A Gentle Introduction to Machine Learning

Third Lecture

Deep Learning – A Closer Look

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LINKÖPINGS UNIVERSITET

Outline of the Deep Learning Lecture

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

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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ever increasing rate.* ***Humans****, who are limited by slow biological evolution, couldn't compete, and* ***would be superseded****."* *–* ***Stephen Hawking***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

Hand-crafted Feature Extractor → “Simple” Trainable Classifier →

”Deep” machine learning

Trainable Feature Extractor *and* Classifier →

(NVIDIA)

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

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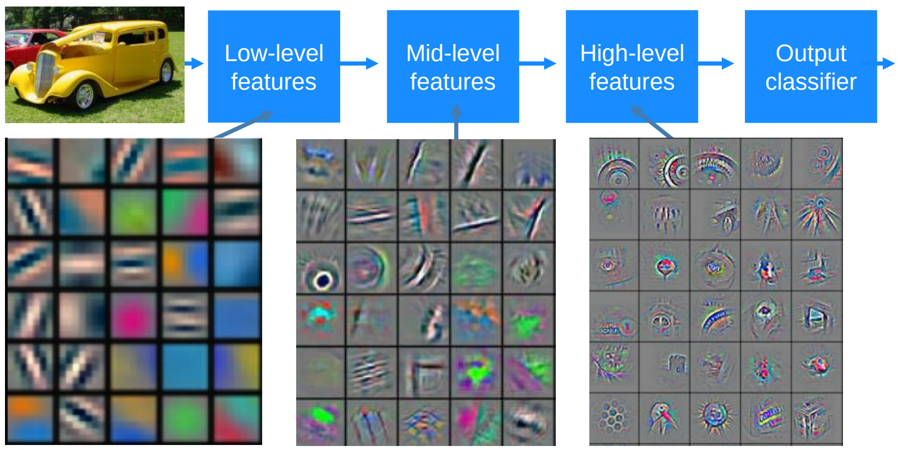
Deep learning = Learning Hierarchical Representations

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?



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

(NVIDIA)

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Many Problems Appear Naturally Hierarchical

Image recognition

- Pixel → edge → texton → motif → part → object

Text

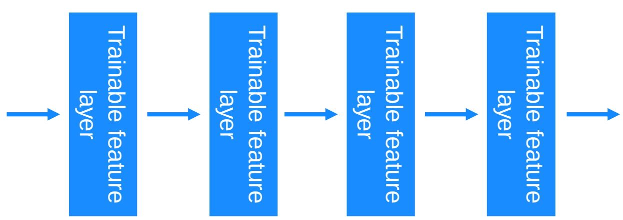
- Character → word → word group → clause → sentence → story

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)

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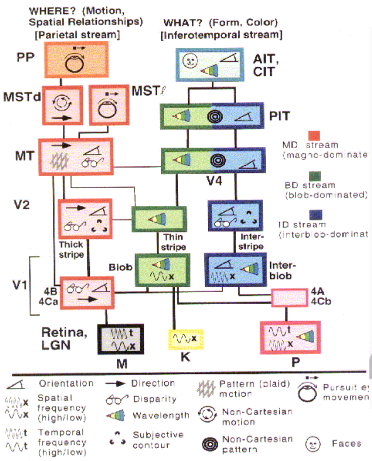
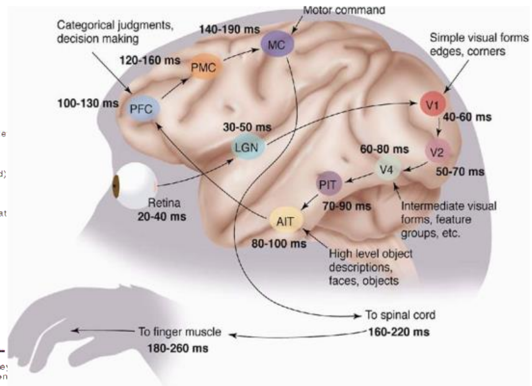
Additional Support: The Visual Cortex is Also Hierarchical

- 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)

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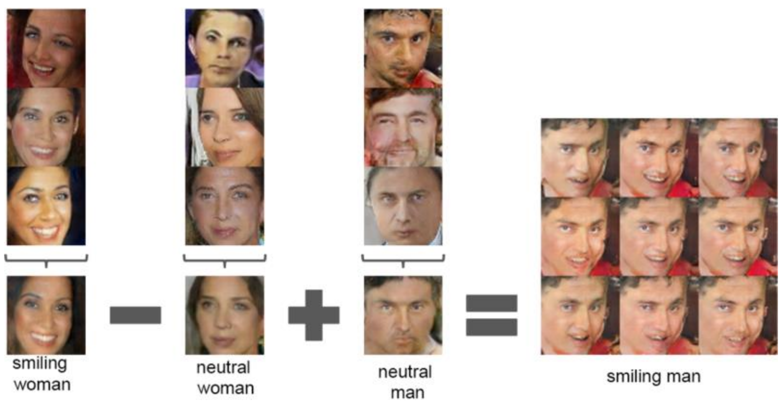
So, Can It Learn Abstractions?

Generated similar examples using learned high-level features



Input examples -> Arithmetic on high-level features -> Results

Clearly learning some kind of abstraction

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

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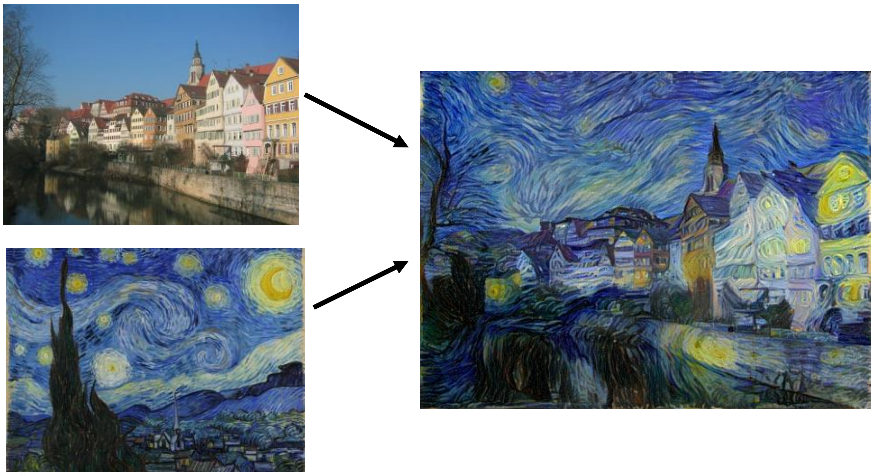
So, Can It Learn Abstractions II

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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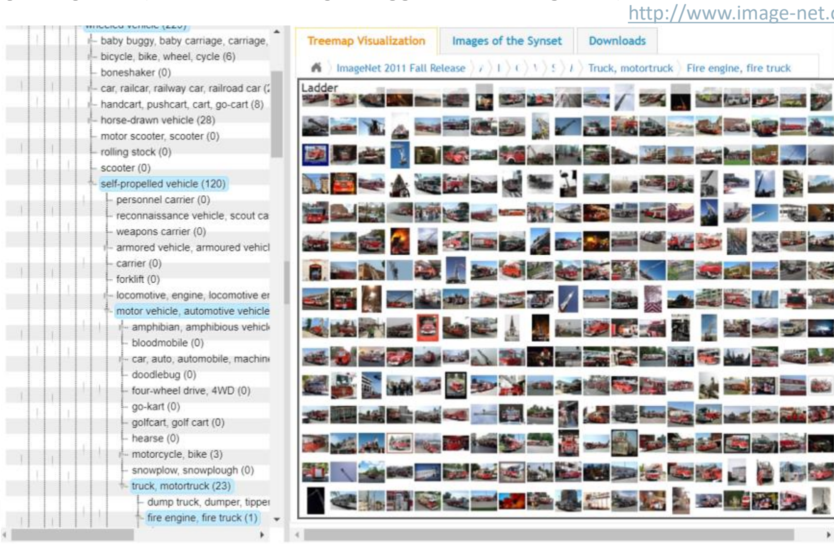
Larger Data Sets

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

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



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Larger Data Sets

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

http://cocodataset.org

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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 **x** often collected automatically, but they still need somebody to provide correct outputs **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 (10^12 **F**loating **P**oint **O**perations **P**er **S**econd)

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

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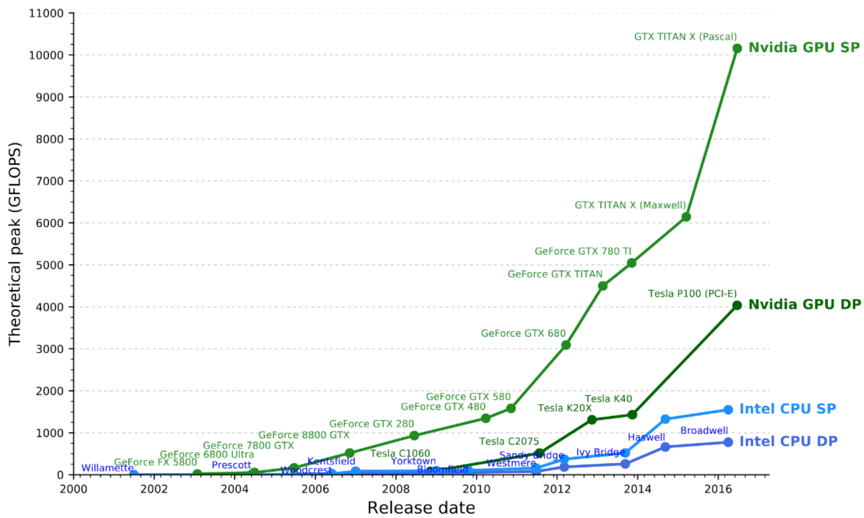
Faster Training - GPUs Increasingly Important



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

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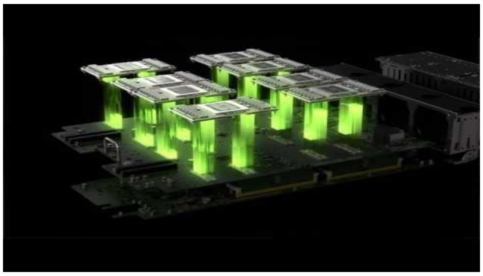
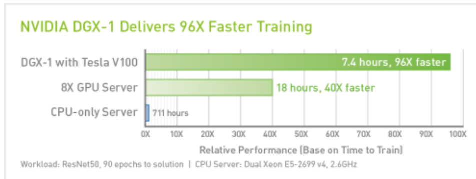
Faster Training - Deep Learning "Supercomputer"

- 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...



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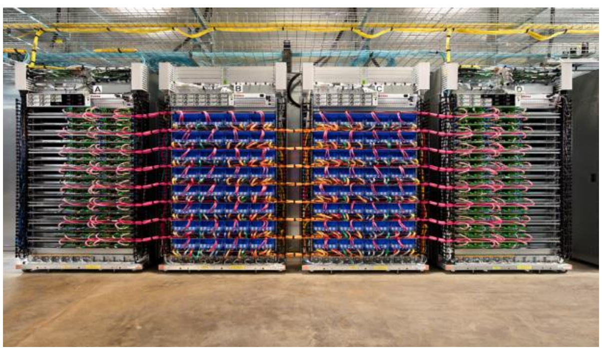
Faster Training - Beyond GPU's -> Custom Hardware

Google recently designed custom chips (ASICs) speficially 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

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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($\boldsymbol{m} \cdot w$), where **m** typically 1-50, much less than n = millions.

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

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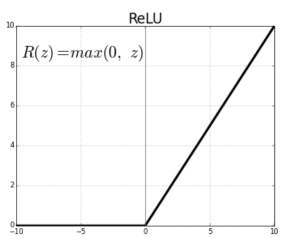
Faster Training – Modifying the Network

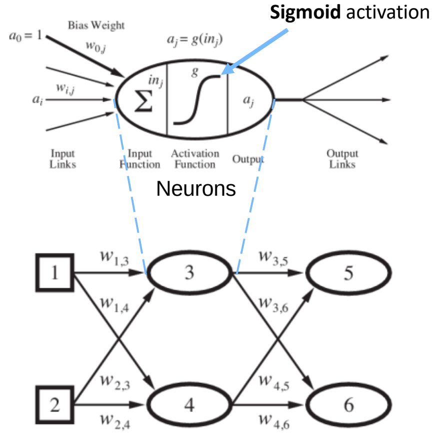
Remember the mathematical structure of neural network models:

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*)

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Training Tools – Generalized Backpropagation

Learning these advanced representations raises two issues:

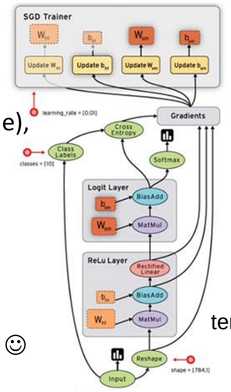
- Deep learning often uses **very large networks** with very large ("Big Data") training set
- **Advanced representations may require modifications to backpropagation**

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

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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 3x1920x1080 = 6M inputs
- Assume 1000 neurons in first layer
- Then each fully-connected neuron will have a weight for each input, 1000x6M = 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

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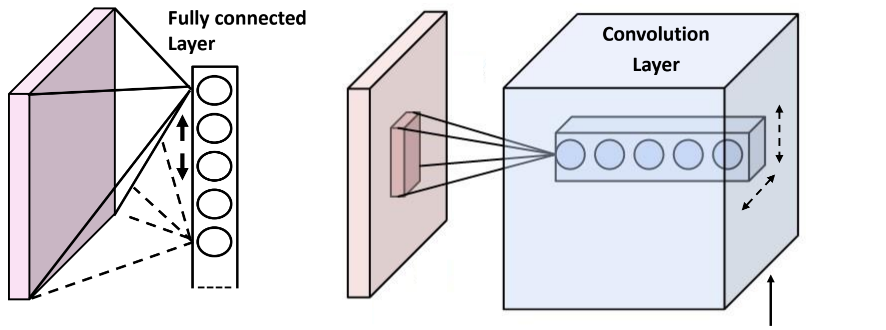
Architectures - Convolutional Layers

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)



Each CNN neuron is a 2D pattern extractor ideal for image data
CNNs retain a lot of information even **with few neurons**

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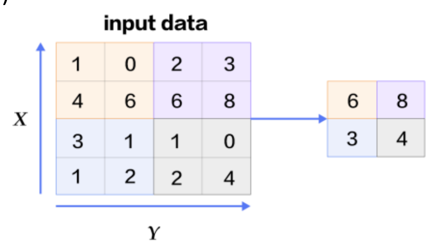
Architectures - CNN Pooling Layers

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)



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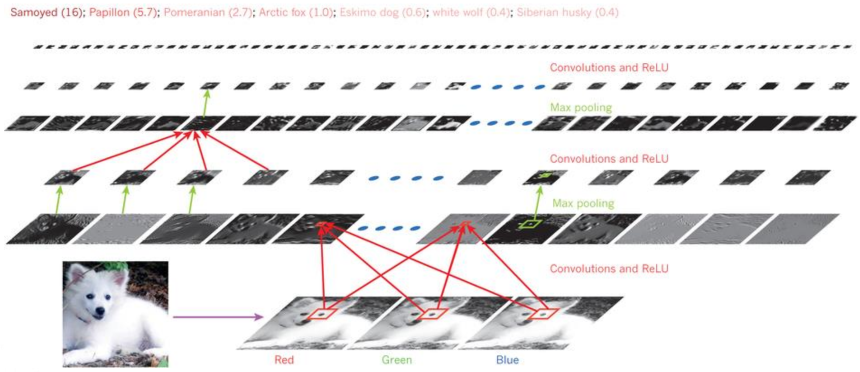
Architectures - Convolutional Neural Networks

- **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



(LeCun, Bengio and Hinton, 2015)

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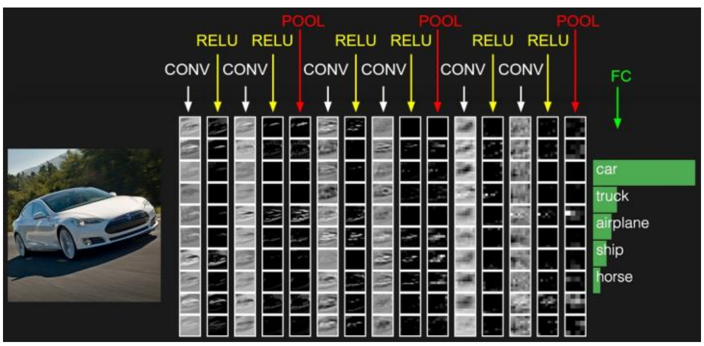
Architectures – CNNs for Object Recognition

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/

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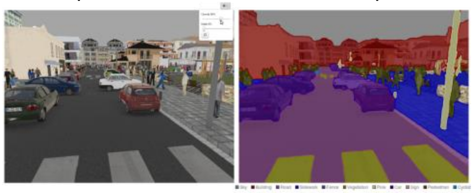
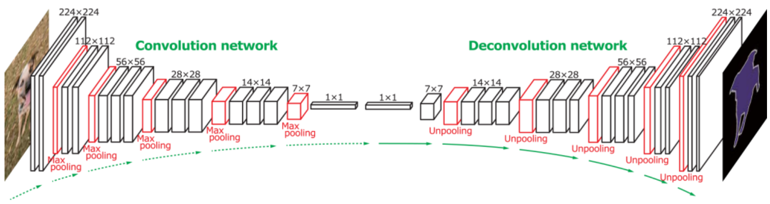
Architectures – CNNs for Segmentation

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



Classes: Road, car, pedestrian, building, pole, etc.
(NVIDIA)

- Deconvolutional networks do reverse convolution and pooling



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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

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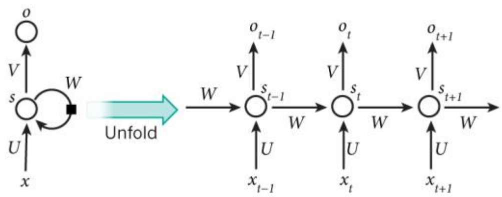
Architectures: Recurrent Neural Networks

- 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)

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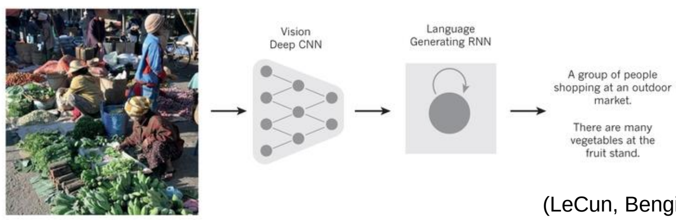
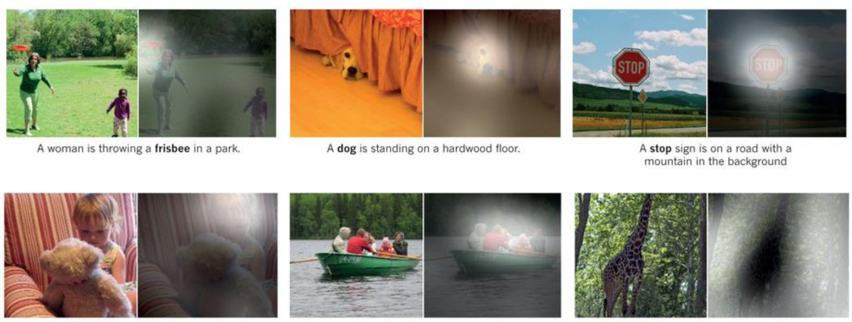
Architectures: Combining Network Structures



(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.

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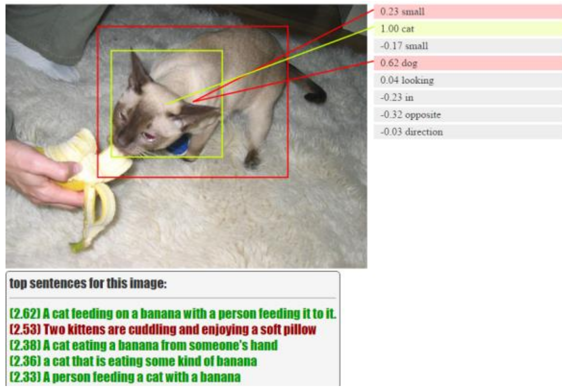
Demo – Visual-Semantic Alignment

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.



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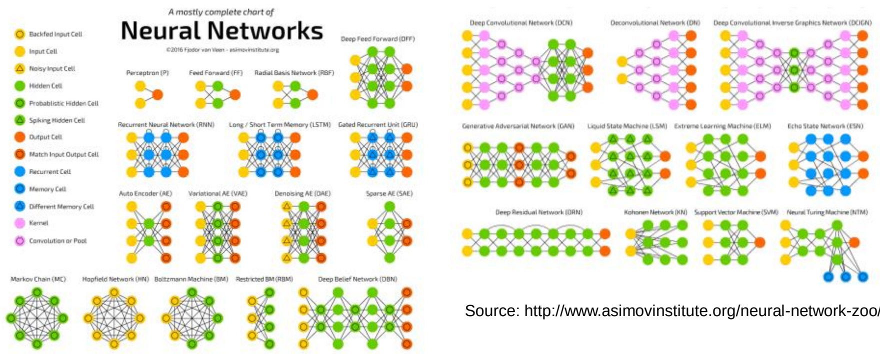
Architectures: The Neural Network Zoo

Many different types of structure, more or less modular components



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

- ...and more keeps being invented

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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

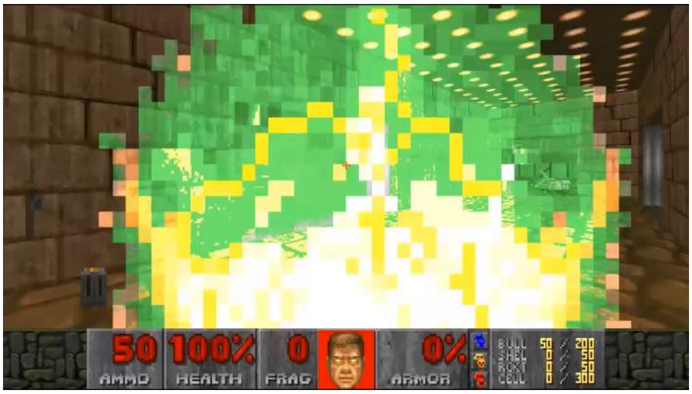
- From 80’s 2D ATARI to 90’s ”3D” Doom in <2 years

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!

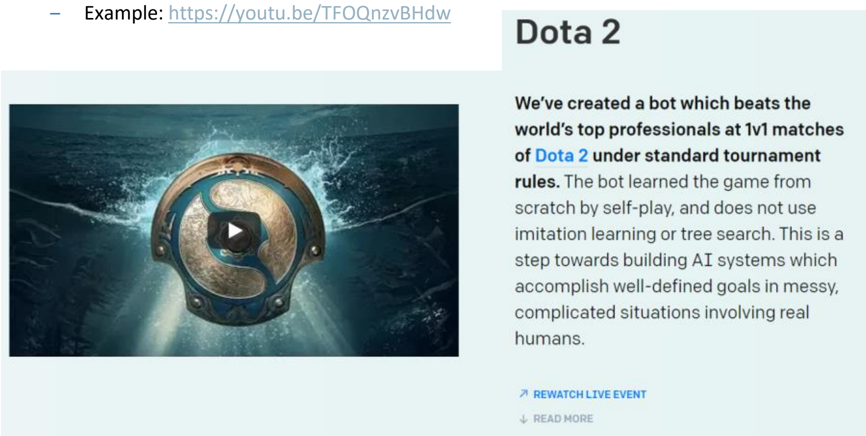
Q-learning Doom directly from **video** by using **CNN + RNN** for Q-function



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



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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.

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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!