# CMPE 297-11 Deep Learning

#### Machine Learning

 Field of study that gives computers the ability to learn without being explicitly programmed

By Arthur Samuel (1959)

## Samuel's Checker Program vs. Human (1956)

#### The IBM 700 Series Computing Comes to Business

01/02

Overview
Transforming the World
Cultural Impacts
The Team
In Their Words





IBM 701 meets the future president

In 1954, Ronald Reagan, who was a TV personality for General Electric at the time, visited the GE Aircraft Jet Engine Plant in Evendale, Ohio. During this visit, GE manager Herbert Grosch spent a few minutes introducing the future US president to the IBM 701.

The IBM 700 series made scientific calculations and commercial operations easier, but the machines also provided the world with some entertainment.



Playing checkers on the 701

On February 24, 1956, Arthur Samuel's Checkers program, which was developed for play on the IBM 701, was demonstrated to the public on television. In 1962, self-proclaimed checkers master Robert Nealey played the game on an IBM 7094 computer. The computer won. Other games resulted in losses for the Samuel Checkers program, but it is still considered a milestone for artificial intelligence, and offered the public in the early 1960s an example of the capabilities of an electronic computer.



## IBM Deep Blue vs. Kasparov (1996 & 1997)





HISTORY TECHNOLOGY

## Did Deep Blue Beat Kasparov Because of a System Glitch?

Jennifer Latson @Jenniel atson Feb. 17, 2015











Feb. 17, 1996: Chess champion Garry Kasparov beats the IBM supercomputer "Deep Blue," winning a six-game chess match

Garry Kasparov was not afraid of a computer. When the world chess champion agreed to play a match against Deep Blue, the IBM supercomputer designed to beat him, he was so confident that, according to TIME, he scoffed at an offer to split the \$500,000 purse 60-



Chess champion Gary Kasparov contemplating a board in 1997, training for his May rematch with a smarter version of Deep Blue

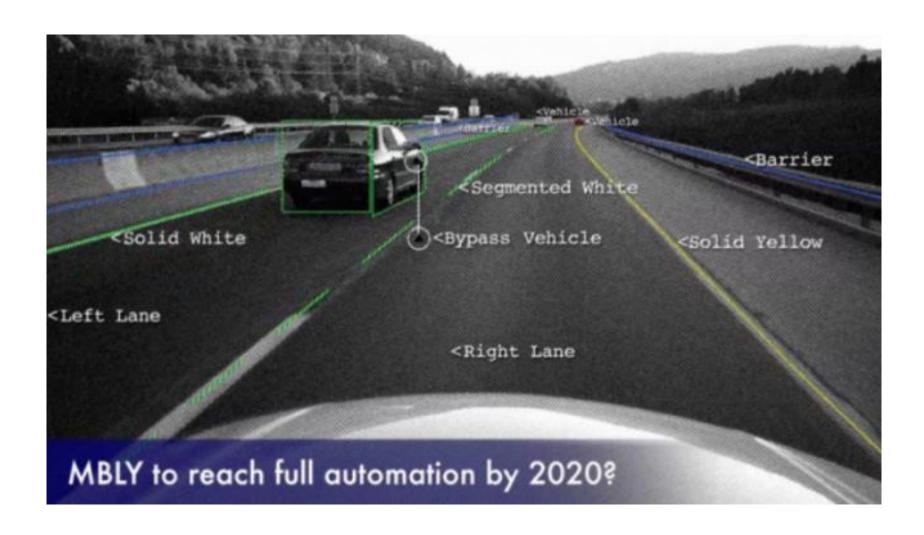
### IBM Watson in Jeopardy! (2011)



#### Fast R-CNN Demo



### Mobileye



## AlphaGo vs. LEe, Sedol (2016)



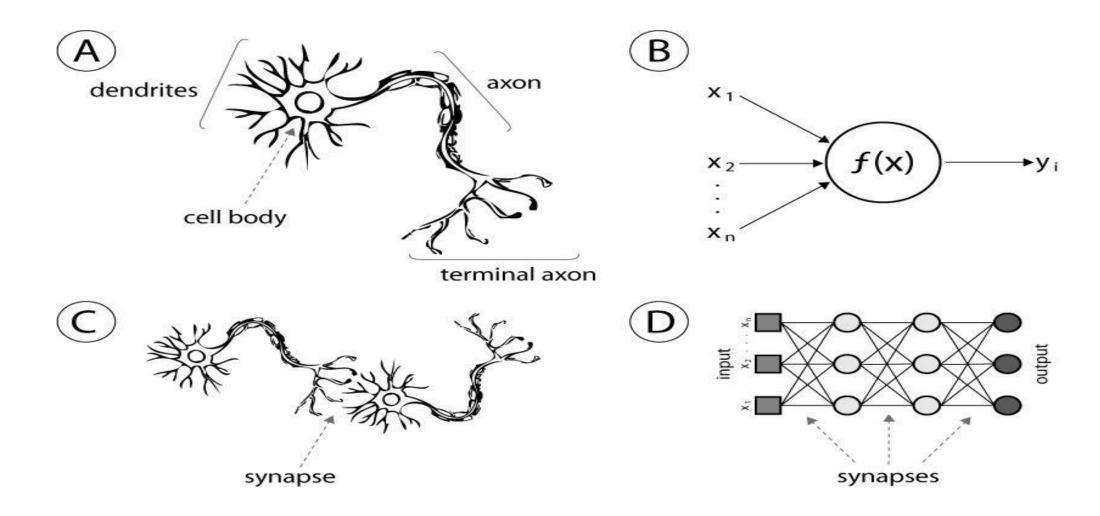
### Machine Learning



#### Neural Network

 Collection of connected units (neurons), inspired by the biological neural networks that constitute human brains

#### **Neural Networks?**

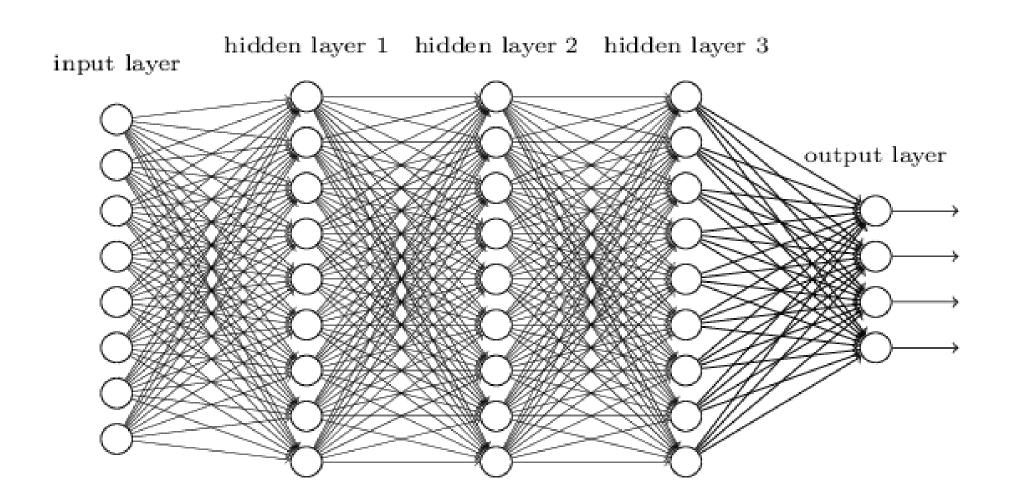


#### Softmax Regression (Multi-Class)

http://vision.stanford.edu/teaching/cs231n-demos/linear-classify

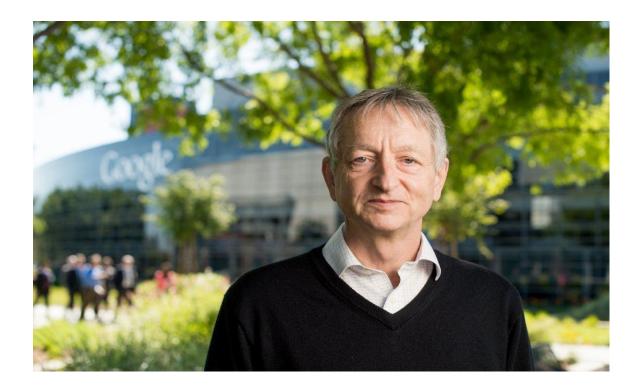
By Andrej Karpahty

## Backpropagation for training



### **Geoffrey Hinton**

Pre-training for deep neural networks



LETTER — Communicated by Yann Le Cun

#### A Fast Learning Algorithm for Deep Belief Nets

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We show how to use "complementary priors" to eliminate the explaining-away effects that make inference difficult in densely connected belief nets that have many hidden layers. Using complementary priors, we derive a fast, greedy algorithm that can learn deep, directed belief networks one layer at a time, provided the top two layers form an undirected associative memory. The fast, greedy algorithm is used to initialize a slower learning procedure that fine-tunes the weights using a contrastive version of the wake-sleep algorithm. After fine-tuning, a network with three hidden layers forms a very good generative model of the joint distribution of handwritten digit images and their labels. This generative model gives better digit classification than the best discriminative learning algorithms. The low-dimensional manifolds on which the digits lie are modeled by long ravines in the free-energy landscape of the top-level associative memory, and it is easy to explore these ravines by using the directed connections to display what the associative memory has in mind.

backpropagation, boltzmann machines



Geoff Hinton Google

convolution



Yann Lecun Facebook

stacked autoencoders



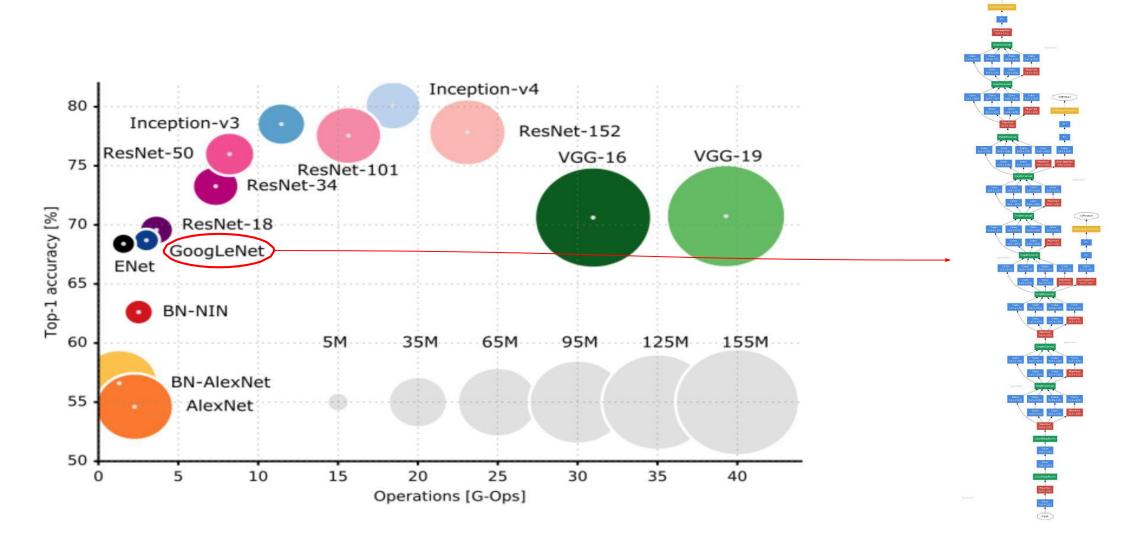
Yoshua Bengio U. of Montreal

GPU utilization



Andrew Ng Baidu

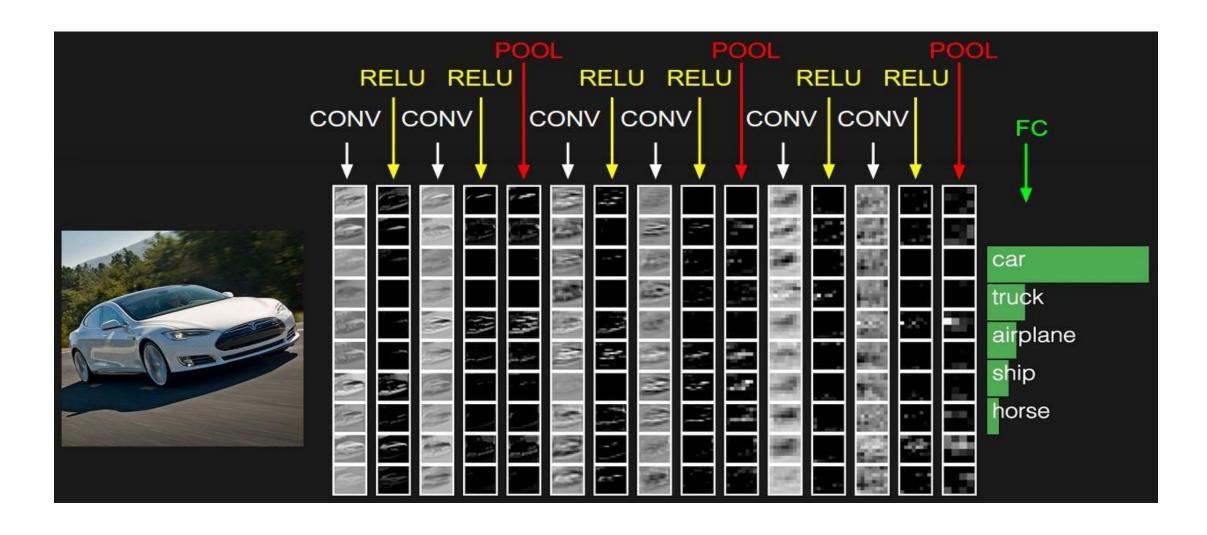
### How Deep?



#### ML, NN & DL Summary

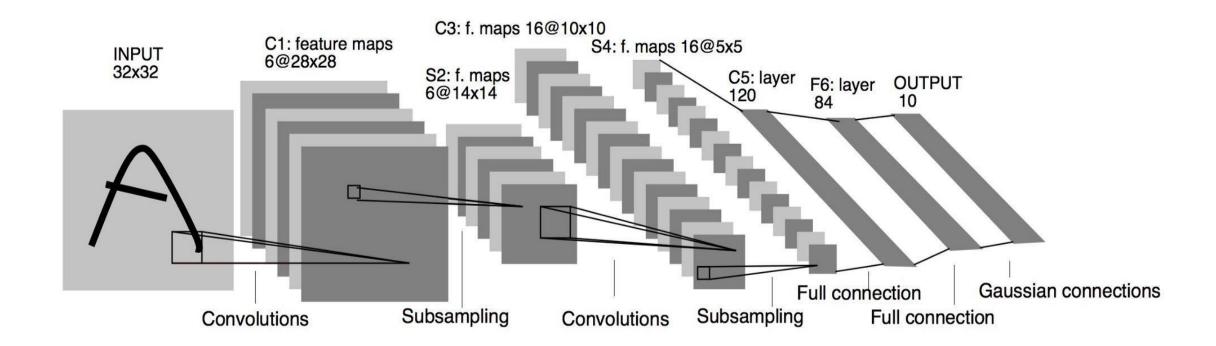
- Machine Learning
  - Field of study that gives computers the ability to learn without being explicitly programmed
- Neural network
  - One of ML classifiers, being trained by backpropagation
  - Extension of logistic & softmax regression
- Deep Learning
  - Framework of using neural networks with deep (many) layers
  - Most of state-of-the-art ML-based products utilized DL!

#### Convolutional Neural Network (CNN)



#### Convolutional Neural Network (CNN)

Yann LeCun's LeNet5



## Image Classification

	Top 5 error
Imagenet 2011 winner (not CNN)	25.7%
Imagenet 2012 winner	16.4% (Krizhesvky et al.)
Imagenet 2013 winner	11.7% (Zeiler/Clarifai)
Imagenet 2014 winner	6.7% (GoogLeNet)
Human: Andrej Karpathy	5.1%
Baidu Arxiv paper: 3 Jan '15	6.0%
MS Research Arxiv paper: 6 Feb '15	4.9%
Google Arxiv paper: 2 Mar '15	4.8%

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#### CNN in TensorFlow

https://www.tensorflow.org/tutorials/layers

### **CNN** in Speech Recognition

#### Deep Speech: Scaling up end-to-end speech recognition

Awni Hannun, Carl Case, Jared Casper, Bryan Catanzaro, Greg Diamos, Erich Elsen, Ryan Prenger, Sanjeev Satheesh, Shubho Sengupta, Adam Coates, Andrew Y. Ng

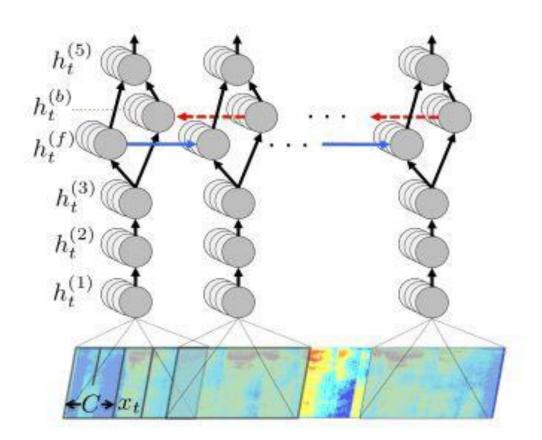
Baidu Research - Silicon Valley AI Lab

#### Abstract

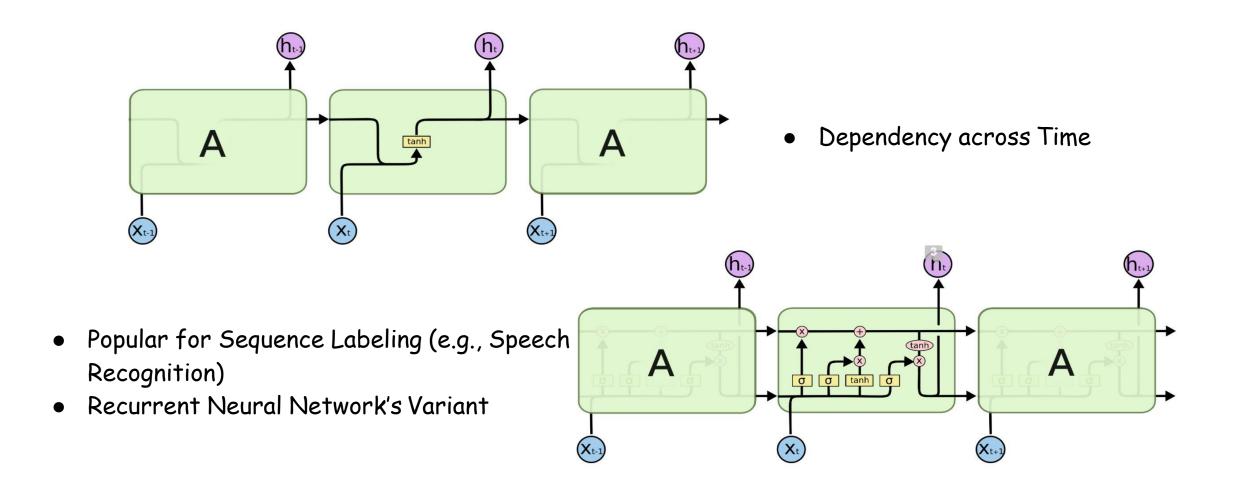
We present a state-of-the-art speech recognition system developed using end-to-end deep learning. Our architecture is significantly simpler than traditional speech systems, which rely on laboriously engineered processing pipelines; these traditional systems also tend to perform poorly when used in noisy environments. In contrast, our system does not need hand-designed components to model background noise, reverberation, or speaker variation, but instead directly learns a function that is robust to such effects. We do not need a phoneme dictionary, nor even the concept of a "phoneme." Key to our approach is a well-optimized RNN training system that uses multiple GPUs, as well as a set of novel data synthesis techniques that allow us to efficiently obtain a large amount of varied data for training. Our system, called Deep Speech, outperforms previously published results on the widely studied Switchboard Hub5'00, achieving 16.0% error on the full test set. Deep Speech also handles challenging noisy environments better than widely used, state-of-the-art commercial speech systems.

#### 1 Introduction

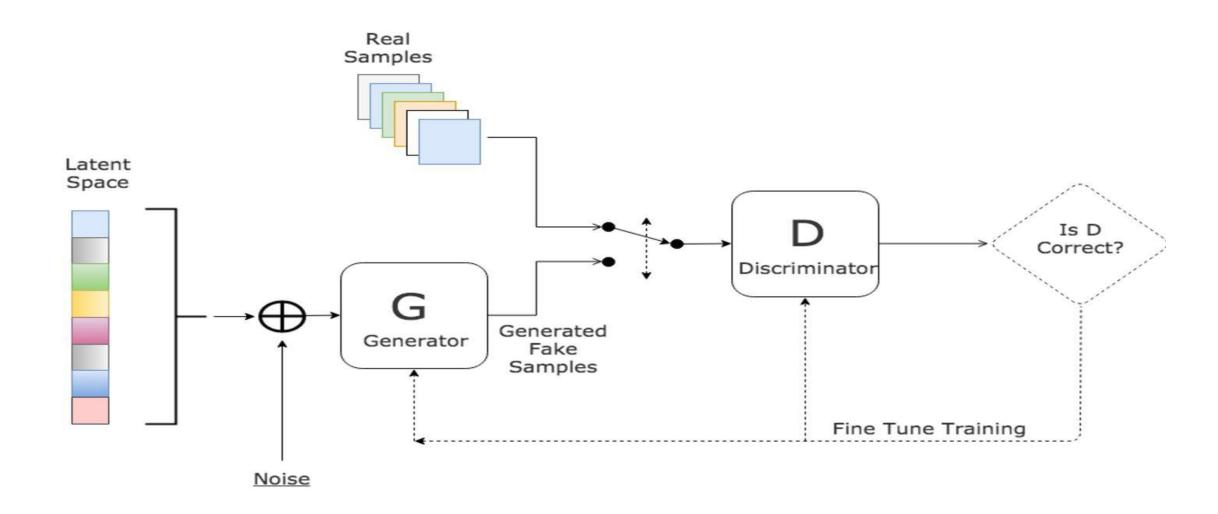
Top speech recognition systems rely on sophisticated pipelines composed of multiple algorithms and hand-engineered processing stages. In this paper, we describe an end-to-end speech system, called "Deep Speech", where deep learning supersedes these processing stages. Combined with a language model, this approach achieves higher performance than traditional methods on hard speech recognition tasks while also being much simpler. These results are made possible by training a large recurrent neural network (RNN) using multiple GPUs and thousands of hours of data. Because this system learns directly from data, we do not require specialized components for speaker adaptation or noise filtering. In fact, in settings where robustness to speaker variation and noise are critical, our system excels: Deep Speech outperforms previously published methods on the Switchboard



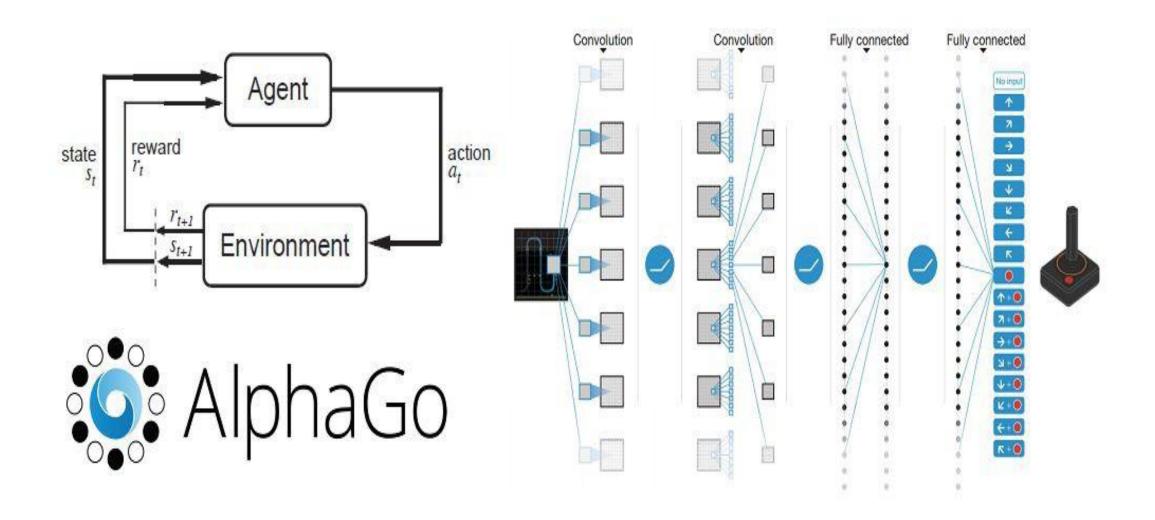
#### RNN and LSTM

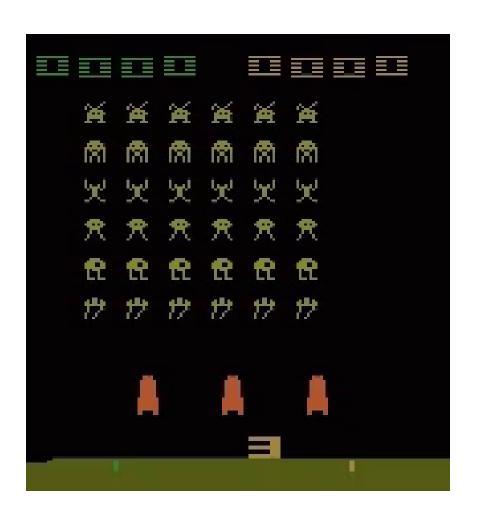


## Generative Adversarial Network (GAN)



#### Deep Reinforcement LEarning



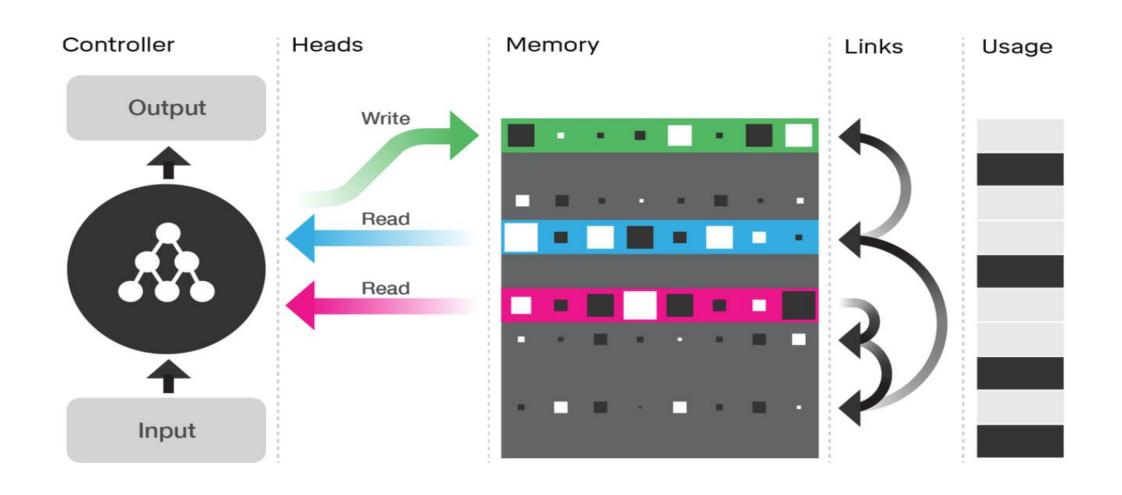




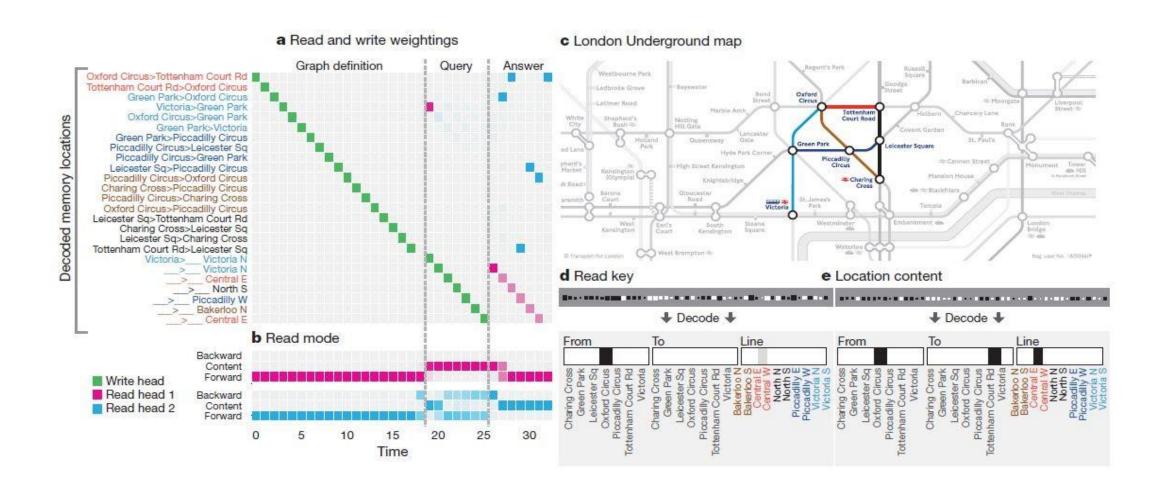
#### **DNN Frameworks**

Language	Library
C++	Caffe
Julia	MOCHA
Lua	Torch
Python	Caffe
Python	Theano
Python/C++	Tensorflow
Python	Karas

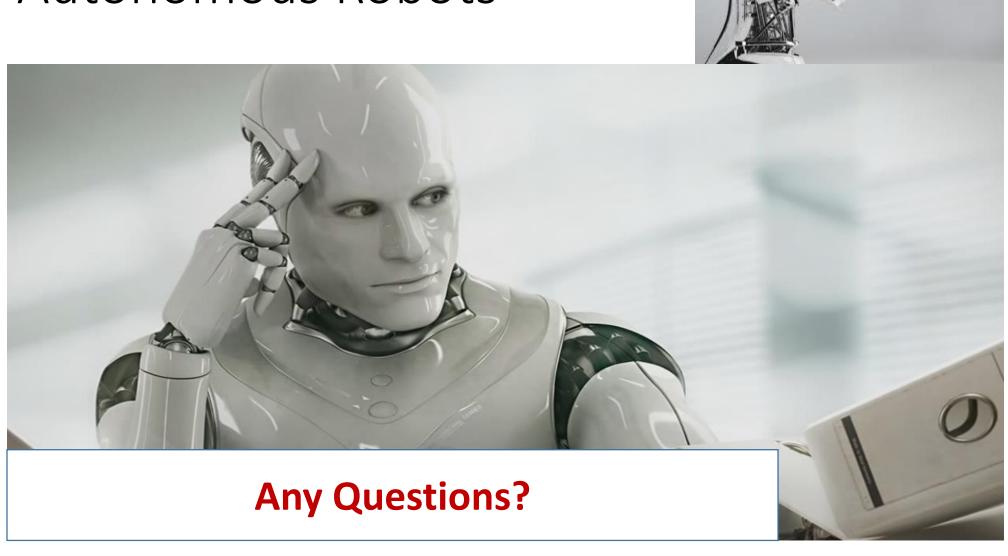
### Differentiable Neural Computer (DNC) 2017



#### Answer Questions



#### Autonomous Robots



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