.UBAfiuba
FACULTAD DE INGENIERÍA

MoEs, Prompting y evaluación

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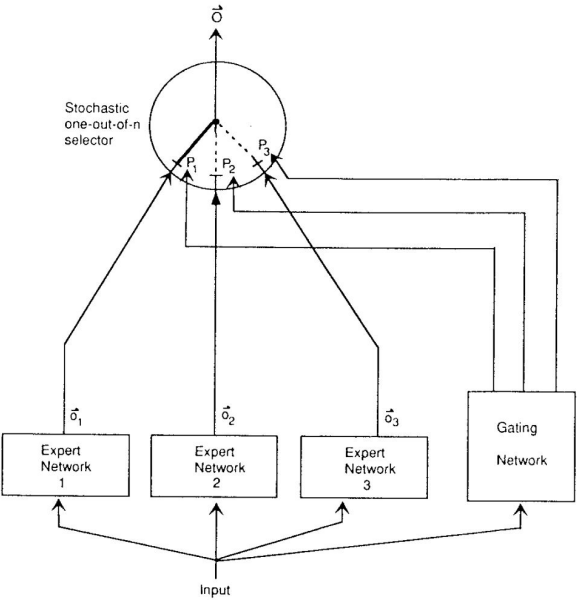
Programa de la materia

1. Repaso de Transformers, Arquitectura y Tokenizers.
2. Arquitecturas de LLMs, Transformer Decoder.
3. Ecosistema actual, APIs, costos, HuggingFace y OpenAI.
4. MoEs, técnicas de prompts, evaluación de LLMs.
5. Modelos locales y uso de APIs.
6. RAG, vector DBs, chatbots y práctica.
7. Agentes, fine-tuning y práctica.
8. Generación multimodal.

Mixture of Experts (MoE)



MoE es un concepto introducido en el paper "Adaptive Mixture of Experts" en 1991, consiste en un conjunto de redes neuronales donde cada una aprende a manejar **subconjuntos** específicos de información.

Cada experto recibe el mismo input y produce el mismo número de outputs, pero existe un mecanismo de selección que **controla** qué expertos contribuyen a la predicción final.

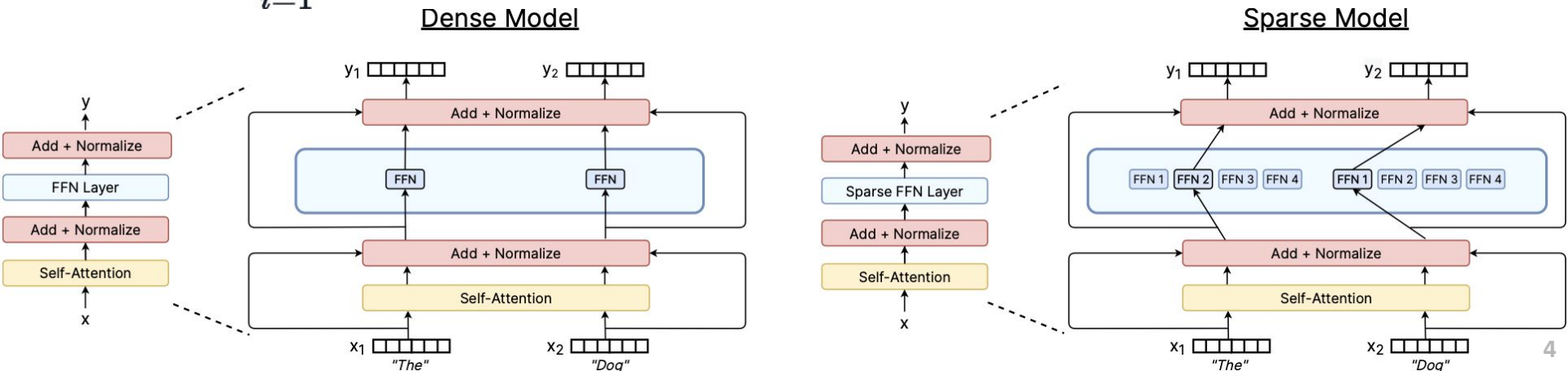
La probabilidad de que se elija la salida de un experto específico *j* es denotada como p_j.

Una red neuronal llamada gating network realiza la selección determinando las contribuciones de cada experto. La gating network aprende las **contribuciones** de cada experto basado en el input.

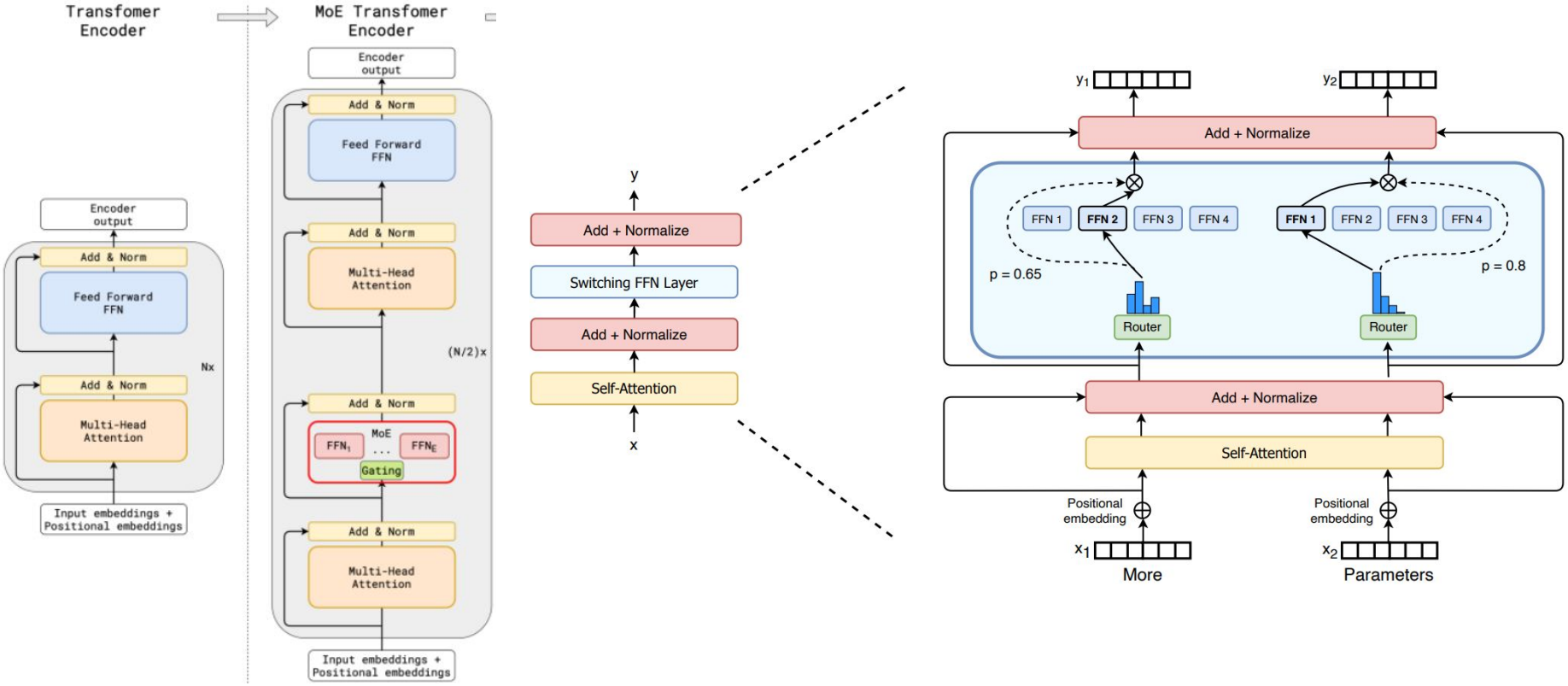
Esparcidad

La esparcidad utiliza la idea de **computación condicional**, en un modelo denso todos los parámetros son utilizados para todos los inputs, en un modelo esparzo utiliza parcialmente los parámetros. La gating network *G* decide que experto *E* ejecutar el input.

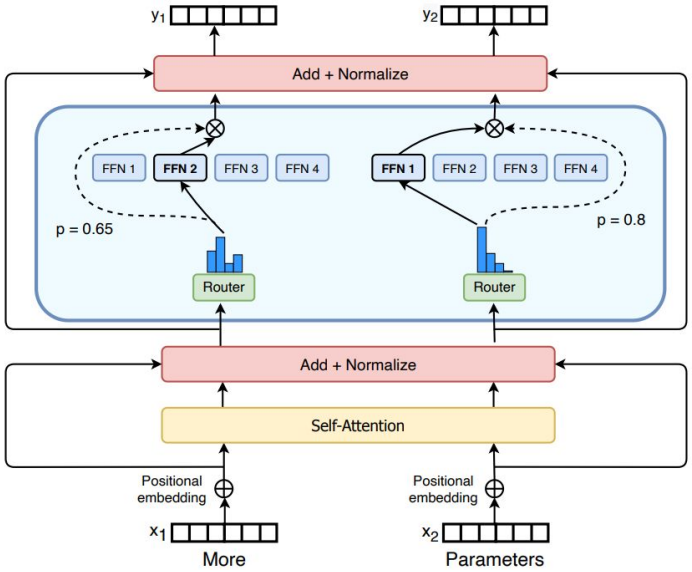
$$y = \sum_{i=1}^{n} G(x)_i E_i(x) \qquad G_\sigma(x) = \text{Softmax}(x \cdot W_g)$$



Mixture of Experts (MoE) en LLMs



Mixture of Experts (MoE) en LLMs



Una MoE permite **escalar** los parámetros del modelo sin necesidad de incrementar la demanda computacional, debido al mecanismo de selección dinámico, permitiendo al modelo alocar los recursos de manera condicional.

Mixture of Experts (MoE) en LLMs

MoE Explained

Why new LLMS use MoE

A Survey on Mixture of Experts

El Paper es un recurso que proporcione un review sobre MoE, tecnicas y arquitecturas, altamente **Recomendable leer.**

Sparse Transformers

A REVIEW OF SPARSE EXPERT MODELS IN DEEP LEARNING **Recomendable leer el paper.**

Mixtral

MistralAI lanzó Mixtral8x7B (2023), el cual consiste en la misma arquitectura que Mistral 7B, pero con 8 capas FFN Spare MoE.

Mixtral tiene en total 47B de parámetros pero utiliza solamente 13B en inferencia, Mixtral supera a Llama-2-70B y GPT-3.5 en múltiples benchmarks.

En conjunto se presentó una versión fine-tuned mediante **SFT** de Mixtral-instruct (similar a instructGPT).

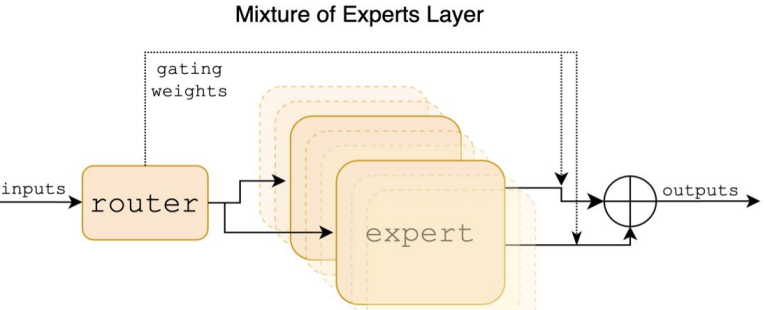
Paper

	LLaMA 2 70B	GPT - 3.5	Mixtral 8x7B
MMLU (MCQ in 57 subjects)	69.9%	70.0%	**70.6%**
HellaSwag (10-shot)	87.1%	85.5%	86.7%
ARC Challenge (25-shot)	85.1%	85.2%	**85.8%**
WinoGrande (5-shot)	**83.2%**	81.6%	81.2%
MBPP (pass@1)	49.8%	52.2%	**60.7%**
GSM-8K (5-shot)	53.6%	57.1%	**58.4%**
MT Bench (for Instruct Models)	6.86	**8.32**	8.30

Mixtral

Mixtral utiliza un router que permite elegir 2 expertos a por token y combinar el output de manera aditiva.

Parameter	Value
dim	4096
n_layers	32
head_dim	128
hidden_dim	14336
n_heads	32
n_kv_heads	8
context_len	32768
vocab_size	32000
num_experts	8
top_k_experts	2



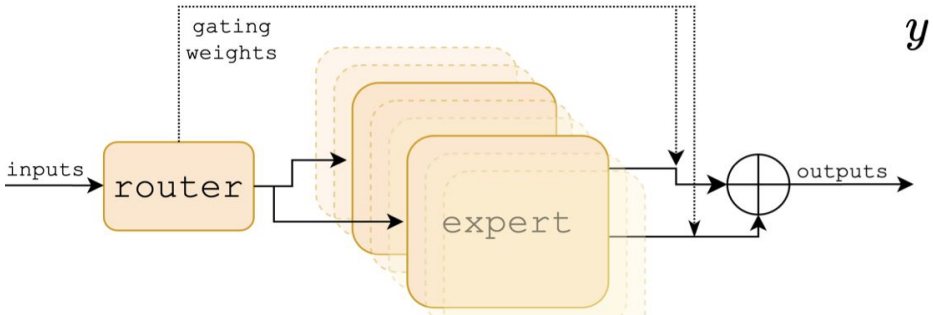
Mixtral Top-K

El router de Mixtral utiliza Top-K logits de una capa lineal, esta técnica fue presentada en el paper "The Sparsely-Gated MoE Layer".

$$(\text{TopK}(\ell))_i := \ell_i \qquad \text{TopK}(v, k)_i = \begin{cases} v_i & \text{if } v_i \text{ is in the top } k \text{ elements of } v, \\ -\infty & \text{otherwise.} \end{cases}$$

$$G(x) := \text{Softmax}(\text{TopK}(x \cdot W_g))$$

Mixture of Experts Layer



$$y = \sum_{i=0}^{n-1} \text{Softmax}(\text{Top2}(x \cdot W_g))_i \cdot \text{SwiGLU}_i(x)$$

DeepSeek V2

DeepSeekV2 utiliza la idea de expertos compartidos, para reducir la redundancia entre expertos seleccionados,

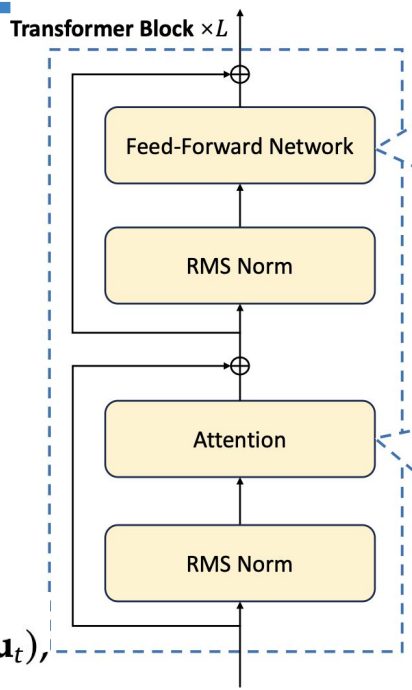
N_s y N_r denotan el # de shared experts y routed experts.

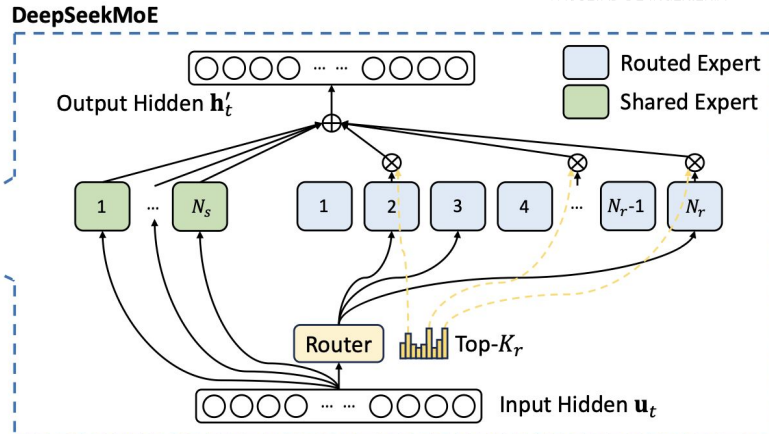
K_r denota el número de experts **activados**.

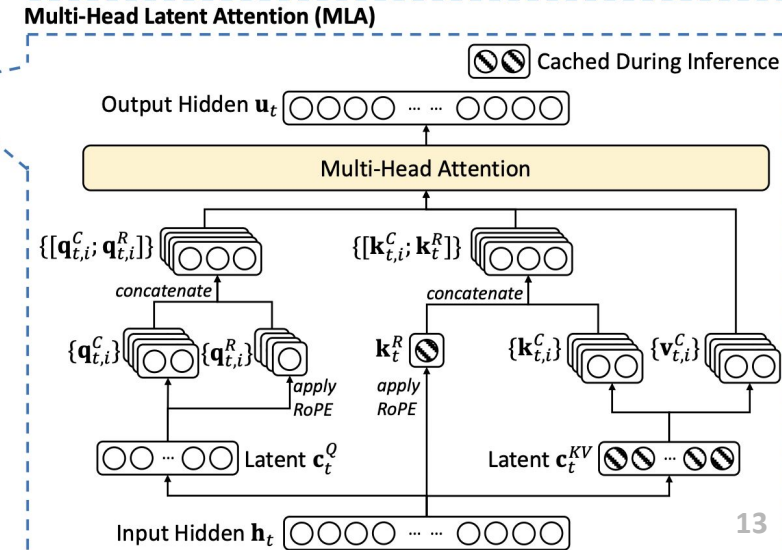
$$\mathbf{h}_t' = \mathbf{u}_t + \sum_{i=1}^{N_s} \mathrm{FFN}_i^{(s)}(\mathbf{u}_t) + \sum_{i=1}^{N_r} g_{i,t}\,\mathrm{FFN}_i^{(r)}(\mathbf{u}_t),$$

$$g_{i,t} = \begin{cases} s_{i,t}, & s_{i,t} \in \mathrm{Topk}(\{s_{j,t} | 1 \leqslant j \leqslant N_r\}, K_r), \\ 0, & \text{otherwise}, \end{cases}$$

$$s_{i,t} = \mathrm{Softmax}_i\left(\mathbf{u}_t^T \mathbf{e}_i\right),$$







Grok-1

Grok-1 es una LLM MoE de xAI, la cual no tiene un paper oficial pero en el blog se da a conocer el uso de MoE, métricas, tamaño, etc.

Visual guide to MoE

Visual guide to MoE (**Recomendable leer**)

MoE Implementaciones

MoE GPT-2
Mistral Transformer layers

Prompting

Chain of Thought

Introducido en el paper "Chain-of-Thought prompting Elicits Reasoning in Large Language Models", 2022, introduce el concepto de realizar **pasos intermedios de razonamiento** para habilitar razonamiento complejo de parte de una LLM. Similar al proceso de descomposición que realiza el ahumado sobre problemas de

Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. ✗

Chain-of-Thought Prompting

Model Input

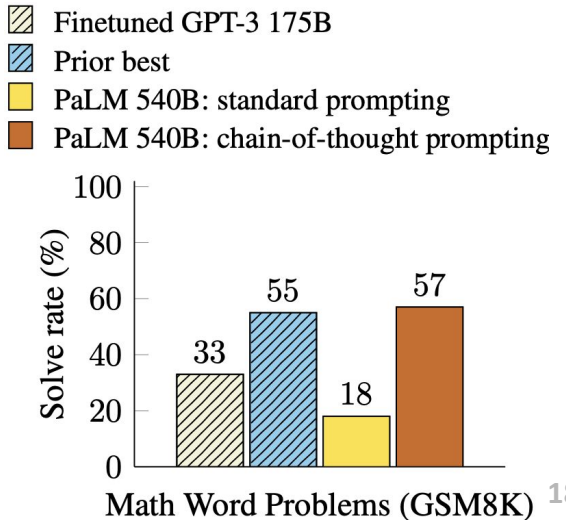
Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9. ✓



Chain of Thought

	Prompting	GSM8K	SVAMP	ASDiv	AQuA	MAWPS
Prior best	N/A (finetuning)	55[a]	57.4[b]	75.3[c]	37.9[d]	88.4[e]
UL2 20B	Standard	4.1	10.1	16.0	20.5	16.6
	Chain of thought	4.4 (+0.3)	12.5 (+2.4)	16.9 (+0.9)	23.6 (+3.1)	19.1 (+2.5)
	+ ext. calc	6.9	28.3	34.3	23.6	42.7
LaMDA 137B	Standard	6.5	29.5	40.1	25.5	43.2
	Chain of thought	14.3 (+7.8)	37.5 (+8.0)	46.6 (+6.5)	20.6 (-4.9)	57.9 (+14.7)
	+ ext. calc	17.8	42.1	53.4	20.6	69.3
GPT-3 175B (text-davinci-002)	Standard	15.6	65.7	70.3	24.8	72.7
	Chain of thought	46.9 (+31.3)	68.9 (+3.2)	71.3 (+1.0)	35.8 (+11.0)	87.1 (+14.4)
	+ ext. calc	49.6	70.3	71.1	35.8	87.5
Codex (code-davinci-002)	Standard	19.7	69.9	74.0	29.5	78.7
	Chain of thought	63.1 (+43.4)	76.4 (+6.5)	80.4 (+6.4)	45.3 (+15.8)	92.6 (+13.9)
	+ ext. calc	65.4	77.0	80.0	45.3	93.3
PaLM 540B	Standard	17.9	69.4	72.1	25.2	79.2
	Chain of thought	56.9 (+39.0)	79.0 (+9.6)	73.9 (+1.8)	35.8 (+10.6)	93.3 (+14.2)

En múltiples benchmarks, CoT trae un aumento considerable sobre el razonamiento matemático.

Zero-Shot Chain of Thought

Las LLMs gozan mucho de fe
y del razonamiento mediante
sin embargo, Zero-shot también
puede mejorarse mediante CoT y la
frase simple "**Let's think step by step**".

	Original GPT-3 (0.3B / 1.3B / 6.7B / 175B)	Instruct GPT-3 (S / M / L / XL-1 / XL-2)
Zero-shot	2.0 / 1.3 / 1.5 / 3.3	3.7 / 3.8 / 4.3 / 8.0 / 17.7
Few-shot	5.2 / 5.2 / 4.0 / 8.1	3.0 / 2.2 / 4.8 / 14.0 / 33.7
Zero-shot-CoT	1.7 / 2.2 / 2.3 / **19.0**	2.0 / 3.7 / 3.3 / **47.8** / **78.7**
Few-shot-CoT	4.3 / 1.8 / 6.3 / **44.3**	2.5 / 2.5 / 3.8 / **36.8** / **93.0**

Zero-Shot	**17.7**	**10.4**
Few-Shot (2 samples)	33.7	15.6
Few-Shot (8 samples)	33.8	15.6
Zero-Shot-CoT	**78.7**	**40.7**
Few-Shot-CoT (2 samples)	84.8	41.3
Few-Shot-CoT (4 samples : First) (*1)	89.2	-
Few-Shot-CoT (4 samples : Second) (*1)	90.5	-
Few-Shot-CoT (8 samples)	93.0	48.7
Zero-Plus-Few-Shot-CoT (8 samples) (*2)	**92.8**	**51.5**
Finetuned GPT-3 175B [Wei et al., 2022]	-	33
Finetuned GPT-3 175B + verifier [Wei et al., 2022]	-	55
PaLM 540B: Zero-Shot	**25.5**	**12.5**
PaLM 540B: Zero-Shot-CoT	**66.1**	**43.0**
PaLM 540B: Zero-Shot-CoT + self consistency	**89.0**	**70.1**
PaLM 540B: Few-Shot [Wei et al., 2022]	-	17.9
PaLM 540B: Few-Shot-CoT [Wei et al., 2022]	-	56.9
PaLM 540B: Few-Shot-CoT + self consistency [Wang et al., 2022]	-	74.4

	Arithmetic					
	SingleEq	AddSub	MultiArith	GSM8K	AQUA	SVAMP
zero-shot	74.6/**78.7**	**72.2/77.0**	17.7/22.7	10.4/12.5	22.4/22.4	58.8/58.7
zero-shot-cot	**78.0/78.7**	69.6/74.7	**78.7/79.3**	**40.7/40.5**	**33.5/31.9**	**62.1/63.7**

	Common Sense		Other Reasoning Tasks		Symbolic Reasoning	
	Common SenseQA	Strategy QA	Date Understand	Shuffled Objects	Last Letter (4 words)	Coin Flip (4 times)
zero-shot	**68.8/72.6**	12.7/**54.3**	49.3/33.6	31.3/29.7	0.2/-	12.8/53.8
zero-shot-cot	64.6/64.0	**54.8**/52.3	**67.5/61.8**	**52.4/52.9**	**57.6**/-	**91.4/87.8**

Zero-Shot Chain of Thought

(a) Few-shot

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?
A: The answer is 11.

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A:

(Output) The answer is 8. ✗

(b) Few-shot-CoT

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?
A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A:

(Output) The juggler can juggle 16 balls. Half of the balls are golf balls. So there are 16 / 2 = 8 golf balls. Half of the golf balls are blue. So there are 8 / 2 = 4 blue golf balls. The answer is 4. ✓

(c) Zero-shot

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: The answer (arabic numerals) is

(Output) 8 ✗

(d) Zero-shot-CoT (Ours)

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: ***Let's think step by step.***

(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls. ✓

CoT Zero-Shot vs Few-shot

Hoy en día las LLMs pueden procesar 32k+ tokens, por ejemplo: chatGPT-4, LLama-3 alcanzan los 128k. Esto permite brindar prompts muy grandes. No hace mucho en modelos como Mistral 7B, LLama 2, el context length rondaba en 8k.

Few-shot era poco escalable en la época, ya que los prompts consumen gran cantidad de tokens y recursos computacionales. En este caso Zero-shot es superior. En especial cuando ocupan tareas complejas con context length o recursos finitos.

Langchain Few-shot examples

Overcoming Context limit for chatgpt text classification (2023)

The crucial role of context Length in LLM for business applications

Prompt Chaining

Esta técnica es común encontrarla en QA de documentos.

Prompt chaining

QA documents with Langchain

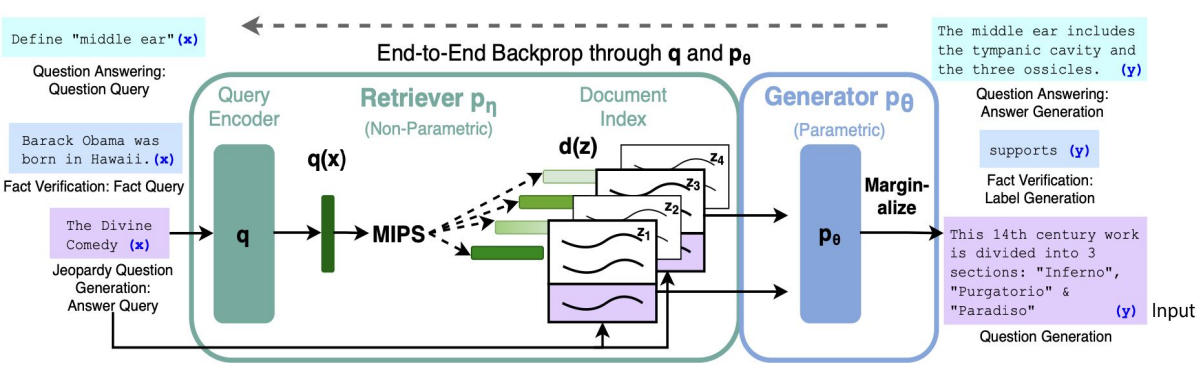
Document chains Langchain

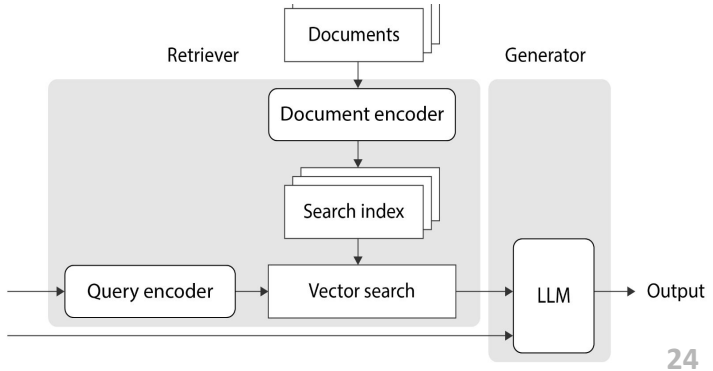
Langchain simple chains

Chain complex prompts for stronger performance

Retrieval Augmented Generation (RAG)

Presentado en el paper "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks" en 2020, lo que implica RAG es introducir al modelo conocimiento externo para completar tareas, esto mitiga la alucinación y mejora la confianza de la respuesta.

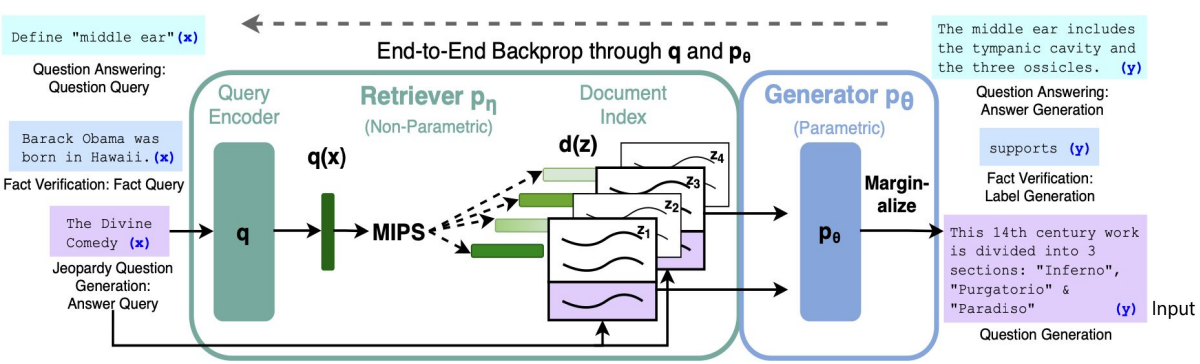


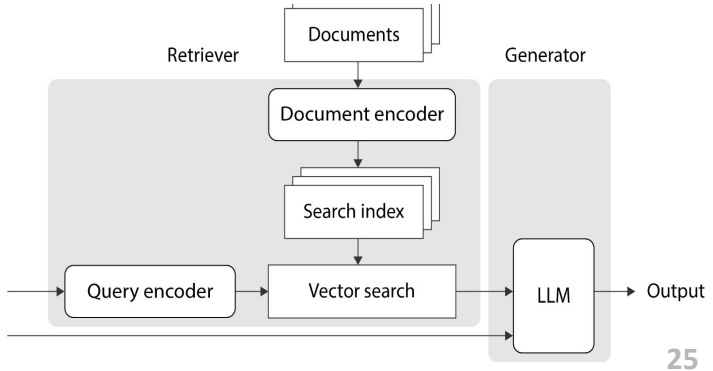


Retrieval Augmented Generation (RAG)

Presentado en el paper "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks" en 2020, RAG implica en **introducir** al modelo contexto nuevo externo para completar tareas, esto mitiga la alucinación y mejora la confianza de la respuesta.

Por ejemplo, documentos privados son desconocidos por la LLM, RAG permite brindar contexto y realizar queries sobre los documentos.





Retrieval Augmented Generation (RAG)

Databricks RAG

Pinecone RAG

Langchain Build a RAG

Evaluación de LLMs

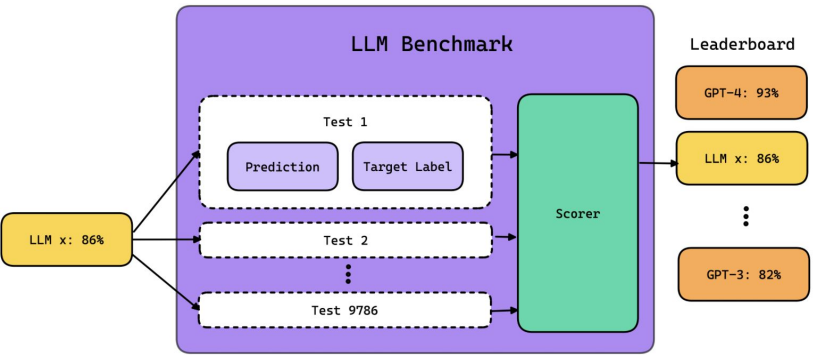
Evaluación de LLMs

En general hay 3 maneras de evaluar LLMs:

- Benchmarks.
- Evaluación Humana.
- Evaluación mediante modelos.

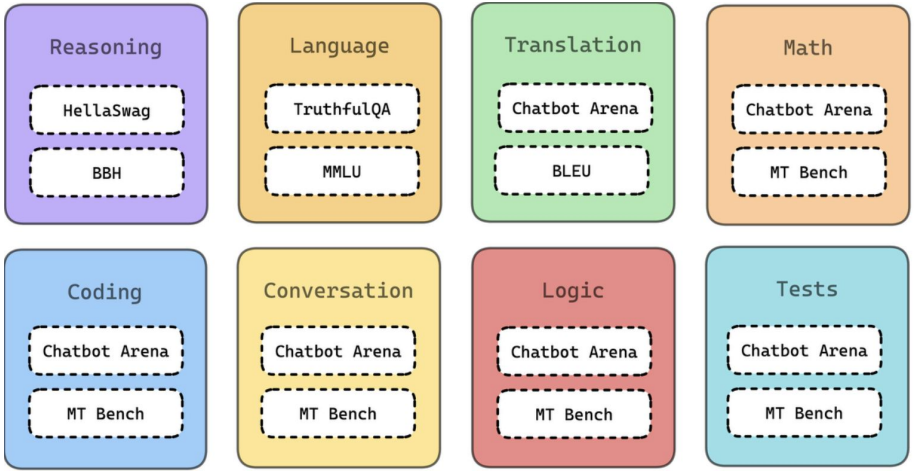
Evaluación de LLMs Benchmarks

Mediante Benchmarks estandarizados es realizable la evaluación medida para múltiples tareas.



Razonamiento y sentido común: Capacidad para aplicar lógica y resolver problemas.
Comprensión de lenguaje y preguntas/respuestas: Habilidad para interpretar texto y responder preguntas con precisión.
Codificación: Capacidad para interpretar y generar código.
Conversación y chatbots: Capacidad para entablar diálogos y responder de manera coherente y relevante.
Traducción: Habilidad para traducir texto de un idioma a otro con precisión.
Matemáticas: Resolución de problemas matemáticos, desde aritmética básica hasta áreas complejas como cálculo.
Pruebas estandarizadas: Exámenes como el SAT o ACT para evaluar el desempeño del modelo en contextos educativos.

Evaluación de LLMs Benchmarks



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GSM-8K (5-shot)	53.6%	57.1%	**58.4%**
MT Bench (for Instruct Models)	6.86	**8.32**	8.30

[LLM benchmarks explained]

Evaluación de LLMs

DeepEval

Documentación DeepEval

Huggingface LLM Eval

List of eval metrics

SuperGLUE

Preguntas?