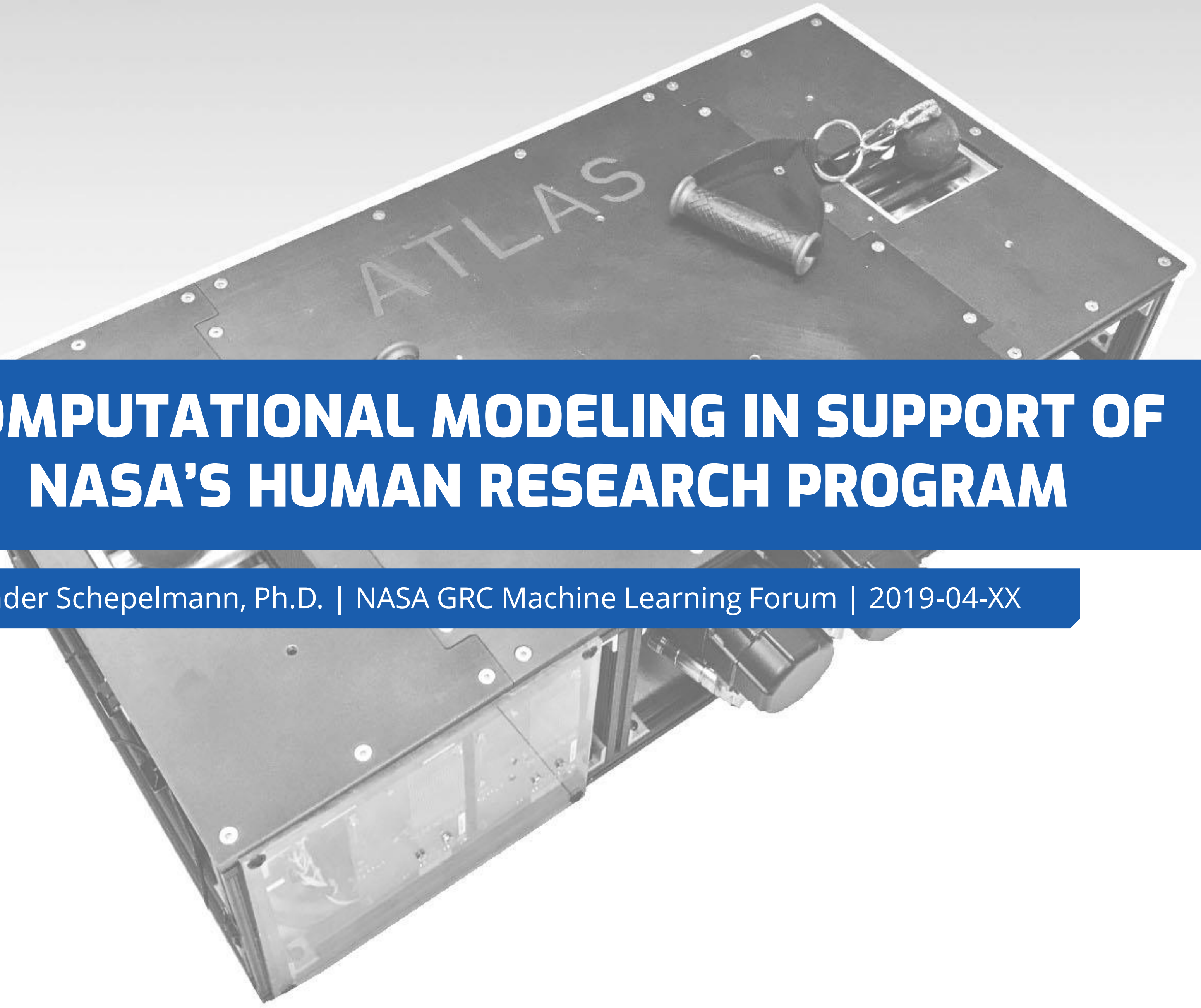

COMPUTATIONAL MODELING IN SUPPORT OF NASA'S HUMAN RESEARCH PROGRAM

Alexander Schepelmann, Ph.D. | NASA GRC Machine Learning Forum | 2019-04-XX

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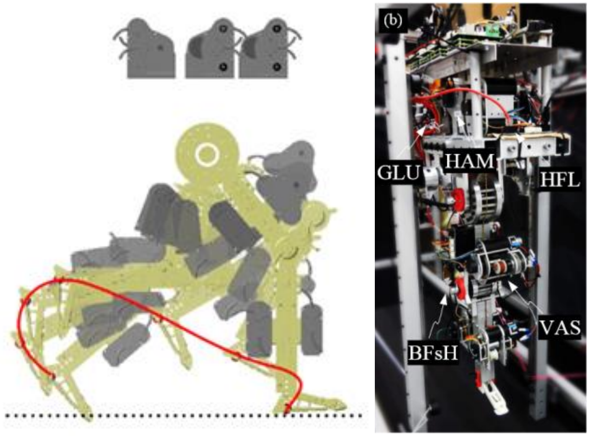
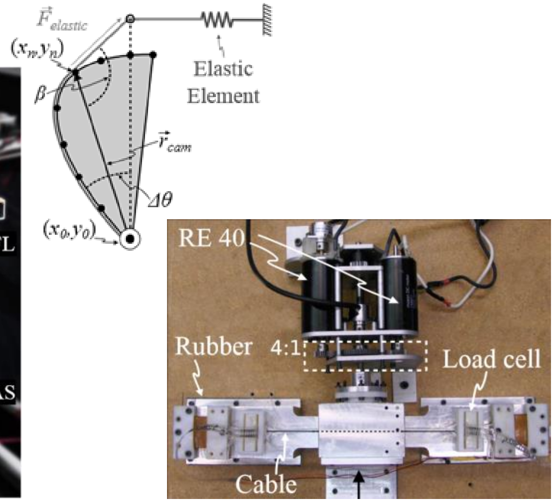
ABOUT ME

CWRU: *CWRU Cutter autonomous lawnmower.*

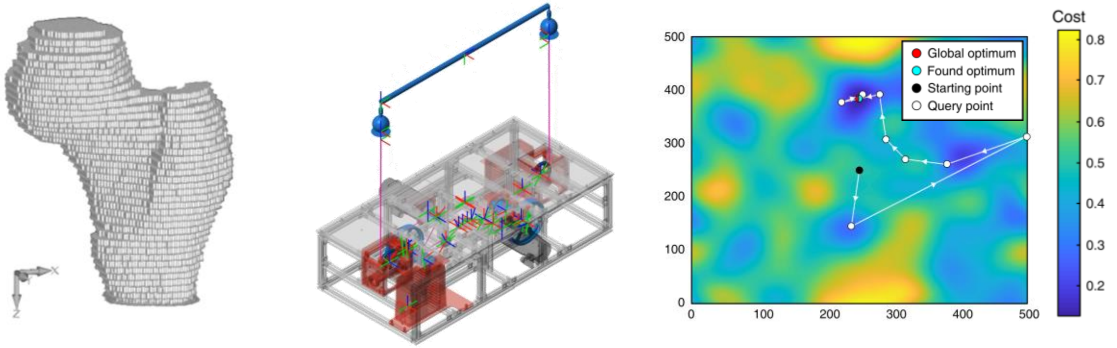


CMU: *Robotic Neuromuscular Leg.*



CMU: *Compact nonlinear SEA springs.*

HEBI Robotics: *Modular series elastic actuators (SEAs).*



ZIN Technologies: *Robotics and computational modeling for human spaceflight.*

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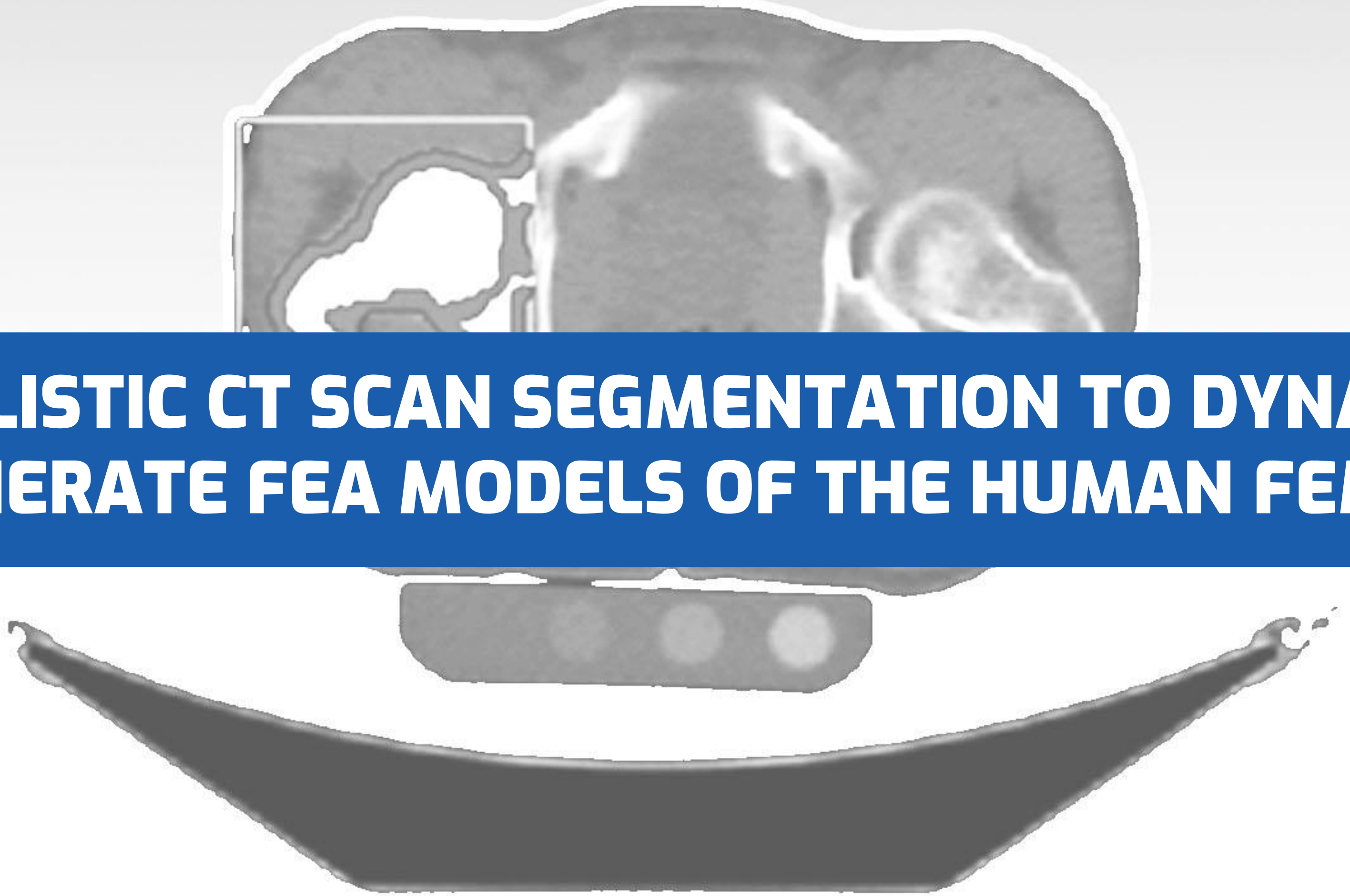


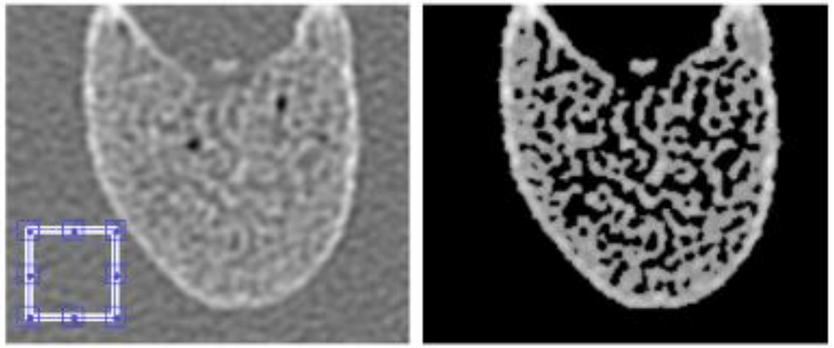
PROBABILISTIC CT SCAN SEGMENTATION TO DYNAMICALLY GENERATE FEA MODELS OF THE HUMAN FEMUR

LONG-DURATION SPACEFLIGHT IS DETRIMENTAL TO BONE HEALTH

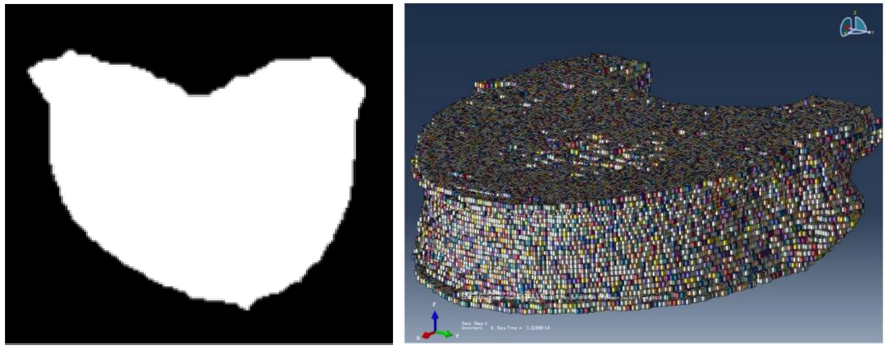
- 0.4-2.7% monthly volumetric bone mineral density (vBMD) loss
- Resistive exercise counters effects of microgravity
- Required frequency and duration of exercise is unclear

Hybrid Ultimate Lifting Kit (HULK) exercise device.

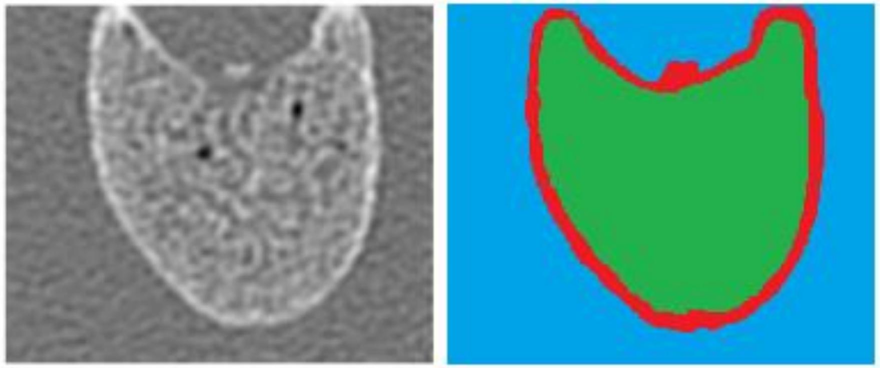
FEA MODELS CAN BE USED TO CALCULATE BMD MAINTENANCE LOADS



Manual calibration results:
Produces noisy output that requires additional, manual post-processing.



Voxel initialization based solely on pixel intensity:
Produces heterogeneous mixture of elements that may be poorly initialized with zero stiffness.



Desired scan processing output (hand-labeled):
Segmented bone cross-section that distinguishes between cortical, trabecular, and non-bone containing regions.

PROBABILISTIC CLASSIFICATION: BETTER, AUTOMATIC SEGMENTATION

"Probability that feature X equals x_i given that sample Y belongs to group y_j"

"Probability that sample Y belongs to group y_j"

$$P(Y = y_j | X = x_i) = \frac{P(X = x_i | Y = y_j) P(Y = y_j)}{P(X = x_i)}$$

"Probability that sample Y belongs to group y_j given that feature X equals x_i"

"Probability that feature X equals x_i"

Bayes' theorem.

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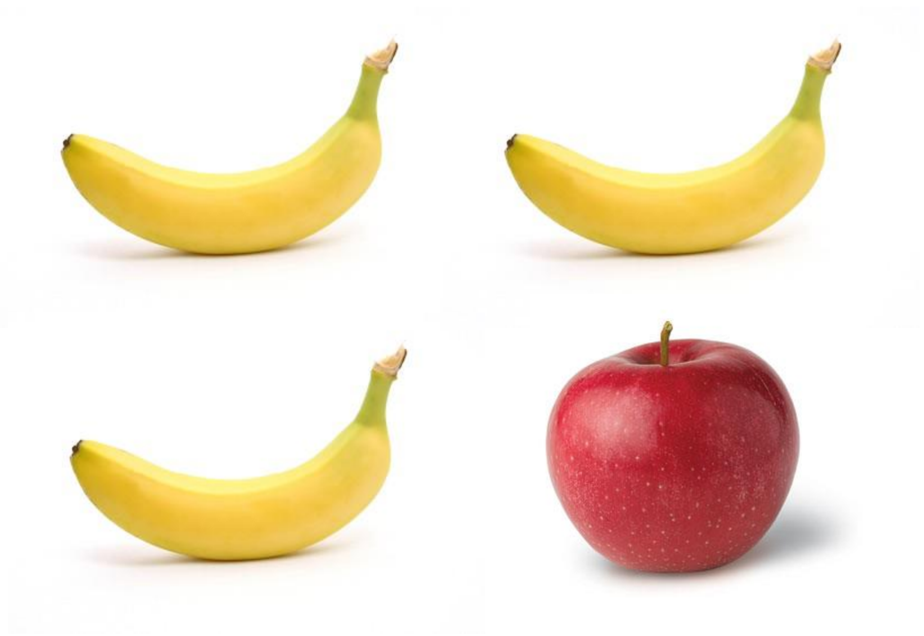
EXAMPLE 1: CLASSIFYING FRUIT BASED ON COLOR

$$P(Y=\text{🍌}|X=\text{🟨}) = \frac{P(X=\text{🟨}|Y=\text{🍌})P(Y=\text{🍌})}{P(X=\text{🟨}|Y=\text{🍌})P(Y=\text{🍌}) + P(X=\text{🟨}|Y=\text{🍎})P(Y=\text{🍎})}$$

$$= \frac{1 * 0.75}{1 * 0.75 + 0 * 0.25} = 1$$

$$P(Y=\text{🍎}|X=\text{🟨}) = \frac{P(X=\text{🟨}|Y=\text{🍎})P(Y=\text{🍎})}{P(X=\text{🟨}|Y=\text{🍎})P(Y=\text{🍎}) + P(X=\text{🟨}|Y=\text{🍌})P(Y=\text{🍌})}$$

$$= \frac{0 * 0.25}{0 * 0.25 + 1 * 0.75} = 0$$



The banana-apple universe, where 75% of all fruit are bananas.

FEATURE CLASSIFICATION ONLY RELIES ON RELATIVE LIKELIHOOD

$$P(Y|X) \propto P(X|Y)P(Y)$$

Bayes' theorem numerator:
The conditional probability is proportional to the joint probability model.

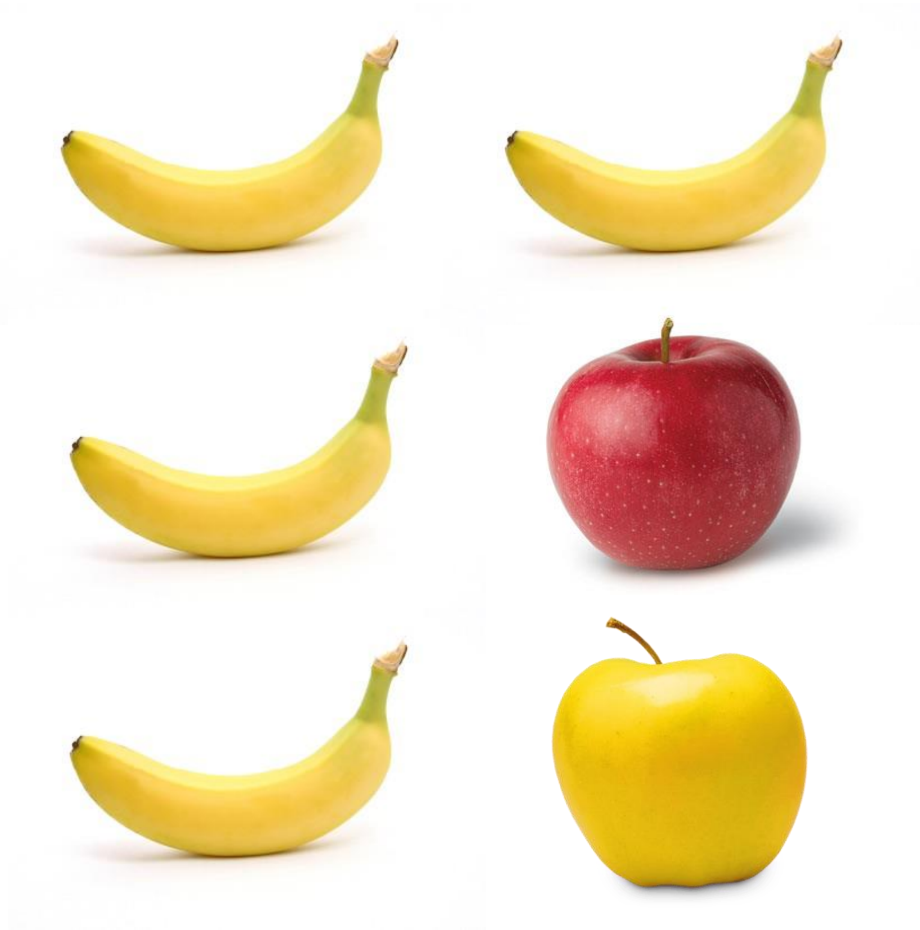
EXAMPLE 2: INSUFFICIENT NUMBER OF FEATURES

$$P(Y = \text{🍌} | X = \boxed{}) \propto P(X = \boxed{} | Y = \text{🍌}) P(Y = \text{🍌})$$

$$\propto 0.8 * 0.66 = 0.53$$

$$P(Y = \text{🍎} | X = \boxed{}) \propto P(X = \boxed{} | Y = \text{🍎}) P(Y = \text{🍎})$$

$$\propto 0.2 * 0.33 = 0.07$$



The banana-apple universe, where 66% of all fruit are bananas and yellow apples exist.

MORE FEATURES WITH NAÏVE ASSUMPTIONS IMPROVE ACCURACY

$$P(Y|X_1, ..., X_n) \propto P(X_1, ..., X_n|Y)P(Y)$$

Assuming statistically independent features: $P(X_1, ..., X_n|Y) = \prod_{i=1}^{n} P(X_i|Y)$

$$P(Y|X_1, ..., X_n) \propto P(Y) \prod_{i=1}^{n} P(X_i|Y)$$

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NAÏVE BAYES = INDEPENDENT FEATURE MODEL + DECISION RULE

Given: $X^{new} =< X_1, ..., X_n >$

$$\hat{y} = \underset{j \in \{1,...,J\}}{\operatorname{argmax}} \propto P(Y = y_j) \prod_{i=1}^{n} P(X_i^{new} | Y = y_j)$$

Naïve Bayes classifier using the maximum a posteriori decision rule:
Based on the features, it is most probable that the item being classified belongs to group.

EXAMPLE 3: CLASSIFYING FRUIT BASED ON COLOR AND SHAPE

$$P(Y = \ |X = \square, round)$$

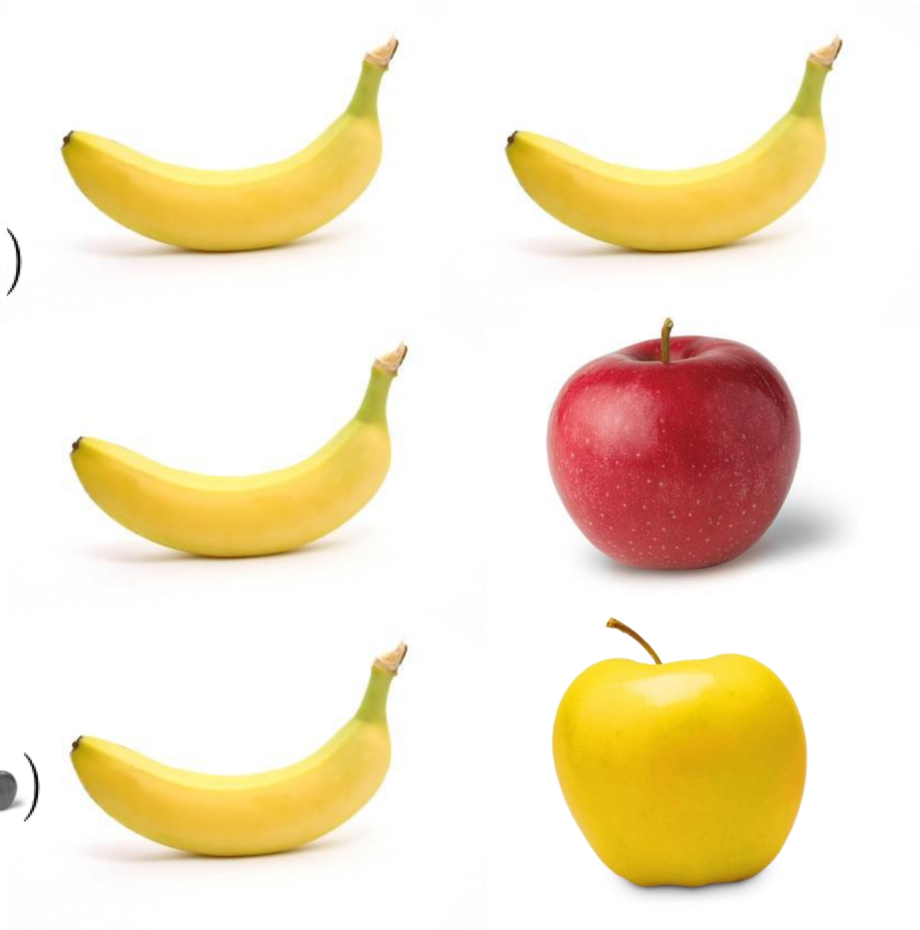
$$\propto P(Y = \ ) * P(X = \square|Y = \ )P(X = round|Y = \ )$$

$$\propto 0.66 * 0.8 * 0 = 0$$

$$P(Y = \ |X = \square, round)$$

$$\propto P(Y = \ ) * P(X = \square|Y = \ )P(X = round|Y = \ )$$

$$\propto 0.33 * 0.2 * 1 = 0.07$$



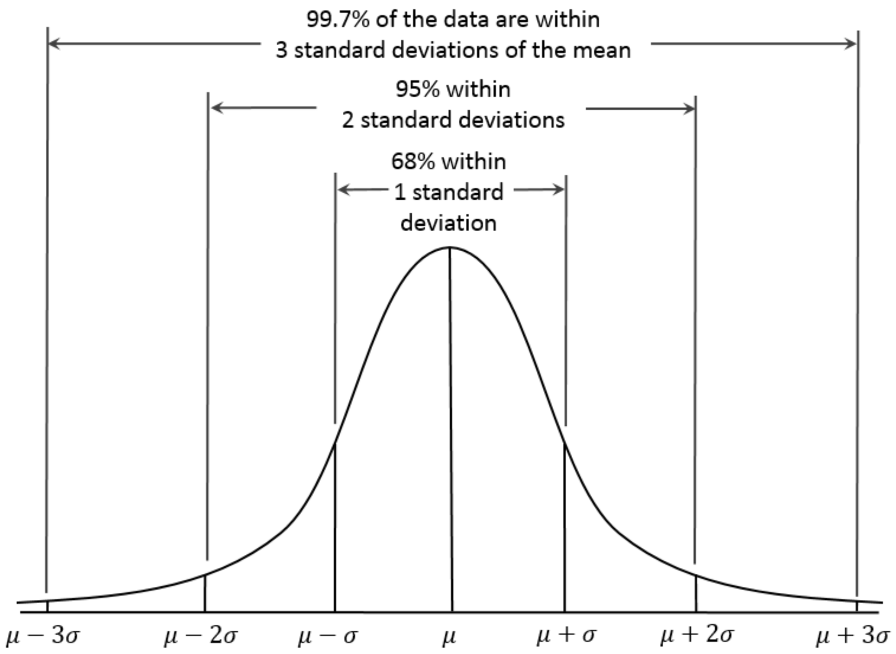
*The banana-apple universe, but fruits are described by color **and** shape.*

GAUSSIAN DISTRIBUTION: ESTIMATING SAMPLE FEATURE LIKELIHOOD

$$P(Y = y_j) \prod_{i=1}^{n} P(X_i | Y = y_j)$$

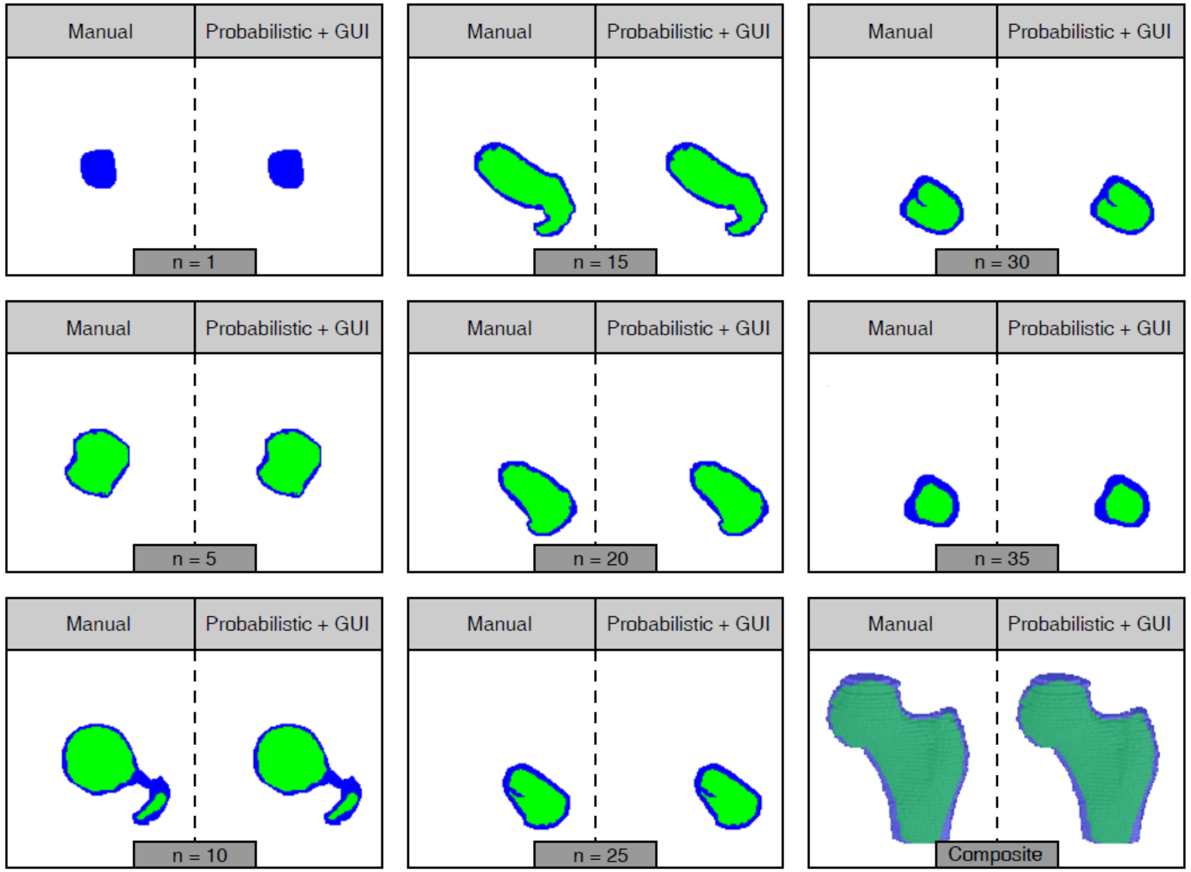
Calculated as (n_{class} / n_{tot})

$$P(X = x_i | Y = y_j) = \frac{1}{\sqrt{2\pi\sigma_{y_j}^2}} e^{-(x_i - \mu_{y_j})^2 / (2\sigma_{y_j}^2)}$$



The probability density function of a Gaussian distribution.

AUTOMATIC CT IMAGE SEGMENTATION TO BUILD FEA BONE MODELS



Manual vs. Probabilistic + GUI segmentation.

- Can generate identical segmentations to manual segmentation by expert
  - **10 minutes vs. 8 hours**
- Combined with computational bone model
- Toolchain accurately predicts post-flight vBMD
  - **-1.16 ± 2.78% mean percent error**

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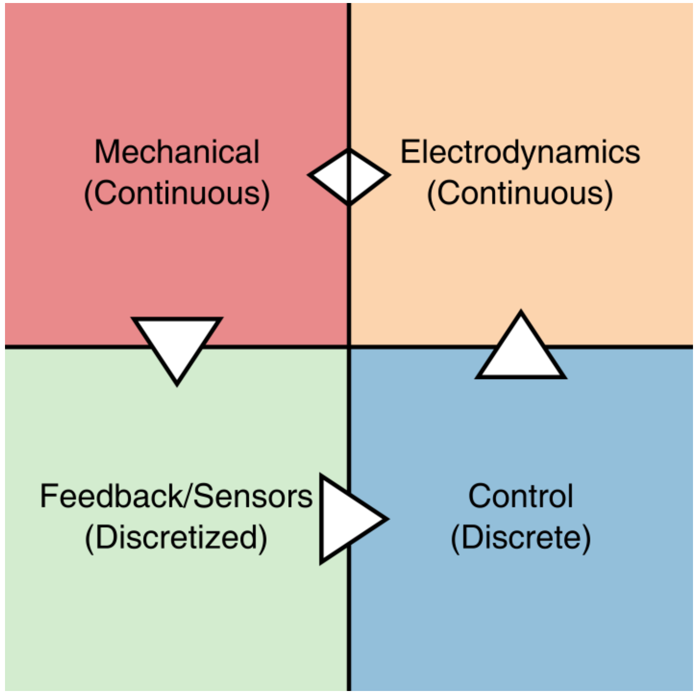
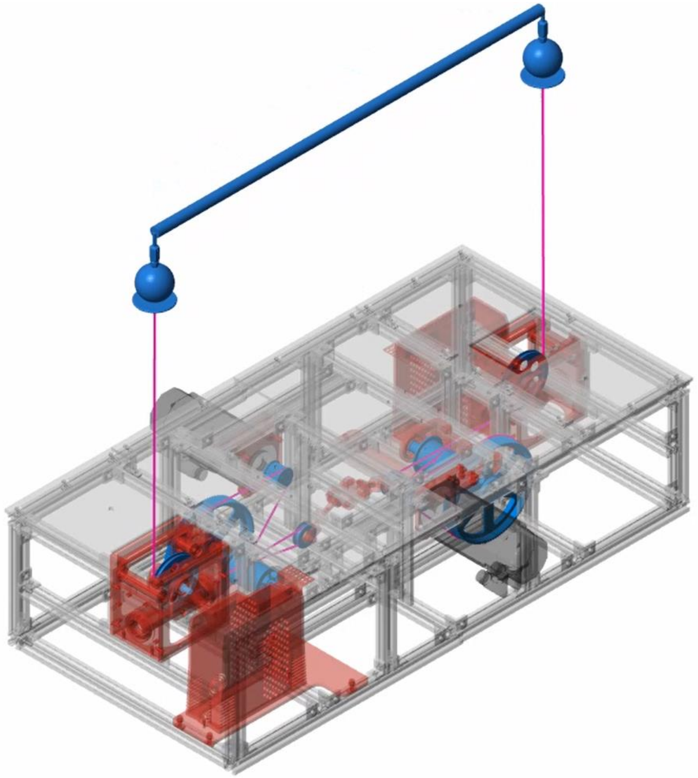
DESIGNING AND TUNING HUMAN-IN-THE-LOOP EXERCISE DEVICES VIA HIGH-FIDELITY SIMULATION

MODEL-BASED HARDWARE DESIGN APPROACH



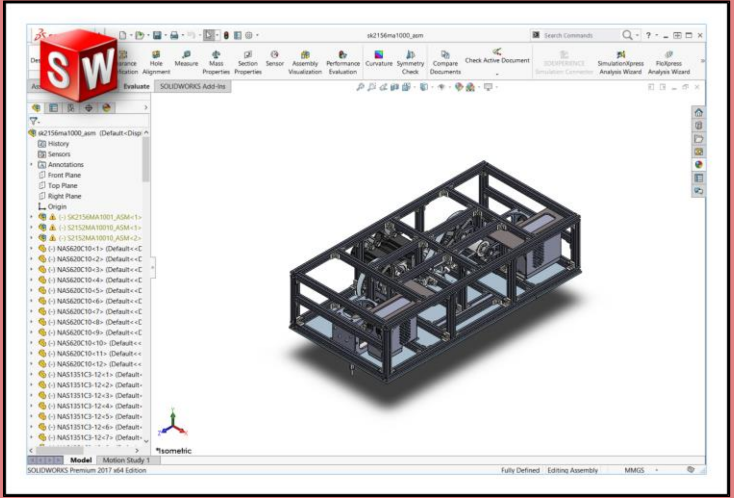
Simulation subsystem interaction diagram.

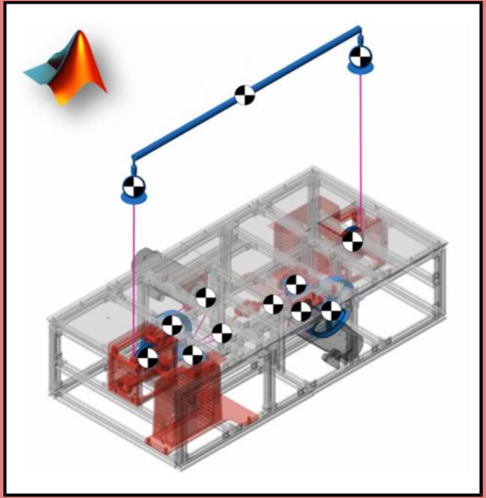


ATLAS breadboard Simulink Simscape model.

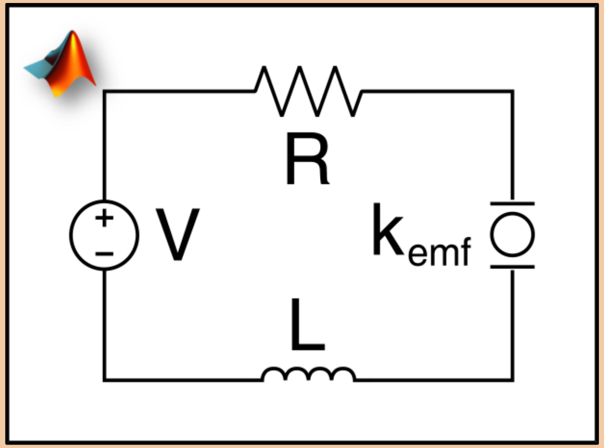
HIGH-FIDELITY DYNAMIC SIMULATION

Mechanical

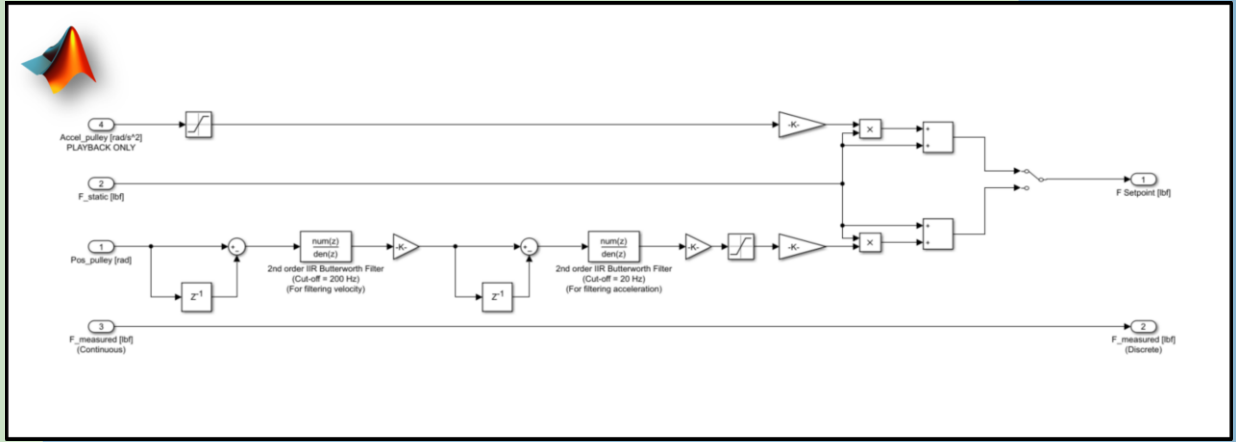




Electrodynamics

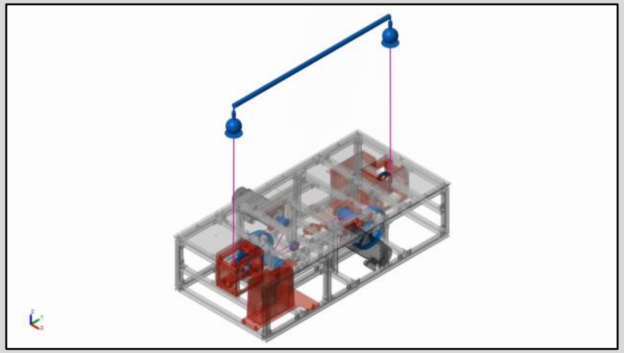


Feedback + Control

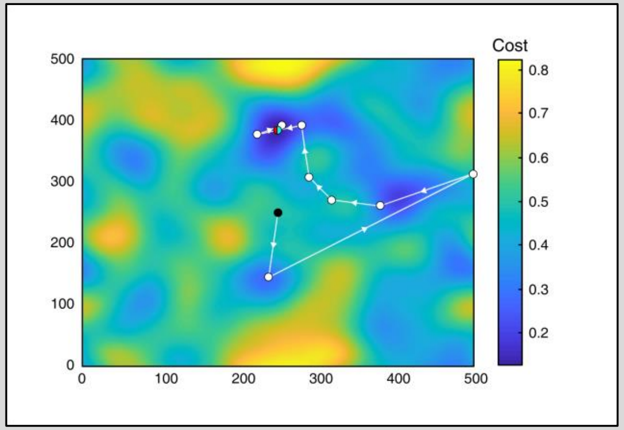


A VIRTUAL TESTBED FOR PLAYBACK AND DEVELOPMENT

Development

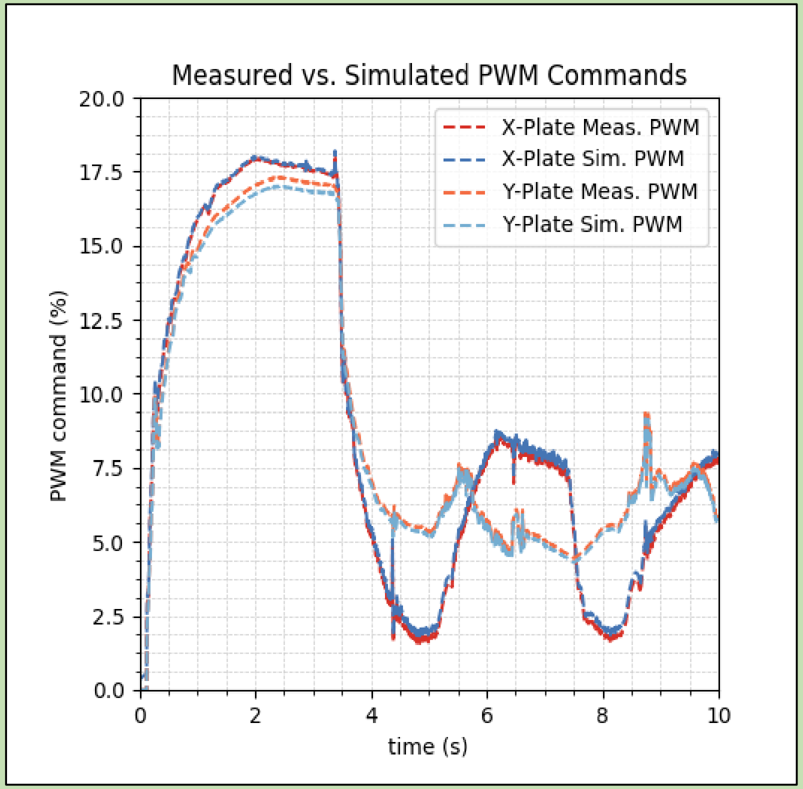


Actuated virtual testbed



Virtual hardware-in-the-loop optimization.

Playback



Log playback for state-observation, development, and debugging.

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DATA-DRIVEN APPROACHES TO TUNING
HUMAN-IN-THE-LOOP CONTROL GAINS

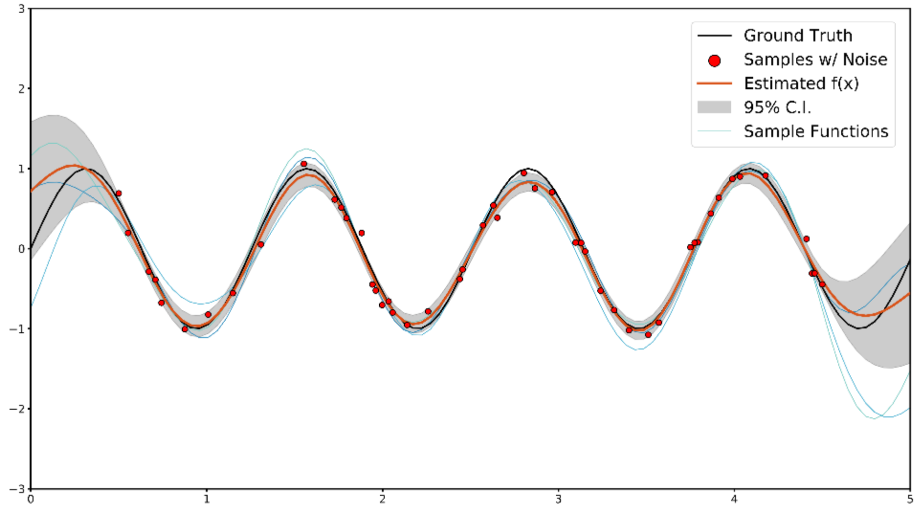
DATA-DRIVEN OPTIMIZATION OF HUMAN-IN-THE-LOOP CONTROL GAINS

- Human-in-the-loop optimization is difficult
  - Trials are expensive
  - Potentially dangerous

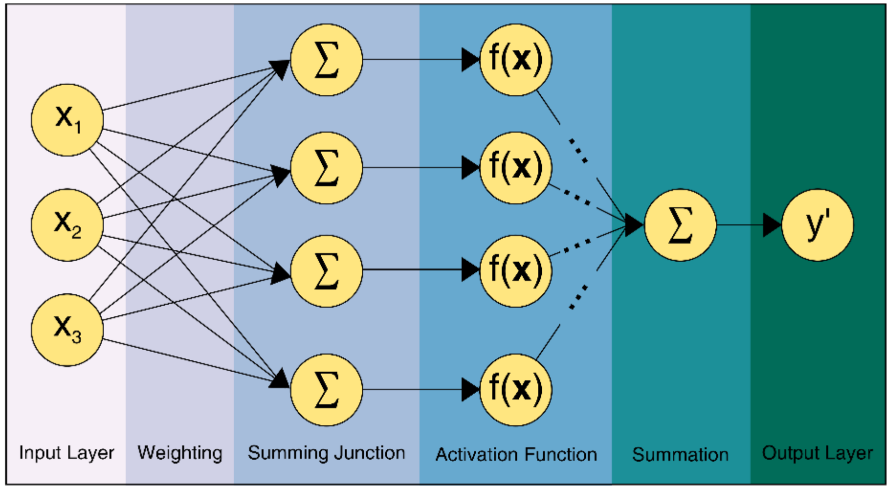
- Preference prediction is complicated
  - Combination of many inter-related factors
  - Human cost-function unknown

- *A priori human* modeling is difficult
  - Models/sub-models that are very complex
  - Incorporates modeler biases
  - May miss important parameter and/or relationships

- Data driven models overcome these limitations
  - Non-parametric, nonlinear function estimators
  - Can augment *a priori* models if necessary
  - **Gaussian Process Regression (GPR)**
  - **Artificial Neural Networks (ANN)**



Gaussian Process Regression.



Artificial Neural Network (Feed-Forward Architecture).

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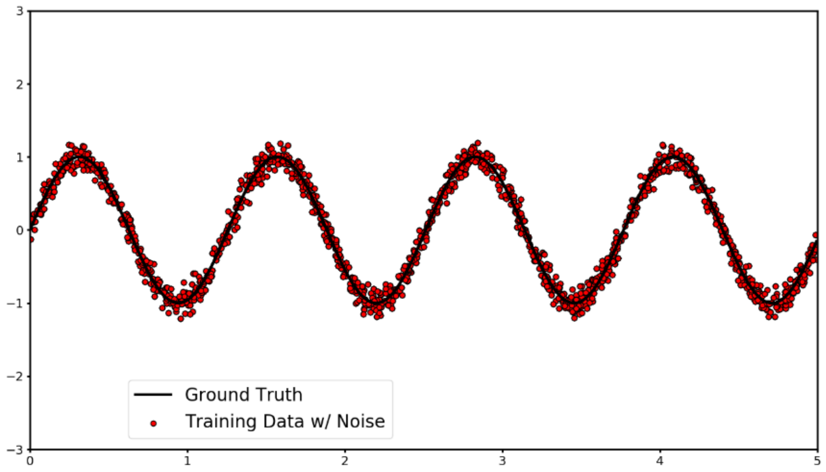
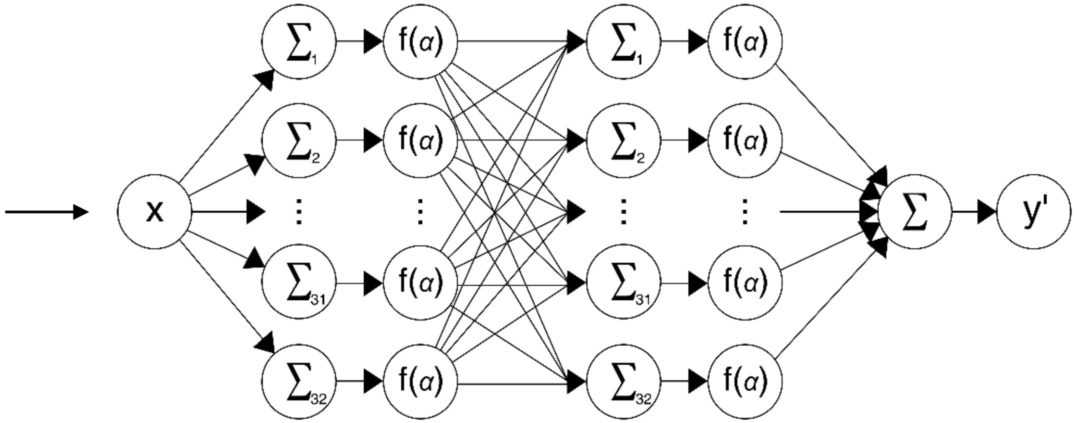
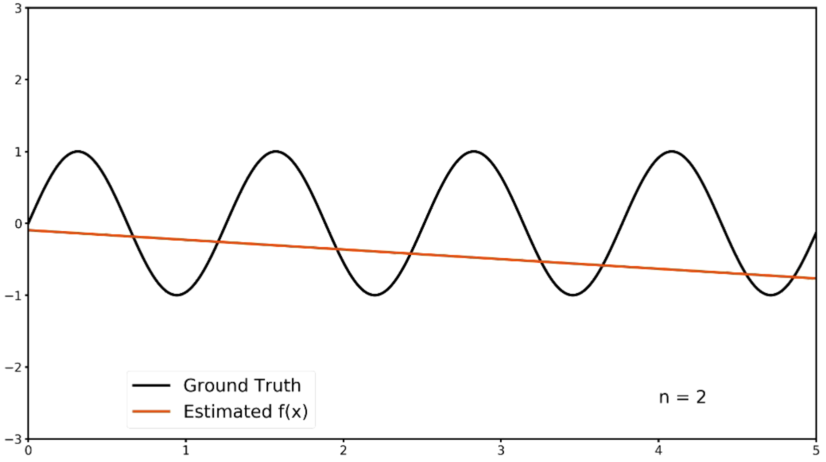
ANNs: TOO MUCH REQUIRED DATA FOR HUMAN-IN-THE-LOOP TUNING



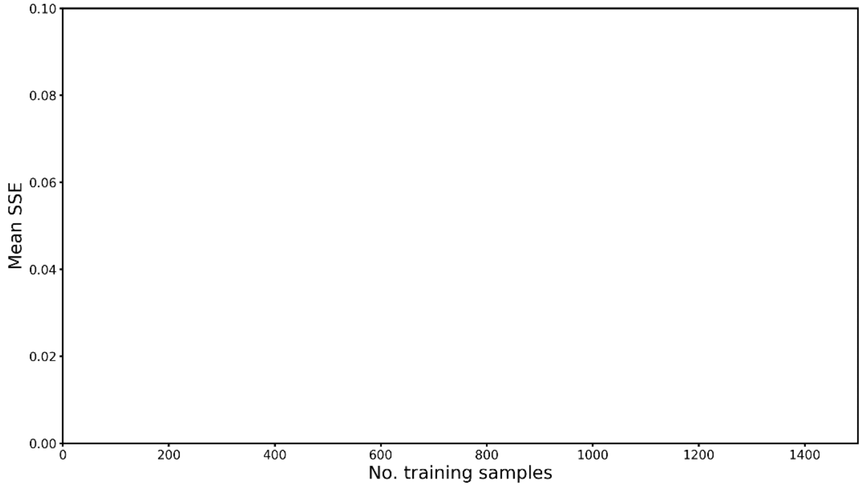
Function y=sin(5x) and noisy ANN training data.



Feed-forward ANN.



ANN estimate of y=sin(5x) from noisy data.



Mean SSE of ANN function estimate.

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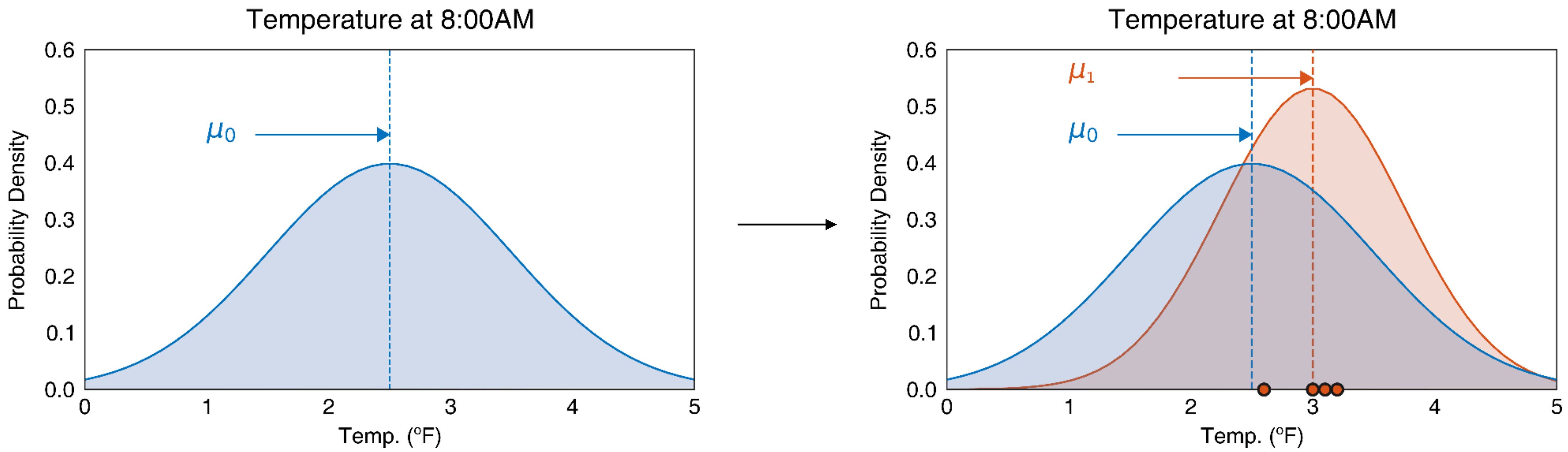
GAUSSIAN PROCESS REGRESSION (GPR)



Posterior update for a univariate Gaussian distribution based on new samples.

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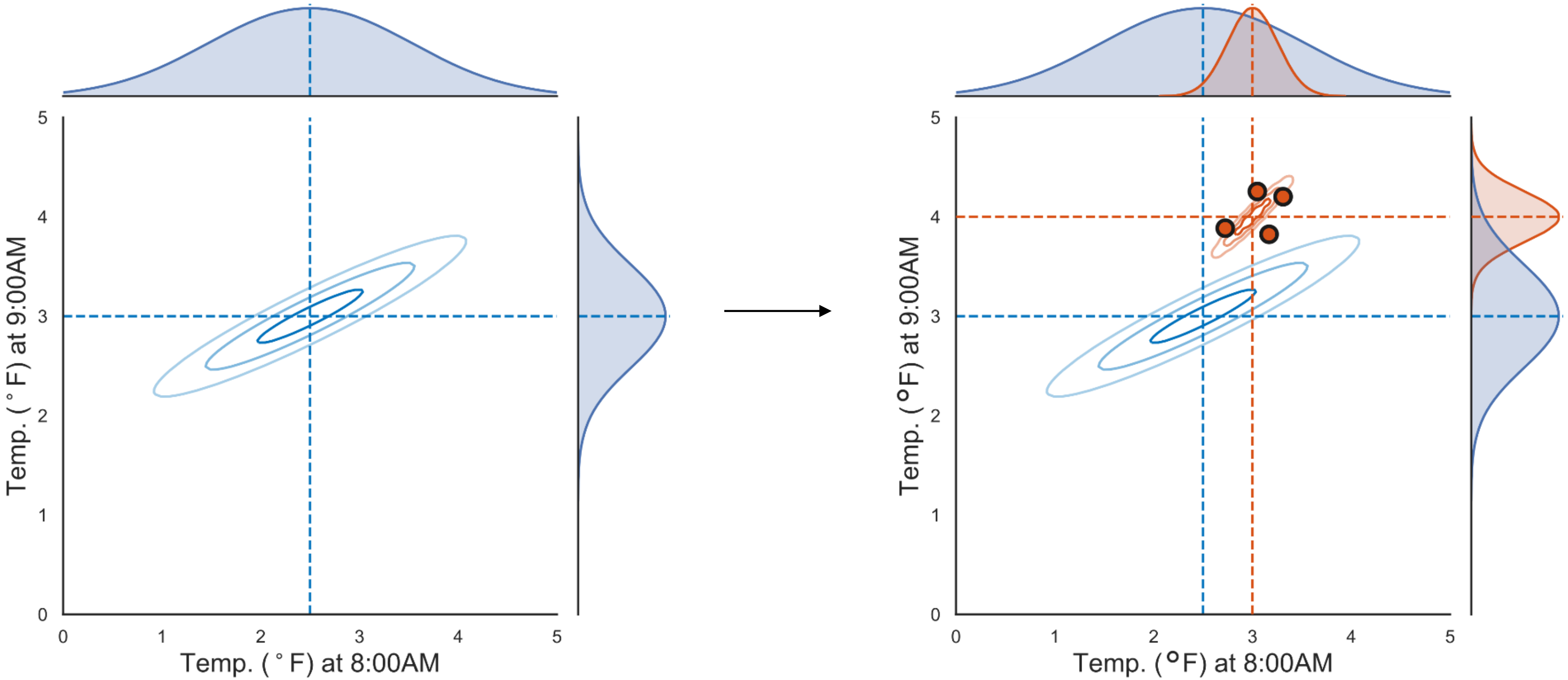
GPR (CONT'D)



Posterior update for a bivariate Gaussian distribution based on new samples.

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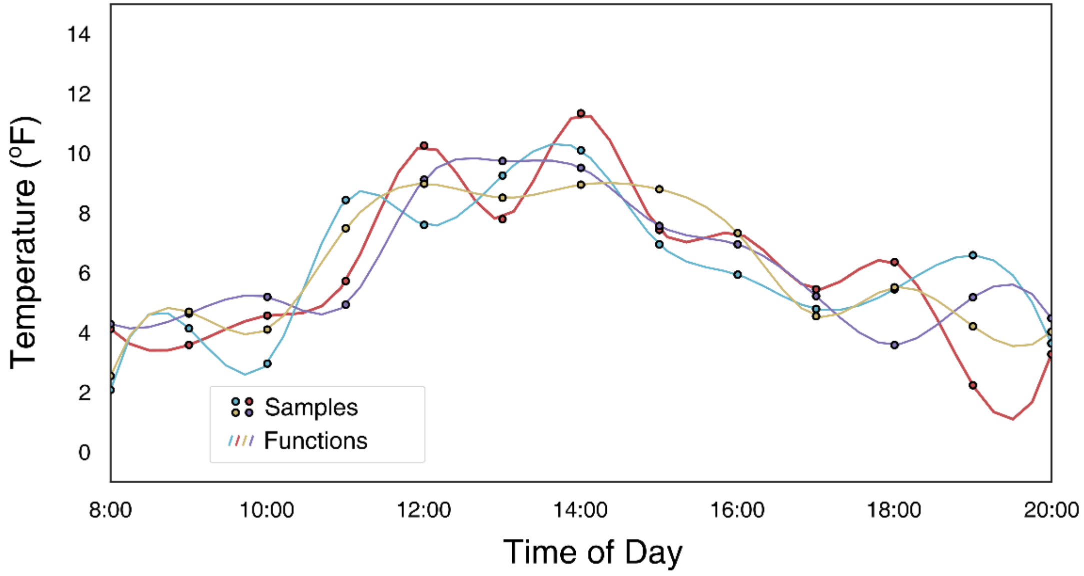
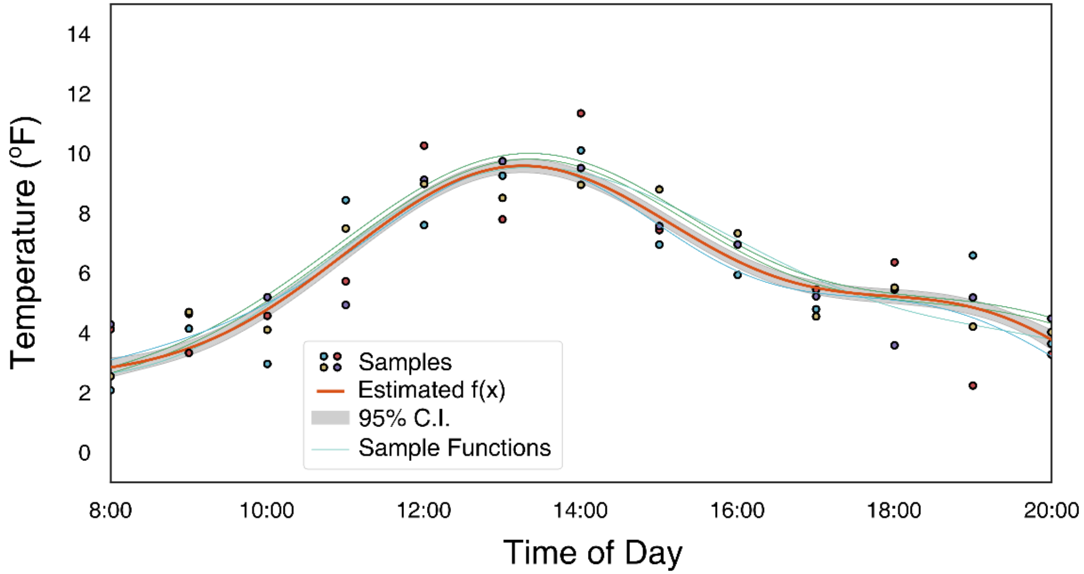
GPR (CONT'D)



$$\boxed{x'} \longrightarrow P(y' | \mathbf{y}, \mathbf{x}, x') \; \alpha \; \mathcal{N}(\vec{\mu}, \vec{\sigma}) \longrightarrow \boxed{y'}$$

Multivariate Gaussian Process Regression.



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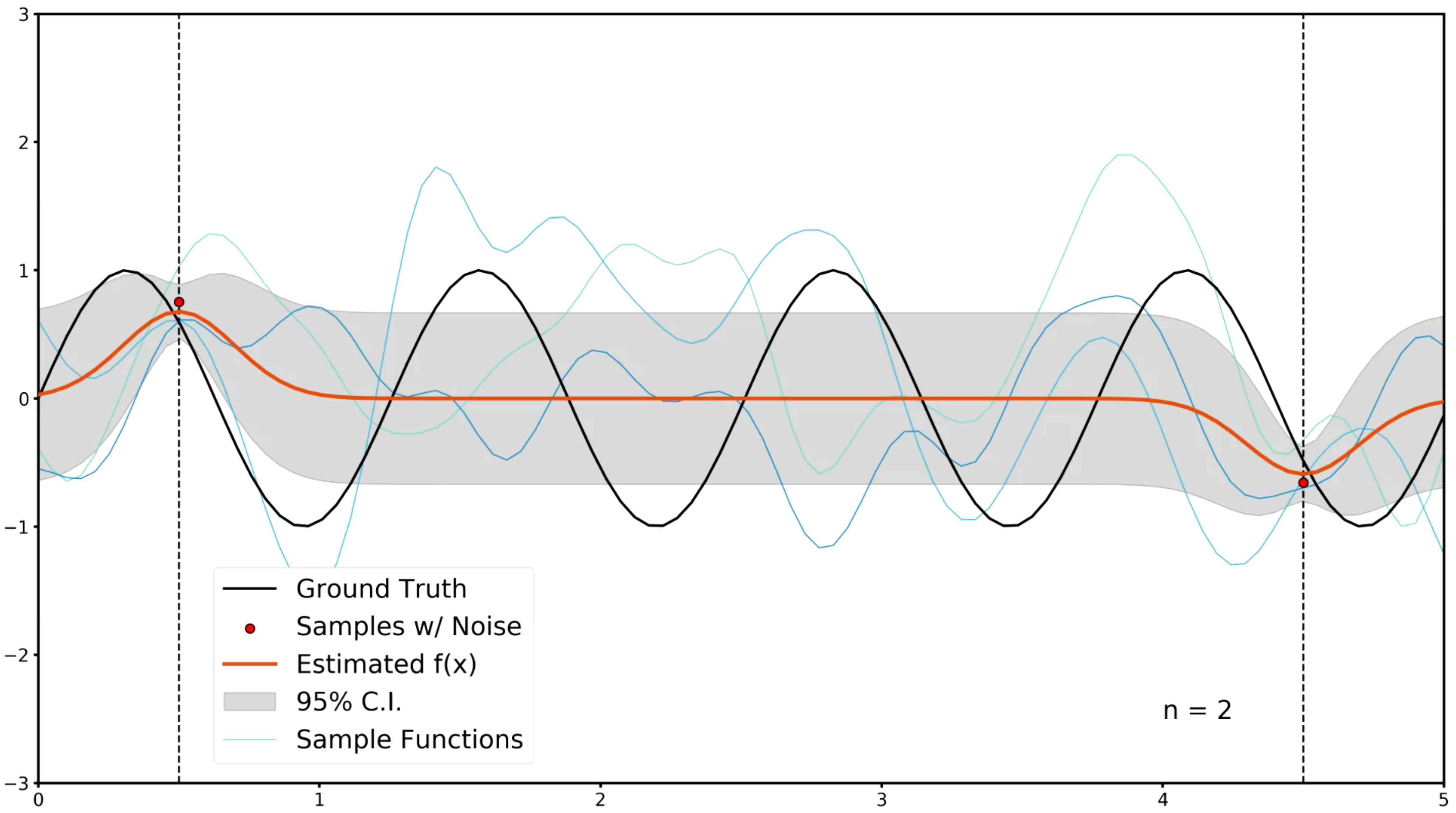
GPR: SAMPLE-BASED ESTIMATION OF Y=SIN(5x)

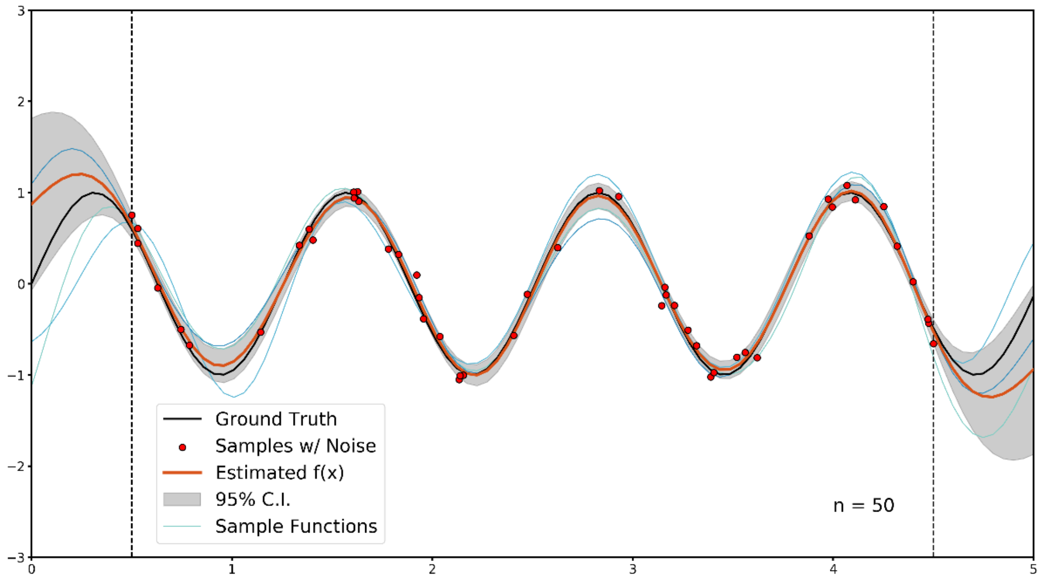


Estimating y=sin(5x) from random samples with noise using GPR.

ADVANTAGES AND DISADVANTAGES OF GPR

+ **Advantages:**
  + Native confidence interval
  + *N*-dimensional datasets
  + Discrete and continuous data
  + Comparatively little data vs. NN
  + Optimal/efficient new data sampling

- **Disadvantages:**
  - Potentially poor at extrapolation
  - Scalability
  - Kernel selection
  - Hyperparameter selection
    - Estimation techniques exist



GPR estimate of y=sin(5x) from noisy data.

ANALOG DATA ASSESSMENT: THE ABALONE DATASET

- Blacklip abalone is a large sea snail
  - Endemic to Australia and Tasmania
  - Used as food source and in jewelry (mother-of-pearl)
- Age can be determined by counting shell rings
  - Time consuming and invasive process
- Physical measurements correlate to age
  - Estimate age with machine learning (ML) techniques?
- **“Abalone” dataset is a classic ML testbed**
  - Contains discrete and continuous variables
    - “Analogous” to human-like data
- **Useful to evaluate GPR and ANN feasibility**

Top: *Blacklip abalone (Haliotis rubra).*
Bottom: *Blacklip abalone shell.*

W.J. Nash *et al*. “The Population Biology of Abalone (Haliotis species) in Tasmania. I. Blacklip Abalone (H. rubra) from the North Coast and Islands of Bass Strait.” *Sea Fisheries Division Technical Report*, No. 48, 1994.

THE ABALONE DATASET (CONT'D)

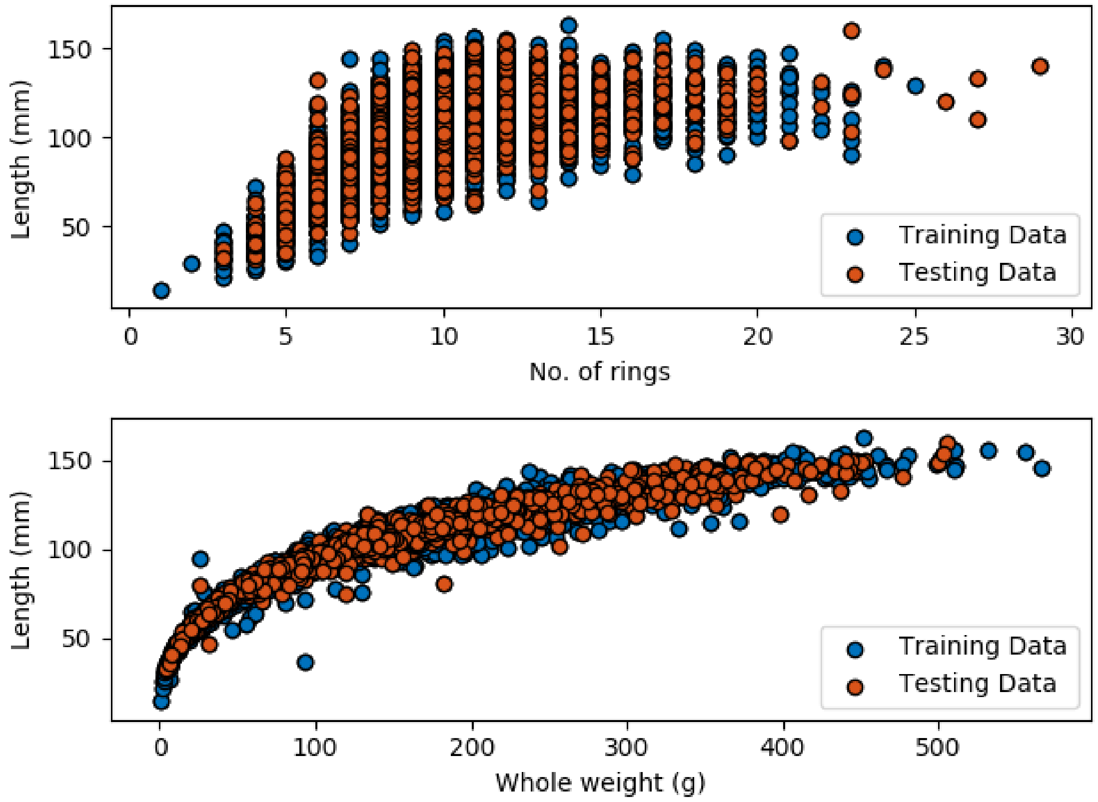
		n=4177
Variable	Unit	Type
No. of rings	[integer]	Discrete
Length	[mm]	Continuous
Diameter	[mm]	Continuous
Height	[mm]	Continuous
Whole weight	[grams]	Continuous
Shucked weight	[grams]	Continuous
Viscera weight	[grams]	Continuous
Shell weight	[grams]	Continuous

Contents of the abalone dataset used to construct GPR and ANN data driven models.

- **Looking to predict continuous variable with model**
  - **Test case:** Use GPR and ANN to predict length from mixed discrete and continuous data

THE ABALONE DATASET (CONT'D)

- Subdivide data into training/testing set
  - *n=4177*
  - Uniformly sample data across length values
  - 75/25 training/testing split
- Train models with increasingly more samples
- Quantify prediction error across entire testing set



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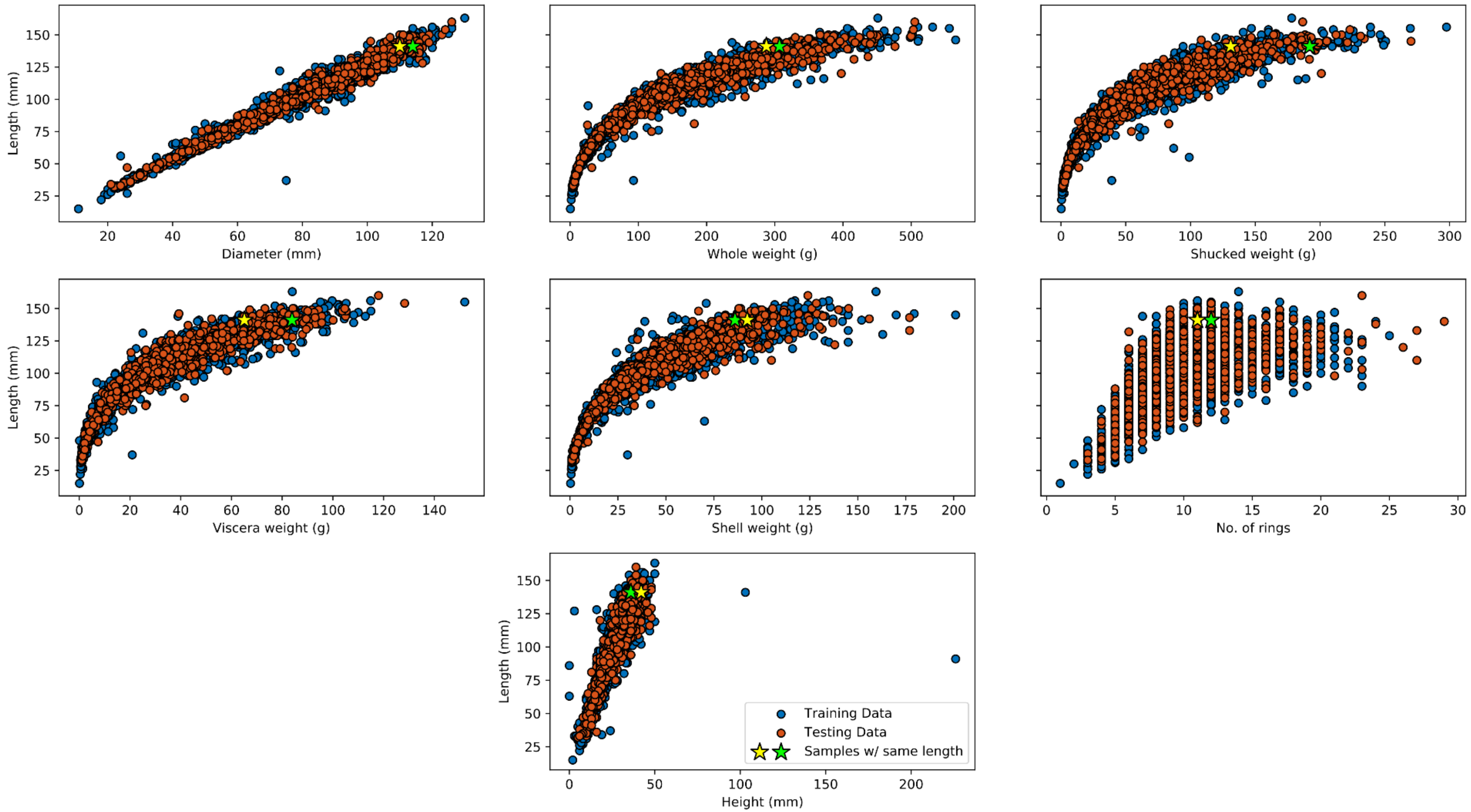
THE ABALONE DATASET (CONT'D)



Abalone training and testing datasets.

PREDICTING ABALONE LENGTH VIA DATA-DRIVEN MODELS

Test set Abalone 1					
		GPR		ANN	
No. training samples	Measured (mm)	Predicted (mm)	Rel. error (%)	Predicted (mm)	Rel. error (%)
2	76.0	48.4	36.3	40.6	46.7
10		72.3	4.5	54.8	28.0
100		116.0	-51.6	86.6	-14.1
1000		89.8	-18.2	78.4	-3.3
3132 (All)		49.8	34.4	82.2	-8.2

Test set Abalone 2					
		GPR		ANN	
No. training samples	Measured (mm)	Predicted (mm)	Rel. error (%)	Predicted (mm)	Rel. error (%)
2	87.0	81.2	6.7	51.8	40.4
10		94.0	-8.1	64.4	26.0
100		88.8	-2.2	78.4	9.9
1000		96.8	-11.3	101.6	-16.8
3132 (All)		95.6	-9.9	98.0	-12.6

Test set Abalone 3					
		GPR		ANN	
No. training samples	Measured (mm)	Predicted (mm)	Rel. error (%)	Predicted (mm)	Rel. error (%)
2	100.0	76.4	23.6	56.8	43.1
10		107.0	-7.0	68.2	31.7
100		75.0	24.9	98.0	2.0
1000		90.4	9.6	127.4	-27.4
3132 (All)		90.8	9.2	132.0	-31.9

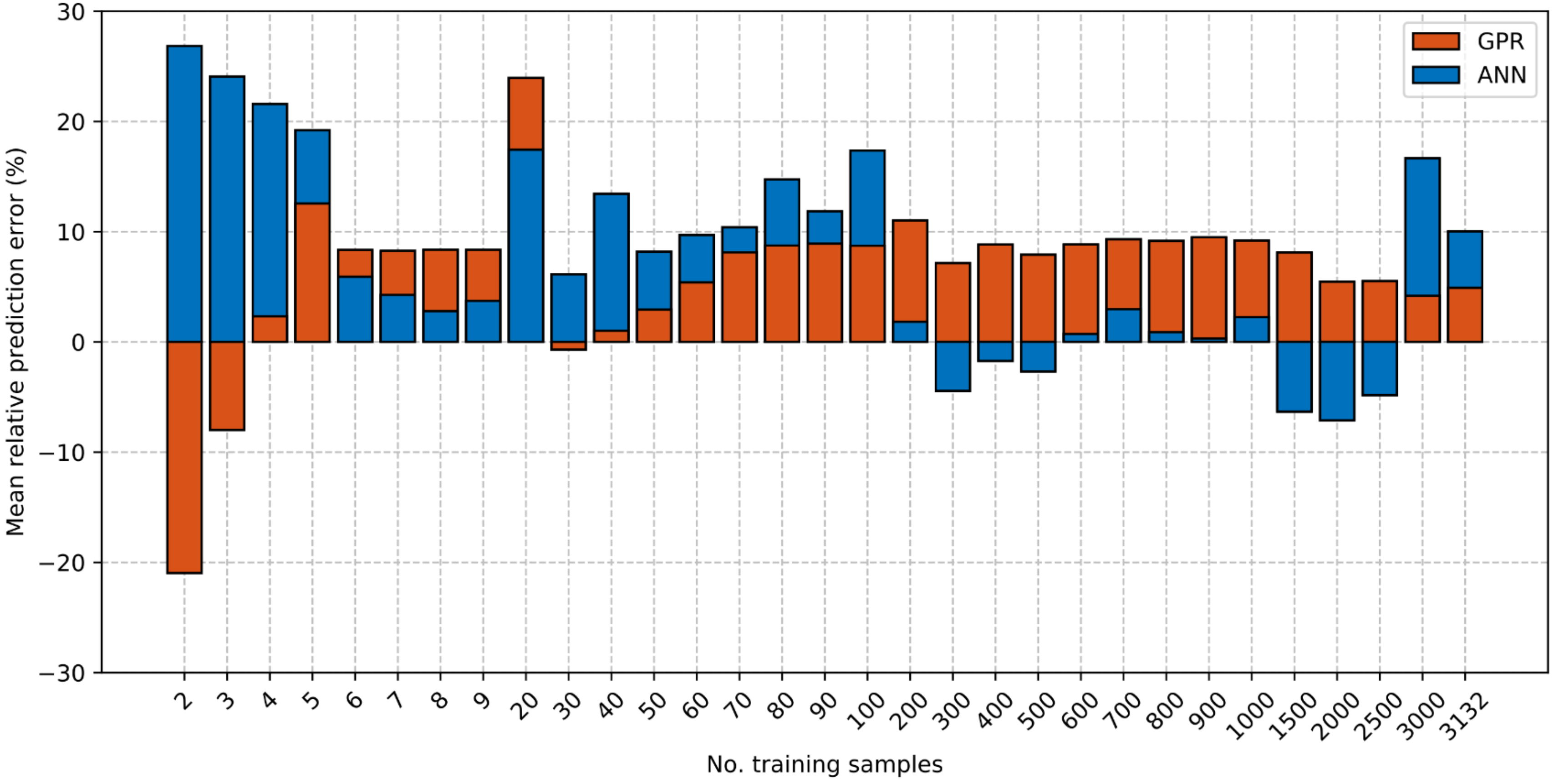
Test set Abalone 4					
		GPR		ANN	
No. training samples	Measured (mm)	Predicted (mm)	Rel. error (%)	Predicted (mm)	Rel. error (%)
2	67.0	76.6	-14.4	39.2	41.36
10		67.4	-0.6	50.8	24.3
100		69.0	-3.1	62.6	6.6
1000		67.4	-0.5	63.2	5.7
3132 (All)		64.6	3.5	59.8	10.7

Test set Abalone 5					
		GPR		ANN	
No. training samples	Measured (mm)	Predicted (mm)	Rel. error (%)	Predicted (mm)	Rel. error (%)
2	104.0	96.2	7.4	64.2	38.3
10		108.0	-3.8	76.6	26.3
100		106.2	-2.0	98.0	5.7
1000		102.2	1.7	121.8	-17.1
3132 (All)		95.0	8.6	128.6	-23.7

Test set Abalone 6					
		GPR		ANN	
No. training samples	Measured (mm)	Predicted (mm)	Rel. error (%)	Predicted (mm)	Rel. error (%)
2	105.0	103.6	1.3	64.6	38.5
10		100.8	4.0	76.4	27.2
100		115.8	-10.4	97.6	7.0
1000		106.8	-1.6	121.8	-15.9
3132 (All)		106.0	-1.0	132.0	-25.6

Sample GPR and ANN Abalone length predictions ($Rel.\ error = ((l_{meas} - l_{pred})/l_{meas}) * 100$).

PREDICTING ABALONE LENGTH (CONT'D)



Mean relative error of predicted length across testing set vs. number of samples used to create GPR and ANN.

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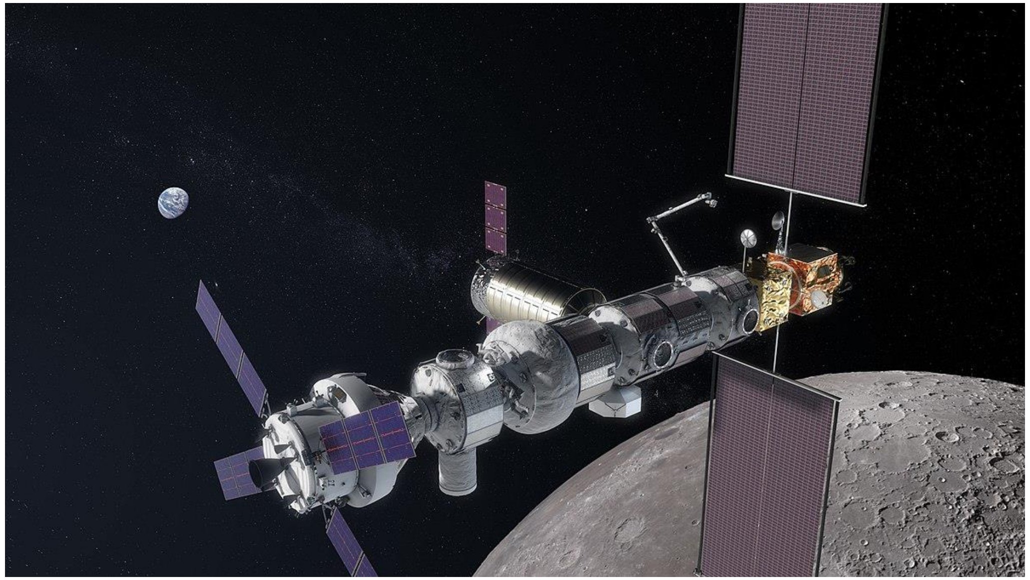
SUMMARY

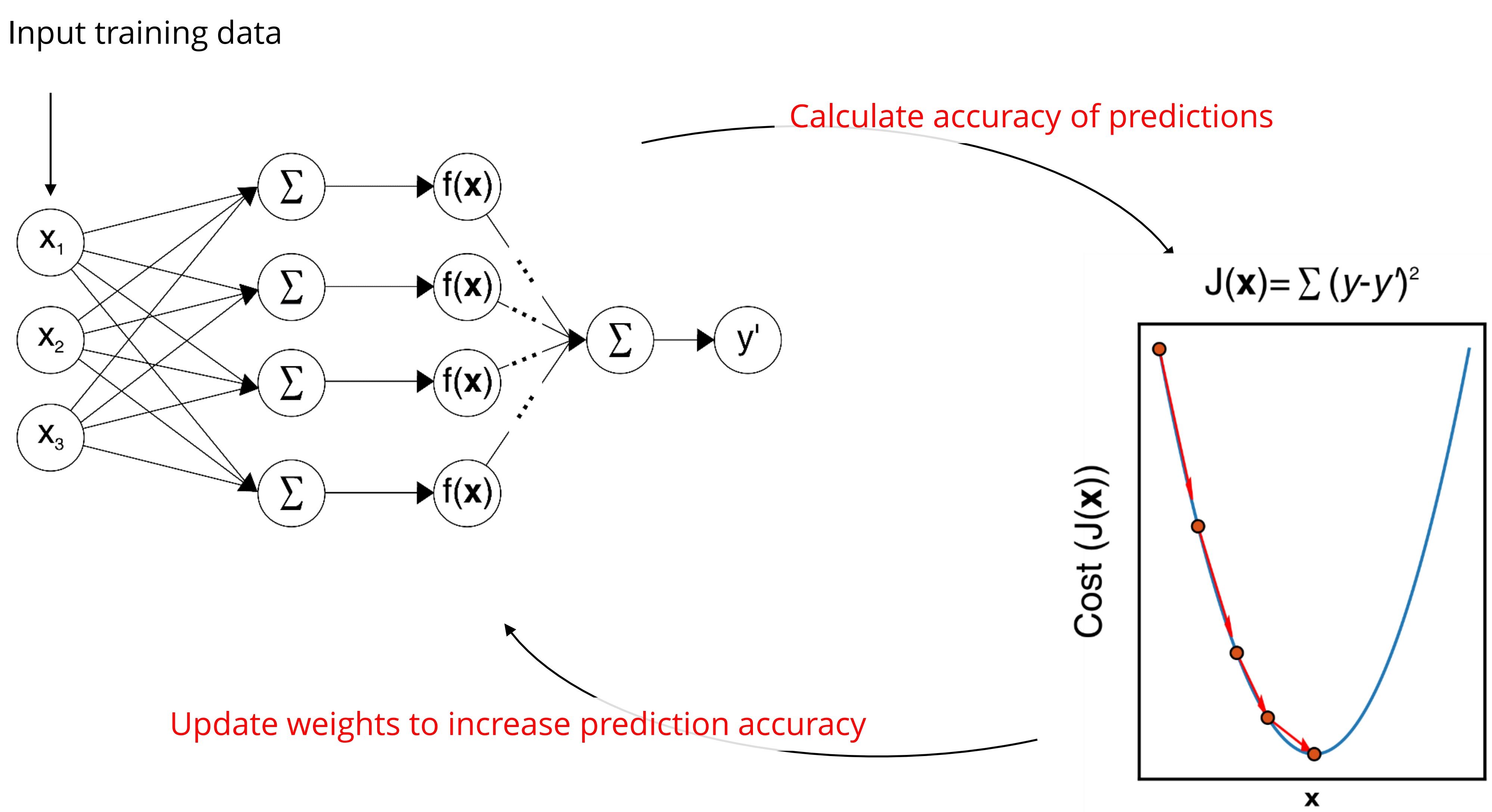
- ATLAS device is currently undergoing human testing at JSC
- Computational modeling is an integral part of robotics effort
- Evaluation planned on Lunar Orbital Platform-Gateway



Lunar Orbital Platform-Gateway concept.

SUPPLEMENTAL SLIDES

ARTIFICIAL NEURAL NETWORKS



Neural network tuning via gradient descent.