



A Gentle Introduction to Machine Learning

Third Lecture

Deep Learning – A Closer Look



Olov Andersson, AIICS

Outline of the Deep Learning Lecture

- What is deep learning
- Some motivation
- Enablers
 - Data
 - Computation
 - Training Algorithms & Tools
 - Network Architectures
- Closing examples



AI In The News Lately

- *“The development of full artificial intelligence could spell the end of the human race ... it would take off on its own, and re-design itself at an ever increasing rate. **Humans**, who are limited by slow biological evolution, couldn’t compete, and **would be superseded.**” – Stephen Hawking*
- *“I think we should be very careful about **artificial intelligence**. If I had to guess at what our biggest **existential threat** is, I’d probably say that. So we need to be very careful.” – Elon Musk*
- *“Artificial intelligence is the future, not only for Russian, but for all of humankind. It comes with colossal opportunities, but also threats that are difficult to predict. **Whoever becomes the leader in this sphere will become the ruler of the world.**” – Vladimir Putin*

There is **a lot of hype** about the capabilities of AI, mainly driven by recent advances in **deep learning**

But Deep Learning Is Not All Hype

No threat to humanity in sight, but **impressive applications...**

- **Google:** "1000 deep learning projects"
 - Extending across search, Android, Gmail, photo, maps, translate, YouTube, and self-driving cars. In 2014 it bought DeepMind, whose deep reinforcement learning project, AlphaGo, defeated the world's Go champion.
- **Microsoft**
 - Speech-recognition products (e.g. Bing voice search, X-Box voice commands), search rankings, photo search, translation systems, and more.
- **Facebook**
 - Uses DL to translate about 2 billion user posts per day in more than 40 languages (About half its community does not speak English.)
- **Baidu** (China's Google)
 - Uses DL for speech recognition, translation, photo search, and a self-driving car project, among others.

Source: Fortune.com

Rapid progress, hardly a day without some new application

The State of Deep Learning

State-of-the-art results in:

- Computer vision (e.g. object detection)
- Natural language processing (e.g. translation)
- Speech recognition/synthesis

Promising results:

- Robotics
- Content generation

Real-world applications are mainly in **supervised learning**, deep reinforcement and unsupervised learning are still less mature

So, what is deep learning?!

General Approach For "AI scale" Real-world ML

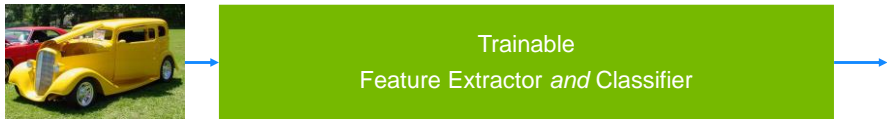
In particular excels at

- Human modalities
- Eg. image, text and speech domains
 - Recognition, segmentation, translation and generation

"Traditional" machine learning



"Deep" machine learning



What Learning Algorithm Goes In The Box?

Why did we want feature extraction in the first place?

- Remember the **limitations and pitfalls** of supervised learning
- **Curse of dimensionality:** Input dimension increases data requirements, *worst-case* exponentially
- If we can also **learn** feature extractors, we can get around this

E.g, $y = f_{\text{classifier}}(g_{\text{features}}(D))$, want to learn both $f()$ and $g()$ from raw data D

- Must be a powerful model, ideally able to approximate arbitrary functions f and $g...$
- Want something that can learn compositions of functions $f(g(...))$, like layers...



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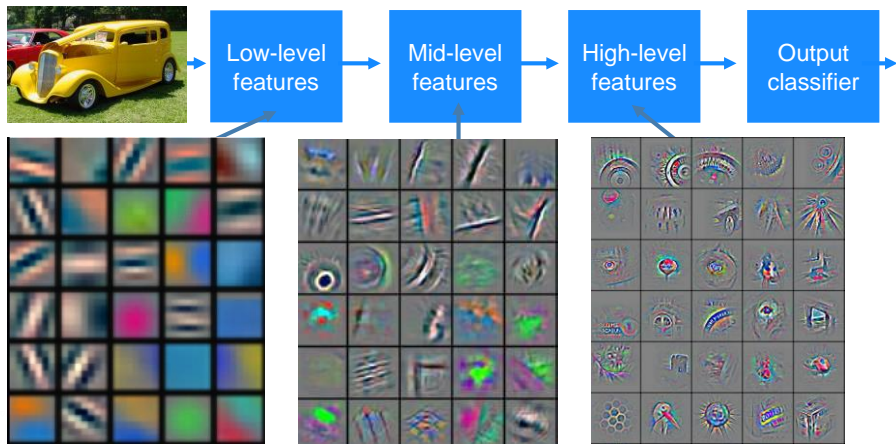
➡ **Multi-layer Neural Networks** is by far the most common choice



Deep learning = Learning Hierarchical Representations

It's **deep** if it has **more than one stage** of non-linear feature transformation

- **More than two layers** of abstractions $f(g())$ might be even better?



Many Problems Appear Naturally Hierarchical

Image recognition

- Pixel → edge → texon → motif → part → object

Text

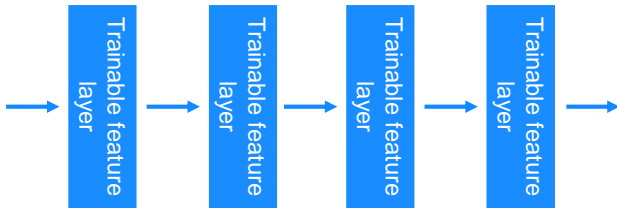
- Character → word → word group → clause → sentence → story

Speech

- Sample → spectral band → sound → ... → phone → phoneme → word

Want to capture this **mathematically** via trainable feature hierarchies

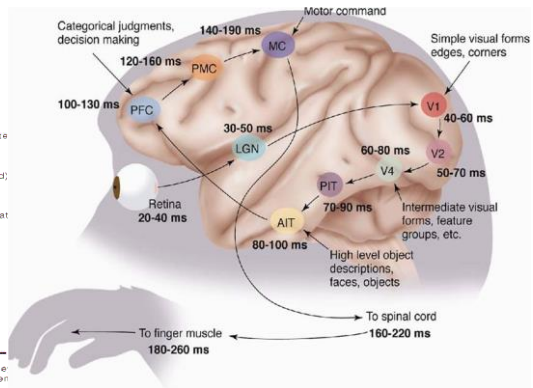
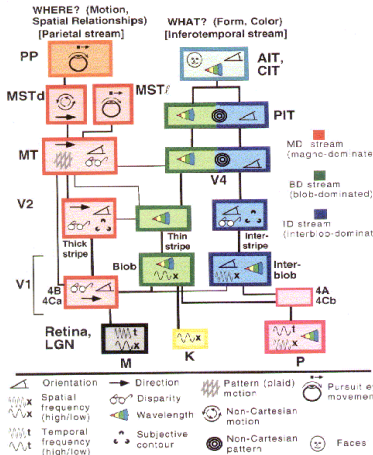
- E.g. NN layers can be seen as feature transform with increasing abstraction



(NVIDIA)

Additional Support: The Visual Cortex is Also Hierarchical

- The ventral (recognition) pathway in the visual cortex has multiple stages
Retina - LGN - V1 - V2 - V4 - PIT - AIT
- Lots of intermediate representations

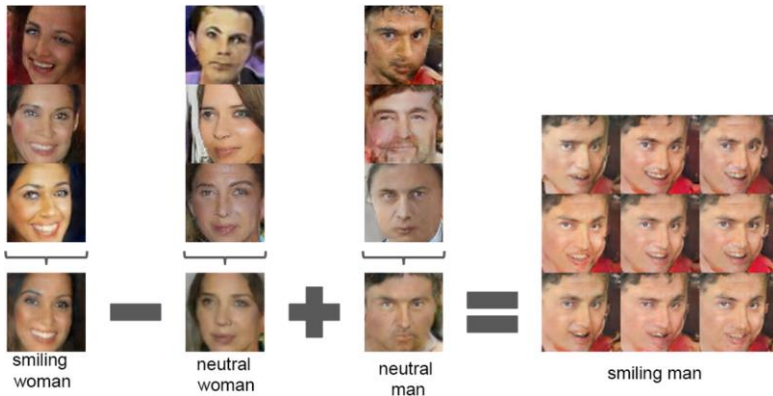


[picture from Simon Thorpe]

[Gallant & Van Essen] (NVIDIA)

So, Can It Learn Abstractions?

Generated similar examples using learned high-level features



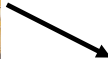
Input examples \rightarrow Arithmetic on high-level features \rightarrow Results

Clearly learning some kind of abstraction

- Such "concept arithmetic" doesn't always work this well...

So, Can It Learn Abstractions II

Neural Style Transfer (deepart.io)



So Why Is Deep Learning Taking Off Now?

People have been using Neural Networks for decades

- BUT, it turns out you need **massive scale** to really see the benefits of multiple layers

Learning deep models means more layers = **more parameters**

- More parameters requires **more data** ("identifiability", overfitting)
- More parameters means **more computation**

Deep Neural Networks (DNNs) may have **millions to billions** parameters, trained on very large data sets

Until recently, this was not feasible



Overview: Deep Learning Driven By...

Larger data sets

- "Big data" trend, cheap storage, internet collaboration

Faster training

- **Hardware**, algorithms and tools (e.g. Tensorflow)

Network architectures tailored for input type

- E.g. images, sequential data. Can be combined (e.g. video)

Heuristics for reducing overfitting during training



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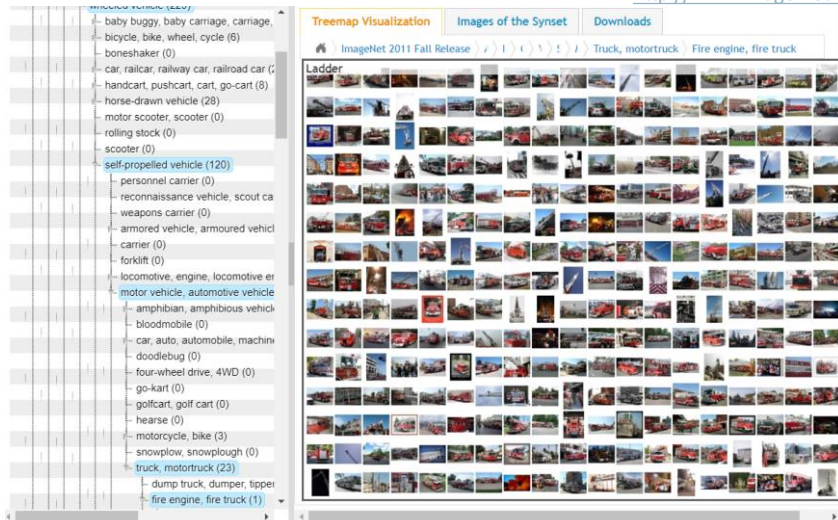
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Larger Data Sets

E.g. ImageNet (> 14 million images **tagged with categories**)

<http://www.image-net.org/>



Larger Data Sets

E.g. Microsoft COCO (> 1 million images **segmented** into categories)



<http://cocodataset.org>



Companies Collect Large Private Data Sets

Internet companies like Google, Facebook and Microsoft collect plenty of data, only some of it is public (e.g. Youtube data set)

- Can get **much for free** from users
- Data is a **competitive advantage**

All major car manufacturers are researching autonomy, many are betting on deep learning

- E.g. Tesla is betting heavily on **object detection from cameras**
 - Can automatically collect raw images from their autopilot(?)

Supervised (deep) learning is the most mature technology, inputs \mathbf{x} often collected automatically, but they still need somebody to provide correct outputs \mathbf{y} (e.g. labels, segmentation etc)

- Such companies can have **large teams just doing labeling**
- Sometimes outsourced to other countries, or Amazon Mechanical Turk



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Faster Training

Consumer Desktop CPU as of 2016

- Speed: ~1 TFLOPS (10¹² Floating Point Operations Per Second)

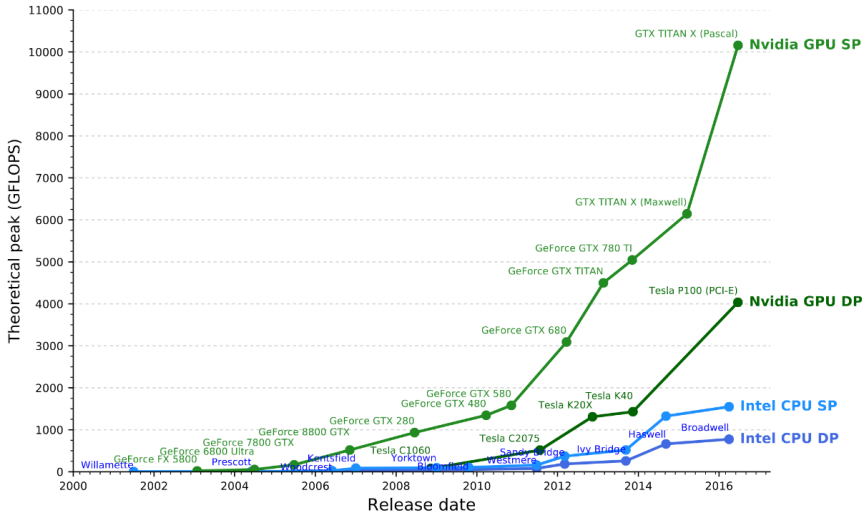


Consumer Graphics Card (GPU)

- ~Speed: **10 TFLOPS** (single precision)
- Cost: ~\$1000
- Task must be extremely parallelizable
- Neural networks are, e.g. all neurons in each layer are **independent** given inputs
- GPUs **key enabler** of deep learning



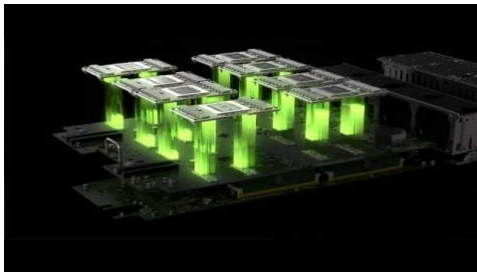
Faster Training - GPUs Increasingly Important



<https://github.com/mgalloy/cpu-vs-gpu/>

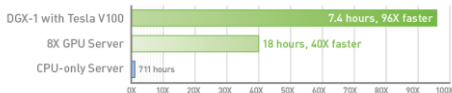
Faster Training - Deep Learning "Supercomputer"

- Computation for deep learning is increasingly **big business**
- NVIDIA has recent integrated solutions based on their GPU-technology



- Speed: **80-170 TFLOPS** (as of 2017)
- Cost: \$150 000 and up...

NVIDIA DGX-1 Delivers 96X Faster Training



Relative Performance [Base on Time to Train]
Workload: ResNet50, 90 epochs to solution | CPU Server: Dual Xeon E5-2699 v4, 2.6GHz

Faster Training - Beyond GPU's -> Custom Hardware

Google recently designed custom chips (ASICs) specifically for neural networks

- These "Tensor Processing Units" are organized into "pods"



- Speed: **11 500 TFLOPS per pod** (2017)
- Cost: Trade secret
- The speed of custom hardware usually comes at the cost of flexibility

Faster Training - Algorithms

Many algorithms proposed to speed up training

Mainly fall into two categories,

- Approximate gradient calculation of your NN
 - E.g. **stochastic** gradient descent (SGD) variants
- *Modifying* your NN for faster derivatives or converging in fewer iterations
 - E.g. different activation functions or network structure



Faster Training – Stochastic Gradient Descent I

Remember, training objective is a loss function against **all examples** (x_i, y_i) for different weights w

$$L(w) = \sum_{i=1}^n (NN_w(x_i) - y_i)^2$$

Want to find w that gives low loss against examples

- Gradient descent: Update w by computing gradient, $O(n \cdot w)$ using the backpropagation algorithm (lecture 1)

If we have millions of data points, do we really need all of it for useful gradients?



Faster Training – Stochastic Gradient Descent

Insight: If we just compute gradients for a **randomly selected subset m** of the total n examples, we get a *faster approximation*

Mini-batch SGD:

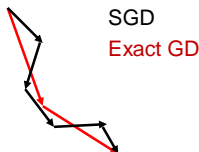
1. Put data set in **random order**, start at position $p = 1$
2. Compute gradients of *partial* loss for **m data points at a time**,

$$\hat{L}(w) = \sum_{i=p}^{p+m} (NN_w(x_i) - y_i)^2$$

3. Set $p = p + m$. When end of data set reached, restart at step 1.

Complexity: $O(m \cdot w)$, where m typically 1-50, much less than $n = \text{millions}$.

- **The approximation over several steps will average out**, and have much **lower computational cost**

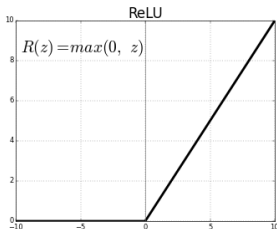


Faster Training – Modifying the Network

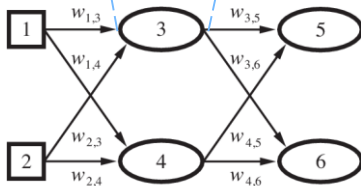
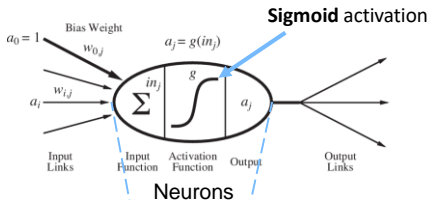
Remember the mathematical structure of neural network models:

To make optimization take fewer steps, we can change **activation function** or **connections**

The **most common** activation function these days is the **ReLU**, $R(z) = \max(0, z)$



Simpler gradients and more stable over time!



Network (fully-connected)

Training Tools – Generalized Backpropagation

Learning these advanced representations raises two issues:

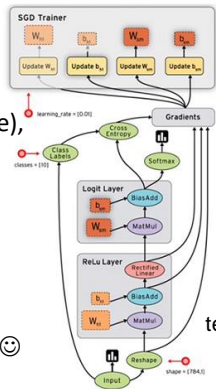
- Deep learning often uses **very large networks** with very large ("Big Data") training set
- **Advanced representations may require modifications to backpropagation**

Reverse-mode Automatic Differentiation is a technique that generalizes backpropagation to differentiate arbitrary scalar (loss) functions

Recent data flow languages like **Tensorflow** (Google), **Torch** and **Theano** let you define **arbitrary models** from primitive mathematical operations and optimize them on or several **GPUs**

Can be orders of magnitude faster!

Will we ever have to manually differentiate again? ☺



tensorflow.org

Code Examples: Tensorflow NN Training

- See workbook at: <https://goo.gl/UHdwBX>
 - Choose File->Save Copy in Drive to run and edit your own version
- Recall, in the ML Lecture 1 code examples we used a `grad()` function to compute the gradients of the loss function.
- This was from the Autograd package which also uses automatic differentiation like Tensorflow, but directly on python code (slower but easier to use)



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Network Architectures Tailored to Input Type

The best results have been achieved mixing in other **network structures** than just fully-connected

Fully connected scales poorly with high-dimensional inputs such as images,

- e.g. RGB HD image is $3 \times 1920 \times 1080 = 6\text{M}$ inputs
- Assume 1000 neurons in first layer
- Then each fully-connected neuron will have a weight for each input, $1000 \times 6\text{M} = 6$ billion weights just in the first layer

The idea is to reduce the number of connections by capturing the **structure in the problem**

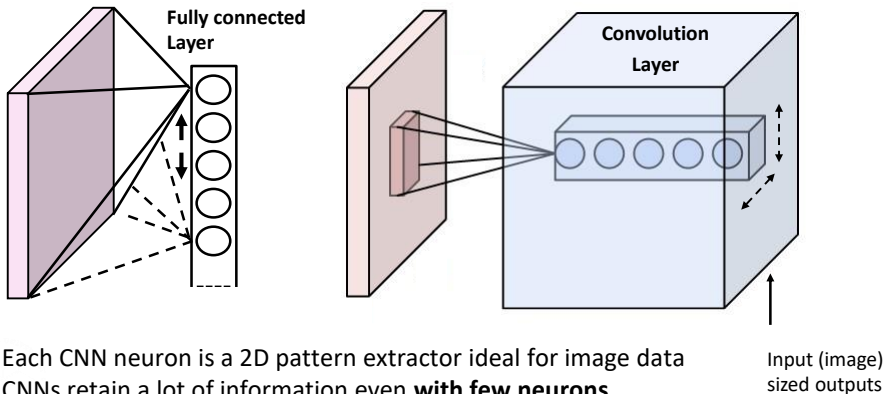
One very successful network structure is **convolutional neural networks**

- "Convolution" layers
- "Pooling" layers
- Fully-connected output layers

Architectures – Convolutional Layers

Insight: Patterns (objects) in an image are translation "invariant"

In a convolutional layer, **the same neurons** are applied to a sliding **window** over the inputs (e.g. image), **for each input coordinate** (e.g. pixel in image)

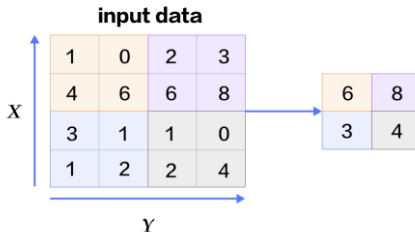


Architectures – CNN Pooling Layers

Insight: Patterns exist at different scales, want capture increasingly higher levels of abstraction

Pooling layers force the network to summarize information by "downsampling"

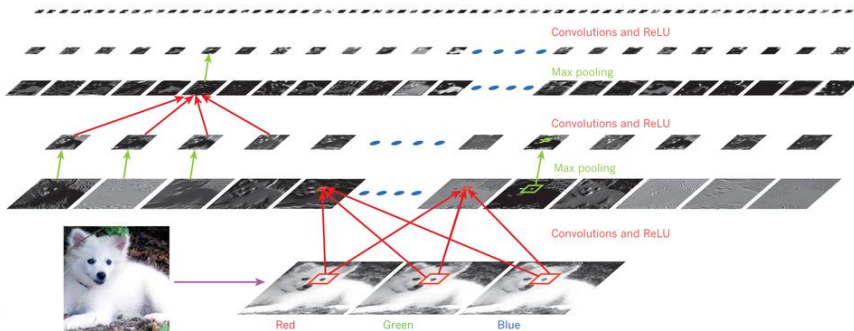
- In an image we **go from higher to lower resolution**
- Typically done by splitting image into regions and taking the **max value**
- E.g, **used after convolutional layers**, selects highest signaling neuron (pattern extractor)



Architectures - Convolutional Neural Networks

- **Bringing it together** into one network, in summary
- "Convolutional" layers are for each pixel only fed inputs only from the local neighborhood to capture **object translation**
- "Pooling" (downsampling) layers to work at different **scales** (abstraction)
- Typically you **interleave convolutions with ReLU and pooling** layers

Samoyed (16); Papillon (5.7); Pomeranian (2.7); Arctic fox (1.0); Eskimo dog (0.6); white wolf (0.4); Siberian husky (0.4)

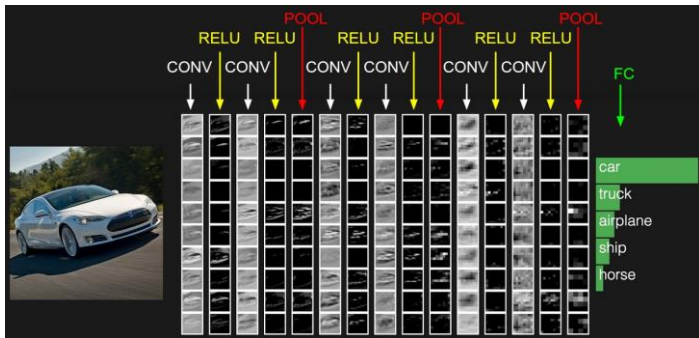


(LeCun, Bengio and Hinton, 2015)

Architectures – CNNs for Object Recognition

Object recognition from images is a typical classification task.

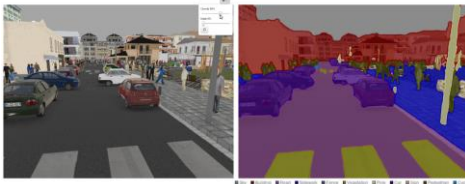
You typically add **fully-connected layer(s) at the end** to train a traditional classifier and the CNN features, jointly



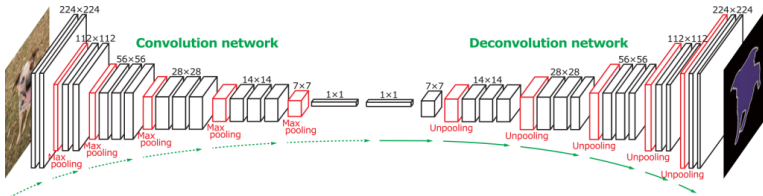
Karpathy, <http://cs231n.github.io/convolutional-networks/>

Architectures – CNNs for Segmentation

- Segmentation (typically images) requires us to classify **each input** (pixel), e.g. network output is same dimension as input



- Deconvolutional networks do reverse convolution and pooling



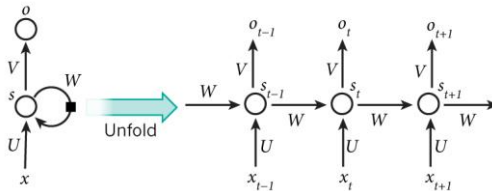
Architectures – CNN Demo

- Online javascript CNN demo:
<http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html>
- See also the CNN code example in our Tensorflow workbook
 - <https://goo.gl/UHdwBX>



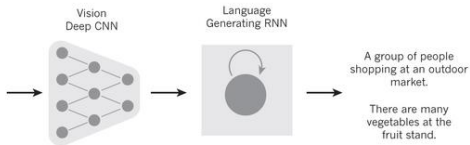
Architectures: Recurrent Neural Networks

- We used the Bag of Words feature vector in the spam classification example. It's simple but it **discards the sequential structure** in text
- This is flawed since the **meaning** of a text strongly depends on the order of the words!
- **Recurrent Neural Networks (RNN)** depend not only on current input x , but also **remembers** internal state s from previous inputs (e.g. words)
- **RNNs can be difficult to train** (variants: "Long Short-Term Memory", "Gated Recurrent Unit")



(LeCun, Bengio and Hinton, 2015)

Architectures: Combining Network Structures



(LeCun, Bengio and Hinton, 2015)



A woman is throwing a **frisbee** in a park.



A **dog** is standing on a hardwood floor.



A **stop** sign is on a road with a mountain in the background



A little **girl** sitting on a bed with a teddy bear.



A group of **people** sitting on a boat in the water.



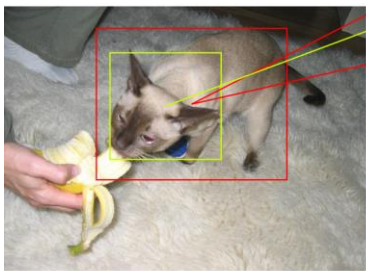
A giraffe standing in a forest with **trees** in the background.

Demo - Visual-Semantic Alignment

Paper: <http://cs.stanford.edu/people/karpathy/deepimagesent/>

Demo: <http://cs.stanford.edu/people/karpathy/deepimagesent/rankingdemo/>

Impressive, but not perfect. Some "weird" mistakes highlight on-going debate on what neural networks have really learned.



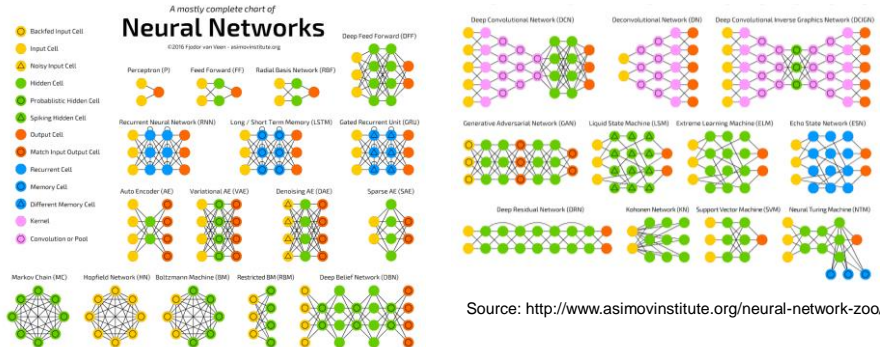
0.23	small
1.00	cat
-0.17	small
0.62	dog
0.04	looking
-0.23	in
-0.32	opposite
-0.03	direction

top sentences for this image:

- (2.62) A cat feeding on a banana with a person feeding it to it.
- (2.53) Two kittens are cuddling and enjoying a soft pillow
- (2.38) A cat eating a banana from someone's hand
- (2.36) a cat that is eating some kind of banana
- (2.33) A person feeding a cat with a banana

Architectures: The Neural Network Zoo

Many different types of structure, more or less modular components



Source: <http://www.asimovinstitute.org/neural-network-zoo/>

- ...and more keeps being invented

Applications - What About Reinforcement Learning?

Examples so far have been mostly supervised learning, as it is the most mature and has most real applications

Several impressive research results, e.g:

- The ATARI video-game playing example from the RL lecture used "fitted" Q-learning, where the **Q-function $Q(s,a)$** was fed raw pixels as state s , enabled by representing it as a **CNN**

That was two years ago, although not as mature as SL, deep RL is a hot research area

- From 80's 2D ATARI to 90's "3D" Doom in <2 years



Deep Reinforcement Learning - Example

In first-person shooters like Doom the player can only observe part of the map at a time

- The agent needs memory!

Q-learning Doom directly from **video** by using **CNN + RNN** for Q-function



Deep Reinforcement Learning – Example II

Last year, the OpenAI research institute beat human experts in the popular game of Dota 2, although a simplified scenario

- Towards learning strategies in **team games**
- This year they played human pro's in full scenarios
 - Example: <https://youtu.be/TFOQnzvBHdw>



Dota 2

We've created a bot which beats the world's top professionals at 1v1 matches of **Dota 2** under standard tournament rules. The bot learned the game from scratch by self-play, and does not use imitation learning or tree search. This is a step towards building AI systems which accomplish well-defined goals in messy, complicated situations involving real humans.

[↗ REWATCH LIVE EVENT](#)

[↓ READ MORE](#)

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Heuristics for **reducing overfitting** during training

- Several: Dropout, BatchNormalization, etc..
- Outside the scope of this course, but lots of DL material out there on the web.

If Time Permits - Exjobb Opportunities

- I do research at intersection of AI, machine learning and robotics
 - Remember e.g. deep learning + quadcopter video in previous lecture
- Students interested in an academic exjobb can mail me at
olov.a.andersson@liu.se
- Example topics include deep learning applications and optimization-based control
 - Math background corresponding to engineering or statistics degree helps



Closing Remarks

- Deep learning tries to learn multiple levels of abstraction to overcome the curse of dimensionality
- Bottlenecks: requires lots of data (and computation) to train
- Mainly based on multi-layer neural networks of various architectures
- An area with great potential. Lots of hype but also some impressive results
- Quickly evolving, best practices for training DNNs change almost every year

Thank you for listening!

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