

Lowering Barriers to AI Adoption with AutoML and Interpretability



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Product Marketing – Machine Learning

AI adoption is hitting barriers

Not explainable like traditional models

Unexpected bias

Pushback against Automation

BlackRock shelves unexplainable AI liquidity models

Risk USA: Neural nets beat other models in tests, but results could not be explained

Card Investigated After Gender Discrimination Complaints

A prominent software developer said on Twitter that the credit card was “sexist” against women applying for credit.

INSIGHTS | January 10, 2020

4 Barriers to Adopting Artificial Intelligence in Healthcare

Outline

Introduction

Optimized models with AutoML

Overcoming Blackbox with Interpretability

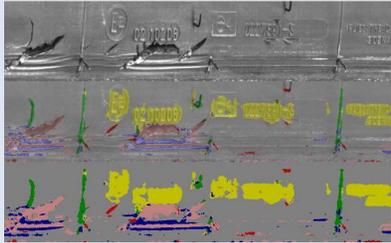
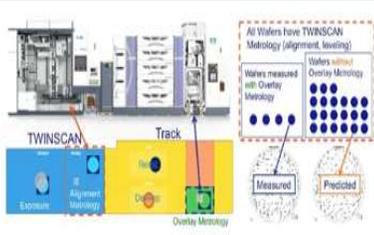
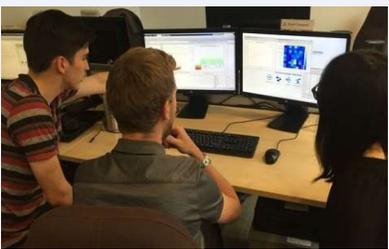
Examples:

- Human Activity Recognition
- ECG Classification

AutoML and Interpretability in Deep Learning

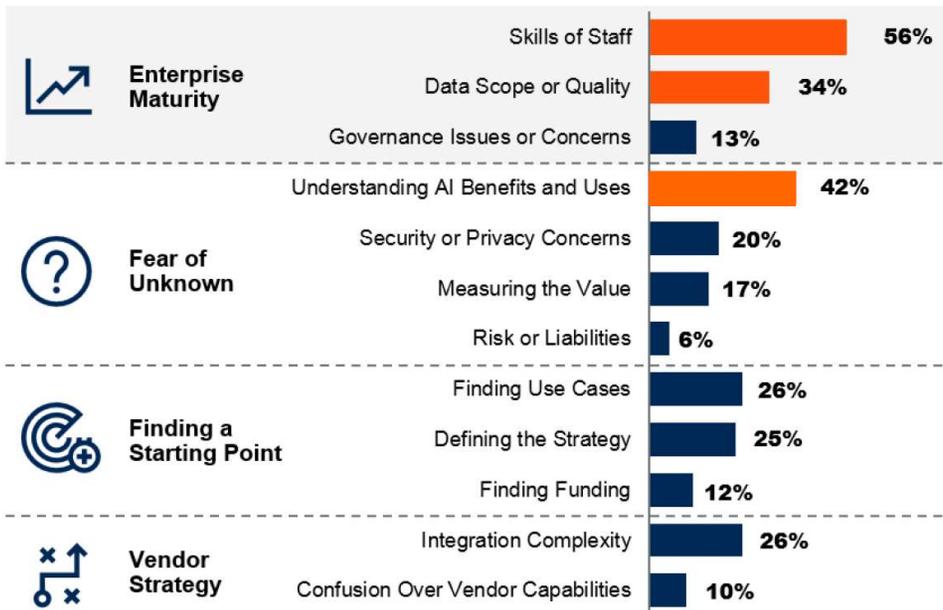
Addressing other Barriers

AI is used in many Industries

Automobile	Manufacturing	Communication & Operations	Energy & Finance
 <p data-bbox="247 776 403 808">Tire Wear</p> 	 <p data-bbox="600 776 886 849"><u>Overlay metrology improvement</u></p> 	 <p data-bbox="1066 776 1352 849"><u>Telecom customer churn prediction</u></p> 	 <p data-bbox="1549 776 1768 849"><u>Forecasting & Risk Analysis</u></p> 
 <p data-bbox="205 1214 361 1287"><u>Detect Oversteer</u></p> 	 <p data-bbox="604 1206 886 1328"><u>Monitor Deployed Compressors using Digital Twin</u></p> 	 <p data-bbox="1079 1214 1339 1287"><u>Building energy use optimization</u></p> 	 <p data-bbox="1577 1214 1732 1287"><u>Portfolio Allocation</u></p> 

Barriers to broader Adoption of AI

Top Challenges to adoption of AI and ML (Gartner Research)

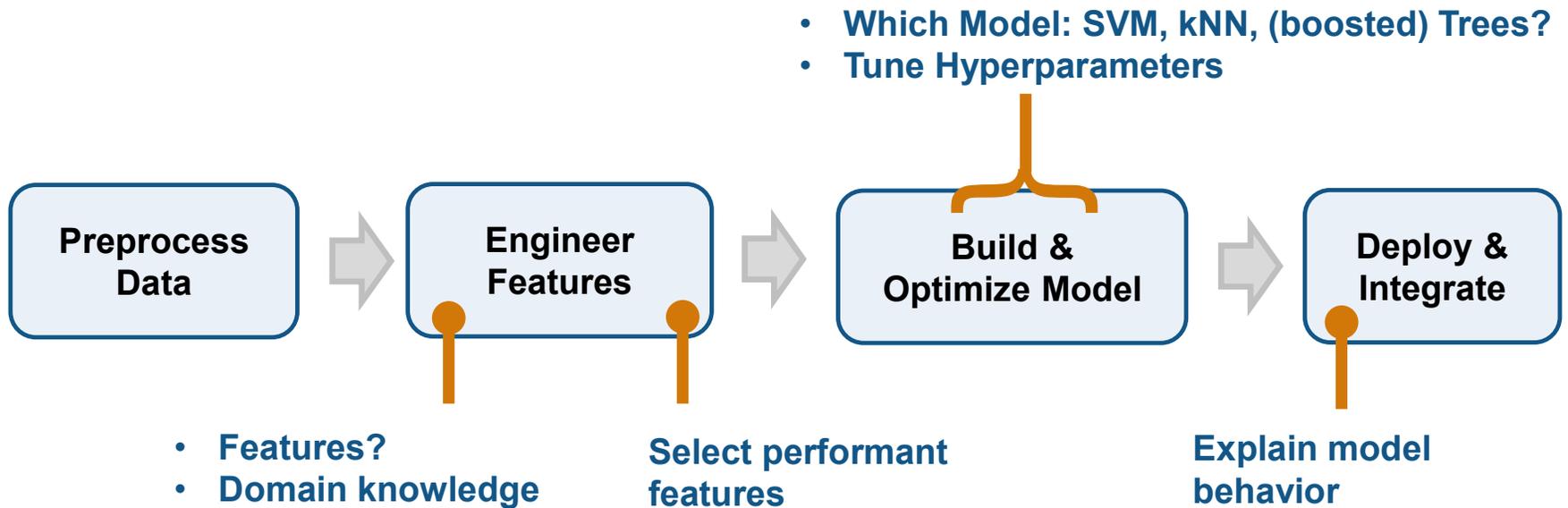


Top barriers to successful adoption of AI

1. Lack of AI skills
2. Black-box nature
3. Data

n = 106
 Gartner Research Circle members, excluding "unsure"
 Source: Gartner AI and ML Development Strategies Survey
 Q: What are the top three challenges or barriers to the adoption of AI and ML within your organization?
 Rank up to three.
 ID: 390794
 published 19 June 2019

Challenges in the Machine Learning Workflow



Chose among many popular models

Build Models interactively

Classification Learner - Scatter Plot

Model History:

Model ID	Model Type	Accuracy	Last change
1	Tree	99.4%	Disabled PCA
2	Logistic Regression	88.4%	Logistic Regression
3	SVM	Canceled	Linear SVM
4	Ensemble	99.8%	Bagged Trees
5	Ensemble	(Draft)	Optimizable Ensemble
6	SVM	94.0%	Fine Gaussian SVM
7	Tree	97.0%	Medium Tree
8	Ensemble	100.0%	Removed feature 'AmplitudeZ'

Current Model: Model 8 Trained

Results: Accuracy 100.0%, Total misclassification cost 5, Prediction speed ~56000 obs/sec, Training time 9.3802 sec

Model Type: Ensemble method: Bag Learner type: Decision tree

Tune Hyperparameters

Classification Learner - Minimum Classification Error Plot

Model 2 Trained

Results: Accuracy 97.3%, Total misclassification cost 4, Prediction speed ~7833 obs/sec, Training time 27.771 sec

Model Type: Preset Optimizable Tree

Optimization Results: Maximum number of epochs: 48, Estimated minimum classification error: 0.024669, Observed minimum classification error: 0.024667

Classification Learner - Confusion Matrix

Model Selection Categories:

- DECISION TREES:** Fine Tree, Medium Tree, Coarse Tree, All Trees, Optimizable Tree
- DISCRIMINANT ANALYSIS:** Linear Discriminant, Quadratic Discriminant, All Discriminants, Optimizable Discriminant
- LOGISTIC REGRESSION CLASSIFIERS:** Logistic Regression
- NAIVE BAYES CLASSIFIERS:** Gaussian Naive Bayes, Kernel Naive Bayes, All Naive Bayes, Optimizable Naive Bayes
- SUPPORT VECTOR MACHINES:** Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, Coarse Gaussian SVM, All SVMs, Optimizable SVM
- NEAREST NEIGHBOR CLASSIFIERS:** Fine KNN, Medium KNN, Coarse KNN, Cosine KNN, Cubic KNN, Weighted KNN, All KNNs, Optimizable KNN
- ENSEMBLE CLASSIFIERS:** Boosted Trees, Bagged Trees, Subspace Discriminant, Subspace KNN, RUSBoosted Trees, All Ensembles

Current Model: Model 8 Trained

Model 8 Trained Results: Accuracy 100.0%, Total misclassification cost 5, Prediction speed ~56000 obs/sec, Training time 9.3802 sec

Model Type: Preset: Bagged Trees, Ensemble method: Bag Learner type: Decision tree, Maximum number of epochs: 48

Confusion Matrix

	Actual Normal	Actual Abnormal
Predicted Normal	901	2647
Predicted Abnormal	906	511

ROC Curve

AUC = 0.87

Plot Options: Number of observations, True Positive Rates, False Negative Rates, Positive Predictive Values, False Discovery Rates

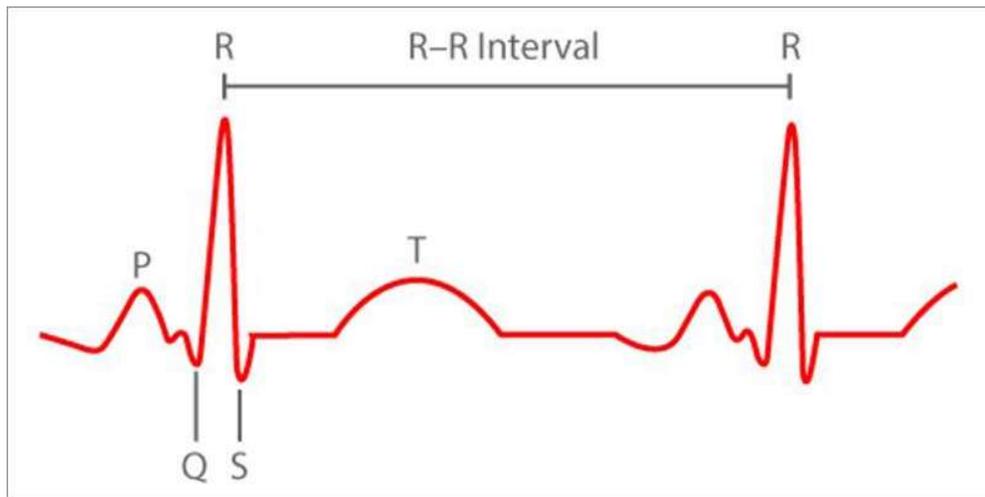
Plot Class: Positive class (Abnormal), Negative classes (Normal)

Evaluate Models using Confusion Matrix and ROC curve

Example: Classify Heart Condition from ECG data

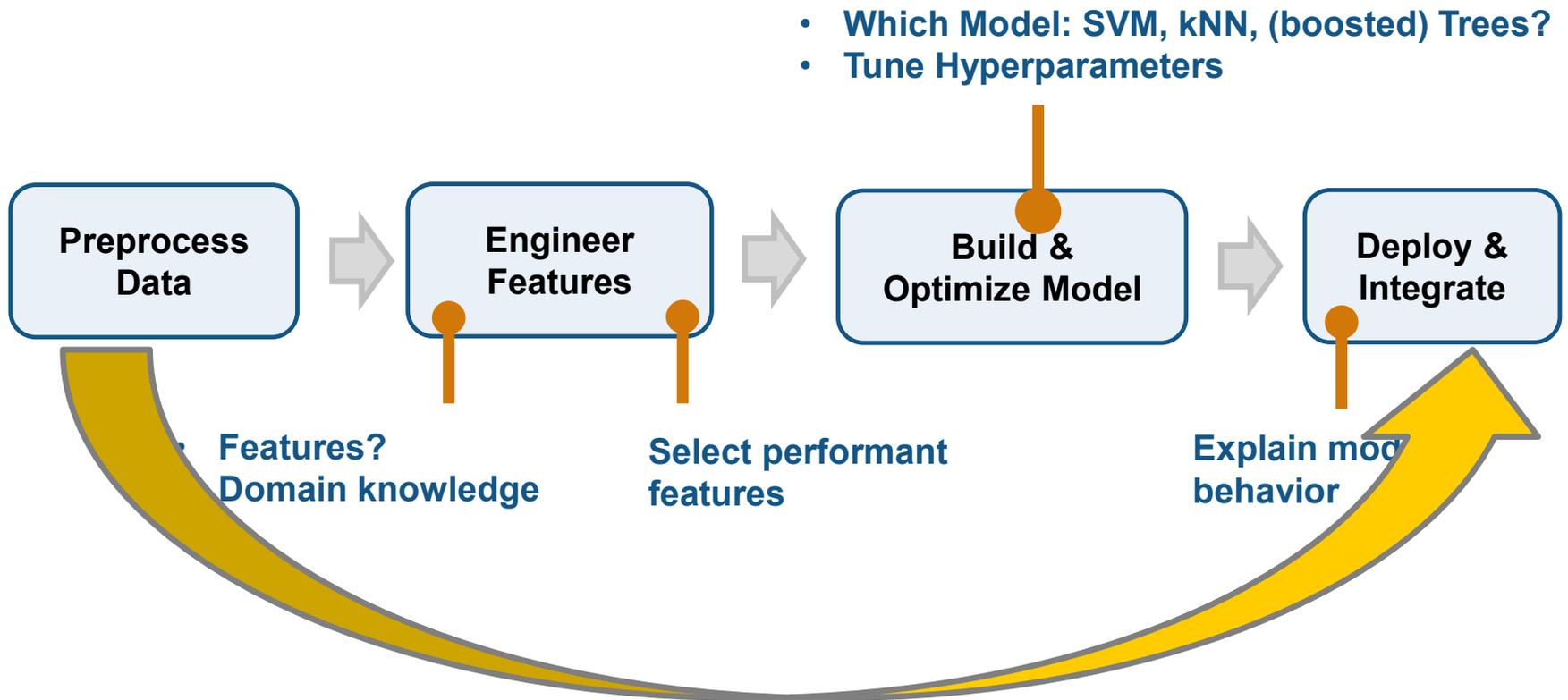


How ECG is characterized:



Dataset was curated for 2017 PhysioNet challenge: "normal" ECG data was obtained from the MIT-BIH Normal Sinus Rhythm database available at <https://physionet.org/content/nsrdb/1.0.0/>, and "abnormal" from MIT-BIH Arrhythmia database at <https://www.physionet.org/content/mitdb/1.0.0/>

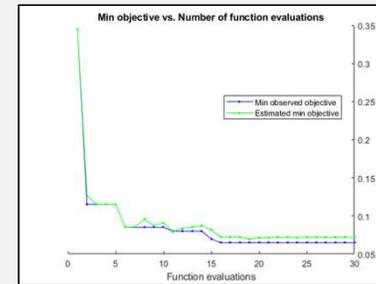
What is AutoML?



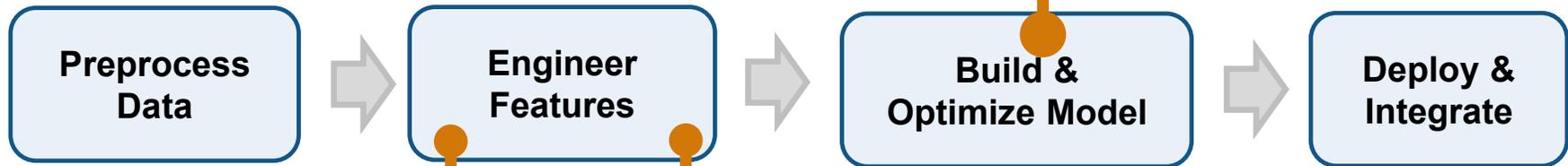
AutoML for Engineering Applications

3

Model Selection with Hyperparameter Optimization

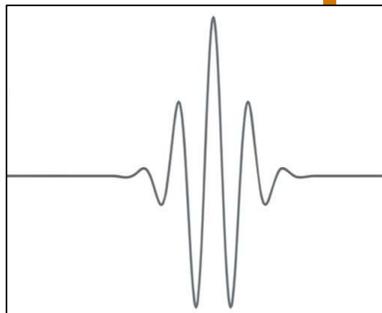


Decision Tree?
SVM?
KNN?
Ensemble?
...?



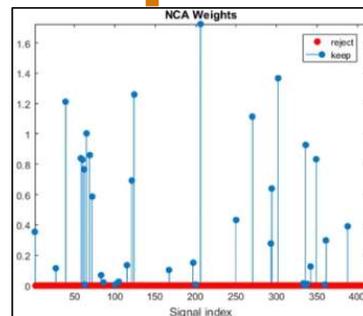
1

Wavelet Scattering



2

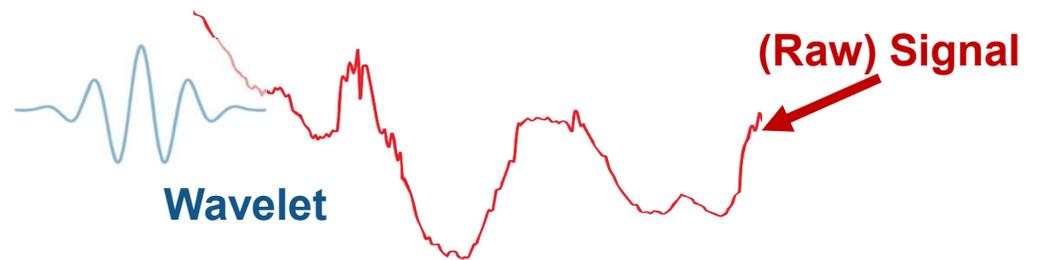
Feature Selection



Feature Generation with Wavelet Scattering

What are Wavelets?

Decompose signal into “wavelets”



Wavelet Scattering Framework [\[Bruna and Mallat 2013\]](#)

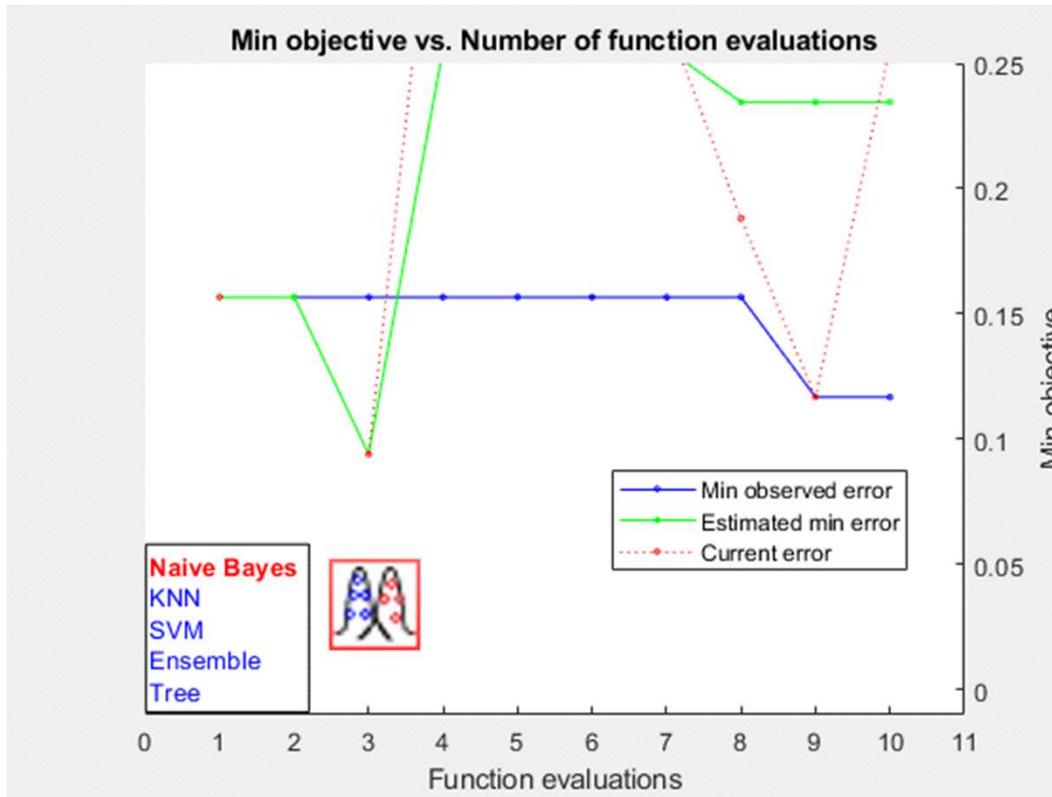
- Reduces data dimensionality and provides compact features
- For Signal and Image data
- Great starting point if you don't have a lot of data



Many Feature Selection methods are available.

Function	Predictors	Machine Learning	Training Speed	Types of Models	Accuracy	Caveats
NCA	Continuous	Classification Regression	Medium	KNN SVM (can use for others)	Strong	Needs manual tuning of regularization lambda (doc page)
MRMR R2019b	Continuous Categorical Mix of both	Classification	Fast	Model Independent	Strong	
ReliefF	Continuous Categorical	Classification Regression	Medium	KNN SVM (can still use for others)	Moderate	Unable to differentiate correlated predictors
Sequentialfs	Continuous Categorical	Classification Regression	Very Slow	Model Independent (define custom loss function)	Strong	Doesn't rank all features
F Test R2020a	Continuous Categorical Mix of both	Regression	Very Fast	Model Independent	Weak	Unable to differentiate correlated predictors
Chi Squared R2020a	Continuous Categorical Mix of both	Classification	Very Fast	Model Independent	Weak	Unable to differentiate correlated predictors

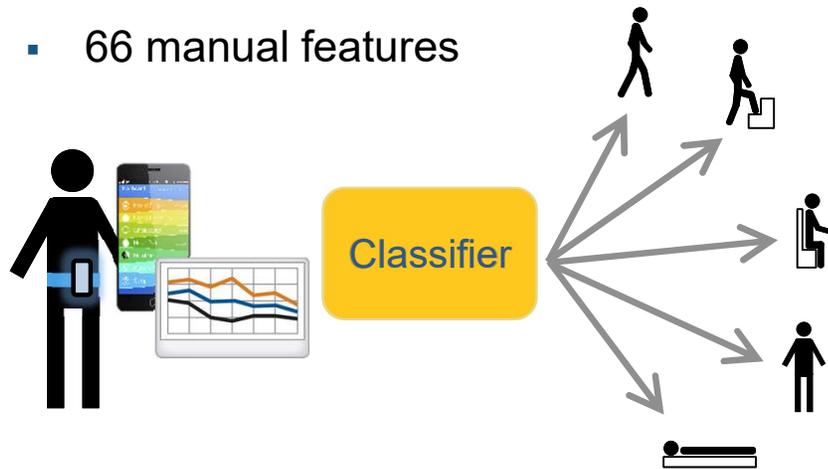
Simultaneous Optimization of Model and Hyperparameters



AutoML matches Manual Optimization in performance.

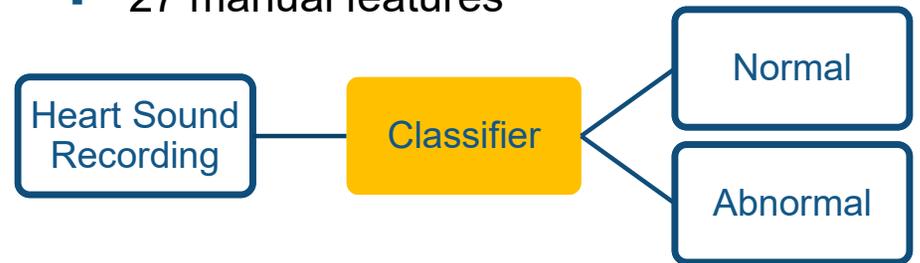
Human Activity Recognition

- Accelerometer from mobile
- 7K observations
- 66 manual features



Heart Sound Classification

- Phonograms
- 10K observations
- 27 manual features

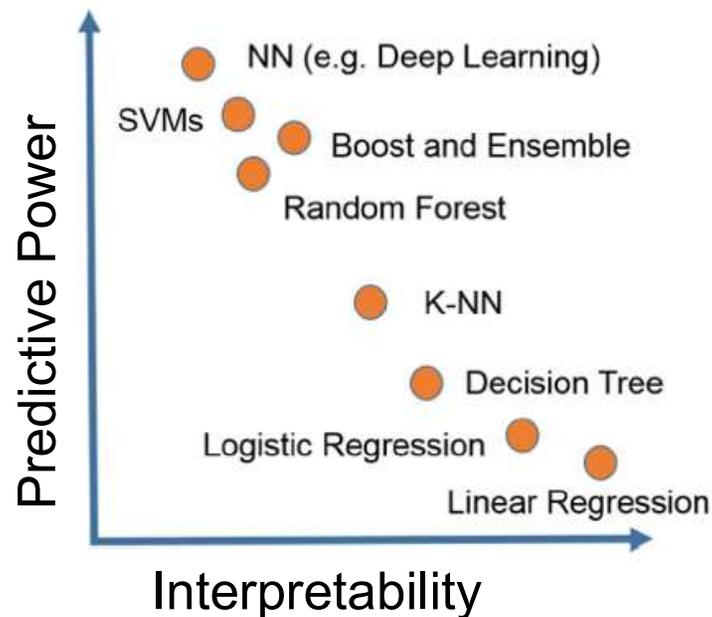


Results:



	Human Activity	Heart Sound
Manual	95%	98%
AutoML	98%	97%

Interpretability and Explainability



Use Cases

1. Overcome black-box model
2. Regulatory requirements
3. Debug models

Interpretability: causality of (mostly machine learning) model decisions

Explainable AI: visualize activations in various layers (deep learning)

Where is Interpretability most needed?

	Finance	Auto & Aero
Why Interpretability	Credit / Market risk models	Safety certification
	Traditional models explainable	
Popular complex models	Gradient-boosted trees Random forests	Deep neural networks
	Neural networks	Reinforcement learning
Popular Interpretability	Shapley values	Network visualizations

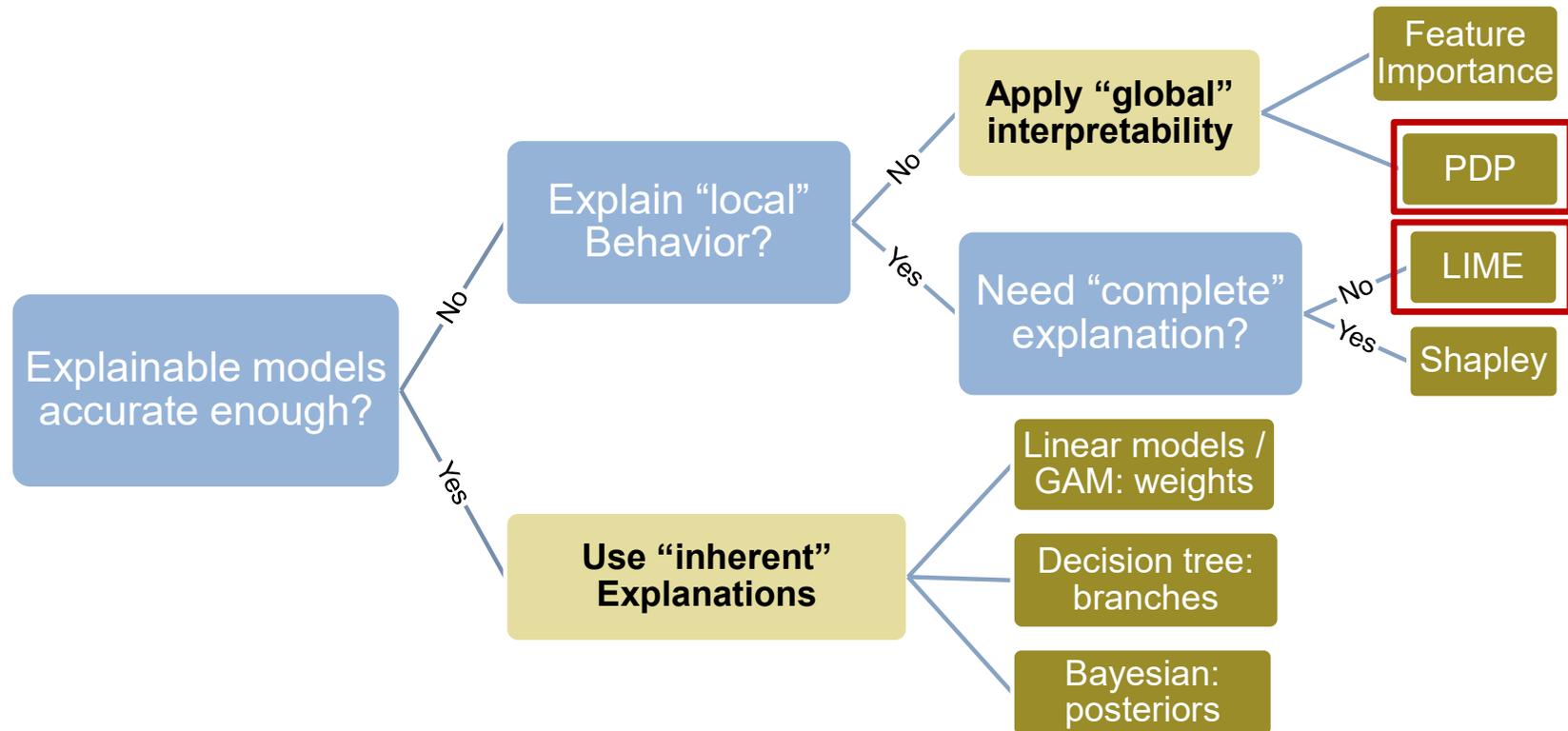


EUROCAE WG-114
"Artificial Intelligence"

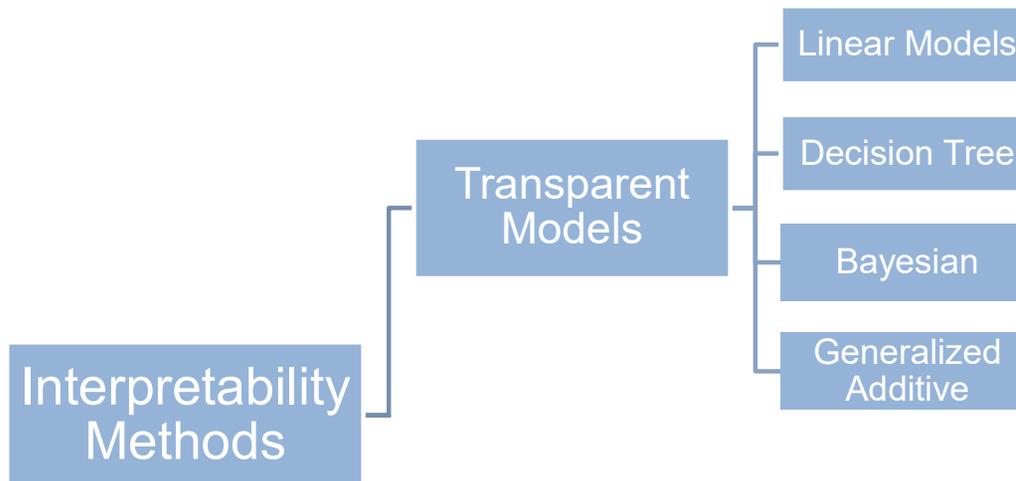


SAE G-34 "Artificial
Intelligence in Aviation"

Which Interpretability method?

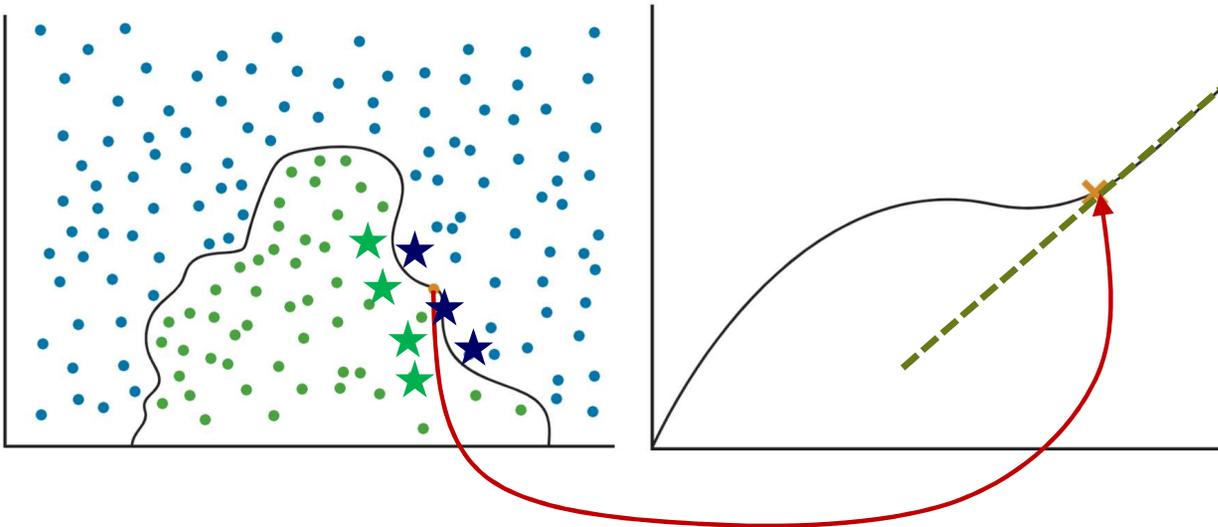


Which Interpretability methods are available?

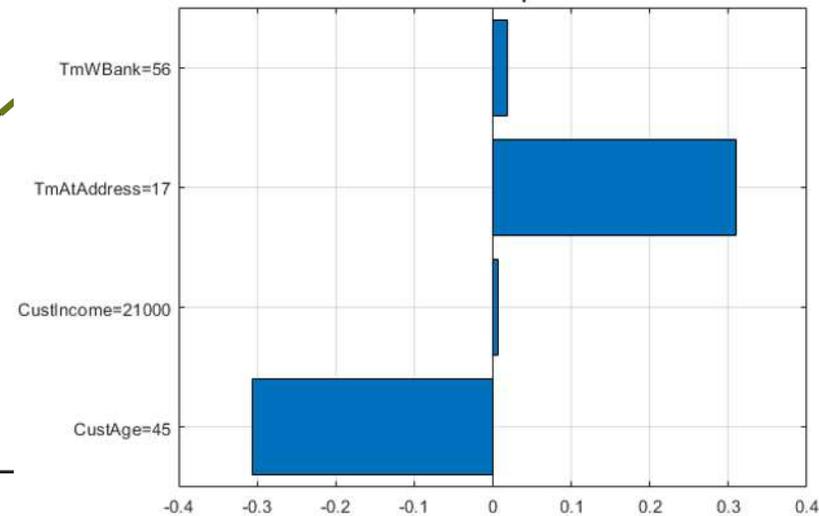


LIME = Local Interpretable Model-Agnostic Explanations

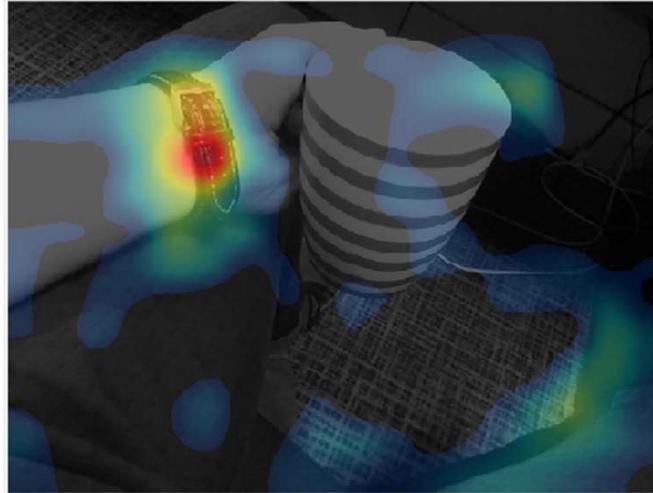
1 Approximate complex model near Point of Interest with simple model



2 “Explain” using weights of simple model



Deep Learning Explainability: “why” behind deep net’s decisions



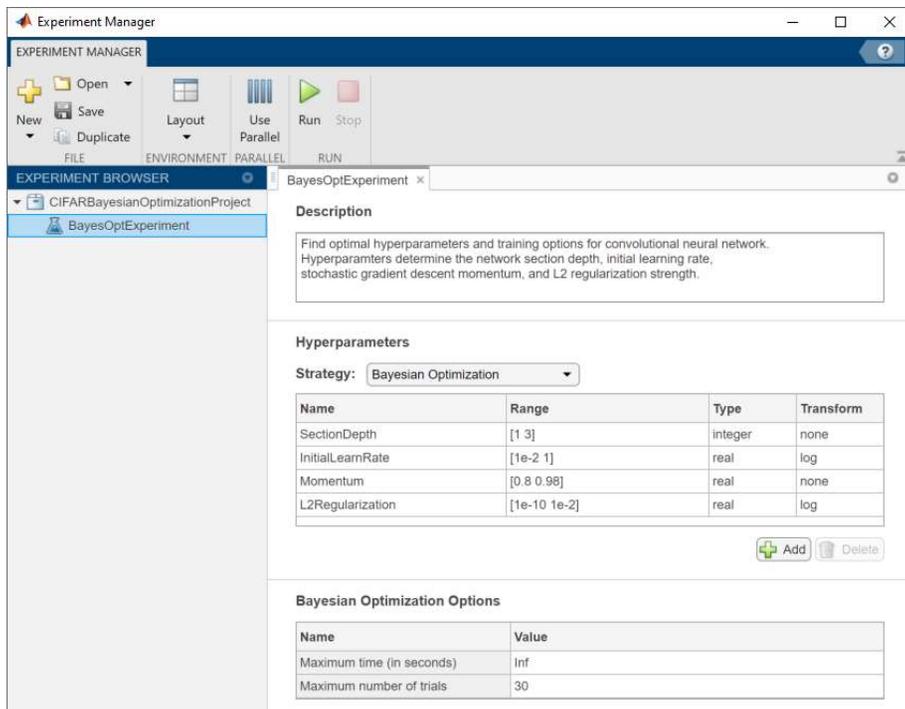
Truth:	Coffee mug
AI:	Buckle (15%) ❌

AI classifies incorrectly as “buckle” due to the watch

- Three techniques:**
- Occlusion Sensitivity
 - GradCAM
 - Image LIME

AutoML in Deep Learning

Neural Net Hyperparameters



The screenshot shows the Experiment Manager interface. The left sidebar displays the project structure: **EXPERIMENT BROWSER** > **CIFARBayesianOptimizationProject** > **BayesOptExperiment**. The main panel shows the experiment details:

- Description:** Find optimal hyperparameters and training options for convolutional neural network. Hyperparameters determine the network section depth, initial learning rate, stochastic gradient descent momentum, and L2 regularization strength.
- Hyperparameters:** Strategy: Bayesian Optimization

Name	Range	Type	Transform
SectionDepth	[1 3]	integer	none
InitialLearnRate	[1e-2 1]	real	log
Momentum	[0.8 0.98]	real	none
L2Regularization	[1e-10 1e-2]	real	log

Buttons: **Add** (with plus icon), **Delete** (with trash icon)

- Bayesian Optimization Options**

Name	Value
Maximum time (in seconds)	Inf
Maximum number of trials	30

Neural Architecture Search

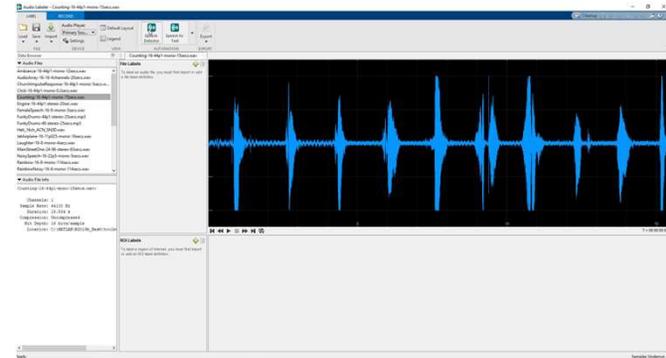
- Identify “optimal” neural net
- Computationally extremely challenging
- Currently: exploring variants of established networks

Addressing other Challenges

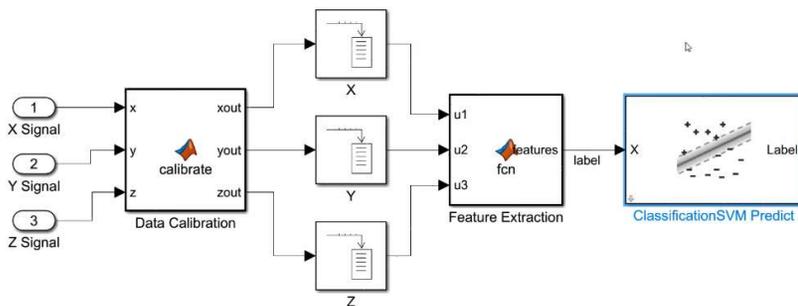
Preprocess with Live Tasks



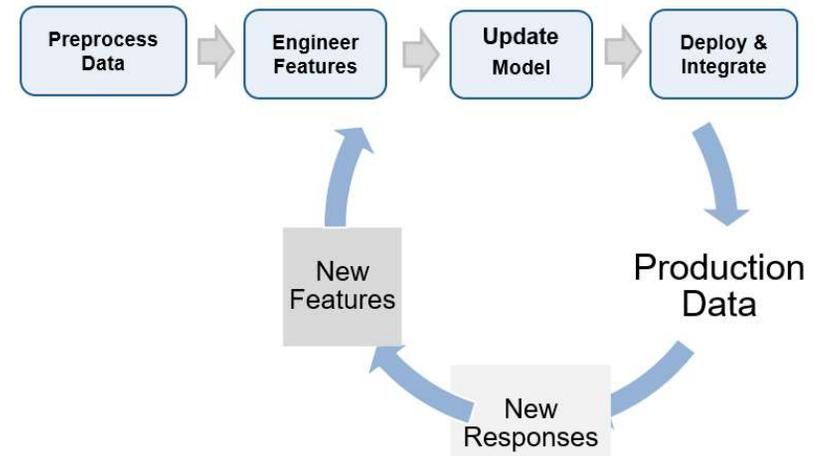
Reduce Labeling Effort



Integrate in Complex Systems



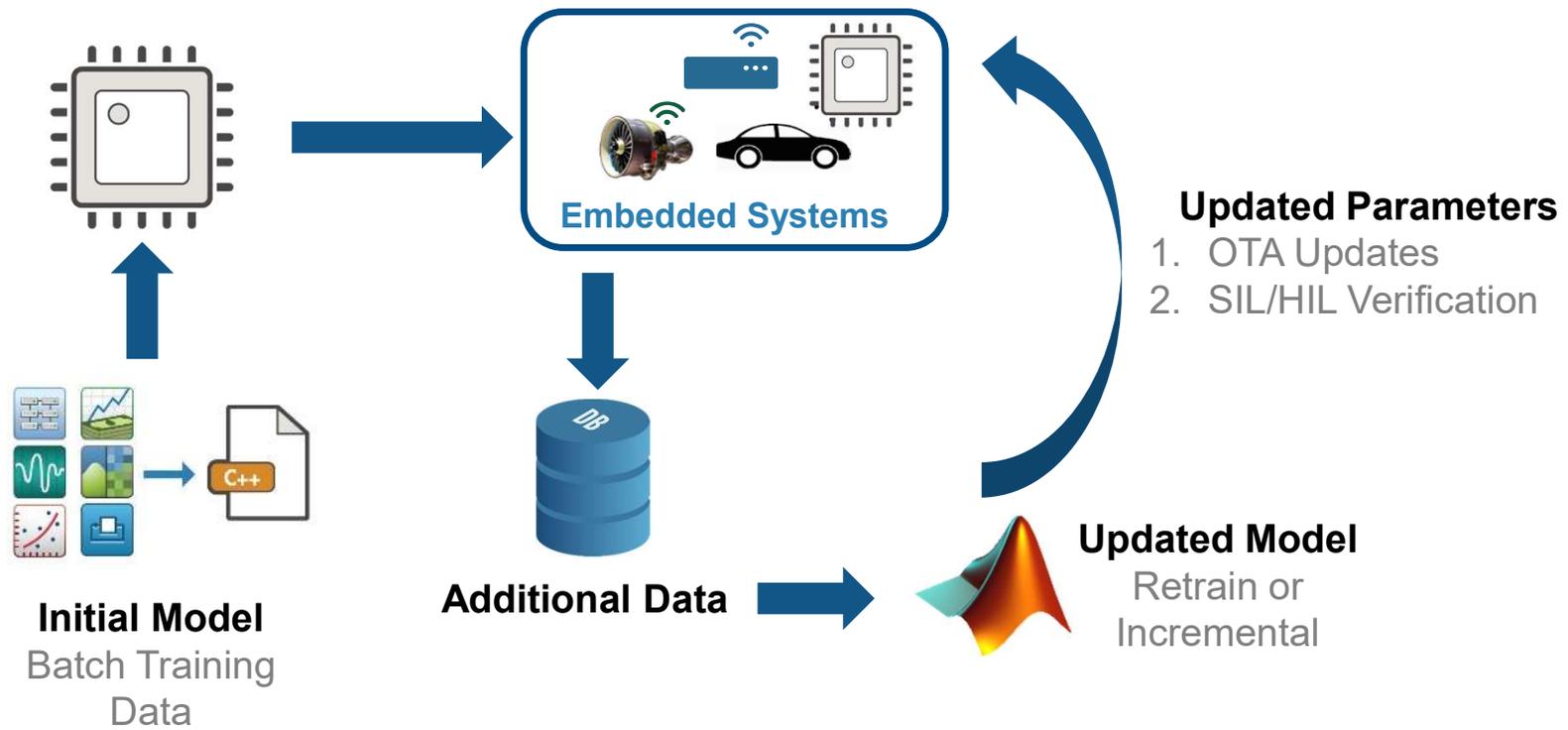
Update deployed models



Updating deployed models

R2019b

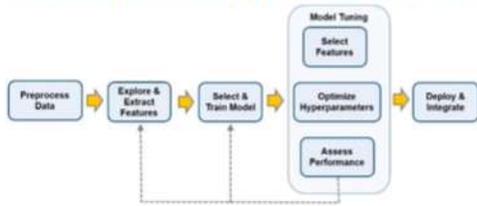
SVM
Linear Models
Decision Trees



Learn more: Tools that facilitate Adoption of Machine Learning

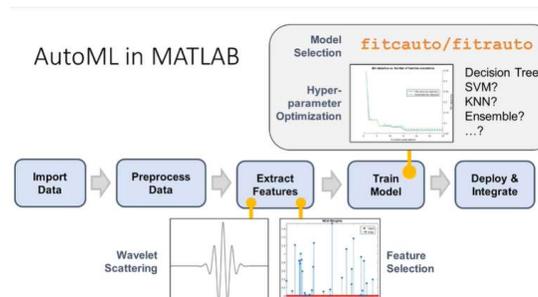
Videos: [Classification Learner](#)

Build Models without Coding using Classification Learner

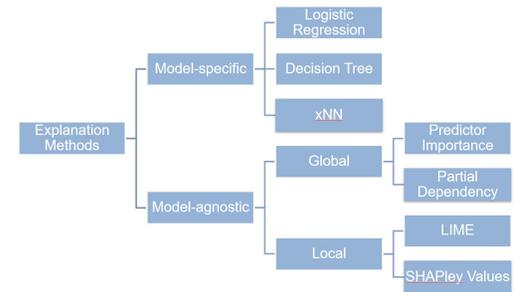


- Explore preprocessed data to determine features
- Train and compare multiple models
- Assess model performance
- Tune hyperparameters

[AutoML in MATLAB](#)



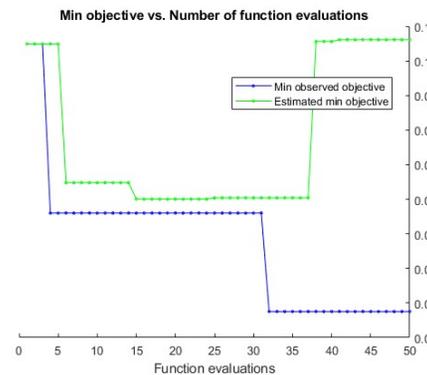
[Applying Model Interpretability](#)



Free 2hr
Machine
Learning
Onramp



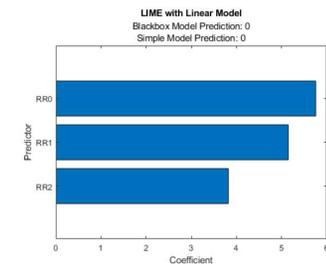
Demo: [Apply AutoML to Human Activity \(Blog\)](#)



Demo: [Machine Learning for ECG Classification \(with Interpretability\)](#)

```
ans = 1x9 table
      RR0      RR1      RR2      R1      R2      Rm      rAmplitude1
      1      0.0528  0.0417  0.0306  1.2667  0.7333  1      0.3287
```

```
% Plot the explanations. This plot consists of the important features recognized by lime
f = plot(limeobj);
```



How MATLAB lowers barriers to adopting Machine Learning

Build models interactively & AutoML

- Empower Engineers & Domain experts with limited expertise
- Make experienced practitioners more productive

Code Generation for Embedded Deployment

- Fixed point for popular Classification and Regression models
- Quantization and C / CUDA code generation for deep learning

Integration with Simulink

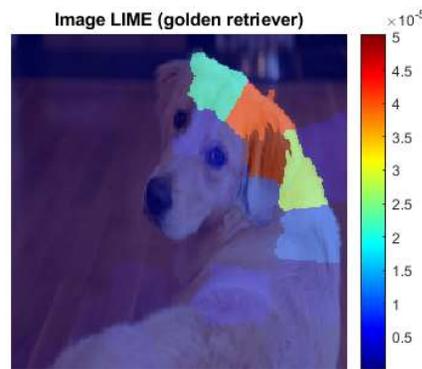
- Native blocks for Machine Learning facilitate Model-Based Design
- Deep Learning blocks for prediction and image classification

Learn more: Deep Learning with MATLAB

Video: [Get Started with Deep Learning in MATLAB](#)



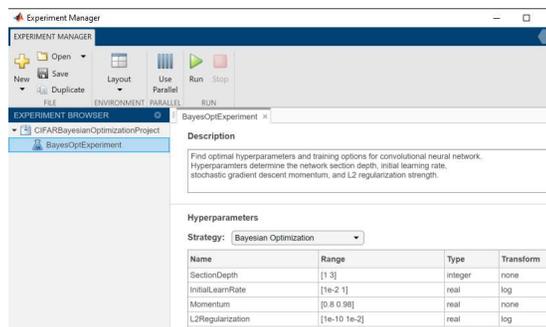
Example: [Understand Network Predictions using \(image\) LIME](#)



Example: [Grad-CAM and Occlusion Sensitivity](#)



Example: [Tuning Hyperparameters in Experiment Manager](#)



mathworks.com/solutions/deep-learning.html
mathworks.com/solutions/machine-learning.html