

CS7015 (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 write 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!



1871-1873



Reticular theory

Staining Technique

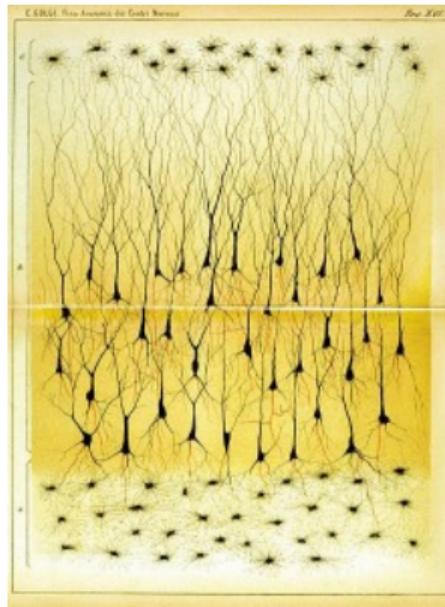
Camillo Golgi discovered a chemical reaction that allowed him to examine nervous tissue in much greater detail than ever before

He was a proponent of Reticular theory.

1871-1873

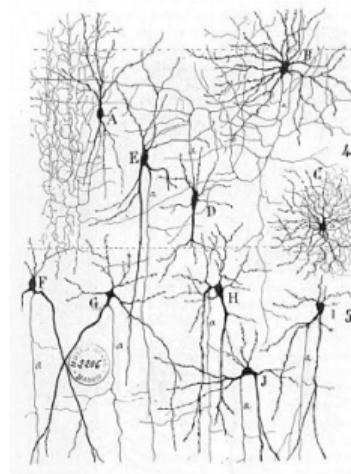


Reticular theory

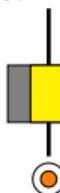


Neuron Doctrine

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 forming a network (as opposed to a single continuous network)

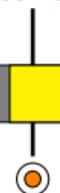


1871-1873



Reticular theory

1888-1891

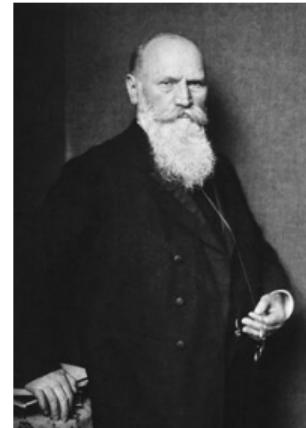


Neuron Doctrine

The Term Neuron

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

He further consolidated the Neuron Doctrine.

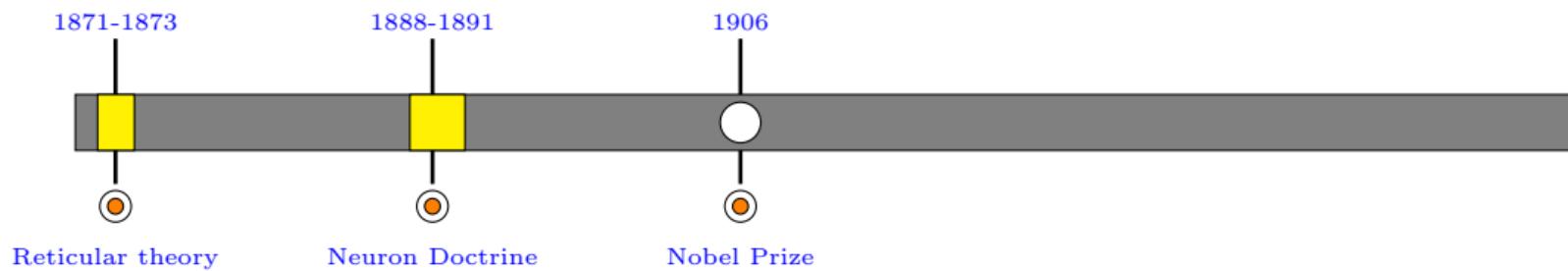
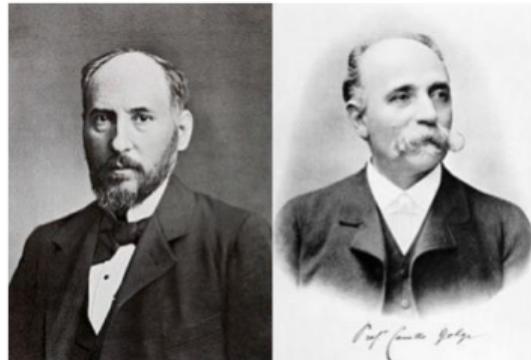


Reticular theory

Neuron Doctrine

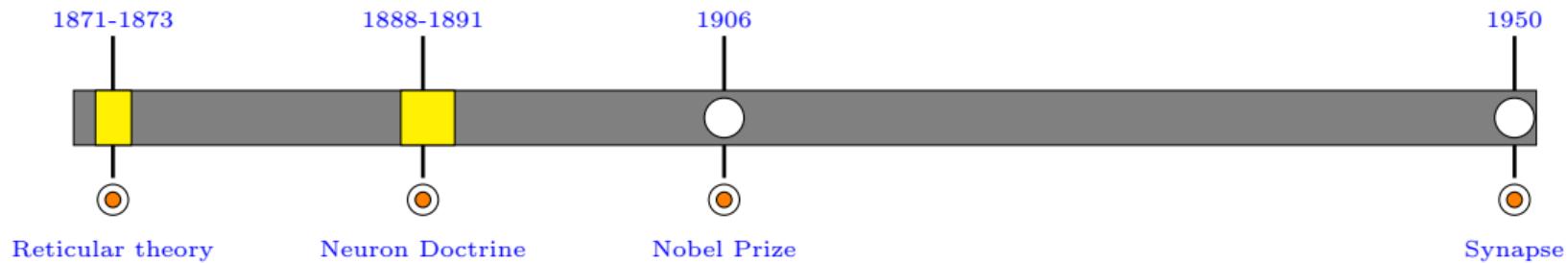
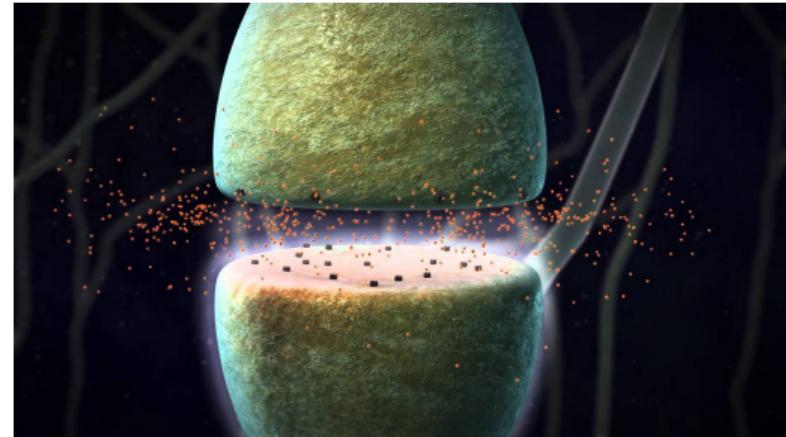
Nobel Prize

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

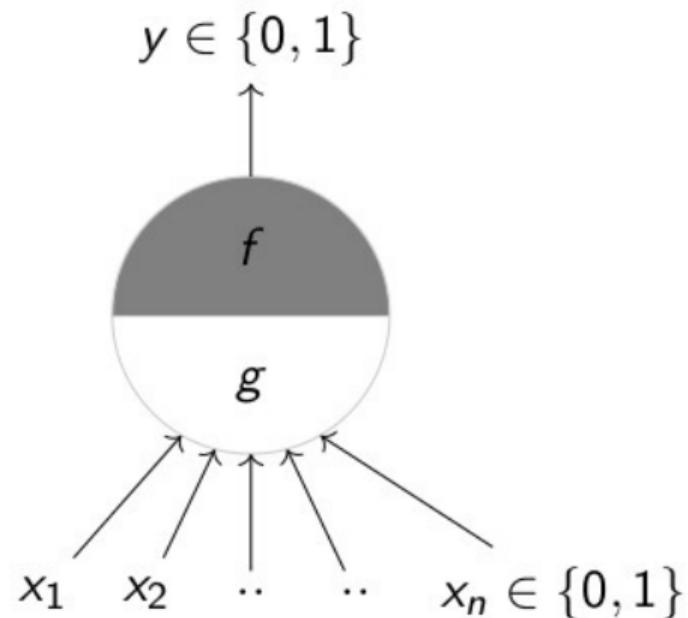
In 1950s electron microscopy finally confirmed the neuron doctrine by unambiguously demonstrated that nerve cells were individual cells interconnected through synapses (a network of many individual neurons).



Chapter 2: From Spring to Winter of AI

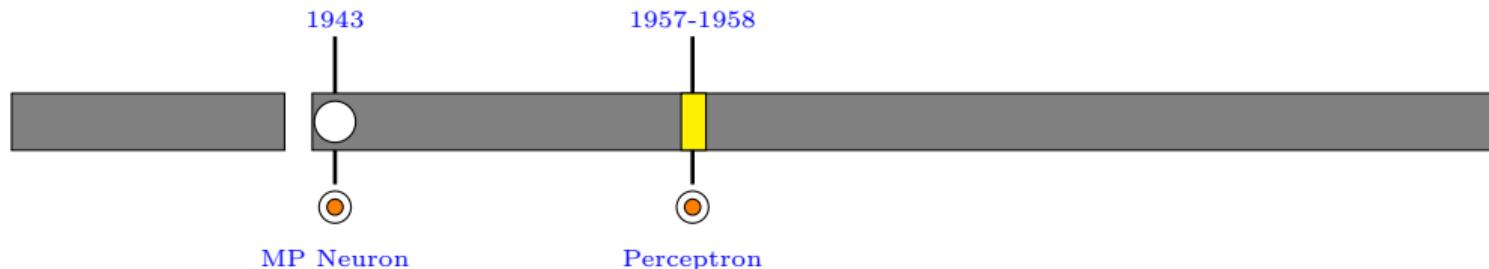
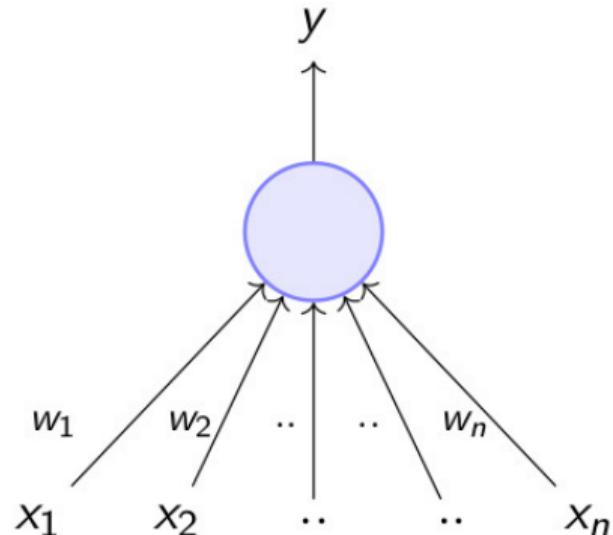
McCulloch Pitts Neuron

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



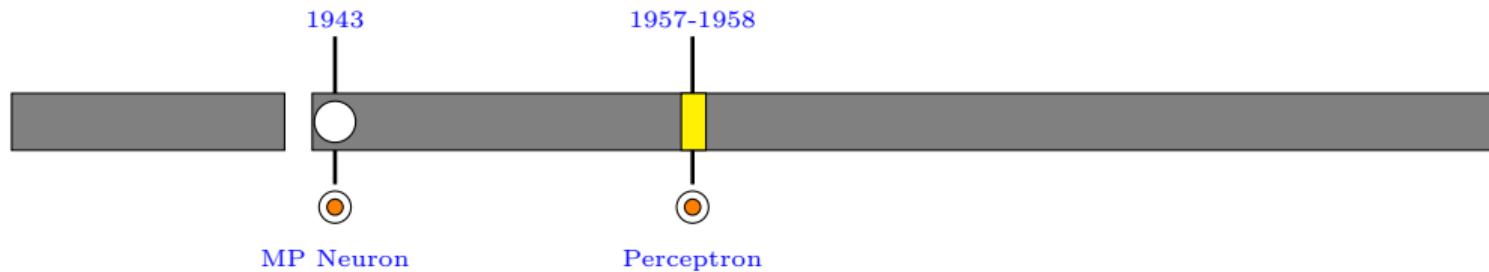
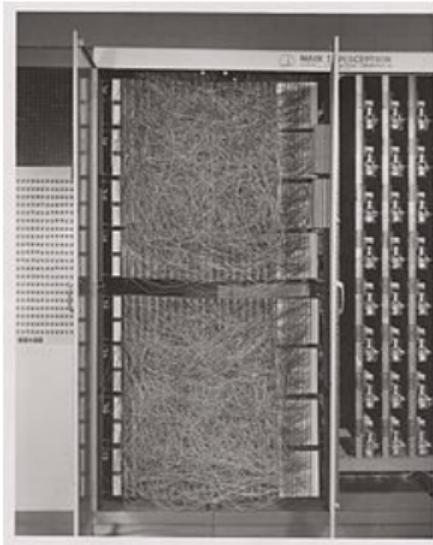
Perceptron

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



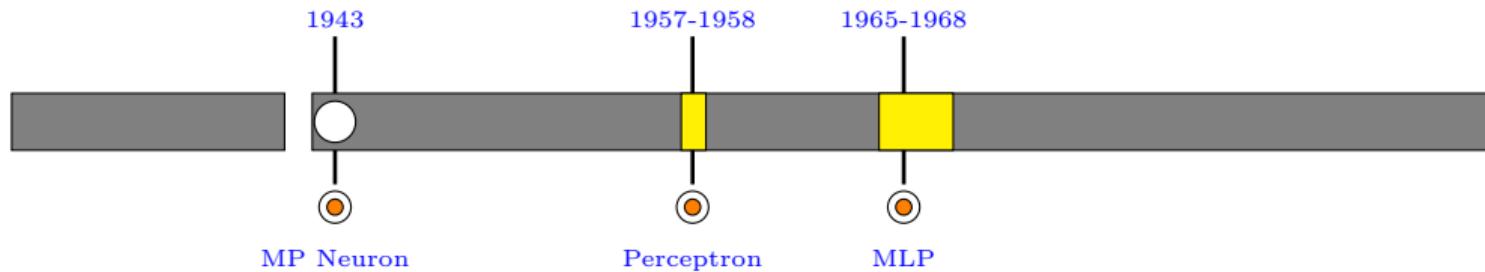
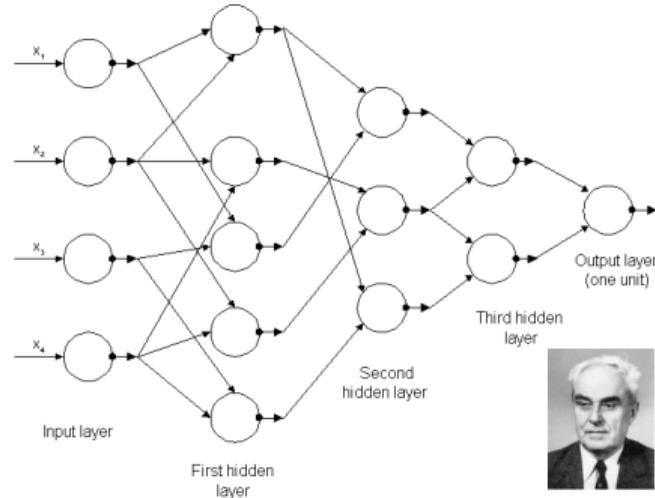
Perceptron

“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



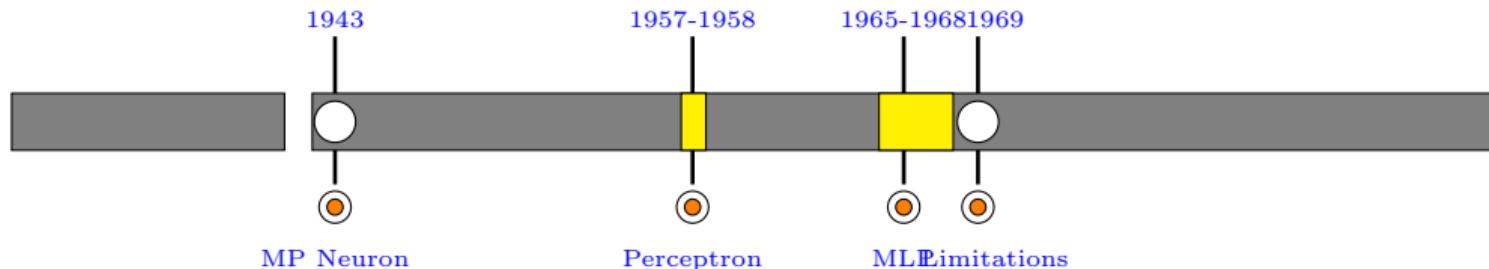
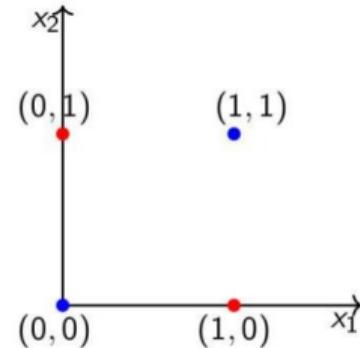
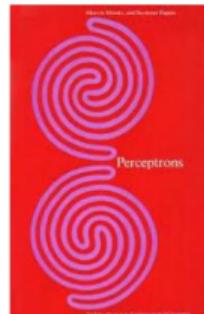
First generation Multilayer Perceptrons

Ivakhnenko et. al. [3]



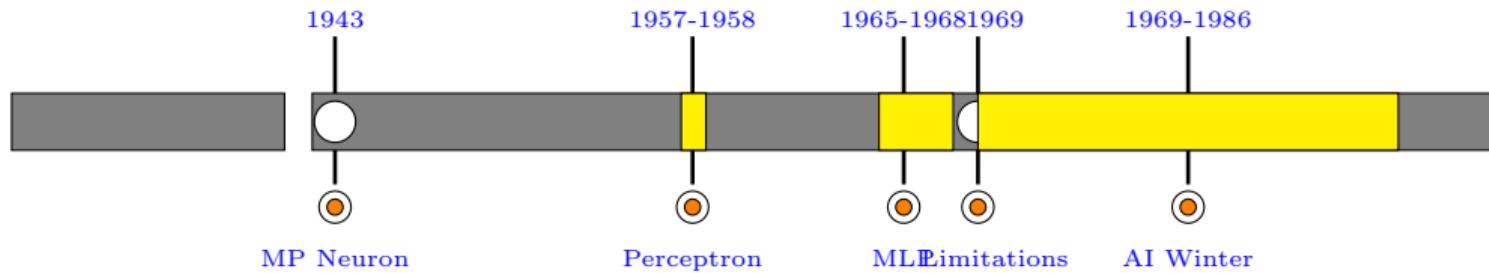
Perceptron Limitations

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



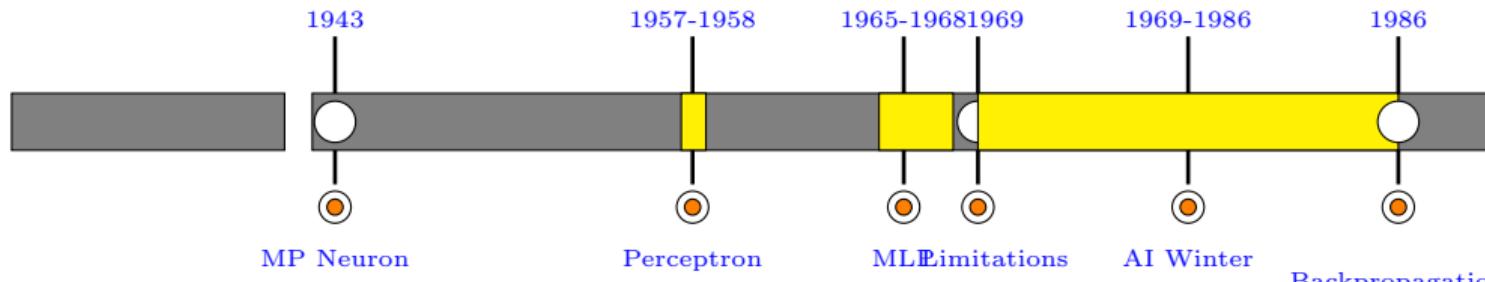
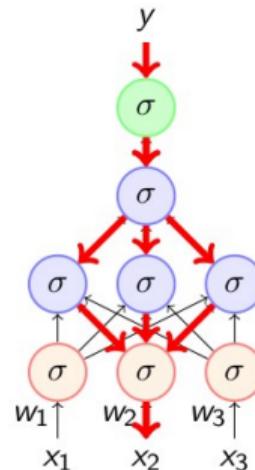
AI Winter of connectionism

Almost lead to the abandonment of connectionist AI



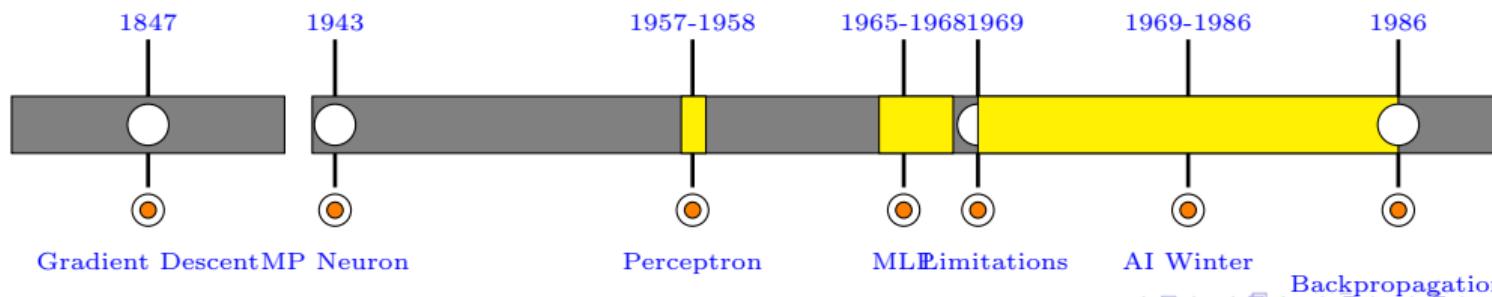
Backpropagation

- 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]



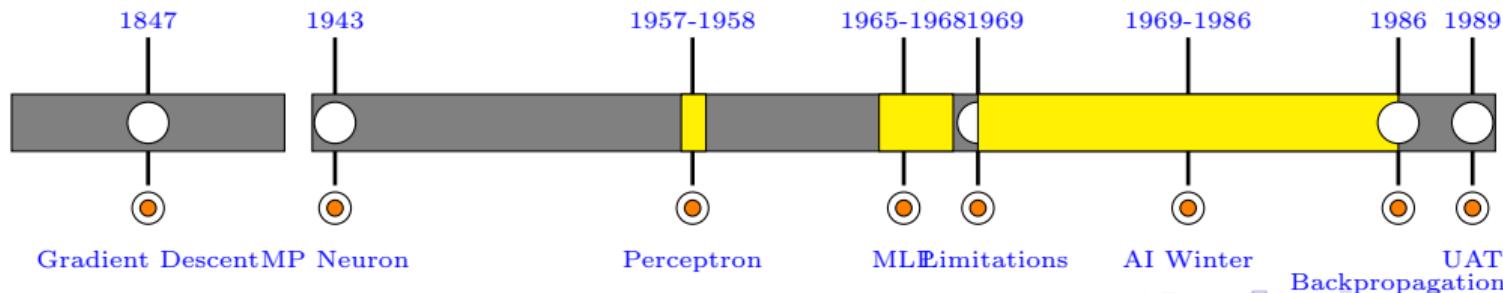
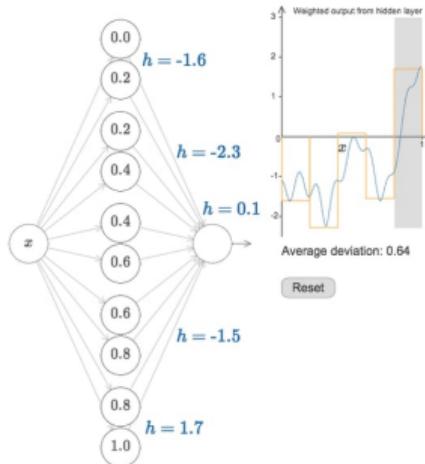
Gradient Descent

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



Universal Approximation Theorem

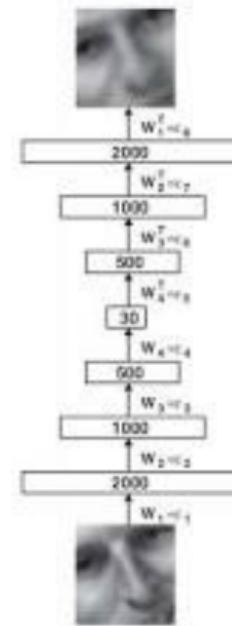
A multilayered network of neurons with a single hidden layer can be used to approximate any continuous function to any desired precision^[7]



Chapter 3: The Deep Revival

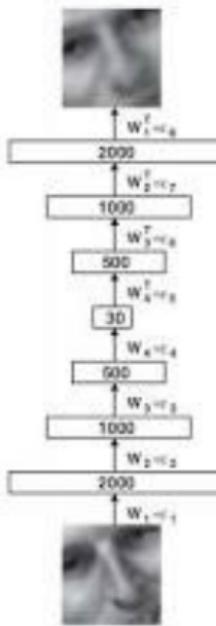
Unsupervised Pre-Training

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”



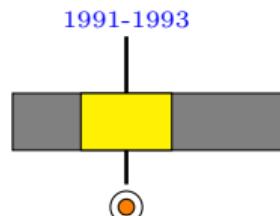
More insights (2007-2009)

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



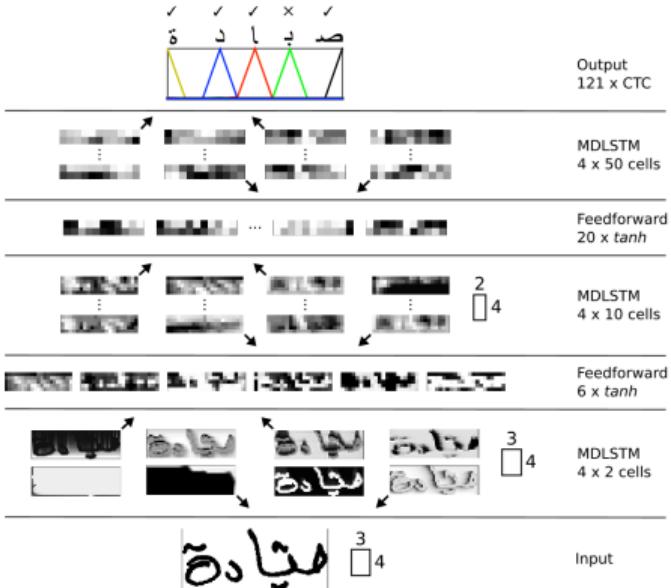
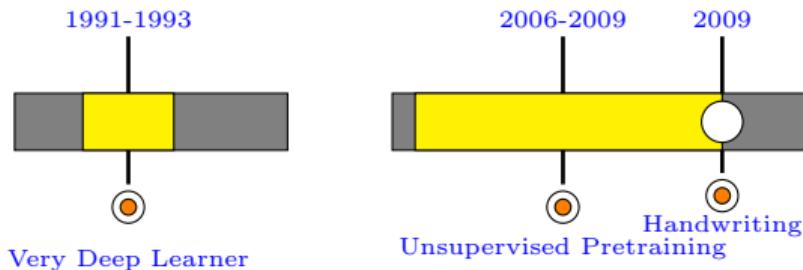
Very Deep Learner



Unsupervised Pretraining

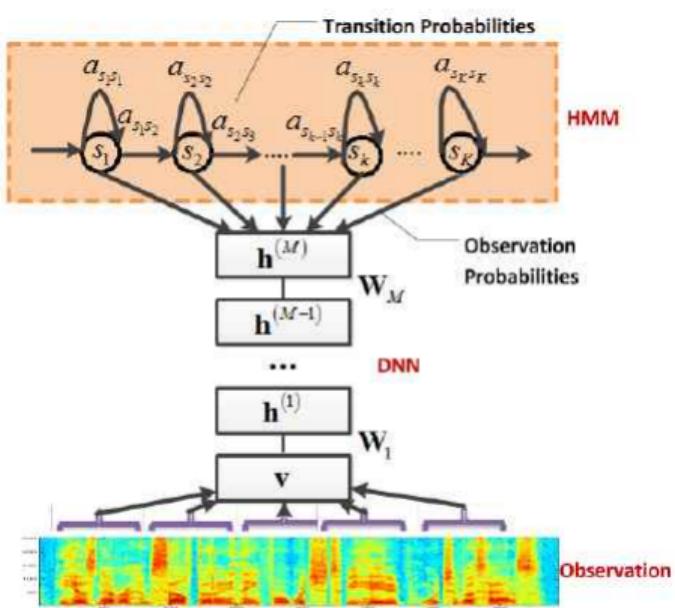
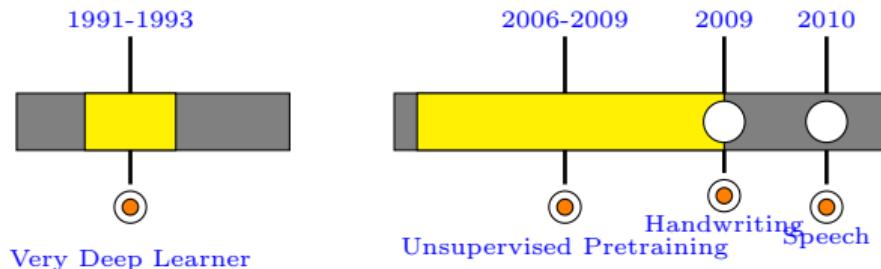
Success in Handwriting Recognition

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



Success in Speech Recognition

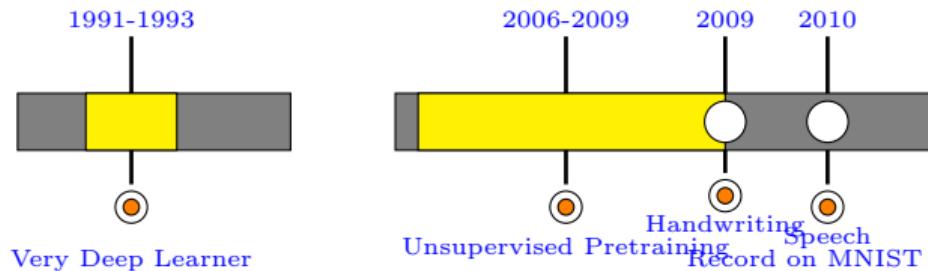
Dahl et. al. showed relative error reduction of 16.0% and 23.2% over a state of the art system^[10]



New record on MNIST

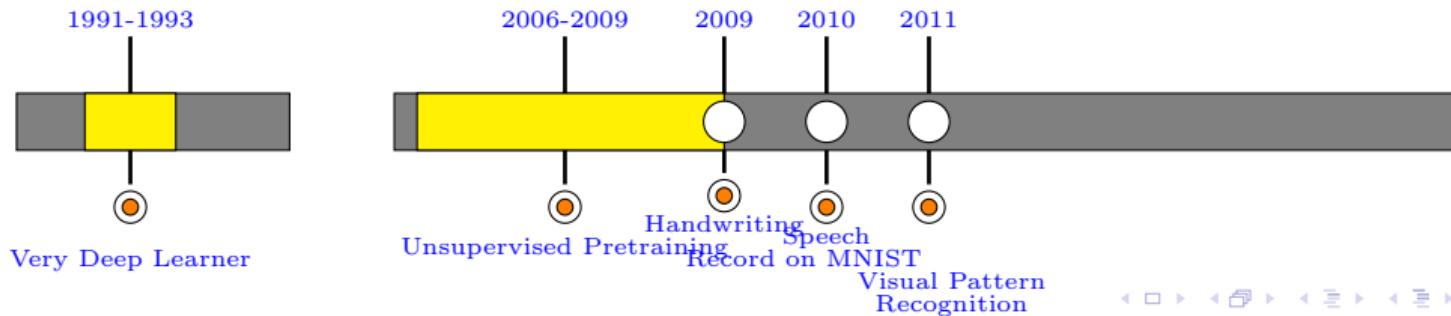
Ciresan et. al. set a new record on the MNIST dataset using good old back-propagation on GPUs (GPUs enter the scene)^[11]

1 2 17	1 1 71	9 8 98	9 9 59	9 9 79	5 5 35	3 8 23
4 9 49	5 5 35	9 4 97	4 9 49	4 4 94	2 2 02	5 5 35
6 6 16	9 4 94	0 0 60	6 6 06	6 6 86	1 1 79	1 1 71
7 9 49	0 0 50	5 5 35	8 8 98	7 9 79	7 7 17	L 1 61
Z 7 27	8 8 58	2 2 78	1 6 16	6 5 65	4 4 94	0 0 60



First Superhuman Visual Pattern Recognition

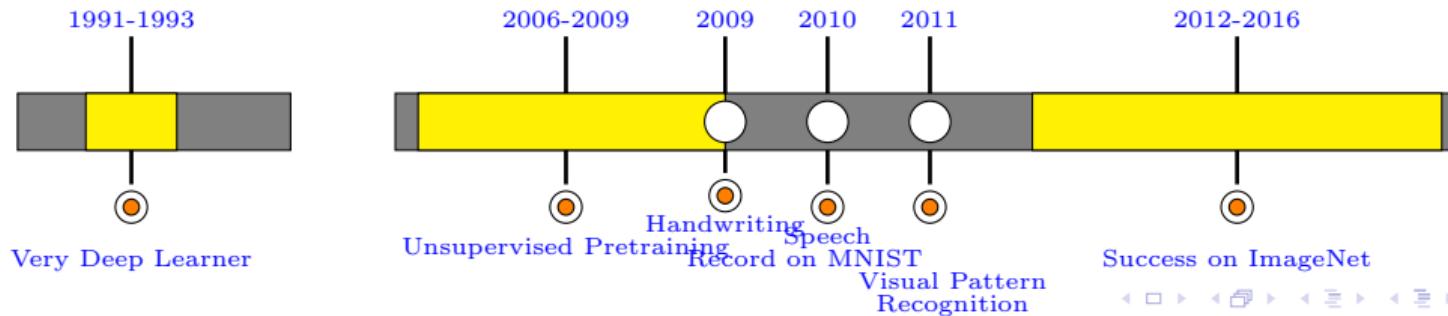
D. C. Ciresan et. al. achieved 0.56% error rate in the IJCNN Traffic Sign Recognition Competition^[12]



Winning more visual recognition challenges



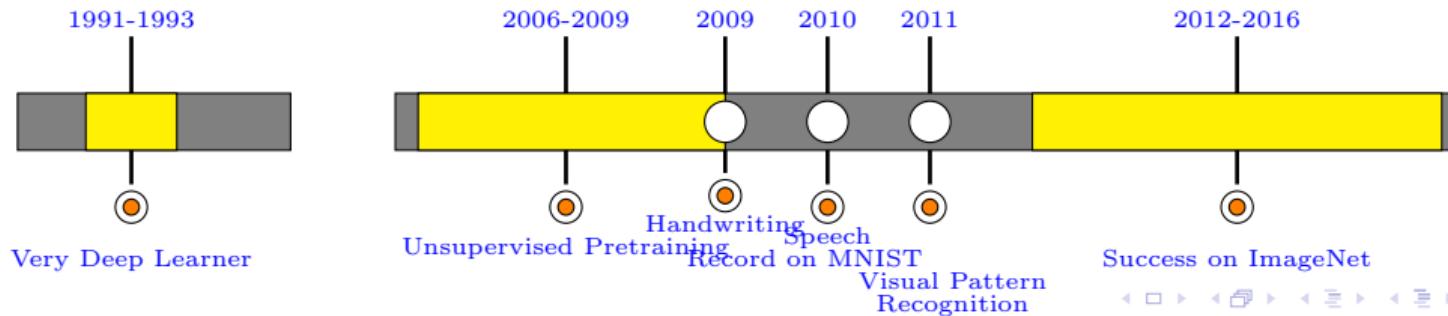
Network	Error	Layers
AlexNet ^[13]	16.0%	8



Winning more visual recognition challenges



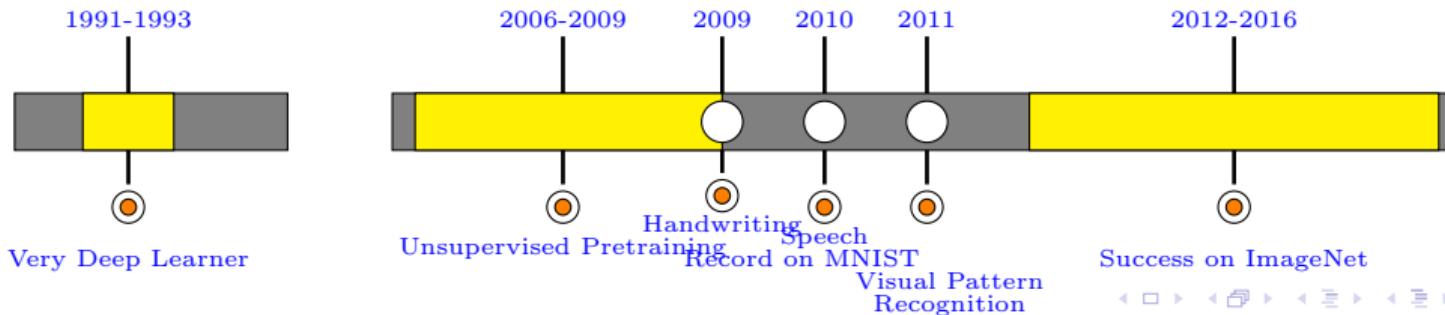
Network	Error	Layers
AlexNet ^[13]	16.0%	8
ZFNet ^[14]	11.2%	8



Winning more visual recognition challenges



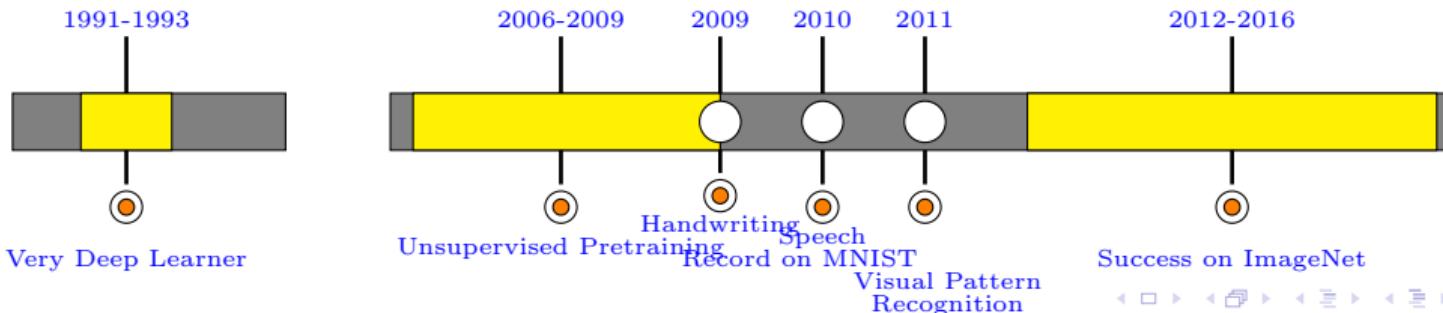
Network	Error	Layers
AlexNet ^[13]	16.0%	8
ZFNet ^[14]	11.2%	8
VGGNet ^[15]	7.3%	19



Winning more visual recognition challenges



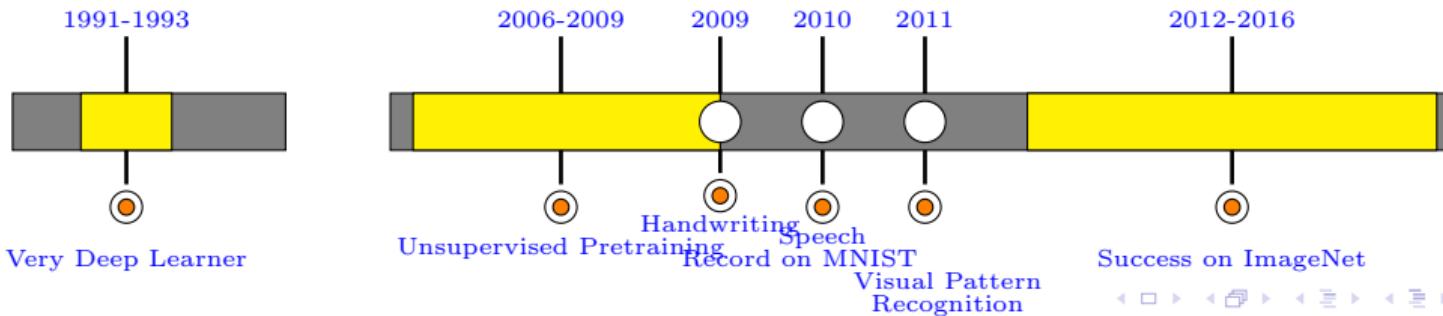
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VGGNet ^[15]	7.3%	19
GoogLeNet ^[16]	6.7%	22



Winning more visual recognition challenges



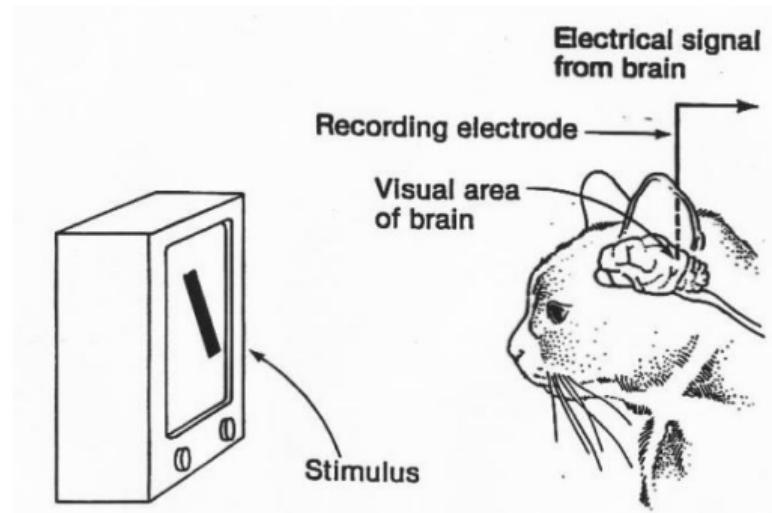
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VGGNet ^[15]	7.3%	19
GoogLeNet ^[16]	6.7%	22
MS ResNet ^[17]	3.6%	152!!



Chapter 4: Cats

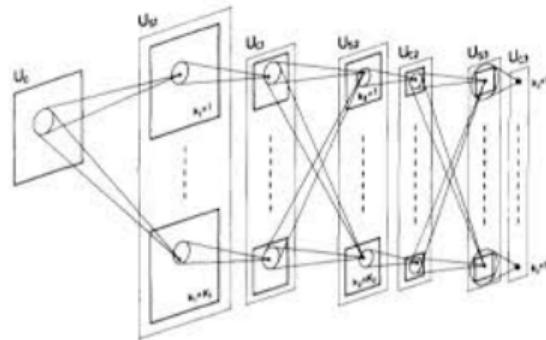
Hubel and Wiesel Experiment

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]



1959



H and W experiment

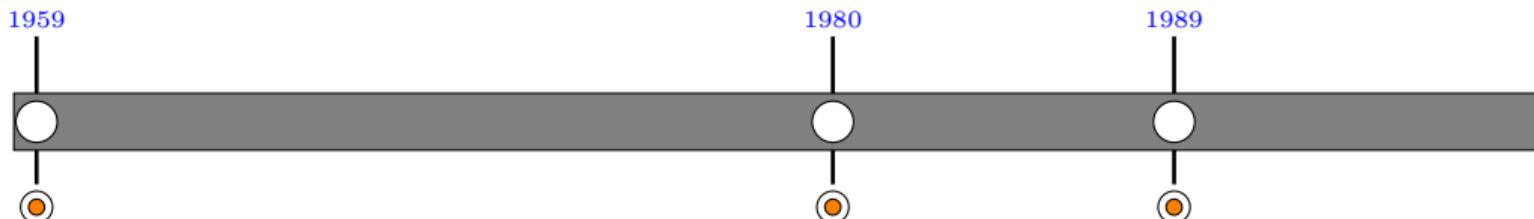
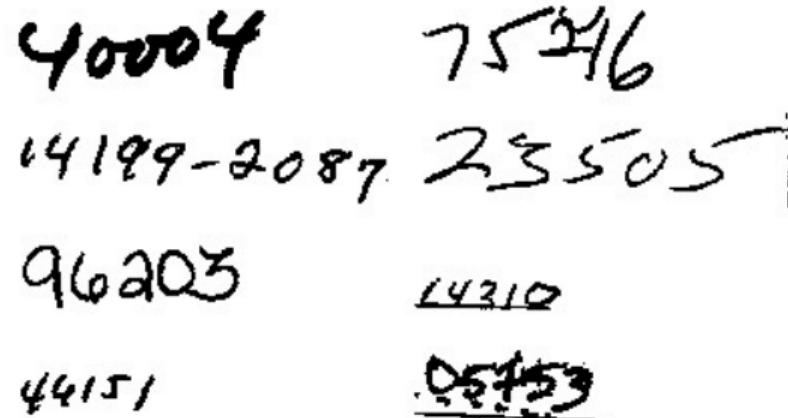
1980



Neocognitron

Convolutional Neural Network

Handwriting digit recognition using back-propagation over a Convolutional Neural Network (LeCun et. al.)^[20]



H and W experiment

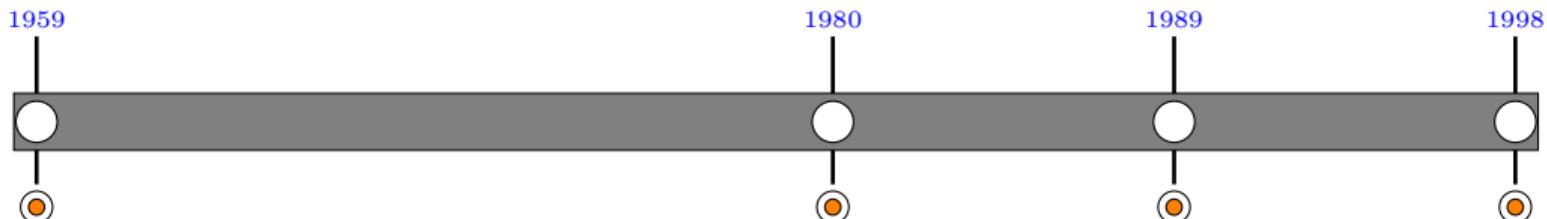
Neocognitron

CNN

LeNet-5

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

3 6 8 1 7 9 6 6 9 1
6 7 5 7 8 6 3 4 8 5
2 1 7 9 7 1 2 8 4 5
4 8 1 9 0 1 8 8 9 4
7 6 1 8 6 4 1 5 6 0
7 5 9 2 6 5 8 1 9 7
2 2 2 2 2 3 4 4 8 0
0 2 3 8 0 7 3 8 5 7
0 1 4 6 4 6 0 2 4 3
7 1 2 8 1 6 9 8 6 1



H and W experiment

Neocognitron

CNN

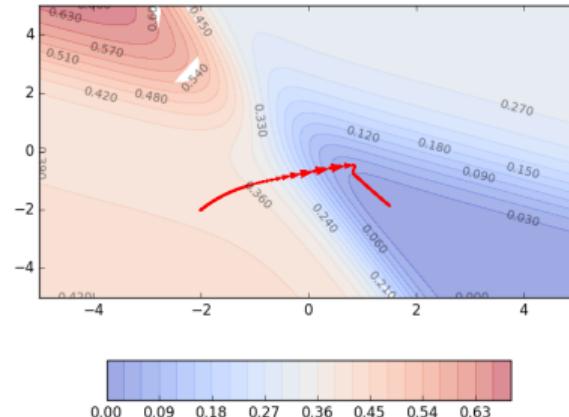
LeNet-5

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



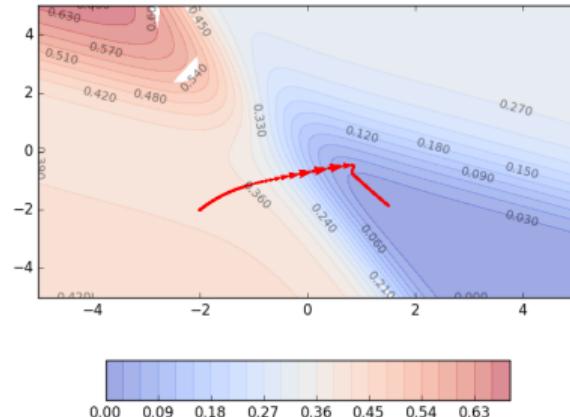
1983



Nesterov

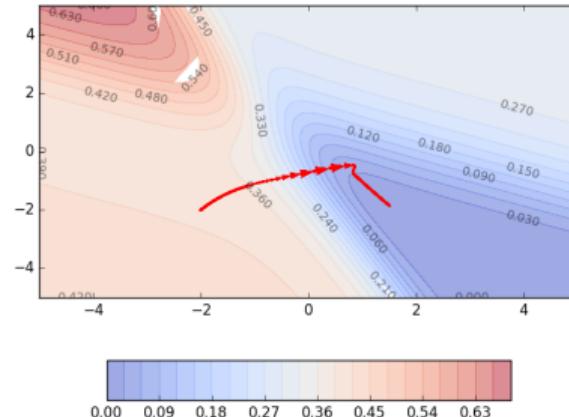
Better Optimization Methods

Faster convergence, better accuracies



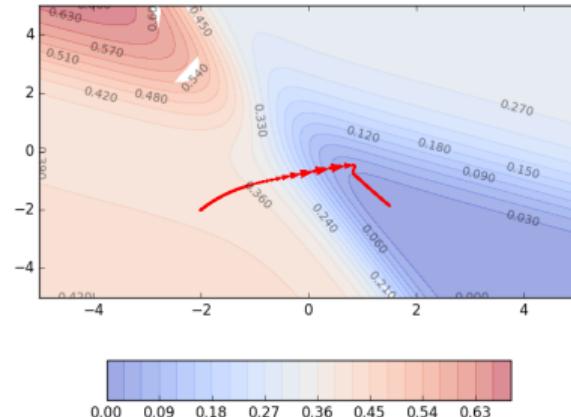
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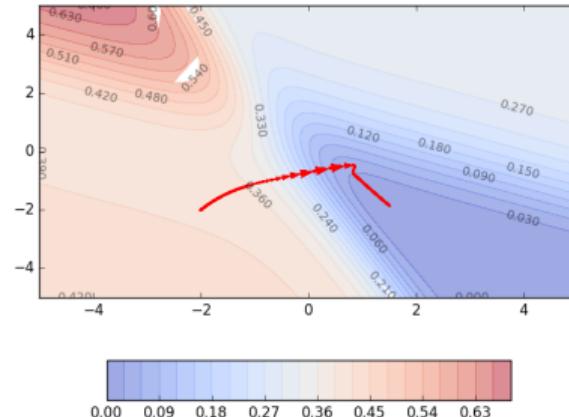
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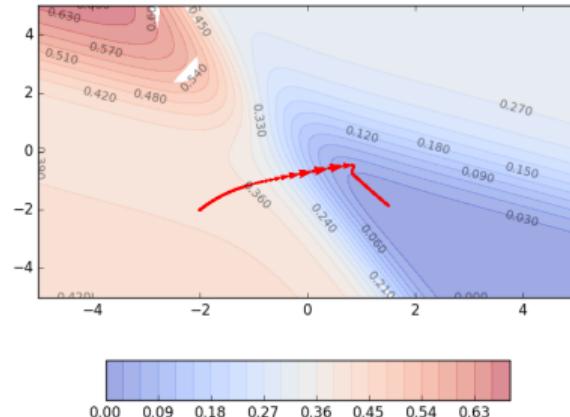
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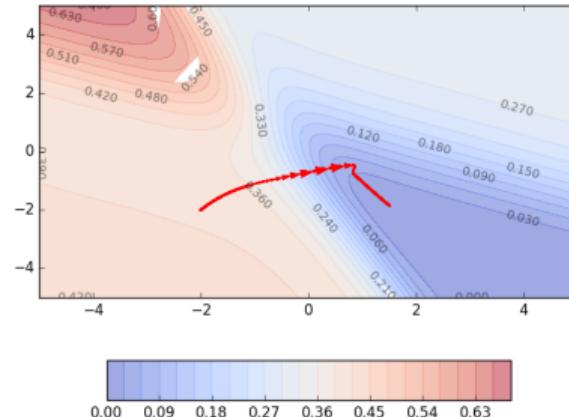
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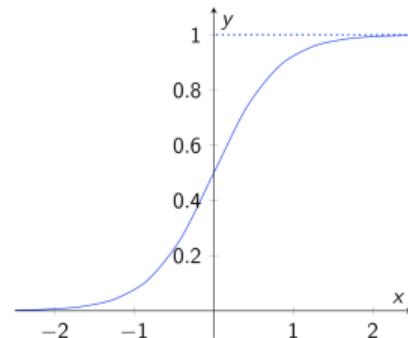
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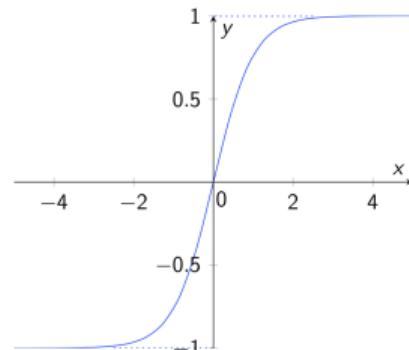
Better Activation Functions

The **logistic function** which is not zero centered was the most popular choice in the 80's



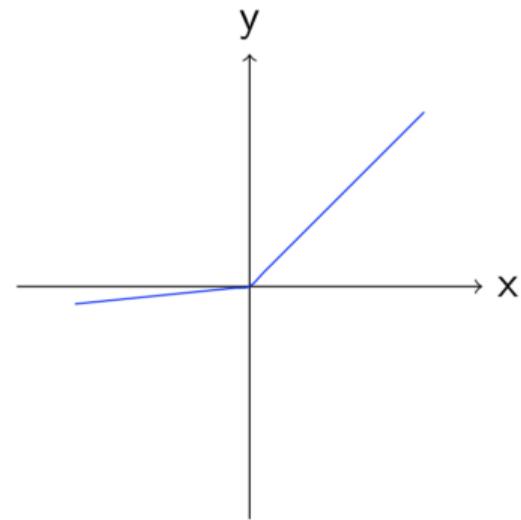
Better Activation Functions

The **tanh** function which is zero centered leads to better convergence^[22]



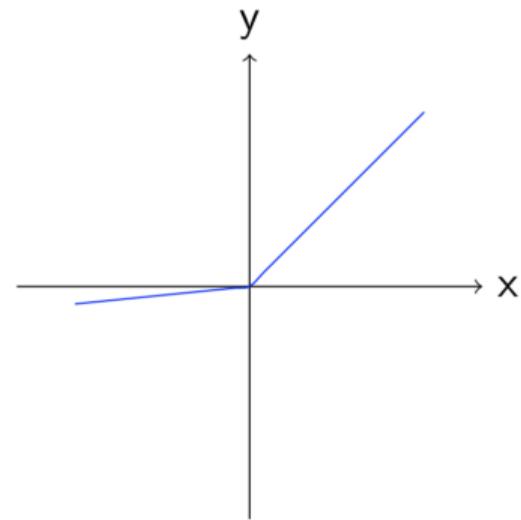
Better Activation Functions

More recently it has been shown that **Rectified Linear Units (ReLUs)** and their variants lead to better performance [23], [24], [25]



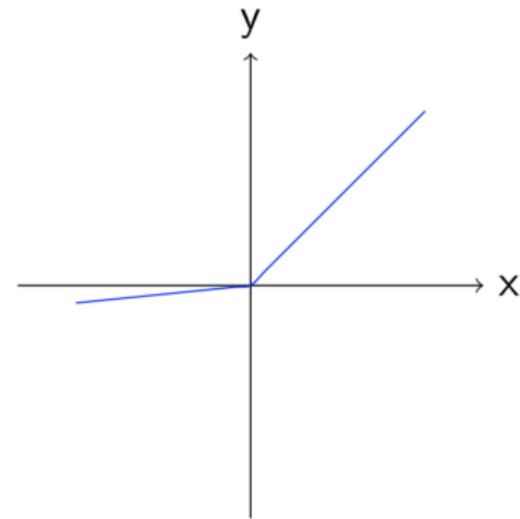
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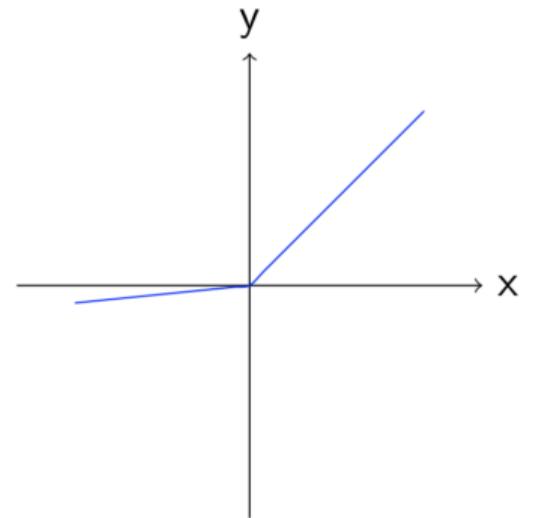
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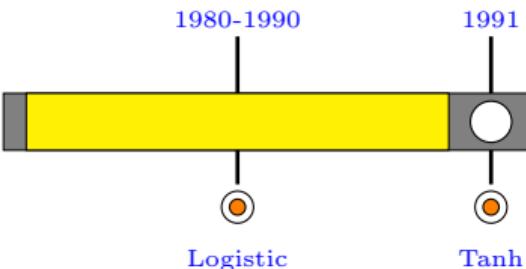
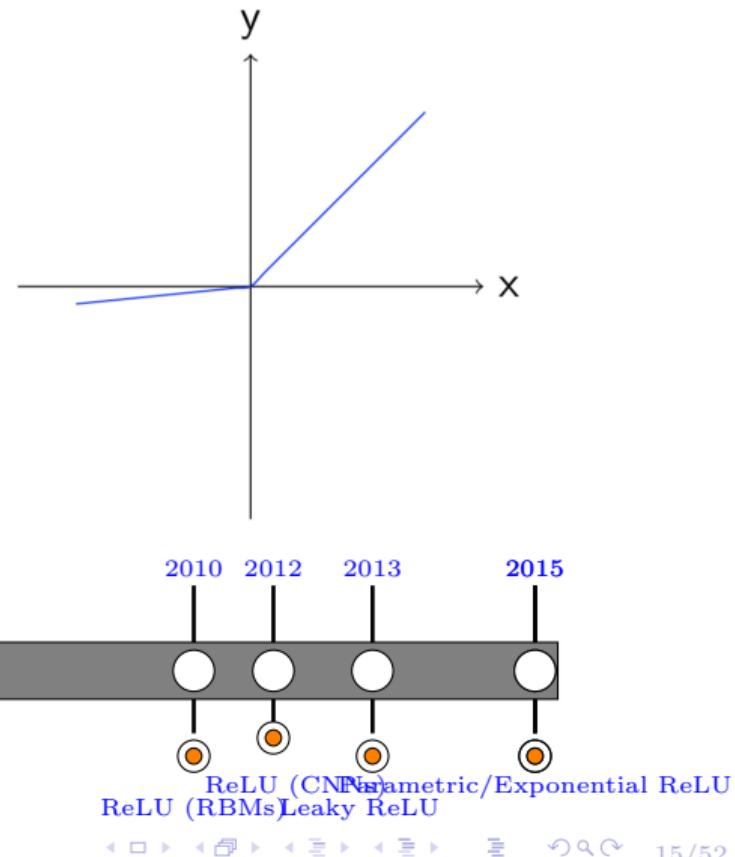
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Better Activation Functions

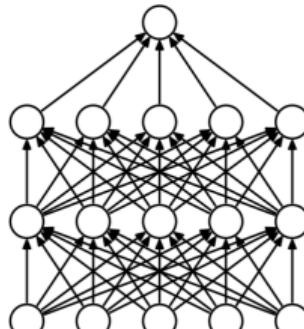
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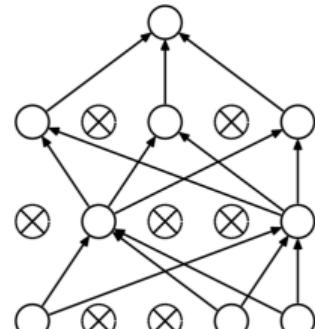
ReLU (CNNs)
Parametric/Exponential ReLU
ReLU (RBMs)

Better Regularization

Dropout: A Simple Way to Prevent Neural Networks from Overfitting^[26]



(a) Standard Neural Net



(b) After applying dropout.



Dropout

Better Regularization

Batch Normalization: Acts as a regularizer in some cases^[27])



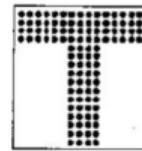
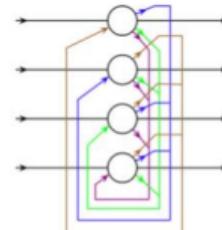
Chapter 6: The Curious Case of Sequences

Sequences

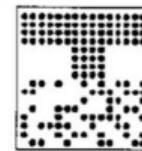
- They are everywhere
- Time series, speech, music, text, video
- Each unit in the sequence interacts with other units
- Need models to capture this interaction

Hopfield Network

Content-addressable memory systems for
storing and retrieving patterns^[28]



Original 'T'

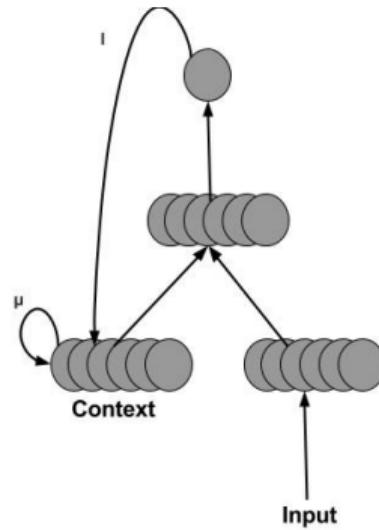


half of image
corrupted by
noise



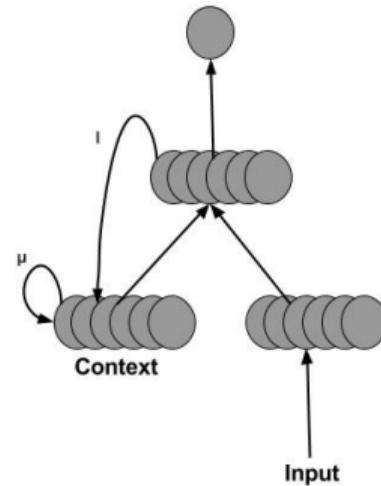
Jordan Network

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



Elman



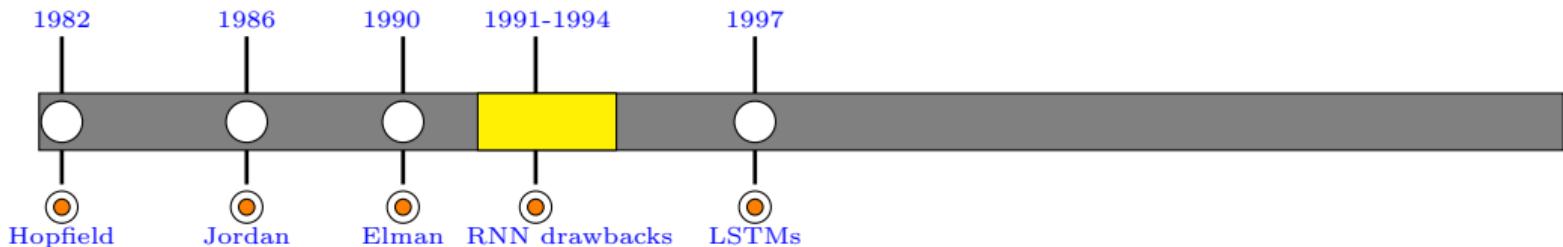
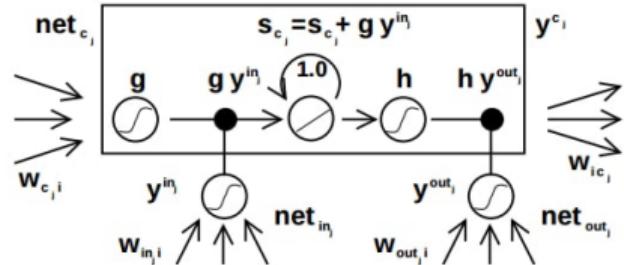
Drawbacks of RNNs

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



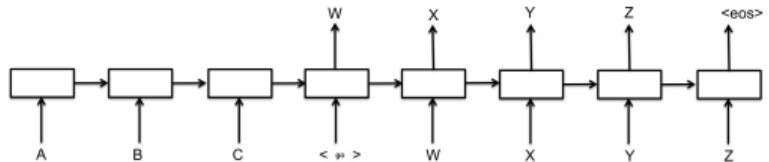
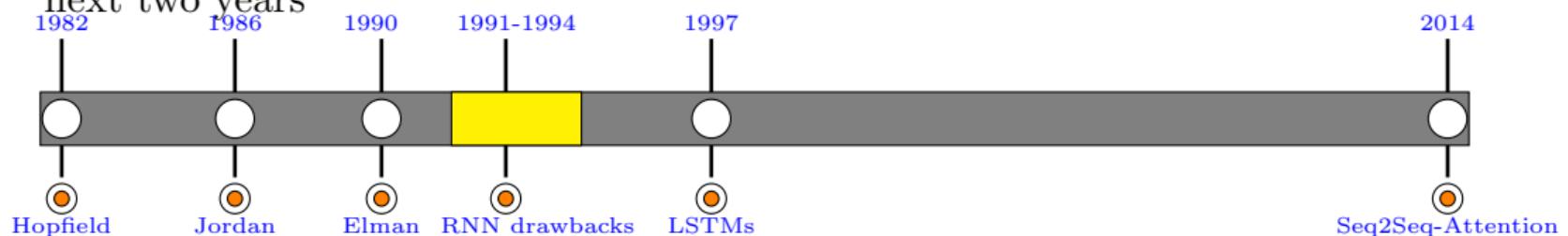
Long Short Term Memory

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



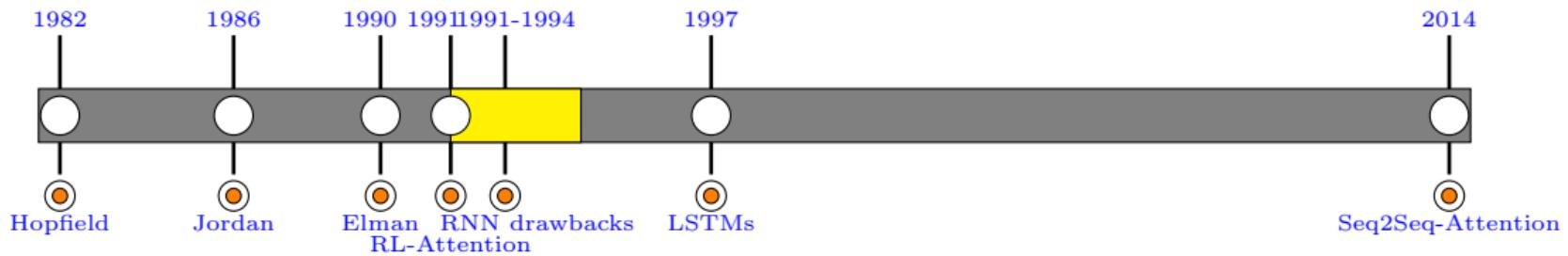
Sequence To Sequence Learning

- Initial success in using RNNs/LSTMs for large scale Sequence To Sequence Learning Problems
- Introduction of Attention which inspired a lot of research over the next two years



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



Let's GO

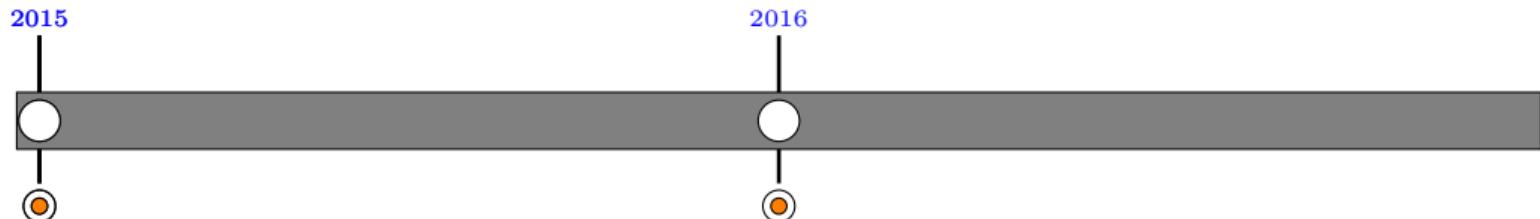
- Alpha Go Zero - Best Go player ever, surpassing human players
- GO is more complex than chess because of number of possible moves.
- No brute force backtracking unlike previous chess agents



DQNs/AlphaGO

Taking a shot at Poker

DeepStack defeated 11 professional poker players with only one outside the margin of statistical significance.

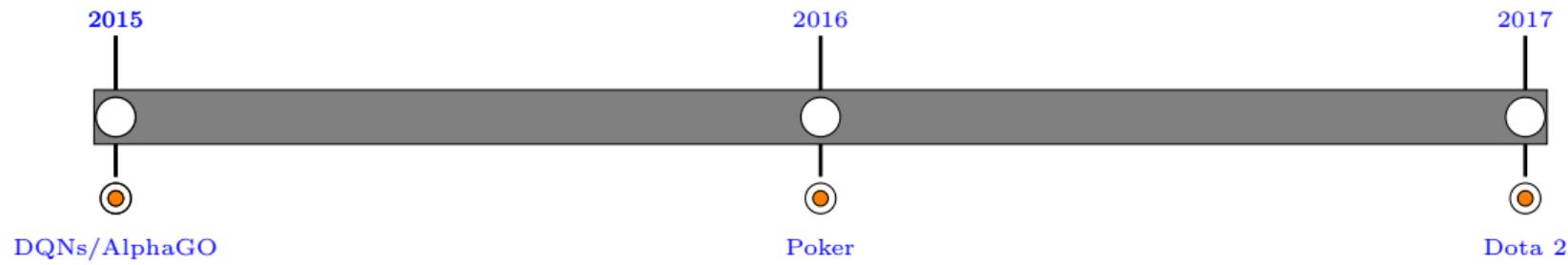


DQNs/AlphaGO

Module 7

Defense of the Ancients

- Widely popular game, with complex strategies, large visual space
- Bot was undefeated against many top professional players .



Chapter 8: The Madness (2013 -)

He sat on a chair.

Language Modeling

- Mikolov et al. (2010)^[29]
- Li et al. (2015)
- Kiros et al. (2015)^[30]
- Kim et al. (2015)^[31]



Speech Recognition

- Hinton et al. (2012)^[32]
- Graves et al. (2013)^[33]
- Chorowski et al. (2015)^[34]
- Sak et al. (2015)^[35]

MACHINE TRANSLATION



Machine Translation

- Kalchbrenner et al. (2013)^[36]
- Cho et al. (2014)^[37]
- Bahdanau et al. (2015)^[38]
- Jean et al. (2015)^[39]
- Gulcehre et al. (2015)^[40]
- Sutskever et al. (2014)^[41]
- Luong et al. (2015)^[42]
- Zheng et al. (2017)^[43]
- Cheng et al. (2016)^[44]
- Chen et al. (2017)^[45]
- Firat et al. (2016)^[46]

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#)"

Conversation Modeling

- Shang et al. (2015)^[47]
- Vinyals et al. (2015)^[48]
- Lowe et al. (2015)^[49]
- Dodge et al. (2015)^[50]
- Weston et al. (2016)^[51]
- Serban et al. (2016)^[52]
- Bordes et al. (2017)^[53]
- He et al. (2017)
- Serban et al. (2017)^[54]
- Lewis et al. (2017)

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 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 2: Two Supporting Facts

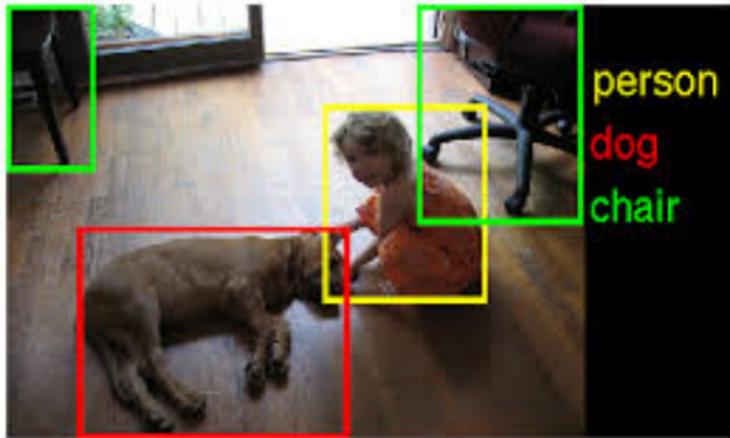
John is in the playground.
John picked up the football.
Bob went to the kitchen.
Where is the football? A:playground

Task 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

Question Answering

- Hermann et al. (2015)^[55]
- Chen et al. (2016)^[56]
- Xiong et al. (2016)^[57]
- Seo et al. (2016)^[58]
- Dhingra et al. (2017)^[59]
- Wang et al. (2017)^[60]
- Hu et al. (2017)^[61]



Object Detection/Recognition

- Semantic Segmentation (Long et al, 2015)^[62]
- Recurrent CNNs (Liang et al., 2015)^[63]
- Faster RCNN (Ren et al., 2015)^[64]
- Inside-Outside Net (Bell et al., 2015)^[65]
- YOLO9000 (Redmon et al., 2016)^[66]
- R-FCN (Dai et al., 2016)^[67]
- Mask R-CNN (He et al., 2017)^[68]
- Video Object segmentation (Caelles et al., 2017)^[69]



Visual Tracking

- Zhang et al. (2017)
- Choi et al. (2017)^[70]
- Yun et al. (2017)^[71]
- Luo et al. (2017)
- Alahi et al. (2017)^[72]
- Van et al. (2016)

Retr.
Gen.



1. Top view of the lights of a city at night, with a well-illuminated square in front of a church in the foreground;
2. People on the stairs in front of an illuminated cathedral with two towers at night;

A square with burning street lamps and a street in the foreground;



1. Tourists are sitting at a long table with beer bottles on it in a rather dark restaurant and are raising their bierglaeser;
2. Tourists are sitting at a long table with a white table-cloth in a somewhat dark restaurant;

Tourists are sitting at a long table with a white table cloth and are eating;

Image Captioning

- Mao et al. (2014)^[73]
- Mao et al. (2015)^[74]
- Kiros et al. (2015)^[75]
- Donahue et al. (2015)^[76]
- Vinyals et al. (2015)^[77]
- Karpathy et al. (2015)^[78]
- Fang et al. (2015)^[79]
- Chen et al. (2015)^[80]



A group of young men playing a game of soccer



A man riding a wave on top of a surfboard.

Video Captioning

- Donahue et al. (2014)^[81]
- Venugopalan at al. (2014)^[82]
- Pan et al. (2015)^[83]
- Yao et al. (2015)^[84]
- Rohrbach et al. (2015)^[85]
- Zhu et al. (2015)^[86]
- Cho et al. (2015)^[37]
- S. Sha 2017



What is the mustache
made of?

AI System

bananas

Visual Question Answering

- Santoro et al. (2017)^[87]
- Hu et al. (2017)^[88]
- Johnson et al. (2017)^[89]
- Ben-younes et al. (2017)^[90]
- Malinowski et al. (2017)^[91]
- Nam et al. (2016)
- Kazemi et al. (2016)^[92]

She ____.

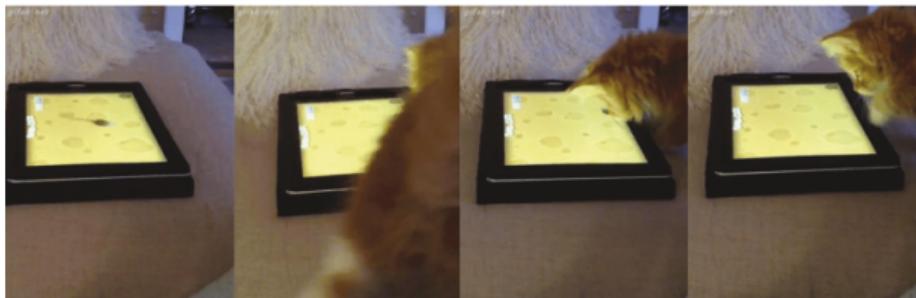


(nods)

She opens the ____.



(door)



Question: What is the cat doing? Answer: playing with a tablet

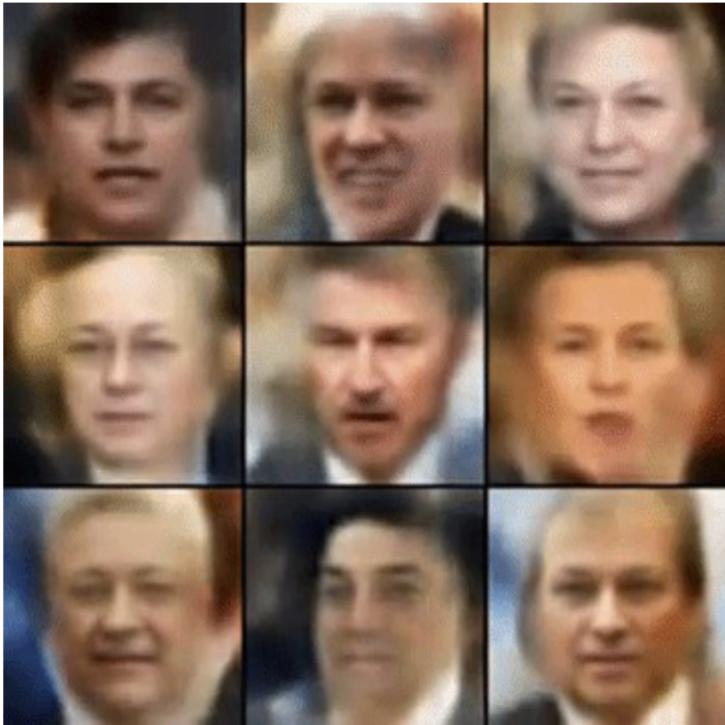
Video Question Answering

- Tapaswi et. al. 2016^[93]
- Zeng et. al. 2016^[94]
- Maharaj et. al. 2017^[95]
- Zhao et. al. 2017^[96]
- Yu Youngjae et. al. 2017^[97]
- Xue Hongyang et. al. 2017^[98]
- Mazaheri et. al. 2017^[99]



Video Summarization

- Chheng 2007^[100]
- Ajmal 2012^[101]
- Zhang Ke 2016^[102]
- Zhong Ji 2017^[103]
- Panda 2017^[104]



Generating Authentic Photos

- Variational Autoencoders (Kingma et. al., 2013)^[105]
- Generative Adversarial Networks (Goodfellow et. al., 2014)^[106]
- Plug & Play generative nets (Nguyen et al., 2016)^[107]
- Progressive Growing of GANs (Karras et al., 2017)^[108]



Generating Raw Audio

- Wavenets (Oord et. al., 2016)^[109]

occluded



completions

original

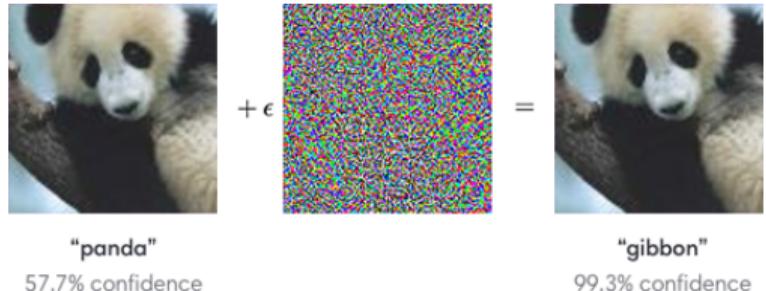
Pixel RNNs

- (Oord et al., 2016)^[110]
- (Oord et al., 2016)^[111]
- (Salimans et al., 2017)^[112]

Chapter 9: (Need for) Sanity

The Paradox of Deep Learning

Why does deep learning work so well despite

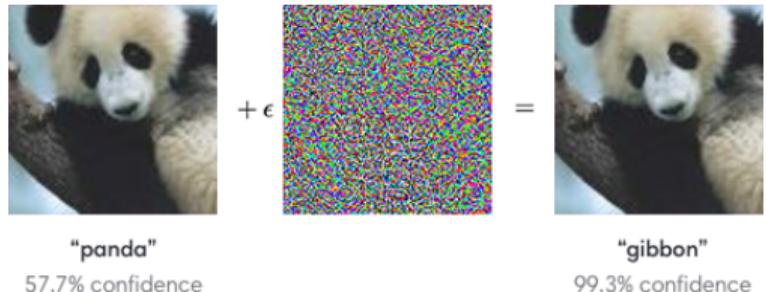


*<https://arxiv.org/pdf/1710.05468.pdf>

The Paradox of Deep Learning

Why does deep learning work so well despite

- high capacity (susceptible to overfitting)

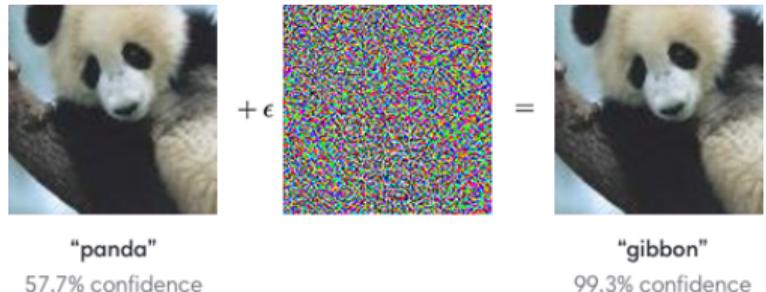


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The Paradox of Deep Learning

Why does deep learning work so well despite

- high capacity (susceptible to overfitting)
- numerical instability (vanishing/exploding gradients)

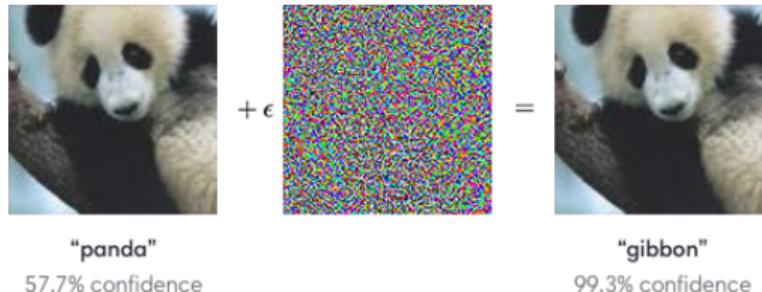


*<https://arxiv.org/pdf/1710.05468.pdf>

The Paradox of Deep Learning

Why does deep learning work so well despite

- high capacity (susceptible to overfitting)
- numerical instability (vanishing/exploding gradients)
- sharp minima (leading to overfitting)

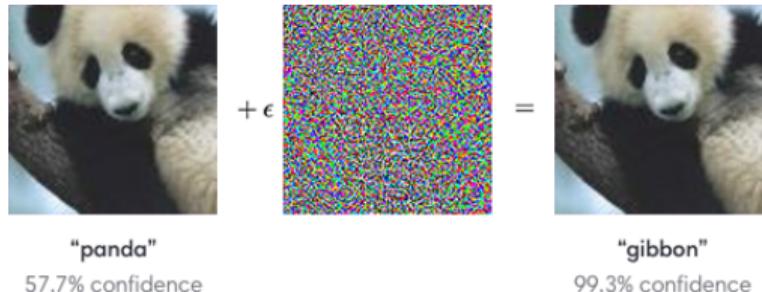


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The Paradox of Deep Learning

Why does deep learning work so well despite

- high capacity (susceptible to overfitting)
- numerical instability (vanishing/exploding gradients)
- sharp minima (leading to overfitting)
- non-robustness (see figure)

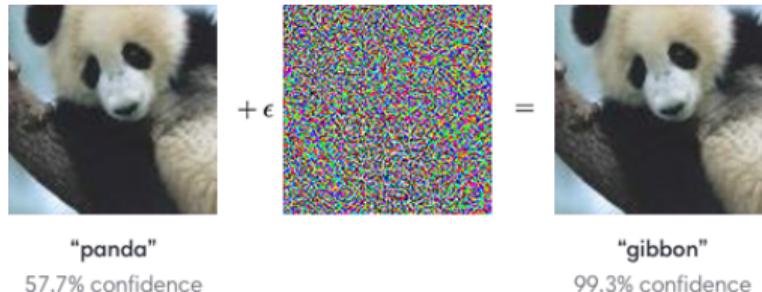


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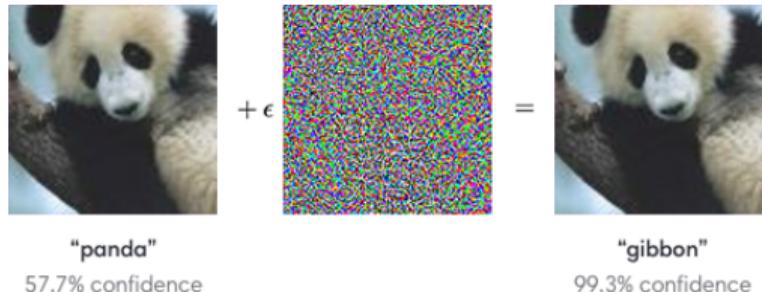
No clear answers yet but ...

*<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)
- numerical instability (vanishing/exploding gradients)
- sharp minima (leading to overfitting)
- non-robustness (see figure)



No clear answers yet but ...

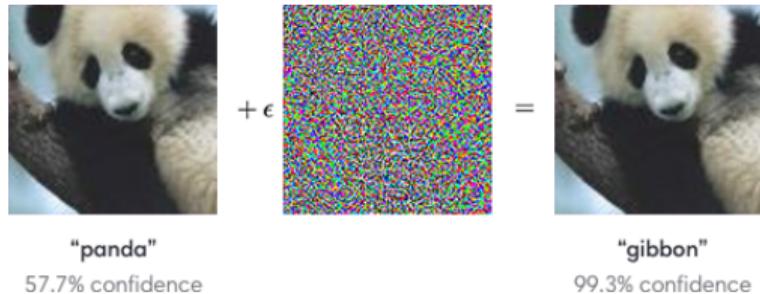
- Slowly but steadily there is increasing emphasis on explainability and theoretical justifications!*

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

The Paradox of Deep Learning

Why does deep learning work so well despite

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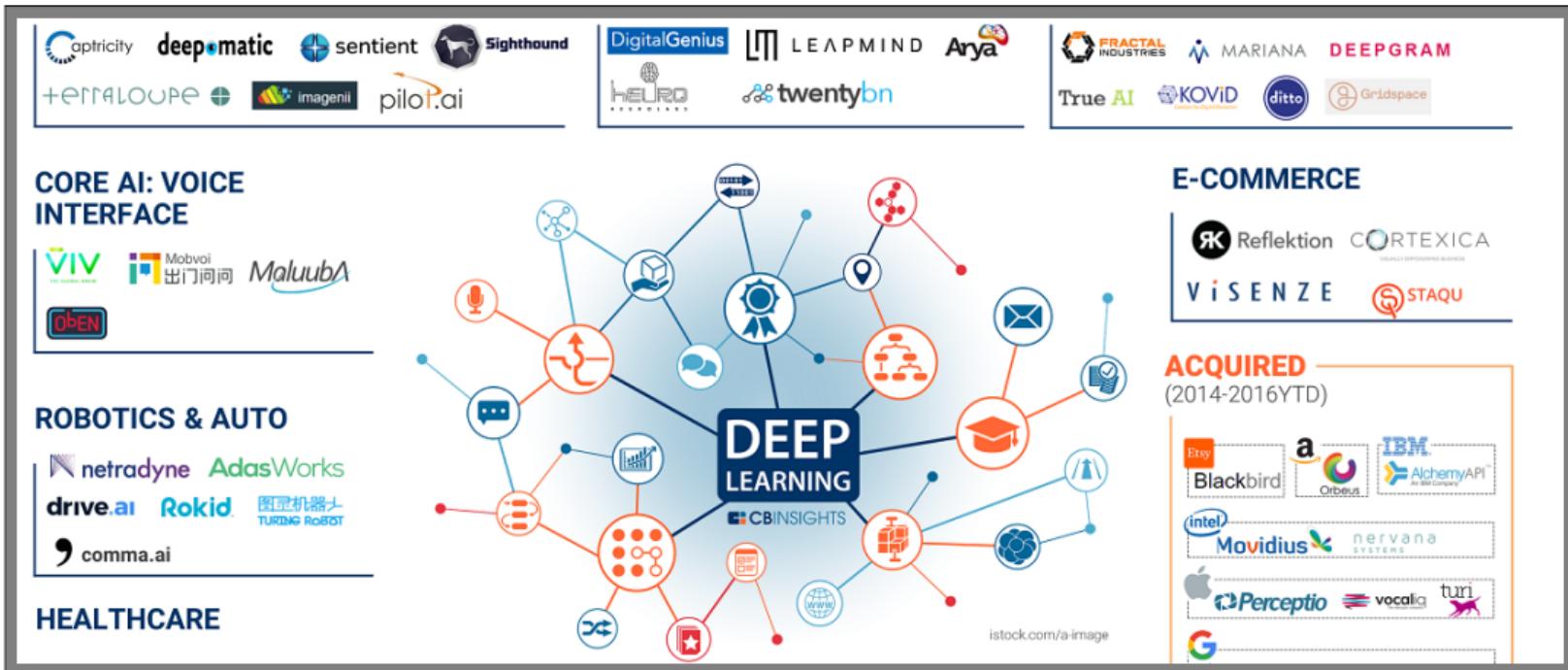


No clear answers yet but ...

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

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

<https://github.com/kjw0612/awesome-rnn>



ⁱSource:

<https://www.cbinsights.com/blog/deep-learning-ai-startups-market-map-company-list/>

References I

- [1] Jürgen Schmidhuber. Deep learning in neural networks: An overview. *Neural Networks*, 61:85–117, 2015.
- [2] W.S.McCulloch and W.Pitts. A logival calculus of the ideas imminent in nervous activity. 1943.
- [3] A.G. Ivakhnenko and V.G. Lapa. Cybernetic predicting devices. 1965.
- [4] M.Minsky and S.Papert. Perceptrons. 1969.
- [5] P. J. Werbos. Applications of advances in nonlinear sensitivity analysis. In *Proceedings of the 10th IFIP Conference, 31.8 - 4.9, NYC*, pages 762–770, 1981.
- [6] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. Learning internal representations by error propagation. In D. E. Rumelhart and J. L. McClelland, editors, *Parallel Distributed Processing*, volume 1, pages 318–362. MIT Press, 1986.
- [7] Kurt Hornik, Maxwell Stinchcombe, and Halbert White. Multilayer feedforward networks are universal approximators. *Neural Networks*, 2(5):359–366, 1989.
- [8] Ruslan Salakhutdinov and Geoffrey Hinton. An efficient learning procedure for deep boltzmann machines. *Neural Comput.*, 24(8):1967–2006, August 2012.
- [9] Alex Graves and Jürgen Schmidhuber. Offline handwriting recognition with multidimensional recurrent neural networks. In D. Koller, D. Schuurmans, Y. Bengio, and L. Bottou, editors, *Advances in Neural Information Processing Systems 21*, pages 545–552. Curran Associates, Inc., 2009.
- [10] G. E. Dahl, Dong Yu, Li Deng, and A. Acero. Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition. *Trans. Audio, Speech and Lang. Proc.*, 20(1):30–42, January 2012.
- [11] Dan Claudiu Ciresan, Ueli Meier, Luca Maria Gambardella, and Jürgen Schmidhuber. Deep big simple neural nets excel on handwritten digit recognition. *CoRR*, abs/1003.0358, 2010.
- [12] Dan C. Ciresan, Ueli Meier, and Jürgen Schmidhuber. Multi-column deep neural networks for image classification. *CoRR*, abs/1202.2745, 2012.
- [13] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc., 2012.

References II

- [14] Matthew D. Zeiler and Rob Fergus. Visualizing and understanding convolutional networks. *CoRR*, abs/1311.2901, 2013.
- [15] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.
- [16] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott E. Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. *CoRR*, abs/1409.4842, 2014.
- [17] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *CoRR*, abs/1512.03385, 2015.
- [18] D. H. Wiesel and T. N. Hubel. Receptive fields of single neurones in the cat's striate cortex. *J. Physiol.*, 148:574–591, 1959.
- [19] K. Fukushima. Neocognitron: A self-organizing neural network for a mechanism of pattern recognition unaffected by shift in position. *Biological Cybernetics*, 36(4):193–202, 1980.
- [20] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel. Back-propagation applied to handwritten zip code recognition. *Neural Computation*, 1(4):541–551, 1989.
- [21] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, November 1998.
- [22] Y. LeCun, I. Kanter, and S. A. Solla. Second order properties of error surfaces: Learning time and generalization. In D. S. Lippman, J. E. Moody, and D. S. Touretzky, editors, *Advances in Neural Information Processing Systems 3*, pages 918–924. Morgan Kaufmann, 1991.
- [23] Vinod Nair and Geoffrey E. Hinton. Rectified linear units improve restricted Boltzmann machines. In *International Conference on Machine Learning (ICML)*, 2010.
- [24] Alex Krizhevsky, I. Sutskever, and G. E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems (NIPS 2012)*, page 4, 2012.
- [25] Andrew L. Maas, Awni Y. Hannun, and Andrew Y. Ng. Rectifier nonlinearities improve neural network acoustic models. In *International Conference on Machine Learning (ICML)*, 2013.

References III

- [26] Geoffrey E. Hinton, Nitish Srivastava, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Improving neural networks by preventing co-adaptation of feature detectors. *CoRR*, abs/1207.0580, 2012.
- [27] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *ICML*, volume 37 of *JMLR Workshop and Conference Proceedings*, pages 448–456. JMLR.org, 2015.
- [28] J. J. Hopfield. Neural networks and physical systems with emergent collective computational abilities. *Proc. of the National Academy of Sciences*, 79:2554–2558, 1982.
- [29] Tomas Mikolov, Martin Karafiat, Lukas Burget, Jan Cernocky, and Sanjeev Khudanpur. Recurrent neural network based language model. In *INTERSPEECH 2010, 11th Annual Conference of the International Speech Communication Association, Makuhari, Chiba, Japan, September 26-30, 2010*, pages 1045–1048, 2010.
- [30] Ryan Kiros, Yukun Zhu, Ruslan Salakhutdinov, Richard S. Zemel, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. Skip-thought vectors. In *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 3294–3302, 2015.
- [31] Yoon Kim, Yacine Jernite, David Sontag, and Alexander M. Rush. Character-aware neural language models. *CoRR*, abs/1508.06615, 2015.
- [32] Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal Process. Mag.*, 29(6):82–97, 2012.
- [33] Alex Graves, Abdel-rahman Mohamed, and Geoffrey E. Hinton. Speech recognition with deep recurrent neural networks. In *IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2013, Vancouver, BC, Canada, May 26-31, 2013*, pages 6645–6649, 2013.
- [34] Jan Chorowski, Dzmitry Bahdanau, Dmitriy Serdyuk, Kyunghyun Cho, and Yoshua Bengio. Attention-based models for speech recognition. In *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 577–585, 2015.
- [35] Hasim Sak, Andrew W. Senior, Kanishka Rao, and Françoise Beaufays. Fast and accurate recurrent neural network acoustic models for speech recognition. In *INTERSPEECH 2015, 16th Annual Conference of the International Speech Communication Association, Dresden, Germany, September 6-10, 2015*, pages 1468–1472, 2015.

References IV

- [36] Nal Kalchbrenner and Phil Blunsom. Recurrent continuous translation models. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, EMNLP 2013, 18-21 October 2013, Grand Hyatt Seattle, Seattle, Washington, USA, A meeting of SIGDAT, a Special Interest Group of the ACL*, pages 1700–1709, 2013.
- [37] Kyunghyun Cho, Bart van Merriënboer, Çaglar Gülcöhre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, EMNLP 2014, October 25-29, 2014, Doha, Qatar, A meeting of SIGDAT, a Special Interest Group of the ACL*, pages 1724–1734, 2014.
- [38] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *CoRR*, abs/1409.0473, 2014.
- [39] Sébastien Jean, KyungHyun Cho, Roland Memisevic, and Yoshua Bengio. On using very large target vocabulary for neural machine translation. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, ACL 2015, July 26-31, 2015, Beijing, China, Volume 1: Long Papers*, pages 1–10, 2015.
- [40] Çaglar Gülcöhre, Orhan Firat, Kelvin Xu, Kyunghyun Cho, Loïc Barrault, Huei-Chi Lin, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. On using monolingual corpora in neural machine translation. *CoRR*, abs/1503.03535, 2015.
- [41] Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. Sequence to sequence learning with neural networks. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pages 3104–3112, 2014.
- [42] Thang Luong, Hieu Pham, and Christopher D. Manning. Effective approaches to attention-based neural machine translation. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015*, pages 1412–1421, 2015.
- [43] Hao Zheng, Yong Cheng, and Yang Liu. Maximum expected likelihood estimation for zero-resource neural machine translation. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, Melbourne, Australia, August 19-25, 2017*, pages 4251–4257, 2017.

References V

- [44] Yong Cheng, Qian Yang, Yang Liu, Maosong Sun, and Wei Xu. Joint training for pivot-based neural machine translation. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, Melbourne, Australia, August 19-25, 2017*, pages 3974–3980, 2017.
- [45] Yun Chen, Yang Liu, Yong Cheng, and Victor O. K. Li. A teacher-student framework for zero-resource neural machine translation. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*, pages 1925–1935, 2017.
- [46] Orhan Firat, Baskaran Sankaran, Yaser Al-Onaizan, Fatos T. Yarman-Vural, and Kyunghyun Cho. Zero-resource translation with multi-lingual neural machine translation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, EMNLP 2016, Austin, Texas, USA, November 1-4, 2016*, pages 268–277, 2016.
- [47] Lifeng Shang, Zhengdong Lu, and Hang Li. Neural responding machine for short-text conversation. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, ACL 2015, July 26-31, 2015, Beijing, China, Volume 1: Long Papers*, pages 1577–1586, 2015.
- [48] Oriol Vinyals and Quoc V. Le. A neural conversational model. *CoRR*, abs/1506.05869, 2015.
- [49] Ryan Lowe, Nissan Pow, Iulian Serban, and Joelle Pineau. The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. In *Proceedings of the SIGDIAL 2015 Conference, The 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue, 2-4 September 2015, Prague, Czech Republic*, pages 285–294, 2015.
- [50] Jesse Dodge, Andreea Gane, Xiang Zhang, Antoine Bordes, Sumit Chopra, Alexander H. Miller, Arthur Szlam, and Jason Weston. Evaluating prerequisite qualities for learning end-to-end dialog systems. *CoRR*, abs/1511.06931, 2015.
- [51] Jason Weston, Antoine Bordes, Sumit Chopra, and Tomas Mikolov. Towards ai-complete question answering: A set of prerequisite toy tasks. *CoRR*, abs/1502.05698, 2015.
- [52] Iulian Vlad Serban, Alessandro Sordoni, Ryan Lowe, Laurent Charlin, Joelle Pineau, Aaron C. Courville, and Yoshua Bengio. A hierarchical latent variable encoder-decoder model for generating dialogues. *CoRR*, abs/1605.06069, 2016.
- [53] Antoine Bordes and Jason Weston. Learning end-to-end goal-oriented dialog. *CoRR*, abs/1605.07683, 2016.

References VI

- [54] Iulian Vlad Serban, Chinnadhurai Sankar, Mathieu Germain, Saizheng Zhang, Zhouhan Lin, Sandeep Subramanian, Taesup Kim, Michael Pieper, Sarah Chandar, Nan Rosemary Ke, Sai Mudumba, Alexandre de Brébisson, Jose Sotelo, Dendi Suhubdy, Vincent Michalski, Alexandre Nguyen, Joelle Pineau, and Yoshua Bengio. A deep reinforcement learning chatbot. *CoRR*, abs/1709.02349, 2017.
- [55] Karl Moritz Hermann, Tomás Kocišký, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. Teaching machines to read and comprehend. In *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 1693–1701, 2015.
- [56] Danqi Chen, Jason Bolton, and Christopher D. Manning. A thorough examination of the cnn/daily mail reading comprehension task. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL 2016, August 7-12, 2016, Berlin, Germany, Volume 1: Long Papers*, 2016.
- [57] Caiming Xiong, Victor Zhong, and Richard Socher. Dynamic coattention networks for question answering. *CoRR*, abs/1611.01604, 2016.
- [58] Min Joon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. Bidirectional attention flow for machine comprehension. *CoRR*, abs/1611.01603, 2016.
- [59] Bhuvan Dhingra, Hanxiao Liu, Zhilin Yang, William W. Cohen, and Ruslan Salakhutdinov. Gated-attention readers for text comprehension. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*, pages 1832–1846, 2017.
- [60] Wenhui Wang, Nan Yang, Furu Wei, Baobao Chang, and Ming Zhou. Gated self-matching networks for reading comprehension and question answering. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*, pages 189–198, 2017.
- [61] Minghao Hu, Yuxing Peng, and Xipeng Qiu. Mnemonic reader for machine comprehension. *CoRR*, abs/1705.02798, 2017.
- [62] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 3431–3440, 2015.

References VII

- [63] Ming Liang and Xiaolin Hu. Recurrent convolutional neural network for object recognition. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 3367–3375, 2015.
- [64] Shaoqing Ren, Kaiming He, Ross B. Girshick, and Jian Sun. Faster R-CNN: towards real-time object detection with region proposal networks. *IEEE Trans. Pattern Anal. Mach. Intell.*, 39(6):1137–1149, 2017.
- [65] Sean Bell, C. Lawrence Zitnick, Kavita Bala, and Ross B. Girshick. Inside-outside net: Detecting objects in context with skip pooling and recurrent neural networks. *CoRR*, abs/1512.04143, 2015.
- [66] Joseph Redmon and Ali Farhadi. YOLO9000: better, faster, stronger. *CoRR*, abs/1612.08242, 2016.
- [67] Jifeng Dai, Yi Li, Kaiming He, and Jian Sun. R-FCN: object detection via region-based fully convolutional networks. In *Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain*, pages 379–387, 2016.
- [68] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross B. Girshick. Mask R-CNN. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 2980–2988, 2017.
- [69] Sergi Caelles, Kevis-Kokitsi Maninis, Jordi Pont-Tuset, Laura Leal-Taixé, Daniel Cremers, and Luc Van Gool. One-shot video object segmentation. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 5320–5329, 2017.
- [70] Janghoon Choi, Junseok Kwon, and Kyoung Mu Lee. Visual tracking by reinforced decision making. *CoRR*, abs/1702.06291, 2017.
- [71] Sangdoo Yun, Jongwon Choi, Youngjoon Yoo, Kimin Yun, and Jin Young Choi. Action-decision networks for visual tracking with deep reinforcement learning. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 1349–1358, 2017.
- [72] Amir Sadeghian, Alexandre Alahi, and Silvio Savarese. Tracking the untrackable: Learning to track multiple cues with long-term dependencies. *CoRR*, abs/1701.01909, 2017.
- [73] Junhua Mao, Wei Xu, Yi Yang, Jiang Wang, and Alan L. Yuille. Deep captioning with multimodal recurrent neural networks (m-rnn). *CoRR*, abs/1412.6632, 2014.

References VIII

- [74] Junhua Mao, Xu Wei, Yi Yang, Jiang Wang, Zhiheng Huang, and Alan L. Yuille. Learning like a child: Fast novel visual concept learning from sentence descriptions of images. In *The IEEE International Conference on Computer Vision (ICCV)*, December 2015.
- [75] Ryan Kiros, Ruslan Salakhutdinov, and Richard S. Zemel. Unifying visual-semantic embeddings with multimodal neural language models. *CoRR*, abs/1411.2539, 2014.
- [76] Jeff Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Trevor Darrell, and Kate Saenko. Long-term recurrent convolutional networks for visual recognition and description. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 2625–2634, 2015.
- [77] Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. Show and tell: A neural image caption generator. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 3156–3164, 2015.
- [78] Andrej Karpathy and Fei-Fei Li. Deep visual-semantic alignments for generating image descriptions. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 3128–3137, 2015.
- [79] Hao Fang, Saurabh Gupta, Forrest N. Iandola, Rupesh Kumar Srivastava, Li Deng, Piotr Dollár, Jianfeng Gao, Xiaodong He, Margaret Mitchell, John C. Platt, C. Lawrence Zitnick, and Geoffrey Zweig. From captions to visual concepts and back. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 1473–1482, 2015.
- [80] Kan Chen, Jiang Wang, Liang-Chieh Chen, Haoyuan Gao, Wei Xu, and Ram Nevatia. ABC-CNN: an attention based convolutional neural network for visual question answering. *CoRR*, abs/1511.05960, 2015.
- [81] Jeff Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Kate Saenko, and Trevor Darrell. Long-term recurrent convolutional networks for visual recognition and description. *CoRR*, abs/1411.4389, 2014.

References IX

- [82] Subhashini Venugopalan, Huijuan Xu, Jeff Donahue, Marcus Rohrbach, Raymond J. Mooney, and Kate Saenko. Translating videos to natural language using deep recurrent neural networks. In *NAACL HLT 2015, The 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Denver, Colorado, USA, May 31 - June 5, 2015*, pages 1494–1504, 2015.
- [83] Yingwei Pan, Tao Mei, Ting Yao, Houqiang Li, and Yong Rui. Jointly modeling embedding and translation to bridge video and language. *CoRR*, abs/1505.01861, 2015.
- [84] Li Yao, Atousa Torabi, Kyunghyun Cho, Nicolas Ballas, Christopher J. Pal, Hugo Larochelle, and Aaron C. Courville. Describing videos by exploiting temporal structure. In *2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015*, pages 4507–4515, 2015.
- [85] Anna Rohrbach, Marcus Rohrbach, Wei Qiu, Annemarie Friedrich, Manfred Pinkal, and Bernt Schiele. Coherent multi-sentence video description with variable level of detail. In *Pattern Recognition - 36th German Conference, GCPR 2014, Münster, Germany, September 2-5, 2014, Proceedings*, pages 184–195, 2014.
- [86] Linchao Zhu, Zhongwen Xu, Yi Yang, and Alexander G. Hauptmann. Uncovering temporal context for video question and answering. *CoRR*, abs/1511.04670, 2015.
- [87] Adam Santoro, David Raposo, David G. T. Barrett, Mateusz Malinowski, Razvan Pascanu, Peter Battaglia, and Tim Lillicrap. A simple neural network module for relational reasoning. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, 4-9 December 2017, Long Beach, CA, USA*, pages 4974–4983, 2017.
- [88] Ronghang Hu, Jacob Andreas, Marcus Rohrbach, Trevor Darrell, and Kate Saenko. Learning to reason: End-to-end module networks for visual question answering. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 804–813, 2017.
- [89] Justin Johnson, Bharath Hariharan, Laurens van der Maaten, Li Fei-Fei, C. Lawrence Zitnick, and Ross B. Girshick. CLEVR: A diagnostic dataset for compositional language and elementary visual reasoning. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 1988–1997, 2017.

References X

- [90] Hedi Ben-younes, Rémi Cadène, Matthieu Cord, and Nicolas Thome. MUTAN: multimodal tucker fusion for visual question answering. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 2631–2639, 2017.
- [91] Mateusz Malinowski, Marcus Rohrbach, and Mario Fritz. Ask your neurons: A neural-based approach to answering questions about images. In *2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015*, pages 1–9, 2015.
- [92] Vahid Kazemi and Ali Elqursh. Show, ask, attend, and answer: A strong baseline for visual question answering. *CoRR*, abs/1704.03162, 2017.
- [93] Makarand Tapaswi, Yukun Zhu, Rainer Stiefelhagen, Antonio Torralba, Raquel Urtasun, and Sanja Fidler. Movieqa: Understanding stories in movies through question-answering. In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016*, pages 4631–4640, 2016.
- [94] Kuo-Hao Zeng, Tseng-Hung Chen, Ching-Yao Chuang, Yuan-Hong Liao, Juan Carlos Niebles, and Min Sun. Leveraging video descriptions to learn video question answering. *CoRR*, abs/1611.04021, 2016.
- [95] Tegan Maharaj, Nicolas Ballas, Anna Rohrbach, Aaron C. Courville, and Christopher Joseph Pal. A dataset and exploration of models for understanding video data through fill-in-the-blank question-answering. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 7359–7368, 2017.
- [96] Zhou Zhao, Qifan Yang, Deng Cai, Xiaofei He, and Yueting Zhuang. Video question answering via hierarchical spatio-temporal attention networks. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, Melbourne, Australia, August 19-25, 2017*, pages 3518–3524, 2017.
- [97] Youngjae Yu, Hyungjin Ko, Jongwook Choi, and Gunhee Kim. End-to-end concept word detection for video captioning, retrieval, and question answering. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 3261–3269, 2017.
- [98] Hongyang Xue, Zhou Zhao, and Deng Cai. The forgettable-watcher model for video question answering. *CoRR*, abs/1705.01253, 2017.

References XI

- [99] Amir Mazaheri, Dong Zhang, and Mubarak Shah. Video fill in the blank with merging lstms. *CoRR*, abs/1610.04062, 2016.
- [100] Tommy Chheng. Video summarization using clustering.
- [101] Muhammad Ajmal, Muhammad Husnain Ashraf, Muhammad Shakir, Yasir Abbas, and Faiz Ali Shah. Video summarization: Techniques and classification. In *Computer Vision and Graphics - International Conference, ICCVG 2012, Warsaw, Poland, September 24-26, 2012. Proceedings*, pages 1–13, 2012.
- [102] Ke Zhang, Wei-Lun Chao, Fei Sha, and Kristen Grauman. Video summarization with long short-term memory. In *Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part VII*, pages 766–782, 2016.
- [103] Zhong Ji, Kailin Xiong, Yanwei Pang, and Xuelong Li. Video summarization with attention-based encoder-decoder networks. *CoRR*, abs/1708.09545, 2017.
- [104] Rameswar Panda, Niluthpol Chowdhury Mithun, and Amit K. Roy-Chowdhury. Diversity-aware multi-video summarization. *IEEE Trans. Image Processing*, 26(10):4712–4724, 2017.
- [105] Diederik P. Kingma and Max Welling. Auto-encoding variational bayes. *CoRR*, abs/1312.6114, 2013.
- [106] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C. Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pages 2672–2680, 2014.
- [107] Anh Nguyen, Jason Yosinski, Yoshua Bengio, Alexey Dosovitskiy, and Jeff Clune. Plug & play generative networks: Conditional iterative generation of images in latent space. *CoRR*, abs/1612.00005, 2016.
- [108] Tero Karras, Timo Aila, Samuli Laine, and Jaakko Lehtinen. Progressive growing of gans for improved quality, stability, and variation. *CoRR*, abs/1710.10196, 2017.
- [109] Aron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alexander Graves, Nal Kalchbrenner, Andrew Senior, and Koray Kavukcuoglu. Wavenet: A generative model for raw audio. In *Arxiv*, 2016.

References XII

- [110] Aaron van den Oord, Nal Kalchbrenner, and Koray Kavukcuoglu. Pixel recurrent neural networks. *arXiv preprint arXiv:1601.06759*, 2016.
- [111] Aaron van den Oord, Nal Kalchbrenner, Lasse Espeholt, koray kavukcuoglu, Oriol Vinyals, and Alex Graves. Conditional image generation with pixelcnn decoders. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 4790–4798. Curran Associates, Inc., 2016.
- [112] Tim Salimans, Andrej Karpathy, Xi Chen, and Diederik P Kingma. Pixelcnn++: Improving the pixelcnn with discretized logistic mixture likelihood and other modifications. *arXiv preprint arXiv:1701.05517*, 2017.
- [113] Albert Haque, Michelle Guo, Alexandre Alahi, Serena Yeung, Zelun Luo, Alisha Rege, Jeffrey Jopling, N. Lance Downing, William Beninati, Amit Singh, Terry Platckew, Arnold Milstein, and Li Fei-Fei. Towards vision-based smart hospitals: A system for tracking and monitoring hand hygiene compliance. *CoRR*, abs/1708.00163, 2017.
- [114] Jifeng Dai, Haozhi Qi, Yuwen Xiong, Yi Li, Guodong Zhang, Han Hu, and Yichen Wei. Deformable convolutional networks. *CoRR*, abs/1703.06211, 2017.
- [115] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, 15:1929–1958, 2014.
- [116] Jayanth Koushik and Hiroaki Hayashi. Improving stochastic gradient descent with feedback. *CoRR*, abs/1611.01505, 2016.
- [117] Matthew D. Zeiler. ADADELTA: an adaptive learning rate method. *CoRR*, abs/1212.5701, 2012.
- [118] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980, 2014.
- [119] Anonymous. On the convergence of adam and beyond. *International Conference on Learning Representations*, 2018.
- [120] John C. Duchi, Elad Hazan, and Yoram Singer. Adaptive subgradient methods for online learning and stochastic optimization. *Journal of Machine Learning Research*, 12:2121–2159, 2011.
- [121] T. Tieleman and G. Hinton. Lecture 6.5—RmsProp: Divide the gradient by a running average of its recent magnitude. COURSERA: Neural Networks for Machine Learning, 2012.