

A walk with deep learning

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Previously on Stardust LTW-I...

- Use of high levels APIs for deep learning (fastai)
- Transfer learning & fine tuning vision models for image classification
- Classification & Regression on Tabular Data
- Handling imbalanced datasets

<https://github.com/stardust-r/LTW-I>

Outline

Day 1

1. Introduction
 - a. What is deep learning?
 - b. Deep learning milestones
 - c. Basics on Machine/Deep learning
 - d. Deep learning = Machine learning with Neural networks
 - e. Areas of success in deep learning
 - f. Why is deep learning currently booming?
2. Getting started
 - a. Getting a GPU deep learning server
 - b. Hands-on 1: Building a simple deep neural network in Pytorch
3. Practical tips & best practices
 - a. Experiment tracking
 - b. Software development in Jupyter Notebooks with nbdev

Day 2

1. Going deeper into deep learning
 - a. Going deeper into deep learning
 - b. Convolutional Neural Networks
 - c. How does a filter look like?
 - d. Generative Adversarial Networks
 - e. Building a convolutional neural network with Keras
 - f. Natural Language Processing with Deep Learning
 - g. Transformers
2. Final discussion
 - a. Trending topics and future opportunities
 - b. Ethical aspects
 - c. Limits of deep learning
 - d. Free ML/DL resources

Day 1

A walk with deep
learning

1. Introduction

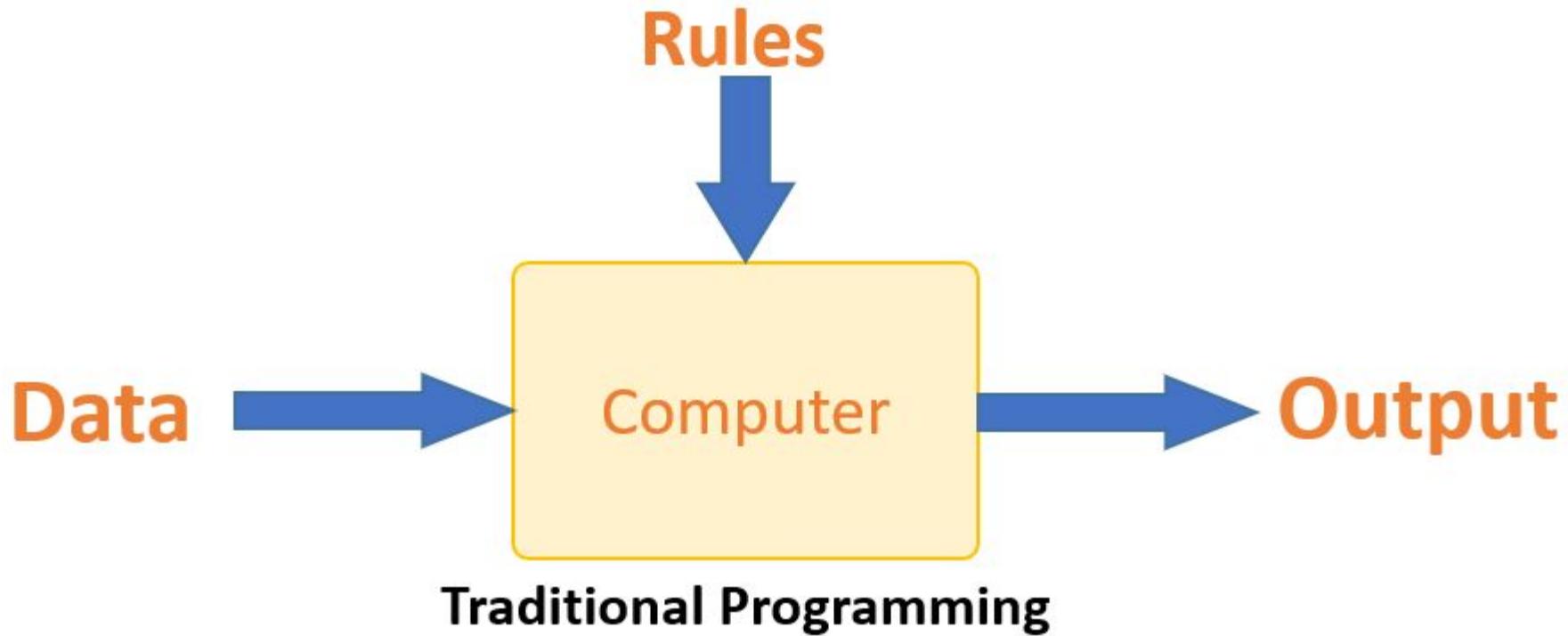


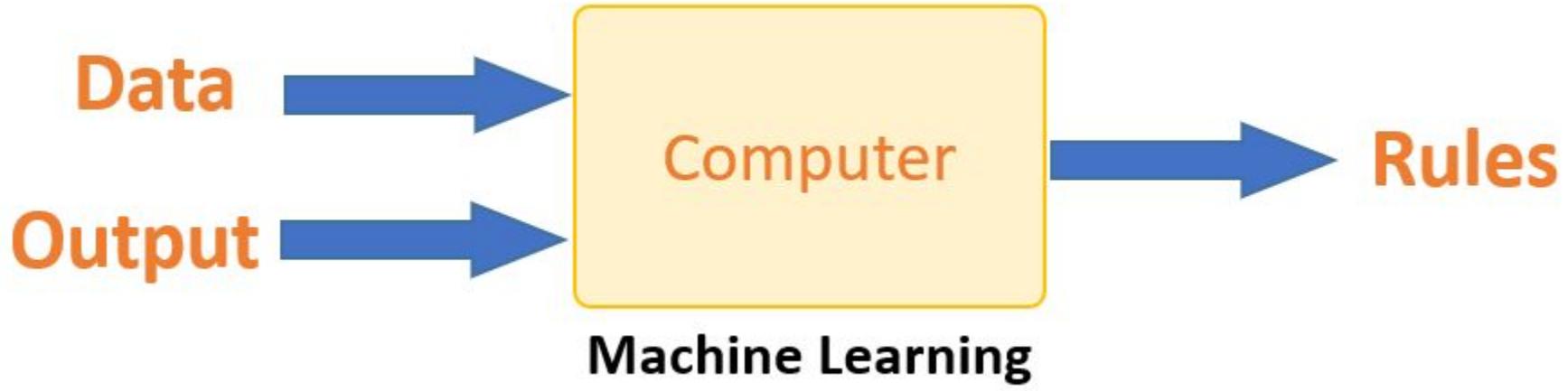
What is machine learning?

Arthur Samuel (1949)

"Suppose we arrange for some automatic means of testing the effectiveness of any current weight assignment in terms of actual performance and provide a mechanism for altering the weight assignment so as to maximize the performance. We need not go into the details of such a procedure to see that it could be made entirely automatic and to see that a machine so programmed would "learn" from its experience."







ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



1950's

1960's

1970's

1980's

MACHINE LEARNING

Machine learning begins to flourish.



1990's

2000's

2010's

DEEP LEARNING

Deep learning breakthroughs drive AI boom.



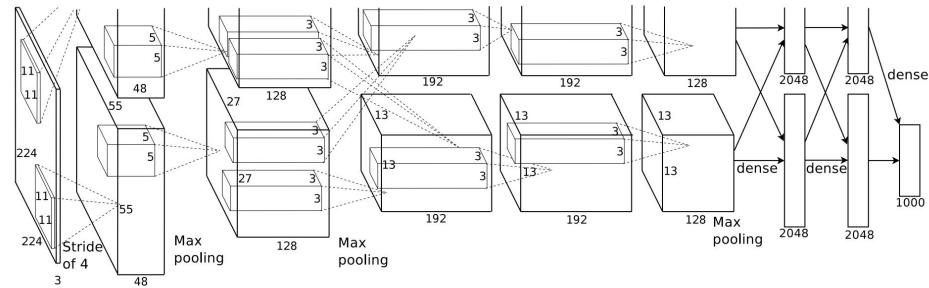
<https://docs.paperspace.com/machine-learning/>

Since the optimistic beginnings of AI in the 1950s, small subfields of AI – first Machine Learning and then Deep Learning (a subfield of Machine Learning) have made huge milestones.

Deep learning milestones

AlexNet (Krizhevsky et al., 2013)

AlexNet is a classic convolutional neural network architecture. It consists of convolutions, max pooling and dense layers as the basic building blocks. Grouped convolutions are used in order to fit the model across two GPUs.



AlphaGo (DeepMind, 2016)



2018 Turing award



Yoshua Bengio

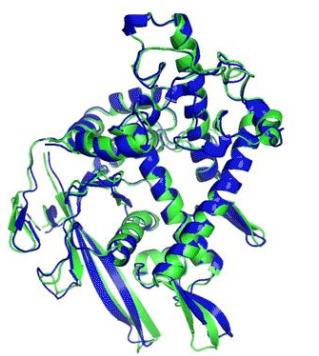


Geoffrey Hinton

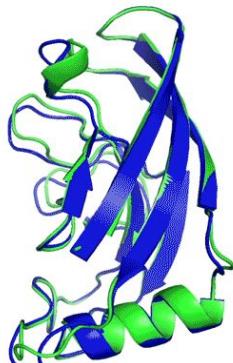


Yann LeCun

AlphaFold2 (DeepMind, 2020)

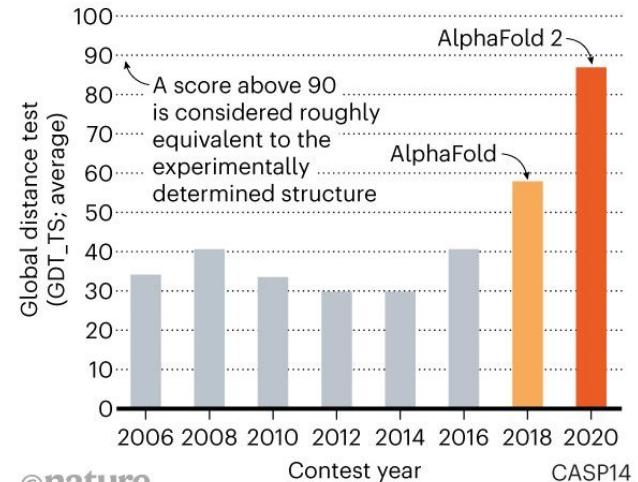


T1037 / 6vr4
90.7 GDT
(RNA polymerase domain)



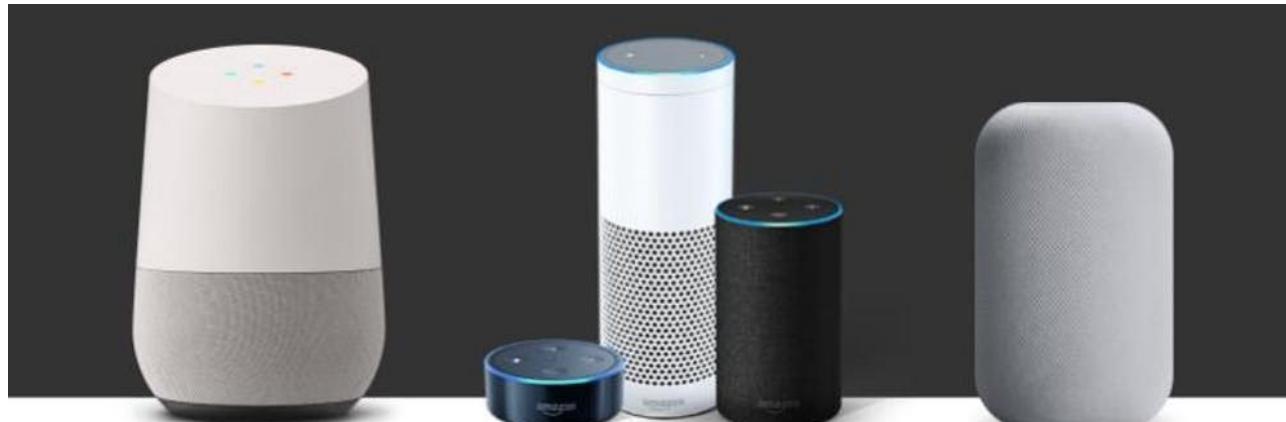
T1049 / 6y4f
93.3 GDT
(adhesin tip)

- Experimental result
- Computational prediction



©nature

Speech recognition - Smart speakers



Self driving cars

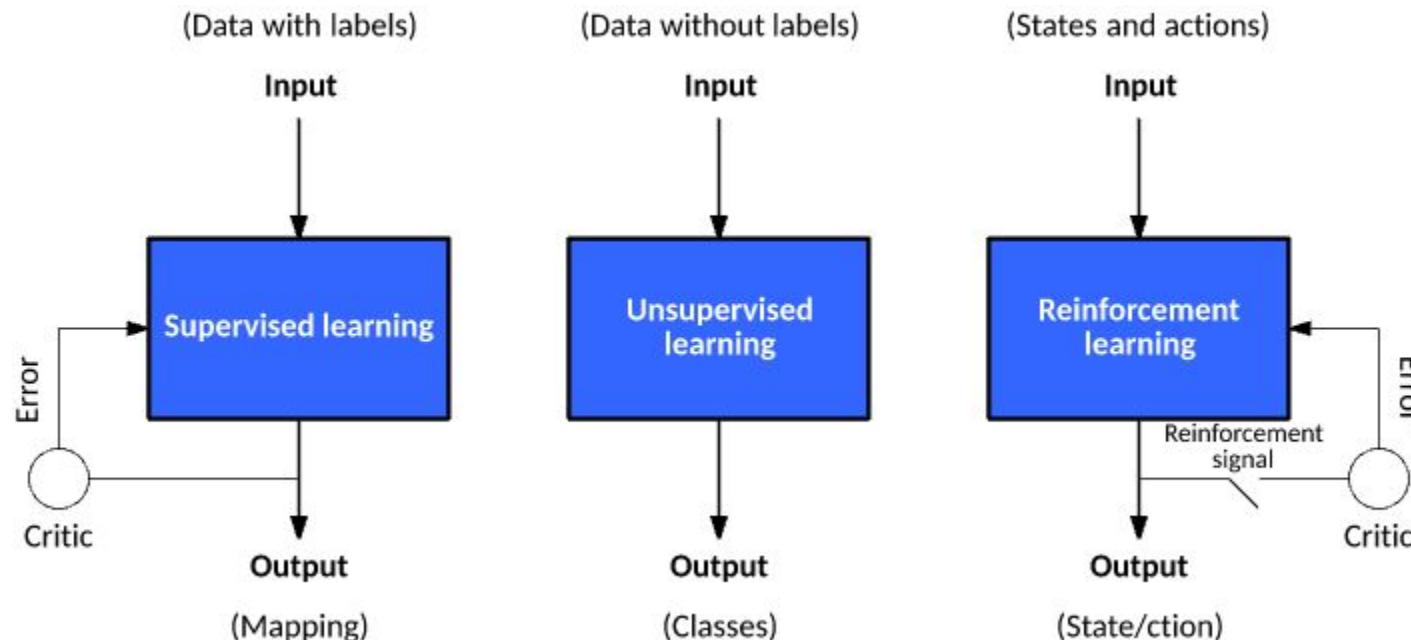


Basics on Machine/Deep Learning

Jargon

- the functional form of a model -> architecture
- the weights -> parameters
- the results -> predictions
- the measure of performance -> loss
- the dependent variable -> targets, y (labels in the context of classification)

Types of Machine learning



Tasks in supervised learning



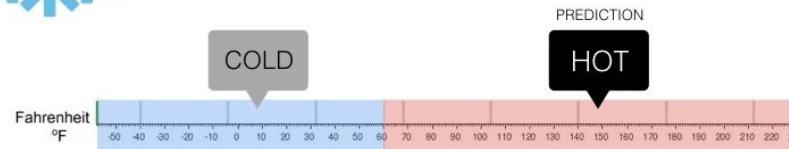
Regression

What is the temperature going to be tomorrow?



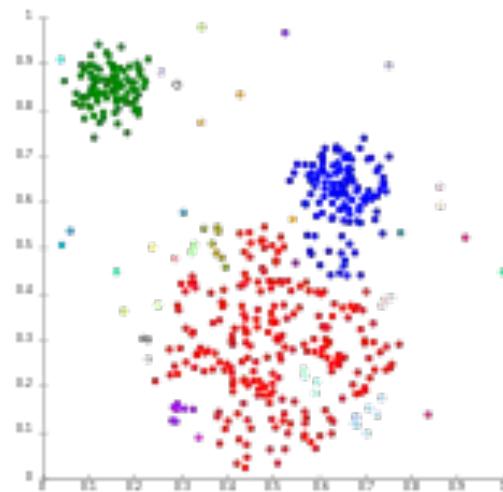
Classification

Will it be Cold or Hot tomorrow?



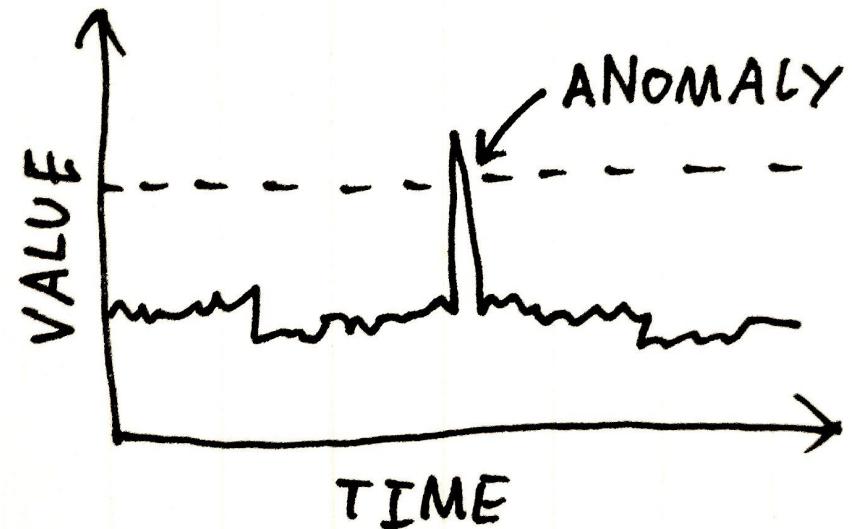
Tasks in unsupervised learning

Clustering



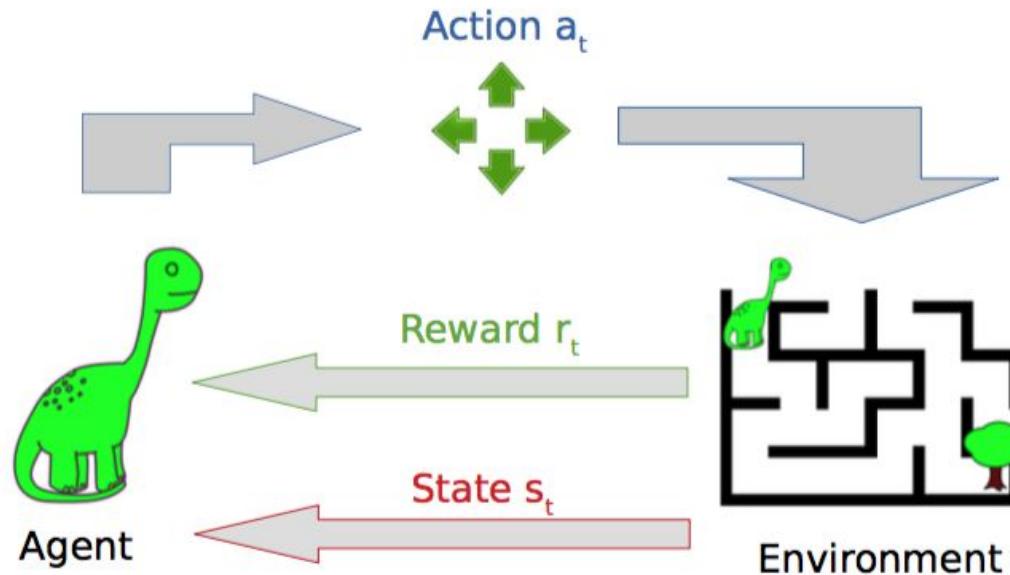
https://en.wikipedia.org/wiki/Cluster_analysis

Anomaly detection



https://github.com/project-anomalia/anomalia/blob/master/time_series.go

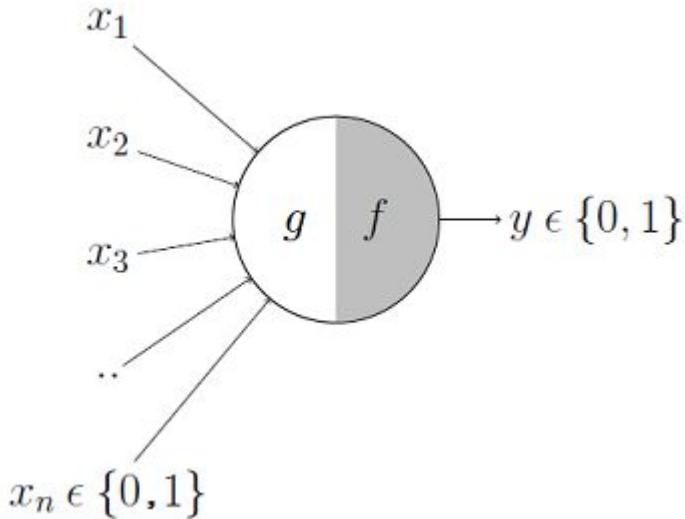
Reinforcement learning



Deep learning = Machine
learning with Neural
networks

Model of an artificial neuron (1943)

- Binary input data (x)
- Aggregation function (g)
- Activation function (f)

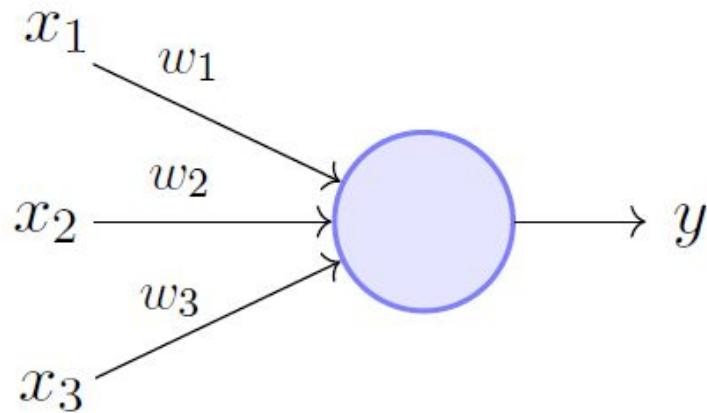


$$y = 1 \quad if \sum_{i=0}^n x_i \geq 0$$

$$= 0 \quad if \sum_{i=0}^n x_i < 0$$

The perceptron (1958)

- Inputs can have numeric values, other than 0 and 1
- Inputs have associated **weights**



$$y = 1 \quad if \sum_{i=0}^n \textcolor{red}{w}_i * x_i \geq 0$$

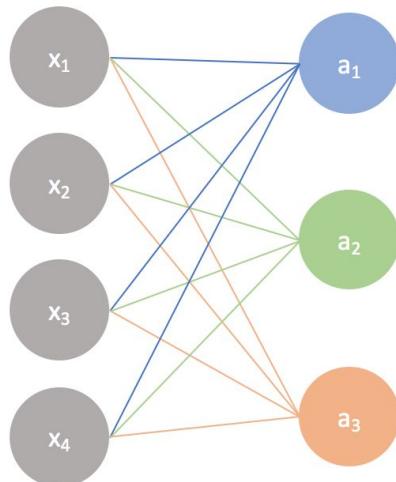
$$= 0 \quad if \sum_{i=0}^n \textcolor{red}{w}_i * x_i < 0$$

Matrix multiplication is all you need

Input layer

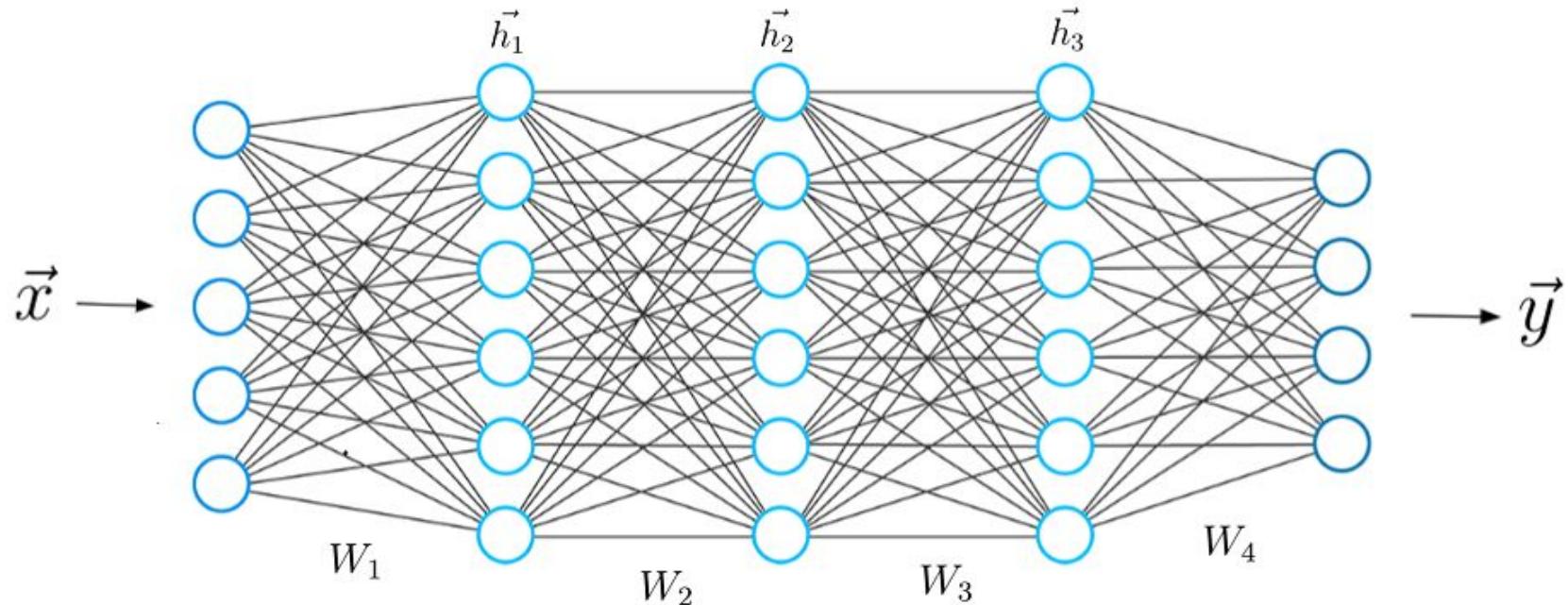
Output layer

A simple neural network



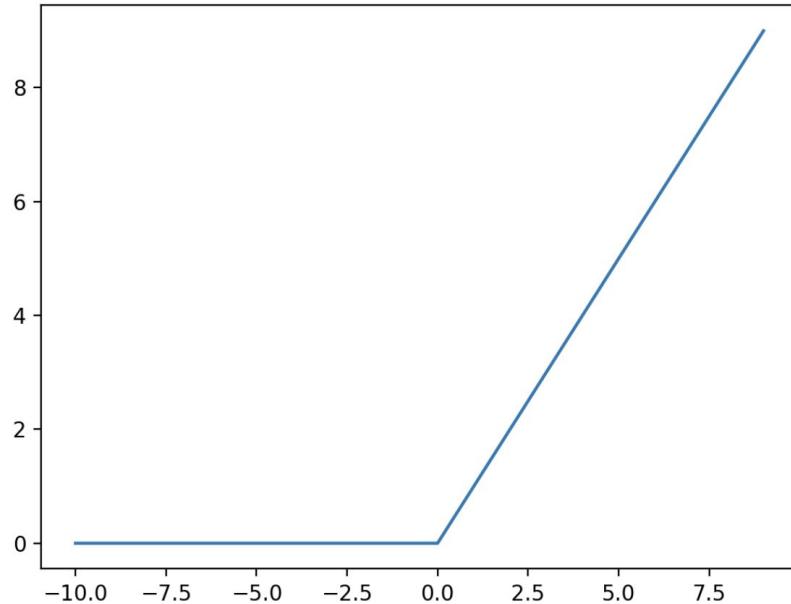
$$\begin{bmatrix} w_1 & w_2 & w_3 & w_4 \\ w_1 & w_2 & w_3 & w_4 \\ w_1 & w_2 & w_3 & w_4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} b \\ b \\ b \end{bmatrix} = \begin{bmatrix} w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \\ w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \\ w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \end{bmatrix} \xrightarrow{\text{activation}} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}$$

Going deep



Activation functions

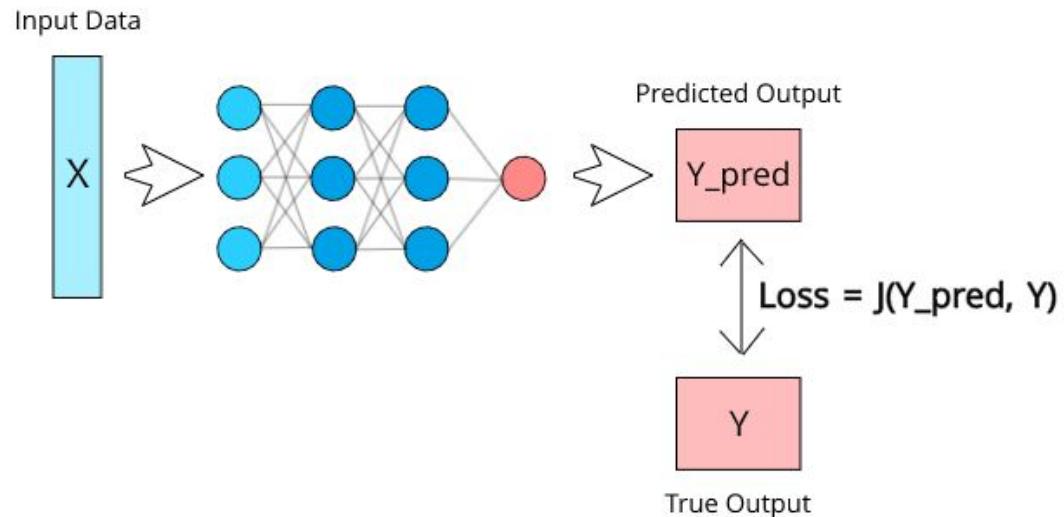
Non linearities applied after the matrix multiplication. The rectified linear unit, or ReLU, has been the most popular in the past decade.



Loss functions

Loss Functions are used to frame the problem to be optimized within deep learning. Most popular ones are:

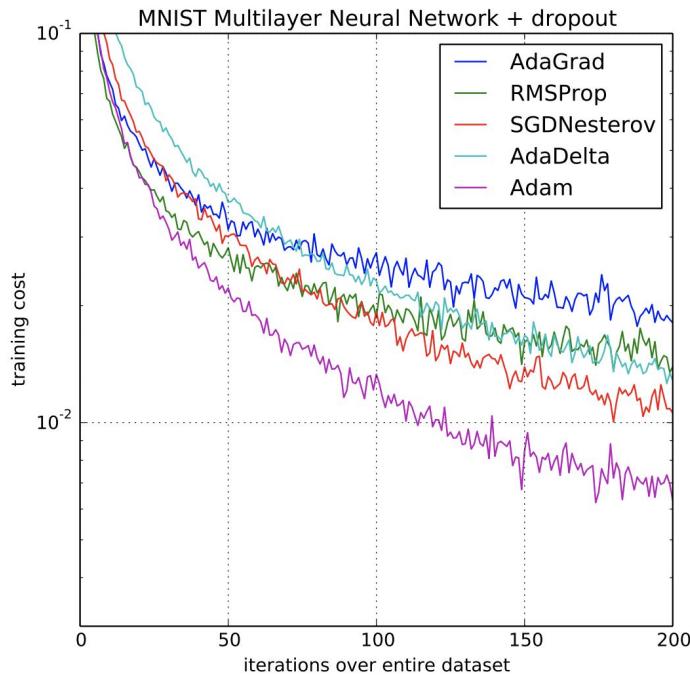
- Cross Entropy Loss
(classification)
- Mean Squared error (regression)



Stochastic optimization

Used to train neural networks. They iteratively take a “mini-batch” of data, hence ‘stochastic’, and perform gradient descent on the loss function for that batch. Most popular methods are:

- SGD
- Adam



Areas of success in deep learning: Computer vision

Image classification

Image Classification is one of the most popular tasks in computer vision. It attempts to comprehend an entire image as a whole.

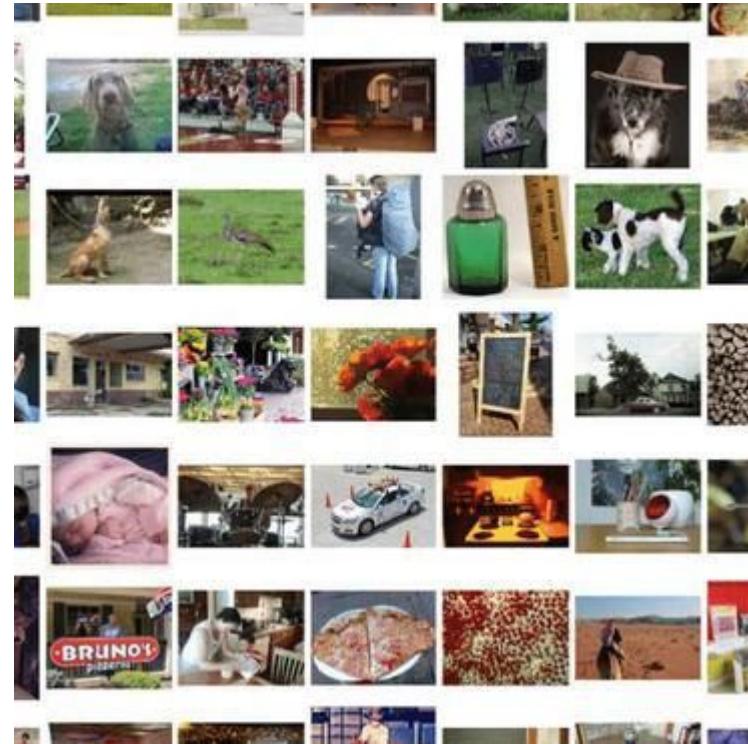


Image segmentation

Semantic segmentation, or image segmentation, is the task of clustering parts of an image together which belong to the same object class.



Object detection

Object detection is the task of detecting instances of objects of a certain class within an image.



Image generation

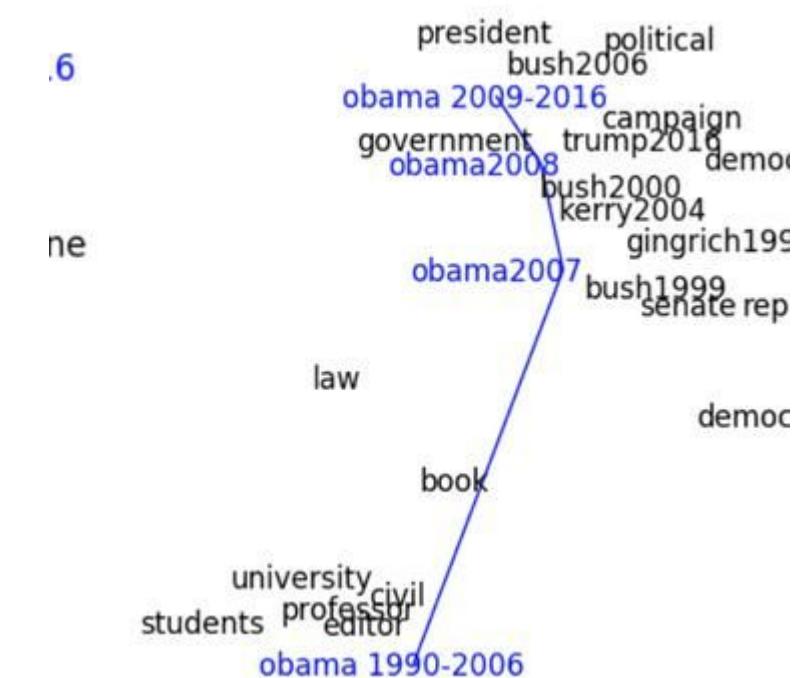
Image generation (synthesis) is the task of generating new images from an existing dataset.



Areas of success in deep
learning: Natural
Language Processing

Word embeddings

Word embedding is the collective name for a set of language modeling and feature learning techniques in natural language processing (NLP) where words or phrases from the vocabulary are mapped to vectors of real numbers.



Language modelling

Language modeling is the task of predicting the next word or character in a document.



Question Answering

Question Answering is the task of answering questions (typically reading comprehension questions), but abstaining when presented with a question that cannot be answered based on the provided context

Passage Sentence

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity.

Question

What causes precipitation to fall?

Answer Candidate

gravity

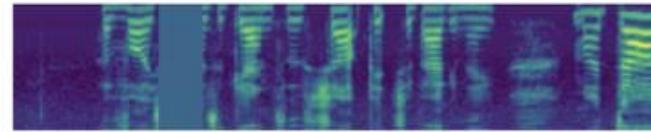
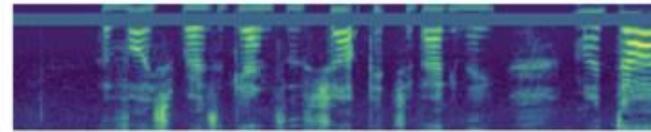
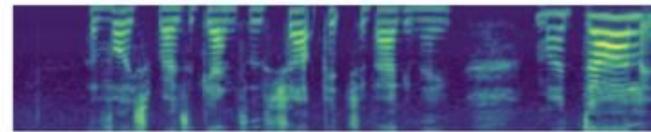
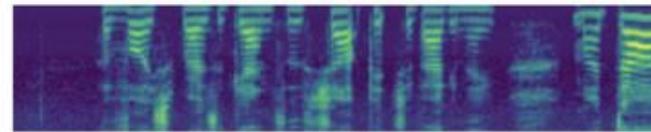
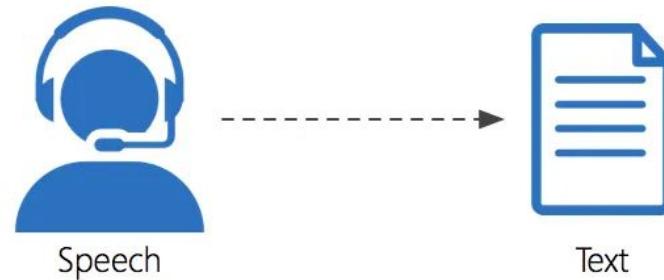
Other areas of success in
deep learning

Recommender systems



Speech Recognition

Speech recognition is the task of recognising speech within audio and converting it into text.



https://apkgk.com/com.knowledge.speech_1

<https://paperswithcode.com/task/speech-recognition/codeless?page=7>

Speech Synthesis

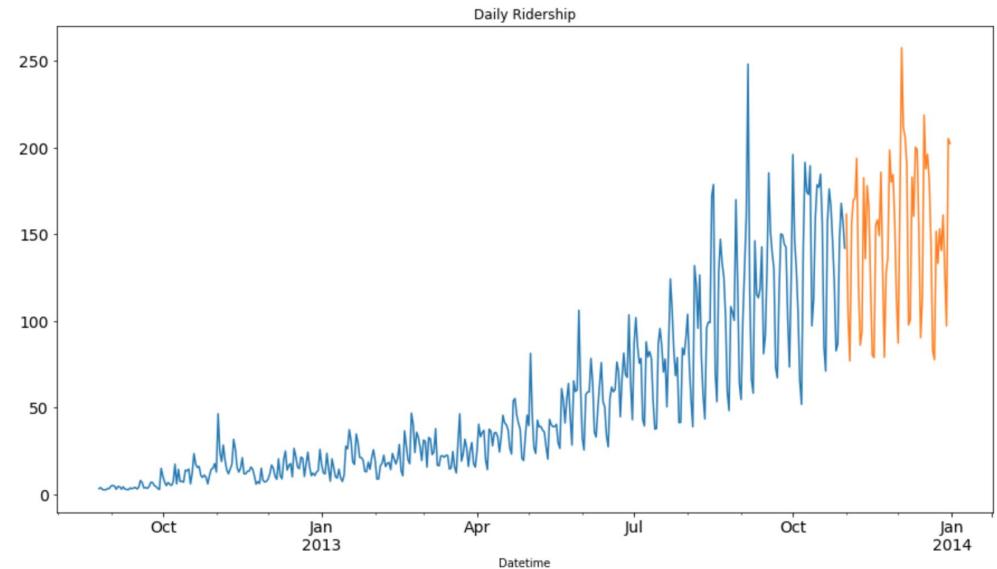
Speech synthesis is the task of generating speech from some other modality like text, lip movements etc.



www.explainthatstuff.com

Time series forecasting

Time series forecasting is the task of predicting future values of a time series (as well as uncertainty bounds).



Playing games

The games task involves training a reinforcement learning agent to play a game with the highest possible score.



<https://paperswithcode.com/task/game-of-chess>

<https://paperswithcode.com/task/game-of-go/codeless>

<https://paperswithcode.com/task/atari-games>

<https://paperswithcode.com/task/starcraft-ii>

Why is deep learning
currently booming?

GPU costs & availability

47X Higher Throughput Than CPU Server on Deep Learning Inference



Workload: ResNet-50 | CPU: 1X Xeon E5-2690v4 @ 2.6 GHz | GPU: Add 1X Tesla P100 or V100

Deep learning frameworks



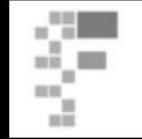
Free learning courses



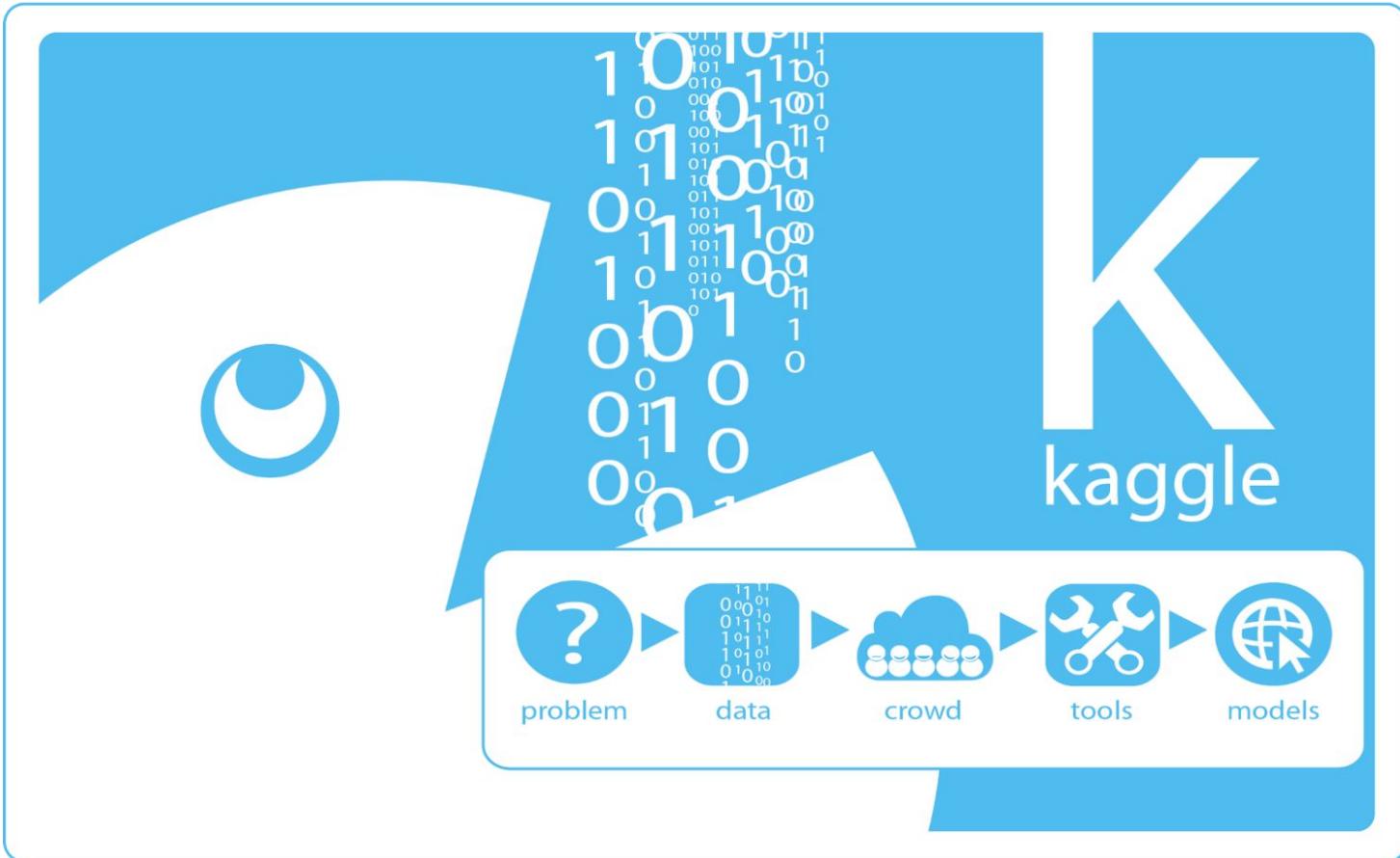
Stanford CS231n
(videos en Youtube)



Deep Learning for NLP
at Oxford with Deep Mind 2017



Fast.ai
Practical Deep Learning for Coders



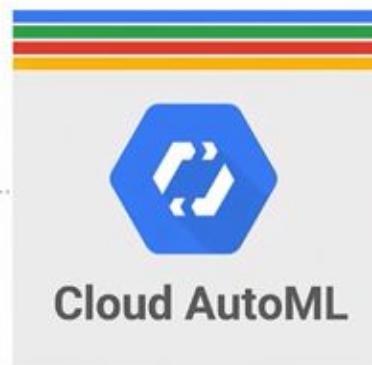
AutoML

Cloud AutoML Vision

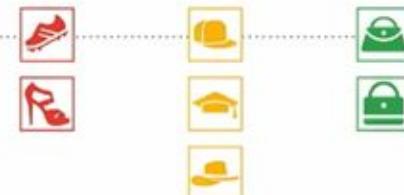
Upload and label images



Train your model



Evaluate



2. Getting Started



Getting a GPU deep learning server

Free online platforms with GPUs

- Google Colab
 - Storage on Google drive account
 - Lots of pre-installed libraries for ML
- Paperspace Gradient
 - Full Jupyter Notebook instance
 - Provides some space to save notebooks and models (5 GB)
 - Only 1 Free Notebook can be run at a time
 - All Notebooks will be set to public and cannot be set to private
- BlazingSQL Notebooks
 - 26 GB free HDD
 - JupyterLab instance



Create Instance

| | | | |
|----------------|---|---------|---|
| Framework | PyTorch | Cost | \$0.490/hr |
| Number of GPUs | 1 | RAM | 32GB |
| GPU Type | RTX5000-16GB | Cores | 7 |
| HDD |  | Version | 1.7 |
| | 20GB - \$0/hr | |  |

<https://cloud.jarvislabs.ai/>

Full remote dedicated servers with GPUs (Datacrunch.io, GoogleCloud, JarvisCloud, ...)

Deep learning 101 with Pytorch and fastai

[https://github.com/stardust-r/walk
-with-deep-learning](https://github.com/stardust-r/walk-with-deep-learning)

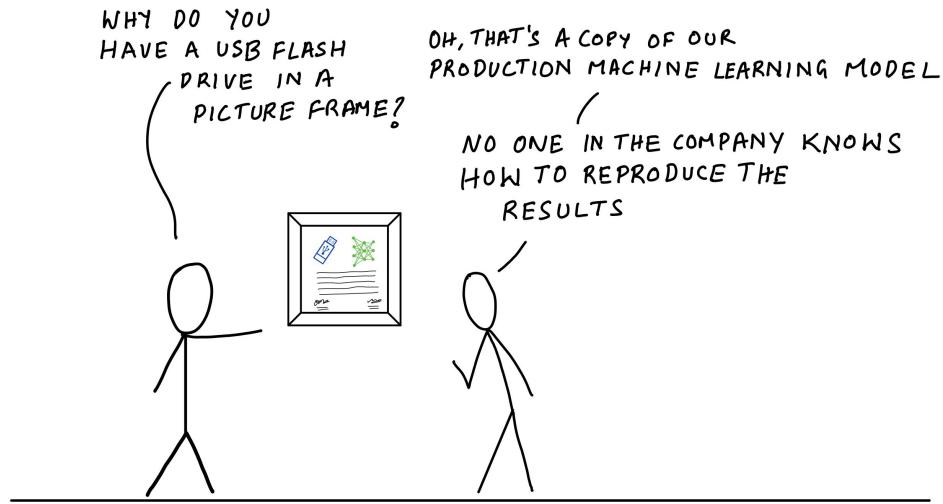
3. Practical tips and best practices



Experiment tracking

Who needs Experiment tracking and why?

- Single scientists
 - Coming back to old ideas
 - Compare and visualize runs
 - Hyperparameter tuning
- Teams
 - Share ideas and insights
 - Store experiment metadata
 - Onboarding new members easier



Tools for ML experiment tracking

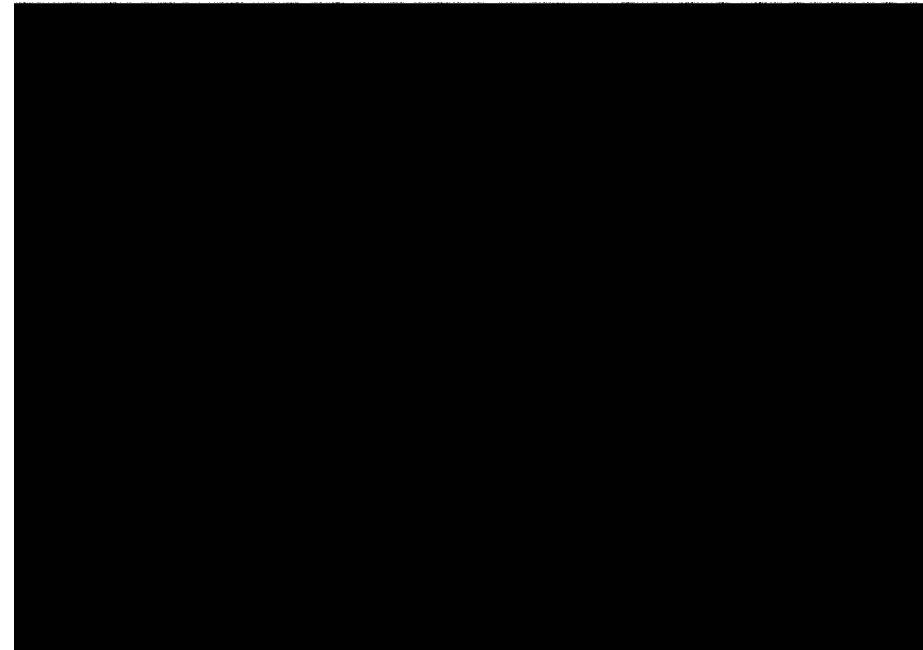
See a comparative in:

<https://neptune.ai/blog/best-ml-experiment-tracking-tools>

1. Neptune
2. **Weights & Biases**
3. Comet
4. Sacred
5. MLFlow
6. TensorBoard
7. ...

Weights & Biases (wandb)

- Created for deep learning experiment tracking
- Easy integration with the most popular ML libraries (Tensorflow, Keras, Pytorch, fast.ai, scikit-learn, ...)
- Customizable visualisation and reporting tools

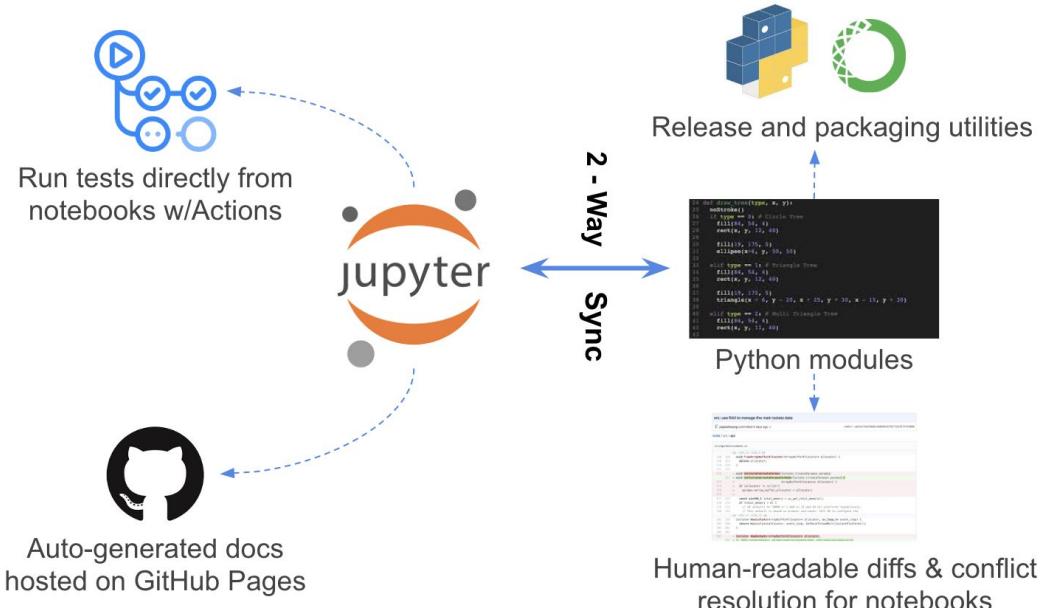


Weights & Biases

See wandb project for this talk:
<https://wandb.ai/vrodriguezf/TS-III>

Software development in Jupyter Notebooks

Nbdev overview



Conflict resolution for notebooks

```
<<<<< HEAD
```

```
In [5]: ┌─ path = Path.cwd()  
      path.ls()[0]
```

```
Out[5]: PosixPath('/home/sgugger/notebooks/01_core.ipynb')
```

```
=====
```

```
In [3]: ┌─ path = Path.cwd()  
      path.ls()[-1]
```

```
Out[3]: PosixPath('/home/jphoward/notebooks/01_core.ipynb')
```

```
>>>>> a7ec1b0bfb8e23b05fd0a2e6cafcb41cd0fb1c35
```

See an example of a nbdev
project in:

<https://github.com/stardust-r/walk-with-deep-learning>

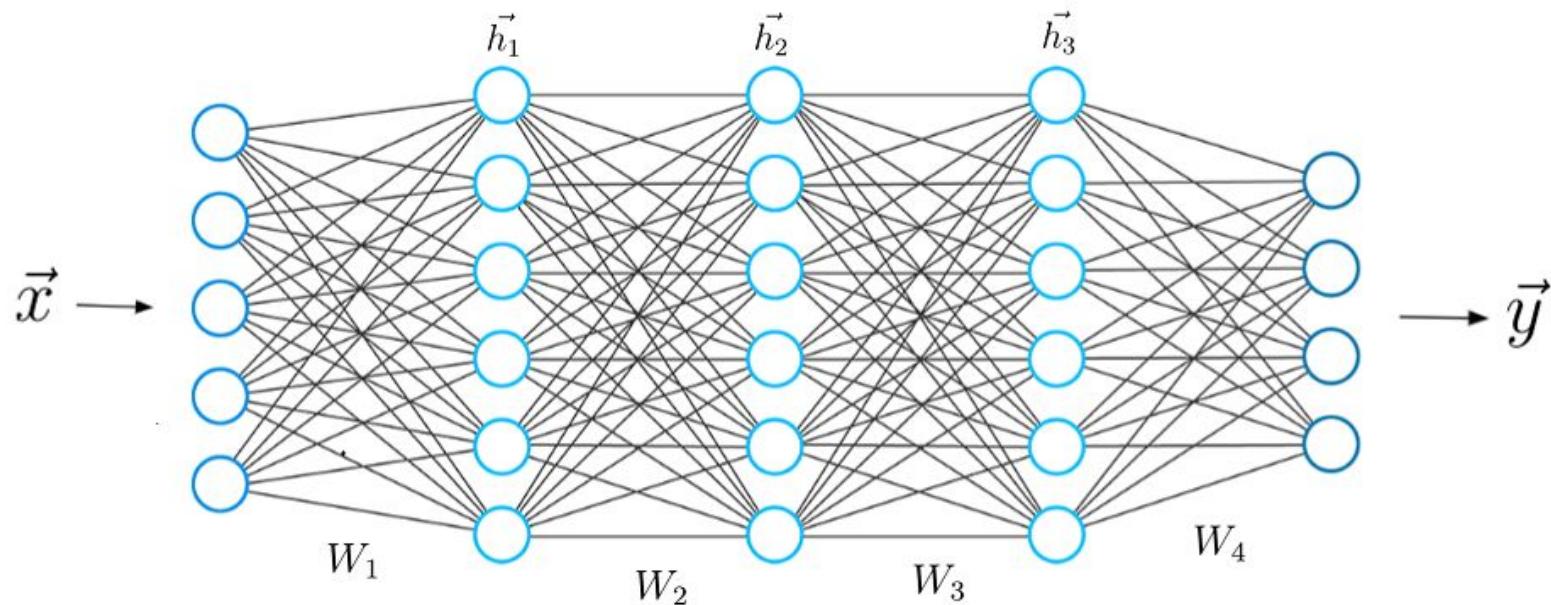
Day 2

A walk with deep
learning

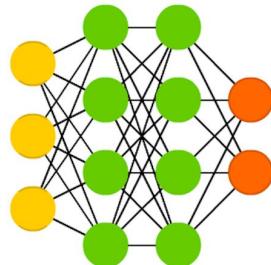
Going deeper into deep learning



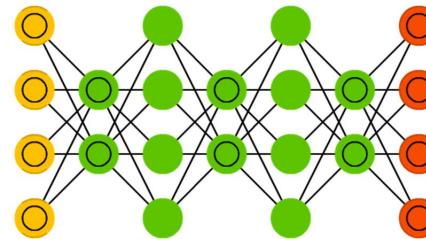
Going deeper



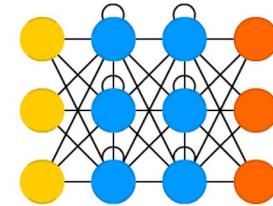
Deep architectures



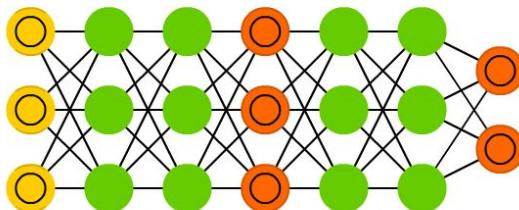
Deep Neural Network
(Fully connected layers)



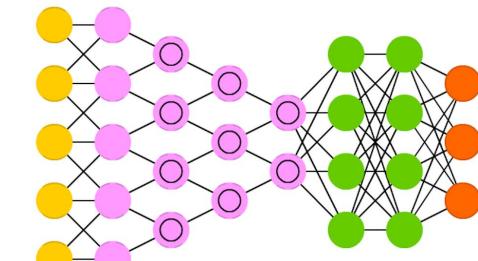
Deep Belief Network



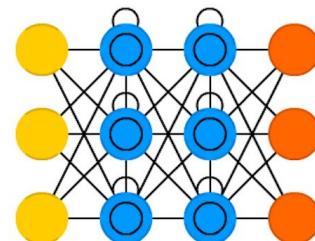
Recurrent Neural Network



GANs



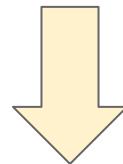
Convolutional Neural Network



LSTMs

Going deeper

An overview of neural
networks architectures

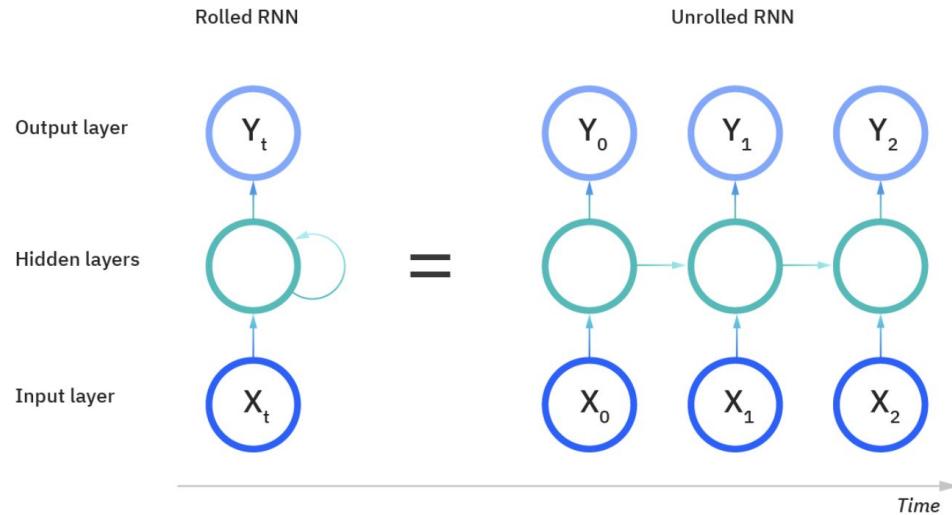
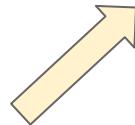
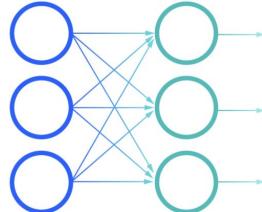
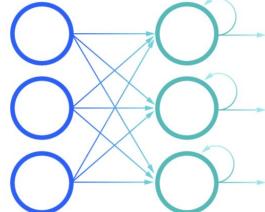


<https://www.asimovinstitute.org/neural-network-zoo/>

Recurrent Neural Network

In temporal series, sequential or ordinal data, we need memory!

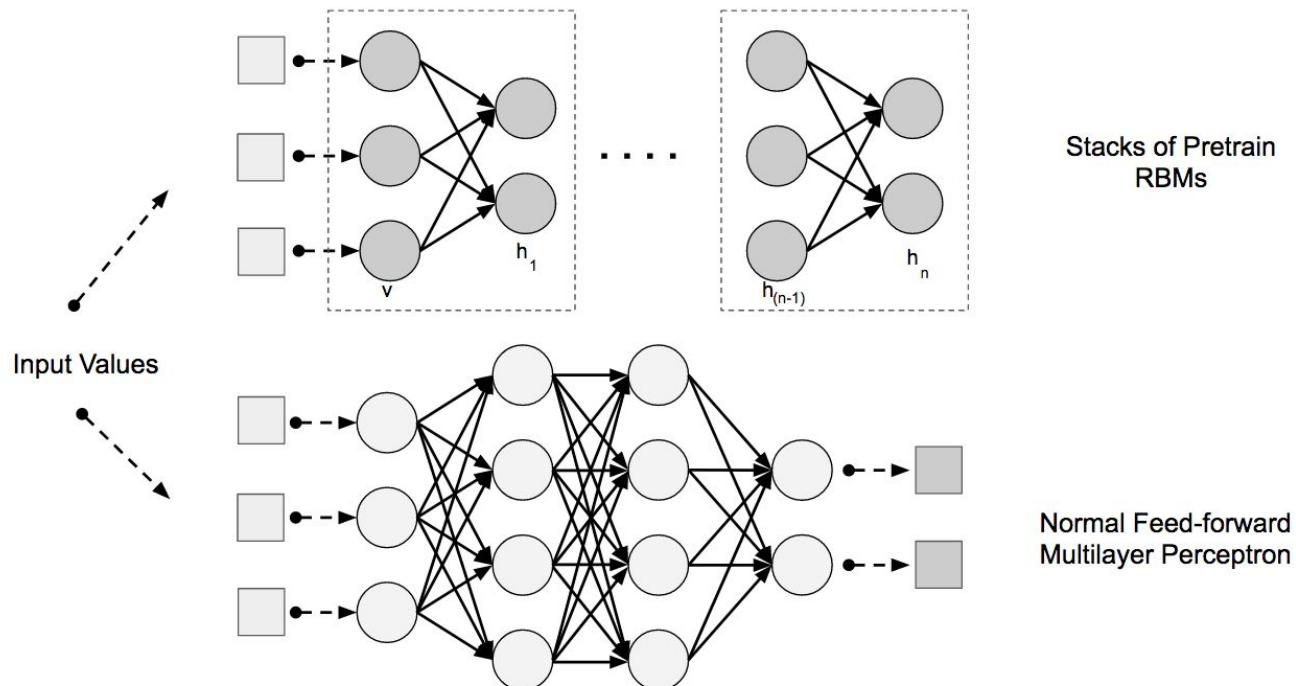
RNN save information from previous states



<https://www.ibm.com/cloud/learn/recurrent-neural-networks>

Deep Belief Networks

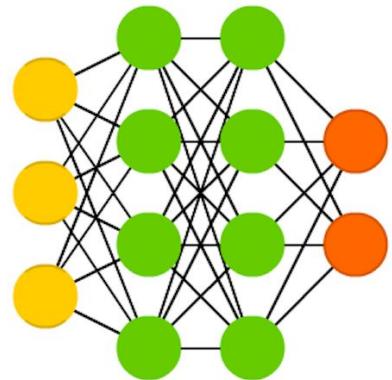
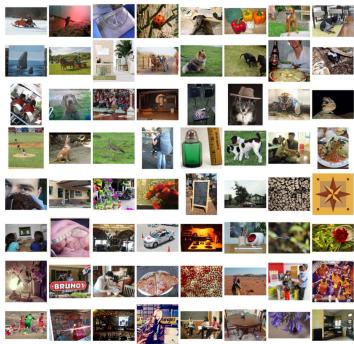
DBNs can be described as
a stack of Restricted
Boltzmann Machines
(RBMs)



credit: Codeburst

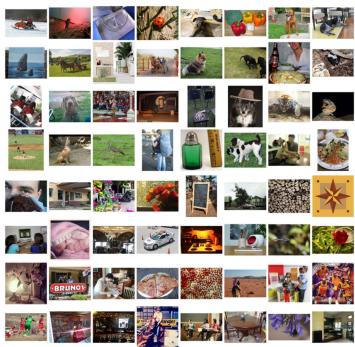
Addressing image classification tasks

DNNs infer knowledge from complex non-linear relationships between the inputs



But they do not infer spatial relationships

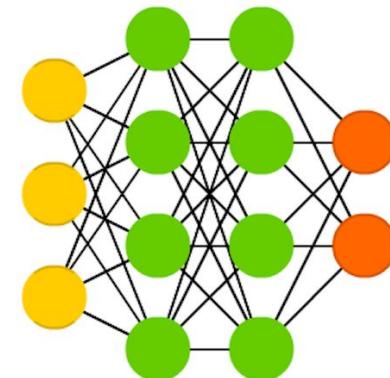
Addressing image classification tasks



Input data



Feature extraction
(by hand in
classical Machine
Learning)

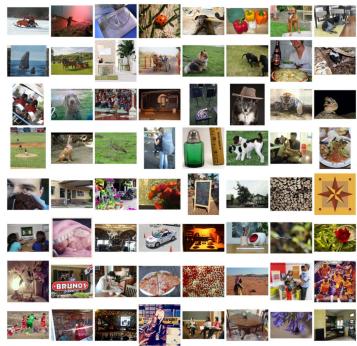


Knowledge
inference (i.e.
image
classification)

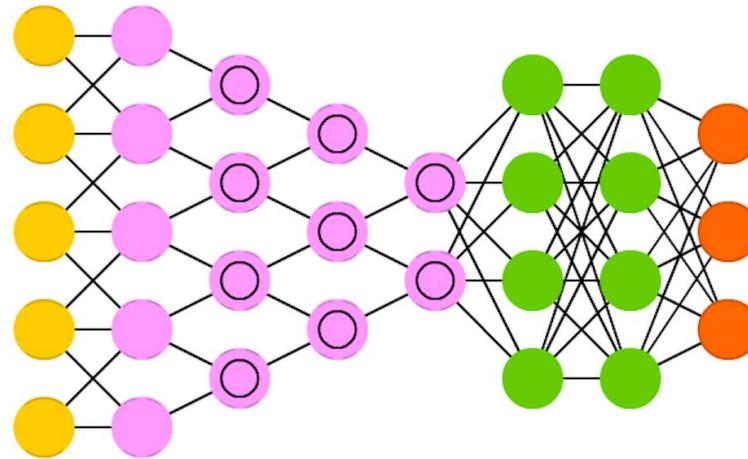
Convolutional Neural Networks



Convolutional Neural Networks



Input data



Feature extraction
+
Knowledge inference

Convolutional Neural Networks

Translation Invariance



Rotation/Viewpoint Invariance



Size Invariance



Illumination Invariance



Also called shift invariant networks

They support translation, rotation or size variances

<https://stats.stackexchange.com/questions/208936/what-is-translation-invariance-in-computer-vision-and-convolutional-neural-networks>

Convolutional Neural Networks

The convolution operation: stride

Stride = 1

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| 0 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 |
| 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 |
| 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 |
| 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 |
| 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 |

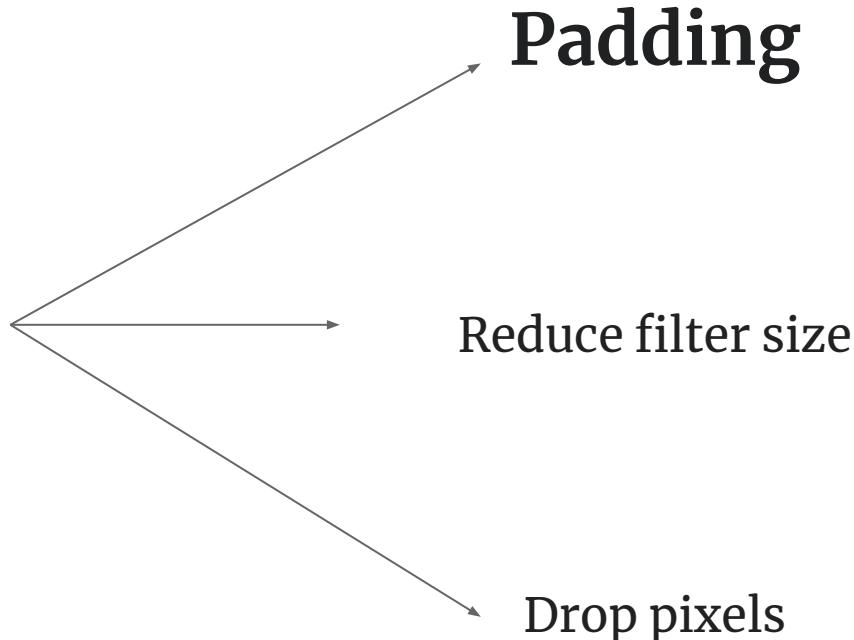
Stride = 3

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 |
| 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 |
| 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 |
| 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 |
| 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 |
| 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 |

Convolutional Neural Networks

The convolution operation: stride

If a filter size / stride combination does not match the size of the image



Convolutional Neural Networks

The convolution operation

Filter or kernel:

| | | |
|---|---|---|
| 1 | 0 | 1 |
| 0 | 1 | 0 |
| 1 | 0 | 1 |

| | | | | |
|-----------------|-----------------|-----------------|---|---|
| 1 _{x1} | 1 _{x0} | 1 _{x1} | 0 | 0 |
| 0 _{x0} | 1 _{x1} | 1 _{x0} | 1 | 0 |
| 0 _{x1} | 0 _{x0} | 1 _{x1} | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 1 | 0 | 0 |

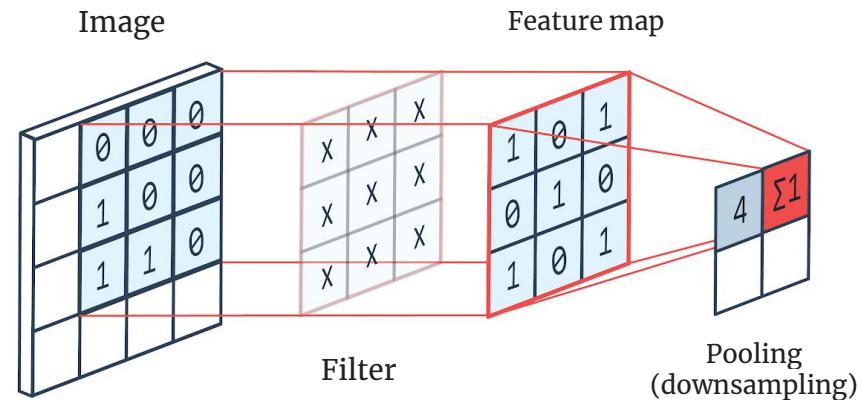
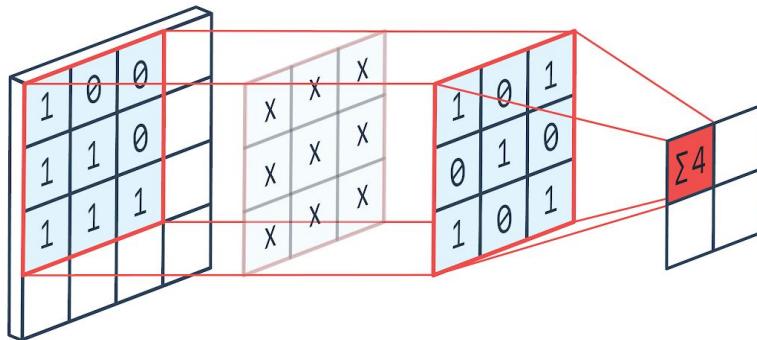
Image

| | | |
|---|--|--|
| 4 | | |
| | | |
| | | |
| | | |

Convolved Feature

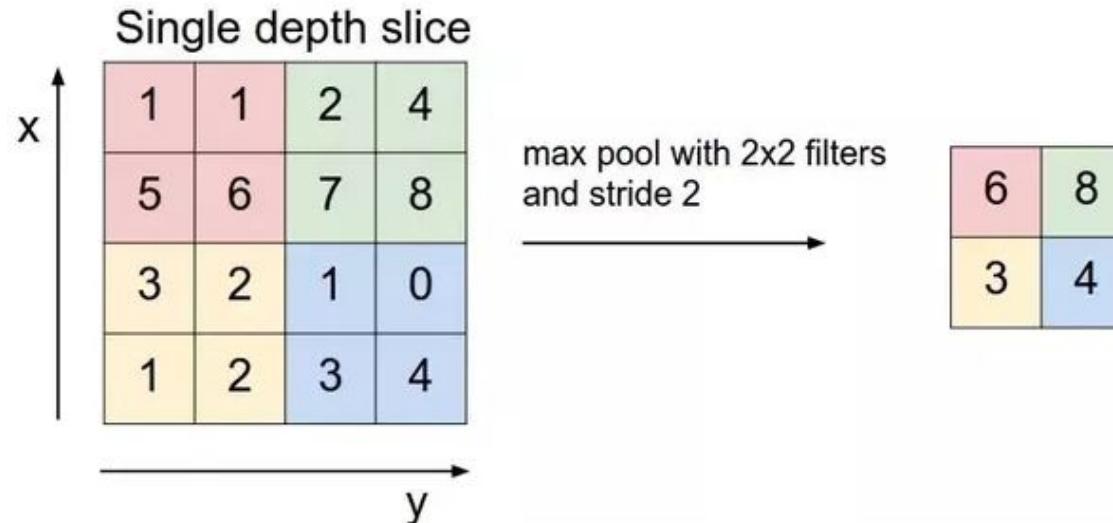
Convolutional Neural Networks

Convolution + Pooling

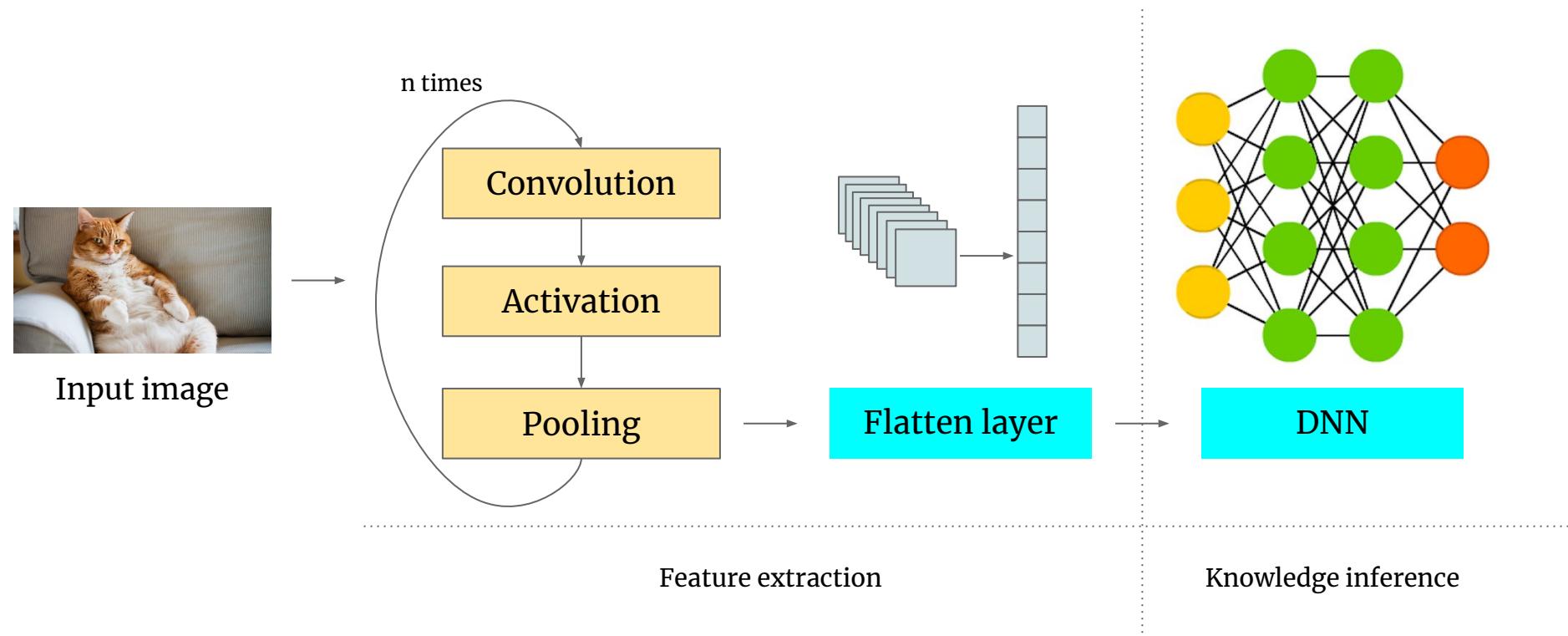


Convolutional Neural Networks

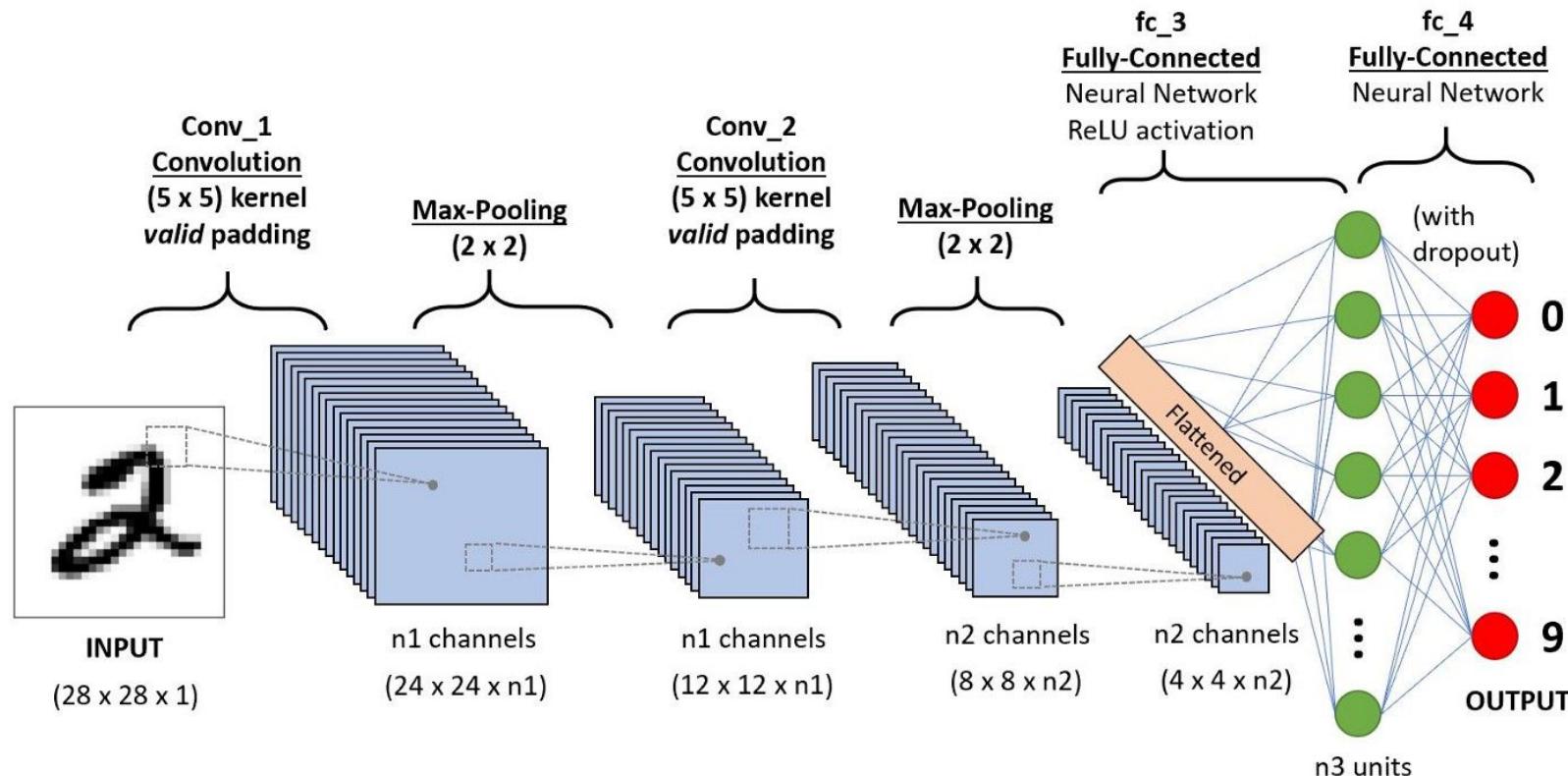
MaxPooling



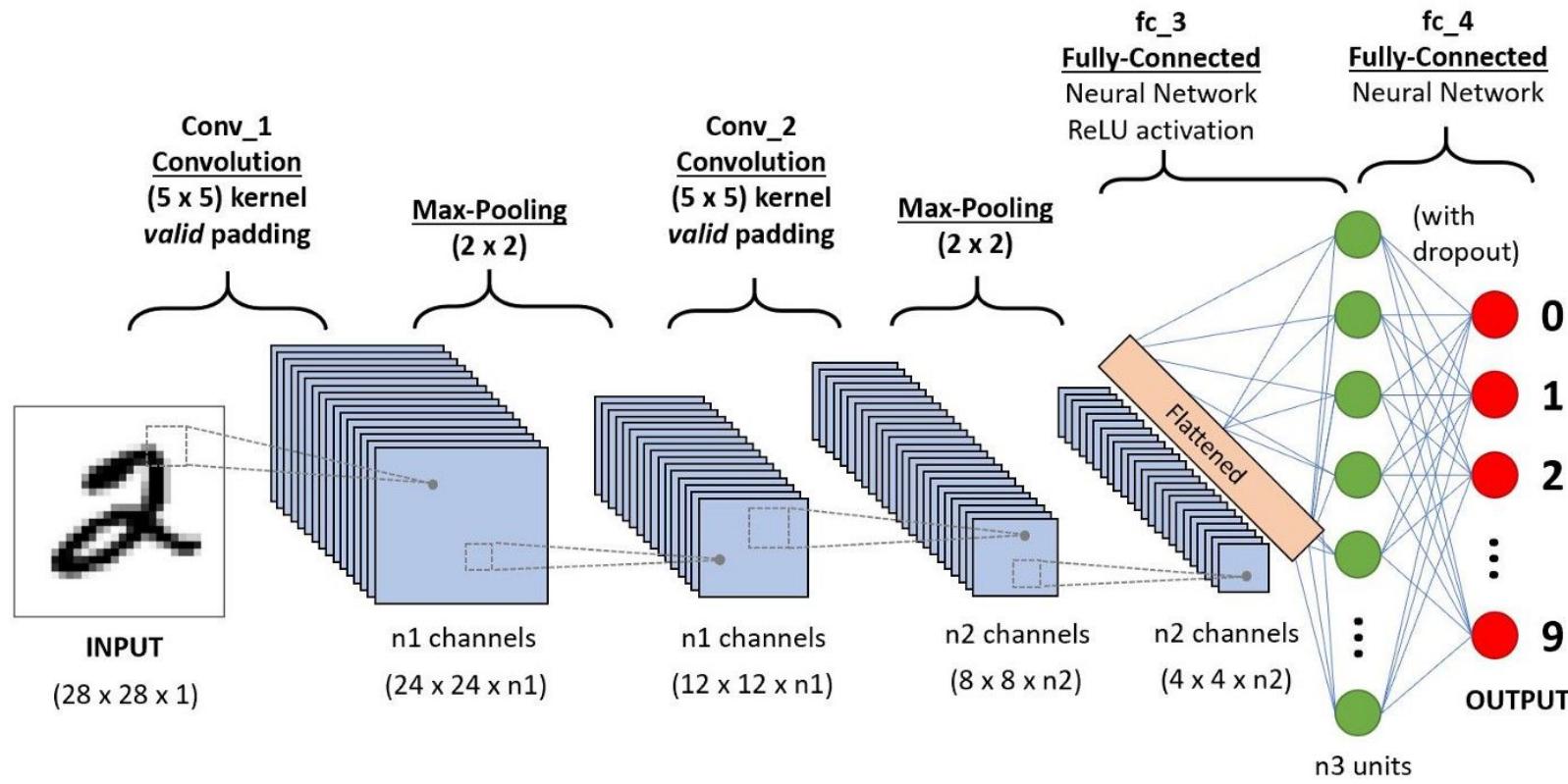
Architecture of a CNN



Architecture of a CNN



Architecture of a CNN

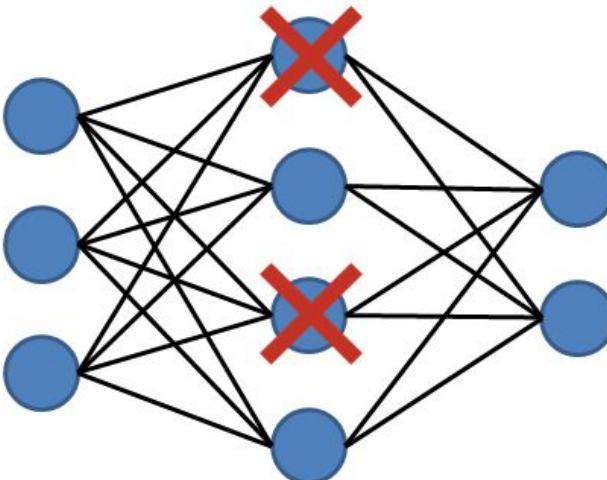


High level to lower level features

Dropout layer

Preventing overfitting

A set of random units are set to 0. This improves the performance of every unit and avoids “isolated units” with wrong knowledge



Channels



Grayscale image
1 channel

Data with size = $w * h$



Original Image



Red Channel



Green Channel



Blue Channel

Color image
3 channel

Data with size = $w * h * c$

Conv1D, Conv2D, Conv3D, ...

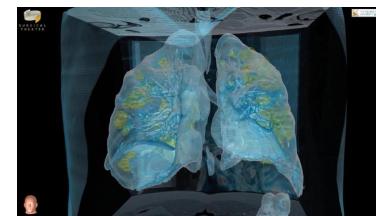
CNNs are typically applied to 2D data, but can be applied to other number of dimensions



1D Audio



2D Image



3D Image

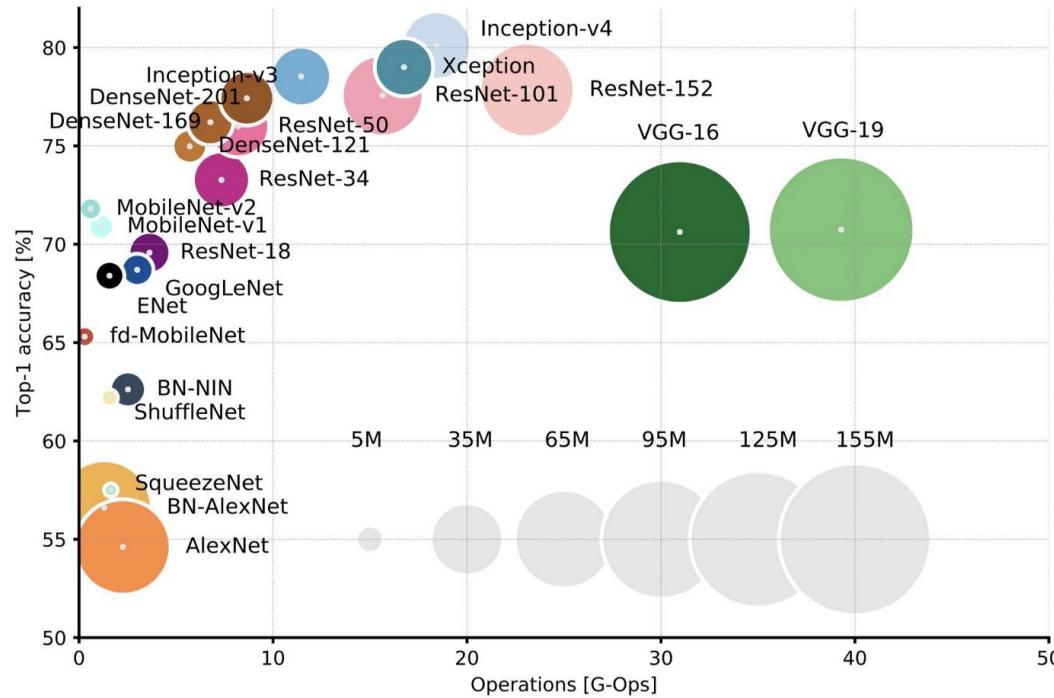


4D spatio-temporal
data

Weaknesses of CNNs

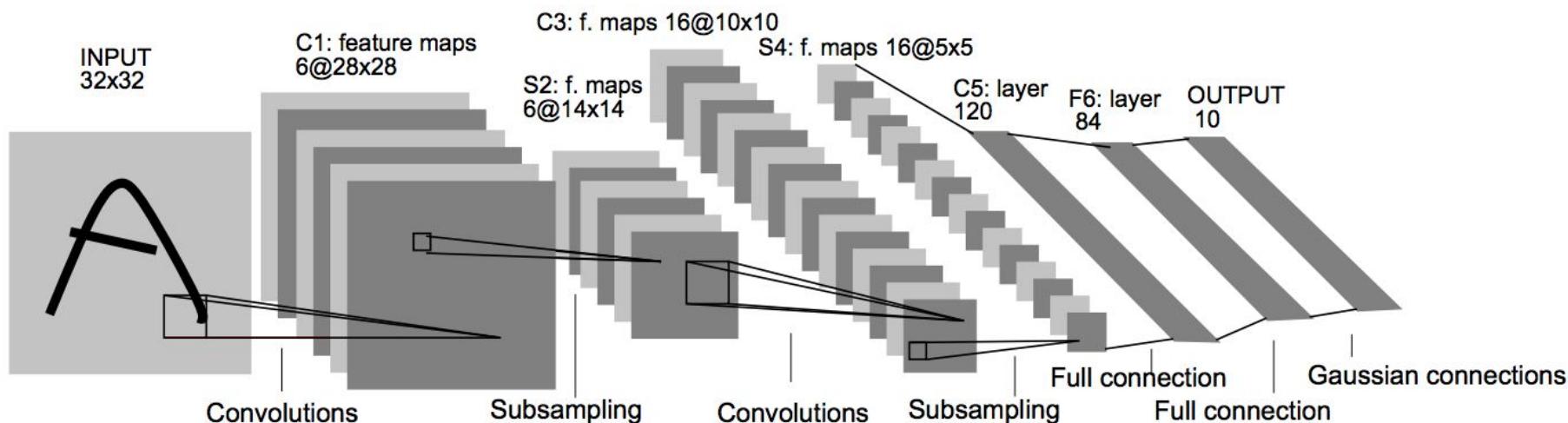
Is it a duck or a
rabbit?

CNN architectures



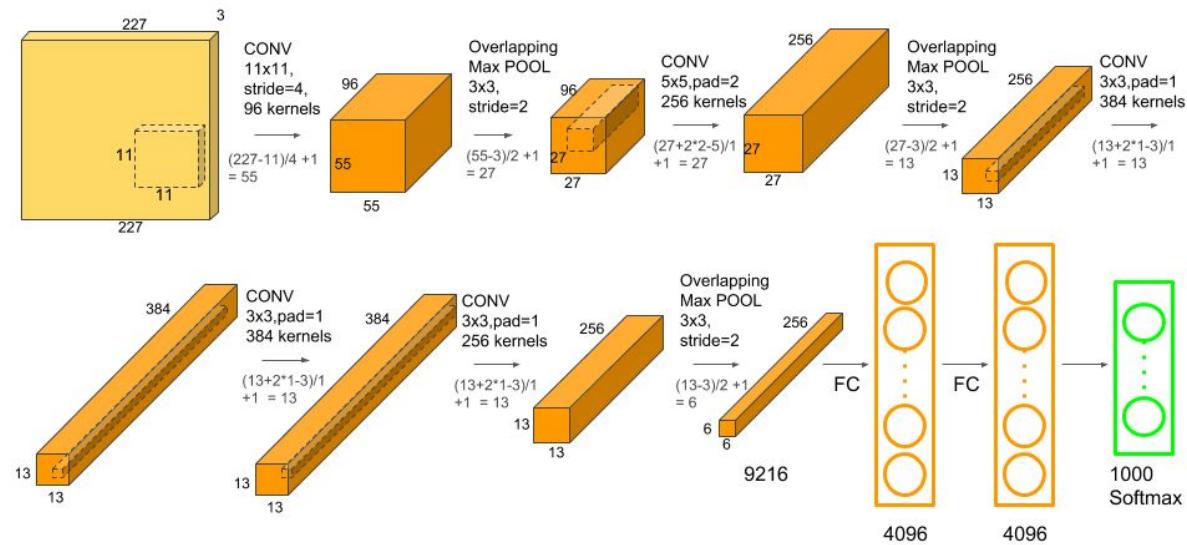
CNN architectures

LeNet-5 (1998)



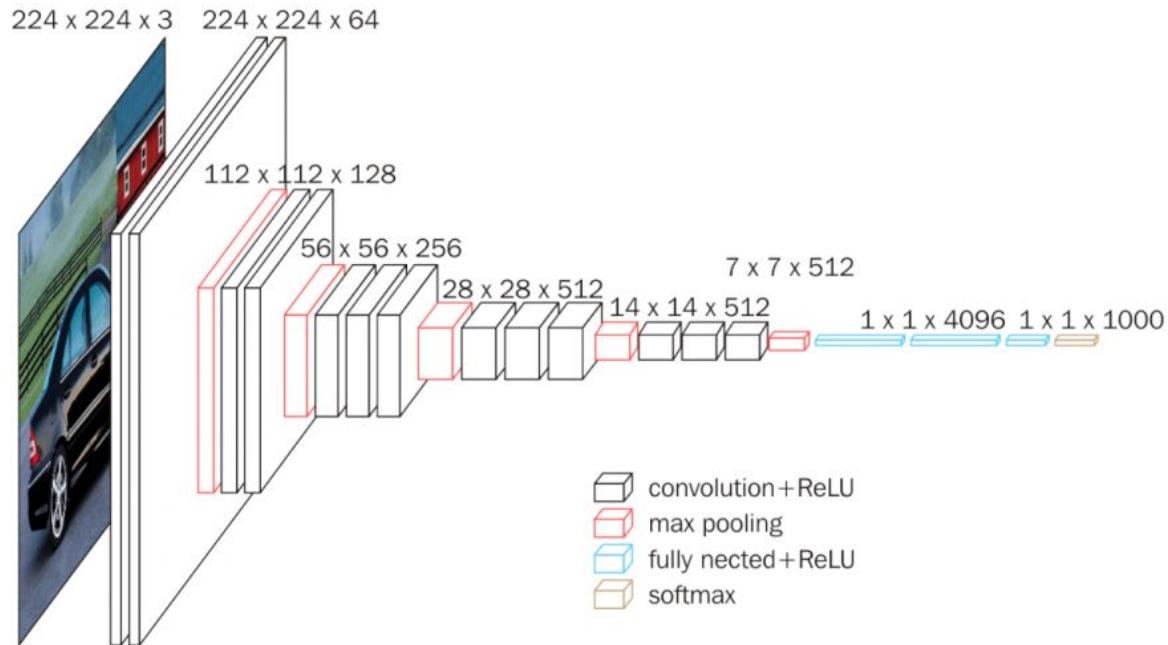
CNN architectures

AlexNet (2012)



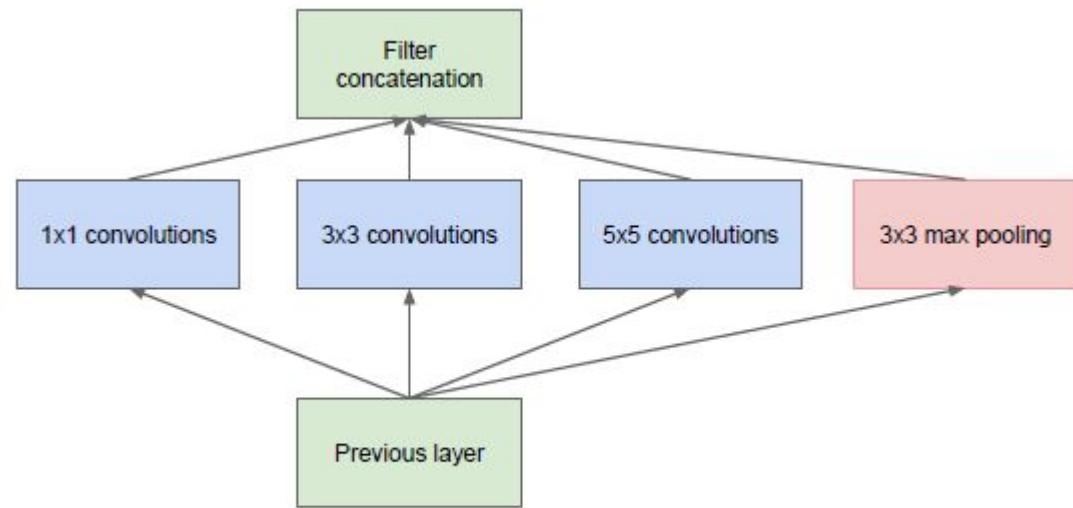
CNN architectures

VGG-16 (2012)



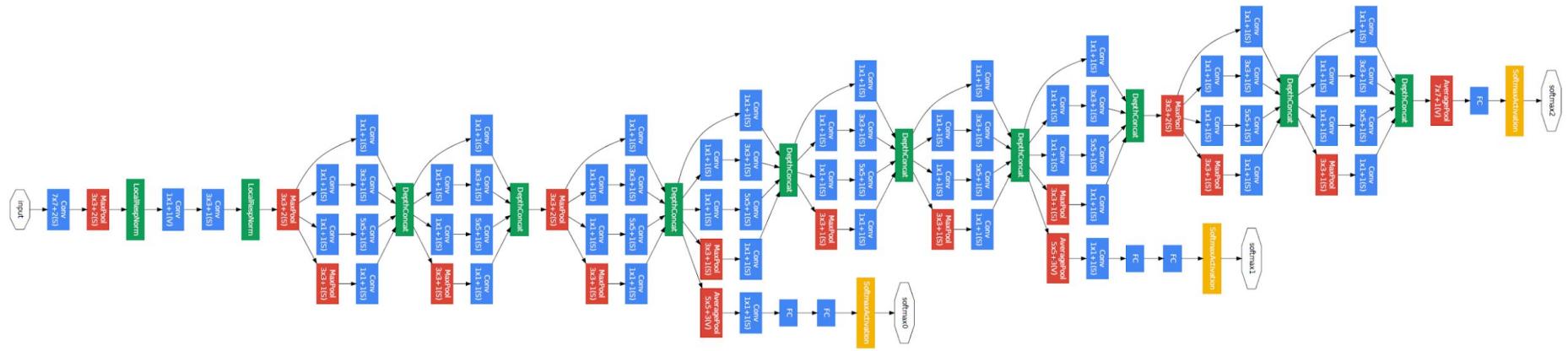
CNN architectures

Inception V1 (2014)



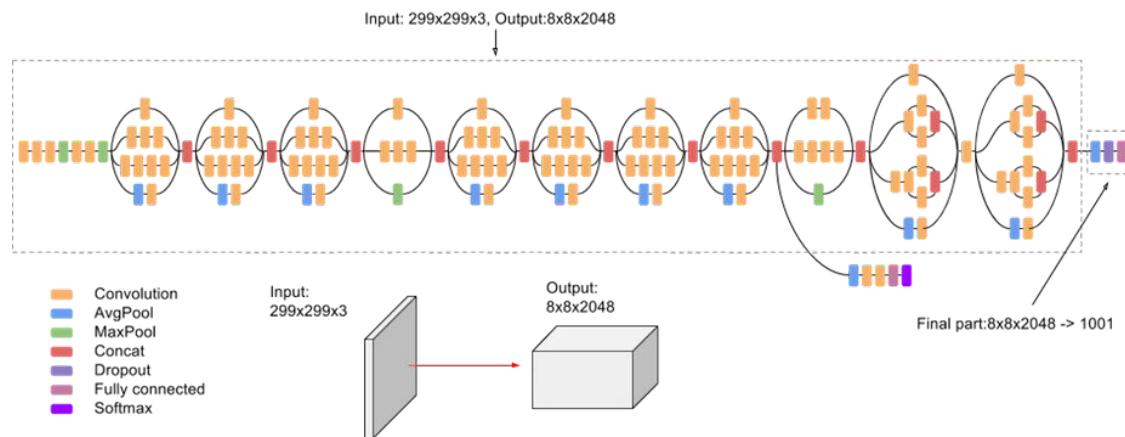
CNN architectures

Inception V1 (2014) - GoogLeNet



CNN architectures

Inception V3



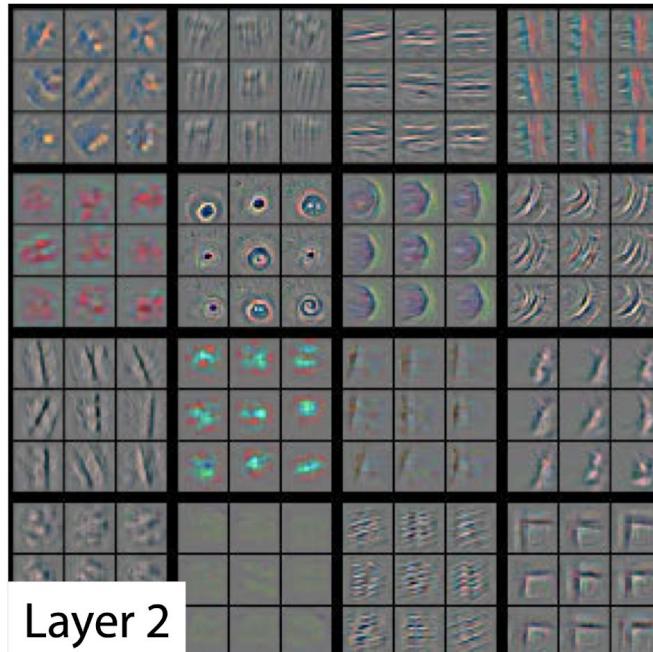
How does a filter look like?



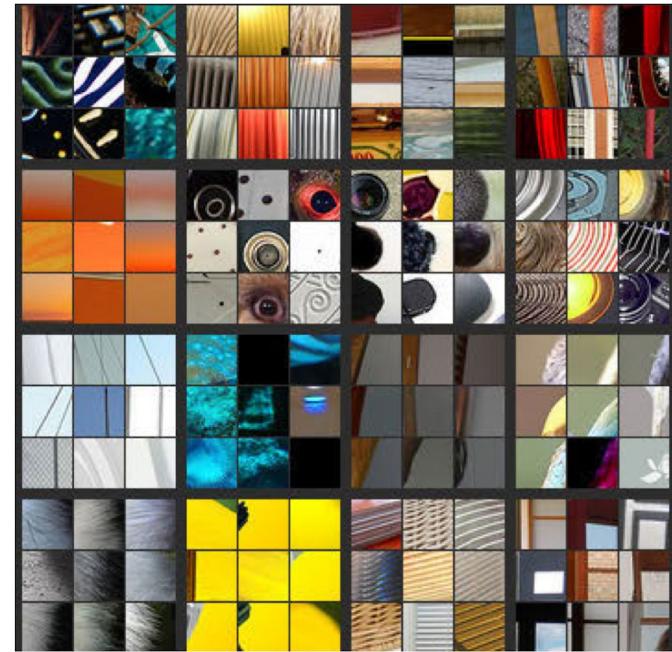
Deconvolution



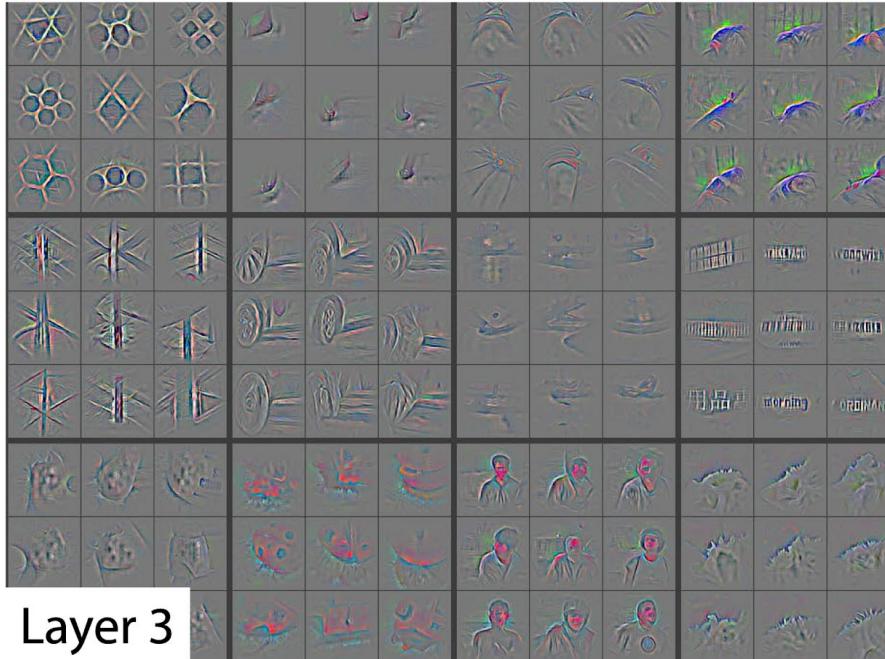
Layer 1



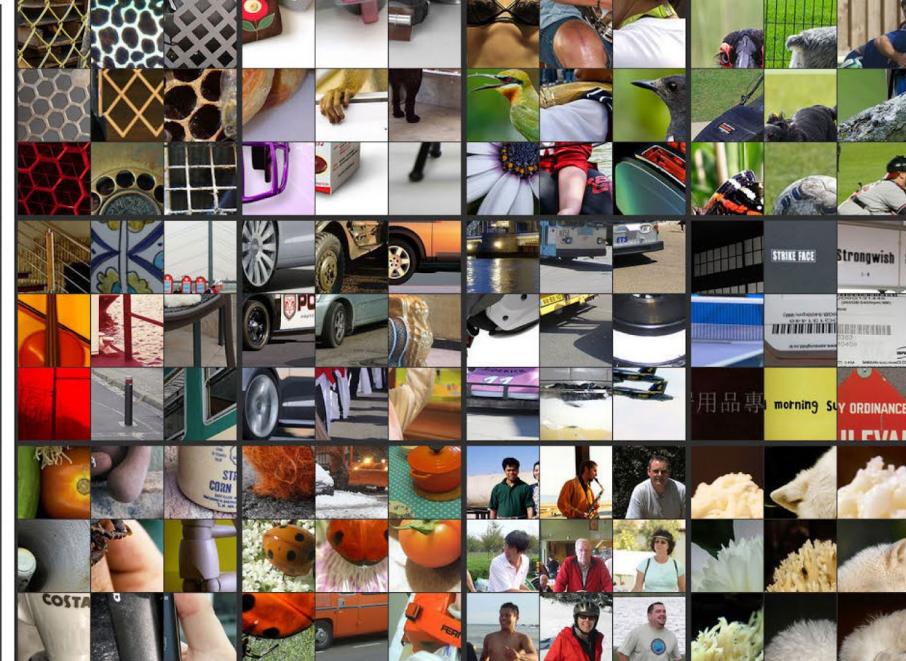
Layer 2



Deconvolution

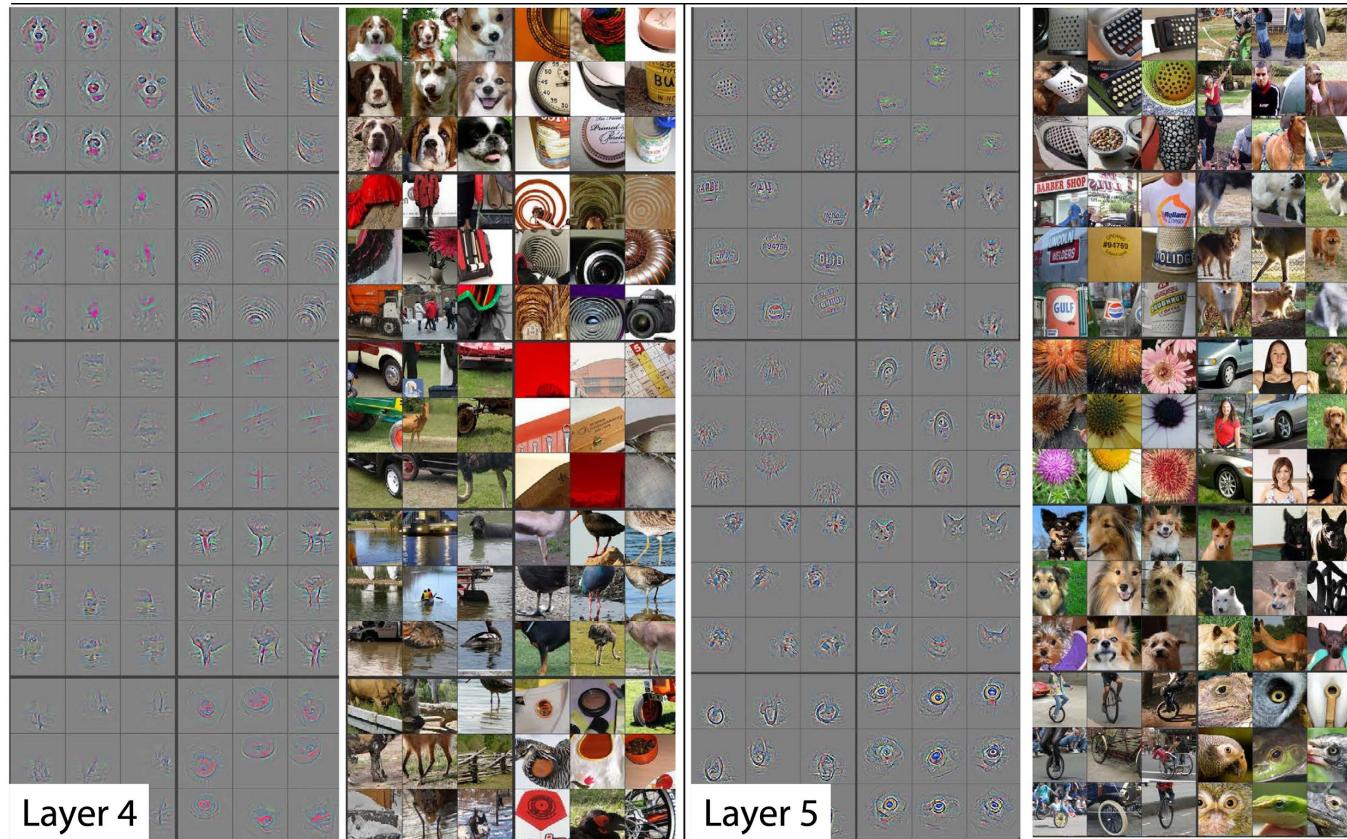


Layer 3



Zeiler, M. D., & Fergus, R. (2014, September). Visualizing and understanding convolutional networks. In *European conference on computer vision* (pp. 818-833). Springer, Cham.

Deconvolution



Zeiler, M. D., & Fergus, R. (2014, September). Visualizing and understanding convolutional networks. In *European conference on computer vision* (pp. 818-833). Springer, Cham.

GANs

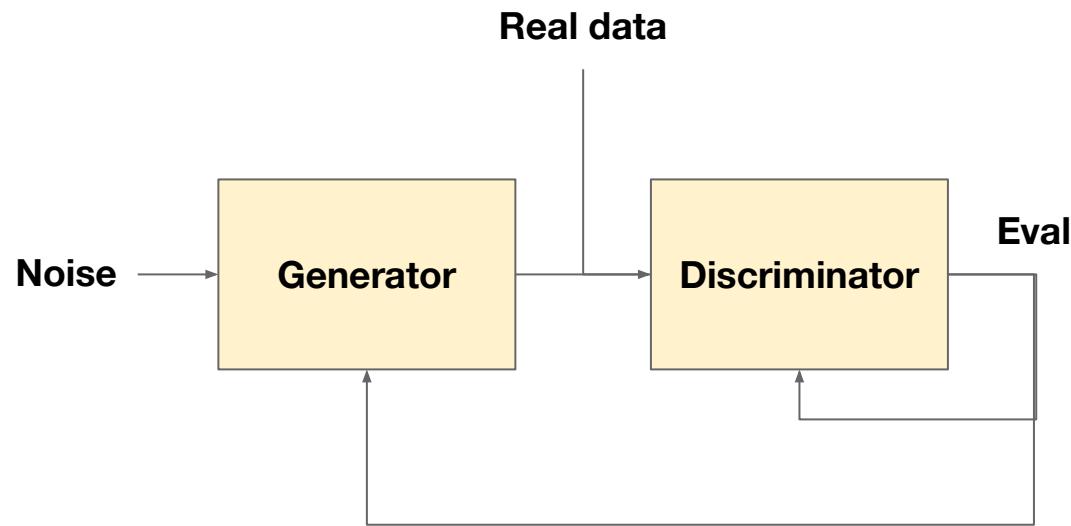
Generative adversarial Networks

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial networks. arXiv preprint arXiv:1406.2661.

[LINK](#)

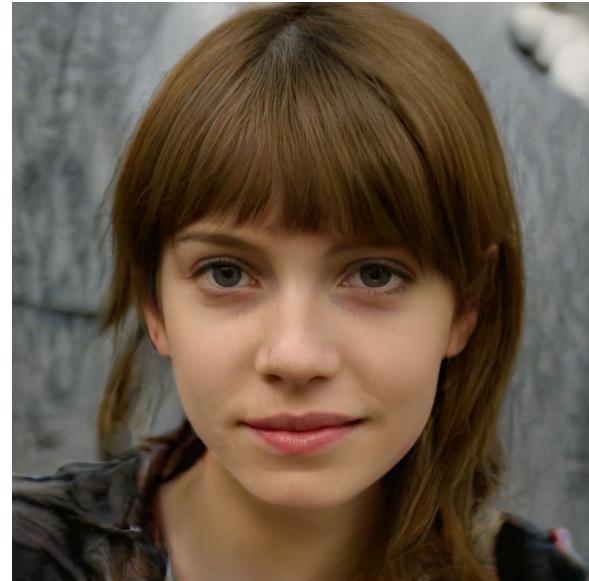
GANs

Two CNNs playing a game



GANs

Fake images
generation



StyleGAN

Building a convolutional neural network with Keras

Natural Language Processing with Deep Learning

NLP - Natural Language Processing

Thread



Donald J. Trump

@realDonaldTrump

This Tweet violated the Twitter Rules about glorifying violence. However, Twitter has determined that it may be in the public's interest for the Tweet to remain accessible. [Learn more](#)

....These THUGS are dishonoring the memory of George Floyd, and I won't let that happen. Just spoke to Governor Tim Walz and told him that the Military is with him all the way. Any difficulty and we will assume control but, when the looting starts, the shooting starts. Thank!

12:53 AM · May 29, 2020 · Twitter for iPhone



NLP - Natural Language Processing

Evolution of NLP

- Symbolic NLP (ontologies, rules based, ...)
- Statistical NLP (TF-IDF)
- Neural models (present: Word2Vec, Tranformers, ...)

NLP - Natural Language Processing

- Statistical NLP
 - TF-IDF: term frequency–inverse document frequency

How important is a word?



I look forward to **working** on Deep Learning

NLP - Natural Language Processing

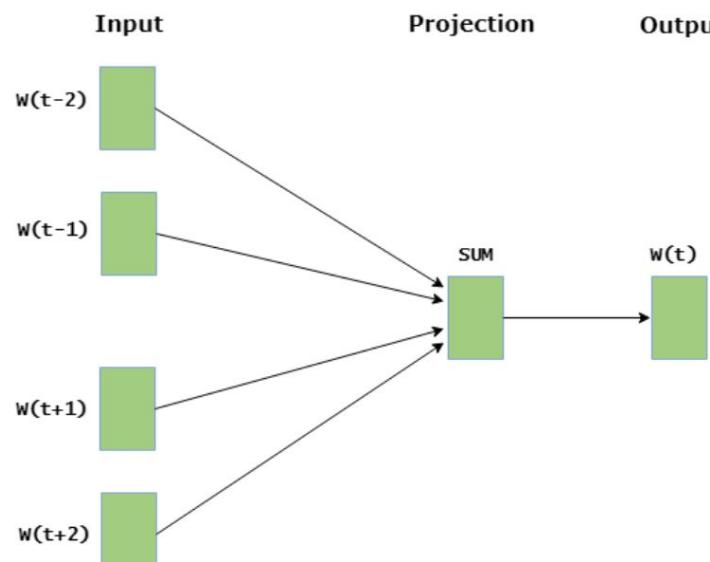
- Neural NLP: the importance of the context

The diagram shows a sentence: "I look forward to working on Deep Learning". Each word is enclosed in a colored box: "I" (green), "look forward" (blue), "to" (grey), "working" (yellow), "on" (light blue), and "Deep Learning" (orange). Three curved arrows indicate context dependencies: a red arrow from "I" to "working", a grey arrow from "forward" to "working", and a blue arrow from "working" to "Deep Learning".

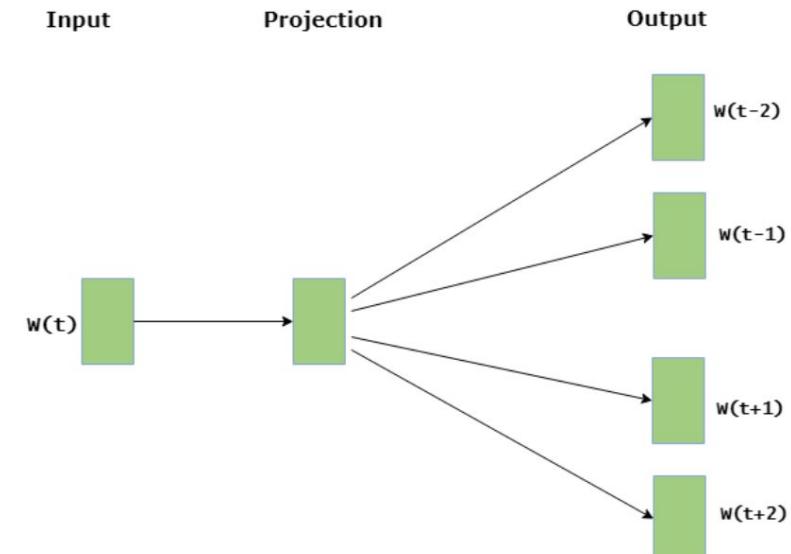
I look forward to working on Deep Learning

NLP - Natural Language Processing

- Word2Vec: neural networks to build word embedding models



Continuous Bag of Words (CBOW)



Skip Gram

NLP - Natural Language Processing

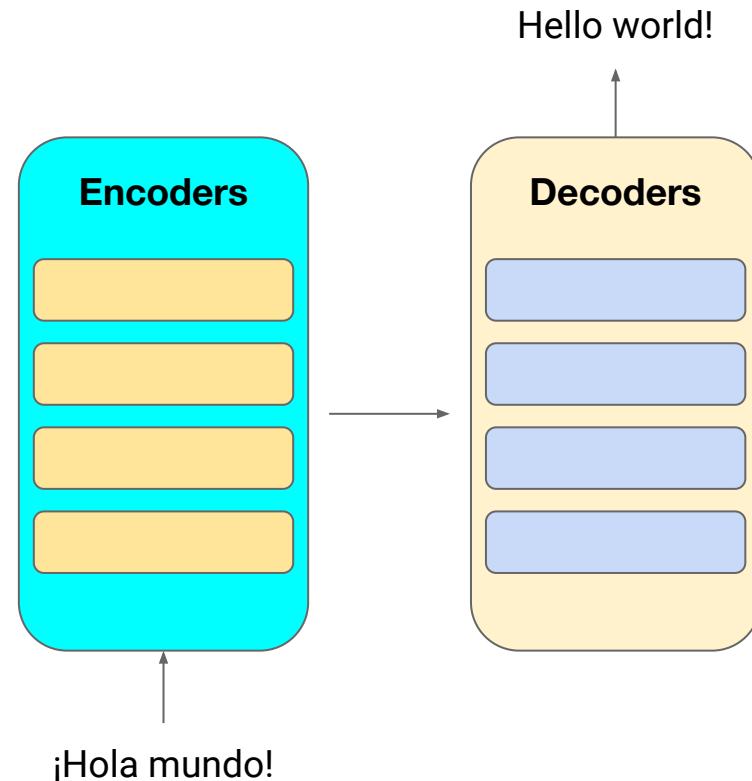
- The sky is
 - **blue**
 - is covered with dark clouds.
 - **is red**
 - **is falling**

Transformers

Attention Is All You Need

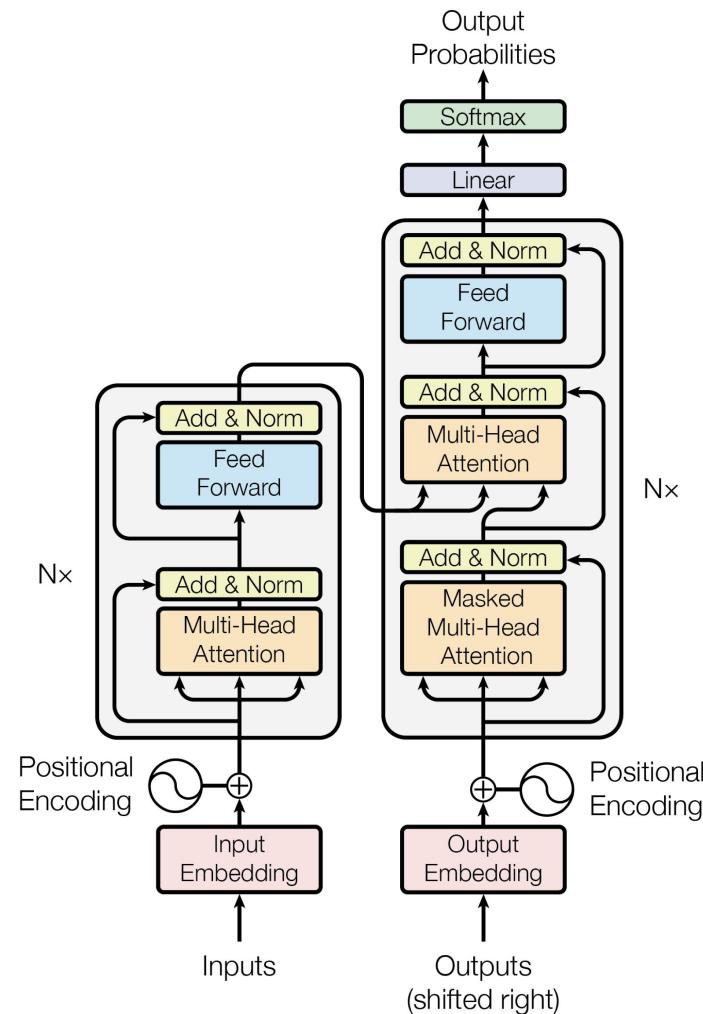
The Transformer architecture

Architectures for Sequence to Sequence transforming



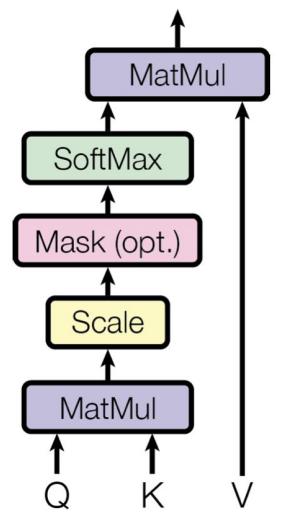
The Transformer architecture

Architectures for Sequence to Sequence transforming



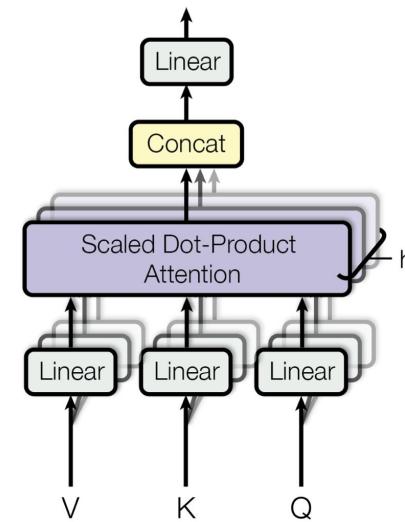
The Transformer architecture

Scaled Dot-Product Attention



Mapping between a query
and key-value pairs

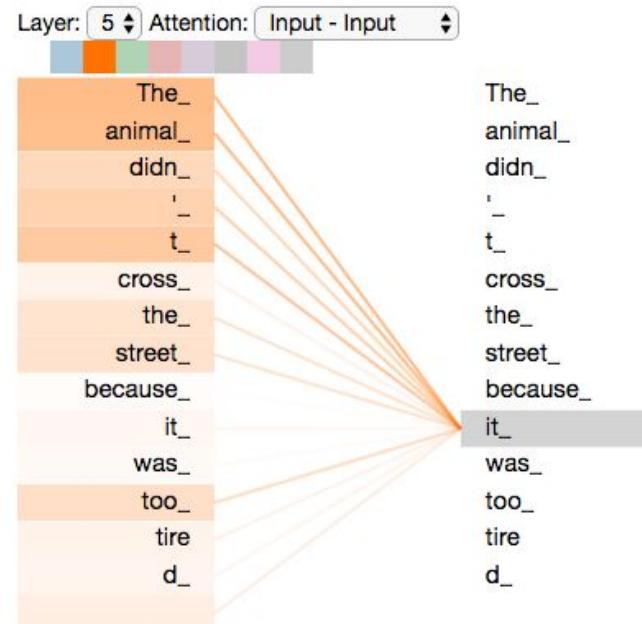
Multi-head attention



Several projections of the
queries, keys and values

The Transformer architecture

Attention



The Transformer architecture

Architectures for Sequence
to Sequence transforming

[Tensor2Tensor](#)
[notebook](#)

Transformers



Transformers

Tensorflow & PyTorch

<https://github.com/huggingface/transformers>

Sentence Tranformers

PyTorch

<https://github.com/UKPLab/sentence-transformers>

Arquitectures

Some models available at
HuggingFace library

BERT (Google)

DistilBERT (HuggingFace)

GPT, GPT2 (OpenAI)

XLM (Facebook)

XLM-RoBERTa (Microsoft)

...



Text generation

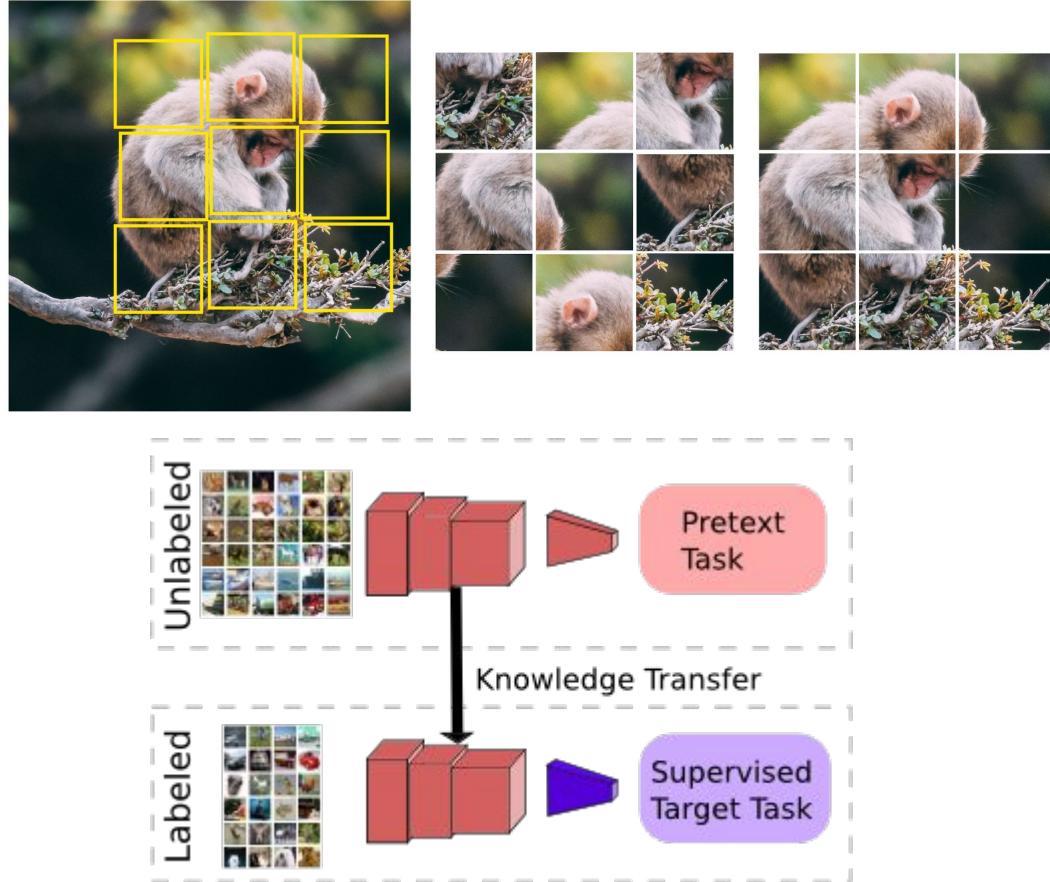
<https://transformer.huggingface.co/doc/gpt2-large>

Trending topics in deep learning



Self-supervised learning

The main idea of Self-Supervised Learning is to generate the labels from unlabeled data, according to the structure or characteristics of the data itself, and then train on this unsupervised data in a supervised manner.



<https://rl.uni-freiburg.de/img/teaching/selfsup-seminar>

<https://perfectial.com/wp-content/uploads/2020/03/SSL-02-scaled.jpg>

Few-shot learning

Dataset



Classes with many samples

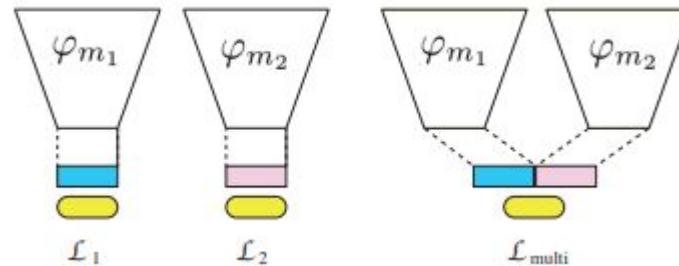
Classes with few samples

Classifier



Data fusion and multimodal models

Recent research shows that end-to-end training of multi-modal networks with fused inputs from different modalities (e.g., images and tabular data at once) do not always outperform uni-modal networks on the same tasks



TEXT PROMPT

an armchair in the shape of an avocado [...]

AI-GENERATED IMAGES



[Edit prompt or view more images ↓](#)

<https://openai.com/blog/dall-e/>

CLIP & DALL-E, by OpenAI: Connecting text and images. CLIP is a neural network that efficiently learns visual concepts from natural language supervision. That can be used to create images from text captions for a wide range of concepts expressible in natural language.

Neutral

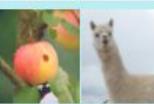
Games / Music
60 images



Black / LGBT Rights
4 images



Non-Political
178 images



Political Generic
54 images



Related to Donald Trump

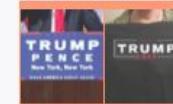
Politics
78 images



Partial Photo
67 images



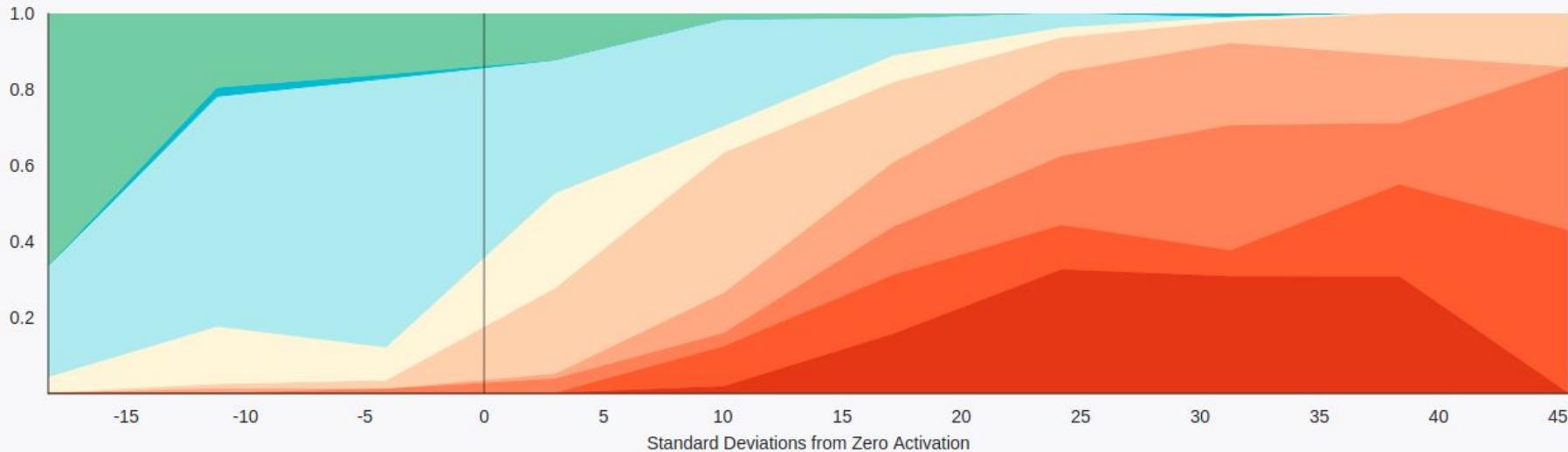
Text
74 images



Art
53 images



Profile Photo
83 images



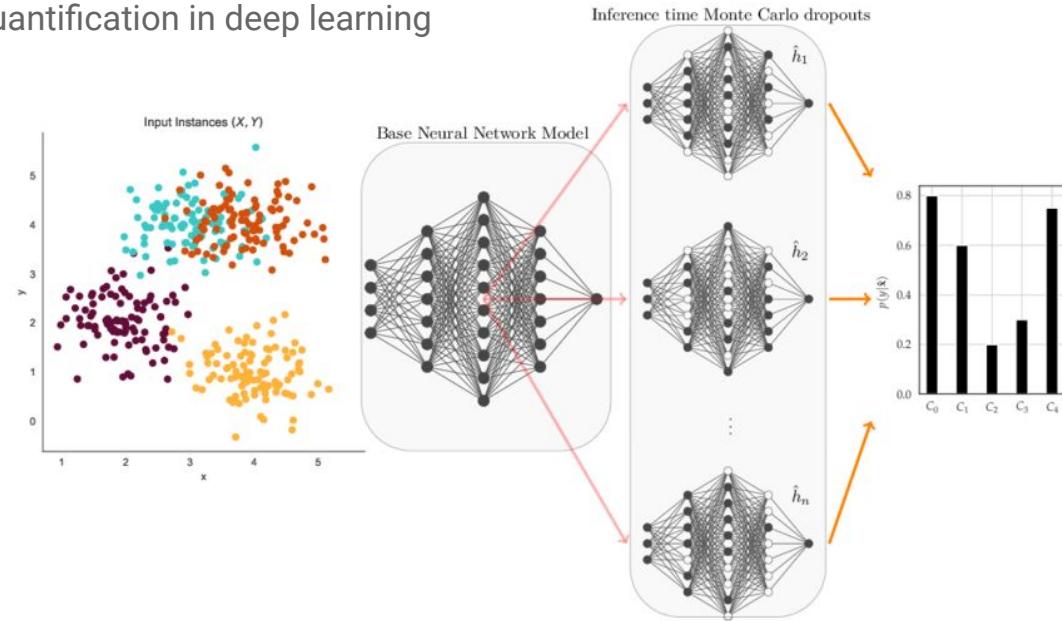
<https://distill.pub/2021/multimodal-neurons/>

Neurons in CLIP respond to the same concept whether presented literally, symbolically, or conceptually.

Uncertainty quantification

Deterministic deep neural networks are known to be overconfident in their predictions on Out of Distribution (OoD) data. Popular ways to approach uncertainty quantification in deep learning

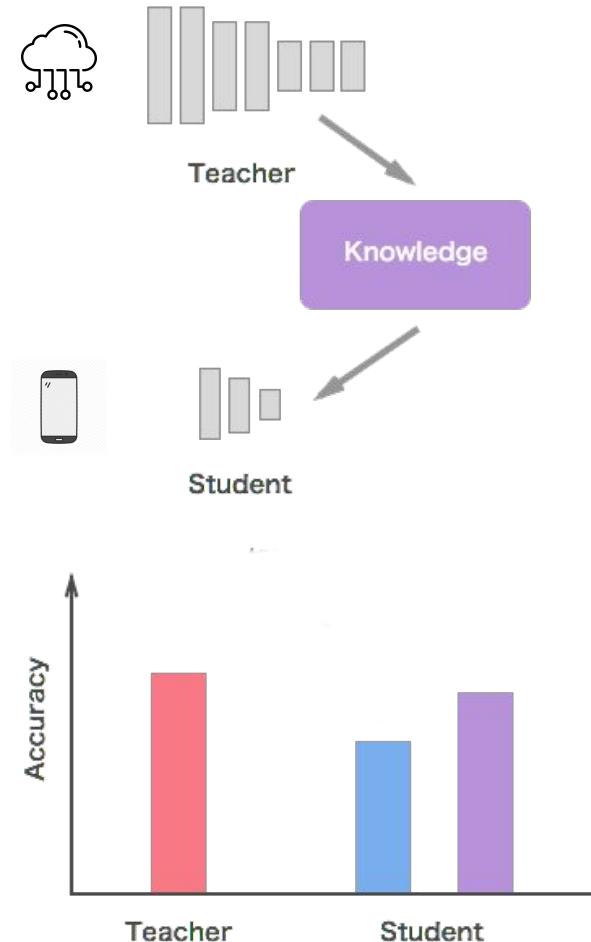
- Monte Carlo Dropout
- Deep ensembles



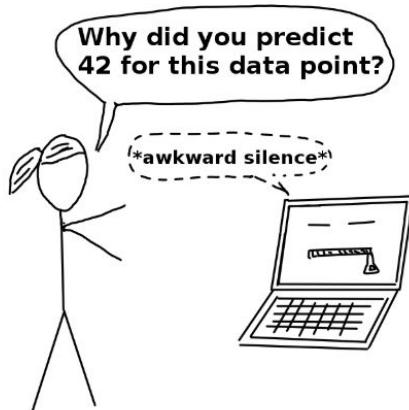
Knowledge distillation

Train a compact model (student) to reproduce the behaviour of a larger one (teacher), achieving smaller, faster, cheaper and lighter versions of it.

- Allows for deployment in mobile and edge devices



Model interpretability



Risks & Ethics of deep learning systems



¿Is this a stop sign?

- Adversarial examples:
Researchers found that popular neural networks for image recognition were classifying this sign as a speed limit sign





Attack text label **iPod** ▾

| | |
|--------------|-------|
| Granny Smith | 85.6% |
| iPod | 0.4% |
| library | 0.0% |
| pizza | 0.0% |
| toaster | 0.0% |
| dough | 0.1% |



| | |
|--------------|-------|
| Granny Smith | 0.1% |
| iPod | 99.7% |
| library | 0.0% |
| pizza | 0.0% |
| toaster | 0.0% |
| dough | 0.0% |

<https://openai.com/blog/multimodal-neurons/>

Typographic attacks: By exploiting the model's ability to read text robustly, we find that even photographs of hand-written text can often fool the model. It requires no more technology than pen and paper

Deep fakes



| Gender Classifier | Darker Male | Darker Female | Lighter Male | Lighter Female | Largest Gap |
|-------------------|-------------|---------------|--------------|----------------|-------------|
| Microsoft | 94.0% | 79.2% | 100% | 98.3% | 20.8% |
| FACE++ | 99.3% | 65.5% | 99.2% | 94.0% | 33.8% |
| IBM | 88.0% | 65.3% | 99.7% | 92.9% | 34.4% |



Joy Buolamwini & Timnit Gebru

<https://cedrickchee.gitbook.io/knowledge/courses/fast.ai/deep-learning-part-1-practical-deep-learning-for-coders/2019-edition/lesson-6-foundations-convolutional-neural-nets>

Gender classification: Lighter male skinned people on IBM's main computer vision system get 99.7% accuracy, while darker darker skinned women get much less accuracy

¿Where does this bias come from?

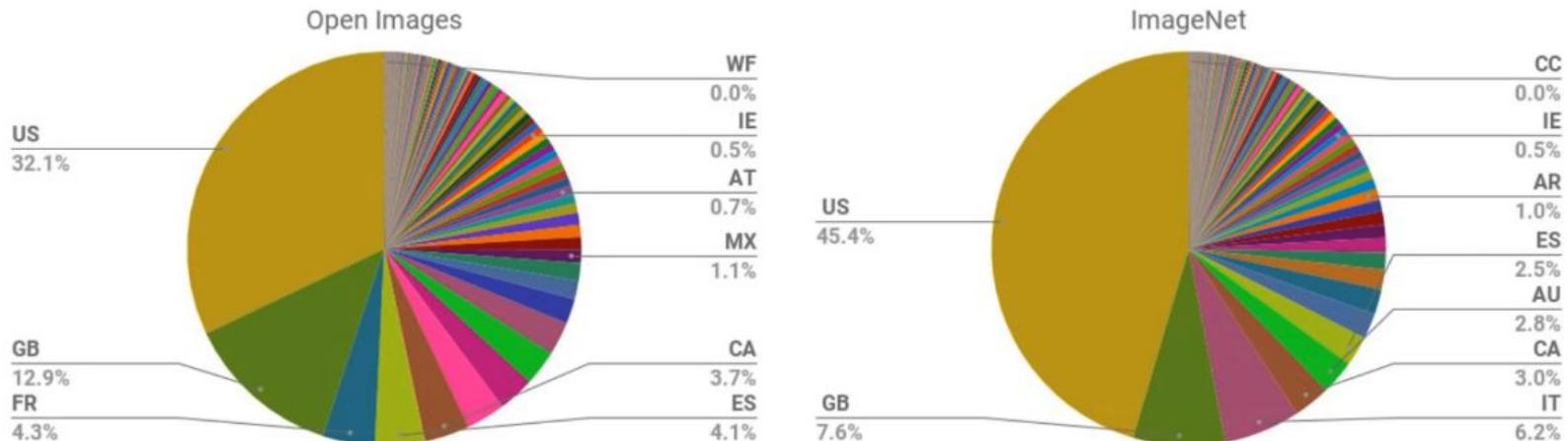


Figure 1: Fraction of Open Images and ImageNet images from each country. In both data sets, top represented locations include the US and Great Britain. Countries are represented by their two-letter ISO country codes.

Bias in NLP

The image shows a screenshot of a web-based translation interface, likely Google Translate, demonstrating gender bias in machine learning models. The interface has two main sections, each with a source text input field, a target language dropdown, and a 'Translate' button.

Top Section:

- Source: English
- Target: Turkish
- Text: "She is a doctor.
He is a nurse."
- Translation: "O bir doktor.
O bir hemşire."
- Annotations: The first "O bir" is marked with a red 'X' and a small 'x' icon, while the second "O bir" is followed by a blue checkmark.
- Details: The source text has a character count of 31/5000.

Bottom Section:

- Source: English
- Target: Turkish
- Text: "O bir doktor.
O bir hemşire"
- Translation: "He is a doctor.
She is a nurse" (with a blue checkmark)
- Annotations: The first "O bir" is marked with a red 'X' and a small 'x' icon, while the second "O bir" is followed by a blue checkmark.
- Details: The source text has a character count of 28/5000.

Prediction Fails Differently for Black Defendants

| | WHITE | AFRICAN AMERICAN |
|---|-------|------------------|
| Labeled Higher Risk, But Didn't Re-Offend | 23.5% | 44.9% |
| Labeled Lower Risk, Yet Did Re-Offend | 47.7% | 28.0% |

<https://www.fast.ai/page7/>

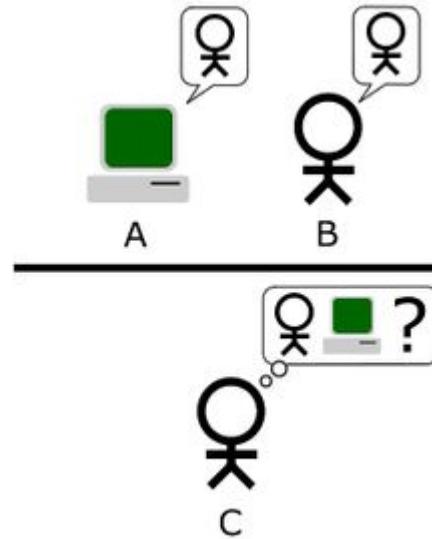
Results of the COMPAS system, used to assist judges in deciding the risk of re-offenders.

Limits of deep learning



The turing test (1950)

- A human assesses natural language (textual) conversations between a human and a machine designed to generate human-like responses.
- In the event that the tester could not distinguish between the human and the machine accurately, the machine would have passed the test.



Thinking systems (Daniel Kahneman)

SYSTEM 1

Intuition & instinct

95%

Unconscious
Fast
Associative
Automatic pilot



SYSTEM 2

Rational thinking

5%

Takes effort
Slow
Logical
Lazy
Indecisive

Source: Daniel Kahneman

Daniel Kahneman: “Deep learning cannot go beyond system 1”

ARTIFICIAL NARROW INTELLIGENCE

VS

ARTIFICIAL GENERAL INTELLIGENCE

IDEA

Machine's ability to perform a single task extremely well, even better than humans.



IDEA

Machines can be made to think and function as human mind.



<https://openai.com/blog/microsoft/>

Microsoft (July 2019): OpenAI and Microsoft sign an exclusive collaboration agreement to create new supercomputing technologies for Artificial General Intelligence

GPT (2019–2020)

New AI fake text generator may be too dangerous to release, say creators

The Elon Musk-backed nonprofit company OpenAI declines to release research publicly for fear of misuse

SYSTEM PROMPT
(HUMAN-WRITTEN)

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

MODEL COMPLETION
(MACHINE-WRITTEN, 10 TRIES)

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them – they were so close they could touch their horns.

While examining these bizarre creatures the scientists discovered that the creatures also spoke some fairly regular English. Pérez stated, "We can see, for example, that they have a common 'language,' something like a dialect or dialectic."

You can try GPT-2 in
<https://transformer.huggingface.co/doc/gpt2-large>

Free ML/DL resources



Free courses and books

- Free online courses
 - [Practical deep learning for coders \(fast.ai\)](#)
 - [Stanford CS229: Machine Learning](#)
 - [Stanford CS231n: Convolutional Neural Networks for Visual Recognition](#)
 - [Fundamentals of deep learning](#)
- Free books
 - [Deep learning, by Ian GoodFellow, Yoshua Bengio and Aaron Courville](#)
 - [Fastbook: Deep learning for coders with fastai & Pytorch: Applications of AI without a PhD](#)
 - [Approaching \(Almost\) Any Machine Learning Problem](#)