A Gentle Introduction to Machine Learning

Third Lecture

Deep Learning – A Closer Look

Originally created by Olov Andersson
Revised and lectured by Yang Liu

LINKÖPINGS UNIVERSITET

1

The Story So Far…

In the previous lectures we talked about **supervised Learning**

- Definition
  - Learn **unknown function** y=f(x) given examples of (x, y)
- We choose a model such as a NN and **train** it on examples
  - Set **loss function** (e.g. square loss) between model and examples
  - Optimize model parameters via gradient descent (local minima)
- Trend: Neural Networks and Deep Learning

2

Outline of the Deep Learning Lecture

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

3

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ever increasing rate.* ***Humans****, who are limited by slow biological evolution, couldn't compete, and* ***would be superseded****."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 hypes** about the capabilities of AI, mainly driven by recent advances in **deep learning**.

4

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

5

5

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 learning and unsupervised learning are still less mature

So, what is deep learning?!

6

6

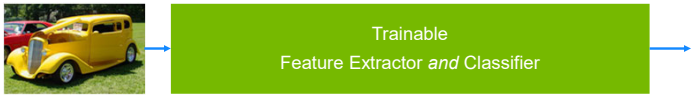
A General Approach For "AI scale" Real-world ML

In particular excels at human modalities:

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

"Traditional" machine learning

"Deep" machine learning



(NVIDIA)

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7

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, $y = f_{classifier}(g_{features}(D))$, 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...

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

8

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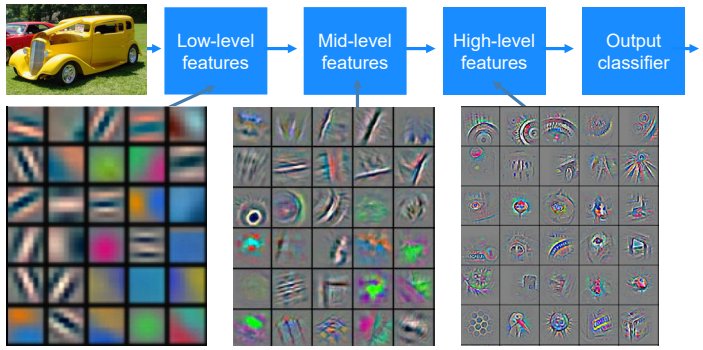
Deep learning = Learning Hierarchical Representations

It's deep if it has more than one layer of non-linear feature transformations

- **More 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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9

Many Problems Appear Naturally Hierarchical

Image recognition

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

Text

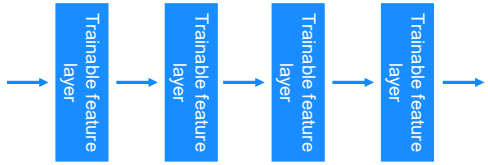
- Character → word → word group → clause → sentence → story

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



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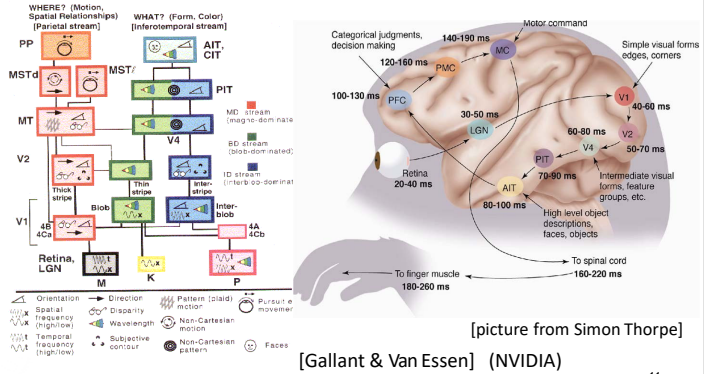
10

10

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]

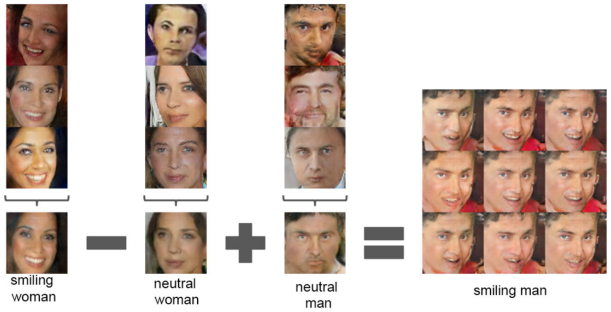
[Gallant & Van Essen] (NVIDIA)

11

11

So, Can Deep NNs Learn Abstractions?

Generated similar examples using learned high-level features



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

Clearly learning some kind of abstraction

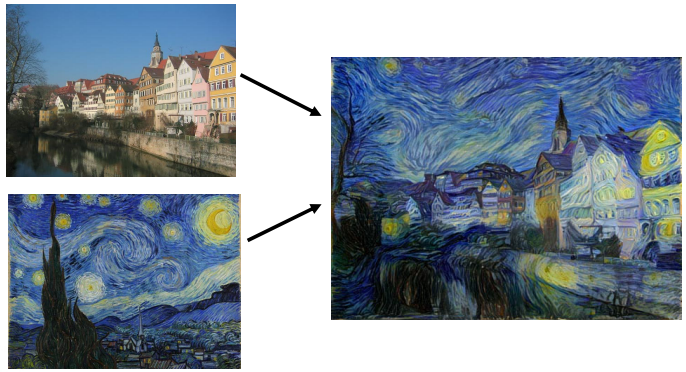
- Such "concept arithmetic" doesn't always work this well...

12

12

So, Can It Learn Abstractions II

Neural Style Transfer (deepart.io)



13

13

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

This was not feasible only until recently.

14

14

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

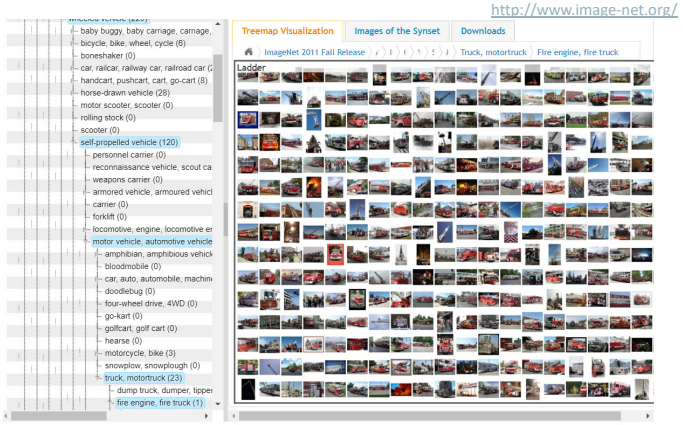
15

15

Larger Data Sets

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

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



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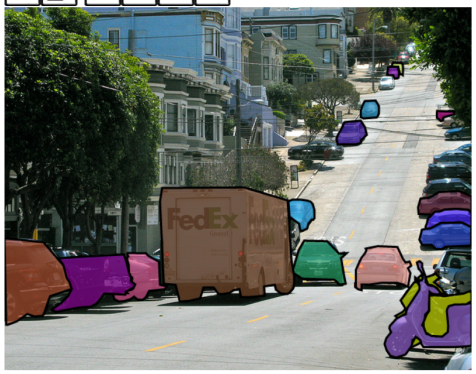
16

Larger Data Sets

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

http://cocodataset.org



17

17

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 often by offering free service to 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 instead of radar**
  - Can automatically collect raw images from their autopilot (not everything)

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 labelling**
- Sometimes outsourced to other countries, or Amazon Mechanical Turk
- By now, human labelling is still far more efficient and accurate

18

18

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19

19

Faster Training

Consumer Desktop CPU

- Speed: ~1 TFLOPS (10^12 **F**loating **P**oint **O**perations **P**er **S**econd)

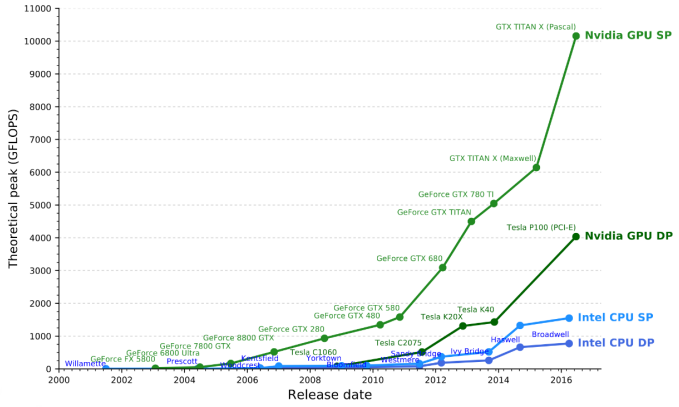
Consumer Graphics Card (GPU)

- 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
- Tesla V100 is the world's first GPU to break the **100 TFLOPS** barrier of deep learning performance

20

20

Faster Training - GPUs Increasingly Important



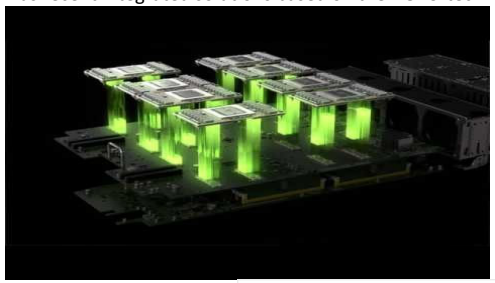
https://github.com/mgalloy/cpu-vs-gpu/

21

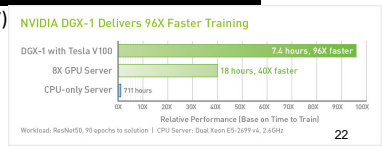
21

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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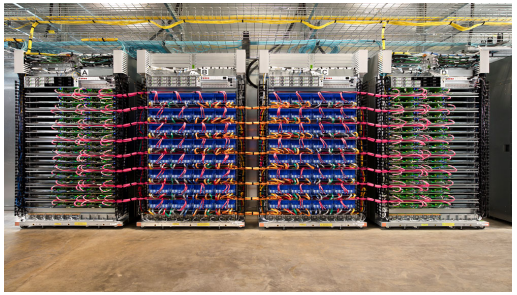
22

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

23

23

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 gradients or converging in fewer iterations
  - E.g. different activation functions or network structure

24

24

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 **on all n examples**
- Computing a gradient is O($n \cdot w$) even using the fast backpropagation algorithm (lecture 1)

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

25

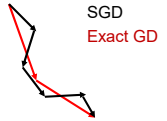
25

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 1-100, much less than n = millions.
- **The approximation over sevaral steps will average out**, and have much **lower computational** cost



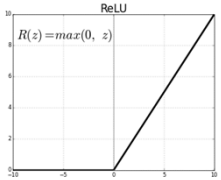
26

26

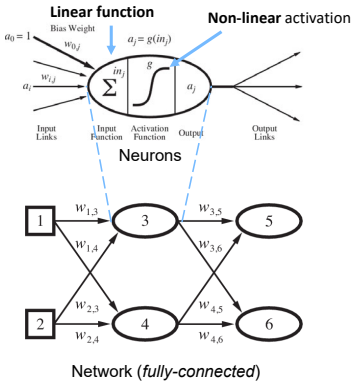
Faster Training – Modifying the Network

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 **rectified linear unit (ReLU),** R(z) = max(0,z)



Simpler gradients and more stable over time!



27

27

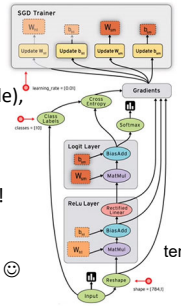
Fast Training Tools via Generalized Backpropagation

Deep learning often uses advanced architectures, not just fully-connected feed-forward ("Dense") neural networks like in the first ML lecture
- These are typically **very large networks** with **very large training sets**
- **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), and **PyTorch** (Facebook) let you define **arbitrary models** by **differentiating graphs of mathematical operations** on one or several **GPUs**
- Orders of magnitude faster than CPU backprop!
- Much easier than manually doing backprop

Will we ever have to manually differentiate again? ☺



28

28

Code Examples: Tensorflow NN Training

- See workbook at: http://bit.ly/2o9NV1o
  - Choose File->Save Copy in Drive to run and edit your own version
  - This is covered in Lab 6.
- 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).

29

29

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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

30

30

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

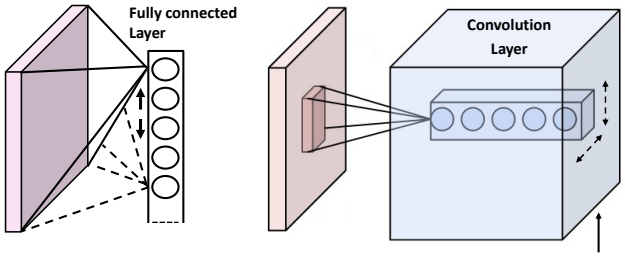
31

31

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**

32

32

Architectures – More on Convolutional Layers

- Animated demo of CNN calculations:
  http://cs231n.github.io/assets/conv-demo/index.html
- For more details, see the excellent resource (some were used in this PPT):
  http://cs231n.github.io/convolutional-networks/

33

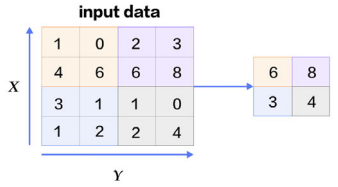
33

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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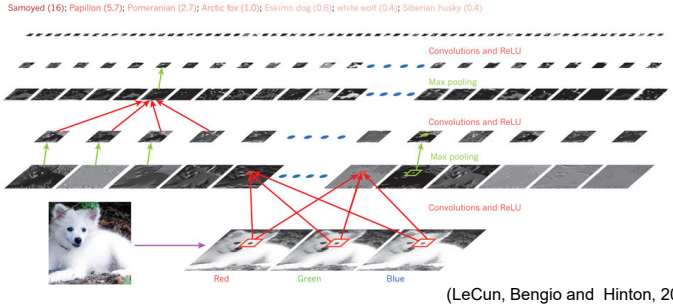
34

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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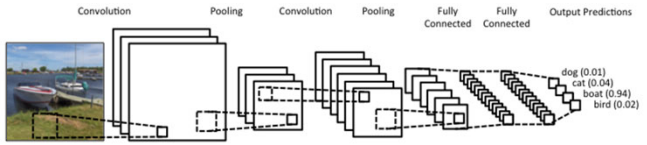
Architectures – CNNs for Object Recognition

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/

36

36

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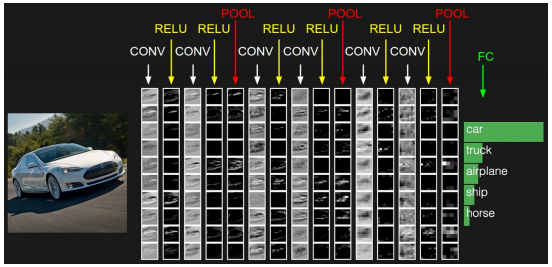

Karpathy, http://cs231n.github.io/convolutional-networks/

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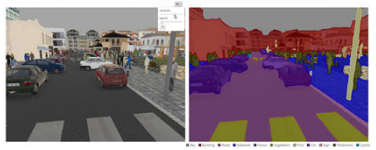
37

Architectures – CNNs for Segmentation

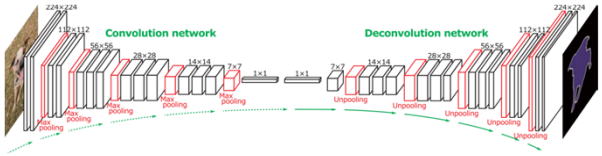
- Segmentation (typically images) requires us to classifiy **each input** (pixel), e.g. network output is same dimension as input



Classes: Road, car, pedestrian, building, pole, etc.

(NVIDIA)

- Deconvolutional networks do reverse convolution and pooling



38

38

Architectures – CNN Demo

- Online CNN demo:
  http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html
  This demo trains a CNN on the CIFAR-10 dataset in the browser, with nothing but JavaScript.

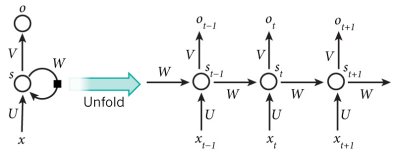
- See also the CNN code example in the previous TensorFlow workbook
  http://bit.ly/2o9NV1o

39

39

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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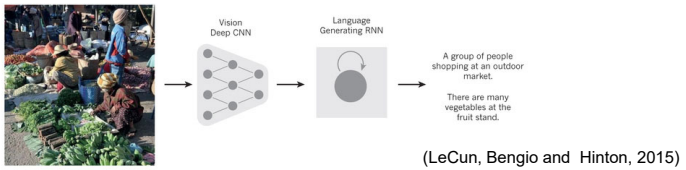
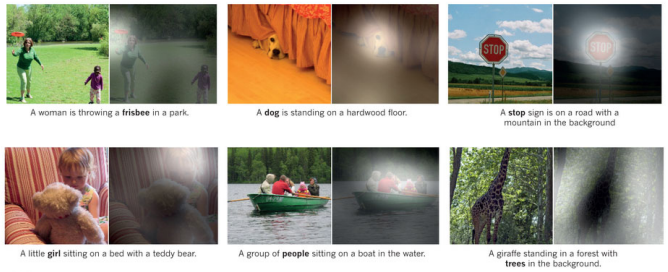
Architectures: Combining Network Structures



(LeCun, Bengio and Hinton, 2015)



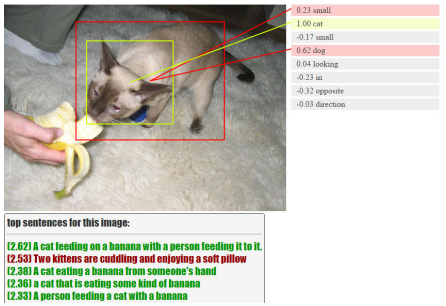
41

41

Demo – Visual-Semantic Alignment

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

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



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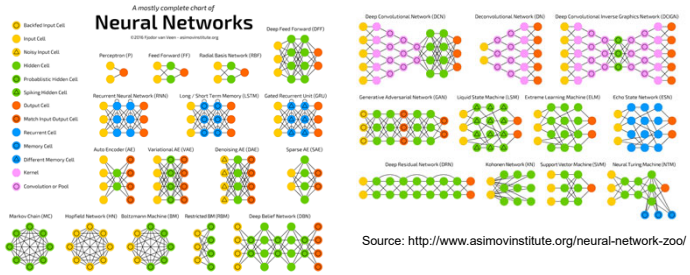
42

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

43

43

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 used Deep Q-learning, where the **Q-function Q(s,a)** was fed raw pixels as state s, enabled by representing it as a **CNN** instead of a table (Lab 5).

That was 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.

44

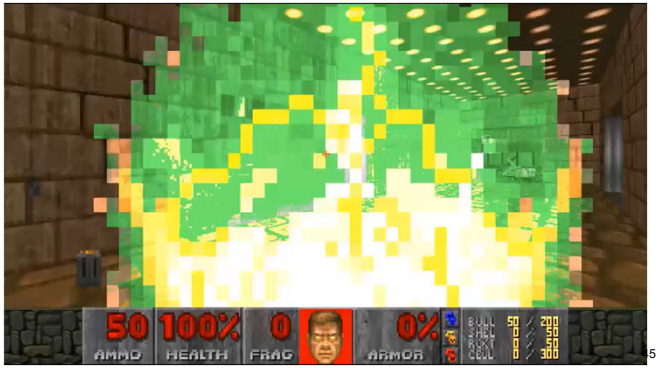
44

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



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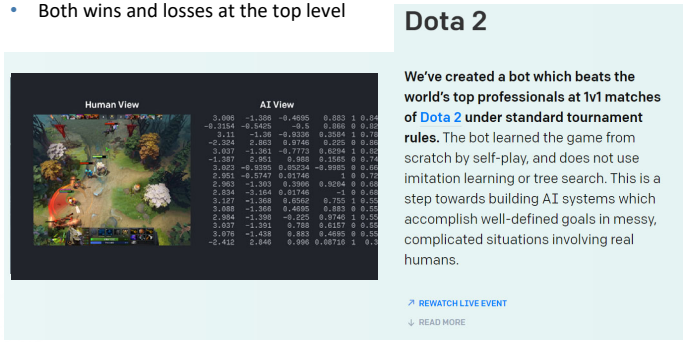
Deep Reinforcement Learning – Example II

The OpenAI research institute plays human experts in the popular game of Dota 2 (https://openai.com/five/)

- Towards learning strategies in **team games**
- Example: https://www.youtube.com/watch?v=LVrpWrvHVNE
- Both wins and losses at the top level

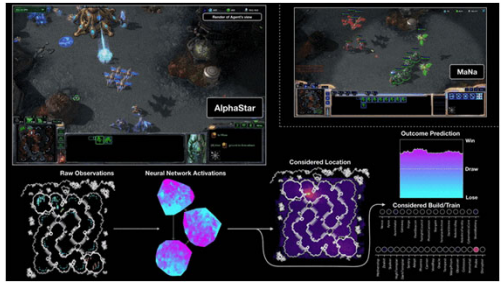


46

46

Deep Reinforcement Learning – Example III

- DeepMind's AlphaStar for Starcraft II
  - https://deepmind.com/blog/article/alphastar-mastering-real-time-strategy-game-starcraft-ii



- NOTE: These examples require **massive compute budgets** and expertize, and how well they generalize remains an open question

47

47

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

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

48

48

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!

49

49

About Lab 6 on Deep Learning

- Lab 6 on Tensorflow and (Deep) Neural Networks
- Teaching you deep learning in just a few hours is a challenge for us, but we think it is important that you get some hands-on experience.
- We are using Google Colab for free computational resources (CPU/GPU) and ease of setup (which can be complicated).
- It is structured more like a tutorial with **only three questions** to answer along the way.
- Ask your TA if you get stuck.
- If you think something could be improved, or find a bug in the lab, feel free to mail me at olov.a.andersson@liu.se

50

50