

# CoNNOR: Convolutional Neural Network for Outsole Recognition

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## Background: Footwear and Forensic Analysis

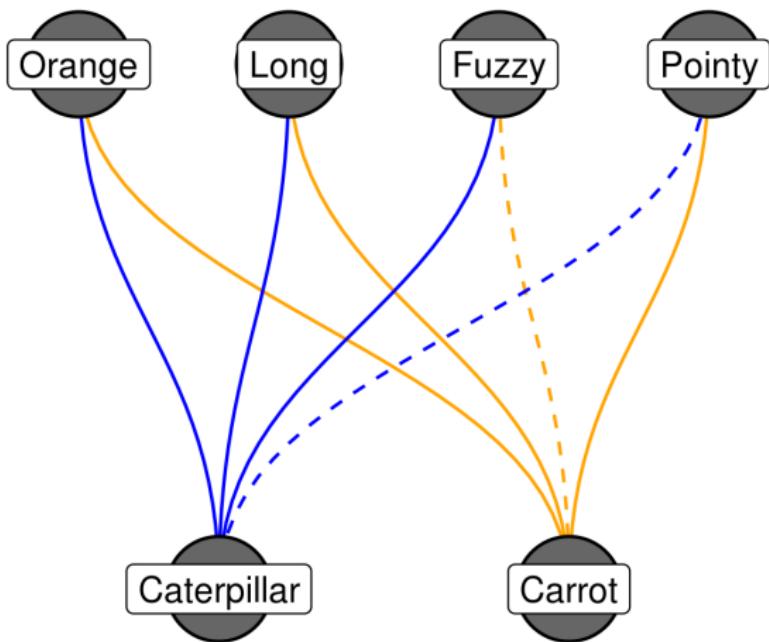
- ▶ Shoe prints and outsole characteristics are pattern evidence
- ▶ May want to identify print at crime scene as made from a certain type of shoe or by a given suspect
- ▶ Also useful to determine the frequency of a given shoe (or features of the shoe) in a local population
- ▶ **Goal:** Develop an efficient method to automatically identify footwear outsole characteristics

# Classification

- ▶ What features does your brain use to classify objects?



# Classification



# Classification



# Convolutional Neural Networks (CNNs)

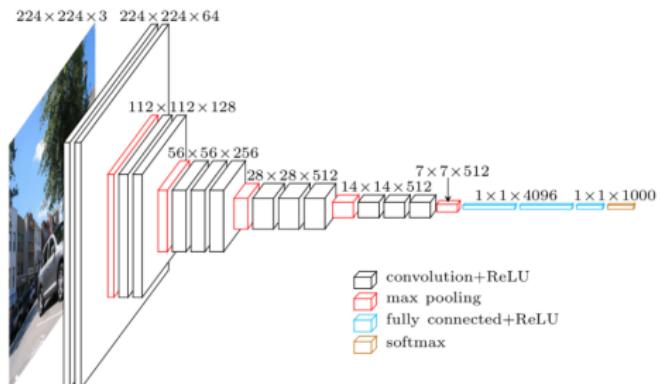
- ▶ Tool for supervised deep-learning, well-suited to image analysis
- ▶ Translation-invariant pattern detection
- ▶ Analogous to how our eyes detect features and our brain weights them for classification
  - ▶ Eyes → Brain → Classification
- ▶ Use combinations of convolutional and pooling layers to filter raw information into features

## Pre-trained CNNs

- ▶ Large, complex networks trained to identify a **subset** of images from **ImageNet**
  - ▶ ~1.2 million images spanning 1,000 categories
- ▶ Examples: LeNet (1998), AlexNet (2012), GoogLeNet/Inception (2014), **VGG** (2014), ResNet (2015)
  - ▶ More on how they compare [here](#) and [here](#)
- ▶ Contain both “eyes” to detect features and “brain” to weight those features for classification

# VGG16 Architecture

- ▶ 16 “functional” layers – 13 convolution and 3 fully connected
- ▶ 5 max-pooling layers, summarize features and structure model



# Filters and Convolution

|   |   |   |   |   |
|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 1 | 0 |
| 0 | 0 | 1 | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 1 | 0 | 0 |

Input

|   |   |   |
|---|---|---|
| 1 | 0 | 1 |
| 0 | 1 | 0 |
| 1 | 0 | 1 |

Filter / Kernel

# Filters and Convolution

|     |     |     |   |   |
|-----|-----|-----|---|---|
| 1x1 | 1x0 | 1x1 | 0 | 0 |
| 0x0 | 1x1 | 1x0 | 1 | 0 |
| 0x1 | 0x0 | 1x1 | 1 | 1 |
| 0   | 0   | 1   | 1 | 0 |
| 0   | 1   | 1   | 0 | 0 |

Input x Filter

|   |  |  |
|---|--|--|
| 4 |  |  |
|   |  |  |
|   |  |  |

Feature Map

# Filters and Convolution

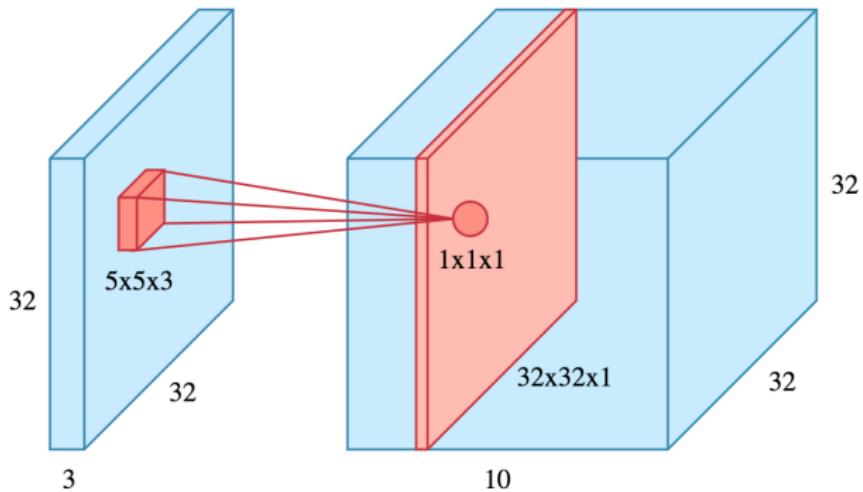
|   |     |     |     |   |
|---|-----|-----|-----|---|
| 1 | 1x1 | 1x0 | 0x1 | 0 |
| 0 | 1x0 | 1x1 | 1x0 | 0 |
| 0 | 0x1 | 1x0 | 1x1 | 1 |
| 0 | 0   | 1   | 1   | 0 |
| 0 | 1   | 1   | 0   | 0 |

Input x Filter

|   |   |  |
|---|---|--|
| 4 | 3 |  |
|   |   |  |
|   |   |  |

Feature Map

# Filters and Convolution



# Max Pooling

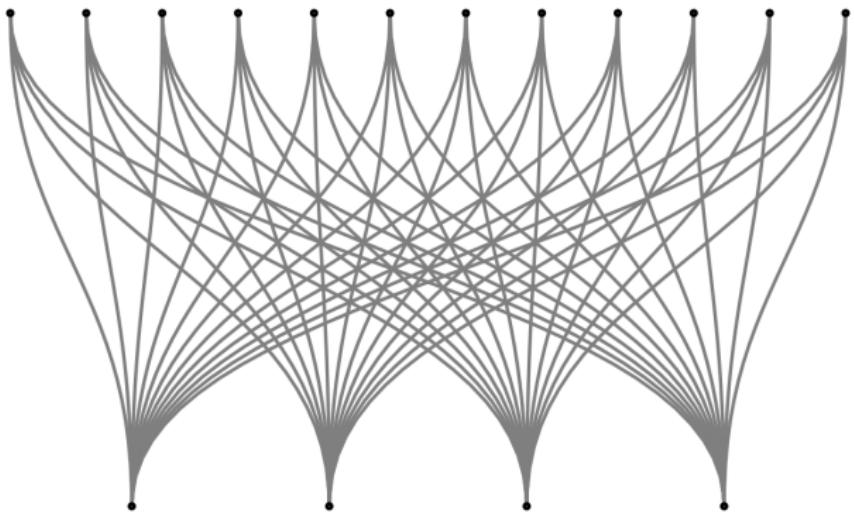
|   |   |   |   |
|---|---|---|---|
| 1 | 1 | 2 | 4 |
| 5 | 6 | 7 | 8 |
| 3 | 2 | 1 | 0 |
| 1 | 2 | 3 | 4 |

max pool with 2x2  
window and stride 2



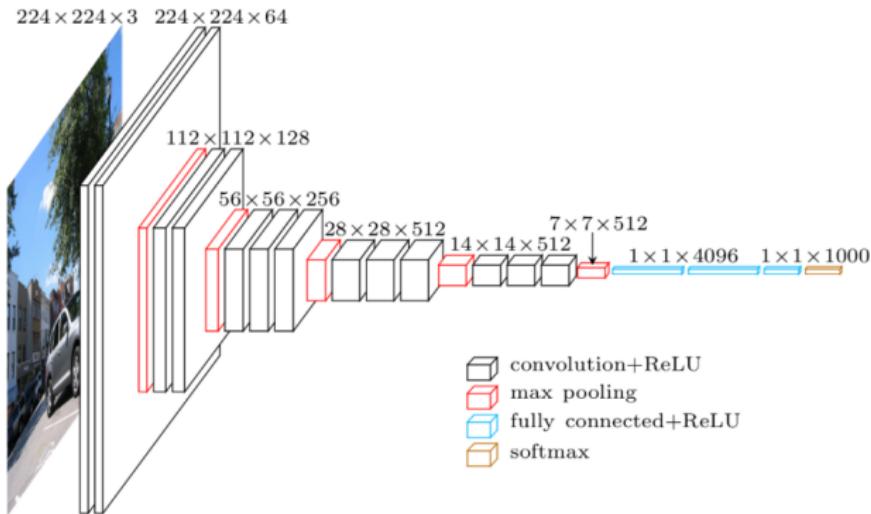
|   |   |
|---|---|
| 6 | 8 |
| 3 | 4 |

# Densely Connected Layers

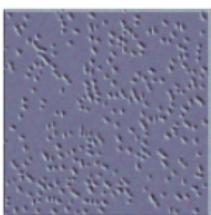
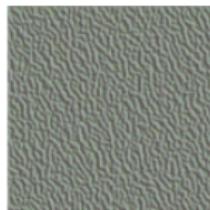
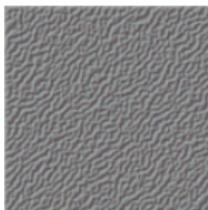


# VGG16 Architecture

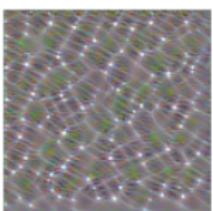
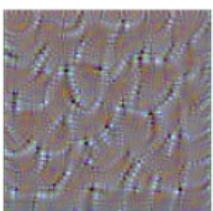
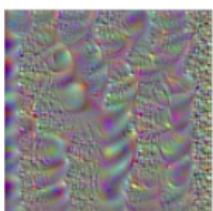
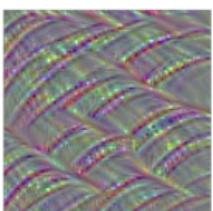
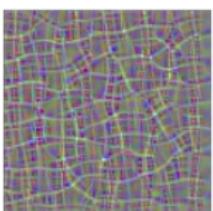
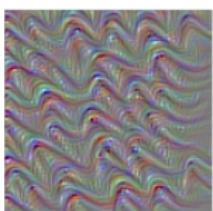
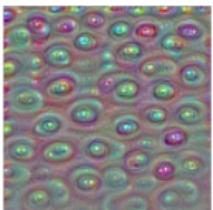
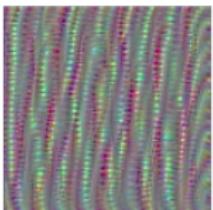
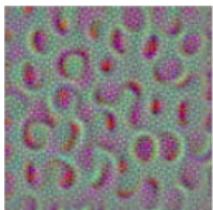
- ▶ Rectified Linear Units (ReLU) =  $x * I_{\{x>0\}}$



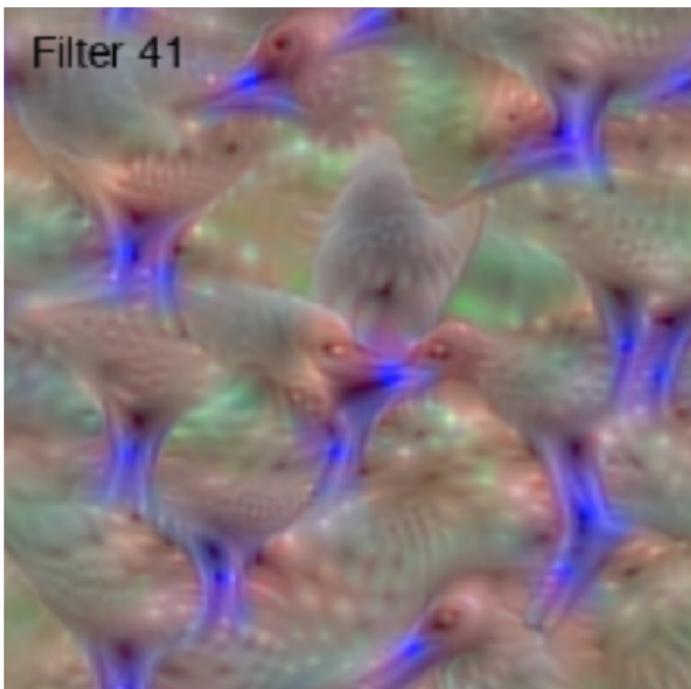
# VGG16 Filters - First Block



# VGG16 Filters - Fourth Block



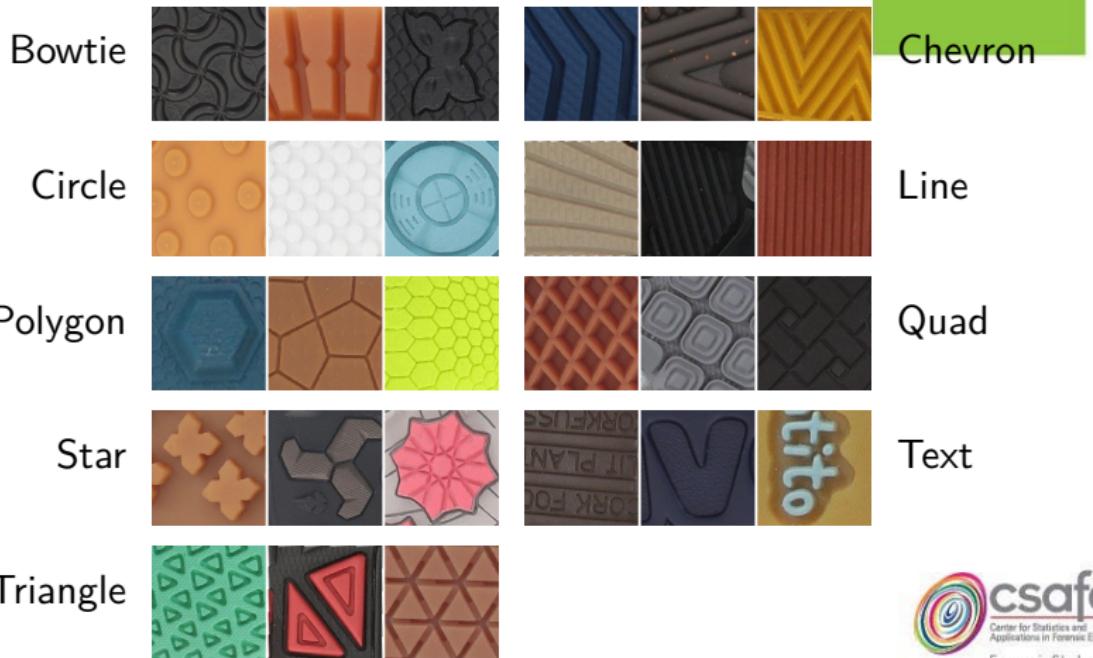
# VGG16 Filters - Fifth Block



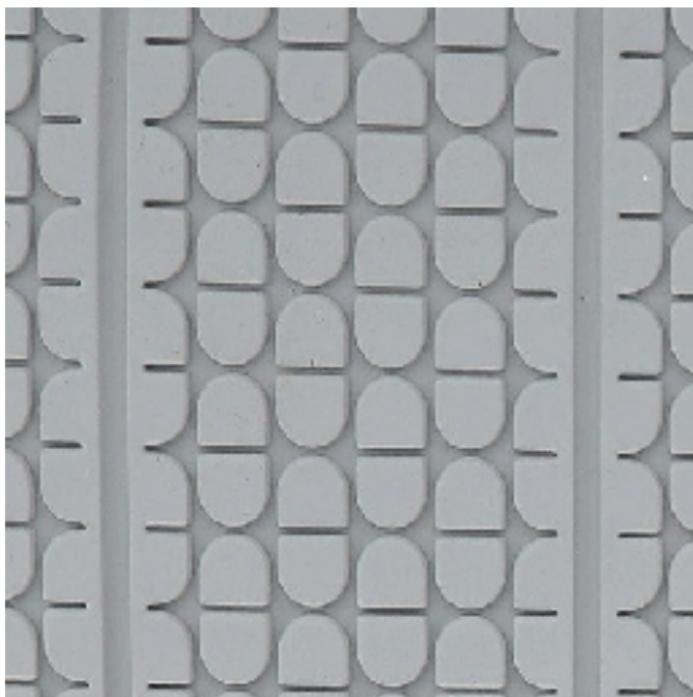
# Using a Pre-trained CNN for a New Task

- ▶ Large CNNs with many layers have millions of parameters to train
  - ▶ VGG16 "eyes" have 14,714,688 trainable parameters
- ▶ Using the existing "eyes" and training only a "brain" brings number of images required from millions to only thousands
  - ▶ "Eyes" = convolutional and pooling layers
  - ▶ "Brain" = fully connected layers

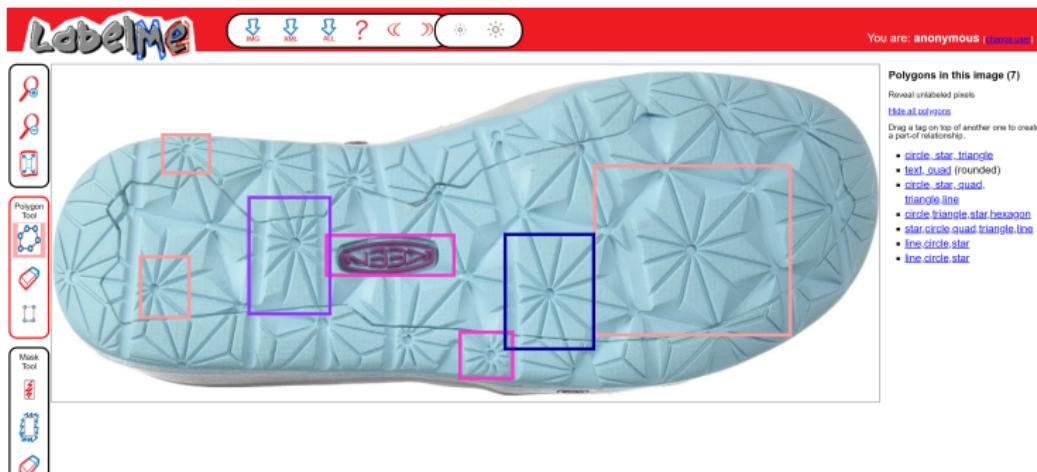
# Outsole Class Characteristics



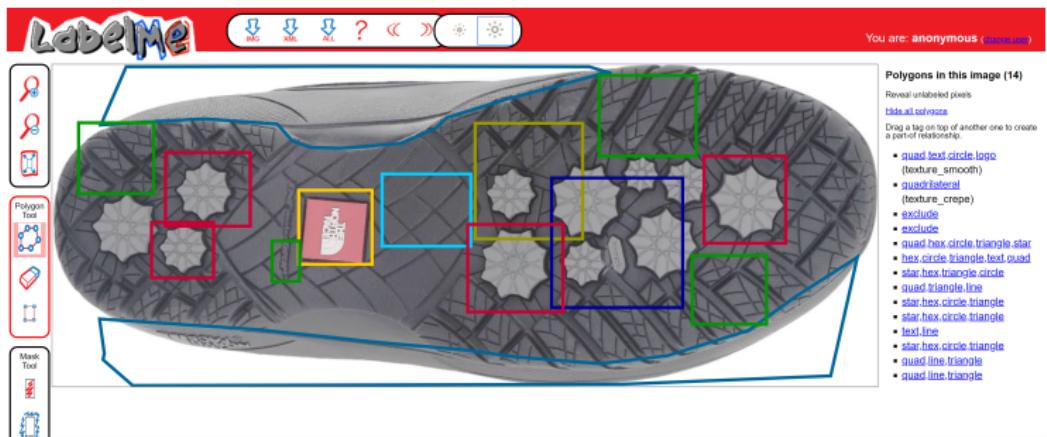
# Circle or Quadrilateral?



# Data Collection

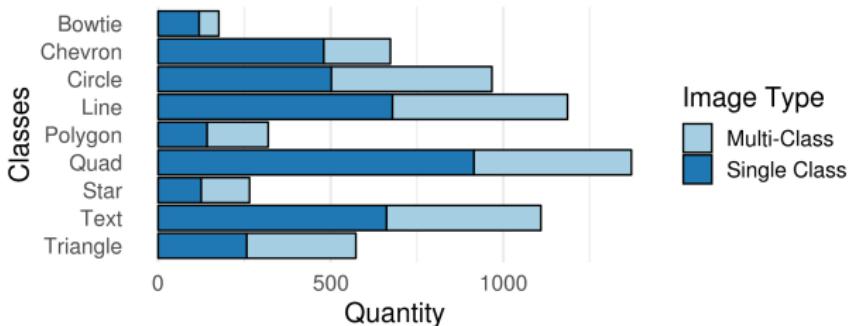


# Data Collection



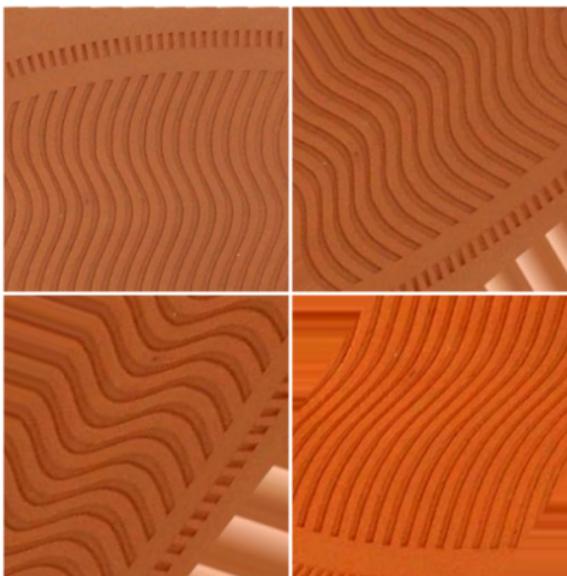
# Training a Neural Network – Data Structure

- ▶ 24,000 **multi-label** images from 2,200 shoes
  - ▶ Outsole images web-scraped from Zappos.com
- ▶ Partition existing data
  - ▶ 50% for training\*
  - ▶ 25% for validation, used to regulate training
  - ▶ 25% for testing, used to evaluate model performance



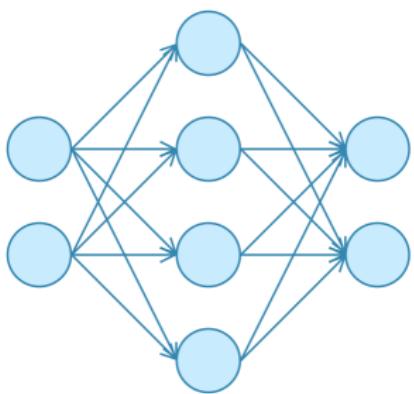
## Training Technique – Augmentation

- ▶ More training data, helps prevent over-fitting

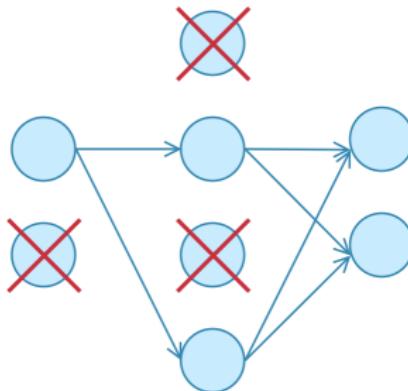


## Training Technique – Drop-out

- ▶ Ensures no neuron is too specialized, helps prevent over-fitting



No Dropout

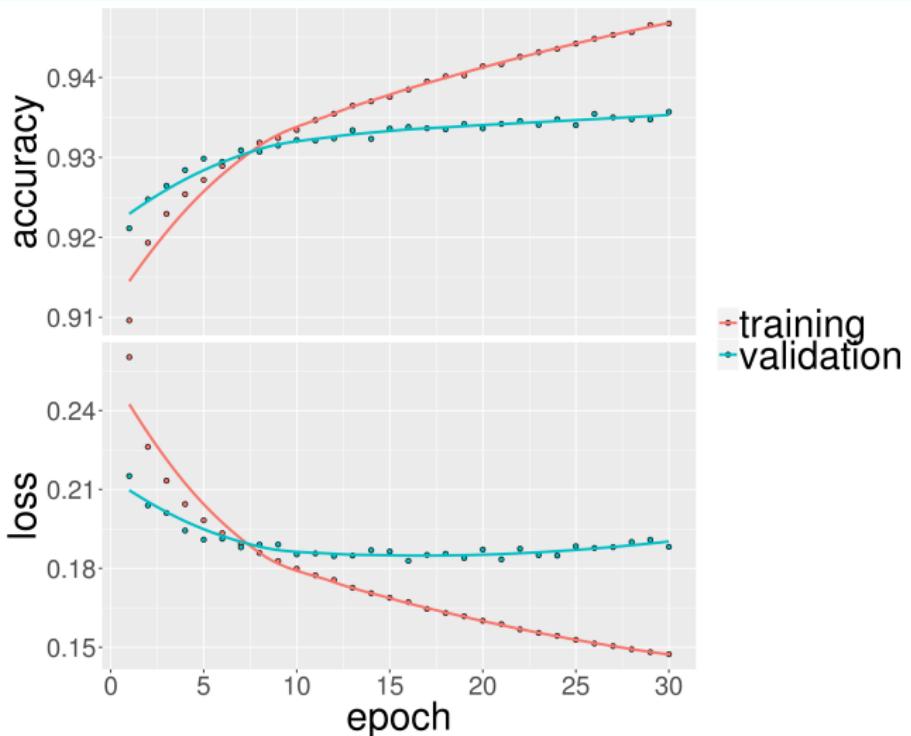


With Dropout

# Training a Neural Network – Computation

- ▶ **Keras:** a neural network API, written in Python
- ▶ Supports **TensorFlow**, CNTK, or Theano as computational backend
- ▶ **Keras:** an R interface to Keras
  - ▶ For more info, see [Deep Learning with R](#)
- ▶ **Note:** Keras requires GPU (or *very* good CPU)
  - ▶ Seriously, don't try this on your personal machine

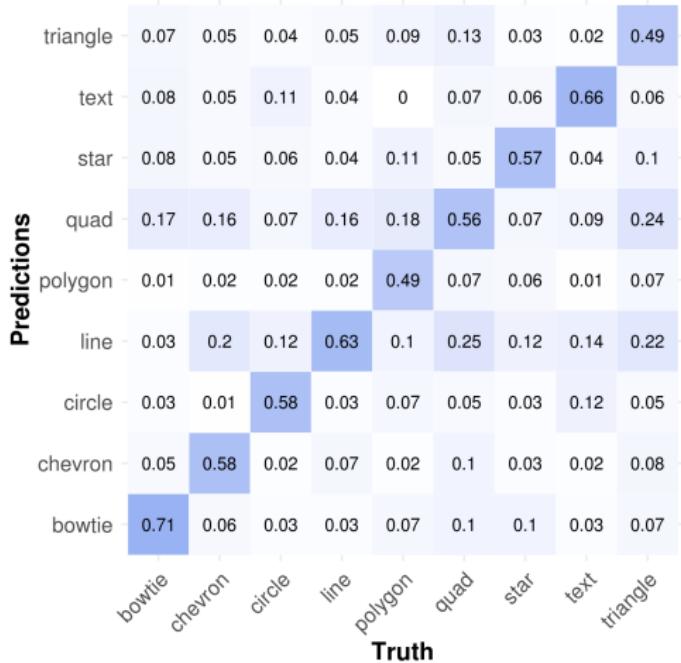
# Training a Neural Network



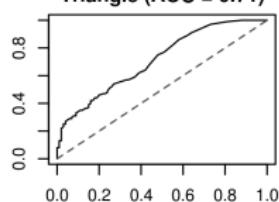
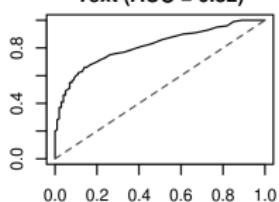
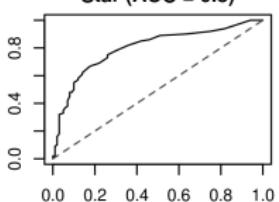
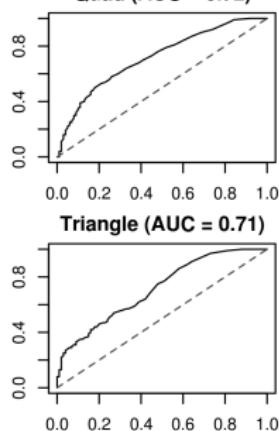
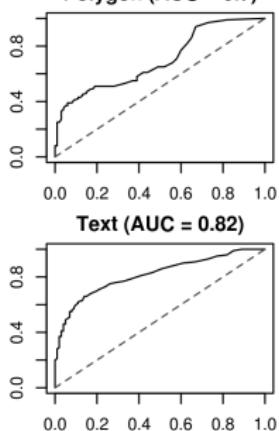
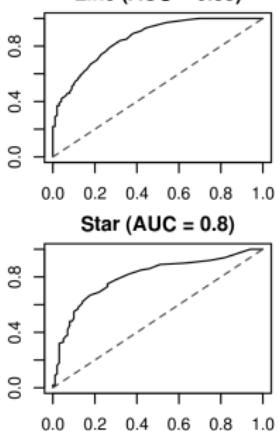
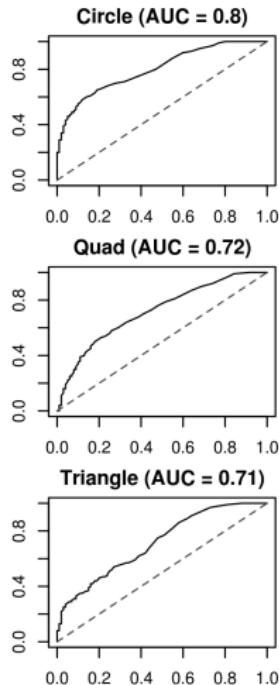
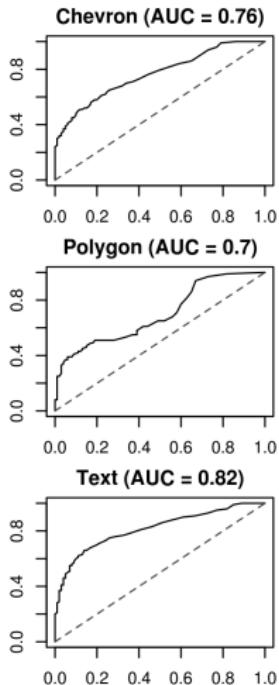
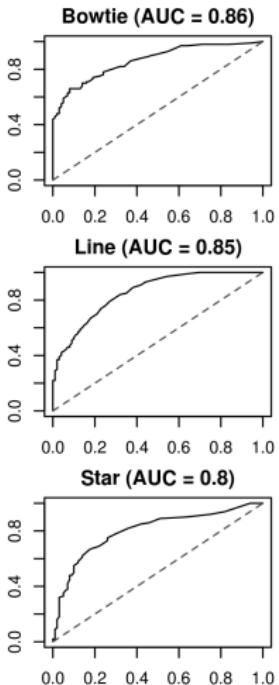
# Visualizing Model Predictions

- ▶ Shiny App

# Prediction Accuracy



# ROC



# Heatmaps



Circle: 0.506

Text: 0.312

Quad: 0.302



Triangle: 0.077

Line: 0.07



Polygon: 0.066



Chevron: 0.019



Star: 0.009

Bowtie: 0.003

# Heatmaps



Circle: 0.783



Quad: 0.543



Line: 0.075



Text: 0.059



Polygon: 0.022



Triangle: 0.017



Chevron: 0.012



Star: 0.004



Bowtie: 0.001

# Heatmaps



Line: 0.044



Quad: 0.04



Text: 0.036



Circle: 0.032



Star: 0.031



Triangle: 0.025



Bowtie: 0.022



Chevron: 0.015

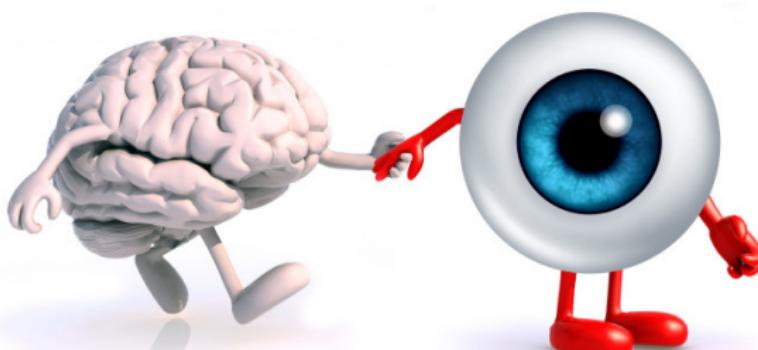


Polygon: 0.013

# Summary

- ▶ CNNs view images as collections of features, then use those features to make classifications
- ▶ Pre-trained CNNs detect complex features and classify images from thousands of categories by learning from large image databases
- ▶ Retraining the classifier on a pre-trained CNN greatly reduces the required number of training images for a new classification task
- ▶ CNNs are well-suited to outsole classification, but the biggest challenge is getting a large amount of consistent data

# Questions?



## References I

- [1] Susan Gross et al. "The Variability and Significance of Class Characteristics in Footwear Impressions". 2013.
- [2] Sheida Hancock et al. "The Interpretation of Shoeprint Comparison Class Correspondences". 2012.
- [3] Alex Krizhevsky et al. "ImageNet Classification with Deep Convolutional Neural Networks". 2012.
- [4] Karen Simonyan and Andrew Zisserman. "Very Deep Convolutional Networks for Large-Scale Image Recognition". Sept. 2014.