



# Deep Learning: State of the Art (2020)

[deeplearning.mit.edu](http://deeplearning.mit.edu)

2020

# Deep Learning Lecture Series



## Deep Learning State of the Art (2020)

Lex Fridman

MIT

Date/Time: Mon, Jan 6, 3-4:30pm

Room: E54-100



## Measures of Intelligence

Francois Chollet

Creator of Keras, Google

Date/Time: Mon, Jan 13, 3-4:30pm

Room: E54-100



## Unlocking AI for Science by Preserving Privacy

Andrew Trask

OpenMined, University of Oxford

Date/Time: Wed, Jan 8, 3-4:30pm

Room: E54-100



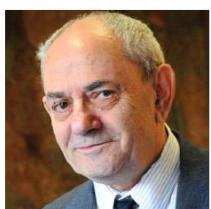
## Deep Learning Hardware Accelerators

Vivienne Sze

MIT

Date/Time: Wed, Jan 15, 3-4:30pm

Room: E54-100



## Complete Statistical Theory of Learning

Vladimir Vapnik

Co-Creator of SVM, Columbia University

Date/Time: Fri, Jan 10, 3-5pm

Room: E54-100



## OpenAI Five

Jakub Pachocki

Dota Team & Reasoning Team Research Lead, OpenAI

Date/Time: Fri, Jan 17, 3-4:30pm

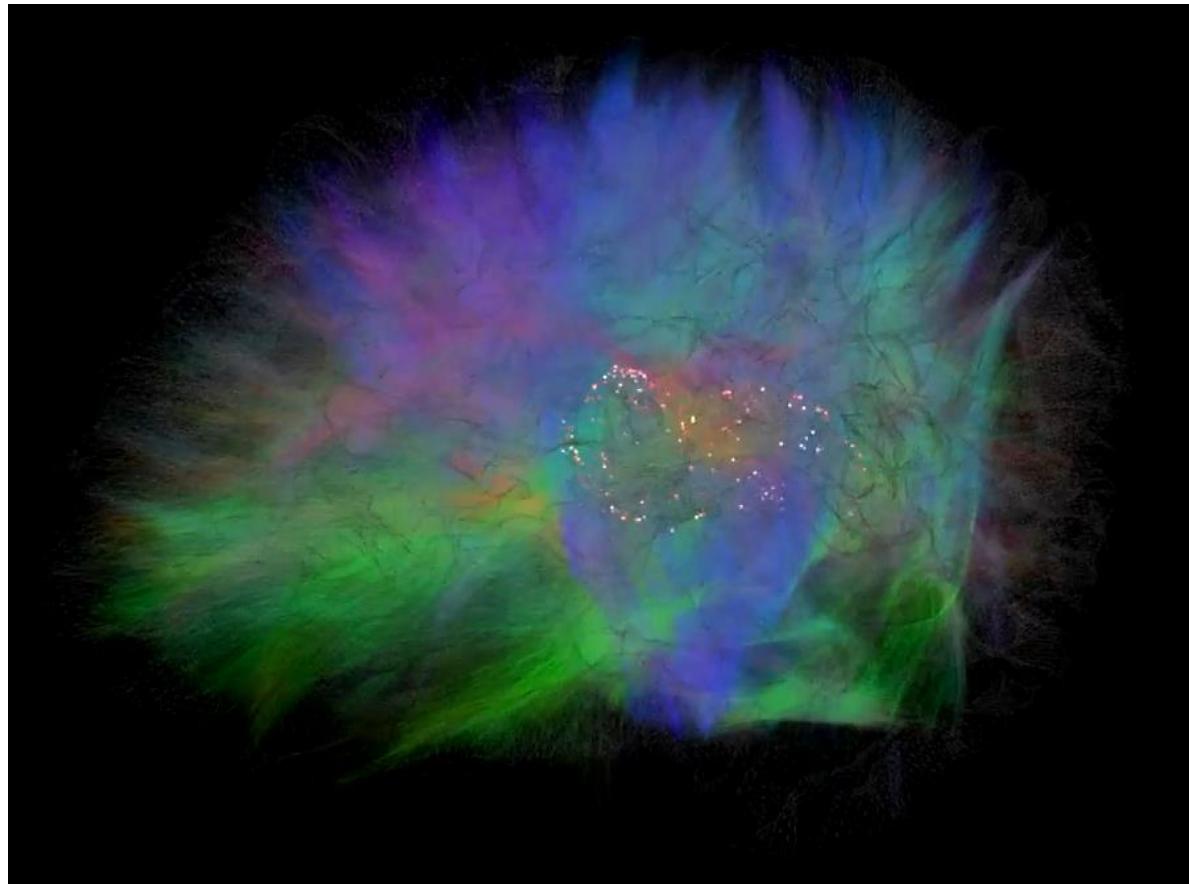
Room: E54-100

# Outline

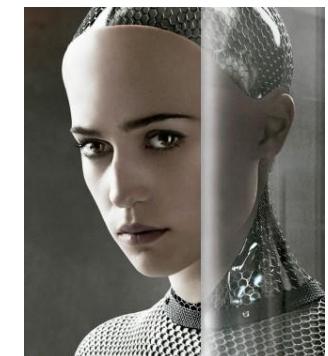
- **Deep Learning Growth, Celebrations, and Limitations**
- Deep Learning and Deep RL Frameworks
- Natural Language Processing
- Deep RL and Self-Play
- Science of Deep Learning and Interesting Directions
- Autonomous Vehicles and AI-Assisted Driving
- Government, Politics, Policy
- Courses, Tutorials, Books
- General Hopes for 2020

# “AI began with an ancient wish to forge the gods.”

- Pamela McCorduck, *Machines Who Think*, 1979



Frankenstein (1818)



Ex Machina (2015)

Visualized here are **3% of the neurons** and **0.0001% of the synapses** in the brain.

Thalamocortical system visualization via DigiCortex Engine.

# Deep Learning & AI in Context of Human History

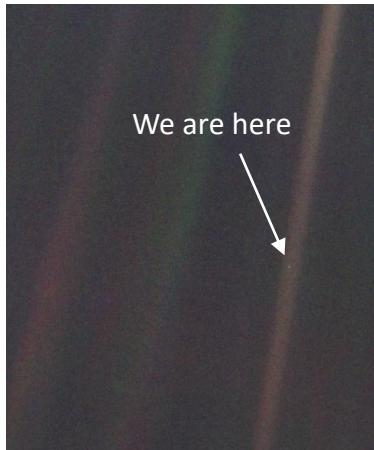


## Perspective:

- Universe created  
13.8 billion years ago
- Earth created  
4.54 billion years ago
- Modern humans  
300,000 years ago
- Civilization  
12,000 years ago
- Written record  
5,000 years ago

**1700s and beyond:** Industrial revolution, steam engine, mechanized factory systems, machine tools

# Artificial Intelligence in Context of Human History



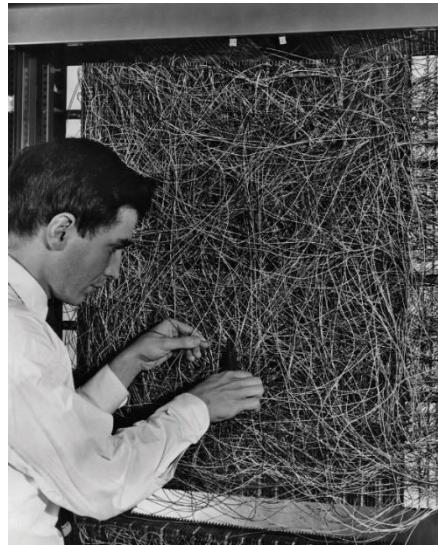
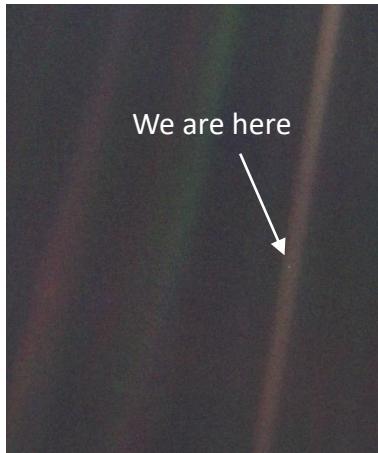
## Perspective:

- Universe created  
13.8 billion years ago
- Earth created  
4.54 billion years ago
- Modern humans  
300,000 years ago
- Civilization  
12,000 years ago
- Written record  
5,000 years ago

**Dreams, mathematical foundations, and engineering in reality.**

**Alan Turing, 1951:** “It seems probable that once the machine thinking method had started, it would not take long to outstrip our feeble powers. They would be able to converse with each other to sharpen their wits. At some stage therefore, we should have to expect the machines to take control.”

# Artificial Intelligence in Context of Human History



## Perspective:

- Universe created  
13.8 billion years ago
- Earth created  
4.54 billion years ago
- Modern humans  
300,000 years ago
- Civilization  
12,000 years ago
- Written record  
5,000 years ago

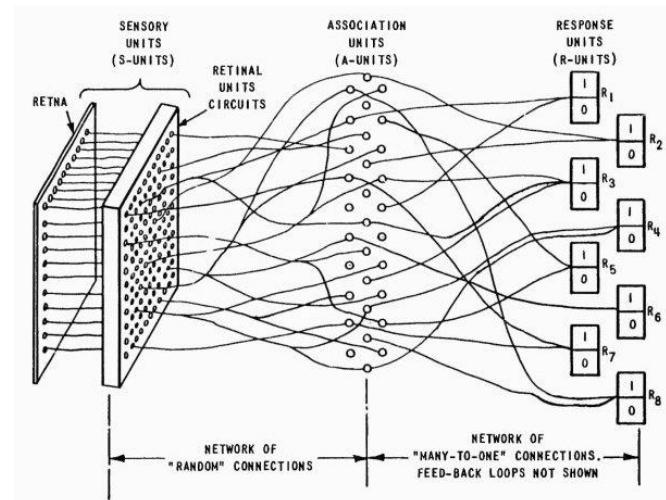
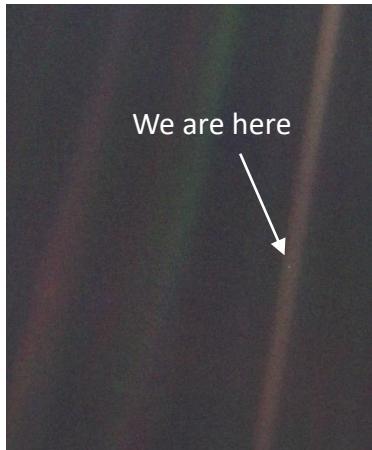


Figure 1 ORGANIZATION OF THE MARK I PERCEPTRON

## Dreams, mathematical foundations, and engineering in reality.

**Frank Rosenblatt, Perceptron (1957, 1962):** Early description and engineering of single-layer and multi-layer artificial neural networks.

# Artificial Intelligence in Context of Human History



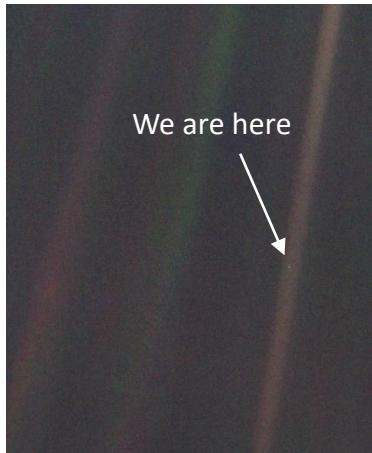
## Perspective:

- Universe created  
13.8 billion years ago
- Earth created  
4.54 billion years ago
- Modern humans  
300,000 years ago
- Civilization  
12,000 years ago
- Written record  
5,000 years ago



Kasparov vs Deep Blue, 1997

# Artificial Intelligence in Context of Human History

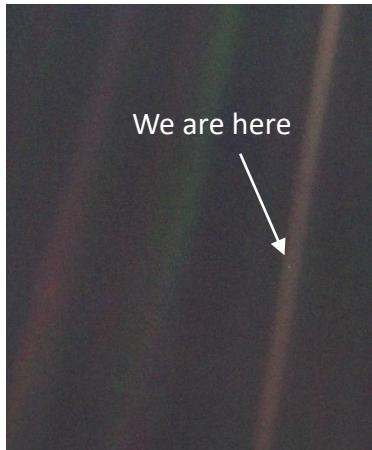


## Perspective:

- Universe created  
13.8 billion years ago
- Earth created  
4.54 billion years ago
- Modern humans  
300,000 years ago
- Civilization  
12,000 years ago
- Written record  
5,000 years ago

Lee Sedol vs AlphaGo, 2016

# Artificial Intelligence in Context of Human History

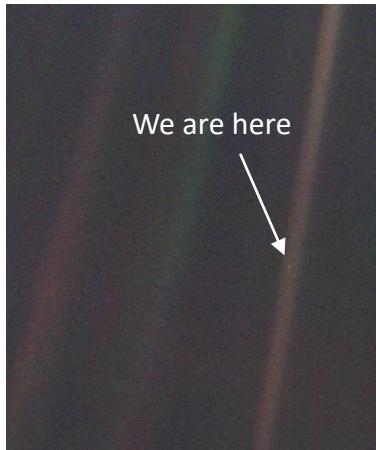


Perspective:

- Universe created  
13.8 billion years ago
- Earth created  
4.54 billion years ago
- Modern humans  
300,000 years ago
- Civilization  
12,000 years ago
- Written record  
5,000 years ago

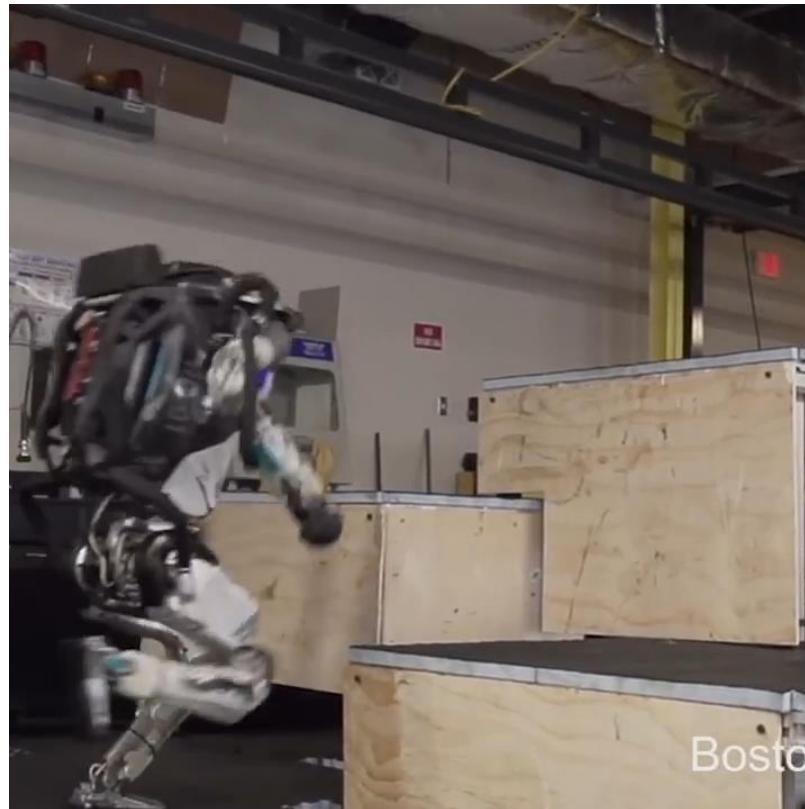
Robots on four wheels.

# Artificial Intelligence in Context of Human History



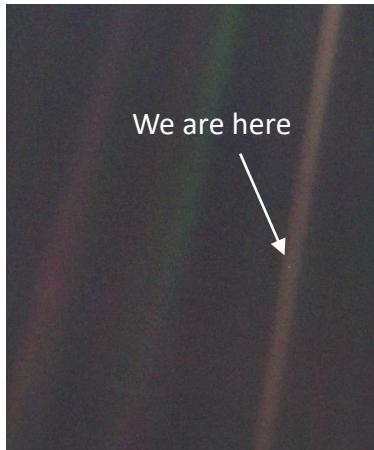
Perspective:

- Universe created  
13.8 billion years ago
- Earth created  
4.54 billion years ago
- Modern humans  
300,000 years ago
- Civilization  
12,000 years ago
- Written record  
5,000 years ago



Robots on two legs.

# History of Deep Learning Ideas and Milestones\*



- 1943: Neural networks
- 1957-62: Perceptron
- 1970-86: Backpropagation, RBM, RNN
- 1979-98: CNN, MNIST, LSTM, Bidirectional RNN
- 2006: “Deep Learning”, DBN
- 2009: ImageNet + AlexNet
- 2014: GANs
- 2016-17: AlphaGo, AlphaZero
- 2017: 2017-19: Transformers

\* Dates are for perspective and not as definitive historical record of invention or credit

## Perspective:

- Universe created  
13.8 billion years ago
- Earth created  
4.54 billion years ago
- Modern humans  
300,000 years ago
- Civilization  
12,000 years ago
- Written record  
5,000 years ago

# Turing Award for Deep Learning



- Yann LeCun
- Geoffrey Hinton
- Yoshua Bengio

Turing Award given for:

- “The conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing.”
- (Also, for popularization in the face of skepticism.)

# Early Key Figures in Deep Learning

(Not a Complete List by Any Means)

- 1943: Walter Pitts and Warren McCulloch  
Computational models for neural nets
- 1957, 1962: Frank Rosenblatt  
Perceptron (Single-Layer & Multi-Layer)
- 1965: Alexey Ivakhnenko and V. G. Lapa  
Learning algorithm for MLP
- 1970: Seppo Linnainmaa  
Backpropagation and automatic differentiation
- 1979: Kunihiko Fukushima  
Convolutional neural networks
- 1982: John Hopfield  
Hopfield networks (recurrent neural networks)

# People of Deep Learning and Artificial Intelligence

- History of science is a story of both **people** and **ideas**.
- Many brilliant people contributed to the development of AI.

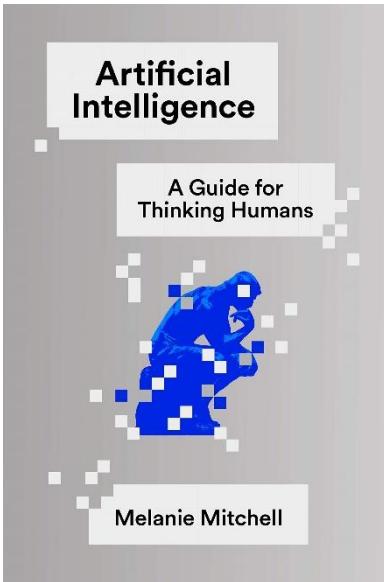
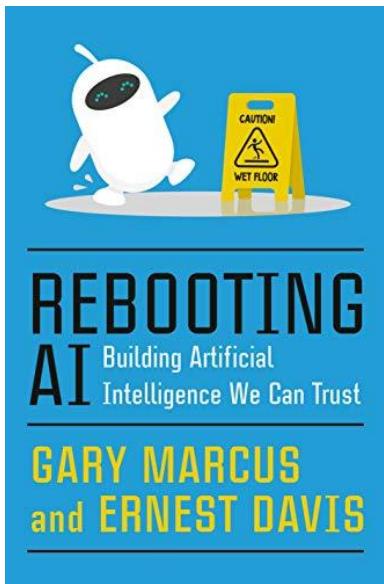


Schmidhuber, Jürgen. "Deep learning in neural networks: An overview." *Neural networks* 61 (2015): 85-117  
<https://arxiv.org/pdf/1404.7828.pdf>

My (Lex) hope for the community:

- More respect, open-mindedness, collaboration, credit sharing.
- Less derision, jealousy, stubbornness, academic silos.

# Limitations of Deep Learning



- 2019 is the year it became cool to say that “deep learning” has limitations.
- Books, articles, lectures, debates, videos were released that learning-based methods cannot do commonsense reasoning.

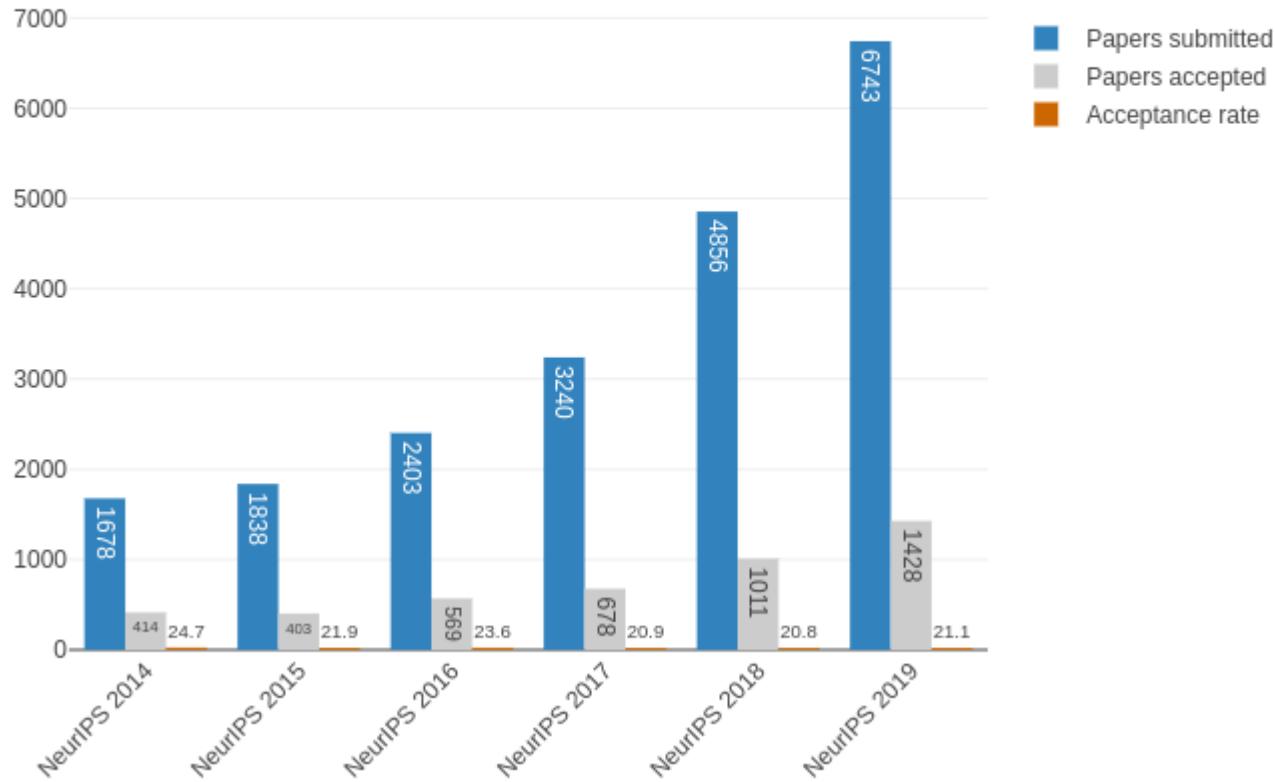
## Prediction from Rodney Brooks:

“By 2020, the popular press starts having stories that the era of Deep Learning is over.”

<http://rodneybrooks.com/predictions-scorecard-2019-january-01/>

# Deep Learning Research Community is Growing

Statistics of acceptance rate NeurIPS



# Hopes for 2020

- **Less Hype & Less Anti-Hype:** Less tweets on how there is too much hype in AI and more solid research in AI.
- **Hybrid Research:** Less contentious, counter-productive debates, more open-minded interdisciplinary collaboration.
- **Research topics:**
  - Reasoning
  - Active learning and life-long learning
  - Multi-modal and multi-task learning
  - Open-domain conversation
  - Applications: medical, autonomous vehicles
  - Algorithmic ethics
  - Robotics

# Outline

- Deep Learning Growth, Celebrations, and Limitations
- **Deep Learning and Deep RL Frameworks**
- Natural Language Processing
- Deep RL and Self-Play
- Science of Deep Learning and Interesting Directions
- Autonomous Vehicles and AI-Assisted Driving
- Government, Politics, Policy
- Courses, Tutorials, Books
- General Hopes for 2020

# Competition and Convergence of Deep Learning Libraries

## TensorFlow 2.0 and PyTorch 1.3



- Eager execution by default (imperative programming)
- Keras integration + promotion
- Cleanup (API, etc.)
- TensorFlow.js
- TensorFlow Lite
- TensorFlow Serving

- TorchScript (graph representation)
- Quantization
- PyTorch Mobile (experimental)
- TPU support

Python 2 support ended on Jan 1, 2020.

```
>>> print "Goodbye World"
```

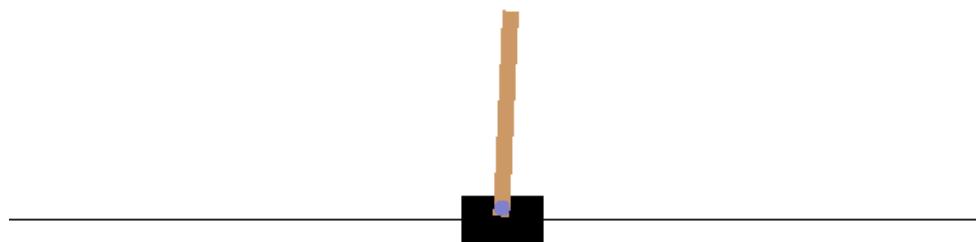
# Reinforcement Learning Frameworks

- TensorFlow
  - OpenAI Baselines
    - Stable Baselines – the one I recommend for beginners
  - TensorForce
  - Dopamine (Google)
  - TF-Agents
  - TRFL
  - RLLib (+ Tune) – great for distributed RL & hyperparameter tuning
  - Coach - huge selection of algorithms
- PyTorch
  - Horizon
  - SLM-Lab
- Misc
  - RLgraph
  - Keras-RL

# Reinforcement Learning Frameworks

- “Stable Baselines” (OpenAI Baselines Fork)
  - A2C, PPO, TRPO, DQN, ACKTR, ACER and DDPG
  - Good documentation (and code commenting)
  - Easy to get started and use

```
1 from stable_baselines import PPO2  
2  
3 # Define and train a model in one line of code !  
4 trained_model = PPO2('MlpPolicy', 'CartPole-v1').learn(total_timesteps=10000)  
5 # you can then access the gym env using trained_model.get_env()
```



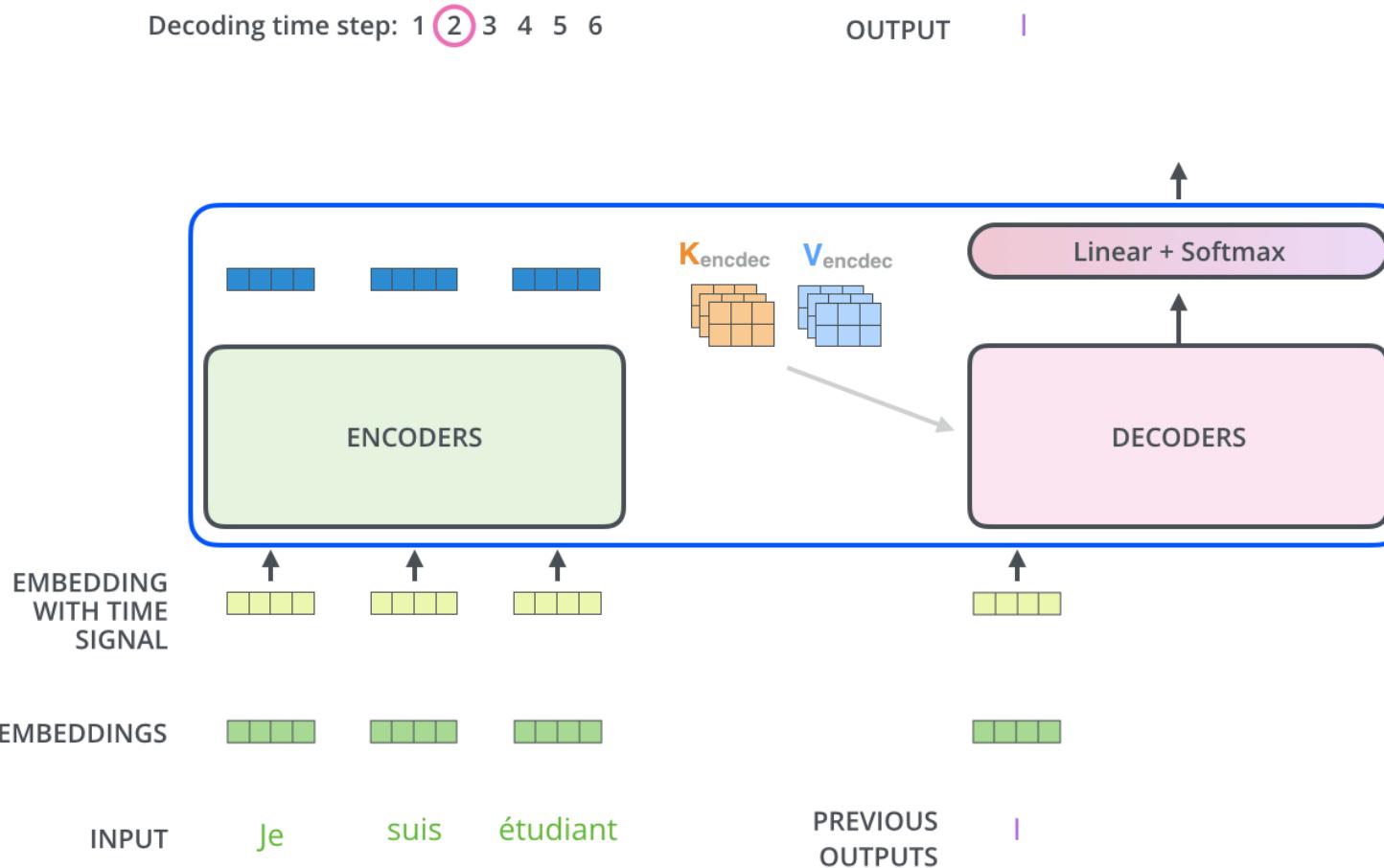
# Hopes for 2020

- **Framework-agnostic Research:** Make it even easier to translate a trained PyTorch model to TensorFlow and vice-versa.
- **Mature Deep RL frameworks:** Converge to fewer, actively-developed, stable RL frameworks that are less tied to TensorFlow or PyTorch.
- **Abstractions:** Build higher and higher abstractions (i.e. Keras) on top of deep learning frameworks that empower researchers, scientists, developers outside of machine learning field.

# Outline

- Deep Learning Growth, Celebrations, and Limitations
- Deep Learning and Deep RL Frameworks
- **Natural Language Processing**
- Deep RL and Self-Play
- Science of Deep Learning and Interesting Directions
- Autonomous Vehicles and AI-Assisted Driving
- Government, Politics, Policy
- Courses, Tutorials, Books
- General Hopes for 2020

# Transformer



Vaswani et al. "Attention is all you need." *Advances in Neural Information Processing Systems*. 2017.

# BERT

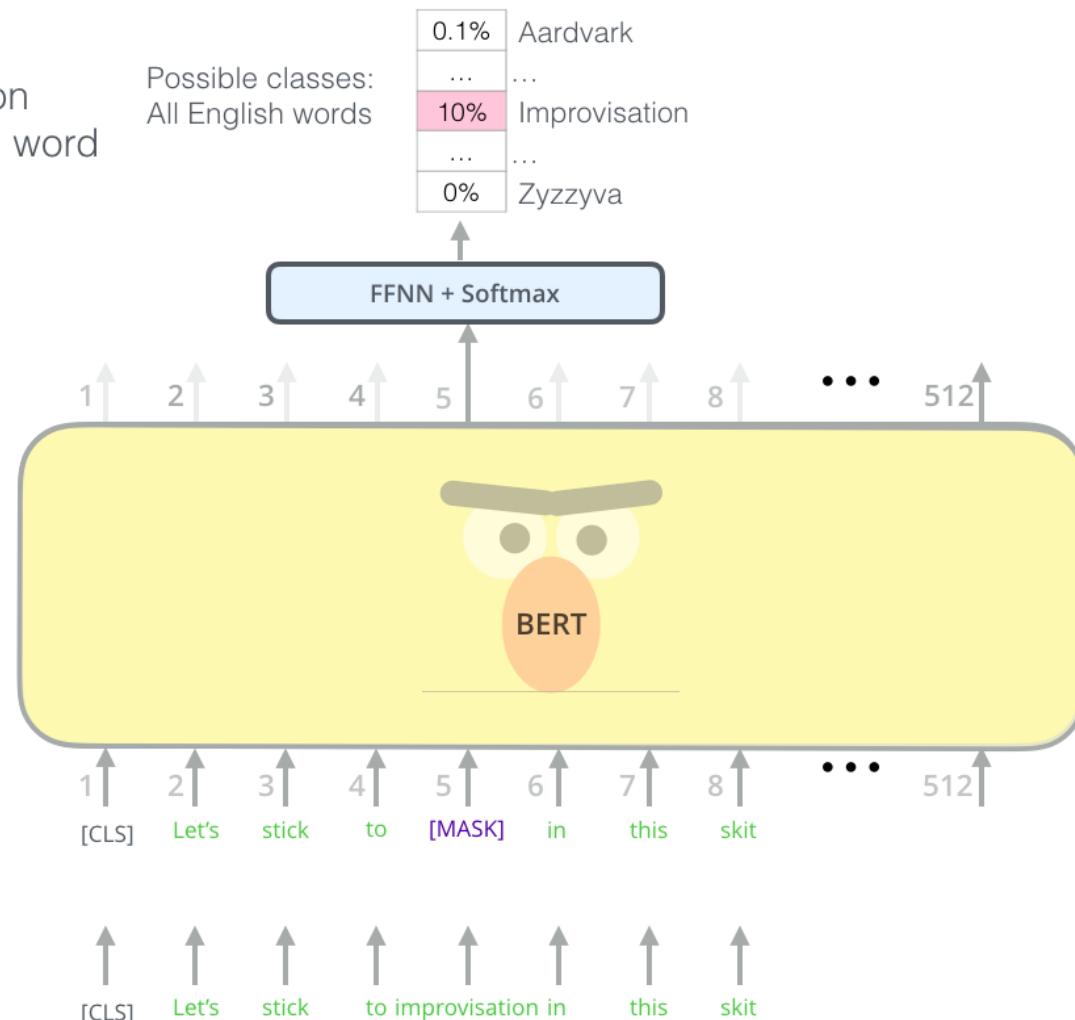
Use the output of the masked word's position to predict the masked word

Possible classes:  
All English words

0.1%	Aardvark
...	...
10%	Improvisation
...	...
0%	Zzyzyva

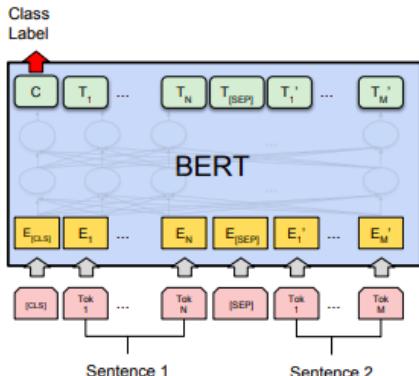
FFNN + Softmax

Randomly mask  
15% of tokens

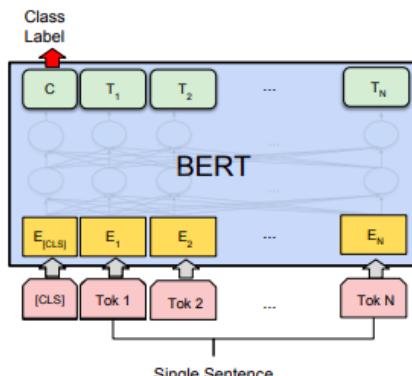


Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." (2018).

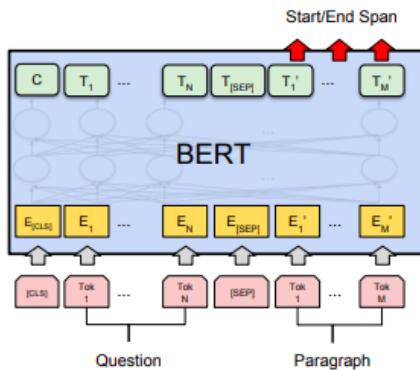
# BERT Applications



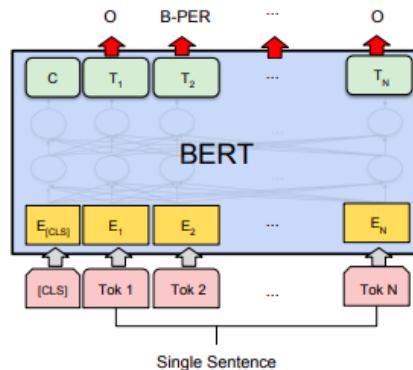
(a) Sentence Pair Classification Tasks:  
MNLI, QQP, QNLI, STS-B, MRPC,  
RTE, SWAG



(b) Single Sentence Classification Tasks:  
SST-2, CoLA



(c) Question Answering Tasks:  
SQuAD v1.1



(d) Single Sentence Tagging Tasks:  
CoNLL-2003 NER

Now you can use BERT:

- Create contextualized word embeddings (like ELMo)
- Sentence classification
- Sentence pair classification
- Sentence pair similarity
- Multiple choice
- Sentence tagging
- Question answering

# Transformer-Based Language Models

- BERT ([Google](#))
- XLNet ([Google/CMU](#))
- RoBERTa ([Facebook](#))
- DistilBERT ([HuggingFace](#))
- CTRL ([Salesforce](#))
- GPT-2 ([OpenAI](#))
- ALBERT ([Google](#))
- Megatron ([NVIDIA](#))



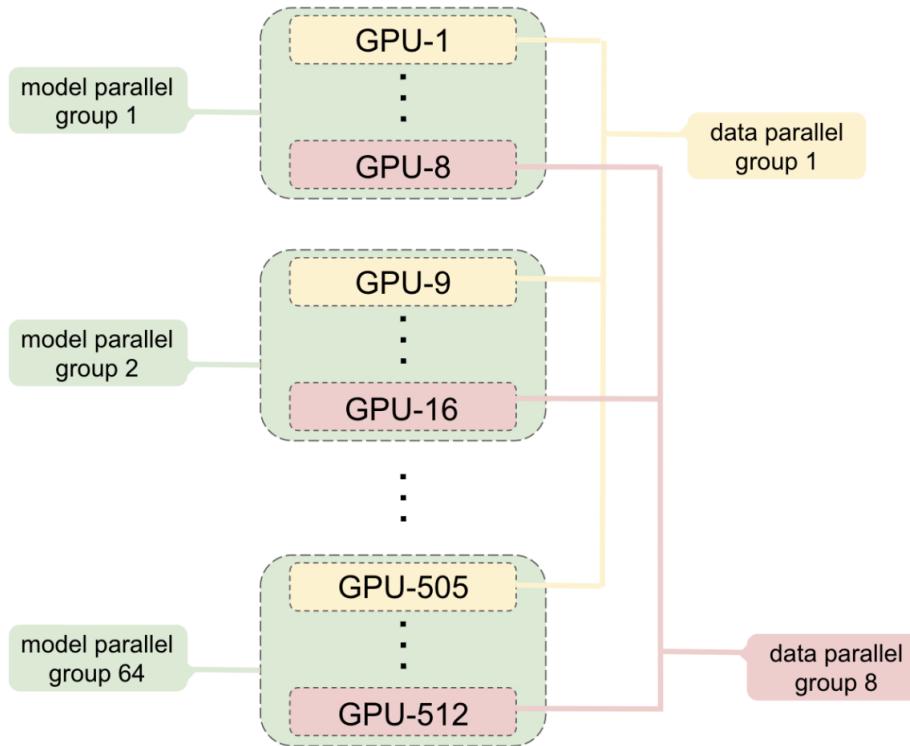
 [sebastianruder / NLP-progress](#)

## NLP-progress

Repository to track the progress in Natural Language Processing (NLP), including the datasets and the current state-of-the-art for the most common NLP tasks.

# Megatron

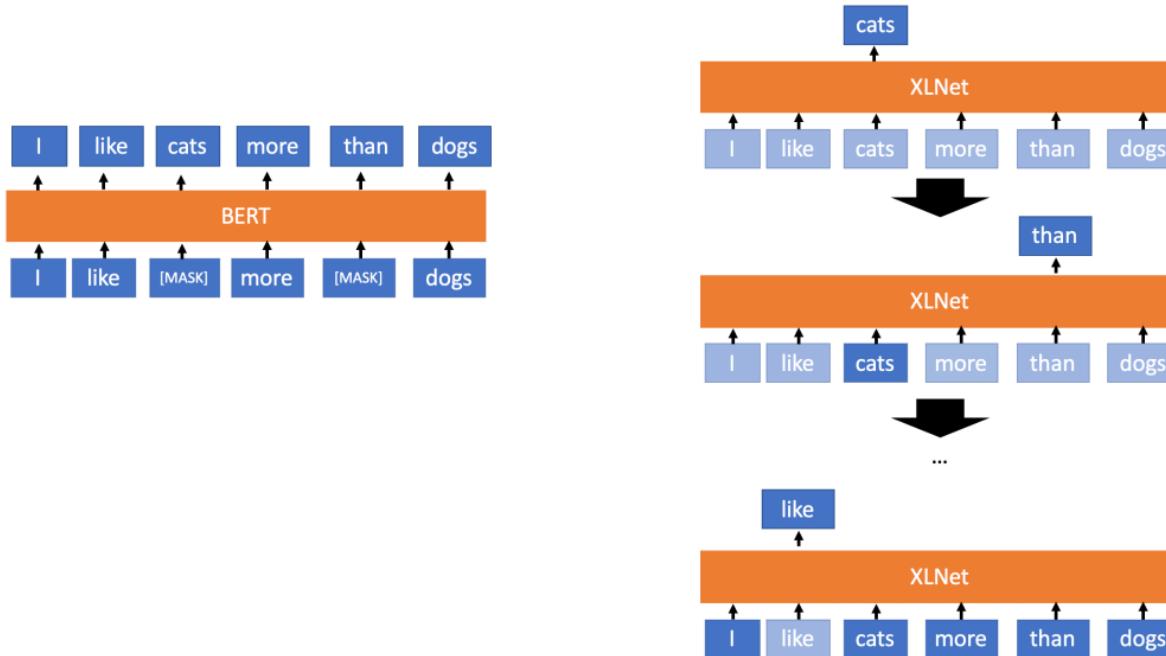
Shoeybi et al. (NVIDIA)



- Megatron-LM is a 8.3 billion parameter transformer language model with 8-way model parallelism and 64-way data parallelism trained on 512 GPUs (NVIDIA Tesla V100)
- Largest transformer model ever trained. 24x the size of BERT and 5.6x the size of GPT-2.

# XLNET

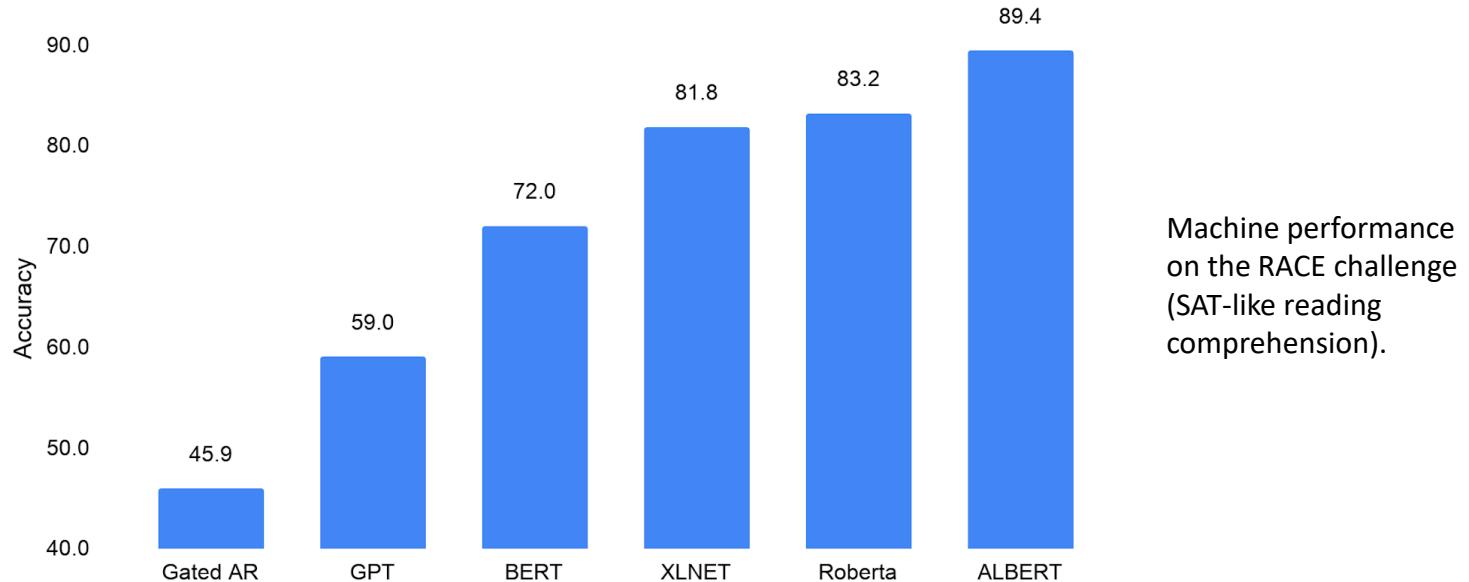
Yang et al. (CMU, Google AI)



- Combine bidirectionality of BERT and the relative positional embeddings and the recurrence mechanism of Transformer-XL.
- XLnet outperforms BERT on 20 tasks, often by a large margin.
- The new model achieves state-of-the-art performance on 18 NLP tasks including question answering, natural language inference, sentiment analysis & document ranking.

# ALBERT

Lan et al. (Google Research & Toyota Technological Institute at Chicago)



- **Idea:** Reduces parameters via cross-layer parameter sharing
- **Results:** An upgrade to BERT that advances the state-of-the-art performance on 12 NLP tasks (including SQuAD2.0)
- **Code:** Open-source TensorFlow implementation, including a number of ready-to-use ALBERT pre-trained language models



## Write With Transformer

gpt2

(i)

The meaning of life is not what I think it is, it's what I do to make it.

The limits of deep learning are still in the process of being figured out.

Most important person in the history of deep learning is probably Andrew Ng.

Lex Fridman's best quality is that he's smart, but I think he gets more attention than he deserves.

# Transformers Model Language They Do Not **Understand** Language. Far from it (for now).

Two plus two is |

a three, five is a six, seven

the result of a simple equation, and the

four, and two plus three is four,

Two minus two is |

seven, plus two is six.

a little too low for me.

a perfect match for the numbers 1 to 20 in

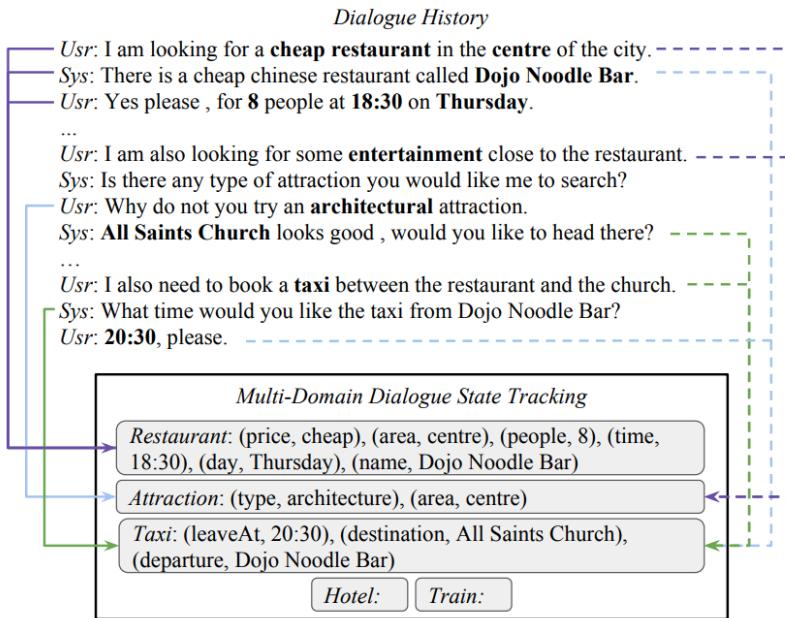
## Release Strategies and the Social Impacts of Language Models

---

- Key takeaways in the report:
  - Coordination during model release between organization is difficult but possible
  - Humans can be convinced by synthetic text
  - Machine-based detection is difficult.
- My takeaways
  - Conversations on this topic are difficult, because the model of sharing between ML organizations and experts is mostly non-existent
  - Humans are still better at deception (disinformation) and detection in text and conversation (see Alexa prize slides)

# Transferable Multi-Domain State Generator for Task-Oriented Dialogue Systems

Wu et al. (Honk Kong UST, Salesforce) – **ACL 2019 Outstanding Paper**



- **Task:** Dialogue state tracking
- **Problem:** Over-dependence on domain ontology and lack of knowledge sharing across domains
- **Details:**
  - Share model parameters across domains
  - Track slot values mentioned anywhere in a dialogue history with a context-enhanced slot gate and copy mechanism
  - Don't require a predefined ontology
- **Results:** State-of-the-art joint goal accuracy of 48.62% on MultiWOZ, a challenging 5-domain human-human dialogue dataset.

# Explain Yourself! Leveraging Language Models for Commonsense Reasoning

Rajani et al. (Salesforce)

---

Question:	While eating a <b>hamburger with friends</b> , what are people trying to do?
Choices:	<b>have fun</b> , tasty, or indigestion
CoS-E:	Usually a hamburger with friends indicates a good time.
Question:	After getting drunk people couldn't understand him,it was because of his what?
Choices:	lower standards, <b>slurred speech</b> , or falling down
CoS-E:	People who are drunk have difficulty speaking.
Question:	People do what during their <b>time off from work</b> ?
Choices:	<b>take trips</b> , brow shorter, or become hysterical
CoS-E:	People usually do something relaxing, such as taking trips,when they don't need to work.

---

Table 1: Examples from our CoS-E dataset.

# Alexa Prize and Open Domain Conversations

- Amazon open-sourced the Topical-Chat dataset.
- Alexa Prize (like the Loebner Prize, etc) are teaching us valuable lessons (from the Alquist 2.0 team):
  - **Parts:** Break dialogue into small parts
  - **Tangents:** Create an interconnected graph of topics. Be ready to jump from context to context and back.
  - **Attention:** Not everything that is said is important. E.g.: *"You know, I'm a really terrible cook. But I would like to ask you, what's your favorite food?"*
  - **Opinions:** Create opinions.
  - **ML**
    - **Content:** ML is okay for generic chitchat, but nothing more for now.
    - **Classification:** ML classifies intent, finds entities or detects sentiment.
  - **Goal:** Goal is to maximize entertainment not information.

# Alexa Prize and Open Domain Conversations

- Alquist: “Have you been in Brazil?”
- User: “What is the population of Brazil?”
- Alquist: “It is around 200 000 000.”
- User: “Well ok.”

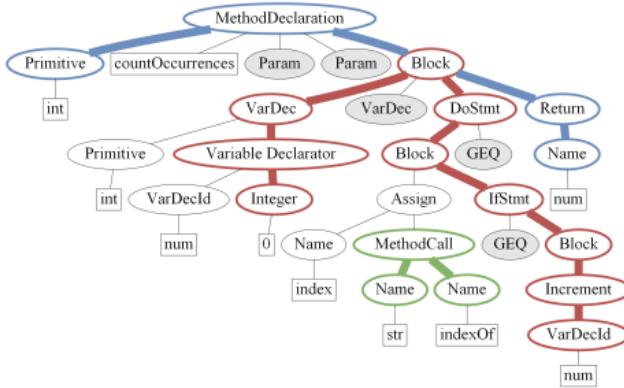
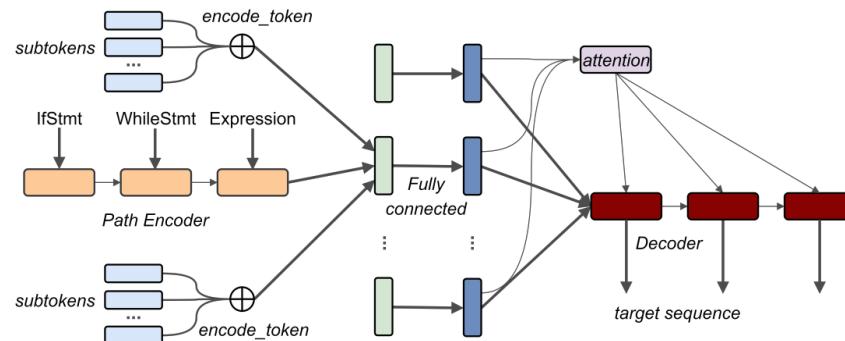
- Alquist: “Have you been in Brazil?”
- User: “What is the population of Brazil?”
- Alquist: “It is around 200 000 000. Anyway, I was saying, have you been in Brazil?”
- User: “No, not yet.”
- Alquist: “Brazil is fascinating country...”

# code2seq: Generating Sequences from Structured Representations of Code

Alon et al. (Technion) – ICLR 2019

- Instead of treating source code as a sequence of tokens, **code2seq** leverages the syntactic structure of programming languages to better encode source code as paths in its abstract syntax tree (AST).

```
int countOccurrences(String str, char ch) {
    int num = 0;
    int index = -1;
    do {
        index = str.indexOf(ch, index + 1);
        if (index >= 0) {
            num++;
        }
    } while (index >= 0);
    return num;
}
```



```
public static int _____(int value) {
    return value <= 0 ? 1 :
        value >= 0x40000000 ? 0x40000000 :
        1 << (32 - Integer.numberOfLeadingZeros(value - 1));
}
```

Model	Prediction
ConvAttention (Allamanis et al., 2016)	get
Paths+CRFs (Alon et al., 2018)	test bit inlz
code2vec (Alon et al., 2019)	multiply
2-layer BiLSTM (no token splitting)	next power of two
2-layer BiLSTM	{ (replaced UNK)
Transformer	get bit length
TreeLSTM (Tai et al., 2015)	get
Gold:	find next positive power of two
code2seq (this work)	get power of two

# Natural Language Processing: Hopes for 2020

- **Reasoning:** Combining (commonsense) reasoning with language models
- **Context:** Extending language model context to thousands of words.
- **Dialogue:** More focus on open-domain dialogue
- **Video:** Ideas and successes in self-supervised learning in visual data.

# Outline

- Deep Learning Growth, Celebrations, and Limitations
- Deep Learning and Deep RL Frameworks
- Natural Language Processing
- **Deep RL and Self-Play**
- Science of Deep Learning and Interesting Directions
- Autonomous Vehicles and AI-Assisted Driving
- Government, Politics, Policy
- Courses, Tutorials, Books
- General Hopes for 2020

# OpenAI & Dota 2

- Dota 2 as a testbed for the **messiness** and continuous nature of the **real world**: teamwork, long time horizons, and hidden information.



Place	Team	Prize money
1st	OG	\$11,190,158
2nd	PSG.LGD	\$4,069,148
3rd	Evil Geniuses	\$2,670,379
4th	Team Liquid	\$1,780,252
5th/6th	Team Secret	\$1,144,448
	Virtus.pro	
7th/8th	OpTic Gaming	\$635,804
	VGJ.Storm	
9th–12th	Mineski	\$381,483
	Team Serenity	
	Vici Gaming	
	Winstrike Team	
13th–16th	Fnatic	\$127,161
	Newbee	
	TNC Predator	
	VGJ.Thunder	
17th–18th	Invictus Gaming	\$63,580
	paiN Gaming	

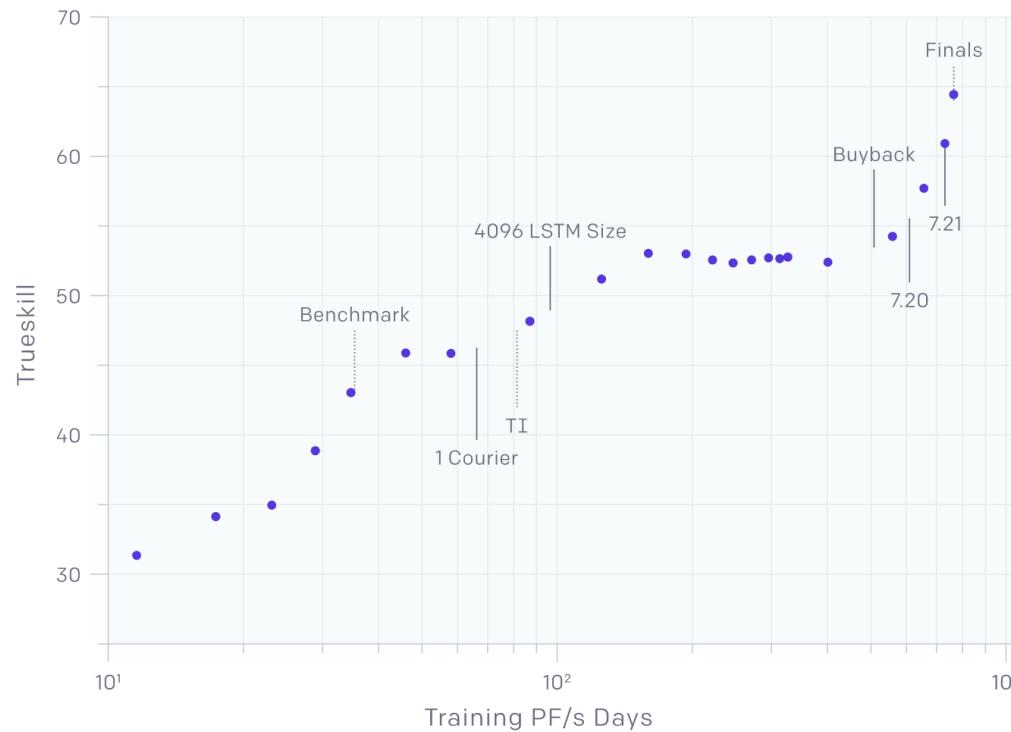
# OpenAI & Dota 2 Progress

- Aug, 2017: 1v1 bot beats top professional Dota 2 players.
- Aug, 2018: OpenAI Five lost two games against top Dota 2 players at The International. “We are looking forward to pushing Five to the next level.”
- Apr, 2019: OpenAI Five beats OG team (the 2018 world champions)



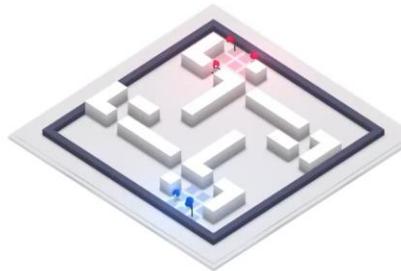
# OpenAI & Dota 2 Progress

- **The Difference:** OpenAI Five's victories in 2019 as compared to its losses in 2018 are due to: **8x more training compute** (training for longer)
- **Compute:** Current version of OpenAI Five has consumed 800 petaflop/s-days and experienced about 45,000 years of Dota self-play over 10 realtime months
- **Performance:** The 2019 version of OpenAI Five has a 99.9% win rate versus the 2018 version.



# DeepMind Quake III Arena Capture the Flag

Agent observation raw pixels

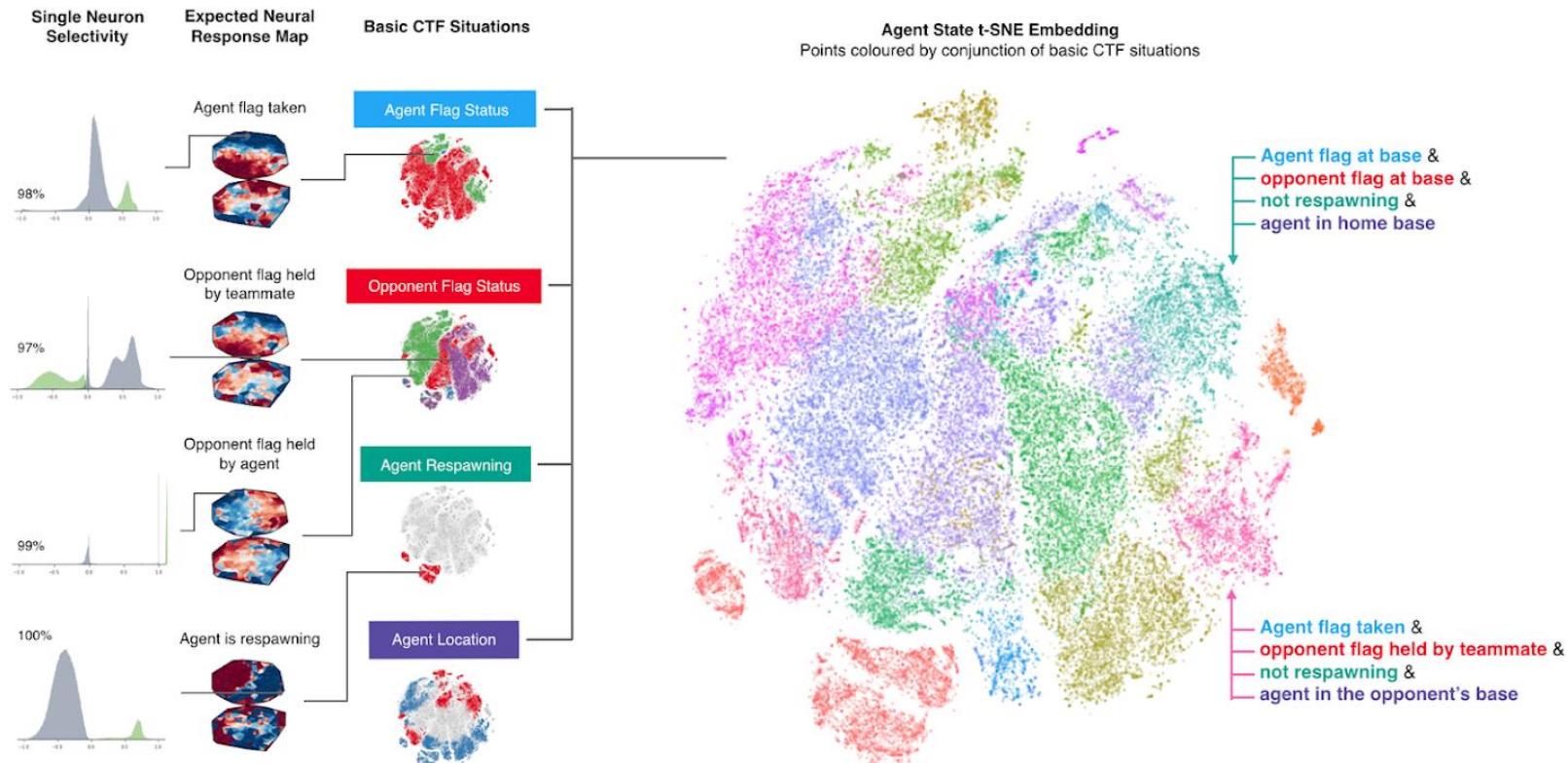


Indoor map overview

- “Billions of people inhabit the planet, each with their own individual goals and actions, but still capable of coming together through teams, organisations and societies in impressive displays of collective intelligence. This is a setting we call multi-agent learning: many individual agents must act independently, yet learn to interact and cooperate with other agents. This is an immensely difficult problem - because with co-adapting agents the world is constantly changing.”

# DeepMind Quake III Arena Capture the Flag

- The agents automatically figure out the game rules, important concepts, behaviors, strategies, etc.



# DeepMind Quake III Arena Capture the Flag

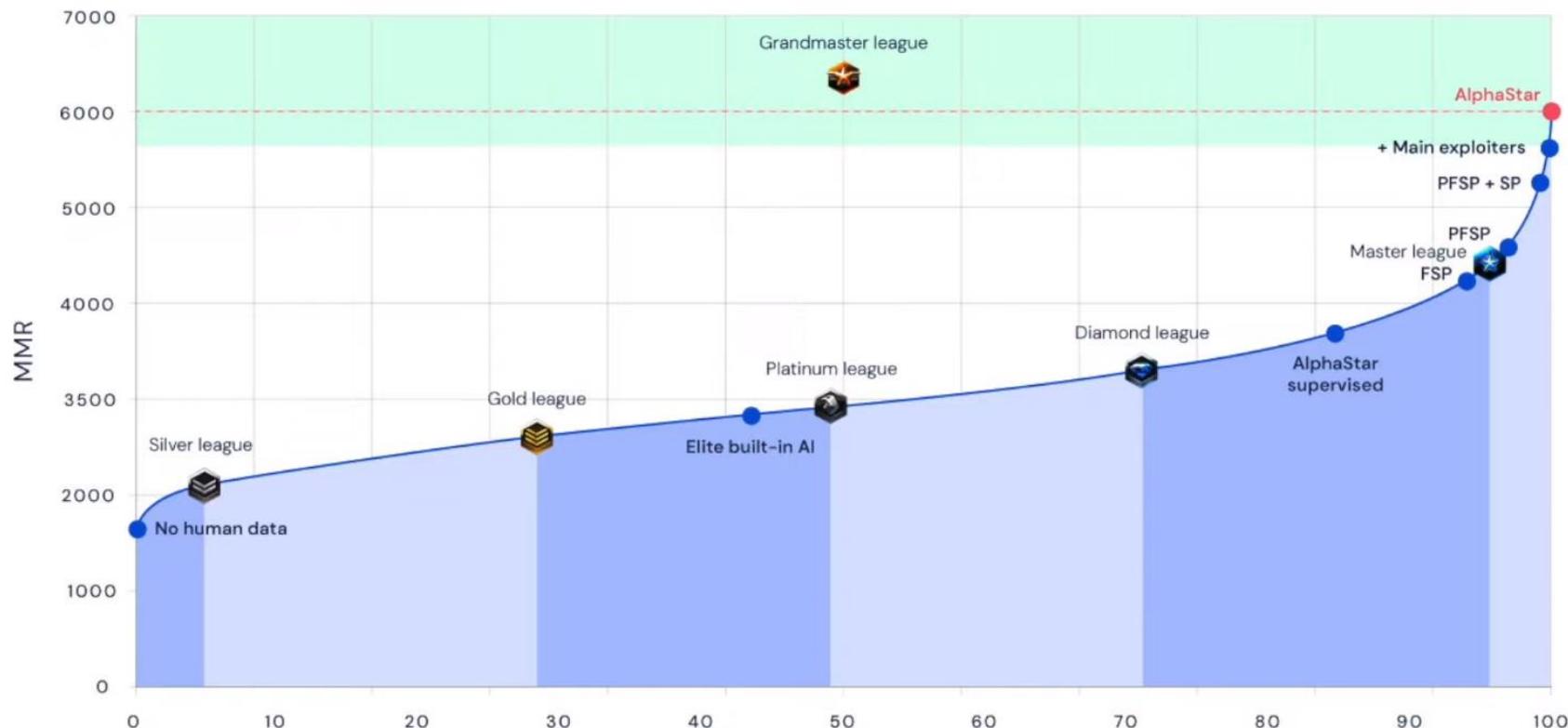
- The agents automatically figure out the game rules, important concepts, behaviors, strategies, etc.

Automatically discovered behaviours



# DeepMind AlphaStar

- Dec, 2018: AlphaStar beats MaNa, one of the world's strongest professional StarCraft players, 5-0.
- Oct, 2019: AlphaStar reaches Grandmaster level playing the game under professionally approved conditions (for humans).



# DeepMind AlphaStar



The main agent (in blue) is beaten by an exploiter agent (in red) which has discovered a strategy known as cannon rush.



As training progresses, the new main agent (in green) has learned how to successfully defend against the cannon rush exploiter (in red).

“AlphaStar is an intriguing and unorthodox player – one with the reflexes and speed of the best pros but strategies and a style that are entirely its own. The way AlphaStar was trained, with agents competing against each other in a league, has resulted in gameplay that’s unimaginably unusual; it really makes you question how much of StarCraft’s diverse possibilities pro players have really explored.”

- Kelazhur, professional StarCraft II player

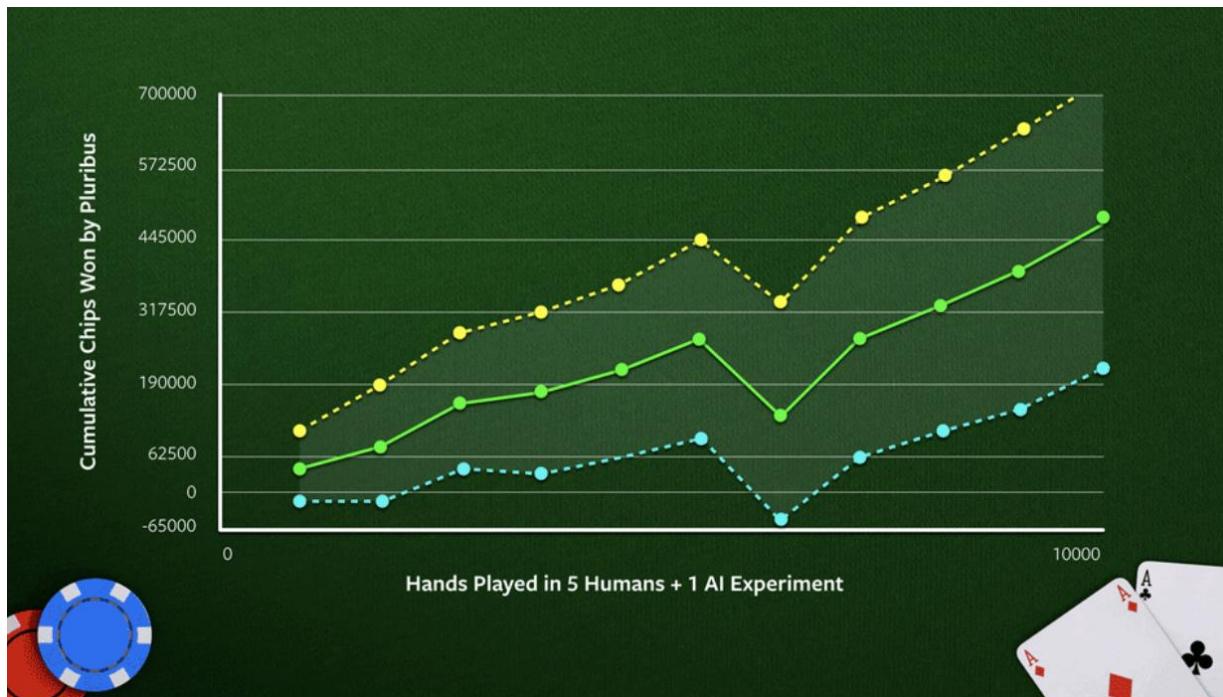
# Pluribus: Six-Player No-Limit Texas Hold'em Poker

Brown et al. (CMU, Facebook AI)

- **Six-Player No-Limit Texas Hold'em Poker**
  - Imperfect information
  - Multi-agent
- **Result:** Pluribus won in six-player no-limit Texas Hold'em poker
- **Offline:** Self-play to generate coarse-grained “blueprint” strategy
  - Iterative Monte Carlo CFR (MCCFR) algorithm
  - Self-play allows for counterfactual reasoning
- **Online:** Use search to improve blueprint strategy based on particular situation
- Abstractions
  - Action abstractions: reduce action space
  - Information abstraction: reduce decision space based on what information has been revealed

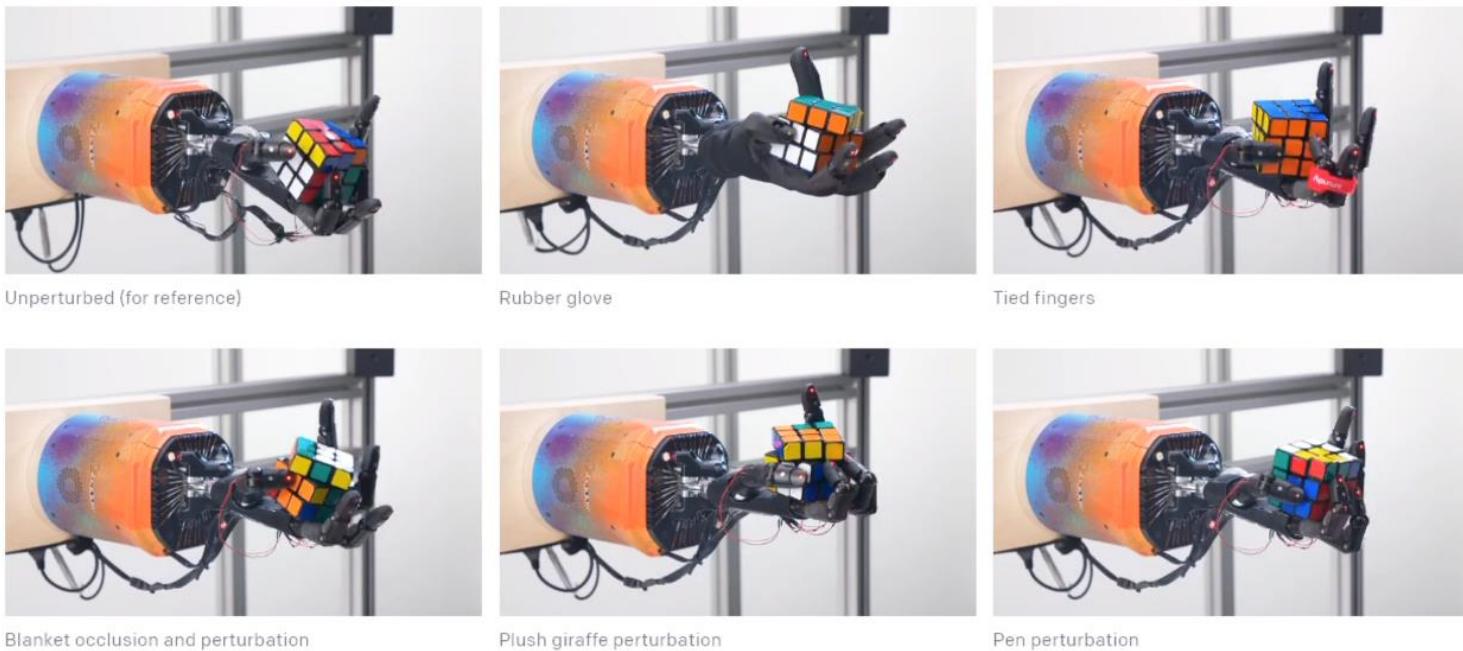
# Pluribus: Six-Player No-Limit Texas Hold'em Poker

Brown et al. (CMU, Facebook AI)



- **Chris Ferguson:** “Pluribus is a very hard opponent to play against. It’s really hard to pin him down on any kind of hand. He’s also very good at making thin value bets on the river. He’s very good at extracting value out of his good hands.”
- **Darren Elias:** “Its major strength is its ability to use mixed strategies. That’s the same thing that humans try to do. It’s a matter of execution for humans — to do this in a perfectly random way and to do so consistently. Most people just can’t.”

# OpenAI Rubik's Cube Manipulation



- **Deep RL:** Reinforcement learning approach from OpenAI Five
- **ADR:** Automatic Domain Randomization (ADR) – generate progressively more difficult environment as the system learns (alternative for self-play)
- **Capacity:** Term of “emergent meta-learning” is used to describe the fact that the network is constrained and the ADR process of environment generation is not

Deep RL and Self-Play:  
**Hopes for 2020**

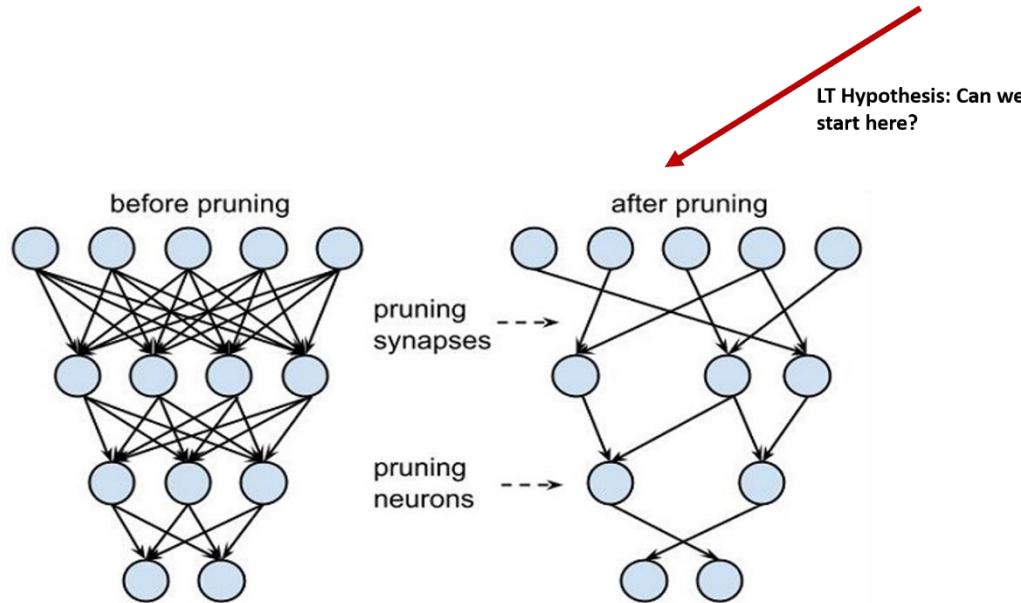
- **Robotics:** Use of RL methods in manipulation and real-world interaction tasks.
- **Human Behavior:** Use of multi-agent self-play to explore naturally emerging social behaviors as a way to study equivalent multi-human systems.
- **Games:** Use RL to assist human experts in discovering new strategies at games and other tasks in simulation.

# Outline

- Deep Learning Growth, Celebrations, and Limitations
- Deep Learning and Deep RL Frameworks
- Natural Language Processing
- Deep RL and Self-Play
- **Science of Deep Learning and Interesting Directions**
- Autonomous Vehicles and AI-Assisted Driving
- Government, Politics, Policy
- Courses, Tutorials, Books
- General Hopes for 2020

# The Lottery Ticket Hypothesis: Finding Sparse, Trainable Neural Networks

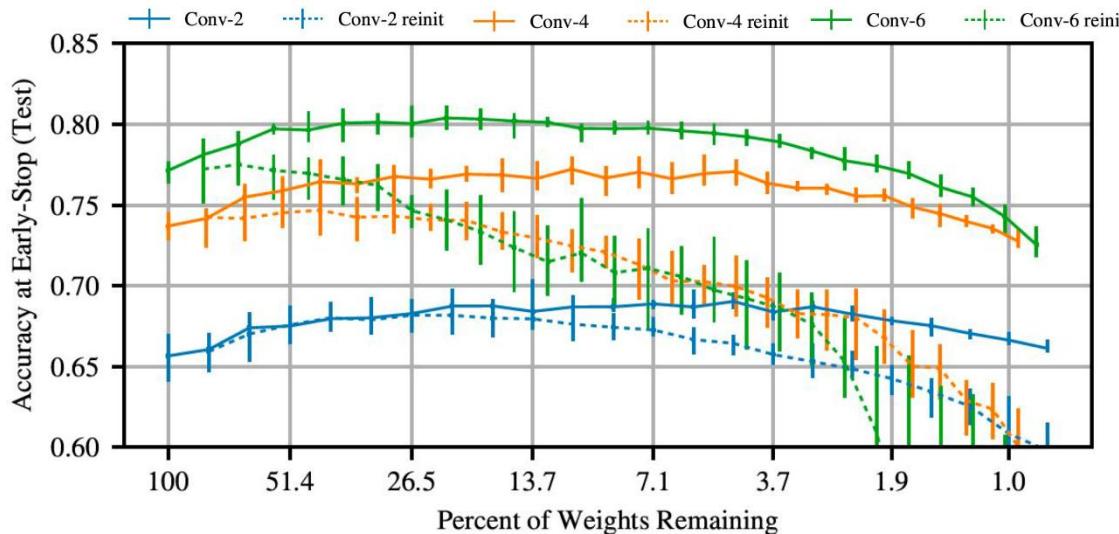
Frankle et al. (MIT) - Best Paper at ICLR 2019



1. Randomly initialize a neural network.
2. Train the network until it converges.
3. Prune a fraction of the network.
4. Reset the weights of the remaining network to initialization values from step 1
5. Train the pruned, untrained network. Observe convergence and accuracy.

# The Lottery Ticket Hypothesis: Finding Sparse, Trainable Neural Networks

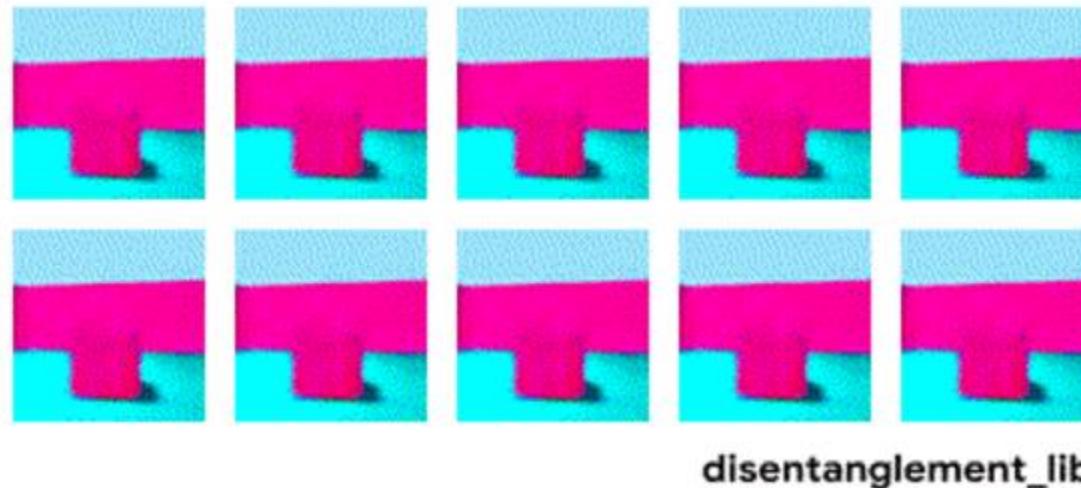
Frankle et al. (MIT) - ICLR 2019 Best Paper



- **Idea:** For every neural network, there is a subnetwork that can achieve the same accuracy in isolation after training.
- **Iterative pruning:** Find this subset subset of nodes by iteratively training network, pruning its smallest-magnitude weights, and re-initializing the remaining connections to their original values. Iterative vs one-shot is key.
- **Inspiring takeaway:** There exist architectures that are much more efficient. Let's find them!

# Challenging Common Assumptions in the Unsupervised Learning of Disentangled Representations

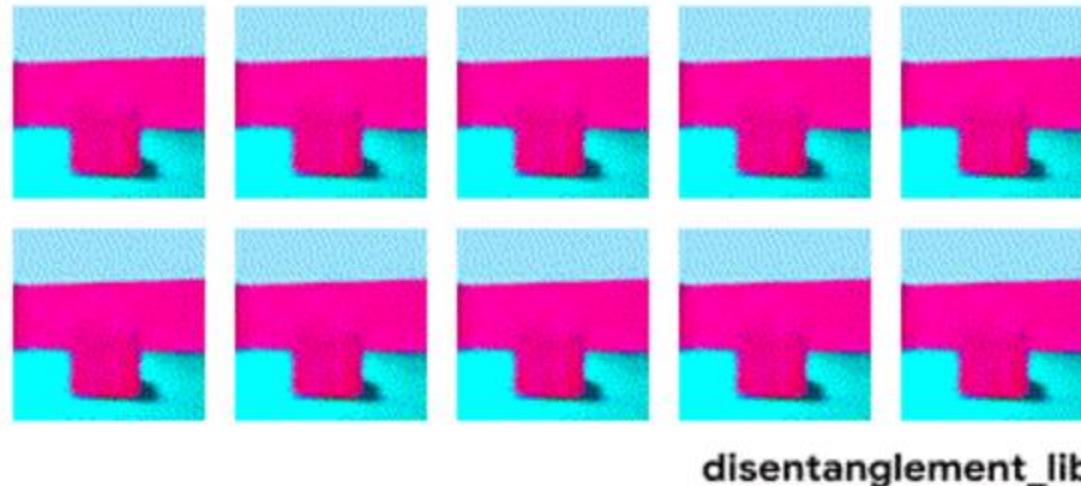
Locatello et al. (ETH Zurich, Max Plank Institute, Google Research) - ICML 2019 Best Paper



- The goal of disentangled representations is to build models that can capture explanatory factors in a vector.
- The figure above presents a model with a 10-dimensional representation vector.
- Each of the 10 panels visualizes what information is captured in one of the 10 different coordinates of the representation.
- From the top right and the top middle panel we see that the model has successfully disentangled floor color, while the two bottom left panels indicate that object color and size are still entangled.

# Challenging Common Assumptions in the Unsupervised Learning of Disentangled Representations

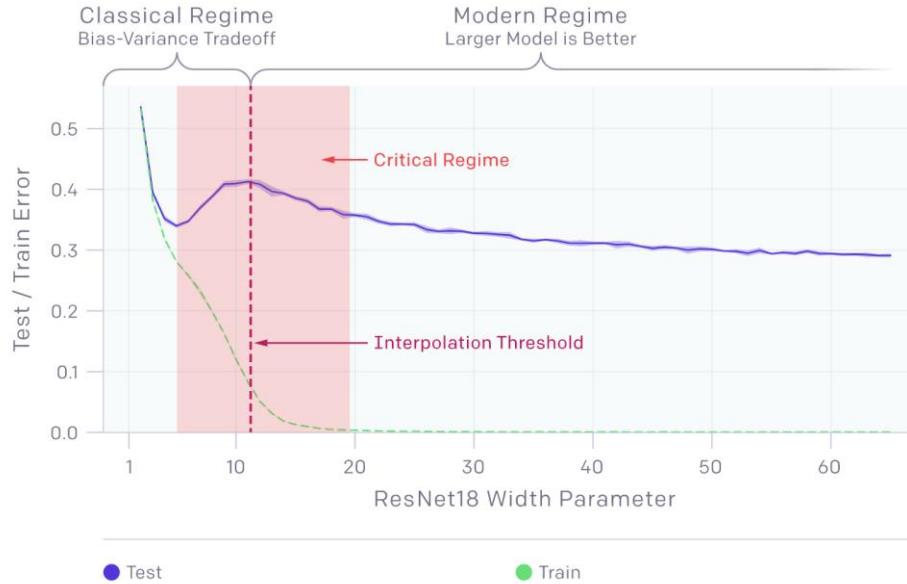
Locatello et al. (ETH Zurich, Max Plank Institute, Google Research) - ICML 2019 Best Paper



- **Proof:** Unsupervised learning of **disentangled representations** without **inductive biases** is impossible.
- **Takeaway:** Inductive biases (assumptions) should be made explicit
- **Open problem:** Finding good inductive biases for unsupervised model selection that work across multiple data sets persists is a key open problem.
- **Open Experiments:** Open source library with implementations of the considered disentanglement methods and metrics, a standardized training and evaluation protocol, as well as visualization tools to better understand trained models.

# Deep Double Descent: Where Bigger Models and More Data Hurt

Nakkiran et al. (Harvard, OpenAI)



- **Double Descent Phenomena:** As we increase the number of parameters in a neural network, the test error initially decreases, increases, and, just as the model is able to fit the train set, undergoes a second descent.
- Applicable to model size, training time, dataset size.

# Science of Deep Learning and Interesting Directions

## Hopes for 2020

- **Fundamentals:** Exploring fundamentals of model selection, training dynamics, and representation characteristics with respect to architecture characteristics.
- **Graph Neural Networks:** Exploring use of graph neural networks for combinatorial optimization, recommendation systems, etc.
- **Bayesian Deep Learning:** Exploring Bayesian neural networks for estimating uncertainty and online/incremental learning.

# Outline

- Deep Learning Growth, Celebrations, and Limitations
- Deep Learning and Deep RL Frameworks
- Natural Language Processing
- Deep RL and Self-Play
- Science of Deep Learning and Interesting Directions
- **Autonomous Vehicles and AI-Assisted Driving**
- Government, Politics, Policy
- Courses, Tutorials, Books
- General Hopes for 2020

# Level 2



# Level 4

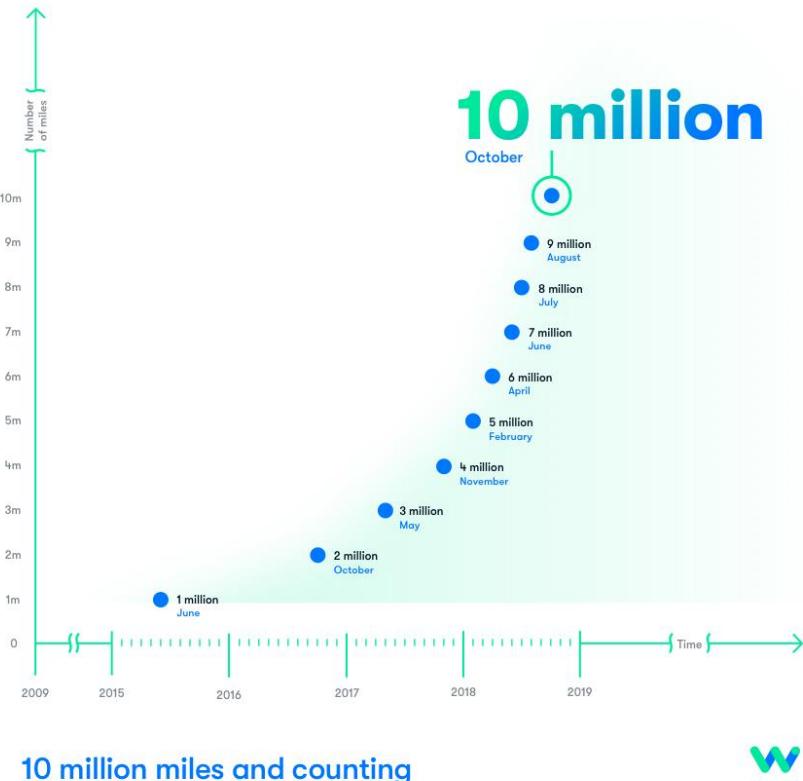


Human is Responsible

Machine is Responsible

# Waymo

October, 2018:

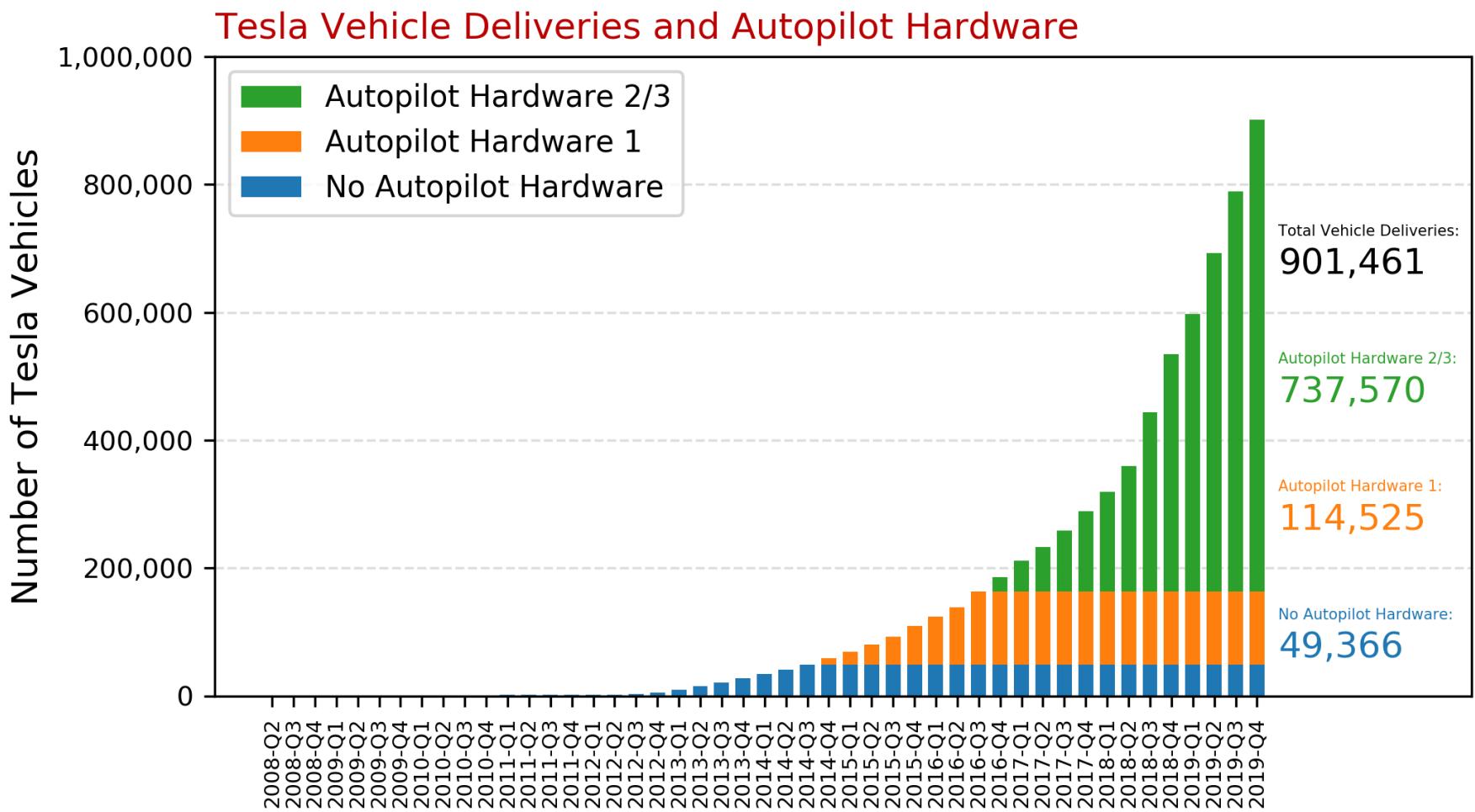


January, 2020:

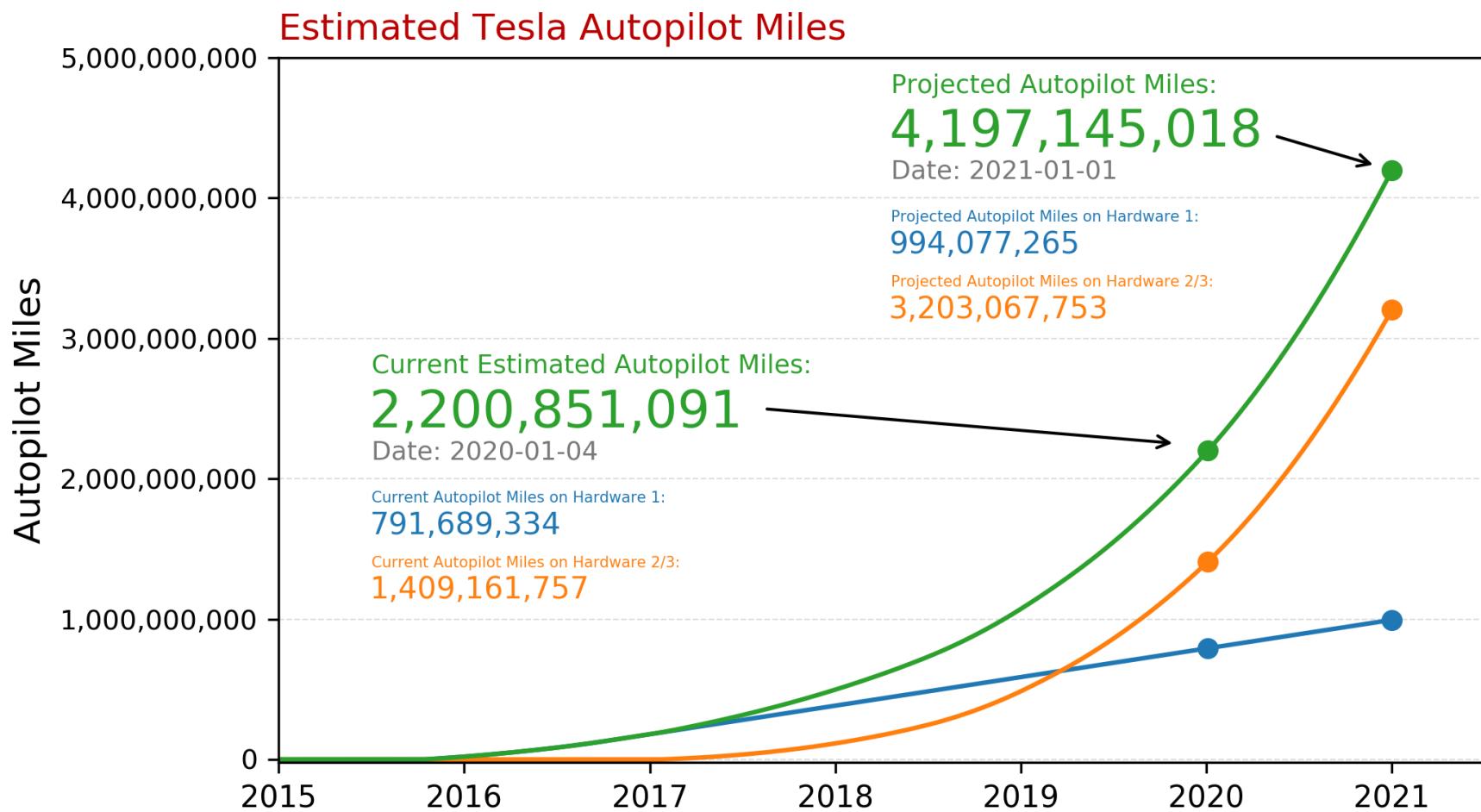
- **On-road:** 20 million miles
- **Simulation:** 10 billion miles
- **Testing & Validation:** 20,000 classes of structured tests
- Initiated testing without a safety driver



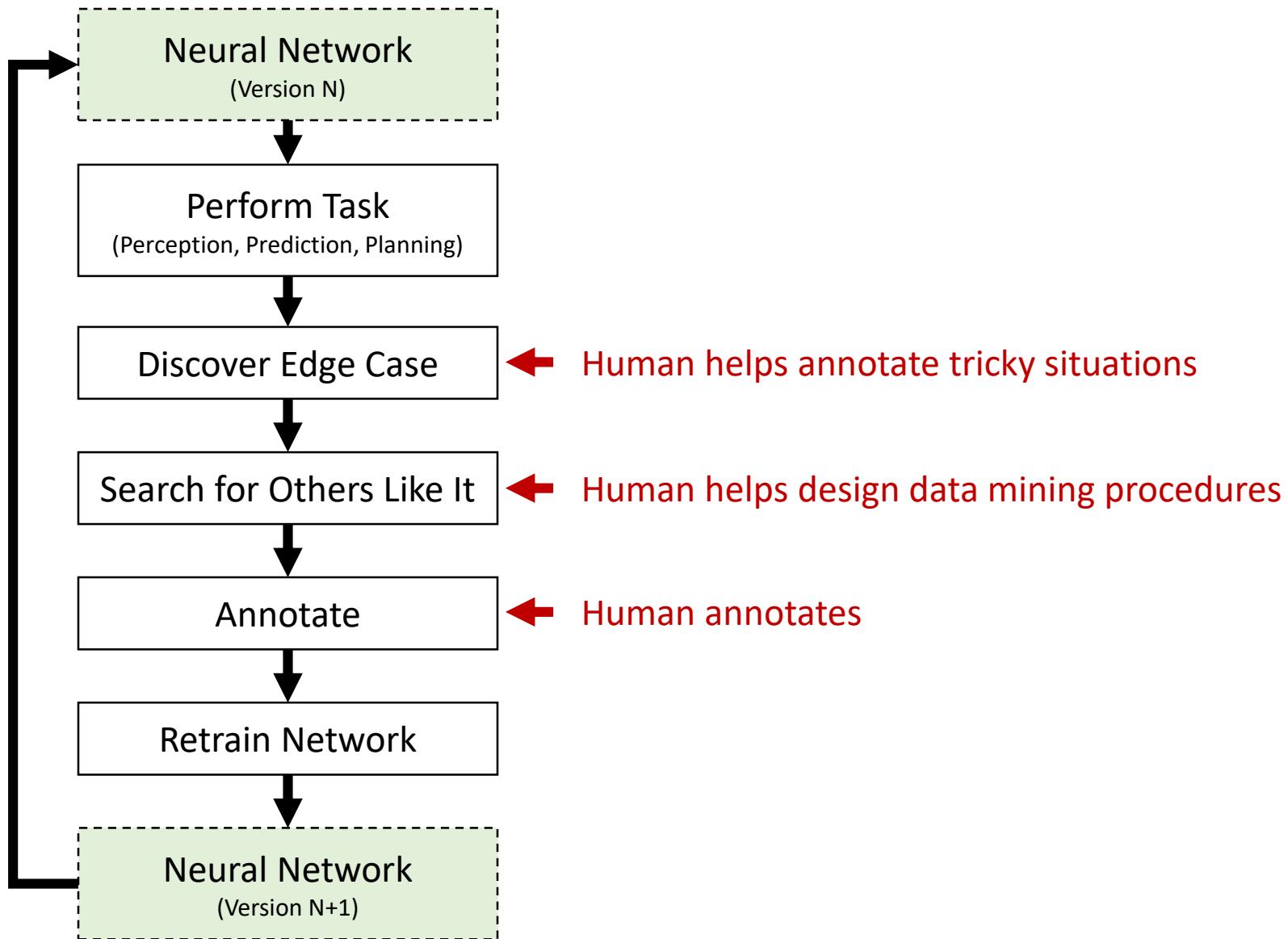
# Tesla Autopilot



# Tesla Autopilot

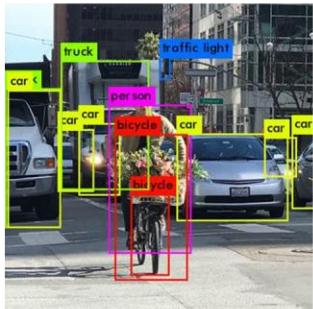


# Active Learning Pipeline (aka Data Engine)



# Single-Task Learning

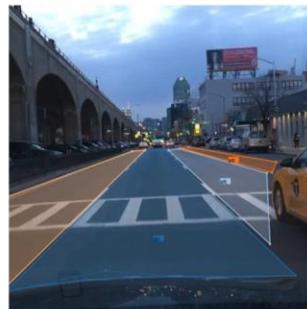
Task 1:  
Object Detection



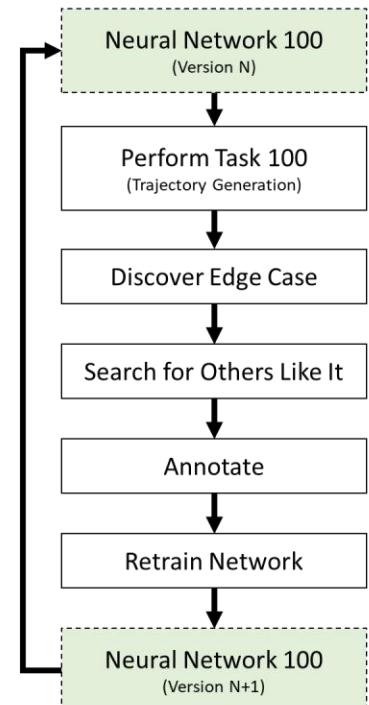
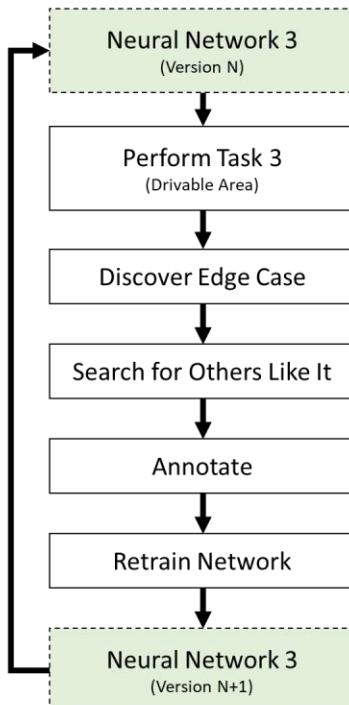
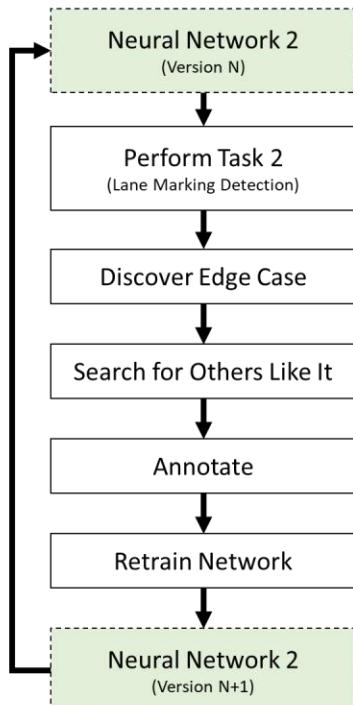
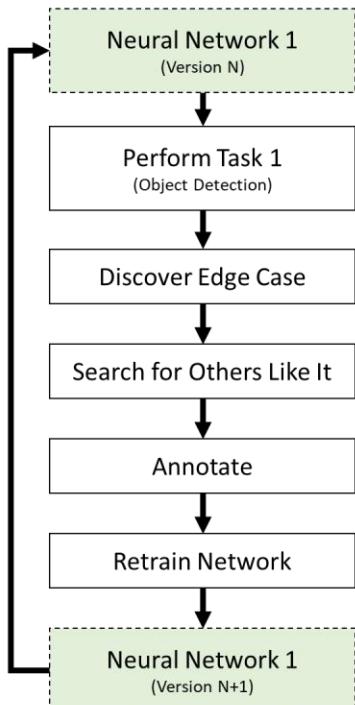
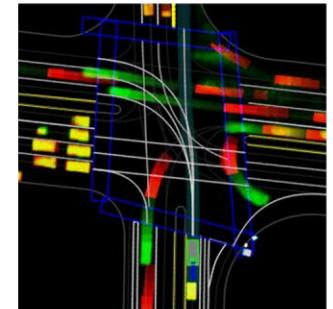
Task 2:  
Lane Markings



Task 3:  
Drivable Area

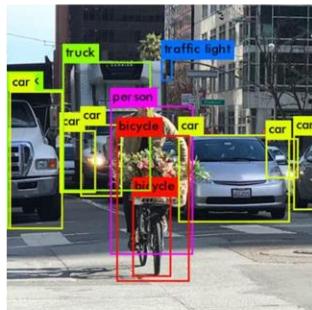


Task 100:  
Trajectory Generation



# Multi-Task Learning

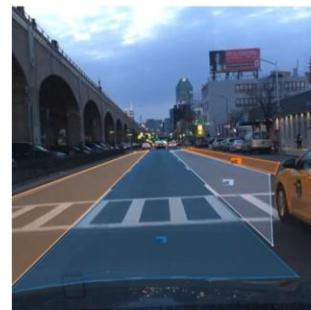
Task 1:  
Object Detection



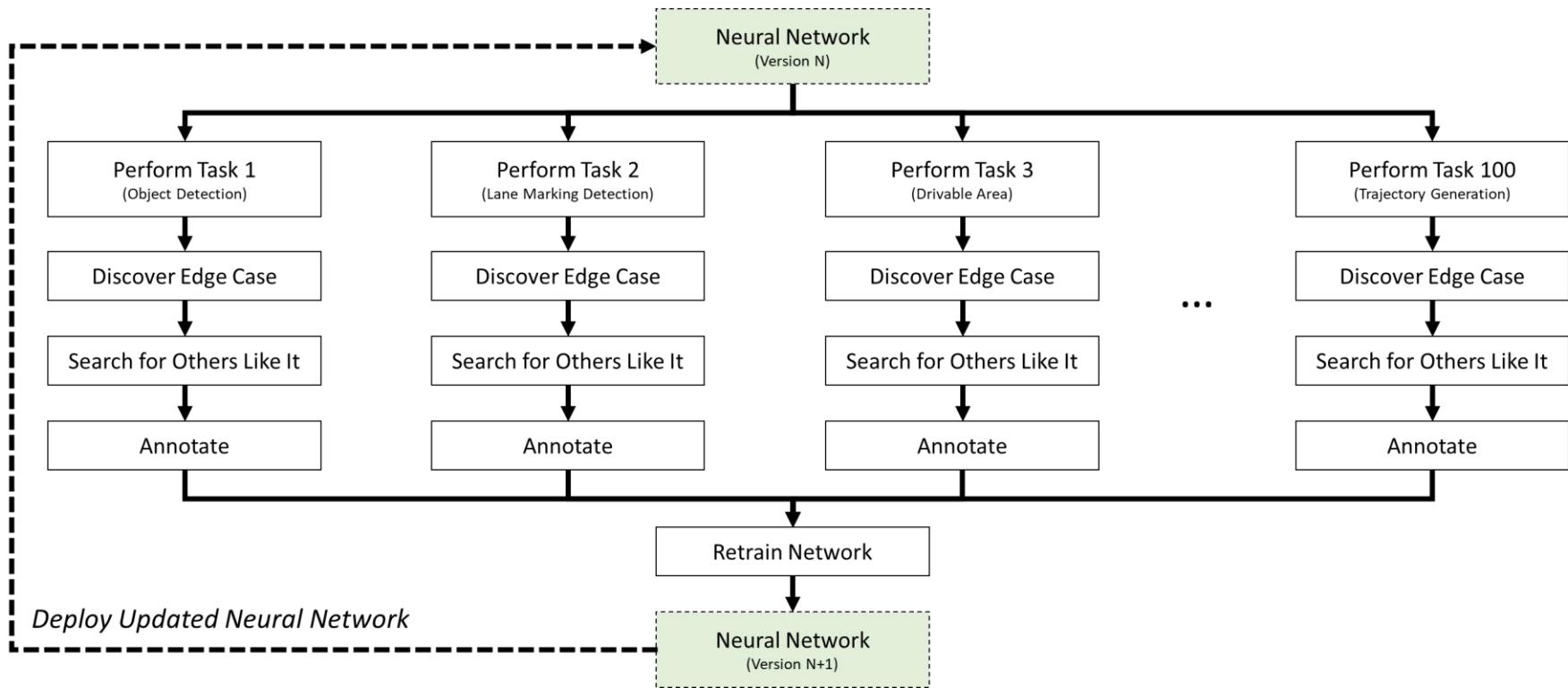
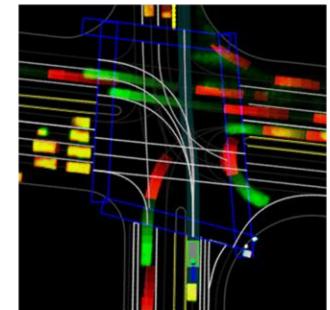
Task 2:  
Lane Markings



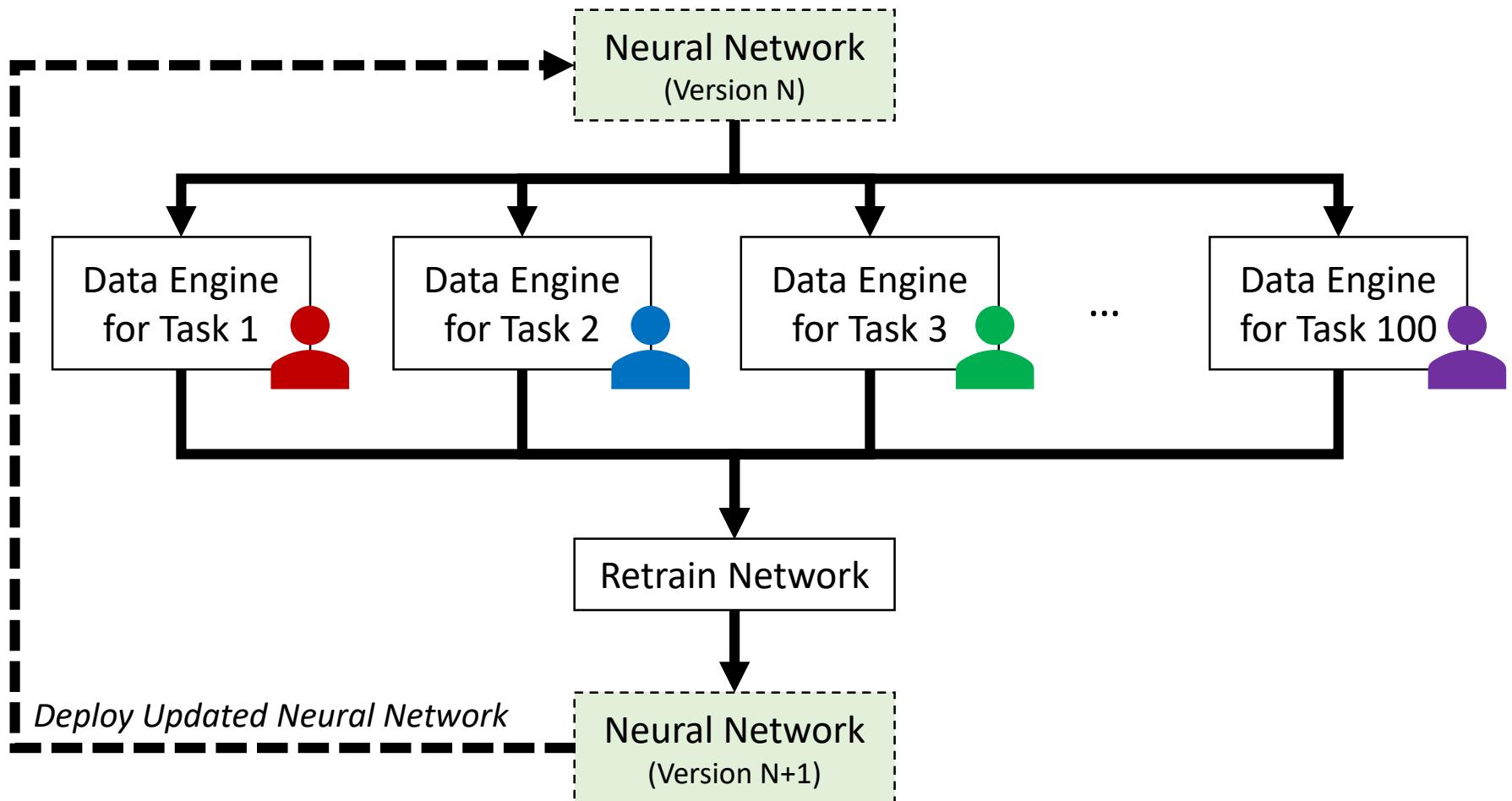
Task 3:  
Drivable Area



Task 100:  
Trajectory Generation



# Collaborative Deep Learning (aka Software 2.0 Engineering)



# Vision vs Lidar

## L2 vs L4

- **Primarily:** Vision Sensors + Deep Learning

- **Pros:**

- Highest resolution information
    - Feasible to collect data at scale and **learn**
    - Roads are designed for human eyes
    - Cheap

- **Cons:**

- Needs a huge amount of data to be accurate
    - Less explainable
    - Driver must remain vigilant

- **Primarily:** Lidar + Maps

- **Pros:**

- Explainable, consistent
    - Accurate with less data

- **Cons:**

- Less amenable to machine learning
    - Expensive (for now)
    - Safety driver or teleoperation fallback



Example L2 System:

**Tesla Autopilot**  
2+ billion miles



Example L4 System:

**Waymo**  
20+ million miles

# Open Questions for Tesla Autopilot

- Deep learning question:

**Problem Difficulty:** How difficult is driving? How many edge-cases does it have? Can it be learned from data?

- Perception (detection, intention modeling, trajectory prediction)
- Action (in a game-theoretic setting)
  - Balancing enjoyability and safety

- Human supervision of deep learning system question:

**Vigilance:** How good can Autopilot get before vigilance decrements significantly?

- And ... will this decrement nullify the safety benefits of automation?

# Open Questions for Waymo

- When we have maps, lidar, and geo-fenced routes:

**Problem Difficulty:** How difficult is driving? How many edge-cases does it have? Can it be learned from data?

- Perception (detection, intention modeling, trajectory prediction)
- Action (in a game-theoretic setting)
  - Balancing enjoyability and safety

- Simulation question:

How much can be learned from simulation?

# Autonomous Vehicles and AI-Assisted Driving

## Hopes for 2020

- **Applied deep learning innovation:** Life-long learning, active learning, multi-task learning
- **Over-the-air updates:** More level 2 systems begin both data collection and over-the-air software updates.
- **Public datasets of edge-cases:** More publicly available datasets of challenging cases.
- **Simulators:** Improvement of publicly available simulators (CARLA, NVIDIA DRIVE Constellation, Voyage Deepdrive)
- **Less hype:** More balanced in-depth reporting (by journalists and companies) on successes and challenges of autonomous vehicle development.

# Outline

- Deep Learning Growth, Celebrations, and Limitations
- Deep Learning and Deep RL Frameworks
- Natural Language Processing
- Deep RL and Self-Play
- Science of Deep Learning and Interesting Directions
- Autonomous Vehicles and AI-Assisted Driving
- **Government, Politics, Policy**
- Courses, Tutorials, Books
- General Hopes for 2020

# AI in Political Discourse: Andrew Yang



- First presidential candidate to discuss artificial intelligence extensively as part of his platform
- Proposals
  - **Department:** Create a new executive department – the Department of Technology – to work with private industry and Congressional leaders to monitor technological developments, assess risks, and create new guidance.
  - **Focus on AI:** The new Department would be based in Silicon Valley and would initially be focused on Artificial Intelligence.
  - **Companies:** Create a public-private partnership between leading tech firms and experts within government to identify emerging threats and suggest ways to mitigate those threats while maximizing the benefit of technological innovation to society.

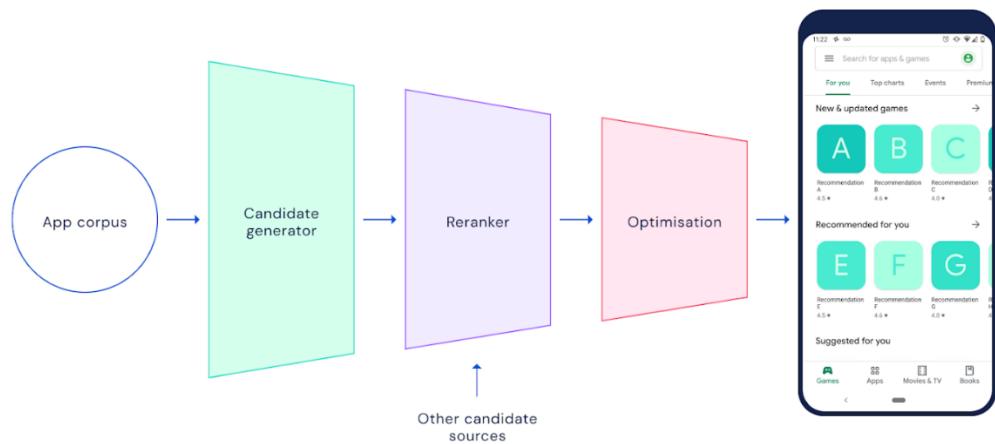
# American AI Initiative

- In February, 2019, the president signed Executive Order 13859 announcing the **American AI Initiative**
- Goals
  - Investment in long-term research
  - Support research in academia and industry
  - Access to federal data
  - Promote STEM education
  - Develop AI in “a manner consistent with our Nation’s values, policies, and priorities.”
  - AI must also be developed in a way that does not compromise our American values, civil liberties, or freedoms.

# Tech Leaders Testifying Before Congress (Ethics of Recommender Systems)



# DeepMind + Google Research: Play Store App Discovery



- **Candidate app generation:**  
LSTM → Transformer → efficient addition attention model
- **Candidate app unbiasing:**
  - The model learns a bias that favors the apps that are shown – and thus installed – more often.
  - To help correct for this bias, impression-to-install rate weighting is introduced.
- **Multiple objectives:** relevance, popularity, or personal preferences

Government, Politics, Policy

# Hopes for 2020

- **Less fear of AI:** More balanced, informed discussion on the impact of AI in society.
- **Experts:** Continued conversations by government officials about AI, privacy, cybersecurity with experts in academia and industry.
- **Recommender system transparency:** More open discussion and publication behind recommender systems used in industry.

# Outline

- Deep Learning Growth, Celebrations, and Limitations
- Deep Learning and Deep RL Frameworks
- Natural Language Processing
- Deep RL and Self-Play
- Science of Deep Learning and Interesting Directions
- Autonomous Vehicles and AI-Assisted Driving
- Government, Politics, Policy
- **Courses, Tutorials, Books**
- General Hopes for 2020

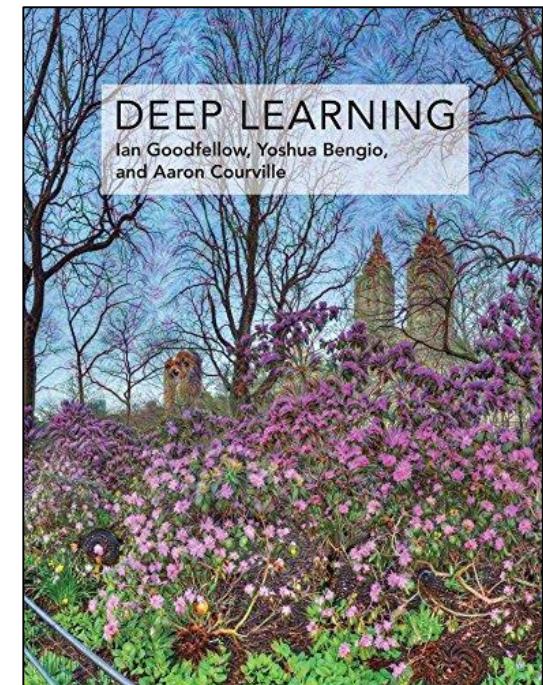
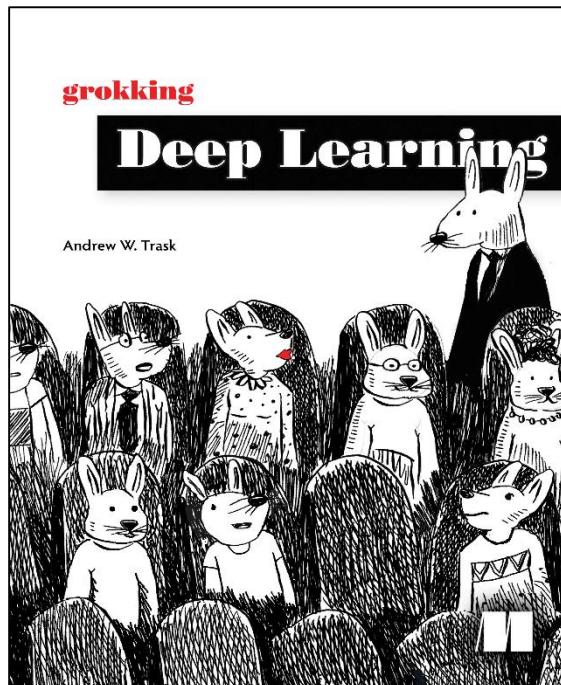
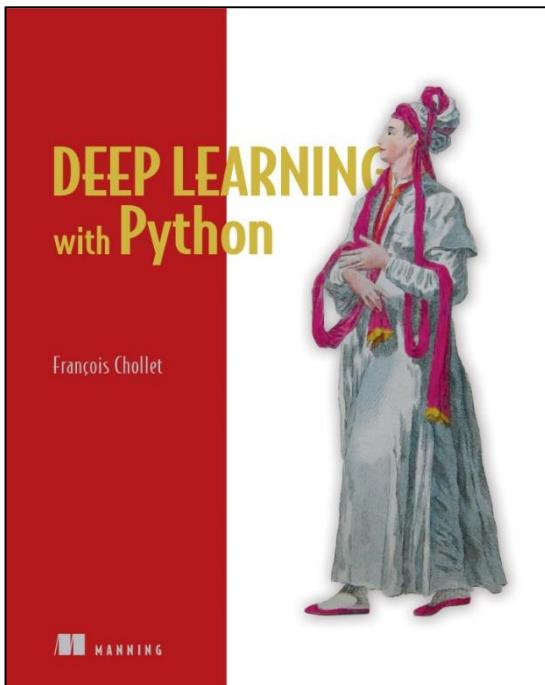
# Online Deep Learning Courses

- Deep Learning
  - Fast.ai: Practical Deep Learning for Coders
    - Jeremy Howard et al.
  - Stanford CS231n: Convolutional Neural Networks for Visual Recognition
  - Stanford CS224n: Natural Language Processing with Deep Learning
  - Deeplearning.ai (Coursera): Deep Learning
    - Andrew Ng
- Reinforcement Learning
  - David Silver: Introduction to Reinforcement Learning
  - OpenAI: Spinning Up in Deep RL

# Tutorials: Over 200 of the Best Machine Learning, NLP, and Python Tutorials (by Robbie Allen)

- Link: <http://bit.ly/36skFE7>
- Topics
  - Machine learning
  - Activation and Loss Functions
  - Bias
  - Perceptron
  - Regression
  - Gradient descent
  - Generative learning
  - Support vector machines
  - Backpropagation
  - Deep Learning
  - Optimization
  - Long Short Term Memory
  - Convolutional Neural Networks
  - Recurrent Neural Nets (RNNs)
  - Reinforcement Learning
  - Generative Adversarial Networks
  - Multi-task Learning
  - NLP
  - Word Vectors
  - Encoder-Decoder
  - TensorFlow
  - PyTorch

# Deep Learning Books



# Outline

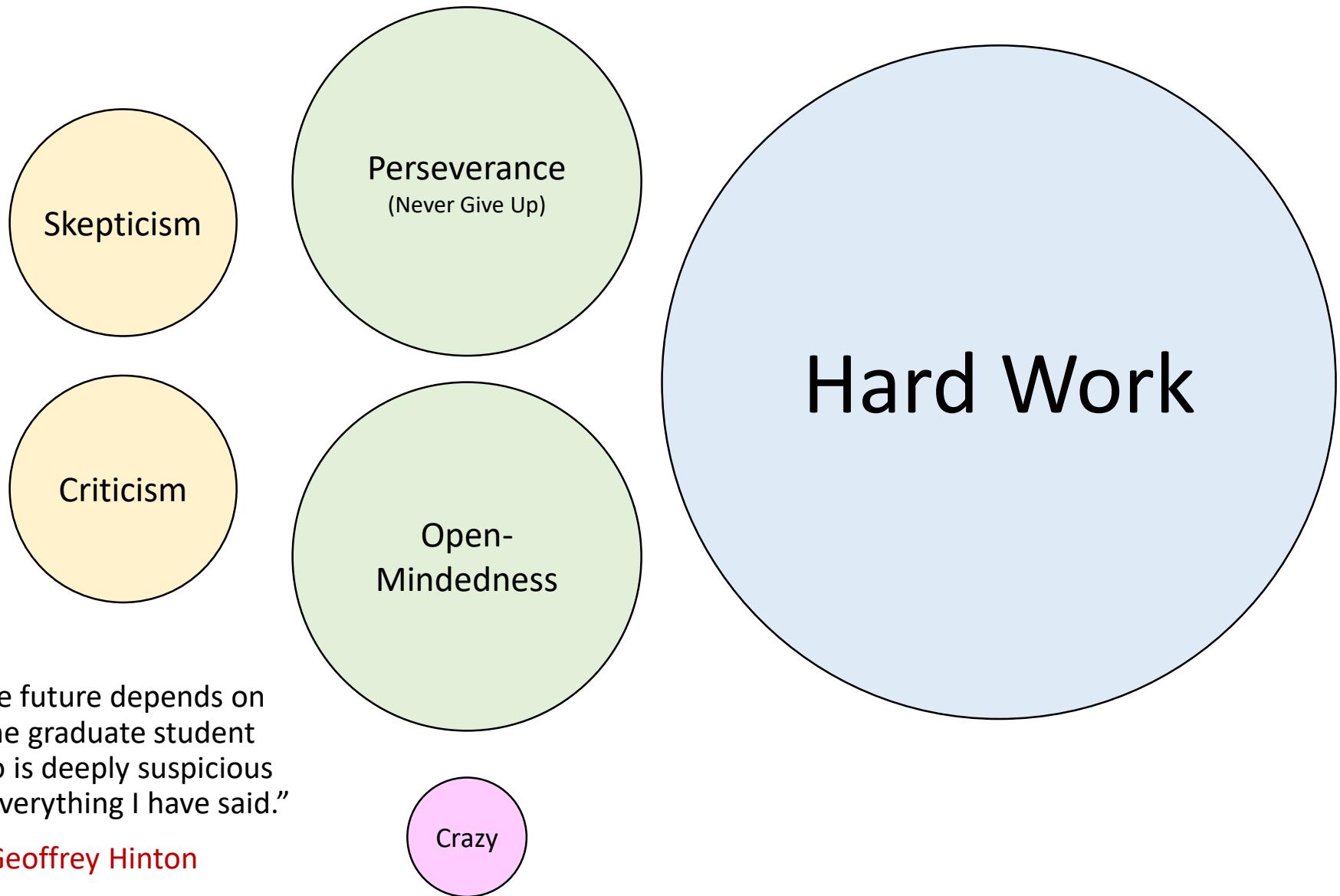
- Deep Learning Growth, Celebrations, and Limitations
- Deep Learning and Deep RL Frameworks
- Natural Language Processing
- Deep RL and Self-Play
- Science of Deep Learning and Interesting Directions
- Autonomous Vehicles and AI-Assisted Driving
- Government, Politics, Policy
- Courses, Tutorials, Books
- **General Hopes for 2020**

# Deep Learning Growth, Celebrations, and Limitations

## Hopes for 2020

- Reasoning
- Active learning and life-long learning
- Multi-modal and multi-task learning
- Open-domain conversation
- Applications: medical, autonomous vehicles
- Algorithmic ethics
- Robotics
- Recommender systems

# Hope for 2020: Recipe for Progress (in AI)



# Thank You

*Videos and slides are posted on the website:*

**deeplearning.mit.edu**