CS7015/CS6910 (Deep Learning) : Lecture 1

(Partial/Brief) History of Deep Learning

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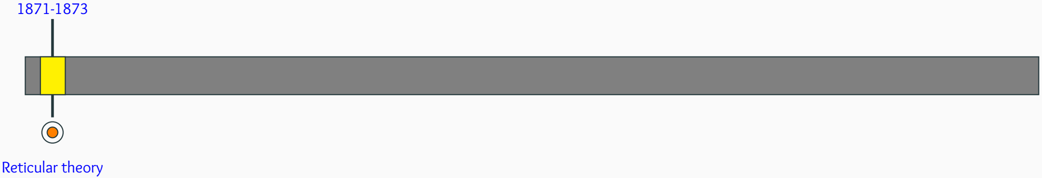
Acknowledgements

- Most of this material is based on the article “Deep Learning in Neural Networks: An Overview" by J. Schmidhuber [1]
- **The errors, if any, are due to me and I apologize for them**
- Feel free to contact me if you think certain portions need to be corrected (please provide appropriate references)

Chapter 1: Biological Neurons

Reticular Theory

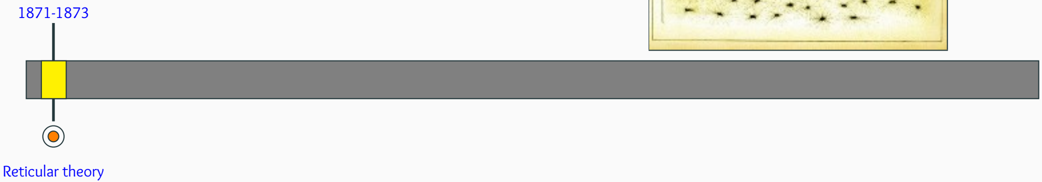
Joseph von Gerlach proposed that the nervous system is a single continuous network as opposed to a network of many discrete cells!



Staining Technique

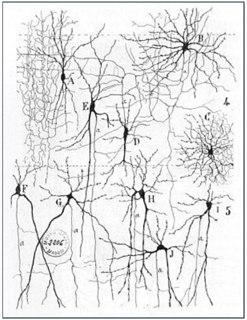
Camillo Golgi discovered a chemical reaction that allowed him to examine nervous tissue in much greater detail than ever before

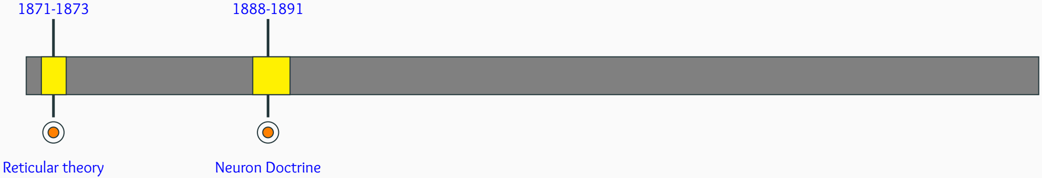
He was a proponent of Reticular theory.



Neuron Doctrine

Santiago Ramón y Cajal used Golgi's technique to study the nervous system and proposed that it is actually made up of discrete individual cells formimg a network (as opposed to a single continuous network)

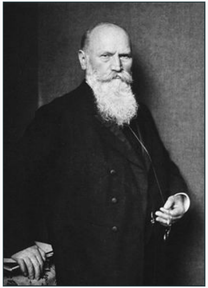


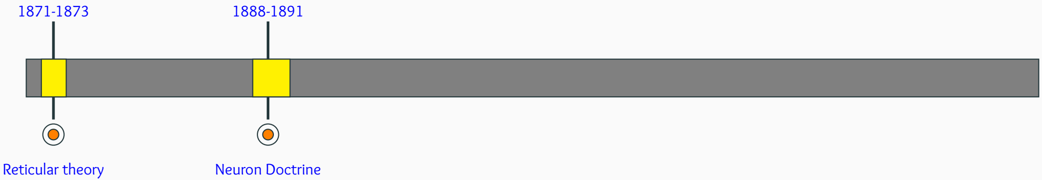


The Term Neuron

The term neuron was coined by Heinrich Wilhelm Gottfried von Waldeyer-Hartz around 1891.

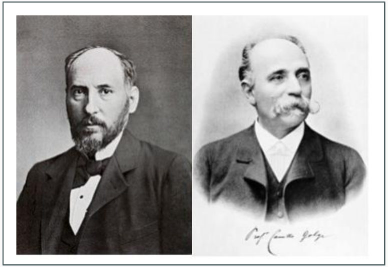
He further consolidated the Neuron Doctrine.

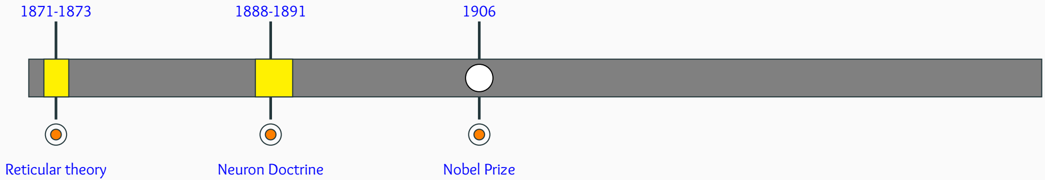




Nobel Prize

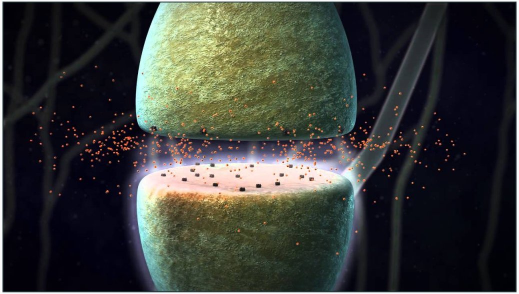
Both Golgi (reticular theory) and Cajal (neuron doctrine) were jointly awarded the 1906 Nobel Prize for Physiology or Medicine, that resulted in lasting conflicting ideas and controversies between the two scientists.

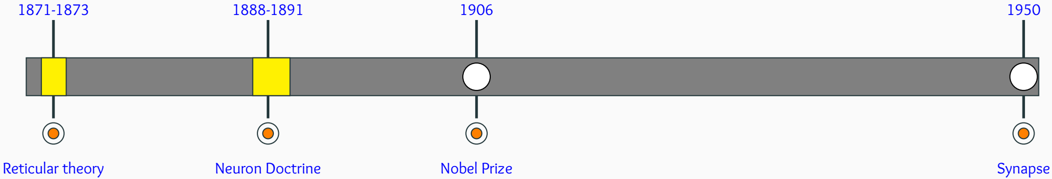




The Final Word

In 1950s electron microscopy finally confirmed the neuron doctrine by unambiguously demonstrating that nerve cells were individual cells interconnected through synapses (a network of many individual neurons).

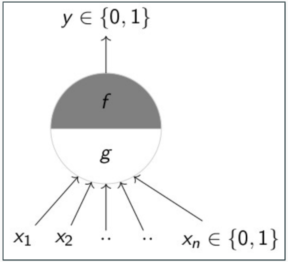


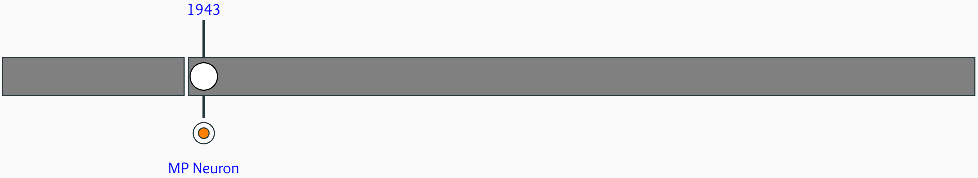


Chapter 2: From Spring to Winter of AI

McCulloch Pitts Neuron

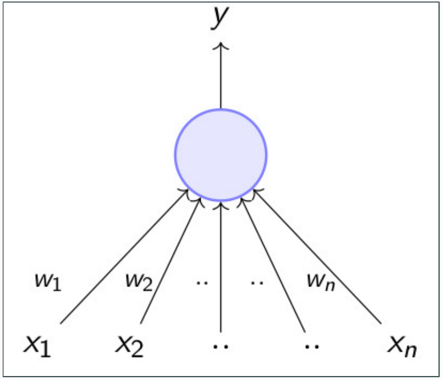
McCulloch (neuroscientist) and Pitts (logician) proposed a highly simplified model of the neuron (1943) [2]

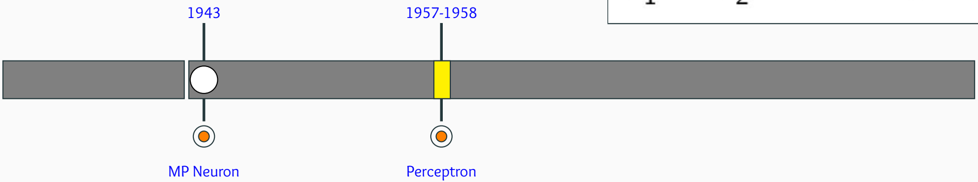




Perceptron

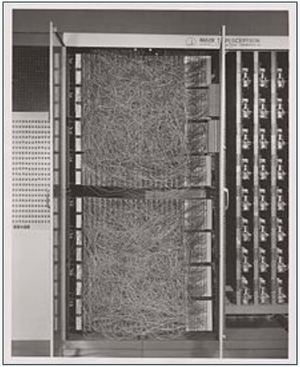
"the perceptron may eventually be able to learn, make decisions, and translate languages" -Frank Rosenblatt

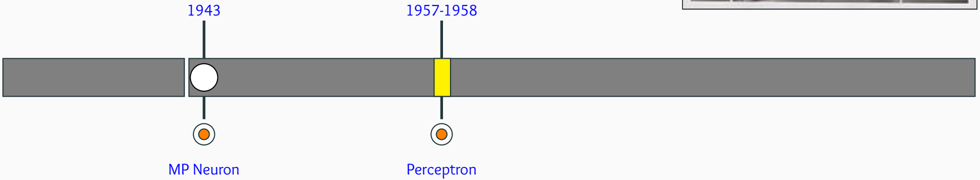




Perceptron

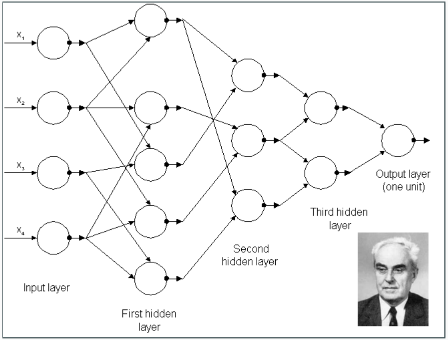
"the embryo of an electronic computer that the Navy expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence." -New York Times

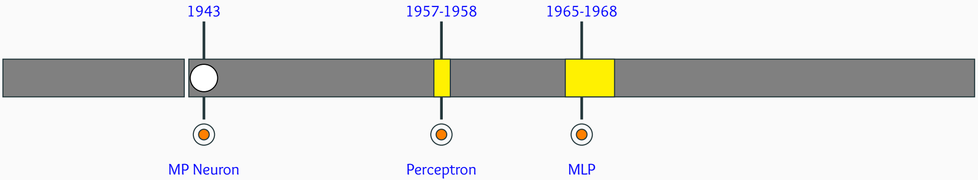




First generation Multilayer Perceptrons

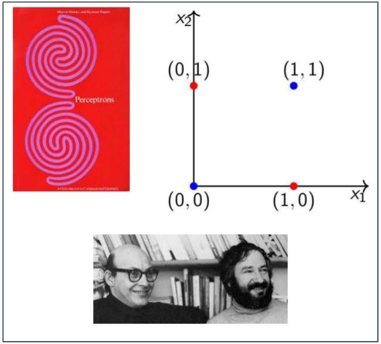
Ivakhnenko et. al. [3]

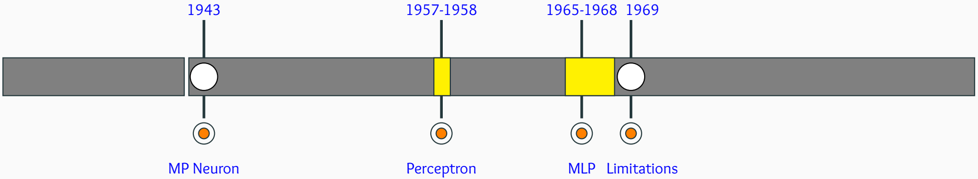




Perceptron Limitations

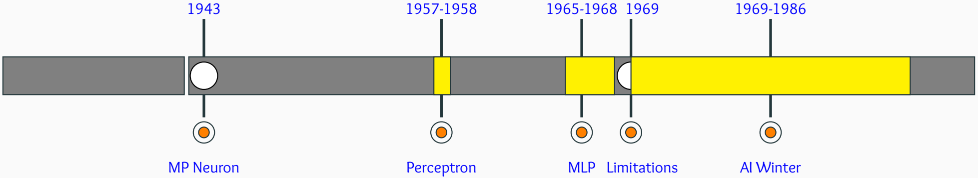
In their now famous book “Perceptrons”, Minsky and Papert outlined the limits of what perceptrons could do [4]





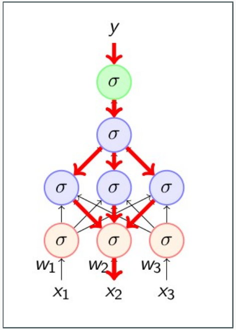
AI Winter of connectionism

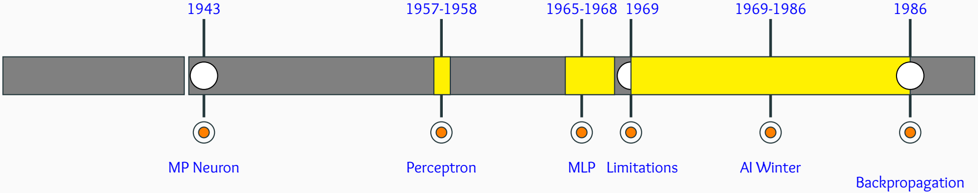
Almost lead to the abandonment of connectionist AI



Backpropagation

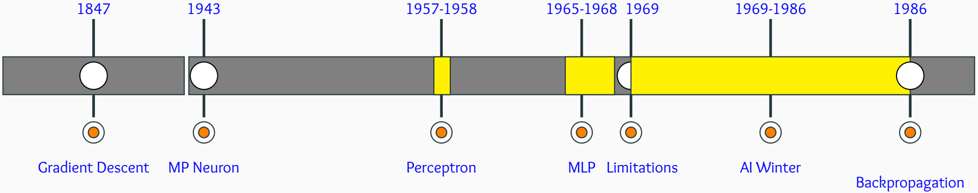
- Discovered and rediscovered several times throughout 1960's and 1970's
- Werbos(1982) [5] first used it in the context of artificial neural networks
- Eventually popularized by the work of Rumelhart et. al. in 1986 [6]





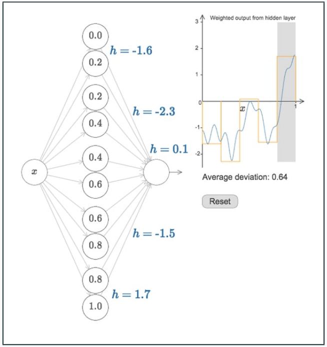
Gradient Descent

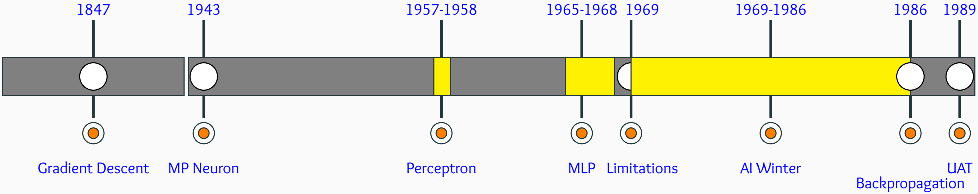
Cauchy discovered Gradient Descent motivated by the need to compute the orbit of heavenly bodies



Universal Approximation Theorem

A multilayered network of neurons with a single hidden layer can be used to approximate any continuous function to any desired precision [7]

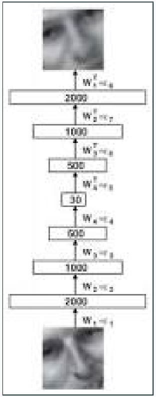




Chapter 3: The Deep Revival

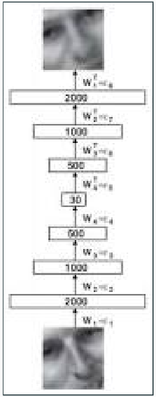
Unsupervised Pre-Training

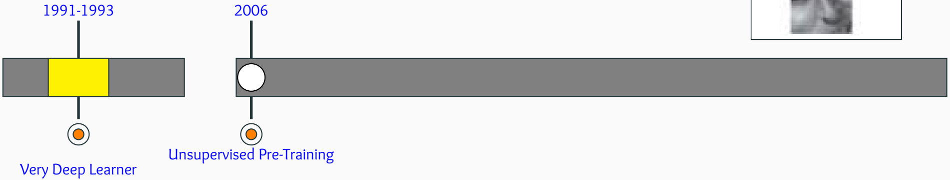
Hinton and Salakhutdinov described an effective way of initializing the weights that allows deep autoencoder networks to learn a low-dimensional representation of data.[8]



Unsupervised Pre-Training

The idea of unsupervised pre-training actually dates back to 1991-1993 (J. Schmidhuber) when it was used to train a “Very Deep Learner”





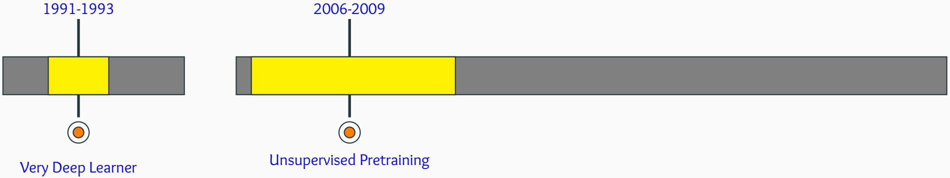
More insights (2007-2009)

Further Investigations into the effectiveness of Unsupervised Pre-training

Greedy Layer-Wise Training of Deep Networks

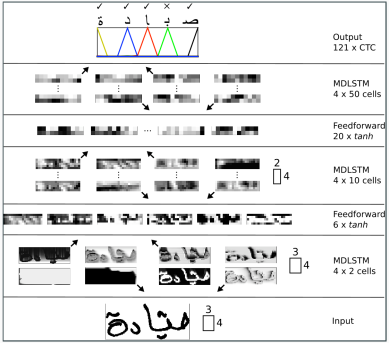
Why Does Unsupervised Pre-training Help Deep Learning?

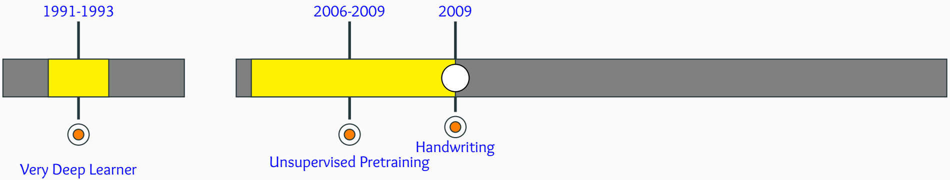
Exploring Strategies for Training Deep Neural Networks



Success in Handwriting Recognition

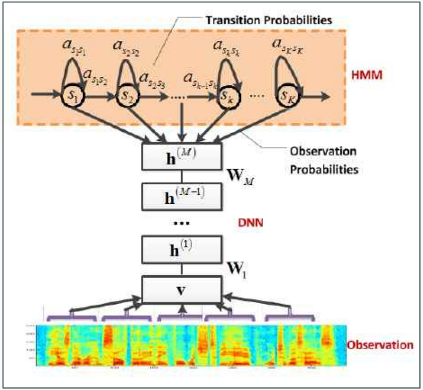
Graves et. al. outperformed all entries in an international Arabic handwriting recognition competition [9]

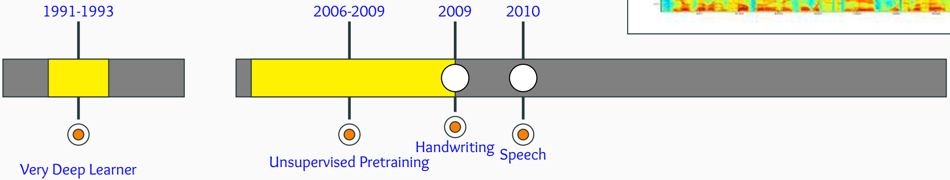




Success in Speech Recognition

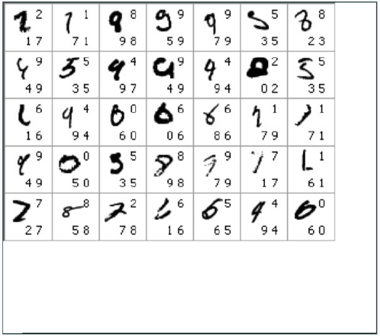
Dahl et. al. showed relative error reduction of 16.0% and 23.2% over a state of the art system [10]

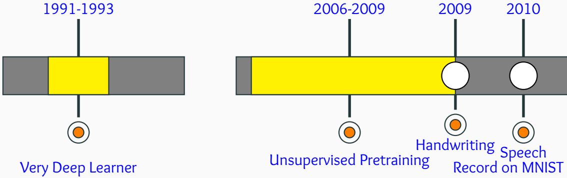




New record on MNIST

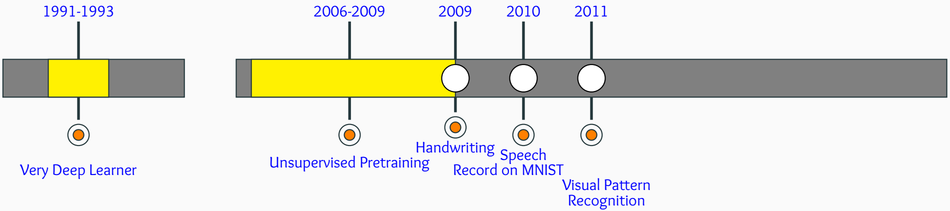
Ciresan et. al. set a new record on the MNIST dataset using good old backpropagation on GPUs (GPUs enter the scene) [11]





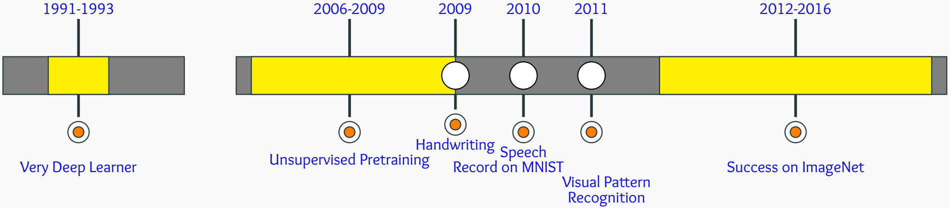
First Superhuman Visual Pattern Recognition

D. C. Ciresan et. al. achieved 0.56% error rate in the IJCNN Traffic Sign Recognition Competition [12]



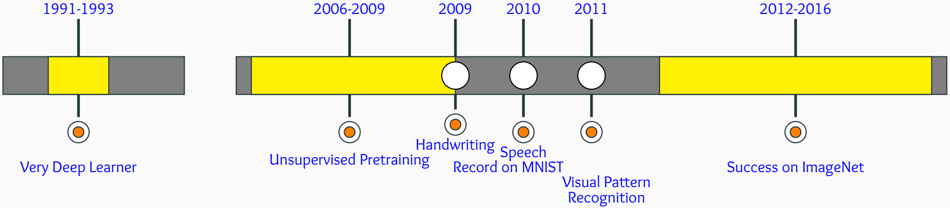
Winning more visual recognition challenges

Network	Error	Layers
AlexNet [13]	16.0%	8



Winning more visual recognition challenges

Network	Error	Layers
AlexNet [13]	16.0%	8
ZFNet [14]	11.2%	8



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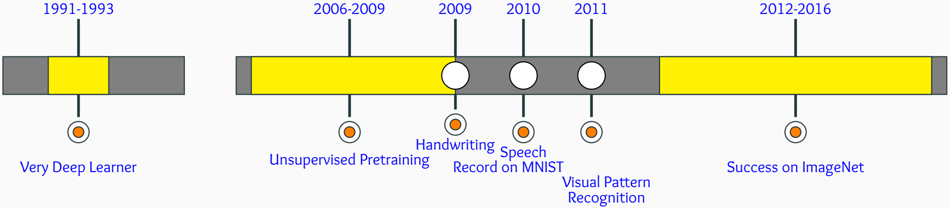
VGGNet [15]	7.3%	19



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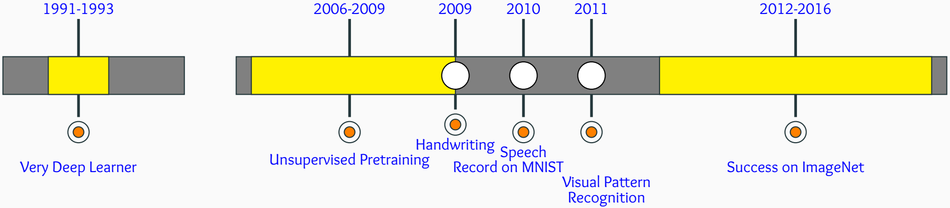
GoogLeNet [16]	6.7%	22



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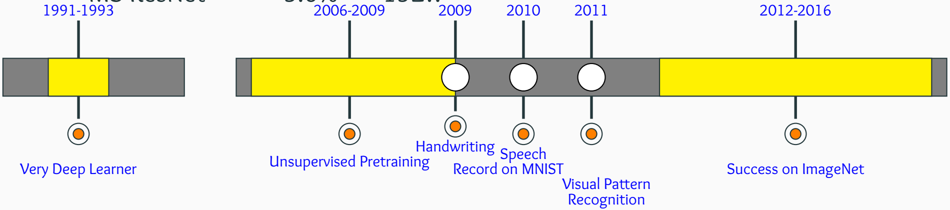
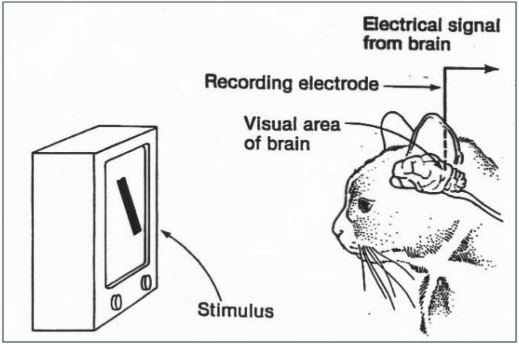
MS ResNet [17]	3.6%	152!!

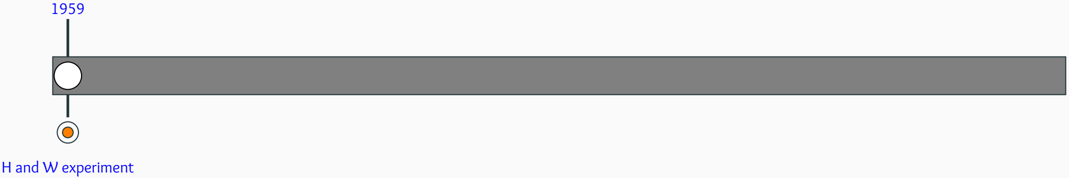


Chapter 4: From Cats to Convolutional Neural Networks

Hubel and Wiesel Experiment

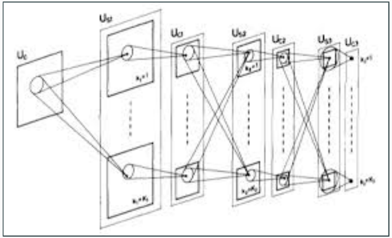
Experimentally showed that each neuron has a fixed receptive field - i.e. a neuron will fire only in response to a visual stimuli in a specific region in the visual space [18]

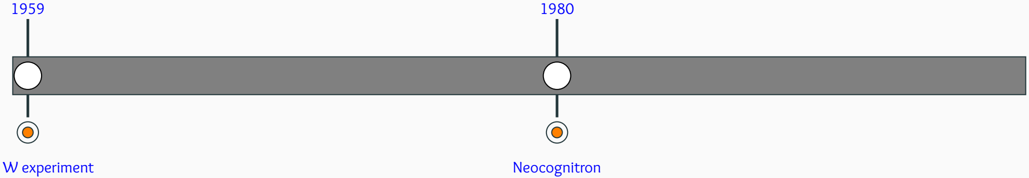




Neocognitron

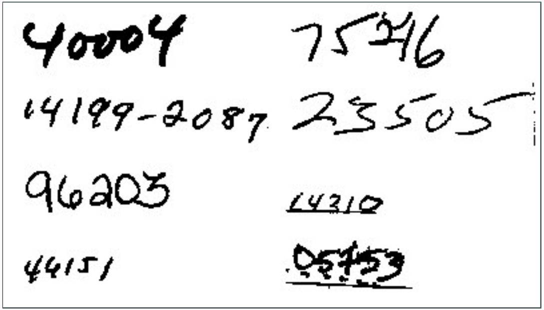
Used for Handwritten character recognition and pattern recognition (Fukushima et. al.) [19]

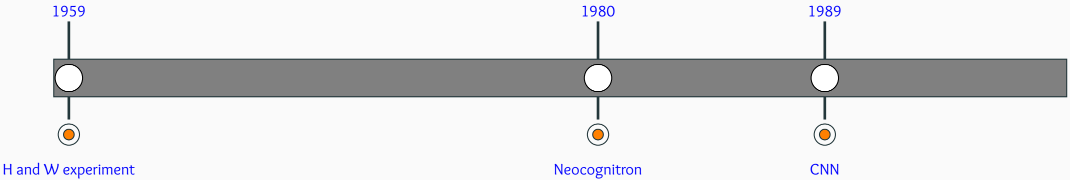




Convolutional Neural Network

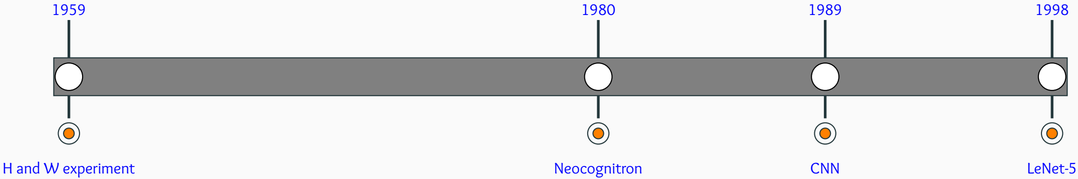
Handwriting digit recognition using backpropagation over a Convolutional Neural Network (LeCun et. al.) [20]





LeNet-5

Introduced the (now famous) MNIST dataset (LeCun et. al.) [21]

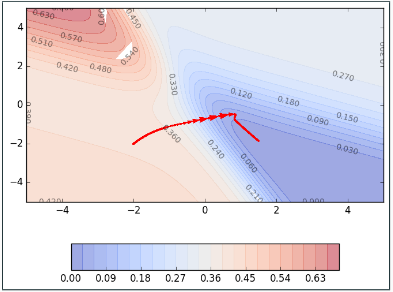


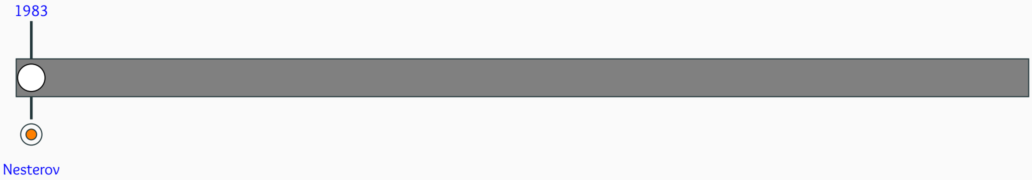
An algorithm inspired by an experiment on cats is today used to detect cats in videos :-)

Chapter 5: Faster, higher, stronger

Better Optimization Methods

Faster convergence, better accuracies





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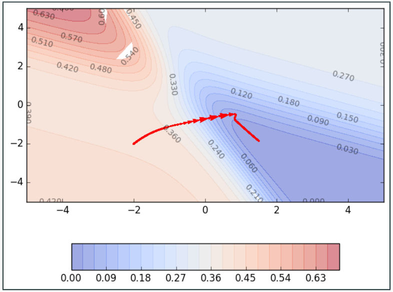

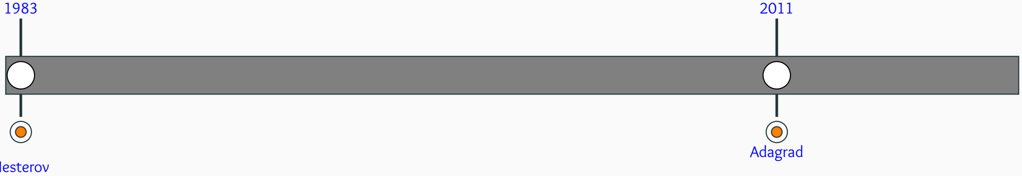

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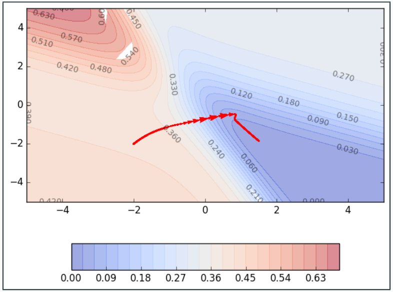

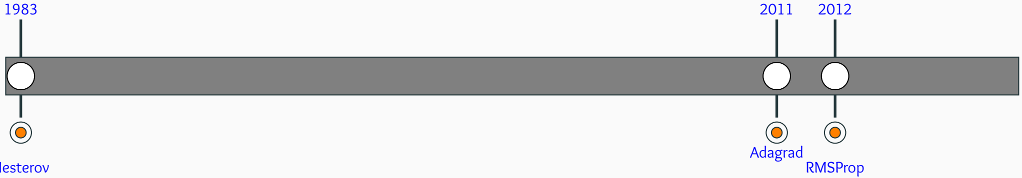

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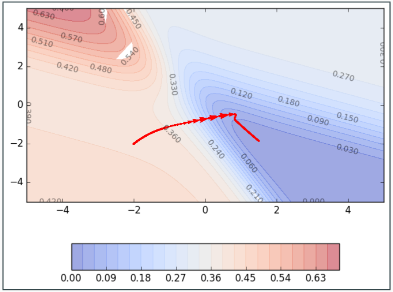

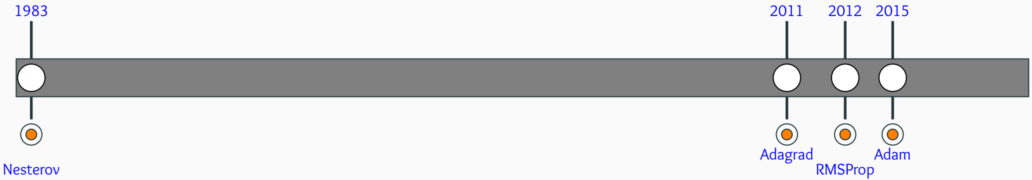

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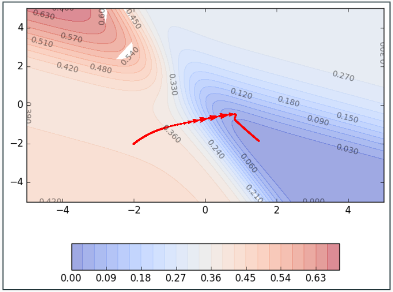

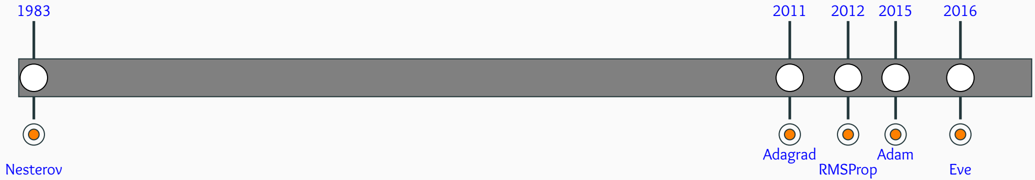

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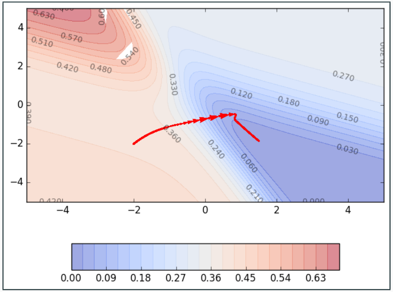

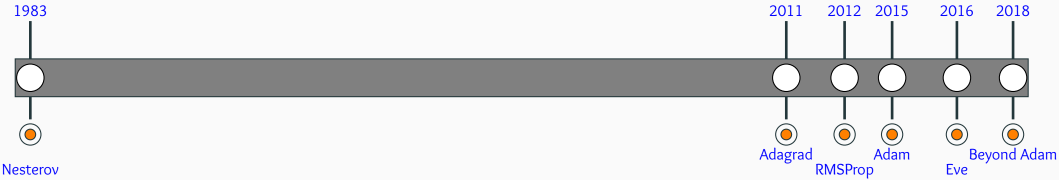

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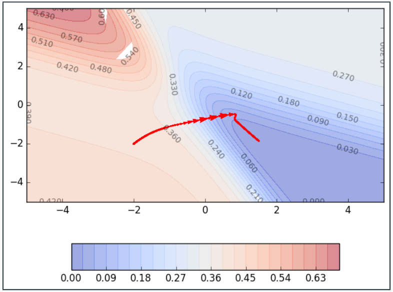
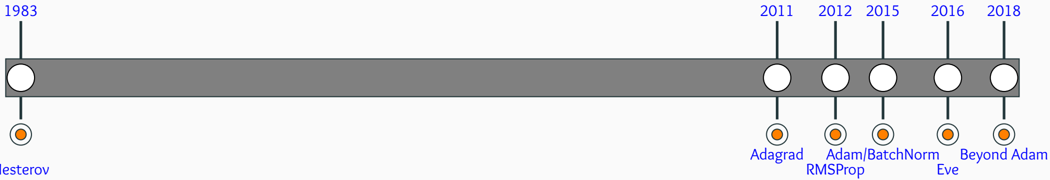
Faster convergence, better accuracies

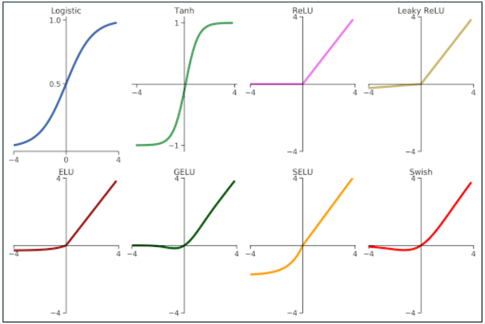


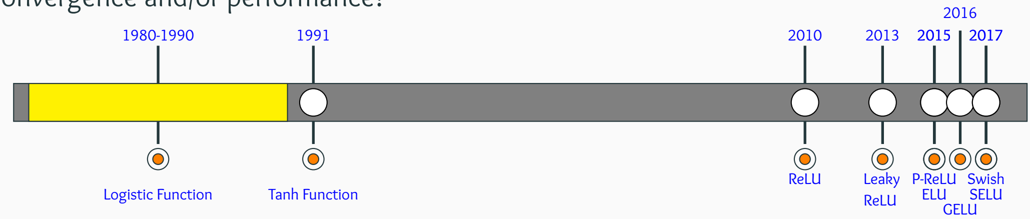


Better Activation Functions

We have come a long way from the initial days when the logistic function was the default activation function in NNs!

Over the past few years many new functions have been proposed leading to better convergence and/or performance!





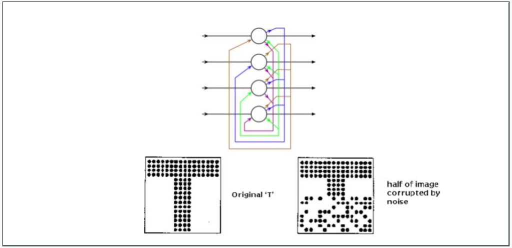
Chapter 6: The Curious Case of Sequences

Sequences

- They are everywhere
- Time series, speech, music, text, video
- Each unit in the sequence interacts with other units
- Need models to capture this interaction

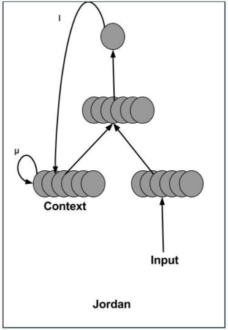
Hopfield Network

Content-addressable memory systems for storing and retrieving patterns [22]



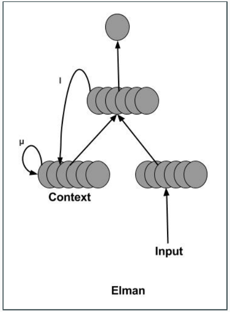
Jordan Network

The output state of each time step is fed to the next time step thereby allowing interactions between time steps in the sequence



Elman Network

The hidden state of each time step is fed to the next time step thereby allowing interactions between time steps in the sequence

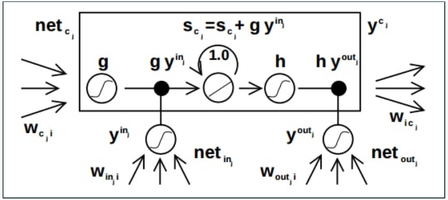


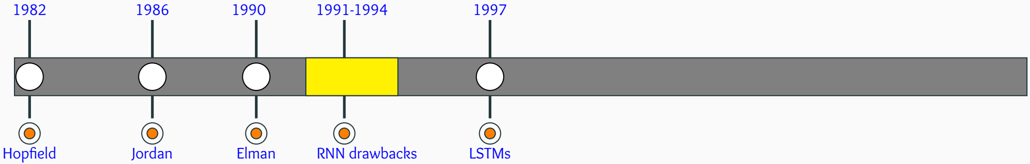
Drawbacks of RNNs

Hochreiter et. al. and Bengio et. al. showed the difficulty in training RNNs (the problem of exploding and vanishing gradients)

Long Short Term Memory

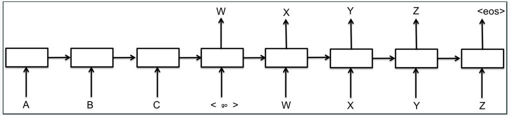
Showed that LSTMs can solve complex long time lag tasks that could never be solved before

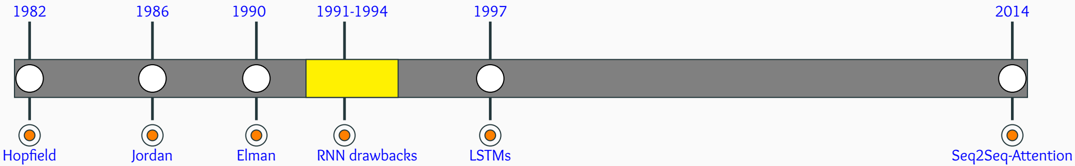




Sequence To Sequence Models

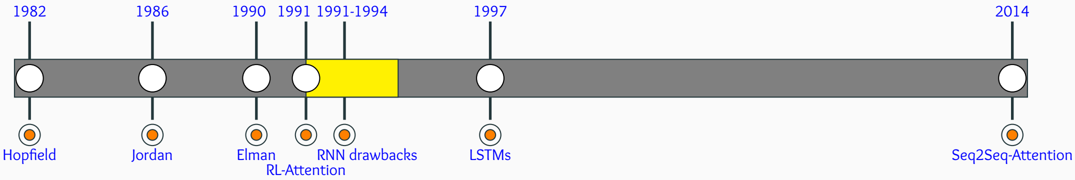
- Initial success in using RNNs/LSTMs for large scale Sequence To Sequence Learning Problems
- Introduction of Attention which is perhaps the idea of the decade!





RL for Attention

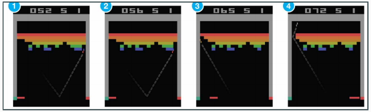
Schmidhuber & Huber proposed RNNs that use reinforcement learning to decide where to look

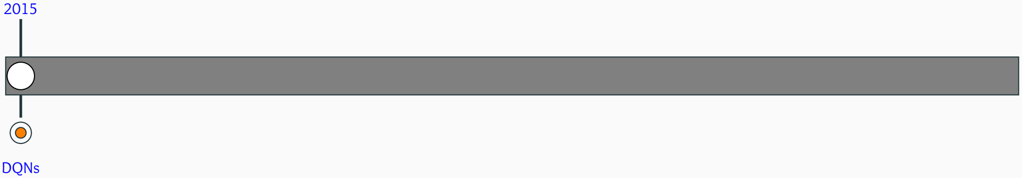


Chapter 7: Beating humans at their own game (literally)

Playing Atari Games

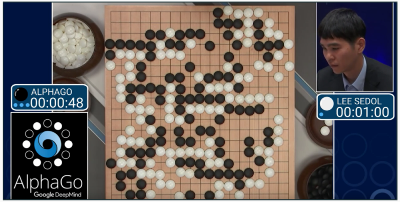
- Human-level control through deep reinforcement learning for playing Atari Games [23]

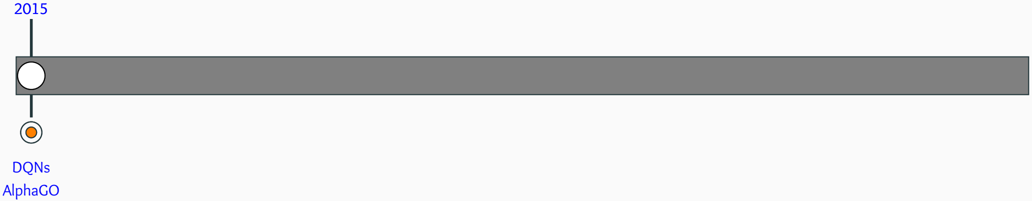




Let’s GO

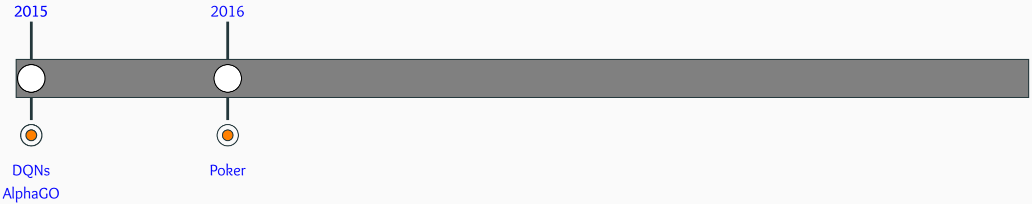
- Alpha Go Zero - Best Go player ever, surpassing human players [24]
- GO is more complex than chess because of number of possible moves
- No brute force backtracking unlike previous chess agents





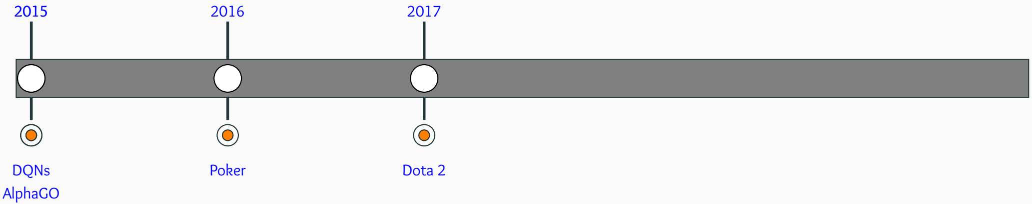
Taking a shot at Poker

DeepStack defeated 11 professional poker players with only one outside the margin of statistical significance [25]



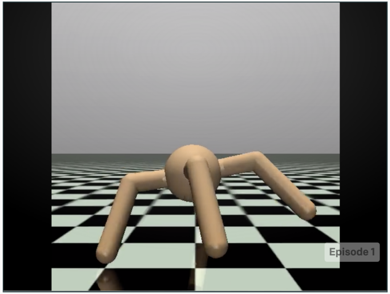
Defense of the Ancients

“Our Dota 2 AI, called OpenAI Five, learned by playing over 10,000 years of games against itself. It demonstrated the ability to achieve expert-level performance, learn human–AI cooperation, and operate at internet scale.” – *OpenAI*

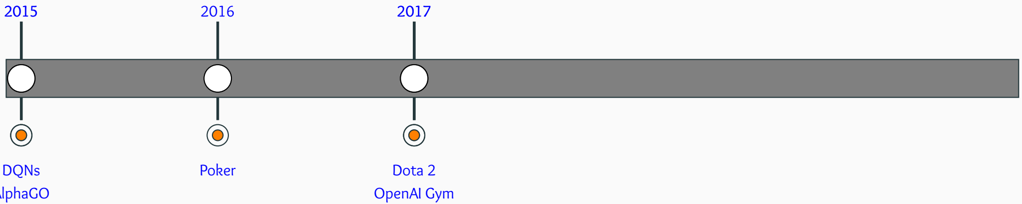


A toolkit for RL

OpenAI Gym[a] is a toolkit for developing and comparing reinforcement learning algorithms. It supports teaching agents everything from walking to playing games like Pong or Pinball.



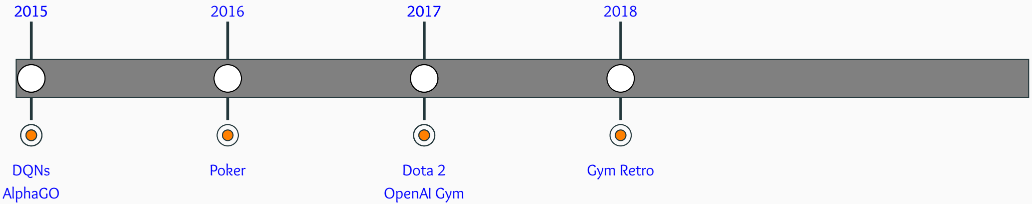
[a] https://gym.openai.com/



RL for a 1000 games!

Open AI Gym Retro[a]: a platform for reinforcement learning research on games which contains 1,000 games across a variety of backing emulators.

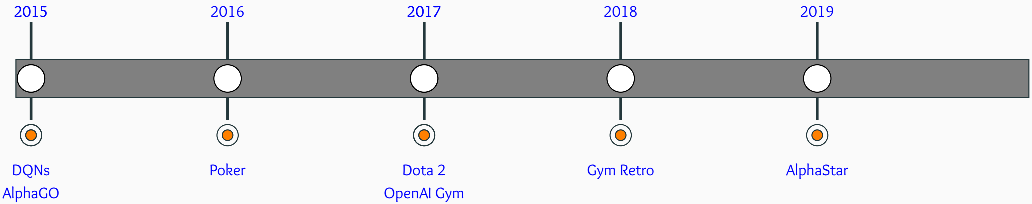
[a] https://openai.com/blog/gym-retro/



Complex Strategy Games

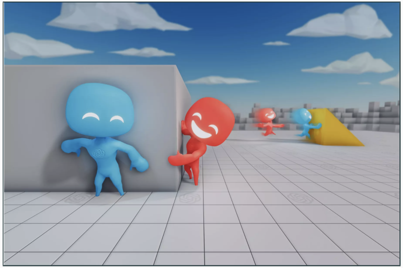
AlphaStar[a] learned to balance short and long-term goals and adapt to unexpected situations while playing using the same maps and conditions as humans

[a] https://deepmind.com/

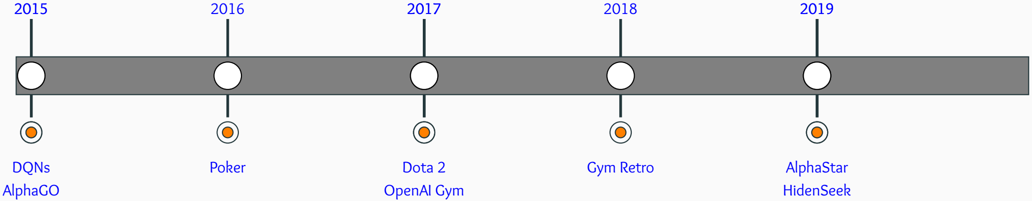


Learning to Hide

OpenAI demonstrated agents which can learn complex strategies such as chase and hide, build a defensive shelter, break a shelter, use a ramp to search inside a shelter and so on!

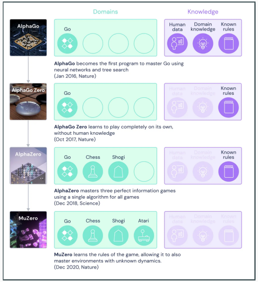


https://openai.com/blog/emergent-tool-use/



Jack of all, Master of all!

MuZero masters Go, chess, shogi and Atari without needing to be told the rules, thanks to its ability to plan winning strategies in unknown environments.



https://deepmind.com/blog

2015	2016	2017	2018	2019	2020
DQNs AlphaGO	Poker	Dota 2 OpenAI Gym	Gym Retro	AlphaStar HidenSeek	MuZero

Chapter 8: The Madness (2013-)

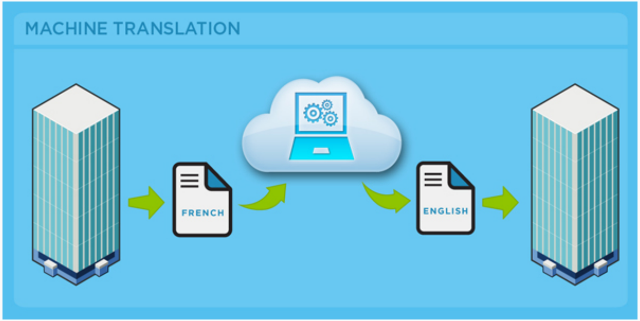
He sat on a chair.

Language Modeling

- Mikolov et al. (2010) [26]
- Kiros et al. (2015) [27]
- Kim et al. (2015) [28]

Speech Recognition

- Hinton et al. (2012) [29]
- Graves et al. (2013) [30]
- Chorowski et al. (2015) [31]
- Sak et al. (2015) [32]



Machine Translation

- Kalchbrenner et al. (2013) [33]
- Cho et al. (2014) [34]
- Bahdanau et al. (2015) [35]
- Jean et al. (2015) [36]
- Gulcehre et al. (2015) [37]
- Sutskever et al. (2014) [38]
- Luong et al. (2015) [39]
- Zheng et al. (2017) [40]
- Cheng et al. (2016) [41]
- Chen et al. (2017) [42]
- Firat et al. (2016) [43]

Time	User	Utterance
03:44	Old	I dont run graphical ubuntu, I run ubuntu server.
03:45	kuja	Taru: Haha sucker.
03:45	Taru	Kuja: ?
03:45	bur[n]er	Old: you can use "ps ax" and "kill (PID#)"
03:45	kuja	Taru: Anyways, you made the changes right?
03:45	Taru	Kuja: Yes.
03:45	LiveCD	or killall speedlink
03:45	kuja	Taru: Then from the terminal type: sudo apt-get update
03:46	_pm	if i install the beta version, how can i update it when the final version comes out?
03:46	Taru	Kuja: I did.

Sender	Recipient	Utterance
Old		I dont run graphical ubuntu, I run ubuntu server.
bur[n]er	Old	you can use "ps ax" and "kill (PID#)"
kuja	Taru	Haha sucker.
Taru	Kuja	?
kuja	Taru	Anyways, you made the changes right?
Taru	Kuja	Yes.
kuja	Taru	Then from the terminal type: sudo apt-get update
Taru	Kuja	I did.

Conversation Modeling

- Shang et al. (2015) [44]
- Vinyals et al. (2015) [45]
- Lowe et al. (2015) [46]
- Dodge et al. (2015) [47]
- Weston et al. (2016) [48]
- Serban et al. (2016) [49]
- Bordes et al. (2017) [50]
- Serban et al. (2017) [51]

Question Answering

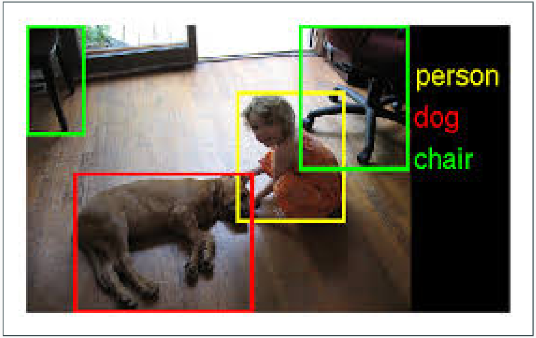
Task 1: Single Supporting Fact
Mary went to the bathroom.
John moved to the hallway.
Mary travelled to the office.
Where is Mary? A:office

Task 2: Two Supporting Facts
John is in the playground.
John picked up the football.
Bob went to the kitchen.
Where is the football? A:playground

Task 3: Three Supporting Facts
John picked up the apple.
John went to the office.
John went to the kitchen.
John dropped the apple.
Where was the apple before the kitchen? A:office

Task 4: Two Argument Relations
The office is north of the bedroom.
The bedroom is north of the bathroom.
The kitchen is west of the garden.
What is north of the bedroom? A: office
What is the bedroom north of? A: bathroom

- Hermann et al. (2015) [52]
- Chen et al. (2016) [53]
- Xiong et al. (2016) [54]
- Seo et al. (2016) [55]
- Dhingra et al. (2017) [56]
- Wang et al. (2017) [57]
- Hu et al. (2017) [58]



Object Detection/Recognition

- Semantic Segmentation (Long et al, 2015) [59]
- Recurrent CNNs (Liang et al., 2015) [60]
- Faster RCNN (Ren et al., 2015) [61]
- Inside-Outside Net (Bell et al., 2015) [62]
- YOLO9000 (Redmon et al., 2016) [63]
- R-FCN (Dai et al., 2016) [64]
- Mask R-CNN (He at al., 2017) [65]
- Video Object segmentation (Caelles et al., 2017) [66]

Visual Tracking

- Choi et al. (2017) [67]
- Yun et al. (2017) [68]
- Alahi et al. (2017) [69]

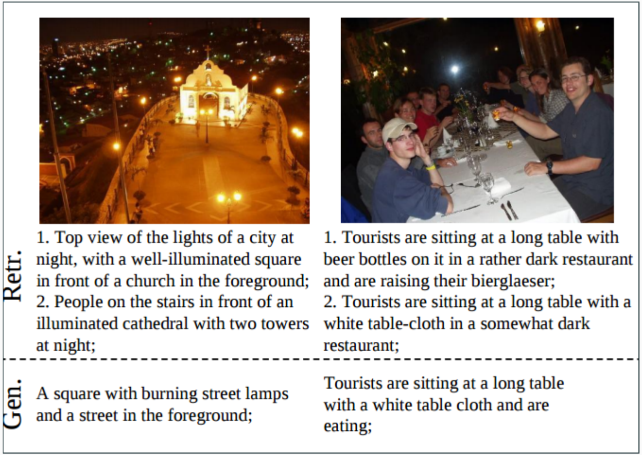


Image Captioning

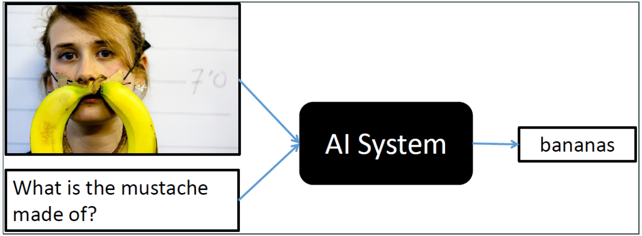
- Mao et al. (2014) [70]
- Mao at al. (2015) [71]
- Kiros et al. (2015) [72]
- Donahue et al. (2015) [73]
- Vinyals et al. (2015) [74]
- Karpathy et al. (2015) [75]
- Fang et al. (2015) [76]
- Chen et al. (2015) [77]

Video Captioning

A group of young men playing a game of soccer

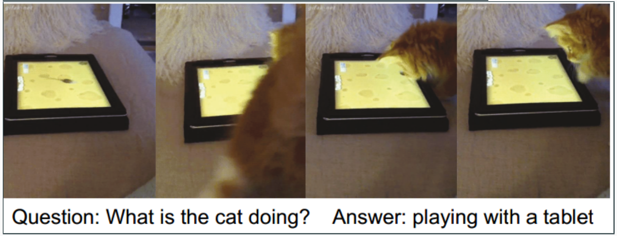
A man riding a wave on top of a surfboard.

- Donahue et al. (2014) [78]
- Venugopalan at al. (2014) [79]
- Pan et al. (2015) [80]
- Yao et al. (2015) [81]
- Rohrbach et al. (2015) [82]
- Zhu et al. (2015) [83]
- Cho et al. (2015) [34]



Visual Question Answering

- Santoro et al. (2017) [84]
- Hu at al. (2017) [85]
- Johnson et al. (2017) [86]
- Ben-younes et al. (2017) [87]
- Malinowski et al. (2017) [88]
- Kazemi et al. (2016) [89]



Video Question Answering

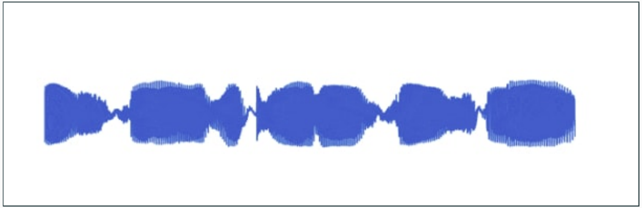
- Tapaswi et. al. 2016 [90]
- Zeng et. al. 2016 [91]
- Maharaj et. al. 2017 [92]
- Zhao et. al. 2017 [93]
- Yu Youngjae et. al. 2017 [94]
- Xue Hongyang et. al. 2017 [95]
- Mazaheri et. al. 2017 [96]

Video Summarization

- Chheng 2007 [97]
- Ajmal 2012 [98]
- Zhang Ke 2016 [99]
- Zhong Ji 2017 [100]
- Panda 2017 [101]

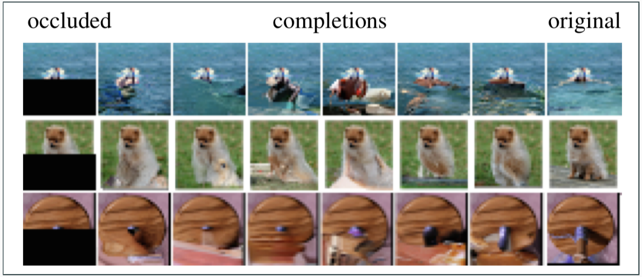
Generating Authentic Photos

- Variational Autoencoders (Kingma et. al., 2013) [102]
- Generative Adversarial Networks (Goodfellow et. al., 2014) [103]
- Plug & Play generative nets (Nguyen et al., 2016) [104]
- Progressive Growing of GANs (Karras et al., 2017) [105]



Generating Raw Audio

- Wavenets (Oord et. al., 2016) [106]



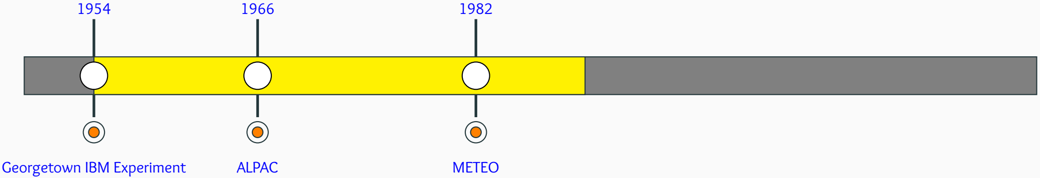
Pixel RNNs

- (Oord et al., 2016) [107]
- (Oord et al., 2016) [108]
- (Salimans et al., 2017) [109]

Chapter 9: The Rise of the Transformers

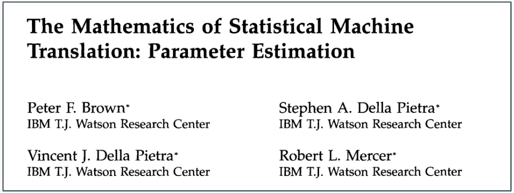
Rule Based Systems

Intial Machine Translation Systems used hand crafted rules and dictionaries to translate sentences between few politically important language pairs (e.g., English -Russian). They could not live upto the initial hype and were panned by the ALPAC report (1966)



Statistical MT

The IBM Models for Machine Translation gave a boost to the idea of data driven statistical NLP which then ruled NLP for the next 2 decades till Deep Learning took over!

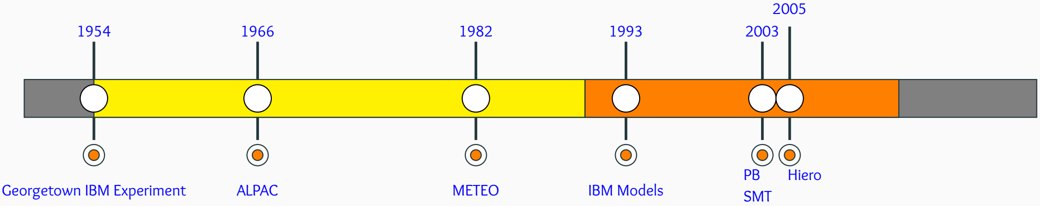

The Mathematics of Statistical Machine Translation: Parameter Estimation

Peter F. Brown*
IBM T.J. Watson Research Center

Stephen A. Della Pietra*
IBM T.J. Watson Research Center

Vincent J. Della Pietra*
IBM T.J. Watson Research Center

Robert L. Mercer*
IBM T.J. Watson Research Center



Neural MT

The introduction of seq2seq models and attention [35] (perhaps, the idea of the decade!) lead to a paradigm shift in NLP ushering the era of bigger, hungrier (more data), better models!

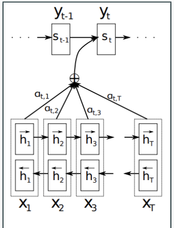
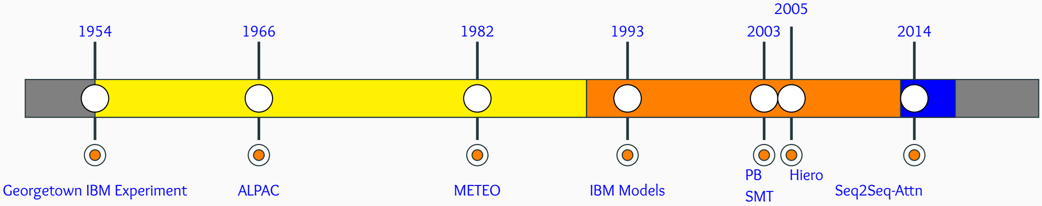


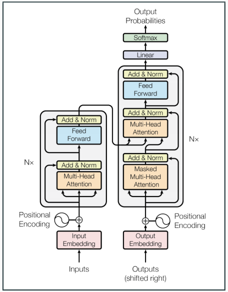
Figure 1: The graphical illustration of the proposed model trying to generate the t-th target word y_t given a source sentence $(x_1, x_2, \ldots, x_T)$.

Source: Bahdanau et. al. [35]

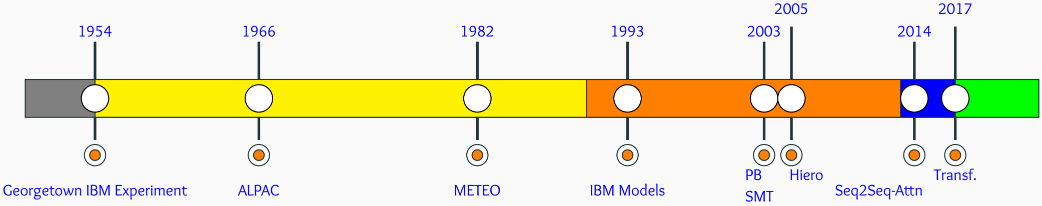


The Transformer Revolution

It is rare for a field to see two dramatic paradigm shifts in a short span of 4 years! Since their inception transformers have taken the NLP world by storm leading to the development of insanely big models trained on obscene amounts of data!

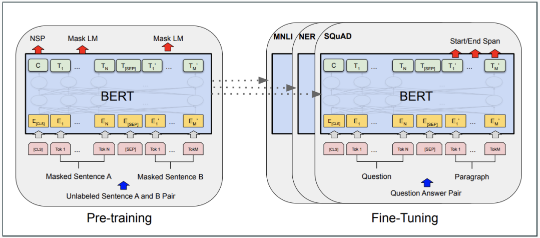


Source: Vaswani et. al. [110]

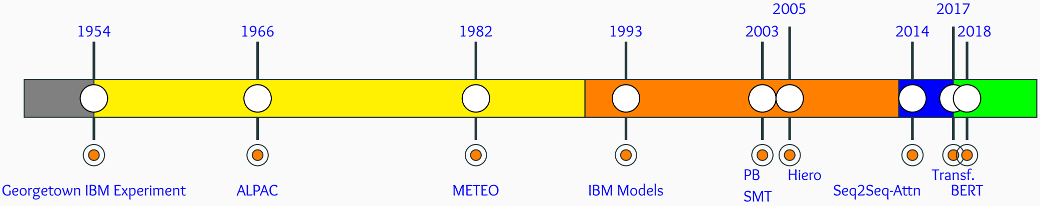


The Transformer Revolution

Most NLP applications today are driven by BERT and its variants. The key idea here was to learn general langauge characteristics using large amounts of unlabeled corpora and then fine-tune the model for specific downstream tasks.



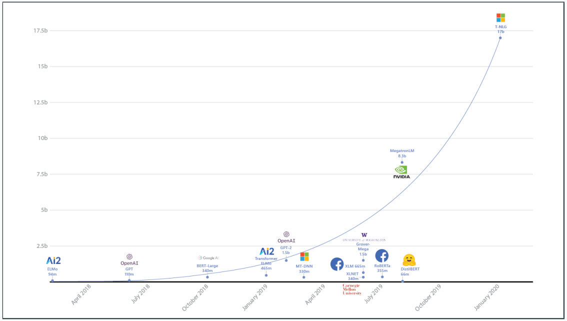
Source: Devlin et. al.[111]

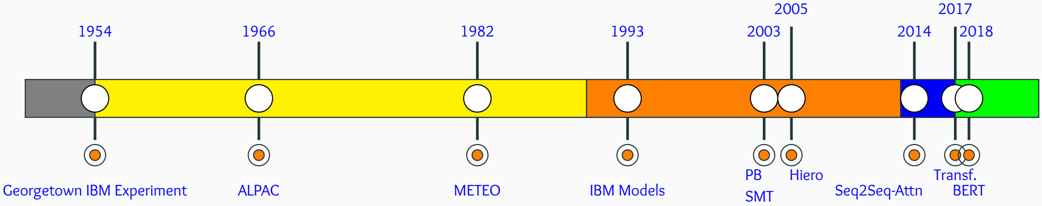


The Billion Parameter Club

The models are becoming bigger and bigger and bigger!

Source: https://msturing.org/

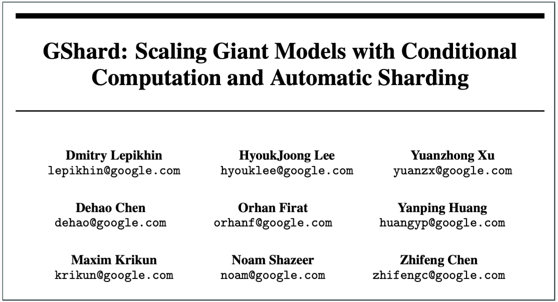




The Trillion Parameter Club

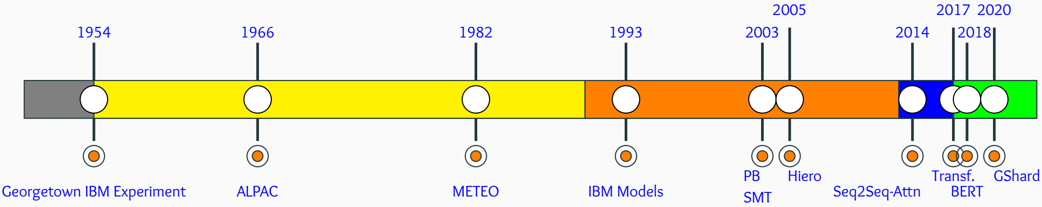
Trained on 100 languages, with a total of 13B examples, 1 Trillion Parameters on 2048 TPUs!

This is insane!



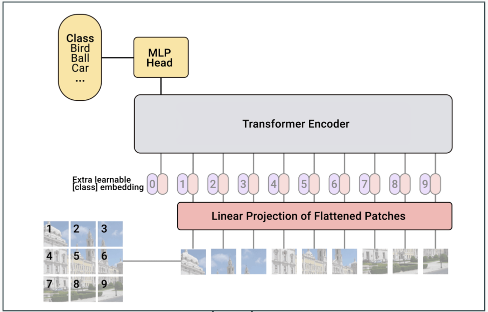
GShard: Scaling Giant Models with Conditional Computation and Automatic Sharding

Dmitry Lepikhin lepikhin@google.com
HyoukJoong Lee hyouklee@google.com
Yuanzhong Xu yuanzx@google.com
Dehao Chen dehao@google.com
Orhan Firat orhanf@google.com
Yanping Huang huangyp@google.com
Maxim Krikun krikun@google.com
Noam Shazeer noam@google.com
Zhifeng Chen zhifengc@google.com

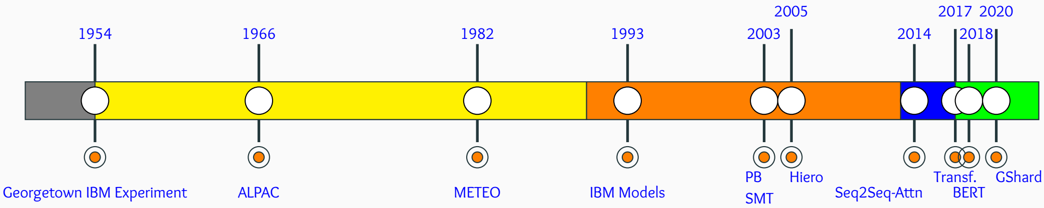


From Language To Vision

A vision model[a] based as closely as possible on the Transformer architecture originally designed for text-based tasks (another paradigm shift from CNNs which have been around since 1980s!)



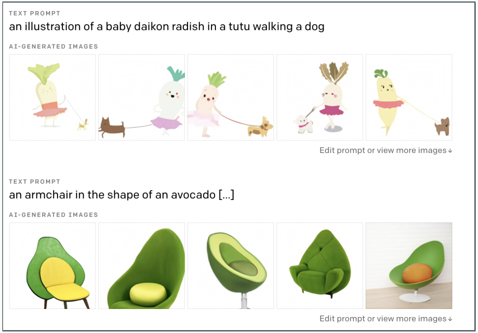
[a] Source:https://ai.googleblog.com/2020/12/transformers-for-image-recognition-at.html

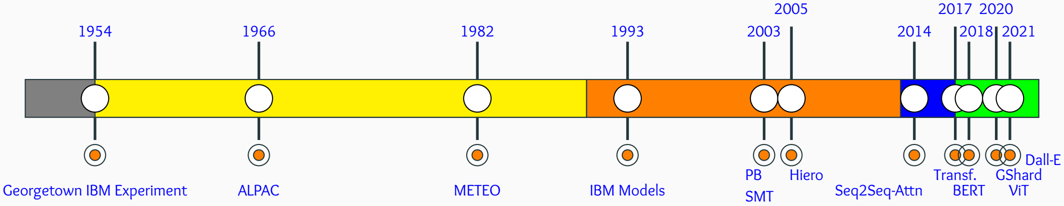


From Language To Vision

DALL·E[a] is a 12-billion parameter version of GPT-3 trained to generate images from text descriptions, using a dataset of text–image pairs.

[a] https://openai.com/blog/dall-e/

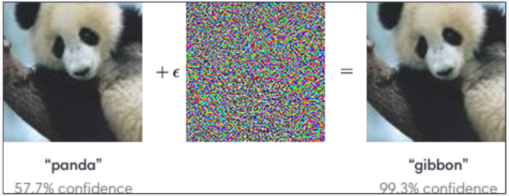




Chapter 10: Calls for Sanity (Interpretable, Fair, Responsible, Green AI)

The Paradox of Deep Learning

Why does deep learning work so well despite

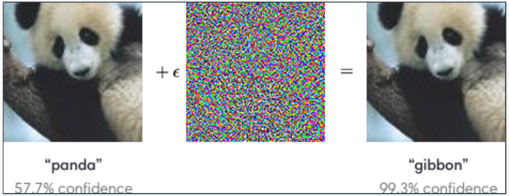


*https://arxiv.org/pdf/1710.05468.pdf

The Paradox of Deep Learning

Why does deep learning work so well despite

- high capacity (susceptible to overfitting)



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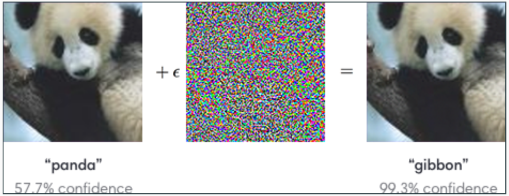

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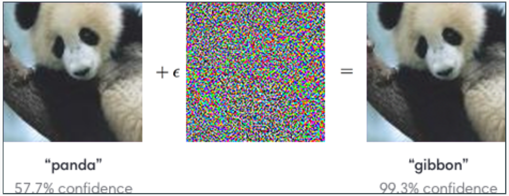

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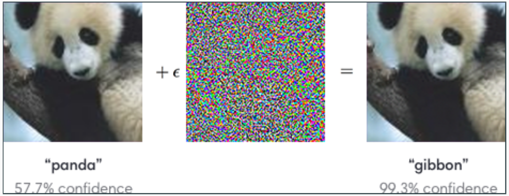

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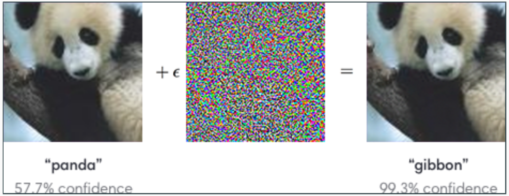

No clear answers yet but ...

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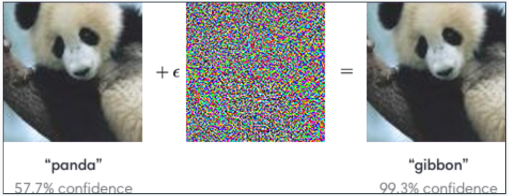

No clear answers yet but ...

- Slowly but steadily there is increasing emphasis on explainability and theoretical justifications!*

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The Paradox of Deep Learning

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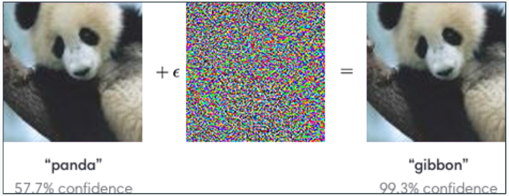

No clear answers yet but ...

- Slowly but steadily there is increasing emphasis on explainability and theoretical justifications!*
- Hopefully this will bring sanity to the proceedings !

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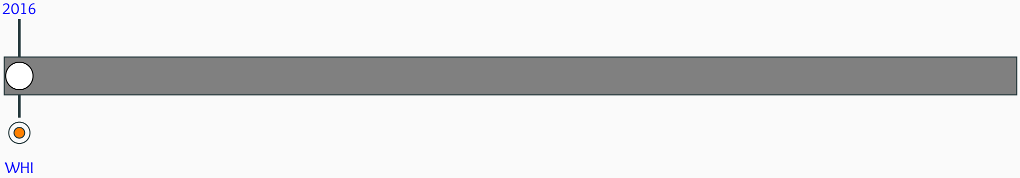
*https://arxiv.org/pdf/1710.05468.pdf

Tell me why!

Workshop on Human Interpretability in Machine Learning

We still do not know much about why DL models do what they do!



Tell me why!

Clever Hans was a horse that was supposed to be able to do lots of difficult mathematical sums and solve complicated problems. Turns out, it was giving the right answers by watching the reactions of the people watching him.

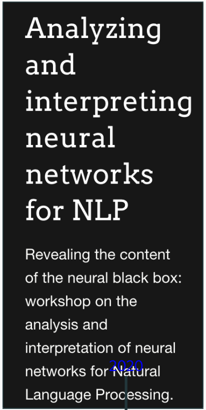
A repository to benchmark machine learning systems' vulnerability to adversarial examples.

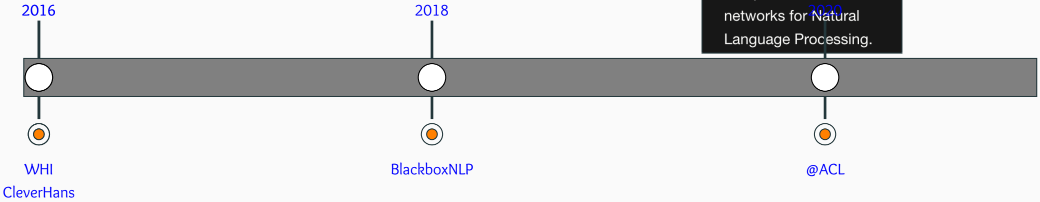
2016

WHI
CleverHans

Tell me why!

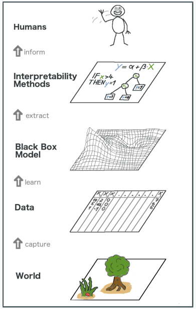
Push for analyzing and interpreting neural networks for NLP



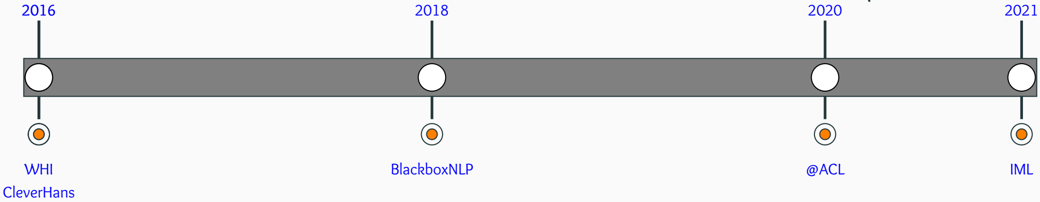


Tell me why!

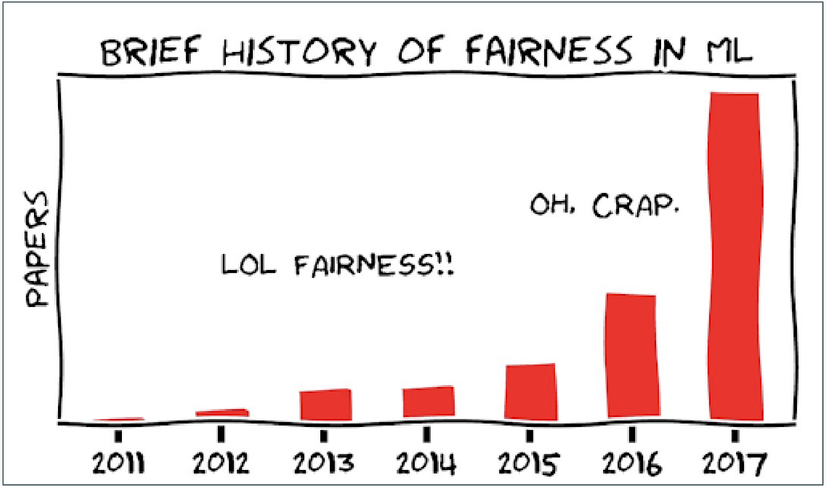
Interpretable Machine Learning: A Guide for Making Black Box Models Explainable. – Christoph Molnar



Source: IML: Christoph Molnar



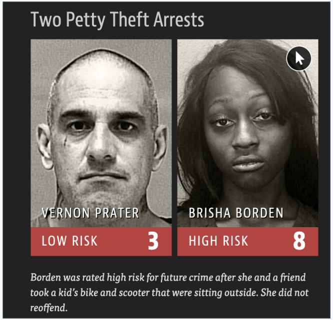
Be Fair and Responsible!



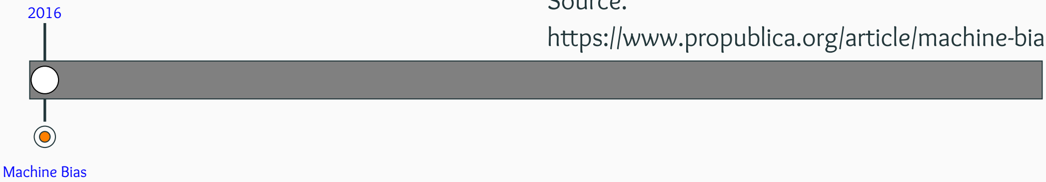
Source: https://fairmlclass.github.io/ (Moritz Hardt)

Be Fair and Responsible!

"There's software used across the country to predict future criminals. And it's biased against blacks." - Propublica



Source:
https://www.propublica.org/article/machine-bias-



Be Fair and Responsible!

"Facial Recognition Is Accurate, if You're a White Guy" - MIT Media

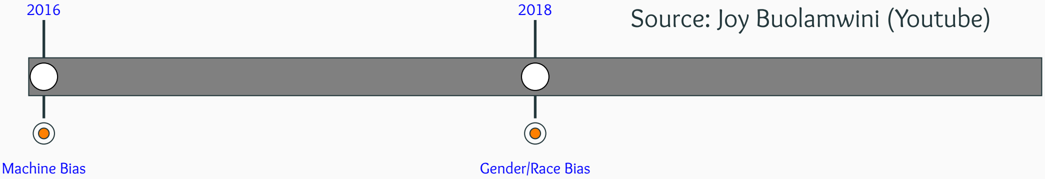
Gender Shades audit, 2018

Accuracy in gender classification

	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
IBM	88.0%	65.3%	99.7%	92.9%	34.4%
Megvii	99.3%	65.5%	99.2%	94.0%	33.8%
Microsoft	94.0%	79.2%	100.0%	98.3%	20.8%

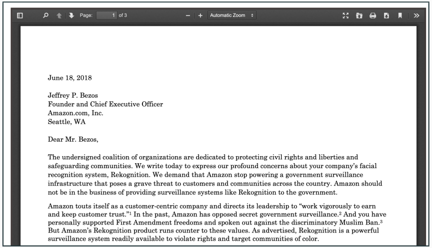
Chart: MIT Technology Review • Source: Joy Buolamwini & Timnit Gebru • Created with Datawrapper

Source: Joy Buolamwini (Youtube)



Be Fair and Responsible!

In 2018, nearly 70 civil rights and research organizations wrote a letter to Jeff Bezos demanding that Amazon stop providing face recognition technology to governments.



Page: 1 of 3 Automatic Zoom

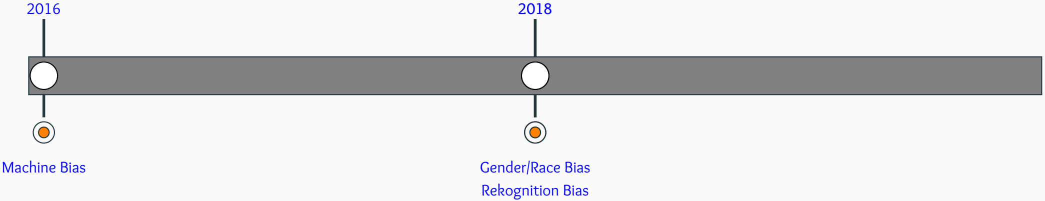
June 18, 2018

Jeffrey P. Bezos
Founder and Chief Executive Officer
Amazon.com, Inc.
Seattle, WA

Dear Mr. Bezos,

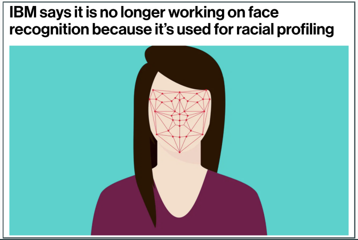
The undersigned coalition of organizations are dedicated to protecting civil rights and liberties and safeguarding communities. We write today to express our profound concerns about your company's facial recognition system, Rekognition. We demand that Amazon stop powering a government surveillance infrastructure that poses a grave threat to customers and communities across the country. Amazon should not be in the business of providing surveillance systems like Rekognition to the government.

Amazon touts itself as a customer-centric company and directs its leadership to "work vigorously to earn and keep customer trust."[1] In the past, Amazon has opposed secret government surveillance.[2] And you have personally supported First Amendment freedoms and spoken out against the discriminatory Muslim Ban.[3] But Amazon's Rekognition product runs counter to these values. As advertised, Rekognition is a powerful surveillance system readily available to violate rights and target communities of color.



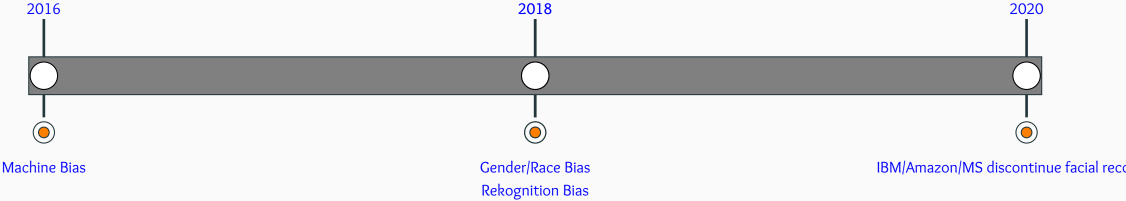
Be Fair and Responsible!

Microsoft refuses to sell police its facial-recognition technology, following similar moves by Amazon and IBM


IBM says it is no longer working on face recognition because it's used for racial profiling

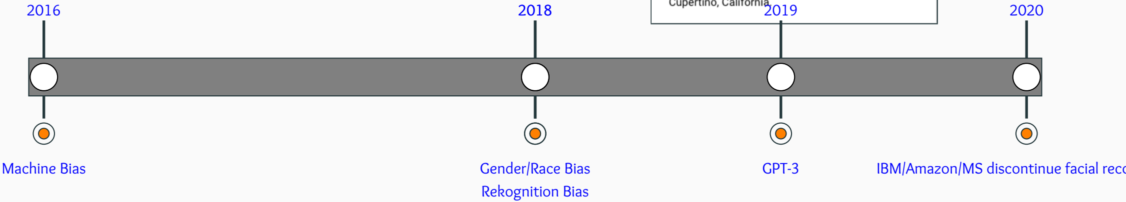

Technology

Microsoft won't sell police its facial-recognition technology, following similar moves by Amazon and IBM



Be Fair and Responsible!

"Due to our concerns about malicious applications of the technology, we are not releasing the trained model." – – *OpenAI*



Be Fair and Responsible!

What started off as an innocuous project for mimicking facial expressions has since lead to many apps and creation of fake videos for blackmailing, pronography and swaying elections!

2016 — Machine Bias

2017 — DeepFakes

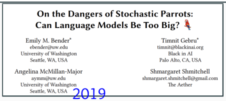
2018 — Gender/Race Bias, Rekognition Bias

2019 — GPT-3

2020 — IBM/Amazon/MS discontinue facial reco

Be Fair and Responsible!

"Models are only as good as the data. Be responsible while curating data." – *Bender et. al.*



On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 🦜

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Palo Alto, CA, USA

Angelina McMillan-Major
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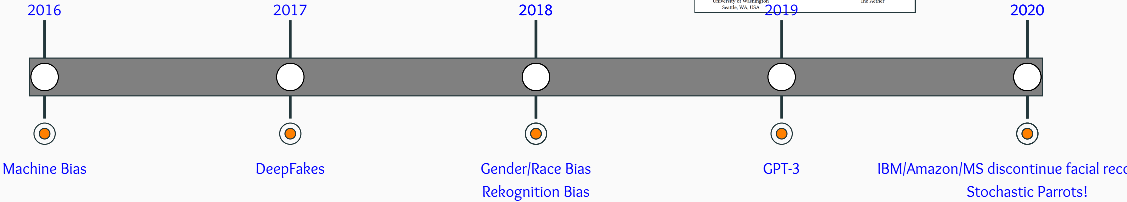
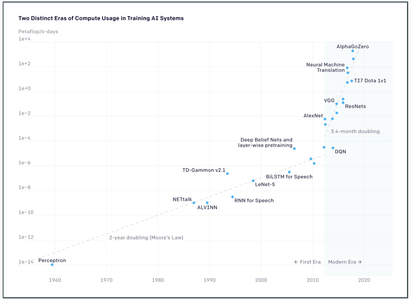
Seattle, WA, USA

Shmargaret Shmitchell
shmargaret.shmitchell@gmail.com
The Aether



Push for Green AI

The computations required for deep learning research have been doubling every few months, resulting in an estimated 300,000x increase from 2012 to 2018 – *AllenAI*



https://openai.com/blog/ai-and-compute/

Ironically, deep learning was inspired by the human brain, which is remarkably energy efficient.

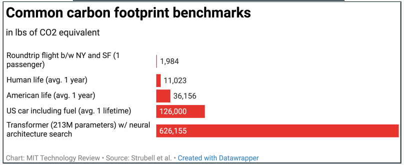
Push for Green AI

Call for energy and policy considerations for Deep Learning

	Date of original paper	Energy consumption (kWh)	Carbon footprint (lbs of CO2e)	Cloud compute cost (USD)
Transformer (65M parameters)	Jun, 2017	27	26	$41-$140
Transformer (213M parameters)	Jun, 2017	201	192	$289-$981
ELMo	Feb, 2018	275	262	$433-$1,472
BERT (110M parameters)	Oct, 2018	1,507	1,438	$3,751-$12,571
Transformer (213M parameters) w/ neural architecture search	Jan, 2019	656,347	626,155	$942,973-$3,201,722
GPT-2	Feb, 2019	-	-	$12,902-$43,008

Note: Because of a lack of power draw data on GPT-2's training hardware, the researchers weren't able to calculate its carbon footprint.

Table: MIT Technology Review • Source: Strubell et al. • Created with Datawrapper

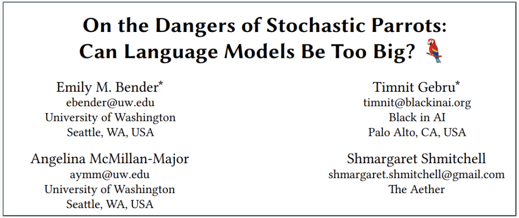


2019

GreenAI
Energy-Aware NLP

Push for Green AI

"Is it fair that the residents of the Maldives (likely to be underwater by 2100) or the 800,000 people in Sudan affected by drastic floods pay the environmental price of training and deploying ever larger English LMs, when similar large-scale models aren't being produced for Dhivehi or Sudanese Arabic?" – *Bender et. al.*


On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 🦜

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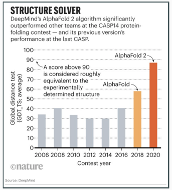
Shmargaret Shmitchell
shmargaret.shmitchell@gmail.com
The Aether

Chapter 11: The AI revolution in Scientific Research (exciting times ahead!)

Accelerating Scientific Discovery[a]



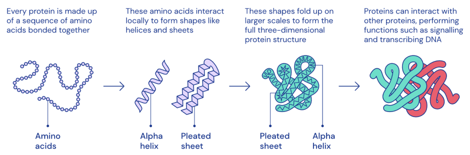
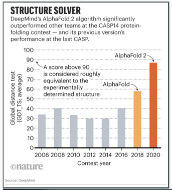
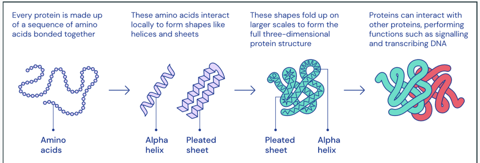


FIGURE 1: COMPLEX 3D SHAPES EMERGE FROM A STRING OF AMINO ACIDS.

[a] https://deepmind.com/blog/article/AlphaFold-Using-AI-for-scientific-discovery
https://ocean.org/stories/spotting-seals-from-space
https://www.quantamagazine.org/how-artificial-intelligence-is-changing-science-20190311/

Accelerating Scientific Discovery[a]





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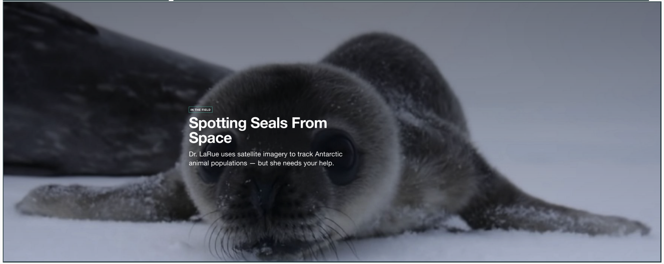

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https://www.quantamagazine.org/how-artificial-intelligence-is-changing-science-20190311/

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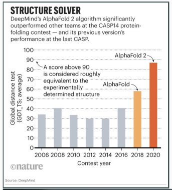

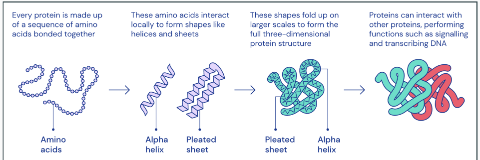

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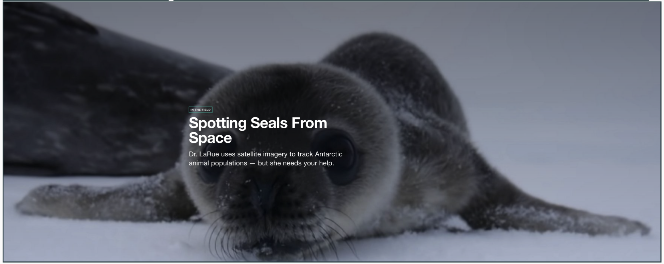
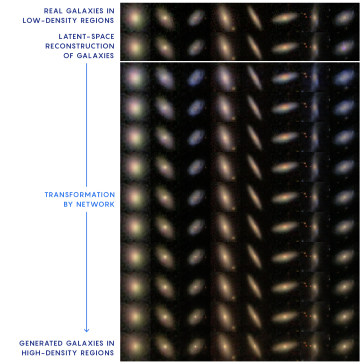


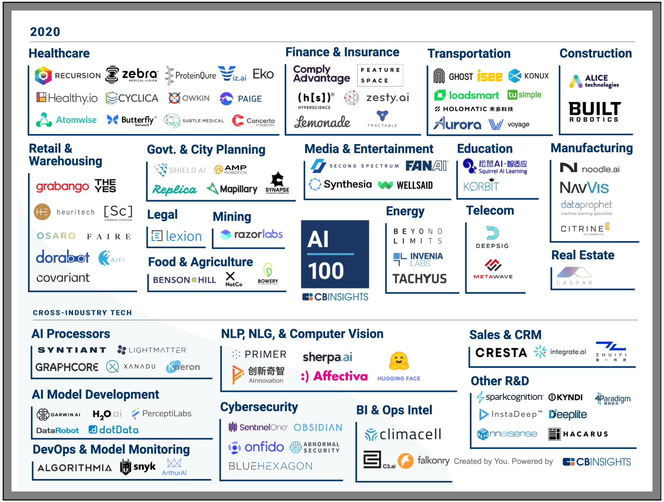


Using generative modeling, astrophysicists could investigate how galaxies change when they go from low-density regions of the cosmos to high-density regions, and what physical processes are responsible for these changes.

Adapted from K. Schawinski et al.; Source doi: 10.1051/0004-6361/201833800

[a] https://deepmind.com/blog/article/AlphaFold-Using-AI-for-scientific-discovery
https://ocean.org/stories/spotting-seals-from-space
https://www.quantamagazine.org/how-artificial-intelligence-is-changing-science-20190311/

https://github.com/ChristosChristofidis/awesome-deep-learning



Source: https://www.cbinsights.com/research/artificial-intelligence-top-startups/

[i] Source: https://www.cbinsights.com/research/artificial-intelligence-top-startups/

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