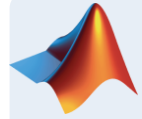


# Hands-On Virtual Lab: Machine Learning

**Reece Teramoto**  
**Application Engineer, MathWorks**

# Agenda



## Machine learning introduction

- Supervised machine learning models
  - Predicting fuel economy (Regression)
  - Human activity learning (Classification)
- Feature extraction and feature selection
- Unsupervised learning (optional)
- Working with big data (optional)
- Deploying Machine Learning Algorithms

# Machine Learning is Everywhere

Automobile	Industrial Automation	CES & Aero Defense	Energy & Finance
 <p data-bbox="300 711 486 746">Tire Wear</p> 	 <p data-bbox="728 711 1072 801"><u>Overlay metrology improvement</u></p> 	 <p data-bbox="1296 711 1640 801"><u>Telecom customer churn prediction</u></p> 	 <p data-bbox="1880 711 2142 801"><u>Forecasting &amp; Risk Analysis</u></p> 
 <p data-bbox="249 1243 435 1333"><u>Detect Oversteer</u></p> 	 <p data-bbox="728 1236 1034 1326"><u>Building energy use optimization</u></p> 	 <p data-bbox="1322 1243 1691 1333">Engine Health (Pred Maintenance)</p> 	 <p data-bbox="1905 1243 2091 1333"><u>Portfolio Allocation</u></p> 

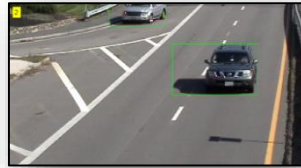
# What is Machine Learning?

*Ability to learn from data without being explicitly programmed*

Solution is too complex for hand written rules or equations



Speech Recognition



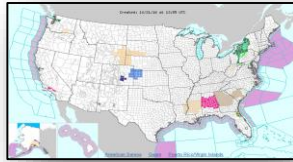
Object Recognition



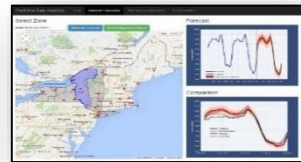
Engine Health Monitoring

*learn complex non-linear relationships*

Solution needs to adapt with changing data



Weather Forecasting



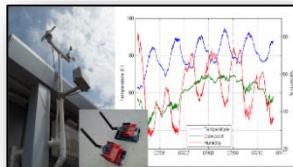
Energy Load Forecasting



Stock Market Prediction

*update as more data becomes available*

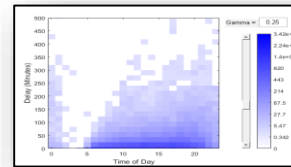
Solution needs to scale



IoT Analytics



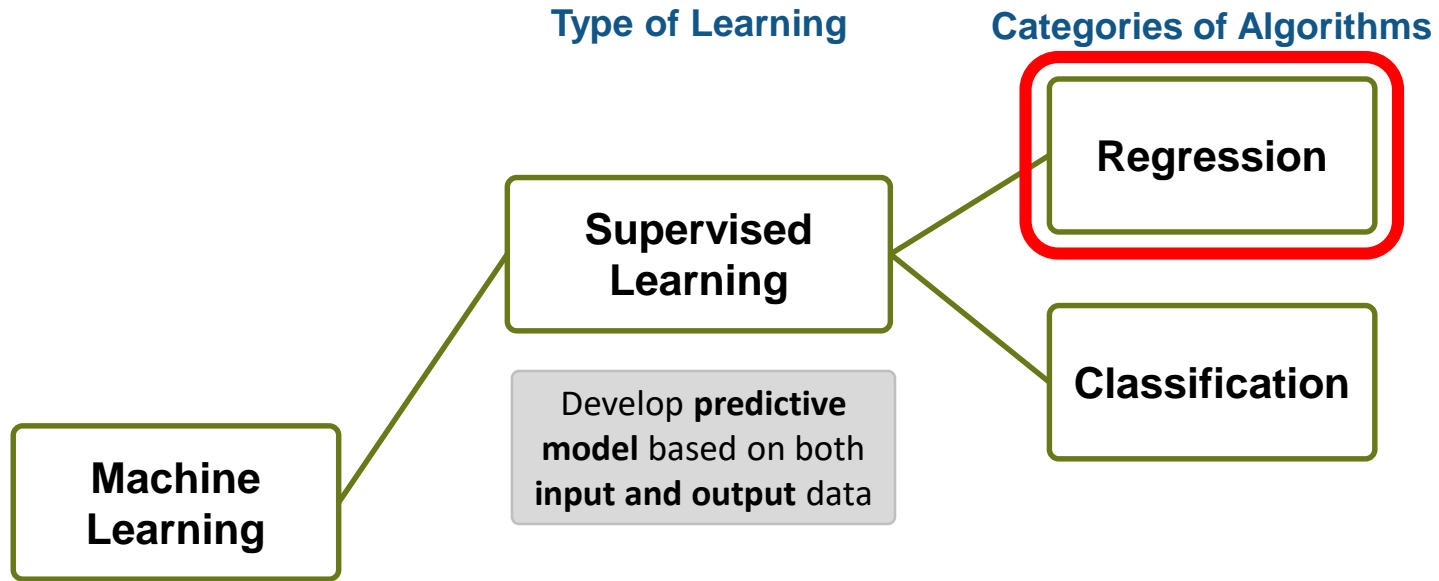
Taxi Availability



Airline Flight Delays

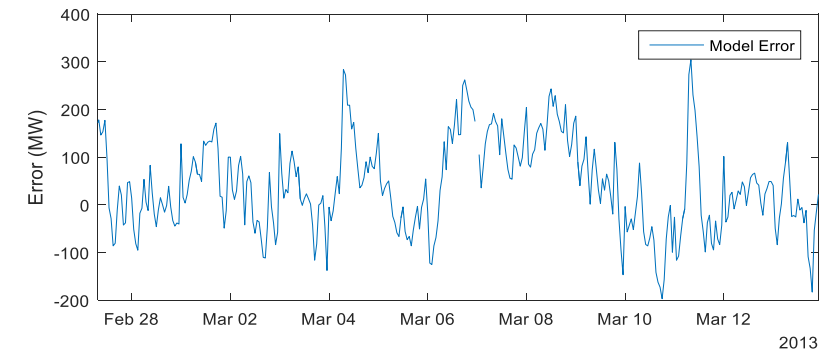
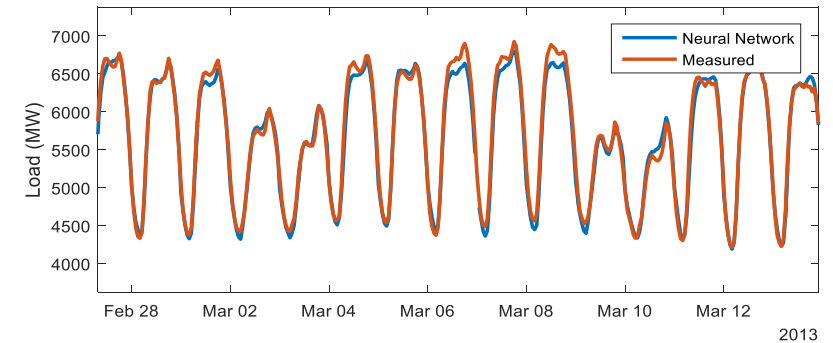
*learn efficiently from very large data sets*

# Types of Machine Learning

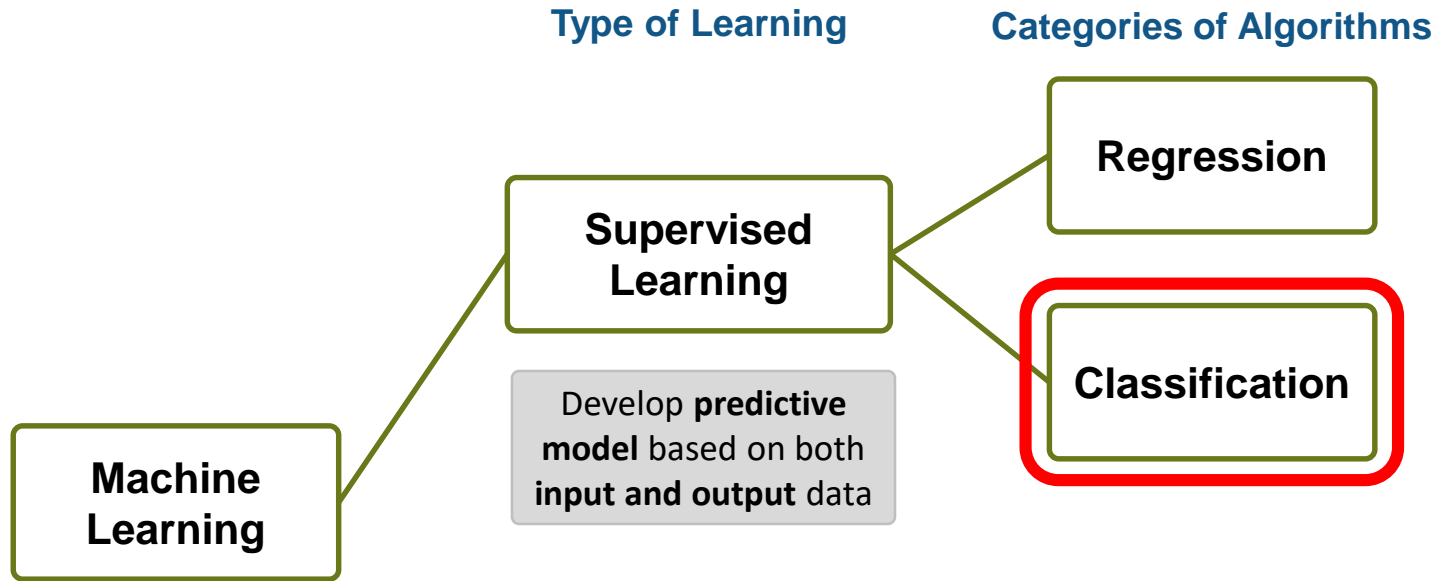


## Objective:

Easy and accurate computation of day-ahead system load forecast





# Types of Machine Learning



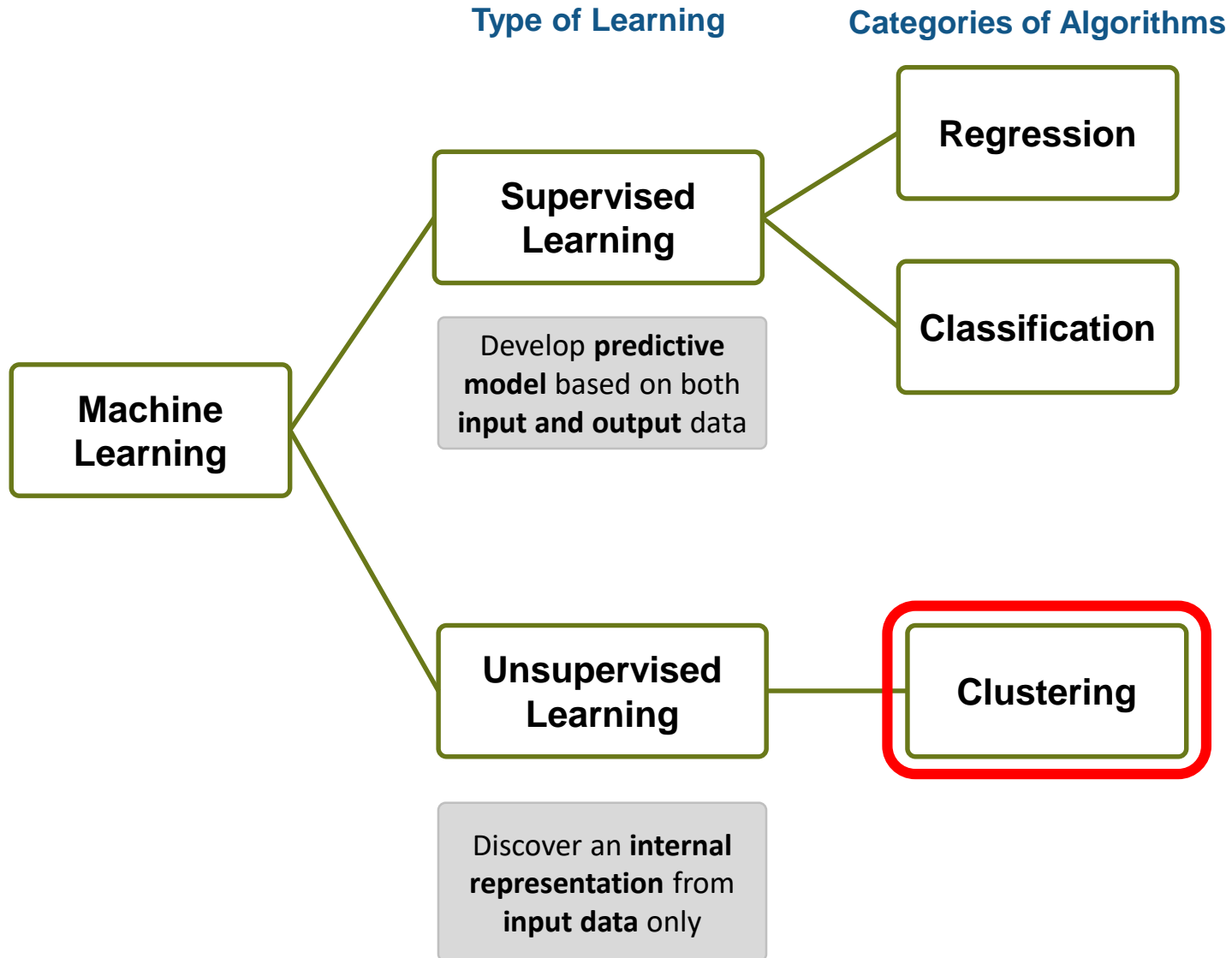
## Objective:

Train a classifier to classify human activity from sensor data

Data:

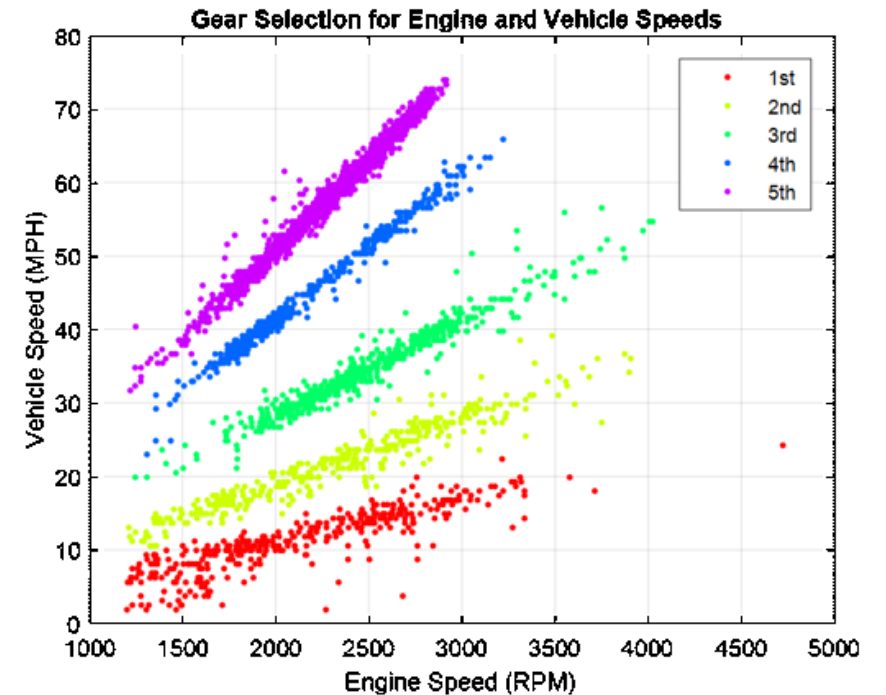
Inputs	3-axial Accelerometer 3-axial Gyroscope	
Outputs		

# Types of Machine Learning

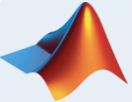


## Objective:

Given data for engine speed and vehicle speed, identify clusters



# Agenda

- Machine learning introduction
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# Exercise 1: Predicting Fuel Economy

## Regression

Goal: Study drivers of

- Build initial models
- Don't need to be a

Approach:

- Load data in MATLAB
- Use the Regression multiple regression
- Create a model which can predict mpg for a new car given characteristics like horsepower, weight, etc

**Let's try it out!**

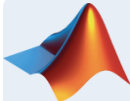
*Exercise: **Predicting Fuel Economy**  
in folder 01-RegressionModels*





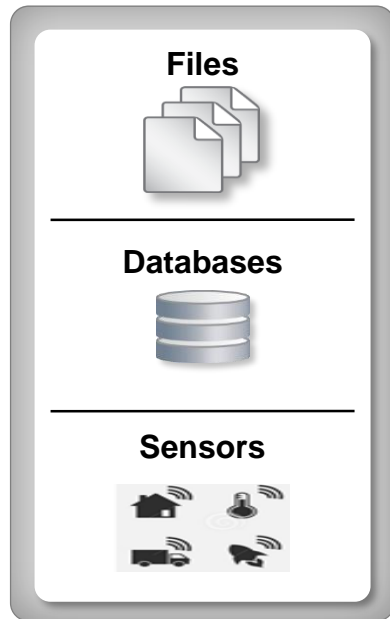
**“essentially, all models are wrong,  
but some are useful”  
– George Box**

# Agenda

- Machine learning introduction
- Supervised machine learning models
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# Machine Learning Workflow

Access and Explore Data



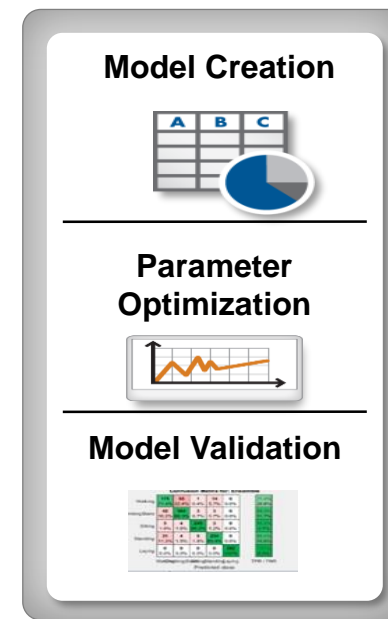
- Data Diversity
- Data clean up
- Working with big data

Preprocess Data



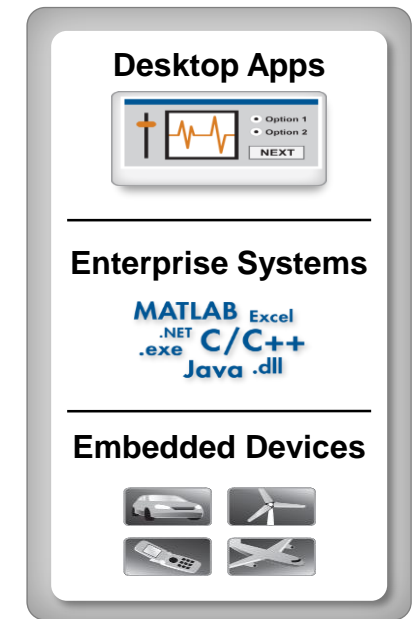
- Data specific processing
- Feature Extraction
- Feature Selection

Develop Predictive Models



- Many different models
- Model tuning
- Computationally intensive

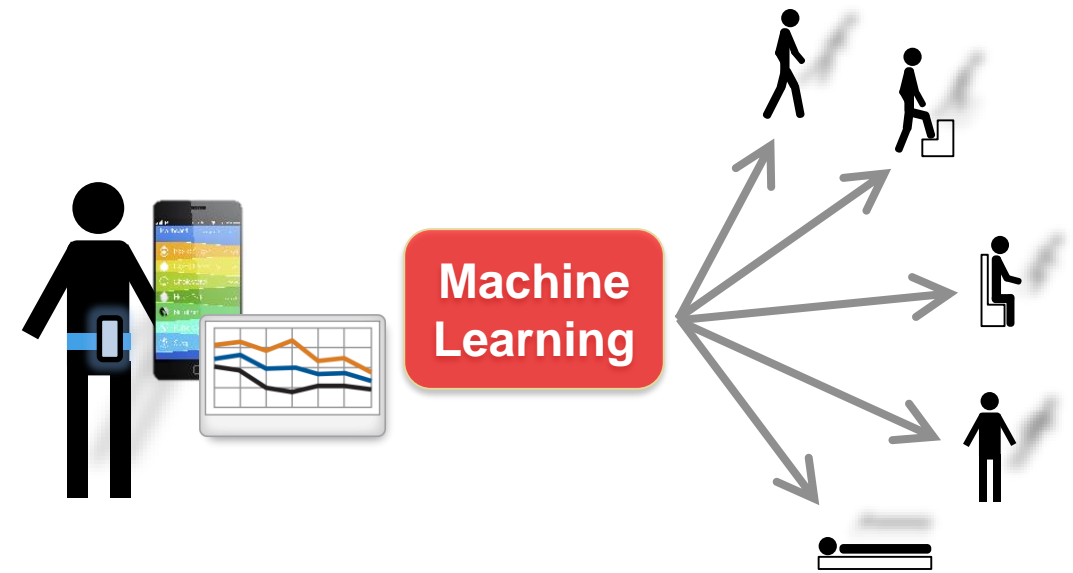
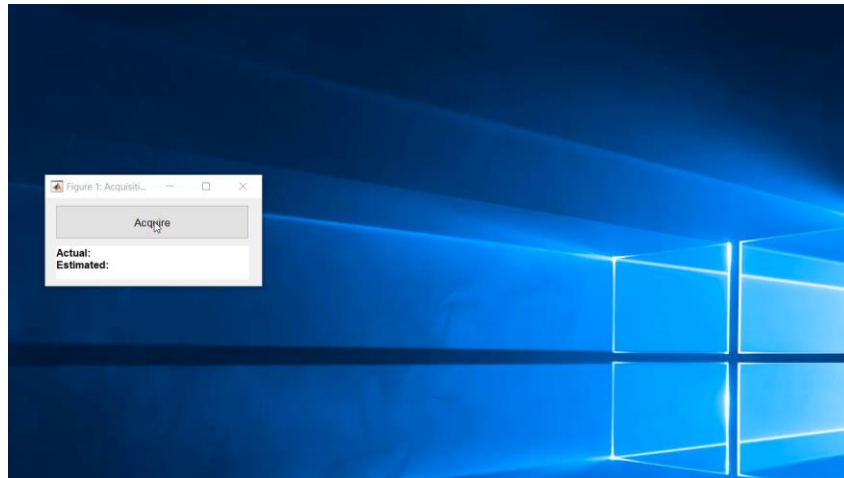
Integrate Analytics with Systems



- Different end users
- Different target platforms
- Different Interfaces

# Human Activity Learning using Smartphones

Example task: Create a model to classify human activity from sensor data



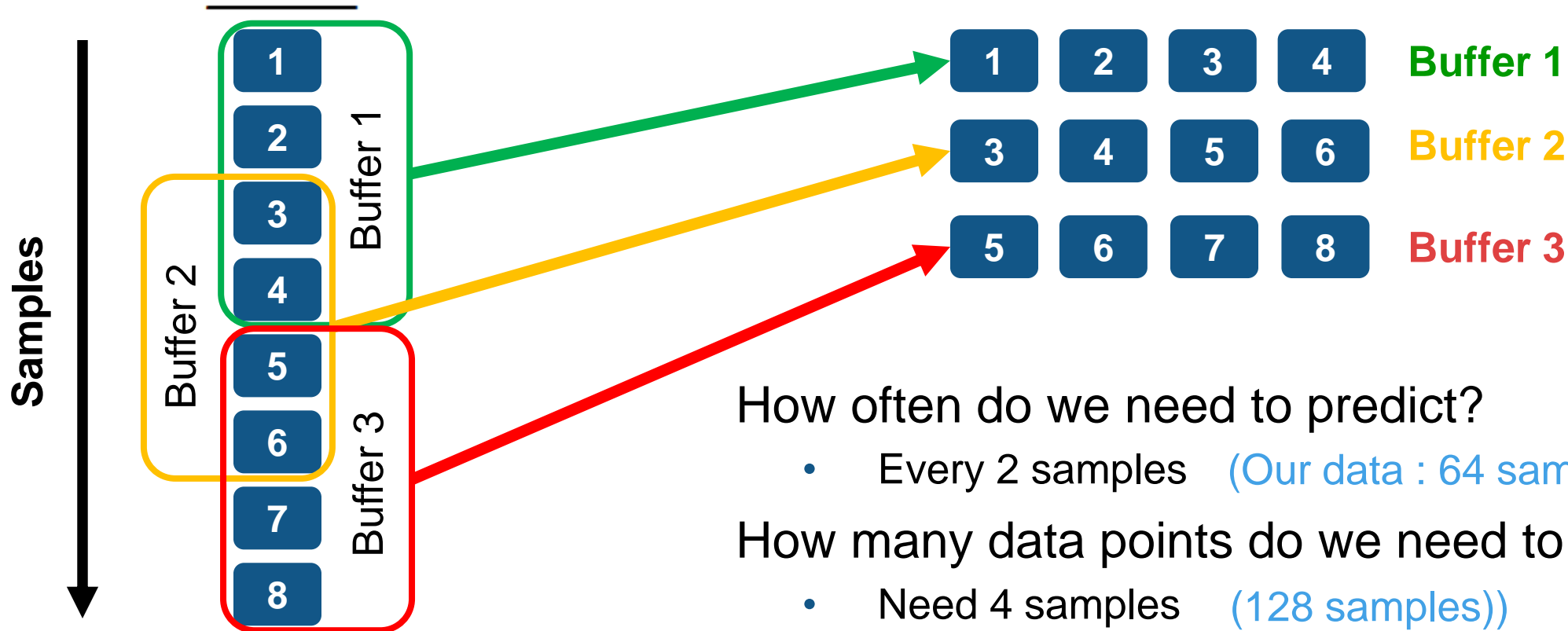
**Dataset courtesy of:**

Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. *Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machine*. International Workshop of Ambient Assisted Living (IWAAL 2012). Vitoria-Gasteiz, Spain. Dec 2012 <http://archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones>

# Signal Buffering

x

**Why?** – Calculate features on “chunks” during which signal doesn’t change (much), increase S/N (in feature)!



How often do we need to predict?

- Every 2 samples (Our data : 64 samples))

How many data points do we need to predict?

- Need 4 samples (128 samples))
- Create overlapping buffers of 4 points (64 samples))

Compute features (e.g. mean) on each buffer

## Exercise 2: Human Activity Learning using Smartphones

Goal: create initial model

- Buffering helps a lot
- Hyperparameter tuning

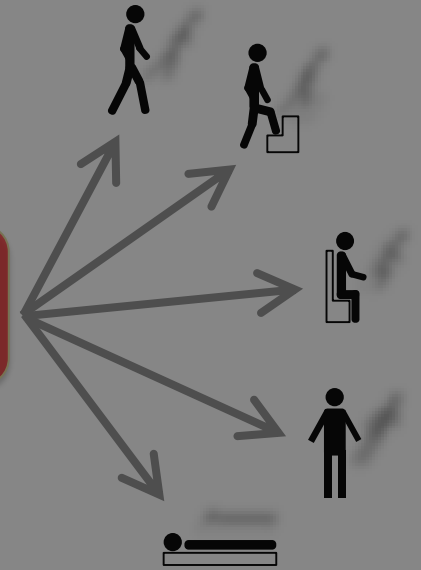
Approach:

- Load buffered data
- Extract statistical features
- Compare various models (interactively)
- Optimize model using hyperparameter tuning

**Let's try it out!**

*Exercise:*  
***humanActivityClassification.mlx***  
*in folder 02-ClassificationModels*

Machine Learning



	30
	25
validateData	3
testData	2

} Combined to held-out validation set

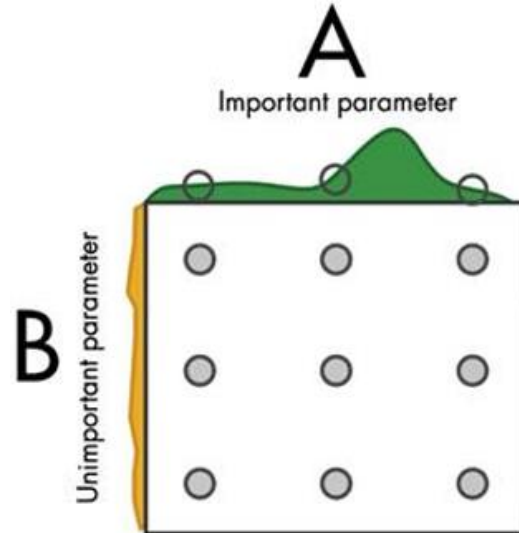
Dataset courtesy of:

Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. *Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machine*. International Workshop of Ambient Assisted Living (IWAAL 2012). Vitoria-Gasteiz, Spain. Dec 2012 <http://archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones>

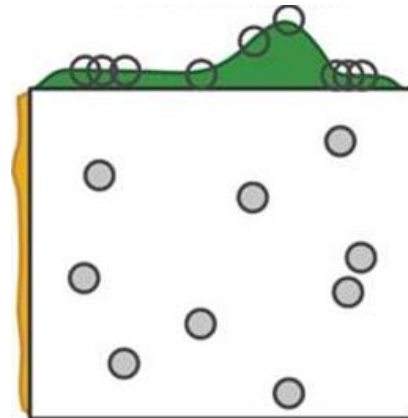
# Hyperparameter Tuning

**Why?** – Model “knobs” (hyperparameters) need to be set properly for optimal performance

Standard:  
Grid Search



Better:  
Random Search



## Best: Bayesian Optimization

- Bayesian model indicates impact of change
- Model picks “good” point to try next
- Much more efficient!
- Scale to multi-cores (using PCT) for larger datasets

Now available inside the (Classification/Regression) Learner app as “Optimizable” model



# Hyperparameter Tuning Workflow inside Learner Apps

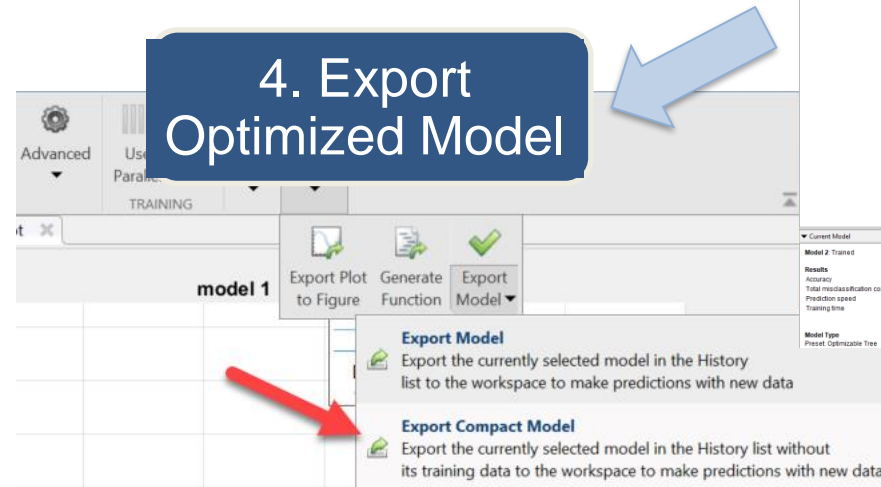
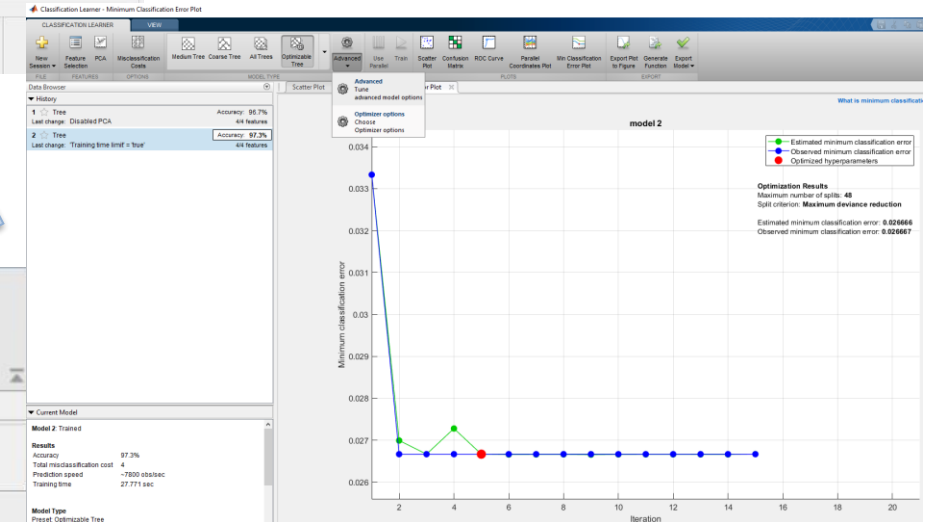
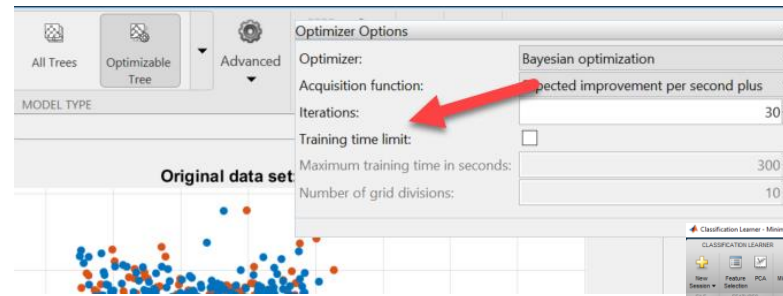
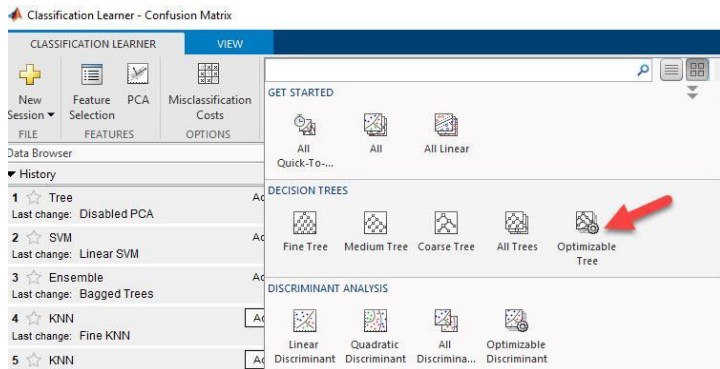
1. Choose "Optimizable" model from gallery

2. Adjust Optimizer Options (control runtime!)

3. "Train": Bayesian Optimization iterates

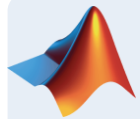
4. Export Optimized Model

5. Iterate OR Prepare for Integration



# Agenda

- Machine learning introduction
- Supervised machine learning models
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  - Human activity learning (Classification)



## Feature extraction and feature selection

- Unsupervised learning (optional)
- Working with big data (optional)
- Deploying Machine Learning Algorithms

# Feature Engineering

*Using domain knowledge to create features for machine learning algorithms*

“... is the art part of data science”

Sergey Yurgenson  
(Kaggle Master)

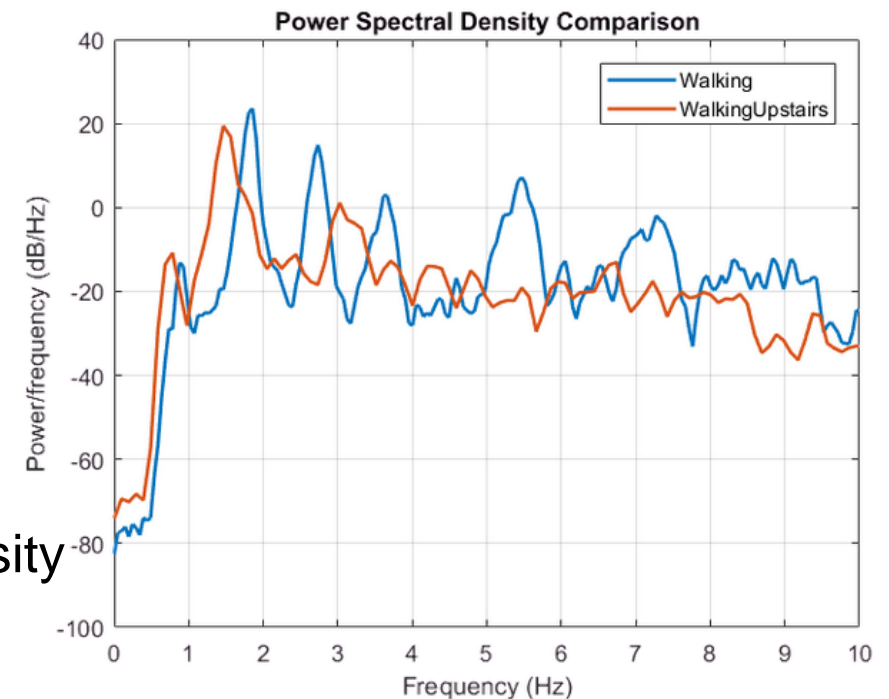


Feature transformation: high dimensionality

Feature selection: subset of relevant features

Possible feature engineering ideas:

- Additional statistics – PCA, NCA etc.
- Signal Processing Techniques – power spectral density, wavelets etc.
- Image Processing Techniques – bag of words, pixel intensity etc.
- Get creative!



[How to use Diagnostic Feature Designer](#) [12 min video]

## Exercise 3 – Feature Engineering for human activity

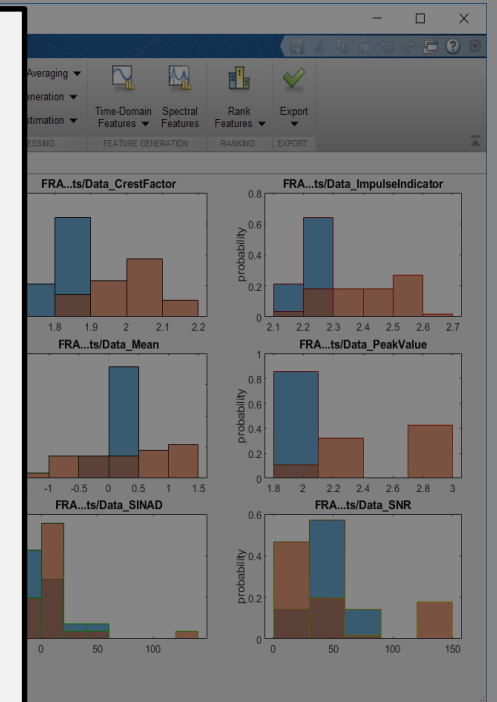
Goal: Explore different techniques for feature engineering

Approach:

- Use signal processing to extract time domain features
- Use feature selection to reduce the set of features to those most relevant
- Browse examples in the documentation for different applications

**Let's try it out!**

*Exercise: **featureEngineering.mlx**  
in folder 03-FeatureEngineering*



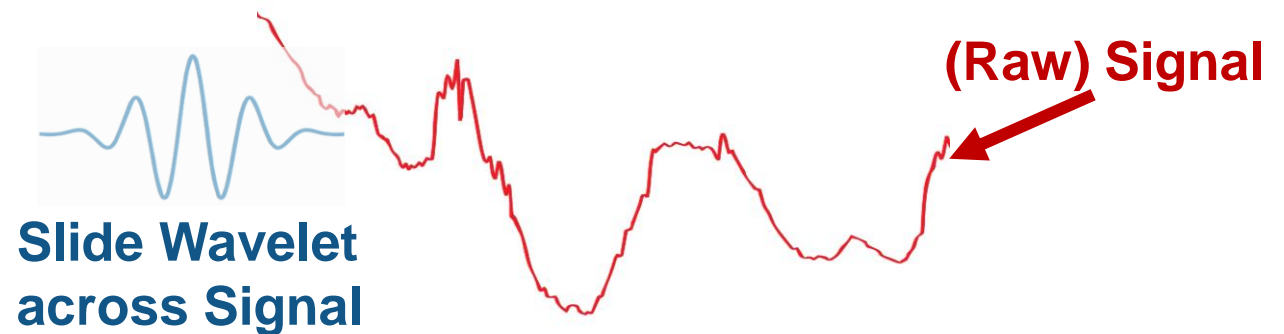
# Feature Generation with Wavelet Scattering

**Why?** – Obtain good features “automagically”, without domain knowledge

## What are Wavelets?

- Instead of decomposing signal into complete sinus waves, decompose into “wavelets”
- [Tech Talks explaining Wavelets](#) [4 videos]
- This conceptually looks like this:

Better than Spectrograms  
because can vary in scale!



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

- Automatic Feature Extraction
- Reduces data dimensionality and provides compact features
- Works with both Signal and Image data [\[Texture example, Digit Classification\]](#)

# Wavelet Scattering Nuts and Bolts



Pseudo-Code:

```
sf = waveletScattering(SignalLength) ;  
Loop over signal  
    waveletFeature = featureMatrix(sf,signal)  
    Append waveletFeature to feature table  
    Add labels  
end
```

Additional Resources:

[Wavelet scattering Tech talk](#) [4 min video]

[Wavelet scattering for ECG](#) [doc example]

[Blog about Wavelet scattering](#) on [towardsdatascience.com](https://towardsdatascience.com)

# Diagnostic Feature Designer App

Predictive Maintenance Toolbox **R2018b** and **R2019a**

**Why? – Empower signal domain expert to try all his favorite features.**

Extract, visualize, and rank features from sensor data

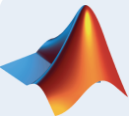
Use both statistical and dynamic modeling methods

Work with out-of-memory data

Explore and discover techniques without writing MATLAB code



# Agenda

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# Big Data in MATLAB: Tall Arrays

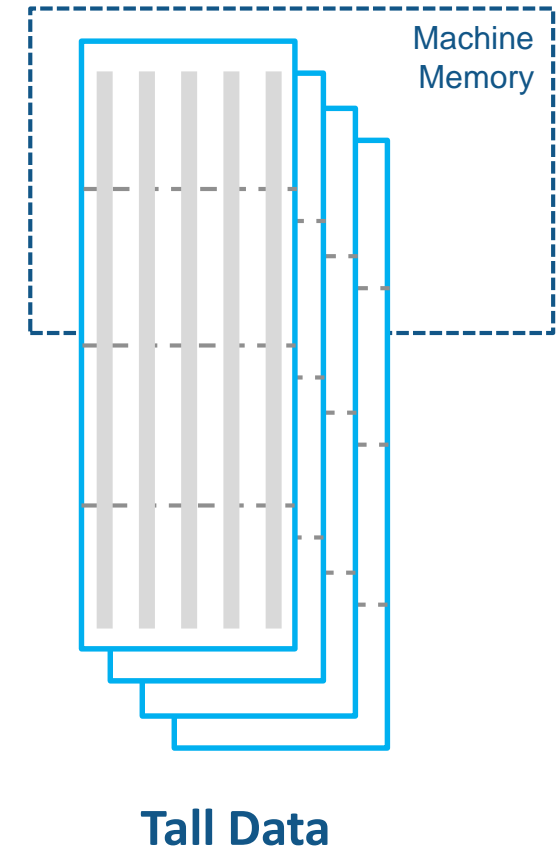
Extends the “array” data type to out-of-memory

- Use like a regular (in-memory) array in supported functions
- (With some setup) Scales processing to clusters with Spark

Applicable when:

- Data is **columnar** – with **many** rows
- Overall data size is **too big to fit into memory**
- Operations are mathematical/statistical in nature

Hundreds of functions supported in MATLAB and Statistics and Machine Learning Toolbox



# Big Data Without Big Changes

## One file

### Access Data

```
measured = readtable('PumpData.csv');
measured = table2timetable(measured);
```

### Preprocess Data

#### Select data of interest

```
measured = measured(timerange(seconds(1),seconds(2)),:)
```

#### Work with missing data

```
measured = fillmissing(measured,'linear');
```

#### Calculate statistics

```
m = mean(measured.Speed);
s = std(measured.Speed);
```

## One hundred files

### Access Data

```
measured = datastore('PumpData*.csv');
measured = tall(measured);
measured = table2timetable(measured);
```

### Preprocess Data

#### Select data of interest

```
measured = measured(timerange(seconds(1),seconds(2)),:)
```

#### Work with missing data

```
measured = fillmissing(measured,'linear');
```

#### Calculate statistics

```
m = mean(measured.Speed);
s = std(measured.Speed);
```

```
[m,s] = gather(m,s);
```

## Exercise 5: Predicting Tips for Cab Drivers

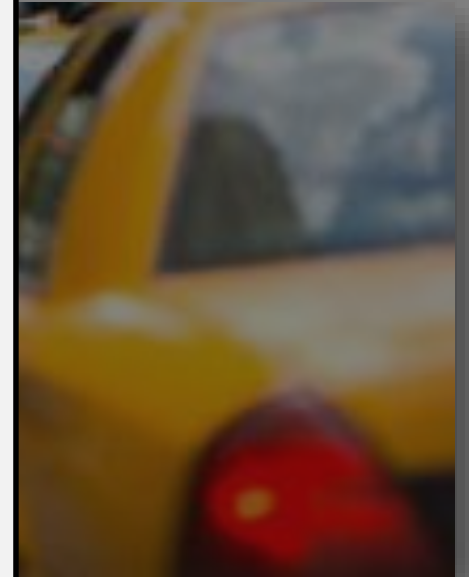
Goal: Create a model on a (simulated)  
large dataset

Approach:

- Access data spread
- Preprocess and Exp
- Train and validate a model

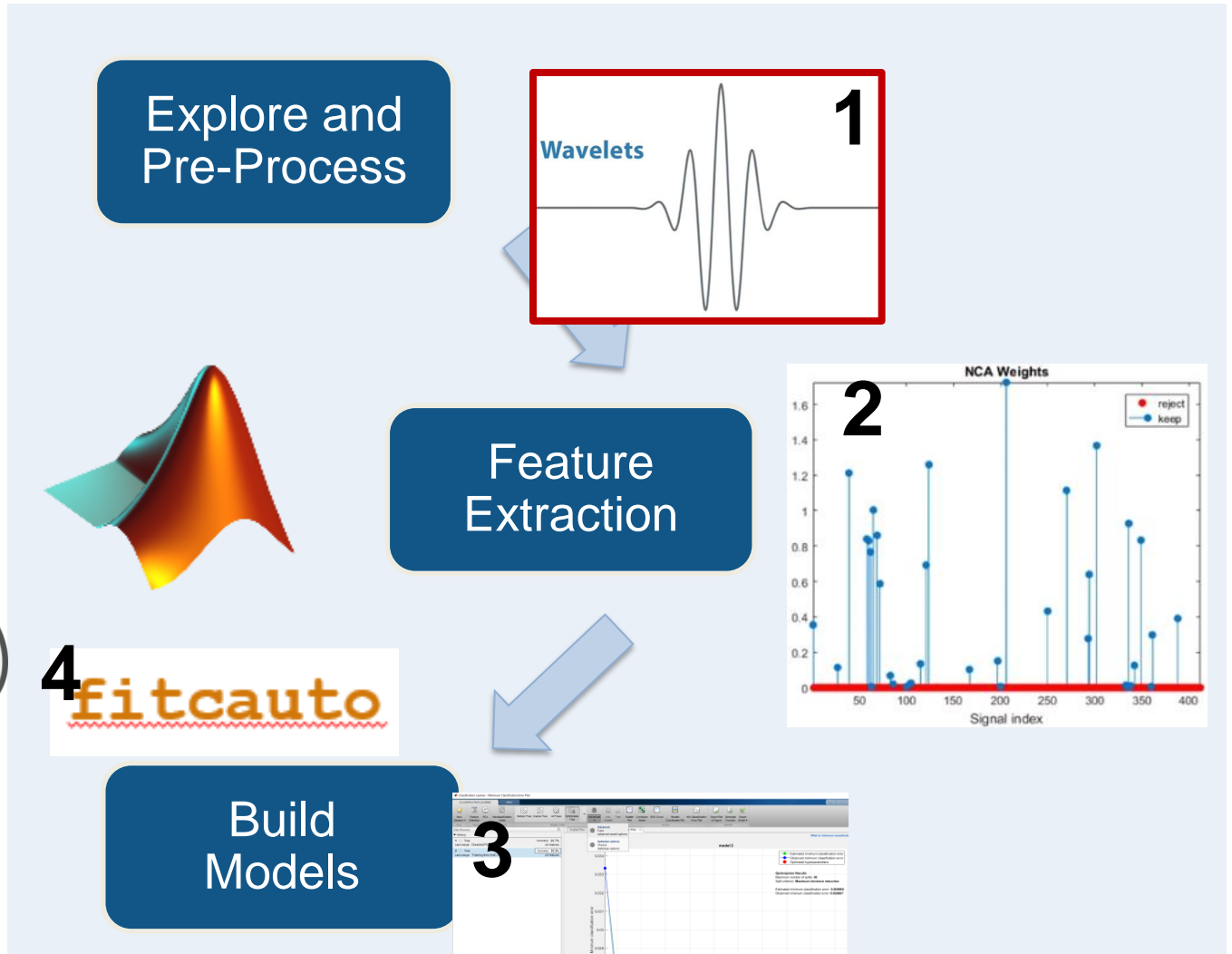
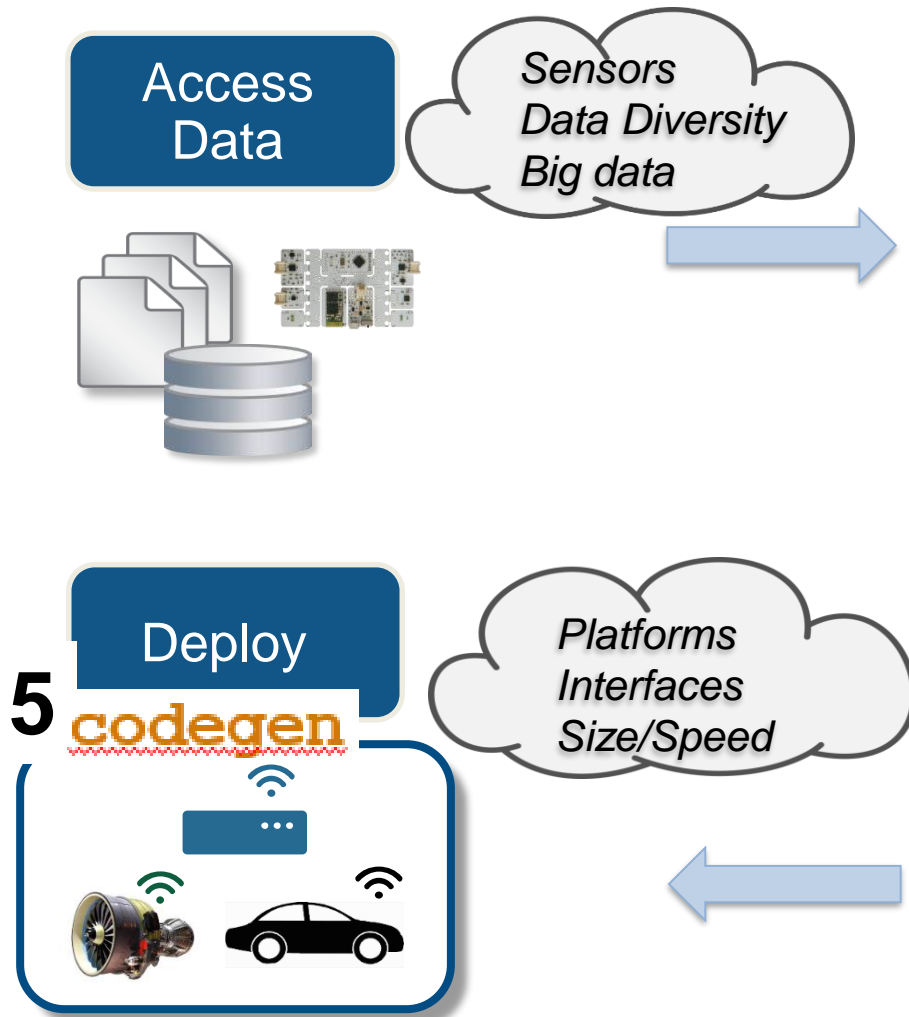
**Let's try it out!**

*Exercise: **predictDriverTip.mlx**  
in folder 05-BigData*

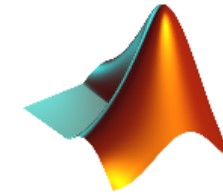


# What's our AutoML?

Automate main steps to minimize expertise needed and increase productivity



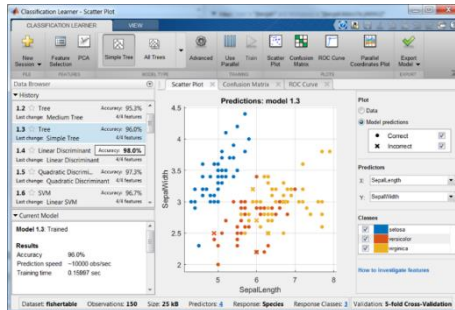
# Summary: Complete Machine Learning Workflow



1. Easy to Learn and Use
2. Engineer Features & Optimize Model
3. Deploy Anywhere: Embedded Device and Enterprise IT/OT

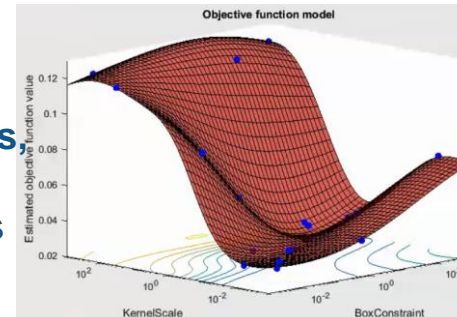
## Learner Apps

Train Classification & Regression models without coding



## Automation

Optimize hyperparameters, Generate and Select features



## C Code Generation

Deploy not just prediction, but also preprocessing

```

MATLAB code
function label = classifyIonosphere(X) %codegen
%classifyIonosphere Classify ionosphere based on pre-trained SVM model
mdl = loadCompactModel('SVMIonosphere');
label = predict(mdl, X);
end

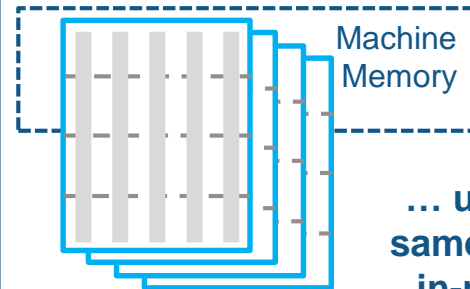
saveCompactModel loadCompactModel

C code
/* #define NUM_FEATURES */
static emlrtSSInfo emlrtSSI = { 4, /* lineNo */
    "classifyIonosphere", /* fileName */
    "C:\\Users\\jcoherrie\\sandbox\\temp\\feature"
};

/* Function Definitions */
void classifyIonosphere(classifyIonosphereStack
const real_T X[[11934], cell_wrap_0_label[351]
{
    real_T t_Alpha[90];
    real_T exp_temp[34];
    }
    
```



## Scale to Big Data

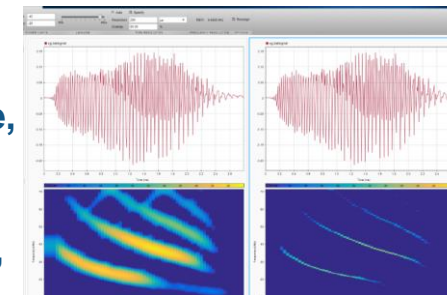


... using the same code as in-memory

Tall Data

## Domain Support

Predictive Maintenance, Text, Signal and Image Processing,



## Where to go from here?

- Finish what you didn't get to - Continue exploring:
  - Keep using **MATLAB Online**: <https://matlab.mathworks.com> (but no GPU!)
  - Your existing desktop MATLAB license (but need to copy content)
- Where to find content? **MATLAB Drive** drive.matlab.com (250MB)
- Apply this to YOUR work
- Take a paid training on Machine Learning or Big Data

# Resources

[Machine Learning Onramp](#) (2 hr online introduction)

## Machine Learning with MATLAB:

- [Overview](#), [Cheat sheet](#)
- [Machine Learning Intro](#) (Tech talk videos)
- [Machine Learning with MATLAB Introduction](#) (eBook)
- [Mastering Machine Learning](#) (eBook)
- [Applied Machine Learning](#) (Tech Talk videos)
- [Practical Data Science with MATLAB](#) (Coursera Specialization)

## Machine and Deep Learning

- [Deep vs. Machine Learning: Choosing the Best Approach](#) (eBook)
- [Deep learning Onramp](#) (2hr online introduction)



# MathWorks® can help you do Machine Learning

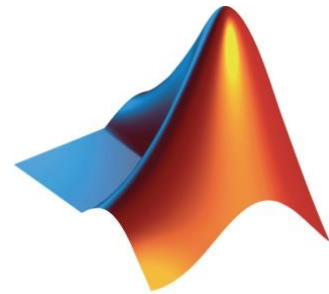
## Free resources:

- Guided evaluations
- Proof-of-concept projects
- Seminars
- Other Hands-on workshops

## More options:

- Paid Training (2-day Machine Learning, 1-day Big Data, see Appendix)
- Advanced customer support
- Enterprise and cloud deployment
- Consulting services





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