MATLAB EXPO 2016

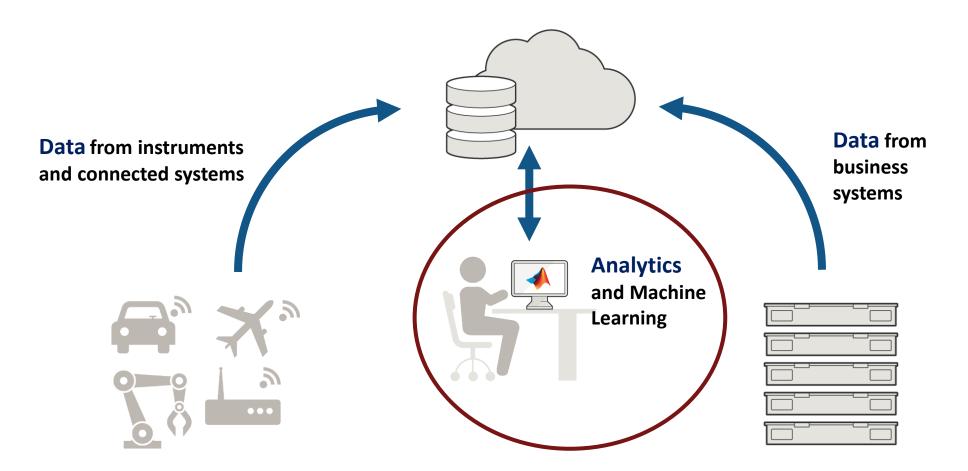
Machine Learning and Deep Learning

Jon Cherrie





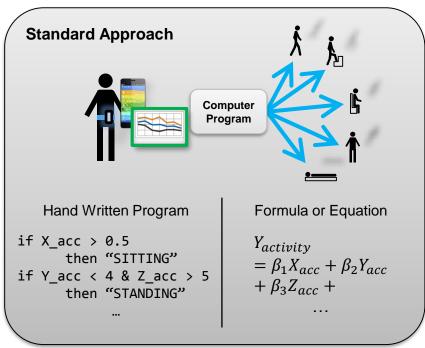
Architecture of an analytics system

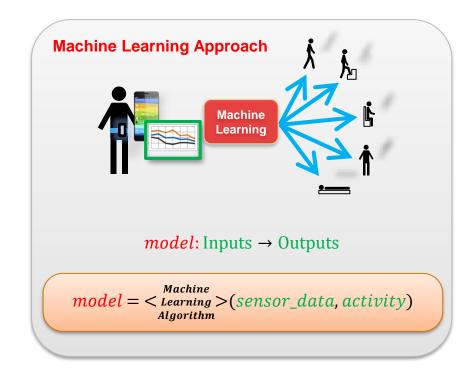




What is Machine Learning

Machine learning uses data and produces a program to perform a task





Task: Human Activity Detection



Classify images into 1000 categories





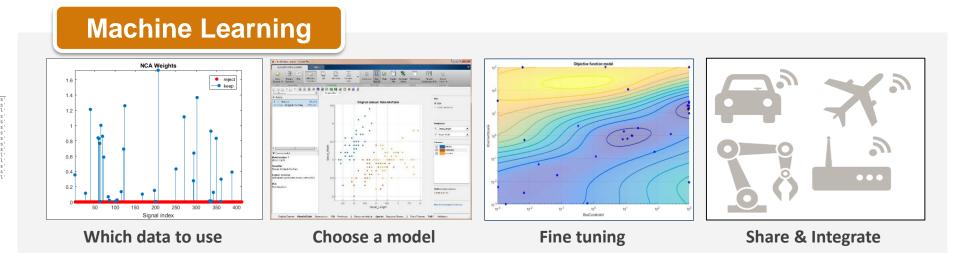
Monitor a manufacturing process

X1	X2	Х3	X4	X5	X6	X7	Y
3030.9	2564	2187.7	1411.1	1.3602	100	97.613	'pass'
3095.8	2465.1	2230.4	1463.7	0.8294	100	102.34	'pass'
2932.6	2559.9	2186.4	1698	1.5102	100	95.488	'fail'
2988.7	2479.9	2199	909.79	1.3204	100	104.24	'pass'
3032.2	2502.9	2233.4	1326.5	1.5334	100	100.4	'pass'
2946.3	2432.8	2233.4	1326.5	1.5334	100	100.4	'pass'
3030.3	2430.1	2230.4	1463.7	0.8294	100	102.34	'pass'
3058.9	2690.2	2248.9	1004.5	0.7884	100	106.24	'pass'
2967.7	2600.5	2248.9	1004.5	0.7884	100	106.24	'pass'
3016.1	2428.4	2248.9	1004.5	0.7884	100	106.24	'pass'
2994.1	2548.2	2195.1	1046.1	1.3204	100	103.34	'fail'
2928.8	2479.4	2196.2	1605.8	0.9959	100	97.916	'fail'
2920.1	2507.4	2195.1	1046.1	1.3204	100	103.34	'pass'
3051.4	2529.3	2184.4	877.63	1.4668	100	107.87	'pass'
2964	2629.5	2224.6	947.77	1.2924	100	104.85	'fail'



Overview

X1	X2	X3	X4	X5	X6	X7	Y
3030.9	2564	2187.7	1411.1	1.3602	100	97.613	'pass
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Deep Learning

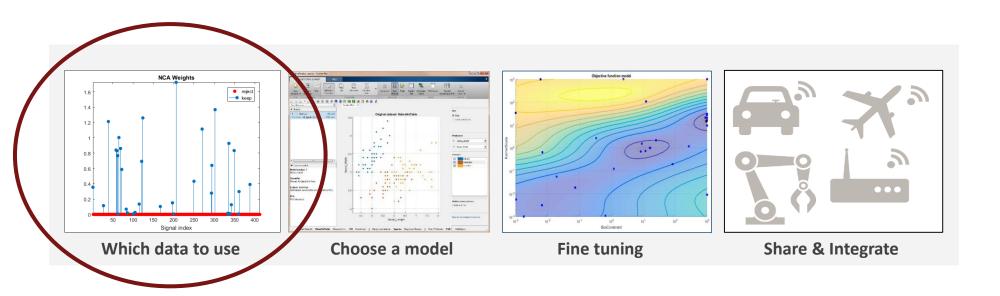
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Deep Learning



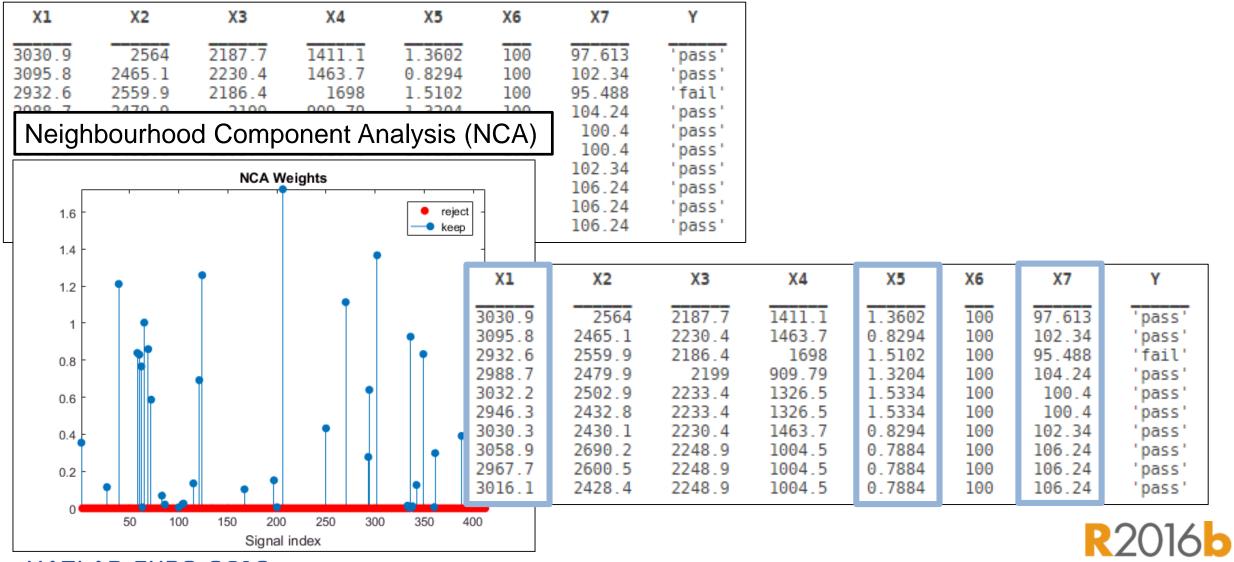


Which data to use? Feature selection



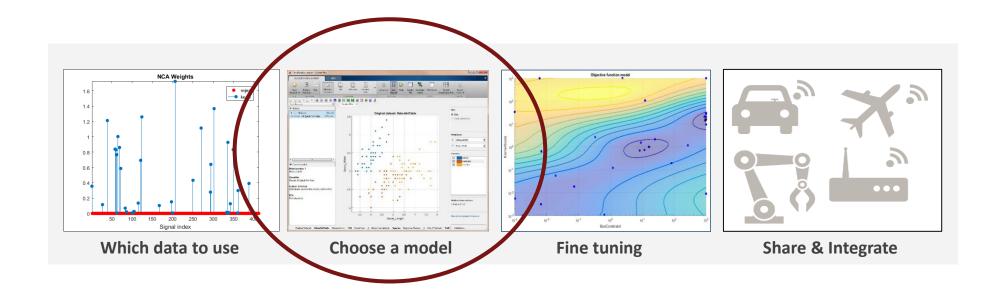
A MathWorks

Which data to use? Feature selection





Which model to use? Classification Learner



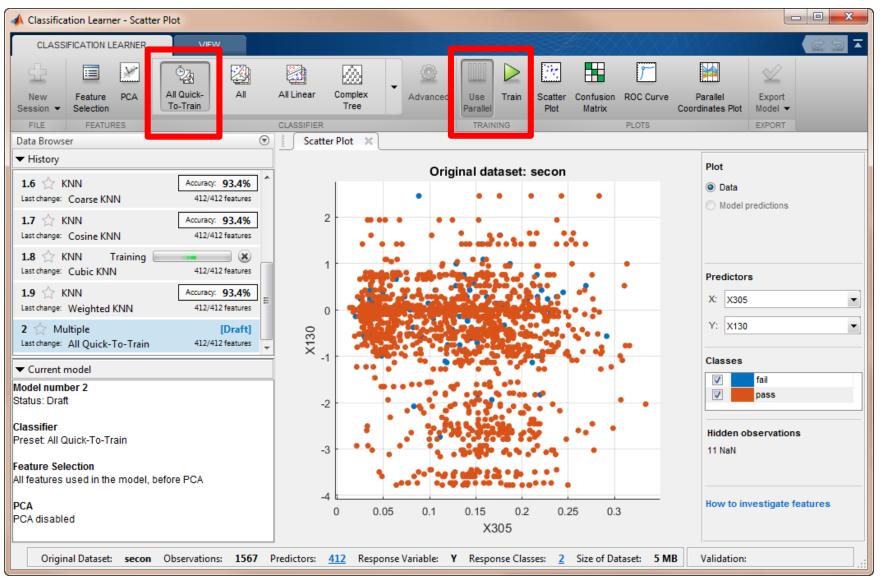


Classification Learner

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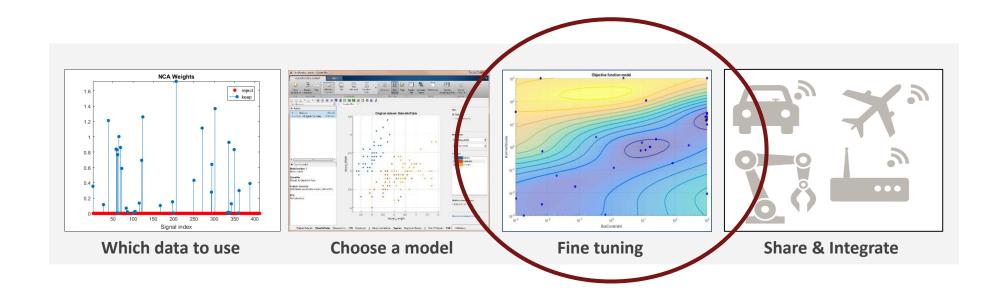
Classification Learner





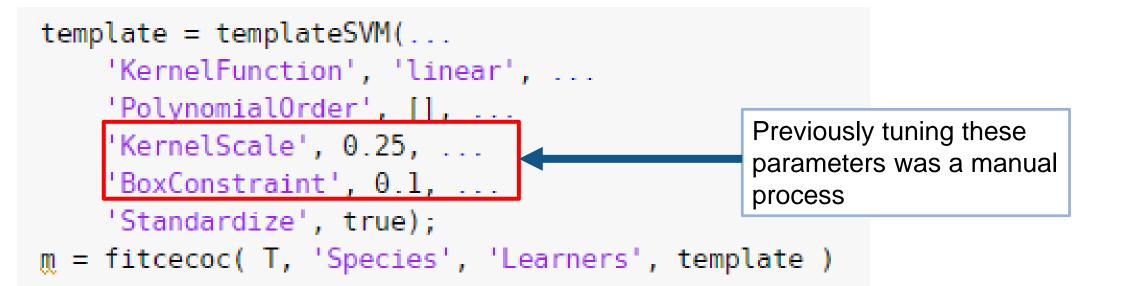


Fine Tuning a Model: Bayesian Optimization





Tune Parameters with Bayesian Optimization





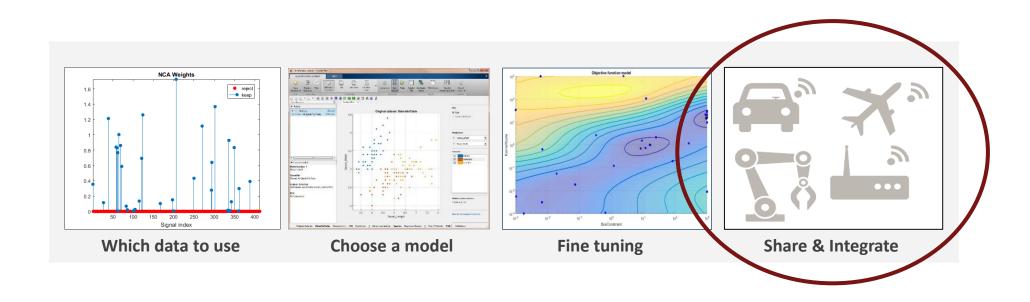


Fine tuning a model – Bayesian Optimization

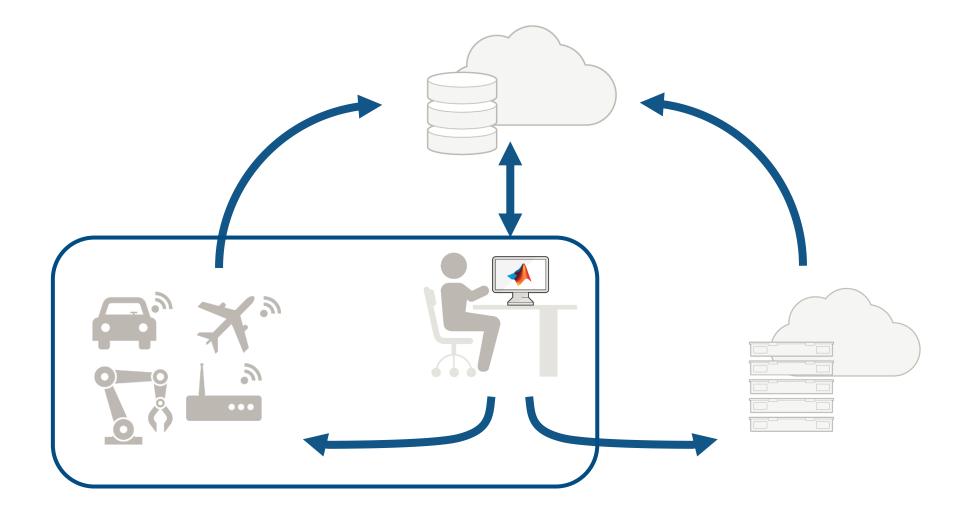
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Figure 2 🗶	<u>.</u>		I	



Share & Integrate

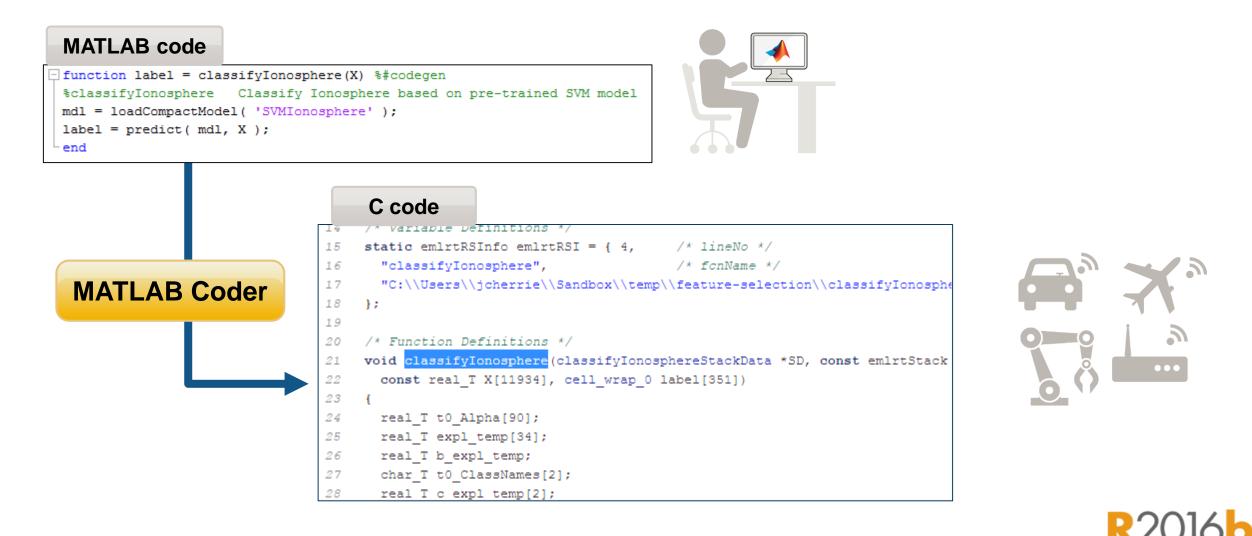


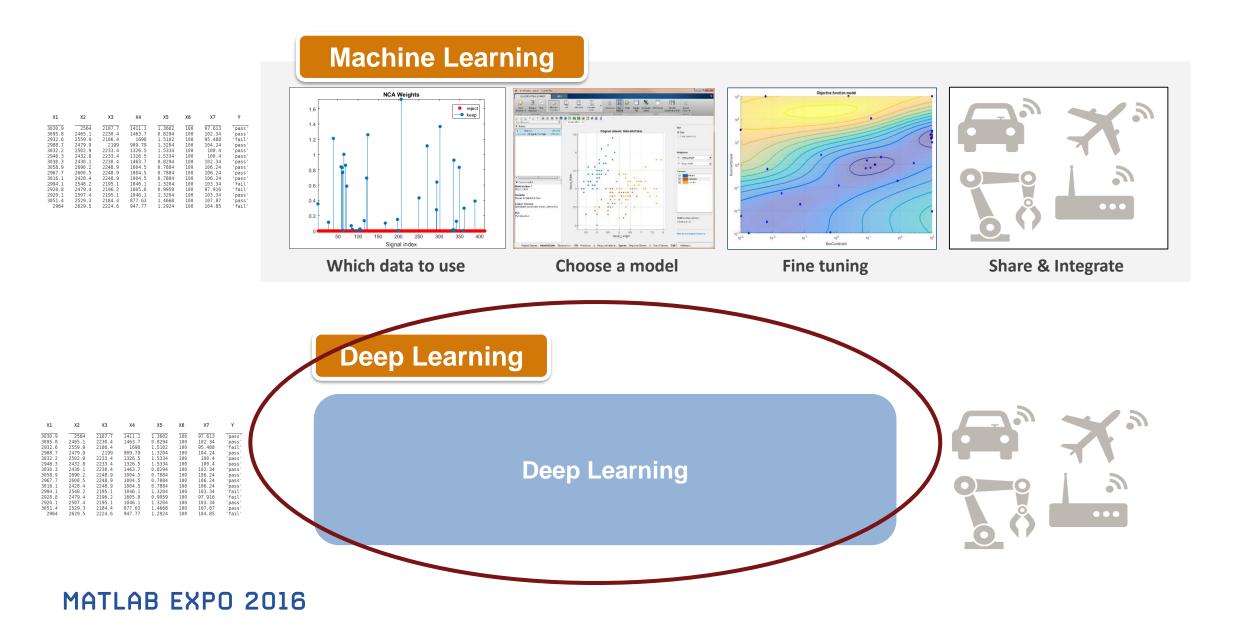






Share & integrate: machine learning models

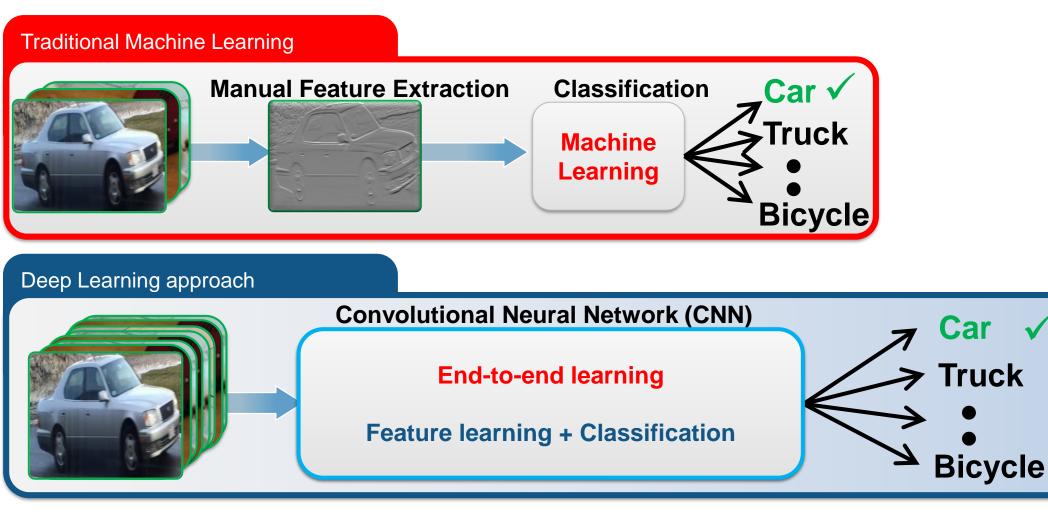






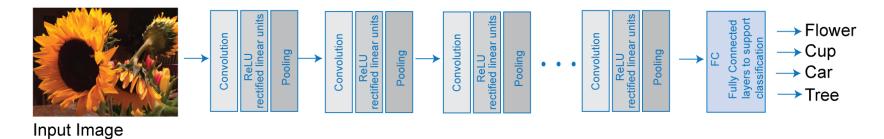
Deep Learning

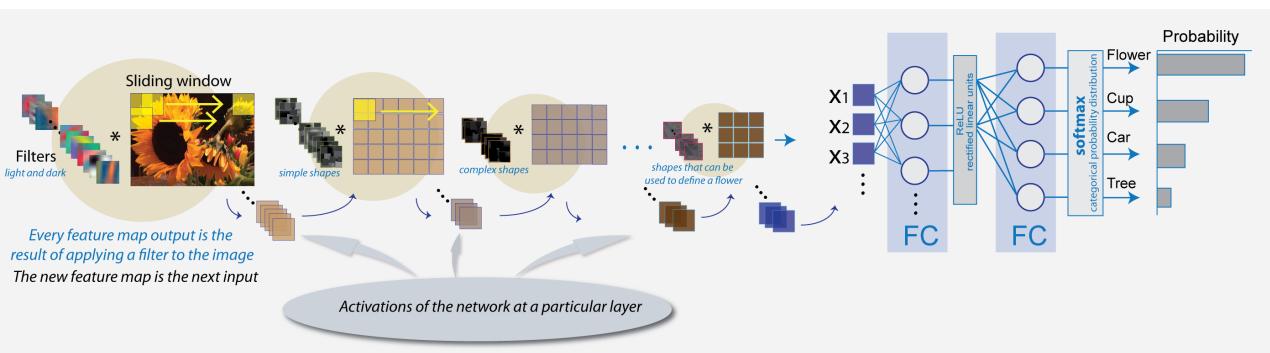
Deep learning performs end-end learning by learning features, representations and tasks directly from images, text and sound





What is Deep Learning?







Object Recognition using Deep Learning

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nmand Win >> de	tectCamera	ImagesWith	CNN							I €

Training (using GPU)	Millions of images from 1000 different categories
Prediction	Real-time object recognition using a webcam connected to a laptop



Why is Deep Learning so Popular?

- Results: Achieved substantially better results on ImageNet large scale recognition challenge
 - 95% + accuracy on ImageNet 1000 class challenge
- Computing Power: GPU's and advances to processor technologies have enabled us to train networks on massive sets of data.
- Data: Availability of storage and access to large sets of labeled data
 - e.g., ImageNet , PASCAL VoC , Kaggle

Year	Error Rate
Pre-2012 (tradition computer vision an machine learning techniques)	
2012 (Deep Learn	ing) ~ 15%
2015 (Deep Learr	ning) <5 %



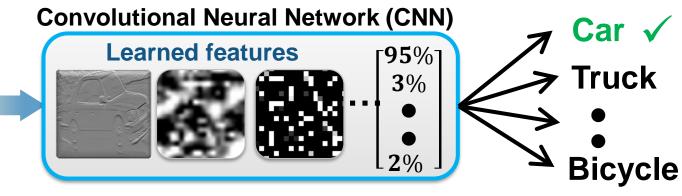


Two Approaches for Deep Learning

1. Train a Deep Neural Network from Scratch



Lots of data



2. Fine-tune a pre-trained model (transfer learning)





Two Deep Learning Approaches Approach 1: Train a Deep Neural Network from Scratch

Convolutional Neural Network (CNN) Learned features 1 (95%) 3%) 2%) Car ✓ Truck 2%) Bicycle

Recommended <u>only</u> when:

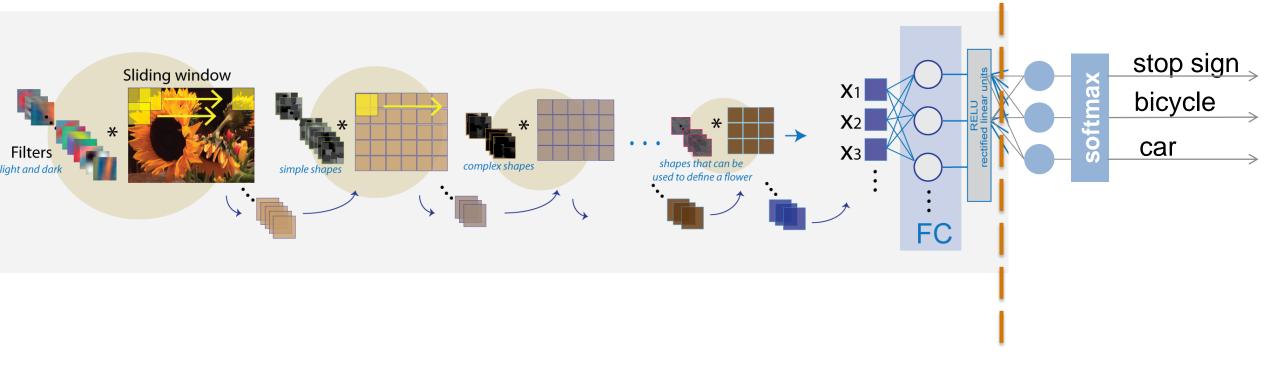
Training data	1000s to millions of labeled images
Computation	Compute intensive (requires GPU)
Training Time	Days to Weeks for real problems
Model accuracy	High (can over fit to small datasets)



Two Deep Learning Approaches *Approach 2: Fine-tune a pre-trained model (transfer learning)*

CNN trained on massive sets of data

- Learned robust representations of images from larger data set
- Can be fine-tuned for use with *new data or task* with small medium size datasets





Two Deep Learning Approaches Approach 2: Fine-tune a pre-trained model

(transfer learning)

CNN trained on massive sets of data

- Learned robust representations of images from larger data set
- Can be fine-tuned for use with *new data or task* with small medium size datasets

Recommended when:

Training data	100s to 1000s of labeled images (small)
Computation	Moderate computation (GPU optional)
Training Time	Seconds to minutes
Model accuracy	Good, depends on the pre-trained CNN model



Deep Learning in MATLAB

```
% Define a CNN architecture
layers = [
    imageInputLayer([32 32 3])
    convolution2dLayer(5,32,'Padding',2)
    reluLayer()
    maxPooling2dLayer(3, 'Stride', 2)
       •••
    fullyConnectedLayer(10)
    softmaxLayer()
    classificationLayer()
    ];
opts = trainingOptions( 'sgdm', 'InitialLearnRate', 0.001 );
```

```
% Train the CNN
[net, info] = trainNetwork(X, Y, layers, opts);
MATLAB EXPO 2016
```





Transfer Learning in MATLAB

% Everything except the last 3 layers.

```
preTrainedLayers = preTrainedNetwork.Layers(1:end-3);
```

% Add new fully connected layer for 2 categories,

- % the softmax layer, and the classification layer which make up the
- % remaining portion of the networks classification layers.

```
layers = [
```

```
preTrainedLayers
fullyConnectedLayer(2)
softmaxLayer
classificationLayer()
```

```
];
```

```
net = trainNetwork(X, Y, layers, opts);
```





Demo Stations



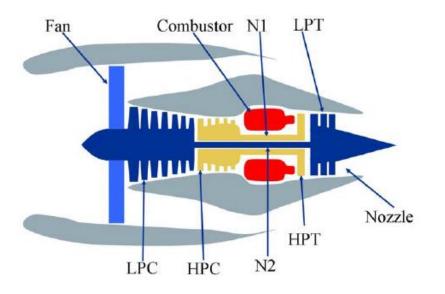
1. Classification Learner Demo Predictive Maintenance of Turbofan Engine

Sensor data from 100 engines of the same model

Predict and fix failures before they arise

- Import and analyze historical sensor data
- Train model to predict when failures will occur
- Deploy model to run on live sensor data
- Predict failures in real time



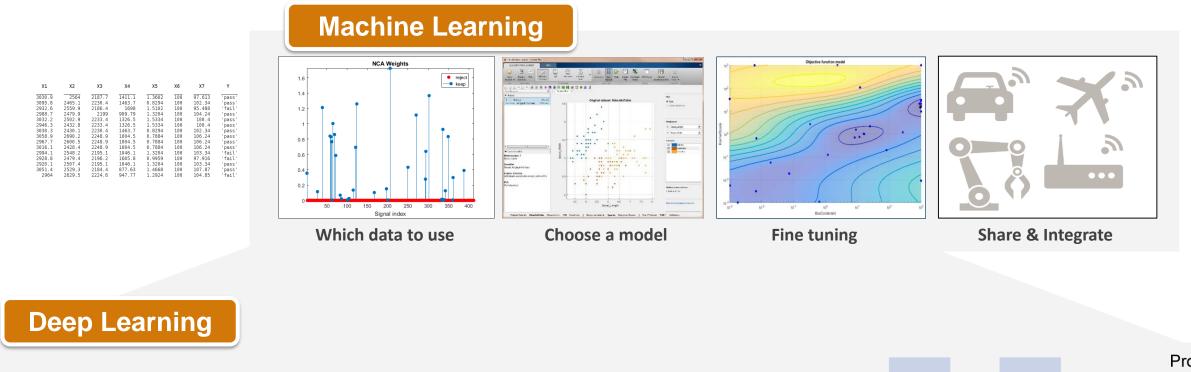


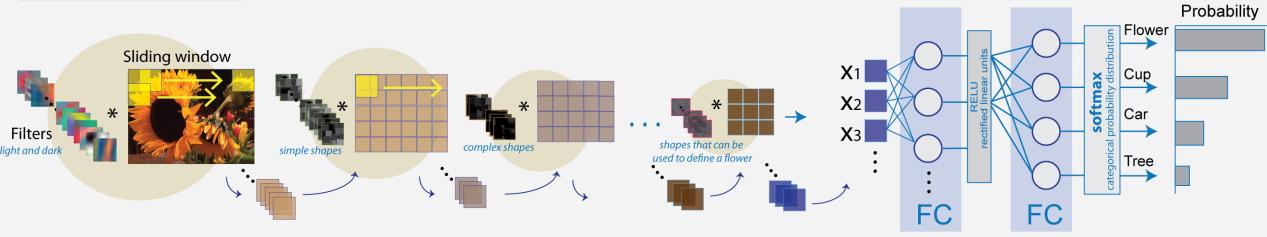
Data provided by NASA PCoE http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/













FIN