Introductory Session: Applied Deep Learning

August 17, 2017

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Agenda

- **Introduction**
    - Machine Learning
- **Deep Learning**
    - Artifical Neural Network
    - Convolution Neural Network (CNN)
    - Recurrent Neural Network (RNN)
    - Generative Adversarial Network (GAN)
    - Use Cases
    - Deep Learning Libraries/Tools
- **Demo - TensorFlow & Keras**
- **Course Preview**

About "Applied Deep Learning"

This is an introductory preview towards a course aimed at

- Graduate students,
- Researchers,
- IT professionals
- Industrial engineers

who already possess basic knowledge in Python programming and machine learning (and possibly, but not necessarily of deep learning) - who wish to learn more about this rapidly growing field of research and its application in the commercial world.

About us:

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Senior Lecturer, Faculty of Computing and Informatics
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Theme Lead, Smart Cities & Digital Services

Co-Organizer,
TensorFlow and Deep Learning Malaysia User Group

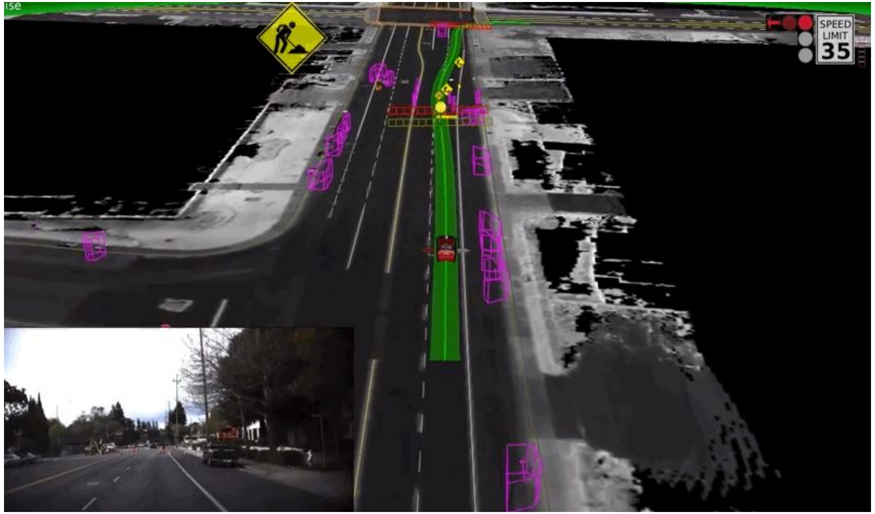
About us:

Poo Kuan Hoong, Ph.D
http://www.linkedin.com/in/kuanhoong

- Senior Data Scientist
- Senior Manager Data Science
- Senior Lecturer
- Chairperson Data Science Institute

- Founder R User Group & TensorFlow User Group
- Speaker/Trainer

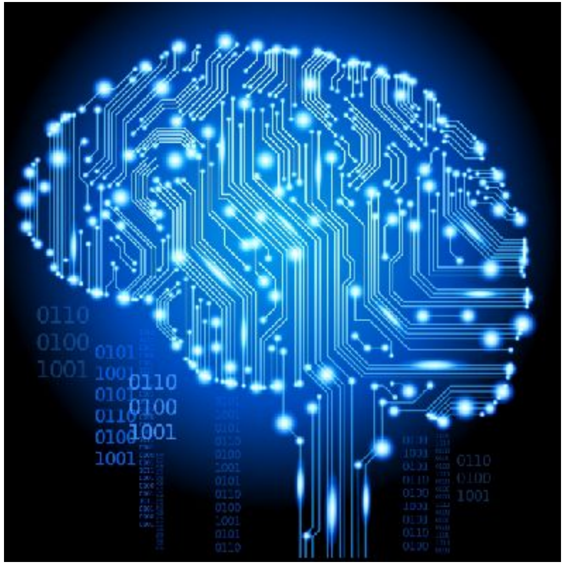
Where are we now..

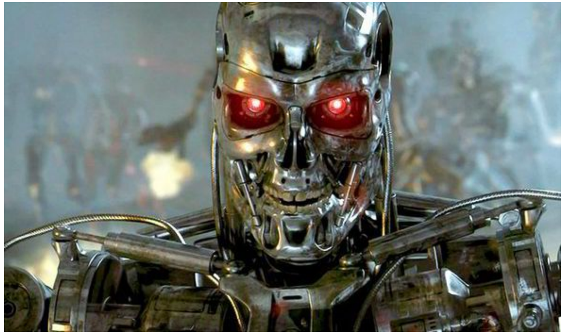


Where are we now..

Introduction

- **Deep Learning**: The fastest growing sub-field in A.I.
    - Computers can now make sense of difficult tasks by crunching large amounts of data
- **See, Hear, Learn, React**
- Many industries and businesses have been impacted by DL, spurring new products and services that are data-driven
- **Machine Learning**: Machines that can learn!

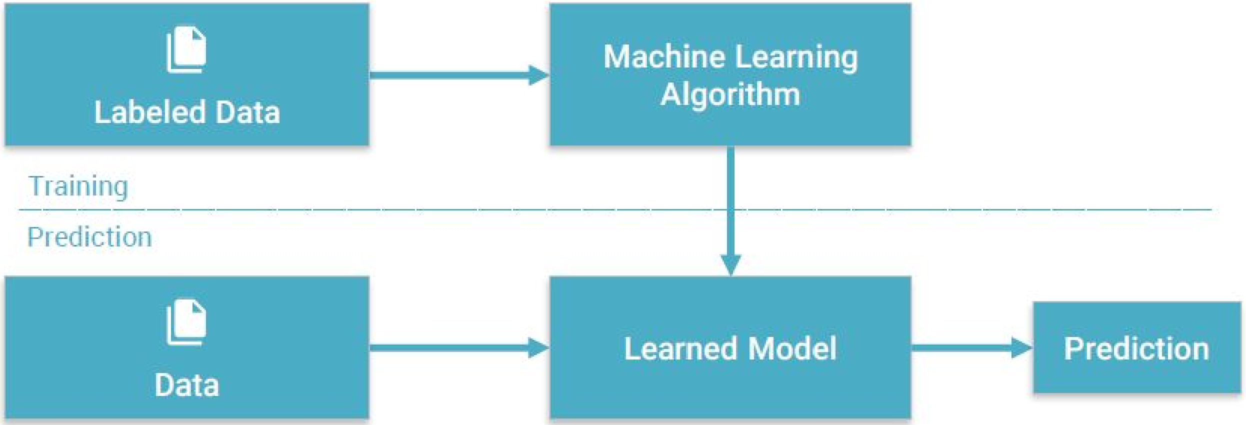




How do we learn?

Machine Learning

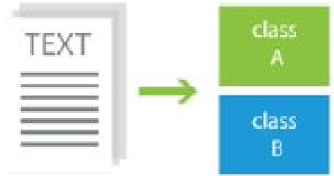
A type of Artificial Intelligence that provides computers with the ability to learn without being explicitly programmed



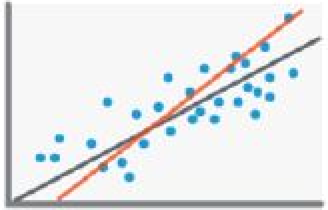
Machine Learning - Approaches

Supervised Learning	Learning from a labeled training set
Unsupervised Learning	Discovering patterns in unlabeled data
Reinforcement Learning	Learning based on feedback or reward

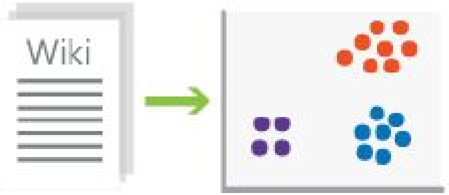
Machine Learning - Types of Problems



Classification



Regression



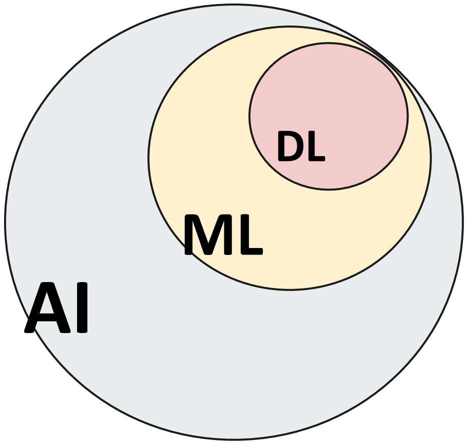
Clustering

Anomaly Detection

Deep Learning

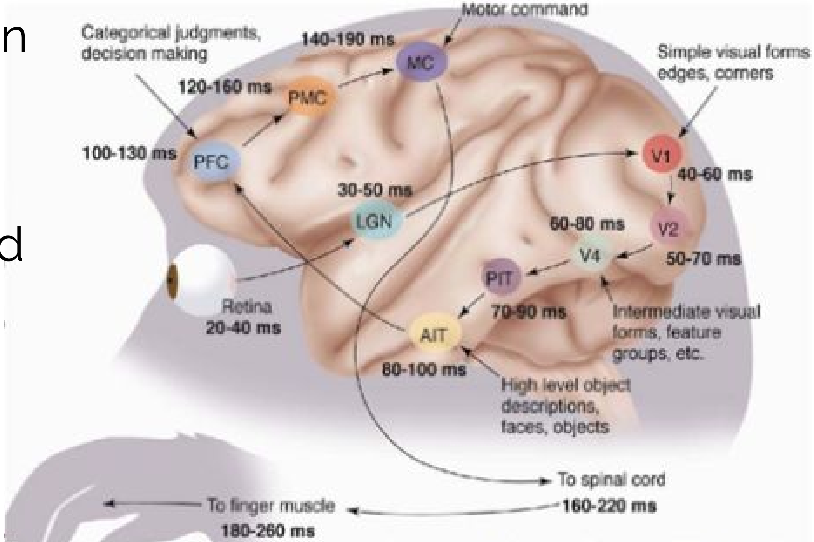
Deep Learning

- In the past 10 years, Artificial Intelligence (AI) particularly ML have shown tremendous progress.
- **Deep Learning**: part of Machine Learning (ML) field of learning representations of data
  - Exceptional effectiveness
  - Hierarchy of multiple “learning” layers that mimic the neurons in our brain
  - Thrives on big amounts of data



Why learn "deeply"?

- Inspired by architectural depth of brain
- Neuroscience findings: Information becomes more complex down the visual pipeline
- No successful attempts were reported before 2006
    - SVM: Vapnik and co. developed Support Vector Machine which was pretty good, but shallow learning

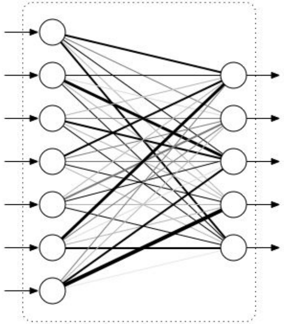


[picture from Simon Thorpe]

2006 Breakthrough: What made Deep Learning possible?

- Explosion of data
- Faster and cheaper computing -- multi-core CPUs and GPUs
- Improvement of ML models -- more complex, more scalable

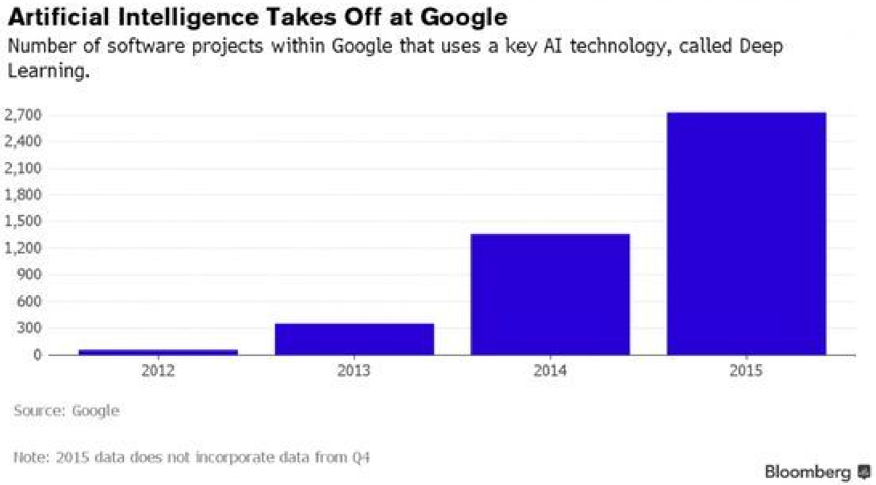
Stacked Restricted Boltzmann Machines (RBM) or **Deep Belief Nets** (DBN), Hinton, 2006
Stacked Autoencoders (AE), Bengio, 2007

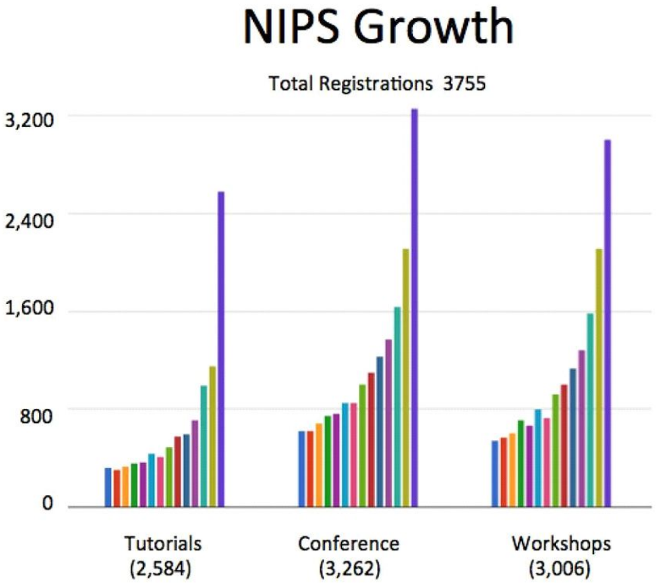


"I've worked all my life in Machine Learning, and I've never seen one algorithm knock over benchmarks like Deep Learning"

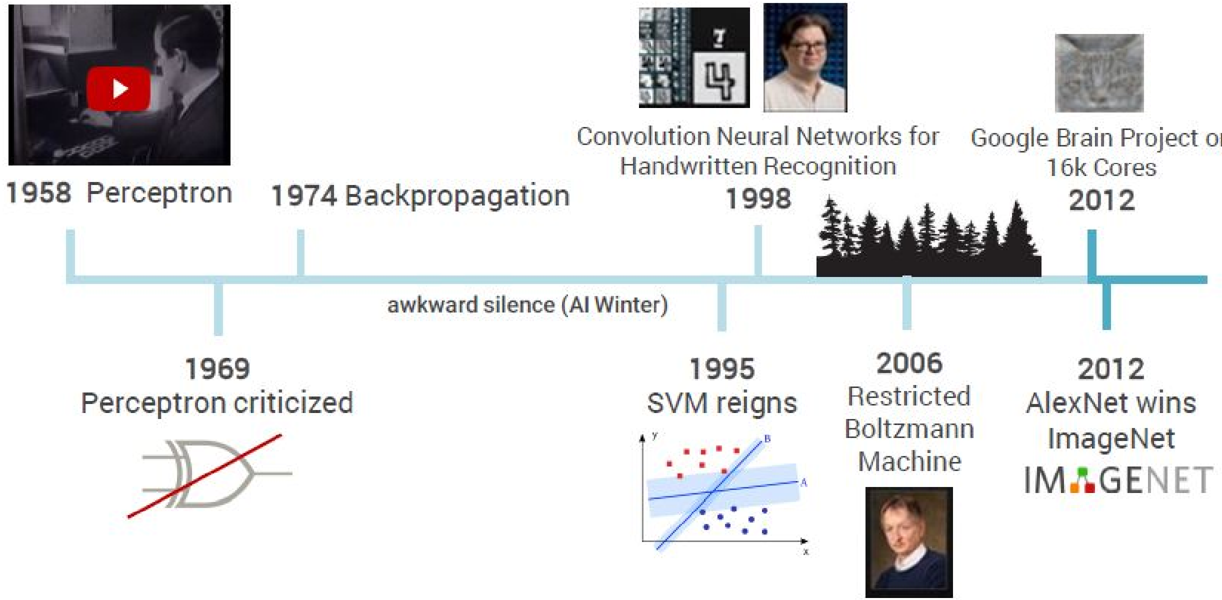
Andrew Ng
Stanford Univ, Baidu (prev.)
Co-Founder of Coursera

Deep Learning: Hype or Reality?

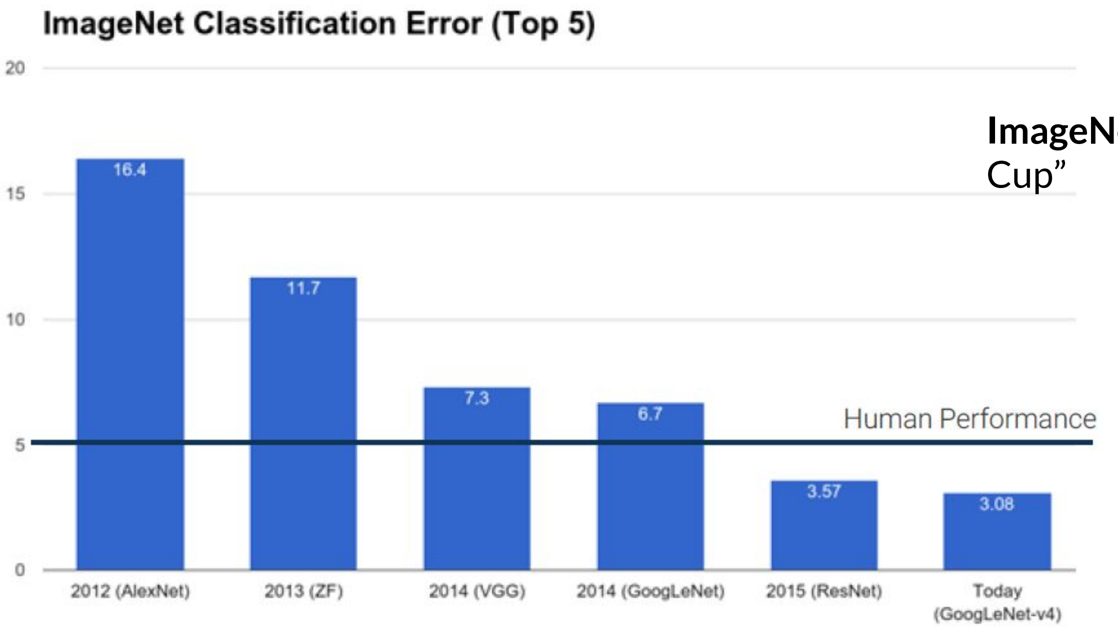




A very brief history...

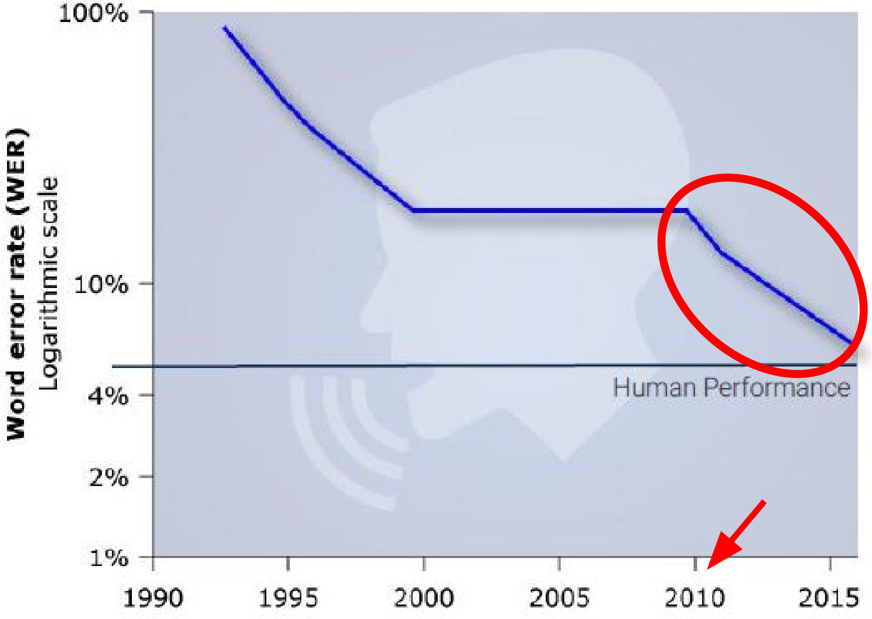


“One algorithm to rule them all”



ImageNet: The “computer vision World Cup”

“One algorithm to rule them all”

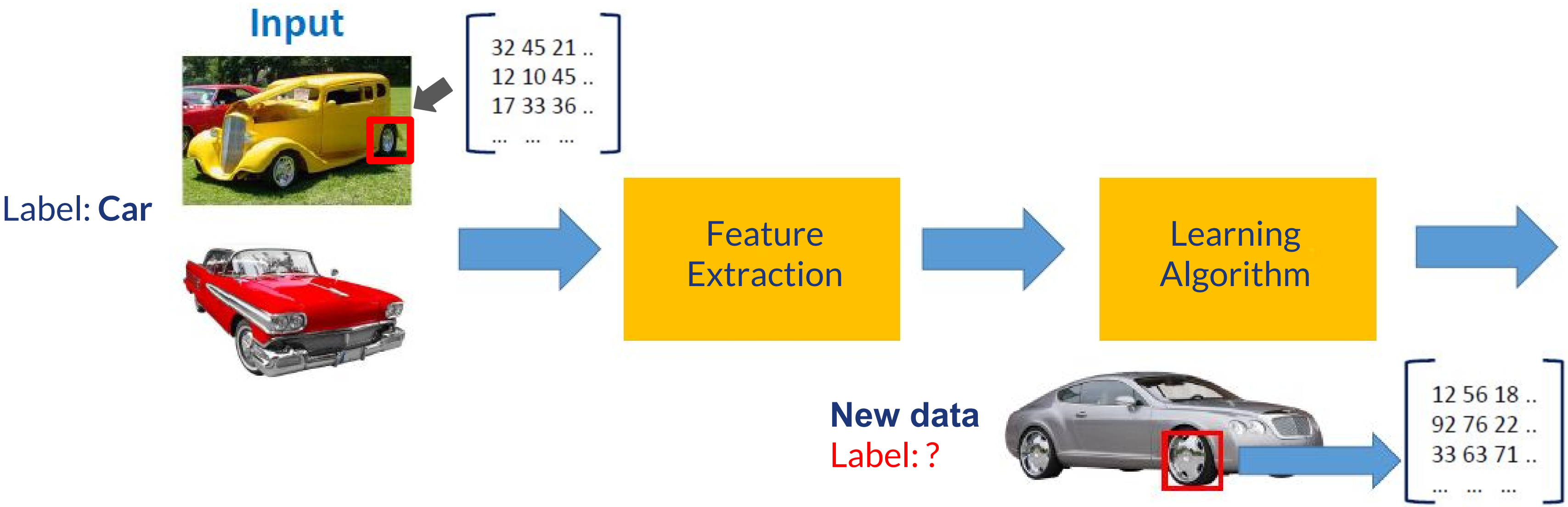


Thanks to DL!

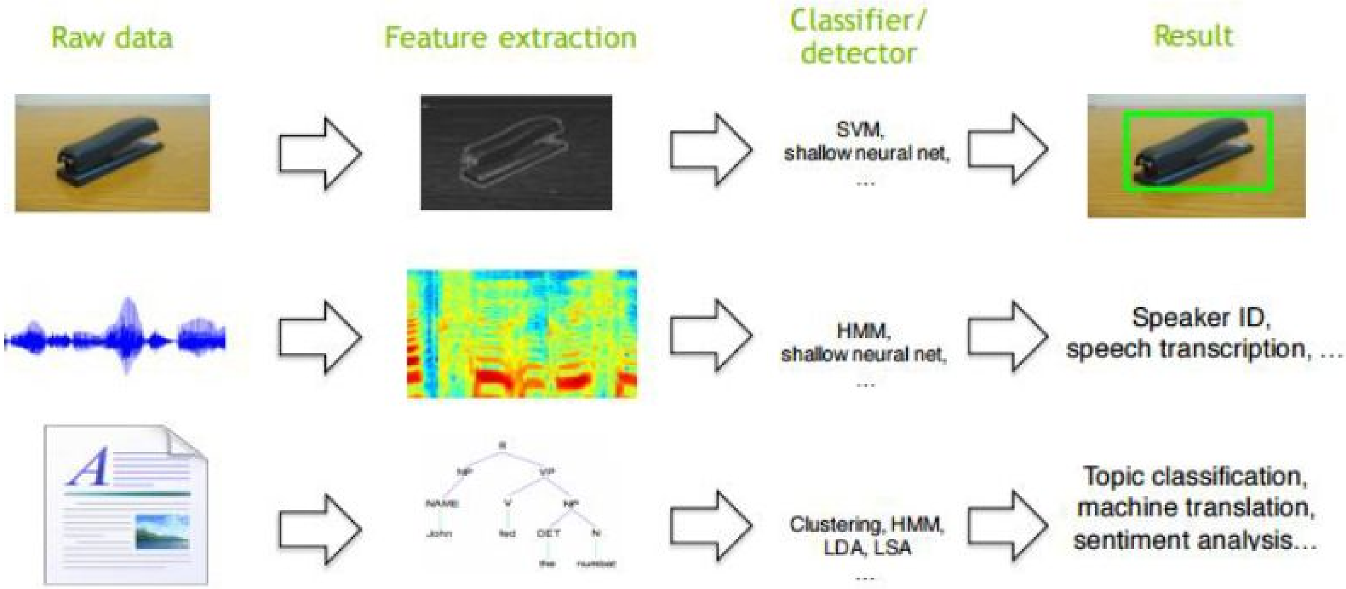
State-of-the-art Performance for Speech Recognition

Revisiting Traditional Machine Learning

- **"Feature Engineering":** Relates to extracting features by "hand-crafted" means. A simple classifier can be trained for recognition.

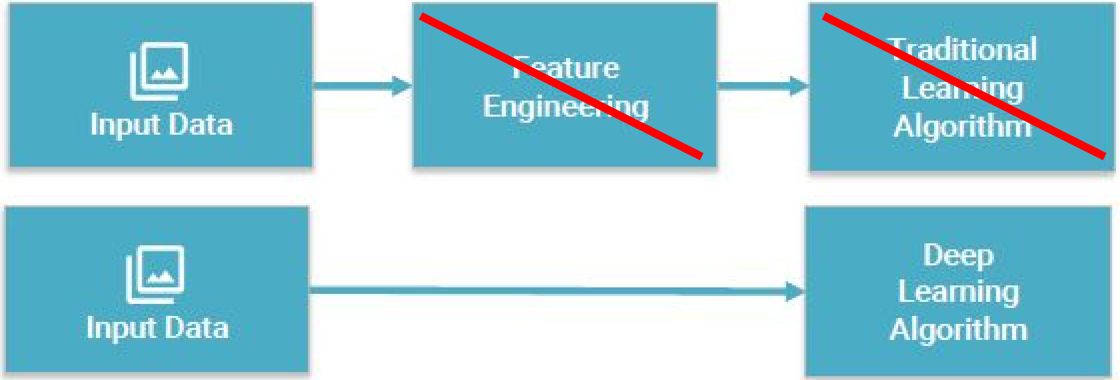


Revisiting Traditional Machine Learning



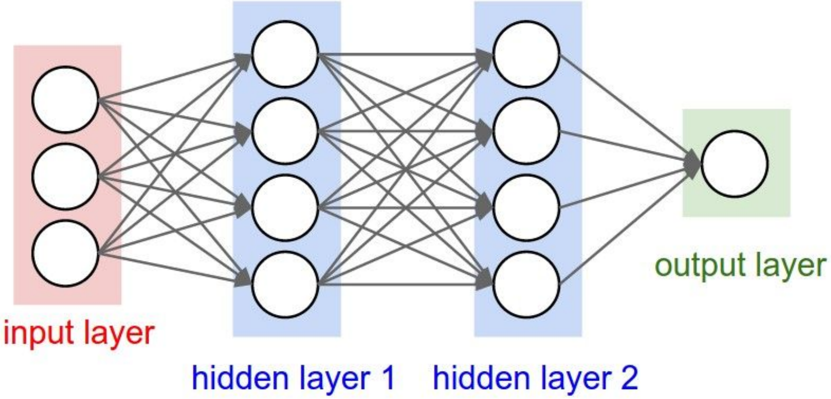
Deep Learning - All-in-one

- Removes the need to manually craft the feature (DL “finds” them instead)
- Removes the need to perform separate learning (DL “learns” them directly)

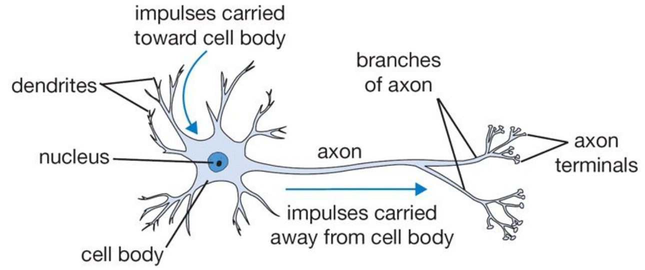


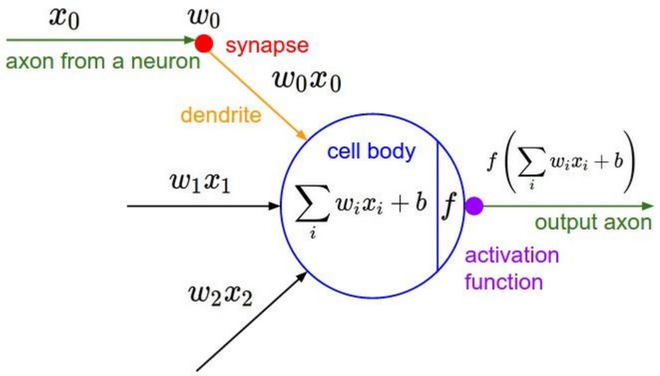
Artificial Neural Networks

- An **artificial neural network** consists of one input, one output and multiple fully-connected hidden layers in between
- Each layer -- a series of neurons, which connects the previous layer to the next



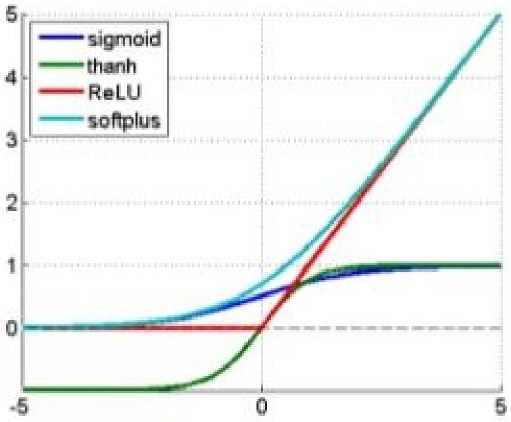
NN Basics: The Neuron

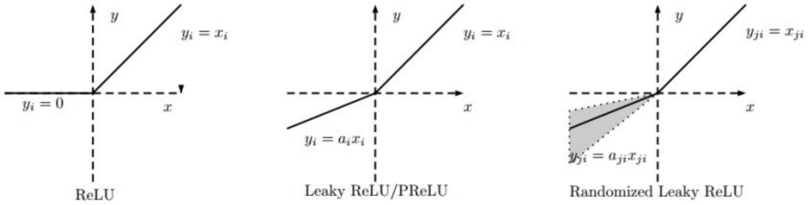




- An **artificial neuron** contains a nonlinear activation function and has several incoming and outgoing weighted connections
- **Neurons**: trained to filter and detect specific features or patterns

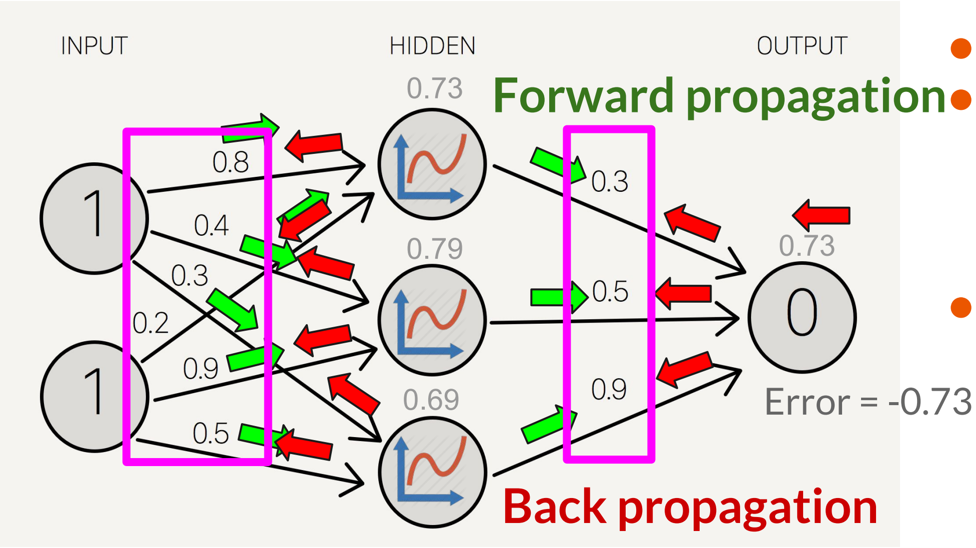
NN Basics: Activation Functions





- Why do activation functions need to be non-linear?
  - To learn complex representations of data
- Among the more popular choices in DL: ReLU (Rectified Linear Units)
  - Creates sparsity
  - Prevents vanishing gradient problem

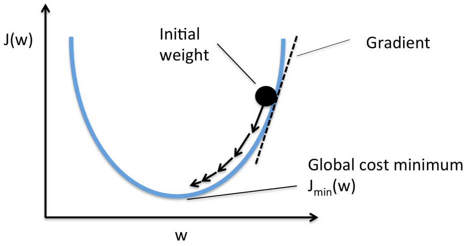
NN Basics: Forward- and Back-propagation

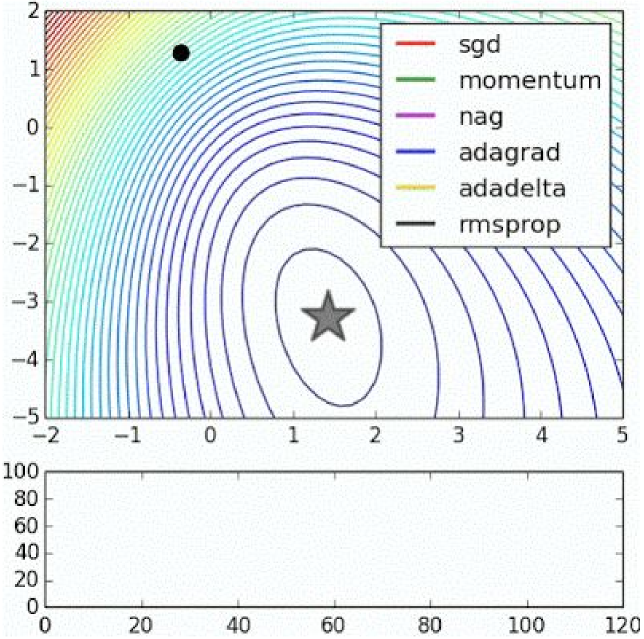


- Multilayer Perceptron (MLP)
- Forward propagation
  - Sum inputs, produce activations at each step forward
- Back propagation
  - Calculates total error, and contributions to error at each step backwards

NN Basics: Optimizing the Cost Function

- Re-adjusting the weights and biases is an optimization problem
- A cost function is defined to measure overall error which needs to be minimized
- Gradients are used to update weight parameters





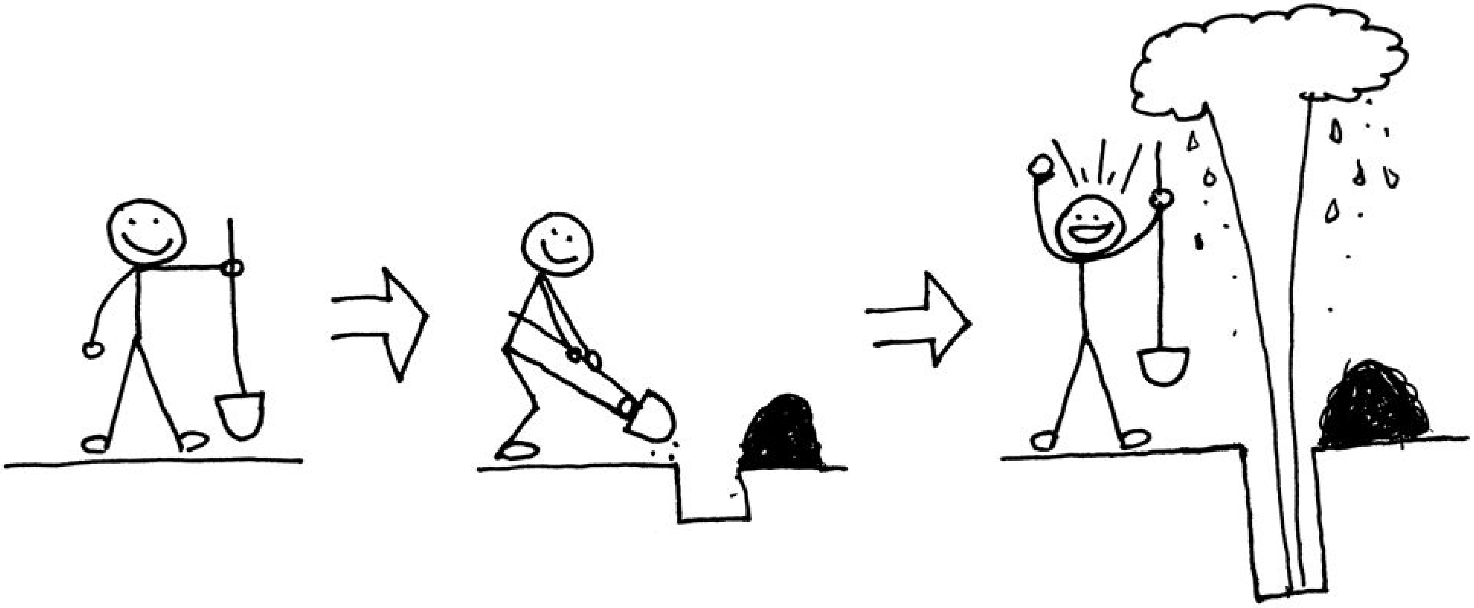
What's wrong with NN and back-propagation?

- It requires a lot of labelled training data
  - Almost all data is unlabelled
- The learning time does not scale well
  - It is very slow in networks with multiple hidden layers
- It can get stuck in poor local optimas
  - Works well most of the time, but suffers when complexity grows

Use unsupervised generative methods

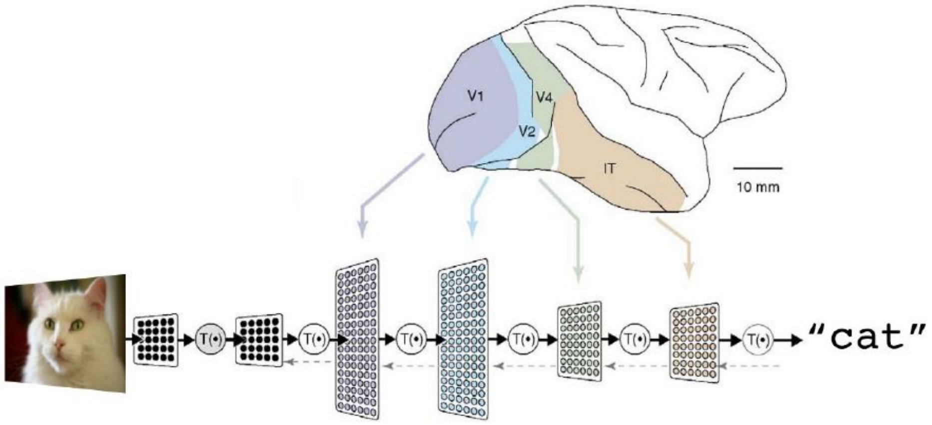
Bring out the GPUs!

Use more robust activation functions like ReLU, dropout layers, etc.



Credits: Ruslan Spivak

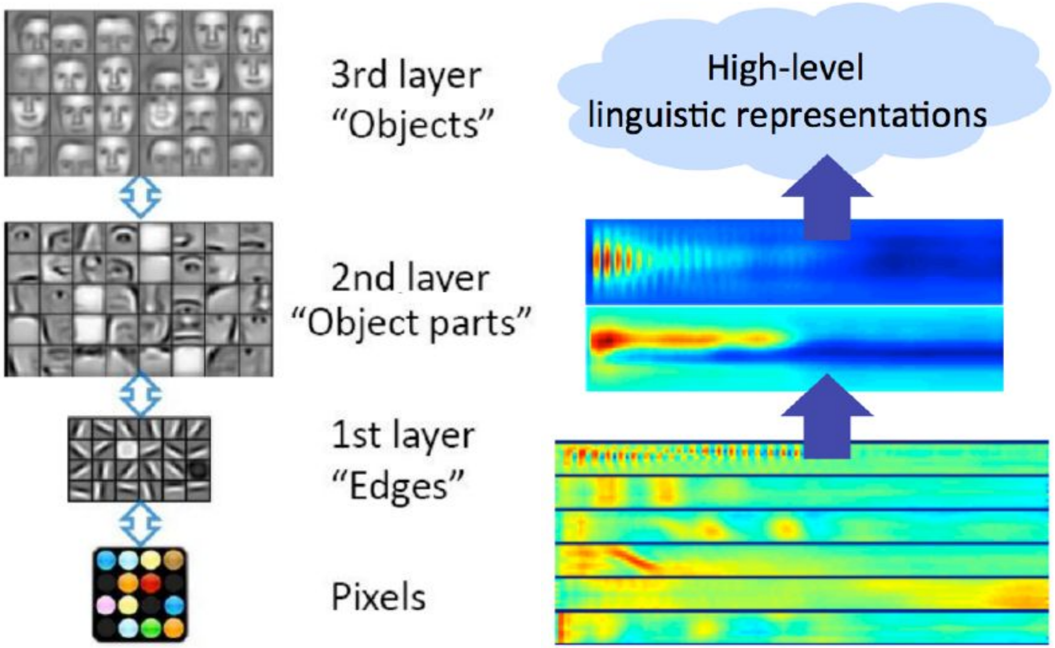
Why Go Deeper in Neural Networks?



1. Biological Justification -- Hierarchical learning
    - A deep neural network consists of a hierarchy of layers, whereby each layer transforms input data into more abstract representations. The output layer combines these features to make predictions

Why Go Deeper in Neural Networks?

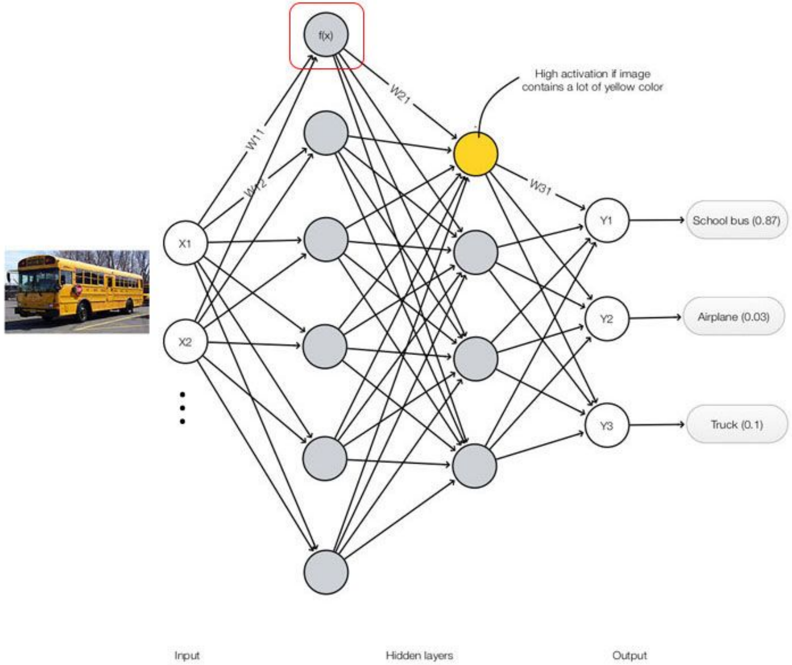
2. Different levels of abstraction
    - Natural progression from low to high level structure as seen in natural complexity



How “deep” is a deep neural network?

- Credit Assignment Path (**CAP**) or (number of hidden layers + 1) more than 2
- CAP > 10 : Very deep

“There is no universally agreed upon threshold of depth dividing shallow learning from deep learning, but most researchers in the field agree that deep learning has multiple nonlinear layers (CAP > 2) and Schmidhuber considers CAP > 10 to be very deep learning”



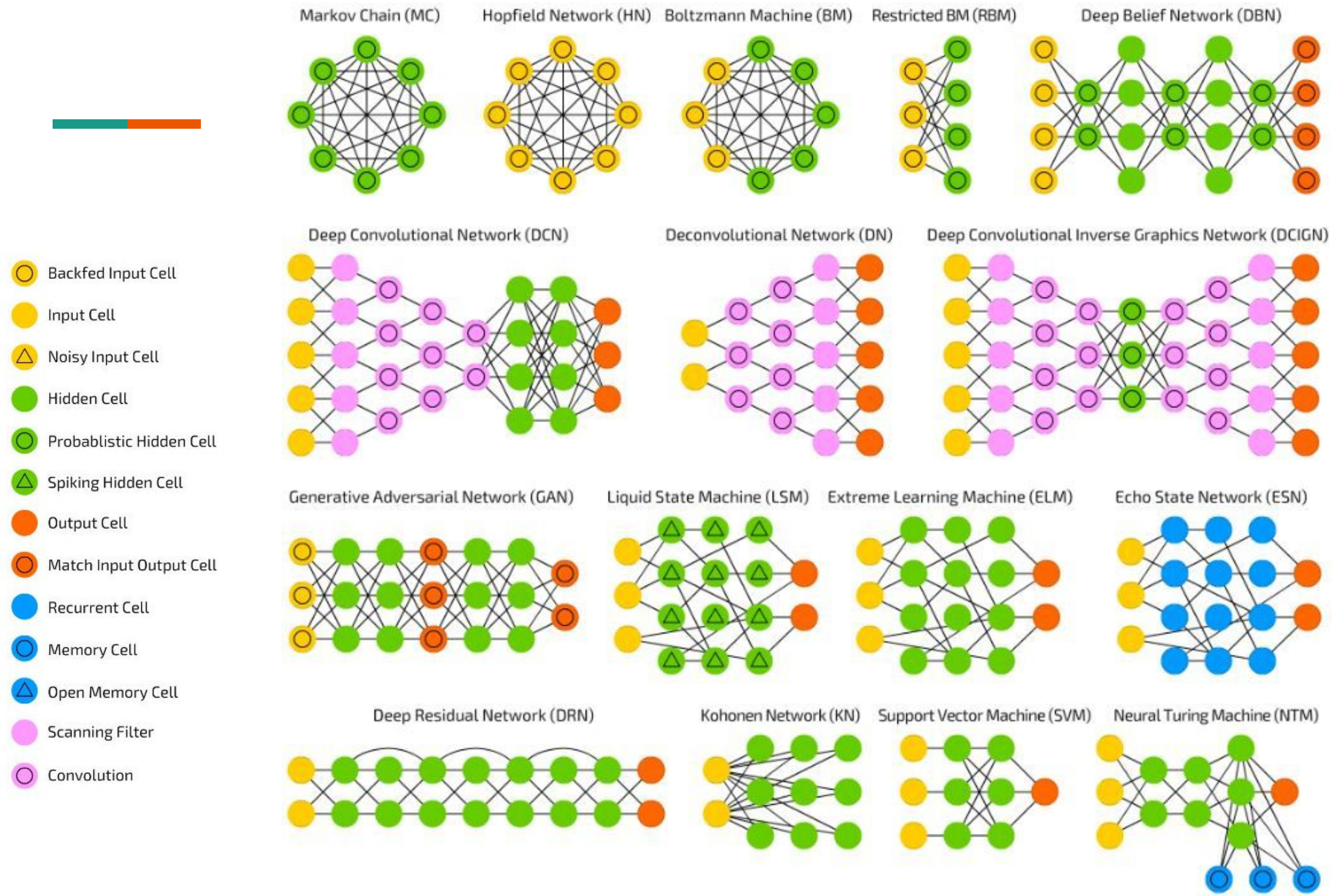
Deep Learning: Strengths

- **Robust**
  - Features are automatically learned to be optimal for the task at hand
- **Generalizable**
  - The same DL approach/architecture can be used for many different applications and data types
- **Scalable**
  - Performance improves with more data, method is massively parallelizable

Deep Learning: Weaknesses

- **Requires large datasets** (typically), also means long training periods.
- **Not necessarily > traditional ML methods** like SVMs, decision trees
- Learned features are often **difficult to understand or explain.**
    - Many vision features are also not really human-understandable (e.g, concatenations/combinations of different features).
- Requires **a good understanding of how to design new models** for new tasks, or using new forms of data, etc.

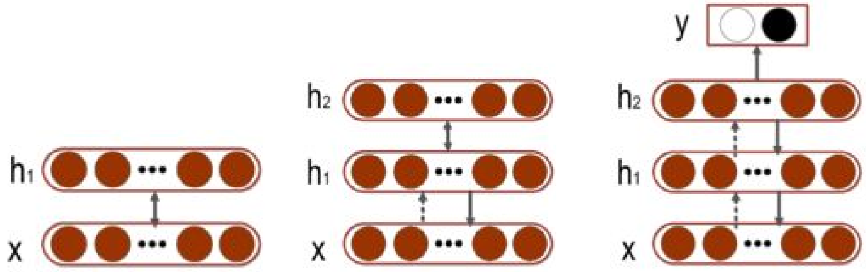
DL Flavours


Backfed Input Cell
Input Cell
Noisy Input Cell
Hidden Cell
Probablistic Hidden Cell
Spiking Hidden Cell
Output Cell
Match Input Output Cell
Recurrent Cell
Memory Cell
Open Memory Cell
Scanning Filter
Convolution
Markov Chain (MC)
Hopfield Network (HN)
Boltzmann Machine (BM)
Restricted BM (RBM)
Deep Belief Network (DBN)
Deep Convolutional Network (DCN)
Deconvolutional Network (DN)
Deep Convolutional Inverse Graphics Network (DCIGN)
Generative Adversarial Network (GAN)
Liquid State Machine (LSM)
Extreme Learning Machine (ELM)
Echo State Network (ESN)
Deep Residual Network (DRN)
Kohonen Network (KN)
Support Vector Machine (SVM)
Neural Turing Machine (NTM)

Stacking Neural Networks

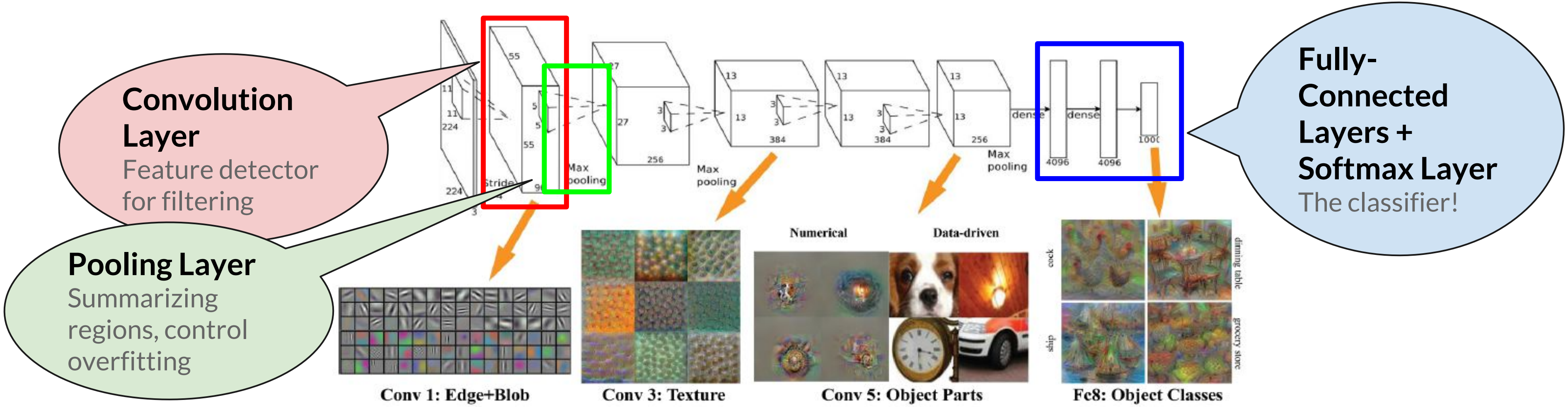
- Early attempts, pioneered by Geoffrey Hinton:
  - Deep Belief Networks (DBN) or Stacked Restricted Boltzmann Machines (RBM),
  - Stacked AutoEncoders (SAE)

- Idea:
  - Layer-wise Unsupervised Pre-training
  - Train last layer in supervised mode



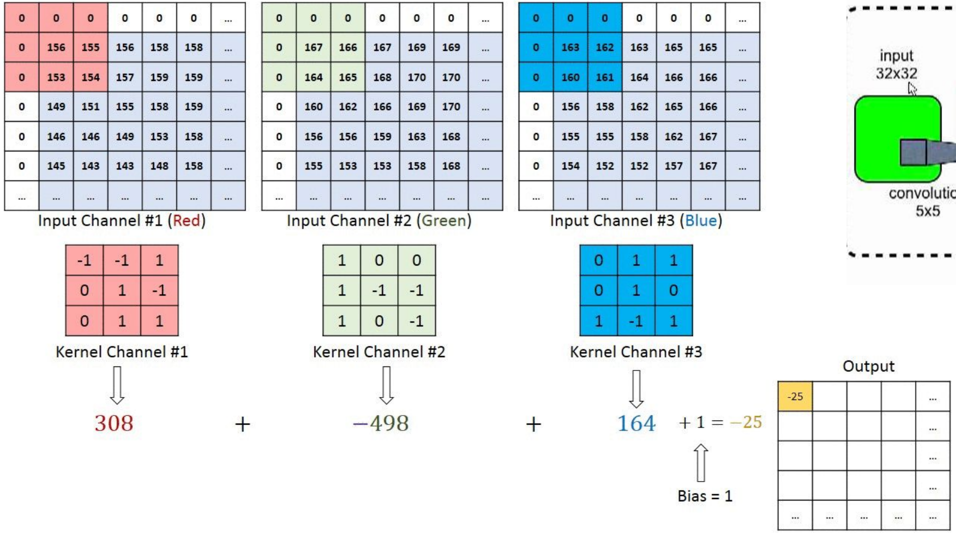
Convolutional Neural Networks (CNN)

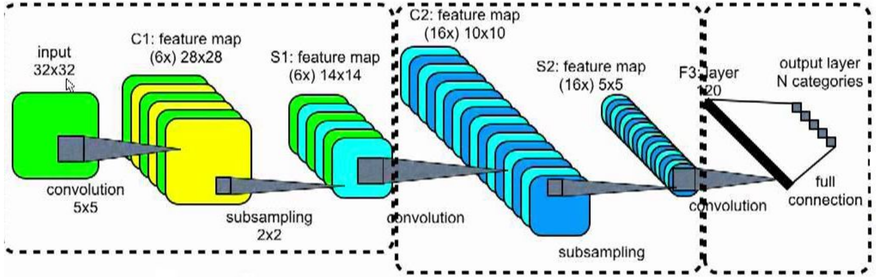
- Learn multiple layers of transformations, stacked to extract a progressively more sophisticated representation of the input



Convolutional Neural Networks (CNN)

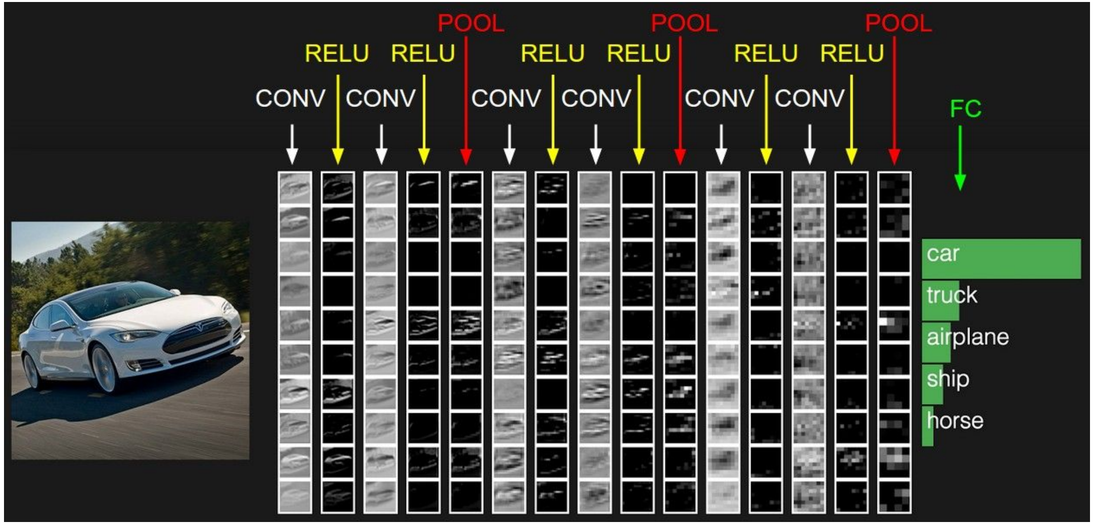
- Each neuron in the Convolutional layer is mapped to a receptive field



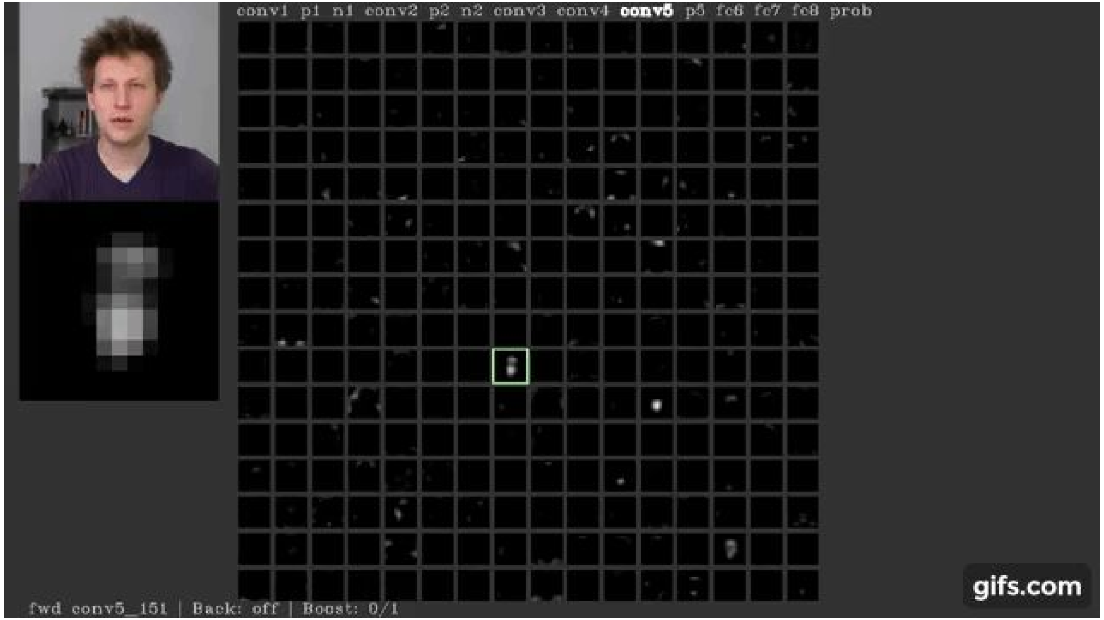


Convolutional Neural Networks (CNN)

- Pioneered by Yann LeCun back in 1989, why didn't it take off then?



Convolutional Neural Networks (CNN)

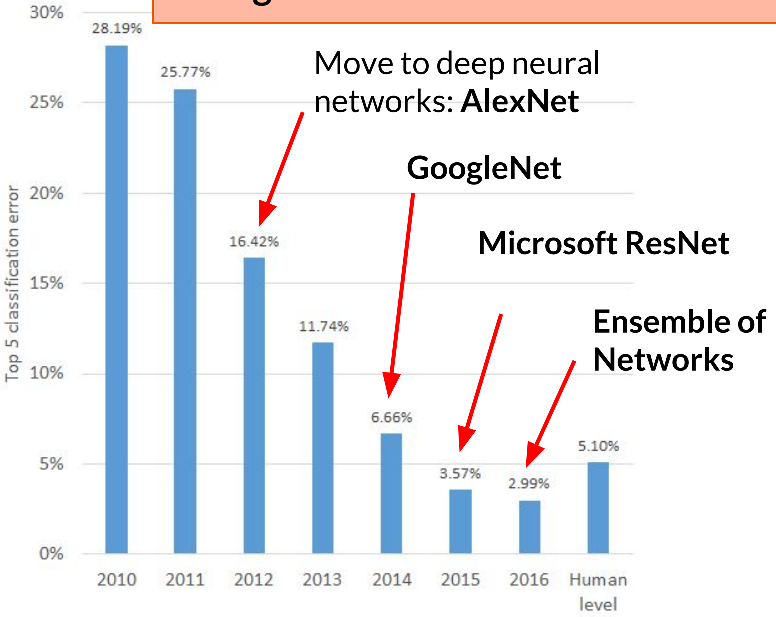


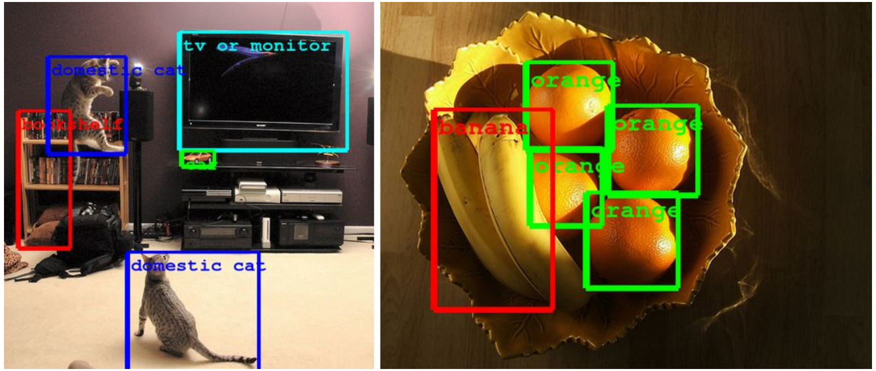
- CNNs can be visualized to gain better understanding of what the network is learning!

https://github.com/yosinski/deep-visualization-toolbox

Object Recognition and Detection/Localization

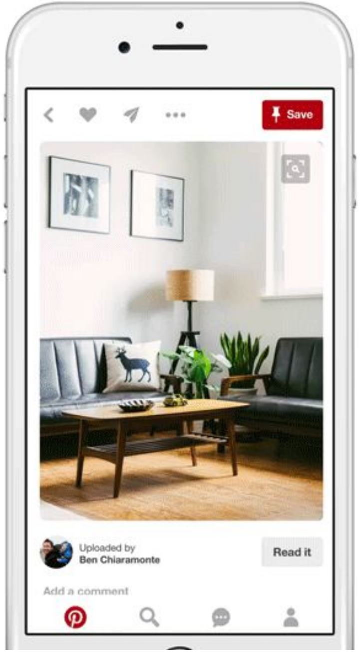
ImageNet ILSVRC: The "CNN War"



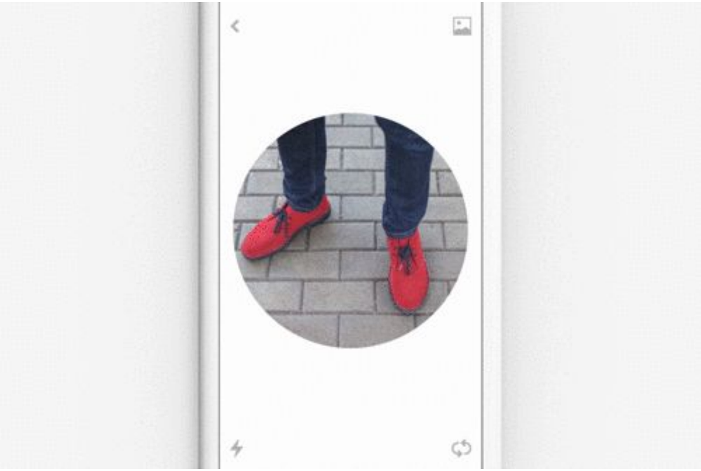


For Detecting objects:
R-CNN, Fast R-CNN, YOLO

Use Case: Visual Search @ Pinterest



Powered by CNNs!



What was used?

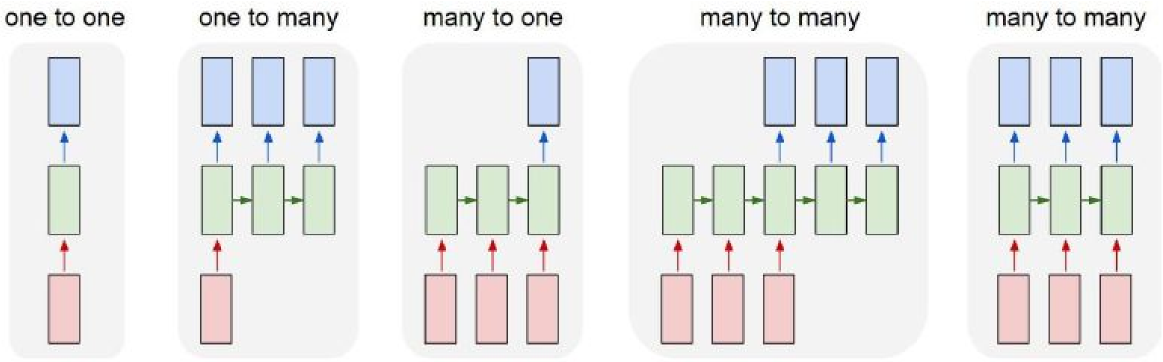
Object detection

Object classification

Recommendation engine: “Related Pins”

Recurrent Neural Networks (RNN)

- Pioneered by Juergen Schmidhuber and Sepp Hochreiter
- Great choice if your data changes over time, or patterns are sequential
- RNNs can map input sequences to output sequences!



Recurrent Neural Networks (RNN)

- Suitable for: Time series prediction, handwriting recognition, speech recognition, stock market forecasting, text translation, sentiment analysis

Single input, Sequential output

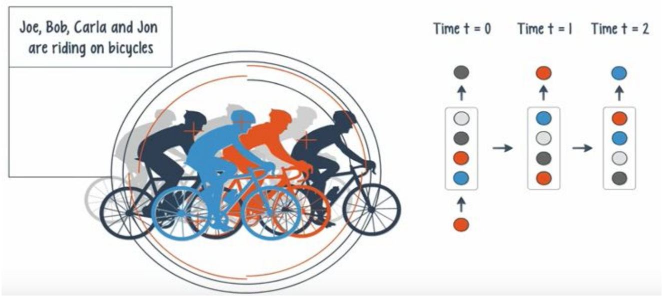
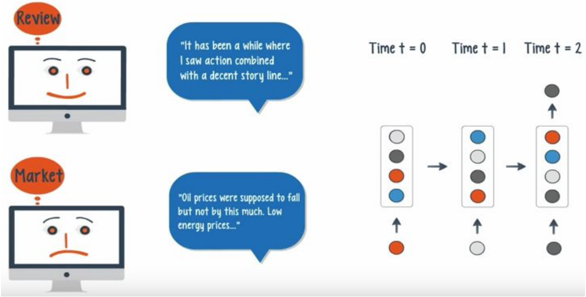


Image captioning

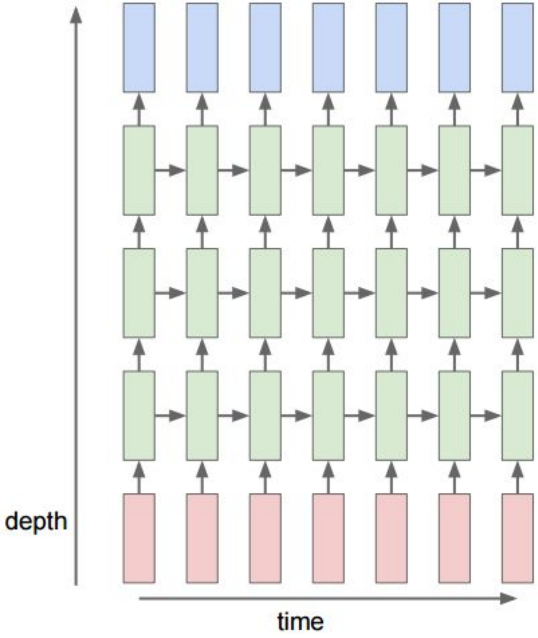
Sequential input, Single output



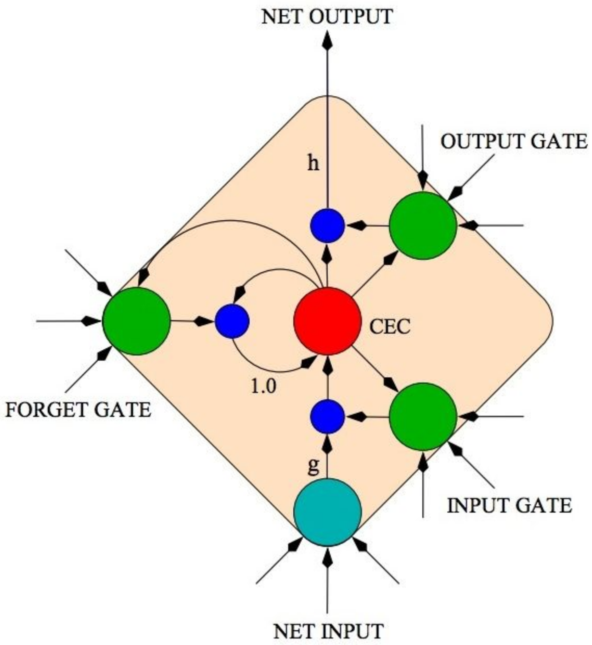
Sentiment analysis

Recurrent Neural Networks (RNN)

- Challenges:
  - Difficult to train, sensitive to parameters
  - Vanishing gradient problem just got worse! (A 100 time step RNN = 100 layer MLP!)
- RNNs can also be stacked into multiple layers to create more complex representations



Long Short-Term Memory (LSTM) RNN



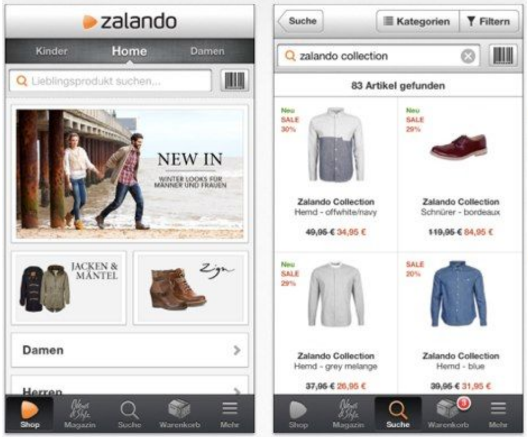
- **LSTM** is a variant of RNN that provides better back-propagation dynamics,
- LSTM units give the network memory cells to read, write and reset operations. During training, the network can learn when it should "remember" and when it should "forget"

LSTM: Modeling Text Data

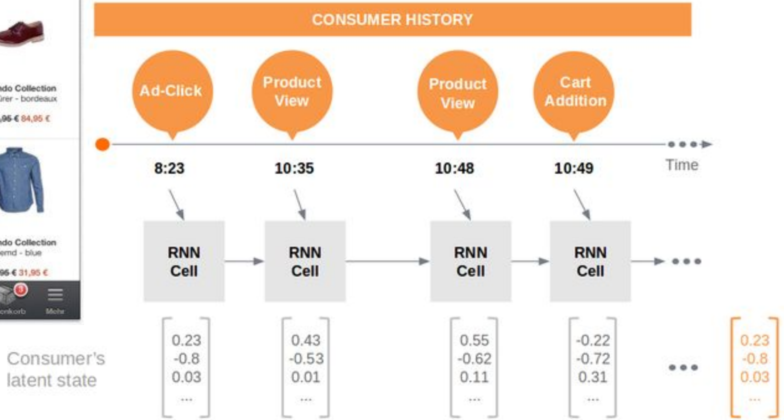
```
This is one of Crichton's best books. The characters of Karen Ross, Peter Elliot,
Munro, and Amy are beautifully developed and their interactions are exciting,
complex, and fast-paced throughout this impressive novel. And about 99.8 percent of
that got lost in the film. Seriously, the screenplay AND the directing were
horrendous and clearly done by people who could not fathom what was good about the
novel. I can't fault the actors because frankly, they never had a chance to make this
turkey live up to Crichton's original work. I know good novels, especially those with
a science fiction edge, are hard to bring to the screen in a way that lives up to the
original. But this may be the absolute worst disparity in quality between novel and
screen adaptation ever. The book is really, really good. The movie is just dreadful.
```

- Text is sequential: Insert characters into LSTM to predict probabilities of the next letter
- Text models can be turned into sentiment classifiers: Cater to longer bunch of sentences, like product/book/movie reviews

Use Case: Forecasting Consumer Preferences @Zalando



Powered by RNNs!

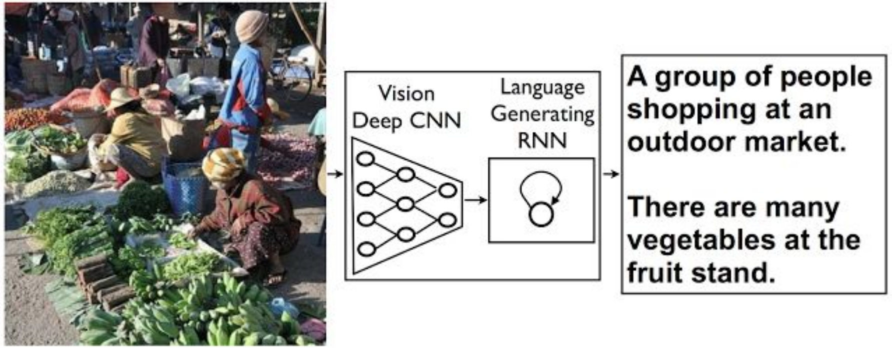


What was achieved?

Track consumer sessions

“Memorize” patterns in consumer behaviour to predict probability of orders

Hybrid Networks

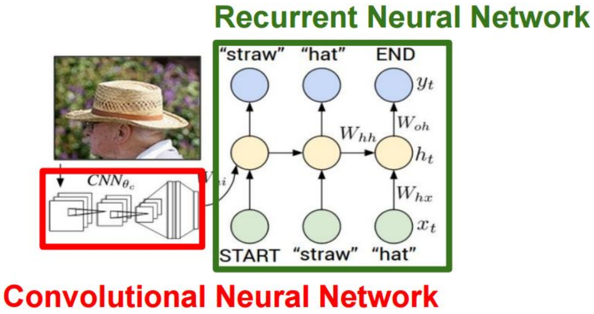


A close up of a child holding a stuffed animal

Two pizzas sitting on top of a stove top oven

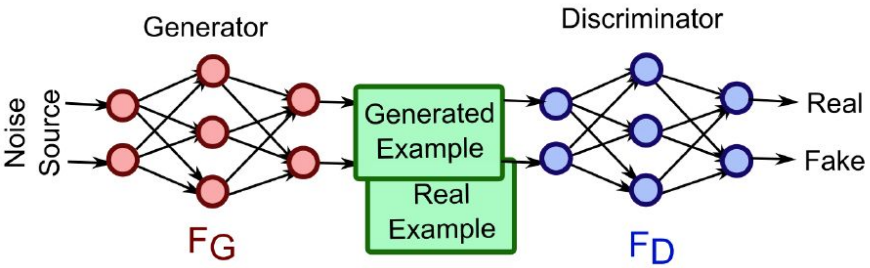
A man flying through the air while riding a skateboard

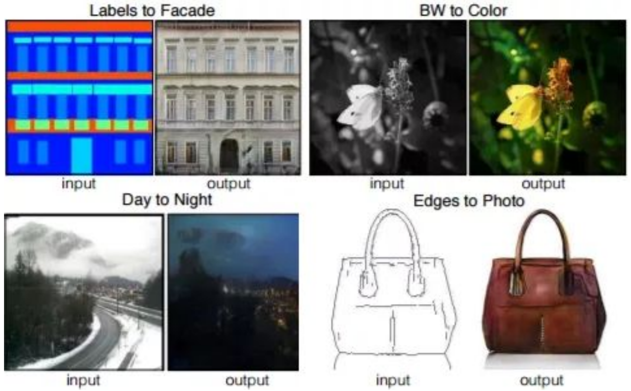
- **Image Captioning**: Combines CNN and RNN
  - Generates fitting natural language captions only based on the pixel data



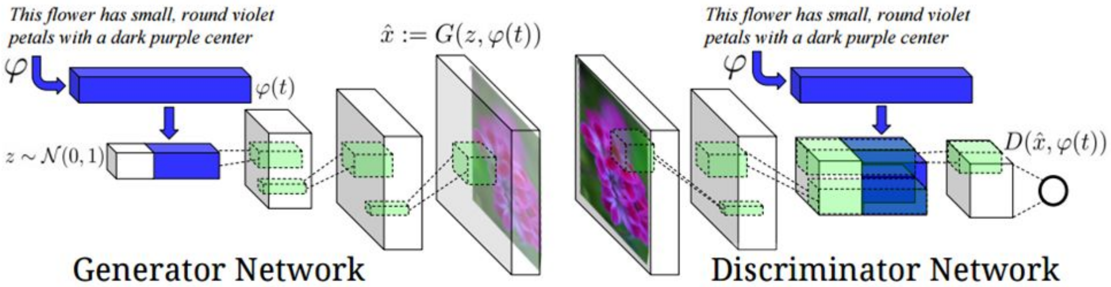
Generative Adversarial Networks (GAN)

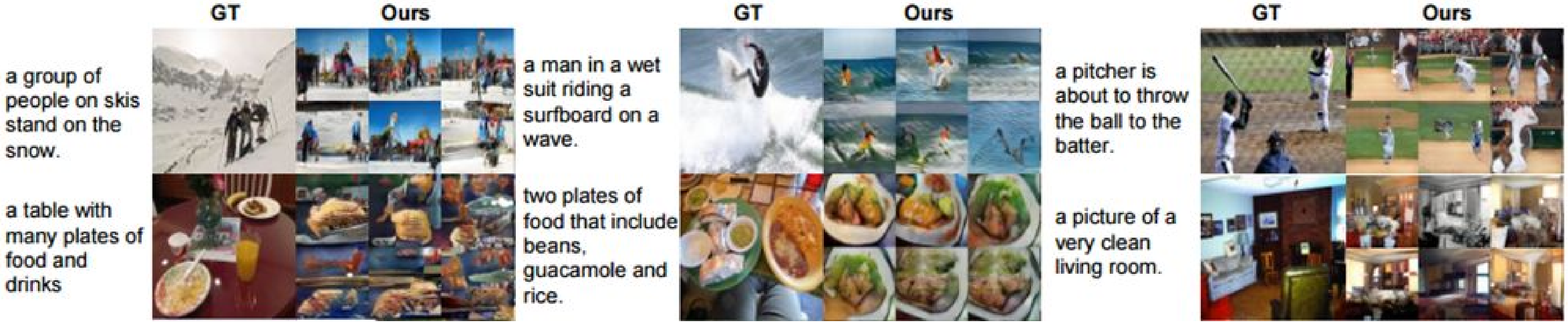
- Inspired by adversarial competition in Game Theory
  - **Two networks**: One tasked to generate content, the other to judge content



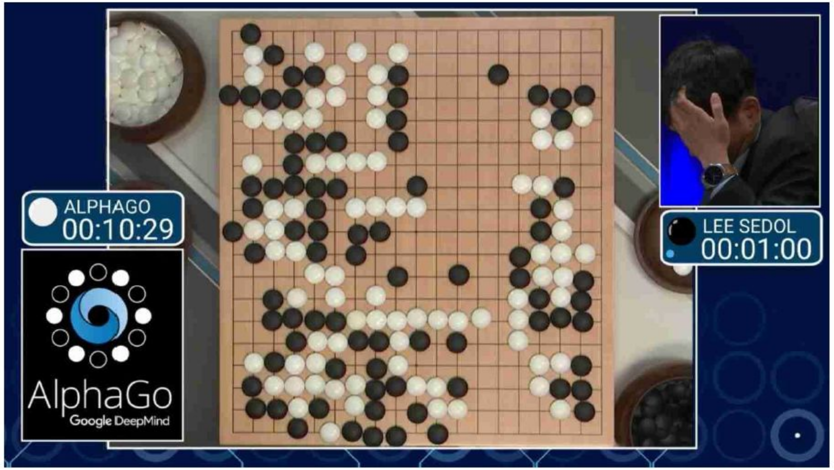


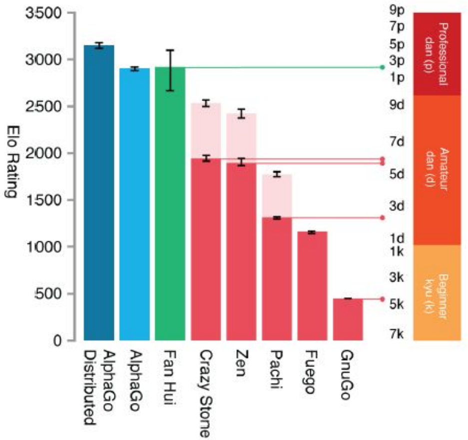
GAN: Text-to-Image Synthesis





Deep Learning for Games

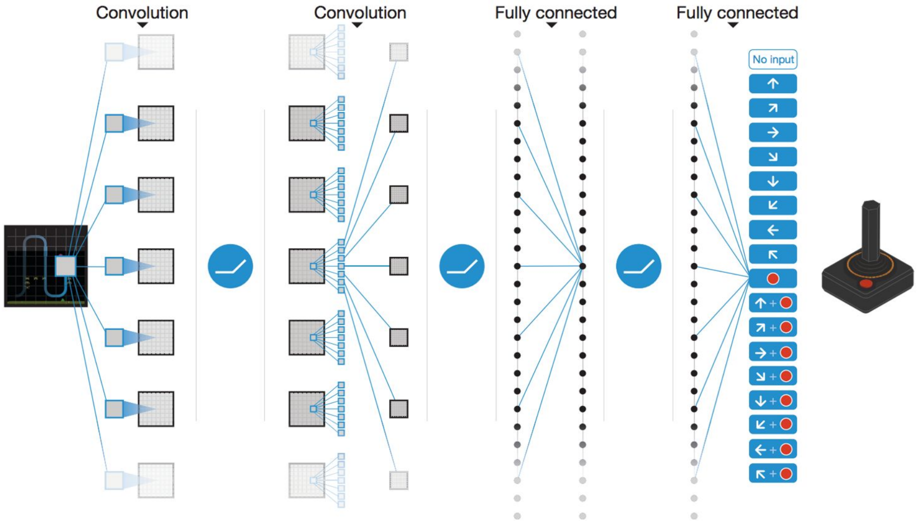




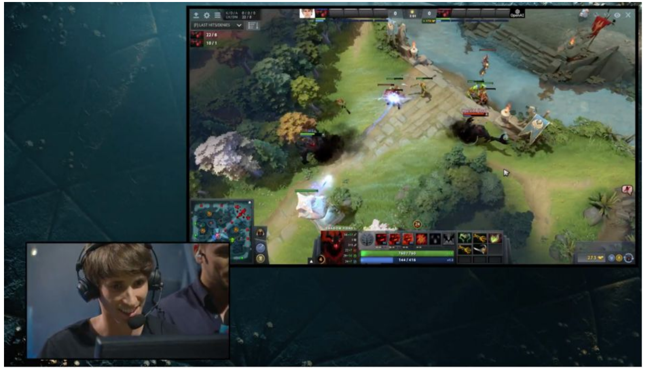
Examines thousands of human GO moves, and then masters it by playing with itself over and over again.

History was made: Google DeepMind's AlphaGo beats Go champion Lee Sedol

Deep Learning for Games



Just In: OpenAI's bot beats professional Dota 2 players

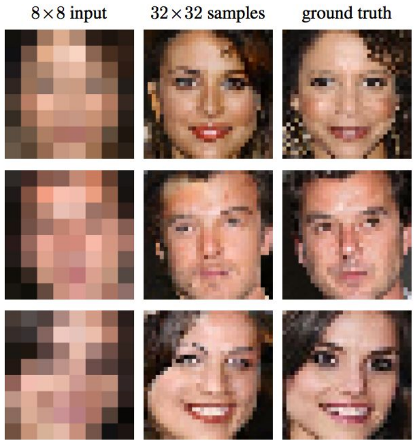


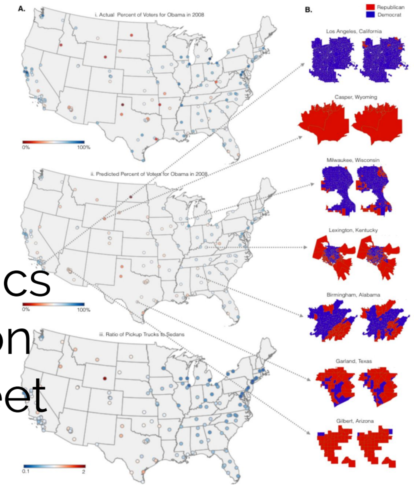
- Deep Q-Network (DQN) is a model-free approach to reinforcement learning using deep networks in environments with discrete action choices

What Else Can Deep Learning Generate?

Generate Expressive Music

Pixel Restoration “CSI-style”

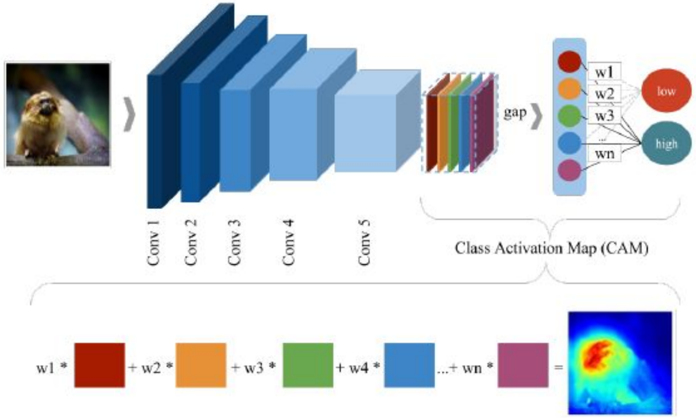


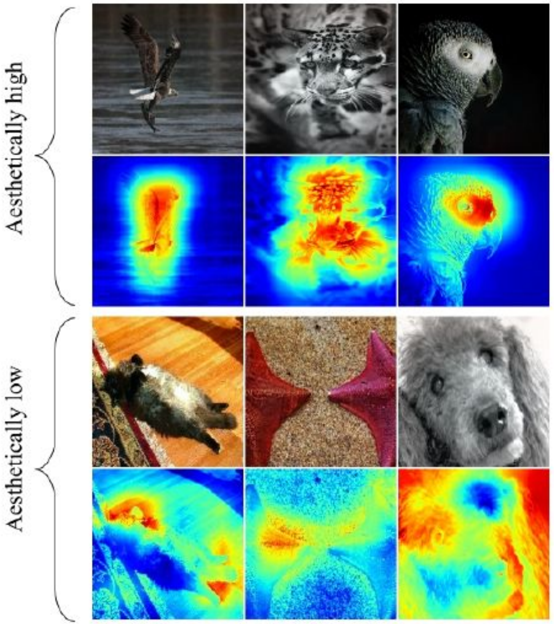


Learning Demographics and Predicting Election Results based on Street View Images

Some Homegrown Research

Predicting and Localizing Aesthetics in Images



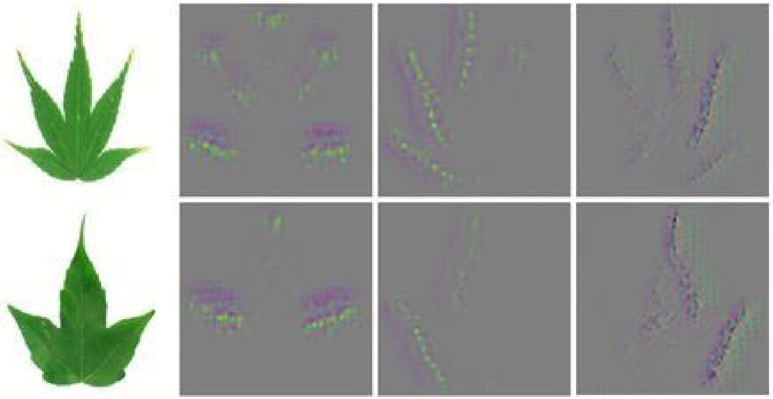


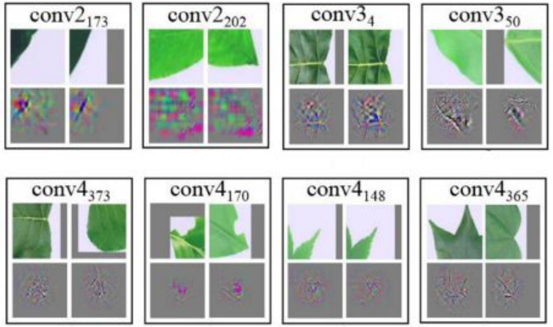
State-of-the-art:
82.27% (Text-augmented MultGAP Network, ICIP 2017)

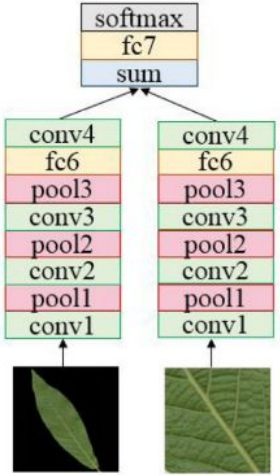
Some Homegrown Research

UNIVERSITY OF MALAYA

Plant Identification & Learning Leaf Features







MalayaKew and Flavia datasets

Top-1 accuracy: 96.3% (Early Fusion conv-sum, PR 2017)

Deep Learning Tools - Open Source!

TensorFlow
DL4J Deep Learning for Java
neon
PaddlePaddle
Keras
theano
torch
Chainer
dmlc mxnet
Caffe
Microsoft CNTK
cuDNN
NVIDIA DIGITS
Lasagne

Is Deep Learning over-hyped?

Is Deep Learning a black box that is unexplainable?

What should I do if I want to get started?

Demo

TensorFlow & Keras

Applied Deep Learning: Course Preview

Deep Learning: 5-day short course

- Fundamental concepts, Hands-on practicals
- Basic knowledge in Python programming & ML (added advantage)
- Tentative course outline:
  1. Machine Learning Primer - Classification & Regression
  2. Fundamentals of Neural Networks (MLPs, Shallow Networks)
  3. Deep Networks I: Convolutional Neural Networks
  4. Deep Networks II: Recurrent Neural Networks
  5. Tricks and Techniques in Deep Learning (Regularization, Data Augmentation, Ensembles)

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thank you
danke
謝謝
ngiyabonga
teşekkür ederim
рахмат
Баярлалаа
спасибо
mersi
barka
wefalin
tack
spas
kia ora
faafetai lava
vinaka
спасибі
blagodaram
dank je
misaotra
matondo
paldies
grazzi
mahalo
tapadh leat
gracias
kiitos
dankie
nanni
nandri
dhanyavad
mauruuru
köszönöm
hvala
bayarlalaa
gracie
bedankt
enkosi
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akun
dankon
aciu
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grafias ago
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go raibh maith agat
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obrigado
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mèsi
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najis tuke
ありがとう
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grazie
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xièxie
감사합니다
merci

Evaluation

Please fill up the online evaluation form for today's preview session

http://bit.ly/magicfeedback