Introduction

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Deep Learning

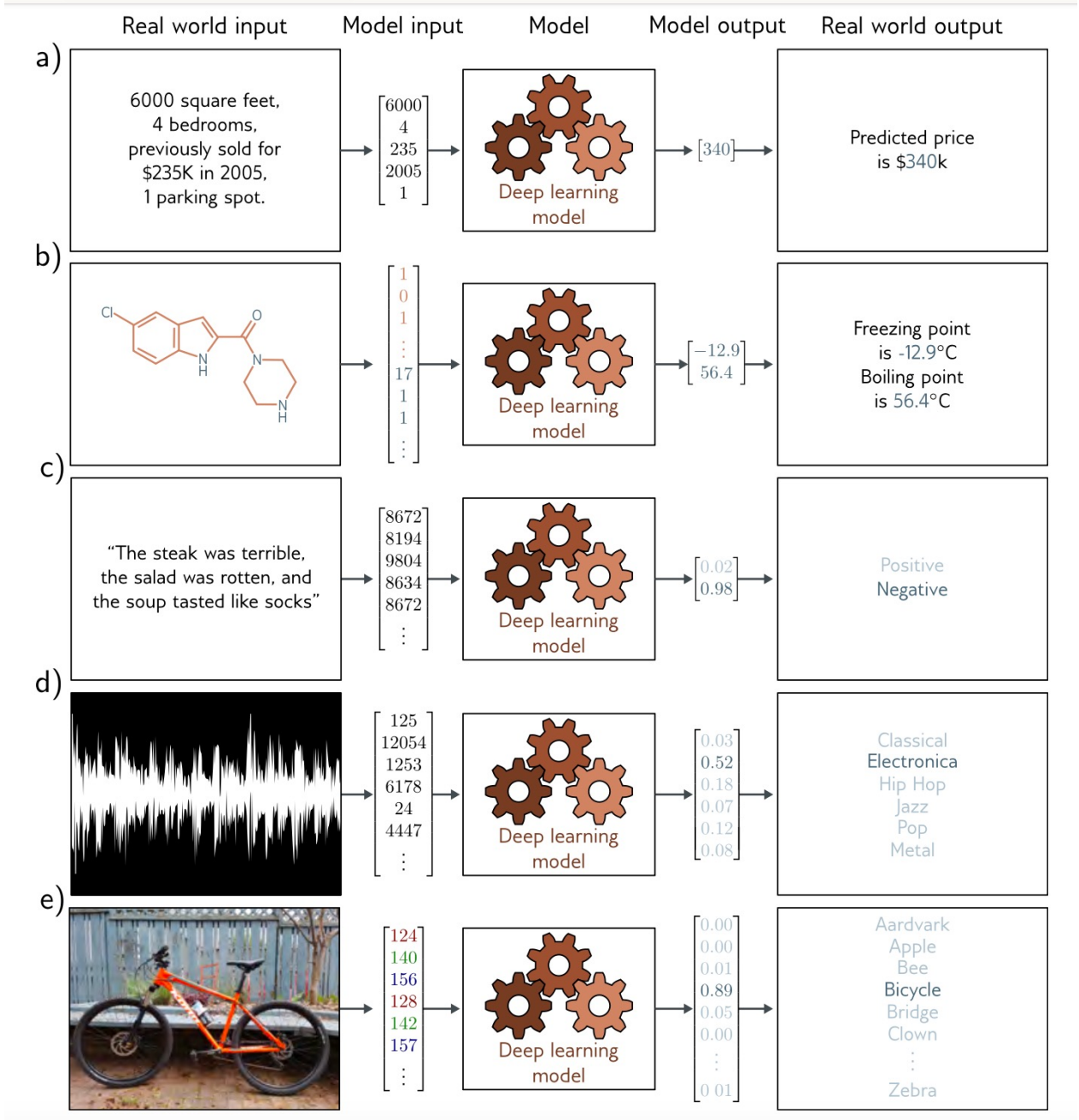
Sharif University of Technology

Spring 2025

Deep learning

- Learning a computational models consists of multiple processing layers
  - learn representations of data with multiple levels of abstraction.

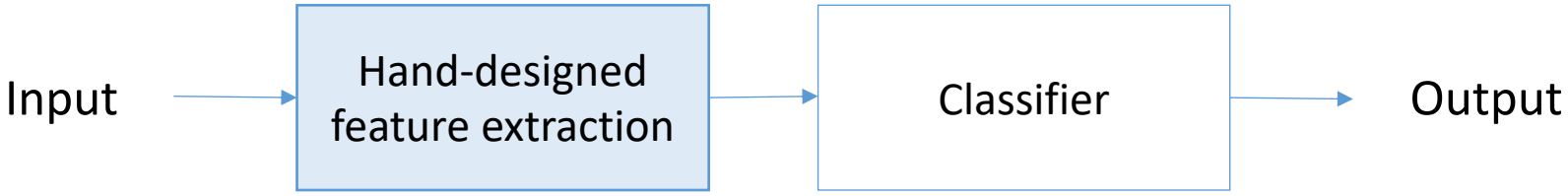
- Dramatically improved the state-of-the-art in many tasks



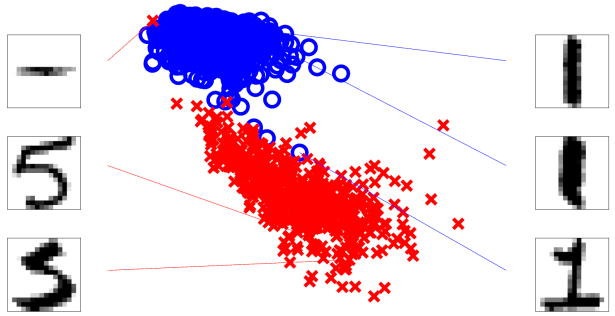
Understanding Deep Learning, 2023

Machine Learning Methods

- Conventional machine learning methods:
  - try to learn the mapping from the input features to the output by samples
  - However, they need appropriately designed hand-designed features



x_1: intensity
x_2: symmetry



[Abu Mostafa, 2012]

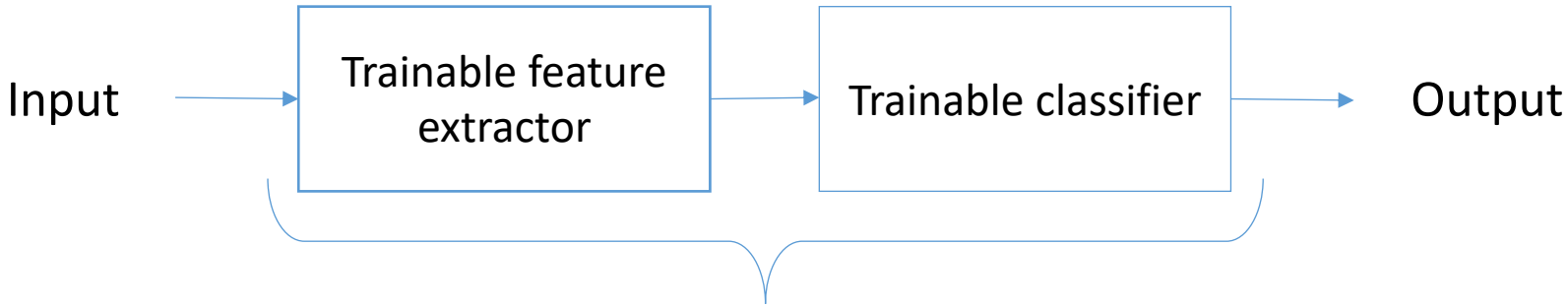
Representation of Data

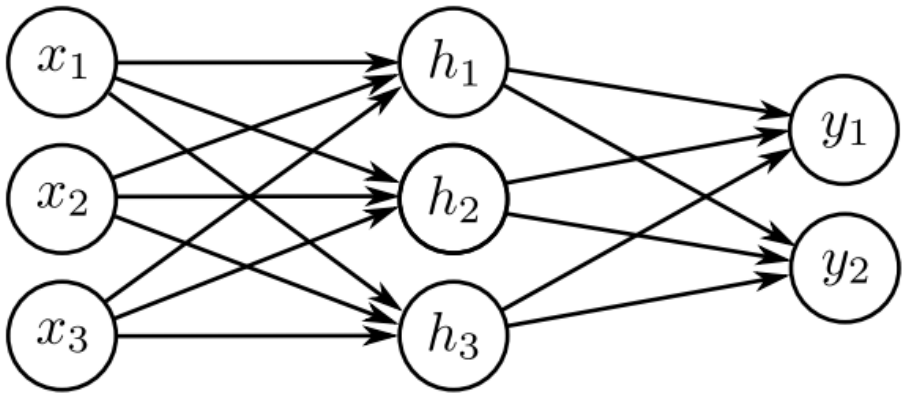
- Traditional learning methods depends heavily on the data representation
  - **Most efforts were on designing proper features**

- However, designing hand-crafted features for inputs like image, videos, time series, and sequences is not trivial at all.
  - It is difficult to know which features should be extracted.
    - Sometimes, it needs long time for a community of experts to find (an incomplete and over-specified) set of these features.

Representation Learning

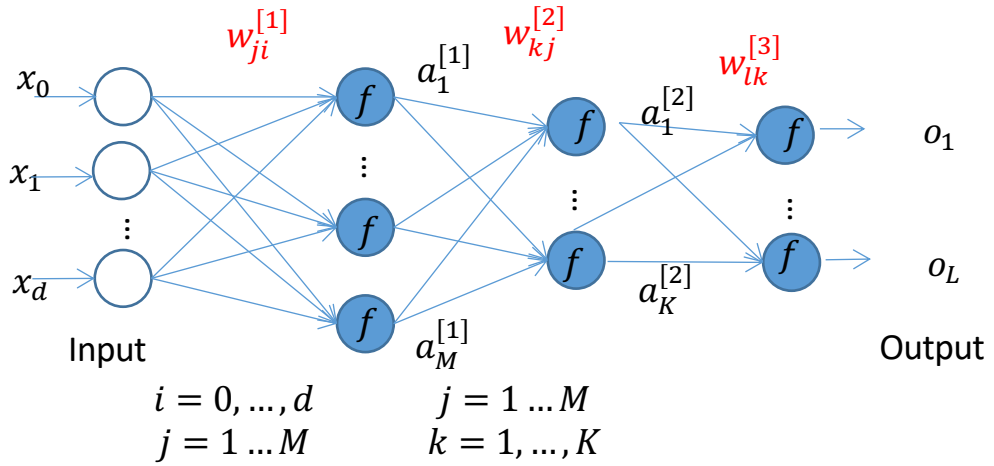
- Using learning to discover both:
  - the representation of data from input features
  - and the mapping from representation to output





Multi-layer Neural Network

- A multilayer perceptron is just a mapping input values to output values.
  - The function is formed by composing many simpler functions.
  - These middle layers are not given in the training data must be determined



Example of f functions:

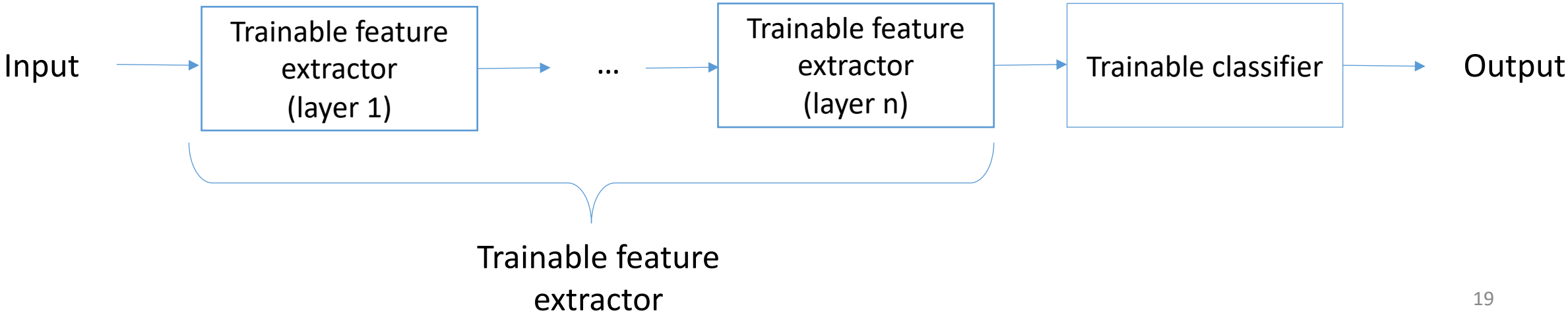
$$f(z) = \max(0, z)$$

$$a_k^{[l]} = f\left(\sum_{i=0}^{M} w_{ki}^{[l]} a_i^{[l-1]}\right)$$

Deep Learning Approach

- Deep breaks the desired complicated mapping into a series of nested simple mappings
  - each mapping described by a layer of the model.
  - each layer extracts features from output of previous layer

- shows impressive performance on many Artificial Intelligence tasks



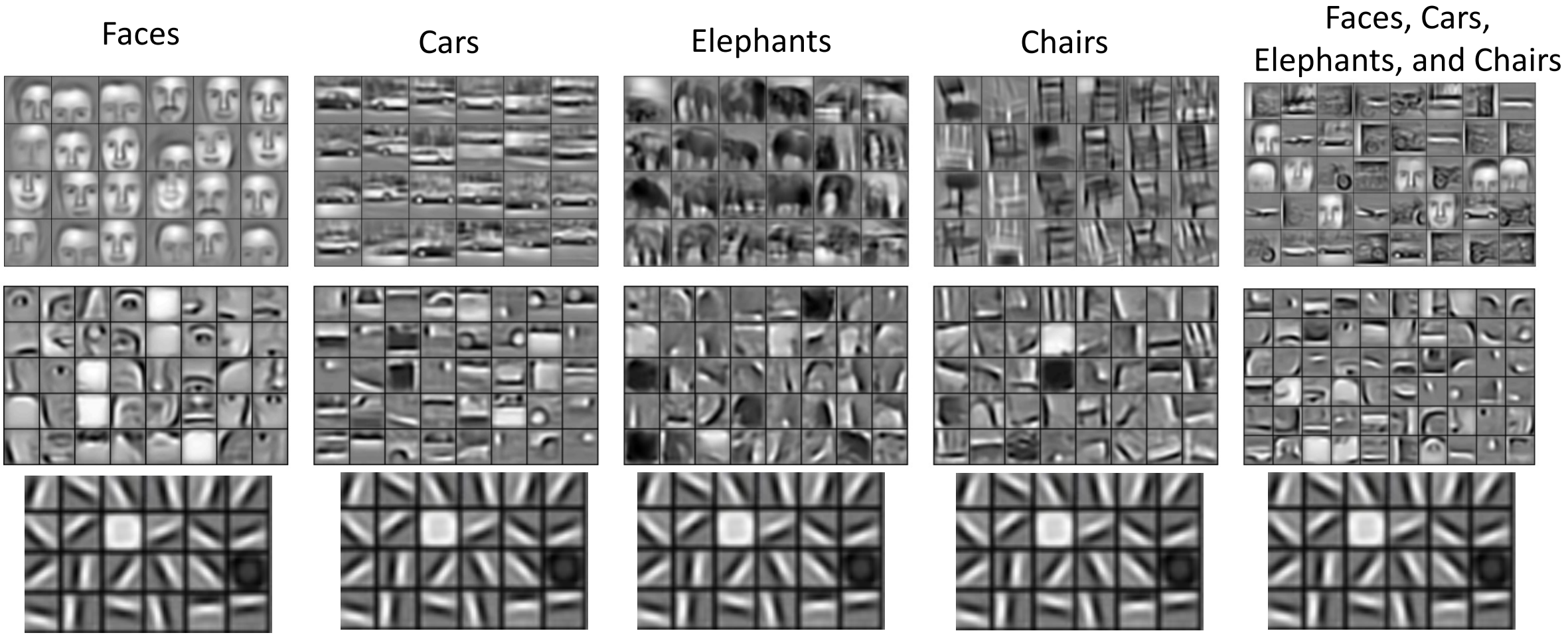
Deep Representations: The Power of Compositionality

- Deep learning has great power and flexibility by learning to represent the world as a nested hierarchy of concepts

- Compositionality is useful to describe the world around us efficiently
  - Learned function seen as a composition of simpler operations
  - Hierarchy of features, concepts, leading to more abstract factors enabling better generalization
    - each concept defined in relation to simpler concepts
    - more abstract representations computed in terms of less abstract ones.
  - Again, theory shows this can be exponentially advantageous

Slice credit: Yoshua Bengio

Example of Nested Representation



Lee et al., ICML 2009

Deep Learning Brief History

- 1940s–1960s:
  - development of theories of biological learning
  - implementations of the first models
    - perceptron (Rosenblatt, 1958) for training of a single neuron.

- 1980s-1990s: back-propagation algorithm to train a neural network with more than one hidden layer
  - too computationally costly to allow much experimentation with the hardware available at the time.
  - Small datasets

- 2006 “Deep learning” name was selected
  - ability to train deeper neural networks than had been possible before
    - Although began by using unsupervised representation learning, later success obtained usually using large datasets of labeled samples

Deep Learning History: Timeline

- **1943 Artificial Neuron**
- 1957 Perceptron
- 1969 Limitations of Neural Networks
- 1979 Neocognitron (inspires CNNs)
- 1982 Recurrent Neural Networks (RNNs)
- 1986 Back propagation
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- 2009 ImageNet
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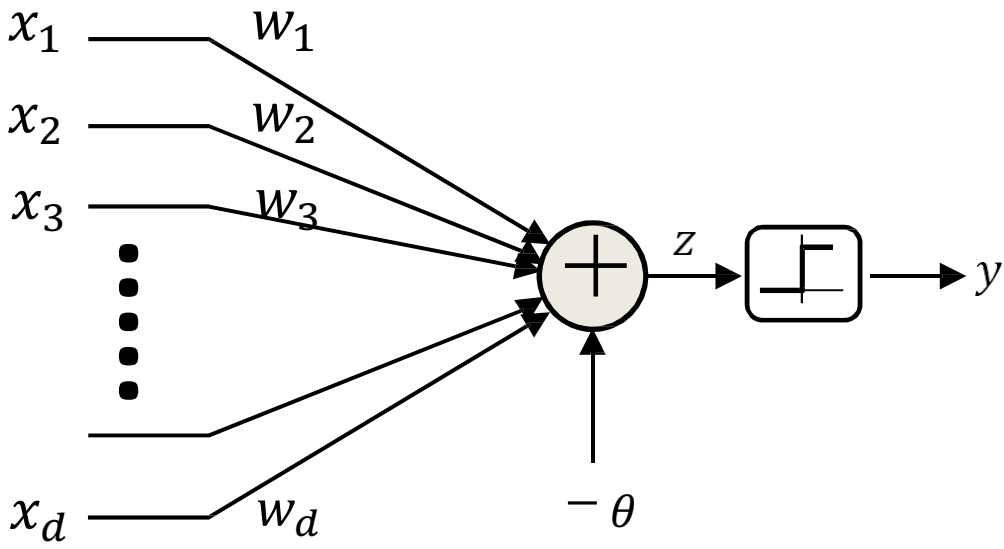

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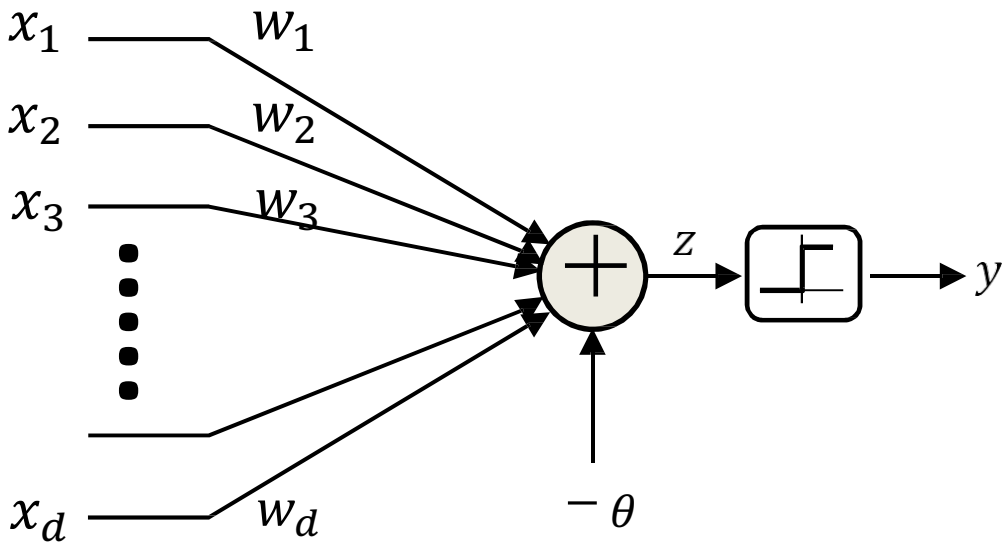

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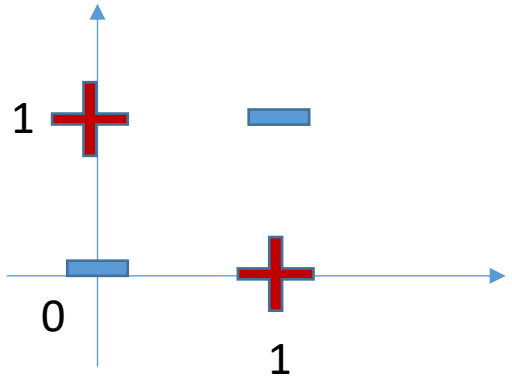

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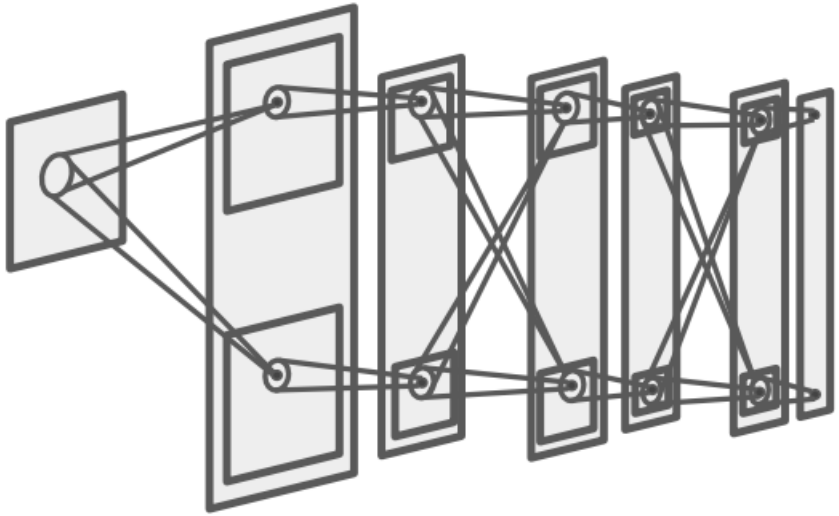

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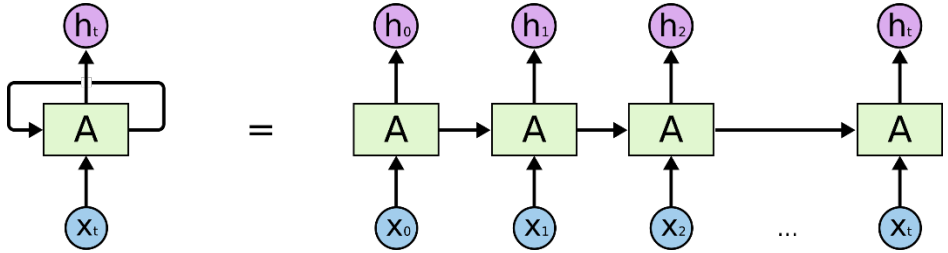

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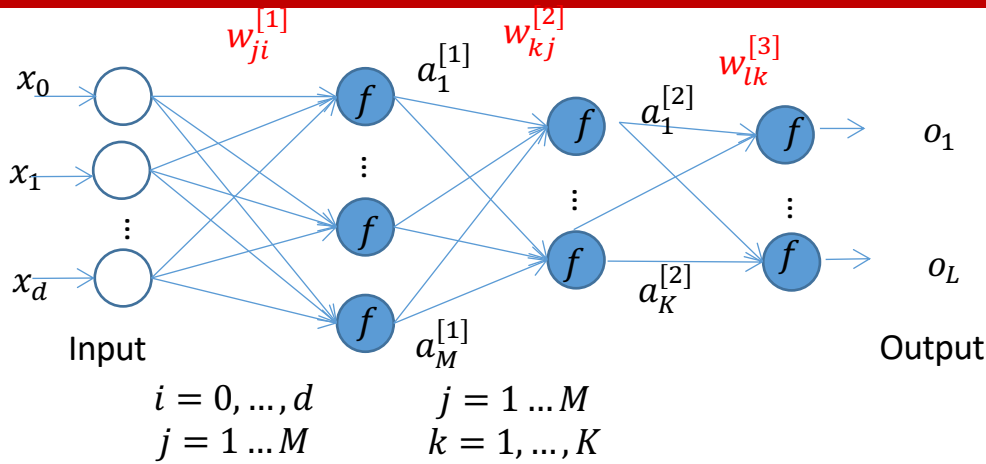

$$\frac{\partial E}{\partial w_{kj}^{[l]}} = \frac{\partial E}{\partial a_k^{[l]}} \frac{\partial a_k^{[l]}}{\partial w_{kj}^{[l]}}$$

$$\frac{\partial E}{\partial a^{[l]}} = \frac{\partial a^{[l+1]}}{\partial a_l^{[l]}} \frac{\partial E}{\partial a^{[l+1]}}$$

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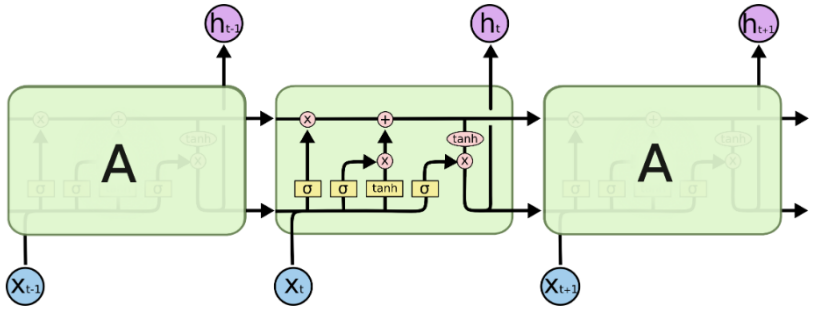

Source: Colah's blog

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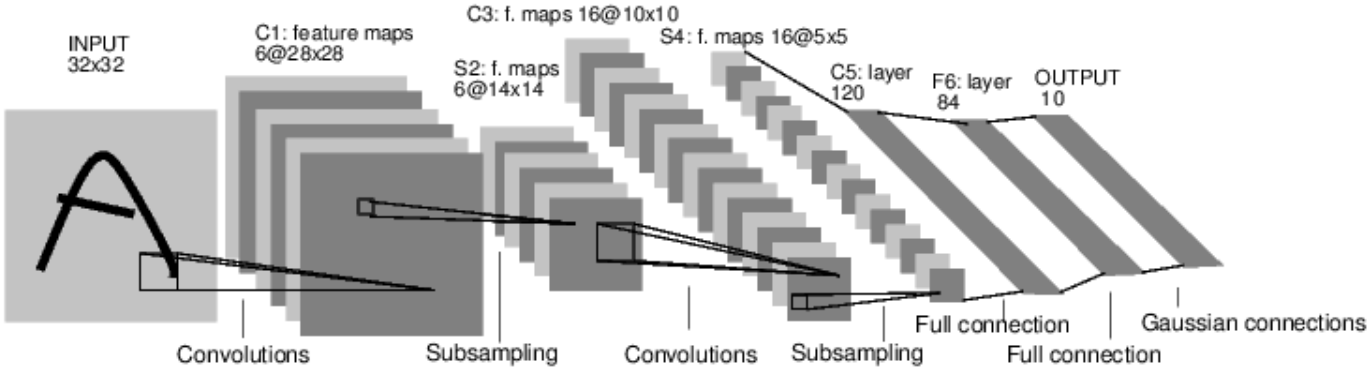
LeNet: Handwritten Digit Recognition (recognizes zip codes)
Training Sample : 9298 zip codes on mails



[LeNet, Yann Lecun, et. al, 1989]

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The training of each layer individually is an easier undertaking
- Training multi layered neural networks became easier
- Per-layer trained parameters initialize further training

ImageNet

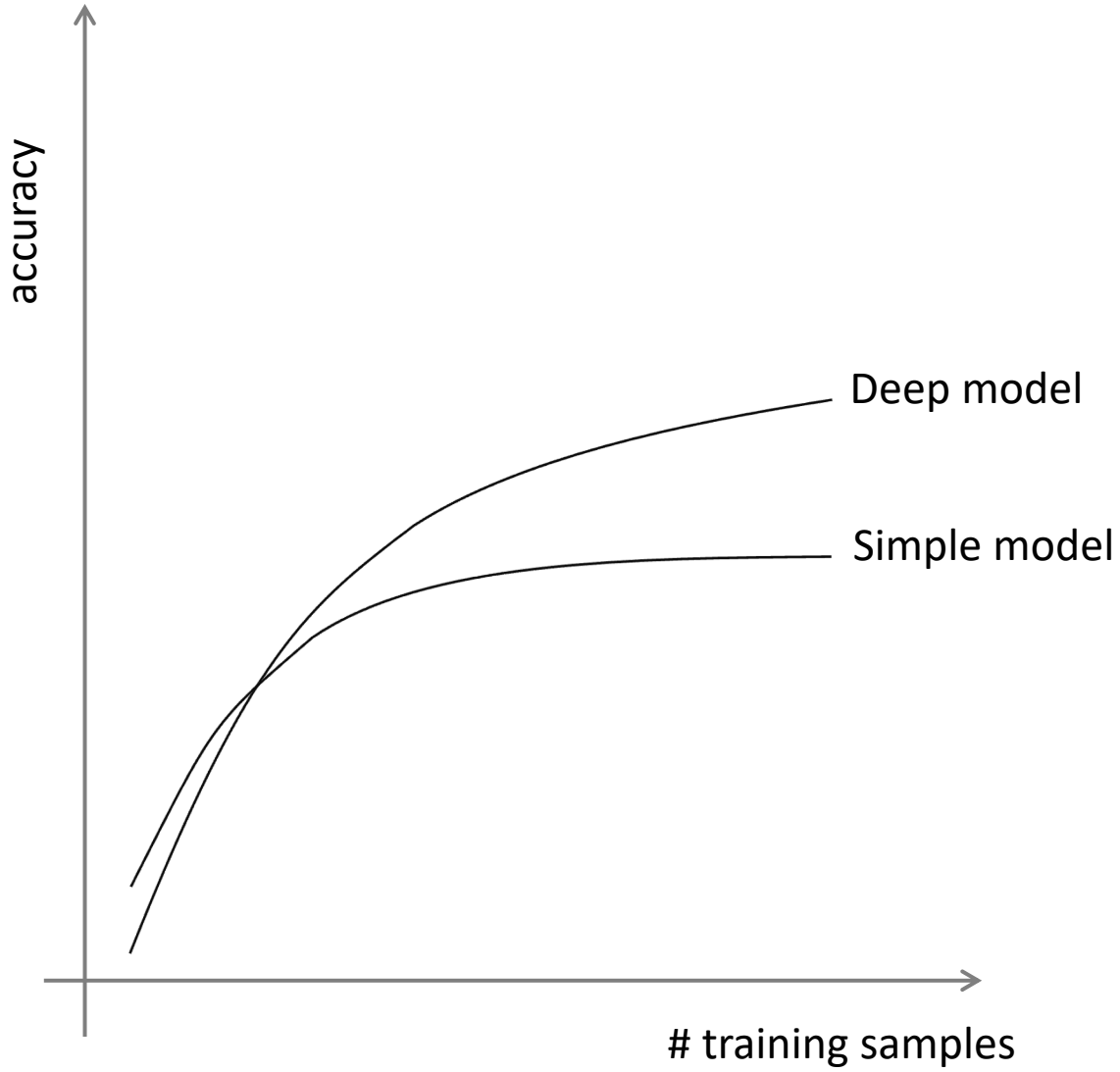
[Deng, Dong, Socher, Li, Li, & Fei-Fei, 2009]

- 22K categories and 14M images
  - Collected from web & labeled by Amazon Mechanical Turk

- The Image Classification Challenge:
  - Imagenet Large Scale Visual Recognition Challenge (ILSVRC)
  - 1,000 object classes
  - 1,431,167 images

- Much larger than the previous datasets of image classification

Large Datasets



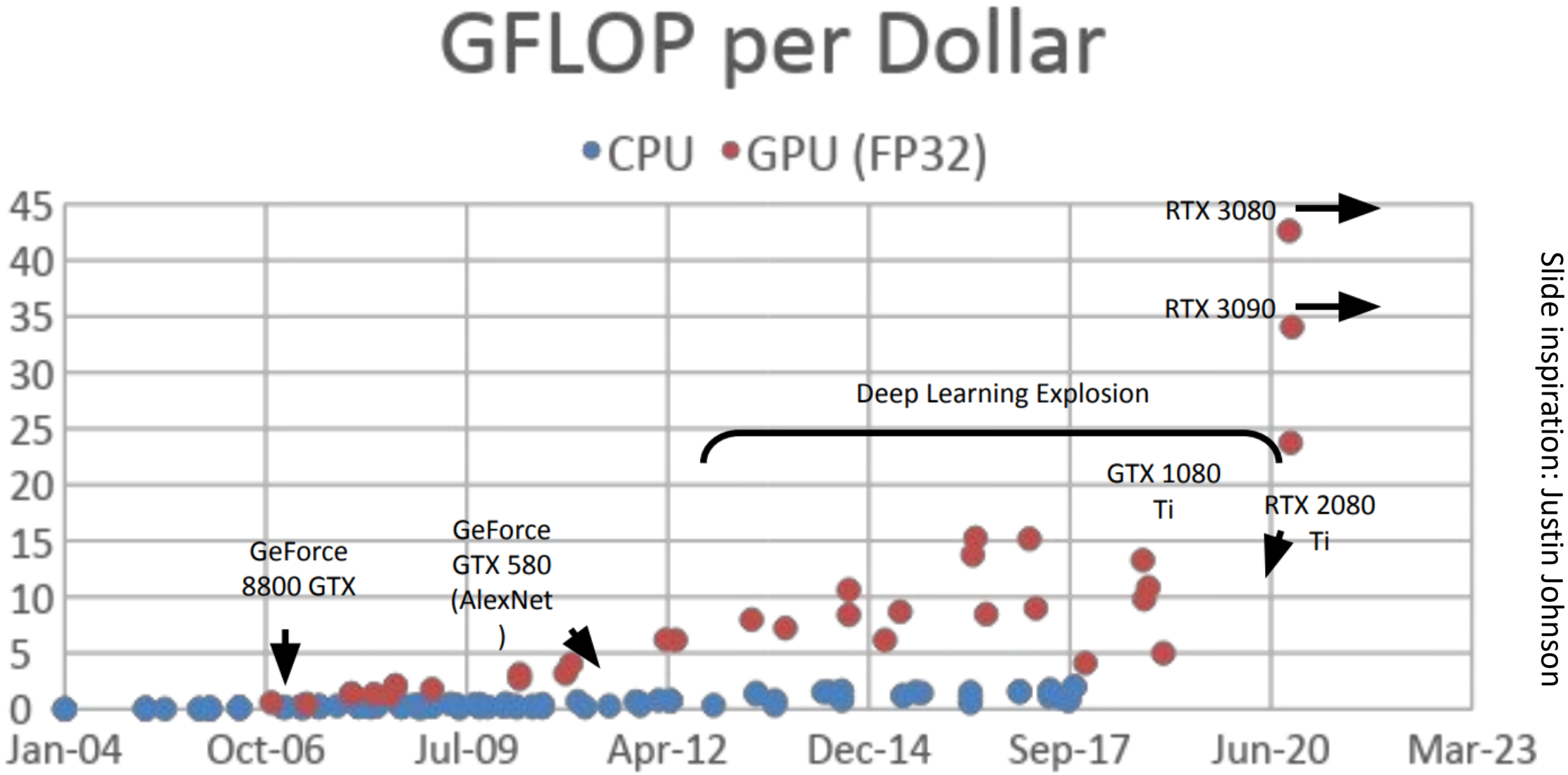
Why does deep learning become popular?

- Data: Large datasets

- Hardware: Availability of the computational resources to run much larger models

- Algorithm
  - New training techniques
  - New models
  - Frameworks

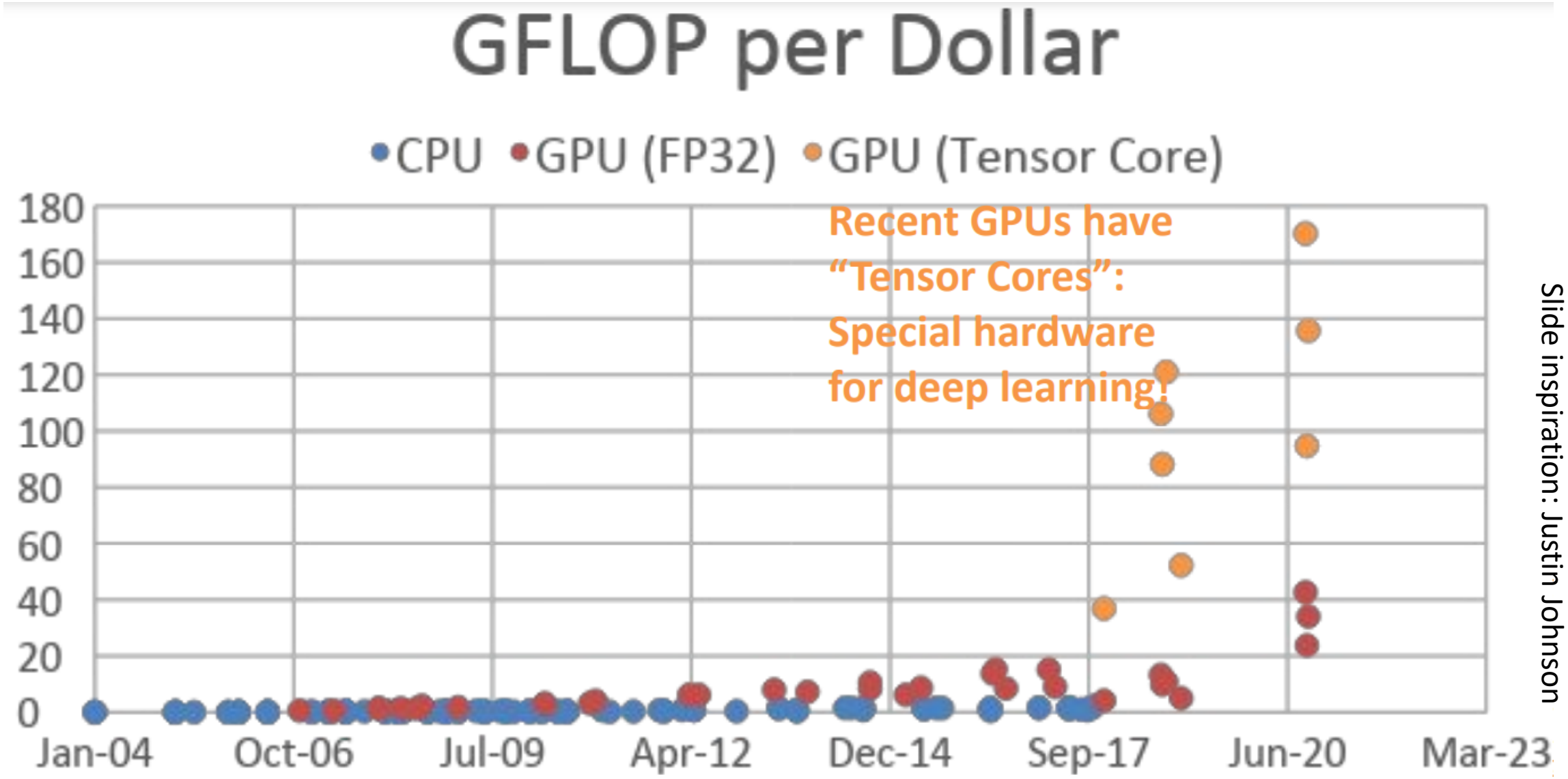
Computational Resources



Slide inspiration: Justin Johnson

Slide credit: Fei-Fei Li & Jiajun Wu & Ruohan Gao, CS231n

Computational Resources



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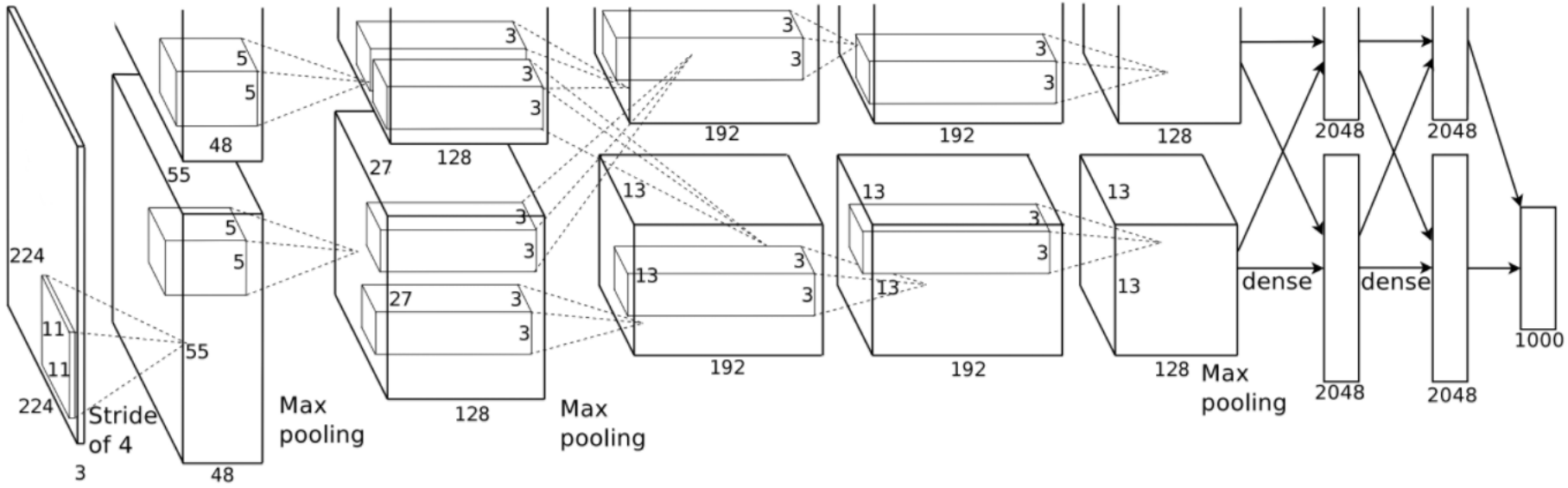
Alexnet (2012)

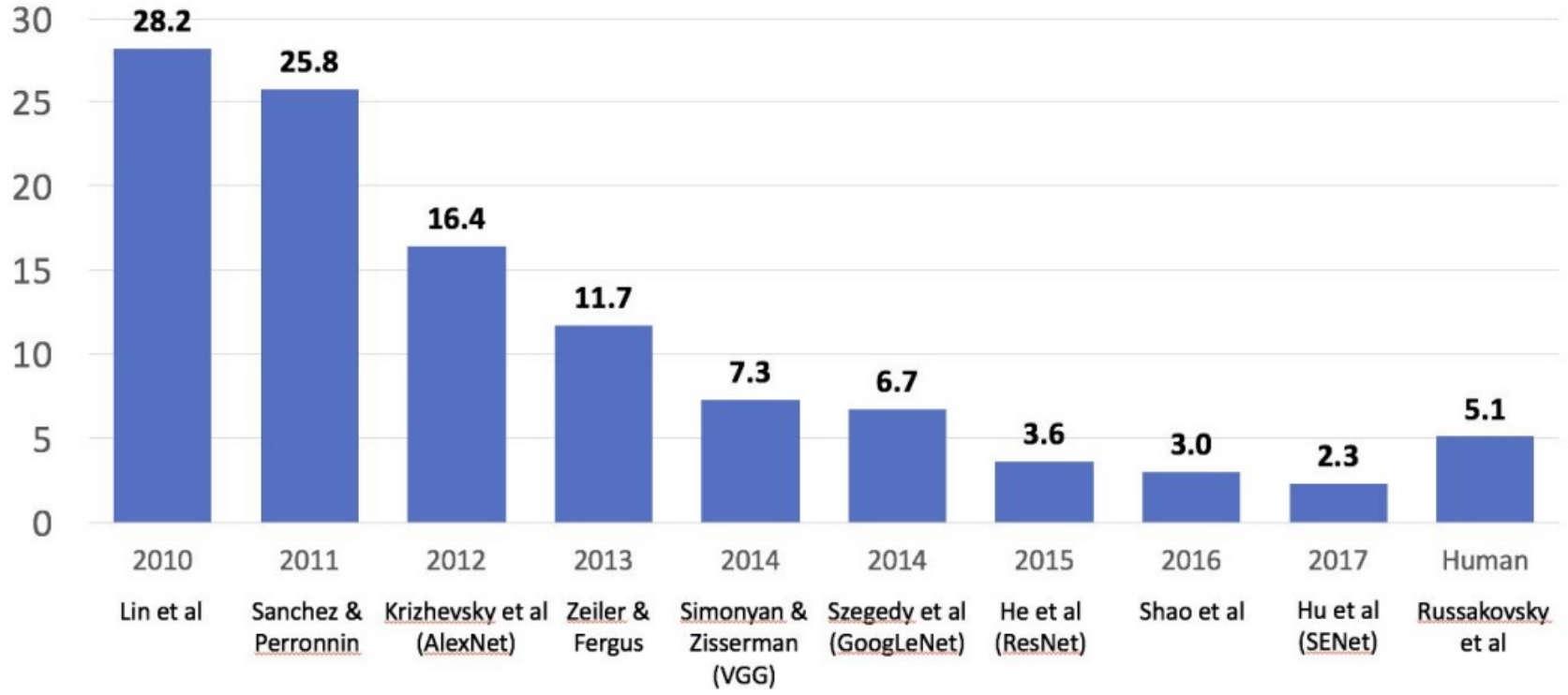


Krizhevsky, Alex, Sutskever, and Hinton, Imagenet classification with deep convolutional neural networks, NIPS 2012

- Reduces 25.8% top 5 error of the winner of 2011 challenge to 16.4%

Deep Models for Image Classification (ILSVRC)

- 5.1% is the performance of human on this data set



Using Pre-trained Models

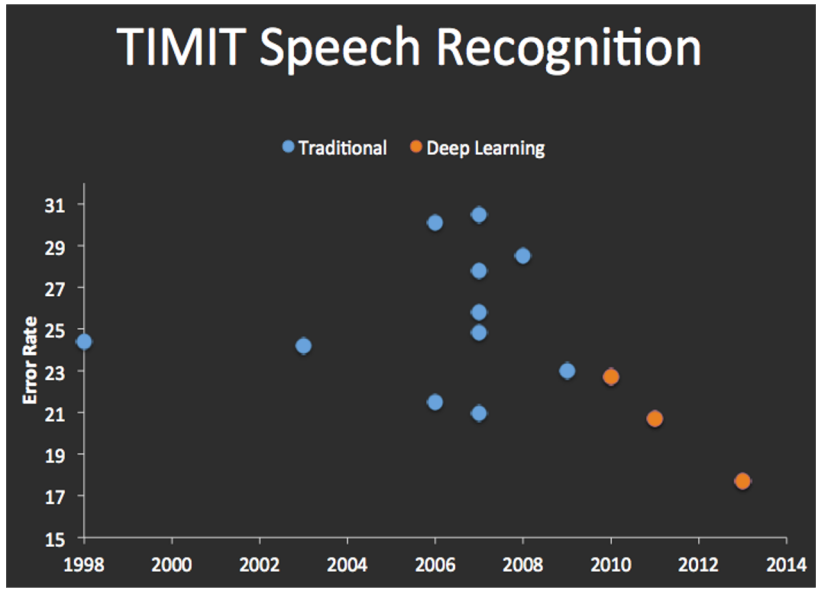
- We don’t have large-scale datasets on all image tasks and also we may not time to train such deep networks from scratch
- On the other hand, learned weights for popular networks (on ImageNet) are available.
- Use pre-trained weights of these networks (other than final layers) as generic feature extractors for images
- Works better than handcrafted feature extraction on natural images

Other Vision Tasks

- After image classification, achievements were obtained in other vision tasks:
  - Object detection
  - Segmentation
  - Image captioning
  - Visual Question Answering (VQA)
  - …

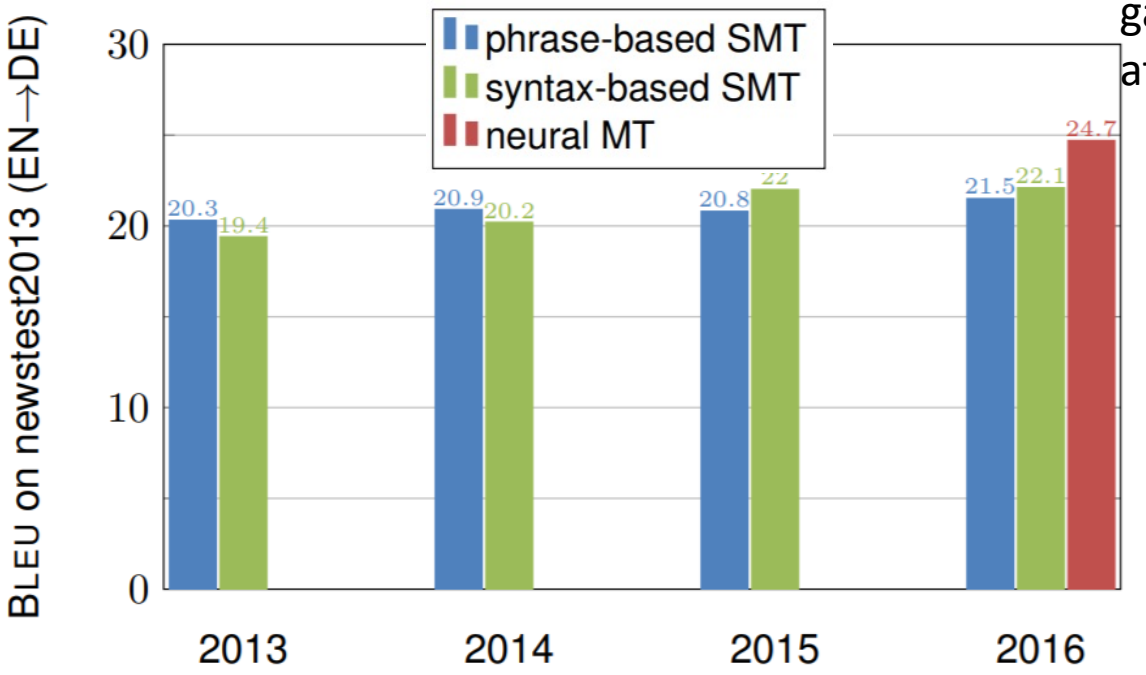
Similar Trends also in Speech and NLP

- Deep learning became SOTA also in speech and NLP tasks



Source: clarifai

Edinburgh's WMT Results Over the Years

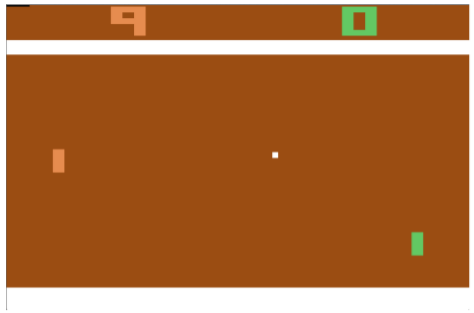


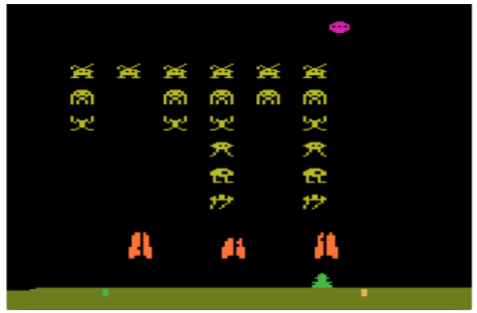
RNN with gating units + attention

Source: http://www.meta-net.eu/events/meta-forum2016/slides/09_sennrich.pdf

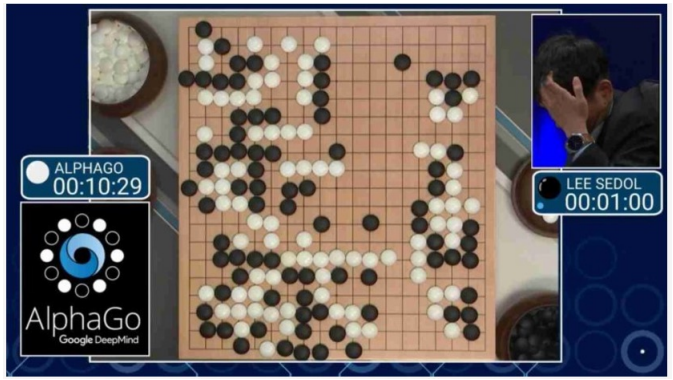
Games

- DQN (2013): Atari 2600 games
  - neural network agent that is able to successfully learn to play as many of the games as possible without any hand-designed feature.



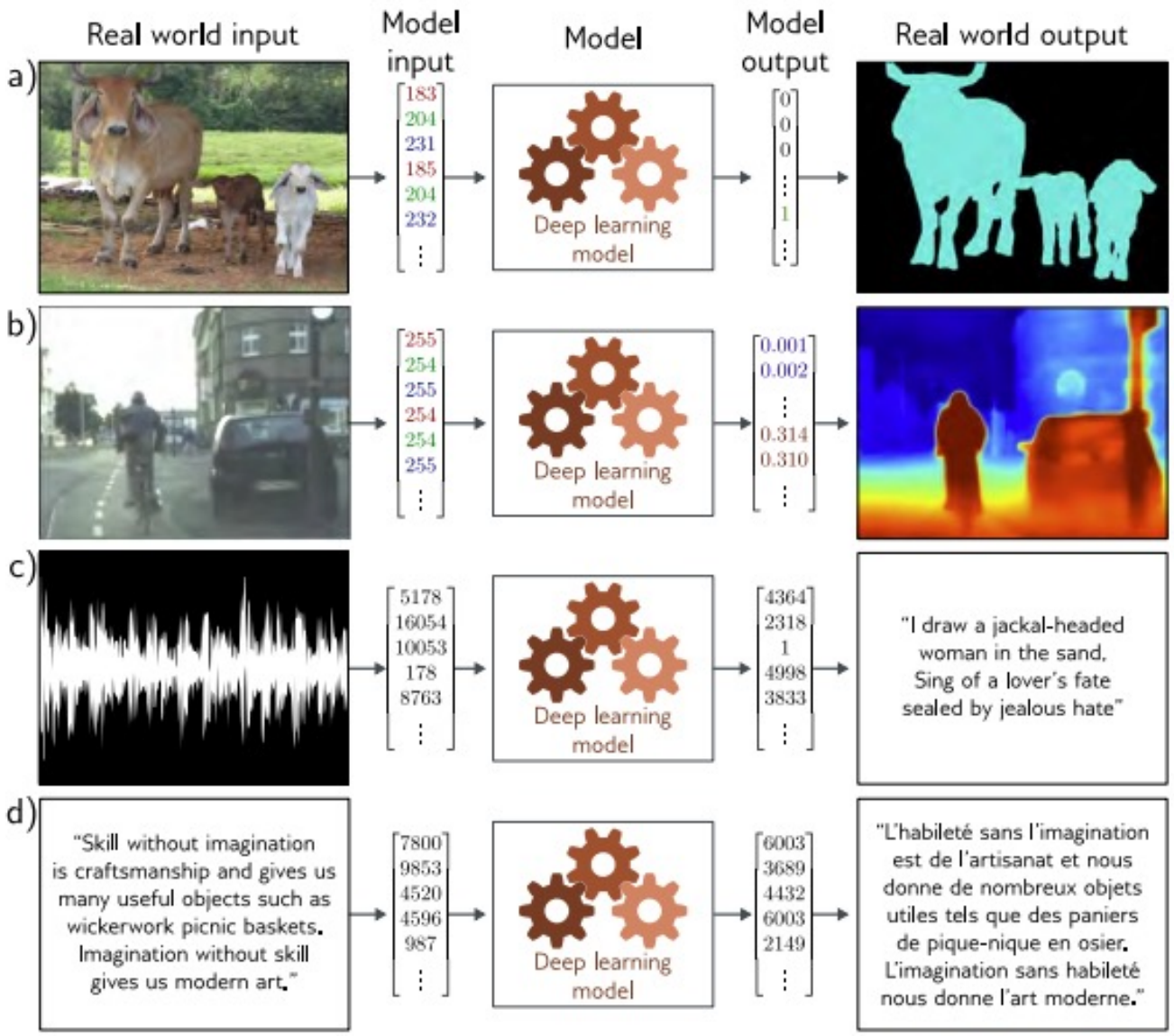



- Deep Mind's alphaGo defeats former world champion in 2016.



Source: https://gogameguru.com/alphago-shows-true-strength-3rd-victory-lee-sedol/

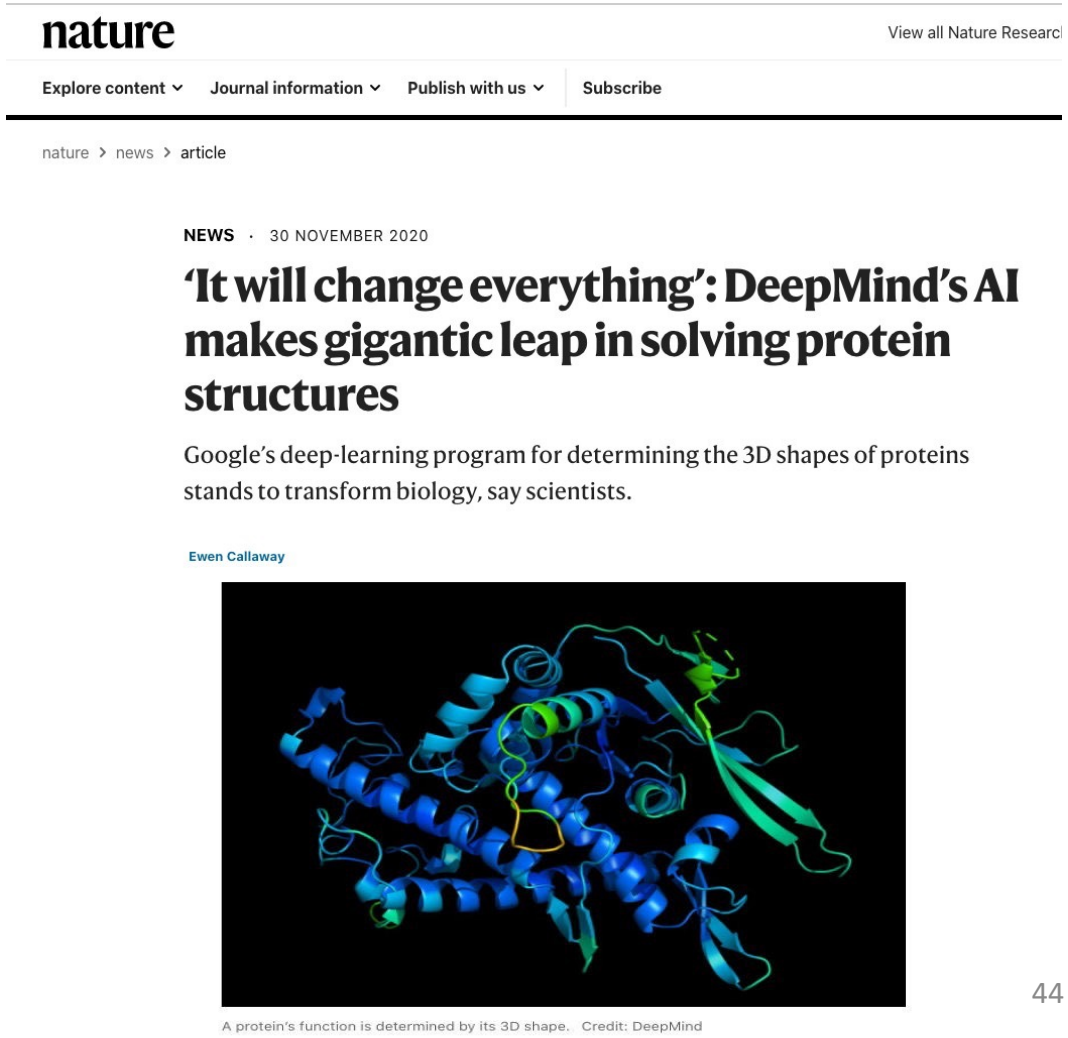
Some Examples



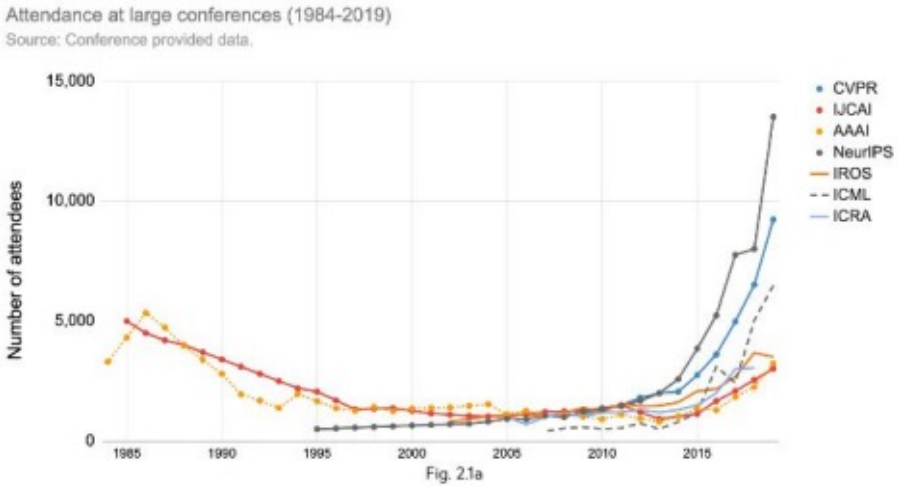
Understanding Deep Learning, 2023

Deep Learning is Everywhere

- Vision
- NLP
- Speech
- Games
- Bioinformatics
- …

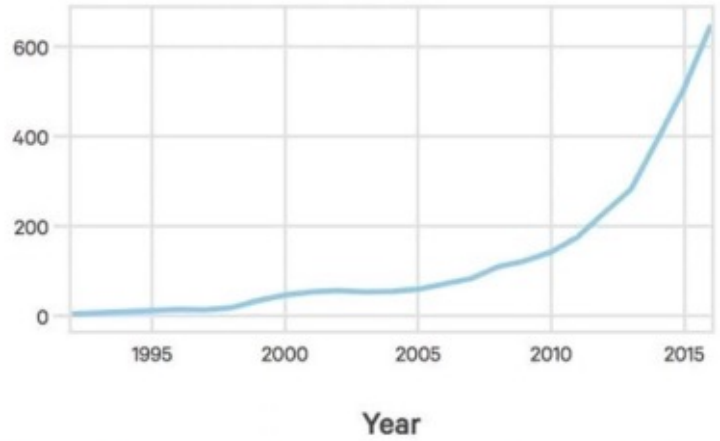


AI's Explosive Growth & Impact



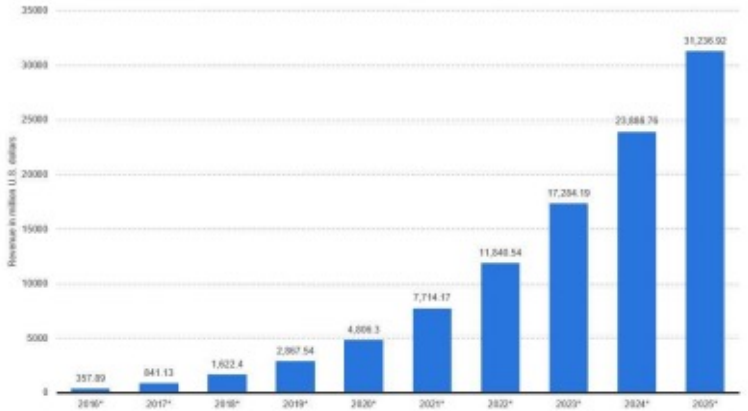
Number of attendance At AI conferences

Source: The Gradient



Startups Developing AI Systems

Source: Crunchbase, VentureSource, Sand Hill Econometrics

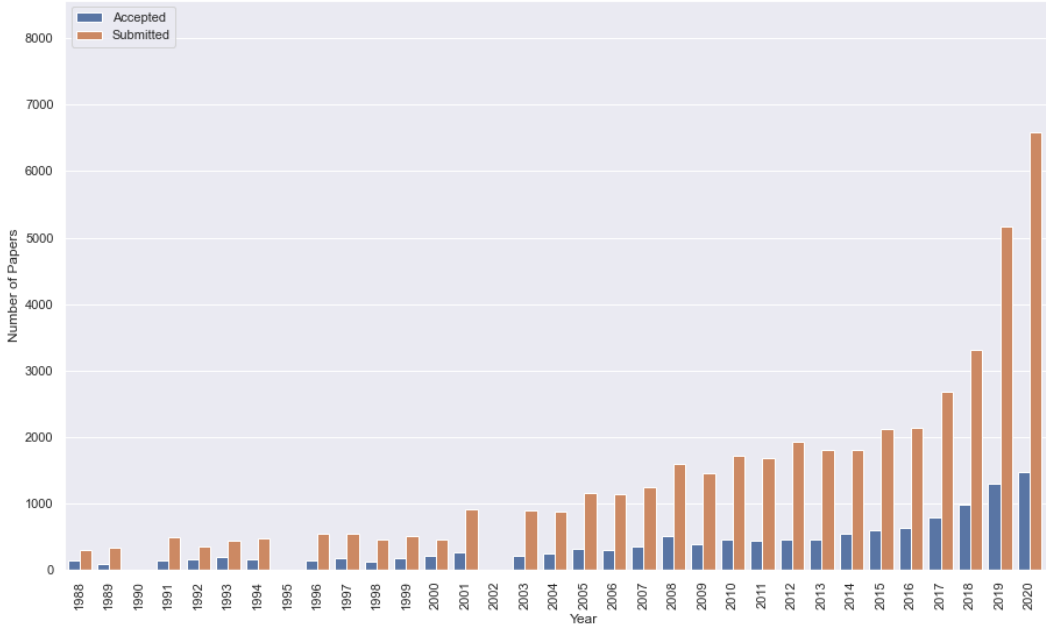


Enterprise Application AI Revenue

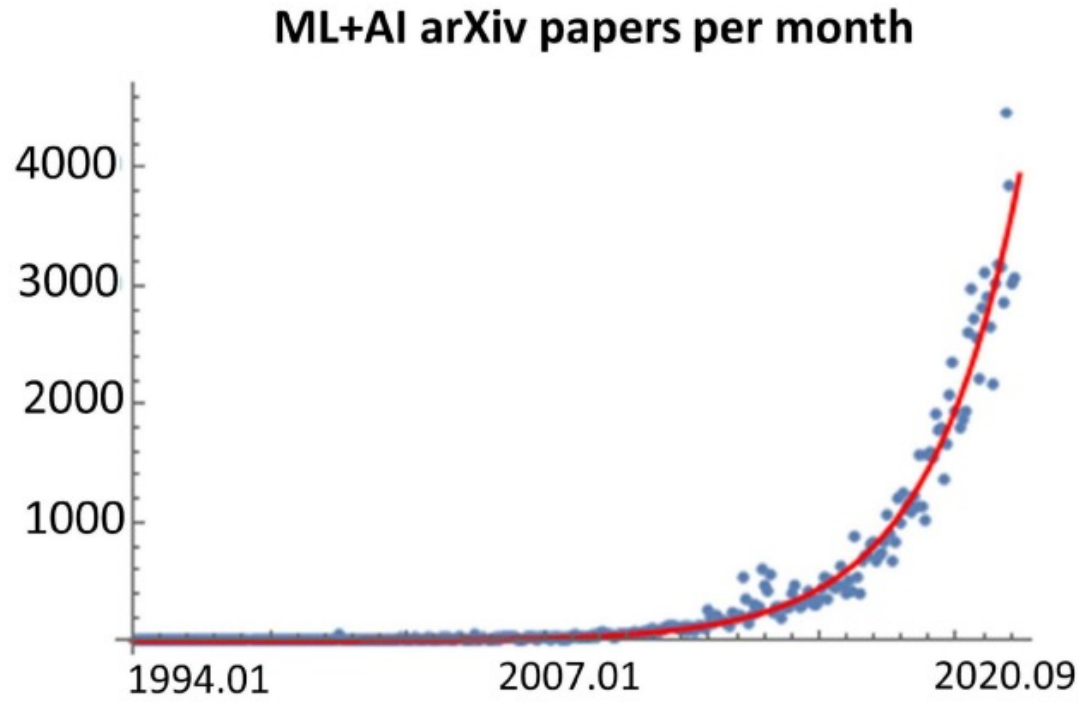
Source: Statista

Slide credit: Fei-Fei Li & Jiajun Wu & Ruohan Gao, CS231n

2012 to Present: Deep Learning Explosion



CVPR papers



ML+AI papers (source)

Language: Transformer

- In 2017, transformer was introduced for NLP tasks.
- Achieved state-of-the-art results on eleven NLP tasks
- Pre-trained transformers (like BERT) can be fine-tuned for a wide range of tasks, such as question answering and language inference
  - without substantial task-specific architecture modifications
  - with just one additional output layer

Attention Is All You Need, NeurIPS 2017

Self-supervised Models

- How do we use unlabeled data for learning representations?
  - Predict next word / patch of image
  - Predict missing word / patch of image
  - Predict if two images are related (contrastive learning)

- Making poweful foundation models using this approach

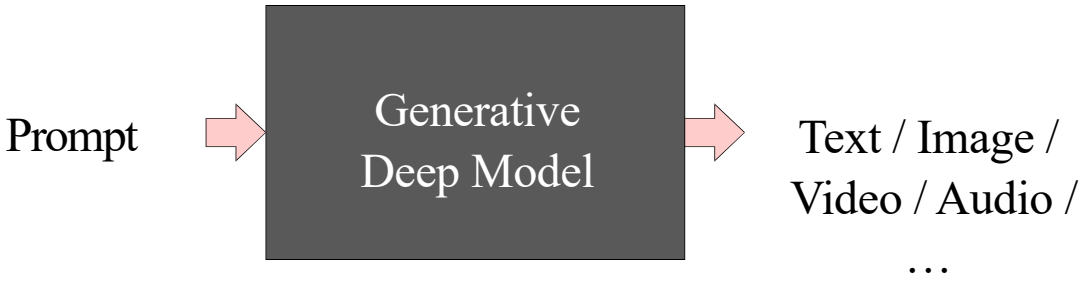
Multi-modal Models

- Using the available large amount of multi-modal data
- CLIP: Learns a multi-modal embedding space by jointly training an image encoder and text encoder
- Zero-shot classification

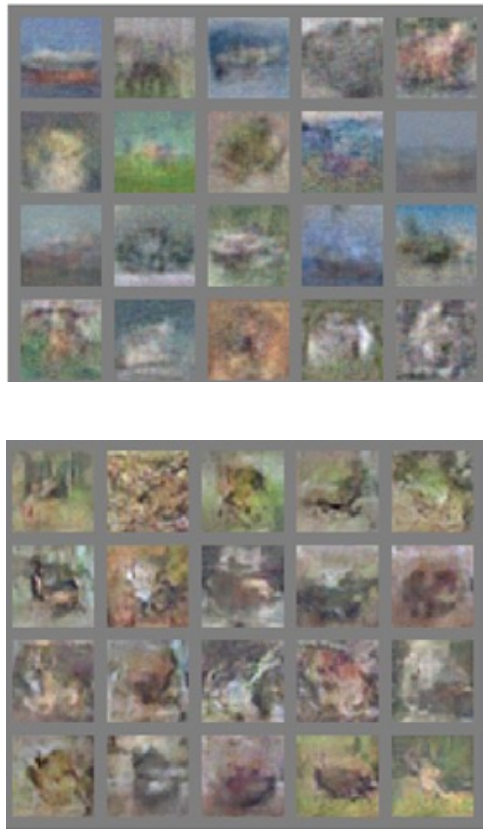
A. Radford, J.W. Kim, et al., “Learning Transferable Visual Models From Natural Language Supervision”, 2021

Generative Models

Output text, image, video, audio, …. given no condition or a partial guidance or prompt

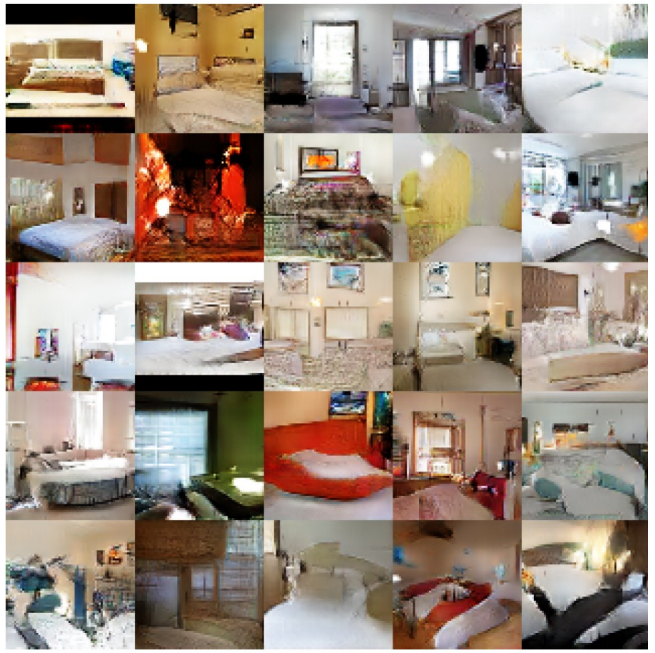


Generate samples by GAN



CIFAR-10

Goodfellow et al., GAN, NIPS 2014



LSUN

Radford et al., DCGAN, ICLR 2016

CelebA

Karras et al., Progressive GAN, ICLR 2018

ImageNet

Brocks et al., BigGAN, ICLR 2019

Denoising Diffusion Models

Emerging as powerful generative models, outperforming GANs

Dhariwal & Nichol, Diffusion Models Beat GANs, OpenAI, 2021

Ho et al., Cascaded Diffusion Models, Google, 2021

DALL-E2 & Imagen

OpenAI DALL·E 2

a teddy bear on a skateboard in times square

[Ramesh et al., Hierarchical Text-Conditional Image Generation with CLIP Latents, 2022]

Google Imagen

A group of teddy bears in suit in a corporate office celebrating the birthday of their friend. There is a pizza cake on the desk.

[Saharia et al., Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding, 2022]

OpenAI GPT3: few-shot and zero-shot learning

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  cheese =>                           ← prompt
```

One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← example
3  cheese =>                           ← prompt
```

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← examples
3  peppermint => menthe poivrée        ←
4  plush girafe => girafe peluche      ←
5  cheese =>                           ← prompt
```

Brown et al., 2020

Large Language Models (LLMs)

- Large language models are one of the most successful applications of transformer models.

- Using massive unlabeled text datasets to learn LLMs (as self-supervised pre-trained models)
  - recognize, summarize, translate, predict and generate text and other content based on knowledge gained from massive datasets.

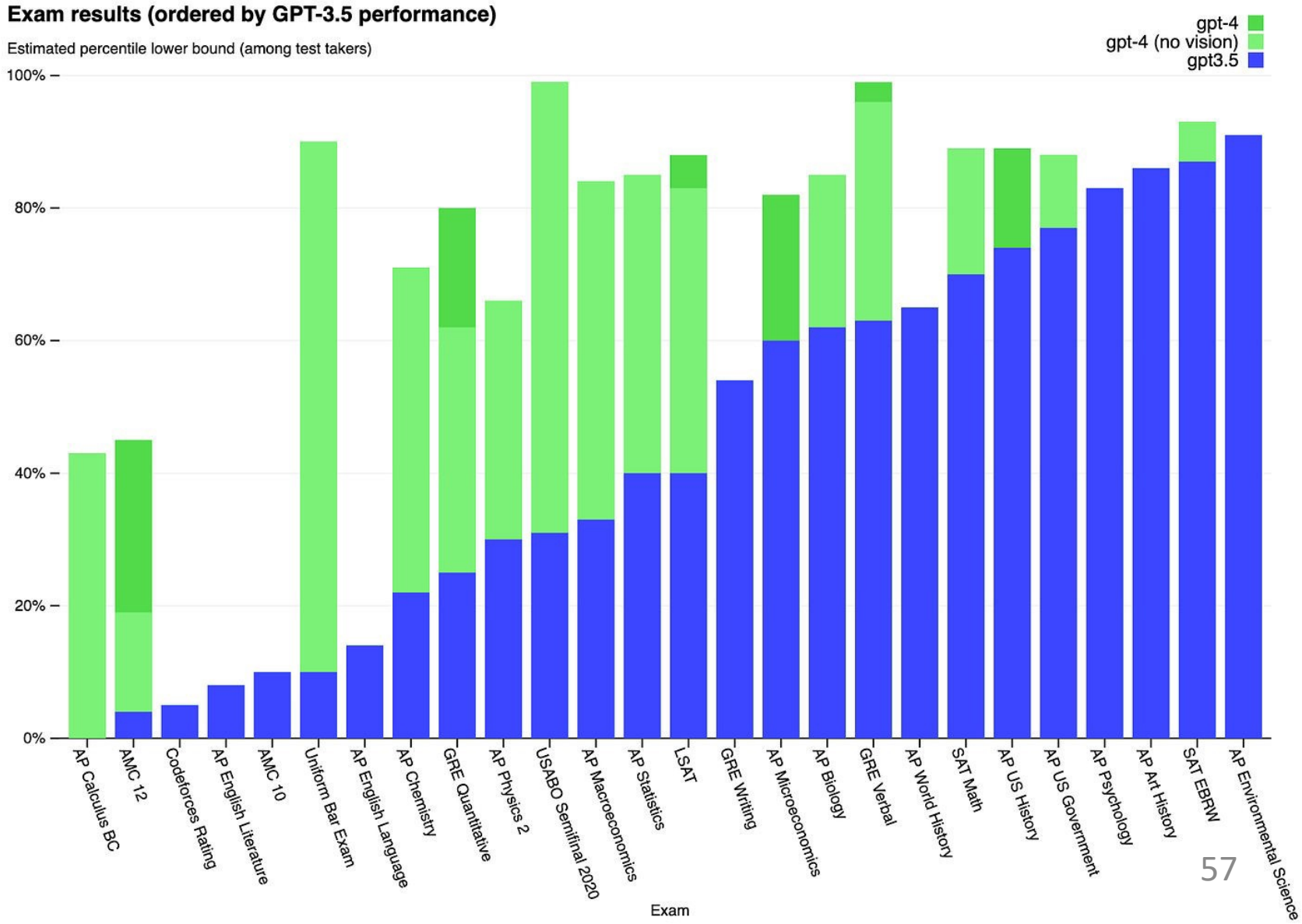
Recent Large Language Models (LLMs)

Conversational generative AI chatbots:

- generate response to a wide range of prompts and questions
- answer questions, translate languages, write different kinds of creative content, generate codes, provide summaries of topics or create stories

Tracking Progress

- How well AI can do human tasks



[OpenAI]

Timeline of Generative Image/text models