Evolving Neural Network Ensembles for Reliable Time Series Prediction

Philip Feldman, PhD

ASRC Federal

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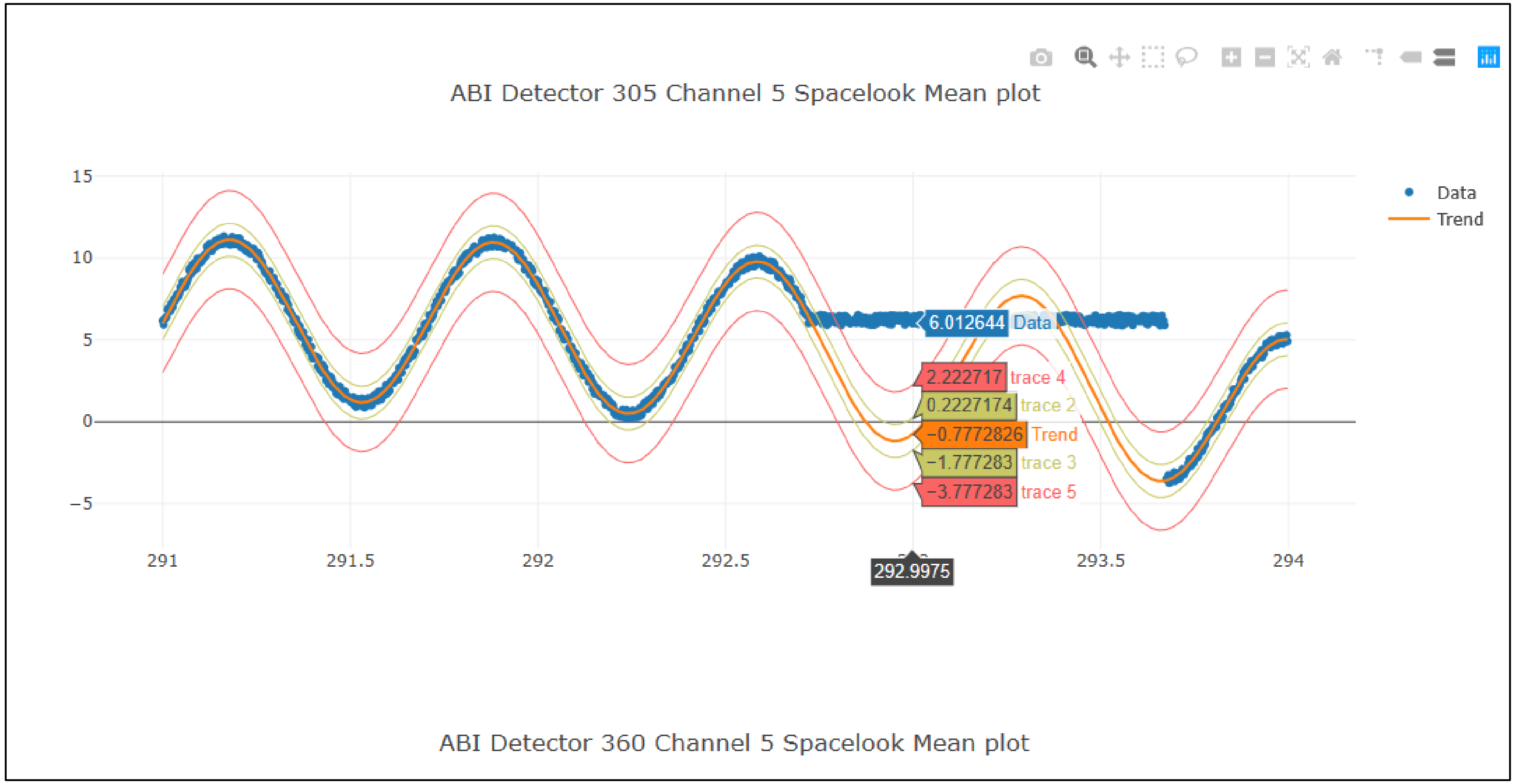
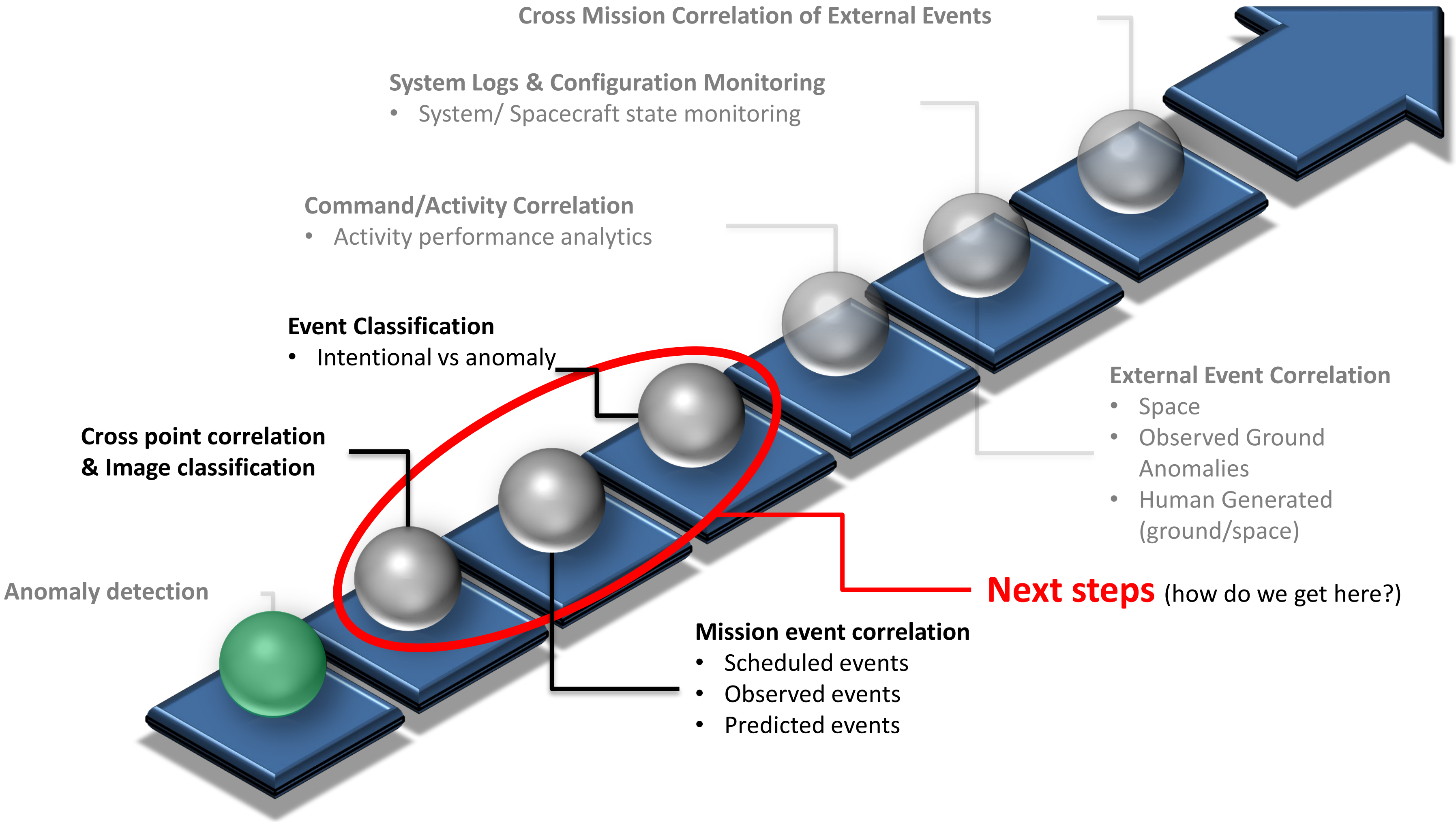
Background

- AIMS: Low-level monitoring and trending for single mnemonics using machine learning

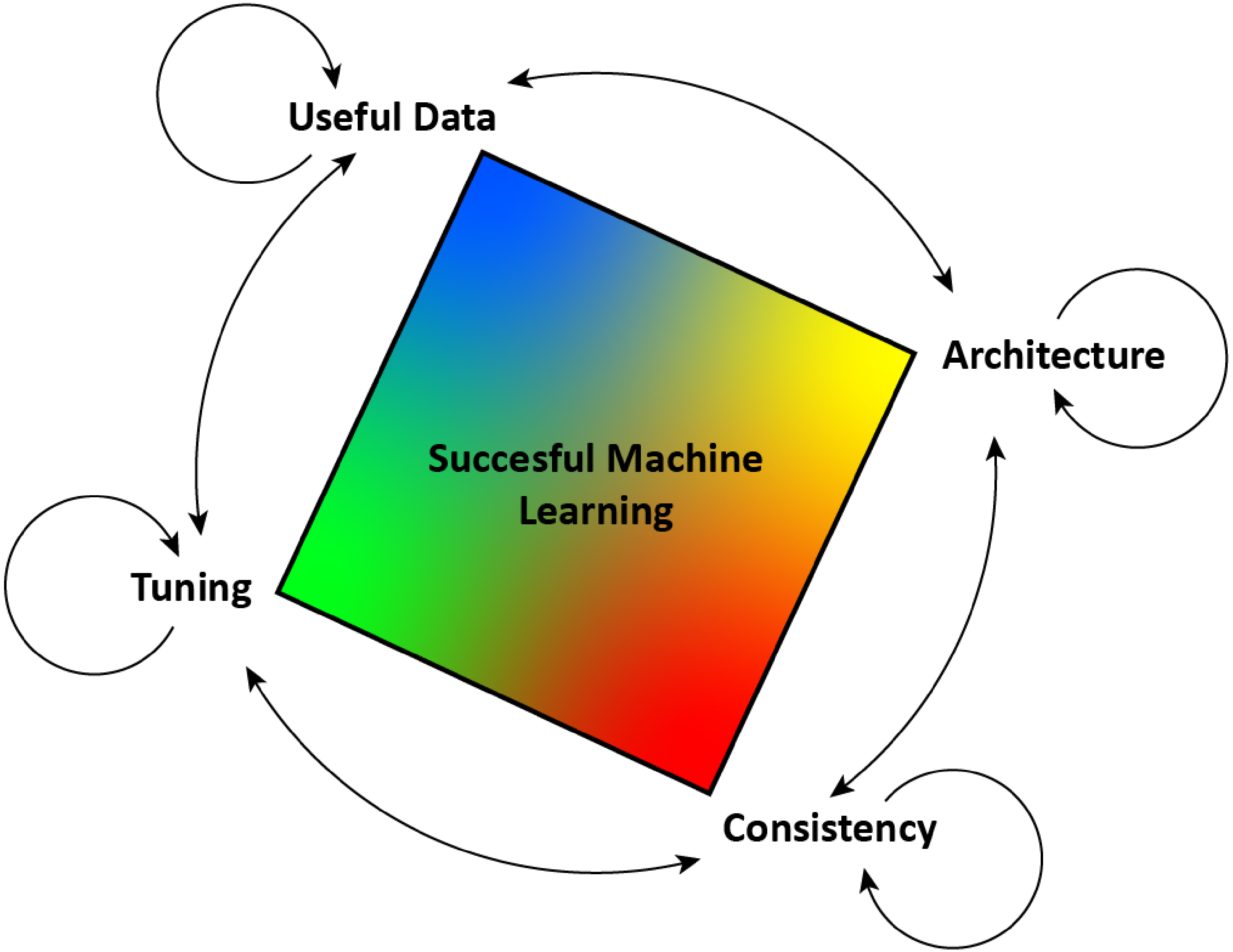


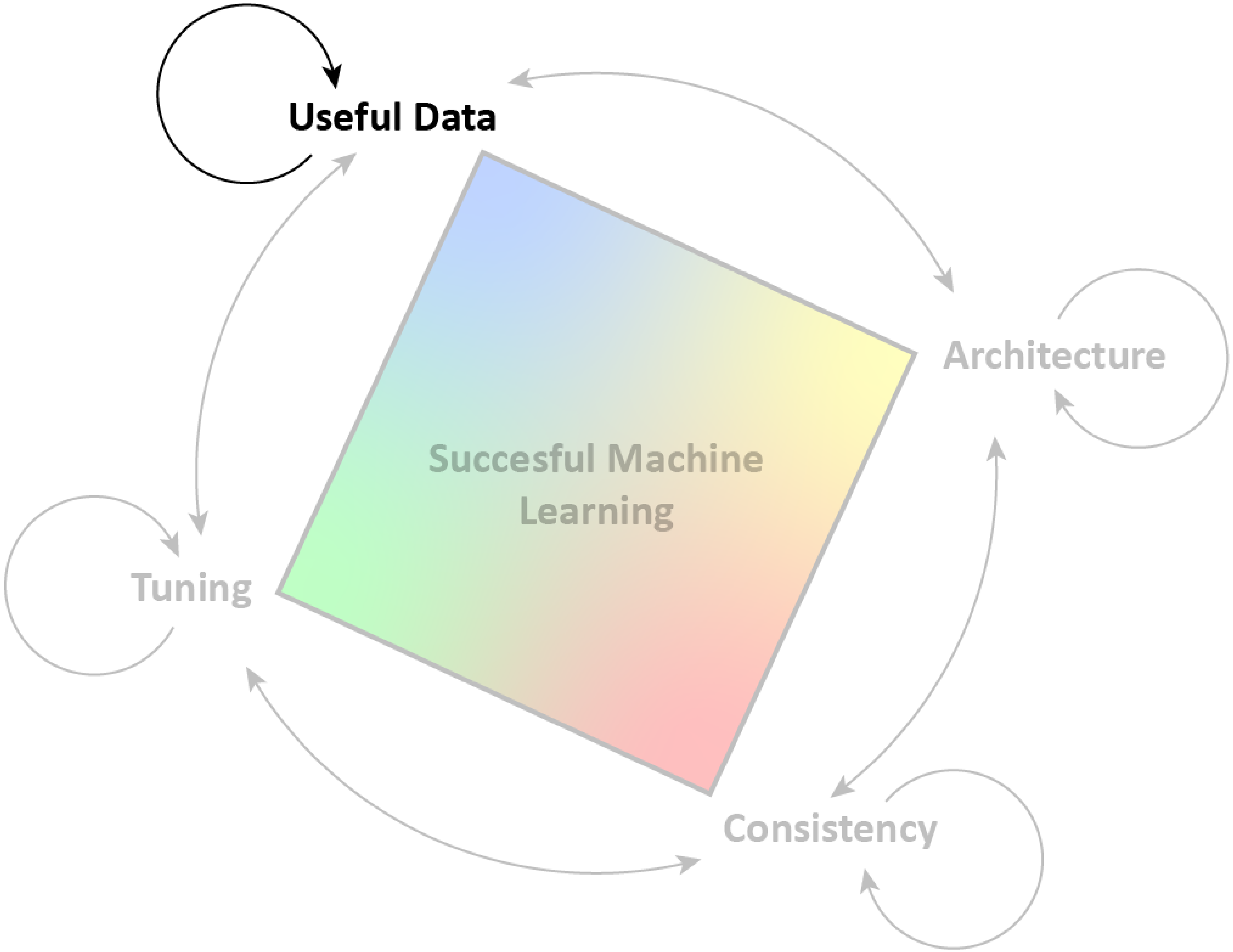
- Goal: High-level monitoring and trending across multiple mnemonics

ASRC Federal Machine Learning Evolution



The 4 parts of successful machine learning




Useful Data
Architecture
Succesful Machine Learning
Tuning
Consistency

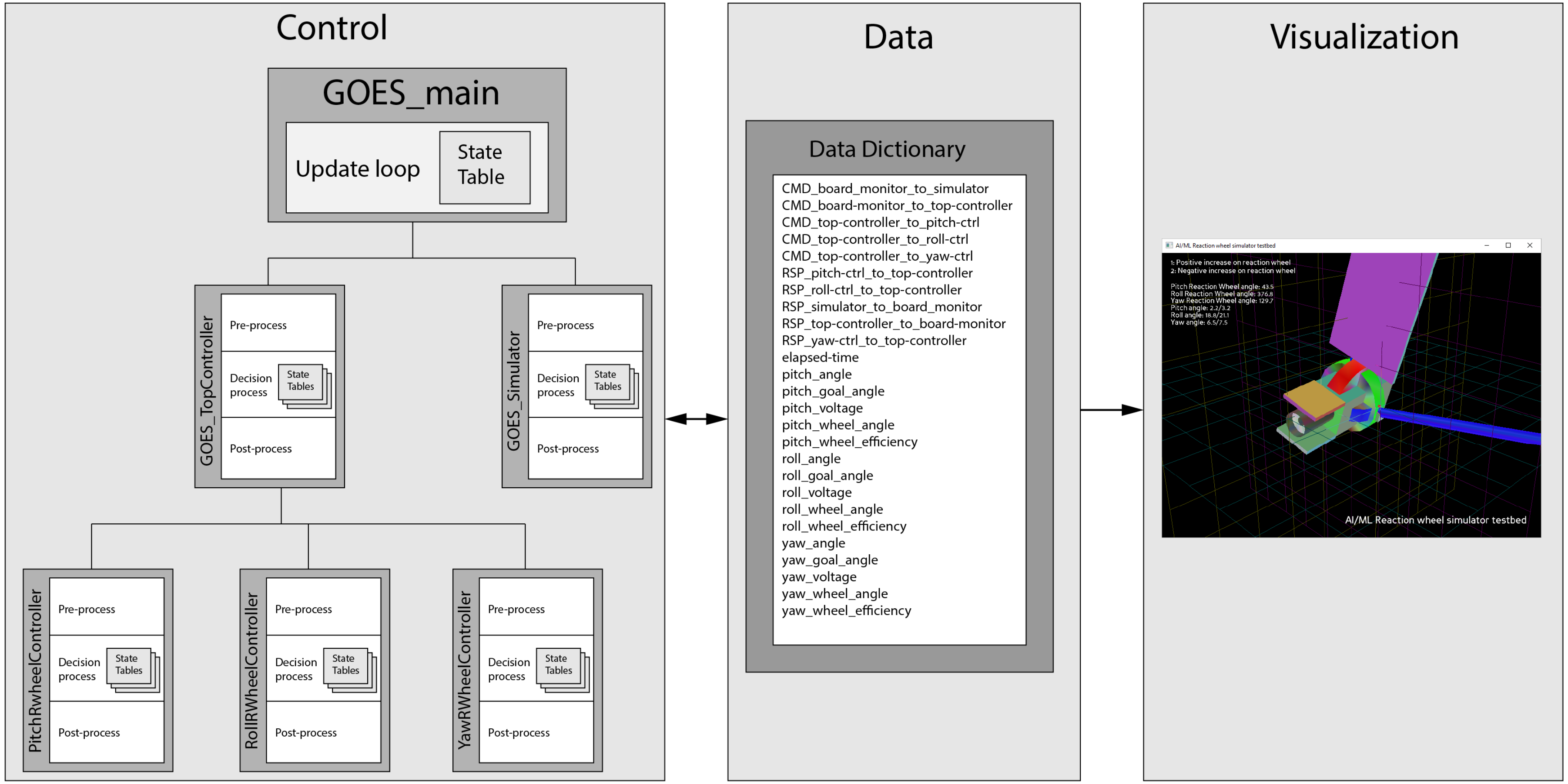
Getting useful data

1. Accidents in real life are rare.
    1. Your chance of a fatal car wreck is 0.00000125% per mile
    2. Your chance of a fatal plane crash is 0.0000000007% per mile
2. Machine learning is based on meeting an objective function, such as accuracy prediction.
    1. Assume no airplane fatalities *ever*: 99.99999999983% accurate
    2. Assume no auto fatalities *ever*: 99.99999875% accurate
3. Simulation lets us change those odds to 50-50, where machines learn best:

Accident simulator *par excellence* – Grand Theft Auto

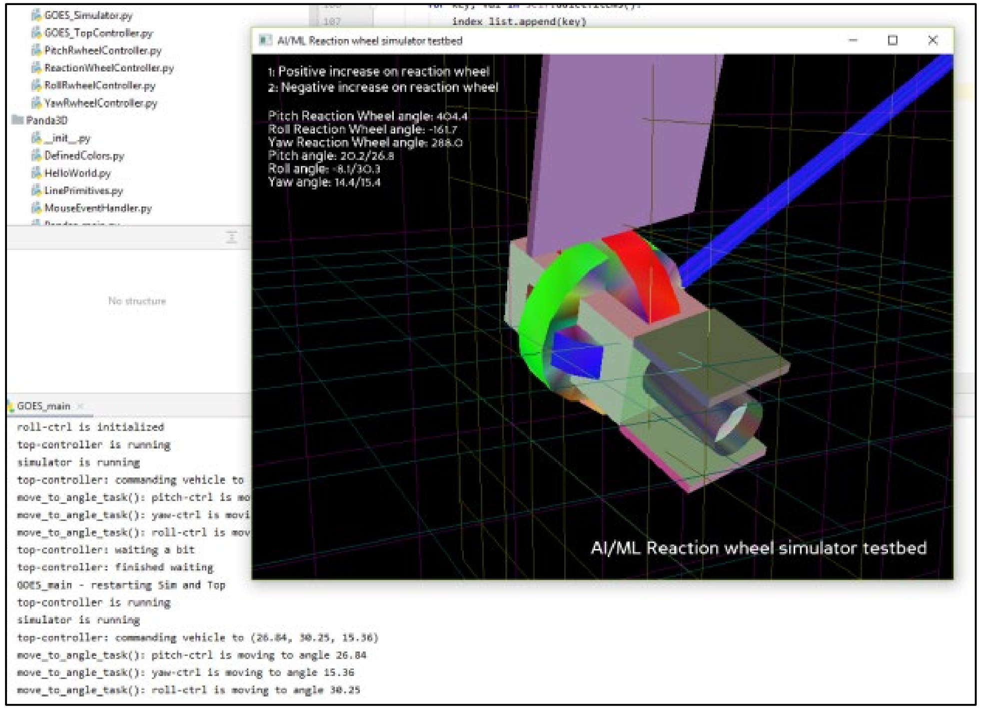
GOES-R Synthetic data generation

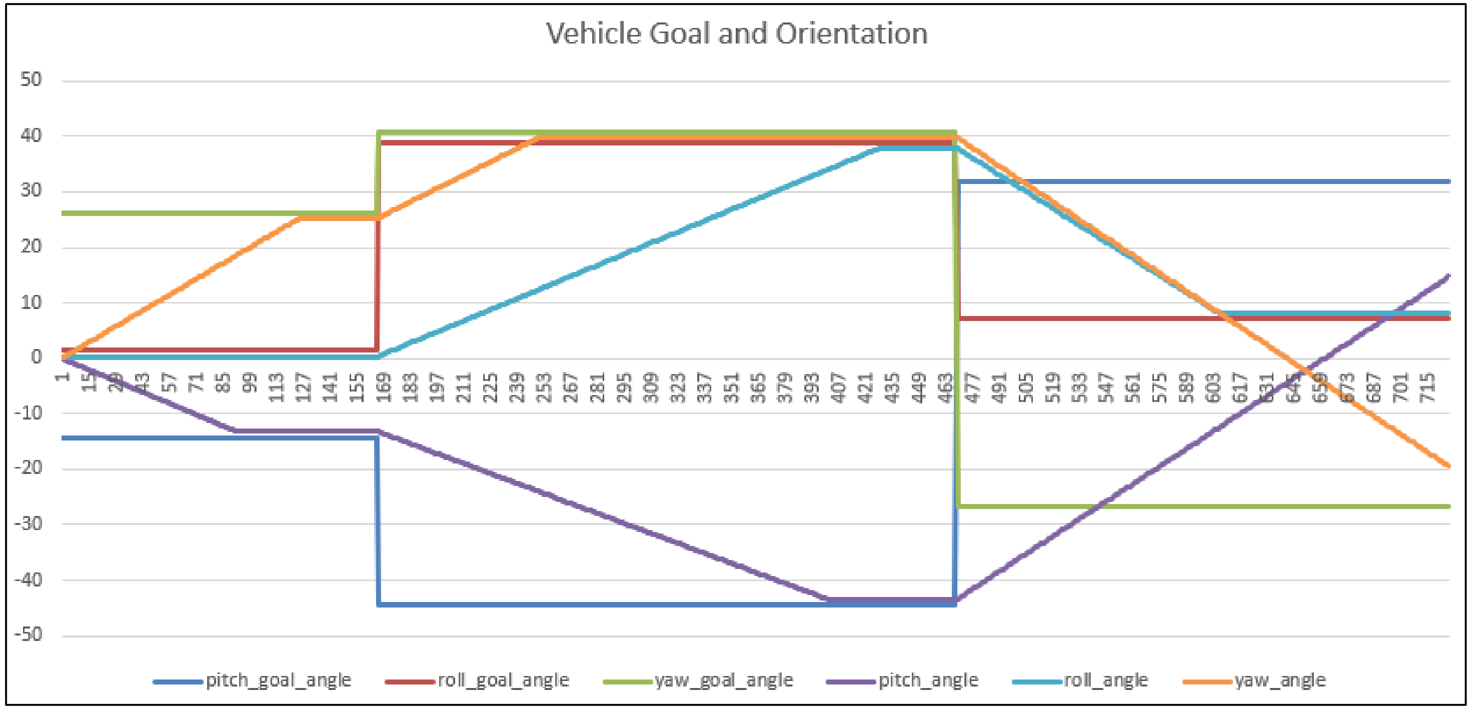
- Designed and implemented a proof-of-concept *control* and *simulation* API
- First use case: Reaction wheel (RW) degradation and failure

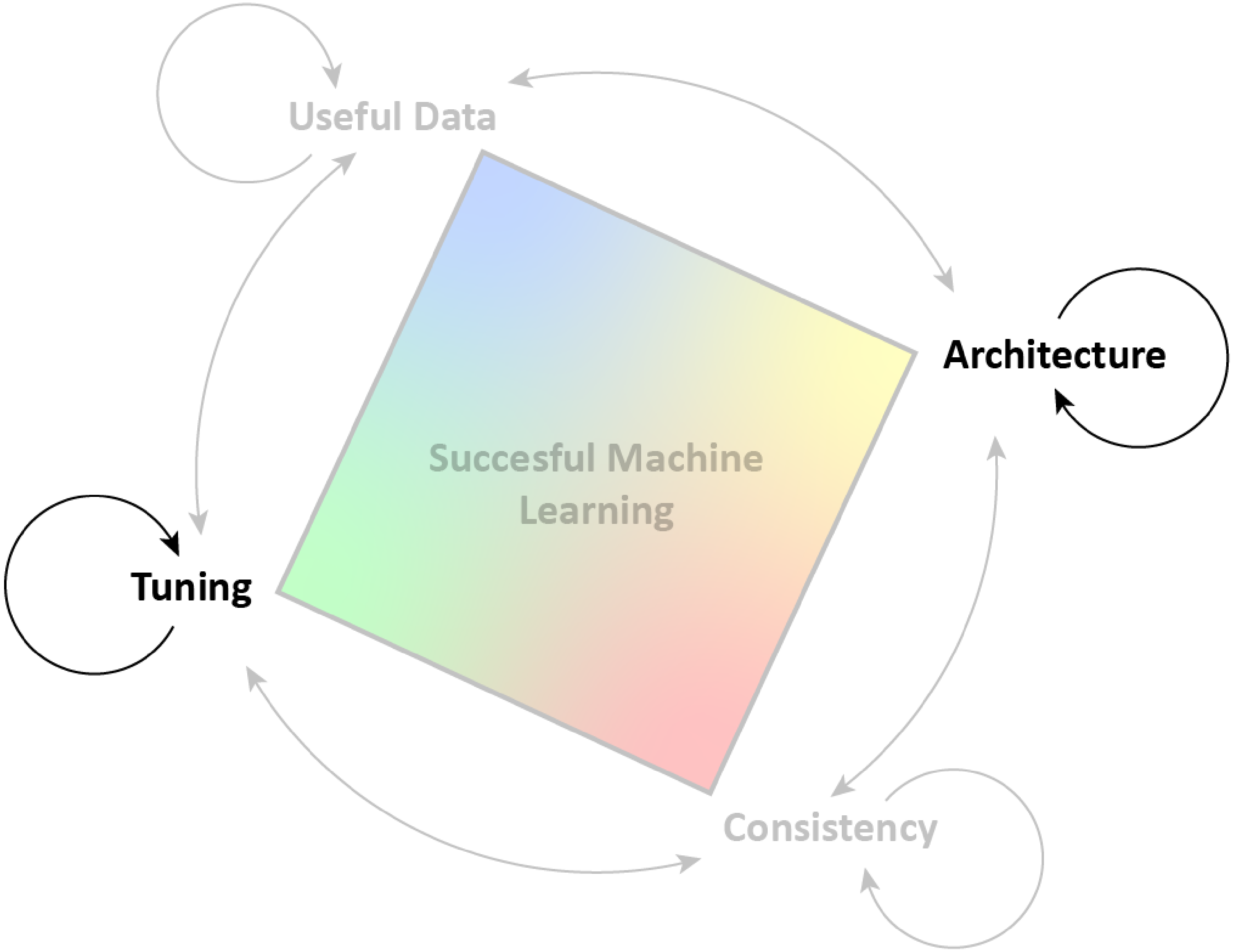


Creating tagged data

- Reaction wheel speed and vehicle slew rate is generated for random efficiencies (50% - 100%)
- The simulation creates an *input vector* of slew rates
- The simulation creates an *output vector* of RW efficiency
- Data is stored for train/test



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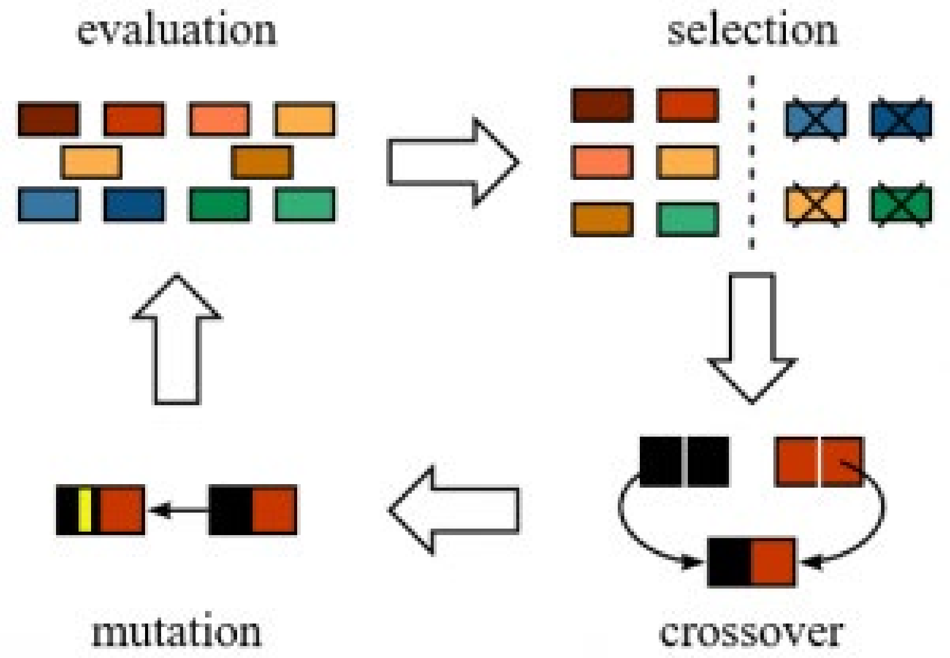
Architecture and tuning

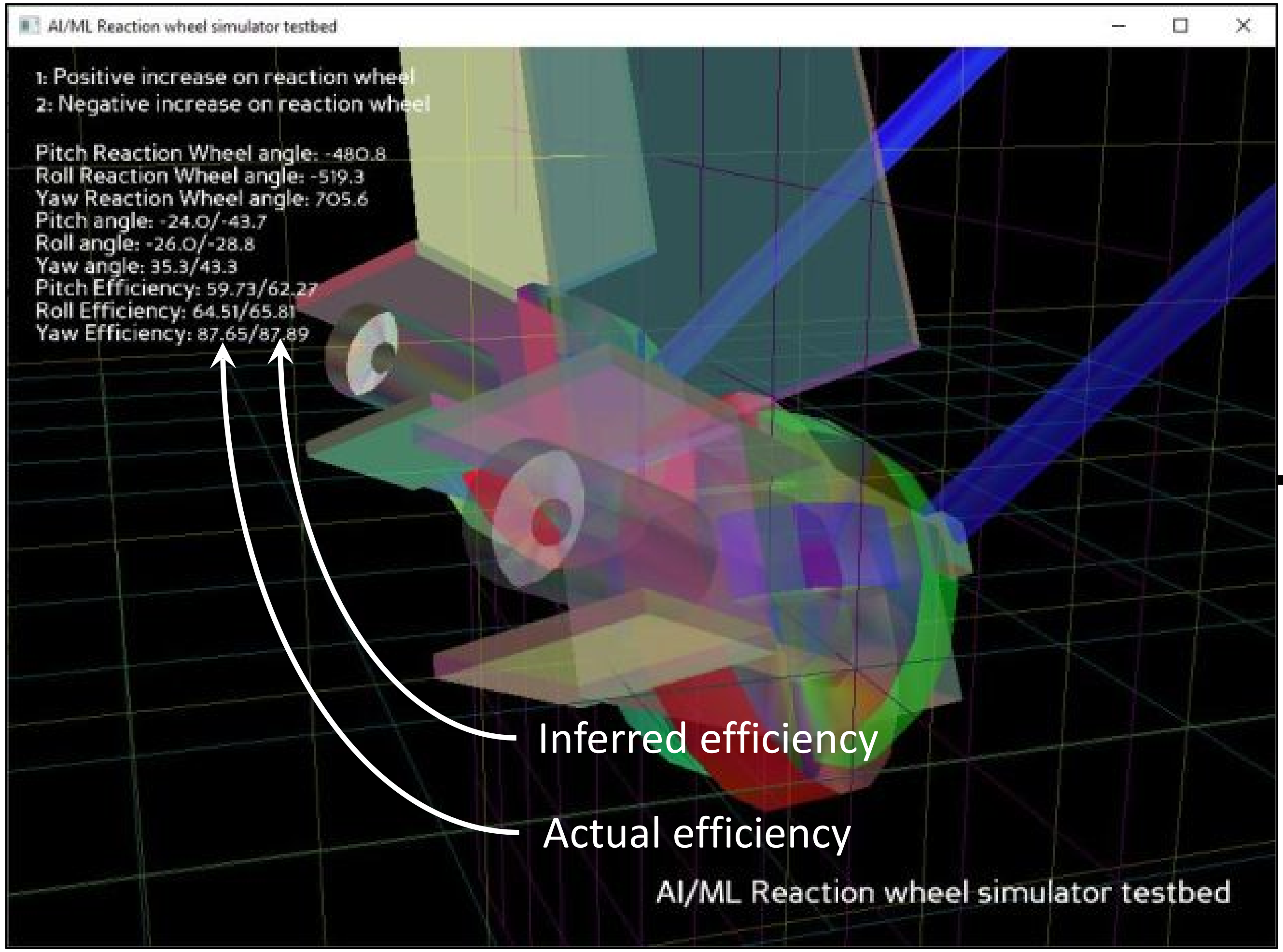
- Initial architecture guess: 1 layers of 100 neuron MLPs
- Initial hyperparameter guess:
  - Optimizer Adam, with learning rate of 0.01
  - Batch size = 10
  - Epochs = 40

- Final architecture : 2 layers of 230 neuron MLPs
- Initial hyperparameter guess:
  - Optimizer Adam, with learning rate of 0.01
  - Batch size = 13
  - Epochs = 70

```
    v1 = VA.EvolveAxis("X", VA.ValueAxisType.FLOAT, min=-5, max=5, step=0.25)
    v2 = VA.EvolveAxis("Y", VA.ValueAxisType.FLOAT, min=-5, max=5, step=0.25)

    vzvals = VA.EvolveAxis("Zvals1", VA.ValueAxisType.FLOAT, parent=vzfunc)
    vzvals = VA.EvolveAxis("Zvals2", VA.ValueAxisType.FLOAT, parent=vzfunc)

    eo = EvolutionaryOpimizer(keep_percent=.5, threads=0)
    eo.add_axis(v1)
    eo.add_axis(v2)

    eo.create_intital_genomes(10)

    evolve_list = []
    num_generations = 20
    for i in range(num_generations):
        fitness = eo.run_optimizer(example_evaluation_function,
example_save_function)
        evolve_list.append(fitness)
```



Real-time inference

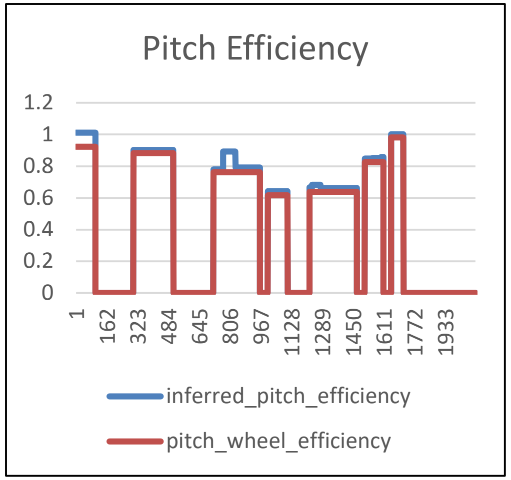


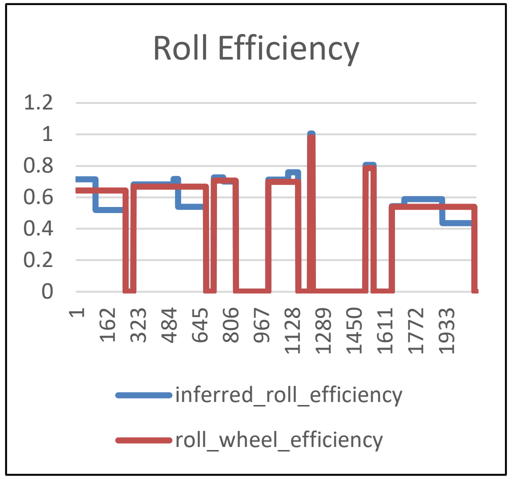
Simulation run

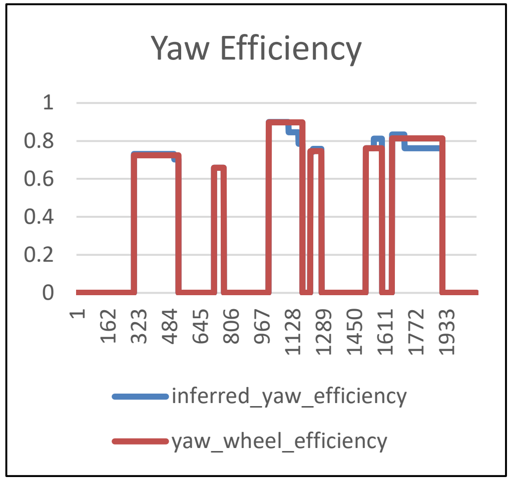
	A	B	C	D	E	F	G	H	I	J	K	L
1		**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2	elapsed-time	0.1	0.1	0.2	0.2	0.3	0.3	0.4	0.4	0.5	0.5	0.6
3	inferred_pitch_efficiency	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
4	inferred_roll_efficiency	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
5	inferred_yaw_efficiency	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	inferred_pitch	-0.1	-0.3	-0.6	-0.8	-1.1	-1.3	-1.6	-1.8	-2.1	-2.3	-2.6
7	inferred_roll	0.0	0.2	0.4	0.6	0.7	0.9	1.1	1.3	1.5	1.6	1.8
8	inferred_yaw	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	pitch_goal_angle	-24.5	-24.5	-24.5	-24.5	-24.5	-24.5	-24.5	-24.5	-24.5	-24.5	-24.5
10	roll_goal_angle	42.5	42.5	42.5	42.5	42.5	42.5	42.5	42.5	42.5	42.5	42.5
11	yaw_goal_angle	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3
12	CMD_board-monitor_to_top-controller	RUN	RUN	RUN	RUN	RUN	RUN	RUN	RUN	RUN	RUN	RUN
13	RSP_top-controller_to_board-monitor	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU
14	pitch_wheel_angle	-1.8	-6.5	-11.1	-15.7	-20.3	-25.0	-29.6	-34.2	-38.8	-43.4	-48.1
15	roll_wheel_angle	1.3	4.5	7.7	10.9	14.1	17.4	20.6	23.8	27.0	30.2	33.4
16	yaw_wheel_angle	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	pitch_wheel_efficiency	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
18	roll_wheel_efficiency	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
19	yaw_wheel_efficiency	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
20	pitch_angle	-0.1	-0.3	-0.6	-0.8	-1.0	-1.2	-1.5	-1.7	-1.9	-2.2	-2.4
21	roll_angle	0.1	0.2	0.4	0.5	0.7	0.9	1.0	1.2	1.4	1.5	1.7
22	yaw_angle	0	0	0	0	0	0	0	0	0	0	0
23	rw_mass	1	1	1	1	1	1	1	1	1	1	1
24	vehicle_mass	20	20	20	20	20	20	20	20	20	20	20
25	CMD_board_monitor_to_simulator	RUN	RUN	RUN	RUN	RUN	RUN	RUN	RUN	RUN	RUN	RUN
26	RSP_simulator_to_board_monitor	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU
27	pitch_voltage	-100	-100	-100	-100	-100	-100	-100	-100	-100	-100	-100
28	yaw_voltage	0	0	0	0	0	0	0	0	0	0	0
29	roll_voltage	100	100	100	100	100	100	100	100	100	100	100
30	CMD_top-controller_to_pitch-ctrl	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI
31	RSP_pitch-ctrl_to_top-controller	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU
32	CMD_top-controller_to_yaw-ctrl	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI
33	RSP_yaw-ctrl_to_top-controller	DONE	DONE	DONE	DONE	DONE	DONE	DONE	DONE	DONE	DONE	DONE
34	CMD_top-controller_to_roll-ctrl	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI	MOVI
35	RSP_roll-ctrl_to_top-controller	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU	EXECU

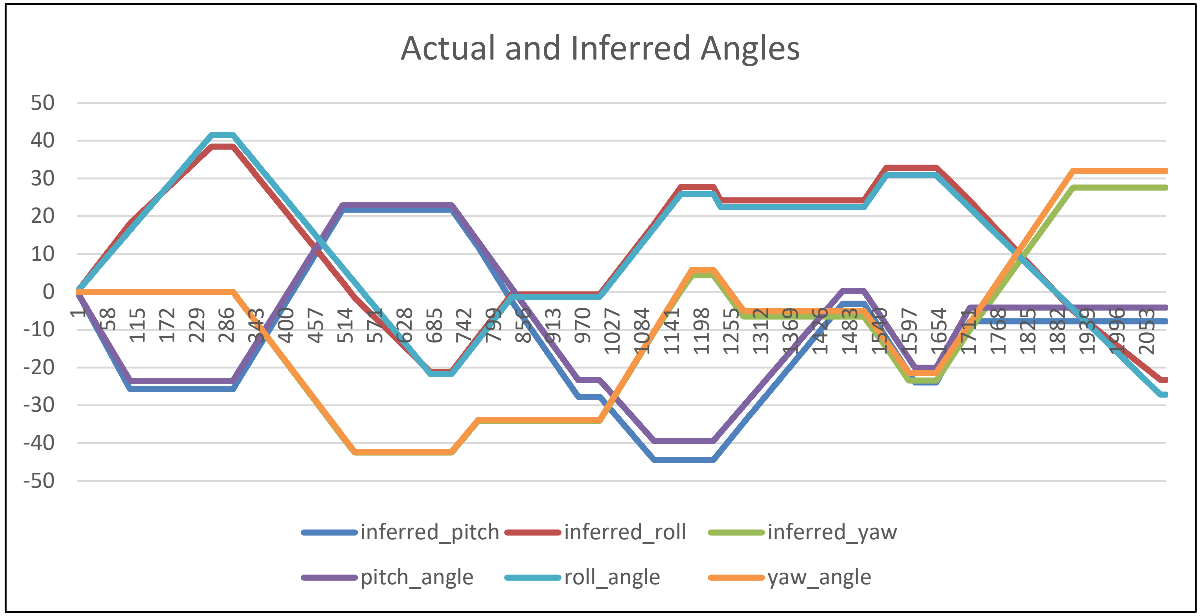
Saved simulation data

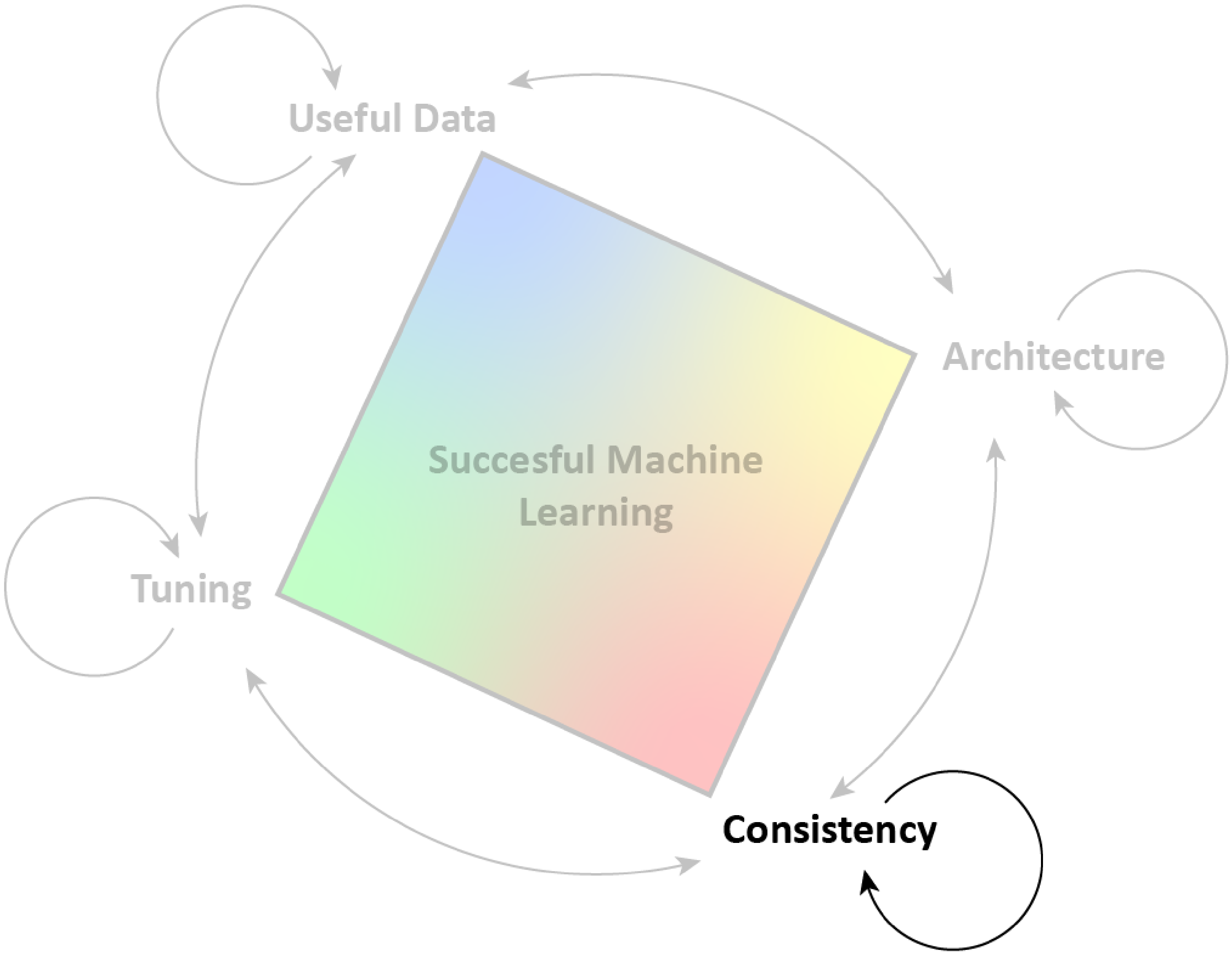
Validation against new synthetic data











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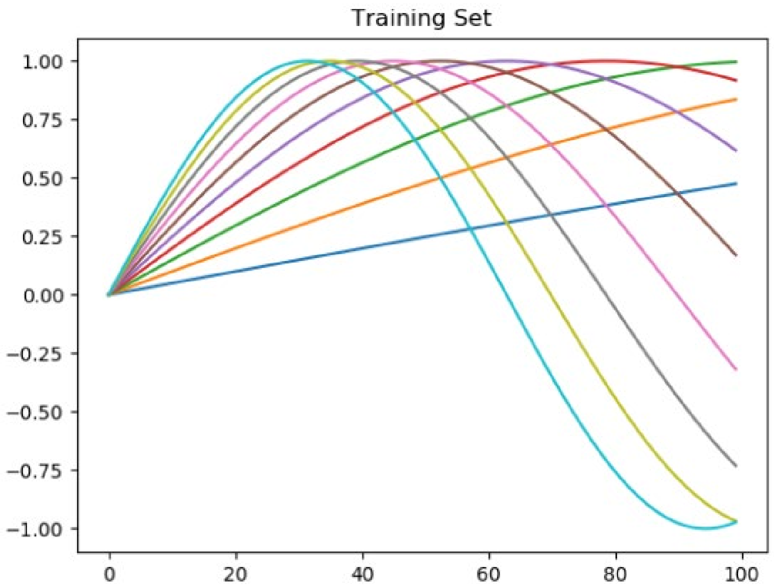
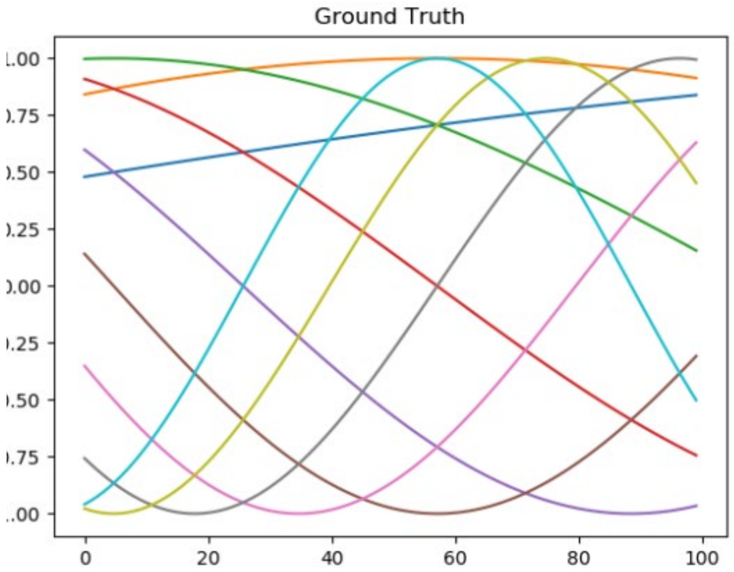
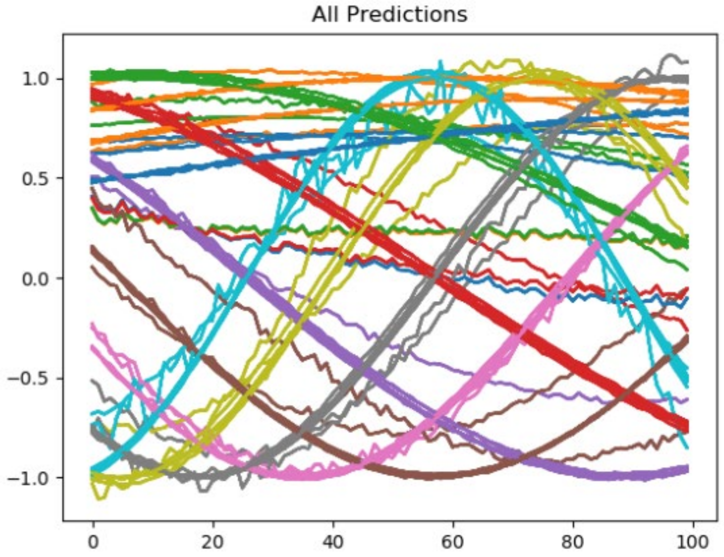
Consistency

1. Neural Networks are initialized with random numbers
2. The same network will train differently *every time*
3. Accuracy differences for the same model can be as high as 50%
4. This makes it very hard to *find* the right hyperparameters!

Let’s use some simple data to see this clearly

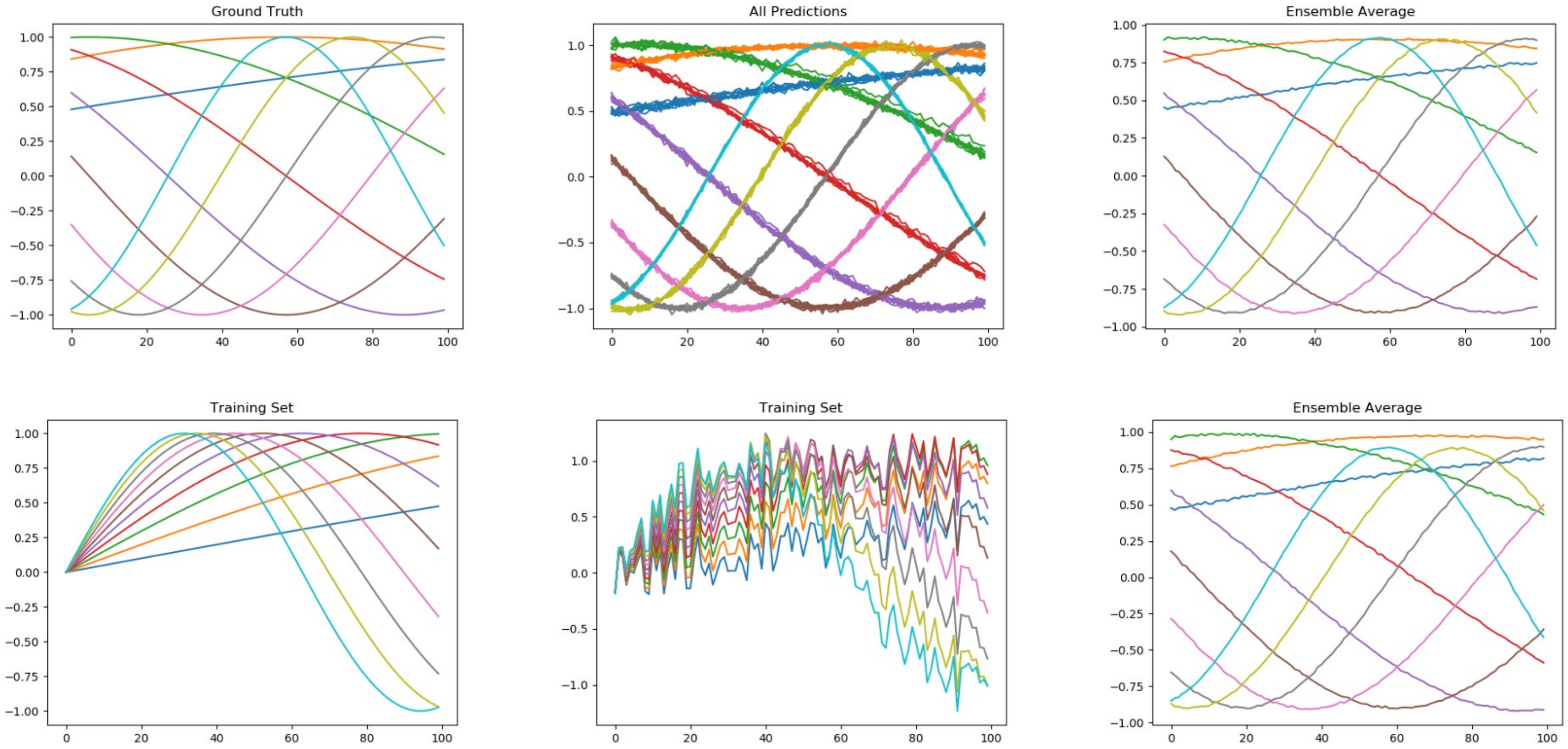






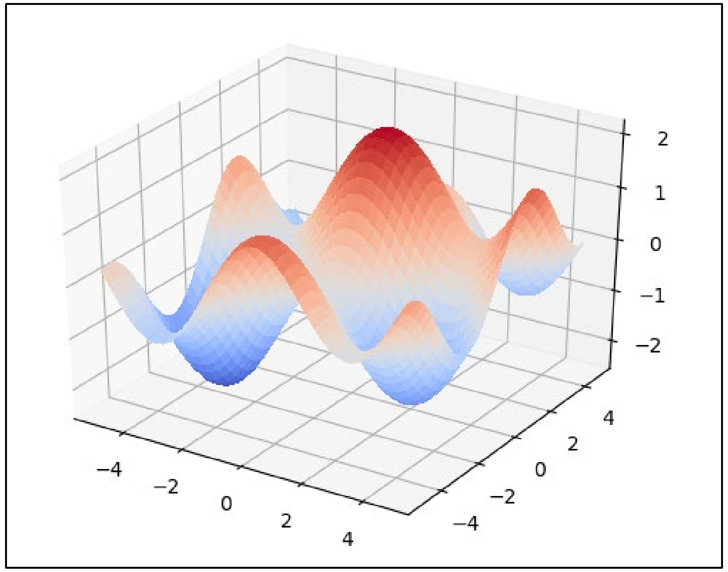
Ensembles

- The best parameters are based on an *Ensemble average* of multiple models
- Multiple models *for the same parameters* are stored
- In *inference*, the average of all model *predictions* is taken as the best value
- Ensembles produce *consistent* and *repeatable* results

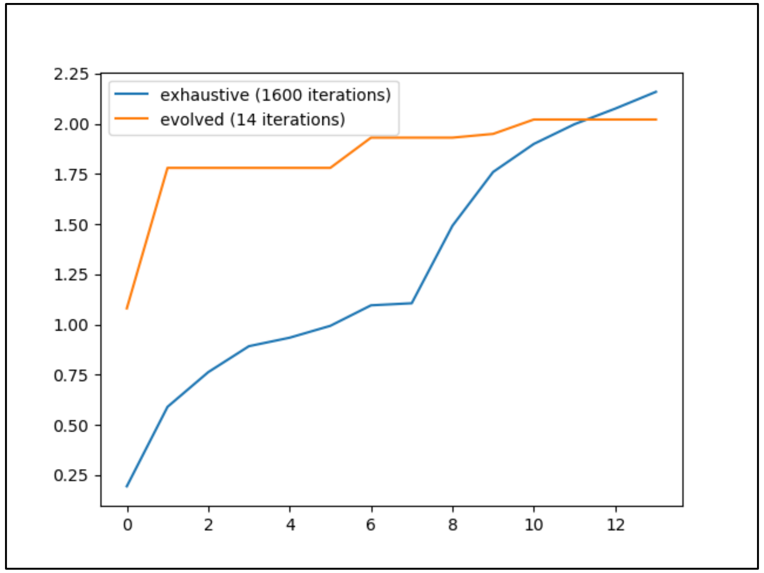


Evolving ensembles

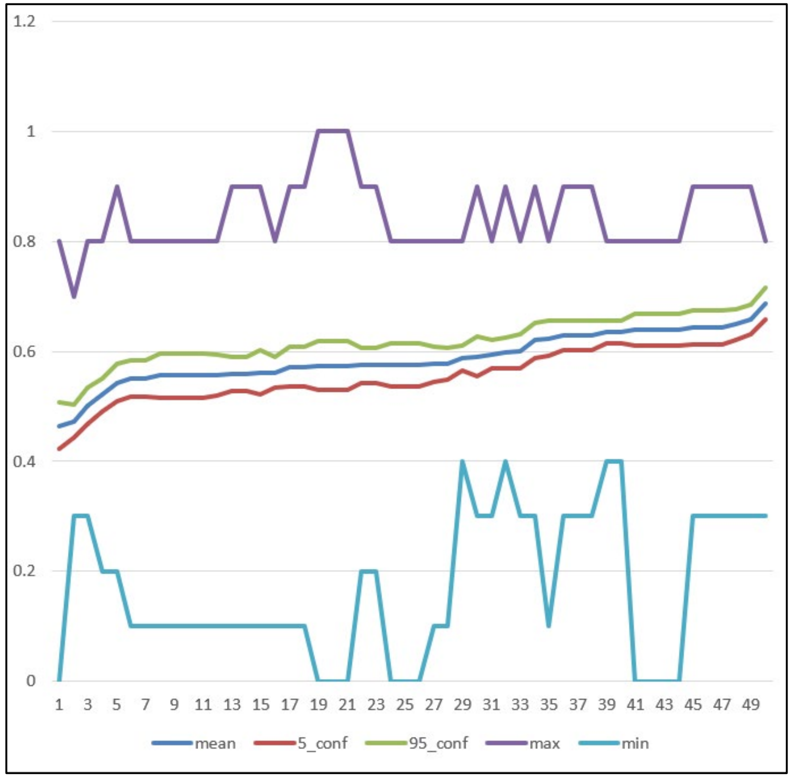
1. We created `Optevolver` – an Ensemble hyperparameter/architecture using GAs
2. Uses a set of models to find average, standard deviation and min/max
3. Much faster, though not quite as good as grid search



Known Fitness landscape



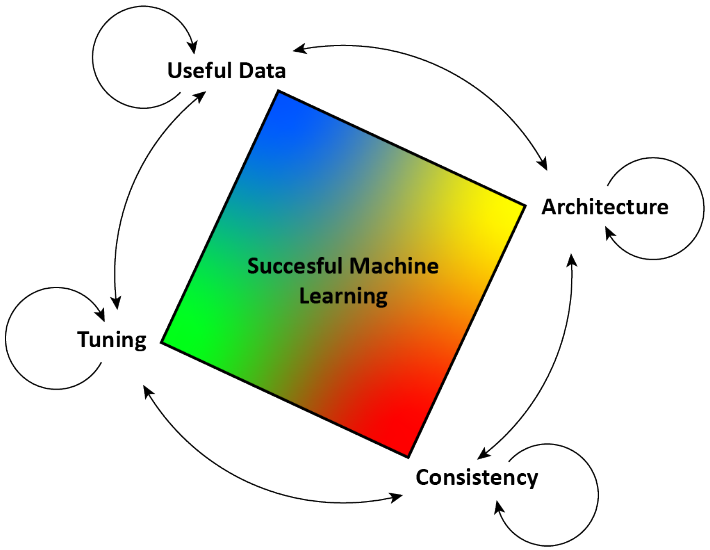
Exhaustive vs. genetic search



Improvement avg 47% - 64% accuracy

Conclusions

Simulation	Genetic Algorithms	Ensemble prediction
• Understandable, explainable models • Creates balanced data sets • Data is clean and perfectly tagged	• Evolutionary hyper-parameter tuning and architecture search • Reduces time spent in model development • Reduced compute cost for model training • Pip install optevolver	• Creates resilient, reliable models • Ensemble models are repeatable and reproducible



Questions?

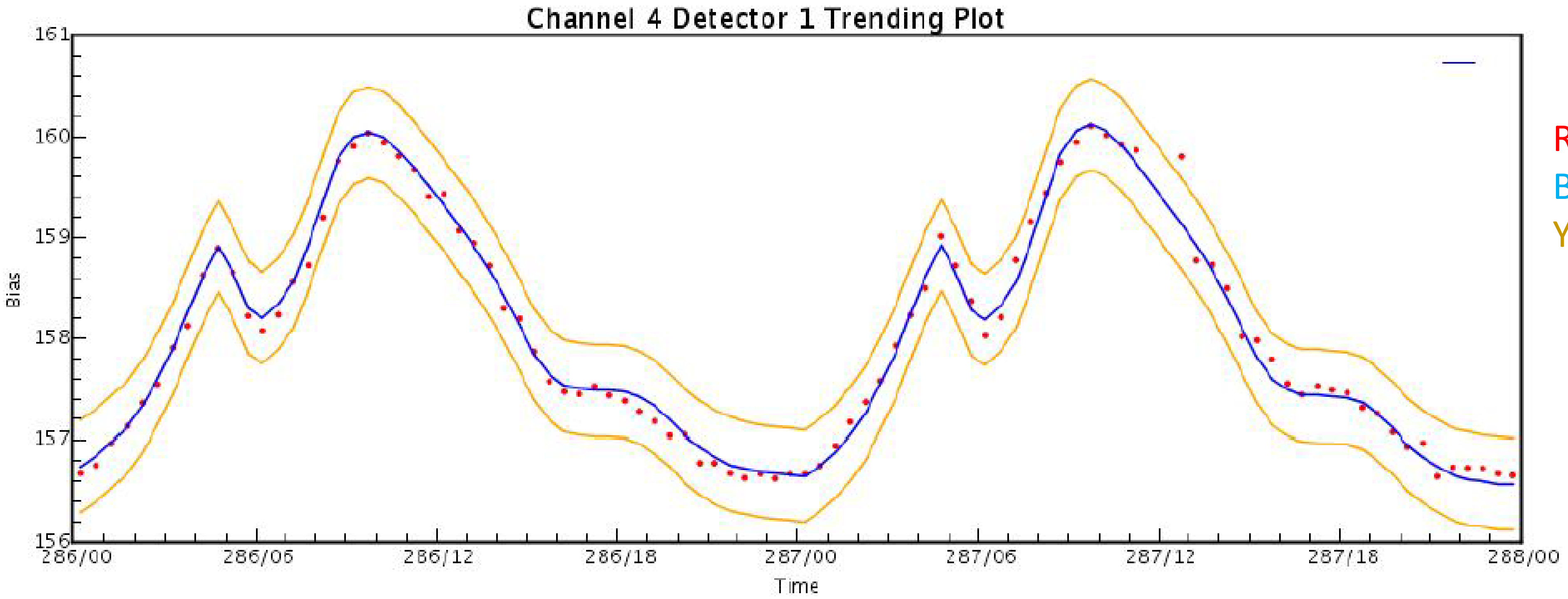
If you can read this, we've gone too far…

Questions?

- Where can I get Optevolver?
  - `pip -install optevolver`
- What does it work on?
  - Just Tensorflow 2.0 right now, but PyTorch soon
- Where can I get the source?
  - https://github.com/pgfeldman/optevolver
- Does it do Bayesian/particle swarm/<other cool algo>
  - Not yet…
  - But feel free to contribute!

Background

- AIMS: Low-level monitoring and trending for single mnemonics using machine learning



Red dots = data
Blue line = ML prediction
Yellow lines = Error bands

- Goal: High-level monitoring and trending across multiple mnemonics