

MATLAB EXPO 2016

KOREA

4월 28일 (목)

등록 하기 matlabexpo.co.kr



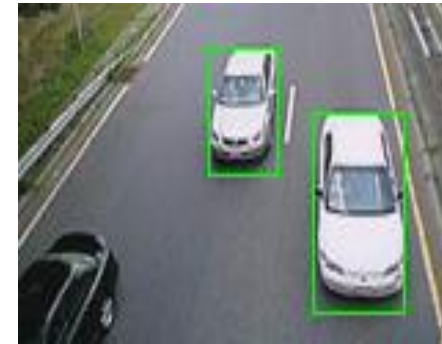
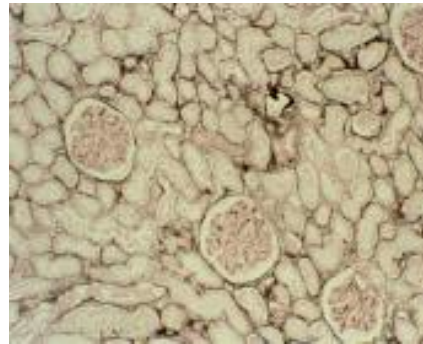
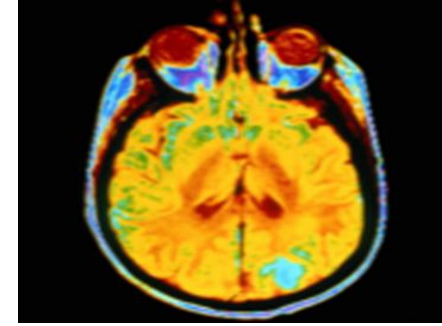
데이터 애널리틱스를 위한 머신 러닝 기법

Application Engineer

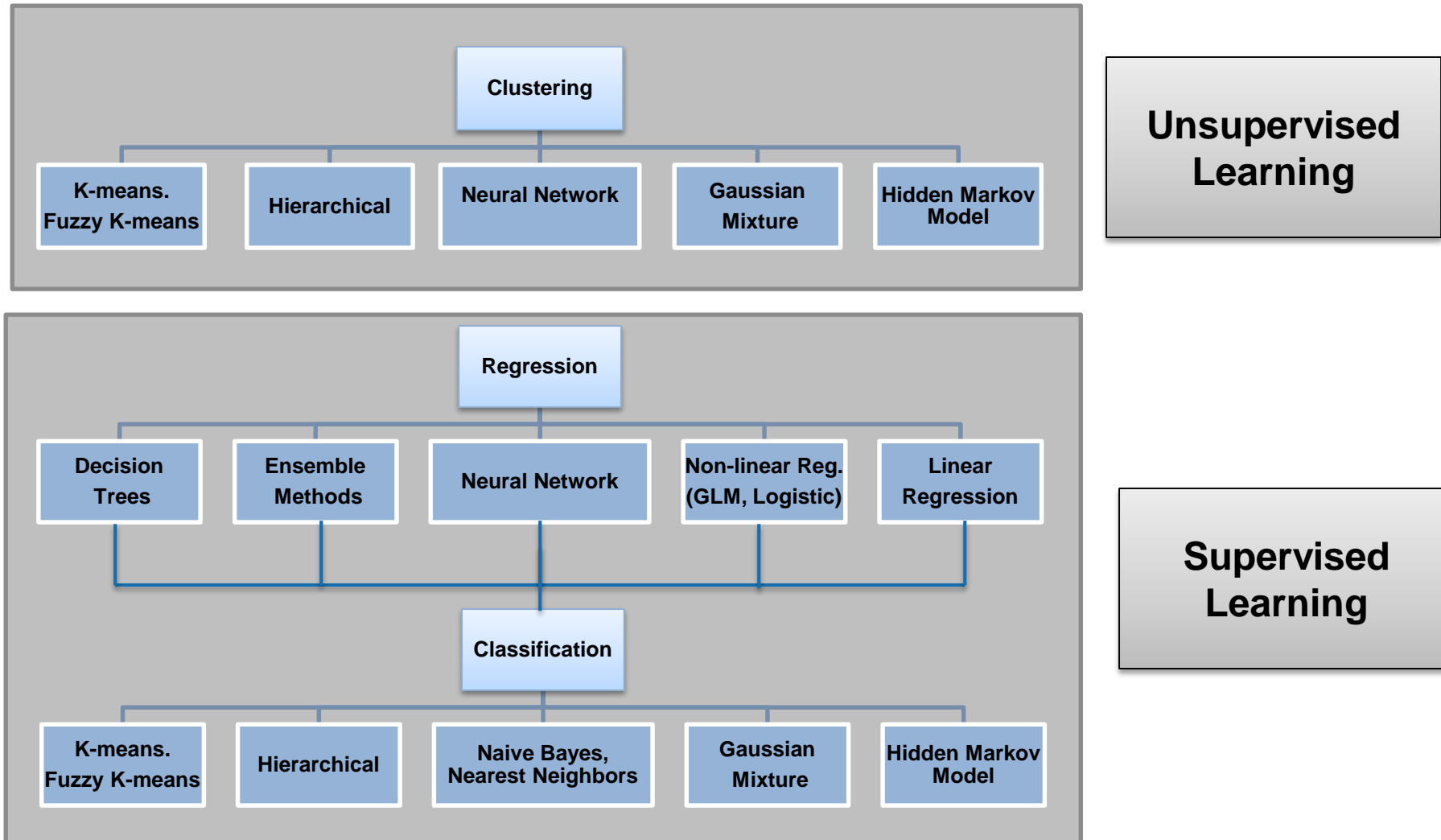
엄준상 과장

Machine Learning is Everywhere

- Image Recognition
- Speech Recognition
- Stock Prediction
- Medical Diagnosis
- Data Analytics
- Robotics
- and more...




Overview of Machine Learning in MATLAB



Challenges in Machine Learning

Hard to get started

Steps	Challenge
Access, explore and analyze data	Data diversity Numeric, Images, Signals, Text – not always tabular
Preprocess data	Lack of domain tools Filtering and feature extraction Feature selection and transformation
Train models	Time consuming Train many models to find the “best”
Assess model performance	Avoid pitfalls Over Fitting Speed-Accuracy-Complexity tradeoffs
Iterate	

Faulty braking system leads to windmill disaster



Why perform predictive maintenance?

- Example: faulty braking system leads to windmill disaster
 - <https://youtu.be/-YJuFvjtM0s?t=39s>
- Wind turbines cost millions of dollars
- Failures can be dangerous
- Maintenance also very expensive and dangerous



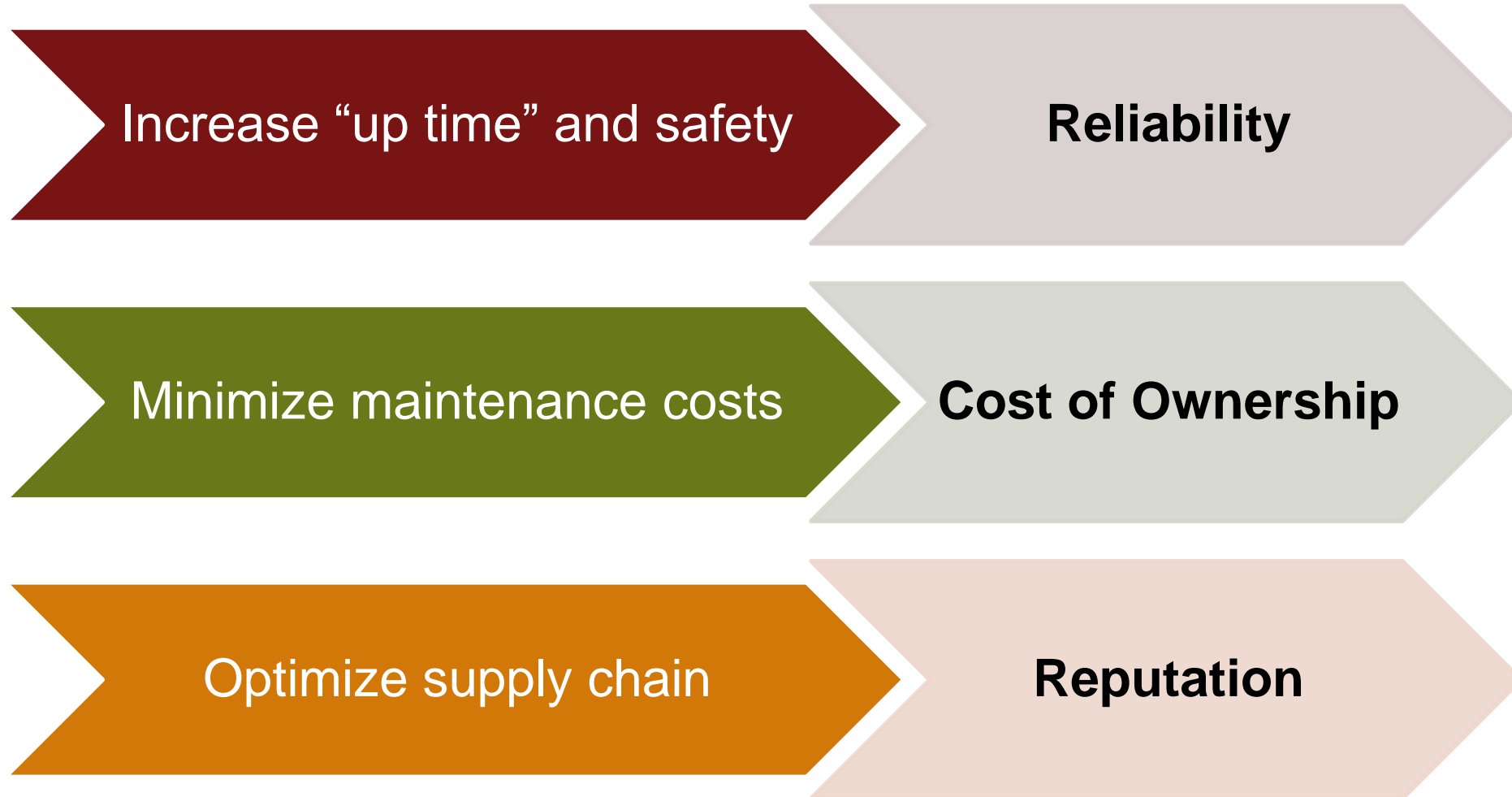
Types of Maintenance

- Reactive – Do maintenance once there's a problem
 - Example: replace car battery when it has a problem
 - Problem: unexpected failures can be expensive and potentially dangerous

- Scheduled – Do maintenance at a regular rate
 - Example: change car's oil every 5,000 miles
 - Problem: unnecessary maintenance can be wasteful; may not eliminate all failures

- Predictive – Forecast when problems will arise
 - Example: certain GM car models forecast problems with the battery, fuel pump, and starter motor
 - Problem: difficult to make accurate forecasts for complex equipment

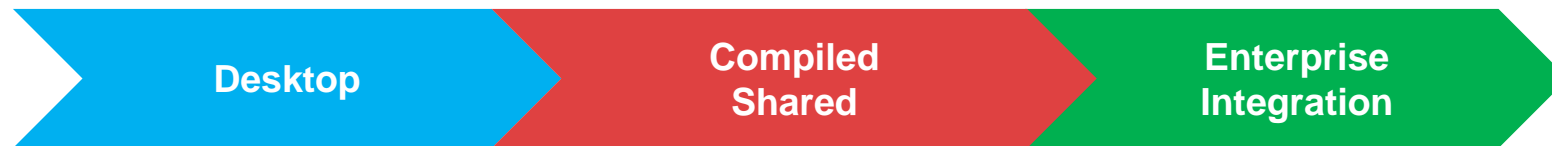
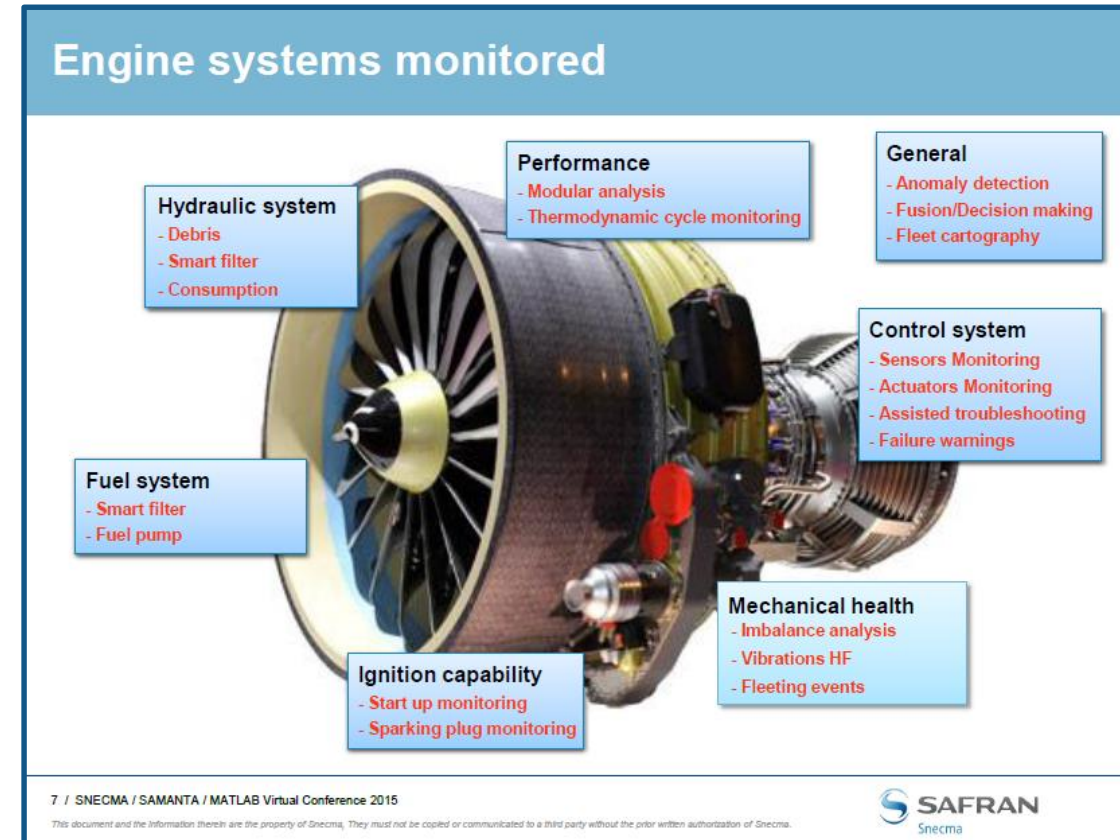
Benefits of Predictive Maintenance



What Does Success Look Like?

Safran Engine Health Monitoring Solution

- Monitor Systems
 - Detect failure indicators
 - Predict time to maintenance
 - Identify components
- Improve Aircraft Availability
 - On time departures and arrivals
 - Plan and optimize maintenance
 - Reduce engine out-of-service time
- Reduce Maintenance Costs
 - Troubleshooting assistance
 - Limit secondary damage



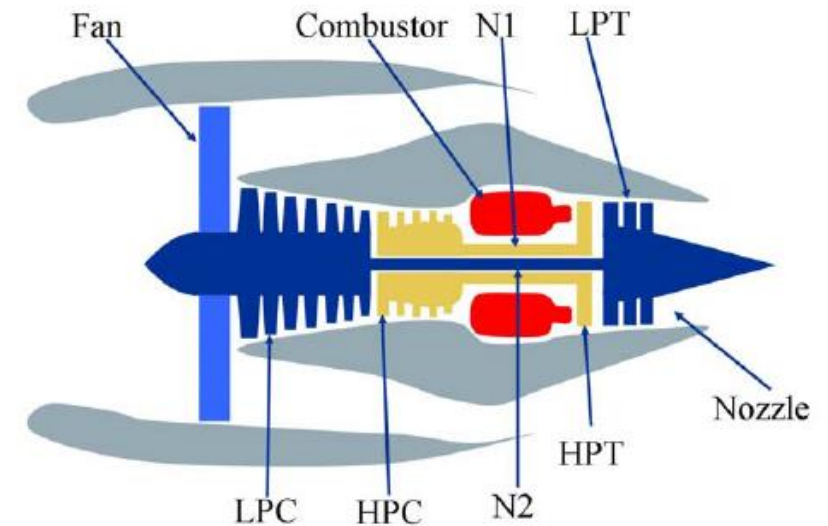
- Ad-hoc data analysis
- Suite of MATLAB Analytics
- Analytics to predict failure
- Shared with other teams
- Proof of readiness
- Real-time analytics
- Integrated with maintenance and service systems

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/>

Predictive Maintenance of Turbofan Engine

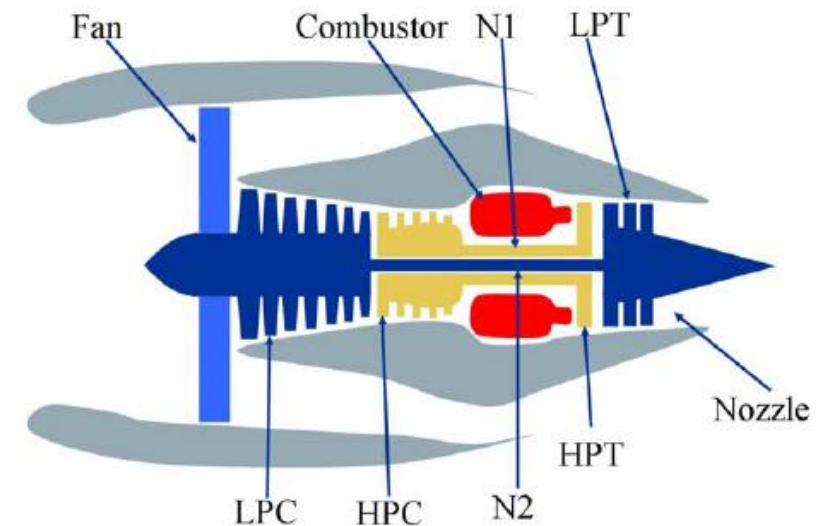
Sensor data from 100 engines of the same model

Scenario 1: No data from failures

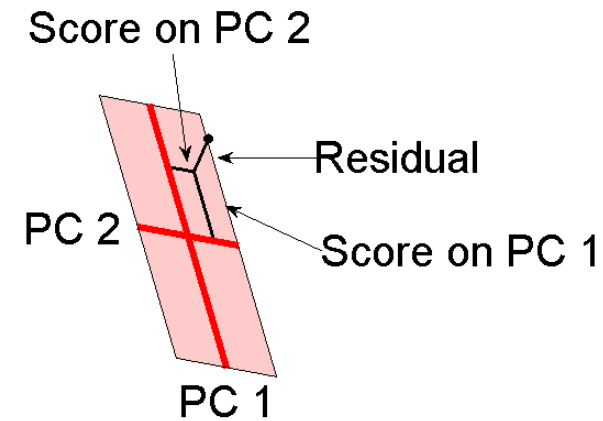
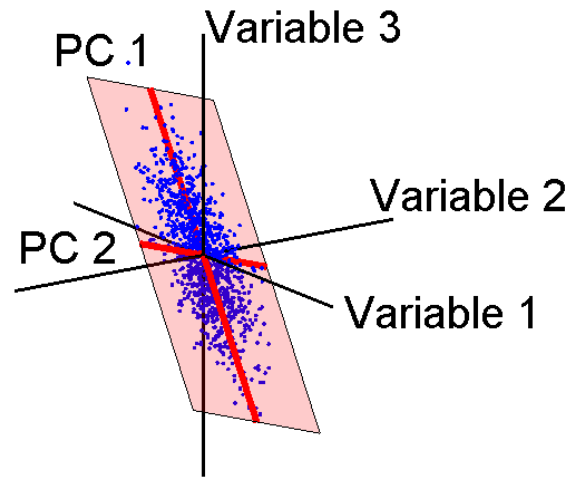
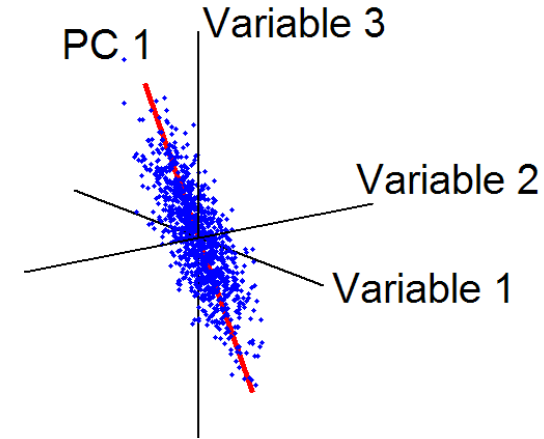
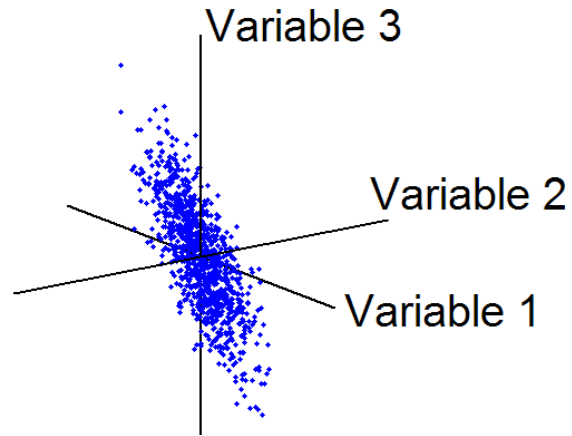
- Performing scheduled maintenance
- No failures have occurred
- Maintenance crews tell us most engines could run for longer
- Can we be smarter about how to schedule maintenance **without** knowing what failure looks like?

Data provided by NASA PCoE

<http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/>

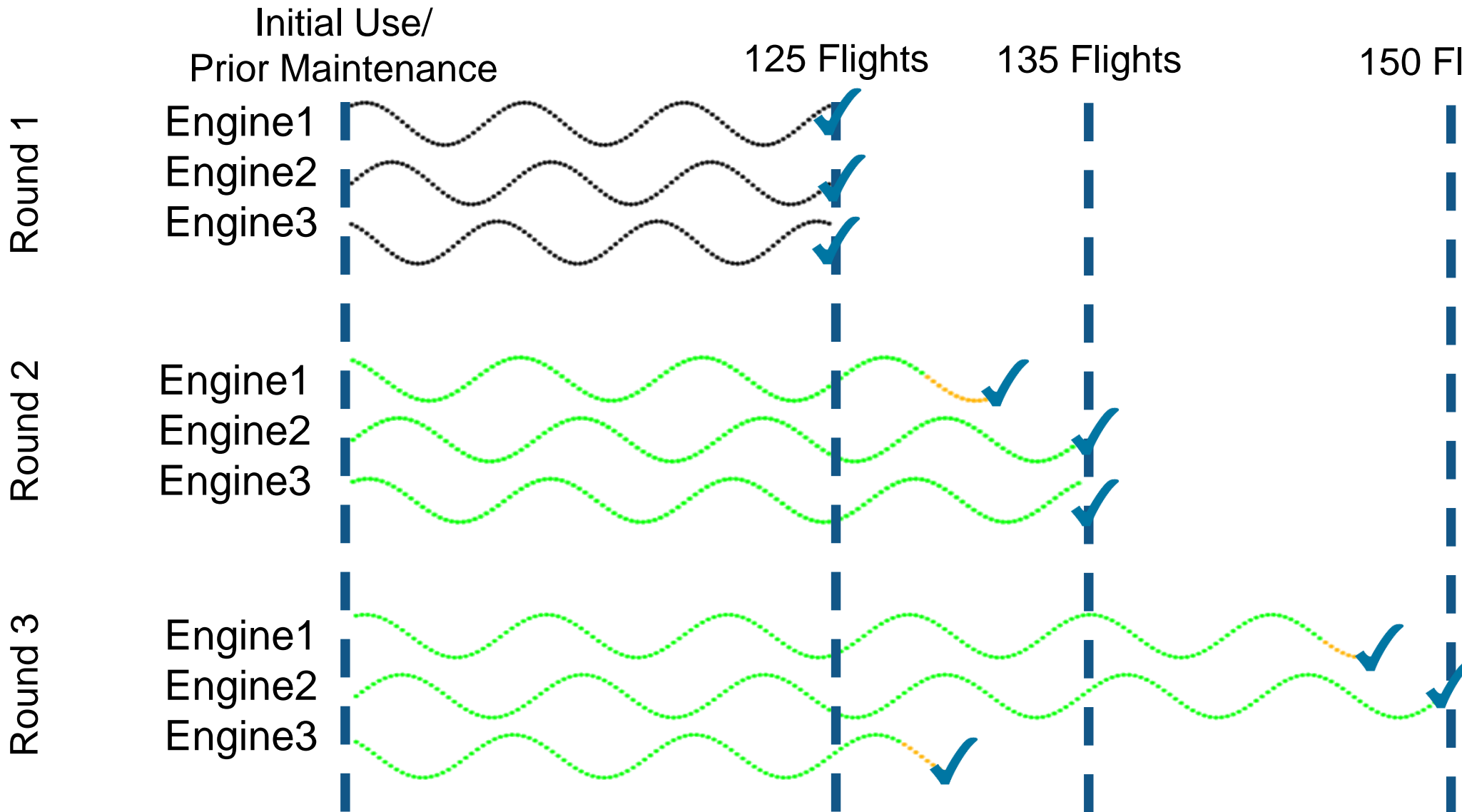


Principal Components Analysis – what is it doing?

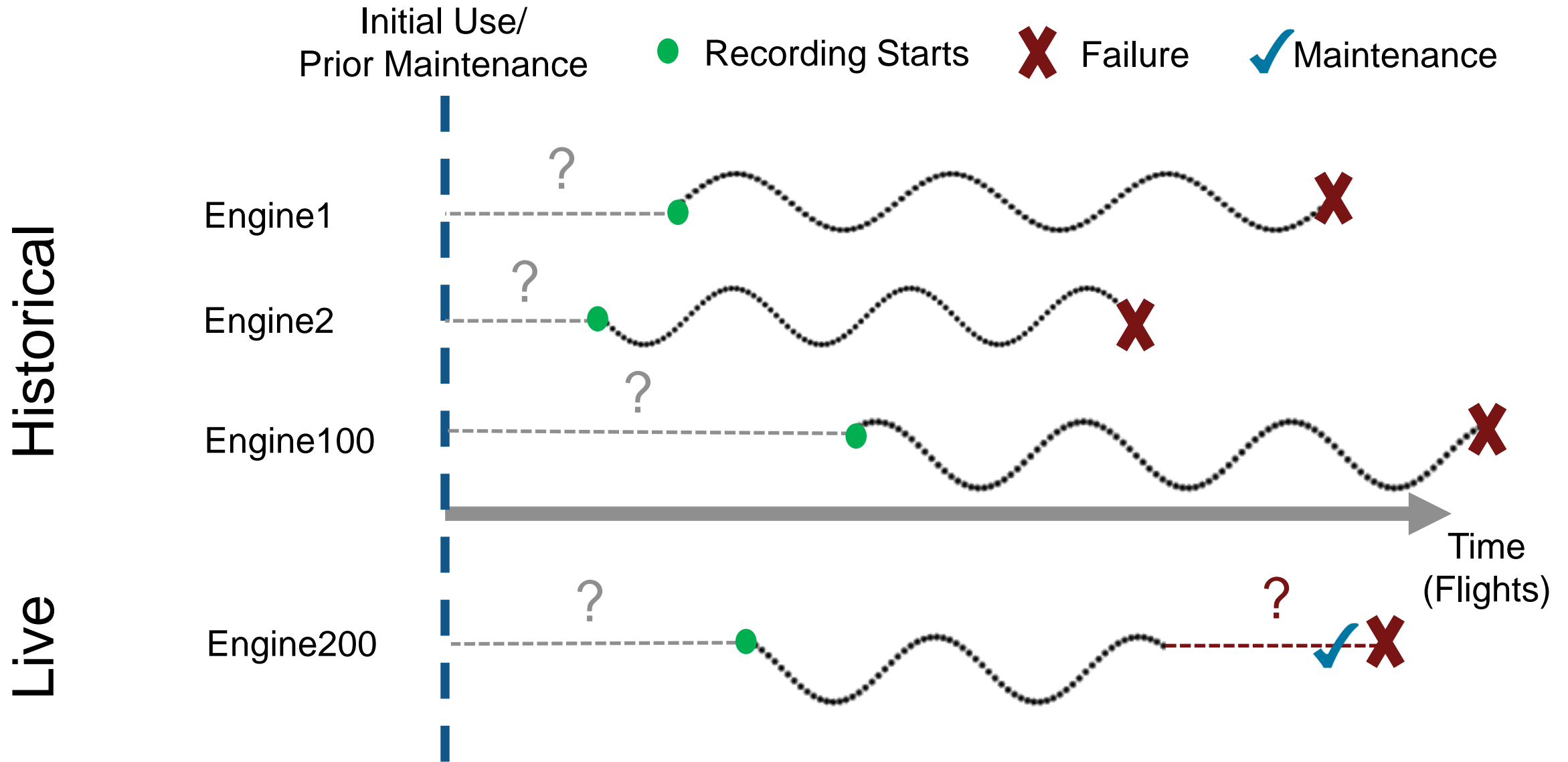


Example Unsupervised Implementation

✓ Maintenance



How Data was Recorded

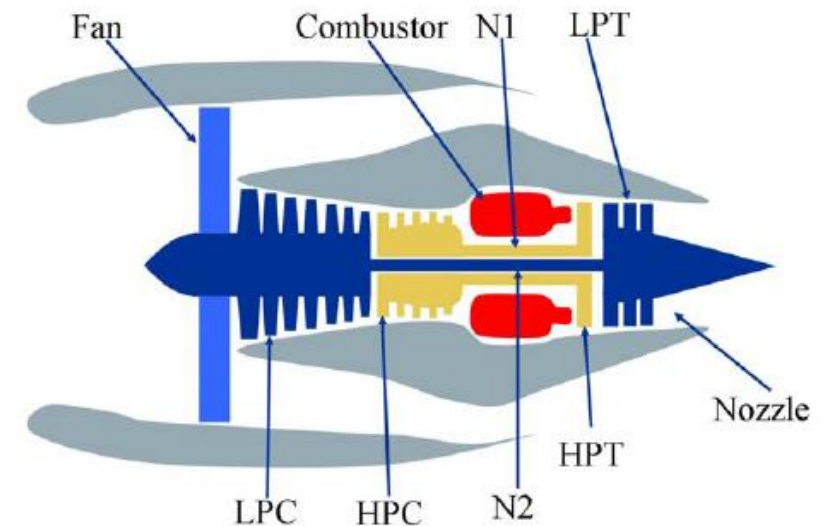


Predictive Maintenance of Turbofan Engine

Sensor data from 100 engines of the same model

Scenario 2: Have failure data

- Performing scheduled maintenance
- Failures still occurring (maybe by design)
- Search records for when failures occurred and gather data preceding the failure events
- Can we predict how long until failures will occur?

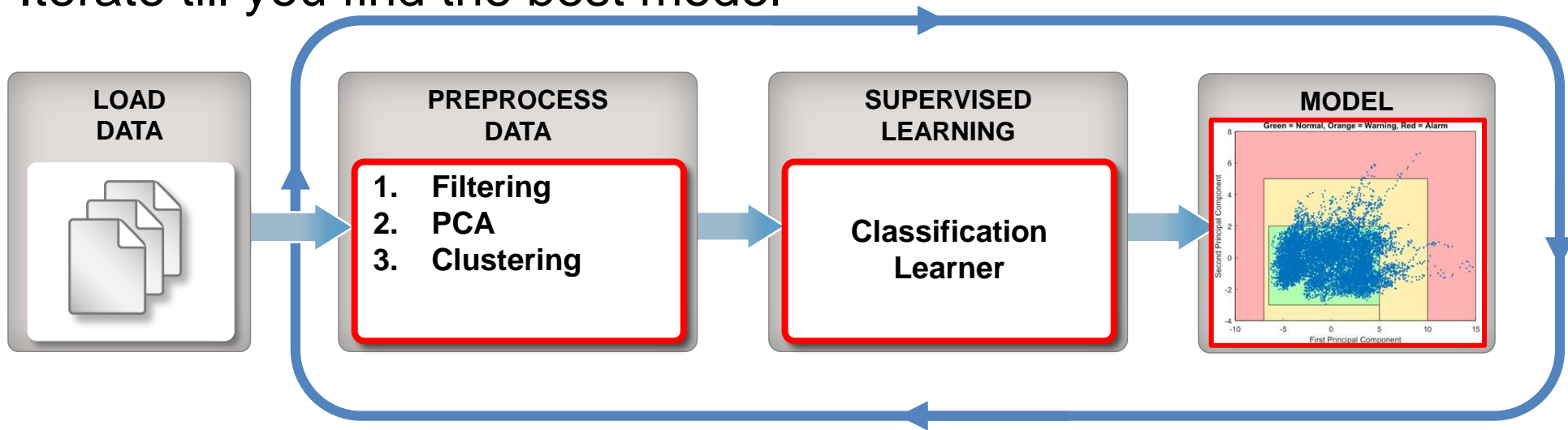


Data provided by NASA PCoE

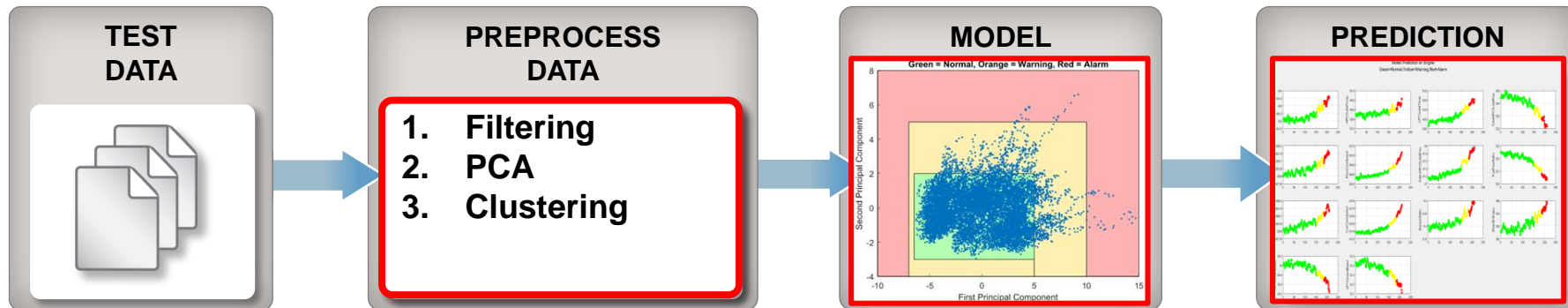
<http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/>

Machine Learning Workflo

Train: Iterate till you find the best model



Predict: Integrate trained models into applications

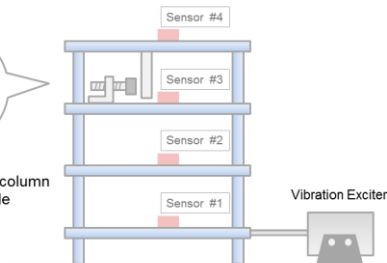


SHMTools

Los Alamos National Laboratory



Gap between center column and bumper is tunable



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SHMTools and mFUSE Beta Users


SHMTools and mFUSE are currently in a beta development stage. While all efforts have been made to ensure stability, from time to time new bugs may be found. We encourage users to submit reports of any bugs found or suggestions for future versions using the Beta Testing Report form in the link to the right. While we are unable to provide technical support on an individual basis, we appreciate feedback from users to allow us to improve on future versions of the software.

SHMTools Software

- [Getting Started with SHMTools \(pdf\)](#)
- [mFUSE Help Manual \(pdf\)](#)
- [Download SHMTools and mFUSE Beta Versions](#)
- [Beta Testing Report](#)

<http://www.lanl.gov/projects/national-security-education-center/engineering/software/shm-data-sets-and-software.php>

MATLAB Strengths for Machine Learning

Challenge	Solution
Data diversity	Extensive data support Import and work with signal, images, financial, Textual, geospatial, and several others formats
Lack of domain tools	High-quality libraries Industry-standard algorithms for Finance, Statistics, Signal, Image processing & more
Time consuming	Interactive, app-driven workflows Focus on machine learning, not programming
Avoid pitfalls Over Fitting, Speed-Accuracy-Complexity	Integrated best practices Model validation tools built into app Rich documentation with step by step guidance
	Flexible architecture for customized workflows Complete machine learning platform

Deep Learning is Ubiquitous

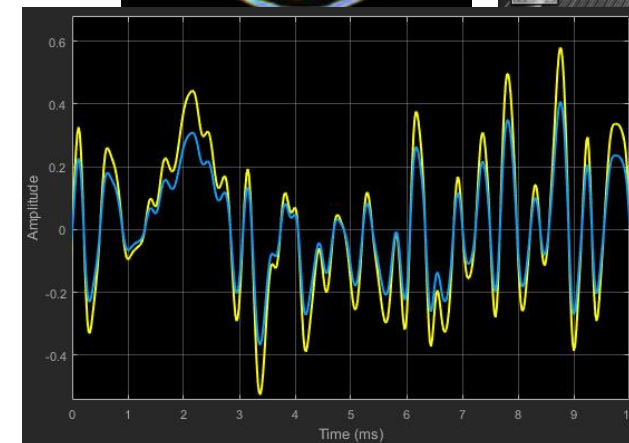
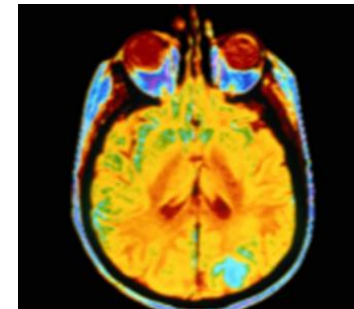
Computer Vision

- Pedestrian and traffic sign detection
- Landmark identification
- Scene recognition
- Medical diagnosis and drug discovery

Text and Signal Processing

- Speech Recognition
- Speech & Text Translation

Robotics & Controls



and many more...

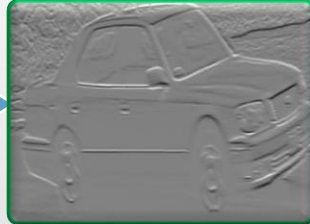
What is Deep Learning ?

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

Traditional Machine Learning



Manual Feature Extraction



Classification

Machine Learning

Car ✓

Truck ✗

⋮

Bicycle ✗

Deep Learning approach



Convolutional Neural Network (CNN)

End-to-end learning

Feature learning + Classification

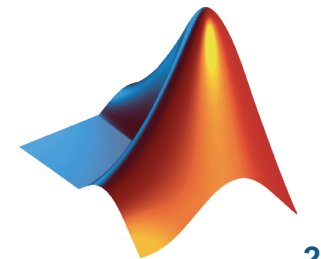
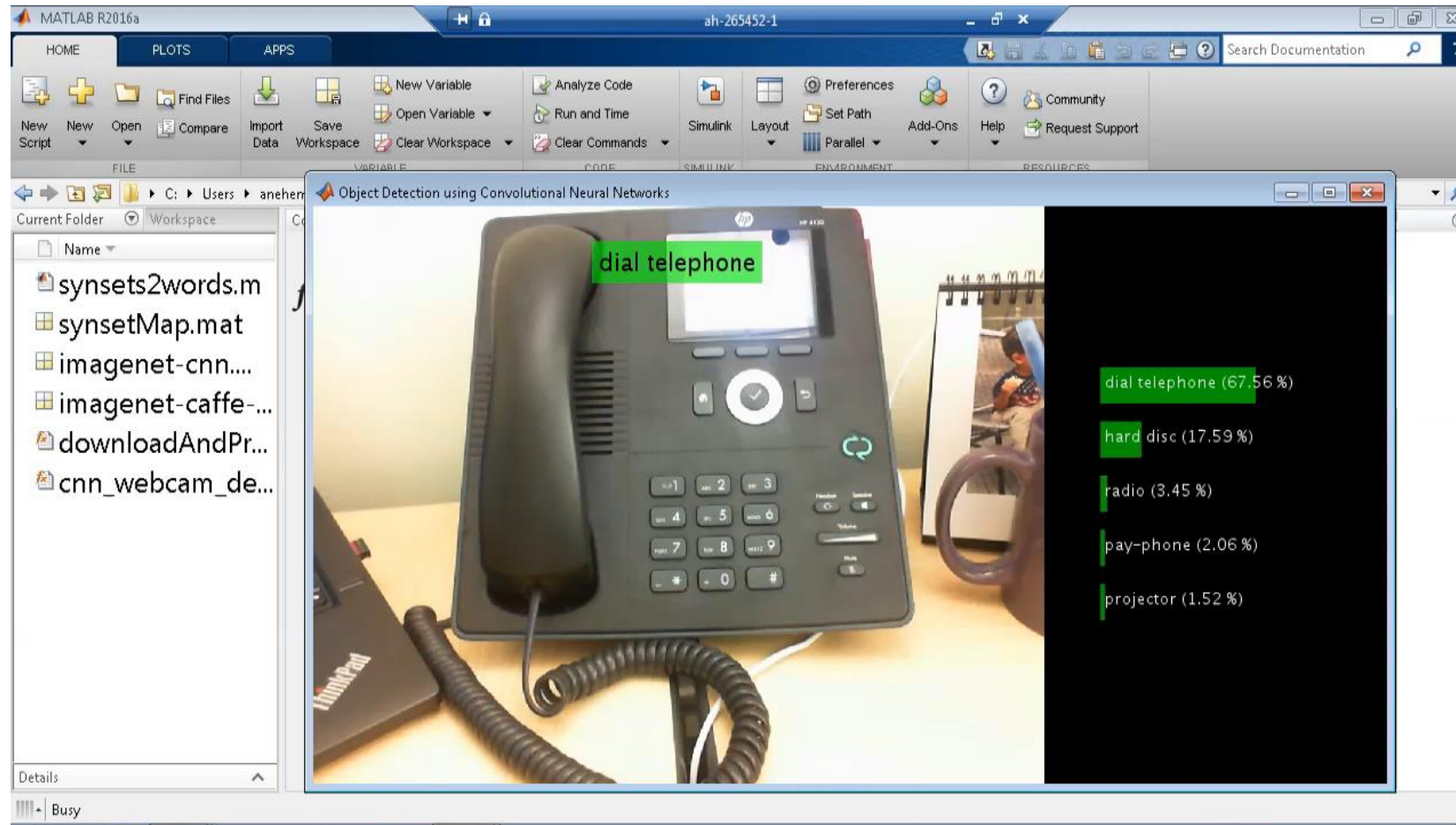
Car ✓

Truck ✗

⋮

Bicycle ✗

Demo : Live Object Recognition with Webcam



Why is Deep Learning so Popular ?

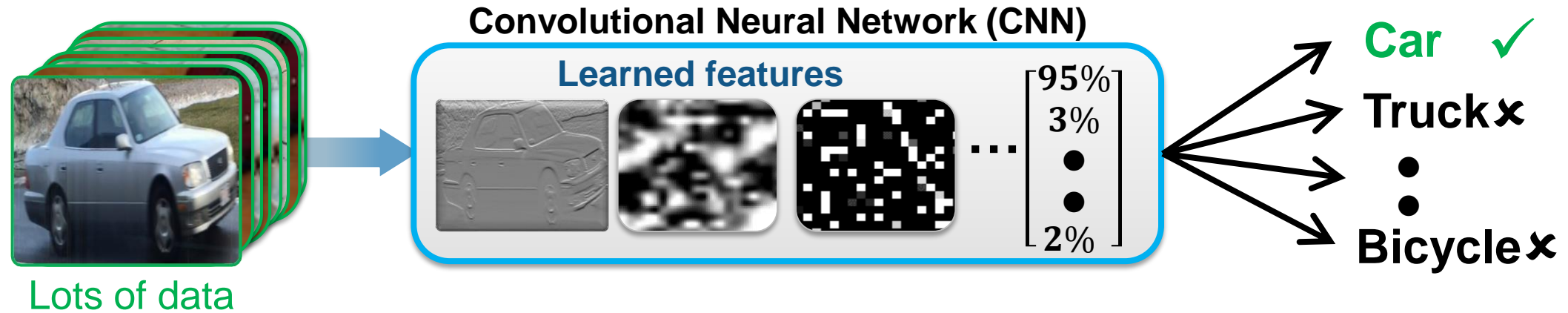
- **Results:** Achieved substantially better results on ImageNet large scale recognition challenge
 - 95% + accuracy on ImageNet 1000 class challenge
- **Computing Power:** GPU's and advances to processor technologies have enabled us to train networks on massive sets of data.
- **Data:** Availability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

Year	Error Rate
Pre-2012 (traditional computer vision and machine learning techniques)	> 25%
2012 (Deep Learning)	~ 15%
2015 (Deep Learning)	<5 %

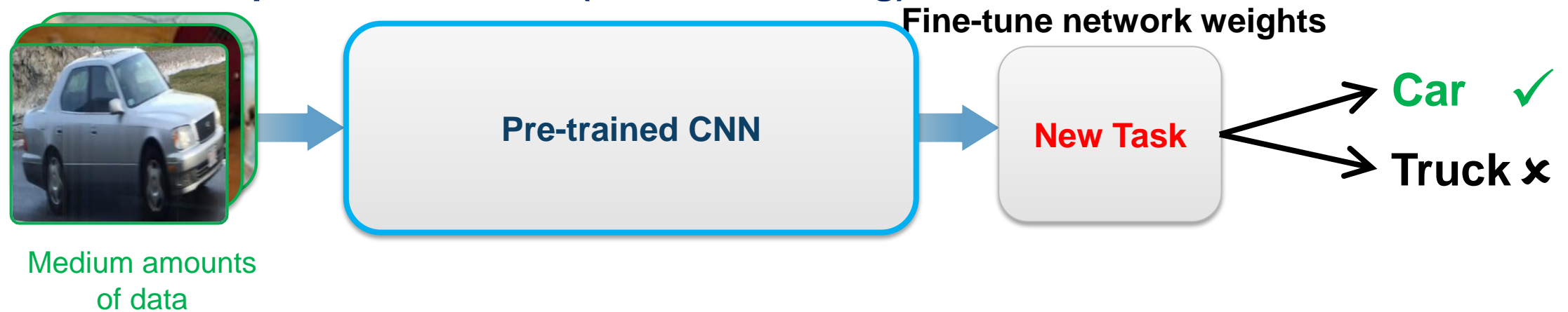


Two Approaches for Deep Learning

1. Train a Deep Neural Network from Scratch

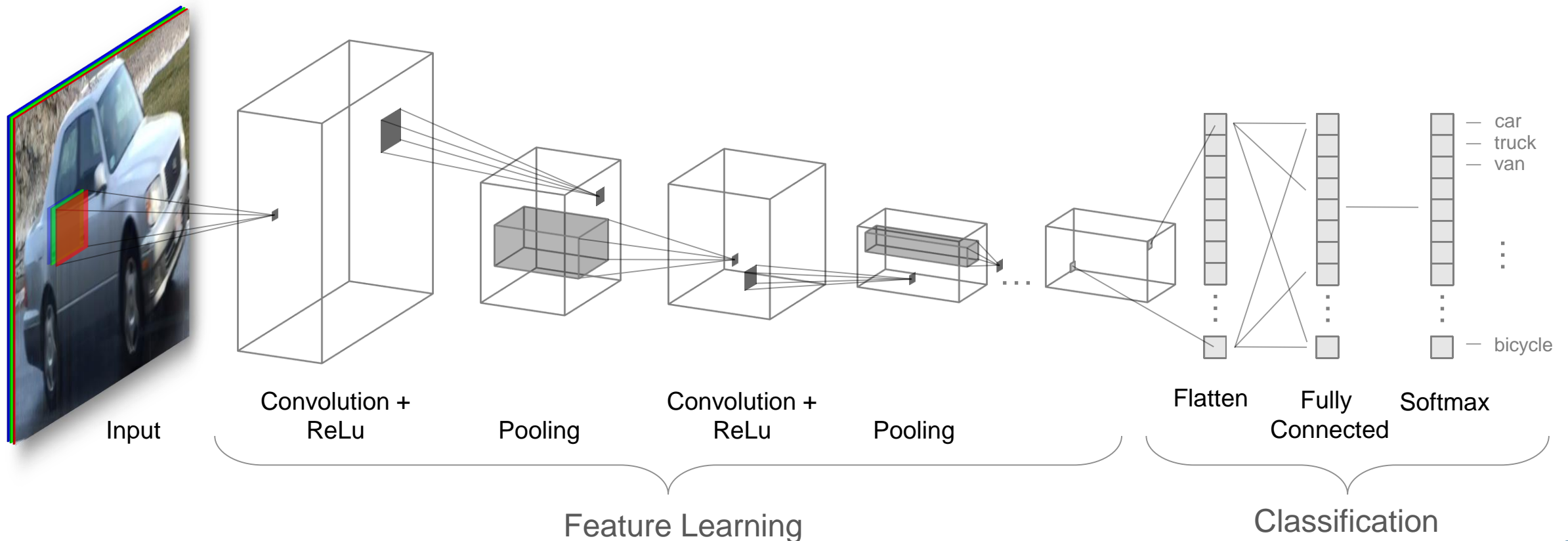


2. Fine-tune a pre-trained model (transfer learning)



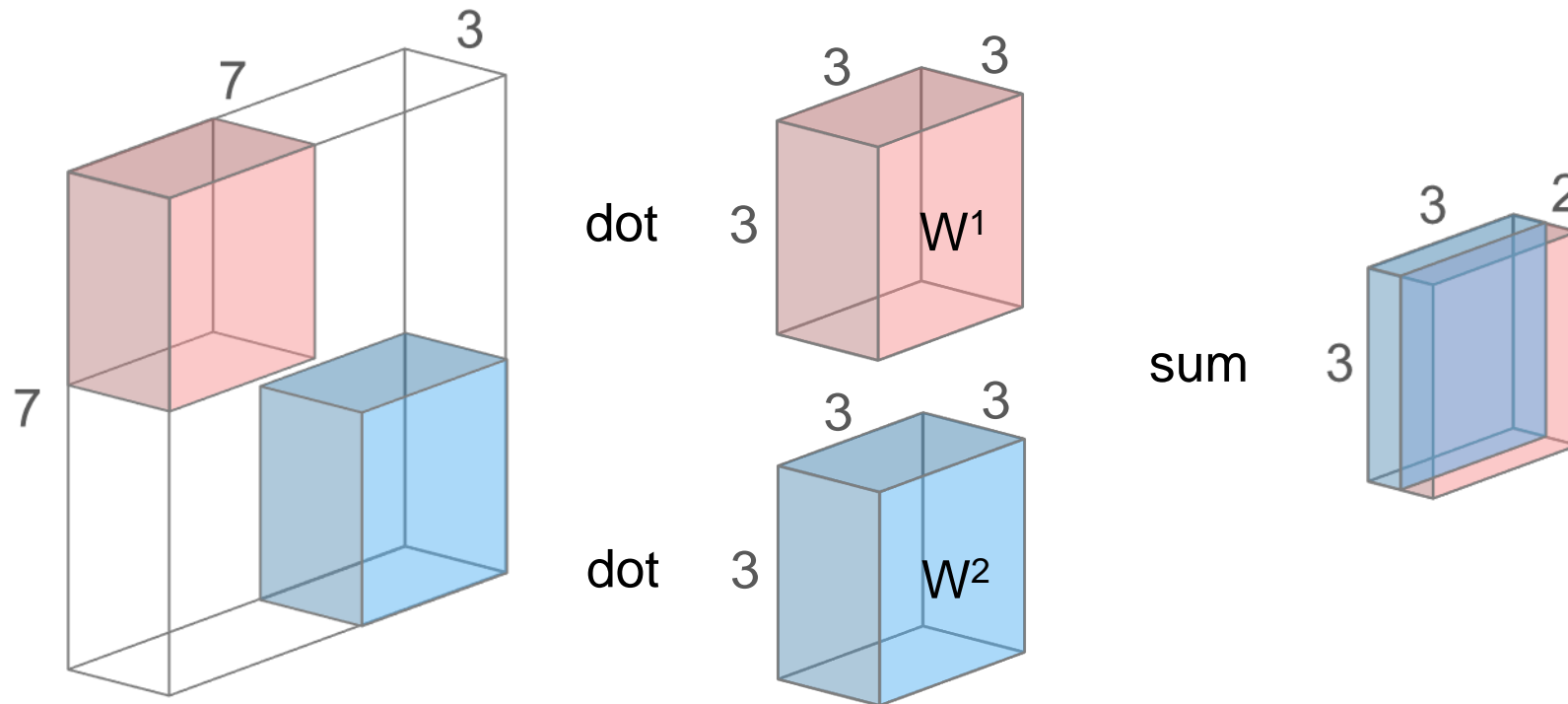
Convolutional Neural Networks

- Train “deep” neural networks on structured data (e.g. images, signals, text)
- Implements Feature Learning: Eliminates need for “hand crafted” features
- Trained using GPUs for performance



Convolution Layer

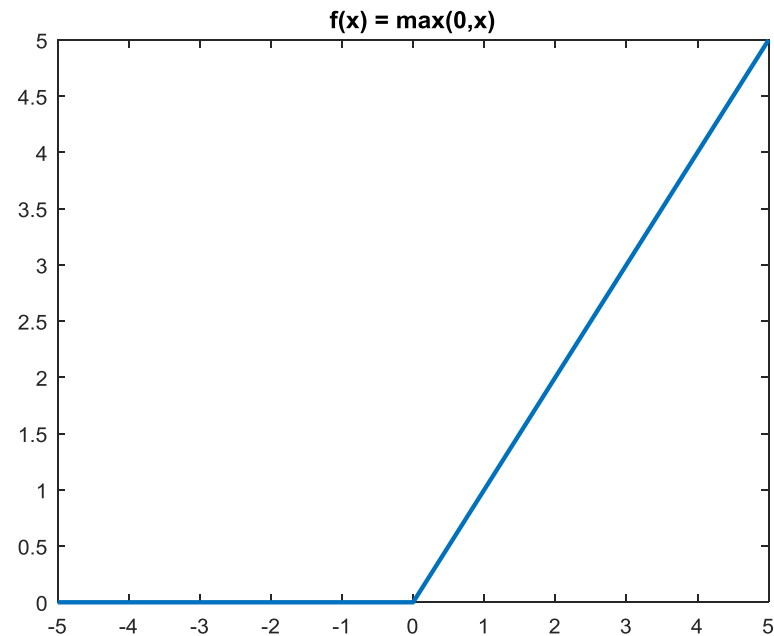
- Core building block of a CNN
- Convolve the filters sliding them across the input, computing the dot product



- Intuition: learn filters that activate when they “see” some specific feature

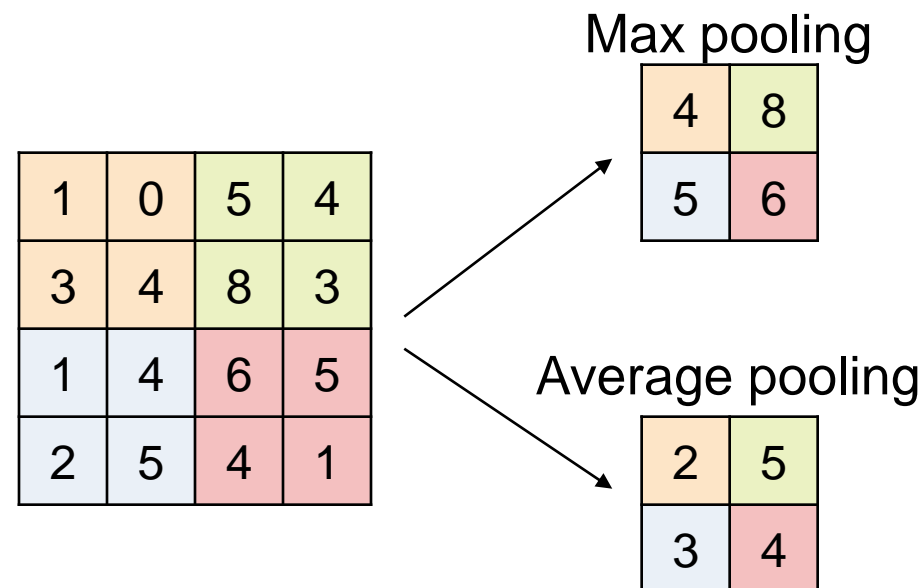
Rectified Linear Unit (ReLU) Layer

- Frequently used in combination with Convolution layers
- Do not add complexity to the network
- Most popular choice: $f(x) = \max(0, x)$, activation is thresholded at 0




Pooling Layer

- Perform a **downsampling** operation across the spatial dimensions
- Goal: progressively decrease the size of the layers
- Max pooling and average pooling methods
- Popular choice: Max pooling with 2x2 filters, Stride = 2

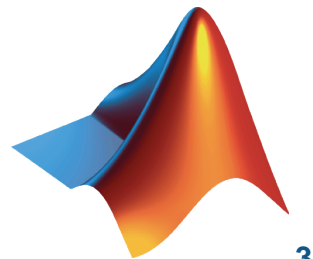


Challenges using Deep Learning for Computer Vision

Steps	Challenge
Importing Data	Managing large sets of labeled images
Preprocessing	Resizing, Data augmentation
Choosing an architecture	Background in neural networks (deep learning)
Training and Classification	Computation intensive task (requires GPU)
Iterative design	

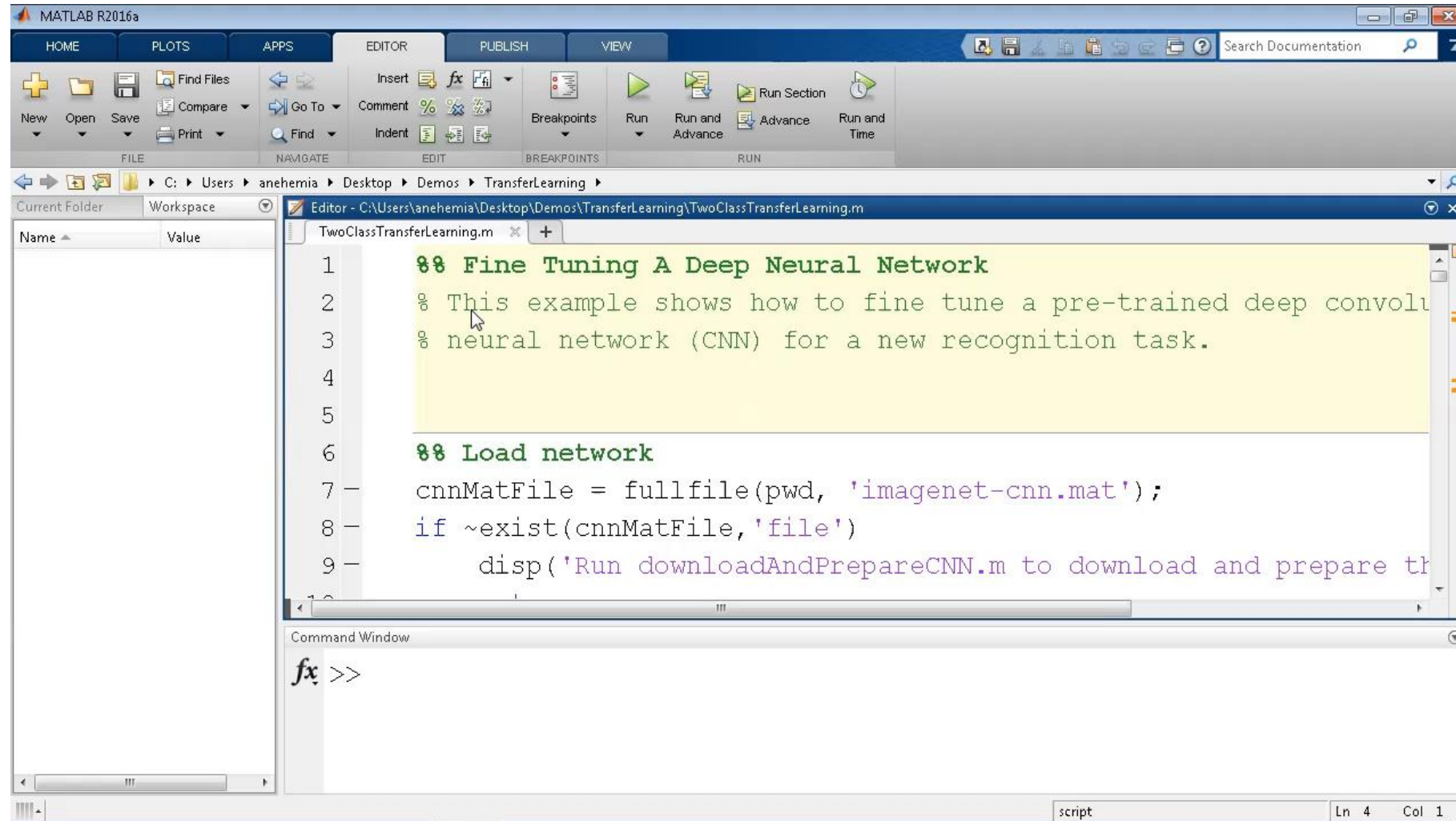
Demo

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



Demo

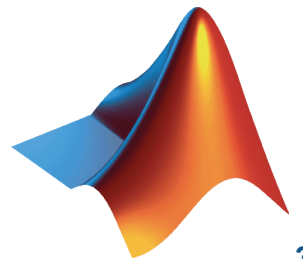
Fine-tune a pre-trained model (transfer learning)





The image shows the MATLAB R2016a software interface. The main window displays a script titled 'TwoClassTransferLearning.m' with the following code:

```
1  %% Fine Tuning A Deep Neural Network
2  % This example shows how to fine tune a pre-trained deep convolu
3  % neural network (CNN) for a new recognition task.
4
5
6  %% Load network
7  cnnMatFile = fullfile(pwd, 'imagenet-cnn.mat');
8  if ~exist(cnnMatFile, 'file')
9      disp('Run downloadAndPrepareCNN.m to download and prepare th
```

The Command Window at the bottom shows the prompt `fx >>`. The status bar at the bottom right indicates the current position is at line 4, column 1.



Addressing Challenges in Deep Learning for Computer Vision

Challenge	Solution
Managing large sets of labeled images	<code>imageSet</code> or <code>imageDataStore</code> to handle large sets of images 
Resizing, Data augmentation	<code>imresize</code> , <code>imcrop</code> , <code>imadjust</code> , <code>imageInputLayer</code> , etc.
Background in neural networks (deep learning)	Intuitive interfaces, well-documented architectures and examples
Computation intensive task (requires GPU)	Training supported on GPUs No GPU expertise is required
	Automate. Offload computations to a cluster and test multiple architectures

Key Takeaways

- MATLAB enables engineers and data scientists to quickly create, test and implement predictive maintenance programs
- Predictive maintenance
 - Saves money for equipment operators
 - Increases reliability and safety of equipment
 - Creates opportunities for new services that equipment manufacturers can provide
- Consider Deep Learning when:
 - Accuracy of traditional classifiers is not sufficient
 - *ImageNet classification problem*
 - You have a pre-trained network that can be fine-tuned
 - Too many image categories (100s – 1000s or more)
 - *Face recognition*

