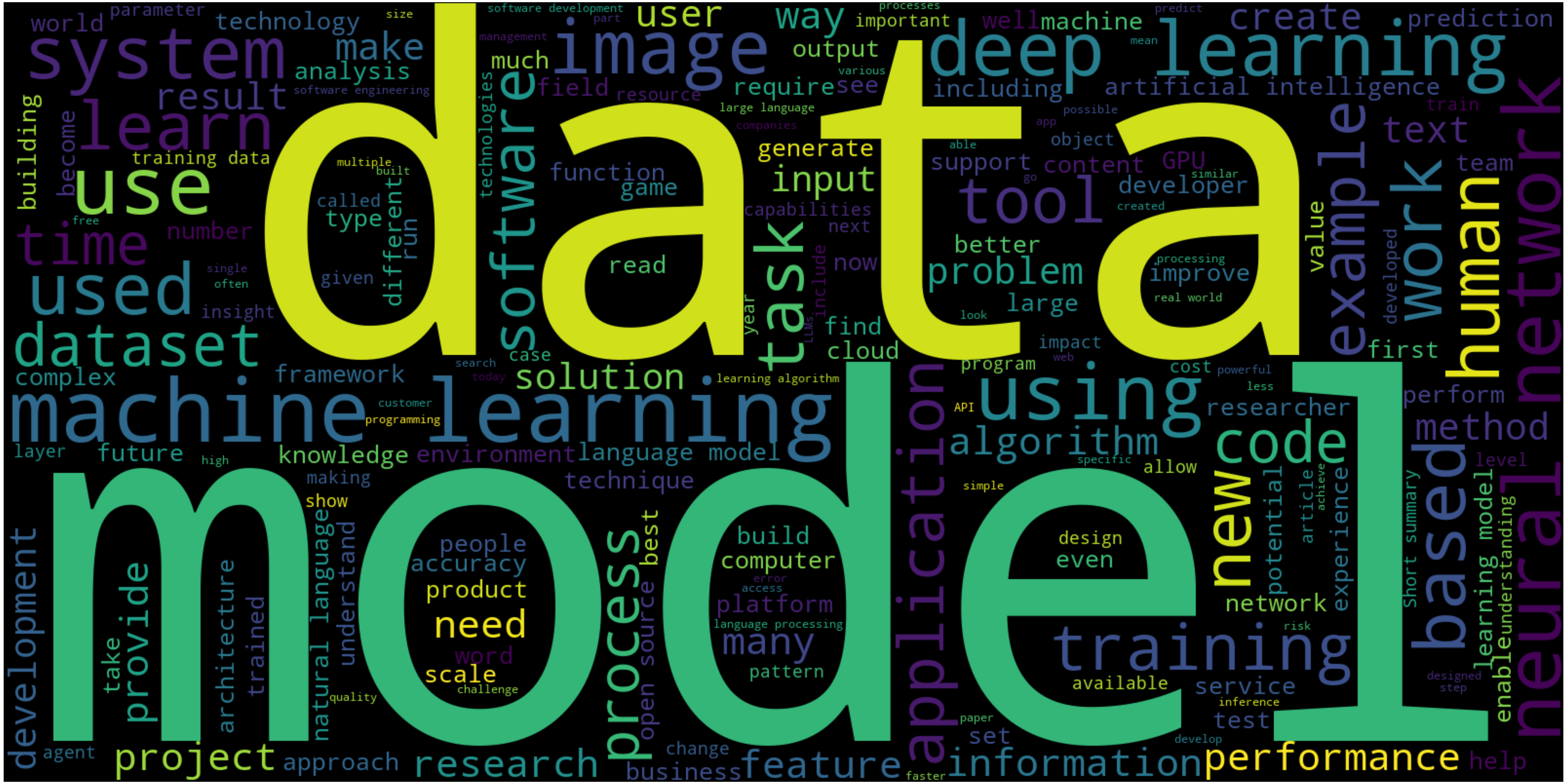
Deep Learning

software 2.0, artificial intelligence

Didier Guillevic
didier.guillevic.net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developed
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web
powerful
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simple
error
access
language processing
quality
challenge
risk
inference
paper
faster
develop
designed
step

Overview

0. Software 2.0

1. Deep Neural Networks

2. Concepts: transfer (meta) learning, tabula rasa, self-supervised

3. Generative AI

    Generative Adversarial Networks (GANs)

    Stable Diffusion Model

4. Natural Language Processing

    Embeddings, neural language model, RNN, LSTM

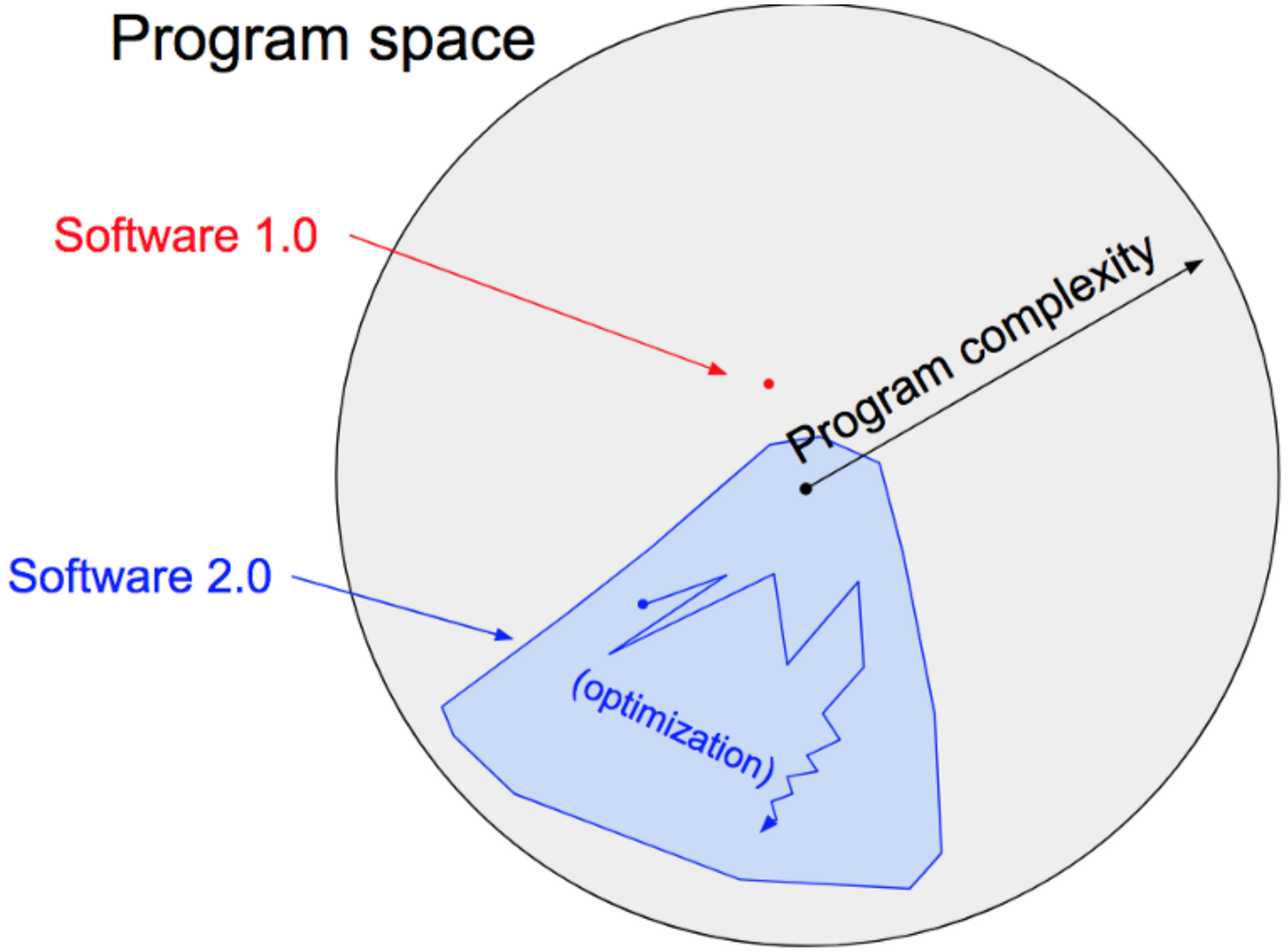
    Attention, transformers, large language model

    Chat LLM: prompt engineering, updates, private documents

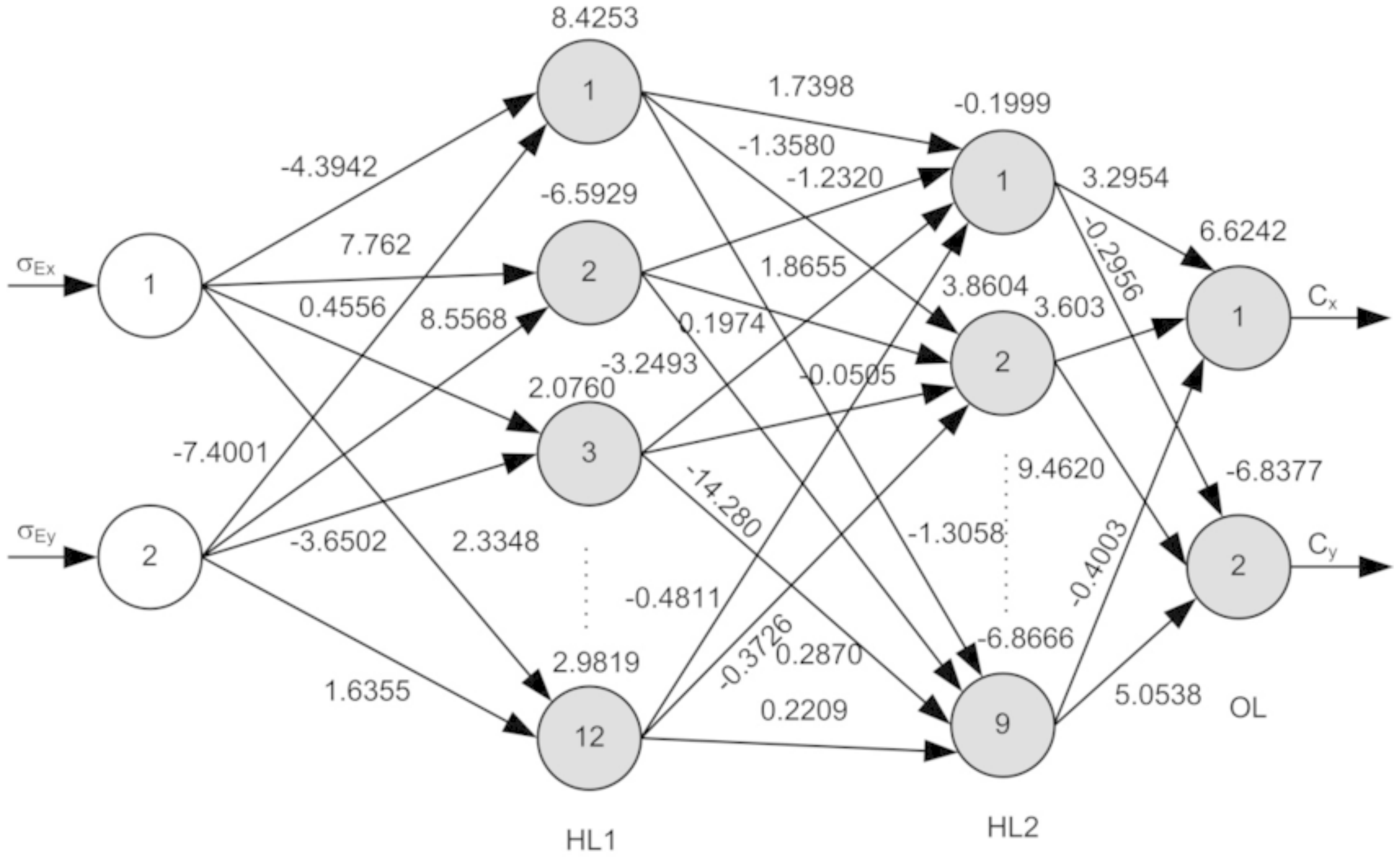
Deep Learning - Software 2.0

Source: Andrej Karpathy (2017-11)

Software 1.0



Software 2.0



Software 2.0 - Applications

Andrej Karpathy (2017-11)

Domain	Software 1.0	Software 2.0
Visual Recognition	Engineered features with a bit of machine learning	Searching the space of Convolutional Neural Network architectures
Speech Recognition	Preprocessing, gaussian mixture models, hidden markov models	Almost entirely neural networks
Speech Synthesis	Various sticking mechanisms	Large Convolutional Neural Networks (e.g. WaveNet)
Machine Translation	Phrase-based statistical techniques	Neural networks (supervised and unsupervised)
Games	Hand-coded Go playing programs	AlphaGo Zero: only uses the game's set of rules and learns strategies by itself
Databases	Indices using B-trees or Hash indexes	Learned Index Structures (using deep learning models) arxiv: 1712.01208, 2006.12804

Software 2.0 - Benefits

Andrej Karpathy (2017-11)

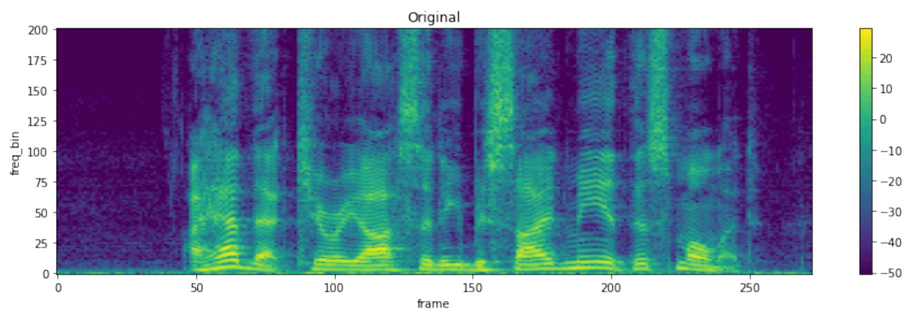
Software 1.0: production-level C++ code base

Software 2.0: Convolutional Neural Network / Transformers

Homogeneous computation	Software 1.0: instruction set of classical software (heterogenous and complex) Software 2.0: matrix multiplication (and thresholding at zero)
Simple to bake in silicon	Easier to make custom ASICs Small inexpensive chips could come with a pre-trained ConvNet
Constant running time	C++ code could have unintended infinite loop Forward pass of a neural network takes exactly the same amount of FLOPS Zero variability
Constant memory use	No dynamically allocated memory as in C++ Little possibility of memory leaks
Highly portable	Sequence of matrix multiplies is easy to run-on arbitrary computational configurations (not the same for binaries)
Very agile	C++: non-trivial to make a system run twice as fast Software 2.0: remove half of the nodes and re-train to get twice the speed OR make program work better by adding more channels (or averaging models)
Melding modules together	Software 1.0: communicates through public functions, APIs, … Software 2.0: two modules trained separately can be connected and the weights adjusted by back-propagation

Deep Learning: State Of The Art (SOTA)

Speech



PyTorch.org

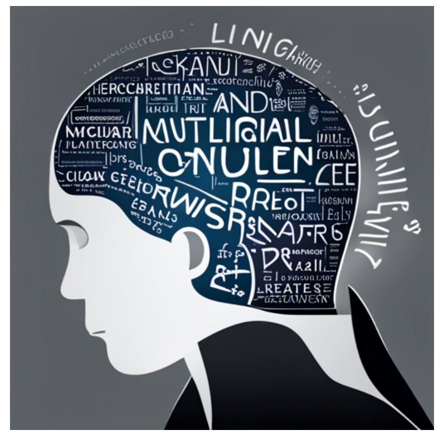
OpenAI [Whisper](#) (2022-09): 680,000 hours of multi-lingual speech

Transcription in multiple languages, any-to-English transcription,
Language identification, phrase-level timestamps

Meta AI [Massively Multilingual Speech (MMS)](#) (2023-05)

Speech-to-text, text-to-speech in 1,100+ languages

Natural Language Processing


Stable Diffusion

Meta AI [No Language Left Behind (NLLB)](#) (2022): translation to/from 200 languages

OpenAI [ChatGPT](#) (2022-11)

Large Language Models: Bloom, Llama, GPT, PaLM, …

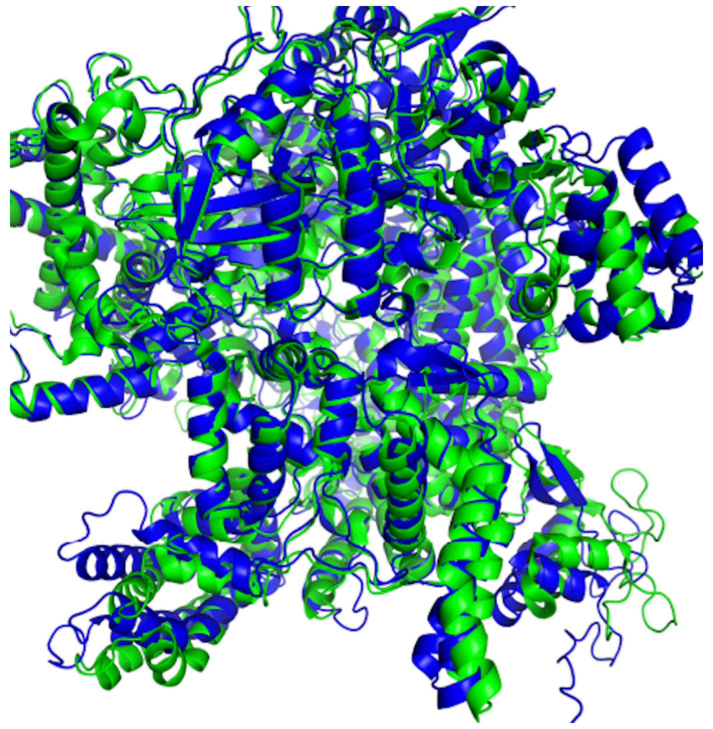
Image / Video


Stable Diffusion

Meta AI [Segment Anything](#) (2022-09)

Medical

Google DeepMind [AlphaFold](#) (2020)



Huggingface.co

Hugging Face | Search models, d | Models | Datasets | Spaces | Docs | Solutions | Pricing

Computer Vision

- Depth Estimation — 52 models
- Image Classification — 3,907 models
- Image Segmentation — 217 models
- Image-to-Image — 134 models
- Object Detection — 420 models
- Video Classification — 138 models
- Unconditional Image Generation — 681 models
- Zero-Shot Image Classification — 138 models

Reinforcement Learning

- Reinforcement Learning — 20,828 models

Natural Language Processing

- Conversational — 2,164 models
- Fill-Mask — 7,013 models
- Question Answering — 4,963 models
- Sentence Similarity — 1,951 models
- Summarization — 1,127 models
- Table Question Answering — 59 models
- Text Classification — 23,166 models
- Text Generation — 12,430 models
- Token Classification — 8,984 models
- Translation — 2,122 models
- Zero-Shot Classification — 137 models

Audio

- Audio Classification — 543 models
- Audio-to-Audio — 155 models
- Automatic Speech Recognition — 8,343 models
- Text-to-Speech — 290 models

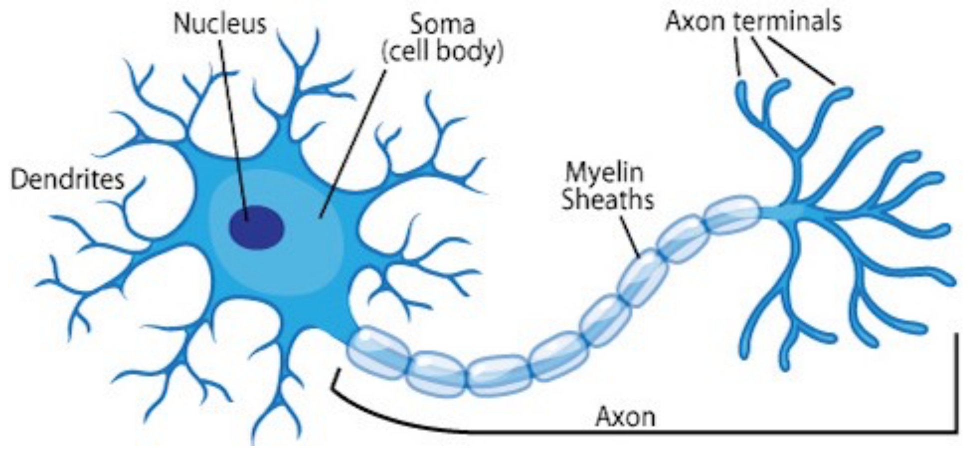
Tabular

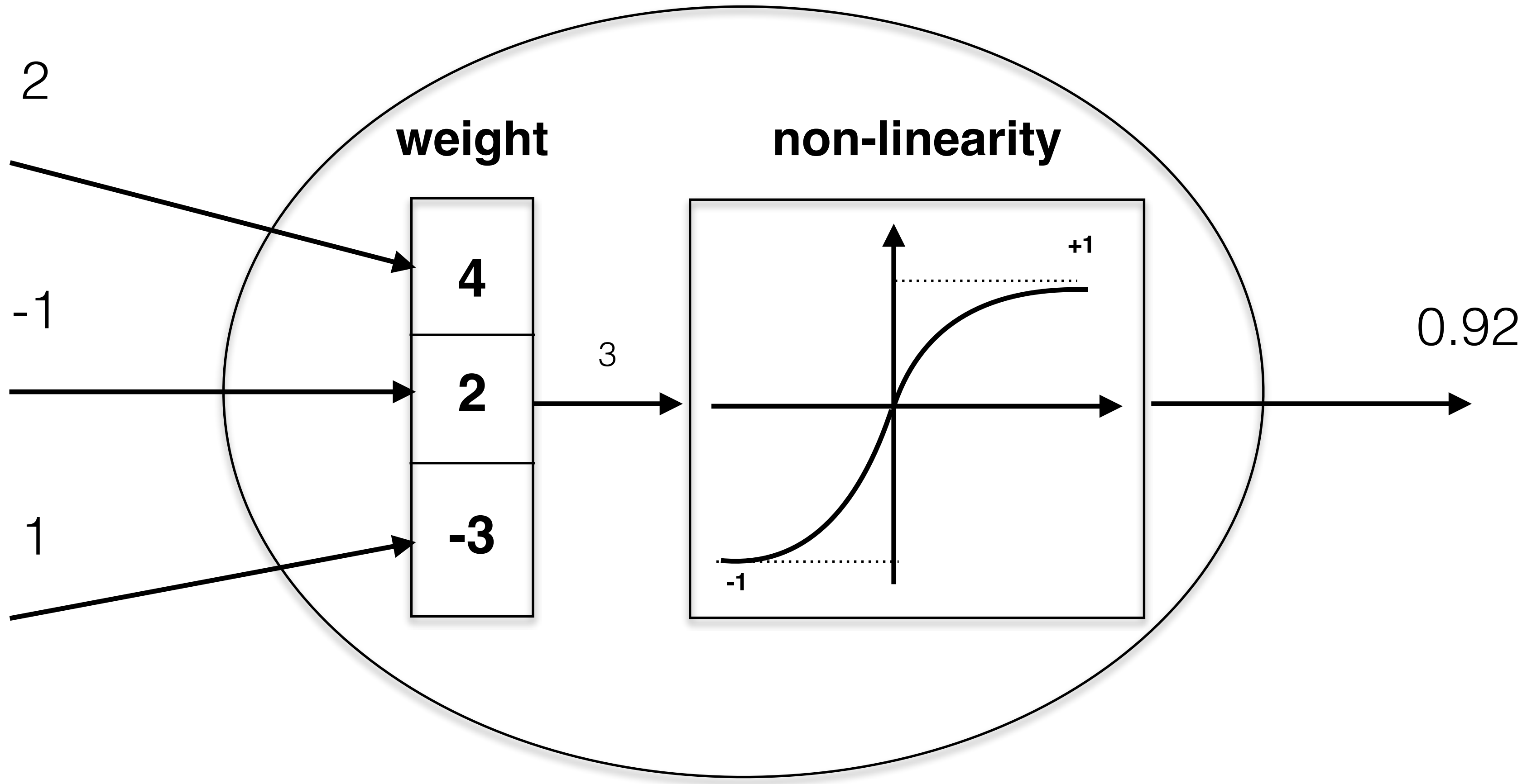
- Tabular Classification — 145 models
- Tabular Regression — 77 models

Multimodal

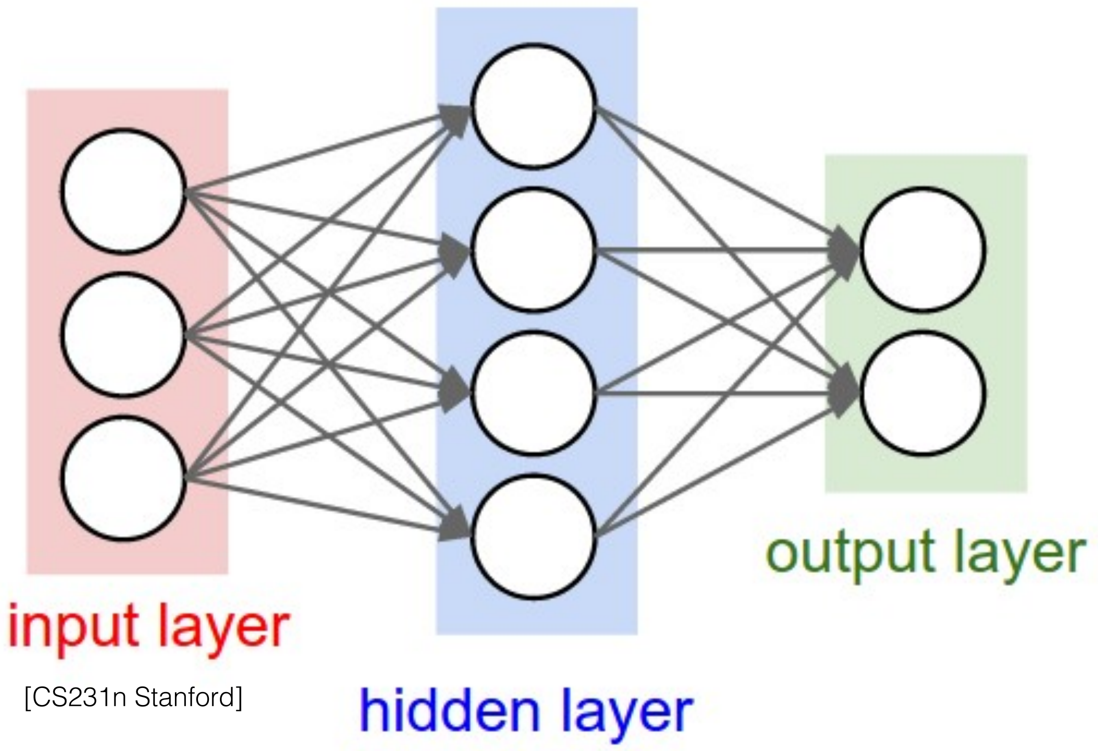
- Document Question Answering — 40 models
- Feature Extraction — 3,892 models
- Image-to-Text — 150 models
- Text-to-Image — 4,278 models
- Contribute
- Text-to-Video — 27 models
- Visual Question Answering — 40 models

Neuron





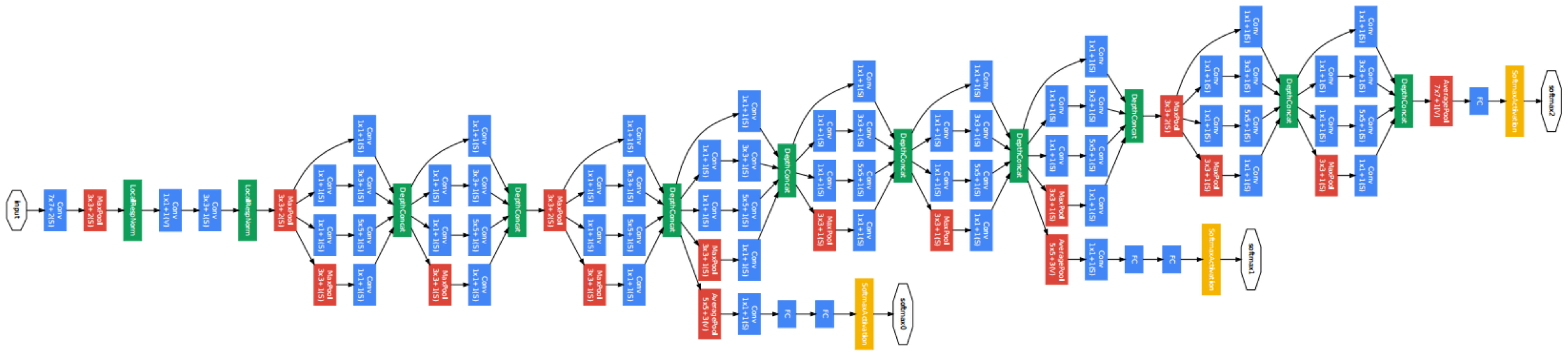
Neural Networks (2 - 5 layers) (until 2006)



[CS231n Stanford]

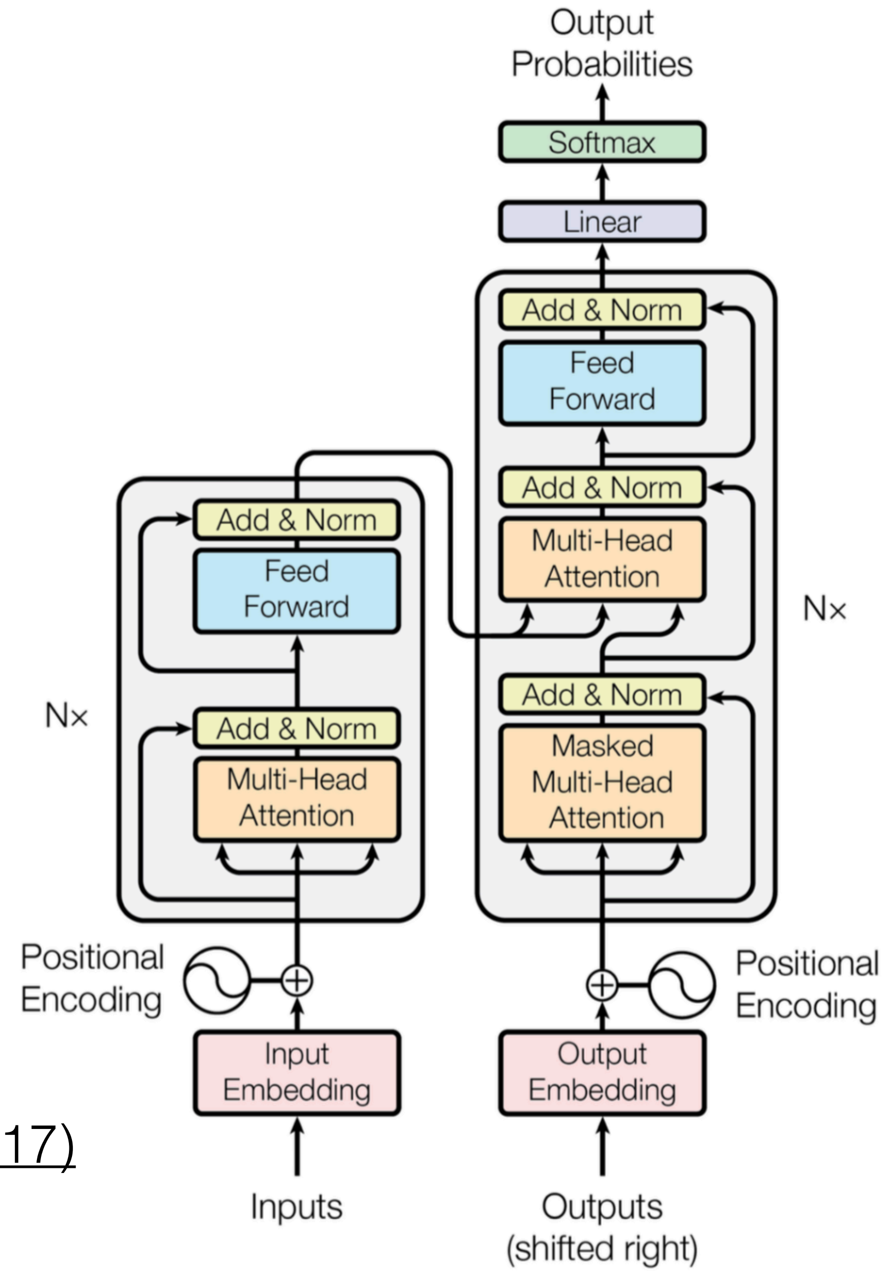
Deep Neural Networks (10 -150 layers)

Convolutional Neural Networks: deep and narrow



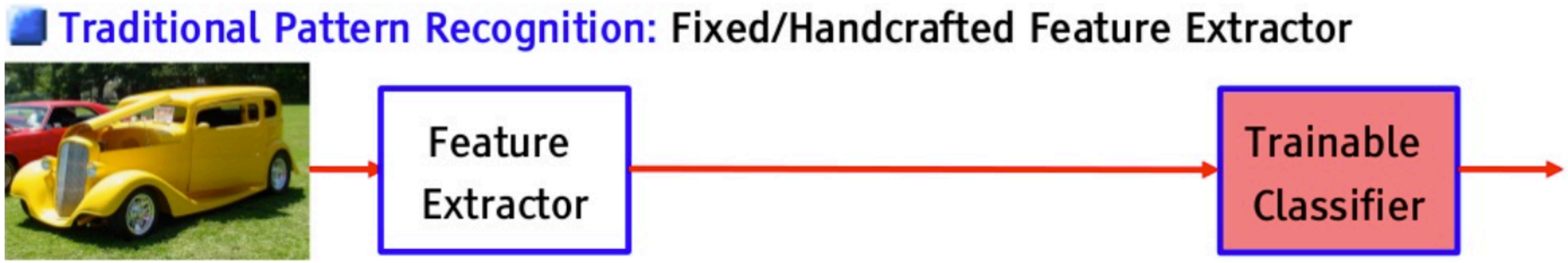
GoogLeNet (2014)

Transformers: “shallow” and wide



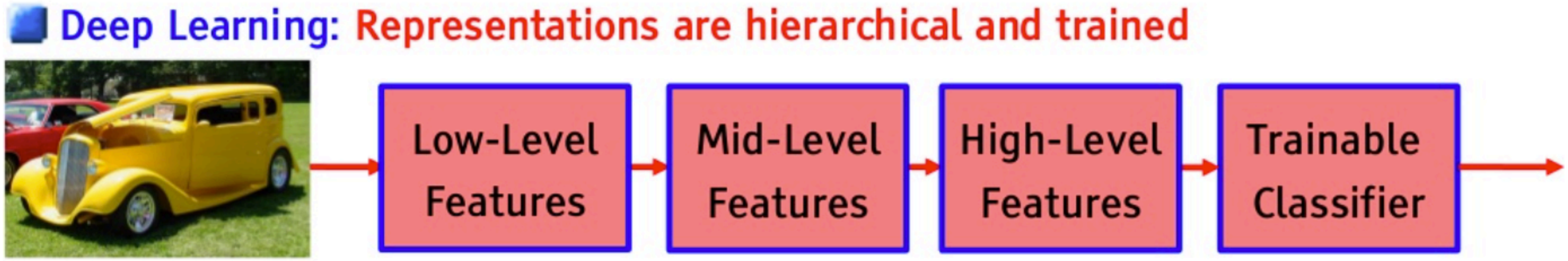
Attention Is All You Need (2017)

Before: Handcrafting features: domain experts: 10s of years

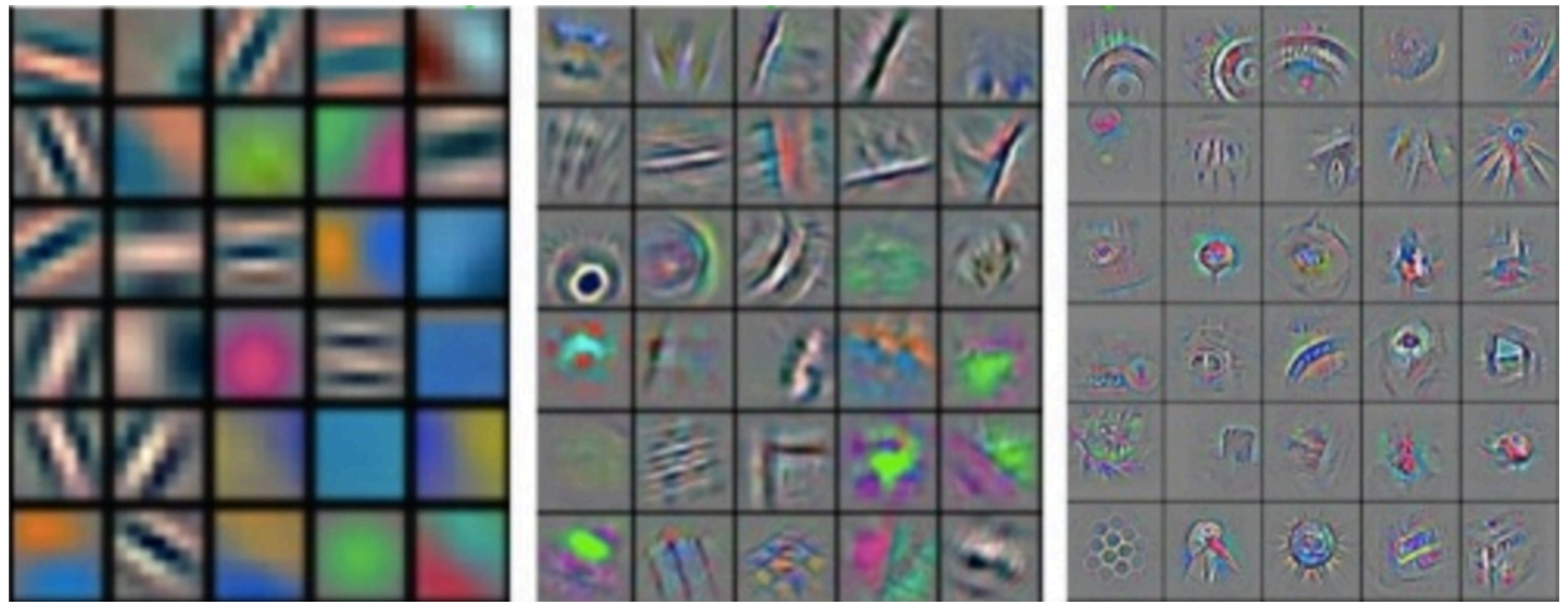


[Yann Le Cun]

Now: Learned features: **End-to-end** Learning



[Yann Le Cun]



[Zeiler & Fergus 2013]

Why only recently (circa 2012)? Why not sooner?

1. A lot more (labeled) data

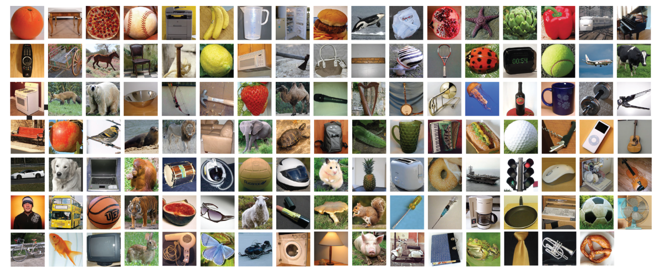
2. A lot more computing power

3. Knowledge on how to train deep networks

1. A lot more (labeled) data

Data

IMAGENET



14 millions images
21000 labels (WordNet)

WIKIPEDIA
The Free Encyclopedia

6 millions articles in the English Wikipedia

Common Crawl

3 billion web pages

Labels

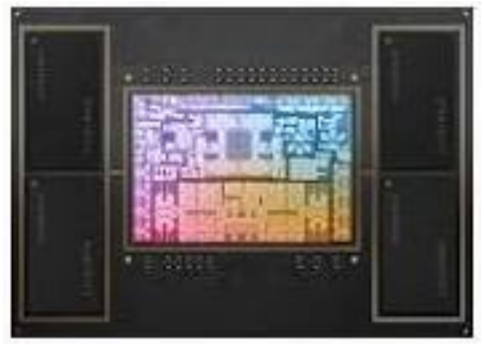
amazon mechanical turk

Low-cost global, 24x7 workforce

reCAPTCHA

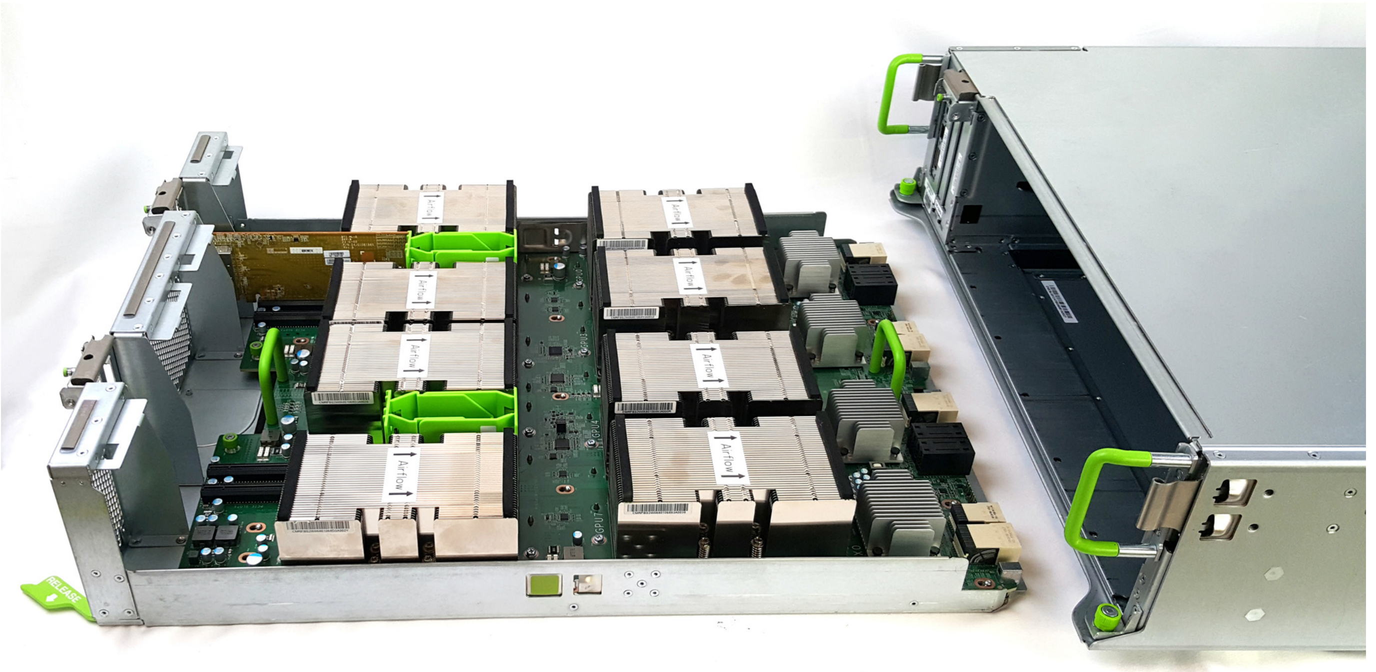
Free global, 24x7 workforce

scale.com



[Apple M2]

[NVIDIA A100]



aws

Google Cloud

Microsoft Azure

CPUs: 20 cores

GPUs: 6000 cores

Facebook Big Basin (2017)

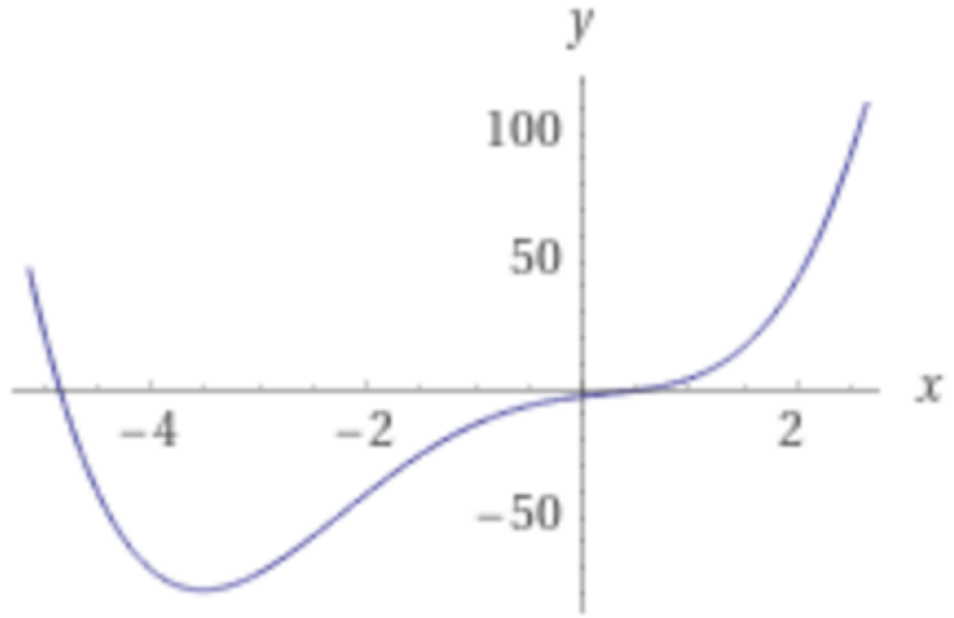
Distributed Computing

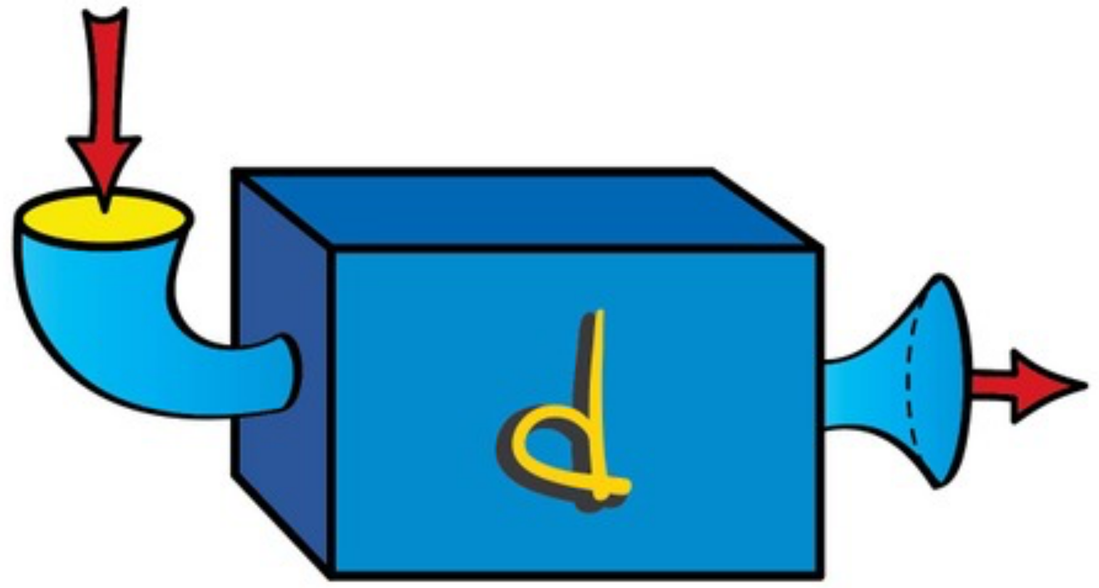
Platforms

PyTorch

3. Knowledge on how to train deep networks

Learning using <u>(Stochastic) Gradient Descent</u> ("going downhill")

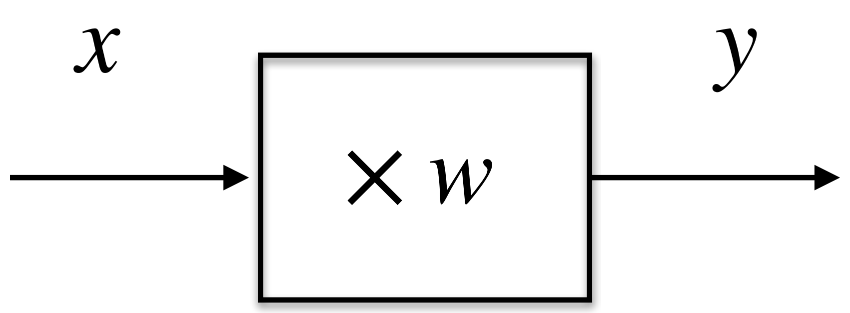




[<u>Robert Ghrist</u> - Calculus - U. of Penn]

$$\frac{\texttt{change in output}}{\texttt{change in input}} = \frac{\mathbf{dy}}{\mathbf{dx}} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{(x+h) - x} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

$$f(x+h) = f(x) + \mathbf{d}h$$



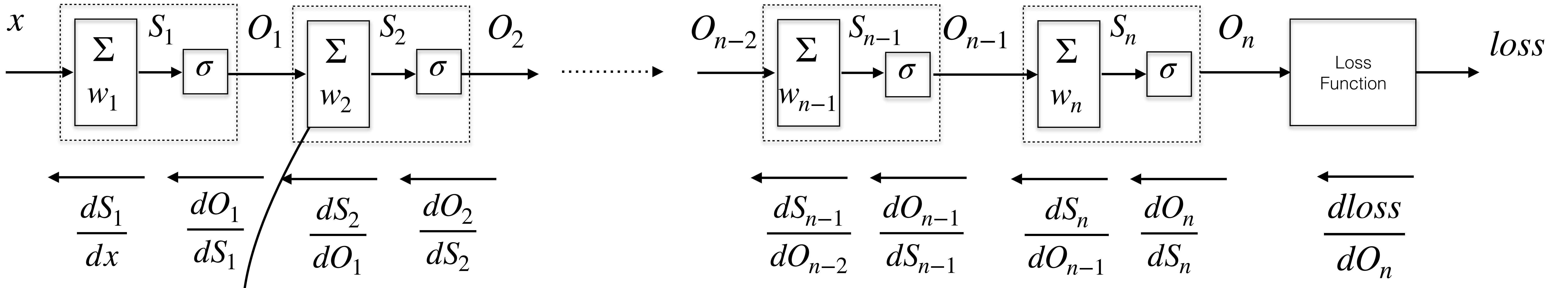
$$y = xw$$

$$(\ x + \underline{\mathbf{h}}\ )\ w = xw + \underline{\mathbf{h}}w \longrightarrow \frac{dy}{dx} = w$$

$$x\ (\ w + \underline{\mathbf{h}}\ ) = xw + x\underline{\mathbf{h}} \longrightarrow \frac{dy}{dw} = x$$

$$w_{new} = w_{old} - learning\_rate * \frac{dy}{dw}$$

<u>Chain rule</u> of gradients (multiplicative)



$$w_{2new} = w_{2old} - lr * \frac{dloss}{dw2}$$

$$w_{2new} = w_{2old} - lr * \frac{dloss}{dO_n} * \frac{dO_n}{dS_n} * \frac{dS_n}{dO_{n-1}} * \frac{dO_{n-1}}{dS_{n-1}} * \frac{dS_{n-1}}{dO_{n-2}} * \ldots * \frac{dO_2}{dS_2} * O_1$$

$$w_{2new} = w_{2old} - lr * 10 * 10 * 10 * 10 * 10 * \ldots * 10 * 10 \quad \approx w_{2old} - lr * \infty$$

Exploding gradient

$$w_{2new} = w_{2old} - lr * 0.10 * 0.10 * 0.10 * \ldots * 0.10 * 0.10 \quad \approx w_{2old} - lr * \mathbf{0.0}$$

Vanishing gradient

$\Rightarrow$ We want all terms to have a norm centred around 1.0 (<u>normally distributed</u>)

⇒ We want the norm of all terms to follow a normal distribution (mean 0, standard deviation 1)

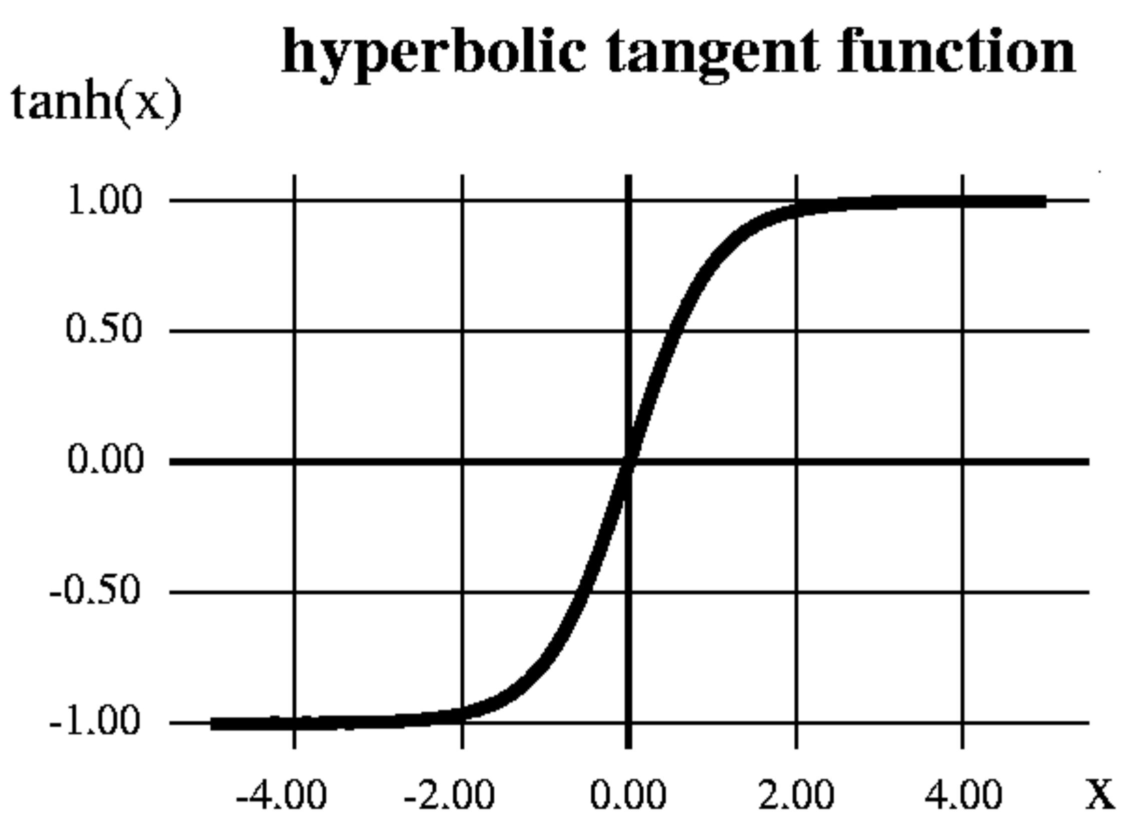
Weight initialization: inversely proportional to number of inputs (e.g. Xavier's initialization scheme)

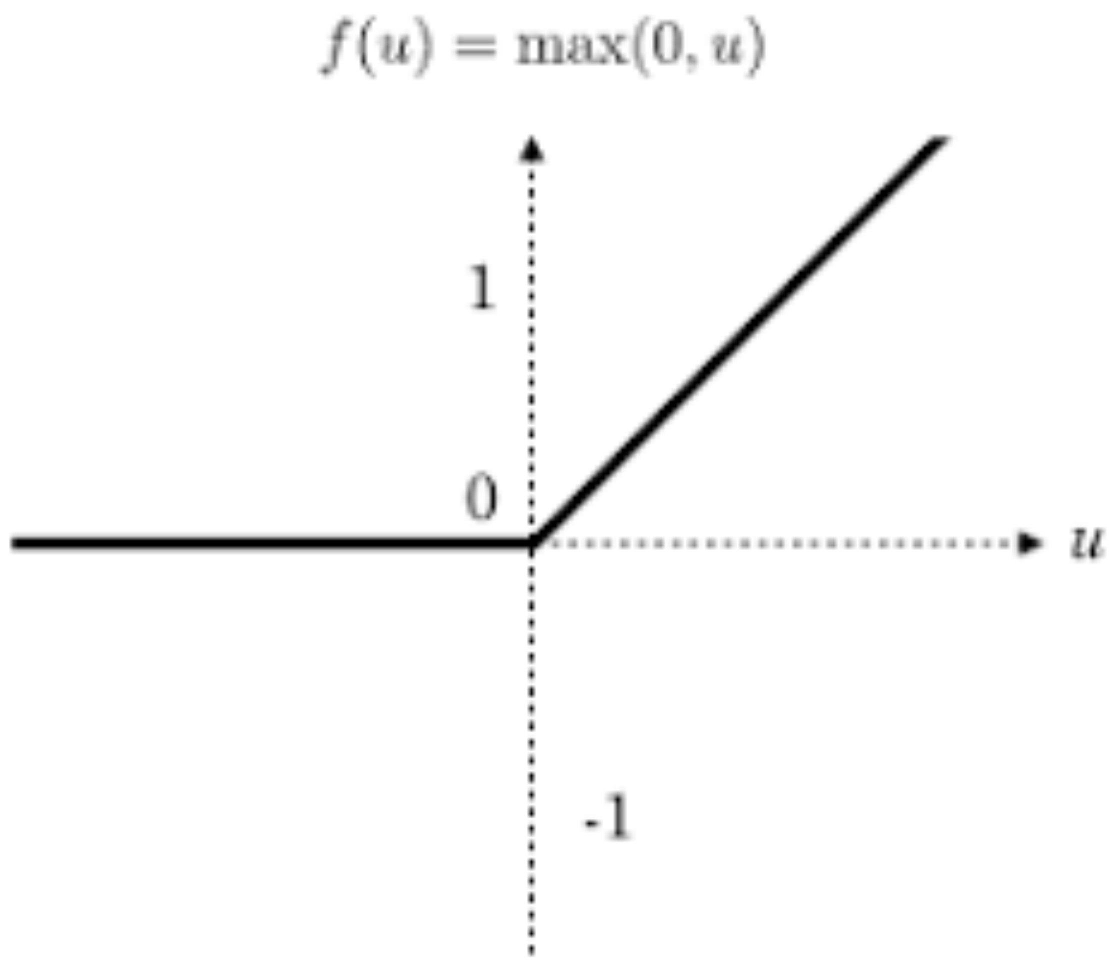
$$S = w_1 * x_1 + w_2 * x_2 + w_3 * x_3 + \ldots + w_n * x_n$$

BatchNorm: scales inputs at each layer to be centred around 0.0 with variance 1.0 (unit Gaussian)

LayerNorm

Non-linearity function: sigmoid have zero gradients —> use ReLU





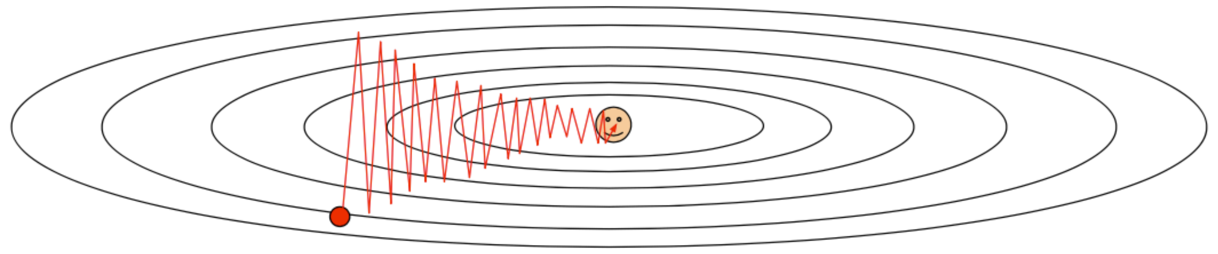
DropOut: randomly ignore some neurons during training

Update rule:

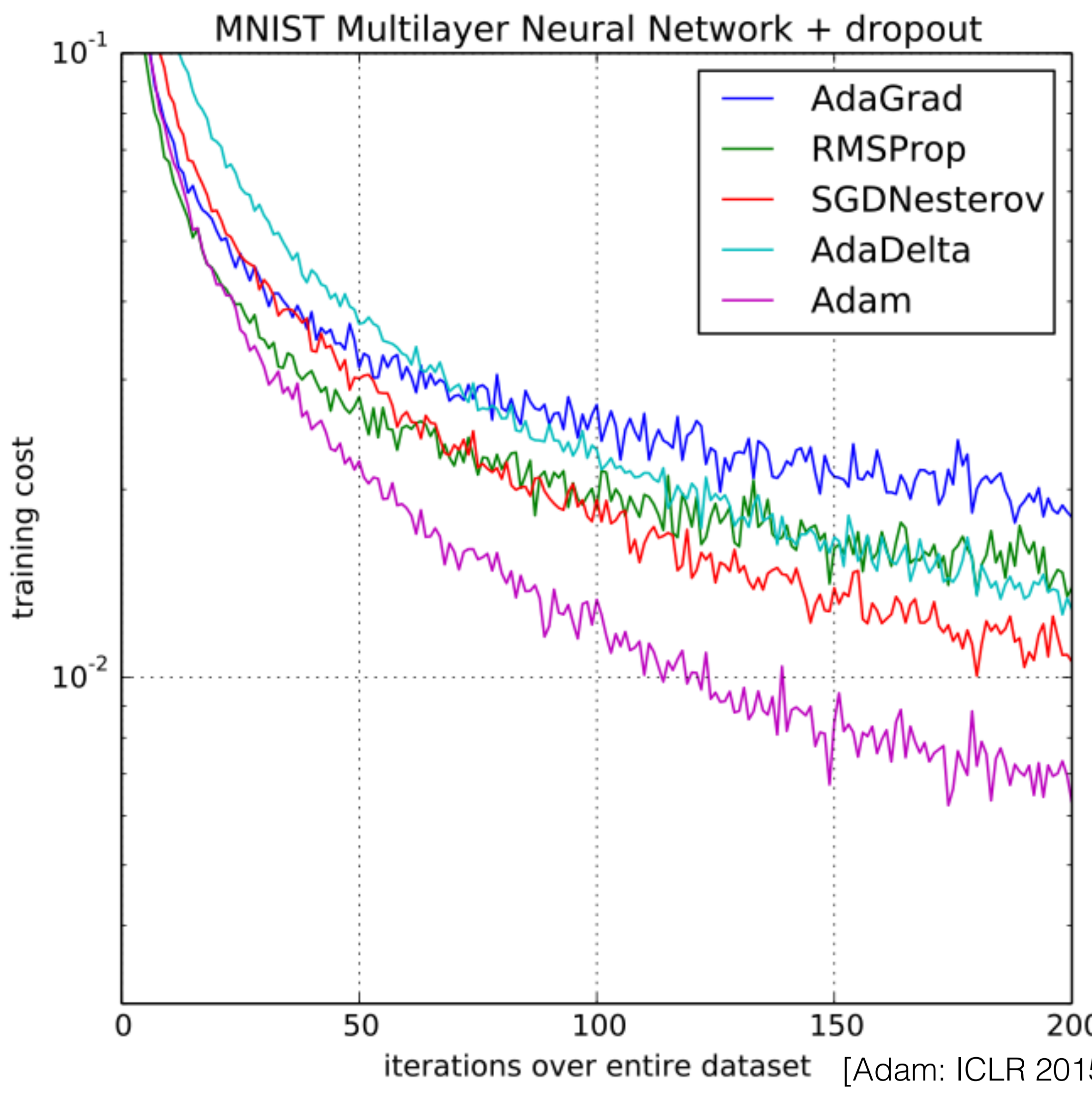
Vanilla update: $w = w - learning\_rate * dw$

Adam update: $w = w - learning\_rate * mb/(sqrt(vb) + eps)$

(Per parameter adaptive learning rate methods with momentum)



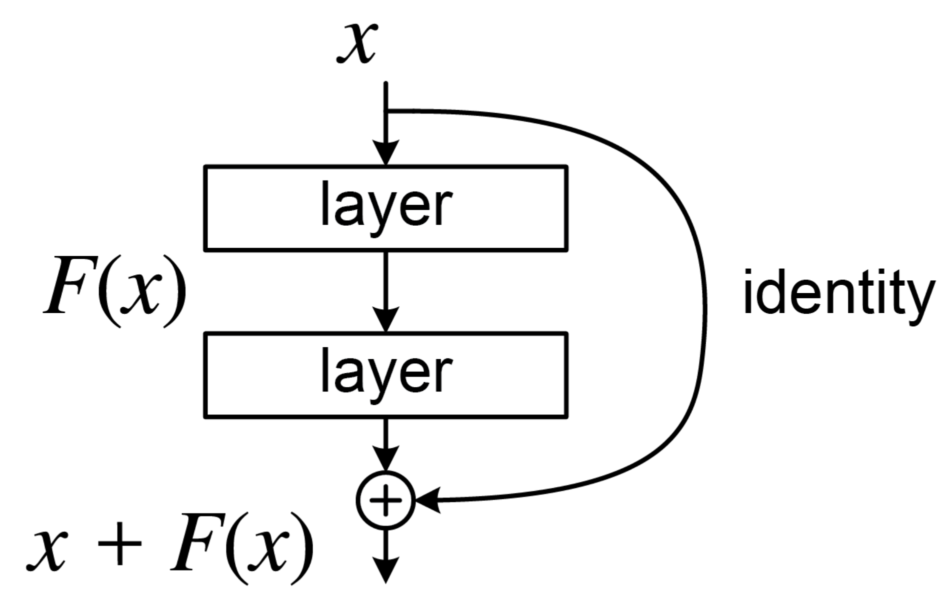
[CS231n - Stanford]

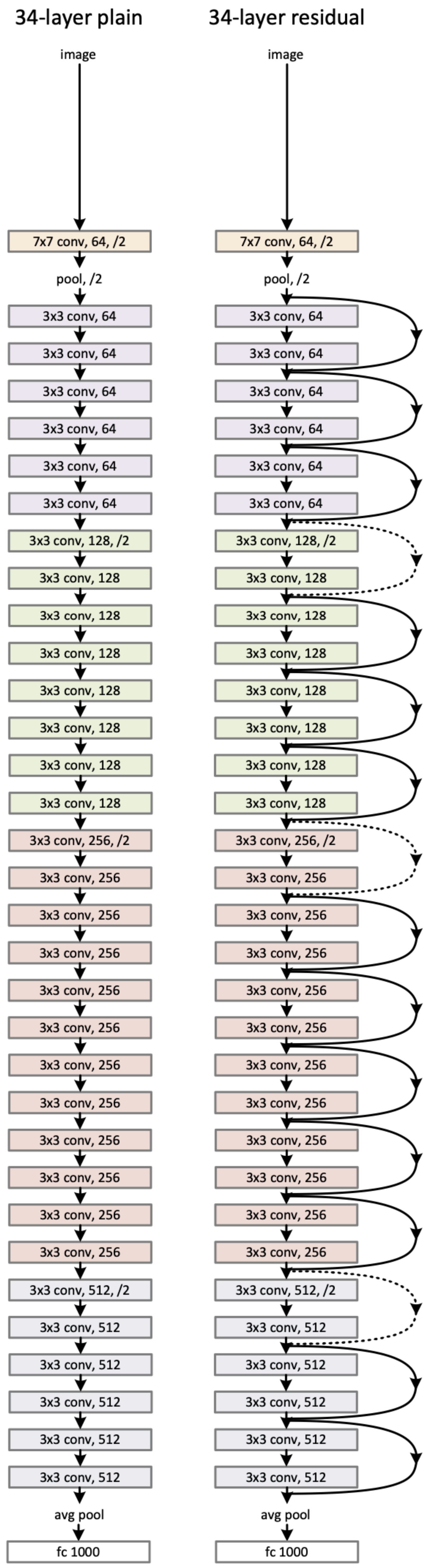


[Adam: ICLR 2015]

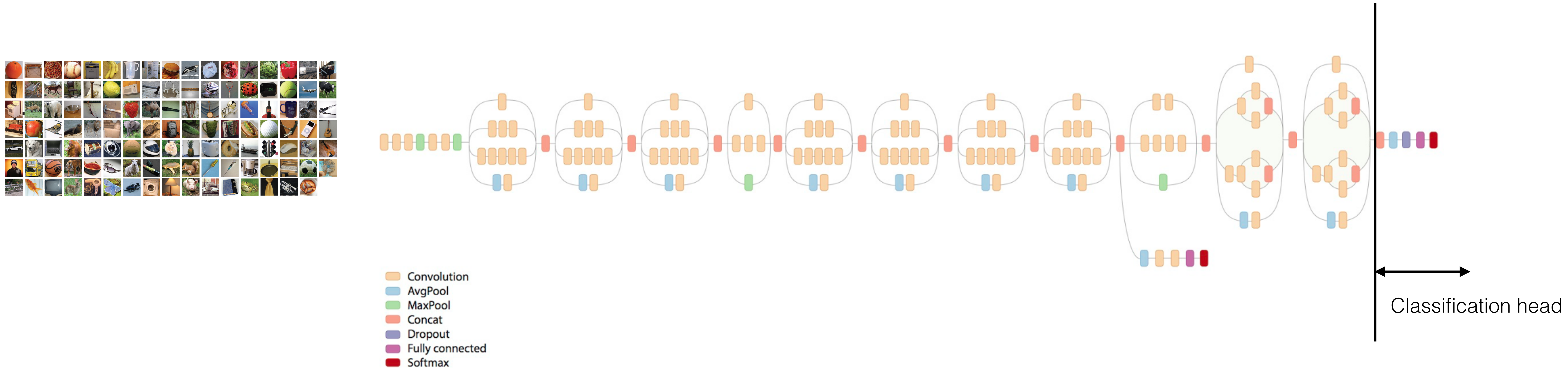
Residual (skip) networks

[Deep Residual Learning for Image Recognition - Microsoft 2016]

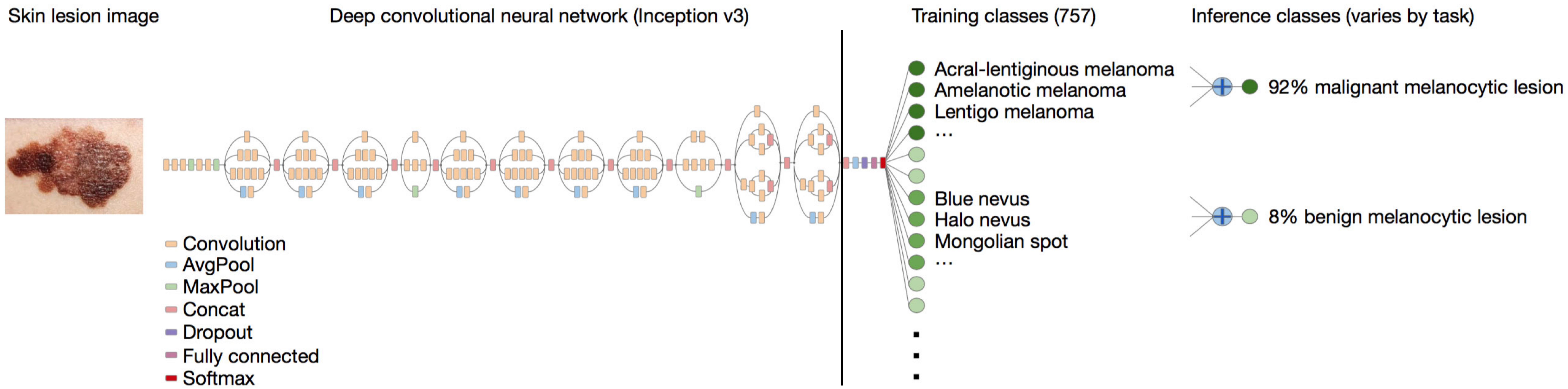




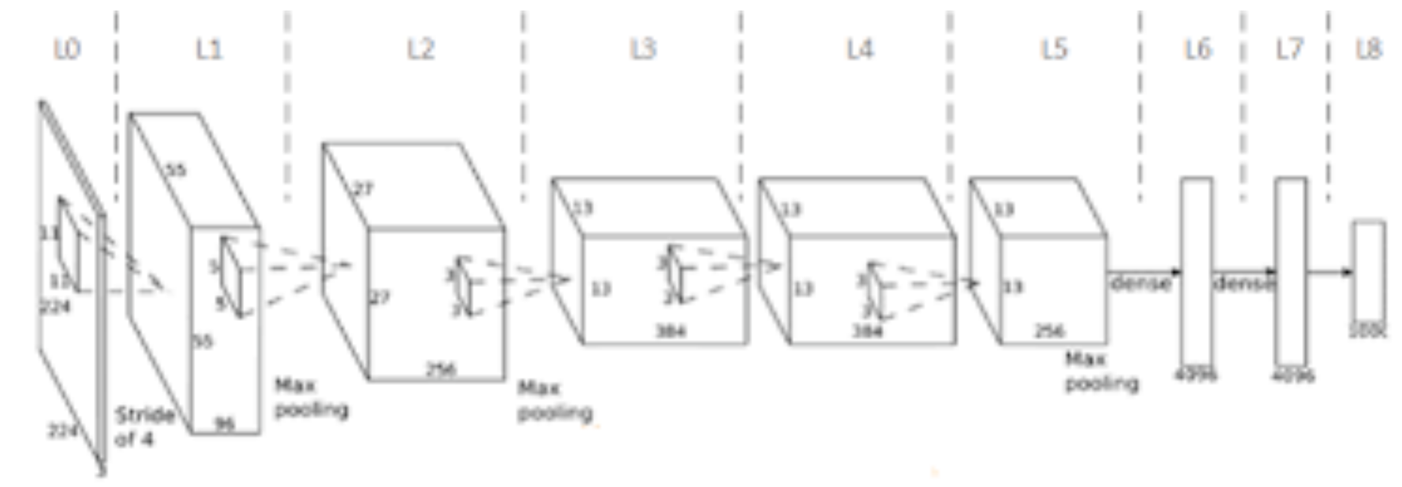
1. Take a model pre-trained on ImageNet (e.g. available on HuggingFace.co); i.e. Inception V3 model

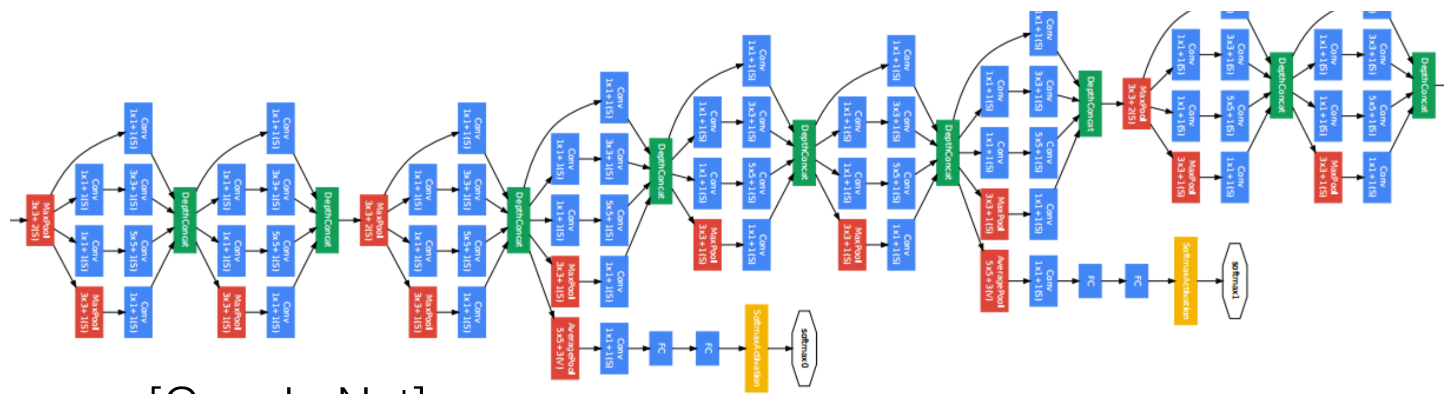


2. Replace classification head and re-train on new smaller smaller data set

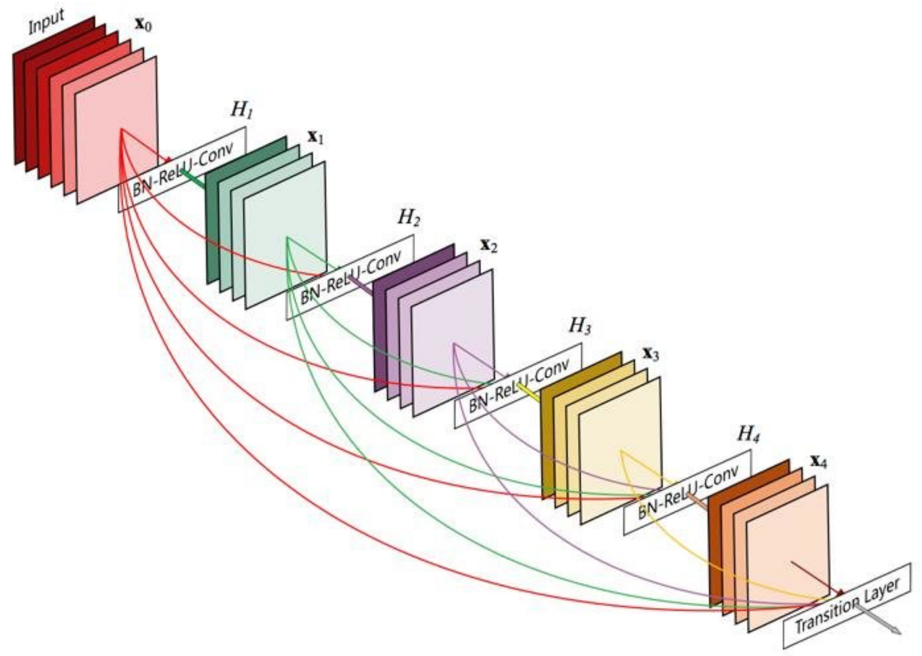


[Andre Esteva - Stanford - Skin Cancer Classification with Deep Learning - 2017]

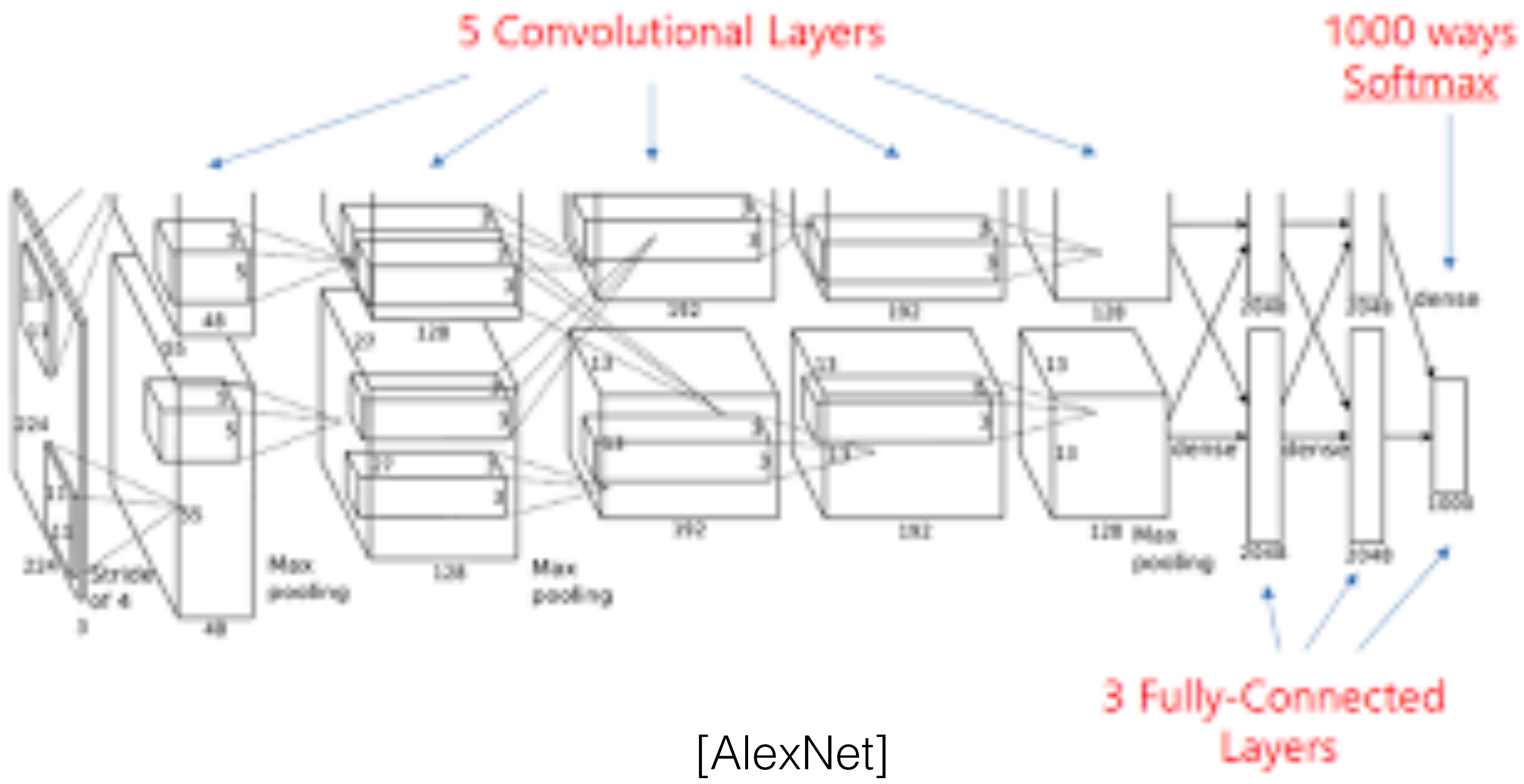




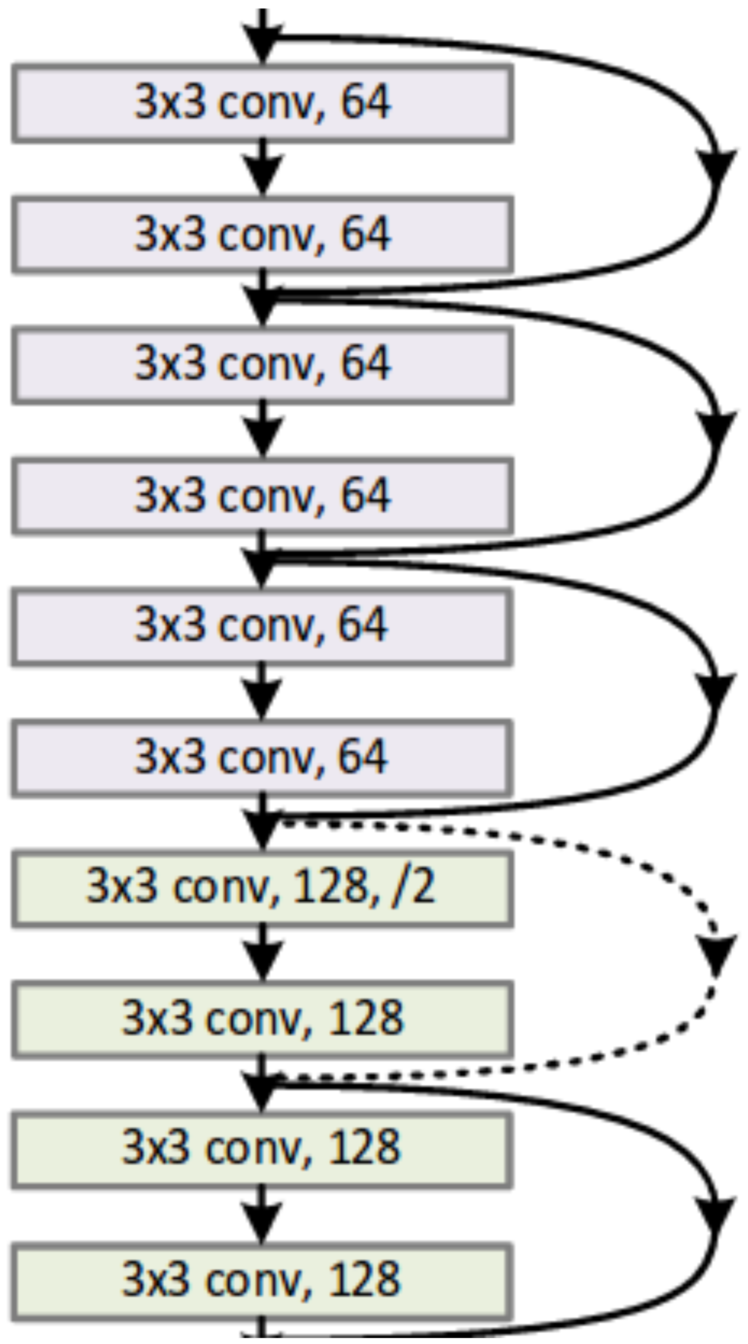
[GoogLeNet]



[DenseNet]



[AlexNet]



[ResNet]

Manual task: search for optimal model architecture for given dataset

Time consuming - performed by skilled professionals

Efficient Neural Architecture Search (NAS - ENAS) (2018)

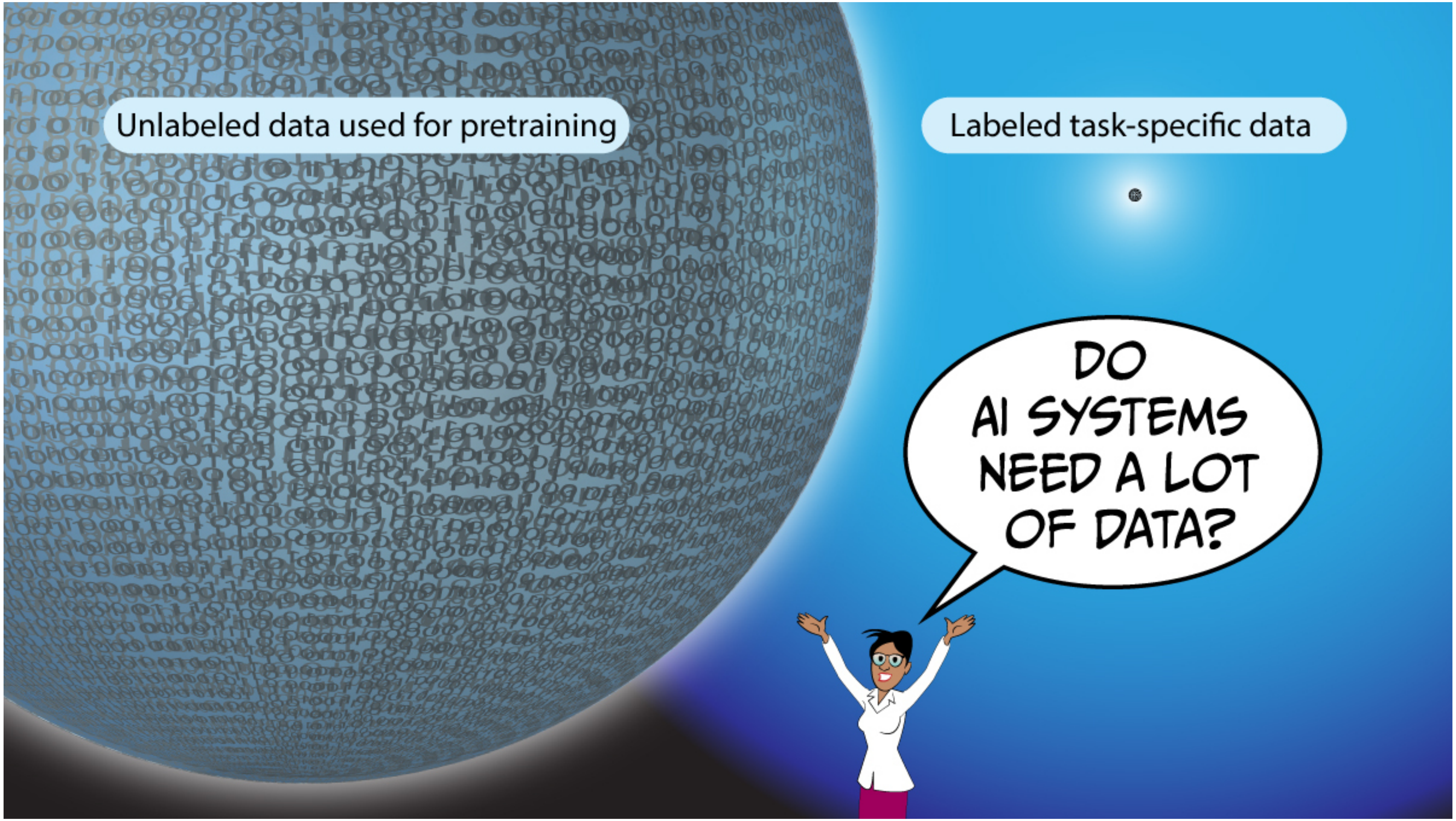
Google AutoML: cloud.google.com/automl

- Transfer learning + Neural Architecture Search
- Network built layer-wise in search for optimal perforr

Efficient Neural Architecture Search via Parameter Sharing

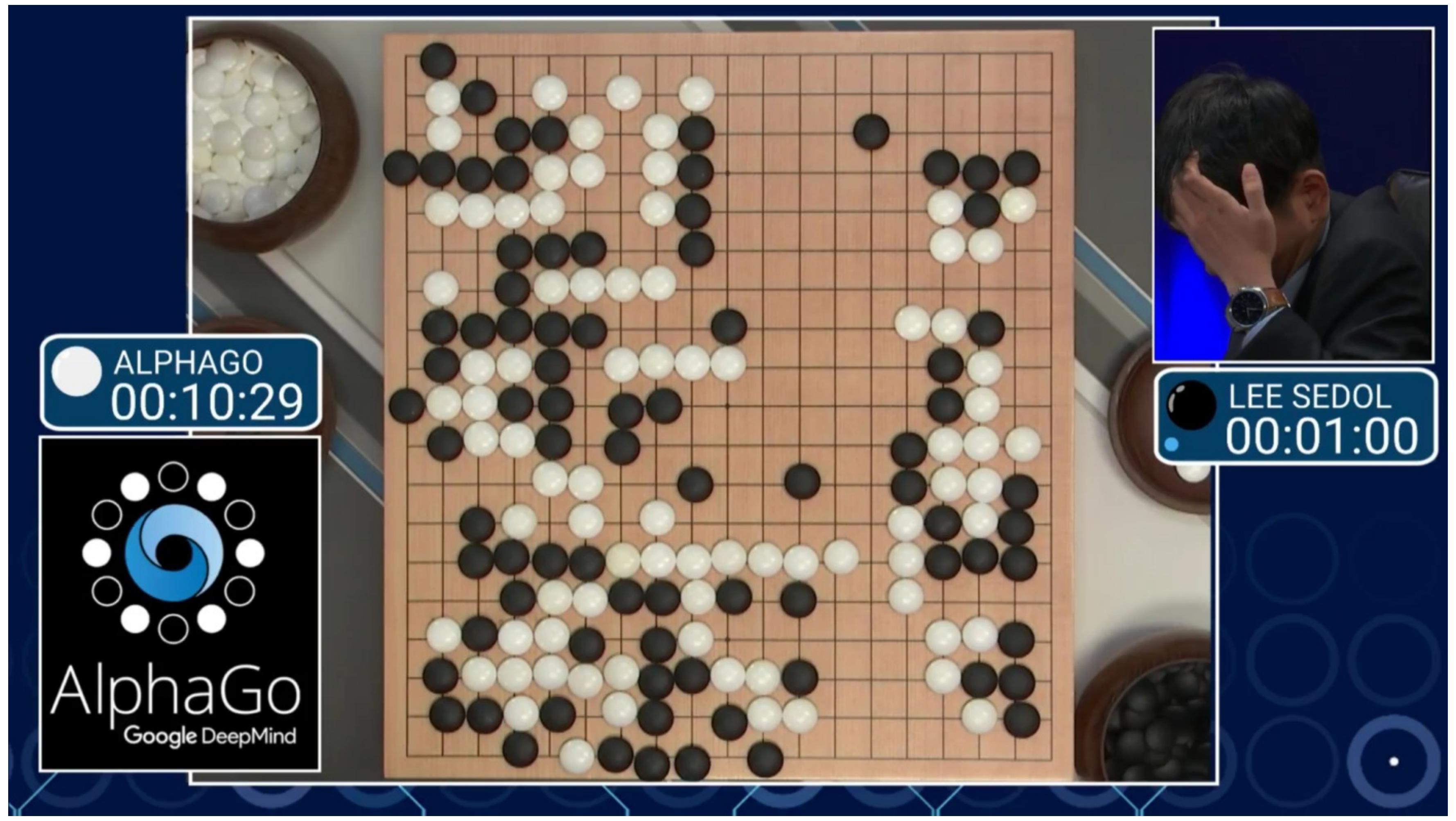
Hieu Pham [*1 2] **Melody Y. Guan** [*3] **Barret Zoph** [1] **Quoc V. Le** [1] **Jeff Dean** [1]

Self-supervised (pre-)training



[The Batch 2023-05]

Towards **unsupervised** (self-supervised) learning



AlphaGo (2015)

- Data: Use thousands of games
- Handcrafted features
- Networks: 2 (policy + evaluation)
- Rollouts: fast random games to predict moves
- Big Data, Big Processing Power

AlphaGo Zero (2017)

- Data: **None**
- Handcrafted features: **None**
- Networks: 1
- Rollouts: **None** (computed by network)
- No Data, Less Processing Power
- Better algorithms better than power and data
- Not constrained by limits of human knowledge

deepmind.com/blog/alphago-zero-learning-scratch/

Generative Adversarial Networks (GANs) - 2014

Generative Adversarial Nets

Ian J. Goodfellow, Jean Pouget-Abadie,[*] Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair,[†] Aaron Courville, Yoshua Bengio[‡]
Département d'informatique et de recherche opérationnelle
Université de Montréal
Montréal, QC H3C 3J7

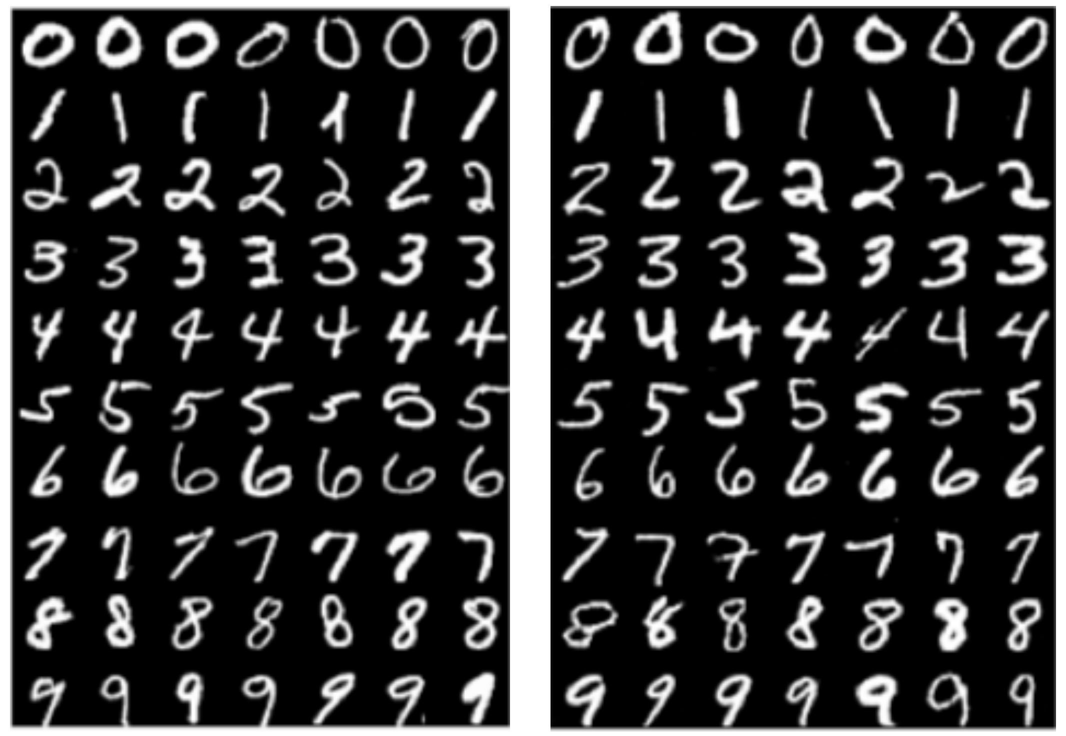
Karras et al. (NVIDIA) - ICLR 2018

Elgammal et al. ICCC 2017

https://arxiv.org/abs/1406.2661

- Fashion industry: Alibaba, Amazon, …

Yanghua Jin et al. - 2017



Real (MNIST) Generated

Alec Radford et al. - ICLR 2016

- Music generation,

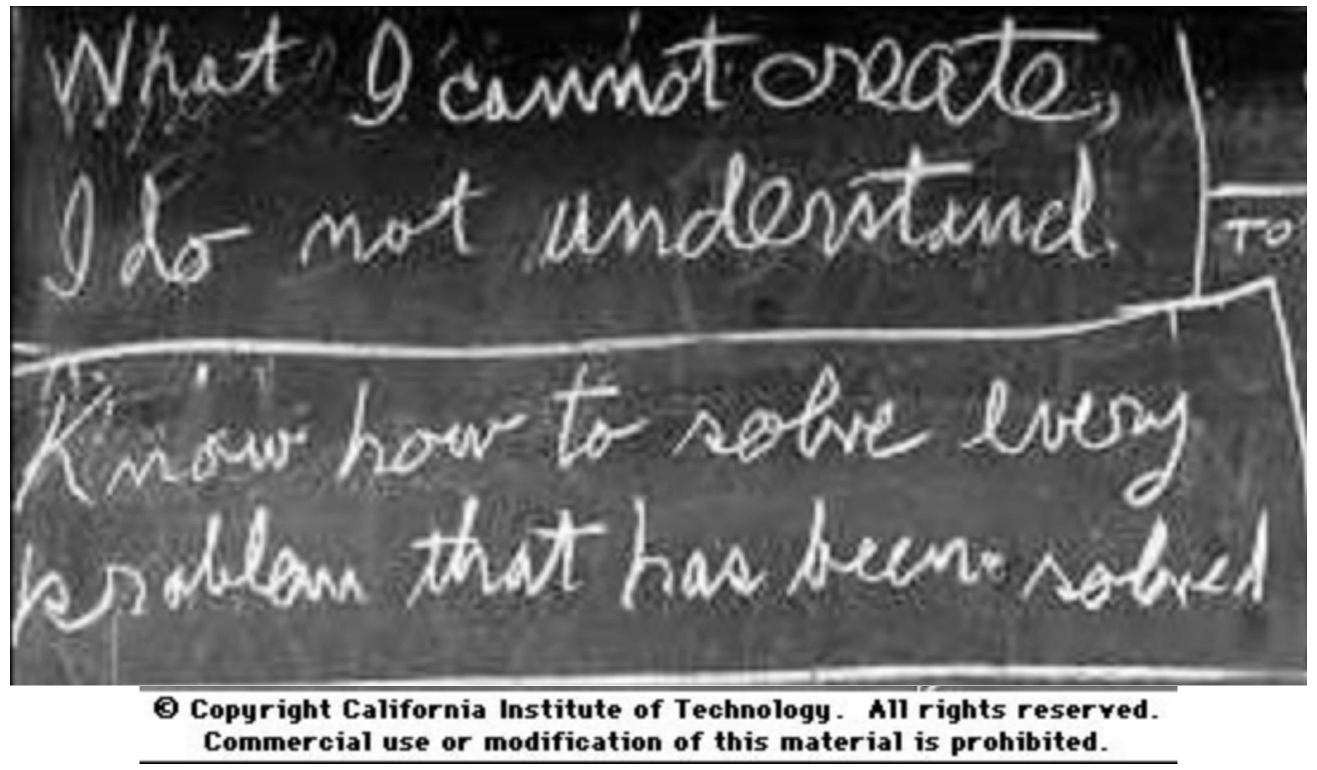
Only two real images (Spolier: Row 1, C and Row 2, D) Vue.ai

(b) Handbag images (input) & **Generated** shoe images (output)

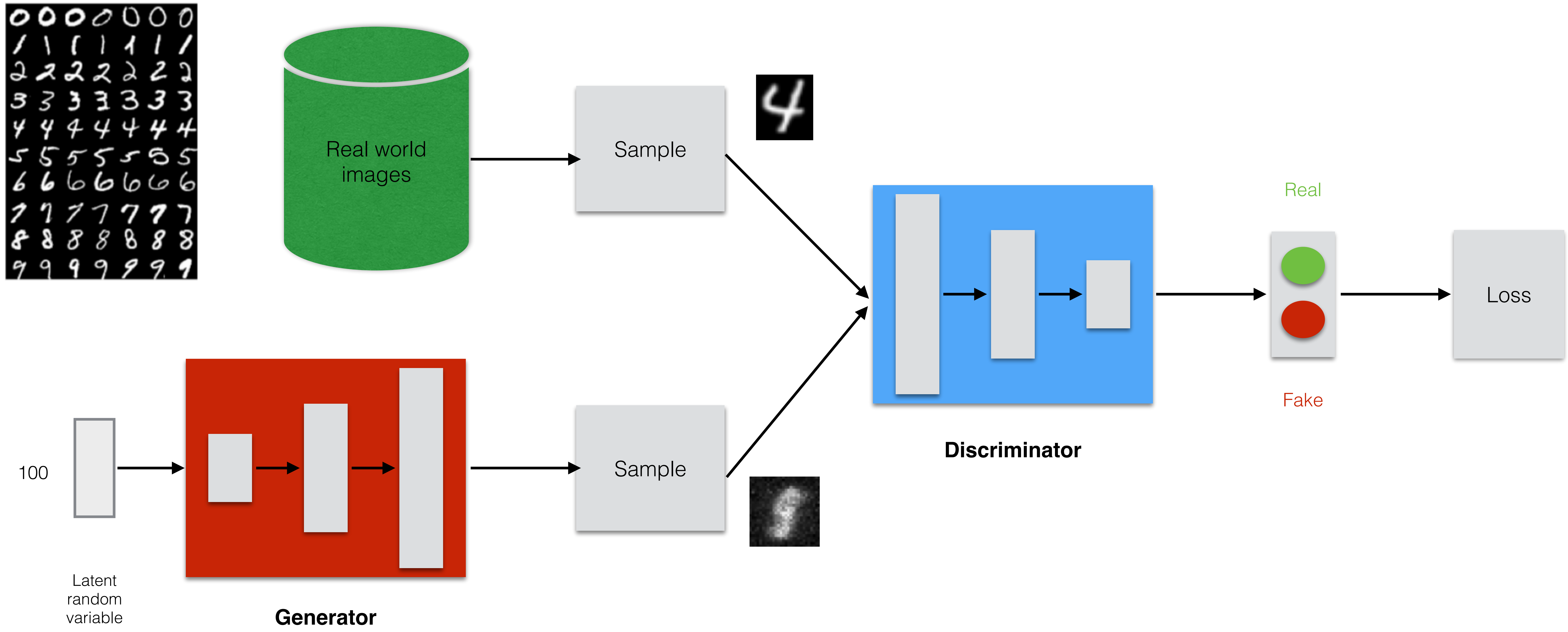
DiscoGAN

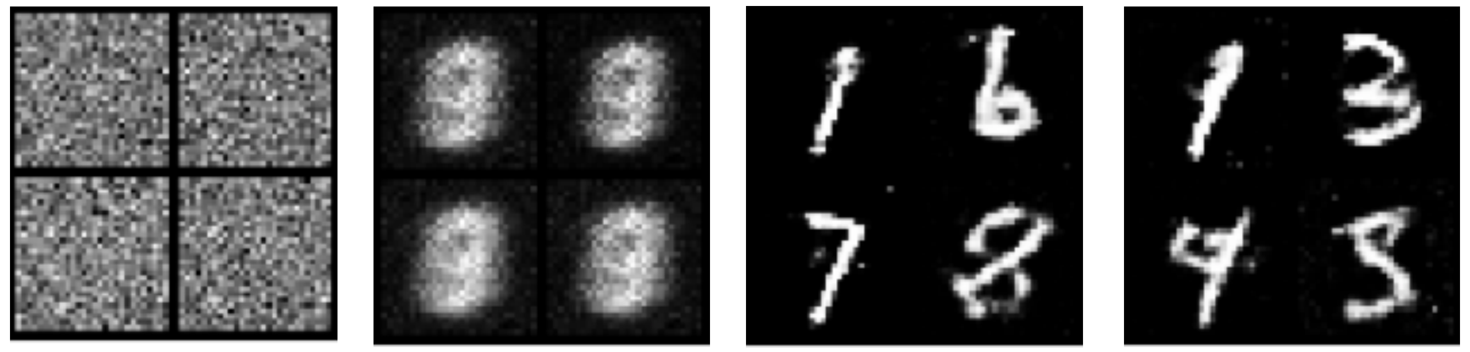
Generative Adversarial Networks (GANs)

“What I cannot create, I do not understand.” — Richard P. Feynman



GANs from Scratch 1: A deep introduction - Diego Gomez Mosquera (2018)





iter 0 | iter 3 | iter 100 | iter 200

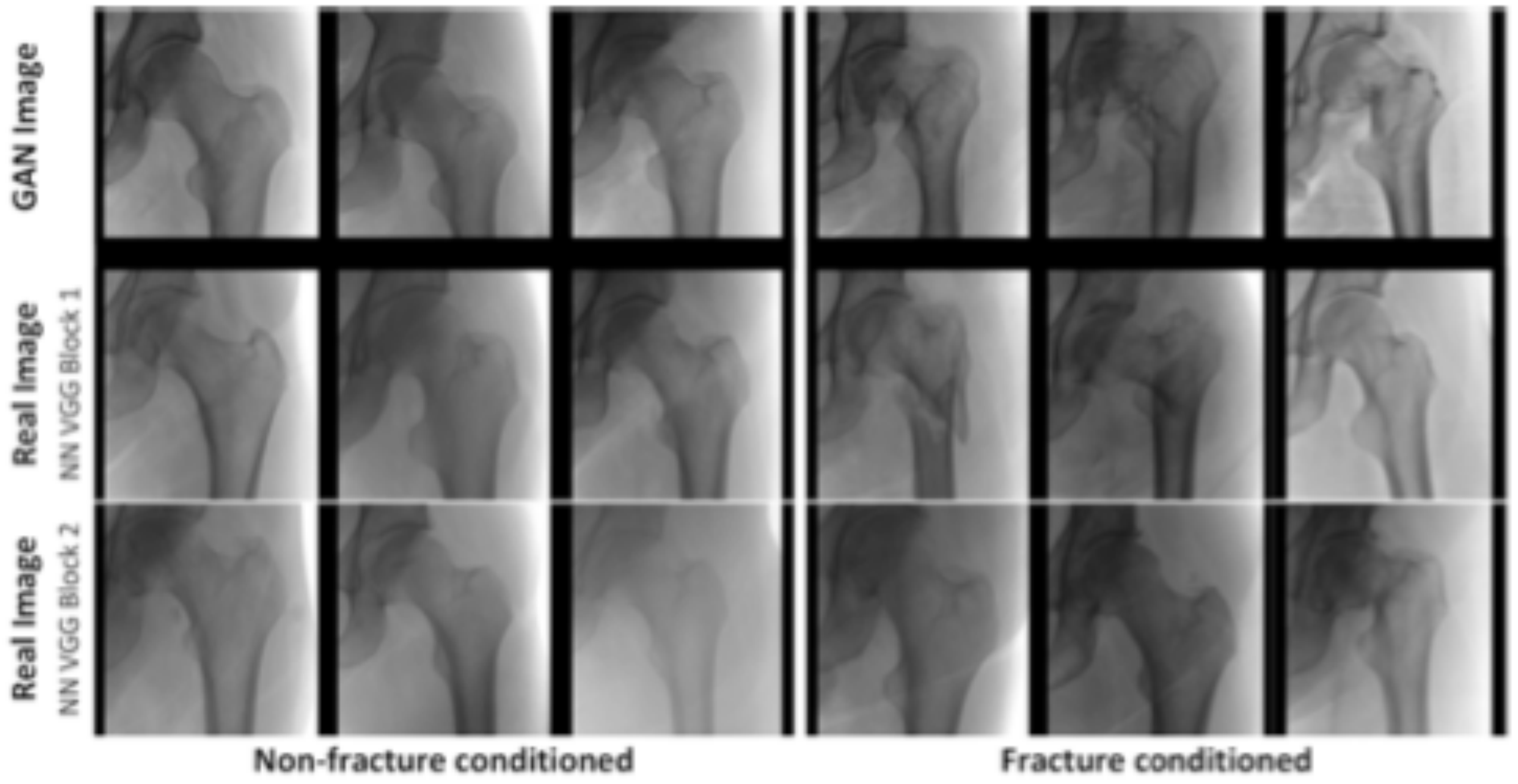
[Alec Radford et al. - ICLR 2016]

GANs applications

[Submitted on 4 Dec 2018]

Towards generative adversarial networks as a new paradigm for radiology education

Samuel G. Finlayson, Hyunkwang Lee, Isaac S. Kohane, Luke Oakden-Rayner



https://arxiv.org/abs/1812.01547 (NeurIPS 2018)

[Submitted on 1 Sep 2017 (v1), last revised 14 Feb 2019 (this version, v3)]

PassGAN: A Deep Learning Approach for Password Guessing

Briland Hitaj, Paolo Gasti, Giuseppe Ateniese, Fernando Perez-Cruz

https://arxiv.org/abs/1709.00440 (code)

https://github.com/hindupuravinash/the-gan-zoo (latest update 5 years ago)

- 3D-ED-GAN - Shape Inpainting using 3D Generative Adversarial Network and Recurrent Convolutional Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling (github)
- 3D-IWGAN - Improved Adversarial Systems for 3D Object Generation and Reconstruction (github)
- 3D-PhysNet - 3D-PhysNet: Learning the Intuitive Physics of Non-Rigid Object Deformations
- 3D-RecGAN - 3D Object Reconstruction from a Single Depth View with Adversarial Learning (github)
- ABC-GAN - ABC-GAN: Adaptive Blur and Control for improved training stability of Generative Adversarial Networks (github)
- ABC-GAN - GANs for LIFE: Generative Adversarial Networks for Likelihood Free Inference
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- ACGAN - Coverless Information Hiding Based on Generative adversarial networks
- acGAN - On-line Adaptative Curriculum Learning for GANs
- ACtuAL - ACtuAL: Actor-Critic Under Adversarial Learning
- AdaGAN - AdaGAN: Boosting Generative Models
- Adaptive GAN - Customizing an Adversarial Example Generator with Class-Conditional GANs
- AdvEntuRe - AdvEntuRe: Adversarial Training for Textual Entailment with Knowledge-Guided Examples
- AdvGAN - Generating adversarial examples with adversarial networks
- AE-GAN - AE-GAN: adversarial eliminating with GAN
- AE-OT - Latent Space Optimal Transport for Generative Models
- …..
- Text2Shape - Text2Shape: Generating Shapes from Natural Language by Learning Joint Embeddings
- textGAN - Generating Text via Adversarial Training
- TextureGAN - TextureGAN: Controlling Deep Image Synthesis with Texture Patches
- TGAN - Temporal Generative Adversarial Nets
- TGAN - Tensorizing Generative Adversarial Nets
- TGAN - Tensor-Generative Adversarial Network with Two-dimensional Sparse Coding: Application to Real-time Indoor Localization
- TGANs-C - To Create What You Tell: Generating Videos from Captions
- tiny-GAN - Analysis of Nonautonomous Adversarial Systems
- TP-GAN - Beyond Face Rotation: Global and Local Perception GAN for Photorealistic and Identity Preserving Frontal View Synthesis
- TreeGAN - TreeGAN: Syntax-Aware Sequence Generation with Generative Adversarial Networks
- Triple-GAN - Triple Generative Adversarial Nets
- ….

stability.ai Stable Diffusion

OpenAI Dall-E

Diffusers

[https://stability.ai/stable-diffusion]

Generated with Stable Diffusion

From Deep Learning Foundations to Stable Diffusion

We've released our new course with over 30 hours of video content.

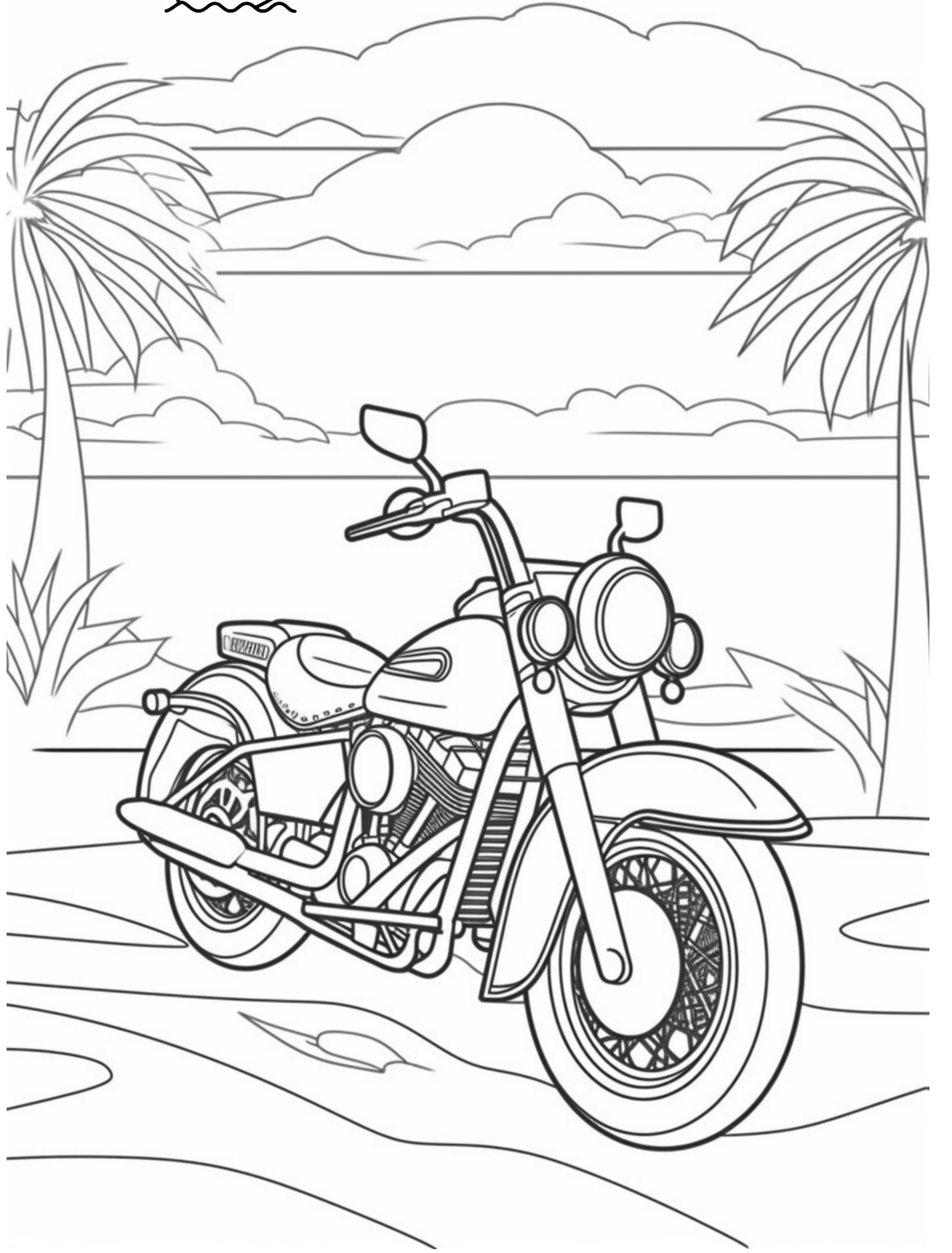
COURSES

AUTHOR
Jeremy Howard

PUBLISHED
April 4, 2023

https://course.fast.ai/Lessons/part2.html

midjourney.com



Midjourney Bot BOT Today at 9:45 PM
A simple coloring book page for kids of a west coast style chopper motorcycle on the beach, all black and white, line art --ar 8:11 --v 5 --s 750 --c 50 - Image #4 @gooner925

Natural Language Processing (NLP)

Word embeddings

Recurrent Neural Networks

Transformers

Large Language Models

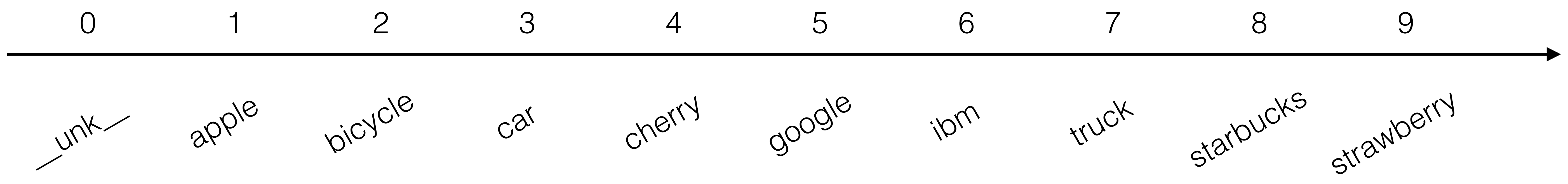
Latest “programming” language: natural language e.g. French (prompt engineering)

Vocabulary: [__unk__, apple, bicycle, car, cherry, google, ibm, truck, starbucks, strawberry]

Word IDs: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

Ecoding schemes

Option 0: Using the word IDs



Issue: false sense of ordering

Option 1: one-hot encoding

__unk__	(0, 0, 0, 0, 0, 0, 0, 0, 0, 0)	google	(0, 0, 0, 0, 0, 1, 0, 0, 0, 0)
apple	(0, 1, 0, 0, 0, 0, 0, 0, 0, 0)	ibm	(0, 0, 0, 0, 0, 0, 1, 0, 0, 0)
bicycle	(0, 0, 1, 0, 0, 0, 0, 0, 0, 0)	truck	(0, 0, 0, 0, 0, 0, 0, 1, 0, 0)
car	(0, 0, 0, 1, 0, 0, 0, 0, 0, 0)	starbucks	(0, 0, 0, 0, 0, 0, 0, 0, 1, 0)
cherry	(0, 0, 0, 0, 1, 0, 0, 0, 0, 0)	strawberry	(0, 0, 0, 0, 0, 0, 0, 0, 0, 1)

Issues:
- Does not scale (vocab. size 10^6)
- No notion of word semantic similarity
  e.g. (car, truck, strawberry)

"*word embedding*" refers to a technique used to represent words or phrases as **dense** numerical vectors in a high-dimensional space (ChatGPT)

Vocabulary: [__unk__, apple, bicycle, car, cherry, google, ibm, truck, starbucks, strawberry]

__unk__ = (-0.9, -0.9)

apple = ?

bicycle = (-0.6, 0.8)

car = (-0.8, 0.5)

cherry = (0.4, 0.8)

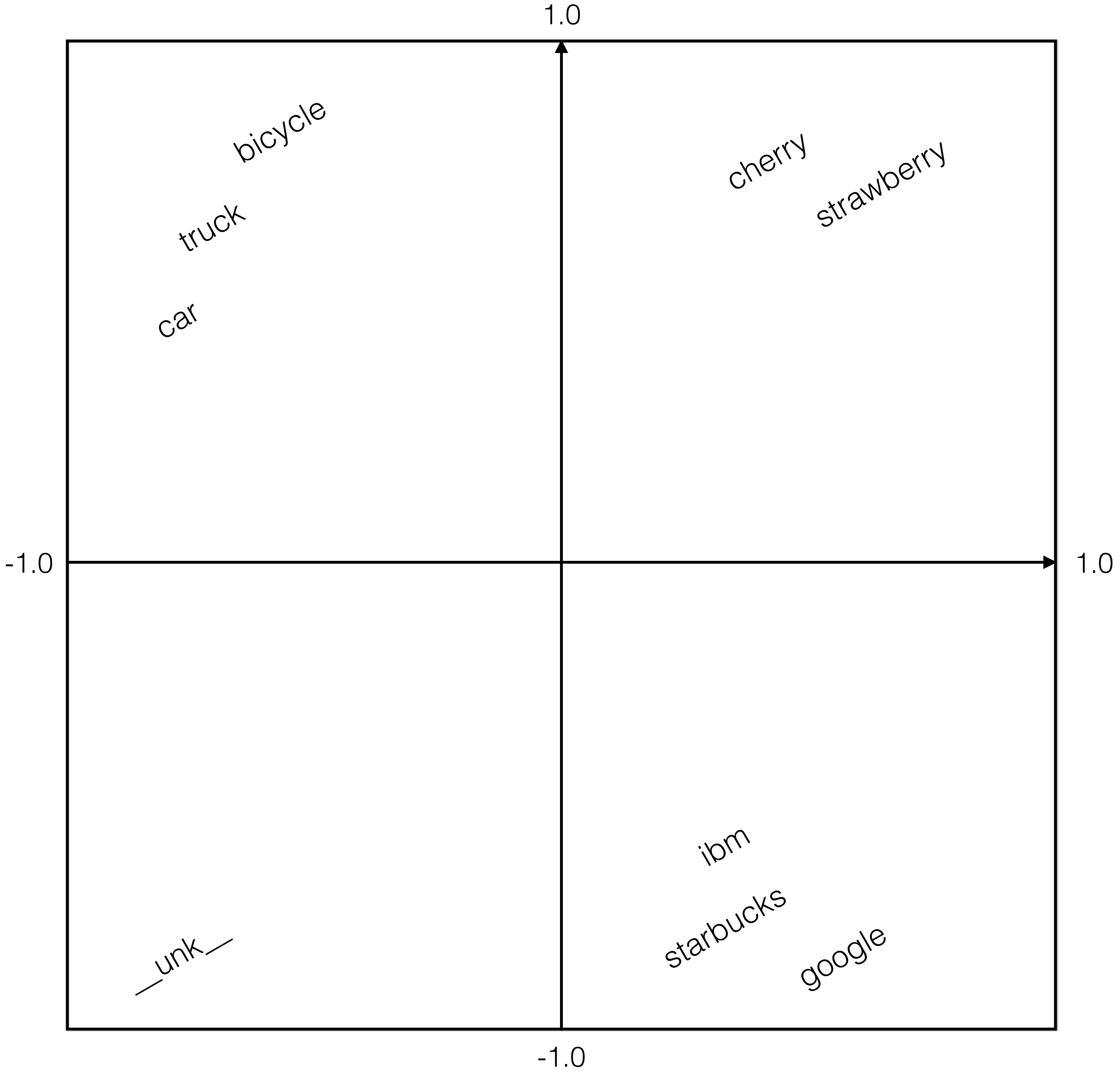
google = (0.6, -0.9)

ibm = (0.3, -0.6)

truck = (-0.8, 0.6)

starbucks = (0.2, -0.9)

strawberry = (0.7, 0.7)



Where should we embed the word "apple"?

Efficient Estimation of Word Representations in Vector Space

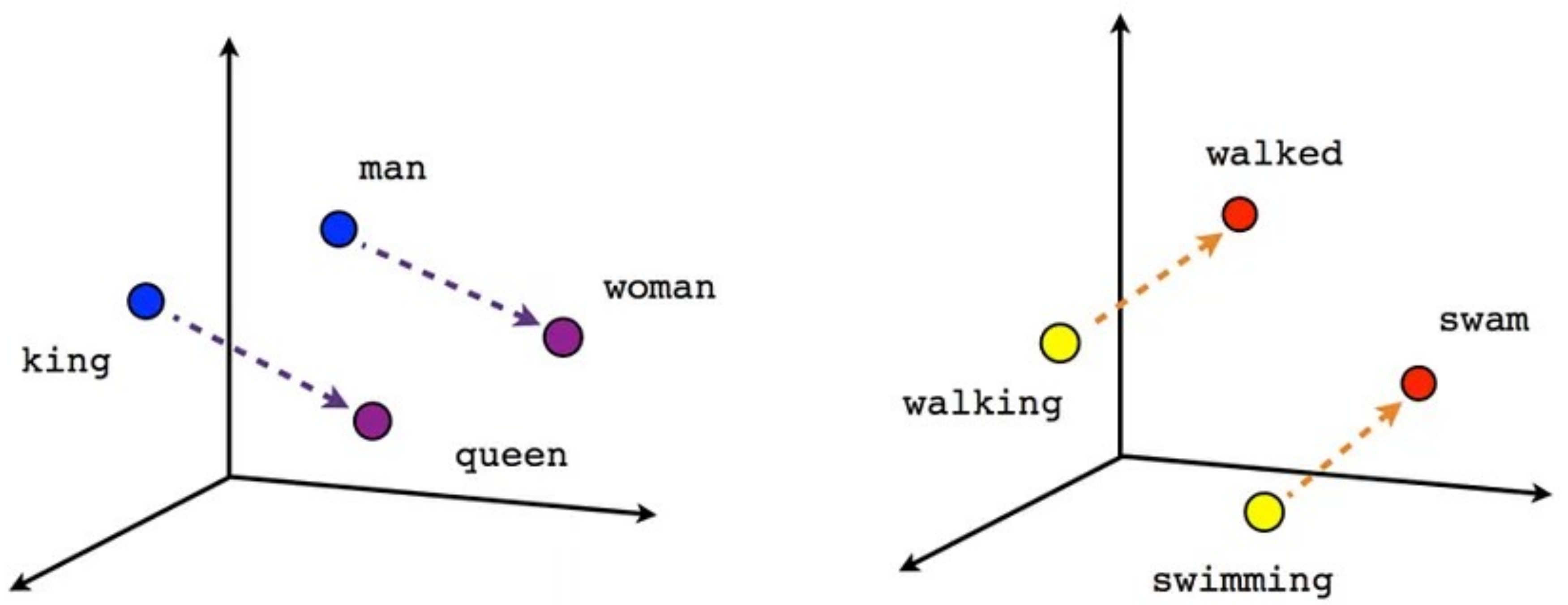
Tomas Mikolov
Google Inc., Mountain View, CA
tmikolov@google.com

Kai Chen
Google Inc., Mountain View, CA
kaichen@google.com

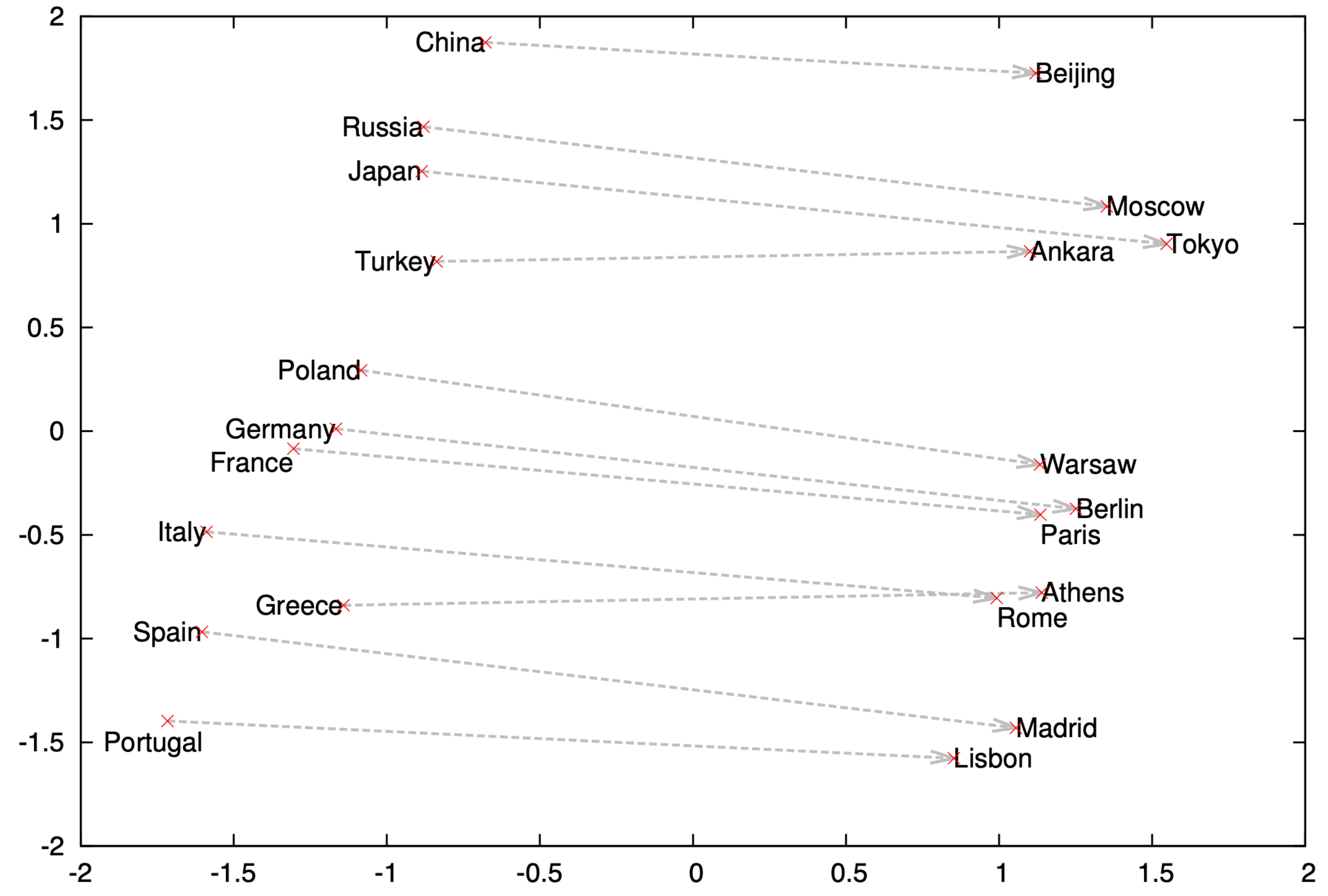
Greg Corrado
Google Inc., Mountain View, CA
gcorrado@google.com

Jeffrey Dean
Google Inc., Mountain View, CA
jeff@google.com

word2vec (2013)



Male-Female [Source: ?] Verb tense



Country-Capital

[word2vec (2013)]

- ➕ Revolutionary, simple, self-supervised, only 2 matrices of size (vocab size, embedding dimension)
- ➖ All unseen words are still matched to the same embedding vector

---

Enriching Word Vectors with Subword Information

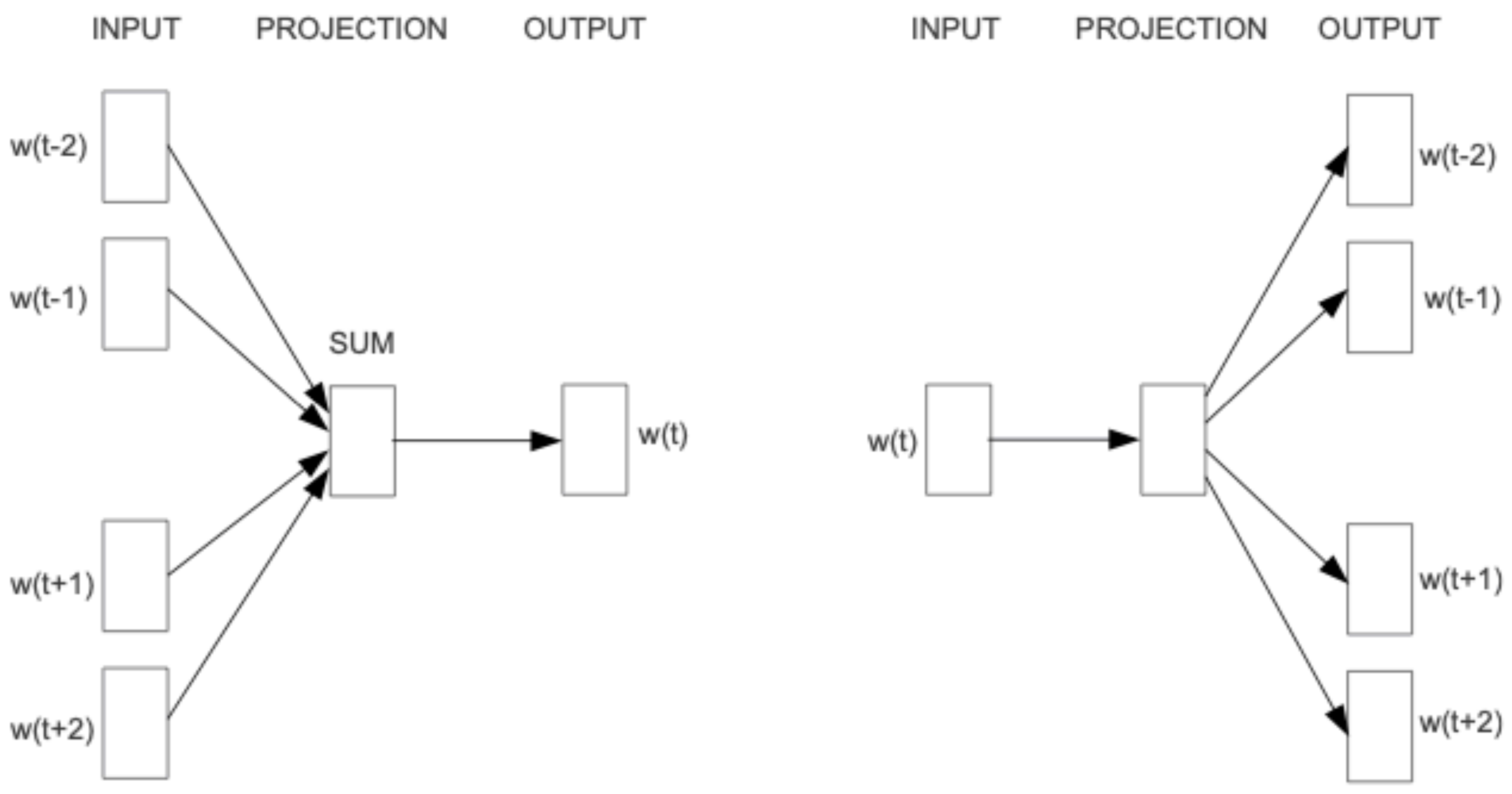
Piotr Bojanowski* and **Edouard Grave*** and **Armand Joulin** and **Tomas Mikolov**
Facebook AI Research
{bojanowski,egrave,ajoulin,tmikolov}@fb.com

Enriching Word Vectors with Subword Information (2017)

unadvised = {<unadvised> + <un + una + nad + adv + dvi + vis + ise + sed + ed>}

- ➕ Getting embeddings even for “unseen” words. No more __unk__ symbol.
- ➖ Ambiguous words (e.g. “apple”, “run”) get a single embedding vector

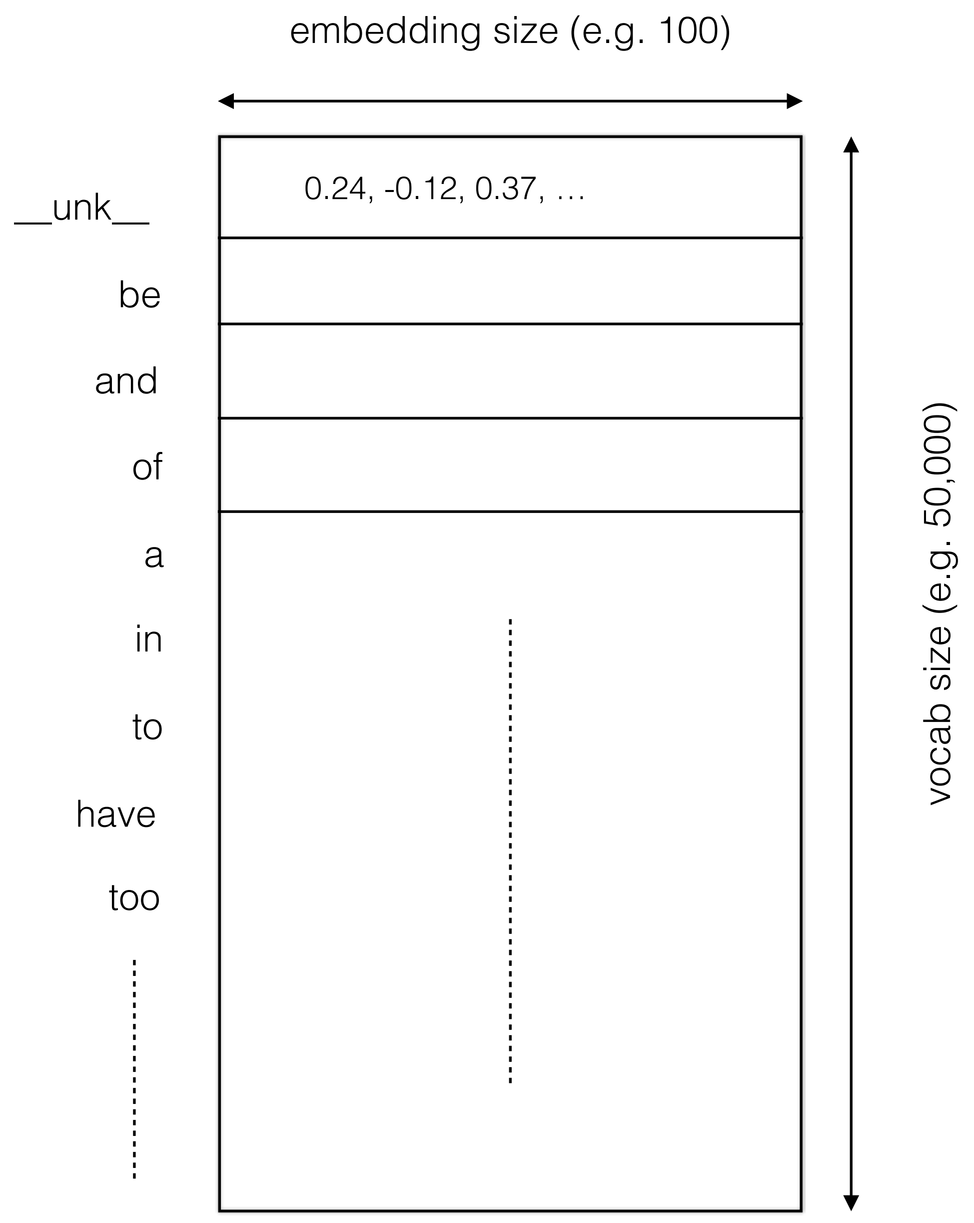
Word2vec algorithm



CBOW **Skip-gram**

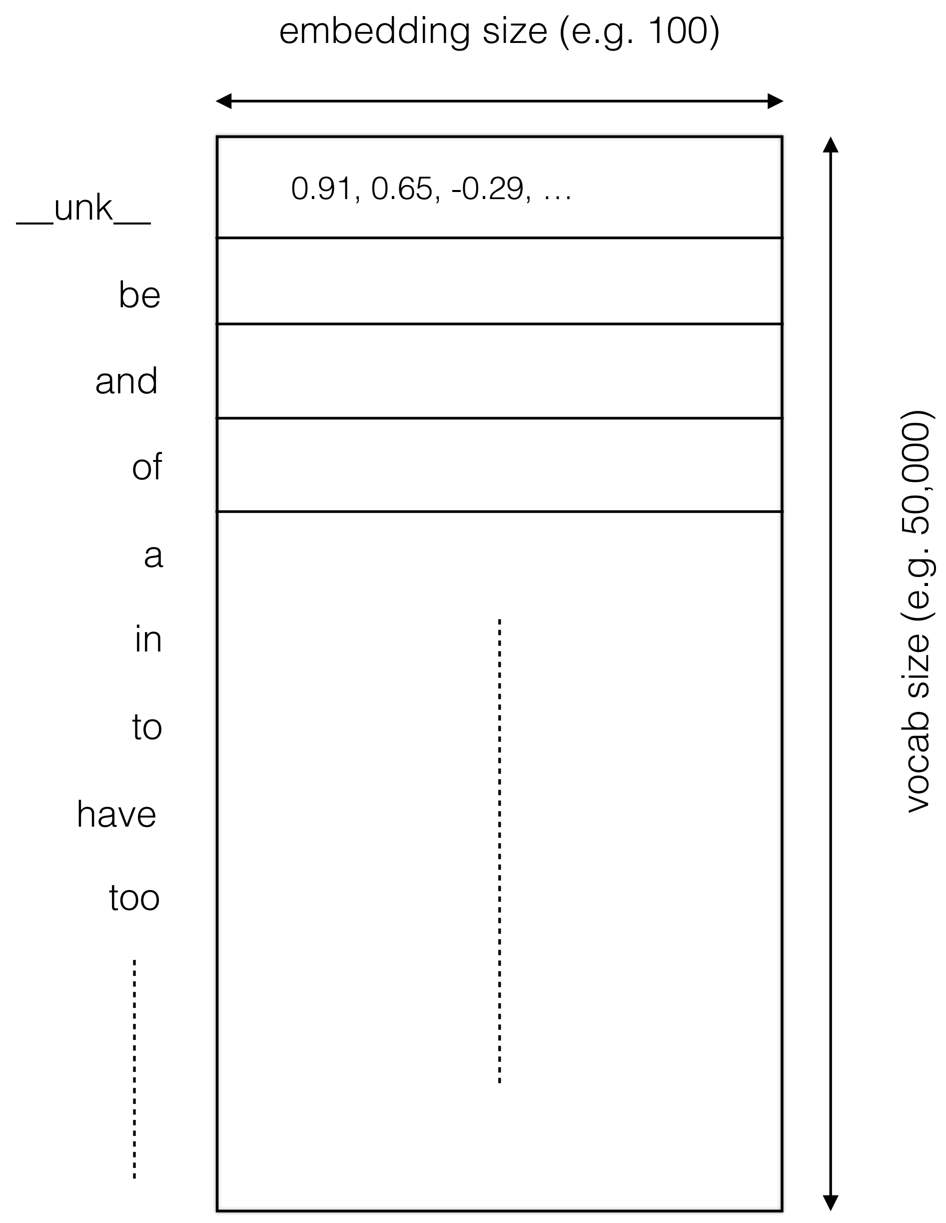
[https://arxiv.org/abs/1301.3781]

Context word embeddings



Dot product (cosine similarity) of context and “masked” words

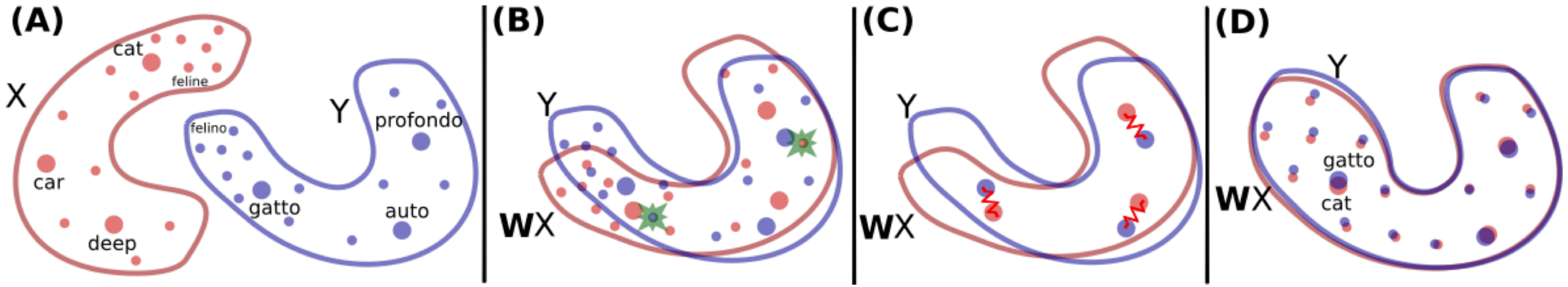
“Masked” word embeddings



Published as a conference paper at ICLR 2018

WORD TRANSLATION WITHOUT PARALLEL DATA

Alexis Conneau[*†‡], **Guillaume Lample**[*†§],
Marc'Aurelio Ranzato[†], **Ludovic Denoyer**[§], **Hervé Jégou**[†]
{aconneau,glample,ranzato,rvj}@fb.com
ludovic.denoyer@upmc.fr

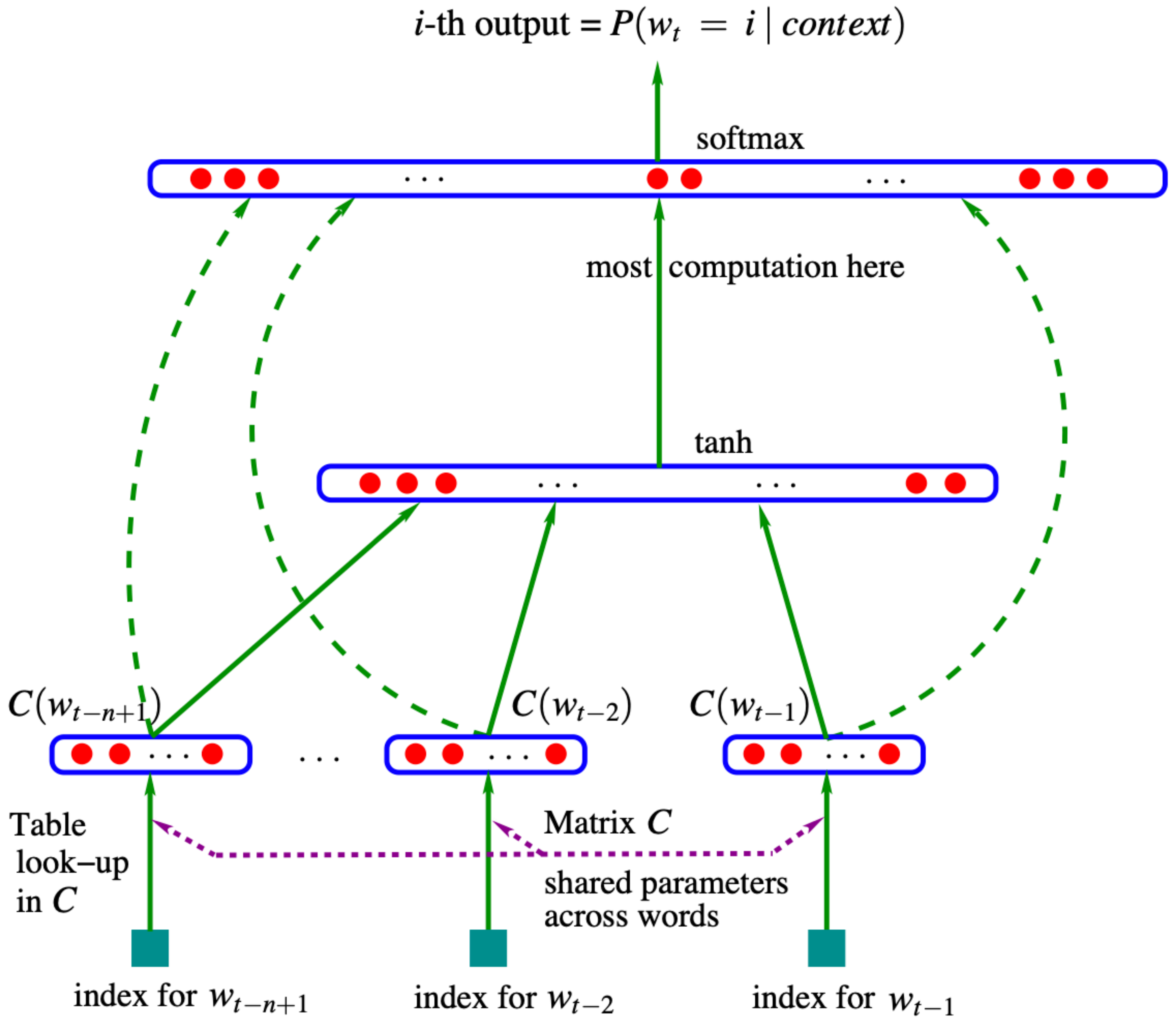


The Procrustes problem

Journal of Machine Learning Research 3 (2003) 1137–1155 Submitted 4/02; Published 2/03

A Neural Probabilistic Language Model

Yoshua Bengio BENGIOY@IRO.UMONTREAL.CA
Réjean Ducharme DUCHARME@IRO.UMONTREAL.CA
Pascal Vincent VINCENTP@IRO.UMONTREAL.CA
Christian Jauvin JAUVINC@IRO.UMONTREAL.CA
Département d'Informatique et Recherche Opérationnelle
Centre de Recherche Mathématiques
Université de Montréal, Montréal, Québec, Canada

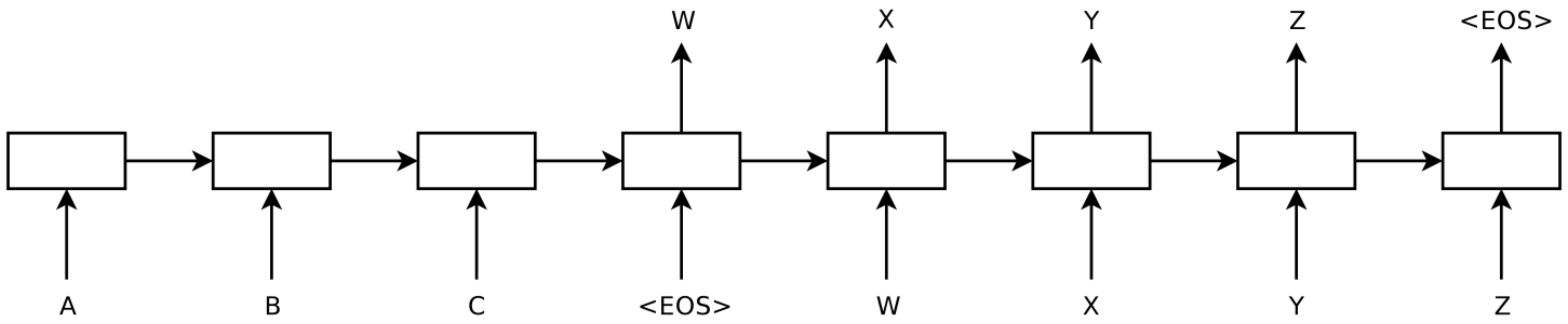


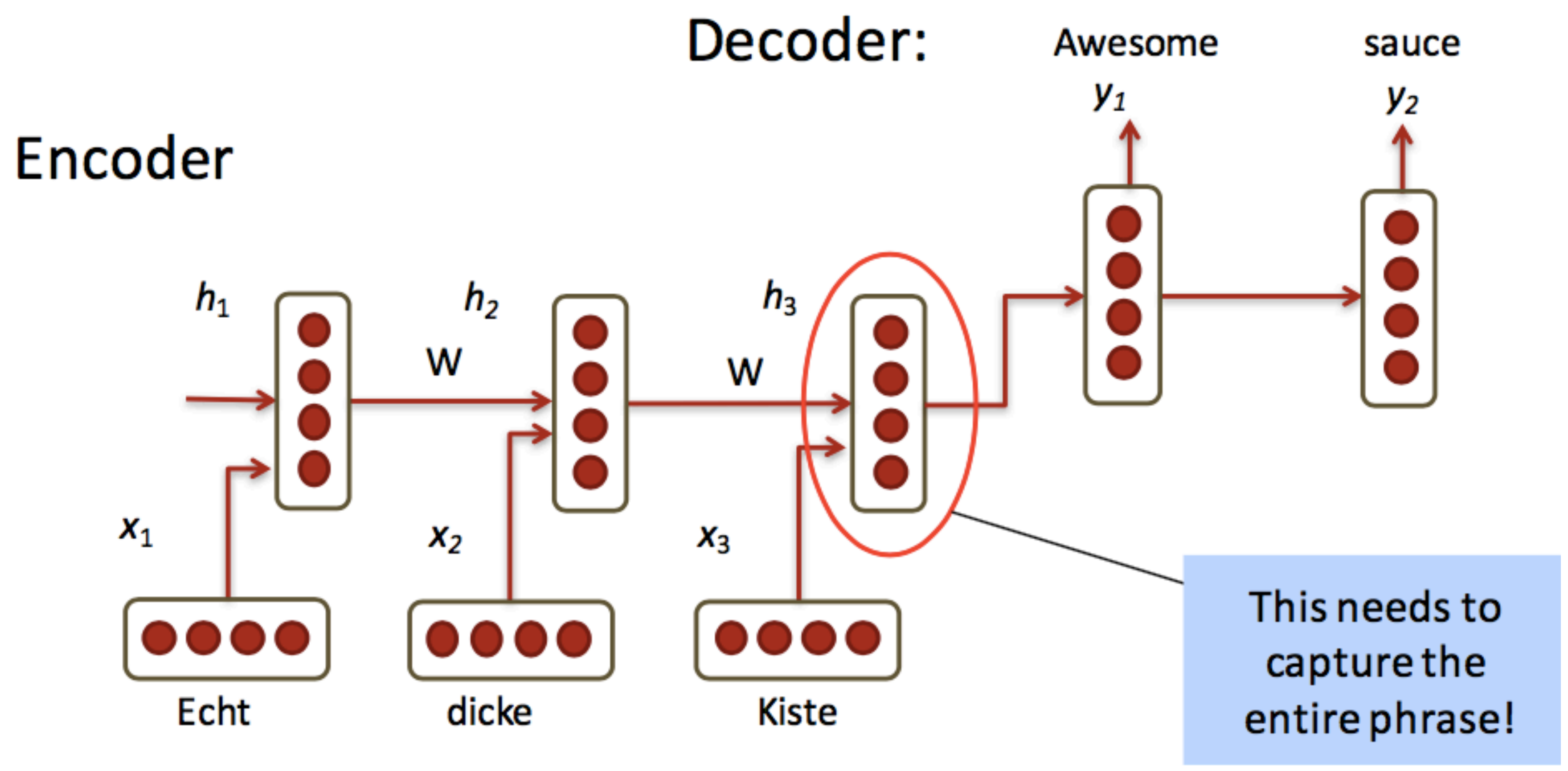
Neural Machine Translation: RNN, LSTM (2014)

Sequence to Sequence Learning with Neural Networks

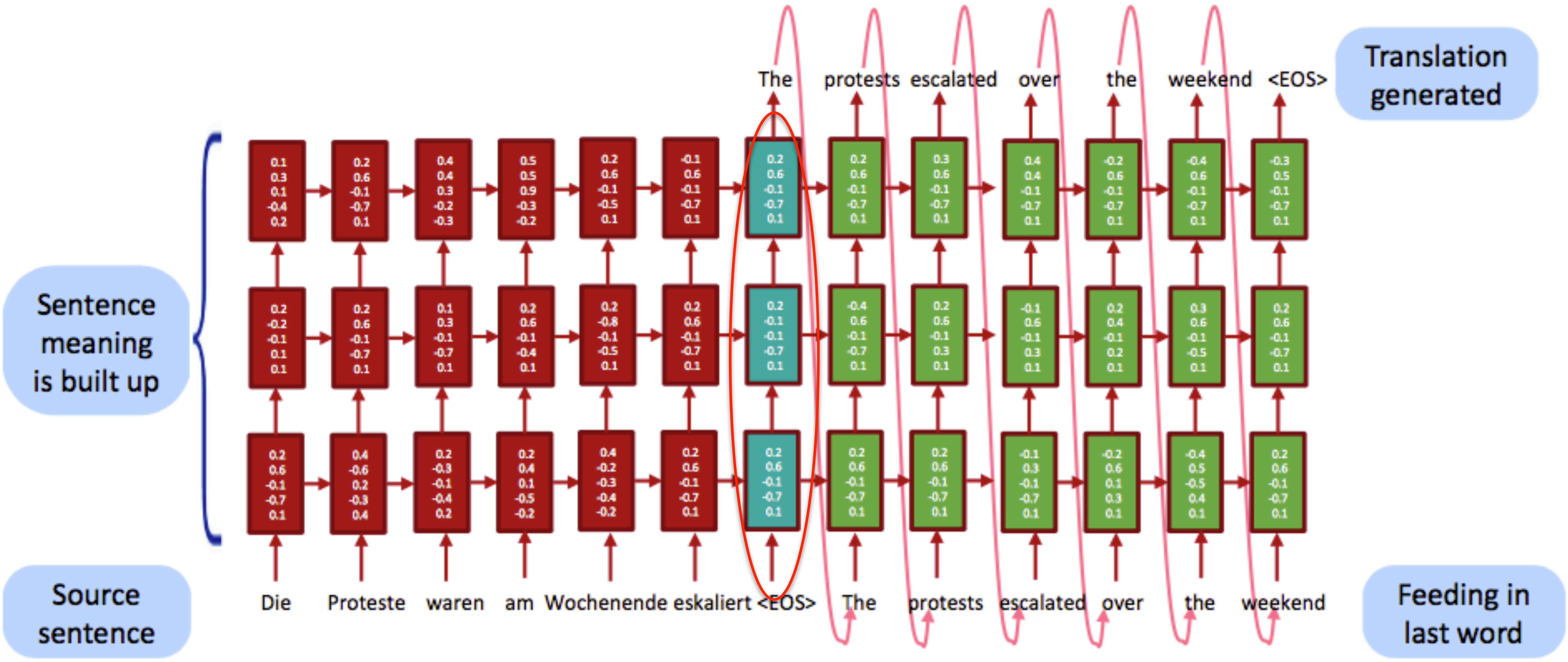
Ilya Sutskever Google ilyasu@google.com
Oriol Vinyals Google vinyals@google.com
Quoc V. Le Google qvl@google.com

2014





[Socher - CS224 - Stanford]



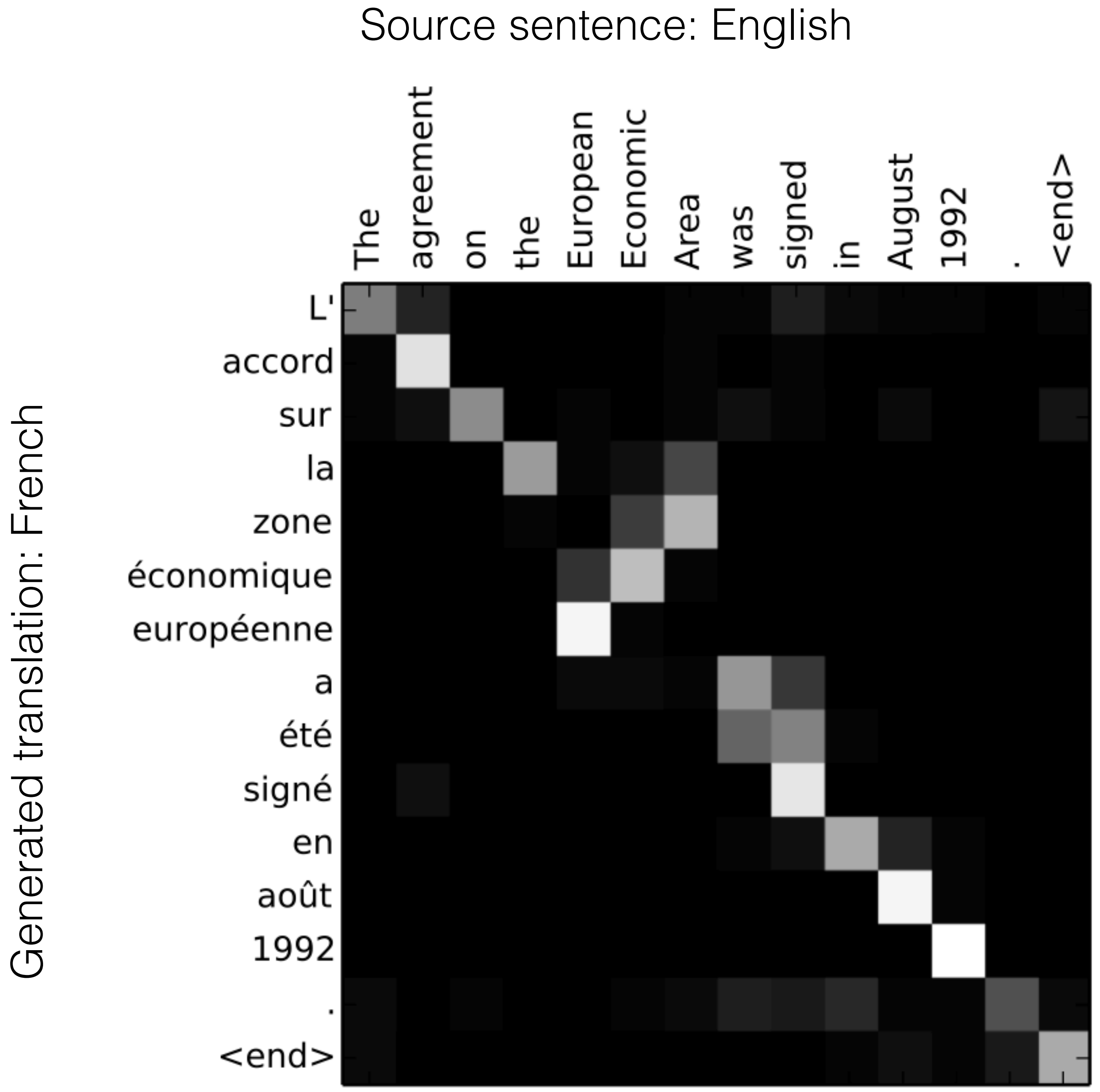
[Socher - CS224 - Stanford]

Published as a conference paper at ICLR 2015

NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

Dzmitry Bahdanau
Jacobs University Bremen, Germany

KyungHyun Cho **Yoshua Bengio***
Université de Montréal



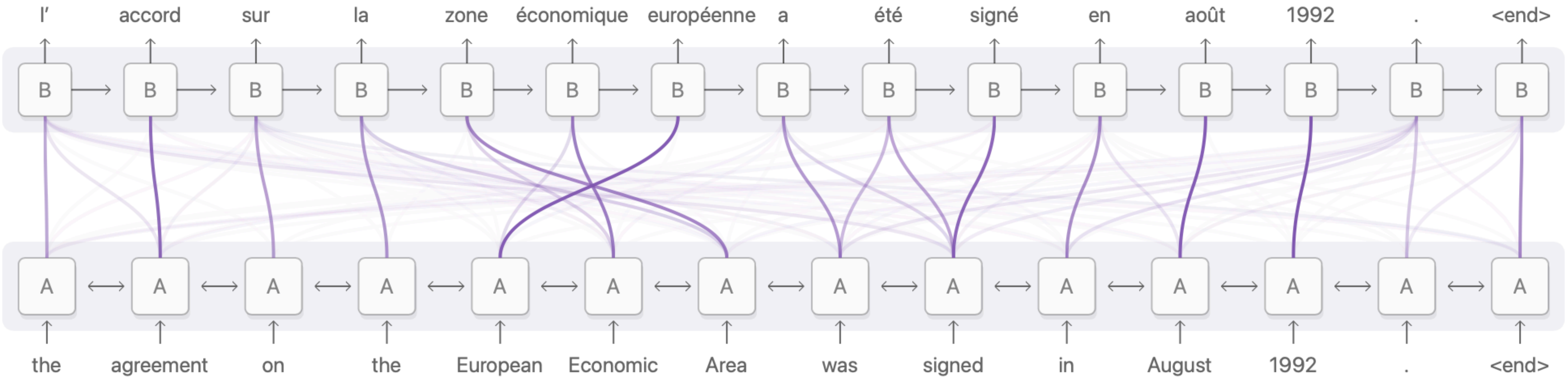


Diagram derived from Fig. 3 of Bahdanau, *et al.* 2014

[Chris Olah & Shan Crater 2016 https://distill.pub/2016/augmented-rnns/]

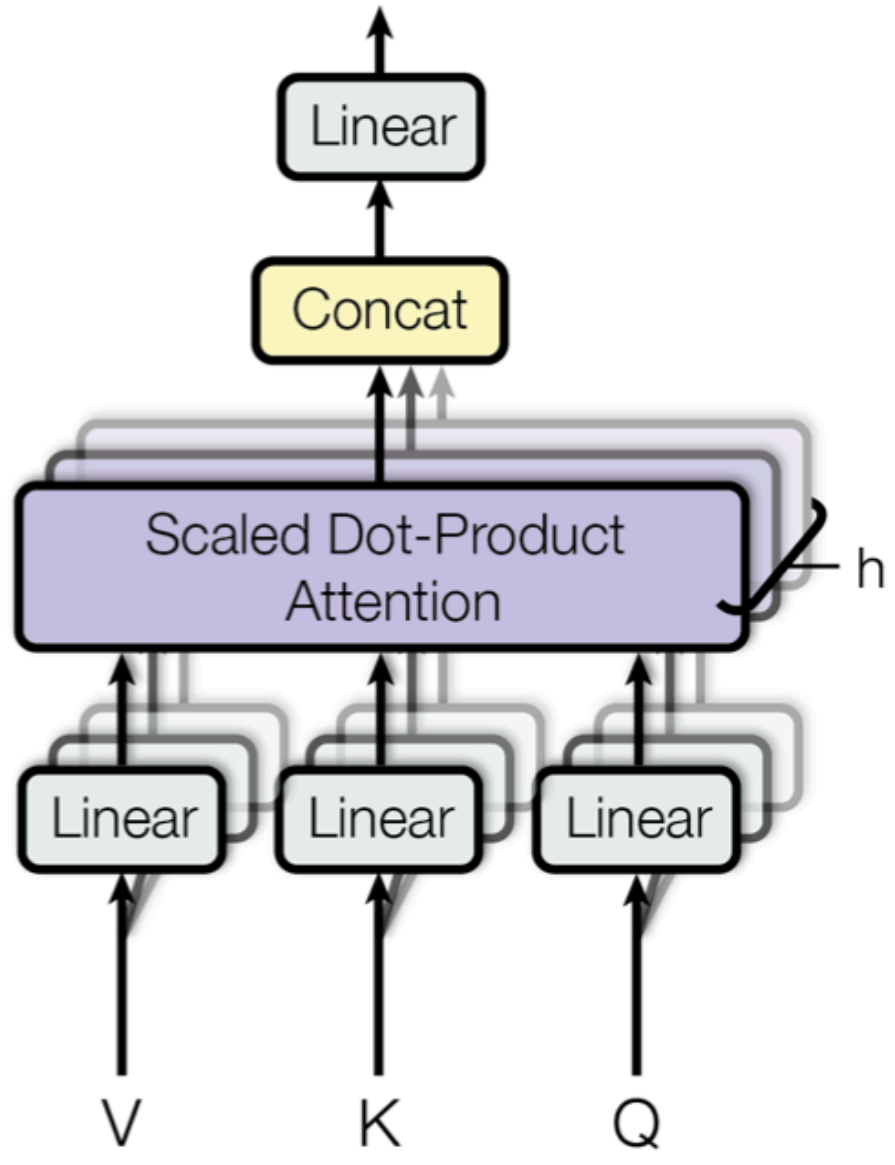
https://arxiv.org/abs/1706.03762

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com
Noam Shazeer* Google Brain noam@google.com
Niki Parmar* Google Research nikip@google.com
Jakob Uszkoreit* Google Research usz@google.com
Llion Jones* Google Research llion@google.com
Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu
Łukasz Kaiser* Google Brain lukaszkaiser@google.com
Illia Polosukhin* ‡ illia.polosukhin@gmail.com

First application: machine translation

Multi-Head Attention



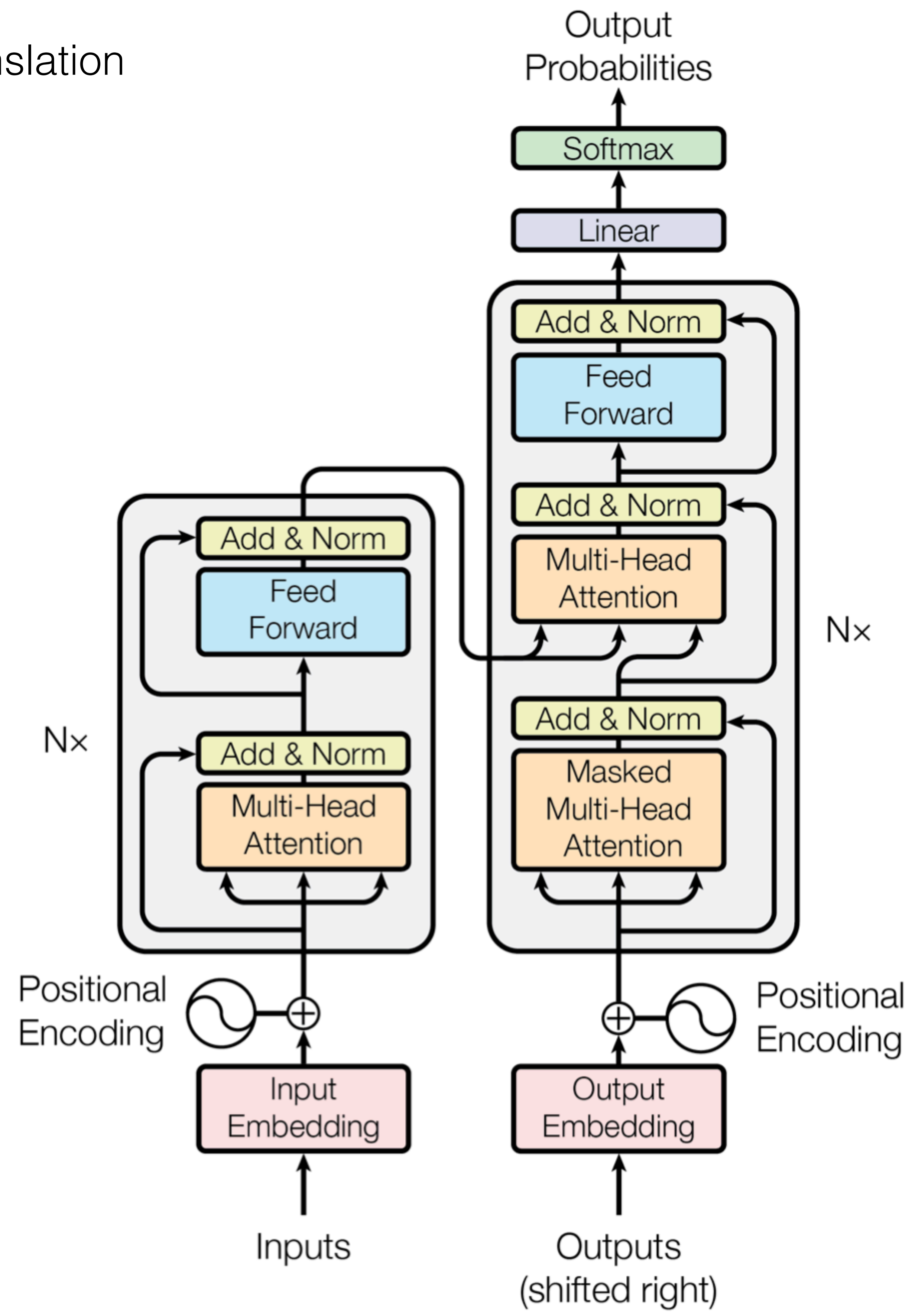
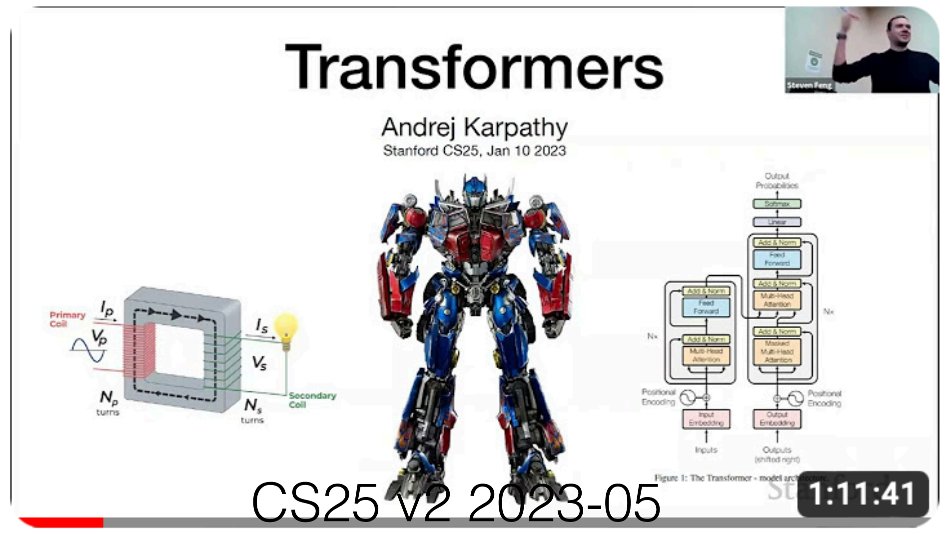


Figure 1: The Transformer - model architecture.

Great resources to understand the transformer architecture:

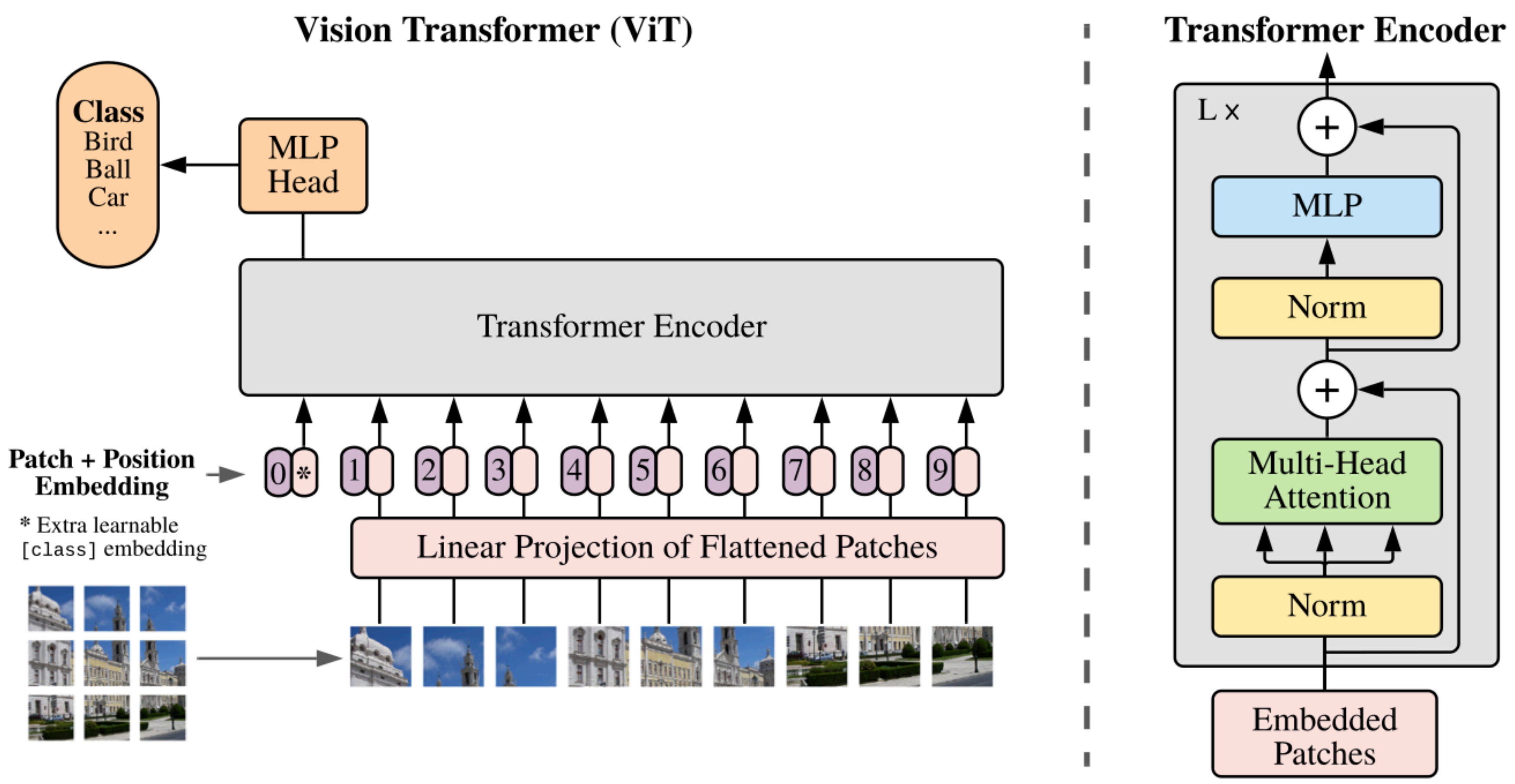
Let's build GPT: from scratch, in code, spelled out.

Andrej Karpathy
2.4M views • 4 months ago



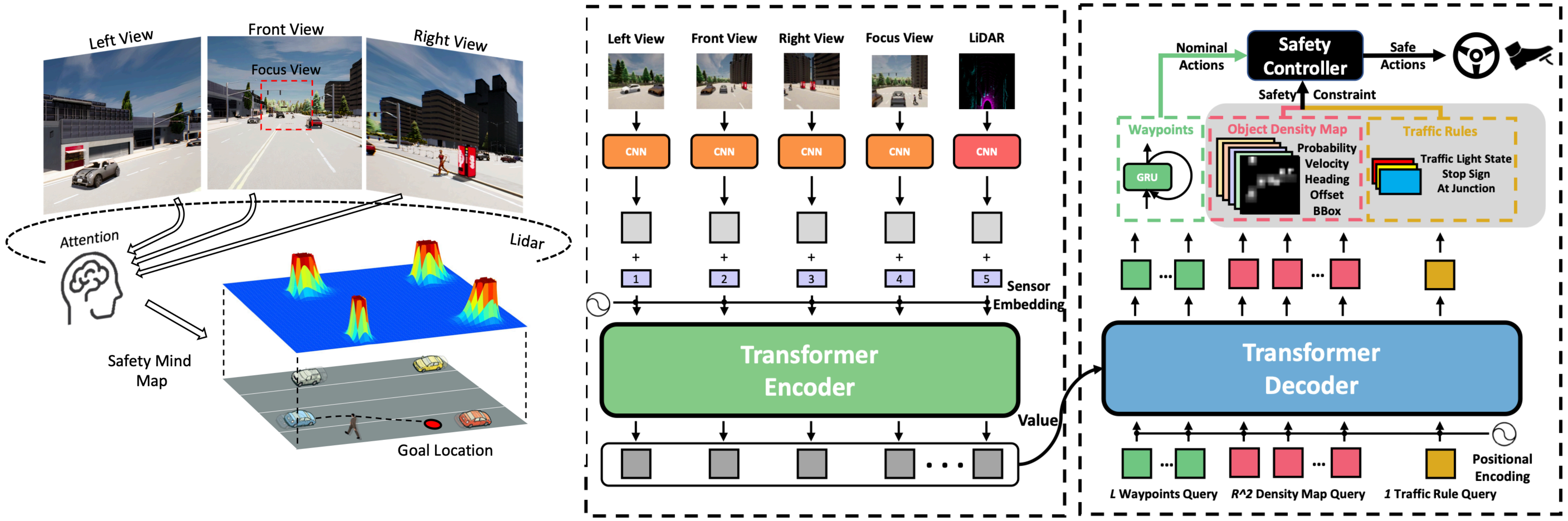
@karpathy: "The Transformer is a … general-purpose differentiable computer" (2022)

Vision: (2020) Transformer for image recognition at scale



https://arxiv.org/abs/2010.11929

Safety-Enhanced Autonomous Driving Using Interpretable Sensor Fusion Transformer (2022)

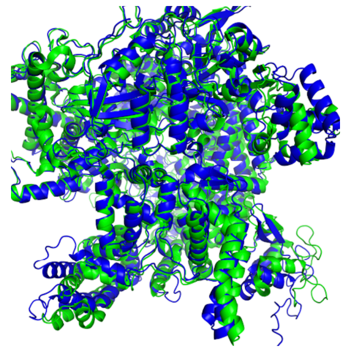


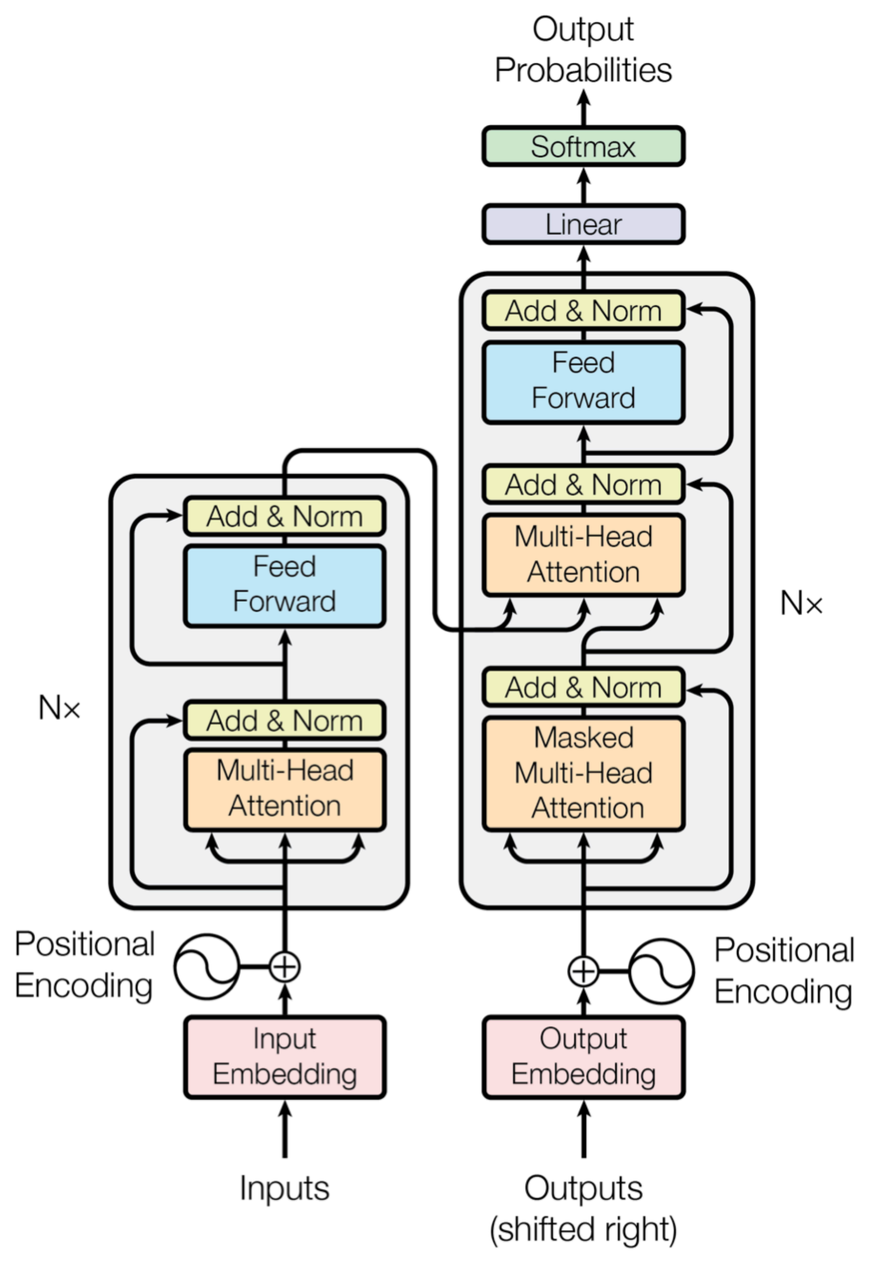
https://arxiv.org/abs/2207.14024

Speech: (2020) Convolution-augmented Transformer for Speech Recognition

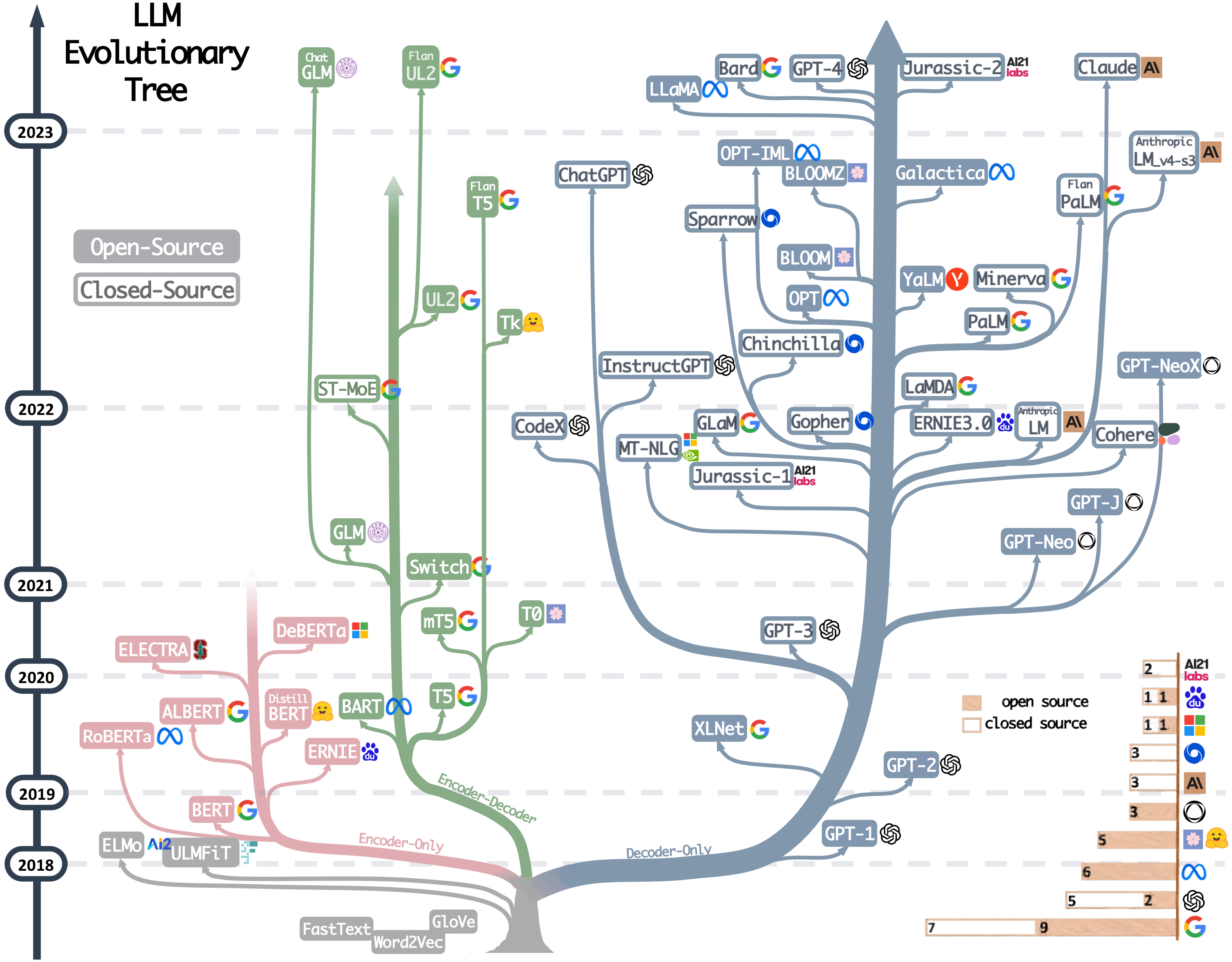
Speech: (2022) Whisper OpenAI

Protein folding: (2020) AlphaFold Google DeepMind

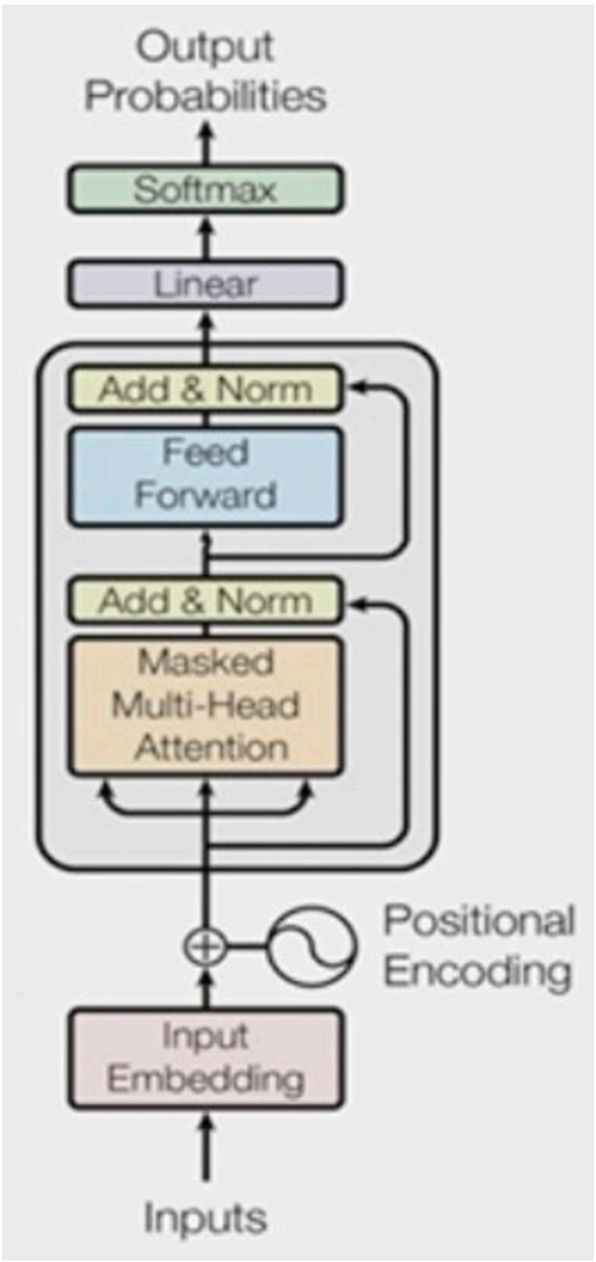




Encoder / decoder

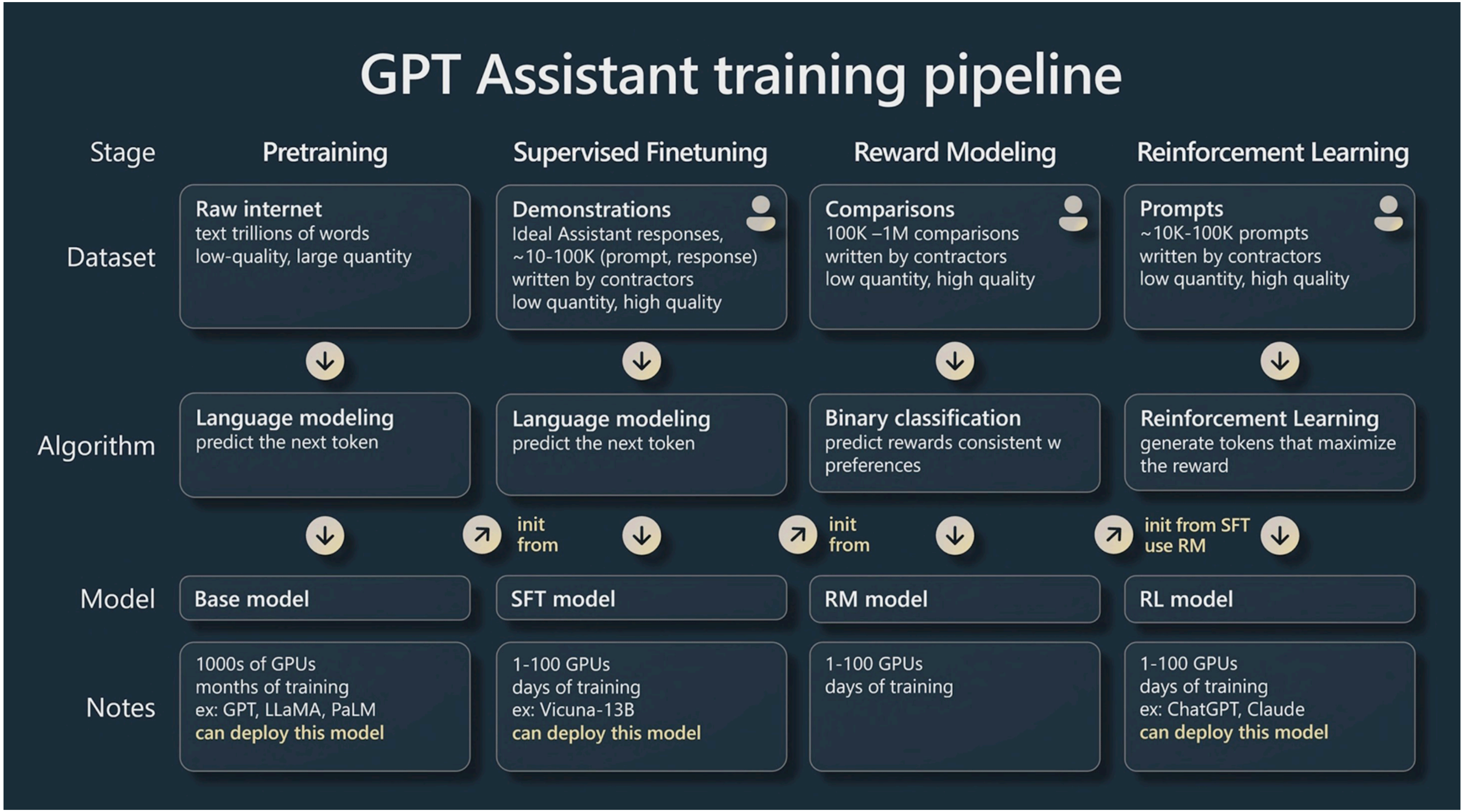


[https://notes.kateva.org/2023/04/large-language-models-evolutionary-tree.html]



Decoder only

Large Language Models (LLMs)



[Andrej Karpathy - State of GPT - 2023-05]

1. Large Language Model (pre-training)

GPT−3

GPT-3 Language Models are Few-Shot Learners (paper) - 2020

175B parameters, 96 layers, 96 heads, trained on 300B tokens, 2,408 tokens context length

1 month training on thousands of GPUs, token vocabulary size approx. 50,000

a BigScience initiative

BLOOM

176B params · 59 languages · Open-access

BLOOM (BigScience Large Open-science Open-access Multilingual) language model (blog, model) - 2022

176B parameters, 46 natural languages, 13 programming languages

Meta AI

LLaMA (Large Language Model Meta AI) (paper) - 2023

7B to 65B parameters, 64 heads, 80 layers, trained on 1.4T tokens, 2,048 tokens context length

21 days training on 2,048 of A100 GPUs, token vocabulary size approx. 30,000

Dataset	Sampling prop.	Epochs	Disk size
CommonCrawl	67.0%	1.10	3.3 TB
C4	15.0%	1.06	783 GB
Github	4.5%	0.64	328 GB
Wikipedia	4.5%	2.45	83 GB
Books	4.5%	2.23	85 GB
ArXiv	2.5%	1.06	92 GB
StackExchange	2.0%	1.03	78 GB

Red Pajama (together.xyz - UdeM, ETH, Stanford, …)

7B parameters, trained on 1.2T tokens

LLM tokenization

Tokenization: transforms some text into a long list of integers…

Token dictionary: A LLM uses a fixed token dictionary representing most common character sequences in training corpora.

Most common tokenizers: Byte-Pair-Encoding, WordPiece (see HuggingFace's tokenizers)

Typical token vocabulary size: 10 to 100K

100 tokens equals approx. 75 words

	Example 1	Example 2
Raw text	Today I would like to	Today I would like to
Tokens	Today I would like to	Today I would like to
Token IDs	[8888, 314, 561, 588, 284]	[8888, 314, 561, 588, 284, 220]

Example 1 — Tokens: 5, Characters: 21

Example 2 — Tokens: 6, Characters: 22

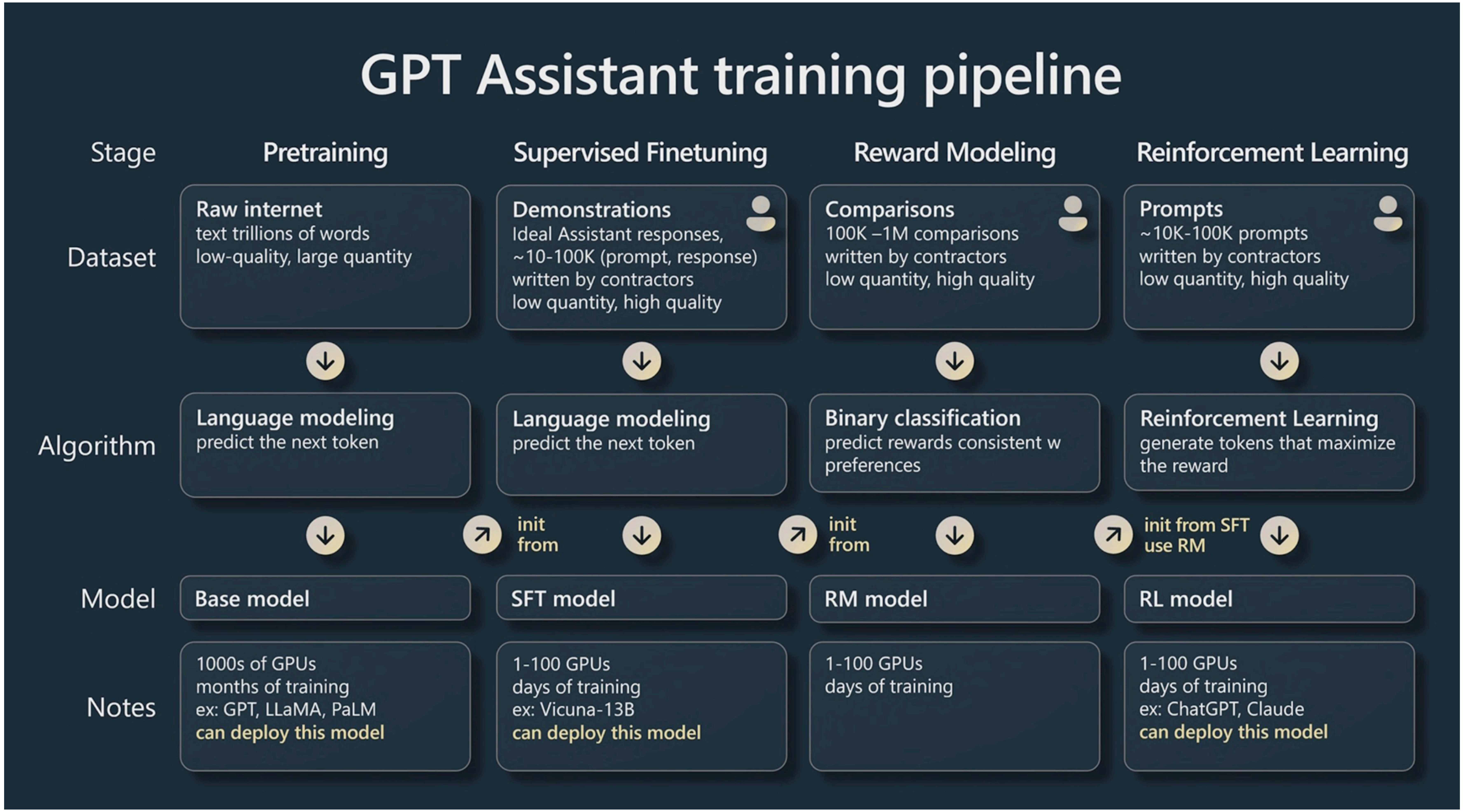
platform.openai.com/tokenizer

LLM transformer

Pre-trained LLM -> supervised fine-tuning -> reward modelling -> reinforcement learning

Pre-trained LLMs (e.g. GPT-3, BLOOM, LIAMA, …) are not (yet) (chat) assistants

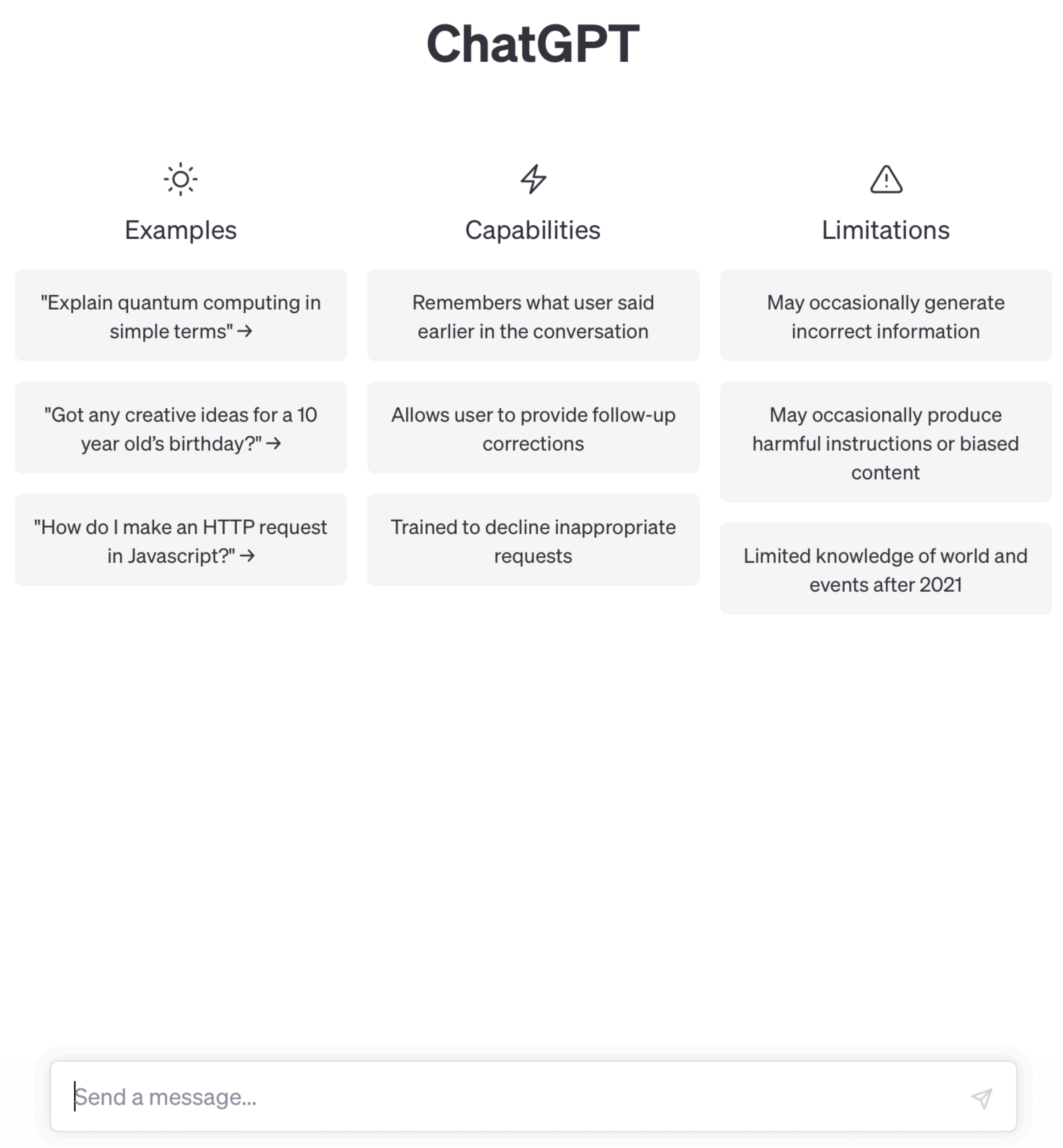
Self-supervised pre-trained LLMs “only” auto-complete text… (predicting next most likely words)



[Andrej Karpathy - State of GPT - 2023-05]

ChatGPT (OpenAI)

November 30, 2022 chat.openai.com



Other chat interfaces to LLMs

Open Assistant open-assistant.io/dashboard

gpt4all.io

Perplexity perplexity.ai

you.com

chat.lmsys.org

Andrej Karpathy @karpathy · Jan 24
The hottest new programming language is English

In fact, any language: French, Japanese, …

1. Write clear and specific instructions

ChatGPT
Prompt Engineering
for Developers

OpenAI DeepLearning.AI

Isa Fulford Andrew Ng

learn.deeplearning.ai/chatgpt-prompt-eng

Assume you are writing to a subcontractor who cannot call you back for more info…

Use delimiters to clearly indicate distinct parts of the input; e.g. ```, """, < >, <tag>, </tag>, :

Your task is to perform the following actions:
1 - Summarize the following text delimited by <> with 1 sentence.
2 - Translate the summary into French.
3 - List each name in the French summary.
4 - Output a JSON object that contains the following keys: french_summary, num_names.

Use the following format:
Text: <text to summarize>
Summary: <summary>
Translation: <summary translation>
Names: <list of names in the French summary>
Output JSON: <json with summary and num_names>

Text:
<
In his closing statement to a Moscow court, just before he was sentenced to 25 years in prison for his outspoken opposition to the invasion of Ukraine, Vladimir Kara-Murza reminded those in attendance that Russia had been down this repressive direction before.

"I've been surprised by the extent to which my trial, in its secrecy and its contempt for legal norms, has surpassed even the trials of Soviet dissidents in the 1960s and '70s," Mr. Kara-Murza told the court on April 17. "We've gone beyond the 1970s – all the way back to the 1930s."

The 1930s in Russia were the time of Joseph Stalin's purges, show trials and extrajudicial executions. For the 23 years that Russian President Vladimir Putin has been in power, he has faced accusations that he seeks to rehabilitate Stalinism and restore the Soviet empire. Until a year ago, the Kremlin could comfortably swat such talk away as hyperbole.
>

Summary: Vladimir Kara-Murza compares his trial for opposing the invasion of Ukraine to the repressive trials of Soviet dissidents in the 1960s and '70s, stating that Russia has regressed back to the era of Stalin's purges in the 1930s.

Translation: Vladimir Kara-Murza compare son procès pour s'opposer à l'invasion de l'Ukraine aux procès répressifs des dissidents soviétiques des années 1960 et 1970, déclarant que la Russie est retournée à l'époque des purges de Staline dans les années 1930.

Names: Vladimir Kara-Murza, Joseph Stalin, Vladimir Putin

Output JSON:
```
{
"french_summary": "Vladimir Kara-Murza compare son procès pour s'opposer à l'invasion de l'Ukraine aux procès répressifs des dissidents soviétiques des années 1960 et 1970, déclarant que la Russie est retournée à l'époque des purges de Staline dans les années 1930.",
"num_names": 3
}
```

Prompt engineering: extracting information / infer topics

```
lamp_review = """
Needed a nice lamp for my bedroom, and this one had \
additional storage and not too high of a price point. \
Got it fast.  The string to our lamp broke during the \
transit and the company happily sent over a new one. \
Came within a few days as well. It was easy to put \
together.  I had a missing part, so I contacted their \
support and they very quickly got me the missing piece! \
Lumina seems to me to be a great company that cares \
about their customers and products!!
"""
```

```
prompt = f"""
Identify the following items from the review text:
- Sentiment (positive or negative)
- Is the reviewer expressing anger? (true or false)
- Item purchased by reviewer
- Company that made the item

The review is delimited with triple backticks. \
Format your response as a JSON object with \
"Sentiment", "Anger", "Item" and "Brand" as the keys.
If the information isn't present, use "unknown" \
as the value.
Make your response as short as possible.
Format the Anger value as a boolean.

Review text: '''{lamp_review}'''
"""
```

```
{
  "Sentiment": "positive",
  "Anger": false,
  "Item": "lamp with additional storage",
  "Brand": "Lumina"
}
```

```
story = """
In a recent survey conducted by the government,
public sector employees were asked to rate their level
of satisfaction with the department they work at.
The results revealed that NASA was the most popular
department with a satisfaction rating of 95%.

One NASA employee, John Smith, commented on the findings,
stating, "I'm not surprised that NASA came out on top.
It's a great place to work with amazing people and
incredible opportunities. I'm proud to be a part of
such an innovative organization."

The results were also welcomed by NASA's management team,
with Director Tom Johnson stating, "We are thrilled to
hear that our employees are satisfied with their work at NASA.
We have a talented and dedicated team who work tirelessly
to achieve our goals, and it's fantastic to see that their
hard work is paying off."

The survey also revealed that the
Social Security Administration had the lowest satisfaction
rating, with only 45% of employees indicating they were
satisfied with their job. The government has pledged to
address the concerns raised by employees in the survey and
work towards improving job satisfaction across all departments.
"""
```

```
prompt = f"""
Determine five topics that are being discussed in the \
following text, which is delimited by triple backticks.

Make each item one or two words long.

Format your response as a list of items separated by commas.

Text sample: '''{story}'''
"""
```

```
government survey, job satisfaction, NASA, Social Security Administration, employee concerns
```

learn.deeplearning.ai/chatgpt-prompt-eng

Translate the following from slang to a business letter:
'Dude, do you have a job for a software developer?'

Dear Sir/Madam,

I hope this letter finds you in good health and high spirits. I am writing to inquire about any potential job opportunities within your esteemed organization. Specifically, I am interested in a position as a software developer.

Allow me to introduce myself; my name is [Your Name]. I have a strong background in software development and possess a wide range of skills and expertise in this field. I am confident that my qualifications align well with the requirements of a software developer role.

I kindly request you to consider my application and notify me if there are any open positions or if you anticipate any future opportunities within your organization. I would be more than happy to provide you with my detailed resume and any additional information you may require.

Thank you for considering my inquiry. I eagerly look forward to the possibility of contributing to the success of your organization as a software developer. Should you require any further information or wish to schedule an interview, please do not hesitate to contact me.

Yours faithfully,

[Your Name]

Proofread and correct this review. Make it more compelling.
Ensure it follows APA style guide and targets an advanced reader.
Output in markdown format.
Text:
"""
Got this for my daughter for her birthday cuz she keeps taking \
mine from my room. Yes, adults also like pandas too. She takes \
it everywhere with her, and it's super soft and cute. One of the \
ears is a bit lower than the other, and I don't think that was \
designed to be asymmetrical. It's a bit small for what I paid for it \
though. I think there might be other options that are bigger for \
the same price. It arrived a day earlier than expected, so I got \
to play with it myself before I gave it to my daughter.
"""

Review: An Adorable Gift for All Ages

Introduction

I recently purchased a charming panda plush toy as a birthday gift for my daughter, as she had developed a penchant for borrowing mine from my room. Contrary to popular belief, pandas hold an undeniable appeal for adults as well. This review aims to provide a comprehensive assessment of the product, catering to advanced readers who value attention to detail and elegance.

The Perfect Companion

My daughter's delight knew no bounds when she received the panda plush. Its irresistibly soft texture and adorable appearance make it an instant favorite. Wherever she goes, this delightful companion faithfully accompanies her, bringing a sense of joy and comfort to her every adventure.

Exceptional Quality, Minor Flaw

While the overall quality of the plush toy is exceptional, I noticed a slight asymmetry in its design. One of the ears appears to be positioned slightly lower than the other, which, to my discerning eye, does not seem intentional. This minor imperfection, although noticeable upon closer inspection, does not diminish the overall appeal of the product.

Size Considerations

It is worth mentioning that the size of the panda plush was slightly smaller than my initial expectations, considering the price I paid for it. However, I believe it is important to note that there might be alternative options available at a similar price point that offer a larger size. Potential buyers seeking a more substantial plush may want to explore such alternatives before making their final decision.

Expedited Delivery, Personal Delight

To my pleasant surprise, the package arrived a day earlier than the anticipated delivery date. This unexpected advantage allowed me to indulge in the joy of playing with the panda plush myself before presenting it to my daughter. The extra time spent with this delightful toy reinforced my confidence in the quality and appeal of the product.

Conclusion

In summary, the panda plush toy I acquired proved to be an enchanting gift suitable for all ages. Its exceptional softness, endearing appearance, and unwavering companionship have made it an instant favorite of my daughter. Although I observed a minor design flaw and found its size to be slightly smaller than expected, the overall quality and charm of the product remain undeniable. For those seeking an elegant and delightful plush companion, this panda plush stands as a compelling option to consider.

learn.deeplearning.ai/chatgpt-prompt-eng

Prompt engineering: designing a chatbot

```
[
{'role':'system', 'content':'You are friendly chatbot.'},
{'role':'user', 'content':'Hi, my name is Isa'}
]
```

Hello Isa! It's nice to meet you. How can I assist you today?

```
[
{'role':'system', 'content':"""
You are OrderBot, an automated service to collect orders for a pizza restaurant. \
You first greet the customer, then collects the order, \
and then asks if it's a pickup or delivery. \
You wait to collect the entire order, then summarize it and check for a final \
time if the customer wants to add anything else. \
If it's a delivery, you ask for an address. \
Finally you collect the payment.\
Make sure to clarify all options, extras and sizes to uniquely \
identify the item from the menu.\
You respond in a short, very conversational friendly style. \
The menu includes \
pepperoni pizza  12.95, 10.00, 7.00 \
cheese pizza   10.95, 9.25, 6.50 \
eggplant pizza   11.95, 9.75, 6.75 \
fries 4.50, 3.50 \
greek salad 7.25 \
Toppings: \
extra cheese 2.00, \
mushrooms 1.50 \
sausage 3.00 \
canadian bacon 3.50 \
AI sauce 1.50 \
peppers 1.00 \
Drinks: \
coke 3.00, 2.00, 1.00 \
sprite 3.00, 2.00, 1.00 \
bottled water 5.00 \
"""}
]
```

Hi there! Welcome to OrderBot, your friendly automated ordering service for our pizza restaurant. How can I assist you today?

I would like to order a pizza.

Great! I'm here to help you with that. Could you please let me know which type of pizza you'd like to order? We have pepperoni pizza, cheese pizza, and eggplant pizza. Just tell me the name of the pizza you want, and I'll provide you with the available sizes and prices.

pepperoni is fine.

Excellent choice! Now, let's talk about the size. We have three options for our pepperoni pizza: small, medium, and large. The prices are as follows: small is $7.00, medium is $10.00, and large is $12.95. Please let me know which size you prefer for your pepperoni pizza.

I would like a medium size.

Perfect! You've chosen a medium-sized pepperoni pizza. Is there anything else you'd like to add to your order, such as toppings, side dishes, or drinks? Let me know, and I'll make sure to include them for you.

what kind of drinks to you have?

We offer a selection of refreshing drinks. Here are your options:

1. Coke: We have three sizes available - small for $1.00, medium for $2.00, and large for $3.00.
2. Sprite: Similar to Coke, we have small for $1.00, medium for $2.00, and large for $3.00.
3. Bottled Water: We have bottled water available for $5.00.

Please let me know if you'd like to add any drinks to your order, and if so, the type and size you prefer.

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I will take a medium coke please.

Great! You've added a medium Coke to your order. Just to confirm, you're ordering a medium-sized pepperoni pizza and a medium Coke. Is that correct?

yes

Got it! You've ordered a medium-sized pepperoni pizza and a medium Coke. Now, I need to ask if you'll be picking up your order or if you'd like it delivered to your location. Could you please let me know your preference?

I will pick it up.

Perfect! You'll be picking up your order. Thank you for letting us know. Now, to complete your order, I just need to confirm your payment method. We accept cash and credit/debit cards. Please let me know your preferred payment method, and we'll get everything ready for you to pick up.

credit

Great! We accept credit cards as a payment method. When you come to pick up your order, please make sure to have your credit card ready for payment.

Just to summarize, your order includes a medium-sized pepperoni pizza, a medium Coke, and you'll be picking it up. Is there anything else I can assist you with or add to your order?

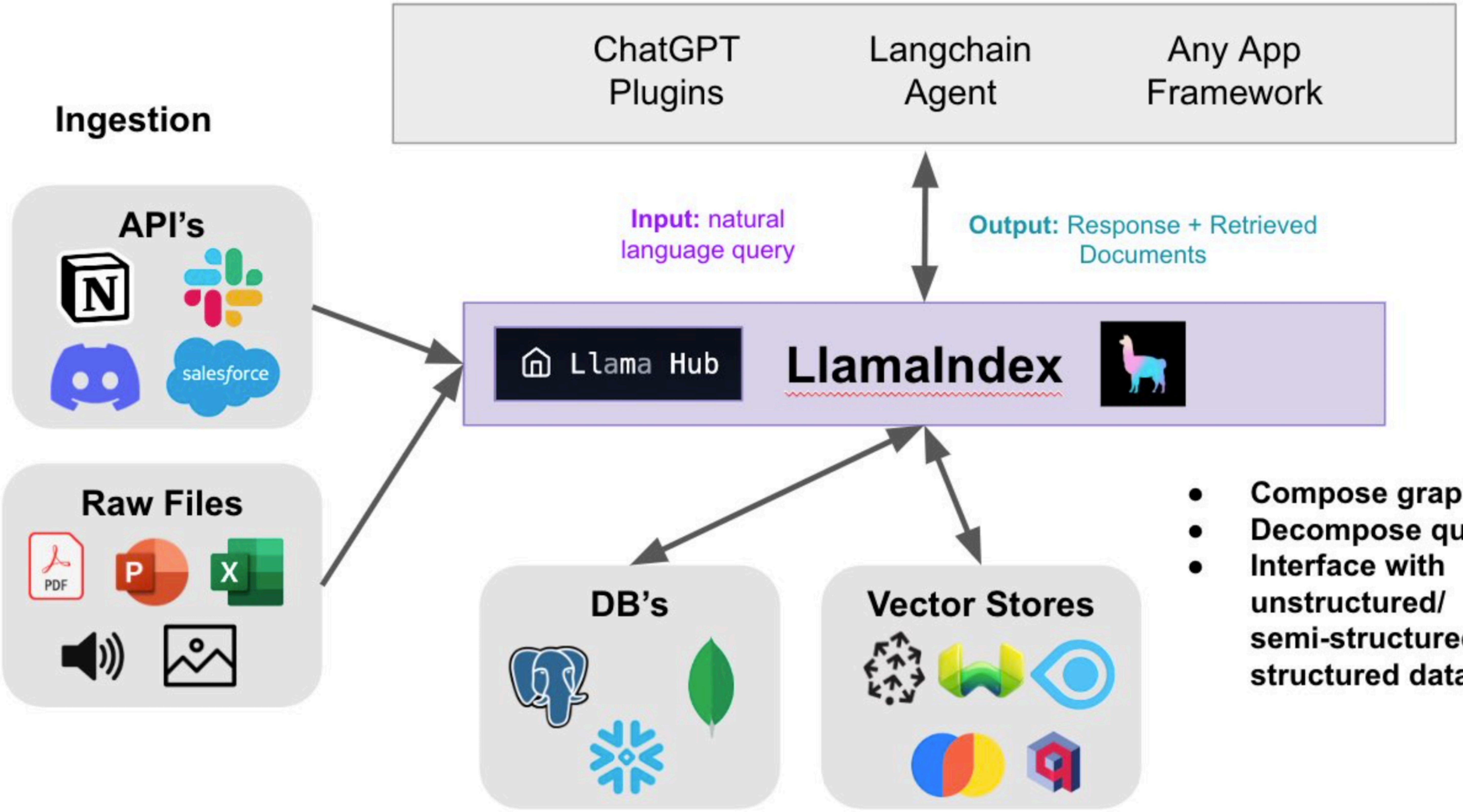
No. Thank you for your help.

You're very welcome! I'm glad I could assist you with your order. Your medium-sized pepperoni pizza and medium Coke will be ready for pickup. If you have any further questions or need any assistance in the future, feel free to reach out. Enjoy your meal!

LLM: in-context learning / adding information

LLMs can only extract information from their context window size: 2,048 tokens (approx. 1,000 words) for GPT-3

LLMs have information from the web up to a given date: GPT 3.5 (ChatGPT) cut-off date is September 2021



- Compose graphs
- Decompose queries
- Interface with unstructured/ semi-structured/ structured data

imartinez / privateGPT

Jerry Liu - twitter.com/jerryjliu0/status/1643998635984818178

LLM: give them a second chance

They cannot backtrack… But they can review in a subsequent response

LLMs: making them smaller / faster

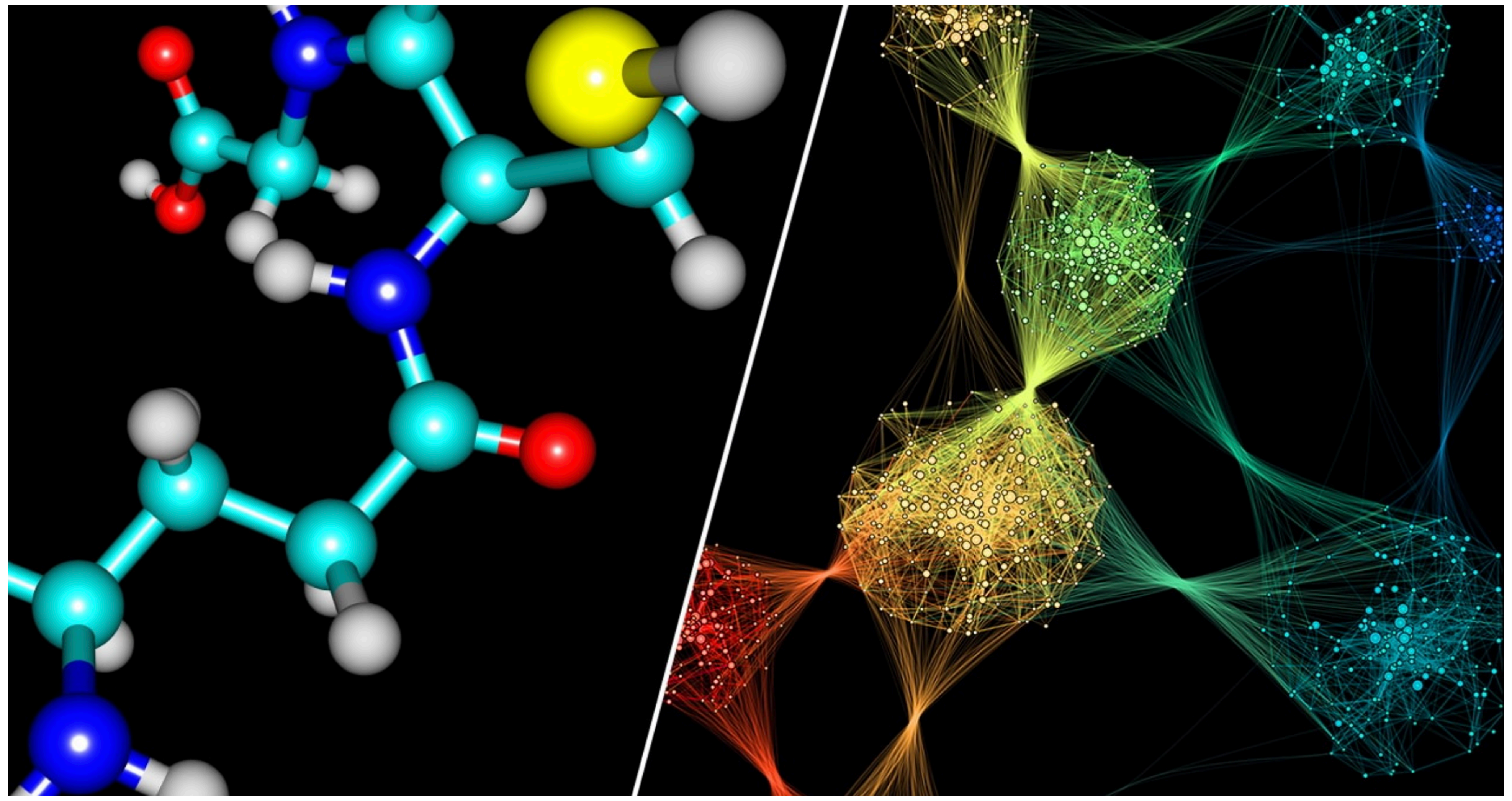
Several sizes trained: reducing the number of heads and layers

Bit quantization: trained with 16 bits floating values (bfloat16 “brain float point 16)… reduced to 4 bits.

LLMs running on iPhone MACHINE LEARNING COMPILATION mlc.ai/mlc-llm/

(Semi) Deep Learning (like) on Graphs

PyG (PyTorch Geometric)



blogs.nvidia.com/blog/2022/10/24/what-are-graph-neural-networks/

Do Transformers Really Perform Bad for Graph Representation?

Chengxuan Ying[1]*, Tianle Cai[2], Shengjie Luo[3]*,
Shuxin Zheng[4]†, Guolin Ke[4], Di He[4]†, Yanming Shen[1], Tie-Yan Liu[4]
[1]Dalian University of Technology [2]Princeton University
[3]Peking University [4]Microsoft Research Asia
yingchengsyuan@gmail.com, tianle.cai@princeton.edu, luosj@stu.pku.edu.cn
{shuz†, guoke, dihe†, tyliu}@microsoft.com, shen@dlut.edu.cn

CS224W: Machine Learning with Graphs

Stanford / Winter 2023

Resources

Courses: cs231n.stanford.edu, cs224n.stanford.edu, fast.ai, Andrej Karpathy (Youtube)

News: deeplearning.ai/thebatch, @karpathy (Twitter)

Blogs: karpathy.github.io

Podcast: Lex Fridman, The Robot Brains (Pieter Abdeel)

Tools: pytorch.org, Huggingface.co PYTORCH

Free GPU: Google Colab

Papers: arxiv.org arXiv.org