TOR VERGATA
UNIVERSITÀ DEGLI STUDI DI ROMA

LARGE LANGUAGE MODELS AND HOW TO INSTRUCTION TUNE THEM

(IN A SUSTAINABLE WAY)

DANILO CROCE
UNIVERSITY OF ROME, «TOR VERGATA»

BERTINORO INTERNATIONAL SPRING SCHOOL 2024
MARCH 11-13, 2024

Tutorial Material

`https://github.com/crux82/BISS-2024`

You can access to the material for the tutorial:

- These slides
- Code

Many thanks to

- **Claudiu Daniel Hromei**
- **Roberto Basili**

for their precious support to this work

Before starting

Remember:

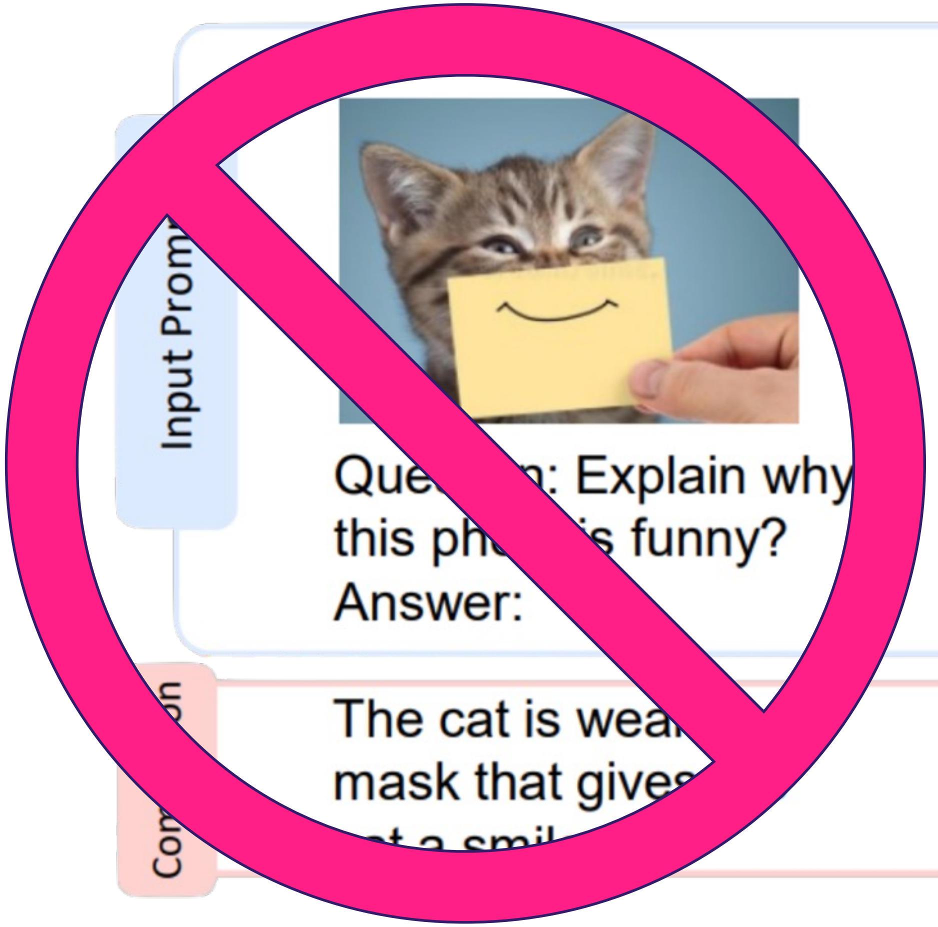
- **There are no *stupid questions*- only *silly answers*!** 😄
- The real goof is the one who's teaching (that's me/us!) 🎓
- Your questions make this journey insightful and fun for everyone!

"In the World of Learning, Every Question is a Step Forward"

- **So, let's make this interactive:**
  - 🙋‍♀️🙋‍♂️ Don't hesitate to ask anything that comes to mind.
  - 🔍 Explore, inquire, and challenge ideas - it's all part of the learning process!
  - 💡 Every question you ask is a chance for us all to learn something new.

Disclaimer(s)

No multi-modality with LLMS, even thought is such an interesting problem..



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Anyway if you are interested in «Multimodal LLMs»

from `https://huyenchip.com/2023/10/10/multimodal.html`

Microsoft COCO Captions: Data Collection and Evaluation Server (Apr 2015)

VQA: Visual Question Answering (May 2015)

VideoBERT: A Joint Model for Video and Language Representation Learning (Google, Apr 3, 2019)

LXMERT: Learning Cross-Modality Encoder Representations from Transformers (UNC Chapel Hill, Aug 20, 2019)

[CLIP] Learning Transferable Visual Models From Natural Language Supervision (OpenAI, 2021)

Unifying Vision-and-Language Tasks via Text Generation (UNC Chapel Hill, May 2021)

BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation (Salesforce, Jan 28, 2022)

Flamingo: a Visual Language Model for Few-Shot Learning (DeepMind, April 29, 2022)

GIT: A Generative Image-to-text Transformer for Vision and Language (Microsoft, May 2, 2022)

MultiInstruct: Improving Multi-Modal Zero-Shot Learning via Instruction Tuning (Xu et al., Dec 2022)

BLIP-2: Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models (Salesforce, Jan 30, 2023)

Cross-Modal Fine-Tuning: Align then Refine (Shen et al., Feb 11, 2023)

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KOSMOS-1: Language Is Not All You Need: Aligning Perception with Language Models (Microsoft, Feb 27, 2023)

PaLM-E: An Embodied Multimodal Language Model (Google, Mar 10, 2023)

LLaMA-Adapter: Efficient Fine-tuning of Language Models with Zero-init Attention (Zhang et al., Mar 28, 2023)

mPLUG-Owl: Modularization Empowers Large Language Models with Multimodality (Ye et al., Apr 2, 2023)

LLaMA-Adapter V2: Parameter-Efficient Visual Instruction Model (Gao et al., Apr 28, 2023)

LLaVA: Visual Instruction Tuning (Liu et al., Apr 28, 2023)

X-LLM: Bootstrapping Advanced Large Language Models by Treating Multi-Modalities as Foreign Languages (Chen et al., May 7, 2023)

InstructBLIP: Towards General-purpose Vision-Language Models with Instruction Tuning (Salesforce, May 11, 2023)

Towards Expert-Level Medical Question Answering with Large Language Models (Singhal et al., May 16, 2023)

Cheap and Quick: Efficient Vision-Language Instruction Tuning for Large Language Models (Luo et al., May 24, 2023)

Shikra: Unleashing Multimodal LLM's Referential Dialogue Magic (SenseTime, Jun 3, 2023)

Macaw-LLM: Multi-Modal Language Modeling with Image, Audio, Video, and Text Integration (Tencent, Jun 15, 2023)

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~~Agenda~~ A long "story"
(made of about 200 slides 😱)

Prologue: A «crazy» idea

Chapter 1: From the distributional hypothesis to word embeddings

Chapter 2: A deep dive into the Transformer

Chapter 3: Training a sentence classifier using BERT-based models 🤗

Chapter 4: From the decoder-only architecture to ChatGPT

Chapter 5: EXTREMITA - one model for all the EVALITA tasks

Chapter 6: Fine-tune a LLaMA-based model for all tasks from EVALITA 🤗

PROLOGUE

A “CRAZY” IDEA

Let’s start from the beginning

EVALITA

- EVALITA is a **periodic evaluation campaign** of Natural Language Processing (NLP) and speech tools for the **Italian language**,
  - an **initiative of the Associazione Italiana di Linguistica Computazionale** (AILC)
- **Shared benchmark for different tracks:**
  - Affect Detection
  - Authorship Analysis
  - Computational Ethics
  - Linguistic Analysis (syntactic/semantic parsing, POS-tagging)
  - Information Extraction (named-entity recognition)
  - Discourse Coherence
  - …

https://www.evalita.it

EVALITA 2023

13 tasks (22 subtasks)

- **Affect**
  - EMit – Categorical Emotion Detection in Italian Social Media
  - EmotivITA – Dimensional and Multi-dimensional emotion analysis
- **Authorship Analysis**
  - PoliticIT – Political Ideology Detection in Italian Texts
  - GeoLingIt – Geolocation of Linguistic Variation in Italy
  - LangLearn – Language Learning Development

https://www.evalita.it

EVALITA 2023

13 tasks (22 subtasks)

- **Computational Ethics**
  - HaSpeeDe 3 – Political and Religious Hate Speech Detection
  - HODI – Homotransphobia Detection in Italian
  - MULTI-Fake-DetectiVE – MULTImodal Fake News Detection and VErification
  - ACTI – Automatic Conspiracy Theory Identification
- **New Challenges in Long-standing Tasks**
  - NERMuD -Named-Entities Recognition on Multi-Domain Documents
  - CLinkaRT – Linking a Lab Result to its Test Event in the Clinical Domain
  - WiC-ITA – Word-in-Context task for Italian
  - DisCoTEX – Assessing DIScourse COherence in Italian TEXts

https://www.evalita.it

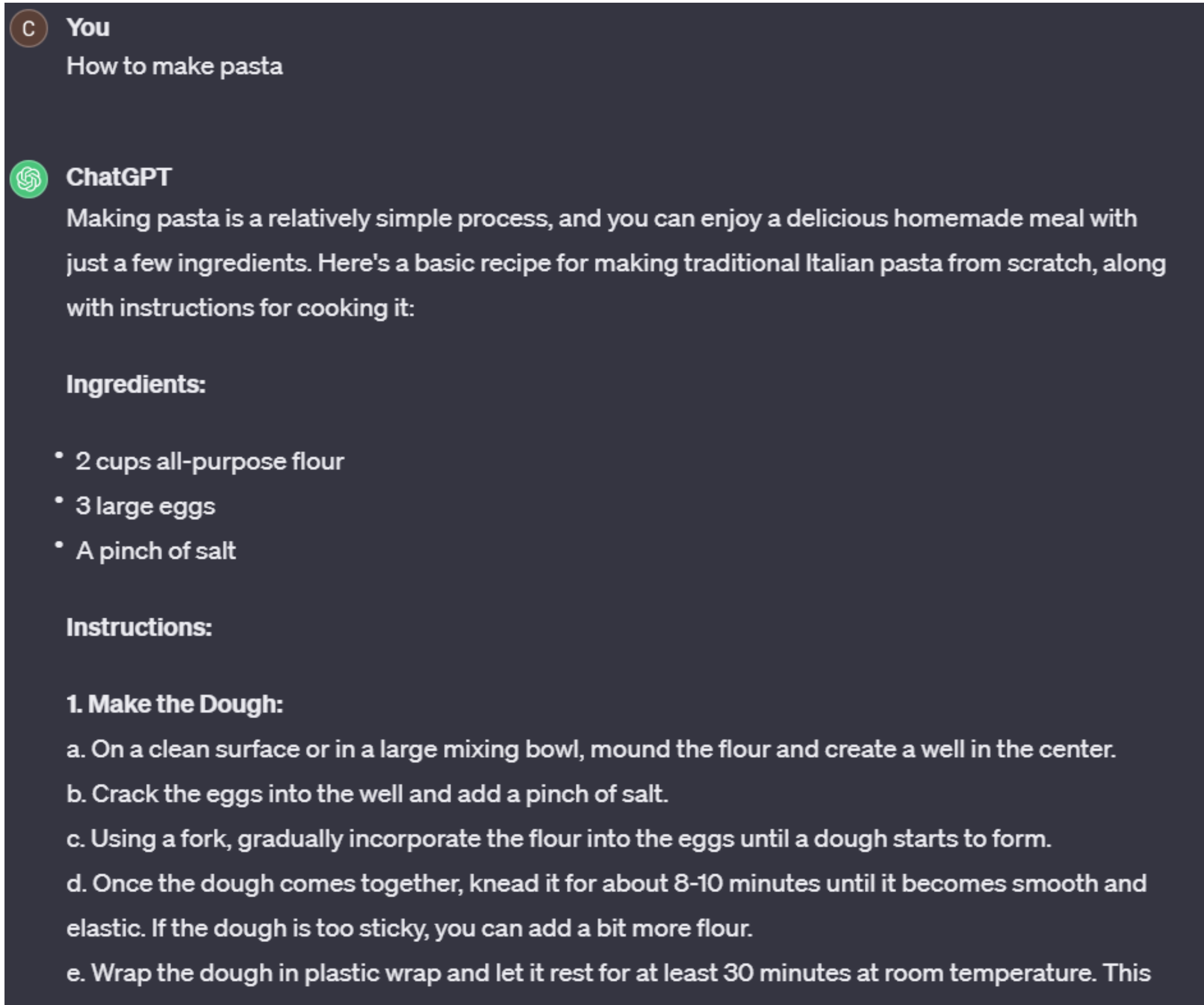
A little «technological» context

- What was the hype in AI/NLP in February 2023?
  (still nowadays)

After one year with, we **ask everything to ChatGPT**

- Even not really smart questions like
  How to make pasta

  and we expect clever/useful/kind answers

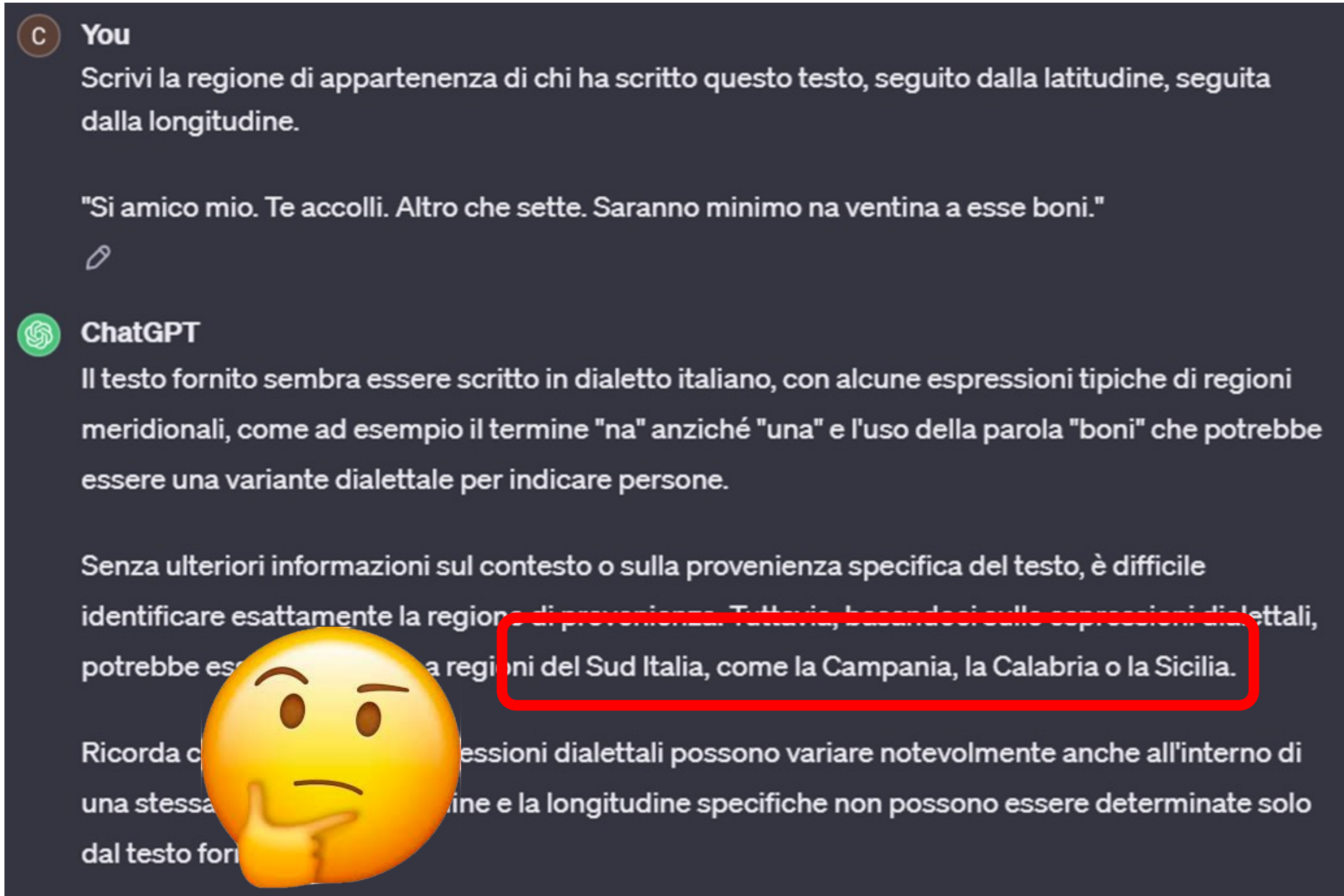


A bit of context (2)

Clearly it could be interesting to use it and ~~participate~~ **win** a task

Let us consider the GeoLingIT task:

“Given the text of **a tweet** exhibiting non-standard Italian language, **predict its region of provenance** [...] and **its location** in terms of longitude and latitude coordinates.”



Leveraging LLMs for Specific Tasks

Can Large Language Models be tailored to address precise language processing challenges?

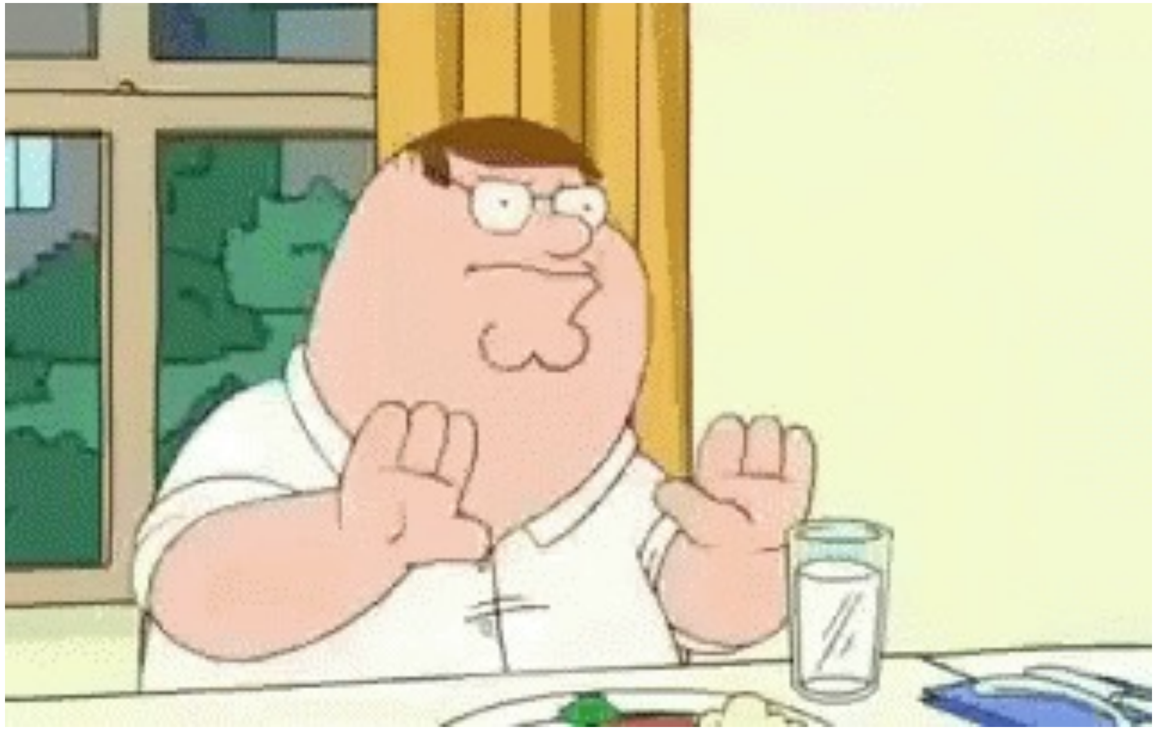
- E.g., NER, POS tagging, Hate Speech Detection, Discourse Coherence…

Our Expectations:

- **Natural Language Interaction**: Use the model using conversational language.
- **Prompt Engineering**: Utilize sophisticated prompt-design techniques for enhanced model performance.
- **Coherent Responses**: Obtain answers that align with our specified tasks.
- **High-Performance Outcomes**: Achieve *good* results in task execution.

The «crazy» idea

Fine-tuning a single LLMs by applying it to **ALL EVALITA tasks**



How did we get here???

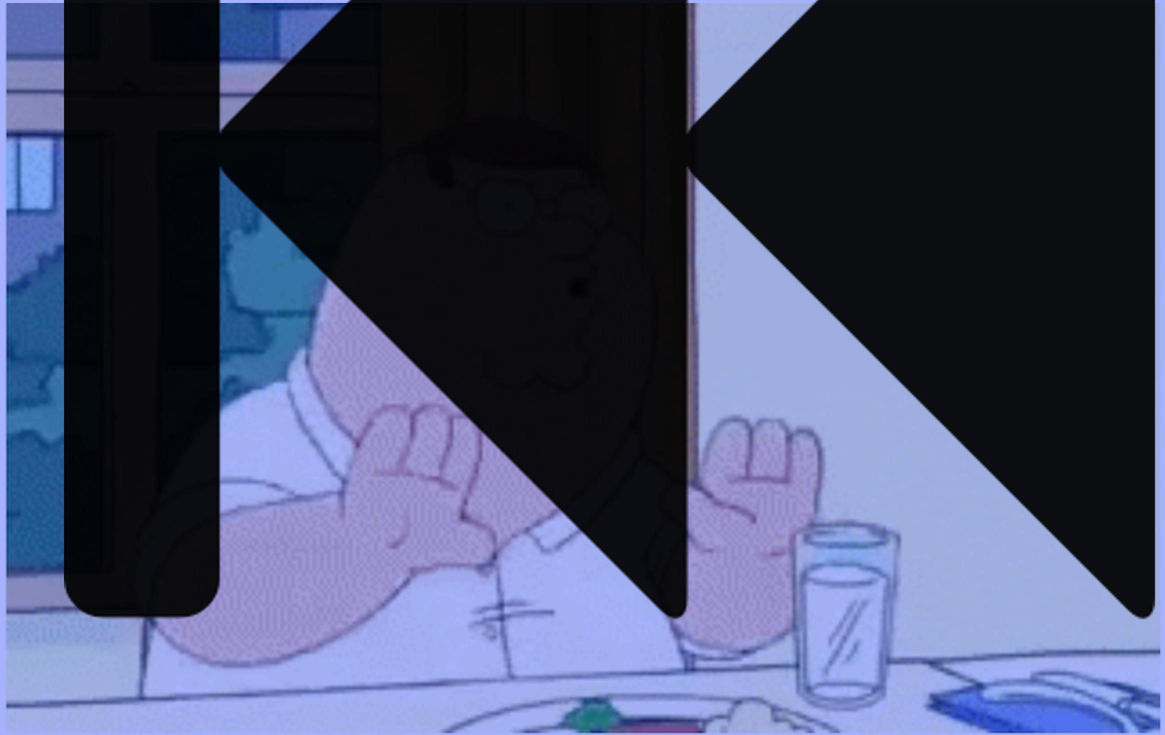
The «crazy» idea

Fine-tuning a single [redacted]y app[redacted] to **ALL EVALITA tasks**

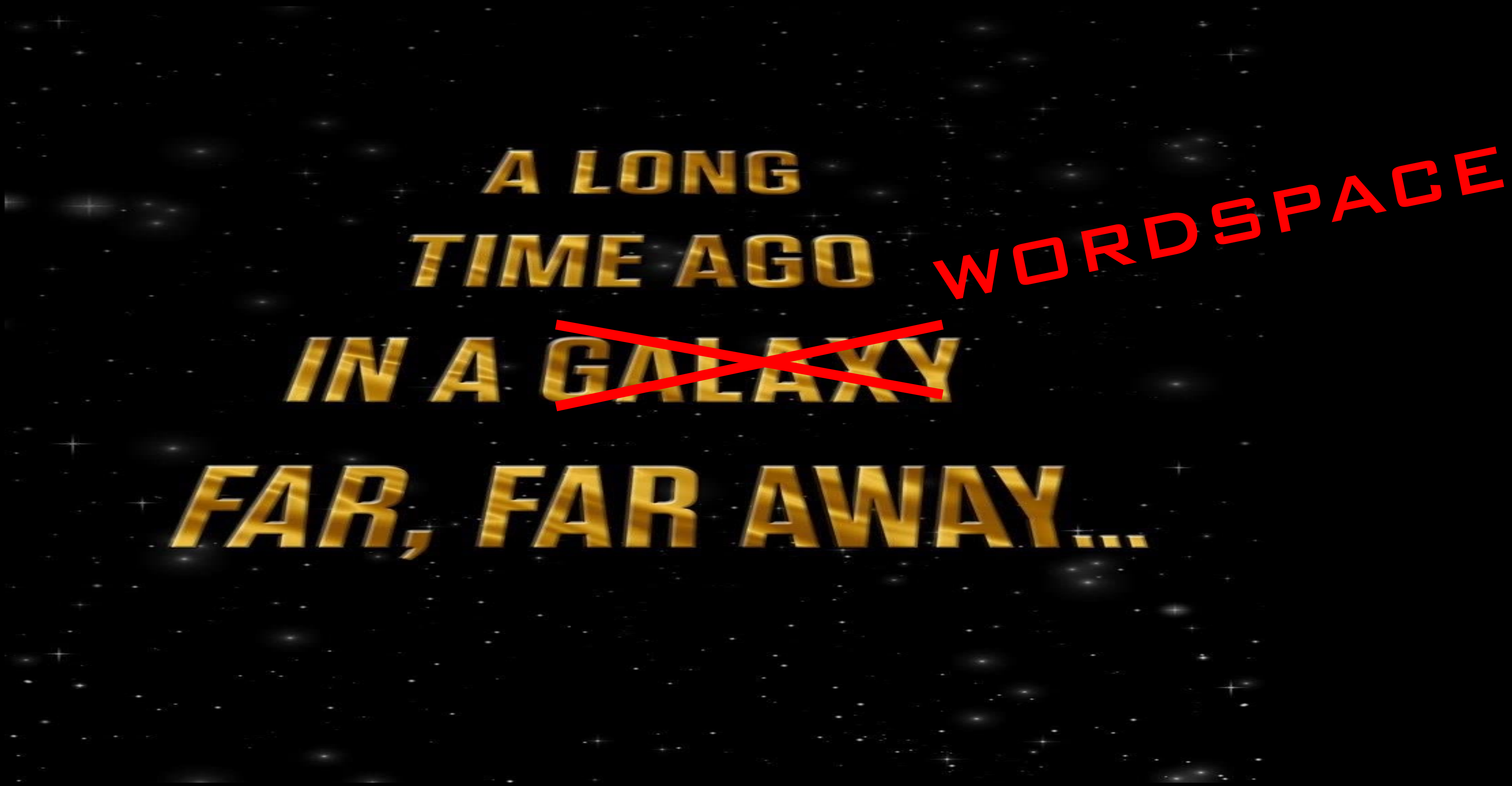
How did we get here???

The «crazy» idea

Fine-tuning a single LLMs by applying it to **ALL EVALITA tasks**



How did we get here???


A LONG
TIME AGO
IN A ~~GALAXY~~
WORDSPACE
FAR, FAR AWAY...

CHAPTER 1

FROM THE DISTRIBUTIONAL HYPOTHESIS TO WORD EMBEDDINGS

The Distributional Hypotesis

STUDIES IN
LINGUISTIC ANALYSIS

John Rupert Firth

IV

The *placing* of a *text* as a constituent in a context of situation contributes to the statement of meaning since situations are set up to recognize *use*. As Wittgenstein says, 'the meaning of words lies in their use.'[4] The day to day practice of playing language games recognizes customs and rules. It follows that a text in such established usage may contain sentences such as 'Don't be such an ass!', 'You silly ass!', 'What an ass he is!' In these examples, the word *ass* is in familiar and habitual company, commonly collocated with *you silly—*, *he is a silly—*, *don't be such an—*. You shall know a word by the company it keeps! One of the meanings of *ass* is its habitual collocation with such other words as those above quoted.[5] Though Wittgenstein was dealing with another problem, he also recognizes the plain face-value, the physiognomy of words. They look at us![6] 'The sentence is composed of the words and that is enough.'

to illustrate changes of meaning. The habitual collocations in which words under study appear are quite simply the mere word accompaniment,

[1] Many of Damon Runyon's 'inventions' follow the features of the fable. See especially 'Pick the Winner', in *Furthermore*, Constable, 1949.

[2] See 'General Linguistics and Descriptive Grammar', pp. 80-1.

[3] *Onomastics* has so far neglected the structural and descriptive study of names in context and collocation.

[4] *Philosophical Investigations*, pp. 80, 109.

[5] See 'Modes of Meaning', pp. 124–7. In this essay, *collocation* is first suggested as a technical term.

[6] See *Philosophical Investigations*, p. 181.

Firth, J.R. (1957). "A synopsis of linguistic theory 1930-1955". Studies in Linguistic Analysis: 1–32. Reprinted in *F.R. Palmer, ed. (1968). Selected Papers of J.R. Firth 1952-1959. London: Longman.*

https://cs.brown.edu/courses/csci2952d/readings/lecture1-firth.pdf

Distributional Hypothesis: Bridging Linguistics and Computational Semantics

- **Foundation**: Linguistic theory positing that **words with similar contexts have similar meanings**.
  - … and **representation** from out computational perspective
- **Computational Leap**: tied to the Vector Space Model (Salton, 1975); represents documents and words as vectors in a metric space.
  - **Key Idea**: Documents are characterized by their words, and words by the documents they appear in.
  - 👶 Initially a Bag of Words model

A distributional perspective of lexical semantics

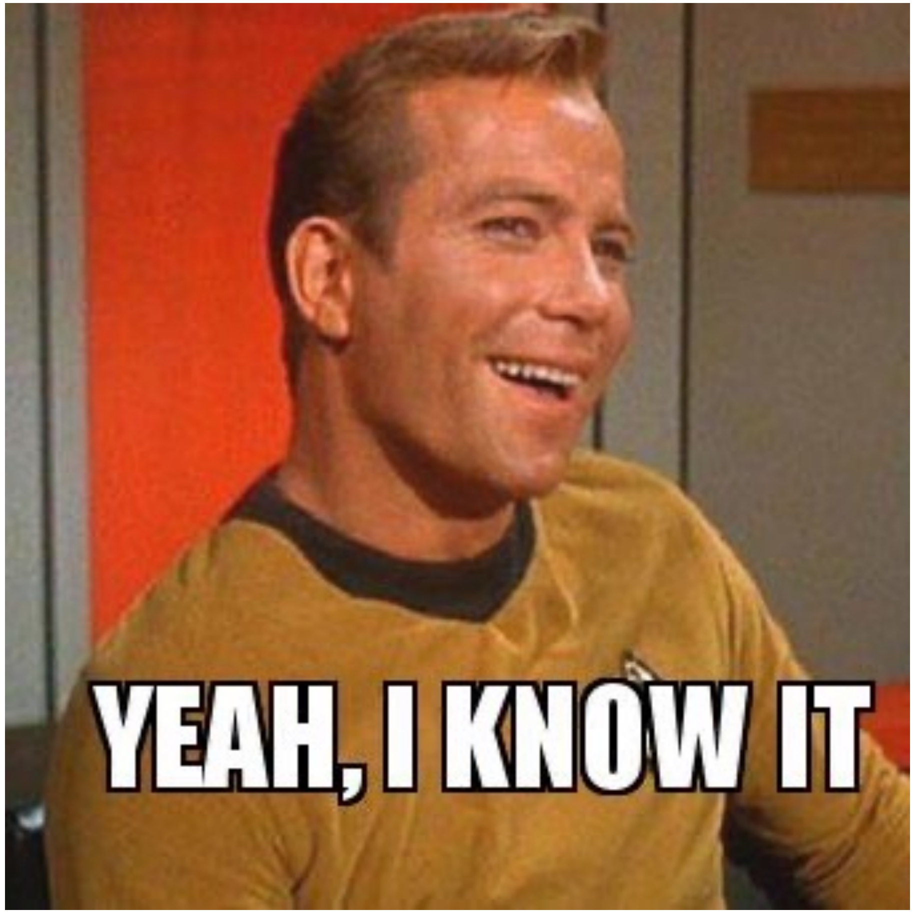
Evolution: Post-1990s, vector representations of word meaning gained prominence with the «rise» of machine learning.

- Words are mapped into vectors expressing their corresponding contexts in the corpus
- The similarity among words is estimated measuring the distance in the space of their vector representations.

(Noble) Goals:

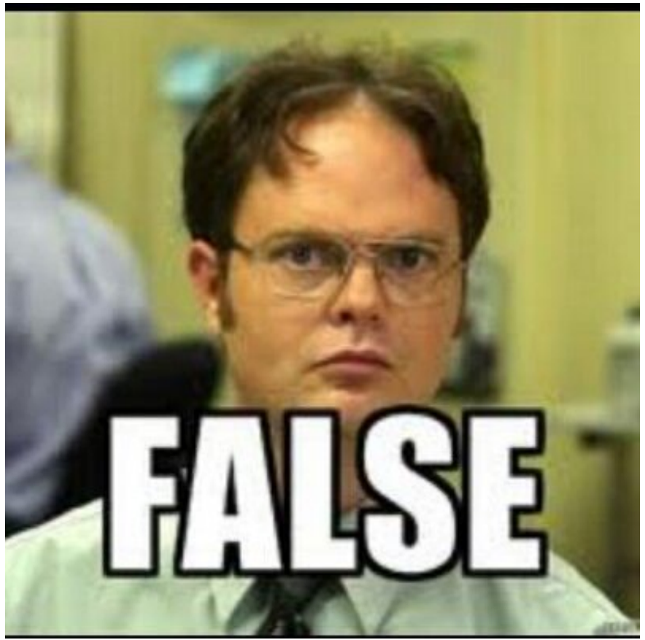
1. design word vectors able to represent in a meaningful fashion the semantics of words
2. surpass the limitations of Bag of Words models by capturing deeper semantic relationships

What was the first model to effectively generate word embeddings?



The answer is:

- `Word2Vec` solved this issue in 2013
- Or maybe some other neural model that generated word embedding



in 1992, the first models were not neural at all (Schutze, 1992) @ Neurips

Word Space

Hinrich Schütze
Center for the Study of Language and Information
Ventura Hall
Stanford, CA 94305-4115

Abstract

Representations for semantic information about words are necessary for many applications of neural networks in natural language processing. This paper describes an efficient, corpus-based method for inducing distributed semantic representations for a large number of words (50,000) from lexical coccurrence statistics by means of a large-scale linear regression. The representations are successfully applied to word sense disambiguation using a nearest neighbor method.

Approaches for Representing Words

Distributional Semantics (*Count*)
- Used since the 90's
- Sparse word-context PMI/PPMI matrix
- Decomposed with SVD

Word Embeddings (*Predict*)
- Inspired by deep learning
- `word2vec` *(Mikolov et al., 2013)*
- GloVe *(Pennington et al., 2014)*

Underlying Theory: **The Distributional Hypothesis** *(Harris, '54; Firth, '57)*

"Similar words occur in similar contexts"

(Baroni et al, 2014) Don't count, predict! A systematic comparison of context-counting vs. context-predicting semantic vectors – ACL
https://aclanthology.org/P14-1023/

Approaches for Representing Words

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"Similar words occur in similar contexts"

An example of “traditional distributional analysis”

- **Remember**: Different types of context define spaces with different semantic properties:
  - Document-based space [Salton, 1975]
    - Contexts are docunment
    - Two words are similar (near in the space) if they appear in the same documents (e.g., *Totti* and *football*)
  - Word-based spaces [Magnus Sahlgren, The Word-Space Model. Ph.D. thesis]
    - Contexts are words (lemmas) appearing in a n-window of the LU
    - Size of n emphasized different aspects
  - Syntax-based spaces [Pado & Lapata 2007]
    - Context is selected through the sentence syntactic structure
    - Words are enriched with syntactic information (e.g. *rebel:Sbj*)

Let’s count… to build a Word Space model

VerbNet (VN) (Kipper-Schuler 2006) is the largest on-line verb lexicon currently available for English. It is a hierarchical domain-independent, broad-coverage verb lexicon with mappings to other lexical resources such as WordNet (Miller, 1990; Fellbaum, 1998), Xtag (XTAG Research Group, 2001), and FrameNet (Baker et al., 1998). VerbNet is organized into verb classes extending Levin (1993) classes through refinement and addition of subclasses to achieve syntactic and semantic coherence among members of a class. Each verb class in VN is completely described by thematic roles, selectional restrictions on the arguments, and frames consisting of a syntactic description and semantic predicates with a temporal function, in a manner similar to the event decomposition of Moens and Steedman (1988).

Let’s count… after a little pre-processing

VerbNet::NNP (::(VN::NNP)::) (::(Kipper-Schuler::JJR 2006::CD)::) is::VBZ the::DT largest::JJS on-line::JJ verb::NN lexicon::NN currently::RB available::JJ for::IN English::NNP .::.
It::PRP is::VBZ a::DT hierarchical::JJ domain-independent::JJ ,::, broad-coverage::JJ verb::NN lexicon::NN with::IN mappings::NNS to::TO other::JJ lexical::JJ resources::NNS such::JJ as::IN WordNet::NNP (::(Miller::NNP ,::, 1990::CD ;::: Fellbaum::NNP ,::, 1998::CD)::) ,::, Xtag::NNP (::(XTAG::NNP Research::NNP Group::NNP ,::, 2001::CD)::) ,::, and::CC FrameNet::NNP (::(Baker::NNP et::CC al::NNP .::.
VerbNet::NN is::VBZ organized::VBN into::IN verb::NN classes::NNS extending::VBG Levin::NNP (::(1993::CD)::) classes::NNS through::IN refinement::NN and::CC addition::NN of::IN subclasses::NNS to::TO achieve::VB syntactic::JJ and::CC semantic::JJ coherence::NN among::IN members::NNS of::IN a::DT class::NN .::.
Each::DT verb::NN class::NN in::IN VN::NNP is::VBZ completely::RB described::VBN by::IN thematic::JJ roles::NNS ,::, selectional::JJ restrictions::NNS on::IN the::DT arguments::NNS ,::, and::CC frames::NNS consisting::VBG of::IN a::DT syntactic::JJ description::NN and::CC semantic::JJ predicates::NNS with::IN a::DT temporal::JJ function::NN ,::, in::IN a::DT manner::NN similar::JJ to::TO the::DT event::NN decomposition::NN of::IN Moens::NNP and::CC Steedman::NNP (::(1988::CD)::) .::.

Example: lexicon::NN

VerbNet::NNP (::(VN::NNP)::) (::(Kipper-Schuler::JJR 2006::CD)::) is::VBZ the::DT largest::JJS on-line::JJ verb::NN lexicon::NN currently::RB available::JJ for::IN English::NNP .::.
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The «contexts» of the word *lexicon*

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Left context – windows 2

VerbNet::NN is::VBZ or … NNS extending::VBG Levin::NNP (::(1993::CD)::) classes::NNS through::IN refinement::NN and::CC addition::NN of::IN subclasses::NNS to::TO achieve::VB syntactic::JJ and::CC semantic::JJ coherence::NN among::IN members::NNS of::IN a::DT class::NN .::.
Each::DT verb::NN class::NN in::IN VN::NNP is::VBZ completely::RB described::VBN by::IN thematic::JJ roles::NNS ,::, selectional::JJ restrictions::NNS on::IN the::DT arguments::NNS ,::, and::CC frames::NNS consisting::VBG of::IN a::DT syntactic::JJ description::NN and::CC semantic::JJ predicates::NNS with::IN a::DT temporal::JJ function::NN ,::, in::IN a::DT manner::NN similar::JJ to::TO the::DT event::NN decomposition::NN of::IN Moens::NNP and::CC Steedman::NNP (::(1988::CD)::) .::.

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semantic::JJ coherence::NN among::IN mem

Right context – window 2

Each::DT verb::NN class::NN in::IN VN::NNP is::VBZ completely::RB described::VBN by::IN thematic::JJ roles::NNS ,::, selectional::JJ restrictions::NNS on::IN the::DT arguments::NNS ,::, and::CC frames::NNS consisting::VBG of::IN a::DT syntactic::JJ description::NN and::CC semantic::JJ predicates::NNS with::IN a::DT temporal::JJ function::NN ,::, in::IN a::DT manner::NN similar::JJ to::TO the::DT event::NN decomposition::NN of::IN Moens::NNP and::CC Steedman::NNP (::(1988::CD)::) .::.

How to «implement» a Word Space

- The word space is expressed by a co-occurrence matrix M
  - **Rows**: The target words occurring more than t are selected (e.g 200)
  - **Columns** : The C most frequent word-context are selected (e.g. 20,000)
  - Each matrix item is the co-occurrence frequency between the target word and contextual word

- Example: the word lexicon::N occurs with
  - *verb::N* Left (feat 8) 2
  - *with::IN* Right (feat 25) 1
  - *available::J* Right (feat 56) 1
  - *online::J* Left (feat 78) 1
  - …

Pointwise Mutual Information (PMI)

- Context with high frequency (e.g. stopwords) have higher score
- PMI is a commonly used metric in Information Theory [Fano, 1961] for measuring this strength of association between two events x and y.

$$I(x,y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$

P(x)= probability of x
P(y)= probability of y
P(x,y)= joint probability of x e y

- Two words x e y that often co-occur (respect to their occurrence) show a high degree of association
- Words with high frequency are penalized

Pointwise Mutual Information (PMI)

- The prevois definition is adaped [Church and Hanks, 1989] to our word-occurrence problem:
  - P(x) = probability of the word x inside a corpus
  - P(y) = probability of the word y inside a corpus
  - P(x,y) = probability that x co-occur with y

- This probability is estimated through the Maximum Likelihood Estimation:

$$I(x,y) \approx \log_2 \frac{\frac{c_{xy}}{N}}{\frac{c_x}{N} \times \frac{c_y}{N}}$$

c_x= number of occurence of x

c_{xy}= number of co-occurence of x and y

N = total number of token

Pointwise Mutual Information (PMI)

- The PMI between lexicon::N and verb::N
  - c_x: lexicon::N occurrs 2 times
  - c_y: verb::N occurrs 4 times
  - c_{xy}: 2 co-occurences (left side)

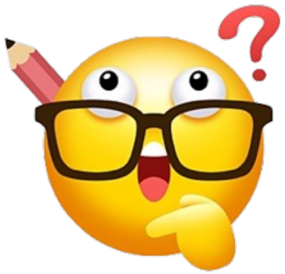
  - N: 142 tokens
  - PMI = 5,14

$$I(x,y) \approx \log_2 \frac{\frac{c_{xy}}{N}}{\frac{c_x}{N} \times \frac{c_y}{N}}$$

- Vectors are then normalized to be comparable

The resulting matrix

Where are my dense embeddings?



- Matrix with $t = 2$ – $C = 100$
- It can be sparse and affected by the "*curse of dimensionality*"

	and::CC R	and::CC L	a::DT R	a::DT L	verb::N R	verb::N L	be::V R	be::V L	class::N R	of::IN R	class::N L	of::IN L	lexicon::N R	verbnet::N L	vn::N R	vn::N L	syntactic::J R	syntactic::J L
and::CC:	0	0	0	0	0	0	0	0	0	0,142	0	0,142	0	0	0	0	0	0,253
a::DT:	0	0	0	0	0	0	0	0,155	0,155	0	0	0,210	0	0	0	0	0,210	0
verb::N:	0	0	0	0	0	0	0	0	0,244	0	0	0	0,302	0	0	0	0	0
be::V:	0	0	0,174	0	0	0	0	0	0	0	0	0	0	0,255	0	0,255	0	0
of::IN:	0,147	0,147	0,219	0	0	0	0	0	0,180	0	0	0	0	0	0	0	0,237	0
class::N:	0	0	0,000	0,184	0	0,271	0	0	0	0	0	0,205	0	0	0,271	0	0	0
the::DT:	0	0	0	0	0	0	0	0,214	0	0	0	0	0	0	0	0	0	0
to::TO:	0	0	0	0	0	0	0	0	0	0	0	0,200	0	0	0	0	0,256	0
in::IN:	0	0	0,295	0	0	0,320	0,320	0	0	0	0,320	0	0	0	0,397	0	0	0
xtag::N:	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
lexicon::N:	0	0	0	0	0	0,331	0	0	0	0	0	0	0	0	0	0	0	0
syntactic::J:	0,344	0	0	0,289	0	0	0	0	0	0	0	0,313	0	0	0	0	0	0
with::IN:	0	0	0,259	0	0	0,280	0	0	0	0	0	0	0	0	0	0	0	0

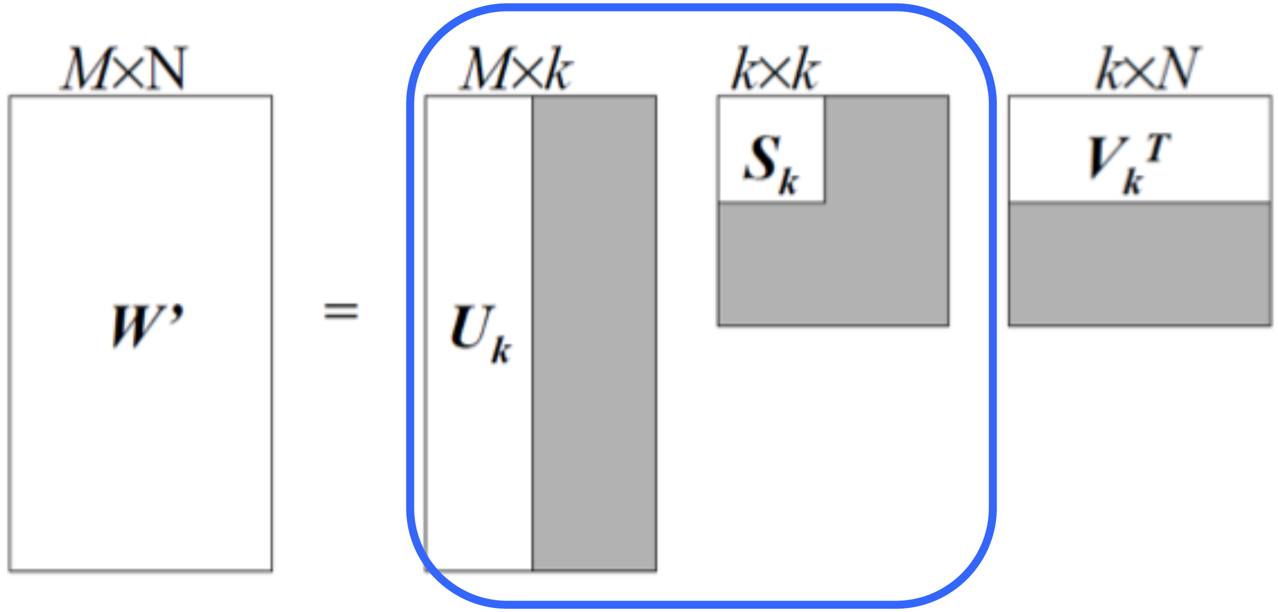
Latent Semantic Analysis

(Landauer and Dumais, 1995) … still for IR systems

- In LSA approach, SVD is applied to source co-occurrence matrix:

Target terms space

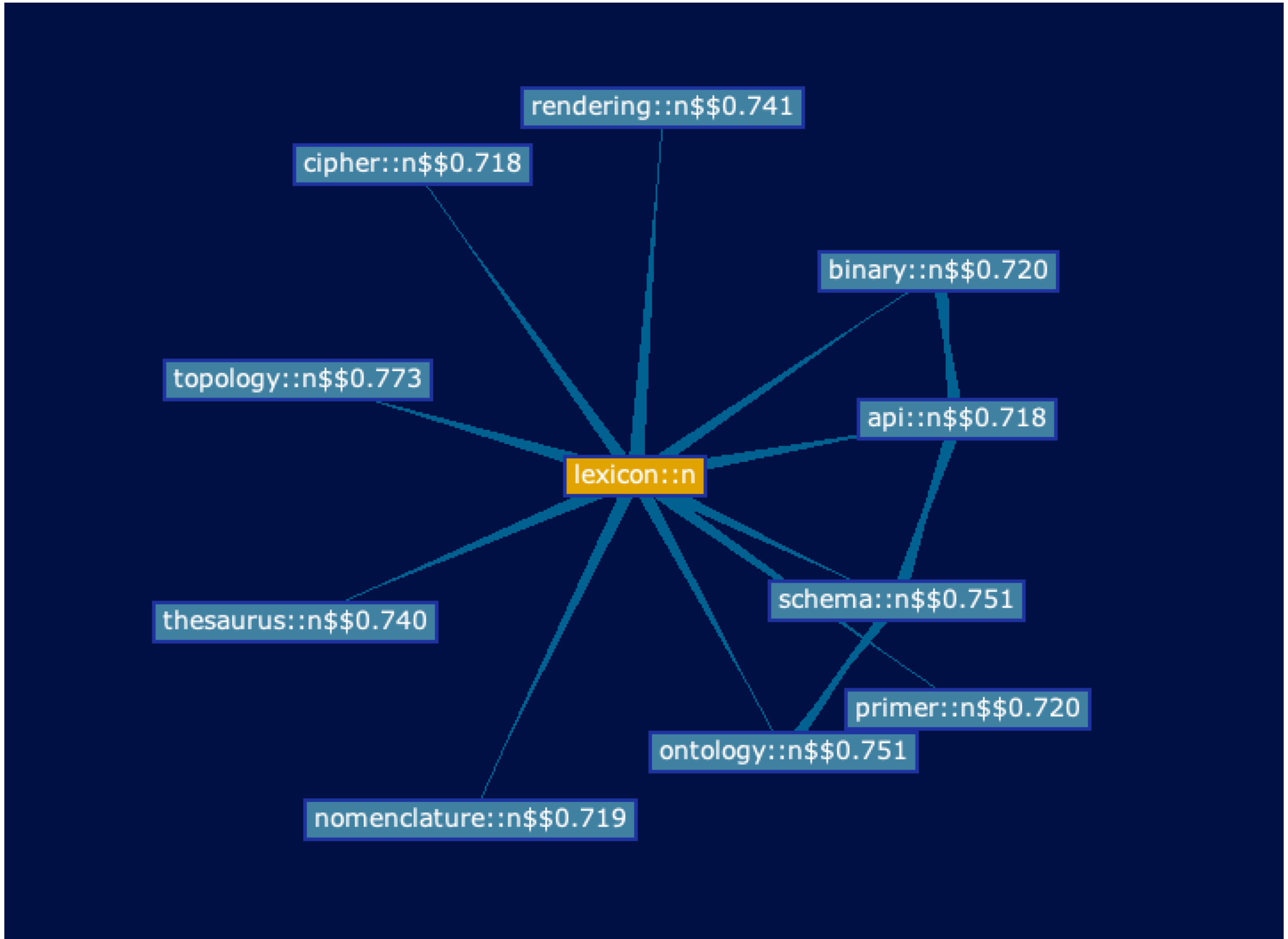
$$M = USV^T \approx U_k S_k V_k^T \rightarrow U_k S_k^{1/2}$$



The advantages

- An effective dimensionality reduction technique
  - **From sparse hi-dimensional** spaces to “small” dense representations
    - The were not called: *embeddings*
- **Minimize** the global **reconstruction error**
  - Reduce noise over the data distribution
  - SVD let the principal components of the distribution emerge (max covariance)
- Principal components are linear combinations of the original dimensions, i.e. pseudo concepts, as captured in the entire space
  - **Capture second order relations among targets words**

What happened to *lexicon::n* ?



Given the noun/vector *lexicon::n*

- The vectors with the highest cosine similarity are show

Approaches for Representing Words

Distributional Semantics (*Count*)

- Used since the 90's
- Sparse word-context PMI/PPMI matrix
- Decomposed with SVD

Word Embeddings (*Predict*)

- Inspired by deep learning
- `word2vec` *(Mikolov et al., 2013)*
- GloVe *(Pennington et al., 2014)*

Underlying Theory: **The Distributional Hypothesis** *(Harris, '54; Firth, '57)*

"Similar words occur in similar contexts"

Let’s «*Predict*». An example: `Word2Vec`

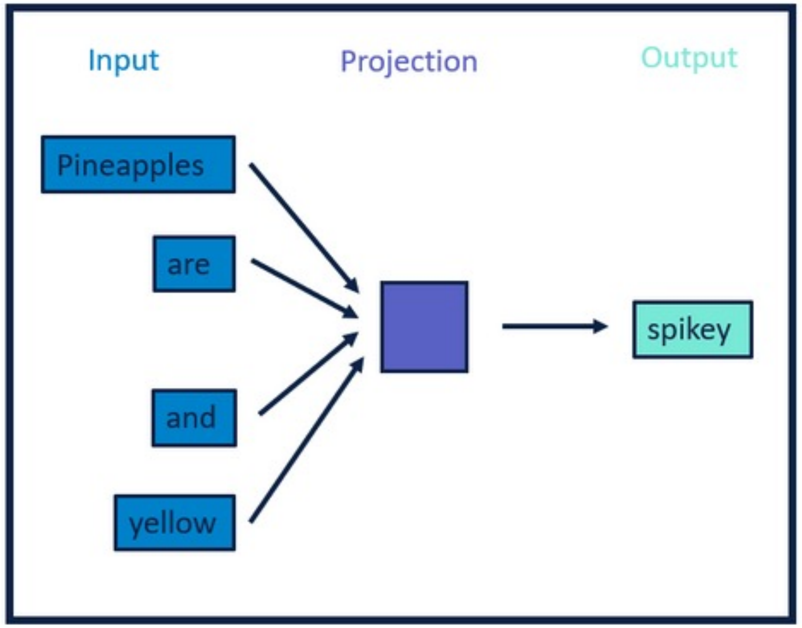
- **Overview**: `Word2Vec` is a neural network-based technique introduced by Mikolov et al. (2013) to efficiently produce word embeddings.
- **Core Principle**: implements distributional hypothesis… again words appearing in similar contexts tend to have similar meanings.
- **Purpose**: Transforms sparse, high-dimensional word vectors into dense, low-dimensional vectors, capturing semantic and syntactic word relationships.

https://proceedings.neurips.cc/paper/2013/file/9aa42b31882ec039965f3c4923ce901b-Paper.pdf

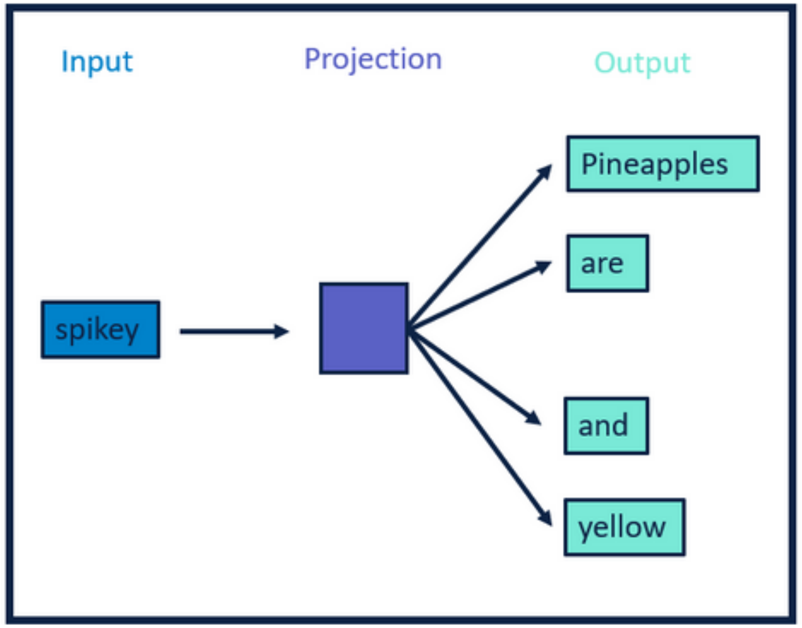
The two models behind `Word2Vec`

Contextual Bag Of Word: Predicts a target word based on context words.

Skip-Gram: Predicts context words from a target word.



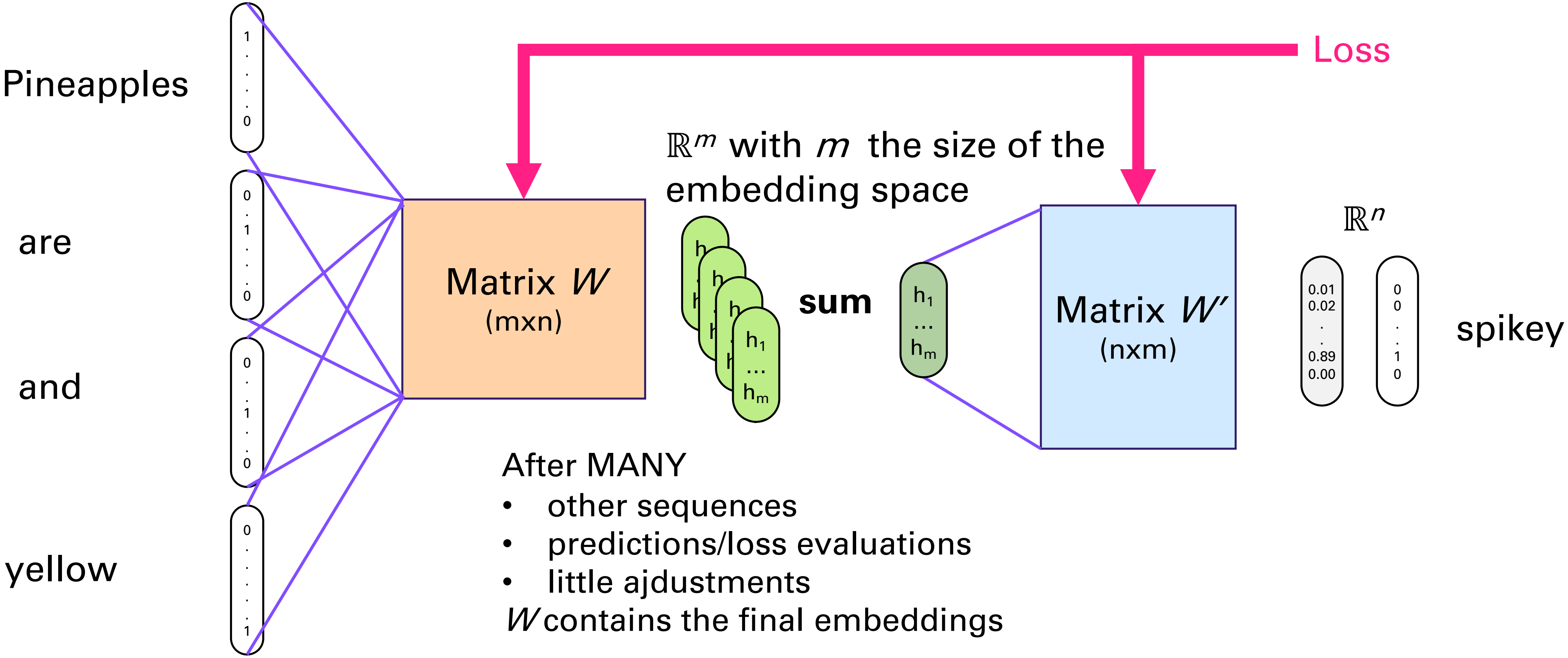
CBOW



Skip-gram

CBOW at work:
It is “just” matrix multiplication

$\mathbb{R}^n$ with n the size of the input dictionary



After MANY
- other sequences
- predictions/loss evaluations
- little ajdustments

W contains the final embeddings

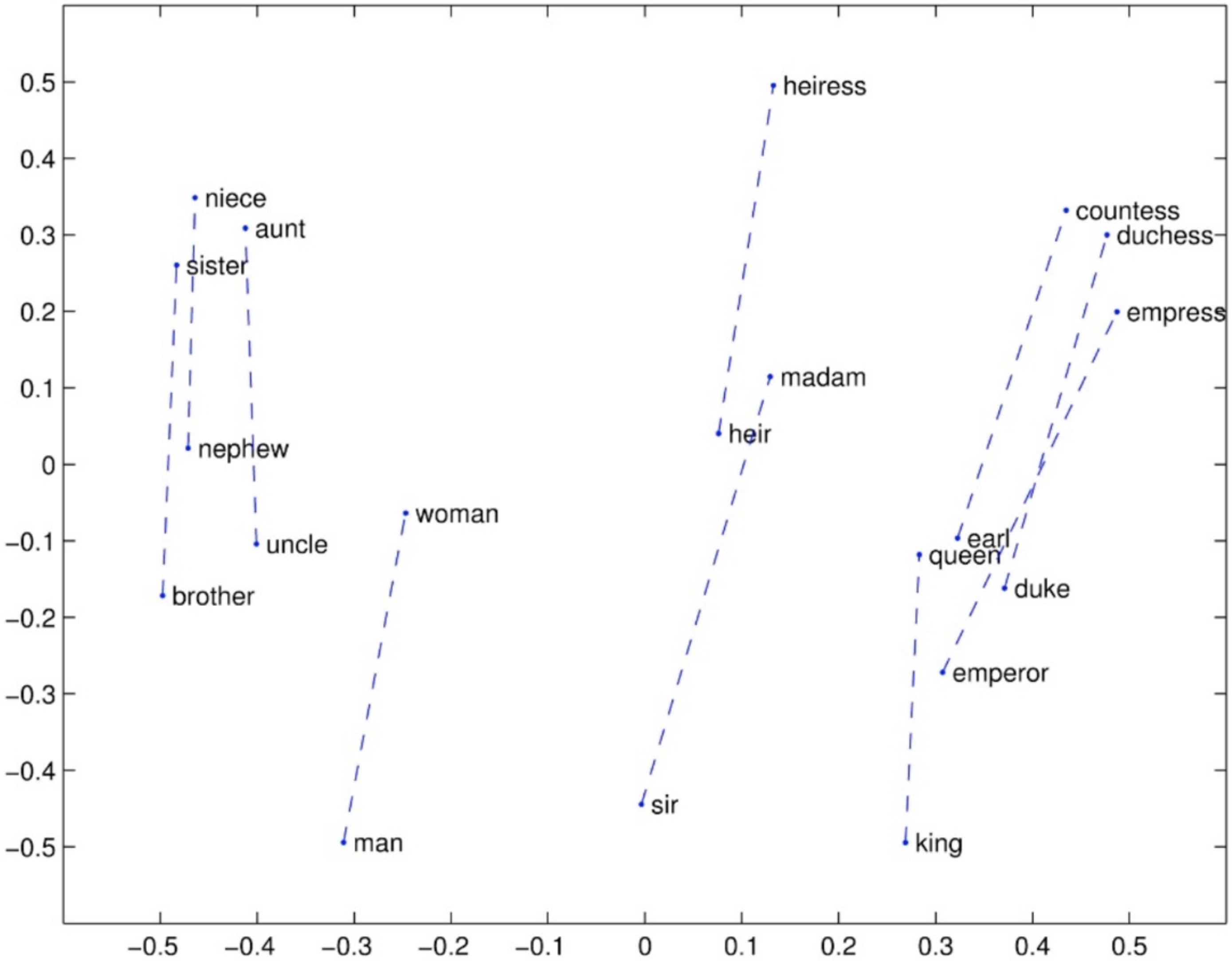
DANILO CROCE

https://lilianweng.github.io/posts/2017-10-15-word-embedding/

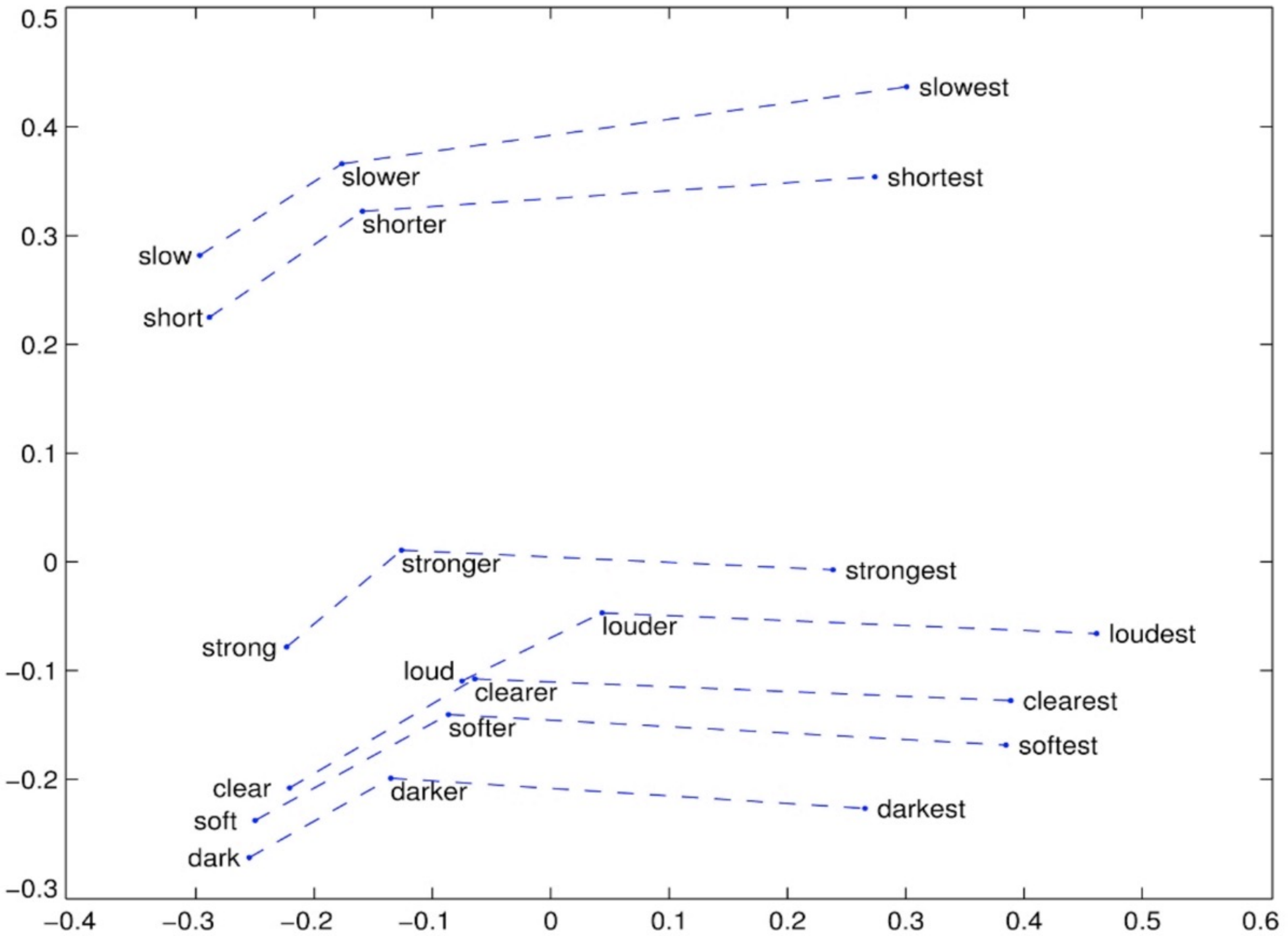
Key Features and Applications

- **Training Efficiency**: Employs techniques like hierarchical softmax and negative sampling to expedite training on large datasets.
- **Semantic and Syntactic Similarity**: Embeddings capture nuanced relationships (e.g., *king* - *man* + *woman* = *queen*)
  - See next slides
- **Impact**: Has set a precedent for subsequent developments in word embedding techniques, influencing both academic research and industry applications.

Geometry, meaning ...



Geometry, meaning ...

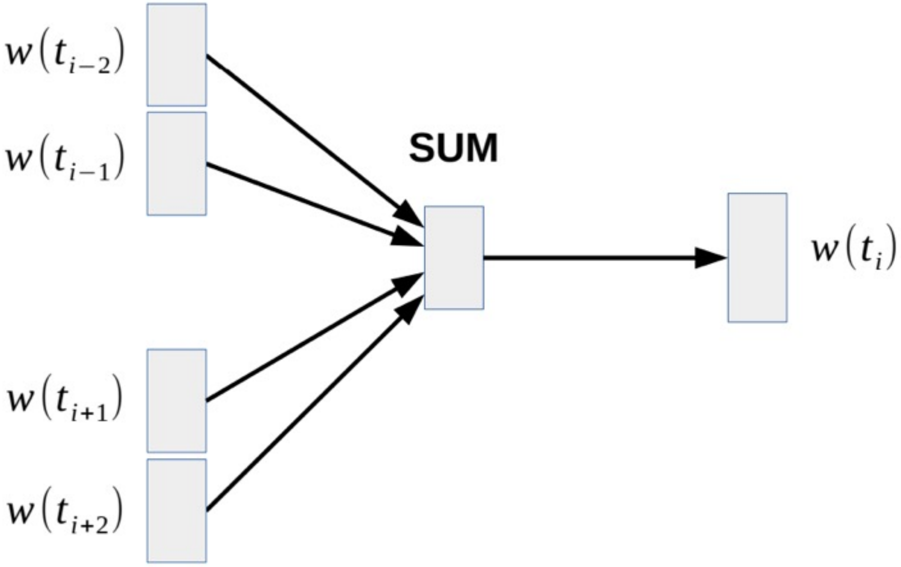


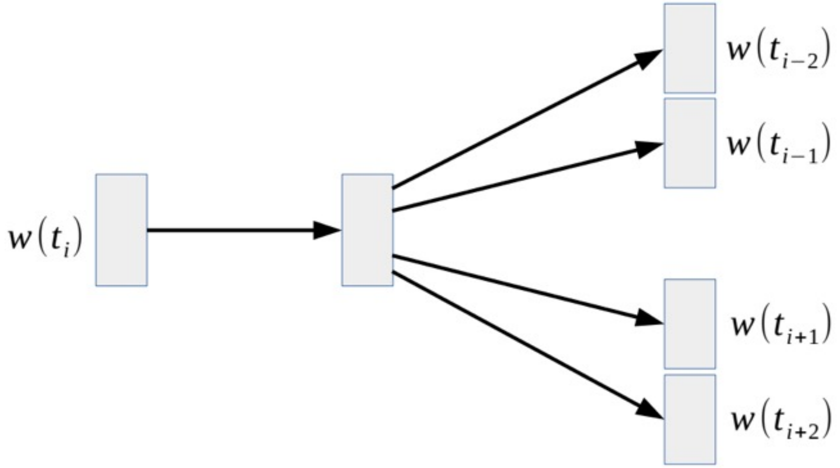
… and funny games

Expression	*Nearest token*
Paris - France + Italy	Rome
bigger - big + cold	colder
sushi - Japan + Germany	bratwurst
Cu - copper + gold	Au
Windows - Microsoft + Google	Android
Montreal Canadiens - Montreal + Toronto	Toronto Maple Leafs

Beyond `Word2Vec`

- **Companions**: Alongside Word2Vec, FastText (Bojanowski et al., 2017) and GloVe (Pennington et al., 2014) emerged as significant models
  - each contributing unique perspectives on handling word representation.
- **Common Principle**: These models predict a word based on its context, as $w(t_{i-2})$, $w(t_{i-1})$, $w(t_{i+1})$, $w(t_{i+2})$ aiming to capture the essence of $w(t_i)$.



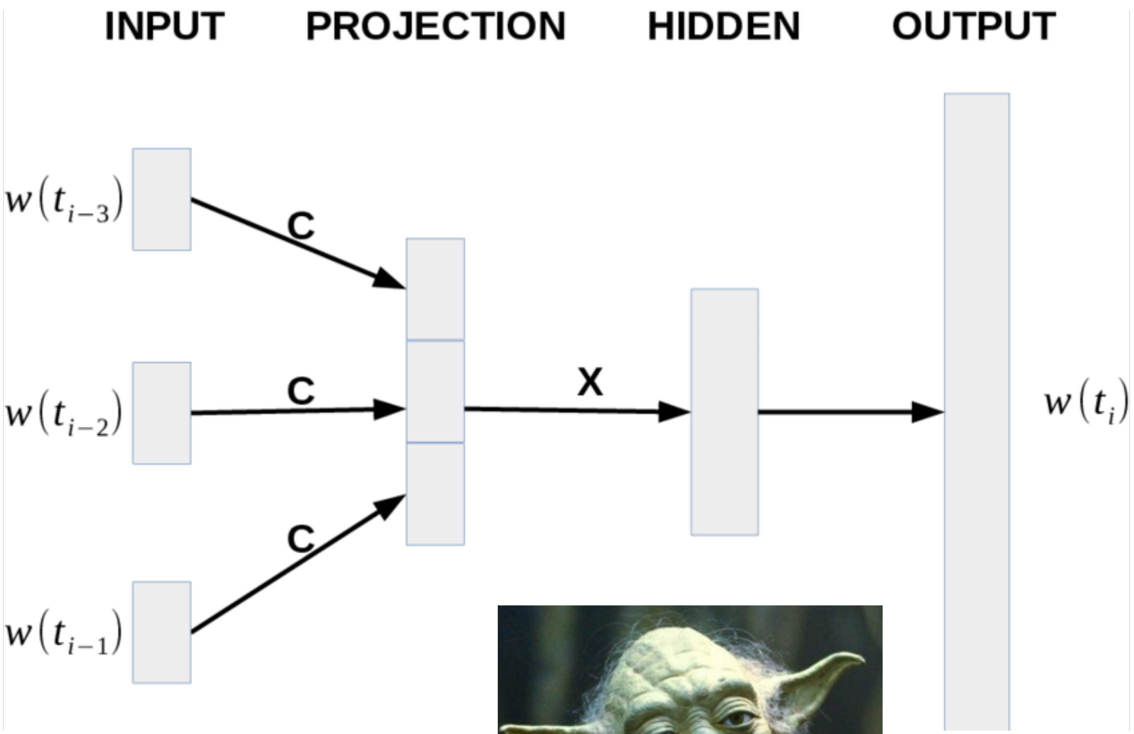


Beyond Word2Vec: Language Models as Word Predictors

- **Evolving Techniques**: While Word2Vec and its contemporaries laid the groundwork, the field has seen advancements with models that incorporate language modeling techniques.

- **Language Model Concept**: These models **predict the next word** in a sequence, $w(t_i)$, based on preceding words, $w(t_{i-3})$, $w(t_{i-2})$, $w(t_{i-1})$, thus understanding language flow.

- **Applications**: Particularly impactful in tasks like speech-to-text
  - selecting the most plausible transcription from multiple candidates is crucial.

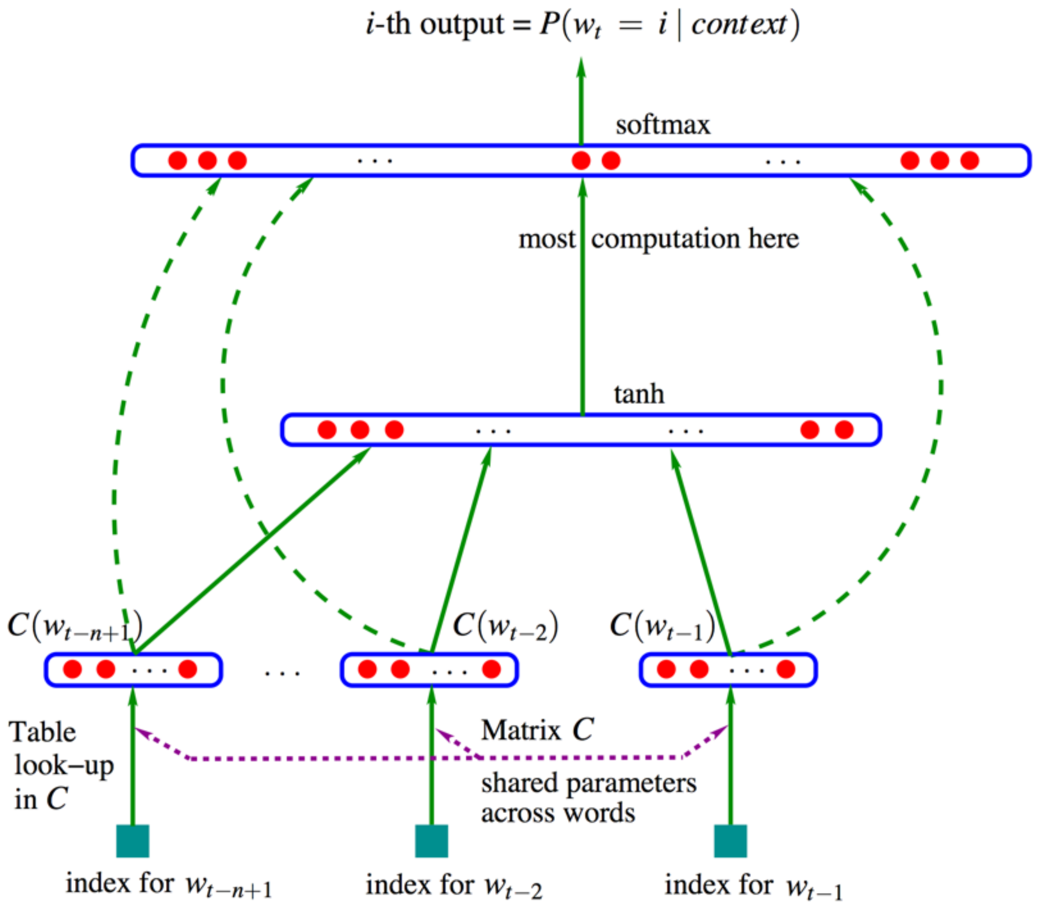


Neural Language modeling

- The objective is to learn a mapping

$$f(w_t, \cdots, w_{t-n+1}) = P(w_t \mid w_1, \ldots, w_{t-1})$$

- **General Idea:**
  - **Associate with each word** in the vocabulary **an embedding**
  - Express the **joint probability function of word sequences in terms of the feature vectors of these words** in the sequence, and
  - **Learn simultaneously both notions:**
    - the word feature vectors as a matrix of lexical feature vectors and
    - the parameters that corresponds to the NN that estimate the probability function of the language model.



(Bengio et al, 2003): Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Janvin. 2003. A neural probabilistic language model. J. Mach. Learn. Res. 3 (March 2003), 1137-1155.

Some Limits of Word Embeddings

- Words not appearing (enough) in the training corpus cannot be learned. At test time they are out-of-vocabulary (OOV) words

- Embeddings are context independent representations of the words
  - A word is represented by the same word, independently from its “companion”
  - Problem with polysemy

Halfway Solution – Subwords

- WordPiece (Wu et al. ‘16):
  - the dictionary includes words and word pieces, i.e., subwords
  - The dictionary is chosen so that it maximizes the likelihood on the language model training data

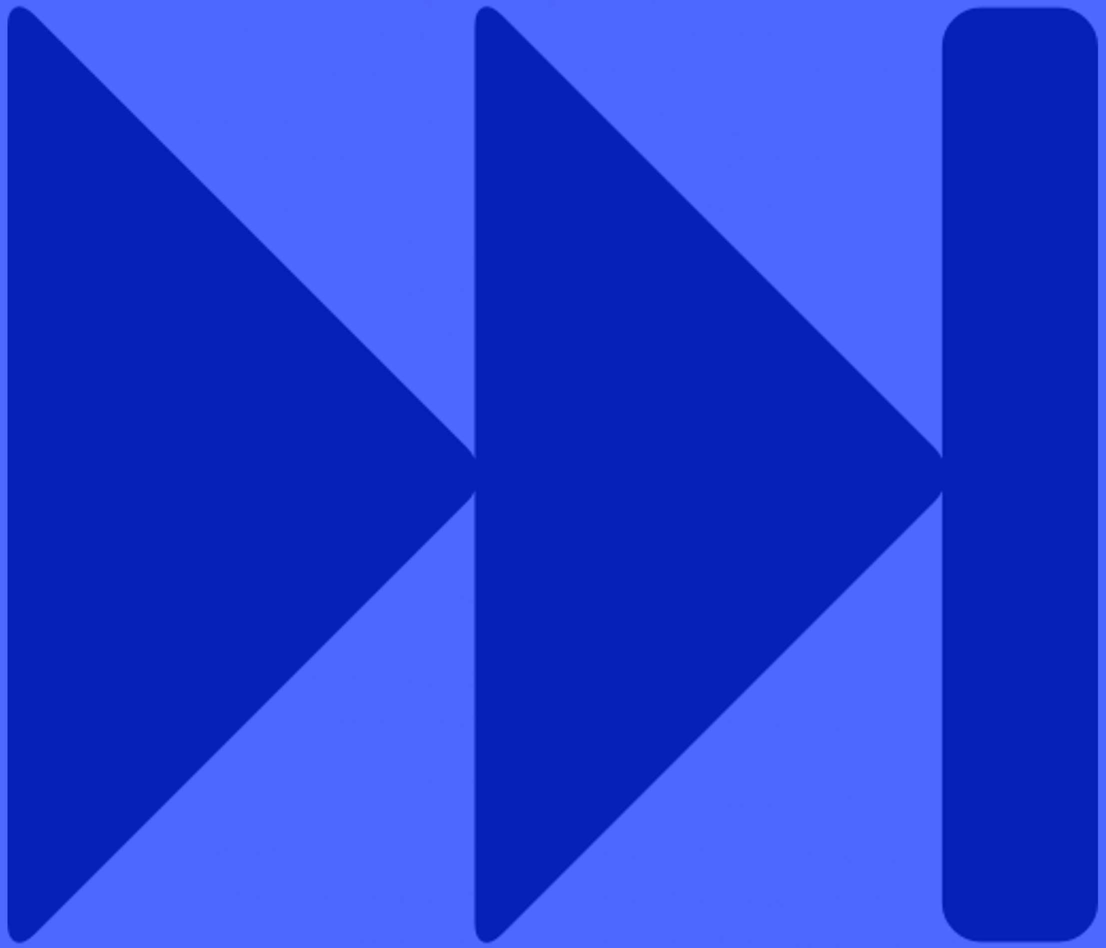
Jet makers feud over seat width with big orders at stake

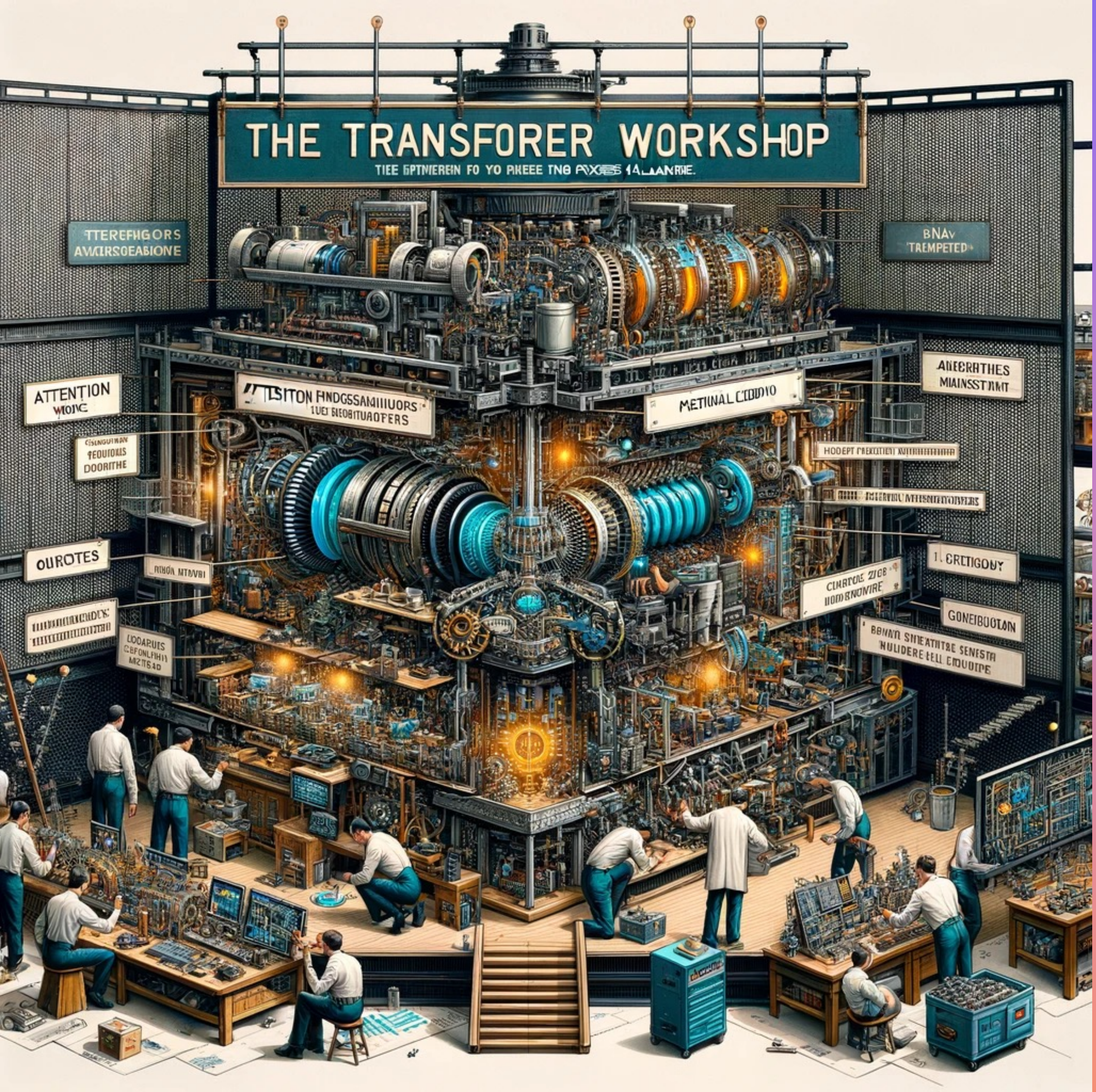
WordPiece Segmentation

_J et _makers _fe ud _over _seat _width _with _big _orders _at _stake

Some interesting references

- Here are some pivotal references that have significantly contributed to the field of NLP and offer a glimpse into the evolution and diversity of approaches during this period:
- **Collobert et al., 2011 - "Natural Language Processing (Almost) from Scratch"**
  - Introduced a groundbreaking unified framework for efficiently handling multiple NLP tasks, illustrating the power of general-purpose models.
  - https://www.jmlr.org/papers/volume12/collobert11a/collobert11a.pdf
- **Yoon Kim, 2014 - "Convolutional Neural Networks for Sentence Classification"**
  - Showcased the adaptability of CNNs for textual data, proving their effectiveness in categorizing sentences and opening new avenues for text analysis.
  - https://aclanthology.org/D14-1181/
- **Yoav Goldberg, 2015 - "A Primer on Neural Network Models for Natural Language Processing"**
  - Offered an accessible overview of neural network models in NLP, bridging the gap between theoretical underpinnings and practical applications in language processing.
  - https://arxiv.org/abs/1510.00726
- **Lenci and Sahlgren - "Distributional Semantics"**
  - Delved into distributional semantics within computational linguistics, providing insights into semantic meaning extraction from linguistic context.
  - https://www.cambridge.org/core/books/distributional-semantics/F7B77FE8EF6152919AC92AC6165BBF53





CHAPTER 2

A DEEP DIVE INTO THE TRANSFORMER

Going back in time to 2017: the Transformer

(Vaswani et al. 2017)

A Transformer: a neural architecture designed for **sequence-to-sequence tasks.**

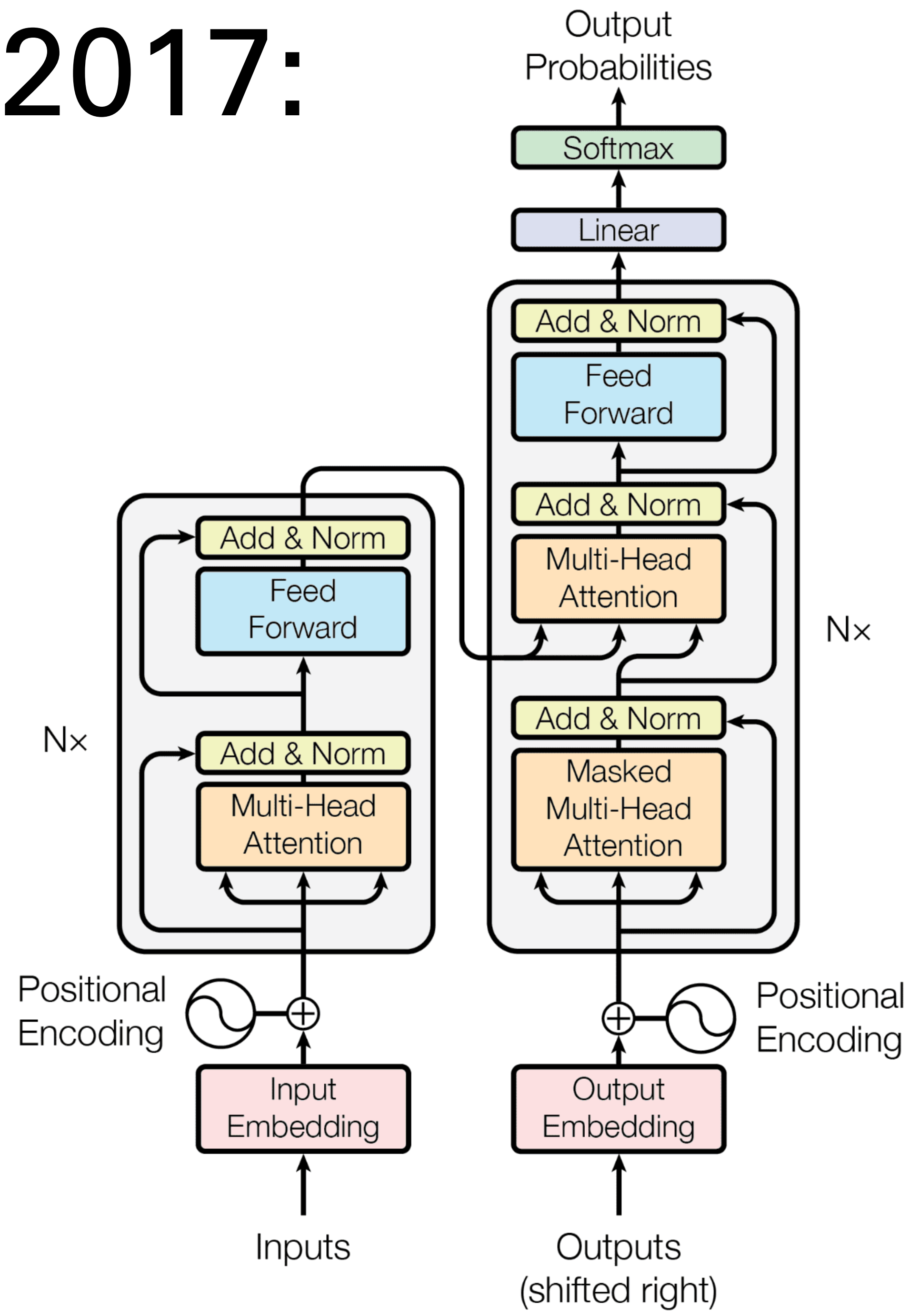
- It takes a sequence of symbols as input and produces a sequence of symbols as output.

Before Transformers:

- Until 2017, these tasks were implemented using **Recurrent Neural Networks** (RNNs).
    - with limitations in handling long sequences.

Emergence of Attention:

- Heavily used since 2015, allowed models to **focus on specific sections of a sequence** for better inference.



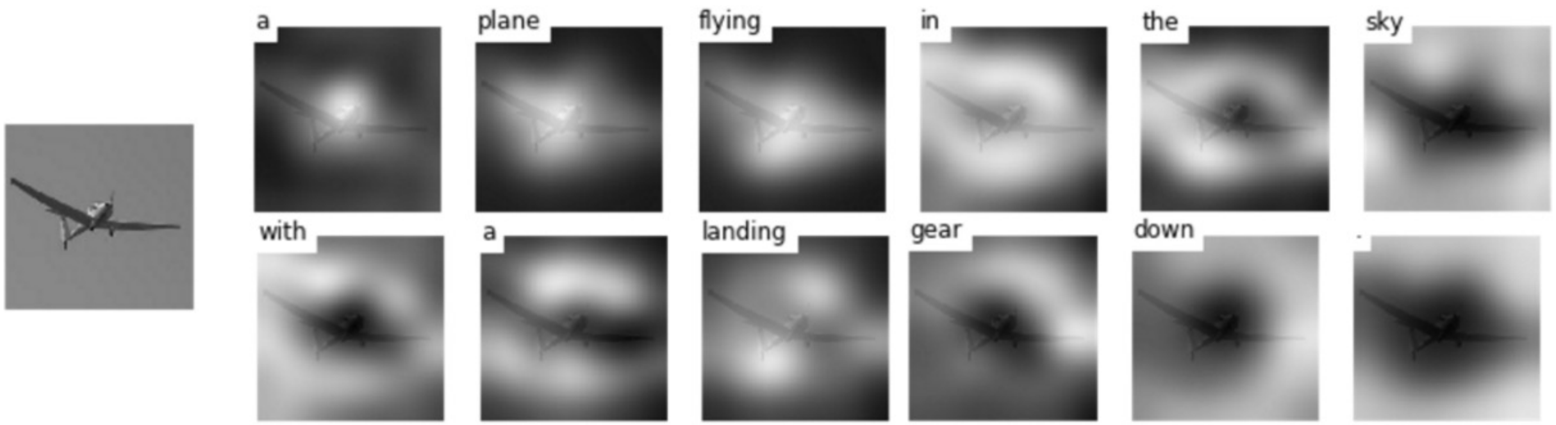
DANILO CROCE

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Luka Polosukhin (2017). Attention Is All You Need. arXiv:1706.03762

The Importance of Attention in Neural Learning

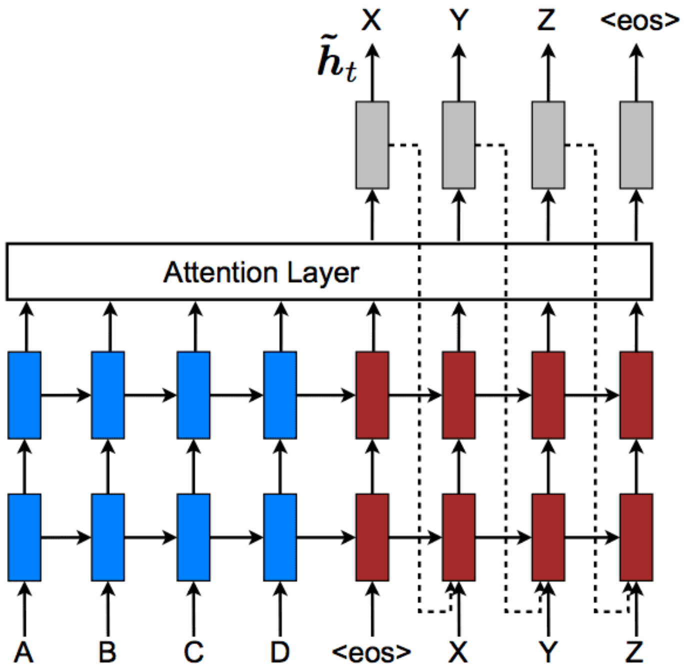
- **Revolution in Computer Vision**
  - It significantly improved **object detection** and **recognition in computer vision**.
  - It enables models to focus on relevant parts of an image, improving accuracy and efficiency.
  - **An interesting Survey:** `https://github.com/MenghaoGuo/Awesome-Vision-Attentions`

- **Breakthrough in tasks such as Image Captioning:**
  - Attention helps in **identifying key components** within images **to generate accurate and contextually relevant descriptions.**
  - **Seminal work:** (Xu et al, 2015) `https://arxiv.org/abs/1502.03044`

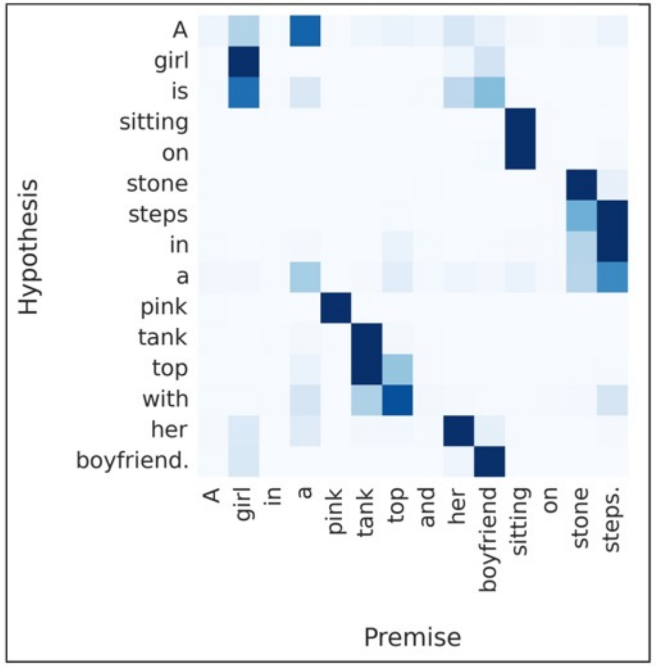


Enhancement in Recurrent Neural Networks

- For RNNs, **attention mechanisms** were used to address the **challenge of handling long sequences.**
- It allows RNNs to **focus on important parts** of the input sequence
  - improving performance in tasks like language translation and speech recognition.



(Luong et al, 2015)
Effective Approaches to Attention-based Neural Machine Translation
https://arxiv.org/abs/1508.04025

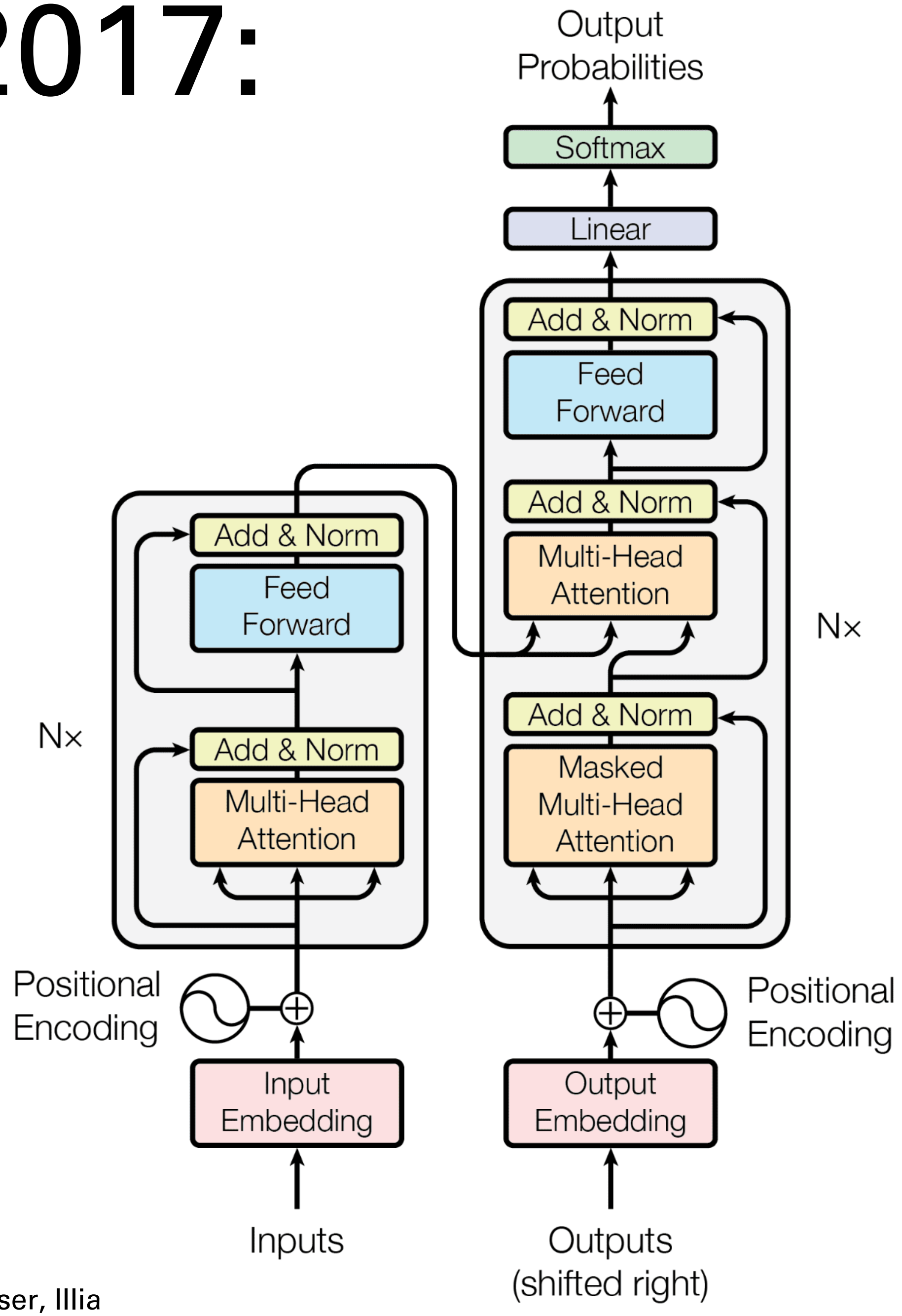


(Rocktäschel et, al., 2015)
Reasoning about Entailment with Neural Attention, 2015.
https://arxiv.org/abs/1508.04025

Going back in time to 2017: the Transformer

(Vaswani et al. 2017)

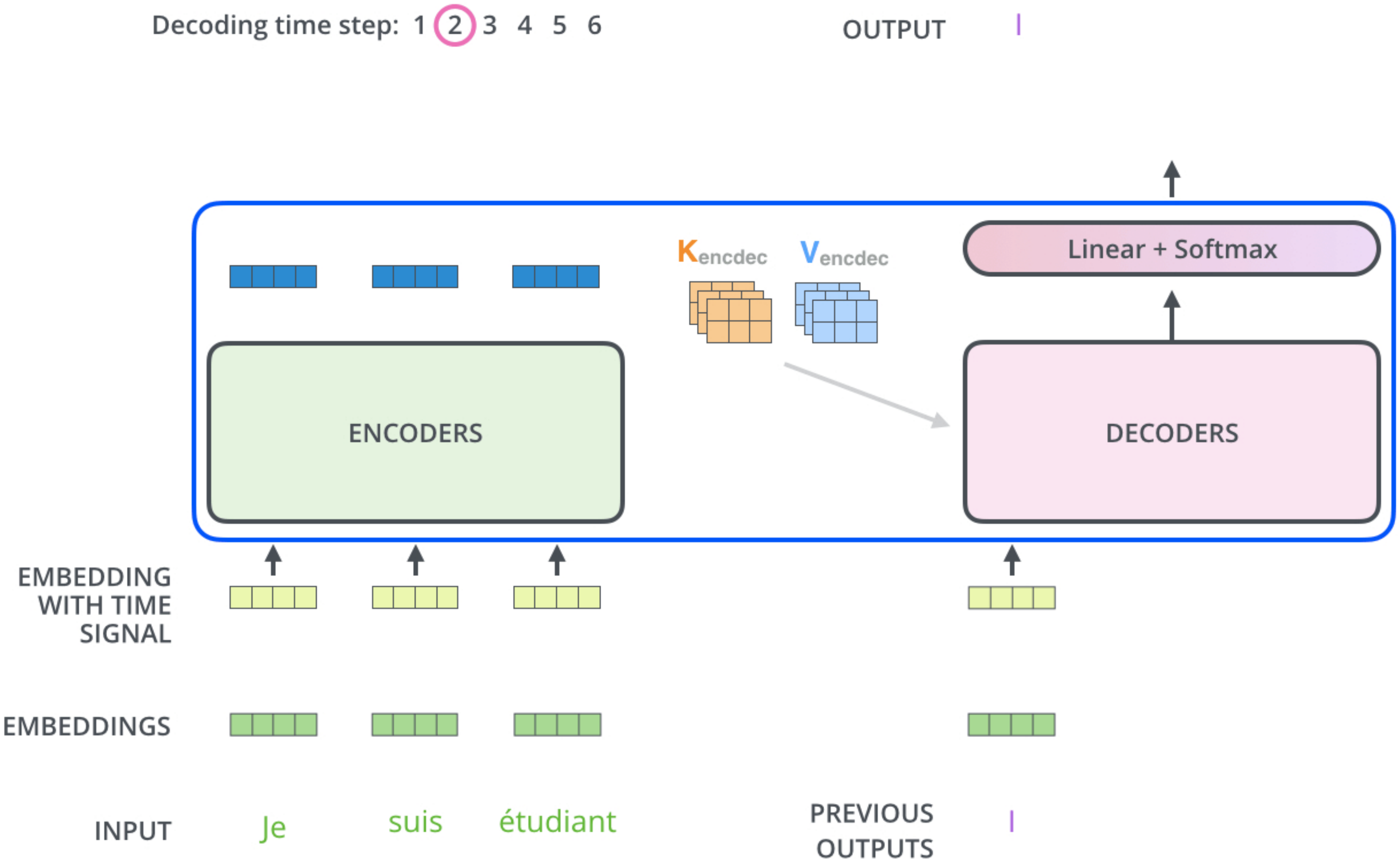
- **Attention in Transformers:**
  - In 2017, the **attention mechanism became an integral part** of this architecture.
  - a **significant evolution in seq2seq modeling**
- **Main advantages:**
  - Better with long range dependencies
  - Parallel processing (more scalable than RNNs)
  - State-of-the-art performances
- **Originally meant for Automatic machine translation:**
  - E.g., French to English



DANILO CROCE

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, Illia Polosukhin (2017). Attention Is All You Need. arXiv:1706.03762

Seq2Seq: A transformer in action



Alammar, J (2018). The Illustrated Transformer [Blog post]. Retrieved from https://jalammar.github.io/illustrated-transformer/

Encoding/Decoding Architecture with Attention Mechanism

- **Two components**
  - **Encoder:** Maps input sequence $X = (x_1, \ldots, x_n)$ to continuous representations $Z = (z_1, \ldots, z_n)$.
  - **Decoder:** Decoder uses Z to generate output sequence $Y = (y_1, \ldots, y_m)$

- Encoder/Decoder process input vectors through **self-attention layer** and feed-forward network.
  - It enables to selectively **concentrate on pertinent parts of the input**
  - It improves **context awareness**
  - It allows to **consider positions** in the that also depends on the output

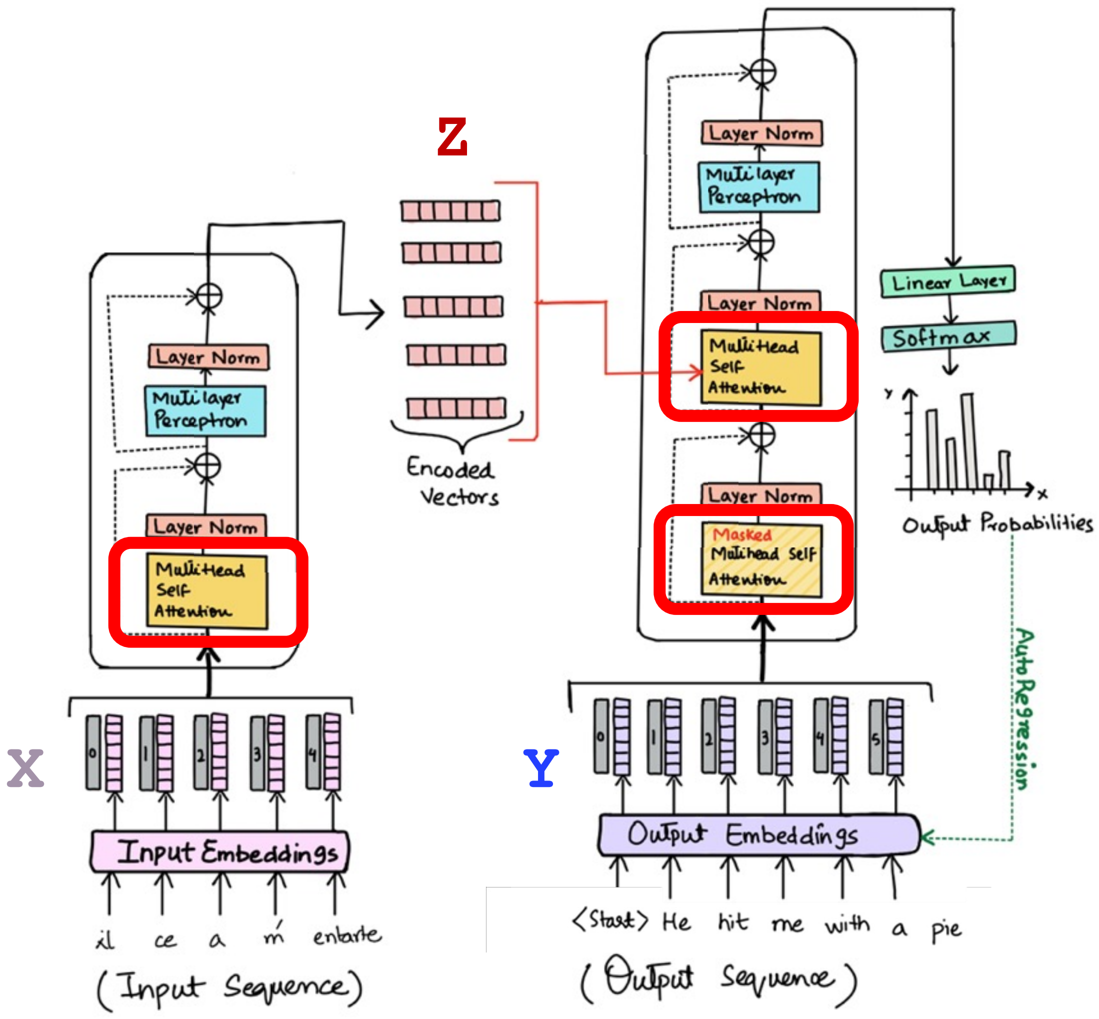
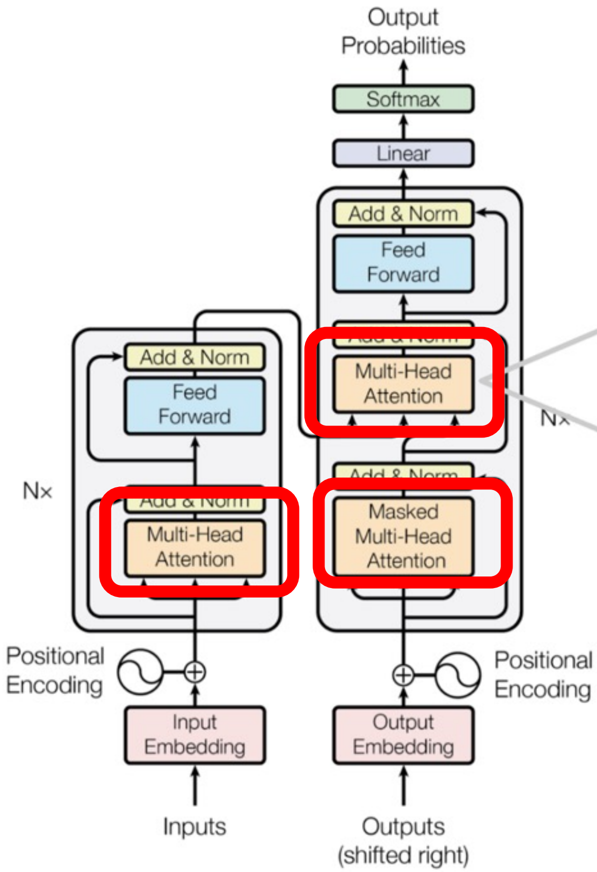
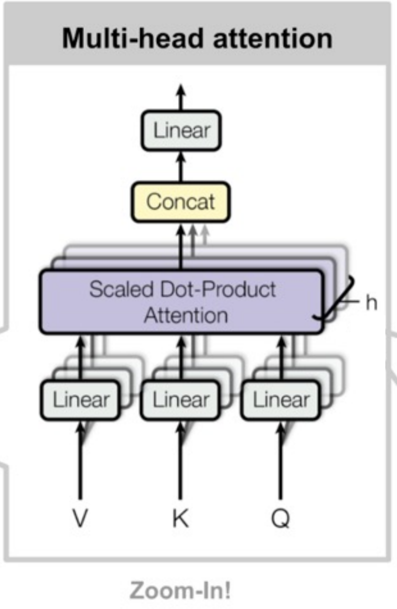


Image from https://medium.com/machine-intelligence-and-deep-learning-lab/transformer-the-self-attention-mechanism-d7d853c2c621

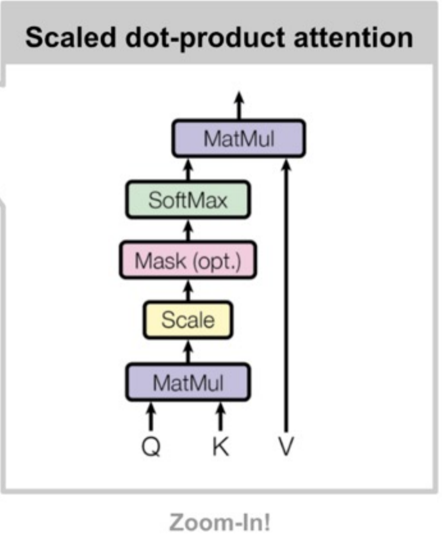
How does Self-attention work?

It is not magic, it is not a human brain, it is **just matrix multiplication**





The core Component
(even many years later in ChatGPT)



It’s «simpler» than it looks

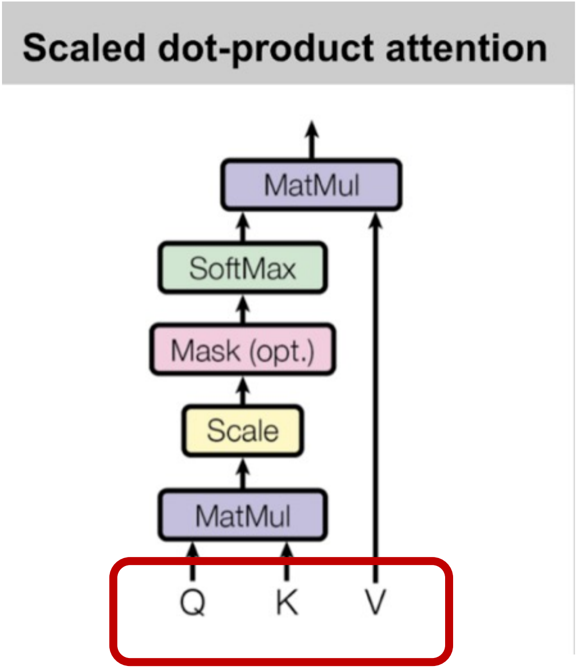
even though I'll be simplifying quite a few things.

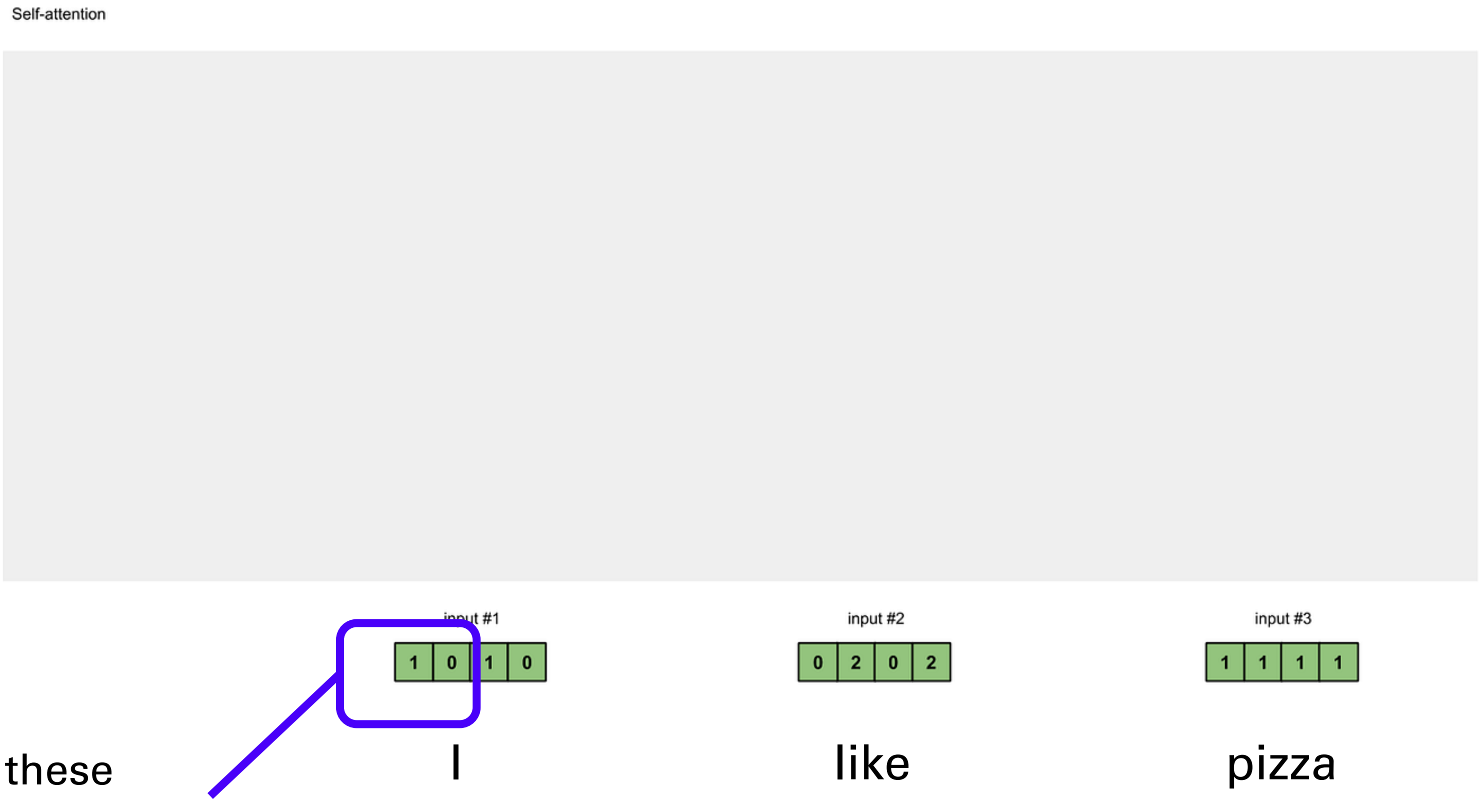
Many thanks to https://towardsdatascience.com/illustrated-self-attention-2d627e33b20a

«Attention in action»

Prepare inputs

Each word is associated to embeddings





Positional Encoding: Part of these vector encodes the tokens' position

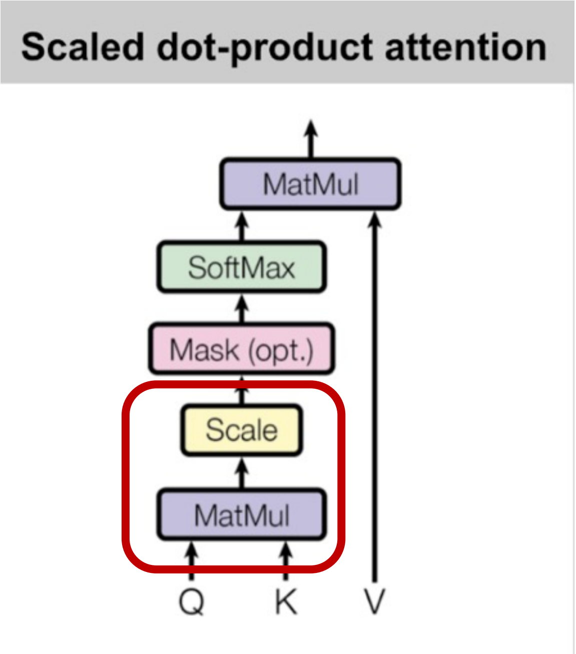
DANILO CROCE

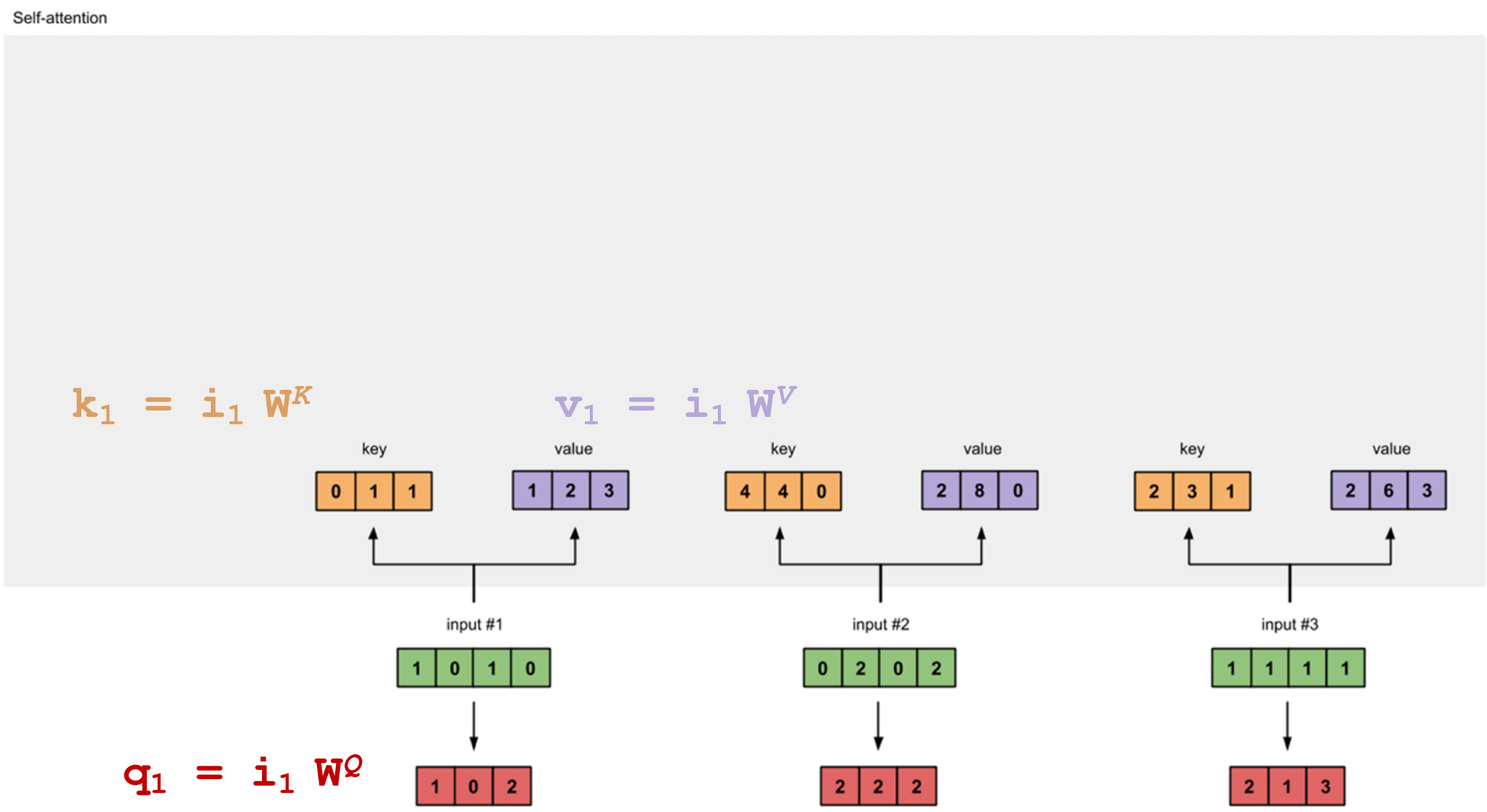
«Attention in action»

Compute Query, Key, and Value Vectors

For each word vector, calculate the Query, Key, and Value vectors by multiplying with respective weight matrices W^Q, W^K, W^V.

- $key_i = input_i \, W^K$
- $value_i = input_i \, W^V$
- $query_i = input_i \, W^Q$

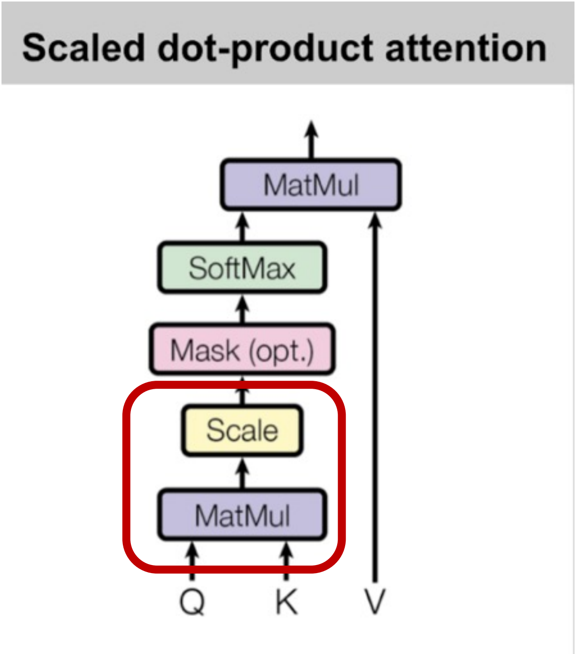




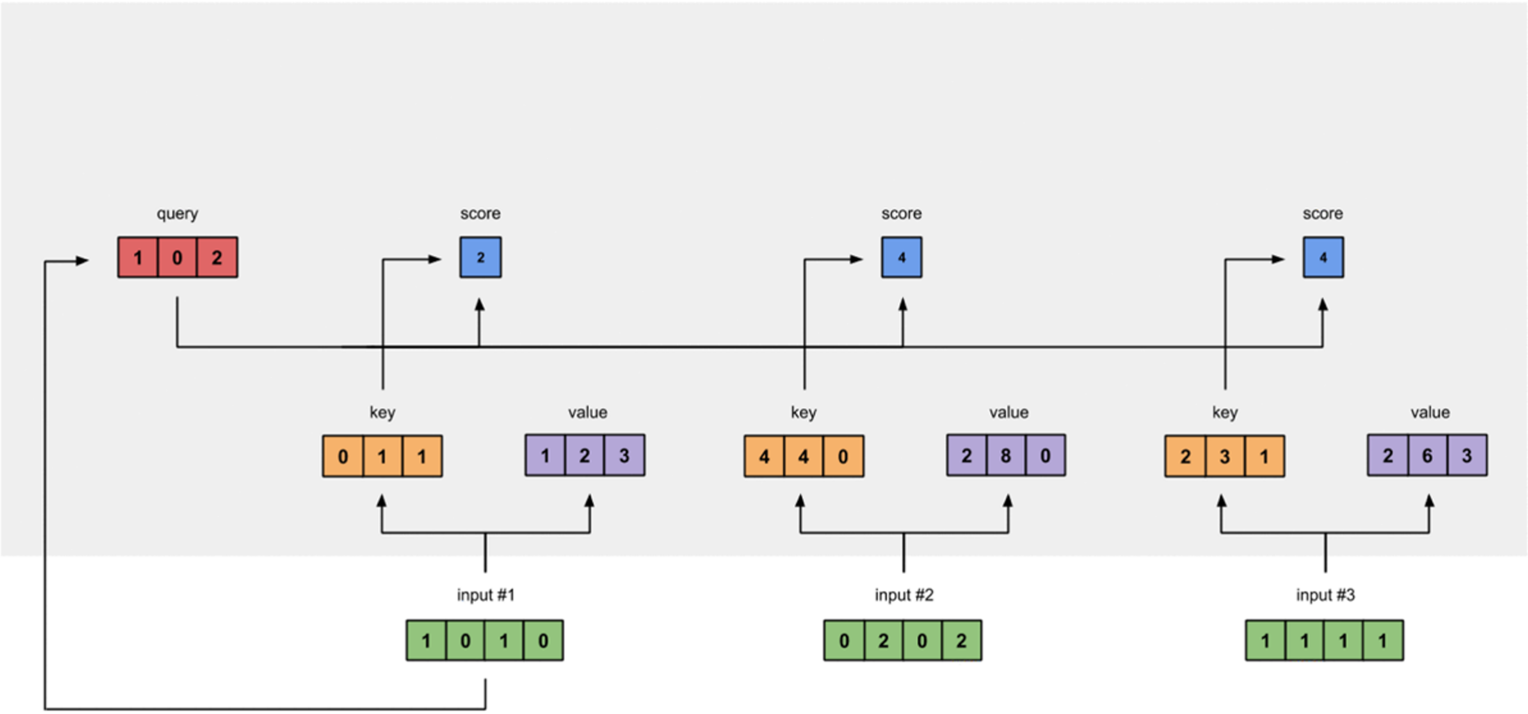
«Attention in action»

Calculate the Attention scores for $\mathtt{input}_1$

Attention scores are computed to «weight » the contribution of ALL words in the input sequence when representing $\mathtt{input}_1$.



Self-attention



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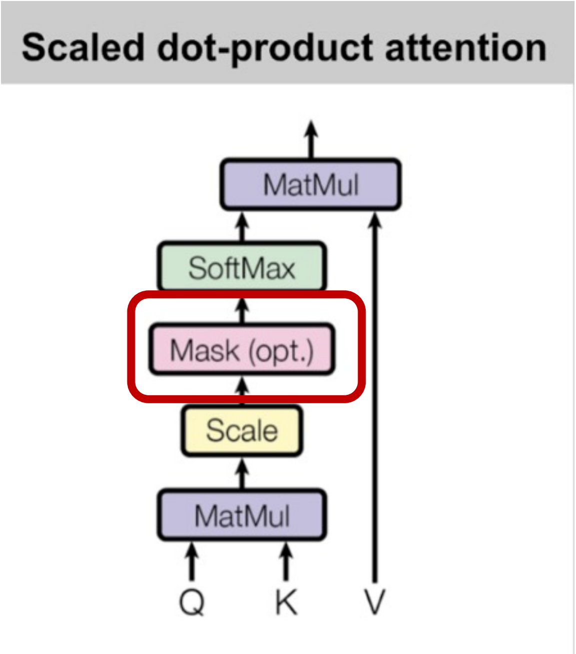
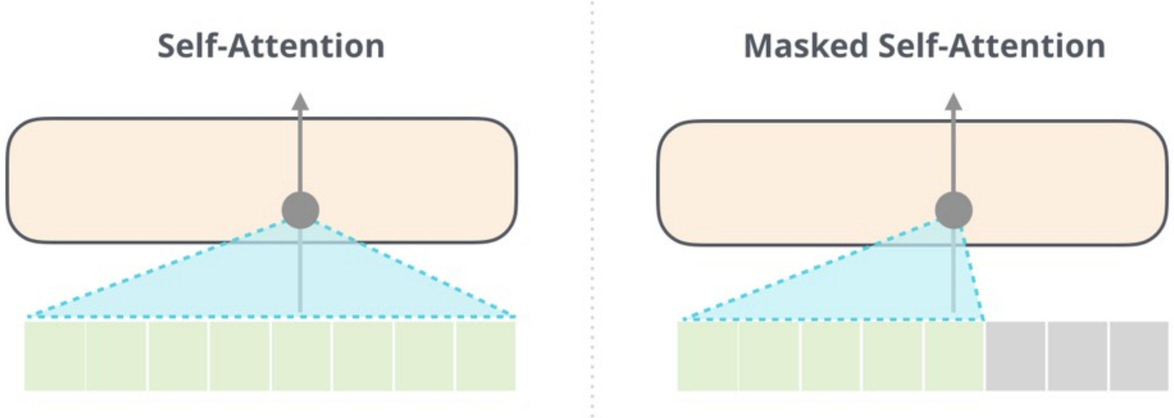
«Attention in action»
Role of Masked Attention

Use masked attention to handle sequences of different lengths

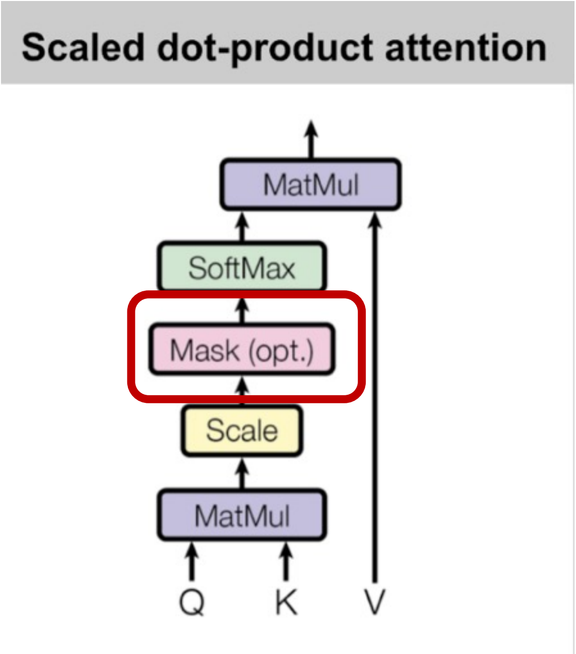


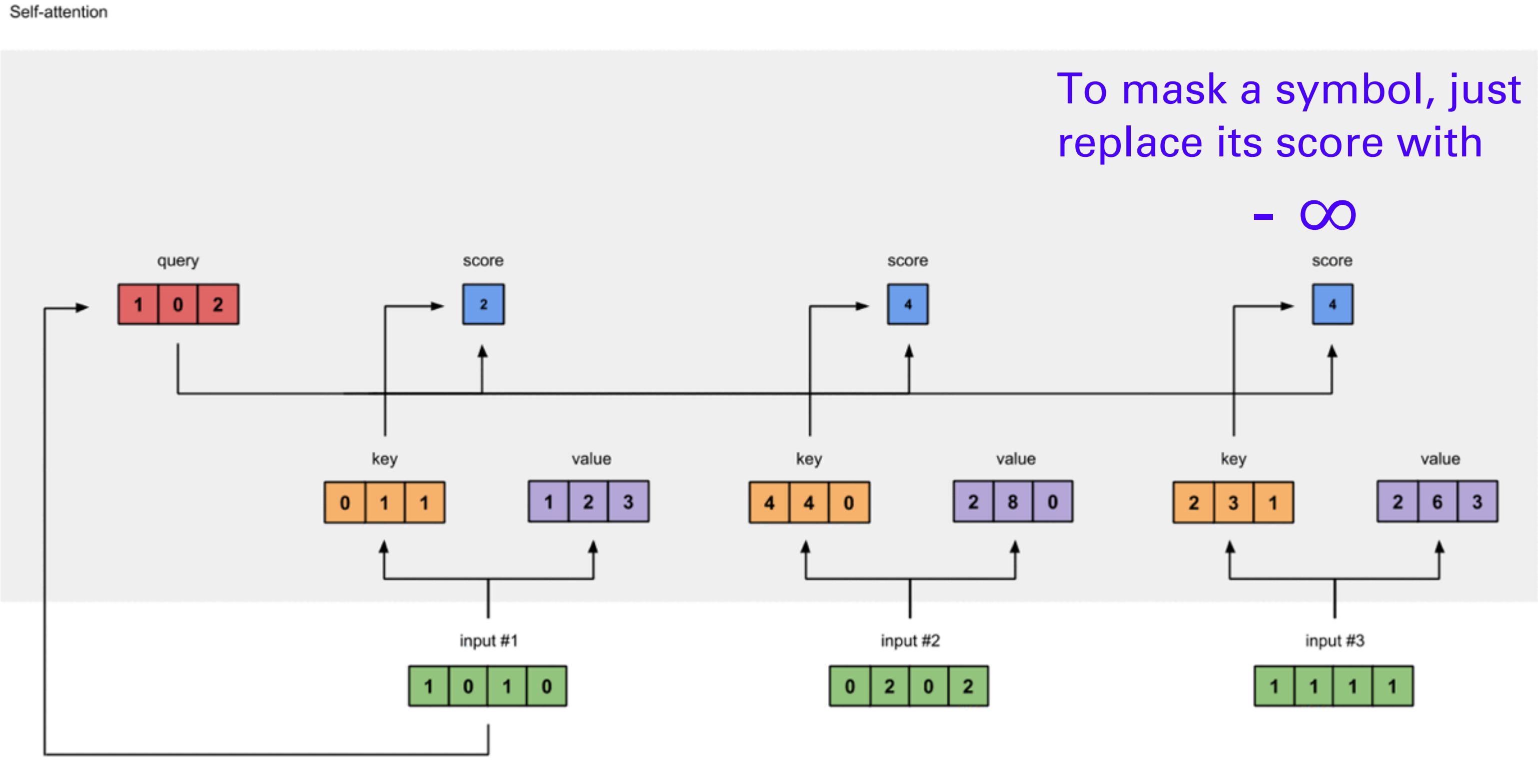


https://jalammar.github.io/illustrated-gpt2/

«Attention in action»
Role of Masked Attention (2)

Use masked attention to handle sequences of different lengths





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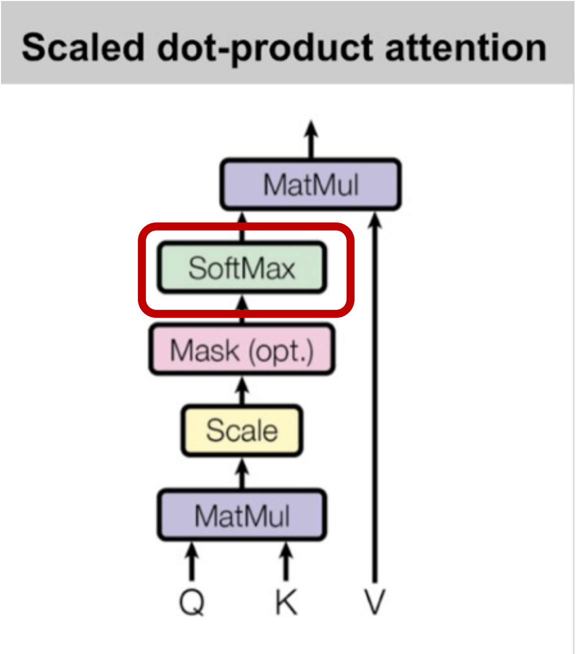
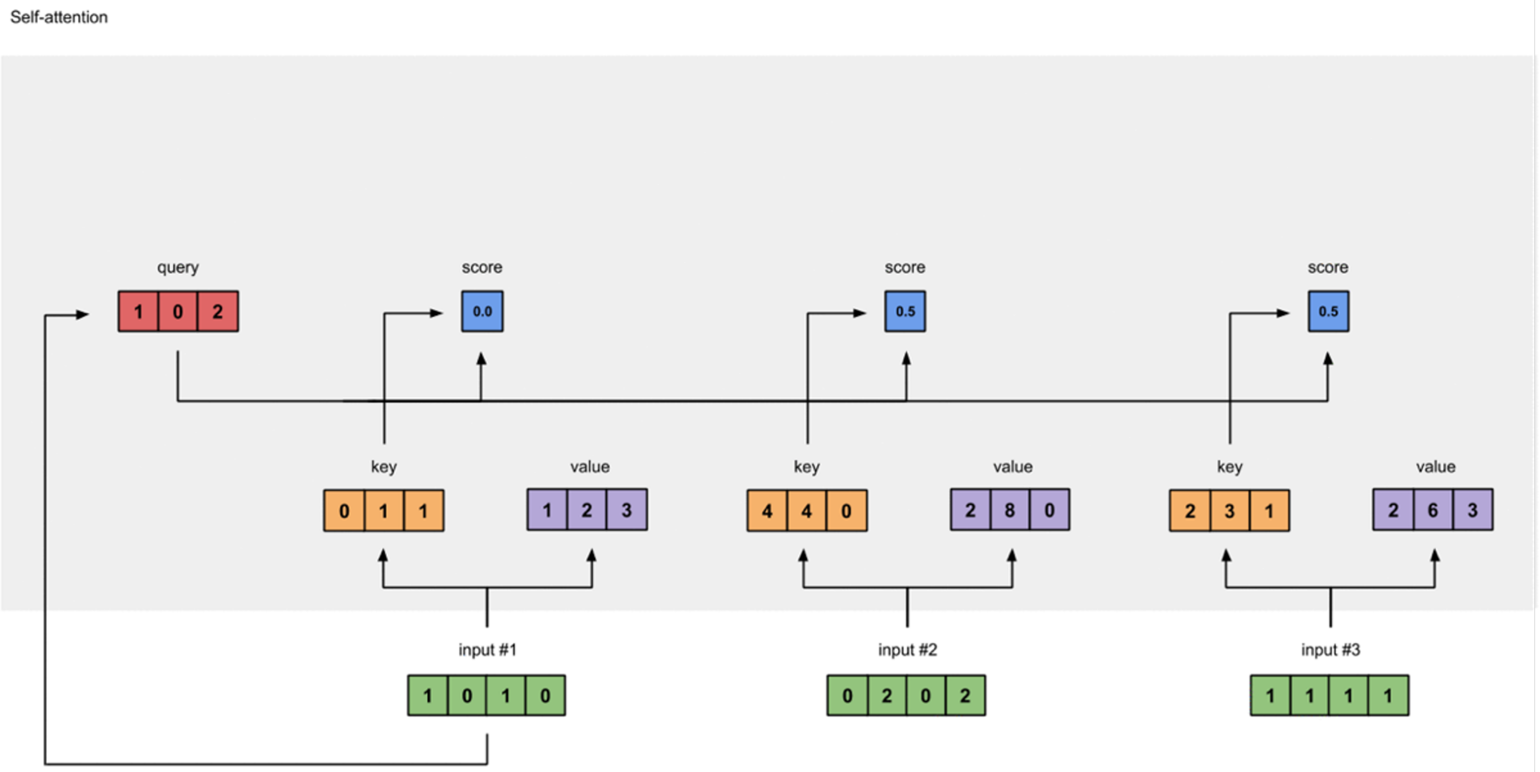
«Attention in action»
Calculate softmax

Softmax «simply» maps attention scores to a «probability» in [0, 1]

- The masked elements (i.e., with - ∞ gets a score near to 0)





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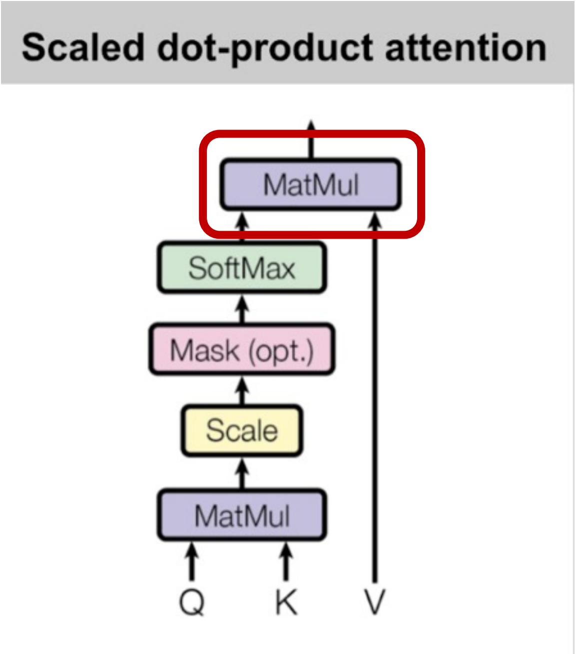
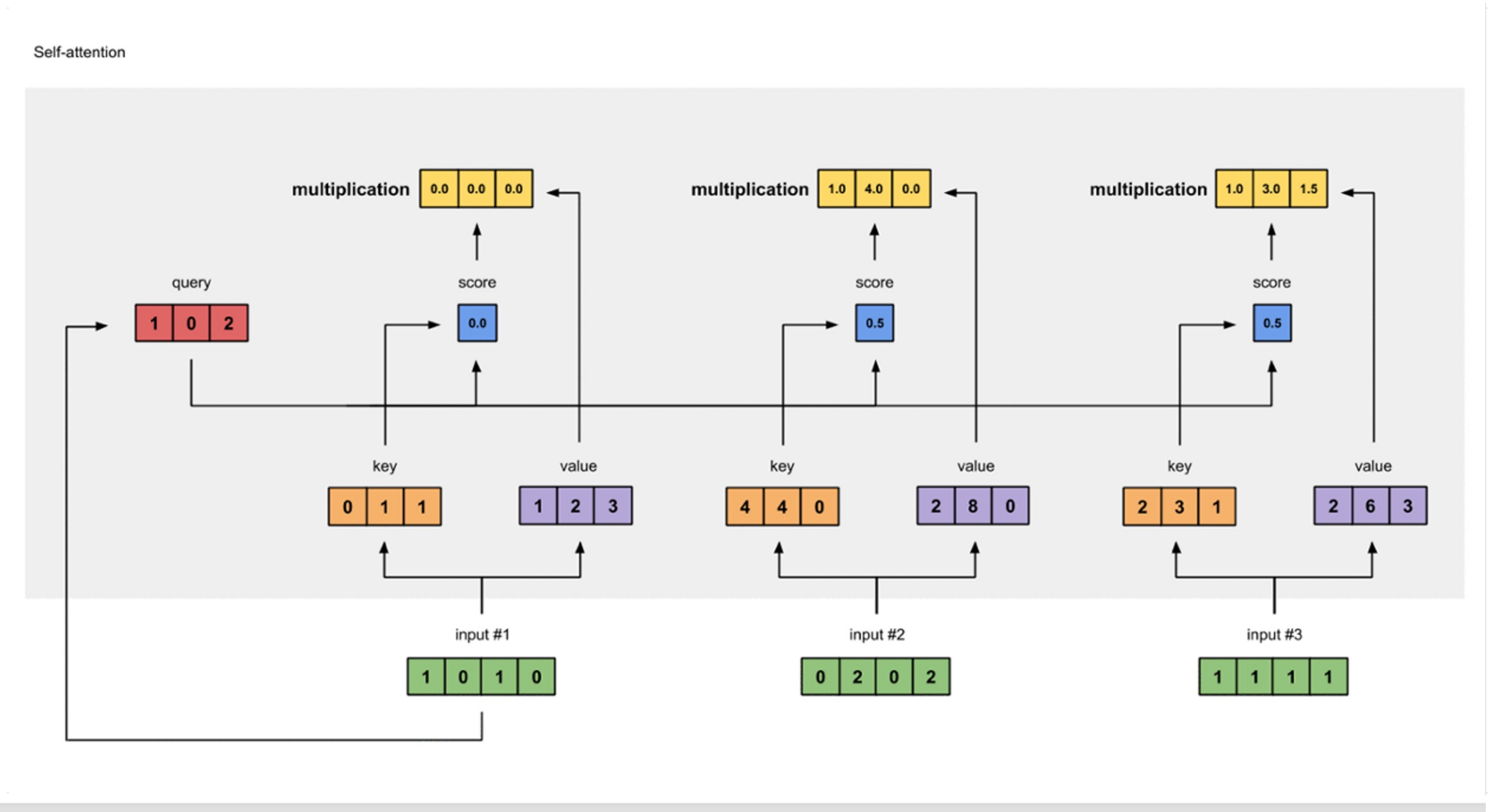
«Attention in action»
Multiply scores with values

Each $\texttt{input}_n$ (through each $\texttt{value}_n$) is weighted based of its importance in representing $\texttt{input}_1$





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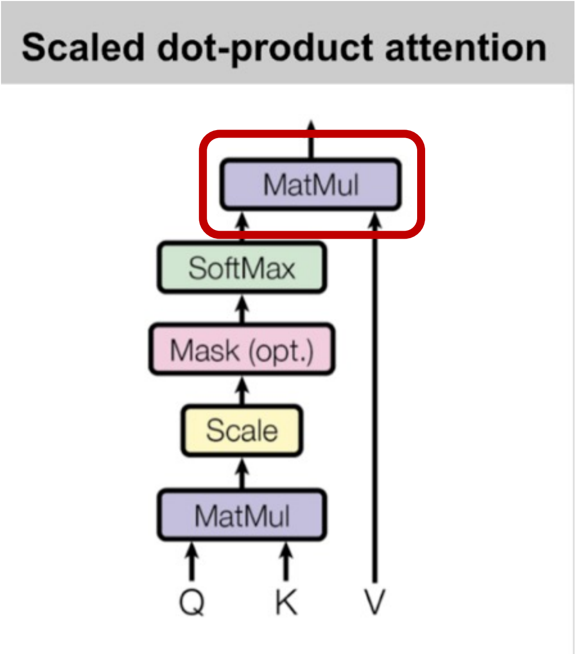
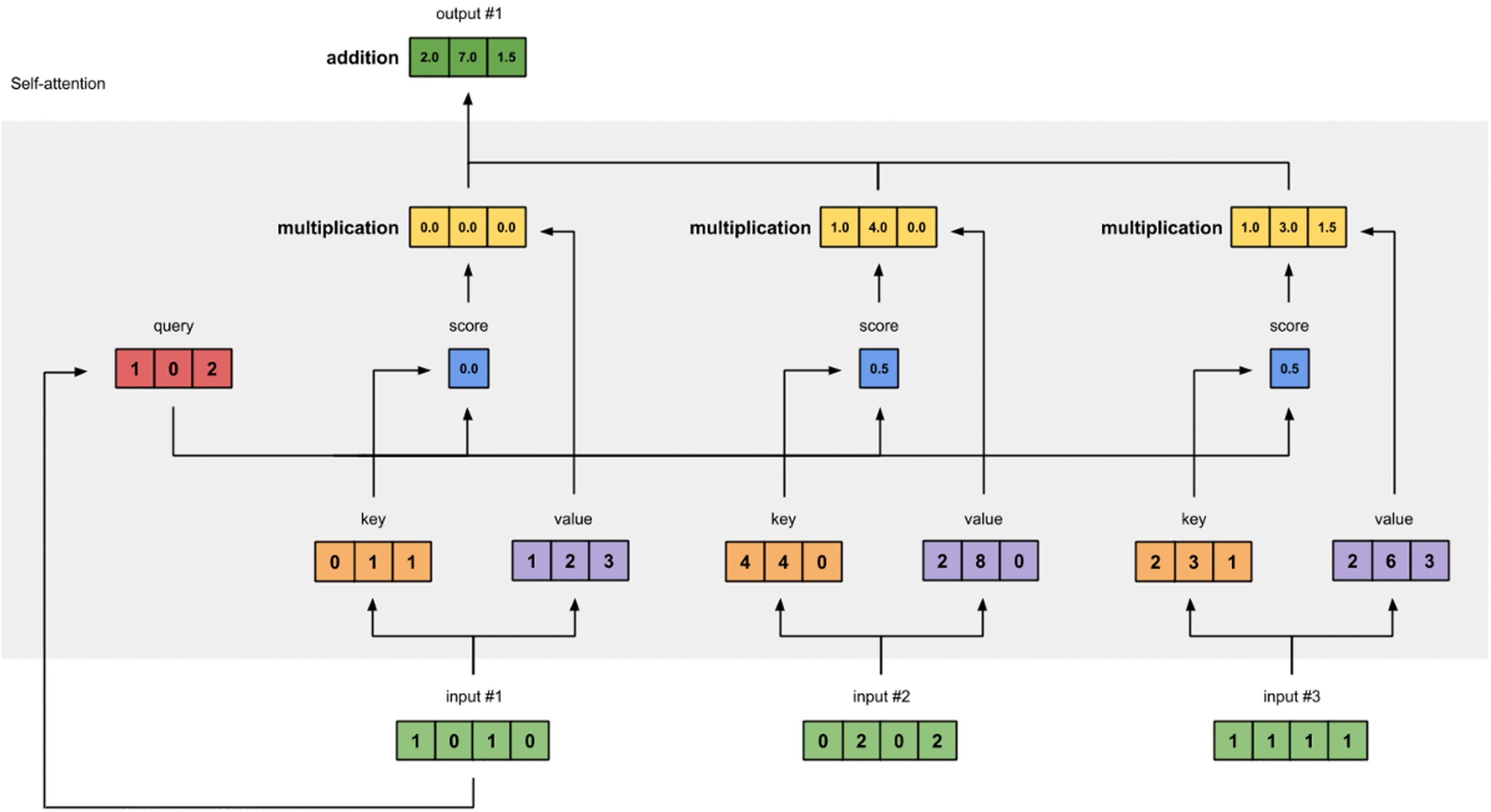
«Attention in action»

Complete the linear combination

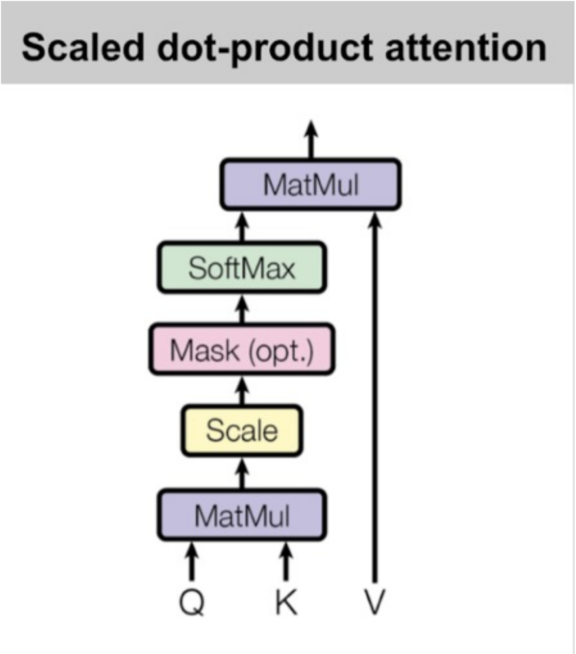
Sum weighted values to get $\texttt{output}_1$ that is the linear combination of all input elements (represented as values) weighted through the attention scores

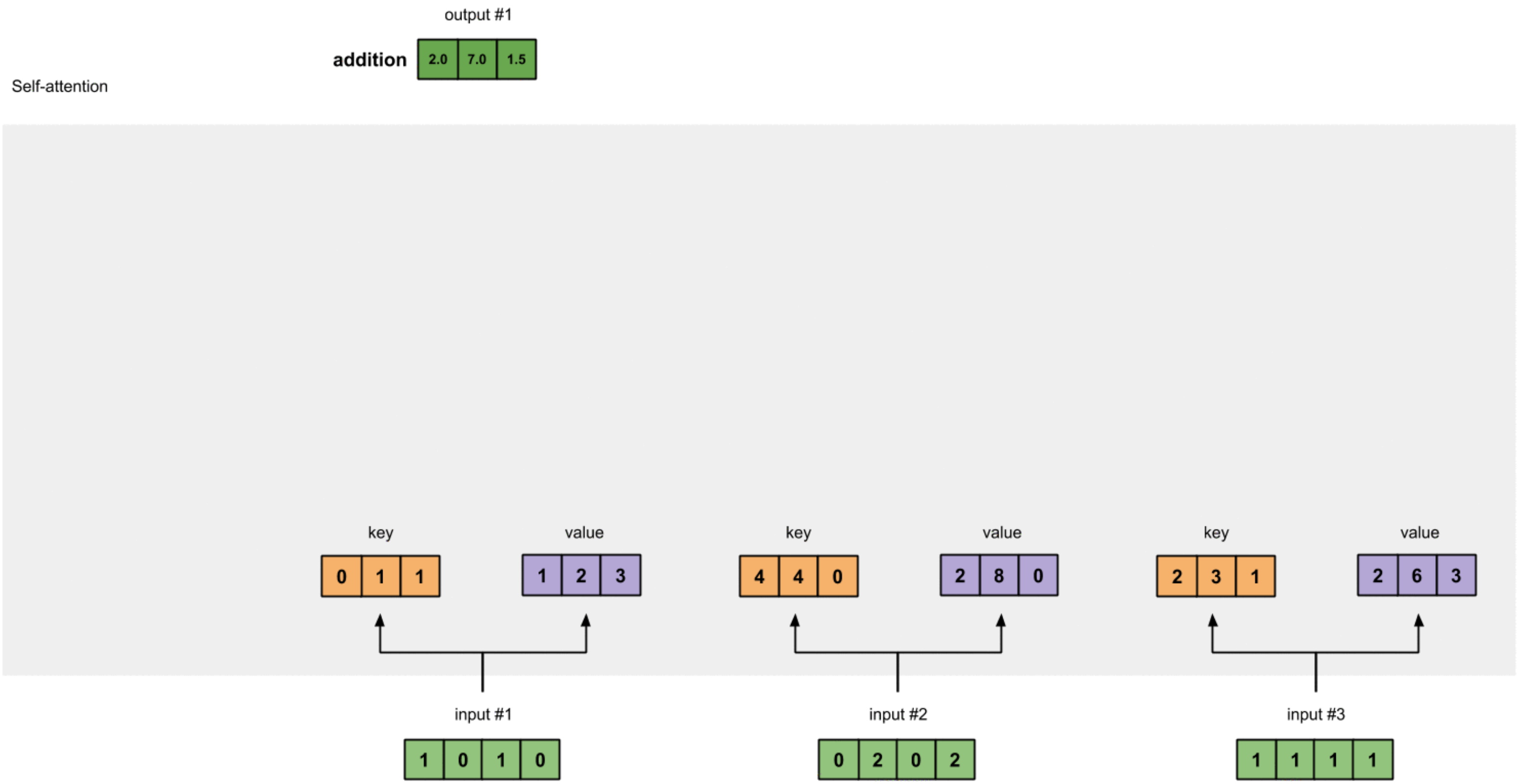




«Attention in action»

Repeat for $\texttt{input}_2$ and $\texttt{input}_3$

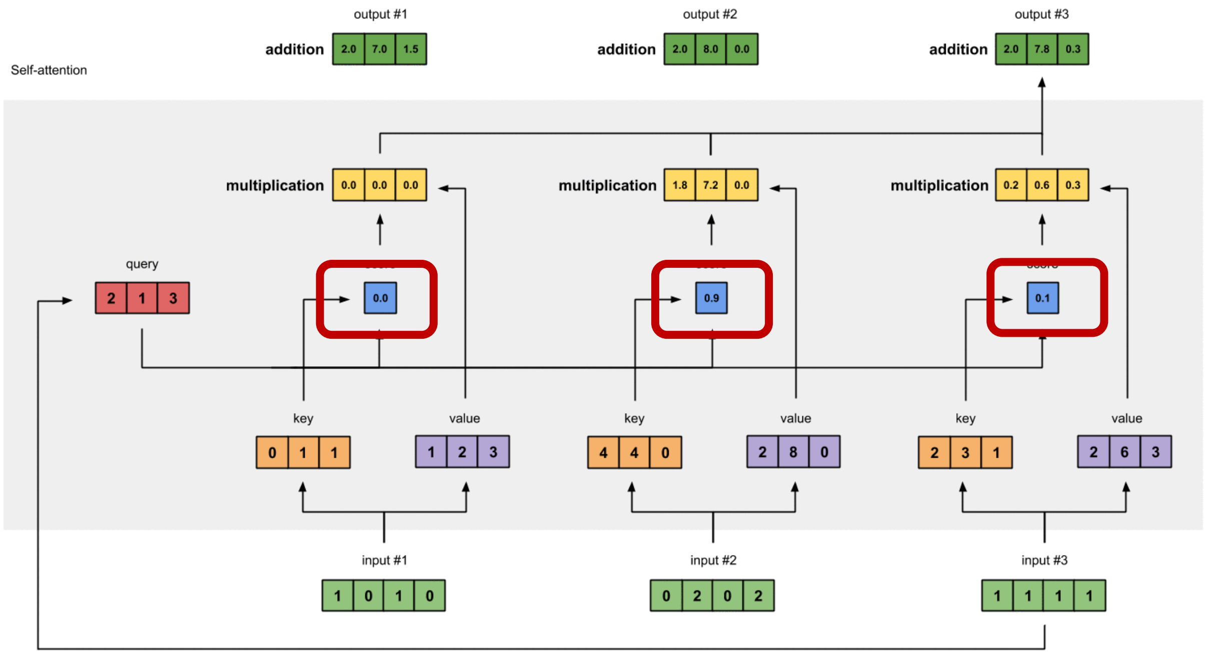




Danilo Croce

So… what is self-attention?

- It is not just a number, but a «probability distribution» for each symbol in input
  - And it allows weighting how **all words** are combined to generate the (hidden) representation of each word



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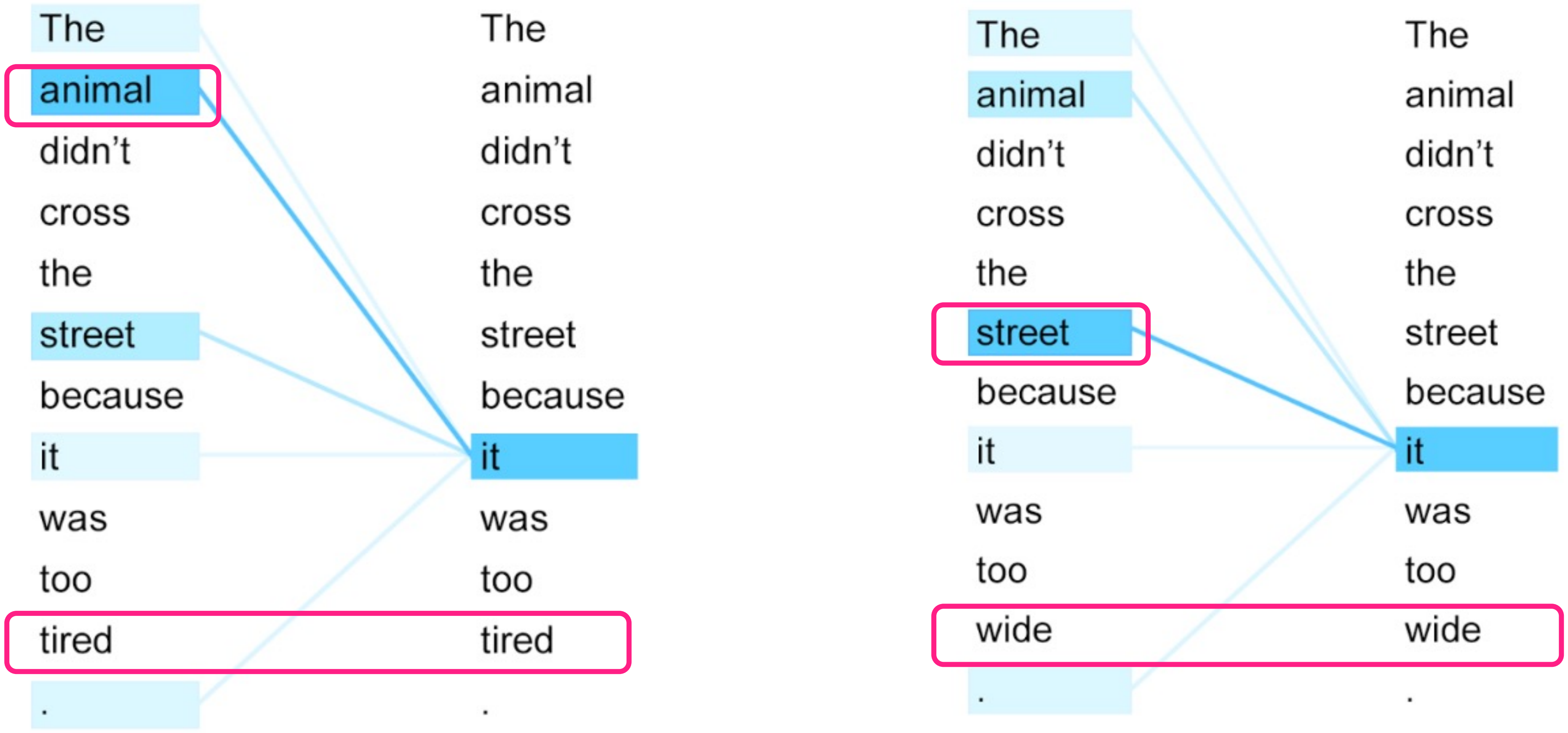
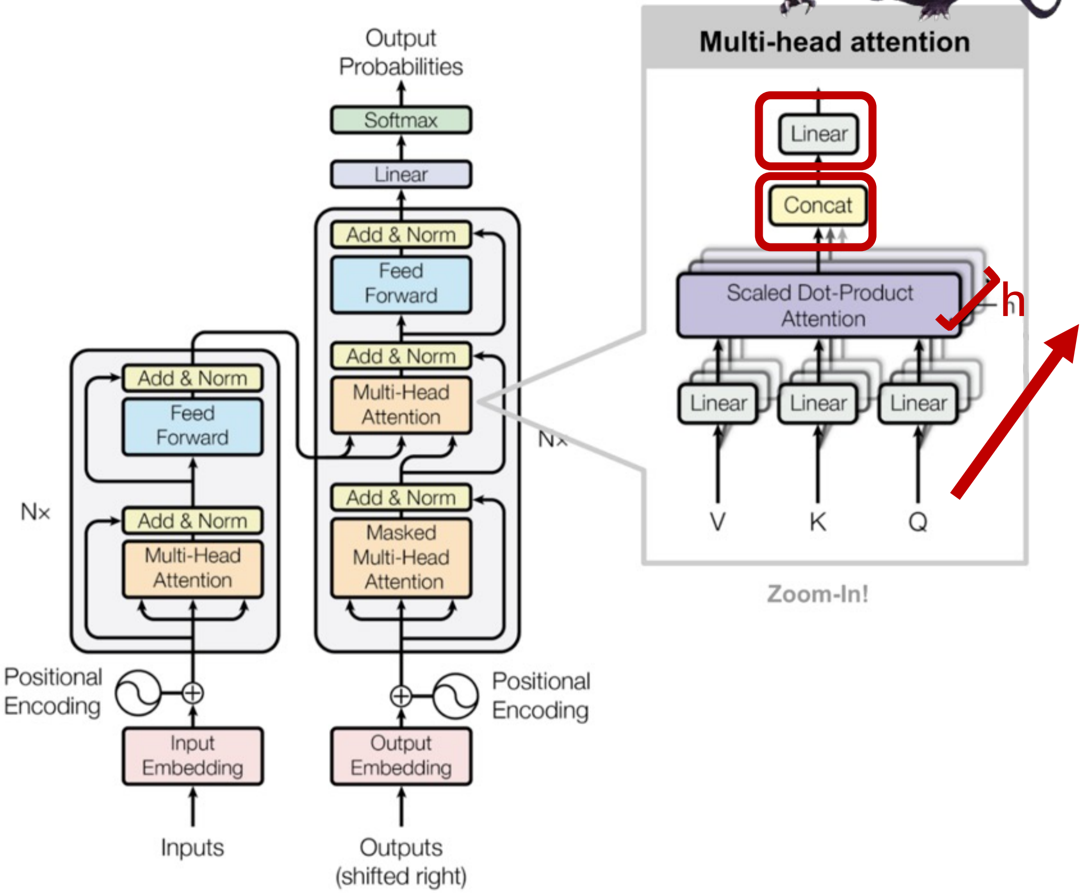
Self-Attention



The Multi-Headed «Beast»

- Humans can attend to many things simultaneously.
- Can we extend attention to achieve the same?

- **Idea**: apply **Redundancy**, i.e., Scaled Dot-Product Attention **multiple times**
  - For each input, just generate h output
    - using h different different $(\mathbf{W}^Q, \mathbf{W}^K, \mathbf{W}^V)$
  - Concatenate the h output vectors of each input
  - Use a linear layer to "restore" the initial dimensionality
    - **But combining all multiple evidences**



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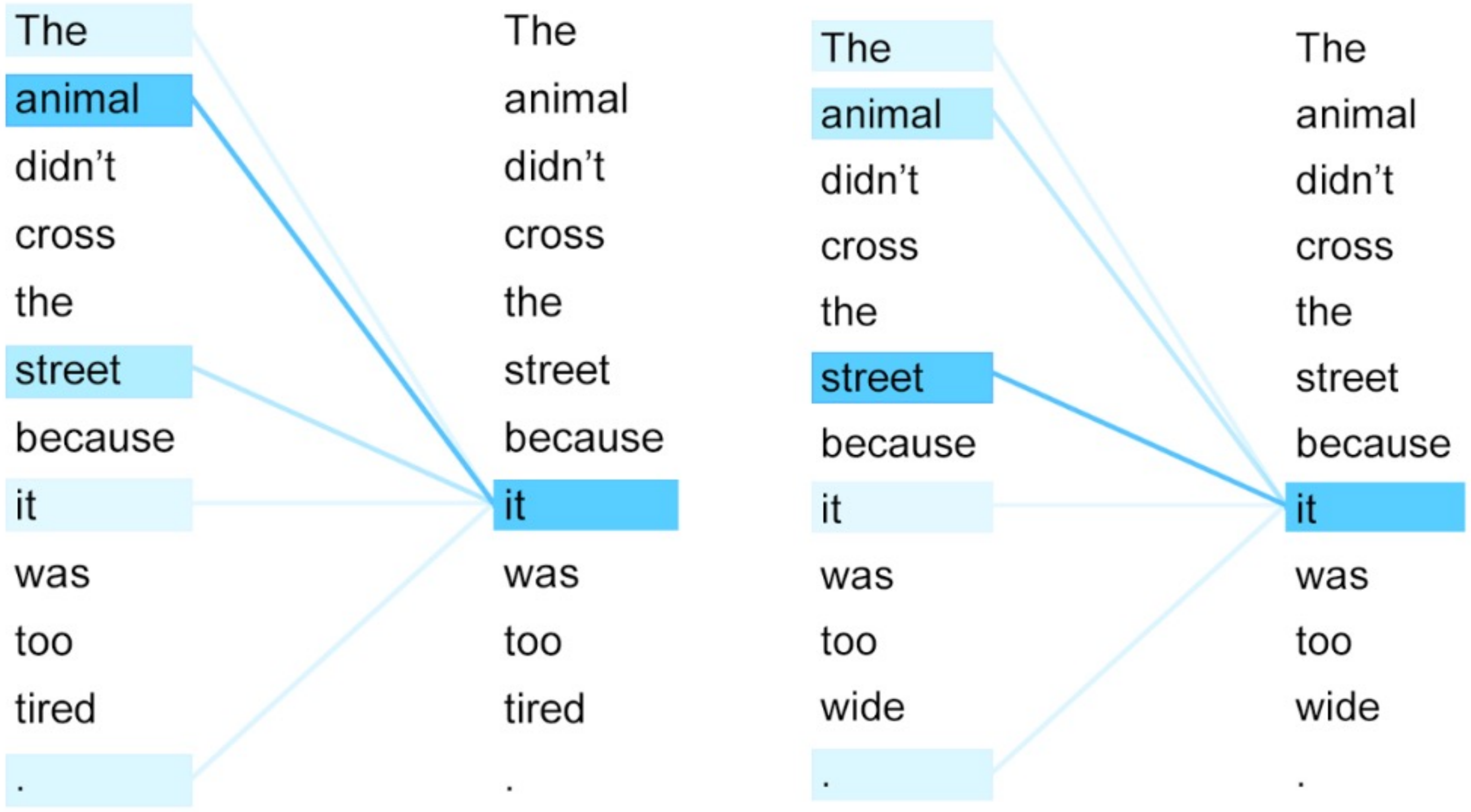
From «simple» attention...



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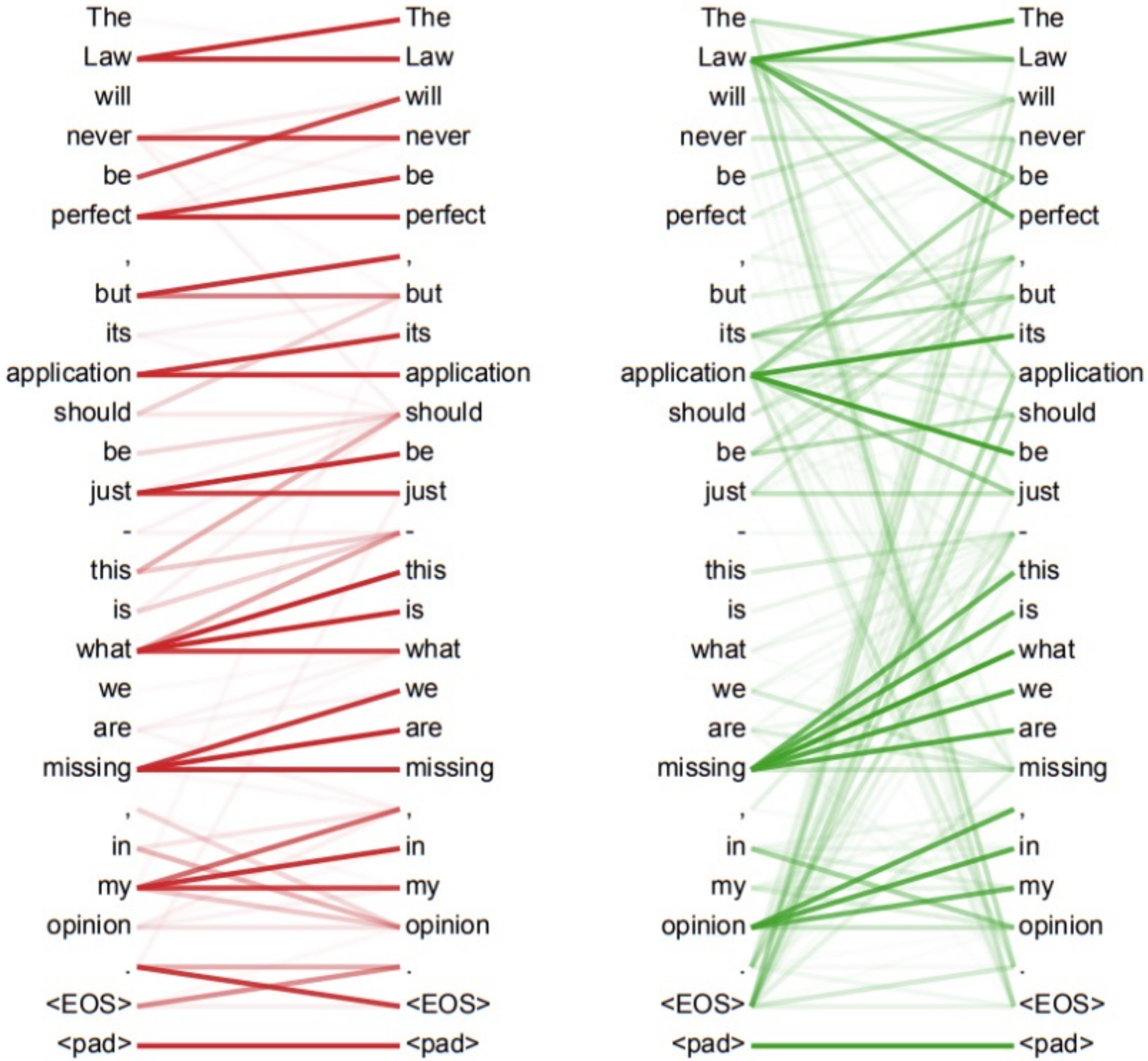
... to Multi-head Attention



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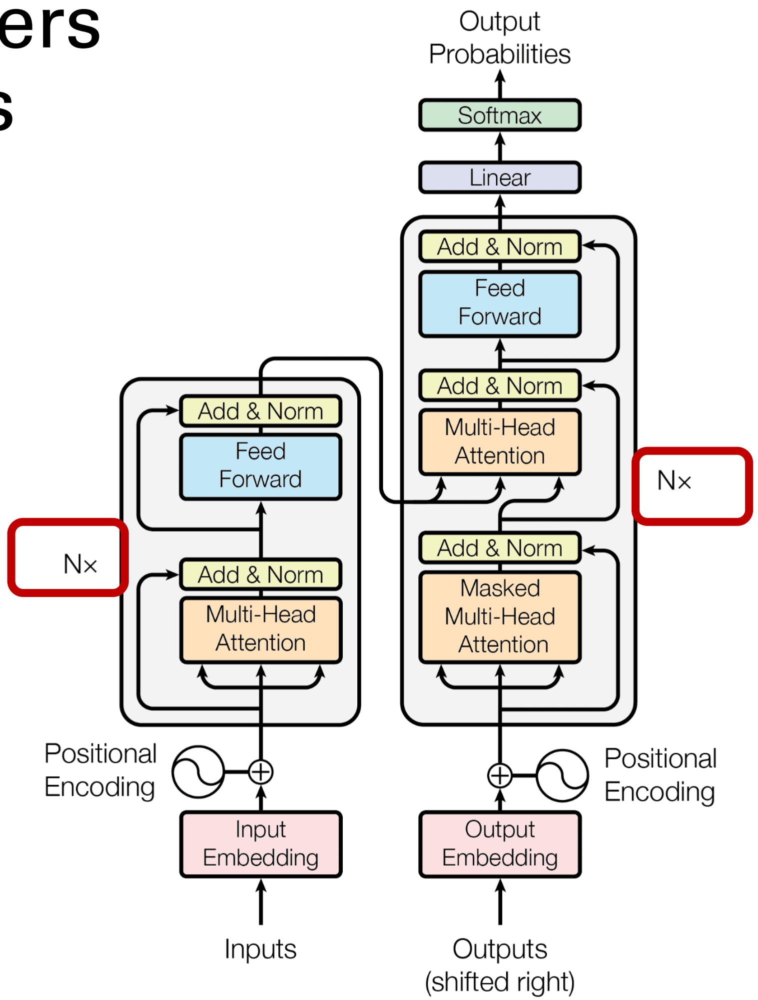
Where is the «Deep Learning»?

Encoders and decoders
are repeated N times



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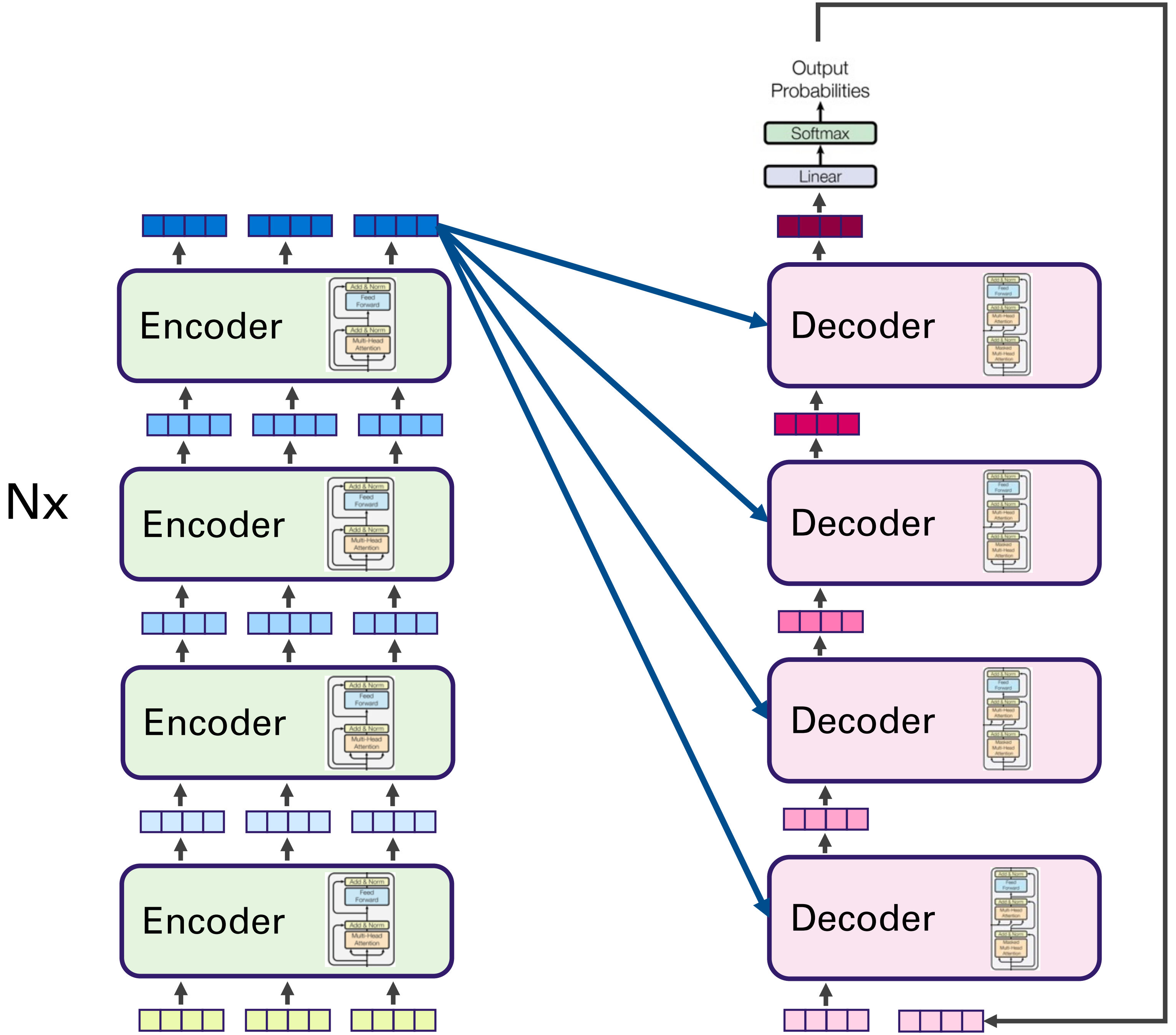
Again: the Transformer in Action

Danilo Croce



Generated hidden representations for each symbol initially rely on the first token, called `<start>`.

These representations are influenced by all hidden representations from the encoder.

Again: the Transformer in Action

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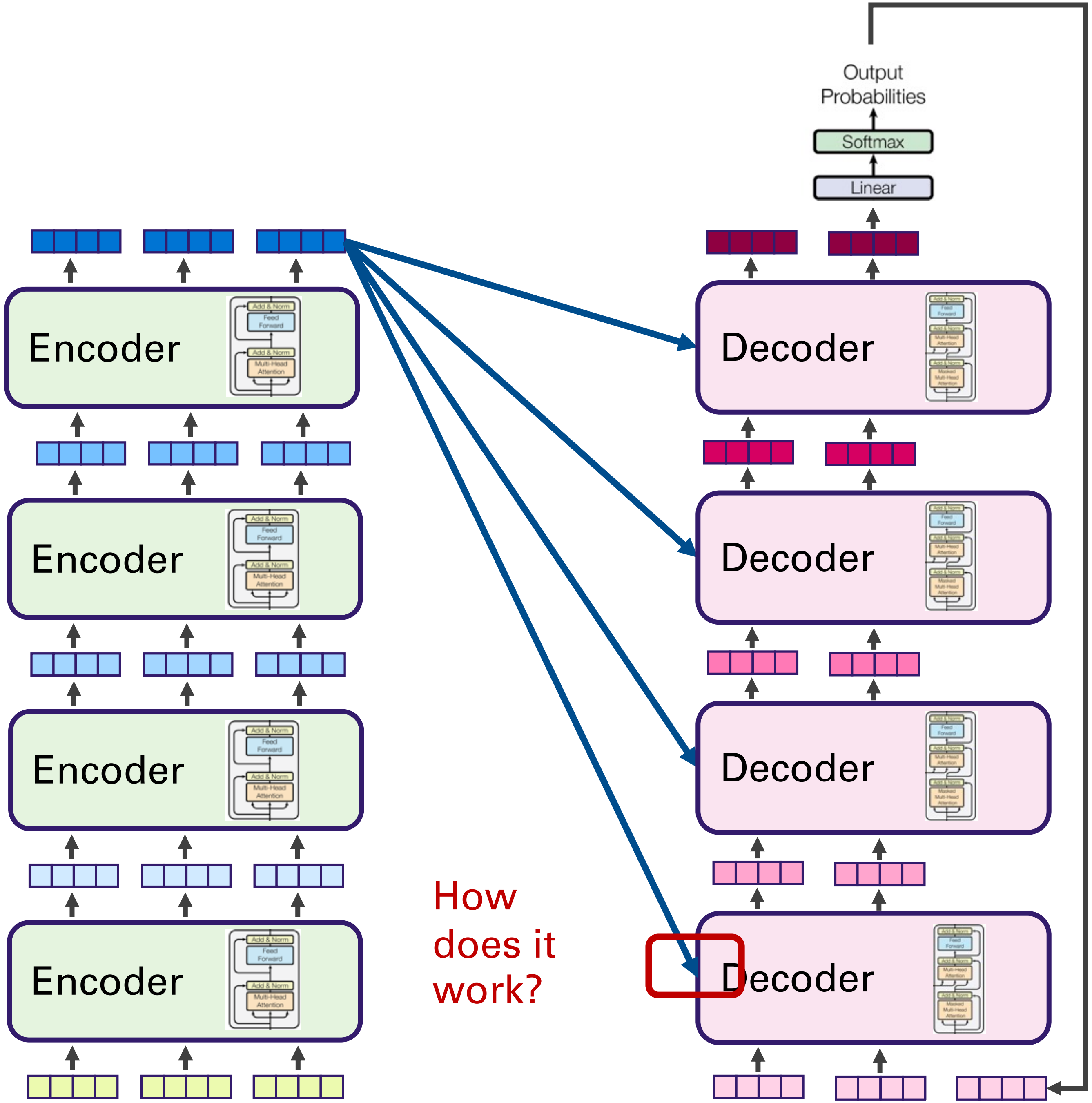


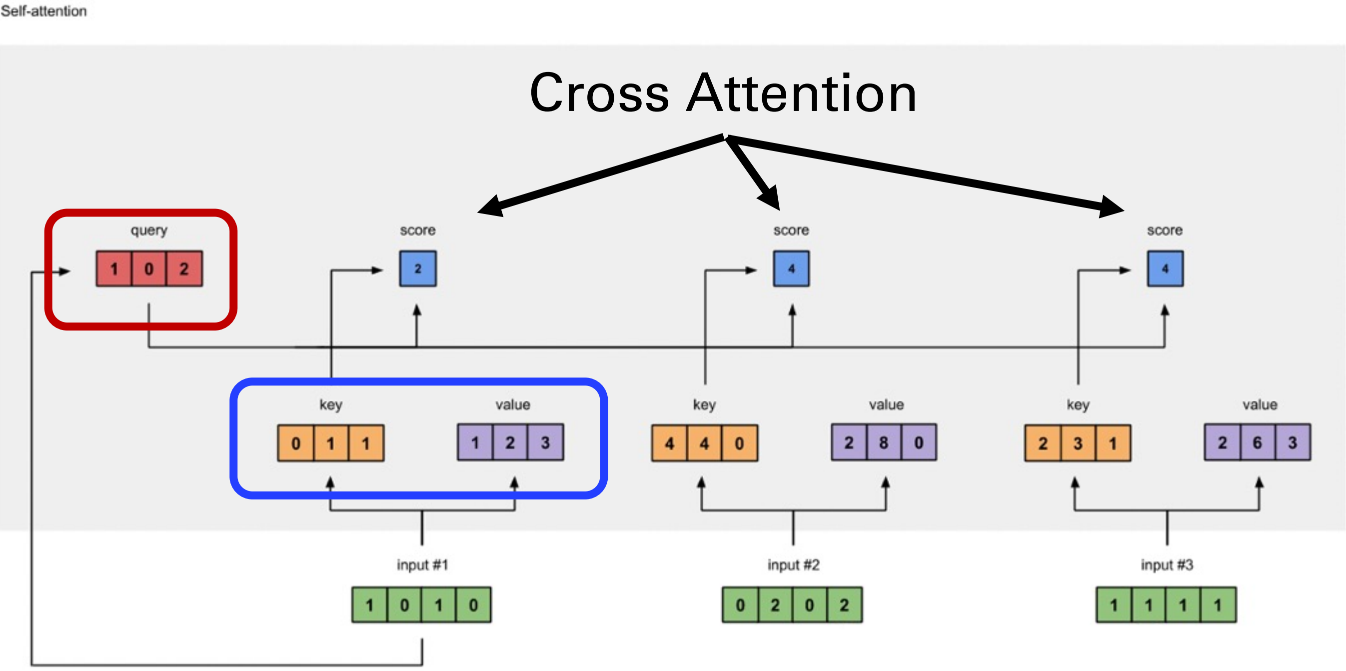
After the generation begins…

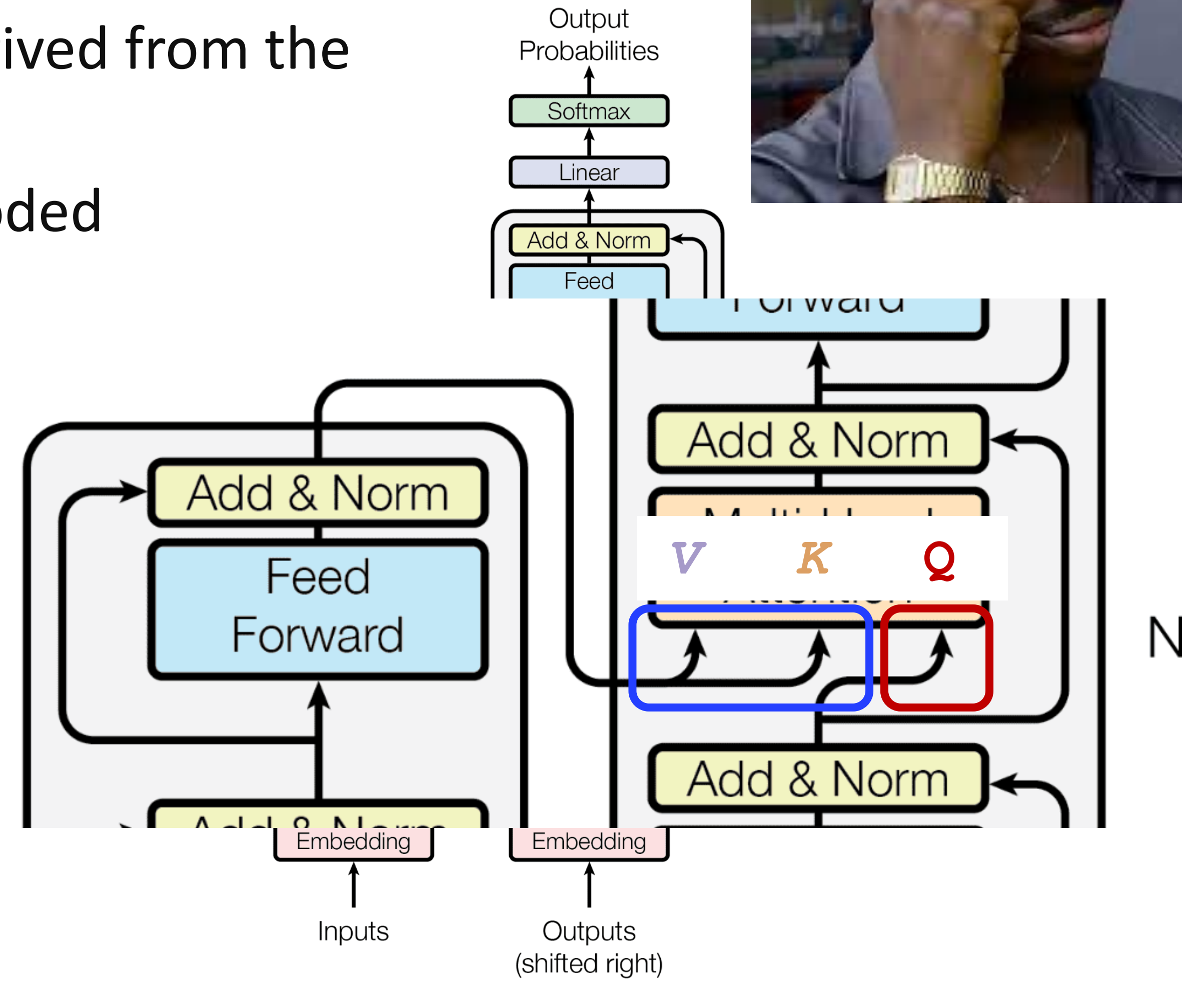
the **decoder's hidden representations simultaneously depend on all input tokens** attended to in the encoder…

but on the decoder's own previously generated hidden representations up to that point.

How to combine Encoders and Decoders?

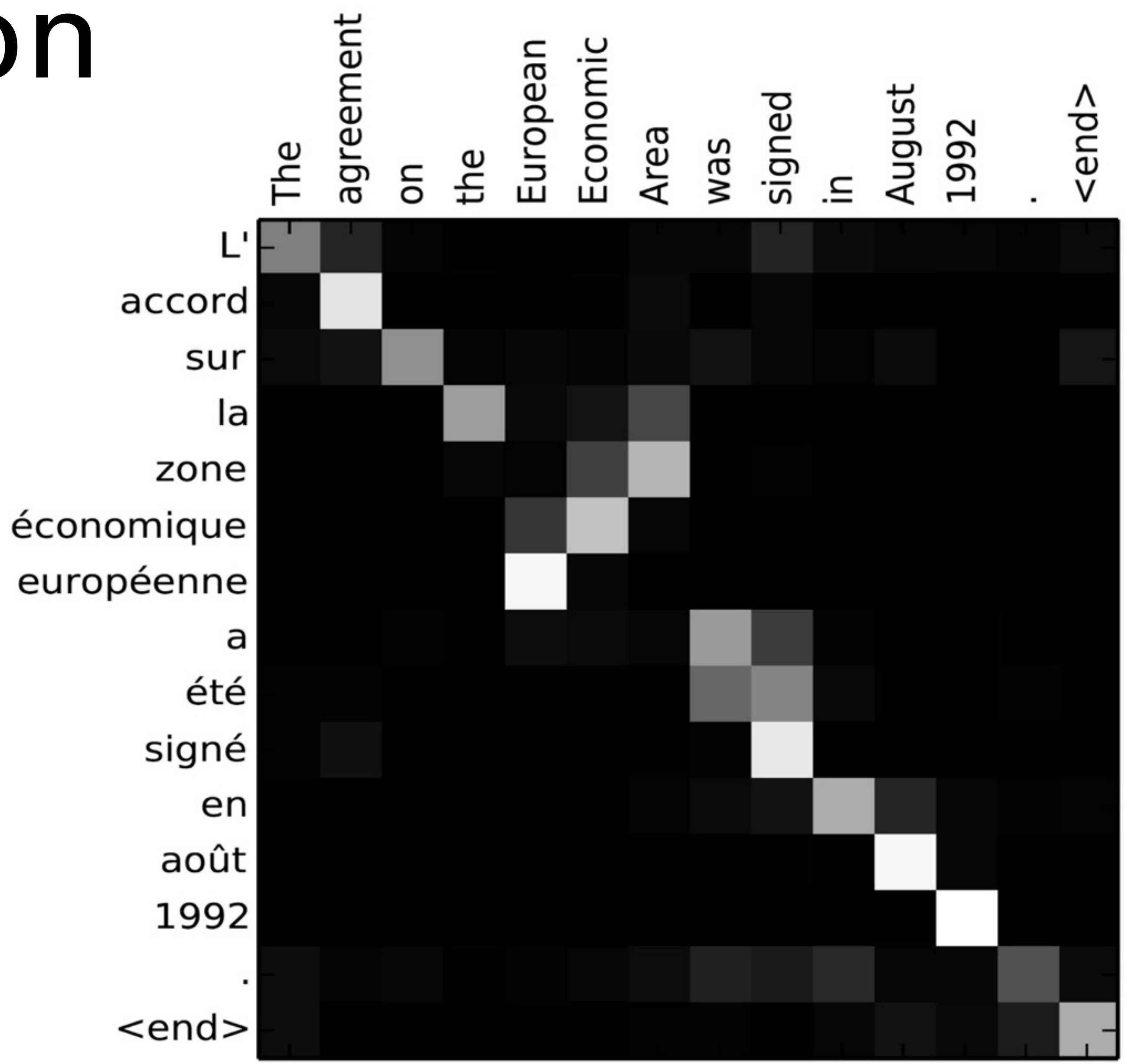
- In the decoder, key and value vector are derived from the input.
- The query, in contrast, depends on the decoded sequence.





Cross-Attention

- Attention scores between input and output words
- White equals higher score
- The diagonal is highly correlated
- The scores reveal the grammatical difference for adjectives for the two languages (*zone économique européenne*)



Advantages of Attention

- **Targeted Focus in Decoding:**
  - The decoder, with attention, can **strategically concentrate on relevant segments** of the source text
  - leading to more coherent and **contextually accurate** translations.
- **Addressing Vanishing Gradient Problem:** The mechanism offers a solution to the vanishing gradients issue
  - creating shortcuts between distant states in the sequence, facilitating smoother gradient flow during backpropagation.
- **Enhancing Model Interpretability:** we gain insights into what the model focuses on at each step

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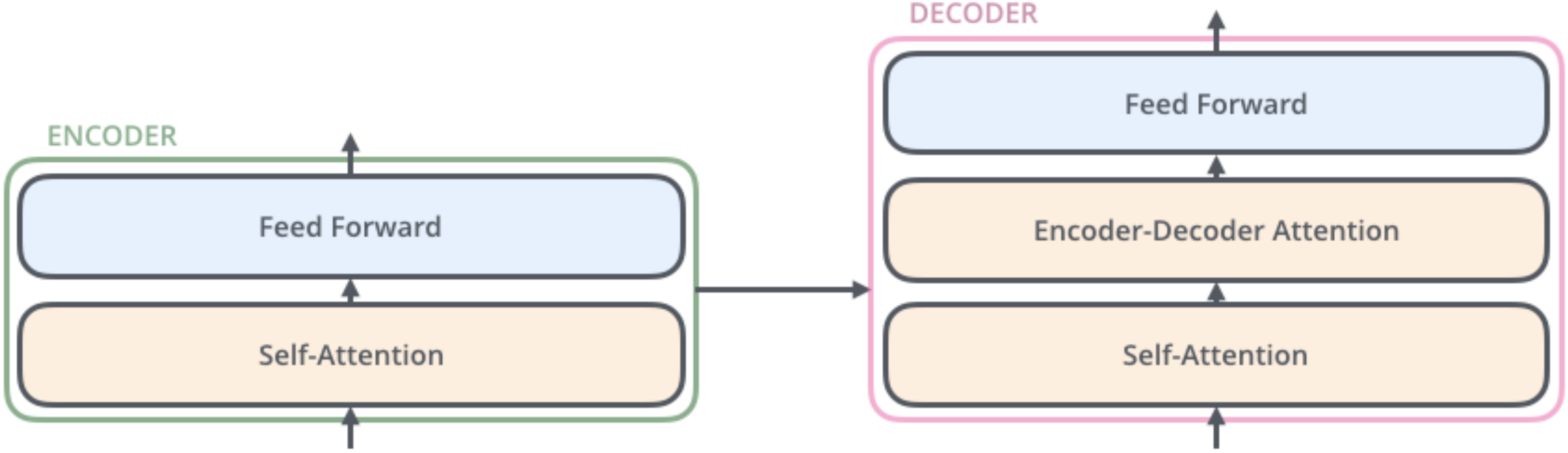
The Transformer was only the beginning

A transformer is made of two components

- Encoder
- Decoder



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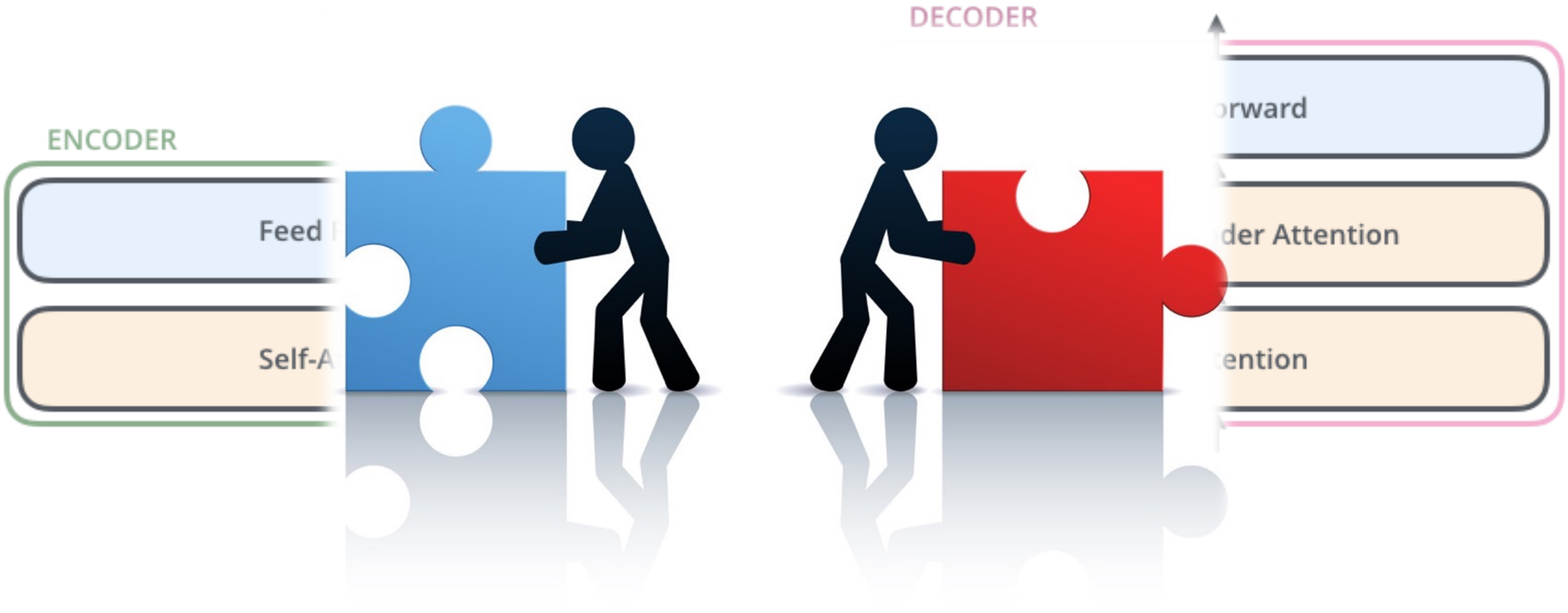
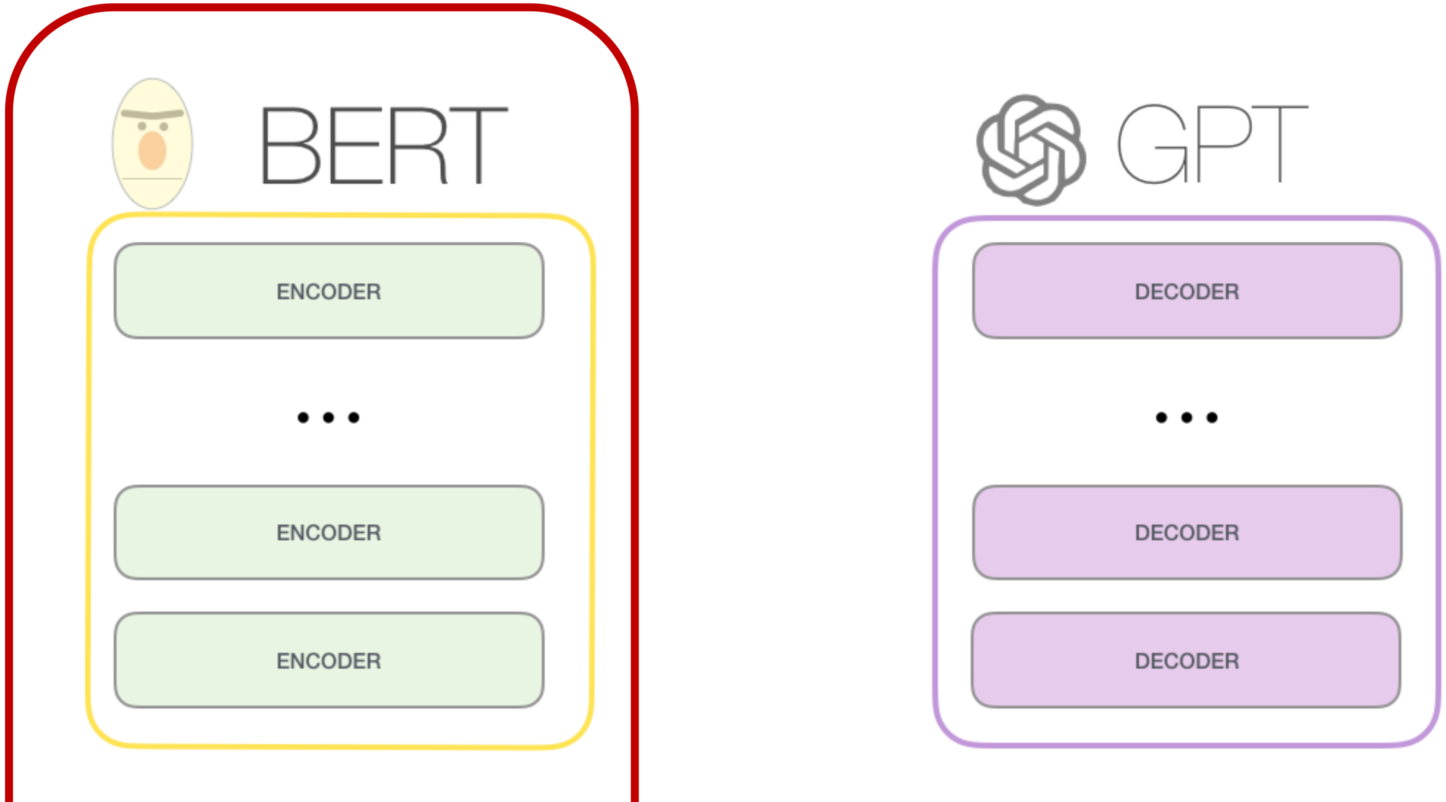


The transformer was only the beginning

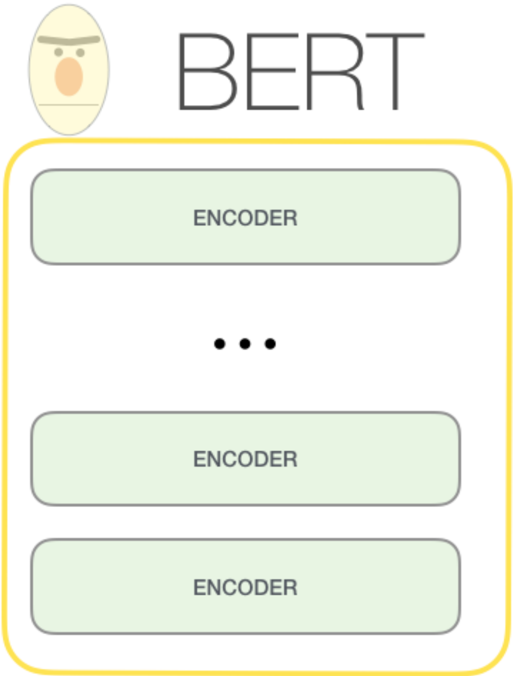
- This separation led to two «classes» of methods
  - **«Encoder-only» models**: the most famous one is BERT
  - **«Decoder–only» models:** the most famous one is GPT



BERT (Devlin et al, 2018)

Bidirectional Encoder Representations from Transformers

- Only the encoder is used
- Designed to generate **contextual meaningful representation** of input words
  - Representations are **context sensitive,** thanks to self-attention
  - Understand the context of a word in a sentence from **both left and right sides** (bidirectionally).
- Representations are embeddings
  - not suitable for text generation
  - … but for many other tasks



Images from `https://jalammar.github.io/illustrated-bert/`

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv:1810.04805.

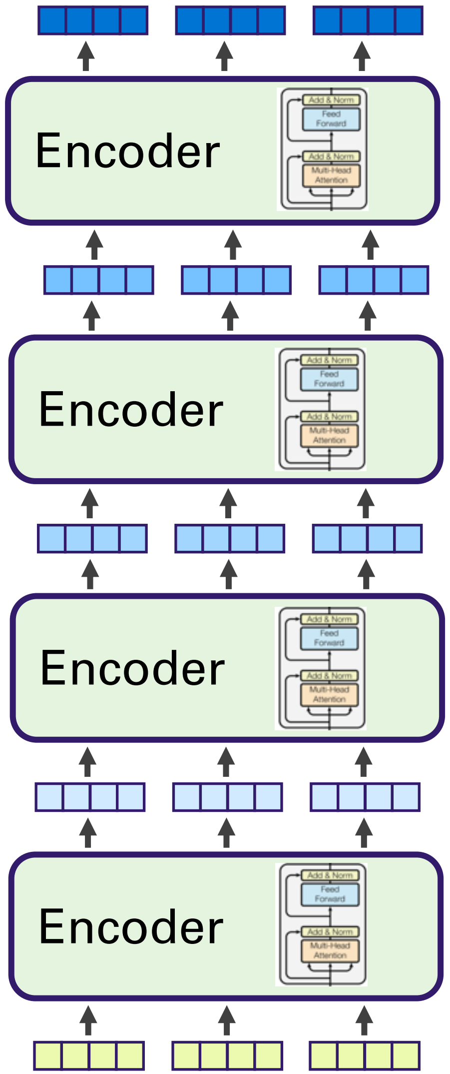
BERT (Devlin et al, 2018)

🤔 **Why should it work?**

- It is just a piece of the Transformer architecture seen a few slides ago.

💡 **The GREAT IDEA: Pre-Training the encoder**

- Pre-trained on a large corpus of text and then fine-tuned for specific tasks like question answering, sentiment analysis, etc.



Images from `https://jalammar.github.io/illustrated-bert/`

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No pre-training no party! The Revolution of Pre-Training in NLP

- **Simple idea:** train a (possibly large) model on a different task and re-use it on your task
  - circumventing the need for training from scratch
  - facilitating “quicker”, more effective deployment of the model
- **Precedent in Computer Vision**:
  - This strategy mirrors developments in computer vision
  - Architectures pre-trained on classification tasks using datasets like ImageNet
  - When applied on related task, these “starting point” achieve very good results
- **Addressing Overfitting in Large Models**:
  - With **increasing model sizes** and parameter counts, the **risk of overfitting grows**
  - Pre-training on vast datasets mitigates this by providing a broad learning base.

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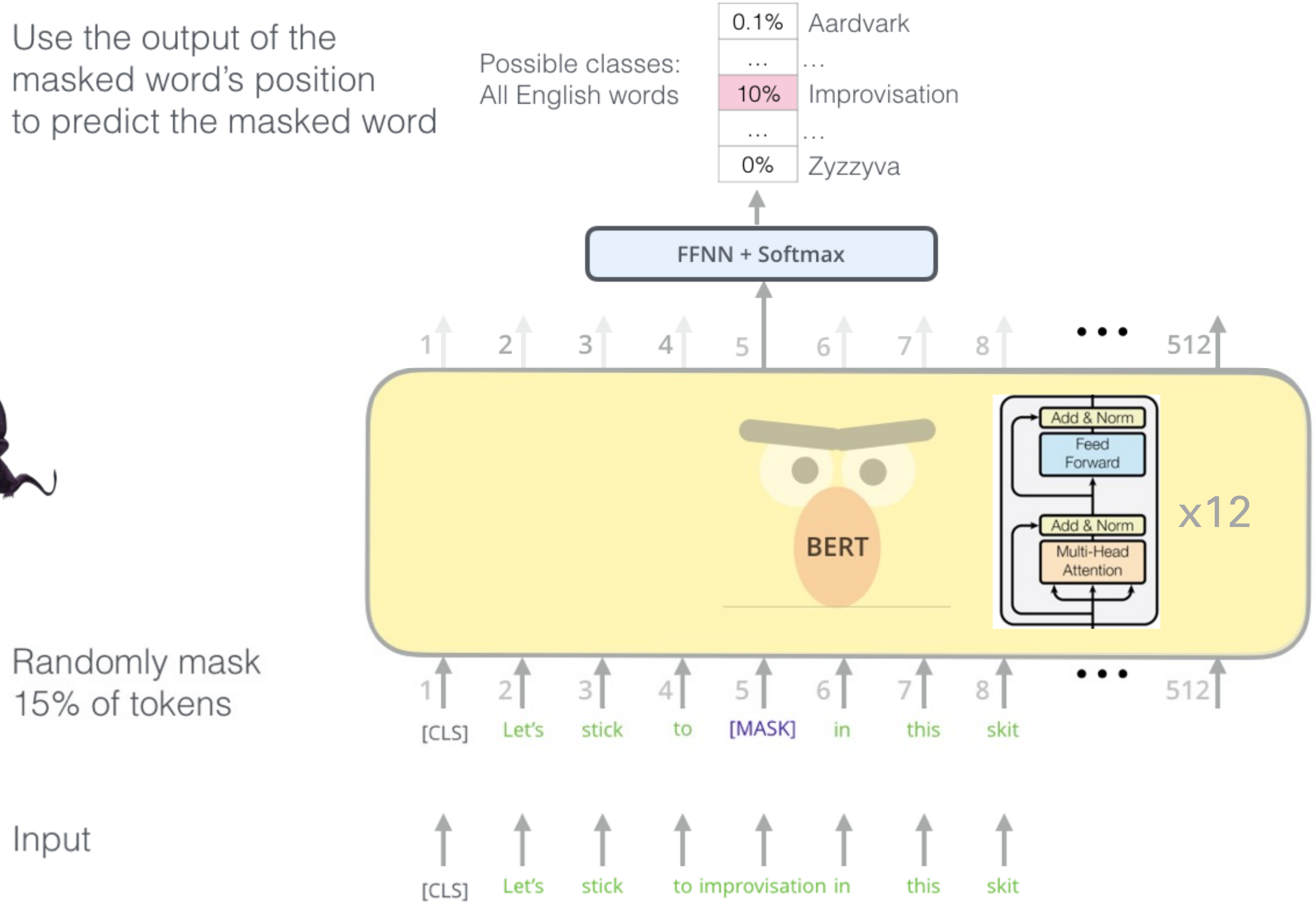
Towards Foundation Models

- **Emergence of Foundation Models in NLP**:
  - Large-scale models trained on linguistic tasks, forming a versatile base that can be fine-tuned for various specific applications.
- **Everybody worked on customizing Foundation Models:**
  - Leverage the extensive knowledge encapsulated in Foundation Models by fine-tuning them for particular NLP tasks.

- If you are interested in foundation models
  - [Zhou et al, 2023] A Comprehensive Survey on Pretrained Foundation Models: A History from BERT to ChatGPT
  - `https://arxiv.org/abs/2302.09419`

Pretraining BERT

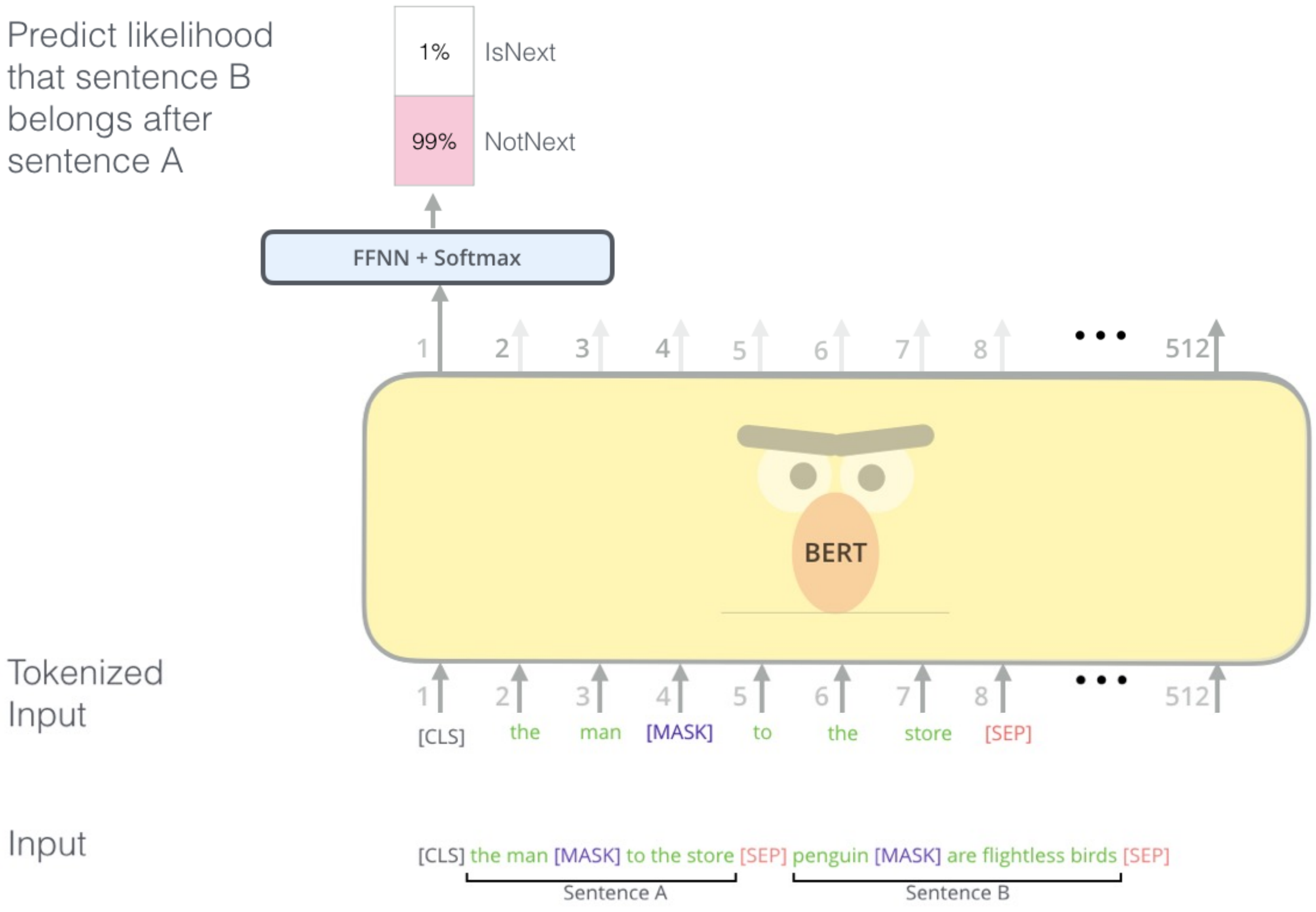
- BERT takes a sequence of tokens as input
  - Utilizes **self-attention across layers** to **generate context-aware** representations of each token in the sequence.
  - In each layer, h=12 $\mathbf{W}^Q, \mathbf{W}^K, \mathbf{W}^V$ matrices
- **Pre-training tasks:**
  - **Masked-language modeling**



Pretraining BERT (2)

- BERT takes a sequence of tokens as input
  - Utilizes **self-attention across layers** to **generate context-aware** representations of each token in the sequence.
  - In each layer, h=12 $\mathbf{W}^Q, \mathbf{W}^K, \mathbf{W}^V$ matrices
- **Pre-training tasks:**
  - Masked-language modeling
  - **Next sentence prediction**

Pretrained using the Toronto BookCorpus (800M words) and English Wikipedia (2,500M words)



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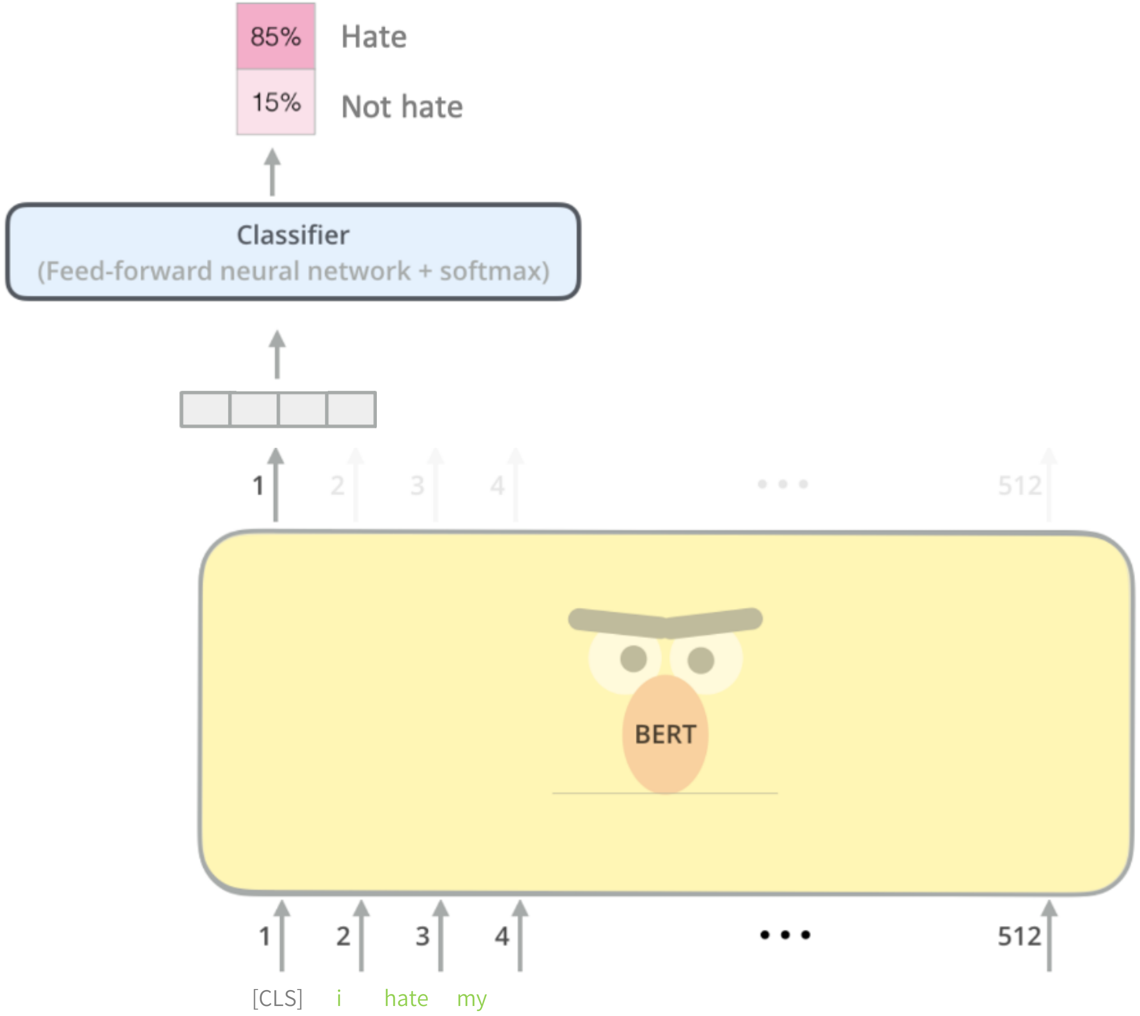
BERT and fine-tuning

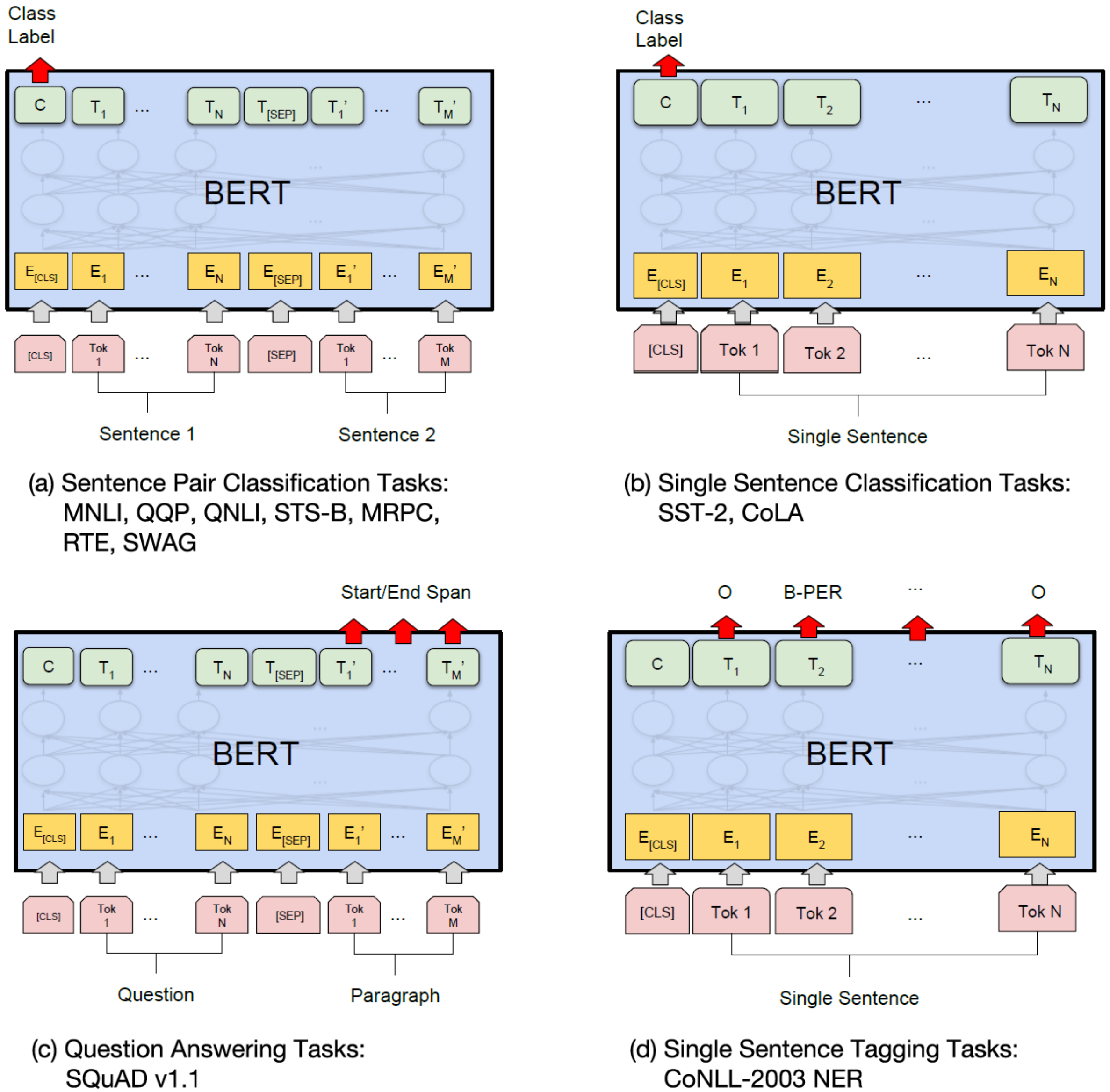
- Once pretrained, we can **apply it to new sentences**
- BERT will **produce encoded representations** for each input symbol
- And it can be used in **different classification tasks**, just adding a new (linear) classifier…
- … through fine-tuning of the entire architecture
- not trivial to forget what learned during the pre-training



Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv:1810.04805.

BERT in action

- The final layer outputs hidden representations, which can be utilized with a simple linear classifier
- to address a broad spectrum of NLP tasks efficiently.



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

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

(c) Question Answering Tasks: SQuAD v1.1

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

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv:1810.04805.

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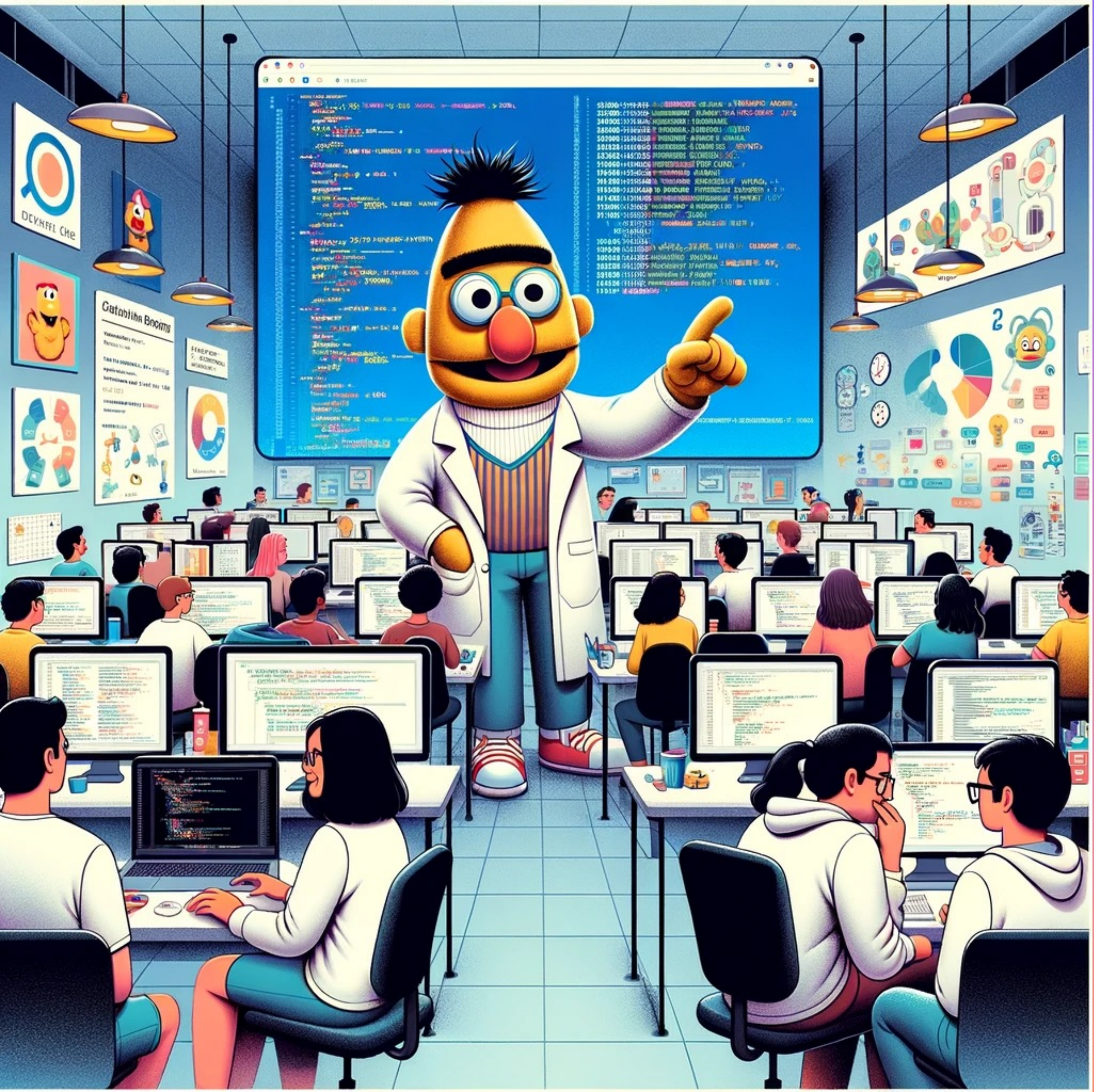
BERT and «sons»

HUGGING FACE

- A wide array of architectures, modeled and pre-trained, draw inspiration from BERT, featuring subtle but impactful variations.
- Selected **Notable Variants**:
  - **RoBERTa**: Streamlines BERT's pre-training approach and leverages an expanded dataset for training.
  - **ELECTRA**: Introduces a unique twist by replacing tokens with similar ones, then focusing on identifying these alterations.
  - **ALBERT**: Implements layer-wise parameter sharing to enhance efficiency.
  - **XLM**: Extends RoBERTa's capabilities across multiple languages.
- **Italian Contributions:**
  - Italy's own spin-offs include Alberto, UMBERTO, and Gilberto, each adding unique flavors to the BERT family.

Everything is very interesting... but



CHAPTER 3

TRAINING A SENTENCE CLASSIFIER USING BERT-BASED MODELS

Let’s Code

Open in Colab

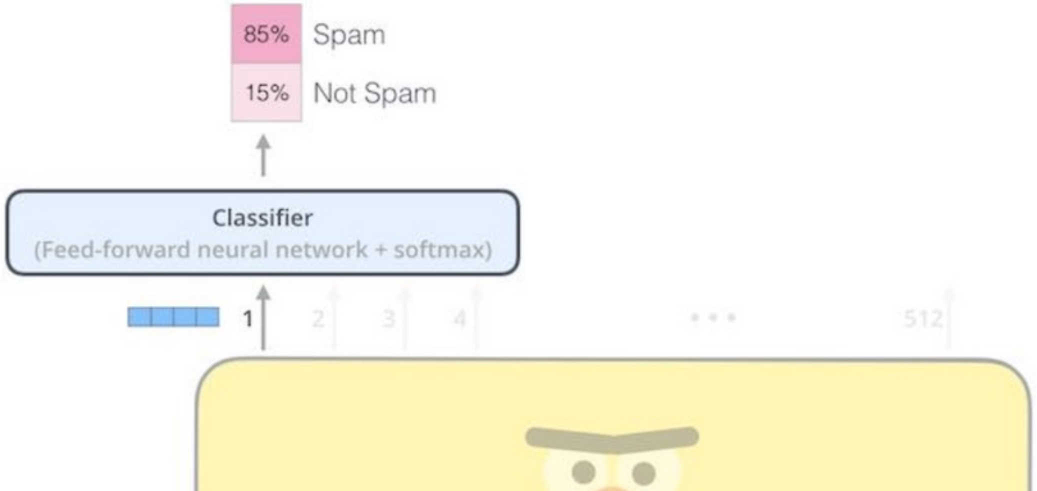
BISS 2024

Tranining a sentence classifier using BERT-based models (in Pytorch and compatible with HuggingFace)

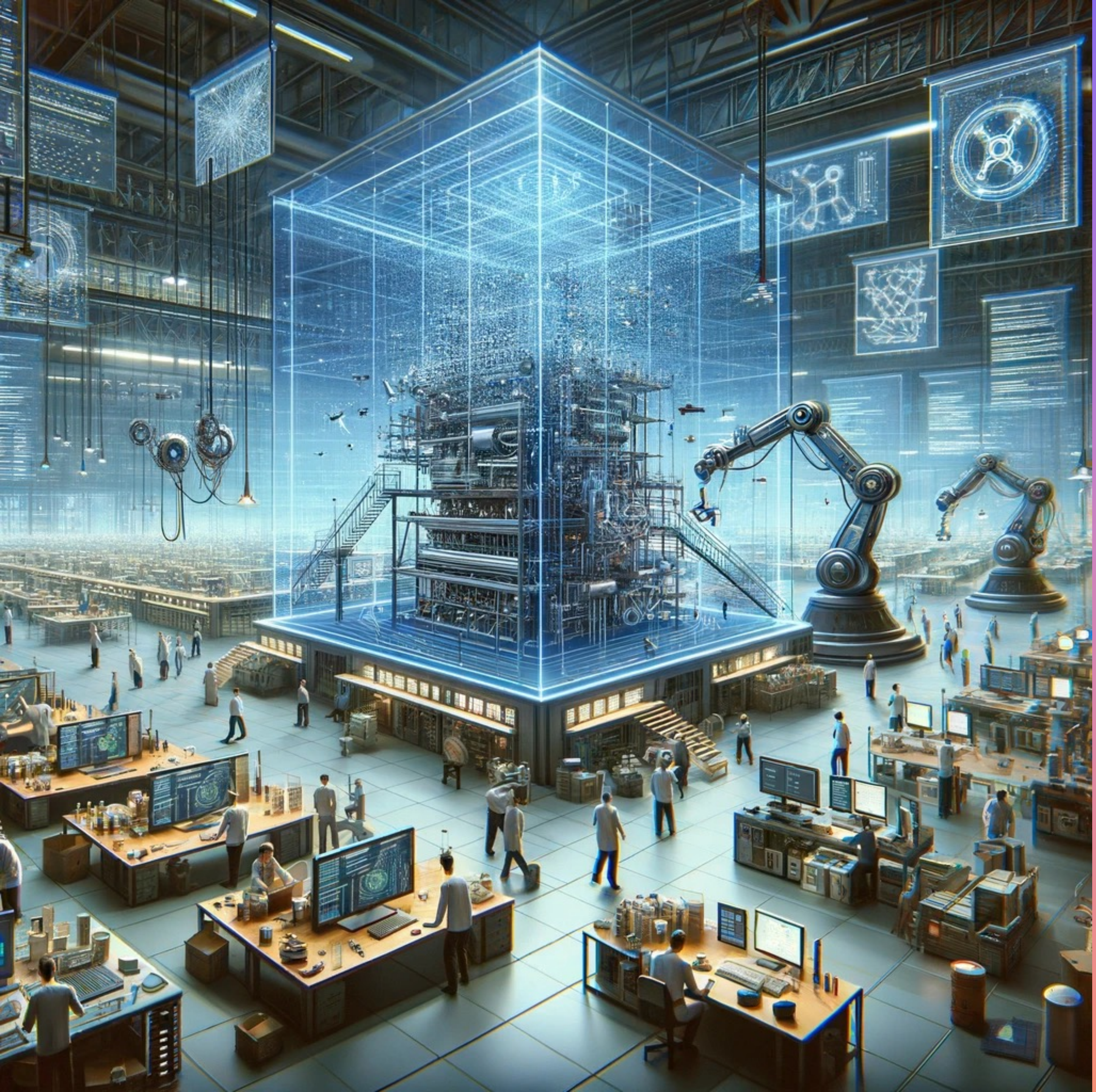
Author: Danilo Croce

This is a Pytorch (+ **Huggingface** transformers) implementation of a "simple" text classifier defined using BERT-based models. In this lab we will see how it is simple to use BERT for a sentence classification task, obtaining state-of-the-art results in few lines of python code.

In a nutshell, we will "implement" this architecture:



DANILO CROCE

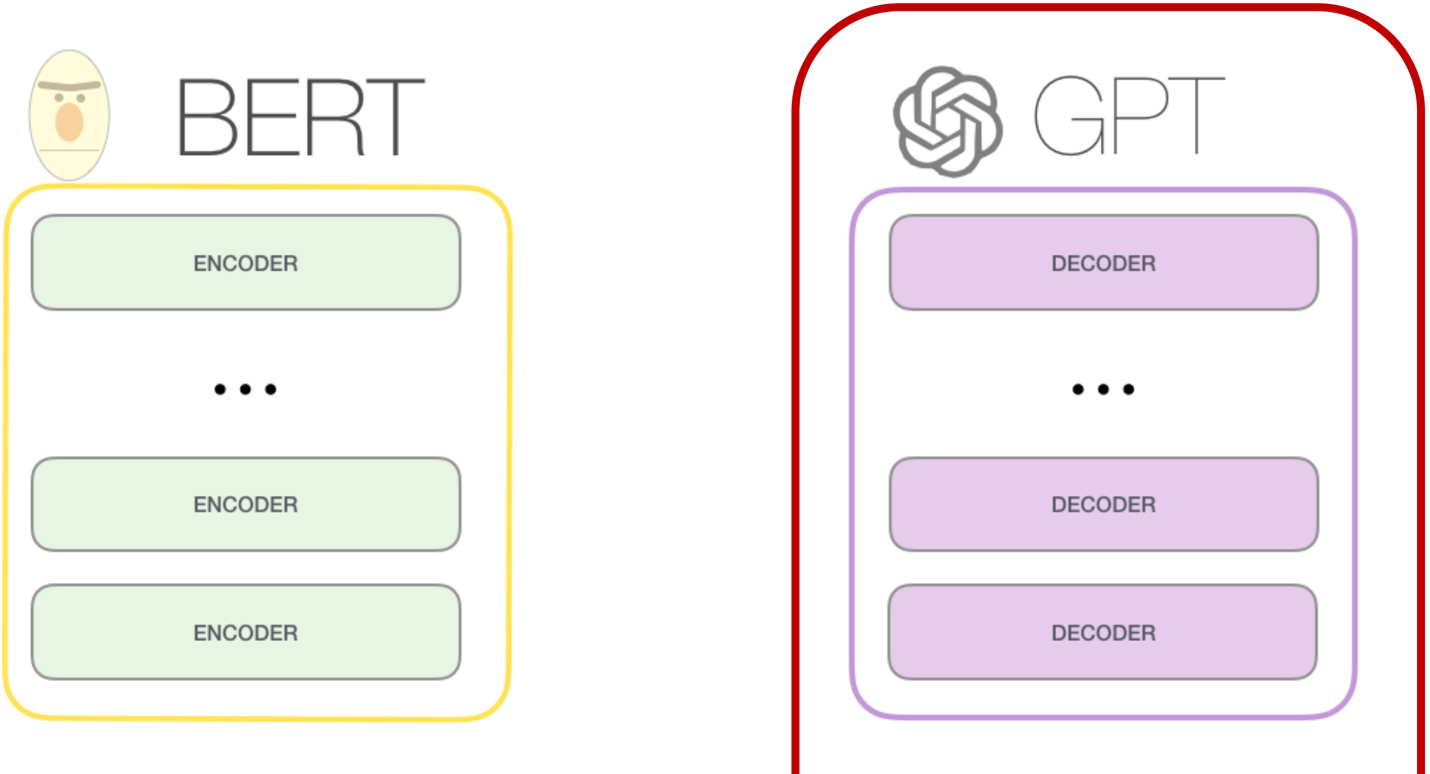


CHAPTER 4

FROM THE DECODER-ONLY ARCHITECTURE TO CHATGPT

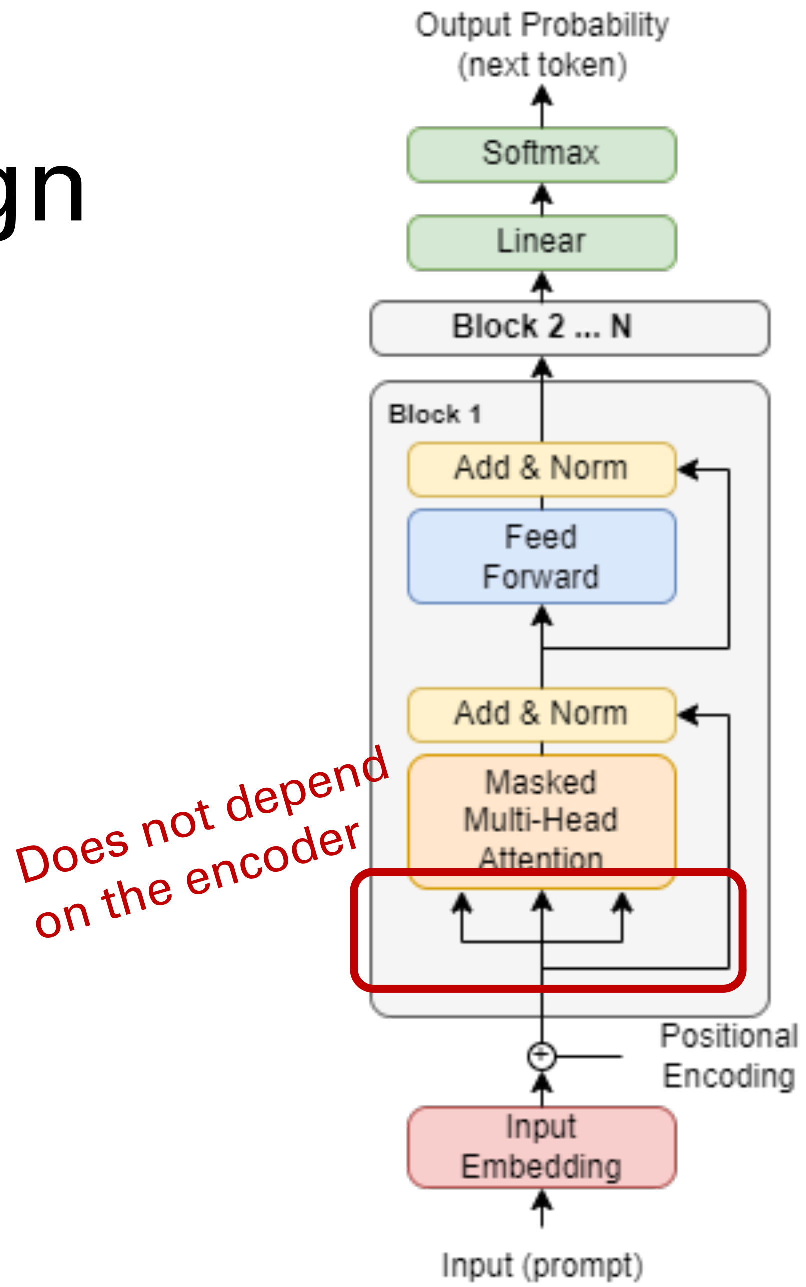
The transformer was only the beginning (2)

- This separation led to two «classes» of methods
  - **«Encoder-only»**: the most famous one is BERT
  - **«Decoder–only»**: the most famous one is GPT



The GPT Architecture
and Its Decoder-Only Design
(Radford et al., 2018)

- **Decoder-Focused Architecture:**
  - GPT (Generative Pre-trained Transformer) is built on a decoder-only framework, exclusively using the decoder part of the original Transformer model.
- **Purpose of Decoder-Only Approach:**
  - to **generate meaningful text**, focusing on producing **coherent and contextually relevant** output sequences.



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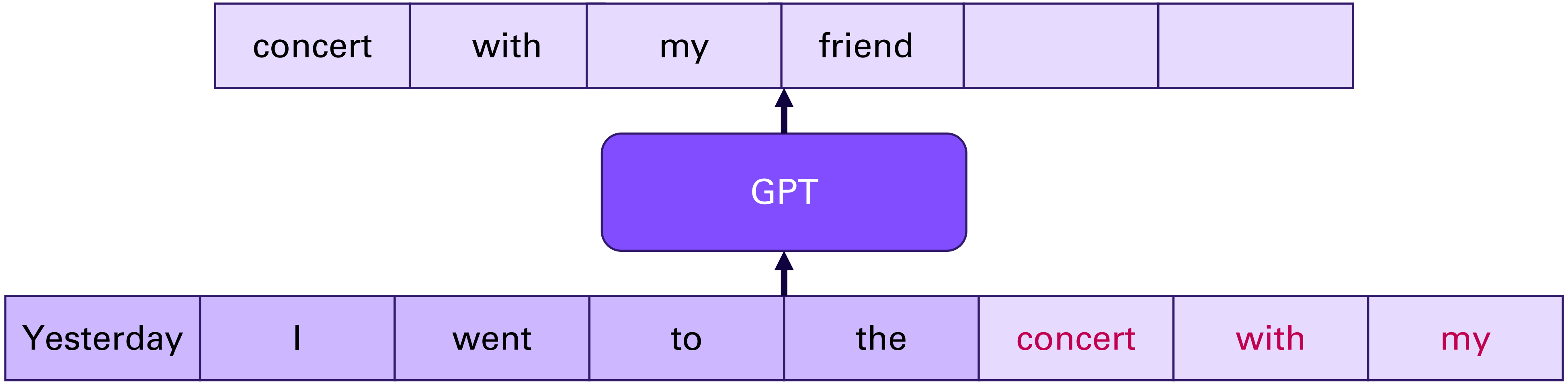
Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by Generative Pre-Training. Technical report, OpenAI.

The task: Next Token Prediction

GPT is trained to **predict the next token in a sequence**, learning to generate text based on the preceding context.

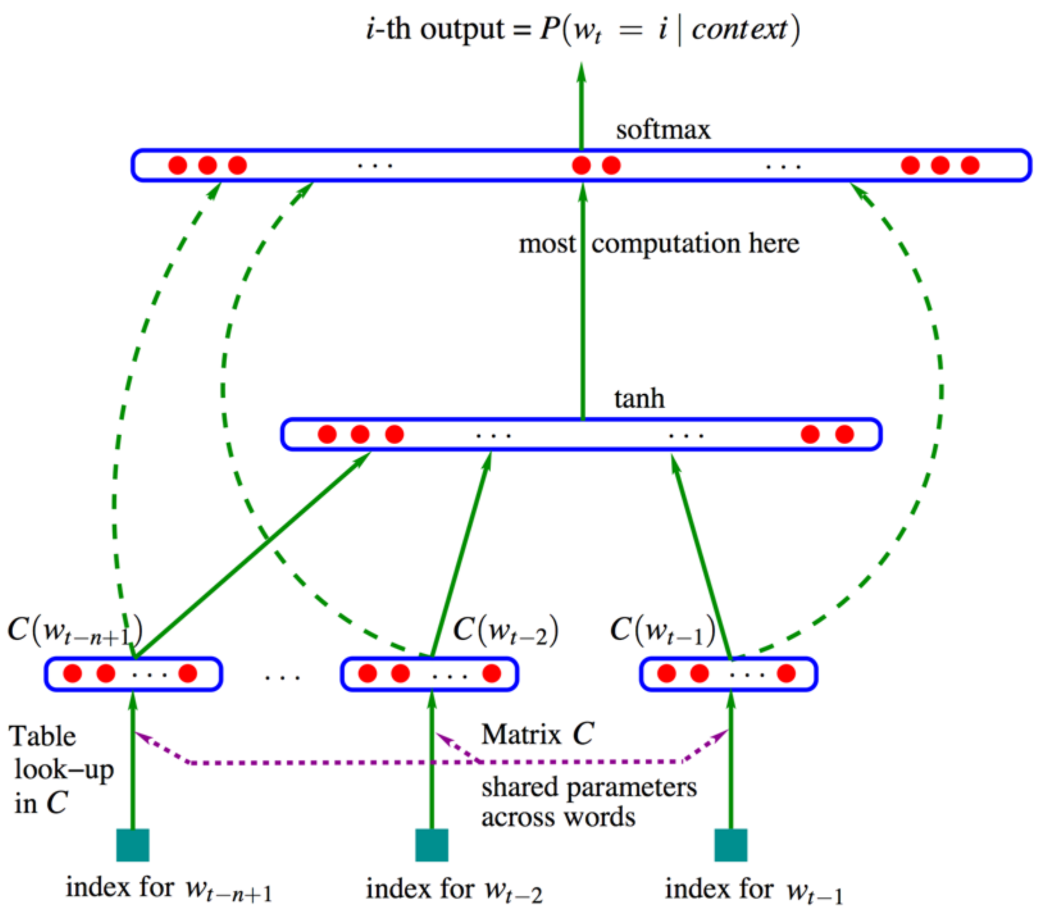


Language modeling is not a new task

- The objective is to learn a mapping

$$f(w_t, \cdots, w_{t-n+1}) = P(w_t \mid w_1, \ldots, w_{t-1})$$

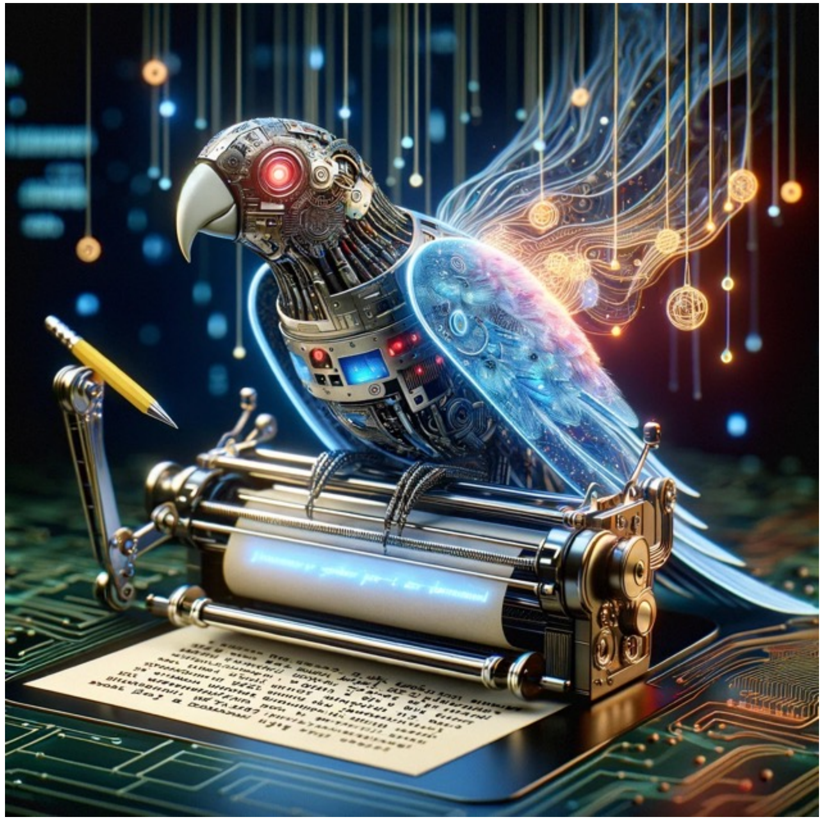
- **General Idea:**
  - **Associate with each word** in the vocabulary **an embedding**
  - Express the **joint probability function of word sequences in terms of the feature vectors of these words** in the sequence, and
  - **Learn simultaneously both notions:**
    - the word feature vectors as a matrix of lexical feature vectors and
    - the parameters that corresponds to the NN that estimate the probability function of the language model.



(Bengio et al, 2003): Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Janvin. 2003. A neural probabilistic language model. J. Mach. Learn. Res. 3 (March 2003), 1137-1155.

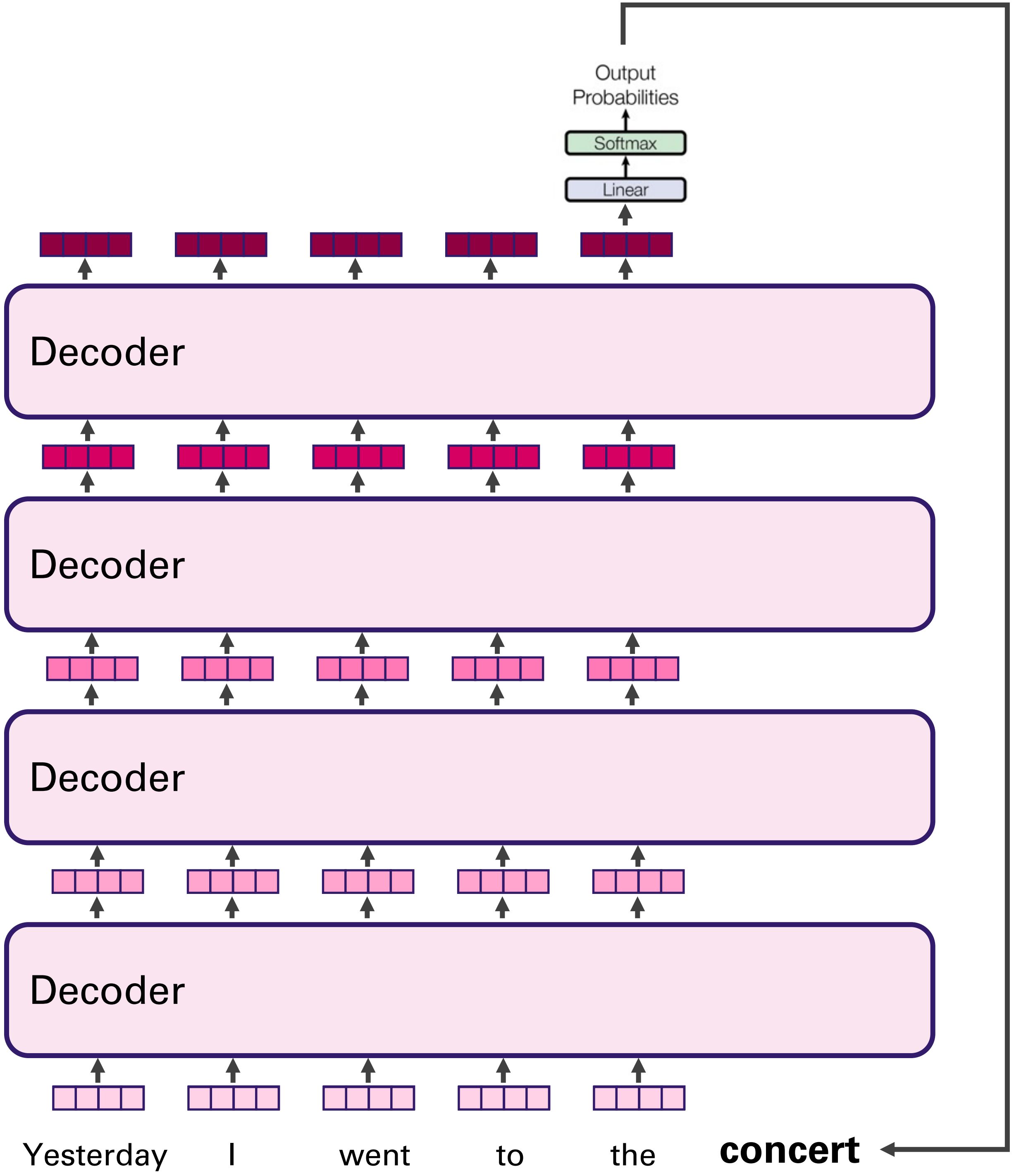
Believe it or not

In the beginning, GPT was not a stochastic parrot, but a complex sentence completion tool based on the multiplication of large matrices.



Generated using GPT4 (it seems it improved)

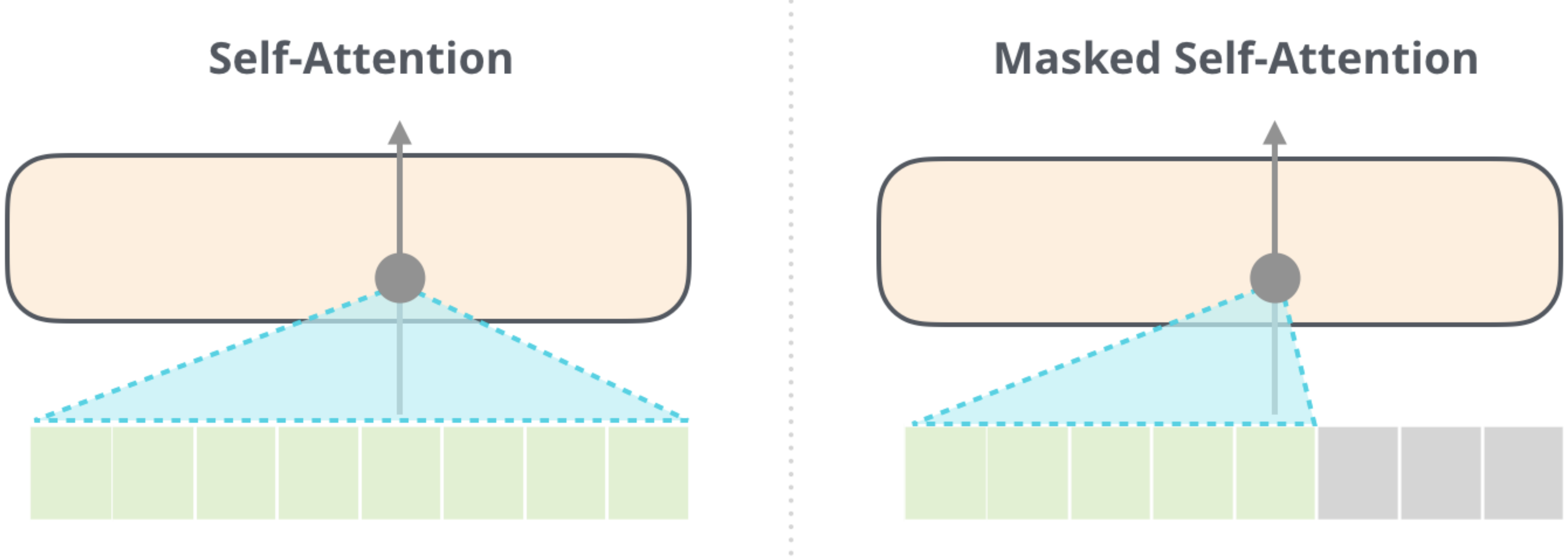
the «Pure» Decoder in Action



- It works similarly as in the Transformer
  - But query, value and key only depends on the input sequence
- Auto-regressive
  - Masked attention is crucial

Role of Masked Attention

Utilizes masked attention to prevent the model from accessing future tokens, ensuring that each prediction is based solely on past and current information.



https://jalammar.github.io/illustrated-gpt2/

What about results?

- At first, in classification tasks BERT seemed more promising, but in few years things changed

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Table 1: GLUE Test results, scored by the evaluation server (https://gluebenchmark.com/leaderboard). The number below each task denotes the number of training examples. The "Average" column is slightly different than the official GLUE score, since we exclude the problematic WNLI set.[8] BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.

DANILO CROCE

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv:1810.04805.

Challenges in Fine-Tuning and Decoding in NLP Models

- **Complexity of Fine-Tuning:**
  - The intricacies of fine-tuning were not delved into deeply due to its complexity and the technical expertise required.
- **Resource Intensive Process:**
  - Fine-tuning is costly, necessitating multiple GPUs
  - Need of Frameworks for Scalable and Distributed Calculus
  - Extensive computational time, sometimes spanning 'years' of processing.

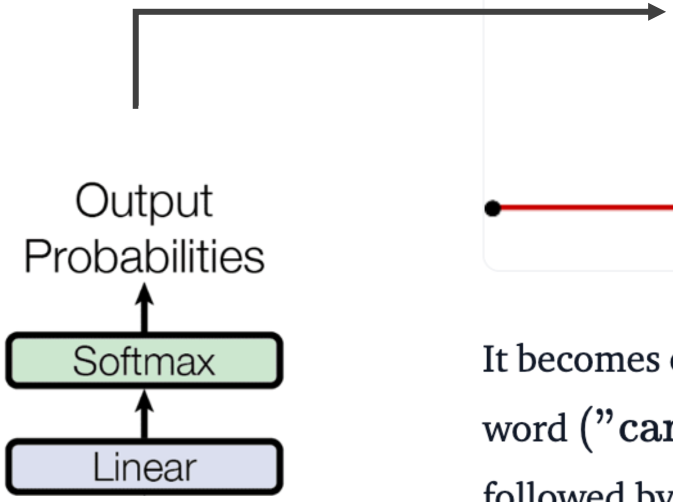
Challenges in Fine-Tuning and Decoding in NLP Models

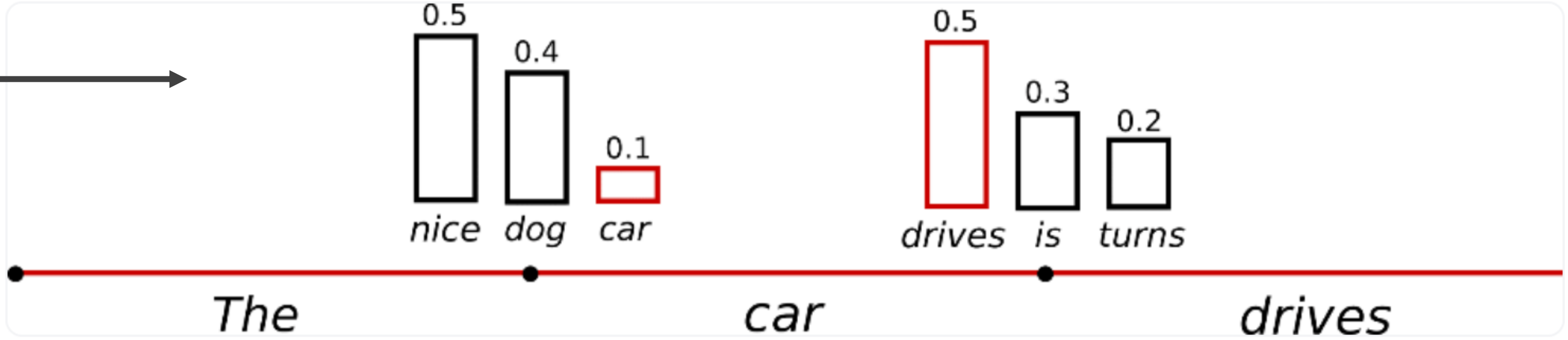
- **Gradient Descent Management:**
  - Careful oversight is needed to manage gradient descent, considering the vast amount of data and billions of adjustments involved.
- **Decoding Process Simplified:**
  - The decoding process has been simplified for this discussion.
  - In reality, various techniques exploit the probability distribution over output symbols, e.g., such as
    - beam search
    - probabilistic methods (*any parrot was involved*)
  - I strongly suggest to read:
    - `https://huggingface.co/blog/how-to-generate`

… why stochastic …

- (also because) the most used decoding tecnique is based on **sampling**
  - In its most basic form, sampling means randomly picking the next word w_t according to its conditional probability distribution:

$$w_t \sim P(w|w_{1:t-1})$$





It becomes obvious that language generation using sampling is not *deterministic* anymore. The word ("car") is sampled from the conditioned probability distribution $P(w|\text{"The"})$, followed by sampling ("drives") from $P(w|\text{"The"}, \text{"car"})$.

But does GPT 'only' know how to predict the next word in a sentence?

- If we are smart enough, we can use the generation capability of GPT to solve a task, but…
  - We can ask GPT to do something, e.g. write an article:

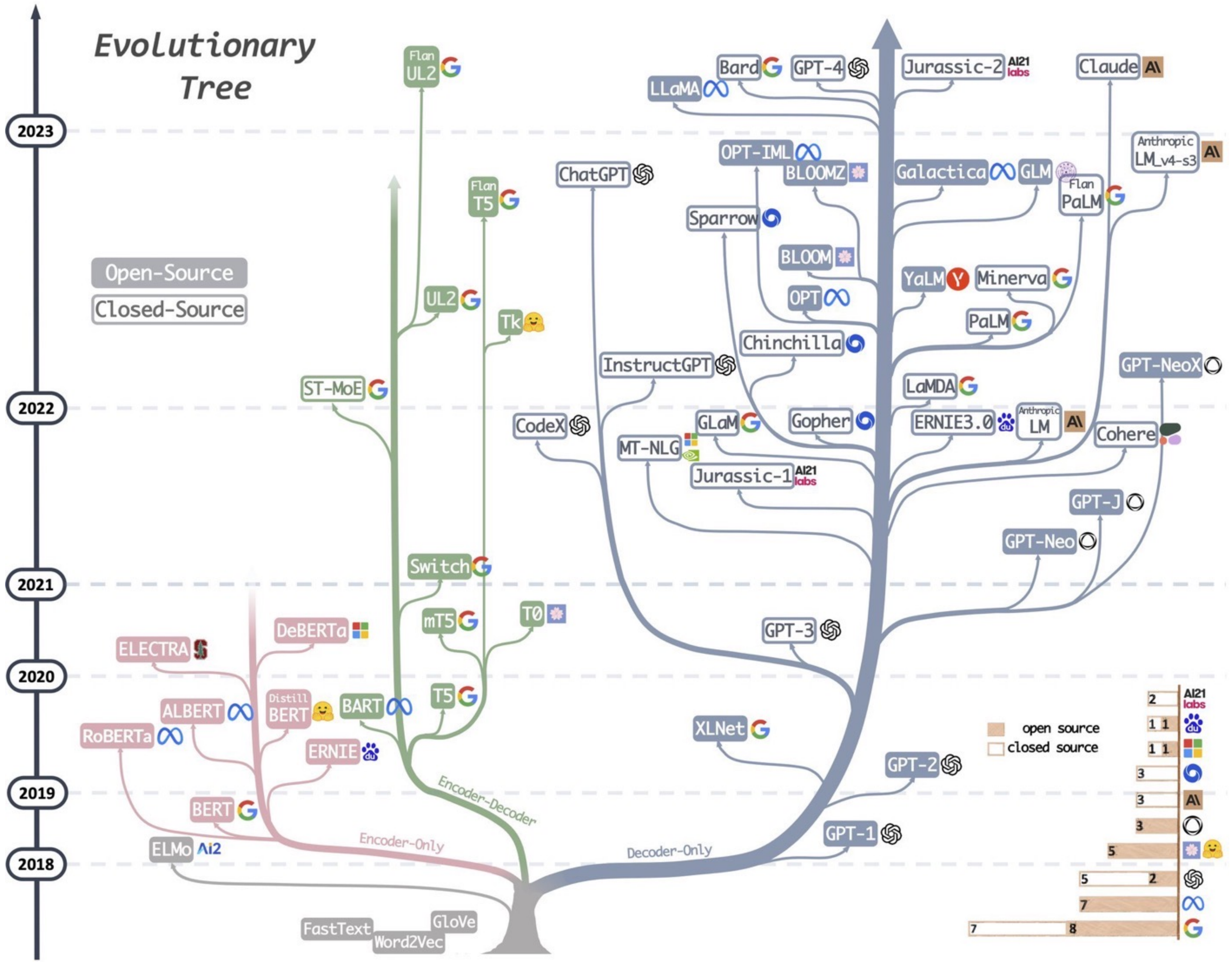
Title: United Methodists Agree to Historic Split

Subtitle: Those who oppose gay marriage will form their own denomination

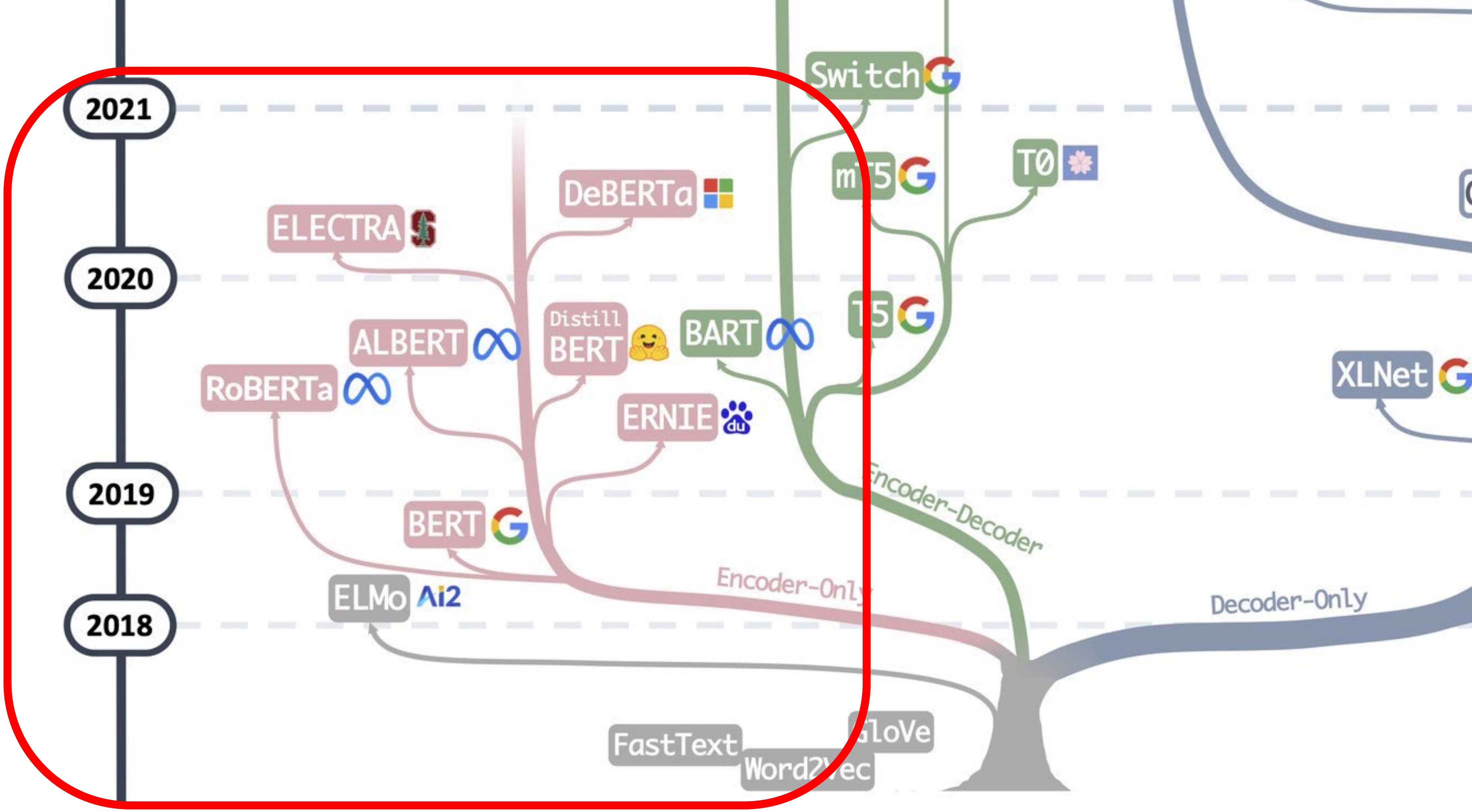
Article: After two days of intense debate, the United Methodist Church has agreed to a historic split - one that is expected to end in the creation of a new denomination, one that will be "theologically and socially conservative," according to The Washington Post. The majority of delegates attending the church's annual General Conference in May voted to strengthen a ban on the ordination of LGBTQ clergy and to write new rules that will "discipline" clergy who officiate at same-sex weddings. But those who opposed these measures have a new plan: They say they will form a separate denomination by 2020, calling their church the Christian Methodist denomination. The Post notes that the denomination, which claims 12.5 million members, was in the early 20th century the "largest Protestant denomination in the U.S.," but that it has been shrinking in recent decades. The new split will be the second in the church's history. The first occurred in 1968, when roughly 10 percent of the denomination left to form the Evangelical United Brethren Church. The Post notes that the proposed

The rest is a family tree

Danilo Croce



The «Encoder Only» family

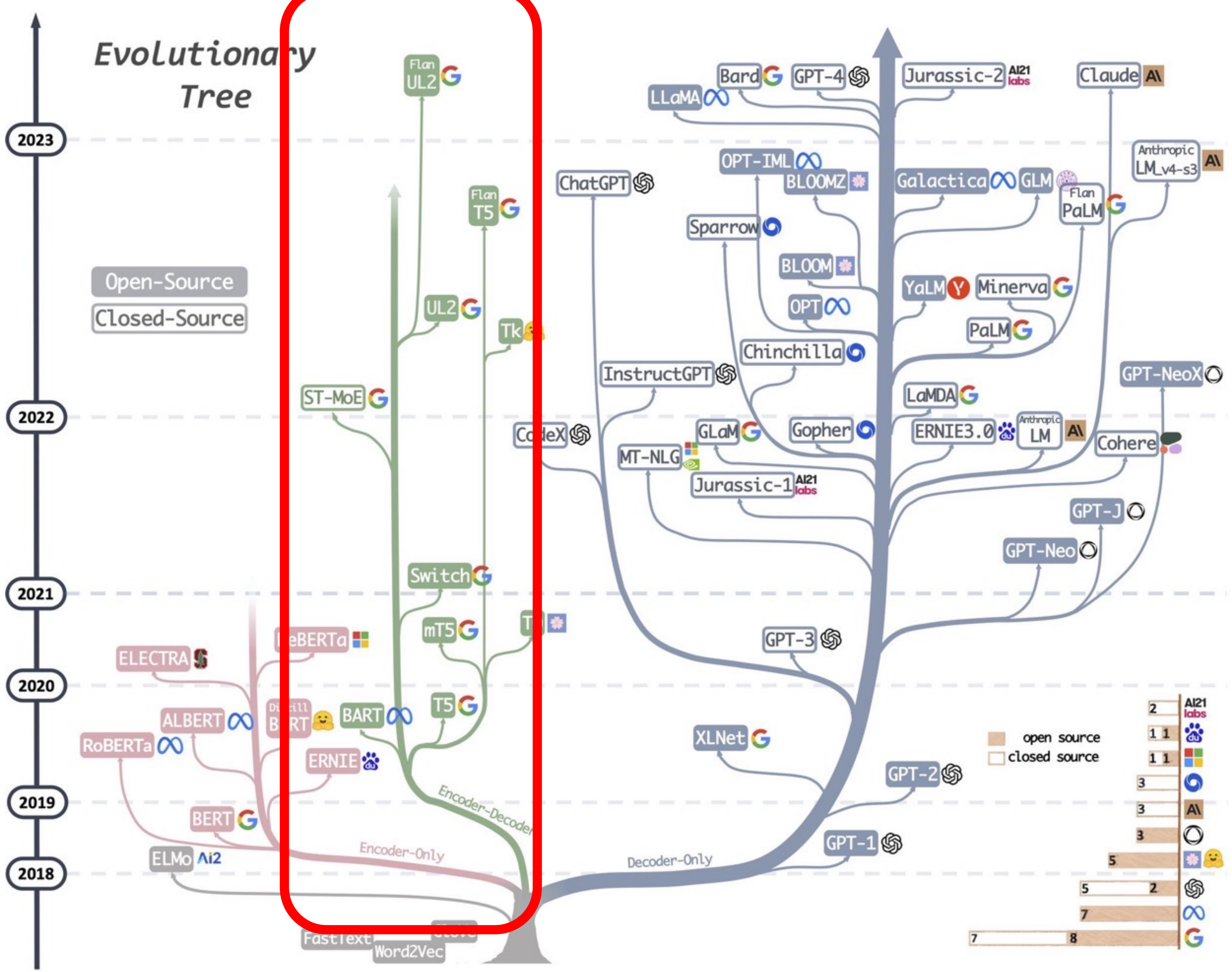


Encoder-based architectures experienced **rapid initial growth** and enormous success until 2021, **after which interest shifted**.

Danilo Croce

The «Encoder/Decoder» family

DANILO CROCE



Encoder-Decoder based architectures experienced **a more limited success but largerly used**, especially tasks requiring generation

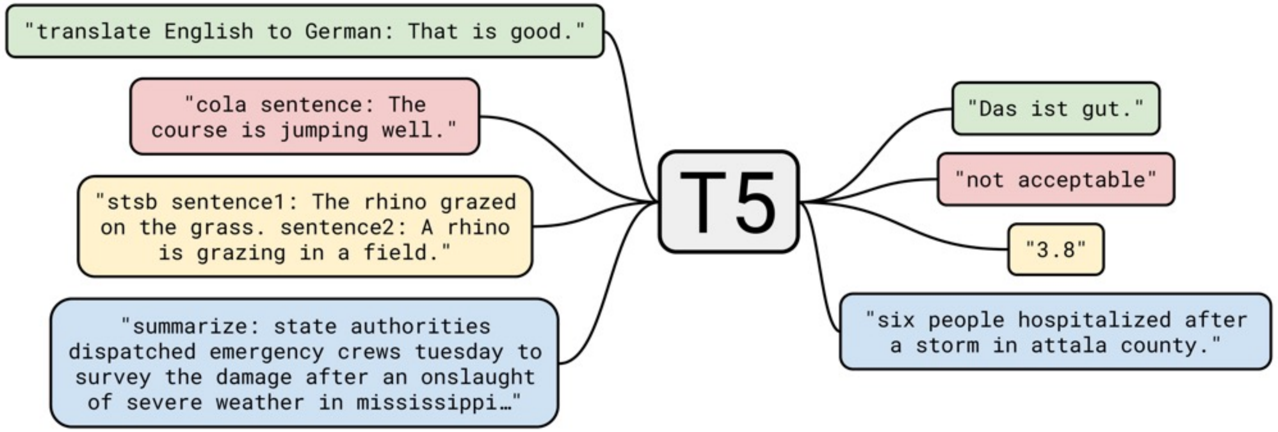
A digression

Introduction to Google's T5 Model

(Raffel et al, 2019)

- **Encoder-Decoder Structure:**
  - T5, or Text-to-Text Transfer Transformer, is based on an encoder-decoder architecture.
  - Trained on large-scale datasets like C4 (Colossal Clean Crawled Corpus) containing a diverse range of internet text.

- **Versatile Pre-Training:**
  - Notably **pre-trained on multiple tasks**
  - Tasks involve reconstructing corrupted versions of input strings, showcasing its adaptability.

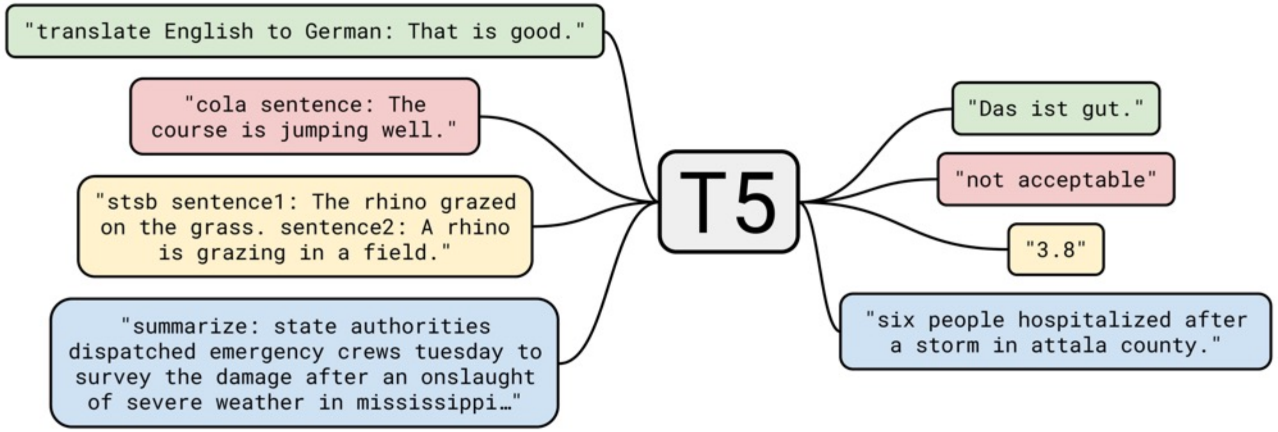


Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., ... & Liu, P. J. (2019). Exploring the limits of transfer learning with a unified text-to-text transformer. The Journal of Machine Learning Research, 21(1), 5485-5551.

T5's Flexibility and Impact

- **Diverse Task Handling:**
  - Classification (inputting a string and task name to output the class),
  - Machine translation,
  - Summarization
  - Regression tasks (outputting a numerical value)

- **Fine-Tuning and Performance:**
  - Served as a precursor to subsequent Google models, including FLAN-T5



Towards
Extreme Multi-task Learning

T5's approach to **framing all tasks** as seq2seq problems has been instrumental in the initial "crazy" idea

- Demonstrating a groundbreaking method in **handling diverse NLP challenges.**
- (Aribandi et al, 2021) `https://openreview.net/pdf?id=Vzh1BFUCiIX`

Published as a conference paper at ICLR 2022

EXT5: TOWARDS EXTREME MULTI-TASK SCALING FOR TRANSFER LEARNING

Vamsi Aribandi*†, Yi Tay†, Tal Schuster, Jinfeng Rao, Huaixiu Steven Zheng, Sanket Vaibhav Mehta, Honglei Zhuang, Vinh Q. Tran, Dara Bahri, Jianmo Ni, Jai Gupta, Kai Hui, Sebastian Ruder♣, Donald Metzler
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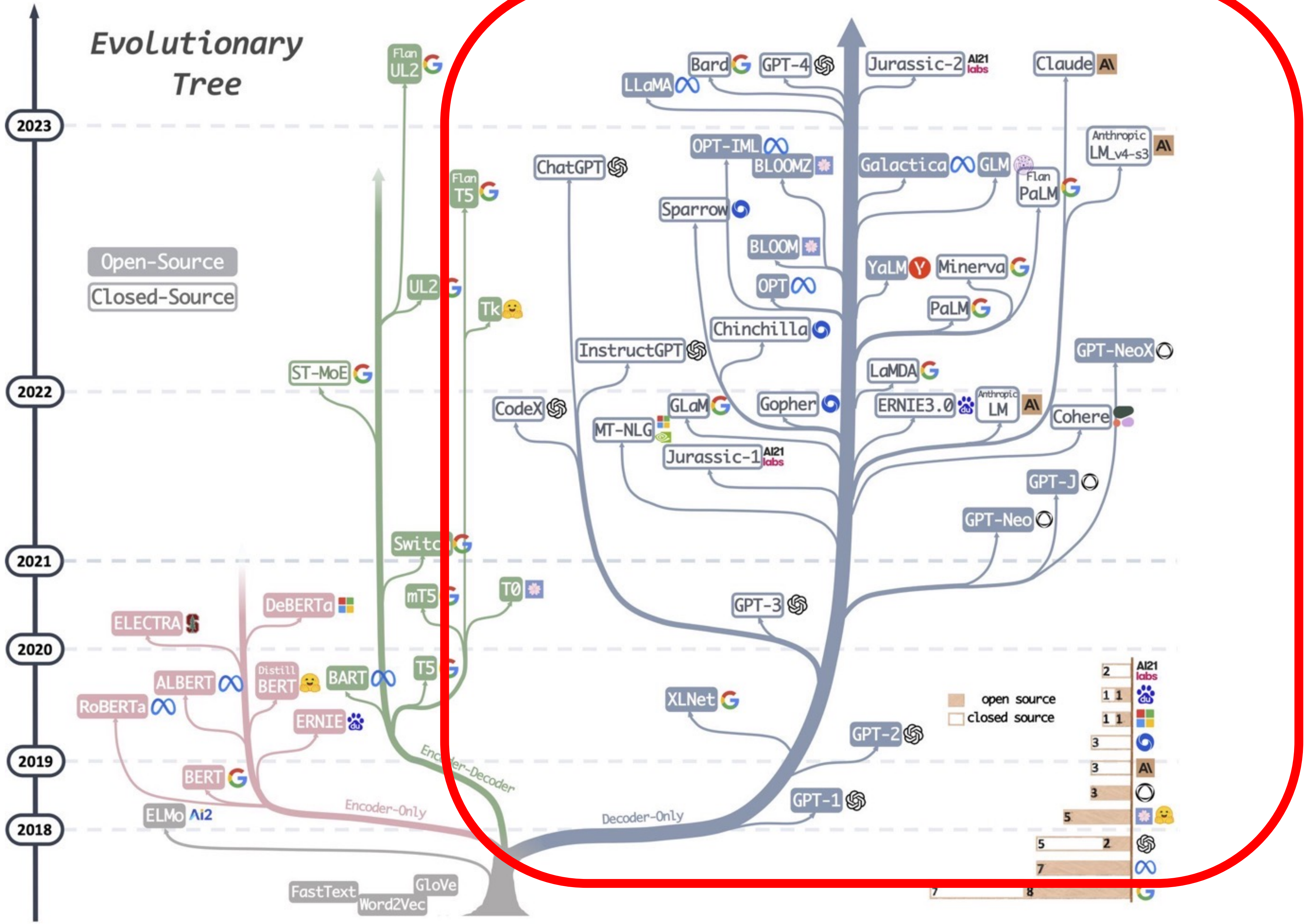
ABSTRACT

Despite the recent success of multi-task learning and transfer learning for natural language processing (NLP), few works have systematically studied the effect of scaling up the number of tasks during pre-training. Towards this goal, this paper introduces EXMIX (**Ex**treme **Mix**ture): a massive collection of 107 supervised NLP tasks across diverse domains and task-families. Using EXMIX, we study the effect of multi-task pre-training at the largest scale to date, and analyze co-

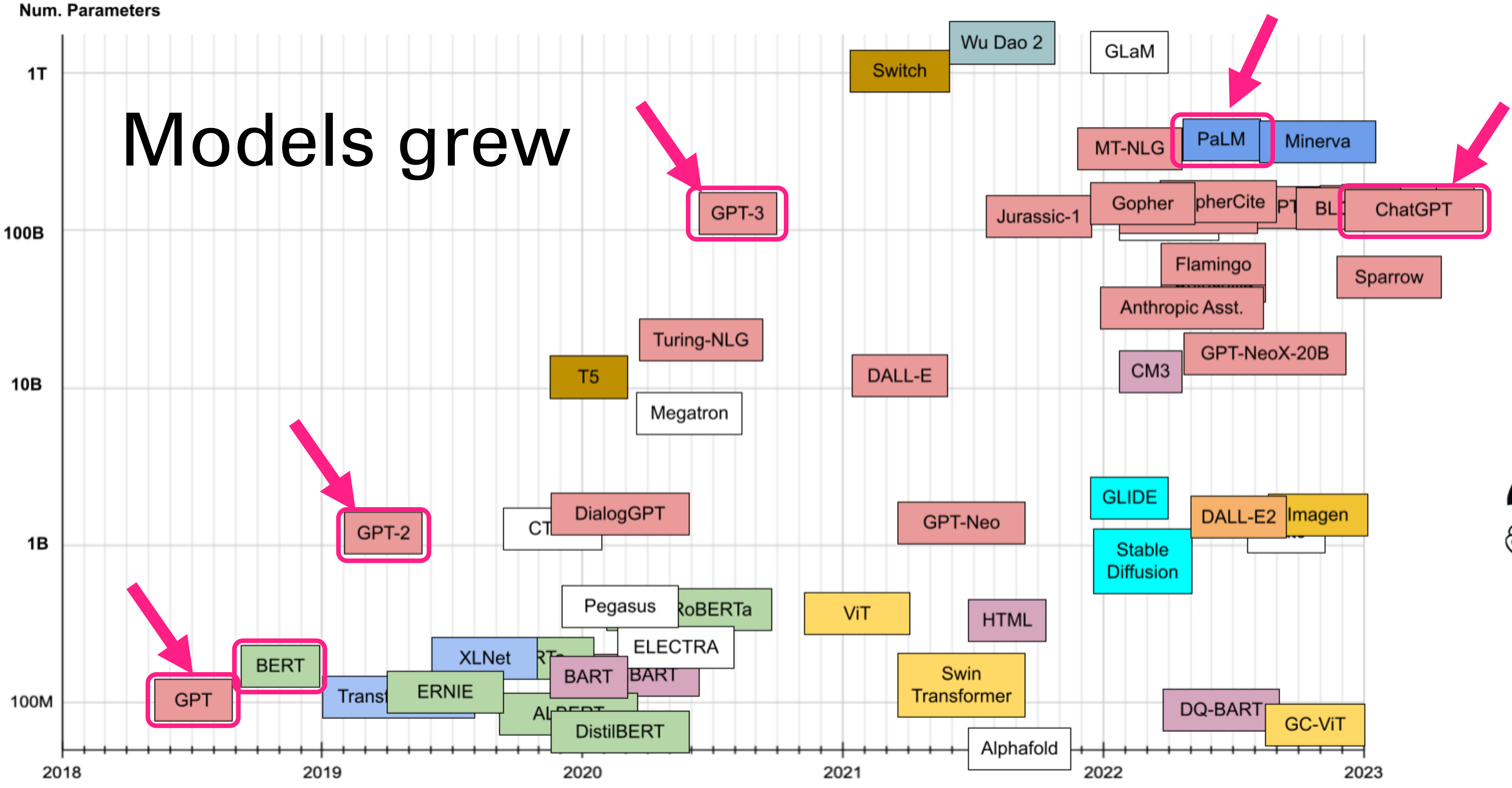
Danilo Croce

The rest is a family tree



Initially, decoder-based architectures **did not attract 'much interest'** (BERT had better performance), but **with the increase in model size, things have radically changed**.

But what happened in 2021 to cause this change of interest?



Xavier Amatriain, Ananth Sankar, Jie Bing, Praveen Kumar Bodigutla, Timothy J. Hazen, Michaeel Kazi (2023). Transformer models: an introduction and catalog. arXiv:2302.07730

But it is not only a matter of size «Ecce GPT-3»

Language Models are Few-Shot Learners

Tom B. Brown* Benjamin Mann* Nick Ryder* Melanie Subbiah*

Jared Kaplan† Prafulla Dhariwal Arvind Neelakantan Pranav Shyam Girish Sastry

Amanda Askell Sandhini Agarwal Ariel Herbert-Voss Gretchen Krueger Tom Henighan

Rewon Child Aditya Ramesh Daniel M. Ziegler Jeffrey Wu Clemens Winter

Christopher Hesse Mark Chen Eric Sigler Mateusz Litwin Scott Gray

Benjamin Chess Jack Clark Christopher Berner

Sam McCandlish Alec Radford Ilya Sutskever Dario Amodei

OpenAI

Abstract

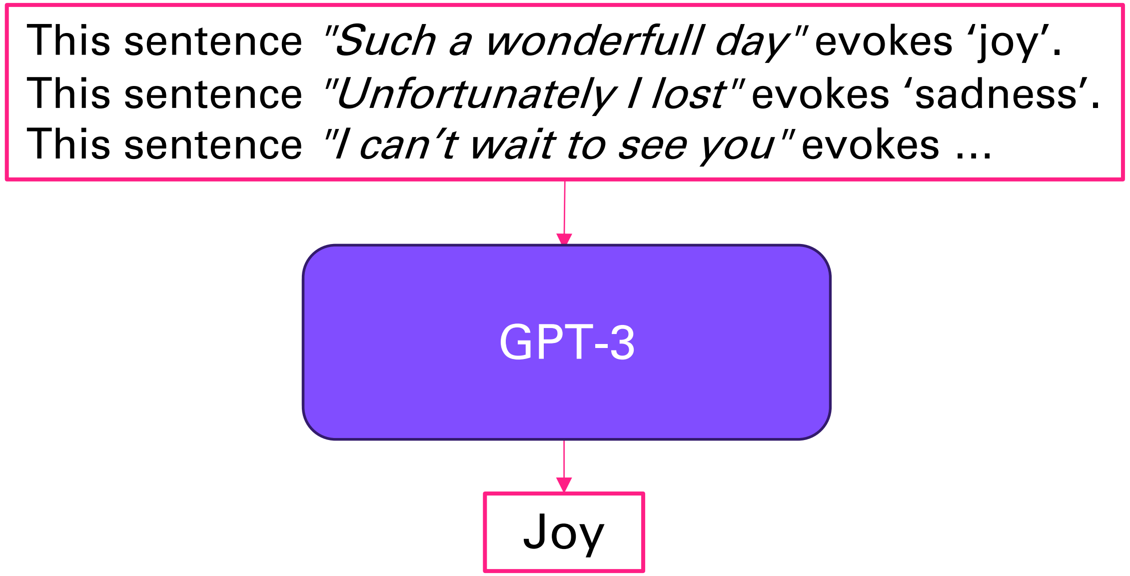
Recent work has demonstrated substantial gains on many NLP tasks and benchmarks by pre-training on a large corpus of text followed by fine-tuning on a specific task. While typically task-agnostic in architecture, this method still requires task-specific fine-tuning datasets of thousands or tens of thousands of examples. By contrast, humans can generally perform a new language task from only a few examples or from simple instructions – something which current NLP systems still largely

Some Data

	Bert-base	GPT-1	GPT-2	GPT-3
Parameters	110 Million	117 Million	1.5 Billion	175 Billion
Layers	12	12	48	96
Context Token Size	512	512	1024	2048
Hidden Layer	768	768	1600	12288
Dataset	BookCorpus + Wikipedia	BooksCorpus	WebText	The Pile
Number of Tokens	~3.3 billion	~1 billion	~8 billion	Hundreds of billions
Memory Size	-	~40 GB (uncompressed)	~40 GB (compressed)	~570 GB (compressed)
Batch Size	256	64	512	3.2M

The «powers» of GPT3

- **Pre-Training and Fine-Tuning Paradigm**
  - Traditional NLP models show **gains by pre-training** on large text corpora and then fine-tuning on specific tasks
  - **but require extensive task-specific datasets.**



- **GPT-3's «Breakthrough» in Few-Shot Learning**
  - GPT-3, with 175 billion parameters, demonstrates substantial **improvement in task-agnostic,**
  - **few-shot performance,**
  - **rivaling traditional fine-tuning methods.**

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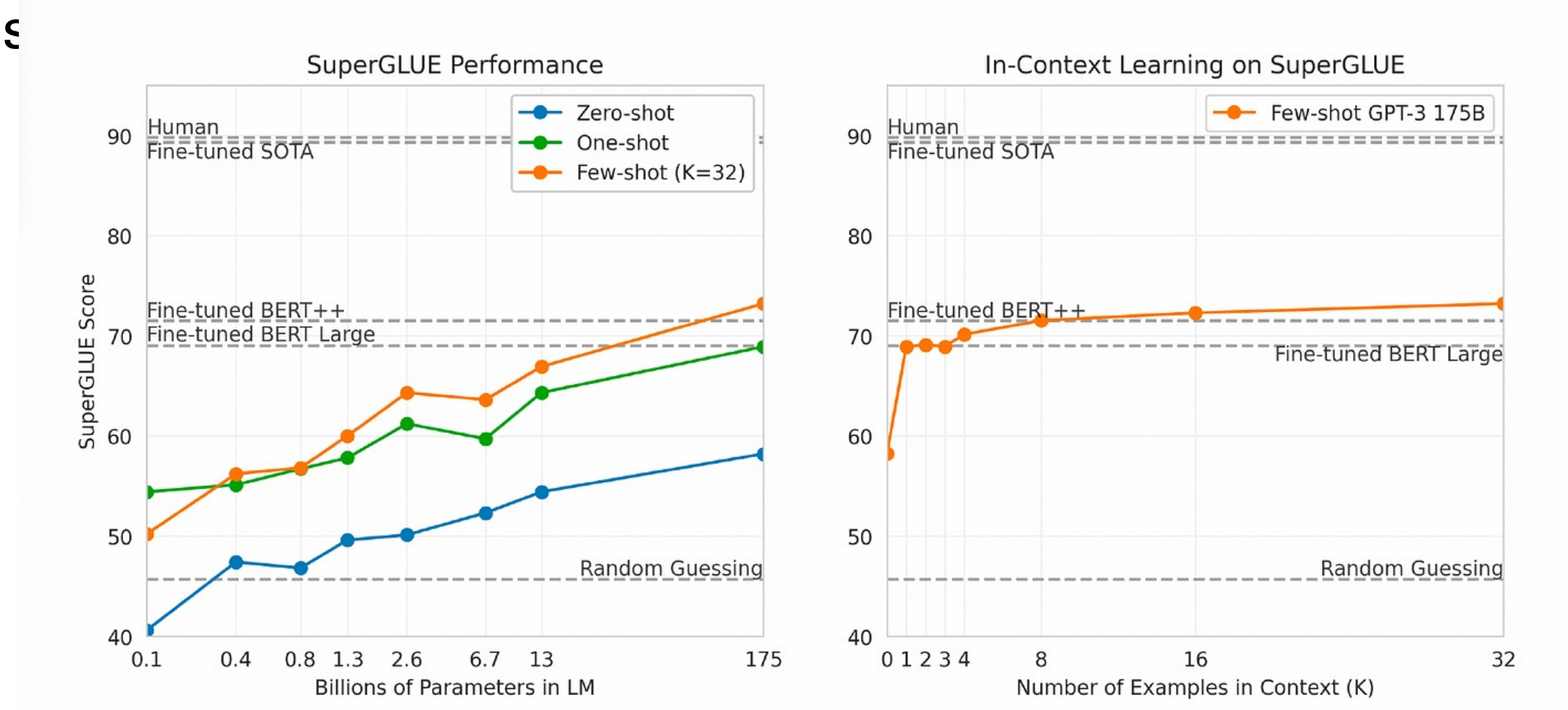
The «powers» of GPT3

Diverse Task Performance Without Fine-Tuning

- Exhibits strong performance across various NLP tasks through text interactions alone, including translation, question-answering, and reas



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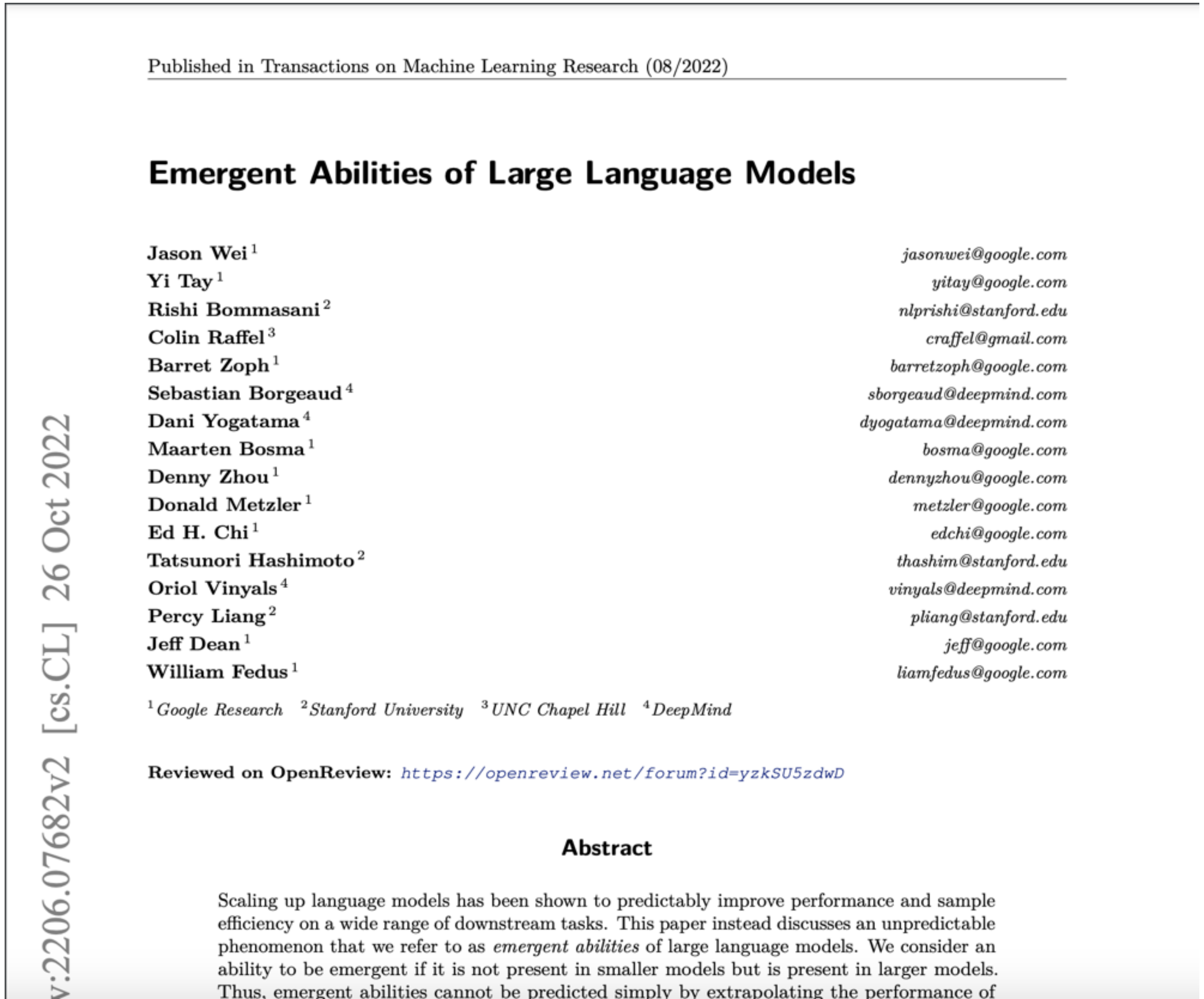
But these models exhibits other capabilities…



Published in Transactions on Machine Learning Research (08/2022)

v:2206.07682v2 [cs.CL] 26 Oct 2022

Emergent Abilities of Large Language Models

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Reviewed on OpenReview: https://openreview.net/forum?id=yzkSU5zdwD

Abstract

Scaling up language models has been shown to predictably improve performance and sample efficiency on a wide range of downstream tasks. This paper instead discusses an unpredictable phenomenon that we refer to as *emergent abilities* of large language models. We consider an ability to be emergent if it is not present in smaller models but is present in larger models. Thus, emergent abilities cannot be predicted simply by extrapolating the performance of

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… many capabilities

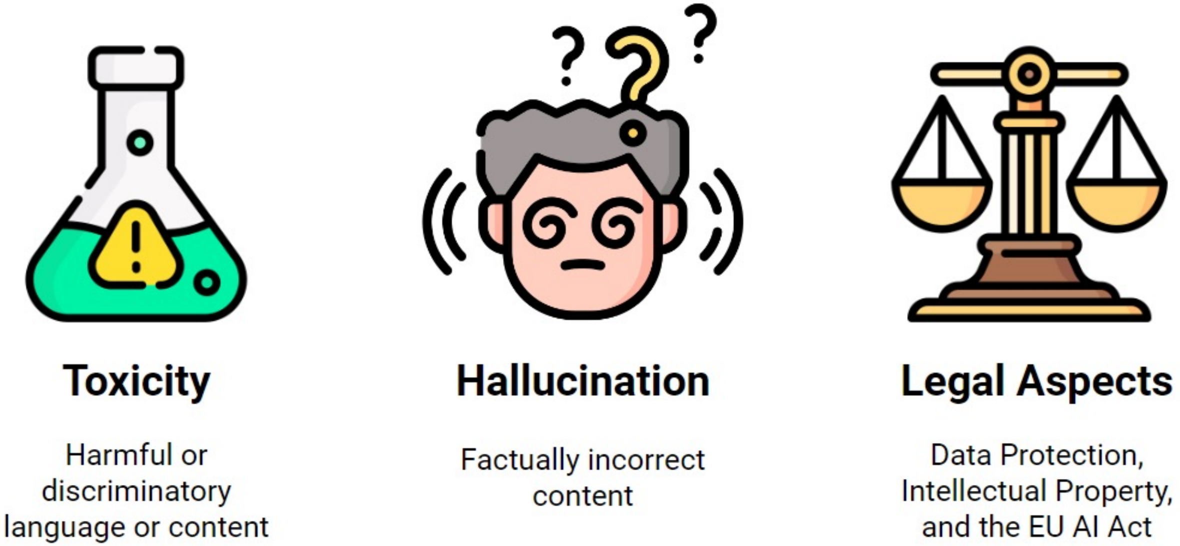
Table 1: List of emergent abilities of large language models and the scale (both training FLOPs and number of model parameters) at which the abilities emerge.

	Emergent scale			
	Train. FLOPs	Params.	Model	Reference
Few-shot prompting abilities				
• Addition/subtraction (3 digit)	2.3E+22	13B	GPT-3	Brown et al. (2020)
• Addition/subtraction (4-5 digit)	3.1E+23	175B		
• MMLU Benchmark (57 topic avg.)	3.1E+23	175B	GPT-3	Hendrycks et al. (2021a)
• Toxicity classification (CivilComments)	1.3E+22	7.1B	Gopher	Rae et al. (2021)
• Truthfulness (Truthful QA)	5.0E+23	280B		
• MMLU Benchmark (26 topics)	5.0E+23	280B		
• Grounded conceptual mappings	3.1E+23	175B	GPT-3	Patel & Pavlick (2022)
• MMLU Benchmark (30 topics)	5.0E+23	70B	Chinchilla	Hoffmann et al. (2022)
• Word in Context (WiC) benchmark	2.5E+24	540B	PaLM	Chowdhery et al. (2022)
• Many BIG-Bench tasks (see Appendix E)	Many	Many	Many	BIG-Bench (2022)
Augmented prompting abilities				
• Instruction following (finetuning)	1.3E+23	68B	FLAN	Wei et al. (2022a)
• Scratchpad: 8-digit addition (finetuning)	8.9E+19	40M	LaMDA	Nye et al. (2021)
• Using open-book knowledge for fact checking	1.3E+22	7.1B	Gopher	Rae et al. (2021)
• Chain-of-thought: Math word problems	1.3E+23	68B	LaMDA	Wei et al. (2022b)
• Chain-of-thought: StrategyQA	2.9E+23	62B	PaLM	Chowdhery et al. (2022)
• Differentiable search index	3.3E+22	11B	T5	Tay et al. (2022b)
• Self-consistency decoding	1.3E+23	68B	LaMDA	Wang et al. (2022b)
• Leveraging explanations in prompting	5.0E+23	280B	Gopher	Lampinen et al. (2022)
• Least-to-most prompting	3.1E+23	175B	GPT-3	Zhou et al. (2022)
• Zero-shot chain-of-thought reasoning	3.1E+23	175B	GPT-3	Kojima et al. (2022)
• Calibration via P(True)	2.6E+23	52B	Anthropic	Kadavath et al. (2022)
• Multilingual chain-of-thought reasoning	2.9E+23	62B	PaLM	Shi et al. (2022)
• Ask me anything prompting	1.4E+22	6B	EleutherAI	Arora et al. (2022)

With great power comes great responsibility

Limitations and Societal Impacts

- Acknowledges **challenges in certain tasks** and **potential methodological issues**, while highlighting the model's ability to produce human-like text, **raising important societal considerations.**

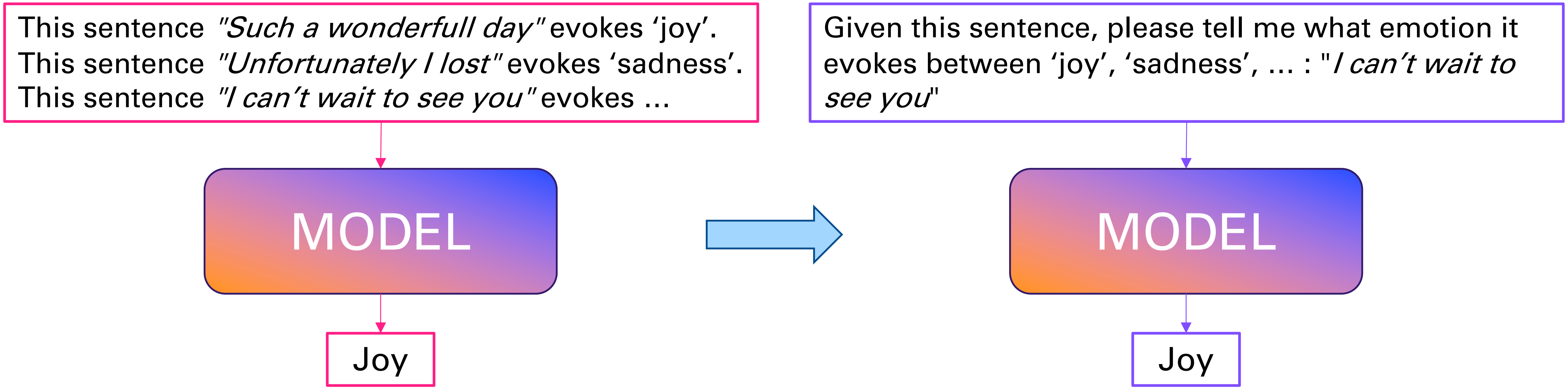


Material for another tutorial

Image from:
https://blog.ml6.eu/navigating-ethical-considerations-developing-and-deploying-large-language-models-llms-d44f3fcde626

We like it, but ...

We just want to move from answers based on completion to **execute instructions**…

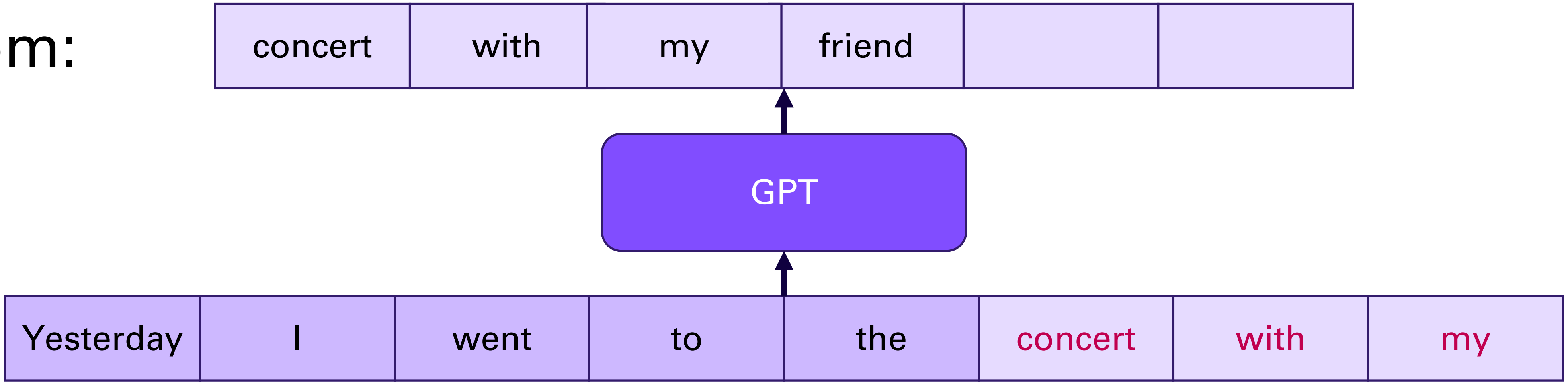


From GPT to Instruct-GPT

Evolving to Instruct-GPT:

- need for a **model that could understand and execute human-like instructions**
- similar to how humans follow commands.

From:



From GPT to Instruct-GPT

Evolving to Instruct-GPT:

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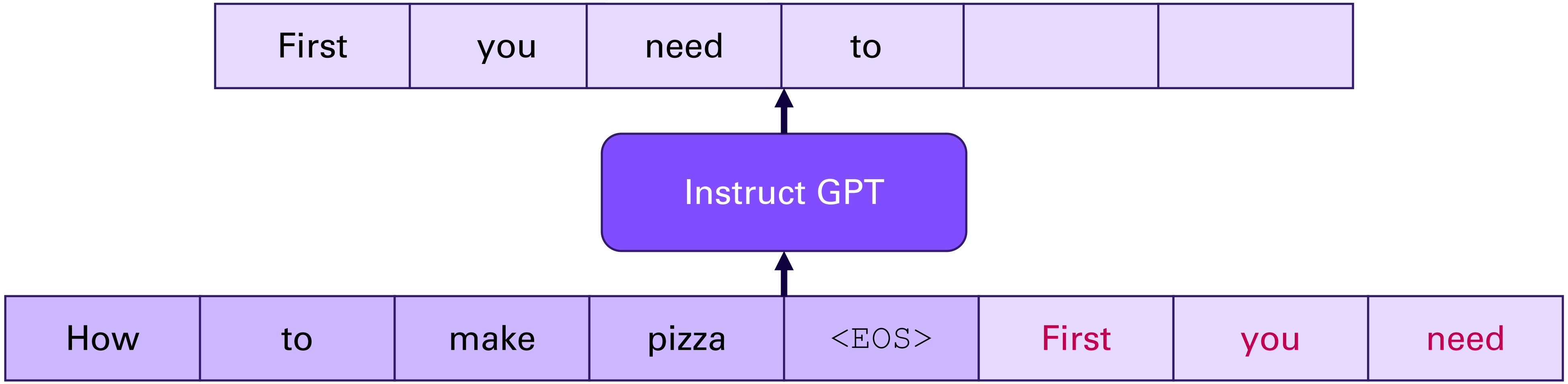
To:



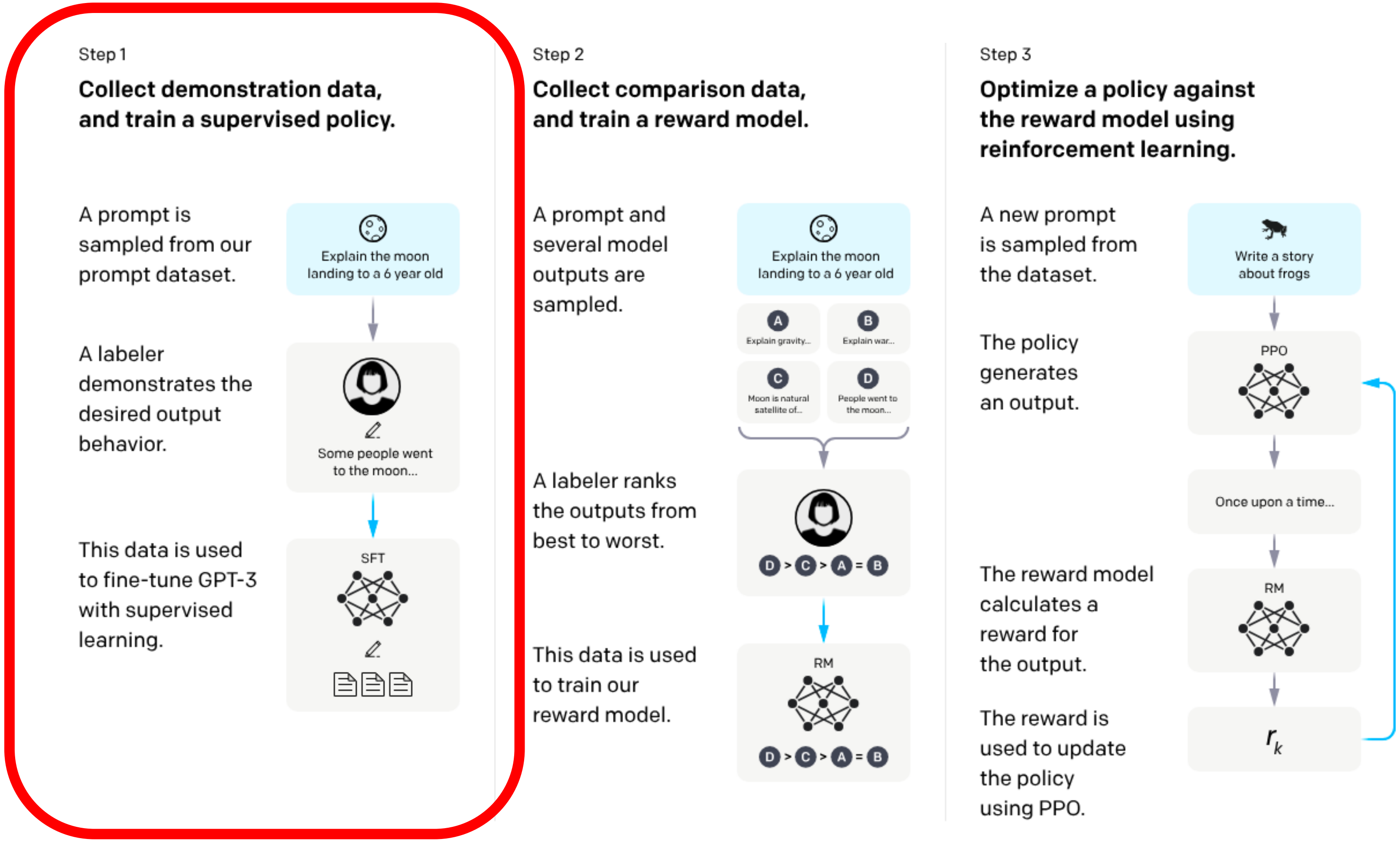
Instruct-GPT in 3 steps
Step 1: Supervised Fine-Tuning

Methodology: Training on a dataset of labeled examples

- each prompt paired with an ideal response

Objective: Teach the model correct responses to various prompts

- Imitating human-like behavior from examples



From: https://openai.com/research/instruction-following

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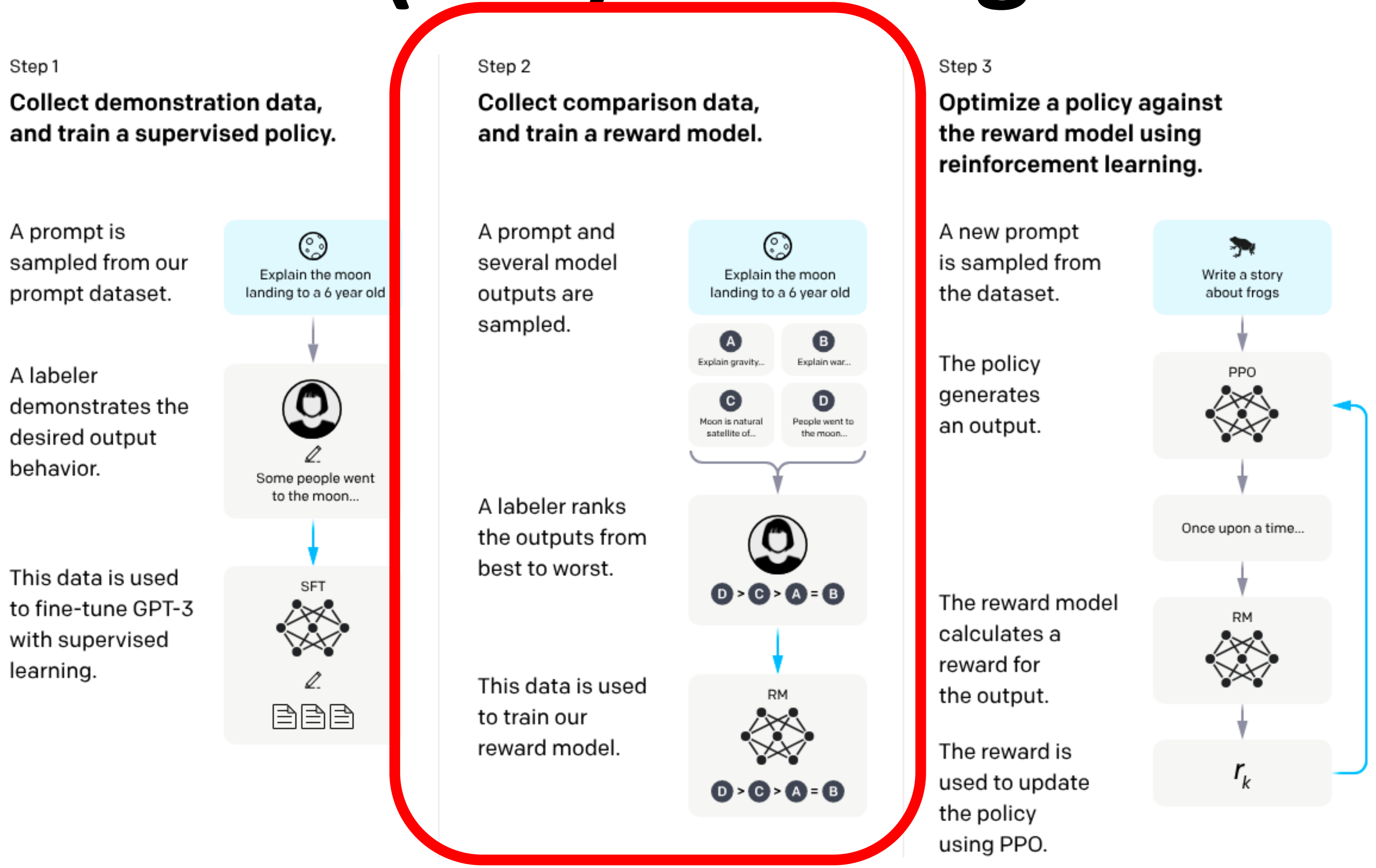
Instruct-GPT in 3 steps
Step 2: Reward Model (RM) Training

Methodology: Develop a model **that assigns rewards to responses** based on human preferences.

- Re-rank the responses

Objective: Prepare the model to **understand and evaluate the quality of its responses**

- beyond just accuracy.



From: `https://openai.com/research/instruction-following`

Instruct-GPT in 3 steps

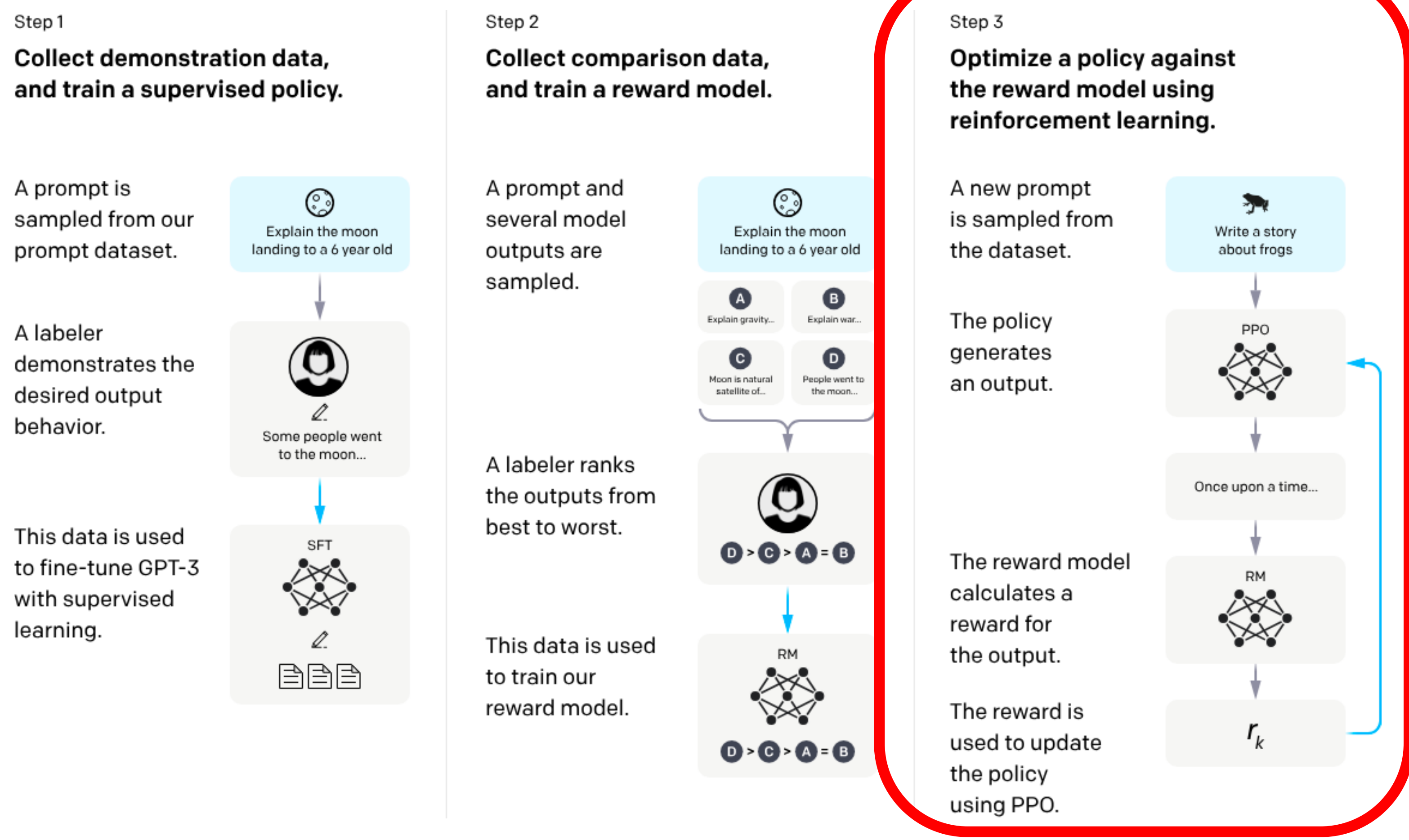
Step 3: Reinforcement Learning via PPO

Methodology: Uses **Reinforcement Learning to fine-tune responses**

- the model is rewarded for high-quality outputs.

Objective: Enhance the model's ability to generate relevant, useful responses in varied and complex scenarios.

- **optimizing responses for quality and contextual appropriateness**
- not just replicating correct answers.



From: https://openai.com/research/instruction-following

Evolution from Transformer architecture in OpenAI

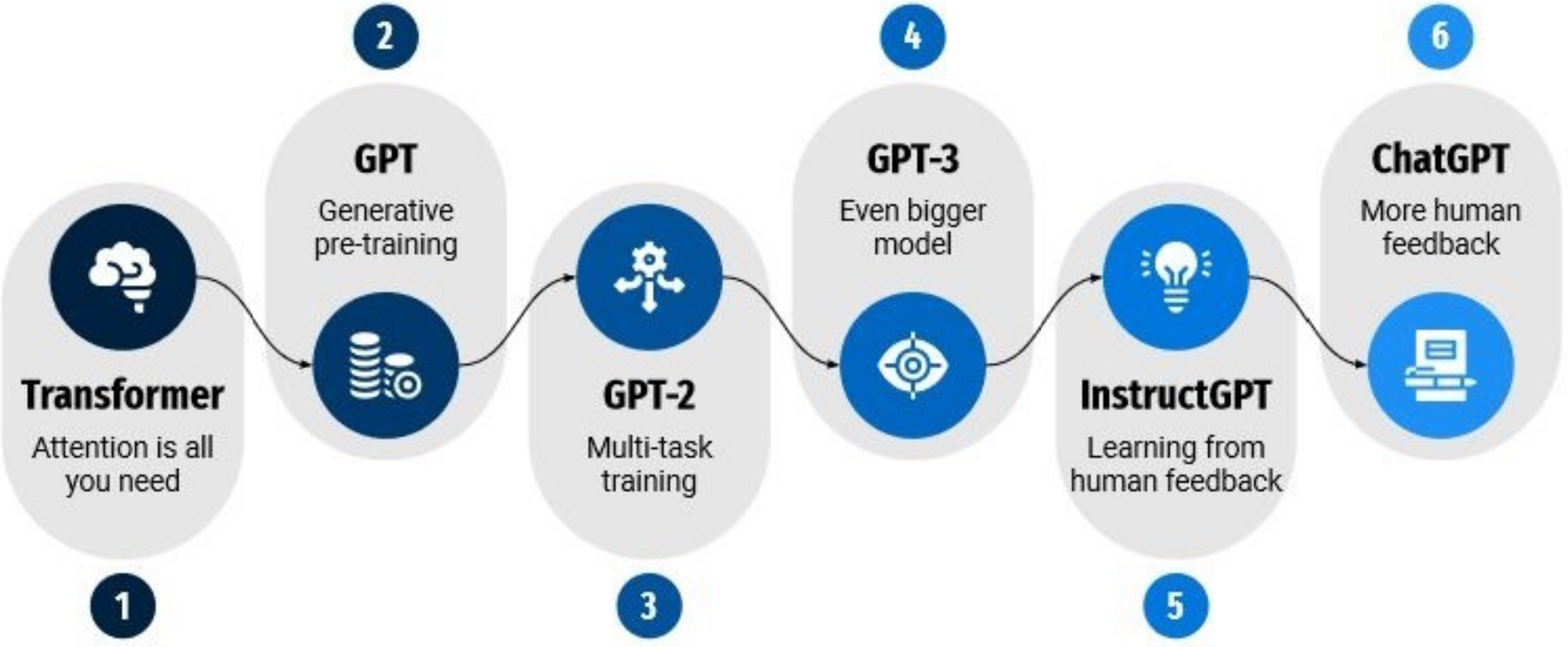


Image from: https://pwr.edu.pl/en/university/news/chatgpt-has-sparked-a-revolution-how-will-it-change-our-lives-10621.html

«Ecce ChatGPT»

Nov 28th, 2022

The prior approaches culminated in OpenAI releasing ChatGPT a 'revolutionary' system capable of:

- Having a human-like dialogue in natural language
- Handle multiple languages
- Answering follow up questions
- Admitting its mistakes
- Challenging incorrect premises
- Rejecting inappropriate requests
- ~~Making a good coffee~~
- …

But at what cost?

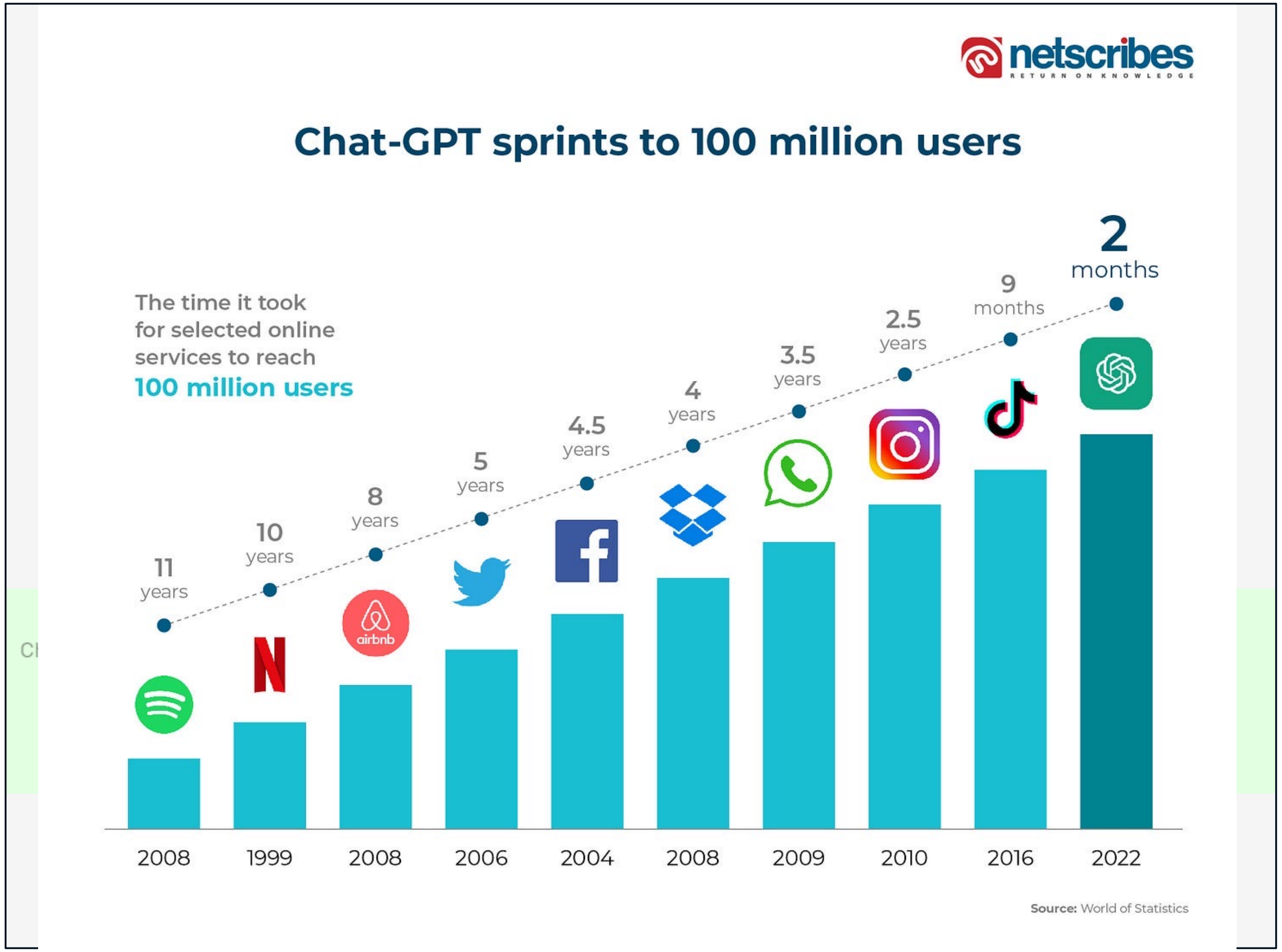


Image from: `https://ai.plainenglish.io/chat-gpt-achieving-100-million-users-in-just-2-month-a-deep-analysis-a453e6f85acf`

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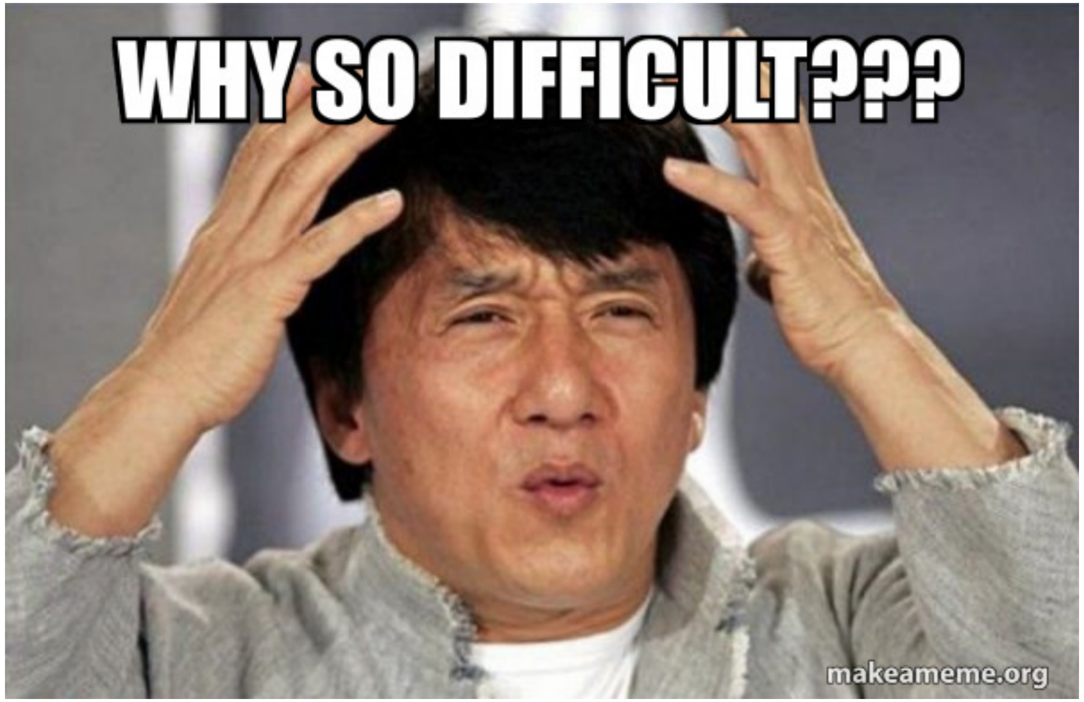
Resources need for ChatGPT

https://lifearchitect.ai/chatgpt/

- **Training hardware**: Access to a supercomputer with ~10,000 GPUs and ~285,000 CPU cores.
- **Staffing**: For training, you'll need access to the smartest PhD-level data scientists in the world. OpenAI paid their Chief Scientist Ilya Sutskever $1.9 million dollars per year (USD) in 2016. Perhaps budget >$200 million for staffing the first year.
- **Time (data collection)**: It took a solid 12-18 months to agree on, collect, clean, and prepare data.
- **Time (training ~300 years)**: Expect a model to take 9-12 months of training, and that's if everything goes perfectly. You may need to run it several times, and you may need to train several models in parallel. Things do go wrong, and they can completely mess up the results (see the GPT-3 paper, China's GLM-130B and Meta AI's OPT-175B logbook).
- **Inference**: Fairly beefy computers, plus devops staffing resources, but this is the least of your worries. Good luck!

Is this a groundbreaking revolution or merely a stochastic parrot?



Material for another tutorial 😅

2022: An odessy in Prompt-Engineering and In-Context Learning

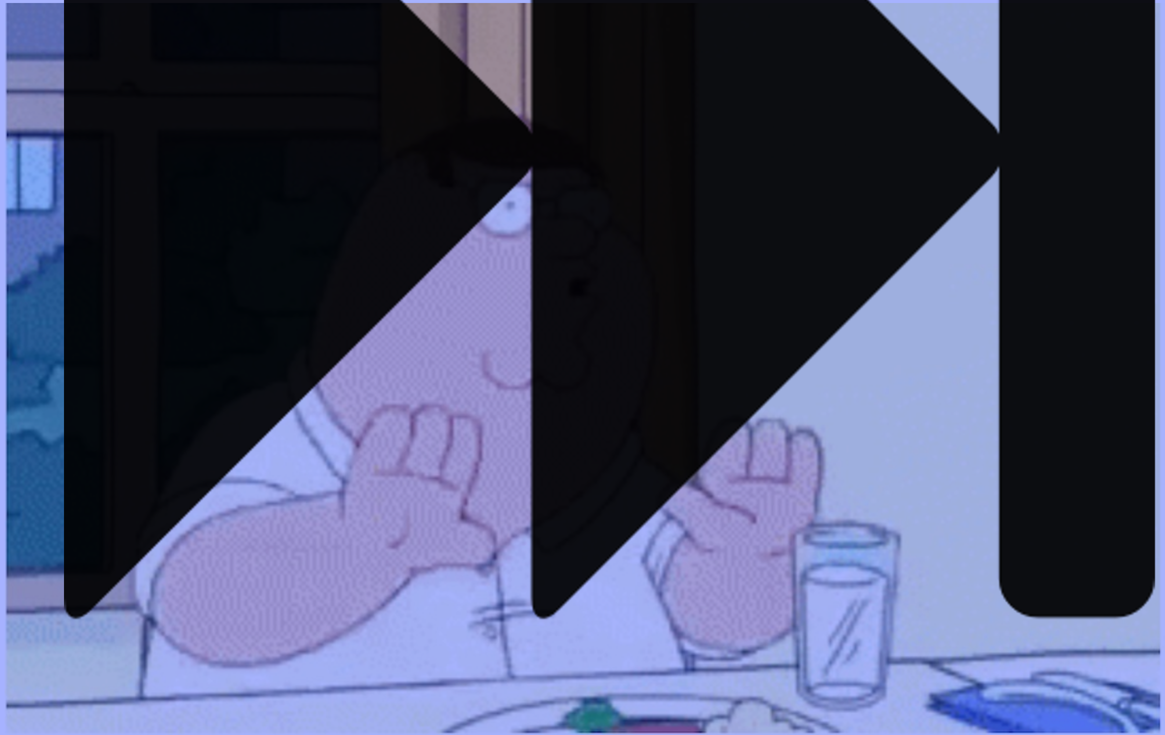
- **Prompt-engineering**, especially **in-context learning**, has become a key research area in 2022.
  - Involves demonstrating or explaining tasks to LLMs through tailored descriptions or examples within prompts (few-shot)
- **Why** Prompt-Engineering?
  - Aims to **leverage the rich, emergent information captured by LLMs** to perform tasks.
- A necessity **driven by resource constraints**?
  - The luxury of fine-tuning **100B models remains inaccessible for many**
  - **Prompt-engineering offers a more resource-efficient and accessible way** to harness the power of LLMs without extensive computational resources.

… but in the end …

- **Transformer-based models are powerful Tools**
  - Suitable for Multi-task learning
- **State-of-the-Art Performance**
  - Thanks to **extensive pre-training**
- **Potentially applicable to EVALITA**

The «crazy» idea

Fine-tuning a single LLMs by applying it to **ALL EVALITA tasks**



How did we get here?

CHAPTER 5

EXTREMITA
ONE MODEL FOR ALL THE EVALITA TASKS

The «crazy» idea

Fine-tuning a single LLMs by applying it to **ALL EVALITA tasks**

- **Modeling Tasks as Prompts**:
  - The core idea is to frame each task as a «linguistic» prompt
  - Enabling a unified approach to diverse NLP challenges
- **Leveraging EVALITA Training Data**:
  - By **aggregating training** examples from EVALITA
  - **Fine-tuning a decoder-based architecture** like GPT
- **Power of Scale**:
  - If the model is sufficiently large, it should possess the capability to solve all tasks.

Why «crazy»?

- **Limited Access to Large Language Models (LLMs)**:
  - We **didn't have an LLM ready**, nor the capacity or resources equivalent to 300 years to develop one.
  - While open-source versions like BLOOM existed, the quality of models with less than 170 billion parameters wasn't optimal.
- **How to handle instructions**:
  - The zero/few-shot capability were not appealing
  - We **lacked a method or resources to** "convert" an LLM to **execute instructions.**
  - Data from the Instruct GPT experience was not available

BLOOM paper: `https://arxiv.org/abs/2211.05100`

Why «crazy»? (2)

- **Computational Constraints**:
  - Even with data available for the initial step of Instruct GPT, **our computational power was limited** (only 1 GPU T4 with 16GB of RAM), insufficient for fine-tuning the model.
- **Language-Specific Model Limitations**:
  - We did not have a model or instruction examples specifically tailored for Italian, presenting a significant language barrier.

BLOOM paper: `https://arxiv.org/abs/2211.05100`

But then many camelids appeared after February 17

- Limited Access to LLMs
  - **FEB 24: LLaMA**

- How to handle instructions
  - **MAR 13: Alpaca**

- Computational Constraints
  - **MAR 23: Alpaca-LoRA**

- Language-Specific Model Limitations
  - **APR 02: Cabrita/Camoscio**

But then many camelids appeared after February 17

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LLAmA: Large Language Model Meta AI (Touvron et al., 2023)

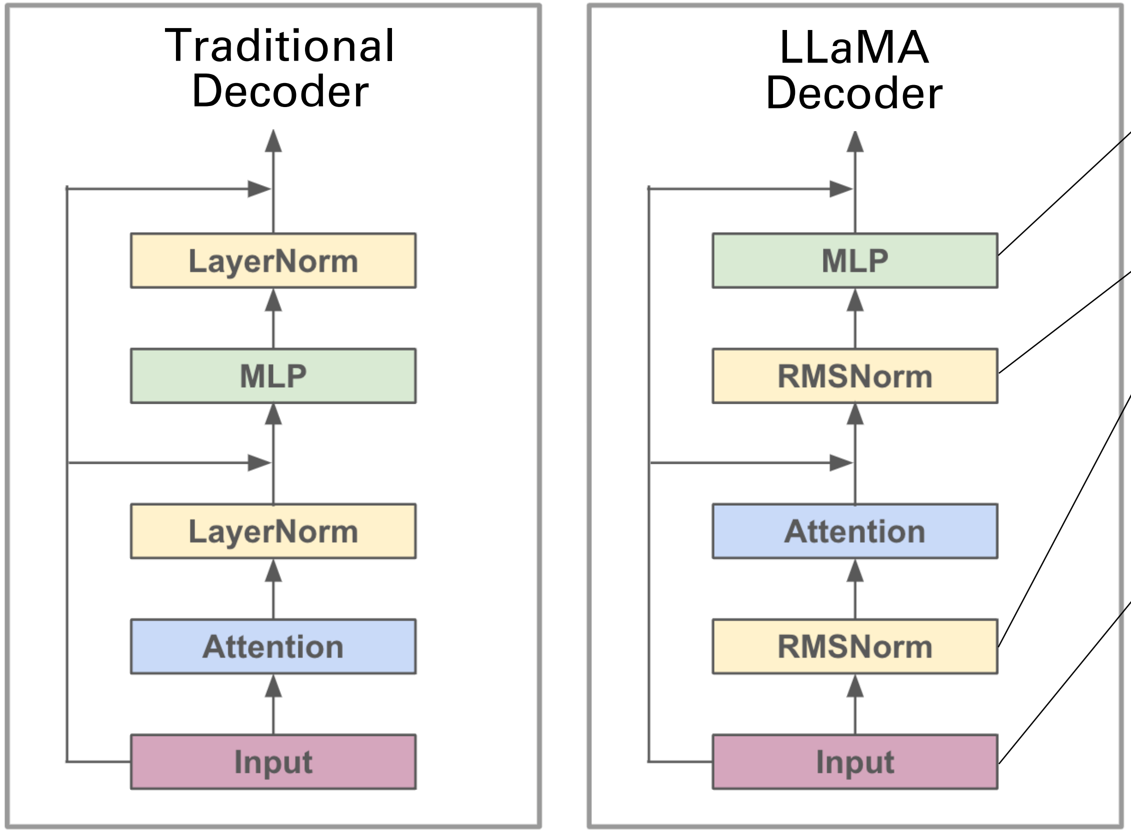
- **LLaMA:** A collection of foundation **language models** with parameters ranging from 7B, 13B to 65B.
- **Training Data:** Models **trained on trillions of tokens** exclusively using publicly available datasets.
- **Performance: LLaMA-13B outperforms GPT-3** (175B) in most benchmarks, while LLaMA-65B competes with Chinchilla-70B and PaLM-540B.
- **Accessibility: All models** ~~leaked~~ **released to the research community** for wide accessibility...
  - https://www.theverge.com/2023/3/8/23629362/meta-ai-language-model-llama-leak-online-misuse

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, Guillaume Lample (2023). LLaMA: Open and Efficient Foundation Language Models. arXiv:2302.13971

Making LMs pubblicly available: LLaMA

(Touvron et al., 2023)

Large **La**nguage Model **M**eta **A**I is a series of Foundational models: 7, 13, 32 and 65 billion parameters

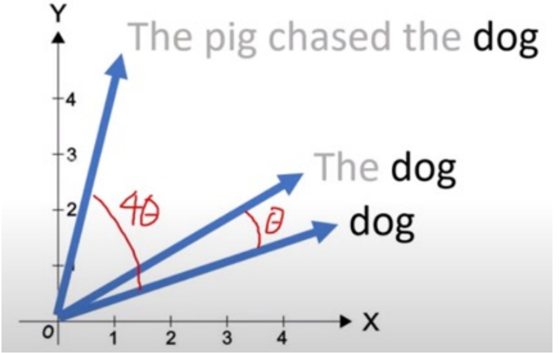


$$\texttt{SwiGLU}(x) = \texttt{Swish}(xW) \cdot xV$$

$$\texttt{Swish}(x) = x \cdot \texttt{Sigmoid}(\beta x)$$

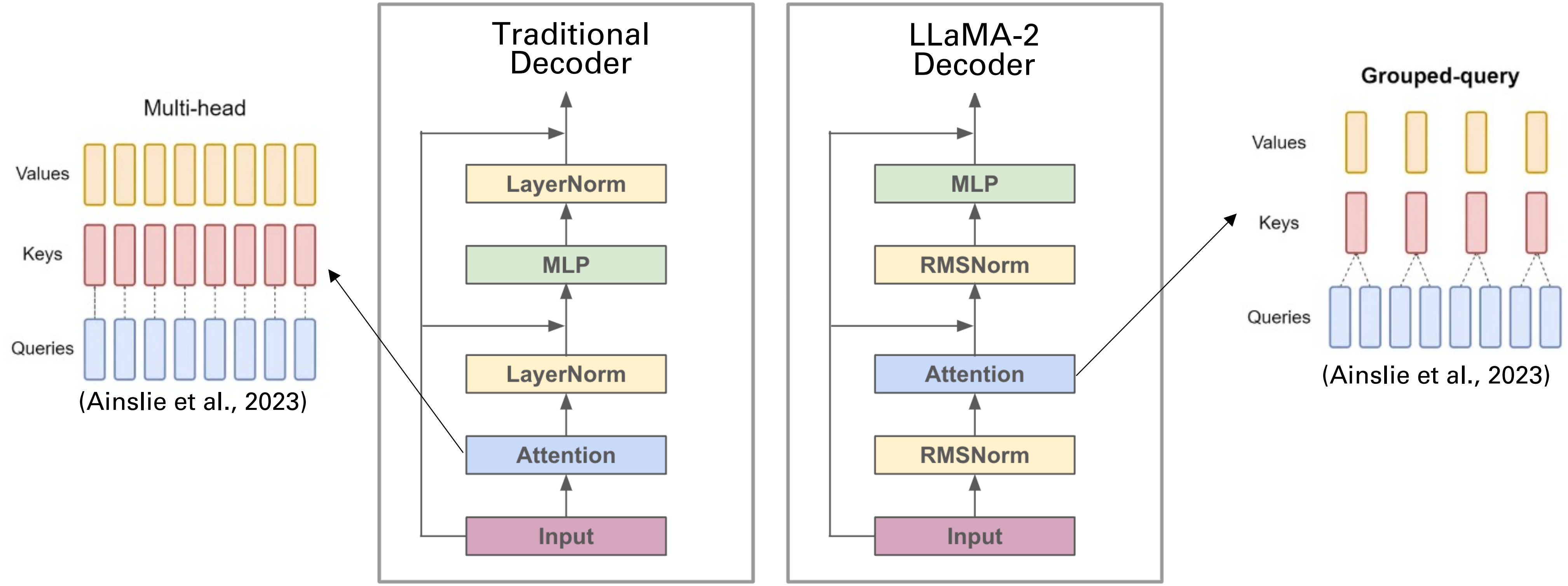
$$\bar{a}_i = \frac{a_i}{\text{RMS}}, \quad where \ \text{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} a_i^2}$$

Rotary Positional Embeddings (RoPE) instead of Absolute/Relative



Making LMs pubblicly available: LLaMA-2

A big difference lies in the Attention block



Joshua Ainslie, James Lee-Thorp, Michiel de Jong, Yury Zemlyanskiy, Federico Lebrón, Sumit Sanghai (2023). GQA: Training Generalized Multi-Query Transformer Models from Multi-Head Checkpoints. arXiv:2305.13245

LLaMA: some cons

- **Bias and Toxicity:** Like other LLMs, LLaMA models encode biases and potential toxicity, necessitating further research in responsible AI.
- **Data Intensity:** Even smaller models require extensive data (up to 1T tokens), posing challenges in terms of data collection and management.
- **Model Scaling:** Determining optimal model size for specific tasks remains a challenge, balancing between compute resources and desired performance levels.

But then many camelids appeared after February 17

- Limited Access to LLMs
  - FEB 24: **LLaMA**

- How to handle instructions
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  - APR 02: **Cabrita/Camoscio**

Instruction-tuning: Alpaca
(Taori et al. 2023)

- **LLaMA Limitations:** Originally a language model, not designed for instruction-following tasks.
- **Challenges in LLMs:** Issues with misinformation, stereotypes, and toxic language.
- **Alpaca**: Fine-tuned from Meta's LLaMA 7B, specifically for instruction-following.
  - Let’s say, only the step 1 from Instruct GPT is used
- **Training:** Utilizes 52K demonstrations in the style of self-instruct from text-davinci-003 (a variant of GPT3).
- **Efficiency:** Smaller, more accessible, and easier to reproduce compared to models like GPT-3.5.

R. Taori, I. Gulrajani, T. Zhang, Y. Dubois, X. Li, C. Guestrin, P. Liang, T. B. Hashimoto, Stanford Alpaca: An instruction-following llama model, 2023

Instruction-tuning: Alpaca
(Taori et al. 2023)

Text-davinci-003

175 Self-Instruct seed tasks

52k Instruction-following examples

Alpaca (Taori et al. 2023)

LLaMA

Example generated task

Instruction:
Brainstorm creative ideas for designing a conference room

Output:
.. Incorporate flexible components, such as..

Instruction: Extract all the entities from the next sentence:
Input: "*Garibaldi , sailing from Caprera, today would know where to go*"

Garibaldi and Caprera

But then many camelids appeared after February 17

- Limited Access to LLMs
  - FEB 24: LLaMA

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  - MAR 13: Alpaca

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  - APR 02: Cabrita/Camoscio

DANILO CROCE

Challenge: 16GB GPU resources

ChatGPT’s resources:
10.000 GPUs

1xTesla T4

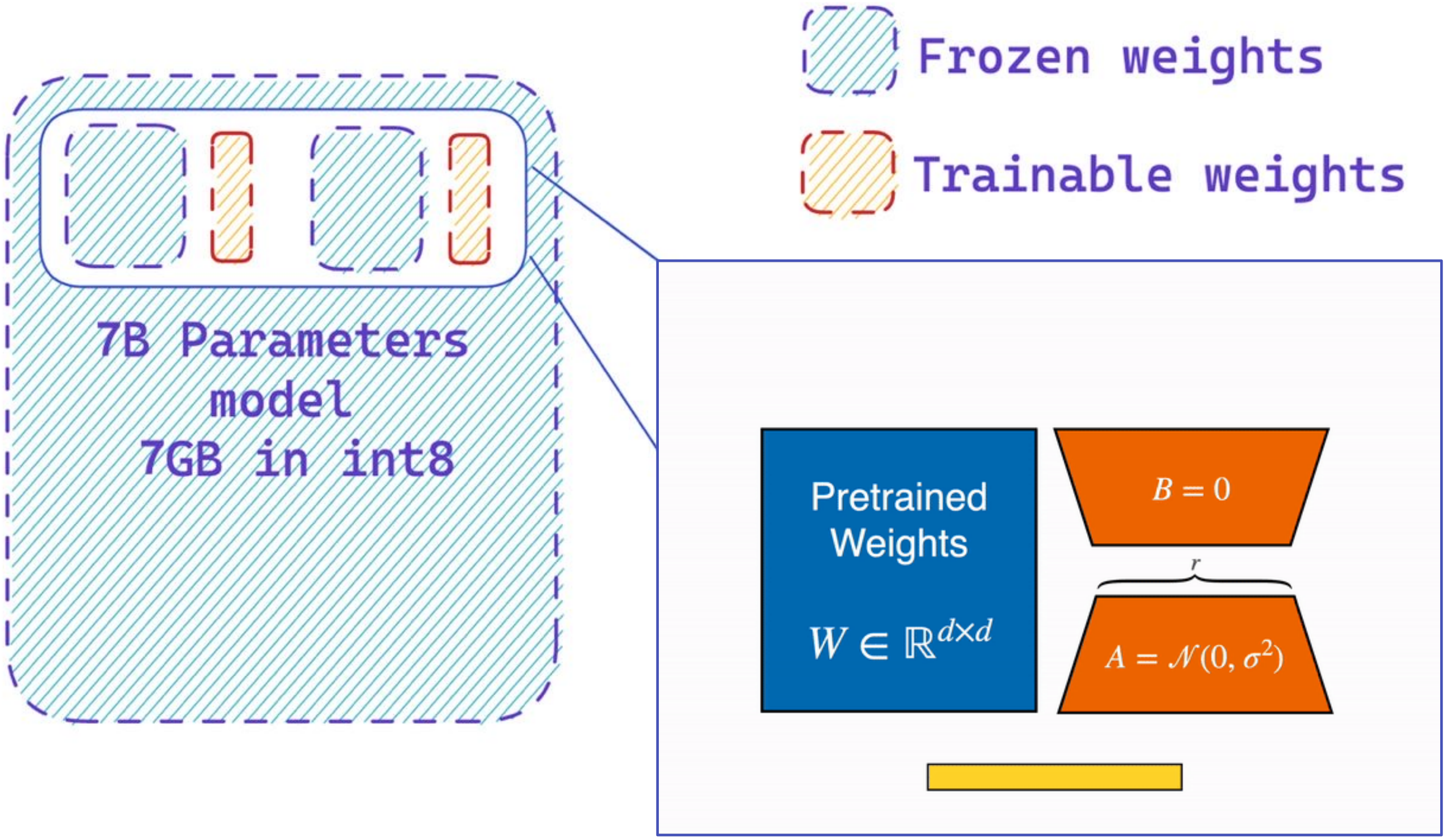
Low-Rank Adaptation (LoRA) (Hu et al., 2021)

Low Rank Adaptation (LoRA: Hu et al., 2021): create the parallel (fine-tunable) adapters as smaller matrices:

- add the adapters to the base model while keeping the base model frozen

LoRA is **NOT** learning any parameter, but the **changes in the parameters**!

$$\underbrace{W_0 + \Delta W}_{\text{Traditional FT}} = \underbrace{W_0 + BA}_{\text{LoRA FT}}$$



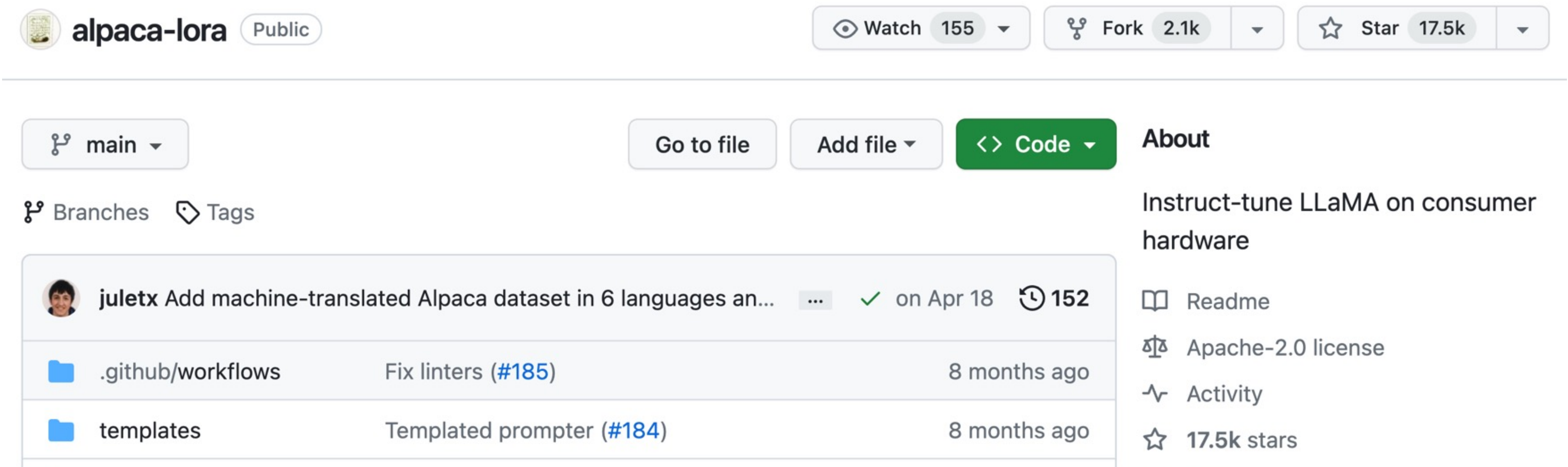
Danilo Croce

Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen (2021). LoRA: Low-Rank Adaptation of Large Language Models. arXiv:2106.09685

Alpaca LoRA

Within just a few days following the release of Alpaca's training material, LoRA was utilized to fine-tune LLaMa into Alpaca efficiently, using only a «small» GPU:

- `https://github.com/tloen/alpaca-lora`



But then many camelids appeared after February 17

- Limited Access to LLMs
  - FEB 24: **LLaMA**

- How to hanlde instructions
  - MAR 13: **Alpaca**

- Computational Constraints
  - MAR 23: **Alpaca-LoRA**

- Language-Specific Model Limitations
  - APR 02: **Cabrita/Camoscio**

Multilingual Adaptation of Alpaca: The Birth of Language-Specific Models

Shortly after Alpaca's dataset release, several groups opted to use automatic translation methods (even using ChatGPT) to translate the Alpaca dataset.

- **Objective:** Enable the training of language-specific versions of Alpaca, adapting LLaMa to each new language.

🇧🇷 https://huggingface.co/22h/cabrita-lora-v0-1
🇨🇳 https://huggingface.co/qychen/luotuo-lora-7b-0.1
🇨🇳 https://huggingface.co/ziqingyang/chinese-alpaca-lora-7b
🇯🇵 https://huggingface.co/kunishou/Japanese-Alapaca-LoRA-7b-v0
🇫🇷 https://huggingface.co/bofenghuang/vigogne-lora-7b
🇹🇭 https://huggingface.co/Thaweewat/thai-buffala-lora-7b-v0-1
🇩🇪 https://huggingface.co/thisserand/alpaca_lora_german
🇵🇱 https://huggingface.co/mmosiolek/polpaca-lora-7b

🇵🇱 https://huggingface.co/chrisociepa/alpaca-lora-7b-pl
🇮🇹 https://huggingface.co/teelinsan/camoscio-7b-llama
🇷🇺 https://huggingface.co/IlyaGusev/llama_7b_ru_turbo_alpaca_lora
🇺🇦 https://huggingface.co/robinhad/ualpaca-7b-llama
🇮🇹 https://huggingface.co/mchl-labs/stambecco-7b-plus
🇪🇸 https://huggingface.co/plncmm/guanaco-lora-7b
🇬🇧 🇪🇸 🇵🇹 https://huggingface.co/HiTZ/alpaca-lora-7b-en-pt-es-ca-eu-gl-at

Among the camelids: Camoscio

Camoscio (Santilli and Rodolà, 2023): A LLaMA-based model capable of executing commands in Italian.

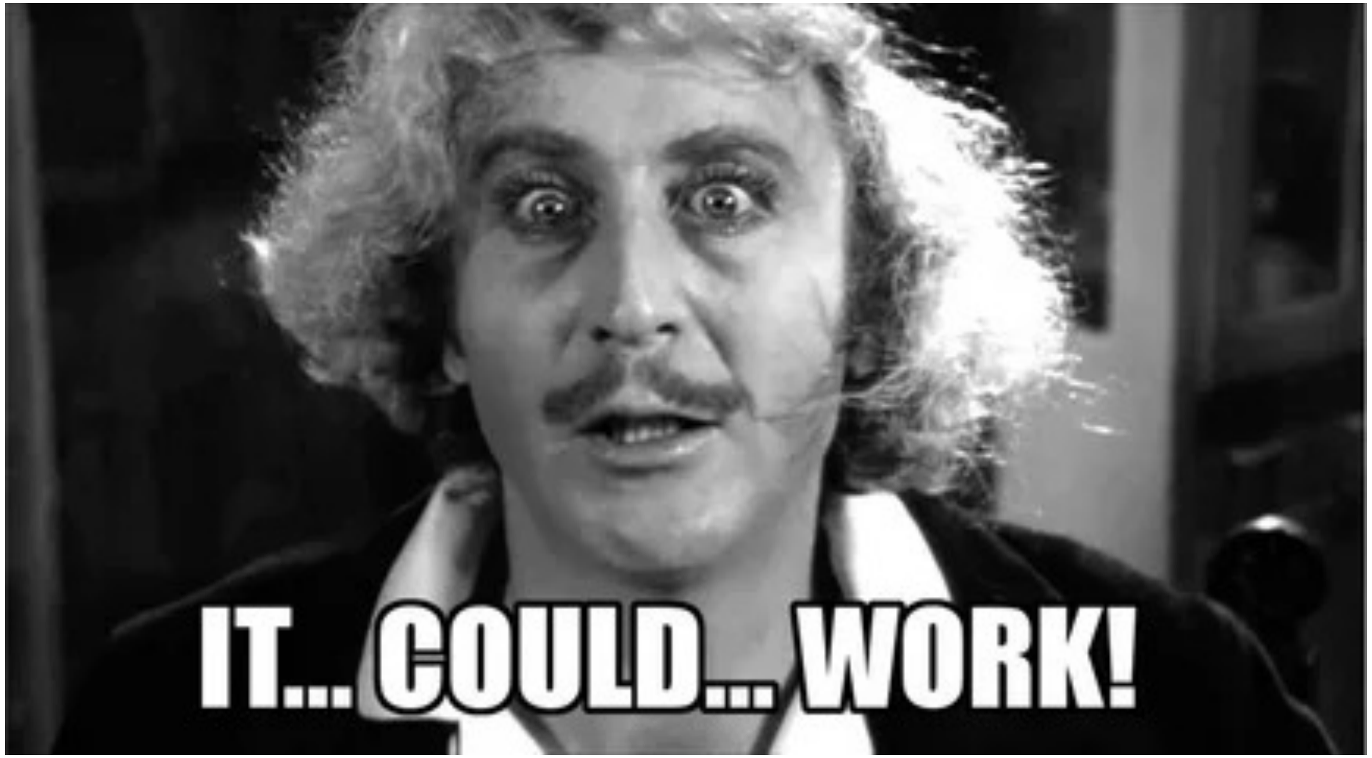
- Fine-tuned using the data from Alpaca translated using ChatGPT

It seemed a good starting point for our «crazy» idea so…

(Santilli and Rodolà, 2023) «Camoscio: an Italian Instruction-tuned LLaMA»
In proceedings of CLiC-IT 2023
https://github.com/teelinsan/camoscio

Danilo Croce

… so, we started thinking



ExtremITA at EVALITA

Evaluation of NLP and Speech Tools for Italian

Multi-Task Sustainable Scaling to Large Language Models at its Extreme

C.D. Hromei, D. Croce, V. Basile, R. Basili

AILC Associazione Italiana di Linguistica Computazionale

UNIVERSITÀ DI TORINO

Università di Roma Tor Vergata

Motivation

- Recent development of LLaMA (Touvron et al., 2023) **foundational models has opened new ways of exploiting natural language** for task specific training through the use of prompting
- **Multitask joint training for a single monolithic architecture** is appealing when coupled with instructions
- **Tasks are modelled as linguistic problems** (see ChatGPT): from traditional classification to solve a task to prompting and natural language inference

H. Touvron, T. Lavril, G. Izacard, X. Martinet, M.-A. Lachaux, T. Lacroix, B. Rozière, N. Goyal, E. Hambro, F. Azhar, A. Rodriguez, A. Joulin, E. Grave, G. Lample, Llama: Open and efficient foundation language models, 2023

Our Method

22

Istruzione: Quali emozioni sono espresse in questo testo? Puoi scegliere una o più emozioni tra ‘Rabbia’, ‘Anticipazione', ‘Disgusto', ‘Paura', ‘Gioia', ‘Amore', ‘Tristezza', ‘Sorpresa', ‘Fiducia', o ‘Neutro'.
Input: “ *Che bella giornata*”

Istruzione: Scrivi le menzioni di entità nel testo, indicandone il tipo: [PER] (persona), [LOC] (luogo), [ORG] (organizzazione).
Input: “ *La Banca d’Italia*”

...

Istruzione: Quanto è coerente questa frase, su una scala da 0 a 5?
Input: “ *Che bella giornata*”

LLM-based Decoder

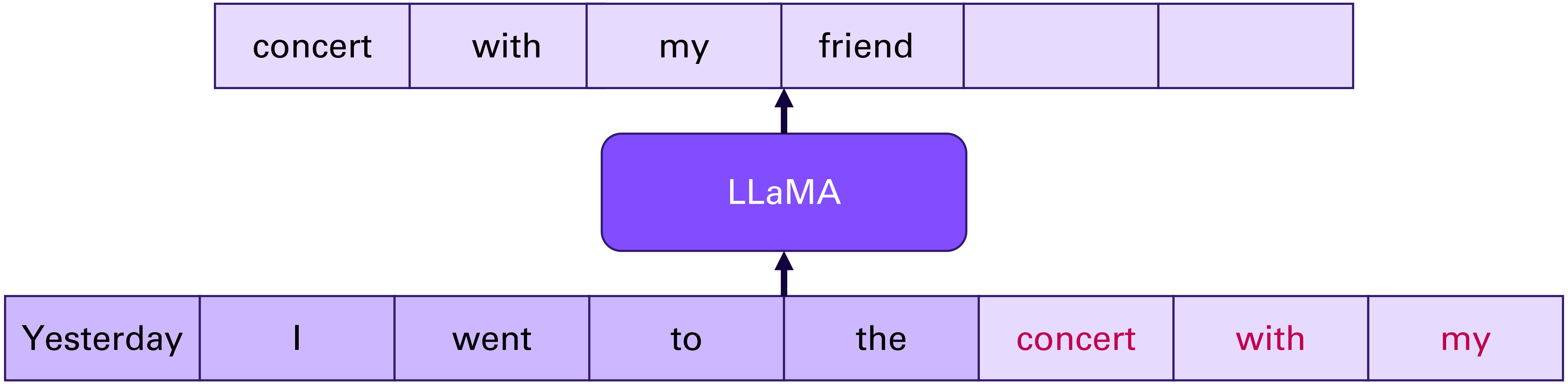
Gioia

[ORG] Banca d’Italia

...

4.0

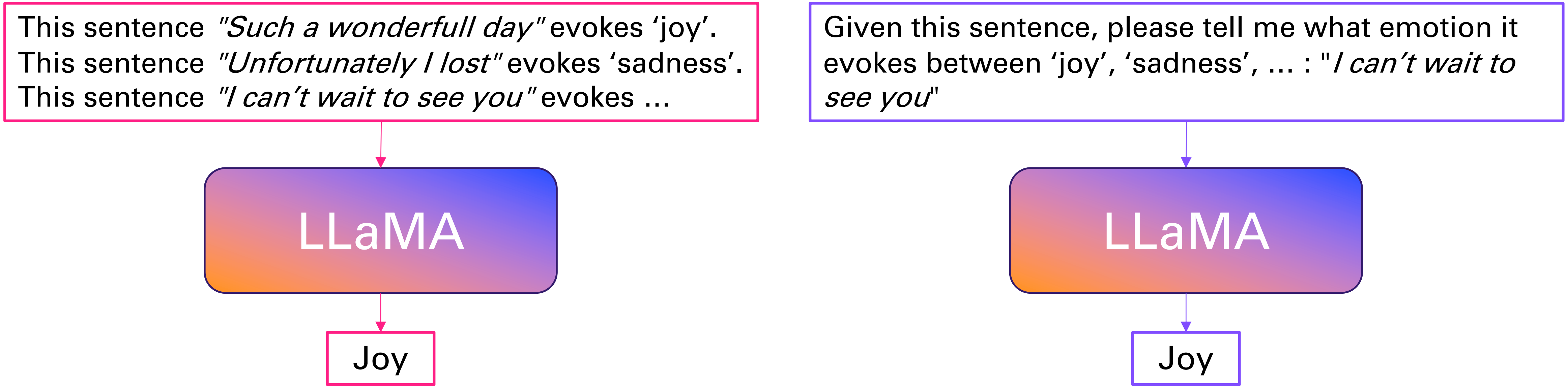
LLaMA (Touvron et. al 2023): Autoregressive Decoder-only



DANILO CROCE

H. Touvron, T. Lavril, G. Izacard, X. Martinet, M.-A. Lachaux, T. Lacroix, B. Rozière, N. Goyal, E. Hambro, F. Azhar, A. Rodriguez, A. Joulin, E. Grave, G. Lample,
Llama: Open and efficient foundation language models, 2023

LLaMA: Few-shot learning vs Instruction-tuning



Objective: fine-tune a multitask architecture (with limited resources) to follow instructions

DANILO CROCE

Large Language Models: the Camelids tree

Text-davinci-003

175 Self-Instruct seed tasks

52k Instruction-following examples

Alpaca (Taori et al. 2023)

LLaMA

Example generated task

Instruction:
Brainstorm creative ideas for designing a conference room

Output:
.. Incorporate flexible components, such as..

Instruction: Extract all the entities from the next sentence:
Input: "*Garibaldi* , *sailing from Caprera, today would know where to go*"

Garibaldi e Caprera

- ✓ Tasks as Natural Language Inference
- ✓ Task independent architecture
- × Italian language support
- × EVALITA training as Few-Shot Learner

R. Taori, I. Gulrajani, T. Zhang, Y. Dubois, X. Li, C. Guestrin, P. Liang, T. B. Hashimoto, Stanford Alpaca: An instruction-following llama model, 2023

Large Language Models: the Camelids tree

Text-davinci-003

175 Self-Instruct seed tasks

52k Instruction-following examples

Alpaca

LLaMA

52k Instruction-following examples

Camoscio(Santilli 2023)

EVALITA Data

ExtremITLLaMA

Example EVALITA data

Istruzione:
In questo testo si parla di una cospirazione? Rispondi sì o no.

Input:
Hanno votato tutti obbligo vaccinale, ...

Risposta:
Sì

- ✓ Tasks as Natural Language Inference
- ✓ Task independent architecture
- ✓ Italian language support
- ✓ EVALITA training with Instructions

Ⓒ Generated with Adobe Firefly

Santilli, A., Rodolà, E.: Camoscio: an Italian instruction-tuned LLaMA 2023

Task Prompts

Task name	Natural language instruction
CLinkaRT	Trova i risultati dei test e delle misurazioni nel testo. Per ogni risultato, scrivi '[BREL]', seguito dal risultato seguito da '[SEP]', seguito dal test, seguito da '[EREL]'. Se non trovi nessun risultato, scrivi '[NOREL]'.

DANILO CROCE

Task Prompts

Task name	Natural language instruction
CLinkaRT	Trova i risultati dei test e delle misurazioni nel testo. Per ogni risultato, scrivi '[BREL]', seguito dal risultato seguito da '[SEP]', seguito dal test, seguito da '[EREL]'. Se non trovi nessun risultato, scrivi '[NOREL]'.
EMit A	Quali emozioni sono espresse in questo testo? Puoi scegliere una o più emozioni tra 'rabbia', 'anticipazione', 'disgusto', 'paura', 'gioia', 'amore', 'tristezza', 'sorpresa', 'fiducia', o 'neutro'.
EMit B	Di cosa parla il testo, tra 'direzione', 'argomento', 'entrambi', 'non specificato'
EmotivITA	Scrivi quanta valenza è espressa in questo testo su una scala da 1 a 5, seguito da quanto stimolo è espresso in questo testo su una scala da 1 a 5, seguito da quanto controllo è espresso in questo testo su una scala da 1 a 5.
PoliticIT	Scrivi se l'autore del testo è 'uomo' o 'donna', seguito dalla sua appartenenza politica tra 'destra', 'sinistra', 'centrodestra', 'centrosinistra'.
GeoLingIT	Scrivi la regione di appartenenza di chi ha scritto questo testo, seguito dalla latitudine, seguita dalla longitudine.
LangLearn	Questi due testi separati da [SEP] sono presentati nell'ordine in cui sono stati scritti? Rispondi sì o no.
HaSpeeDe 3	In questo testo si esprime odio? Rispondi sì o no.
HODI A	In questo testo si esprime odio omotransfobico? Rispondi sì o no.
HODI B	Con quali parole l'autore del testo precedente esprime odio omotransfobico? Separa le sequenze di parole con [gap].
Multifake-Detective	L'evento riportato nel testo è 'certamente vero', 'probabilmente vero', 'probabilmente falso', o 'certamente falso'?
ACTI A	In questo testo si parla di una cospirazione? Rispondi sì o no.
ACTI B	Di quale teoria cospirazionista parla questo testo, tra 'Covid', 'Qanon', 'Terrapiattista', 'Russia'?
NERMuD	Scrivi le menzioni di entità nel testo, indicandone il tipo: [PER] (persona), [LOC] (luogo), [ORG] (organizzazione).
WiC-ITA	La parola compresa tra [TGTS] e [TGTE] ha lo stesso significato in entrambe le frasi? Rispondi sì o no.
DisCoTEX 1	Le due frasi precedenti, separate da '[SEP]', sono coerenti tra loro? Rispondi sì o no.
DisCoTEX 2	Quanto è coerente questa frase, su una scala da 0 a 5?

Acceptable Answers

Task name	Output Templates
EMit A	{“Rabbia", “Anticipazione", “Disgusto", “Paura", “Gioia", “Amore", “Tristezza", “Sorpresa", “Fiducia"}$^{+}$ ∨ “Neutrale"
EMit B	{“Direzione", “Argomento", “Entrambi", “Non specificato"}
EmotivITA	“Valenza: {0-5} Stimolo: {0-5} Controllo: {0-5}"
PoliticIT	“Gender: {“Uomo”, “Donna”} PIB: {“Sinistra”, “Destra”} PIM: {“Sinistra”, “Destra”, “Centro Sinistra”, “Centro Destra”}"
GeoLingIT	“Regione: {Abruzzo, .., Veneto} Latitudine: {} Longitudine: {}"
LangLearn	{“Sì", “No"}
HaSpeeDe 3	{“Sì", “No"}
HODI A	{“Sì", “No"}
HODI B	<Homotransphobia_mention>
Multifake-Detective	{“Certamente Falso", “Probabilmente Falso", “Probabilmente Vero", “Certamente Vero"}
ACTI A	{“Sì", “No"}
ACTI B	{“Terrapiattista", “Covid", “Qanon", “Russia"}
NERMuD	[<entity_type>] <text_span_that_evokes_entity>
CLinkaRT	“[BREL] <Rml_entity_mention> [SEP] <Event_entity_mention> [EREL]"
WiC-ITA	{“Sì", “No"}
DisCoTEX 1	{“Sì", “No"}
DisCoTEX 2	{0-5}

Prompting in  CLinkaRT

- From a Clinical Information Extraction to a sequence to sequence generation
- Heuristics applied to reconstruct back the original form of the desired output

Istruzione: Trova i risultati dei test e delle misurazioni nel testo. Per ogni risultato, scrivi '[BREL]', seguito dal risultato seguito da '[SEP]', seguito dal test, seguito da '[EREL]'. Se non trovi nessun risultato, scrivi '[NOREL]'.

Input: [...] *Gli ESAMI di laboratorio sono normali, se si fa eccezione per una lieve anemia, così come normali sono lo STUDIO radiologico del piccolo e del grosso intestino.* [...]

[BREL] *normali* [SEP] *Gli ESAMI di laboratorio* [EREL] [BREL] *normali* [SEP] *lo STUDIO radiologico del piccolo e del grosso intestino* [EREL]

DANILO CROCE

Sustainable training with Low-Rank Adaptation (Hu et al., 2021)

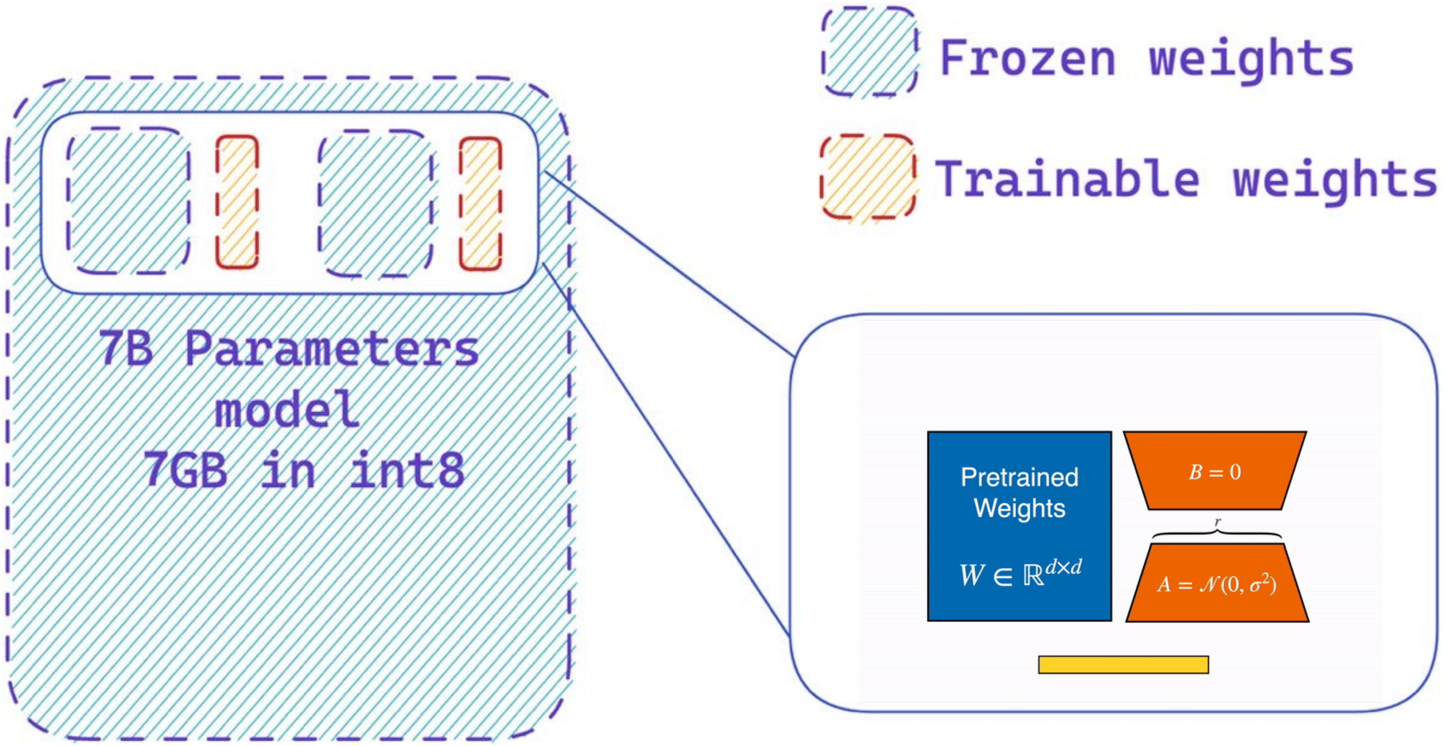
Low Rank Adaptation (LoRA: Hu et al., 2021): create the parallel (fine-tunable) adapters as smaller matrices

- add the adapters to the base model while keeping the base model frozen

We can further **scale down the memory** required by using **int8 approximation**, instead of float32

As a result, **we successfully fine-tuned a 7B parameters model with a T4 GPU** (16GB memory).

Training took 144 hours for 2 epochs on a dataset composed of 134,018 examples.

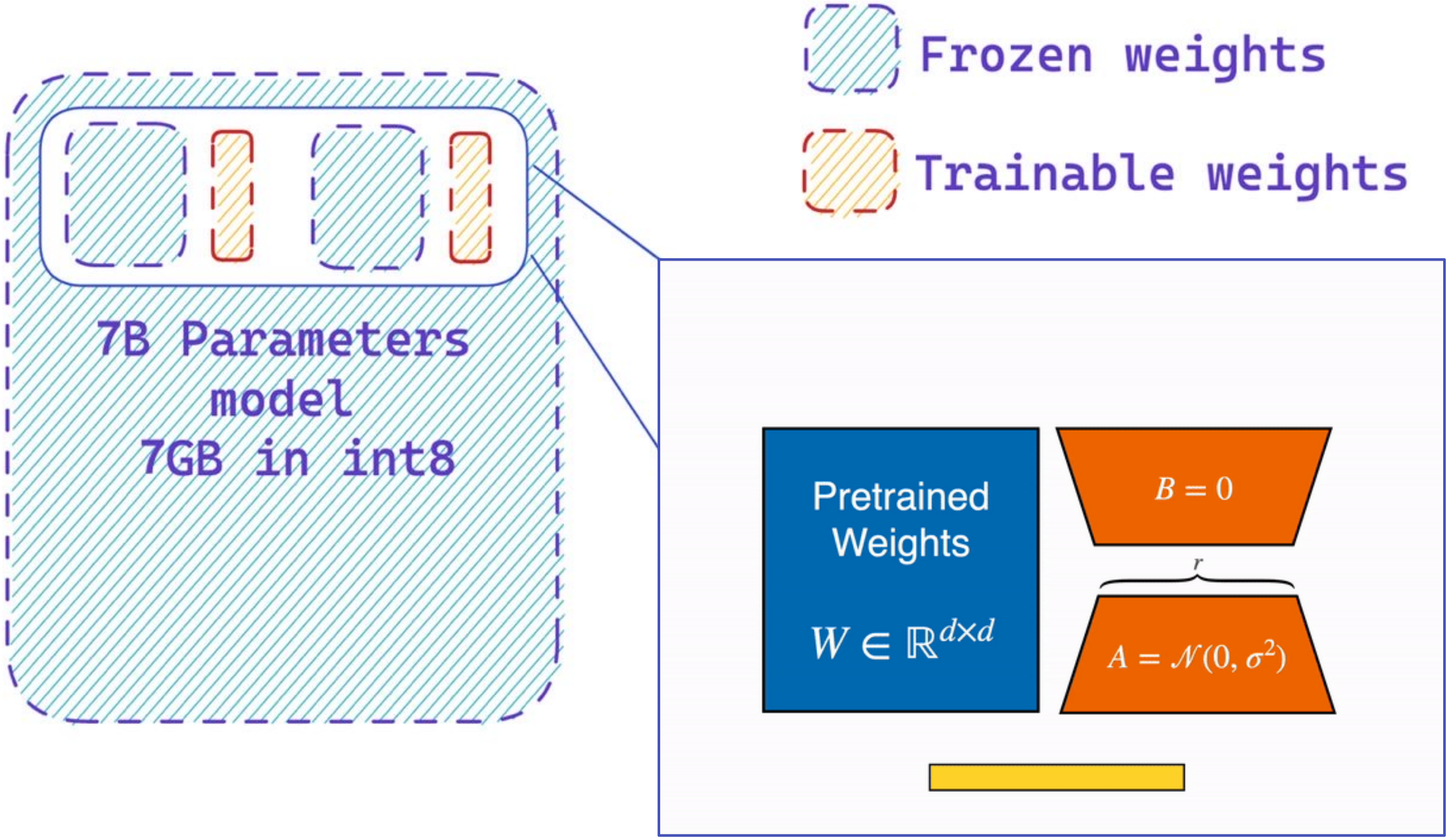


Hu, E.J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., Chen, W.: Lora: Low-rank adaptation of large language models. 2021

Sustainable training with Low-Rank Adaptation (Hu et al., 2021)

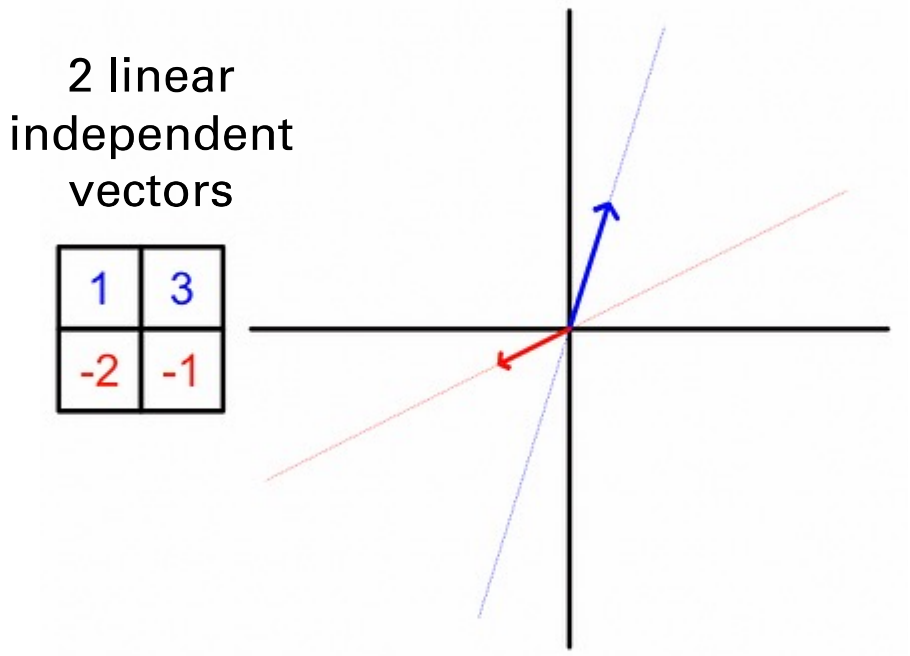
LoRA is **NOT** learning any parameter, but the **changes in the parameters**!

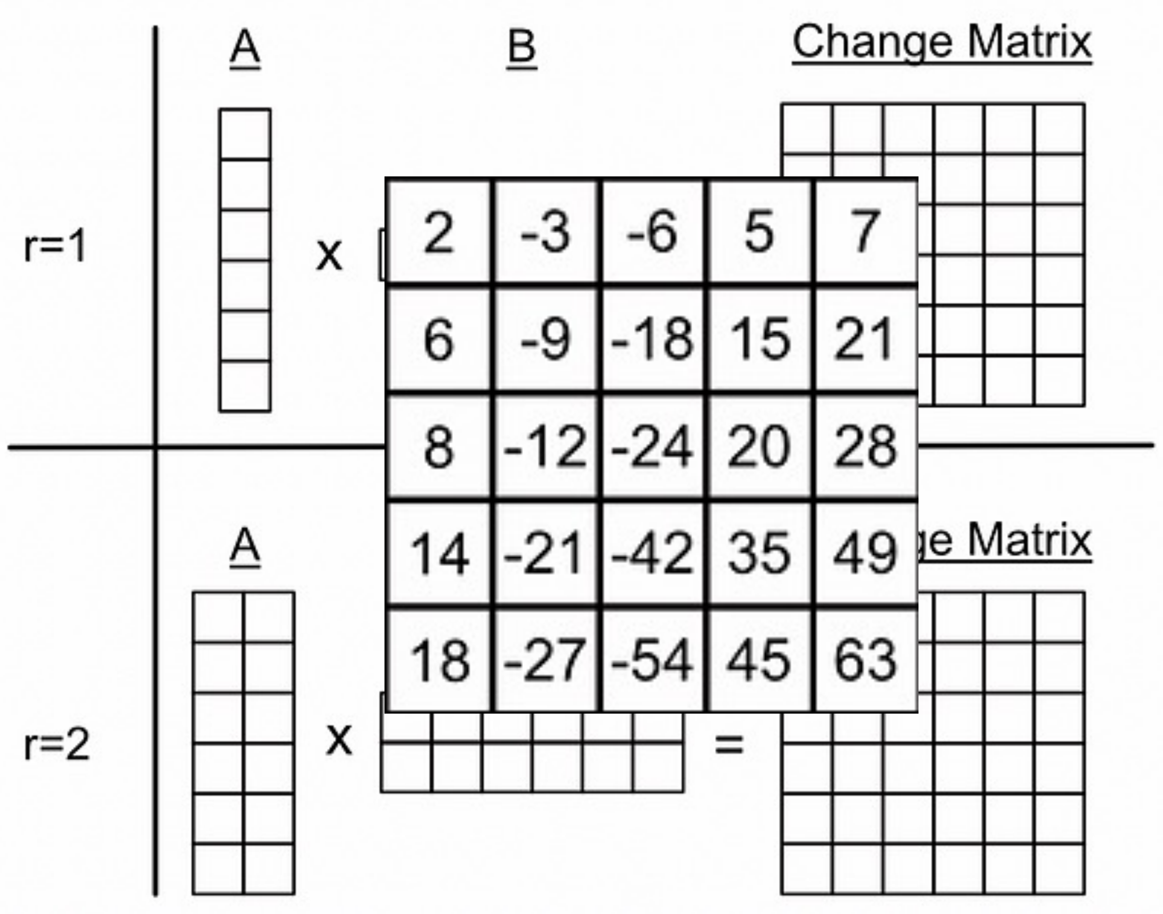
$$\underbrace{W_0 + \Delta W}_{\text{Traditional FT}} = \underbrace{W_0 + BA}_{\text{LoRA FT}}$$



Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen (2021). LoRA: Low-Rank Adaptation of Large Language Models. arXiv:2106.09685

Independence and matrix rank

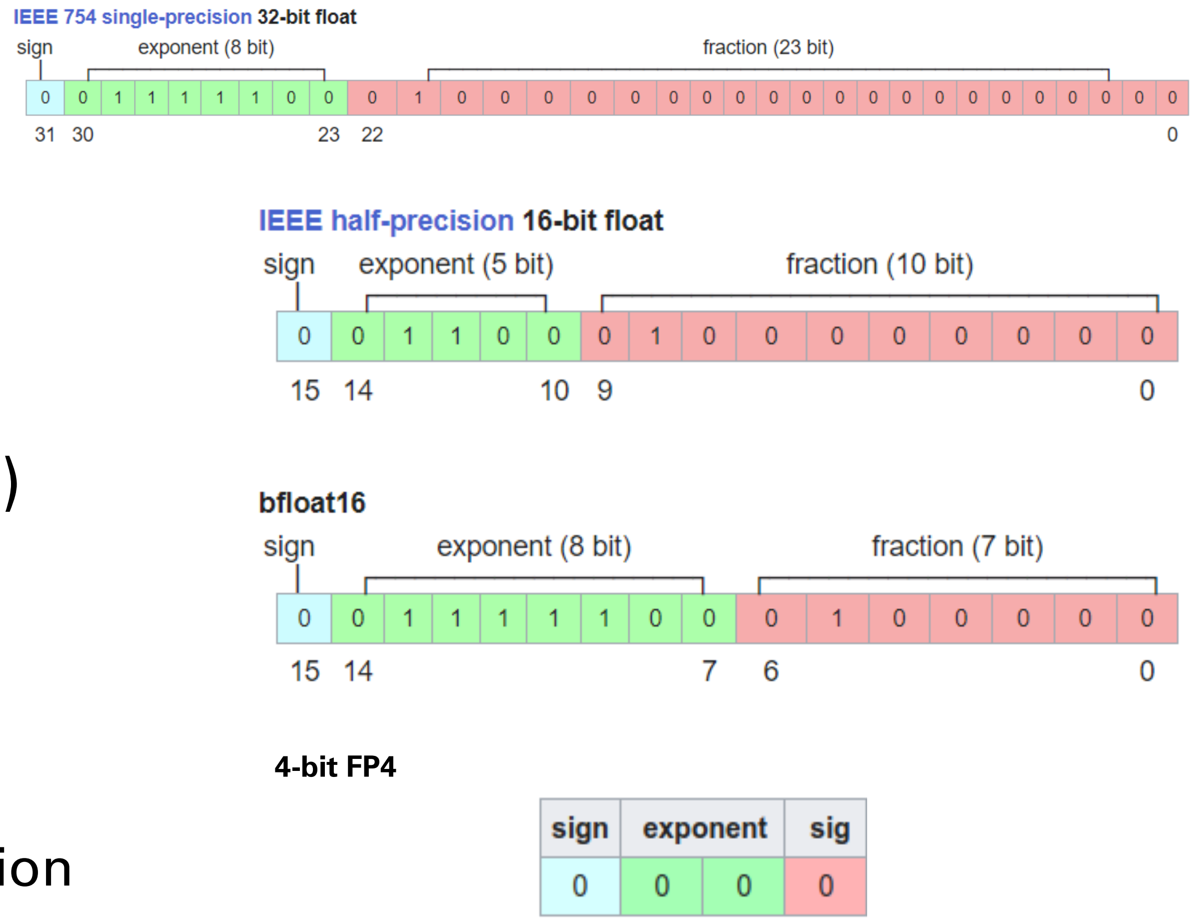




Images from https://towardsdatascience.com/lora-intuitively-and-exhaustively-explained-e944a6bff46b

Model Quantization

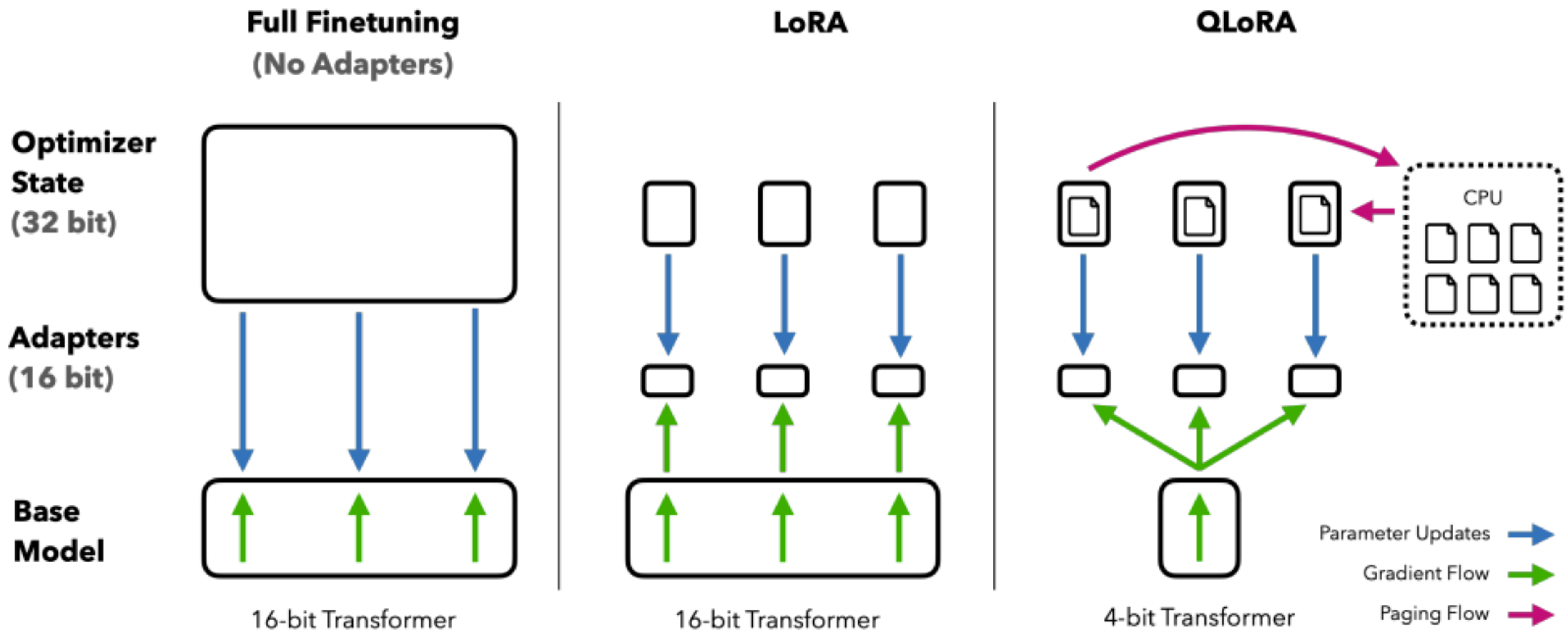
- Technique to reduce the computational and memory costs of running inference
- Represents the weights and activations with low-precision data types: 32-bit floating point (`float32`) → 8-bit integer (`int8`)
- Advantages:
  - Requires less memory storage
  - Consumes less energy (in theory)
  - Faster operations like matrix multiplication



Images from https://towardsdatascience.com/16-8-and-4-bit-floating-point-formats-how-does-it-work-d157a31ef2ef

QLoRA: Quantized LLMs (Dettmers et al., 2023)

- 4-bit quantization to compress a pretrained language model
- Double quantization of constants (save additional 0.37 bits)
- LoRA fine-tuning
- Paged optimizers for memory spikes (drop on CPUs)



Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, Luke Zettlemoyer (2023). QLoRA: Efficient Finetuning of Quantized LLMs. arXiv:2305.14314

Results

Task name	Eval Metric	ExtremITLLaMA Score	ExtremITLLaMA Rank	Best Competitor Score	Best Competitor Rank
EMit	F1	**0.6028** **0.6459**	**1** **1**	0.4994 0.6184	3 3
EmotivITA	Pears Val Pears Aro Pears Dom	**0.8110** **0.6330** **0.6300**	**1**	0.8110 0.6520 0.6540	2
PoliticIT	F1	0.7719	3	**0.8241**	**1**
GeoLingIT	F1 Avg Km	0.3818 145.15	11 9	**0.6630** **97.74**	**1** **1**
LangLearn	F1 F1	0.5500 0.6100	8 8	**0.7500** **0.9300**	**1** **1**
HaSpeeDe 3	F1 – text/context/xPolitic F1 – xRel	0.9034 **0.6525**	3 **1**	**0.9128** 0.6461	**1** 2
HODI	F1 F1	0.7942 **0.7228**	5 **1**	**0.8108** 0.7051	**1** 2
Multifake-Detective	F1 F1	0.5070 **0.4640**	2 **1**	**0.5120** 0.4600	**1** 2
ACTI	F1 F1	0.8565 0.8556	2 5	**0.8571** **0.9123**	**1** **1**
NERMuD	F1	**0.8900**	**1**	na	na
CLinkaRT	F1	0.5916	2	**0.6299**	**1**
WiC-ITA	F1 it-it F1 it-en	0.5100 0.5400	10 8	**0.7300** **0.7400**	**1** **1**
DisCoTEX	Acc HM*	**0.8150** **0.6500**	**1** **1**	0.7200 0.6300	2 2

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Prompting in NERMuD

- From a token classification problem to a sequence to sequence generation
- Heuristics applied to reconstruct back the original form of the desired output

Istruzione: Scrivi le menzioni di entità nel testo, indicandone il tipo: [PER] (persona), [LOC] (luogo), [ORG] (organizzazione).

Input: *Le dispute tuttavia fra cattolici non cessarono […] gli argomenti che furono opposti in Germania alla nomina di Marx e […] collaborazione coi socialisti vennero fatte in Italia.*

[LOC] Germania [PER] Marx
[LOC] Italia

Construction of NERMuD data

Original data

Transformation in sequence to sequence

Le	O
dispute	O
tuttavia	O
...	...
in	O
Germania	LOC
alla	O
nomina	O
di	O
Marx	PER
...	...

Input data

Le dispute tuttavia ... in Germania ...	[LOC] Germania [PER] Marx [LOC] Italia
L' ordine n. 14 è senza dubbio una misura ...	nessuna
Chi è questo Flor ?	[PER] Flor

[LOC] Germania [PER] Marx [LOC] Italia

Look up indexes and pair words with labels

DANILO CROCE

NERMuD: error analysis

Text	Gold Standard	ExtremITLLaMA
Informa il Consiglio che Nenni gli ha chiesto se il governo porrà ostacoli all' ingresso in Italia di dieci membri dell' Esecutivo internazionale dei partigiani della pace .	[ORG] Consiglio [PER] Nenni [LOC] Italia [ORG] Esecutivo internazionale dei partigiani della pace ✓	[ORG] Consiglio [PER] Nenni [LOC] Italia ✗
Occorre ricordare che l' America vincerà , passerà molto tempo ma vincerà e questa adesione nostra salva il futuro dell' Italia .	[ORG] America [ORG] Italia ✓	[LOC] America [LOC] Italia ✗
Intervento al Senato della Repubblica	[ORG] Senato [ORG] Repubblica ✗	[ORG] Senato della Repubblica ✓
Bisognava capire una buona volta che con un Governo come il nostro , con partiti nemici come abbiamo noi , a dir « tutto o nulla » ci restava e ci resterà sempre la seconda parte .	nessuna ✗	[ORG] Governo ✓
Netflix rimuove un documentario sull' AIDS a seguito di alcune proteste	nessuna ✗	[ORG] Netflix ✓
Russia	[ORG] Russia ?	[LOC] Russia ?

DiscoTEX: prompts and examples

Task	Instruction
DisCoTEX 1	Le due frasi precedenti, separate da '[SEP]', sono coerenti tra loro? Rispondi sì o no.
DisCoTEX 2	Quanto è coerente questa frase, su una scala da 0 a 5?

Istruzione: Le due frasi precedenti, separate da '[SEP]', sono coerenti tra loro? Rispondi sì o no.
Input: *"Ah... domani piove..." Mi assecondarono come si fa coi pazzi. In effetti io mi sentivo completamente folle. Non ero molto convinta. [SEP] Perché il movimento trasforma, impregna, informa di sé.*

Istruzione: Quanto è coerente questa frase, su una scala da 0 a 5?.
Input: *Lo fa allo stadio. Se lo fa alle poste è una cosa un po' strana. Ma non è l'esercizio il problema, è il contesto. Nel contesto giusto, tutti insieme per 30 secondi.*

No

3.0

Danilo Croce

DiscoTEX: Error analysis

First Sentence	Second Sentence	Gold Standard	ExtremITLLaMA
Quando la paura non supera l'incontro? Quando ciò non lo consideriamo normale. Ma esiste la normalità?	E, quindi, ritornando un po' indietro a quando rispondere a quei bimbi è complicato, e deve essere per forza una bugia.	Sì	No
Per l'orografia del luogo il lato secondario ha un piano in più. Questo lato è in laterizio con tre fornici. L'ingresso è incorniciato da lesene e posto tra due aperture.	L'aspetto è molto monumentale, ha ordine regolare di finestre architravate con timpano curvilineo, e finto bugnato agli angoli.	No	Sì

LangLearn: prompts and examples

Task name	Natural language instruction
LangLearn	Questi due testi separati da [SEP] sono presentati nell'ordine in cui sono stati scritti? Rispondi sì o no.

Istruzione: Questi due testi separati da [SEP] sono presentati nell'ordine in cui sono stati scritti? Rispondi sì o no.
Input: *Io e Luca siamo molto amici, ci conosciamo dall' asilo, siamo molto legati infatti certa gente ci invidia per la nostra grande amicizia. [SEP] Sono pronto a calciare la palla mi tremano le mani. Sono eccitato. Calcio, sento. Uno strappo alla gamba. Cado a Terra. Fuori la palla.*

Sì

LangLearn: error analysis

First Sentence	Second Sentence	Gold Standard	ExtremITLLaMA
I gruppi sono formati da amici, stretti tra loro da un legame di amicizia pura. Purtroppo questo legame anche quando è ben "saldo", anche per causa di un piccolo scherzo ..., il gruppo anche per il comportamento non adeguato di una persona potrebbe sciogliersi.	Sin dall'inizio l'uomo è nomade, si sposta in cerca di animali -per poi ricavarne carne,latte e pellicce- e in cerca di frutti e radici. Con il tempo il territorio sfruttato al massimo, si impoverì. ... Le tribù così diventarono sedentarie; cominciarono ad esplorare i territori dove vi erano insediati.	Sì	No
Il mio fratellino ha gli occhi azzurri come il cielo, dei capelli gialli come il sole, e la pelle bianca come il ghiaccio.	Un giorno due bambini si avventurarono in un bosco. Camminando i bambini si accorsero che si stava facendo buglio , ... Entrarono e videro otto bare, scapparono al piano di sopra e dal buglio spuntarono un esercito di zombi non morti.	No	Sì

Danilo Croce

MultiFake-Detective: prompts and error analysis

Task name	Natural language instruction
MultiFake-Detective	L'evento riportato nel testo è 'certamente vero', 'probabilmente vero', 'probabilmente falso', o 'certamente falso'?

Task name	Output Templates
MultiFake-Detective	{“Certamente Falso", “Probabilmente Falso", “Probabilmente Vero", “Certamente Vero"}

Input text	Gold Standard	ExtremITLLaMA
E niente gli sputa inchiostro dell' AnZa non riescono a dare una notizia senza cadere nella subdola propaganda. Il contestato è Letta colpevole di favorire l'invio di armi all'Ucraina e loro pubblicano una foto contro Putin. Buffoni!!! #buonafestadellaliberaZione https://t.co/wh9fY0UeVN	Probabilmente vero ?	Probabilmente Falso ?

Conclusions

9/22
(41%)

14/22
(64%)

- ✓ One architecture for all tasks
- ✓ Task-independent architecture
- ✓ Sequence to sequence
- ✓ Excellent performance
- ✓ Straightfoward NL prompts
- ✓ Task dependent prompts
- ✓ Code on GitHub and models on HuggingFace

- × Data hungry
- × GPUs and time hungry
- × Non satisfactory performance on all tasks:
  - × GeoLingIT
  - × LangLearn
  - × WiC-ITA

DANILO CROCE AND CLAUDIU D. HROMEI

Again…
Everything is very interesting… but

CHAPTER 6

FINE-TUNE A LLAMA-BASED MODEL FOR ALL TASKS FROM EVALITA 2023

Now: Let’s fine-tune an LLM

The objective is to take some data, transform it into a sequence to sequence format and train the model. The tutorial is split into 4 steps, reflecting the aforementioned process:

- Step 1 - Encoding the data
- Step 2 - Training the LLaMA model
- Step 3 - Inference: generating answers
- Step 4 - Deconding the data

LET'S CODE!

https://github.com/crux82/BISS-2024

Open in Colab

BISS-2024 Tutorial

LAB 2.2: Large Language Models and How to Instruction Tune Them (in a Sustainable Way)

Authors: C.D. Hromei & D. Croce

This is an implementation for training and using a Large Language Model (based on LLaMA) with instructions in order to solve the linguistic tasks of EVALITA. In this lab, we will see how to encode datasets from any format to a sequence to sequence format, train the model using Q-LoRA, perform the inference using the previous trained model for generating answers to instructions, and finally, how to encode back the data to the original format.. all of it using the only available *T4 GPU with 15GB from Google Colab*.

The tutorial is split into 4 steps, reflecting the aforementioned process:

- Step 1 - Encoding the data
- **Step 2 - Training the LLaMA model**
- Step 3 - Inference: generating answers
- Step 4 - Deconding the data

Index:

A not so comprehensive list here https://sapling.ai/llm/index

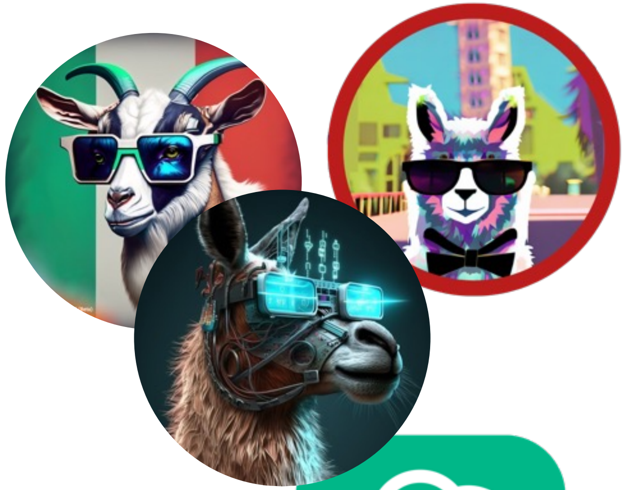
The wave of other «camelids»

Instruction-Tuned Models:

- Vicuna (03/2023)
- ColossalChat (03/2023)
- Koala (04/2023)
- Guanaco (05/2023)
- Orca (06/2023)
- LLaMA2Chat (07/2023)
- OpenChat (07/2023)
- Code-LLaMA (08/2023)
- Orca2 (11/2023)

Large Language Models:

- Colossal-LLaMA-2 (09/2023)
- Falcon (05/2023)
- LLaMA2 (07/2023)
- Mistral (09/2023)
- Zephyr (10/2023)
- CausalLM (10/2023)



...

A complete bibliography on LLMs

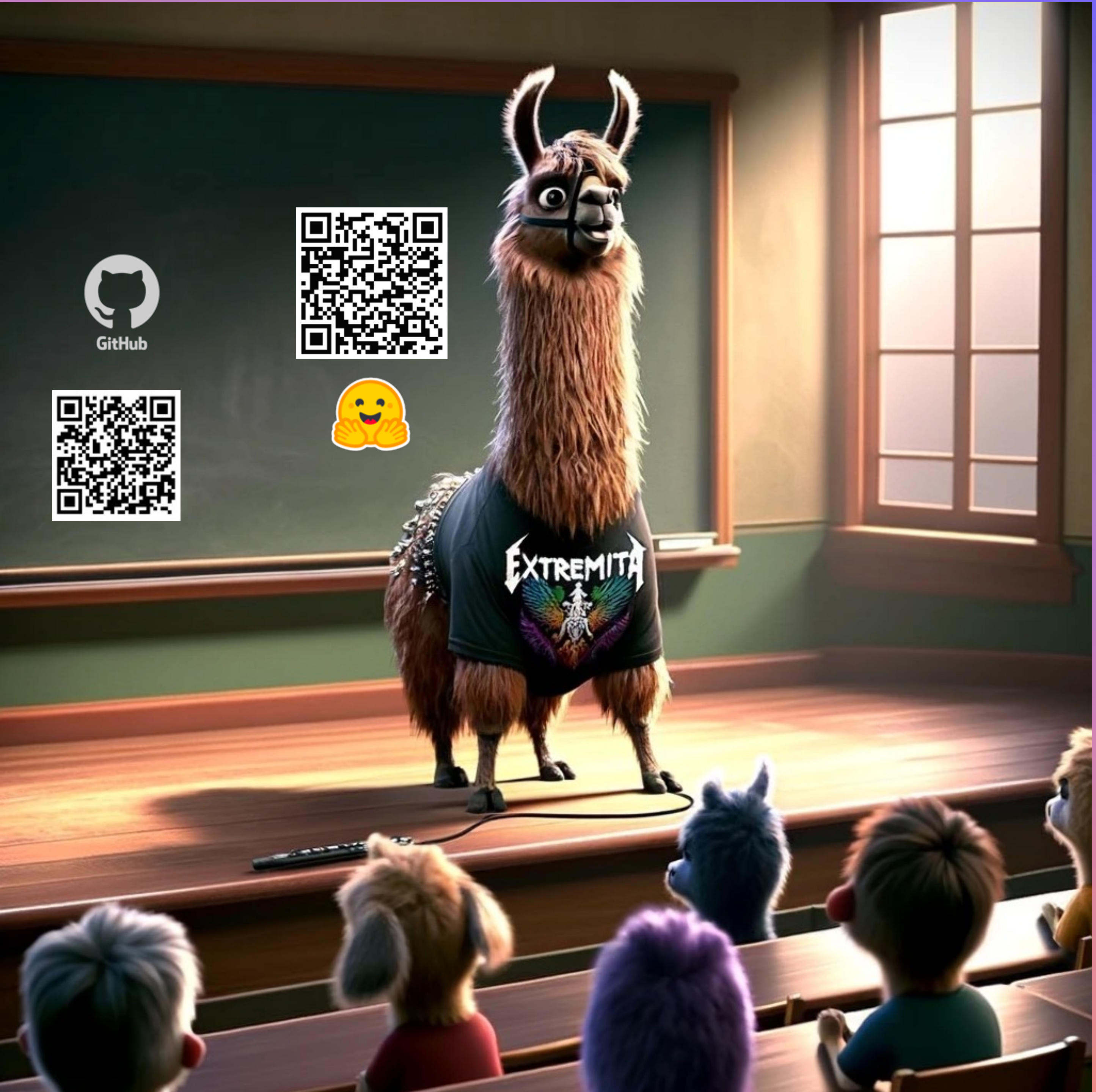
https://github.com/RUCAIBox/LLMSurvey

https://arxiv.org/pdf/2303.18223.pdf

A Survey of Large Language Models

Wayne Xin Zhao, Kun Zhou*, Junyi Li*, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, Yifan Du, Chen Yang, Yushuo Chen, Zhipeng Chen, Jinhao Jiang, Ruiyang Ren, Yifan Li, Xinyu Tang, Zikang Liu, Peiyu Liu, Jian-Yun Nie and Ji-Rong Wen

Abstract—Ever since the Turing Test was proposed in the 1950s, humans have explored the mastering of language intelligence by machine. Language is essentially a complex, intricate system of human expressions governed by grammatical rules. It poses a significant challenge to develop capable artificial intelligence (AI) algorithms for comprehending and grasping a language. As a major approach, *language modeling* has been widely studied for language understanding and generation in the past two decades, evolving from statistical language models to neural language models. Recently, pre-trained language models (PLMs) have been proposed by pre-training Transformer models over large-scale corpora, showing strong capabilities in solving various natural language processing (NLP) tasks. Since the researchers have found that model scaling can lead to an improved model capacity, they further investigate the scaling effect by increasing the parameter scale to an even larger size. Interestingly, when the parameter scale exceeds a certain level, these enlarged language models not only achieve a significant performance improvement, but also exhibit some special abilities (*e.g.,* in-context learning) that are not present in small-scale language models (*e.g.,* BERT). To discriminate the language models in different parameter scales, the research community has coined the term *large language models (LLM)* for the PLMs of significant size (*e.g.,* containing tens or hundreds of billions of parameters). Recently, the research on LLMs has been largely advanced by both academia and industry, and a remarkable progress is the launch of ChatGPT (a powerful AI chatbot developed based on LLMs), which has attracted widespread attention from society. The technical evolution of LLMs has been making an important impact on the entire AI community, which would revolutionize the way how we develop and use AI algorithms. Considering this rapid technical progress, in this survey, we review the recent advances of LLMs by introducing the background, key findings, and mainstream techniques. In particular,



THANK YOU FOR THE ATTENTION

CONTACTS

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https://github.com/crux82/ExtremITA

https://github.com/crux82/BISS-2024