

Machine Learning with MATLAB on SNIC

A hands-on MATLAB workshop

Antti Löytynoja, *Senior Application Engineer, MathWorks*
Emelie Andersson, *Application Engineer, MathWorks*
Sagar Zade, *Customer Success Engineer, MathWorks*
Anders Sjöström, *System Administrator, Lund University*

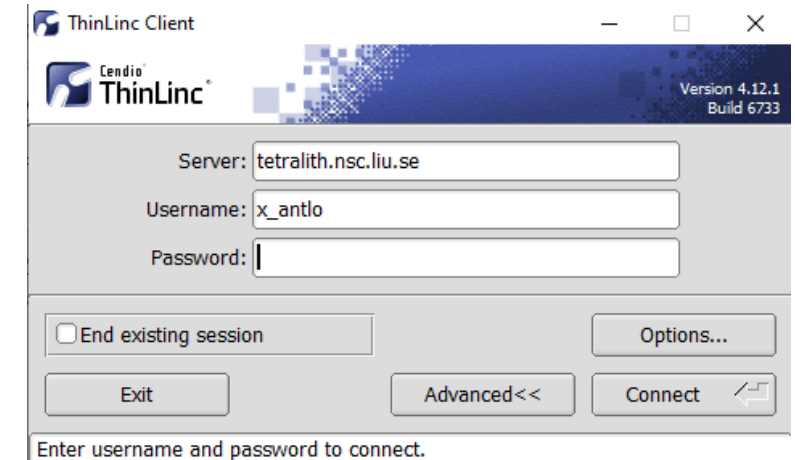
How can you participate?

You have three options:

1. Run exercises yourself on Tetralith (you need to have SNIC and Tetralith credentials)
 1. Bonus: you have access to at least 8 cores (and even more outside the workshop)
2. Run exercises on your own computer (if you don't have access to Tetralith)
 1. Download exercise material: tinyurl.com/rebrxfz
3. Get your popcorn and just follow along

In case you want to run on Tetralith

- Login to Tetralith using Thinlinc
- Open terminal window
 - Copy workshop material:
 - `cp -r /home/x_antlo/Public/ExerciseFiles .`
 - Get on a compute node:
 - `interactive --reservation=matlab-monday -n8 -t 03:00:00`
 - This gives you 8 cores for three hours on a node that has been reserved for us
- Start MATLAB (from terminal)
 - `module load MATLAB/R2021a-nsc1`
 - `matlab -softwareopengl`



What's Machine Learning About?



Source: <https://xkcd.com/1838/>

↻ Internet of Shit Retweeted



Computer Facts
@computerfact

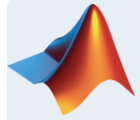


concerned parent: if all your friends jumped off a bridge would you follow them?

machine learning algorithm: yes.

2:20 PM · Mar 15, 2018

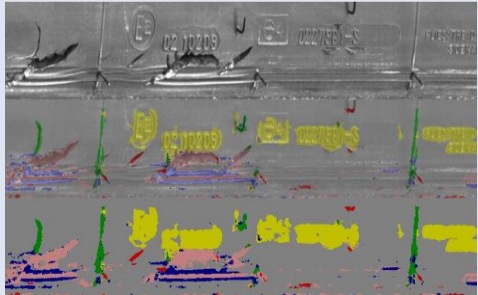

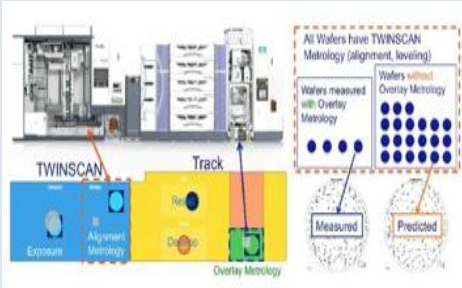






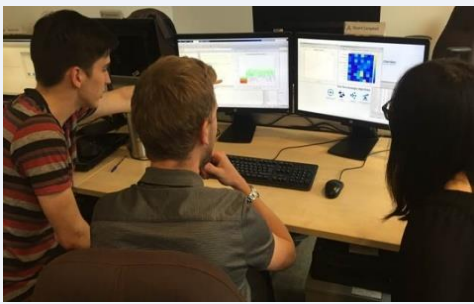

Agenda



Machine learning introduction

- Supervised machine learning models
 - Predicting fuel economy (Regression)
 - Human activity learning (Classification)
 - Feature engineering
 - AutoML
 - Interpretability
- Unsupervised learning (optional)
- Working with big data (optional)
- Text Analytics (demo)

Machine Learning is Everywhere

| Automobile | Manufacturing | Comms & Operations | Energy & Finance |
|---|--|---|---|
|  <p data-bbox="300 668 489 706">Tire Wear</p>  |  <p data-bbox="726 668 1075 763"><u>Overlay metrology improvement</u></p>  |  <p data-bbox="1294 668 1643 763"><u>Telecom customer churn prediction</u></p>  |  <p data-bbox="1872 668 2140 763"><u>Forecasting & Risk Analysis</u></p>  |
|  <p data-bbox="249 1199 438 1292"><u>Detect Oversteer</u></p>  |  <p data-bbox="733 1192 1070 1335"><u>Monitor Deployed Compressors using Digital Twin</u></p>  |  <p data-bbox="1312 1199 1617 1292"><u>Building energy use optimization</u></p>  |  <p data-bbox="1905 1192 2102 1292"><u>Portfolio Allocation</u></p>  |

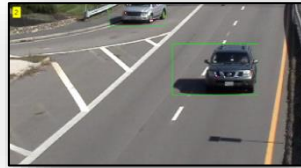
What is Machine Learning?

Ability to learn from data without being explicitly programmed

Solution is too complex for hand written rules or equations



Speech Recognition



Object Recognition



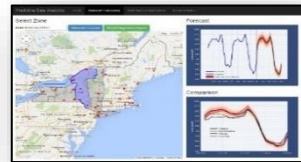
Engine Health Monitoring

learn complex non-linear relationships

Solution needs to adapt with changing data



Weather Forecasting



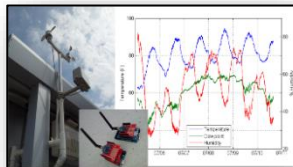
Energy Load Forecasting



Stock Market Prediction

update as more data becomes available

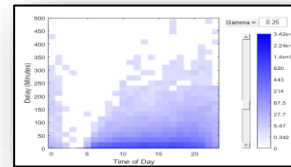
Solution needs to scale



IoT Analytics



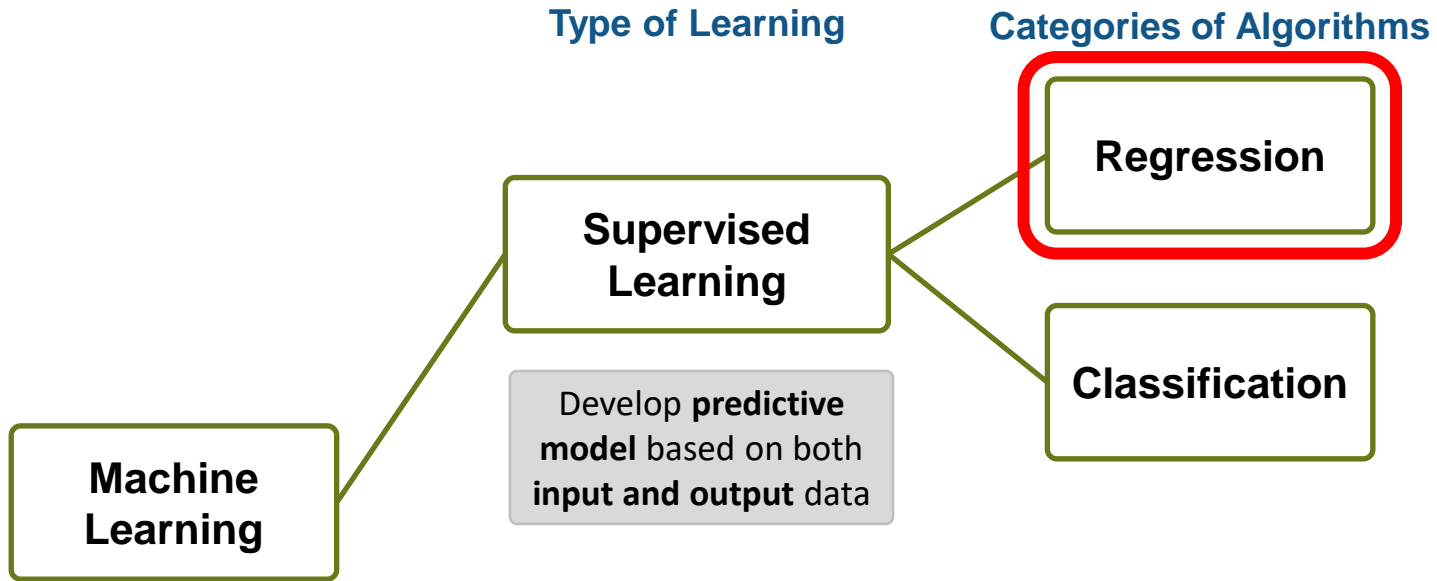
Taxi Availability



Airline Flight Delays

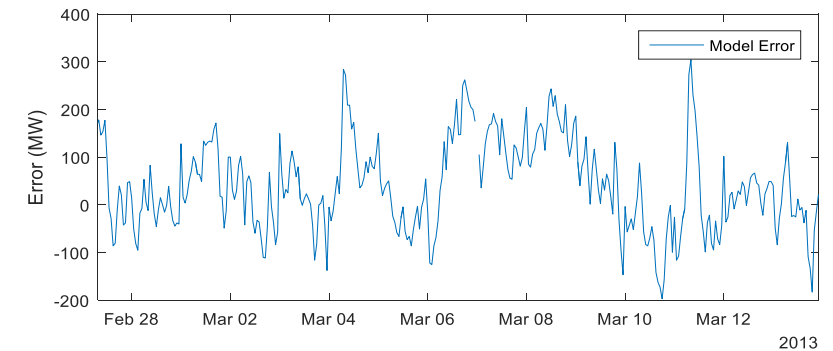
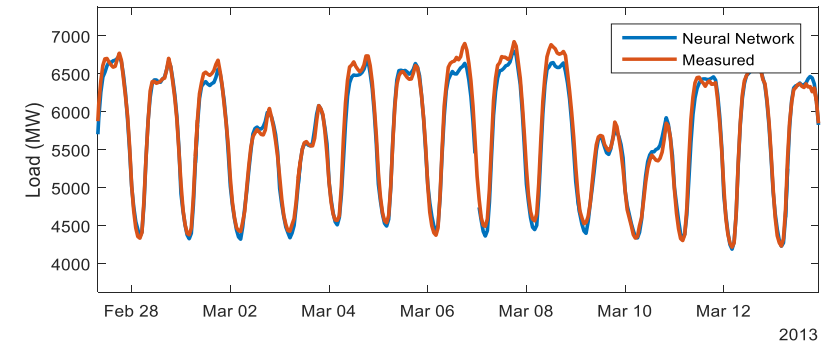
learn efficiently from very large data sets

Types of Machine Learning

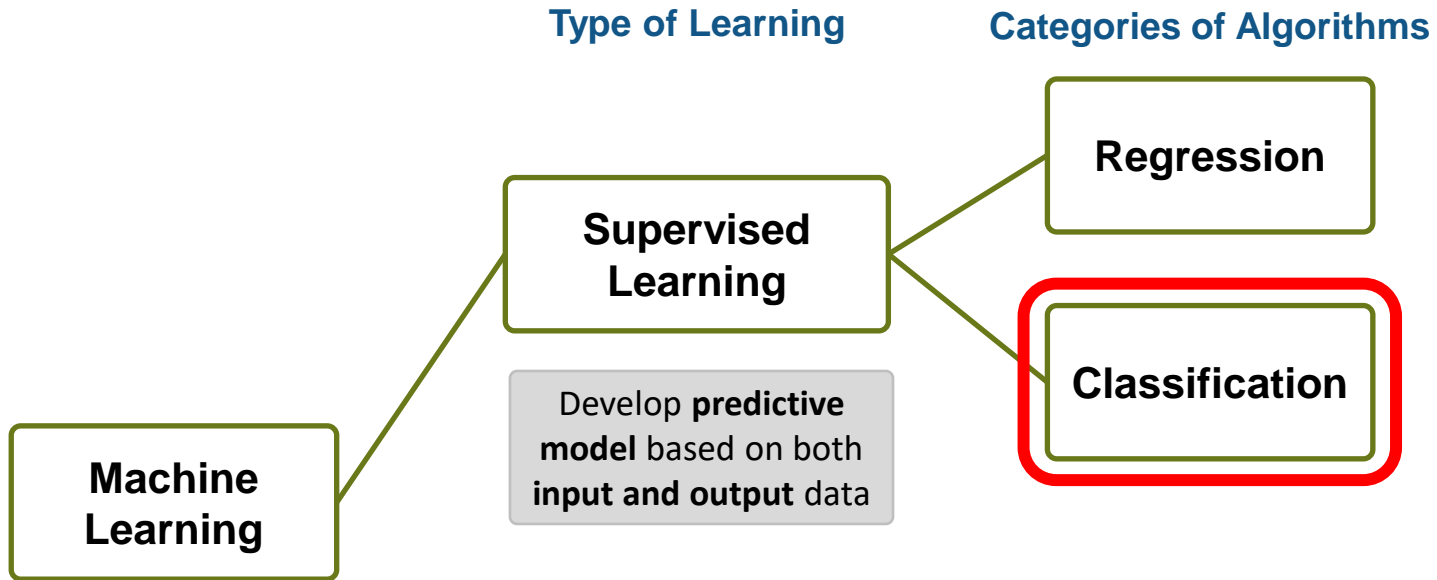


Objective:

Easy and accurate computation of day-ahead system load forecast





Types of Machine Learning



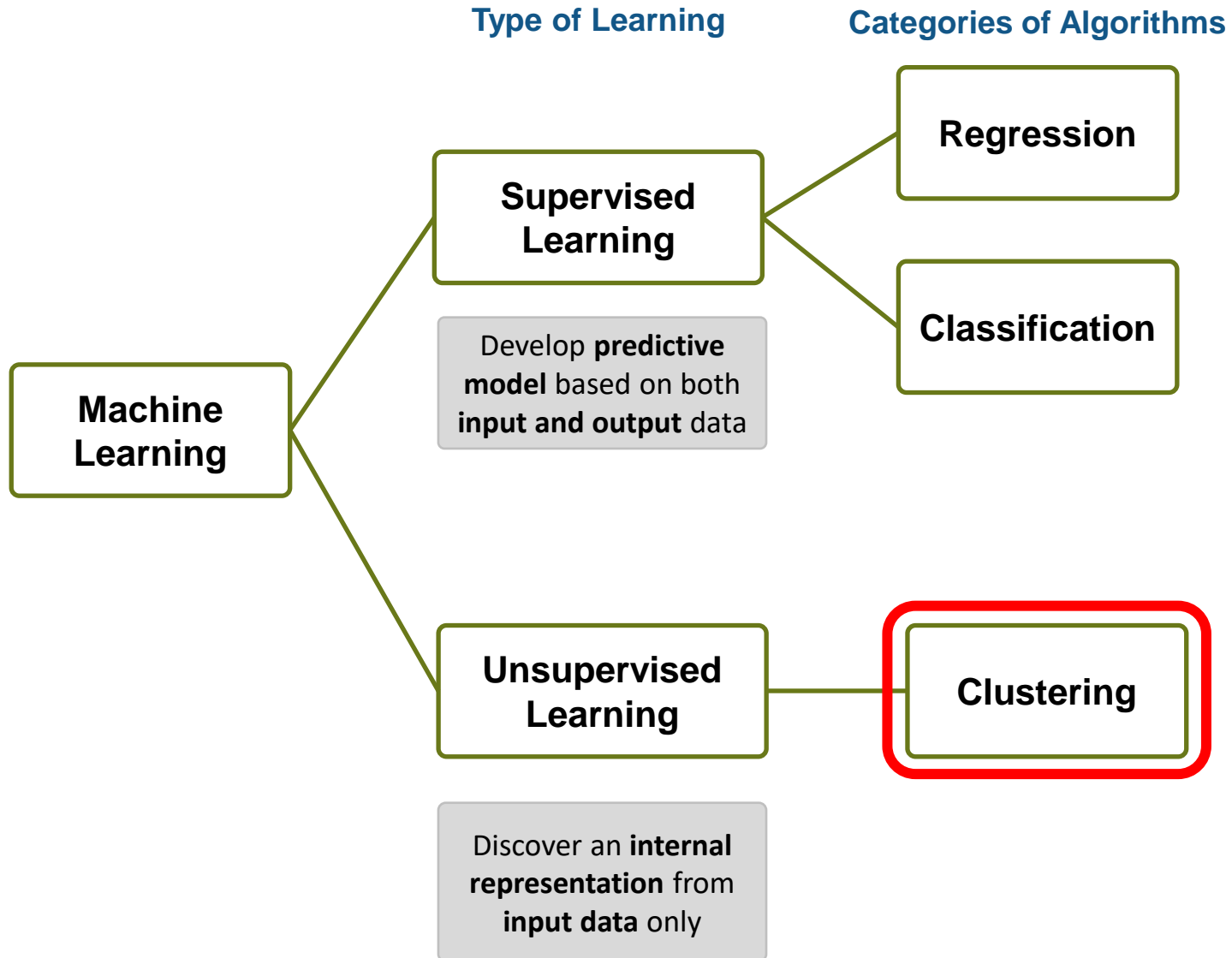
Objective:

Train a classifier to classify human activity from sensor data

Data:

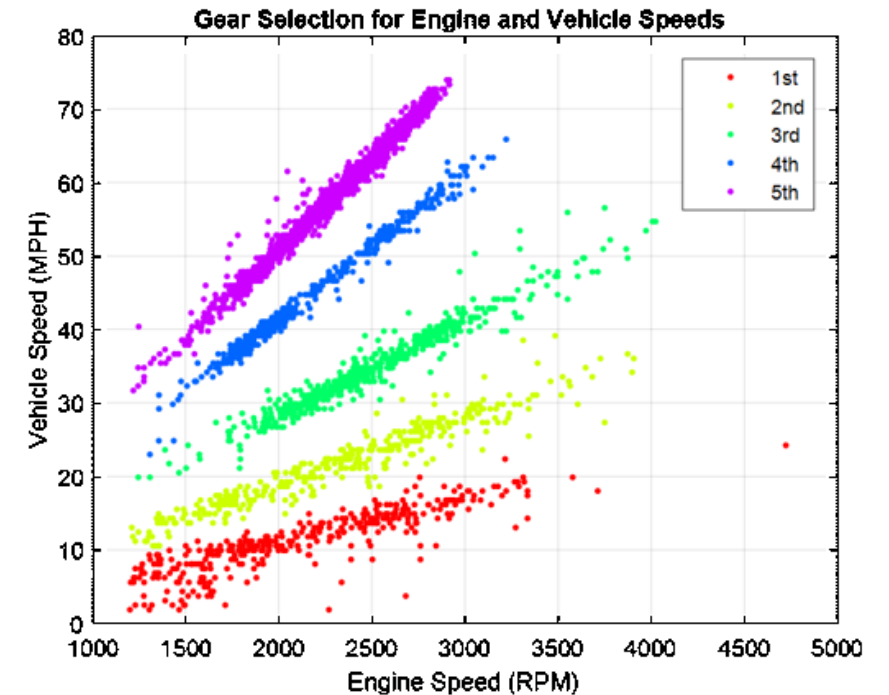
| | | |
|---------|---|---|
| Inputs | 3-axial Accelerometer 3-axial Gyroscope |  |
| Outputs |  | |

Types of Machine Learning

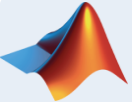


Objective:

Given data for engine speed and vehicle speed, identify clusters



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

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!

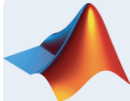
*Exercise: **Predicting Fuel Economy**
in folder 01-RegressionModels*





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

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Machine Learning Workflow

Access and Explore Data

Files

Databases

Sensors

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

Preprocess Data

Noisy Data

Data Transformation

Feature Extraction

- Data specific processing
- Feature Extraction
- Feature Selection

Develop Predictive Models

Model Creation

Parameter Optimization

Model Validation

- Many different models
- Model tuning
- Computationally intensive

Integrate Analytics with Systems

Desktop Apps

Enterprise Systems

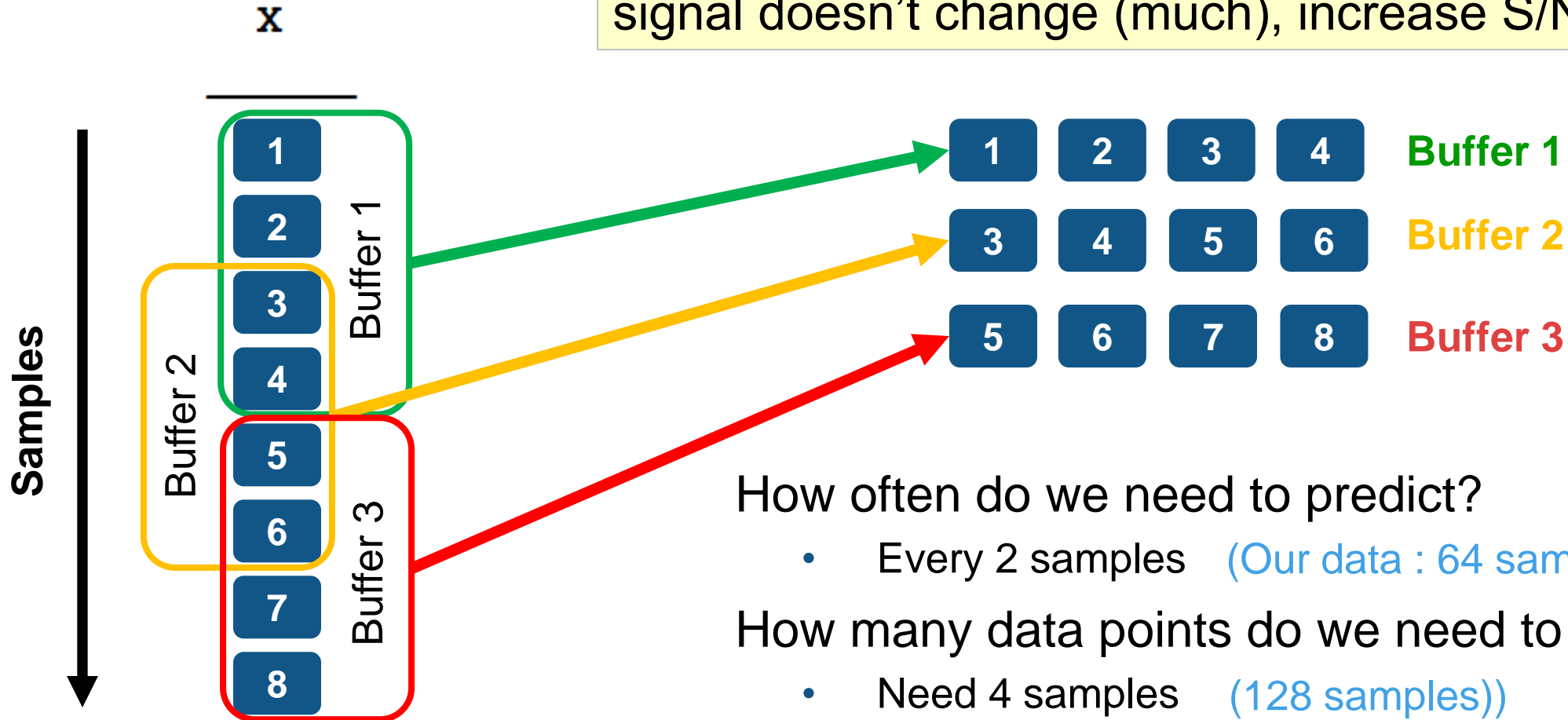
MATLAB Excel
.NET C/C++
.exe Java .dll

Embedded Devices

- Different end users
- Different target platforms
- Different Interfaces

Signal Buffering

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

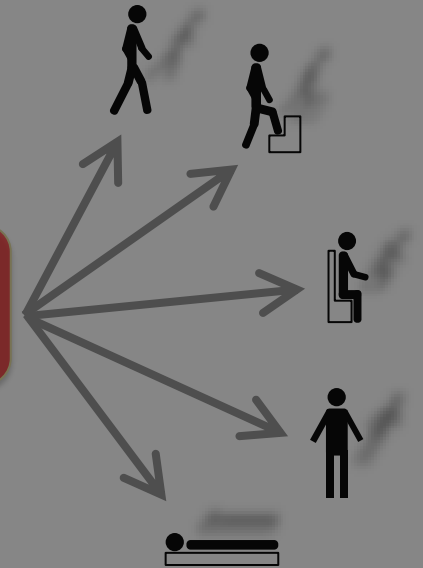
Approach:

- Load buffered data
- Extract statistical features
- Compare various machine learning 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

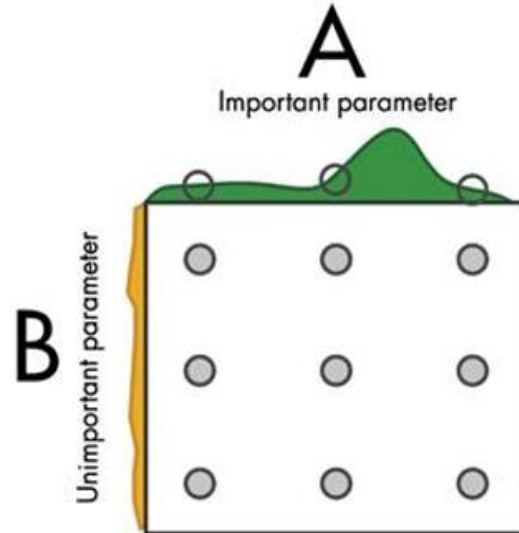
Dataset courtesy of:

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>

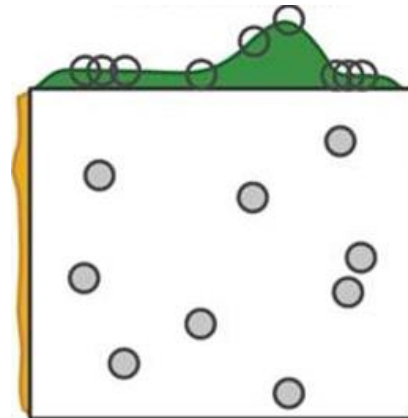
Hyperparameter Tuning

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

Classification Learner - Confusion Matrix

CLASSIFICATION LEARNER VIEW

GET STARTED

DECISION TREES

DISCRIMINANT ANALYSIS

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

Hyperparameter Tuning Workflow inside Learner Apps

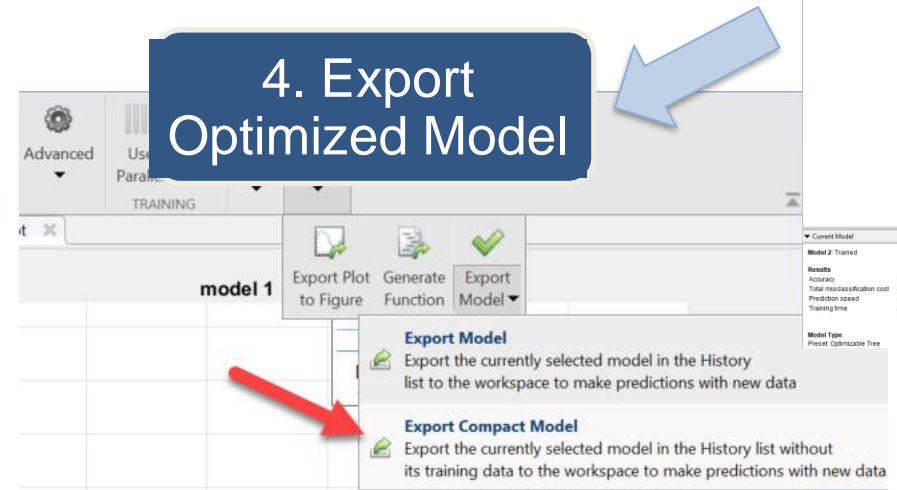
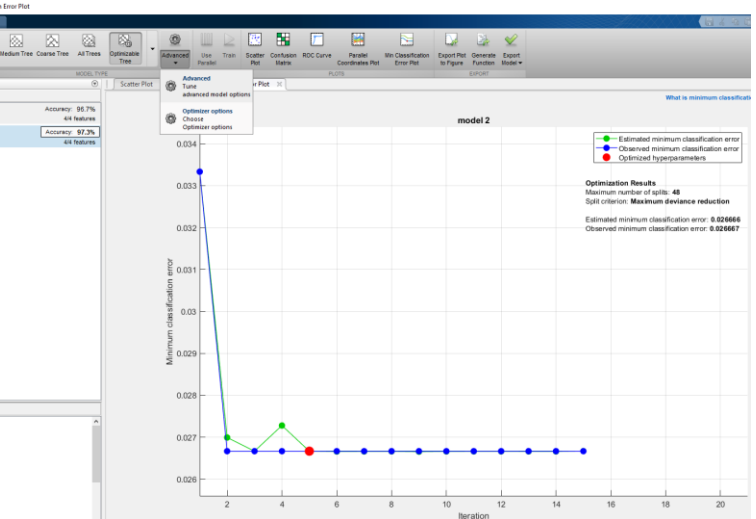
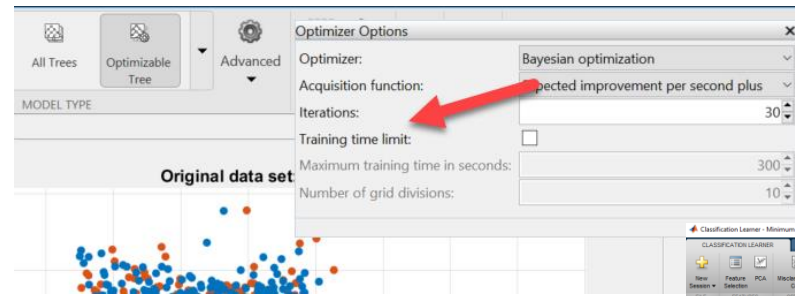
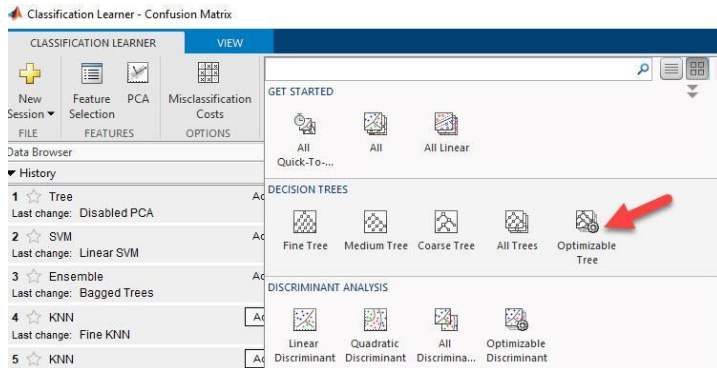
1. Choose "Optimizable" model from gallery

2. Adjust Optimizer Options (control runtime!)

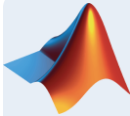
3. "Train": Bayesian Optimization iterates

4. Export Optimized Model

5. Iterate OR Prepare for Integration



Agenda

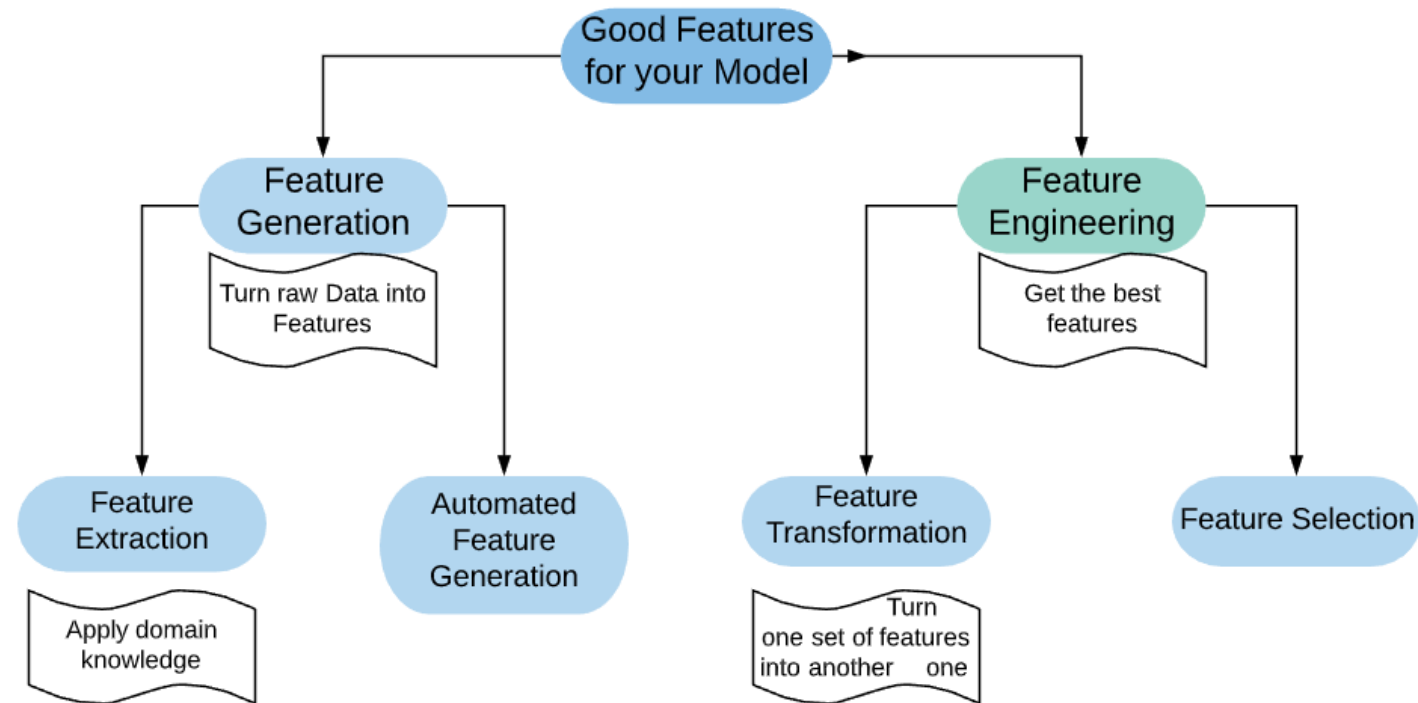
- Machine learning introduction
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Feature Engineering

Using domain knowledge to create features for machine learning algorithms

“... is the art part of data science”

Sergey Yurgenson
(Kaggle Master)



What could you try?

- 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

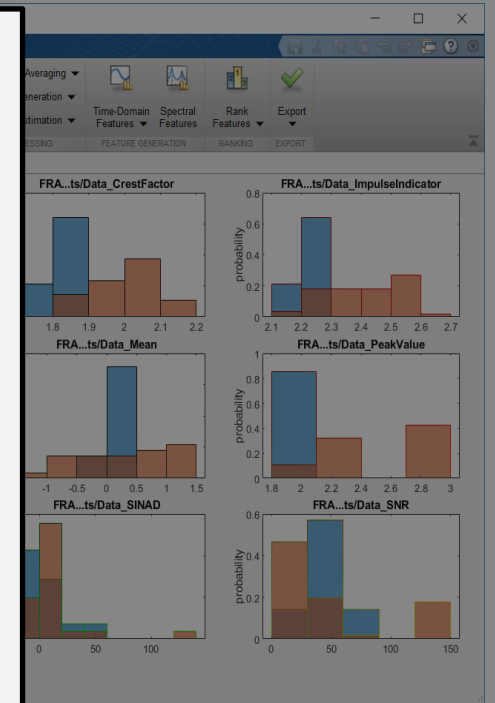
Goal: Explore different techniques for feature engineering

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*



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

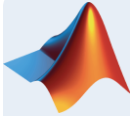
Use both statistical and dynamic modeling methods

Work with out-of-memory data

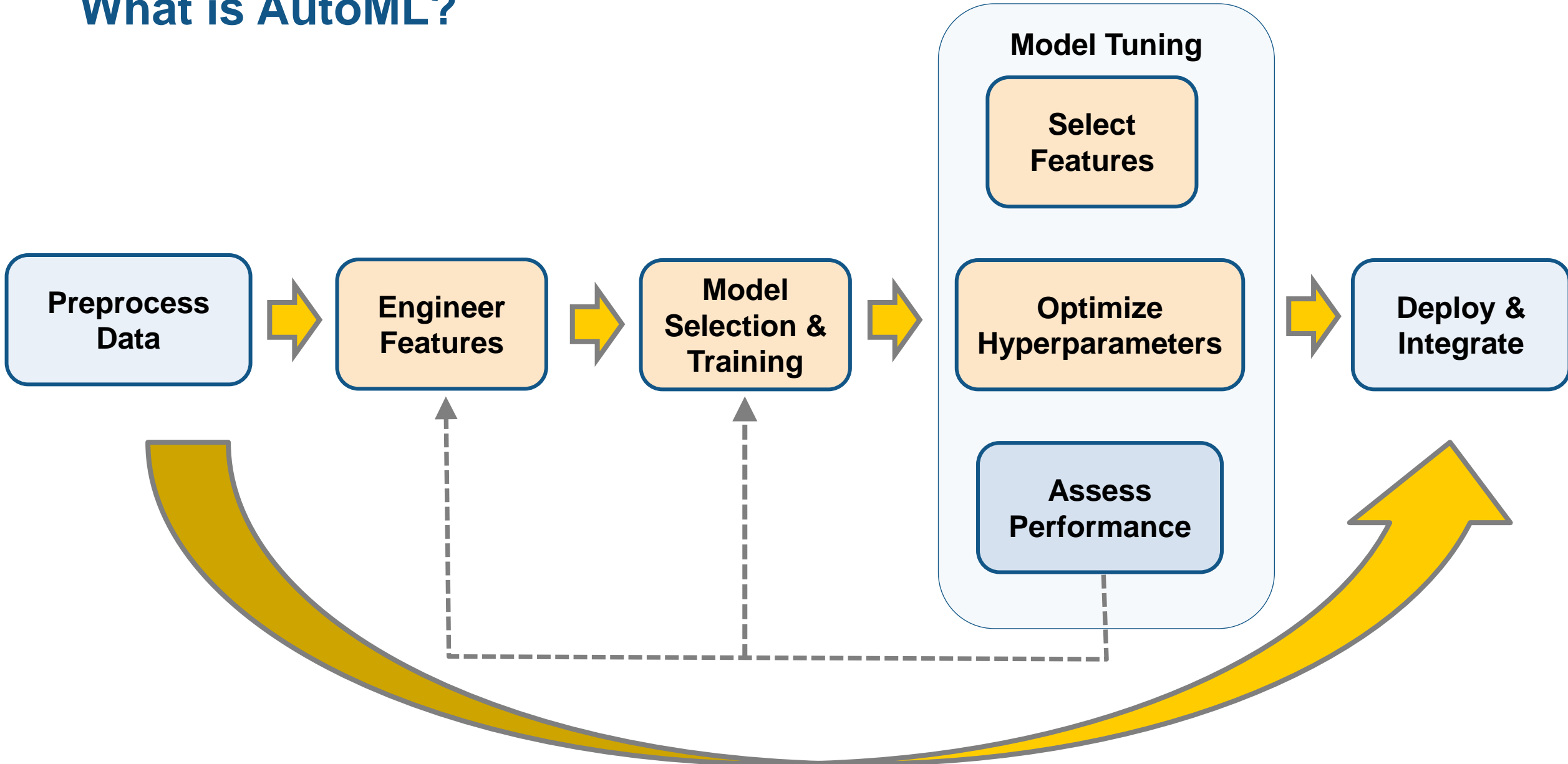
Explore and discover techniques without writing MATLAB code



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What is AutoML?



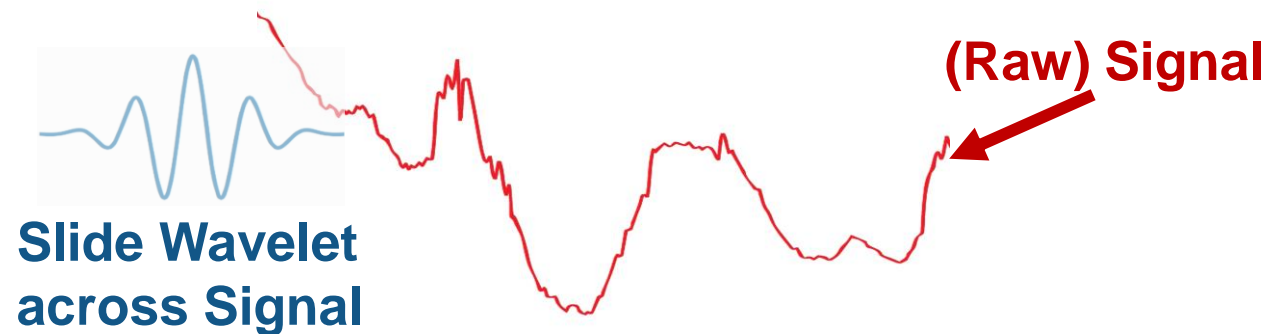
Feature Generation with Wavelet Scattering

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
```

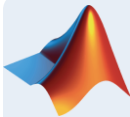
Additional Resources:

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

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

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

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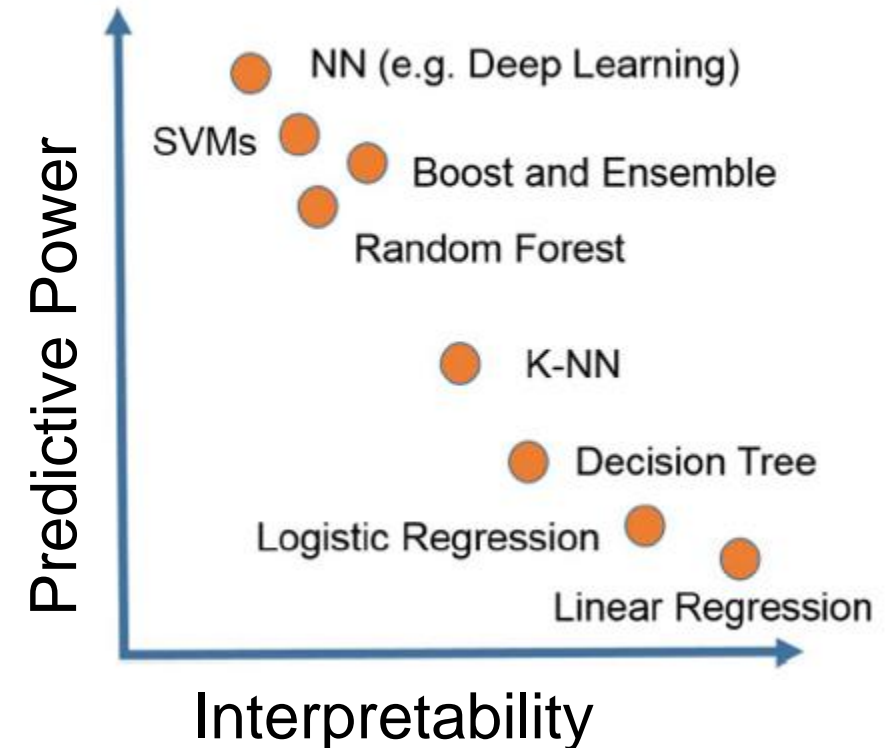
Interpretability and Explainability

Both terms describe the process of making “blackbox” models understandable

- “Interpretability”: primarily “classic” machine learning, causality of specific model decisions
- “**Explainable AI**” often refers to AI=Deep Learning, sometimes explaining how model works

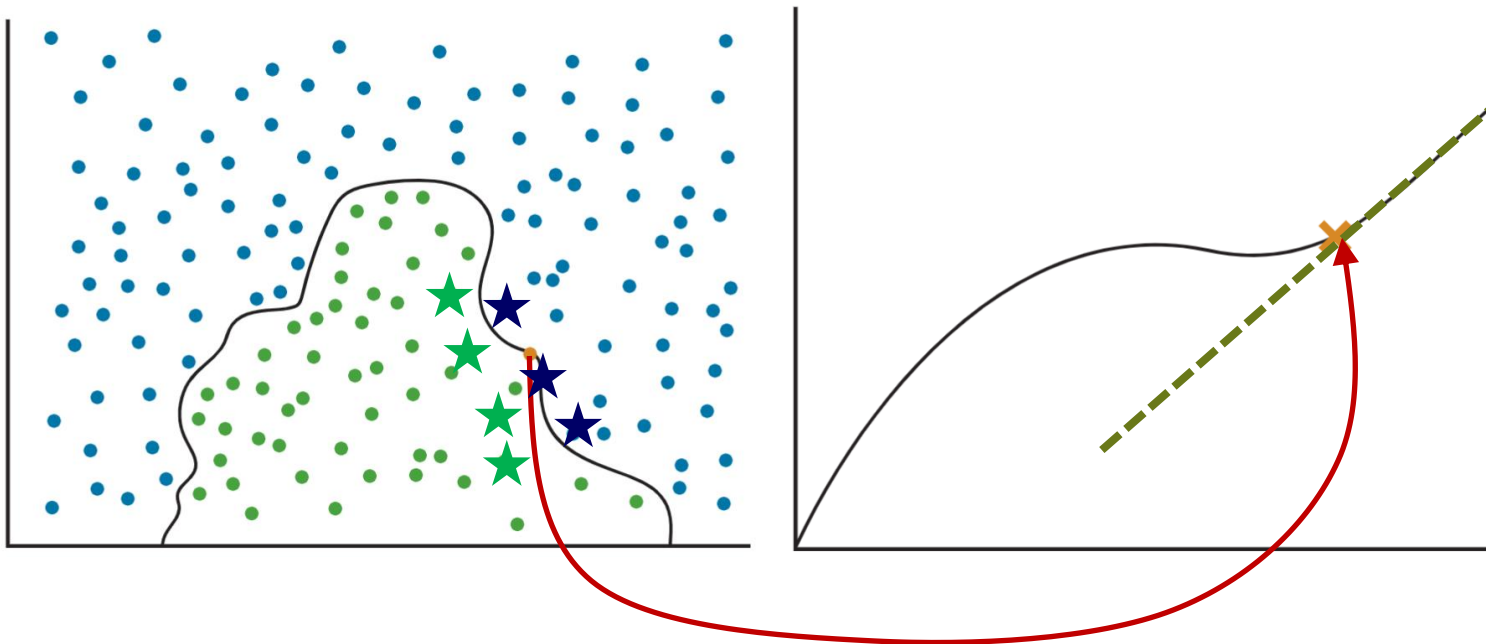
Why Interpretability?

1. Overcome “blackbox” model
 - Not acceptable by company guidelines
 - Build trust for users unfamiliar with machine learning
 - Pick model that looks at “right” evidence
2. Regulatory requirements (Finance, Europe’s GDPR):
3. Debug models

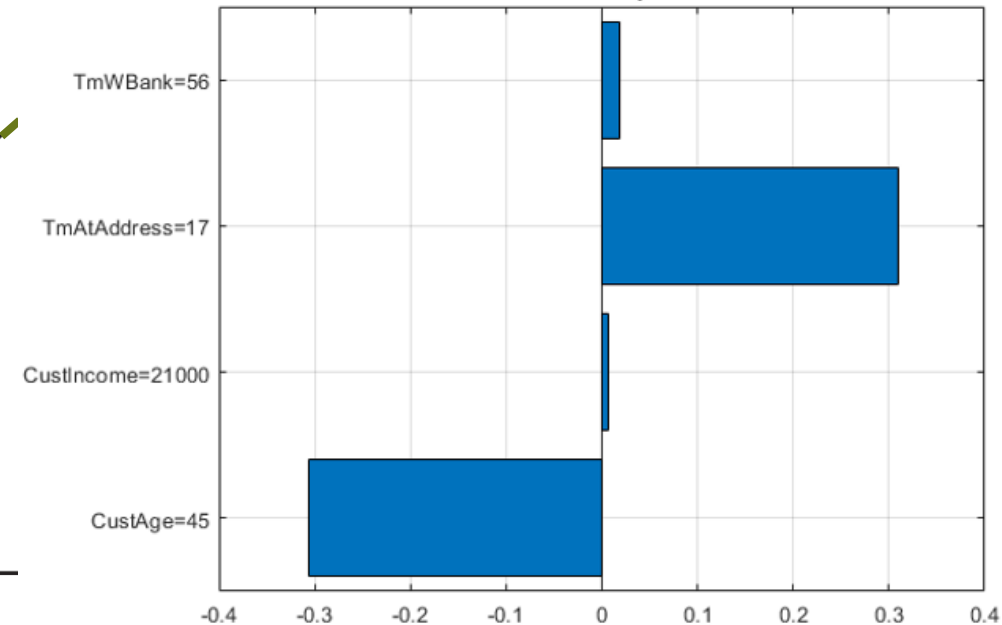


LIME = Local Interpretable Model-Agnostic Explanations

1 Approximate complex model near Point of Interest with simple model

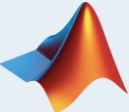


2 “Explain” using weights of simple model



```
l0bj = lime mdl, 'QueryPoint', queryPt, 'NumImportantPredictors', 4);  
plot(l0bj);
```

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Clustering

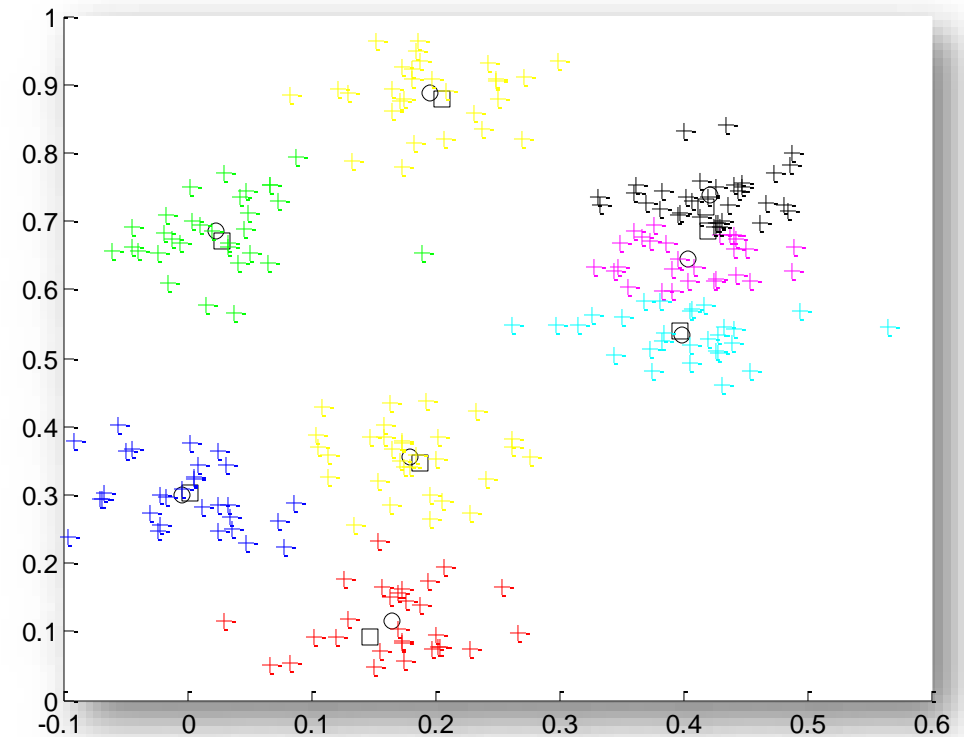
Why? Discover patterns, identify possible features, check for outliers

What is clustering?

Segment data into groups,
based on data similarity

How is clustering done?

- Can be achieved by various algorithms
- It is an iterative process (*involving trial and error*)



Exercise 4: Clustering Human Activity

Goal: find additional options to improve human activity classification

Approach:

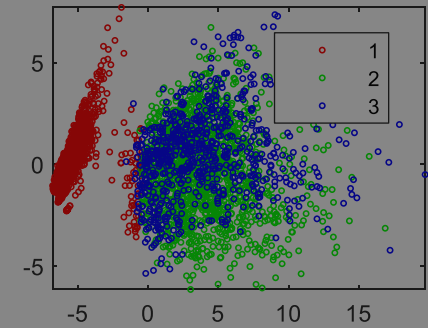
- Reduce dimensionality and simplify structure of data
- Evaluate different clustering algorithms to identify groups of similar data points

Let's try it out!

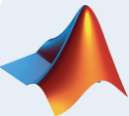
*Exercise: **`clusteringHumanActivity.mlx`**
in folder 04-UnsupervisedLearning*

1 vs 2

1 vs 3



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Big Data in MATLAB: Tall Arrays

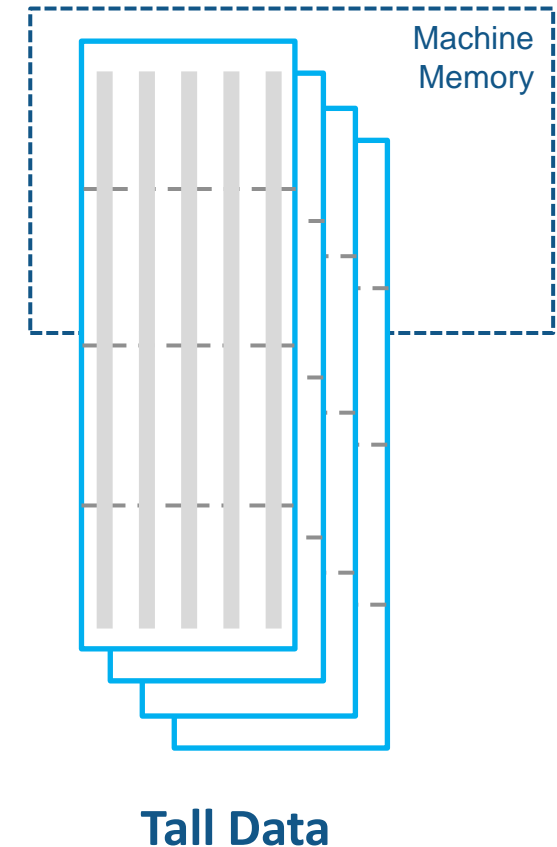
Extends the “array” data type to out-of-memory

- 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

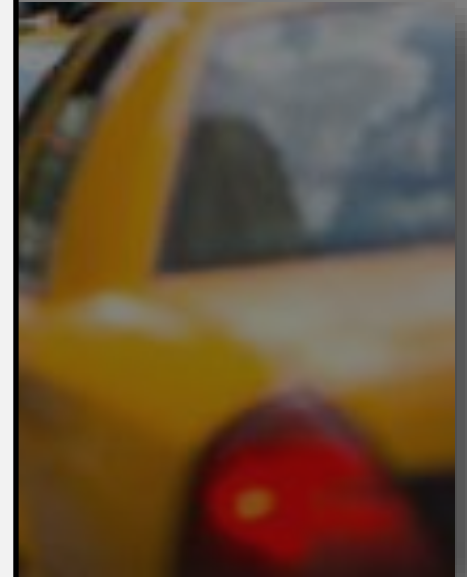
Goal: Create a model on a (simulated)
large dataset

Approach:

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

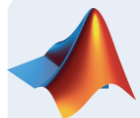
Let's try it out!

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



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Deploying Machine Learning Algorithms

Deploying MATLAB Algorithms

- Royalty-free deployment
- Point-and-click workflow

desktop and server apps

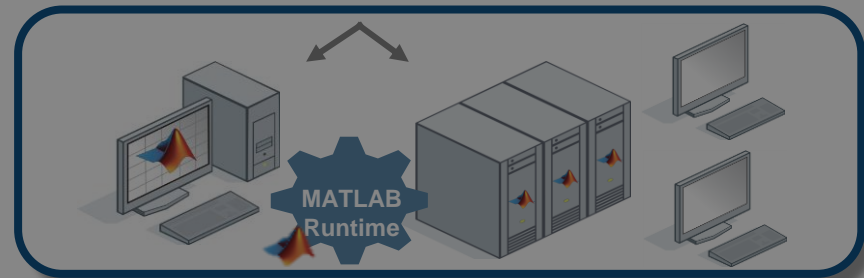
Let's observe!

```
for k=1:max
  x = fft(dat
  y = 20*log1
```

Embedded Hardware



ns



Beyond traditional Machine Learning: Deep Learning

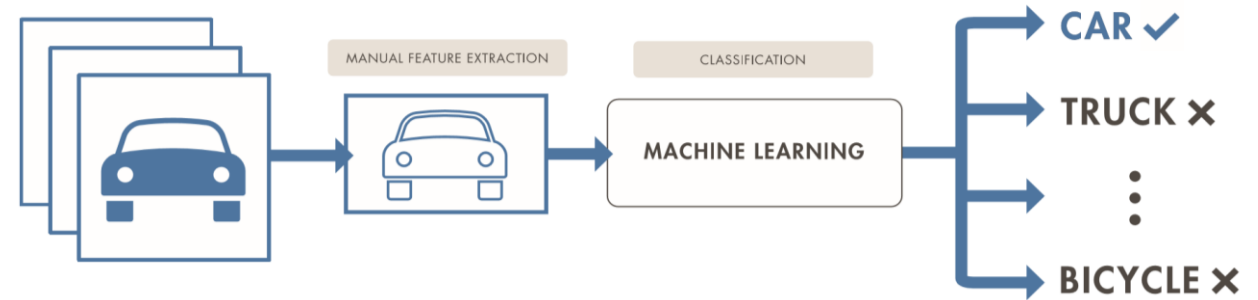
Machine Learning

Deep Learning

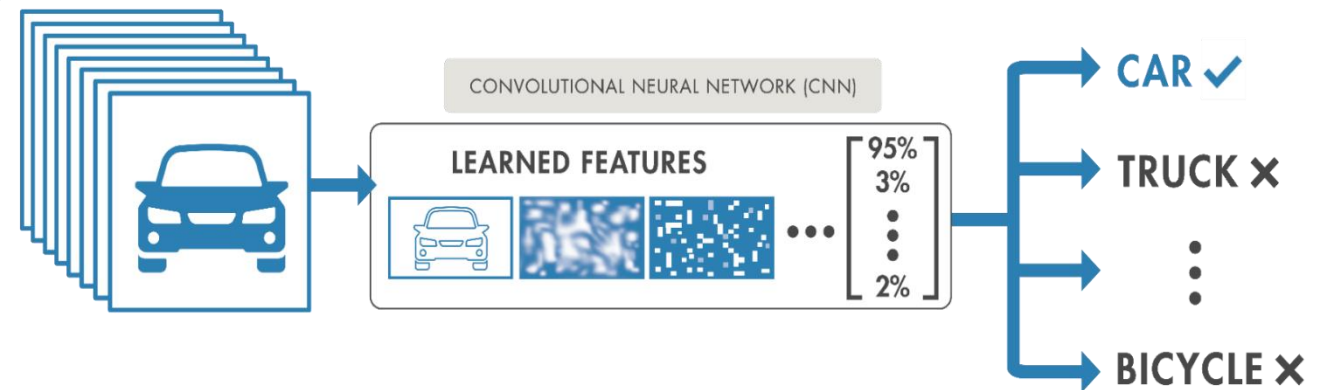
Neural Networks
with many Hidden
Layers

- Learns directly from data
- More Data = better model
- Computationally Intensive
- **Not interpretable**

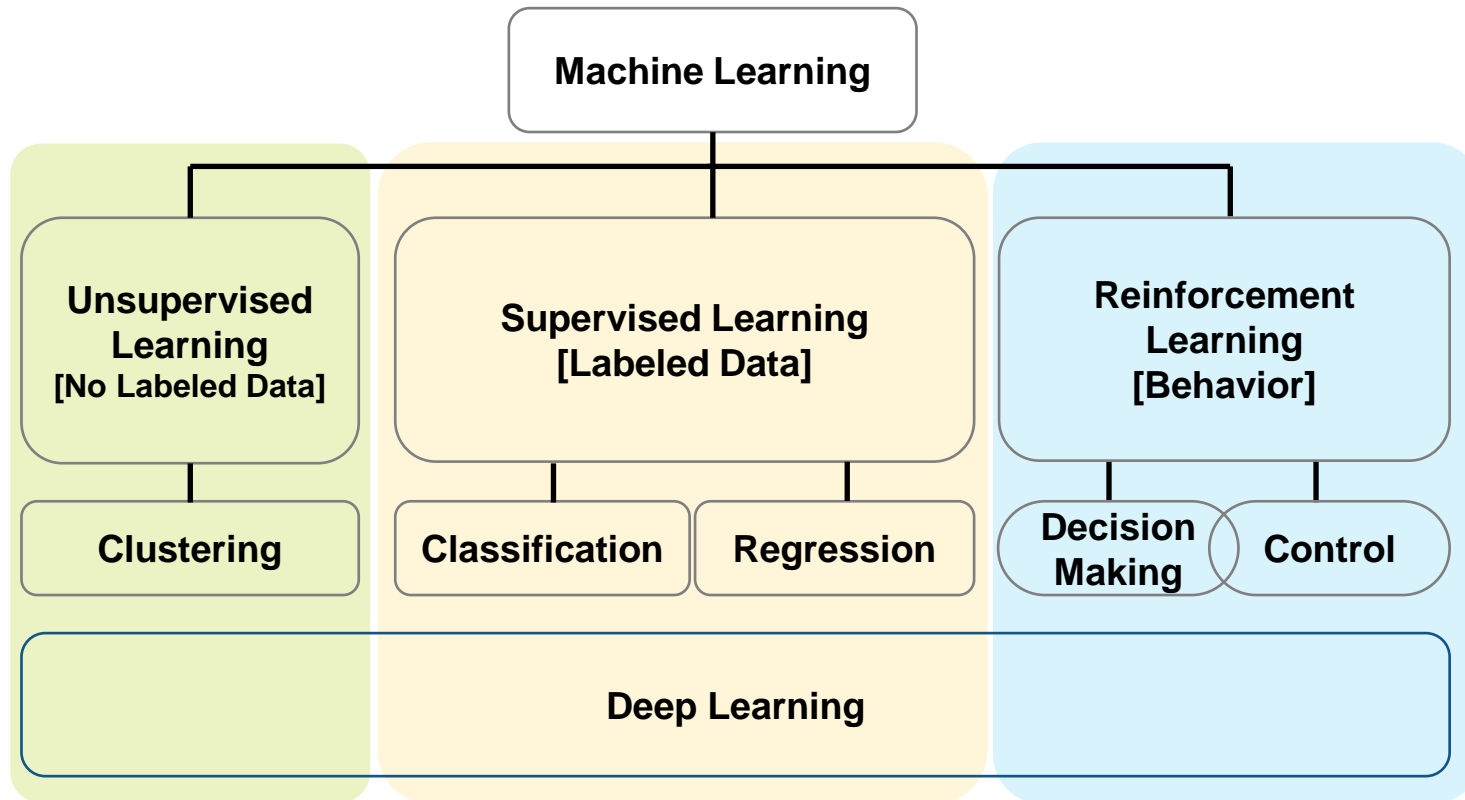
Machine Learning



Deep Learning



Beyond Machine Learning: Reinforcement Learning



Reinforcement learning:

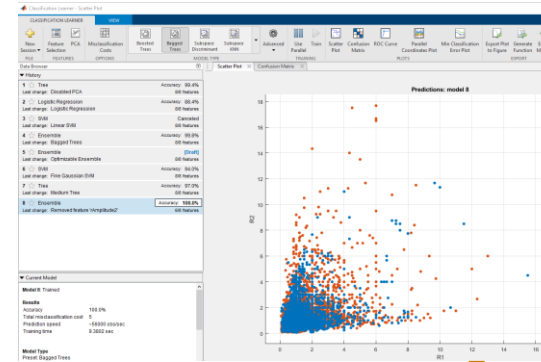
Learning through trial & error
[*interaction data*]

Complex problems typically
need deep learning

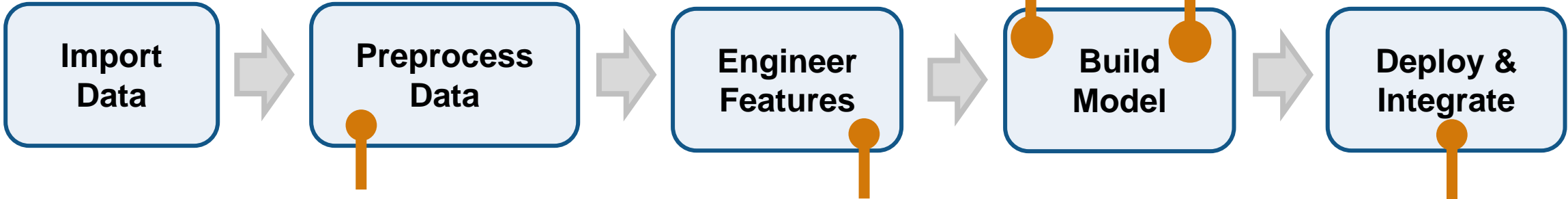
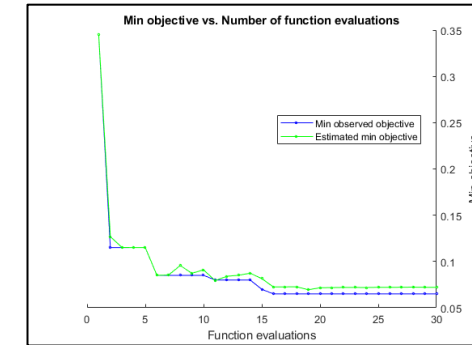
It's about learning a **behavior**
or accomplishing a **task**

Summary: Tools for building & deploying Machine Learning

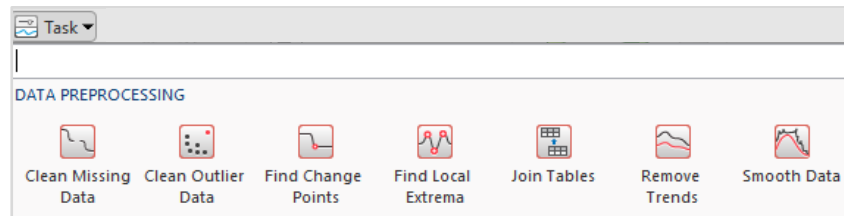
Interactive Model Training



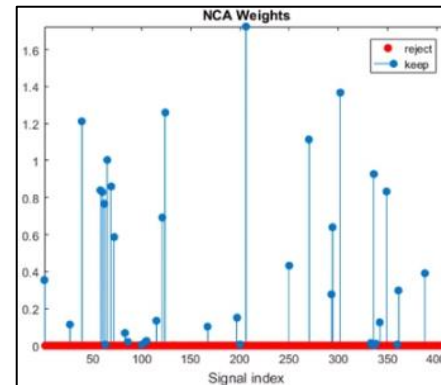
Automated Model Optimization



Clean Messy Raw Data



Feature Selection



Automated Code Generation

```

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

```

C code
14 // Define the SVM model
15 static emlTrInfo emlTrS1 = { 4, // LineNo //
16 "classifyIonosphere", // SrcName
17 "C:\Users\johanna\Documents\temp\feature-
18 };
19
20 // Function Definitions //
21 void classifyIonosphere(classifyIonosphereSrc
22 const real_T X[11934], cell_wrap_0_label[34]
23 {
24 real_T to_Alpha[90];
25 real_T expl_temp[34];
  
```



Resources

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

[Practical Data Science with MATLAB](#) (4 course Specialization)

Machine Learning with MATLAB:

- [Overview](#), [Cheat sheet](#)
- [Machine Learning Intro](#) (Tech talks)
- [Machine Learning with MATLAB Introduction](#) (eBook)
- [Mastering Machine Learning](#) (eBook)
- [Applied Machine Learning](#) (Tech Talk videos)

Machine and Deep Learning

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

Five Interactive Apps for Machine Learning

No matter what type of problem you're trying to solve, MATLAB® is here to help. Discover apps to interactively model, fit, and label data for machine learning.

Classification Learner

Regression Learner

Curve Fitting

Image Labeler

Signal Labeler

MathWorks can help you apply Machine Learning



Training



Guided Evaluations



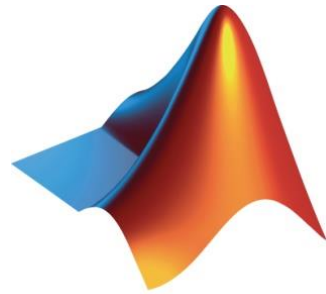
Onsite Workshops



Consulting



Technical Support



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Accelerating the pace of engineering and science

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Additional Material

- Working with Data in MATLAB
- Reinforcement Learning Example
- Explain different accuracies
- Alternative for Wavelet Scattering, drawing comparison to CNN filters

Working with Data

Business and Transactional Data

Repositories

- Databases (SQL/NoSQL)
- Hadoop

File I/O

- Text
- Spreadsheet

Web Sources

- RESTful/SOAP
- JSON
- HTML/XML
- Mapping
- Financial datafeeds
- FTP

Recent Additions

File I/O

- PDF
- Microsoft Word
- Parquet
- Vector BLF
- STL (Stereolithography)

Web Sources

- Amazon Web Services
- Azure Blob Storage

Internet of Things (IOT)

- ThingSpeak

Engineering, Scientific and Field Data

File I/O

- CDF/HDF
- Audio/Image/ Video
- Geospatial
- Microarrays
- CAD Models
- MDF

Communication Protocols

- CAN (Controller Area Network)
- DDS (Data Distribution Service)
- OPC (OLE for Process Control) (e.g. PI)
- XCP (eXplicit Control Protocol)
- TCP/IP
- Serial/Bluetooth/USB

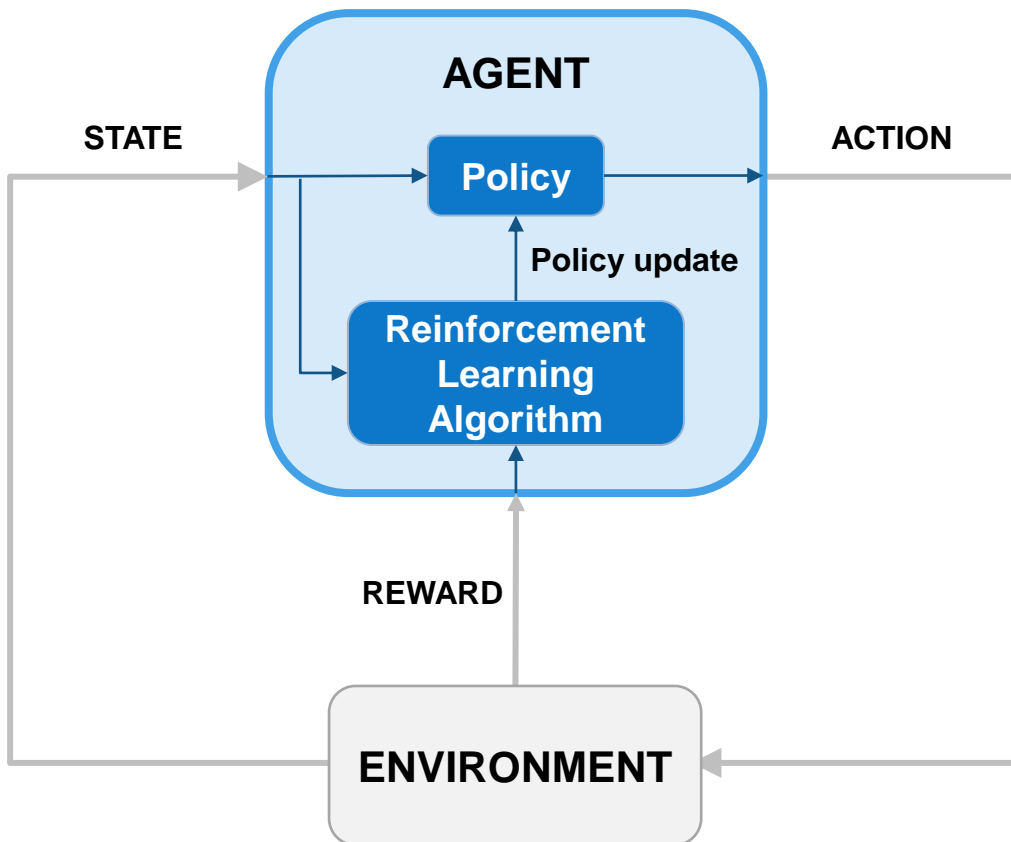
Real-Time Sources

- Sensors/Instrumentation/Cameras
- GPS
- Communication systems
- Machines (embedded systems)
- Robot Operating System (ROS)

The above list is not all-inclusive, but is intended for guidance only

A Practical Example of Reinforcement Learning

Training a Self-Driving Car



Vehicle's computer learns how to drive... (agent)
 using sensor readings from LIDAR, cameras,... (state)
 that represent road conditions, vehicle position,... (environment)
 by generating steering, braking, throttle commands,... (action)
 based on an internal state-to-action mapping... (policy)
 that tries to optimize driver comfort & fuel efficiency... (reward).

The policy is updated through repeated trial-and-error by a **reinforcement learning algorithm**

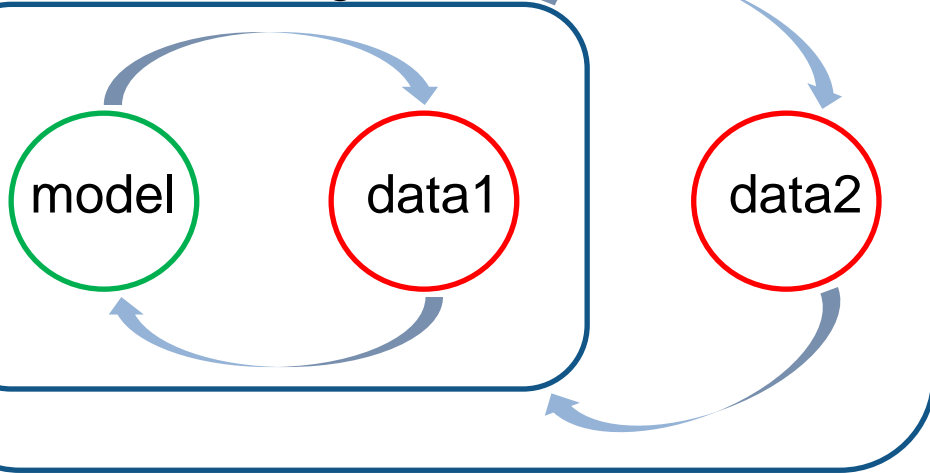
Evaluating Model Accuracy, properly.

Common Customer Workflow

Learner App Workflow

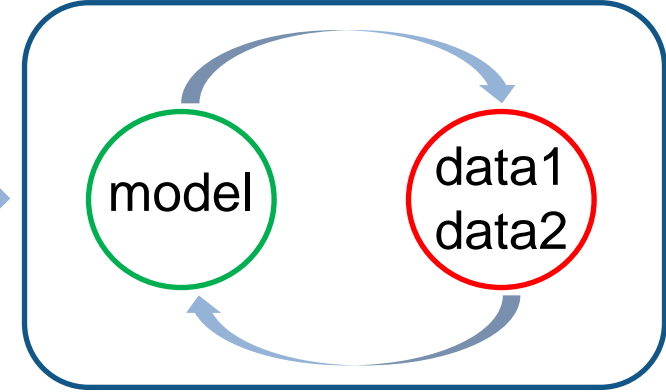
Hyperparameter Tuning

Model Training

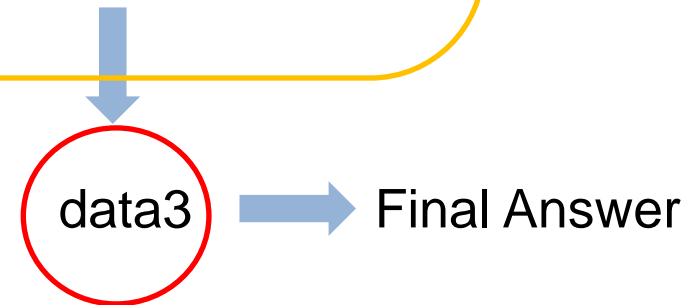


Pick winning model based on data2 accuracy

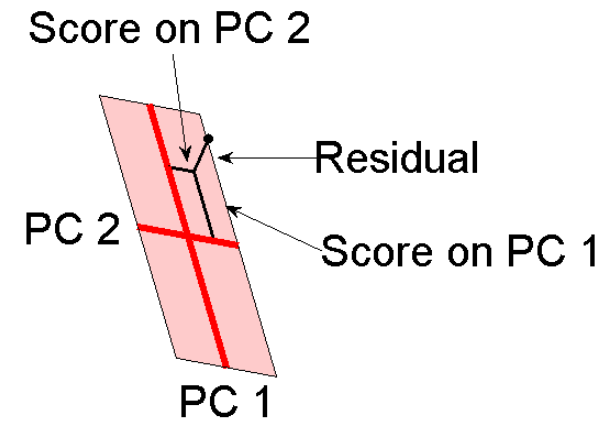
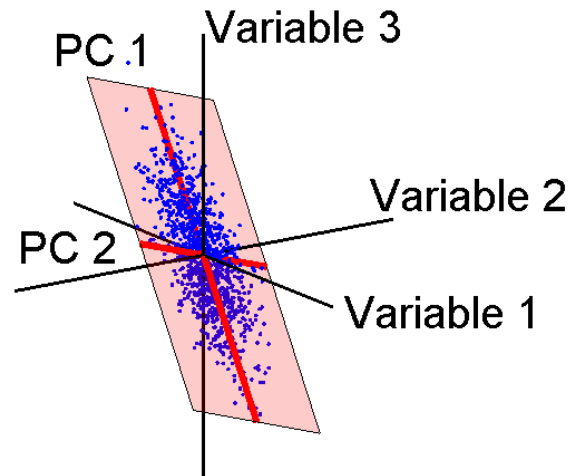
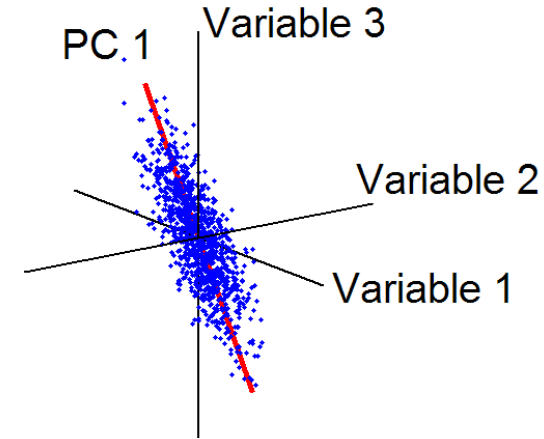
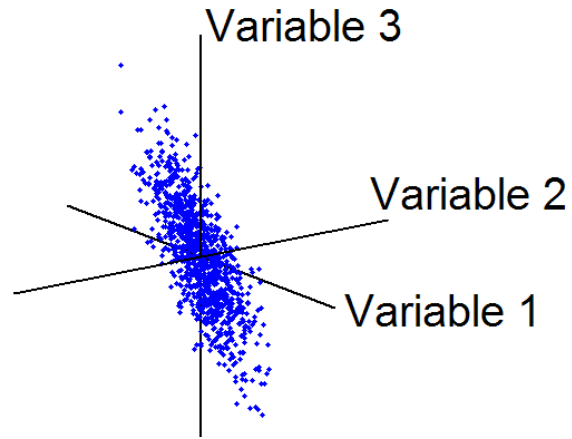
Model Training



data1 = training data
 data2 = validation data
 data3 = test data



Principal Components Analysis (PCA)

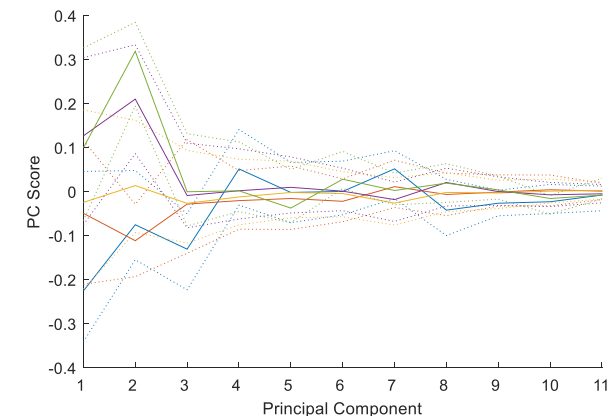
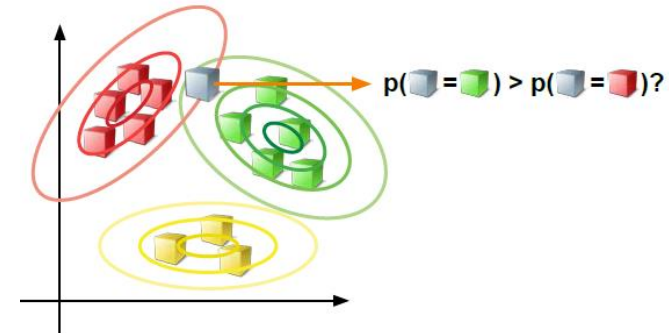
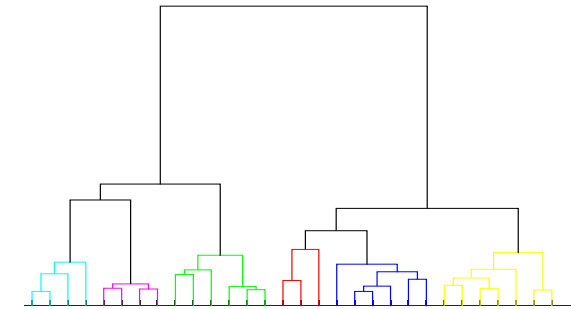


Training: *Machine Learning with MATLAB*

After this 2-day course you will be able to:

- Discover natural patterns in data
- Create predictive models
- Validate the predictions of a model
- Simplify and improve models

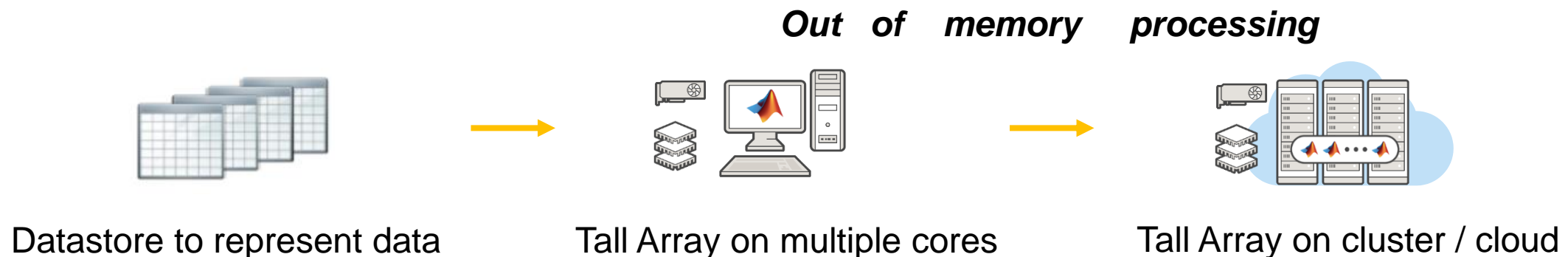
<http://www.mathworks.com/training-schedule/machine-learning-with-matlab>



Training: *Processing Big Data with MATLAB*

In this 1-day course, you will apply your data science code to **big** data

- Overcome physical memory limitations.
- Work with many gigabytes or terabytes of data.
- Access data and process it on the cloud.



<https://www.mathworks.com/training-schedule/processing-big-data-with-matlab.html>