Deep Neural Nets Brass Tacks

Nebojsa Bozanic

Slides: `bit.ly/deepNets`

Hey

Kindly introduce yourself

Brass Tacks

- Brass

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Brass- an alloy of copper and zinc

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Brass- an alloy of copper and zinc

A tack

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A tack- a small wide-head nail

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- Roll up one's sleeves

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Brass tacks has a meaning

- Roll up one’s sleeves
- Get down to business

Brass Tacks

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Brass tacks has a meaning

- Roll up one’s sleeves
- Get down to business
- **Deal with the important details**

An ambitious goal

An ambitious goal

Everyone that knows nothing or have a partial knowledge about Deep Learning should be able to use state-of-the-art DNN models

Today’s to do list

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1. What are Deep Neural Networks?

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2. Their Performance?

Today’s to do list

1. What are Deep Neural Networks?

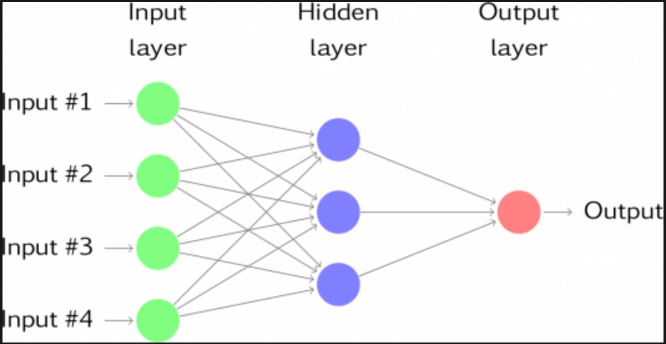
2. Their Performance?

3. How to use them in my research/production?

Deep Neural Networks

What is a ’Neural Network’ in Deep Neural Networks?

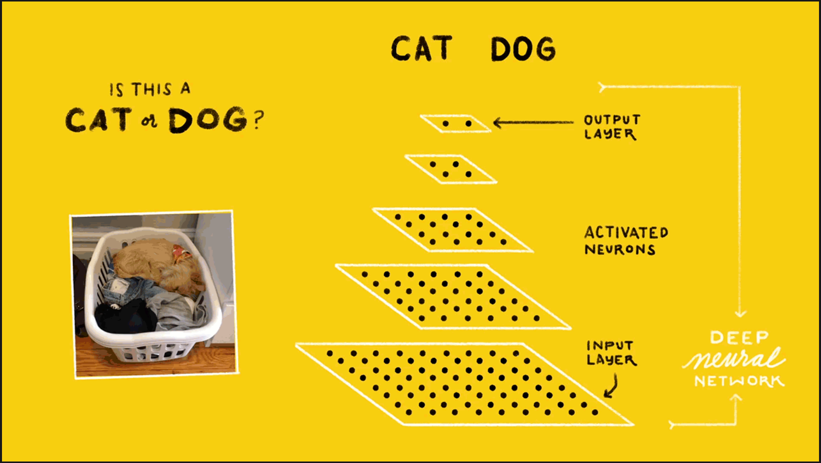
Neural Networks



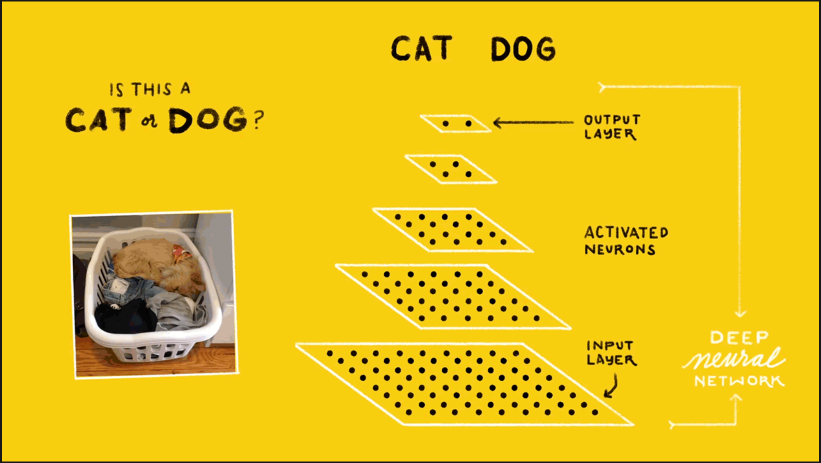
"A Neural Network is inspired by our knowledge the inner-workings of the human brain."

`How Does Deep Learning Work? Two Minute Papers # 24 by Karoly Zsolnai Feher`

Neural Networks



Neural Networks



Deep Learning for Intelligent Computer Systems by Jeff Dean

Neural Nets

Let’s take a look first at two examples of sensory processing networks;

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One is technological, the other is biological;

Neural Nets

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One is technological, the other is biological;

Both handle visual information.

Neural Nets

Let’s take a look first at two examples of sensory processing networks;

One is technological, the other is biological;

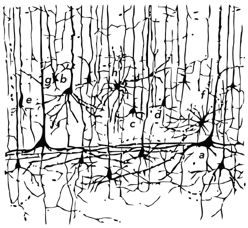
Both handle visual information.

Biological Inspiration

Ramón y Cajal's Retina

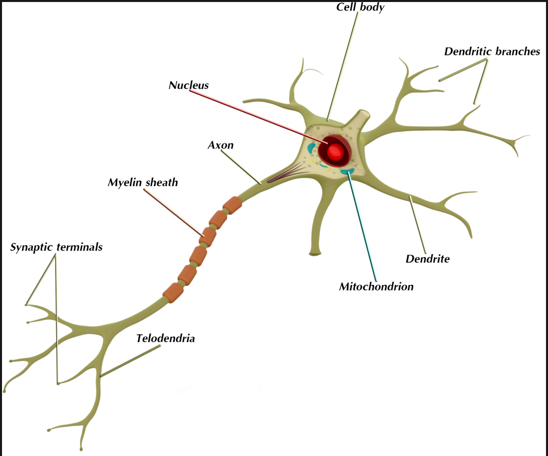
Mammalian retinal structure – note the apparent layers that are very clearly depicted. Different anatomical Layers are associated with different functional properties of cells.

The *layered* structure is typical of neural circuitry involved in sensory perception.



c.1900 By Santiago Ramón y Cajal.

Biological Inspiration



A Neuron

The Complexity of Vision

Some ’statistics’ on the human retina:

- 120 million photoreceptors in each human retina.
- Approximately 5 distinct layers of cells.
- Various areas of the retina:
  - Central Fovea
  - Fovea
  - Periphery
- Variation of properties/ratios of photoreceptors/ganglion cells across the retina.

Receptive fields

Spike-triggered averaging (STA) – also known as reverse 'correlation': a probabilistic characterisation of receptive fields.

Run through a random series of spatial patterns, and empirically estimate:

- – P(spike|spatial pattern stimulus; t)

Provides a systematic way of capturing response characteristics of cells.

The 'Optimal' Stimulus

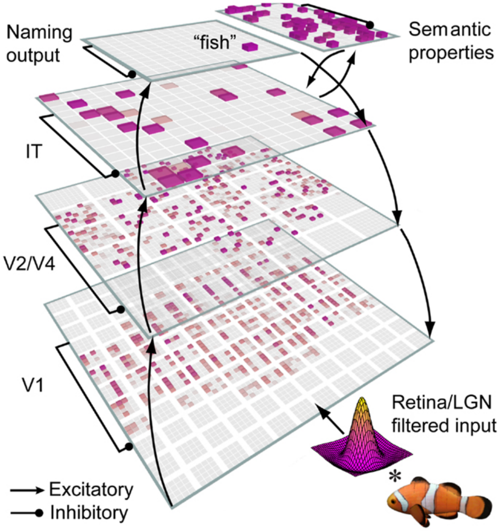
- A visual Interpretation of a retinal receptive Field
  - The 'optimal visual stimuli': probability of firing of two classes of retinal ganglion cells might be highest for these stimuli*.
  - Examples:
    OFF Centre ON Centre
    *This is a simplified, but 'on average' response.

Visual Information: The Path

Retina -> LGN -> V1 -> Projections to other brain areas;

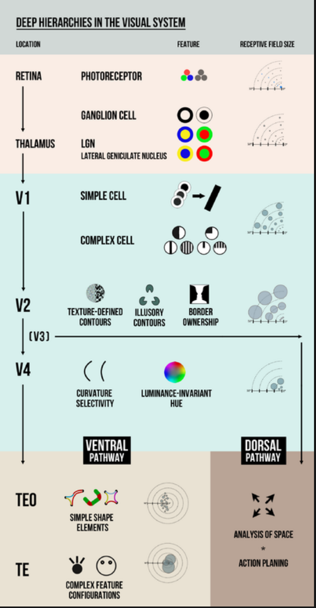
Anatomically distinct brain regions that can be captured by painstaking histopathology (for example, see Van Essen's work);

Visual Information: The Path



Biological architecture of a visual pathway

Visual Information: The Path



Cortical Layers

Cortex uses layered architecture for different types of function.

For vision, we know that we can associate different visual receptive field properties with different layers;

Staining for cell bodies in (left) visual cortex and (right) motor cortex of human adult. From Santiago Ramón y Cajal 'Comparative study of the sensory areas of the human cortex', 1899. Reprinted by Nabu Press, 2010.

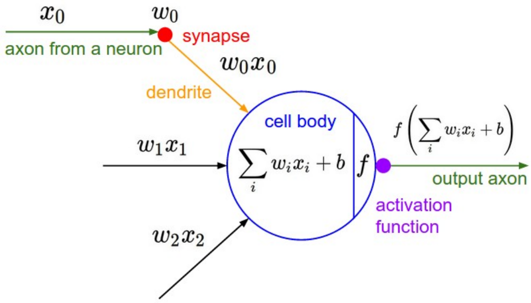
Possible, though not easy to experimentally find receptive fields for higher visual areas.

However, we do not suggest a grandmother cell so much as a joint encoding of visual structure by many cells.

Rough idea of selectivity to properties; however, selectivity is usually ’soft’ and not ’hard’: e.g. orientation tuning curves.

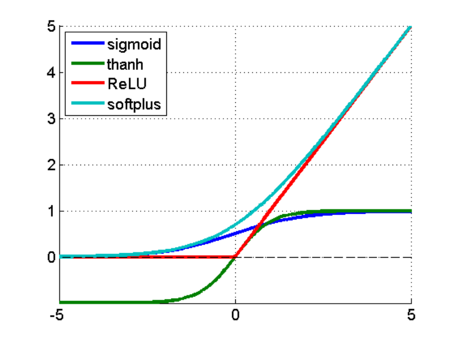
And now, the machines…

A Neuron Model



Stanford CS class by Andrej Karpathy

Activation Function



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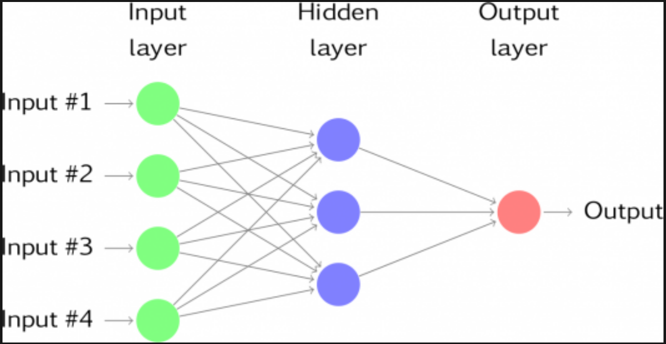
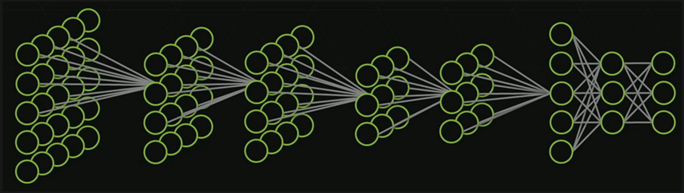
1D Convolutional Network



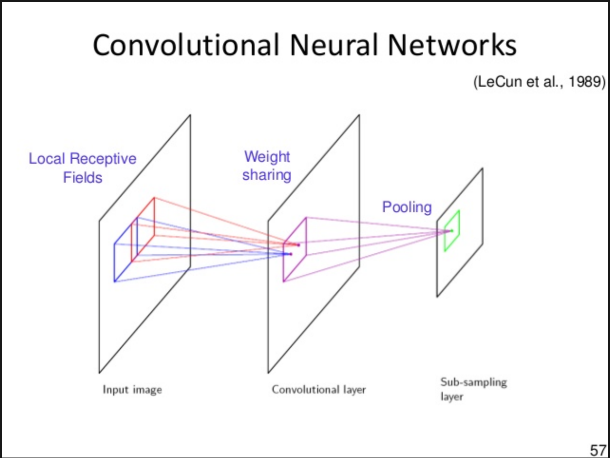
1D Network

2D Convolutional Network



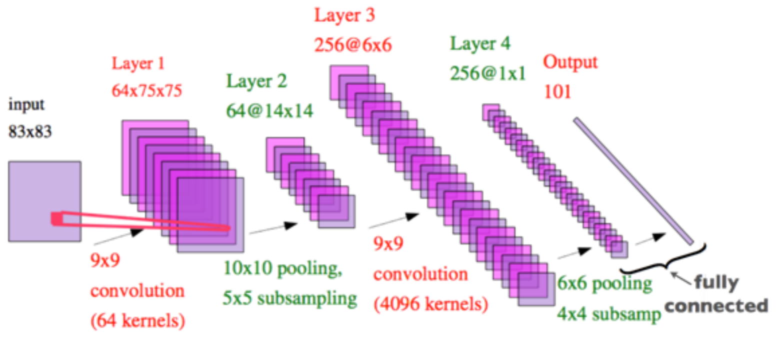
2D Network

Analyzing results



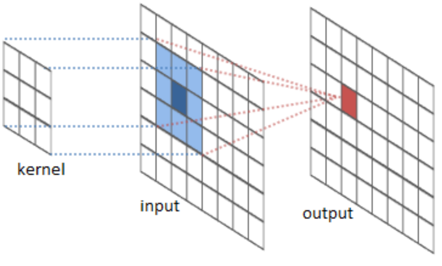
LeCun ConvNets, ICML 1989

Convolutional Multilayer Network



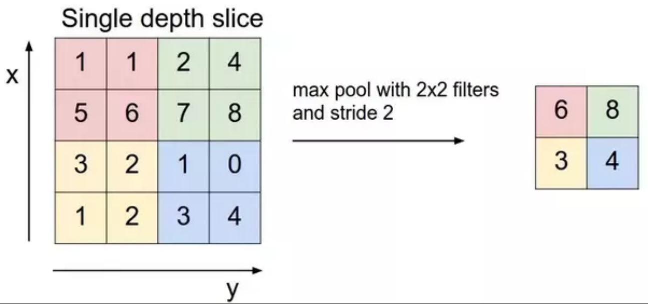
LeCun ConvNets, ICML 2012

(Matrix) Convolution



Stanford CS class by Andrej Karpathy

Max Pooling



Stanford CS class by Andrej Karpathy

Let’s try again...

Deep Learning systems

Multi-layered networks of units, that are based on simple artificial neurons, which encode and classify sensory data.

Start with the single artificial neuron to revise some terminology and concepts;

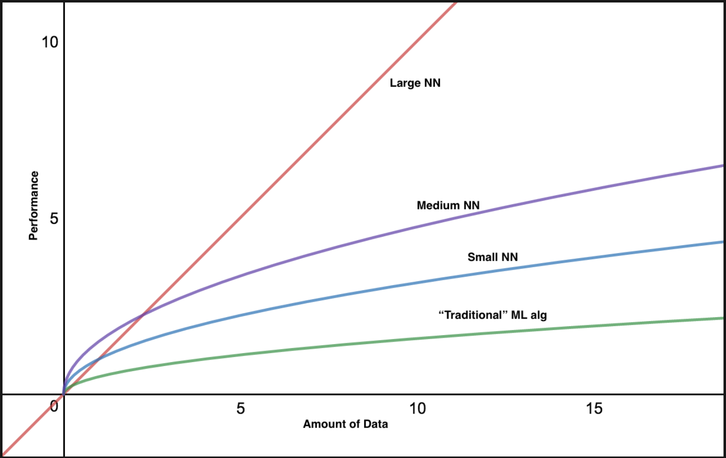
Objectives in training a DNN

- Accurately encoding ’stimuli’
  - generally, at the lower levels of the network
  - classifying accurately at the top level
- Sparsity: all levels – not all units are ac0ve in response to stimuli from the layer below;
- Robustness to noise (e.g. denoising autoencoder), usually at the lower level(s), but see MacKay for a more general view of neuronal capacity in the noisy channel-coding sense.

Convolutional Deep Learning Systems

- Training on small patches (non-convolutional) leads to good performance, particularly if:
  - There is no clutter in the images;
  - The objects are centered in the field of view;
  - The field of view is small;
- Recently, convolutional deep learning systems have been used by the DL community very successfully.
- Some debate about benefits of convolutional networks vs non-convolutional; experimental results are pretty convincing, though.

Capacity



Nuts and Bolts of Applying Deep Learning Andrew Ng at Deep Learning School

Deep Neural Networks

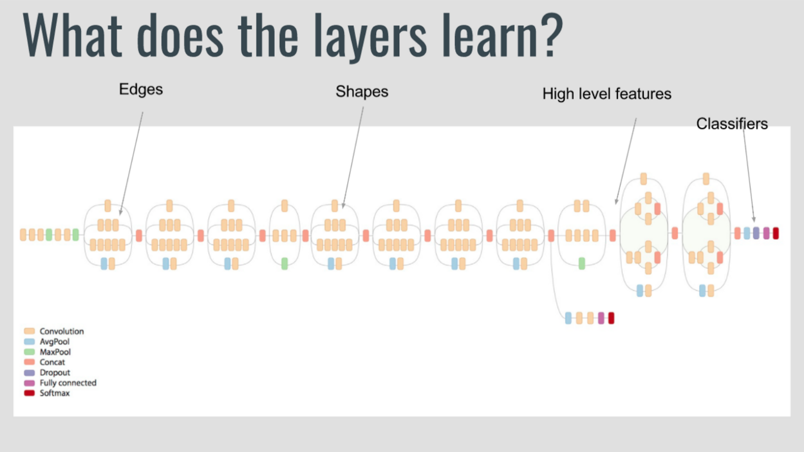
Deep Neural Networks

Why ’deep’ in Deep Neural Networks?

Deep Neural Networks

- A Deep Neural Networks (DNN) system contains multiple hidden layers of network between input and output layers;
- DNN systems are reminiscent of multi-layer perceptrons, BUT:
  - DNN systems are often trained by exploiting both **supervised** and **unsupervised** training in the same network;
  - DNN systems may mixed architectures from layer to layer, that often conform to hybrid probabilistic models;
  - Training regimes may differ depending on layer, reflecting a balance between the need to represent and to classify data

Architecture: Inception



Google Inception V3 model

Inception V3

Architectures / Models

Architectures / Models

what is a Neural Model?

Architectures / Models

what is a Neural Model?

Acronyms

Deep Neural Networks

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Performance

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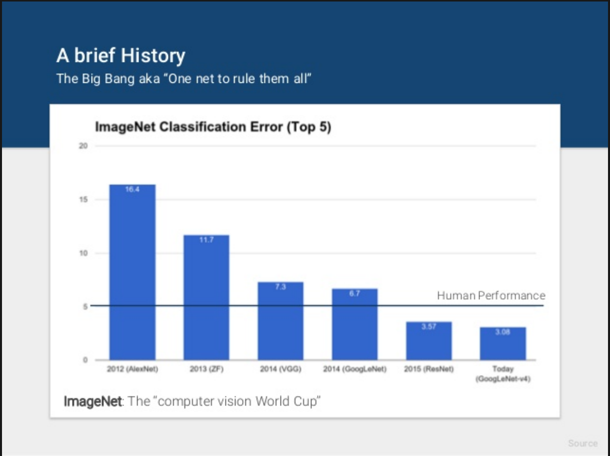

Performance

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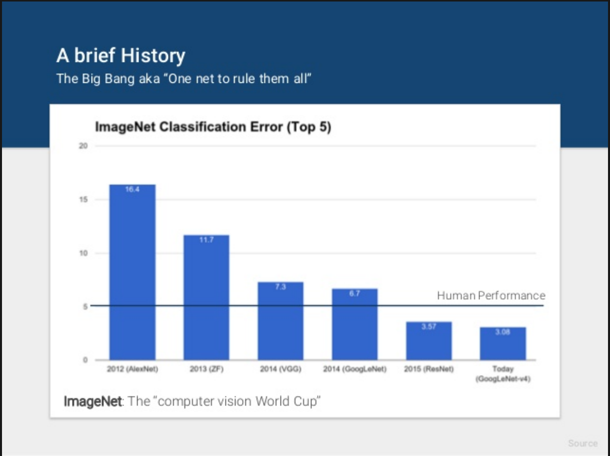

Krizhevsky et al. 2012: AlexNet

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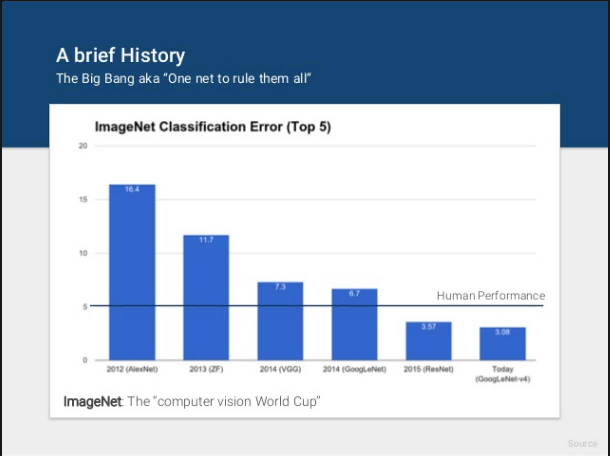
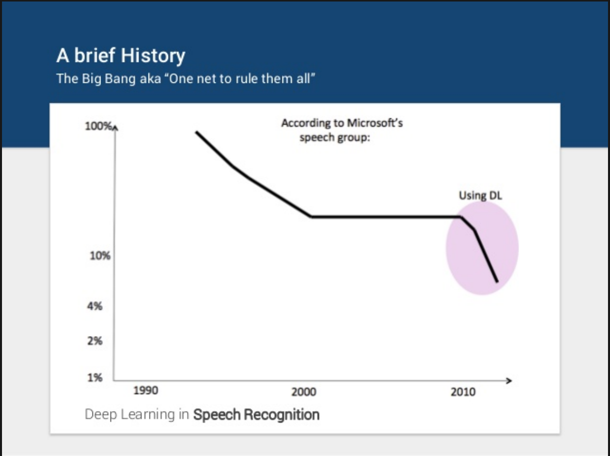


Krizhevsky et al. 2012: AlexNet

`ImageNet Classification Challenge`

Performance



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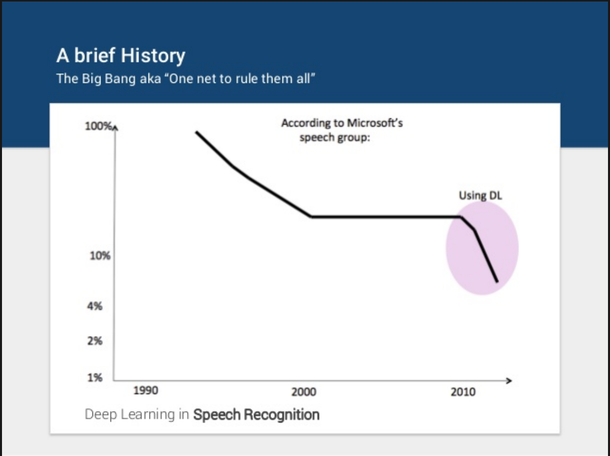
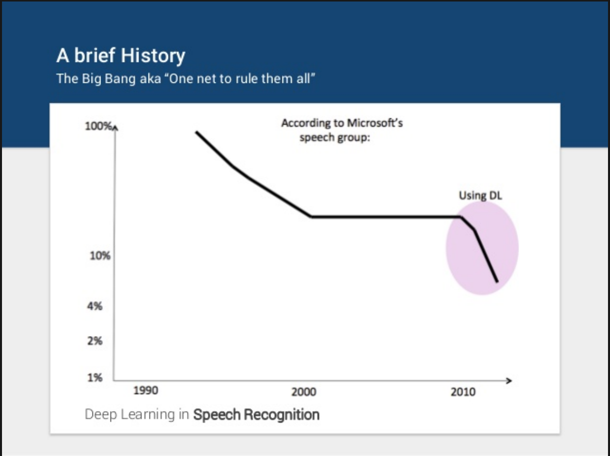


Superhuman accuracy in Face Verification

Performance



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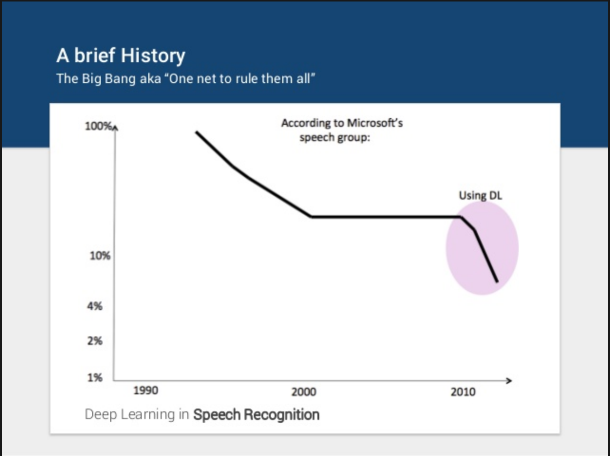

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Setup

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To use a DNN

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Frameworks - Part I

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Tensorflow

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Tensorflow

Theano

Frameworks - Part I

Tensorflow

Theano

Keras

Frameworks - Part I

Tensorflow

Theano

Keras

Lasagne

Frameworks - Part I

Tensorflow

Theano

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Caffe

Frameworks - Part II

Frameworks - Part II

DSSTNE

Frameworks - Part II

DSSTNE

Torch

Frameworks - Part II

DSSTNE

Torch

mxnet

Frameworks - Part II

DSSTNE

Torch

mxnet

DL4J

Frameworks - Part II

DSSTNE

Torch

mxnet

DL4J

Cognitive Toolkit

Frameworks - Part II

- DSSTNE
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Python IDEs

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PyCharm

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VIM

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Pydev

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Pydev

Spyder Python

Python IDEs

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Task-Tailored Practical End-to-End Setup of a Neural Network

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Let’s build an image classifier

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Choose an object you want to classify

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Let's build an image classifier

Choose an object you want to classify

We can choose to:

- train a cnn ourselves
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  or
- use a pretrained model

Build a Classifier

Build a Classifier

Object: X

Build a Classifier

Object: X

Pretrained model:

Build a Classifier

Object: X

Pretrained model:

- Inception V3

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What if Inception was not trained on Object X?

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Object: X

Pretrained model:

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What if Inception was not trained on Object X?

- Transfer learning
  - Applying learnings from a previous training session to a new training session

Building a Classifier (Steps)

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1. Build a TensorFlow Image Classifier in 5 Min by Siraj Raval

Building a Classifier

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What if there are more objects?

Building a Classifier

What if there are more objects?

Difference between objects X and Y?

Building a Classifier

What if there are more objects?

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or n objects?

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Train an Image Classifier with TensorFlow for Poets by Josh Gordon

Obtaining Results

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85 - 99% accuracy

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and then what?

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Accuracy:

- Model (Training Set) / Cross-Validation

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Accuracy:

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Accuracy:

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- Test

Obtaining Results

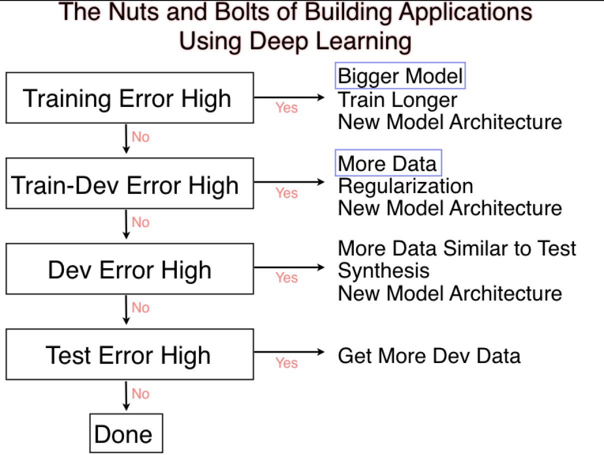
85 - 99% accuracy

and then what?

Accuracy:

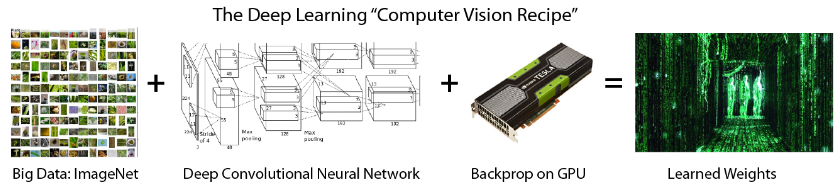
- Model (Training Set) / Cross-Validation
- Validation
- Test
  - Overall accuracy (ROC, PR)

Analyzing results



Nuts and Bolts of Applying Deep Learning Andrew Ng at Deep Learning School

A good recipe



Pipeline

Bibliography & Suggested Reading

Stanford Course: Convolutional Neural Networks for Visual Recognition Karpathy

- For starters:

  - Bengio, Y., 'Learning Deep Architectures for AI', Foundations and Trends in Machine Learning Vol. 2, No. 1 (2009) 1–127, DOI: 10.1561/2200000006.
  - David J.C. MacKay, 'Information Theory, Inference, and Learning Algorithms', CUP, 2006, for brushing up on single neuron models, learning rules and links between statistics and physics.
  - NIPS 2010 tutorial

Links:

Anil Bharath: Shallow Introduction to Deep Learning

Andrew Ng: Nuts and bolts of building AI applications using Deep Learning

kbroman Beamer Presentation Template

Tensorflow For Poets

Tensorflow Models GitHub Repo

Google Research Blog on Tensorflow Models

Skipped Theoretical

Initialization

Regularization

Backpropagation

Softmax

Fully conected layers

Skipped Practical

Data Augmentation

DNN can be easily fooled

Tensorboard

Training with less data

- Meta Learning
  - One Shot Learning