Algorithmic Perspectives on the Certification of Machine Learning

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Outline

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Properties and AI Regulations

- trained on WPAFB 2009 dataset [12]: The images were taken by a camera system with six optical sensors that had already been stitched to cover a wide area of around 35km^2. Image size: 12,000×10,000. The frame rate is 1.25Hz.

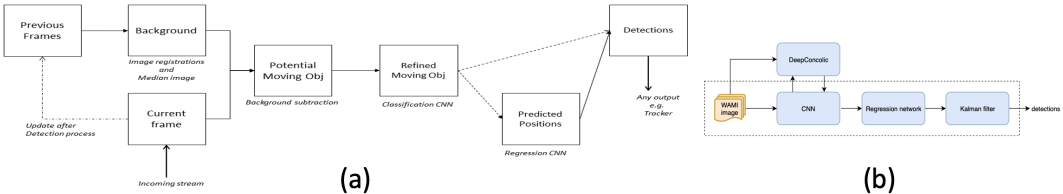


Figure: (a) The architecture of the vehicle detector. (b) Workflow for testing the WAMI tracking system.

[36] Reliability Validation of Learning Enabled Vehicle Tracking. ICRA2020

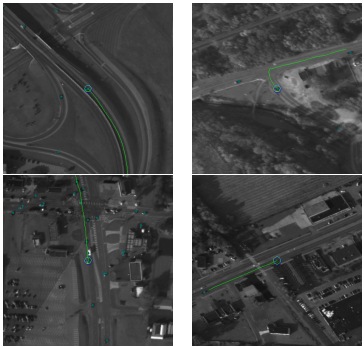


Figure: Original detected tracks

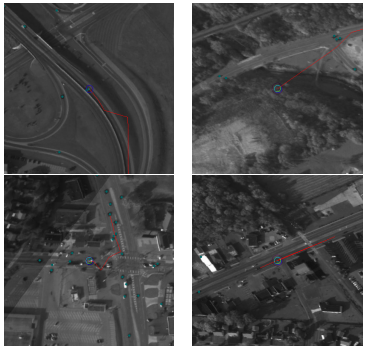
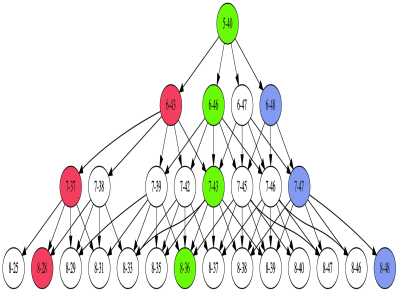


Figure: Distorted tracks

[36] Reliability Validation of Learning Enabled Vehicle Tracking. ICRA2020

(a) Heuristic search

(b) Verification

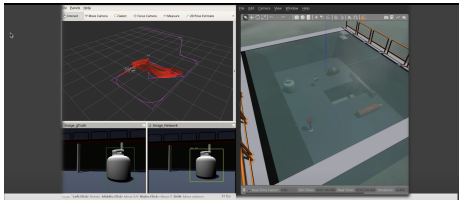


(c) Enumeration of all possible Tracks

[21] Practical Verification of Neural Network Enabled State Estimation System for Robotics. IROS2020.

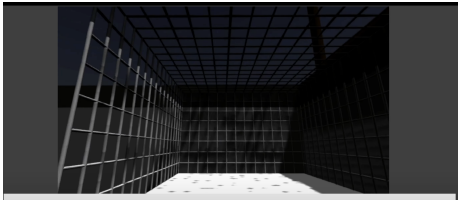
- Scenario: `https://youtu.be/akY8f5sSFpY?t=13`
- simulation / testing: `https://youtu.be/akY8f5sSFpY?t=155`
- verification: `https://youtu.be/WNjUP_qL6W4?t=475`

Underwater Vehicle



Scene 1:
The AUV mission

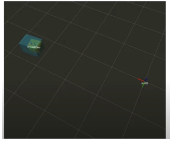
- An autonomous inspection/survey mission with several waypoints and docking.
- 6 simulated objects per mission: pipe, barrel, dock-cage, etc.
- The mission is subject to dynamic noise factors.

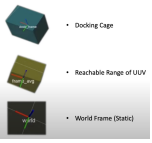


Scene 2:
Statistical testing based on repeated missions

- Only 5 dynamic missions are demonstrated (with acceleration).
- Hundreds/thousands of missions are simulated for collecting the statistical data.
- Reliability modelling is based on the collected images of objects.

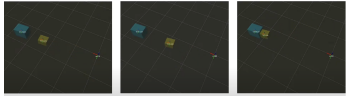
Case Demo without Crash



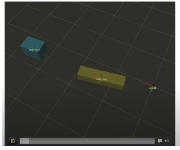


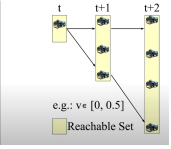
- Docking Cage
- Reachable Range of UUV
- World Frame (Static)

Case Demo without Crash



Case Demo with Crash





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- EU
  - GDPR [1], AI Act [9], Data Act [10]
- UK
  - Data Protection Act [2] and pro-innovative approach to regulate AI [11]
- US
  - Blueprint for an AI Bill of Rights [7] and AI Risk Management Framework [4]
- China
  - regulations for recommendation algorithms [5], deep synthesis [3], and algorithm registry [8]

Different principles w.r.t. the risk levels:

1. unacceptable-risk AI: banned
2. high-risk AI:
   - human oversight,
   - technical robustness,
   - compliance with data protection rules,
   - appropriate explainability, non-discrimination and fairness,
   - social and environmental well-being
3. limited and minimal-risk:
   - transparency

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Translated into technical terms:

- robustness
- security
- privacy
- accountability
- fairness
- explainability
- safety
- human-centricity

Properties

Technical terms:

- robustness
- security
- privacy
- accountability
- fairness
- explainability
- safety
- human-centricity

Known threats, e.g.,

- generalisation
- uncertainty
- robustness
- data poisoning
- backdoor
- model stealing
- membership inference
- model inversion

Formalised into **logical specifications** with statistical atomic propositions

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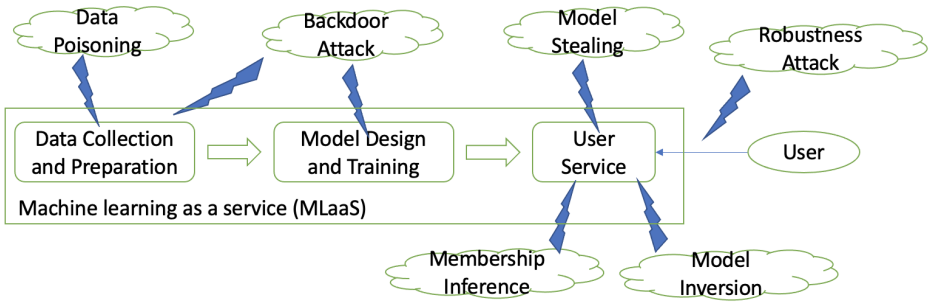
[26] Bridging Formal Methods and Machine Learning with Global Optimisation. ICFEM, 2022.
[22] Machine Learning Safety. Springer, 2023.

Attack in ML Development Cycle



[22] Machine Learning Safety. Springer, 2023.

Trustworthiness = Certification (for information) + Explanation (for communication)

- Certification can be property-based, considering properties including safety, security, accountability, fairness, privacy, transparency, etc.
- Explanation is for the communication with stakeholders in a proper level of details.

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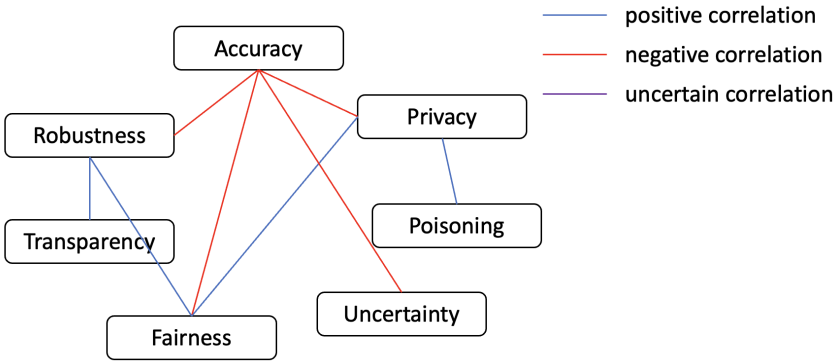
[23]: A Survey of Safety and Trustworthiness of Deep Neural Networks: Verification, Testing, Adversarial Attack and Defence, and Interpretability, Computer Science Review. 37 (2020): 100270.

Certification Framework – F.E.V.E.R.

Complex Relations between Properties



- Uncompleted, even for a given ML model
- Relations may change wrt dataset, model, etc

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For example:

Robustness: $\phi_{rob}(\mathbf{w}, \mathbf{x}) \triangleq \square(\textbf{inference} \Rightarrow \phi^1_{rob}(\mathbf{w}, \mathbf{x}))$ where $\phi^1_{rob}(\mathbf{w}, \mathbf{x}) \triangleq \forall \mathbf{r} : ||\mathbf{r}||_2 \leq c \Rightarrow |P(Y|\mathbf{x}+\mathbf{r}, \mathbf{w})(\hat{y}) - P(Y|\mathbf{x}, \mathbf{w})(\hat{y})| \leq \epsilon_{rob}$

Backdoor: $\phi_{bac}(\mathbf{w}, \mathbf{d}_{train}, \mathbf{d}_{adv}) \triangleq \neg(training \wedge \phi^2_{bac}(\mathbf{d}_{train}) \wedge \neg\phi^2_{bac}(\mathbf{d}_{train} \cup \mathbf{d}_{adv}))$ where $\phi^1_{bac}(\mathbf{w}) \triangleq \neg\exists \mathbf{r} \forall \mathbf{x} \forall y : P(Y|\mathbf{x}+\mathbf{r}, \mathbf{w})(y_{adv}) \geq P(Y|\mathbf{x}+\mathbf{r}, \mathbf{w})(y)$ and $\phi^2_{bac}(\mathbf{d}) \triangleq \neg\exists \mathbf{r} \forall \mathbf{x} \forall y : \mathbb{E}_{\mathbf{w} \sim P(W|\mathbf{d})}(P(Y|\mathbf{x}+\mathbf{r}, \mathbf{w})(y_{adv})) \geq \mathbb{E}_{\mathbf{w} \sim P(W|\mathbf{d})}(P(Y|\mathbf{x}+\mathbf{r}, \mathbf{w})(y))$. It expresses that, there does not exist any time in the future that the model is resistant to the backdoor trigger if trained on the usual training dataset but is not resistant if trained on the poisoned dataset.

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[26] Bridging Formal Methods and Machine Learning with Global Optimisation. ICFEM, 2022.

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We end up have to deal with several probabilistic atoms such as

- Posterior Distribution $P(W|\mathbf{d})$
- Data Distribution $\mathcal{D}$
- Distribution of Predictive Labels $P(\hat{Y}|\mathbf{d}, \mathbf{w})$
- distance between distributions such as $D_{KL}(\mu, \mu)$ or $||\mu - \mu||_p$

Nevertheless, the most tricky part (and the most drastic difference with existing safety critical software) is

- Environmental uncertainty, and
- Dynamic evolution of learning

So, there does not exist "one method rules all".

[26] Bridging Formal Methods and Machine Learning with Global Optimisation. ICFEM, 2022

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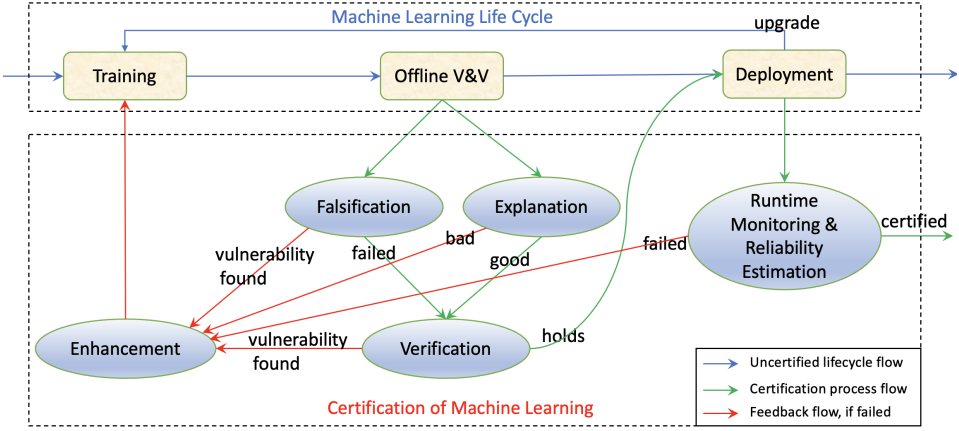
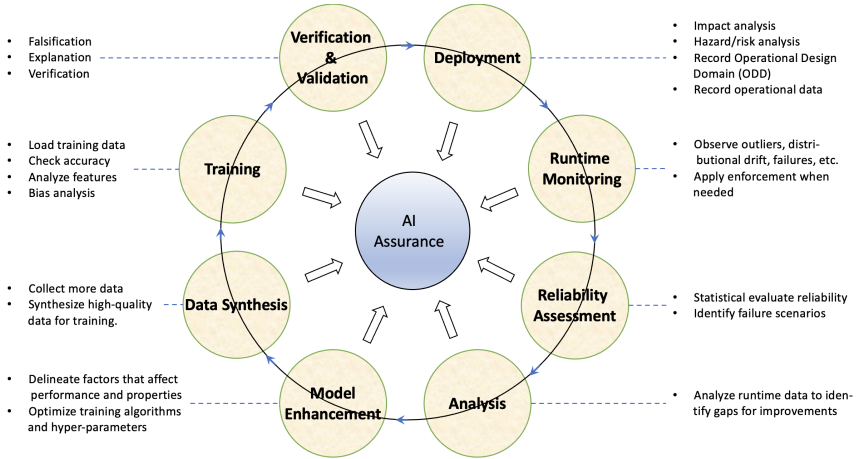


[23] A survey of safety and trustworthiness of deep neural networks: Verification, testing, adversarial attack and defence, and interpretability. Computer Science Survey, 2020



[22] Machine Learning Safety. Springer, 2023.

Assurance is a description of what high-quality software *development processes* should be put in-place to create (safety-critical) software that performs its desired function.

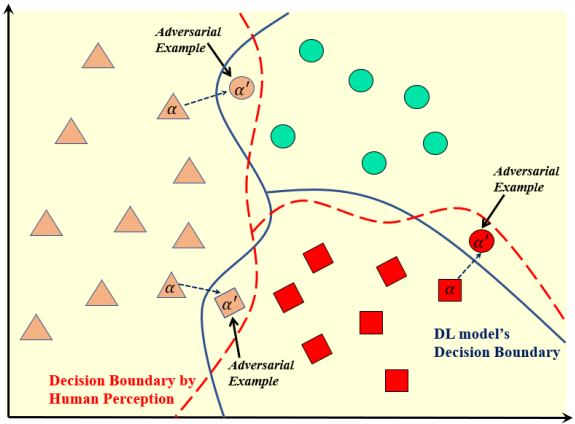
If *life cycle evidence* can be produced to demonstrate that these processes have been correctly and appropriately implemented, then such software should be assured.

leads to software standards such as

- DO-178B/C, Software Considerations in Airborne Systems and Equipment Certification
- ISO 26262: standards for the functional safety of road vehicles

Falsification aims to find evidence to demonstrate the weaknesses of a trained machine learning model or a machine learning training process. Popular techniques include

- adversarial attack
- testing
- Monte Carlo sampling based methods,
- genetic algorithm based methods,
- etc



DL model: classifies α and α' **differently**

Human: should remain the **same**

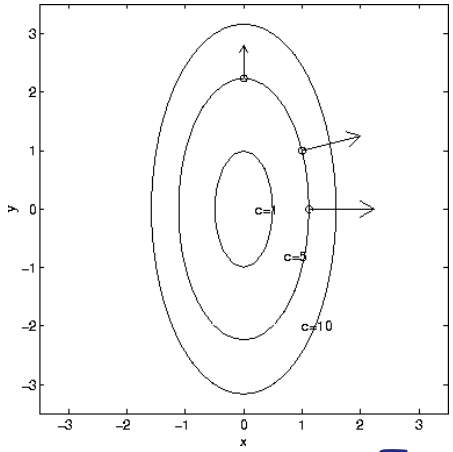
For robustness, one of earliest adversarial attack : optimization based formulation with L_2-norm metric

- Model $f : R^{s_1} \rightarrow \{1 \dots s_K\}$ with s_K labels
- $x \in R^{s_1} = [0, 1]^{s_1}$ is an input
- $t \in \{1 \dots s_K\}$ is a target misclassification label

Find the adversarial perturbation r via

$$\begin{aligned} & \min ||r||_2 && \text{assure human-decision unchanged} \\ \textit{s.t.} \quad & \arg\max_l f_l(x + r) = t && \text{assure misclassification} \\ & x + r \in R^{s_1} && \text{assure perturbed image feasible} \end{aligned} \tag{1}$$

The gradient vector $\nabla f(x, y)$ points in the direction of greatest rate of increase of $f(x, y)$



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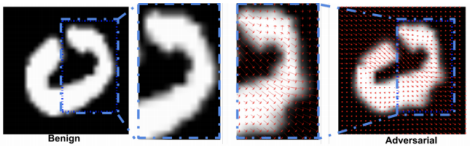
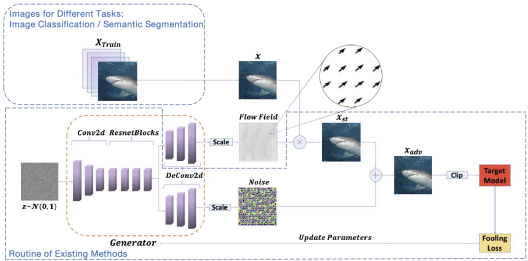
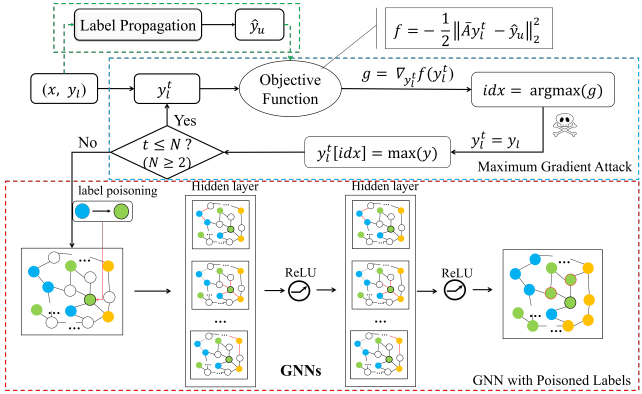




- Instead of perturbing the pixel values, adversarial attacks can be achieved by **spatial transformation** – on MNIST: digit "0" is misclassified as "2" (left figure)
- Different metric is required to measure pixel's **spatial displacement**
- Perturb spatial location and values of pixels simultaneously on **a set of images**?

[35] Generalizing Universal Adversarial Perturbations for DNNs. ICDM2020 & Machine Learning, 2023

1. label propagation to generate predictive labels
2. maximum gradient attack to poison data labels
3. GNN training with poisoned labels



[30] Adversarial Label Poisoning Attack on Graph Neural Networks via Label Propagation. ECCV2022

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- Well established in many industrial standard for software used in safety critical systems, such as ISO26262 for automotive systems and DO 178B/C for avionic systems.

- Coverage-guided testing
  - (step 1) generate as many as possible the test cases according to the structural information of the model, and
  - (step 2) use the test cases to evaluate if the model performs well with respect to certain properties

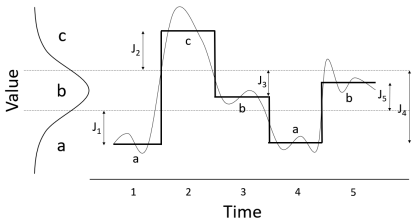
- Coverage Metrics
  - Structural Coverage, e.g., MC/DC coverage metrics [34] (Core idea: not only the presence of a feature needs to be tested but also the causal effects of less complex features on a more complex feature must be tested.)
  - Scenario Coverage
- Test Case Generation Methods
  - Fuzzing
  - Symbolic/Concolic execution [35], etc

- check DeepConcolic: `https://github.com/TrustAI/DeepConcolic`

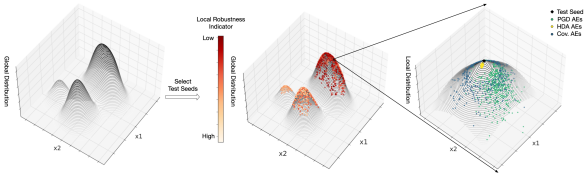
[34] Structural Test Coverage Criteria for Deep Neural Networks. ICSE2019

[35] Concolic Testing for Deep Neural Networks. ASE2018

Coverage-Guided Testing for Recurrent Neural Networks [18]



Hierarchical Distribution-Aware Testing of Deep Learning [19]



[18] Coverage-Guided Testing for Recurrent Neural Networks. IEEE trans. on Reliability, 2021

[19] Hierarchical Distribution-Aware Testing of Deep Learning. ACM Trans. on Software Engineering and Methodology, 2023

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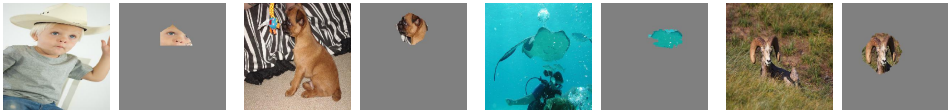
The black-box nature of deep neural networks (DNNs) makes it impossible to understand why a particular output is produced, creating demand for "Explainable AI".



(a) 'cowboy hat' (b) 'dog' (c) 'numbfish' (d) 'sheep'

Figure: Input images and explanations from for Xception (red labels highlight misclassification or counter-intuitive explanations) [33]

For certification, we need not only correct classification but also correct explanation.

[33] Explaining Image Classifiers using Statistical Fault Localization. ECCV2020

Adopting the definition of explanations by Halpern and Pearl, which is based on their definition of actual causality. What we required:

1. an explanation is a *sufficient* cause of the outcome;
2. an explanation is a *minimal* such cause (that is, it does not contain irrelevant or redundant elements);
3. an explanation is *not obvious*; in other words, before being given the explanation, the user could conceivably imagine other explanations for the outcome.

What we propose:

- SFL (stochastic fault localisation) measures to rank the set of pixels of x by slightly abusing the notions of passing and failing tests

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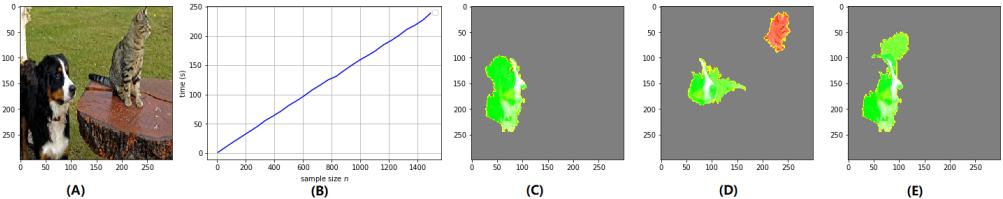
[33] Explaining Image Classifiers using Statistical Fault Localization. ECCV2020

Utilising Bayesian variant to deal with

- consistency in repeated explanations of a single prediction (as shown below, with LIME, different explanations can be generated for the same prediction)



- explanation fidelity
- robustness to kernel settings

[42] BayLIME: Bayesian Local Interpretable Model-Agnostic Explanations. UAI2021

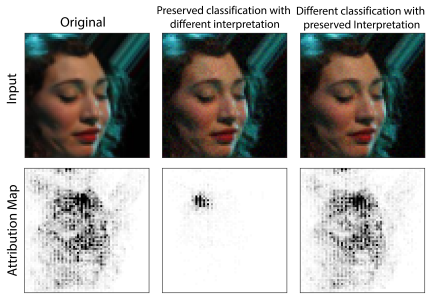


Figure: Two types of misinterpretations after perturbation

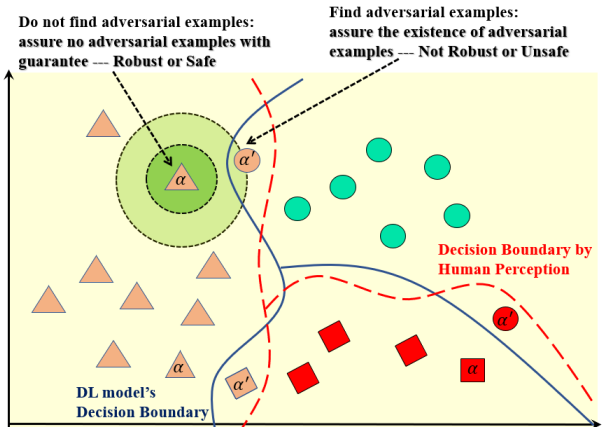
Novel black-box evaluation methods:

- based on Genetic Algorithm
- for both *worst-case* and *overall* robustness of explanations
- new interpretation Discrepancy Metrics

[20] SAFARI: Versatile and Efficient Evaluations for Robustness of Interpretability. ArXiv, 2022.

Verification aims to determine if a model satisfies certain properties. Popular techniques include

- reduction to constraint solving
- over-approximation
- global optimisation based methods
- statistical evaluation
- coverage-guided testing
- etc



(Robustness) Verification: verify if a certain input area can exclude misclasssification with **guarantees**

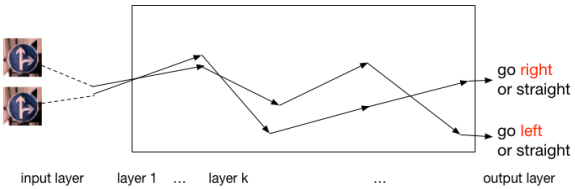
- (step 1) encode the entire network
- (step 2) encode the robustness constraint over the input
- (step 3) compute the result by solving the constraints

- encode the network
- Let $\vec{t}_{i+1}$ have value 0 or 1 in its entries and have the same dimension as $\vec{v}_{i+1}$, and M be a very large constant number that can be treated as ∞.
- we have the following MILP constraints for every layer $i = 1..K-2$

$$\begin{aligned} \vec{v}_{i+1} &\geq \mathbf{W}_i \vec{v}_i + \vec{b}_i, \\ \vec{v}_{i+1} &\leq \mathbf{W}_i \vec{v}_i + \vec{b}_i + M\vec{t}_{i+1}, \\ \vec{v}_{i+1} &\geq \mathbf{0}, \\ \vec{v}_{i+1} &\leq M(1 - \vec{t}_{i+1}), \end{aligned} \tag{2}$$

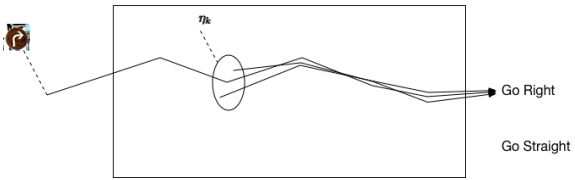
Verification by Region Propagation

How does neural network process (two very similar) inputs?



How does verification work?

A layer-by-layer explicit search with SMT solver



[24] Safety verification of deep neural networks. CAV2017

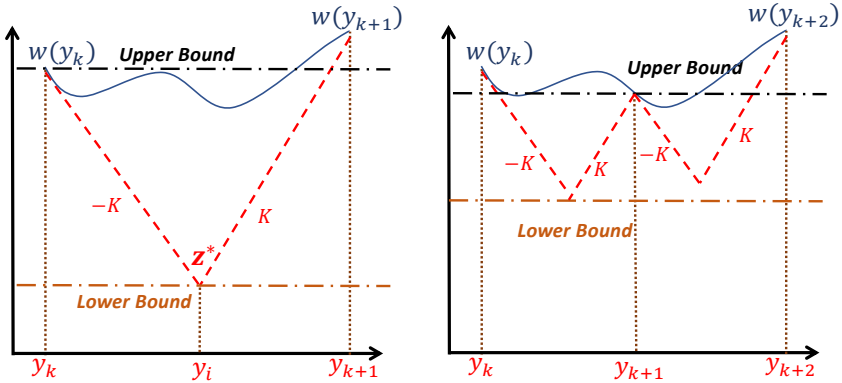


Figure: A lower-bound function designed via Lipschitz constant

[31] Reachability Analysis of Deep Neural Networks with Provable Guarantees. IJCAI2018

- Reduction to Monte-Carlo Tree Based Search
- Reduction to Other Global Optimisation Method
- Reduction to Two-player Game

[37] Feature-guided black-box safety testing of deep neural networks. TACAS2018.
[32] Global robustness evaluation of deep neural networks with provable guarantees for the Hamming distance. IJCAI2019
[38] A game-based approximate verification of deep neural networks with provable guarantees. Theoretical Computer Science, 2020.

- Scalability
- Mostly work with Robustness
- Can only deal with deterministic variables/neurons, but machine learning problems are mostly statistical ...

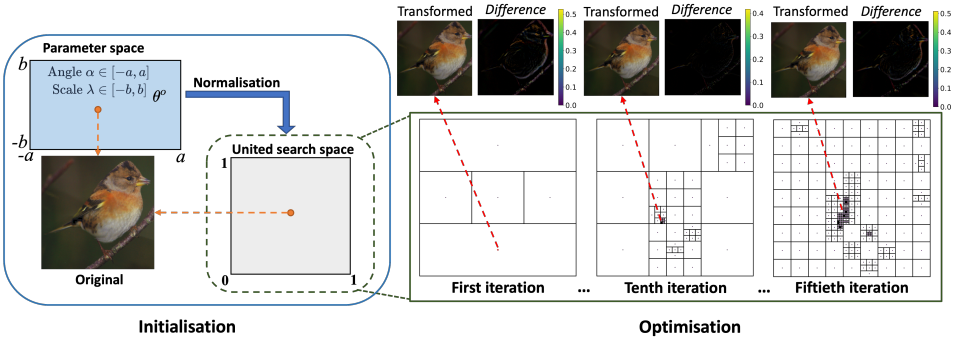
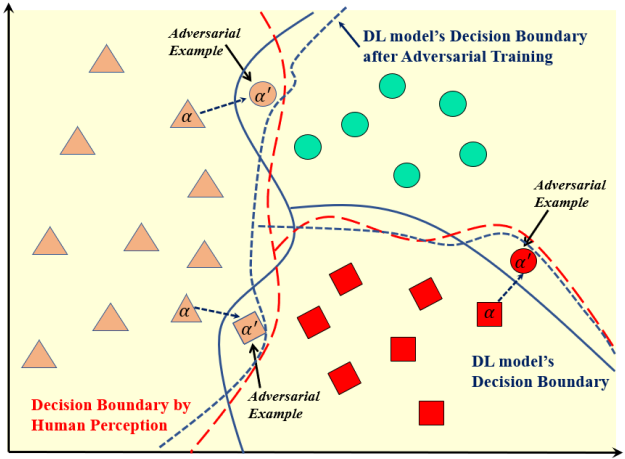


Figure: After normalising the parameter space to a unit search space, GeoRobust performs a sequence of space divisions to find the global worst-case transformation.

[6] Towards Verifying the Geometric Robustness of Large-scale Neural Networks. IJCAI2023

Rectification aims to enhance the machine learning training process or the trained machine learning model, so that the resulting machine learning model performs better with respect to the properties. Popular techniques include

- adversarial training
- regularisation
- outlier detection
- randomisation (based on differential privacy)
- etc


Adversarial Example
DL model's Decision Boundary after Adversarial Training
α′
α
Adversarial Example
α′
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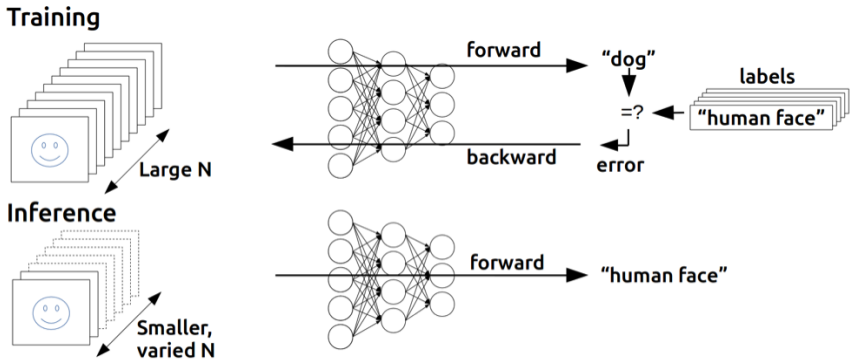
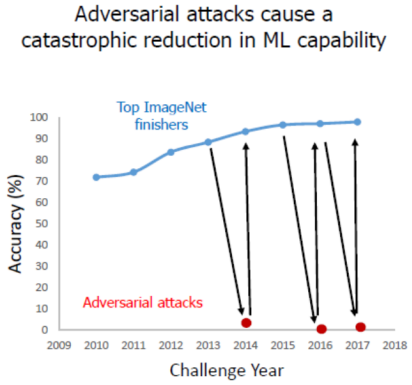
α′
α
DL model's Decision Boundary
Decision Boundary by Human Perception
Adversarial Example


Training
Large N
forward
"dog"
labels
=?
"human face"
backward
error
Inference
Smaller,
varied N
forward
"human face"

Attack vs. Defence: An Endless Game



@ DARPA's GARD programme

Consider weight correlation during the training

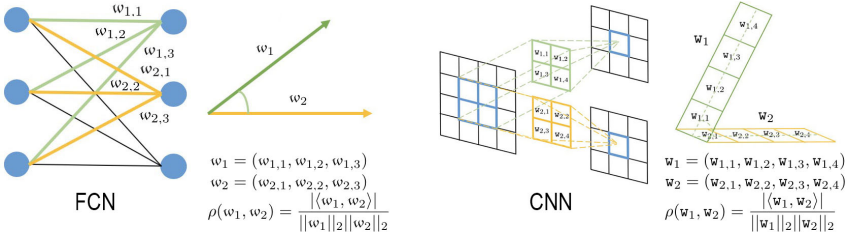
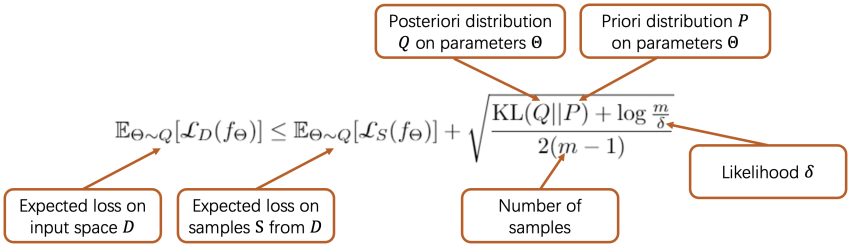


Figure: For fully connected networks, the weight correlation of any two neurons is the cosine similarity of the associated weight vectors. For convolutional neural networks, the weight correlation of any two filters is the cosine similarity of the reshaped filter matrices.

[29] How does Weight Correlation Affect Generalisation Ability of DNNs? NeurIPS2020

(McAllester, 1999) considers a generalization bound on the parameters



KL divergence plays a key role in the generalization bound

- a small KL term will help tighten the bound
- a larger KL term will loose the bound

[28] How does Weight Correlation Affect Generalisation Ability of DNNs? NeurIPS2020

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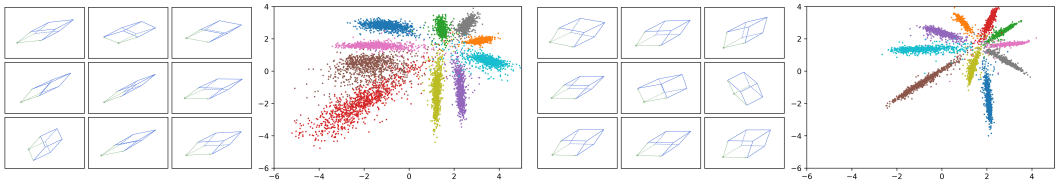

Figure: Visualization of weight volume and features of the last layer in a CNN on MNIST, with and without dropout during training

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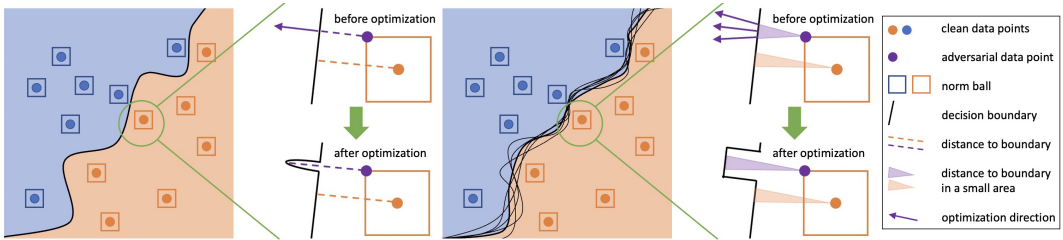
[29] Weight Expansion: A New Perspective on Dropout and Generalization. Transactions on Machine Learning Research. 2022

- treating model weights as random variables allows for enhancing adversarial training through **S**econd-Order **S**tatistics **O**ptimization (S^2O) with respect to the weights
- derive an improved PAC-Bayesian adversarial generalization bound, which suggests that optimizing second-order statistics of weights can effectively tighten the bound.
- through experiments, we show that S^2O not only improves the robustness and generalization of the trained neural networks when used in isolation, but also integrates easily in state-of-the-art adversarial training techniques like TRADES, AWP, MART, and AVMixup, leading to a measurable improvement of these techniques.

[27] Enhancing Adversarial Training with Second-Order Statistics of Weights. CVPR2022

Probabilistic View Helps Training

- embedding neural network weights with random noise
- utilize Taylor series to expand the objective function over weights (e.g., zeroth term, first term, second term, etc).

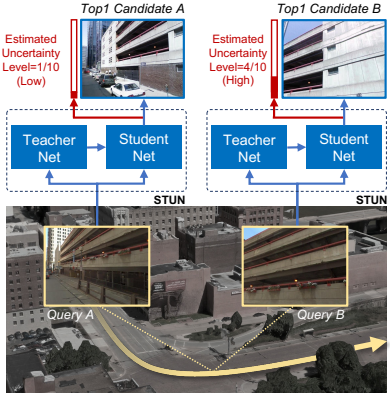


(a) Adversarial Training of TRADES (b) Our Method

[27] Randomized Adversarial Training via Taylor Expansion. CVPR2023

1. train a teacher net
2. supervised by the pretrained teacher net, a student net with an additional variance branch is trained
3. During the online inference phase, we only use the student net to generate both a place prediction and the uncertainty

This can not only generate uncertainty for each prediction but also improve the accuracy (i.e., generalisation).

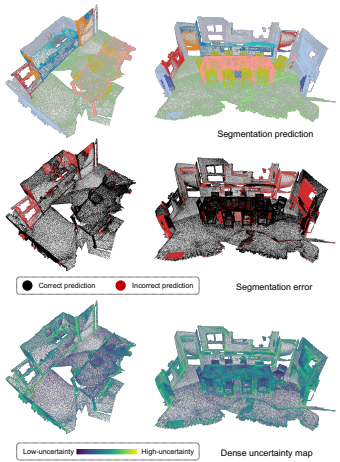


[14] STUN: Self-Teaching Uncertainty Estimation for Place Recognition. IROS2022

- building a probabilistic embedding model and then
- enforcing metric alignments of massive points in the embedding space

Figure 1 for 3D semantic segmentation. We have segmentation prediction (top), segmentation error (middle) and dense uncertainty map (bottom) of two scenes from ScanNet.

- Incorrect predictions tend to have high uncertainties.



[13] Uncertainty Estimation for 3D Dense Prediction via Cross-Point Embeddings. RA-L. 2023

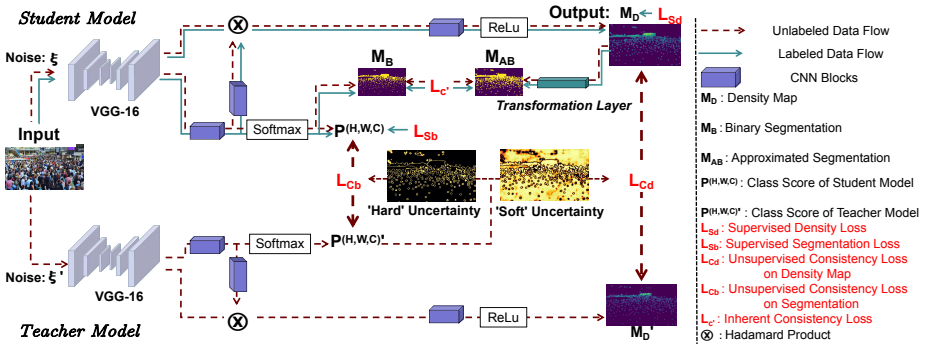


Figure: The pipeline of our uncertainty-aware framework for semi-supervised crowd counting.

[13] Spatial Uncertainty-Aware Semi-Supervised Crowd Counting. ICCV2021

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- Software reliability: the probability of failure-free software operation for a specified period of time in a specified environment

Approach: a reliability assessment model to construct probabilistic safety argument by deriving reliability requirements from low-level ML functionalities

A RAM built upon statistical testing evidence, while inspired by conventional partition-based testing and operational profile (OP)-based testing

$$\textbf{Reliability} = \textbf{Generalisation} \times \textbf{Local Robustness/Safety/Security/...} \quad (3)$$

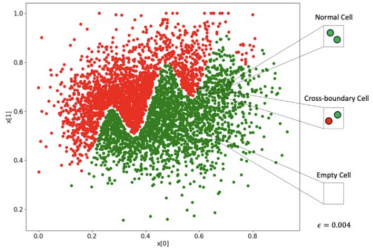
Specifically,

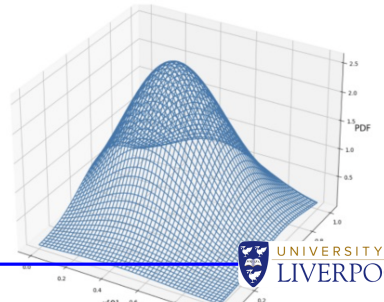
$$\lambda := \int_{x \in \mathbb{R}^{s_1}} I_{\{x \text{ causes a misclassification}\}}(x) \mathsf{Op}(x)\, \mathrm{d}x \ , \quad (4)$$

where x is an input in the input domain $\mathbb{R}^{s_1}$, and $I_{\mathsf{S}}(x)$ is an indicator function—it is equal to 1 when S is true and equal to 0 otherwise. The function $\mathsf{Op}(x)$ returns the probability that x is the next random input.

[39] A safety framework for critical systems utilising deep neural networks. SafeCOMP2020.
[40] Assessing Reliability of Deep Learning Through Robustness Evaluation and Operational Testing. AISafety2021

- Partition the input space into "cells", with the guidance of r-separation
- Approximation the operational profile OP
- Cell robustness evaluation
- "Assemble" cell-wise estimates for reliability $\lambda = \sum_{i=1}^{m} Op_i \lambda_i$. Then we can have the mean and variance of λ





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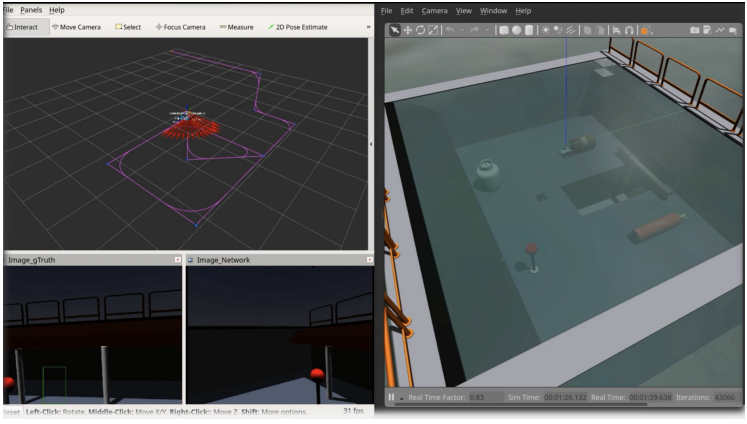
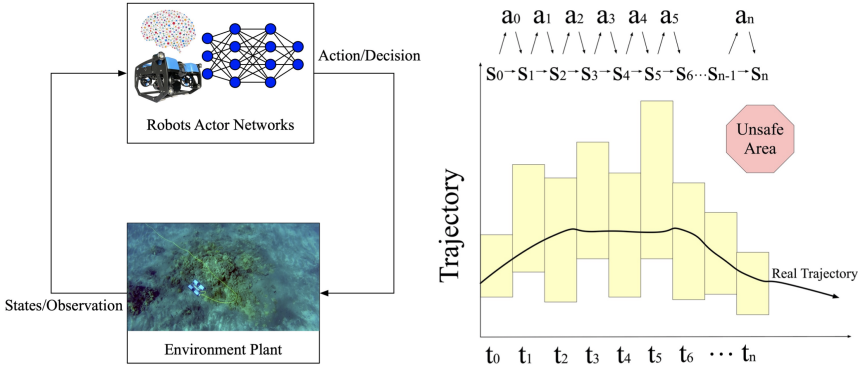
[15] Reliability Assessment and Safety Arguments for Machine Learning Components in System Assurance. ACM trans. Embedded Syst. 2022.

** Won SIEMENS AI-DA (AI Dependability Assessment) Challenge "most original approach"*

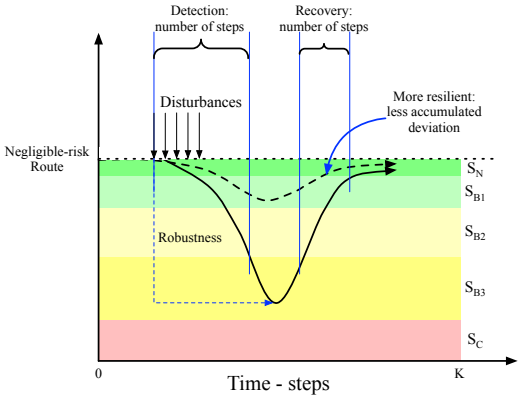
- An autonomous inspection/survey mission with several waypoints and docking
- 6 simulated objects per mission: pipe, barrel, dock-cage, etc
- the mission is subject to dynamic noise factors

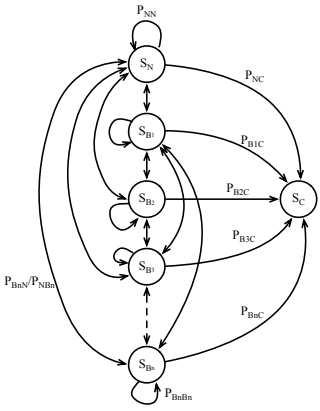


[41] Reliability Assessment and Safety Arguments for Machine Learning Components in System Assurance. ACM Trans. Embedded Computing Systems, 2022.



[16] Dependability Analysis of Deep Reinforcement Learning based Robotics and Autonomous Systems through Probabilistic Model Checking. IROS2022.





[16] Dependability Analysis of Deep Reinforcement Learning based Robotics and Autonomous Systems through Probabilistic Model Checking. IROS2022.

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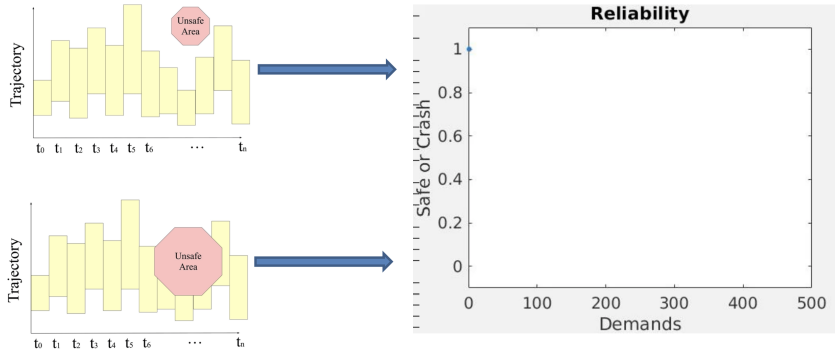
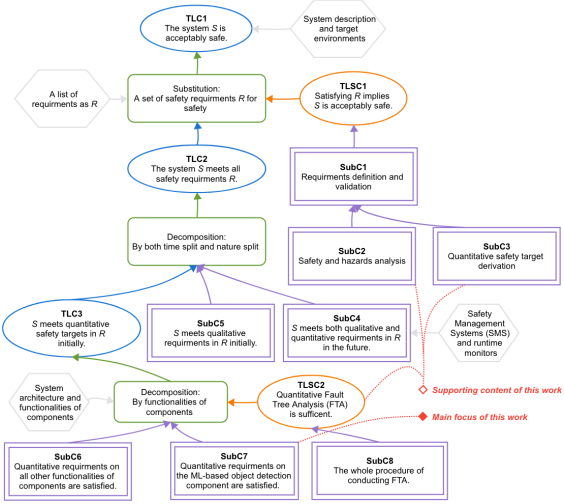


[16] Dependability Analysis of Deep Reinforcement Learning based Robotics and Autonomous Systems through Probabilistic Model Checking. IROS2022.

To pull the above elements (falsification, explanation, verification, enhancement, reliability) together, we use

- Safety assurance: processes that function systematically to ensure the performance and effectiveness of safety risk controls and that the organization meets or exceeds its safety objectives through the collection, analysis, and assessment of information

A Safety Argument Framework

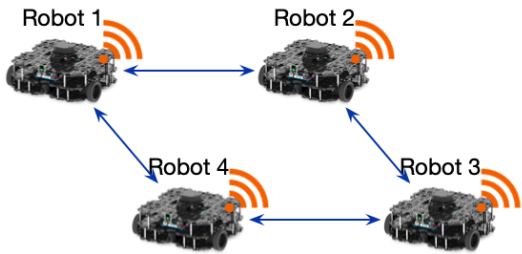


[15] Reliability Assessment and Safety Arguments for Machine Learning Components in System Assurance. ACM trans. Embedded Syst., 2022.

- There is no single tool/method that can work for the certification of deep learning
- None of the F.E.V.E.R. has been sophisticated – many to be done for not only each analysis technique but also the interfacing between them
- More than one properties to work with – probably an expressive formal language with a model checking algorithm will help.

Looking ahead: distributed/federated learning

- systems are more complex: topology, communication, etc
- more attackers: Byzantine attacker, etc
- more problems: convergence, etc.
- more trade-offs: model vs data, privacy vs security, etc



[17] Decentralised and Cooperative Control of Multi-Robot Systems through Distributed Optimisation. AAMAS2023

Looking ahead: distributed/federated learning

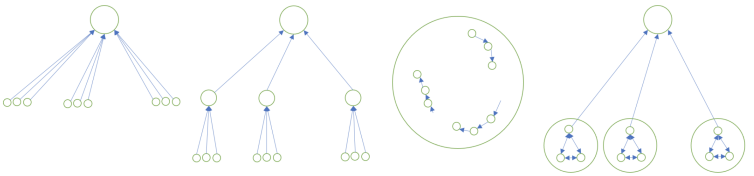
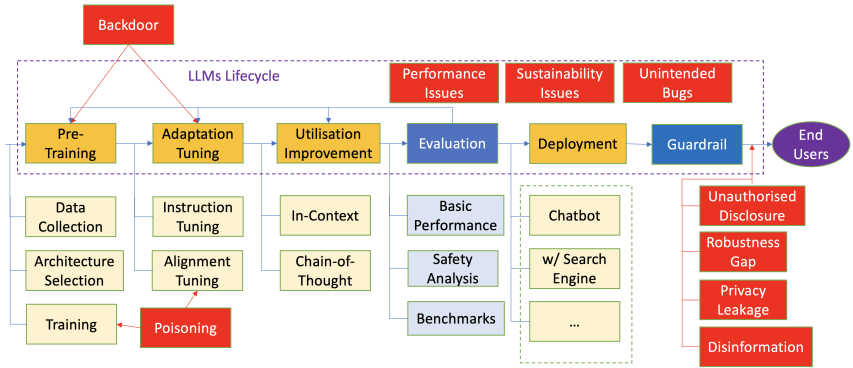


Fig. 1: An Illustrative Comparison with State-of-the-Art

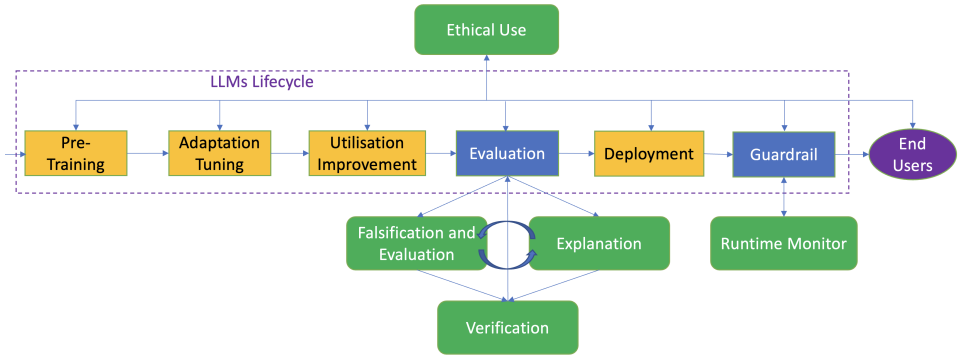
	Local Differential Privacy [5]	FL with Worker [9]	Secure Multiparty Computation [11]	Our SPAC^{2}E
Scalability	3	1	4	1
Privacy	4	2	1	2
Accuracy	4	3	1	2
Communication Complexity	1	4	2	2
Efficiency	3	1	4	2
Overall Score	15	11	12	9

TABLE I: Comparison with State-of-the-Art with respect to the Five Properties

** Won the UK-US privacy-enhancing technologies prize challenges, "Novel Modelling/Design"*



[25] A Survey of Safety and Trustworthiness of Large Language Models through the Lens of Verification and Validation. ArXiv, 2023



[25] A Survey of Safety and Trustworthiness of Large Language Models through the Lens of Verification and Validation, ArXiv, 2023

Looking ahead: Sustainability

Model	Parameter size	Dataset size	Hardware	Energy
BERT-base [77]	110 million	3.3b words	16 TPU chips	-
BERT-large [77]	340 million	3.3b words	64 TPU chips	-
GPT-3 [50]	175 billion	499 billion tokens	10,000 NVIDIA V100	1287 MWh
Megatron Turing NLG [231]	530 billion	338.6 b	4480 NVIDIA A100-80GB	>900MWh
ERNIE 3.0 [238]	260 billion	4Tb texts	384 NVIDIA V100 GPU	-
GLaM [81]	1.2 trillion	1.6 trillion	1,024 Cloud TPU-V4	456MWh
Gopher [201]	280 billion	300 billion	4096 TPUv3	1066 MWh
PanGu-α [284]	200 billion	1.1TB	2048 Ascend 910 AI processors	-
LaMDA [242]	137 billion	1.56T words	1024 TPU-v3	451MWh
GPT-NeoX [45]	20 billion	825 GiB	96 NVIDIA A100-SXM4-40GB	43.92MWh
Chinchilla [112]	70 billion	1.4 trillion	TPUv3/TPUv4	-
PaLM [66]	540 billion	780 billion	6144 TPU v4	$\sim$ 640MWh
OPT [289]	175 billion	180b	992 NVIDIA A100-80GB	324 MWh
YaLM [273]	100 billion	300B	800 NVIDIA A100	$\sim$ 785MWh
BLOOM [220]	176 billion	1.61 terabytes of text	384 NVIDIA A100 80GB	433 MWh
Galactica [241]	120 billion	450b	128 NVIDIA A100 80GB	-
AlexaTM [233]	20 billion	1 trillion	128 NVIDIA A100	$\sim$ 232MWh
LLaMA [244]	65 billion	1.4 trillion	2048 NVIDIA A100-80GB	449 MWh
GPT-4 [143, 85]	1.8 trillion	1 petabyte	-	-
Cerebras-GPT [80]	13 billion	260b	16 Cerebras CS-2	-
BloombergGPT [268]	50.6 billion	569b	512 NVIDIA A100 40GB	$\sim$ 325MWh
PanGu-Σ [209]	1.085 trillion	329 billion	512 Ascend 910 accelerators	-

Table 1: Costs of different large language models.

[25] A Survey of Safety and Trustworthiness of Large Language Models through the Lens of Verification and Validation, ArXiv, 2023

- Small models
- Energy efficient variants of neural networks such as spiking neural networks, which require
  - specialised hardware implementation
  - a complete re-investigation of the safety and trustworthiness issues?

FOCETA

Thank you

http://www.foceta-project.eu/

https://www.linkedin.com/company/foceta-project

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