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Microsoft

De-mystifying Deep Learning

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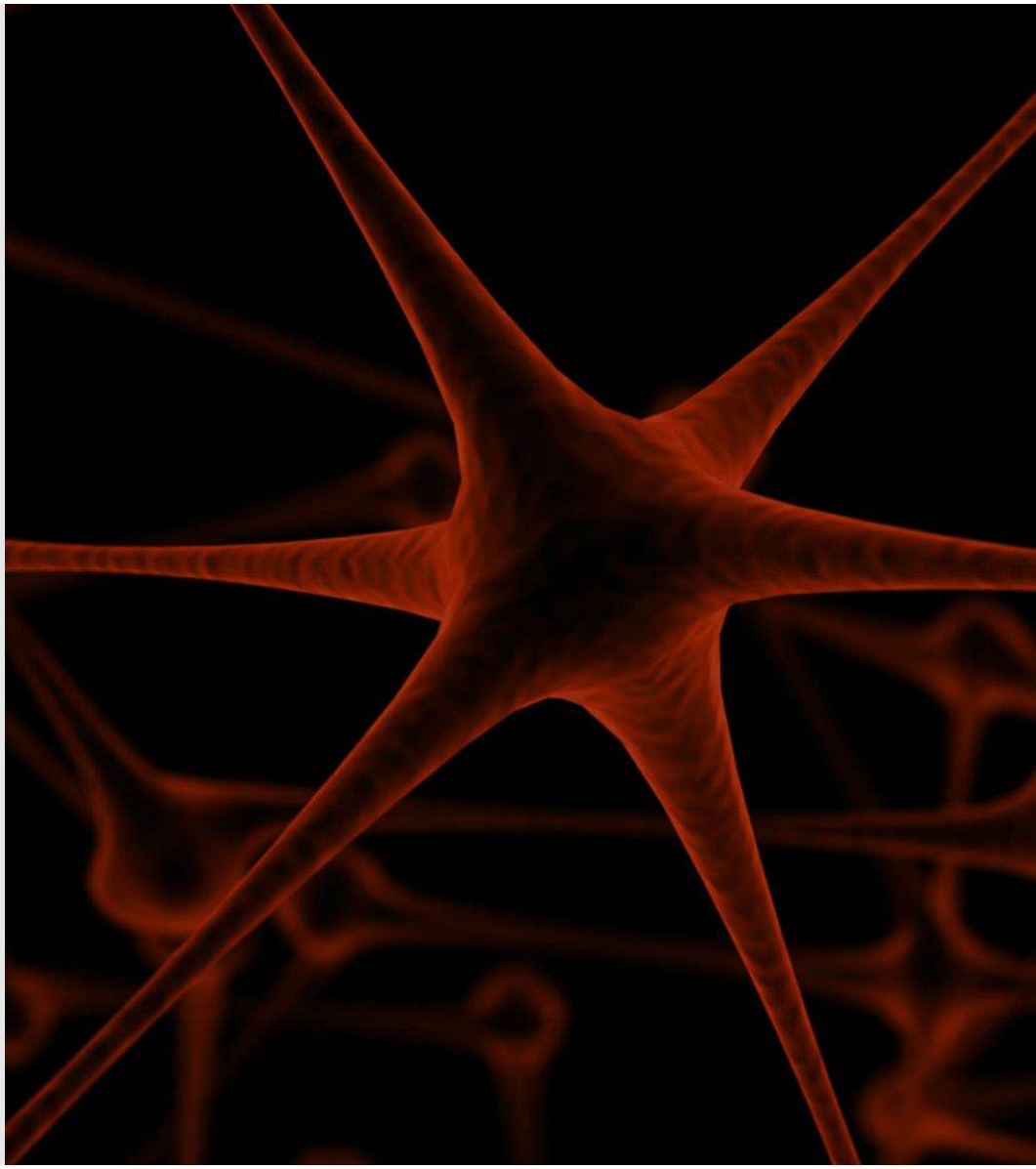


Talk Outline

- Deep Learning (DL)
- Deep Neural Networks (DNN)
- Types of DNNs
- DL Frameworks
- Use Cases

Resources

MLADS_2018_deeplearning

Traditional ML Vs DL

Traditional ML requires manual feature extraction/engineering

Feature extraction for unstructured data is very difficult

Deep learning can automatically learn features in data

Deep learning is largely a "black box" technique, updating learned weights at each layer

Why is DL popular?

- DL models has been here for a long time
  - Fukushima (1980) – Neo-Cognitron
  - LeCun (1989) – Convolutional Neural Network

- DL popularity grew recently
  - With growth of Big Data
  - With the advent of powerful GPUs

Deep learning begins with a little function

It all starts with a humble linear function called a perceptron.

weight1 ✕ input1
weight2 ✕ input2
\+ weight3 ✕ input3
sum

Perceptron:
If sum > threshold: output 1
Else: output 0

Example: The inputs can be your data. Question: Should I buy this car?

0.2 ✕ gas mileage
0.3 ✕ horsepower
\+ 0.5 ✕ num cup holders
sum

Perceptron:
If sum > threshold: buy
Else: walk

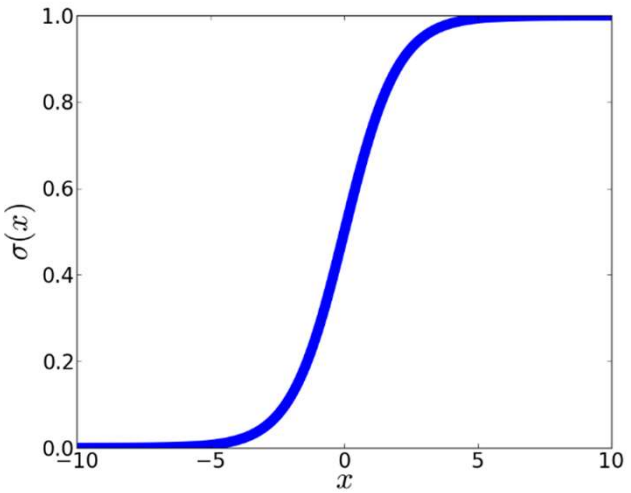
These little functions are chained together

- Deep learning comes from chaining a bunch of these little functions together. Chained together, they are called neurons.
- To create a neuron, we add a nonlinearity to the perceptron to get extra representational power when we chain them together.
- Our nonlinear perceptron is sometimes called a sigmoid.

$$\sigma\left(\sum_i w_i x_i + b\right)$$

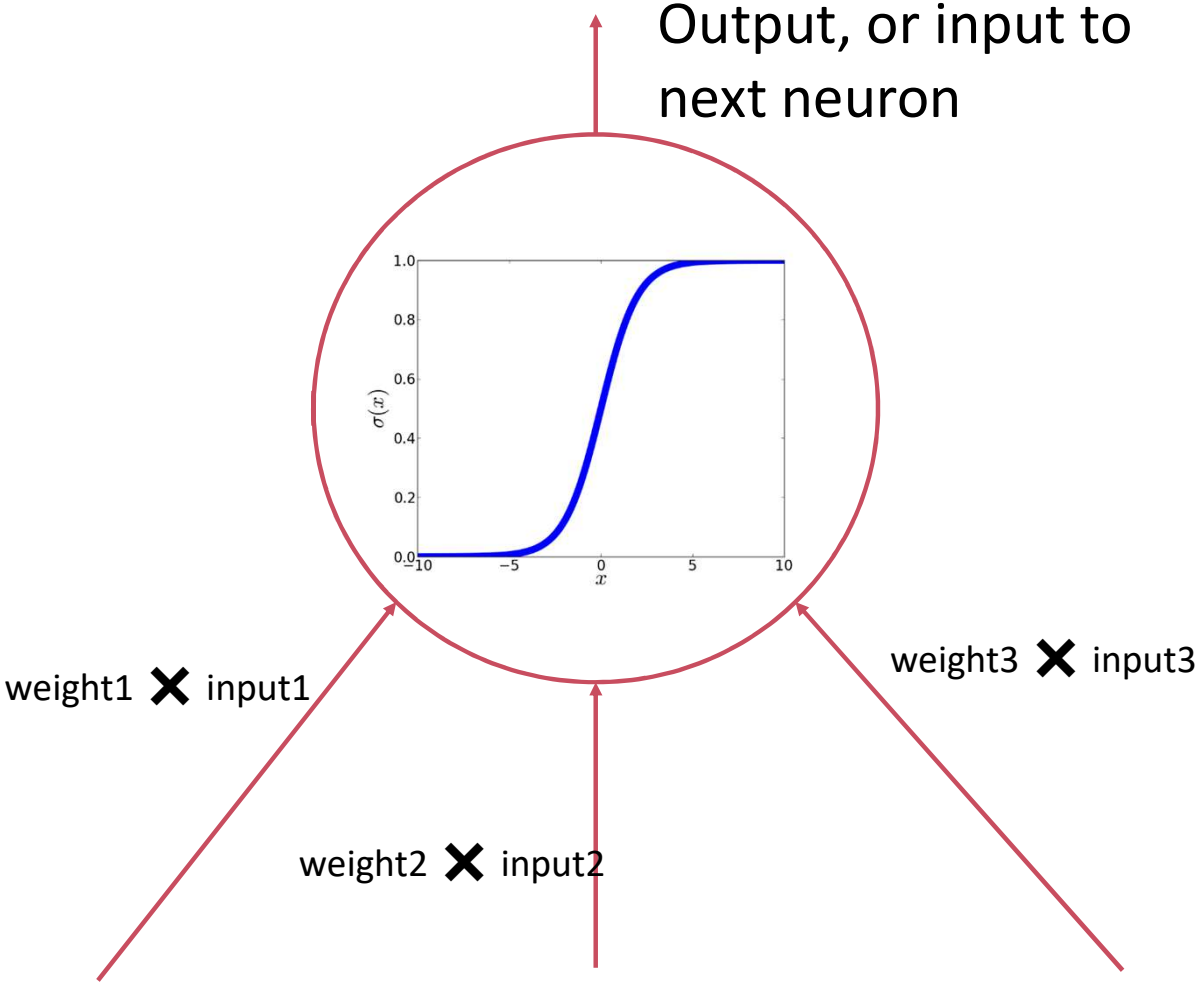
where $$\sigma(x) = \frac{1}{1 + \frac{1}{e^x}}$$

The value b just offsets the sigmoid so the center is at 0.

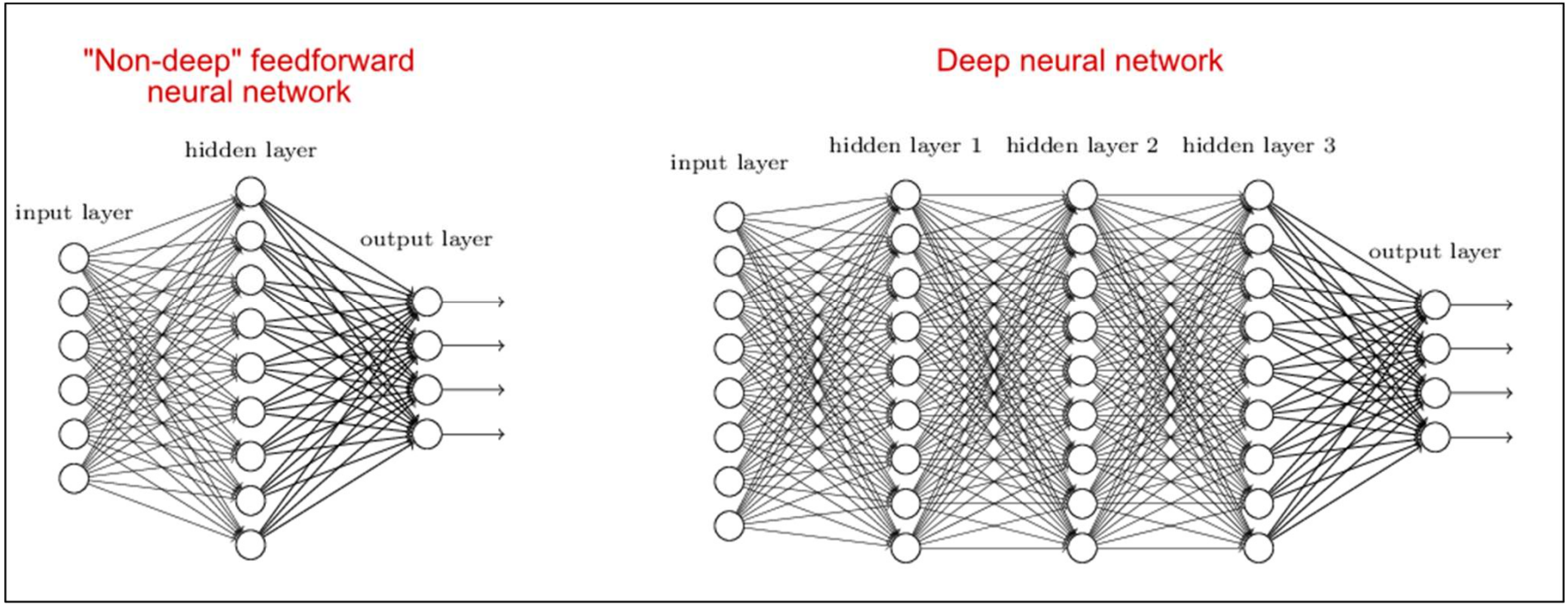


Plot of a sigmoid

Single artificial neuron



Deep Neural Network (DNN)



*http://neuralnetworksanddeeplearning.com/chap5.html

Common DNNs

- Deep Convolutional Neural Network (DCNN)
  - To extract representation from images
- Recurrent Neural Network (RNN)
  - To extract representation from sequential data
- Deep Belief Neural Network (DBN)
  - To extract hierarchical representation from a dataset

Comparing Representations

Vector representation

taco = $[17.32, 82.9, -4.6, 7.2]$

- Vectors have a similarity score.
  A taco is not a burrito but similar.
- Vectors have internal structure [Mikolov et al., 2013].
  Italy – Rome = France – Paris
  King – Queen = Man – Woman
- Vectors are grounded in experience.
- Meaning relative to predictions.

Symbolic representation

taco = $taco$

- Symbols can be the same or not.
- A taco is just as different from a burrito as a Toyota.
- Symbols have no structure.
- Symbols are arbitrarily assigned.
- Meaning relative to other symbols.

Common Open-Source DL Frameworks

Non-symbolic

Torch, Caffe

Manual optimization

Memory intensive

Symbolic

CNTK, MXNET, Theano, TensorFlow

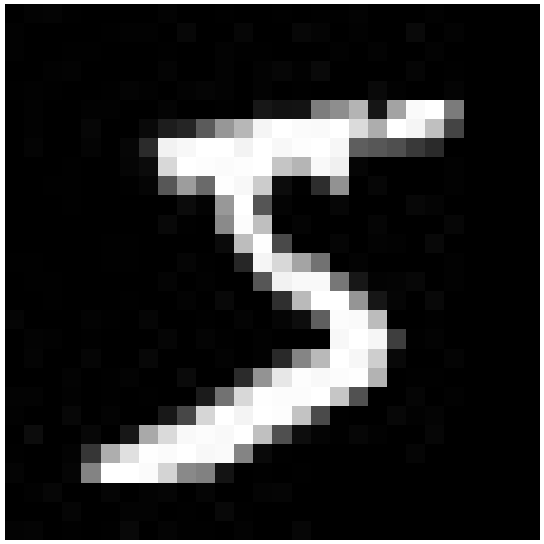
Automatic optimization

Memory reuse

Deep learning and computer vision

Vision is hard

Vision is hard because images are big matrices of numbers.



Example from MNIST handwritten digit dataset [LeCun and Cortes, 1998].

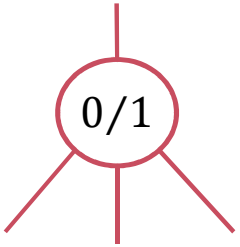
How a computer sees an image

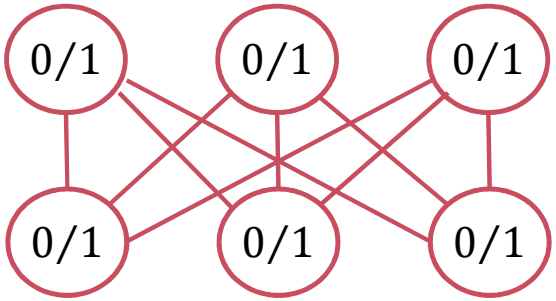
[22, 81, 44, 88, 17, 0, ..., 45]

- Even harder for 3D objects.
- You move a bit, and everything changes.

RBM: Unsupervised Model

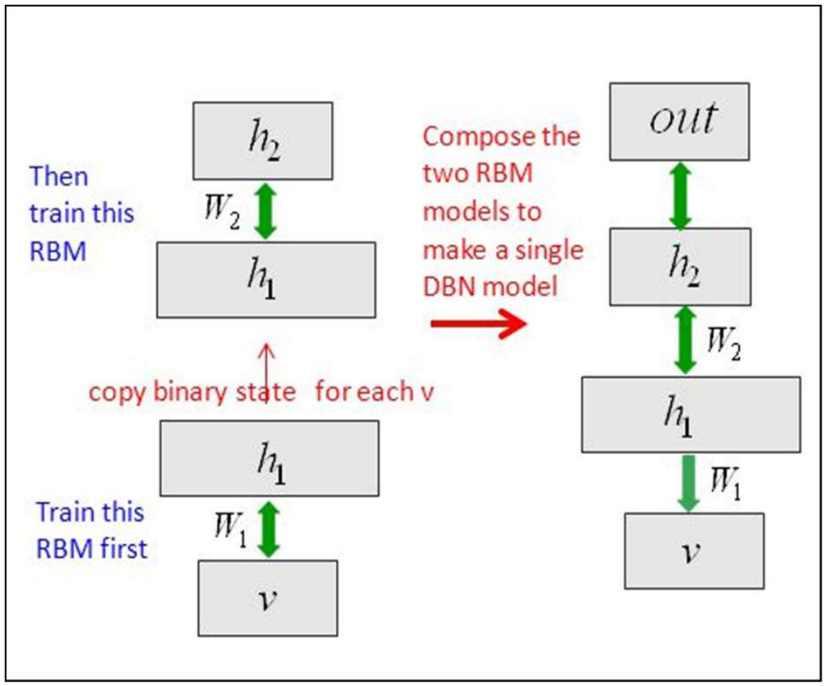
- Stochastic binary neuron
- Probabilistically outputs 0 (turns off) or 1 (turns on) based on the weight of the inputs from on units.





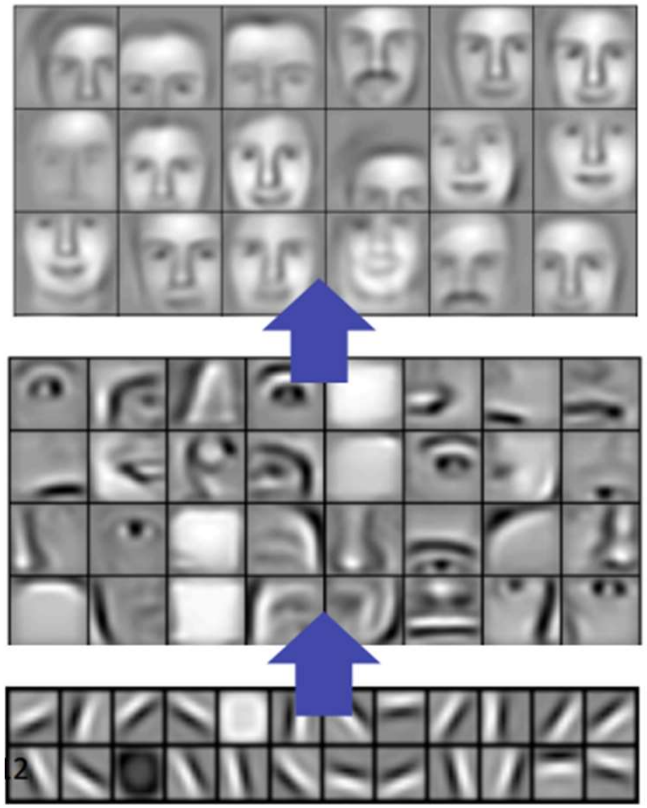
- Limit connections to be from one layer to the next.
- Fast because decisions are made locally.
- Trained in an unsupervised way to reproduce the data.

Stack up the layers to make a DBN



*Huang et al., Communications ACM 01/2014

Computer vision, scaling up



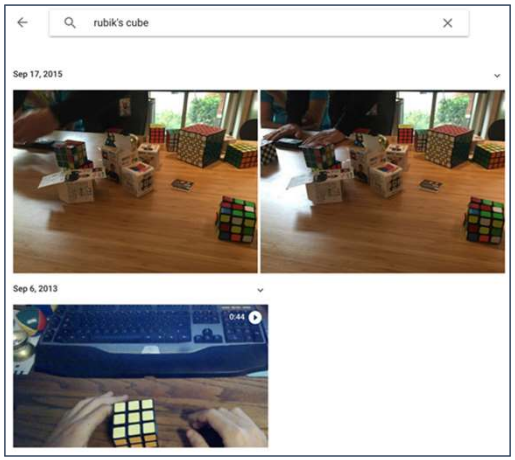
[Lee et al., 2009]

Unsupervised learning was scaled up by Honglak Lee et al. [2009] to learn high-level visual features.

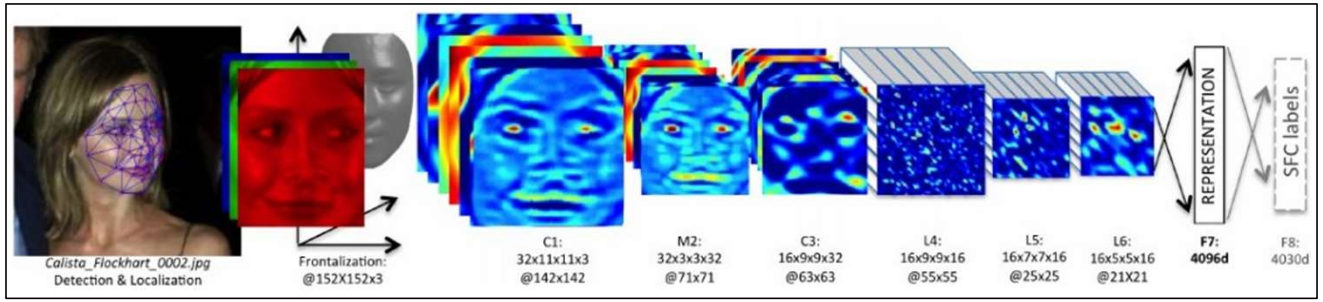
Further scaled up by Quoc Le et al. [2012].

- Used 1,000 machines (16,000 cores) running for 3 days to train 1 billion weights by watching YouTube videos.
- The network learned to identify cats.
- The network wasn't told to look for cats, it naturally learned that cats were integral to online viewing.

Supervised: ConvNets are everywhere



e.g. Google Photos search



Face Verification, Taigman et al. 2014 (FAIR)

[Goodfellow et al. 2014]

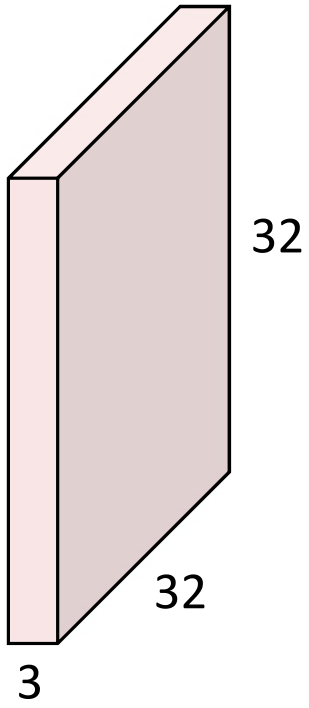
Self-driving cars

*Andrej Karpathy's recent presentation

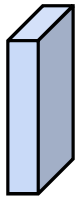
Convolution Layer

32x32x3 image

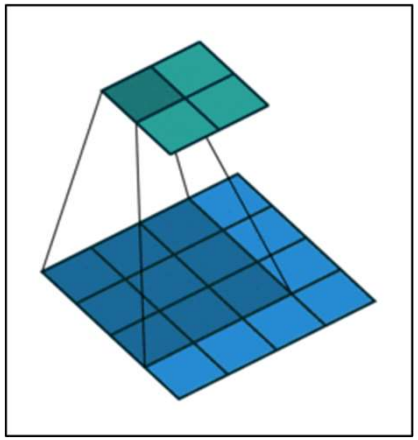
Filters always extend the full depth of the input volume



5x5x3 filter



Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”



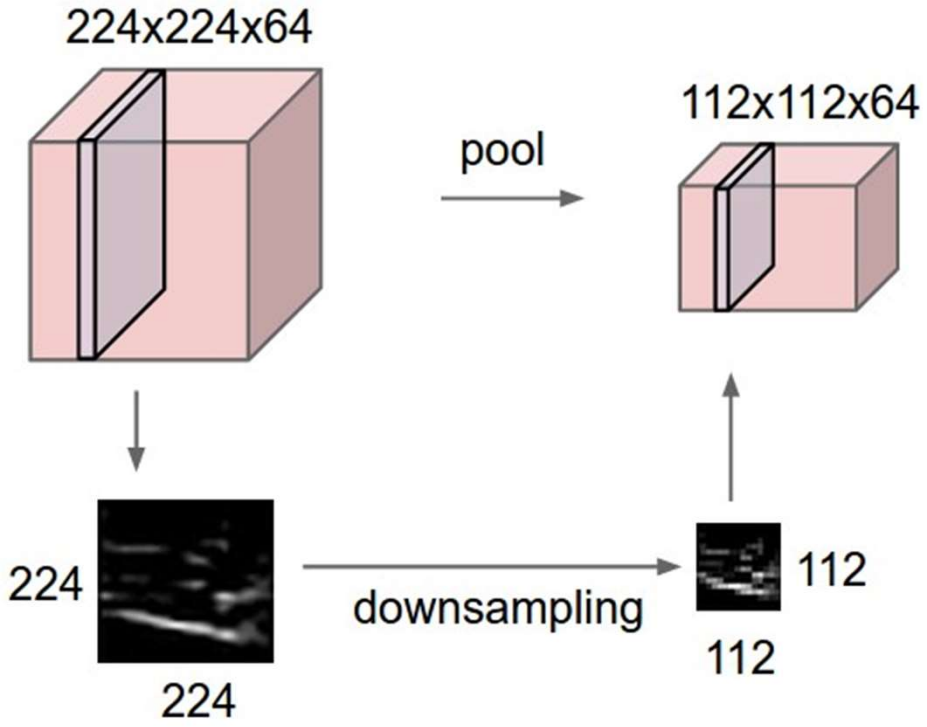
Convolving a 3 X 3 kernel over a 4 X 4 input

*Andrej Karpathy’s recent presentation

*http://iamaaditya.github.io/2016/03/one-by-one-convolution/

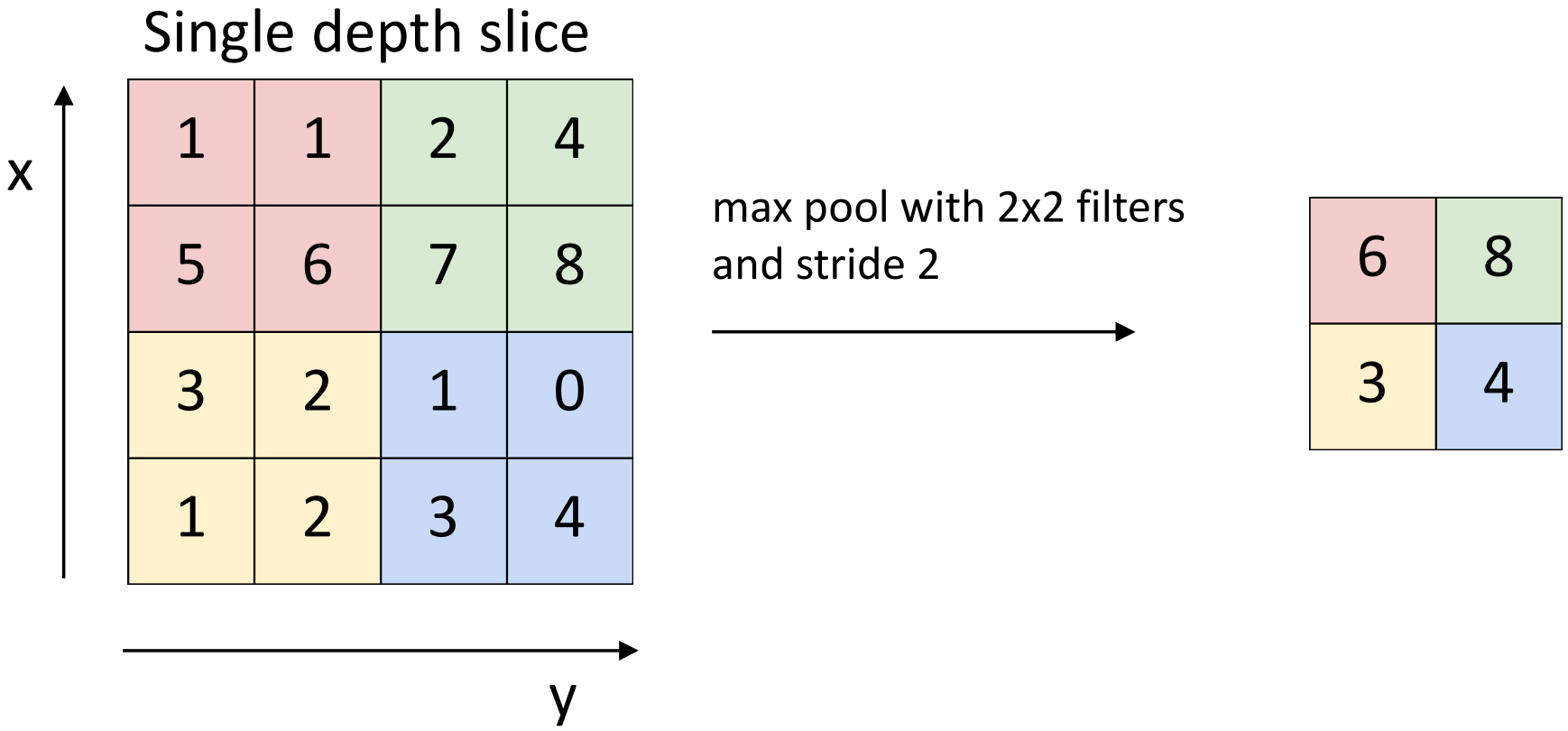
Pooling layer

- makes the representations smaller and more manageable
- operates over each activation map independently



*Andrej Karpathy's recent presentation

Max Pooling



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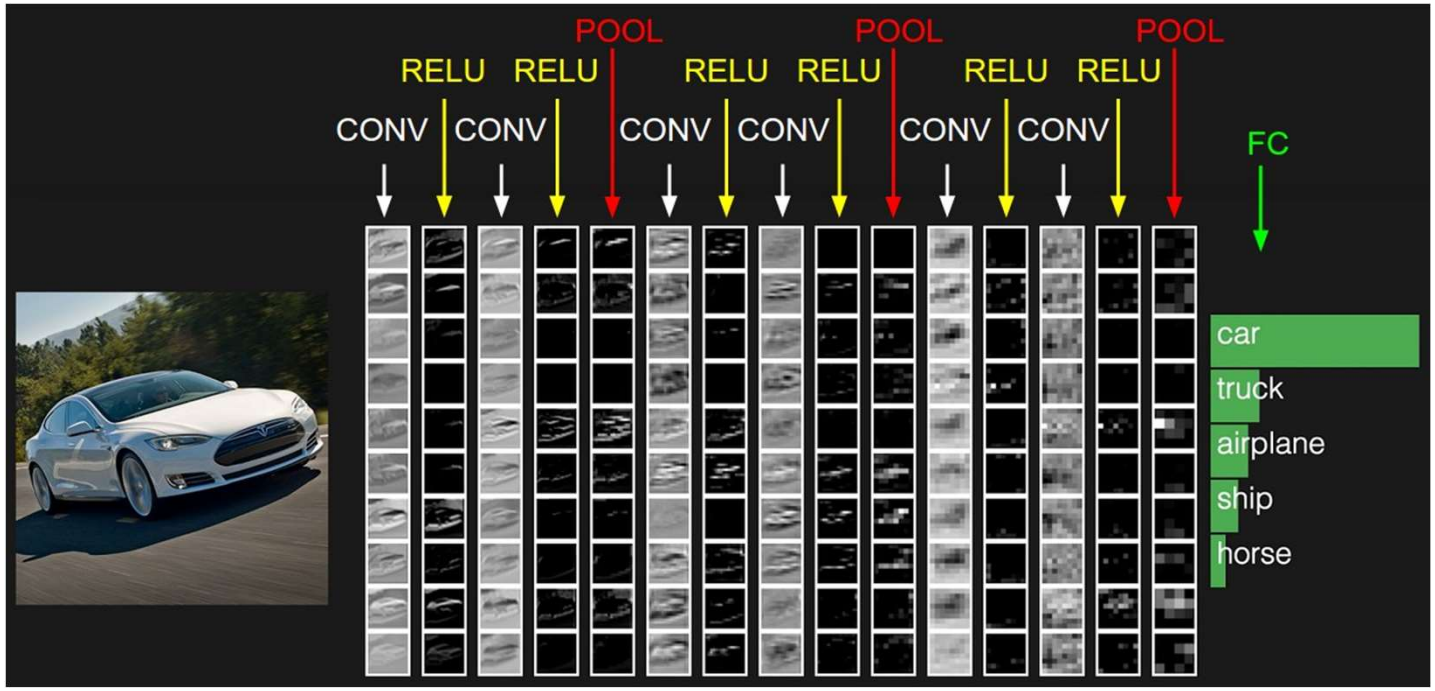
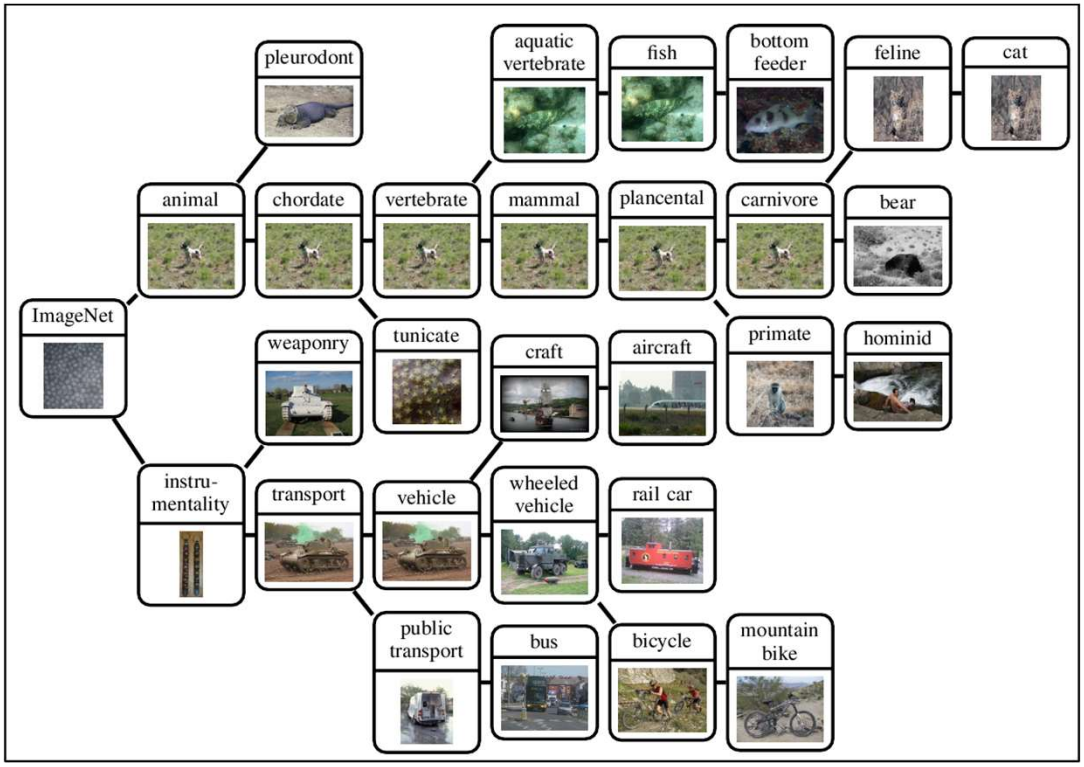
Fully Connected Layer (FC layer)



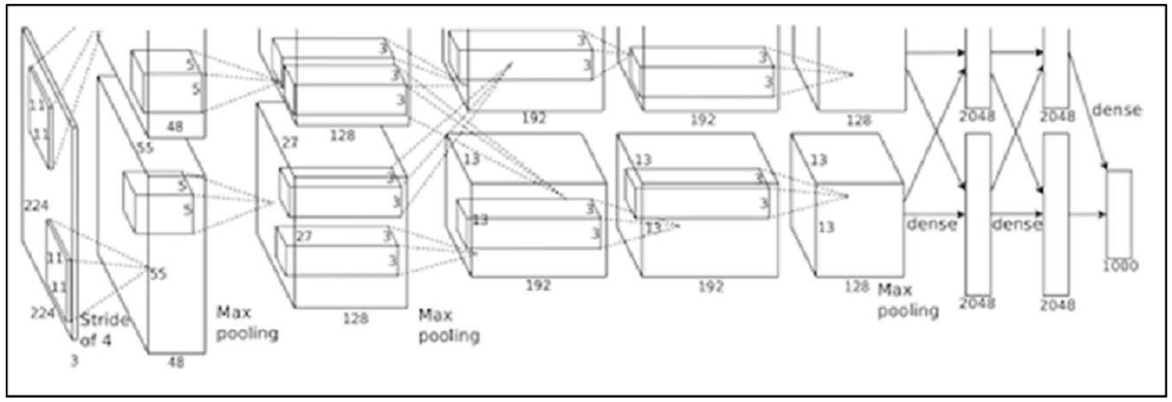
*Andrej Karpathy's recent presentation

IMAGENET



*http://groups.inf.ed.ac.uk/calvin/imagenet/prototypes.html

AlexNet



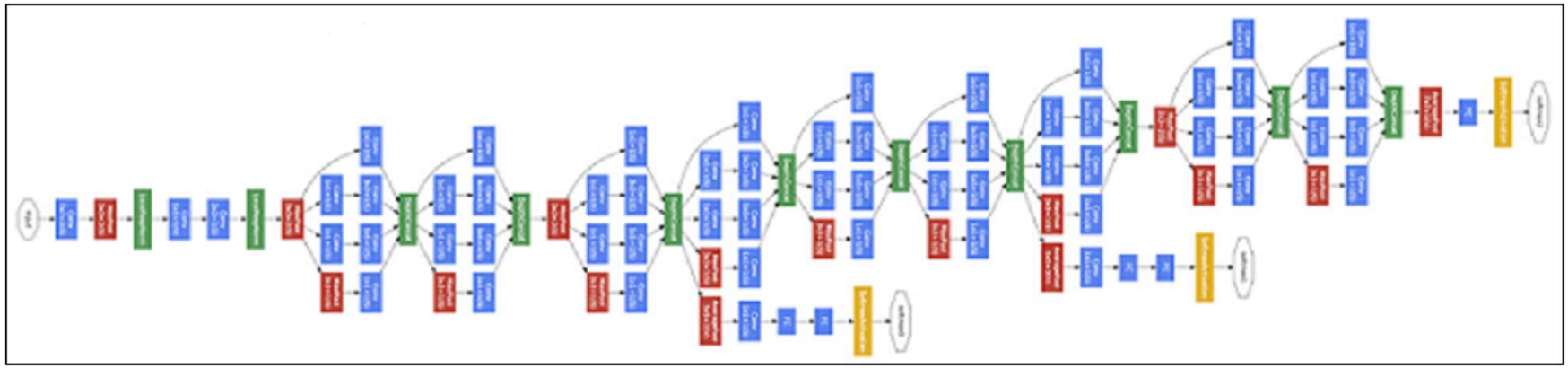
*https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf

VGGNet

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB imag)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

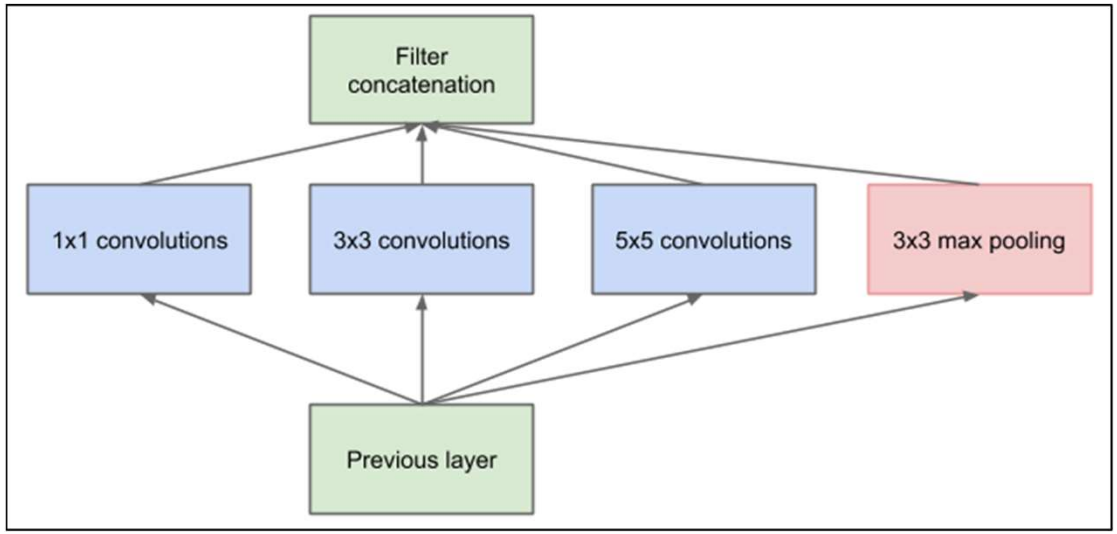
*http://arxiv.org/pdf/1409.1556v6.pdf

GoogLeNet



*http://www.csc.kth.se/~roelof/deepdream/bvlc_gnet.html

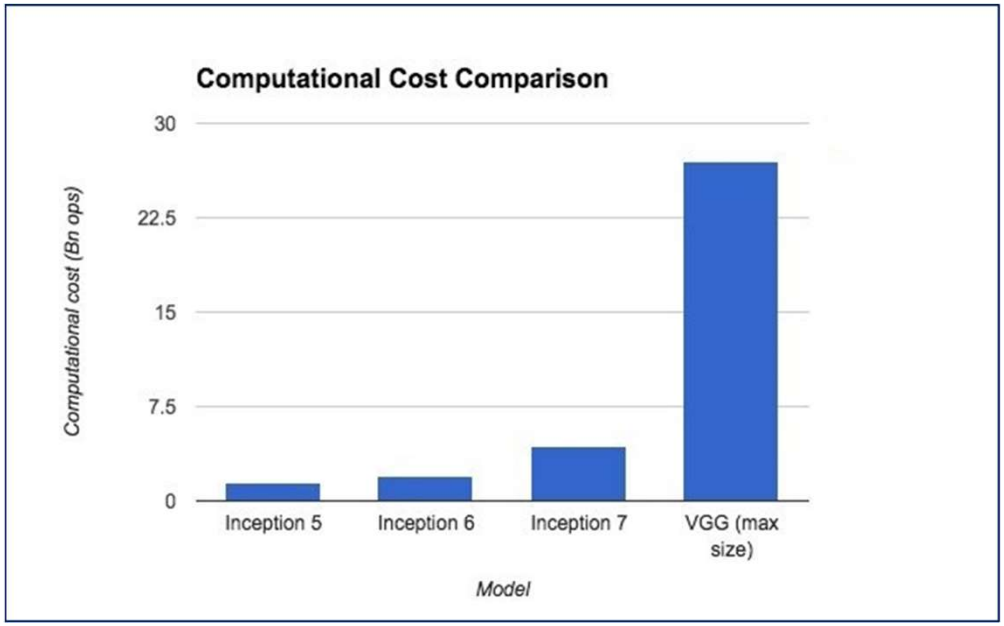
GoogLeNet uses Inception



Inception Module

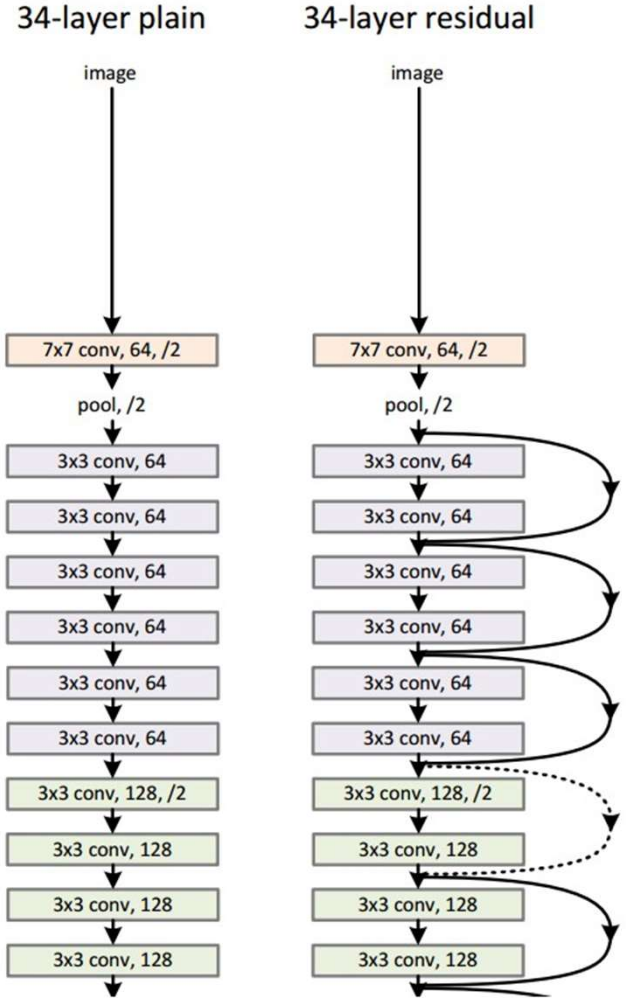
*https://arxiv.org/pdf/1409.4842v1.pdf

Inception Performance comparison

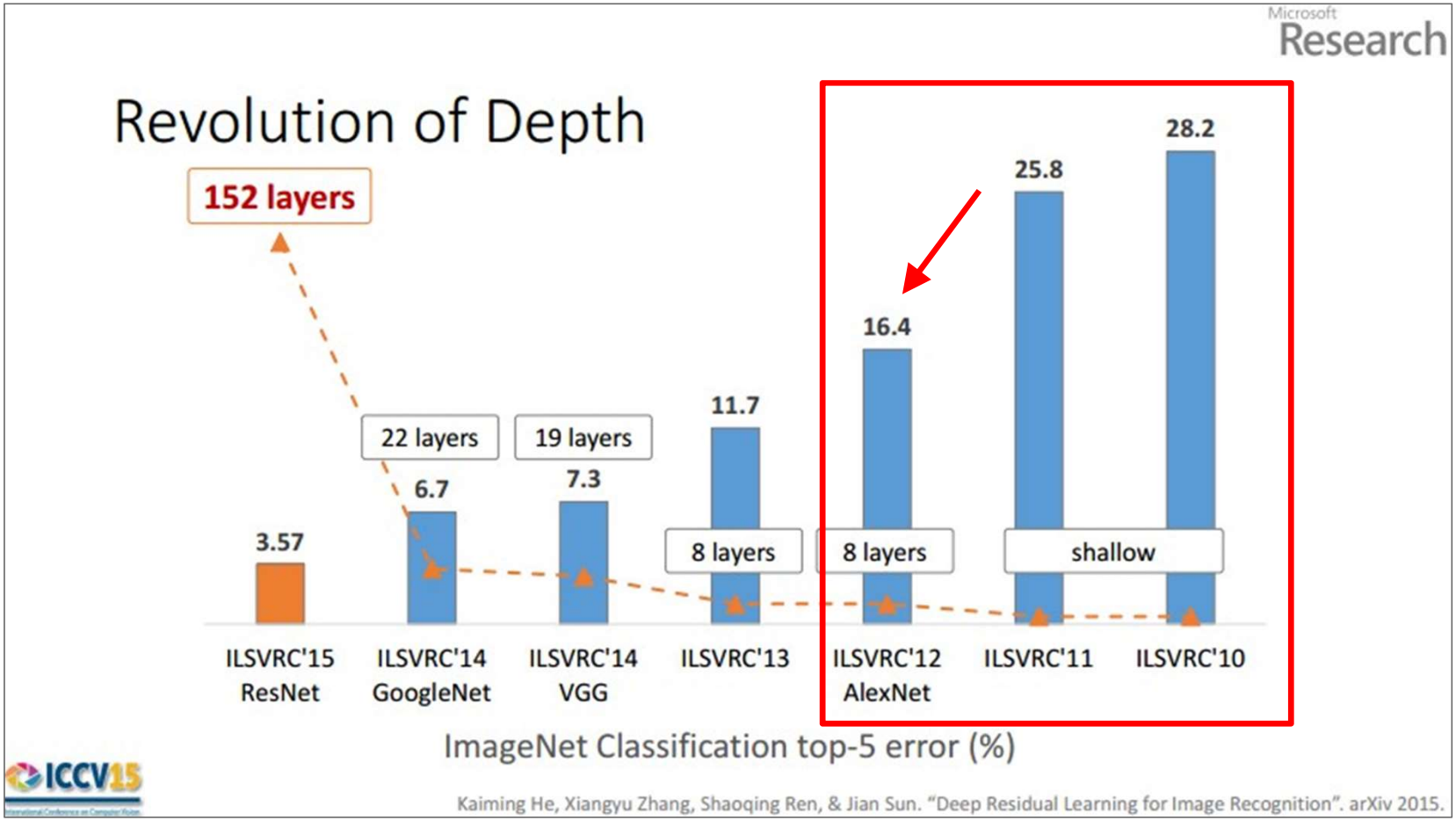


*http://lsun.cs.princeton.edu/slides/Christian.pdf

Microsoft ResNet



*https://arxiv.org/pdf/1512.03385v1.pdf



*Andrej Karpathy's recent presentation

Deep learning and natural language processing

Deep learning enables sub-symbolic processing

I	<i>
bought	<bought>
a	<a>
car	<car>
.	<.>

You have to remember to represent “purchased” and “automobile.”

What about “truck”?

How do you encode the meaning of the entire sentence?

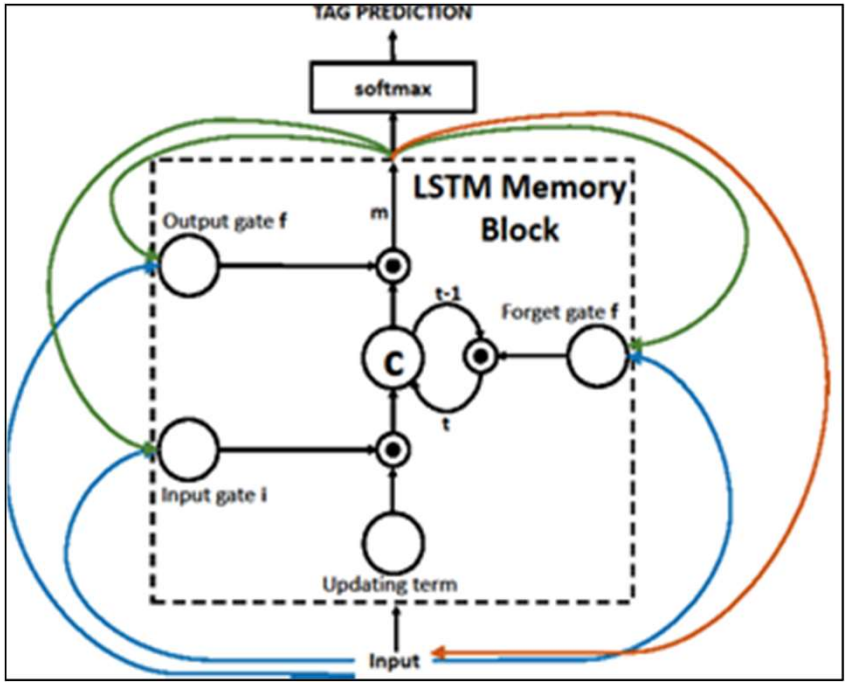
But what about a sentence?

Algorithm for generating vectors for sentences

1. Make the sentence vector be the vector for the first word.
2. For each subsequent word, combine its vector with the sentence vector.
3. The resulting vector after the last word is the sentence vector.

Can be implemented using a recurrent neural network (RNN)

LSTM RNN



*Huang et al., Communications ACM 01/2014

What can you do with a Sentence Vector?

You can feed it to a classifier.

You can unwind in the other direction to do machine translation.

Called a seq2seq model, or Neural Machine Translation, or encoder-decoder model.

Deep learning and question answering

Bob went home.
Tim went to the junkyard.
Bob picked up the jar.
Bob went to town.
Where is the jar? A: town

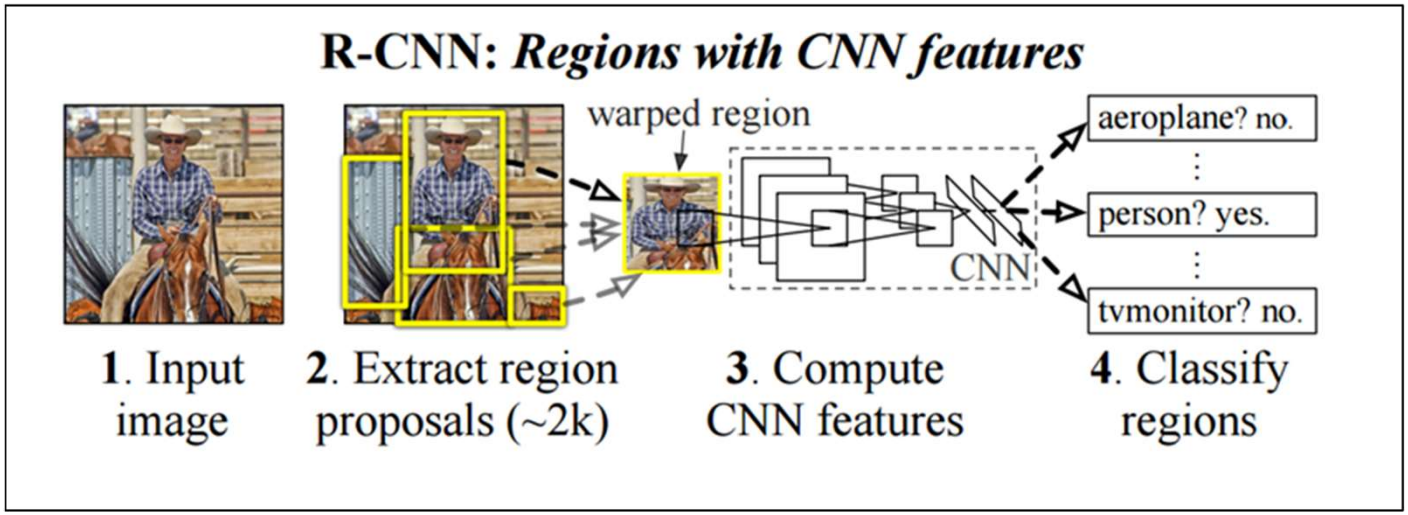
Memory Networks [Weston et al., 2014]: Updates memory vectors based on a question and finds the best one to give the output.

The office is north of the yard.
The bath is north of the office.
The yard is west of the kitchen.
How do you go from the office to the kitchen? A: south, east

Neural Reasoner [Peng et al., 2015]: Encodes the question and facts in many layers, and the final layer is put through a function that gives the answer.

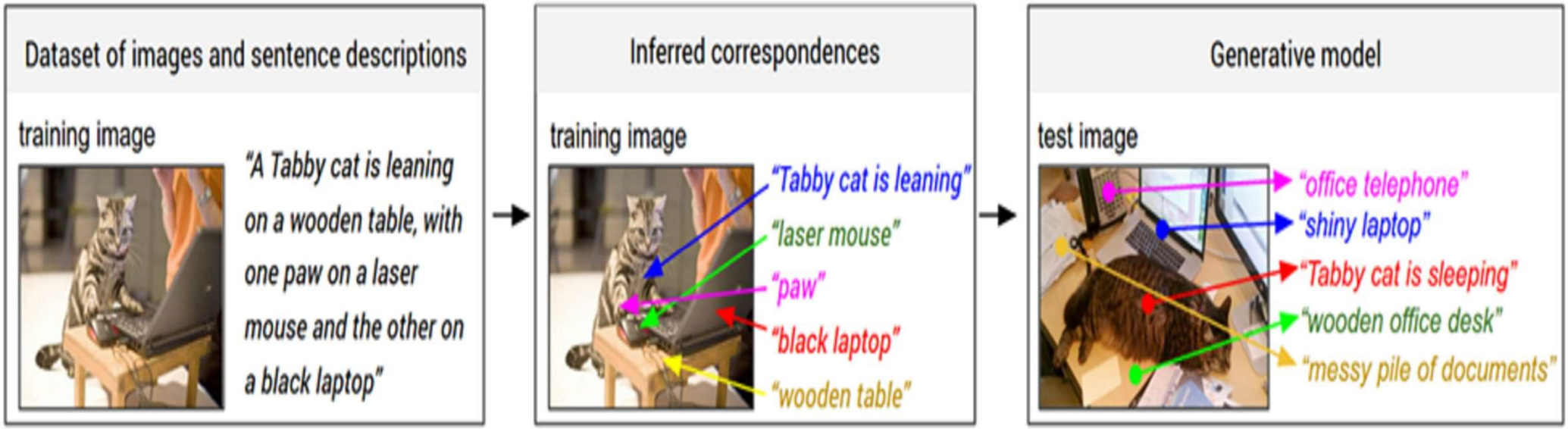
Other commonly used DNNs

Region Based CNN (RCNN)



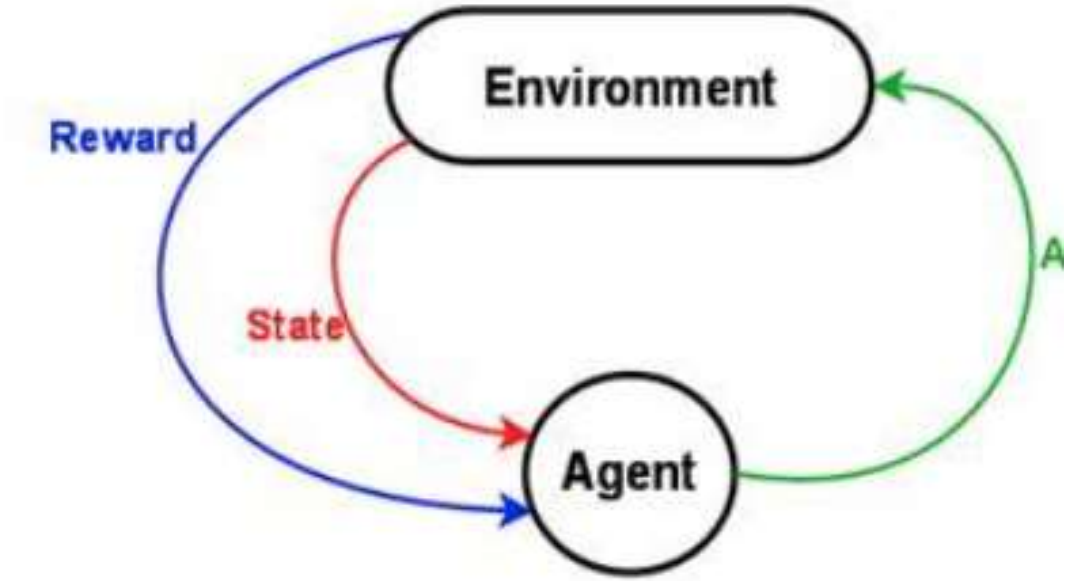
*https://arxiv.org/pdf/1311.2524v5.pdf

Generating Image Descriptions (CNN-RNN)



*https://arxiv.org/pdf/1412.2306v2.pdf

Deep Reinforcement Learning



Deep Learning – Some use-cases in next 5 years?

Advanced Melanoma Screening and Detection

- Researchers at the University of Michigan are putting advanced image recognition to work, detecting one of the most aggressive, but treatable in early stages, types of cancer.

- The team trained a neural network to isolate features (texture and structure) of moles and suspicious lesions for better recognition and detecting melanoma known to date.

Neural Networks for Brain Cancer Detection

- A team of French researchers is working on spotting invasive brain cancer cells during surgery.

- They found that using neural networks in conjunction with Raman spectroscopy during operations allows them to detect the cancerous cells easier and reduce residual cancer post-operation.

Neural Networks in Finance

- Trading and risk management are two areas where we would expect to see developments for neural networks

- Popular technical indicators along with neural networks and genetic algorithms are used to generate buy and sell signals for each stock and for portfolios of stocks

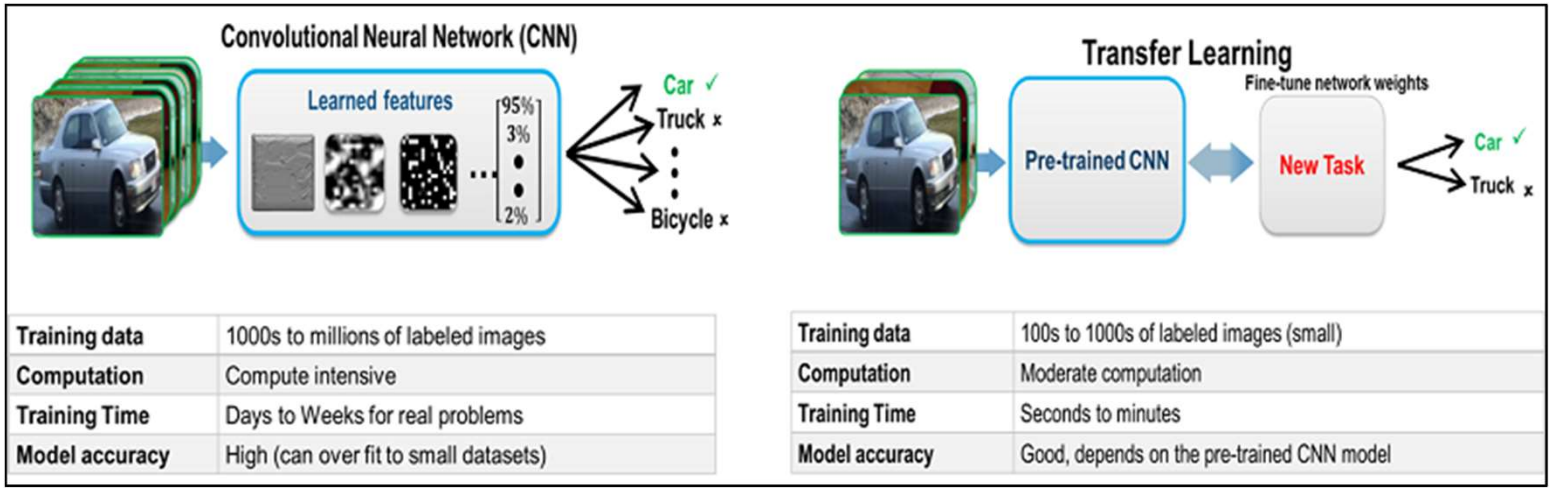
Example: Predicting the 2016 Presidential Election, and the Resulting Market Impact

- Use a DNN and features to predict the Trump election and the expected market reaction
- Python utilizing Tensorflow
- https://github.com/athaker/econ_136
- Identify the sources of data and the resulting outputs
- What features do you think are most important to the model?

Candidate	Party	Electoral Votes	Popular Votes
Donald J. Trump	Republican	304	62,980,160
Hillary R. Clinton	Democratic	227	65,845,063
Gary Johnson	Libertarian	0	4,488,931
Jill Stein	Green	0	1,457,050
Evan McMullin	Independent	0	728,830

Increasing Re-usability of Deep Learning models

Transfer Learning & Fine-tuning



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

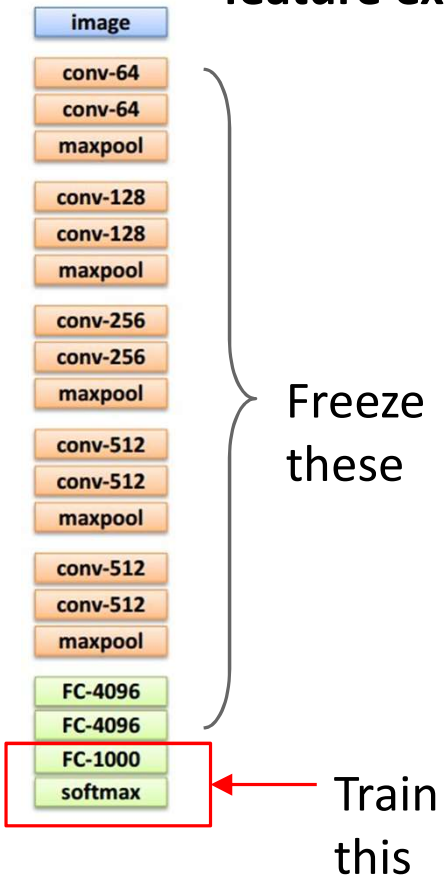
Training data	100s to 1000s of labeled images (small)
Computation	Moderate computation
Training Time	Seconds to minutes
Model accuracy	Good, depends on the pre-trained CNN model

*http://www.mathworks.com/discovery/deep-learning.html?requestedDomain=uk.mathworks.com

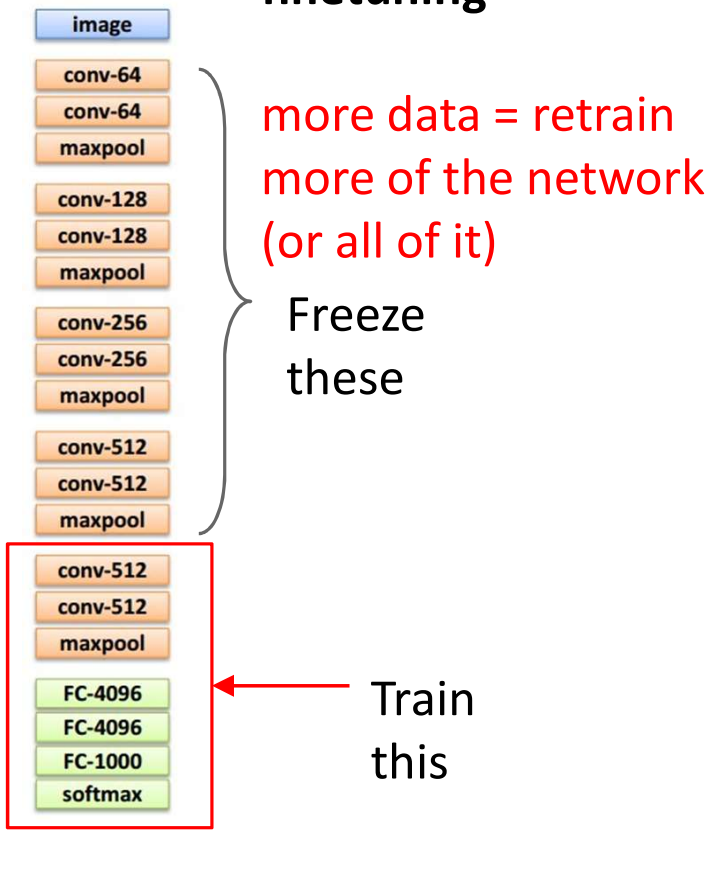
Transfer Learning

1. Train on Imagenet

2. Small dataset: **feature extractor**



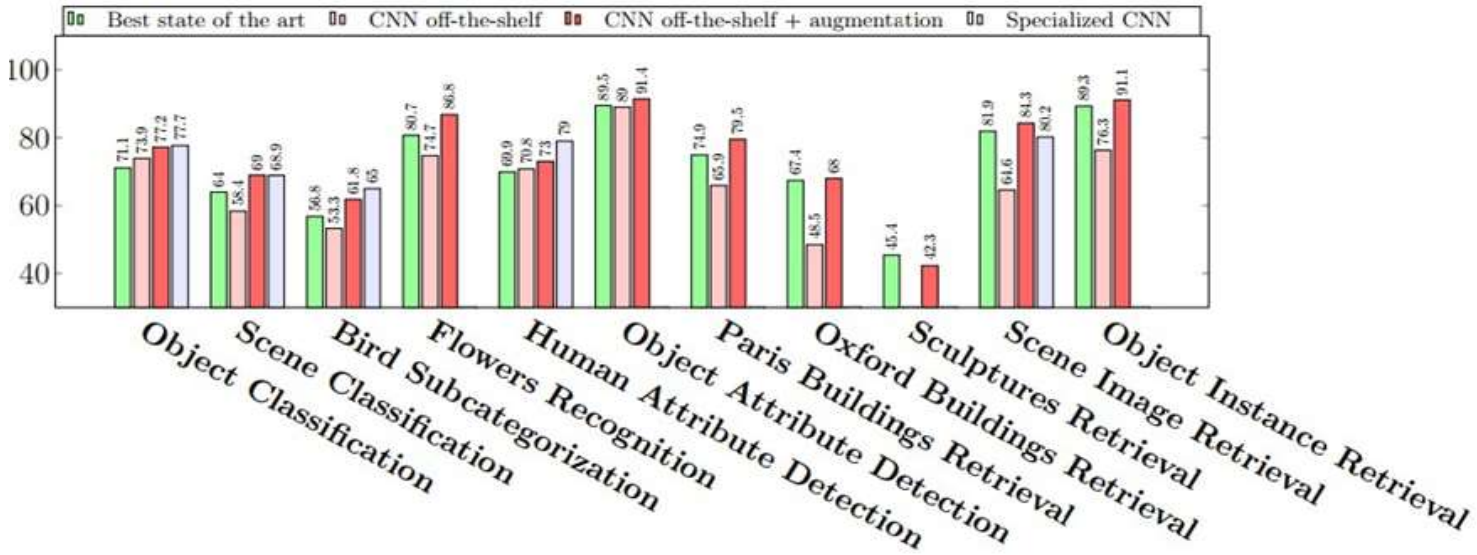
3. Medium dataset: **finetuning**



*Andrej Karpathy's recent presentation

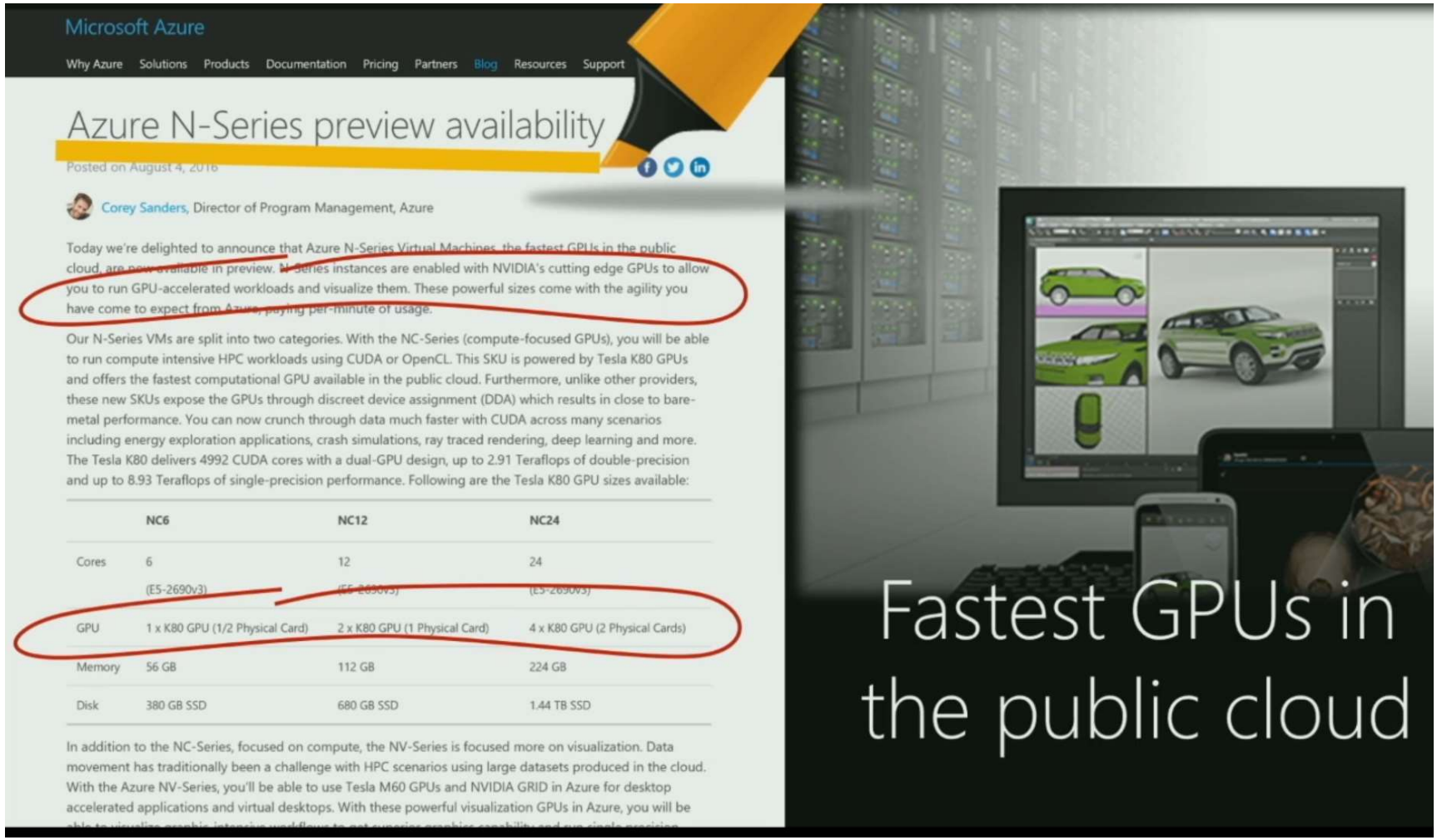
Transfer Learning

CNN Features off-the-shelf: an Astounding Baseline for Recognition [Razavian et al, 2014]



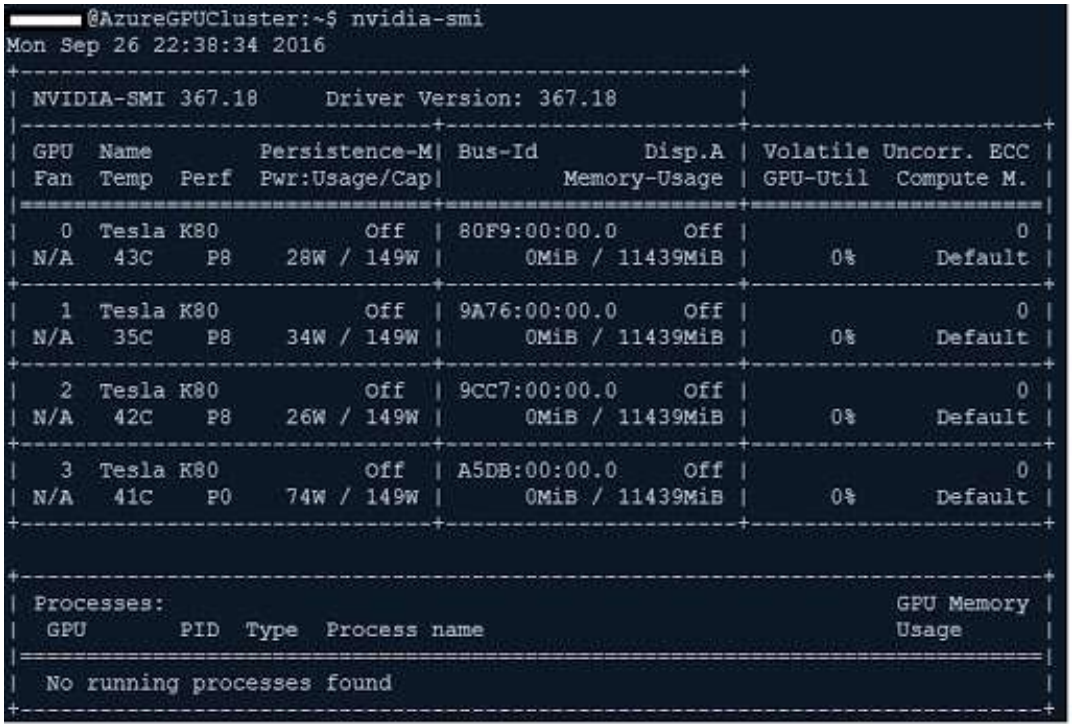
*Andrej Karpathy's recent presentation

GPUs in Azure

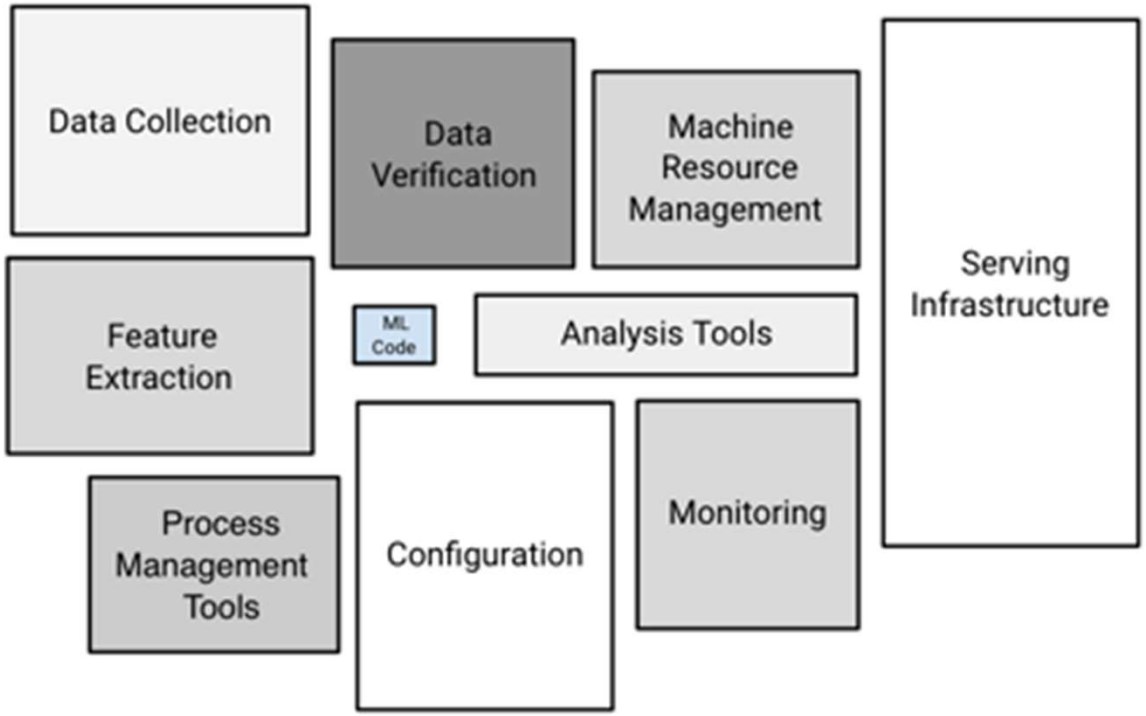


Azure GPU VM

- Used Ubuntu 16.04 N-Series VM
- NC24 VM with 4 NVIDIA Tesla K80



ML/DL is Only a Small Fraction, Toolkits speed up the process



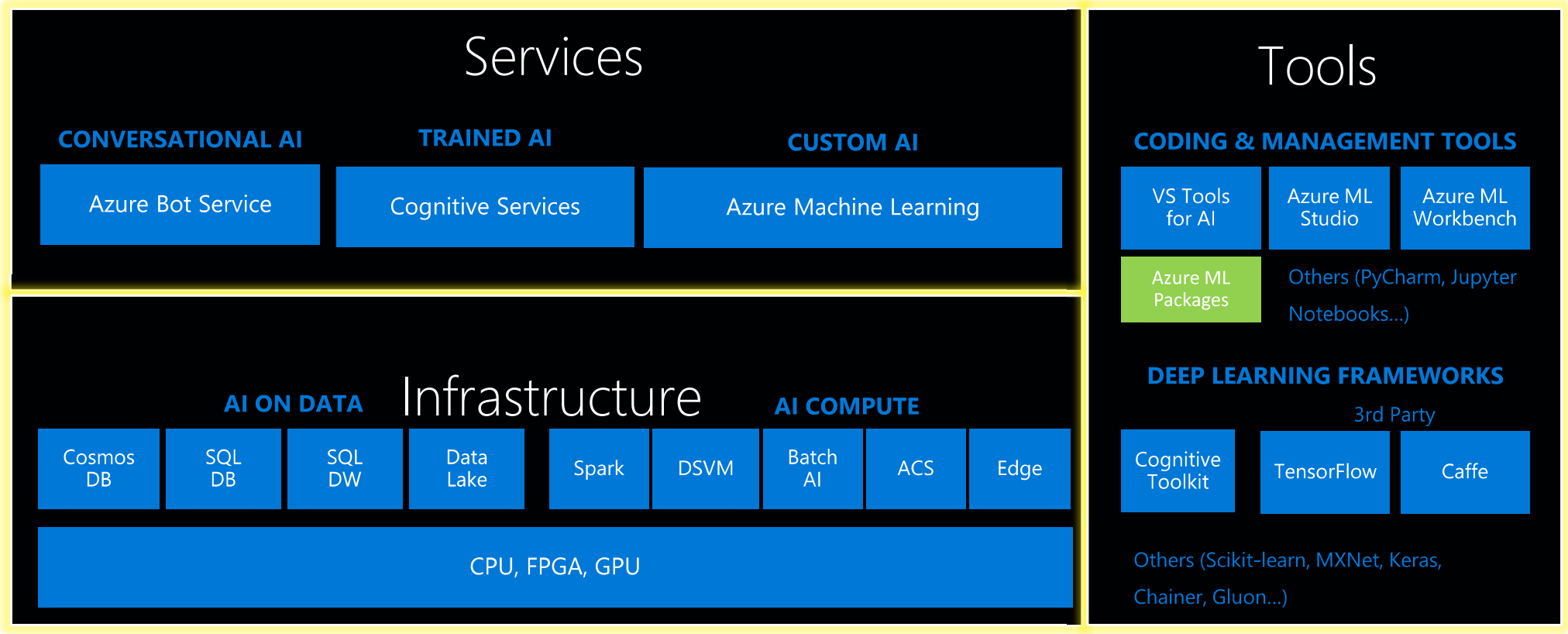
https://developers.google.com/machine-learning/crash-course

Toolkits for Practical re-usability of DL Models

Azure ML Packages

The Microsoft AI platform

Cloud-powered AI for every developer



What are Azure ML Packages?

- Python packages extensions for Azure Machine Learning enabling data scientist and AI developers to build high AI quality pipelines for

Computer Vision	Text Analytics	Forecasting

- Provides high level APIs for data preparation, augmentation, training, evaluating and deployment.

- Model experimentation and comparison, run history, model management and deployment through AML Workbench

Easily build and deploy models on Microsoft AML platform

Value Proposition

Accurate

Packages support State of the Art algorithms and include optimized parameters to provide out of the box highly accurate models.

Flexible

Powerful and composable Python API. Optimize the best algorithm for your application. Provides control over all the aspects that are available to the power user.

Scalable

Train models at large scale with multi GPU

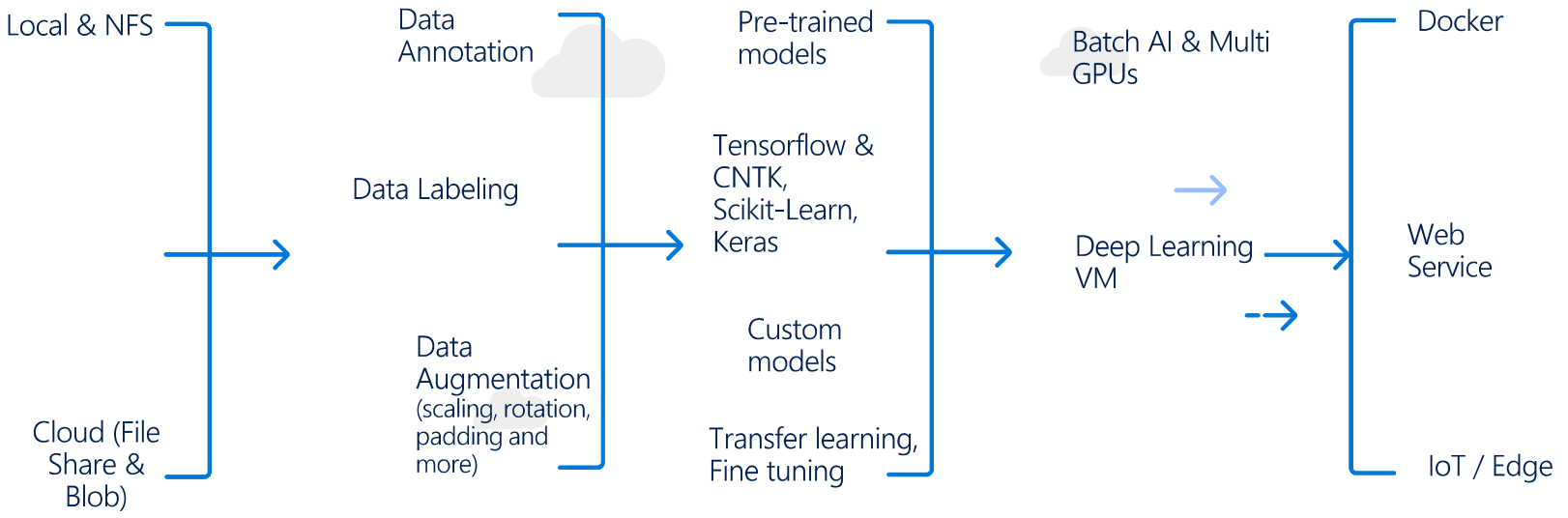
Time to Solution

Automates many tedious tasks (data alignment, cleaning and preparation), easily model experimentations and deploy in production.

Best in class package in Quality, Flexibility, Scale and Time to solution.

Deep Dive on AML Package For Computer Vision

AML Packages - Pipeline



Sample Code (less than 20 lines)

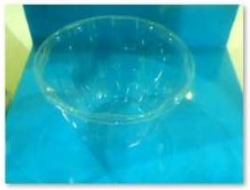
```
# create a dataset from a directory with folders representing different classes
dataset = Dataset.create_from_dir(dataset_name, dataset_location)

# split the full dataset into a train and test set
train_set_orig, test_set = Splitter(dataset).split(train_size=.8, stratify='label’)

# Image augmentation
rotate_and_flip = augmenters.Sequential([augmenters.Affine(rotate=(-45, 45)), augmenters.Fliplr(.5)])
crop = augmenters.Sequential([augmenters.Crop(percent=(0, .1))])
train_set = augment_dataset(train_set_orig, [rotate_and_flip, crop])

# create the model
model = TransferLearningModel(num_classes = num_classes, base_model_name = 'ResNet18_ImageNet_CNTK’)

# train the model using cntk
num_epochs = 45
mb_size = 32
t = Trainer(model, train_set, num_epochs=num_epochs, mb_size=mb_size)
t.start_training()
```

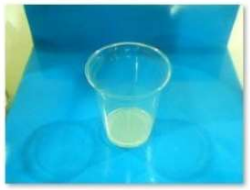
Microsoft Confidential

Image Classification

Prepare Dataset

1


bowl


cup


cutlery

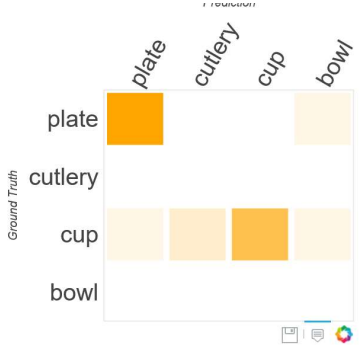
2

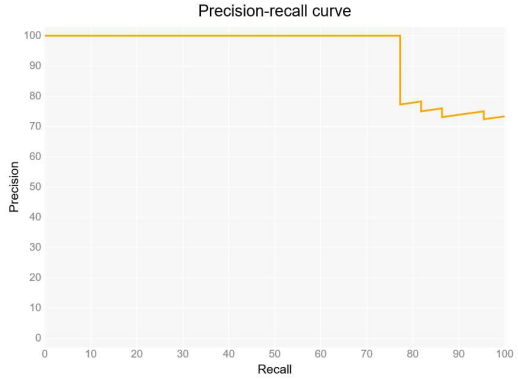
Model Definition & Training

```
# CVTK default parameters (224 x 224 pixels resolution, Resnet-18)
lr_per_mb = [0.05]*7 + [0.005]*7 +  [0.0005]
mb_size = 32
input_resoluton = 224
base_model_name = "ResNet18_ImageNet_CNTK"
```

3

Evaluate the model





Score the model

```
# Parse result from json string
import numpy as np
parsed_result = CNTKTLModel.parse_serialized_result(r.text)
print("Parsed result:", parsed_result)
# Map result to image class
class_index = np.argmax(np.array(parsed_result))
print("Class index:", class_index)
dnn_model.class_map
print("Class label:", dnn_model.class_map[class_index])
```

```
Parsed result: ['[0.07414770871400833, -0.03261350095272064, -2.57250714302063,
Class index: 0
Class label: bowl
```

4

5

Deploy the model

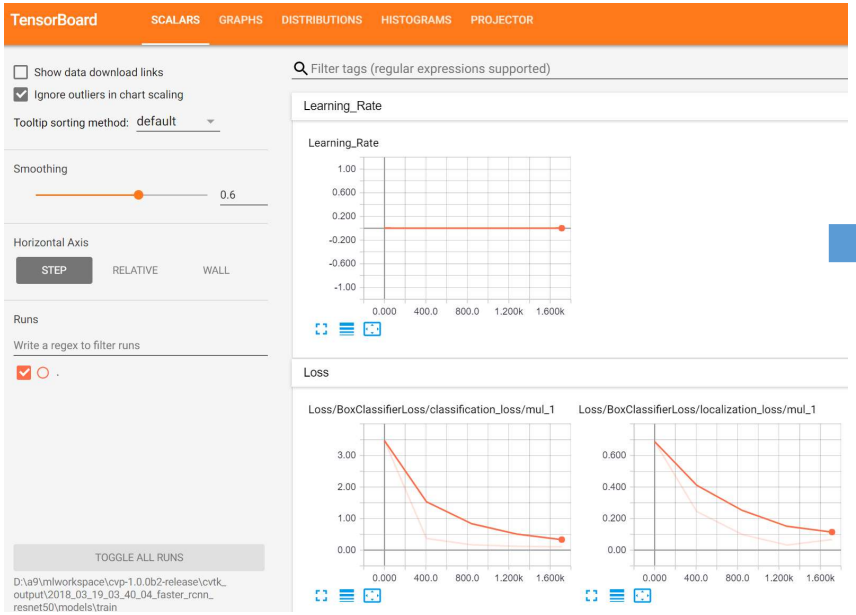
Deploy the model as an Azure web service, Dockers Container or IoT Edge

The evaluation module provides functionality to evaluate the performance of the trained model. Some of the evaluation metrics : accuracy, precision and recall, confusion matrix

Object Detection

Object Detection is one of the main problems in Computer Vision. The Computer Vision Package makes it easy to perform all these steps easily and with high accuracy , and internally uses Tensorflow's implementation of Faster R-CNN

Train the model



Score an image

```
image_path = '../sample_data/liebherr/liebherr_val/JPEGImages/WIN_20160803_11_46_03_Pro.jpg'
# scores = my_detector.score_image(frozen_model_path, image_path)
dectections_dict = detection_utils.score(frozen_model_path, image_path)
```

```
Object 0: label=butter     , score=0.99,
Object 1: label=tomato     , score=0.97,
Object 2: label=gerkin     , score=0.96,
Object 3: label=pepper     , score=0.95,
Object 4: label=eggBox     , score=0.94,
Object 5: label=tomato     , score=0.94,
Object 6: label=avocado    , score=0.94,
Object 7: label=champagne  , score=0.59,

Found 8 objects in image ../sample_data/
```

Computer Vision Simplified in Python

High Accuracy out of the box

Include optimized parameters and pre trained weights to provide out of the box highly accurate models.

Time To Solution

Get from a data set to a highly accurate deployed model quickly

```
# CVTK default parameters (224 x 224 pixels resolution, Resnet-18)
lr_per_mb = [0.05]*7 + [0.005]*7 +  [0.0005]
mb_size = 32
input_resoluton = 224
base_model_name = "ResNet18_ImageNet_CNTK"

# CVTK suggested parameters for 500 x 500 pixels resolution, Resnet-50
# (see in the Appendix "How to improve accuracy", last row in table)
# lr_per_mb   = [0.01] * 7 + [0.001] * 7 + [0.0001]
# mb_size     = 8
# input_resoluton = 500
# base_model_name = "ResNet50_ImageNet_CNTK"

# Initialize model
dnn_model = CNTKTLModel(train_set.labels,
                        base_model_name=base_model_name,
                        image_dims = (3, input_resoluton, input_resoluton))
```

```
# Optional azure machine learning deployment cluster name (environment name) and resource group
# If you don't provide here. It will use the current deployment environment (you can check with
azureml_rscgroup = "<resource group>"
cluster_name = "<cluster name>"

# If you provide the cluster information, it will use the provided cluster to deploy.
# Example: deploy_obj = AMLDeployment(deployment_name=deployment_name, associated_DNNModel=dnn_m
#                            aml_env="cluster", cluster_name=cluster_name, resource_group=azurem

# Create deployment object
deploy_obj = AMLDeployment(deployment_name=deployment_name, aml_env="cluster", associated_DNNMod

# Check if the deployment name exists, if yes remove it first.
if deploy_obj.is_existing_service():
    AMLDeployment.delete_if_service_exist(deployment_name)

# create the webservice
print("Deploying to Azure cluster...")
deploy_obj.deploy()
print("Deployment DONE")
```

What customers are saying ?

“Using the AML Package for Computer Vision we were able to reach 97% accuracy on our production images and deploying the models to the Azure Cluster Servers is incredibly fast and easy ” (Jocelyn Desbiens, Ph.D)

“The Azure Machine Learning Package for Computer Vision package different parts (data load, annotation, split, augmentation, training, evaluation, etc.) into separate modules, which reduces the coding effort for data scientist when building the model. In addition, the visualization utils provide a straightforward and visual understanding of the image data and model evaluation results.” (MS Data Scientist)

“The Azure Machine Learning Package for Computer Vision model out of the box with 10 epochs outperforms 4 out of the 6 human experts on a cell identification problem. ” (MS ADS Data Sceintist)

Demo – Object Detection

Drone Demo –Powered by AML Packages

https://youtu.be/EruH-4Fvecc?t=249

Thank you. Questions?