1. Artificial Intelligence Overview

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UAO - Universidad Autónoma de Occidente, Cali, Colombia www.uao.edu.co

Jesús Alfonso López Sotelo

Nacido en Cali, Colombia. Es Ingeniero Electricista, Magíster en Automática y Doctor en Ingeniería.

Tiene más de 25 años de experiencia en docencia y en desarrollo de proyectos relacionados con Inteligencia Artificial. Sus áreas de interés son las redes neuronales artificiales y el aprendizaje profundo (Deep Learning), la Inteligencia Artificial en dispositivos de borde, los sistemas difusos, la computación evolutiva, la enseñanza de la inteligencia artificial y el impacto que esta tecnología pueda tener en nuestra sociedad.

Es investigador Asociado del sistema nacional de ciencia tecnología e innovación en Colombia de MinCiencias. Es miembro profesional de la IEEE donde pertenece al capítulo nacional de la sociedad de Inteligencia Computacional. Actualmente está vinculado a la Universidad Autónoma de Occidente en Cali y pertenece al Grupo de Investigación en Energías, GIEN. Ha publicado diversos artículos, capítulos de libro y libros en las temáticas de Redes Neuronales Artificiales, Deep Learning y otras técnicas de inteligencia artificial.

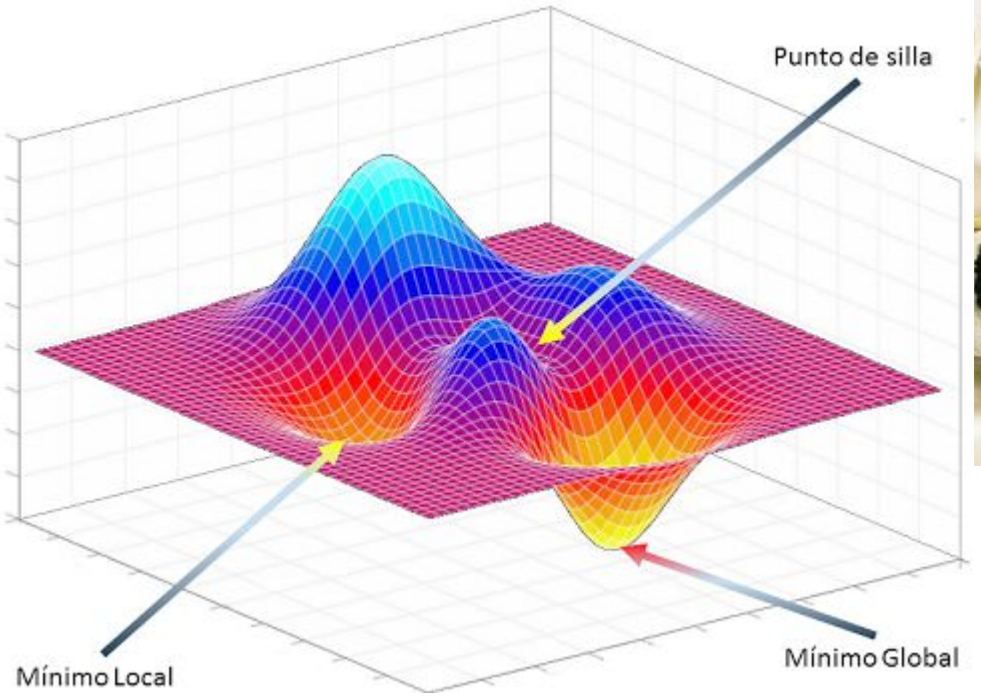
Perfil Linkedin

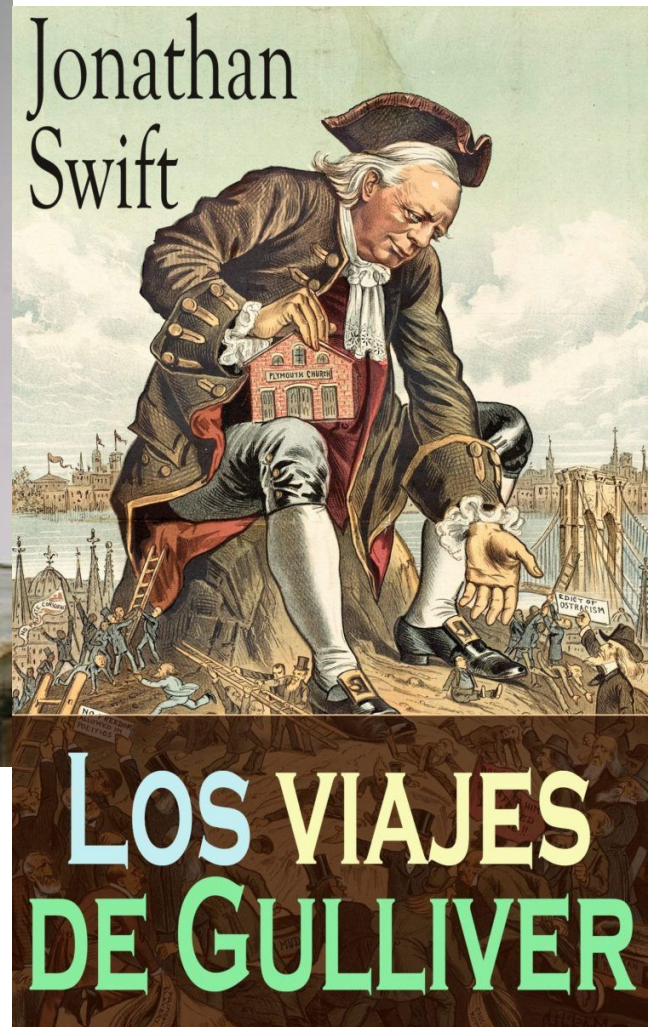
https://www.linkedin.com/in/jesus-alfonso-lópez-sotelo-76100718/

¿Qué es la Inteligencia Artificial (IA) y el Aprendizaje Automático?

¿Qué es Inteligencia Artificial?

Los antecedentes de la IA se pueden rastrear en la filosofía, en la técnica, en la literatura y en la matemáticas.



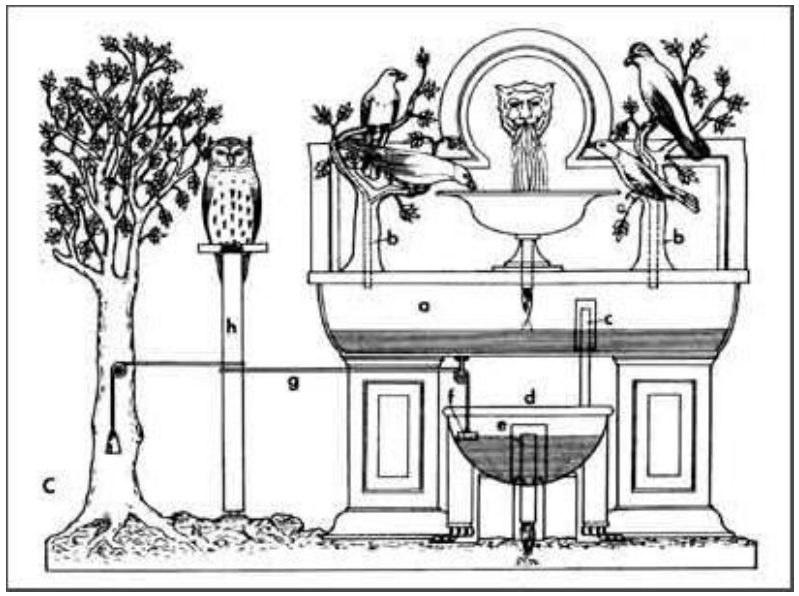


¿Qué es Inteligencia Artificial?

Mito de Talos

https://mitologia.guru/personajes-mitologicos/talos/

Autómata de Herón



http://automata.cps.unizar.es/Historia/Webs/automatas_en_la_historia.htm

¿Qué es Inteligencia Artificial?

Autómatas de Pierre Jacques-Droz

https://www.xatakaciencia.com/robotica/los-primeros-automatas-de-la-historia

https://www.youtube.com/watch?v=vr0e_WsjkvY

¿Qué es Inteligencia Artificial?

Frankestein

https://www.elperiodico.com/es/ciencia/20180309/frankenstein-ciencia-responsabilidad-y-estereotipos-de-genero-6679506

R.U.R. (Robots Universales Rossum)

https://es.wikipedia.org/wiki/R.U.R._(Robots_Universales_Rossum)

¿Qué es Inteligencia Artificial?

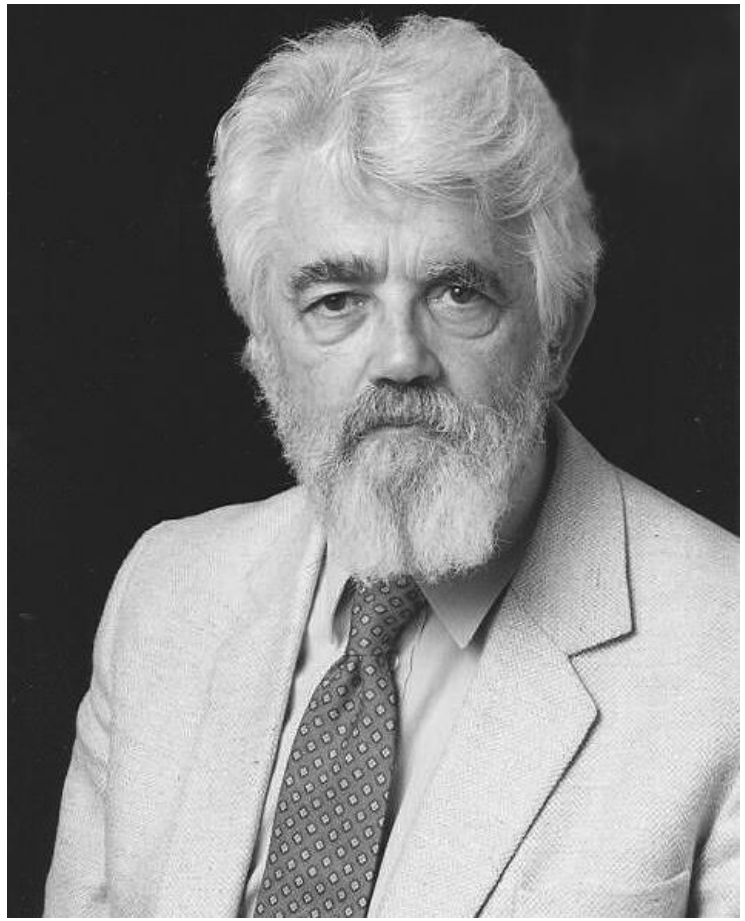
Tres Leyes de la Robótica de Asimov

https://historia.nationalgeographic.com.es/a/isaac-asimov-maestro-ciencia-ficcion_15035

¿Qué es Inteligencia Artificial?

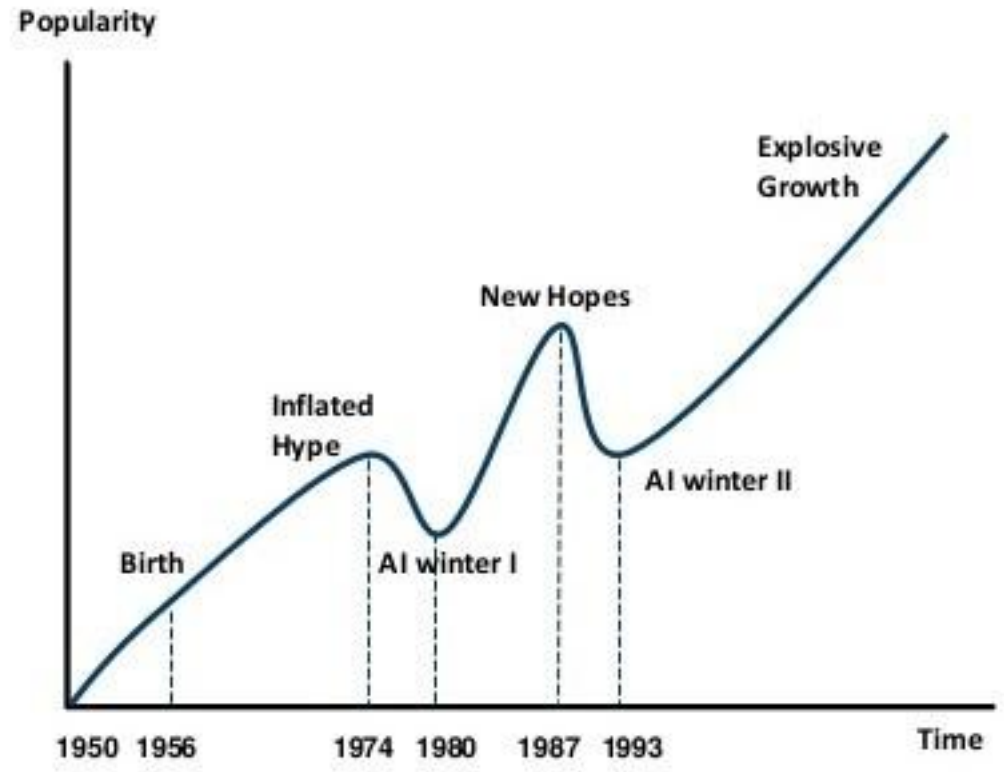
La Escuela de Verano en Dartmouth sobre Inteligencia Artificial (1956) se considera un evento importante en la historia de la IA y donde surgió el término inteligencia artificial, seleccionado por el informático John McCarthy.

La inteligencia artificial (IA) se puede definir como el campo de estudio y desarrollo de sistemas informáticos que pueden realizar tareas que normalmente requieren inteligencia humana. Estas tareas incluyen el aprendizaje, la percepción, el razonamiento, la resolución de problemas y la comprensión del lenguaje natural.



https://francis.naukas.com/2011/10/25/john-mccarthy-1927-2011-el-padre-de-la-inteligencia-artificial/

¿Qué es Inteligencia Artificial?



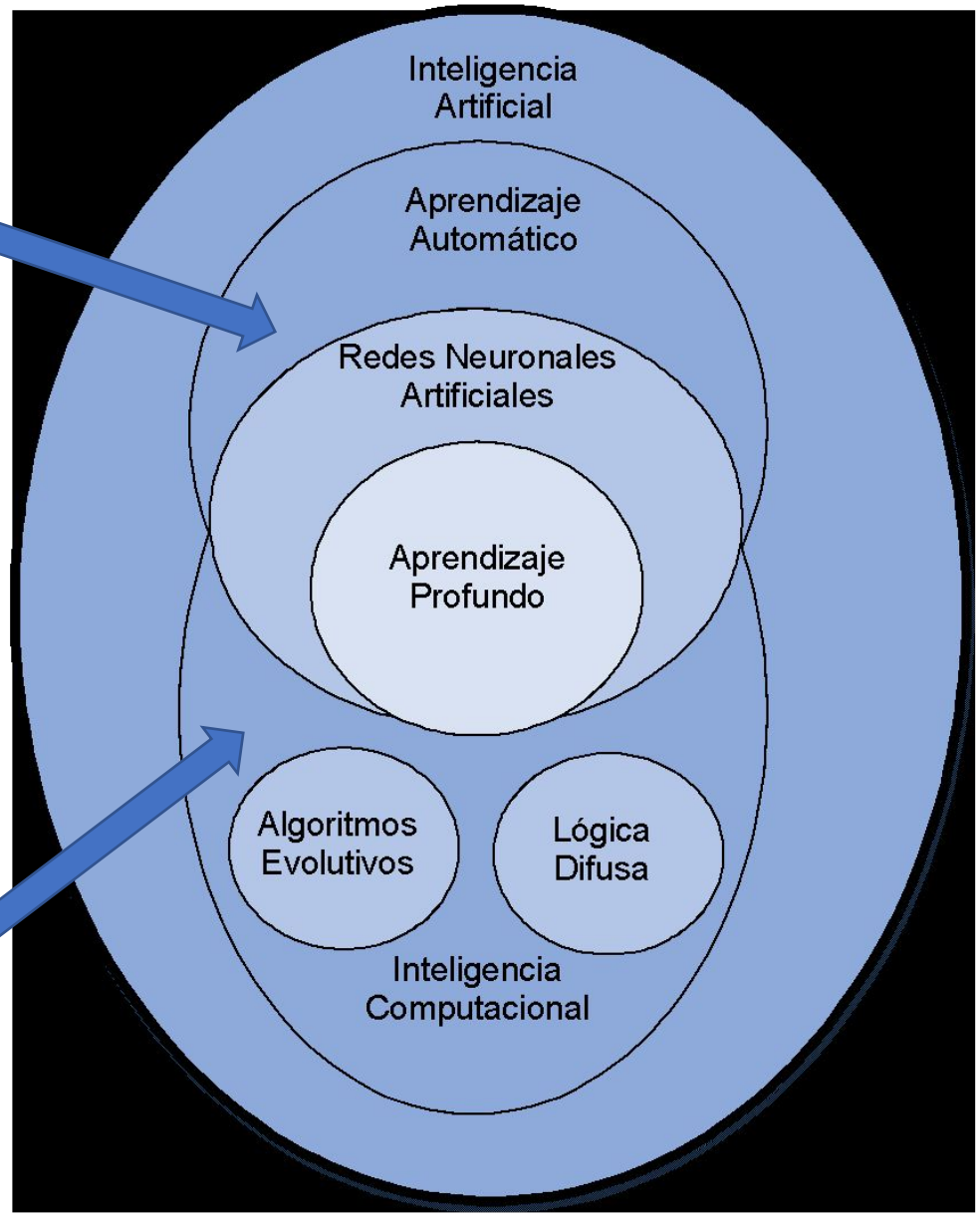
Timeline of AI Development

- **1950s-1960s**: First AI boom - the age of reasoning, prototype AI developed
- **1970s**: AI winter I
- **1980s-1990s**: Second AI boom: the age of Knowledge representation (appearance of expert systems capable of reproducing human decision-making)
- **1990s**: AI winter II
- **1997**: Deep Blue beats Gary Kasparov
- **2006**: University of Toronto develops Deep Learning
- **2011**: IBM's Watson won Jeopardy
- **2016**: Go software based on Deep Learning beats world's champions

https://www.actuaries.digital/2018/09/05/history-of-ai-winters/

¿Qué es Inteligencia Artificial?

Machine Learning
(Aprendizaje Automático)



Algoritmos Bio-inspirados

Aprendizaje Automático

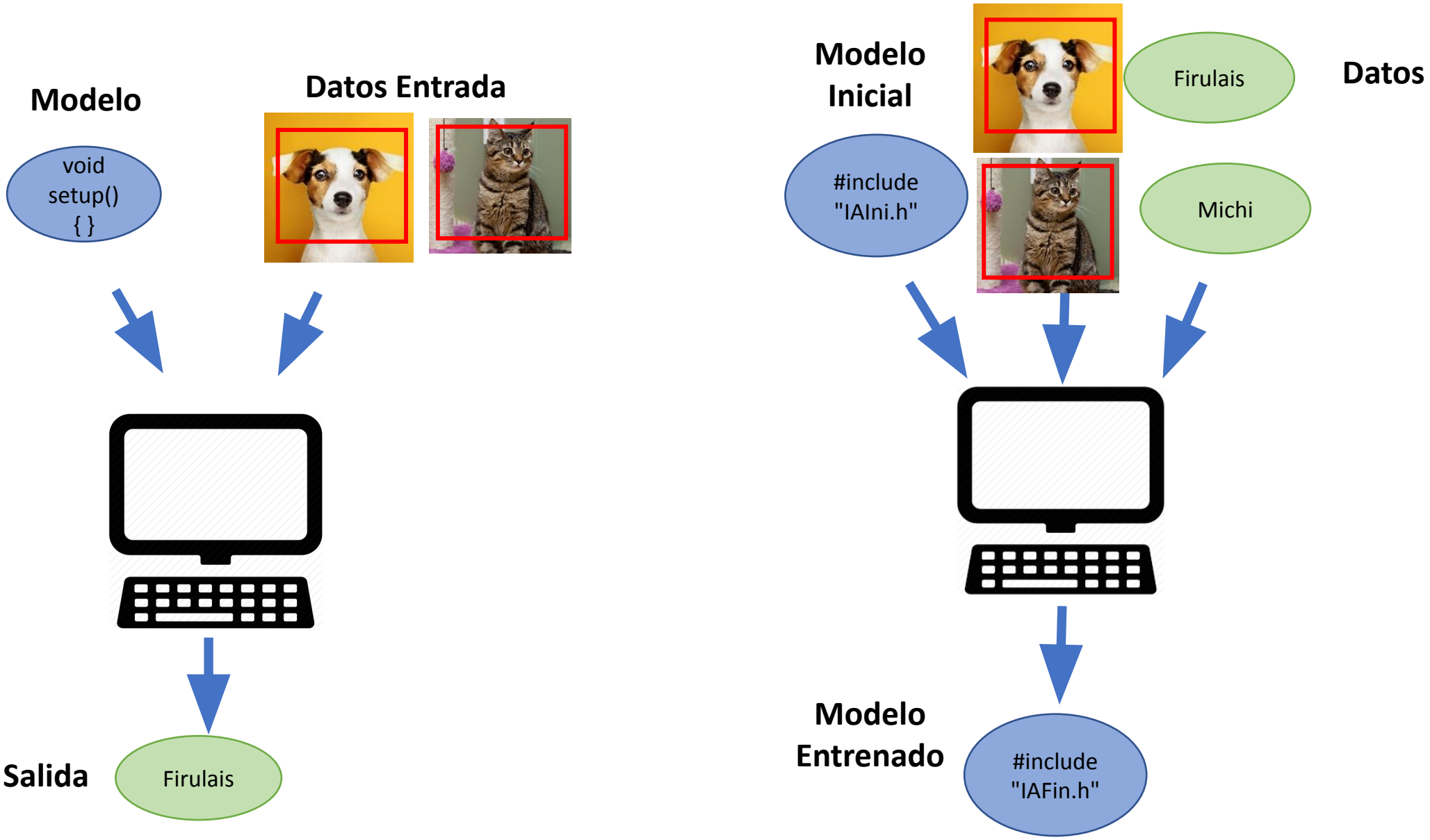
Datos es lo que Hay!

El aprendizaje automático es un subconjunto de la inteligencia artificial que tiene la capacidad de "aprender" (es decir, mejorar progresivamente el rendimiento en una tarea específica) con datos, sin ser programado explícitamente

Aprendizaje Automático

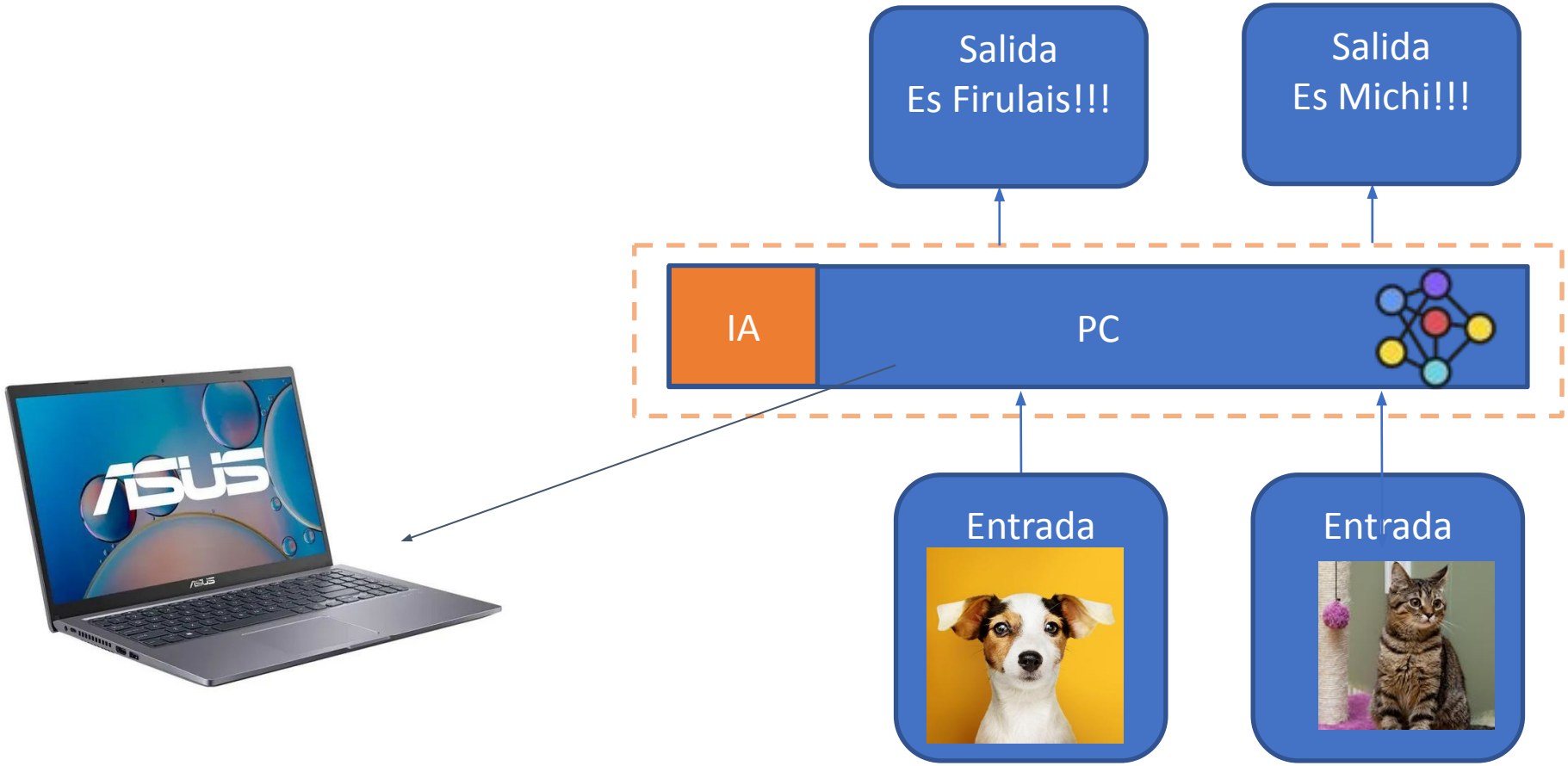
Detector de Firulais y Michis

Aprendizaje Automático



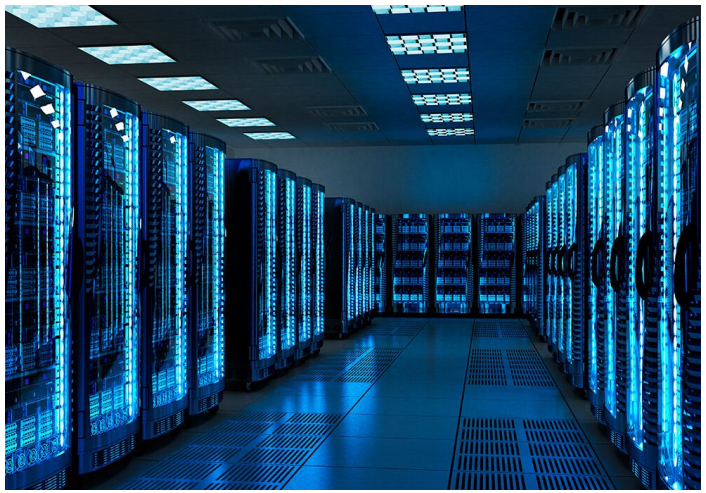
¿Cómo Utilizo el Modelo?

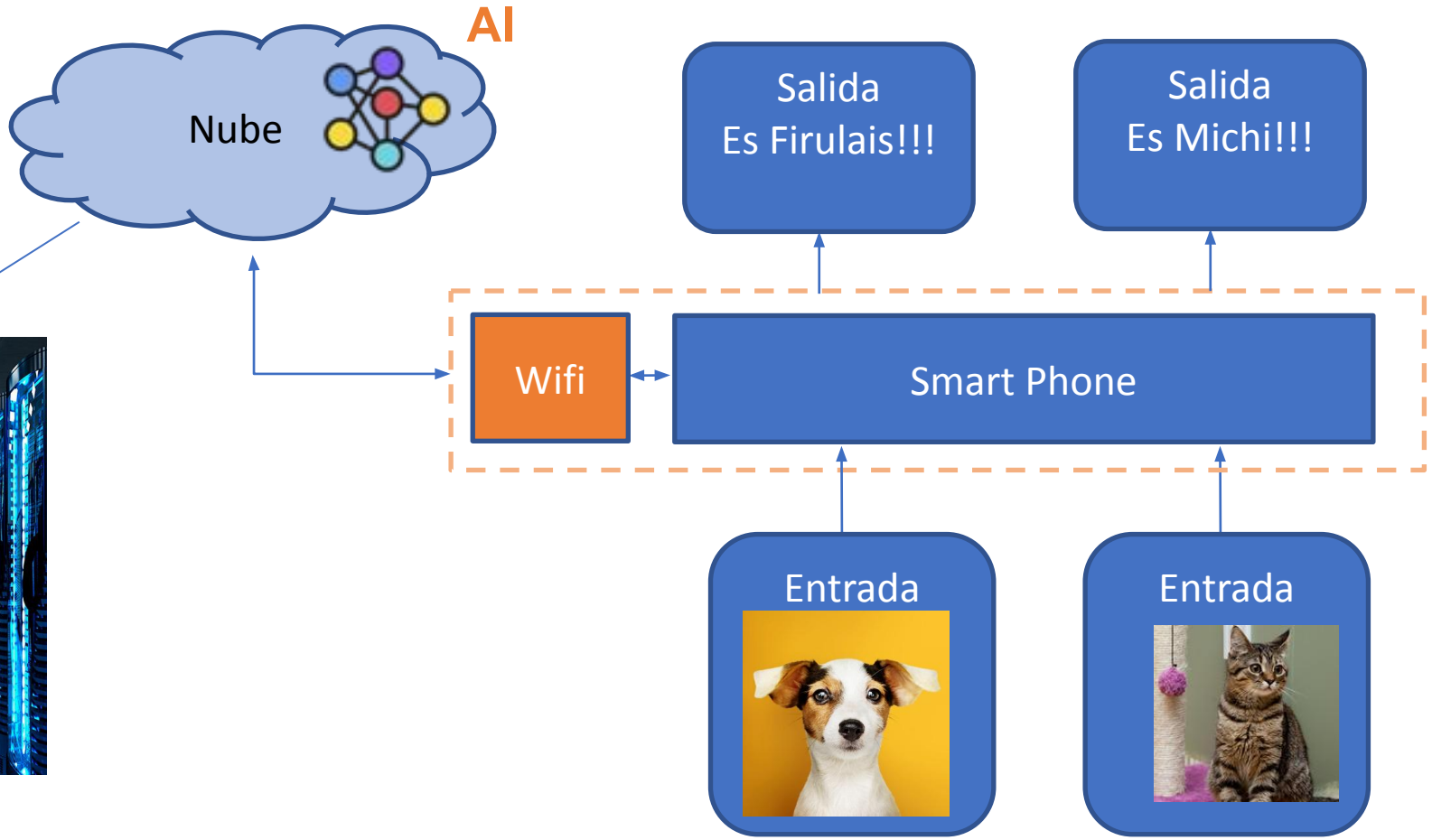
Despliegue Local (PC o Web Page)



¿Cómo Utilizo el Modelo?

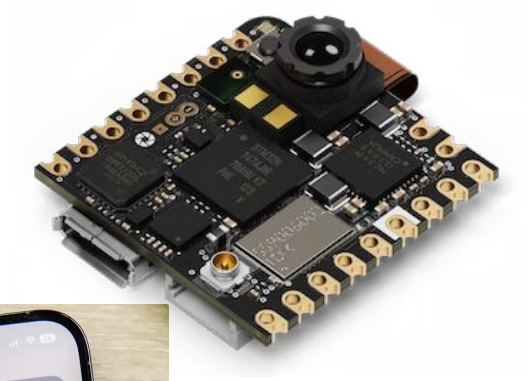
Inteligencia Artificial en la Nube

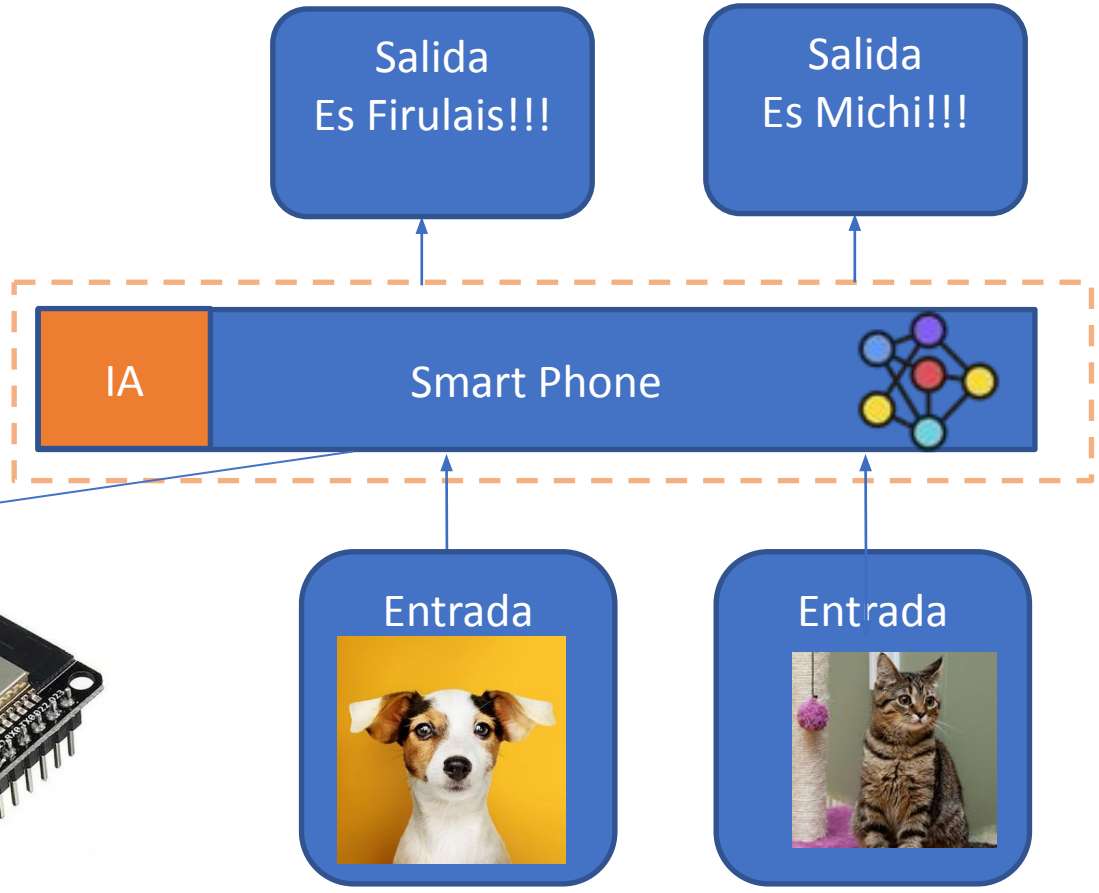




¿Cómo Utilizo el Modelo?

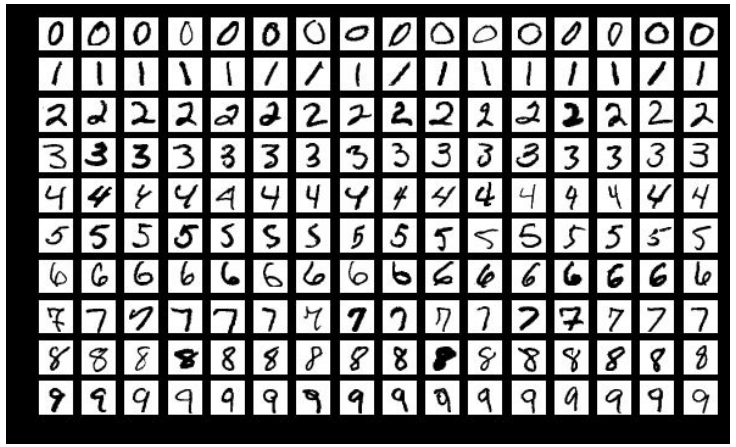
Edge AI





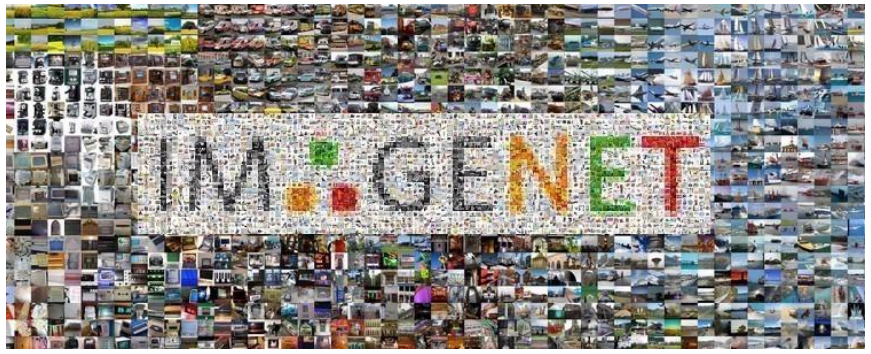
Facilitadores del Estado Actual de la Inteligencia Artificial

Accesibilidad a diversos data sets



By Josef Steppan - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=64810040

https://www.facebook.com/kaggle/



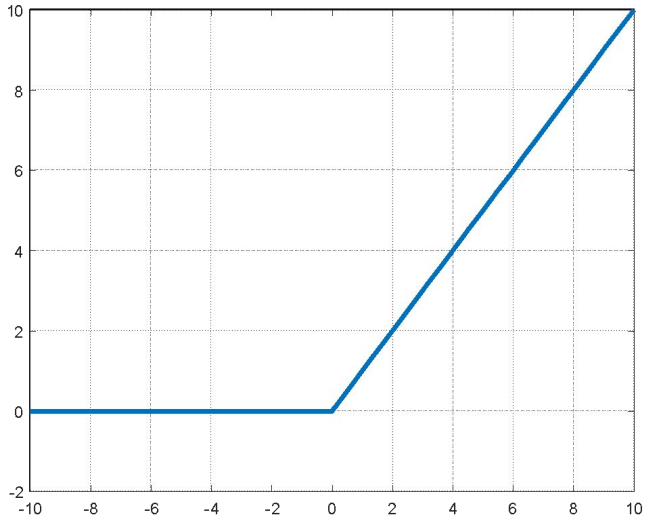
(http://image-net.org/)

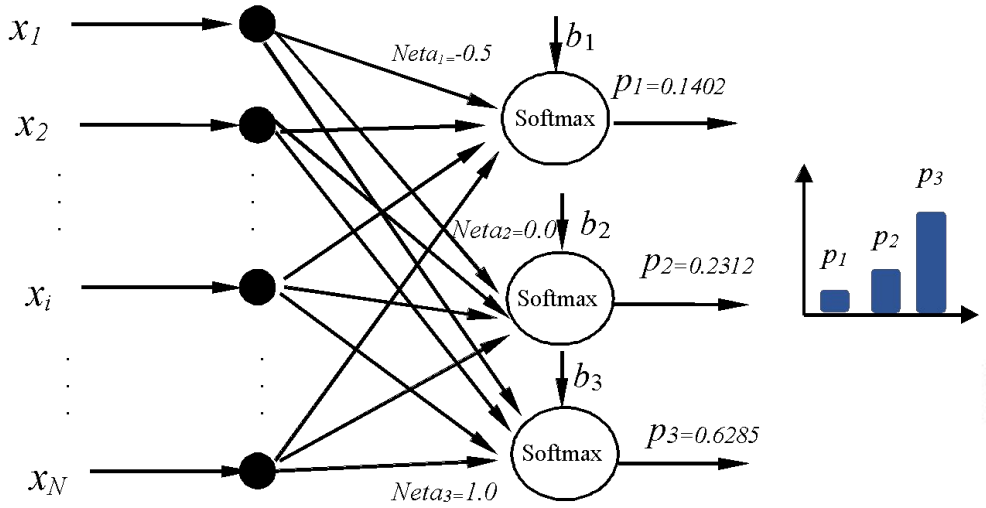
https://datasetsearch.research.google.com/

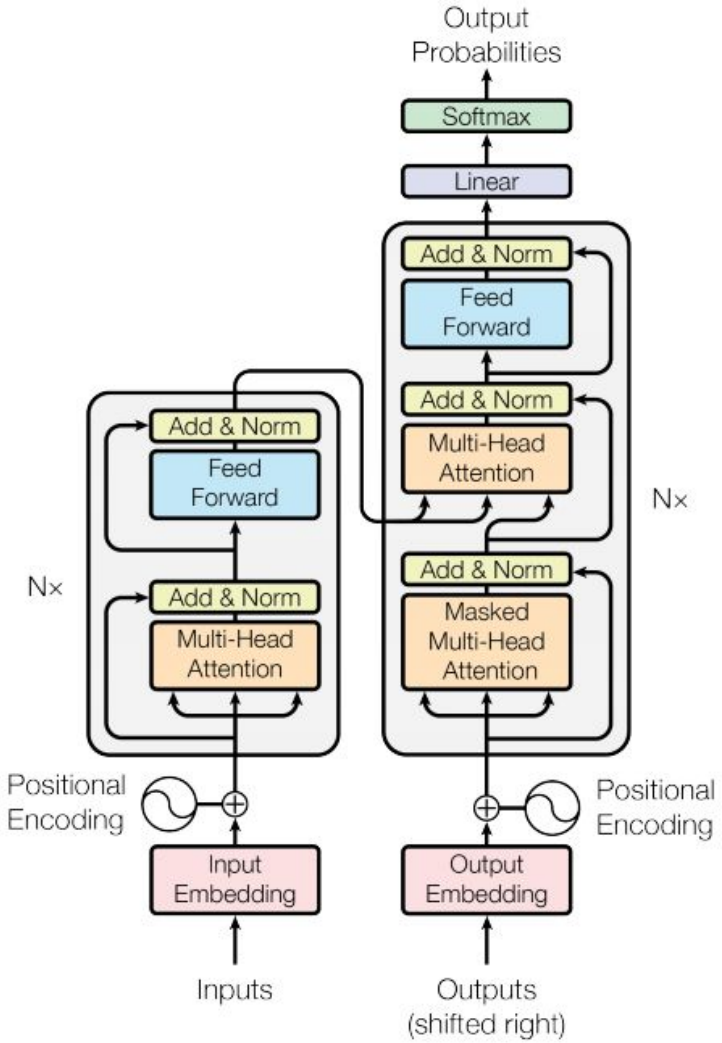
Facilitadores del Estado Actual de la Inteligencia Artificial

Mejoras conceptuales

- Entrenamiento por lotes
- Mejoras en las arquitecturas (p.e. Nuevas funciones de activación)
- Nuevas arquitecturas







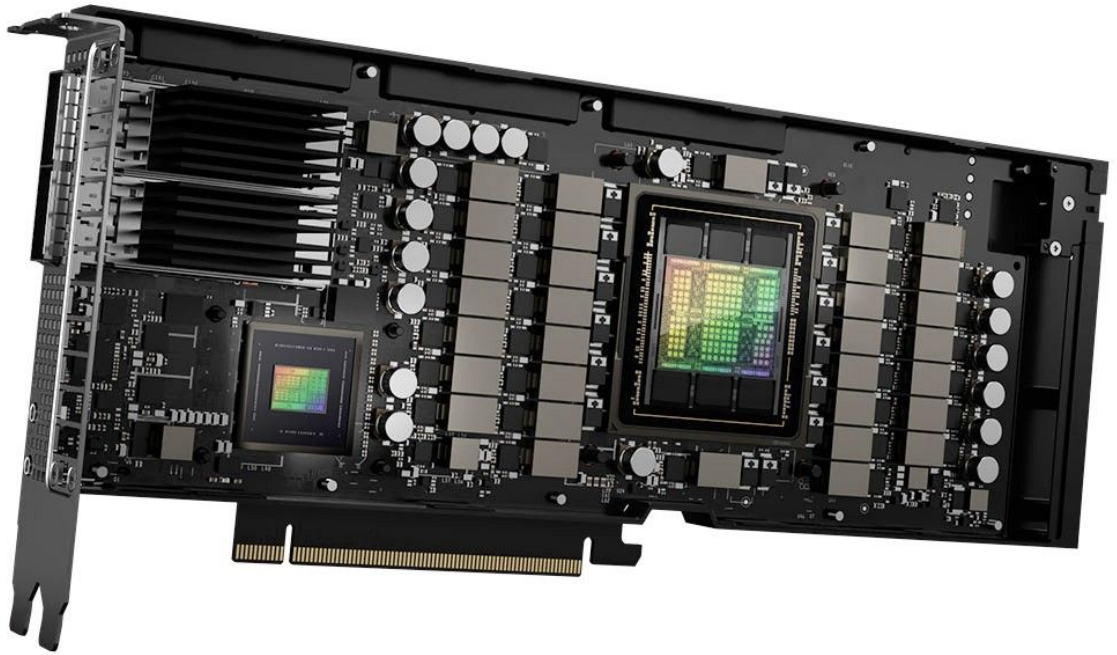
Fuente: Deep Learning. Teoría y Aplicaciones.. Jesus Alfonso López. 2021

https://arxiv.org/pdf/1706.03762.pdf

Facilitadores del Estado Actual de la Inteligencia Artificial

Se requiere una alta capacidad de cómputo

- Uso de GPU
- GPU especiales para data centers



http://www.funkykit.com/news/pc-computers/nvidia-abandon-3-way-4-way-sli-configurations/

https://www.viperatech.com/product/nvidia-h100-tensor-core-gpu/

Facilitadores del Estado Actual de la Inteligencia Artificial

Otros elementos

- Open source
- Software especializado (Diferenciación automática)

https://arxiv.org/

https://github.com/

https://paperswithcode.com/

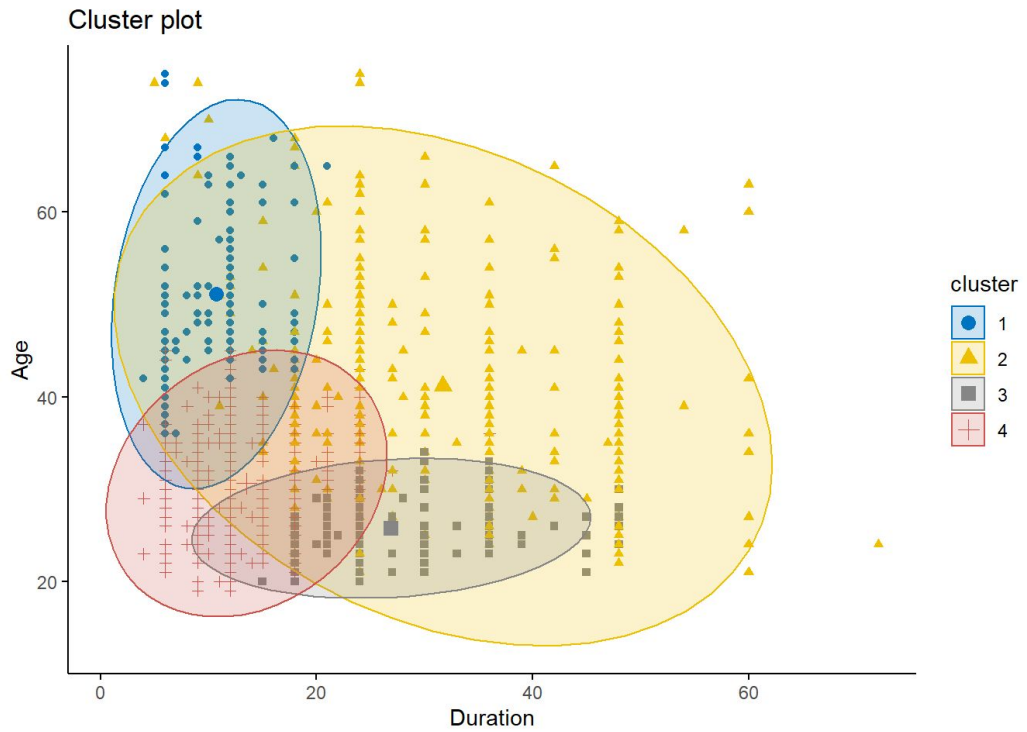
https://huggingface.co/

Datos Para Modelos de IA

Datos Tabulados o Estructurados

Credit Risk Data											
Loan Purpose	Checking	Savings	Months Customer	Months Employed	Gender	Marital Status	Age	Housing	Years	Job	Credit Risk
Small Appliance	$0	$739	13	12	M	Single	23	Own	3	Unskilled	Low
Furniture	$0	$1,230	25	0	M	Divorced	32	Own	1	Skilled	High
New Car	$0	$389	19	119	M	Single	38	Own	4	Management	High
Furniture	$638	$347	13	14	M	Single	36	Own	2	Unskilled	High
Education	$963	$4,754	40	45	M	Single	31	Rent	3	Skilled	Low
Furniture	$2,827	$0	11	13	M	Married	25	Own	1	Skilled	Low
New Car	$0	$229	13	16	M	Married	26	Own	3	Unskilled	Low
Business	$0	$533	14	2	M	Single	27	Own	1	Unskilled	Low
Small Appliance	$6,509	$493	37	9	M	Single	25	Own	2	Skilled	High
Small Appliance	$966	$0	25	4	F	Divorced	43	Own	1	Skilled	High
Business	$0	$989	49	0	M	Single	32	Rent	2	Management	High
New Car	$0	$3,305	11	15	M	Single	34	Rent	2	Unskilled	Low
Business	$322	$578	10	14	M	Married	26	Own	1	Skilled	Low
New Car	$0	$821	25	63	M	Single	44	Own	1	Skilled	High
New Car	$396	$228	13	26	M	Single	46	Own	3	Unskilled	Low
Used Car	$0	$129	31	8	M	Divorced	39	Own	4	Management	Low
Furniture	$652	$732	49	4	F	Divorced	25	Own	2	Skilled	High
New Car	$708	$683	13	33	M	Single	31	Own	2	Skilled	Low
Repairs	$207	$0	28	116	M	Single	47	Own	4	Skilled	Low
Education	$287	$12,348	7	2	F	Divorced	23	Rent	2	Skilled	High
Furniture	$0	$17,545	34	16	F	Divorced	22	Own	4	Skilled	High
Furniture	$101	$3,871	13	5	F	Divorced	26	Rent	4	Skilled	High
Furniture	$0	$0	25	23	M	Married	19	Own	4	Skilled	High
Furniture	$0	$485	37	23	F	Divorced	27	Own	2	Management	High

https://media.cheggcdn.com/media/d52/d52c60c8-60d4-4e55-882f-3ed24306f8cb/phpR8NHxM

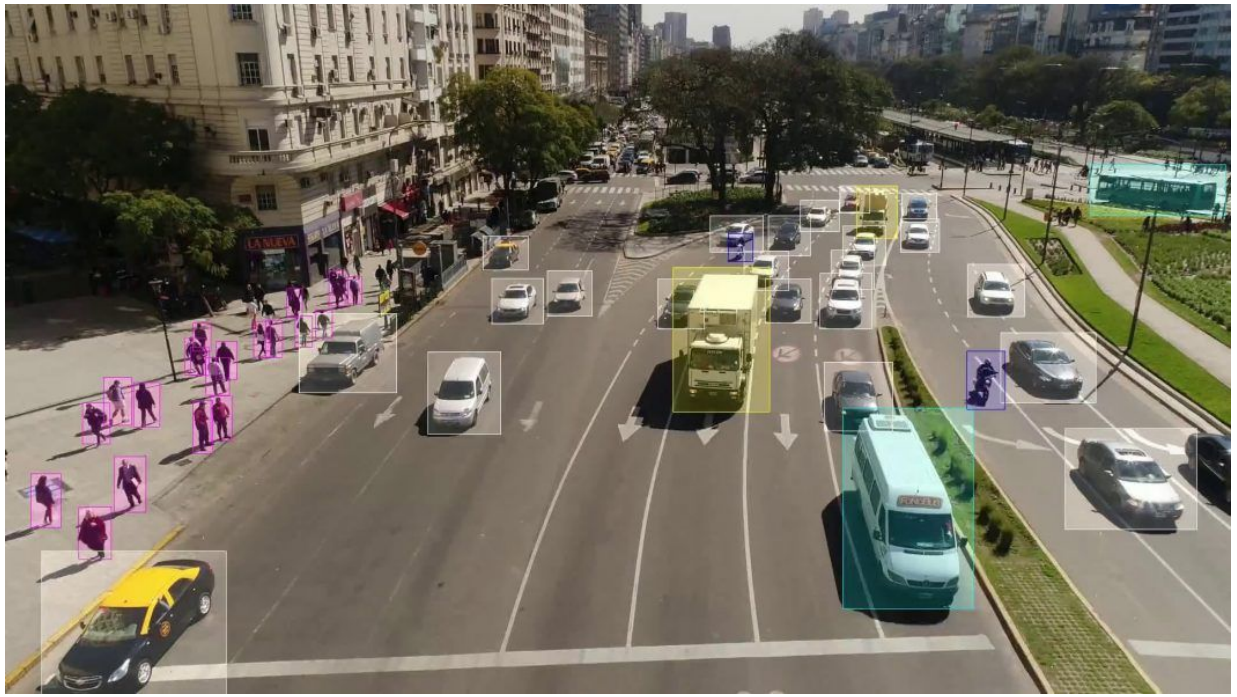


https://rpubs.com/sid9715/580607

Datos Para Modelos de IA

Datos en Imágenes

https://www.youtube.com/watch?v=KS_4xjXNTxg&



https://viso.ai/applications/computer-vision-applications/

Datos Para Modelos de IA

Datos de Lenguaje (hablado y escrito)

https://www.grupoftp.com/noticias/el-futuro-de-los-chatbots/

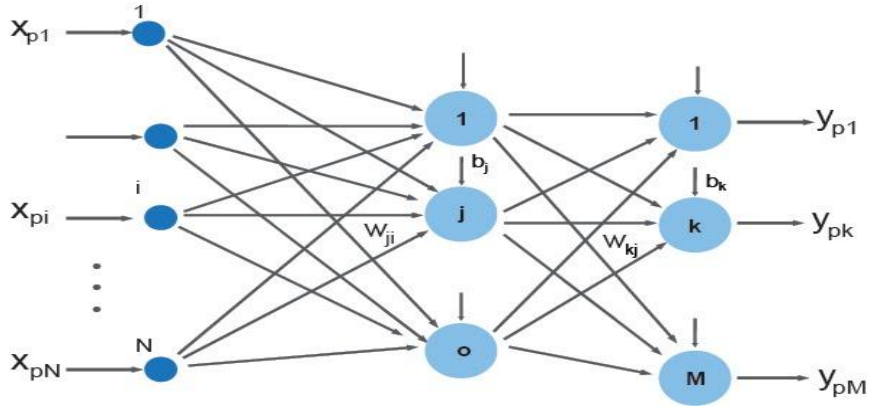
https://analyticsindiamag.com/google-translate-machine-learning/

Redes Neuronales Artificiales Alias Aprendizaje Profundo (Deep Learning)

Redes Neuronales Artificiales (Alias Deep Learning)

https://medium.com/espanol/avances-en-redes-neuronales-705c2efe53d2

https://medicine.wustl.edu/news/slow-steady-waves-keep-brain-humming/



Fuente: Deep Learning. Teoría y Aplicaciones. Jesus Alfonso López. Alpha Editorial 2021

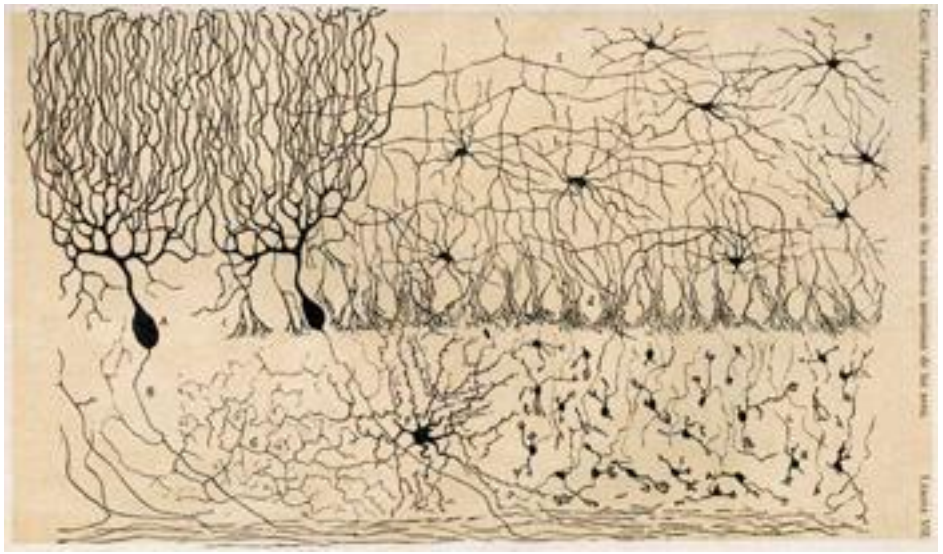
Los Bloques Básicos del Deep Learning

Capas Densas

La Doctrina de la Neurona

Santiago Ramón y Cajal

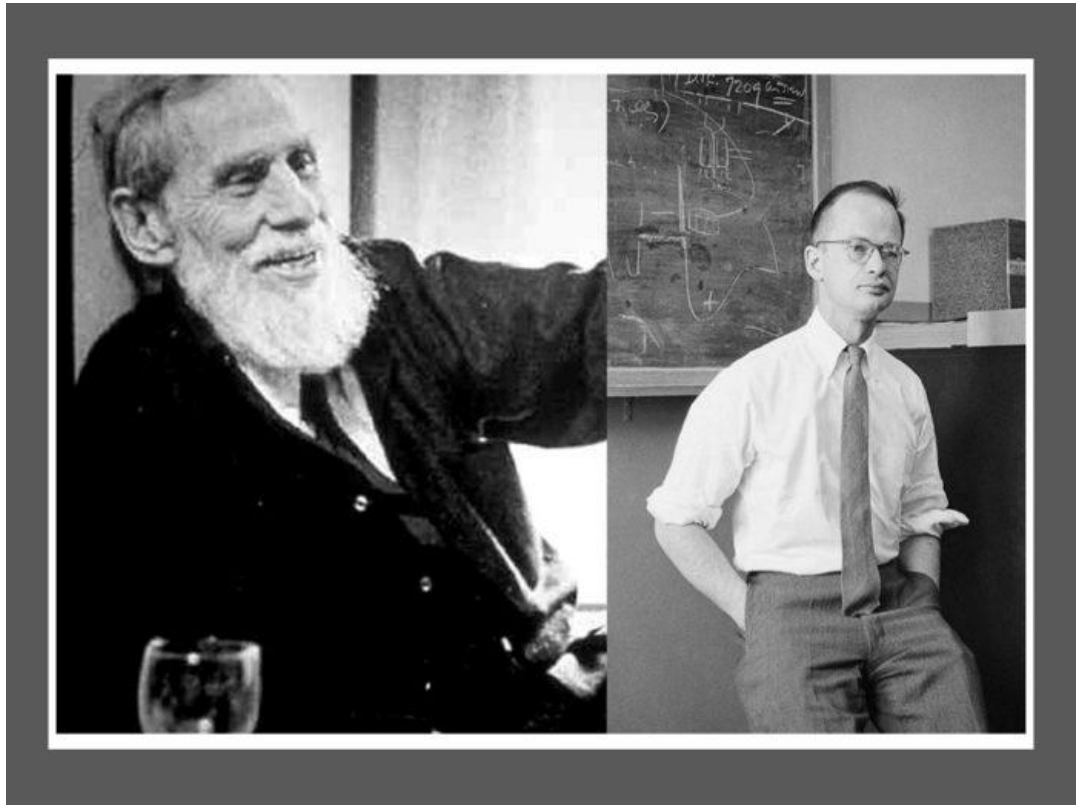
https://es.wikipedia.org/wiki/Santiago_Ram%C3%B3n_y_Cajal



https://es.wikipedia.org/wiki/Doctrina_de_la_neurona

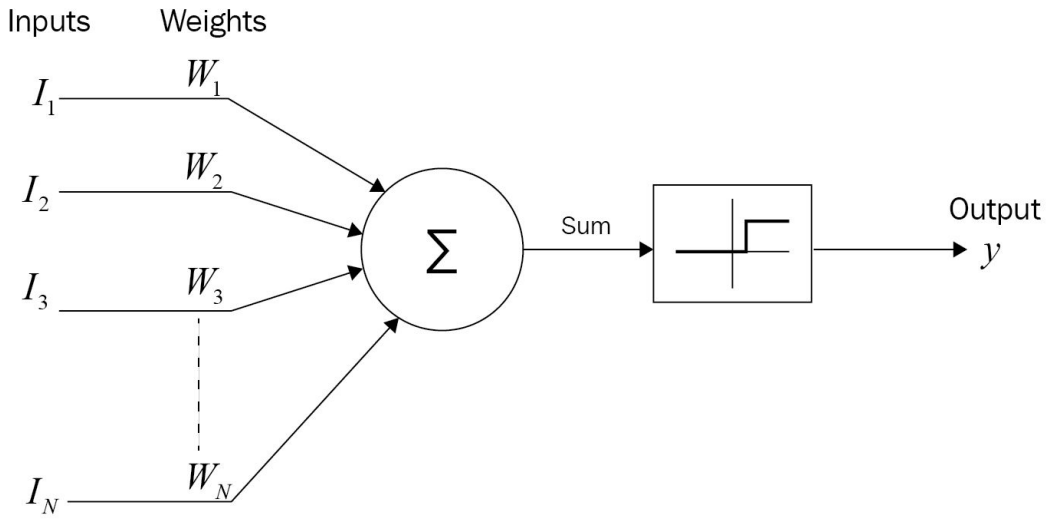
Capas Densas

McCulloch and Pitts



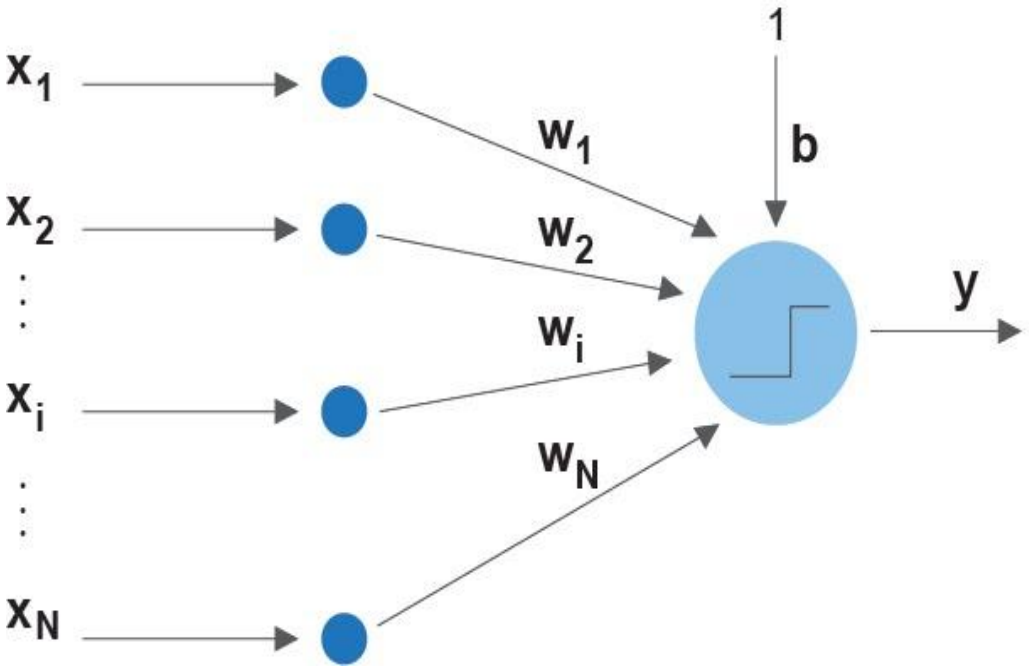
https://machinelearningknowledge.ai/timeline/mcculloch-pitts-neuron-the-beginning/

Modelo de Neurona Artificial

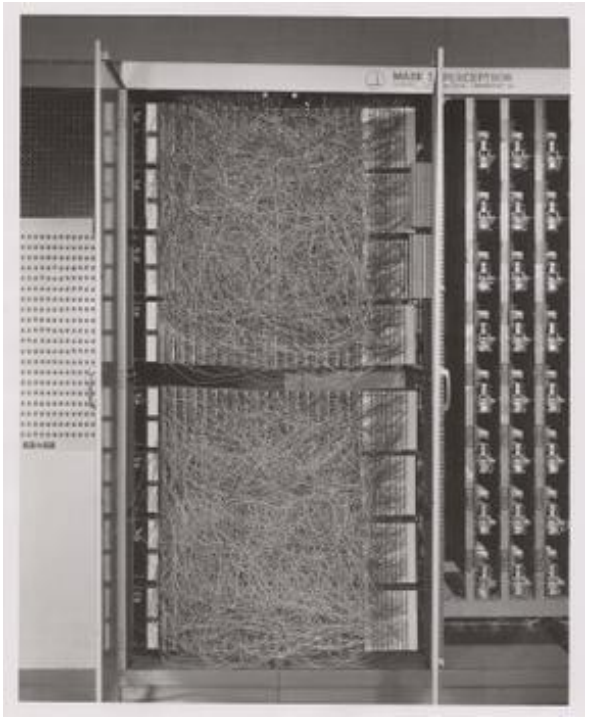


Capas Densas

Perceptron



The Mark I Perceptron machine was the first implementation of the perceptron algorithm



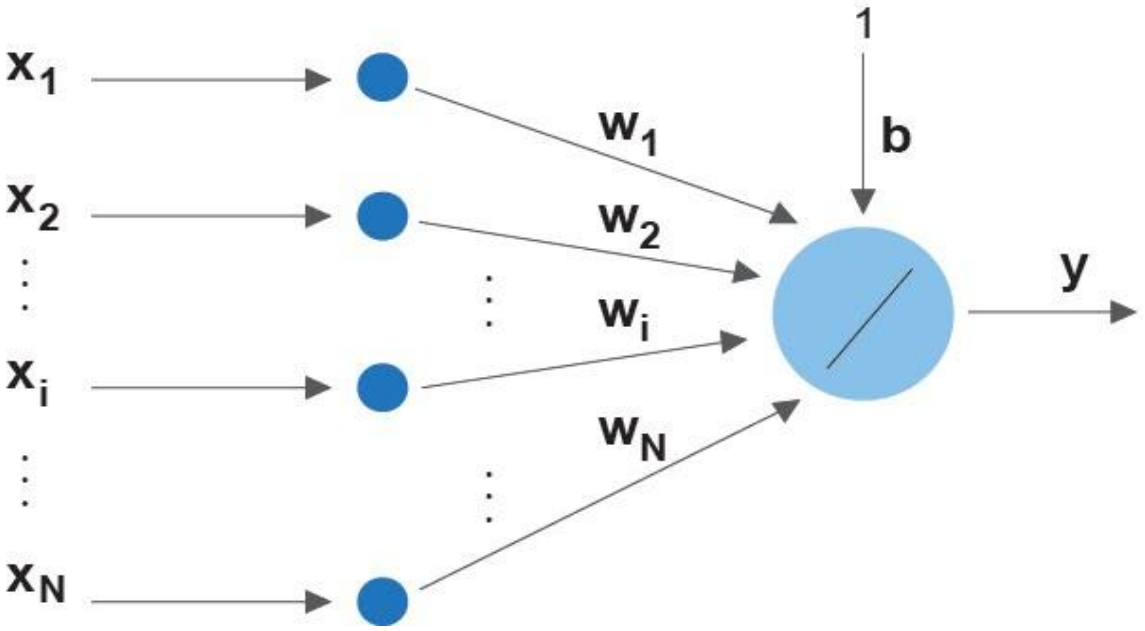
Frank Rossenblatt

https://en.wikipedia.org/wiki/Perceptron

https://blogs.umass.edu/comphon/2017/06/15/did-frank-rosenblatt-invent-de
-learning-in-1962/

Capas Densas

Adaline. Gradiente Descendente

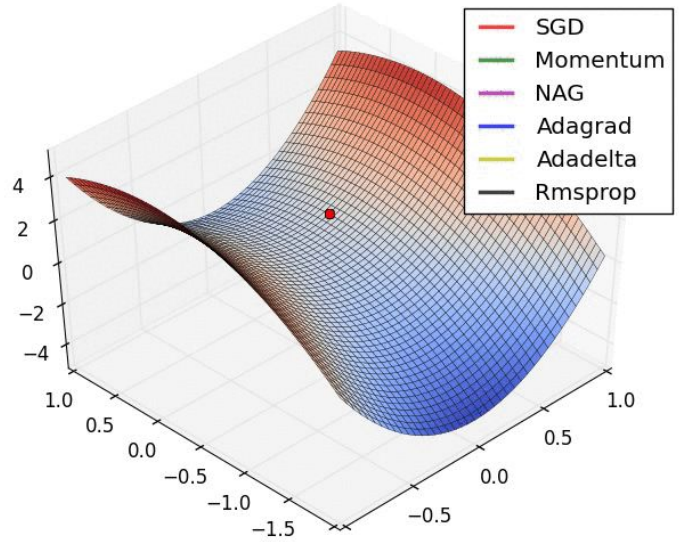


https://medium.com/invisible-illness/the-mountaineer-897387f8a902

Regla Delta

$$w_i(t+1) = w_i(t) + \Delta w_i(t)$$

$$w_i(t+1) = w_i(t) + \alpha(d_i - y_i)\, x_i$$



http://dsdeepdive.blogspot.com/2016/03/optimizations-of-gradient-descent.html

Capas Densas

Adaline. Gradiente Descendente

Augustin-Louis Cauchy

1847

https://en.wikipedia.org/wiki/Augustin-Louis_Cauchy

Haskell Brooks Curry

1944

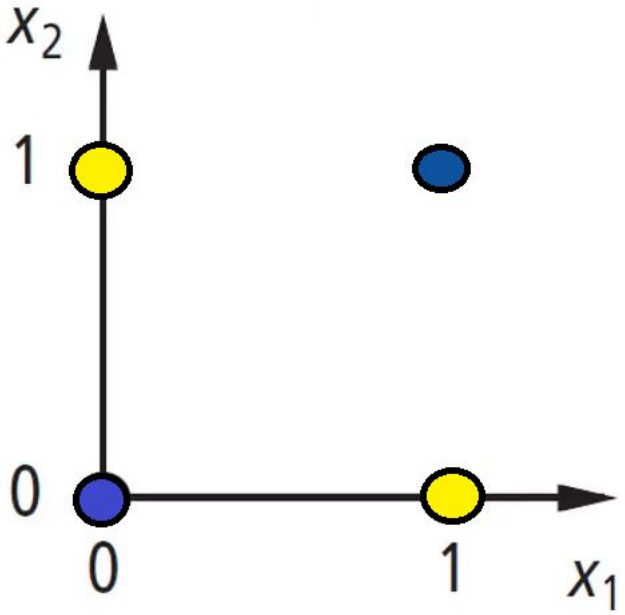
https://en.wikipedia.org/wiki/Haskell_Curry

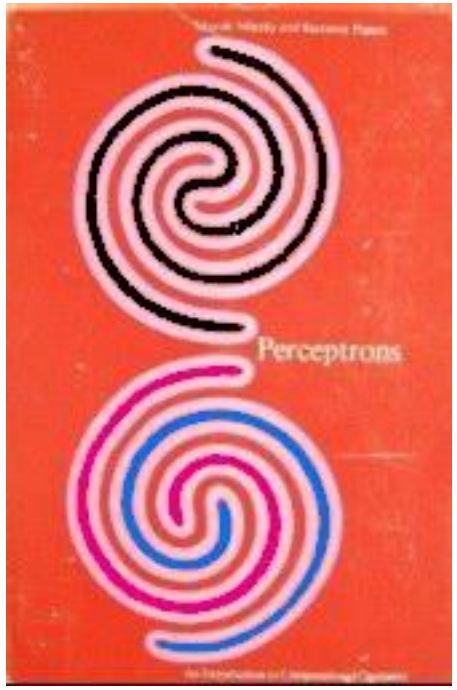
Capas Densas

Problemas de las Redes Monocopa

Marvin Minsky and Seymour Papert

Problema de la XOR: Separatividad No Lineal



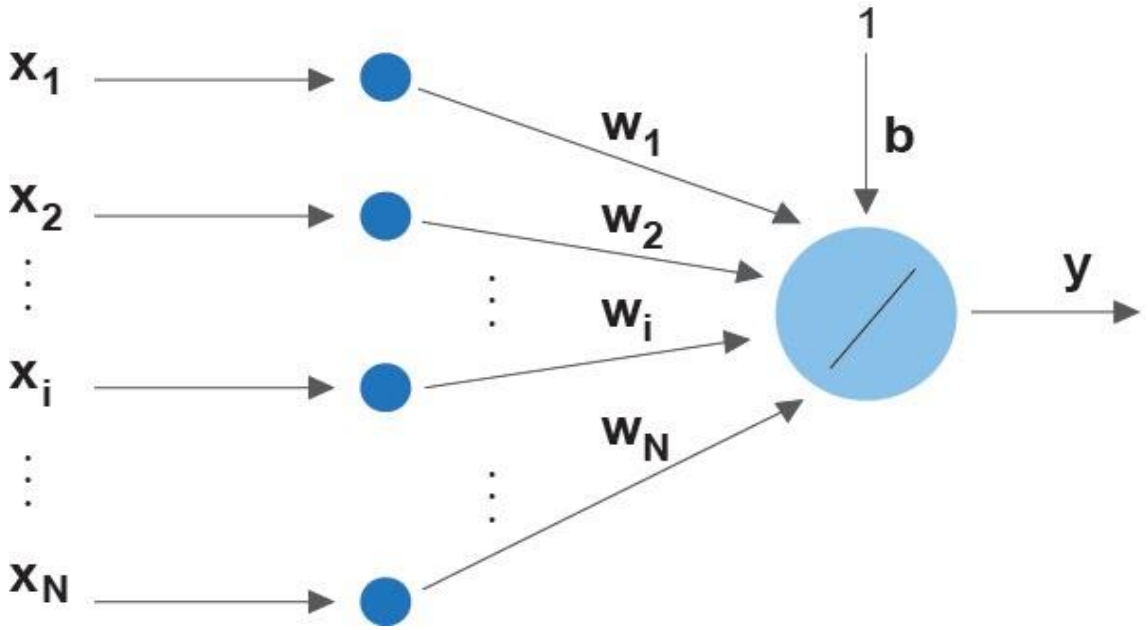


http://harveycohen.net/image/perceptron.html

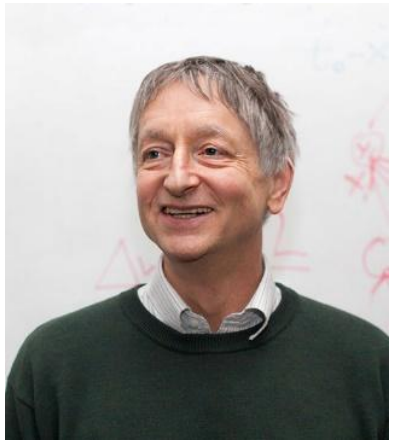
Winter!!!

Capas Densas

Backpropagation



David Rumelhart



Geoffrey Hinton

Regla Delta Generalizada

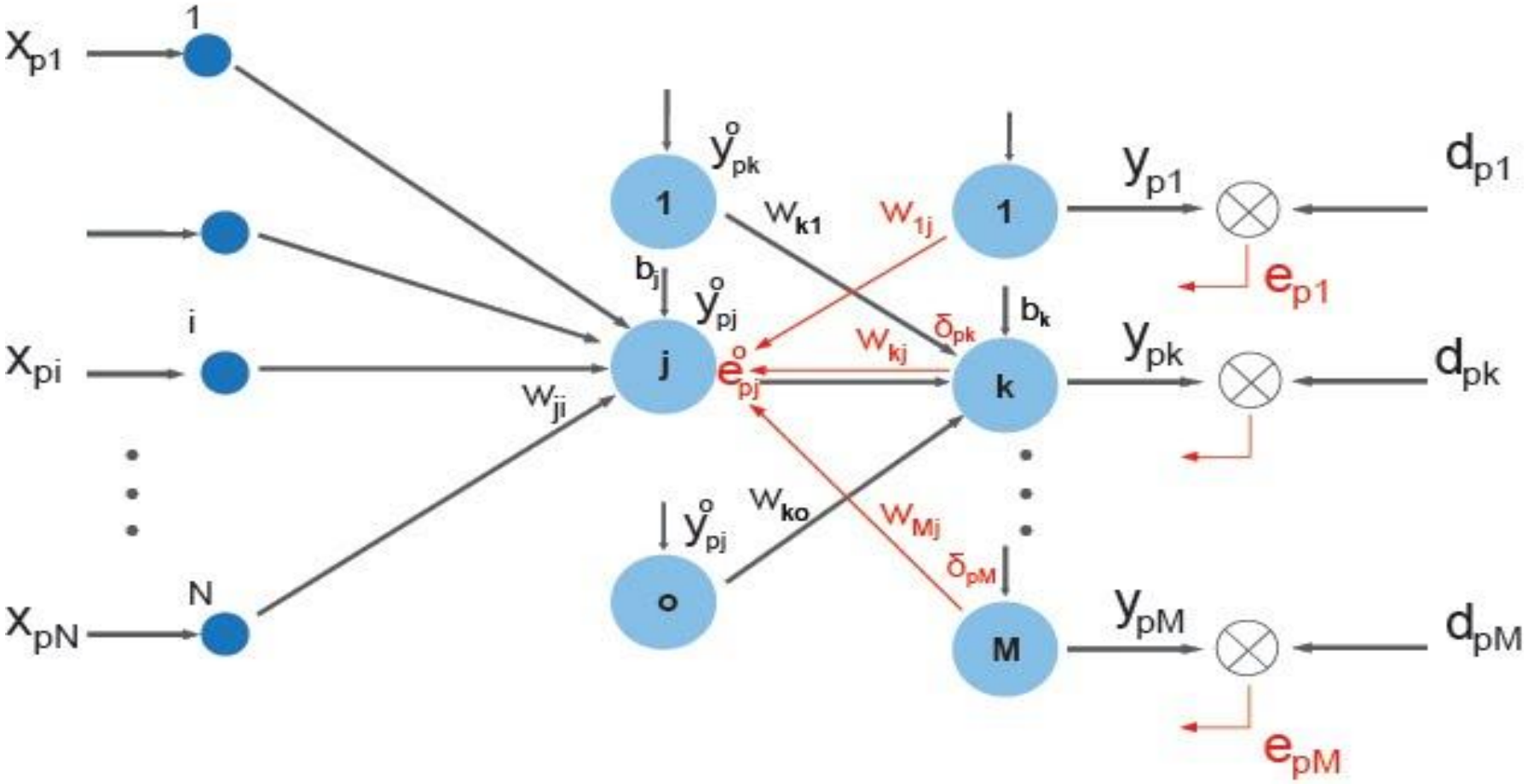
$$w_i(t+1) = w_i(t) + \Delta w_i(t)$$

$$w_i(t+1) = w_i(t) + \alpha(d_i - y_i)\ Fact'(neta)x_i$$

Es evidente en la capa de Salida pero
¿Cómo se calcula en las capas ocultas?

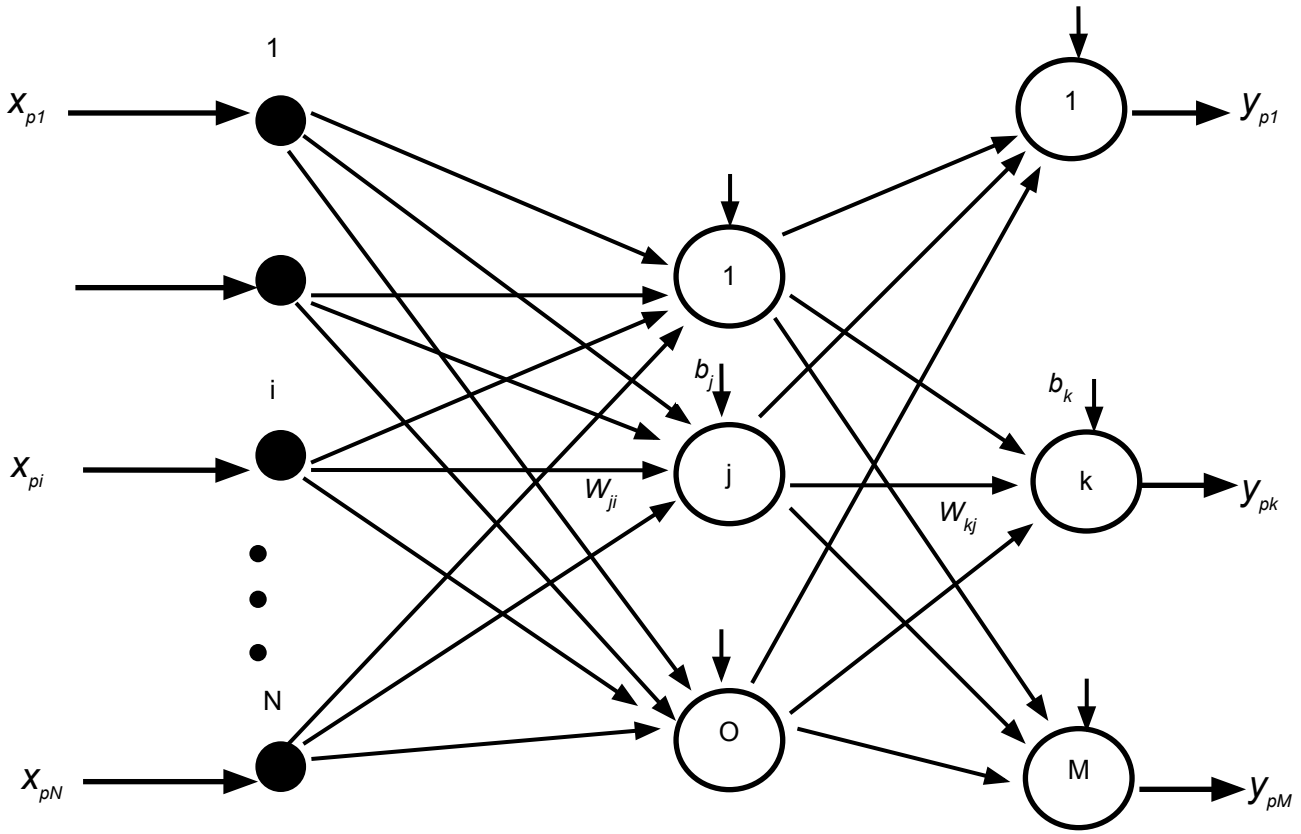
Capas Densas

Backpropagation



Fuente: Deep Learning. Teoría y Aplicaciones Jesus Alfonso López. Alpha Editorial. 2021

Capas Densas



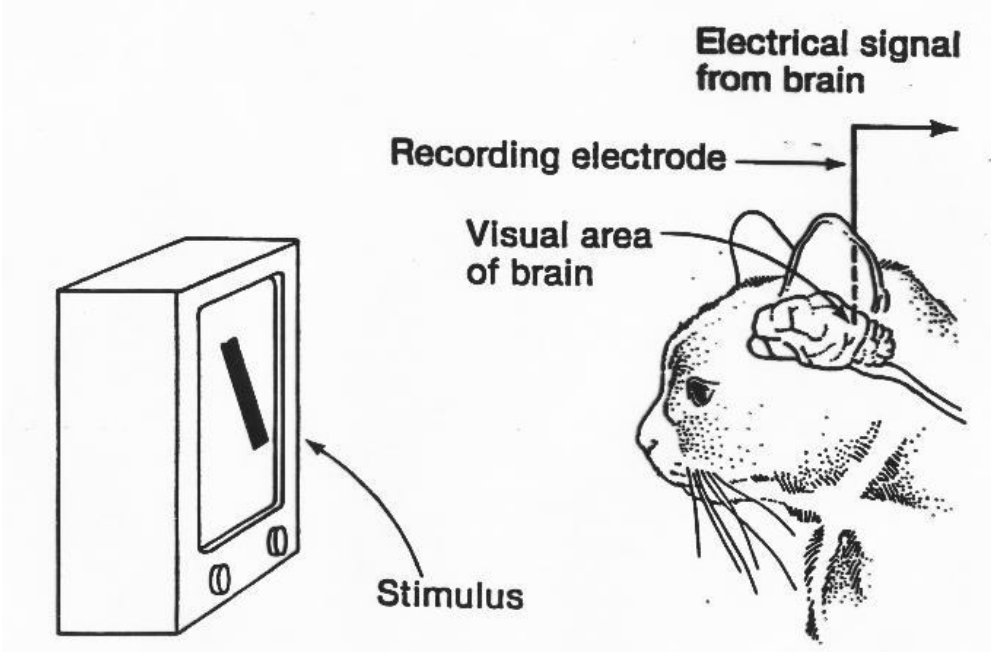
Fuente: Deep Learning. Teoría y Aplicaciones.. Jesus Alfonso López. 2021

Los Bloques Básicos del Deep Learning

Capas Convolucionales

Hubel and Wiesel Cat Experiment (60s)

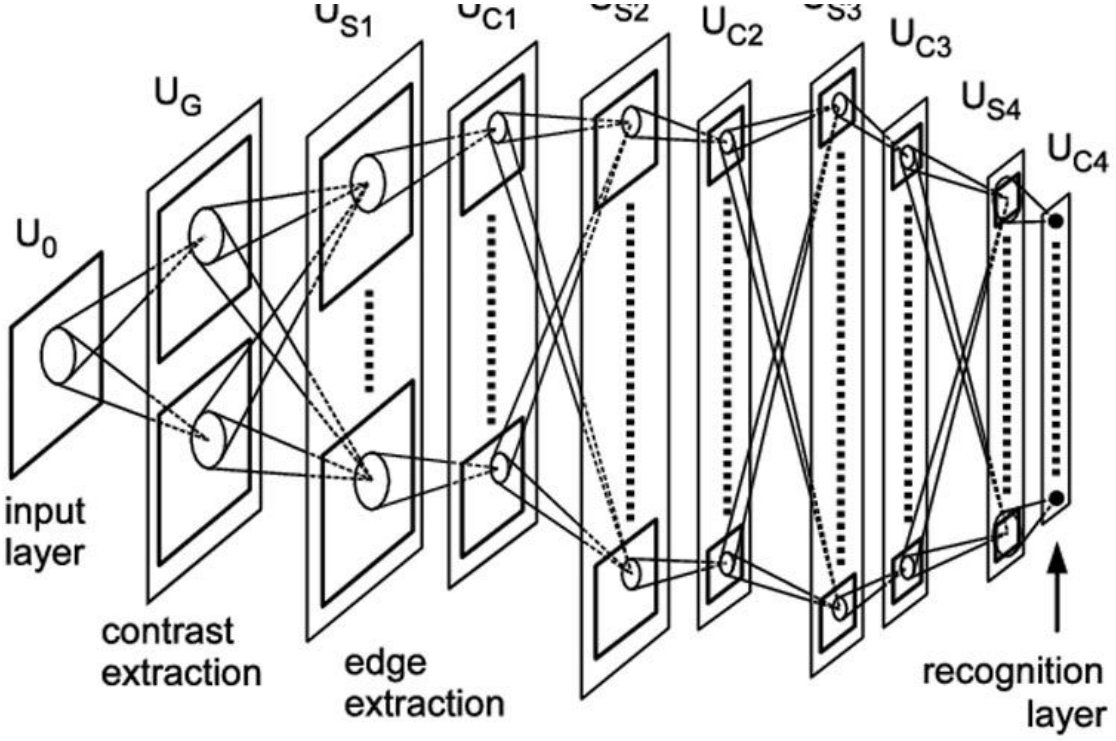
- Patrones sencillos = luz y oscuridad, células simples
- Patrones intermedios = Bordes o movimientos en determinadas direcciones, células complejas
- Patrones complejos = Dos bordes formando un ángulo recto , células hipercomplejas
- Neuronas especializadas en detectar bordes, movimientos, profundidad estereoscópica o color.



https://jralonso.es/2016/01/11/la-suma-para-construir-un-todo/

Capas Convolucionales

Kunihiko Fukushima and the architecture of the Neocognitron (1979)

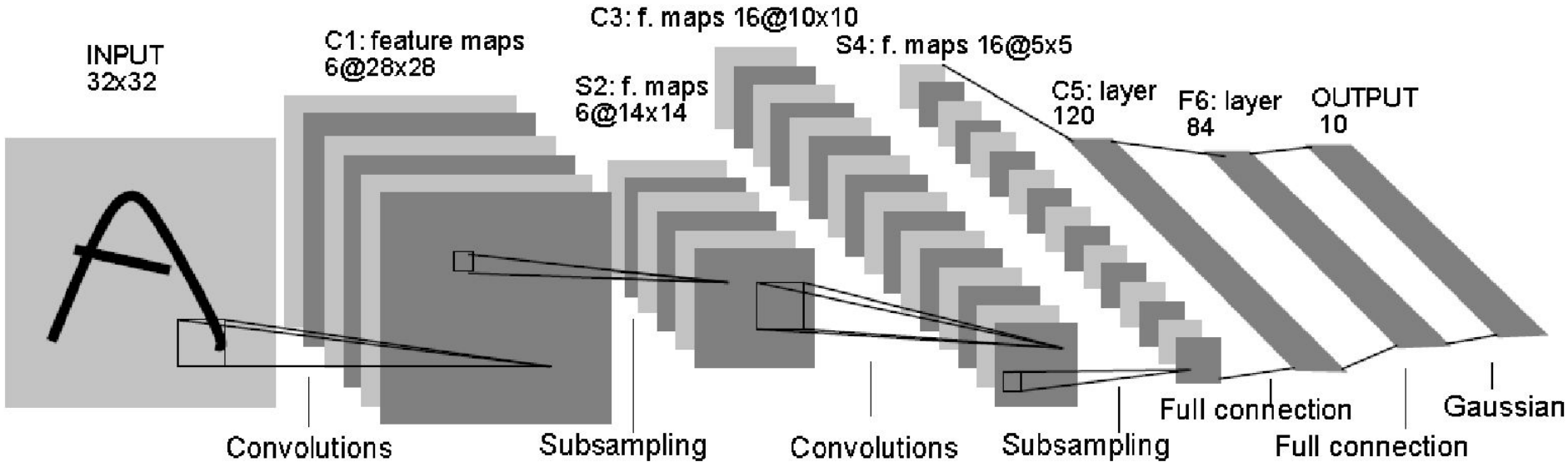


https://labelyourdata.com/articles/history-of-machine-learning-how-did-it-all-start#1979

Capas Convolucionales

Yann LeCun

LeNet-5 (1989)



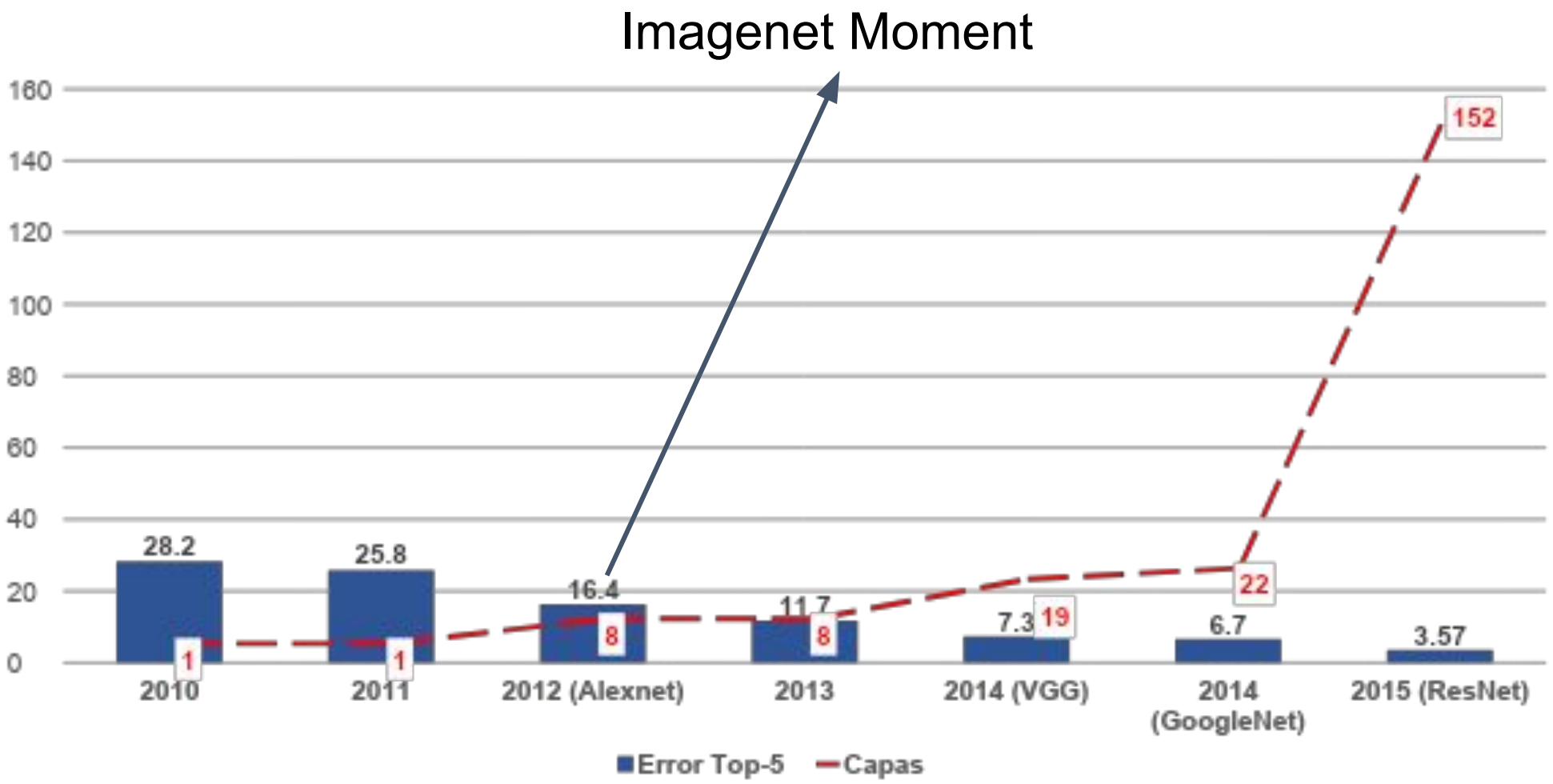
https://es.wikipedia.org/wiki/Yann_LeCun

http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf

LeNet- 1 Demo Video

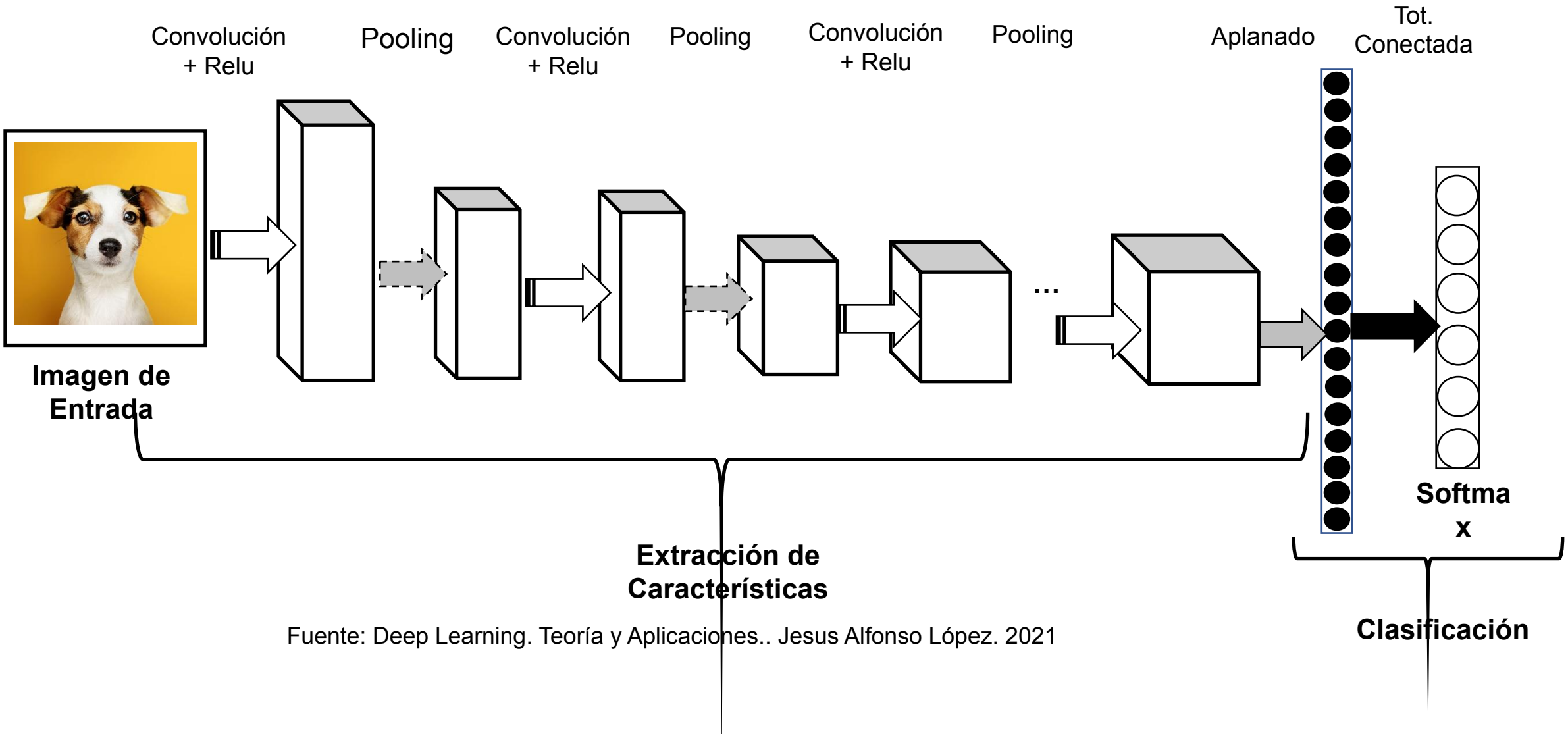
https://www.youtube.com/watch?v=FwFduRA_L6Q

Capas Convolucionales



Fuente: Deep Learning. Teoría y Aplicaciones.. Jesus Alfonso López. 2021

Capas Convolucionales

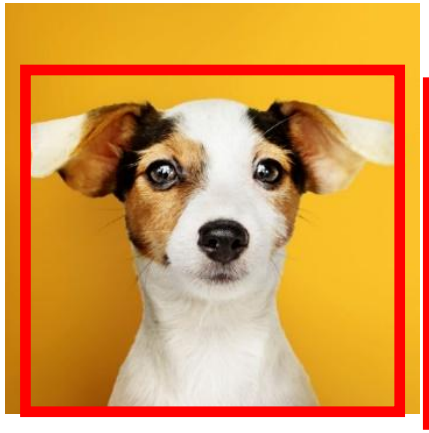


Fuente: Deep Learning. Teoría y Aplicaciones.. Jesus Alfonso López. 2021

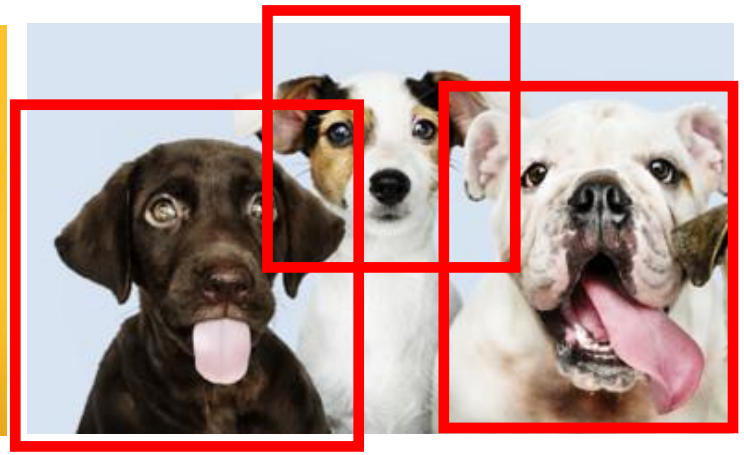
Capas Convolucionales

Clasificación

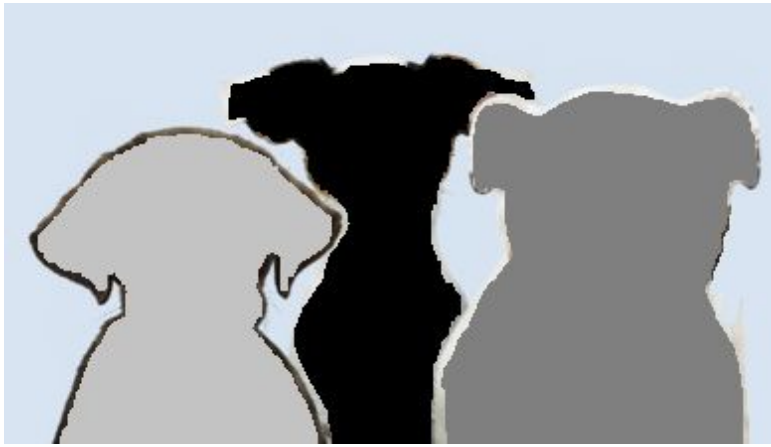
Clasificación y Localización



Detección



Segmentación Semántica



Un Objeto

Varios Objetos

Fuente: Deep Learning. Teoría y Aplicaciones.. Jesus Alfonso López. 2021

Capas Convolucionales

https://securitytoday.com/articles/2019/03/01/the-flaws-and-dangers-of-facial-recognition.aspx

https://www.v7labs.com/blog/human-pose-estimation-guide

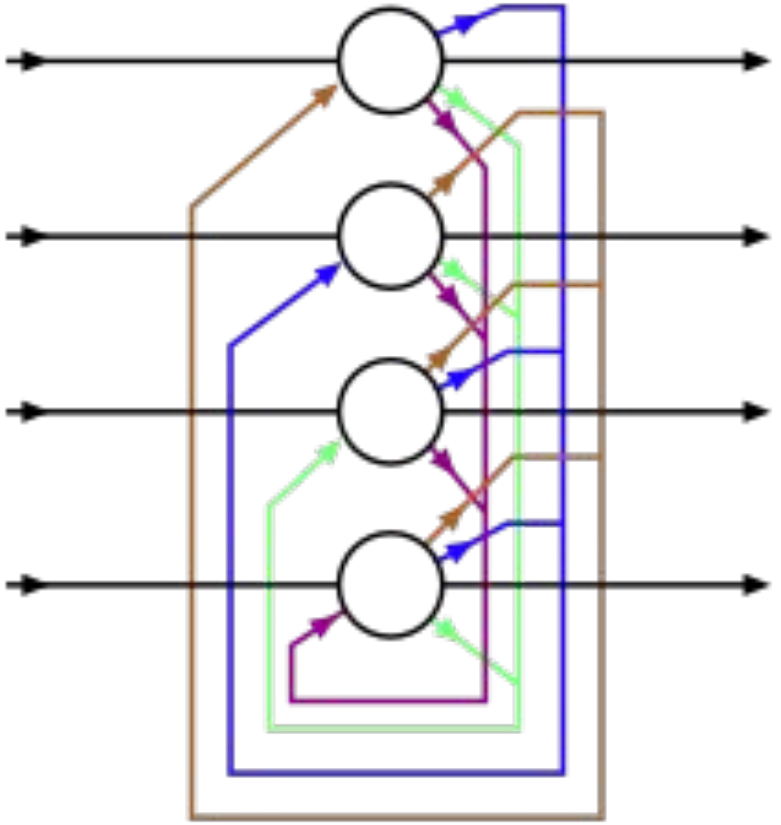
Los Bloques Básicos del Deep Learning

Capas Recurrentes

Red neuronal de Hopfield (1982)

John Joseph Hopfield

https://www.swarthmore.edu/bulletin/archive/wp/october-2009_john-hopfield-54.html



https://en.wikipedia.org/wiki/Hopfield_network

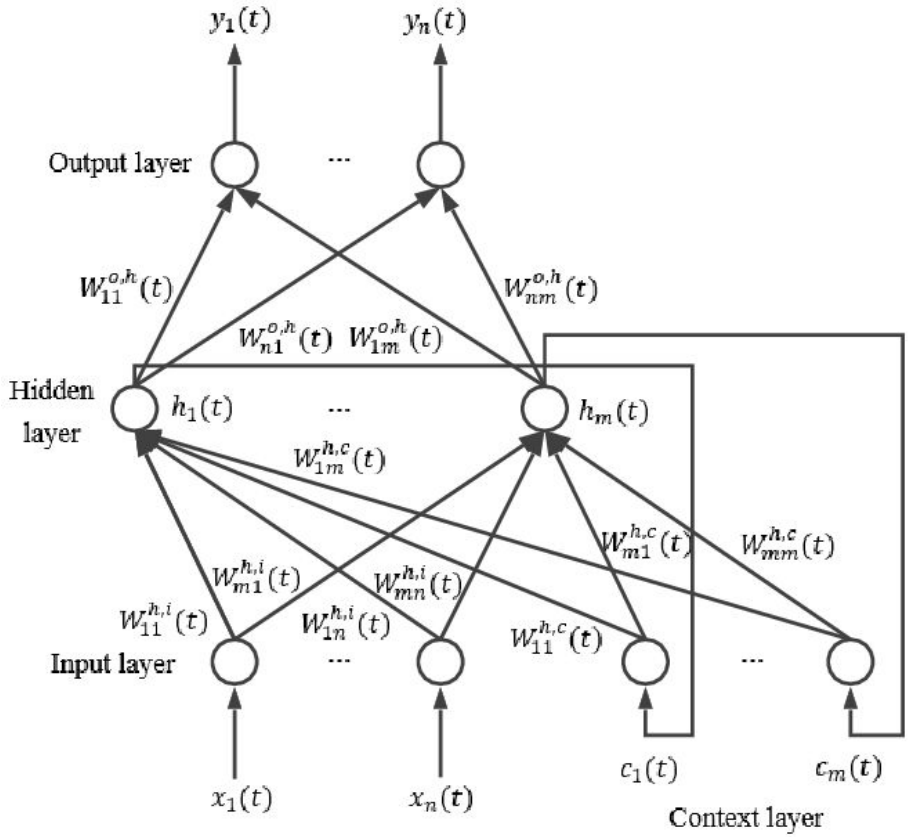
Los Bloques Básicos del Deep Learning

Capas Recurrentes

Red neuronal de Elman (1990)

Jeffrey Locke Elman

https://crl.ucsd.edu/elman/obituary/

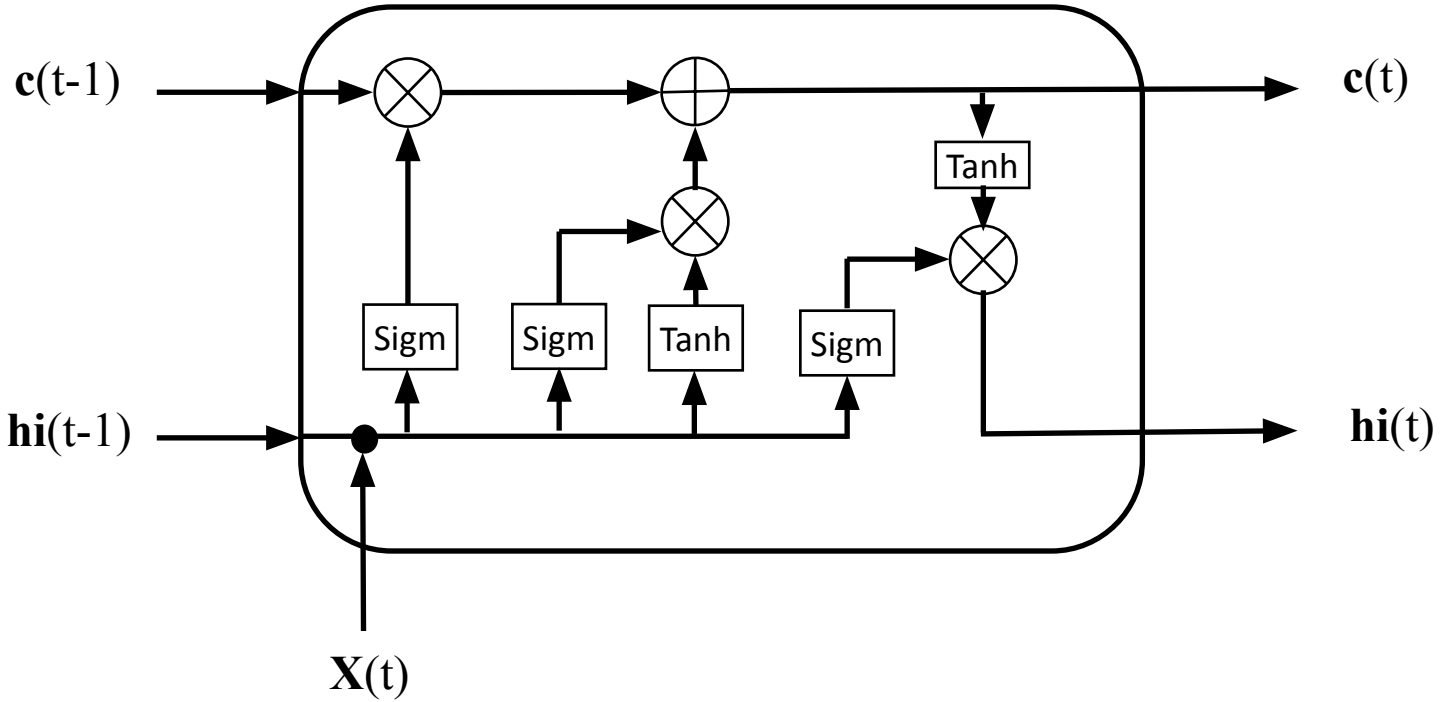


https://www.researchgate.net/figure/The-Structure-of-Elman-Neural-Network_fig1_322843098

Capas Recurrentes

Red neuronal de LSTM (1997)

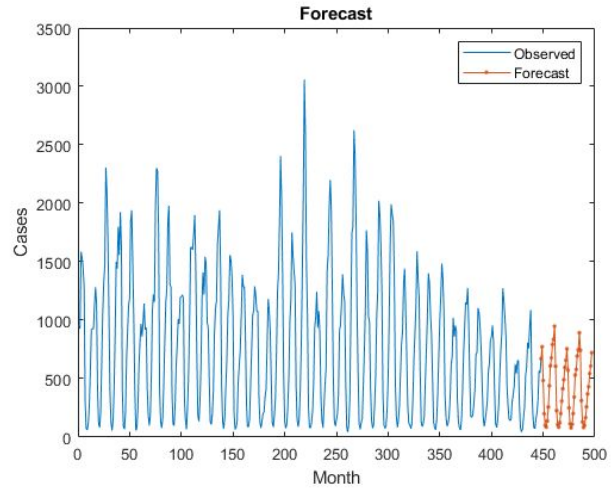
Jürgen Schmidhuber



Fuente: Deep Learning. Teoría y Aplicaciones.. Jesus Alfonso López. 2021

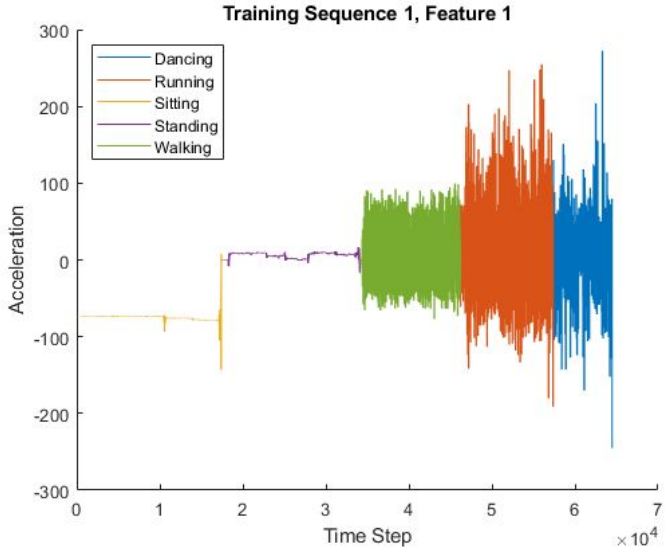
Capas Recurrentes

['1,2,3,4,5'] → Red Recurrente → [6]



https://la.mathworks.com/help/deeplearning/examples/time-series-forecasting-using-deep-learning.html

['1,2,3,4,5'] → Red Recurrente → [Clase]



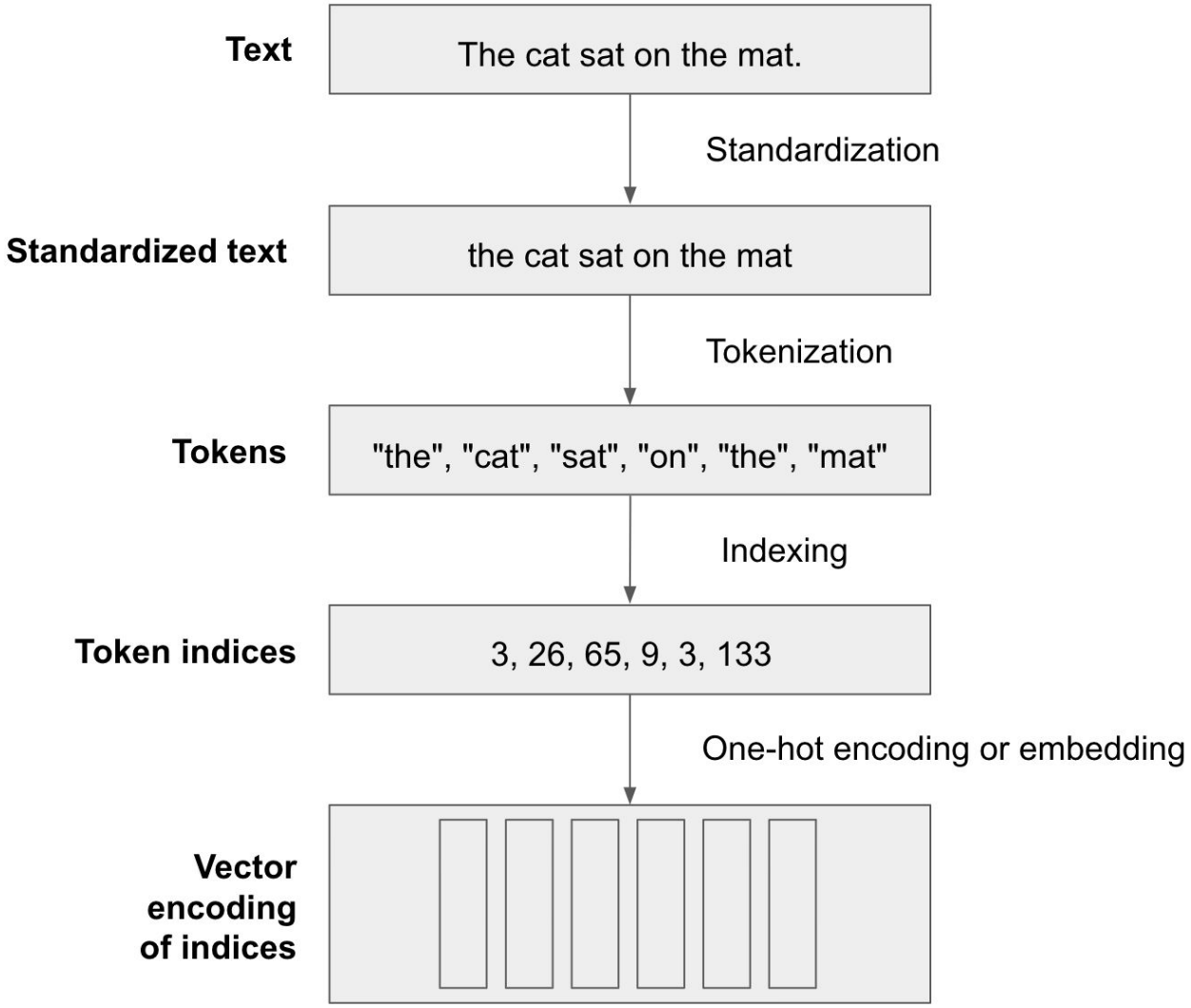
https://la.mathworks.com/help/deeplearning/examples/sequence-to-sequence-classification-using-deep-learning.html

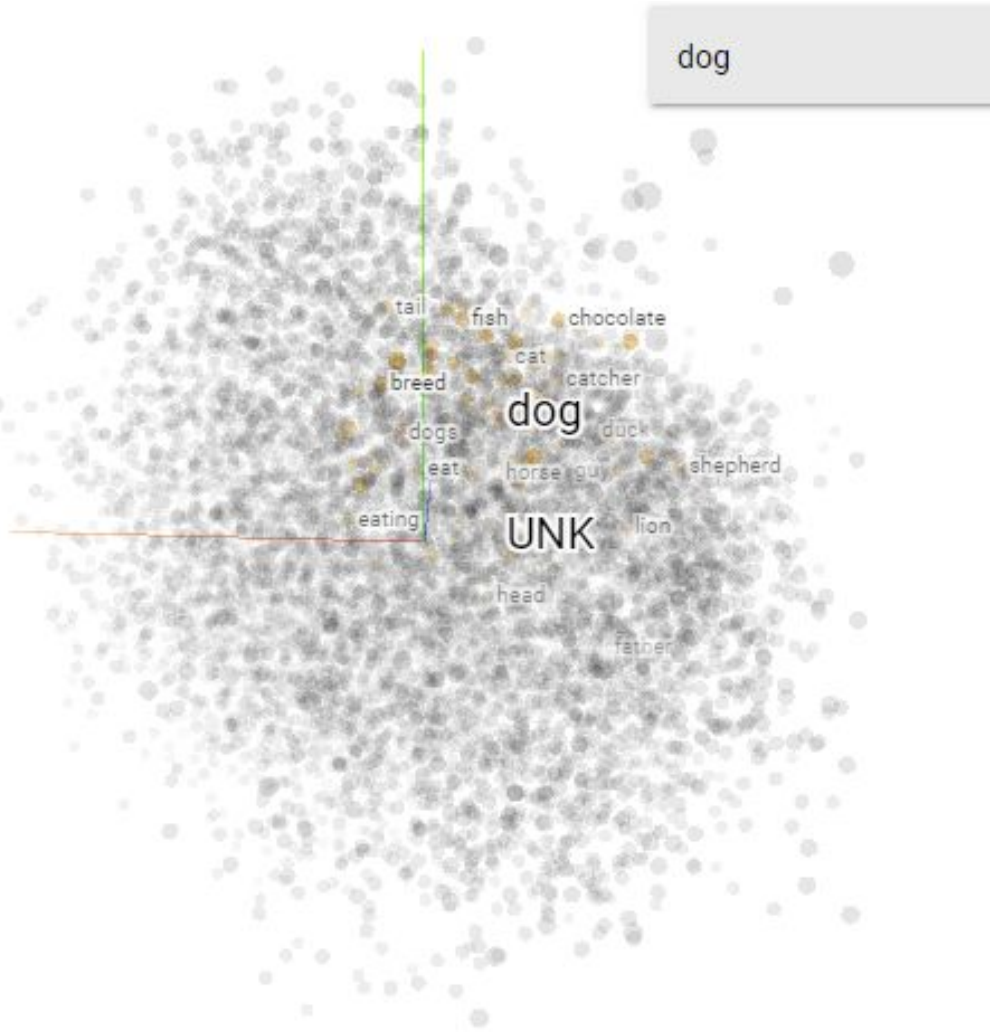
Capas Recurrentes

PLN (Procesamiento de Lenguaje Natural)

Modelos de Lenguaje

Embedding





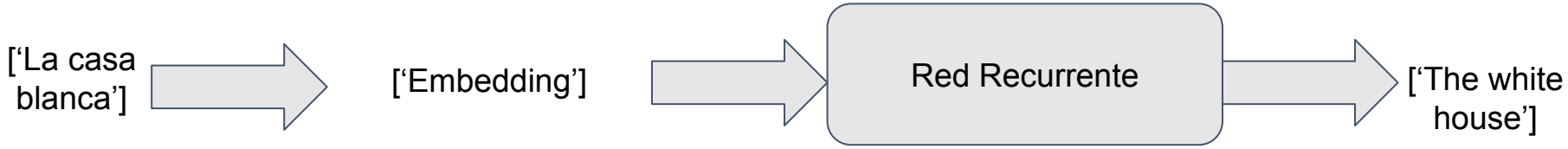
https://projector.tensorflow.org/

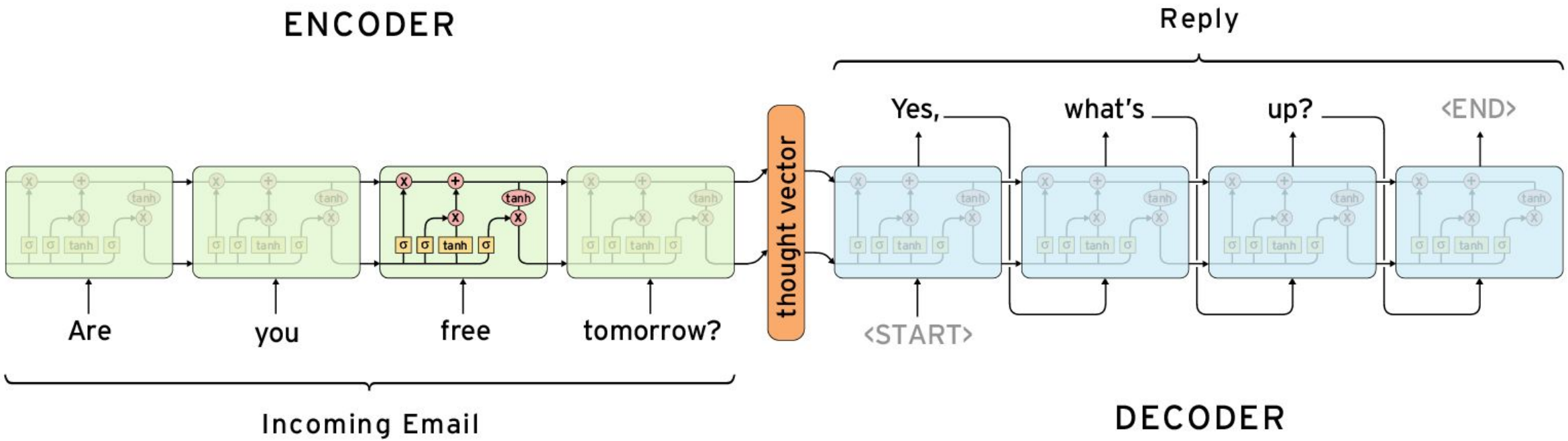
https://livebook.manning.com/book/deep-learning-with-python-second-edition/chapter-11/v-6/28

Modelos de Lenguaje

Secuencia a secuencia

Aplicación tipo seq2seq. Por ejemplo traducción, sistemas de recomendación, chatbots
Tienen un Codificador y un Decodificador

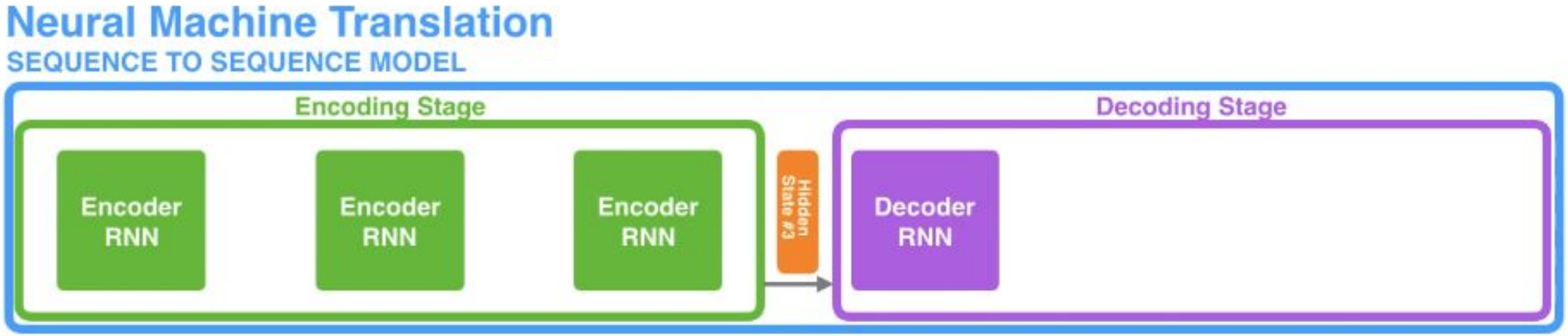




https://github.com/nicolas-ivanov/debug_seq2seq

Modelos de Lenguaje

Con entrada al decodificador se usan el último estado del codificador

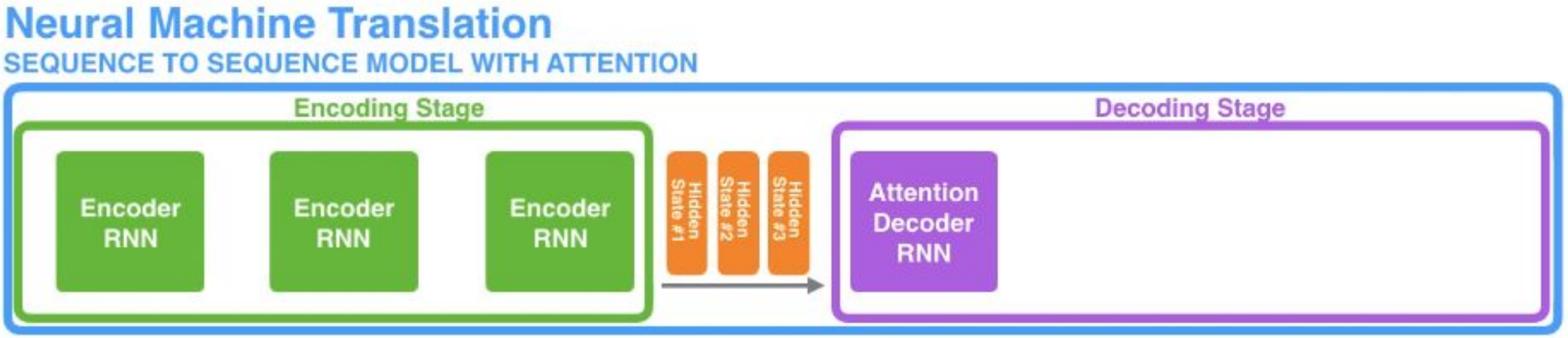


https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

Modelos de Lenguaje

Uso de la Atención

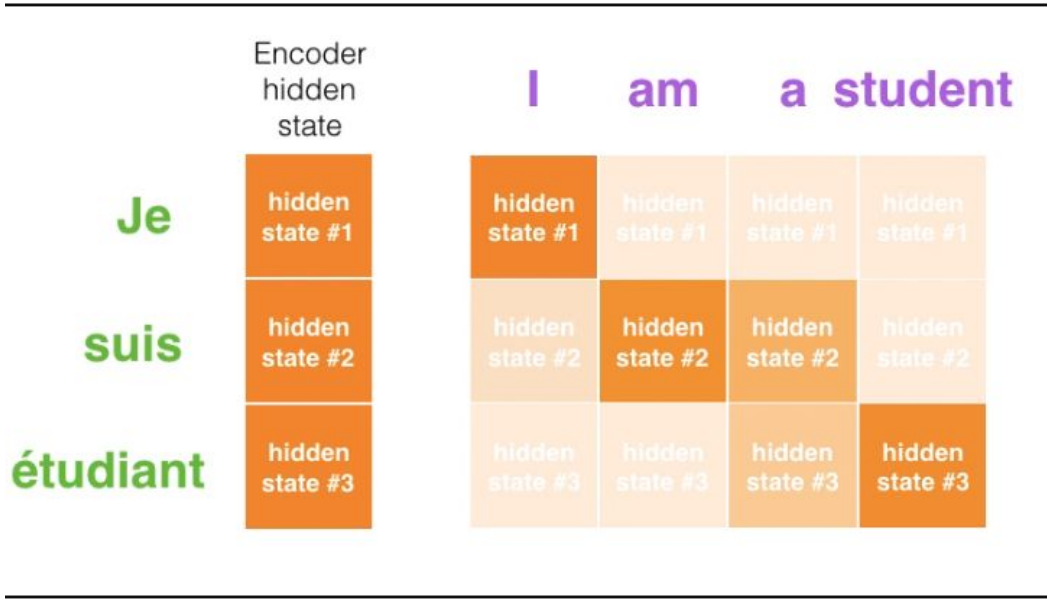
Teniendo en cuenta la atención se usan todos los estados ocultos del codificador

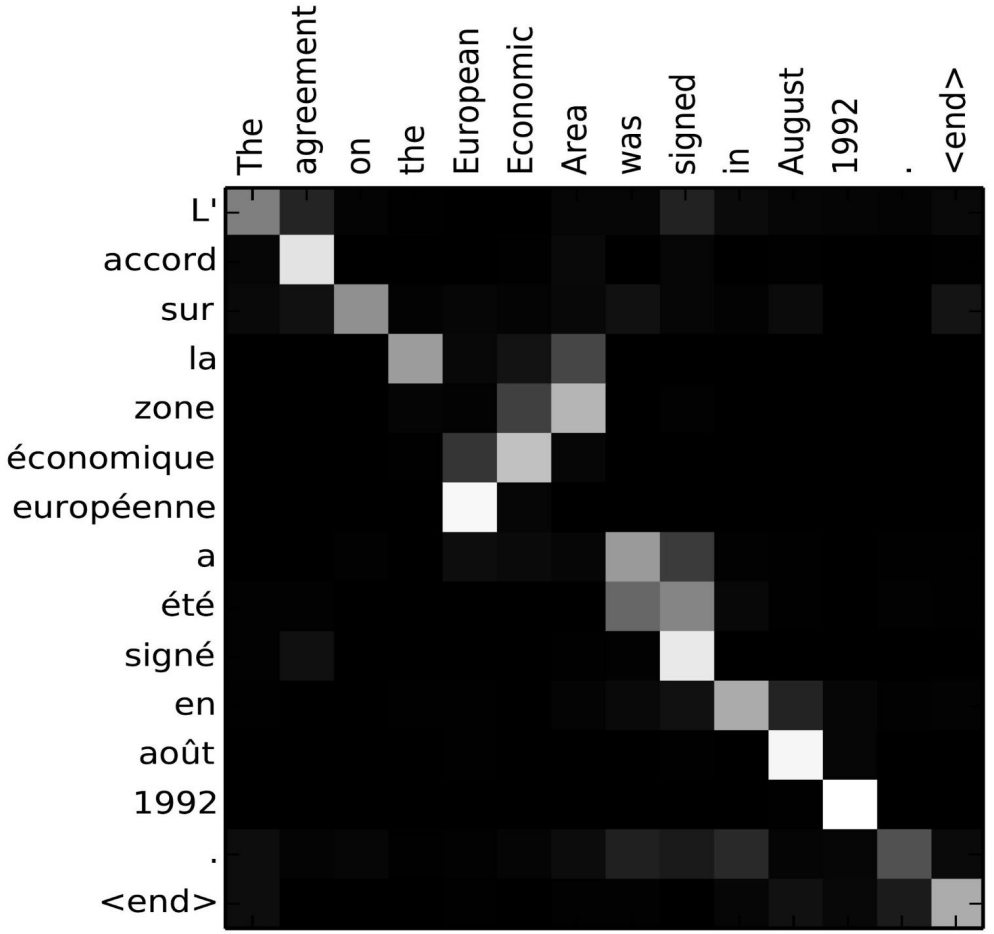


https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

Atención

Esta es otra forma de ver a qué parte del texto de entrada prestamos atención en cada paso de decodificación

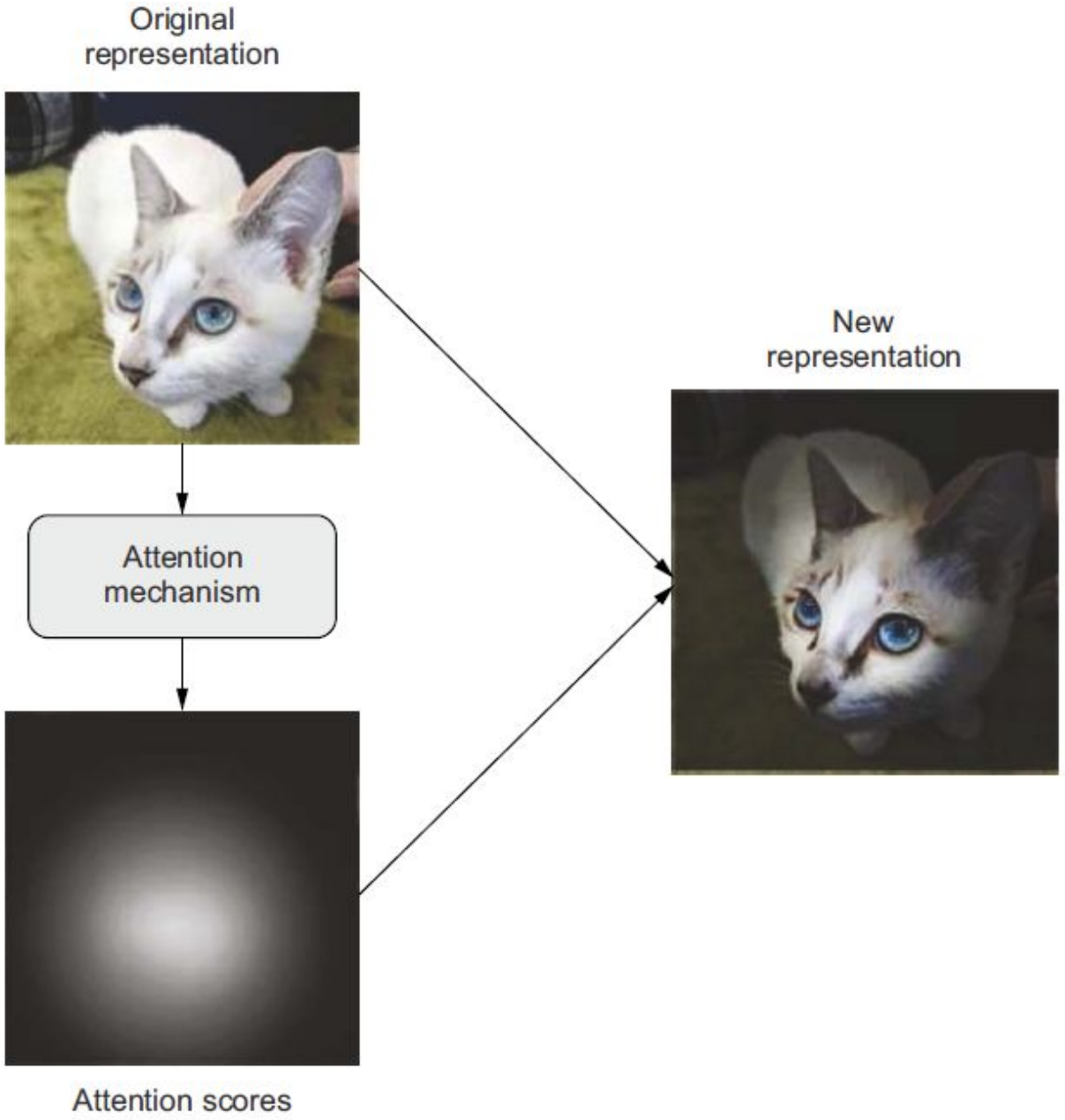




https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html

Atención



Atención como mecanismo de representar el contexto de una información de entrada

Deep Learning with Python,
François Chollet
Manning; 2nd edición (21 Diciembre 2021)

Los Bloques Básicos del Deep Learning

Capas de Auto Atención

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com

Noam Shazeer* Google Brain noam@google.com

Niki Parmar* Google Research nikip@google.com

Jakob Uszkoreit* Google Research usz@google.com

Llion Jones* Google Research llion@google.com

Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu

Łukasz Kaiser* Google Brain lukaszkaiser@google.com

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

Abstract

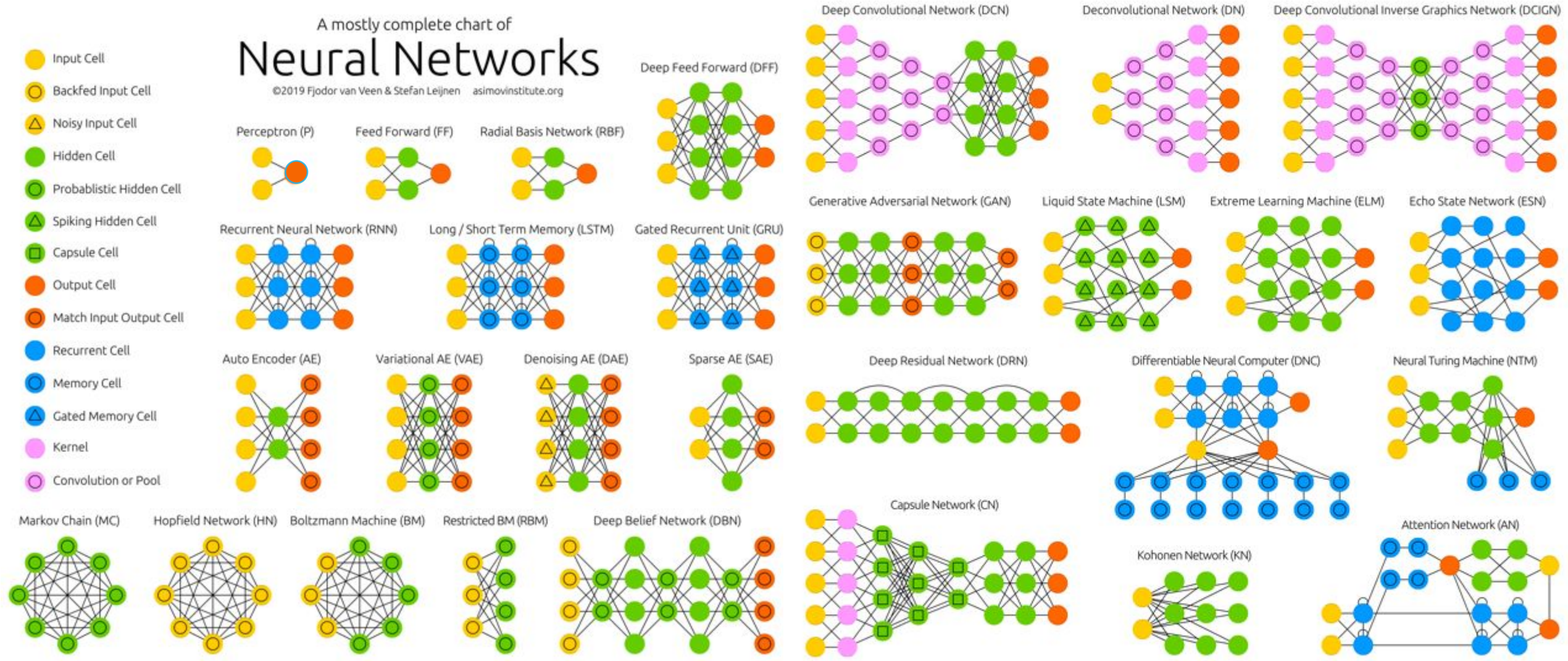
The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

Fórmula de la Self-Attention

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\intercal}{\sqrt{d_{keys}}}\right)\mathbf{V}$$

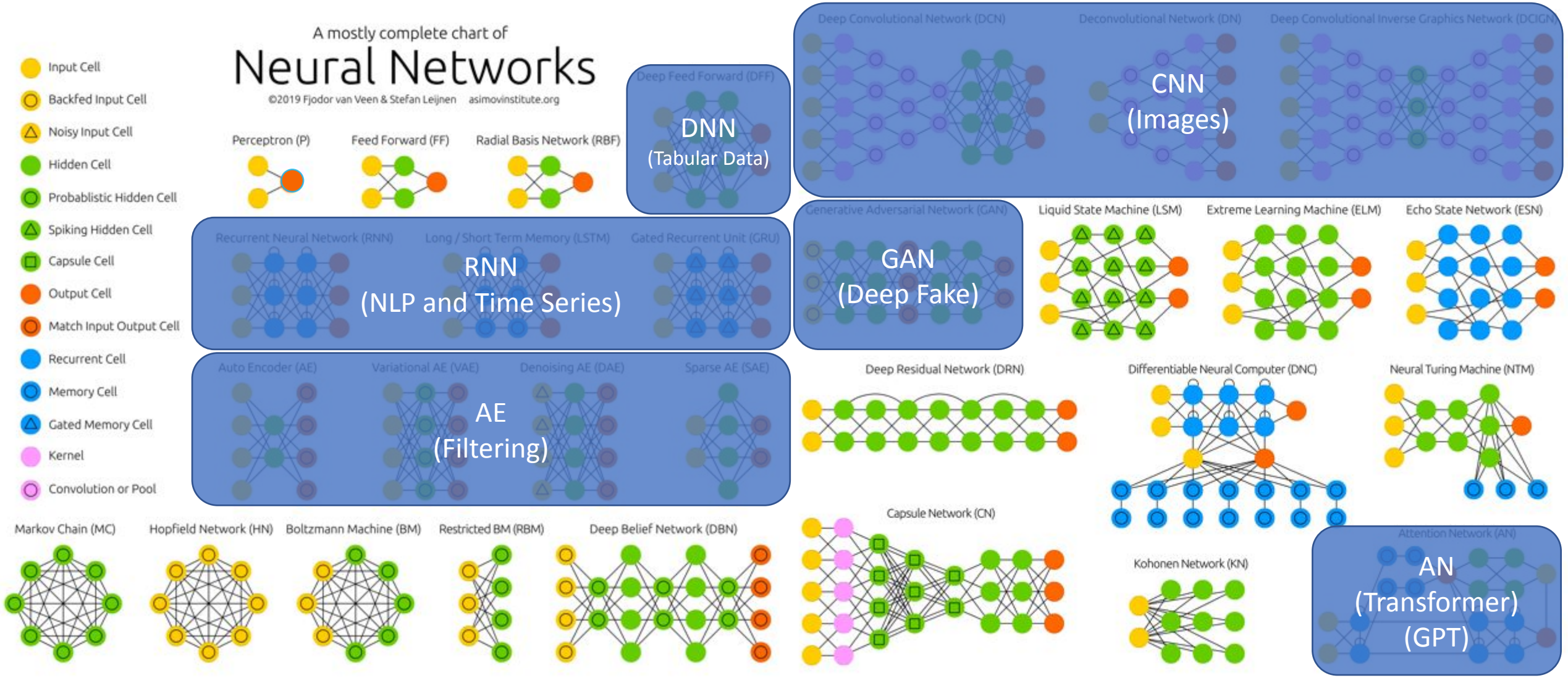
https://arxiv.org/pdf/1706.03762.pdf

Deep Learning ZOO



https://www.asimovinstitute.org/neural-network-zoo/

Deep Learning ZOO

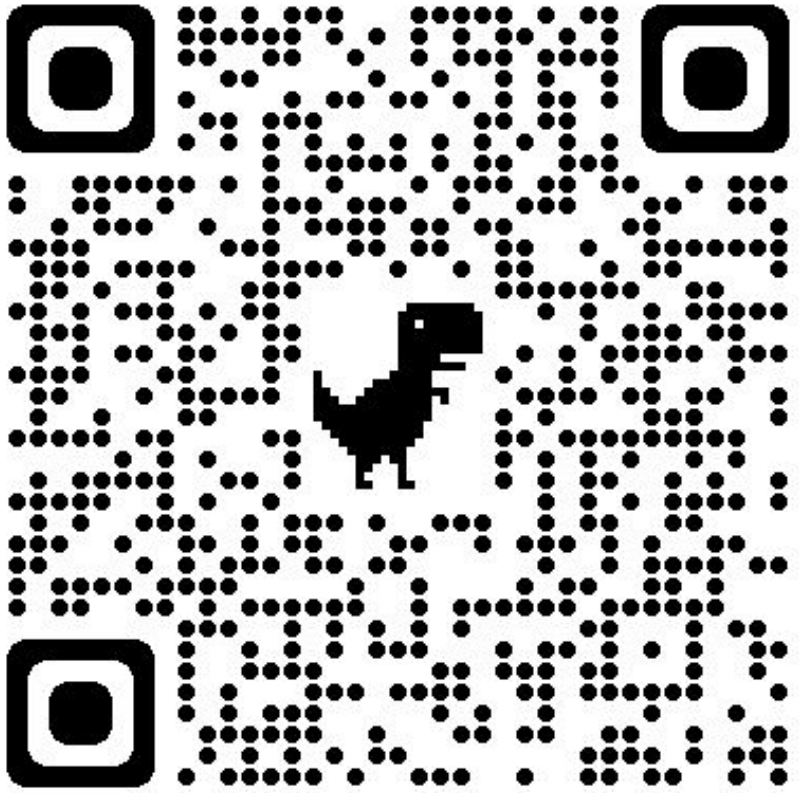


https://www.asimovinstitute.org/neural-network-zoo/

Modelos de IA Basados en Transformers

¿Qué se te viene a la mente cuando escuchas la palabra transformers?

https://app.wooclap.com/ROJGUC?from=status-bar



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* † University of Toronto aidan@cs.toronto.edu

Łukasz Kaiser* Google Brain lukaszkaiser@google.com

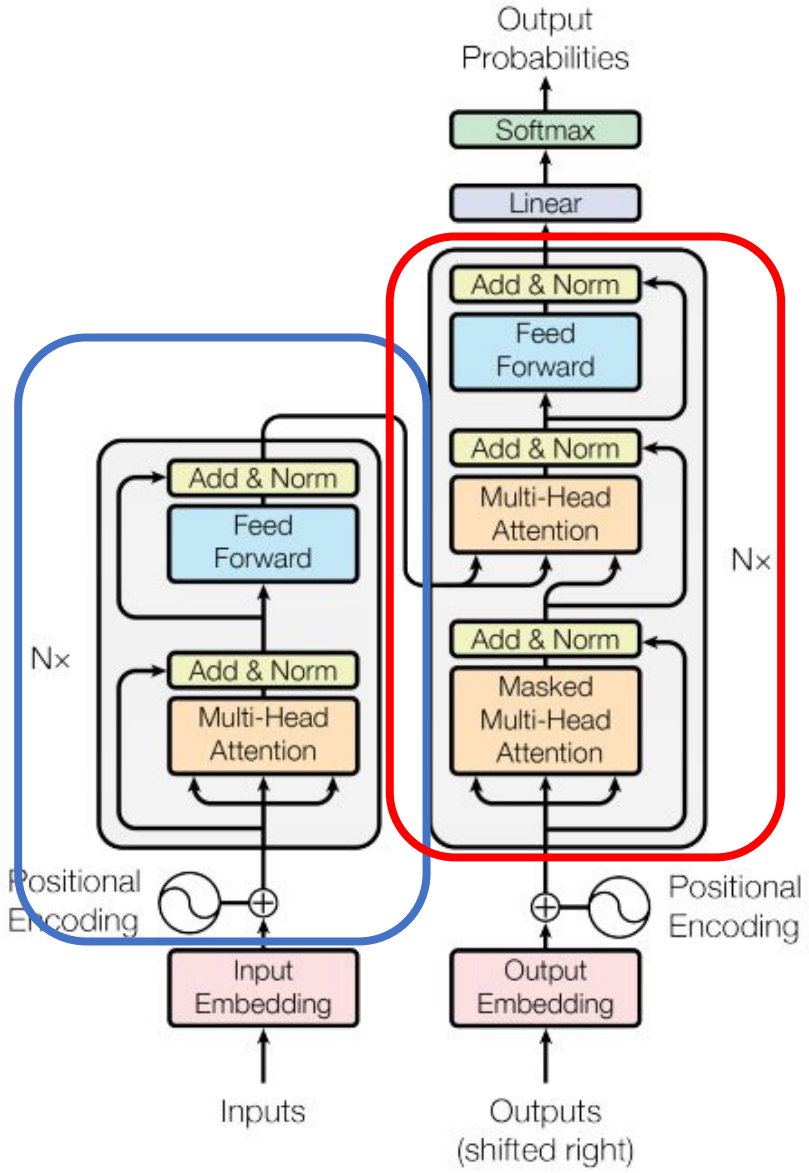
Illia Polosukhin* ‡ illia.polosukhin@gmail.com

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 propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

https://arxiv.org/pdf/1706.03762.pdf

Transformer

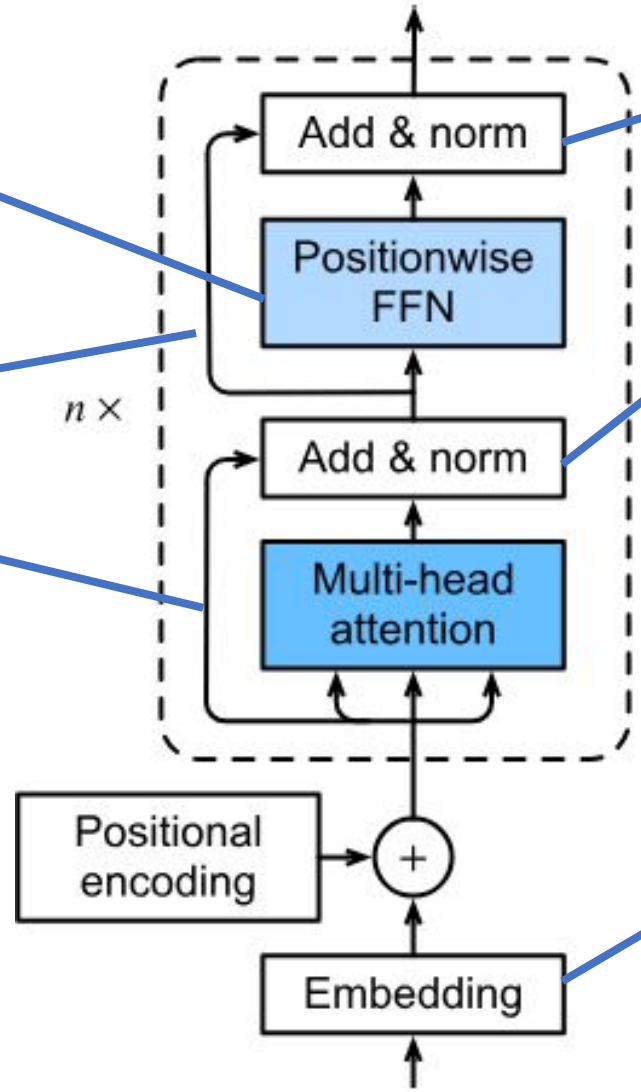


Transformers

Capas Densas

Conexiones Residuales
(CNN)

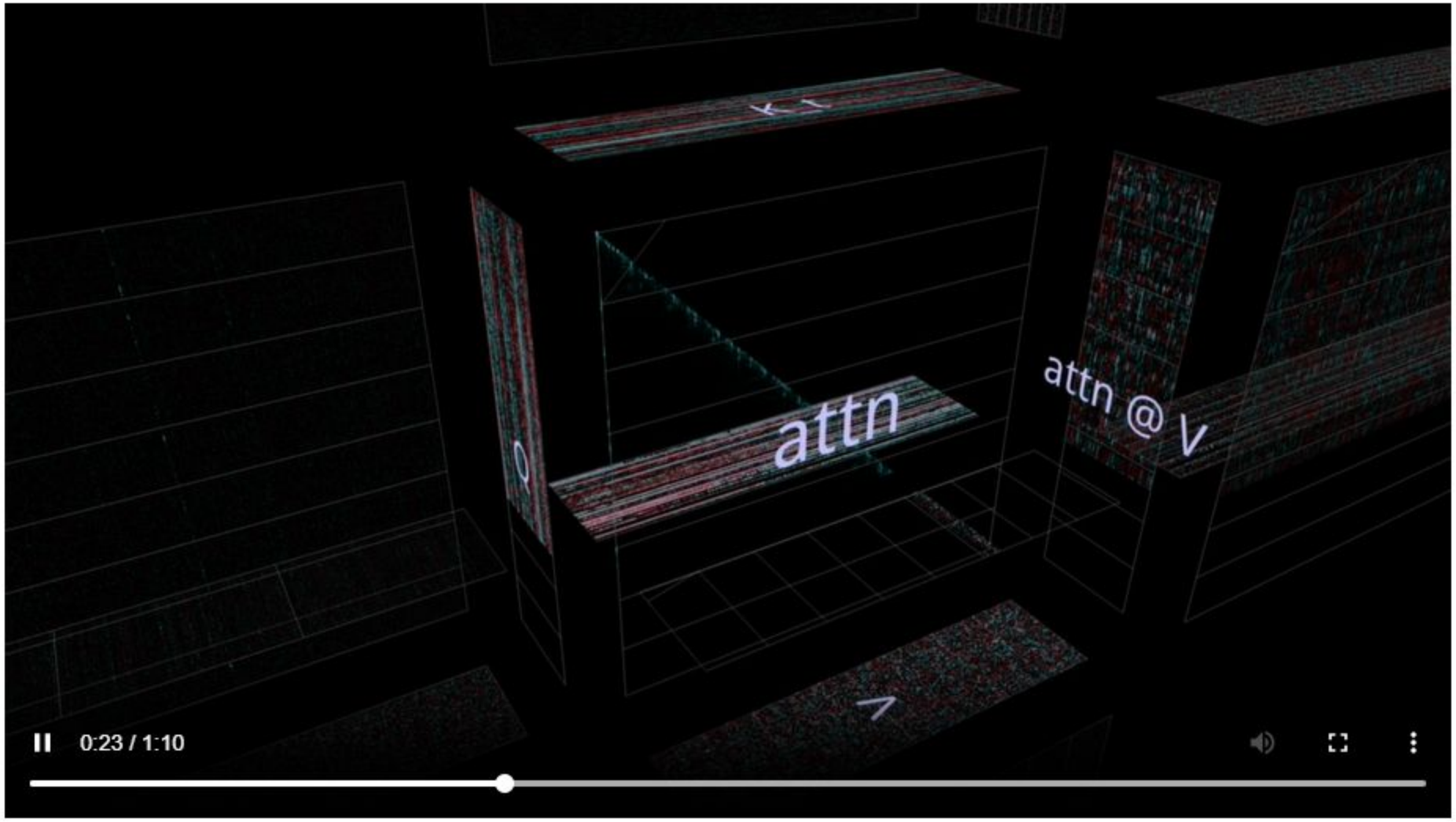
Normalización
(CNN)



PLN basado en RNN

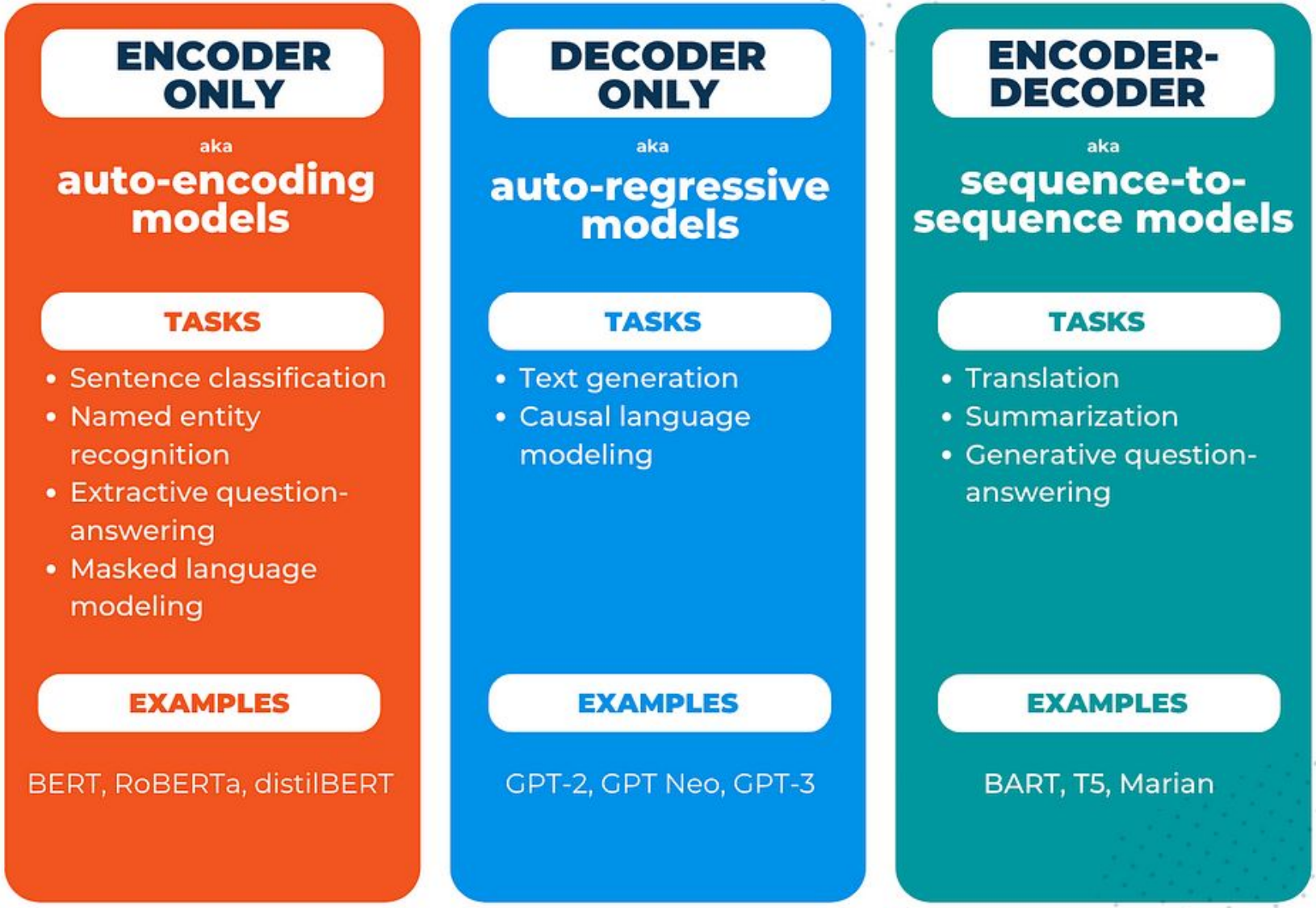
https://d2l.ai/_images/transformer.svg

Transformers



https://pytorch.org/blog/inside-the-matrix/

Transformers y Modelos de Lenguaje



https://mlops.community/explainable-ai-visualizing-attention-in-transformers/

Transformers y Modelos de Lenguaje

BERT (Bidirectional Encoder Representations from Transformers)

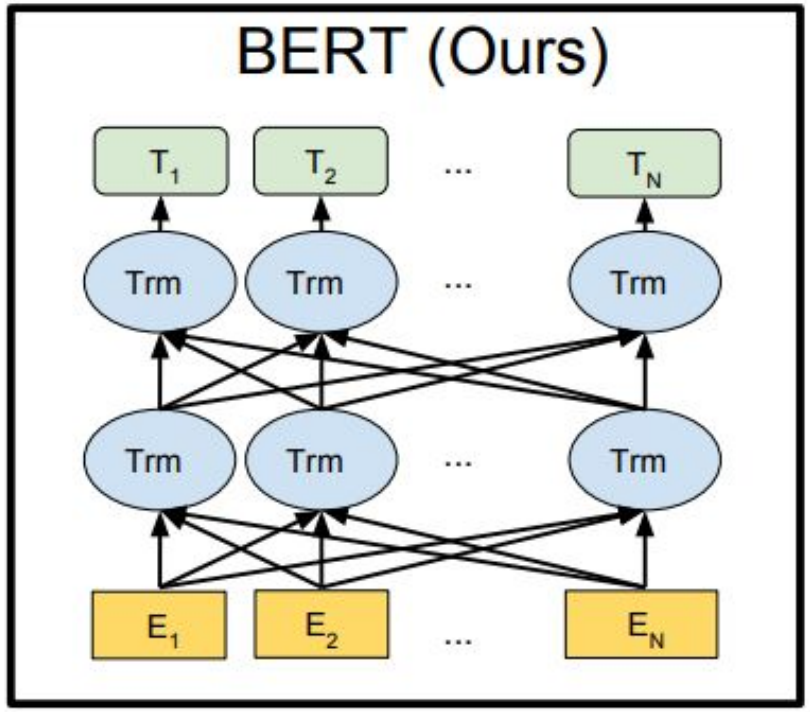
BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

Abstract

We introduce a new language representation model called **BERT**, which stands for **B**idirectional **E**ncoder **R**epresentations from **T**ransformers. Unlike recent language representation models (Peters et al., 2018a; Radford et al., 2018), BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer

There are two existing strategies for applying pre-trained language representations to downstream tasks: *feature-based* and *fine-tuning*. The feature-based approach, such as ELMo (Peters et al., 2018a), uses task-specific architectures that include the pre-trained representations as additional features. The fine-tuning approach, such as the Generative Pre-trained Transformer (OpenAI GPT) (Radford et al., 2018), introduces minimal task-specific parameters, and is trained on the downstream tasks by simply fine-tuning *all* pre-

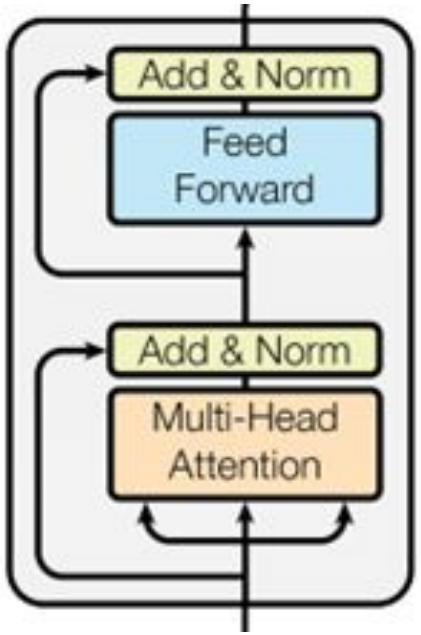


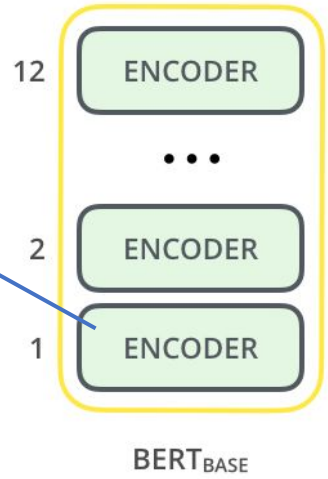
https://arxiv.org/pdf/1810.04805.pdf

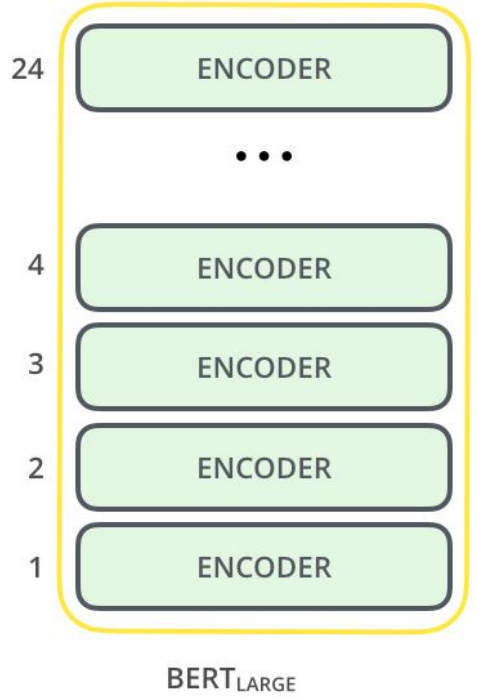
Transformers y Modelos de Lenguaje

BERT (Bidirectional Encoder Representations from Transformers)

BERT-Base: 12-layers, 768-hidden, 12-attention-heads, 110M parameters
BERT-Large: 24-layers, 1024-hidden, 16-attention-heads, 340M parameters

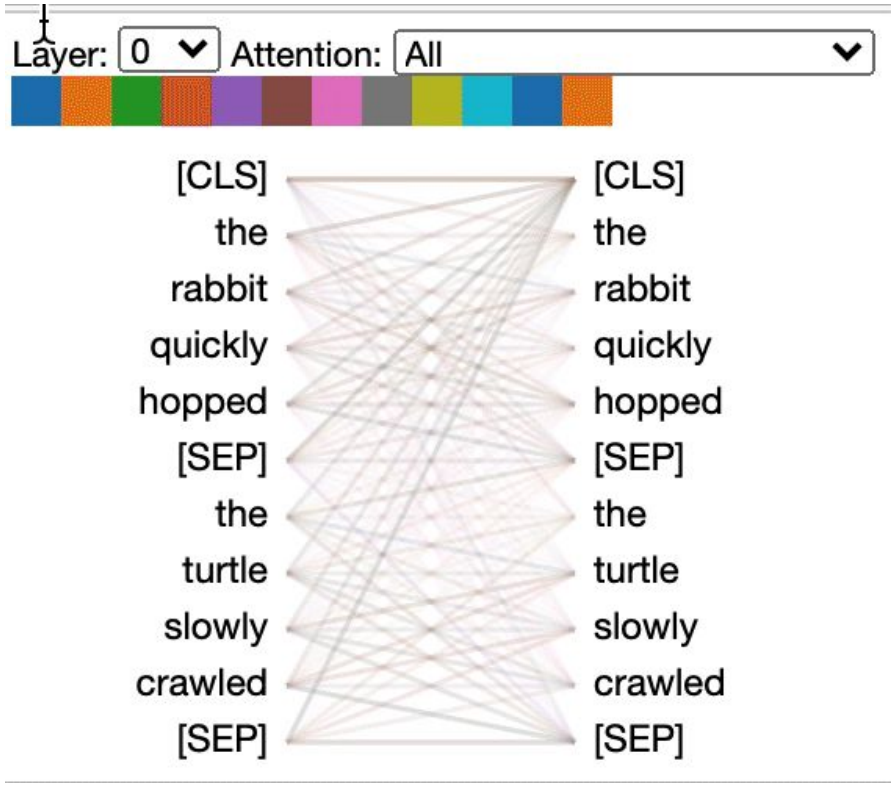


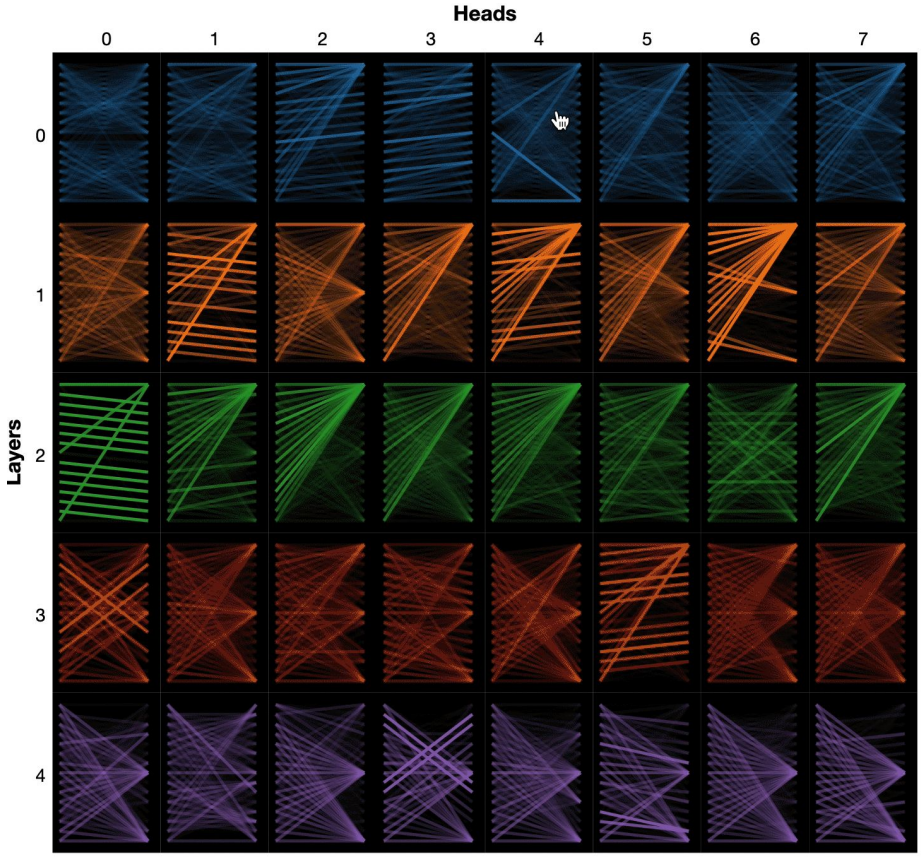




http://jalammar.github.io/illustrated-bert/

Transformers y Modelos de Lenguaje





https://github.com/jessevig/bertviz

https://colab.research.google.com/drive/1hXIQ77A4TYS4y3UthWF-Ci7V7vVUoxmQ

Transformers y Modelos de Lenguaje

GPT (Generative Pretrained Transformers**)**

12-layers, 768-hidden, 12-attention-heads, 117M parameters. Tamaño de secuencia 512

Improving Language Understanding by Generative Pre-Training

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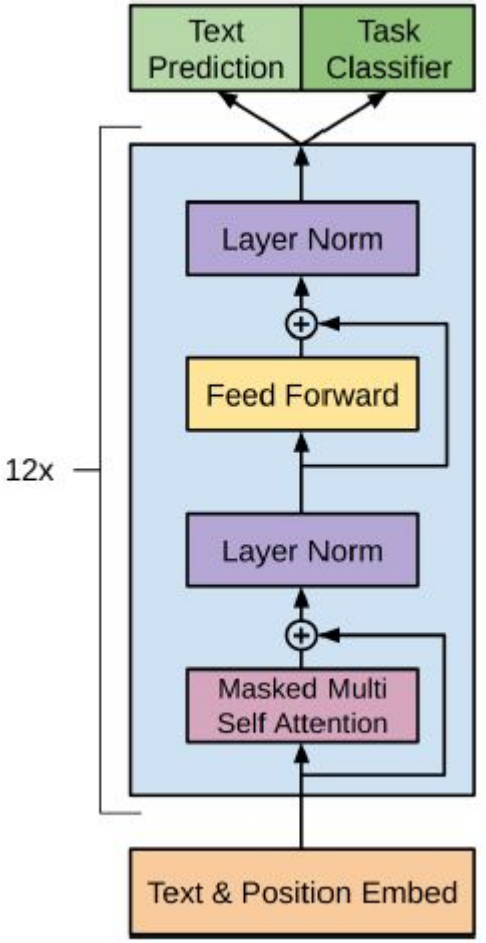
Ilya Sutskever OpenAI ilyasu@openai.com

Abstract

Natural language understanding comprises a wide range of diverse tasks such as textual entailment, question answering, semantic similarity assessment, and document classification. Although large unlabeled text corpora are abundant, labeled data for learning these specific tasks is scarce, making it challenging for discriminatively trained models to perform adequately. We demonstrate that large gains on these tasks can be realized by *generative pre-training* of a language model on a diverse corpus of unlabeled text, followed by *discriminative fine-tuning* on each specific task. In contrast to previous approaches, we make use of task-aware input transformations during fine-tuning to achieve effective transfer while requiring minimal changes to the model architecture. We demonstrate the effectiveness of our approach on a wide range of benchmarks for natural language understanding. Our general task-agnostic model outperforms discriminatively trained models that use architectures specifically crafted for each task, significantly improving upon the state of the art in 9 out of the 12 tasks studied. For instance, we achieve absolute improvements of 8.9% on commonsense reasoning (Stories Cloze Test), 5.7% on question answering (RACE), and 1.5% on textual entailment (MultiNLI).

seq/language_understanding_paper.pdf



https://openai.com/blog/language-unsupervised/

Transformers y Modelos de Lenguaje

GPT-2

Language Models are Unsupervised Multitask Learners

Alec Radford [*1] Jeffrey Wu [*1] Rewon Child [1] David Luan [1] Dario Amodei [**1] Ilya Sutskever [**1]

Abstract

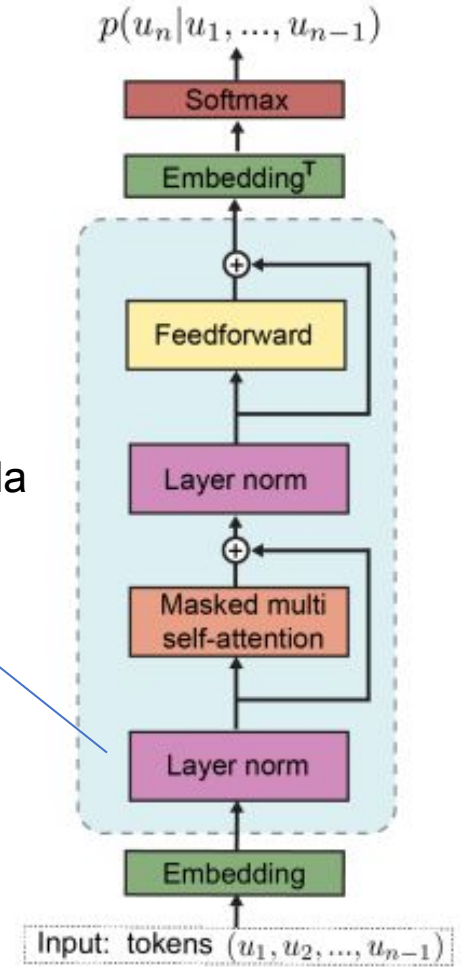
Natural language processing tasks, such as question answering, machine translation, reading comprehension, and summarization, are typically approached with supervised learning on task-specific datasets. We demonstrate that language models begin to learn these tasks without any explicit supervision when trained on a new dataset of millions of webpages called WebText. When conditioned on a document plus questions, the answers generated by the language model reach 55 F1 on the CoQA dataset - matching or exceeding the performance of 3 out of 4 baseline systems without using the 127,000+ training examples. The capacity of the language model is essential to the success of zero-shot task transfer and in-

competent generalists. We would like to move towards more general systems which can perform many tasks – eventually without the need to manually create and label a training dataset for each one.

The dominant approach to creating ML systems is to collect a dataset of training examples demonstrating correct behavior for a desired task, train a system to imitate these behaviors, and then test its performance on independent and identically distributed (IID) held-out examples. This has served well to make progress on narrow experts. But the often erratic behavior of captioning models (Lake et al., 2017), reading comprehension systems (Jia & Liang, 2017), and image classifiers (Alcorn et al., 2018) on the diversity and variety of possible inputs highlights some of the shortcomings of this approach.

Our suspicion is that the prevalence of single task training

https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf



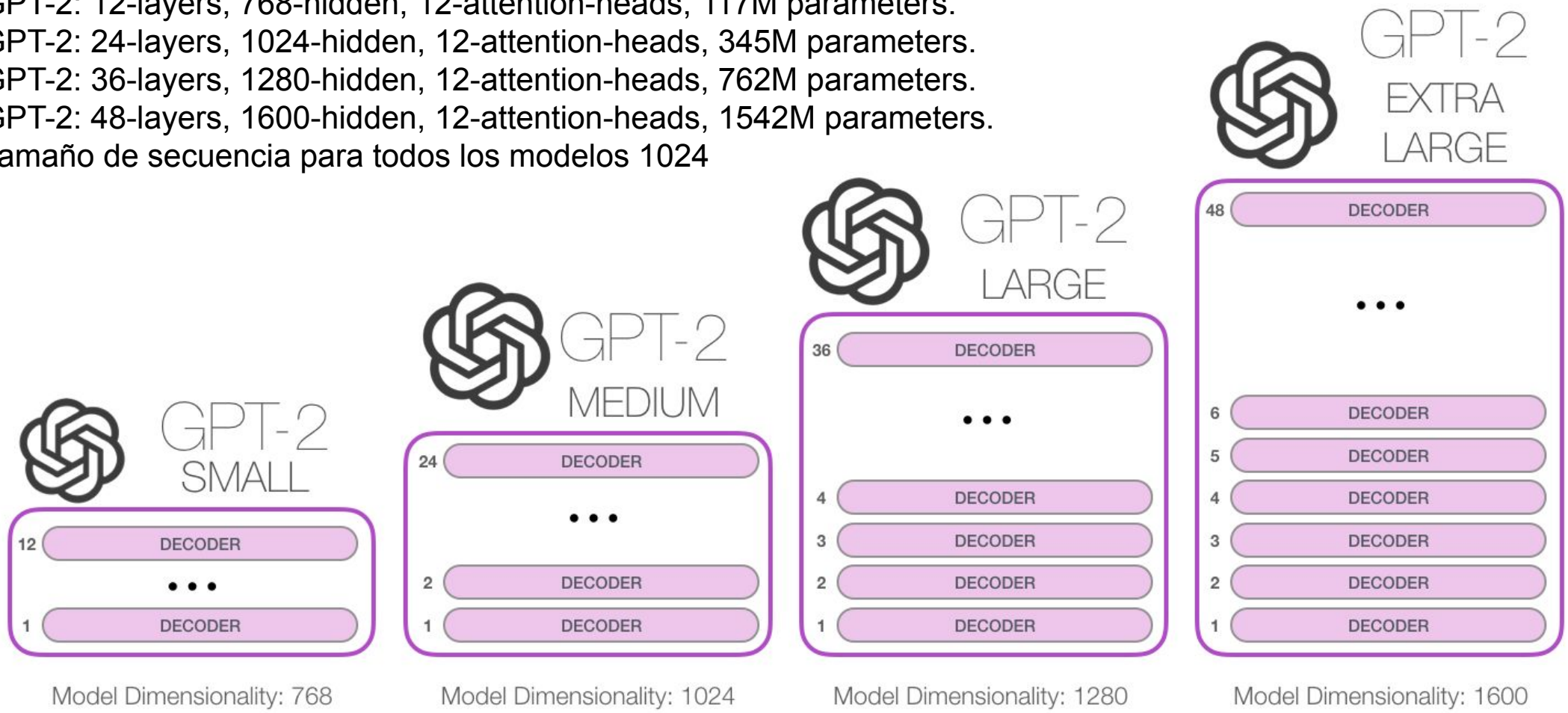
Se cambia de posición la capa de normalización

https://www.researchgate.net/publication/335737829_Tracking_Naturalistic_Linguistic_Predictions_with_Deep_Neural_Language_Models

Transformers y Modelos de Lenguaje

GPT-2

GPT-2: 12-layers, 768-hidden, 12-attention-heads, 117M parameters.
GPT-2: 24-layers, 1024-hidden, 12-attention-heads, 345M parameters.
GPT-2: 36-layers, 1280-hidden, 12-attention-heads, 762M parameters.
GPT-2: 48-layers, 1600-hidden, 12-attention-heads, 1542M parameters.
Tamaño de secuencia para todos los modelos 1024



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

Transformers y Modelos de Lenguaje

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 struggle to do. Here we show that scaling up language models greatly improves task-agnostic, few-shot performance, sometimes even reaching competitiveness with prior state-of-the-art fine-tuning approaches. Specifically, we train GPT-3, an autoregressive language model with 175 billion parameters, 10x more than any previous non-sparse language model, and test its performance in the few-shot setting. For all tasks, GPT-3 is applied without any gradient updates or fine-tuning, with tasks and few-shot demonstrations specified purely via text interaction with the model. GPT-3 achieves strong performance on many NLP datasets, including translation, question-answering, and cloze tasks, as well as several tasks that require on-the-fly reasoning or domain adaptation, such as unscrambling words, using a novel word in a sentence, or performing 3-digit arithmetic. At the same time, we also identify some datasets where GPT-3's few-shot learning still struggles, as well as some datasets where GPT-3 faces methodological issues related to training on large web corpora. Finally, we find that GPT-3 can generate samples of news articles which human evaluators have difficulty distinguishing from articles written by humans. We discuss broader societal impacts of this finding and of GPT-3 in general.

Se explota la capacidad para Zero Shot Learning
No se hace fine tuning
Es un modelo de lenguaje masivo

https://arxiv.org/pdf/2005.14165.pdf

Transformers y Modelos de Lenguaje

GPT-3

GPT-3: 96-layers, 12288-hidden, 96-attention-heads, 175x10^9 parameters.
Tamaño de secuencia 2048

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

https://arxiv.org/pdf/2005.14165.pdf

Transformers y Modelos de Lenguaje

Evaluating Large Language Models Trained on Code

Mark Chen [*1] Jerry Tworek [*1] Heewoo Jun [*1] Qiming Yuan [*1] Henrique Ponde de Oliveira Pinto [*1]
Jared Kaplan [*2] Harri Edwards [1] Yuri Burda [1] Nicholas Joseph [2] Greg Brockman [1] Alex Ray [1] Raul Puri [1]
Gretchen Krueger [1] Michael Petrov [1] Heidy Khlaaf [3] Girish Sastry [1] Pamela Mishkin [1] Brooke Chan [1]
Scott Gray [1] Nick Ryder [1] Mikhail Pavlov [1] Alethea Power [1] Lukasz Kaiser [1] Mohammad Bavarian [1]
Clemens Winter [1] Philippe Tillet [1] Felipe Petroski Such [1] Dave Cummings [1] Matthias Plappert [1]
Fotios Chantzis [1] Elizabeth Barnes [1] Ariel Herbert-Voss [1] William Hebgen Guss [1] Alex Nichol [1] Alex Paino [1]
Nikolas Tezak [1] Jie Tang [1] Igor Babuschkin [1] Suchir Balaji [1] Shantanu Jain [1] William Saunders [1]
Christopher Hesse [1] Andrew N. Carr [1] Jan Leike [1] Josh Achiam [1] Vedant Misra [1] Evan Morikawa [1]
Alec Radford [1] Matthew Knight [1] Miles Brundage [1] Mira Murati [1] Katie Mayer [1] Peter Welinder [1]
Bob McGrew [1] Dario Amodei [2] Sam McCandlish [2] Ilya Sutskever [1] Wojciech Zaremba [1]

Abstract

We introduce Codex, a GPT language model fine-tuned on publicly available code from GitHub, and study its Python code-writing capabilities. A distinct production version of Codex powers GitHub Copilot. On HumanEval, a new evaluation set we release to measure functional correctness for synthesizing programs from docstrings, our model solves 28.8% of the problems, while GPT-3 solves 0% and GPT-J solves 11.4%. Furthermore, we find that repeated sampling from the model is a surprisingly effective strategy for producing working solutions to difficult prompts. Using this method, we solve 70.2% of our problems with 100 samples per problem. Careful investigation of our model reveals its limitations, including difficulty with docstrings describing long chains of operations and with binding operations to variables. Finally, we discuss the potential broader impacts of deploying powerful code generation technologies, covering safety, security, and economics.

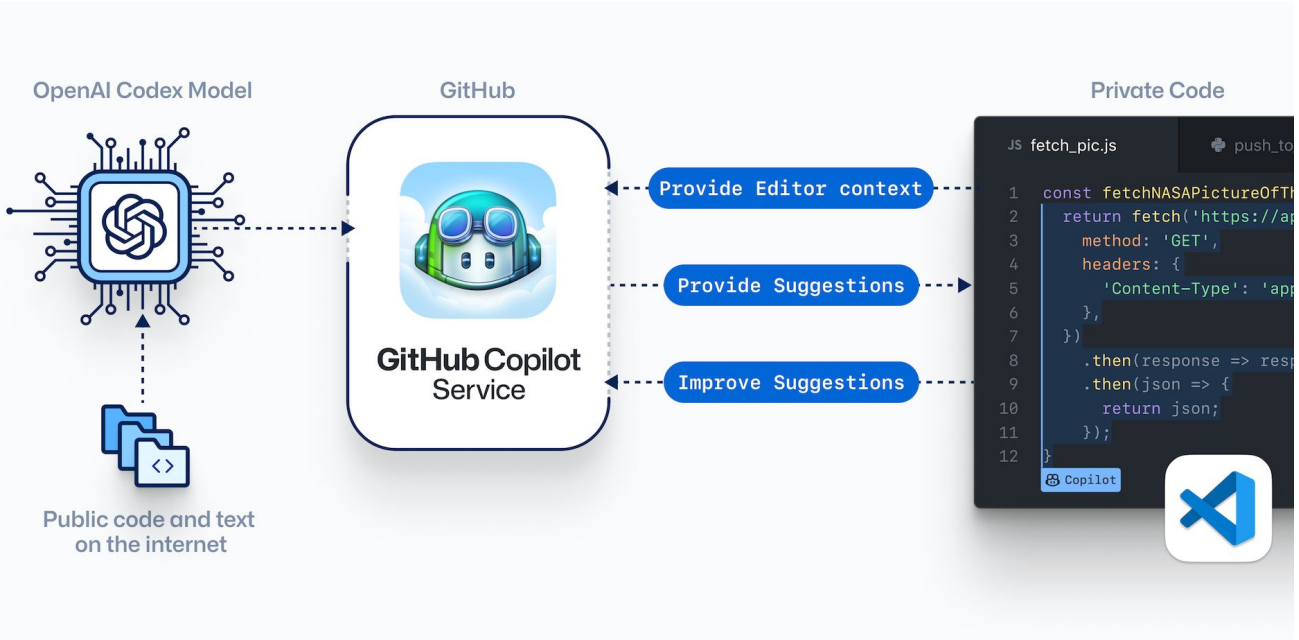
1. Introduction

Scalable sequence prediction models (Graves, 2014; Vaswani et al., 2017; Child et al., 2019) have become a general-purpose method for generation and representation learning in many domains, including natural language processing (Mikolov et al., 2013; Sutskever et al., 2014; Dai & Le, 2015; Peters et al., 2018; Radford et al., 2018; Devlin et al., 2018), computer vision (Van Oord et al., 2016; Menick & Kalchbrenner, 2018; Chen et al., 2020; Bao et al., 2021), audio and speech processing (Oord et al., 2016; 2018; Dhariwal et al., 2020; Baevski et al., 2020), biology (Alley et al., 2019; Rives et al., 2021), and even across multiple modalities (Das et al., 2017; Lu et al., 2019; Ramesh et al., 2021; Zellers et al., 2021). More recently, language models have also fueled progress towards the longstanding challenge of program synthesis (Simon, 1963; Manna & Waldinger, 1971), spurred by the presence of code in large datasets (Husain et al., 2019; Gao et al., 2020) and the resulting programming capabilities of language models trained on these datasets (Wang & Komatsuzaki, 2021). Popular language modeling objectives like masked language modeling (Devlin et al., 2018) and span prediction (Raffel et al., 2020) have also been adapted to train their programming counterparts CodeBERT (Feng et al., 2020) and PyMT5 (Clement et al.,

https://arxiv.org/pdf/2107.03374.pdf

Codex

https://copilot.github.com/



Transformers y Modelos de Lenguaje

Palm

Explaining a joke

Prompt

```
Explain this joke:

Joke: Did you see that Google just hired an eloquent whale for
their TPU team? It showed them how to communicate between two
different pods!
```

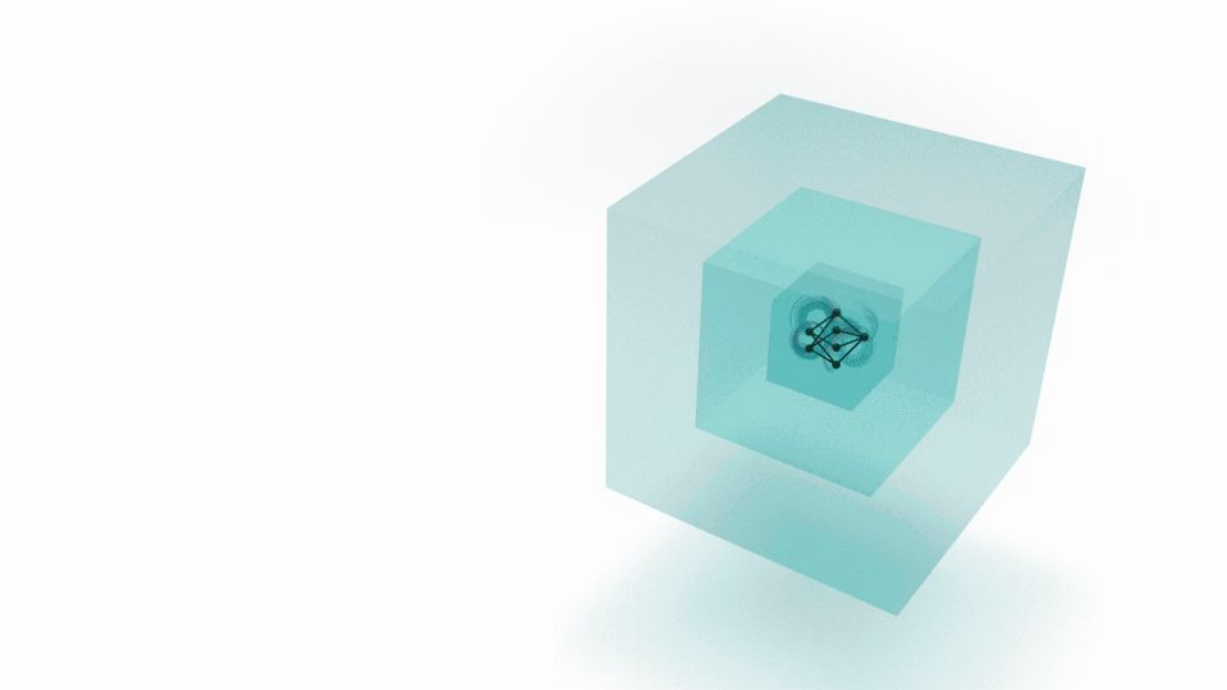
Model Response

```
Prediction: TPUs are a type of computer chip that Google uses
for deep learning. A "pod" is a group of TPUs. A "pod" is also a
group of whales. The joke is that the whale is able to
communicate between two groups of whales, but the speaker is
pretending that the whale is able to communicate between two
groups of TPUs.
```

PaLM explains an original joke with two-shot prompts.

https://ai.googleblog.com/2022/04/pathways-language-model-palm-scaling-to.html

OPT



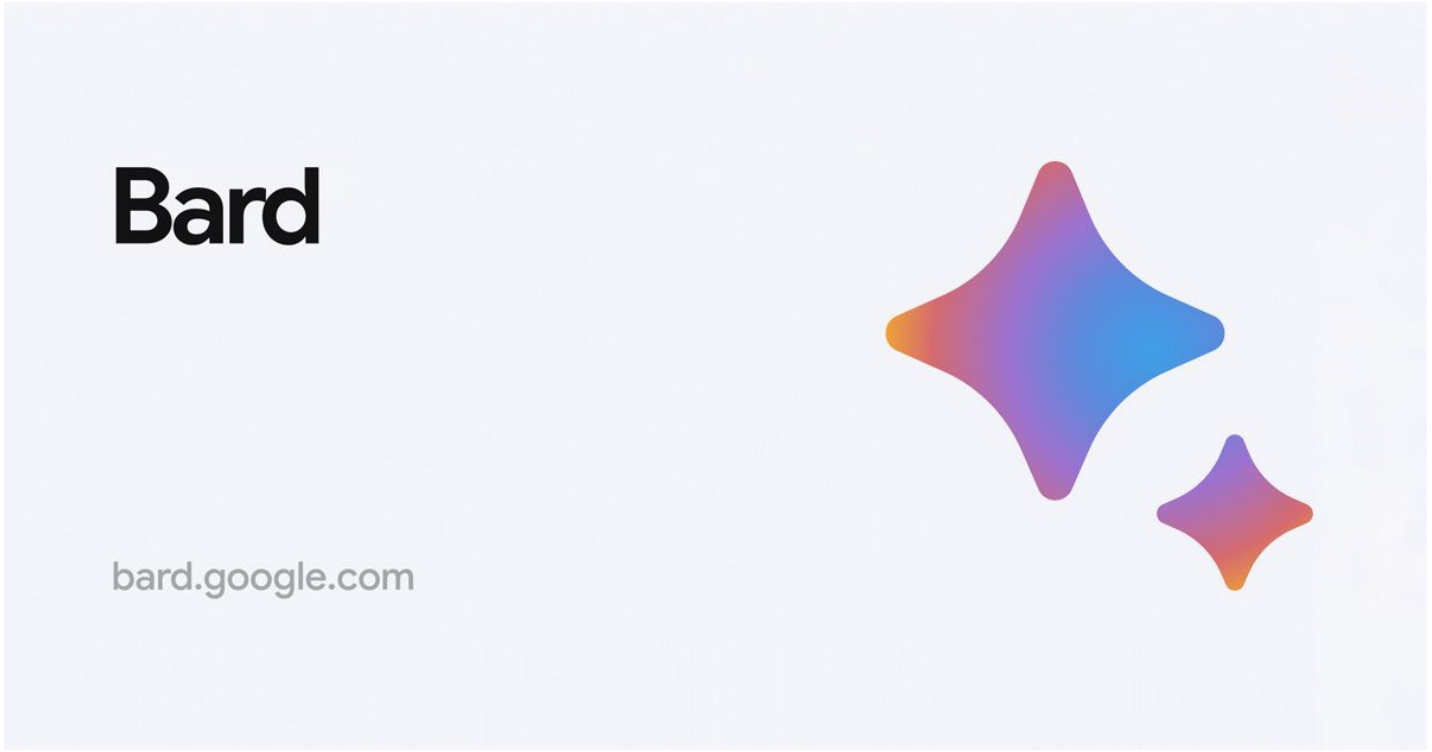
https://ai.facebook.com/blog/democratizing-access-to-large-scale-language-models-with-opt-175b/

Transformers y Modelos de Lenguaje

LaMDA

https://blog.google/technology/ai/lamda/

Transformers y Modelos de Lenguaje



Bard

https://bard.google.com/

Transformers y Modelos de Lenguaje

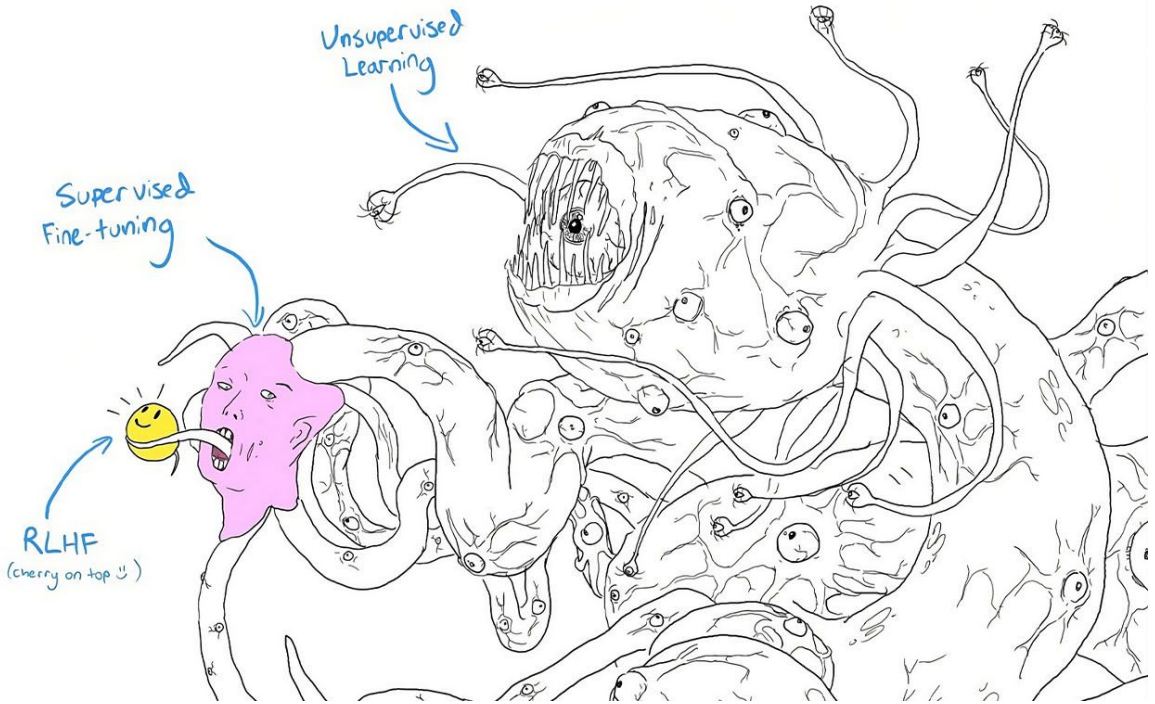
El caso ChatGPT

https://openai.com/blog/chatgpt/

Chat GPT

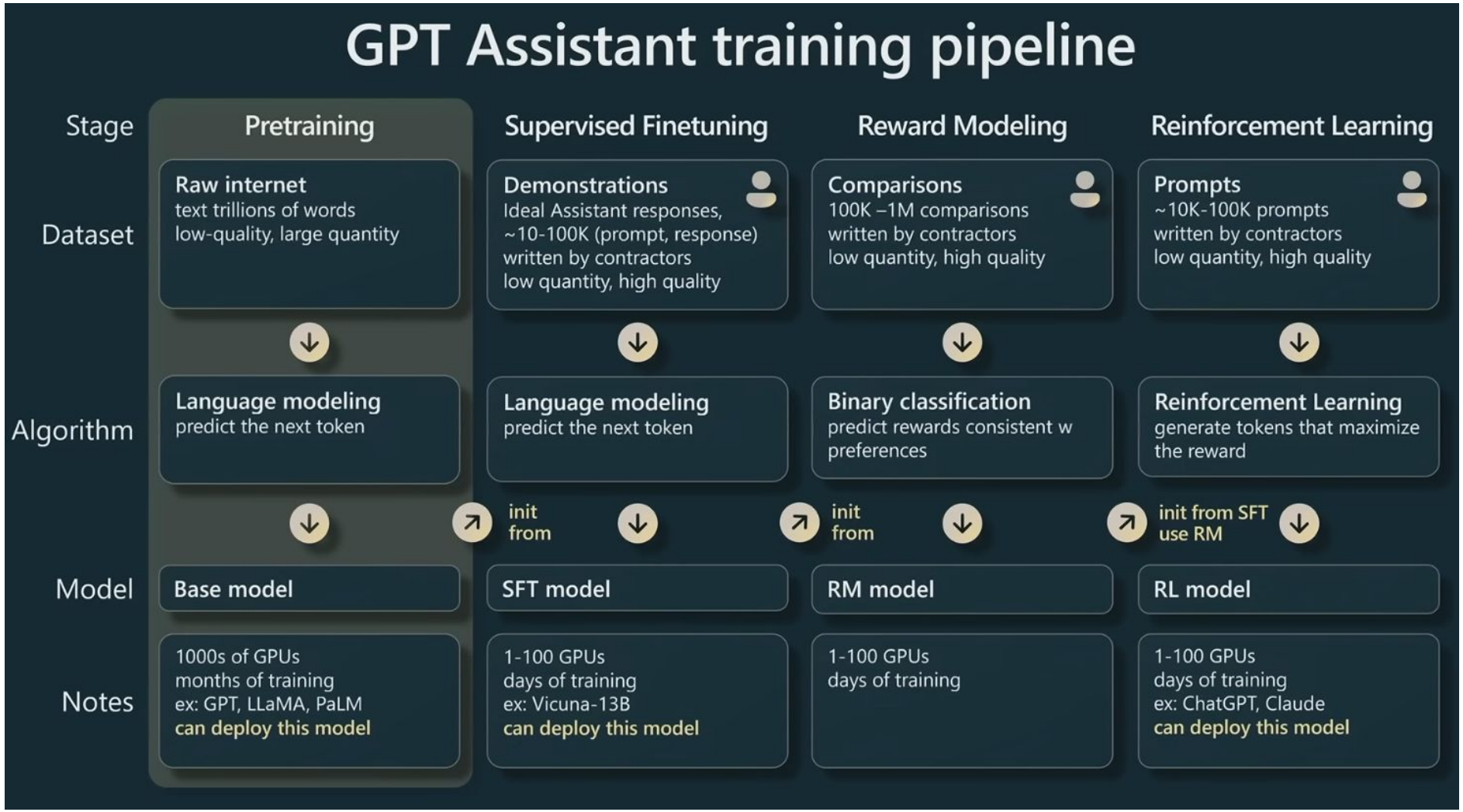
Reinforcement learning from Human Feedback

“Los modelos entrenados por RLHF pueden proporcionar respuestas que se alineen con los valores humanos, generar respuestas más detalladas y rechazar preguntas que sean inapropiadas o estén fuera del espacio de conocimiento del modelo” Por lo tanto pueden ser usados para disminuir el sesgo en la respuestas de los LLM



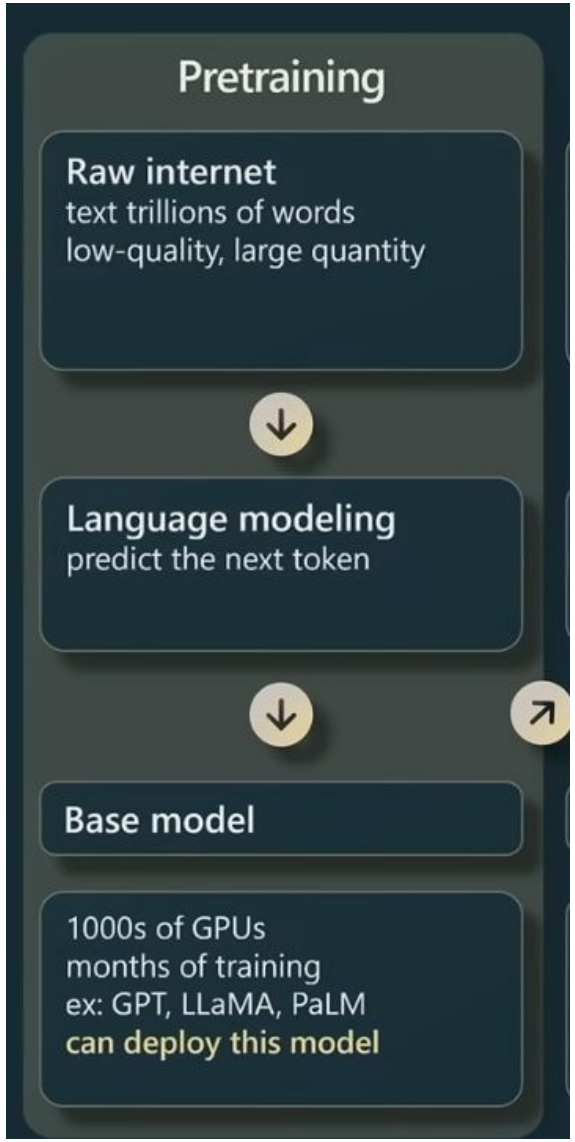
https://i.kym-cdn.com/entries/icons/original/000/044/025/shoggothhh_header.jpg

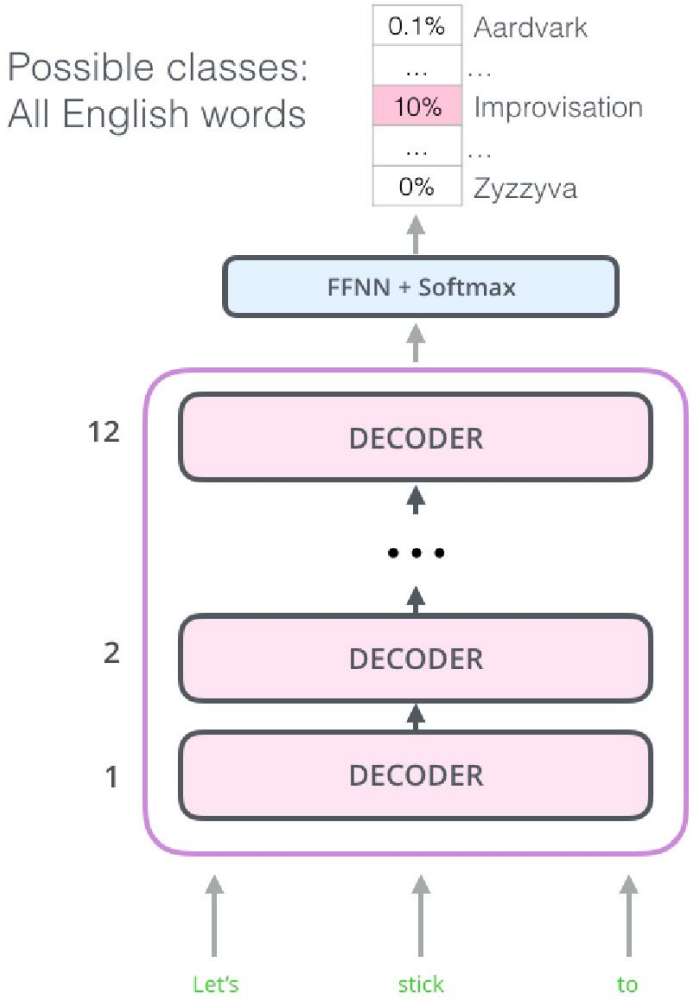
Chat GPT

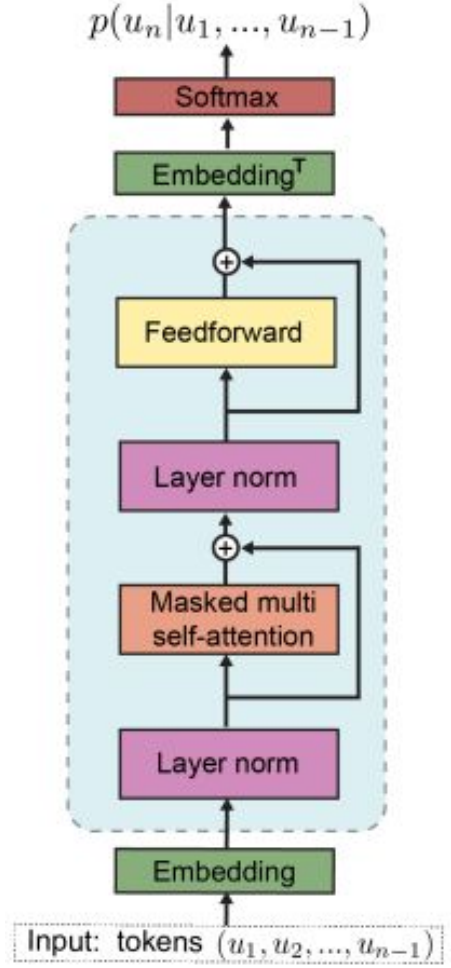


https://www.youtube.com/watch?v=bZQun8Y4L2A&t=16s

Chat GPT

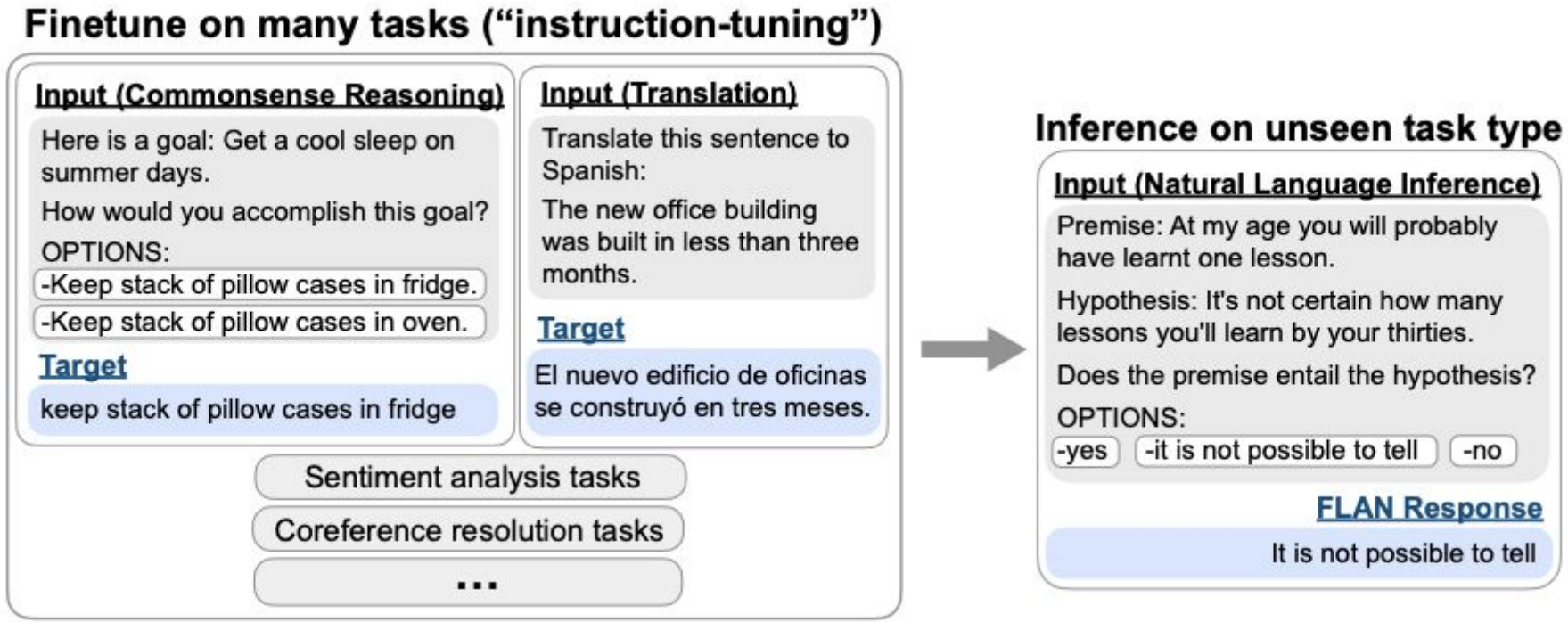






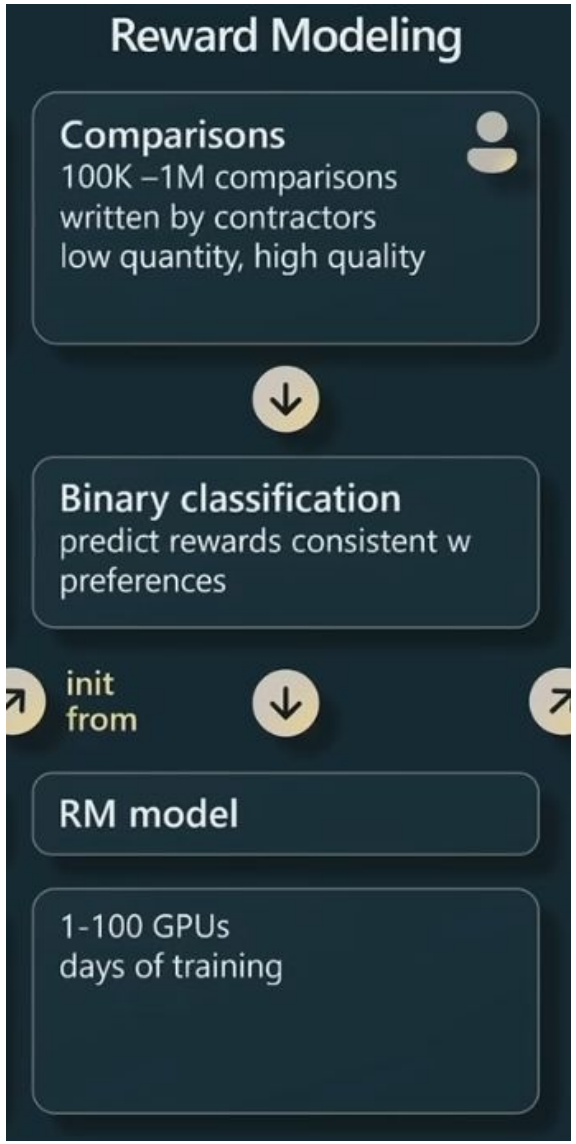
https://www.youtube.com/watch?v=bZQun8Y4L2A&t=16s

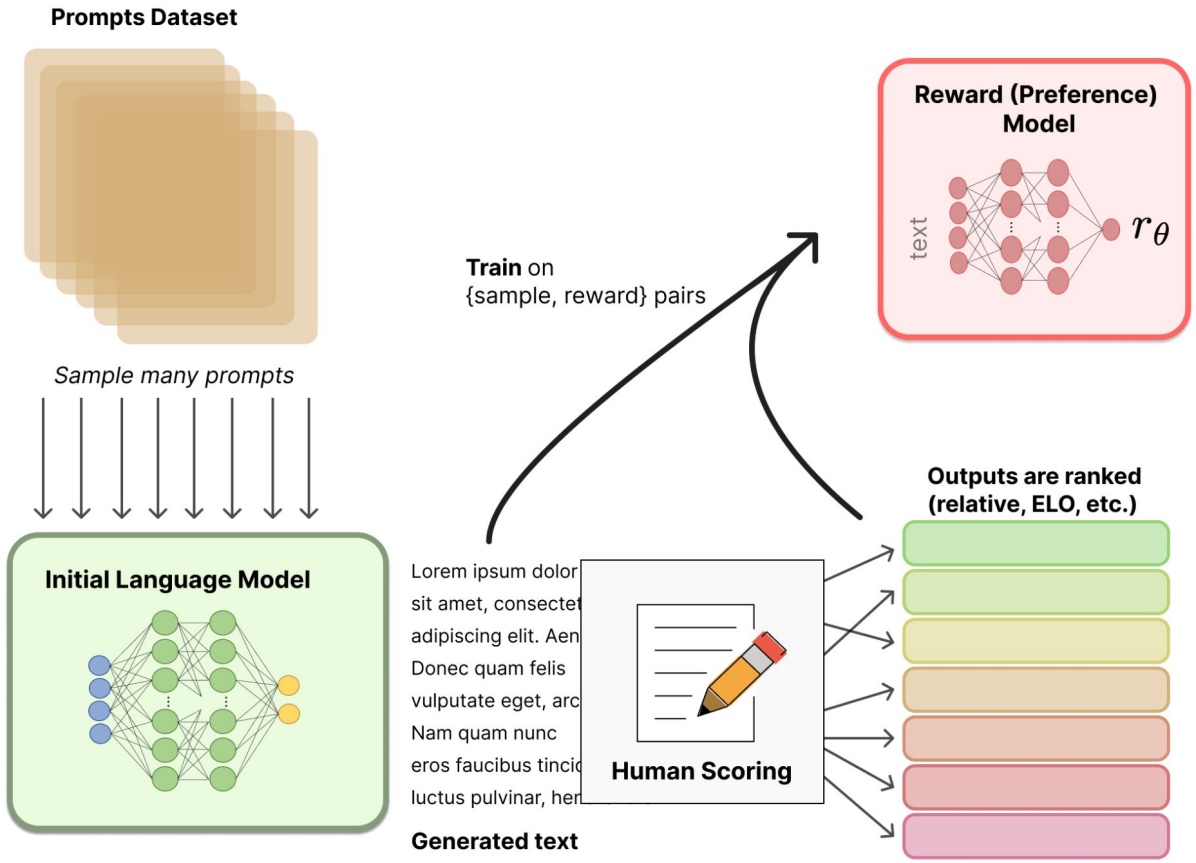
Chat GPT



https://www.youtube.com/watch?v=bZQun8Y4L2A&t=16s

Chat GPT

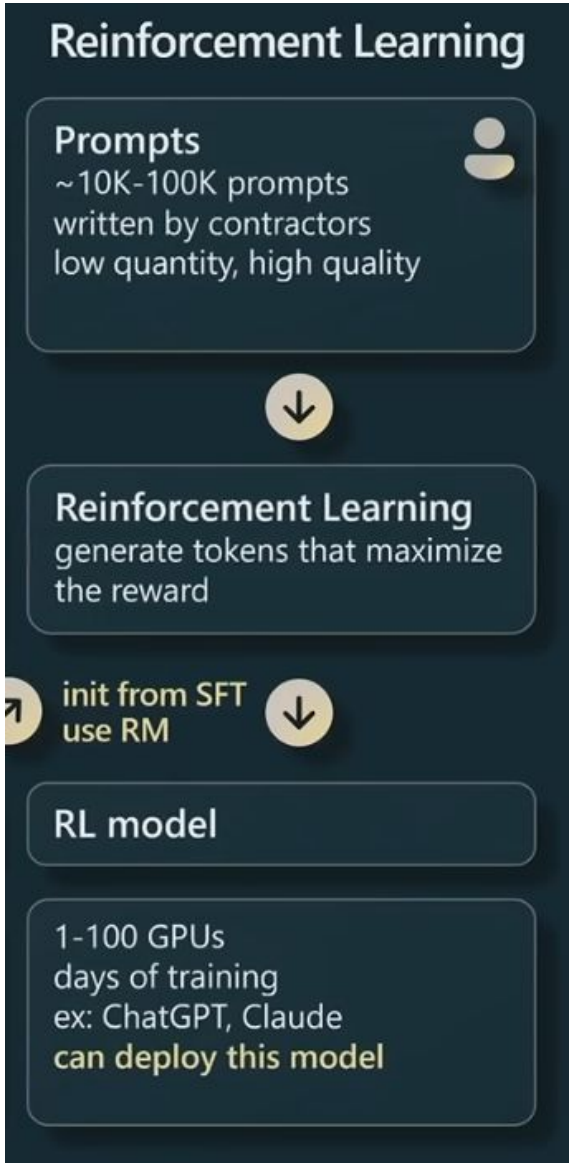


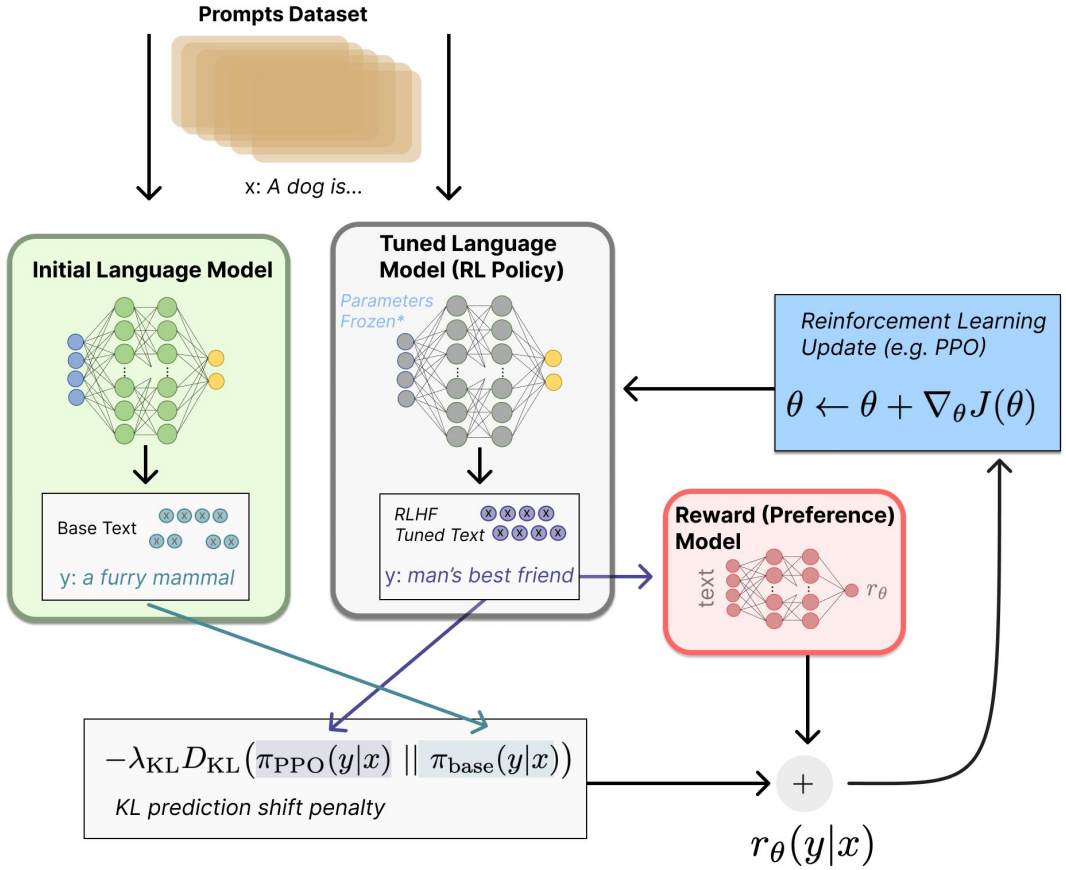


https://www.youtube.com/watch?v=bZQun8Y4L2A&t=16s

https://huggingface.co/blog/rlhf

Chat GPT





https://www.youtube.com/watch?v=bZQun8Y4L2A&t=16s

https://huggingface.co/blog/rlhf

Transformers y Modelos de Imágenes

Vision Transformer

AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

Alexey Dosovitskiy[*,†], **Lucas Beyer**[*], **Alexander Kolesnikov**[*], **Dirk Weissenborn**[*], **Xiaohua Zhai**[*], **Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby**[*,†]

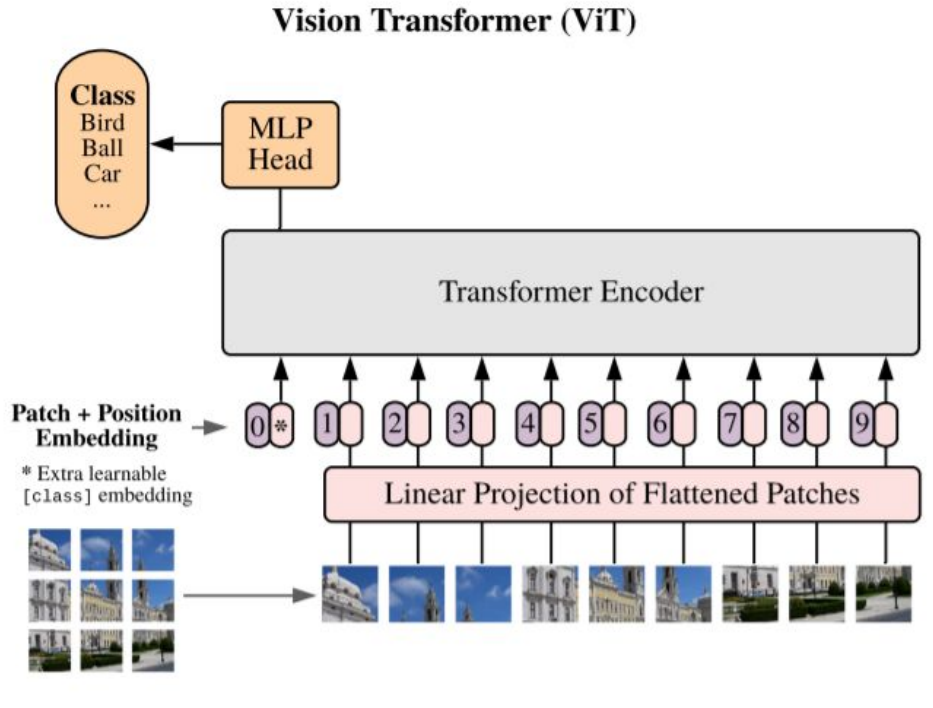
[*]equal technical contribution, [†]equal advising

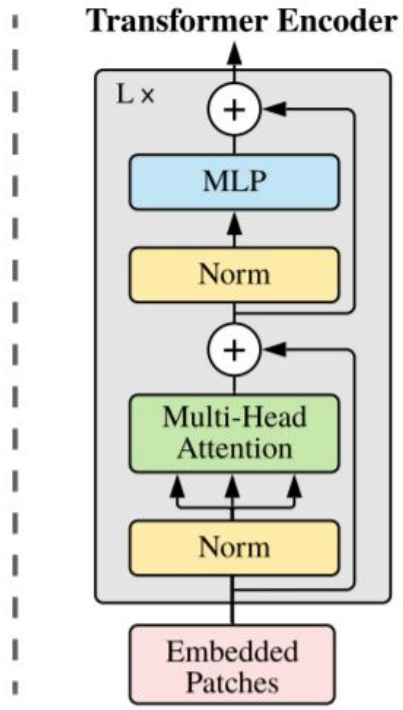
Google Research, Brain Team

{adosovitskiy, neilhoulsby}@google.com

ABSTRACT

While the Transformer architecture has become the de-facto standard for natural language processing tasks, its applications to computer vision remain limited. In vision, attention is either applied in conjunction with convolutional networks, or used to replace certain components of convolutional networks while keeping their overall structure in place. We show that this reliance on CNNs is not necessary and a pure transformer applied directly to sequences of image patches can perform very well on image classification tasks. When pre-trained on large amounts of data and transferred to multiple mid-sized or small image recognition benchmarks (ImageNet, CIFAR-100, VTAB, etc.), Vision Transformer (ViT) attains excellent results compared to state-of-the-art convolutional networks while requiring substantially fewer computational resources to train.[1]





https://arxiv.org/pdf/2010.11929.pdf

Transformers y Modelos de Imágenes

Image GPT

Generative Pretraining from Pixels

Mark Chen [1] Alec Radford [1] Rewon Child [1] Jeff Wu [1] Heewoo Jun [1] Prafulla Dhariwal [1] David Luan [1]
Ilya Sutskever [1]

Abstract

Inspired by progress in unsupervised representation learning for natural language, we examine whether similar models can learn useful representations for images. We train a sequence Transformer to auto-regressively predict pixels, without incorporating knowledge of the 2D input structure. Despite training on low-resolution ImageNet without labels, we find that a GPT-2 scale model learns strong image representations as measured by linear probing, fine-tuning, and low-data classification. On CIFAR-10, we achieve 96.3% accuracy with a linear probe, outperforming a supervised Wide ResNet, and 99.0% accuracy with full fine-tuning, matching the top supervised pre-trained models. An even larger model trained on a mixture of ImageNet and web images is competitive with self-supervised benchmarks on ImageNet, achieving 72.0% top-1 accuracy on a linear probe

ported strong results using a single layer of learned features (Coates et al., 2011), or even random features (Huang et al., 2014; May et al., 2017). The approach fell out of favor as the state of the art increasingly relied on directly encoding prior structure into the model and utilizing abundant supervised data to directly learn representations (Krizhevsky et al., 2012; Graves & Jaitly, 2014). Retrospective study of unsupervised pre-training demonstrated that it could even hurt performance in modern settings (Paine et al., 2014).

Instead, unsupervised pre-training flourished in a different domain. After initial strong results for word vectors (Mikolov et al., 2013), it has pushed the state of the art forward in Natural Language Processing on most tasks (Dai & Le, 2015; Peters et al., 2018; Howard & Ruder, 2018; Radford et al., 2018; Devlin et al., 2018). Interestingly, the training objective of a dominant approach like BERT, the prediction of corrupted inputs, closely resembles that of the Denoising Autoencoder, which was originally developed for images.

https://openai.com/blog/image-gpt/

https://cdn.openai.com/papers/Generative_Pretraining_from_Pixels_V2.pdf

Transformers y Modelos de Imágenes

Image GPT

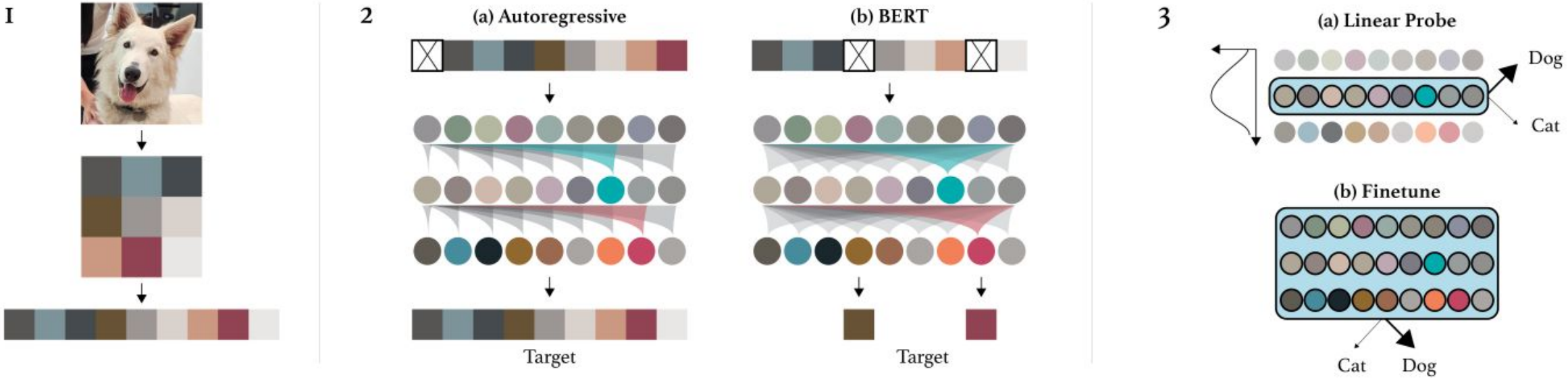


Figure 1. An overview of our approach. First, we pre-process raw images by resizing to a low resolution and reshaping into a 1D sequence. We then chose one of two pre-training objectives, auto-regressive next pixel prediction or masked pixel prediction. Finally, we evaluate the representations learned by these objectives with linear probes or fine-tuning.

https://openai.com/blog/image-gpt/

https://cdn.openai.com/papers/Generative_Pretraining_from_Pixels_V2.pdf

Transformers y Modelos de Imágenes

CLIP

Learning Transferable Visual Models From Natural Language Supervision

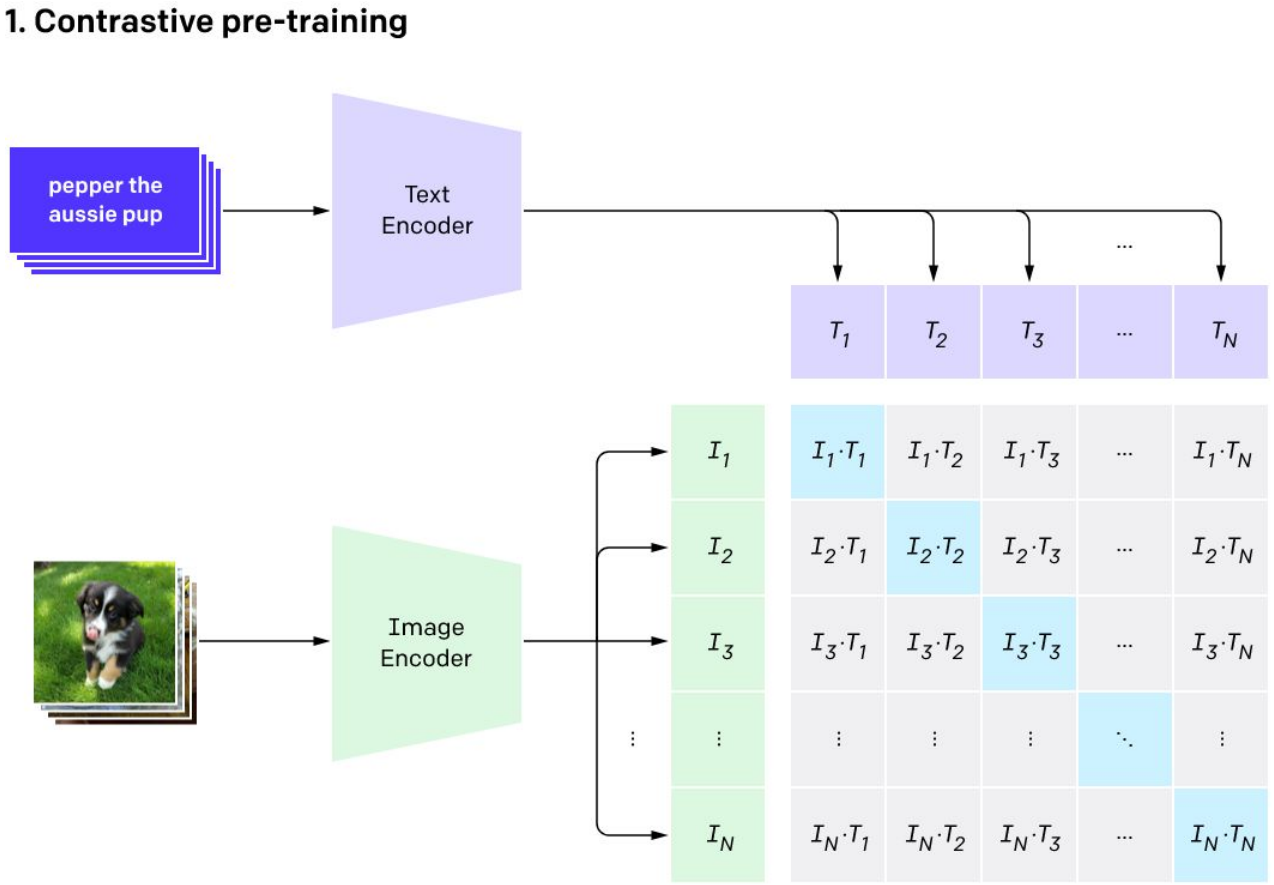
Alec Radford [*1] Jong Wook Kim [*1] Chris Hallacy [1] Aditya Ramesh [1] Gabriel Goh [1] Sandhini Agarwal [1]
Girish Sastry [1] Amanda Askell [1] Pamela Mishkin [1] Jack Clark [1] Gretchen Krueger [1] Ilya Sutskever [1]

Abstract

State-of-the-art computer vision systems are trained to predict a fixed set of predetermined object categories. This restricted form of supervision limits their generality and usability since additional labeled data is needed to specify any other visual concept. Learning directly from raw text about images is a promising alternative which leverages a much broader source of supervision. We demonstrate that the simple pre-training task of predicting which caption goes with which image is an efficient and scalable way to learn SOTA image representations from scratch on a dataset of 400 million (image, text) pairs collected from the internet. After pre-training, natural language is used to reference learned visual concepts (or describe new ones) enabling zero-shot transfer

Task-agnostic objectives such as autoregressive and masked language modeling have scaled across many orders of magnitude in compute, model capacity, and data, steadily improving capabilities. The development of "text-to-text" as a standardized input-output interface (McCann et al., 2018; Radford et al., 2019; Raffel et al., 2019) has enabled task-agnostic architectures to zero-shot transfer to downstream datasets removing the need for specialized output heads or dataset specific customization. Flagship systems like GPT-3 (Brown et al., 2020) are now competitive across many tasks with bespoke models while requiring little to no dataset specific training data.

These results suggest that the aggregate supervision accessible to modern pre-training methods within web-scale collections of text surpasses that of high-quality crowd-labeled NLP datasets. However, in other fields such as computer vision it is still standard practice to pre-train models on



https://openai.com/blog/clip/

https://arxiv.org/pdf/2010.11929.pdf

Transformers y Modelos Generadores de Imágenes

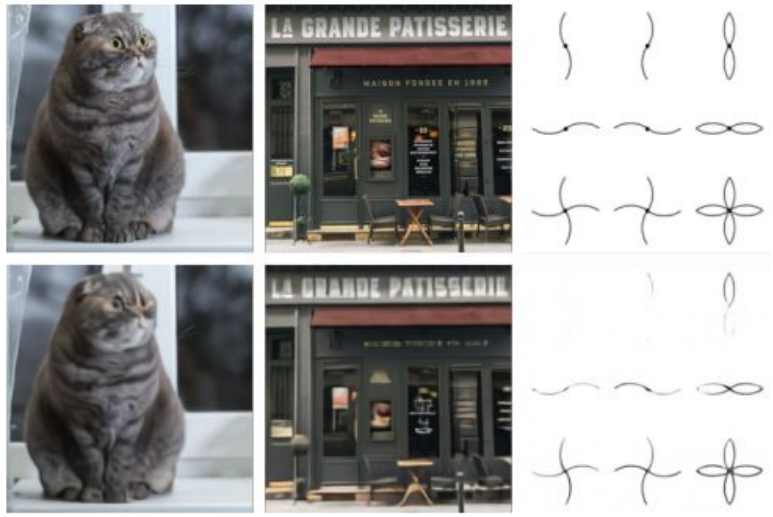
Dalle-1

Zero-Shot Text-to-Image Generation

Aditya Ramesh [1] Mikhail Pavlov [1] Gabriel Goh [1] Scott Gray [1]
Chelsea Voss [1] Alec Radford [1] Mark Chen [1] Ilya Sutskever [1]

Abstract

Text-to-image generation has traditionally focused on finding better modeling assumptions for training on a fixed dataset. These assumptions might involve complex architectures, auxiliary losses, or side information such as object part labels or segmentation masks supplied during training. We describe a simple approach for this task based on a transformer that autoregressively models the text and image tokens as a single stream of data. With sufficient data and scale, our approach is competitive with previous domain-specific models when evaluated in a zero-shot fashion.



https://openai.com/blog/dall-e/

https://arxiv.org/pdf/2102.12092.pdf

Transformers y Modelos Generadores de Imágenes

Dalle-2

Hierarchical Text-Conditional Image Generation with CLIP Latents

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Prafulla Dhariwal* OpenAI prafulla@openai.com

Alex Nichol* OpenAI alex@openai.com

Casey Chu* OpenAI casey@openai.com

Mark Chen OpenAI mark@openai.com

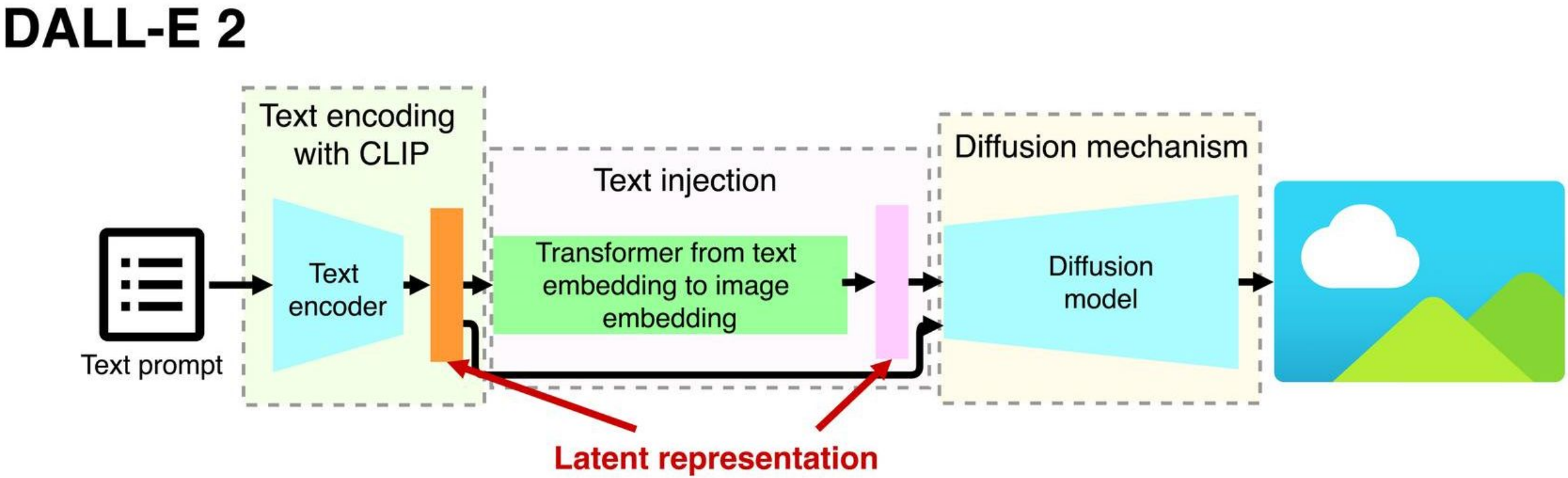
Abstract

Contrastive models like CLIP have been shown to learn robust representations of images that capture both semantics and style. To leverage these representations for image generation, we propose a two-stage model: a prior that generates a CLIP image embedding given a text caption, and a decoder that generates an image conditioned on the image embedding. We show that explicitly generating image representations improves image diversity with minimal loss in photorealism and caption similarity. Our decoders conditioned on image representations can also produce variations of an image that preserve both its semantics and style, while varying the non-essential details absent from the image representation. Moreover, the joint embedding space of CLIP enables language-guided image manipulations in a zero-shot fashion. We use diffusion models for the decoder and experiment with both autoregressive and diffusion models for the prior, finding that the latter are computationally more efficient and produce higher-quality samples.

https://openai.com/dall-e-2/

https://arxiv.org/pdf/2204.06125.pdf

Transformers y Modelos Generadores de Imágenes



https://newsletter.theaiedge.io/p/everything-you-need-to-know-about

Transformers y Modelos Generadores de Imágenes

Imagen

Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding

Chitwan Saharia*, William Chan*, Saurabh Saxena†, Lala Li†, Jay Whang†, Emily Denton, Seyed Kamyar Seyed Ghasemipour, Burcu Karagol Ayan, S. Sara Mahdavi, Rapha Gontijo Lopes, Tim Salimans, Jonathan Ho†, David J Fleet†, Mohammad Norouzi*

{sahariac,williamchan,mnorouzi}@google.com
{srbs,lala,jwhang,jonathanho,davidfleet}@google.com

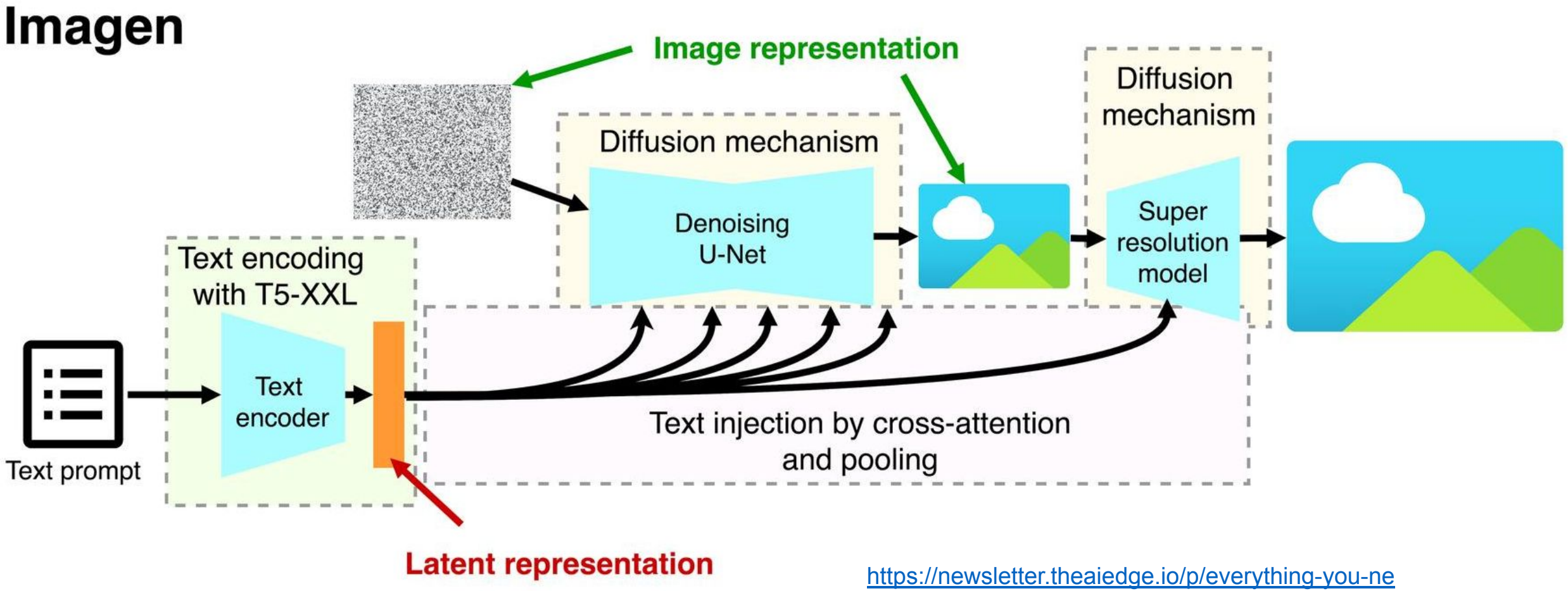
Google Research, Brain Team
Toronto, Ontario, Canada

Abstract

We present Imagen, a text-to-image diffusion model with an unprecedented degree of photorealism and a deep level of language understanding. Imagen builds on the power of large transformer language models in understanding text and hinges on the strength of diffusion models in high-fidelity image generation. Our key discovery is that generic large language models (e.g. T5), pretrained on text-only corpora, are surprisingly effective at encoding text for image synthesis: increasing the size of the language model in Imagen boosts both sample fidelity and image-text alignment much more than increasing the size of the image diffusion model. Imagen achieves a new state-of-the-art FID score of 7.27 on the COCO dataset, without ever training on COCO, and human raters find Imagen samples to be on par with the COCO data itself in image-text alignment. To assess text-to-image models in greater depth, we introduce DrawBench, a comprehensive and challenging benchmark for text-to-image models. With DrawBench, we compare Imagen with recent methods including VQ-GAN+CLIP, Latent Diffusion Models, GLIDE and DALL-E 2, and find that human raters prefer Imagen over other models in side-by-side comparisons, both in terms of sample quality and image-text alignment. See imagen.research.google for an overview of the results.

https://arxiv.org/pdf/2205.11487.pdf

Transformers y Modelos Generadores de Imágenes



https://newsletter.theaiedge.io/p/everything-you-need-to-know-about

Transformers y Modelos Generadores de Imágenes

Stable Diffusion

High-Resolution Image Synthesis with Latent Diffusion Models

Robin Rombach[1] * Andreas Blattmann[1] * Dominik Lorenz[1] Patrick Esser[R] Björn Ommer[1]
[1]Ludwig Maximilian University of Munich & IWR, Heidelberg University, Germany [R]Runway ML
https://github.com/CompVis/latent-diffusion

Abstract

By decomposing the image formation process into a sequential application of denoising autoencoders, diffusion models (DMs) achieve state-of-the-art synthesis results on image data and beyond. Additionally, their formulation allows for a guiding mechanism to control the image generation process without retraining. However, since these models typically operate directly in pixel space, optimization of powerful DMs often consumes hundreds of GPU days and inference is expensive due to sequential evaluations. To enable DM training on limited computational resources while retaining their quality and flexibility, we apply them in the latent space of powerful pretrained autoencoders. In contrast to previous work, training diffusion models on such a representation allows for the first time to reach a near-optimal point between complexity reduction and detail preservation, greatly boosting visual fidelity. By introducing cross-attention layers into the model architecture, we turn diffusion models into powerful and flexible generators for general conditioning inputs such as text

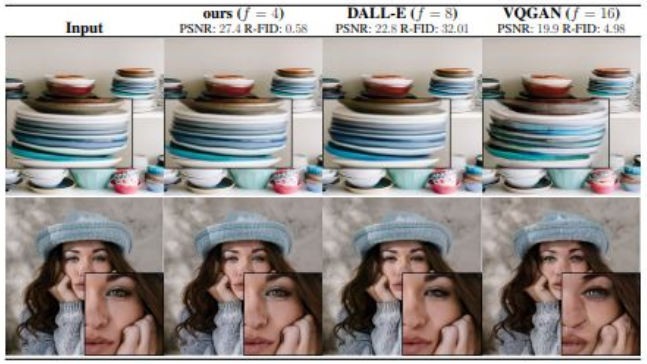


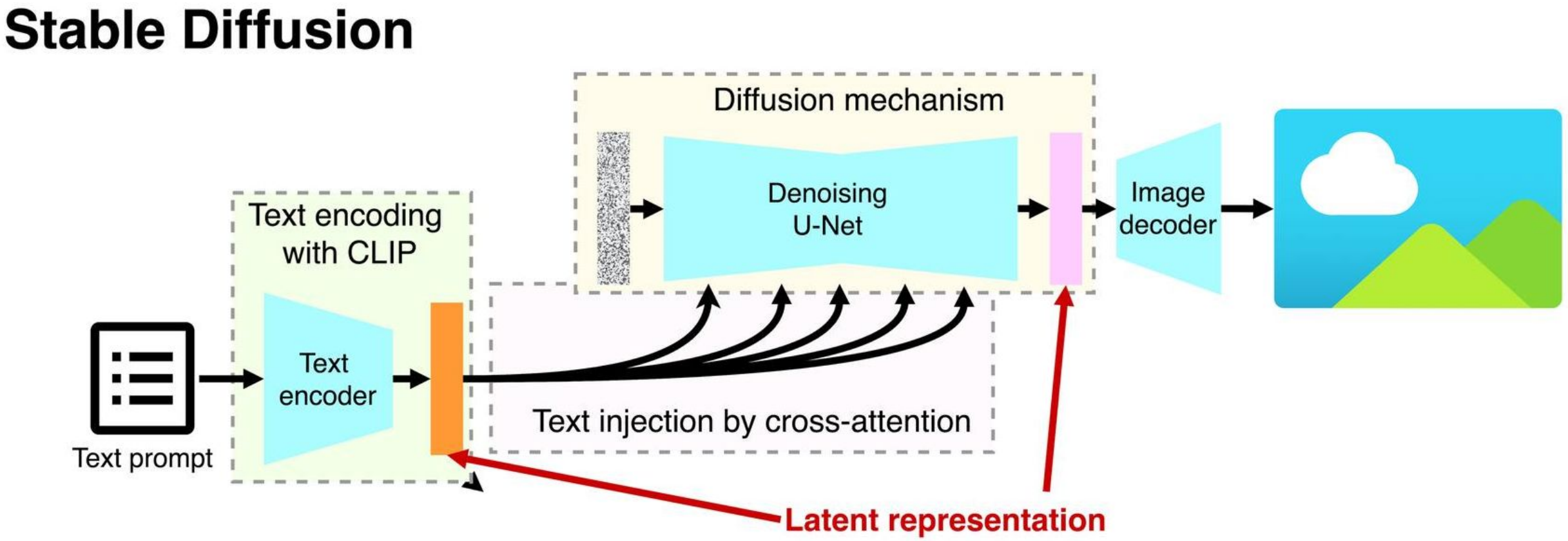
Figure 1. Boosting the upper bound on achievable quality with less agressive downsampling. Since diffusion models offer excellent inductive biases for spatial data, we do not need the heavy spatial downsampling of related generative models in latent space, but can still greatly reduce the dimensionality of the data via suitable autoencoding models, see Sec. 3. Images are from the DIV2K [1] validation set, evaluated at 512^2 px. We denote the spatial downsampling factor by f. Reconstruction FIDs [29] and PSNR are calculated on ImageNet-val. [12]; see also Tab. 8.

results in image synthesis [30, 85] and beyond [7, 45, 48, 57]

https://jalammar.github.io/illustrated-stable-diffusion/

https://arxiv.org/pdf/2112.10752.pdf

Transformers y Modelos Generadores de Imágenes

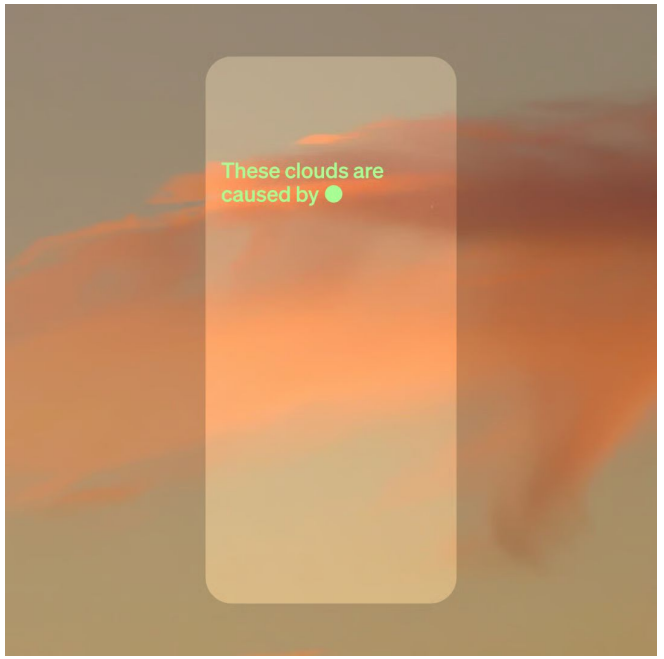


https://newsletter.theaiedge.io/p/everything-you-need-to-know-about

Transformers y Modelos Multimodales

https://openai.com/research/gpt-4

GPT-4V
Recibe Imágenes y Texto



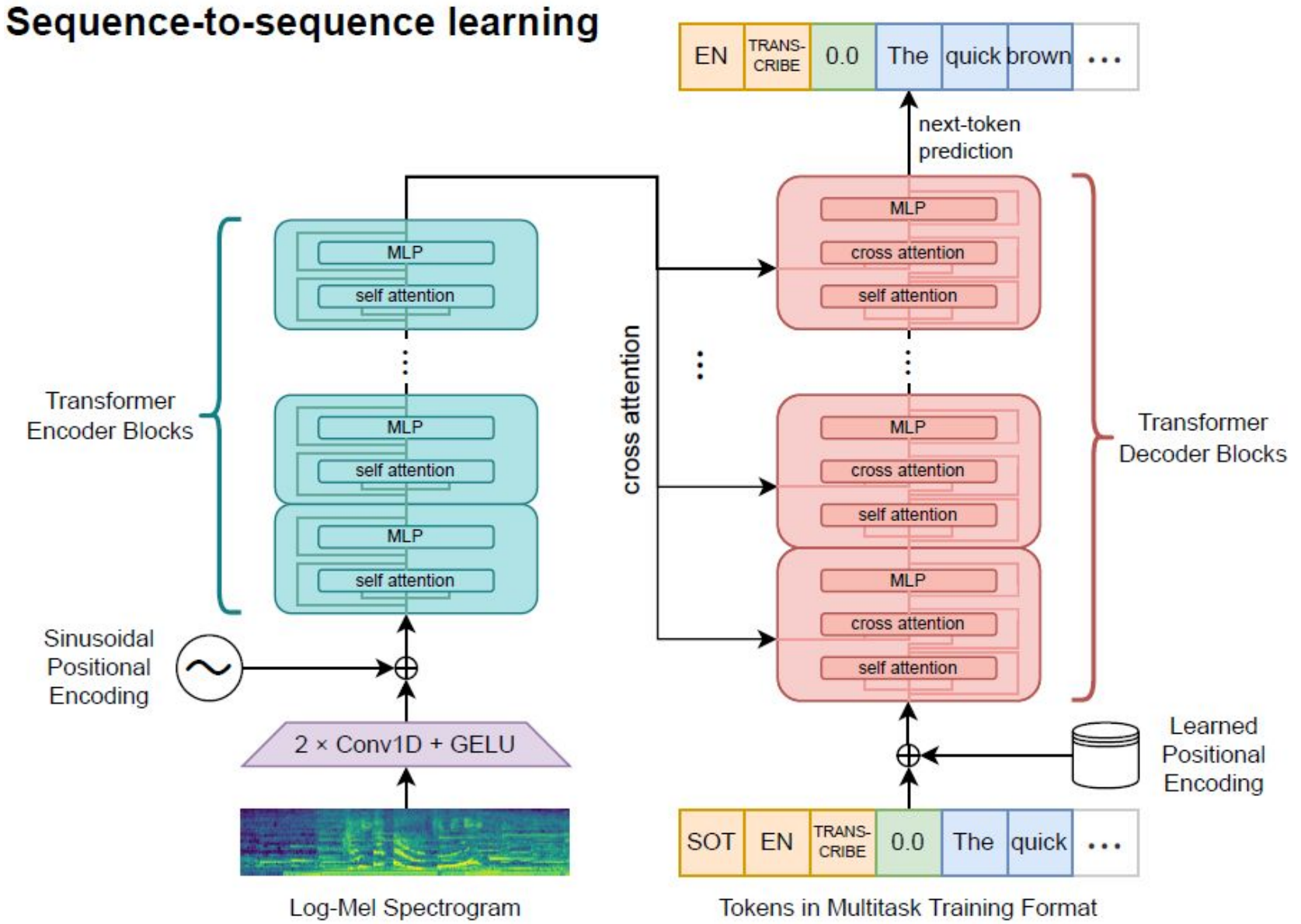
https://openai.com/blog/chatgpt-can-now-see-hear-and-speak?s=03

Transformers y Modelos Multimodales

Inteligencia Artificial Multimodal o Polivalente

GEMINI
Sistema multimodal de Google
Actualmente en entrenamiento y/o pruebas privadas

Transformers y Modelos de Audio

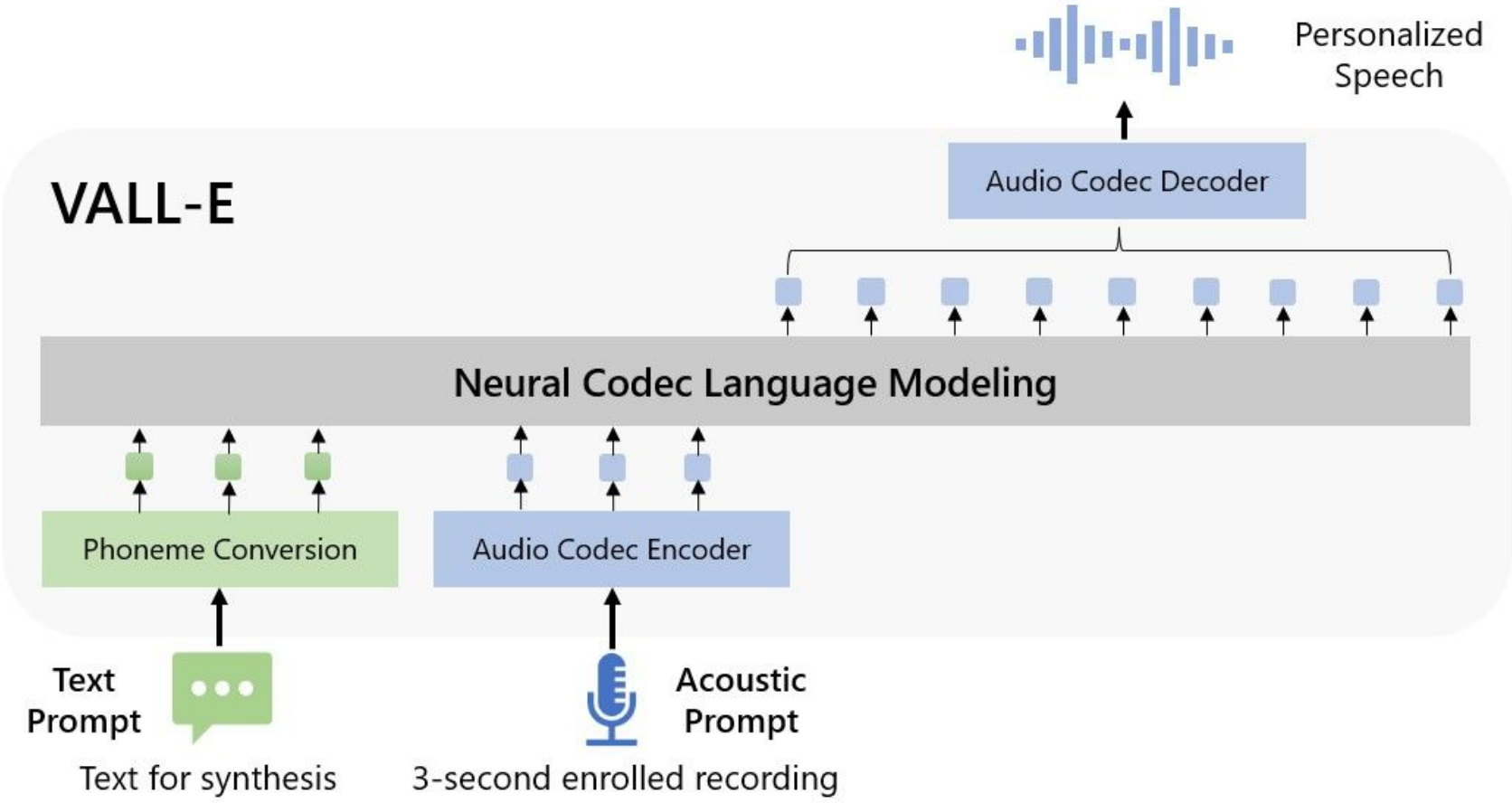


Whisper

https://openai.com/blog/whisper/

https://cdn.openai.com/papers/whisper.pdf

Transformers y Modelos Generadores de Audio



VALL-E

https://valle-demo.github.io/

Transformers y Modelos Generadores de Audio

Music LM

MusicLM: Generating Music From Text

Andrea Agostinelli [*1] Timo I. Denk [*1]
Zalán Borsos [1] Jesse Engel [1] Mauro Verzetti [1] Antoine Caillon [2] Qingqing Huang [1] Aren Jansen [1]
Adam Roberts [1] Marco Tagliasacchi [1] Matt Sharifi [1] Neil Zeghidour [1] Christian Frank [1]

Abstract

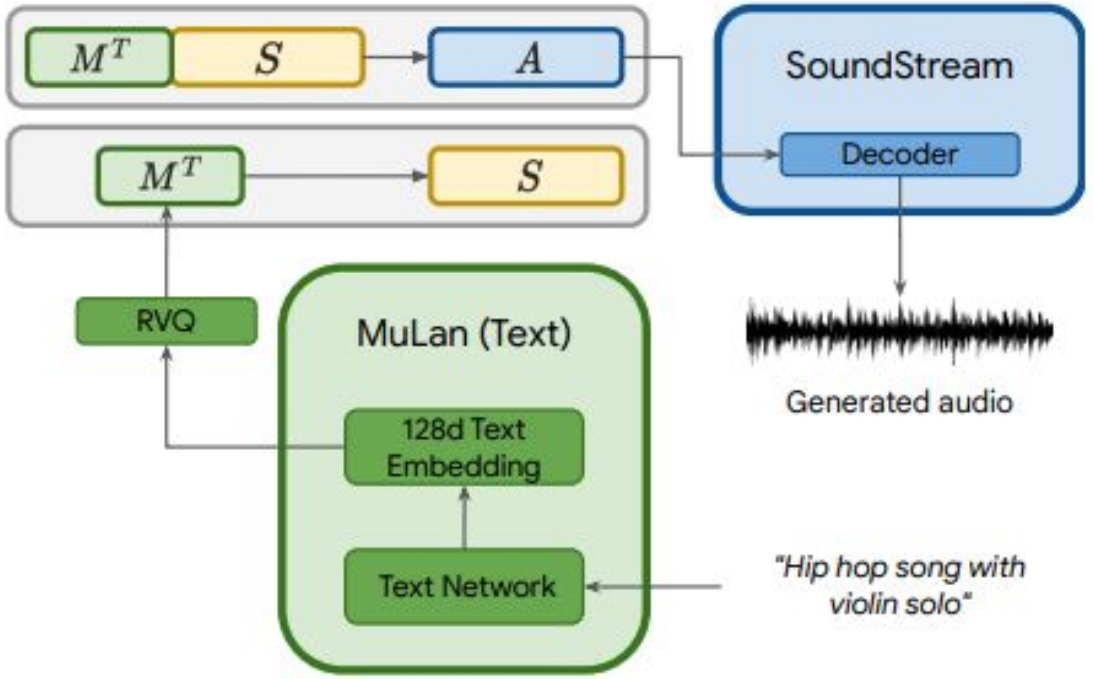
We introduce MusicLM, a model for generating high-fidelity music from text descriptions such as *"a calming violin melody backed by a distorted guitar riff"*. MusicLM casts the process of conditional music generation as a hierarchical sequence-to-sequence modeling task, and it generates music at 24 kHz that remains consistent over several minutes. Our experiments show that MusicLM outperforms previous systems both in audio quality and adherence to the text descriptions. Moreover, we demonstrate that MusicLM can be conditioned on both text and a melody in that it can transform whistled and hummed melodies according to the style described in a text caption. To support future research, we publicly release MusicCaps, a dataset composed of 5.5k music-text pairs, with rich text descriptions provided by human experts.

google-research.github.io/seanet/musiclm/examples

period of seconds. Hence, turning a single text caption into a rich audio sequence with long-term structure and many stems, such as a music clip, remains an open challenge.

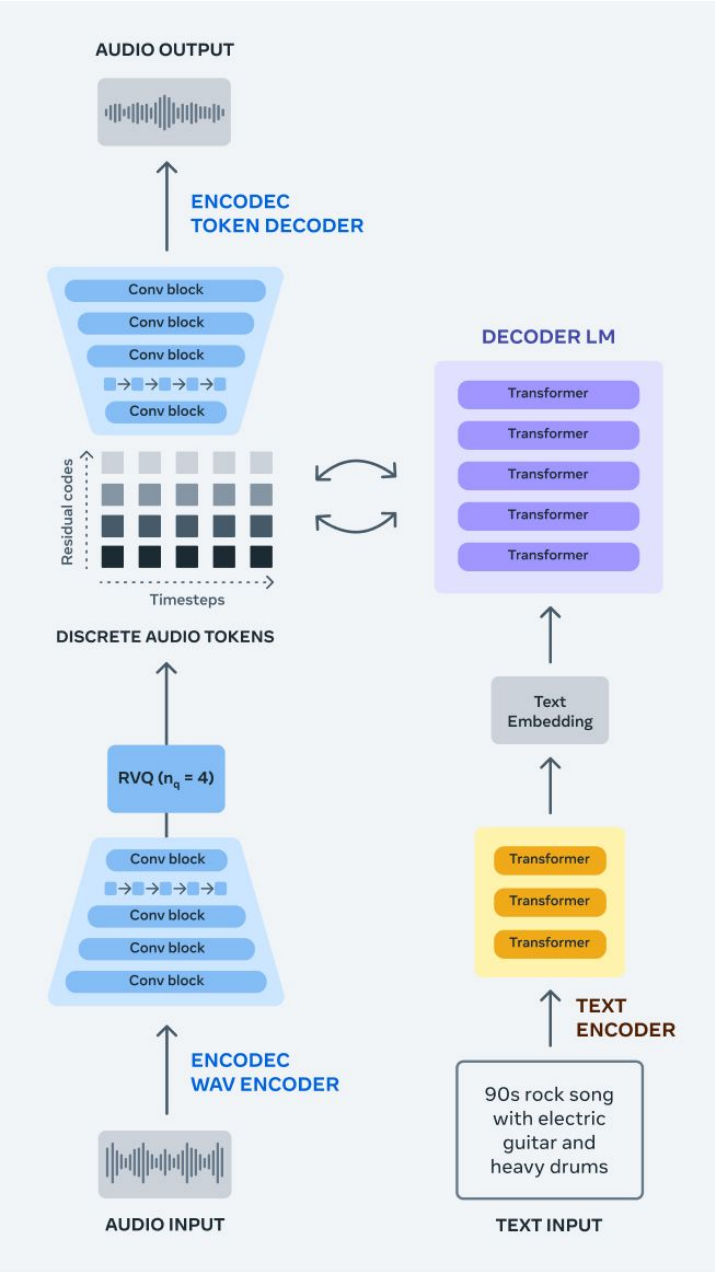
AudioLM (Borsos et al., 2022) has recently been proposed as a framework for audio generation. Casting audio synthesis as a language modeling task in a discrete representation space, and leveraging a hierarchy of coarse-to-fine audio discrete units (or *tokens*), AudioLM achieves both high-fidelity and long-term coherence over dozens of seconds. Moreover, by making no assumptions about the content of the audio signal, AudioLM learns to generate realistic audio from audio-only corpora, be it speech or piano music, without any annotation. The ability to model diverse signals suggests that such a system could generate richer outputs if trained on the appropriate data.

Besides the inherent difficulty of synthesizing high-quality and coherent audio, another impeding factor is the scarcity of paired audio-text data. This is in stark contrast with the image domain, where the availability of massive datasets



https://arxiv.org/pdf/2301.11325.pdf

Transformers y Modelos Generadores de Audio



Audiocraft

https://audiocraft.metademolab.com/

Transformers y Modelos Generadores de Video

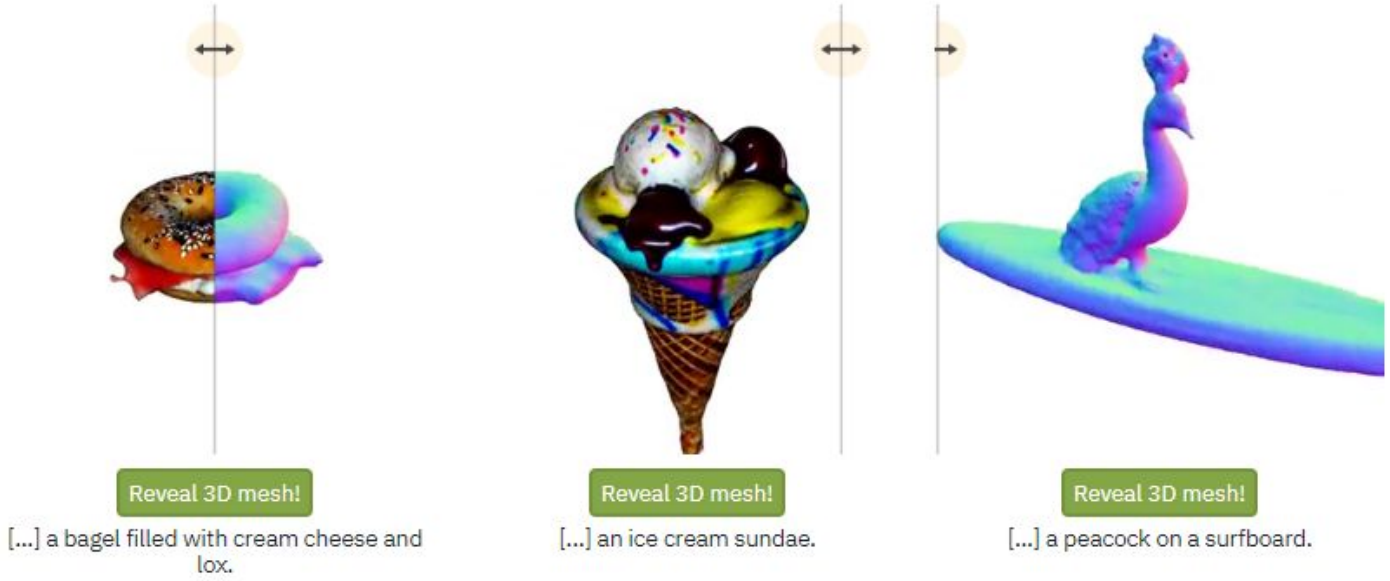
Texto a Video

https://makeavideo.studio/

https://www.nvidia.com/en-us/gpu-cloud/picasso/

Transformers y Modelos Generadores de 3D

Texto a 3D



https://research.nvidia.com/labs/dir/magic3d/

https://www.nvidia.com/en-us/gpu-cloud/picasso/

Inteligencia Artificial Generativa

Text generation
(ChatGPT, Bard, Llama, etc.)

Input prompts

"Write a lullaby about cats and dogs to help a child fall asleep, include a golden shepherd"

Real-life application of this platform

- Communications,
- Journalism,
- Publishing,
- Creative writing
- Writing assistance

Image generation
(Stable Diffusion, MidJourney, etc.)

Input prompts

"Super cute fluffy cat warrior in armor"

Real-life application of this platform

- Advertisements
- Published illustrations
- Corporate visuals
- Novel image generation

Code generation
(Codex, etc.)

Input prompts

"Create code for a pool cleaning website with tab for cleaning, repairs, and testimonials"

A beautiful website is created in seconds

Real-life application of this platform

- Web design
- Software development
- Coding
- Technology

What is generative AI?

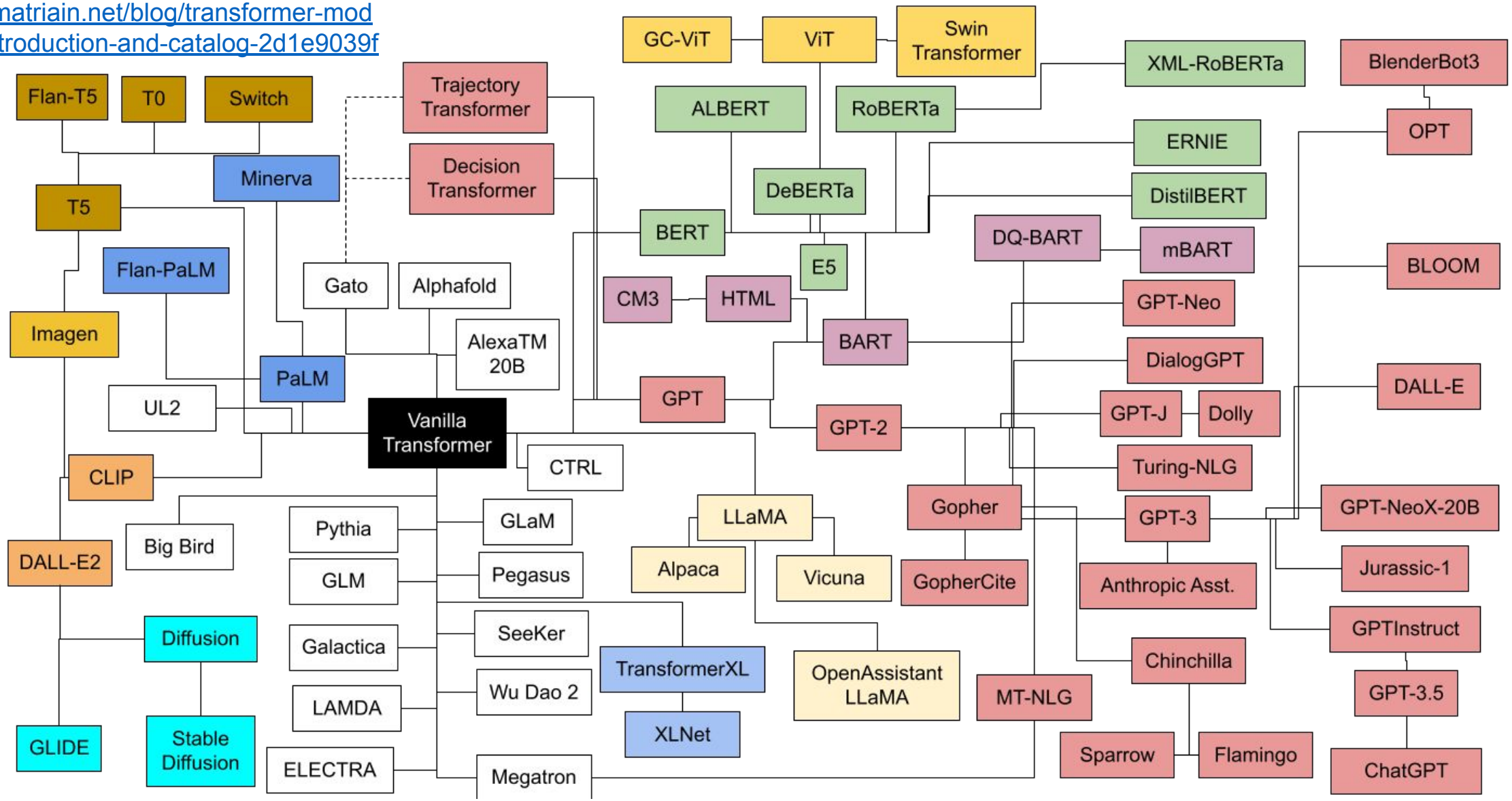
AI models that create new and original content like text, images, video, audio, or other data

Generative AI, foundational models, and large language models are sometimes used interchangeably

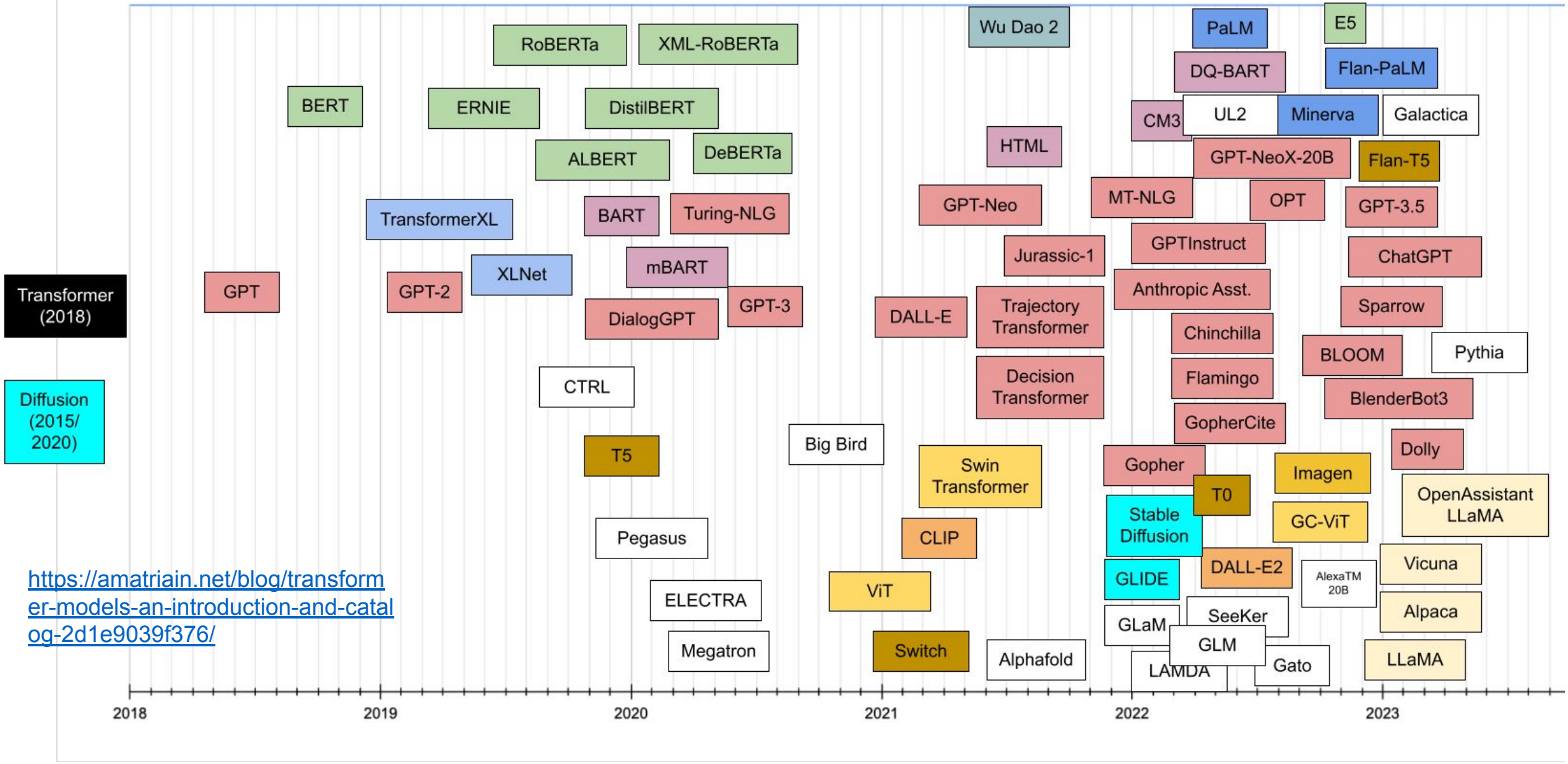
Generative AI at the edge. Joseph Soriaga Qualcomm Technologies, Inc. Nov. 8 2023

Transformers ZOO

https://amatriain.net/blog/transformer-models-an-introduction-and-catalog-2d1e9039f376/

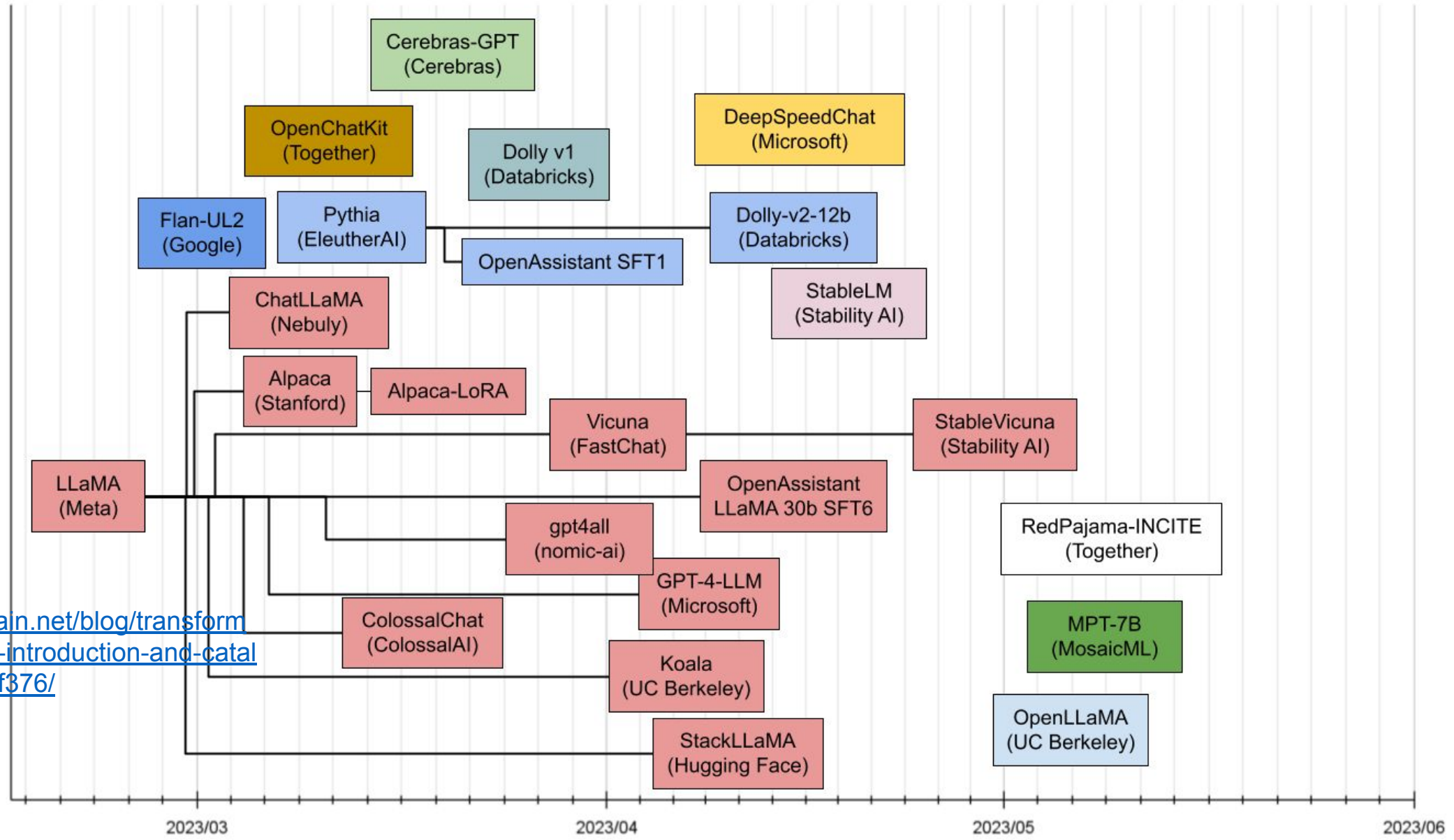


Transformers ZOO



https://amatriain.net/blog/transformer-models-an-introduction-and-catalog-2d1e9039f376/

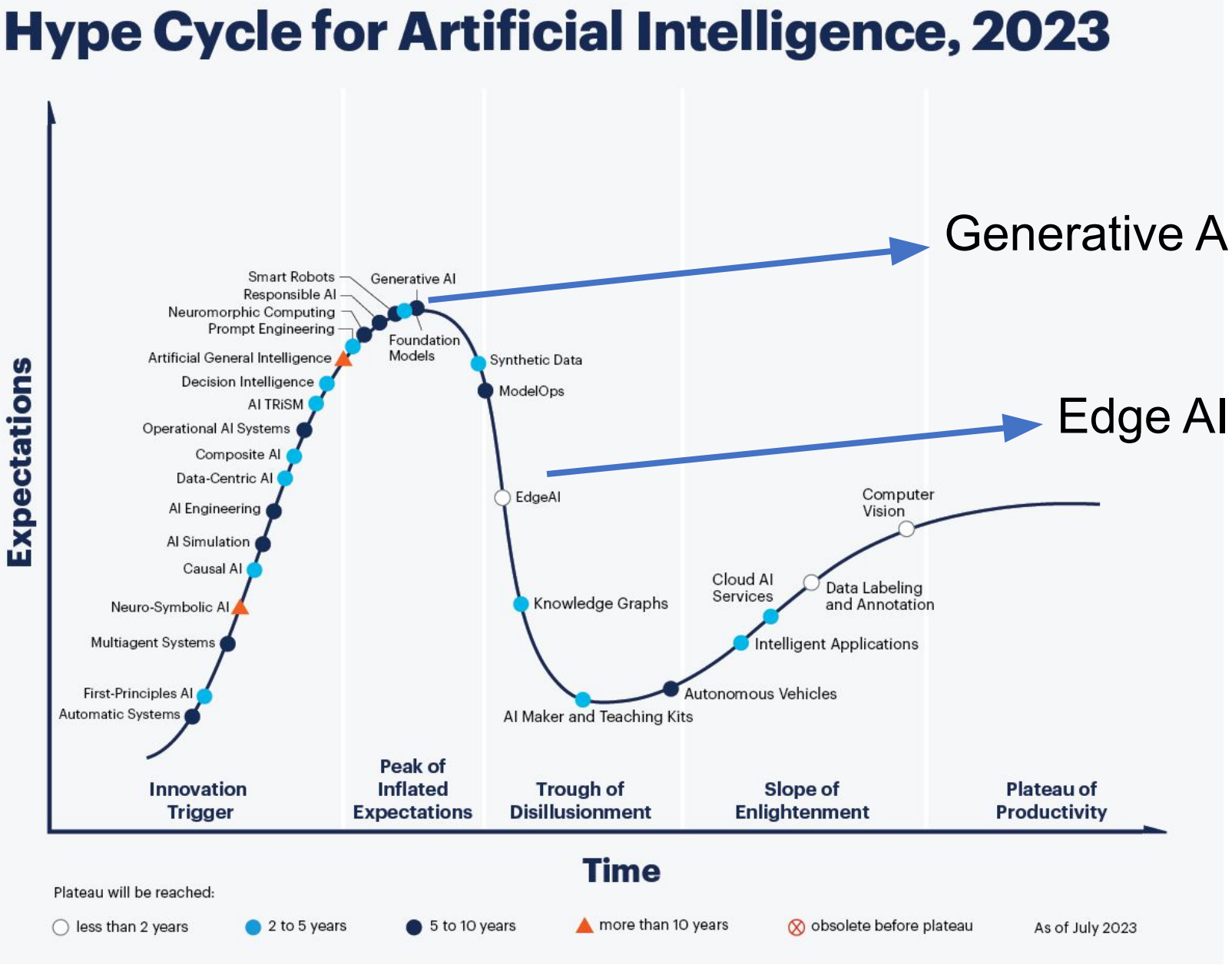
Transformers ZOO (Modelos Libres)



https://amatriain.net/blog/transformer-models-an-introduction-and-catalog-2d1e9039f376/

Los Extremos se Encuentran

Edge AI y Generative AI

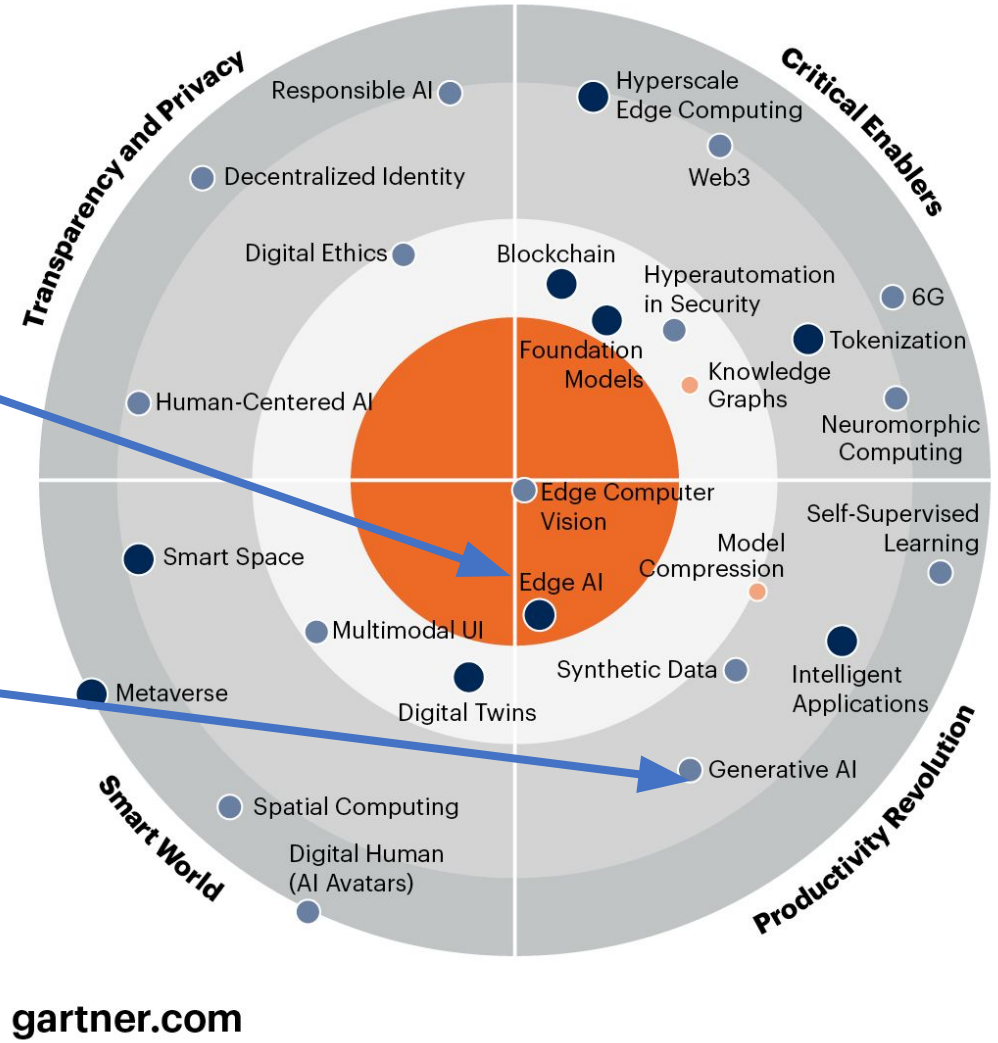


https://www.gartner.com/en/articles/what-s-new-in-artificial-intelligence-from-the-2023-gartner-hype-cycle

Edge AI y Generative AI

Edge AI

Generative AI



https://www.gartner.com/en/articles/4-emerging-technologies-you-need-to-know-about

Edge AI y Generative AI

Costo Económico y Ambiental

	GPU Type	GPU Power consumption	GPU-hours	Total power consumption	Carbon emitted (tCO_2eq)
OPT-175B	A100-80GB	400W	809,472	356 MWh	137
BLOOM-175B	A100-80GB	400W	1,082,880	475 MWh	183
LLaMA-7B	A100-80GB	400W	82,432	36 MWh	14
LLaMA-13B	A100-80GB	400W	135,168	59 MWh	23
LLaMA-33B	A100-80GB	400W	530,432	233 MWh	90
LLaMA-65B	A100-80GB	400W	1,022,362	449 MWh	173

Table 15: **Carbon footprint of training different models in the same data center.** We follow the formula from Wu et al. (2022) to compute carbon emission of train OPT, BLOOM and our models in the same data center. For the power consumption of a A100-80GB, we take the thermal design power (TDP) for NVLink systems, that is 400W. We take a PUE of 1.1 and a carbon intensity factor set at the national US average of 0.385 kg CO_2e per KWh.

https://research.facebook.com/publications/llama-open-and-efficient-foundation-language-models/

... estimamos que utilizamos 2048 A100-80GB durante un período de aproximadamente 5 meses para desarrollar nuestros modelos

Esto muestra que el modelo más pequeño, LLaMA-7B, fue entrenado con 82.432 horas de GPU A100-80GB, con un costo de 36MWh y generando 14 toneladas de CO2.
(Eso son aproximadamente 28 personas que vuelan de Londres a Nueva York).

Se estima que el costo del entrenamiento fue $7,372,800

https://simonwillison.net/2023/Mar/17/beat-chatgpt-in-a-browser/

Edge AI y Generative AI

Costo Económico y Ambiental

HOME > TECH

ChatGPT could cost over $700,000 per day to operate. Microsoft is reportedly trying to make it cheaper.

CLEAN ENERGY

Microsoft is hiring a nuclear energy expert to help power its AI and cloud data centers

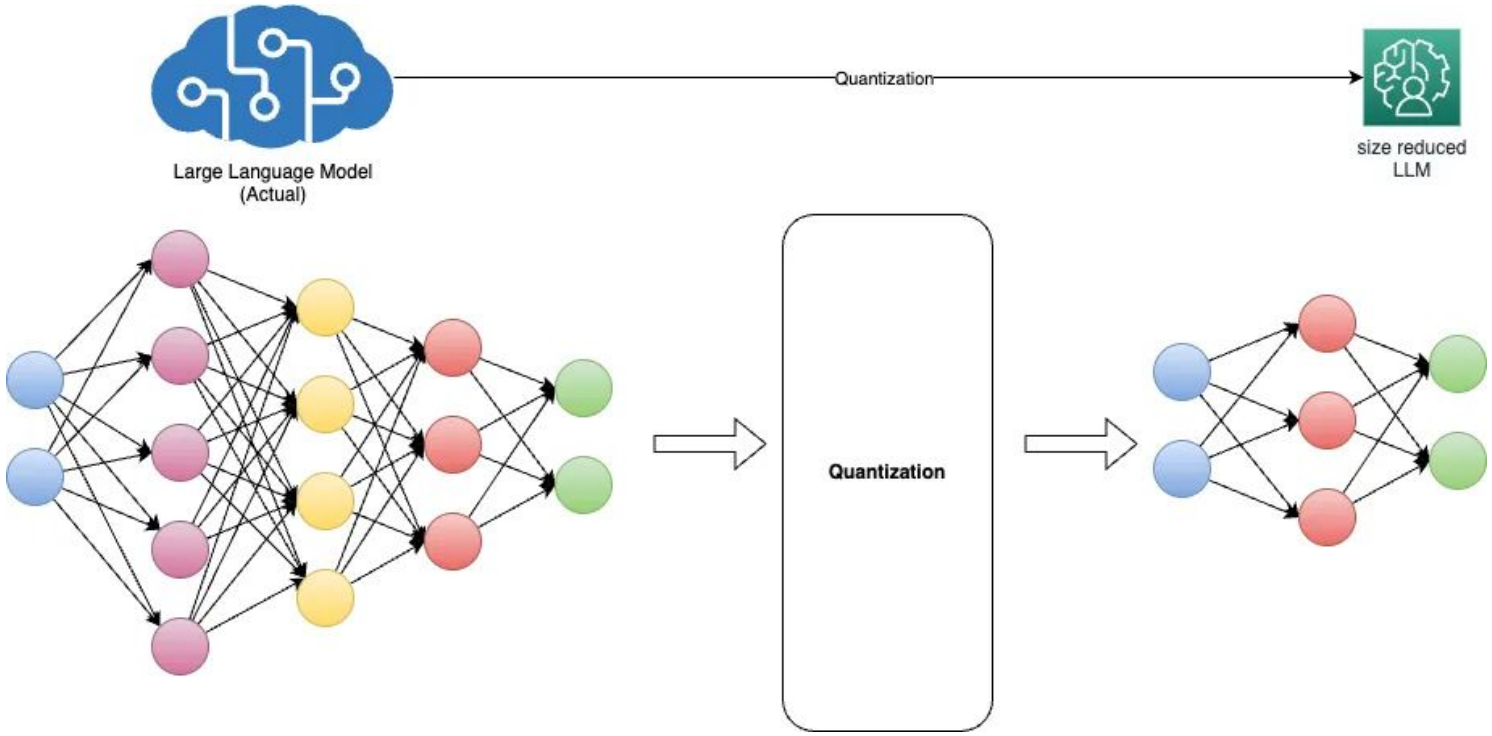
La inteligencia artificial requiere mucha potencia informática y Microsoft está elaborando una hoja de ruta para impulsar ese proceso con pequeños reactores nucleares

https://www.cnbc.com/2023/09/25/microsoft-is-hiring-a-nuclear-energy-expert-to-help-power-data-centers.html

https://www.businessinsider.com/how-much-chatgpt-costs-openai-to-run-estimate-report-2023-4

Edge AI y Generative AI

- Optimización de los modelos de IA
- Cuantización
- Pruning
- Knowledge distillation

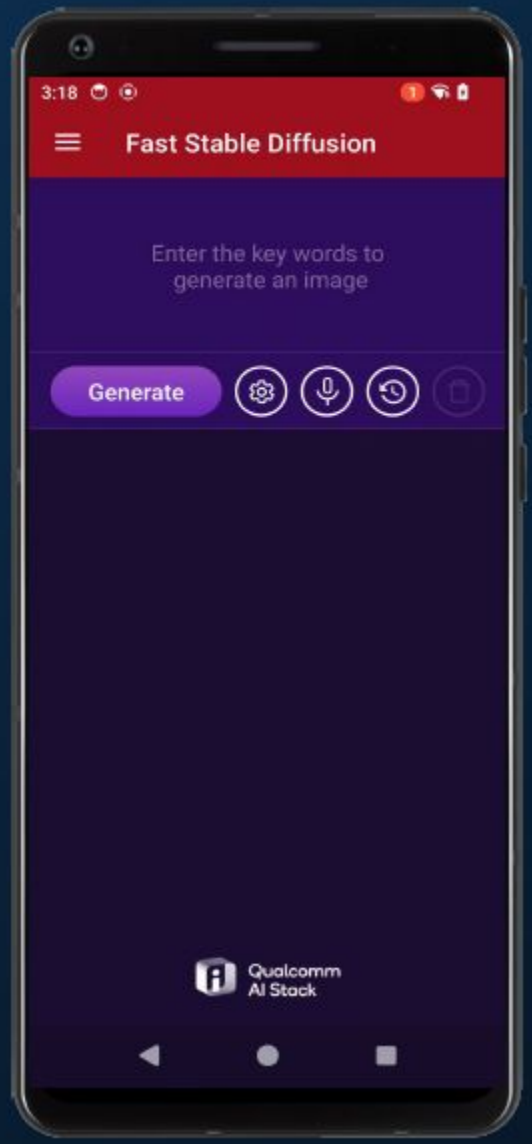


https://int8.io/local-large-language-models-beginners-guide/

https://www.linkedin.com/pulse/quantization-what-you-should-understand-want-run-llms-pavan-mantha

Edge AI y Generative AI

World's fastest AI text-to-image generative AI on a phone



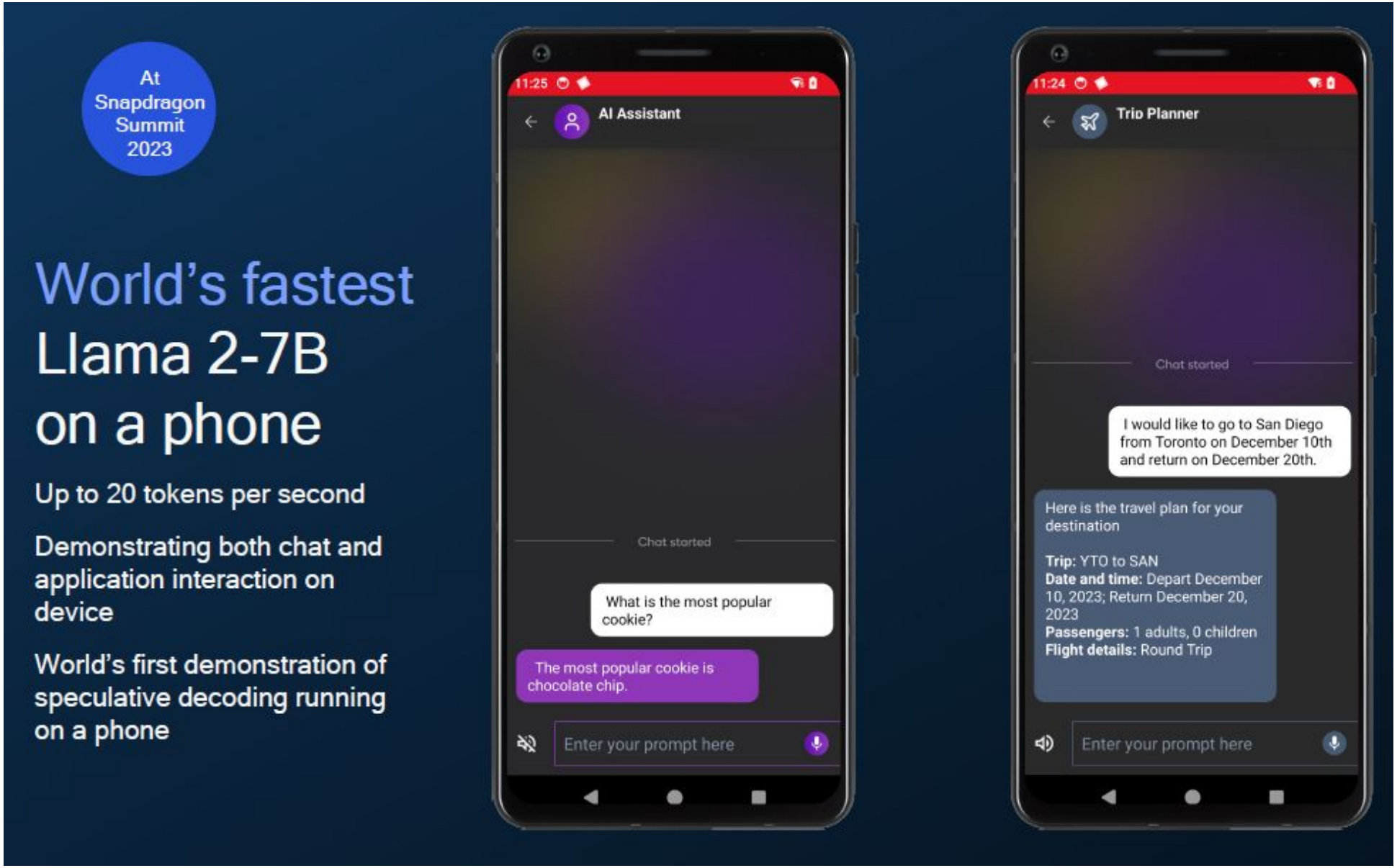
Takes less than 0.6 seconds for generating 512x512 images from text prompts

Efficient UNet architecture, guidance conditioning, and step distillation

Full-stack AI optimization to achieve this improvement

Generative AI at the edge. Joseph Soriaga Qualcomm Technologies, Inc. Nov. 8 2023

Edge AI y Generative AI



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Gracias

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