Innovation Network

EASA AI Task Force

Daedalean AG

Public Report Extract

Concepts of Design Assurance for Neural Networks (CoDANN)

March 31, 2020

Version 1.0

An agency of the European Union

Authors

EASA
Jean Marc Cluzeau
Xavier Henriquel
Georges Rebender
Guillaume Soudain

Daedalean AG
Dr. Luuk van Dijk
Dr. Alexey Gronskiy
David Haber
Dr. Corentin Perret-Gentil
Ruben Polak

Disclaimer

Contents

Chapter 1

Executive summary

This is a public extract of the report that resulted from the collaboration between EASA and Daedalean in the frame of an Innovation Partnership Contract (IPC) signed by the Agency. The project ran from June 2019 to February 2020.

The project titled "Concepts of Design Assurance for Neural Networks" (CoDANN) aimed at examining the *challenges posed by the use of neural networks in aviation*, in the broader context of allowing machine learning and more generally artificial intelligence on-board aircraft for safety-critical applications.

Focus was put on the "Learning Assurance" building-block of the EASA AI Roadmap 1.0 [EAS20] which resulted in significant progress on three essential aspects of the "Learning Assurance" concept:

1. The *definition of the W-shaped Learning Assurance life-cycle* as a foundation for future guidance from EASA for machine learning / deep learning (ML/DL) applications. It provides an outline of the essential steps for Learning Assurance and their connection with traditional Development Assurance processes.

2. The *investigation of the notion of "generalization" of neural networks*, which is a crucial characteristic of neural networks when ensuring the level of confidence that a ML model will perform as intended. The reviewed theoretical and practical "generalization bounds" should contribute to the definition of more generic guidance on how to account for NNs in Safety Assessment processes.

3. The approach to accounting for *neural networks in safety assessments*, on the basis of a realistic use case. Guidance that is more generic will have to be developed but this report paves the way for a practical approach to achieve certification safety objectives when ML/DL are used in safety-critical applications. The Safety Assessment in this report includes an outline of a failure mode and effect analysis (FMEA) for an ML component to derive quantitative guarantees.

Many concepts discussed in this report apply to machine learning algorithms in general, but an emphasis is put on the specific challenges of deep neural networks or deep learning for computer vision systems.

It was one of the primary goals to keep the guidelines for Learning Assurance on a generic level, in an attempt to motivate these guidelines from a theoretical perspective. Where applicable, reference is made to concrete methods.

A note about this document

This extract is a public version of the original IPC report. Several parts have been shortened for conciseness and some details from the original report have been removed for confidentiality reasons. The main outcomes from the work between EASA and Daedalean have been retained for the benefit of the public.

Chapter 2

Introduction

2.1 Background

In recent years, the scientific discipline known as *machine learning* (ML) has demonstrated impressive performances on visual tasks relevant to the operation of General Aviation aircraft, autonomous drones, or electric air-taxis. For this reason, the application of machine learning to complex problems such as object detection and image segmentation is very promising for current and future airborne systems. Recent progress has been made possible partly due to a simultaneous increase in the amount of data available and in computational power (see for example the survey [LBH15]). However, this increase of performance comes at the cost of more complexity in machine learning models, and this complexity might pose challenges in safety-critical domains, as it is often difficult to verify their design and to explain or interpret their behavior during operation.

Machine learning therefore provides major opportunities for the aviation industry, yet the trustworthiness of such systems needs to be guaranteed. The EASA AI Roadmap [EAS20, p. 14] lists the following challenges with respect to trustworthiness:

- *"Traditional Development Assurance frameworks are not adapted to machine learning"*;
- *"Difficulties in keeping a comprehensive description of the intended function"*;
- *"Lack of predictability and explainability of the ML application behavior"*;
- *"Lack of guarantee of robustness and of no 'unintended function'"*;
- *"Lack of standardized methods for evaluating the operational performance of the ML/DL applications"*;
- *"Issue of bias and variance in ML applications"*;
- *"Complexity of architectures and algorithms"*;
- *"Adaptive learning processes"*.

This report investigates these challenges in more detail. The current aviation regulatory framework and in particular Development Assurance do not provide a means of compliance for these new systems. As an extension to traditional Development Assurance, the elements of the Learning Assurance concepts defined in the EASA AI Roadmap are investigated to address these challenges.

2.2 Learning Assurance process elements

This report has identified crucial elements for *Learning Assurance in a W-shaped development cycle*, as an extension to traditional Development Assurance frameworks (see Figure 6.1 and the details on Page 43). They summarize the key activities required for the safe use of neural networks (and more generally machine learning models) during operation.

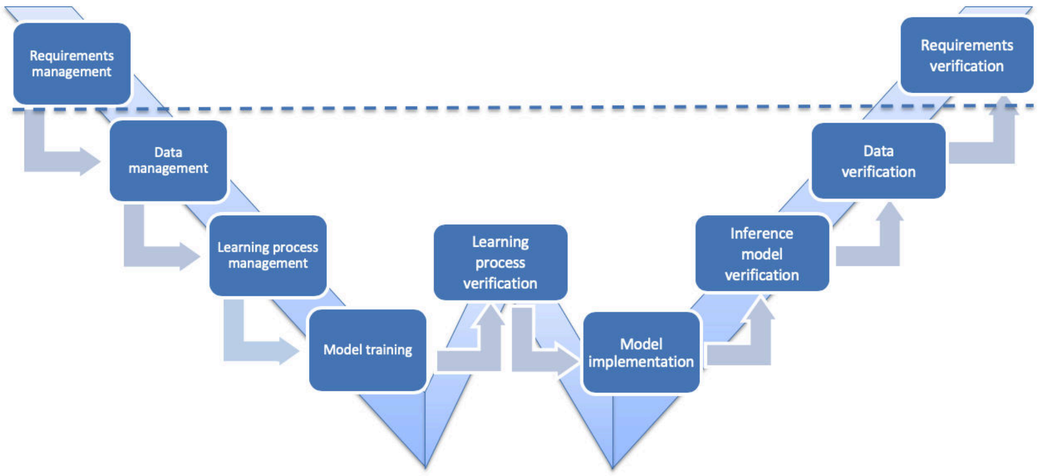

Requirements management
Data management
Learning process management
Model training
Learning process verification
Model implementation
Inference model verification
Data verification
Requirements verification

Figure 6.1: W-shaped development cycle for Learning Assurance.

The reader is encouraged to use these as a guide while reading the report. Each of these items will be motivated from a theoretical perspective and exemplified in more detail in the context of the identified use case in Chapter 4.

2.3 Other key takeaways from the IPC

To cope with the difficulties in keeping a comprehensive description of the intended function, this report introduces data management activities to ensure the quality and completeness of the datasets used for training or verification processes. In particular, the concepts outlined in this document advocate the creation of a *distribution discriminator* to ensure an evaluation of the *completeness of the datasets*.

The lack of predictability of the ML application behavior could be addressed through the concept of *generalizability* that is introduced in Section 5.3 as a means of obtaining theoretical guarantees on the expected behavior of machine learning-based systems during operation. Together with *data management*, introduced in Section 6.2, this allows to obtain such guarantees from the performance of a model during the design phase.

The report identified risks associated with two types of robustness: *algorithm robustness and model robustness*. The former measures how robust the learning algorithm is to changes in the underlying training dataset. The latter quantifies a trained model's robustness to input perturbations.

The evaluation and mitigation of bias and variance is a key issue in ML applications. It was identified that *bias and variance must be addressed on two levels*. First, bias and variance inherent to the datasets need to be captured and minimized. Second, model bias and variance need to be analyzed and the associated risks taken into account.

This report assumes a *system architecture which is non-adaptive* (i.e. does not learn) during operation. This does not impair the capability of retraining or reusing portions of NNs (transfer learning) but creates boundaries which are easily compatible with the current aviation regulatory frameworks.

2.4 Aim of the report

The aim of this report is to present the outcome of the collaboration between EASA and Daedalean AG, in an Innovation Partnership Contract (IPC) on the *Concepts of Design Assurance for Neural Networks (CoDANN)*.

The purpose of this IPC was to investigate ways to gain confidence in the use of products embedding machine learning-based systems (and more specifically neural networks), with the objective of identifying the enablers needed to support their future introduction in aviation.

More precisely, the collaboration aimed at:

1. Proposing a first set of guidelines for machine learning-based systems facilitating future compatibility with the Agency regulatory framework (e.g. [CS-25]/[CS-27]/[CS-29].1309 or [CS-23]/[SC-VTOL-01].2510), using one of the specific examples (landing guidance) proposed by Daedalean;
2. Proposing possible reference(s) for evaluating the performance/accuracy of machine learning-based system in the context of real-scale safety analyses.

The scope of this assessment will include but may not be limited to airworthiness and operations. Note however that only software questions are addressed in detail: specific hardware might have to be used and certified for neural networks, but we leave discussions on this subject for future work.

This report has been prepared under the conditions set within the IPC. Its duration has been of ten months, between May 2019 and February 2020.

The European Union Aviation Safety Agency (EASA) is the centerpiece of the European Union's strategy for aviation safety. Its mission is to promote the highest common standards of safety and environmental protection in civil aviation. The Agency develops common safety and environmental rules at the European level. It monitors the implementation of standards through inspections in the Member States and provides the necessary technical expertise, training and research. The Agency works hand in hand with the national authorities which continue to carry out many operational tasks, such as certification of individual aircraft or licensing of pilots.

Daedalean AG was founded in 2016 by a team of engineers who worked at companies such as Google and SpaceX. As of February 2020, the team includes 30+ software engineers, as well as avionics specialists and pilots. Daedalean works with eVTOL companies and aerospace manufacturers to specify, build, test and certify a fully autonomous autopilot system. It has developed systems demonstrating crucial early capabilities on a path to certification for airworthiness. Daedalean has offices in Zürich, Switzerland and Minsk, Belarus.

2.5 Outline of the report

Chapter 3 investigates the existing regulations, standards, and major reports on the use of machine learning-based systems in safety-critical systems.

Afterwards, Chapter 4 presents the identified use cases and Concepts of Operations of neural networks in aviation applications. These will be used to illustrate the findings on a real-world example for the remainder of the report.

Chapter 5 provides the reader with the necessary background knowledge required for the concepts of Learning Assurance.

In Chapters 6 and 7, guidelines for Learning Assurance are introduced. Furthermore, a set of activities that appear to be necessary to guarantee a safe use of neural networks are detailed. Each of these activities are visited in detail and motivated from a theoretical perspective. This framework is kept in a flexible way such that the concrete implementation of each activity can be tailored to the specific use case of future applicants.

Chapter 8 explains how the overall system described in Chapter 4 is evaluated. Chapter 9 discusses the Safety Assessment aspects of the system.

A use case summary is given in Chapter 10, with a few more concrete ideas for implementation.

Finally, the conclusion (Chapter 11) revisits assumptions made throughout and discusses subjects for future work.

2.6 Terminology

In this section, the definition of machine learning is recalled, and common terminology that will be used throughout the report is set up.

Automation is the use of control systems and information technologies reducing the need for human input and supervision, while **autonomy** is the ultimate level of automation, the ability to perform tasks without input or supervision by a human during operations.

Artificial intelligence (AI) is the theory and development of computer systems which are able to perform tasks that "normally" require human intelligence. Such tasks include visual perception, speech recognition, decision-making, and translation between languages. As "normally" is a shifting term, the definition of what constitutes AI changes over the years. This report will therefore not discuss this specific term in more detail.

Machine learning (ML) is the scientific field rooted in statistics and mathematical optimization that studies algorithms and mathematical models that aim at achieving artificial intelligence through learning from data. This data might consists of samples with labels (**supervised learning**), or without (**unsupervised learning**).

More formally, machine learning aims at approximating a mathematical function $f : X \to Y$ from a (very large and possibly infinite) input space X to an output space Y, given a *finite* amount of data.

In supervised learning, the data consists of sample pairs $(x, f(x))$ with $x \in X$. This report will mostly consider **parametric machine learning algorithms**, which work by finding the optimal parameters in a set of models, given the data.

An approximation $\hat{f} : X \to Y$ to f is usually called a **model**. Together, the computational steps required to find these parameters are usually referred to as **training** (of the model). Once a model $\hat{f}$ for f has been obtained, it can be used to make approximations/predictions $\hat{f}(x)$ for values $f(x)$ at points x which were not seen during training. This phase is called **inference**. The sample pairs $(x, f(x))$ (or simply the values $f(x)$) are often called **ground truth**, as opposed to the approximation $\hat{f}(x)$.

Artificial neural networks (or simply *neural networks*) are a class of machine learning algorithms, loosely inspired by the human brain. They consist of connected nodes ("neurons") that define the order in which operations are performed on the input. Neurons are connected by edges which are parametrized by weights and biases. Neurons are organized in layers, specifically an input layer, several intermediate layers, and an output layer. Given a fixed topology (neurons and connections), a model is found by searching for the optimal weights and other parameters. **Deep learning** is the name given to the study and use of "deep" neural networks, that is neural networks with more than a few intermediate layers.

Convolutional neural networks (CNN) are a specific type of deep neural networks that are particularly suited to process image data, based on convolution operators. A **feature** is a derived property/attribute of data, usually lower dimensional than the input. While features used to be handcrafted, deep learning is expected to learn features automatically. In a CNN, they are encoded by the convolutional filters in the intermediary layers.

A system is **adaptive** when it continues to change (e.g. learn) during real-time operation. A system is **predictable/deterministic** if identical inputs produce identical outputs. In the scope of this report, only non-adaptive and deterministic systems will be considered.

A machine learning model is **robust** if small variations in the input yield small variations in the output (see also Section 6.4 for a precise definition).

Refer to the index at the end of the document for an exhaustive list of the other technical terms used throughout the report.

Chapter 3

Existing guidelines, standards and regulations, and their applicability to machine learning-based systems

3.1 EASA AI Roadmap

As far as EASA is concerned, AI will have an impact on most of the domains under its mandate. AI not only affects the products and services provided by the industry, but also triggers the rise of new business models and affects the Agency's core processes (certification, rule-making, organization approvals, and standardization). This may in turn affect the competency framework of EASA staff.

EASA developed an AI Roadmap [EAS20] that aims at creating a consistent and risk-based "AI trustworthiness" framework to enable the processing of AI/ML applications in any of the core domains of EASA, from 2025 onward. The EASA approach is driven by the seven key requirements for trustworthy AI that were published in the report from the EC High Level Group of Experts on AI (see also Section 3.2). Version 1.0 of the EASA AI Roadmap focuses on machine learning techniques using, among others, learning decision trees or neural network architectures. Further development in AI technology will require future adaptations to this Roadmap.

3.1.1 Building blocks of the AI Trustworthiness framework

The EASA AI Roadmap is based on four building blocks that structure the AI Trustworthiness framework. All four building blocks are anticipated to have an importance in gaining confidence in the trustworthiness of an AI/ML application.

- The *AI trustworthiness analysis* should provide guidance to applicants on how to address each of the seven key guidelines in the specific context of civil aviation;
- The objective of *Learning Assurance* is to gain confidence at an appropriate level that an ML application supports the intended functionality, thus opening the "AI black box" as much as practically possible and required;
- *Explainability* of AI is a human-centric concept that deals with the capability to explain how an AI application is coming to its results and outputs;

- *AI safety risk mitigation* is based on the anticipation that the "AI black box" may not always be opened to a sufficient extent and that supervision of the function of the AI application may be necessary.

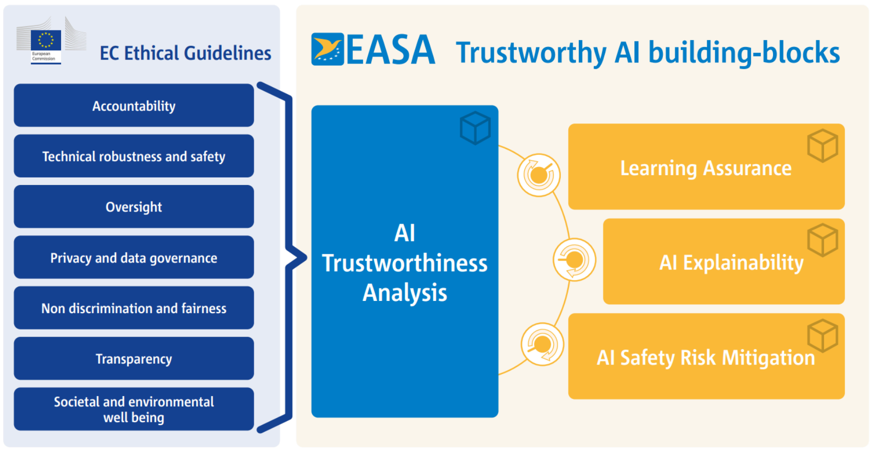

EC Ethical Guidelines
Accountability
Technical robustness and safety
Oversight
Privacy and data governance
Non discrimination and fairness
Transparency
Societal and environmental well being
EASA Trustworthy AI building-blocks
AI Trustworthiness Analysis
Learning Assurance
AI Explainability
AI Safety Risk Mitigation

Figure 3.1: Relationship between AI Roadmap building blocks and AI trustworthiness.

3.1.2 Key objectives

The main action streams identified in the EASA AI Roadmap are to:

1. "Develop a human-centric Trustworthiness framework";
2. "Make EASA a leading certification authority for AI";
3. "Support European Aviation leadership in AI";
4. "Contribute to an efficient European AI research agenda";
5. "Contribute actively to EU AI strategy and initiatives".

3.1.3 Timeline

The EASA AI Roadmap foresees a phased approach, the timing of which is aligned with the industry AI implementation timeline. Phase I will consist of developing a first set of guidelines necessary to approve first use of safety-critical AI. This will be achieved in partnership with the industry, mainly through IPCs, support to research, certification projects, and working groups. Phase II will build on the outcome of Phase I to develop regulations, Acceptable Means of Compliance (AMC) and Guidance Material (GM) for certification/approval of AI. A phase III is foreseen to further adapt the Agency process and expand the regulatory framework to the future developments in the dynamic field of AI.

3.2 EU guidelines for trustworthy AI

On April 8th, 2019, the European Commission's High-Level Expert Group on Artificial Intelligence (AI HLEG) issued a report titled "Ethics and Guidelines on Trustworthy AI" [EGTA], which lays out four ethical principles and seven requirements that AI systems should meet in order to be trustworthy, each further split out into multiple principles that should be adhered to.

3.2.1 EGTA, EASA, and this report

The seven EGTA requirements, their constituting principles, the four building blocks of the EASA AI Roadmap and this report form a narrowing sequence of scopes. The EGTA report intends to address any kind of AI the European citizens might encounter, many of which will deal with end-user data, affecting them directly.

This report is not focused on all possible applications of AI in all of EASA's domain of competency, but specifically on machine-learned systems applied to make better and safer safety-critical avionics. This report is not intended or expected to be the end-all and be-all of this topic, but addresses a subset of the concerns raised by the guiding documents. As an aid to the reader, Table 3.1 presents an overview of how parts of this report may be traced to the EASA building blocks, and to the principles and the requirements.

EGTA key requirement	**Constituting principles**	**(Example of) applicability to AI in safety-critical avionics**	**EASA building block**	**This report**
Human agency and oversight	Fundamental rights	Must improve safety of life and goods	TA	–
	Human agency	Public must be allowed choice of use		
	Human oversight	Human-in-command		
Technical robustness and safety	Resilience to attack and security	Potential for sabotage	TA	–
	Fallback plan	Runtime monitoring, Fault mitigation	TA	Chapter 9
	General safety	Hazard analysis, proportionality in DAL	TA/SRM	Chapter 9
	Accuracy	Correctness and accuracy of system output	LA	Ch. 5, 6, 7
	Reliability and reproducibility	Correctness and accuracy of system design		
Privacy and data governance	Privacy and data protection	Passenger/pilot privacy when collecting training/testing data	[GDPR]	–
	Quality and integrity of data	Core to quality of ML systems	LA	Ch. 5 and 6

EGTA key requirement	**Constituting principles**	**(Example of) applicability to AI in safety-critical avionics**	**EASA building block**	**This report**
	Access to individual's data	(n/a, Individual passenger/pilot data not required)	TA	–
Transparency	Traceability	Datasets and ML process documentation	LA/EX	Chapter 6
	Explainability	Justification and failure case analysis of ML system outputs	EX	Chapter 11
	Communication	Mixing human and AI on ATC/comms	TA	–
Diversity, non-discrimination and fairness	Avoidance of unfair bias	Must not unfairly trade off safety of passenger vs public	TA	–
	Accessibility and universal design	May enable more people to fly		
	Stakeholder participation	EASA, pilots and operators, passengers, public at large		
Societal and environmental well-being	Sustainable and environmentally friendly AI	Increase ubiquity of flying, with environmental and societal consequences	TA	–
	Social impact			
	Society and democracy			
Accountability	Auditability	Core competency of the regulator (EASA)	TA	–
	Minimization and reporting of negative impacts			
	Trade-offs			
	Redress			

Table 3.1: EGTA requirements and principles, EASA building blocks and this report. The EASA building blocks are referred to as TA (Trustworthiness Analysis), LA (Learning Assurance), SRM (Safety Risk Mitigation) and EX (Explainability).

3.3 Existing guidelines and standards

3.3.1 ARP4754A / ED-79A

The *Guidelines for Development of Civil Aircraft and Systems* [ED-79A/ARP4754A] were released in 2010. The purpose of this guidance is to define a structured development process to minimize the risk of development errors during aircraft and system design. It is recognized by EASA as a recommended practice for system Development Assurance. In conjunction with [ARP4761], it also provides a Safety Assessment guidance used for the development of large aircraft and their highly integrated system.

It is essentially applied for complex and highly integrated systems, as per AMC25.1309:

> *"A concern arose regarding the efficiency and coverage of the techniques used for assessing safety aspects of highly integrated systems that perform complex and interrelated functions, particularly through the use of electronic technology and software based techniques. The concern is that design and analysis techniques traditionally applied to deterministic risks or to conventional, non-complex systems may not provide adequate safety coverage for more complex systems. Thus, other assurance techniques, such as Development Assurance utilizing a combination of process assurance and verification coverage criteria, or structured analysis or assessment techniques applied at the aeroplane level, if necessary, or at least across integrated or interacting systems, have been applied to these more complex systems. Their systematic use increases confidence that errors in requirements or design, and integration or interaction effects have been adequately identified and corrected."*

One key aspect is highlighted by [ED-79A/ARP4754A, Table 3]: When relying on Functional Development Assurance Level A (FDAL A) alone, the applicant may be required to substantiate that the development process of a function has sufficient independent validation/verification activities, techniques, and completion criteria to ensure that all potential development errors, capable of having a catastrophic effect on the operations of the function, have been removed or mitigated. It is EASA's experience that development errors may occur even with the highest level of Development Assurance.

3.3.2 EUROCAE ED-12C / RTCA DO-178C

The *Software Considerations in Airborne Systems and Equipment Certification* [ED-12C/DO-178C], released in 2011, provide the main guidance used by certification authorities for the approval of aviation software. From [ED-12C/DO-178C, Section 1.1], the purpose of this standard is to

> "*provide guidance for the production of software for airborne systems and equipment that performs its intended function with a level of confidence in safety that complies with airworthiness requirements.*"

Key concepts are the flow-down of requirements and bidirectional traceability between the different layers of requirements. Traditional "Development Assurance" frameworks such as [ED-12C/DO-178C] are however not adapted to address machine learning processes, due to specific challenges, including:

- Machine learning shifts the emphasis on other parts of the process, namely data preparation, architecture and algorithm selection, hyperparameter tuning, etc. There is a need for a change in paradigm to develop specific assurance methodologies to deal with learning processes;

- Difficulties in keeping a comprehensive description of the intended function and in the flow-down of traceability within datasets (e.g. definition of low level requirements);
- Lack of predictability and explainability of the ML application behavior.

The document also has the following three supplements:

- [ED-128/DO-331]: *Model-Based Development and Verification*;
- [ED-217/DO-332]: *Object-Oriented Technology and Related Techniques*;
- [ED-216/DO-333]: *Formal Methods*.

The two first supplements are addressing specific Development Assurance techniques and will not be applicable to address machine learning processes. The Formal Methods supplement could on the contrary provide a good basis to deal with novel verification approaches (e.g. for the verification of the robustness of a neural network).

Finally, for tool qualification aspects, it is also worth mentioning:

- [ED-215/DO-330]: *Tool Qualification Document* that could also be used in a Learning Assurance framework to develop tools that would reduce, automate or eliminate those process objective(s) whose output cannot be verified.

3.3.3 EUROCAE ED-76A / RTCA DO-200B

The *Standards for Processing Aeronautical Data* [ED-76A/DO-200B] provides the minimum requirements and guidance for the processing of aeronautical data that are used for navigation, flight planning, terrain/obstacle awareness, flight deck displays, flight simulators, and for other applications. This standard aims at providing assurance that a certain level of data quality is established and maintained over time.

Data Quality is defined in the standard as the degree or level of confidence that the provided data meets the requirements of the user. These requirements include levels of accuracy, resolution, assurance level, traceability, timeliness, completeness, and format.

The notion of data quality can be used in the context of the preparation of machine learning datasets and could be instrumental in the establishment of adequate data completeness and correctness processes as described in Section 6.2.

3.3.4 ASTM F3269-17

The *Standard Practice for Methods to Safely Bound Flight Behavior of Unmanned Aircraft Systems Containing Complex Functions* [F3269-17] outlines guidance to constrain complex function(s) in unmanned aircraft systems through a runtime assurance (RTA) system.

Aspects of safety monitoring are encompassed in the building block "Safety Risk Mitigation" from the EASA AI Roadmap (see Section 3.1).

3.4 Other documents and working groups

3.4.1 EUROCAE WG-114 / SAE G-34

An EUROCAE working group on the "certification of aeronautical systems implementing artificial intelligence technologies", WG-114, was announced in June 2019 (see `https://eurocae.net/about-us/working-groups/`). It recently merged with a similar SAE working group, G-34 ("Artificial Intelligence in Aviation"). Their objectives are to:

- "Develop and publish a first technical report to establish a comprehensive statement of concerns versus the current industrial standards. [. . .]"
- "Develop and publish EUROCAE Technical Reports for selecting, implementing, and certifying AI technology embedded into and/or for use with aeronautical systems in both aerial vehicles and ground systems."
- "Act as a key forum for enabling global adoption and implementation of AI technologies that embed or interact with aeronautical systems."
- "Enable aerospace manufactures and regulatory agencies to consider and implement common sense approaches to the certification of AI systems, which unlike other avionics software, has fundamentally non-deterministic qualities. (sic)"

At the time of writing, draft documents list possible safety concerns and potential next steps. Most of these are addressed in this report and a detailed comparison can be released when the WG-114 documents are finalized.

The working group includes representatives from both EASA and Daedalean, in addition to experts from other stakeholders.

3.4.2 UL-4600: Standard for Safety for the Evaluation of Autonomous Products

A working group, led by software safety expert Prof. Phil Koopman, is currently working with UL LLC on a standard proposal for autonomous automotive vehicles (with the goal of being adaptable to other types of vehicles). The idea is to complement existing standards such as ISO 26262 and ISO/PAS 21488 that were conceived with human drivers in mind. Notice that this is very similar to what this IPC aimed to achieve for airborne systems. A preliminary draft [UL-4600] has been released in October 2019, and the standard is planned to be released in the course of 2020.

Section 8.5 of the current draft of UL-4600 is dedicated to machine learning, but the treatment of the topic remains fairly high-level. In this report, the aim is to provide a more in-depth understanding of the risks of modern machine learning methods and ways to mitigate them.

3.4.3 "Safety First for Automated Driving" whitepaper

In June 2019, 11 major stakeholders in the automative and automated driving industry, including Audi, Baidu, BMW, Intel, Daimler, and VW, published a 157-page report [SaFAD19] on safety for automated driving. Their work focuses on safety by design and verification & validation methods for SAE levels 3-4 autonomous driving (conditional/high automation).

In particular, the report contains an 18-page appendix on the use of deep neural networks in these safety-critical scenarios, with the running example of 3D object detection. The conclusions that surface therein are compatible with those in this IPC report.

3.4.4 FAA TC-16/4

The U.S. Federal Aviation Administration (FAA) report on *Verification of adaptive systems* [TC-16/4], released in April 2016, is the result of a two-phase research study in collaboration with the NASA Langley Research Center and Honeywell Inc., with the aim of analyzing the certifiably of adaptive systems in view of [ED-12C/DO-178C].

Adaptive systems are defined therein as "*software having the ability to change behavior at runtime in response to changes in the operational environment, system configuration, resource availability, or other factors*".

At this stage, adaptive machine learning algorithms are anticipated to be harder to certify than models that are *frozen* after training. Restricting ourselves to non-adaptive models creates a set of realistic assumptions in which the development of Learning Assurance concepts is possible. Following this, aspects of recertification of existing but changed models (i.e. retrained models) are very briefly discussed in Section 7.1.3.

3.4.5 FDA April 2019 report

The *Proposed Regulatory Framework for Modifications to AI/ML-based Software as a Medical Device* [FDA19], released by the U.S. Food and Drugs Administrations in April 2019, focuses on risks in machine learning-based systems resulting from software modifications, but also contains more general information on the regulation/certification of AI software. Note that such software modifications include the adaptive algorithms studied in length in the FAA report [TC-16/4] discussed above.

3.4.6 AVSI's AFE 87 project on certification aspects of machine learning

This is a one-year project launched in May 2018 and includes Airbus, Boeing, Embraer, FAA, GE Aviation, Honeywell, NASA, Rockwell Collins, Saab, Thales, and UTC. According to a presentation given in the April 2019 EUROCAE symposium, the goal is to address the following questions (quoting from [Gat19]):

1. "*Which performance-based objectives should an application to certify a system incorporating machine learning contain, so that it demonstrates that the system performs its intended function correctly in the operating conditions?*"
2. "*What are the methods for determining that a training set is correct and complete?*"
3. "*What is retraining, when is it needed, and to which extent?*"
4. "*What kind of architecture monitoring would be adapted to complex machine learning applications?*"

Note that these questions are all addressed in this report, respectively in Chapter 10, Section 6.2, Section 7.1.3/Section 7.1 and Section 6.6.

3.4.7 Data Safety Guidance

The *Data Safety Guidance* [SCSC-127C], from the Data Safety Initiative Working Group of the Safety Critical Systems Club, aims at providing up-to-date recommendations for the use of data (under a broad definition) in safety-critical systems. Along with definitions, principles, processes, objectives, and guidance, it contains a worked out example in addition to several appendices (including examples of accidents due to faulty data). Section 6.2 will explain the importance of data in systems based on machine learning.

3.5 Comparison of traditional software and machine learning-based systems

3.5.1 General considerations

A shift in paradigm In aviation, system and software engineering are traditionally guided through the use of industrial standards on Development Assurance like [ED-79A/ARP4754A] or [ED-12C/DO-178C]. The use of learning algorithms and processes constitutes a shift in paradigm compared to traditional system and software development processes.

Development processes foresee the design and coding of software from a set of functional requirements to obtain an intended behavior of the system. Whereas in the case of learning processes, the intended behavior is captured in data from which a model is derived through the training phase, as an approximation of the expected function of the system. This conceptual difference comes with a set of challenges that requires an extension to the traditional Development Assurance framework that was used for complex and highly integrated system development so far. Machine learning shifts the emphasis of assurance methods on other parts of the process, namely data management, learning model design, etc.

Still some similarities. . . It is anticipated that Development Assurance processes could still apply to higher layers of the system design, namely to capture, validate and verify the functional system requirements.

Also the core software and the hardware used for the inference phase are anticipated to be developed with traditional means of compliance such as [ED-12C/DO-178C] or [ED-80/DO-254].

In addition, some of the processes integral to Development Assurance are nevertheless anticipated to be still compatible and required with Learning Assurance methods. This concerns mainly processes such as planning, configuration management, quality assurance and certification liaison.

Planning, quality assurance, and certification liaison processes These elements of traditional Development Assurance require adaptations for the Learning Assurance process, in particular for the definition of transition criteria but their principles are anticipated to remain unchanged.

3.5.2 Configuration management principles

The principles from existing standards are anticipated to apply with no restriction. For applications involving modification of parameters through learning, a strong focus should be put on the capability to maintain configuration management of those parameters (e.g. weights of a neural network) for any relevant configuration of the resulting application. Specific consideration may be required for the capture of hyperparameters configurations.

Considerations on the use of PDIs Considering the nature of neural networks, parametrized by weights and biases that define the behavior of the model, it may be convenient to capture these parameters in a separate configuration file.

It is however important to mention that the Parameter Data Item (PDI) guidance as introduced in [ED-12C/DO-178C] cannot be used as such, due to the fact that the learned parametrized model is inherently driving the functionality of the software and cannot be separated from the neural network architecture or executable object code.

As indicated in [ED-12C/DO-178C, Section 6.6], PDIs can be verified separately under four conditions:

1. The Executable Object Code has been developed and verified by normal range testing to correctly handle all Parameter Data Item Files that comply with their defined structure and attributes;
2. The Executable Object Code is robust with respect to Parameter Data Item Files structures and attributes;
3. All behavior of the Executable Object Code resulting from the contents of the Parameter Data Item File can be verified;
4. The structure of the life-cycle data allows the parameter data item to be managed separately.

At least the third condition is not realistic in the case of a learning model parameter data item.

In conclusion, even if PDIs can be conveniently used to store and manage the parameters of a machine learning model resulting from a learning process, the PDI guidance from [ED-12C/DO-178C] (or equivalent), which foresees a separate verification of the PDI from the executable object code, is not a practicable approach.

Chapter 4

Use case definition and Concepts of Operations (ConOps)

The use of neural networks in aviation applications should be regulated such that it is proportionate to the risk of the specific operation. As a running example throughout the report, a specific use case (*visual landing guidance*) will be considered, described in detail in this chapter.

Chapter 9 will use this example to outline a safety analysis and Chapter 10 aims to present a summary of the Learning Assurance activities in the context of the use case.

The contents of Chapters 5 to 8 are generic, and apply to general (supervised) machine learning algorithms.

4.1 Use case and ConOps

Visual landing guidance (VLG) facilitates the task of landing an aircraft on a runway or vertiport. Table 4.1 proposes two operational concepts for our VLG system, one for General Aviation [CS-23] Class IV and another for Rotorcraft [CS-27] or eVTOL [SC-VTOL-01] (cat. enhanced), with corresponding operating parameters.

To assess the risk of the operation, two levels of automation are proposed for each operational concept: *pilot advisory* (1a and 2a) and *full autonomy* (1b and 2b).

	Operational Concept 1	**Operational Concept 2**
Application	Visual landing guidance (Runway)	Visual landing guidance (Vertiport)
Aircraft type	General Aviation [CS-23] Class IV	Rotorcraft [CS-27] or eVTOL [SC-VTOL-01] (cat. enhanced)
Flight rules	Visual Flight Rules (VFR) in daytime Visual Meteorological Conditions (VMC)	
Special considerations	Marked concrete runways, no ILS equipment assumed	Vertiports in urban built-up areas, no ILS equipment assumed

	Operational Concept 1		**Operational Concept 2**	
Level of automation	Pilot advisory **(1a)**	Full autonomy **(1b)**	Pilot advisory **(2a)**	Full autonomy **(2b)**
System interface	Glass cockpit flight director display	Flight computer guidance vector and clear/abort signal	Glass cockpit flight director display	Flight computer guidance vector and clear/abort signal
Cruise/Pattern	Identify runway		Identify vertiport	
Descent	Disambiguate alternatives, eliminate taxiways, find centerline, maintain tracking over 3^o descents (even if runway out of sight)		Find centerpoint and bounds, maintain tracking over 15^o descents (assume platform stays in line of sight)	
Final approach	Maintain tracking, identify obstruction/clear at 150m AGL		Maintain tracking, identify obstruction/clear at 30 – 15m AGL	
Decision point	Decide to land/Abort at any point including after touchdown		Decide to land/Abort down to flare	
Go Around	Maintain tracking until back in pattern			
	Relevant Operating Parameters			
Number of airfields	50’000		100’000	
Distance	100 – 8000m		10 – 1000m	
Altitude	800m AGL		150m AGL	
Angle of view	160^o			
Time of day (sun position)	3^o below horizon and 3^o after sunset (VFR definition)			
Time of year	Every month sampled			
Visibility	$>$ 5km		$>$ 1km	
Runways visible	At most 1			
Temporary runway changes	Landing lights out, temporary signs obstructing aircraft		Obstructing aircraft, person or large object (box, plastic bag)	

Table 4.1: Concepts of Operations (ConOps). Note that these are only meant to be an illustration, in the scope of the report and, for example, do not address all possible sources of uncertainty (e.g. other traffic, runway incursions, etc.).

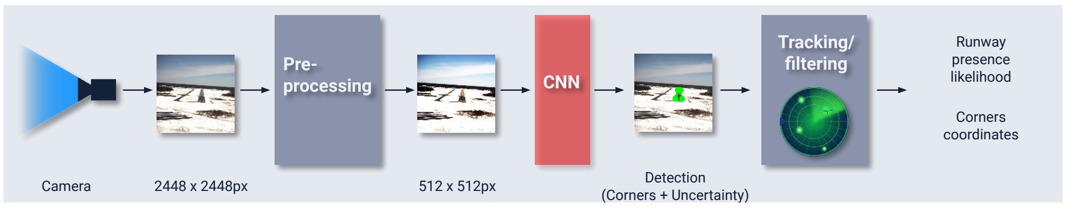


Figure 4.1: System architecture overview (perception).

4.2 System description

This section describes and analyzes the system that performs visual landing guidance from the above ConOps. It consists of traditional (non machine learning-based) software and a neural network. A focus will be put on the machine learning components and their interactions with the traditional software parts, since the existing certification guidelines can be followed otherwise.

End-to-end learning The proposed system includes several smaller more dedicated, components to simplify the design and achieve an isolation of the machine learning components. This split will make the performance and safety assessments easier and more transparent (see Chapters 8 and 9).

This is in contrast to recently proposed systems that attempt to learn complex behavior such as visual landing guidance *end-to-end*, i.e. learning functions that directly map sensor data to control outputs. While end-to-end learning is certainly an exciting area of research, it will not be considered in this report for simplicity.

4.2.1 System architecture: perception

The system used in operation is shown in Figure 4.1 and consists of a combination of a camera unit, a pre-processing component, a neural network and a tracking/filtering component.

Sensor The camera unit is assumed to have a global shutter and output 5 megapixels RGB images at a fixed frequency.

Pre-processing The pre-processing unit reduces the resolution of the camera output to 512×512 pixels and normalizes the image (e.g. so that it fits a given distribution). This is done with "classical software" (i.e. no machine learning).

Neural network A *convolutional neural network* (CNN) as shown in Figure 4.2 is chosen as the reference architecture for this document. The model's input space X consists of 512×512 RGB images from a camera fixed on the nose of the aircraft. The model's output space Y consists of:

- A likelihood value (in $[0, 1]$) that the input image contains a runway;
- The normalized coordinates (e.g. in $[0, 1]^2$) of each of the four runway corners (in a given ordering with respect to image coordinates).

The model approximates the "ground truth" function $f : X \to \{0, 1\} \times [0, 1]^{4\times2}$ defined similarly.

Such networks are usually called *object detection networks*. They are generally based on a feature extraction network such as ResNet [ResNet], followed by fully connected or convolutional layers. Examples of such models (for multiple objects detection) are the Single Shot MultiBox

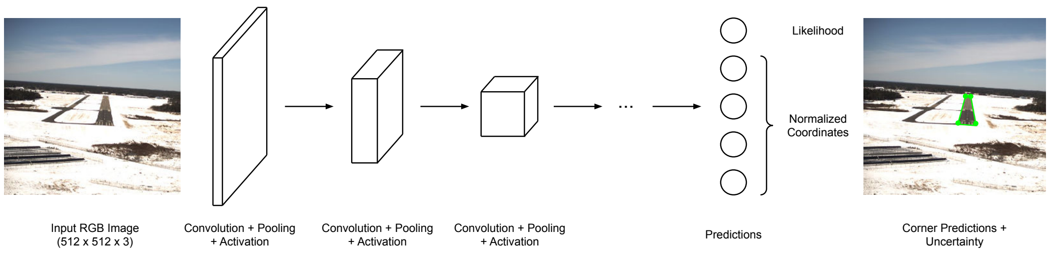


Figure 4.2: A generic convolutional neural network as considered in this report. This corresponds to the red box in Figure 4.1.

Detector (SSD) [Liu+16], Faster R-CNN [Ren+15] or Mask R-CNN [He+17] (the first two output only bounding boxes, while the third one provides object masks; our proposed model outputs quadrilaterals corresponding to the detected object and therefore, lies in-between).

The neural network satisfies all hypotheses that will be made in Chapter 5. In particular, all operations in the CNN are fully defined and differentiable, the network's topology is a directed acyclic graph (so that there are no recurrent connections), it is trained in a supervised manner, and the whole system is non-adaptive, as defined in Section 2.6.

Post-processing (tracking/filtering) The *tracking/filtering unit* post-processes the neural network output to:

- Threshold the runway likelihood output to make a binary runway/no runway decision;
- Reduce the error rate of the network, using information on previous frames, and eventually on the movement/controls of the aircraft.

Similarly to pre-processing, this post-processing is also implemented with "classical software".

4.2.2 System architecture: actuation

The second part of the system takes as input the output of the perception component, namely an indication whether a runway is present or not, and corner coordinates (these are relevant only if the runway likelihood is high enough). It then uses those to perform the actual visual landing guidance described in Section 4.1, in full autonomy or for pilot advisory only.

As the report focuses on certification concerns related to the use of machine learning, the actuation subsystem is not described further and assumed to be developed with conventional technologies. Similarly, the Safety Assessment outlined in Chapter 9 will only consider the perception system.

4.2.3 Hardware

Pre-/post-processing The pre- and post-processing software components described above run on classical computing hardware (CPUs), for which existing guidance and standards apply.

Neural network While it is possible to execute neural networks on CPUs as well, circuits specialized in the most resource-heavy operations (e.g. matrix multiplications, convolutions) can yield significantly higher performance. This can be especially important for applications requiring high resolution input or throughput.

Nowadays, this is mostly done using graphics processing units (GPUs), originally developed for 3D graphics, even though there is an increase in the use of application-specific integrated circuits[1] (ASICs) or field-programmable gate arrays (FPGAs). For example, a recent study [WWB20] shows an improvement of 1-100 times on inference speed for GPUs over CPUs, and $1/5 - 10$ times for TPUs over GPUs on different convolutional neural networks, depending on various parameters (see also Table 4.2).

An important part to prove the airworthiness of the whole system described in this chapter would be to demonstrate compliance of such specialized compute hardware with [ED-80/DO-254] and applicable EASA airborne electronic hardware guidance. This will not be addressed in this report, which focuses on novel software aspects relevant to the certification of machine learning systems.

Platform	**Peak TFLOPS**	**Memory (GB)**	**Memory bandwidth (GB/s)**
CPU (Skylake 32 threads)	2 (single prec.)	120	16.6
GPU (NVIDIA V100)	125	16	900
ASIC (Google TPUv3)	420	16	3600

Table 4.2: Neural network inference hardware compared in [WWB20].

4.3 Notes on model training

The computational operations required to train a neural network are similar to those performed during inference. Therefore, the observations made on hardware in Section 4.2.3 still apply, with the difference that requirements are a bit less stringent: one needs to ensure the correctness of computations, but the training hardware does not need to be airworthy itself.

A typical environment for training neural networks consists of a desktop computer equipped with a GPU (e.g. NVIDIA K80 or P100), running a Linux-based operating system, with device-specific acceleration libraries (such as CUDA and cuDNN), and a neural network training framework. Popular neural network frameworks are TensorFlow[2], Keras[3], PyTorch[4], and CNTK[5]. These are all open-source, i.e. their source code is publicly available.

System errors could be introduced through malfunctioning hardware or data corruption. This is relevant to both the learned model and datasets used for training, validation, and testing. Another risk could come from deliberate third-party attacks on the learning algorithm and/or model in training. Adversarial attacks are popular examples to *fool neural networks* during operation. During the design phase, one could imagine that malicious attackers obtain access to the training machine and insert modifications (e.g. backdoors) to the resulting model.

Again, this report will not address these risks further and leave them for future work. Note that they could for example be mitigated in part by performing evaluations on the certified operational hardware once the training has finished.

Use of cloud computing It is very common nowadays for complex consumer-grade machine learning models to be trained in the cloud, given the advantages provided by the hardware abstractions of remote compute and storage (such as large amount of resources available,

[1] See for example Google's Tensor processing units (TPUs): https://cloud.google.com/tpu/
[2] https://tensorflow.org
[3] https://keras.io
[4] https://pytorch.org
[5] https://github.com/microsoft/CNTK

lack of maintenance needs, etc.). Popular cloud providers include Google Cloud Platform[6], Amazon Web Services (AWS)[7], and Microsoft Azure[8]. Each of them allows the creation of virtual instances which provide access to a full operating system and hardware including GPUs or ASICs for machine learning.

This would introduce additional challenges in a safety-critical setting. For example, the user has no control over which specific hardware unit the training algorithms are executed on. The hardware is (at least for the time being) not provisioned with any certifications or qualifications relevant to safety-critical applications. In this setting, third-party attacks and data corruption error are particularly important to keep in mind.

Hence, training safety-critical machine learning models in the cloud is not excluded per se, but should be the subject of extended discussion and analysis (e.g. with respect to hardware certification, cybersecurity, etc.), which are also left to future work.

4.4 Selection criteria

The use case and system presented in this chapter were chosen because they are a representative and at the same time a fairly simple example for a machine learning system in aviation.

In this setting, a human pilot has the following cognitive functions:

- *Perception* (processing visual input). The quality of the image input is equivalent to perfect human vision in specified VFR conditions.
- *Representation of knowledge* (information organization in memory and learning/construction of new knowledge from information stored in memory).
- *Reasoning* (computation based on knowledge represented in memory).
- *Capability of communication and expression*. This requires identification of the human/machine interface and communication protocol.
- *Decision making*: modeling of executive decisions (e.g. landing: yes/no, if no, go around or diversion).

This report focuses on the emulation of the perception function.

[6]https://cloud.google.com
[7]https://aws.amazon.com
[8]https://azure.microsoft.com

Chapter 5

Learning process

This chapter provides a background tour of the learning algorithms considered in this document. The reader will obtain a more precise technical understanding that is fundamental to comprehend the theoretical guarantees and challenges of the framework for *Learning Assurance* described in Chapter 6. This chapter also provides formal definitions for supervised and parametric learning and explains strategies to quantify model errors. While most of this chapter applies to the broader use of general machine learning algorithms, it concludes with a discussion of generalization behavior specific to neural networks.

For more detailed accounts of learning algorithms, the reader is referred to textbooks including [LFD; ESL].

5.1 What is a learning algorithm?

The goal of a (supervised) learning algorithm $\mathcal{F}$ is to learn a function $f : X \to Y$ from an input space X to an output space Y, using a finite number of example pairs $(x, f(x))$, with $x \in X$. More precisely, given a finite *training dataset*

$$D_{\text{train}} = \{(x_i, f(x_i)) : 1 \leq i \leq n_{\text{train}}\},$$

the goal of the training algorithm $\mathcal{F}$ is to generate a function (also called *model*, or *hypothesis*)

$$\hat{f}^{(D_{\text{train}})} : X \to Y$$

that approximates f "well", as measured by error metrics that are defined below. In the following, we will use the notation

$$\mathcal{F}(D_{\text{train}}) = \hat{f}^{(D_{\text{train}})}, \tag{5.1}$$

with the meaning "the model $\hat{f}^{(D_{\text{train}})}$ is the result of learning algorithm $\mathcal{F}$ trained on dataset D_{train}".

With a slight abuse of notation, we will also refer to $\mathcal{F}$ as a *set of possible models* produced by the learning algorithm $\mathcal{F}$, sometimes called *hypothesis space*:

$$\hat{f} \in \mathcal{F}.$$

Error metrics The pointwise quality of the approximation of f by $\hat{f}$ is measured with respect to a predefined choice of *error metric(s)* $m : Y \to \mathbb{R}_{\geq 0}$, demanding that

$$m\big(\mathcal{F}(D_{\text{train}}), f(x)\big)$$

be low on all $x \in X$. These will not be simply called "metrics" to emphasize that "lower value means better performance", nor "losses" to make a distinction with the losses that are introduced below.

For example, if Y is a subset of the real numbers, one could simply use the absolute values (resp. squares) of differences $m(y_1, y_2) = |y_1 - y_2|$ (resp. $(y_1 - y_2)^2$). For further illustrations in the context of the ConOps, see Sections 5.2.5 and 8.1. In particular, these will explain that *several* error metrics can and should be used.

Generalizability Most importantly, the goal is to perform well on unseen data from $\mathcal{X}$ during operation (and not simply memorize the subset D_{train}). This is called *generalizability*.

Design phase The process of using D_{train} to obtain $\hat{f}^{(D_{\text{train}})}$ from $\mathcal{F}$ is called the *training phase*. The *design phase* of a final model $\hat{f}^{(D_{\text{train}})}$ comprises of multiple rounds of choosing learning algorithms, training them, and comparing them using validation datasets (see below).

The models that will be considered are *parametric*, in the sense that the algorithm $\mathcal{F}$ chooses the model $\hat{f}$ from a family $\{\hat{f}_{\boldsymbol{\theta}} : X \to Y : \boldsymbol{\theta} \in \Theta\}$ parametrized by a set of parameters $\boldsymbol{\theta}$. For neural networks, $\boldsymbol{\theta}$ would include the weights and biases. The choice of $\boldsymbol{\theta}$ is usually done by trying to minimize a function of the form

$$J(\boldsymbol{\theta}) = \frac{1}{|D_{\text{train}}|} \sum_{(x, f(x)) \in D_{\text{train}}} L\left(\hat{f}_{\boldsymbol{\theta}}^{(D_{\text{train}})}(x), f(x)\right),$$

where L is a differentiable *loss function* that is related or equal to one or several of the error metrics m. Usually, the loss function acts as a differentiable proxy to optimize the different error metrics.

For binary classification tasks (i.e. the number of output classes is two), a popular loss function is binary cross-entropy:

$$L(\hat{y}, y) = \mathrm{CE}(\hat{y}, y) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y}), \qquad (y, \hat{y} \in [0, 1]). \tag{5.2}$$

Hyperparameters In addition to the *learned* parameters $\boldsymbol{\theta}$, the algorithm $\mathcal{F}$ might also come with parameters, called *hyperparameters*. For the widely used gradient descent minimization algorithm, the *learning rate* is an important hyperparameter.

Validation dataset A second dataset, the *validation dataset*

$$D_{\text{val}} = \{(x_i, f(x_i)) : 1 \le i \le n_{\text{val}}\},$$

disjoint from D_{train}, is used during the design phase to

- monitor the performance of models on unseen data, and
- compare different models (i.e. different choices of $\boldsymbol{\theta}$).

For example, an algorithm simply memorizing D_{train} would certainly perform badly on D_{val}.

Note that D_{val} is not used explicitly by the algorithm, but the information it contains might influence the design of the model, leading to an overestimation of the performance on unseen data. To illustrate this, an extreme example would involve tweaking $\mathcal{F}$ at each round of the design phase depending on the validation scores. This would essentially become equivalent to using D_{val} as a training set.

Test dataset To get a more precise estimation of generalizability (and hence of performance during the operational phase), remedying the issue just mentioned, the final model is evaluated on a third disjoint dataset, the *test dataset*

$$D_{\text{test}} = \{(x_i, f(x_i)) : 1 \le i \le n_{\text{test}}\}.$$

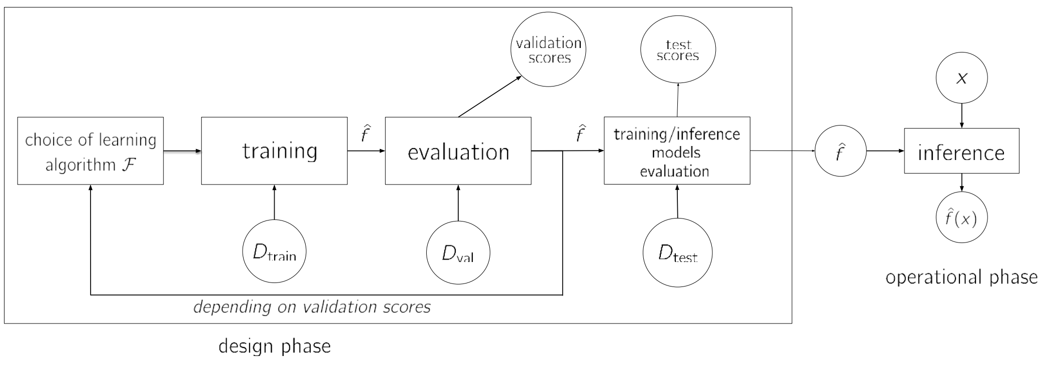


Figure 5.1: The training, design, and operational phases of a learning algorithm. See also the development life-cycle exposed in Section 6.1.

As Section 6.2.9 will explain, D_{test} should also be disjoint from D_{val} and D_{train}. Importantly, D_{test} should be *kept hidden* from the training phase, i.e., it should not influence the training of the model in any manner.

Operational phase During the *inference* or *operational phase*, the model can be fed data and make predictions. It is important to note that once a model has been obtained during the design phase, it will be *frozen and baselined*. In other words, its behavior will not be changed in operation.

5.2 Training, validation, testing, and out-of-sample errors

In this section, different types of errors are considered. These will allow to understand a model's behavior on both known and, to a possible extent, on unknown data (i.e. data it will encounter during operation).

5.2.1 Probability spaces

To be able to quantify performance on unseen data accurately, X is equipped with a probability distribution P, yielding a probability space[1] $\mathcal{X} = (X, P)$, so that more likely elements are assigned a higher probability. When evaluating and comparing learning algorithms, worse performance on more likely elements will be penalized more strongly. As described later, identifying the probability space corresponding to the target operational scenario is essential.

5.2.2 Errors in data

In a real-world scenario, the pairs (x_i, y_i) in the training, validation, and test datasets might contain small errors coming from sources such as annotation mistakes or imprecisions in measurements arising from sensor noise. Namely, one rather has[2]

$$y_i = f(x_i) + \delta_i$$

[1]The σ-algebra of events will be left implicit for simplicity.

[2]For the sake of simplicity, the focus is put here on additive errors. Advanced texts would consider the joint distribution of (x, y).

for some small but nonzero $\delta_i \in \mathbb{R}^t$, assuming that $Y \subset \mathbb{R}^t$ for some $t \geq 1$ (as will be assumed from now on). These δ_i are typically modeled as normal independent variables with mean zero and common variance σ^2.

This aspect will be addressed in detail in Section 6.2.3.

5.2.3 In-sample errors

The *training error* of a model $\hat{f} : X \to Y$ with respect to an error metric m is defined as the mean

$$E_{\text{in}}(\hat{f}, D_{\text{train}}, m) = \frac{1}{|D_{\text{train}}|} \sum_{(x, f(x)) \in D_{\text{train}}} m\left(\hat{f}(x), f(x)\right),$$

and the *validation and testing errors* $E_{\text{in}}(\hat{f}, D_{\text{val}}, m)$, $E_{\text{in}}(\hat{f}, D_{\text{test}}, m)$ are defined similarly. These are called *in-sample errors*.

5.2.4 Out-of-sample errors

The *out-of-sample error* (or *expected loss*) of a model $\hat{f}$, with respect to an error metric m, can be measured formally by the expected value[3]

$$E_{\text{out}}(\hat{f}, m) = \mathbb{E}_{\delta, x \sim \mathcal{X}}\left[m\left(f(x) + \delta, \hat{f}(x)\right)\right],$$

with the expectation taken over the distribution of the input space $\mathcal{X}$ and the errors δ.

Given a dataset size n, one can also consider the average

$$E_{\text{out}}(\mathcal{F}, m, n) = \mathbb{E}_{D \sim \mathcal{X}^n}\left[E_{\text{out}}\left(\mathcal{F}(D), D, m\right)\right], \tag{5.3}$$

over all datasets D obtained by sampling n points independently from $\mathcal{X}$, where $\mathcal{F}(D) = \hat{f}^{(D)}$ is the model resulting from training $\mathcal{F}$ on D.

One would generally have

$$\begin{aligned} E_{\text{in}}\left(\mathcal{F}(D_{\text{train}}), D_{\text{train}}, m\right) < E_{\text{in}}\left(\mathcal{F}(D_{\text{train}}), D_{\text{val}}, m\right) &< E_{\text{in}}\left(\mathcal{F}(D_{\text{train}}), D_{\text{test}}, m\right) \\ &< E_{\text{out}}\left(\mathcal{F}(D_{\text{train}}), m\right), \end{aligned}$$

and a desirable property is to have all inequalities as tight as possibly because it would imply that the performance on unseen data (during the operational phase) can be precisely estimated during the design phase (see Section 5.3 on generalizability below).

5.2.5 Example

This section gives an example of the above in the context of the ConOps from Chapter 4. As described in Section 4.2.1, the input space $\mathcal{X}$ consists of 512×512 RGB images from a camera fixed on the nose of the aircraft (with the image distribution depending on the conditions/locations where the plane is expected to fly), while the output space is $Y = [0, 1] \times [0, 1]^{4 \times 2}$. The goal is to obtain a model $\hat{f} : X \to Y$ approximating the function $f : X \to Y$ indicating the presence or not of a runway in the input image, and the corner coordinates if relevant.

[3]Here, $\mathbb{E}$ denotes the expected value of a random variable, and $x \sim \mathcal{X}$ denotes a random variable sampled from the probability space $\mathcal{X}$.

Datasets A large representative dataset of images $x \in X$ in the operating conditions is collected, and the "ground truth" $f(x)$ is manually annotated. Care is given to cover all parameters correctly (see Sections 6.2.7 and 6.2.8), particularly those that correlate with the presence of a runway. Splitting the resulting set of pairs $(x, f(x))$ randomly with the ratios 70%–15%–15% yields training, validation, and test datasets D_{train}, D_{val}, D_{test} respectively.

Error metric The error metric m has to take into account both the runway presence likelihood, and the corner coordinates prediction. A linear combination of the cross-entropy (5.2) and the L^2 (Euclidean) norm could be used:

$$m(\hat{f}(x), f(x)) := f_0(x) \sum_{1 \leq i \leq 4} \|\hat{f}_i(x) - f_i(x)\| + \lambda \cdot \mathrm{CE}(\hat{f}_0(x), f_0(x)),$$

where $\lambda > 0$ is a parameter to determine during the design/training phase, and

$$\begin{aligned} f &= (f_0, \ldots, f_4) \in \{0, 1\} \times [0, 1]^2 \times \cdots \times [0, 1]^2, \\ \hat{f} &= (\hat{f}_0, \ldots, \hat{f}_4) \in [0, 1] \ \ \times [0, 1]^2 \times \cdots \times [0, 1]^2, \end{aligned}$$

with $\hat{f}_0$ the runway presence likelihood and $\hat{f}_1, \ldots, \hat{f}_4$ the corner coordinates (similarly for the ground truth f).

Note that one could also compare the two runway masks using the Jaccard distance; see Section 8.1 for a discussion of different metrics.

Design phase An algorithm is selected, as described in Section 4.2.1. For example, a first round gives a model $\hat{f}$ with a validation error $E_{\text{in}}(\hat{f}, D_{\text{val}}, m)$ of 0.20. A subsequent modification of the algorithm yields another model $\hat{f}$ with a lower validation error $E_{\text{in}}(\hat{f}, D_{\text{val}}, m) = 0.15$. This second model is chosen as the end result of the design phase, fixed and baselined.

Verification phase The fixed model is evaluated on D_{test}, and gives an error of $E_{\text{in}}(\hat{f}, D_{\text{test}}, m) = 0.17$. This gives further evidence that the performance that will be observed during operation is close to the performance measured during the design phase.

Operational phase The average error observed during the operational phase (say on ten 5-minute runway approaches, after a posteriori data annotation) is 0.18. Section 8.2.1 addresses system evaluation details.

This example illustrates that both in-sample and out-of-sample errors can be measured, respectively estimated. One observes that, in line with (5.4), the errors vary slightly between the different datasets and during operation. Assuming that the different datasets were prepared and used according to the requirements for *Dataset correctness* (Section 6.2), these observations provide an estimate of how the model performs on unseen data.

This motivates an investigation of methods to determine the model's generalization performance more rigorously which will be discussed in the following section.

5.3 Generalizability

As already mentioned in Section 5.1, a learning algorithm could simply memorize[4] the training data and therefore perform very poorly on validation or test data. A fundamental task of machine learning, which if neglected can pose severe safety risks during the operational phase, is to *assess model performance on previously unseen data*. The ability of a learning algorithm to produce models that perform well on unseen data is referred to as *generalizability*, or *generalization capacity*.

[4] In machine learning, the term "memorization" is always used as a synonym of "overfitting".

In the context of safety-critical systems, to guarantee good generalizability, an estimation of the out-of-sample errors (Section 5.2.4) is required. This section will review the concept of *generalization gap* as a means to characterize the difference in model performance during design and operational phases.

5.3.1 Definitions

For the sake of structural clarity, we first provide the definitions that will be used throughout the text. These notions will be put into the context of a concrete example in the following sections.

Generalization gap Ideally, the in-sample errors (i.e. the errors computed during the design phase) should be a good approximation of out-of-sample (i.e. operational) errors; however, the former will usually underestimate the latter. The *generalization gap* of a model $\hat{f}$ with respect to an error metric m and a dataset D is illustrated in Figure 5.2 and can be defined as the difference:

$$G(\hat{f}, D) = \left|E_{\text{out}}(\hat{f}, m) - E_{\text{in}}(\hat{f}, D, m)\right|. \tag{5.4}$$

Note that in the equation above, the in-sample error E_{in} can be computed exactly *during* the design phase, while E_{out} is an average over the *unknown* true distribution and can only be estimated (*after* the design phase).

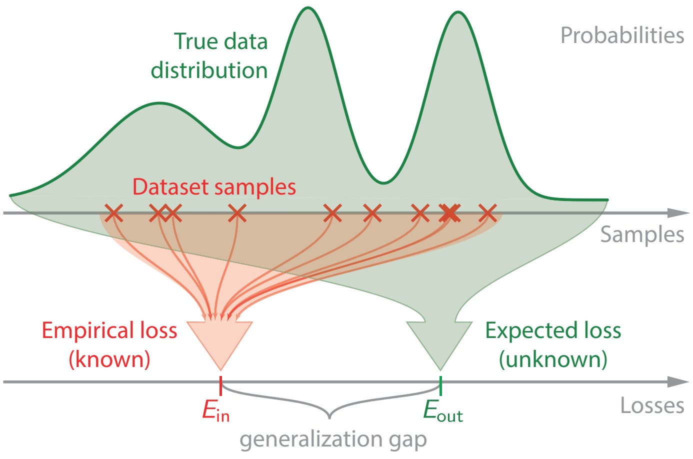


Figure 5.2: In-sample error E_{in} (empirical loss), out-of-sample error E_{out} (expected loss), and the generalization gap between them. The difficulty in guaranteeing any bounds on the latter raises from the fact that the true distribution is unknown and can only be estimated.

An important objective would be to ensure during the design phase that the generalization gap is low, which can be used as a guarantee of robust performance during the operational phase, given that the in-sample error is small. We will address this objective in more detail in the subsequent sections.

Average model Let $\mathcal{F}$ be a fixed learning algorithm to learn a model for a function $f : X \to Y$. Recall (5.1) that for every dataset $D \subset \mathcal{X}$, a model $\hat{f}^{(D)}$ is obtained by training $\mathcal{F}$ on D, i.e.

$$\hat{f}^{(D)} = \mathcal{F}(D).$$

Let us define a function $\overline{f}_n : X \to Y$ by[5]

$$\overline{f}_n(x) = \mathbb{E}_{D\sim\mathcal{X}^n}\big[\mathcal{F}(D)(x)\big] \qquad (x \in X),$$

where the average over D is as in (5.3). The average model is mostly a theoretical tool which is not possible to compute in most cases. Intuitively, the average model can be interpreted as a "theoretically idealized" model which one could produce by training algorithm $\mathcal{F}$ on *all possible datasets* of size n.

Bias The quantity bias$(\mathcal{F}, n)$ named *bias* is the average over all points $x \in X$ of the difference between the average model and the target function, that is[6]

$$\text{bias}^2(\mathcal{F}, n) = \mathbb{E}_{x\sim\mathcal{X}}\left[\left(\overline{f}_n(x) - f(x)\right)^2\right].$$

Intuitively, the bias of a learning algorithm can be interpreted as a measure of how well the average model deviates from the true one and thus is a measure of model quality. One wants to make the bias small to have the average model close to the true function f.

Variance First, for every *fixed* $x \sim \mathcal{X}$, the variance of $\mathcal{F}\colon D \mapsto \hat{f}^{(D)}$ is the average distance to the value of the average model $\overline{f}_n$:

$$\text{var}(\mathcal{F}, n, x) = \mathbb{E}_{D\sim\mathcal{X}^n}\left[\left(\hat{f}^{(D)}(x) - \overline{f}_n(x)\right)^2\right].$$

Second, averaging this quantity over all $x \sim \mathcal{X}$ gives the *variance* of the learning algorithm

$$\text{var}(\mathcal{F}, n) = \mathbb{E}_{x\sim\mathcal{X}}\big[\text{var}(\mathcal{F}, n, x)\big].$$

Intuitively, variance of a learning algorithm can be interpreted as a measure of its fluctuations around the average model and thus reflects how stable it is.

5.3.2 Classical ML – Risks

In this section, examples of problems that are related to generalizability in the setting of classical machine learning will be discussed. The setting of deep neural networks as a special case will be presented in the subsequent sections.

Bias-variance (approximation-generalization) trade-off As discussed before, in supervised learning, one typically wants to obtain a model that can both capture the important characteristics of the dataset and at the same time generalize well to unseen data. Conventional knowledge tells us that it is typically impossible to achieve both simultaneously. This is often referred to as the *approximation-generalization trade-off* or *bias-variance trade-off* as illustrated in Figure 5.3. One has (see e.g. [LFD, Section 2.3]):

$$E_{\text{out}}(\mathcal{F}, m, n) = \text{bias}^2(\mathcal{F}, n) + \text{var}(\mathcal{F}, n) + \text{var}(\delta), \tag{5.5}$$

if the random error δ has mean zero, and is independent from $x \sim \mathcal{X}$. The third term is usually called *irreducible error*, since it does not depend on the learning algorithm. It originates from the errors in data (see Section 5.2.2). The whole decomposition is called *bias-variance decomposition*.

[5]Here, $\mathbb{E}$ denotes the expected value of a random variable, with the subscript indicating the variable and the probability space. In other words, this is an average (possibly over infinitely many elements), taking into account the likelihood of each event/set of events.

[6]Some authors (e.g. [LFD]) also alternatively define the bias to be $\mathbb{E}_{x\sim\mathcal{X}}\left[\left(\overline{f}_n(x) - f(x)\right)^2\right]$, i.e. the square of bias$(\mathcal{F}, n)$ as defined here.

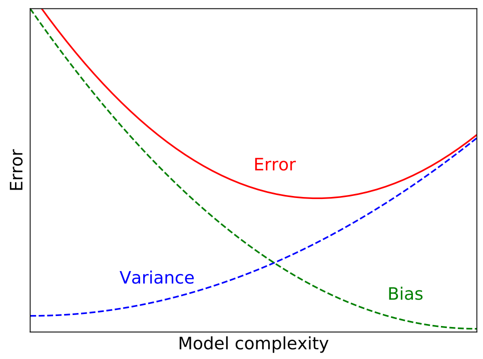


Figure 5.3: Bias-variance trade-off. As the model becomes more complex, it can fit the data better (i.e. bias decreases) but will become very sensitive to it (i.e. variance increases). Both facts yield a specific error curve shape (red).

Then, for a fixed irreducible error:

- a high bias means poor approximation of the target, which also means large in-sample error E_{in}, while
- a high variance means poor generalization, since small fluctuations in the training data might lead to large variations in the final model on testing data.

Both bias and variance pose a risk for the operational phase and should be mitigated. For many machine learning algorithms one can observe that reducing the bias leads to increased variance and reducing the variance leads to increased bias.

Associated risks Simple models usually have high bias and low variance (sometimes called *underfitting*), while more complicated ones have lower bias, but higher variance (sometimes called *overfitting*), as illustrated in Figures 5.3 and 5.4. This can easily be observed by taking the simple case where the algorithm $\mathcal{F}$ chooses among a finite set of models:

- When $\mathcal{F}$ contains a single model, the variance will be zero, but the bias might be large if the single model does not approximate well the target;
- When $\mathcal{F}$ contains many models, the bias should be smaller, since there is more flexibility to find a model that approximates f well, but the variance will be non-zero.

Both overfitting and underfitting come with risks: overfitting will lead to models that do not generalize well, while underfitted models will not achieve a satisfactory performance. A trade-off between these two extremes must be reached, depending on the performance and safety requirements.

Domain bias (shift) The hypothesis that the dataset is independently sampled from the input space $\mathcal{X}$ (in particular, with the right probability distribution) is extremely important for these theoretical results to apply. The operational performance of a model can significantly decrease if the dataset is sampled from a different distribution, even if the two distributions seem similar to a human observer. This phenomenon will for example happen if the model is used on a different input space than the one planned initially.

Associated risks Following [Hof+16], several levels of domain shifts could be envisioned, for example:

1. City to city (small/medium shift);

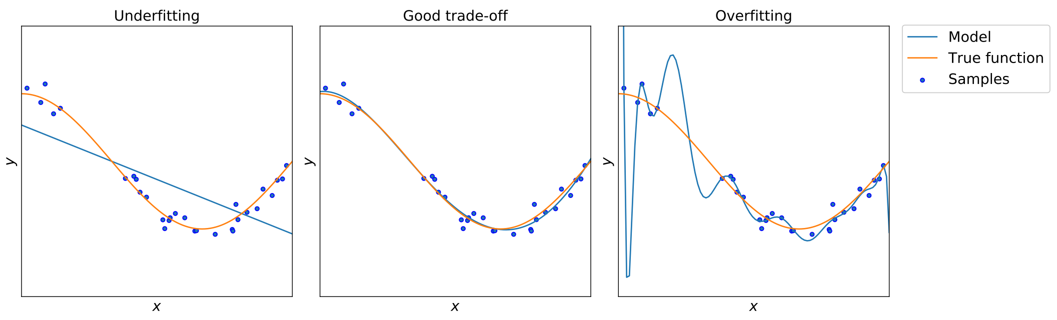


Figure 5.4: Given samples (blue dots) from a function (in orange), three models (in blue) that underfit (left), overfit (right), or provide a good trade-off (center).

2. Season to season, in the same city (small/medium shift);
3. Synthetic to real images (large shift; see also Section 7.2).

For example,

- Chen et al. [Che+17] observe a drop of 25-30% mean Intersection over Union (IoU; see Figure 8.3) (higher scores being better here) when a semantic segmentation[7] model trained on cities in Germany and Switzerland (the Cityscapes dataset) is used to make predictions on similar scenes in Rome, Rio, Taipei and Tokyo;
- Similarly, a segmentation model trained by Handa et al. [Han+16] on synthetic 3D data achieves a global accuracy of only 54% on the dataset of real images NYUv2 [Sil+12], while further training increases this number to 68% (the best result at the time being 69.5%).

Note that some of the domain shift comes from the fact that most training data is gathered under natural conditions (called "human filter" in [KKB19, Sec. 2.2.5]) and it is often difficult or even impossible to obtain data for highly non-standard operational conditions (e.g. for emergency landings in marginal visual weather or unusual approach angles), see Figure 5.5 for illustration.

5.3.3 Classical ML – Mitigation (Theory)

The field of *statistical learning theory* (SLT) has a two-fold objective:

1. It provides ways to obtain well-generalizing machine learning models, and
2. it provides the means to guarantee bounds on the generalization gap (5.4) (see Figure 5.2). In other words, it makes the statement that *predicting unseen data accurately from a finite training sample is possible.*

This section mainly focuses on the second objective, because guaranteeing performance bounds is more crucial for the use of machine learning in safety-critical settings. It will first focus on the classical ML algorithm setting before exploring approaches to mitigate risks specific to neural networks.

[7]Semantic segmentation of an image means to classify each of the image's pixels into a predefined set of class labels (e.g. road, tree, unknown, etc.).

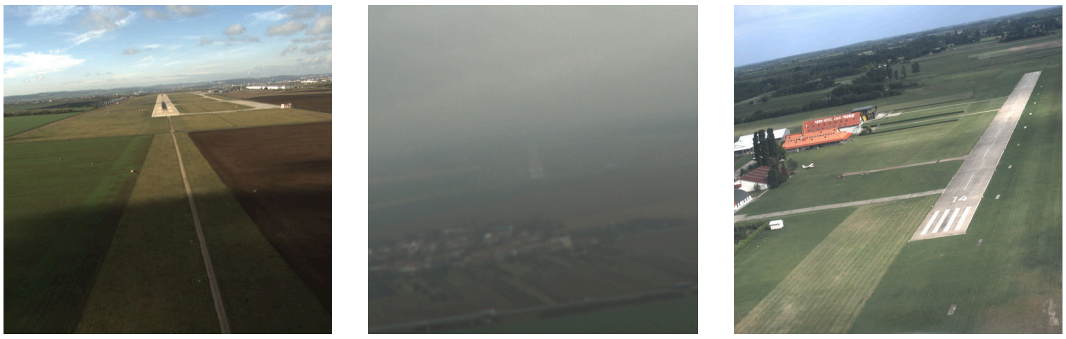

(a) Normal operation (b) Non-standard operation mode (marginal weather) (c) Non-standard operation mode (geometry)

Figure 5.5: Domain bias due to inherently non-standard conditions. Example of a final approach to a runway (see Table 4.1, "ConOps"). (a): Most data is naturally coming from standard approaches under standard VFR conditions. (b, c): Operational domain shift due to marginal weather or non-standard approach angles, often irreducible due to the inherent danger of obtaining such data.

	Learning algorithm $\mathcal{F}$	
Data $\mathcal{X}$	Independent	Dependent
Independent	Bounding $G(\dots)$ uniformly over all possible models and for worst-case datasets: VC-dimension bounds [VC71]	—
Dependent	Bounding $G(\dots)$ uniformly over all possible models and for particular dataset: Rademacher complexity [BM03]	PAC-Bayesian bounds on weighted $G(\dots)$ based on distributional information over learned models [McA03].

Table 5.1: Summary of theoretical approaches to bounding the generalization gap (5.4). Such approaches can be dependent on the properties of the data ($\mathcal{X}$) or the learning algorithm ($\mathcal{F}$). Exploiting information in the data leads to tighter bounds but makes such bounds use case-specific.

Guarantees on generalization gap Ensuring theoretical guarantees on the generalization gap (5.4), also called *generalization bounds*, has a rich history starting with seminal work by Vapnik and Chervonenkis [VC71], who established the relation of the generalization capability of a learning algorithm with its *hypothesis space complexity*. Various forms of such bounds have been derived since then. This section provides a brief overview of them and discusses the underlying assumptions of each approach.

A generalization bound is by its nature a *probabilistic statement* with the probability taken over possible datasets of a fixed size drawn from $\mathcal{X}$. Because of this, such bounds usually output a *probability tolerance* $\delta \in (0, 1)$ for some given *generalization gap tolerance* ε:

$$P_{D\sim\mathcal{X}^{|D|}}\left(\left|E_{\text{out}}(\hat{f}, m) - E_{\text{in}}(\hat{f}, D, m)\right| < \varepsilon\right) > 1 - \delta. \tag{5.6}$$

This yields a more common, "inverted" (i.e. solved for generalization gap tolerance ε while probability tolerance δ is considered given) form of generalization bounds, which is given below and used throughout the section:

$$\underbrace{\text{with probability} > 1-\delta:}_{\text{"Probably"}} \qquad \underbrace{G(\hat{f}, D) < \varepsilon(\delta, |D|, \dots)}_{\text{"Approximately Correct"}}. \tag{5.7}$$

The above form is related to *Probably Approximately Correct (PAC)*-learning setting. The ingredients behind "..." are dependent on a specific bound, and there are several approaches for deriving such bounds. For instance, they may or may not rely on knowing the underlying distribution of $\mathcal{X}$, or properties of the learning algorithm $\mathcal{F}$. These types of bounds are summarized in Table 5.1 and discussed in detail below.

The bounds listed below represent involved theoretical results, however they all manifest an intuitive idea: models that are more complex are more prone to overfitting and generalize worse. While the precise meaning of "complex" varies, all bounds have a complexity term on the right-hand side which controls looseness. It is worth comparing that with the approximation-generalization trade-off showcased in Section 5.3.2, which identifies learning algorithm variance as an "overfitting term".

As the reader will see below, all bounds roughly follow the specific form

$$\begin{aligned}&\text{with probability} > 1-\delta,\\ &\text{and for any model } \hat{f} \in \mathcal{F}: \qquad G(\hat{f}, D) \le \sqrt{\frac{\text{func(model class } \mathcal{F} \text{ complexity}) + \log(1/\delta)}{|D_{\text{train}}|}}.\end{aligned} \tag{5.8}$$

Note the inverse dependence on the dataset size $|D_{\text{train}}|$, which implies that the more data one has at hand, the tighter the gap becomes:

$$G(\hat{f}, D_{\text{train}}) \to 0 \quad \text{as} \quad |D_{\text{train}}| \to \infty.$$

Below, several of the most prominent types of bounds are outlined.

- *Data-independent, algorithm-independent bounds*:

  This class of bounds was the first to be derived by Vapnik and Chervonenkis [VC71] who related the gap to the complexity of the class of possible models,

  (a) without any explicit information about the learning algorithm (e.g. uniformly over all possible models) and
  (b) independently of the underlying data distribution.

  The most important ingredient of this type of bounds is the *hypothesis space complexity* expressed in terms of *VC-dimension* d_{vc}. Informally, VC-dimension defines how "powerful" the models are in their ability to fit *any* data[8]. Intuitively, this makes sense: the more complex patterns the model class is able to fit, the more it will overfit, hence the bound will be higher.

- *Data-dependent, algorithm-independent bounds*:

  The notion of VC-dimension *does not* take into account properties of a particular dataset, hence yielding worst-case generalization bounds. However, using dataset information, i.e.

[8]E.g. for the binary classification task, the VC-dimension is the maximal amount of points that can be arbitrarily labeled by a given set of classifiers. In this sense, linear classifiers have VC-dimension of 3, while more powerful quadratic classifiers have VC-dimension of 4. Note that the VC-dimension is *data-independent*.

exploiting the structure of the data, can help in tightening such bounds. This can be captured through a more modern measure of complexity which is data-dependent, for example the *Rademacher complexity* [cf. BM03]. Omitting technical details[9], one can informally define Rademacher complexity $\mathfrak{R}(\mathcal{F}, D)$ as an ability of a class of models $\mathcal{F}$ to fit the dataset D.

- *Data-dependent, algorithm-dependent bounds*:

  Finally, one can take into account the distributional properties of the learning algorithm $\mathcal{F}$. An example of such an approach is the *PAC-Bayesian* framework [McA03]. Informally, it operates with distributions over models, which involve

  (a) a *prior* distribution $P_{\mathcal{F}}$, i.e. the one chosen before seeing any data and defining what is the designer's belief about the complexity of possible solutions to the problem;

  (b) a *posterior* distribution $Q_{\mathcal{F}}$, i.e. the distribution of the learned models once seeing the data.

  Typical PAC-Bayesian bounds then enjoy the advantage of being both data- and algorithm-dependent through $P_{\mathcal{F}}$, $Q_{\mathcal{F}}$ and the measure of complexity, expressed as a *Kullback–Leibler-divergence* $\mathrm{KL}(Q_{\mathcal{F}}||P_{\mathcal{F}})$. The prior $P_{\mathcal{F}}$ defines the foreseen complexity of the model class, while the posterior $Q_{\mathcal{F}}$ determines the complexity of the models trained on given data. The discrepancy $\mathrm{KL}(Q_{\mathcal{F}}||P_{\mathcal{F}})$ between the two naturally explains how much complexity is added by observing the data.

Theoretical guarantees using validation Section 5.3.5 below will explain that, in the current state of knowledge, the values of the generalization upper bounds $\varepsilon(\delta, |D|, \dots)$ (cf. (5.7)) obtained for large models (such as neural networks) are often too loose without an unreasonable amount of training samples.

However, sharper bounds can be obtained during the validation phase (introduced in Section 5.1). Assuming that r models $\hat{f}_1, \dots, \hat{f}_r$ (trained on D_{train}) are considered during validation, one can can derive bounds similar to the above, where the dependency in δ is only logarithmic, and there is no dependency on the complexity of the underlying model. The key is that the in-sample error is now computed over the *validation* set. This would require to have a large validation dataset in addition to the training dataset.

For the use case in this report, the size of such a validation dataset is determined in the analysis in Section 9.5.

5.3.4 Classical ML – Mitigation (Practice)

Mitigating high model bias/variance As mentioned above, high model bias and variance contribute to suboptimal performance. One can see from (5.5), that it is important to both estimate and minimize them in order to be able to guarantee good out-of-sample (see Section 5.2) performance.

An individual analysis and mitigation of the three terms in (5.5) can provide a better understanding of the weaknesses of an algorithm (or dataset) and give stronger safety evidence. It can also serve as a decision factor in the choice of a model during the design phase: one would aim for a model whose complexity is high enough to provide a low bias, but not too high as to cause a high variance.

However, determining $\mathrm{bias}(\mathcal{F}, n)$ and $\mathrm{var}(\mathcal{F}, n)$ is not possible in practice since it would require full knowledge of the ground truth $\mathcal{X}$ and the class of all possible models. However, these terms can be estimated using random resampling methods:

[9]For precise formulation, refer e.g. to [BM03].

- *Bootstrapping*: a class of methods that was introduced by Efron [Efr79] consists in resampling B "bootstrapped" datasets D_i uniformly with replacement from the given dataset D and training on them. This process produces several models

$$\mathcal{F}(D_0), \dots, \mathcal{F}(D_B),$$

  which can be used to estimate $\text{var}(\mathcal{F}, n)$ with good accuracy for a broad family of data-generating distributions [Efr79].

- *Jackknife*: a method (see [Efr82]) that consists in sequentially removing a single datapoint from the dataset D and re-training on such a "reduced" version of the original dataset. The method can be used to both produce an average model with reduced $\text{bias}(\mathcal{F}, n)$ and simultaneously estimate $\text{var}(\mathcal{F}, n)$.

Regularization When working with complex models (such as neural networks), *regularization* is often needed to prevent overfitting. A common and simple method for parametric models is to set constraints on the size of the parameters (which can otherwise take any real value). The intuition behind this regularization method is that models with smaller weights are less complex and therefore generalize better. See for example [ESL, Sections 2.8.1, 3.4, Chapter 5].

Mitigating domain bias For solutions towards using models in the presence of domain shift, see also Section 7.1 on transfer learning.

5.3.5 Deep Learning – Risks

This section is devoted to bringing examples of possible shortcomings of classical approaches (e.g. outlined in Section 5.3.3) when applied to neural networks.

Neural networks are usually highly overparametrized, in the sense that they contain many more parameters than training samples are available. From a "classical" perspective, this would mean that the hypothesis space is extremely rich, allowing to easily overfit to any data. For example, the ResNet101 model [ResNet] contains over 44 million trainable parameters, while the ImageNet [ImageNet] and CIFAR-10 [CIFAR10] datasets contain respectively 14 million and 60'000 images.

As mentioned and discussed below, despite overparametrization and thus high risks of overfitting, neural networks still generalize well.

Classical generalization bounds applied to neural networks As one has seen from (5.8), any such bound where the complexity function is at least linear in the number of parameters will not be usable in practice. This is for example the case for the VC-dimension bounds.

In their seminal paper [Zha+17], Zhang et al. also showed that deep neural networks can memorize the training data (in this case [CIFAR10; ImageNet] or random noise), by achieving zero training error on the datasets paired with random labels. In this case, the expected test error is not better than random guessing. Zhang et al. additionally show theoretically that a two-layer neural network with $2n + d$ parameters is enough to memorize a training set of size n in dimension d. This also shows that the Rademacher complexity is close to maximal, implying that bounds based on it will be converging slowly, thus requiring extensive amounts of data to become practical.

Good generalizability of neural networks trained on little data The fact that deep neural networks still generalize well in practice poses a risk of uncontrollable generalizability.

In the context of this chapter, the *uncontrollable generalizability* means that despite good (much better than classical ML algorithms) generalization performance in *practice*, the associated *theoretical* generalization bounds (5.7) are large, which renders them unusable to theoretically guarantee, and hence control, generalization performance.

It is important to note that the ability to overfit or to fit random data alone doesn't imply poor generalizability, but merely that existing approaches are not sufficient to capture this fact[10].

Many different approaches to explain the generalization behavior of neural networks have been proposed since, for example using *margin* distributions. Essentially, margins measure how much the input has to be altered to change the output classification and it is believed that large margins indicate good generalization behavior. They play an important role in the SVM models. For example, they have recently been used by Bartlett et al. [BFT17] to derive upper generalization bounds, by Jiang et al. [Jia+19] to estimate the generalization gap, or by Lampinen and Ganguli [LG19] in the setting of deep linear networks (deep neural networks with linear activation functions).

5.3.6 Deep Learning – Mitigation

Theoretical approaches Several approaches are worth highlighting in this section, similar to Section 5.3.3:

- *Vapnik–Chervonenkis type bounds*:

  Recent advances in applying the VC-type bounds resulted in work by [Bar+19] which derives practical bounds by using a corrected definition of VC-dimension for the case of neural networks.

- *Model compression bounds*:

  Another promising approach is that of *model compression*[11]. The basic idea is that of Occam's Razor: if a complex model can be replaced by a simpler one, up to some small admissible error, it might be possible to obtain stronger generalization bounds on the simple model. Before theoretical considerations, the idea of reducing the complexity of models has been very popular for applications of machine learning in low resources scenarios (e.g. local inference on smartphones), see the survey [Che+18].

- *PAC-Bayesian bounds for NNs*:

  Recent advances in PAC-Bayes bounds that are usable for neural networks include the work by Dziugaite and Roy [DR17], where the authors optimize the original PAC-Bayes bound directly and show that one can bound the generalization gap of a two-layer *stochastic* neural network.

  A *stochastic neural network* (or *stochastic ensemble*) can be seen as a family of neural networks with a probability distribution Q, where a random model is selected at each evaluation according to Q (see Section 5.3.3). One might get stronger generalization bounds for stochastic neural network than for single models, which intuitively makes sense, but the trade-off is that inference is not deterministic anymore.

- *Hybrid model compression/PAC-Bayesian bounds*:

  The recent work of Zhou et al. [Zho+19] gives PAC-Bayesian bounds valid for any compression algorithm, obtained by setting a prior that assigns more weight to models with a

[10] This phenomenon is not new to neural networks. Some classical machine learning algorithm have the same behavior, for example the k-nearest neighbor (k-nn) algorithm. The latter predicts the outcome of an unseen data point x by using the majority vote based on the training data of the k nearest neighbors of x. By definition, it therefore memorizes the entire dataset, but is still able to generalize to unseen data. For more on that, the reader is referred to [CH67].

[11] There is earlier work considering *data* compression as well, see e.g. [LW86].

small compression. Like PAC-Bayesian bounds, the bounds apply only to a whole stochastic ensemble, but the results obtained with a simple pruning/quantization compression are usable in practice both for MNIST and ImageNet, unlike previous works (including [Aro+18]).

The reader is also referred to [JGR19] for a comprehensive and up-to-date survey of generalization bounds for deep neural networks.

Practical approaches From a practical perspective, regularization (introduced in Section 5.3.2) in various forms is still important to prevent overfitting (and hence improve generalization). Common methods that can be applied during training are:

- Bounding the sizes of the weights/bias as in simpler models (e.g. ℓ_1, ℓ_2 regularization);
- Activation dropout [Sri+14], that sets to zero certain neuron activations at each step, leading to implicit model averaging, see Section 6.3.3. More generally, ensemble methods (see [ESL, Chapter 16]);
- Data augmentation (see Section 7.2 below) is an implicit method;
- Batch normalization [Luo+19] has been shown to have a regularizing effect;
- Early stopping, namely stopping the training process as validation scores stop improving.

5.3.7 Conclusion

Generalization is a key aspect for building robust machine learning models. Without it, models simply memorize training samples but cannot make predictions on unseen data during operation. This chapter showed that theoretical guarantees of generalization can be established for deep neural networks and that two approaches can be identified:

1. (*Training/model complexity approach*) This approach applies generalization bounds as described earlier in this chapter. They depend in particular on the complexity of the model architecture/algorithm $\mathcal{F}$ and/or information on the training process/data. These bounds usually show that

   $$P_{D_{\text{train}} \sim \mathcal{X}^{|D_{\text{train}}|}} \left(|E_{\text{in}}(\hat{f}^{(D_{\text{train}})}, D_{\text{train}}, m) - E_{\text{out}}(\hat{f}^{(D_{\text{train}})}, m)| < \varepsilon \right) > 1 - \delta(\varepsilon, \mathcal{F}, n, m).$$

   However, these bounds are sometimes too loose to explain the generalization behavior of neural networks: they generalize better than the bounds predict, given the fairly high complexity (e.g. with respect to the number of parameters) of neural networks. Understanding this phenomenon and finding tighter bounds is an area of active research and one expects more results in the future.

2. (*Validation evaluation-based approach*) This approach does not rely on the model complexity, but only on the performance on the validation dataset.

   The advantage of this approach consists in the fact that dependency of the generalization bound on the probability tolerance δ (see (5.8)) is only logarithmic, so that one might easily make δ very small, at the price of a reasonable increase in the size of the validation dataset.

   For the use case in this report, the size of such a validation dataset is determined in the analysis in Section 9.5.

Chapter 6
Learning Assurance

Following from the theoretical considerations in the previous chapter, a framework that could provide a viable path to *Learning Assurance* is now presented. For any type of safety-critical application, *Learning Assurance* needs to impose strict requirements on the datasets used for development, the development process itself, and verification of the system behavior both during development and operation. In fact, [ED-12C/DO-178C, Section 6.0] says that *"verification is not simply testing. Testing, in general, cannot show the absence of errors"*. Thus, for some aspects of Learning Assurance, this chapter will formulate stricter requirements than what is known from traditional Development Assurance.

6.1 Learning Assurance process overview

An outline of the Learning Assurance process can be defined using a typical V-shaped development cycle in which specific steps are added to cover aspects pertaining to the learning processes. These additional steps are related to the data life-cycle management as well as to the training phase and its verification. As a result, the V-shaped cycle becomes a W-shaped cycle as shown in Figure 6.1.

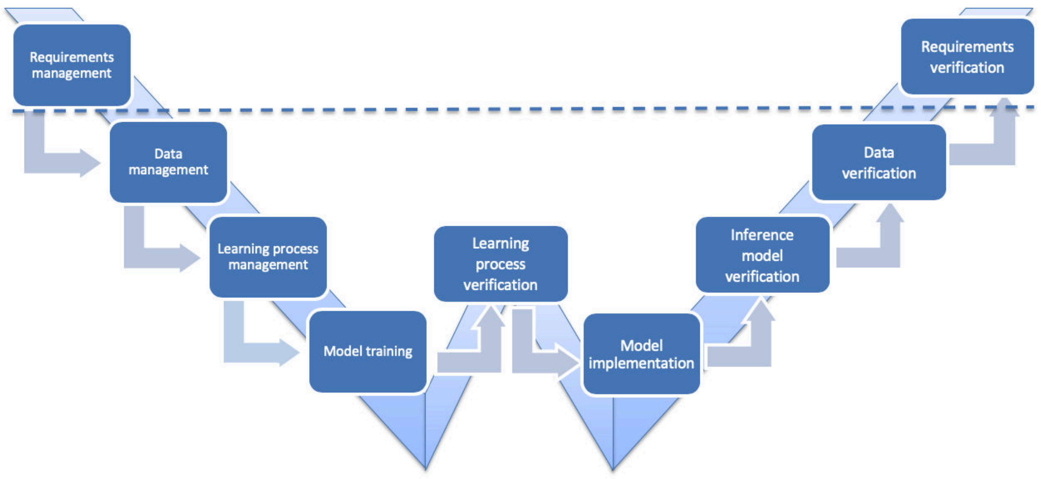

Requirements management
Data management
Learning process management
Model training
Learning process verification
Model implementation
Inference model verification
Data verification
Requirements verification

Figure 6.1: W-shaped development cycle for Learning Assurance.

Requirements management and verification The *requirements management* and *requirements verification processes* are considered to be covered by traditional system development methods (e.g. [ED-79A/ARP4754A]).

The novel Learning Assurance processes start below the dotted line. It is however important to note that this dotted line is not meant to split specific assurance domains (e.g. system/software).

Data management The *data management process* is the first step of the data life-cycle management. It covers the identification of the various datasets used for training and evaluation (typically the training, validation, and test datasets) and the dataset preparation (including collection, labeling and processing). It also addresses the validation objective of completeness and correctness of the datasets with respect to the product/system requirements and to the ConOps, as well as considerations on the quality of the datasets. Finally, it should cover objectives on the independence between datasets and an evaluation of the bias and variance inherent to the data.

Learning process management The *learning process management* considers the preparatory step of the formal training phase. It drives the selection and validation of key elements such as the training algorithm, the activation function, the loss function, the initialization strategy, and the training hyperparameters, which all have the potential to influence the result of the training in terms of performance. Another consideration is on the training environment, including the host hardware and software frameworks, whose selection should be recorded and analyzed for potential risks. The metrics that will be used for the various validation and verification steps should be selected (derived from the requirements) and justified.

Model training The *training* consists primarily of executing the training algorithm in the conditions defined in the previous step, using the training dataset originating from the data management process step. Once trained, the model performance, bias and variance are evaluated, using the validation dataset.

Learning process verification The *learning process verification* then aims at evaluating the trained model performance on the test dataset. An evaluation of the bias and variance of the trained model should be performed, as well. The training phase and its verification can be repeated iteratively until the trained model reaches the expected performance. Any shortcoming in the model quality can lead to iterate again on the data management process step, by correcting or augmenting the dataset.

Model implementation The *model implementation* consists of transforming the training model into an executable model that can run on a target hardware. The environment (e.g. software tools) necessary to perform this transformation should be identified and any associated assumptions, limitations or optimizations captured and validated. Any optimization (e.g. pruning, quantization or other model optimizations) should be identified and validated for its impact on the model properties. The inference hardware should be identified and peculiarities associated with the learning process managed (e.g. specificities due to GPU usage, memory/cache management, real time architecture).

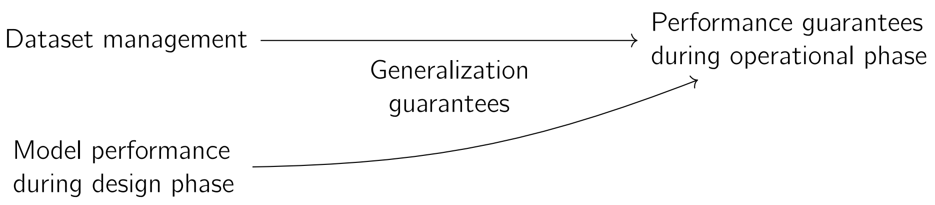
Inference model verification The *inference model verification* aims at verifying that the inference model behaves adequately compared to the trained model, by evaluating the model performance with the test dataset and explaining any differences in the evaluation metric compared to the one used in the training phase verification (e.g. execution time metrics). This process step should also include a verification that the model properties have been preserved (e.g. based on the implementation analysis or through the use of formal methods) and any differences explained. Finally, it includes typical software verification steps (e.g. memory/stack usage, WCET, . . .) that could be strictly conventional (e.g. per [ED-12C/DO-178C]) but for which any specificity linked to the learning approach should be identified and managed.

Data verification The *data verification* step is meant to close the data management life-cycle, by verifying with independence that the datasets were adequately managed.

6.2 Dataset management and verification

Section 5.3 introduced theoretical results bounding the generalization gap of machine learning models. In other words, these give performance guarantees of a model on unseen data during the operational phase, depending on the model performance during the design phase and the model details.

These results crucially depend on hypotheses on the design datasets, which we call *dataset management*:


Dataset management
Performance guarantees during operational phase
Generalization guarantees
Model performance during design phase

This section defines the requirements for dataset management that would allow to apply the generalization guarantees from Section 5.3. The *Standards for Processing Aeronautical Data* [ED-76A/DO-200B] will be taken as a starting point and supplemented in this chapter.

Chapter 9 (Safety Assessment) will illustrate how these can lead to quantitative performance guarantees during the operational phase, as in the figure above.

6.2.1 Operational domain identification

Recall that the goal of machine learning is to approximate a function $f : X \to Y$. A crucial step, before considering data quality, is to correctly identify the input space X and its distribution (i.e. the probability space $\mathcal{X}$).

Failing to do so would prevent establishing any learning guarantees, even though the data is "correct" according to the requirements below. This is the common issue of "domain bias", that will be illustrated in Section 5.3.2. Recall that [ED-79A/ARP4754A] defines "airworthiness" as the ability to accomplish the *intended function* safely.

Then, one of the requirements (see Section 6.2.8) is that the training, validation and, test datasets are independently sampled according to the input distribution, and that the distribution during the operational phase also corresponds to $\mathcal{X}$.

For example, in the setting of the ConOps (Chapter 4), that would require to identify precisely the possible locations of operations, weather conditions, sensor specifications, likelihood of different inputs (i.e. the distribution on X), etc.

The issue of verifying that the domain $\mathcal{X}$ has been correctly identified, and ways to transfer from one domain to another, will be addressed in Section 6.6 and Section 7.1 respectively.

6.2.2 Data quality characteristics

[ED-76A/DO-200B, Section 2.3.2, Appendix B] provides an outline of data quality characteristics in the scope of aeronautical databases. The quality of data is "*its ability to satisfy* *the requirements for its safe application in the end system*". In the following sections, an analysis is provided of how the requirements from [ED-76A/DO-200B] could apply to modern machine learning systems and whether they need modifications. The requirements from [ED-76A/DO-200B] are:

Accuracy Based upon its intended use. See Section 6.2.3 for details.

Resolution Based upon its intended use. The original formulation applies.

Assurance level Confidence that the data is not corrupted while stored or in transit. Original formulation applies.

Traceability Ability to determine the origin of the data. See Section 6.2.4 for details.

Timeliness Confidence that the data is applicable to the period of intended use. Original formulation applies.

Completeness Definition of any requirements that define the minimum acceptable set of data to perform the intended function. See Sections 6.2.7, 6.2.8 and 6.2.10 for details.

Format When loaded into the end application, the data can be interpreted in a way consistent with its intent. Original formulation applies.

The reader is referred to [SCSC-127C] for a modern overview of data best practices and implementation guidelines.

6.2.3 Data accuracy

Sufficient evidence should be gathered to show that the data errors δ_i from Section 5.2.2 are *minimal and independent*. This means that the model was provided on average with correct pairs (x_i, y_i) during the learning process.

More precisely, "minimal errors" means zero mean and low variance σ^2, which can be assessed using statistical testing. Systematic errors in the data (i.e. nonzero mean or non-independence of the errors) are also called *data bias*.

At a minimum, the following type of errors should be addressed:

Capture errors One possible source of errors stems from how the data (x or $f(x)$) was captured. For example, a degraded camera sensor may introduce erroneous information in the data samples. Similarly, humans are prone to introducing a bias through unconscious yet specific collection patterns, for example by making erroneous assumptions, such as rounding all measurements. From a data perspective, it is also very important that the design phase takes into account the sensors that will be used during the operational phase. If the data is collected with one particular type of sensor and another type of sensor is used during operation, this may lead to significantly degraded performance and erroneous behavior.

Single-source errors If the data used to train a model has only been collected from a single source, there exists a risk that the resulting dataset (and therefore model) encodes undesired artifacts of that particular source. In addition to showing functional correctness of individual sources, one should demonstrate that the model will either only be used with that single source during operation or, in a more general setting, that the model has been trained, validated, and tested on multiple capture sources.

Labeling errors If the value $f(x)$ is evaluated from x by manual or automatic *labeling*, instead of being captured, this process creates another source of possible errors. This could be mitigated by having all annotations verified by multiple independent processes.

In the case of manual labeling, this could be achieved through the use several independent annotators. Then, disagreements can be measured, monitored and reported. Any disagreement should be flagged and the corresponding samples considered for re-annotation. As the number of independent annotations per datapoint grows and assuming that each annotator has roughly the same probability of making a mistake, the error rate decreases exponentially (see the discussion and examples on ensemble learning in Section 6.3.3).

This double- (or multiple-)reading practice is widespread in radiology and is continued in related machine learning datasets. For example, Google's work on diabetic retinopathy prediction [Gul+16] used 54 independent human expert annotators.

It is crucial that the annotators' errors are independent. If all make the same faulty assumption (e.g. because of incorrect requirements), then the errors that follow will not be detected.

6.2.4 Traceability

Similar to the definition of *traceability* in [ED-76A/DO-200B], the ability to determine the origin of each data item is required. For data used to train and evaluate machine learning models, each data pair (x_i, y_i) needs to contain artifacts that allow full back-to-birth traceability. Depending on how each data pair is obtained, the following aspects need to be considered:

- Data pairs are obtained by collecting *both* x_i and y_i as part of the data recording process, i.e. both are measured directly. A trace of changes from the origin of each data pair to when it is used by the learning algorithm needs to be established;
- Input data x_i is measured as part of the data recording process and y_i requires additional (human) annotation. If y_i requires annotation, additional information about the annotation process need to be provided to guarantee traceability. The volumes for such annotations are usually quite large and so the annotation process needs to be carefully designed and documented. Each y_i is annotated according to a set of *annotation requirements* which need to become part of the item's trace. See a list of potential artifacts below in Section 6.2.6 for more details.

In both cases, the aim of such traceability is that the root cause of any errors or anomalies can be identified and traced back to their origin.

6.2.5 Digital error protection

To protect the integrity and to detect loss or alteration of the data, an error-detection scheme such as Cyclic Redundancy Check (CRC) needs to be employed at all relevant stages of the development process. This is particularly relevant during the transfer between different (cloud) compute machines, but also during storage, or even after deliberate modification of the data.

6.2.6 Data artifacts

Following from the previous section, each data pair (x_i, y_i) should have the following artifacts to provide full back-to-birth traceability:

- Link to higher-level requirement(s);
- Collection protocols to describe procedures that are used to gather the data, date and location of recording, checksums for digital error protection, and any other relevant information;

- Annotation details, if relevant, including input data item, annotation requirements, annotator identification, name of annotation tool, date and time of annotation, disagreement between annotators, and any other notes;
- Data transformation steps that are applied to each data item after collection/annotation for reproducibility, including code artifacts, if applicable.

6.2.7 Explicit operating parameters

It is often possible to associate explicit and interpretable *operating parameters* to the complex input space $\mathcal{X}$. These could originate from the system requirements, derived software requirements and the application ConOps.

One can make the simplifying assumption that there is a finite number of operating parameters $\varphi_1, \dots, \varphi_n$, each belonging to either a compact interval or a finite set, say $\varphi_i \in P_i$, forming an *operating space*

$$\mathrm{OS} = P_1 \times \cdots \times P_n,$$

with a surjective map

$$\varphi : X \to \mathrm{OS}, \quad x \mapsto (\varphi_1(x), \dots, \varphi_n(x)),$$

i.e. every point of the operating space gives the parameters of at least one point in the input space. By definition, the parameters are *well-defined*, in the sense that $\varphi_i(x) \in P_i$ for every datapoint $x \in X$.

Example If $\mathcal{X}$ is the space of all 512×512 RGB aerial images captured with a camera on the nose of an aircraft in the context of the ConOps, one might consider φ_1 as the altitude in $P_1 = [0, \mathrm{MAX\_ALT}]$, φ_2 the time of day in $P_3 = [6, 21]$ for daylight operations, etc. See Chapter 10 for an extended example.

Limitations It is important to note that the operating parameters will invariably fail to describe subtleties from $\mathcal{X}$. While classical software tends to operate on a lower-dimensional space like OS, machine learning models tend to directly process the full input from $\mathcal{X}$ and therefore require the full consideration of the latter.

Nevertheless, the development of explicit operating parameters is still useful since:

- This is reminiscent of "classical" aeronautical tests, where parameters can be enumerated and combinations exhaustively tested;
- This might be easier to verify, interpret and visualize, due to lower dimensionality and/or compactness;
- They provide necessary (although not sufficient) conditions that can be checked as "sanity checks" during verification.

6.2.8 Dataset completeness

From Section 5.1, the training, validation, and test datasets should each be independently sampled in the input space $\mathcal{X}$ (i.e. a dataset of size n is obtained by sampling a point from $\mathcal{X}^n$ with the product distribution). This means in particular that the datasets should be "complete", in the sense that "most elements[1] in $\mathcal{X}$ should be close to a datapoint".

[1] If $\mathcal{X}$ is infinite, this can be made sense of by discretizing $\mathcal{X}$ and its distribution with respect to an arbitrary threshold.

Hence, this requirement replaces the "completeness" requirement ("all the data needed to support the function") of aeronautical data quality from [ED-76A/DO-200B, Section 2.3.2]. This is vital to ensure that all the work done during the design phase actually translates to guarantees for the operational phase.

One example where this is violated is data collected in a specific region while it is supposed to cover a much larger area. Another example is a pilot flying similar maneuvers towards a runway throughout the collection process, while the data is supposed to cover a much larger variety of patterns.

Distribution of operating parameters A *necessary* condition for the above is that the elements of the datasets have operating parameters that are independently distributed in

$$\mathrm{OS} = \varphi(X)$$

with respect to the image by φ of the distribution on $\mathcal{X}$.

However, as described above under *Limitations of operating parameters*, this is not sufficient. For example, one can easily imagine a dataset covering all possible altitudes, angles of approaches, time of day, and presence of rain, but missing a whole class of images likely to appear during operation (i.e. from $\mathcal{X}$). Therefore, one needs to consider the more complex approaches below.

A general verification framework In this section, a high-level framework is described, under which candidates to certification could provide evidence that they possess datasets independently sampled from the input probability space $\mathcal{X}$. The framework is *general* in the sense that it does not require the regulator to specify explicit methods or to provide costly annotated datasets.

The framework demands that, in addition to the trained model $\hat{f}$, one develops

- *an input distribution discriminator* $\mathcal{D} : \coprod_{n\geq 1} \mathcal{X}^n \to [0, 1]$;
- *an out-of-distribution dataset* D_{ood}: see Section 6.6.2.

The former should estimate the likelihood that a sample of size n is independently sampled from distribution X, while D_{ood} is used to test $\mathcal{D}$ and prevent it from simply outputting 1 for any dataset. The following properties should then be satisfied:

1. $\mathcal{D}(D)$ is close to 1 for all datasets considered that should be independently sampled from $\mathcal{X}$ (e.g. the training/validation/testing datasets);
2. $\mathcal{D}(D)$ is small for all subsets $D \subset D_{\mathrm{ood}}$.

Note that further testing of the discriminator $\mathcal{D}$ can be performed at very low cost, since testing only requires *unannotated* data from or outside the input distribution. Once verified, $\mathcal{D}$ can be used to check the representativity of a dataset at any point, to perform runtime monitoring and to help assess the similarity between different datasets (e.g., real-world vs. synthetic datasets).

Of course, there is a risk of making a circular argument, since $\mathcal{D}$ also has to satisfy learning assurances if it is a machine learning model. For example, one should make sure that $\mathcal{D}$ did not simply overfit to $D_{\mathrm{train}} \cup D_{\mathrm{val}} \cup D_{\mathrm{test}} \cup D_{\mathrm{ood}}$. However, this concern is alleviated by noting that $\mathcal{D}$ is a binary classification problem, where the input space is well-defined (any input that could be produced by the sensor, e.g. all 512×512 RGB images).

Example constructions Note that this framework essentially asks to develop ways to correctly identify the operational space $\mathcal{X}$ and to check the datasets for independence and goodness of fit. There is a large body of work on outlier/anomaly/novelty detection, goodness of fit and independence testing (see e.g. [Pim+14; Hub+12]) and it would not make sense to impose a single method. However, the above conditions formulate the desirable properties in an implementation-agnostic manner. Still, explicit examples will be given in Section 6.6.3.

6.2.9 Independence between datasets

Chapter 5 showed the importance of having independent training, validation, and test datasets to be able to correctly estimate the operational performance of a machine learning model. More precisely:

- Training/validation and test datasets need to be prepared by independent individuals, so that the latter can truly be used to estimate real-world performance of the model;
- The test dataset should be elaborated as a first step of the design phase, at the same time as the selection of the error metrics. The next steps of the design phase should have *no access to the test dataset at all*: only the validation dataset can be used for intermediate evaluations and model tuning;
- At the very end of the design phase, the evaluation on the test set should be done without knowledge of the detailed test data characteristics and by individuals having either no involvement in curating it or no involvement in the past or future design phases.

These considerations are motivated by the independence of verification activities from [ED-12C/DO-178C, Section 6.2] which states that:

> *"Verification independence is achieved when the verification activity is performed by a person(s) other than the developer of the item being verified."*
>
> [. . .]
>
> *"The person who created a set of low-level requirements-based test cases should not be the same person who developed the associated Source Code from those low-level requirements."*

In the context of machine learning systems, the learned *model* becomes the equivalent of *source code*. Therefore, independence between the person who developed the *model* and the individual that created the corresponding set of requirements-based test cases is required.

Intra-dataset independence Note that it is also required that the elements of the datasets be independent; this has already been taken care of in Section 6.2.8.

6.2.10 Dataset sizes

The validation and test datasets need to be large enough such that good model performance on these leads to adequate guarantees on the required operational performance. This is dictated by the theoretical bounds on generalization gaps introduced in Section 5.3.

The training set must be large enough to be able to train a model having adequate performance on the validation and test sets.

The training, validation, and test sets must also be large enough to cover the entire ConOps space with large enough precision, as required by Section 6.2.8.

General criteria cannot be given, as the required sizes depend on the precise model, design phase details, error metrics, and bounds used. These would typically be determined during the model design phase and the system Safety Assessment. A numerical example will be given in Chapter 9 in the context of the use case.

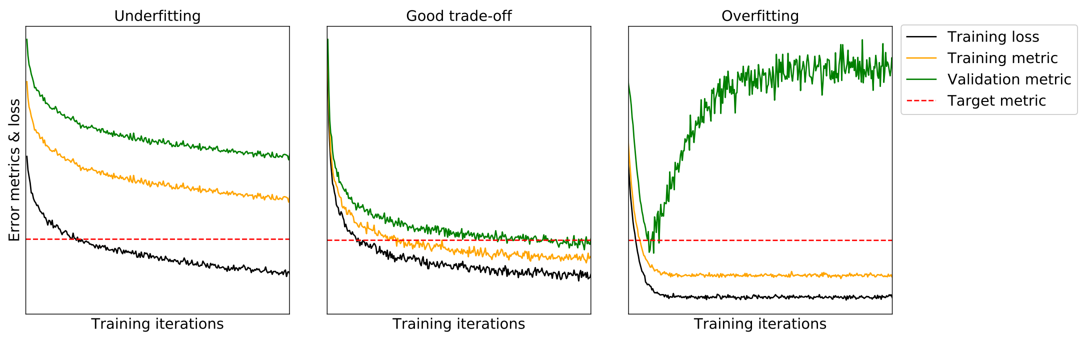


Figure 6.2: Three cases of approximation-generalization behaviors when training models. Early stages of model training are typically underfitting (left), as the model parameters have not fully approximated the target function yet. Overfitting behavior (right) can be observed when the model parameters have memorized the training data, resulting in the model's inability to generalize to unseen data. Good model parameters (center) both approximate the training data well and generalize to unseen data at the same time. Note that each of the three cases visualizes a single error metric computed on the training and validation datasets (where lower is better), but there might be several error metrics.

6.3 Training phase verification

6.3.1 Training curves

Early indications of adequate learning properties can be obtained by examining the approximation-generalization behavior (see Section 5.3.2) of the model as training progresses. This behavior is captured by gathering losses and metrics during the training phase and plotting them into so-called training *curves*.

Most notably, the relationship between the training loss, the training error metrics, and the validation error metrics are indicative signs of whether the model parameters are in an underfitted state, an overfitted state, or a "satisfactory" state. This satisfactory state is often referred to as a state where the model has *converged* into an optimal trade-off between approximation and generalization.

Examples of training curves and how they relate to various levels of over-/underfitting and training process stages can be found in Figure 6.2. These training curves should be provided as part of the design phase artifacts to validate that trained model has converged correctly.

6.3.2 Reproducibility and replicability

Reproducibility and replicability are key elements of the scientific method and so are they for certification of machine learning-based systems, since learning assurances are based on experiments and measurements.

In particular, any learning process that is run with the same inputs (training dataset D_{train}, learning parameters) should produce equivalent or similar models, despite parts of the learning process being random (weight initialization, sampling, stochastic optimization, . . .).

Model equivalence will be defined in Section 6.4.1: the model outputs are the same for every input, up to some tolerance factor. From there, performance assurances of one model would follow from performance assurances of the other.

There are further ways to measure model similarity, such as:

- Distances between the parameters/weights (from which model equivalence could follow);
- Correlation of network activations (on intermediary and final layers), using various correlations measures (see the survey and new methods given in [Kor+19]).

These are distinct notions from model equivalence and the similarity measure to use should be determined and analyzed as part of the Safety Assessment.

6.3.3 Multiple version dissimilarity considerations

From [ED-12C/DO-178C, Section 2.4.2]:

> "*Multiple-version dissimilar software is a system design technique that involves producing two or more components of software that provide the same function in a way that may avoid some sources of common errors between the components.*"

It is also possible to take advantage of multiple version dissimilarity for machine learning systems, in a strategy called *ensemble learning* [ESL, Chapter 16].

In ensemble learning, multiple models are combined to perform the same function. Typically, through the "wisdom of the crowd effect", the final predictions will be more accurate and/or with less variance. This can be easily seen through the following two examples:

1. Given 21 classifiers each having independent error rate $\varepsilon = 30.0\%$, one forms a classifier by taking the majority vote. The error rate of the new classifier is only
$$\sum_{i=12}^{20} \binom{20}{i} \varepsilon^i (1-\varepsilon)^{20-i} < 0.52\%;$$
2. If $X_1, \ldots, X_n$ are independent variables with mean μ and variance σ^2, then the average $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$ still has mean μ, but has lower variance σ^2/n.

Models in an ensemble can differ in multiple ways, for example:

- The model parameters are initialized differently at the beginning of training, as proposed by Lakshminarayanan et al. [LPB17];
- They are trained with different learning algorithms;
- They could be shown a different subset of data (but evaluated on the same test set).

There exist several methods for combining models, see [Zho12]. For example:

- Given a learning algorithm, *Bootstrap aggregating (bagging)* proposes to train a certain number of models using random subsets of the training dataset and then average (or take majority voting for classification) the predictions. The goal is to reduce variance, as in the second example above. See also e.g. [ESL, Section 8.7];
- *Boosting* algorithms work by successively training models, where previously misclassified example are given higher weights for the training of the subsequent models. The models are then combined with a weighted average or majority vote. The goal is to reduce bias and eventually variance. For example, *random forests* combine simple *decision trees* with boosting (see e.g. [ESL, Chapter 10]).

Usually, a requirement of ensemble learning is that the errors of each model are independent (as seen in the examples above). This could be probed using statistical testing and the performance gains can be mathematically estimated. An example will be given in Chapter 9.

Measuring ensemble agreement An ensemble allows to measure the agreement score of the individual classifiers during the design phase. Section 6.6.4 explains how this can be used for runtime/uncertainty monitoring during the operational phase.

6.4 Machine learning model verification

The ability to verify model behavior during the design phase helps establish trust in the model's performance during operation. This section explores several verification strategies, from running systematic tests to formally proving model properties, and discusses their limitations and applicability in the context of safety-critical applications.

6.4.1 Definitions

Algorithm robustness and model robustness According to the definitions of Section 5.1, the *learning algorithm* $\mathcal{F}$ during the training phase produces a trained model $\hat{f}^{(D_{\text{train}})} : X \to Y$, which represents a function mapping from the data input space X to prediction space Y. It is often important to understand, which properties this function exhibits when it comes to *perturbations of input*, i.e. how *stable* it is. This task is known as *sensitivity analysis*.

Phase	Input	Output	Relevant fluctuations	Type
design	D_{train}	$\mathcal{F}(D_{\text{train}})$	Those in the training dataset (replacement of data points, additive noise, label errors etc).	learning algorithm stability
operational	$x \in X$, $\mathcal{F}(D_{\text{train}})$	$\mathcal{F}(D_{\text{train}})(x)$	Those in the data input and prediction output *or* in the model itself (model alteration).	model stability

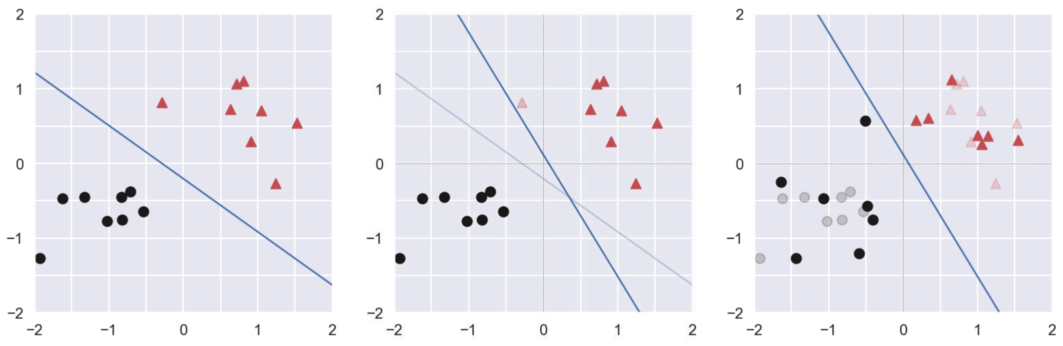
Table 6.1: Two sources of robustness: *algorithm* and *model* stability.

To this end, there are two sources of instability which might be considered here and they naturally stem from the fact that there are two inputs contributing to the final prediction of such a trained function: the *training dataset* and the *datapoint* which is fed to a trained model. This is summarized in Table 6.1.

The above two sources of fluctuations allow for slight variability in definitions of robustness. *Robustness of learning algorithms* (Figure 6.3, (a,b)) is the type of robustness which ensures that the produced model does not change a lot under perturbations of the training dataset D_{train}. Traditionally, this is referred to as *learning algorithm stability*. *Robustness of trained models* (Figure 6.3 or *model stability*, (b,c)) refers, on the contrary, to keeping input-output relations[2] of a trained model, e.g.:

$$\|x' - x''\| < \delta \;\Rightarrow \|\hat{f}(x') - \hat{f}(x'')\| < \varepsilon, \quad \text{where } x', x'' \in X \text{ and } \delta, \varepsilon \in \mathbb{R}_{>0}.$$

[2]Here and below the notion of "closeness" is deliberately not defined. It can be any norm or any distance in any respective space, whose choice is specific to the task at hand. For example, in case of adversarial attacks, the "closeness" is typically defined as per-pixel p-norm. In case of rotation invariance, the "closeness" is a more complex notion, captured by norms such as the Wasserstein norm.



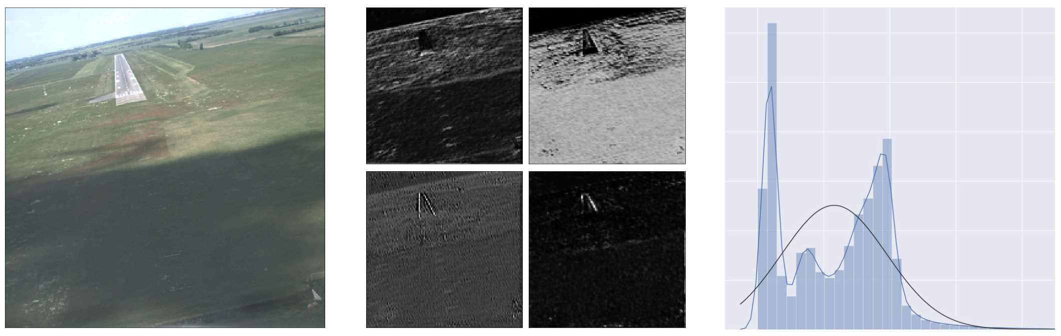
(a) Original classification (b) Training phase perturbation (c) Operational phase perturbation

Figure 6.3: A simple showcase illustrating the notions of learning stability and inference robustness. Margin-maximization classifier (in this case, linear SVM) is (a → b): not robust to perturbations during training — one datapoint is removed leading to change in the resulting model, but (b → c): is robust to perturbations during inference — all datapoints are now perturbed and classification result yet remains the same.

6.4.2 Overview of neural network verification methods

There is a tendency (see Sun et al. [SKS19] and Liu et al. [Liu+19]) to divide all verification methods into several (partially intersecting) categories:

- *Coverage-based white-box testing*: aims at running trained models through a systematic testing of both the *extrinsic* (outputs) and *intrinsic* (architecture-dependent properties) behaviors of the model;
- *Falsification*: adversarial attacks that make use of special artifacts of the training process to generate corner-cases for the trained models;
- *Formal verification*: aims at obtaining formally-derived worst case robustness bounds.



(a) Input image (b) Intrinsics: activations (c) Analysis of statistics

Figure 6.4: White-box testing aims at analyzing the network extrinsics and intrinsics when being run through a set of tests. Example of a final approach to a runway (see the ConOps, Table 4.1). (a → b): Input image results in a set of inner activations "reacting" to runway semantics (approach lights and touchdown) or geometry (lines) (b → c): the latter is analyzed to check that the intrinsics behaves as expected, or to generate new test examples.

Soundness and completeness Verification algorithms can be *sound* and *complete* (those properties are not mutually exclusive). Informally speaking, one says that a verifier is *sound*, if the fact that it returns "property holds" implies that the property actually holds. One says that a verifier is *complete*, if the fact that the property actually holds will imply that such a verifier returns "property holds". Intuitively, a sound verifier minimizes false positive returns and a complete verifier minimizes false negative returns (see Figure 6.5).

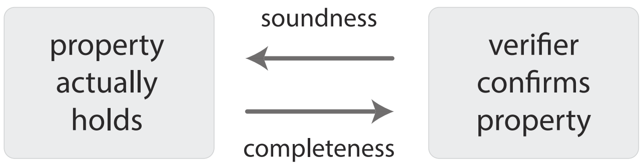


Figure 6.5: Soundness ensures that if the verifier returns "property holds", then it actually holds. Vice versa, completeness ensures that if the property holds, the verifier will be able to "catch" this.

Verification via white-box testing Methods of this group aim at efficient procedures to explore the behavior of a neural network through testing. "White-box" in this context (see Figure 6.4) refers to the fact that the test is allowed to see not only the final output behavior ("extrinsics tests"), but the behavior of the neural network's internal parameters — such as neural coverage, activation patterns, etc. Typical examples of the methods are DeepXplore [Pei+17] and DeepTest [Tia+18].

Verification via semi-formal falsification Methods of this group apply a white-box approach in an attempt to generate "hard" test examples for the neural networks, hence "falsification". However, they do not provide any formal guarantees of the existence or non-existence of an edge/failure case for the network, hence "semi-formal". Such methods typically do not guarantee completeness, but attempt to maximize soundness, i.e. expand test coverage in meaningful and efficient ways. Recent examples include [DDS19] and [Zha+18b], which use specialized search procedures for finding hard test cases.

Verification via formal approaches This set of methods attempts to solve the main issue of the verification approaches above: it is impossible to test the network outputs on the set X of *all possible inputs*, due to the continuum cardinality of the latter. To circumvent this issue, it is suggested to formally verify *verification properties* which are generally defined [Liu+19] as "if-then" statements of a predicate form:

$$\text{prop}_{\hat{f}}(X_c, Y_c): \quad x \in X_c \;\Rightarrow\; \mathcal{F}(D_{\text{train}})(x) \in Y_c,$$

for $X_c \subseteq X, Y_c \subseteq Y$. The pair $C = (X_c, Y_c)$ is called *verification constraint*.

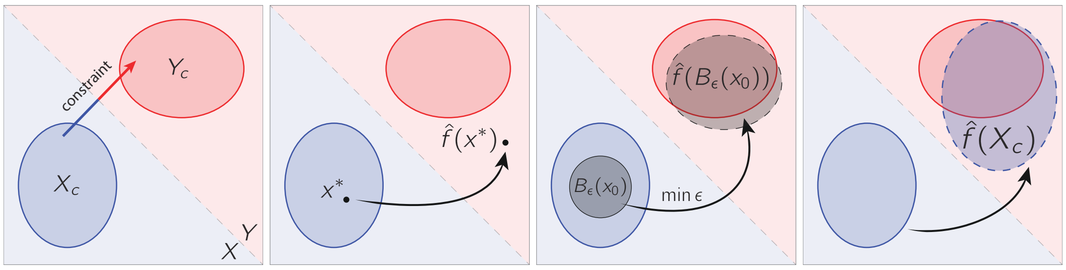
For a given verification constraint C, a typical formal verification algorithm shall output one of the following types of *verification results* (see Liu et al. [Liu+19]):

- *Counterexample result*: the verification algorithm finds an input $x^* \in X_c$ that violates the constraint: $\hat{f}(x^*) \notin Y_c$ (Figure 6.6b). In plain language, it answers the question: *"Are there any inputs that violate the given constraint?"*.

  Methods that can be mentioned here include Reluplex [Kat+17] or ReluVal [Wan+18];

- *Adversarial result*: for any given input $x_0 \in X_c$, the verification algorithm finds perturbation guarantees, that is, the largest possible ε-ball around x_0, such that the constraint is satisfied:

$$\min \varepsilon \quad \text{such that} \quad \hat{f}(B_\varepsilon(x_0)) \not\subseteq Y_c,$$



(a) Legend (b) Counterexample result (c) Adversarial result (d) Reachability result

Figure 6.6: Three types of formal verification results. (a): notation. Light-blue and light-red areas X, Y depict input and output spaces; blobs X_c, Y_c depict the constraint sets. (b): a counterexample result represents a single datapoint x^* that violates the constraint. (c): an adversarial result represents the minimum perturbation ε of the input around x_0 that still violates the constraint. (d): reachability result represents the image $\hat{f}(X_c)$ in the output space.

effectively ensuring that if the constraint input set X_c does not exceed this perturbation, the whole constraint is satisfied (Figure 6.6c). In plain language, it answers the question: *"What is the largest tolerable perturbation to the input constraint such that the output constraint is still satisfied?"*

Formal verification methods that return adversarial results include for example DLV [Hua+17] which aims at searching adversarial guarantees along with falsifying the properties;

- *Reachability result*: for the constraint X_c, the reachability result outputs its image $\hat{f}(X_c)$ (Figure 6.6d). In plain language, it answers the question: *"What are the outputs for the given set of inputs?"*

  Methods of this group include maximum sensitivity approach [XTJ18] (called MaxSens in [Liu+19]), exact reachability analysis of [XTJ18] or DeepZ, a method of [Sin+18]. The latter method uses a framework of *abstract interpretation* [CC77] which aims at constructing tight over-approximation bounds for each of the transformations in the neural network.

6.4.3 Challenges and issues of formal verification methods

Verification of machine learning models and, more precisely, deep learning models has gained significant attention from the research and industrial community, primarily as a means to mitigate the risks typically exhibited by such models (learning instability, model instability, inequivalence, etc.). This has led to extensive work in various specific sub-domains. Despite this ongoing extensive effort, several challenges yet persist, as outlined by Leofante et al. [Leo+18]:

Computational costs and scalability Verifying NNs is a computationally hard problem (falling into the category of NP-complete ones, see [Kat+17]). The approaches outlined above generally struggle to scale well both in the number of hidden units and the number of hidden layers. An intuitive reason for that is the fact that the amount of constraints for the underlying optimization problems (primal, dual, SAT, SMT) grows exponentially with the number of layers.

Guarantees There is an inherent trade-off between the runtime of a verification algorithm and the completeness of results it returns. A possible intuitive explanation would refer to the fact that many methods (especially those returning *reachability results*) make use of various over-approximations for network operations (e.g. ReLU activations). Such approximations trade exactness with computational simplicity.

Applicability The applicability of formal verification methods depends on:

- *The type of network activations*. Verification methods are generally not universal, i.e. most of them target specific activations such as ReLU or piecewise linear. There are only a few methods that extend to arbitrary types of activations and typically come at a cost of runtime, completeness or over-approximation;
- *The type of network architecture*. Very few methods aim at verifying recurrent neural networks (RNNs). An advantage of the feed-forward architecture is that the algorithm does not need to unroll complicated looping execution branches. Recent work that investigates RNNs is [Aki+19].

Lack of benchmarking Since there are many desirable properties that may be required from typical verifiers (speed, completeness, soundness), it would be natural to benchmark them on some common tasks, similar to how modern machine learning models are benchmarked on common datasets.

Comparison with software formal verification It is worth noting that a software engineering counterpart to model verification is provided in [ED-216/DO-333]. However, given the complexity of the input space and the number of parameters for a modern deep neural network (on the order of millions), it is infeasible to exhaustively or nearly-exhaustively verify all possible computation branches and build exact reachable sets of outputs. This is the reason why there exist a lot of sub-divisions in neural network verification methods, ranging from exact to approximate.

6.4.4 Conclusion

Machine learning model verification represents a rich class of methods which can provide rigorous performance guarantees that are highly desirable for safety-critical applications, e.g. to mitigate unexpected behavior. These methods establish robustness properties of neural networks, such as stability under random or adversarial perturbations, or full coverage of possible outputs.

More recent verification methods, including semi-formal approximate methods, provide a promising path to overcome the computational challenges described in this chapter. The applicability of new approaches coming from this field should be constantly evaluated.

6.5 Inference stage verification

The inference model verification consist of identifying the differences introduced by the implementation phase and verifying the conservation of the training model properties after the transformation to the inference model.

This report does not focus on these verification steps, which will be addressed in future work.

6.6 Runtime monitoring

[ED-12C/DO-178C, Section 2.4.3] describes safety monitoring as a means to protect "against specific failure conditions by directly monitoring a function for failures that would result in a failure condition". This section investigates how such monitoring should be done for machine learning models during the operational phase.

Correct operational space As seen in the previous chapter, most of the arguments guaranteeing correct output rely on the assumption that *the input data follows the target distribution $\mathcal{X}$ against which the model has been trained*. Therefore, a first concern is to verify that this hypothesis holds during operation.

Quantification of uncertainty Furthermore, in line with the system architecture (Section 4.2.1), it is assumed that machine learning models receive raw sensory input, perform low-level feature extraction and classification. Their outputs are then fed into higher-level systems, such as tracking algorithms or decision making systems. In this setting, *models must not only be accurate, but one would also like to obtain a measure of their uncertainty*. If the network were to output an accurate uncertainty alongside its predictions, results with high uncertainty could be discarded by higher-level systems. Understanding a model's uncertainty can avoid that higher-level systems blindly rely on incorrect results. For example, in assistive systems, a good fallback option would be to pass control back to a human.

6.6.1 Traditional software considerations

While [ED-12C/DO-178C] mentions that monitoring functions can be implemented in hardware, software, or a combination of both, the following focuses on software only.

Separation of concerns A common approach is to separate separate functionality execution from monitoring. For example, Koopman, Kane and Black [KKB19] refer to this as the "*Doer*" and "*Checker*" separation. The *Doer* subsystem executes the normal, untrusted functionality (e.g., execution of a neural network) while the *Checker* subsystem implements failsafe behavior. That way, if the *Checker* knows how the behavior of the *Doer* looks like in normal conditions, it can flag any abnormal output which can be taken into account by higher-level decision making systems.
This can and should of course be applied to the operation of machine learning models.

6.6.2 What can be encountered during operation?

Ideally, the distribution of the input provided to machine learning models during operation should precisely match that of the input space $\mathcal{X}$ identified during the design phase. This can however not be fully guaranteed in practice and, unfortunately, it is as easy to come up with aphorisms about *expecting the unexpected* as it is hard to define it in practice. Nonetheless, it is important to at least obtain a broad categorization of any input that could be practically observed during operation, so that risks associated with out-of-distribution scenarios can be properly mitigated. Below, such a classification is attempted:

Expected input These are samples coming from the distribution $\mathcal{X}$, say having high enough probability.

Long-tail examples / edge cases These are samples coming from the distribution $\mathcal{X}$, but that have low or very low probability. This implies that the model might not perform well on these inputs, even though the model metrics are high (since these are often taken as averages over datasets).

Static Aberrations These are sensor artifacts that perturb samples from $\mathcal{X}$, such as (in the case of a camera) humidity condensation, unexpected aircraft parts in view, camera misplacements, bent parts, etc. They can be, but are not exclusively malicious in nature.

Dynamic Aberrations These are dynamic sensor artifacts that perturb samples from $\mathcal{X}$ such as (in the case of a camera) laser pointing, physically blocking camera view, image capture processing noise, etc. They can be, but are not exclusively malicious in nature. This input category relates to the data accuracy errors described in Section 6.2.3.

Adversarial attacks These are methods to purposely produce input (in the target distribution $\mathcal{X}$ or not) on which the model $\hat{f}$ gives "bad" approximation to f (say with respect to one of the metrics m).

- White-box adversarial attacks require access to the model intrinsics (architecture, weights, training data, ...);
- Black-box adversarial attacks are model-agnostic: one assumes that the adversary only has access to the output of the model.

Others The final category comprises other types of out-of-distribution samples, such as (in the context of the ConOps from Chapter 4) images of a geographic region not contained in $\mathcal{X}$, or images taken after 9pm.

6.6.3 Detecting out-of-distribution data

Out-of-distribution/anomaly/novelty/outlier detection was already touched on in Section 6.2.8 and the generic distribution discriminator $\mathcal{D} : \sqcup_{n\geq 1}\mathcal{X}^n \to [0, 1]$ used to verify the distribution of the design phase datasets can directly be used to ensure that the inputs during the operational phase match the design distribution $\mathcal{X}$. For example, one can set thresholds $0 < \delta_1 < \delta_2 < 1$, such that a sample $x \in X$ satisfying

- $\mathcal{D}(x) > \delta_2$ is considered *in-distribution*;
- $\mathcal{D}(x) \in [\delta_1, \delta_2]$ is considered an *edge case*;
- $\mathcal{D}(x) < \delta_1$ is considered *out-of-distribution*.

Note that more generally, discriminators can be agnostic to the model $\hat{f}$ that they might be used with, or actually use parts of it.

Section 6.2.8 referenced two surveys on outlier detection methods. Another recent example, this time using the intrinsics of the model, is the *Out-of-DIstribution detector for Neural networks* (ODIN) method by Liang et al. [LLS18].

6.6.4 Estimating uncertainty during operation

Uncertainty types Understanding which different types of uncertainty a machine learning model has, can help understand and mitigate operational risks. Der Kiureghian and Ditlevsen [DD09] identified seven high level sources of uncertainty, which they categorize into two types of uncertainty:

1. *Epistemic uncertainty* refers to the situation where the model $\hat{f}$ has not been exposed to the relevant input domain area $\mathcal{X}$. In other words, the function's parameters $\boldsymbol{\theta}$ do not correctly fit the input data.
2. *Aleatory uncertainty* refers to the intrinsic randomness in the data, which was introduced in Section 5.2.2. This can come from data collection errors, sensor noise, or noisy labels. In other words, the model has seen such data during training but expects it to be difficult.

Crucially, the main difference is that epistemic uncertainty can be reduced by adding more data to the training set, while aleatory uncertainty will always be present to a certain extent. Given that there is complete dataset with a correct learning process as defined in Sections 6.2 and 6.3 respectively, one can consider that all epistemic uncertainty has been sufficiently minimized within the ConOps input domain.

Probability outputs and miscalibration of models Many machine learning models already output a probability as their prediction (often the output of a *logistic function*, the result of mapping any real number to $[0, 1]$). An example of this is the model described in Section 4.2.1 (runway presence likelihood).

However, it has been shown that these probabilities are usually *not calibrated*, in the sense that they measure likelihood, but do not match with the empirical error rates that would be observed on data. For example, Guo et al. [Guo+17] showed that modern neural network architectures tend to suffer from overconfident probability estimates. Furthermore, Hendrycks and Gimpel [HG17] used this approach as a baseline to empirically demonstrate that model predictions are not directly useful as confidence estimate to distinguish in- from out-of-distribution samples.

Still, there are methods to address this issue, such as simply rescaling the probabilities a posteriori (a variant of *Platt scaling*), as suggested by [Guo+17].

Other methods for measuring uncertainty There also exist multiple methods to estimate the uncertainty of arbitrary models, that do not already intrinsically estimate it:

- Section 6.3.3 explained that instead of training a single model, one can train an *ensemble of models*. When used in operation, one expect the members of the ensemble to mostly agree on their outputs (i.e. have low variance). On the other hand, "disagreement" can be used to measure uncertainty.
- *Variational dropout* [KSW15], or *Monte Carlo dropout*, is a Bayesian view on dropout which applies dropout during both training and testing. It follows that if dropout is applied during test time repeatedly, a probability distribution is obtained instead of a point estimate. That probability distribution can then be used to obtain statistics such as mean value and variance. For samples that the model has seen during training, one intuitively expect a low variance around the mean. However, for unseen samples, a high variance is expected among the forward passes. More generally, this implies that one can estimate how well the model fits the mean and variance and use that as a measure of confidence.

6.6.5 Risks and mitigation

Monitoring the operational input- and output space during operation by functionality separation (Section 6.6.1) is subject to the following non-exhaustive set of possible risks that one needs to be mindful of. Sculley et al. [Scu+14] have identified several risks that are relevant to the runtime monitoring of machine learning models in operation and are referred to where applicable. Aside risks specific to runtime monitoring, Sculley et al. identify other machine learning related risks, but these are considered to be mitigated by [ED-79A/ARP4754A] and [ARP4761] standards and the strict specification of ConOps in Chapter 4.

Assumption turns into fallacy First and foremost, it is important to realize that any means to introduce robustness to undefined phenomena comes with inescapable assumption-making. It is equally important to treat these assumptions as such at each stage during development and testing. [ED-79A/ARP4754A] and [ARP4761] define assumptions as "Statements, principles and/or premises offered without proof" and provide guidelines and methods on how to assess the assumptions made as a part of Functional Hazard Assessments. Consequently, every assumption made on the unknown space described by the designer should be held to iterative scrutiny at each evaluation stage, which is described in more detail in Chapter 9. For illustrative reference, assumption validation and adjustment is one of the first steps — the "*first iterations*" — in the *Fault Tree Analysis* example given by [ARP4761, Appendix D.3.b].

Edge case or out-of-distribution? There is a fine line between edge cases (in-distribution elements that are unlikely) and out-of-distribution samples. Given Operational Concept 1 from Table 4.1, one can try to decide whether the following illustrative scenarios are edge cases or out-of-distribution examples:

1. The input images are taken from an altitude of 1800M AGL, instead of the specified 800M AGL;
2. A solar eclipse darkens the camera view;
3. An airshow is being held next to the runway, resulting in an abnormal amount of visual obstructions and distractions around the runway;
4. An unusual springtime flower "super bloom" happens around the runway.

The above examples highlight the difficulty of deciding whether a particular scenario is out-of-distribution or an edge case. The classification can be subjective to the reader without careful analysis. As an example, the first scenario is only clearly out-of-distribution after reviewing the altitude parameters specified in the ConOps from this report.

Empirical out-of-distribution thresholds do not hold during operation Most methods that estimate the distribution origins of inputs are *thresholded methods*, whether that is a threshold on uncertainty, entropy, or other measures.

These thresholds are typically estimated during test phases and validated using more annotated data. Specifically, *human bias* in selecting in- and out-of-distribution samples may be skewed towards certain unknown distributions. For example, the list of scenarios in the previous risk is a display of the author's bias; an unbiased observer, i.e. somebody that has not seen that list, may think of entirely different cases.

The discriminating threshold that was found during the test phase may not hold during operation, resulting in unjustified amounts of in-distribution samples labeled as out-of-distribution (a false positive; the threshold was placed too high), or out-of-distribution samples labeled as in-distribution (a false negative; the threshold was placed too low).

Scully et al. [Scu+14] address this risk in section "*Fixed Thresholds in Dynamic Systems*", under the scenario that these thresholds are tuned manually. The authors propose to mitigate this strategy by tuning these thresholds on held-out data, which is exactly the method outlined above. Rather, an emphasis should be placed on validating this held-out dataset and its representativity of the target ConOps, as described in Section 6.2.

Common mode failures in ensembles This final risk of common mode failure applies to using multiple versions of the same model architecture for joint decision making as described in Section 6.3.3. A common mode failure describes the event of multiple instances failing in the same manner, where they were otherwise considered independent and therefore should not fail in such a way.

It specifically addresses the risk of *assuming* that having more versions of slightly different, but still the same component increases independence, when they actually have a common unseen flaw and/or vulnerability. Similar to the first risk (that addresses assumptions specifically), these assumption should be thoroughly tested through safety assessments. Section 9.4 is dedicated to the description of the way in which such assessments should be conducted to prevent common mode failure.

Sculley et al. [Scu+14] address a similar risk in "*Monitoring and Testing*", under the scenario of a single operational model. The authors propose two starting points for mitigation strategies. The first mitigation approach is using the prediction bias as a diagnostic for indicating sudden changes in the environment. The second mitigation proposal suggests to enforce a limit on the system's actions as a sanity check.

6.7 Learning Assurance artifacts

The following list provides a summary of the *minimum* (i.e. not exhaustive) artifacts whose generation is recommended during the development of airworthy machine learning models:

PLAC: Plan for Learning Aspects of Certification A summary of all aspects of machine learning safety and how it relates to certification.

The training, validation, and test datasets $D_{\text{train}}, D_{\text{val}}, D_{\text{test}} \subset X$. alongside evidence that the datasets satisfy the data quality requirements outlined in Section 6.2.

The design phase details. Model architecture (including the type of NN, number of layers/neurons, activation function(s), loss function), training procedure and hyperparameters (including random seeds), training curves (see Section 6.3).

The end model $\hat{f} : X \to Y$.

The input distribution discriminator $\mathcal{D} : \sqcup_{n\geq 1}\mathcal{X}^n \to [0, 1]$. To ensure that the datasets considered are independently sampled from the input space $\mathcal{X}$, see Section 6.2.8. This discriminator should satisfy the conditions therein with respect to the training, validation, test, and out-of-distribution datasets.

An out-of-distribution dataset D_{ood}. To test the distribution discriminator.

The error metrics m used to evaluate the model, and corresponding performance thresholds. These should be determined prior to the training process and included here.

Chapter 7

Advanced concepts for Learning Assurance

In the last chapter, elements of *Learning Assurance* that can be considered *absolutely necessary* for the operation of complex machine learning algorithms in any safety-critical application are provided. This chapter gives a discussion of more advanced concepts alongside their potential risks and benefits. Some of the concepts presented here are *active areas of research* and the reader is invited to follow progress in these closely.

7.1 Transfer learning

In real-world applications, data collection and model training is often expensive, and models for related tasks and domains should be able to share characteristics. In short, the idea of *transfer learning* is to use information from one model to help obtain another one on related tasks and/or domains, in a less data- and/or computation-intensive way. Parallels can be drawn with human behavior: it is easier to learn how to drive a truck, if one already knows how to drive a car.

There exist multiple variants of transfer learning: transfer between tasks, between input types, between input domains, etc. For simplicity, this section will focus on the important category of *homogeneous domain transfer* (albeit a majority of the remarks apply to other variants). Namely,

- one has a model $\hat{f} : X \to Y$ that has performance guarantees when the inputs $x \in X$ follow a probability distribution P (i.e. $\mathcal{X} = (X, P)$), and
- one would like to obtain a model $\hat{f}_T : X \to Y$ that performs well when the inputs $x \in X$ are sampled from a probability distribution P_T (i.e. the new domain is $\mathcal{X}_T?(X, P_T)$).

In other words, the type of outputs and the task remain the same, but the underlying probability distributions change. A simple but important example is when X is a set of RGB images collected over a specific geographical region and one would like to make the model work in a different region (with different visual characteristics).

7.1.1 Domain transfer methods

There are many methods to perform transfer learning, up to the extent that giving a complete overview would deserve a report of its own. Instead, the reader is referred to [PY09; WD18]

Training	Model 1		Model 2	
	Accuracy	Precision	Accuracy	Precision
Real data (baseline)	.719	.792	.781	.792
Synthetic data	.643	.753	.637	.755
Synthetic data, fine-tuning on real data	.767	.809	.787	.800

Table 7.1: Training on synthetic data, table from [Gai+16]. Higher scores are better.

and the following rather explains a few selected methods to motivate the discussion on risks in the next section.

Based on the availability of labels, the methods can be classified into *supervised* (requires labels), *semi-unsupervised* (partially requires labels) and *unsupervised* (does not require labels). If the domain gap is small enough, unsupervised methods would be a prime choice, as they require no additional annotated data, only data from the new domain. In any case, these methods usually have trade-offs between the amount of data (annotated or not) necessary, and the complexity added on top of the original learning algorithm.

Note that the results presented below are mostly empirical. While general patterns can be observed, no general statement can be made, and performance gains must be assessed on a case-by-case basis, in the setting of Chapters 5 and 6. In other words, it is the final model that has to be evaluated, and no credit can be directly taken from the performance of the original model on its original input space. This will be further explained in Section 7.1.2.

Fine-tuning To perform homogeneous domain transfer, one might simply resume the learning algorithm $\mathcal{F}$ used to obtain the original model at the end of the training phase, and continue training with data from $\mathcal{X}_T$ instead of the data from $\mathcal{X}$ used so far. Note that fine-tuning is a supervised approach.

At the beginning, the loss will be higher than the one seen at the end of the first training phase, but the additional training steps should help bring the loss closer to the earlier one.

A few examples of this approach are the following:

- Girshick et al. [Gir+14] have demonstrated that supervised, domain-specific fine-tuning is an effective method to learn high capacity models even when the target domain data is scarce. Using a model that was trained on the large ILSVRC dataset, the authors observe an 8% increase in the mean average precision metric when fine-tuning using the smaller PASCAL dataset compared to a model trained on the PASCAL dataset from scratch.
- Gaidon et al. [Gai+16] observe the scores in Table 7.1 on a multi-object tracking model, evaluated on real data. Note that for evaluation on real data, synthetic-only training is always worse than real-only training, which is also always improved by synthetic training followed by fine-tuning on real data.
- Raghu and Zhang et al. [Rag+19] provide insights into the effect of transfer learning between a benchmark natural image domain [ImageNet] and two medical image domains. Among other findings, the authors most notably demonstrate that transfer learning does not always significantly improve model performance, and that smaller model architectures trained solely on the target domain can perform comparably to larger, fine-tuned architectures. This underpins the point made earlier that performance gains must be measured on case-by-case bases.

Bridging the domain gap as a pre-processing step Another approach is to try to make input from the new domain "look similar" (i.e. have the same distribution) to the original inputs as a pre-processing step. If $\mathcal{X}$ (resp. $\mathcal{X}_T$) is constituted of synthetic (resp. real) images, this pre-processing might make "real images look synthetic", for example by adding some blur or sharpening edges. Of course, this pre-processing function can also be learned through as complex machine learning model, trained on samples the two domains.

As an example of this approach, Zhang et al. [Zha+18a] train (among other strategies) a model on synthetic data, and evaluate it on real data as is, or after transforming it with a domain adaptation function. The first naive method gives a mean intersection over union score of 29%, while the second one improves this to 46%.

More advanced approaches More complex methods for domain adaptations can for example:

- Adapt not only the domain, but the representations/features inherent to the original domain;
- Perform the adaptation while jointly optimizing for the performance of the task at hand (this could be semi-supervised or supervised).

For such examples, the reader is referred to [GL15; Zha+18a; Shr+17; SS14] (as well as the survey [WD18]. In there, Ganin and Lempitsky [GL15] propose an approach where the final predictions are based on input representations that are discriminative and invariant to target domain transfer. In digit image classification, the authors show performance increases ranging from 42.6% – 79.7% when comparing their method to models that were only trained on the source domain. The work of Zhang et al. [Zha+18a] is an example of joint task optimization.

7.1.2 Risks and mitigation

Transfer learning can provide the advantage of reducing the cost of creating models (be it in terms of data, computations, or other), but new risks are also added, compared with the design pipeline handled in the previous sections. In this section, important risks are underlined and suggestions to mitigate them are provided.

Performance verification As already noted in Section 7.1.1, it is fundamental that the performance of the "transferred" models are evaluated on the target input space, rather than taking any safety credit from the performance of the original model on the original input space. Domain transfer is mainly an empirical method, whose results must be verified. The risk in not doing so can be seen in the phenomenon exposed in the next paragraph.

Negative transfer When the source domain and target domain are sufficiently unrelated, it gives rise to the risk of *negative transfer*. This is a phenomenon where the source domain $\mathcal{X}$ contributes to poor performance of the target model $\hat{f}_T$. A prerequisite for transfer learning, regardless of the availability of target domain labels, is the availability of a representative test set for the target function. See also "Correct optimization target" below for a possible mitigation stratgy.

Transfer from publicly available models A common form of transfer learning is through the use models pre-trained on public datasets (see e.g. He et al. [HGD19]; for neural networks, this is also sometimes called "weights initialization"), which can be seen as domain and/or task transfer. When used for safety-critical applications, one should consider:

1. It may be more difficult to verify that the correct Learning Assurance requirements have been fulfilled;

2. The "link to the intended function/absence of unintended function" is lost or harder to keep track of;
3. The ability to train several models on different random weight initializations (see Section 6.3.3) is lost.

In other words, the *full* training process should be done in a way to follow the recommendations exposed in this document.

Correct optimization target As mentioned in Chapter 6, the loss function (whose value is minimized during the training process) should be a good proxy for the metrics of interest. In transfer learning, the function optimized might however not be directly related to the metrics (or a loss) of the target task anymore.

Ideally, the link between the transfer learning method and the optimization of the target metrics should be shown.

Transfer algorithms Recall that transfer methods can be learning algorithms, as well as classical algorithms. In the first case, the transfer algorithm should as well satisfy the Learning Assurance requirements outlined in this chapter. In the second case, the transfer algorithm should follow usual software airworthiness requirements, e.g. [ED-12C/DO-178C].

7.1.3 Retraining and recertification

Transfer learning is a means to modify a model that complies with the concepts of Learning Assurance from Chapter 6. Potential risks and possible mitigation strategies were described in the sections above. This leads to a discussion of requirements for (re-)certification of a newer or retrained version of such a model. Such modifications can be grouped into:

1. *model update*, the model is retrained with new or additional data without further changes to its original functionality;
2. *model upgrade*, the model is retrained such that its original functionality is (partly) changed.

These types of changes and the possible implications for recertification will not be addressed further in this report and left for future work. In the meantime, the reader is referred to [ED-79A/ARP4754A, Chapter 6].

7.2 Synthesized data

Acquiring high-quality data satisfying the requirements of Section 5.1 can be very costly, while it is crucial that machine learning algorithms are tested and trained on a very large amount of data. Consequently, the design and testing of safety-critical machine learning models should rely on *simulated/synthesized data*, for which new data can be acquired at a very low cost once a system is setup. By synthesized data, it is meant *any data that was computer-generated or any data from the target sensors that underwent a processing step that is not included in the target operational system.*

7.2.1 Examples and classification of synthesized data

To better understand the possible benefits and risks of using synthesized data, it is useful to first give a categorized list of examples, roughly in increasing order of complexity/syntheticity:

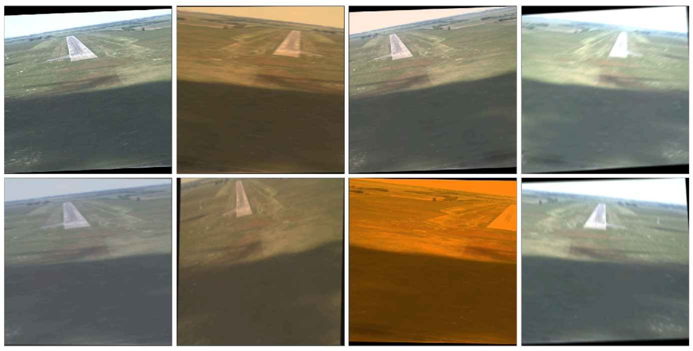


Figure 7.1: Various transformations of the runway image on the top left.

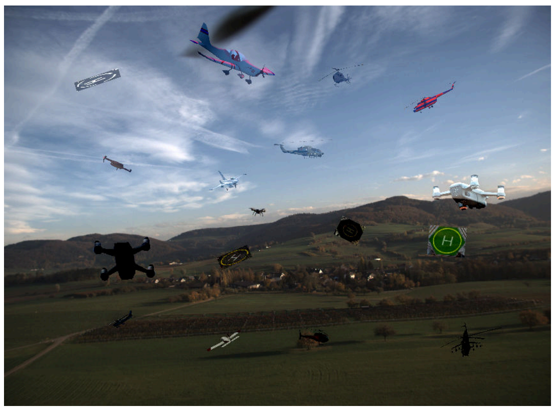


Figure 7.2: Augmentation of real data for the task of object detection: pictures of objects to be detected are pasted against a background. Note that some additions appear realistic (the aircraft), while some do not (the helipads).

Basic transformations of real data This type of synthesized data includes applying geometric transformations (translation, rotation, scaling, flipping, cropping, deformation, . . .) or transformations of image attributes (brightness, noise, hue, . . .) to real data. See Figure 7.1. It is widely used in machine learning and usually known as "data augmentation": see for example [SK19].

More advanced transformations of real data It is also possible to perform transformations that go beyond applying basic transformations to the existing pixels. A common example is to "paste" new objects into existing images, e.g. adding cars randomly on empty roads, or adding images of aircraft against a background (see Figure 7.2). The bounding boxes of the objects added are by definition known, so that there is no need to do new manual annotations. This was studied by Peng et al. [Pen+15], among others.

Fully or mostly synthetic data Finally, one can also generate data that is fully or almost entirely synthetic, for example a 3D urban scene as in Figure 7.3 using textures and geometries partially collected from the real world. Such examples can be found in [Gai+16; Ric+16], along with analyses of machine learning models trained on this data.

7.2.2 Risks and mitigation

Section 5.3.2 explained that having data independently sampled from the target input space $\mathcal{X}$ is essential to obtain models that perform well during the operational phase and to estimate the expected operational performance. Thus, the problem of domain shift/bias (see Section 5.3.2) is a particular concern when using synthesized data in the training/validation sets D_{train}, D_{val} or in the test set D_{test}.

Handa et al. [Han+16] noted that fine-tuning a synthetic semantic segmentation dataset (with added noise) on real (target) data leads to an improvement of 5% in the per-class accuracy, compared to simply evaluating the model trained on synthetic data on real images. Further examples were given in Section 7.1, on transfer learning:

- Gaidon et al. [Gai+16], who observe drops of up to 15% when passing from synthetic to real data (while combining both leads to better results than using real data only);
- Zhang et al. [Zha+18a], who report that a model segmenting road scenes trained on a photorealistic video game (GTA5 [Ric+16], see Figure 7.3) only achieves 29% mean intersection over union on similar real images from the Cityscapes dataset [Cor+16] (while an improved transfer strategy raises this number to 46%).

Similarly, even natural transformations of real data could end up changing the distribution of the training data (which would therefore not match anymore the target distribution of $\mathcal{X}$).

Hence, the key requirement is that *synthetic data should never be used without proper analysis and mitigation of the domain biases*, no matter how realistic it looks. The risks and mitigations for transfer learning from Section 7.1 apply to this situation.

It is useful to note that there is a dissension between the recent claims of companies producing synthesized data for training (e.g. that one can train high-quality models using *only* their data), and the observations made in academic research (such as the aforementioned works) which question such claims.

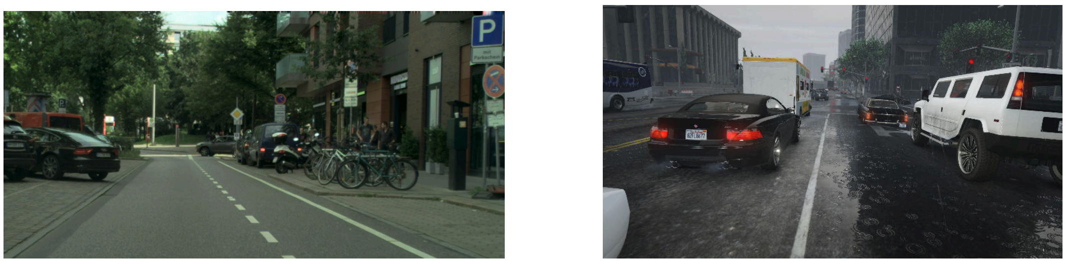

(a) Real image (b) Synthetic image

Figure 7.3: An image from the GTA5 synthetic dataset [Ric+16] and from the Cityscapes [Cor+16] real dataset.

Use of synthesized data for testing Testing machine learning systems using synthesized data is extremely useful and important, as it helps to find edge cases that almost never happen in the real world or that would be difficult or very costly to reproduce.

However, testing using synthesized data can only supplement testing using actual data from the distribution $\mathcal{X}$ that is expected in the operational phase and not to replace it. Otherwise, the learning assurances (such as the theoretical guarantees) would not apply.

Here, one can diverge from [EAS19] and [UL-4600] (at least in the current version), that claim respectively that

“Partial certification credits may still be granted while using a non-conformed test article, provided that the item to be evaluated is simulated with an adequate level of representativity.”

“In order to ensure that credit may be taken from the [simulator/test rig] tests, the [simulator/test rig] must be adequately representative for aircraft systems and flight dynamics. At the same time the limitations for using the [simulator/test rig] must be established. This objective can be achieved by a combination of a controlled development process of the [simulator/test rig], simulator configuration management, system models behavior (crosschecked when necessary with partial system bench or flight test results, analysis, desktop simulation) and engineering/operational judgment. Currently, there is no detailed guidance available on the qualification of simulators or test rigs for use as a Means of Compliance for certification. [. . .] Relying upon simulation results in arguing safety is typically a practical necessity. Simulation results can be used so long as their accuracy is justified, simulation run coverage is justified, and an appropriate non-zero amount of physical testing is used to validate simulation results.”

7.2.3 Conclusion

Many safety-critical applications require a significant amount of training and evaluation data to obtain strong performance guarantees. Both transfer learning and synthesized data (eventually used jointly) allow to palliate a lack of data in the target domain and/or task, by taking advantage of existing or easy to generate data from different domains/tasks. Beyond that, the use of synthesized data can help identify edge cases and simulate scenarios that are difficult or impossible to produce in the real world.

However, this comes with additional risks, highlighted in the sections above, that need to be mitigated to obtain the same levels of performance garantees as those given by the primary learning assurance processes exposed in this chapter until Section 7.1. For example, no claim can be made on the real-world performance of models trained on synthesized data, as photorealistic as it might be, without a careful analysis.

Chapter 8
Performance assessment

In this chapter, the performance assessment of machine learning components, and systems including these, is discussed. In particular, the choice of adequate error metrics is analyzed, along with possible risks of performing the model and system evaluations.

8.1 Metrics

Chapter 5 introduced a machine learning model $\hat{f} : X \to Y$ as the approximation of a function $f : X \to Y$, learned through samples $(x, f(x) + \delta_x) \in D_{\text{train}}$. The quality of the approximation is measured by error metrics $m : Y \to \mathbb{R}_{\geq 0}$, requiring that

$$m\left(\hat{f}(x), f(x)\right) \quad \text{be small on all } x \in X. \tag{8.1}$$

The learning guarantees presented in Chapters 5 to 7 ensure that (8.1) holds during the operational phase, on average and up to some small failure probability. Therefore, one should:

1. Discuss adequate choices of error metrics and potential pitfalls, which is the goal of this section;
2. Understand how to control the failure probability and strengthen the "on average" statement into the validity of (8.1) for all expected inputs. This will be done in Chapter 9 (Safety Assessment).

8.1.1 Context

Section 4.2 outlined that the machine learning systems considered in this report are part of larger (sub)systems, and do not perform "end-to-end" functions by themselves (for example, from perception to actuation). This is the case for the model involved in the example of Chapter 4 (ConOps), which is solely responsible for the perception component of the visual landing guidance.

Therefore, it is important to realize that *the choice of error metrics must be understood in the scope of the whole subsystem* and use case, and not in isolation. To illustrate this risk, one can easily imagine two systems using the same model $\hat{f}$, where good performance of $\hat{f}$ with respect to m (in the sense of (8.1)) translates to adequate performance for the first system but not the second. For example, assuming the model performs object detection, an error metric might penalize false positives and false negatives differently:

- the first system aims at identifying runways, as in Chapter 4. In this case, one might want to avoid false positives above all, i.e. avoid that the system predicts the existence of runways even when they are not present;
- the second system aims at identifying other aircraft to avoid collisions. In this case, it is better to have false positives than to risk a collision, i.e. avoid that the system misses other aircraft even when they are present.

The error metrics must be chosen so that they ensure good performance for the whole system (ultimately the whole aircraft) in the context of the application and must become an artifact of the development process for certification.

8.1.2 Different tasks and metrics

By definition, error metrics depend not on the input space X of the model but on the output space Y. In machine learning, one usually distinguishes between two main types of tasks:

Classification When Y is a finite/discrete set, a model $\hat{f} : X \to Y$ has to assign to each input $x \in X$ a "category" or "class" $y \in Y$. Rather than predicting directly a class, these models usually predict a *soft score* , or a probability distribution over Y, namely a likelihood for each class. This allows for finer decision making and error measurements. An example is the runway presence detection from Section 4.2.1.

Regression When Y is an infinite/a continuous set, such as an interval $[a, b] \subset \mathbb{R}$, a model $\hat{f}$ aims at estimating the continuous responses $f(x) \in Y$ to the inputs $x \in X$ that the function f represents. Predicting bounding boxes in an image (e.g. $Y = [0, 1]^{4\times2}$, as in the runway corner detection from Section 4.2.1) is an example of a regression task. As discussed for classification, the predicted values can be provided along with uncertainty measures.

A model can perform a combination of classification and regression, such as the one described in Section 4.2.1. Keeping the slicing philosophy from Section 4.2 in mind, the performances with respect to the two task types are usually considered separately, before being combined. The latter can be done by simply using several error metrics or by combining several error metrics into one (e.g. through a weighted sum, see Section 5.2.5).

There are usually many possible metrics for any classification or regression task, and these should be carefully selected taking Section 8.1.1 into consideration. Generally, all relevant metric choices should be analyzed and the validity and precedence of the ones chosen justified. In practice it is recommended to consider several metrics throughout the whole process and this should be preferred over dismissing an important metric or because of computational overhead.

In the next sections, a (non-exhaustive) selection of common metrics is given for both types of tasks. Recall also that Section 5.2.5 gave a complete example for the runway detection case.

8.1.3 Examples of classification metrics

As explained in Section 8.1.2, it is best to phrase a classification task into d categories as finding a model

$$\hat{f} : X \to [0, 1]^d,$$

such that the ith coordinate $\hat{f}_i(x)$ gives the likelihood that x belongs to class i, enforcing $\sum_{i=1}^{d} \hat{f}_i(x) = 1$. The model approximates the "ground truth" function $f : X \to [0, 1]^d$, where $f_i(x) = 1$ if and only if x belongs to class i. The predicted class for $x \in X$ can be set as

$$\hat{g}(x) = \arg\max_{1\leq i\leq d} \hat{f}_i(x). \tag{8.2}$$

		Prediction	
		Runway	No Runway
Ground truth	Runway	*True positive*	*False negative*
	No Runway	*False positive*	*True negative*

Figure 8.1: A confusion matrix that summarizes binary classification outputs.

Binary classification Any classification task into d categories can be viewed as d *separate* binary classification tasks (i.e. $d = 2$ and for each class $1 \leq i \leq d$, whether a sample belongs to class i or not). The binary classification task, as defined in Chapter 4, to decide if a runway is visible in the image or not, is a suitable example for this section.

The output of a binary classification model can fall into four categories: true positives, false positives, false negatives and true negatives. For example, true (resp. false) positives represent the case where the classifier predicts that a runway is visible and the image does (resp. not) contain it. False (resp. true) negatives represent the case where the classifier predicts that a runway is not visible and the image does (resp. not) contain it. Figure 8.1 summarizes these outcomes as a *confusion matrix*.

Class imbalances Even in a binary classification setting (but also for multi-class classification discussed later in this section), calculating average metrics has to be done carefully. In particular, the underlying class distribution will likely influence the evaluation results. *Class imbalances* can cause *significant* misinterpretations of model performance. For example, the accuracy metric

$$\sum_{i=1}^{2} I\left(f_i(x) \neq (\hat{g}(x) = i)\right),$$

where I is the indicator function taking value 1 if its boolean argument is true, and 0 otherwise, could be chosen. However, if most $x \in X$ have class 1 (corresponding for example to background), the model will have high performance with respect to class 1 while having abysmal performance on all other classes. A complete evaluation of a classification model's performance always requires considering the distribution of classes and different error types.

False positives and false negatives For each of the outcomes $1 \leq i \leq d$, *true (false) positives* and *true (false) negatives* can be counted using the metrics

$$\begin{aligned}
m_{\mathrm{TP}}(\hat{f}_i(x), f_i(x)) &= I\left(f_i(x) = 1,\ \hat{g}(x) = i\right), \\
m_{\mathrm{FP}}(\hat{f}_i(x), f_i(x)) &= I\left(f_i(x) = 0,\ \hat{g}(x) = i\right), \\
m_{\mathrm{TN}}(\hat{f}_i(x), f_i(x)) &= I\left(f_i(x) = 0,\ \hat{g}(x) \neq i\right) \text{ and} \\
m_{\mathrm{FN}}(\hat{f}_i(x), f_i(x)) &= I\left(f_i(x) = 1,\ \hat{g}(x) \neq i\right).
\end{aligned}$$

According to the definitions of Chapter 5, the numbers of true (false) positives and true (false) negatives in a dataset D are given by

$$|D| \cdot E_{\text{in}}(\hat{f}_i, D, m_\zeta) = \sum_{(x,f(x)) \in D} m_\zeta(\hat{f}_i(x), f_i(x)),$$

where $\zeta \in \{\text{TP}, \text{FP}, \text{TN}, \text{FN}\}$.

Precision is the proportion of correct of positive predictions by the classifier:

$$\begin{aligned} \text{Precision}(\hat{f}_i, D) &= \frac{E_{\text{in}}(\hat{f}_i, D, m_{\text{TP}})}{E_{\text{in}}(\hat{f}_i, D, m_{\text{TP}}) + E_{\text{in}}(\hat{f}_i, D, m_{\text{FP}})} \\ &= \frac{\#\text{ of true positives}}{\#\text{ of true positives} + \#\text{ of false positives}}. \end{aligned} \tag{8.3}$$

Recall Conversely, *recall* measures how many of the positive samples were detected by the classifier:

$$\begin{aligned} \text{Recall}(\hat{f}_i, D) &= \frac{E_{\text{in}}(\hat{f}_i, D, m_{\text{TP}})}{E_{\text{in}}(\hat{f}_i, D, m_{\text{TP}}) + E_{\text{in}}(\hat{f}_i, D, m_{\text{FN}})} \\ &= \frac{\#\text{ of true positives}}{\#\text{ of true positives} + \#\text{ of false negatives}} \end{aligned} \tag{8.4}$$

Note that the definition of recall is similar to that of precision but takes into account false negatives instead of false positives. In the runway example above, this measures how many of the runways were detected by the classifier.

F_1 score If necessary, precision (8.3) and recall (8.4) can be combined into a single score. The F_1 *measure* considers both and is defined as

$$\text{F}_{1,}(\hat{f}_i, D) = \frac{2 \cdot \text{Precision}(\hat{f}_i, D) \cdot \text{Recall}(\hat{f}_i, D)}{\text{Precision}(\hat{f}_i, D) + \text{Recall}(\hat{f}_i, D)} \tag{8.5}$$

A classifier with high precision and recall has a high F_1 score.

A more general form of the F_1 score is the F_β measure where $\beta \in \mathbb{R}^+$:

$$\text{F}_\beta(\hat{f}_i, D) = \frac{(1+\beta^2) \cdot \text{Precision}(\hat{f}_i, D) \cdot \text{Recall}(\hat{f}_i, D)}{\beta^2 \cdot \text{Precision}(\hat{f}_i, D) + \text{Recall}(\hat{f}_i, D)} \tag{8.6}$$

While the F_1 score is the harmonic mean, F_β allows a different weighting of precision and recall. For example, F_2 weights recall higher than precision and $\text{F}_{0.5}$ places more emphasis on precision than on recall.

Decision thresholds In (8.2), the predicted class i was the one with the maximal soft score $\hat{f}_i(x)$. In the binary case $d = 2$, this is equivalent to setting a *decision threshold* at $t = 0.5$, namely

$$\hat{g}(x) = \begin{cases} 1 & \text{if } \hat{f}_1(x) \geq 0.5 \\ 2 & \text{if } \hat{f}_1(x) < 0.5, \end{cases}$$

Other thresholds $t \in (0, 1)$ may be used, leading to the decision functions

$$\hat{g}_t(x) = \begin{cases} 1 & \text{if } \hat{f}_1(x) \geq t \\ 2 & \text{if } \hat{f}_1(x) < t, \end{cases} \qquad \hat{g} = \hat{g}_{1/2}$$

and having different rates of false negatives/positives (and therefore precision/recall).

During operation, this threshold can also be used as a *rejection threshold* and prevent the classifier from outputting a class at all. This is discussed further in Section 6.6.

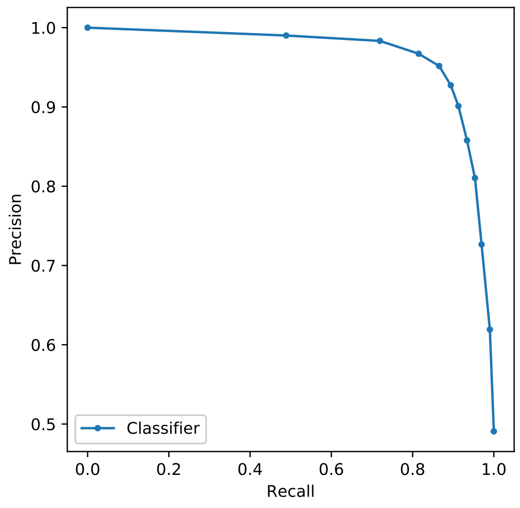


Figure 8.2: Precision-recall curve for binary classifier

Precision/recall curve The influence of the threshold t_i on the precision and recall values can be illustrated in a *precision-recall curve* as shown in Figure 8.2. As t_i is varied, different values for precision and recall are obtained. A higher t_i generally results in higher precision and lower recall (or lower false positive and higher false negative counts). As t_i is lowered, one expects lower precision and higher recall (or higher false positive and lower false negative counts). This is often referred to as the *precision-recall trade-off*.

For example, one would typically choose a high t_i to ensure that the model only predicts that particular class (e.g. predicts that the runway is present) if it is "very confident". Conversely, a lower t_i would ensure that the model predicts a class even if it is "less confident", i.e. less runways are missed.

The favorable classifiers are those that maintain a high precision as recall increases. Such classifiers have a high *area under the curve*.

Costs A downside of the aggregated F_1 score (and in fact many other aggregating metrics) is that it gives equal importance to precision and recall. As illustrated in Section 8.1.1, in practice, different types of error types have different associated costs with it. One may want to penalize certain erroneous outcomes more than others. This is why it is recommended to always report precision and recall separately.

Multiclass classification False positive and false negatives among *all* classes can be counted by considering the error metrics

$$\begin{aligned} m(\hat{f}(x), f(x)) &= \sum_{i=1}^{d} I\left(f_i(x) = 0,\ \hat{g}(x) = i\right), \text{ resp.} \\ m(\hat{f}(x), f(x)) &= \sum_{i=1}^{d} I\left(f_i(x) = 1,\ \hat{g}(x) \neq i\right). \end{aligned}$$

Micro vs. macro averages The above considered any classification task into d categories as d binary classification tasks and the performance was evaluated separately for each class. Calculating an aggregated score over all classes could, for example, be helpful to compare several models against each other. For this, two approaches can be considered:

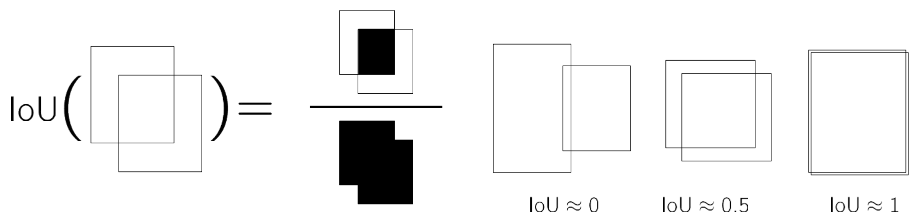


Figure 8.3: Computation of the intersection over union (IoU) of two masks and examples. The Jaccard distance is respectively 1, 0.5 and 0.

- Per-class metrics are first calculated independently and then averaged (macro-average);
- True positives, false positives, and false negatives are summed up across all classes before computing the average metric (micro-average).

It can be seen that the *macro-average* considers all classes to be equally important while the *micro-average* takes into account the underlying class distribution. For multi-class classification problems it is not uncommon that the evaluation differs *significantly* depending on the type of average used. This again motivates a careful use of evaluation metrics, especially when some error types have higher costs than others. [FS10] provides further details on aggregating metrics and their associated risks.

For a more in-depth analysis of classification metrics, the reader is referred to [SL09].

8.1.4 Examples of regression metrics

Given a general regression task of estimating a function $f : X \to Y \subset \mathbb{R}^d$, an obvious metric to use is one of the L^p norms

$$m(y, \hat{y}) = \|y - \hat{y}\|_p, \qquad (p \in [1, \infty]),$$
$$\|z\|_p^p = \sum_{i=1}^{d} z_i^p \qquad (p \geq 1), \quad \|z\|_\infty = \max_{1 \leq i \leq d} |z_i|$$

(note that $p = 2$ is the Euclidean norm; $d = 1$ simply yields the absolute value mentioned in Section 5.1).

While these are straightforward, other metrics might be more adapted for more structured or geometric tasks such as predicting corner points of an object in an image. For example, the *Jaccard distance* (complement of *intersection over union*)

$$1 - \frac{\mu(A \cap B)}{\mu(A \cup B)} = \frac{\mu(A \triangle B)}{\mu(A \cup B)} \in [0, 1]$$

allows to compare two shapes $A, B \subset \mathbb{R}^d$ (e.g. bounding boxes) in a scale-invariant manner, where μ is a measure on $\mathbb{R}^d$ (see Figure 8.3).

8.2 Model evaluation

An important part of the Learning Assurance process described in the earlier chapters involves evaluating models $\hat{f}$ on datasets (training, validation, testing) with respect to the chosen metrics m. More specifically, the in-sample error averages

$$E_{\text{in}}(\hat{f}, D_{\text{train}}, m), \quad E_{\text{in}}(\hat{f}, D_{\text{val}}, m), \quad E_{\text{in}}(\hat{f}, D_{\text{test}}, m)$$

as defined in Chapter 5 will be computed to serve as approximations for the out-of-sample operational errors. The following paragraphs give a brief overview of risks to consider.

Software and hardware concerns An important requirement is that the evaluation software and hardware need to be qualified to ensure the correctness and faithfulness (with respect to the target hardware) of the evaluation results. See [ED-215/DO-330] on software tool qualification, and [EAS19] (mentioned in Section 7.2.2). Without this assurance, none of the learning guarantees would be valid.

Ideally, the evaluation should be run on the target system for representativity. However, this might not be possible if there is a very large amount of data to evaluate. In this case, it is important to demonstrate the equivalence of the target and evaluation systems.

Particular concerns arise if cloud computing is used (see Section 4.3), such as cybersecurity, data integrity, hardware qualification, etc. These are not addressed further in this report.

Beyond averages Recall that the errors evaluated (at least in the setting adopted therein) are averages over datapoints. However, an average only gives a partial view of the underlying data: an average equal to 1/2 might mean that all samples are equal to 1/2, or that half of them are equal to 1, the other half to 0. Obviously, these two cases would give a very different safety perspective, and it becomes clear that "average performance" alone is not sufficient. For example, Csurka et al. [CLP13] give an interesting analysis of the pitfalls of averaging in the case of semantic segmentation (a case of multiclass classification).

The discussion on the Safety Assessment (Chapter 9) will show how to pass from average statements to probabilistic guarantees about individual datapoints. In particular, this might require a deeper understanding of the distribution of the model errors.

More generally, the safety argument might necessitate more detailed evaluations than the averages above. In addition to providing averages, it is strongly recommended to include variances, higher moments, confidence intervals or maximally-observed error.

8.2.1 System evaluation

As already noted in Section 8.1.1, a machine learning component will likely be part of a larger (sub)system. Therefore, it is crucial to also evaluate the system as a whole, in particular to verify the correctness of the assumptions that might have been required to link model performance and system performance. This report will outline a possible safety analysis in the next chapter.

Chapter 9

Safety Assessment

The Safety Assessment process aims at showing compliance with certification requirements such as [CS-25]/[CS-27]/[CS-29].1309 or [CS-23]/[SC-VTOL-01].2510. This process is performed in parallel with the development, which is highlighted in details in [ARP4761, Figure 7] (Safety Assessment Process Model and the associated paragraph).

The goal of this chapter is to look at the Safety Assessment in the scope of safety-critical systems *involving a machine learning component*, in particular for the landing guidance use case defined in Chapter 4. It concludes with a quantitative neural network Failure Mode and Effect Analysis (FMEA), that shows how the theoretical results from Chapter 5 can lead to quantitative estimations of failure rates of machine learning systems.

9.1 Safety Assessment process

The Safety Assessment process contains the following analyses at each design iteration:

- *Functional Hazard Assessment* (FHA) evaluates the hazard associated to each aircraft and system and classifies them according to their severity.
- *Preliminary Aircraft Safety Assessment* (PASA) and *Preliminary System Safety Assessment* (PSSA) establish a set of aircraft and system safety requirements and the associated preliminary analysis that the aircraft and system architecture will meet these requirements. The PASA and PSSA are updated throughout the development process to become the *Aircraft Safety Assessment* (ASA) and *System Safety Assessments* (SSA) that supports the compliance demonstration of the final system.
- *Common Cause Analysis* (CCA). Safety analysis often relies on the assumption that failures are independent. Dedicated analyses are thus necessary to guarantee that independence is actually ensured. This is the purpose of the "common cause analysis" which is typically divided into three complementary studies. [AC23.1309-1E] is defining these analyses as per below:
  - *Zonal Safety Analysis* (ZSA) has the objective to ensure that the equipment installations per structural zone of the aircraft are at an adequate safety standard, with regard to design and installation standards, interference between systems, and maintenance errors.
  - *Particular Risk Analysis* (PRA). Particular risks are defined as those events or influences outside the systems concerned (e.g., fire, leaking fluids, bird strike, tire

burst, HIRF exposure, lightning, uncontained failure of high energy rotating machines, etc.). Each risk should be the subject of a specific study to examine and document the simultaneous or cascading effects, or influences, which may violate independence.

– *Common Mode Analysis* (CMA). This analysis is performed to confirm the assumed independence of the events that were considered in combination for a given failure condition. The effects of specification, design, implementation, installation, maintenance errors, manufacturing errors, environmental factors other than those already considered in the particular risk analysis and failures of system components should be taken into account.

With respect to the particular use case analyzed in this report (see Chapter 4):

- Section 9.2 below will provide the outline of a FHA.
- Some aspects of the CCA will be discussed in Section 9.4.
- No particular considerations related to the usage of machine learning have been identified for the ZSA and PRA. These analyses will therefore not be developed further herein.
- *The full report contained a quantitative FMEA for the neural network component in Section 9.5, which has been redacted for confidentiality reasons.*

9.2 Functional Hazard Assessment

A Functional Hazard Assessment is usually performed at the aircraft and system levels. The intent of the aircraft level analysis is to identify possible multiple system failures that would have a higher severity when analyzed in conjunction than when analyzed independently. In the scope of this report, only the system level analysis will be presented for the use cases under consideration, since it is not anticipated that the aircraft level analysis would bring additional insights.

A prerequisite to proceed with the functional hazard assessment is to identify all the functions of the level (aircraft or system) under assessment.

9.2.1 Reminders on the use case

Recall that, using a RGB camera mounted on the aircraft, the goal of the perception system described in Chapter 4 is to output at a given frequency:

1. the four points defining a runway in sight, where “in sight/visible” means “with an area larger than 1px^2 on the screen”. For the purposes of this analysis, when a runway is partially visible, it is considered visible and the corners are clipped to the screen.
2. a runway presence likelihood. A threshold can be fixed, and the condition “likelihood $\geq$ threshold” is interpreted as the presence (resp. absence) of runway in sight.

To do so, the system functions as follows:

1. (Sensing) At a given frequency, a RGB image is captured by the camera at a 5 megapixels resolution.

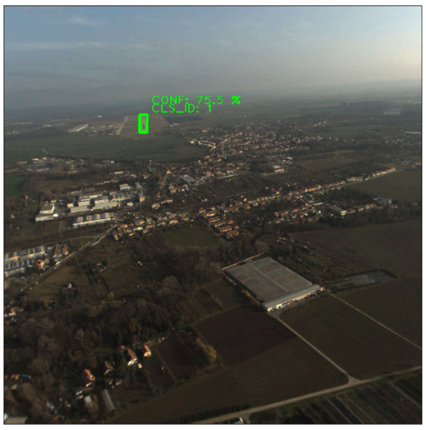


Figure 9.1: Example of system input and output: runway detected, with given confidence level.

2. (Pre-processing) The image is pre-processed to reduce its size to 512×512 pixels and to normalize its values (say, so that it has the same channel-wise mean and variance than images in the training set). The resulting space is denoted by $\mathcal{X}$ (with the right probability distribution).
3. (Neural network) The output of the previous step is processed by a convolutional neural network to output corner coordinates, as well as a confidence score. Given the operating conditions provided initially[1], there is a well-defined "ground truth" function, in the sense that the four corners of the runway can always be perfectly identified at the pixel level from images in $\mathcal{X}$.
4. (Post-processing/filtering) As the output of the neural network might contain errors or noise, the last step is to filter the predictions, eventually using information on the state of the aircraft.

Another system (using for example a global positioning system and terrain elevation data) could then use this output to compute the eventual runway corners in WGS84 coordinates and/or control commands to perform a landing, etc.

9.2.2 Functional analysis

In the ConOps example, for the four identified use cases, the following functional decomposition has been identified:

- F1: To land on a runway/vertiport.
  - F1.1: To detect the runway/vertiport position.
    This function is implemented through machine learning-based perception.
    - F1.1.1: To sense the aircraft's environment and provide the flight computer with an image of the environment.
    - F1.1.2: To pre-process the image.
    - F1.1.3: To detect the runway/vertiport position in a given image (neural network).

[1]In the scope of the ConOps, it is assumed in particular that there is at most one runway visible at all times and that the visibility is clear.

Hardware item	Allocated function
Optical sensor	F1.1.1, F2.1, F3.4
Processing unit — main processing	F1.1.2, F1.1.4, F1.2, F2.2, F2.4
	F3.1, F3.2, F3.3, F3.4, F3.5, F3.6
Processing unit — NN processing	F1.1.3, F2.3
Autopilot / Pilot	F4

Table 9.1: Functional allocation

    * F1.1.4: To track the target position.
  - F1.2: To compute the flight director order to the runway/vertiport.
    This function computes the flight director order to reach the runway/vertiport from the identified runway/vertiport position and aircraft parameters.

- F2: To monitor the system.
  - F2.1: To monitor sensors.
  - F2.2: To monitor internal databuses.
  - F2.3: To monitor the neural network behavior.
    This function is running independently from function F1.1.3 and monitors key characteristics of the neural network to determine whether its inputs and outputs remain in the defined boundaries and the neural network behavior is as intended.
  - F2.4: To monitor the flight computer.

- F3: To interface with the aircraft systems.
  - F3.1: to receive GPS data.
  - F3.2: to receive digital terrain elevation data.
  - F3.3: to receive phase of flight.
  - F3.4: to receive electrical power.
  - F3.5: to provide flight director data to the autopilot.
  - F3.6: to provide monitoring data to the avionics.

- F4: To track the flight director.
  This function is responsible for the aircraft tracking the flight director command. It sends commands to the flight control system such that the flight director command is tracked with a minimal error. It is either performed by the pilot itself (in use cases 1a, 2a) or by an autopilot system (use cases 1b, 2b).

9.2.3 Preliminary architecture

As a starting point for the use cases, the preliminary architecture in Figure 9.2 is considered.

It is assumed that two identical processing units are running in an active-standby configuration. Redundancy is deemed necessary on this basic configuration to ensure the availability of the system function at all times during operation.

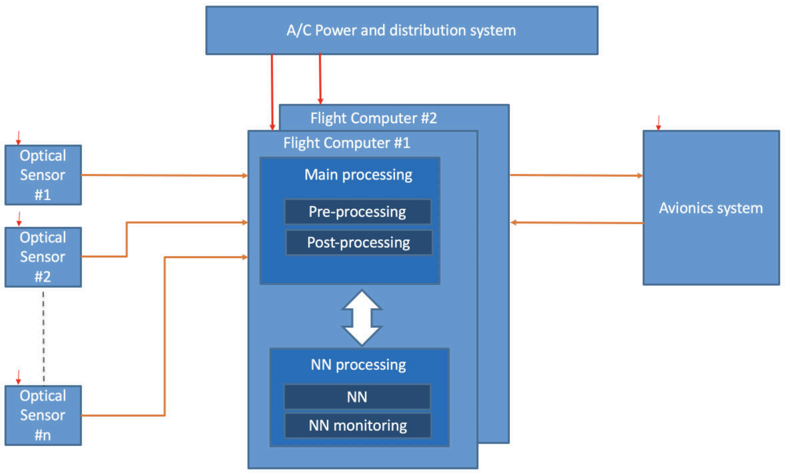


Figure 9.2: Preliminary system architecture.

Failure conditions list Once a functional analysis has been performed, various methodologies such as the one in [ARP4761, Appendix A] may be used to establish the list of failures conditions and associated classifications. Still, existing certification requirements and associated guidance material provide flexibility on the FHA process. The following key aspects were also discussed with EASA when reviewing the use case FHAs:

- Assessment of failure conditions at aircraft level.
  This assessment is expected to cover in particular handling qualities, performances, impact on structures and human factor. For the latter, particular attention shall be paid when failure condition severity is justified by assumptions made on human factor aspects (flight crew alert, AFM procedures, flight deck controls, . . .) and/or the need for a particular training such as CTASE (Candidate for Training Area of Special Emphasis). A process should be implemented to ensure that these assumptions are properly traced and checked during aircraft development. In view of the novelty of the machine learning application, this interface between the Safety Assessment process and human factor is likely to be subject to scrutiny by certification authorities.

- Validation of failure condition classification (e.g. is there an organized way to validate the classification?).

Beyond this area of interest, no further aspects compared to the Safety Assessment of conventional designs were identified for this step of the Safety Assessment process.

Table 9.3 lists some of the failure conditions that will be considered in the remainder of the report, with a proposed severity.

Additional assumption for this report In practice, the FHA would be analyzed in detail during the Preliminary System Safety Assessment (PSSA) to derive precise criteria defining the maximum errors and durations after which a function output is considered lost or misleading. This step is crucial for the design and safety teams, so that they can properly develop monitoring and filtering functions, and precisely characterize failure modes.

In the use case under consideration, to proceed with the Safety Assessment, it would not only be necessary to be able to establish the reliability of the detection algorithm on a given image but also the overall performance of the runway position detection on multiple frames for the approach duration. From the perspective of the safety analysis, what matters is not only the reliability of the machine learning model detection on a given image but also the overall reliability of the system achieved during the approach sequences.

ID	**Severity (FW) Use Case 1a/b**	**Severity (RW and VTOL) Use Case 2a/b**
FC1.1-1	MIN	MIN
FC1.1-2	MAJ	MAJ
FC1.1-3	MIN	MIN
FC1.1-4	HAZ	HAZ
FC1.1-5	HAZ	HAZ
FC1.1-6	HAZ	HAZ
FC2.1	HAZ	HAZ
FC2.2	HAZ	HAZ
FC2.3	CAT	CAT

- MIN = Minor Failure condition as defined in applicable guidance.
- MAJ = Major Failure condition as defined in applicable guidance.
- HAZ = Hazardous Failure condition as defined in applicable guidance.
- CAT = Catastrophic Failure condition as defined in applicable guidance.
  For example, an applicable guidance for VTOL is [SC-VTOL-01].2510.

Table 9.3: Failure conditions with their severities. Rows in white are related to use case 1a, 2a (advisory guidance provided to the pilot), rows in gray are related to use case 1b, 2b (Autonomous landing). *Details from the full report have been removed.*

To do that, one may have to determine upper level characteristics such as:

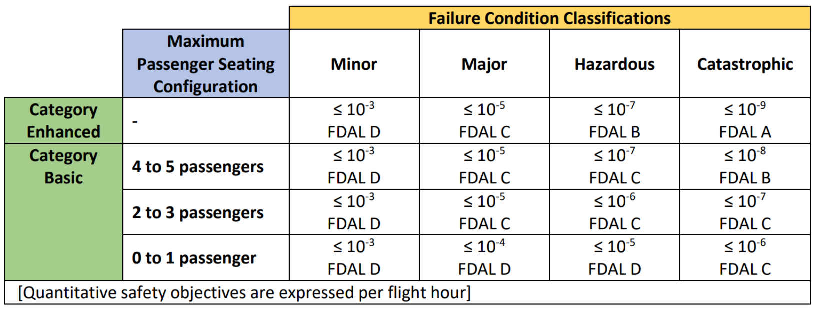
- the maximum duration for which a missed detection is acceptable;
- the maximum duration for which the guidance function can be lost;
- the maximum acceptable trajectory deviation.

This refinement of the FHA is typically done based on the ConOps, engineering judgment and possibly applicable Minimum Operational Performance Standard (MOPS) or Minimum Aviation System Performance Standard (MASPS). This step is not detailed in the report and is left for future work. The following discussions on improvements to the system architecture to be able to reach the safety objectives are therefore only qualitative.

9.2.4 Safety objectives definition

Safety objectives are allocated to each of the Failure Conditions (FC) identified in the FHA based on applicable certification guidances.

For example for Use Cases 2a and 2b, for the type of vehicle considered in the ConOps, allocation is done according to the first row of the table in Figure 9.3. The safety objective for Hazardous (respectively Catastrophic) failure conditions would be 10^{-7} per flight hour (resp. 10^{-9} per flight hour).



		Failure Condition Classifications			
	Maximum Passenger Seating Configuration	**Minor**	**Major**	**Hazardous**	**Catastrophic**
Category Enhanced	-	≤ 10^{-3} FDAL D	≤ 10^{-5} FDAL C	≤ 10^{-7} FDAL B	≤ 10^{-9} FDAL A
Category Basic	**4 to 5 passengers**	≤ 10^{-3} FDAL D	≤ 10^{-5} FDAL C	≤ 10^{-7} FDAL C	≤ 10^{-8} FDAL B
	2 to 3 passengers	≤ 10^{-3} FDAL D	≤ 10^{-5} FDAL C	≤ 10^{-6} FDAL C	≤ 10^{-7} FDAL C
	0 to 1 passenger	≤ 10^{-3} FDAL D	≤ 10^{-4} FDAL D	≤ 10^{-5} FDAL D	≤ 10^{-6} FDAL C
[Quantitative safety objectives are expressed per flight hour]					

Figure 9.3: Safety objective allocation table, [SC-VTOL-01] – AMC VTOL.2510. Quantitative safety objectives are expressed as probabilities per flight hour.

Additionally, beyond the above quantitative objectives, CAT failure conditions are also subject to qualitative requirements from [SC-VTOL-01].2510 or [AC23.1309-1E].1309 that requires that "*each catastrophic failure condition is extremely improbable and does not result from a single failure*".

This qualitative requirement ensures that at least two independent failures must occur before a catastrophic failure condition can develop. In practice, in the early stages of the system design, independence requirements will be generated through the PSSA to ensure that the system is designed according to this requirement. In the verification stage, a dedicated set of analyses (Common Cause Analyses, including a Common Mode Analysis) will be used to ensure that this qualitative requirement is achieved.

9.2.5 Architectural means to meet safety objectives

1. The Hazardous (HAZ) and Catastrophic (CAT) safety objectives identified in the above FHA are mostly associated with misoperation of the system function (i.e. the *integrity*

of the system function). These are for example FC1.3, 1.4, 2.2, 2.3. However, in some cases such as the autonomous landing use case, the loss of function is also critical (i.e. the *availability* of the system function; FC2.1).

Integrity and availability are two different aspects that may drive different architectural constraints:

- A Control/Monitor architecture is often used to guaranteeing the integrity of a function;
- The availability of a function is more likely to be achieved by having redundant independent instances of the system function running.

2. Function 1.1.3 — Detecting runway/vertiport in a given image (through a machine learning model) — is a direct contributor to some failure conditions classified as MAJ, HAZ, and CAT. This brings one of the first challenges in the introduction of machine learning as for severity higher than MAJ, quantitative demonstration is necessary.

   Indeed, for traditional airborne software functions, reliability of a given piece of software is not quantified per se: it is considered that since known Development Assurance methodologies such as [ED-12C/DO-178C] are used throughout, the risk of having an error resulting in a failure is minimized to an adequate level of confidence. The contribution of software components taken into account in the quantitative safety analysis is then usually limited to the reliability of the software function input parameters and to the reliability of the platform executing the software code. Assuming a reliability between 10^{-3} to 10^{-5} per hour is a classical hypothesis for platforms commonly used in the aerospace industry. This typically drives the need for duplex or even triplex implementations to meet safety objectives associated with HAZ or CAT failure conditions.

   However, beyond this first aspect, machine learning applications have a certain probability of misoperation due to their intrinsic nature. To reflect this particular aspect, based on considerations developed in Chapter 8, this report has been exploring the possibility to additionally derive failure rates for the machine learning model itself by performing a Failure Mode and Effect Analysis (FMEA) (see consideration developed in Section 9.5 below). The output of this FMEA is then fed into the quantitative analysis (e.g. Fault Tree Analysis) to demonstrate that each FC meets its quantitative objective.

   Based on Chapter 8 and Section 9.5 below, improving the performance of the machine learning model to reduce the probability of a faulty output is a task that requires a level of effort that grows with the desired level of performance.

To meet quantitative objectives associated to critical failure conditions such as Hazardous (10^{-7} per flight hour) or Catastrophic (10^{-9} per flight hour) with practical test set size and training time, it seems necessary to rely on system architecture mitigations, in particular by:

1. Having a *control/monitor architecture* which would improve system integrity. Considerations on runtime monitoring functions and associated assumptions have been provided in Section 6.6. This kind of architectural mitigation is typically expected to improve the system integrity at the detriment of its availability.

2. Relying on *post-processing* through a *tracking* of the runway position (F1.1.4) over several images. A post-processing tracking layer would be expected to improve the performance, availability, continuity, and integrity of the detection and guidance functions.

3. Having *different instances* of independent machine learning models running in parallel to both improve integrity and possibly availability (see Sections 6.3.3 and 9.4). For example, the probability that two systems, each with *independent* failure probability 10^{-5}, fail at the same time is only 10^{-10}.

4. Having the aircraft make short maneuvers during the approach to change runway/vertiport perception. This is not a system architecture change but rather a change in the operational concept. The maneuver would contribute to limit the risk of having the network making erroneous predictions, by forcing a different perception and thus a different image to be analyzed.

Provided that reliable performance monitoring and tracking algorithms can be implemented, this would allow breaking down the 10^{-9} per flight hour budget between several subfunctions (identification, monitoring, tracking).

During the design phase, through the Preliminary System Safety Assessment (PSSA):

- Independence requirements would be generated to ensure independence between these various subfunctions;
- Each subfunction would receive a safety requirement defining its contribution to the overall safety objectives. This contribution is expected to be on the order of 10^{-2} to 10^{-5} per flight hour, in which case it would be easier to achieve the safety objectives. Obviously, investigating further how these broken-down safety requirements can be achieved is one of the key aspects for future work.

9.3 DAL Assignment

The Development Assurance Level (DAL) assignment process is a top-down process described in [ED-79A/ARP4754A]. The Safety Assessment process assigns a DAL to the various components of the system.

For the application considered in this use case, the usual aircraft and system processes defined in [ED-79A/ARP4754A], in particular paragraph 5.2.3.2.2, were deemed relevant to allocate a Development Assurance Level.

Item Development Assurance Level (IDAL), allocation at item level, can be the reference point for the level of rigor of the Learning Assurance process.

Per the FHA above, for some of the use cases under consideration, Catastrophic failure conditions have been identified. Based on [ED-79A/ARP4754A, Table 3, note 1]:

> *"When a FFS has a single Member and the mitigation strategy for systematic errors is to be FDAL A alone, then the applicant may be required to substantiate that the development process for that Member has sufficient independent validation/verification activities, techniques and completion criteria to ensure that potential development error(s) having a catastrophic effect have been removed or mitigated."*

Certification agencies such as EASA have been exposed to occurrences of common mode errors on critical in-service systems. Even software or complex electronic hardware design developed to the highest level of design assurance (DAL A) by highly experienced teams could contain development errors that could cause simultaneous failures in redundant items.

Depending on the system under consideration, relying solely on the Development Assurance may not be deemed adequate and could justify the need for architectural mitigation. Likewise for machine learning Development Assurance, until proper field experience is gained, it is expected that for most critical applications, architectural mitigations are considered as part of the mitigation strategy for systematic errors.

The demonstration that the proposed architectural mitigations are sufficient is typically done by performing a Common Mode Analysis (CMA) early in the development phase. Early coordination with the certification agency on the conclusion of the CMA is advised.

9.4 Common Mode Analysis

The Common Mode Analysis should be initiated as soon as possible during the design phase to gain confidence that the identified independence requirements will actually be met by the architecture under consideration.

For instance, in the example given in Section 9.2.5, at least the following aspects should be considered:

- *Independence between processing and runtime monitoring.*
  Independence between control and monitoring functions is a classical aerospace design practice. Designing monitoring functions for a classical software application is a well-documented question. In the case of machine learning applications, the capability to probe the model behavior independently of its processing is one aspect that will need further evaluation. Performing a check of the statistical characteristics of the image used by the model to ensure that its characteristics match those of the design datasets is a first step. More advanced monitoring techniques could also be considered, such as the distribution discriminator introduced in Section 6.2.8.
- *Independence between the processing and the tracking algorithms.*
- *Independence between the various instances of the machine learning model.*
  If credit is taken from using independent neural networks, the first step could be to introduce during the design phase some dissimilarities in the key characteristics of the neural networks. This could be done by having:
  - Different architectures (number of layers, different loss function, etc.);
  - Independent/distinct datasets: coming from different sources, designed by different teams;
  - Different training software/hardware;
  - etc.

  In a second step, once independent models have been designed, dissimilarity between the outputs shall be verified through a statistical test to demonstrate the independence of their errors. See also Section 6.3.3 (multiple version dissimilarity).

9.5 Neural network Failure Mode and Effect Analysis (FMEA)

The original report contained a detailed quantitative FMEA for the neural network component of the use case, demonstrating how the theoretical results surveyed in Chapter 6 allow to obtain a reasonable failure probability per frame (given adequate error metrics and failure definitions).

The general strategy, which can be extended to other use cases, is the following:

1. Describe precisely the desired inputs and outputs of the system and the pre-/post-processing steps.
2. Identify the right metrics to evaluate the model performance and how these allow to reach the required system performance (see Section 8.1).

3. Understand and quantify generalization guarantees (see Chapter 5), either through the model complexity approach or through the validation/evaluation approach. This leads to guarantees for almost all datasets on average over all inputs.

4. Identify how guarantees on average translate to performance guarantees on each input (with respect to the chosen metrics), up to a controlled failure probability.

5. Analyze the post-processing system to show how it modifies the latter guarantees/failure probabilities. Usually, the post-processing allows to improve performance (with respect to the chosen metrics) and/or reduce the model failures.

6. Understand what performance guarantees (up to the chosen failure probability) follow from the sizes of the chosen datasets, the models, and their in-sample errors (with respect to the chosen metrics).

7. Study the elevated values of the error metrics for the model on the training/validation (eventually testing) datasets, and develop adequate external mitigations such as those discussed in Sections 9.2.5 and 9.4 (monitoring, tracking, etc.). This will allow to prevent errors from exponentially accumulating over time. For example, one could try to characterize properties of inputs triggering erroneous outputs.

For the use case described in this report, following the quantitative analysis above yields results that show the feasibility of guaranteeing safety for neural networks at the appropriate levels of criticality.

The remainder of this section has been redacted for confidentiality reasons.

Chapter 10

Use case: Learning Assurance

For this chapter, the full report included more concrete guidance on following the Learning Assurance concepts from Chapter 6 in the context of the specific use case from Chapter 4 and the Safety Assessment from Chapter 9. It described details for a selection of activities required to build safety-critical machine learning systems.

Chapter 11

Conclusion & future work

This project constituted a first major step in the definition of the "Learning Assurance" process, which is a key building-block of the "AI trustworthiness framework" introduced in the EASA AI Roadmap 1.0 [EAS20]. Consequently, this is an enabler towards the certification and approval of machine learning applications in safety-critical applications.

EASA greatly appreciated technical inputs and investigations from the Daedalean team which allowed opening promising directions for several key elements of the "Learning Assurance" concept.

To summarize the findings made by the EASA and Daedalean teams, the following revisits the challenges from the EASA AI Roadmap that are listed in Chapter 2 (Introduction) and describes how they were covered in this report:

Traditional Development Assurance frameworks are not adapted to machine learning The concepts of Learning Assurance are formulated in Chapter 6 to provide extensions to traditional Development Assurance. In this respect, the definition of the W-shaped Learning Assurance life-cycle (see Figure 6.1) provides an outline of the essential steps for Learning Assurance and their connection with traditional Development Assurance processes.

Difficulties in keeping a comprehensive description of the intended function This report argued that higher-level system and software requirements are derived with traditional means to capture the intended functionality of the system. Then, the concepts outlined in this report advocate a shift from Development Assurance to Learning Assurance. For this purpose, the report put a dedicated focus on the data lifecycle management, introducing a set of guidelines on data quality management and in particular the use of a distribution discriminator to ensure an evaluation of the completeness of the datasets. Fulfilling the dataset requirements from Section 6.2 is a key element to ensure that the higher-level requirements are satisfied for the intended functionality.

Lack of predictability and explainability of the ML application behavior The concept of "generalizability" was introduced in Section 5.3 as a means of obtaining theoretical guarantees on the expected behavior of machine learning-based systems during operation. Together with "data management", introduced in Section 6.2, this allows to obtain such guarantees from the performance of a model during the design phase. The topic of "explainability" was left for future work.

Lack of guarantee of robustness and of no "unintended function" The report identified two types of robustness to investigate: algorithm robustness and model robustness (see Section 6.4.1). The former measures how robust the learning algorithm is to changes in the underlying training dataset. The latter quantifies a trained model's robustness to input perturbations (e.g. viewpoint changes, adversarial attacks). Section 6.6.2 provided more examples of perturbations and "randomness" that the system can encounter during operation. Both types of robustness are discussed in Section 6.4, which also covered aspects of "unintended functions". More specific examples are included in Chapter 10.

Lack of standardized methods for evaluating the operational performance of the ML/DL applications This aspect is addressed in several sections throughout the report. Section 5.2 introduced the general ideas of in- and out-of-sample errors which were used to describe the generalization gap. Chapter 8 discussed the choice of metrics and how to measure model performances during both design and operational phases in detail.

Issue of bias and variance in ML applications Bias and variance must be addressed on two levels. First, bias and variance inherent to the datasets need to be captured and eliminated. This was discussed as part of the data quality characteristics in Section 6.2.2, specifically the requirements on the completeness and distribution of the datasets. See Section 6.2.8 for details on the latter. Second, model bias and variance need to be analyzed and the associated risks be taken into account. This was covered in Section 5.3.2. Examples for both are included in Chapter 10.

Complexity of architectures and algorithms This work considered convolutional neural network architectures as described in Section 4.2. Convolutional neural networks (CNNs) were chosen for two reasons: 1) they are complex architectures that allow for in-depth analyses of many common aspects and difficulties associated with modern machine learning systems; 2) they are ubiquitously used in computer vision applications and beyond. A generic discussion of learning algorithms was included in Chapter 5 with more concrete examples in Chapter 10.

Adaptive learning processes Following from the definition of adaptive learning in Section 2.6, Section 4.2 described a system architecture which is non-adaptive (i.e. does not learn) during operation. This architecture was used for subsequent analyses which therefore assume that the model behavior is frozen and baselined (i.e. does not change anymore) once the design phase has been completed.

While most of the concepts outlined in this report apply to machine learning more generally, it is important to note that the details of any such analyses are highly dependent on the specific applications, techniques, and methodologies used.

As can be seen above, many of the major challenges and risks associated with machine learning systems in safety-critical applications were discussed. They were addressed with certain assumptions and based on a specific use case. The next step for EASA will be to generalize, abstract, and complement these promising guidelines, in order to outline a first set of applicable *guidance* for safety-critical machine learning applications.

In addition, a set of future work streams have been left aside in this report and are highlighted in the following section.

Future work

To further prepare machine learning systems for future certification, additional aspects need to be addressed.

This report focused merely on the training phase and did not push the barriers of the implementation and inference phase verifications. In particular, risks associated with various types of training frameworks (e.g. cloud computing) and of inference platforms, especially hardware accelerators specific to the highly parallel execution of deep neural networks (GPUs, FPGAs, etc.) were not investigated further.

Furthermore, the different types of changes that can be made to a model after certification and deployment were not discussed in detail in this report and need to be analyzed more elaborately.

The proportionality of the framework has not been investigated as part of this report as it will require the complete set of guidance elements to be defined before assessing adequate criteria and levels of proportionality towards the definition of a risk-based assurance framework.

The idea of adaptive learning was not covered in this report. Despite the popularity of the term in the industry, it was considered that it would add significant complexity and that it is not absolutely necessary for a general first use of machine learning systems in aviation. In case there is future interest to make use of adaptive learning, this topic needs specific attention, as well.

Finally, this work only focused on non-recurrent convolutional neural networks, which are suitable for a wide range of computer vision applications. At the same time, the machine learning community produces novel neural network architectures at an outstanding pace. It is almost certain that new architectures which can improve the performance of systems described in this document will appear. For this reason, the report was intentionally kept at a level that is generic enough to hopefully apply to future developments in the machine learning community, too. Yet, any new architecture and similarly any new application deserve careful analysis to mitigate the risks associated with their specific design choices and intended functionality.

References

[AC23.1309-1E] FAA. *Advisory Circular AC23.1309-1E : System Safety Analysis and Assessment for Part 23 Airplanes*. Standard. Nov. 2011.

[Aki+19] Michael E. Akintunde, Andreea Kevorchian, Alessio Lomuscio, and Edoardo Pirovano. "Verification of RNN-Based Neural Agent-Environment Systems". In: *The Thirty-Third AAAI Conference on Artificial Intelligence*. 2019, pp. 6006–6013.

[Aro+18] Sanjeev Arora, Rong Ge, Behnam Neyshabur, and Yi Zhang. "Stronger generalization bounds for deep nets via a compression approach". In: *35th International Conference on Machine Learning (ICML)*. Ed. by Andreas Krause and Jennifer Dy. International Machine Learning Society (IMLS), 2018, pp. 390–418.

[ARP4761] *ARP-4761, Guidelines and Methods for Conducting the Safety Assessment Process on Civil Airborne Systems and Equipment*. Standard. ARP, Dec. 1996.

[Bar+19] Peter L. Bartlett, Nick Harvey, Christopher Liaw, and Abbas Mehrabian. "Nearly-tight VC-dimension and Pseudodimension Bounds for Piecewise Linear Neural Networks". In: *Journal of Machine Learning Research* 20.63 (2019), pp. 1–17.

[BFT17] Peter L. Bartlett, Dylan J. Foster, and Matus J. Telgarsky. "Spectrally-normalized margin bounds for neural networks". In: *Advances in Neural Information Processing Systems*. 2017, pp. 6240–6249.

[BM03] Peter L. Bartlett and Shahar Mendelson. "Rademacher and Gaussian Complexities: Risk Bounds and Structural Results". In: *Journal of Machine Learnnig Research* 3 (2003), pp. 463–482.

[CC77] P. Cousot and R. Cousot. "Abstract interpretation: a unified lattice model for static analysis of programs by construction or approximation of fixpoints". In: *Conference Record of the Fourth Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages*. 1977, pp. 238–252.

[CH67] Thomas Cover and Peter Hart. "Nearest neighbor pattern classification". In: *IEEE transactions on information theory* 13.1 (1967), pp. 21–27.

[Che+17] Yi-Hsin Chen et al. "No More Discrimination: Cross City Adaptation of Road Scene Segmenters". In: *2017 IEEE International Conference on Computer Vision (ICCV)*. Venice, Italy, 2017.

[Che+18]	Y. Cheng, D. Wang, P. Zhou, and T. Zhang. "Model Compression and Acceleration for Deep Neural Networks: The Principles, Progress, and Challenges". In: *IEEE Signal Processing Magazine* 35.1 (Jan. 2018), pp. 126–136.
[CIFAR10]	Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton. *CIFAR-10 (Canadian Institute for Advanced Research)*. 2009.
[CLP13]	Gabriela Csurka, Diane Larlus, and Florent Perronnin. "What is a good evaluation measure for semantic segmentation?" In: *Proceedings of the British Machine Vision Conference*. BMVA Press, 2013.
[Cor+16]	Marius Cordts et al. "The Cityscapes Dataset for Semantic Urban Scene Understanding". In: *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Las Vegas, Nevada, USA, 2016.
[CS-23]	EASA. *Certification Specification for Normal, Utility, Aerobatic, and Commuter Category Aeroplanes*. Standard. Amendment 5. Mar. 2017.
[CS-25]	EASA. *Certification Specifications for Large Aeroplanes*. Standard. Amendment 24. Jan. 2020.
[CS-27]	EASA. *Certification Specifications and Acceptable Means of Compliance for Small Rotorcraft*. Standard. Amendment 6. Dec. 2019.
[CS-29]	EASA. *Certification Specifications for Large Rotorcraft*. Standard. Amendment 7. July 2019.
[DD09]	Armen Der Kiureghian and Ove Ditlevsen. "Aleatory or epistemic? Does it matter?" In: *Structural Safety* 31.2 (2009), pp. 105–112.
[DDS19]	Tommaso Dreossi, Alexandre Donzé, and Sanjit A. Seshia. "Compositional Falsification of Cyber-Physical Systems with Machine Learning Components". In: *Journal of Automated Reasoning* 63.4 (2019), pp. 1031–1053.
[DR17]	Gintare Karolina Dziugaite and Daniel M. Roy. "Computing Nonvacuous Generalization Bounds for Deep (Stochastic) Neural Networks with Many More Parameters than Training Data". In: *Proceedings of the Thirty-Third Conference on Uncertainty in Artificial Intelligence, UAI 2017, Sydney, Australia, August 11-15, 2017*. 2017.
[EAS19]	EASA. *EASA Generic Means of Compliance Certification Review Item (MOC CRI): Certification credit for Simulator and Rig Testing*. Tech. rep. 2019.
[EAS20]	EASA. *Artificial Intelligence Roadmap: A human-centric approach to AI in aviation*. Tech. rep. Feb. 2020. URL: `https://www.easa.europa.eu/sites/default/files/dfu/EASA-AI-Roadmap-v1.0.pdf`.
[ED-128/DO-331]	*ED-128/DO-331, Model-based development and verification, supplement to ED-12C/DO-178C and ED-109A/DO-278A*. Standard. EUROCAE/RTCA, Dec. 2011.
[ED-12C/DO-178C]	*ED-12C/DO-178C, Software Considerations in Airborne Systems and Equipment Certification*. Standard. EUROCAE/RTCA, Jan. 2011.
[ED-215/DO-330]	*ED-215/DO-330, Software Tool Qualification Considerations*. Standard. EUROCAE/RTCA, Dec. 2011.
[ED-216/DO-333]	*ED-216/DO-333, Formal Methods, Supplement to DO-178C and DO-278A*. Standard. EUROCAE/RTCA, Dec. 2011.

[ED-217/DO-332]	*ED-217/DO-332, Object-Oriented Technology and Related Techniques, Supplement to ED-12C/DO-178C and ED-109A/DO-278A*. Standard. EUROCAE/RTCA, Dec. 2011.
[ED-76A/DO-200B]	*ED-76A/DO-200B: Standards for Processing Aeronautical Data*. Standard. EUROCAE/RTCA, June 2015.
[ED-79A/ARP4754A]	*ED-79A/ARP4754A: Guidelines for Development of Civil Aircraft and Systems*. Standard. EUROCAE/RTCA, Dec. 2010.
[ED-80/DO-254]	*ED-80/DO-254, Design Assurance Guidance for Airborne Electronic Hardware*. Standard. EUROCAE/RTCA, Apr. 2000.
[Efr79]	Bradley Efron. "Bootstrap Methods: Another Look at the Jackknife". In: *The Annals of Statistics* 7.1 (Jan. 1979), pp. 1–26.
[Efr82]	Bradley Efron. *The jackknife, the bootstrap, and other resampling plans*. Vol. 38. Siam, 1982.
[EGTA]	*Ethics and Guidelines on Trustworthy AI*. Tech. rep. European Commission's High-Level Expert Group on Artificial Intelligence, Apr. 2019.
[ESL]	Trevor Hastie, Robert Tibshirani, and Jerome Friedman. *The Elements of Statistical Learning*. Springer Series in Statistics. Springer, 2001.
[F3269-17]	*F3269-17, Standard Practice for Methods to Safely Bound Flight Behavior of Unmanned Aircraft Systems Containing Complex Functions*. Standard. ASTFM, Sept. 2017.
[FDA19]	*Proposed Regulatory Framework for Modifications to Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD) - Discussion Paper and Request for Feedback*. Tech. rep. The U.S. Food and Drug Administration, Apr. 2019.
[FS10]	George Forman and Martin Scholz. "Apples-to-apples in cross-validation studies: pitfalls in classifier performance measurement". In: *ACM SIGKDD Explorations Newsletter* 12.1 (2010), pp. 49–57.
[Gai+16]	A. Gaidon, Q. Wang, Y. Cabon, and E. Vig. "VirtualWorlds as Proxy for Multi-object Tracking Analysis". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Las Vegas, Nevada, USA, 2016, pp. 4340–4349.
[Gat19]	Marc Gatti. *AVSI AFE 87 Machine Learning: Development Assurance of Machine Learning Systems*. EUROCAE 2019 Symposium & 56th General Assembly, Toulouse, France. Thales Avionics. Apr. 2019. URL: https://www.eurocae.net/media/1587/2019-eurocae-symposium_presentations_final.pdf.
[GDPR]	*General Data Protection Regulation (EU)*. 2016/679. European Parliament and Council, Apr. 2016.
[Gir+14]	Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. "Rich feature hierarchies for accurate object detection and semantic segmentation". In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Columbus, Ohio, USA, 2014, pp. 580–587.
[GL15]	Yaroslav Ganin and Victor Lempitsky. "Unsupervised Domain Adaptation by Backpropagation". In: *Proceedings of the 32nd International Conference on International Conference on Machine Learning*. Vol. 37. Lille, France, 2015, pp. 1180–1189.

[Gul+16] Varun Gulshan et al. "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs". In: *JAMA* 316.22 (Dec. 2016), pp. 2402–2410.

[Guo+17] Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q Weinberger. "On calibration of modern neural networks". In: *Proceedings of the 34th International Conference on Machine Learning*. Vol. 70. 2017, pp. 1321–1330.

[Han+16] A. Handa, V. Patraucean, V. Badrinarayanan, S. Stent, and R. Cipolla. "Understanding RealWorld Indoor Scenes with Synthetic Data". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2016, pp. 4077–4085.

[He+17] K. He, G. Gkioxari, P. Dollár, and R. Girshick. "Mask R-CNN". In: *2017 IEEE International Conference on Computer Vision (ICCV)*. Venice, Italy, 2017, pp. 2980–2988.

[HG17] Dan Hendrycks and Kevin Gimpel. "A Baseline for Detecting Misclassified and Out-of-Distribution Examples in Neural Networks". In: *International Conference on Learning Representations (ICLR)*. 2017.

[HGD19] Kaiming He, Ross Girshick, and Piotr Dollár. "Rethinking ImageNet pre-training". In: *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Long Beach, California, USA, 2019.

[Hof+16] Judy Hoffman, Dequan Wang, Fisher Yu, and Trevor Darrell. "FCNs in the Wild: Pixel-level Adversarial and Constraint-based Adaptation". Unpublished, https://arxiv.org/abs/1612.02649. 2016.

[Hua+17] Xiaowei Huang, Marta Kwiatkowska, Sen Wang, and Min Wu. "Safety Verification of Deep Neural Networks". In: *Computer Aided Verification - 29th International Conference*. Vol. 2. Heidelberg, Germany, 2017, pp. 3–29.

[Hub+12] Catherine Huber-Carol, Narayanaswamy Balakrishnan, M Nikulin, and M Mesbah. *Goodness-of-fit tests and model validity*. Springer, 2012.

[ImageNet] Olga Russakovsky et al. "ImageNet Large Scale Visual Recognition Challenge". In: *International Journal of Computer Vision (IJCV)* 115.3 (2015), pp. 211–252.

[JGR19] Daniel Jakubovitz, Raja Giryes, and Miguel R. D. Rodrigues. "Generalization Error in Deep Learning". In: *Compressed Sensing and Its Applications: Third International MATHEON Conference 2017*. Ed. by Holger Boche et al. Cham: Springer, 2019, pp. 153–193.

[Jia+19] Yiding Jiang, Dilip Krishnan, Hossein Mobahi, and Samy Bengio. "Predicting the Generalization Gap in Deep Networks with Margin Distributions". In: *7th International Conference on Learning Representations (ICLR)*. New Orleans, LA, USA, 2019.

[Kat+17] Guy Katz, Clark W. Barrett, David L. Dill, and Kyle Julian andMykel J. Kochenderfer. "Reluplex: An Efficient SMT Solver for Verifying Deep Neural Networks". In: *Computer Aided Verification - 29th International Conference*. Vol. 1. Heidelberg, Germany, 2017, pp. 97–117.

[KKB19] P. Koopman, A. Kane, and J. Black. "Credible Autonomy Safety Argumentation". In: *Safety-Critical Systems Symposium*. 2019.

[Kor+19] Simon Kornblith, Mohammad Norouzi, Honglak Lee, and Geoffrey Hinton. "Similarity of neural network representations revisited". In: *Proceedings of the 36th International Conference on Machine Learning (ICML)*. Long Beach, California, USA, 2019.

[KSW15] Durk P Kingma, Tim Salimans, and Max Welling. "Variational Dropout and the Local Reparameterization Trick". In: *Advances in Neural Information Processing Systems 28*. Ed. by C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett. Curran Associates, Inc., 2015, pp. 2575–2583.

[LBH15] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. "Deep learning". In: *Nature* 521 (2015).

[Leo+18] Francesco Leofante, Nina Narodytska, Luca Pulina, and Armando Tacchella. "Automated Verification of Neural Networks: Advances, Challenges and Perspectives". Unpublished, arXiv:1805.09938. 2018.

[LFD] Yaser S. Abu-Mostafa, Malik Magdon-Ismail, and Hsuan-Tien Lin. *Learning From Data*. AMLBook, 2012.

[LG19] Andrew K. Lampinen and Surya Ganguli. "An analytic theory of generalization dynamics and transfer learning in deep linear networks". In: *International Conference on Learning Representations (ICLR)*. New Orleans, Louisiana, USA, 2019.

[Liu+16] Wei Liu et al. "SSD: Single Shot MultiBox Detector". In: *Proceedings of the European Conference on Computer Vision (ECCV)*. Amsterdam, Netherlands, 2016.

[Liu+19] Changliu Liu, Tomer Arnon, Christopher Lazarus, Clark Barrett, and Mykel J. Kochenderfer. "Algorithms for Verifying Deep Neural Networks". In: *International Conference on Learning Representations (ICLR)*. New Orleans, Lousiana, USA, 2019.

[LLS18] Shiyu Liang, Yixuan Li, and Rayadurgam Srikant. "Enhancing the reliability of out-of-distribution image detection in neural networks". In: *International Conference on Learning Representations (ICLR)*. Vancouver, Canada, 2018.

[LPB17] Balaji Lakshminarayanan, Alexander Pritzel, and Charles Blundell. "Simple and scalable predictive uncertainty estimation using deep ensembles". In: *Advances in Neural Information Processing Systems*. 2017, pp. 6402–6413.

[Luo+19] Ping Luo, Xinjiang Wang, Wenqi Shao, and Zhanglin Peng. "Towards understanding regularization in batch normalization". In: *7th International Conference on Learning Representations (ICLR)*. New Orleans, USA, 2019.

[LW86] Nick Littlestone and Manfred K. Warmuth. "Relating Data Compression and Learnability". Unpublished, https://users.soe.ucsc.edu/~manfred/pubs/lrnk-olivier.pdf. 1986.

[McA03] David A. McAllester. "PAC-Bayesian Stochastic Model Selection". In: *Machine Learning* 51.1 (2003), pp. 5–21.

[Pei+17] Kexin Pei, Yinzhi Cao, Junfeng Yang, and Suman Jana. "DeepXplore: Automated Whitebox Testing of Deep Learning Systems". In: *Proceedings of the 26th Symposium on Operating Systems Principles*. Shanghai, China, 2017, pp. 1–18.

[Pen+15] X. Peng, B. Sun, K. Ali, and K. Saenko. "Learning Deep Object Detectors from 3D Models". In: *2015 IEEE International Conference on Computer Vision (ICCV)*. Araucano Park, Las Condes, Chile, 2015, pp. 1278–1286.

[Pim+14] Marco A.F. Pimentel, David A. Clifton, Lei Clifton, and Lionel Tarassenko. "A review of novelty detection". In: *Signal Processing* 99 (2014), pp. 215–249.

[PY09] Sinno Jialin Pan and Qiang Yang. "A survey on transfer learning". In: *IEEE Transactions on knowledge and data engineering* 22.10 (2009), pp. 1345–1359.

[Rag+19] Maithra Raghu, Chiyuan Zhang, Jon M. Kleinberg, and Samy Bengio. "Transfusion: Understanding Transfer Learning for Medical Imaging". In: *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019*. Vancouver, BC, Canada, 2019, pp. 3342–3352.

[Ren+15] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". In: *Advances in Neural Information Processing Systems 28*. Ed. by C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett. 2015, pp. 91–99.

[ResNet] K. He, X. Zhang, S. Ren, and J. Sun. "Deep Residual Learning for Image Recognition". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Las Vegas, Nevada, USA, 2016, pp. 770–778.

[Ric+16] Stephan R. Richter, Vibhav Vineet, Stefan Roth, and Vladlen Koltun. "Playing for Data: Ground Truth from Computer Games". In: *European Conference on Computer Vision (ECCV)*. Ed. by Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling. Vol. 9906. LNCS. Amsterdam, Netherlands: Springer, 2016, pp. 102–118.

[SaFAD19] Aptiv, Audi, Baidu Apollo, BMW, Continental, Daimler, FCA Group, Here, Infineon, Intel, Volkswagen. *Safety first for automated driving*. Tech. rep. June 2019. URL: https://www.daimler.com/innovation/case/autonomous/safety-first-for-automated-driving-2.html.

[SC-VTOL-01] EASA. *Special Condition for small-category VTOL aircraft*. Standard. July 2019.

[SCSC-127C] *SCSC-127C: Data Safety Guidance*. Tech. rep. The Data Safety Initiative Working Group, Jan. 2018.

[Scu+14] D. Sculley et al. "Machine Learning: The High Interest Credit Card of Technical Debt". In: *SE4ML: Software Engineering for Machine Learning (NIPS 2014 Workshop)*. Montreal, Canada, 2014.

[Shr+17] A. Shrivastava et al. "Learning from Simulated and Unsupervised Images through Adversarial Training". In: *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Honolulu, Hawaii, USA, 2017, pp. 2242–2251.

[Sil+12] Nathan Silberman, Derek Hoiem, Pushmeet Kohli, and Rob Fergus. "Indoor segmentation and support inference from RGBD images". In: *European Conference on Computer Vision (ECCV)*. Springer. Munich, Germany, 2012, pp. 746–760.

[Sin+18] Gagandeep Singh, Timon Gehr, Matthew Mirman, Markus Püschel, and Martin Vechev. "Fast and Effective Robustness Certification". In: *Proceedings of the 32nd International Conference on Neural Information Processing Systems (NeurIPS)*. Montreal, Canada, 2018, pp. 10825–10836.

[SK19] Connor Shorten and Taghi M. Khoshgoftaar. "A survey on Image Data Augmentation for Deep Learning". In: *Journal of Big Data* 6.1 (2019), p. 60.

[SKS19] Xiaowu Sun, Haitham Khedr, and Yasser Shoukry. "Formal Verification of Neural Network Controlled Autonomous Systems". In: *Proceedings of the 22nd ACM International Conference on Hybrid Systems: Computation and Control*. Montreal, Quebec, Canada: ACM, 2019, pp. 147–156.

[SL09] Marina Sokolova and Guy Lapalme. "A systematic analysis of performance measures for classification tasks". In: *Information processing & management* 45.4 (2009), pp. 427–437.

[Sri+14] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. "Dropout: a simple way to prevent neural networks from overfitting". In: *Journal of Machine Learning Research* 15.1 (2014), pp. 1929–1958.

[SS14] Baochen Sun and Kate Saenko. "From Virtual to Reality: Fast Adaptation of Virtual Object Detectors to Real Domains". In: *Proceedings of the British Machine Vision Conference*. Nottingham, United Kingdom: BMVA Press, 2014.

[TC-16/4] *DOT/FAA/TC-16/4: Verification of Adaptive Systems*. Report. The U.S. Federal Aviation Administration, Apr. 2016.

[Tia+18] Yuchi Tian, Kexin Pei, Suman Jana, and Baishakhi Ray. "DeepTest: Automated Testing of Deep-neural-network-driven Autonomous Cars". In: *Proceedings of the 40th International Conference on Software Engineering (ICSE)*. Gothenburg, Sweden, 2018, pp. 303–314.

[UL-4600] Edge Case Research Inc. "UL-4600: Standard for Safety for the Evaluation of Autonomous Products". Work in progress. 2019.

[VC71] V. N. Vapnik and A. Ya. Chervonenkis. "On the Uniform Convergence of Relative Frequencies of Events to their Probabilities". In: *Theory of Probability and its Applications* 16 (1971), pp. 264–280.

[Wan+18] Shiqi Wang, Kexin Pei, Justin Whitehouse, Junfeng Yang, and Suman Jana. "Formal Security Analysis of Neural Networks Using Symbolic Intervals". In: *Proceedings of the 27th USENIX Conference on Security Symposium (SEC)*. SEC'18. Berkeley, California, USA, 2018, pp. 1599–1614.

[WD18] Mei Wang and Weihong Deng. "Deep visual domain adaptation: A survey". In: *Neurocomputing* 312 (2018), pp. 135–153.

[WWB20] Yu Wang, Gu-Yeon Wei, and David Brooks. “A Systematic Methodology for Analysis of Deep Learning Hardware and Software Platforms”. In: *Proceedings of Machine Learning and Systems 2020*. Austin, Texas, USA, 2020, pp. 30–43.

[XTJ18] Weiming Xiang, Hoang-Dung Tran, and Taylor T. Johnson. “Output Reachable Set Estimation and Verification for Multilayer Neural Networks”. In: *IEEE Transansactions on Neural Networks and Learning Systems* 29.11 (2018), pp. 5777–5783.

[Zha+17] Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, and Oriol Vinyals. “Understanding deep learning requires rethinking generalization”. In: *5th International Conference on Learning Representations (ICLR)*. Toulon, France, 2017.

[Zha+18a] Yiheng Zhang, Zhaofan Qiu, Ting Yao, Dong Liu, and Tao Mei. “Fully Convolutional Adaptation Networks for Semantic Segmentation”. In: *2018 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2018.

[Zha+18b] Zhenya Zhang, Gidon Ernst, Sean Sedwards, Paolo Arcaini, and Ichiro Hasuo. “Two-Layered Falsification of Hybrid Systems Guided by Monte Carlo Tree Search”. In: *IEEE Transansactions on CAD of Integrated Circuits and Systems* 37.11 (2018), pp. 2894–2905.

[Zho+19] Wenda Zhou, Victor Veitch, Morgane Austern, Ryan P. Adams, and Peter Orbanz. “Non-Vacuous Generalization Bounds at the ImageNet Scale: A PAC-Bayesian Compression Approach”. In: *International Conference on Learning Representations (ICLR)*. New Orleans, Louisiana, USA, 2019.

[Zho12] Zhi-Hua Zhou. *Ensemble Methods: Foundations and Algorithms*. Chapman & Hall/CRC, 2012.

Notations

D_{test}	Test dataset	p. 30
D_{train}	Training dataset	p. 28
D_{val}	Validation dataset	p. 29
$E_{\text{in}}(\hat{f}, D_{\text{test}}, m)$	Testing error	p. 31
$E_{\text{in}}(\hat{f}, D_{\text{train}}, m)$	In-sample error	p. 31
$E_{\text{in}}(\hat{f}, D_{\text{val}}, m)$	Validation error	p. 31
$E_{\text{out}}(\mathcal{F}, m, n)$	Average out-of-sample error	p. 31
$E_{\text{out}}(\mathcal{F}, m, n)$	Out-of-sample error (over datasets of size n)	p. 31
$E_{\text{out}}(\hat{f}, m)$	Out-of-sample error	p. 31
X	Input space (as a set)	p. 28
Y	Output (prediction) space	p. 28
CE	Cross-entropy	p. 29
$\mathbb{E}$	Expected value of a random variable	p. 31
$\mathcal{F}$	Learning algorithm *or* hypothesis space	p. 28
$\mathcal{X}$	Input (probability) space	p. 30
$\text{bias}(\mathcal{F}, n)$	Bias	p. 34
$\hat{f}^{(D_{\text{train}})}$	Trained model	p. 29
$\text{var}(X)$	Variance of a random variable	p. 34
$\text{var}(\mathcal{F}, n)$	Variance of a learning algorithm	p. 34
d_{vc}	VC-dimension	p. 38
f	True (unknown) function to approximate	p. 28
$m(y_1, y_2)$	Metric evaluated on two predictions	p. 29
$x \in X$	Input datapoint	p. 28
$x \sim \mathcal{X}$	Sample from a probability space	p. 31
$y \in Y$	Output prediction	p. 28

Index

Acronyms

Above Ground Level (AGL) 23
Acceptable Means of Compliance (AMC) 13
Aircraft Safety Assessment (ASA) 77
Application-Specific Integrated Circuit (ASIC) 26
Artificial Intelligence (AI) 10

Candidate for Training Area of Special Emphasis (CTASE) 81
Common Cause Analysis (CCA) 77
Common Mode Analysis (CMA) 78
Convolutional Neural Network (CNN) 11

Development Assurance Level (DAL) 85

Ethics and Guidelines on Trustworthy AI (EGTA) 13
European Union Aviation Safety Agency (EASA) 9

Failure Condition (FC) 83
Failure Mode and Effect Analysis (FMEA) 77
Federal Aviation Administration (FAA) 19
Field-Programmable Gate Array (FPGA) 26
Functional Development Assurance Level (FDAL) 16
Functional Hazard Assessment (FHA) 77

Graphics Processing Unit (GPU) 25
Guidance Material (GM) 13

Innovation Partnership Contract (IPC) 9
Instrument Landing System (ILS) 22
Item Development Assurance Level (IDAL) 85

Kullback–Leibler divergence (KL) 39

Machine Learning (ML) 10

Neural Network (NN) 10

Parameter Data Item (PDI) 20
Particular Risk Analysis (PRA) 77
Plan for Learning Aspects of Certification (PLAC) 62
Preliminary Aircraft Safety Assessment (PASA) 77
Preliminary System Safety Assessment (PSSA) 77
Probably Approximately Correct (PAC) 38