IS813: Gen AI - Implementation

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Neural Nets in Language Modeling

Continued…

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Fast Forward…

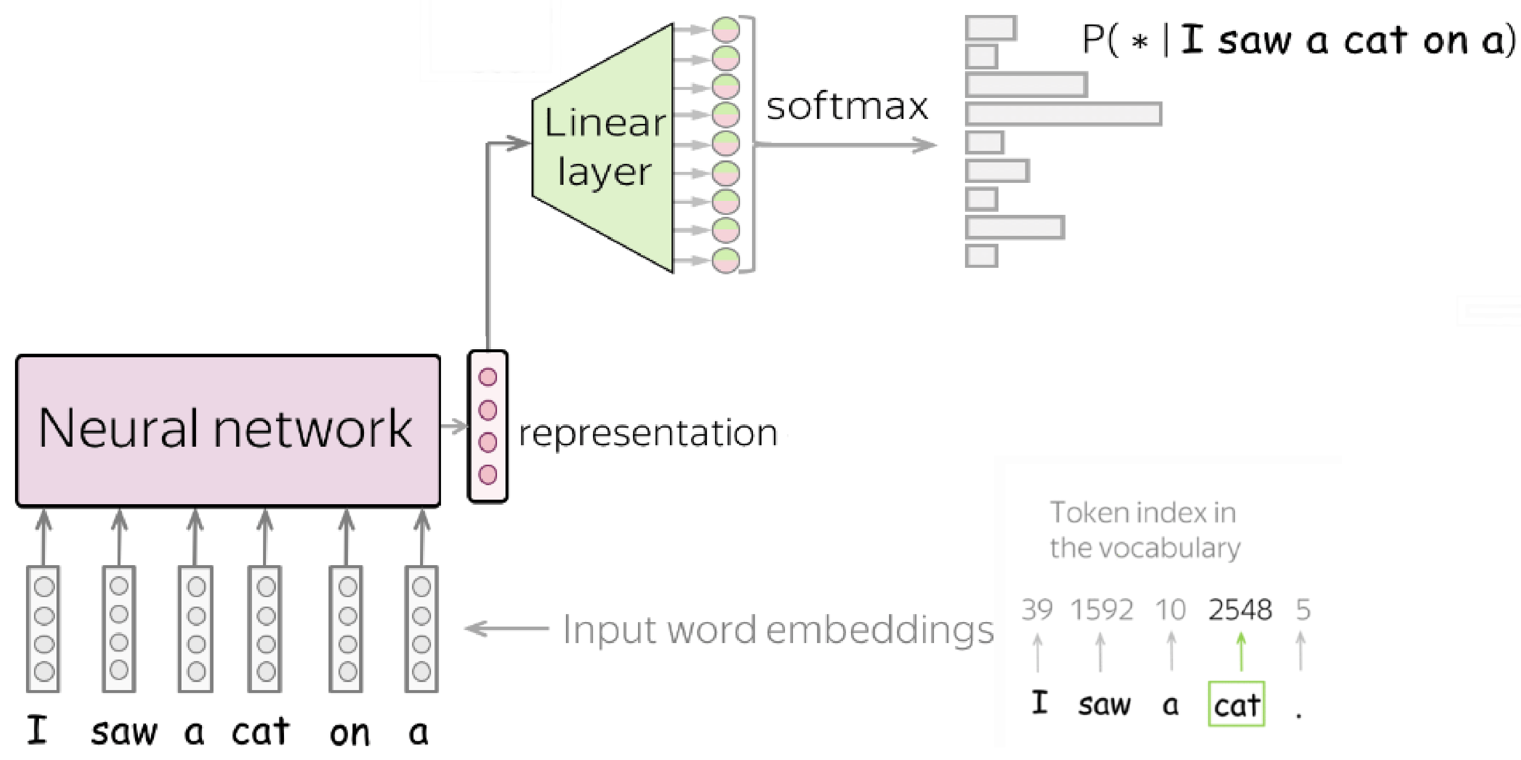
As neural networks arrived at the scene, they were utilized for language modeling.

- N-grams look for exact prefixes, which is limiting…
- However, neural networks can learn more interesting relationships between the words.

Example: All humans are mortal. Socrates is a human. Therefore,

Socrates is mortal.

General Model Architecture



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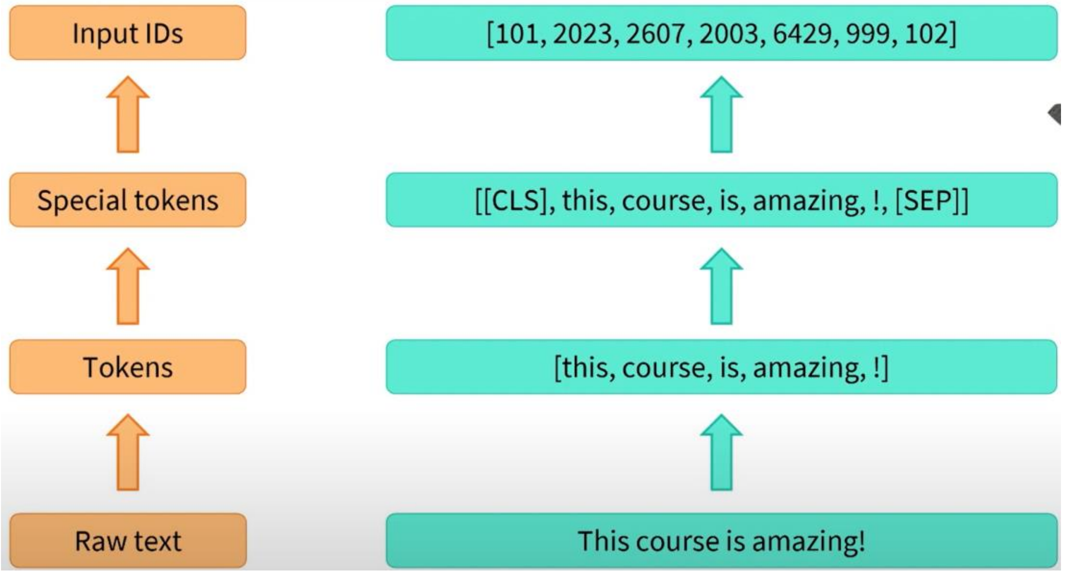
Can you see any issue with inputting words in an NN?

Tokenization

- Computers only understand numbers.
- We need to convert the text into tokens (e.g., words).
- Each token can then be represented as a number.
- Demo

Huggingface



What is an embedding?

- It is the numeric representation of data.
- Example for images.

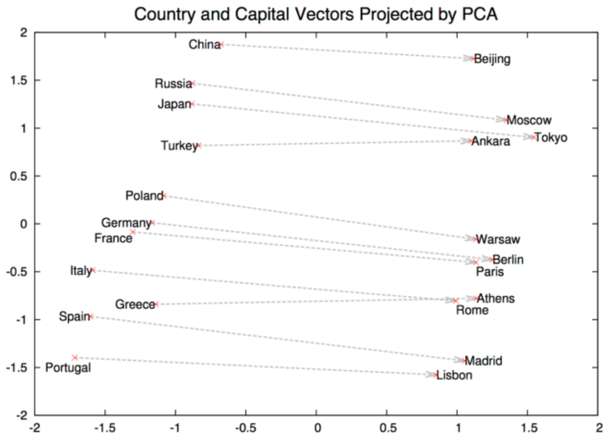
Word Embeddings

- We ideally want related words (i.e., *similar* meanings) to have smaller distances.
- [Demo]
- Examples:
  1. Word2Vec (Google)
  2. GloVe (Stanford)
  3. Train your own!

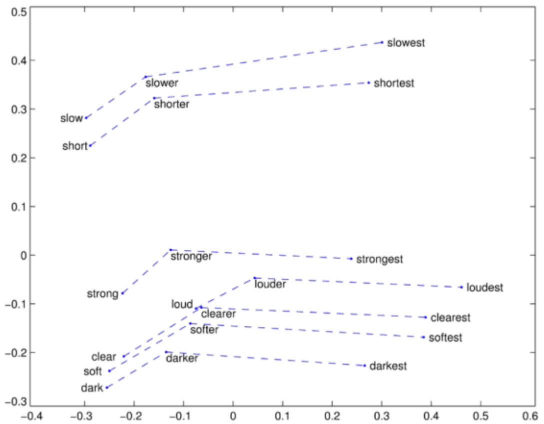
Word Embeddings

Since word embeddings carry *meaning*, certain directions in their space carry certain significance:

- Demo (dimensionality)



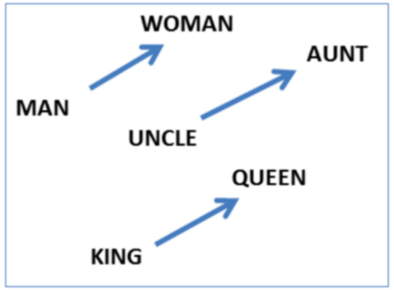
Word2Vec

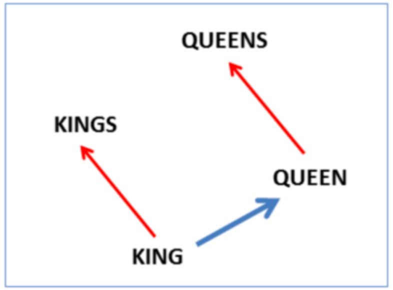


GloVe

semantic: v(king) – v(man) + v(woman) ≈ v(queen)

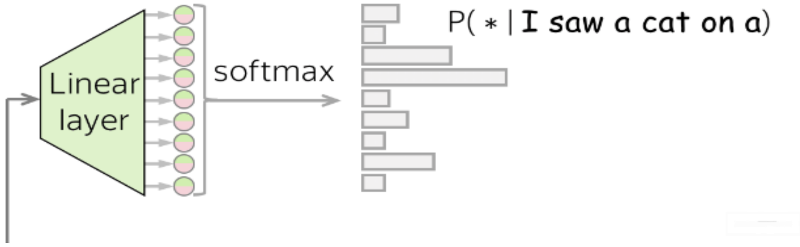
syntactic: v(kings) – v(king) + v(queen) ≈ v(queens)

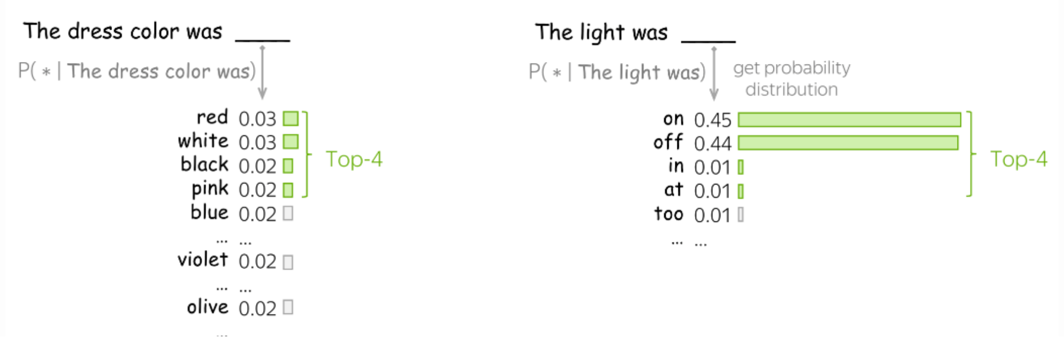


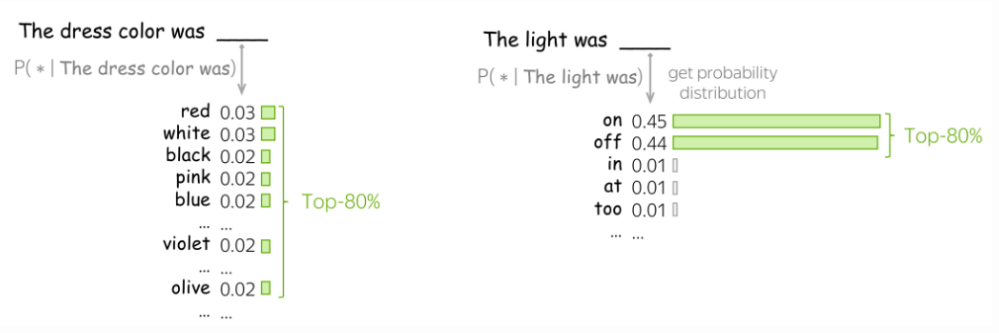


Sampling The Distribution

- Always take top probability?
  - That makes the model deterministic (no creativity).
- Alternative?
  - Top-k or top-p.







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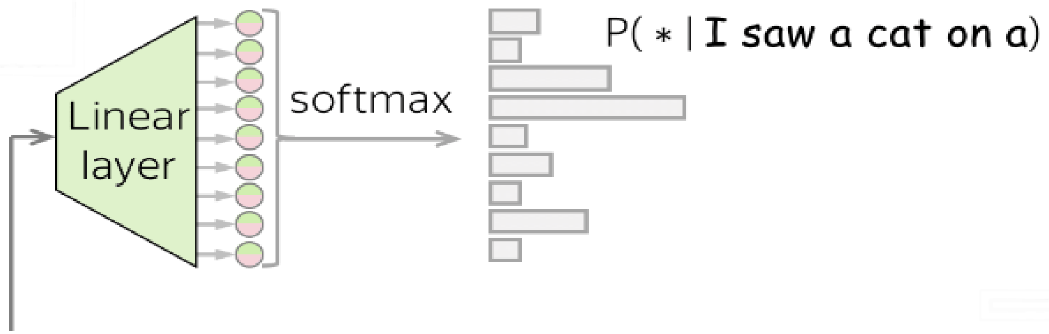
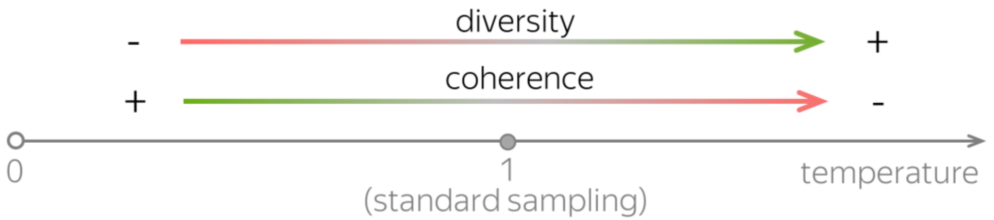
Sampling The Distribution

- Some words have way higher probability than others.
- This can be manually tuned through temperature.
- Demo





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Measuring The Metric

- What are we looking for?
  - A model that is not surprised by the new text it seen.
- We use perplexity.
  - Takes values between 1 and number of possible tokens.
  - Smaller is better.
  - Perplexity calculations: Demo
  - Next word probability: Demo

Fast Forward…

- There exists many types of Neural Nets for language modeling:
  - CNNs
  - RNNs
  - LSTMs…

- Generally, Neural Nets learn an *embedding* that represents the *entire prefix* to predict the next word.

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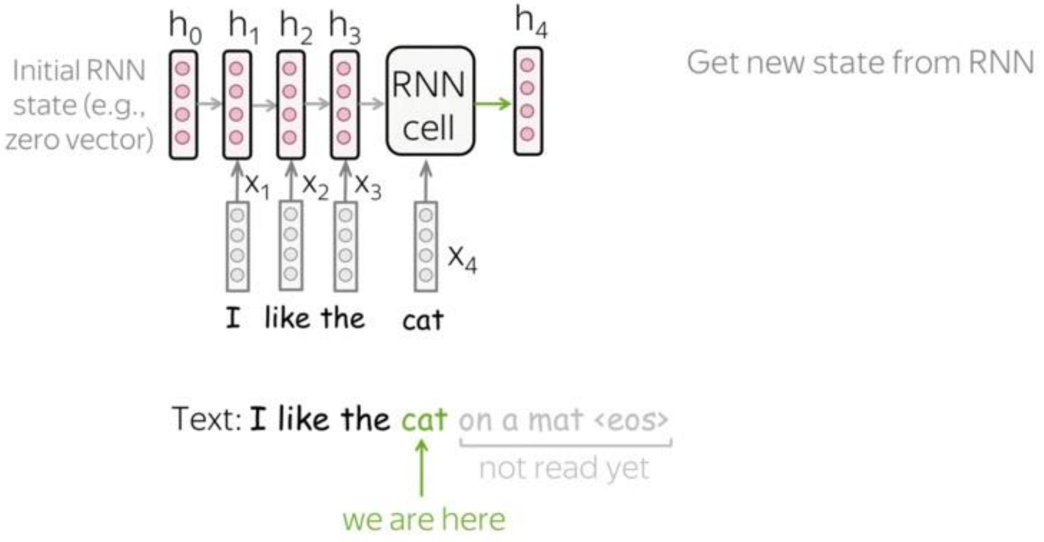


Attention!

- These types of Neural Nets, however, suffered from various issues:
    - E.g., *catastrophic forgetting*, where earlier context in longer sentences tends to be forgotten.

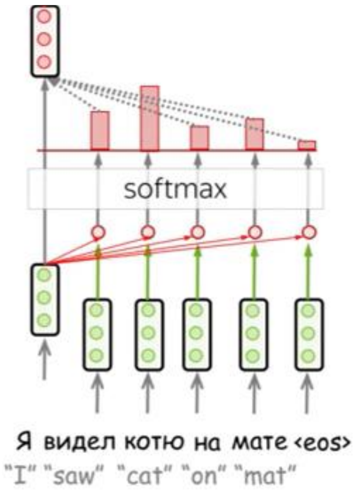
- In 2015, *attention* in Neural Nets was invented:
    - It allowed models to attend to different parts of the sentence (instead of a single representation).

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



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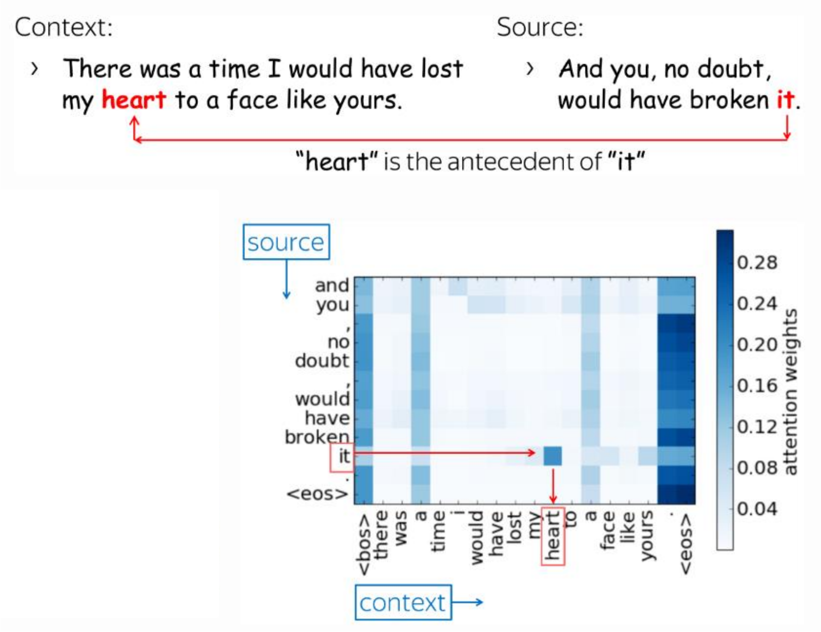
Attention!

- Once each part has its own embedding, different types of *relationships* can be learned!



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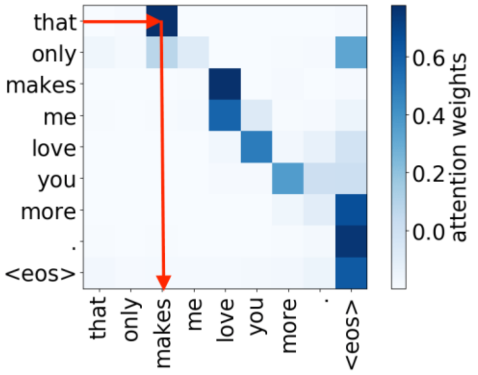
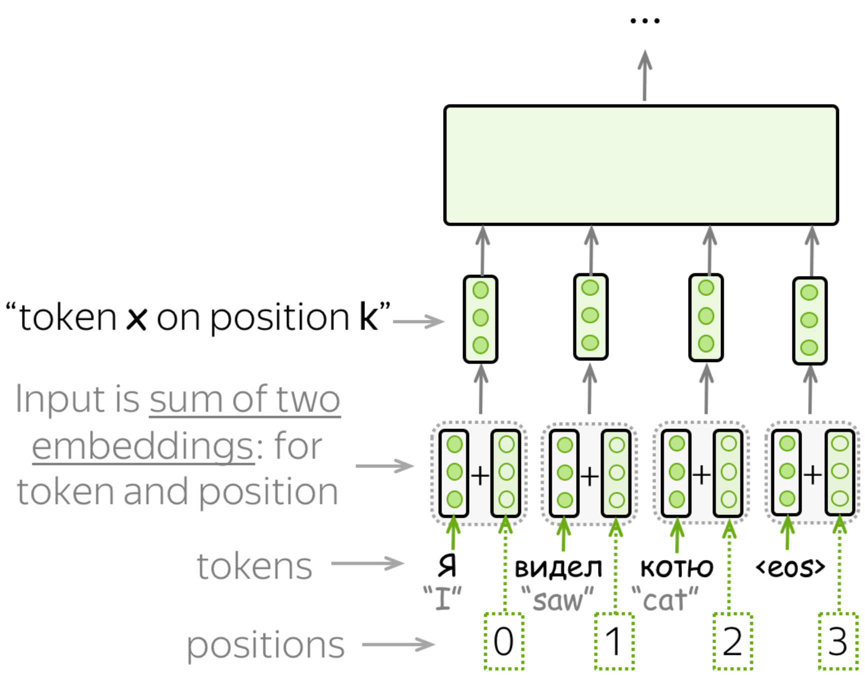


Subject -> verb

Order Matters: Positional Encoding!

- Since token embeddings do not contain information about the location of the word, they should be combined with a *positional encoding.*



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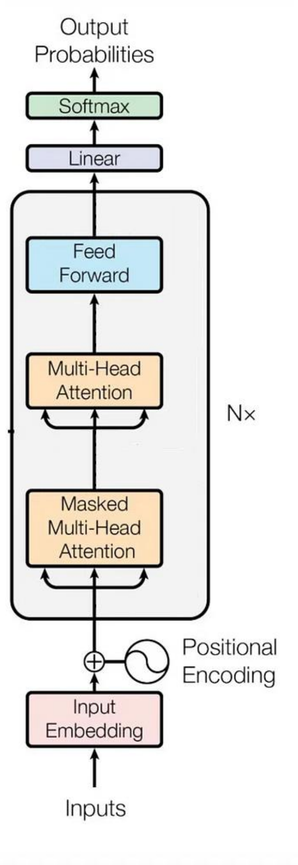
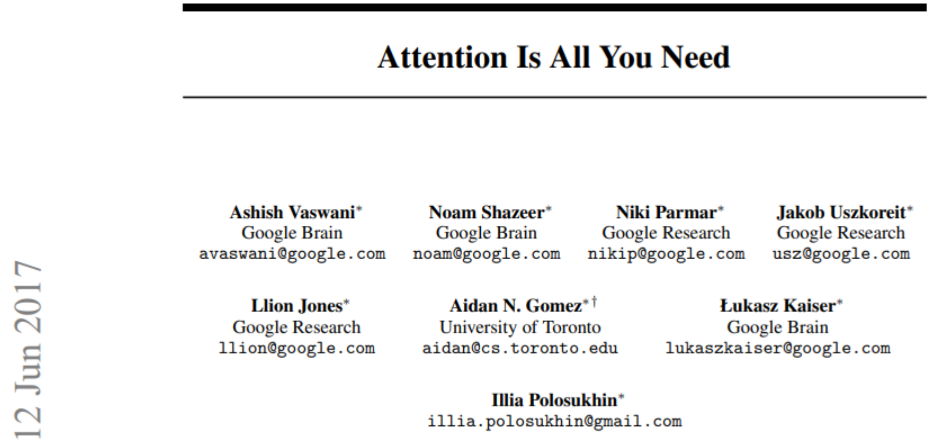
The Transformer is born!



Javinkarla



12 Jun 2017

Attention Is All You Need

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Models in the wild

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Model Types

We are not going to get into technical details, but certain models may be more fit for certain tasks:

Model	Examples	Tasks
Encoder	ALBERT, BERT, DistilBERT, ELECTRA, RoBERTa	Sentence classification, named entity recognition, extractive question answering
Decoder	CTRL, GPT, GPT-2, Transformer XL	Text generation
Encoder-decoder	BART, T5, Marian, mBART	Summarization, translation, generative question answering

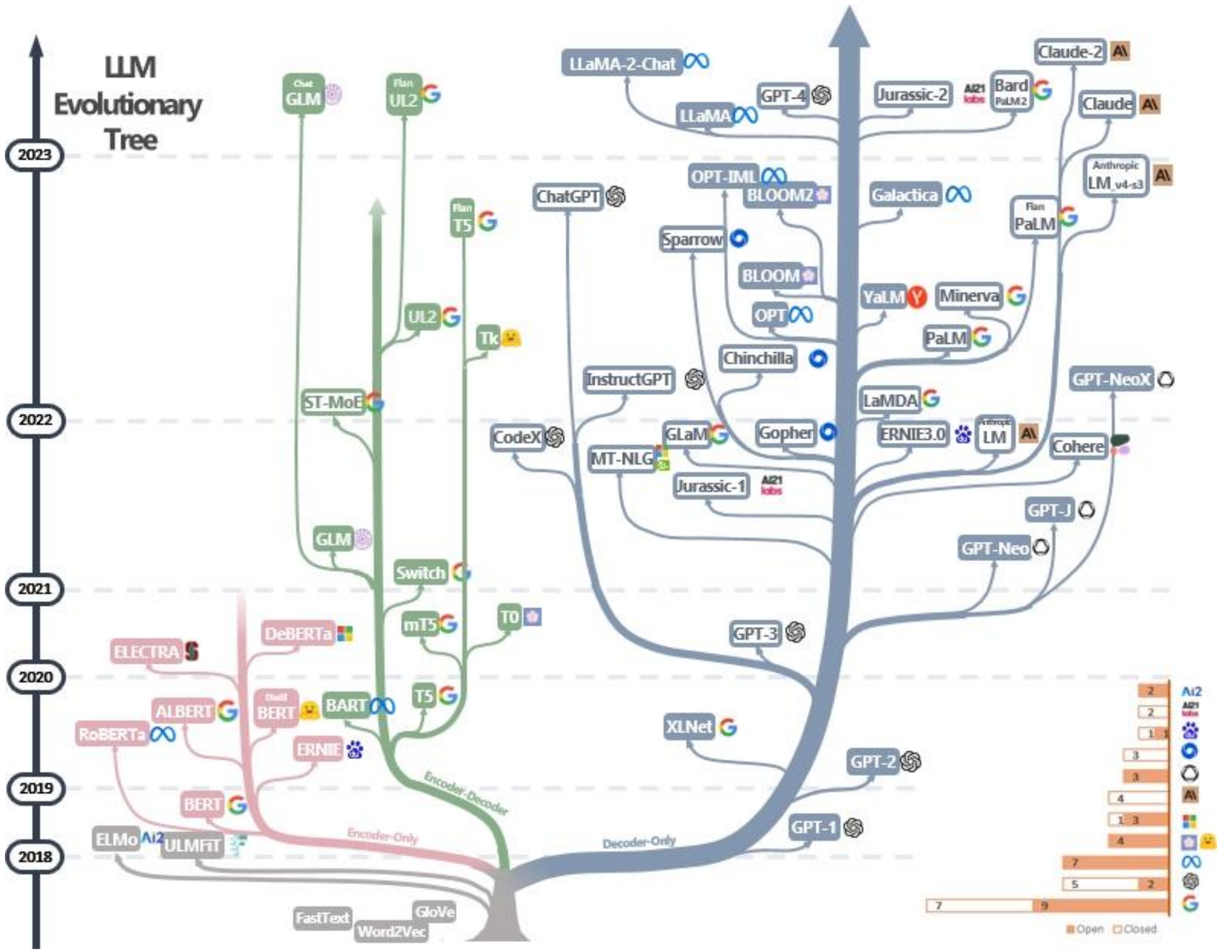
Javinkarla

Why so many?

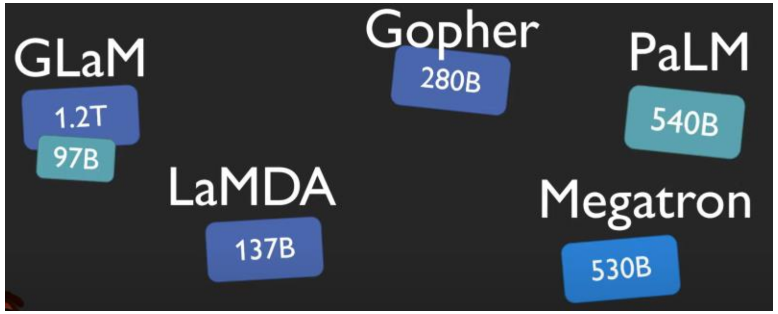
Where do the differences come from?

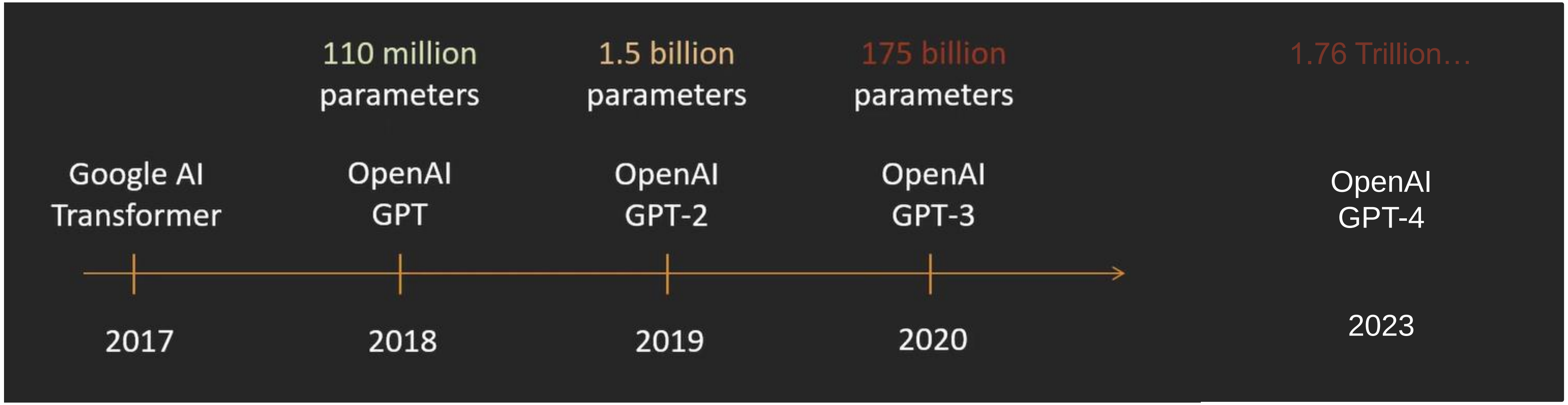
- Data.
- Model type and size.
- Hyperparameters (context size, embedding size,…).
- Training process (the cost function, fine-tuning, human feedback, etc.).

Yang et al.



The GPT Evolution…





AI Coffee Beak with Letitia

[Book Corpus](#)
[WebText](#)

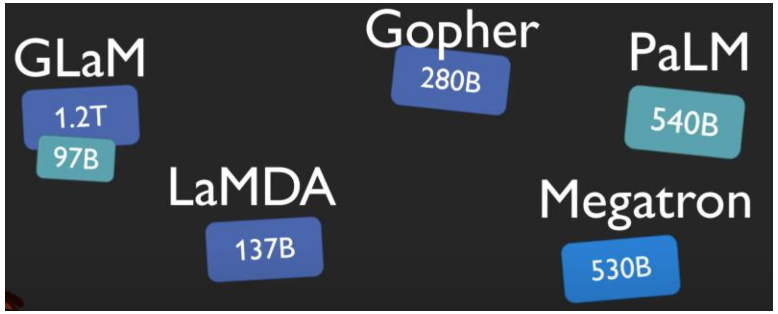
1,038 books (around 74M sentences and 1G words) of 16 different sub-genres (e.g., Romance, Historical, Adventure, etc.)

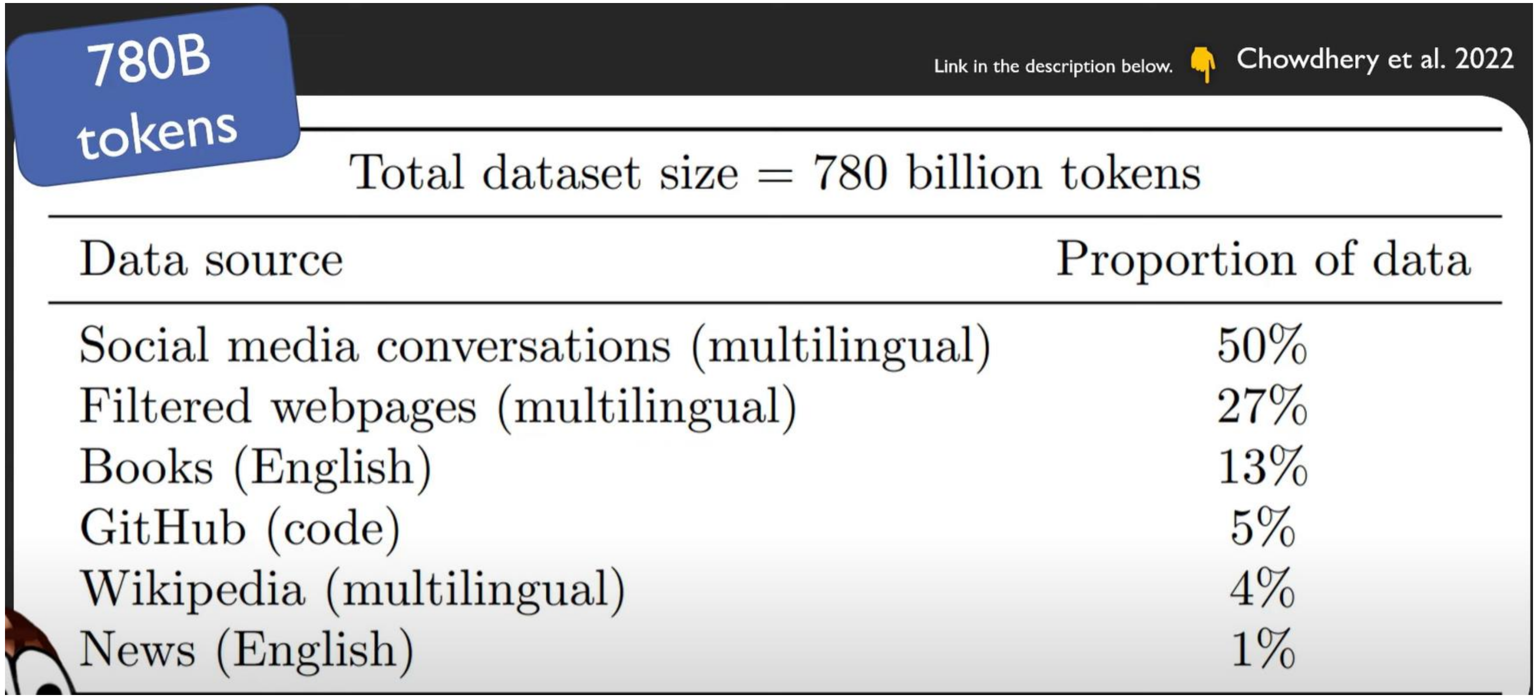
[Common Crawl + ...](#)

Over 240 billion pages.
Petabytes of data.

????

The GPT Evolution...



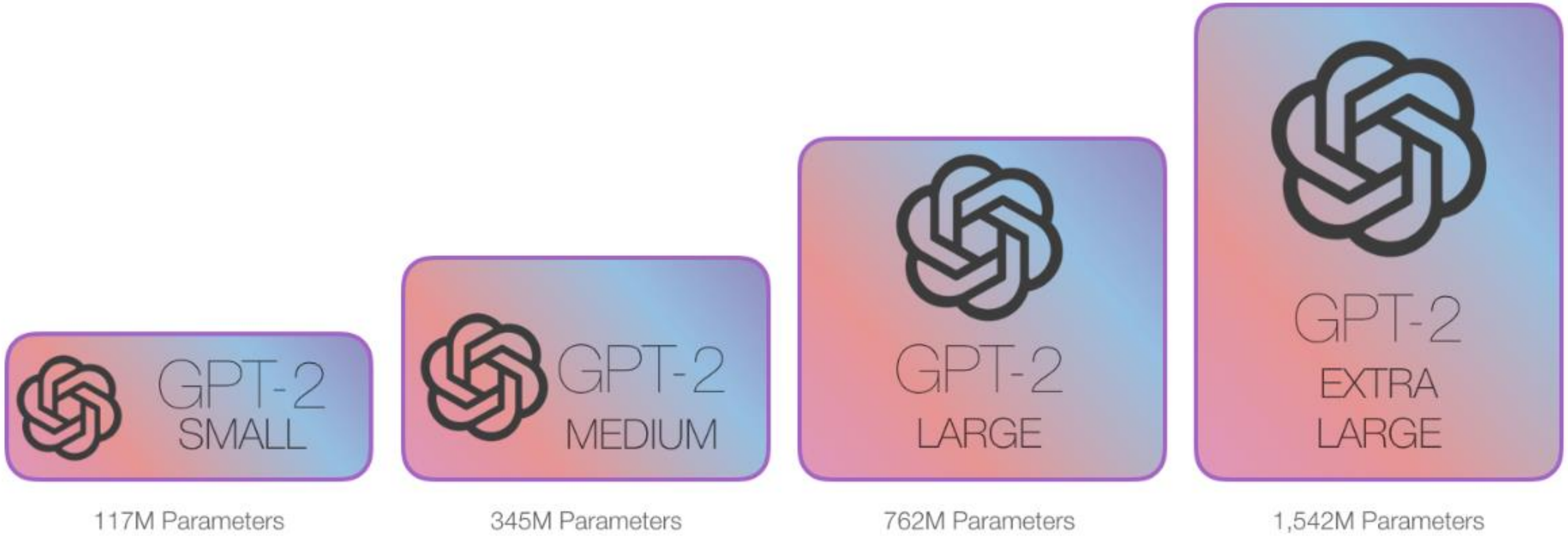


Total dataset size = 780 billion tokens

Data source	Proportion of data
Social media conversations (multilingual)	50%
Filtered webpages (multilingual)	27%
Books (English)	13%
GitHub (code)	5%
Wikipedia (multilingual)	4%
News (English)	1%

AI Coffee Beak with Letitia

Different model sizes



[Jay Alammar]

Exploring Your Options

- OpenAI model reference

- HuggingFace tasks
- HuggingFace models

How much training does it take?

2 example models

GPT-3 (2020)

50,257 vocabulary size
2048 context length
175B parameters
Trained on 300B tokens

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	1.6×10^{-4}
GPT-3 6.7B	6.7B	32	4096	32	128	2M	1.2×10^{-4}
GPT-3 13B	13.0B	40	5140	40	128	2M	1.0×10^{-4}
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	0.6×10^{-4}

Table 2.1: Sizes, architectures, and learning hyper-parameters (batch size in tokens and learning rate) of the models which we trained. All models were trained for a total of 300 billion tokens.

Training: (rough order of magnitude to have in mind)

- O(1,000 - 10,000) V100 GPUs
- O(1) month of training
- O(1-10) $M

LLaMA (2023)

32,000 vocabulary size
2048 context length
65B parameters
Trained on 1-1.4T tokens

params	dimension	n heads	n layers	learning rate	batch size	n tokens
6.7B	4096	32	32	$3.0e^{-4}$	4M	1.0T
13.0B	5120	40	40	$3.0e^{-4}$	4M	1.0T
32.5B	6656	52	60	$1.5e^{-4}$	4M	1.4T
65.2B	8192	64	80	$1.5e^{-4}$	4M	1.4T

Table 2: **Model sizes, architectures, and optimization hyper-parameters.**

Training for 65B model:

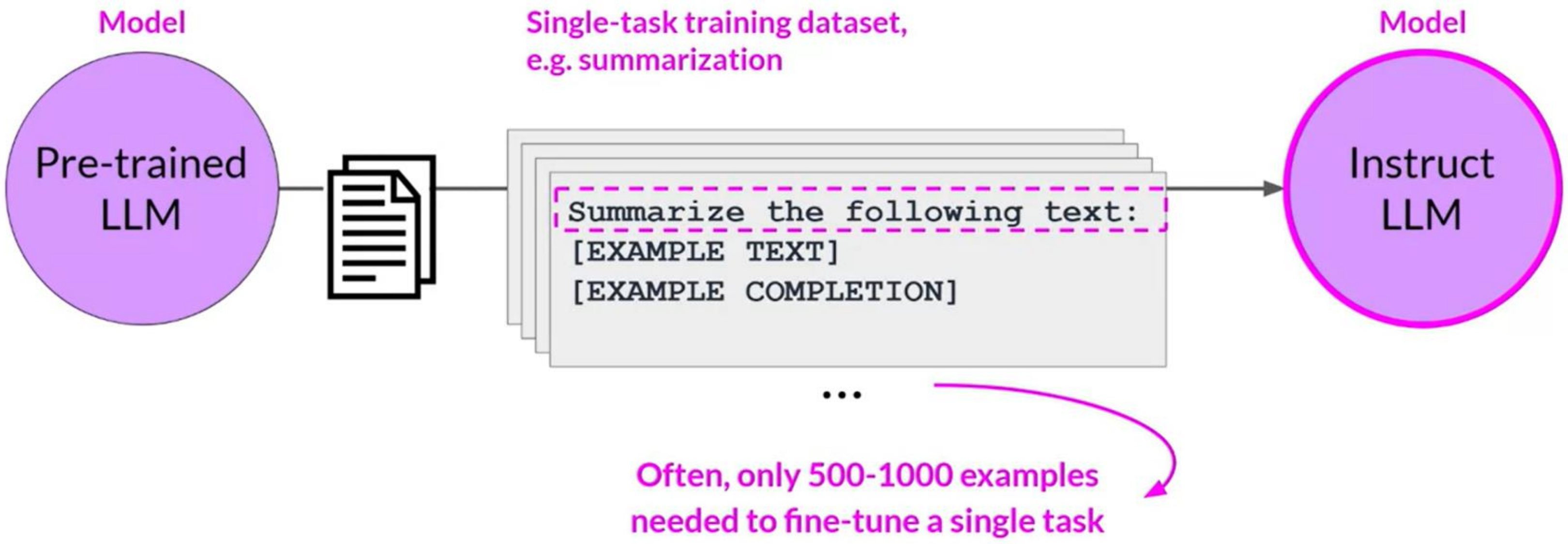
- 2,048 A100 GPUs
- 21 days of training
- $5M

[Language Models are Few-Shot Learners, OpenAI 2020]
[LLaMA: Open and Efficient Foundation Language Models, Meta AI 2023]

Pre-trained Models: Democratizing AI

- Most of us don’t have the expertise, data, or resources to train anything close to these impressive large models.
- Instead:
  - *Zero-shot Learning:* We can use open-source models out-of-the-box, even though they have never seen our data before.
  - *Transfer learning/Fine-Tuning:* Can be used as a base for further training (e.g., if the training data is non-public legal documents).

Example: Instruct LLMs



Coursera

In-Class Work

HuggingFace

Resources

- Meaning and calculation of perplexity.
- Video: LLMs vs The Brain
- Video: Deciding which pre-trained model to fine-tune