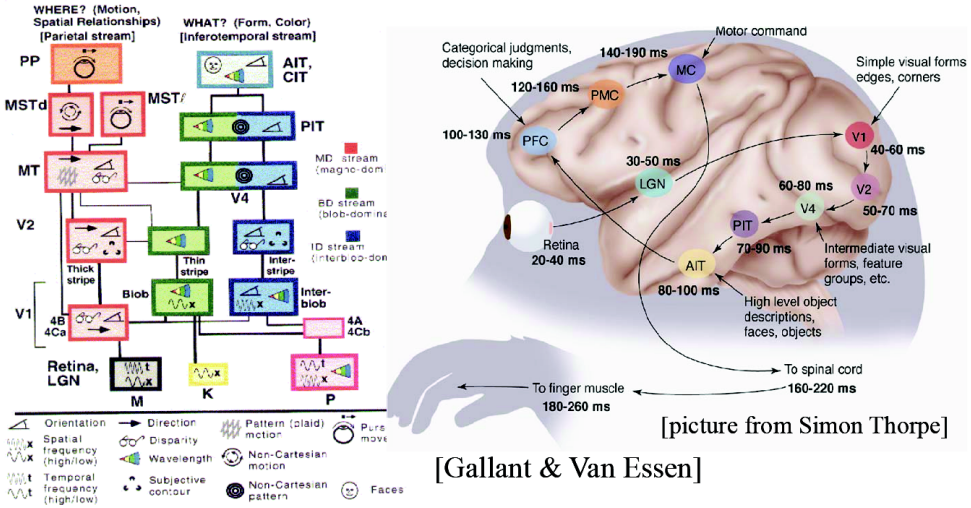
Deep Learning

Machine Learning Lecture

Yoonsuck Choe

What Is Deep Learning?

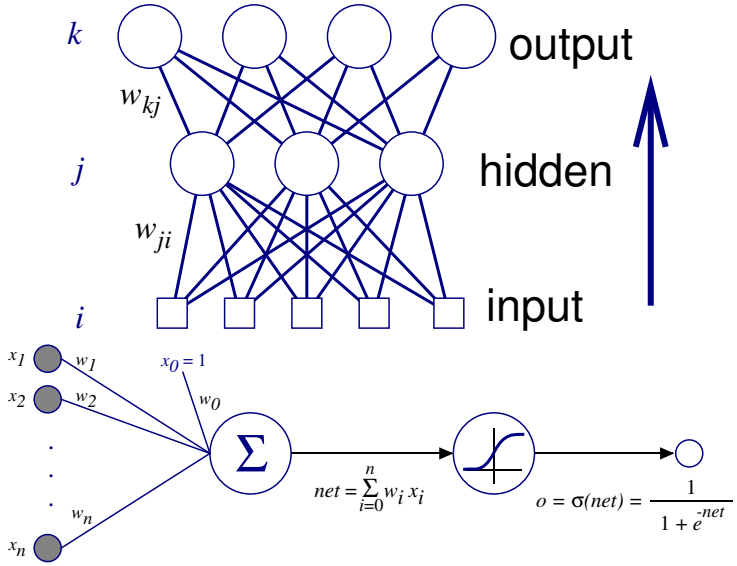
- Learning higher level abstractions/representations from data.
- Motivation: how the brain represents and processes sensory information in a hierarchical manner.
  - The ventral (recognition) pathway in the visual cortex has multiple stages
  - Retina - LGN - V1 - V2 - V4 - PIT - AIT ....



[Gallant & Van Essen]

From LeCun's Deep Learning Tutorial

Brief Intro to Neural Networks

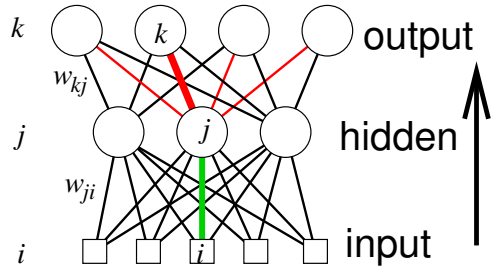


Deep learning is based on neural networks.

- Weighted sum followed by nonlinear activation function.
- Weights changed w/ *gradient descent* (η = learning rate, E=err):

$$w_{ij} \leftarrow w_{ij} - \eta \frac{\partial E}{\partial w_{ij}}$$

Intro to Neural Network: Backpropagation



Weight w_{ji} is updated as: $w_{ji} \leftarrow w_{ji} + \eta \delta_j a_i$, where

- a_i : activity at input side of weight w_{ji}.
- Hidden to output weights (thick red weight). T_k is target value.

$$\delta_k = (T_k - a_k)\sigma'(net_k)$$

- Deeper weights (green line in figure above).

$$\delta_j = \left[\sum_k w_{kj}\delta_k\right] \sigma'(net_j)$$

What Neurons Do in a Neural Network

Two points of view (both are valid):

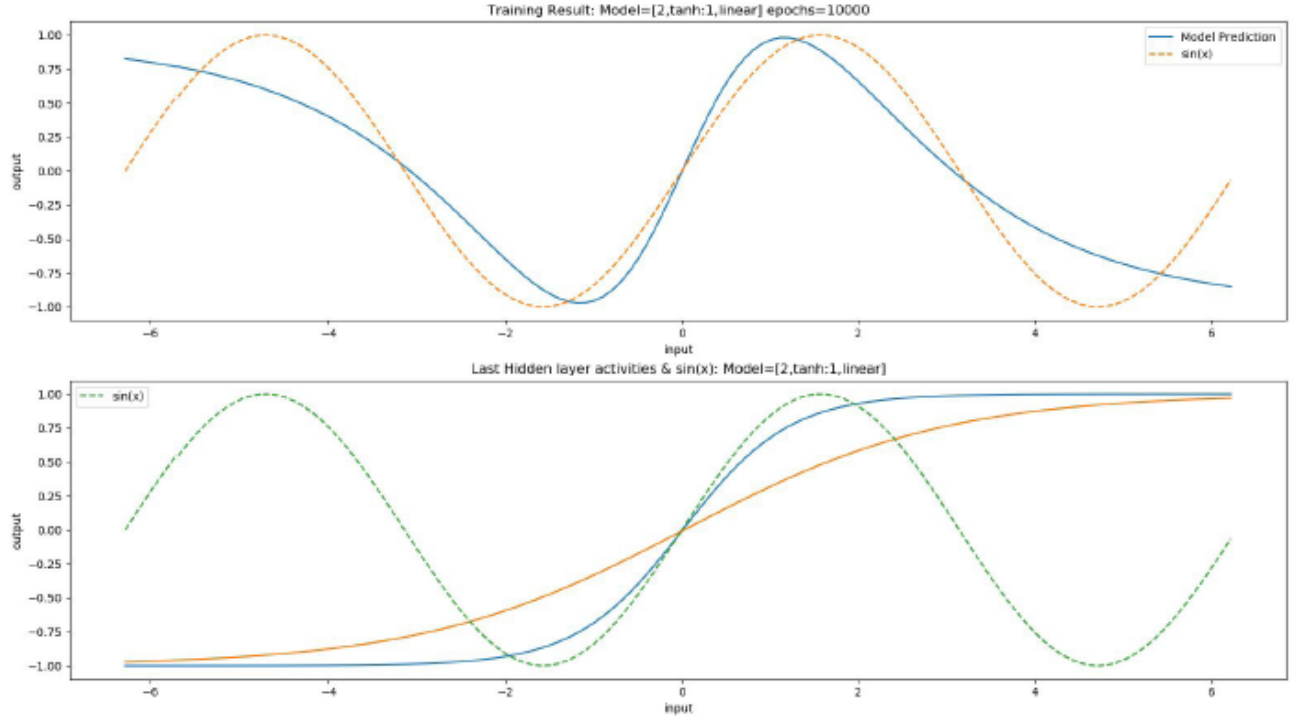
- Function approximation
- Decision boundary

* Represent input features – more on this later.

Function Approximation

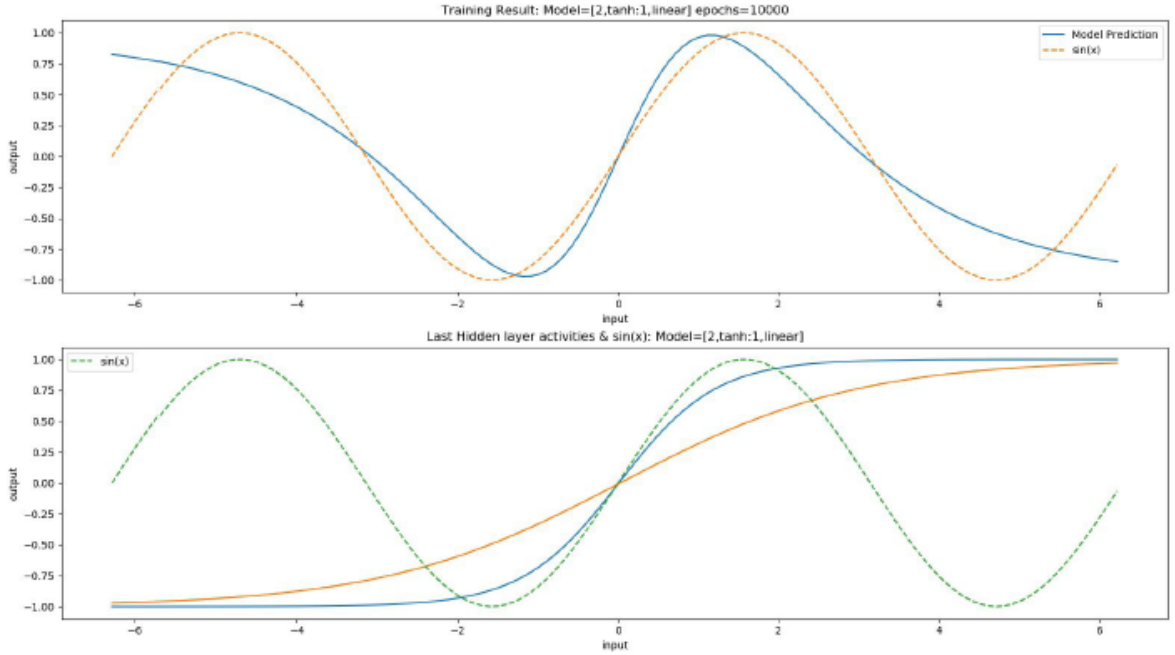
- Assume one input unit (scalar value).
- Depending on # of hidden layers, # of hidden units, etc., function with any complex shape can be learned. Ex: $y = \sin(x)$.

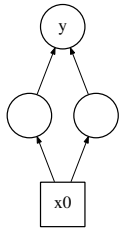
Example: $y = \sin(x)$



- Top: $\sin(x)$ nnet: Model=[# of units, activation func, [next layer spec], ...]
- Bottom: $\sin(x)$ vs. the hidden unit's output of last hidden layer.

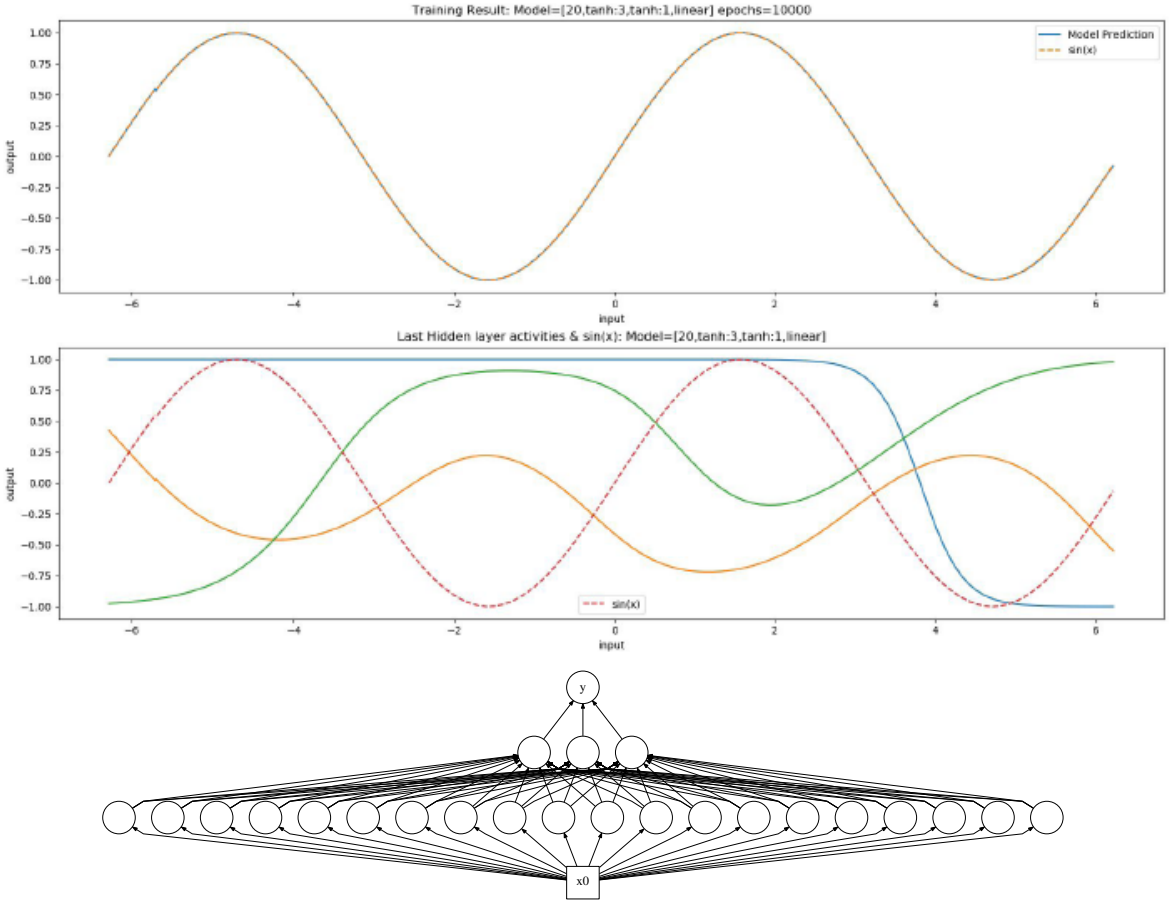
Ex: $y = \sin(x)$ Model=[2,tanh:1,linear]





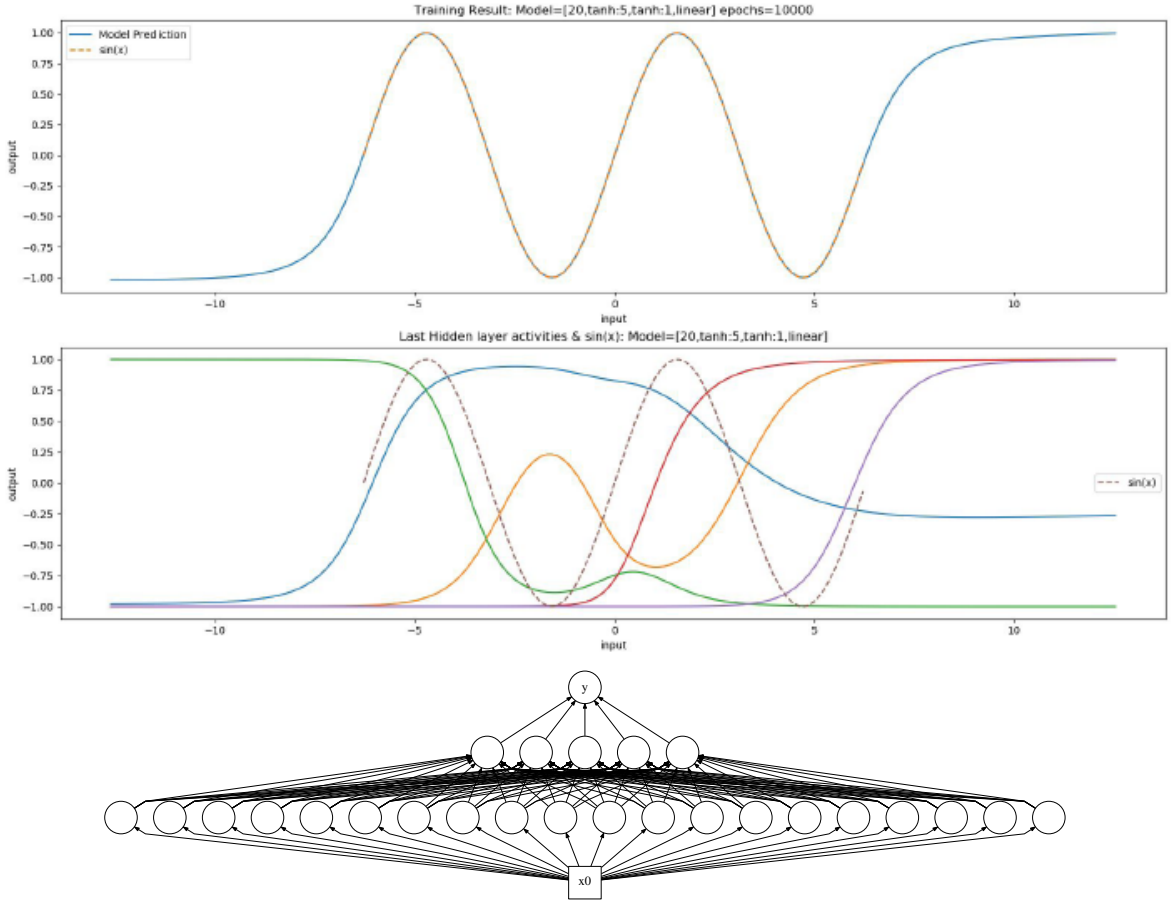
- One hidden layer with 2 units, One output unit. [2,tanh:1,linear]
- Bottom plot: Hidden neurons represent sigmoids.
- Top plot: Output unit is a linear combination of two sigmoids.

Ex: $y = \sin(x)$ Model=[20,tanh:3,tanh:1,linear]



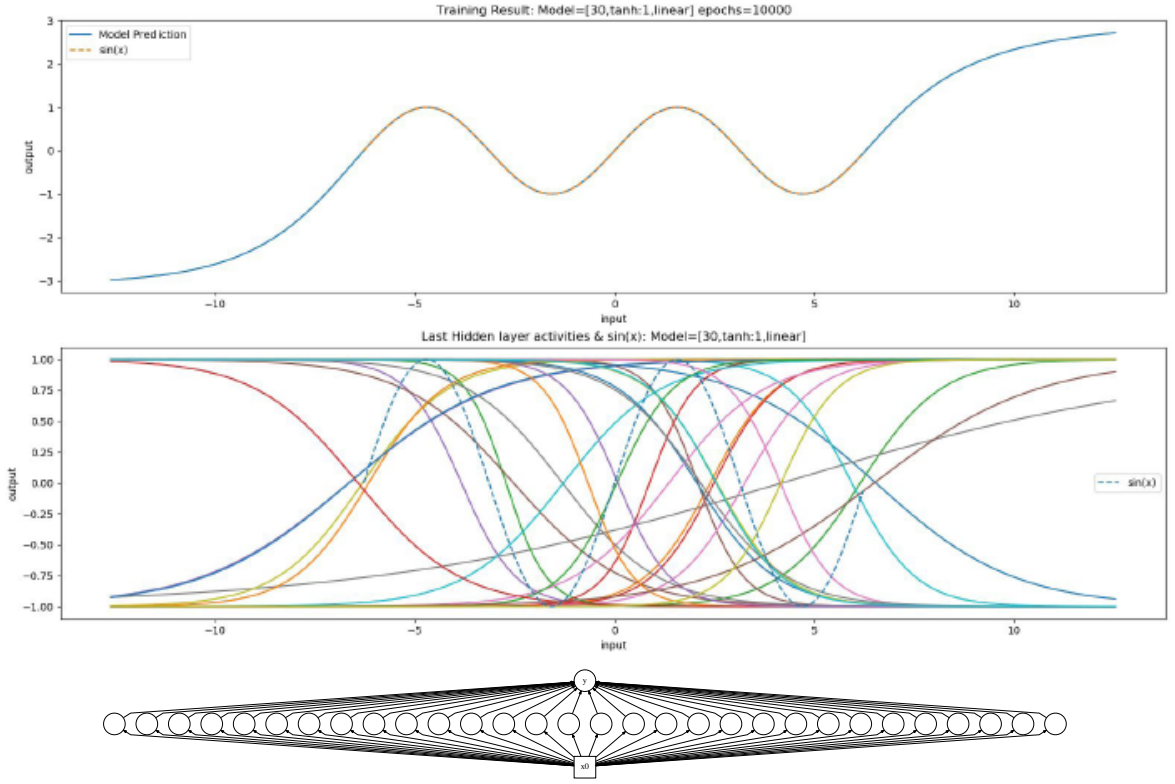
- 2nd hidden layer represents linear combination of 20 sigmoids.

Ex: $y = \sin(x)$ Model=[20,tanh:5,tanh:1,linear]



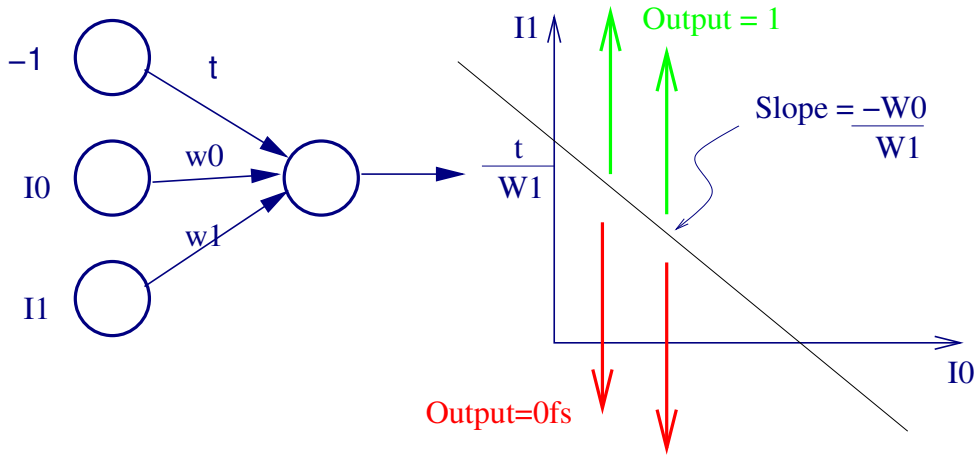
- Out-of-range inputs illustrate the limitation of DL.

Ex: $y = \sin(x)$ Model=[30,tanh:1,linear]



- Does a single hidden layer suffice? – Yes, with enough neurons.

Decision Boundary



Perceptrons (step function activation) can only represent **linearly separable** functions.

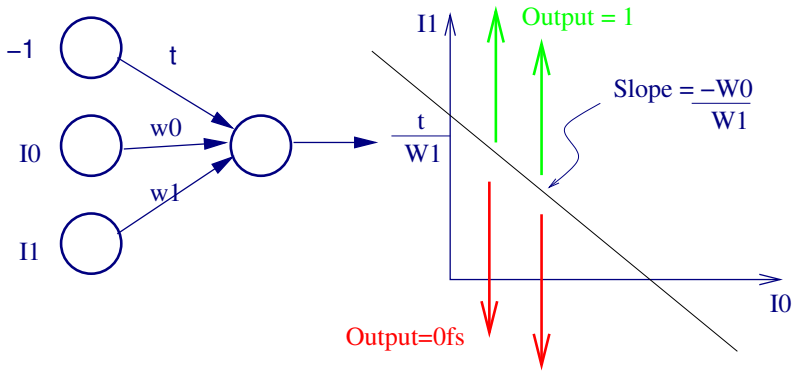
- Output of the perceptron:

$$W_0 \times I_0 + W_1 \times I_1 - t > 0, \text{ then output is } 1$$

$$W_0 \times I_0 + W_1 \times I_1 - t \leq 0, \text{ then output is } -1$$

If activation function is sigmoid, decision is a smooth ramp.

Decision Boundary



- Rearranging

$$W_0 \times I_0 + W_1 \times I_1 - t > 0, \text{ then output is } 1,$$

we get (if $W_1 > 0$)

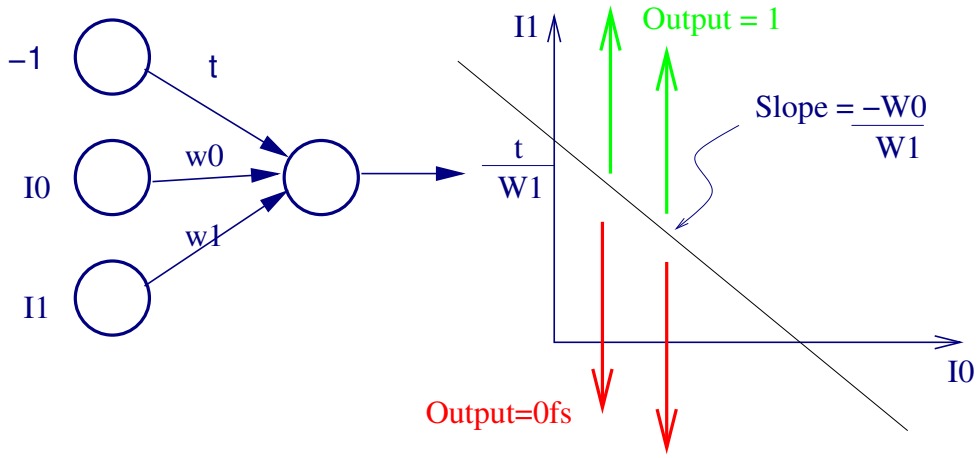
$$I_1 > \frac{-W_0}{W_1} \times I_0 + \frac{t}{W_1},$$

where points above the line, the output is 1, and -1 for those below the line.

Compare with

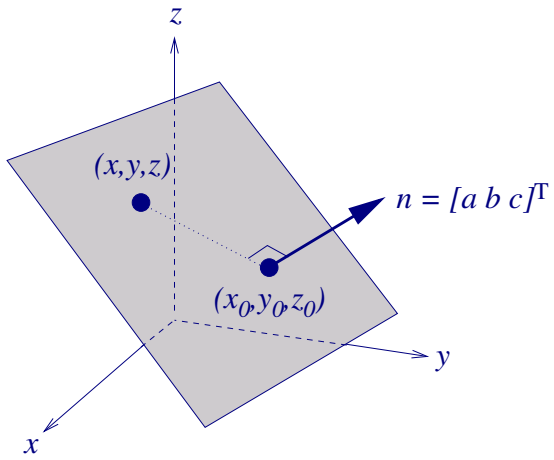
$$y = \frac{-W_0}{W_1} \times x + \frac{t}{W_1}.$$

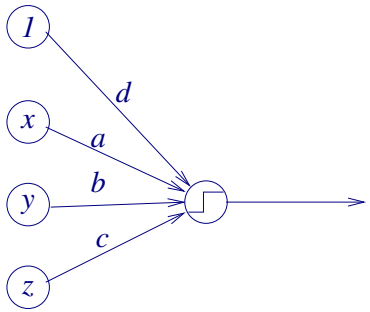
Limitation of Perceptrons



- Only functions where the -1 points and 1 points are clearly separable can be represented by perceptrons.
- The geometric interpretation is generalizable to functions of n arguments, i.e. perceptron with n inputs plus one threshold (or bias) unit.

Generalizing to n-Dimensions

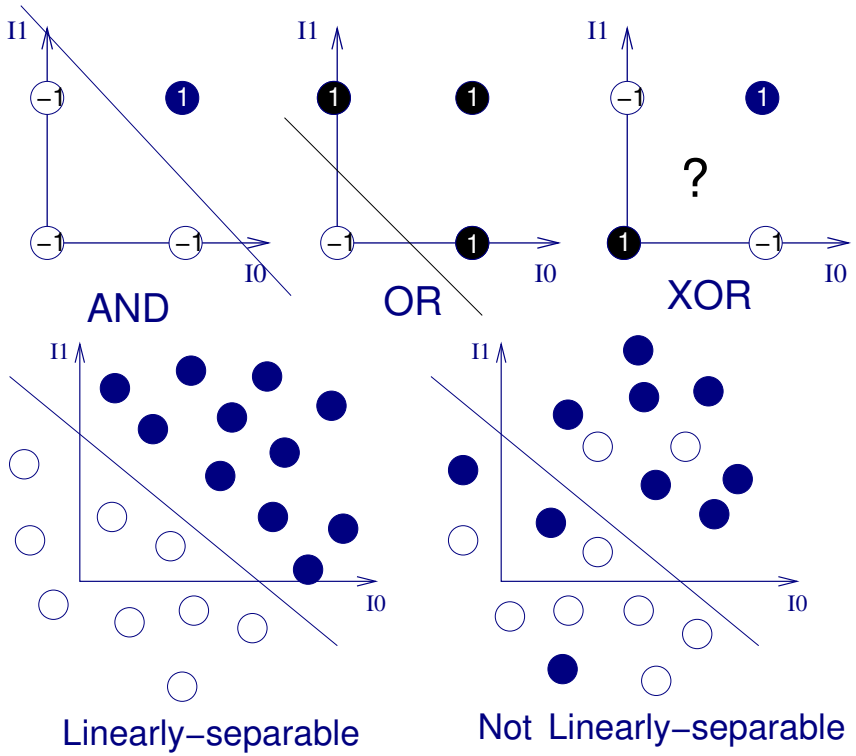




http://mathworld.wolfram.com/Plane.html

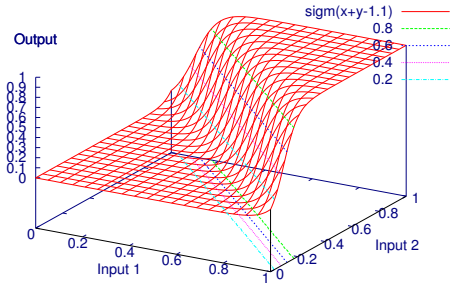
- $\vec{n} = (a, b, c), \vec{x} = (x, y, z), \vec{x_0} = (x_0, y_0, z_0)$.
- Equation of the plane: $\vec{n} \cdot (\vec{x} - \vec{x_0}) = 0$
- In short, $ax + by + cz + d = 0$, where a, b, c can serve as the weight, and $d = -\vec{n} \cdot \vec{x_0}$ as the bias.
- For n-D input space, the decision boundary becomes a $(n - 1)$-D hyperplane (1-D less than the input space).

Linear Separability

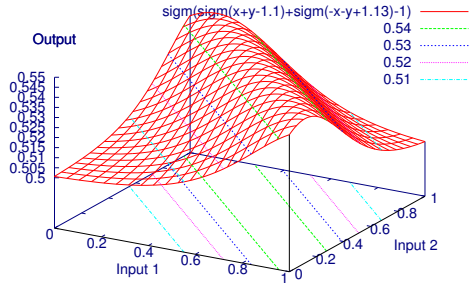


- Functions/Inputs that can or cannot be separated by a linear boundary.

Decision Boundary in Multilayer Networks

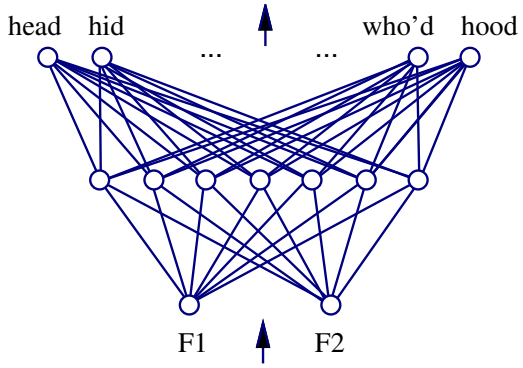


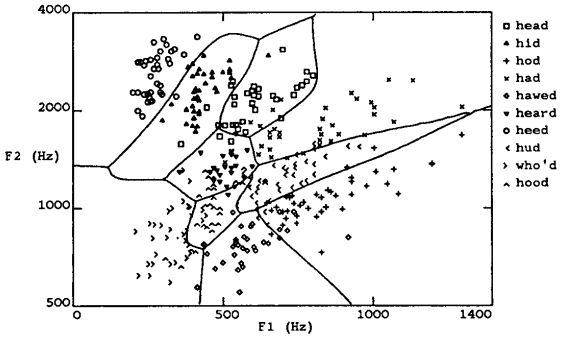
(a) One output



(b) Two hidden, one output

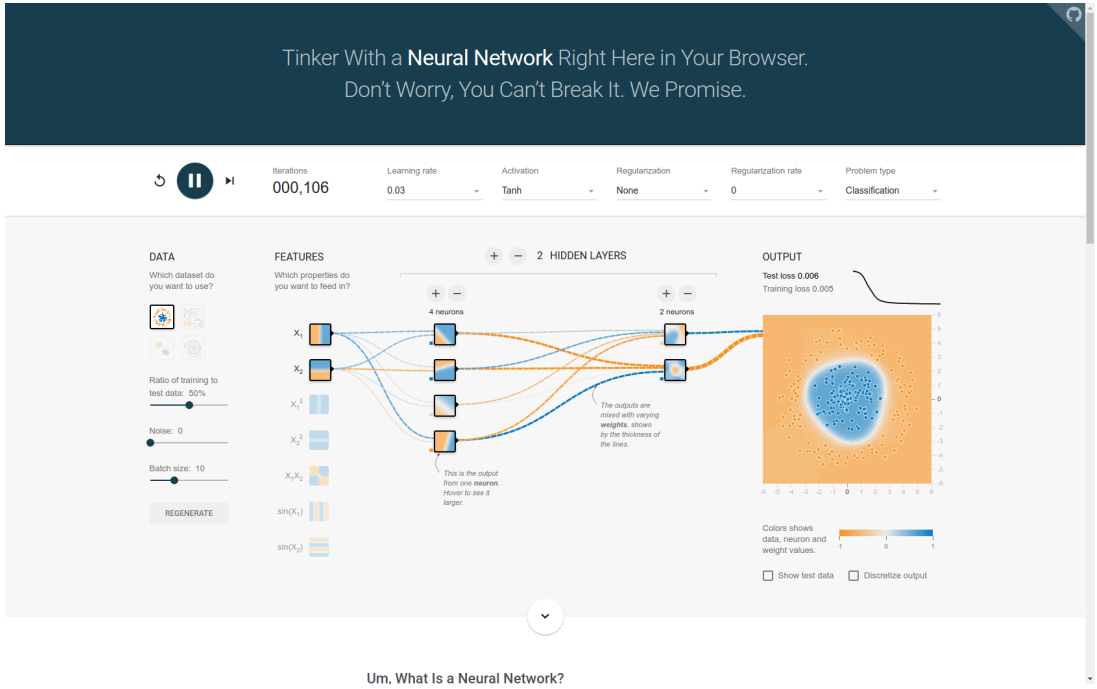
- Example: XOR





- Multiple decision regions.

Decision Boundary Demo with Tensorflow Playground



- http://playground.tensorflow.org

Deep Learning

- Complex models with large number of parameters
  - Hierarchical representations
  - More parameters = more accurate on training data
  - Simple learning rule for training (gradient-based).
- Lots of data
  - Needed to get better generalization performance.
  - High-dimensional input need exponentially many inputs (curse of dimensionality).
- Lots of computing power: GPGPU, etc.
  - Training large networks can be time consuming.

Deep Learning, in the Context of AI/ML

Deep Learning:
Automating
Feature Discovery

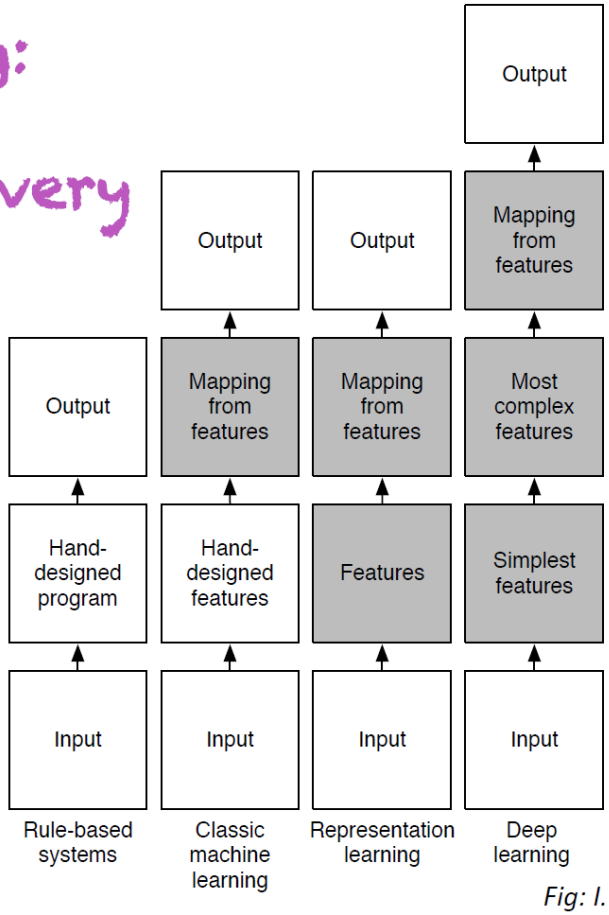


Fig: I. Goodfellow

From LeCun's Deep Learning Tutorial

The Rise of Deep Learning

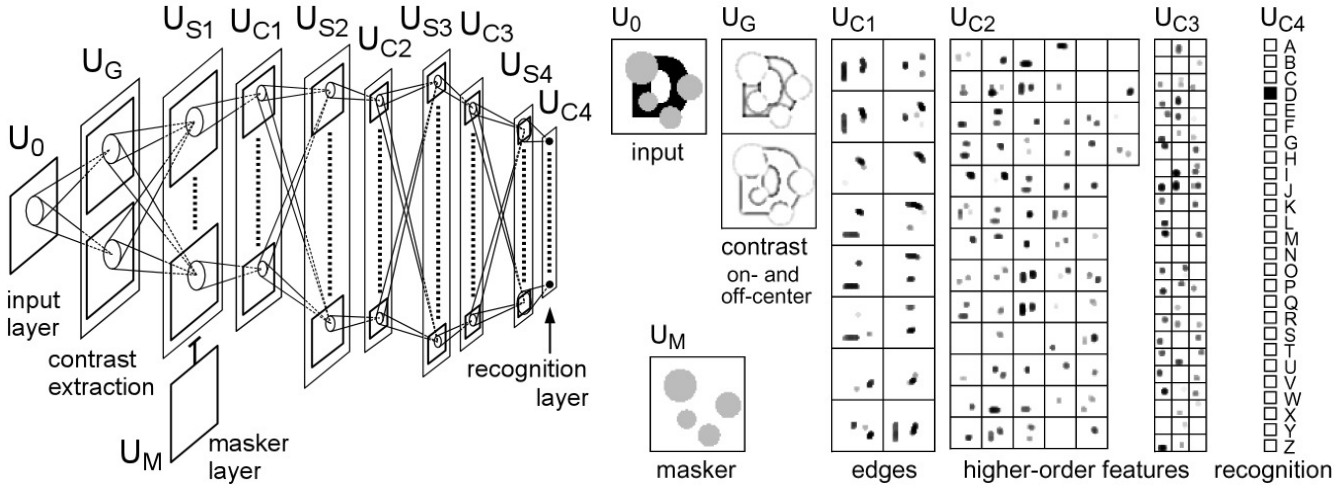
Made popular in recent years

- Geoffrey Hinton et al. (2006).
- Andrew Ng & Jeff Dean (Google Brain team, 2012).
- Schmidhuber et al.'s deep neural networks (won many competitions and in some cases showed super human performance; 2011–). Recurrent neural networks using LSTM (Long Short-Term Memory).
- Google Deep Mind: Atari 2600 games (2015), AlphaGo (2016).
- ICLR, International Conference on Learning Representations: First meeting in 2013.

Long History (in Hind Sight)

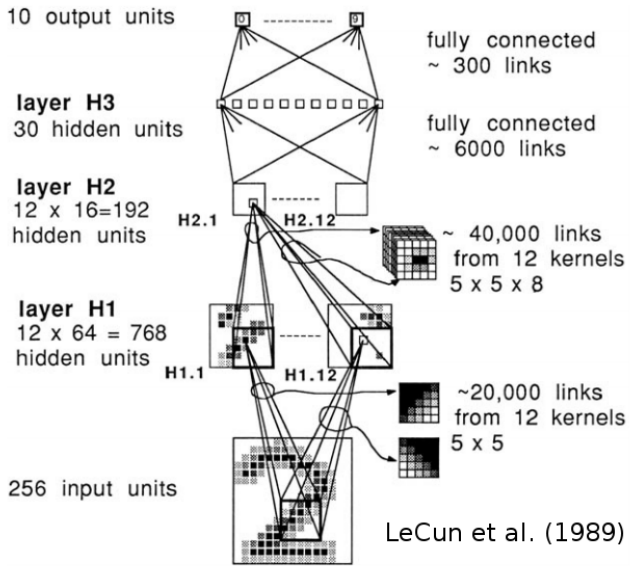
- Fukushima's Neocognitron (1980).
- LeCun et al.'s Convolutional neural networks (1989).
- Schmidhuber's work on stacked recurrent neural networks (1993). Vanishing gradient problem.
- See Schmidhuber's extended review: Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, 61, 85-117.

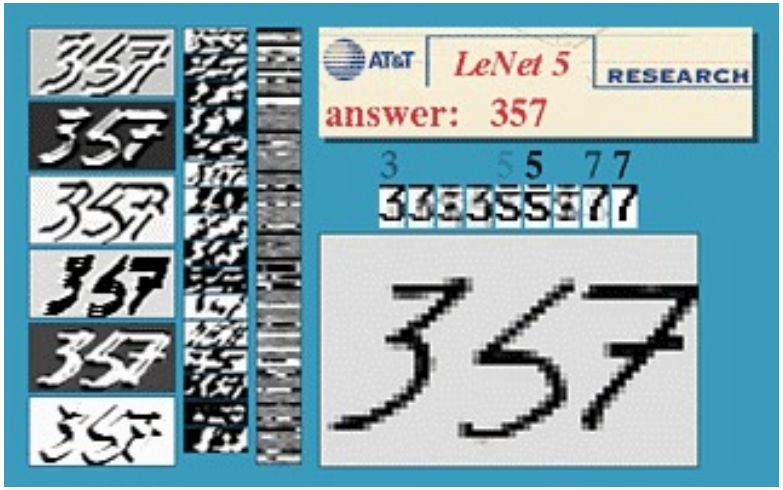
History: Fukushima's Neocognitron



- Appeared in journal *Biological Cybernetics* (1980).
- Multiple layers with local receptive fields.
- S cells (trainable) and C cells (fixed weight).
- Deformation-resistent recognition.

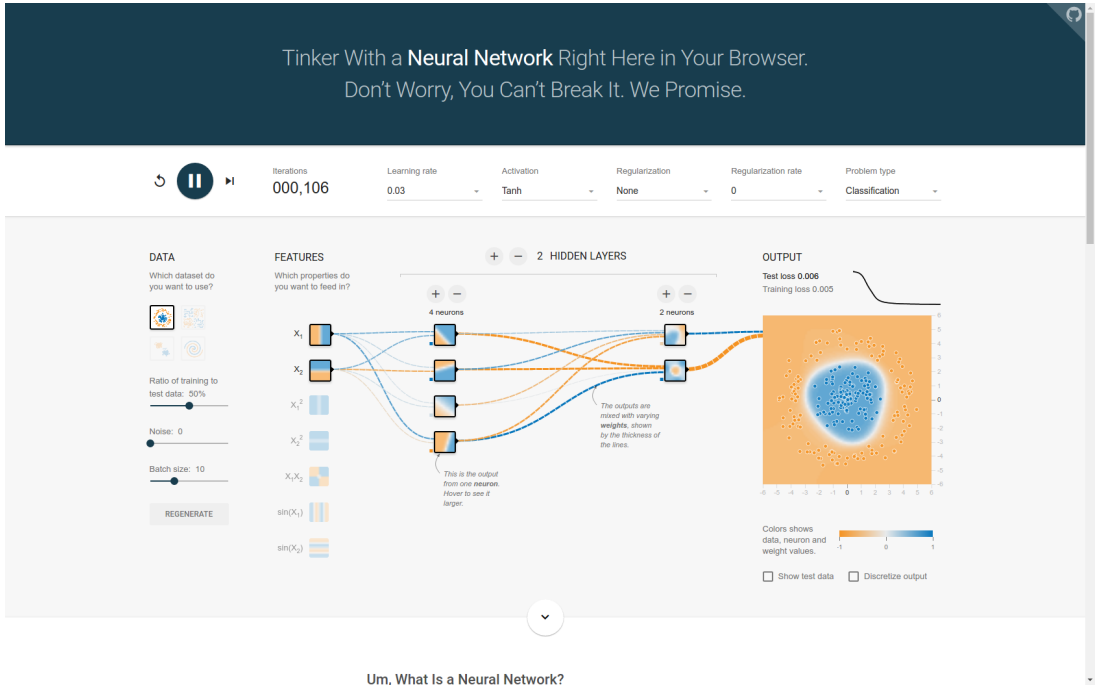
History: LeCun's Colvolutional Neural Nets





- Convolution kernel (weight sharing) + Subsampling
- Fully connected layers near the end.
- Became a main-stream method in deep learning.

Motivating Deep Learning: Tensorflow Demo



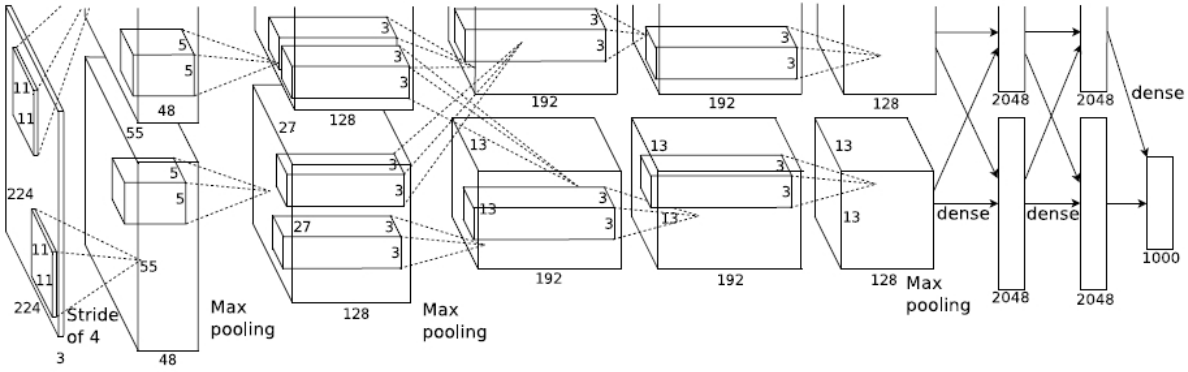
- http://playground.tensorflow.org
- Demo to explore why deep nnet is powerful and how it is limited.

Current Trends

Focusing on ground-breaking works in Deep Learning:

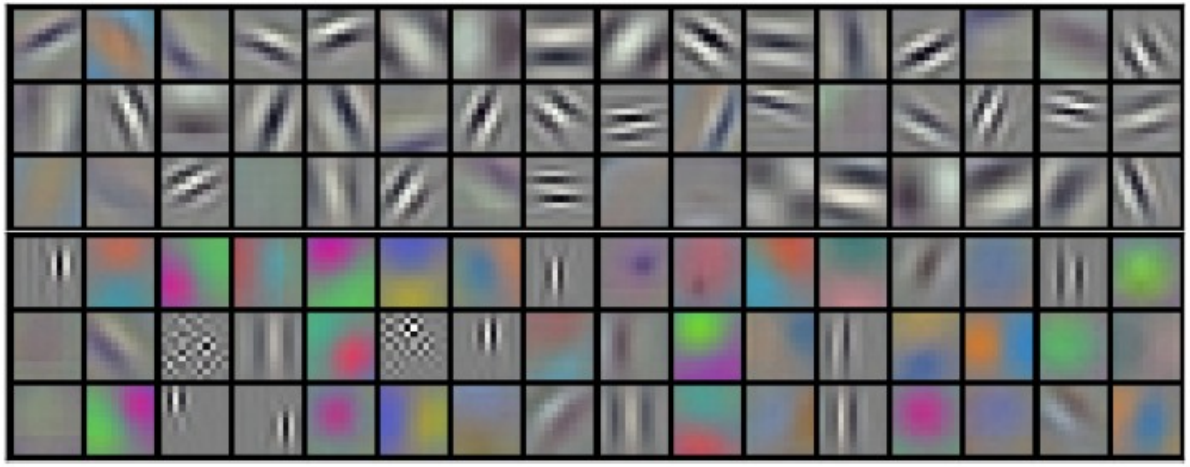
- Convolutional neural networks
- Deep Q-learning Network (extensions to reinforcement learning)
- Deep recurrent neural networks using (LSTM)
- Applications to diverse domains.
  - Vision, speech, video, NLP, etc.
- Lots of open source tools available.

Deep Convolutional Neural Networks (1)



- Krizhevsky et al. (2012)
- Applied to ImageNet competition (1.2 million images, 1,000 classes).
- Network: 60 million parameters and 650,000 neurons.
- Top-1 and top-5 error rates of 37.5% and 17.0%.
- Trained with backprop.

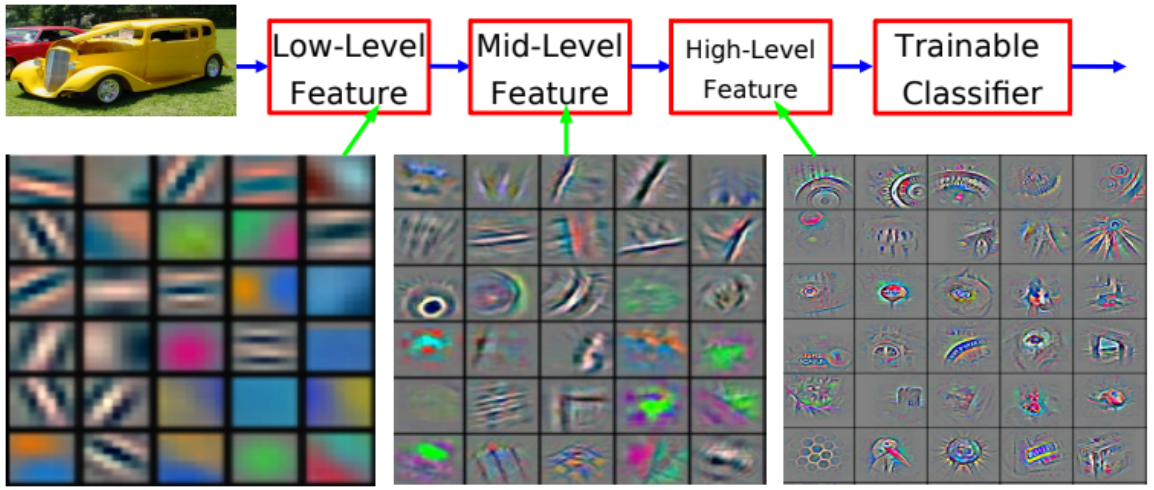
Deep Convolutional Neural Networks (2)



- Learned kernels (first convolutional layer).
- Resembles mammalian RFs: oriented Gabor patterns, color opponency (red-green, blue-yellow).

Deep Convolutional Neural Networks (3)

Natural is data is compositional => it is efficiently representable hierarchically

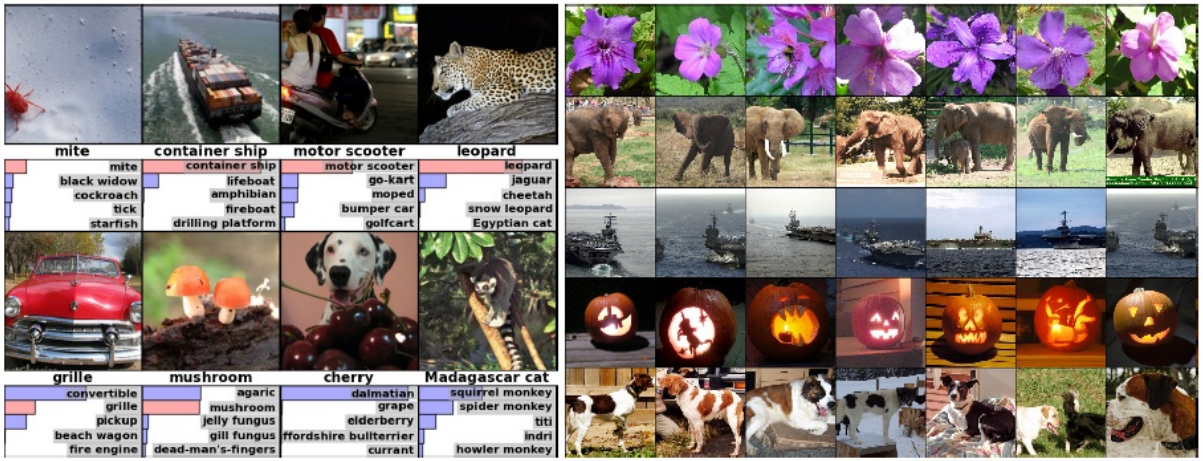


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

- Higher layers represent progressively more complex features.

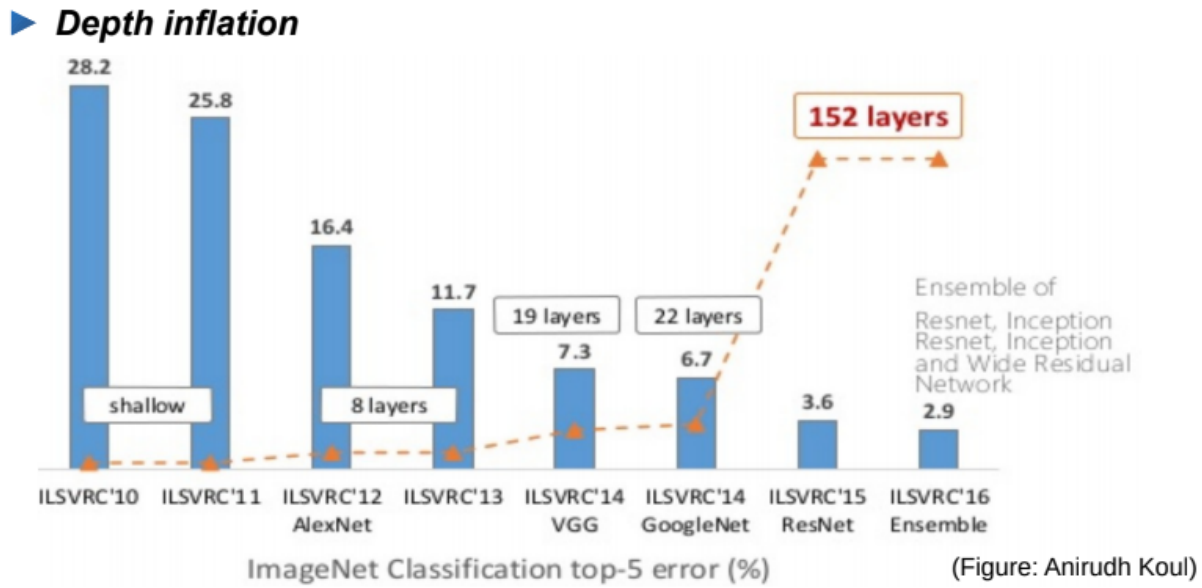
* From Yann LeCun's Harvard lecture (2019)

Deep Convolutional Neural Networks (4)



- Left: Bold = correct label. 5 ranked labels: model's estimation.
- Right: Test (1st column) vs. training images with closest hidden representation to the test data.

Deep Convolutional Neural Networks (5)

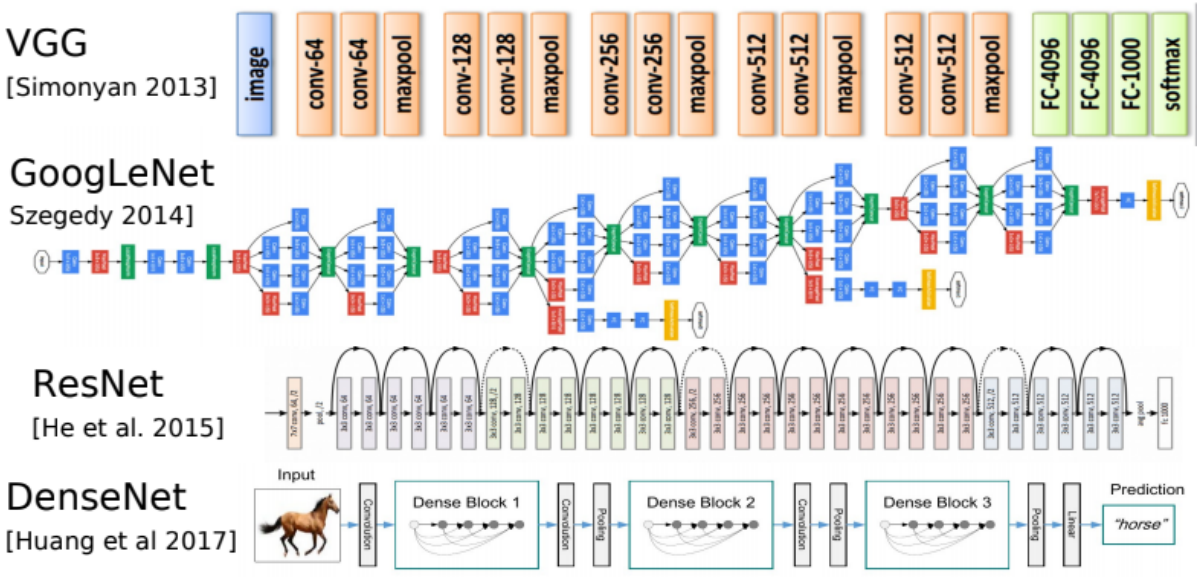


(Figure: Anirudh Koul)

- Depth inflation: Deeper is better!

* From Yann LeCun's Harvard lecture (2019)

Deep Convolutional Neural Networks (6)

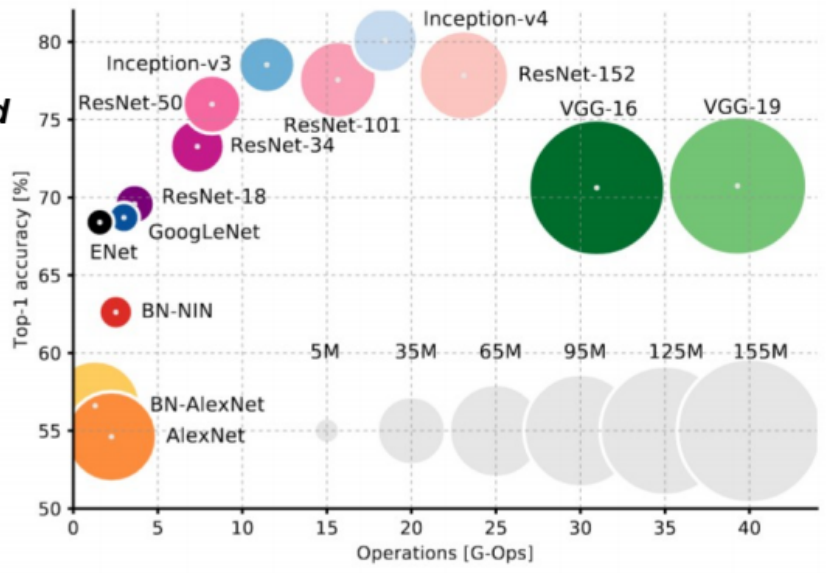


- Not just depth but architecture also matters!

* From Yann LeCun's Harvard lecture (2019)

Deep Convolutional Neural Networks (7)

- ***[Canziani 2016]***
- ***ResNet50 and ResNet 100 are used routinely in production.***



- Computation vs. performance

* From Yann LeCun's Harvard lecture (2019)

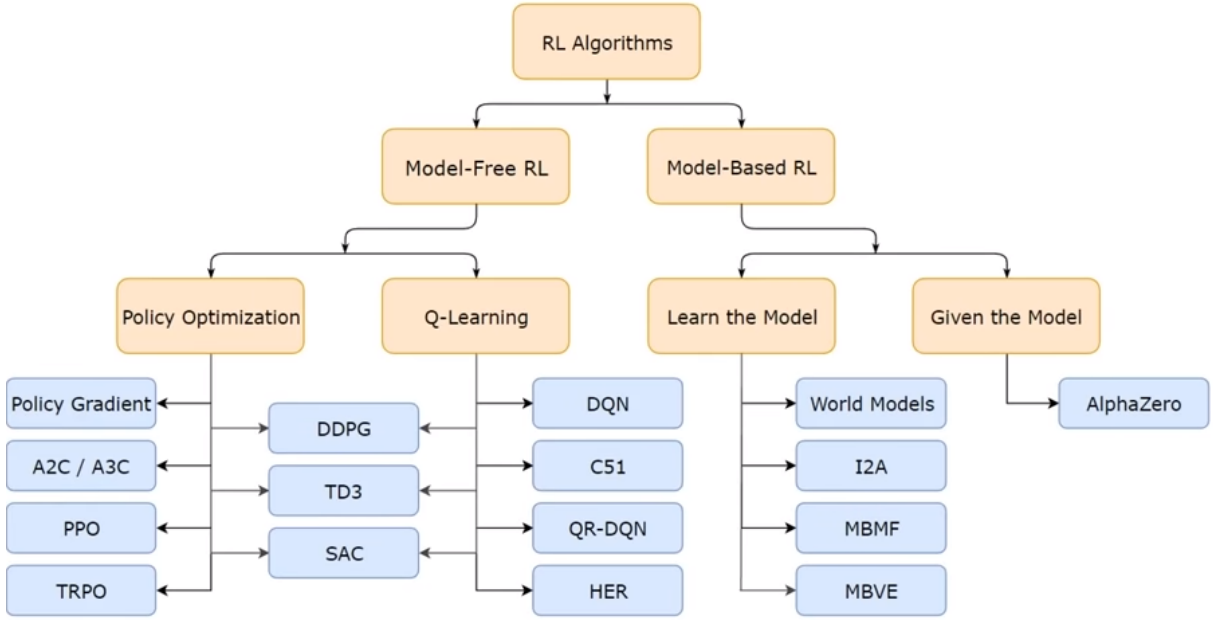
Deep Reinforcement Learning

- Deep = can process complex sensory input
- Reinforcement learning = can choose complex actions

Current Status of Deep Reinforcement Learning

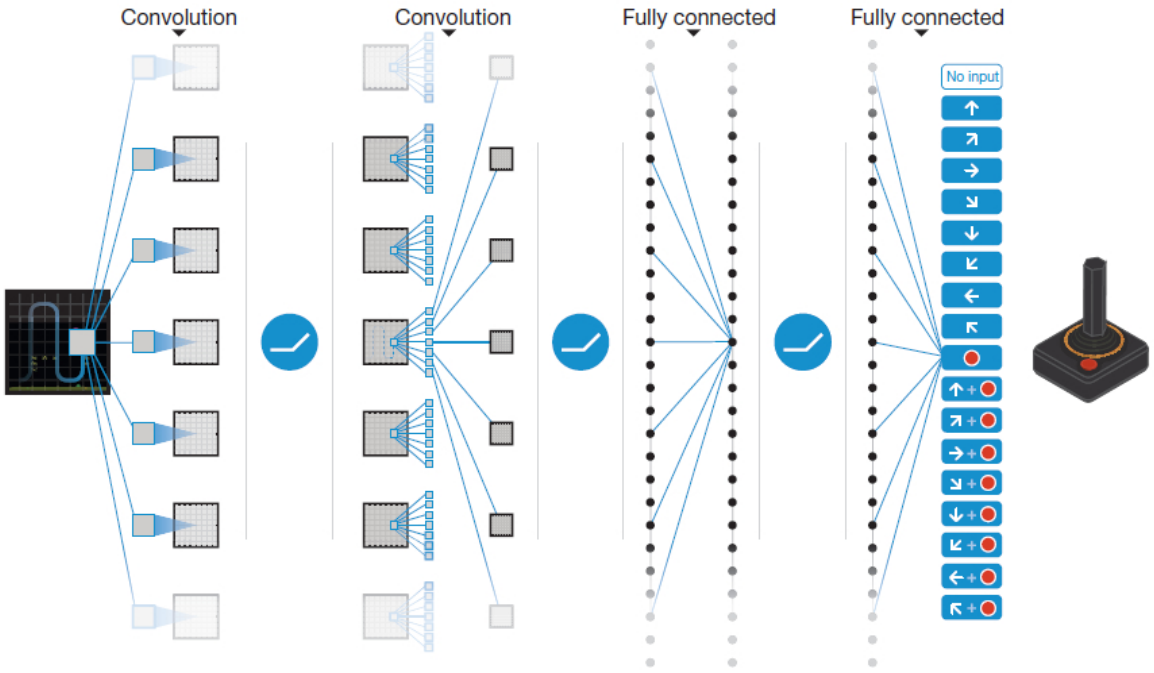
- Rapidly advancing subfield of reinforcement learning.
- Replace various components of RL with deep neural networks:
  - Convolutional neural network for input processing
  - value function (e.g. Q function), policy function ($\pi(s)$)
- Various innovations:
  - Experience replay (replay buffer)
  - Multitask learning, transfer learning, meta learning, immitation learning,

Variations in Deep Reinforcement Learning



- Value-based: fit $Q(s_t, a_t)$, and construct $\pi(s_t)$ based on it (e.g. ϵ-greedy). DQN is an example
- Policy gradient: fit $\pi(s_t)$ directly
- Actor-critic: fit $Q(s_t, a_t)$ and use that to improve fit of $\pi(s_t)$
- Model-based RL: directly model $p(s_{t+1}|s_t, a_t)$, then plan.

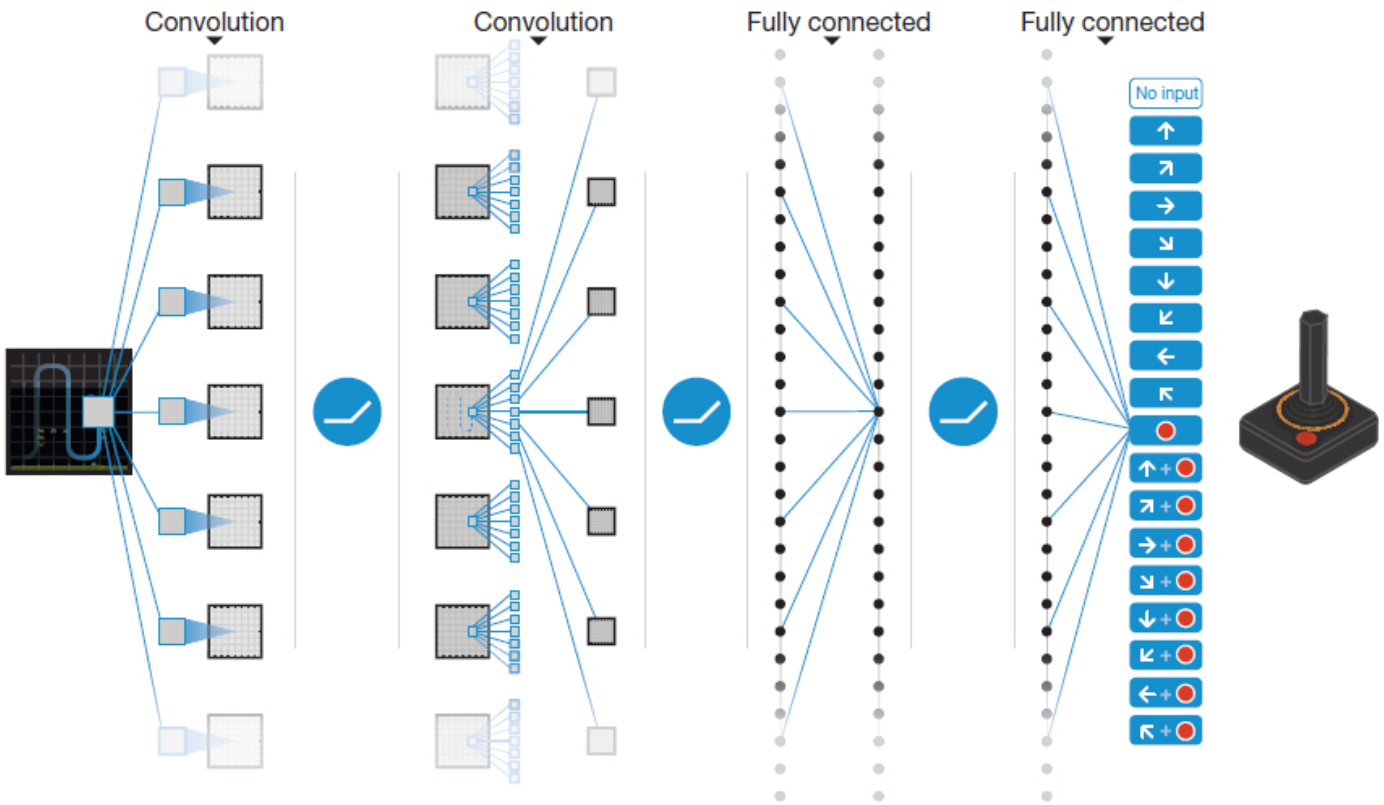
Deep Q-Network (DQN)



Google Deep Mind (Mnih et al. *Nature* 2015).

- One of the earliest deep learning method applied to a *reinforcement learning* domain (Q as in Q-learning).
- Applied to *Atari 2600* video game playing.

DQN Overview



- Input: video frames; Output: $Q(s, a)$; Reward: game score.
- Network output $Q(s, a)$: action-value function
  - Value of taking action a when in state s.

DQN Overview

- Input preprocessing $\phi(s_t)$: takes 4 video frames and stack up.
- Experience replay (collect and replay state, action, reward, and resulting state $< s_t, a_t, r_t, s_{t+1} >$)
- Delayed (periodic) update of target $\hat{Q}$.
  - Moving target $\hat{Q}$ value used to compute target reward value y_t (loss function L, parameterized by weights θ_i).
  - Gradient descent:

$$\frac{\partial L}{\partial \theta_i}$$

- ϵ-greedy policy based on the learned $Q(s, a)$.

DQN Algorithm

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N

Initialize action-value function Q with random weights θ

Initialize target action-value function $\hat{Q}$ with weights $\theta^{-} = \theta$

For episode = 1, M **do**

Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$

For $t = 1$,T **do**

With probability ε select a random action a_t

otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$

Execute action a_t in emulator and observe reward r_t and image x_{t+1}

Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$

Store transition $\left(\phi_t, a_t, r_t, \phi_{t+1}\right)$ in D

Sample random minibatch of transitions $\left(\phi_j, a_j, r_j, \phi_{j+1}\right)$ from D

Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}\left(\phi_{j+1}, a'; \theta^{-}\right) & \text{otherwise} \end{cases}$

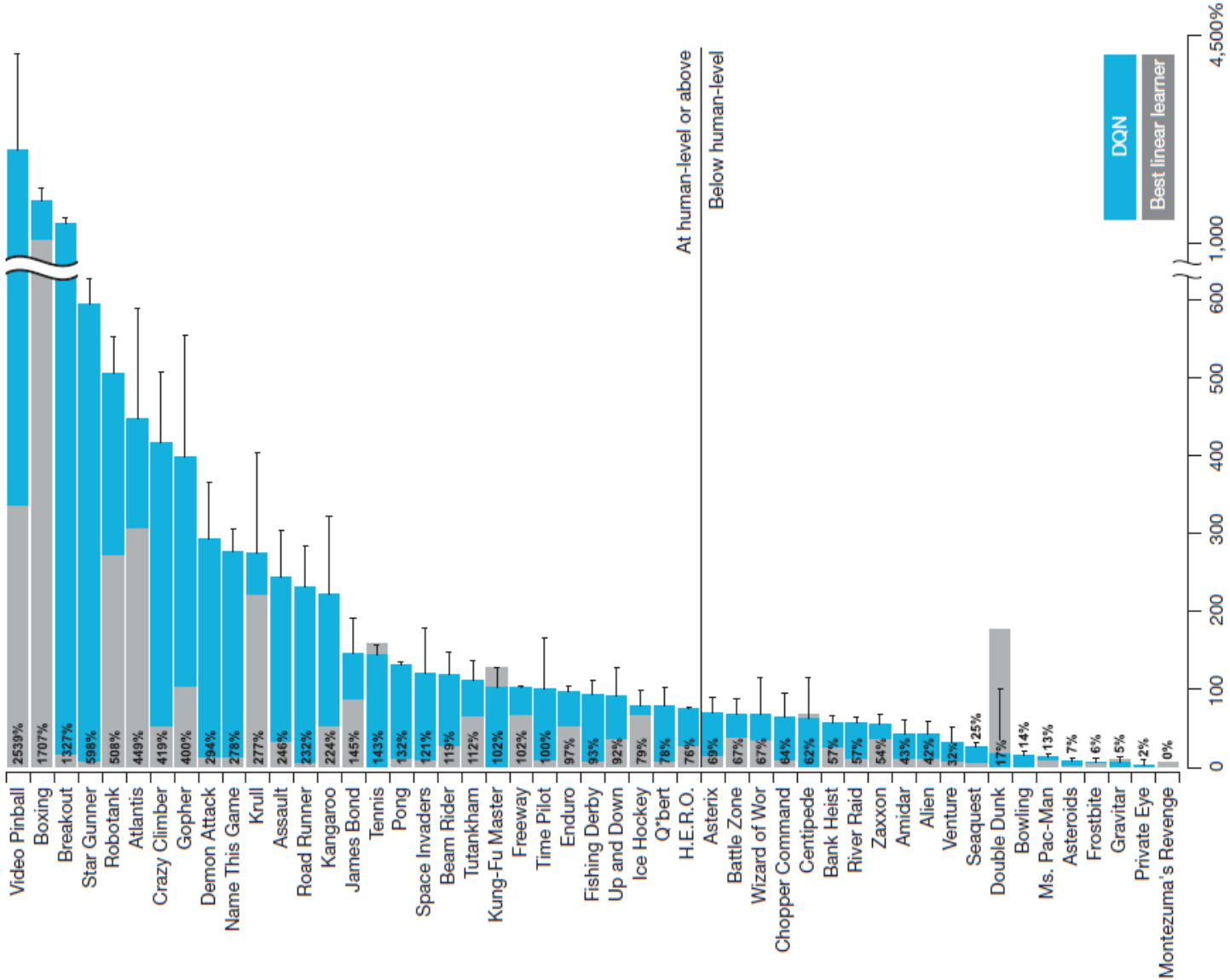
Perform a gradient descent step on $\left(y_j - Q\left(\phi_j, a_j; \theta\right)\right)^2$ with respect to the network parameters θ

Every C steps reset $\hat{Q} = Q$

End For

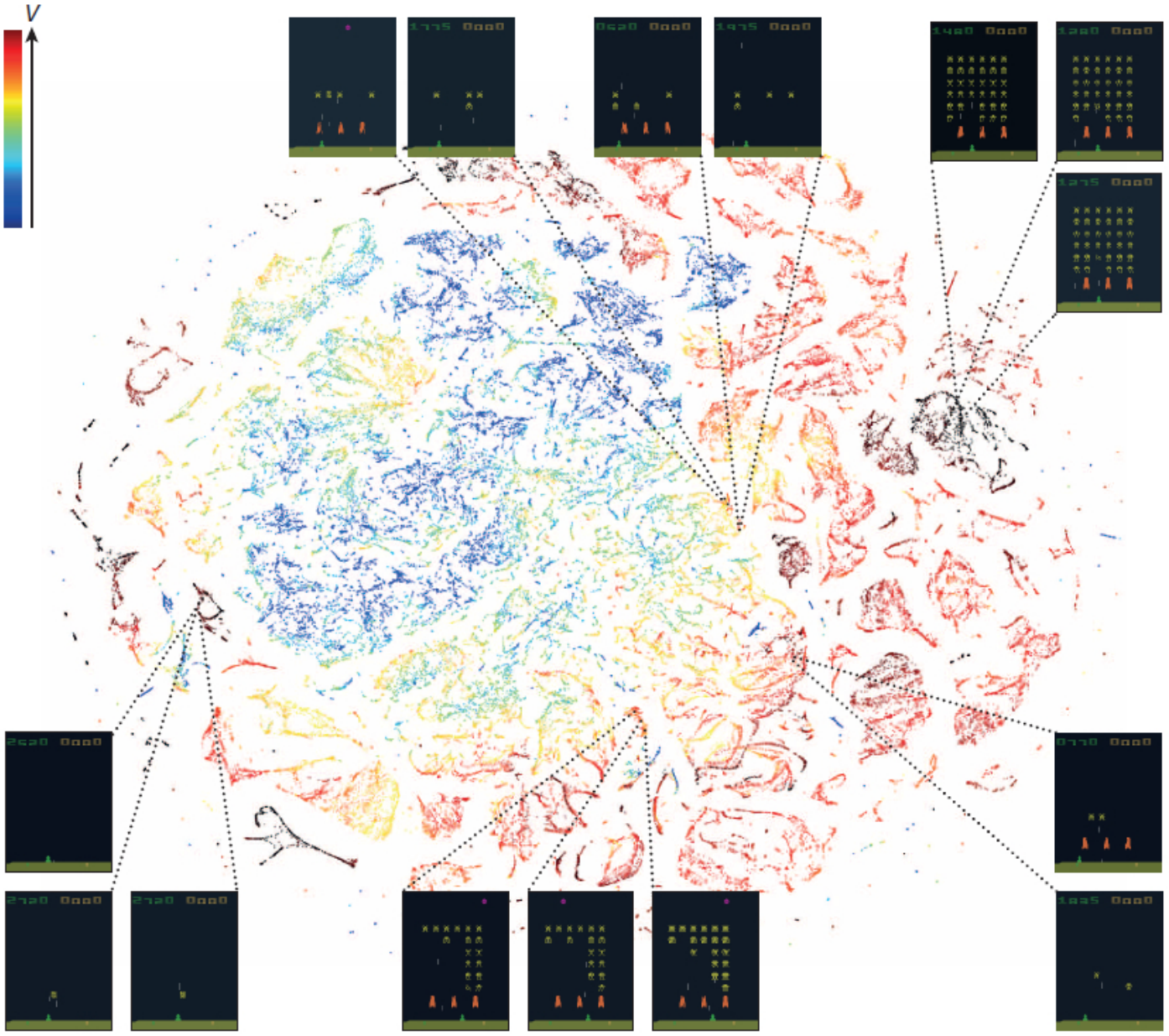
End For

DQN Results

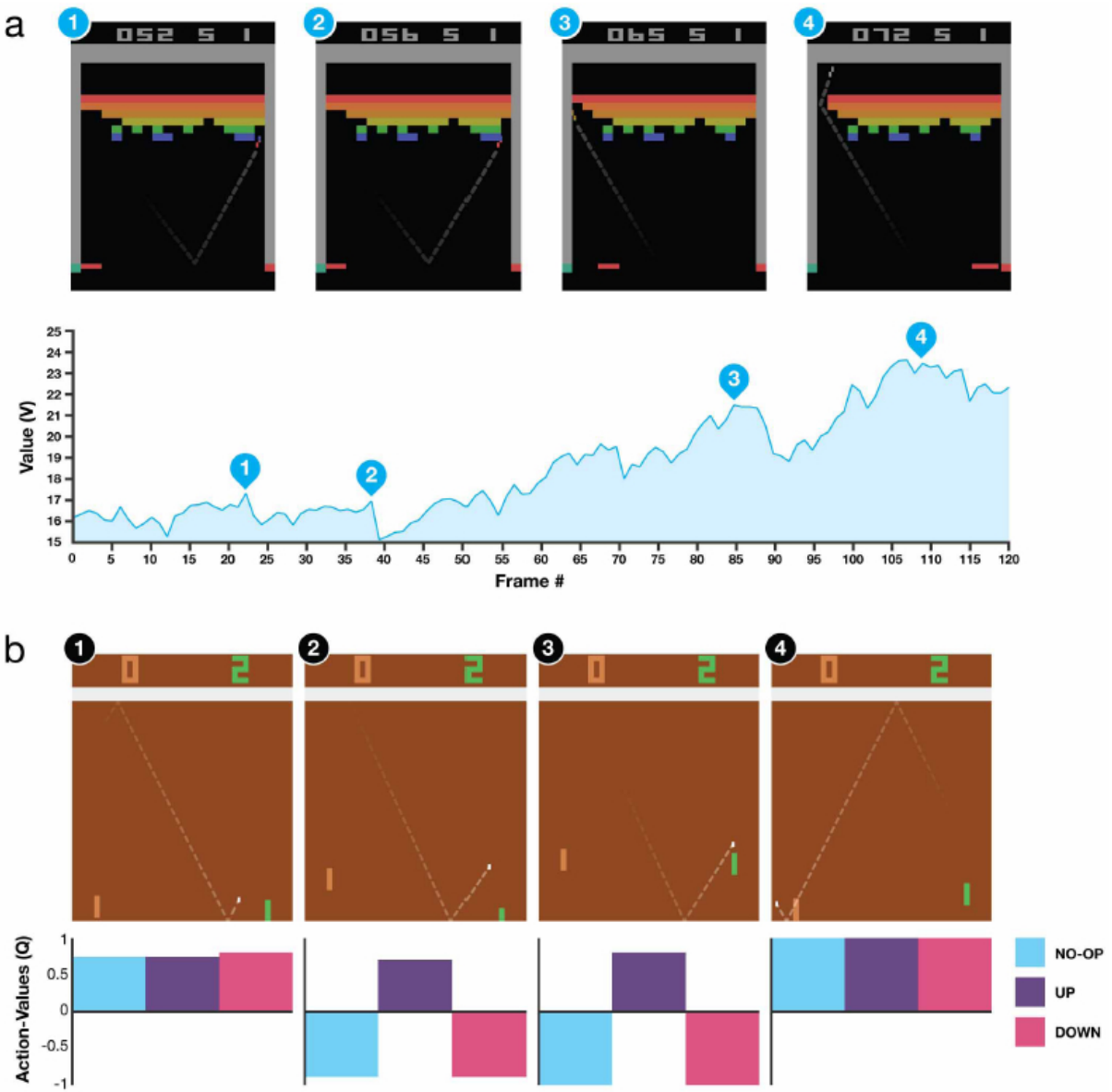


- Superhuman performance on over half of the games.

DQN Hidden Layer Representation (t-SNE map)



DQN Operation



- Value vs. game state; Game state vs. action value.

DQN: Summary

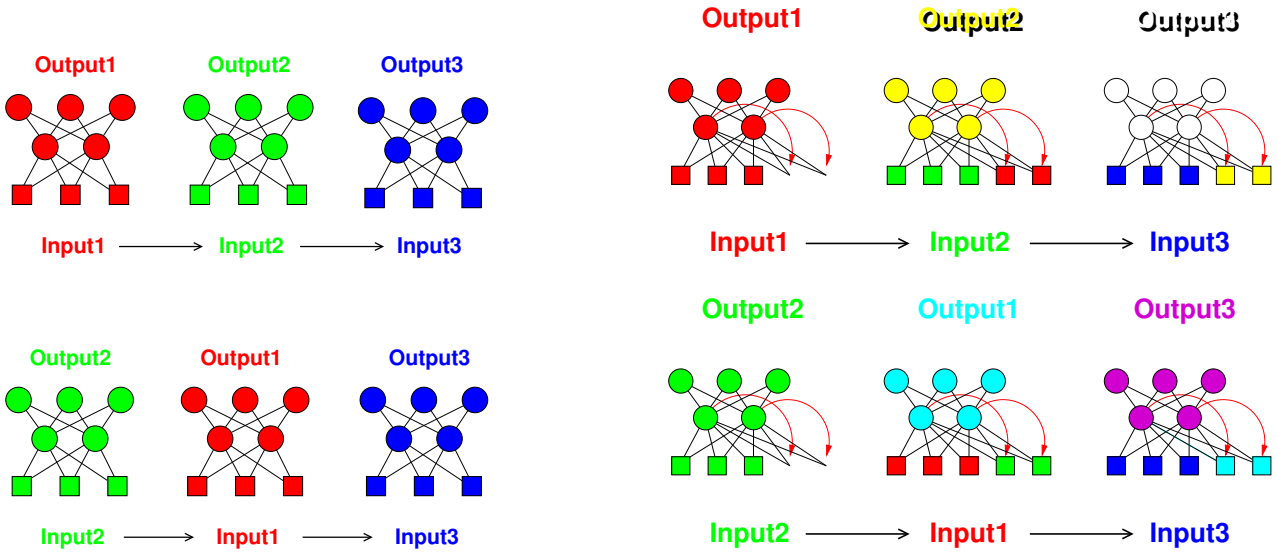
- Convolutional network part enables continous video input.
- Weights trained end-to-end.
- Outputs $Q(s, a)$.
- Limitations: cannot do complex planning requiring long term memory, e.g., Montezuma's revenge game.

Alternatives to Deep Reinforcement Learning

- Evolution strategies (OpenAI)
- Deep Neuroevolution (Uber, OpenAI)
  - NEAT (NeuroEvolution of Augmenting Topologies) – Stanley and Miikkulainen

Source: https://openai.com/blog/evolution-strategies/, https://arxiv.org/abs/1712.06567

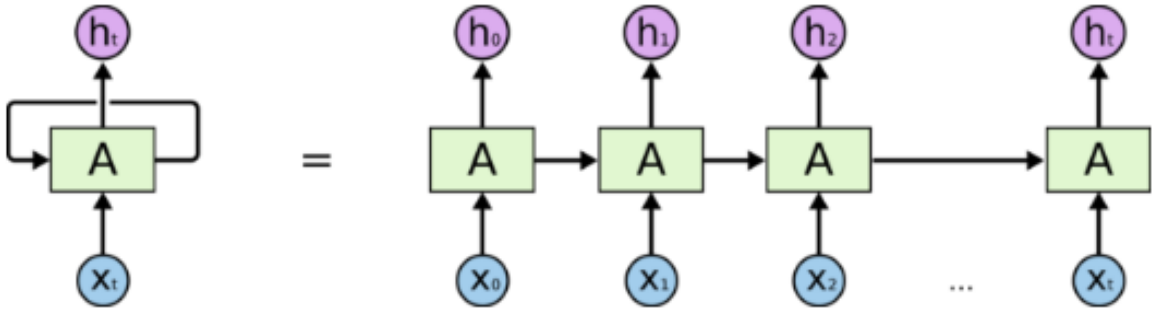
Deep Recurrent Neural Networks



Feedforward **Recurrent**

- Feedforward networks: No memory of past input.
- Recurrent networks:
  - Good: Past input affects present output.
  - Bad: Cannot remember far into the past.

RNN Training: Backprop in Time

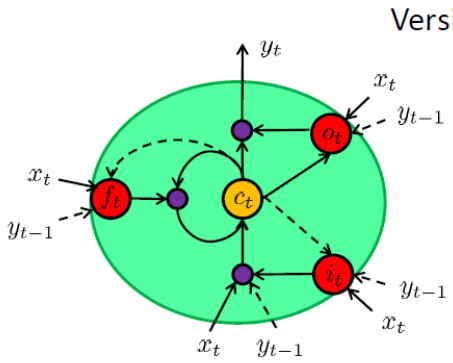


An unrolled recurrent neural network.

- Can unfold recurrent loop: Make it into a feedforward net.
- Use the same backprop algorithm for training.
- Again, cannot remember too far into the past.

Fig from http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short-Term Memory



i_t, f_t, o_t - input, forget and output gates from 0 to 1

c_t - memory

x_t - input, y_t - output

$$i_t = \sigma(w_{ix}x_t + w_{ic}c_{t-1} + w_{iy}y_{t-1} + b_i)$$

$$f_t = \sigma(w_{fx}x_t + w_{fc}c_{t-1} + w_{fy}y_{t-1} + b_f)$$

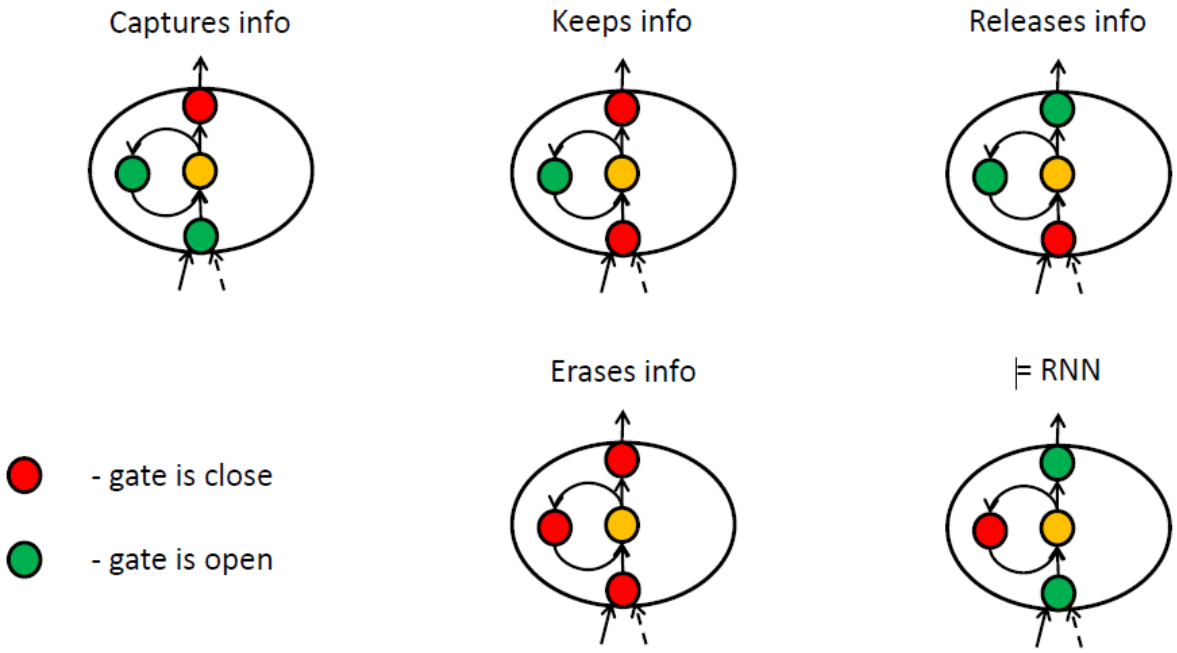
$$o_t = \sigma(w_{ox}x_t + w_{oc}c_t + w_{oy}y_{t-1} + b_o)$$

$$c_t = f_t c_{t-1} + i_t \cdot tanh(w_{cx}x_t + w_{cy}y_{t-1}) \qquad y_t = o_t \cdot tanh(c_t)$$

- LSTM to the rescue (Hochreiter and Schmidhuber, 1997).
- Built-in recurrent memory that can be written (Input gate), reset (Forget gate), and outputted (Output gate).

From `http://www.machinelearning.ru/wiki/images/6/6c/RNN_and_LSTM_16102015.pdf`

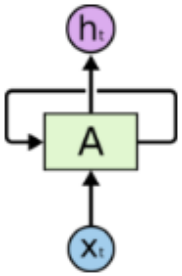
Long Short-Term Memory



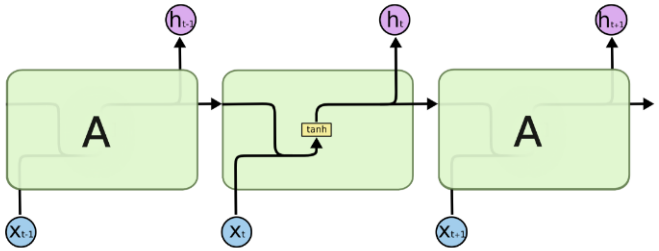
- Long-term retention possible with LSTM.

From http://www.machinelearning.ru/wiki/images/6/6c/RNN_and_LSTM_16102015.pdf

Long Short-Term Memory in Action

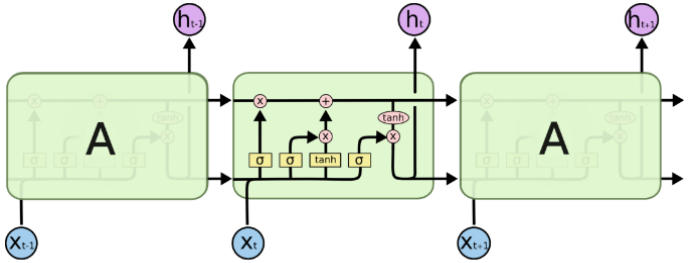


RNN



The repeating module in a standard RNN contains a single layer.

Vanilla RNN Unit



The repeating module in an LSTM contains four interacting layers.

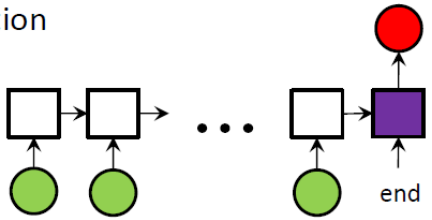
LSTM Unit

- Unfold in time and use backprop as usual.

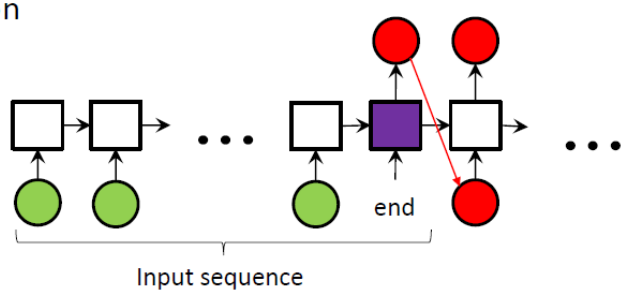
Fig from http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM Applications

- Sequence classification



- Sequence translation



- Applications: Sequence classification, Sequence translation.

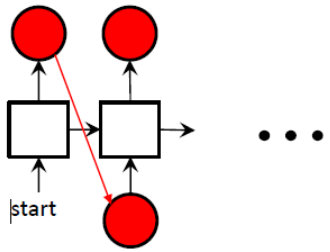
From http://machinelearning.ru

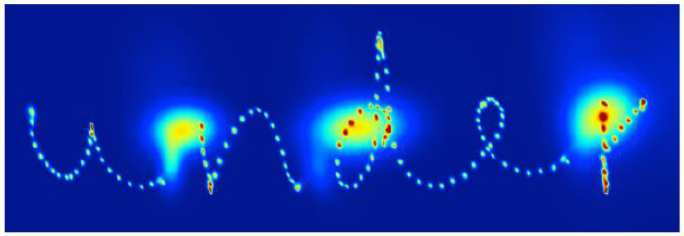
LSTM Applications

handwriting -> handwriting

Next pen position (we predict parameters):
x1,x2 - mixture of bivariate Gaussians
x3 - Bernoulli distribution

Current pen position:
x1,x2 – pen offset
x3 – is it end of the stroke



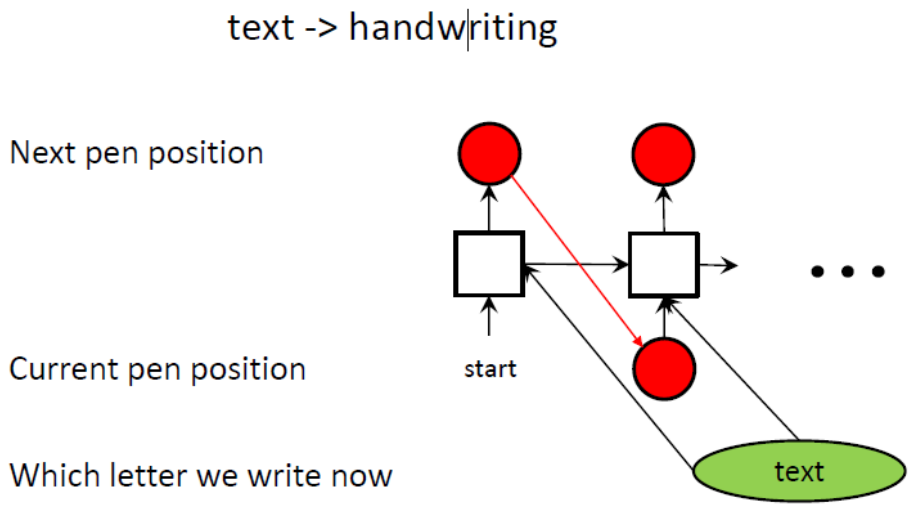


- Applications: Sequence prediction

From

https://blog.acolyer.org/2017/03/23/recurrent-neural-network-models/

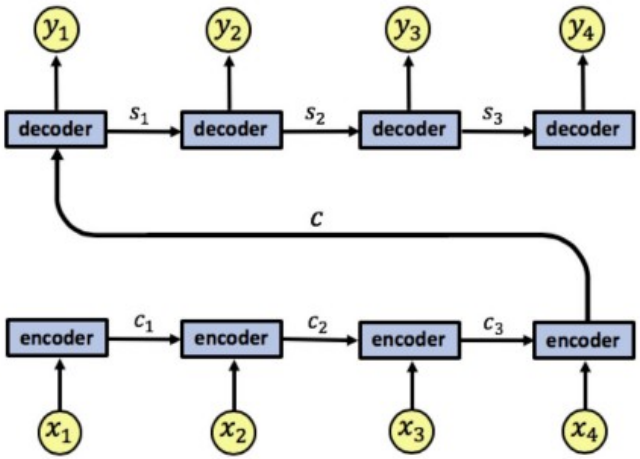
LSTM Applications

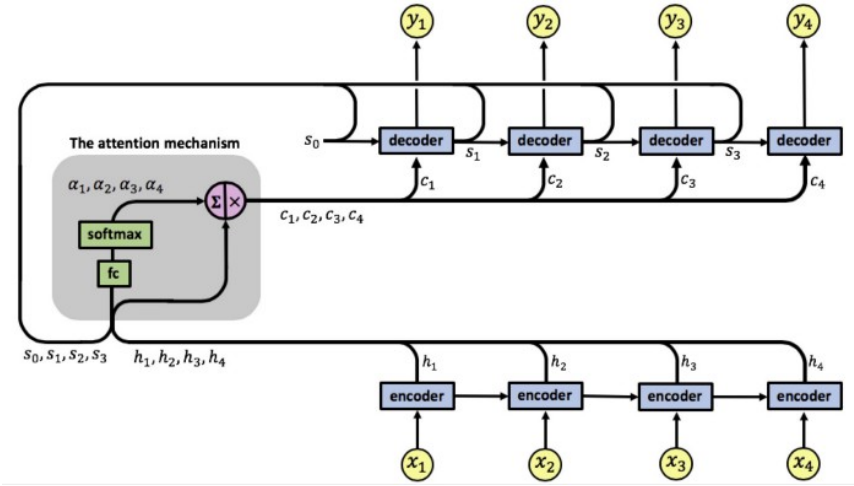


- Applications: Sequence classification, Sequence prediction, Sequence translation.

From http://machinelearning.ru

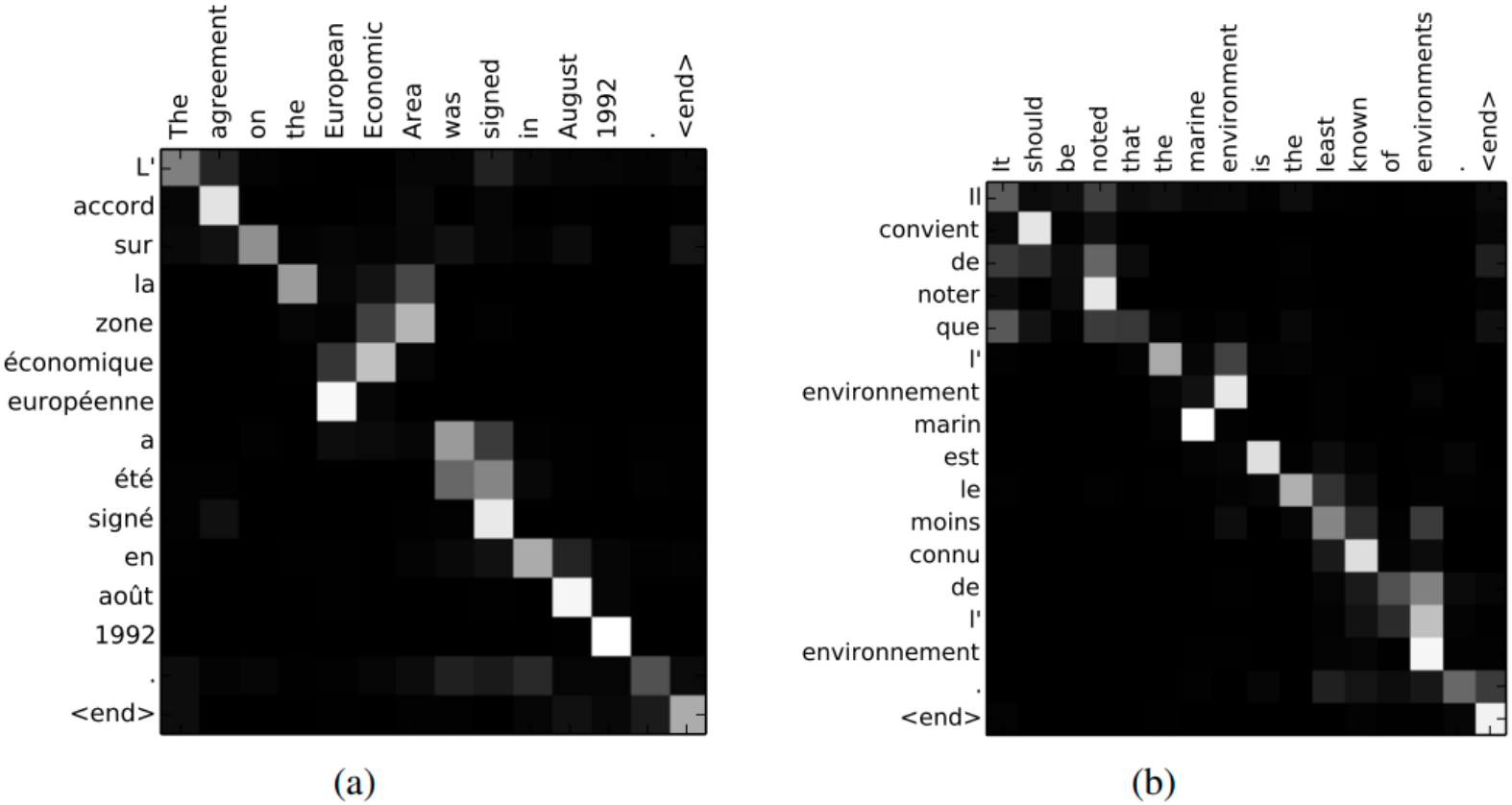
RNN with Attention Mechanism





- RNN uses the last hidden vector from the encoder as input to the decoder.
- RNN with Attention (Bahdanau et. al. 2015):
  - Uses weighted sum of all hidden vectors, not just the last one from the decoder.
  - Uses the states of the encoder and the hidden vectors to compute the weighting of the hidden vectors (the attention weight): simple FFW net is used.
  - The attention weights dynamically change based on the input and output.
  - Attention weights are determined by the FFW net (trained, end-to-end).

RNN with Attention: Example (NMT)



- x-axis: source language; y-axis: target language
- pixels: attention weight α_{ij} (j-th source to i-th target)

Source: Bahdanau, Cho, and Bengio (ICLR 2015)

Deep Learning Applications: Vision

- Give the name of the dominant object in the image
- Top-5 error rates: if correct class is not in top 5, count as error
  - Red:ConvNet, blue: no ConvNet

2012 Teams	%error
Supervision (Toronto)	15.3
ISI (Tokyo)	26.1
VGG (Oxford)	26.9
XRCE/INRIA	27.0
UvA (Amsterdam)	29.6
INRIA/LEAR	33.4

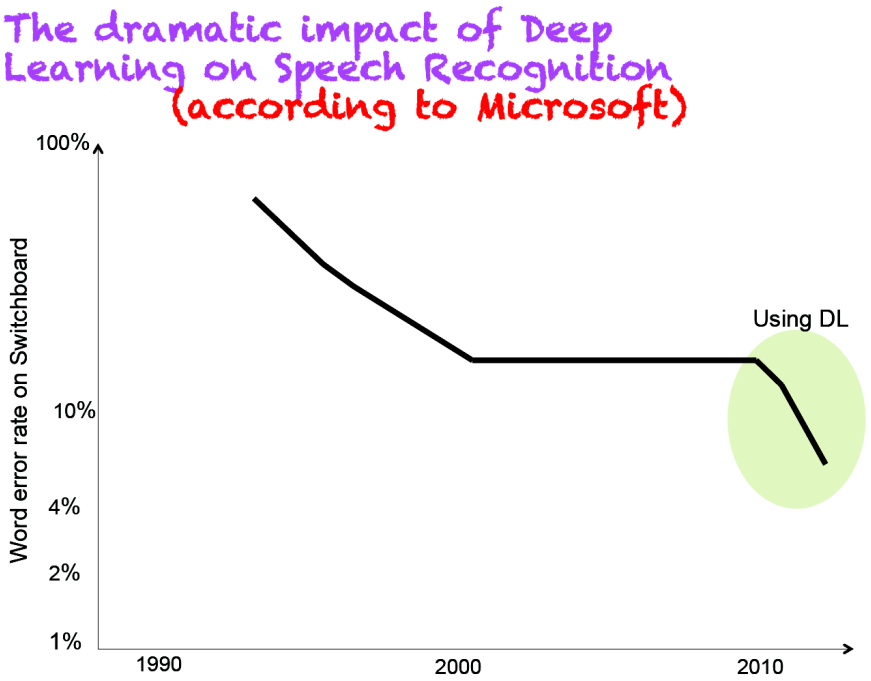
2013 Teams	%error
Clarifai (NYU spinoff)	11.7
NUS (singapore)	12.9
Zeiler-Fergus (NYU)	13.5
A. Howard	13.5
OverFeat (NYU)	14.1
UvA (Amsterdam)	14.2
Adobe	15.2
VGG (Oxford)	15.2
VGG (Oxford)	23.0

2014 Teams	%error
GoogLeNet	6.6
VGG (Oxford)	7.3
MSRA	8.0
A. Howard	8.1
DeeperVision	9.5
NUS-BST	9.7
TTIC-ECP	10.2
XYZ	11.2
UvA	12.1

- ConvNet sweepting image recognition challenges.

From LeCun's Deep Learning Tutorial

Deep Learning Applications: Speech

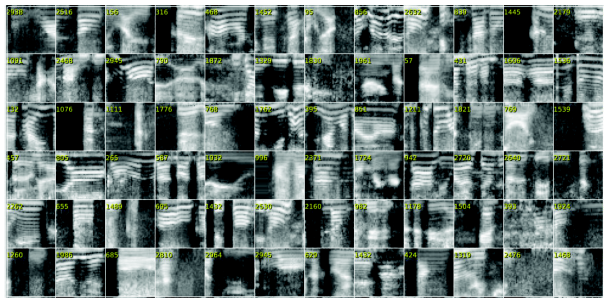


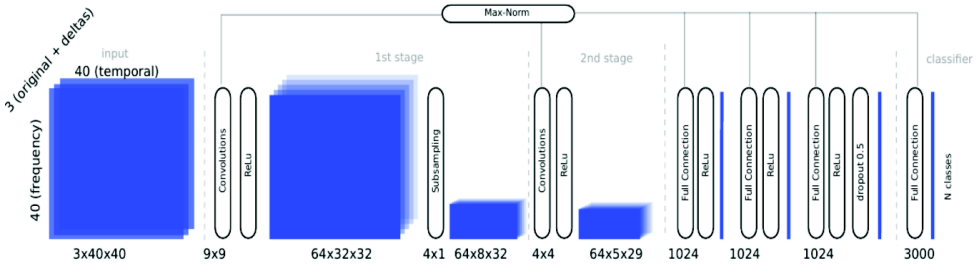
- Deep learning led to major improvement in speech recognition.

From LeCun's Deep Learning Tutorial

Deep Learning Applications: Speech

Training samples.
- 40 MEL-frequency Cepstral Coefficients
- Window: 40 frames, 10ms each



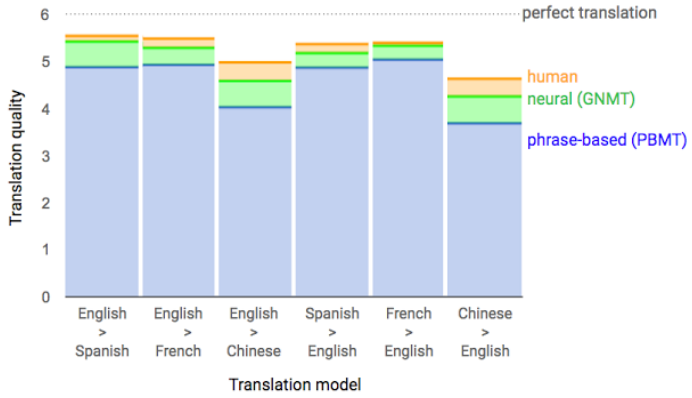


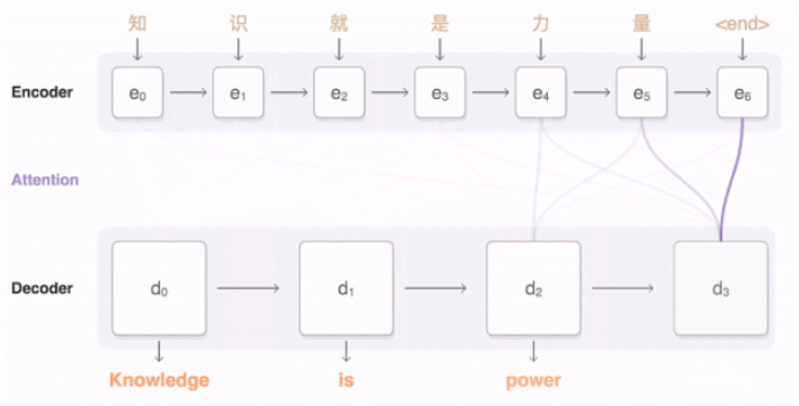
- Acoustic Model: ConvNet with 7 layers. 54.4 million parameters.
- Classifies acoustic signal into 3000 context-dependent subphones categories
- ReLU units + dropout for last layers
- Trained on GPU. 4 days of training

- ConvNet can also be applied to speech recognition.
- Use spectrogram and treat it like a 2D image.
- SOTA: end-to-end attention-based RNN (w/ LSTM, GRU, ...)

From LeCun's Deep Learning Tutorial

Deep Learing Applications: NLP

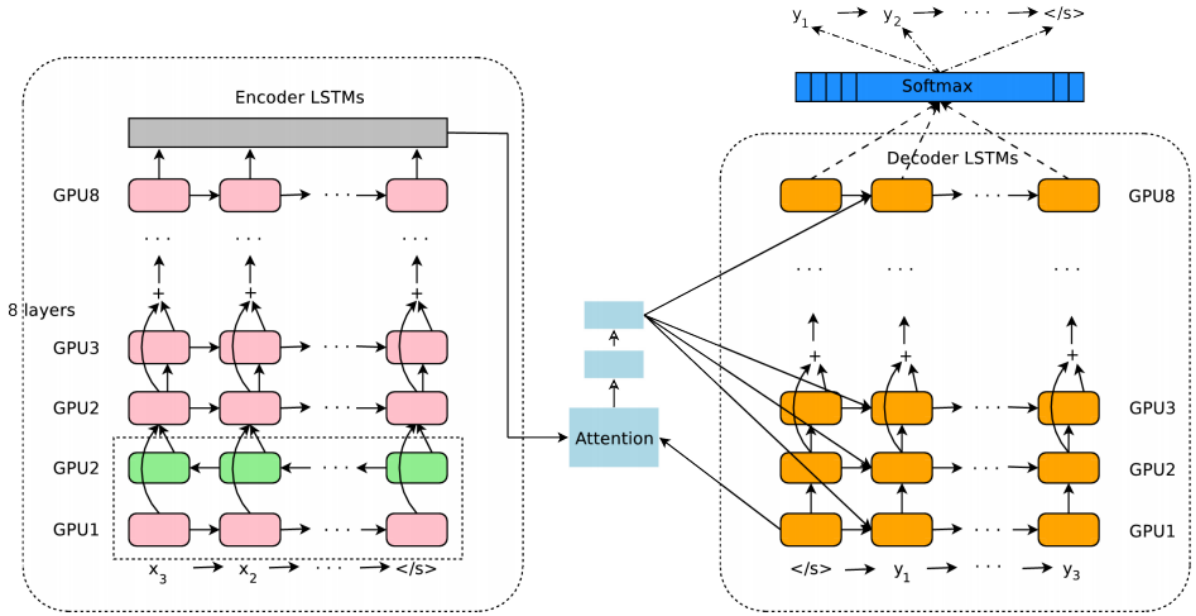




- Based on encoding/decoding and attention.

From `https://research.googleblog.com/2016/09/a-neural-network-for-machine.html`

Deep Learing Applications: NLP

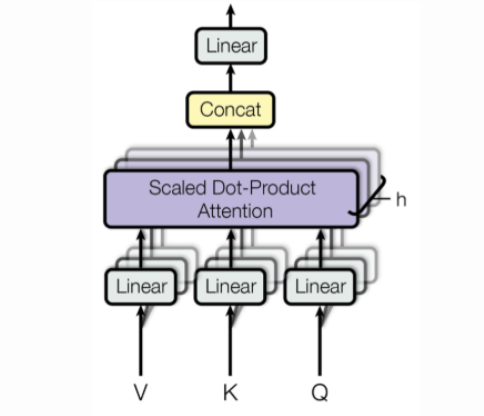


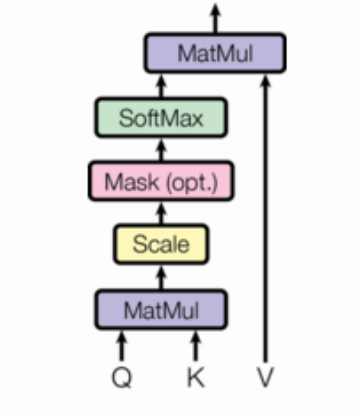
- Google's LSTM-based machine translation.

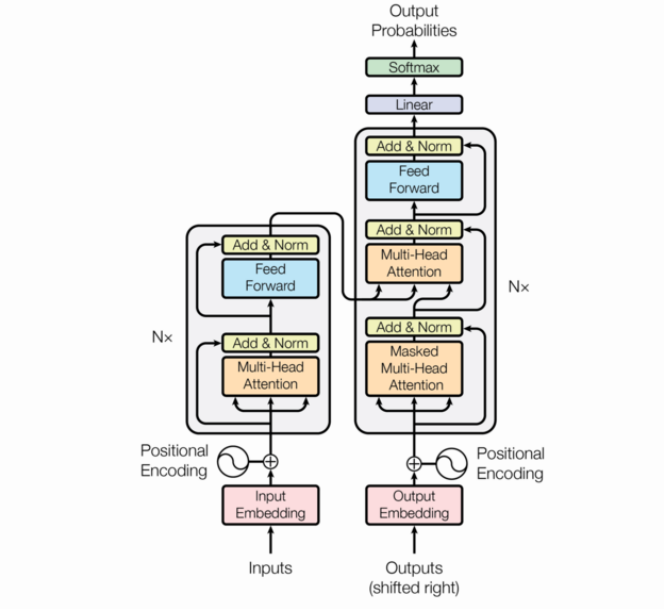
Wu et al. *arXiv:1609.08144* (2016).

How attention works: `https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attenti`

Deep Learning for NLP: Transformers







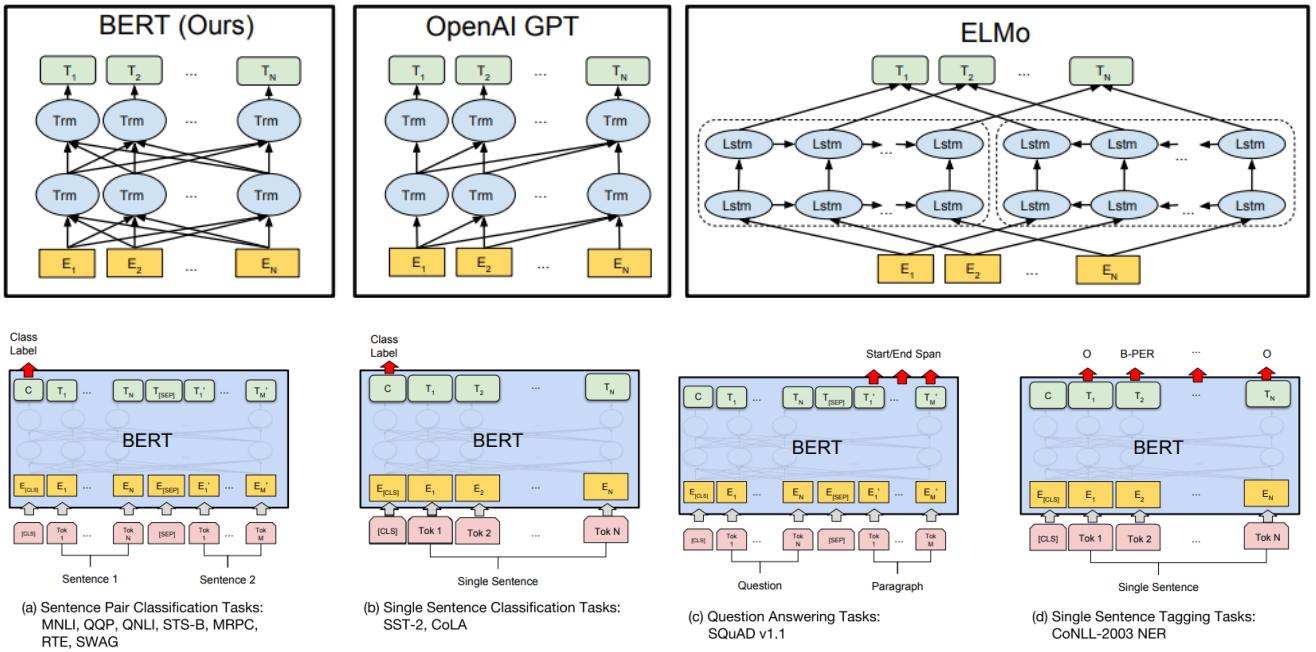
Multihead Self-attention Scaled Dot-Product Attention Transformer

- Highly parallelizable, Reduces serial computation
- Multi-head self-attention + position-encoding/position-wise FFW
- Organized over Query, Key, Value (Q,K,V)

s://medium.com/@adityathiruvengadam/transformer-architecture-attention-is-all-you-need-ae

vani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... , and Polosukhin, I. (2017). Attention is all you need. arXiv preprint arXiv

Deep Learning for NLP: Transformers & BERT



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

(b) Single Sentence Classification Tasks: SST-2, CoLA

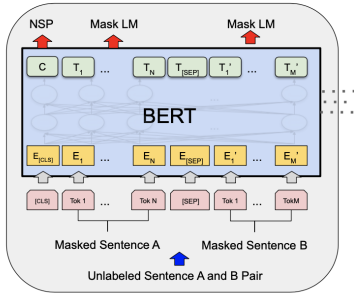
(c) Question Answering Tasks: SQuAD v1.1

(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

from Devlin et al. 2018

- BERT, based on Transformer: Powerful new approach for NLP

Deep Learning for NLP: BERT pretraining



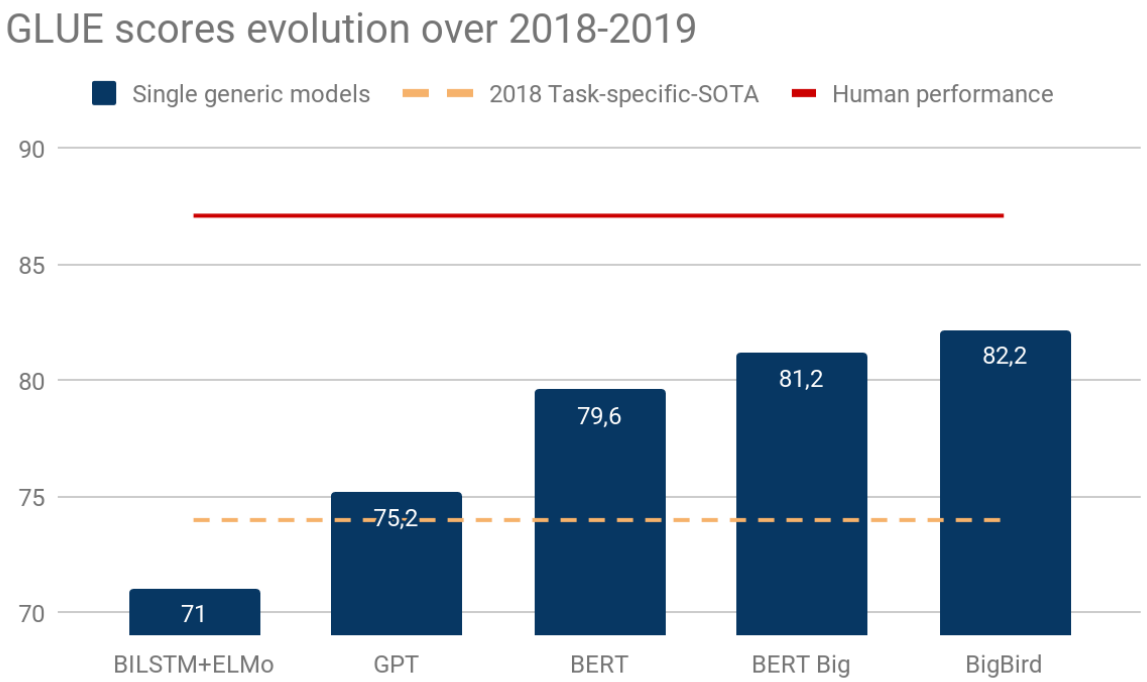
Pre-training

- Learn language model based on a large corpus of unlabled data (e.g. Wikipedia).
- Two sentences go in as input, and output depends on the task, below.
- Task 1: Masked Language Model
  - Predict masked words from a sentence: My dog is [MASK] $\longrightarrow$ My dog is hairy.
- Task 2: Next sentence prediction
  - Check if the second sentence follows the first sentence in the text (binary classification).

ttps://medium.com/swlh/bert-pre-training-of-transformers-for-language-understanding-5214f

Source: *https://medium.com/dair-ai/a-light-introduction-to-bert-2da54f96b68c*

Deep Learning for NLP: Transformers & BERT



- Transformer-based NLP led to big leap in performance.

https://medium.com/synapse-dev/understanding-bert-transformer-attention-isnt-all-you-need-5839ebd396db

Very Big Transformers: OpenAI's GPT-3

- GPT-3: Generative Pre-Trained Transformer
- Huge model: 175 billion parameters
- Extremely high quality text generation.
- Example: `https://philosopherai.com/` (not free any longer: some examples below)
  - `https://philosopherai.com/philosopher/can-consciousness-survive-after-death-c3bbf5`
  - `https://philosopherai.com/philosopher/is-the-universe-fundamentally-computational-9df1fc`
  - `https://philosopherai.com/philosopher/isnt-buddhism-more-of-a-philosophical-system-than-830bcf`

Source: *https://arxiv.org/abs/2005.14165* *https://openai.com/blog/gpt-3-apps/*

More Language Models: PaLM

Cause & Effect

Prompt

```
Which of the following sentences makes more sense?

1. I studied hard because I got an A on the test.
2. I got an A on the test because I studied hard.
```

Model Response

```
I got an A on the test because I studied hard.
```

Emoji Movie Game

Prompt

```
What movie does this emoji describe? 🤖👨🌱🌎

1. l.a. confidential
2. wall-e
3. léon: the professional
4. big
5. rush
```

Model Response

```
wall-e
```

Synonym Game

Prompt

```
Try to identify the 2 words best associated with the word STUMBLE
from the following list: table, jam, kangaroo, lock, australia,
centaur, ham, calf, web, robin, battery, spell, pilot, ruler,
trip, jack, dragon, fall. Give your answer in alphabetical order.
```

Model Response

```
fall, trip
```

Counterfactuals

Prompt

```
Q: A president rides a horse. What would have happened if the
president had ridden a motorcycle?

1. She or he would have enjoyed riding the horse.
2. They would have jumped a garden fence.
3. She or he would have been faster.
4. The horse would have died.
```

Model Response

```
She or he would have been faster.
```

Conceptual Understanding

Prompt

```
Concept: moving definition. Question: Which of the following
sentences best characterizes moving definitions?

1. Moving definitions can be very fast.
2. Moving definitions define movements.
3. Moving definitions can be expensive.
4. Moving definitions change often.
```

Model Response

```
Moving definitions change often.
```

- PaLM : Pathways Language Model https://ai.googleblog.com/2022/04/pathways-language-model-palm-scaling-to.html

More Advanced Topics

- DALL·E 2 : https://openai.com/dall-e-2/
- Generative Adversarial Networks (GAN): style transfer, data augmentation, deep fake, etc.
- Graph Neural Networks (GNN): molecular fingerprinting, combinatorial optimization, vision, etc.
- Meta learning, Transfer learning, Multi-task learning, Imitation learning
- Optimizers: Adam, RMSprop, etc.
  https://ruder.io/optimizing-gradient-descent/
- Applications: autonomous driving, chat bots, retail, etc.
- Continous learning, semisupervised learning, active learning, federated learning
- Model compression, Model distillation

Limitations of Deep Learning

- Requires massive amounts of (labeled) data.
- Long training time. Large trained models.
- Catastrophic forgetting.
- Designing good model is done mostly manually.
- Vulnerable to adversarial inputs.
- Hard to explain how it works / what it learned.

Overcoming Limitations of DL

Pretty much well known problems, and solutions emerging.

- Data: Active learning, Core sets, data augmentation, etc.
- Computing time: Train with reduced data. Compact models.
- Large trained models: Compression, distillation
- Catastrophic forgetting: Various approaches, not perfect yet.
- Issue of manual design: AutoML, NAS, ENAS, Evolution, etc.
- Adversarial inputs: Adversarial training, defensive distillation, ...
- Explainability: DARPA XAI effort - explanation generation, Bayesian program induction, semantic associations, etc.

Advanced/Fundamental Issues in Deep Learning

- Reasoning, Common-sense reasoning, Causality
- Self-supervised learning, Combining unsupervised and supervised/reinforcement learning
- Human-like learning
- Meaning/semantic-level processing
- Problem posing, Coping with new tasks
- Tool construction and tool use
- Open-endedness, Artificial General Intelligence (AGI)

Summary

- Deep convolutional networks (DNN): High computational demand, over the board great performance in vision tasks.
- Deep Q-Network: unique apporach to reinforcement learning. End-to-end machine learning. Super-human performance.
- Deep recurrent neural networks: sequence learning. LSTM is a powerful mechanism.
- Transformers, based on self-attention, surpasses RNNs, and even infringe on CNN territory.
- Diverse applications. Top performance.
- Lots of practical and fundamental limits
- Flood of deep learning tools available.