TTIC 31230, Fundamentals of Deep Learning

David McAllester, Autumn 2020

A Timeline of Deep Learning

and A Course Overview

Early History

1943: McCullock and Pitts introduced the linear threshold "neuron". Words in red are important — we will discuss them in detail in this class.

1962: Rosenblatt applies a "Hebbian" learning rule. Novikoff proved the perceptron convergence theorem.

1969: Minsky and Papert publish the book *Perceptrons*.

The Perceptrons book greatly discourages work in artificial neural networks. Symbolic methods dominate AI research through the 1970s.

80s Renaissance

1980: Fukushima introduces the neocognitron — a form of convolutional neural Network or CNN. CNNs created the deep revolution in 2012.

1984: Valiant defines PAC learnability and stimulates learning theory. Wins the Turing Award in 2010.

1985: Hinton and Sejnowski introduce the Boltzman machine

1986: Rummelhart, Hinton and Williams demonstrate empirical success with backpropagation (itself dating back to 1961).

90s and 00s: Research In the Shadows

1997: Schmidhuber et al. introduce LSTMs (a form of recurrent neural network or RNN).

1998: LeCunn draws attention to convolutional neural networks (CNNs) (LeNet).

2003: Bengio introduces neural language modeling.

Current Era

2012: Alexnet dominates the Imagenet computer vision challenge.

Google speech recognition converts to deep learning.

Both developments come out of Hinton's group in Toronto.

2013: Refinement of AlexNet continues to dramatically improve computer vision.

Current Era

2014: Neural machine translation appears (Seq2Seq models).

Variational auto-encoders (VAEs) appear.

Generative Adversarial Networks (GANs) appear.

Graph neural networks appear (GNNs) revolutionizing the prediction of molecular properties.

Dramatic improvement in computer vision and speech recognition continues.

Current Era

2015: Google converts to neural machine translation leading to dramatic improvements.

Batch Normalization appears improving the performance of image classification.

Residual Connections appear. This makes yet another dramatic improvement in computer vision.

Diffusion Models are formulated which become important in 2021.

2016: Reinforcement Learning is used to develop Alphago which defeats Lee Sedol.

Current Era

2017: AlphaZero learns both go and chess at super-human levels in a mater of hours entirely form self-play and advances computer go far beyond human abilities.

Unsupervised machine translation is demonstrated.

Progressive GANs demonstrate high resolution realistic face generation.

The Transformer appears greatly improving language modeling.

Current Era

2018: Unsupervised pre-training significantly improves a broad range of NLP tasks including question answering.

Contrastive learning is formulated which ultimately becomes the foundation of various systems.

AlphaFold revolutionizes protein structure prediction.

2019: Vector quantized VAEs (VQ-VAE) demstrate that VAEs can be competative with GANs for high-resolution image generation.

Super-human performance is achieved on the GLUE natural langauge understanding benchmark.

Current Era

2020: A neural langauge model (GPT-3) writes a fake blog post that landed in the No. 1 spot on Hacker News.

Natural Language Understanding

Unsuperfived pre-training leads to dramatic improvements on benchmarks for language understanding.

GLUE: General Language Understanding Evaluation

ArXiv 1804.07461

Corpus	|Train|	|Test|	Task	Metrics	Domain
			Single-Sentence Tasks		
CoLA	8.5k	**1k**	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
			Similarity and Paraphrase Tasks		
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	**391k**	paraphrase	acc./F1	social QA questions
			Inference Tasks		
MNLI	393k	**20k**	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	**146**	coreference/NLI	acc.	fiction books

Table 1: Task descriptions and statistics. All tasks are single sentence or sentence pair classification, except STS-B, which is a regression task. MNLI has three classes; all other classification tasks have two. Test sets shown in bold use labels that have never been made public in any form.

BERT and GLUE

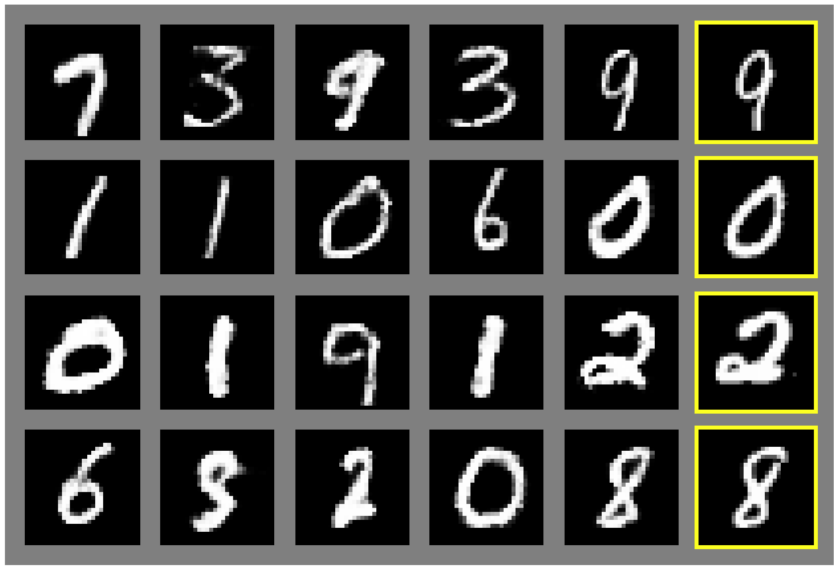
Rank	Name	Model	URL	Score
1	T5 Team - Google	T5		90.3
2	ERNIE Team - Baidu	ERNIE		90.1
3	Microsoft D365 AI & MSR AI & GATECH	MT-DNN-SMART		89.9
4	王玮	ALICE v2 large ensemble (Alibaba DAMO NLP)		89.7
5	Microsoft D365 AI & UMD	FreeLB-RoBERTa (ensemble)		88.4
6	Junjie Yang	HIRE-RoBERTa		88.3
7	Facebook AI	RoBERTa		88.1
8	Microsoft D365 AI & MSR AI	MT-DNN-ensemble		87.6
9	GLUE Human Baselines	GLUE Human Baselines		87.1

BERT and SuperGLUE

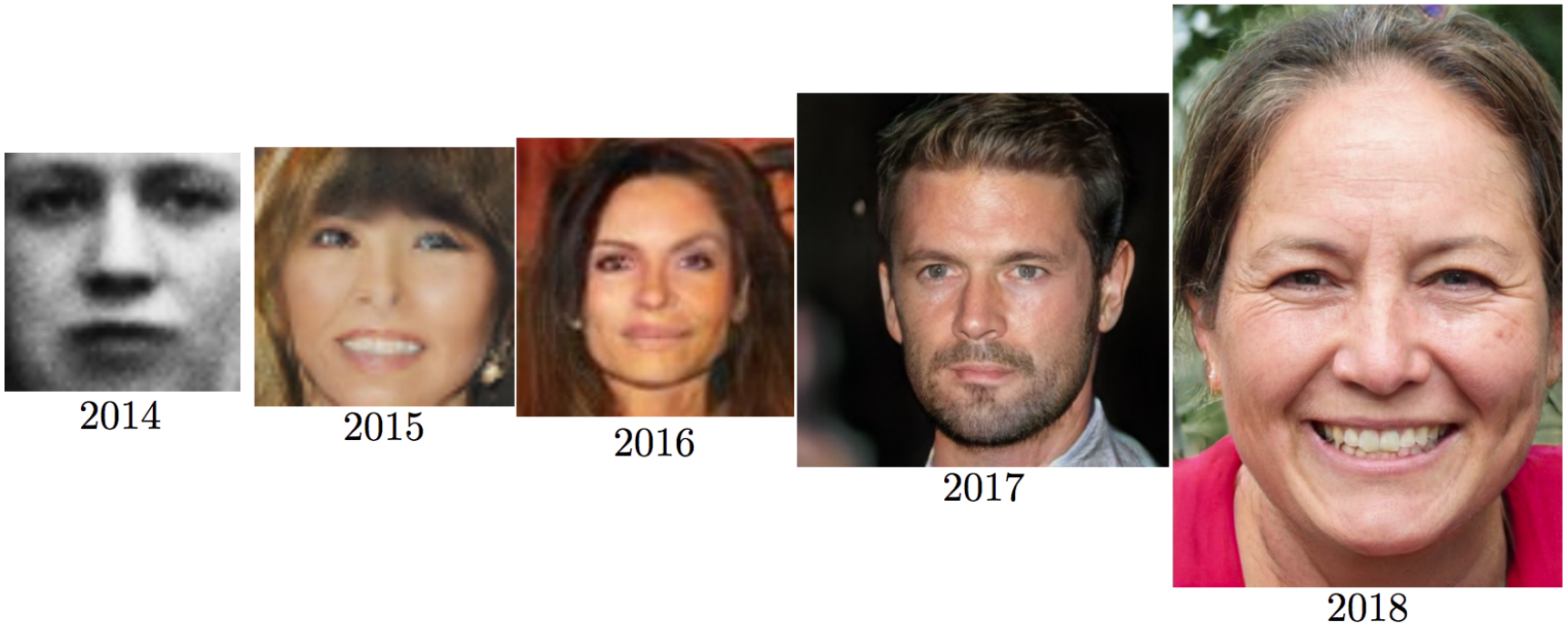
	Rank	Name	Model	URL	Score
	1	SuperGLUE Human Baselines	SuperGLUE Human Baselines		89.8
+	2	T5 Team - Google	T5		89.3
	3	Zhuiyi Technology	RoBERTa-mtl-adv		85.7
	4	Facebook AI	RoBERTa		84.6
	5	IBM Research AI	BERT-mtl		73.5

Generative Adversarial Nets (GANs)

Goodfellow et al., 2014



Moore's Law of AI
4.5 years of progress on faces



(Goodfellow 2019)

ArXiv 1406.2661, 1511.06434, 1607.07536, 1710.10196, 1812.04948
Goodfellow, ICLR 2019 Invited Talk

GANs for Imagenet

(Odena 2018)

BigGANs, Brock et al., 2018

Figure 1: Class-conditional samples generated by our model.

Variational Auto Encoders (VAEs, 2015)

[Alec Radford, 2015]

VAEs in 2019

VQ-VAE-2, Razavi et al. June, 2019

VAEs in 2019

Figure 1: Class-conditional 256x256 image samples from a two-level model trained on ImageNet.

VQ-VAE-2, Razavi et al. June, 2019

Wav2vec 2.0, June 2020, Facebook

Trained on 53k hours of unlabeled audio (no text) they use contrastive learning to convert speech to a sequence of discrete quantized vectors they call "pseudo-text units".

By training on only one hour of human-transcribed audio, and using the Wav2vec transcription into pseudo-text, the outperform the previous state of the art in word error rate for 100 hours of human-transcribed text.

GLSM, February 2021, Facebook

Generative Spoken Language Model (GSLM)

Using a form of VQ-VAE They then train a generative model of the sequences of pseudo-text units learned from unlabeled audio.

This model can continue speech from a speech prompt in much the same way that GPT-3 continues text from a text prompt.

Semantic and grammatical structure in a "unit language model" is recovered from speech alone.

Codex, July 2021, OpenAI

Using an unsupersided pretrained language model they fine-tune on code, including comments, from public repositories.

Starting from an English prompt Codex continues with code — a form of automatic programming.

There is a published version (58 authors) and a production version that powers **GitHub Copilot**.

Copilot may supplant Stack Overflow for finding out how to do x in language y.

CLIP, January 2021, OpenAI

CLIP: Contrastive Language-Image Pre-training.

Trained on images and associated text (such as image captions or hypertext links to images) CLIP computes embeddings of text and embeddings of images ("co-embeddings") trained to capture the mutual information between the two.

This is done with contrastive learning.

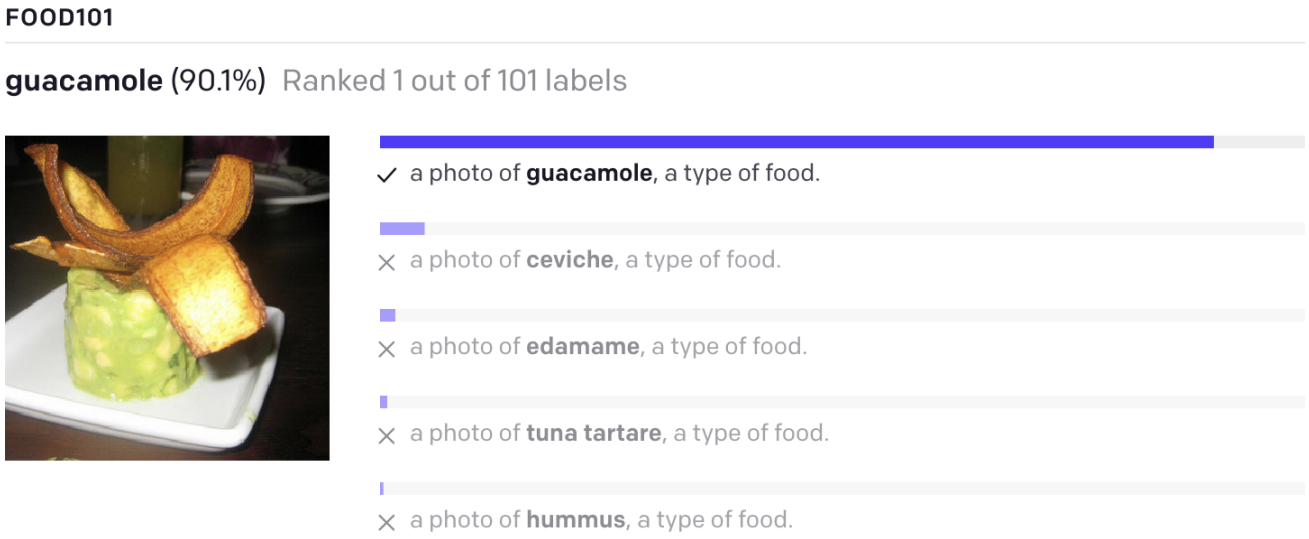
CLIP, January 2021, OpenAI

The model computes a probability of text given the co-embedding of the image.

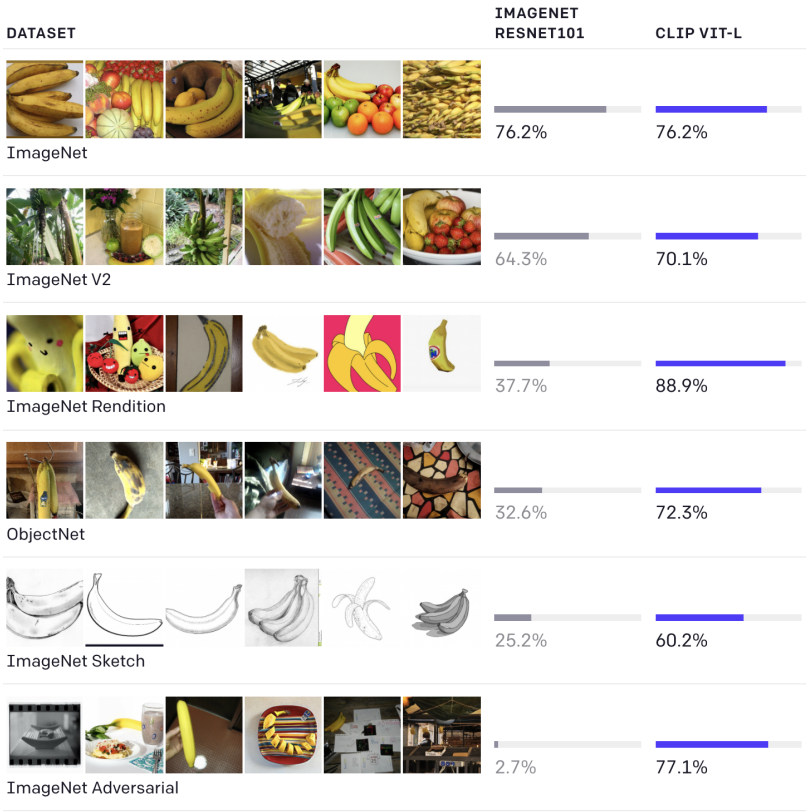
It is then used for zero-shot image classification on various datasets.

One can classify an image by comparing the probabilities that the model assigns to "prompts". There is a prompt for each class.

Zero-Shot Image Classification



Zero-Shot Image Classification



Although both models have the same accuracy on the ImageNet test set, CLIP's performance is much more representative of how it will fare on datasets that measure accuracy in different, non-ImageNet settings. For instance, ObjectNet checks a model's ability to recognize objects in many different poses and with many different backgrounds inside homes while ImageNet Rendition and ImageNet Sketch check a model's ability to recognize more abstract depictions of objects.

DALL·E, January 2021, OpenAI

DALL·E-2, April 2022

DALL·E-3 has been announced.

The name DALL·E is simply some kind of homage to the painter Dali and the Disney character WALL·E.

Both versions of DALL·E uses CLIP's co-embeddings of images and text.

Given text, DALL·E generates an image using a diffusion model.

DALL·E-1 Zero-Shot Image Rendering from Language

TEXT PROMPT an illustration of a baby daikon radish in a tutu walking a dog

AI-GENERATED IMAGES

Edit prompt or view more images↓

TEXT PROMPT an armchair in the shape of an avocado. . . .

AI-GENERATED IMAGES

Edit prompt or view more images↓

DALL·E-2

vibrant portrait painting of Salvador Dalí with a robotic half face

a shiba inu wearing a beret and black turtleneck

a close up of a handpalm with leaves growing from it

an espresso machine that makes coffee from human souls, artstation

panda mad scientist mixing sparkling chemicals, artstation

a corgi's head depicted as an explosion of a nebula

a dolphin in an astronaut suit on saturn, artstation

a propaganda poster depicting a cat dressed as french emperor napoleon holding a piece of cheese

a teddy bear on a skateboard in times square

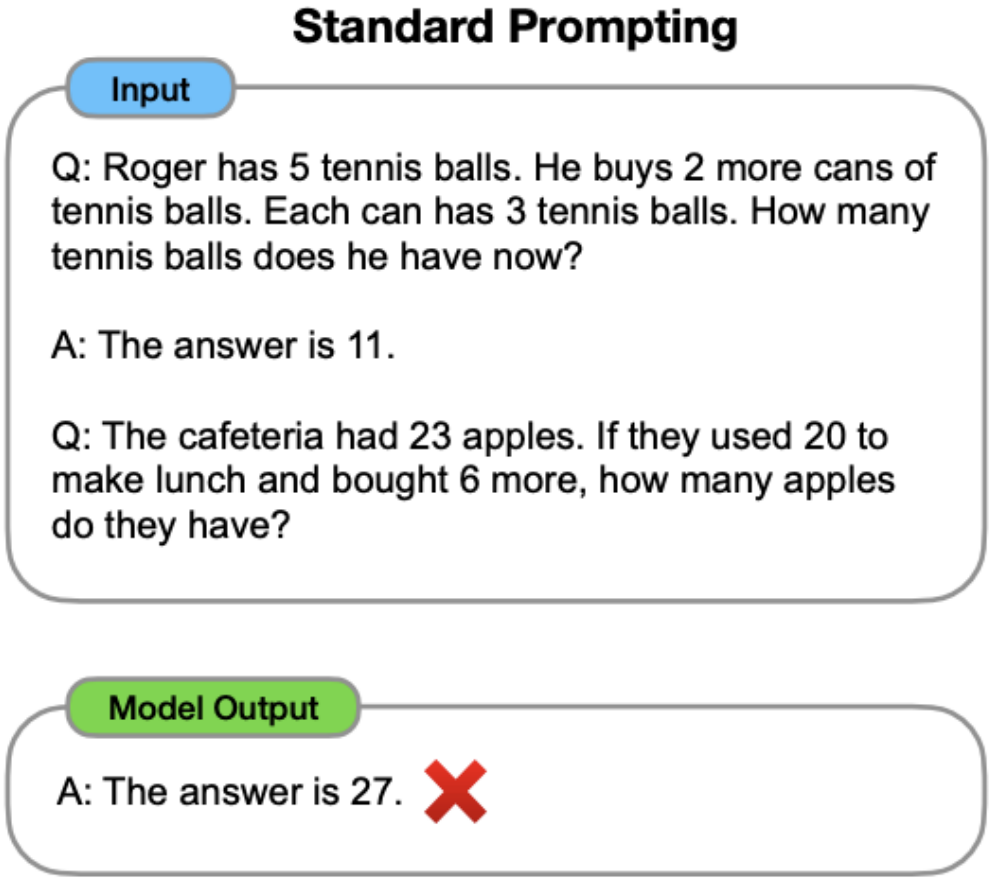
Diffusion Models

DALL·E-2 uses diffusion models. Although originally defined in 2015, they have become very prominent in the last year.

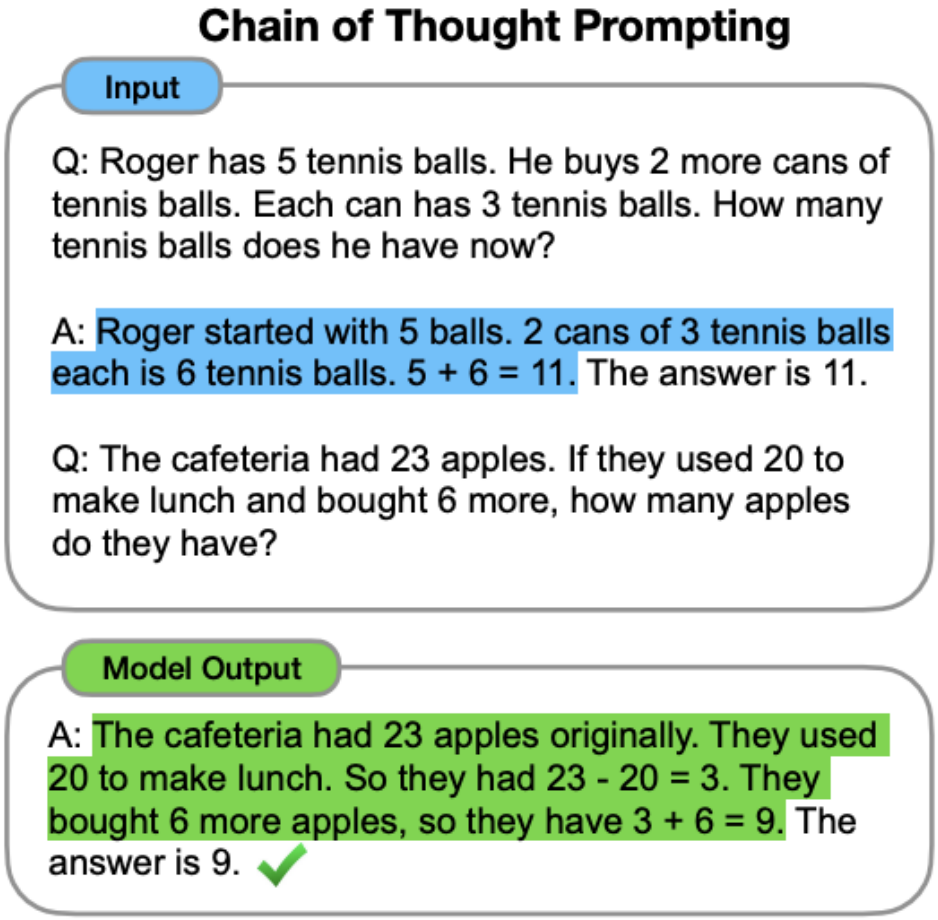
Chain of Thought Prompting, January 2022

Give examples of "chains of thought" for few shot learning of reasoning steps.

Naive Prompting



Chain of Thought Prompting, January 2022



Step by Step Prompting, June 2022

It turns out that adding the simple instruction "take it step by step" elicits powerful chain of thought reasoning in GPT-3.

Humanoid Soccer, September 2022, Deep Mind

Deep mind demonstrated two-on-two humanoid soccer in simulation (MuJoCo).

This a startling advance in the state of the art in humanoid humanoid control.

It also continues Deep Mind's effort in reinforcement learning.

Application Advancements vs. Architecture Advancements

Advancements in the general principles of learning are having applications over very diverse applications.

When considering Moore's law of AI it seems worth distinguishing architectural advancements (new general learning methods) from new applications of established architectures.

This course will focus on general, architectural, ideas.

Architectural Ideas

- Linear Threshold "neuron"
- Convolutional Neural Network or CNN
- Backpropagation
- Recurrent Neural Network or RNN
- Neural Language Modeling
- Variational Auto-Encoders (VAEs)
- Generative Adversarial Networks (GANs)
- Graph Neural Networks
- Batch Normalization
- Residual Connections
- Diffusion Models

- Reinforcement Learning
- The Transformer
- Unsupervised pre-training
- Contrastive Learning
- Prompting

END