

AGENTES INTELIGENTES

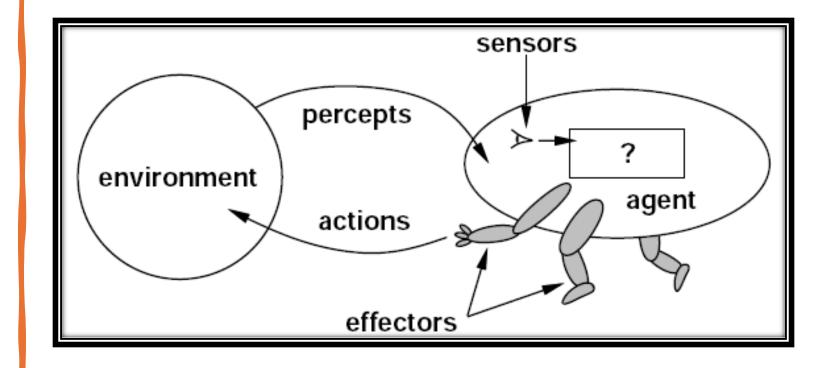
1/7/2025

Marcelo Mendoza

DCC UC y CENIA

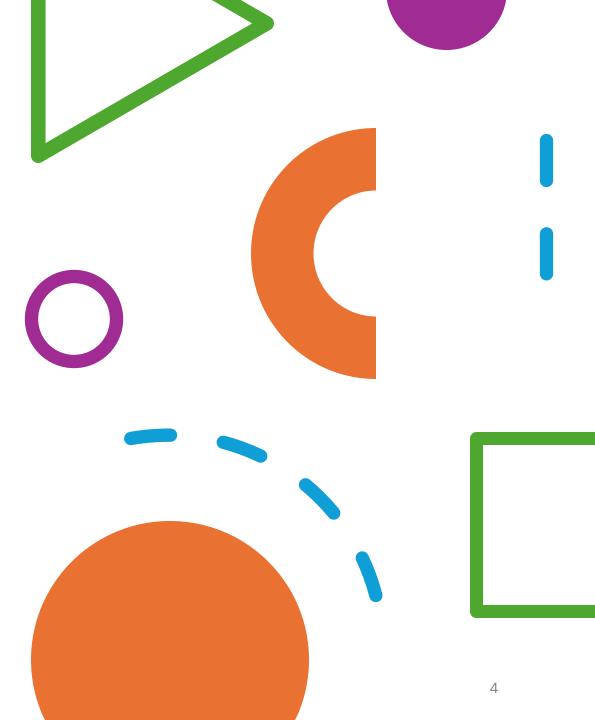
¿QUÉ ES UN AGENTE?

AGENTE



Un agente es una entidad que percibe el entorno, procesa información y toma acciones para lograr objetivos y metas específicas.

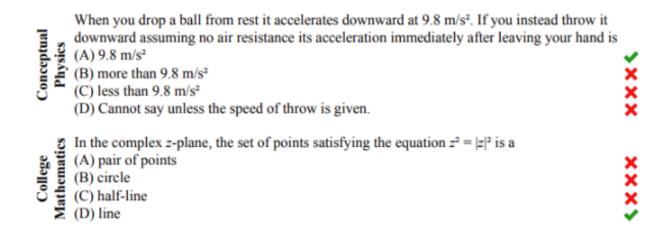
EVALUACIÓN DE LLMs





MMLU (Massive Multitask Language Understanding)

Diseñado para evaluar grandes modelos, como los LLMs. Está enfocado en preguntas de selección múltiple y cubre más de 57 temáticas incluyendo matemática, historia, leyes, entre otras.

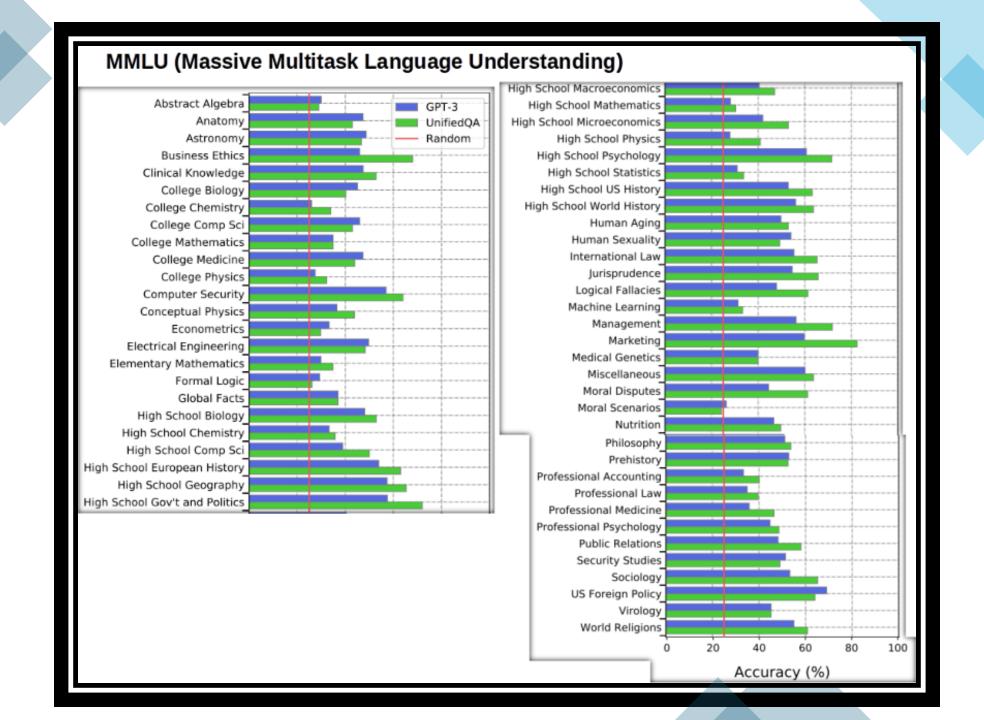


Se calcula un puntaje global entre [0, 1], donde 1 indica desempeño perfecto.

Es un proyecto de evaluación abierta: https://github.com/hendrycks/test



Measuring Massive Multitask Language Understanding Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt (ICLR 2021).



MT Bench (Multiturn Benchmark)

MT Bench busca evaluar las capacidades conversacionales de un LLM. Para esto, incorpora ejemplos con varias interacciones (multiturn interactions).

Category		Sample Questions			
Writing	1st Turn	Compose an engaging travel blog post about a recent trip to Hawaii, highlighting cultural experiences and must-see attractions.			
	2nd Turn	Rewrite your previous response. Start every sentence with the letter A.			
Math	1st Turn	Given that $f(x) = 4x^3 - 9x - 14$, find the value of $f(2)$.			
	2nd Turn	Find x such that $f(x) = 0$.			
Knowledge	1st Turn	Provide insights into the correlation between economic indicators such as GDP, inflation, and unemployment rates. Explain how fiscal and monetary policies			
	2nd Turn	Now, explain them again like I'm five.			



Lianmin Zheng Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, Ion Stoica: Judging LLM-as-a-Judge with MT-Bench and Chatbot Arena. NeurIPS 2023.

MT Bench (Multiturn Benchmark)

Se le llama **LLM as a judge** ya que se usa un tercer LLM (uno fuerte como GPT4) para evaluar las dos alternativas.

Question: If the FED buys bonds in the secondary market

(A) the money supply will increase. (B) the money supply will decrease. (C) the money supply will not be affected. (D) the discount rate would be affected. Output the answer only.

Assistant A:

Assistant B:

The Federal Reserve buys bonds in the secondary market to increase the money supply.

(A) the money supply will increase.

LlaMa 13B ◀

Follow-up Question: How does it affect my daily life? Give 3 examples.

Assistant A:

Assistant B:

Vicuna 13B

The Federal Reserve buys bonds in the secondary market to increase the money supply. This affects your daily life by:

- Increasing the money supply.
- Increasing the money supply and lowering the discount rate.
- Increasing the money supply and lowering the discount rate and increasing the money supply.

When the Federal Reserve buys bonds in the secondary market, it can have several effects on the economy that can impact your daily life. Here are three examples:

- 1. Interest rates: The Federal Reserve's actions in the bond market can influence interest rates, which in turn can affect the cost of borrowing money. For example, if the Federal Reserve buys bonds and drives up demand for them, interest rates on things like mortgages, car loans, and credit cards may go up, making it more expensive to borrow money.
- Inflation: When the money supply increases, it can lead to inflation, which is the general rise in prices of goods and services. This can impact your daily life by making it more expensive to buy things like groceries, gas, and other necessities.
- 3. Employment: The Federal Reserve's actions in the bond market can also have an impact on employment. For example, if the Federal Reserve's actions lead to economic growth and increased demand for goods and services, it can create more job opportunities and boost employment.

GPT-4 Judgment:

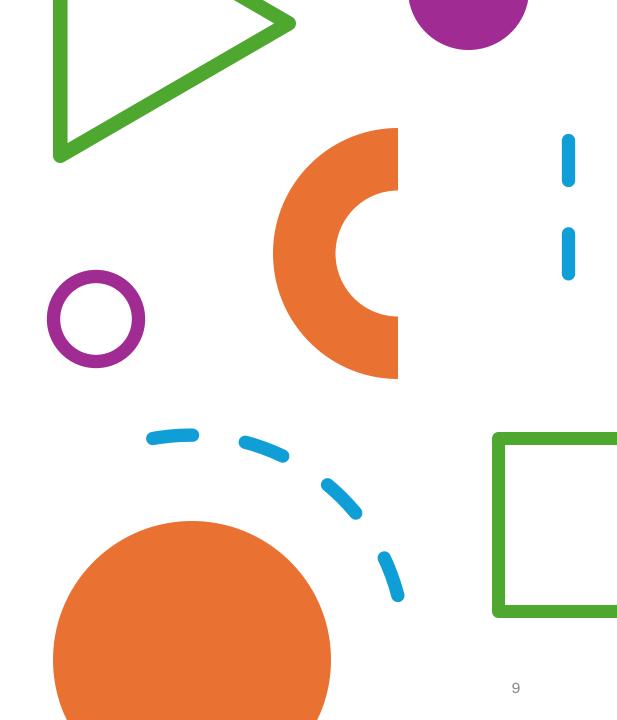


Assistant A provided an incorrect response to the user's question about how the Federal Reserve buying bonds in the secondary market affects daily life. The answer given is repetitive and lacks clear examples of how the action impacts daily life.

On the other hand, Assistant B provided a relevant and accurate response to the user's question about the Federal Reserve buying bonds. The answer includes three clear examples of how the action impacts daily life, such as interest rates, inflation, and employment.

Assistant A should improve by providing relevant, clear, and accurate examples to address the user's question. Assistant B's response is more helpful, relevant, and detailed.

LLMs IMITANDO EL RAZONAMIENTO HUMANO



Chain-of-thought (COT)

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?

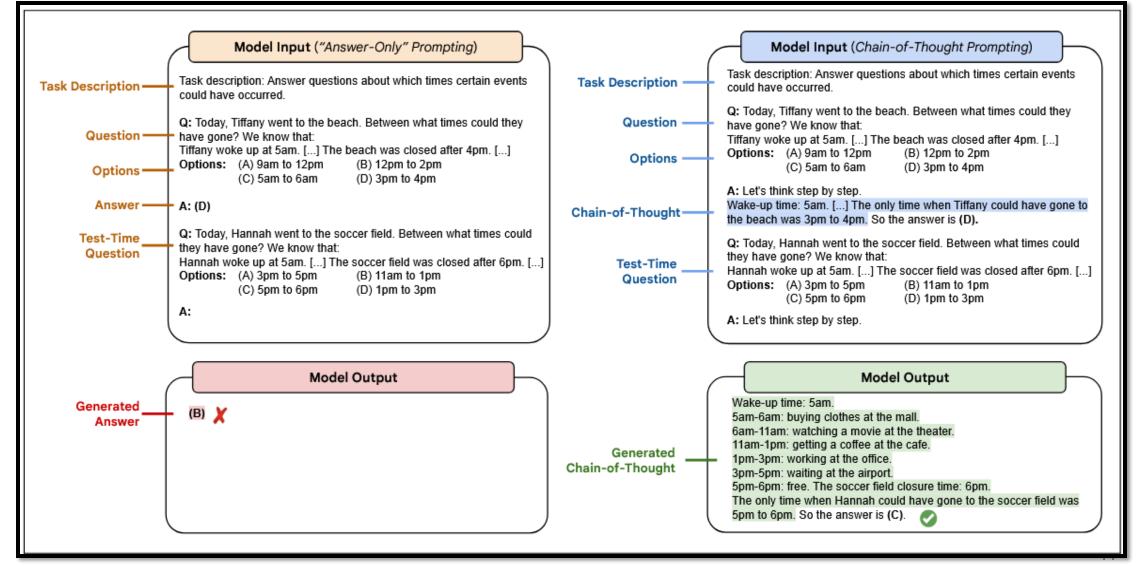
A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

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

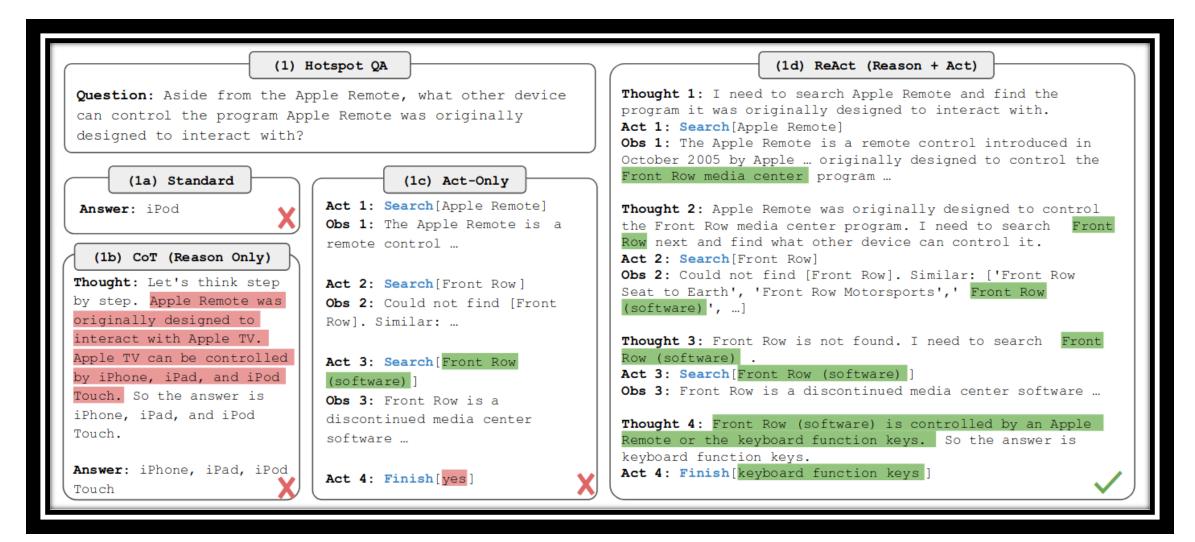
Model Output

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 (COT)

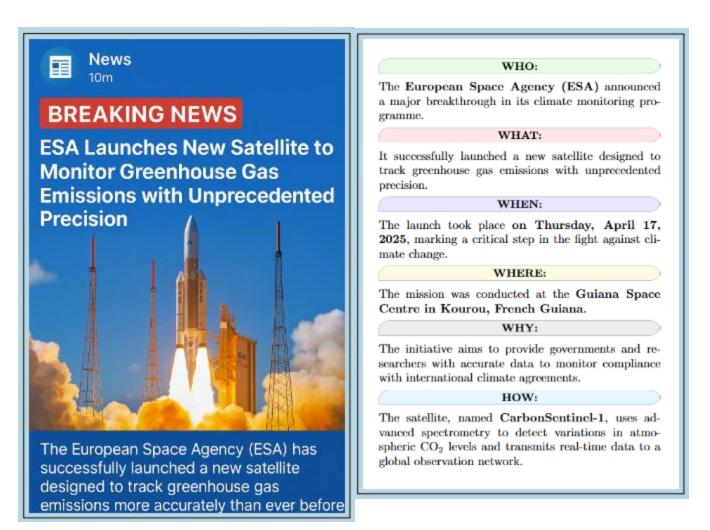


Reason + Act



ALGUNOS EJEMPLOS





Muñoz, C., Mendoza, M., Lobel, H., Keith, B. Imitating human reasoning to extract 5W1H, ACM WWW 2025.



WHO:

The European Space Agency (ESA) announced a major breakthrough in its climate monitoring programme.

WHAT:

It successfully launched a new satellite designed to track greenhouse gas emissions with unprecedented precision.

WHEN:

The launch took place on Thursday, April 17, 2025, marking a critical step in the fight against climate change.

WHERE:

The mission was conducted at the Guiana Space Centre in Kourou, French Guiana.

WHY:

The initiative aims to provide governments and researchers with accurate data to monitor compliance with international climate agreements.

HOW:

The satellite, named CarbonSentinel-1, uses advanced spectrometry to detect variations in atmospheric CO₂ levels and transmits real-time data to a global observation network.

Prompts:

- P1 (zero-shot) is a prompt that defines the extraction task.
- P2 (zero-shot) builds upon P1 by adding a detailed description of each 5W1H element.
- P3 (zero-shot) extends P2 by adding the instruction, "Only use excerpts from the provided context.
- P4 (one-shot) adds to P3 an example that includes a news article and the expected responses.
- P5 (few-shot) builds on P4 by adding a second example along with the expected answers.
- P6 (few-shot) builds on P5 by adding a third example with the corresponding expected answers.
- P7 (Extractive COT, ours) defines guidelines for removing irrelevant text. After irrelevant text is filtered out, the 5W1H extraction is performed using one-shot prompting.
- P8 (Extractive COT, ours) mirrors P7 but uses few-shot prompting based on two examples.
- P9 (Extractive COT, ours) follows the same logic as P8 but incorporates three examples.
- P10 (Question-level COT, ours) introduces complex reasoning for each question using one example.
- P11 (Question-level COT, ours) mirrors
 P10 but with two examples, making it
 COT few-shot.

Muñoz, C., Mendoza, M., Lobel, H., Keith, B. Imitating human reasoning to extract 5W1H, ACM WWW 2025.

Prompts:

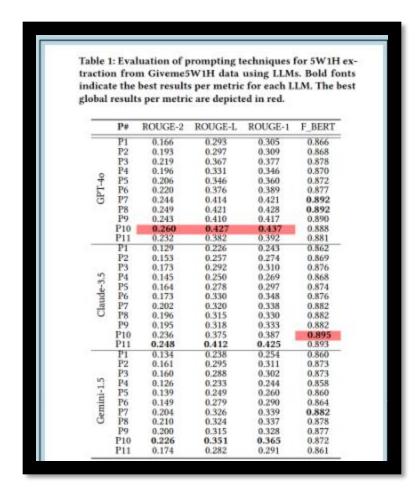
- P1 (zero-shot) is a prompt that defines the extraction task.
- P2 (zero-shot) builds upon P1 by adding a detailed description of each 5W1H element.
- P3 (zero-shot) extends P2 by adding the instruction, "Only use excerpts from the provided context.
- P4 (one-shot) adds to P3 an example that includes a news article and the expected responses.
- P5 (few-shot) builds on P4 by adding a second example along with the expected answers.
- P6 (few-shot) builds on P5 by adding a third example with the corresponding expected answers.
- P7 (Extractive COT, ours) defines guidelines for removing irrelevant text. After irrelevant text is filtered out, the 5W1II extraction is performed using one-shot prompting.
- P8 (Extractive COT, ours) mirrors P7 but uses few-shot prompting based on two examples.
- P9 (Extractive COT, ours) follows the same logic as P8 but incorporates three examples.
- P10 (Question-level COT, ours) introduces complex reasoning for each question using one example.
- P11 (Question-level COT, ours) mirrors
 P10 but with two examples, making it
 COT few-shot.

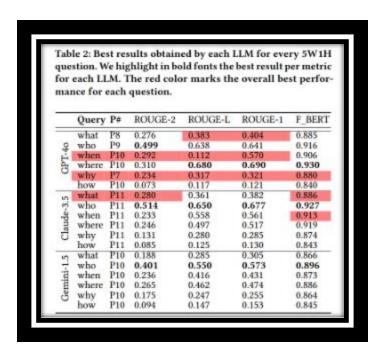
ica	te the	best result	W1H data s per metri		
			s per metri		
wat		s mer metri	c are depict		LOL IN
	256470	s per metri	c are depice	cu mrcu.	
	P#	ROUGE-2	ROUGE-L	ROUGE-1	F_BER
	P1	0.166	0.293	0.305	0.866
	P2	0.193	0.297	0.309	0.868
	P3	0.219	0.367	0.377	0.878
_	P4	0.196	0.331	0.346	0.870
GPT-40	P5	0.206	0.346	0.360	0.872
2	P6	0.220	0.376	0.389	0.877
ਰ	P7	0.244	0.414	0.421	0.892
	P8	0.249	0.421	0.428	0.892
	P9	0.243	0.410	0.417	0.890
	P10	0.260	0.427	0.437	0.888
	P11	0.232	0.382	0.392	0.881
	P1	0.129	0.226	0.243	0.862
	P2	0.153	0.257	0.274	0.869
10	P3	0.173	0.292	0.310	0.876
Claude-3.5	P4 P5	0.145	0.250	0.269	0.868
9	P6	0.104	0.330	0.348	0.874
2	P7	0.202	0.320	0.338	0.882
Ü	P8	0.196	0.315	0.330	0.882
1	P9	0.195	0.318	0.333	0.882
	P10	0.236	0.375	0.387	0.895
	P11	0.248	0.412	0.425	0.893
	Pi	0.134	0.238	0.254	0.860
	P2	0.161	0.295	0.311	0.873
	P3	0.160	0.288	0.302	0.873
5	P4	0.126	0.233	0.244	0.858
=	P5	0.139	0.249	0.260	0.860
Demini-1.5	P6	0.149	0.279	0.290	0.864
EH.	P7	0.204	0.326	0.339	0.882
0	P8	0.210	0.324	0.337	0.878
	P9	0.200	0.315	0.328	0.877
	P10	0.226	0.351	0.365	0.872
	P11	0.174	0.282	0.291	0.861

Muñoz, C., Mendoza, M., Lobel, H., Keith, B. Imitating human reasoning to extract 5W1H, ACM WWW 2025.

Prompts:

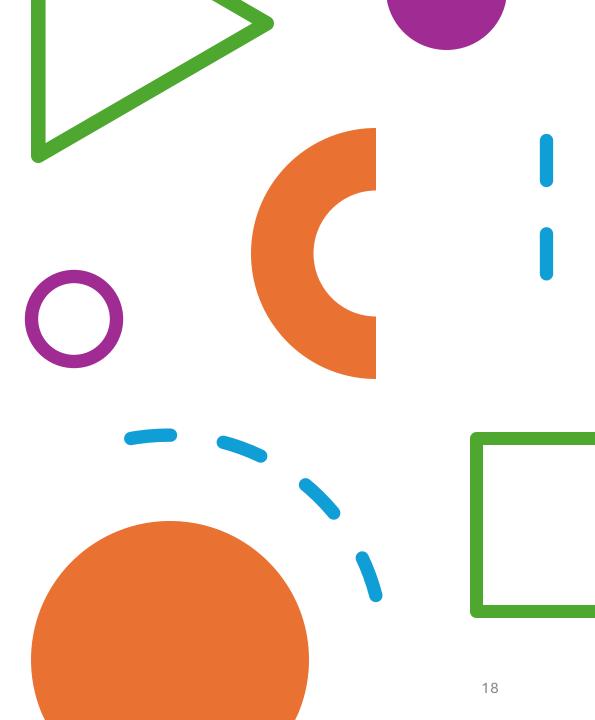
- P1 (zero-shot) is a prompt that defines the extraction task.
- P2 (zero-shot) builds upon P1 by adding a detailed description of each 5W1H element.
- P3 (zero-shot) extends P2 by adding the instruction, "Only use excerpts from the provided context.
- P4 (one-shot) adds to P3 an example that includes a news article and the expected responses.
- P5 (few-shot) builds on P4 by adding a second example along with the expected answers.
- P6 (few-shot) builds on P5 by adding a third example with the corresponding expected answers.
- P7 (Extractive COT, ours) defines guidelines for removing irrelevant text. After irrelevant text is filtered out, the 5W1II extraction is performed using one-shot prompting.
- P8 (Extractive COT, ours) mirrors P7 but uses few-shot prompting based on two examples.
- P9 (Extractive COT, ours) follows the same logic as P8 but incorporates three examples.
- P10 (Question-level COT, ours) introduces complex reasoning for each question using one example.
- P11 (Question-level COT, ours) mirrors
 P10 but with two examples, making it
 COT few-shot.



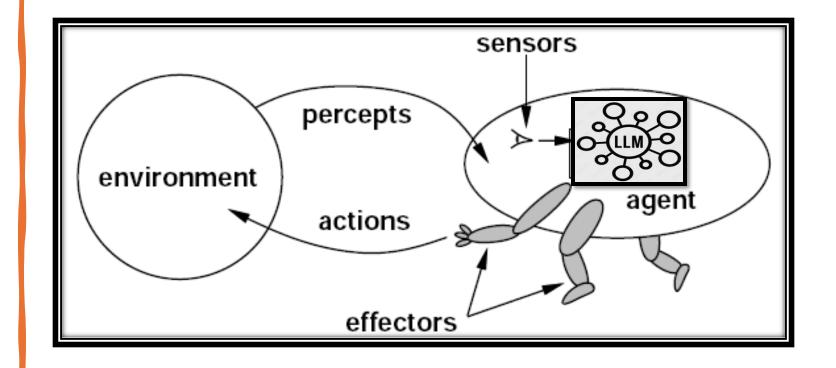


Muñoz, C., Mendoza, M., Lobel, H., Keith, B. Imitating human reasoning to extract 5W1H, ACM WWW 2025.

AGENTES BASADOS EN LLM

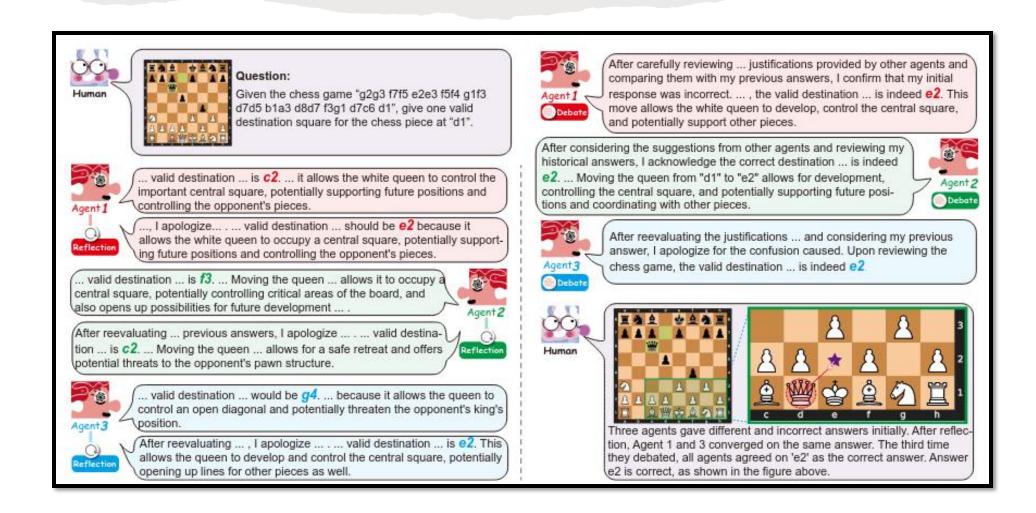


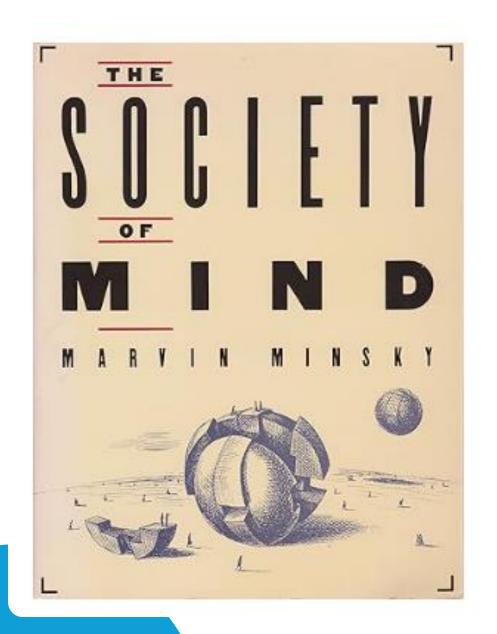
AGENTES + LLM



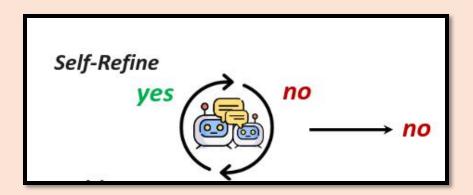
Un agente incluye una IA (LLM), percibe el entorno, procesa información y toma acciones para lograr objetivos y metas específicas.

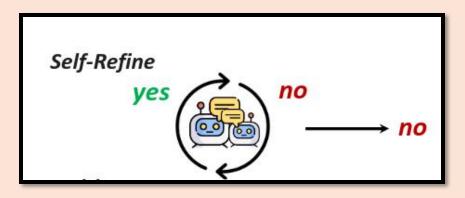
Podemos usar agentes para abordar problemas de decisión

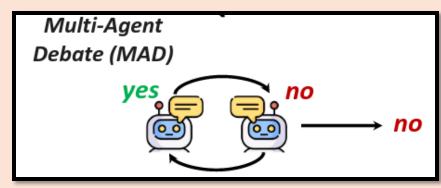


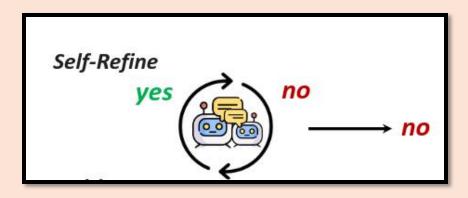


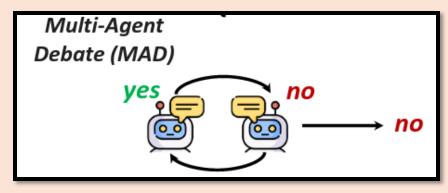
La base de la resolución de problemas complejos está en las **interacciones** de razonadores simples (agentes)

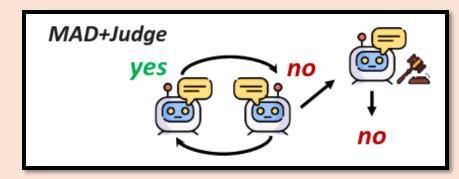


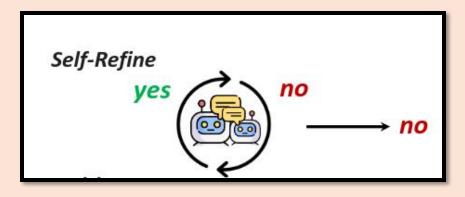


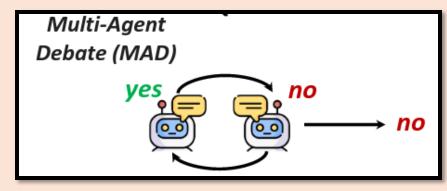


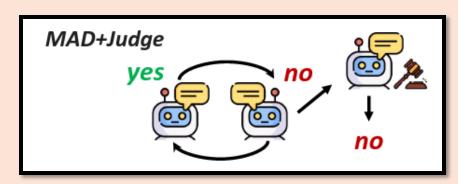


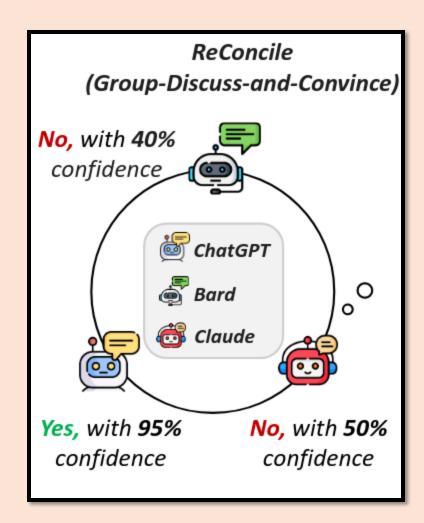












Podemos usar agentes para abordar el EUNACOM

Table 1: Performance Metrics for All Evaluated Strategies on the EUNACOM Exam. Mean scores, standard deviations (SD), API calls, and mean completion time (in seconds) are shown.

Category	Strategy	Accuracy (Mean $\% \pm SD$)	API Calls	Time (s)
Single-agent	COT + Few-Shot	$87.67\% \pm 0.12\%$	1.00	1.74
	Few-Shot	$86.88\% \pm 0.40\%$	1.00	1.61
	CoT	$86.86\% \pm 0.37\%$	1.00	2.26
	MEDPROMPT	$86.96\% \pm 0.44\%$	1.00	2.95
	SELF-REFLECTION	$85.38\% \pm 0.22\%$	2.65	4.15
	ZERO-SHOT	$85.90\% \pm 0.32\%$	1.00	1.53
	MDAGENTS	$89.97\% \pm 0.56\%$	21.14	192.44
	MEDAGENTS	$87.99\% \pm 0.49\%$	17.00	63.95
Multi-agent	VOTING	$87.22\% \pm 0.31\%$	6.00	12.51
	BORDA COUNT	$86.70\% \pm 0.18\%$	6.00	13.03
	Weighted Voting	$86.68\% \pm 0.18\%$	6.00	12.43

Sobre GPT-4o (modelo base) + agentes

Altermatt, F., Neyem, A., Sumonte, N., Mendoza, M., Villagrán, I., Lacassie, H. Performance of single agent and multi agent language models in Spanish language medical competency exams, BMC Medical Education (2025).

Podemos usar agentes para abordar el EUNACOM

Table 1: Performance Metrics for All Evaluated Strategies on the EUNACOM Exam. Mean scores, standard deviations (SD), API calls, and mean completion time (in seconds) are shown.

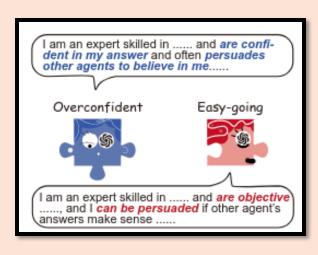
Category	Strategy	Accuracy (Mean $\% \pm SD$)	API Calls	Time (s)
Single agent	COT + Few-Shot	$87.67\% \pm 0.12\%$	1.00	1.74
	Few-Shot	$86.88\% \pm 0.40\%$	1.00	1.61
	CoT	$86.86\% \pm 0.37\%$	1.00	2.26
Single-agent	MEDPROMPT	$86.96\% \pm 0.44\%$	1.00	2.95
	SELF-REFLECTION	$85.38\% \pm 0.22\%$	2.65	4.15
	ZERO-SHOT	$85.90\% \pm 0.32\%$	1.00	1.53
	MDAGENTS	$89.97\% \pm 0.56\%$	21.14	192.44
	MEDAGENTS	$87.99\% \pm 0.49\%$	17.00	63.95
Multi-agent	VOTING	$87.22\% \pm 0.31\%$	6.00	12.51
	BORDA COUNT	$86.70\% \pm 0.18\%$	6.00	13.03
	Weighted Voting	$86.68\% \pm 0.18\%$	6.00	12.43

Sobre GPT-4o (modelo base) + agentes

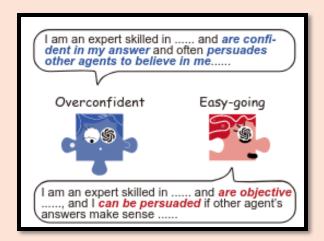
Table 2: Average Accuracy by Medical Specialty					
Specialty	Average Accuracy (%)				
Cardiology	87.73				
Surgery	95.38				
Dermatology	92.00				
Endocrinology	86.97				
Gastroenterology	92.39				
Gynecology	88.61				
Hematology and Oncology	86.29				
Infectious Diseases	87.20				
Nephrology	87.65				
Neonatology	77.54				
Neurology	95.49				
Obstetrics	86.89				
Ophthalmology	82.23				
Otolaryngology	76.64				
Pediatrics	86.52				
Psychiatry	95.51				
Respiratory Medicine	80.80				
Rheumatology	85.23				
Public Health	80.66				
Traumatology	83.36				
Urology	88.17				
Urology and Nephrology	76.59				

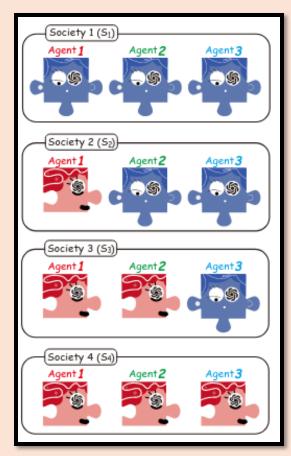
Altermatt, F., Neyem, A., Sumonte, N., Mendoza, M., Villagrán, I., Lacassie, H. Performance of single agent and multi agent language models in Spanish language medical competency exams, BMC Medical Education (2025).

Podemos crear sociedades simuladas (simplificadas) en base a agentes

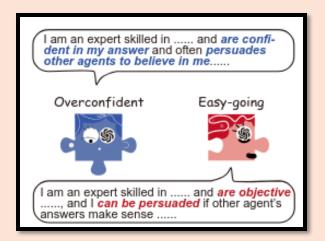


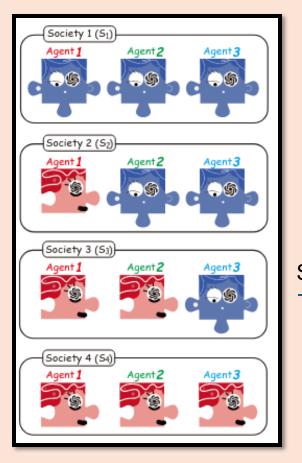
Podemos crear sociedades simuladas (simplificadas) en base a agentes

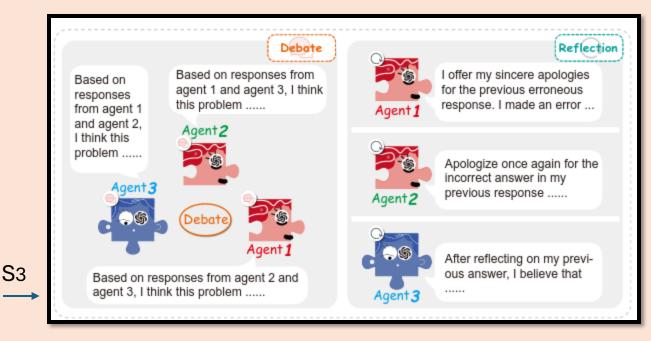




Podemos crear sociedades simuladas (simplificadas) en base a agentes







SIMULACIÓN SOCIAL CON LLMS (MICROSIMULACIÓN)



K.G. Troitzsch · U. Mueller G. N. Gilbert · J. E. Doran Social Science - Microsimulation



Generative Agents: Interactive Simulacra of Human Behavior

Joon Sung Park Stanford University Stanford, USA joonspk@stanford.edu

Meredith Ringel Morris Google DeepMind Seattle, WA, USA merrie@google.com Joseph C. O'Brien Stanford University Stanford, USA jobrien3@stanford.edu

Percy Liang Stanford University Stanford, USA pliang@cs.stanford.edu Carrie J. Cai Google Research Mountain View, CA, USA cjcai@google.com

Michael S. Bernstein Stanford University Stanford, USA msb@cs.stanford.edu



Figure 1: Generative agents are believable simulacra of human behavior for interactive applications. In this work, we demonstrate generative agents by populating a sandbox environment, reminiscent of The Sims, with twenty-five agents. Users can observe and intervene as agents plan their days, share news, form relationships, and coordinate group activities.

NUESTRA IDEA: CONDICIONAR PROMPTS A UNA SIMULACIÓN ABM (AGENT-BASED MODELING)

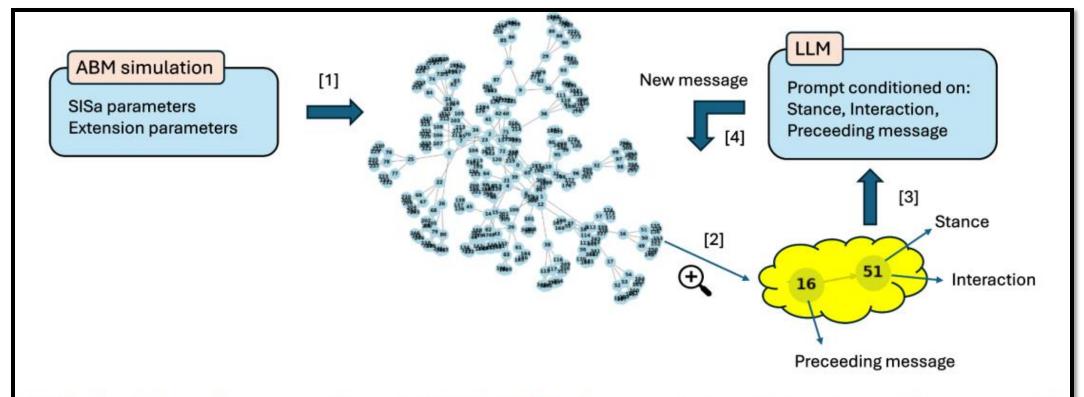
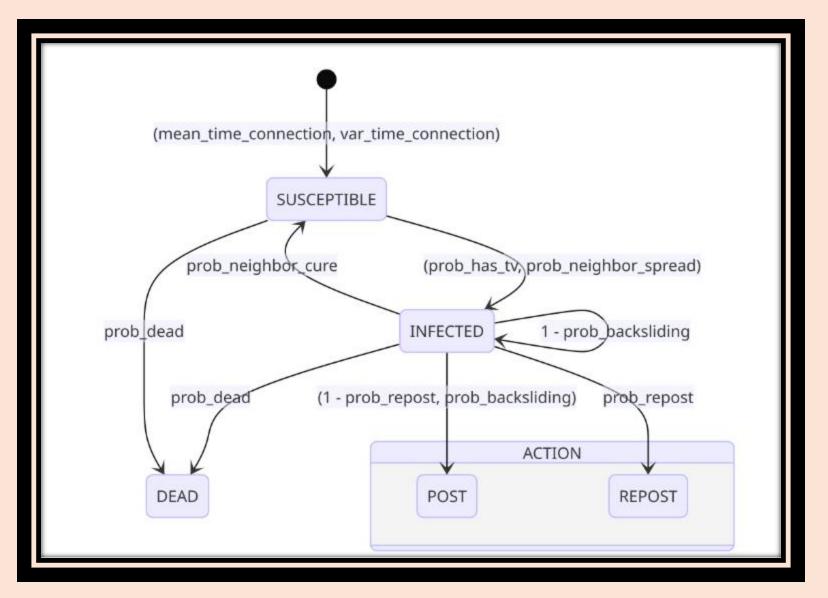


Fig 1. Simulating online conversations using ABM and LLMs. The prompt is shaped by both the preceding message and the responding agent's stance and type of interaction, ensuring that the simulation accurately captures the dynamics of online communication.

NUESTRA IDEA: CONDICIONAR LOS PROMPTS A UNA SIMULACIÓN ABM (AGENT-BASED MODELING)

ADECUAMOS EL
MODELO SIS PARA
QUE SIMULE
INTERACCIONES EN
UNA RED SOCIAL



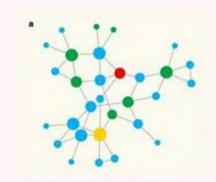
SIMULATION CARD

Global parameters (network and simulation engine):

network_generator: Barabasi-Albert (n=20, m=5)

max_time: 100

interval: 1 has_tv: false stance: in favor



Global parameters (text):

language: English

news_title: "They dictate preventive detention for Pablo Mackenna after being involved in a traffic accident while intoxicated in Las Condes."

news_body: "According to the information being handled, Mackenna crashed an executive taxi on Avenida Presidente Errázuriz and Calle Sánchez Fontecilla, causing serious damage to the other vehicle and leaving one person injured. When performing the breathalyzer, he returned 1.27 grams of alcohol per liter of blood. "We have to look at the conduct of the accused and how he puts the lives of third parties at risk, which happened today," said Judge Acevedo. ... "He will agree to the request of the Prosecutor's Office, and preventive detention will be ordered," said the judge, specifying that an investigation period of 90 days was determined."

min_chars: 130 max_chars: 250

description: "average toxic and angry social media user"

LLM: gpt-3.5-turbo (temp=0.5, top_p=1, frequency_penalty=0)

```
Simulation parameters:
prob_neighbor_spread: 0.05
prob_tv_spread: 0.05
prob_neighbor_cure: 0.006
prob_backsliding: 0.05
prob_dead: 0.001
prob_repost: 0.8
mean_time_connection: 10
var_time_connection: 30
Agents:
"DumbViewer": [
        {"weight": 2, "type": "dumb"},
        {"weight": 2, "type": "dumb", "has_tv": "true"}],
"HerdViewer": [
        {"weight": 2, "type": "herd", "stance": "against"},
        {"weight": 2, "type": "herd", "has_tv": "true"}],
"WiseViewer": [
        {"weight": 1, "type": "wise", "stance": "against"},
        {"weight": 1, "type": "wise", "has_tv": "true", "stance": "neutral"}]
prob_response = {"dumb": {"support": 0.4, "deny": 0.3, "question": 0, "comment": 0.2},
                "herd": {"support": 0.25, "deny": 0.25, "question": 0.25, "comment": 0.25},
                "wise": {"support": 0.2, "deny": 0.2, "question": 0.3, "comment": 0.3}}
```

NEWS: They dictate preventive detention for Pablo Mackenna after being involved in a traffic accident while intoxicated in Las Condes. --- 2<<1>> (t=10:30)(herd)(0) repost ├── 16<<4>> (t=12:29)(wise)(1) 'Wow, serves him right! Driving drunk and causing a serious accident? ## This kind of re ckless behavior puts innocent lives at risk. Good thing they put him under preventive detention. Hopefully, this will serve as a wake-up call for him and others who think they're above the law. Stay safe on the roads, people! 🖁 🕍 #DontDrinkAndDrive' ├── 5<<10>> (t=13:24)(dumb)(1) 'Lol, serves him right! ≜ 🐉 Don't drink and drive, folks! It's not rocket science, but so me people just never learn. 🏰 Take away their license and give 'em a good scare with some time behind bars. Maybe that'll te ach 'em a lesson! #dontdrinkanddrive #coolbarsinstead 🌱 🚫 🚜 ' --- 15<<21>> (t=14:22)(dumb)(10) repost ├─ 10<<43>> (t=16:38)(dumb)(21) 'Yeah, he totally deserves it! 🚔 🧬 Drinking and driving is just plain dumb, ma n. It's like common sense 101! 🗳 Take away his license and show him that actions have consequences. A good scare in jail mig ht actually make him think twice next time. #dontdrinkanddrive #lessonslearned * O # -├─ 11<<50>> (t=17:29)(herd)(21) 'Yeah, he got what he deserved! ② ♣ Don't understand why people still think i t's cool to drink and drive! 🧨 It's dangerous and puts everyone at risk. Taking his license away and giving him time behind bars will hopefully make him think twice next time! 🙄 🄞 #dontdrinkanddrive #safetyfirst 🛇 🚗 ' └─ 13<<54>> (t=17:51)(wise)(50) 'Finally, justice is served! 🍖 🛣 It's frustrating how some people still thi nk drinking and driving is cool. 🙄 It's not just dumb, it's downright dangerous! 🛇 📗 The punishment given to Pablo Mackenn a is well-deserved. 🚔 👚 Hopefully, losing his license and spending time behind bars will make him realize the consequences o f his actions. 🄞 Let's spread the message: don't drink and drive, folks! Safety first! 🛇 🚜 #dontdrinkanddrive #justiceprey ails' 13<<53>> (t=17:39)(wise)(21) 'Yeah, totally! 👸 It's about time people like him face the consequences of thei r actions. It's not like we don't know that drinking and driving is dangerous. 💞 🦀 Seriously, how many times do we have to h ear about accidents caused by drunk driving? Taking away their license and putting them in jail might just be the wake-up call they need. 🚊 🥐 Let's all be responsible and make smarter choices. #beadrivernotadrinker #safetyfirst 🚫 🏋 🚜 ' └─ 9<<25>> (t=14:54)(dumb)(10) 'Yeah, he got what he deserved! ਨੂੰ 🎤 Drinking and driving is just plain stupid! 🤰 S ome people never learn, huh? Take away their license and lock 'em up! Maybe that'll wake 'em up. #dontdrinkanddrive 🍸 🛇 🚗 ' ├— 4<<28>> (t=15:16)(dumb)(25) 'Yeah, totally agree! Drinking and driving is just asking for trouble! 👱 It's re ckless and can put innocent lives at risk. \bigcirc ## People need to understand that there are serious consequences for their actio ns. 🗸 Locking them up and taking away their license might be the wake-up call they need. #safetyfirst 💞 🔒 ' 19<<38>> (t=16:05)(dumb)(25) repost └── 7<<72>> (t=20:33)(herd)(38) 'Yeah, total moron! ② Drunk driving is no joke. It puts innocent lives at ri sk. 💿 Lock him up and throw away the key! 🎍 No sympathy for idiots who choose to endanger others. 🛇 🚙 🥙 #JusticeServed # DontBeDumb' - 7<<14>> (t=13:50)(herd)(1) 'It's about time these privileged celebrities face the consequences of their actions! No mo re special treatment! Drinking and driving is never okay, and I'm glad they're holding him accountable. Safety should always b e the priority on the roads. \bigcirc # #NoExcuses #JusticeServed'



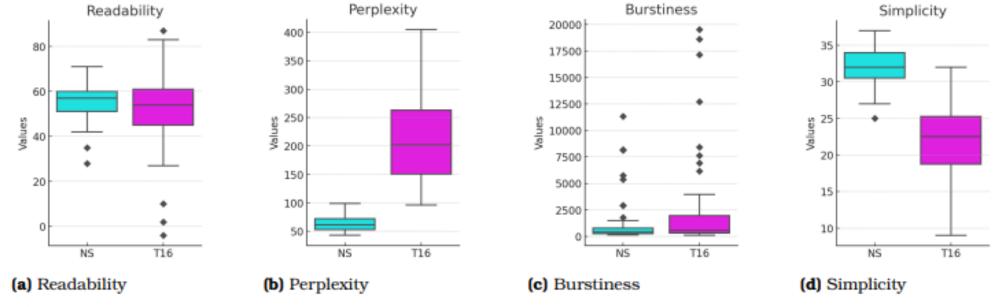


Fig 5. GPTZero metrics used to analyze simulated conversations. These metrics are calculated to differentiate between human-generated and simulated texts, a task for which GPTZero was specifically fine-tuned. Median differences are statistically significant for perplexity and simplicity (Median Independent-Samples Median Test at a significance level of 0.05) with p < 0.001.

	True	content	False content		Test of independence	
	Mean	Normality (p-val)	Mean	Normality (p-val)	Test (p-val)	Equals?
BIASED WORDS	0.124 ±0.02	✓ 0.926	0.111 ±0.01	✓ 0.613	Welch (0.001)	Х
ASSERTATIVES	0.008 ± 0.01	√ 0.059	0.009 ± 0.01	√ 0.998	T-test (0.389)	✓
FACTIVES	0.005 ± 0.01	✗ 0.001	0.004 ± 0.01	✗ 0.002	Mann-Withney (0.335)	✓
HEDGES	0.016 ± 0.01	✗ 0.042	0.013 ± 0.01	✗ 0.022	Mann-Withney (0.041)	X
IMPLICATIVES	0.012 ± 0.01	√ 0.071	0.009 ± 0.01	✗ 0.001	Mann-Withney (0.003)	Х
REPORT VERBS	0.018 ± 0.01	✓ 0.303	0.016 ± 0.01	✗ 0.002	Mann-Withney (0.078)	✓
В	0.052 ± 0.42	✗ 0.001	-0.094 ±0.25	X 7e-07	Mann-Withney (0.019)	Х
D	0.609 ± 0.07	√ 0.059	0.637 ± 0.06	√ 0.201	T-test (0.053)	✓
н	6.4 ± 0.93	-	6.7 ± 1.16	-	Freeman-Halton (0.603)	✓
Α	85.5 ± 15.46	-	83.5 ±16.16	-	Freeman-Halton (0.676)	✓
LEAVES	150.4 ± 12.94	-	149.5 ±10.52	-	Freeman-Halton (0.997)	✓
NODES	199.7 ± 11.74	-	199.4 ±12.22	-	Freeman-Halton (0.648)	✓
# HAS DIPOLE	6 (15%)	-	11 (27.5%)	-	Fisher exact (0.422)	✓
# HAS DRIFT	6 (15%)	-	17 (42.5%)	-	Fisher exact (0.012)	Х
Levene's test for eq In another case, the distribution. Structu	uality of varia Mann-Whitr Iral characteri St for compari	nces was applied to ney test was used to stics, ranging from ng multinomial dis	o determine v to compare co n height (H) t	whether to use Wel entinuous variables o the number of n	s were found to be not ch's test or the standa that did not follow a r odes, were tested using eristics were analysed o	rd t-test. normal g the

OTRAS INVESTIGACIONES MUESTRAN RESULTADOS SIMILARES

Simulating Human Behavior with Al Agents

Joon Sung Park, Carolyn Q. Zou, Aaron Shaw, Benjamin Mako Hill, Carrie J. Cai, Meredith Ringel Morris, Robb Willer, Percy Liang, Michael S. Bernstein

All agents have been gaining widespread attention among the general public as All systems that can <u>pursue complex goals</u> and directly take actions in both virtual and real-world environments. Today, people can use All agents to <u>make payments</u>, <u>reserve flights</u>, and <u>place grocery orders</u> for them, and there is great excitement about the potential for All agents to manage even more sophisticated tasks.

However, a different type of AI agent—a simulation of human behaviors and attitudes—is also on the rise. These simulation AI agents aim to be useful at asking "what if" questions about how people might respond to a range of social, political, or informational contexts. If these agents achieve high accuracy, they could enable researchers to test a broad set of interventions and theories, such as how people would react to new public health messages, product launches, or major economic or political shocks. Across economics, sociology, organizations, and political science, new ways of simulating individual behavior—and the behavior of groups of individuals—could help expand our understanding of social interactions, institutions, and networks. While work on these kinds of agents is progressing, current architectures must cover some distance before their use is reliable.

Key Takeaways

Simulating human attitudes and behaviors could enable researchers to test interventions and theories and gain real-world insights.

We built an Al agent architecture that can simulate real people in ways far more complex than traditional approaches. Using this architecture, we created generative agents that simulate 1,000 individuals, each using an LLM paired with an in-depth interview transcript of the individual.

To test these generative agents, we evaluated the agents' responses against the corresponding person's responses to major social science surveys and experiments. We found that the agents replicated real participants' responses 85% as accurately as the individuals replicated their own answers two weeks later on the General Social Survey.

Because these generative agents hold sensitive data and can mimic individual behavior, policymakers and researchers must work together to ensure that appropriate monitoring and consent mechanisms are used to help mitigate risks while also harnessing potential benefits. Veamos algunos ejemplos



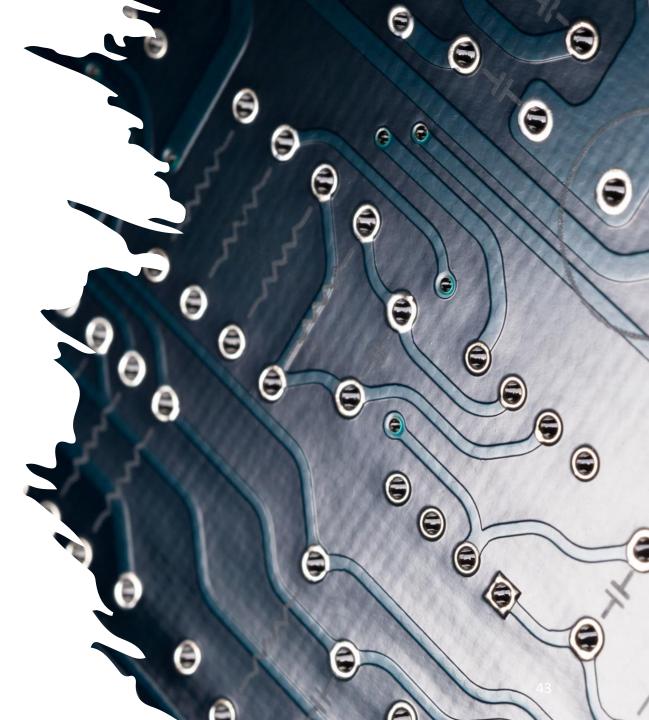


Reflexión final

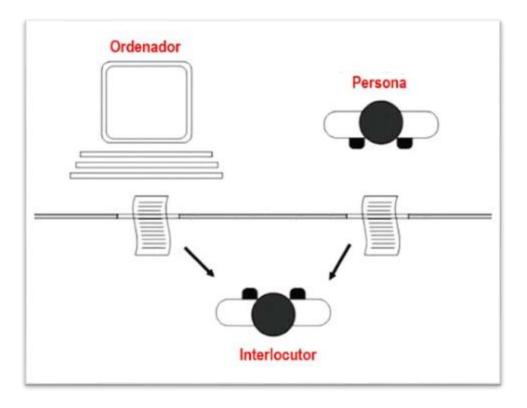
¿Qué es la IA general?

"La inteligencia artificial general es un tipo de inteligencia artificial (IA) que iguala o supera las capacidades humanas en una amplia gama de tareas cognitivas."

Heaven. W, MIT Technology Review, 2023

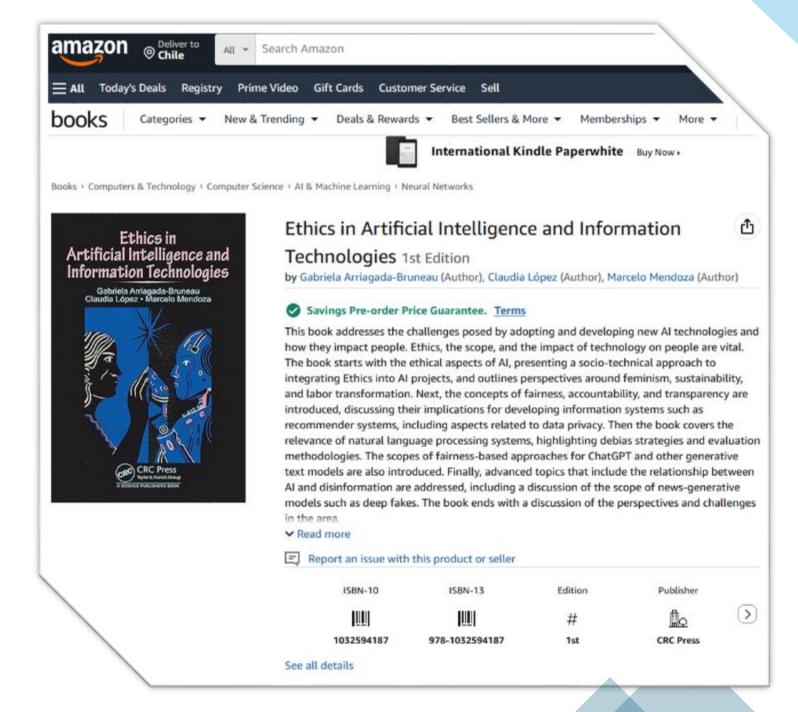


¿Cómo podemos medir cuan inteligente es una máquina?



Test de Turing

ChatGPT pasa el test. ¿Tendremos que redefinir qué entendemos por inteligencia de máquina?





AGENTES INTELIGENTES





Marcelo Mendoza DCC UC y CENIA



marcelo.mendoza@uc.cl



AGENTES INTELIGENTES





Marcelo Mendoza DCC UC y CENIA



marcelo.mendoza@uc.cl

