MATLAB을 활용한 컴퓨터 비전 (3차원 비전 및 기계학습)

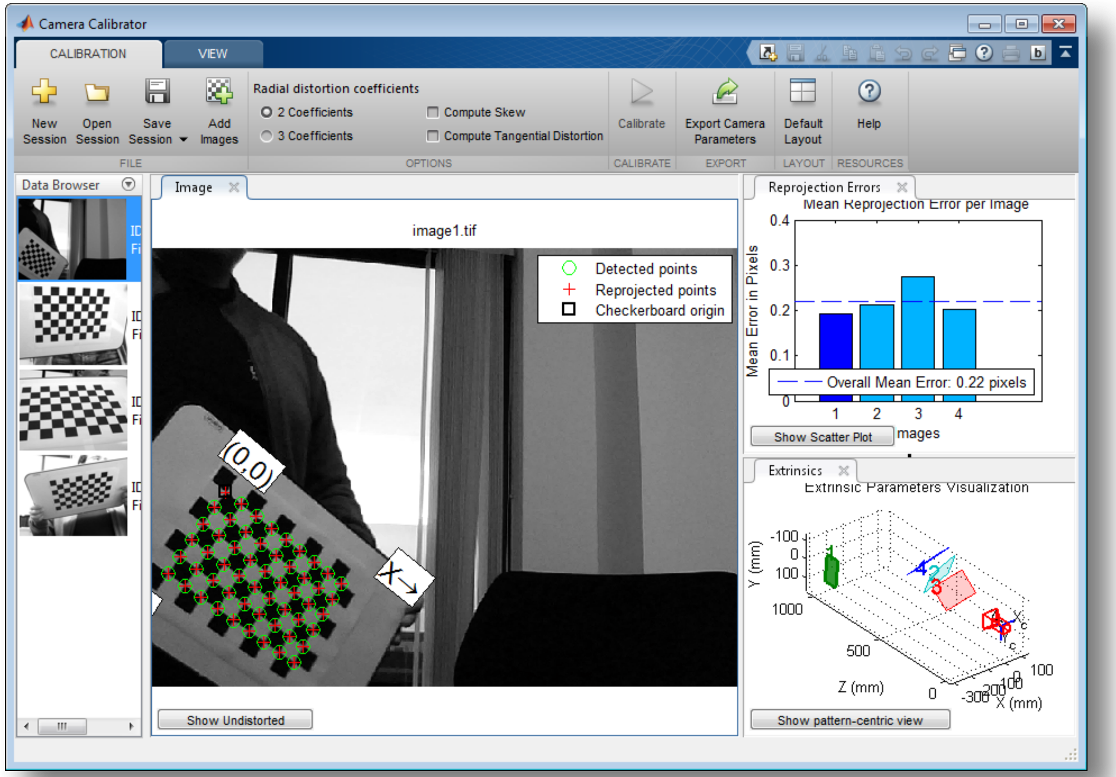
Application Engineer
Caleb Kim

Contents

- Stereo and 3D Vision
- Machine Learning
- Deep Learning

Camera Calibration App

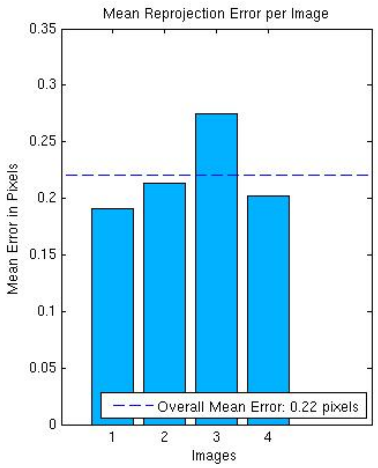
- Simplified workflow for estimating camera intrinsic and extrinsic parameters
- Removes the effects of lens distortion from an image
- Automatically detects checkerboard patterns

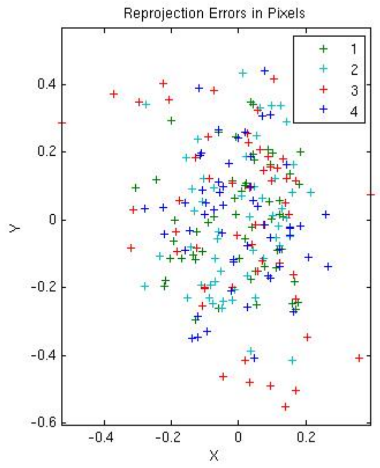


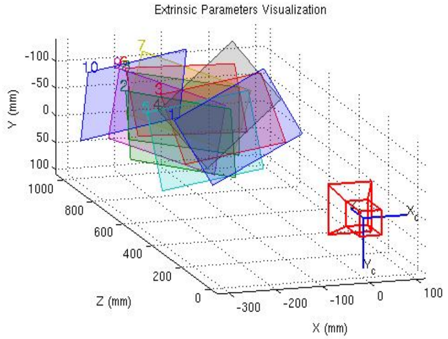
Evaluate Calibration Accuracy

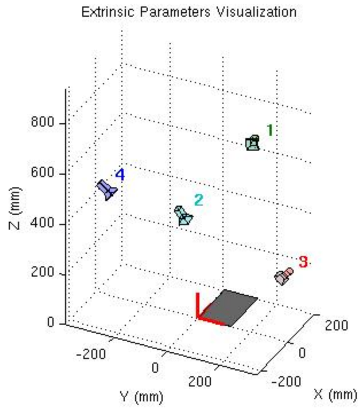
Determine the accuracy of estimated camera parameters

- Plot re-projection errors as a bar graph or as a scatter plot
- Visualize the 3-D locations of the calibration patterns relative to the camera, or the cameras relative to the pattern.







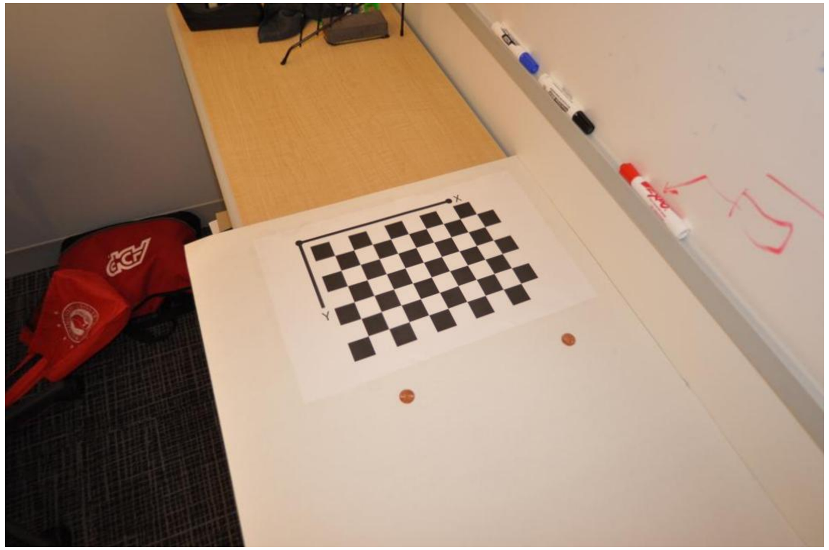



```
» showReprojectionErrors(cameraParameters)
» showExtrinsics(cameraParameters)
```

Remove Lens Distortion From an Image

Removes radial and tangential distortion.

- Radial distortion (“barrel” or “pincushion”) is caused by the curvature of the lens
- Tangential distortion is caused by misalignment between the lens and the sensor



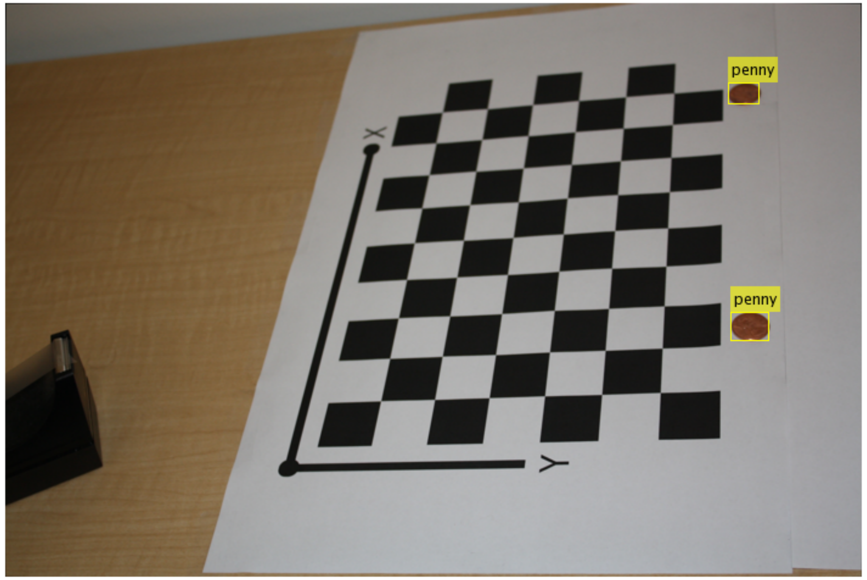
```
» J = undistortImage(I, cameraParameters)
```

Measuring Planar Objects With a Calibrated Camera

Featured example: measure the diameter of a penny in millimeters.

- Undistort the image
- Detect the penny
- Project points from the image into the world
- Measure the diameter in millimeters

Detected Coins

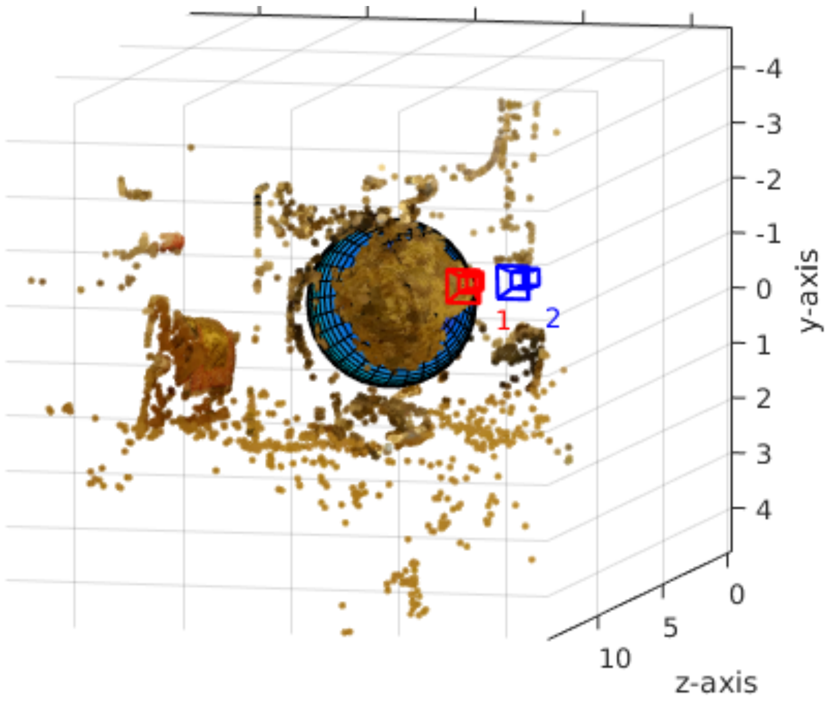


» `MeasuringPlanarObjectsExample`

Structure From Motion

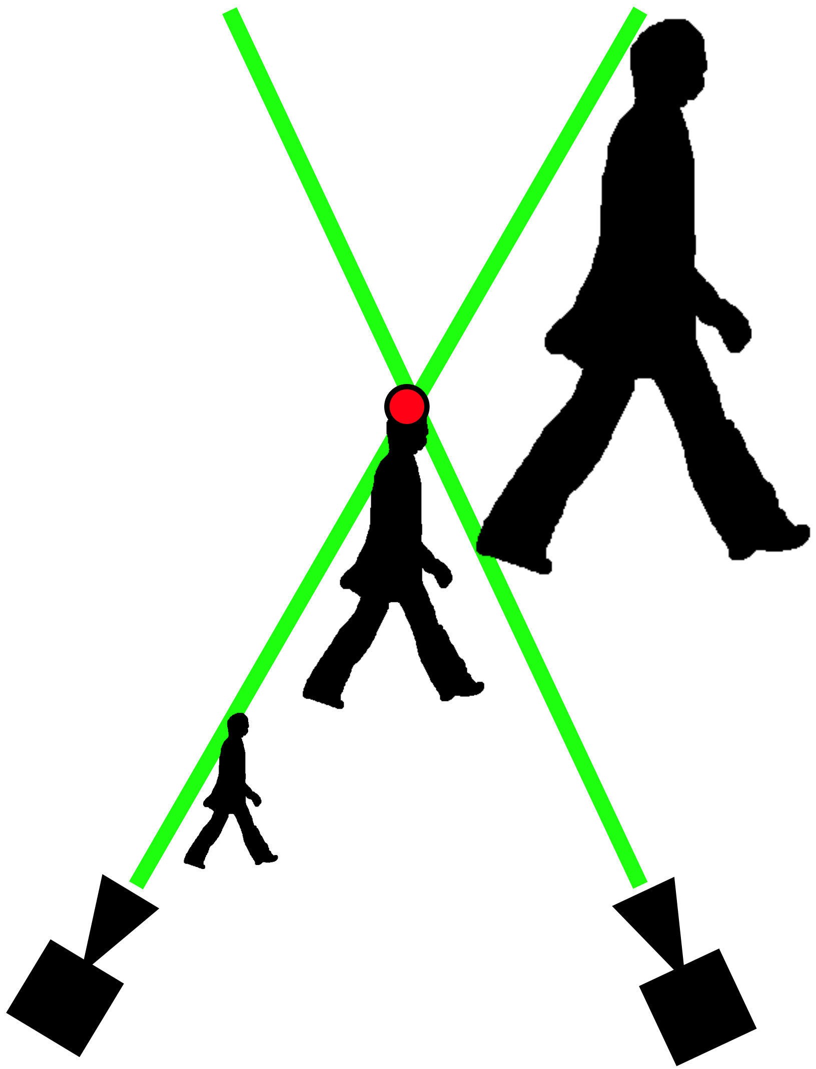
Estimating 3-D structure of a scene from a set of 2D-images

- Match a set of points between the two images
- Estimate the fundamental Matrix
- Compute the motion of camera
- 3D reconstruction
- Detect an Object

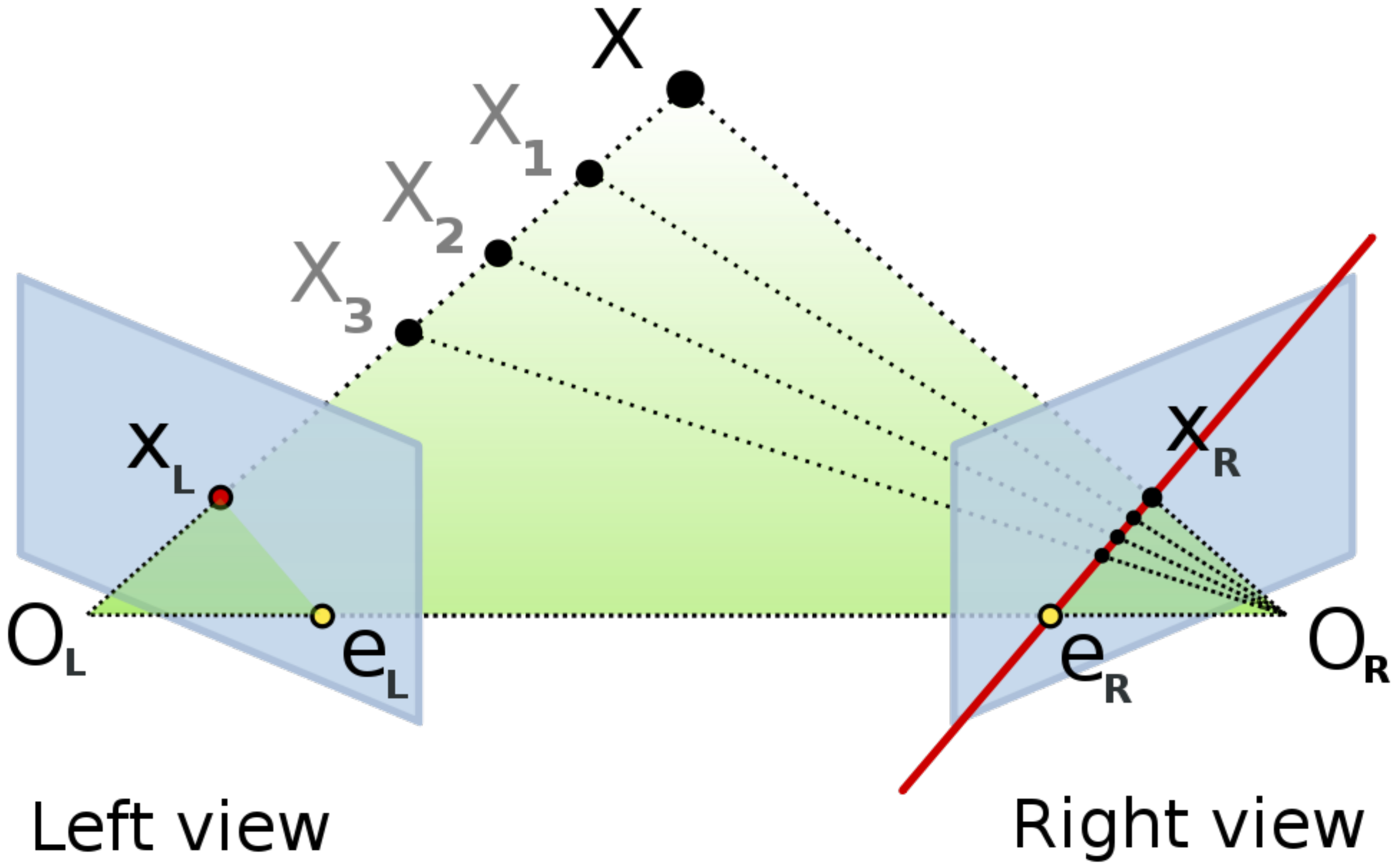


» StructureFromMotionExample.m

Recovering Scene Depth with Stereo Cameras

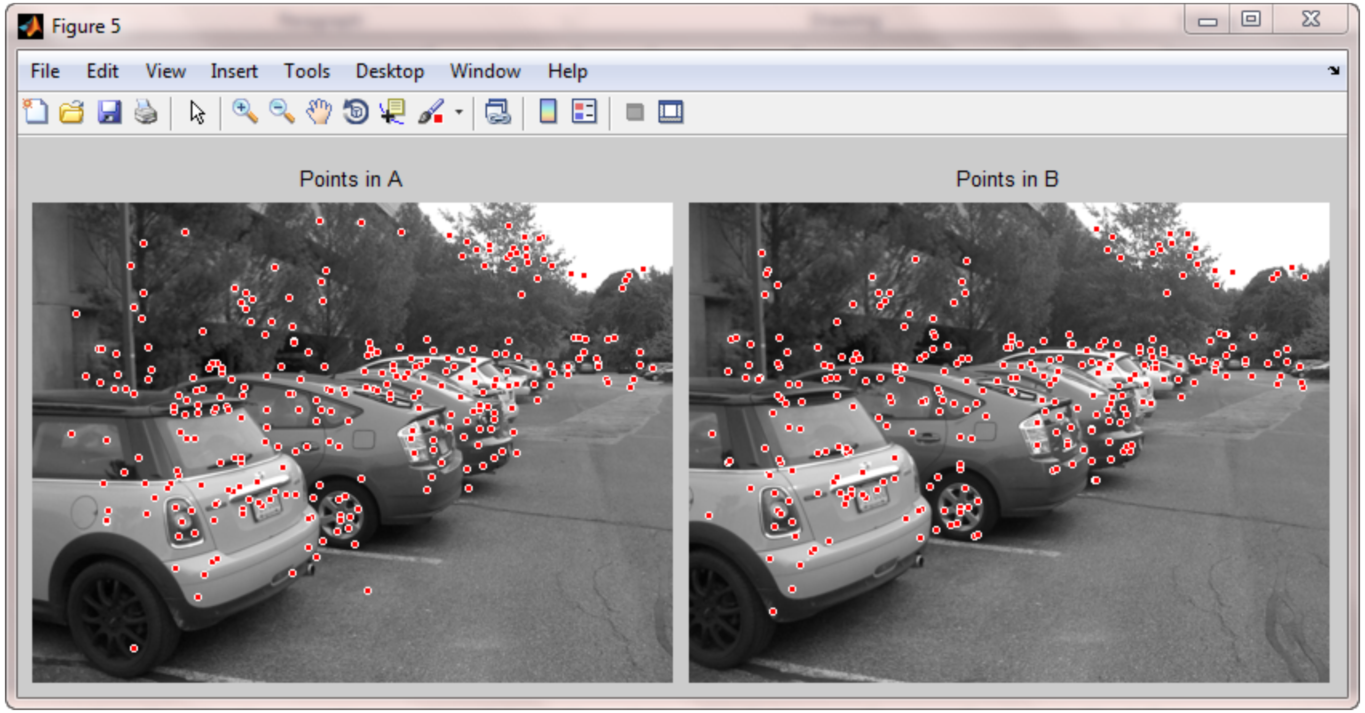


Epipolar Geometry

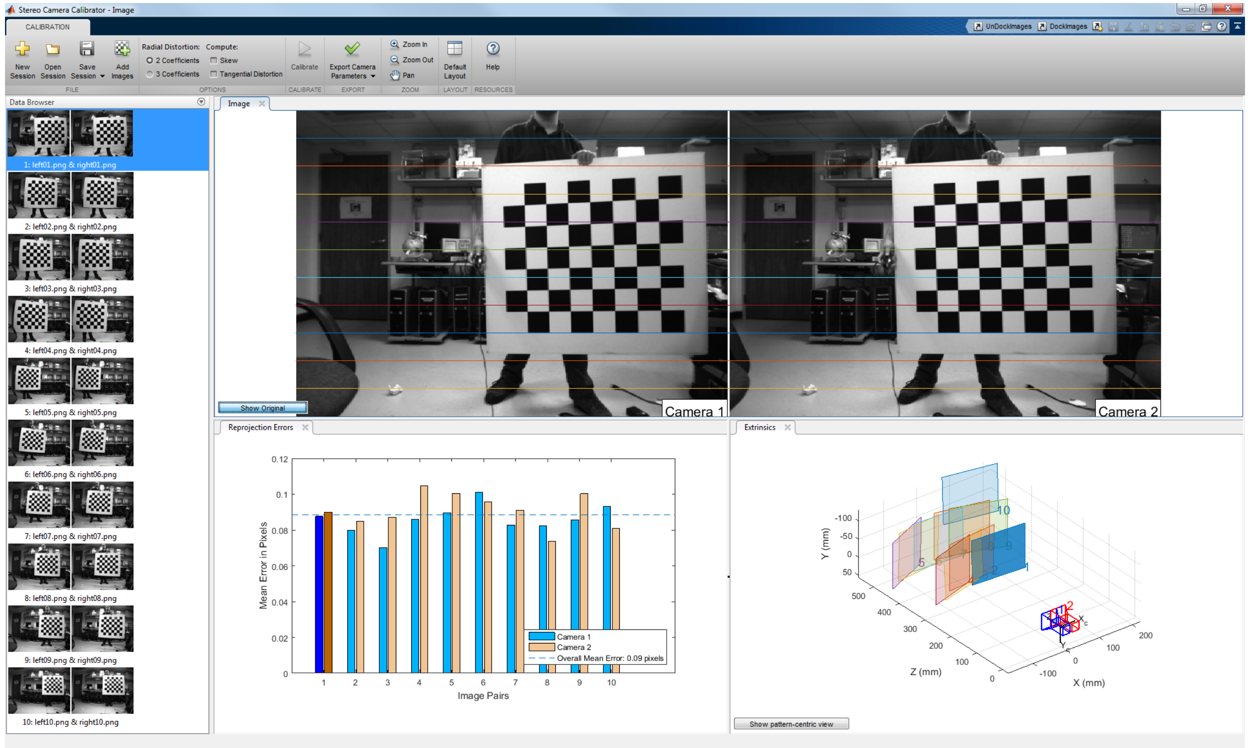


Fundamental Matrix   Demo

$$X_L^T F X_R = 0$$

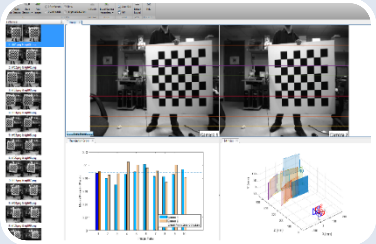


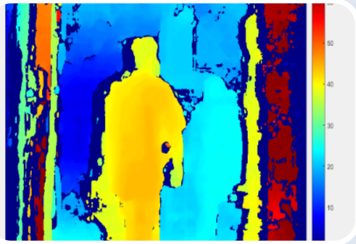
Stereo Camera Calibration

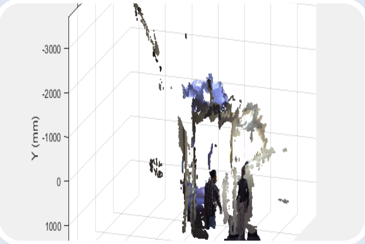


- Simplifies and automates calibration process

Stereo Vision Workflow







Calibration

- App (14b)

Rectification

-Codegen (15a)

Disparity Estimation

-Block matching, semi-global matching (14b)

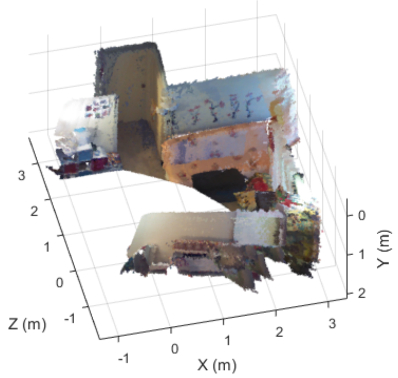
-Codegen (14b)

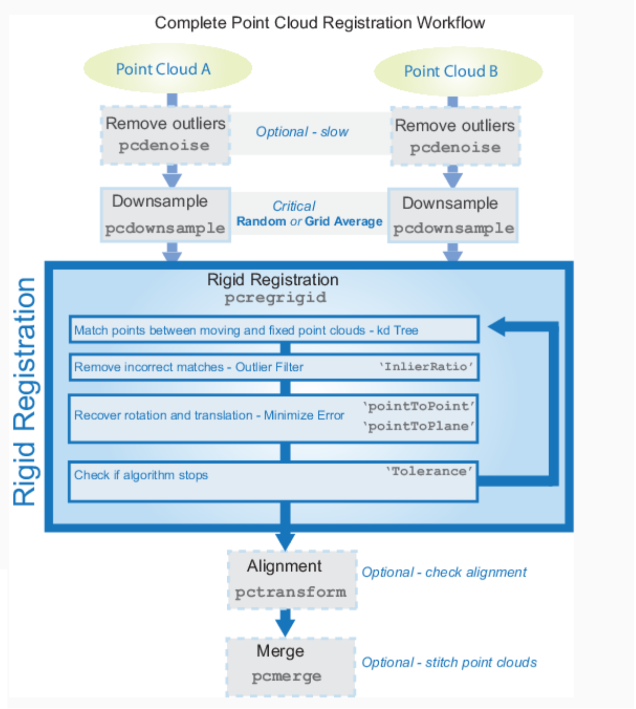
3-D Reconstruction

-Codegen (15a)

Point Cloud Registration

- Rigid registration
  - *pcregrigid*: Fundamental operation across point cloud applications
  - 'Iterative Closest Point' Algorithm
  - Comparable to state-of-the-art c++ package on academic benchmarks
  - *3-D Point Cloud Registration and Stitching* Featured Example

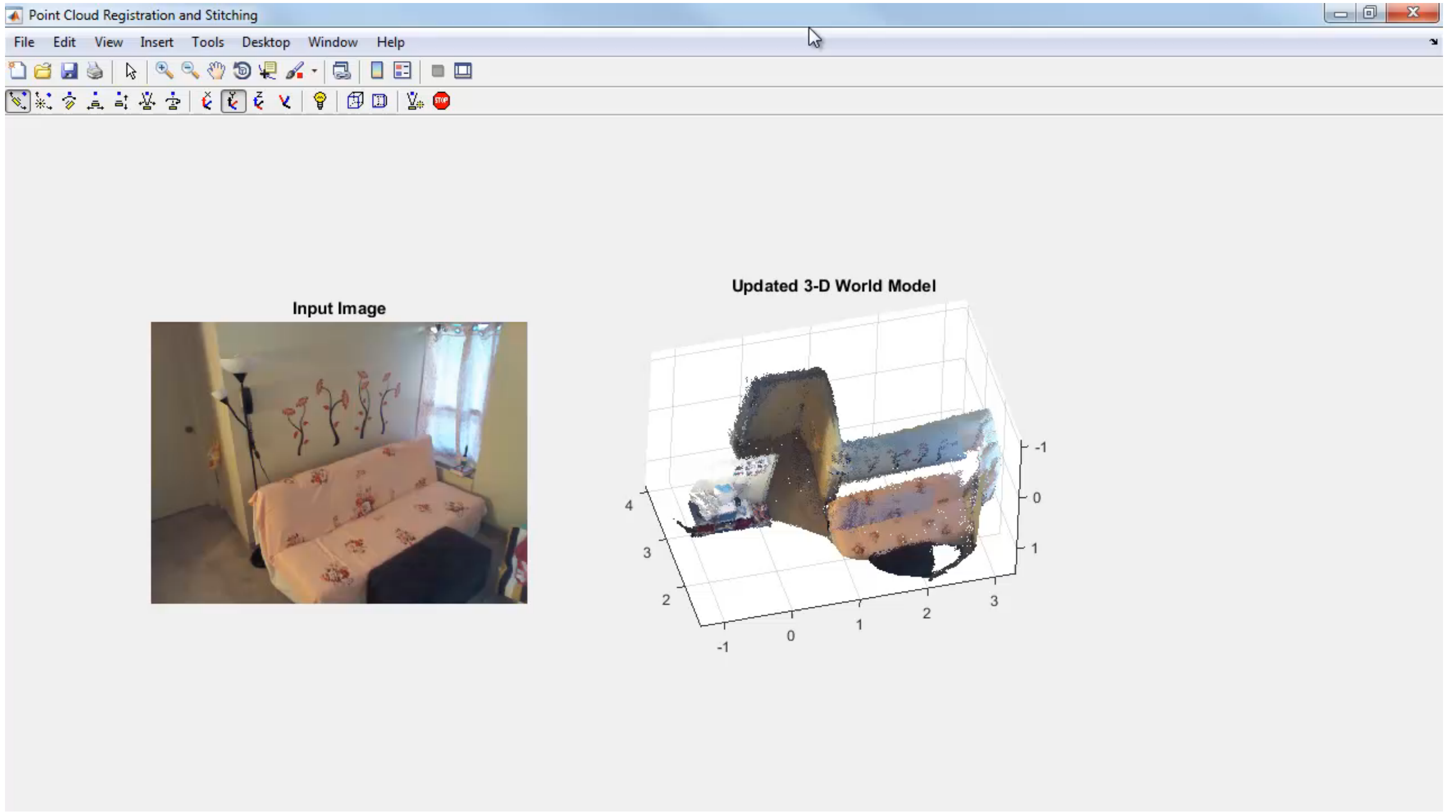




Demo

Point Cloud Processing

R2015a



- 3-D point cloud processing
  - File I/O , Viewers
  - Registration, denoising, downsampling, geometric transformation

Point Cloud Application – Robot Vision

- Robot Navigation



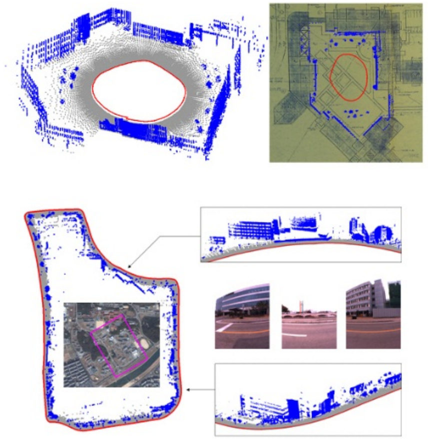
- Robot Perception



Point Cloud Application – Advanced Driver Assistance Systems (ADAS)

- Collision Detection

- Visual SLAM (Simultaneous localization and mapping) / Visual Odometry



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Today's Objectives

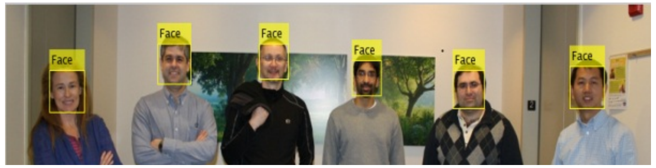
Use examples to solve real-world problems to:

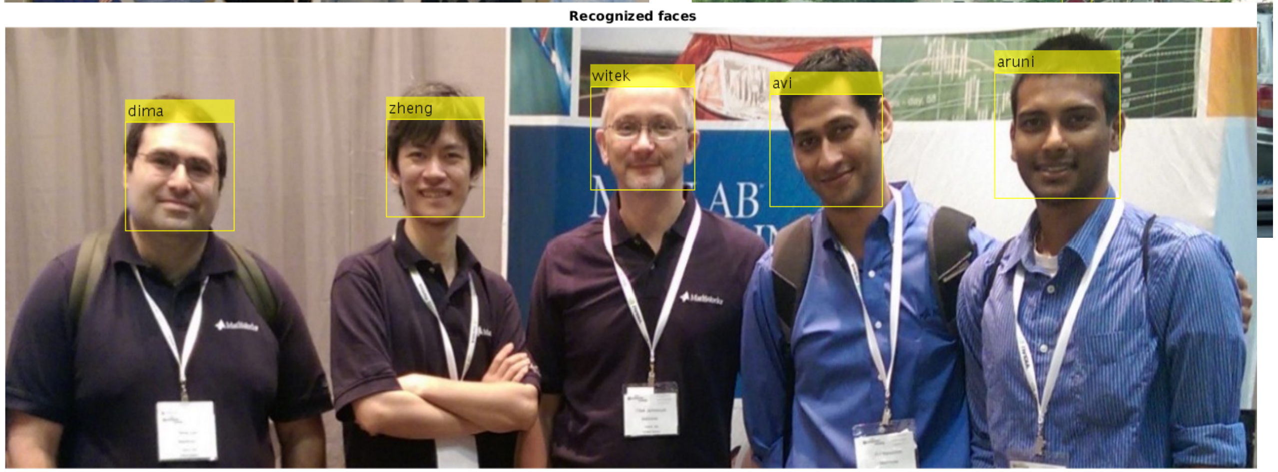
- See how MATLAB *simplifies the machine learning workflow*
- Quickly go from idea to prototype
- What's new for machine learning, deep learning, image processing and computer vision

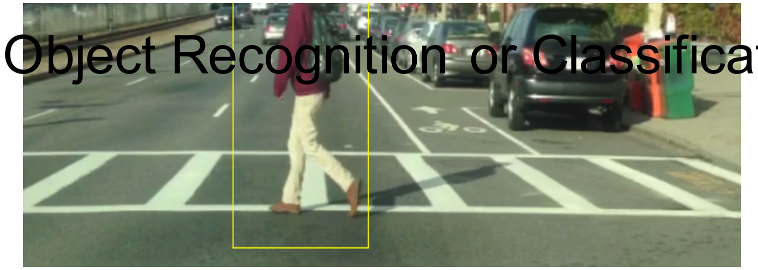
Agenda

- Introduction
  - Applications
  - Workflow
  - Common Challenges
- Demonstrations
  - Object **recognition** using live video
  - Deep learning for **recognition**
  - Training object **detectors**
  - Grouping or **clustering** images by visual similarity
- Conclusion

What Problems Can You Solve ?







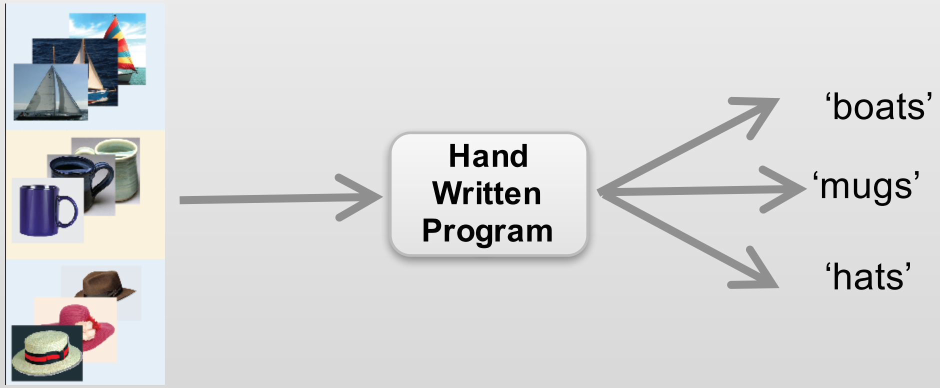
Object Recognition or Classification

Object Detection

Machine Learning

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

Task: Image Category Recognition



If **brightness** > 0.5

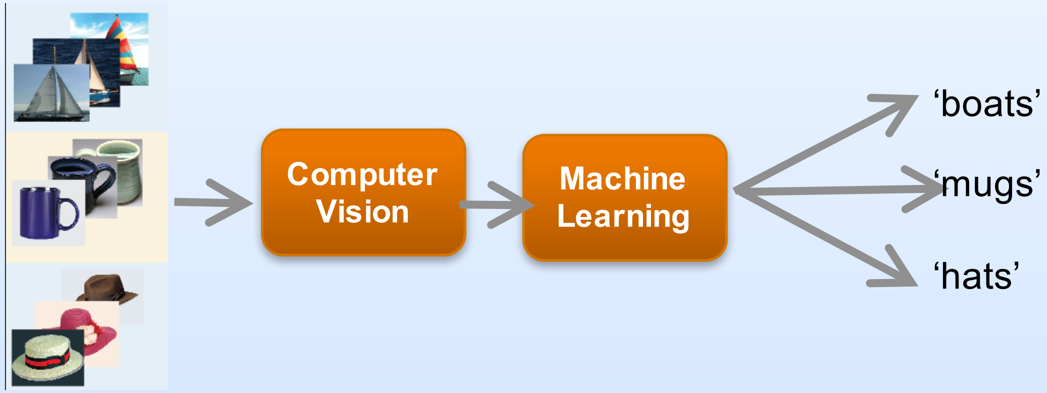
then 'hat'

If **edge_density** < 4 and

major_axis > 5

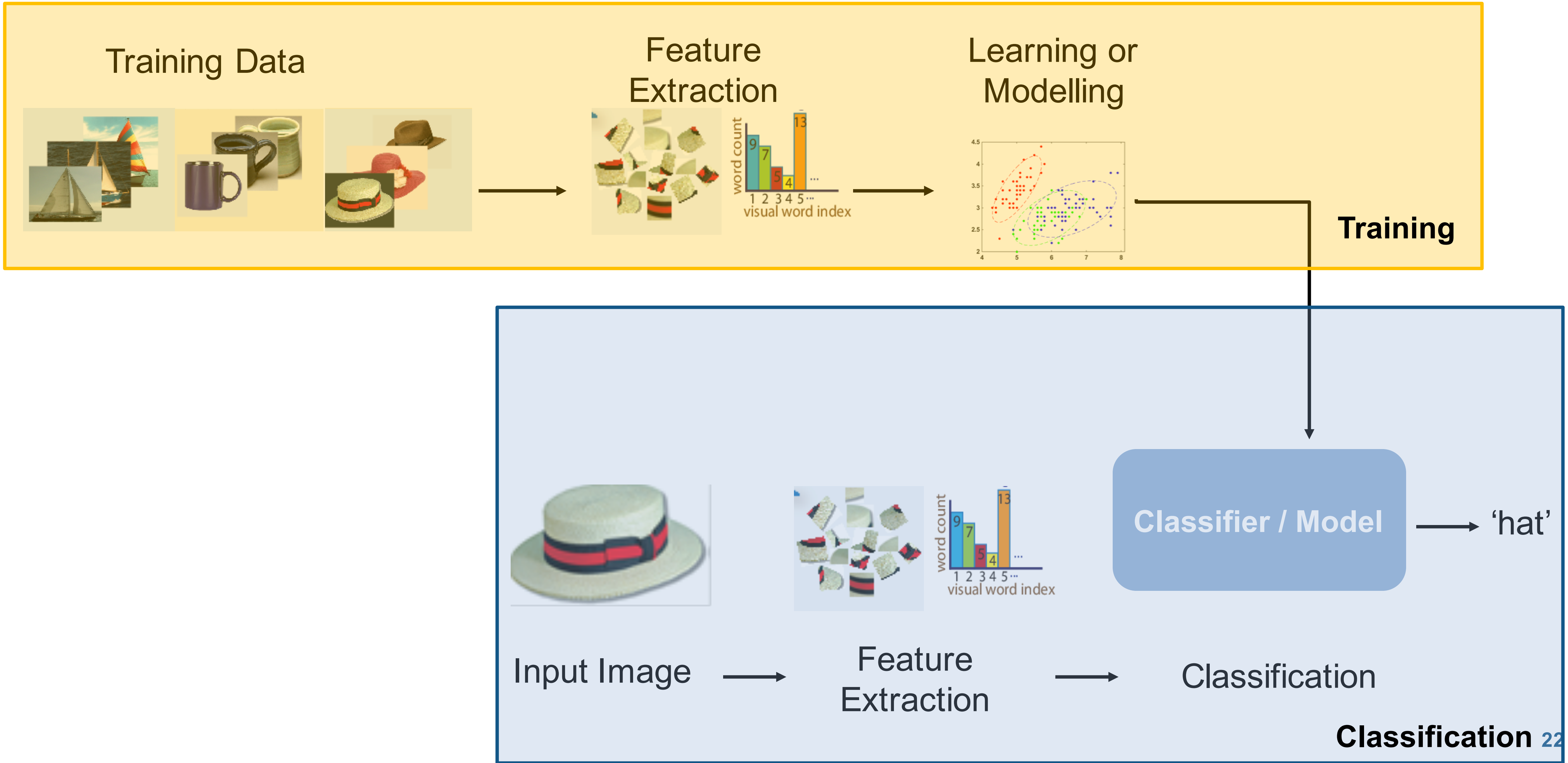
then "boat"

…



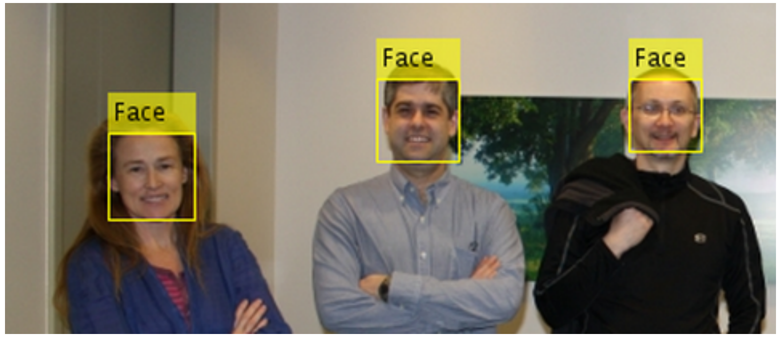
$$model = < \underset{Algorithm}{\overset{Machine}{Learning}} > (\text{data}, \text{label})$$

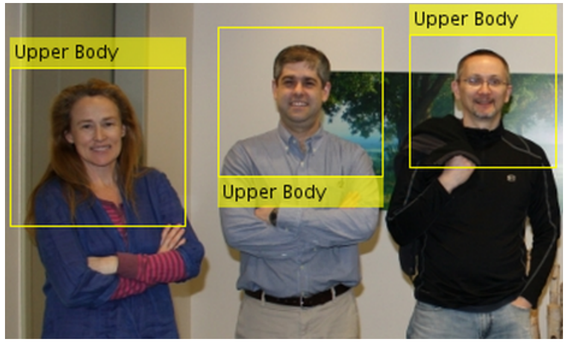
Machine Learning Workflow Using Images



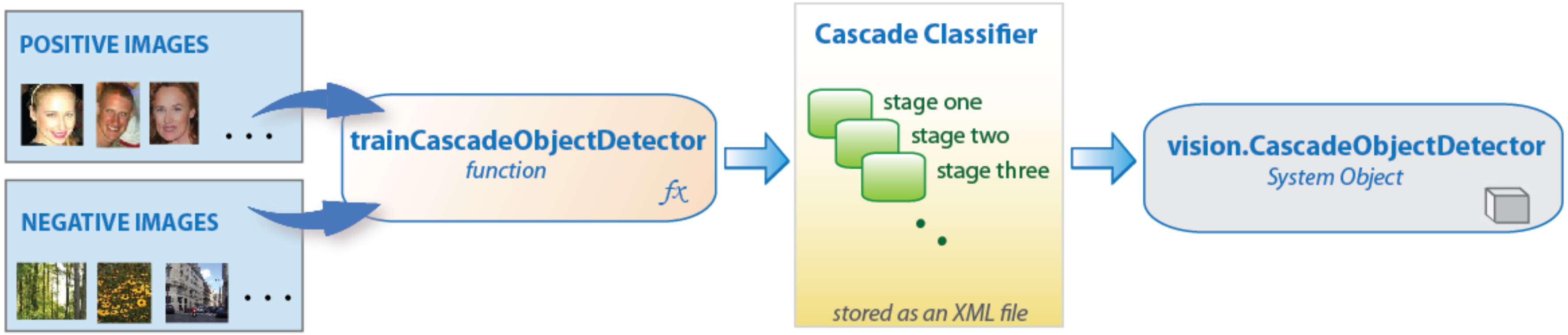
Viola Jones – Cascade Object Detectors

- Algorithm to detect people's faces, noses, eyes, mouth, or upper body.
- Ability to train custom classifiers using the Training Image Labeler





Cascade of Classifiers in CascadeObjectDetector



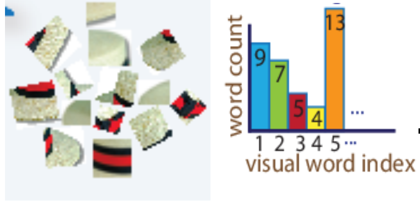
- Each stage of cascade is Gentle Adaboost, an ensemble of weak learners
- Each stage rejects negative samples using a weighted vote of these weak learners
- The samples not rejected are passed to the next stage
- Positive detection means the sample passed all stages of the cascade

Challenges: Machine Learning Workflow Using Images

Training Data

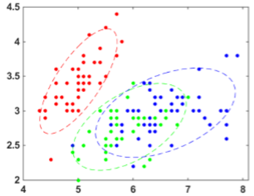
Challenge 1

Feature Extraction



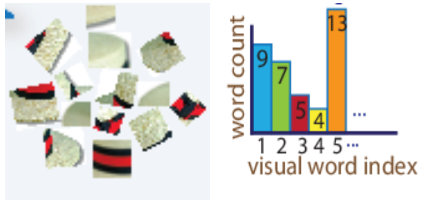
Challenge 2

Learning or Modelling



Challenge 3

Challenge 2



Classifier / Model

→ ‘hat’

Input Image → Feature Extraction → Classification

Common Challenges for Machine Learning with Images

- **Challenge 1:** Handling large sets of images
- **Challenge 2:** How to extract discriminative information from images
- **Challenge 3:** How to model tasks or data using machine learning

Goal: Recognize/ Classify Objects in Live Video

vs

vs

'hat'

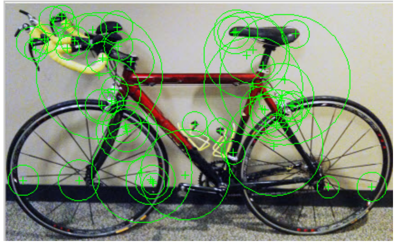
'mug'

'boat'

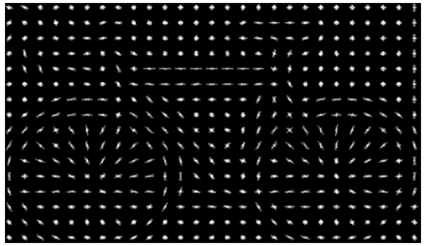
Known as **object classification or recognition**

What is Feature Extraction ?

Bag of Words



SURF



HOG

Image Pixels

Feature Extraction
- Representations often **invariant to** changes in scale, rotation, illumination
- More compact than storing pixel data
- Feature selection based on nature of problem

Sparse → Dense

Bag of Words

Image Processing Toolbox

Class / Label

Perform **image processing**, **analysis**, and algorithm development

Image Processing Toolbox™ provides a comprehensive set of reference-standard algorithms, functions, and apps for **image processing**, **analysis**, visualization, and algorithm development. You can perform **image analysis**, **image** segmentation, **image enhancement**, noise reduction, geometric transformations, and **image** registration. Many toolbox functions support multicore processors, GPUs, and C-code generation.

Image Processing Toolbox supports a diverse set of **image** types, including high dynamic range, gigapixel resolution, embedded ICC profile, and tomographic. Visualization functions and apps let you explore **images** and videos, examine a region of **pixels**, adjust color and contrast, create contours or histograms, and manipulate regions of interest (ROIs). The toolbox supports workflows for **processing**, displaying, and navigating large **images**.

Training Data

Vocabulary / Bag of Words

Bag of “Visual Words” (features)

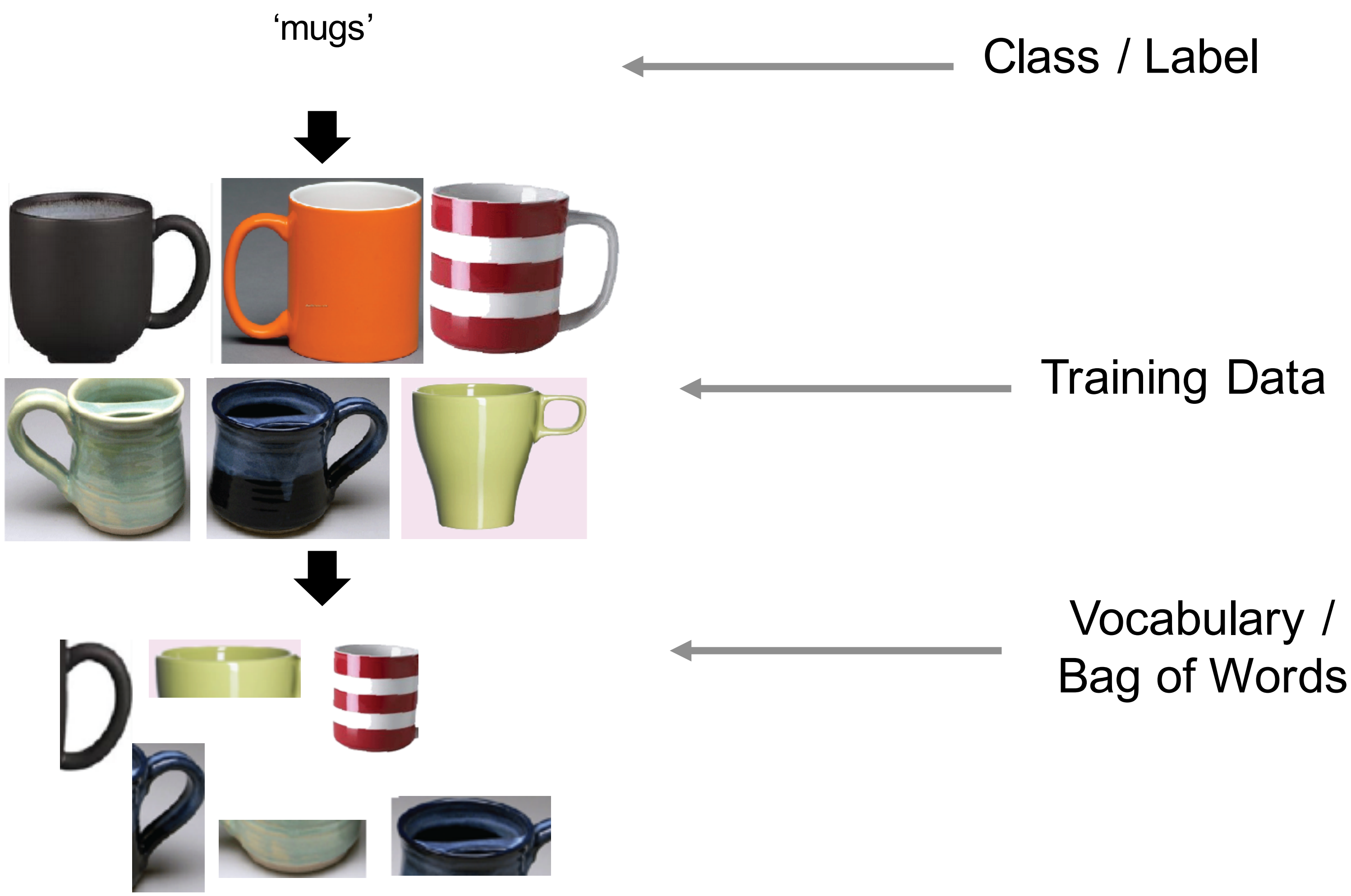
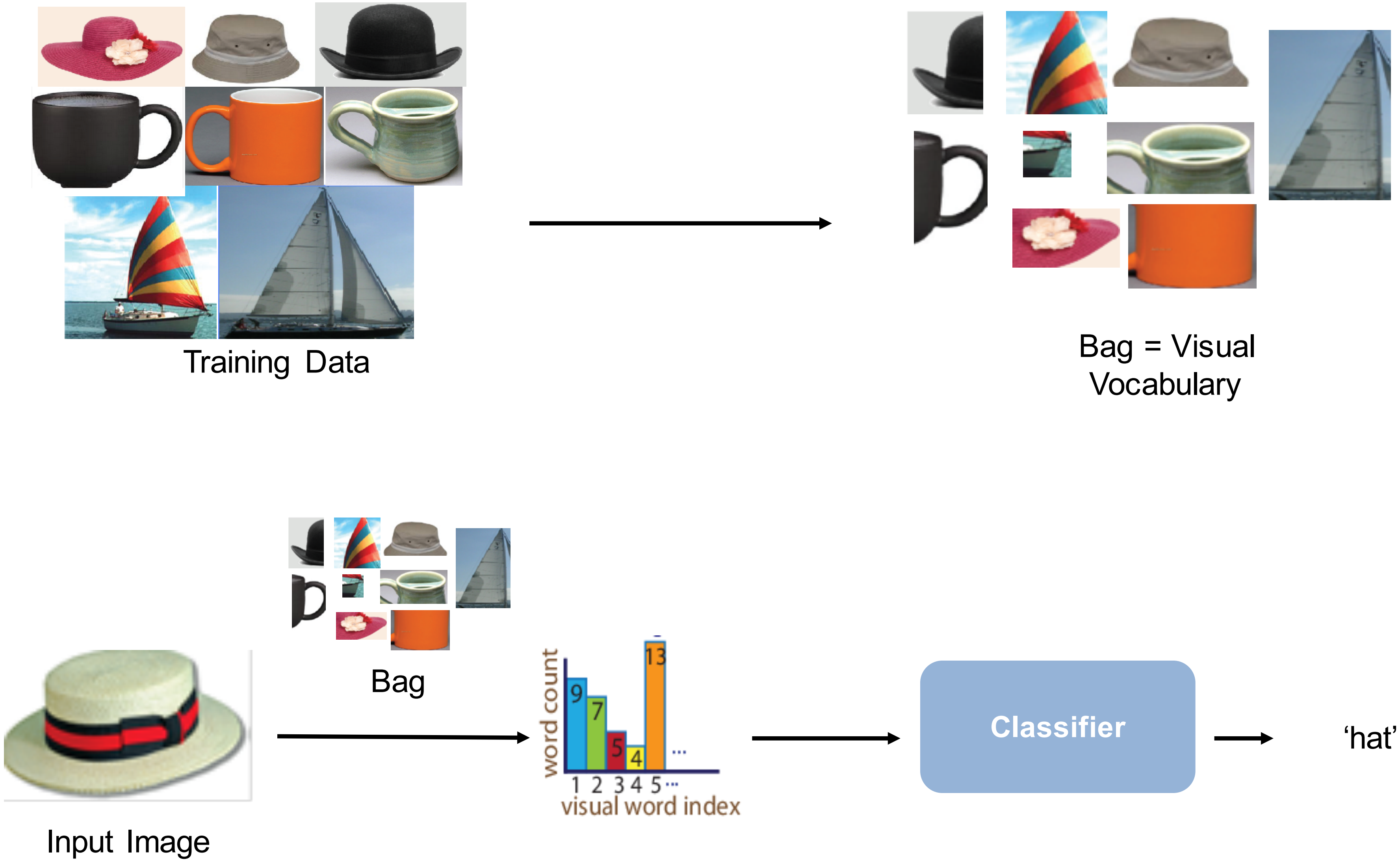


Image Classification with Bag of Words



Many Options for Features and Machine Learning

Feature Extraction

- BRISK,FREAK, SURF
- Histogram of Oriented Gradients (HoG)
- Using box filters(integral images)
- Bag of visual words
- Color-based features
- Frequency-domain features

Machine Learning

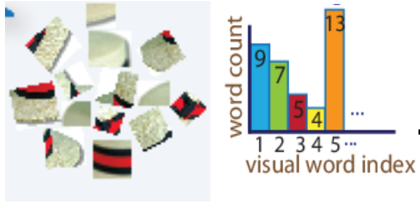
- SVM
- Decision trees
- AdaBoost
- Bagged trees
- k-NN
- Discriminant analysis
- Bayes classifiers

Bottom Line: Many permutations and combinations to fit the needs of your problem

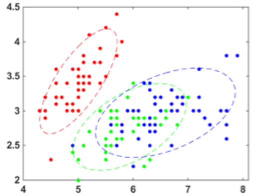
Challenges: Machine Learning Workflow Using Images

Training Data

Feature Extraction



Learning or Modelling

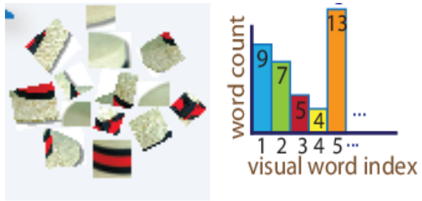


Challenge 1

Challenge 2

Challenge 3

Challenge 2



Classifier / Model

‘hat’

Input Image

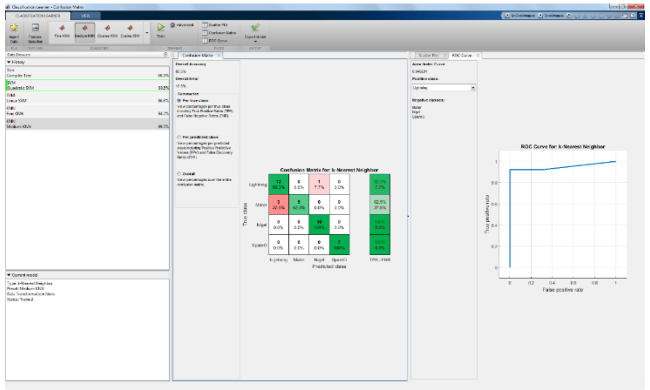
Feature Extraction

Classification

Common Challenges for Machine Learning with Images

- **Challenge 1:** Handling large sets of images
- **Challenge 2:** How to extract discriminative information from images
- **Challenge 3:** How to model problem using machine learning techniques

- Easy to handle large sets of images
  - `imageSet`
- Bag of words for feature extraction
  - More available in Computer Vision System Toolbox



Examples of Object Recognition/Classification

- Automatic scene categorization
- Biometrics
  - Face recognition
  - IRIS recognition
  - Fingerprint recognition
- Part recognition for factory automation
- Autonomous robotics

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Deep Learning is Ubiquitous

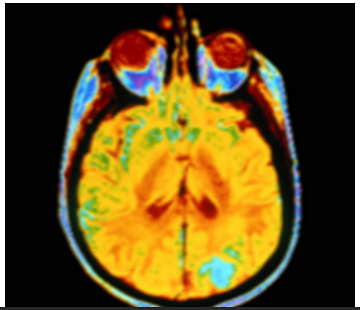
Computer Vision

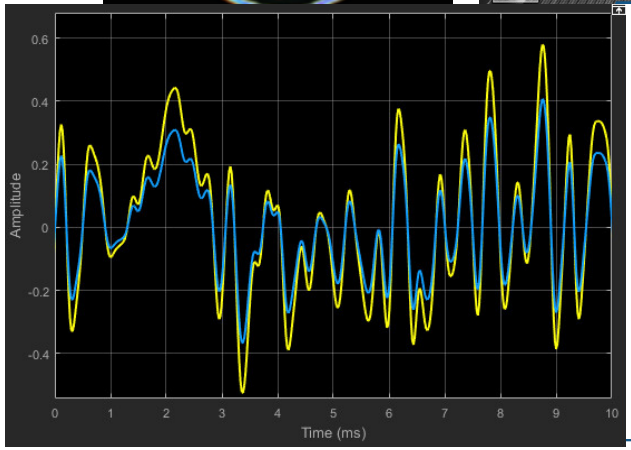
- Pedestrian and traffic sign detection
- Landmark identification
- Scene recognition
- Medical diagnosis and drug discovery

Text and Signal Processing

- Speech Recognition
- Speech & Text Translation

Robotics & Controls

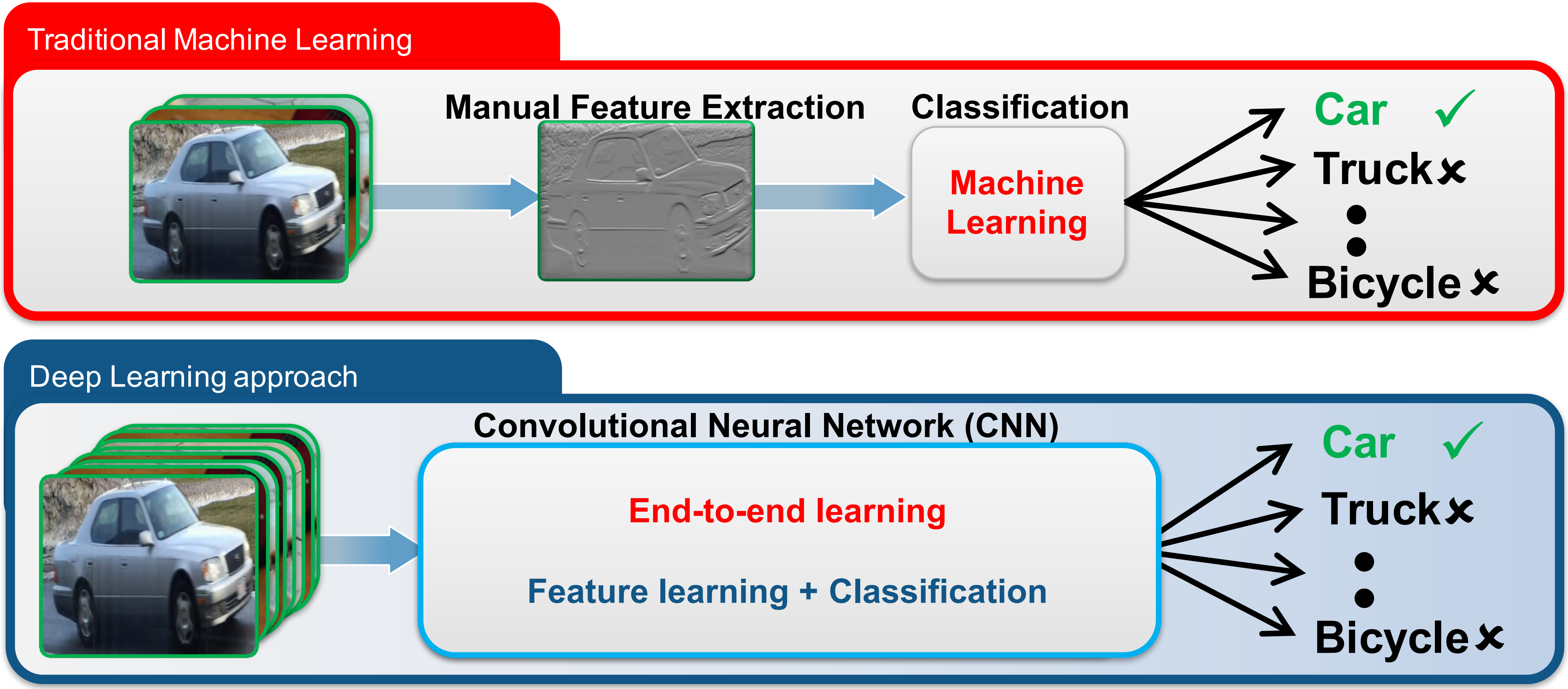


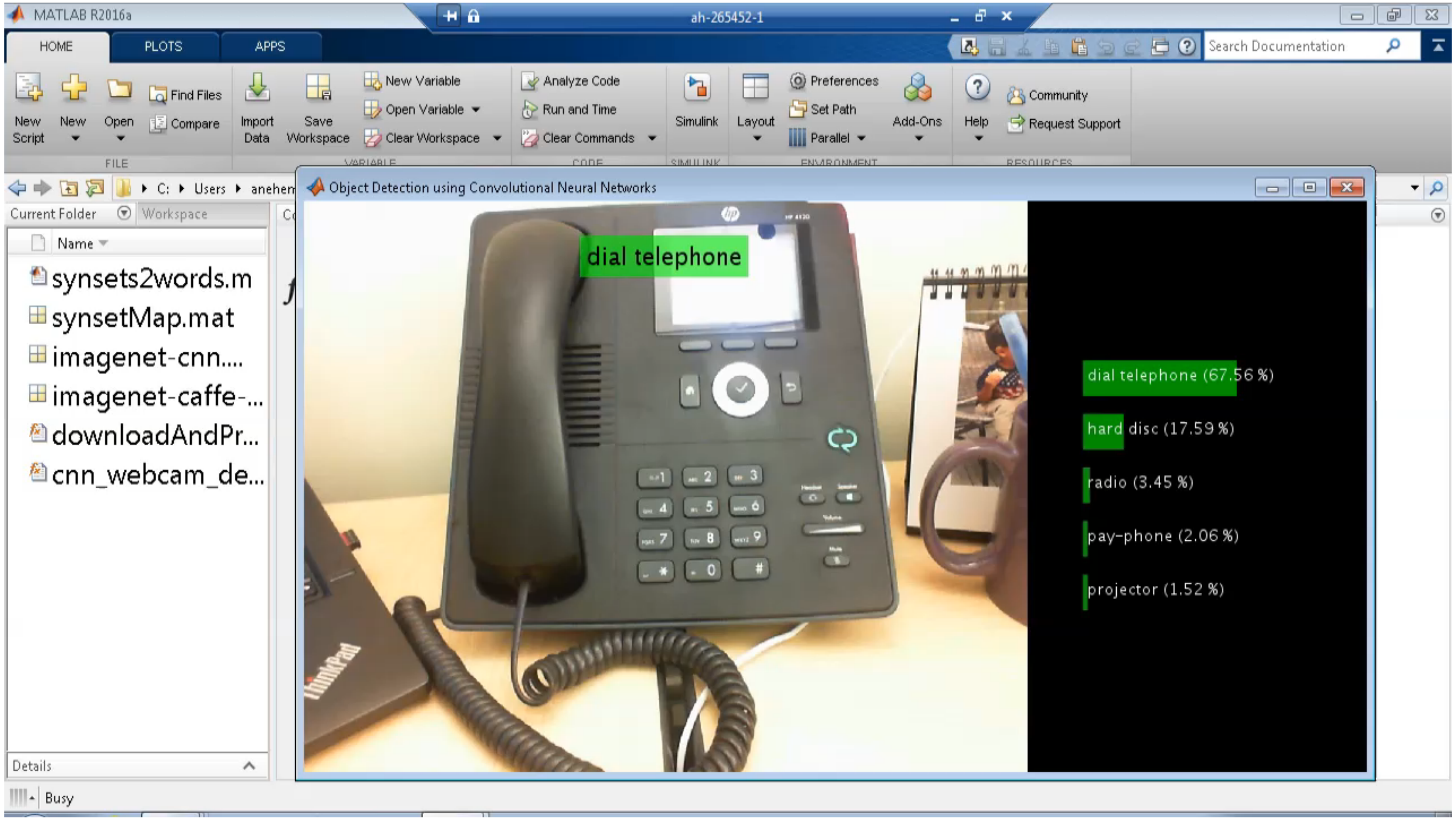
and many more…

What is Deep Learning ?

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



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

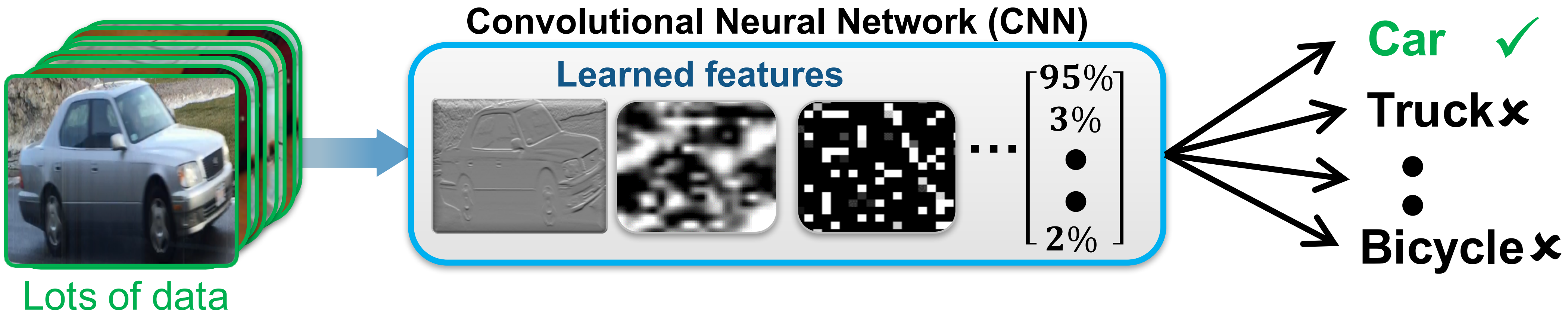
Year	Error Rate
Pre-2012 (traditional computer vision and machine learning techniques)	> 25%
2012 (Deep Learning)	~ 15%
2015 (Deep Learning)	<5 %

- **Computing Power:** GPU's and advances to processor technologies have enabled us to train networks on massive sets of data.

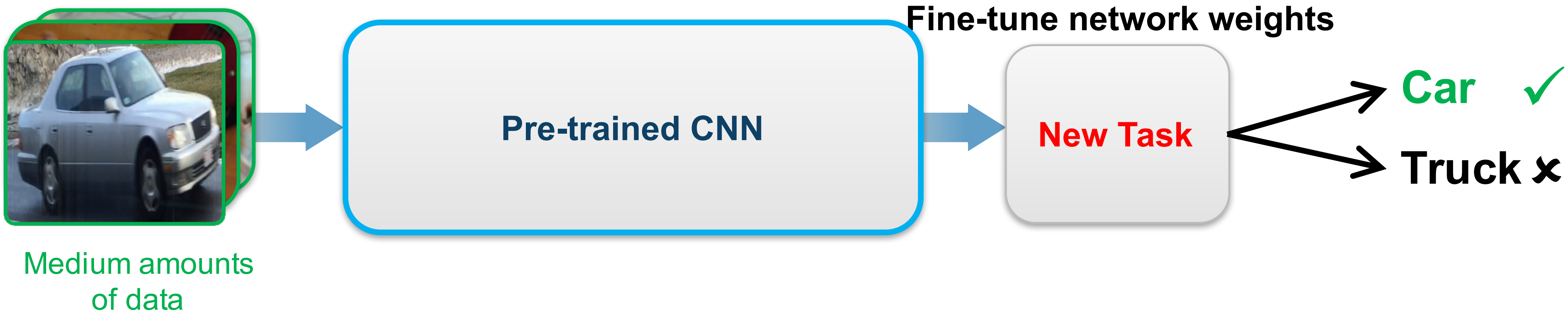
- **Data:** Availability of storage and access to large sets of labeled data
  – E.g. ImageNet , PASCAL VoC , Kaggle

Two Approaches for Deep Learning

1. Train a Deep Neural Network from Scratch

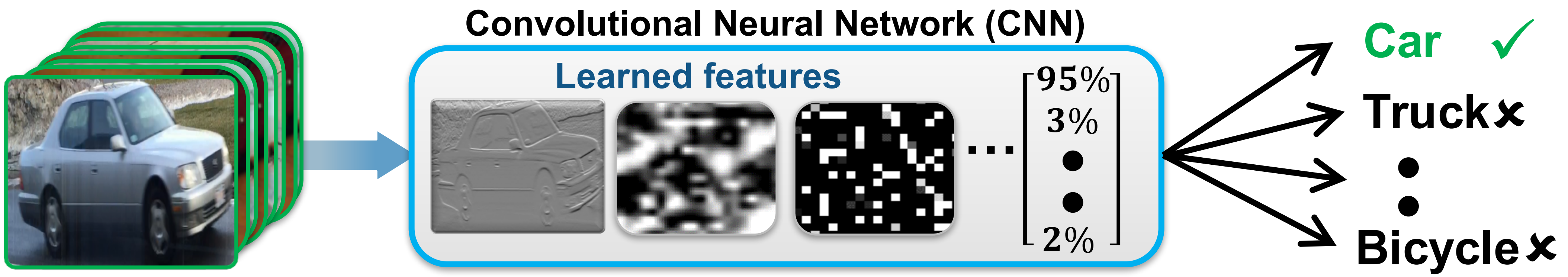


2. Fine-tune a pre-trained model (transfer learning)



Two Deep Learning Approaches

Approach 1: Train a Deep Neural Network from Scratch



Recommended only when:

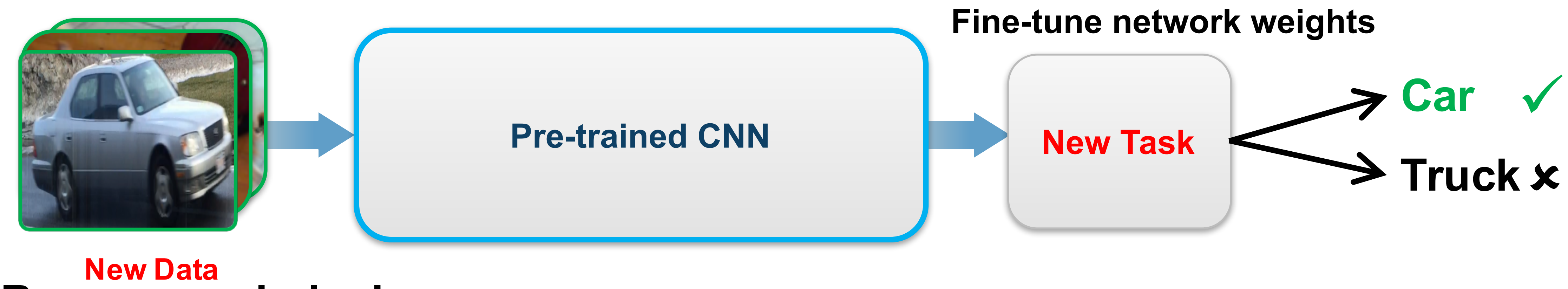
Training data	1000s to millions of labeled images
Computation	Compute intensive (requires GPU)
Training Time	Days to Weeks for real problems
Model accuracy	High (can over fit to small datasets)

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

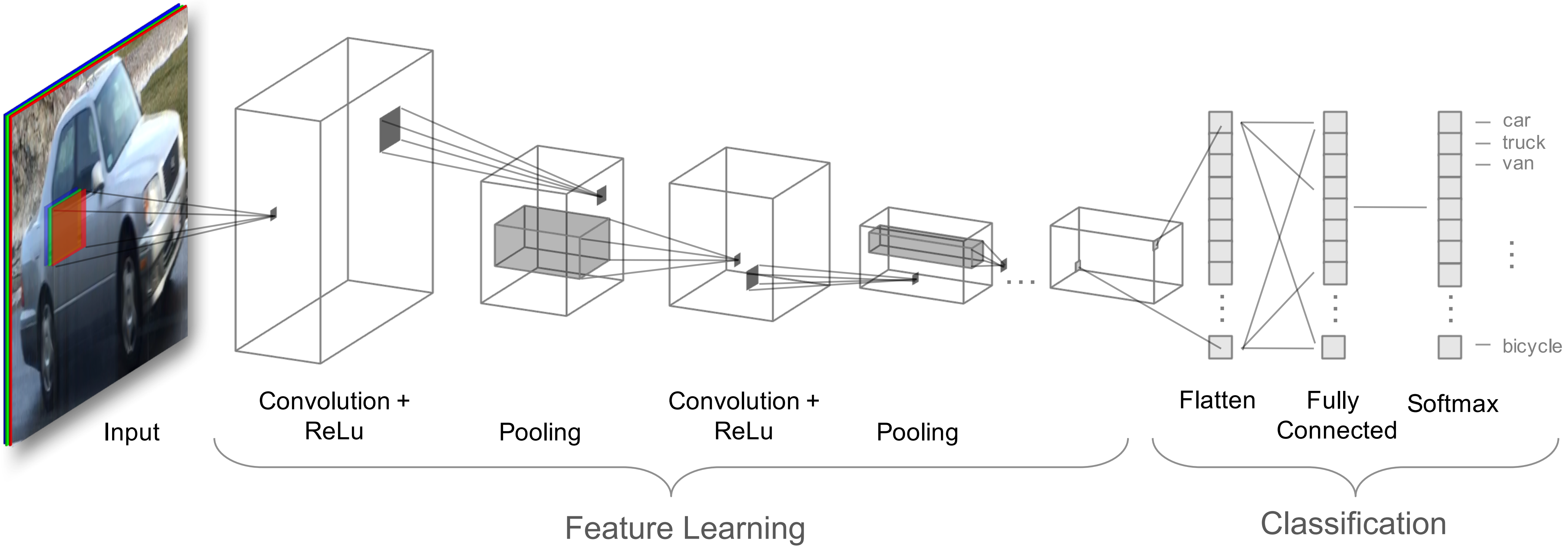


Recommended when:

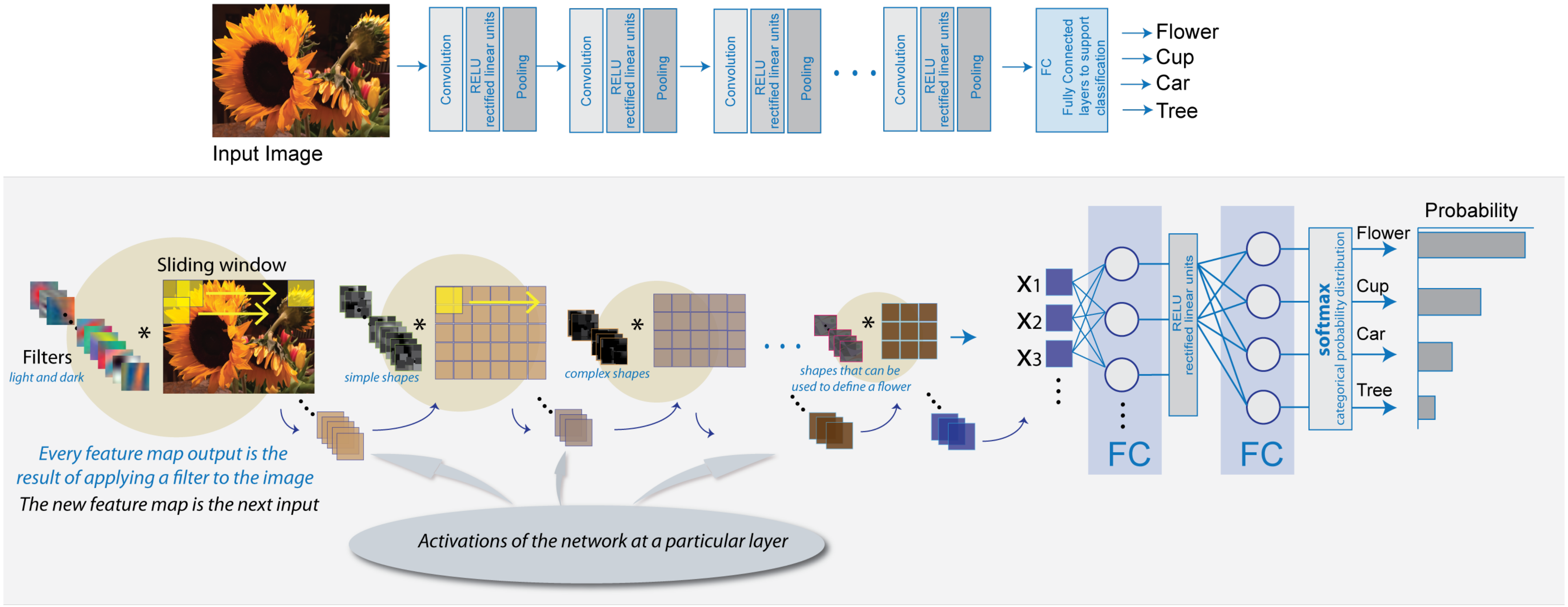
Training data	100s to 1000s of labeled images (small)
Computation	Moderate computation (GPU optional)
Training Time	Seconds to minutes
Model accuracy	Good, depends on the pre-trained CNN model

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

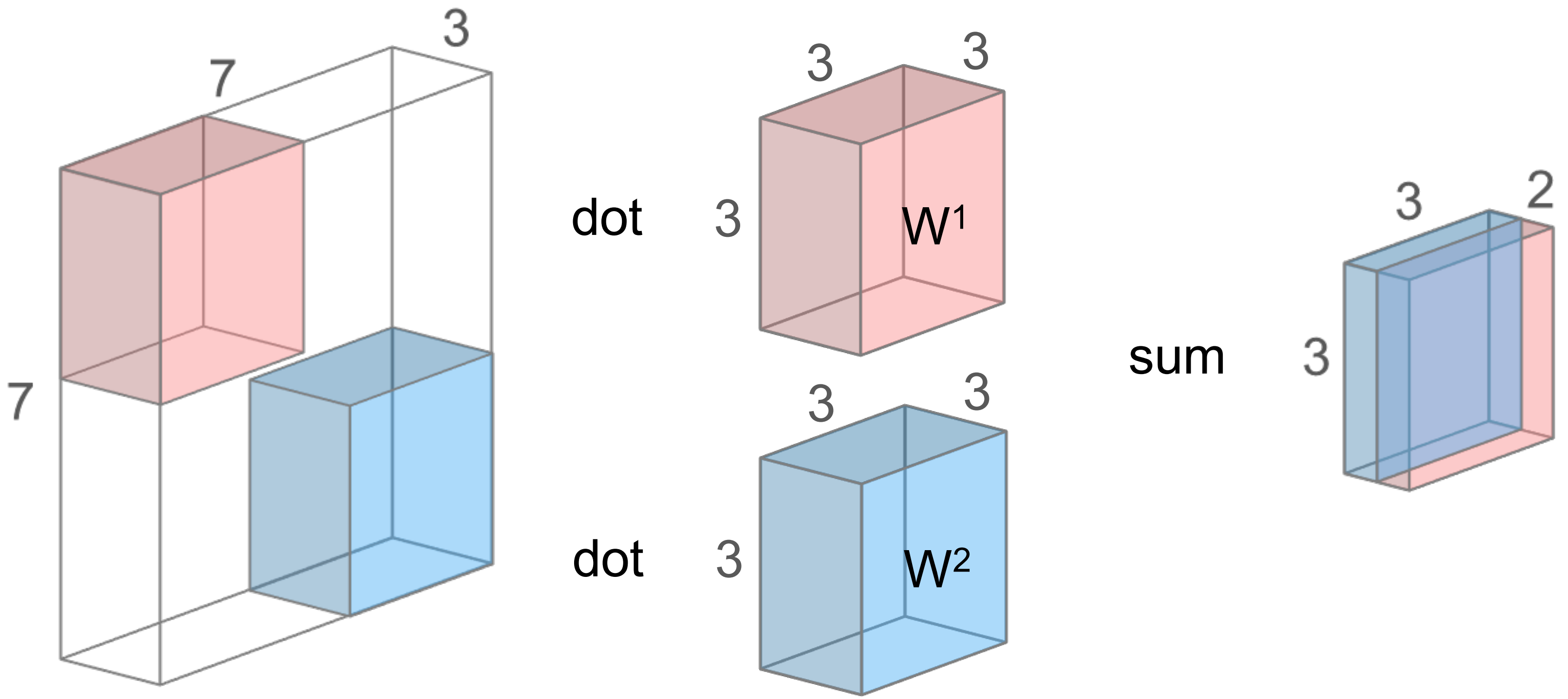


Convolutional Neural Networks



Convolution Layer

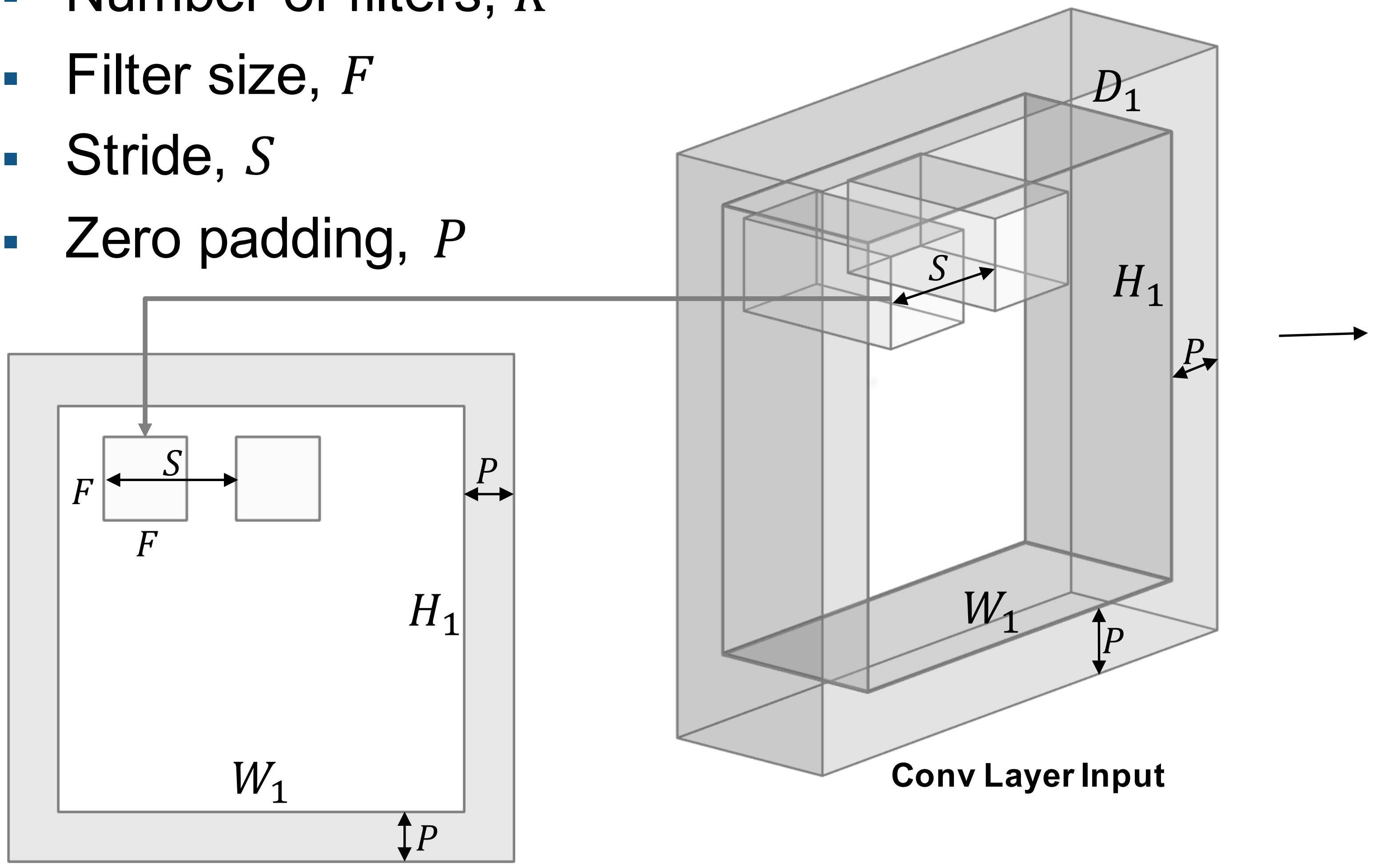
- Core building block of a CNN
- Convolve the filters sliding them across the input, computing the dot product

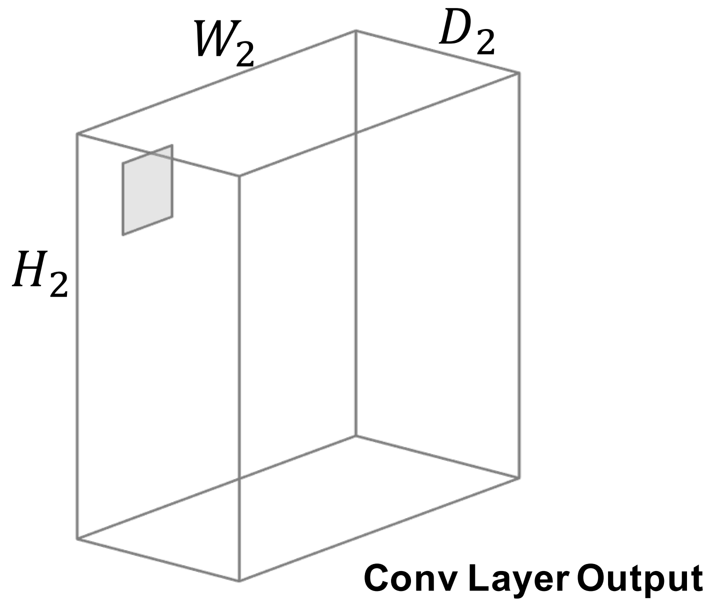


- Intuition: learn filters that activate when they “see” some specific feature

Convolution Layer – Choosing Hyperparameters

- Number of filters, K
- Filter size, F
- Stride, S
- Zero padding, P

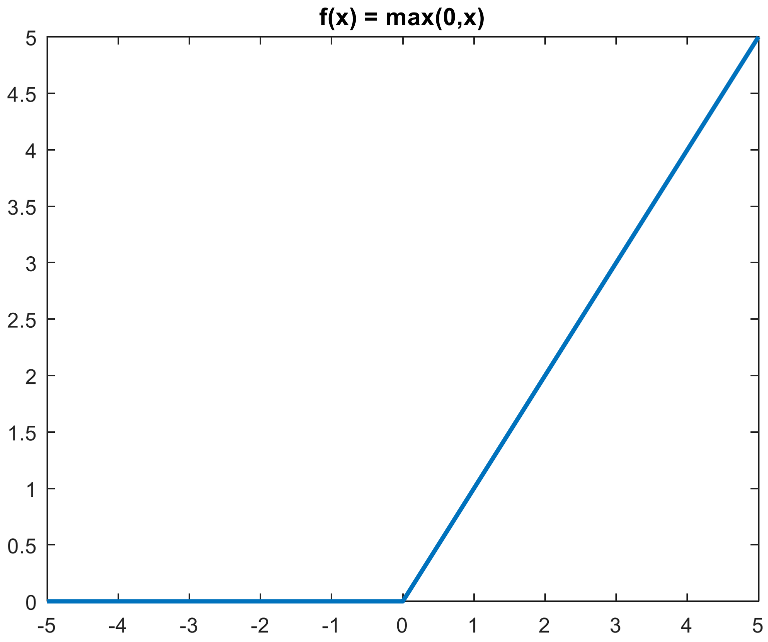




$$W_2 = (W_1 - F + 2P)/S + 1$$
$$H_2 = (H_1 - F + 2P)/S + 1$$
$$D_2 = K$$

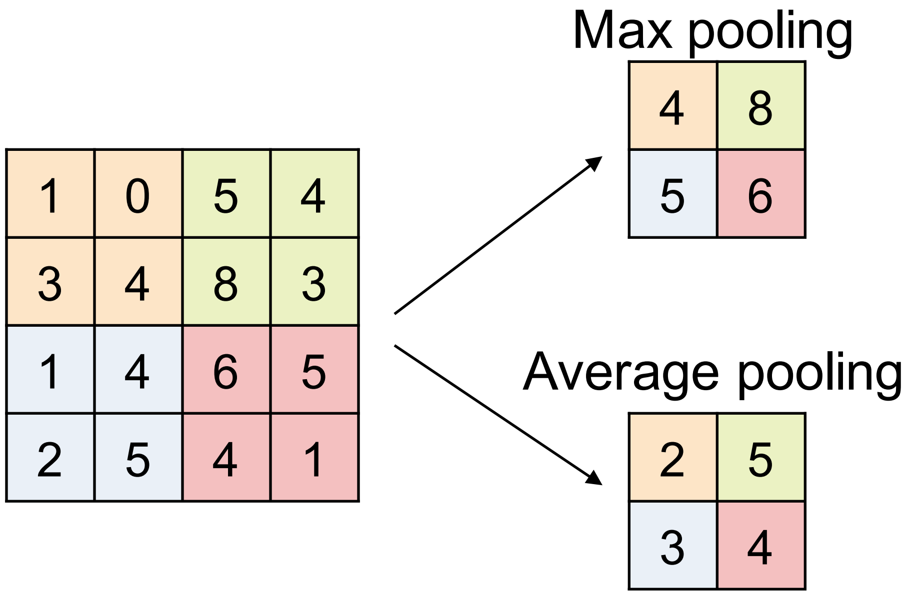
Rectified Linear Unit (ReLU) Layer

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

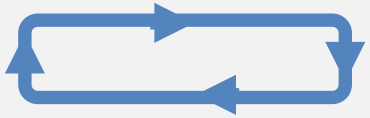


Pooling Layer

- 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: Classifying the CIFAR-10 dataset

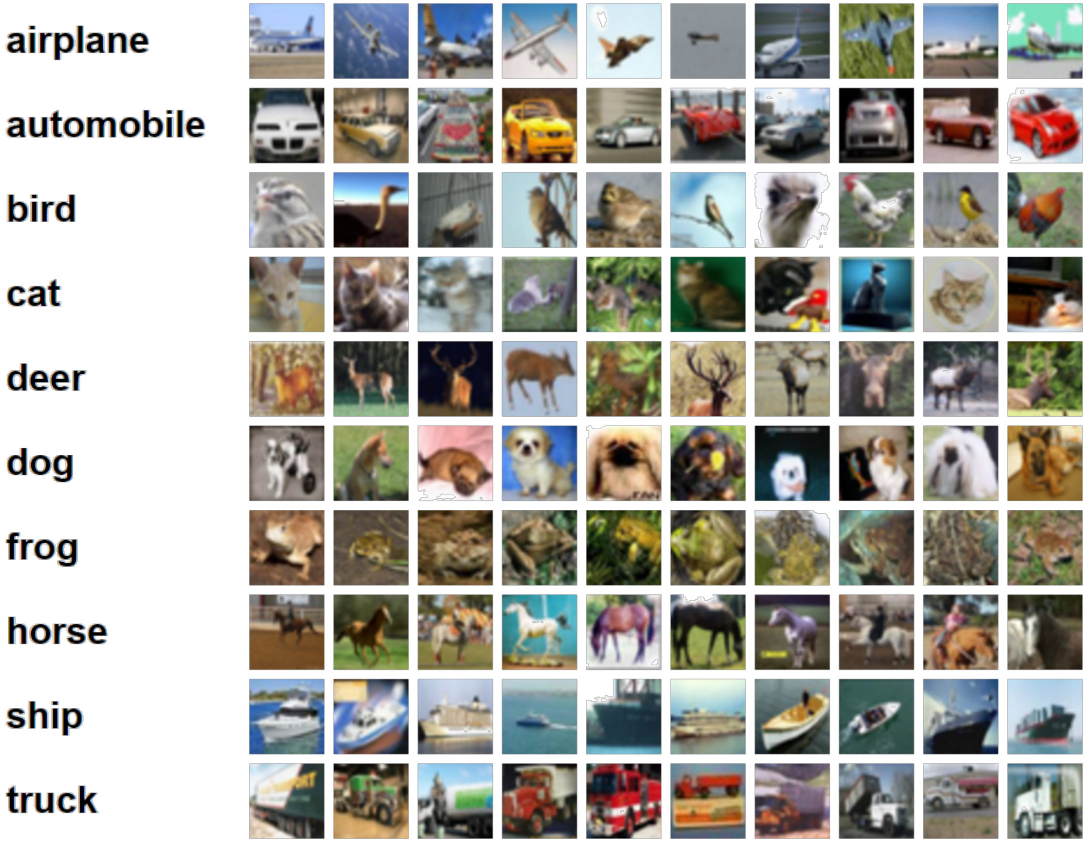
Objective: Train a Convolutional Neural Network to classify the CIFAR-10 dataset

Data:

Input Data	Thousands of images of 10 different Classes
Response	**AIRPLANE, AUTOMOBILE, BIRD, CAT, DEER, DOG, FROG, HORSE, SHIP, TRUCK**

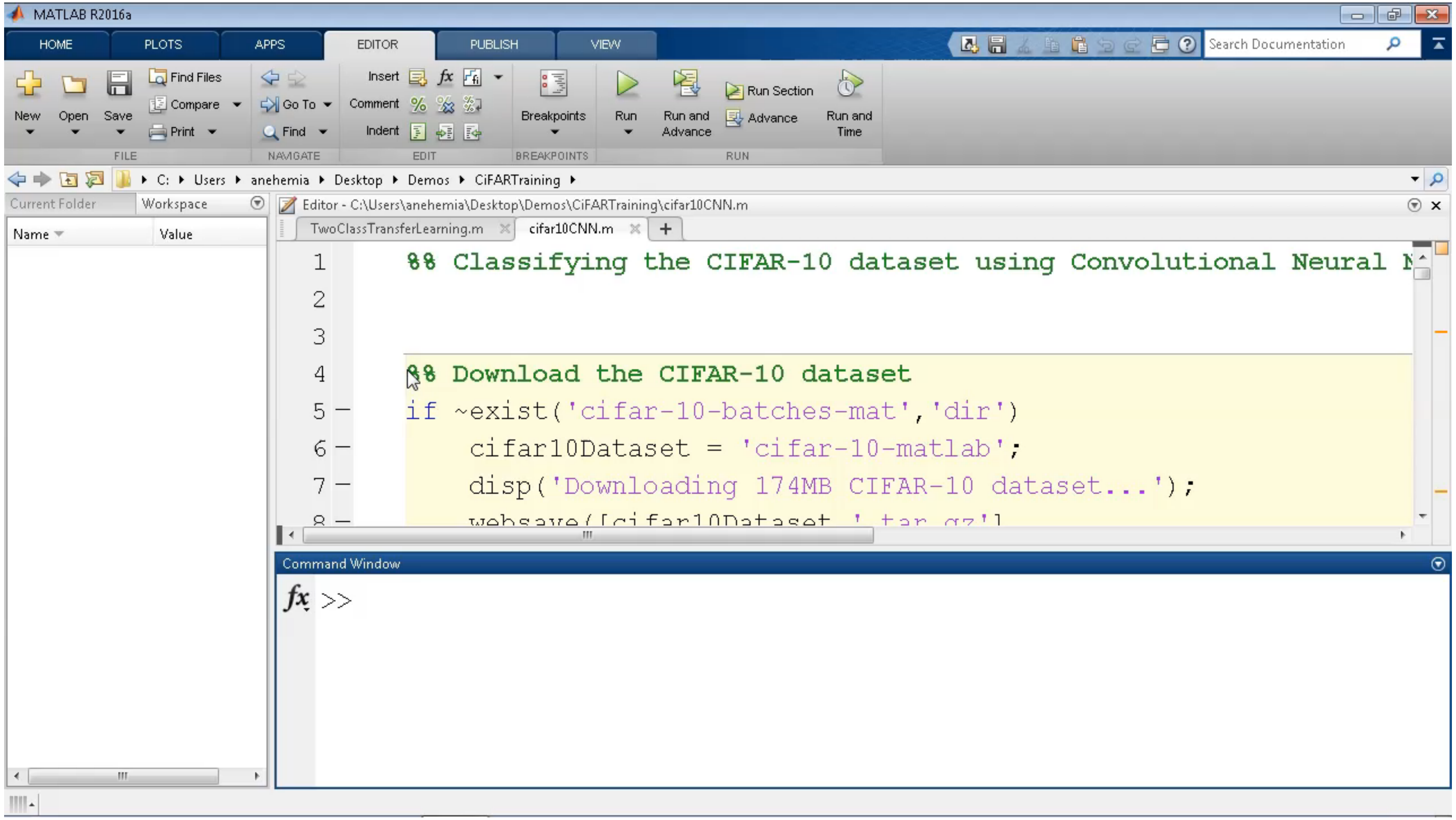
Approach:

- Import the data
- Define an architecture
- Train and test the CNN

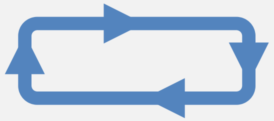


Data Credit: Learning Multiple Layers of Features from Tiny Images, Alex Krizhevsky, 2009.
https://www.cs.toronto.edu/~kriz/cifar.html

Demo: Classifying the CIFAR-10 dataset



Addressing Challenges in Deep Learning for Computer Vision

Challenge	Solution
Managing large sets of labeled images	`imageSet` or `imageDataStore` to handle large sets of images
Resizing, Data augmentation	`imresize`, `imcrop`, `imadjust`, `imageInputLayer`, 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

Demo

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

New Data

Pre-trained CNN
(AlexNet – 1000 Classes)

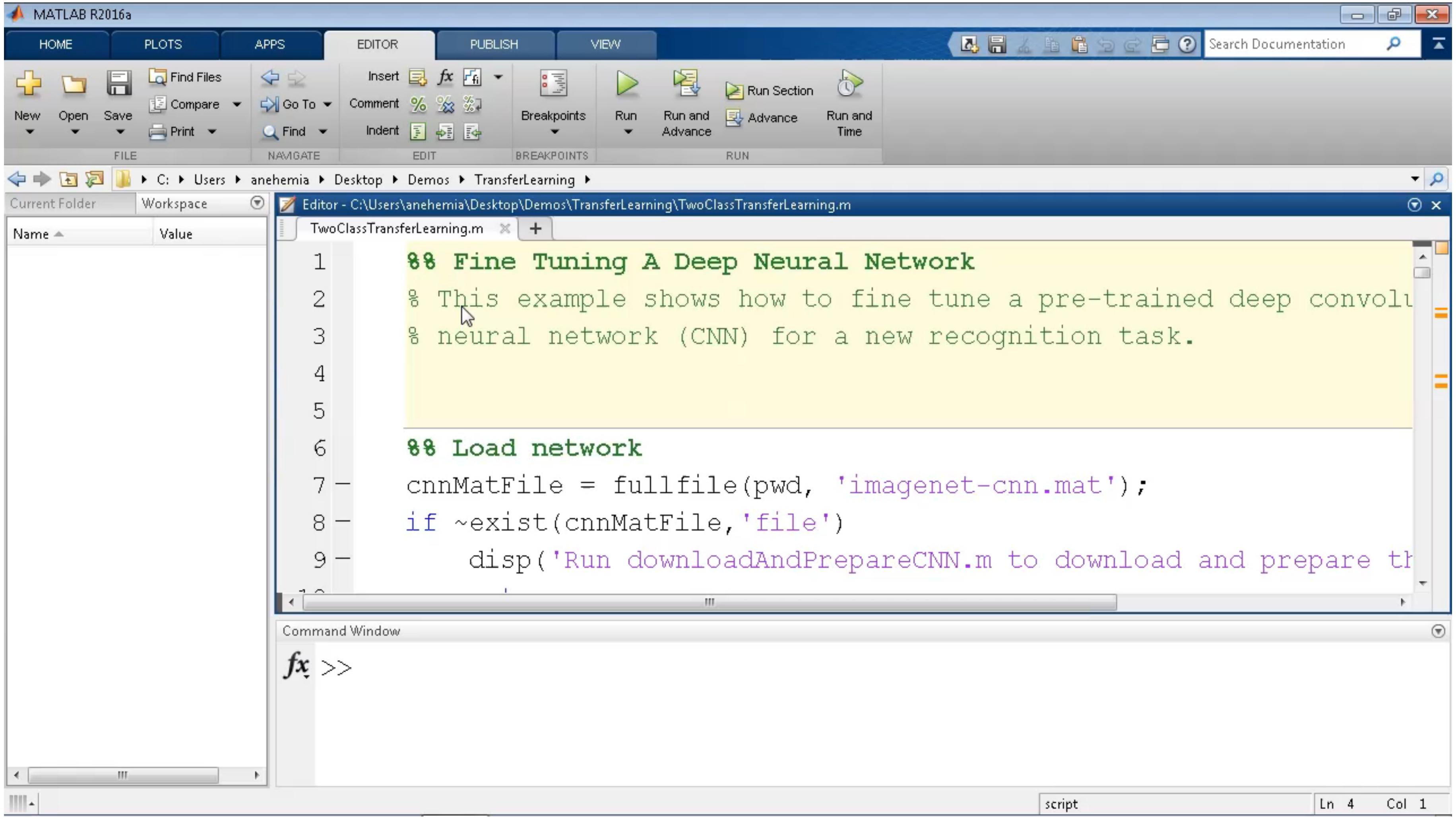
Car

SUV

New Task – 2 Class Classification

Demo

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



Addressing Challenges in Deep Learning for Computer Vision

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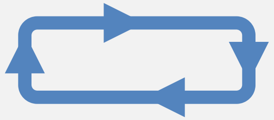	Automate. Offload computations to a cluster and test multiple architectures

Key Takeaways

- 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*

MATLAB for Deep Learning and Computer Vision

Email us:

Challenges using Deep Learning for Computer Vision

Steps	Challenge

Thank You!

Questions?