Assessing Robustness and Resilience of AI: The ALC Project

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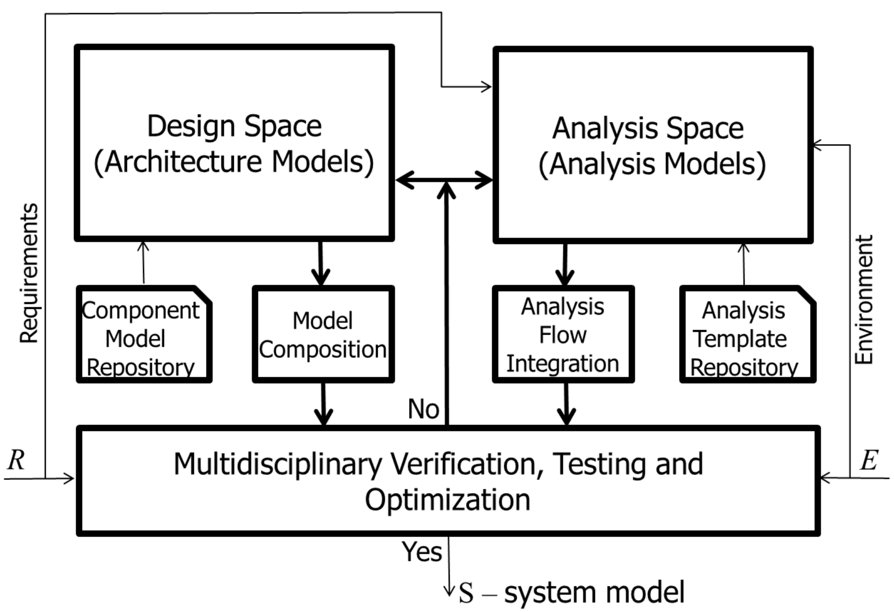
with contributions by Taylor Johnson, Xenofon Koutsoukos
Supported by DARPA under
Assurance of Learning-Enabled Cyber-Physical Systems

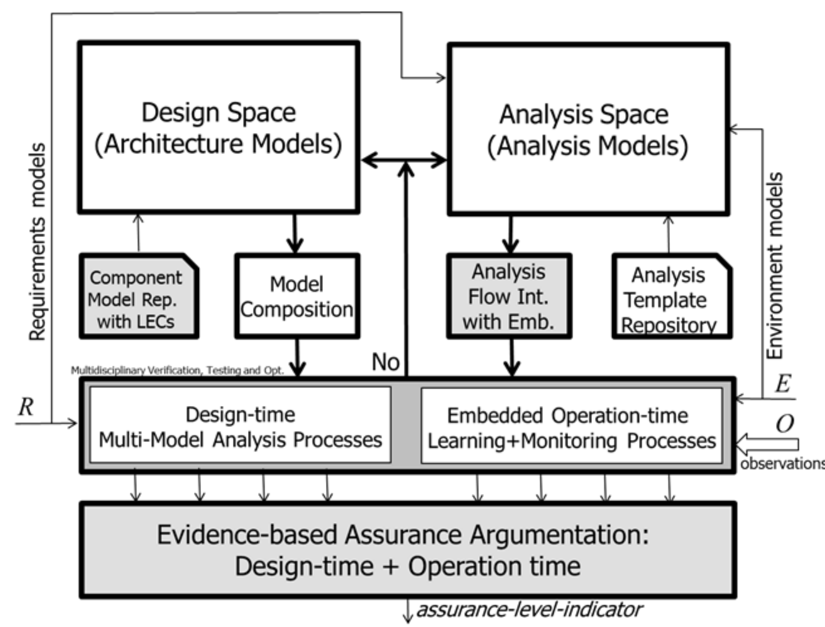
Project vision

"The proposed research effort will address the ... technical areas with overall goal of delivering an <u>integrated design tool suite</u> *and* <u>reusable operation support components</u> *for constructing autonomous CPS including Learning Enabled Components (LECs). Our vision is to … create a new design flow that extends from design-time to operation time, re-interprets the traditional assurance argumentation to become a dynamic, operational concept. Our ultimate goal is to establish a fusion of model- and component-based methods with data-driven methods."*

Model-driven design flow

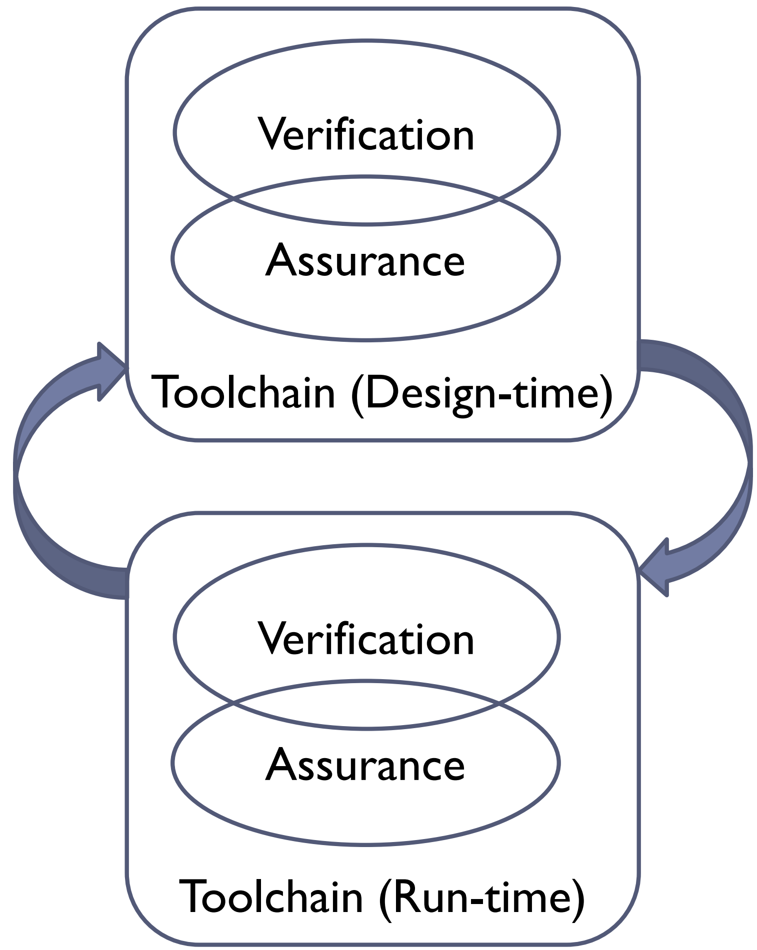


Model-driven design flow with LEC-s



Project activities

- Thrusts:
  - Verification: formal and/or coverage-driven verification of safety and liveness properties of components, subsystems, and systems, at design-time and at run-time, to provide evidence for assurance arguments
  - Assurance: construction and continuous evaluation of logical arguments that demonstrate the *truth* or *strength* of a safety claim based on available evidence
  - Toolchain: design-time and run-time software tools to implement and support the above, for real systems
- Learning (component adaptation)
  - Design-time: in design tools, while the system is not operational
  - Run-time: in the running system, on-the-fly
  - Mixed – learning from operational, 'overnight'



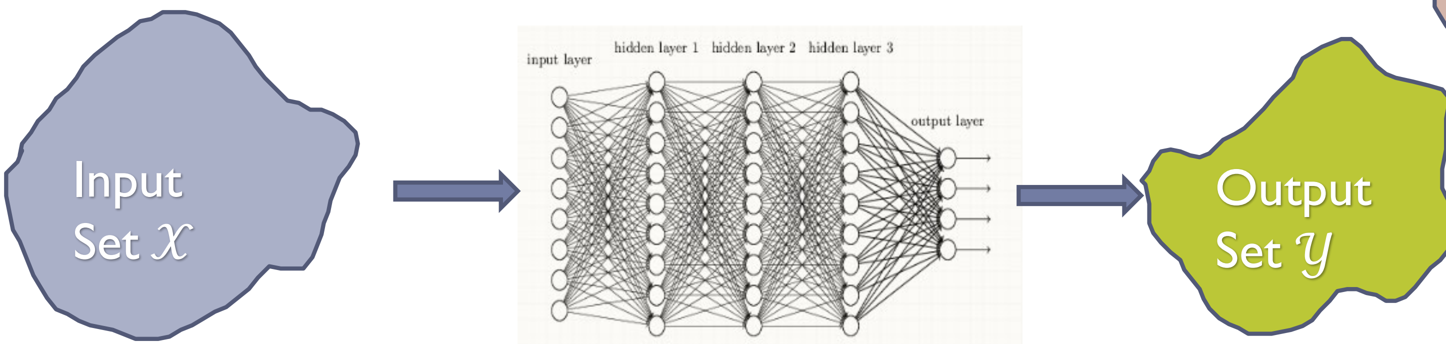
Verification Technology

Example-1: Robustness Assessment
Example-2: Run-time Verification

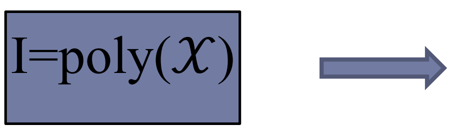
Prof. Taylor Johnson and team

LEC Verification: Reachability Analysis of Feedforward/Convolutional Neural Networks

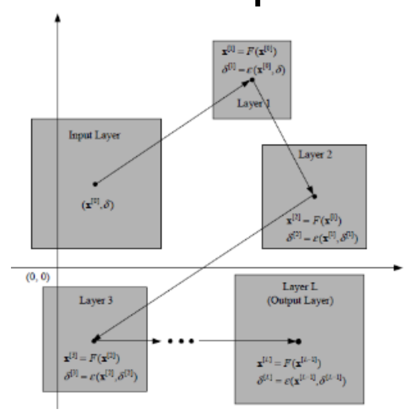
- Given a NN F & an input set $\mathcal{X}$, the **<u>output reachable set</u>** of F is
$$\mathcal{Y} = \{y \mid y = F(x), x \in \mathcal{X}\}$$

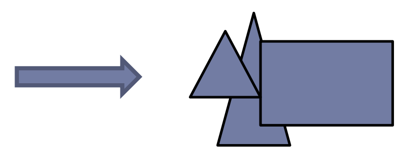


- Computationally: Given a NN F, a convex initial set of inputs I represented as a polytope $\mathrm{poly}(\mathcal{X})$, compute the output set Y = F(I) of the network



$I = \{x \mid Ax \leq B, x \in R^n\}$





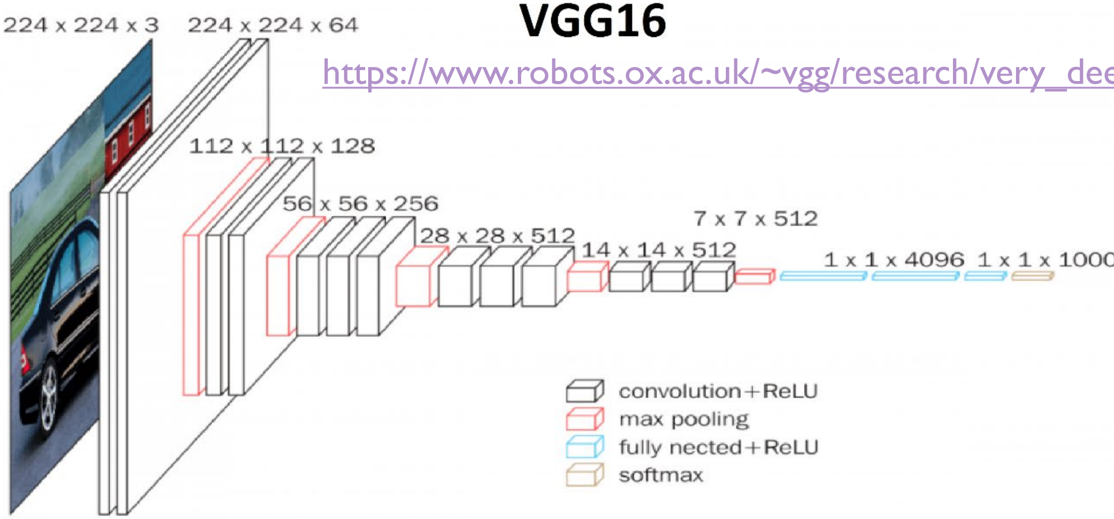
$Y = F(I) = ?$

Layer-by-Layer Propagation of Polytopes

CNN Robustness Verification [CAV'20]

VGG16

https://www.robots.ox.ac.uk/~vgg/research/very_deep/



Original image | **Noise** | **a = 1e-6%** | **a = 8e-6%**

Disturbed images = Original image + *a* x Noise

Is VGG16/19 robust to FGSM attacks for $a \leq 2 \times 10^{-8}$?

VGG Classifiers: **~93% accuracy in top-5 classification on ImageNet**

VGG16: **16** layers, **138M** parameters

VGG19: **19** layers, **144M** parameters

Classify images into **1000 classes**, e.g., car, horse, bell pepper, …

Layers of interest

- Convolutional
- Average pooling
- Max pooling
- Fully connected
- ReLU

Tran HD., Bak S., Xiang W., Johnson T.T. (2020) Verification of Deep Convolutional Neural Networks Using ImageStars. In: Lahiri S., Wang C. (eds) Computer Aided Verification. CAV 2020. https://doi.org/10.1007/978-3-030-53288-8_2

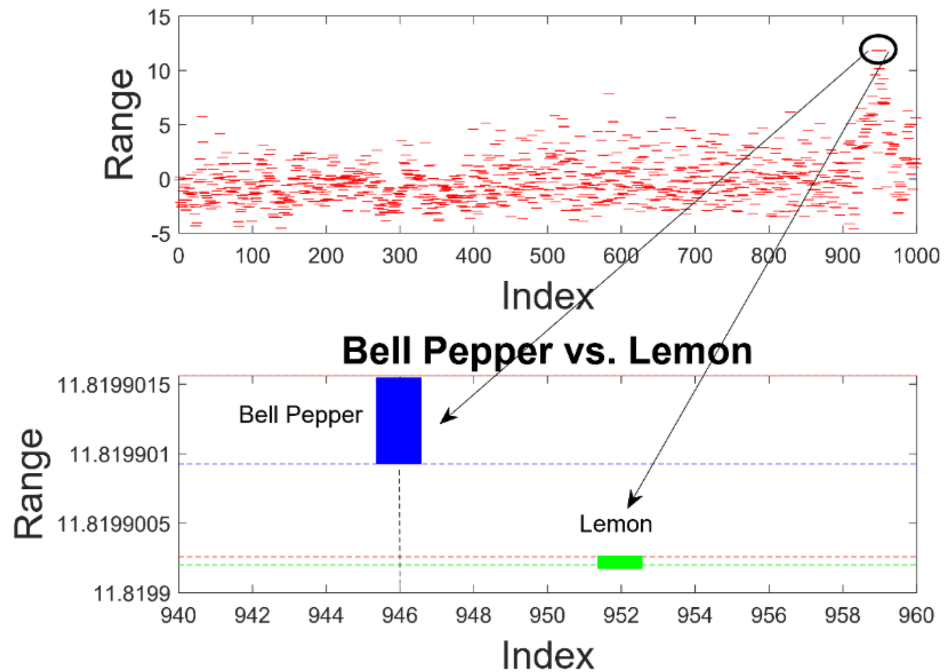
CNN Classification Robustness Analysis: ImageStars

- **ImageStar** $\Theta = \{x | x = c + \Sigma_{i=1}^{m} \alpha_i v_i, P(\alpha)\}$
  - $c \in R^{h \times w \times nc}$ is the **center image**
  - $V = \{v_1, v_2, \cdots, v_m\}, v_i \in R^{h \times w \times nc}$ is a set of **basis images**
  - $P(\alpha) \triangleq C\alpha \leq d$, is a predicate
  - $\alpha = [\alpha_1, \alpha_2, \cdots, \alpha_m]^T$, is predicate variable
  - Extension of Star Sets [Tran et al, FM'19]
  - Represent infinite sets of multi-channels images

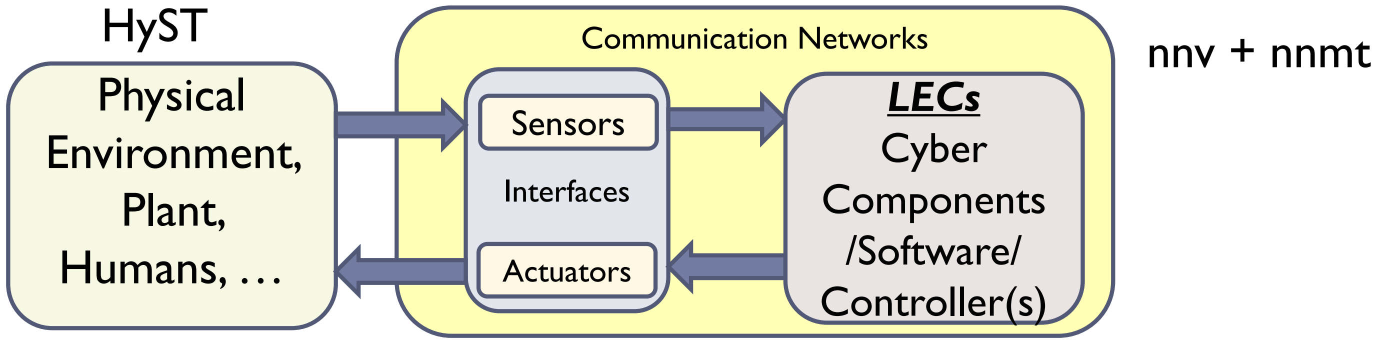
$$\Theta = c + \alpha v = \underbrace{\begin{bmatrix} 0 & 4 & 1 & 2 \\ 2 & 3 & 2 & 3 \\ 1 & 3 & 1 & 2 \\ 2 & 1 & 3 & 2 \end{bmatrix}}_{c \in R^{4 \times 4 \times 1}} + \alpha \underbrace{\begin{bmatrix} 0 & \boxed{1} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}}_{v \in R^{4 \times 4 \times 1}}, P \equiv \begin{pmatrix} 1 \\ -1 \end{pmatrix} \alpha \leq \begin{pmatrix} 2 \\ 2 \end{pmatrix}$$

VGG16 Robustness Verification

- Is VGG16/19 robust to FGSM attacks for $a \leq 2 \times 10^{-8}$?
- Reachable set computation time: **518** seconds
- Verifying Robustness Time: **56** seconds
- Number of ImageStars in the output reachable set: **8**
- Total Verification Time: **574** seconds ($\approx$ 10 minutes)
- Number of cores: **1**
- **Robust? Yes**



Closed-Loop CPS with LECs: Verification Flow and Tools

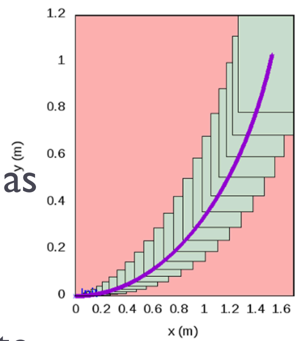


https://github.com/verivital/hyst
https://cps-vo.org/group/hyst
https://github.com/verivital/nnv
https://github.com/verivital/nnmt

- Plant models: **hybrid automata**, or networks thereof, represented in HyST/SpaceEx/CIF formats
  - Hybrid automaton: **finite state machine** + set of real-valued variables that evolve continuously over intervals of real time according to **ordinary differential equations (ODEs)**
  - **Hybrid** behaviors: discrete transitions and continuous trajectories over real time
  - Plant dynamics: linear, nonlinear, hybrid, continuous-time, discrete-time, …
- LEC and cyber models: feedforward **neural networks**, represented in **ONNX** format (compatible with Keras, Tensorflow, Matlab, etc.)
- Specifications: primarily **safety properties** for now, some **reachability properties**
- Verification: composed LEC and plant analysis: autonomous closed-loop CPS
  - **Bounded model checking**: k control periods, alternating reachability analysis of controller and plant

Runtime (Online) Verification of Autonomous Systems with Real-Time Reachability

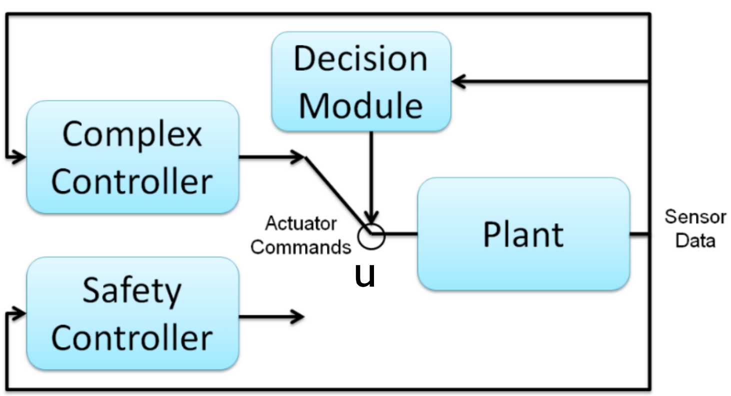
- For controller LECs **online monitoring at runtime** is essential
- How can we provide formal and provable guarantees of system-level behaviors, such as safety, **online at runtime**?
  - Key idea: abstract LEC behaviors (see other approaches on out of distribution detection, etc.) and simply ***observe the influence of their behavior on plant/system-level at runtime***
  - Necessary technology: **online reachability analysis** of plant models, ideally with worst-case execution time (**WCET**) guarantees for implementation in embedded hardware
  - Builds on **real-time reachability** of linear/nonlinear ordinary differential equations (ODEs) and hybrid automata with WCET guarantees, implemented as an **anytime** algorithm [FORTE'19, TECS'16, RTSS'14]
  - Based on **mixed face lifting reachability** [Dang and Maler, HSCC'98 & HSCC'19 Test of Time Award Winner], using hyperrectangles (intervals) as state-space representation



[Tran et al, "Decentralized Real-Time Safety Verification for Distributed Cyber-Physical Systems", **FORTE'19**]
[Johnson et al, "Real-Time Reachability for Verified Simplex Design", **TECS'16**]
[Bak et al, "Real-Time Reachability for Verified Simplex Design", **RTSS'14**]
http://www.verivital.com/rtreach/

Runtime (Online) Verification of Autonomous Systems with Real-Time Reachability: Supervisory Control and Monitoring of LECs in the Loop

- Complex controller: can do **<u>anything</u>**, be output from LECs, etc., abstracted to just produce control inputs (u) for the plant
- Assumptions: analytical (linear or nonlinear ordinary differential equation [ODE]) plant model available, and controller input remains fixed over finite time horizon
- **Supervisory control** via **Simplex architecture**
- Check these control inputs on closed-loop for a finite time horizon using **reachability analysis with real-time (WCET) guarantees**, if there's a problem, fall back to safety strategy

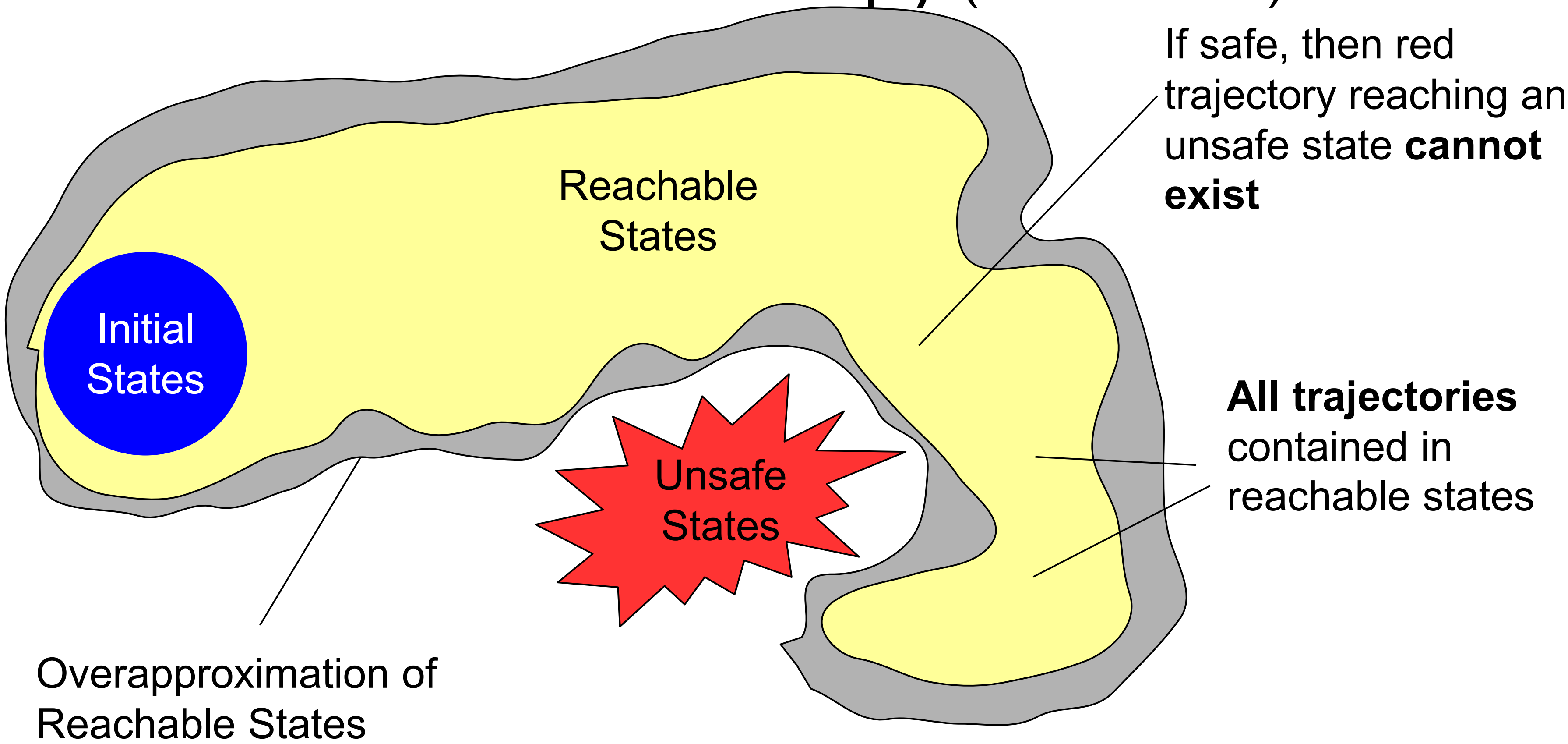


Real-time reachability algorithm implementation is cross-platform C (x86, ARM, AVR, etc.) with no dynamic memory allocation, recursion, or library dependencies: https://github.com/verivital/rtreach

[Taylor T. Johnson, Stanley Bak, Marco Caccamo, Lui Sha, "Real-Time Reachability for Verified Simplex Design", In ACM Transactions on Embedded Computing Systems (TECS), 2016 / RTSS'14]

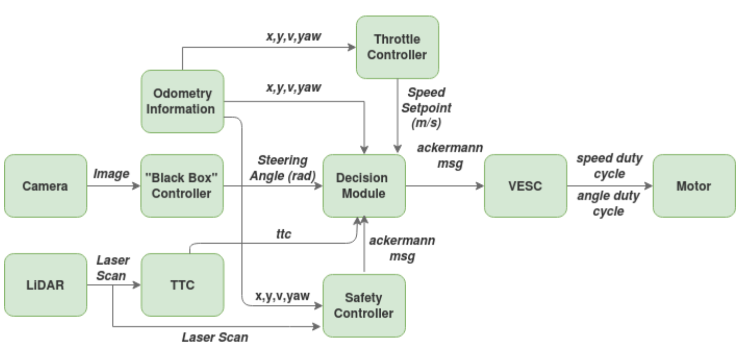
Safety Verification with Reachability

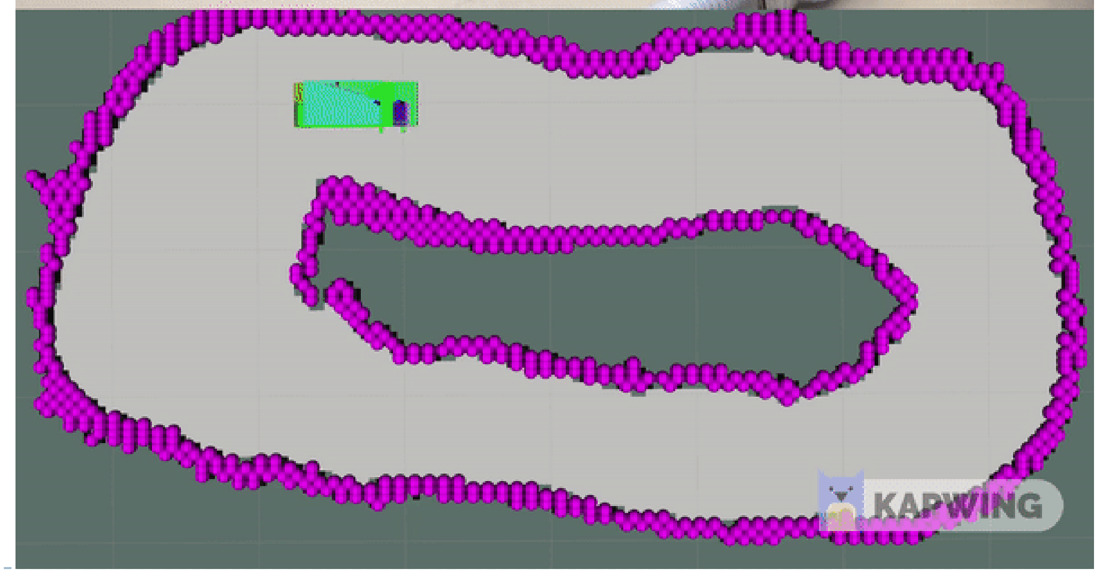
- **<u>Safe</u>** if intersection of overapproximation of reachable states with unsafe states is empty (**soundness**)



F1/10 Ground Vehicle End-to-End (E2E) LEC Demo

- End-to-end (E2E) controller: takes images and produces steering control inputs
- Classification-based control: determining steering angle (straight, weak left, weak right, etc.) with fixed speed
- Reachable sets visualized below right: if intersection with obstacles occurs, use fallback safety controller
- Plant model: nonlinear ODEs (bicycle, Ackermann steering)





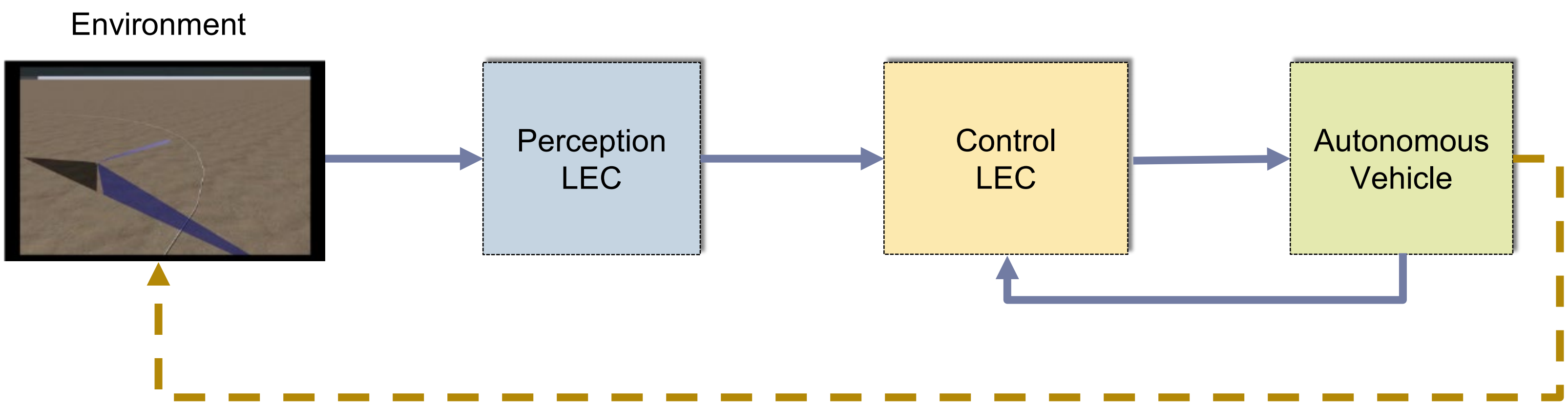
Assurance Monitoring Technology

Example-1: Detecting distribution shifts

Example-2: Detecting adversarial attacks

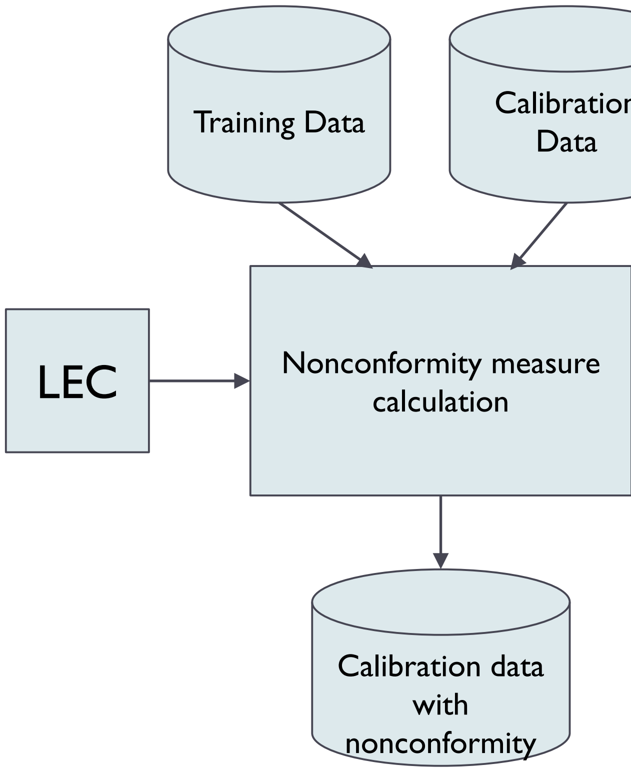
Prof. Xenofon Koutsoukos and team

Assurance Monitoring: Can we trust the output of the LEC?



- **Assurance Monitoring Based on Inductive Conformal Prediction**
  - Characterize how close the LEC behavior is to a model that represents the *expected safe behavior* obtained during the training phase.
  - Compute measures of confidence associated with predictions from LECs
  - Nonconformity measure is used to evaluate the degree to which a new example disagrees from a set of examples
  - Confidence is computed based how different is a test example compared to a set of calibration examples

Inductive Conformal Prediction (ICP)



- **Nonconformity measure**: A function that measures the disagreement between the actual label and the prediction using the neural network

1. Split the training set into
   - The proper **training** set
   - The **calibration** set
2. Use the proper training set to train the neural network
3. For each example in the calibration set:
   - Supply the input to the trained neural network to obtain the prediction
   - Calculate the nonconformity scores
   - Sort the calibration examples using descending order of the **nonconformity scores** in the set A
4. For each new example, compute the fraction of examples that are equally or more nonconforming (p-values)
5. Compute a *predictor* with a given confidence based on the p-values

Shafer, G., & Vovk, V. (2008). A tutorial on conformal prediction. *Journal of Machine Learning Research*, *9*(Mar), 371-421.

Anomaly Detection

- The nonconformity measure can be used to evaluate the degree to which a new example disagrees from a set of examples
- For test examples, we compute the fraction of nonconformity scores for the calibration data that are larger than the nonconformity score of the test input (**empirical** ***p*****-value**)
- If the empirical p-value < ε the example is classified as a conformal anomaly
- There are at least three explanations for a conformal anomaly
  - A rare or previously unseen example from the *same* probability distribution as the training set
  - A *true novelty* not generated from the same probability distribution as the training set
  - The training examples are *not* IID

Laxhammar, R. & Falkman, G. , Inductive conformal anomaly detection for sequential detection of anomalous subtrajectories, *Annals of Mathematics and Artificial Intelligence*, (2015) 74: 67.

Online Out-of-Distribution Detection in Multidimensional Time Series

- In CPS, examples arrive one by one and after observing each new example, we would like to quantify the degree to which the examples disagree with the training data
- If the examples are IID, the inductive conformal anomaly detection algorithm produces *p*-values that are independent and uniformly distributed in [0,1]
- Out-of-distribution detection can be performed by testing the hypothesis that *p*-values that are independent and uniformly distributed in [0,1] – or not

V. Fedorova, A. Gammerman, I. Nouretdinov, and V. Vovk. 2012. Plug-in martingales for testing exchangeability on-line. In Proceedings of the 29th International Conference on International Conference on Machine Learning (ICML'12).

Exchangeability Martingales

- Given the sequence of p-values, a martingale is calculated as a function of the p-values
  - Power martingale

$$M_n^{\varepsilon} = \prod_{i=1}^{n} \varepsilon p_i^{\varepsilon-1}$$

  - Simple mixture martingale

$$M_n = \int_0^1 M_n^{\varepsilon} \, d\varepsilon$$

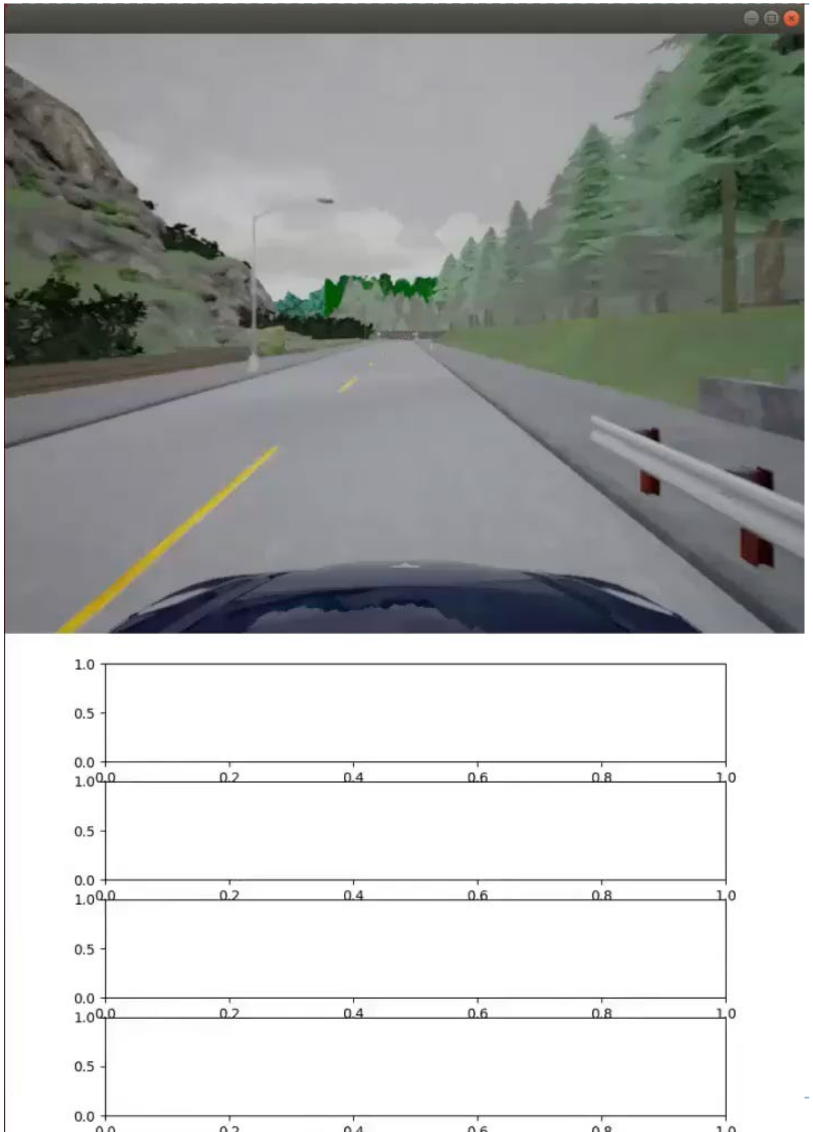
- The value of the martingale reflects the strength of evidence *against the exchangeability assumption*, i.e. that the examples are generated from the same probability distribution independently
- Such a martingale will grow only if there are many small p-values in the sequence
- If the generated p-values concentrate in any other part of the unit interval, we cannot expect the martingale to grow

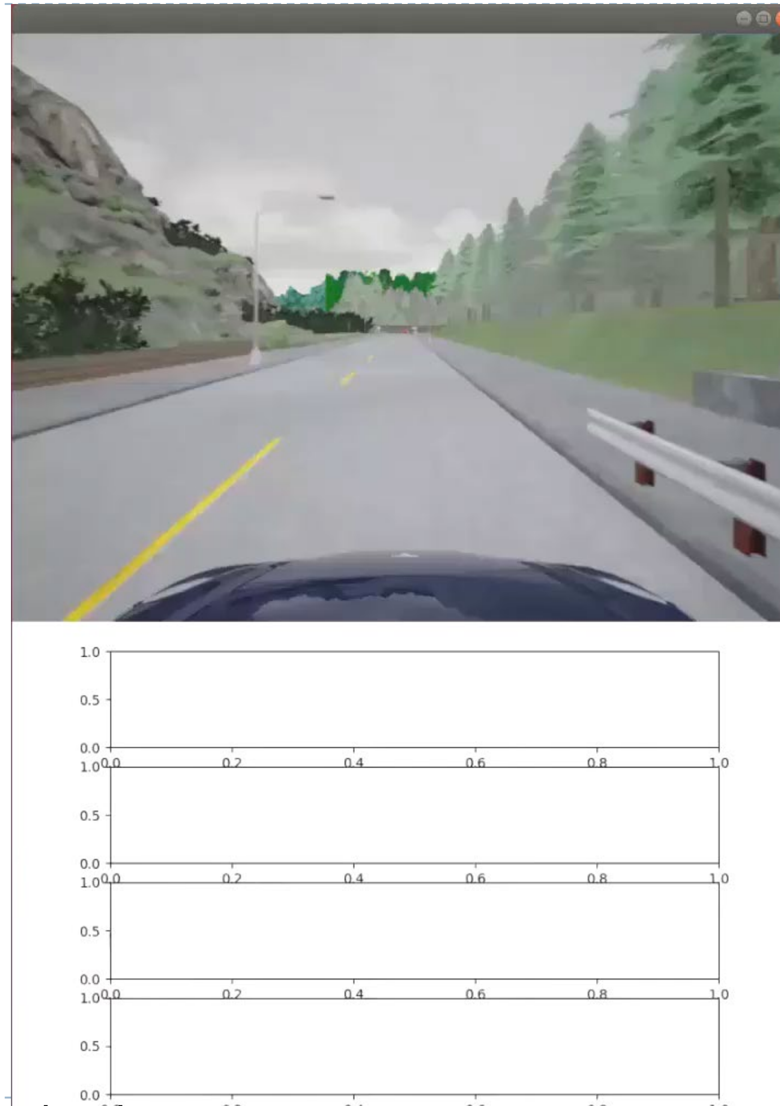
V. Fedorova, A. Gammerman, I. Nouretdinov, and V. Vovk. 2012. Plug-in martingales for testing exchangeability on-line. In Proceedings of the 29th International Conference on International Conference on Machine Learning (ICML'12).

Nonconformity Measure (NCM)

- Computing the NCM using k-nearest neighbors requires storing the training data which may be infeasible for autonomous CPS → Reduce the memory/time requirements
- Train an appropriate neural network architecture which can be used to compute efficiently the NCM
- 1. Autoencoders
  - Use the reconstruction error as the NCM
  - Based on current experiments, the method is not robust
- 2. Variational autoencoders
  - Use the generative model to sample multiple IID examples for the input of the current time step
  - Use the reconstruction error (probability) as the NCM
- 3. Deep One-Class Classification
  - Deep Support Vector Description (SVDD)

Assurance Monitoring
Distribution Shift Detection Example



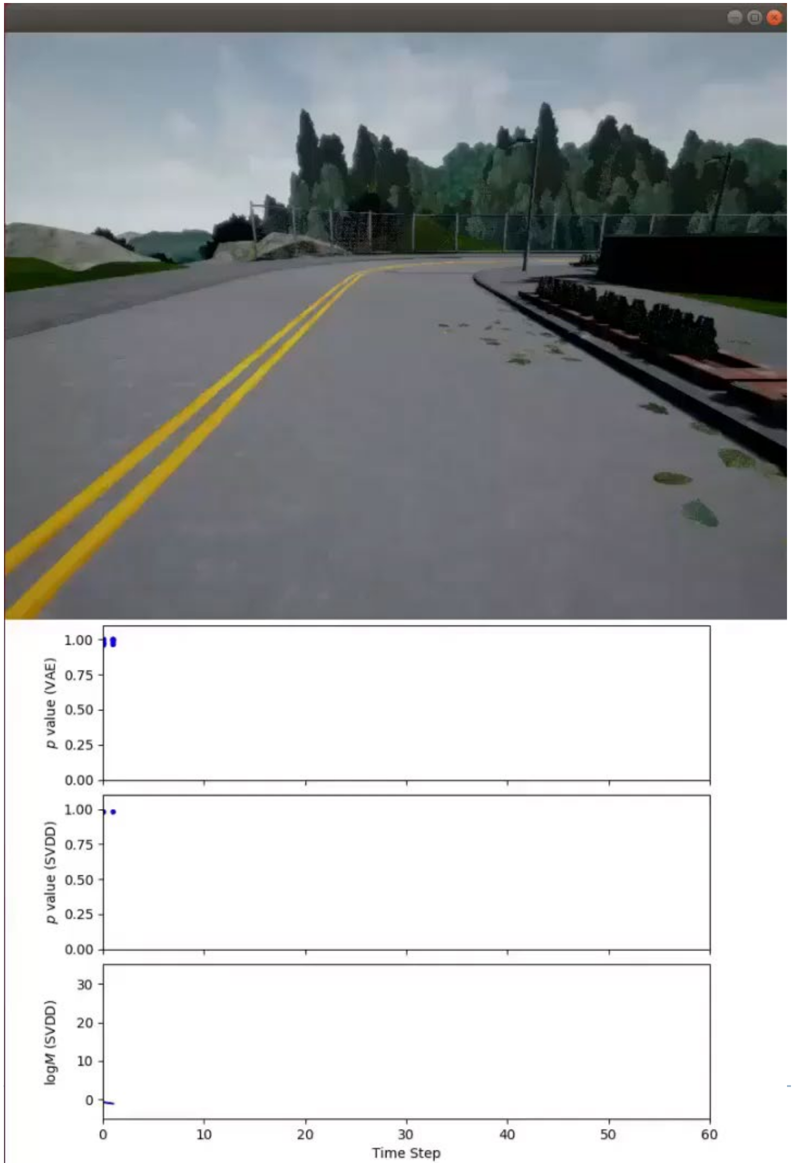


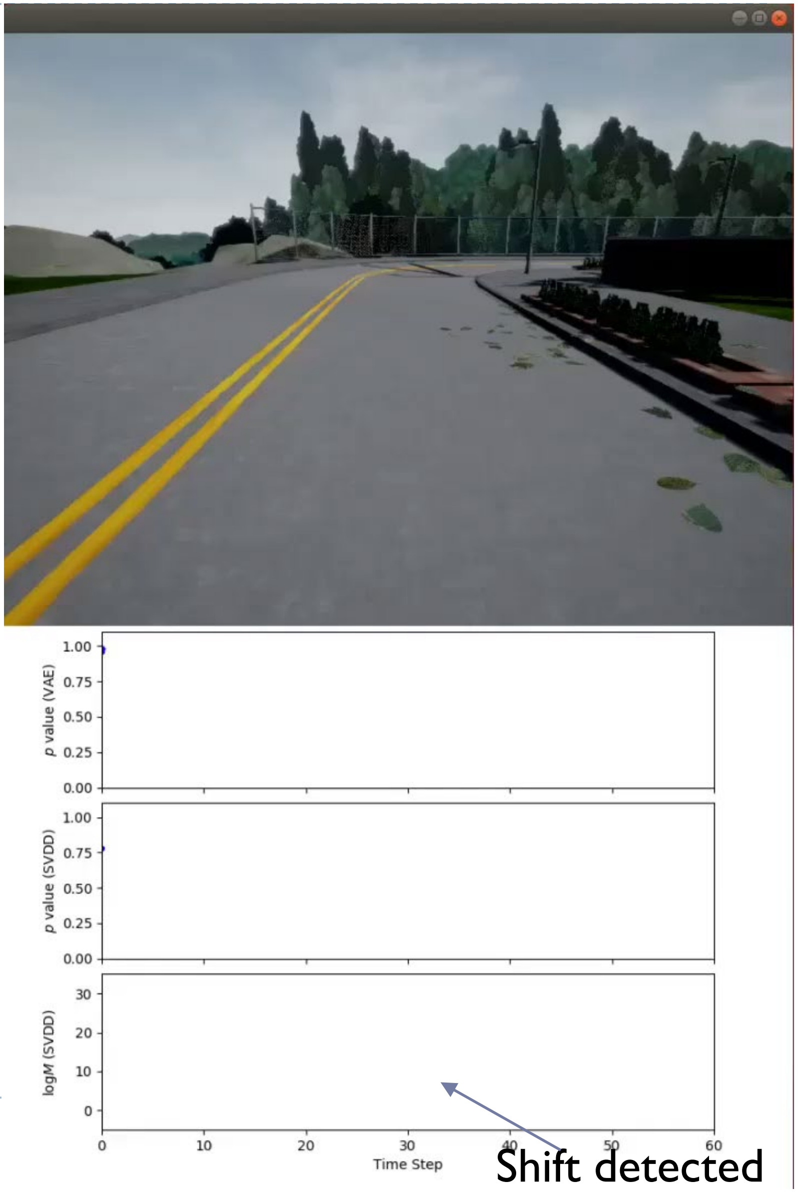
In distribution

Out of distribution

Precipitation parameter [0,100] is the full range. Precipitation [0,20] is in distribution

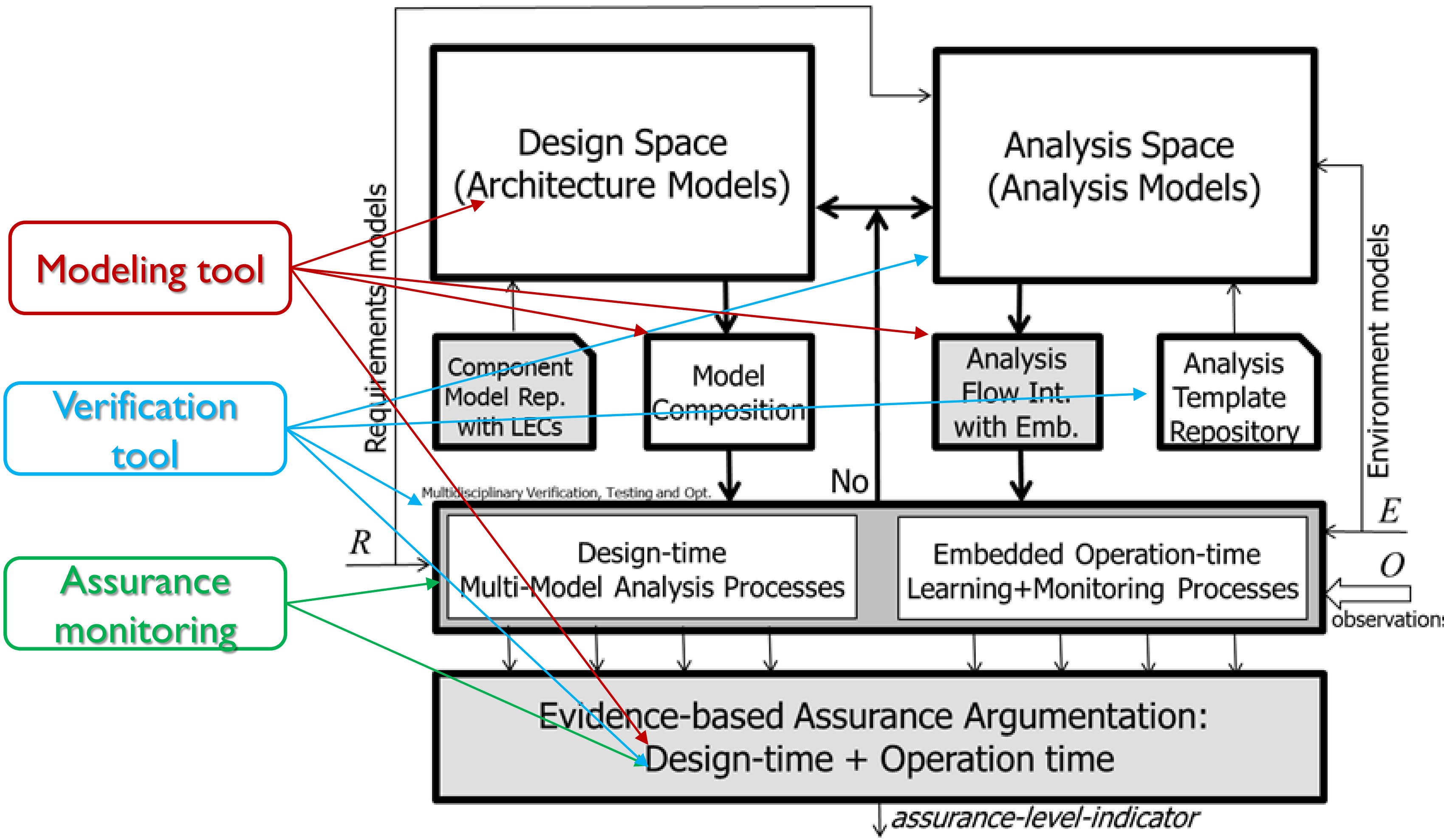
Assurance Monitoring:
Distribution Shift Detection in adversarial scenarios





ALC Toolchain

Tool architecture - coverage



ALC Toolchain Approach

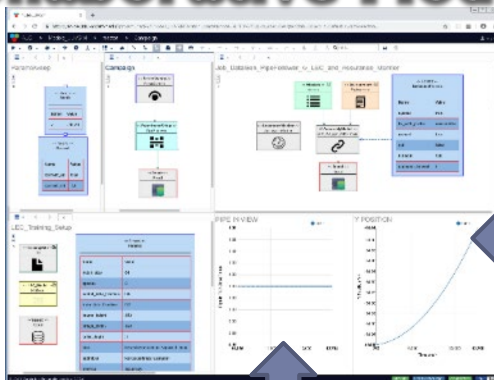
ALC Workflows

System Integrator

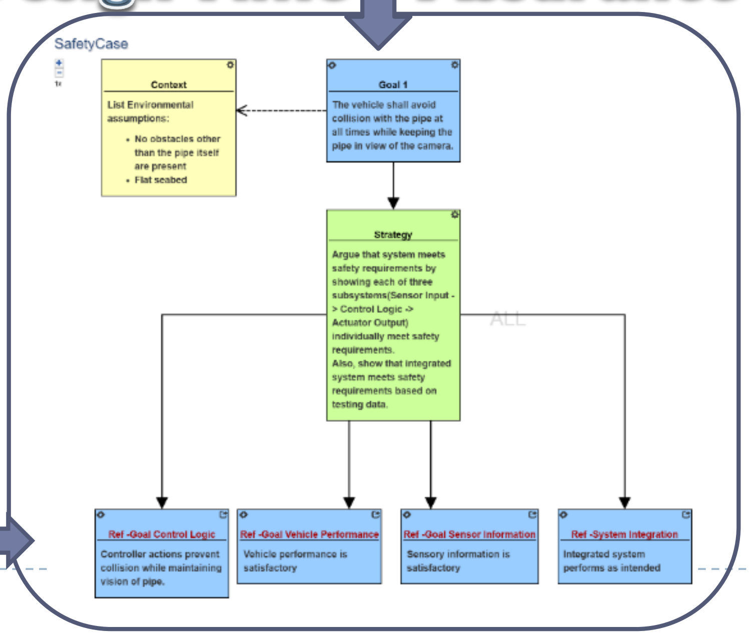
LEC Developer

Assurance Engineer

Collaborative Modeling

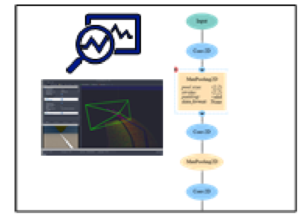


Design Time Assurance

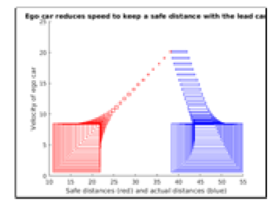


- *The model driven toolchain supports training, verification and design-time assurance of learning enabled components.*
- *Toolchain helps with developing safety assurance cases for the system using collected evidence.*
- *Complete provenance tracking of Experimental runs and data collection is supported.*

Execution, Training, Data Collection, Verification

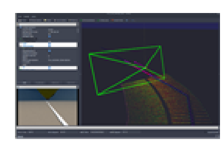


(d) Run System with LEC



(c) Verify Closed-Loop System With LEC

(b) Train LECs

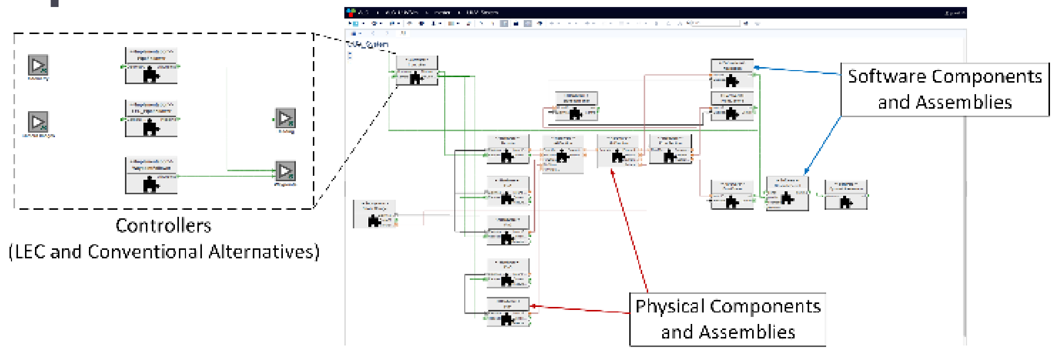


(a) Run Scenarios To Collect Data

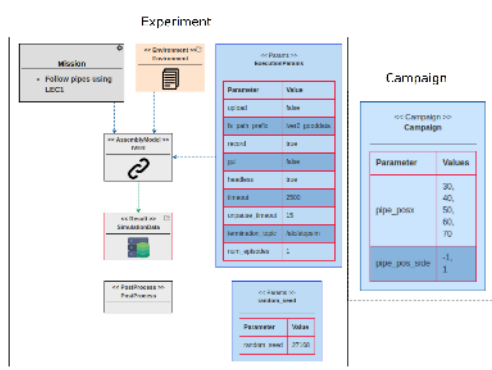
Typical Workflow Sequence

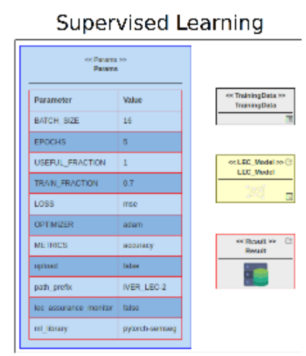
ALC Toolchain Concepts

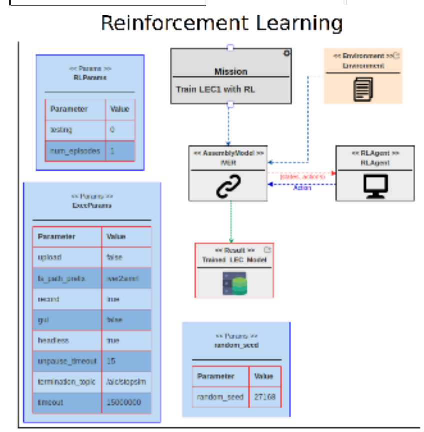
- Modeling
  - System Architecture / SysML



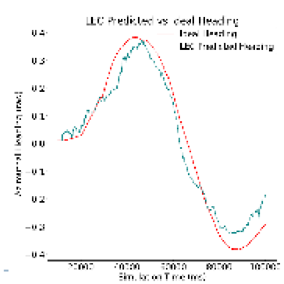
- LEC Construction
  - Data collection
  - Training
  - Evaluation

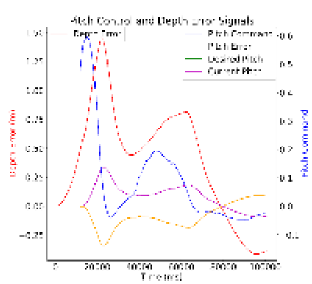


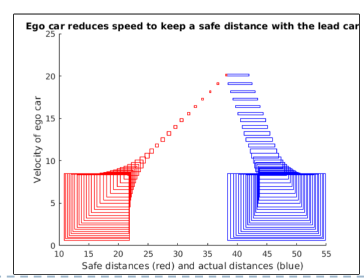


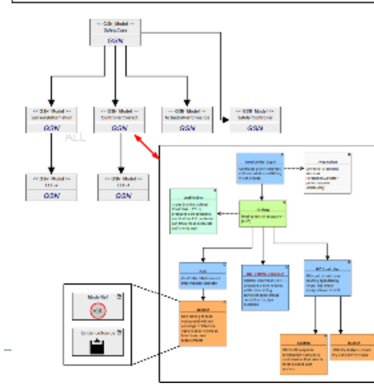


- Testing -- Verification/Validation/Assurance



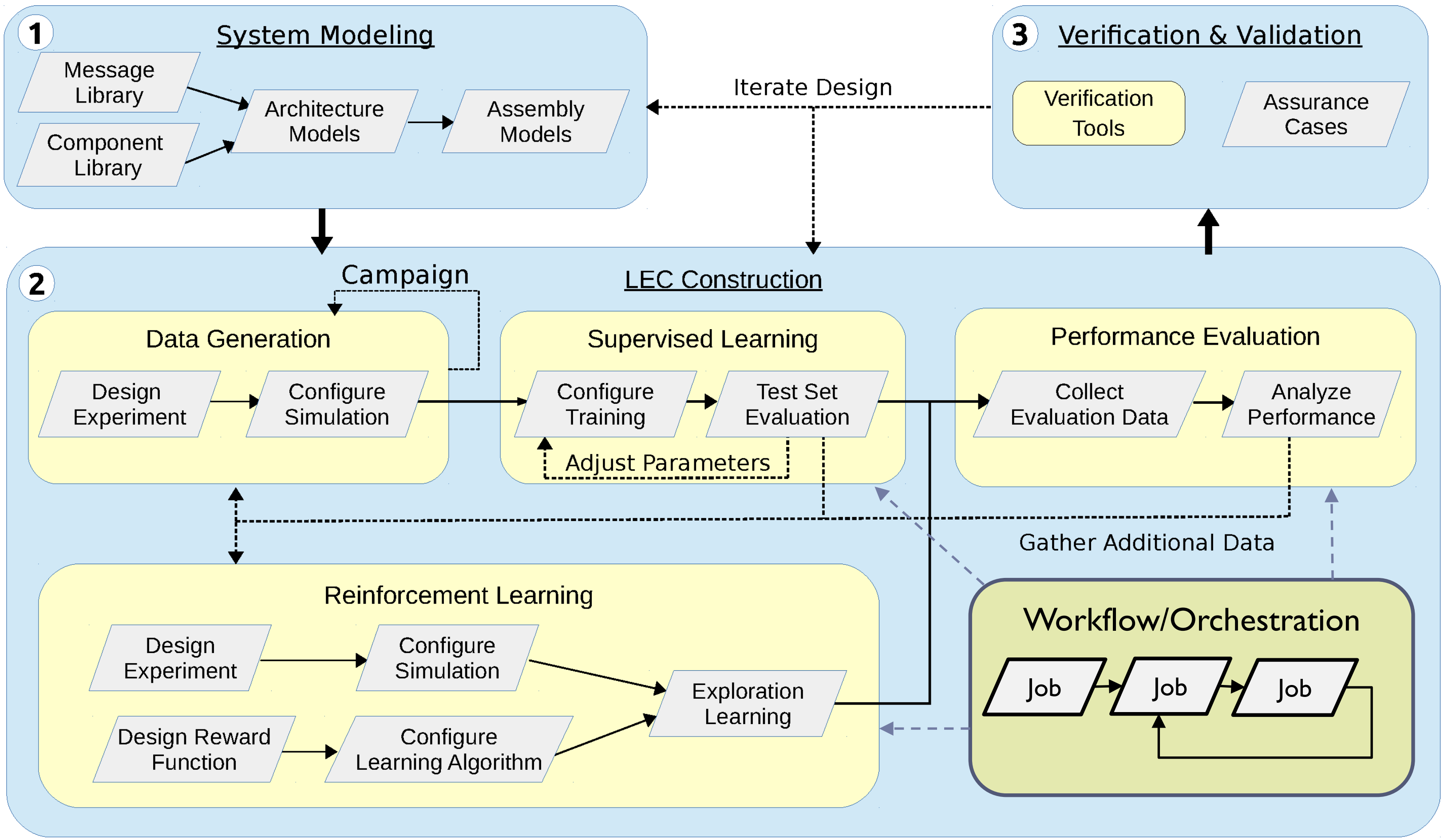




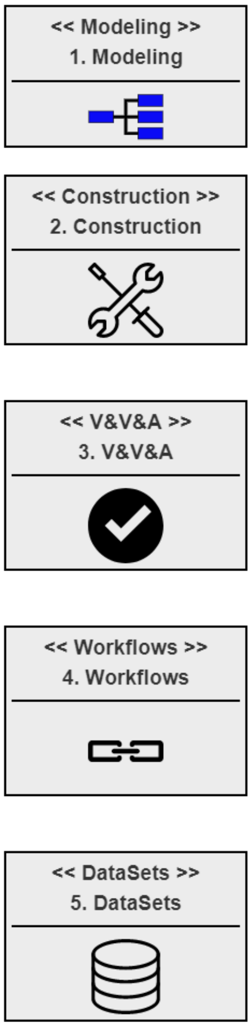


ALC Workflow

- MDE with support for LEC development + Assurance



Models in the ALC Toolchain



Model Systems using:
- Component blocks (hardware/software)
- Messages/datatypes for software
- System architecture

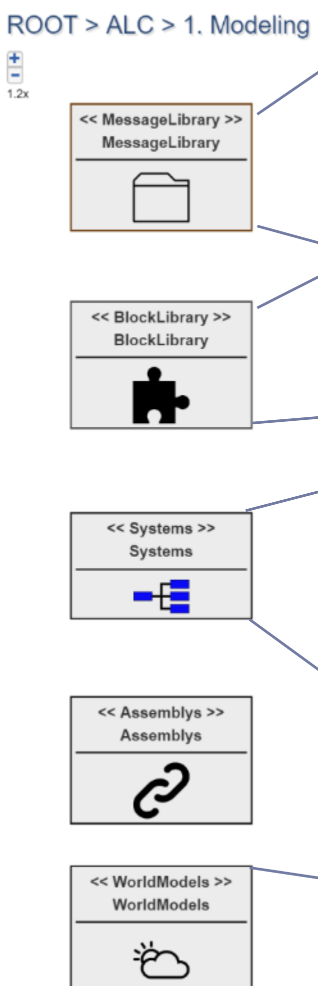
Construct Experiments consisting of:
- Data collection
- LEC training
- Assurance Monitor construction

Verification, Validation, and Assurance via:
- Formal Verification (Design-time)
- LEC testing
- Assurance argument construction

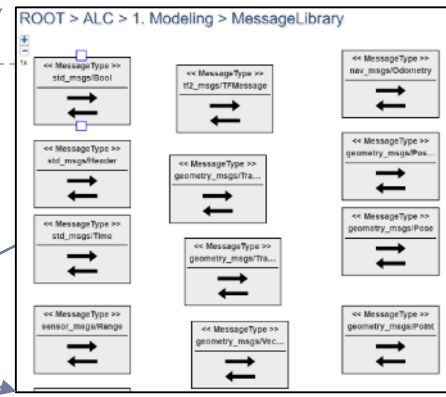
Workflow automation:
- Create/Execute sequences of operations

Datasets to:
- Manage all data produced by Experiments and Workflows
- Track data provenance
- Perform automated analysis/evaluation of data

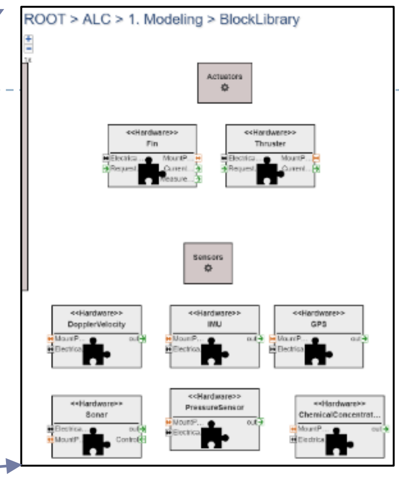
System Modeling

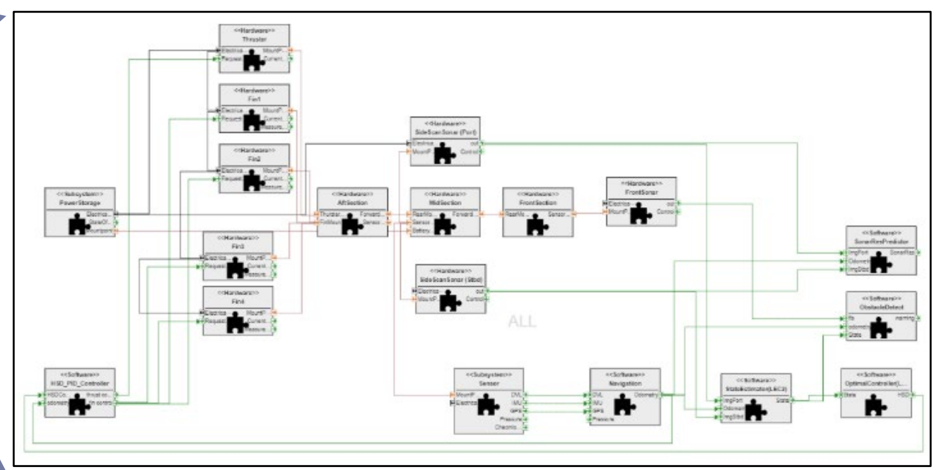


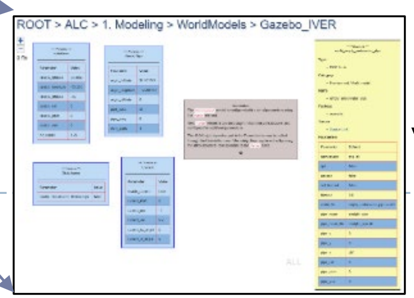
Data Models, Messages



Components:
Hardware, Software/LEC



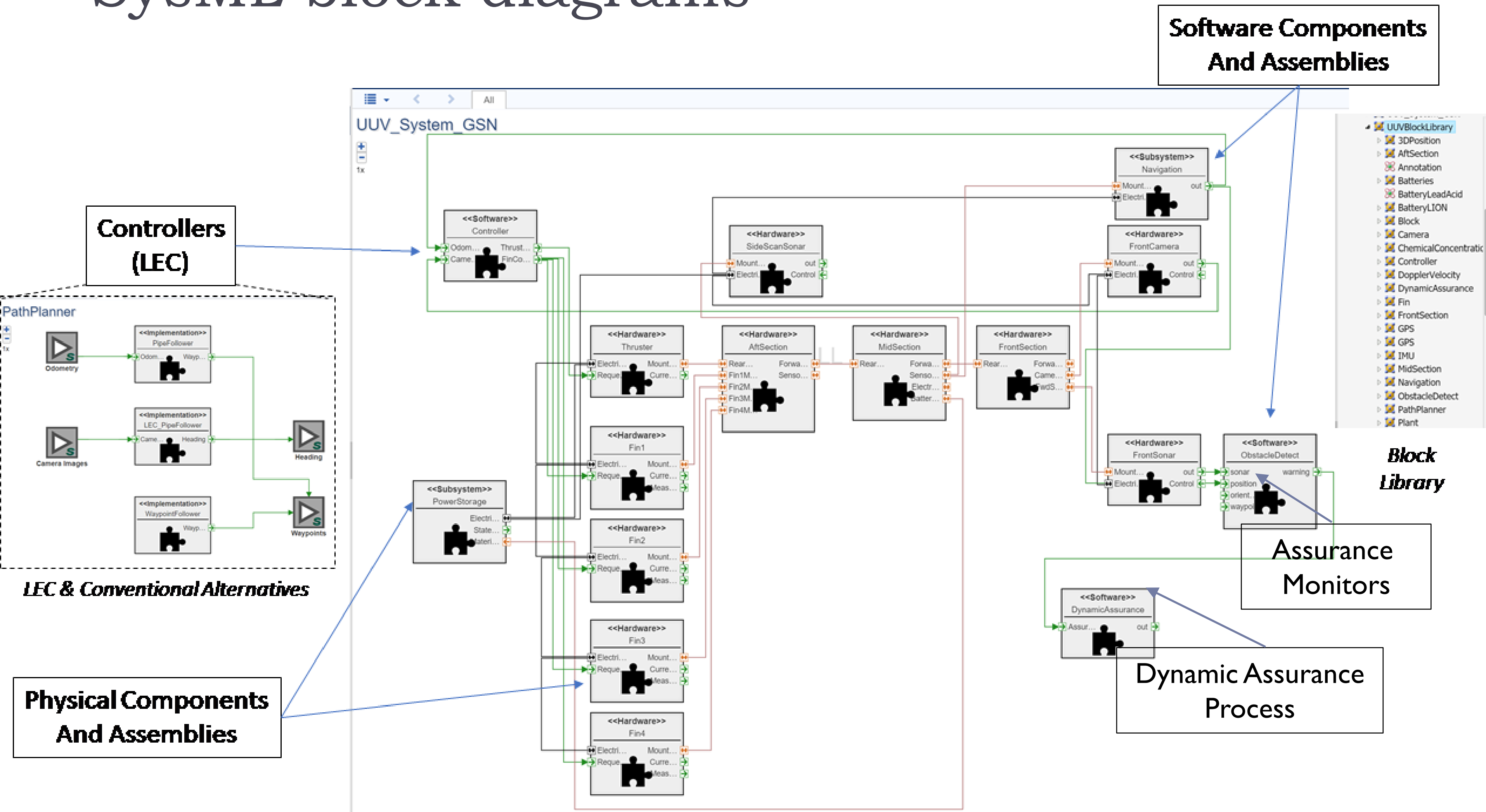




Systems: Components/ Subsystems; Parameters,...

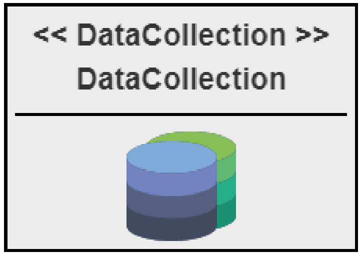
World models: Scenarios, Environments, Parameters

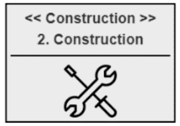
System architecture SysML block diagrams

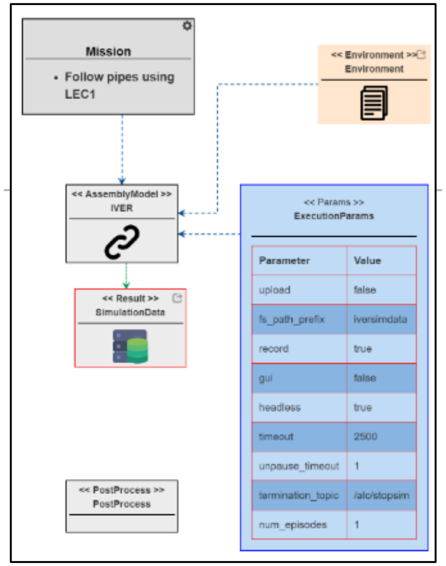


Subset of SysML Blocks, IBD to model all blocks, implementation alternatives for flexibility

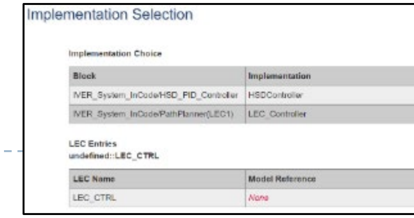
LEC Construction



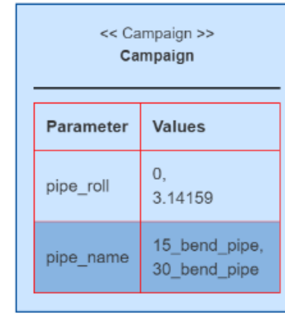


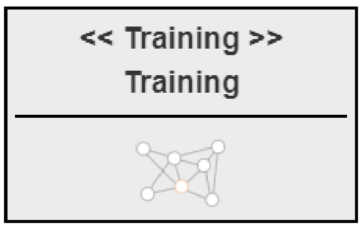


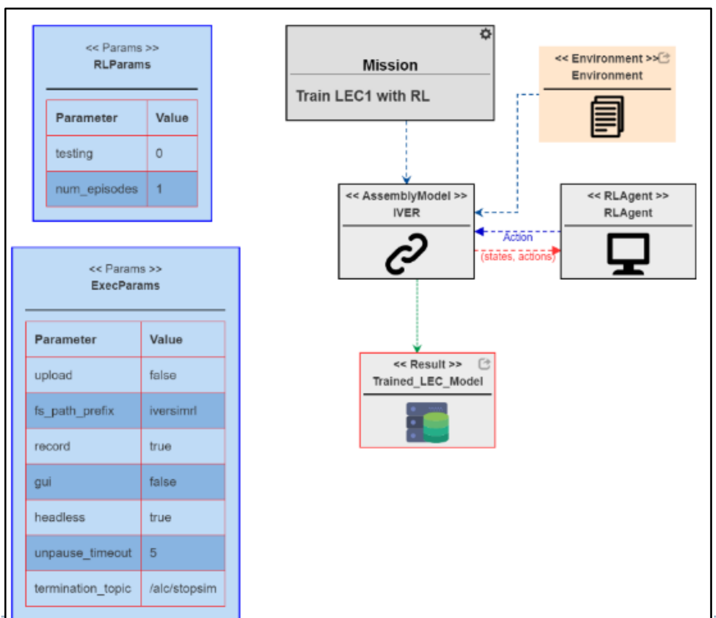
1. Data Collection



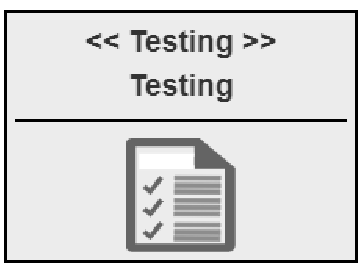
Select Configuration

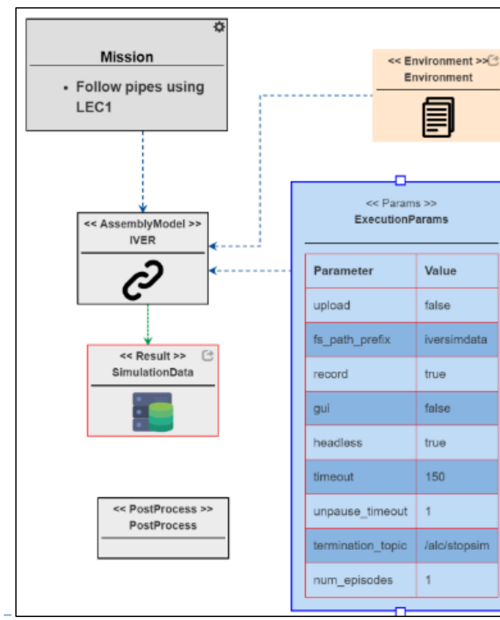






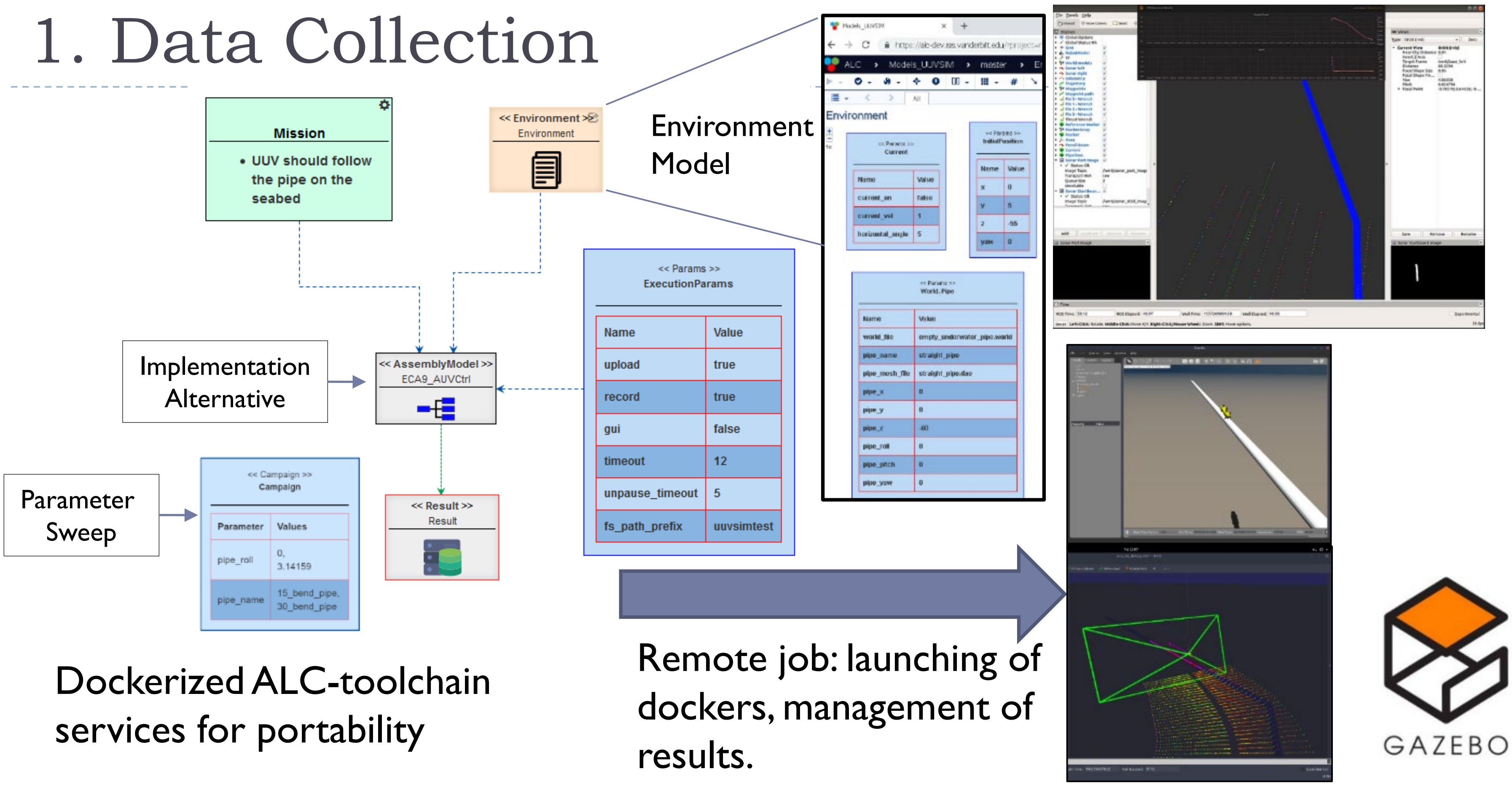
2. Training LEC + A/M





3. Testing

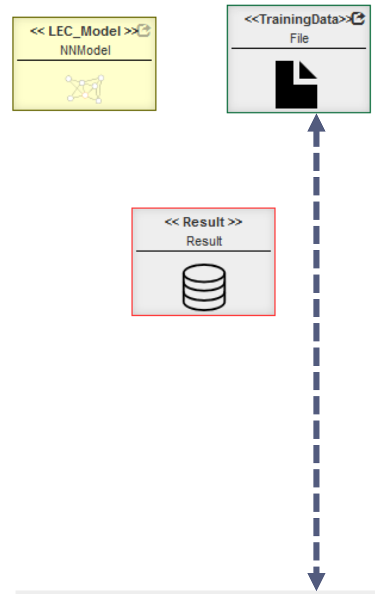
LEC Construction: 1. Data Collection



- *Assembly model* selects a specific implementation variant of a system architecture
- *Mission*, *Environment*, and *Execution parameters* set up the experiment scenario
- *Campaigns* across parameters a configurations related to system and environments
- Tool generates configuration for running the simulation, capture results + metadata for all trials

LEC Construction: 2. Training

- Neural Net model and parameters specified in "LEC Model"
- "Training Data" links to data generated from previous experiments
- Training job is dispatched to worker machines (typically with GPUs)
- Results and metadata are saved from the training sessions

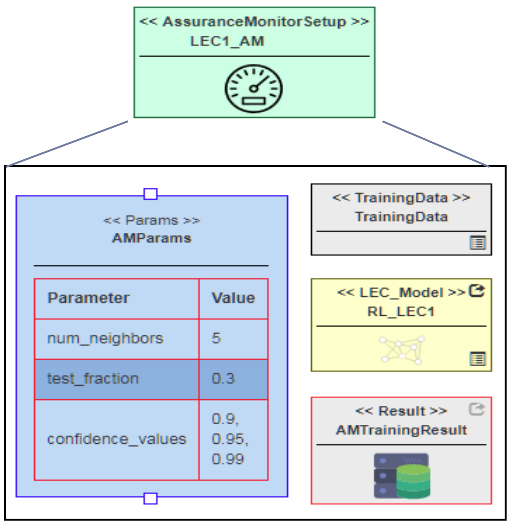


<< Params >>
Params

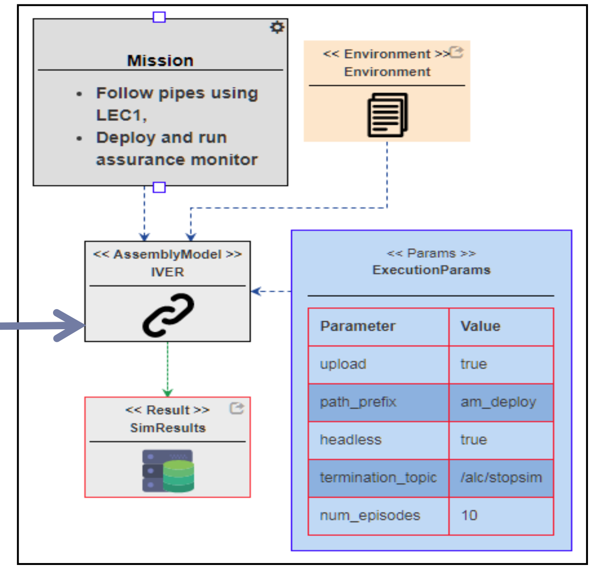
Name	Value
batch_size	64
epochs	5
useful_data_fraction	0.5
train_data_fraction	0.7
image_height	492
image_width	768
color_depth	3
loss	keras.losses.mean_squared_error
optimizer	keras.optimizers.Adam()
metrics	accuracy
upload	true

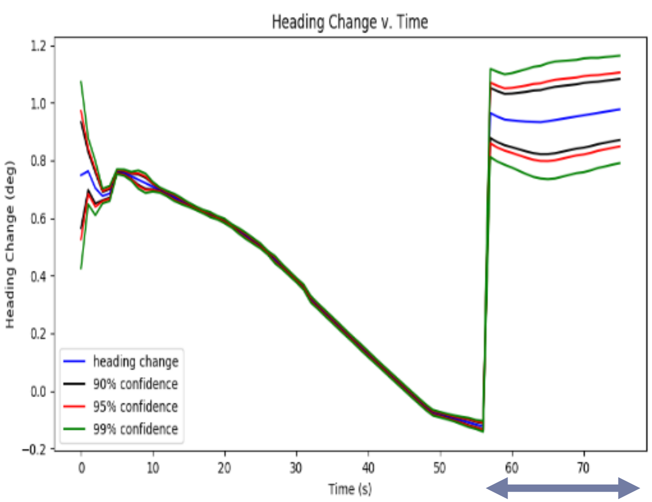
Name	Type
result-DataGen_PipeFollower-1542125401110	*metadata.json*
result-DataGen_PipeFollower-1542129035690	*metadata.json*
result-DataGen_PipeFollower-1542140169160	*metadata.json*

LEC Construction
2. Training: Assurance Monitor

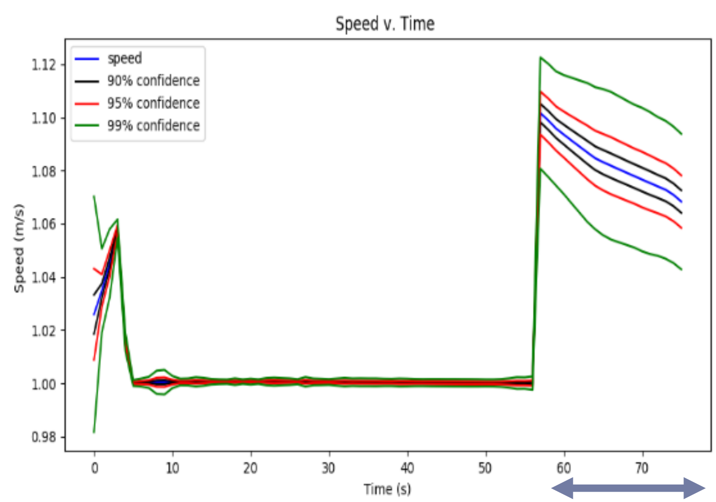


Deploy trained LEC, build assurance monitor.



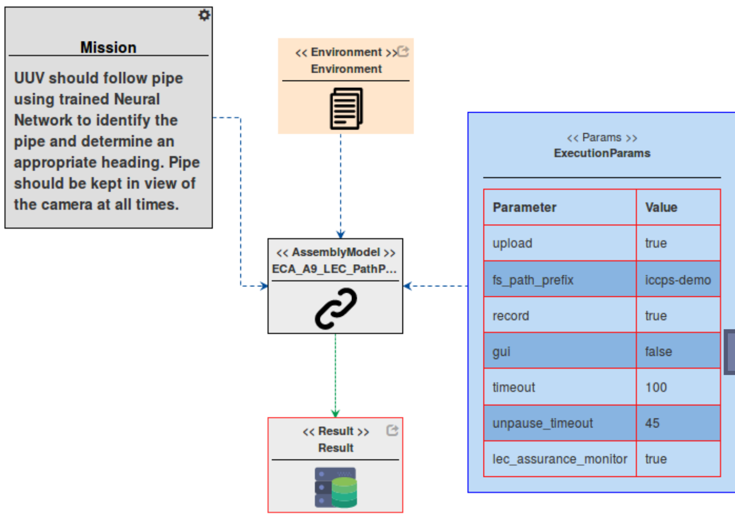


Pipe Visibility Lost



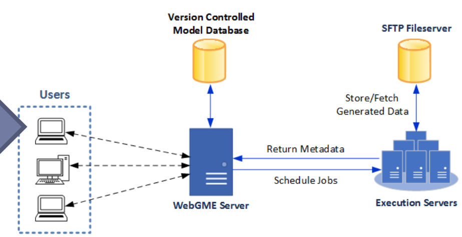
Pipe Visibility Lost

LEC Construction:
3. Evaluation: Testing/Verification

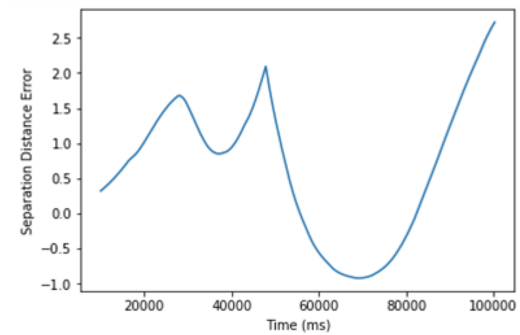


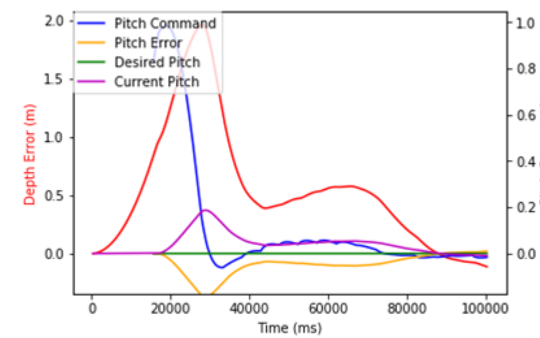
Analysis in Jupyter Notebook

Also, "single step" the process for debugging



Execute on Remote Server/s





Training Model Data Managed on GitLab

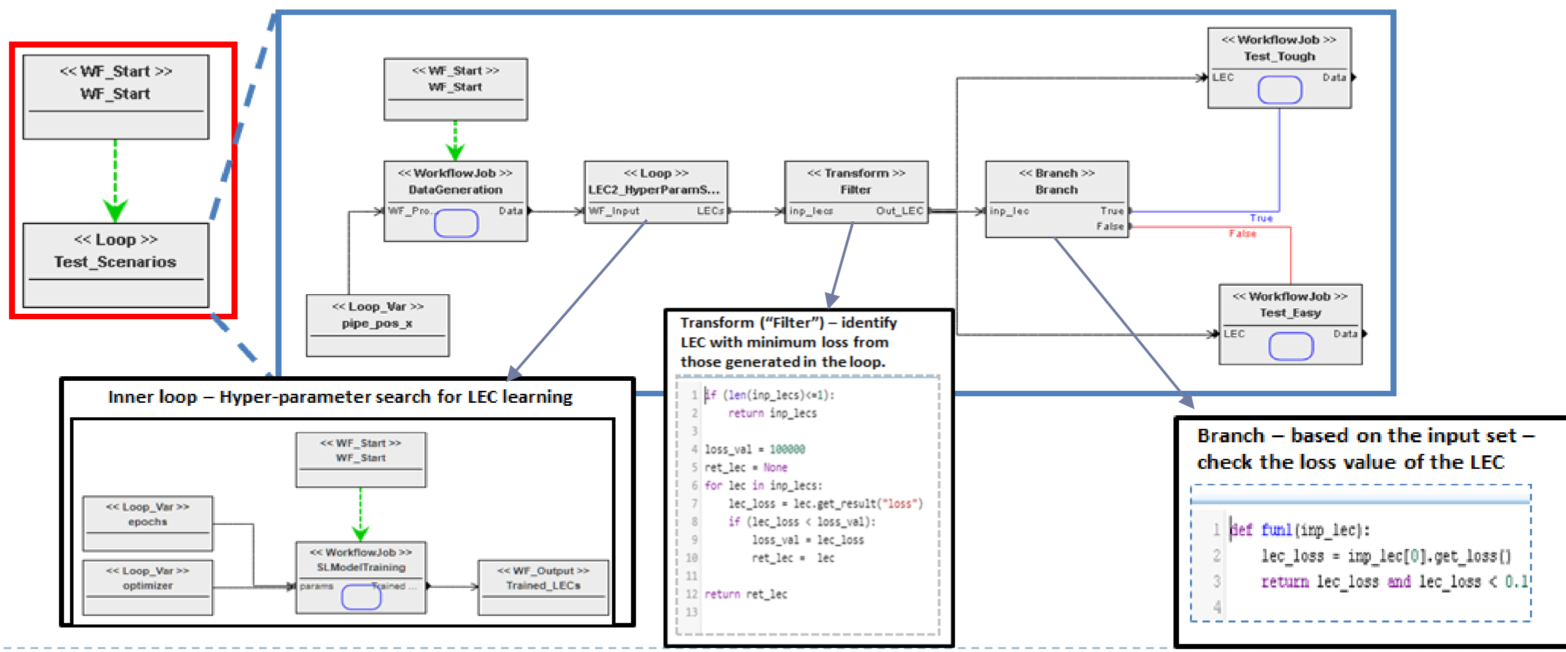
- Trained Neural Net can be tested in the simulator with another experiment model
- Performance metrics are recorded for LEC evaluation, e.g.:
  - Distance from ideal path
  - Pipe within camera field of view

Name	Type	Size	Creation Date
result-NN_Training_Test-1542127634867	model.keras	267 B	11/13/2018
result-NN_Training_Test-1542128784700	model.keras	267 B	11/13/2018

Results in file store + git, cross-linked for data provenance

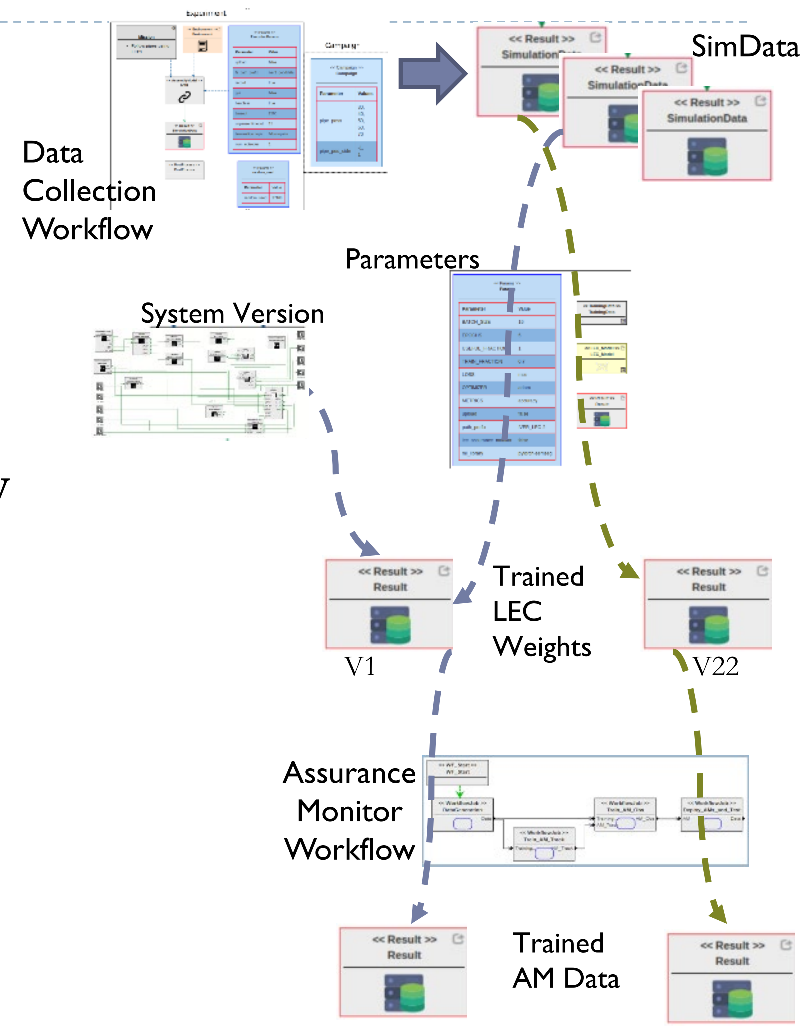
Tool Automation
Workflow Models

- Workflow models are for the specification and execution of job graphs
  - Each workflow job specifies execution of one or more activity models
  - Data dependencies between jobs are handled automatically
- Workflow supports
  - Loops – For (parallel), while/ do-while (sequential)
  - Transforms - Filter / Join (subset or aggregation of results)
  - Branch – execution path based on user-specified condition
- Example workflow to train and optimize a LEC

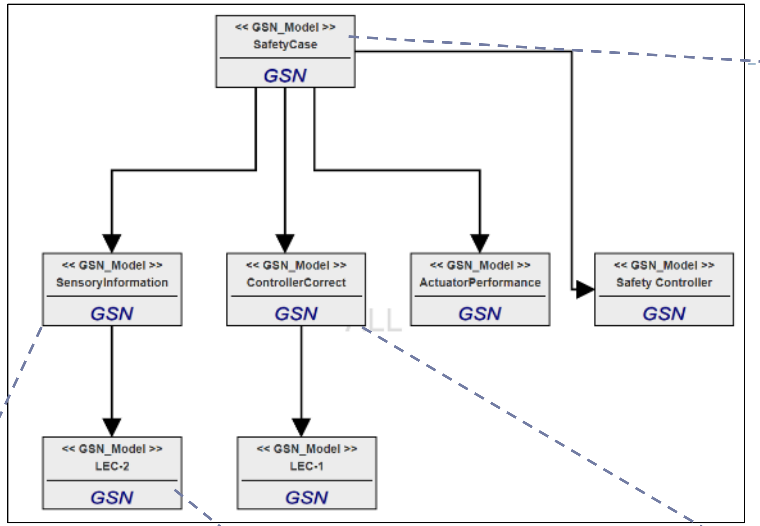


Tool automation
Support for Data Provenance

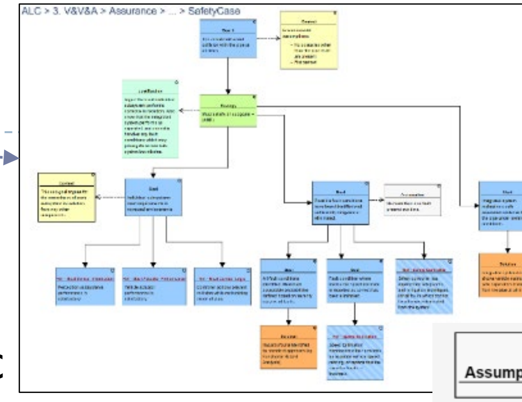
- All artifacts – generated during data collection, training, evaluation
- Recorded for each execution:
  - Parameter settings
  - LEC(s) Models (Deployed/Initial)
  - Data used in training, validation and evaluation
- Allows re-execution of any step/workflow
- Track the evolution of data/ LECs/ Assurance
- Maintain traceability links at each stage to:
  - Data used in training LECs
  - Initial trained model used in training LECs
  - LECs used in generating data sets/Assurance

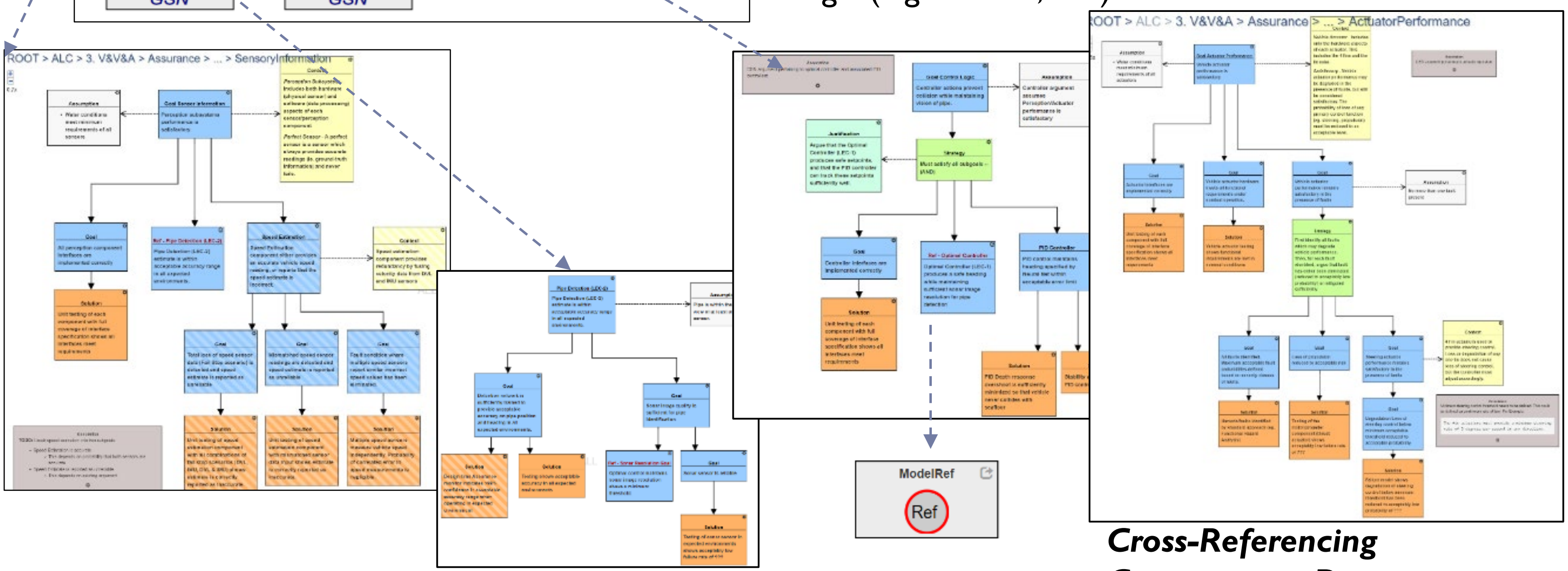


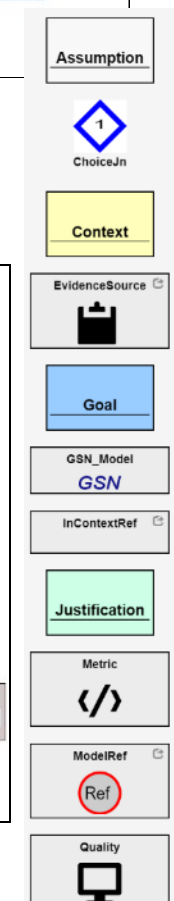
System Assurance Case: GSN



- Top-level goals correspond to high level safety claims
- Leaf goals correspond to claims which can be directly supported by evidence/solutions
- Evaluation metrics from LEC experiments can be used as evidence for leaf goals
- User Defined Combination Logic (E.g. M-of-N, etc.)







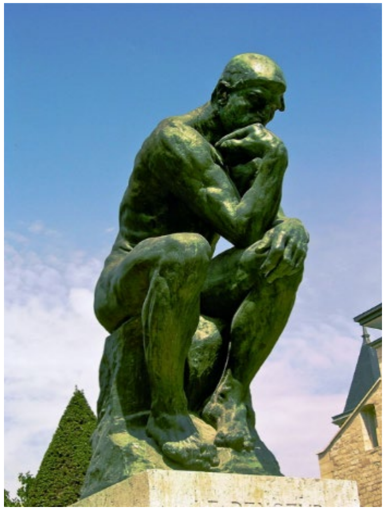
Cross-Referencing Components, Datasets, for Context/Evidence

Example GSN Model for UUV

Summary

ALC Project

- Verification:
  - Design-time: reachability + robustness of AI/LEC components
  - Run-time: safety given in the given situation
- Assurance monitoring:
  - Detect distribution shift
  - Assess confidence/credibility in the output
- Toolchain:
  - Automation for evaluating LECs
  - Modeling for assurance arguments (with evidence)



Publications:
https://alc.isis.vanderbilt.edu/redmine/projects/alc-project-public/documents
Portal for AA program tools:
https://assured-autonomy.org/

Credits

- Ted Bapty
- Dimitrios Boursinos
- Feiyang Cai
- Abhishek Dubey
- Charles Hartsell
- Taylor Johnson
- Xenofon Koutsoukos
- Jiani Li
- Nagabhushan Mahadevan
- Diego Manzanas Lopez
- Mary Metelko
- Patrick Musau
- Harmon Nine
- Shreyas Ramakrishnan
- Joel Rosenfeld
- Janos Sztipanovits
- Hoang-Dung Tran
- Ayana Wild
- Weiming Xiang
- Xiaodong Yang