OPEN DATA SCIENCE CONFERENCE

#ODSC

@ODSC

Boston | May 1 - 4 2018

http://bit.ly/aiconfny18cv

Introductions & Networking

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Agenda

- Computer Vision Overview
- Overview of Keras & TensorFlow
- Getting started with Keras
- Anatomy of Keras Model
- Computer Vision Models using Keras
  - Image Classification
  - Transfer Learning
  - Object Detection
- Workign with Computer Vision Datasets
- Deploying Keras Model
- Computer Vision next...

Computer Vision Overview

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http://bit.ly/odsckerascv

Computer Vision 101

- Image Properties
  - Pixels
  - Dimension
  - Channels
  - Color Depth

Width (800 pixels)

Height (600 pixels)

8-bit Image

Color Depth	Channel Range
1-Bit	0-1
8-Bit	0-255
16-Bit	0-65,535
24-Bit	0-16,777,215

One Pixel

Channel	Red	Green	Blue
Value	0-255	0-255	0-255

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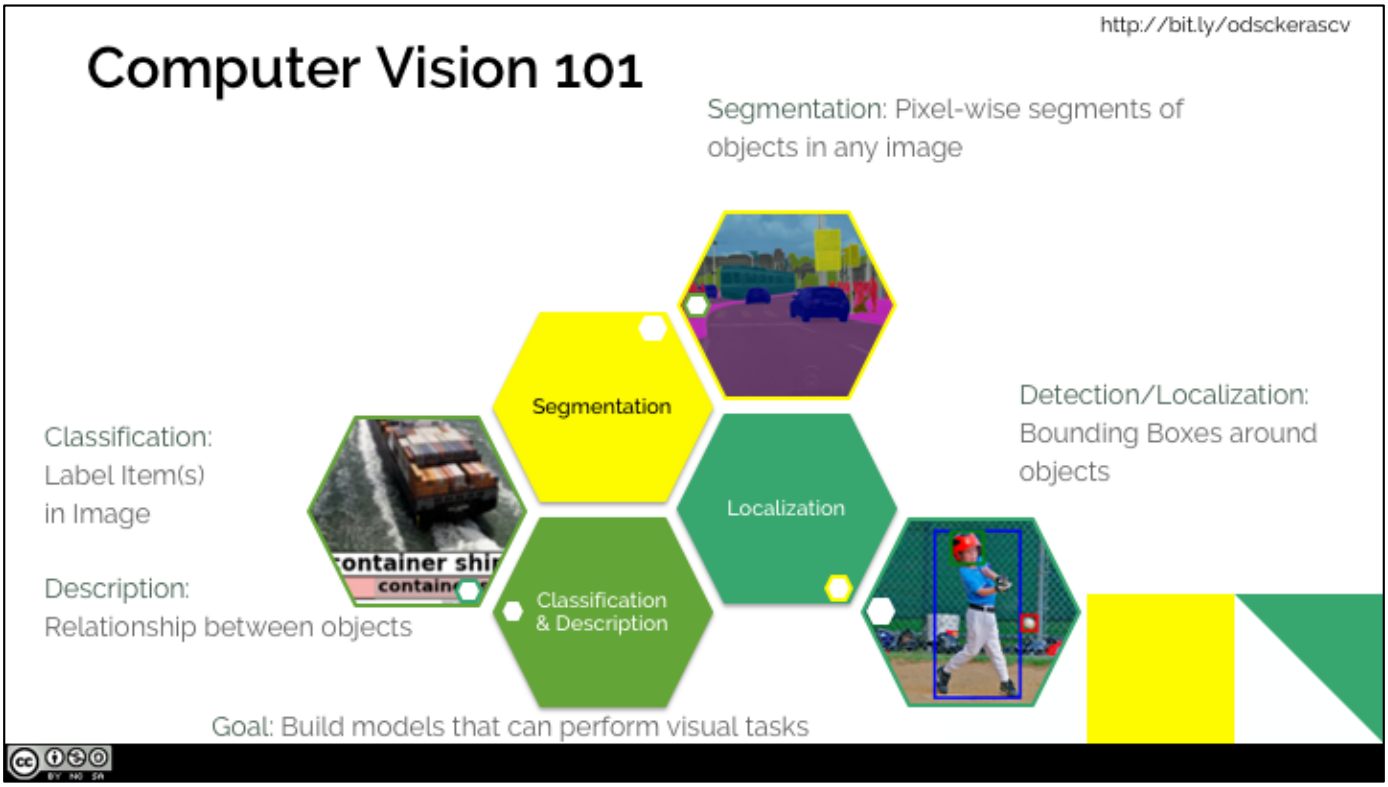

- Classification Image: https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks
- Segmentation Image:https://www.cityscapes-dataset.com/examples/
- Detection Image: http://image-net.org/challenges/LSVRC/2015/ui/det.html

http://bit.ly/odsckerascv

Classification & Description

What is the man doing?

Submit

Predicted top-5 answers with confidence:

playing tennis	99.126%
tennis	0.553%
skateboarding	0.139%
serving	0.075%
jumping	0.033%

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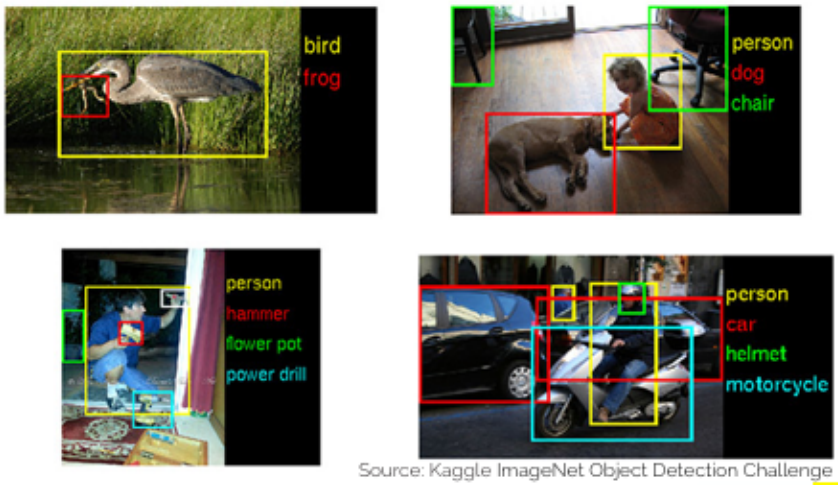
Localization



Source: Kaggle ImageNet Object Detection Challenge

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Segmentation

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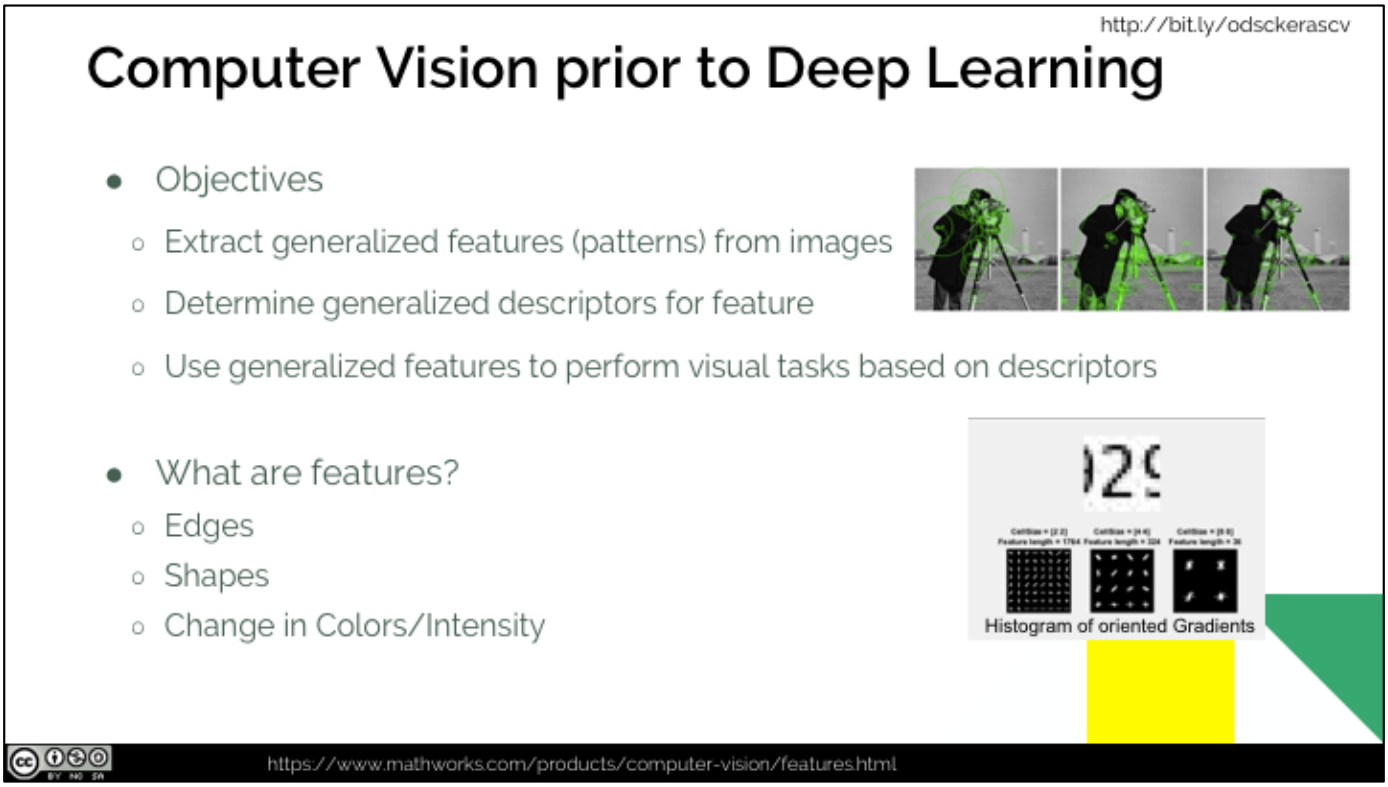
Source: The Cityscapes Dataset - Semantic, instance-wise, dense pixel annotations of 30 classes



- Histogram of oriented gradients (HOG) feature extraction of image (top). Feature vectors of different sizes are created to represent the image by varying cell size.
- SURF: Speeded-up robust features (left), MSER: maximally stable extremal regions (center), and corner detection (right). Using the same image, three different feature types are detected and results plotted over the original image.

Traditional Machine Learning → Deep Learning

- Featuring engineering challenges
  - Human scaling: Time consuming to create rules for each object
  - Computational scaling: Translating human curated features to algorithms that machines can perform at scale is tedious
- Feature Learning
  - Design computational models to learn features
- Feature Learning Challenges
  - Need large datasets with annotations
  - Model architectures become complex both to design and run

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Convolutional Neural Networks

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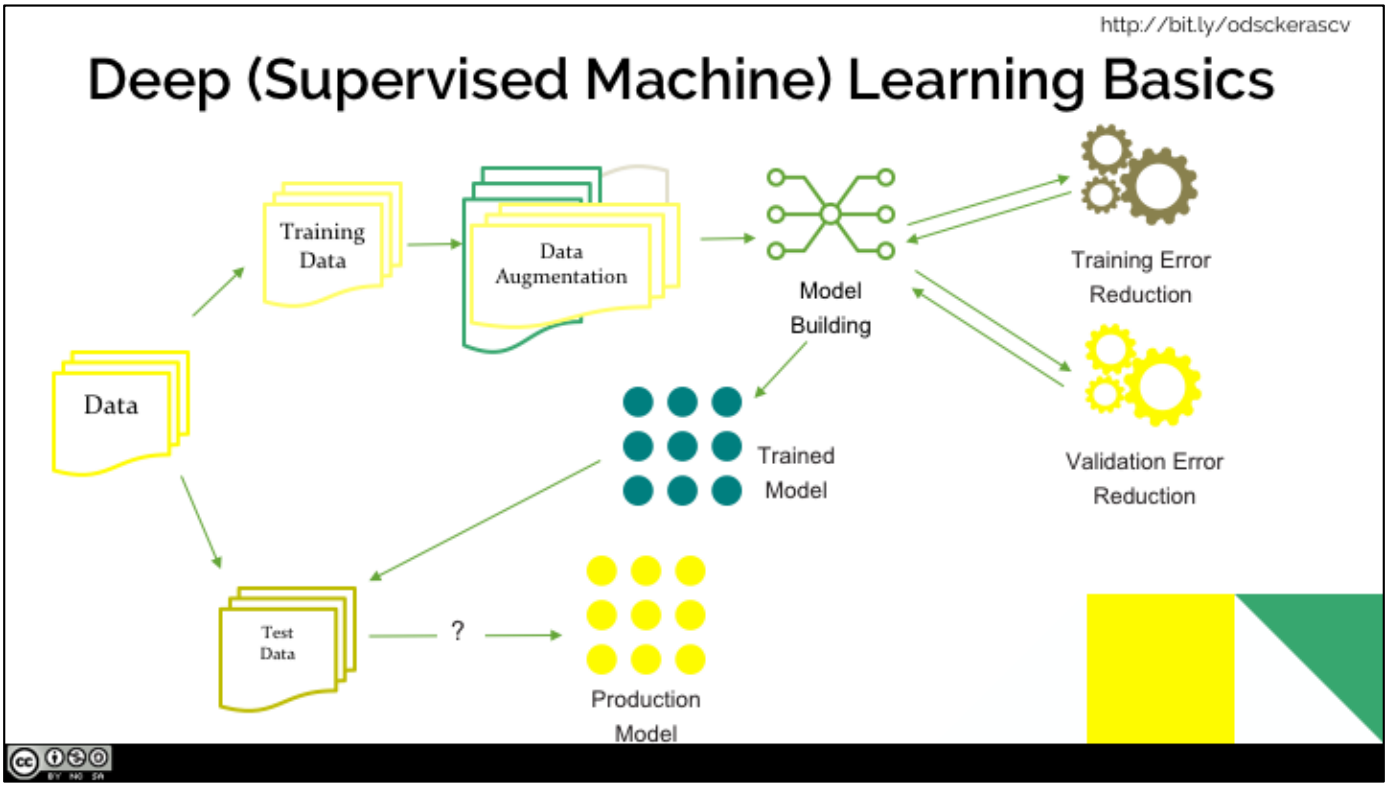
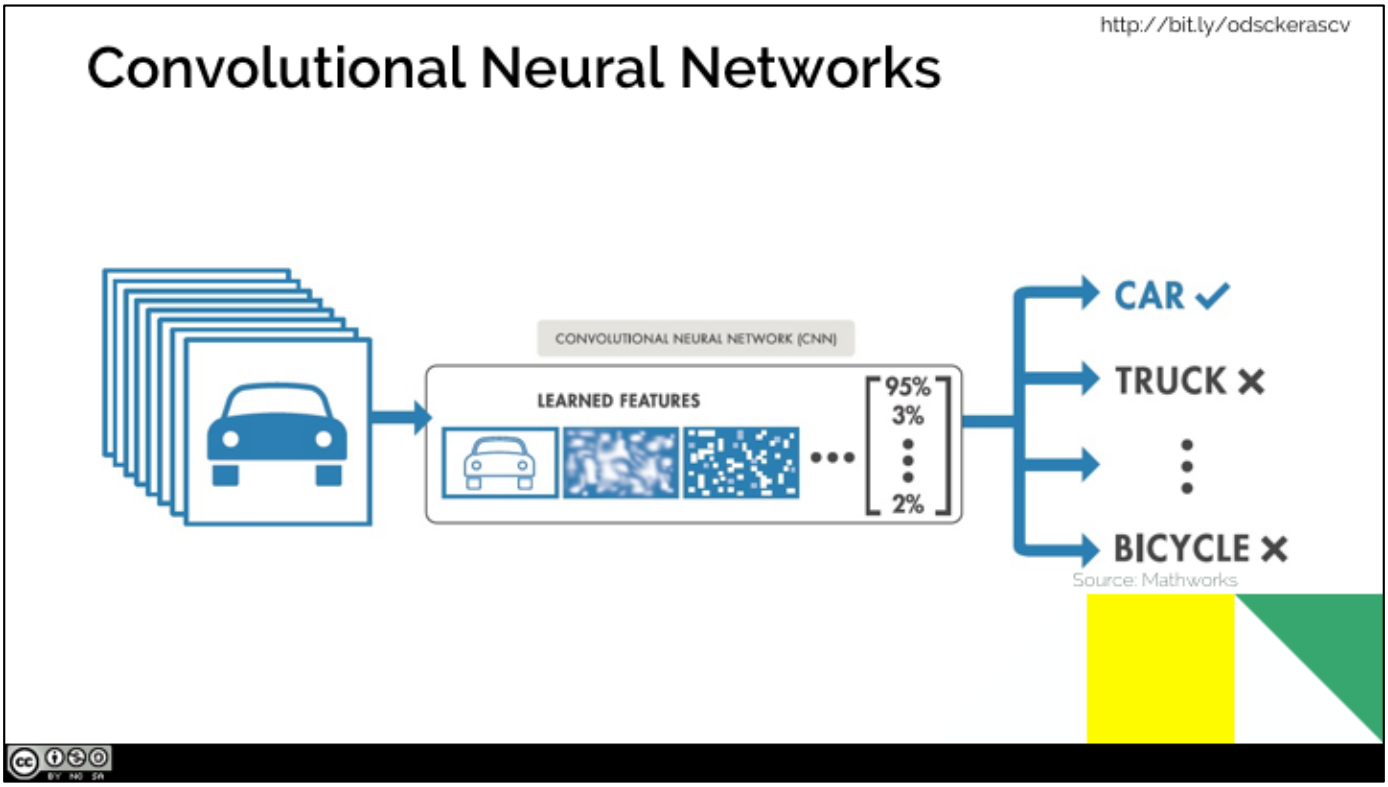
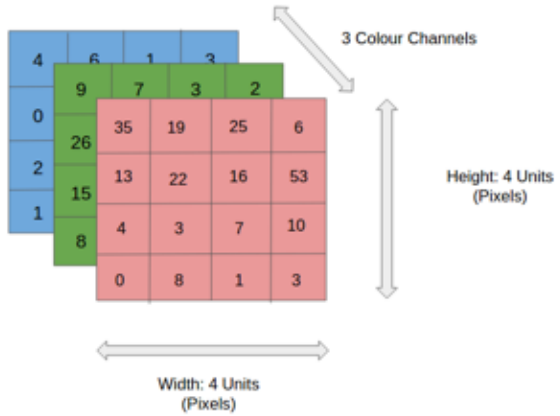

http://bit.ly/odsckerascv
Deep (Supervised Machine) Learning Basics
Training Data
Data Augmentation
Model Building
Training Error Reduction
Validation Error Reduction
Data
Trained Model
Test Data
?
Production Model



- https://www.mathworks.com/discovery/convolutional-neural-network.html

Convolutional Neural Network Properties

- Learning Low Level Features from High Dimensional Data
- Must Have Data Properties:
  - Shift Invariant
  - Correlated
- Simply put: Changing column order should not change meaning of Data
- Naturally Suitable Data Types:
  - Images, Audio, Video
  - Time Series



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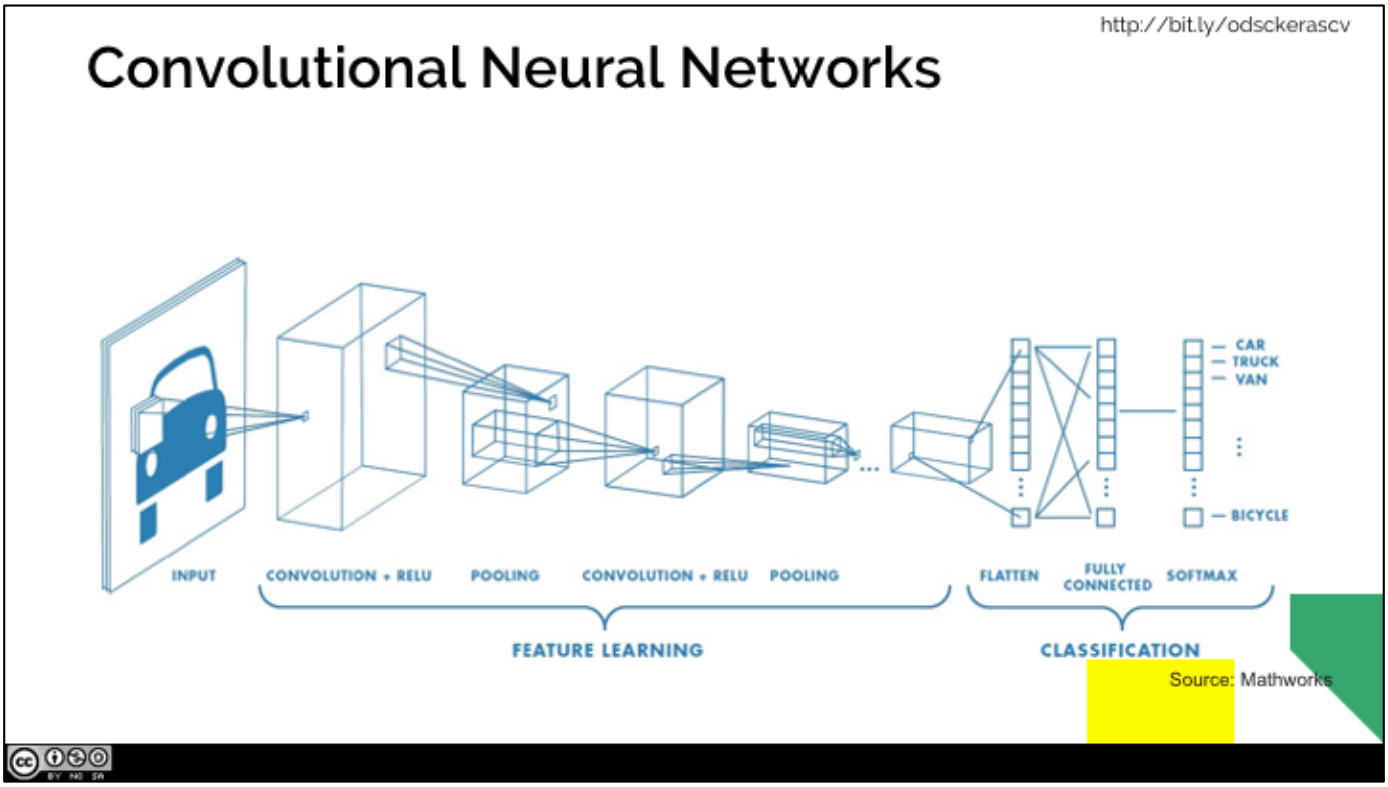
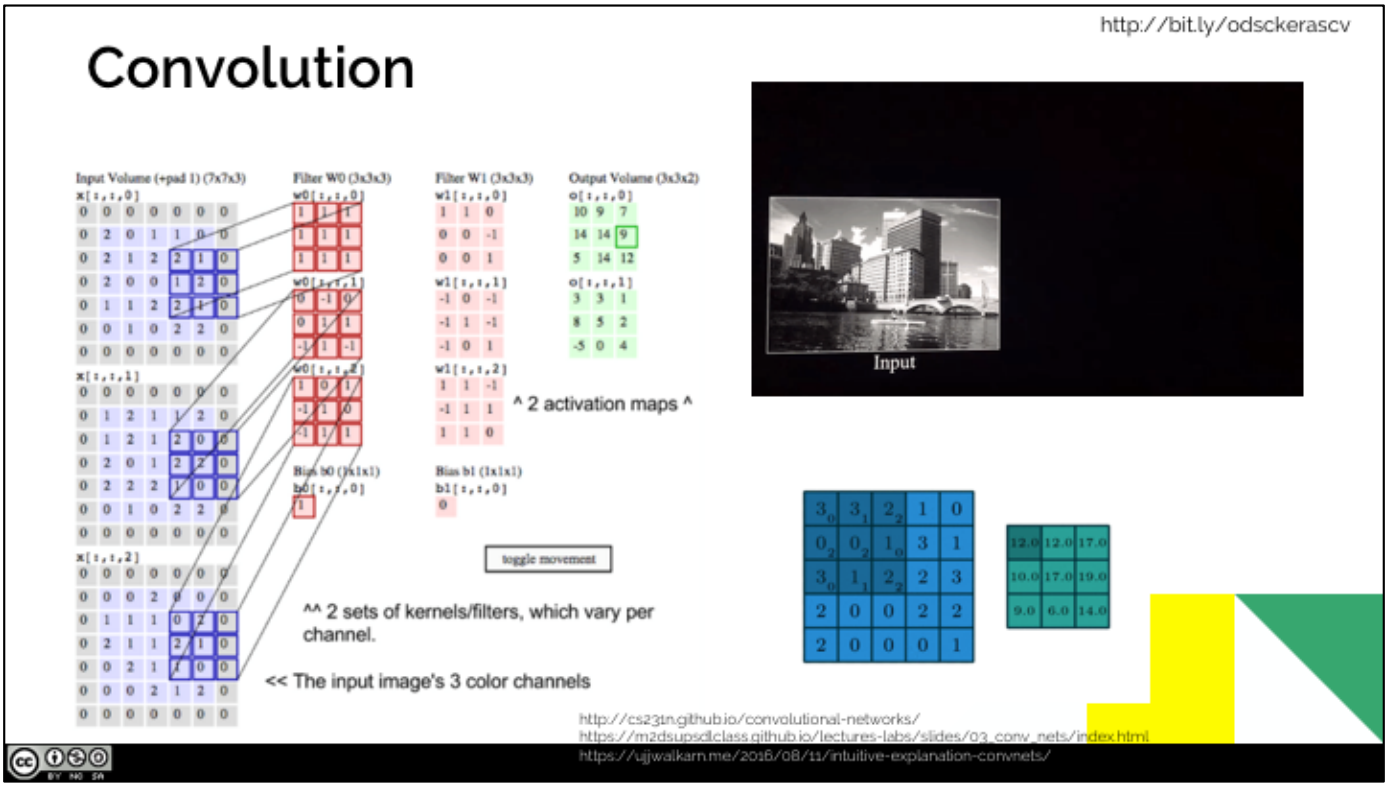


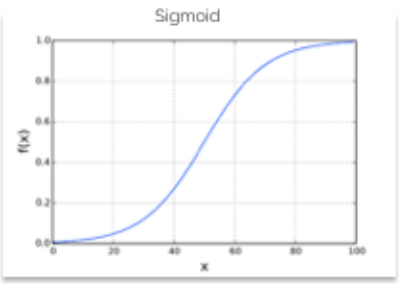
- https://www.mathworks.com/discovery/convolutional-neural-network.html

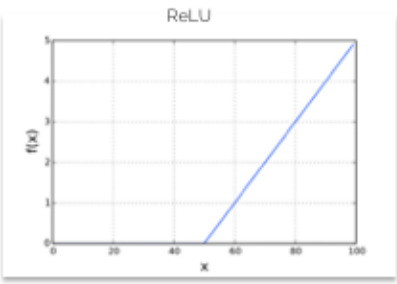


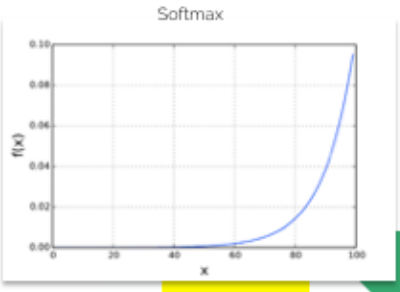
- http://cs231n.github.io/convolutional-networks/
- https://m2dsupsdlclass.github.io/lectures-labs/slides/03_conv_nets/index.html
- https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

Activation

- Mechanism that decides to activate or not activate a neuron in a neural network







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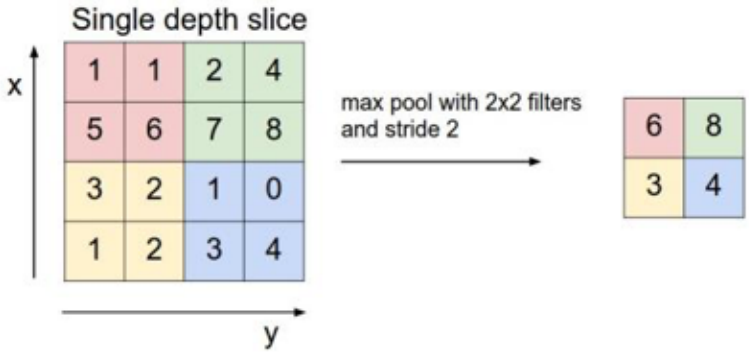
Pooling



Source: Stanford University CS 231 Course:
http://cs231n.github.io/convolutional-networks/#pool

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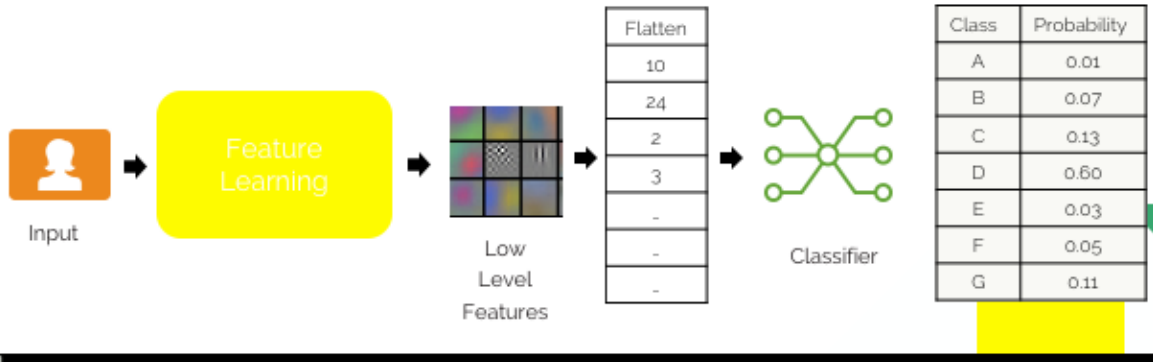
Fully Connected

- Traditional Machine Learning: Feature Engineering
- Deep Learning: Feature Learning
- Learned Features are fed to traditional classifier such as Multivariate Logistic Regression (Softmax)



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Loss Reduction

Class	Probability	Truth	Loss/ Error
A	0.01	0	0
B	0.07	0	0
C	0.13	0	0
D	0.60	1	0.22
E	0.03	0	0
F	0.05	0	0
G	0.11	0	0

Cross Entropy Loss

One-Hot Encoded Vector of Class Label

Back Propagation

- Account for loss across the weights and biases in the network
- Use cost function provided by Back Propagation to optimize the weights and biases to reduce loss
- Variety of Stochastic Gradient Descent techniques used for optimization

Overview of Gradient Descent Techniques:
http://ruder.io/optimizing-gradient-descent/

https://rdipietro.github.io/friendly-intro-to-cross-entropy-loss/

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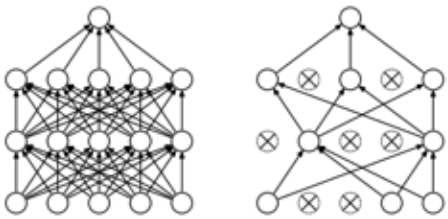
Generalization

Dropout

Randomly remove learned nodes from network



(a) Standard Neural Net (b) After applying dropout.

Dropout: A Simple Way to Prevent Neural Networks from Overfitting
http://www.jmlr.org/papers/volume15/srivastava14a/srivastava14a.pdf

Batch Normalization

- During training input data shifts as weights and parameter adjust values
- To prevent internal covariate shift, normalize each batch by mean and variance

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift
https://arxiv.org/abs/1502.03167

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Keras & TensorFlow

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TensorFlow & Keras

- TensorFlow: A system for movement of Tensors
- A general purpose framework for machine learning
- Intermediate to Advanced Users
- Extensive Ecosystem
- Large Community

- Keras: "It's a play on the words κέρας (horn) / κραίνω (fulfill), and ἐλέφας (ivory) / ἐλεφαίρομαι (deceive)."
- Best for beginners and prototyping
- Simple API that works with multiple backends
- TensorFlow now primary backend

Getting started with Keras

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Deep Learning Software Quick-Start

Simple:

```
python3 -m pip install --upgrade pip
pip install keras
python3 -m pip install jupyter
```

- Get Anaconda Python Distribution
  - https://www.anaconda.com/download/
- Install Keras*
  - Open Anaconda Navigator
  - Go to Environments
  - Click on Channels, Click on Add, Add conda-forge and click on Update Channels
  - Search for TensorFlow and check the box in Name column
  - Search for Keras and check the box in Name column
  - Click Apply
- Launch Jupyter Notebook
  - Open Anaconda Navigator
  - From Home, click on Launch button for Jupyter Notebook

*your mileage may vary

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Anatomy of a Keras Model

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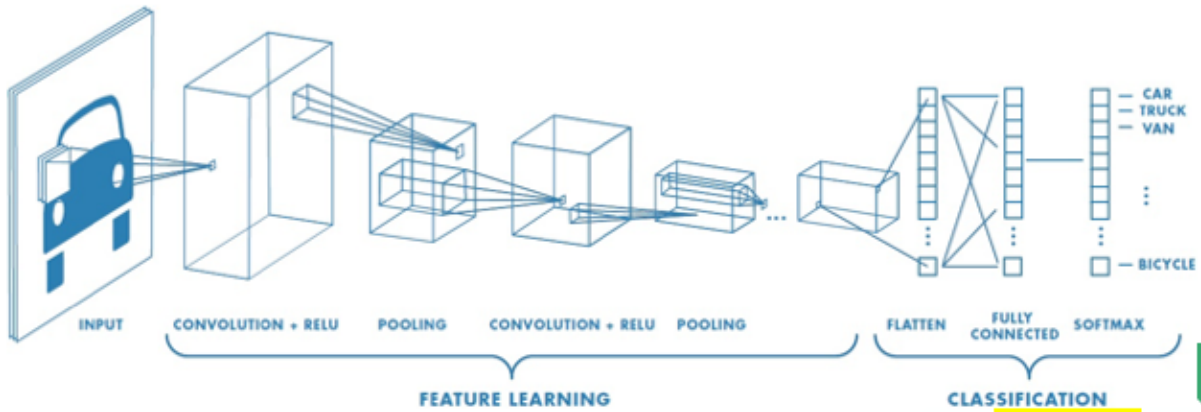
Image Classification



Source: Mathworks

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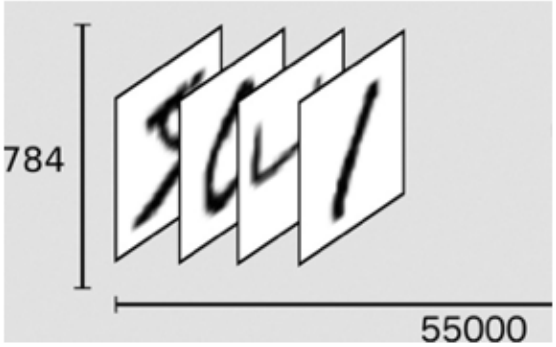
http://bit.ly/odsckerascv

Learning by example: MNIST Handwritten Digit Classifcation

- Ten classes
  - 0,1,2,3,4,5,6,7,8,9
- Dataset
  - 55,000 28x28 Black and White images for training
  - 10,000 28x28 Black and White images for testing



- https://www.tensorflow.org/get_started/mnist/pros

Anatomy of a Keras Model

- Using Jupyter Notebook, please open `Keras_MNIST.ipynb` from the tutorial repository on Github.

Computer Vision Models

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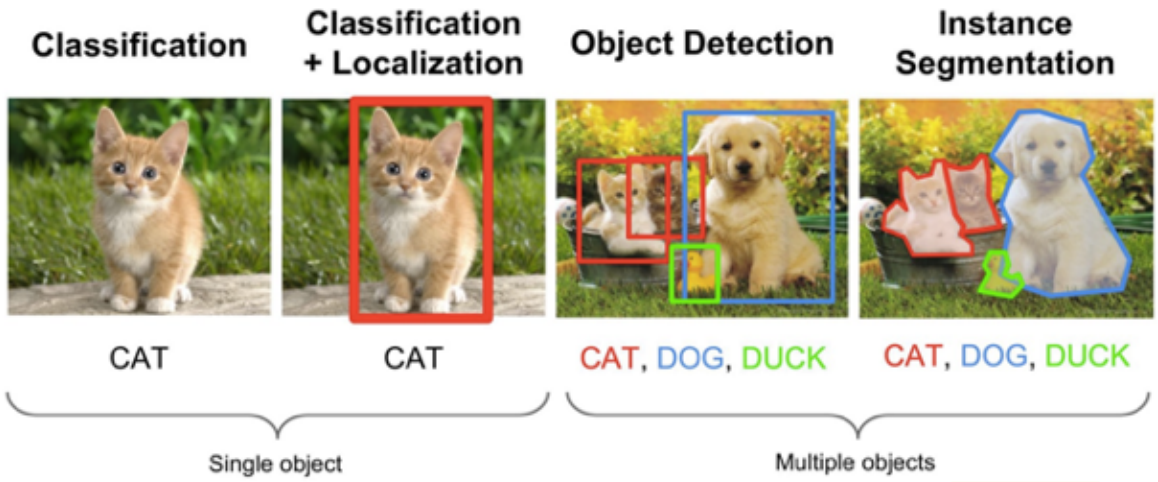
Object Detection & Segmentation



https://medium.com/comet-app/review-of-deep-learning-algorithms-for-object-detection-c1f3d437b852

Image Classification

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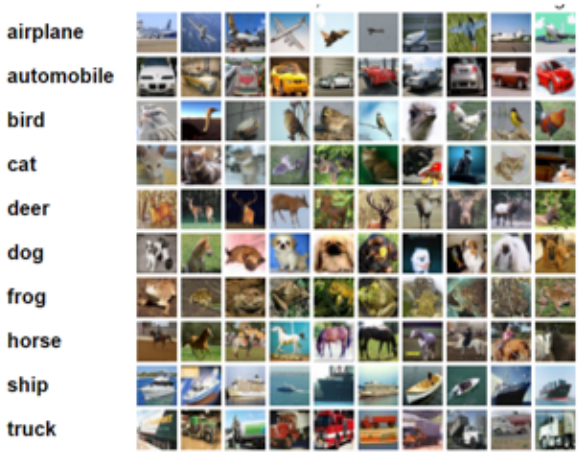
PyTorch CIFAR10 Tutorial

- Ten classes
- Dataset:
  - 60,000 32x32 color images in 10 classes
  - 6000 images per class.
  - 50,000 training images
  - 10,000 test images



https://www.cs.toronto.edu/~kriz/cifar.html

PyTorch CIFAR10 Tutorial

- Using Jupyter Notebook, please open `Keras_CIFAR10_Walk_Through.ipynb` from the tutorial repository on Github.

Transfer Learning

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Why Transfer Learning?

Deep Learning Challenges

- Not enough data
- Not enough labeled data
- Not enough hardware
- Training time too long

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Transfer Learning

Domain to Domain Learning

- Learn Features, Weights, Biases in one domain
- Find domain with similar data characteristics and distribution
- Apply model in new domain

Retraining

- Freeze layers in a "good" model up to tunable depth of feature extraction but before final prediction layer
- Remove final layer(s)
- Relearn final and classification layers using your own data

Bonus: Combine Domain to Domain and Retraining

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Freezing Layers in Keras

Existing Model

```
model = Sequential()
model.add(Conv2D(32, (3, 3), padding='same',
input_shape=x_train.shape[1:]))
model.add(Activation('relu'))
model.add(Conv2D(32, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes))
model.add(Activation('softmax'))
opt = keras.optimizers.rmsprop(lr=0.0001, decay=1e-6)
model.compile(loss='categorical_crossentropy',
optimizer=opt,metrics=['accuracy'])
```

Retraining Model

```
model = Sequential()
model.add(Conv2D(32, (3, 3), padding='same',
input_shape=x_train.shape[1:]),trainable=False)
model.add(Activation('relu'),trainable=False)
model.add(Conv2D(32, (3, 3)),trainable=False)
model.add(Activation('relu'),trainable=False)
model.add(MaxPooling2D(pool_size=(2, 2)) ,trainable=False)
model.add(Dropout(0.25))
model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
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model.compile(loss='categorical_crossentropy',
optimizer=opt,metrics=['accuracy'])
```

Object Detection & Segmentation

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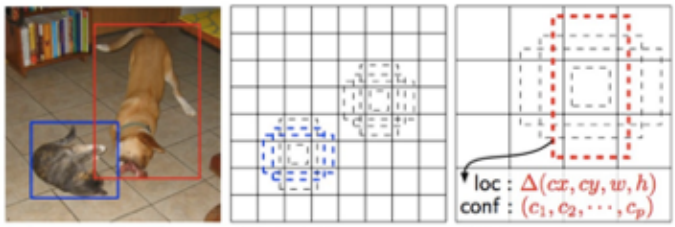
Single Shot Multi-box Detector

- Keras: SSD_tutorial.ipynb



(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

Fig. 1: **SSD framework.** (a) SSD only needs an input image and ground truth boxes for each object during training. In a convolutional fashion, we evaluate a small set (e.g. 4) of default boxes of different aspect ratios at each location in several feature maps with different scales (e.g. 8×8 and 4×4 in (b) and (c)). For each default box, we predict both the shape offsets and the confidences for all object categories ($(c_1, c_2, \cdots, c_p)$). At training time, we first match these default boxes to the ground truth boxes. For example, we have matched two default boxes with the cat and one with the dog, which are treated as positives and the rest as negatives. The model loss is a weighted sum between localization loss (e.g. Smooth L1 [6]) and confidence loss (e.g. Softmax).

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Paper: https://arxiv.org/pdf/1512.02325v5.pdf

YOLO: You Only Look Once

- Keras: https://github.com/xiaochus/YOLOv3

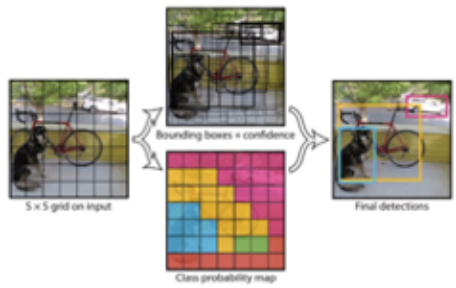

Figure 2: The Model. Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

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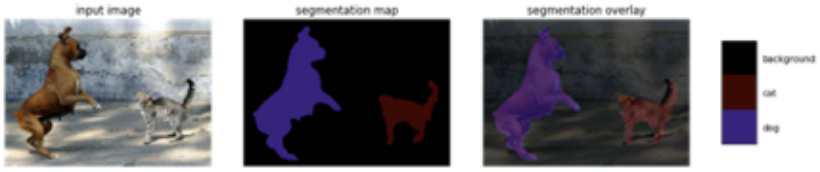
Image Segmentation in Keras & TensorFlow

- Keras – DeepLab: https://github.com/bonlime/keras-deeplab-v3-plus
- TensorFlow: https://research.googleblog.com/2018/03/semantic-image-segmentation-with.html



Keras - DeepLab

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Working with Computer Vision Datasets

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Working with video

Extract Frames and Compose Video using FFMPEG
https://www.ffmpeg.org/

Extract
```
ffmpeg -i <video.file> image%03d.jpg
```

Compose
```
ffmpeg -framerate 24 -i img%03d.jpg <output_video.file>
```

Data Augmentation

- Data Augmentation in Keras
  - keras.preprocessing.image.ImageDataGenerator

```
featurewise_center
samplewise_center
featurewise_std_normalization
samplewise_std_normalization
zca_whitening
zca_epsilon
rotation_range
width_shift_range
height_shift_range
```

```
shear_range
zoom_range
channel_shift_range
fill_mode
cval
horizontal_flip
vertical_flip
rescale
```

Image Source: Deep Image: Scaling up Image Recognition (Baidu)
https://arxiv.org/abs/1501.02876

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Data Annotation


```
{"coco_url":"http://mscoco.org/images/405628",
"date_captured":"2013-11-21 00:26:09",
"file_name":"COCO_train2014_000000405628.jpg",
"flickr_url":"http://farm5.staticflickr.com/4130/5133418813_61f33c
9633_z.jpg",
"height":426,
"id":405628,
"license":5,
"width":640}
```

```
{"area":7581.427150000003,
"bbox":[95.28,146.43,131.92,142.0],
"category_id":1,"id":188293,
"image_id":405628,
"iscrowd":0,
"segmentation":[[219.87,177.58,224.45,172.08,225.37,157.42,218.95
,146.43,208.88,149.18,208.88,149.18,202.46,151.92,198.8,153.76,19
8.8,153.76,196.97,154.67,184.14,153.76,183.23,153.76,158.49,157.4
2,133.75,157.42,95.28,186.74,105.35,183.99,153.91,164.75,169.48,1
74.83,169.48,197.73,135.59,231.63,131.92,235.29,133.75,247.2,152.
99,247.2,155.74,247.2,175.9,241.71,179.56,228.88,184.14,278.35,19
5.14,280.18,194.22,288.43,200.63,282.93,198.8,271.02,224.45,227.0
5,224.45,227.05,227.2,196.82,219.87,183.99]]},
```

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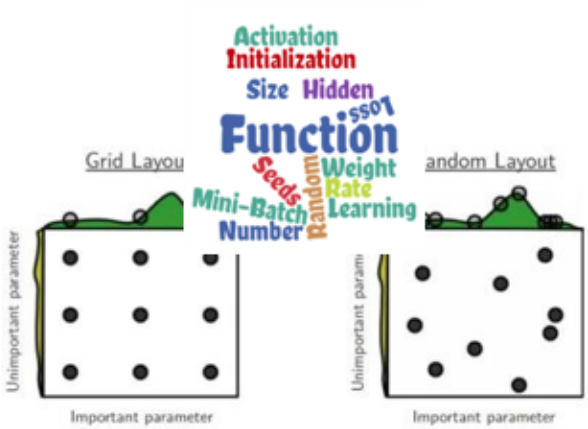
Data Annotation

	BOUNDING BOX	DOTS	POLYGON	SEMANTIC SEGMENTATION
COST	Least expensive	More expensive	More expensive	Most expensive
TIME COMMITMENT	Lowest	Medium	Medium	Highest
PRECISION	Good	Great	Great	Excellent
INSTANCE-BASED (OUTPUT CONTAINS DISCRETE OBJECTS)	Yes	Yes	Yes	No
POSSIBLE TO LABEL SEVERAL OBJECTS?	Yes	Yes	Yes	Yes
POSSIBLE TO LABEL SEVERAL CLASSES OF OBJECT IN A SINGLE JOB?	No	No	No	Yes
OUTPUT*	X,Y coordinate, width and length of each box	Series of x,y coordinates	Series of x,y coordinates, with shapes resolving	Coded RGB pixels as an image

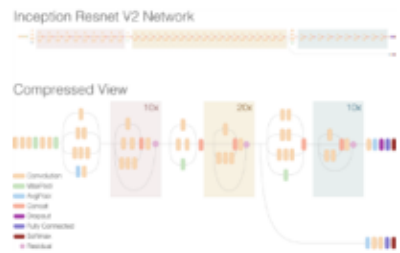
Source: CrowdFlower WHAT WE LEARNED LABELING 1 MILLION IMAGES

http://bit.ly/odsckerascv

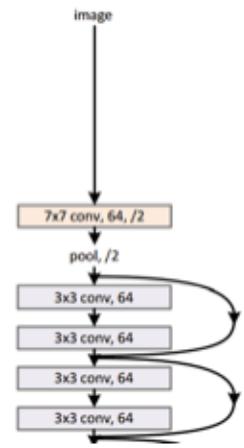
Training Challenges



Hyper-Parameter Optimization



Google Inception v3

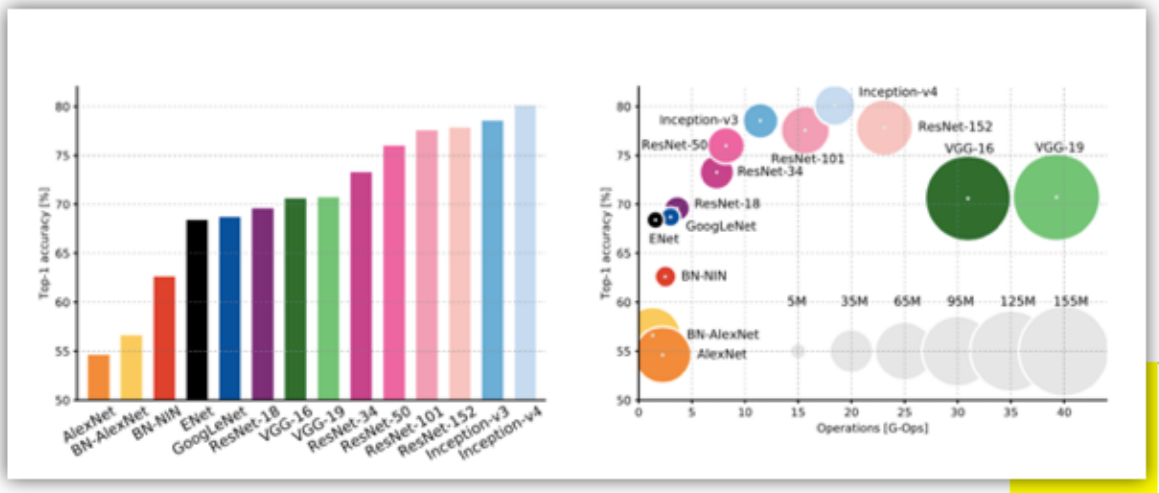


Microsoft Resnet

https://adeshpande3.github.io/adeshpande3.github.io/The-9-Deep-Learning-Papers-You-Need-To-Know-About.html
http://colinraffel.com/wiki/neural_network_hyperparameters

http://bit.ly/odsckerascv

Analysis from training Computer Vision Models



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An Analysis of Deep Neural Network Models for Practical Applications https://arxiv.org/abs/1605.07678

Training Computer Vision Models: Time & Cost

Batch Size	epochs	Top-1 Accuracy	hardware	cost ($)	time
256	100	58.7%	8-core CPU + K20 GPU	3,000	144h
512	100	58.8%	1 DGX station	129,000	6h 10m
4096	100	58.4%	1 DGX station	129,000	2h 19m
32K	100	58.5%	512 KNLs	1.2 million	24m

Table 7: The speed and hardware cost for training AlexNet.
For batch size=32K, we changed local response norm in AlexNet to batch norm.

Batch Size	epochs	Top-1 Accuracy	hardware	cost ($)	time
256	90	73.0%	1 DGX station	129,000	21h
8192	90	72.7%	1 DGX station	129,000	21h
8192	90	72.7%	32 DGX stations	4.1 million	1h
32K	90	72.4%	512 KNLs	1.2 million	1h

Table 8: The speed and hardware cost for training ResNet50. We did not use data augmentation.

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ImageNet Training in 24 Minutes https://arxiv.org/abs/1709.05011

Deploying Keras Models

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Deploying Keras Models

- Prototype using Keras Predict API: Building a simple Keras + deep learning REST API
  - `output = model.predict(input)`
  - https://blog.keras.io/#exporting-a-model-with-tensorflow-serving
- Production: TensorFlow* Serving
  - `estimator_model = keras.estimator.model_to_estimator(keras_model=model)`
  - Converting a Keras model to a TensorFlow Estimator: https://cloud.google.com/blog/big-data/2017/12/new-in-tensorflow-14-converting-a-keras-model-to-a-tensorflow-estimator
  - https://github.com/tensorflow/workshops/blob/master/extras/keras-to-estimator/keras-to-estimator.ipynb

*TensorFlow 1.4 or higher

Computer Vision *Next...*

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New ideas in Deep Learning Computer Vision

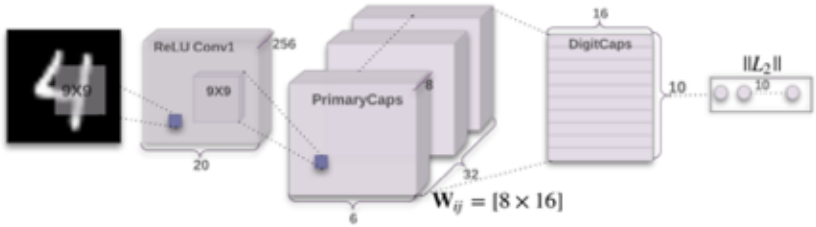
- Generative Adversarial Networks (GANs) https://arxiv.org/abs/1406.2661

https://github.com/eriklindernoren/Keras-GAN

- Capsule Networks

Dynamic Routing Between Capsules (https://arxiv.org/abs/1710.09829)

https://github.com/XifengGuo/CapsNet-Keras



https://medium.com/ai%C2%B3-theory-practice-business/understanding-hintons-capsule-networks-part-i-intuition-b4b559d1159b

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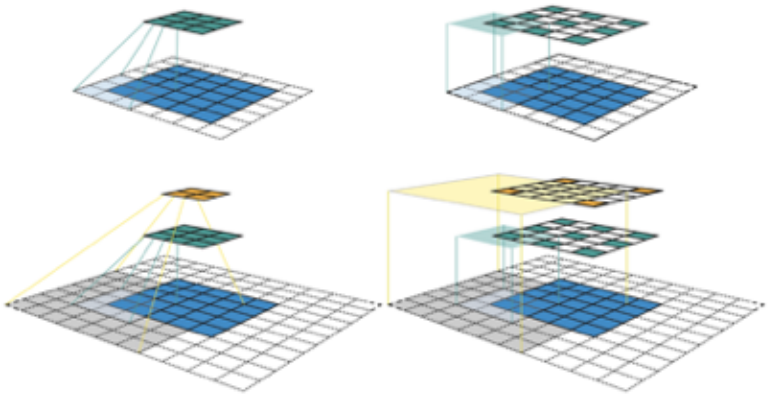
Features and Receptive Field

- A guide to receptive field arithmetic for Convolutional Neural Networks



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https://medium.com/mlreview/a-guide-to-receptive-field-arithmetic-for-convolutional-neural-networks-e0f514068807

POWER UP YOUR COMPUTER VISION SKILLS WITH TENSORFLOW-KERAS

DISCUSSION