



# TRANSFORMERS

SISTEMAS DE INTELIGENCIA ARTIFICIAL - 2025

---

# TABLA DE CONTENIDOS

**O1.** INTRODUCCIÓN

**O4.** APLICACIONES

**O2.** ARQUITECTURA

**O5.** INDUSTRIA

**O3.** ENTRENAMIENTO

**O6.** BIBLIOGRAFÍA

01

---

## INTRODUCCIÓN

¿Qué es un Transformer?

# TRANSFORMERS

## Attention Is All You Need

Ashish Vaswani\*

Google Brain

avaswani@google.com

Noam Shazeer\*

Google Brain

noam@google.com

Niki Parmar\*

Google Research

nikip@google.com

Jakob Uszkoreit\*

Google Research

usz@google.com

Llion Jones\*

Google Research

llion@google.com

Aidan N. Gomez\*<sup>†</sup>

University of Toronto

aidan@cs.toronto.edu

Lukasz Kaiser\*

Google Brain

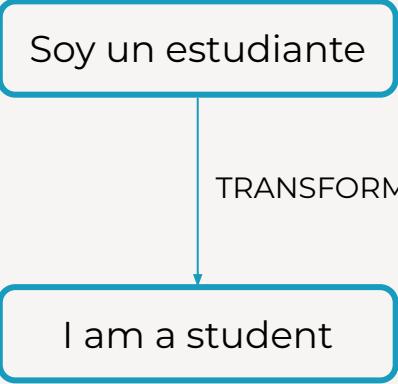
lukaszkaiser@google.com

Illia Polosukhin\*<sup>‡</sup>  
illia.polosukhin@gmail.com

### Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We show that we can obtain comparable results without such a complex architecture. To do so, we introduce a new model architecture based on attention which performs well on several tasks.

Paper



```
graph TD; A["Soy un estudiante"] -- TRANSFORMER --> B["I am a student"]
```

# ¿QUÉ ES UN TRANSFORMER?

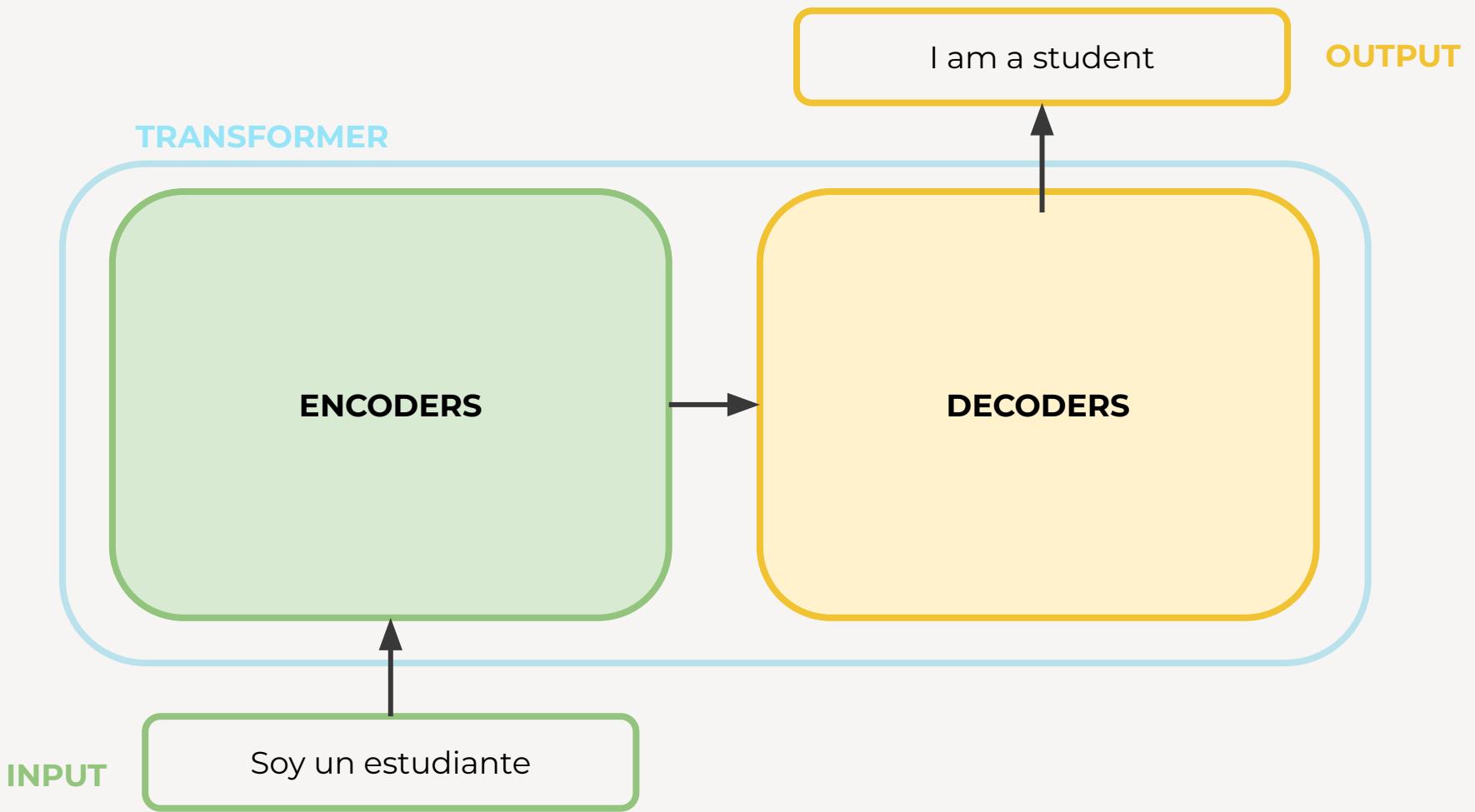
**Red neuronal** utilizada para transformar una secuencia en otra basada en un mecanismo de **atención**.

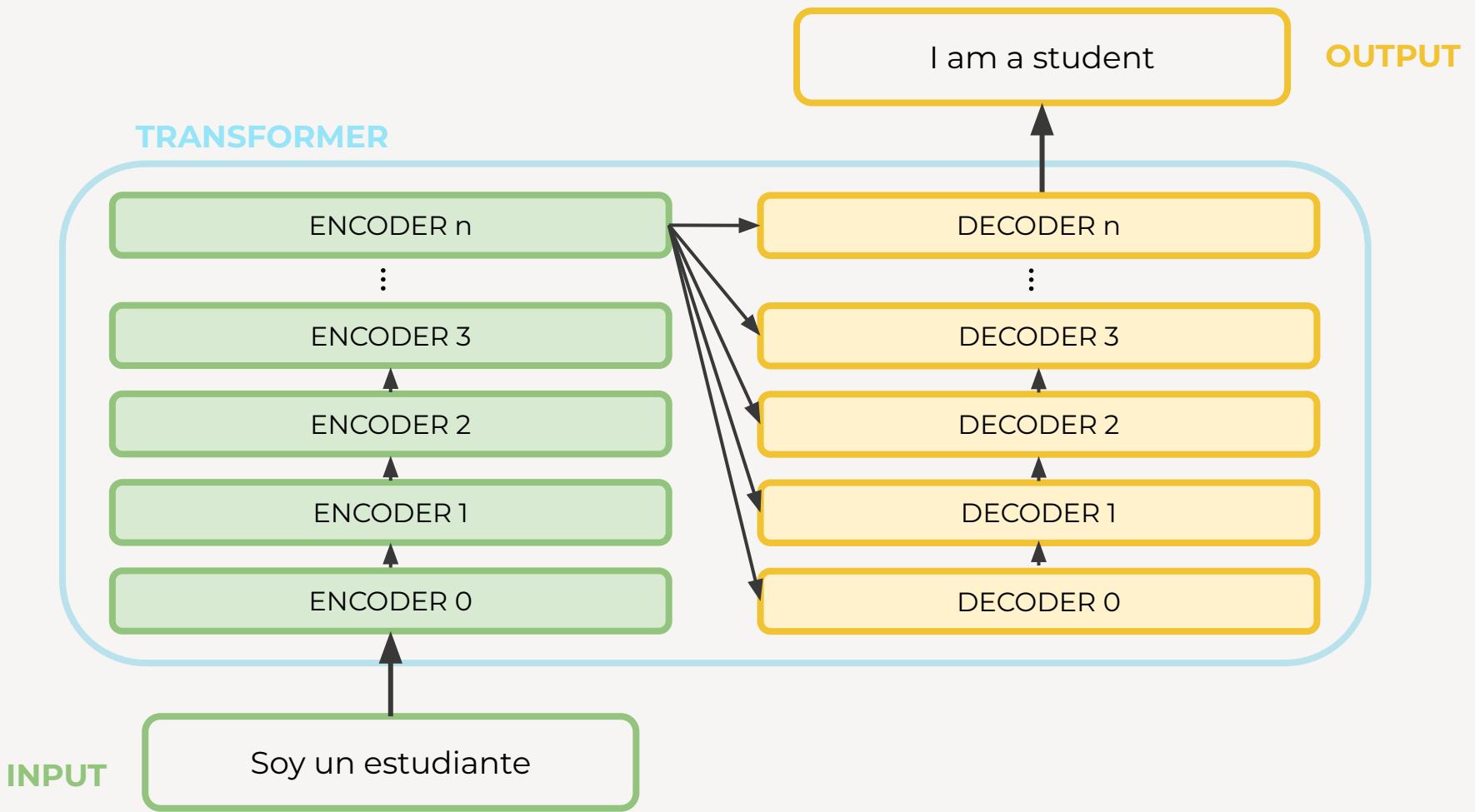
02

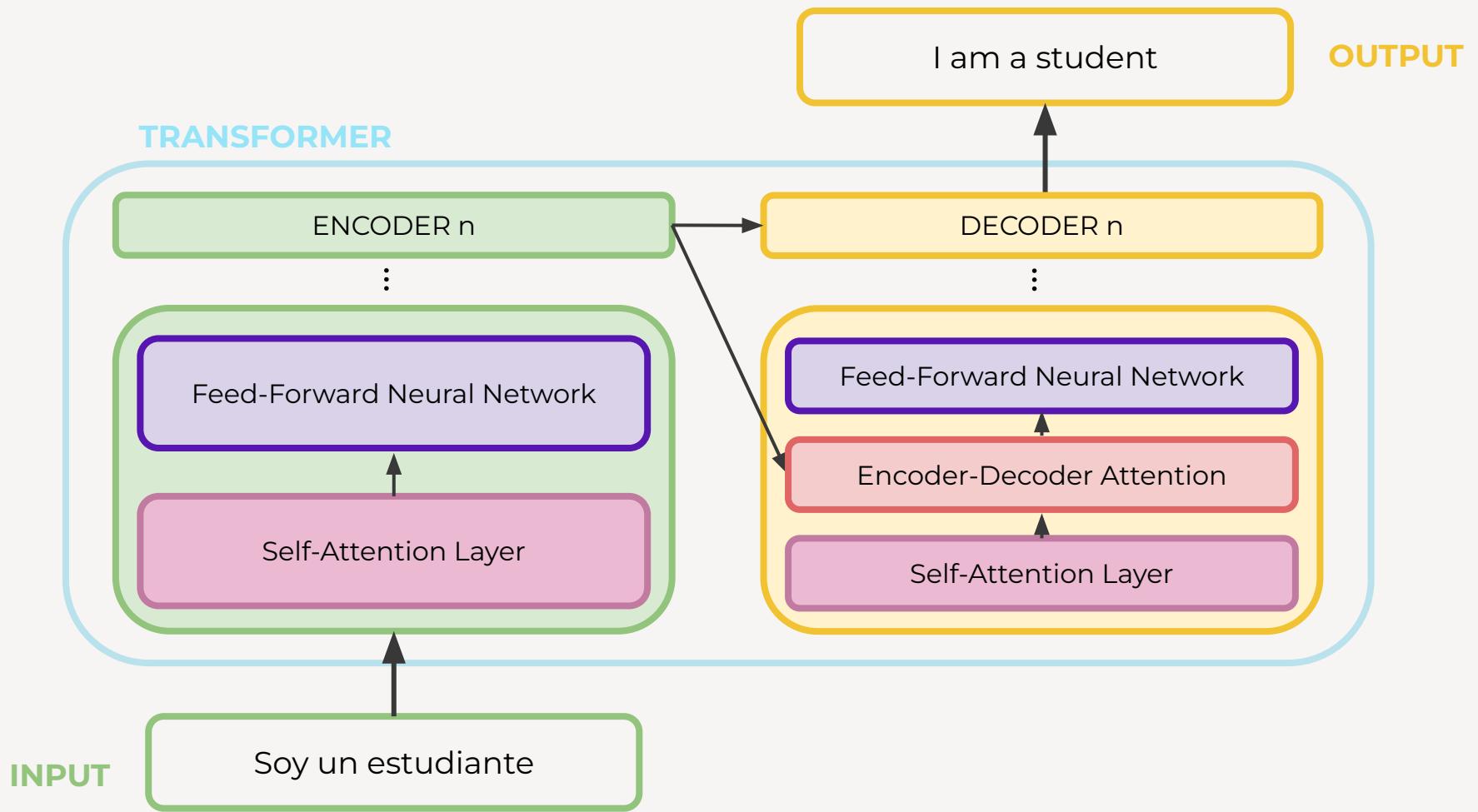
---

# ARQUITECTURA

¿Cuáles son las capas  
ocultas de un Transformer?







# SELF-ATTENTION LAYER

---

Ayudar al Encoder a **mirar otras palabras** en la secuencia de input mientras analiza una palabra en particular.

En el Decoder solo puede mirar palabras previas en la secuencia de output.

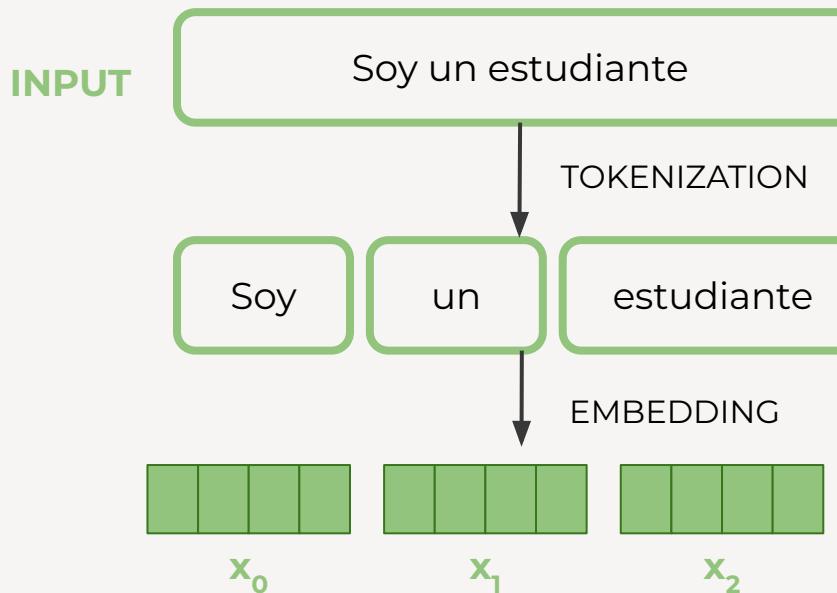
**INPUT**

The animal didn't cross the street because **it** was tired

¿La palabra “*it*” se refiere al animal o a la calle ?

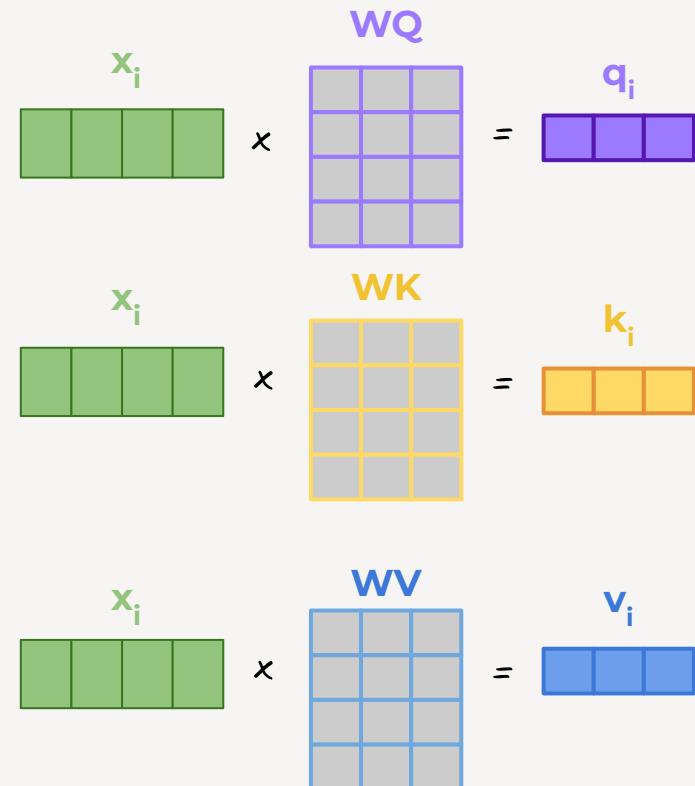
# EMBEDDING

- Cada token es representado en un vector de números reales de dimensión 512. A esto se lo llama **embedding** (algoritmos: *GloVe* o [word2vec](#): *SkipGram - CBOW*)
- El primer encoder recibe como input el *embedding*.



# CÁLCULO DE SELF-ATTENTION

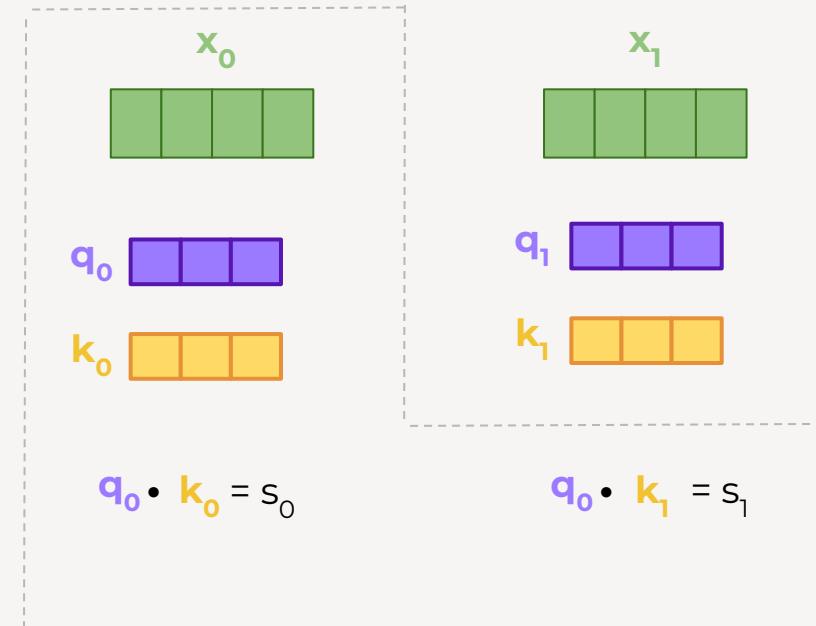
1. Por cada embedding  $x_i$ , se calculan 3 vectores llamados **query**, **key** y **value** multiplicando los embeddings por 3 matrices de pesos (*Attention Weights*) **WQ**, **WK** y **WV**



# CÁLCULO DE SELF-ATTENTION

2. Se calcula un “score” por cada embedding que determina cuánta atención se le pone a ese embedding mientras se está procesando otro.

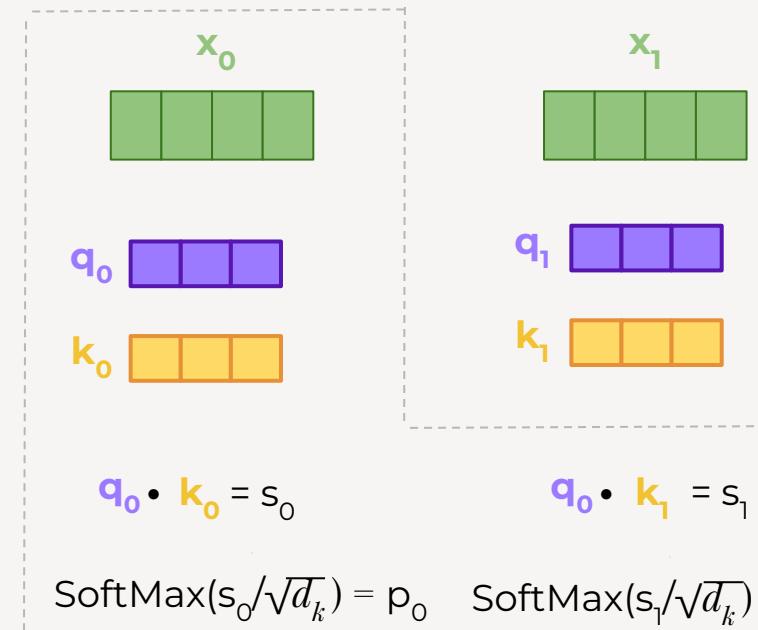
Se hace el producto escalar entre **q** y el vector **k** de cada embedding.



# CÁLCULO DE SELF-ATTENTION

3. Se dividen los scores por la raíz de la dimensión de vector **k** ( $d_k$ )

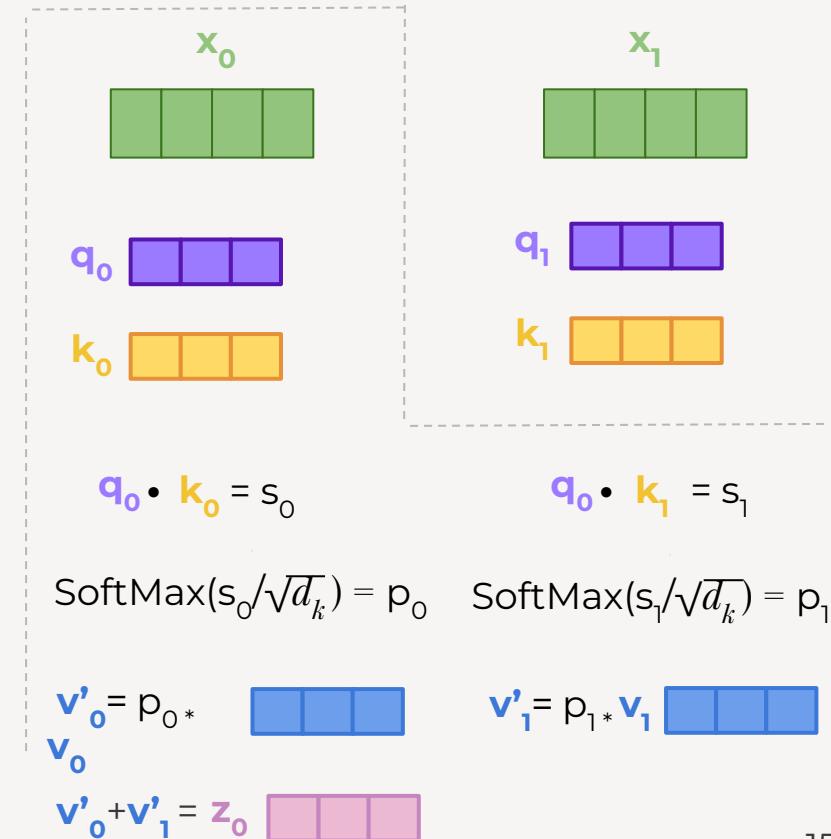
4. Usando Softmax para los scores se obtienen probabilidades ( $p_i$ ).



# CÁLCULO DE SELF-ATTENTION

5. Se multiplica cada vector  $v$  por lo obtenido en la función de Softmax.

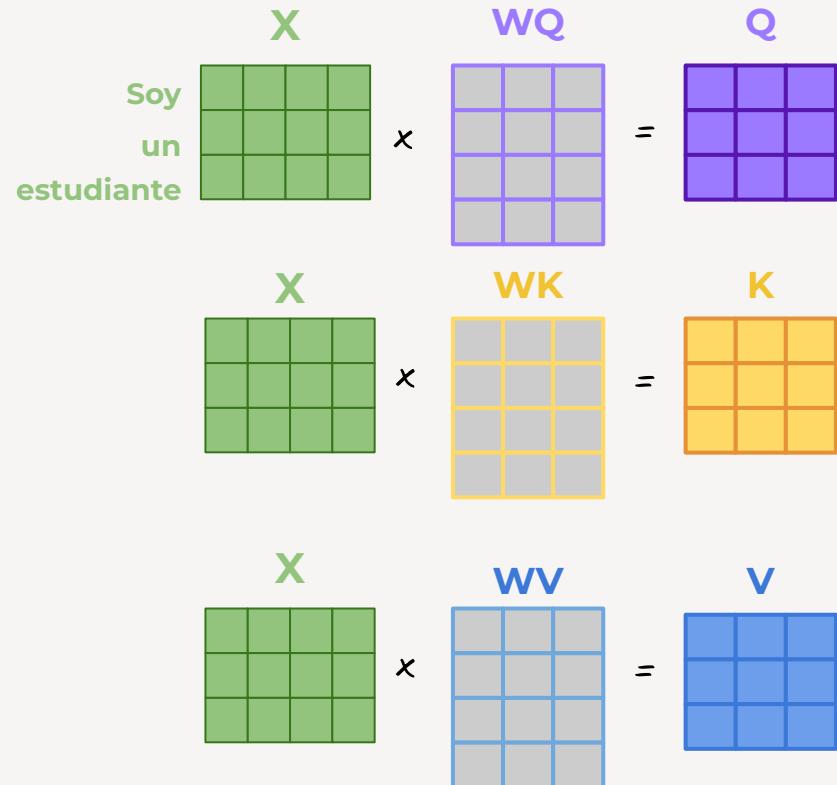
6. Se suman los vectores ponderados  $v'$  obteniendo el output de la capa de Self-Attention para cada token (en este ejemplo, para el primero)

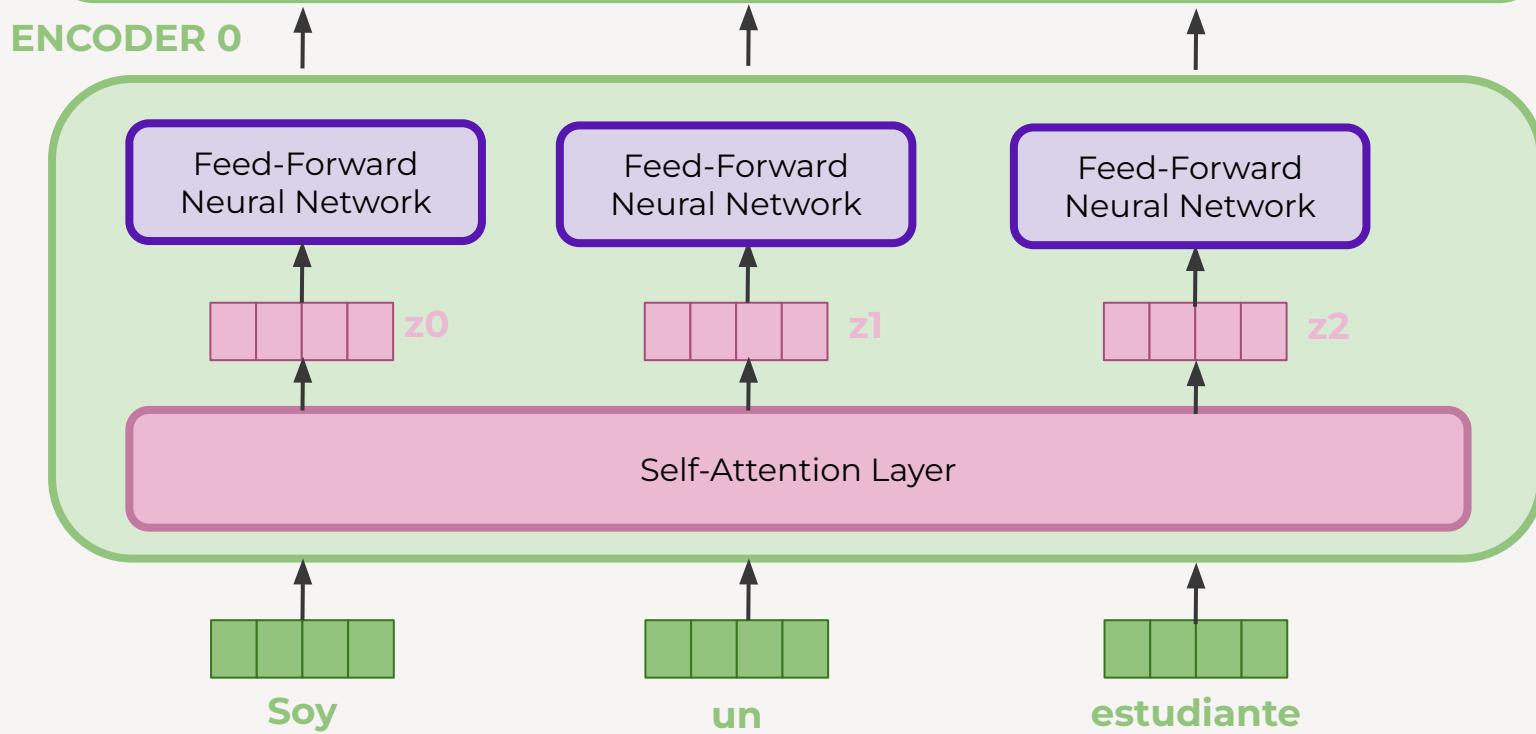


# CÁLCULO DE SELF-ATTENTION

Para implementarlo se calcula de forma matricial para un procesamiento más rápido

$$\text{Attention}(K, Q, V) = \text{SoftMax}\left(\frac{QK'}{\sqrt{d_k}}\right) * V = Z$$



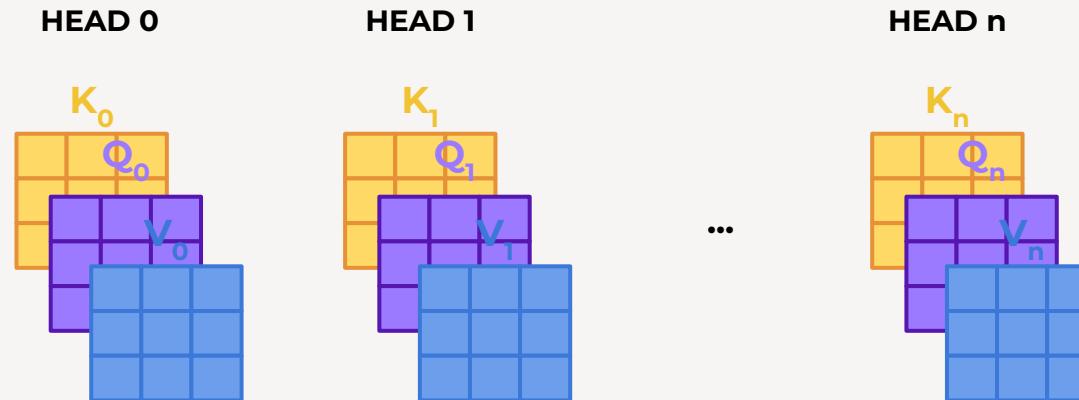


- Cada token sigue su **propio camino** en el encoder.
- Hay **dependencias** entre los caminos en la self-attention layer pero no en la red feed-forward.
- Los caminos se pueden ejecutar en **paralelo**, pasando por **redes feed-forward idénticas**

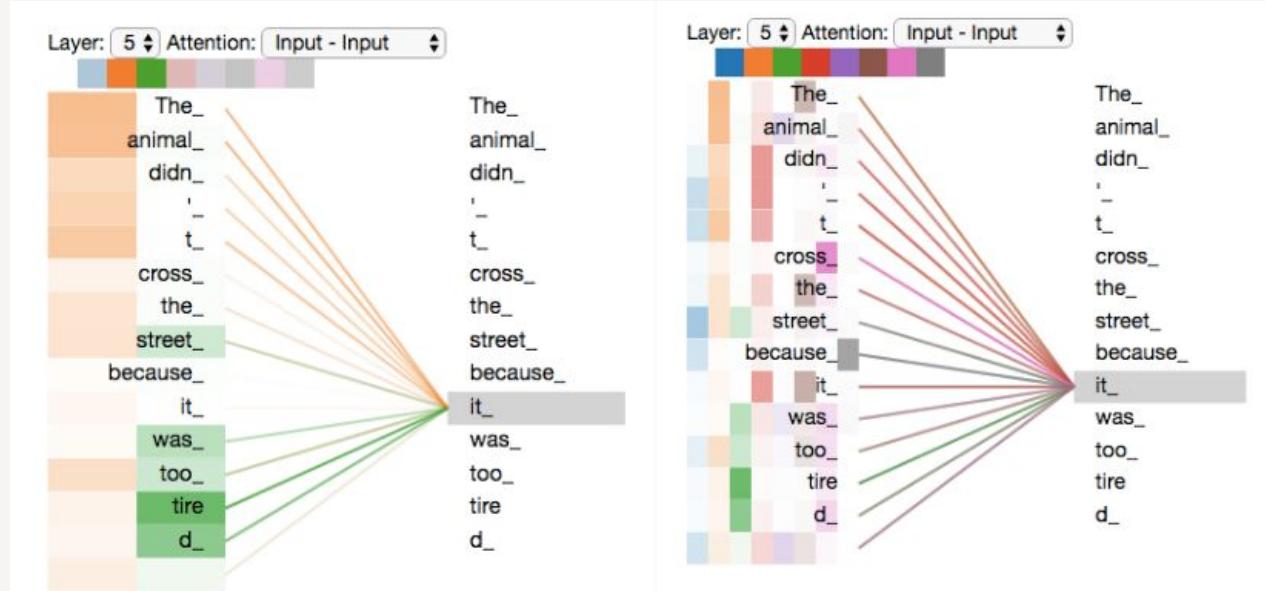
# MULTI-HEADED ATTENTION

Mecanismo que mejora la performance de la capa de self-attention:

- El Encoder se puede enfocar en distintas posiciones de la secuencia **simultáneamente**
- Se tienen múltiples sets **K Q V**, llamados “heads”



# MULTI-HEADED ATTENTION



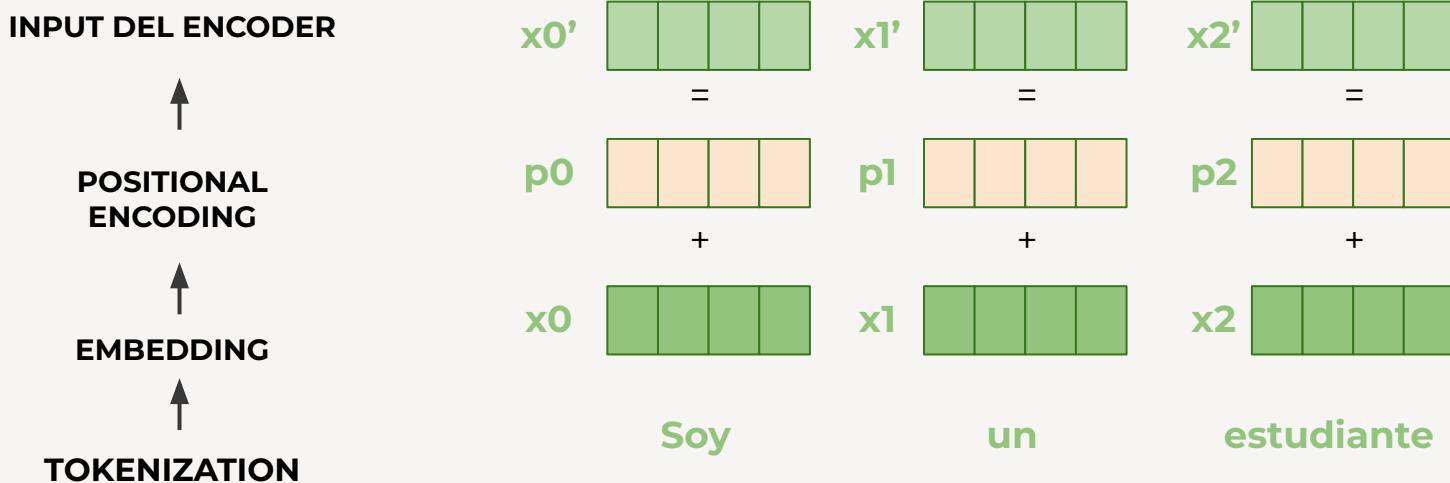
Multi-Headed Attention

# POSITIONAL ENCODING

Representa el orden de los tokens en la secuencia tomada como input

A cada embedding se le agrega un vector **p**

Los vectores p siguen un patrón que el modelo aprende para determinar la distancia entre tokens



# POSITIONAL ENCODING

---

$$PE(pos, 2i) = \sin(pos / 10000^{2i/d})$$

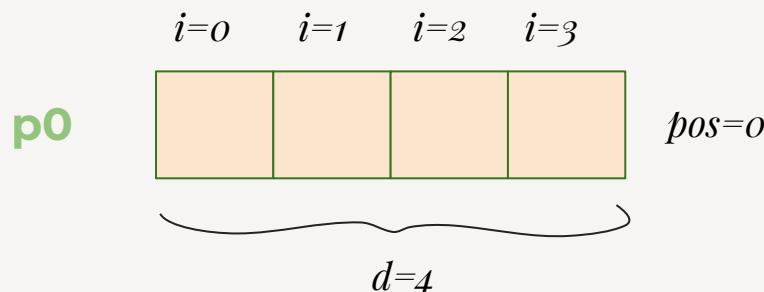
$$PE(pos, 2i+1) = \cos(pos / 10000^{2i/d})$$

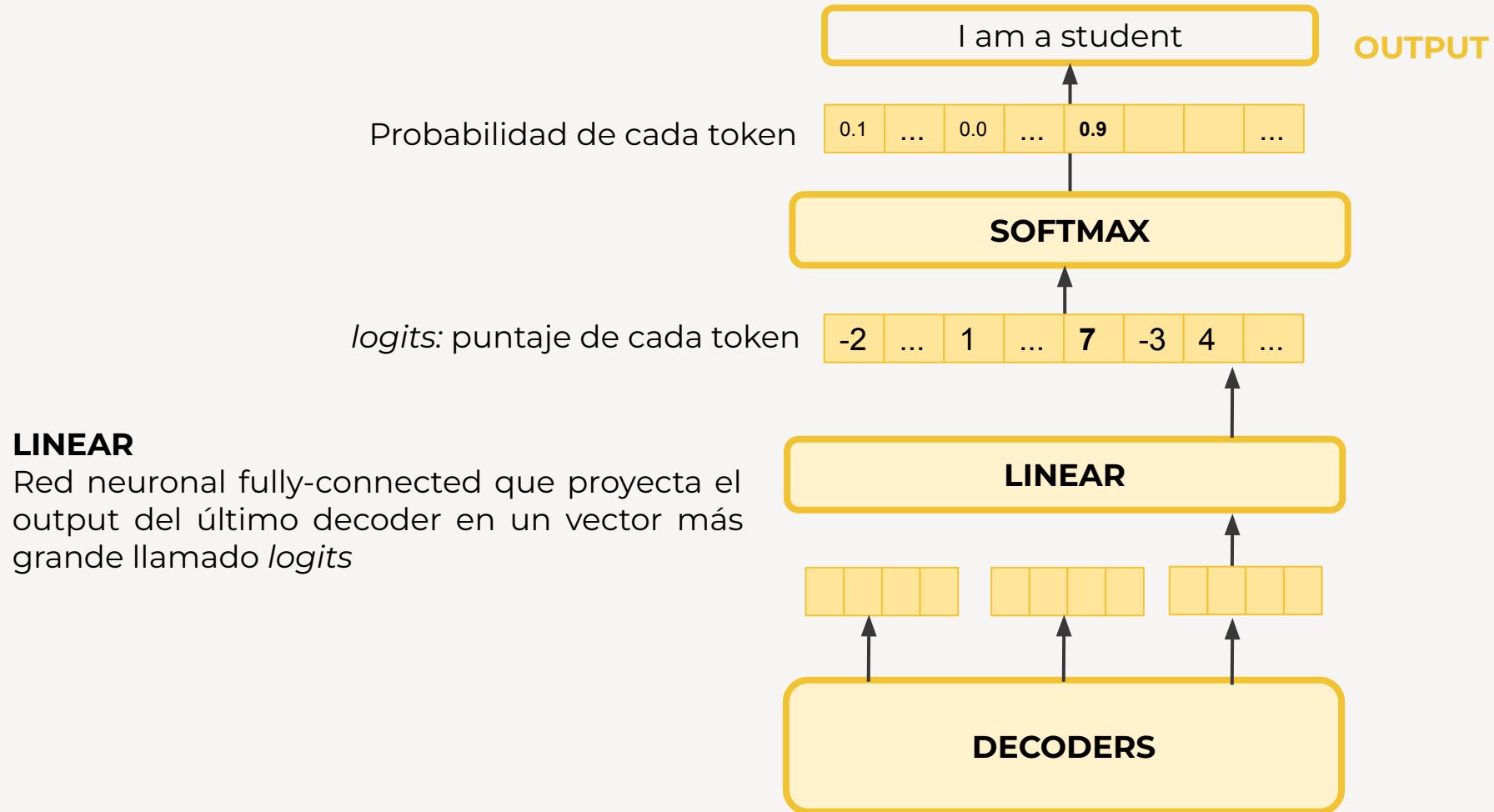
Donde:

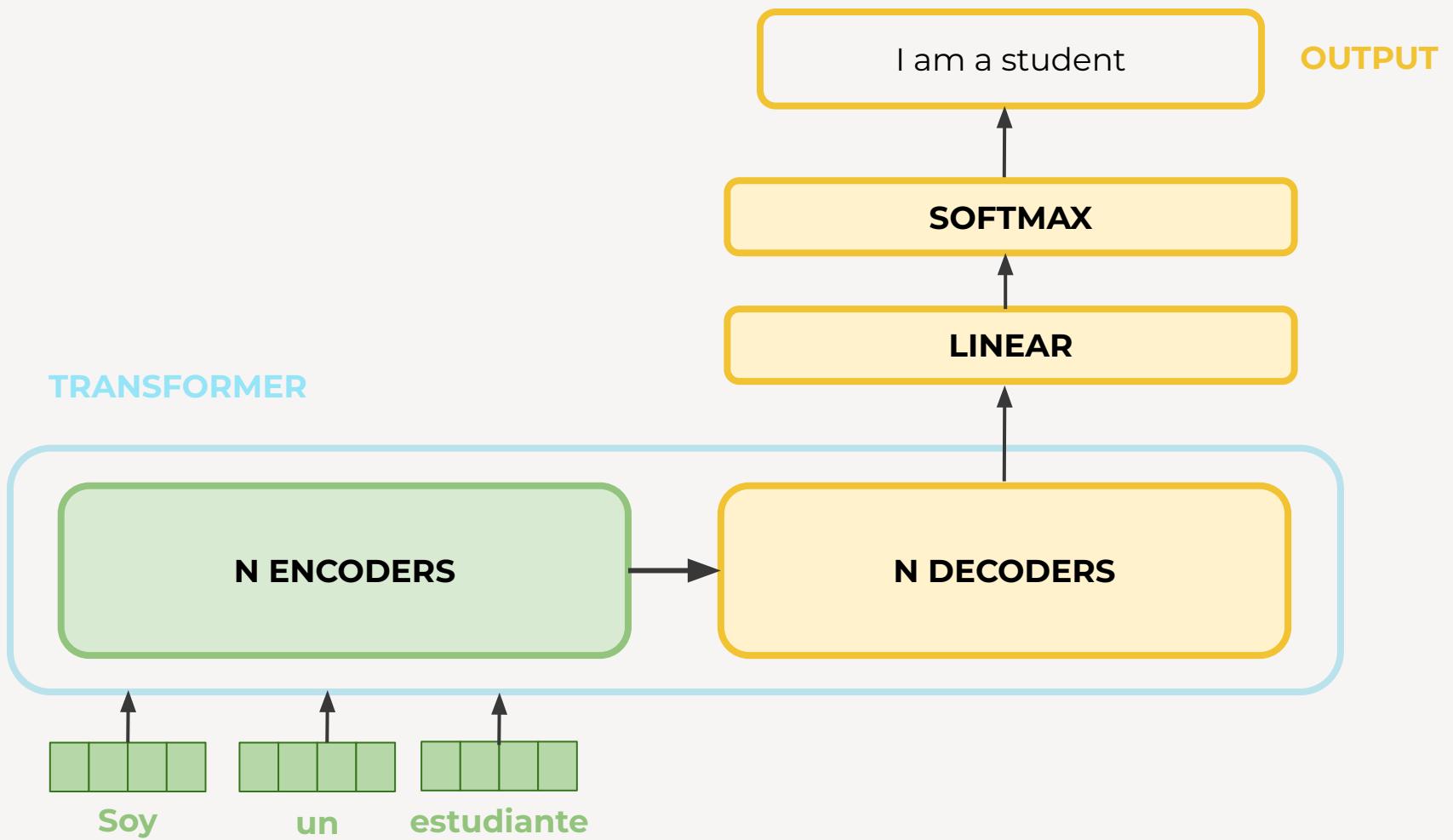
$pos$  es la posición del token en la secuencia

$i$  es el índice del vector de posición

$d$  es la dimensión de un embedding, la misma del vector de posición  $p_i$







03

## ENTRENAMIENTO

¿Cómo aprende un  
Transformer?

# CASO DE USO - TRADUCCIÓN

---

Se quiere traducir “*gracias*” a “*thanks*”.

Se tiene un vocabulario de salida  $v = (a, am, i, \text{thanks}, \text{student}, \langle\text{eof}\rangle)$ .

# ENTRENAMIENTO

Los **pesos se inicializan de forma aleatoria**, entonces el modelo sin entrenar devuelve una distribución de probabilidades con valores arbitrarios para cada token

Se pueden comparar las probabilidades y por **backpropagation** nos vamos acercando al output deseado.

OUTPUT OBTENIDO

|     |     |     |     |     |     |
|-----|-----|-----|-----|-----|-----|
| 0.2 | 0.2 | 0.1 | 0.2 | 0.2 | 0.1 |
|-----|-----|-----|-----|-----|-----|

OUTPUT DESEADO

|     |     |     |     |     |     |
|-----|-----|-----|-----|-----|-----|
| 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 |
|-----|-----|-----|-----|-----|-----|

a            am            i            ***thanks***            student            <eof>

# COSTO

---

Entrenar un Transformer requiere de gran costo computacional

## 6 Results

### 6.1 Machine Translation

On the WMT 2014 English-to-German translation task, the big transformer model (Transformer (big) in Table 2) outperforms the best previously reported models (including ensembles) by more than 2.0 BLEU, establishing a new state-of-the-art BLEU score of 28.4. The configuration of this model is listed in the bottom line of Table 3. Training took 3.5 days on 8 P100 GPUs. Even our base model surpasses all previously published models and ensembles, at a fraction of the training cost of any of the competitive models.

# VARIACIÓN DE PARÁMETROS

Table 3: Variations on the Transformer architecture. Unlisted values are identical to those of the base model. All metrics are on the English-to-German translation development set, newstest2013. Listed perplexities are per-wordpiece, according to our byte-pair encoding, and should not be compared to per-word perplexities.

|      | $N$                                       | $d_{\text{model}}$ | $d_{\text{ff}}$ | $h$  | $d_k$ | $d_v$ | $P_{\text{drop}}$ | $\epsilon_{ls}$ | train steps | PPL (dev)   | BLEU (dev)  | params $\times 10^6$ |  |
|------|---|--------------------|-----------------|------|-------|-------|-------------------|-----------------|-------------|-------------|-------------|----------------------|--|
| base | 6   | 512                | 2048            | 8    | 64    | 64    | 0.1               | 0.1             | 100K        | 4.92        | 25.8        | 65                   |  |
| (A)  |   |                    |                 | 1    | 512   | 512   |                   |                 |             | 5.29        | 24.9        |                      |  |
|      |   |                    |                 | 4    | 128   | 128   |                   |                 |             | 5.00        | 25.5        |                      |  |
|      |   |                    |                 | 16   | 32    | 32    |                   |                 |             | 4.91        | 25.8        |                      |  |
|      |   |                    |                 | 32   | 16    | 16    |                   |                 |             | 5.01        | 25.4        |                      |  |
| (B)  |   |                    |                 |      | 16    |       |                   |                 |             | 5.16        | 25.1        | 58                   |  |
|      |   |                    |                 |      | 32    |       |                   |                 |             | 5.01        | 25.4        | 60                   |  |
| (C)  |   |                    |                 | 2    |       |       |                   |                 |             | 6.11        | 23.7        | 36                   |  |
|      |   |                    |                 | 4    |       |       |                   |                 |             | 5.19        | 25.3        | 50                   |  |
|      |   |                    |                 | 8    |       |       |                   |                 |             | 4.88        | 25.5        | 80                   |  |
|      |   |                    |                 | 256  |       | 32    | 32                |                 |             | 5.75        | 24.5        | 28                   |  |
|      |   |                    |                 | 1024 |       | 128   | 128               |                 |             | 4.66        | 26.0        | 168                  |  |
|      |   |                    |                 | 1024 |       |       |                   | 5.12            | 25.4        | 53          |             |                      |  |
|      |   |                    |                 | 4096 |       |       |                   | 4.75            | 26.2        | 90          |             |                      |  |
| (D)  |   |                    |                 |      |       |       | 0.0               |                 |             | 5.77        | 24.6        |                      |  |
|      |   |                    |                 |      |       |       | 0.2               |                 |             | 4.95        | 25.5        |                      |  |
|      |   |                    |                 |      |       |       | 0.0               |                 |             | 4.67        | 25.3        |                      |  |
|      |   |                    |                 |      |       |       | 0.2               |                 |             | 5.47        | 25.7        |                      |  |
| (E)  | positional embedding instead of sinusoids |                    |                 |      |       |       |                   |                 |             | 4.92        | 25.7        |                      |  |
| big  | 6   | 1024               | 4096            | 16   |       |       | 0.3               | 300K            |             | <b>4.33</b> | <b>26.4</b> | 213                  |  |

04

---

## APLICACIONES

¿Para qué puedo usar un  
Transformer?

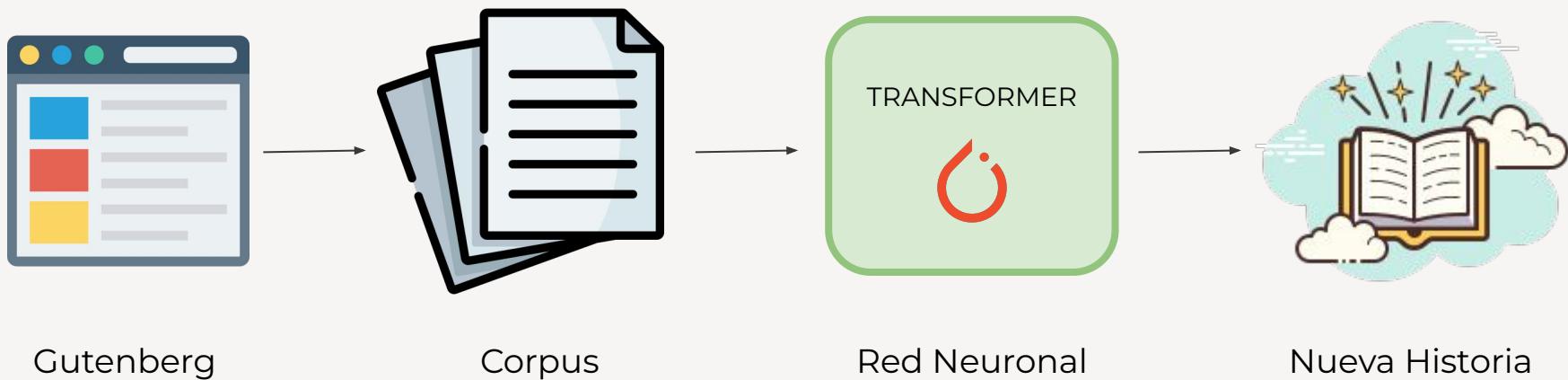
4.1

## TEXTO

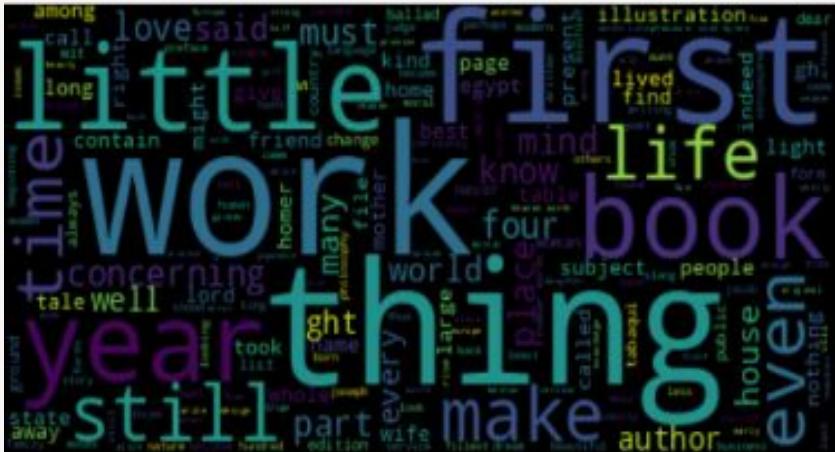
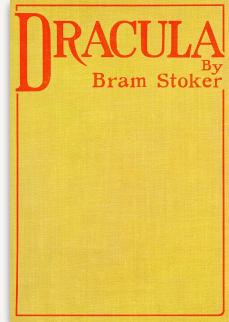
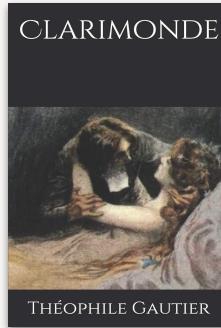
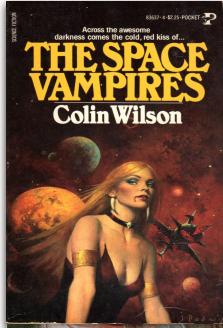
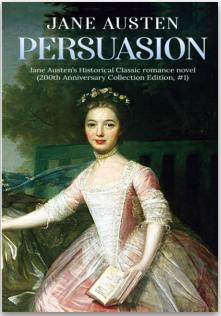
Aplicaciones

# BARD TEXT GENERATOR

---



# CORPUS



# GENERACIÓN

---

Época 1/100: "This story is about a woman"

Época 2/100: "This story is about a jungle for one , that he was the"

...

Época 20/100: "This story is about a good fortune and messages"

...

Época 60/100: "This story is about a to new truth , and be impossible for \_us \_ to visit"

...

Época 100/100: this story is about a man of the to names of ten years say ,

# GENERACIÓN

---



A small, tightly **wound** body found in San Bernardino County that **police** say may have come from the former San Bernardino **shooter**.

Police at San Bernardino County State Police began searching for the 32-month-old San Bernardino resident, who it said was in the early morning hours of Nov. 7, 2015.

Authorities were also interviewing a man the county's first **responders found at the scene**.

**The woman's death** is the latest in a string of shootings in

# GENERACIÓN

---



A dark shadow has been found in the sky. The **ghostly creature's** name has not been found in the sky with **no explanation**, and no one knows the cause of it.

You can see it coming out of your mouth on this little piece of paper. It's tiny, yet you need only look at it to know if it actually was the ghost of the man who had killed the Earth

She was in the throes of **madness and insanity. He had her hands clenched around her neck** and she could hear her breathing on the floor of his room.

"Ahm...**what's your name?**" I looked over at her face. "Ahm...you haven't seen me like before."

# TEXT COMPLETION

---



**He loved her so much that** she cried and tried again to **express her grief** and to let that **tears fall upon her heart**; not only because of the great loss on which she took at once to love herself, but because of the great sorrow that had had arisen upon her by accident; and because of the great grief she had caused at once to **love herself**, as an expression of **remorse** when she was taken as such; when she cried and cried again, because of the great joy that had arisen upon

# CHAT-GPT

---

Generative Pre-trained Transformer

## Introducing ChatGPT

We've trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests.

[Try ChatGPT ↗](#)

[Read about ChatGPT Plus](#)

# OPEN AI

[OpenAI - Playground](#)

[OpenAI - API Docs](#)

[OpenAI - Examples](#)

Classify the sentiment in these tweets:

1. "I can't stand homework"
2. "This sucks. I'm bored 😞"
3. "I can't wait for Halloween!!!!"
4. "My cat is adorable ❤️❤️"
5. "I hate chocolate"

Tweet sentiment ratings:

1. Negative
2. Negative
3. Positive
4. Positive
5. Negative

The following is a conversation with a teacher. The teacher is helpful and clever

Teacher: Hi there! How can I help you?

Student: I'm having trouble with my math homework.

Teacher: Let's take a look. What are you stuck on?

Translate this into French, Spanish and Japanese:

What rooms do you have available?

French: Quels sont les chambres que vous avez disponibles?

Spanish: ¿Qué habitaciones tienen disponibles?

Japanese: あなたはどんな部屋を用意していますか？

# GPT4

---

GPT-4 is OpenAI's most advanced system, producing safer and more useful responses

[Try on ChatGPT Plus ↗](#)

[Join API waitlist](#)

## 4.2

# IMÁGENES

Aplicaciones

## A Transformer-Based Anomaly Detection System for OCT Image Embeddings

1<sup>st</sup> Eugenia Sol Piñeiro

Dpto. Ingeniería Informática  
Instituto Tecnológico de Buenos Aires  
Buenos Aires, Argentina  
epineiro@itba.edu.ar

2<sup>nd</sup> Ariel Schlaen

Sección Uveítis, Servicio de Oftalmología  
Hospital de Clínicas "José de San Martín"  
Universidad de Buenos Aires  
Buenos Aires, Argentina  
riel.schlaen@gmail.com

3<sup>rd</sup> Rodrigo Ramele

Dpto. Ingeniería Informática  
Instituto Tecnológico de Buenos Aires  
Buenos Aires, Argentina  
rramele@itba.edu.ar

4<sup>th</sup> Juliana Gambini

LIDEC, UNAHur  
dad Nacional de Hurlingham  
sidad Tecnológica Nacional  
e Buenos Aires, Argentina  
a.gambini@unahur.edu.ar

### Variational Autoencoder as a Data Augmentation tool for Confocal Microscopy Images

1<sup>st</sup> Eugenia Sol Piñeiro

Dpto. Ingeniería Informática  
Instituto Tecnológico de Buenos Aires  
Buenos Aires, Argentina  
epineiro@itba.edu.ar

2<sup>nd</sup> Rodrigo Ramele

Dpto. Ingeniería Informática  
Instituto Tecnológico de Buenos Aires  
Buenos Aires, Argentina  
rramele@itba.edu.ar

3<sup>rd</sup> Juliana Gambini

Centro de Investigación CIDIA - CEPSI  
Universidad Nacional de Hurlingham  
Universidad Tecnológica Nacional  
Universidad Nacional de Tres de Febrero  
Buenos Aires, Argentina  
juliana.gambini@unahur.edu.ar

**Abstract**—Retinoblastoma is an ocular tumor characterized by malignant cells in the retina of the eye. For its treatment, doctors apply different methods, one of them is the localized injection of a chemotherapy drug called Topotecan. Scientists in the area of medicine are interested in study the speed of Topotecan penetration in tumor clusters. In order to do this, several sequences of microscopy images of Retinoblastoma cell cultures were taken. However, this process is very complex because Retinoblastoma's tumor clusters require stringent growth and maintenance conditions. That is why there is only one reduced set of images, unique in Argentina. Nonetheless, for this same reason statistical studies applied to uncover this penetration dynamics

out a predictive analysis and evaluate the results obtained for drawing conclusions.

Hence, in this work we are proposing the usage of Variational Autoencoder to augment this dataset, aiming to imitate the process of Topotecan penetration, while using Transformers to verify that this imitation preserves the dynamics found in the original dataset.

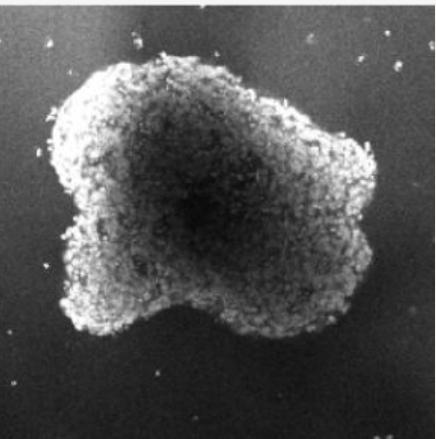
#### II. BACKGROUND

Deep Learning is a very successful artificial intelligence

visual transduction by converting light into electrical signals. These signals travel through the optic nerve to the brain, where they are interpreted to form visual images. The disruption of the outer retina can result in vision loss, which may become a complete loss if not identified and treated at an early stage.

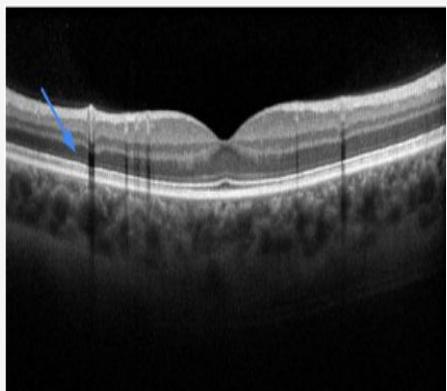
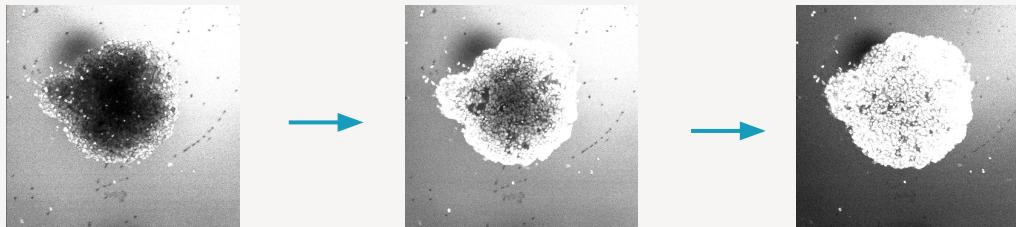
This study arises from the need to estimate the likelihood of a patient having retinal damage caused by AIR by detecting the differences from other similar diseases. The first step to do so, is to propose a method to identify pathological from non-pathological retinal images, using a Transformer-based Deep Learning model capable of capturing subtle clinical variations.

The Transformer has been widely used since its introduction in [2] for several applications, such as Natural Language models or Computer Vision, among others. In this work, it is used to develop an image feature detection of AIR disease.



## RETINOBLASTOMA

Tumor intraocular caracterizado por células malignas en la retina



## RETINOPATÍA AUTOINMUNE

Alteraciones patológicas en la retina que pueden llevar a una **pérdida parcial o total de la visión**

# DALL-E 3

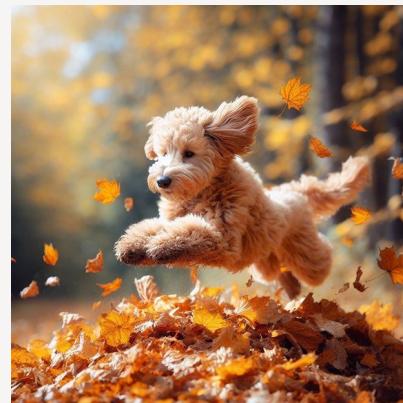


Research

# DALL-E 3

DALL-E 3 understands significantly more nuance and detail than our previous systems, allowing you to easily translate your ideas into exceptionally accurate images.

[Read research paper ↗](#) [Try in ChatGPT ↗](#)



[DALL-E 3](#)

[Ejemplos](#)

# IMAGE GENERATION

 Adobe Firefly

## Lo mejor para dejar volar tu imaginación

Utiliza la inteligencia artificial generativa y las instrucciones sencillas de texto para crear imágenes bonitas, efectos de texto y paletas de colores vivos con la máxima calidad. Crea contenido innovador a partir de imágenes de referencia y explora más posibilidades.



Dog in a sweater, primary colors, big smile Generate

 NVIDIA > Main Menu

Generative AI for Visual Applications

## NVIDIA Picasso

A foundry for building and deploying generative AI image, video, 3D assets and 360 HDRi



# GPT4-O

[OpenAI - GPT4-omni](#)



Research

Products

Safety

Company



May 13, 2024

# Hello GPT-4o

We're announcing GPT-4o, our new flagship model that can reason across audio, vision, and text in real time.

[Contributions >](#) [Try on ChatGPT ↗](#) [Try in Playground ↗](#) [Rewatch live demos >](#)

## 4.3

## AUDIO

Aplicaciones

# WHISPER

## Open AI - Whisper model

### Robust Speech Recognition via Large-Scale Weak Supervision

Alec Radford<sup>\* 1</sup> Jong Wook Kim<sup>\* 1</sup> Tao Xu<sup>1</sup> Greg Brockman<sup>1</sup> Christine McLeavey<sup>1</sup> Ilya Sutskever<sup>1</sup>

#### Abstract

We study the capabilities of speech processing systems trained simply to predict large amounts of transcripts of audio on the internet. When scaled to 680,000 hours of multilingual and multitask supervision, the resulting models generalize well to standard benchmarks and are often competitive with prior fully supervised results but in a zero-shot transfer setting without the need for any fine-tuning. When compared to humans, the models approach their accuracy and robustness. We are releasing models and inference code to serve as a foundation for further work on robust speech processing.

#### 1. Introduction

Progress in speech recognition has been energized by the development of unsupervised pre-training techniques exemplified by Wav2Vec 2.0 (Baevski et al., 2020). Since these methods learn directly from raw audio without any labeled data, they have the potential to be more robust than supervised models. However, they also have significant limitations. For example, they can only recognize words and phrases that were present in the training data, and they are less accurate at identifying speakers and other features of speech than supervised models.

methods are exceedingly adept at finding patterns within a training dataset which boost performance on held-out data from the same dataset. However, some of these patterns are brittle and spurious and don't generalize to other datasets and distributions. In a particularly disturbing example, Radford et al. (2021) documented a 9.2% increase in object classification accuracy when fine-tuning a computer vision model on the ImageNet dataset (Russakovsky et al., 2015) without observing any improvement in average accuracy when classifying the same objects on seven other natural image datasets. A model that achieves "superhuman" performance when trained on a dataset can still make many basic errors when evaluated on another, possibly precisely because it is exploiting those dataset-specific quirks that humans are oblivious to (Geirhos et al., 2020).

This suggests that while unsupervised pre-training has improved the quality of audio encoders dramatically, the lack of an equivalently high-quality pre-trained decoder, combined with a recommended protocol of dataset-specific fine-tuning, is a crucial weakness which limits their usefulness and robustness. The goal of a speech recognition system

# MÚSICA

## Music Transformer: Generating Music with Long-Term Structure

**BBC**

Home News Sport Business Innovation Culture Travel Earth Video Live

Rapper Bad Bunny has released a furious rant about a viral TikTok song that uses artificial intelligence (AI) to replicate his voice.

The track has hundreds of thousands of views and also uses fake vocals from Justin Bieber and Daddy Yankee.

In a post on his WhatsApp channel, Bad Bunny said anyone who liked the song NostalgIA should leave the group chat.

"You don't deserve to be my friends," the singer wrote in Spanish. "I don't want them on the tour either."

The track was uploaded by a user under the name flowgptmusic, but there's no evidence to say they're linked to the AI platform FlowGPT - which is powered in a similar way to ChatGPT.



## 4.4

# APLICACIONES

Otros

# APLICACIONES

---

- Comprensión, generación y traducción de textos: [OpenAI Language Model](#)
- Predecir la siguiente palabra de una oración: [IntelliSense in Visual Studio Code](#)
- Juegos de Estrategia Real-Time: [AlphaStar - StarCraft II](#)
- Detección de Anomalías: [Spacecraft Anomaly Detection](#)
- Reconocimiento de Imágenes: [Patches Are All You Need?  
An Image is Worth 16x16 Words](#)
- Generar música: [Music Transformer: Generating Music with Long-Term Structure](#)

05.

## INDUSTRIA

¿Cómo se usa hoy en día?

# DEEP LEARNING FRAMEWORKS

---



# HUGGING-FACE

Existen distintos modelos de Transformers: GPT-2/3/4, BERT, RoBERTa, DistilBERT, T5

The screenshot shows the official Hugging Face Transformers documentation page. The top navigation bar includes a search bar, a documentation version (V4.35.0), language selection (EN), and a user count (114,893). The main content area features a large title "Transformers" with a smiling emoji icon. Below it, a sub-section title "State-of-the-art Machine Learning for PyTorch, TensorFlow, and JAX." is also preceded by a smiling emoji. The main text explains that Transformers provides APIs and tools for downloading and training pretrained models, which can reduce compute costs and save time. It lists several modalities supported by the models: Natural Language Processing, Computer Vision, Audio, and Multimodal.

• **Transformers** ▾

Search documentation Ctrl+K

V4.35.0 EN 114,893

GET STARTED

Transformers

Quick tour

Installation

TUTORIALS

Run inference with pipelines

Write portable code with AutoClass

Preprocess data

Fine-tune a pretrained model

Transformers

State-of-the-art Machine Learning for PyTorch, TensorFlow, and JAX.

(Transformers) Transformers provides APIs and tools to easily download and train state-of-the-art pretrained models. Using pretrained models can reduce your compute costs, carbon footprint, and save you the time and resources required to train a model from scratch. These models support common tasks in different modalities, such as:

- (file) **Natural Language Processing**: text classification, named entity recognition, question answering, language modeling, summarization, translation, multiple choice, and text generation.
- (camera) **Computer Vision**: image classification, object detection, and segmentation.
- (microphone) **Audio**: automatic speech recognition and audio classification.
- (person) **Multimodal**: table question answering, optical character recognition, information extraction from scanned documents, video classification, and visual question answering.

# MLOps CLOUD



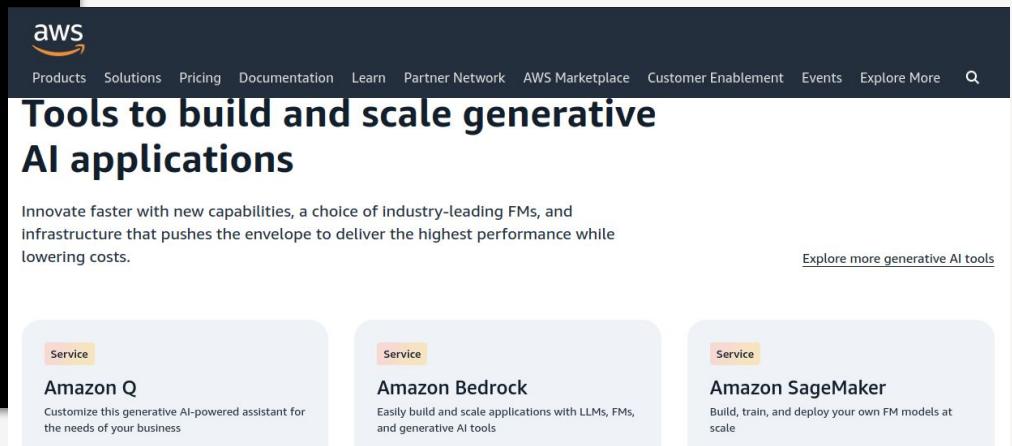
## Hugging Face on Azure

Deploy tens of thousands of pretrained Hugging Face Transformers models in Azure Machine Learning using Hugging Face endpoints.

[Try Azure for free](#)

Already using Azure? Try Hugging Face on Azure >

| PRODUCT                     | aws                             | Microsoft Azure          | Google Cloud Platform                          |
|-----------------------------|---------------------------------|--------------------------|--|
| Machine learning            | Amazon SageMaker                | Azure Machine Learning   | Google Cloud AI Platform                       |
| Image recognition           | Amazon Rekognition              | Azure Cognitive Services | Google Cloud Vision                            |
| Speech                      | Amazon Polly, Amazon Transcribe | Azure Cognitive Services | Google Cloud Speech-to-Text and Text-to-Speech |
| Natural language processing | Amazon Comprehend               | Azure Cognitive Services | Google Cloud Natural Language API              |
| Big Data Analytics          | Databricks                      | Databricks               | Databricks                                     |
| Chat Bot                    | AWS Chatbot                     | Azure Bot Service        | Dialogflow                                     |



**Tools to build and scale generative AI applications**

Innovate faster with new capabilities, a choice of industry-leading FMs, and infrastructure that pushes the envelope to deliver the highest performance while lowering costs.

[Explore more generative AI tools](#)

**Service** **Amazon Q** Customize this generative AI-powered assistant for the needs of your business

**Service** **Amazon Bedrock** Easily build and scale applications with LLMs, FMs, and generative AI tools

**Service** **Amazon SageMaker** Build, train, and deploy your own FM models at scale

06

---

## BIBLIOGRAFÍA

¿Dónde puedo profundizar?

# BIBLIOGRAFÍA

---

[Attention Is All You Need - Paper](#)

[GPT-2](#) - [GPT-3](#) - [BERT](#)

[Inside Machine Learning](#)

[Illustrated Transformer](#)

[Positional Encoding - Visualization](#)

[Word Embedding - Visualization](#)

[Simple Transformer in Python - Github](#)

[Interactive Transformer](#)

# CÓMO PROFUNDIZAR

---

## 73.64 Temas Avanzados en Deep Learning

- LLMs
- Responsible AI y Safety
- Industria



¡ GRACIAS !