

# OPEN DATA SCIENCE CONFERENCE

Boston | May 1 - 4 2018



@ODSC



# POWER UP YOUR COMPUTER VISION SKILLS WITH TENSORFLOW-KERAS

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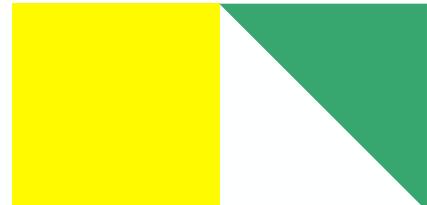
ODSC East - Boston May 2018

<http://bit.ly/odsckerascv>

# Keras & TensorFlow

# 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

# Deep Learning Software Quick-Start

- 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

Simple:

```
python3 -m pip install --upgrade pip
```

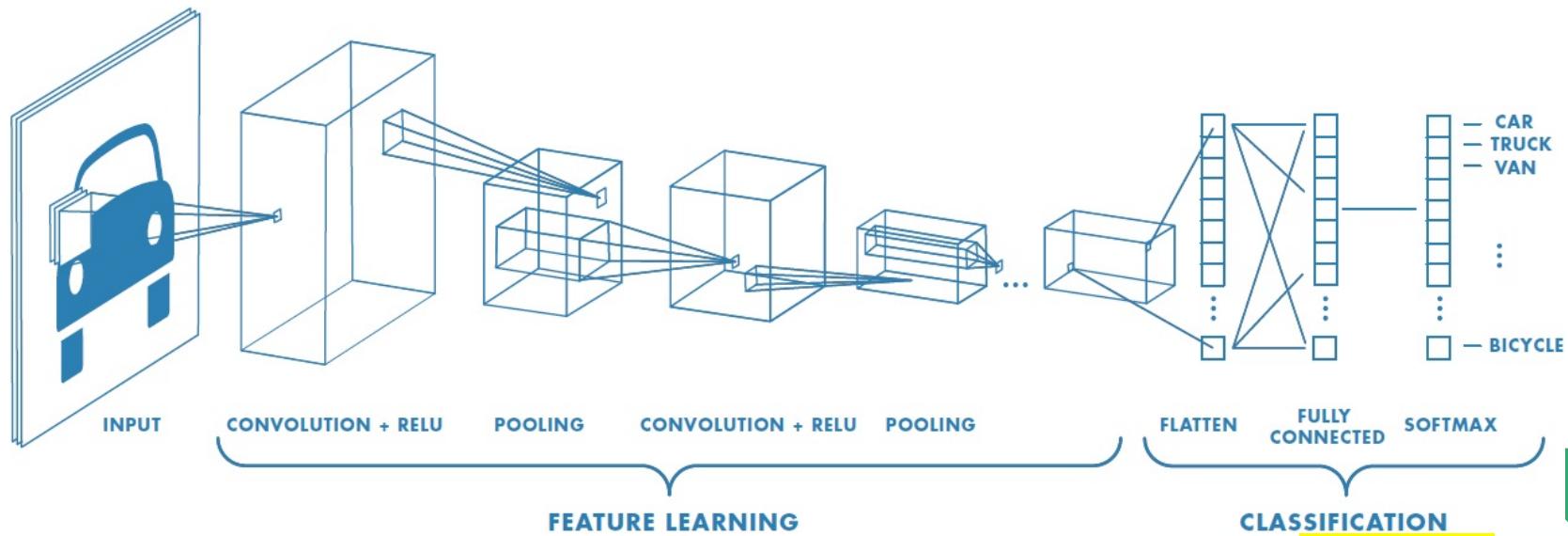
```
pip install keras
```

```
python3 -m pip install jupyter
```

\*your mileage may vary

# Anatomy of a Keras Model

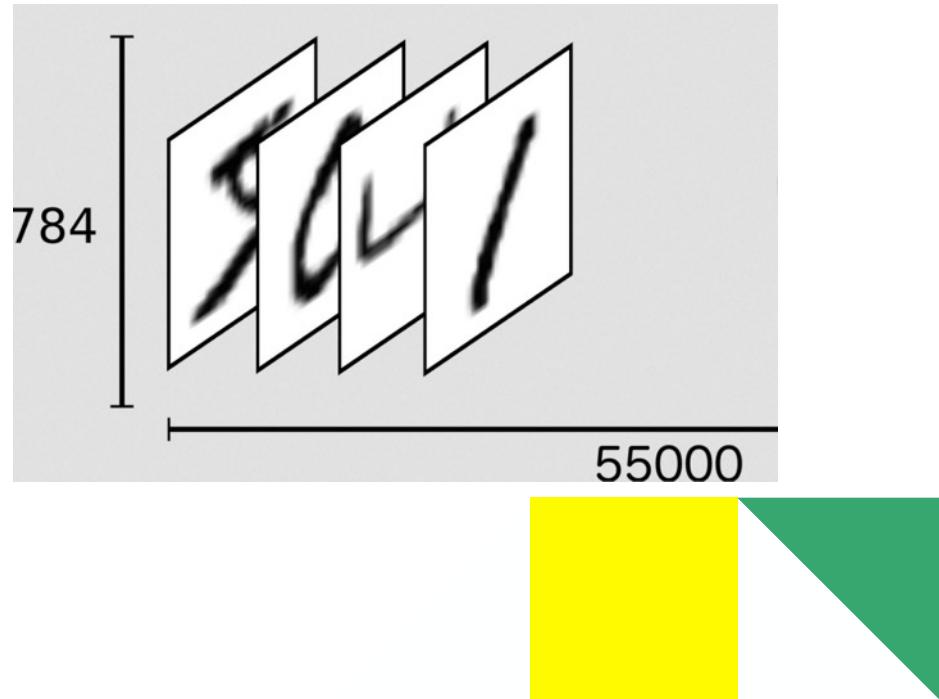
# Image Classification



Source: Mathworks

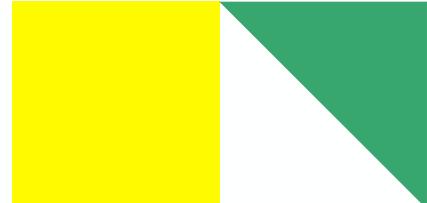
# Learning by example: MNIST Handwritten Digit Classification

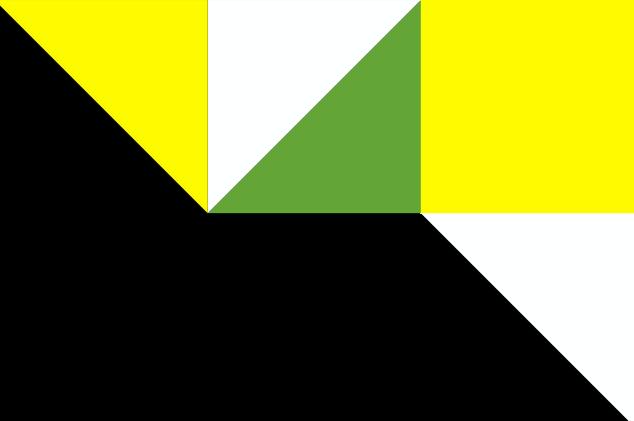
- Ten classes
  - 0,1,2,3,4,5,6,7,8,9
- Dataset
  - 55,000 28x28 Black and White images for training
  - 10,000 28x28 Black and White images for testing



# Anatomy of a Keras Model

- Using Jupyter Notebook, please open *Keras\_MNIST.ipynb* from the tutorial repository on Github.





# Computer Vision Models

# Object Detection & Segmentation

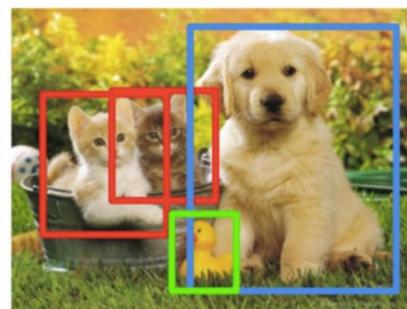
**Classification**



**Classification + Localization**



**Object Detection**



**Instance Segmentation**



CAT

CAT

CAT, DOG, DUCK

CAT, DOG, DUCK

Single object

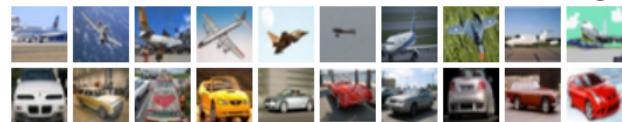
Multiple objects

# Image Classification

# 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

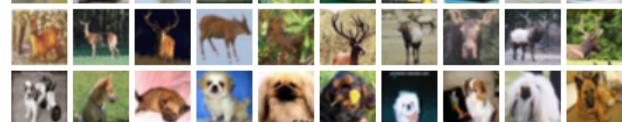
**airplane**



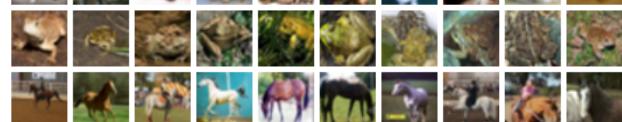
**automobile**



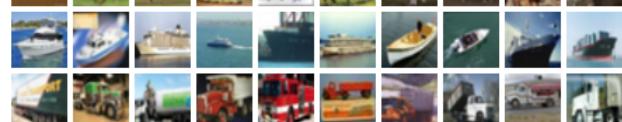
**bird**



**cat**



**deer**



**dog**



**frog**



**horse**



**ship**



**truck**



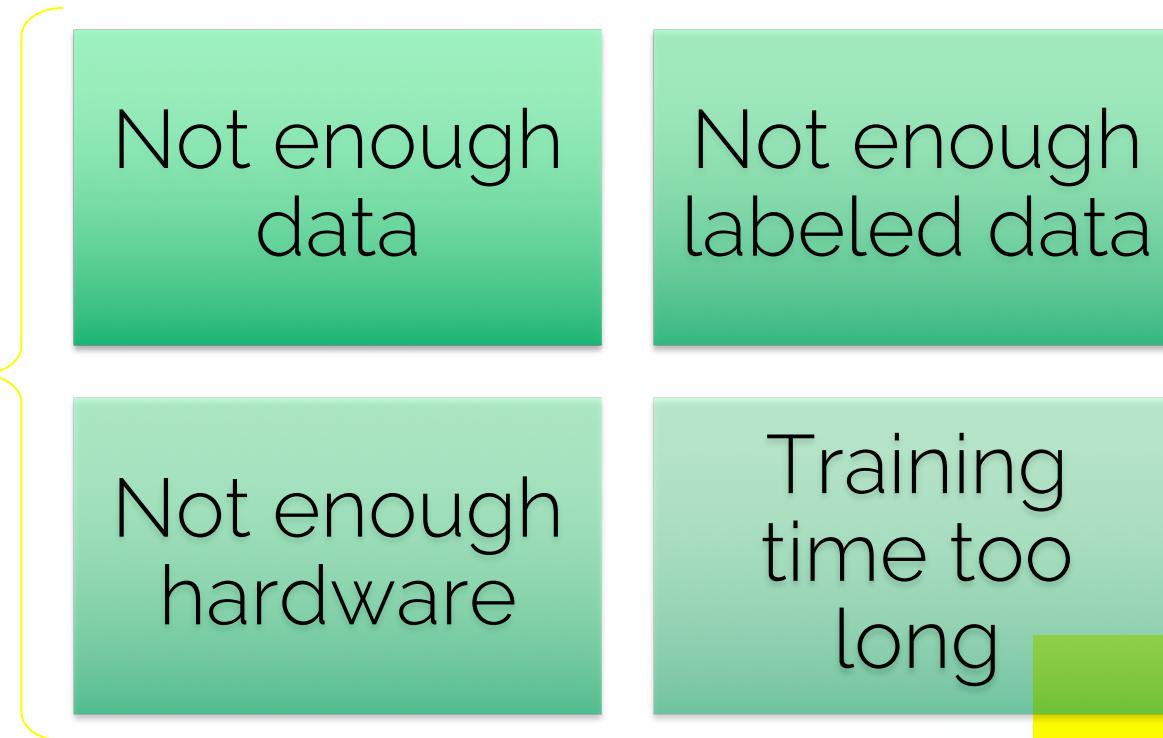
# PyTorch CIFAR10 Tutorial

- Using Jupyter Notebook, please open  
*Keras\_CIFAR10\_Walk\_Through.ipynb* from the tutorial repository on Github.

# Transfer Learning

# Why Transfer Learning?

Deep  
Learning  
Challenges



# 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

# 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'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
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optimizer=opt,metrics=['accuracy'])
```

# Object Detection & Segmentation

# Single Shot Multi-box Detector

- Keras: SSD\_tutorial.ipynb

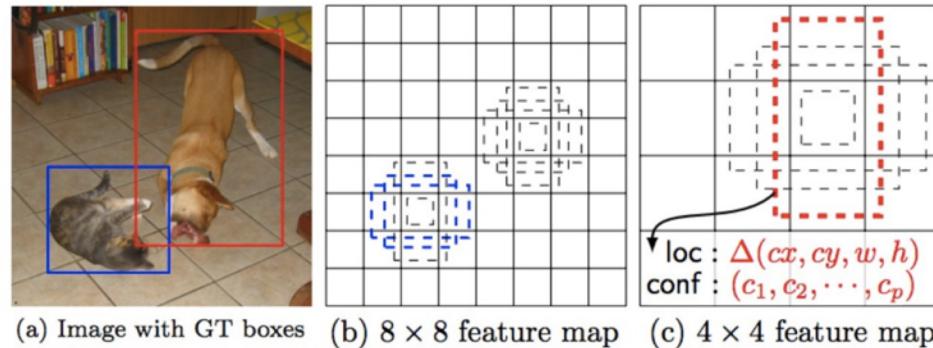
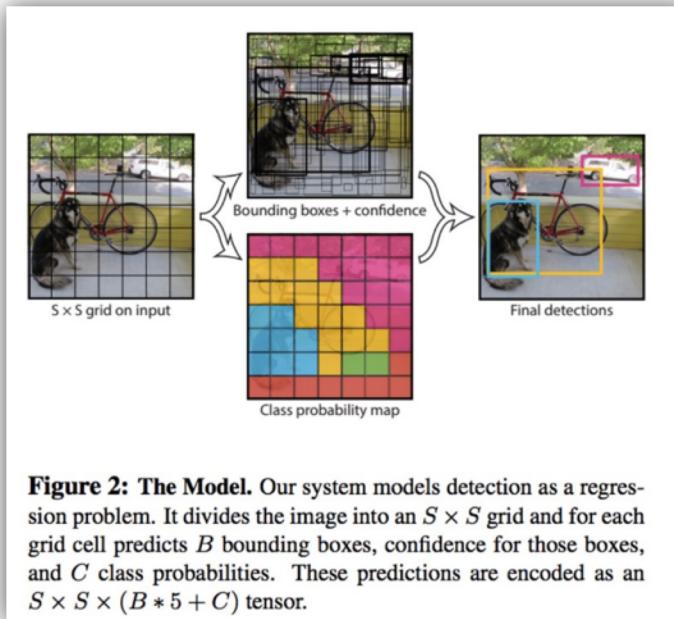


Fig. 1: **SSD framework.** (a) SSD only needs an input image and ground truth boxes for each object during training. In a convolutional fashion, we evaluate a small set (e.g. 4) of default boxes of different aspect ratios at each location in several feature maps with different scales (e.g.  $8 \times 8$  and  $4 \times 4$  in (b) and (c)). For each default box, we predict both the shape offsets and the confidences for all object categories ( $(c_1, c_2, \dots, c_p)$ ). 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).

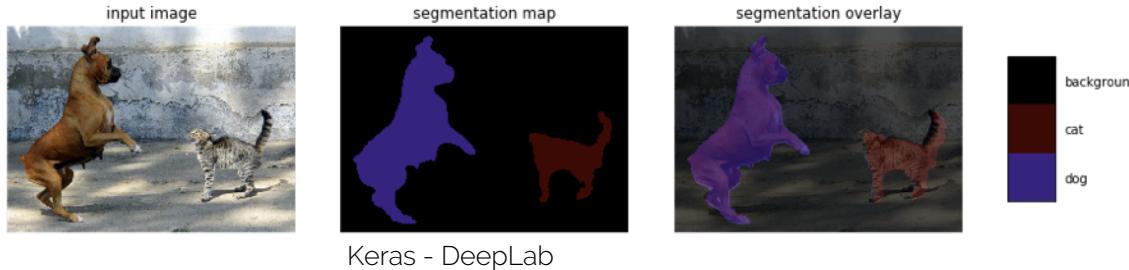
# YOLO: You Only Look Once

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



# 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>



# Working with Computer Vision Datasets

# 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
```

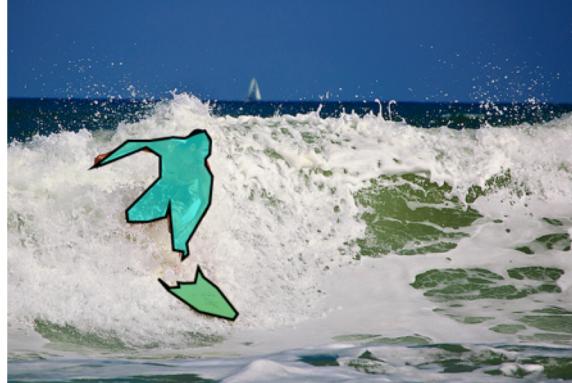


Image Source: Deep Image: Scaling up  
Image Recognition (Baidu)  
<https://arxiv.org/abs/1501.02876>

# Data Annotation

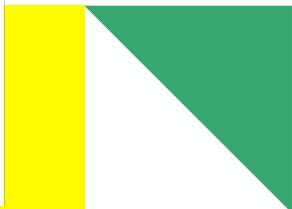
```
{"coco_url": "http://mscoco.org/images/405628",
"date_captured": "2013-11-21 00:26:09",
"file_name": "COCO_train2014_00000405628.jpg",
"flickr_url": "http://farm5.staticflickr.com/4130/5133418813_61f33c9633_z.jpg",
"height": 426,
"id": 405628,
"license": 5,
"width": 640}
```

```
{"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, 198.8, 153.76, 196.97, 154.67, 184.14, 153.76, 183.23, 153.76, 158.49, 157.42, 133.75, 157.42, 95.28, 186.74, 105.35, 183.99, 153.91, 164.75, 169.48, 174.83, 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, 195.14, 280.18, 194.22, 288.43, 200.63, 282.93, 198.8, 271.02, 224.45, 227.05, 224.45, 227.05, 227.2, 196.82, 219.87, 183.99]]},
```

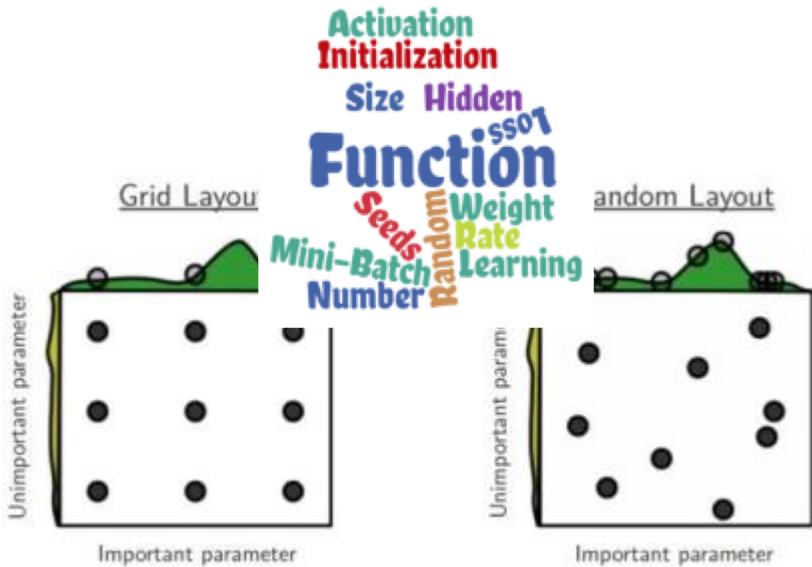


# Data Annotation

	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

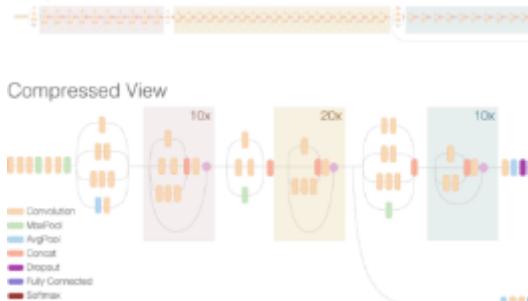


# Training Challenges



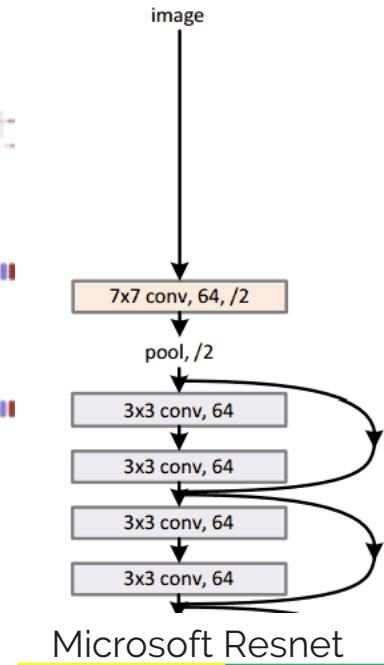
Hyper-Parameter Optimization

Inception Resnet V2 Network



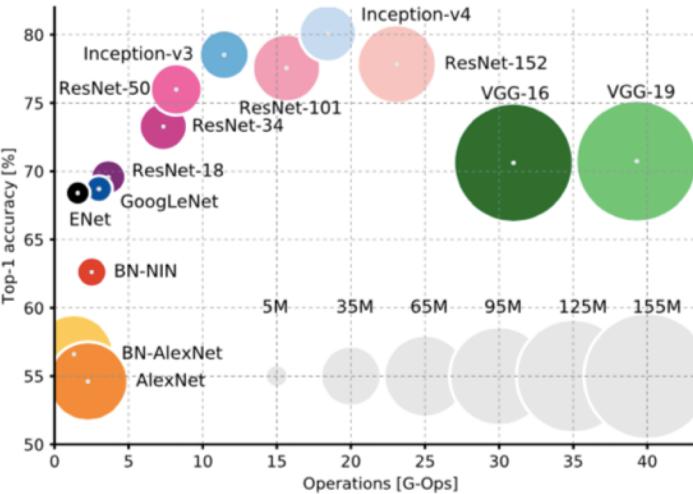
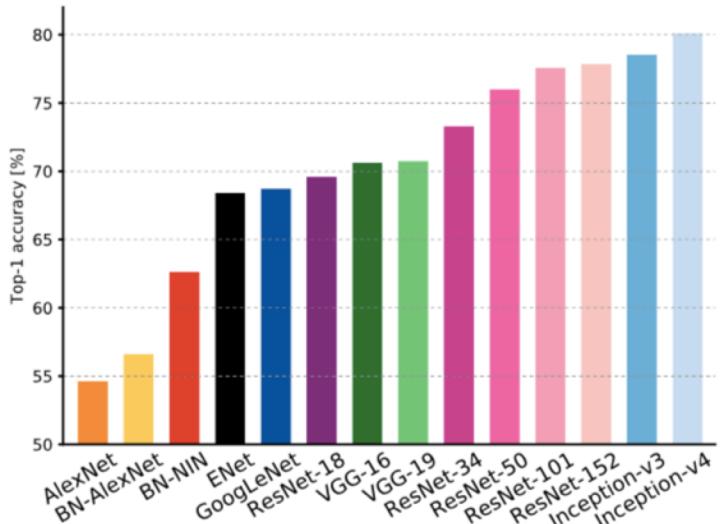
Google Inception v3

34-layer residual



Microsoft Resnet

# Analysis from training Computer Vision Models



# 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.

# Deploying Keras Models

# 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





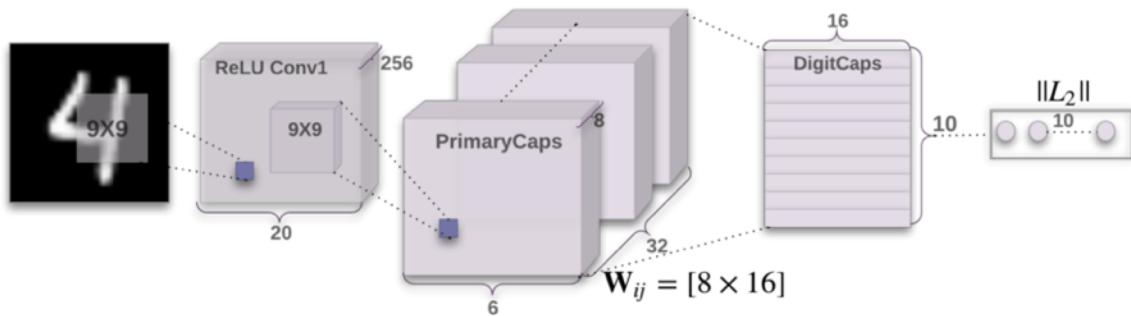
# Computer Vision *Next...*

# 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>

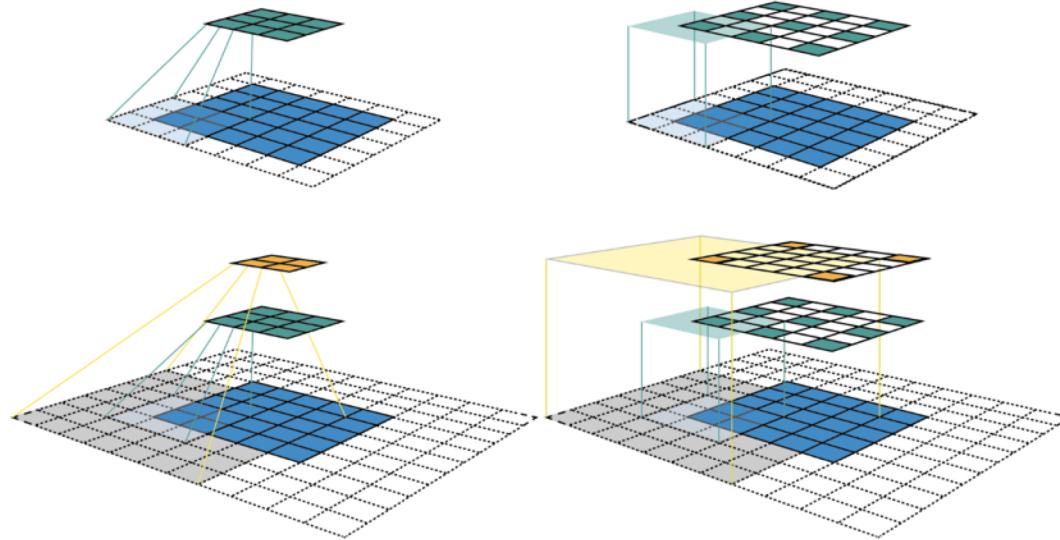


<https://medium.com/ai%C2%B3-theory-practice-business/understanding-hintons-capsule-networks-part-i-intuition-b4b559d1159b>



# Features and Receptive Field

- A guide to receptive field arithmetic for Convolutional Neural Networks





# **POWER UP YOUR COMPUTER VISION SKILLS WITH TENSORFLOW-KERAS**

## **DISCUSSION**