55 AÑOS

PUCP
Departamento Académico de Ingeniería

IA PUCP

Fundamentos de Procesamiento de Lenguaje Natural

Summer Camp
en Inteligencia Artificial

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- Bachiller en Ingeniería de Computación y Sistemas: Universidad San Martín de Porres.
- Maestría en Informática con Mención en Ciencias de la Computación: Pontificia Universidad Católica del Perú.
- PhD. in Medical Image Analysis, Computer Vision and Machine Learning: The University of Adelaide.
- Current: Chief Scientist - Kashin

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Web: https://renato145.github.io

Índice

0. Some tools

- https://aistudio.google.com
- https://console.anthropic.com
- https://web2md.answer.ai/

1.

Intro

- IMDB challenge
- Classic methods for NLP
- Deep learning for NLP
- Language models
- Fine-tuning
- Transformer
- Large language models
- Future

1.1 Preguntas

Experiencia con:

- NLP?
- CV?
- DL?
- ML?
- Usando Llms?

1.2 Setup

- https://colab.google/
- https://github.com/renato145/pucp_bootcamp_202401

1.3 Que es NLP (Natural Language Processing)?

El Procesamiento de Lenguaje Natural (NLP) es un campo amplio abarca una variedad de tareas que incluyen:

- Part-of-speech tagging: etiquetado de sustantivos, verbos, adjetivos.
- Named entity recognition NER: identificar nombres de personas, organizaciones, ubicaciones.
- Question answering.
- Speech recognition.
- Topic modeling: identificar los temas principales en un conjunto de documentos.
- Sentiment classification: Determinar si un comentario es positivo, negativo o neutral.
- Language modeling: predecir la siguiente palabra.
- Translation.

1.4 NLP: un campo cambiante

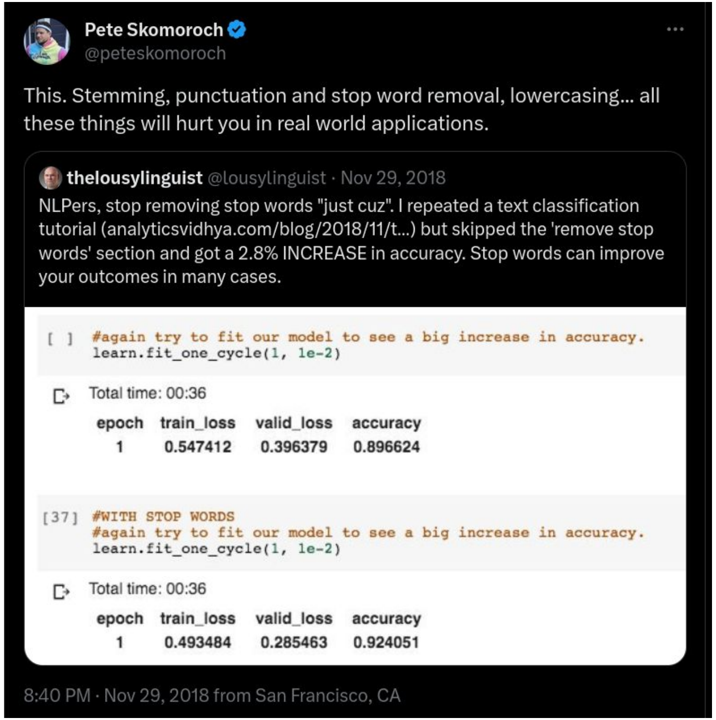
Case: spell checkers

Históricamente los correctores ortográficos han requerido miles de líneas de código para expresar reglas (Whitelaw et al., 2009).

Usando métodos estadísticos se puede escribir un corrector ortográfico en muchas menos líneas de código (norvig-spell-correct).

1.5 NLP: un campo cambiante

Case: best practices



Pete Skomoroch
@peteskomoroch

This. Stemming, punctuation and stop word removal, lowercasing... all these things will hurt you in real world applications.

thelousylinguist @lousylinguist · Nov 29, 2018
NLPers, stop removing stop words "just cuz". I repeated a text classification tutorial (analyticsvidhya.com/blog/2018/11/t...) but skipped the 'remove stop words' section and got a 2.8% INCREASE in accuracy. Stop words can improve your outcomes in many cases.

```
[ ]  #again try to fit our model to see a big increase in accuracy.
     learn.fit_one_cycle(1, 1e-2)
```

Total time: 00:36

epoch	train_loss	valid_loss	accuracy
1	0.547412	0.396379	0.896624

```
[37] #WITH STOP WORDS
     #again try to fit our model to see a big increase in accuracy.
     learn.fit_one_cycle(1, 1e-2)
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Total time: 00:36

epoch	train_loss	valid_loss	accuracy
1	0.493484	0.285463	0.924051

8:40 PM · Nov 29, 2018 from San Francisco, CA

link-to-tweet

1.6 NLP: complejidad

"She killed the man with the tie."

- Was the man wearing the tie?
- Or was the tie the murder weapon?

1.7 NLP: presente

- Large language models (LLMs)
- ChatGPT

1.8 NLP: futuro

- Accesibilidad
- Modelos abiertos
- Regulaciones
- Problemas éticos

1.9 Timeline

1997: LSTM (Hochreiter and Jürgen, 1997)

2007: Google translate: SMT

2011: IMDB dataset (Mass et. al., 2011)

2015: ImageNet (Russakovsky et. al., 2015)

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2017: ULMFiT (Howard and Ruder, 2018), Transformer architecture (Vaswani et al., 2017)

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2019: GPT-2 (Solaiman et al., 2019)

2020: GPT-3 (Brown et al., 2020)

2023: GPT-4

1.10 Librerías

- scikit-learn
- hugging-face
- PyTorch
- FastAI
- Axolotl

2.

Intro

IMDB challenge

Classic methods for NLP
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2.1 IMDB challenge

[Large Movie Review Dataset](#) (Mass et. al., 2011)

```
imdb_dataset['train'][99]
```

```
{'text': "This film is terrible. You don't really need to read this review further. If you are planning on watching
it, suffice to say - don't (unless you are studying how not to make a good movie).<br /><br />The acting is horrendo
us... serious amateur hour. Throughout the movie I thought that it was interesting that they found someone who speak
s and looks like Michael Madsen, only to find out that it is actually him! A new low even for him!!<br /><br />The p
lot is terrible. People who claim that it is original or good have probably never seen a decent movie before. Even b
y the standard of Hollywood action flicks, this is a terrible movie.<br /><br />Don't watch it!!! Go for a jog inste
ad - at least you won't feel like killing yourself.",
 'label': 0}
```

```
imdb_dataset['train'][-6]
```

```
{'text': "Very smart, sometimes shocking, I just love it. It shoved one more side of David's brilliant talent. He im
pressed me greatly! David is the best. The movie captivates your attention for every second.",
 'label': 1}
```

2.2 IMDB challenge

Features	PL04	Our Dataset	Subjectivity
Bag of Words (bnc)	85.45	87.80	87.77
Bag of Words (bΔt'c)	85.80	88.23	85.65
LDA	66.70	67.42	66.65
LSA	84.55	83.96	82.82
Our Semantic Only	87.10	87.30	86.65
Our Full	84.65	87.44	86.19
Our Full, Additional Unlabeled	87.05	87.99	87.22
Our Semantic + Bag of Words (bnc)	88.30	88.28	88.58
Our Full + Bag of Words (bnc)	87.85	88.33	88.45
Our Full, Add'l Unlabeled + Bag of Words (bnc)	88.90	88.89	88.13
Bag of Words SVM (Pang and Lee, 2004)	87.15	N/A	90.00
Contextual Valence Shifters (Kennedy and Inkpen, 2006)	86.20	N/A	N/A
tf.Δidf Weighting (Martineau and Finin, 2009)	88.10	N/A	N/A
Appraisal Taxonomy (Whitelaw et al., 2005)	90.20	N/A	N/A

Table 2: Classification accuracy on three tasks. From left to right the datasets are: A collection of 2,000 movie reviews often used as a benchmark of sentiment classification (Pang and Lee, 2004), 50,000 reviews we gathered from IMDB, and the sentence subjectivity dataset also released by (Pang and Lee, 2004). All tasks are balanced two-class problems.

3.

Intro
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3.1 Classic methods for NLP

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 'label': 0}
```

?

```
[0.96, 1.73, 0.67, 1.24, 0.41, 0.32, 0.68, 0.76, 0.56, 0.23, 0.92,
 0.53, 0.46, 0.35, 1.24, 0.89, 0.09, 1.06, 0.77, 1.11, 0.22, 1.92,
 2.22, 0.5 , 1.25, 1.2 , 1.06, 1.08, 0.19, 0.18, 0.69, 1.42, 0.6 ,
 0.36, 0.53, 0.74, 0.49, 0.66, 1.11, 0.86, 0.58, 0.13, 0.58, 1.08]
```

3.2 Classic methods for NLP

	Word 1	Word 2	Word 3	Word 4	Word 5	...
Document 1		5		4		
Document 2	1		2		1	
Document 3	2	3		2		
...						

3.3 Classic methods for NLP: TF-IDF

- TF: term-frequency.
- IDF: inverse document-frequency.

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Ej:

- El **término** “playa” aparece 10 veces en un **documento**.
- En el **documento** aparecen un total de 100 **términos**.

$$TF = \frac{10}{100} = 0.1$$

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- TF: term-frequency.
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Ej:

- El **término** “playa” aparece 10 veces en un **documento**.
- En el **documento** aparecen un total de 100 **términos**.
- Hay un total de 5000 **documentos.**
- El **término** “playa” aparece en 50 **documentos**.

$$TF = \frac{10}{100} = 0.1 \qquad IDF = \log(\frac{5000}{50}) = 2$$

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- TF: term-frequency.
- IDF: inverse document-frequency.

Ej:

- El **término** “playa” aparece 10 veces en un **documento**.
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$$TF = \frac{10}{100} = 0.1 \qquad IDF = \log(\frac{5000}{50}) = 2$$

$$\text{TF-IDF} = 0.1 * 2 = 0.2$$

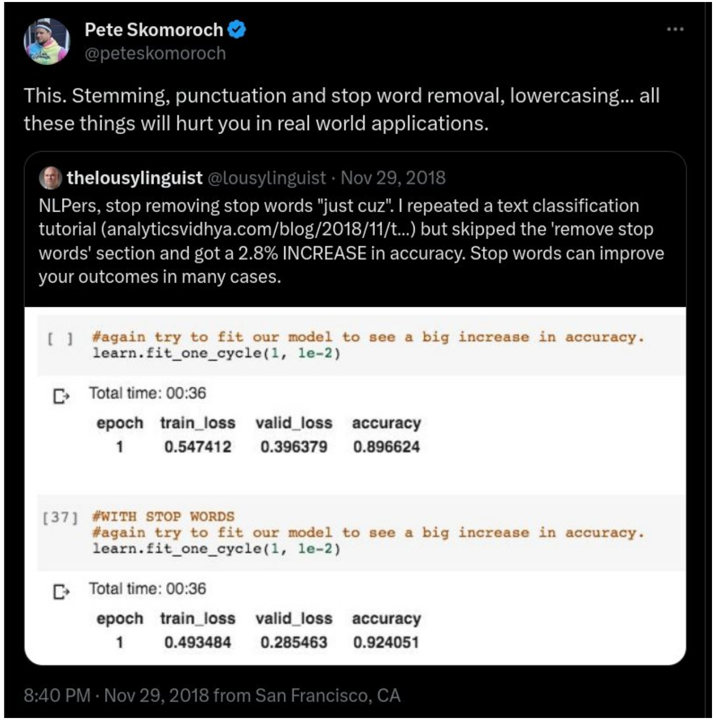
3.4 Classic methods for NLP: stemming and lemmatization

Reducir palabras a su raíz:

- **Lemmatization:** usa reglas del lenguaje, los resultados son palabras existentes.
- **Stemming** (poor-man's lemmatization)**:** corta la terminación de las palabras para aproximar la raíz de las palabras, los resultados pueden no ser palabras reales.

1.5 NLP: un campo cambiante

Case: best practices



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[link-to-tweet]

3.5 Classic methods for NLP: stemming and lemmatization

Librerías:

- NLTK (natural language toolkit)
- spacy

3.6 Classic methods for NLP

Notebook 1

4.

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4.1 Deep learning for NLP: embeddings

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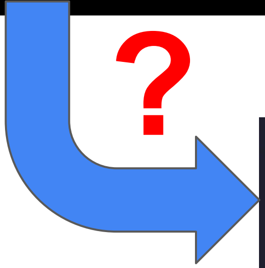


```
[0.96, 1.73, 0.67, 1.24, 0.41, 0.32, 0.68, 0.76, 0.56, 0.23, 0.92,
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```
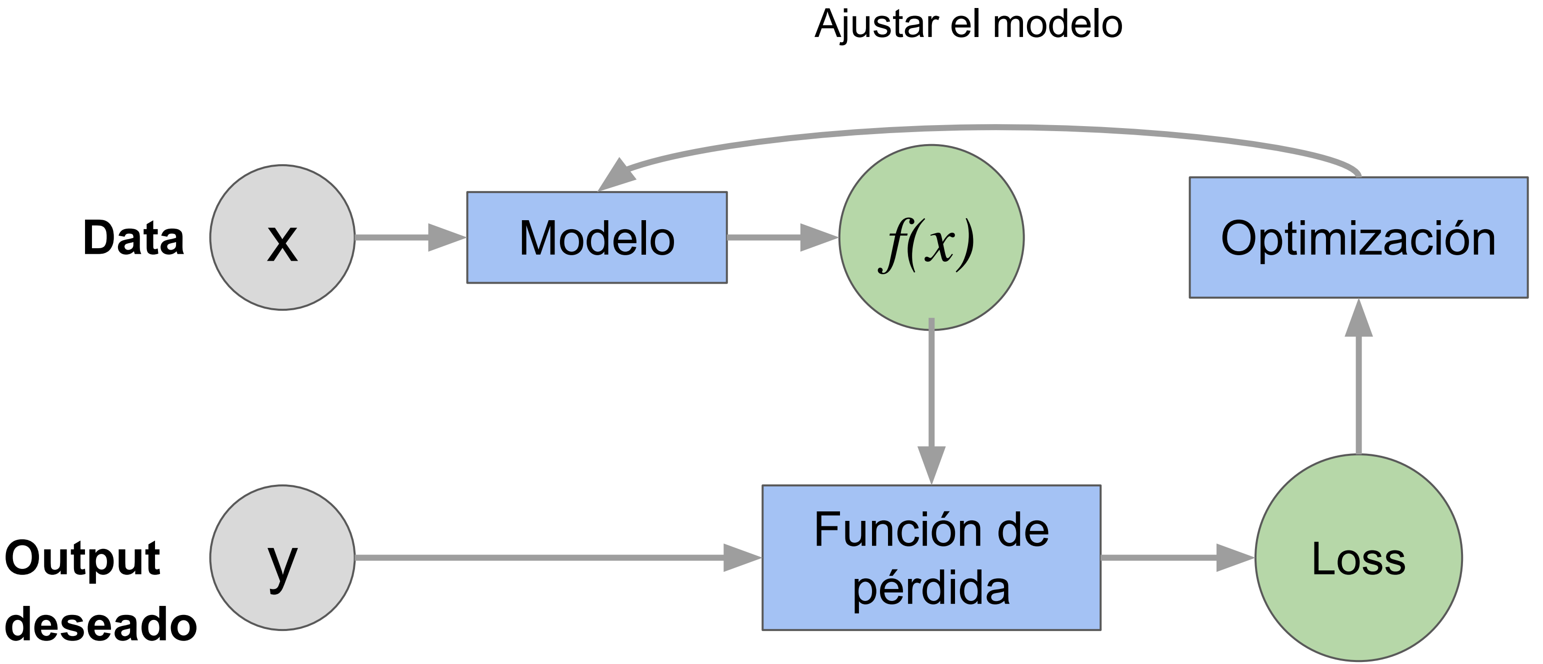

4.2 Deep learning for NLP: embeddings

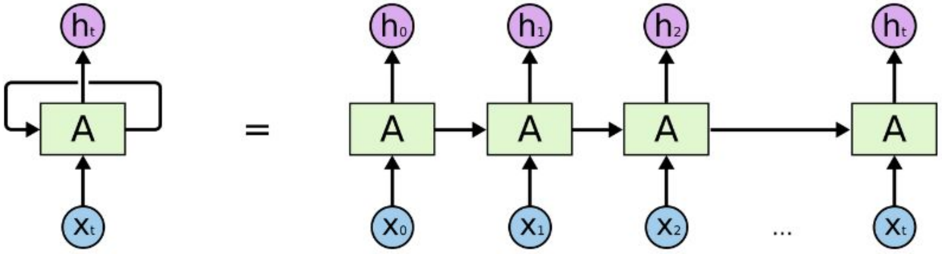
	x1	x2	x3	x4	x6	...
Token 1	0.86	0.41	0.49	0.13	0.72	
Token 2	1.03	0.34	0.31	0.25	0.69	
Token 3	0.77	0.13	0.05	0.31	0.64	
...						

4.3 Deep learning for NLP



4.4 Deep learning for NLP: RNN

Recurrent neural networks

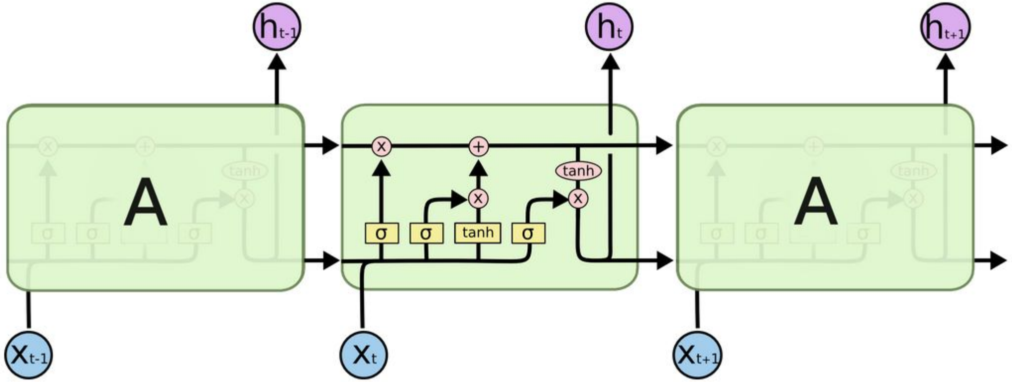


An unrolled recurrent neural network.

[Understanding LSTMs by Chris Olah]

4.5 Deep learning for NLP: LSTM

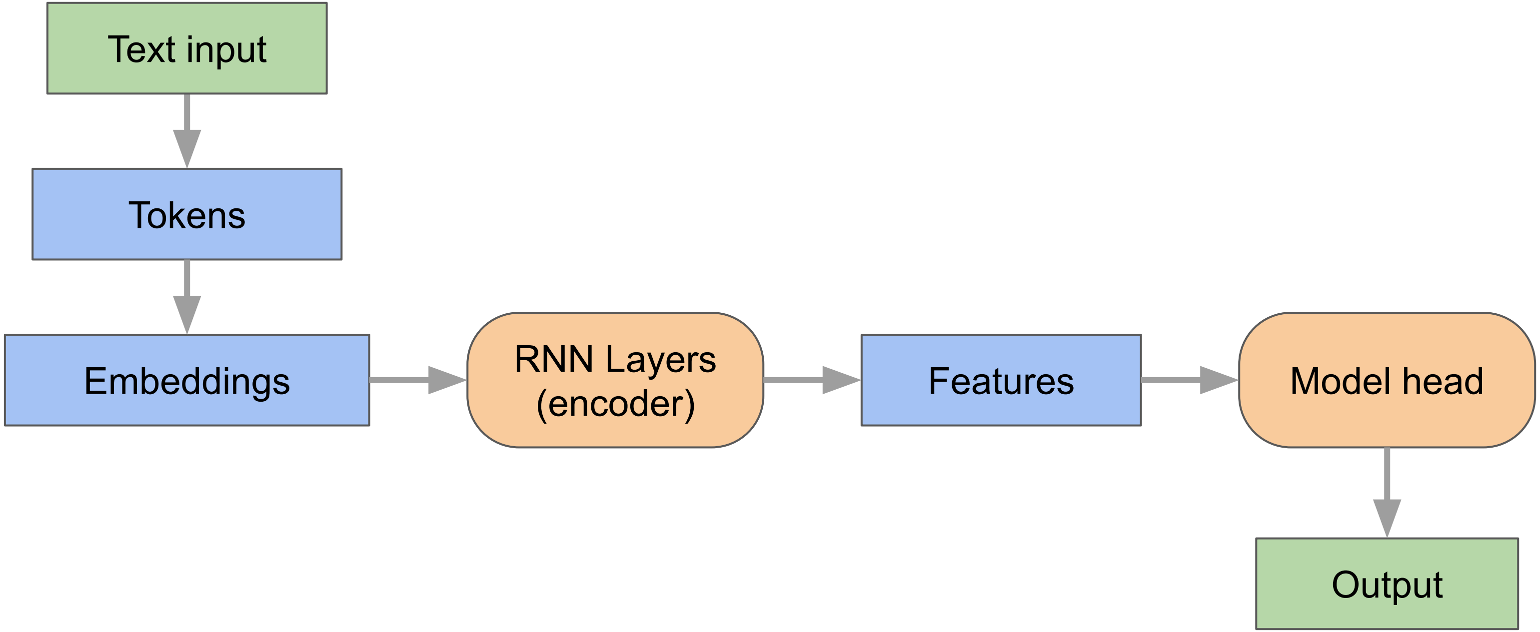
Long Short Term Memory (Hochreiter and Jürgen, 1997)



The repeating module in an LSTM contains four interacting layers.

[Understanding LSTMs by Chris Olah]

4.6 Deep learning for NLP: LSTM



4.7 Timeline

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2007: Google translate: SMT

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4.8 Deep learning for NLP

Notebook 2

5.

Language models

5.1 Language models

Tarea: estimar la siguiente palabra

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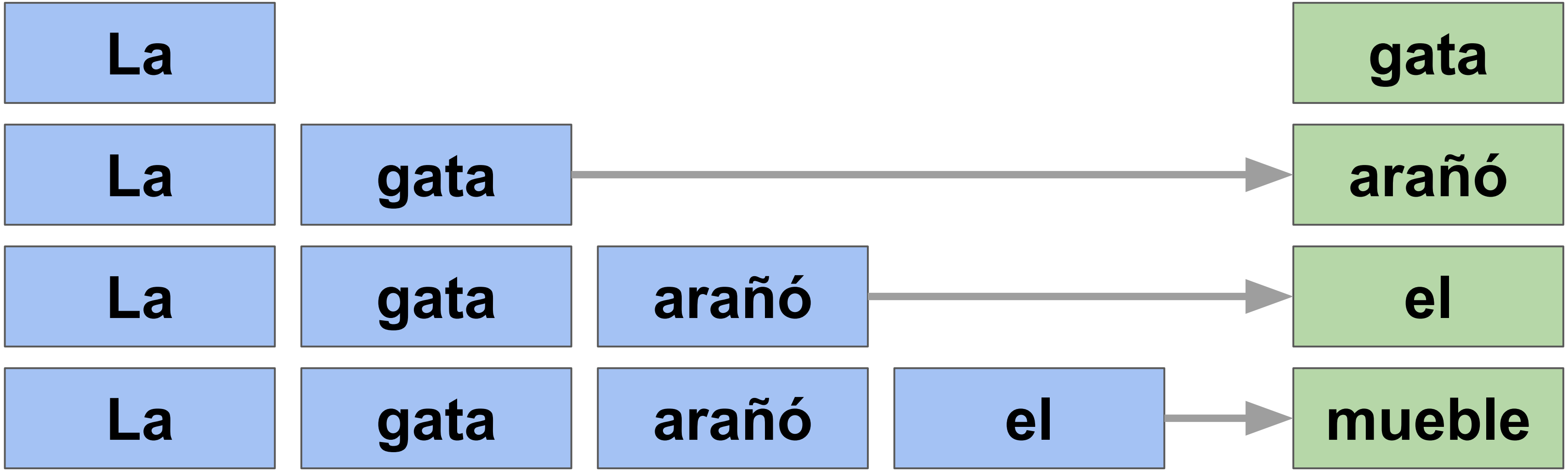
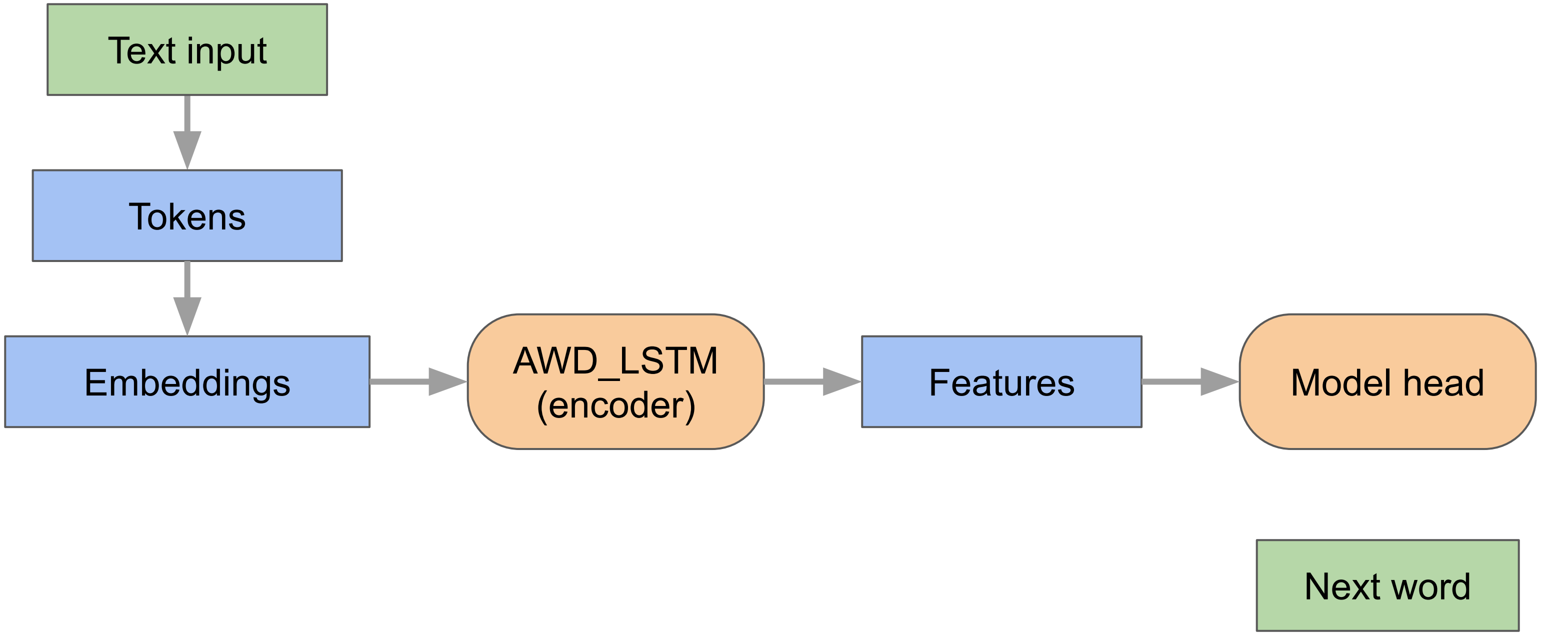
Tarea: estimar la siguiente palabra



5.2 Language models



5.3 Language models

Notebook 3

6.

Fine-tuning

6.1 Fine-tuning

ImageNet (Russakovsky et. al., 2015)

IMAGENET

- 1,000 object classes (categories).
- Images:
  - 1.2 M train
  - 100k test.

6.2 Fine-tuning

IMAGENET

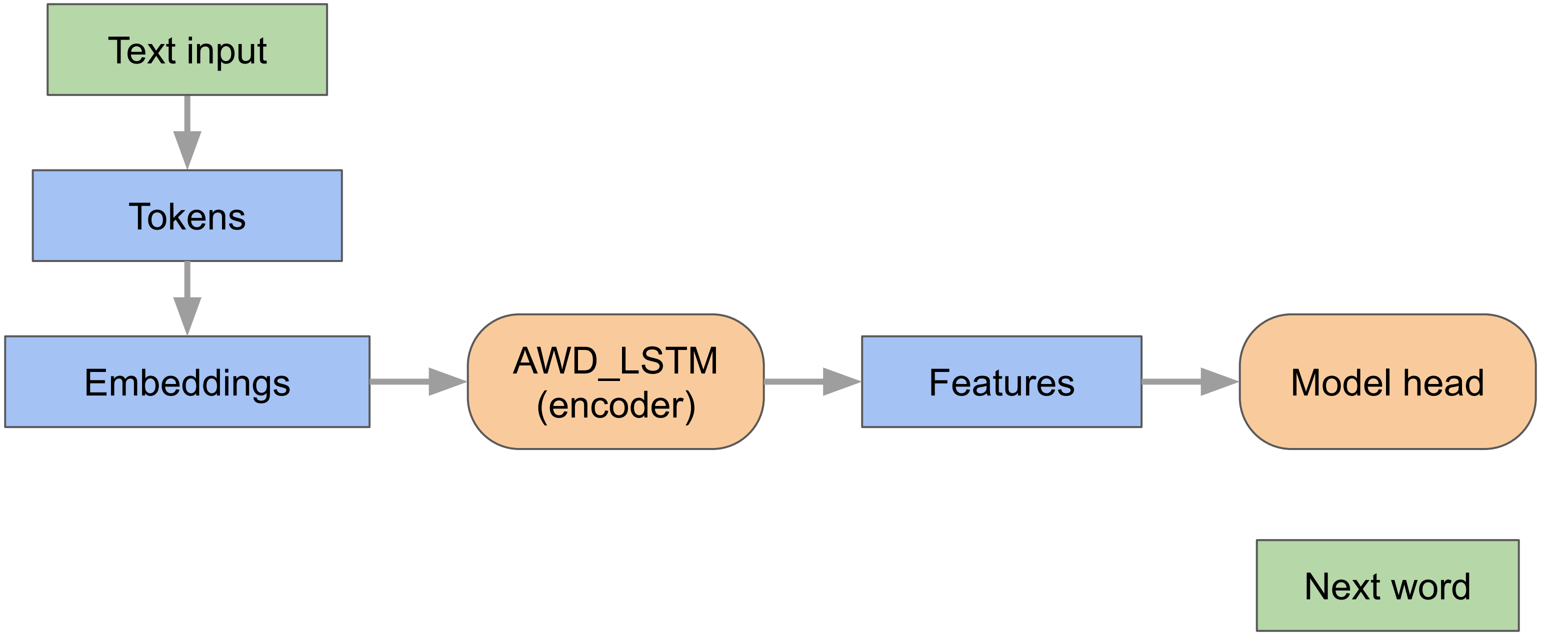
(Red pre-entrenada)

Convoluciones

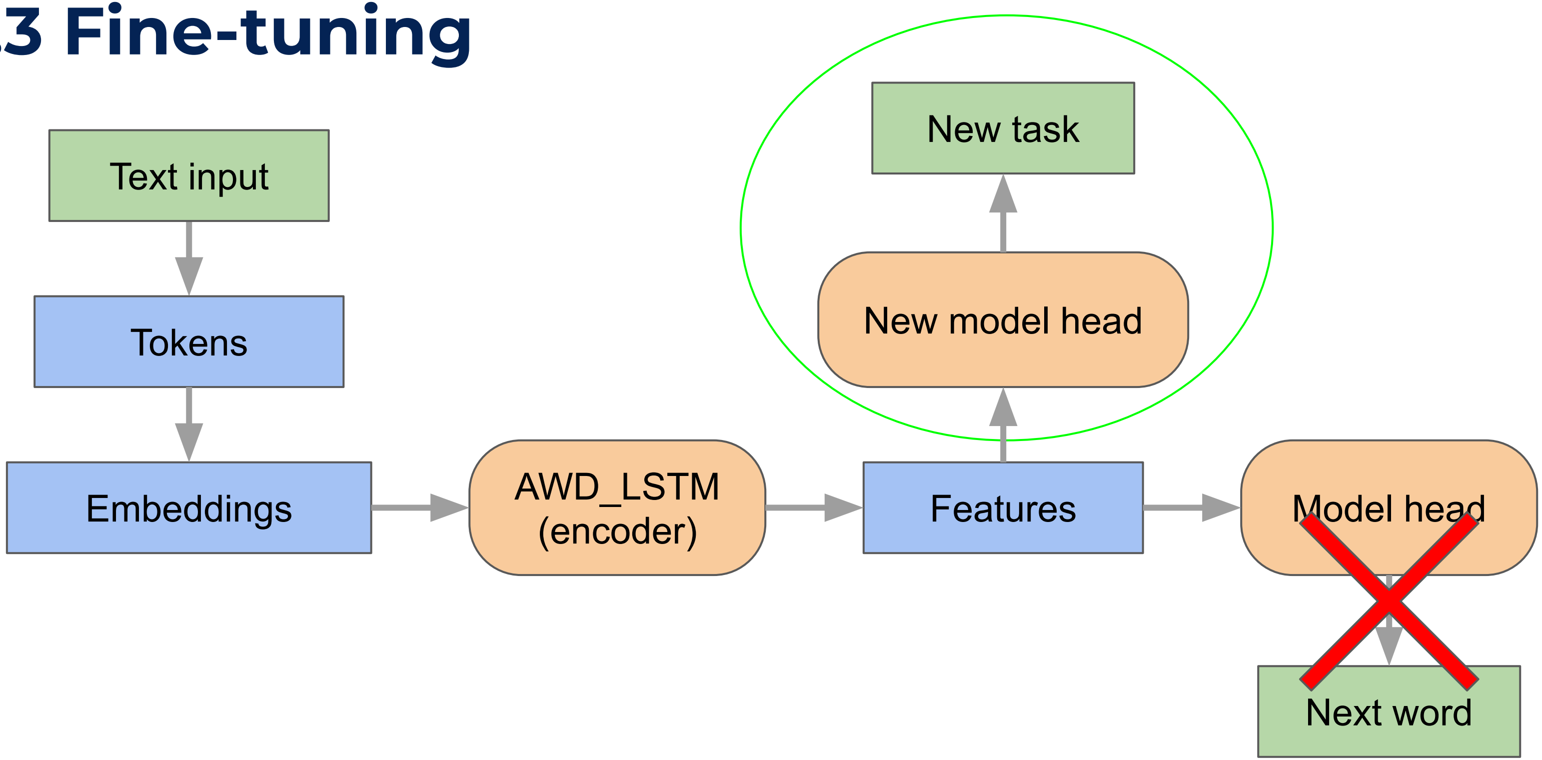
Features o Características

Clasificación
Segmentación
Detección
Survival
....

6.3 Fine-tuning



6.3 Fine-tuning



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6.5 Language models

Notebook 4

7.

Transformer

7.1 Transformers

Attention Is All You Need (Vaswani et al., 2017).

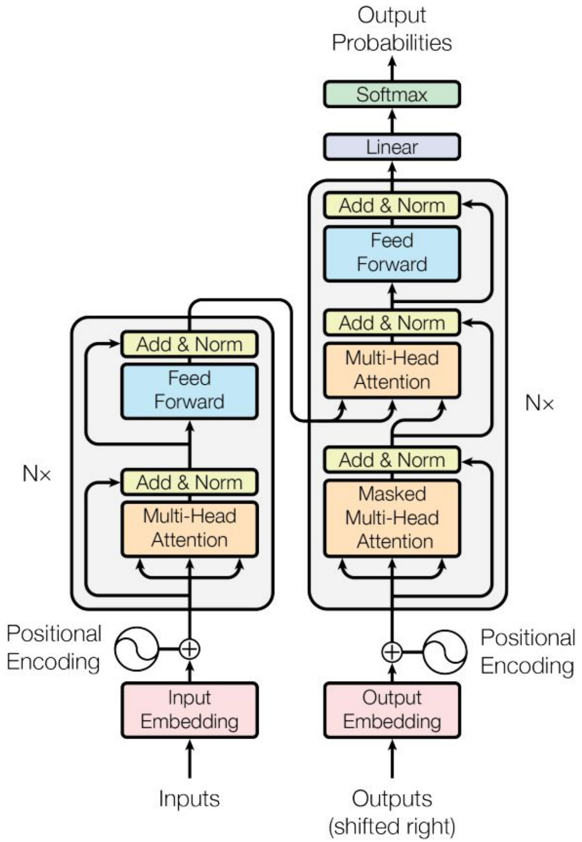

Figure 1: The Transformer - model architecture.

7.1 Transformers

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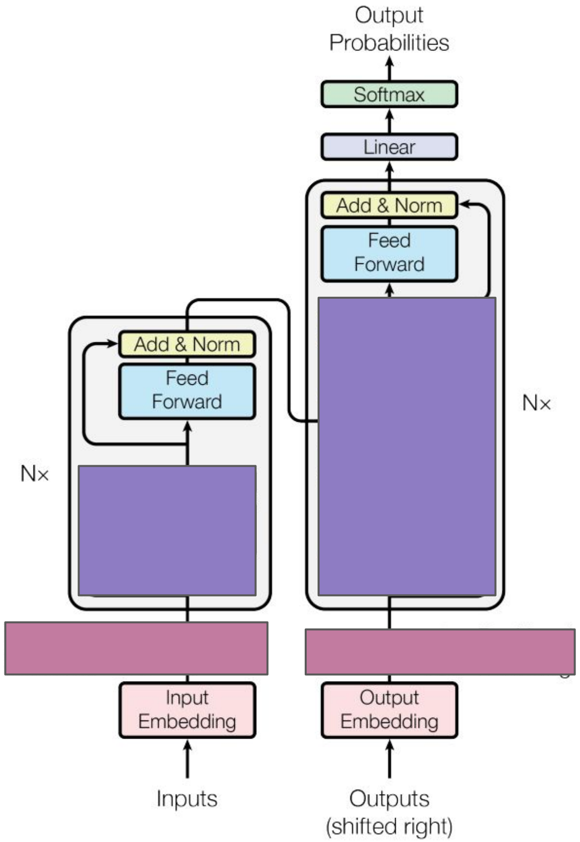

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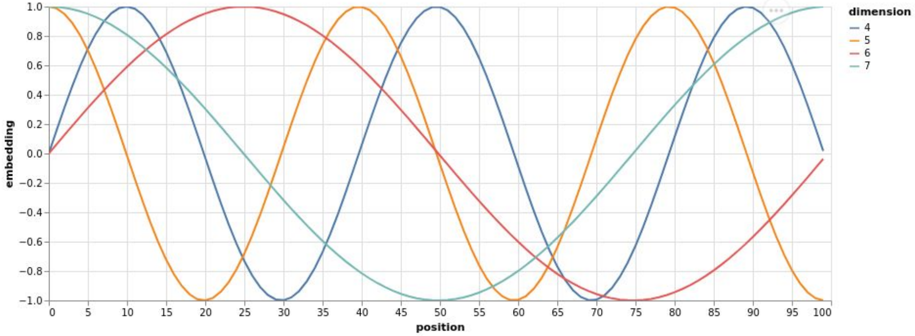
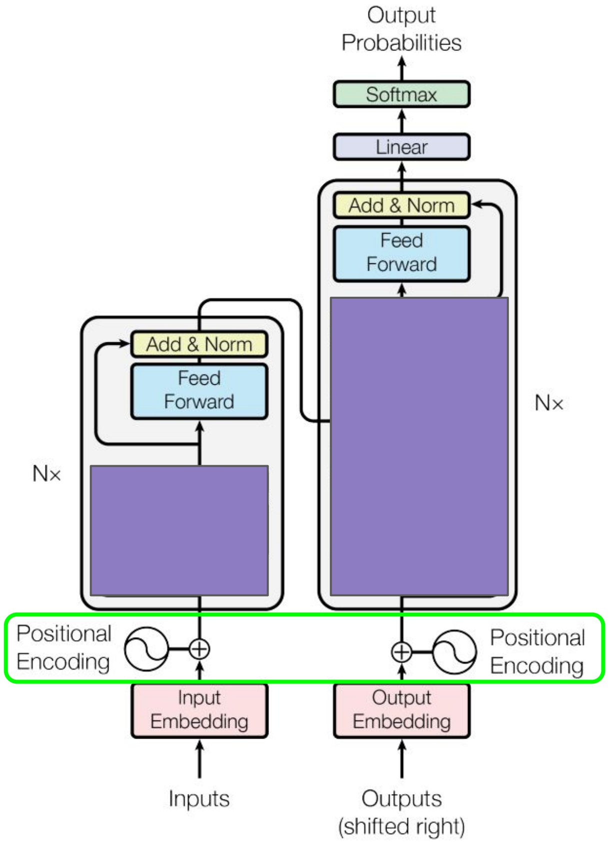


Source: [The annotated transformer]

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$



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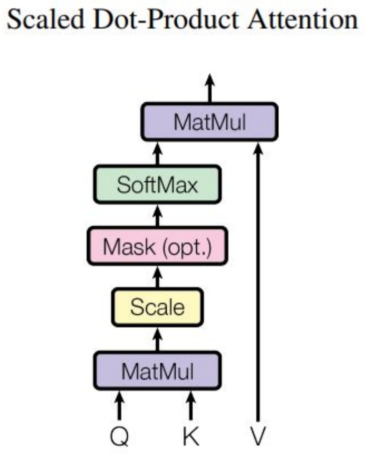
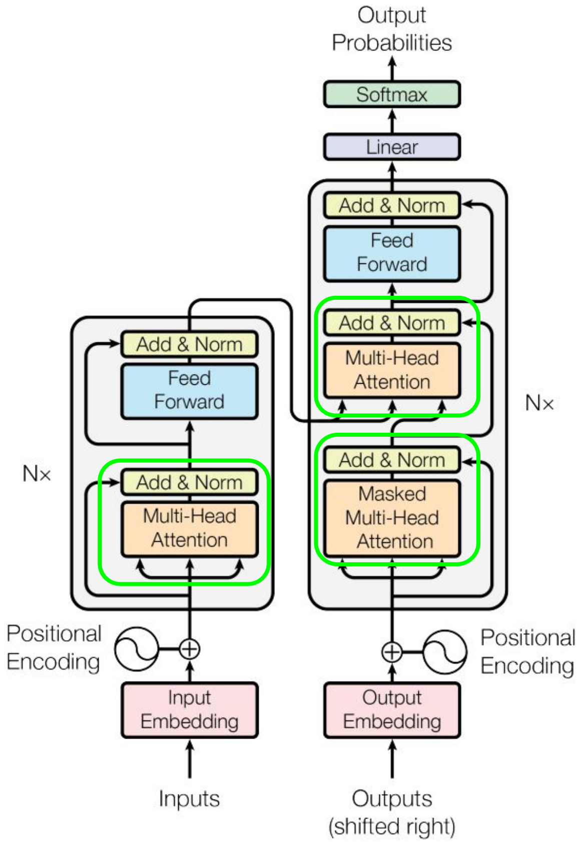


$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$



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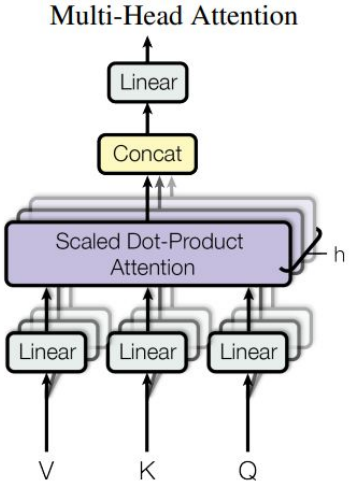
7.1 Transformers

Attention Is All You Need (Vaswani et al., 2017).



$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head_1}, ..., \mathrm{head_h})W^O$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

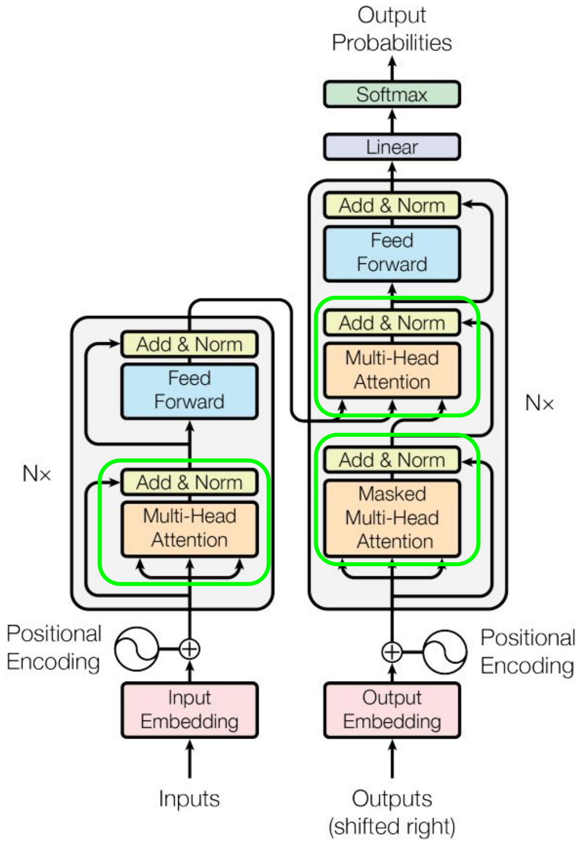
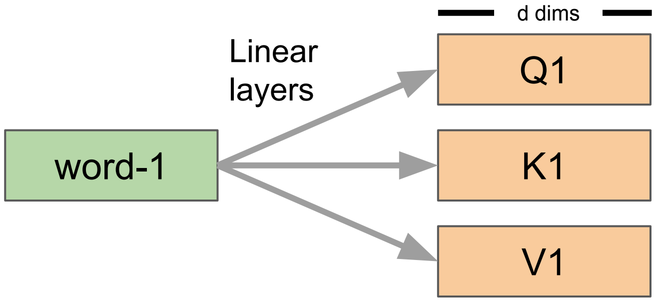


Figure 1: The Transformer - model architecture.

7.2 Transformers: attention

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



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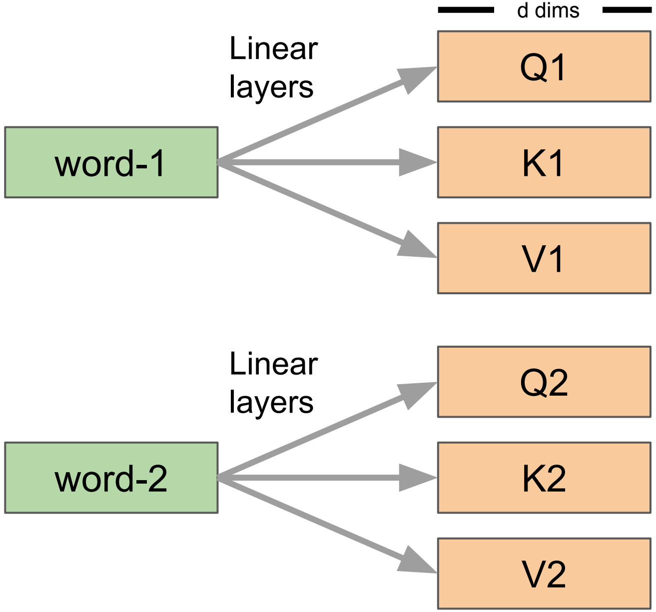

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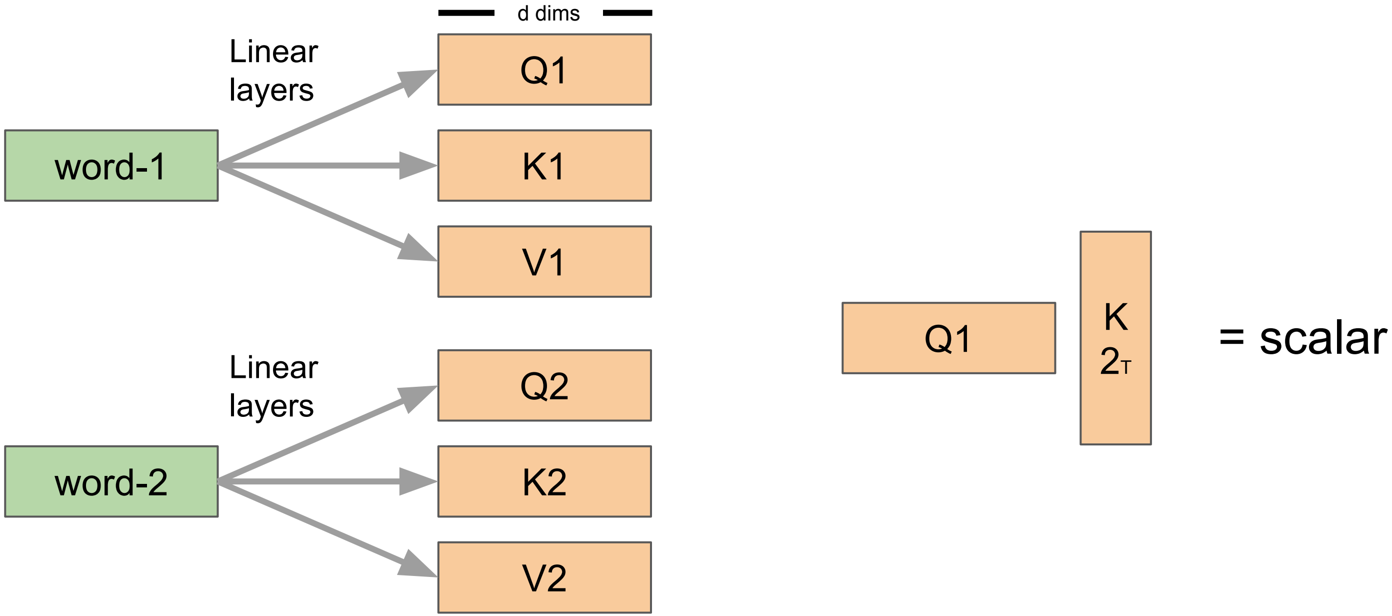

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$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

	word-1	word-2	word-3	word-4
word-1	x11	x12	x13	x14
word-2	x21	x22	x23	x24
word-3	x31	x32	x33	x34
word-4	x41	x42	x43	x44

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	word-1	word-2	word-3	word-4
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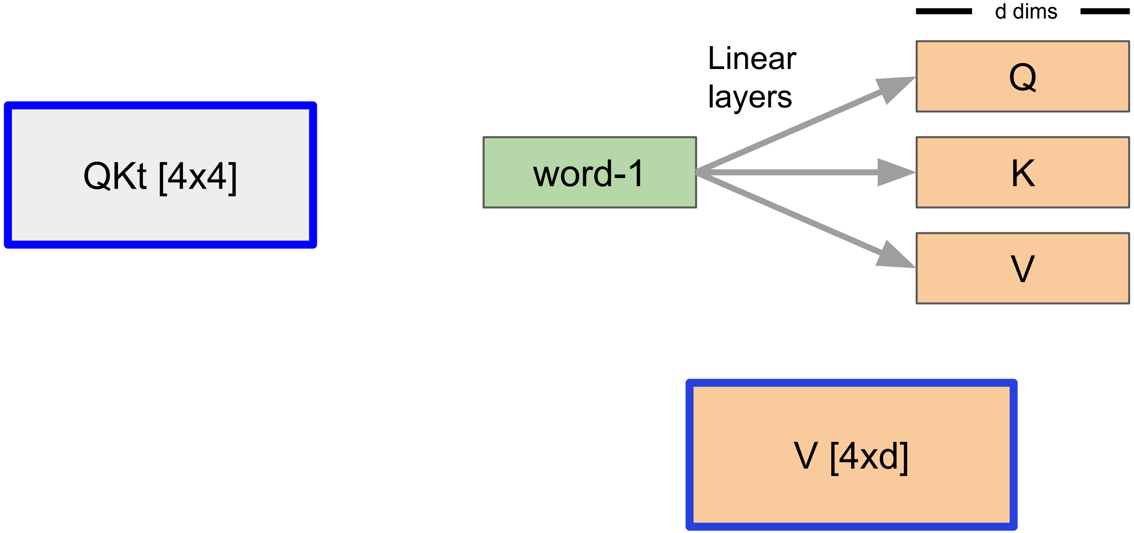
word-3	x31	x32	x33	x34
word-4	x41	x42	x43	x44

QKt [4x4]

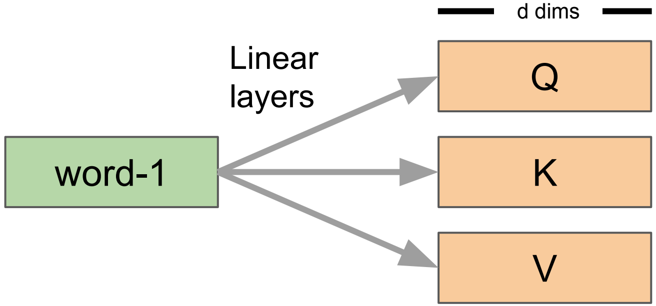
7.4 Transformers: attention

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



7.4 Transformers: attention

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$



QKt [4x4]

$\mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})$ [4x4]

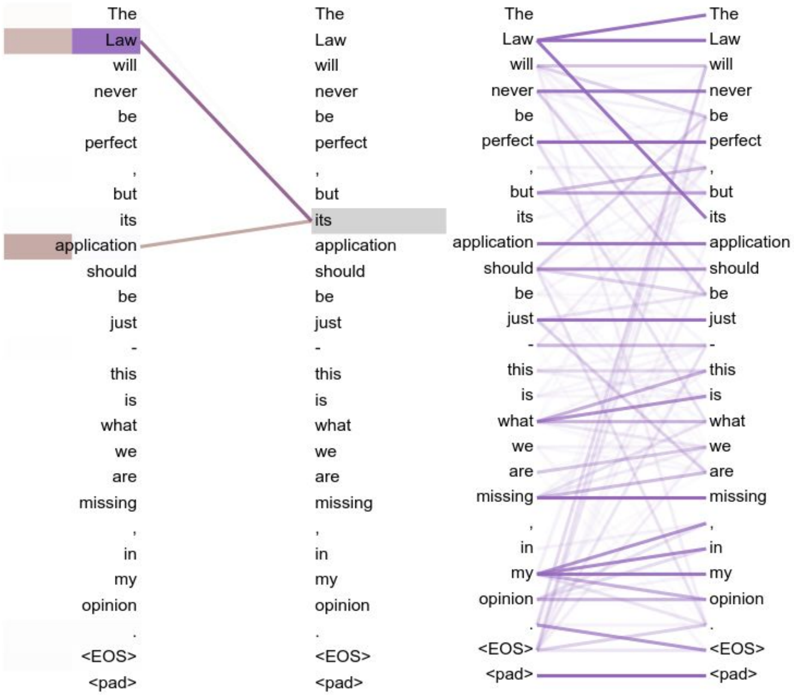
V [4xd]

7.4 Transformers: attention

$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

$\mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})$ [4x4] | V [4xd] $\rightarrow$ Attention [4xd]

7.5 Transformers: attention



From Vaswani et al., 2017.

7.6 Transformers

Input

word-1 word-2 word-3 word-4 word-5 ... word-n

7.6 Transformers

Input

word-1 | word-2 | word-3 | word-4 | word-5 | ... | word-n

Embeddings (eg: 50 dims), shape: [50, n]

embs-1 | embs-2 | embs-3 | embs-4 | embs-5 | ... | embs-n

7.6 Transformers

Input

word-1	word-2	word-3	word-4	word-5	...	word-n

Embeddings (eg: 50 dims), shape: [50, n]

embs-1	embs-2	embs-3	embs-4	embs-5	...	embs-n

Positional encoding, shape: [50, n]

embs+pos-1	embs+pos-2	embs+pos-3	embs+pos-4	embs+pos-5	...	embs+pos-n

7.6 Transformers

Input

word-1	word-2	word-3	word-4	word-5	...	word-n

Embeddings (eg: 50 dims), shape: [50, n]

embs-1	embs-2	embs-3	embs-4	embs-5	...	embs-n

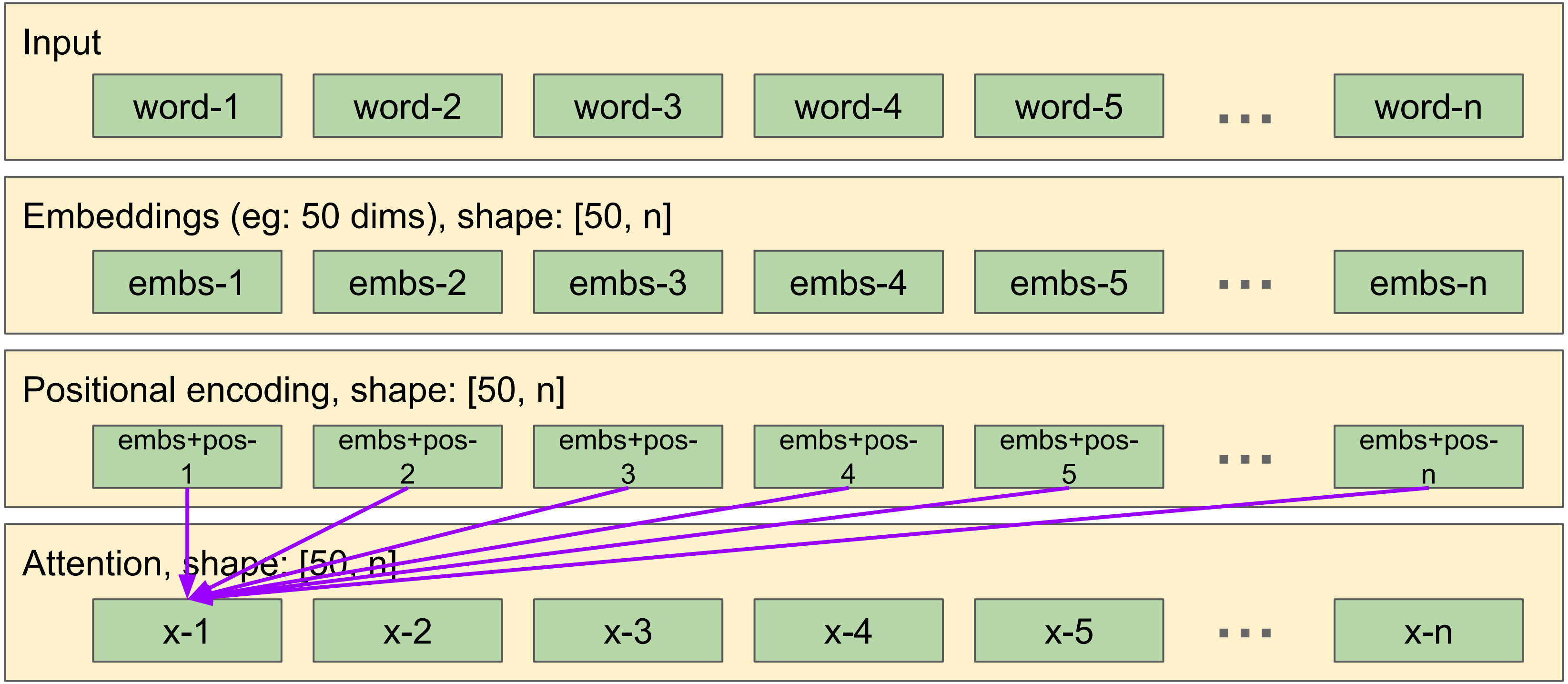
Positional encoding, shape: [50, n]

embs+pos-1	embs+pos-2	embs+pos-3	embs+pos-4	embs+pos-5	...	embs+pos-n

Attention, shape: [50, n]

x-1	x-2	x-3	x-4	x-5	...	x-n

7.6 Transformers



7.7 Transformers

Attention Is All You Need (Vaswani et al., 2017).

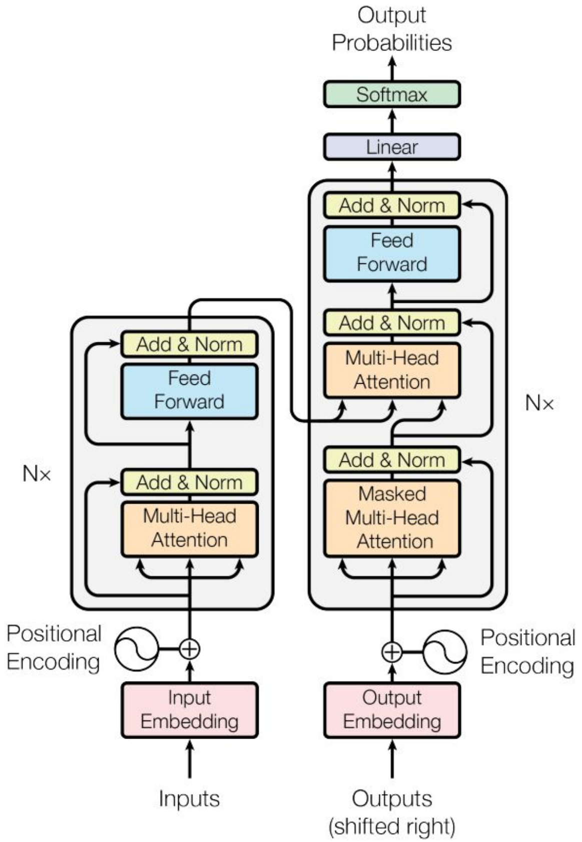


Figure 1: The Transformer - model architecture.

7.8 Timeline

1997: LSTM (Hochreiter and Jürgen, 1997)

2007: Google translate: SMT

2011: IMDB dataset (Mass et. al., 2011)

2015: ImageNet (Russakovsky et. al., 2015)

2016: Google translate: GNMT

2017: ULMFiT (Howard and Ruder, 2018), **Transformer architecture** (Vaswani et al., 2017)

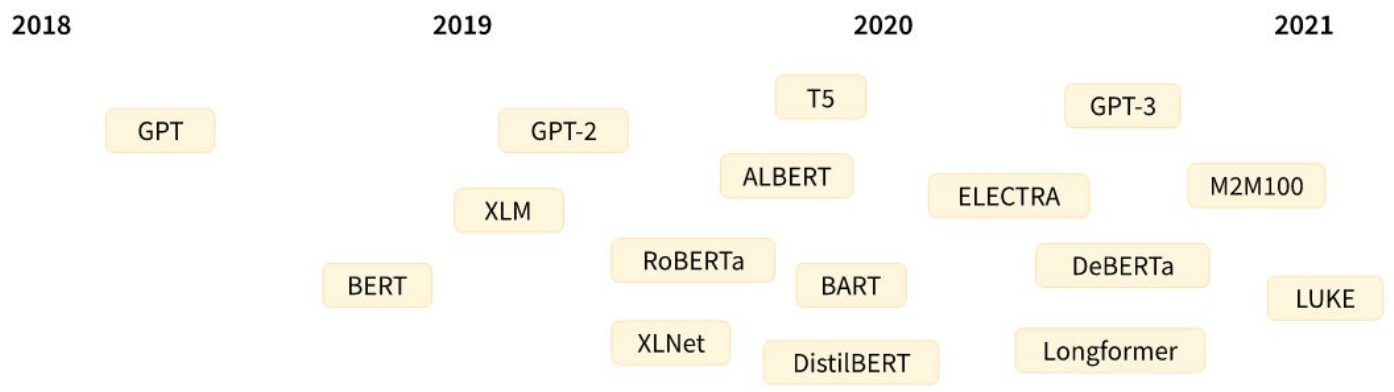
2018: ELMo (Peters et al., 2018), **GPT-1** (Radford et al., 2018)

2019: GPT-2 (Solaiman et al., 2019)

2020: GPT-3 (Brown et al., 2020)

2023: GPT-4

7.9 Transformers



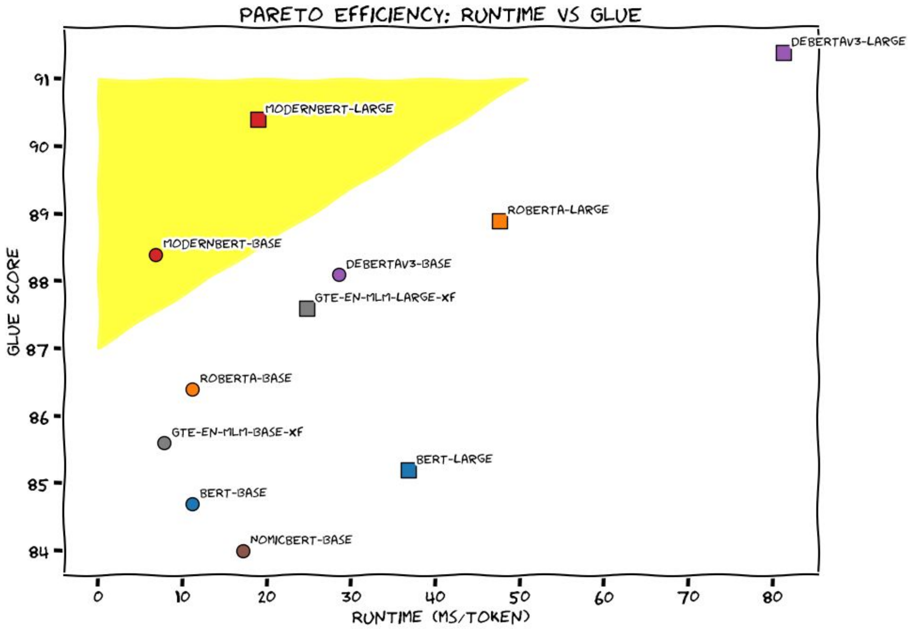
From Hugging-Face.

7.10 Transformers

Notebook 5

7.11 Modern Bert

https://huggingface.co/blog/modernbert



7.11 Modern Bert

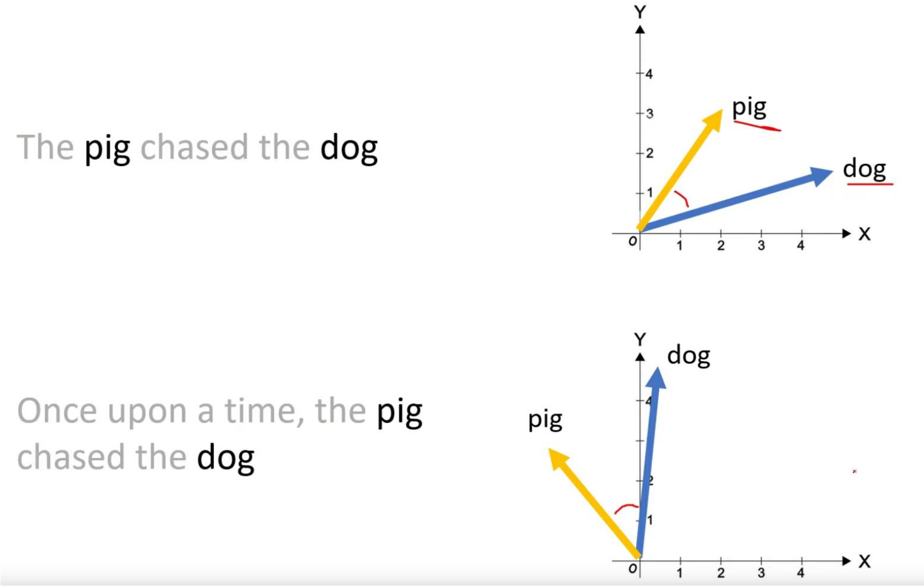
https://huggingface.co/blog/modernbert

Principales mejoras:

- **RoPE:** Rotary Positional Embeddings (detalles).
- Alternating Attention.

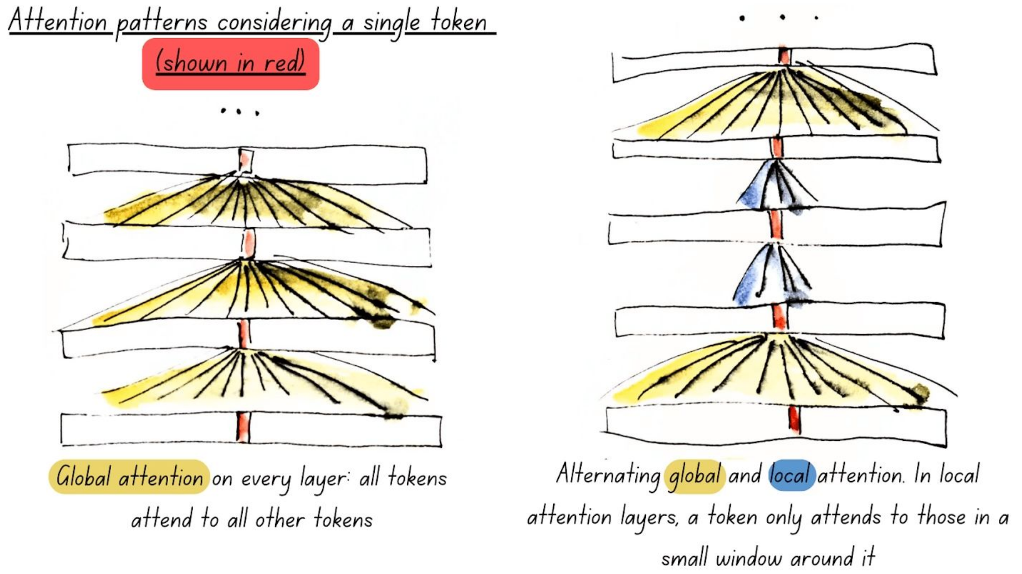
7.11 Modern Bert

RoPE: Rotary Positional Embeddings (detalles).



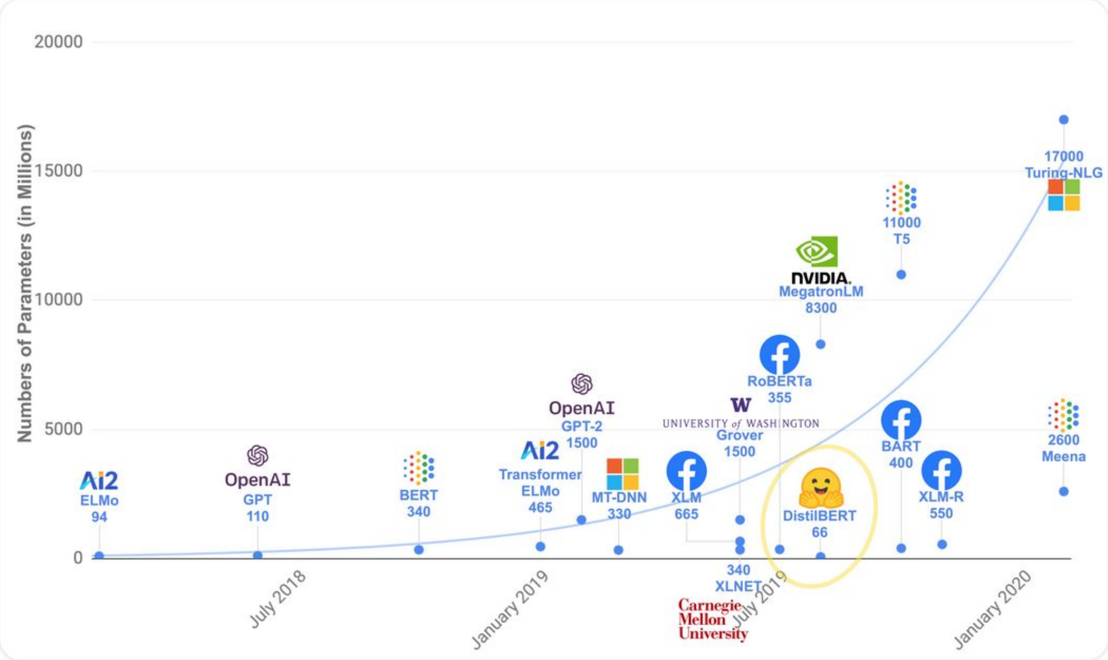
7.11 Modern Bert

Alternating Attention.



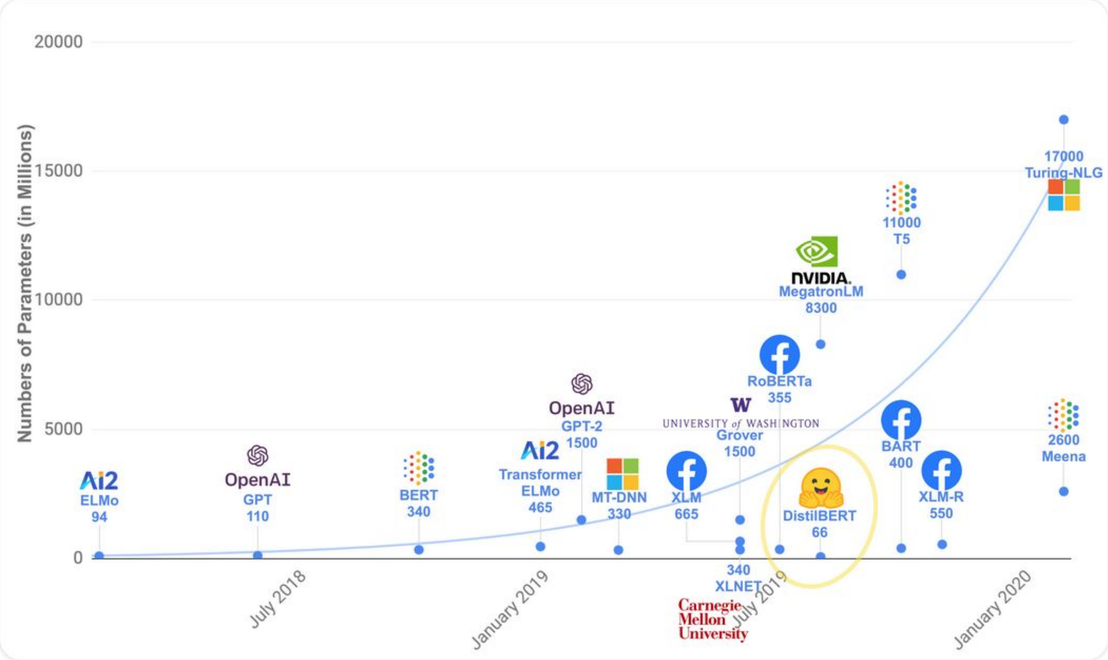
8. Large language models

8.1 Large language models



From Hugging-Face.

8.1 Large language models



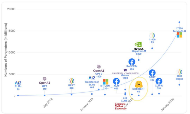
- GPT-3 (175 billion parameters)

From Hugging-Face.

8.1 Large language models

GPT-4 (1.76 trillion parameters)

GPT-3 (175 billion parameters)



From Hugging-Face.

8.2 Large language models

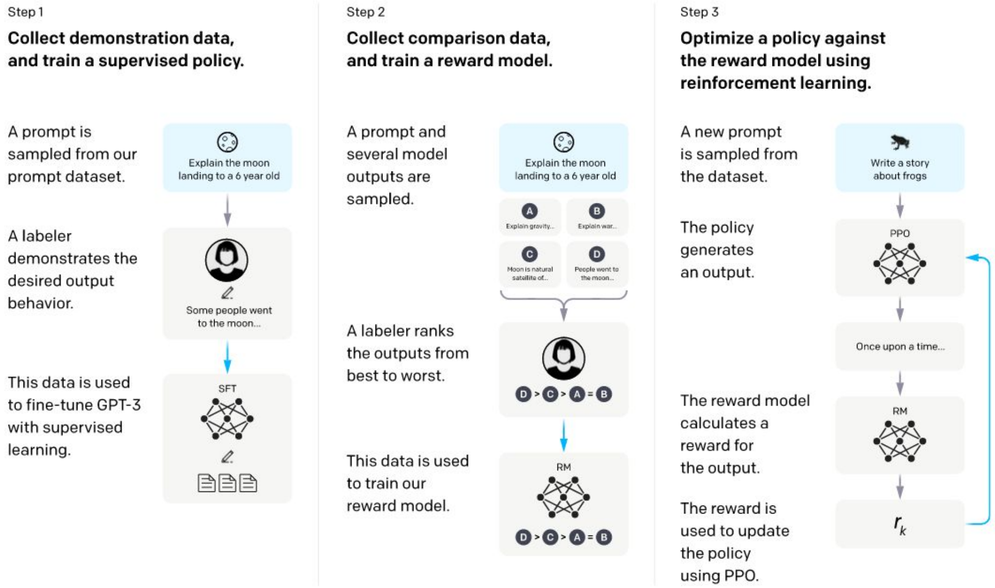
Instruction tuning datasets:

- https://huggingface.co/datasets/Open-Orca/OpenOrca
- https://huggingface.co/datasets/Anthropic/hh-rlhf

id string · *lengths* 4 12	system_prompt string · *classes* 17 values	question string · *lengths* 12 40.6k	response string · *lengths* 0 15k
niv.242684		You will be given a definition of a task first, then some input of the task. This task is about using the specified…	[["AFC Ajax (amateurs)", "has ground", "Sportpark De Toekomst"], ["Ajax Youth Academy", "plays at", "Sportpark…
flan.564327	You are an AI assistant. You will be given a task. You must generate a detailed and long answer.	Generate an approximately fifteen-word sentence that describes all this data: Midsummer House eatType…	Midsummer House is a moderately priced Chinese restaurant with a 3/5 customer rating, located near All Bar One.
flan.1875913	You are a helpful assistant, who always provide explanation. Think like you are answering to a five year…	What happens next in this paragraph? She then rubs a needle on a cotton ball then pushing it onto a pencil and wrappin…	C. She then dips the needle in ink and using the pencil to draw a design on her leg, rubbing it off with a rag in the…
t0.408370	You are an AI assistant. You will be given a task. You must generate a detailed and long answer.	Please answer the following question: I want to test the ability of students to read a passage and answer questions…	Based on the passage, discuss the primary motivations and outcomes of the 1901 Federation of Australia, including th…
cot.86217	You are an AI assistant that helps people find information.	James runs a TV show and there are 5 main characters and 4 minor characters. He pays the minor characters $15,000 eac…	James pays the minor characters $15,000 each episode. Since there are 4 minor characters, he pays them a total of 4 *…
cot.18180	You are an AI assistant that helps people find information.	Given the stream of consciousness rationale, provide a reasonable question and answer. Rationale: Here the game…	Question: What is the proper technique for a female beach volleyball player to serve the ball effectively in a game?…
flan.2136716	You are an AI assistant. User will you give you a task. Your goal is to complete the task as faithfully as you can…	Multi-choice question: What is the sentiment of the following tweet? Tweet: @nikkigreen I told you Choose your…	To determine the sentiment of the tweet, we need to analyze it thoroughly. Tweet: @nikkigreen I told you Step 1:…
cot.84626	You are an AI assistant that helps people find information. User will you give you a question. Your task is to answer…	John was a terrible writer. To practice, his teacher suggest that he consider people he knows and do what?…	Step 1: Analyze the situation - John is a terrible writer and needs practice to improve his skills. His teacher give…

8.3 Large language models

RLHF: Reinforcement Learning from Human Feedback (Christiano et al., 2017).



From OpenAI.

8.4 Large language models

DPO: Direct Preference Optimization (Rafailov, Rafael, et al. 2024).

prompt string · *lengths* 10 1.99k	initial_reason_steps string · *lengths* 33 2.35k	chosen string · *lengths* 15 2.57k	rejected string · *lengths* 14 3.72k
In the month of July, the bookstore has a…	Let's think step by step. Step 1:	Find the dates on which both stores have sales. The bookstore has a sal…	Find the dates when the shoe store has …
Two different prime numbers between 4 an…	Let's think step by step. Step 1: Choosing two different prime numbers…	Comparing the results with the given options. Comparing the results with…	Comparing the results with the…
If $h(x) = x^3 + f(x)$ where $f(x) = 2x^2 - 3…	Let's think step by step. Step 1: First, we need to find $g(1)$ and…	We are given that $g(x) = x^2 - 2x + 3$. So, to find $g(1)$, we…	Given $g(x) = 2x - 3$, we can find…
If Jeremy played a three-letter word on a…	Let's think step by step. Step 1: The word is a three-letter word, and the…	The word score was tripled to earn 30 points, so the original word…	The word score was tripled to earn 30…
Let $A=2+i$, $B=3-2i$, $O=-4$, $P=-i$,…	Let's think step by step. Step 1: First, we need to find the sum of all…	Let's add all the complex numbers together. First, add A and B: $…	First, let's add all the given complex…
Hannah aims to achieve the highest grade in…	Let's think step by step. Step 1: Determine the score for the student…	Determine how many questions Hannah needs to answer correctly to surpas…	Determine how many questions Hannah…

https://huggingface.co/datasets/xinlai/Math-Step-DPO-10K

8.5 Timeline

1997: LSTM (Hochreiter and Jürgen, 1997)

2007: Google translate: SMT

2011: IMDB dataset (Mass et. al., 2011)

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2019: GPT-2 (Solaiman et al., 2019)

2020: GPT-3 (Brown et al., 2020)

2023: GPT-4

8.6 Large language models

Notebook 6

8.8 Large language models

https://github.com/axolotl-ai-cloud/axolotl

Usage

```
# preprocess datasets - optional but recommended
CUDA_VISIBLE_DEVICES="" python -m axolotl.cli.preprocess examples/openllama-3b/lora.yml

# finetune lora
accelerate launch -m axolotl.cli.train examples/openllama-3b/lora.yml

# inference
accelerate launch -m axolotl.cli.inference examples/openllama-3b/lora.yml \
    --lora_model_dir="./outputs/lora-out"

# gradio
accelerate launch -m axolotl.cli.inference examples/openllama-3b/lora.yml \
    --lora_model_dir="./outputs/lora-out" --gradio
```

9.

Future

9.1 Future

https://www.fast.ai/p osts/2023-09-04-learning-jumps/

Can LLMs learn from a single example?

We've noticed an unusual training pattern in fine-tuning LLMs. At first we thought it's a bug, but now we think it shows LLMs can learn effectively from a single example.

TECHNICAL

Loss chart from 3 epoch training on Kaggle comp

9.2 Future

Open source LLMs:

- https://huggingface.co/
- https://ai.meta.com/llama/
- https://mistral.ai/

9.3 Future

https://www.nytimes.com/es/2023/12/27/espanol/new-york-times-demanda-openai-microsoft.html

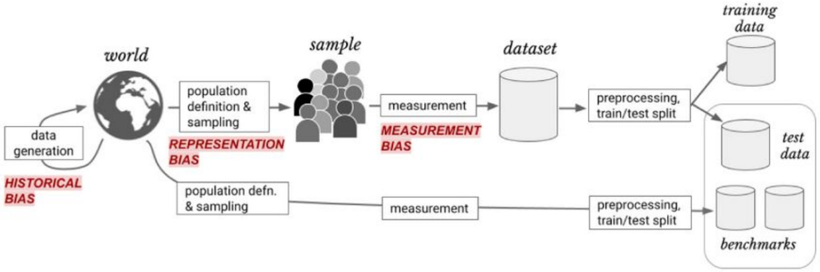
The New York Times

The New York Times demanda a OpenAI y Microsoft por el uso de obras con derechos de autor en la IA

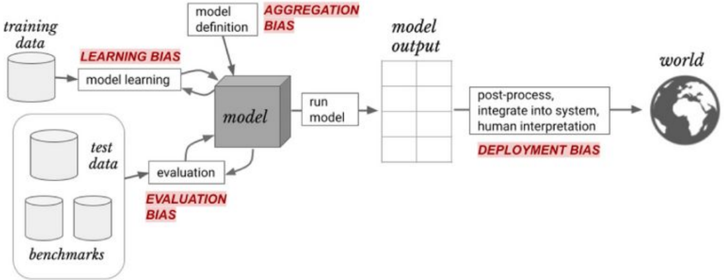
Millones de artículos del diario fueron empleados para entrenar chatbots que ahora representan una competencia para el medio de comunicación, según la demanda.

9.4 Future

"A framework for understanding unintended consequences of machine learning." (Suresh and Guttag, 2019).



(a) Data Generation



(b) Model Building and Implementation

9.5 Future

Algorithmic Bias

- Computers make mistakes.
- Unjust algorithmic bias is one of those mistakes.
- Machine learning involves algorithms learning from data– that data is often biased.
- Algorithmic systems are disproportionately used on the poor.

The privileged are processed by people; the poor are processed by algorithms. -- Cathy O'Neil, Weapons of Math Destruction

Algorithms are used differently than human decision makers:

- People are more likely to assume algorithms are **objective or error-free** (even if they're given the option of a human override)
- Algorithms are more likely to be implemented with **no appeals process** in place.
- Algorithms are often used **at scale**.
- Algorithmic systems are **cheap.**

9.6 Future

Technology is power.
With that, comes responsibility.

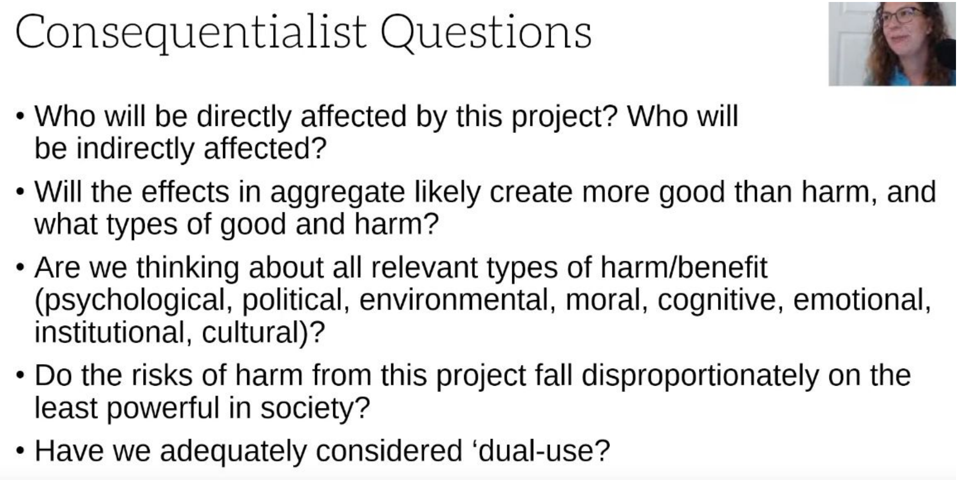
Of the global population:

- 56% have internet access
- 7% have college degree
- 0.5% know how to code

9.7 Future

Ethics for Data Science

https://www.youtube.com/watch?v=krIVOb23EH8



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