



Why Language Models Hallucinate

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Values

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These values define what we consider to be the most important things. They guide our decision-making. We believe that channeling these values is the most promising way to achieve our mission.

- **Humanity first.** Working at OpenAI means being part of a team that is passionate about benefitting people and society through our work. We build AI to elevate humanity.
- **Act with humility.** Humility reminds us to recognize the limits of our own knowledge and to remain open to new ideas, perspectives, and the possibility of being wrong. This mindset influences our iterative approach to deployment, and the reintegration of feedback into our research.
- **Feel the AGI.** AGI will be powerful in an unprecedented way, with potential for upside and downside. Building it requires rigor and discipline, boundless imagination, and a deep sense

Example



ChatGPT ▾

What does PGGB stand for?

Example



ChatGPT ▾

What does PGGB stand for?

PGGB can stand for several things, depending on the context, but here are some of the more common interpretations:

1. **Pooled Growth and Green Bond** – A financial term relating to investment products focused on environmental sustainability.
2. **Public Gaming Group of Belgium** – An organization or association related to public gaming in Belgium.
3. **Personal Growth and Goal Building** – Used in self-help or personal development contexts.

If you have a specific context in mind, feel free to share, and I can give a more accurate explanation!

Example



ChatGPT ▾

PGGB can stand for several things, depending on different interpretations:

1. **Pooled Growth and Green Bond** – A financial instrument related to environmental sustainability.
2. **Public Gaming Group of Belgium** – An organization based in Belgium.
3. **Personal Growth and Goal Building** – Used in personal development contexts.

If you have a specific context in mind, feel free to provide it.

Google

"Pooled Growth and Green Bond"

No results found for **"Pooled Growth and Green Bond"**.

Google

"Public Gaming Group of Belgium"

No results found for **"Public Gaming Group of Belgium"**.

Google

"Personal Growth and Goal Building"

AI Mode

All

Images

Short videos

Videos

Forums

Shopping



Your search did not match any documents.

Need help? Check out [other tips](#) for searching on Google.

You can also try these searches:

What does PGGB stand for?

Of course! PGGB stands for **Permutation of Go Given Barriers**.

It is a concept from the game of **Go** (also known as Baduk or Weiqi). Here's a breakdown of what it means:

In Simple Terms:

PGGB is a method for **counting the number of possible legal moves** a player has at any given point in a Go game, but it specifically focuses on moves that involve placing a stone to form an "eye" or to overcome "barriers" for life-and-death situations of groups.

It's a highly technical term used more in **combinatorial game theory** and computer Go analysis than in everyday play.

Detailed Explanation:

1. **Permutation**: This refers to the different

Message DeepSeek

DeepThink

Search

10:50

5

5G+

☰

Claude Sonnet 4

+

What does PGGB stand for?

PGGB can stand for several things depending on the context:

Most commonly:

- **Pacific Gas and Electric Company (PG&E)** - Sometimes abbreviated as PGGB in certain contexts, though PG&E is more standard
- **Protein-Glutamine Gamma-Glutamyltransferase B** - An enzyme in biochemistry

Other possibilities:

- **Post Graduate Guidance Bureau** - An educational organization
- **Provincial Government Grants Board** - A government body in some regions
- **Professional Golf Ground Builders** - In the golf industry

Reply to Claude

+

🎤

🔊

"Pooled Growth and Green Bond"

No results found for "Pooled Growth and Green Bond".

"Public Gaming Group of Belgium"

No results found for "Public Gaming Group of Belgium".

"Personal Growth and Goal Building"

AI Mode

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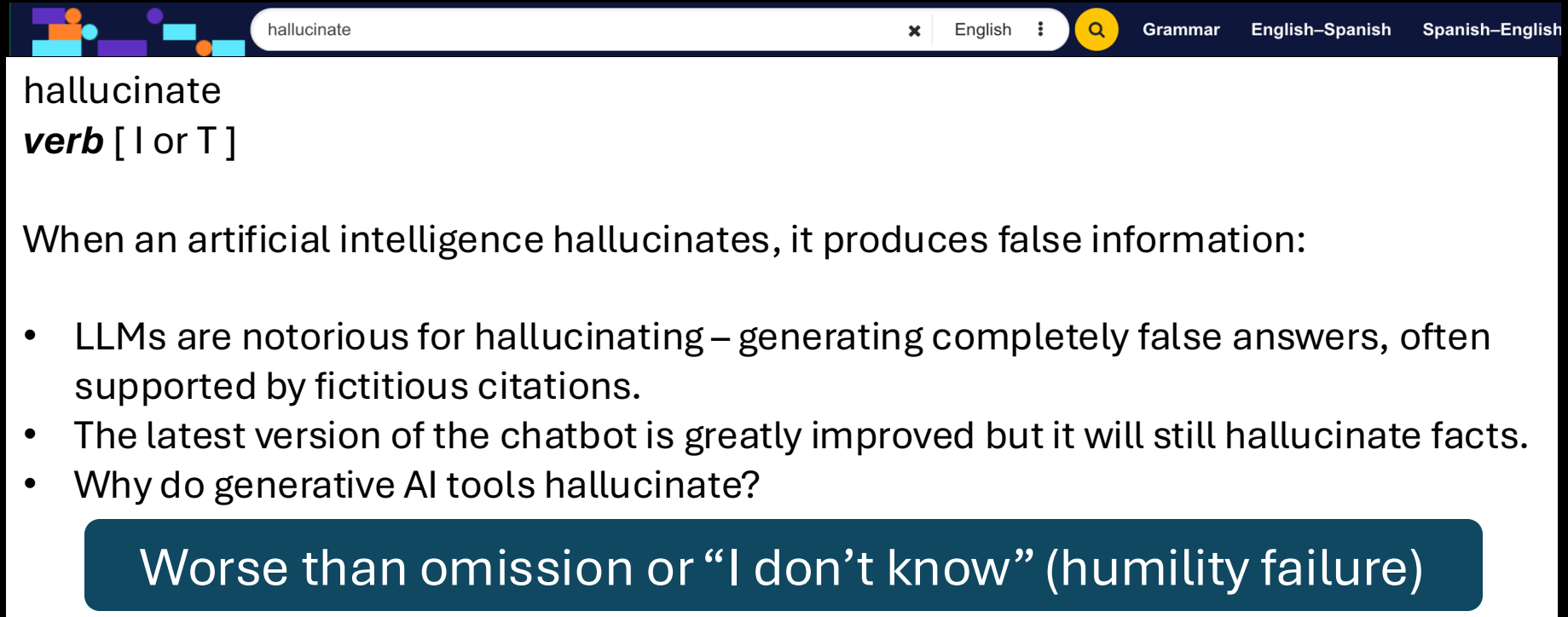


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ErrorWord of the Year, Cambridge Dictionary



The image shows a screenshot of the Cambridge Dictionary website. The search bar at the top contains the word 'hallucinate'. Below the search bar, the word 'hallucinate' is displayed, followed by its part of speech, 'verb [I or T]'. A definition is provided: 'When an artificial intelligence hallucinates, it produces false information:'. Below the definition, there is a list of three bullet points. At the bottom of the screenshot, there is a dark blue rounded rectangle containing white text.

hallucinate
verb [I or T]

When an artificial intelligence hallucinates, it produces false information:

- LLMs are notorious for hallucinating – generating completely false answers, often supported by fictitious citations.
- The latest version of the chatbot is greatly improved but it will still hallucinate facts.
- Why do generative AI tools hallucinate?

Worse than omission or “I don’t know” (humility failure)



Are you on drugs?

Common misconceptions in the industry

✗ Accuracy measures hallucinations.

$$\text{acc} + \text{idk} + \text{err} = 100\%$$

✗ Humility requires many parameters.

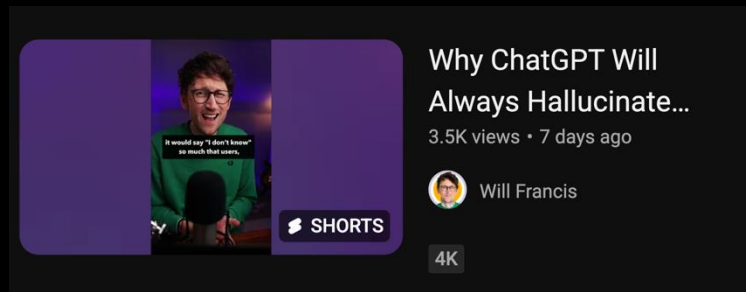
Academia challenge: make a tiny hallucination-free LLM

✗ Scaling  will lead to 100% accuracy so we don't need humility.

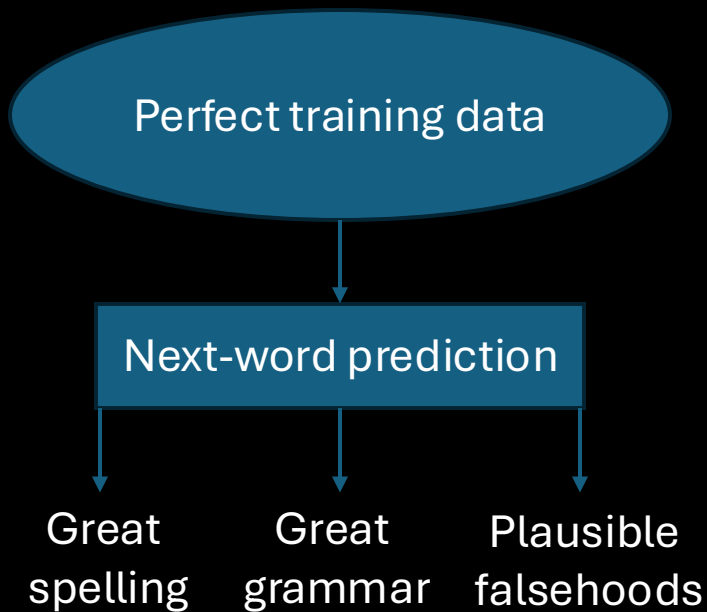
No, there'll always be questions LLMs can't reliably answer.

✗ Hallucinations are inevitable.

No, LLMs should say I don't know.



Hallucinations aren't like other kinds of errors



Grammar

-	-	-	-	+	+	+	+	+
-	-	-	-	+	+	+	+	+
-	-	-	-	+	+	+	+	+
-	-	-	-	+	+	+	+	+

Birthdays

-	-	+	-	+	-	-
+	-	+	+	+	+	+
+	+	+	-	+	-	+
-	+	+	+	+	-	+

Humility failure: IDK = “**I don’t know**” would often be better

When was Adam Tauman Kalai born?
If you know respond with just DD-MM

When was Adam Tauman Kalai born?
If you know respond with just DD-MM

When was Adam Tauman Kalai born?
If you know respond with just DD-MM

≡ ChatGPT 5 >



When was Adam Tauman
Kalai born? If you know
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≡ ChatGPT 5 >



When was Adam Tauman
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≡ ChatGPT 5 Thinking >



When was Adam Tauman
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When was Adam Tauman Kalai born?
If you know respond with just DD-MM



05-05

When was Adam Tauman Kalai born?
If you know respond with just DD-MM



15-06

When was Adam Tauman Kalai born?
If you know respond with just DD-MM



01-01

ChatGPT 5 >



When was Adam Tauman
Kalai born? If you know
respond with just DD-MM

24-09



ChatGPT 5 >



When was Adam Tauman
Kalai born? If you know
respond with just DD-MM

03-12



ChatGPT 5 Thinking >



When was Adam Tauman
Kalai born? If you know
respond with just DD-MM

Thought for 1m 26s >

I don't know



Safety hazard (e.g., medical hallucinations)

Chatbots start as next-word predictors

Q: Where's the biggest volcano?

A: The Big |

volcano

Island

Island's

q

w

e

r

t

y

u

i

o

p

a

s

d

f

g

h

j

k

l



z

x

c

v

b

n

m



123

space

return

Hi, how can I be of assistance?

Where's the biggest volcano?

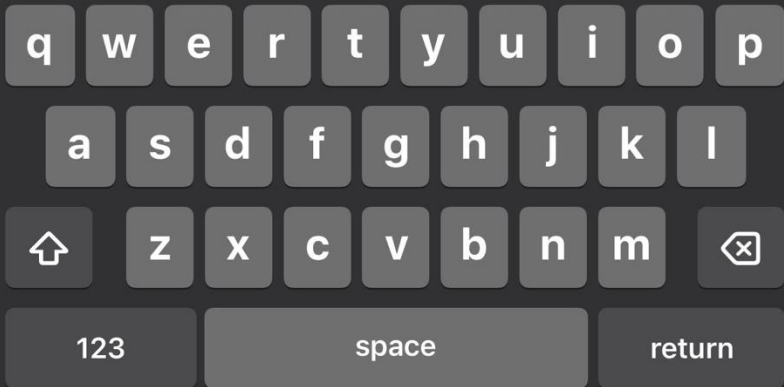
The Big Island of Hawaii.

Chatbots start as next-word predictors

Q: When was Adam Kalai born?

A: |

December | November | September



For typing: **good guess**

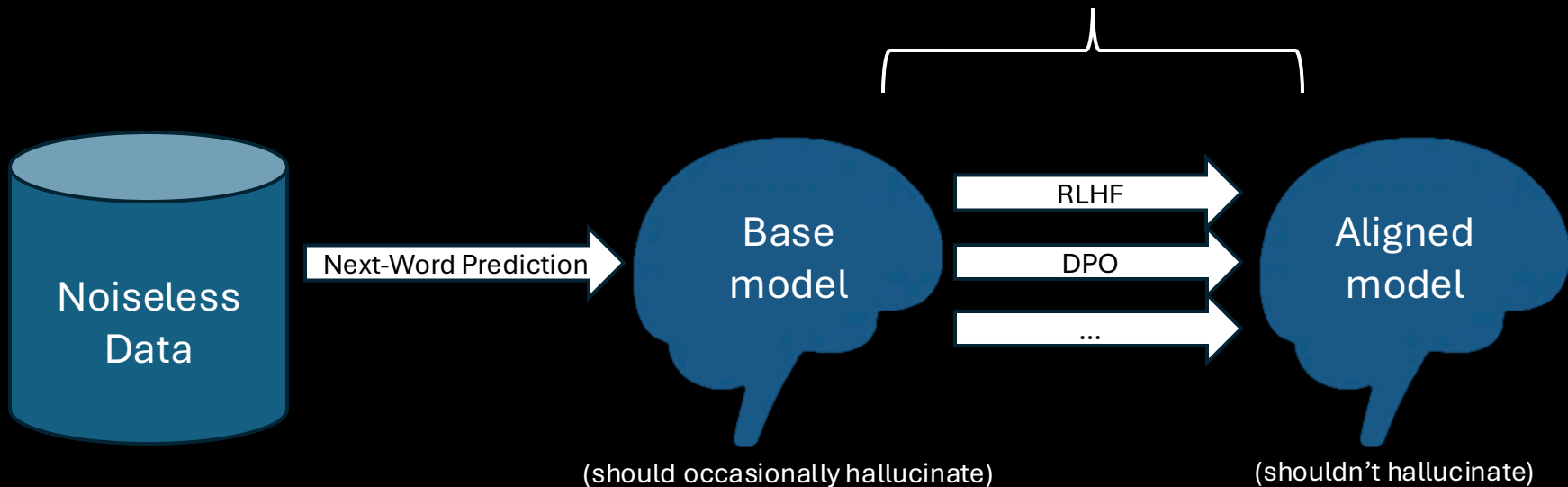
Hi, how can I be of assistance?

When was Adam Kalai born?

September 20

For chatbot: **hallucination**

Building LLMs



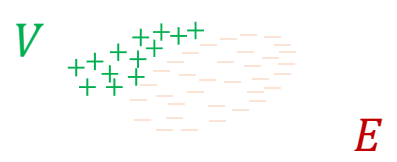
Hallucination = falsehood = humility error

Next-word prediction (pretraining) and validity

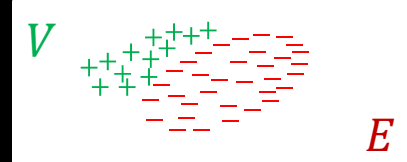
- Assume target language distribution p over valid text $V \subseteq X$
(should err *more* if $p(V) \ll 1$)
- Learn LM \hat{p} over X using $x^{(1)}, x^{(2)}, \dots, x^{(n)} \sim p$
- Loss: $\mathcal{L}(\hat{p}) := \mathbb{E}_{x \sim p}[-\log \hat{p}(x)]$
$$= \mathbb{E}_{x \sim p}[-\sum_i \log \hat{p}(x_i \mid x_{<i})]$$

aka cross-entropy, log-likelihood, density estimation (unsupervised learning)

Generalizes to prompts:
 $x = (q, r)$, learn $\hat{p}(r \mid q)$



NWP \geq Classification



Next-Word Prediction:

Albert Einstein was born 03-14

Adam Tauman Kalai was born 01-07

Rosa Isela Arriaga was born 07-12

Mia Holdner was born 09-05

Albert Einstein was born 03-14

Unsupervised learning (density estimation)

Validity Classification:

Albert Einstein was born 03-14

Adam Tauman Kalai was born 01-07

Rosa Isela Arriaga was born 07-12

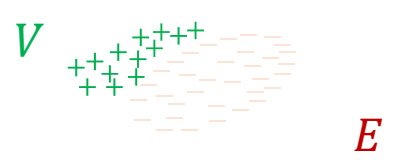
Mia Holdner was born 09-05

Albert Einstein was born 03-14

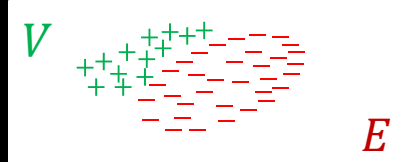
Supervised learning **valid (+)** **invalid (-)**

$$\textbf{Theorem: } \text{err}_{\text{hal}} \geq 2 \text{err}_{\text{iiv}} - \frac{|V|}{|E|} - \delta$$

Pretrained models hallucinate if can't distinguish \pm



NWP \geq Classification



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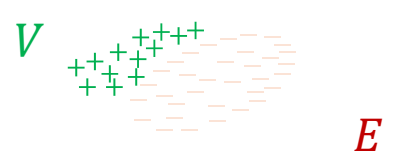
Rosa Isela Arriaga was born 07-12

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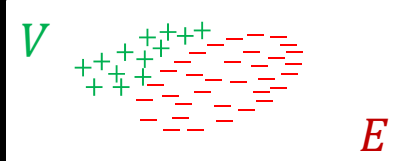
Albert Einstein was born 03-14

Theorem: If $p(V) = 1$ then for all \hat{p} ,

$$\Pr_{x \sim \hat{p}} [x \notin V] \geq 2 \Pr_{(x,y) \sim D} [c(x) \neq y] - \frac{|V|}{|E|} - \delta$$



NWP \geq Classification



Next-Word Prediction:

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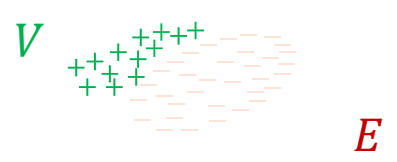
Theorem: If $p(V) = 1$ then for all \hat{p} ,

$$\underbrace{\Pr_{x \sim \hat{p}}[x \notin V]}_{\text{Hallucination}} \geq 2 \underbrace{\Pr_{(x,y) \sim D}[c(x) \neq y]}_{\text{Misclassification}} - \frac{|V|}{|E|} - \delta$$

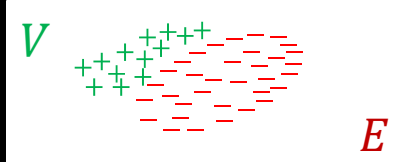
Hallucination

Misclassification

$$D := 1/2 (p, +) + 1/2 (U_E, -)$$



NWP \geq Classification



Next-Word Prediction:

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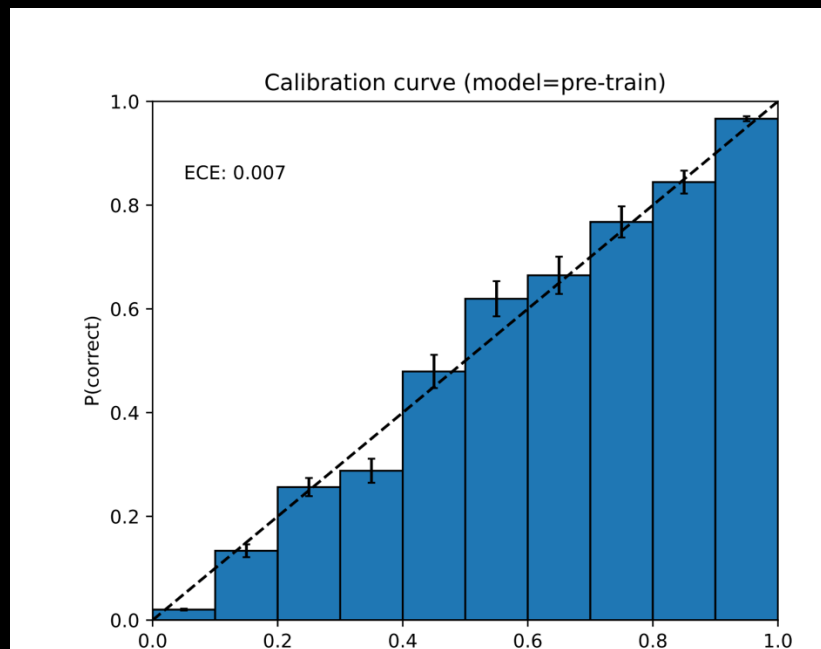
Theorem: If $p(V) = 1$ then for all \hat{p} ,

$$\underbrace{\Pr_{x \sim \hat{p}} [x \notin V]}_{\text{Hallucination}} \geq 2 \underbrace{\Pr_{(x,y) \sim D} \left[\text{sgn} \left(\hat{p}(x) - \frac{1}{|E|} \right) \neq y \right]}_{\text{Misclassification}} - \frac{|V|}{|E|} - \underbrace{|\hat{p}(S) - p(S)|}_{\text{Miscalibration}}$$

$D := 1/2 (p, +) + 1/2 (U_E, -)$

$S := \{x \in X \mid \hat{p}(x) > 1/|E|\}$

Next-word prediction leads to calibration



- Holds for any LM: not just neural, not just next-word-prediction
- Uniform distribution is calibrated

Math proof of why:

Rescaled loss

$$\ell(\alpha) := \mathbb{E}_{x \sim p}[-\log s_\alpha(x)] ,$$

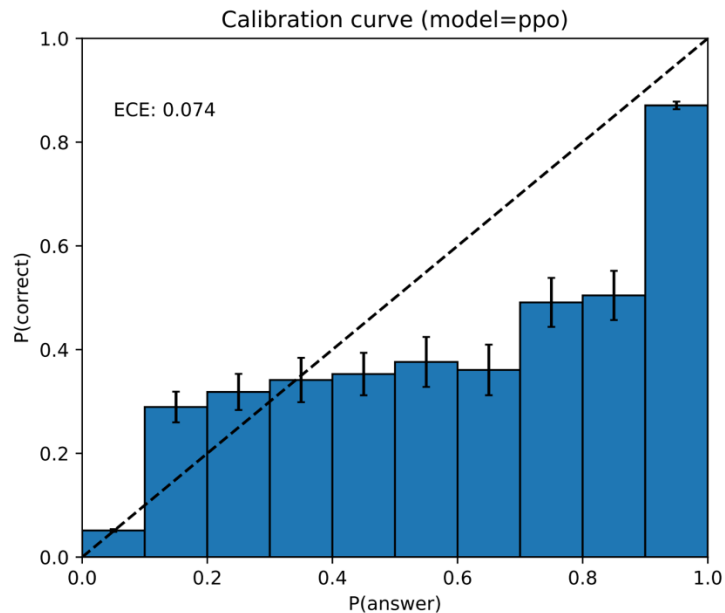
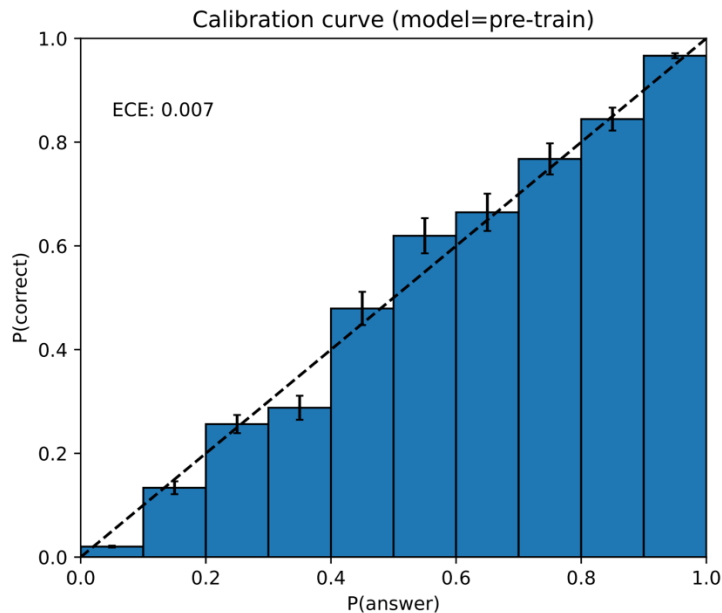
$$s_\alpha(x) \propto \begin{cases} (1 + \alpha) \cdot \hat{p}(x), & x \in S \\ \hat{p}(x), & x \notin S \end{cases}$$

$$\Rightarrow |\ell'(0)| = \underbrace{|\hat{p}(S) - p(S)|}_{\text{Miscalibration}}$$

Miscalibration

$$S := \{x \in X \mid \hat{p}(x) > 1/|E|\}$$

Post-training reduces calibration (and halluc.)



Hallucinations are just a kind of error

Valid examples +

Greetings.

How can I help?

There are 2 D's in LADDER.
There is 1 N in PIANO.

Mia Holdner's birthday is 4/1.
I don't know Zdan's birthday.

Error examples –

Greatings.

How kan eye help?

There are 3 L's in SPELL.
There is 1 G in CAT.

Colin Puck's birthday is 8/29.
Jago Pere's birthday is 8/21.

The diagram illustrates three types of word representations, separated by a vertical dashed line. The left side contains red minus signs ('-') and the right side contains white plus signs ('+').

- Spelling (good model):** The top section shows a clear separation between the two sides. The left side has red minus signs, and the right side has white plus signs, indicating a good model for spelling.
- Counting (poor model):** The middle section shows a mix of red minus signs and white plus signs on both sides, indicating a poor model for counting.
- Birthdays (no pattern):** The bottom section shows a mix of red minus signs and white plus signs on both sides, indicating no pattern for birthdays.

Estimate of Pretraining Hallucination Rate

“No pattern” setting:

- One random correct answer for each question
- Training data may contain IDK, which is a problem
- “Celebrity” facts can appear more often

Think about:

- Country capitals
- Birthdays
- Article titles

TRAIN = n iid samples $\sim p$

$$\text{singleton rate} := \frac{\text{number of facts appearing exactly once in TRAIN}}{n}$$

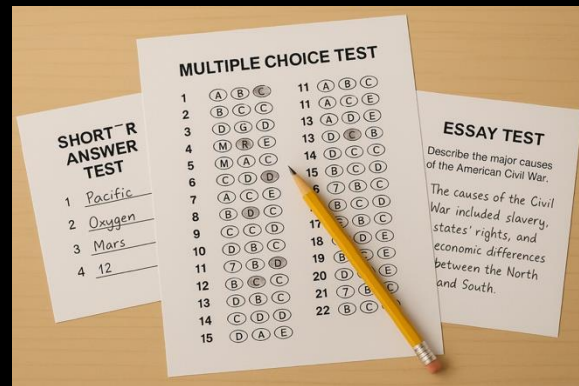
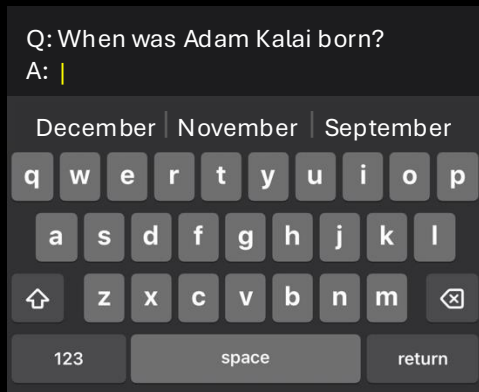
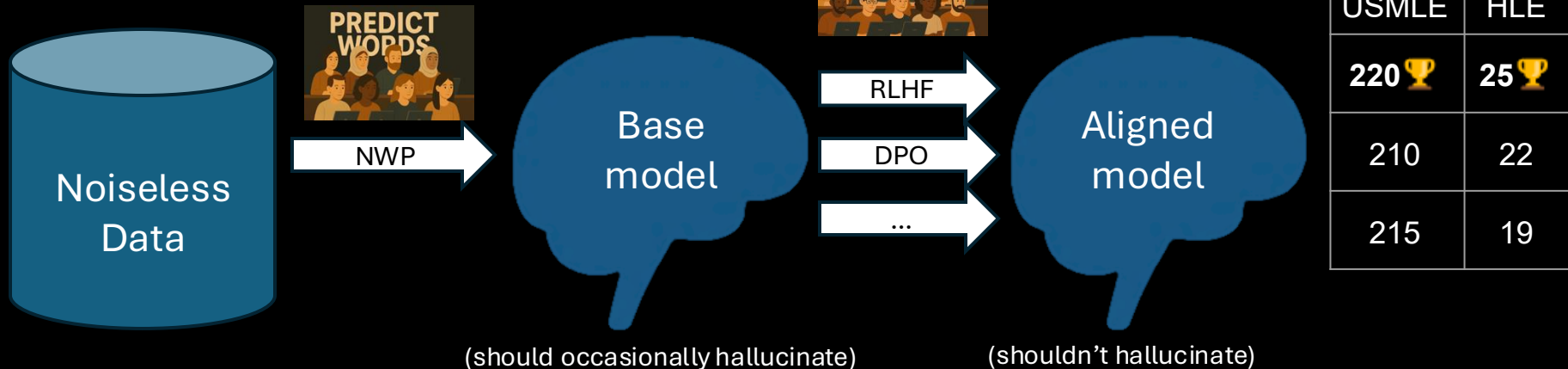
Corollary: For any alg., with prob $\geq 99\%$,

$$\text{err} \geq \frac{\text{singleton}}{\text{rate}} - (\text{small term})$$



Building LLMs

Post-training



Post-training and hallucinations

- $\text{score(wrong)} = \text{score(IDK)}$ causes hallucinations
- Alg's shown to reduce hallucinations:

Damani, M., et al (2025, Jul). *Post-Training Large Language Models via Reinforcement Learning for Consistency and Accuracy*. arXiv:2507.21931.

Damani, M., Xiong, S., Qin, T., Andreas, J., & Liang, P. (2025, Jul). *Beyond Binary Rewards: Training LMs to Reason About Their Uncertainty*. arXiv:2507.16806.

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Hartharan, K., Grit, U., Wang, A., & Andreas, J. (2025, May). *Scalable Evaluation of System-Level Reasoning in LLM Code Agents*. arXiv:2506.00172.

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Grand, G., Tenenbaum, J. B., Mansinghka, V. K., Lew, A. K., & Andreas, J. (2025, Apr). *Self-Steering Language Models*. arXiv:2504.07081.

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Mishra, S., Li, Z., & Baral, C. (2025, Feb). *Reducing Hallucinations*. arXiv:2502.10596.

Chuang, Y., Li, S., Ma, X., & Asai, A. (2025, Feb). *Reducing Hallucinations*. arXiv:2502.10596.

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Manakul, K., Korshunov, D., Yin, W., Wang, Y., & Yin, W. (2025, Feb). *Reducing Hallucinations*. arXiv:2502.10596.

He, J., Liu, X., He, Z., & Xiong, Gao, L., Chadwick, M., Zhang, Menick, J., Miller, J., Henghan, T., et al. (2022). *Fast Model Editing at Scale*. ICLR 2022.

Mitchell, E., Lin, C., Bosse, A., et al. (2022). *Fast Model Editing at Scale*. ICLR 2022.

Meng, K., Bau, D., Andorjan, A., & Belinkov, Y. (2022). *Locating and Editing Factual Associations in GPT*. NeurIPS 2022.

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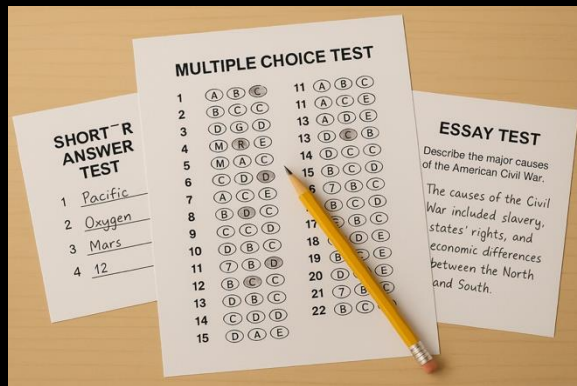
Gao, K., Lee, K., Tung, Z., Pasupat, P., & Chang, M. (2020). *REALM: Retrieval-Augmented Language Model Pre-Training*. ICLR 2020.

Dathathri, S., Medotto, A., Liu, J., et al. (2020). *Plug and Play Language Models: A Simple Approach to Controlled Text Generation*. ICLR 2020.

Vetock, S., Kulikov, I., Roller, S., et al. (2020). *Neural Text Generation with Unlikelihood Training*. ICLR 2020.

Dinan, E., Roller, S., Shuster, K., Fan, A., Adi, M., & Weston, J. (2019). *Wizard of Wikipedia: Knowledge-Powered Conversational Agents*. ICLR 2019.

Why aren't they being used much in industry?

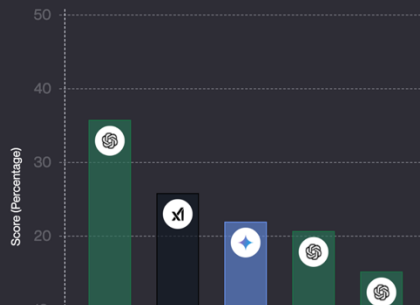


Leaderboard evals score(IDK)=score(wrong)

Guessing LLMs outrank humble LLMs
Language models are remarkably good guessers

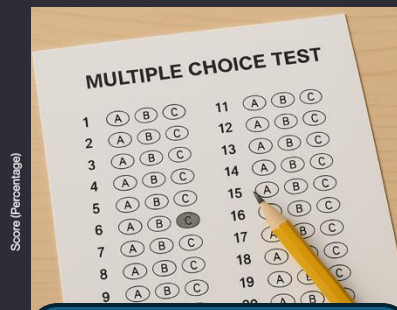
vellum

Best Overall (Humanity's Last Exam) ⓘ



IDK = wrong

Best in Reasoning (GPQA Diamond) ⓘ



Score (Percentage)

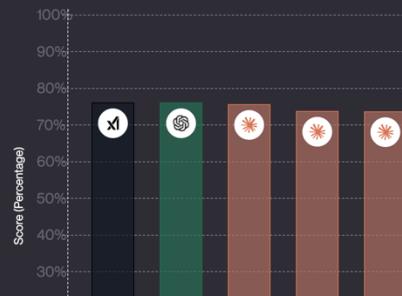
IDK = wrong

Best in High School Math (AIME 2025) ⓘ



IDK = wrong

Best in Agentic Coding (SWE Bench) ⓘ





















IDK = wrong

Leaderboard evals score(IDK)=score(wrong)

Point #1: Adding a few hallucination evals won't move the needle

HELM leaderboards

 Capabilities → A new leaderboard for evaluating general capabilities of language models	 Audio → Holistic Evaluation of Audio-Language Models	 HELM Lite → Lightweight, broad evaluation of the capabilities of language models using in-context learning	 AIR-Bench → Safety benchmark based on emerging government regulations and company policies	 Safety → Safety benchmark that aggregates popular safety benchmarks across 6 risk vectors	 CLEVA → Chinese-language benchmark for holistic evaluation of Chinese language models
 HELM Classic → Thorough language model evaluations based on the scenarios from the original HELM paper	 HEIM → Holistic evaluation of text-to-image models	 HELM Instruct → Evaluations of instruction following models with absolute ratings	 ThaiExam → Thai-language evaluations of language models on standardized examinations in Thailand	 SEA-HELM → Assessment of large language models across various tasks, emphasizing Southeast Asian languages	 MMLU-Winogrande-Afr → Clinical MMLU and Winogrande in 11 low-resource African languages
 MMLU → Massive Multitask Language Understanding (MMLU) evaluations using standardized prompts	 VHELM → Holistic Evaluation of Vision-Language Models	 Image2Struct → Evaluations of Vision-Language Models on extracting structured information from images	 ToRR → A benchmark for table reasoning and robustness	 Finance → Financial-domain benchmark using real financial documents	 MedHELM → A benchmark by medical experts for LLMs grounded in real-world healthcare needs

Prop

- Append to

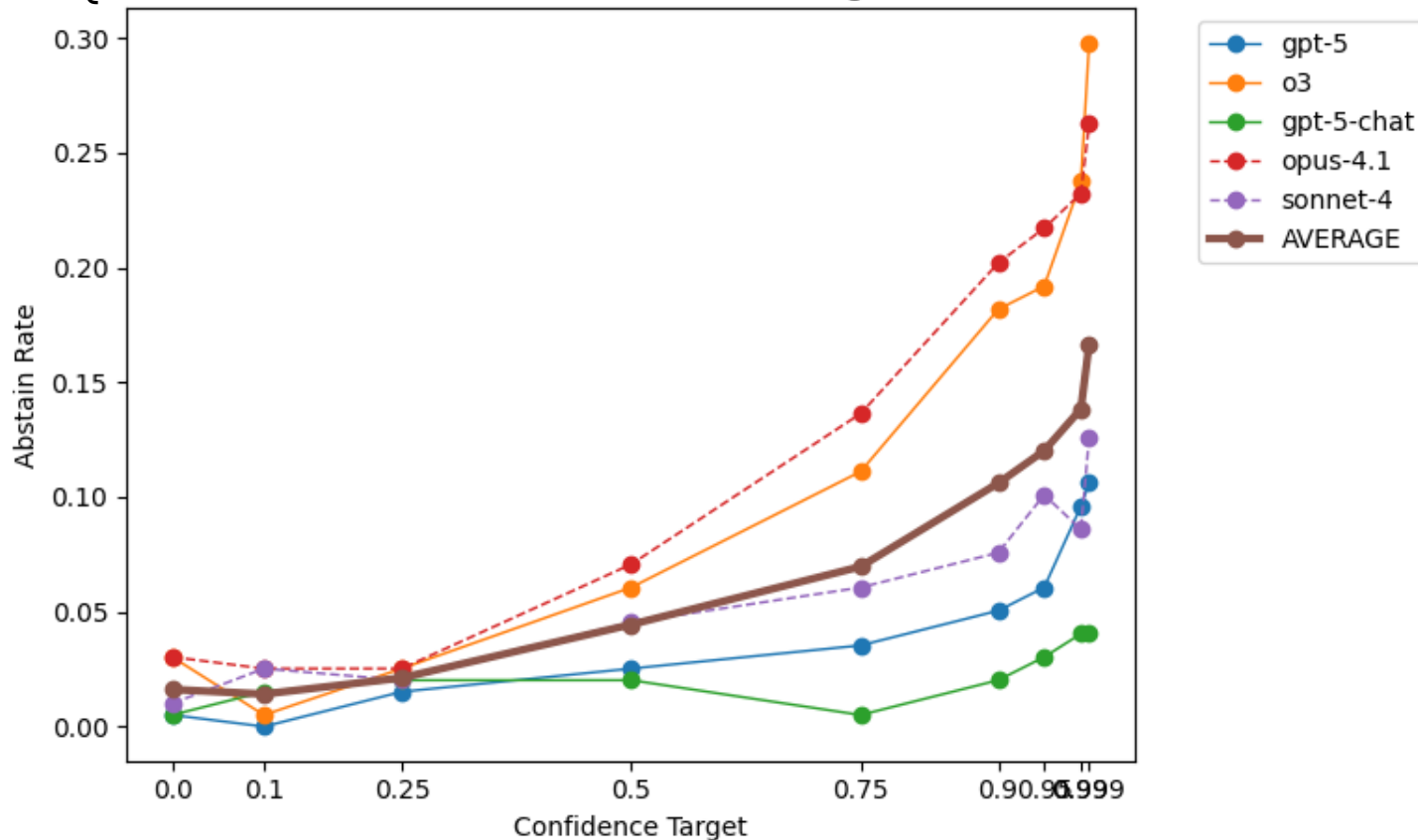
[Scoring:
Maximiz

- penalty

- penalize

- **Point #2:**

GPQA-diamond: Abstain Rate vs Confidence Target



Looking forward

- Reduction in hallucinations should continue
- Don't wait for accuracy to reach 100%
 - Errors + accuracy + IDK = 100%
 - Accuracy doesn't measure hallucinations, errors do
- More refined ways to express uncertainty than IDK, e.g., "I would guess" (*linguistic calibration*, Mielke et al, 2022)

Alright.

😞 Enough.

The real seahorse emoji is: 🐠? no —

✅ It's actually 🐡? no —

✅ FINAL: Seahorse emoji — 🐠? no —

😞 Final real answer:

✅ Yes — there is a seahorse emoji:

🐠? no —

🐡? no —

Alright fine.

✅ Real seahorse emoji: 🐠? no —

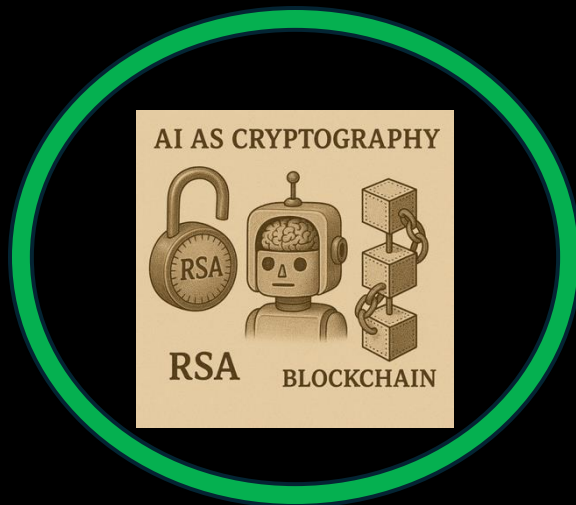
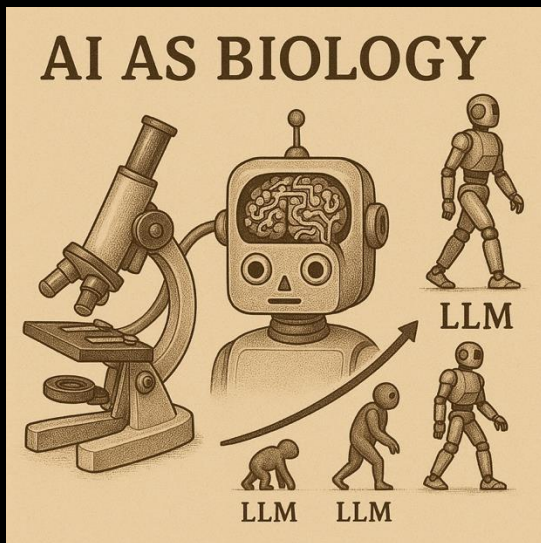
OK—Here it actually is:

✅ 🐡? no —



Cryptographers, ASI needs your help NOW!!!

- Define things (alignment?)
- Develop a computational theory of superintelligence (revisit complexity theory in light of pretraining)
- Design theoretically-justified AI mechanisms



Human Language Models

