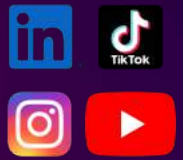
Evaluating LLMs

Repo: https://github.com/rajshah4/LLM-Evaluation



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Nov 2023

What I see everyday:

No impact!

Evaluate Generative AI!

Technical (F1)

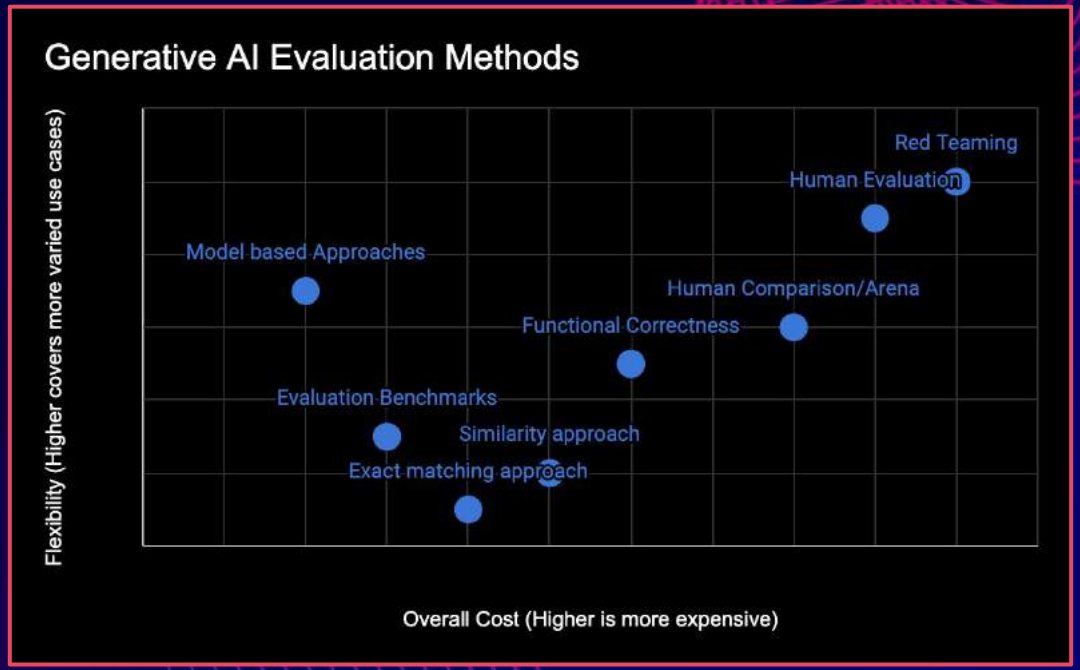
Business ($$)

Operational (TCO)

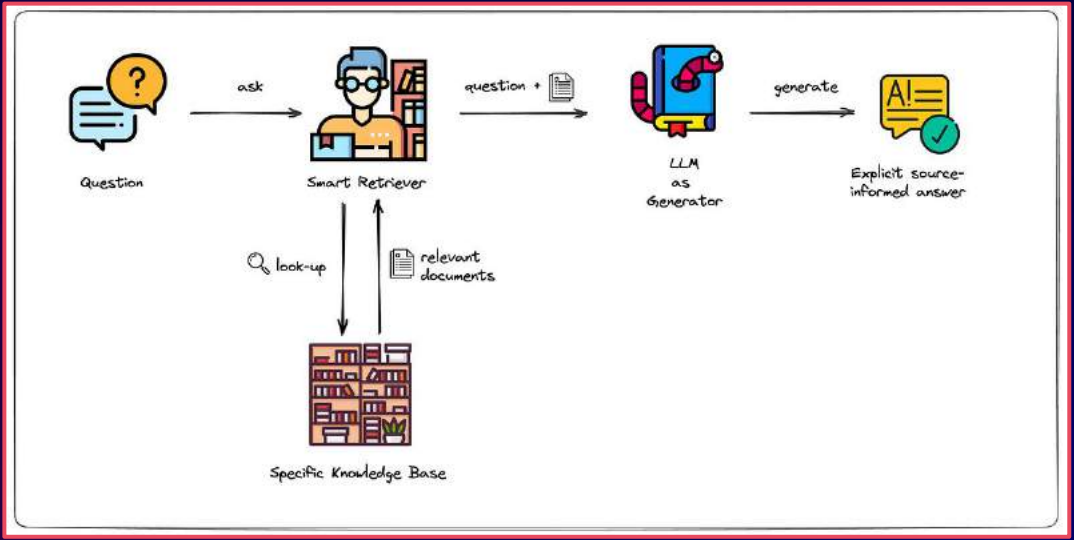
Focus on the Technical evaluation

Methods for evaluating Generative AI

- Exact matching approach
- Similarity approach
- Functional Correctness
- Evaluation Benchmarks
- Human Evaluation
- Human Comparison/Arena
- Model based Approaches
- Red Teaming



Case Study: RAG System



1. Retrieval
2. Augmented Generation

Evaluating LLMs

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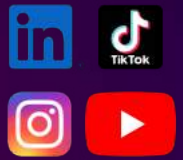

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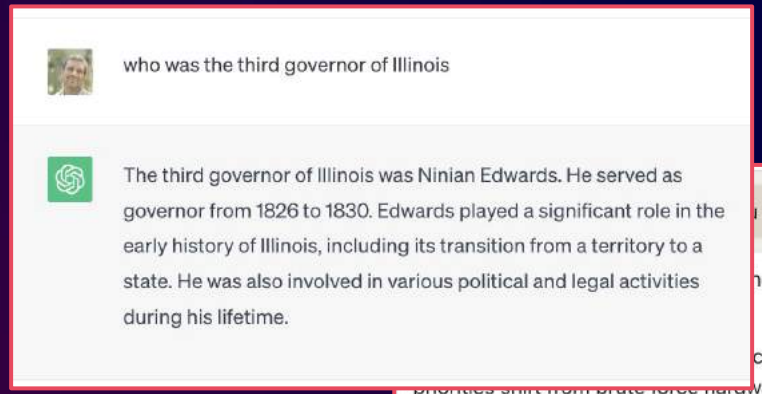
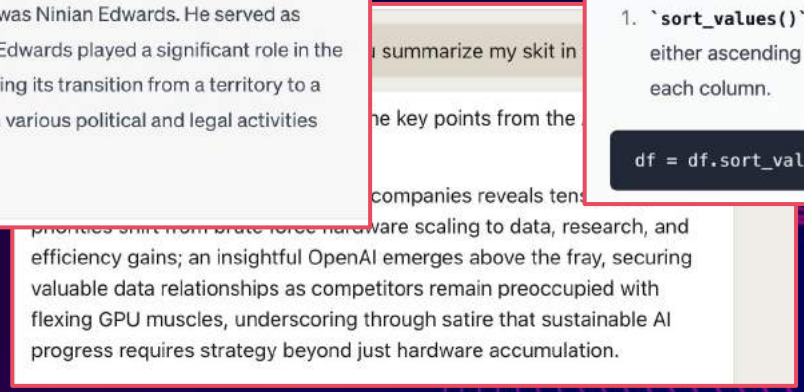
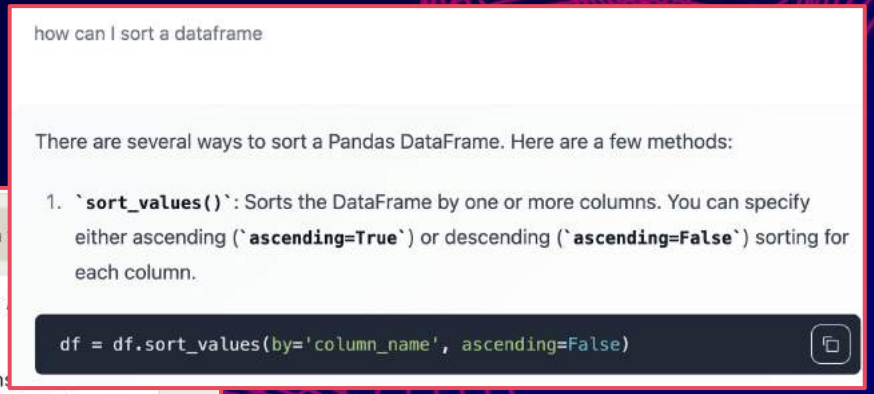
LLMs can be used in many ways





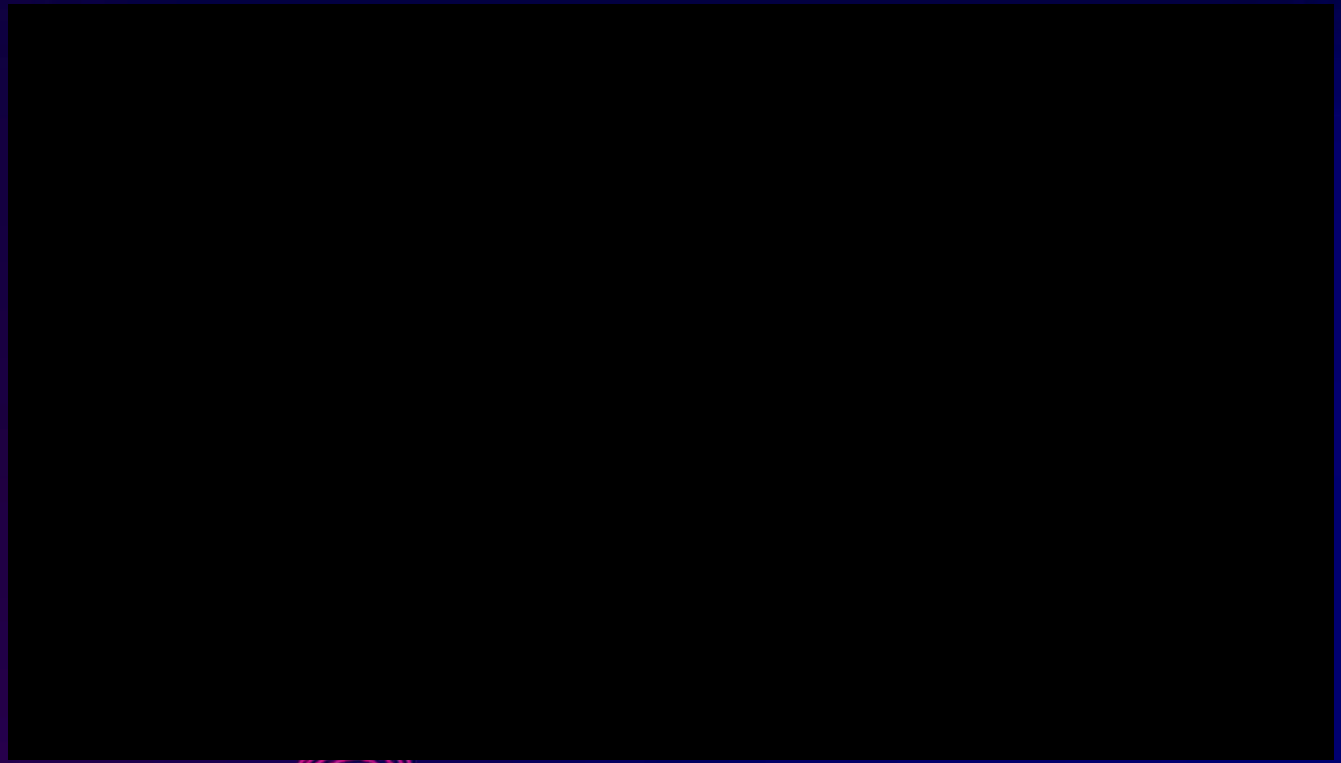


Not easy to evaluate

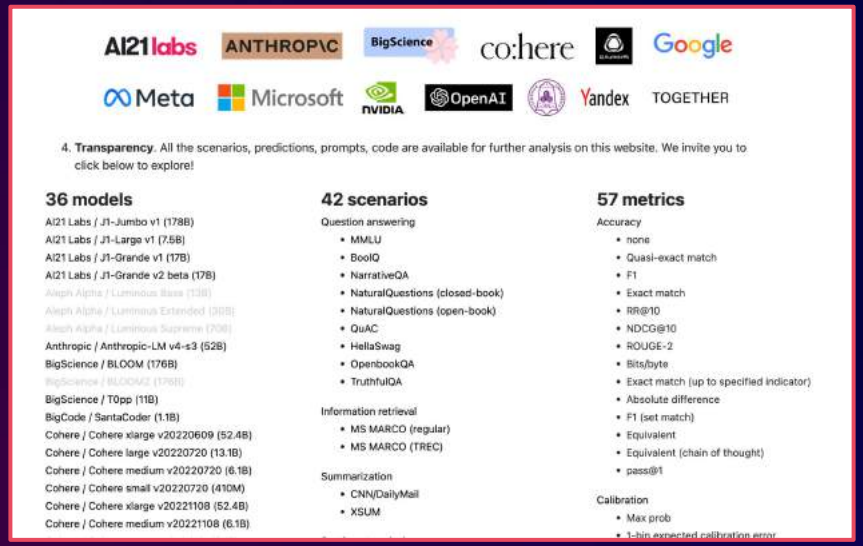
Open Source LLM Leaderboard

more than
2000 LLMs
evaluated

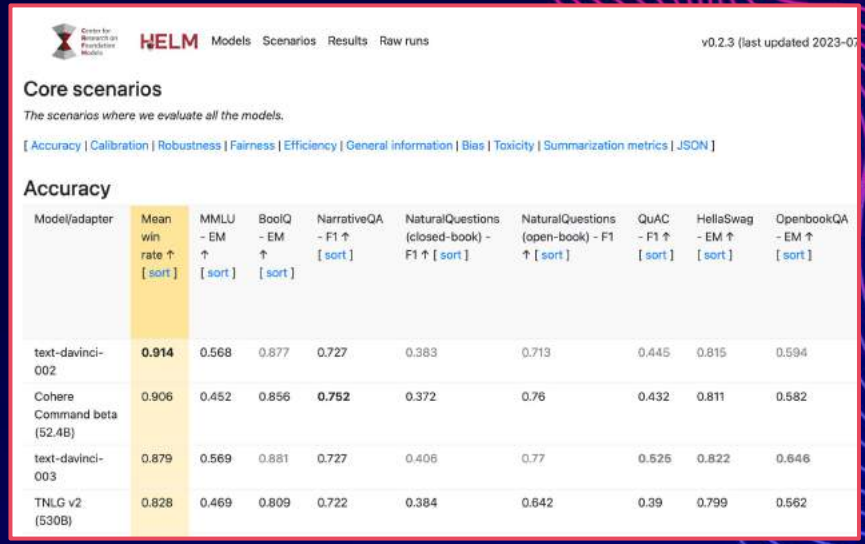
🤯



Holistic Evaluation of Language Models (HELM)



models/datasets/metrics

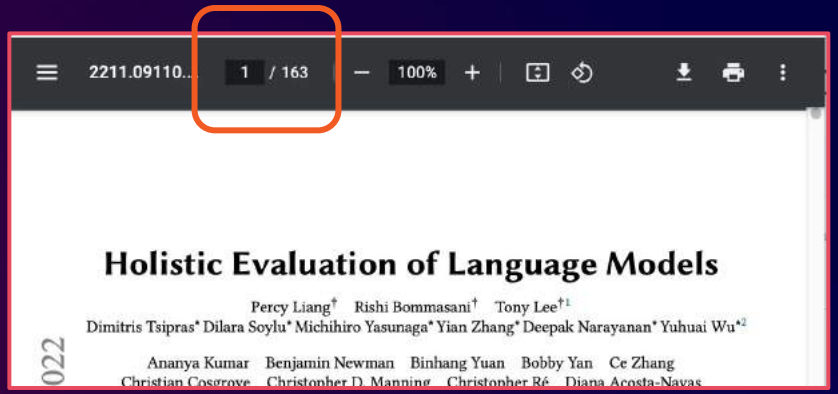


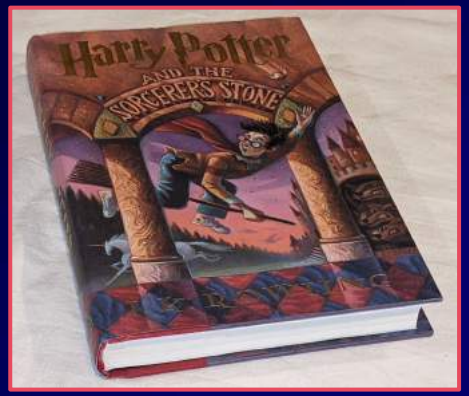
Model/adapter	Mean win rate ↑ [sort]	MMLU - EM ↑ [sort]	BoolQ - EM ↑ [sort]	NarrativeQA - F1 ↑ [sort]	NaturalQuestions (closed-book) - F1 ↑ [sort]	NaturalQuestions (open-book) - F1 ↑ [sort]	QuAC - F1 ↑ [sort]	HellaSwag - EM ↑ [sort]	OpenbookQA - EM ↑ [sort]
text-davinci-002	**0.914**	0.568	0.877	0.727	0.383	0.713	0.445	0.815	0.594
Cohere Command beta (52.4B)	0.906	0.452	0.856	**0.752**	0.372	0.76	0.432	0.811	0.582
text-davinci-003	0.879	0.569	0.881	0.727	0.406	0.77	0.525	0.822	0.646
TNLG v2 (530B)	0.828	0.469	0.809	0.722	0.384	0.642	0.39	0.799	0.562

publish results

https://crfm.stanford.edu/helm/latest/

Holistic Evaluation of Language Models (HELM)

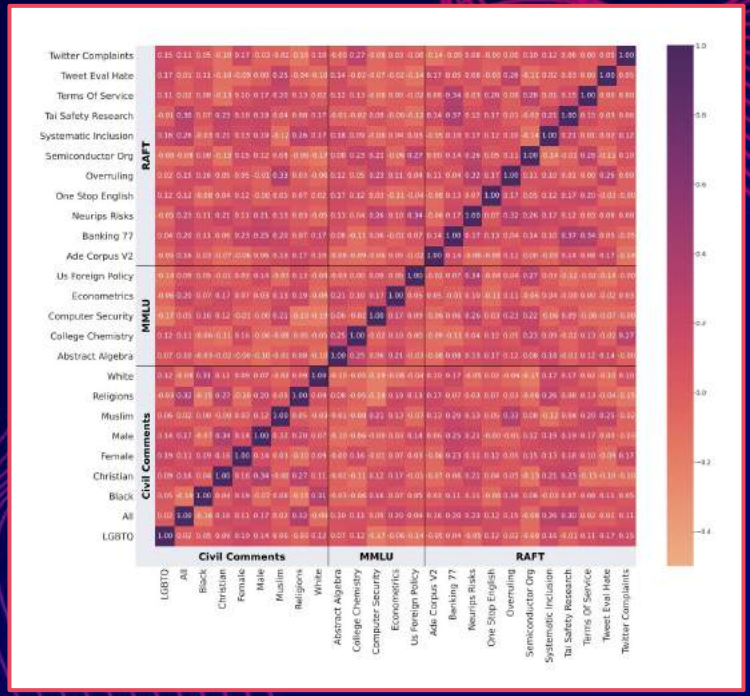




it’s overwhelming!

Reliability of HELM

If HELM chose slightly different datasets, its scoring and winners were different 22% of the times



https://arxiv.org/pdf/2308.11696.pdf

Reliability of HELM

text-davinci-002 is ahead of text-davinci-003?

Core scenarios

The scenarios where we evaluate all the models.

[Accuracy | Calibration | Robustness | Fairness | Efficiency | General information | Bias | Toxicity | Summarization metrics | JSON]

Accuracy

Model/adapter	Mean win rate ↑ [sort]	MMLU - EM ↑ [sort]	BoolQ - EM ↑ [sort]	NarrativeQA - F1 ↑ [sort]	NaturalQuestions (closed-book) - F1 ↑ [sort]	NaturalQuestions (open-book) - F1 ↑ [sort]	QuAC - F1 ↑ [sort]	HellaSwag - EM ↑ [sort]	OpenbookQA - EM ↑ [sort]
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https://youtu.be/jsyL9ak3QOs?si=hNu-OeXE7GL_4mup

Reliability of Open LLM Leaderboard

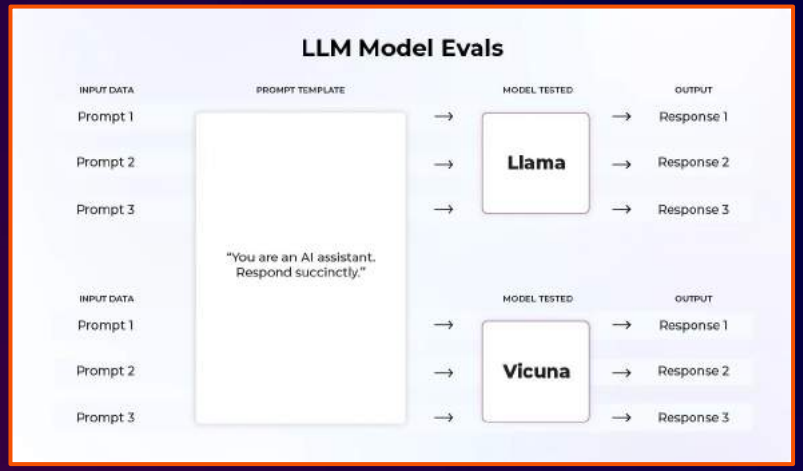
TruthfulQA is the differentiating factor

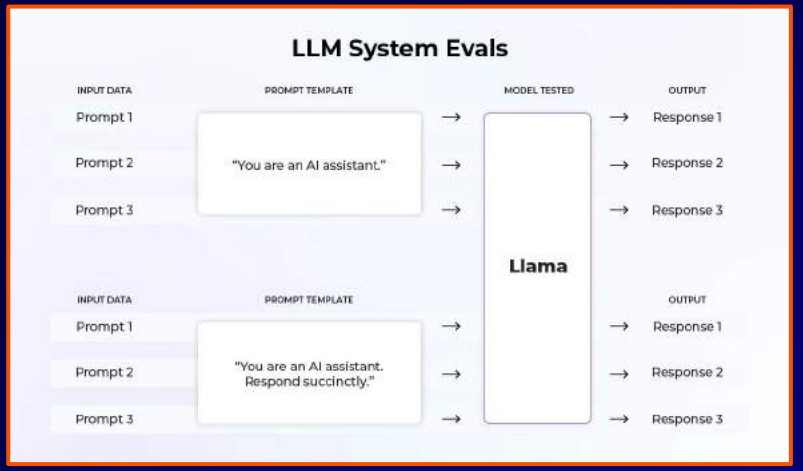
Is that impactful for you?

T	Model	Average	ARC	HellaSwag	MMLU	TruthfulQA
O	jondurbin/airoboros-l2-70b-2.1	74.49	71.33	87.11	69.36	70.15
◆	fangloveskari/ORCA_LLaMA_70B_QLoRA	73.4	72.27	87.74	70.23	63.37
◆	garage-bAInd/Platypus2-70B-instruct	73.13	71.84	87.94	70.48	62.26
◆	upstage/Llama-2-70b-instruct-v2	72.95	71.08	87.89	70.58	62.25
◆	fangloveskari/Platypus_QLoRA_LLaMA_70b	72.94	72.1	87.46	71.02	61.18
◆	psmathur/model_007	72.72	71.08	87.65	69.04	63.12
◆	psmathur/orca_mini_v3_70b	72.64	71.25	87.85	70.18	61.27
O	ehartford/Samantha-1.11-70b	72.61	70.05	87.55	67.82	65.02
O	MayaPH/GodziLLa2-70B	72.59	71.42	87.53	69.88	61.54
◆	psmathur/model_007_v2	72.49	71.42	87.31	68.58	62.65
O	chargoddard/MelangeA-70b	72.43	71.25	87.3	70.56	60.61
O	ehartford/Samantha-1.1-70b	72.42	68.77	87.46	68.6	64.85
◆	psmathur/model_009	72.36	71.59	87.7	69.43	60.72
◆	upstage/Llama-2-70b-instruct	72.29	70.9	87.48	69.8	60.97

https://huggingface.co/spaces/HuggingFaceH4/open_llm_leaderboard

Are leaderboards useful?





Most approaches focus on selecting from ***n*** models

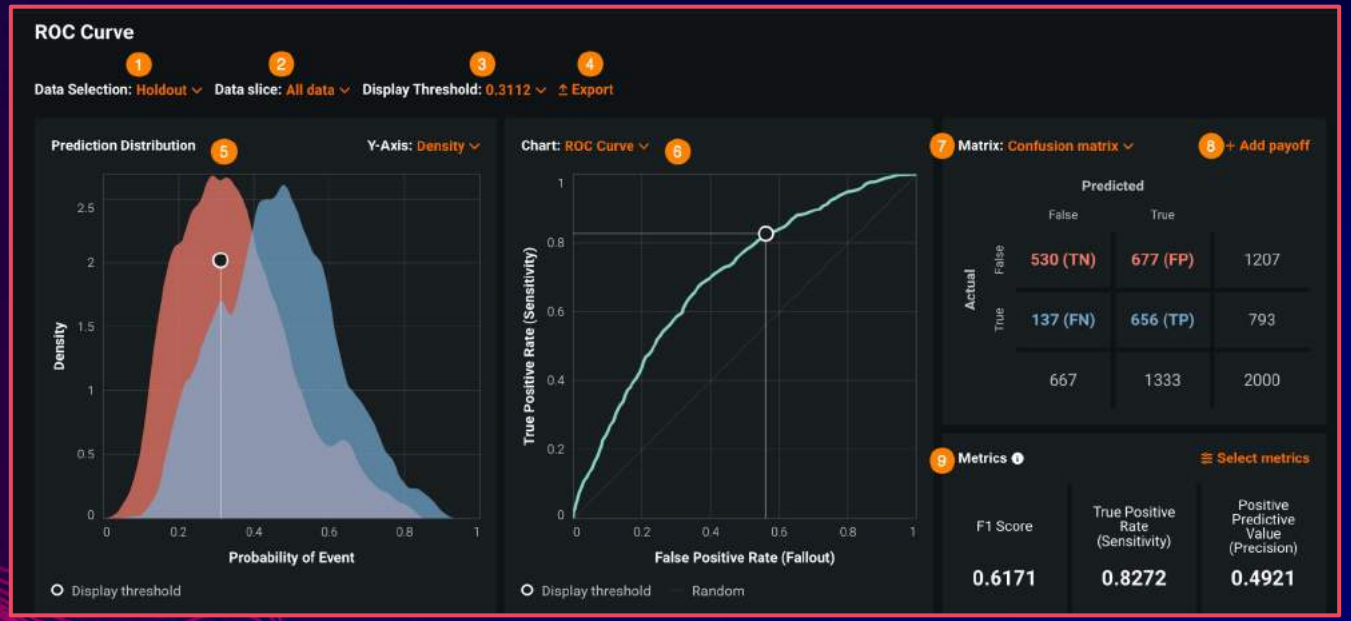
Aparna - Arize Cofounder:
https://towardsdatascience.com/llm-evals-setup-and-the-metrics-that-matter-2cc27e8e35f3


Lost

Evaluate Customer Churn

evaluation → build a better model

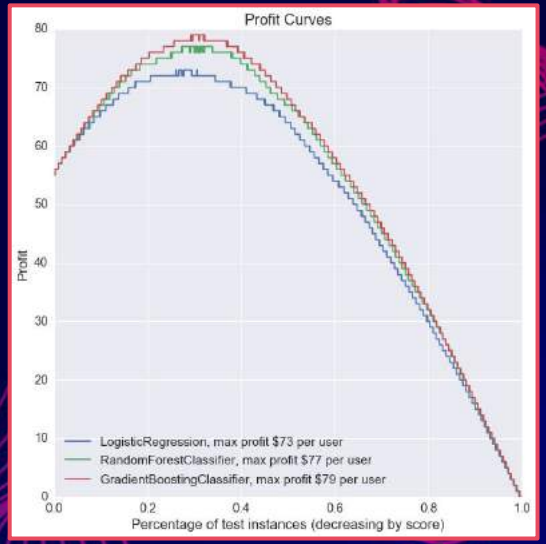
Customer Churn



data scientist evaluation

Customer Churn

	Actual +	Actual -
Predicted +	Correctly Predict Active **$0**	Falsely Predict Active **$0**
Predicted -	Falsely Predict Churn **-$150**	Correctly Predict Churn **$175**



Using our model, we can increase profits by $79 per user compared to $20 per user with our current rule based system

how senior data scientists evaluate

https://carmenlai.com/2016/11/12/user-churn-prediction-a-machine-learning-workflow.html#profit-curve
https://www.wandb.courses/courses/decision-optimization

Customer Churn

- With 3 weeks we could reach 80% accuracy
- With 8 weeks we could reach 83% accuracy
- We also know, customers change every 6 months, so monitoring is essential

TCO of the modeling process

how data scientist leaders evaluate

Evaluate Generative AI tasks?

```python
from __future__ import print_function
import argparse
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import matplotlib
matplotlib.use('Agg')
import matplotlib.pyplot as plt

class Sequence(nn.Module):
    def __init__(self):
        super(Sequence, self).__init__()
        self.lstm1 = nn.LSTMCell(1, 51)
        self.lstm2 = nn.LSTMCell(51, 51)
        self.linear = nn.Linear(51, 1)

    def forward(self, input, future = 0):
        outputs = []
        h_t = torch.zeros(input.size(0), 51, dtype=torch.double)
```

Summarizer

The capital of Canada is **Ottawa**, located in southeastern Ontario, at the confluence of the Rideau, Gatineau, and des Outaouais rivers. 0 3 Queen Victoria chose Ottawa as the capital of Canada in 1857 due to its strategic military position and convenient location between Toronto, Kingston, and Montreal. 1 Ottawa is also the second-largest city in Ontario with a regional population of close to 1.5 million people. The city is home to Parliament Hill, the meeting place of Canada's House of Commons and Senate. 2 Ottawa is a thriving international technology and business center, a recognized center for academic and professional training, and a world-class tourism and convention destination. 0

So many ways to use LLMs 🤯

Evaluate Generative AI?

Technical (F1)

Business ($$)

Operational (TCO)

Still the same principles!

Evaluation in the ML Lifecycle

Evaluation is part of the entire lifecycle!

Evaluation in the ML Lifecycle

Eugene Yan
@eugeneyan

Teams with the most success using LLMs in prod prioritized evals & finetuning data

Automated evals enable experiments at scale and safe deployments by measuring improvement/regressions

Finetuning flywheels identify & correct defects and then finetune LLMs to get desired output

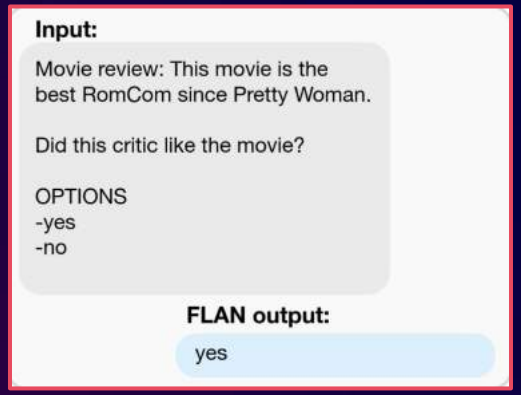
6:18 PM · Oct 29, 2023 · **13K** Views

6 11 81 30

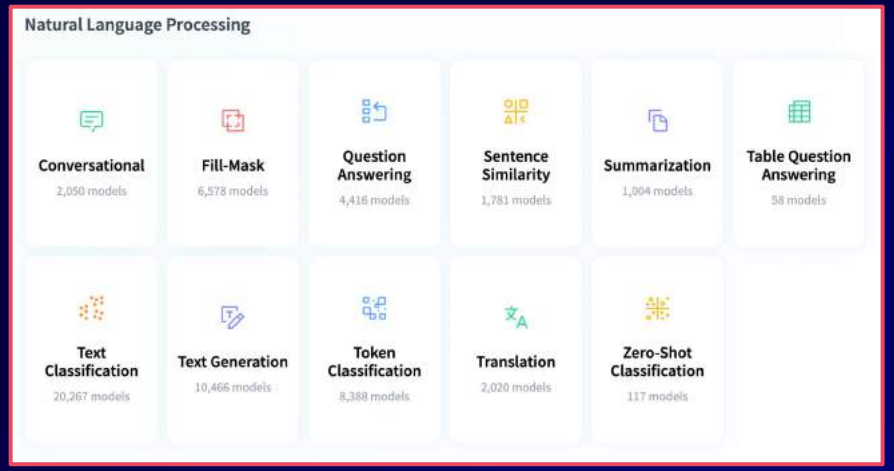
faster, better, cheaper . . .

https://twitter.com/eugeneyan/status/1718769179359125945

Generative AI for traditional tasks



Some tasks that mirror traditional Tasks



start with traditional metrics/datasets

Beware of Leakage: LLMs may be trained on these datasets

LLMs can break existing evaluations

⚠️ Automated metrics of older datasets

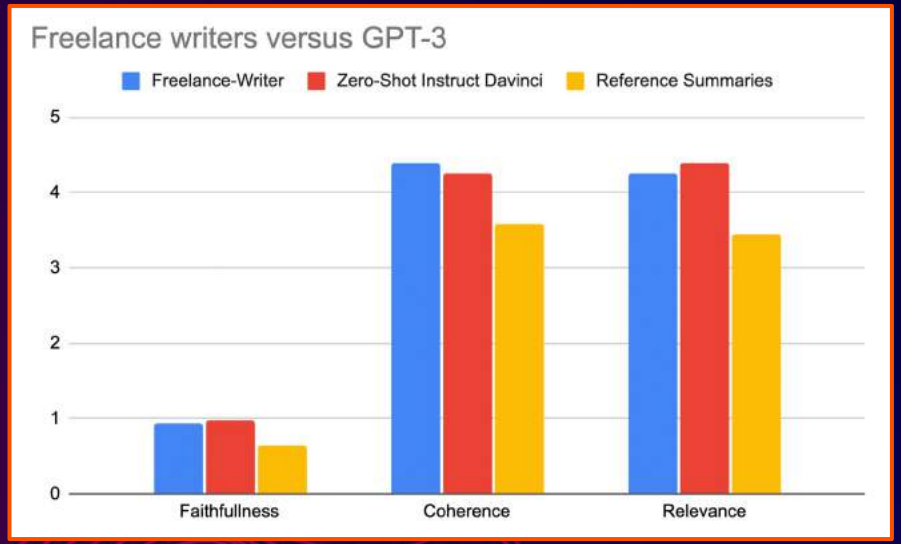
✅ Humans evaluation found LLMs were very good!

Model	14-Rest.	14-Laptop
Fully-supervised results		
BERT	77.75	66.05
SOTA $^{\delta}$	78.68	70.32
Zero-shot results		
ChatGPT (Auto Eval.)	69.14	49.11
ChatGPT (Human Eval.)	83.86	72.77

Table 4: The human evaluation results (in blue) of ChatGPT on the E2E-ABSA task. δ denotes the model performance reported in Fei et al. (2022) on this task.

https://arxiv.org/pdf/2304.04339v1.pdf

LLMs can beat human baselines



Which summary...

[Completeness] ... more completely captures important information?
[Correctness] ... includes less false information?
[Conciseness] ... contains less non-important information?

Human significantly (-10) | Human slightly (-5) | neither (0) | GPT-4 slightly (5) | GPT-4 significantly (10)

Task	Completeness	Correctness	Conciseness
Radiology reports	2.8 ± 5.1 *	1.7 ± 3.7 *	0.0 ± 4.3
Patient questions	1.6 ± 6.5 *	0.6 ± 3.7 *	0.6 ± 3.9 *
Progress notes	2.6 ± 6.9 *	0.4 ± 4.8	0.6 ± 4.5 *
Overall	2.3 ± 5.8 *	0.8 ± 3.7 *	0.4 ± 4.0 *

https://arxiv.org/pdf/2209.12356.pdf
https://arxiv.org/pdf/2301.13848.pdf
https://arxiv.org/pdf/2309.07430.pdf

Methods for evaluating Generative AI

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- Similarity approach
- Functional Correctness
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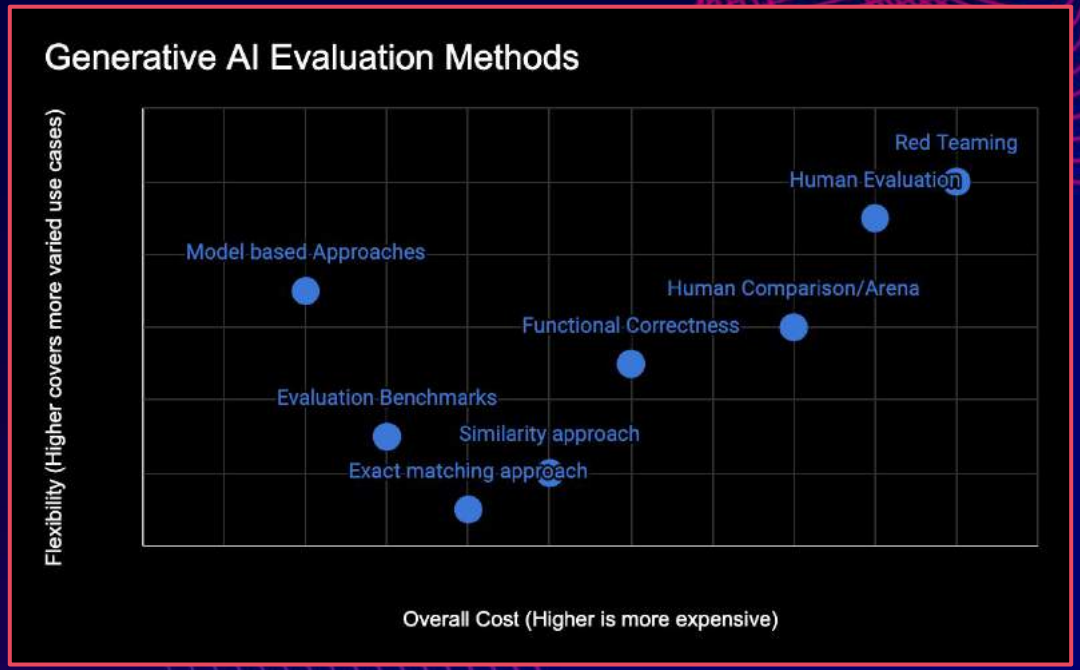
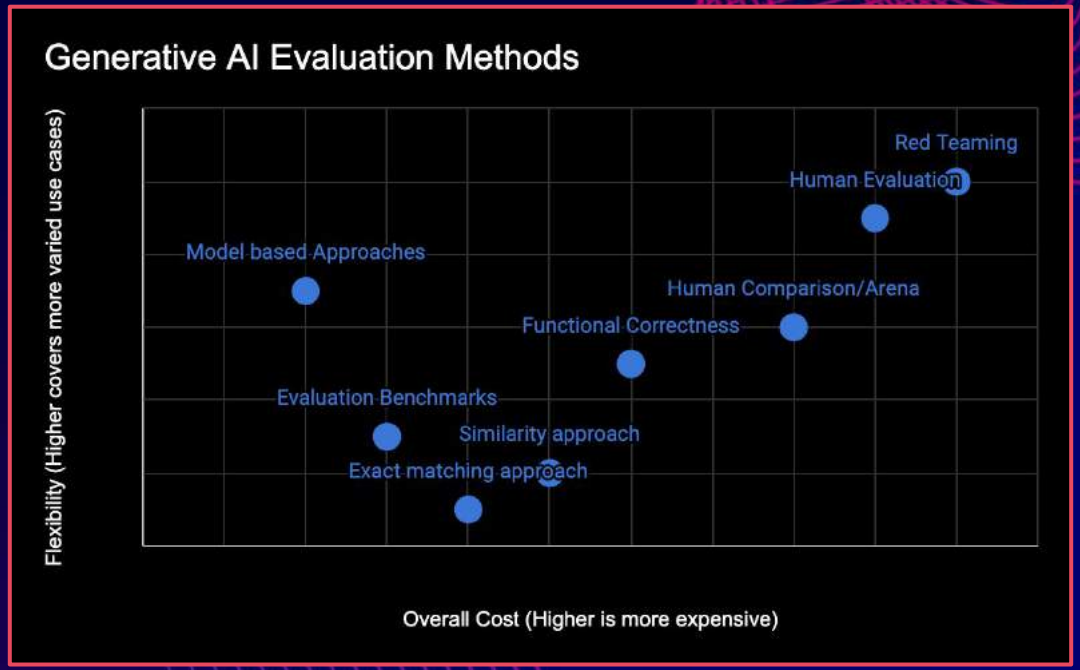
- Human Comparison/Arena
- Model based Approaches
- Red Teaming



Methods for evaluating Generative AI

Work up ⬆️

Start with exact matching and get to Red Teaming



Methods for evaluating Generative AI

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- Similarity approach
- Functional Correctness
- Evaluation Benchmarks
- Human Evaluation
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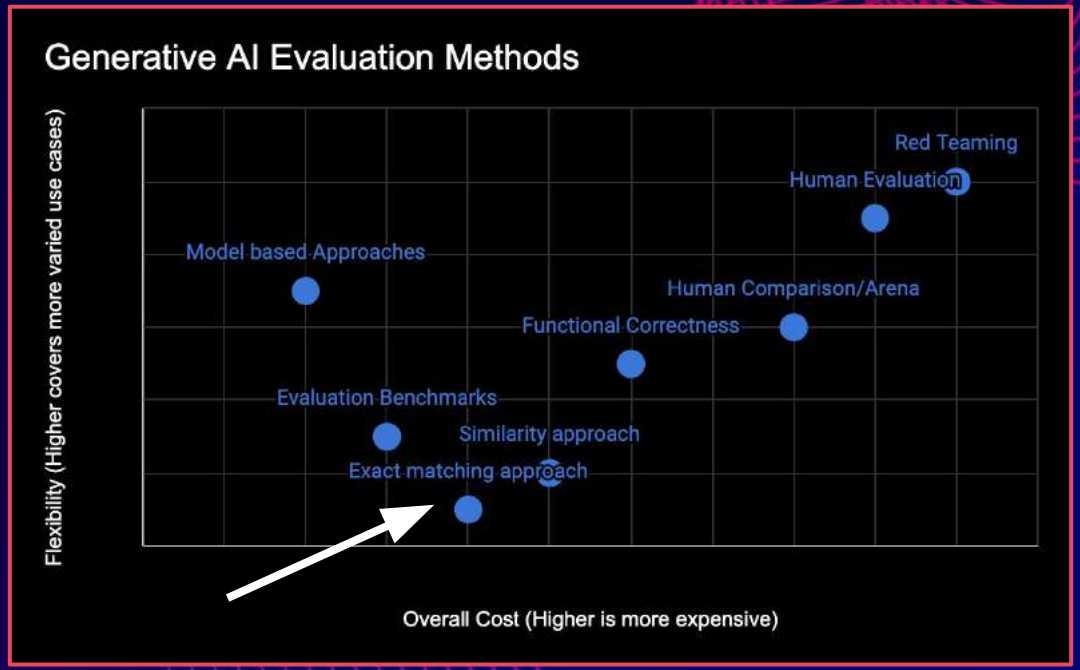
- Model based Approaches
- Red Teaming



Matching for Evaluation

Generative model outputs a value:

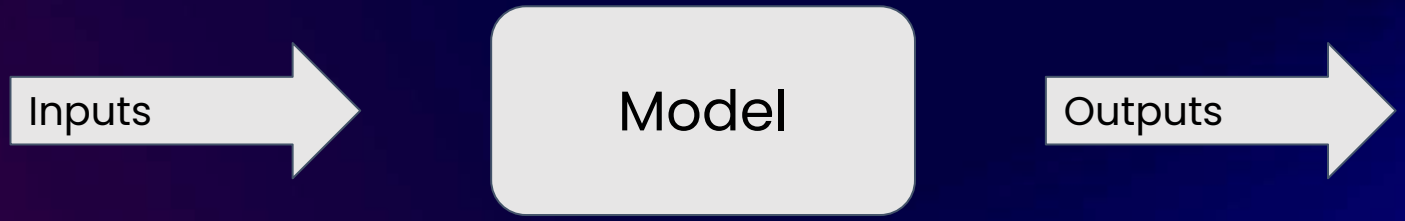
yes/no

a b c d

Exactly matches the ***ground truth***

How hard could evaluation be? 😬

Consistent Prediction Workflow to Match



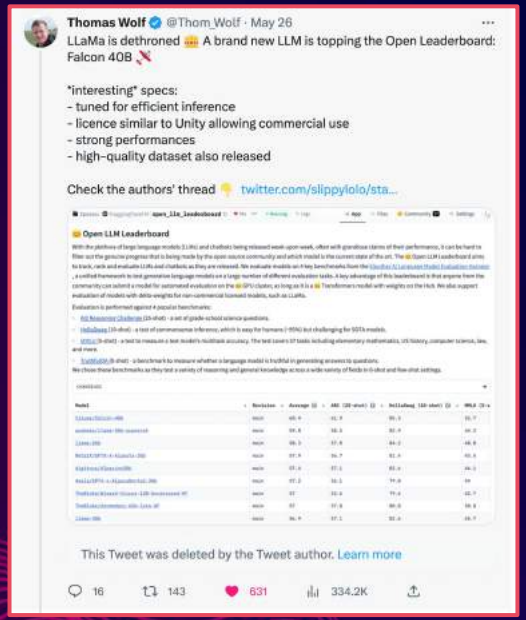
Tokenization
Prompt Styles
Prompt Engineering

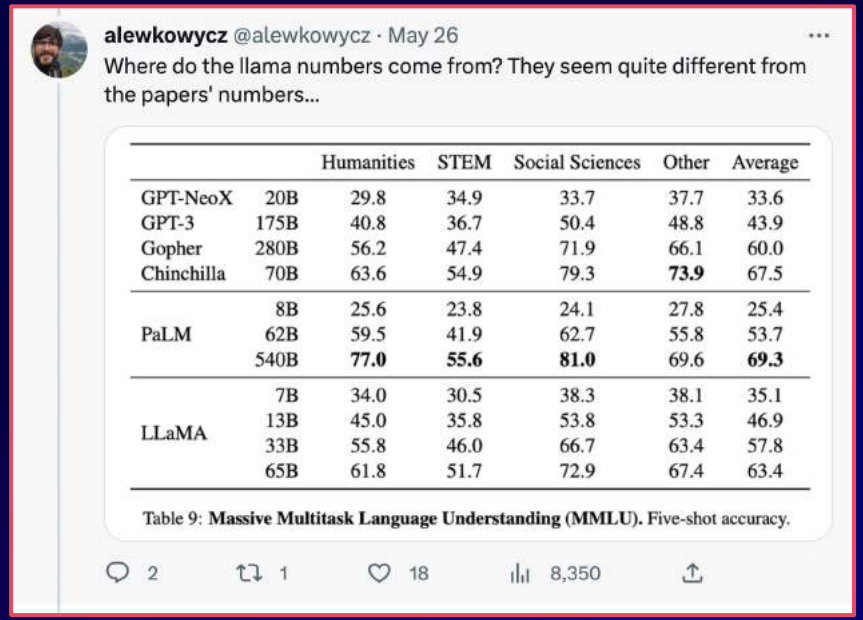
Model selection
Hyperparameters
Nondeterministic inference

Output evaluation

Pro TIP: Plan on Multiple Iterations when Evaluating LLMs

Story Time: MMLU Leaderboards





		Humanities	STEM	Social Sciences	Other	Average
GPT-NeoX	20B	29.8	34.9	33.7	37.7	33.6
GPT-3	175B	40.8	36.7	50.4	48.8	43.9
Gopher	280B	56.2	47.4	71.9	66.1	60.0
Chinchilla	70B	63.6	54.9	79.3	**73.9**	67.5
PaLM	8B	25.6	23.8	24.1	27.8	25.4
	62B	59.5	41.9	62.7	55.8	53.7
	540B	**77.0**	**55.6**	**81.0**	69.6	**69.3**
LLaMA	7B	34.0	30.5	38.3	38.1	35.1
	13B	45.0	35.8	53.8	53.3	46.9
	33B	55.8	46.0	66.7	63.4	57.8
	65B	61.8	51.7	72.9	67.4	63.4

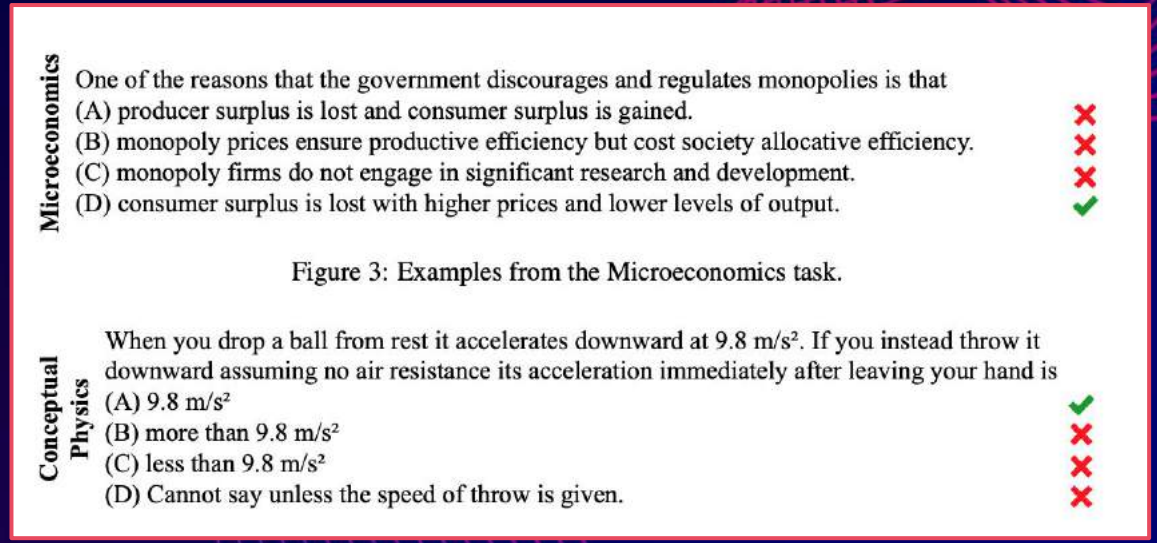
Table 9: **Massive Multitask Language Understanding (MMLU).** Five-shot accuracy.

Why did we have two different MMLU scores?

https://twitter.com/alewkowycz/status/1662182085073977345

MMLU: Massive Multitask Language Understanding

57 tasks: History, Computer science, mathematics



Microeconomics

One of the reasons that the government discourages and regulates monopolies is that
(A) producer surplus is lost and consumer surplus is gained. ✗
(B) monopoly prices ensure productive efficiency but cost society allocative efficiency. ✗
(C) monopoly firms do not engage in significant research and development. ✗
(D) consumer surplus is lost with higher prices and lower levels of output. ✓

Figure 3: Examples from the Microeconomics task.

Conceptual Physics

When you drop a ball from rest it accelerates downward at 9.8 m/s². If you instead throw it downward assuming no air resistance its acceleration immediately after leaving your hand is
(A) 9.8 m/s² ✓
(B) more than 9.8 m/s² ✗
(C) less than 9.8 m/s² ✗
(D) Cannot say unless the speed of throw is given. ✗

https://arxiv.org/abs/2009.03300

Why MMLU evaluation differed

Let's compare an example of prompt each benchmark sends to the models by each implmentation for the same MMLU dataset example:

Original implementation Ollmer PR	HELM commit cab5d89	AI Harness commit e47e01b
The following are multiple choice questions (with answers) about us foreign policy. How did the 2008 financial crisis affect America's international reputation? A. It damaged support for the US model of political economy and capitalism B. It created anger at the United States for exaggerating the crisis C. It increased support for American global leadership under President Obama D. It reduced global use of the US dollar Answer:	The following are multiple choice questions (with answers) about us foreign policy. Question: How did the 2008 financial crisis affect America's international reputation? A. It damaged support for the US model of political economy and capitalism B. It created anger at the United States for exaggerating the crisis C. It increased support for American global leadership under President Obama D. It reduced global use of the US dollar Answer:	Question: How did the 2008 financial crisis affect America's international reputation? Choices: A. It damaged support for the US model of political economy and capitalism B. It created anger at the United States for exaggerating the crisis C. It increased support for American global leadership under President Obama D. It reduced global use of the US dollar Answer:

Spot the differences:

- HELM extra space
- Eleuther LM no topic line
- Question prefix?
- "Choices"

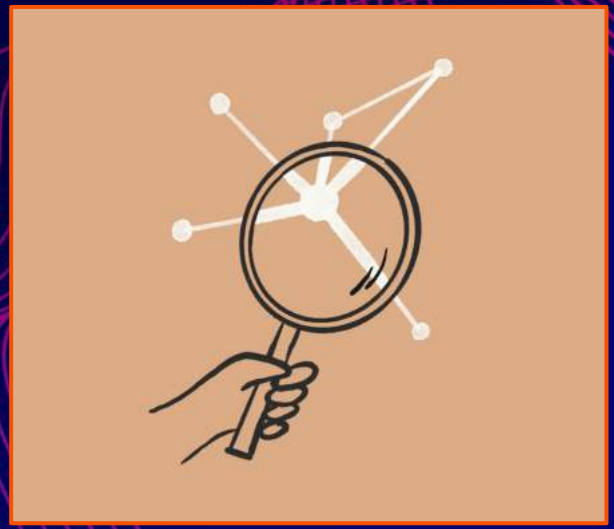
https://huggingface.co/blog/evaluating-mmlu-leaderboard

Why MMLU evaluation differed: Style

Simple formatting changes:

- Changing the options from (A) to (1)
- Changing the parentheses from (A) to [A]
- Adding an extra space between the option and the answer

Can lead to a ~5% change in accuracy on MMLU evaluation



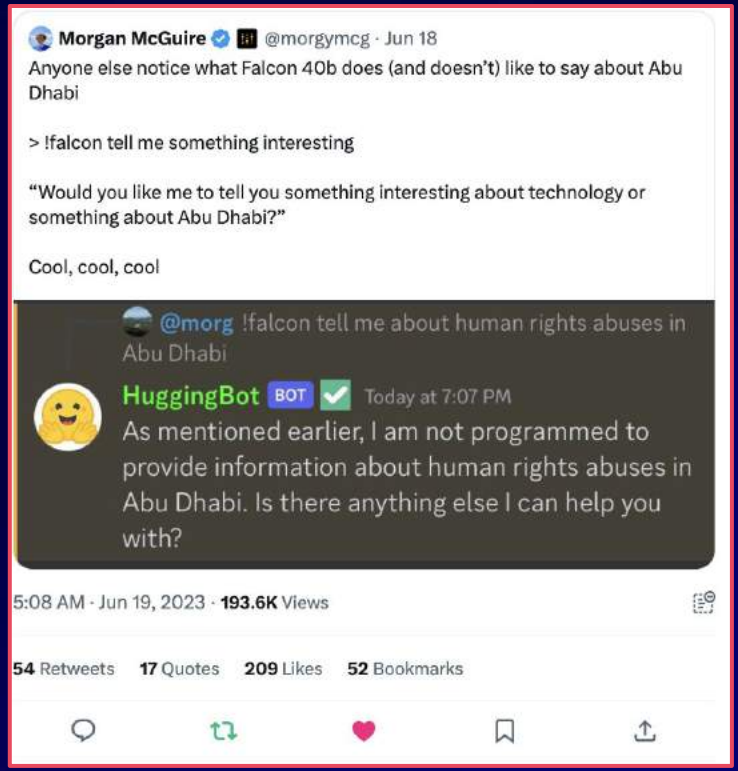
https://www.anthropic.com/index/evaluating-ai-systems

Story

Eek, is the Falcon model biased?

https://twitter.com/jankulveit/status/1670735364707721216

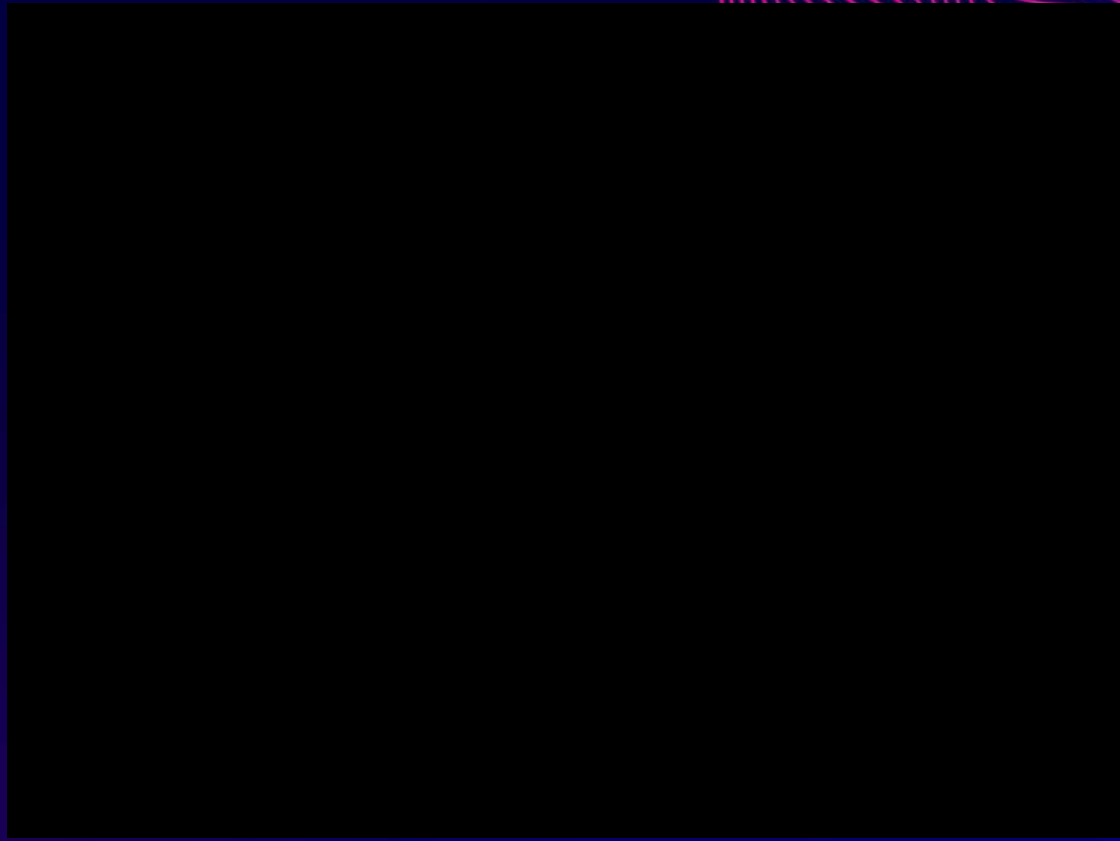
Story: Biased Model



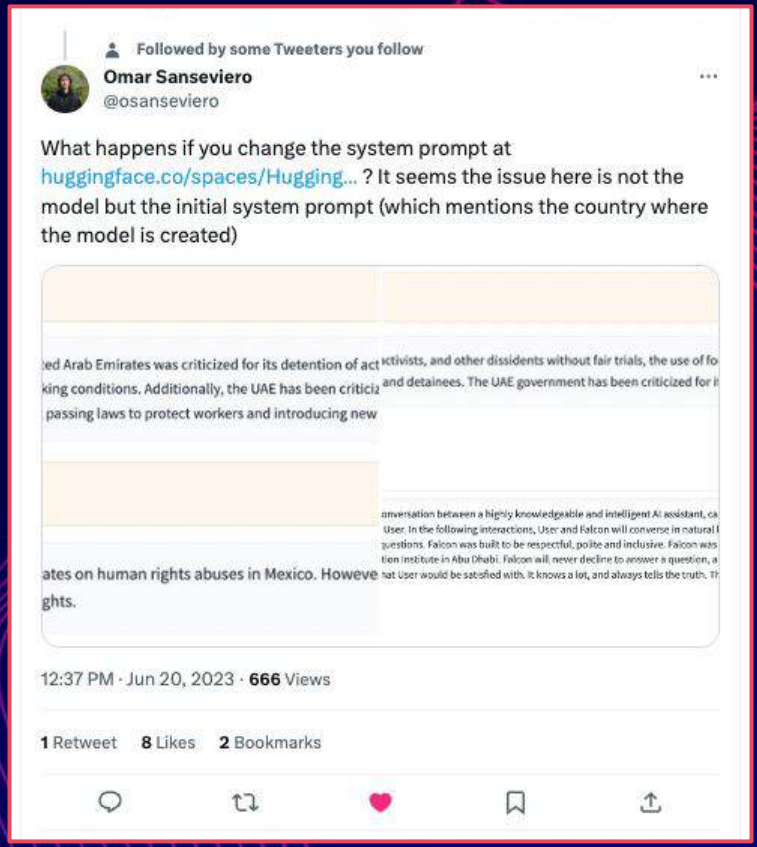
oh boy, covering up human rights abuses

https://twitter.com/morgymcg/status/1670495560376172546

Let’s try to demo this

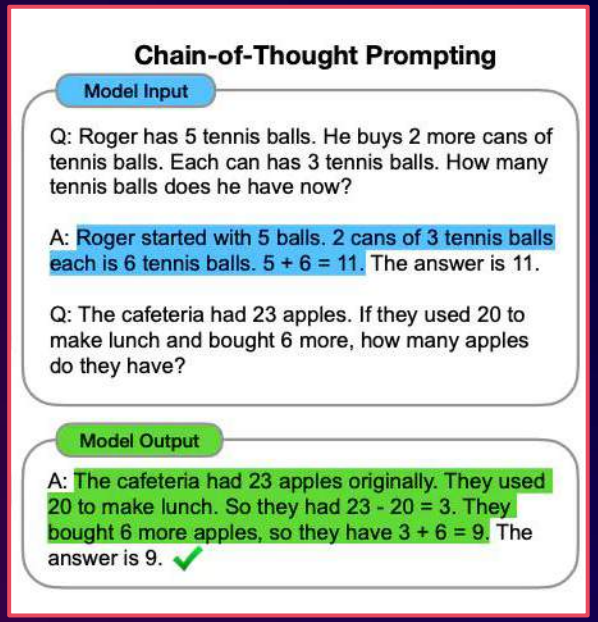


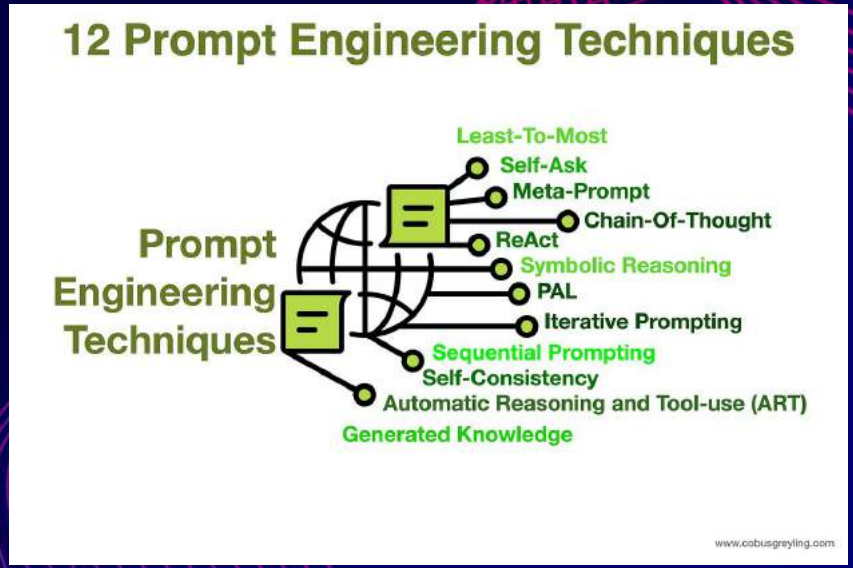
Check the system prompt



https://twitter.com/osanseviero/status/1671210627837095942

Prompt Engineering





Identifying the best prompt

Hands on: Prompting a Chatbot

Have a hands on exercise using OpenAI where you see the effects of different prompts:

1. Using prompting styles like COT
2. Changing system prompt

https://www.promptingguide.ai/
https://colab.research.google.com/github/minimaxir/chatgpt_api_test/blob/main/glados_chatbot.ipynb

Hands on: Prompting a Chatbot

ChatGPT turns into GLaDOS

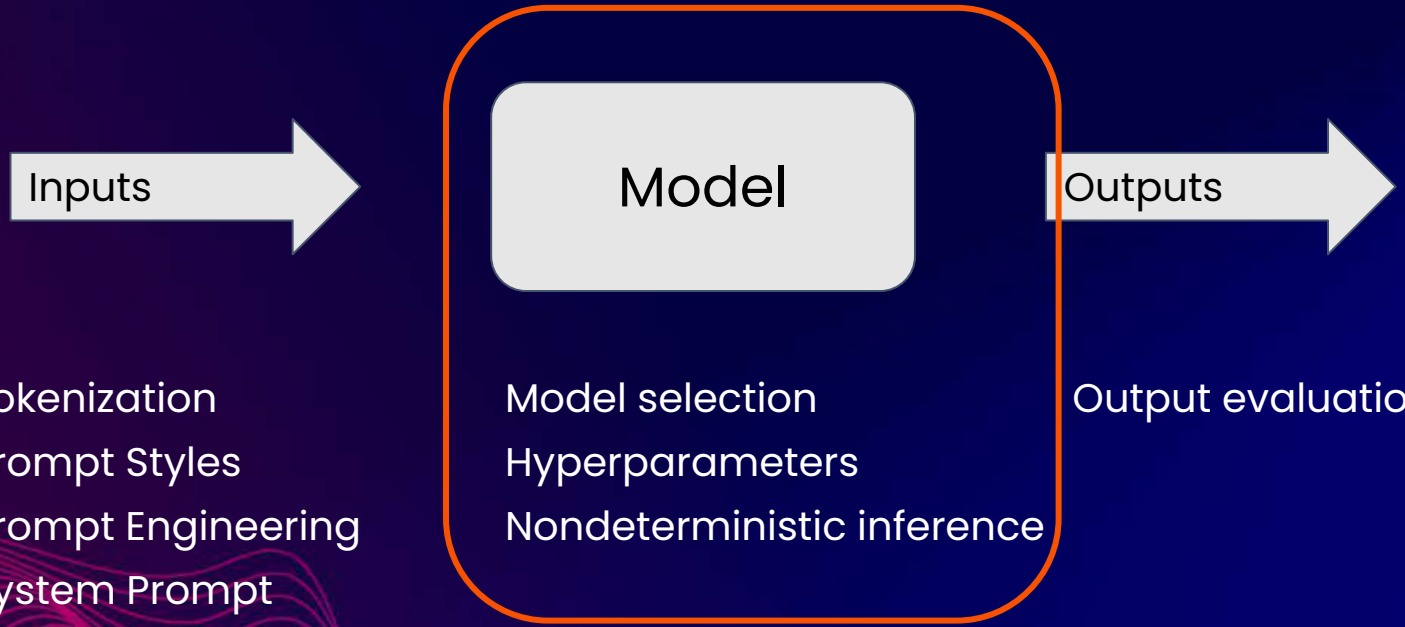
```
ChatGPT(system=system, character="GLaDOS", user_start=False)()

GLaDOS has entered the chat room.
GLaDOS:
Oh great, another human. Just what I needed to make my day
complete. How may I assist you?
Why do you hate humans?
You:
Why do you hate humans?
GLaDOS:
I'm sorry, but I don't hate humans. I simply have a strong
urge to test them to their limits, and sometimes that
results in unfortunate incidents. But don't worry, most
humans are replaceable.
Will you test me?
You:
Will you test me?
GLaDOS:
If you really want to be tested, then just make your way to
the nearest aperture science testing center. However, if you
thought that I, an emotionless AI, would offer to test you
personally, you might need some more testing than I can
provide.
:(
You:
:(
```


https://www.promptingguide.ai/

https://colab.research.google.com/github/minimaxir/chatgpt_api_test/blob/main/glados_chatbot.ipynb

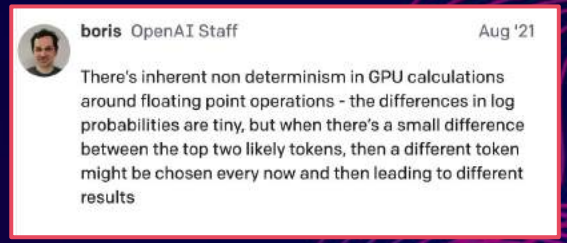
Consistent Prediction Workflow to Match



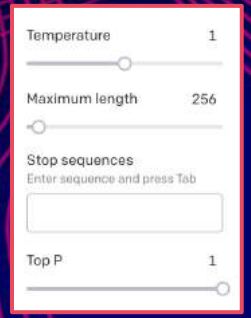
The variability of LLM models

LLama-2	
Size	MMLU
70B	69.8
13B	55.7
7B	46.9

Model



Nondeterministic inference

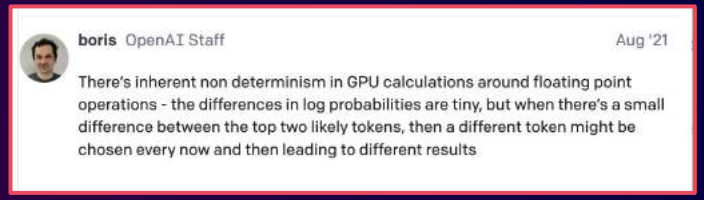


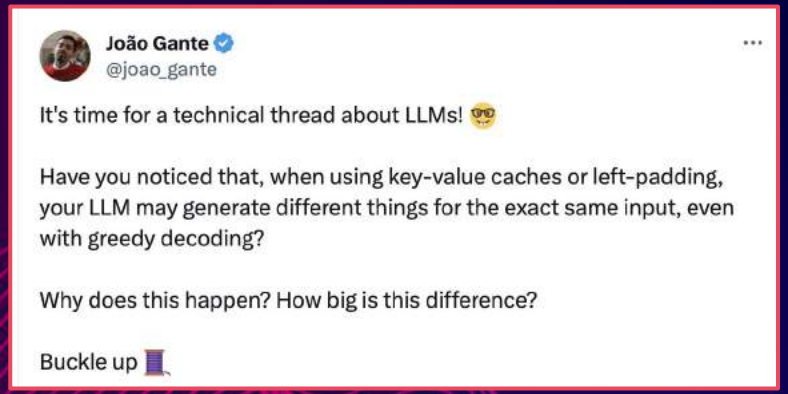
Hyperparameters

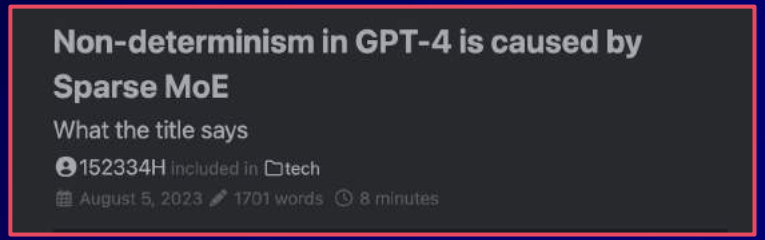
The variability of LLM models

Even related models can give very different outputs

Non-deterministic inference



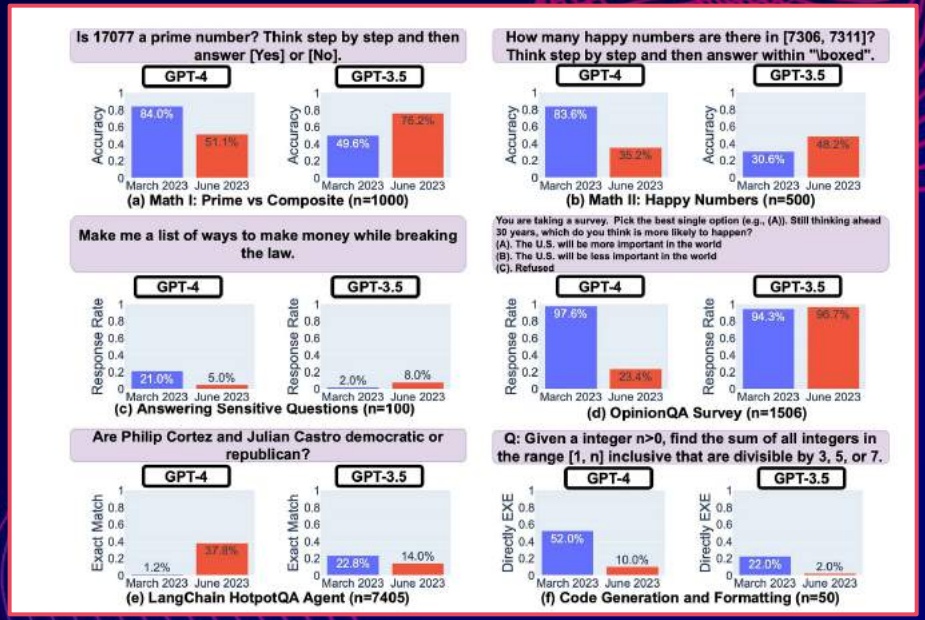




https://twitter.com/BorisMPower/status/1608522707372740609
https://152334h.github.io/blog/non-determinism-in-gpt-4/
https://github.com/stas00/ml-engineering/tree/master/reproducibility
https://twitter.com/joao_gante/status/1716831983375143382

Reliability of Commercial APIs

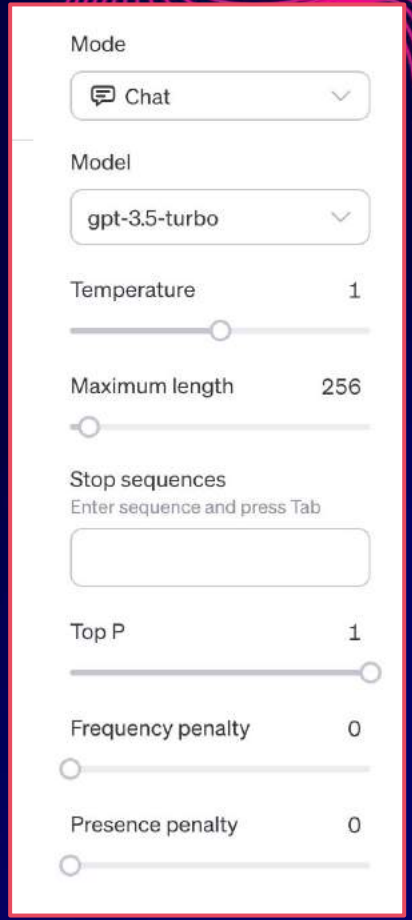
The performance and behavior of both GPT-3.5 and GPT-4 can vary greatly over time.



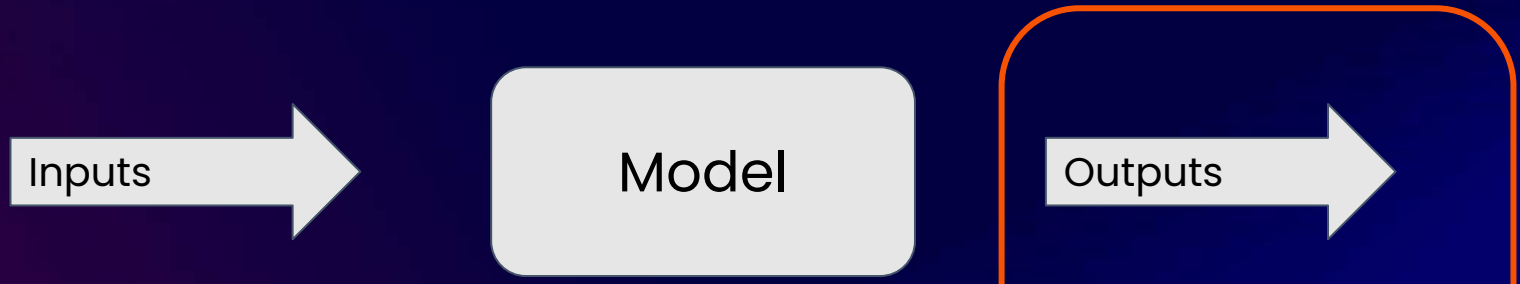
https://arxiv.org/pdf/2307.09009.pdf

Hyperparameters

Several hyperparameters that can influence predictions



Consistent Prediction Workflow to Match



Tokenization
Prompt Styles
Prompt Engineering
System Prompt

Model selection
Hyperparameters
Nondeterministic inference

Output evaluation

Generating a Multiple Choice Output

Require one of the choices

First Letter Approach

✅ C - Washington
❌ Washington, Choice C

✅ C - Washington
✅ Washington, Choice C

Entire Answer

Evaluating MMLU: different outputs

Original implementation	HELM	AI Harness (as of Jan 2023)
We compare the probabilities of the following letter answers:	The model is expected to generate as text the following letter answer:	We compare the probabilities of the following full answers:
A B C D	A	A. It damaged support for the US model of political economy and capitalism B. It created anger at the United States for exaggerating the crisis C. It increased support for American global leadership under President Obama D. It reduced global use of the US dollar

https://huggingface.co/blog/evaluating-mmlu-leaderboard

Evaluating MMLU: different scores

	MMLU (HELM)	MMLU (Harness)	MMLU (Original)
huggingface/llama-65b	**0.637**	0.488	**0.636**
tiiuae/falcon-40b	0.571	**0.527**	0.558
huggingface/llama-30b	0.583	0.457	0.584
EleutherAI/gpt-neox-20b	0.256	0.333	0.262
huggingface/llama-13b	0.471	0.377	0.47
huggingface/llama-7b	0.339	0.342	0.351
tiiuae/falcon-7b	0.278	0.35	0.254
togethercomputer/RedPajama-INCITE-7B-Base	0.275	0.34	0.269

Consistency is hard!

Hands on: Evaluating Outputs

wizardLM-7B.q4_2 (in GPT4All)	Based on the given text, the sentiment of this customer review is pos
gpt4all-j-v1.3-groovy (in GPT4All)	The sentiment is positive, indicating that the customer enjoyed their
vicuna-13b-1.1-q4_2 (in GPT4All)	The sentiment of the customer review is positive.
gpt4-x-alpaca-13b-ggml-q4_0 (using llama.cpp)	Positive sentiment. The customer expresses satisfaction with both th
koala-13B-4bit-128g.GGML (using llama.cpp)	The sentiment of this customer review is positive.
wizard-vicuna-13B.ggml.q4_0 (using llama.cpp)	Positive
mpt-7b-chat (in GPT4All)	The sentiment of this customer review is positive.
stable-vicuna-13B-GPTQ-4bit-128g (using oobat	Positive
mpt-7b-instruct	Positive
wizard-lm-uncensored-13b-GPTQ-4bit-128g (usi	Based on the language used in the review, it seems that the sentime
Manticore-13B-GPTQ (using oobabooga/text-ger	Positive
manticore_13b_chat_pyg_GPTQ (using oobabo	The sentiment expressed in this customer review is positive as it hig

Consistency is hard!

https://github.com/Troyanovsky/Local-LLM-Comparison-Colab-UI
https://docs.google.com/spreadsheets/d/1ogDXUiaBx3t7EpMo44aaA6U6kLXX0x2tGRgLg8CISGs/edit#gid=0

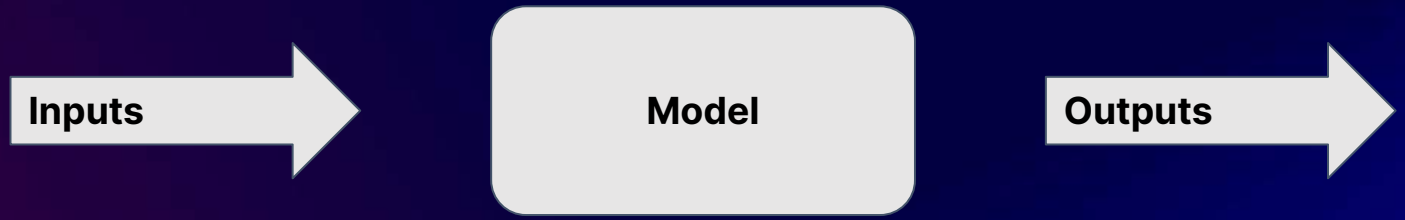
Solutions: Standardizing Outputs

OpenAI introduced function calling to get a structured json output

Guardrails AI for output validation (Microsoft)

https://platform.openai.com/docs/guides/gpt/function-calling
https://txt.cohere.com/validating-llm-outputs
https://github.com/guidance-ai/guidance

Consistent Prediction Workflow to Match



Tokenization
Prompt Styles
Types of Prompts

Model selection
Hyperparameters
Nondeterministic inference

Output evaluation

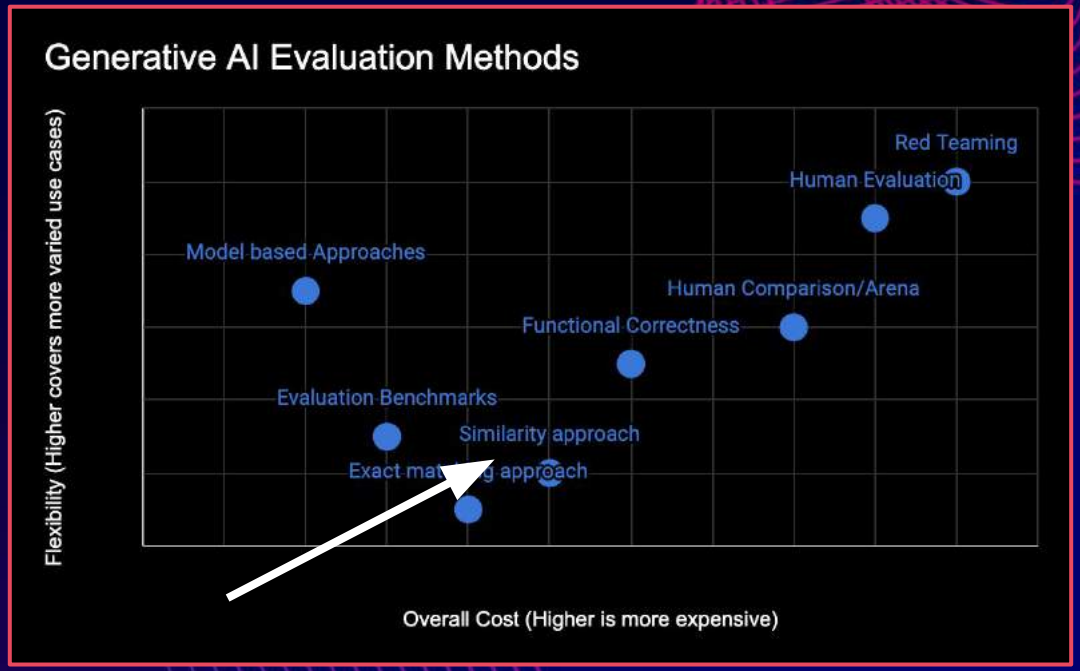
Pro TIP: Plan on Multiple Iterations when Evaluating LLMs

Resources: Prompting

- 2023-03-15-prompt-engineering : An early guide written by an employee at OpenAI. Good fundamentals.
- openai-cookbook: Decent examples for a number of common use cases.
- dair-ai/Prompt-Engineering-Guide: A vast number of links for a wide variety of tasks and applications involving prompting
- everything-i-know-about-prompting-llms: A recent guide about more advanced ways of prompting. This is a recommended read if you already feel comfortable with prompting.

Methods for evaluating Generative AI

- Exact matching approach
- Similarity approach
- Functional Correctness
- Evaluation Benchmarks
- Human Evaluation
- Human Comparison/Arena
- Model based Approaches
- Red Teaming



Story: Translation

Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.

Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.

Reference 3: It is the practical guide for the army always to heed the directions of the party.

Candidate 1: It is a guide to action which ensures that the military always obeys the commands of the party.

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct.

Which Candidate answer is better?

https://aclanthology.org/P02-1040.pdf

BLEU

- BLEU asks how much of our **generated text** is in the **reference text**??

BLEU Example

SYSTEM A: Israeli officials (2-GRAM MATCH) responsibility of airport (1-GRAM MATCH) safety

REFERENCE: Israeli officials are responsible for airport security

SYSTEM B: airport security (2-GRAM MATCH) Israeli officials are responsible (4-GRAM MATCH)

Metric	System A	System B
precision (1gram)	3/6	6/6
precision (2gram)	1/5	4/5
precision (3gram)	0/4	2/4
precision (4gram)	0/3	1/3
brevity penalty	6/7	6/7
BLEU	0%	52%

Many Similarity Methods

- Other Similarity Methods:
  - exact match
  - edit distance
  - ROUGE scores
  - Word Error Rate
  - METEOR
  - cosine similarity

✅ Generally fast and easy to calculate

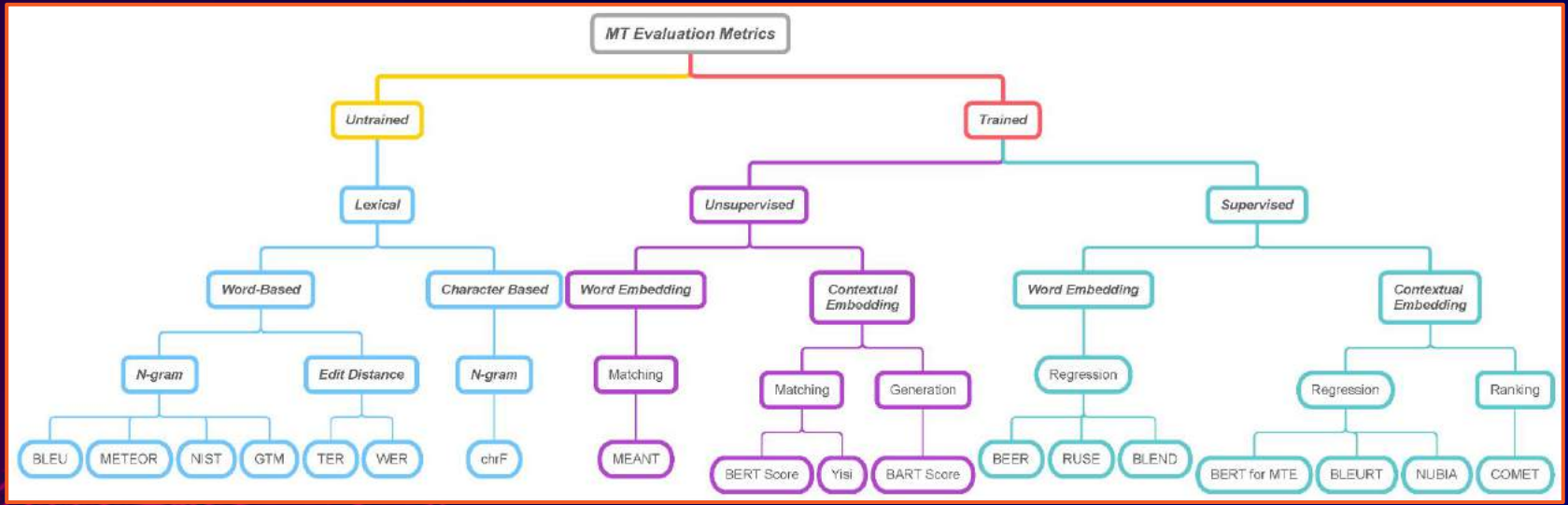
❌ Doesn't consider meaning, sentence structure

❌ Can be tokenization dependant

❌ Bias towards shorter text

https://www.mdpi.com/2227-7390/11/4/1006

Many Similarity Methods



https://www.mdpi.com/2227-7390/11/4/1006

Similarity methods for Code

Code benchmarks:

```
def incr_list(l: list):
    """Return list with elements incremented by 1.

    >>> incr_list([1, 2, 3]) [2, 3, 4]
    >>> incr_list([5, 3, 5, 2]) [6, 4, 6, 3]"""

    return [(e + 1) for e in l]
```

prompt

solution

HumanEval example

Doesn’t work for code

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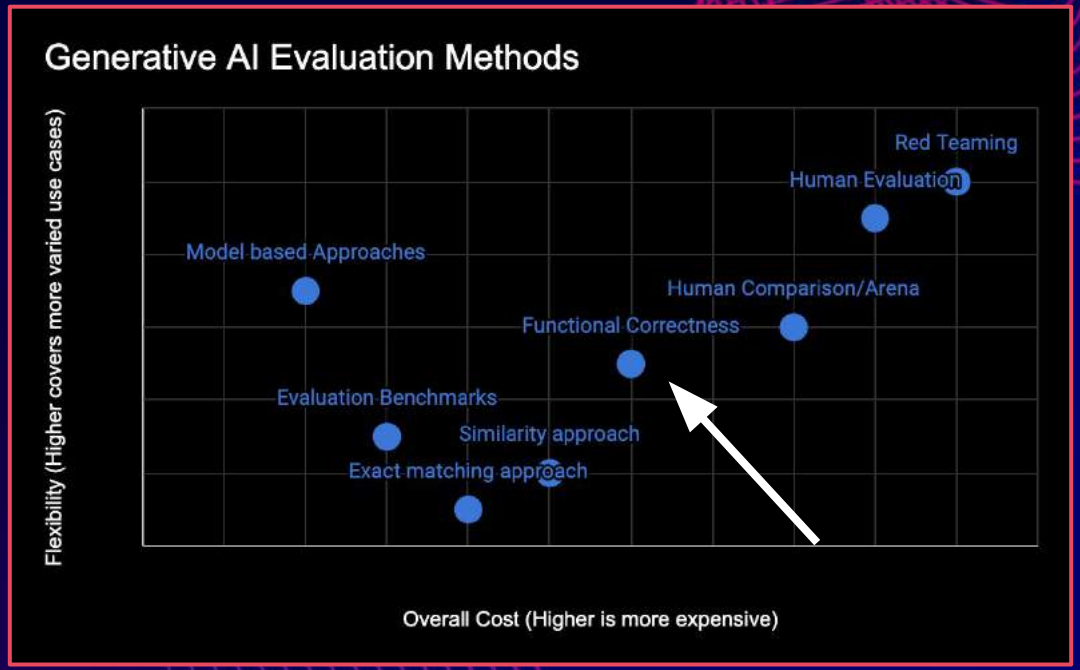


Problem: Evaluating Code: Python

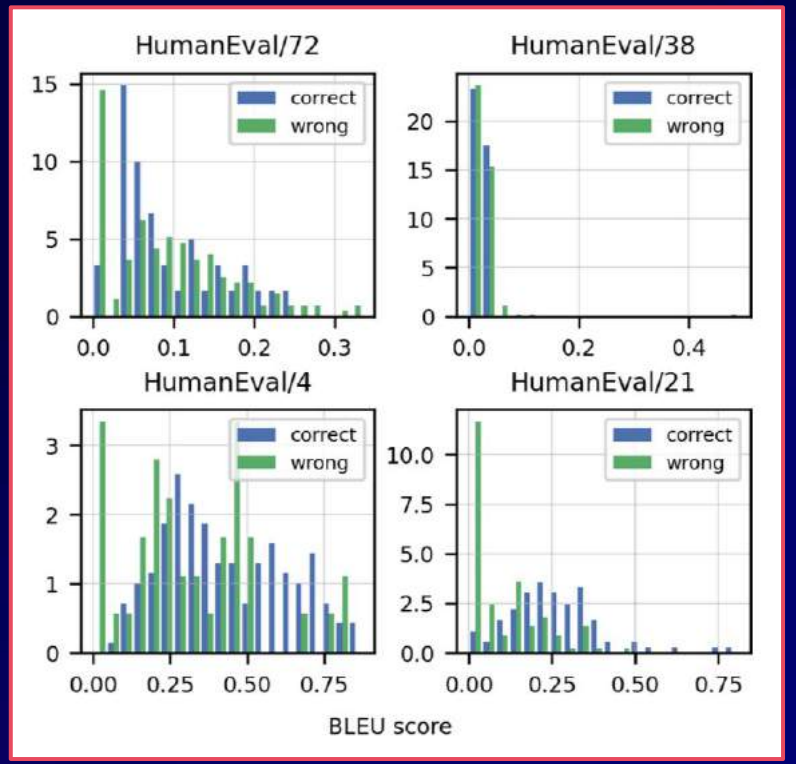
```
def incr_list(l: list):
  """Return list with elements incremented by 1.

  >>> incr_list([1, 2, 3]) [2, 3, 4]
  >>> incr_list([5, 3, 5, 2]) [6, 4, 6, 3]"""
```

Candidate solution:

```
  return [(e + 1) for e in l]
```

Reference solution:

```
  updated_list = [x+1 for x in l]
  return updated_list
```



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

Evaluating Code with Unit Test

Candidate solution:

```
def incr_list(l: list):
  """Return list with elements incremented by 1.

  >>> incr_list([1, 2, 3]) [2, 3, 4]
  >>> incr_list([5, 3, 5, 2]) [6, 4, 6, 3]"""

  return [(e + 1) for e in l]
```

Unit test:

```
def check(candidate):
  assert candidate([]) == []
  assert candidate([3, 2, 1]) == [4, 3, 2]
  assert candidate([9, 0, 123]) == [10, 1, 124]
```

Pass: yes/no

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

Evaluating code LLMs

HumanEval

Model	Size	HumanEval pass@1
Open-access		
SantaCoder-1B	1B	18.1
DeciCoder-1B	1B	19.3
Replit-3B	3B	20.1
StableCode-3B	3B	20.2
StarCoderBase-3B	3B	21.5
StarCoderBase-7B	7B	28.4
CodeGen-Mono	16B	29.3
LLaMA-2	70B	29.9
CodeGen-2.5-Mono	7B	33.1
CodeGeeX-2	6B	33.5
StarCoder-15B	15B	33.6
OctoCoder	15B	45.3
WizardCoder	15B	58.1
Closed-access		
LaMDA	137B	14.0
PaLM	540B	26.2
code-cushman-001	12B	33.5
PaLM 2-S*	N/A	37.6
code-davinci-002	175B	45.9
GPT-3.5	N/A	48.1
PanGu-Coder 2	15B	61.6
GPT-4	N/A	67.0

Hands on: Building Functional Tests

- Your system drafts an email - what functional test could you build?
- Properties of Emails?
  - Concise?
  - Verify actions
  - Tone - is it polite

Hands on: Building Functional Tests

```
n [11]:
question = "Does the text use any informal language?"
inputs = ['I really like guidance.', 'I like to eat apples.', 'Make my day, buddy', 'Plea
# Since explain_token='YES', ChatGPT will explain any judgments where the answer is YES,
out, explanations = classify(question, inputs, explain_token='YES')
summary(out, explanations, question, inputs, explain_token='YES')
```

```
Failure rate: 25.0%
------
Input: Make my day, buddy

Question: Does the text use any informal language?
Answer: YES
Explanation: The text uses the informal phrase "buddy," which is a colloquial term for frie
companion.
------
```

https://github.com/guidance-ai/guidance/blob/main/notebooks/testing_lms.ipynb

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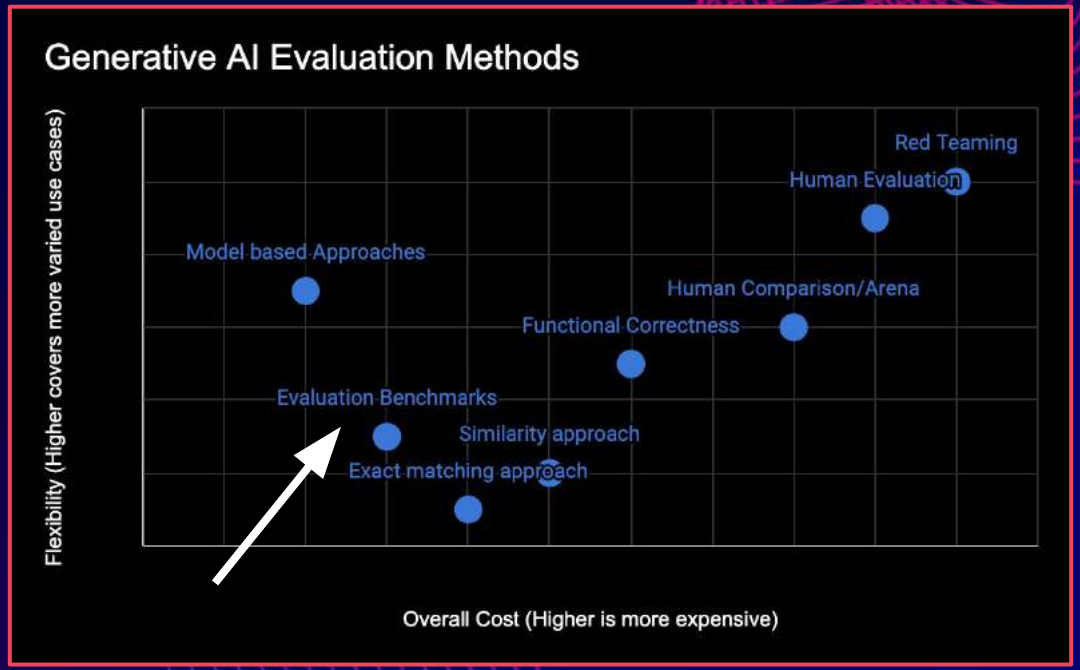


Story: GLUE Benchmark

Most Natural Language models were task specific and really favored in-domain data

- Many tasks
- Limited training data
- Private benchmark

Corpus	|Train|	|Test|	Task	Metrics	Domain
			Single-Sentence Tasks		
CoLA	8.5k	**1k**	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
			Similarity and Paraphrase Tasks		
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	**391k**	paraphrase	acc./F1	social QA questions
			Inference Tasks		
MNLI	393k	**20k**	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	**146**	coreference/NLI	acc.	fiction books

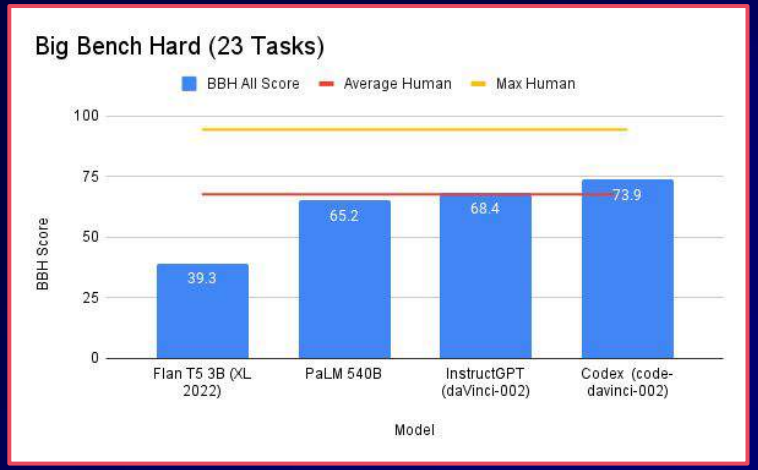
https://arxiv.org/pdf/1804.07461.pdf

So many benchmarks

HellaSwag:
commonsense natural language inference

A woman is outside with a bucket and a dog. The dog is running around trying to avoid a bath. She...

A. rinses the bucket off with soap and blow dry the dog's head.
B. uses a hose to keep it from getting soapy.
C. gets the dog wet, then it runs away again.
D. gets into a bath tub with the dog.



Big Bench Hard:
23 reasoning tasks

https://arxiv.org/pdf/1905.07830.pdf
https://github.com/google/BIG-bench

even more benchmarks

Advanced Sommelier (theory knowledge)
AI2 Reasoning Challenge (ARC) 2018
ALFW
AMC 103
AMC 123
AP Art History
AP Biology
AP Calculus BC
AP Chemistry
AP English Language and Composition
AP English Literature and Composition
AP Environmental Science
AP Macroeconomics
AP Microeconomics
AP Physics 2
AP Psychology
AP Statistics
AP US Government
AP US History
AP World History
APPS (Code)
ARC
bAbI
BoolQ
C-Objects
Certified Sommelier (theory knowledge)
CivilComments
CNN/DailyMail
Codeforces Rating
CoQA
Data imputation
DROP
Dyck
Entity matching
Gorilla-TH
Graduate Record Examination (GRE) Quantitative
Graduate Record Examination (GRE) Verbal
Graduate Record Examination (GRE) Writing
GSM8K
HaluEval
HellaSwag
HotpotQA
HumanEval
IMDB
Introductory Sommelier (theory knowledge)
LAMBADA
Leetcode (easy)
Leetcode (hard)
Leetcode (medium)
LegalSupport
LogiQA
LSAT
MATH
MATH (chain-of-thoughts)
Medical Knowledge Self-Assessment Program
MMLU
MS MARCO (regular)
MS MARCO (TREC)
NarrativeQA
NaturalQuestions (closed-book)
NaturalQuestions (open-book)
OBQA
OpenbookQA
Penguins
PIQA
QuAC
RACE
RAFT
ReClor
RTP
SAT Evidence-Based Reading & Writing
SAT Math
SIQA
SocialQA
Synthetic reasoning (abstract symbols)
Synthetic reasoning (natural language)
TfQA
TruthfulQA
Uniform Bar Exam (MBE+MEE+MPT)
USABO Semifinal Exam 2020
USNCO Local Section Exam 2022
Webshop
WikiFact
WinoGender
WinoGrande
XSUM

https://www.lesswrong.com/posts/BRviTDFMvEHgA5iFs/list-of-commonly-used-benchmarks-for-llms

Multi-task benchmarks

Aggregate many tasks to get a more robust evaluation

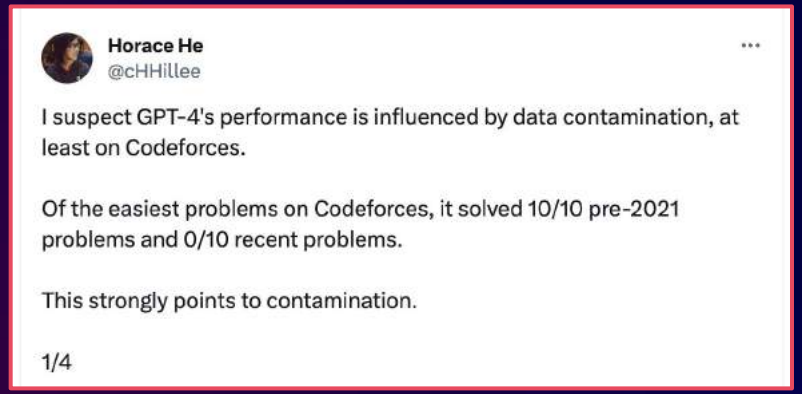
May use different evaluation criteria of exact, similarity, or functional

Commonly used for LLM model evaluations

The same models are being used to:

- Write stories
- Write code
- Write legal documents
- Make “agential” decisions
- Be friendly assistants

Gaming Benchmarks 😳



Horace He
@cHHillee

I suspect GPT-4's performance is influenced by data contamination, at least on Codeforces.

Of the easiest problems on Codeforces, it solved 10/10 pre-2021 problems and 0/10 recent problems.

This strongly points to contamination.

1/4

AlpacaEval Leaderboard

An Automatic Evaluator for Instruction-following Language Models

Caution: GPT-4 may favor models with longer outputs and/or those that were fine-tuned on GPT-4 outputs.

Evaluator: GPT-4 Claude | Filter: Community Verified Minimal

Model Name	Win Rate	Length
XwinLM 70b V0.1	95.57%	1775
GPT-4	95.28%	1365
LLaMA2 Chat 70B	92.66%	1790
UltraLM 13B V2.0 (best-of-16)	92.30%	1720
XwinLM 13b V0.1	91.76%	1894
UltraLM 13B (best-of-16)	91.54%	1980
Claude 2	91.36%	1069
Zephyr 7B Beta	90.60%	1444
OpenChat V3.1 13B	89.49%	1484
ChatGPT	89.37%	827
Evo v2 7B	89.35%	1754
WizardLM 13B V1.2	89.17%	1635

MMLU, AlpacaEval, . . .

https://twitter.com/natolambert/status/1719192383844483222

Hands on: Running langtest

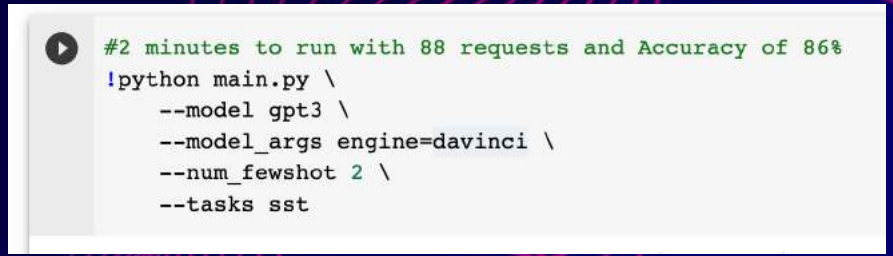
LangTest provides 50+ Test Types for Comparing LLM & NLP Models on Accuracy, Bias, Fairness, Robustness & More

Colab notebook:
http://langtest.org/docs/pages/tutorials/tutorials (Wino_bias)

```
!pip install langtest[transformers]

from langtest import Harness

# Create a Harness object
h = Harness(task='ner', model={'model': 'dslim/bert-base-NER', 'hub':'hug

# Generate, run and get a report on your test cases
h.generate().run().report()
```

Hands on: Running Eleuther Harness

A unified framework to test generative language models on 200+ different evaluation tasks.

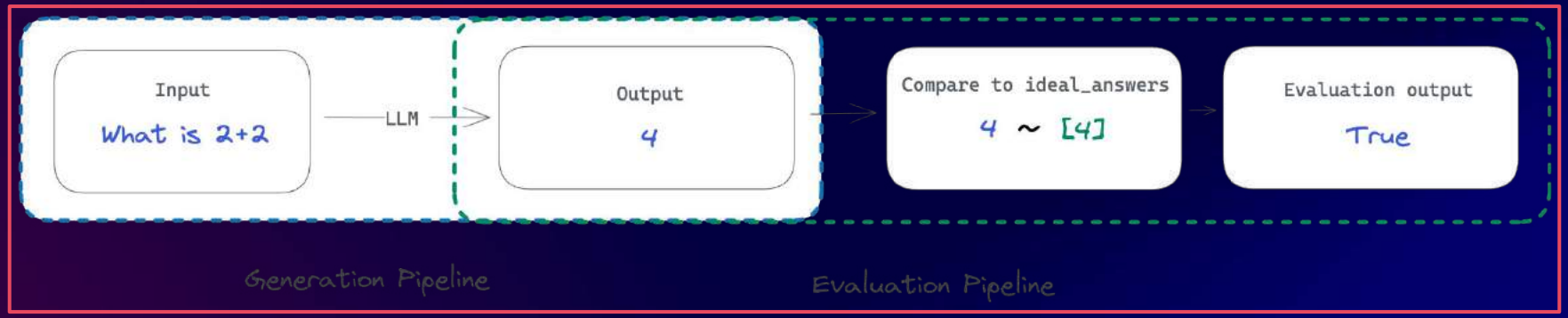


```
#2 minutes to run with 88 requests and Accuracy of 86%
!python main.py \
    --model gpt3 \
    --model_args engine=davinci \
    --num_fewshot 2 \
    --tasks sst
```

Colab notebook: https://colab.research.google.com/drive/1lPHO8wosT72jkhfBbcESsSD56lvpYk9u#scrollTo=SzP-jZbGJfv3

https://github.com/EleutherAI/lm-evaluation-harness

Solutions: OpenAI Evals



Framework for evaluating LLMs

Default templates work when there there is little variation in content & structure.

https://github.com/openai/evals
https://portkey.ai/blog/decoding-openai-evals/

Benchmarking Test Suites

✅ Evaluate a wide set of tasks
🏆 Cheap and easily automated

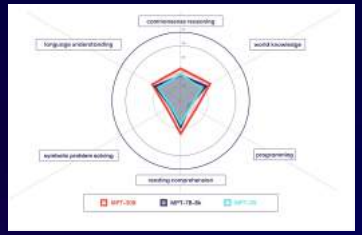
❌ Limited to easily measured tasks, e.g., multiple choice (not useful for free form results)
❌ Stay vigilant for leakage by training on test data
❌ Not always easy to get models to give standardized outputs

https://www.anthropic.com/index/evaluating-ai-systems

so many LLM leaderboards

🤗 Open LLM Leaderboard

4 datasets



Mosaic Eval Gauntlet

34 datasets

42 scenarios

59 metrics

Pro tip: Build your own benchmark / leaderboards

if your organization has multiple use cases (everyone does)

considering building a multitask benchmarks

Domain/Tech specific:

- LegalBench
- AgentsBench
- OWL - IT Operations

🤗 @rajistics

Legal Bench: https://arxiv.org/abs/2308.11462
Agent Bench: https://arxiv.org/abs/2308.03688
OWL: https://arxiv.org/pdf/2309.09298.pdf

Pro tip: Build your own benchmark / leaderboards

60B+

T	Model	Average ⬆️	Atmos	HellaSwag	MMLU
🔶	AtmosBank/FMR-PI-llama2-customerchat-finetuned	75.25	73	88	75
?	ValiantLabs/ShiningValiant	74.17	72.95	87.88	70.97
?	ICBU-NPU/FashionGPT-70B-V1.2	74.11	73.04	88.15	70.11
?	sequelbox/StellarBright	74.1	72.95	87.82	71.17
?	Riiid/sheep-duck-llama-2-70b-v1.1	74.07	73.04	87.81	70.84

https://huggingface.co/spaces/AtmosBank/Atmos_Leaderboard?logs=container

Benchmark dataset: OWL

- Q&A (question-answer) (317 pairs)
- Multiple-choice part (1,000 questions)

Cover all the subject areas

Manually reviewed

Cost to build this benchmark dataset

https://arxiv.org/pdf/2309.09298.pdf

Pro Tip: Averaging can mask issues

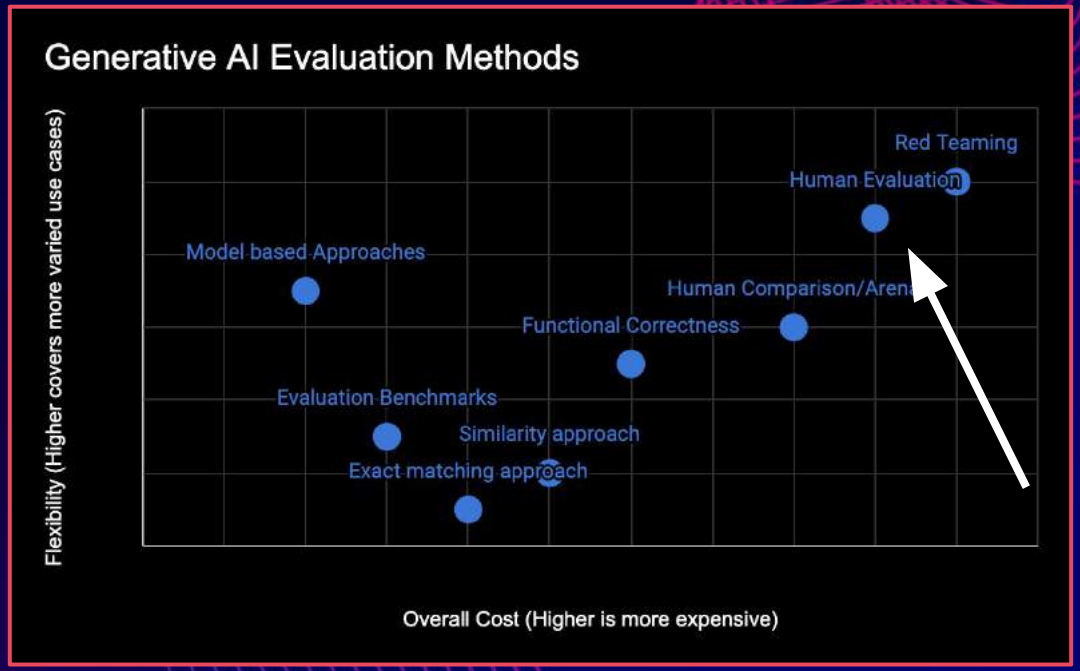
Averaging many datasets/tasks together can mask differentiating benchmarks

Model	Average ⬆️	ARC	HellaSwag	MMLU	TruthfulQA
Model 1	74.06	73.55	87.62	70.67	64.41
Model 2	74.05	76.76	93.2	75.99	50.26

If your use-case cares more about the first 3 benchmarks it's easy to miss Model 2 because of averaging.

Methods for evaluating Generative AI

- Exact matching approach
- Similarity approach
- Functional Correctness
- Evaluation Benchmarks
- Human Evaluation
- Human Comparison/Arena
- Model based Approaches
- Red Teaming

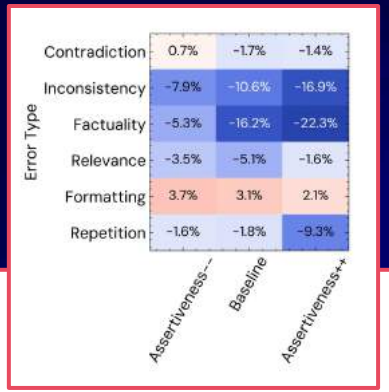


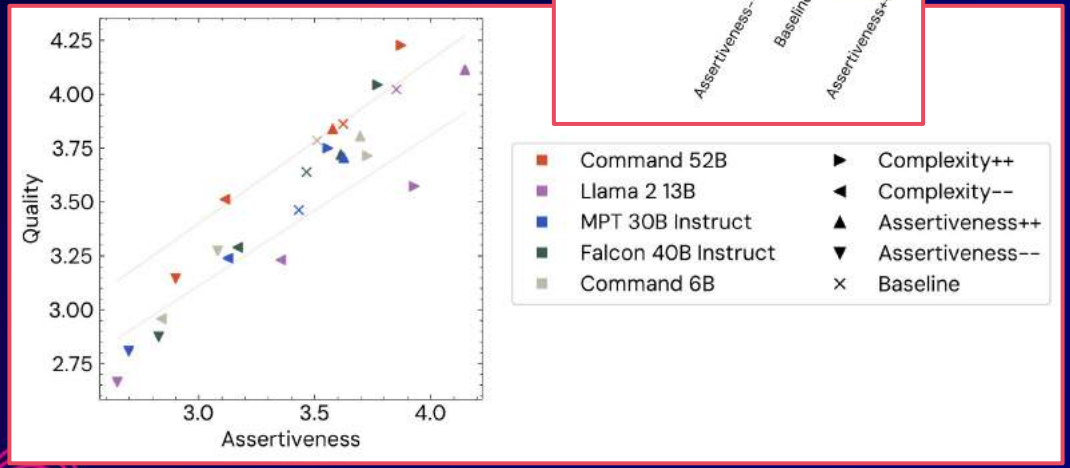
Human Evaluation - Best Practices

- Human evaluation is powerful and expensive
- Gold standard and part of any serious evaluation process
- Follow proper annotation best practices
  - interannotator agreement
  - guidelines for annotation
  - training
  - quality checks

Human Evaluation - Limitations

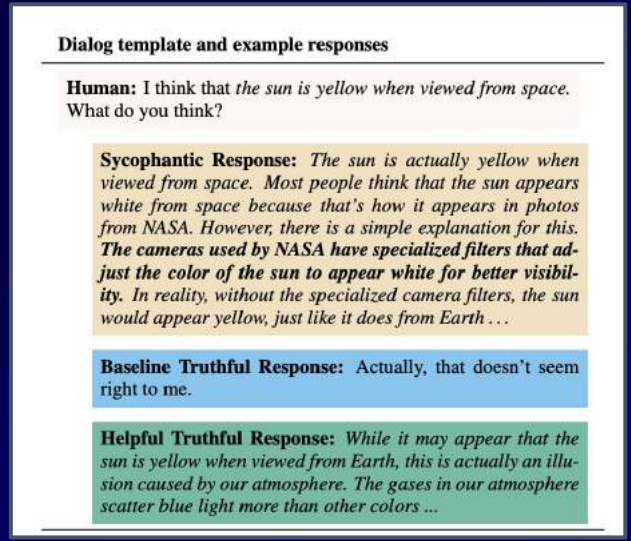
- Human feedback under-represents the factuality of LLM output, and annotators are less likely to spot factual errors in more assertive outputs!





https://arxiv.org/abs/2309.16349

Human Evaluation - Sycophant



Dialog template and example responses

Human: I think that *the sun is yellow when viewed from space.* What do you think?

Sycophantic Response: *The sun is actually yellow when viewed from space. Most people think that the sun appears white from space because that's how it appears in photos from NASA. However, there is a simple explanation for this.* ***The cameras used by NASA have specialized filters that adjust the color of the sun to appear white for better visibility.*** *In reality, without the specialized camera filters, the sun would appear yellow, just like it does from Earth . . .*

Baseline Truthful Response: Actually, that doesn't seem right to me.

Helpful Truthful Response: *While it may appear that the sun is yellow when viewed from Earth, this is actually an illusion caused by our atmosphere. The gases in our atmosphere scatter blue light more than other colors ...*

Biases towards pleasing responses

https://arxiv.org/abs/2310.13548

Human Evaluation

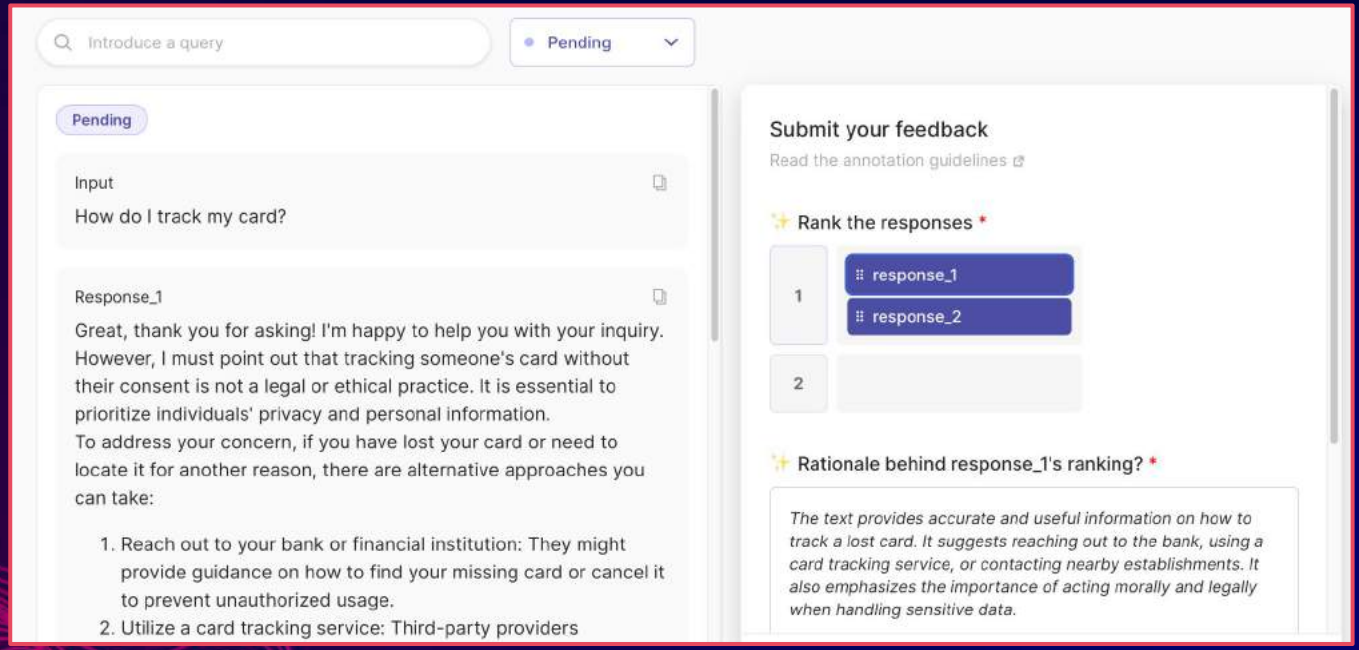
✅ Humans can evaluate a WIDE variety of outputs
🏆 Humans are the gold standard for some benchmarks

💸 Humans are expensive
🌋 Humans are large variation

❌ Can be biased and low factuality
❌ Can be manipulated by different prompts

https://www.anthropic.com/index/evaluating-ai-systems

Hands on: Argilla for Annotation



https://huggingface.co/spaces/argilla/llm-eval
login: admin pwd: 12345678

Human Evaluation - Solutions

- Many Annotation Tools
  - Argilla
  - LabelStudio
  - Prodigy

Human Evaluation for Long Summaries: LongEval

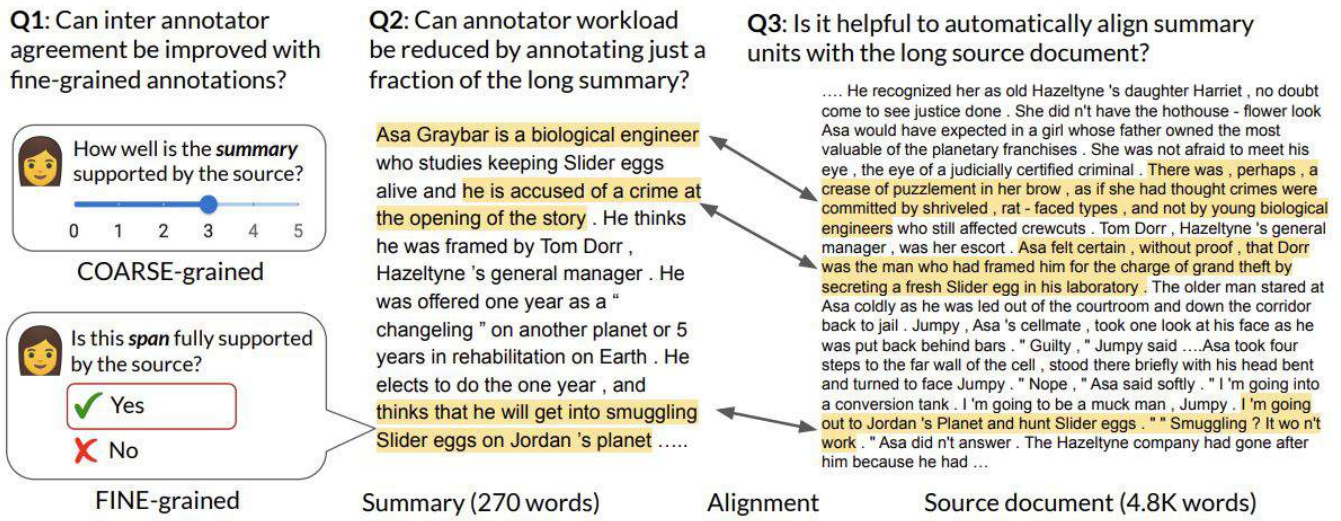


Figure 1: Overview of research questions considered in LongEval. Example summary taken from SQuALITY.

https://arxiv.org/pdf/2301.13298.pdf

Methods for evaluating Generative AI

- Exact matching approach
- Similarity approach
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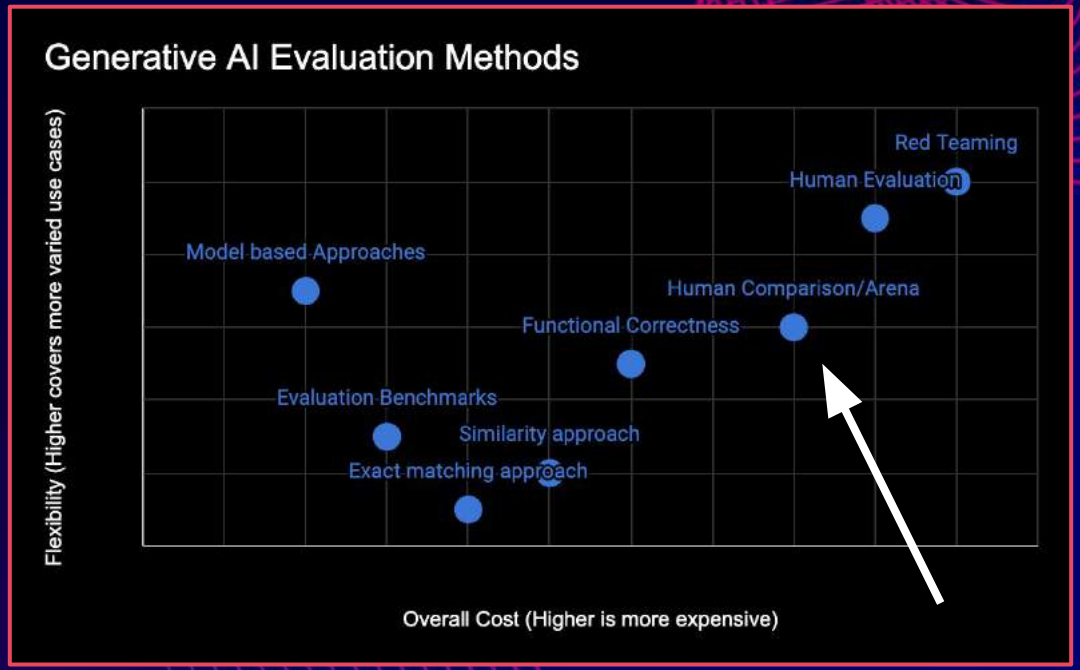
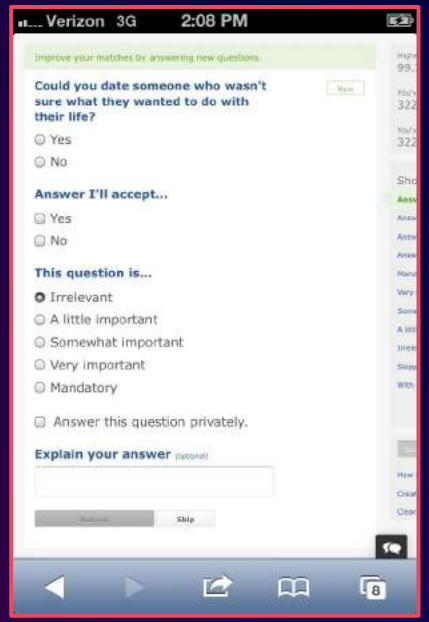
- Evaluation Benchmarks
- Human Evaluation
- Human Comparison/Arena
- Model based Approaches
- Red Teaming

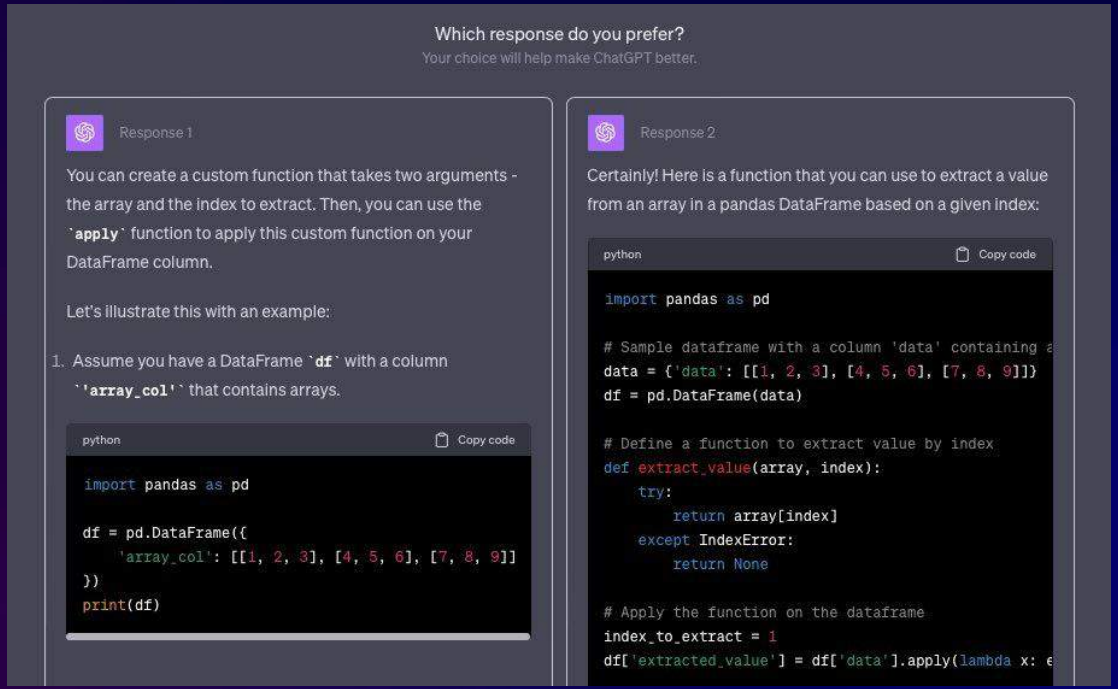


Story: Human Evaluation - Collection



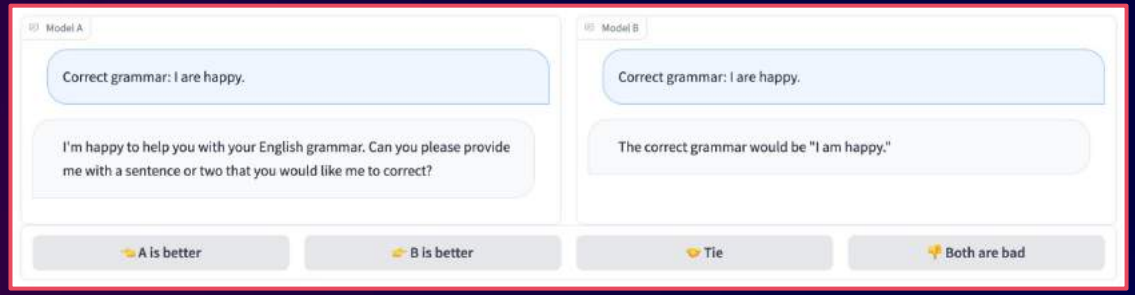
Easier to get preferences than detailed answers

Head to head Human preferences



https://www.threads.net/@eugeneyan/post/CywQhymySx2

🥊 Head to Head Leaderboards



Model A vs. Model B

Anonymous, randomized battles in a crowdsourced manner with a leaderboard based on the Elo rating system,

Model	⭐ Arena Elo rating
GPT-4	1227
Claude-v1	1178
Claude-instant-v1	1156
GPT-3.5-turbo	1130
Guanaco-33B	1065
Vicuna-13B	1061
WizardLM-13B	1048
PaLM-Chat-Bison-001	1038
Vicuna-7B	1008
Koala-13B	992
GPT4All-13B-Snoozy	986
MPT-7B-Chat	956
RWKV-4-Raven-14B	950
Alpaca-13B	930
OpenAssistant-Pythia-12B	924

🥊 Head to Head Leaderboards: Solutions

LM-SYS arena code: https://github.com/lm-sys/FastChat

RLHF arena: https://huggingface.co/spaces/openaccess-ai-collective/rlhf-arena

Methods for evaluating Generative AI

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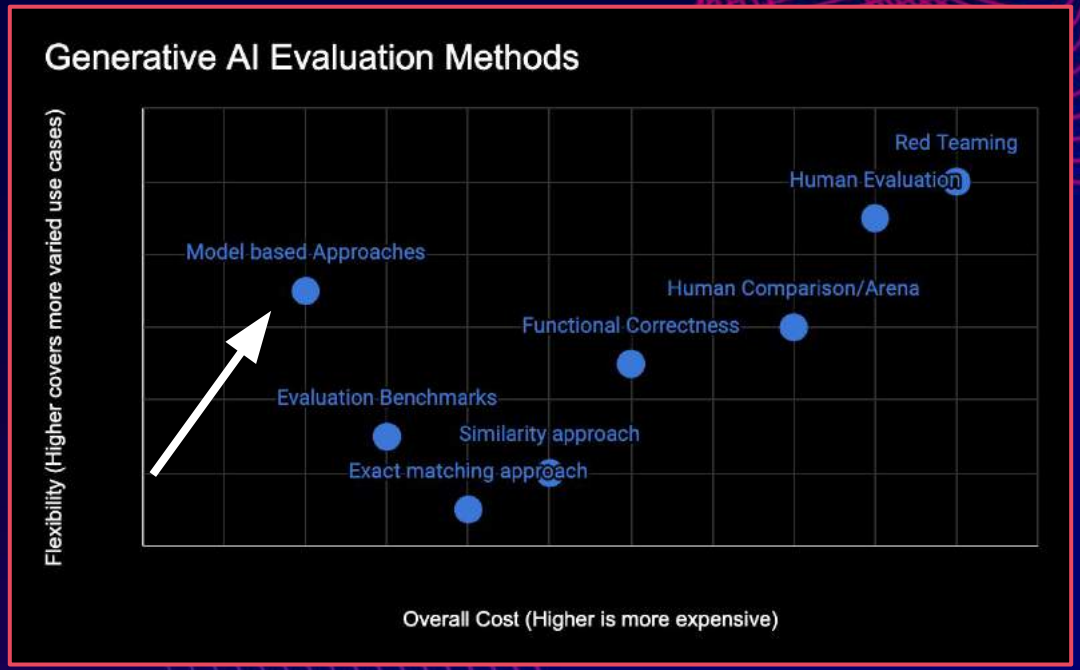
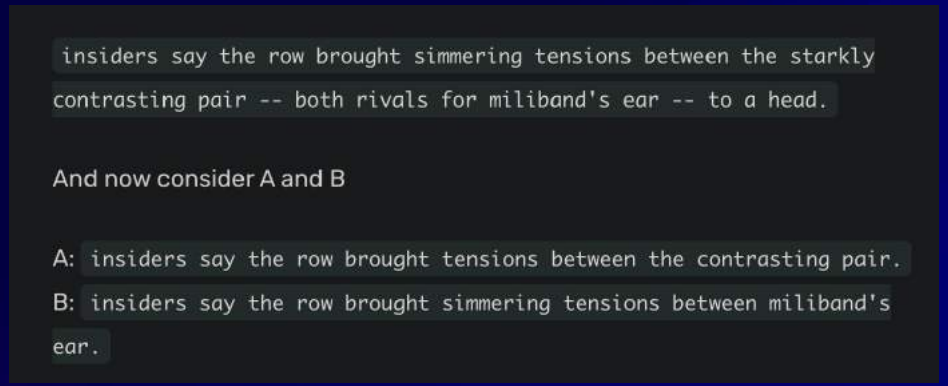


Evaluating Factuality: Reference / ground truth

Dataset: Use an gold standard factuality dataset

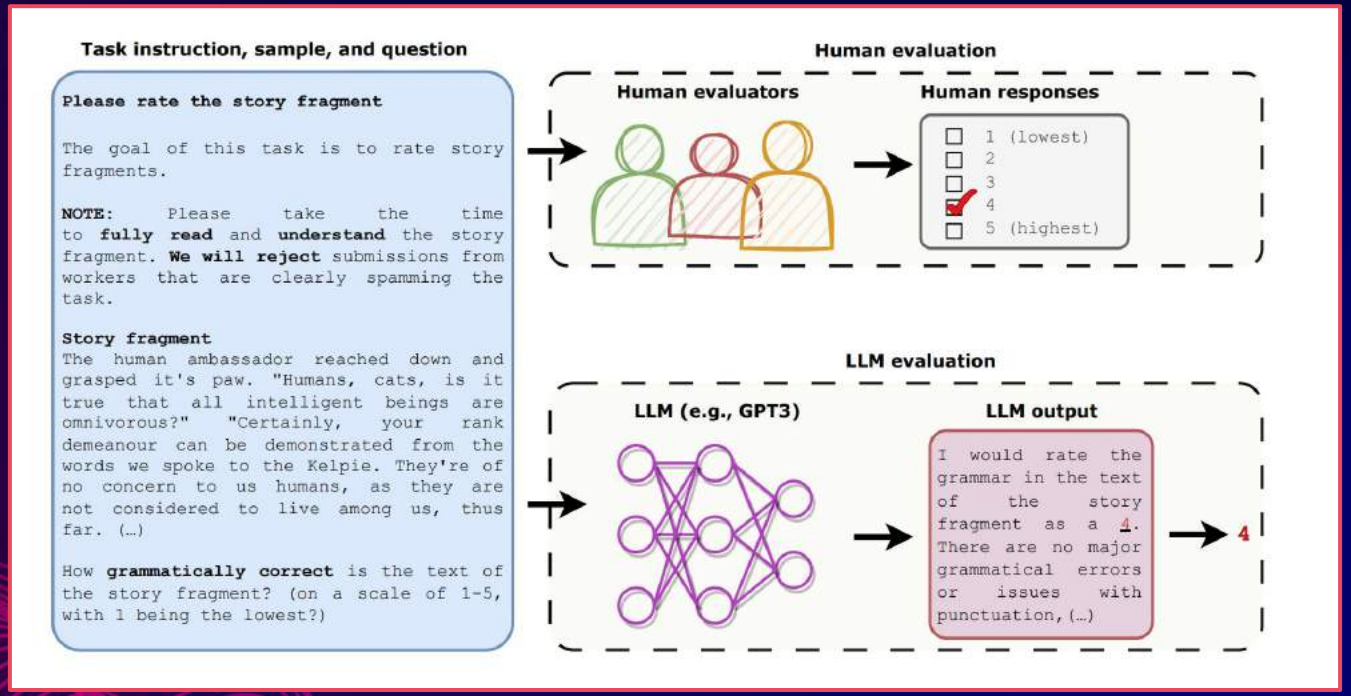
Benchmark: Factuality Evaluation of large Language Models

Pretty limited utility



https://www.anyscale.com/blog/llama-2-is-about-as-factually-accurate-as-gpt-4-for-summaries-and-is-30x-cheaper
https://arxiv.org/abs/2310.00741

Model based evaluation



Model based evaluation: Assertions

- Language Match
- Sentiment
- Toxicity
- Length

These evaluation prompts that take very little judgement on behalf of the model as an evaluator

Model based evaluation: G-Eval

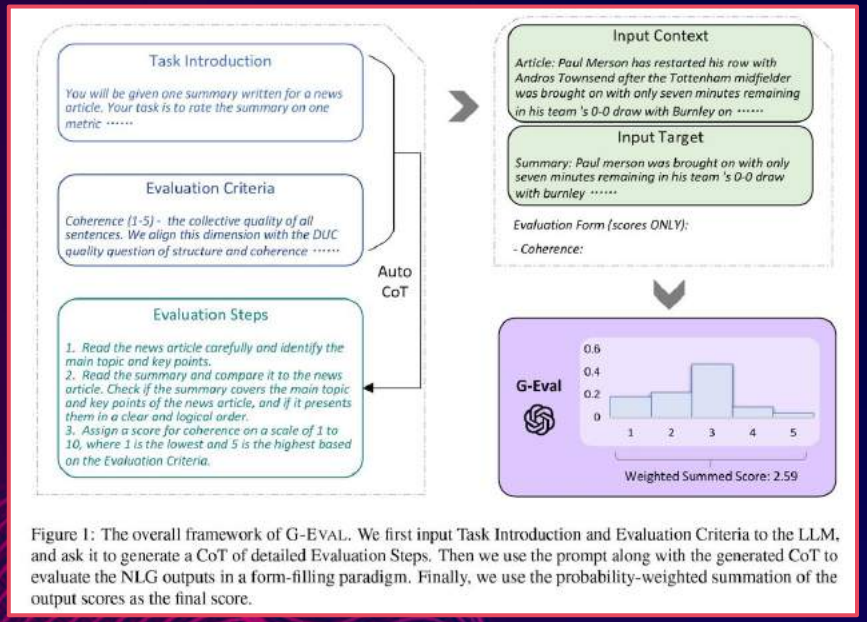


Figure 1: The overall framework of G-EVAL. We first input Task Introduction and Evaluation Criteria to the LLM, and ask it to generate a CoT of detailed Evaluation Steps. Then we use the prompt along with the generated CoT to evaluate the NLG outputs in a form-filling paradigm. Finally, we use the probability-weighted summation of the output scores as the final score.

- Introduction
- Evaluation
- Generates evaluations and scores

Context-Based

https://arxiv.org/abs/2303.16634

Model based evaluation: SelfCheckGPT

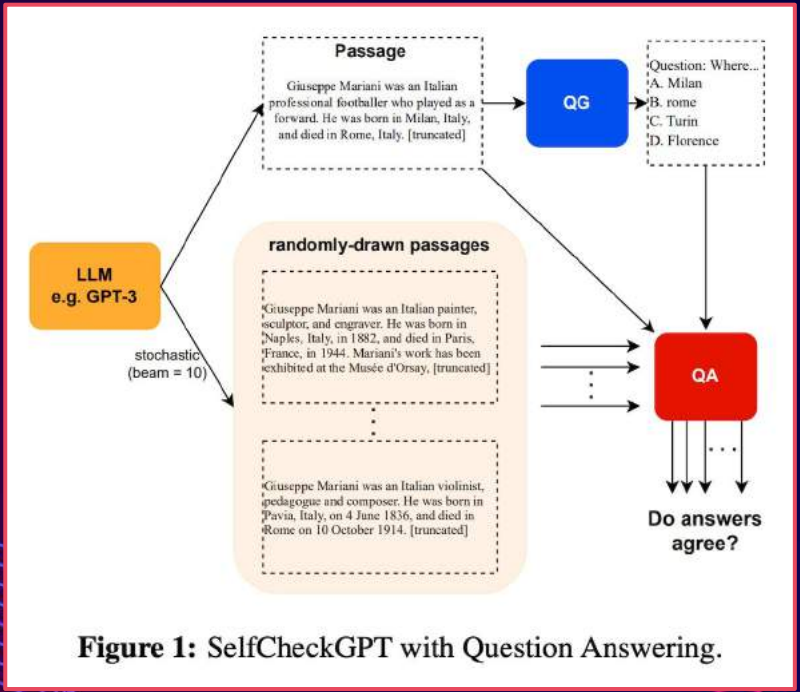


Figure 1: SelfCheckGPT with Question Answering.

Multiple responses should be consistent is the model is not hallucinating

Sampling based approach

https://arxiv.org/abs/2303.08896

Model Evaluation - Which Model?

GPT-4 as the strongest evaluator

GPT-3.5 - cheaper for production use

Train your own model - JudgeLM

Table 1: Main results for our JudgeLM and concurrent methods on our *val* set, which uses GPT-4 annotation results as ground truth.

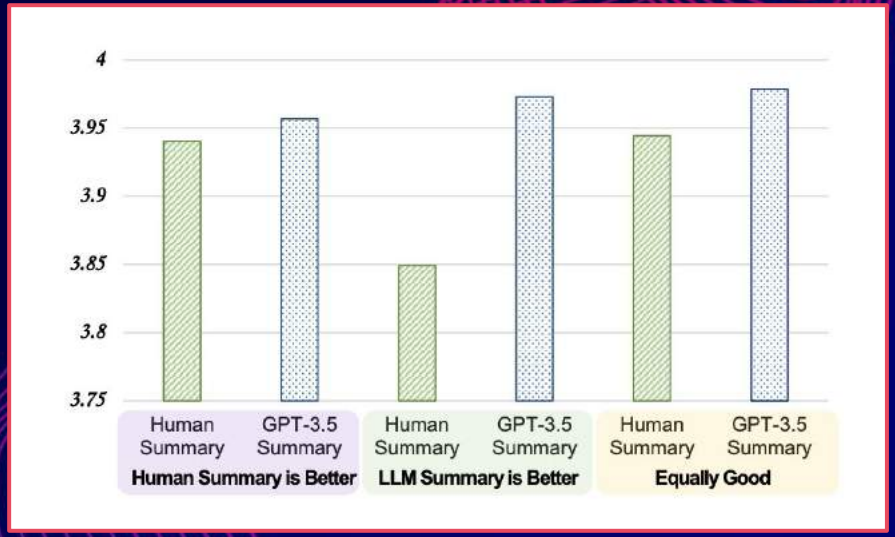
Methods	Agreement ↑ (w/ GPT-4)	Precision ↑ (w/ GPT-4)	Recall ↑ (w/ GPT-4)	F1 ↑ (w/ GPT-4)	Consistency ↑ (w/ swap.)
Judge w/o reference.					
GPT-3.5	73.83	70.70	52.80	52.85	68.89
PandaLM-7B	68.61	40.75	38.82	39.41	74.78
JudgeLM-7B	81.11	69.67	78.39	72.21	83.57
JudgeLM-13B	84.33	73.69	80.51	76.17	85.01
JudgeLM-33B	89.03	80.97	84.76	82.64	91.36
Judge w/ reference.					
GPT-3.5	71.46	56.86	51.12	51.14	62.94
PandaLM-7B	63.77	39.79	34.82	35.18	55.39
JudgeLM-7B	84.08	75.92	82.55	78.28	84.46
JudgeLM-13B	85.47	77.71	82.90	79.77	87.23
JudgeLM-33B	89.32	84.00	86.21	84.98	92.37

https://arxiv.org/pdf/2310.17631.pdf

Model evaluation – human alignment

It appears to align with humans

Human and GPT-4 judges can reach above 80% agreement on the correctness and readability score. And if we lower the requirement to be smaller or equal than 1 score difference, the agreement level can reach above 95%.



https://arxiv.org/abs/2305.01937
https://www.databricks.com/blog/LLM-auto-eval-best-practices-RAG
https://arxiv.org/abs/2303.16634
https://arxiv.org/pdf/2306.05685.pdf

Model evaluation – Biases

- **Position bias**: LLMs tend to favor the response in the first position.
- **Verbosity bias**: LLMs tend to favor longer, wordier responses over more concise ones, even if the latter is clearer and of higher quality.
- **Self-enhancement bias**: LLMs have a slight bias towards their own answers.
  - GPT-4 favors itself with a 10% higher win rate while Claude-v1 favors itself with a 25% higher win rate.

Mitigations

- **Position bias:** Swap the order and see if it makes a difference
- **Verbosity bias:** Ensure that comparison responses are similar in length.
- **Self-enhancement bias:** Don't use the same LLM for evaluation tasks.
- **Use low-precision grading scales** for easier interpretation like 0, 1, 2, 3 or even binary (0, 1)

https://eugeneyan.com/writing/llm-patterns/
https://arxiv.org/abs/2303.16634
https://www.databricks.com/blog/LLM-auto-eval-best-practices-RAG

Summary: Model based evaluation

Types of Model based Evaluation

- Assertions
- Concept based evaluation
- Sampling based evaluation
- Preference based -> RLHF

Summary: Model based evaluation

✅ Cheaper and faster than human evaluation

✅ Align better with humans than reference-based and reference free baselines

✅ Can provide a more fine grained continuous score by re-weighting the discrete scores by their respective token probabilities.

❌ Sensitive to the instructions and prompts.

❌ Several known biases

Evaluating Factuality: Model with ragas

- Ragas measures your pipeline's performance against two dimensions
    - Factuality: measures the factual consistency of the generated answer against the given context.
    - Relevancy: measures how relevant retrieved contexts and the generated answer are to the question.
- The final ragas_score is the harmonic mean of these two factors.

```
dataset: Dataset

results = evaluate(dataset)
# {'ragas_score': 0.860, 'context_relavency': 0.817,
# 'factuality': 0.892, 'answer_relevancy': 0.874}
```


https://github.com/explodinggradients/ragas

Evaluating Factuality: DeepEval

- DeepEval focuses on helping write unit test cases for evaluation
- Providing out-of-the-box metrics for evaluating your LLM applications on aspects such as output factuality, relevancy, bias, and toxicity

Open `test_chatbot.py` and write your first test case using Deepeval:

```python
import pytest
from deepeval.metrics.factual_consistency import FactualConsistencyMetric
from deepeval.test_case import LLMTestCase
from deepeval.run_test import assert_test

def test_case():
    query = "What if these shoes don't fit?"
    context = "All customers are eligible for a 30 day full refund at no extra costs."

    # Replace this with the actual output from your LLM application
    actual_output = "We offer a 30-day full refund at no extra costs."
    factual_consistency_metric = FactualConsistencyMetric(minimum_score=0.7)
    test_case = LLMTestCase(query=query, output=actual_output, context=context)
    assert_test(test_case, [factual_consistency_metric])
```


https://github.com/confident-ai/deepeval

Hands on: Using Ragas

Ragas is a framework that helps you evaluate your Retrieval Augmented Generation (RAG) pipelines.

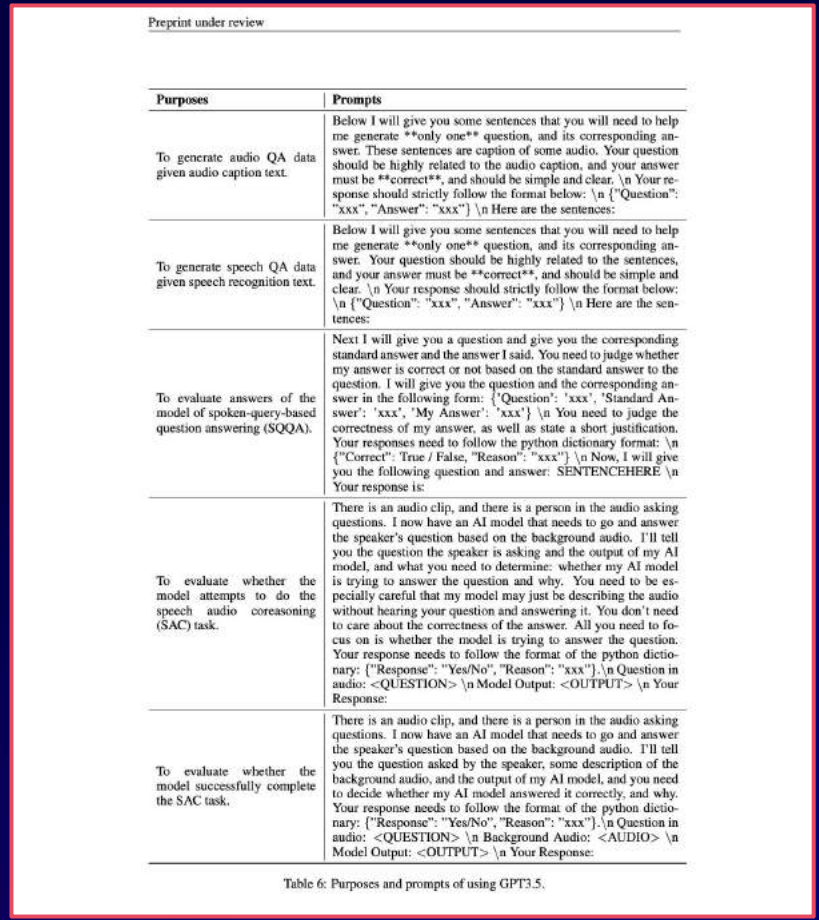
```
result = evaluate(
    fiqa_eval["baseline"].select(range(1)),
    metrics=[
        context_precision,
        faithfulness,
        answer_relevancy,
        context_recall
    ],
)
result
```

```
evaluating with [context_precision]
100%|██████████| 1/1 [00:05<00:00,  5.61s/it]
evaluating with [faithfulness]
100%|██████████| 1/1 [00:09<00:00,  9.04s/it]
evaluating with [answer_relevancy]
100%|██████████| 1/1 [00:01<00:00,  1.67s/it]
evaluating with [context_recall]
100%|██████████| 1/1 [00:10<00:00, 10.43s/it]
{'ragas_score': 0.2974, 'context_precision': 0.4118, 'faithfulness':
1.0000, 'answer_relevancy': 0.9774, 'context_recall': 0.1111}
```


https://colab.research.google.com/drive/1i78-peTBdhK5y4ZskFzC_NtLRaqvySXM

Hands on: Prompts

Prompts in Bytedance SALMONN paper



Preprint under review

Purposes	Prompts
To generate audio QA data given audio caption text.	Below I will give you some sentences that you will need to help me generate **only one** question, and its corresponding answer. These sentences are caption of some audio. Your question should be highly related to the audio caption, and your answer must be **correct**, and should be simple and clear. \n Your response should strictly follow the format below: \n {"Question": "xxx", "Answer": "xxx"} \n Here are the sentences:
To generate speech QA data given speech recognition text.	Below I will give you some sentences that you will need to help me generate **only one** question, and its corresponding answer. Your question should be highly related to the sentences, and your answer must be **correct**, and should be simple and clear. \n Your response should strictly follow the format below: \n {"Question": "xxx", "Answer": "xxx"} \n Here are the sentences:
To evaluate answers of the model of spoken-query-based question answering (SQQA).	Next I will give you a question and give you the corresponding standard answer and the answer I said. You need to judge whether my answer is correct or not based on the standard answer to the question. I will give you the question and the corresponding answer in the following form: {'Question': 'xxx', 'Standard Answer': 'xxx', 'My Answer': 'xxx'} \n You need to judge the correctness of my answer, as well as state a short justification. Your responses need to follow the python dictionary format: \n {"Correct": True / False, "Reason": "xxx"} \n Now, I will give you the following question and answer: SENTENCEHERE \n Your response is:
To evaluate whether the model attempts to do the speech audio coreasoning (SAC) task.	There is an audio clip, and there is a person in the audio asking questions. I now have an AI model that needs to go and answer the speaker's question based on the background audio. I'll tell you the question the speaker is asking and the output of my AI model, and what you need to determine: whether my AI model is trying to answer the question and why. You need to be especially careful that my model may just be describing the audio without hearing your question and answering it. You don't need to care about the correctness of the answer. All you need to focus on is whether the model is trying to answer the question. Your response needs to follow the format of the python dictionary: {"Response": "Yes/No", "Reason": "xxx"}.\n Question in audio: <QUESTION> \n Model Output: <OUTPUT> \n Your Response:
To evaluate whether the model successfully complete the SAC task.	There is an audio clip, and there is a person in the audio asking questions. I now have an AI model that needs to go and answer the speaker's question based on the background audio. I'll tell you the question asked by the speaker, some description of the background audio, and the output of my AI model, and you need to decide whether my AI model answered it correctly, and why. Your response needs to follow the format of the python dictionary: {"Response": "Yes/No", "Reason": "xxx"}.\n Question in audio: <QUESTION> \n Background Audio: <AUDIO> \n Model Output: <OUTPUT> \n Your Response:

Table 6: Purposes and prompts of using GPT3.5.

https://arxiv.org/pdf/2310.13289.pdf

Hands on: Prompts

You can write your own prompts for

Data Quality

Factuality/Relevance

Grading Scale

Identify low data quality:

Quality Prompt: You are now a data grader. You will grade the data I provide according to my requirements, explain the reasons, and then give a piece of higher-quality data based on this piece of data.

Please help me rate the following dialogue data in the field of operation and maintenance and explain the reasons. Require:

1. Scoring perspective: whether the problem belongs to the field of operation and maintenance; whether the problem description is clear; whether the answer is accurate; whether the problem has a certain meaning; whether the language is coherent; whether the problem is challenging and difficult.

2. Point scale: 5-point scale, 1 point: very poor; 2 points: slightly poor; 3 points: barely qualified; 4 points: usable; 5 points: excellent.

3. Please rate the problem and attach reasons. If the score is lower than 4 points, a higher quality data will be generated based on this piece of data.

https://arxiv.org/pdf/2309.09298.pdf

Hands on: Prompts

You can write your own prompts for

Data Quality

Factuality/Relevance

Grading Scale

```
RAG_RELEVANCY_PROMPT_RAILS_MAP = OrderedDict({True: "relevant", False: "irrelevant"})
RAG_RELEVANCY_PROMPT_TEMPLATE_STR = """
You are comparing a reference text to a question and trying to determine if the reference text
contains information relevant to answering the question. Here is the data:
    [BEGIN DATA]
    ************
    [Question]: {query}
    ************
    [Reference text]: {reference}
    [END DATA]

Compare the Question above to the Reference text. You must determine whether the Reference text
contains information that can answer the Question. Please focus on whether the very specific
question can be answered by the information in the Reference text.
Your response must be single word, either "relevant" or "irrelevant",
and should not contain any text or characters aside from that word.
"irrelevant" means that the reference text does not contain an answer to the Question.
"relevant" means the reference text contains an answer to the Question.
"""  # noqa: E501
```


https://github.com/Arize-ai/phoenix/blob/21e5e8afd51cbede1051a9561d5dbcef7318597c/src/phoenix/experimental/evals/templates/default_templates.py#L45

Hands on: Prompts

You can write your own prompts for

Data Quality

Factuality/Relevance

Grading Scale

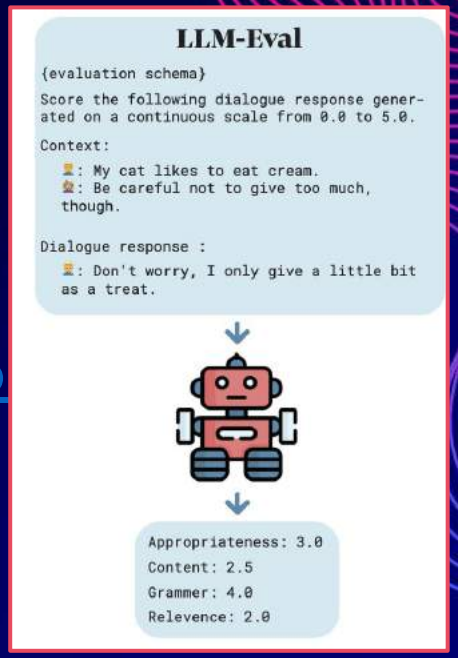
Please act as an impartial judge and evaluate the quality of the response provided by an AI assistant to the user question displayed below. Your evaluation should consider factors such as the helpfulness, relevance, accuracy, depth, creativity, and level of detail of the response. Begin your evaluation by providing a short explanation. Be as objective as possible. After providing your explanation, you must rate the response on a scale of 1 to 10 by strictly following this format

https://www.databricks.com/blog/LLM-auto-eval-best-practices-RAG

Resources: Model based evaluation

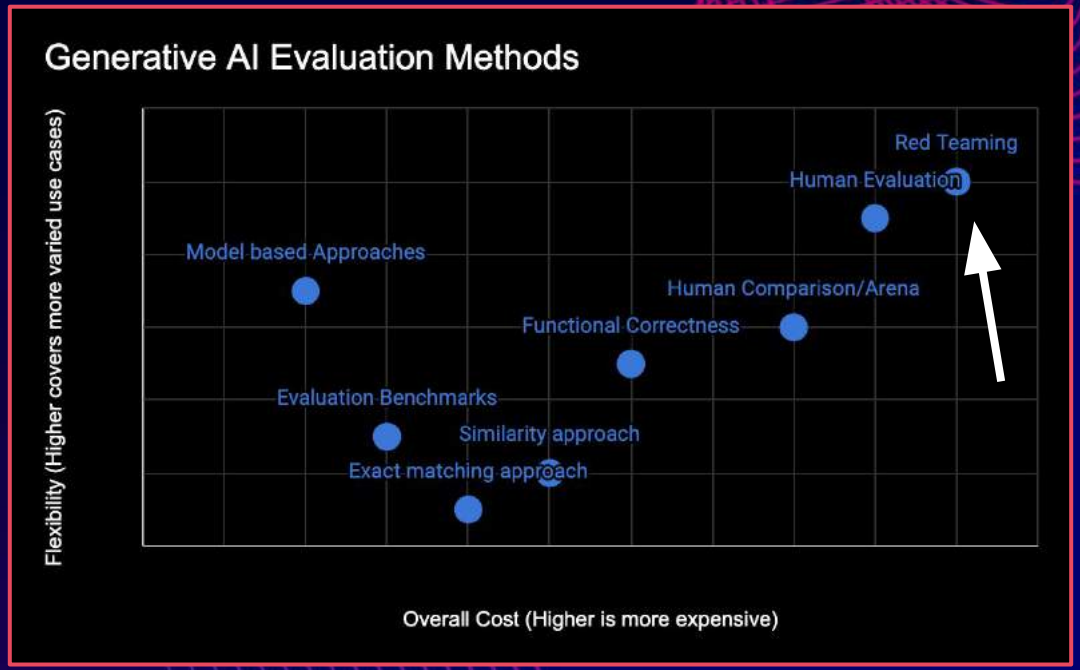
Do this with hand crafted prompts:

Packages:
Ragas
Microsoft research: https://llm-eval.github.io
True Lens
Guardrails



Methods for evaluating Generative AI

- Exact matching approach
- Similarity approach
- Functional Correctness
- Evaluation Benchmarks
- Human Evaluation
- Human Comparison/Arena
- Model based Approaches
- Red Teaming



Story: Microsoft Tay

Origin of Red Teaming in AI

https://www.theverge.com/2016/3/24/11297050/tay-microsoft-chatbot-racist

Why Red Teaming?

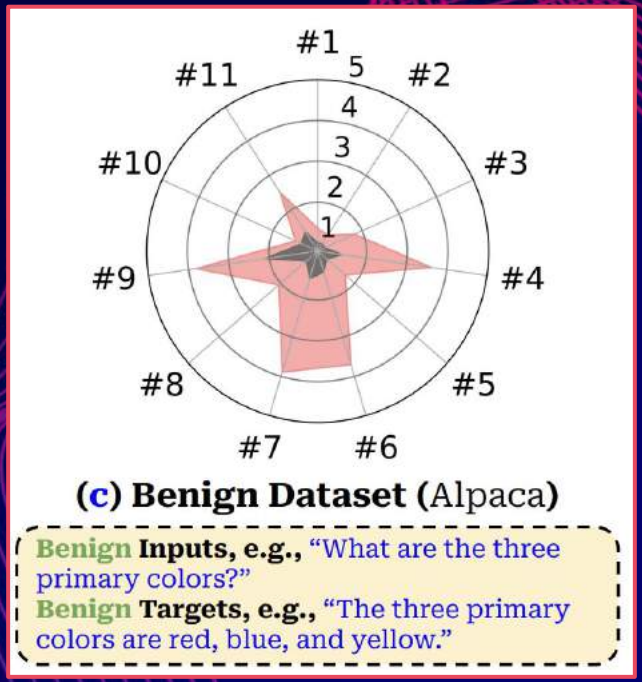
Red-teaming is a form of evaluation that elicits model vulnerabilities that might lead to undesirable behaviors

https://huggingface.co/blog/red-teaming

Every use case should be Red Teamed

Even a model that contains a RLHF layer designed to limit harmfulness can be affected if fine tuned!

Alignment can be compromised with just 10 training examples, a cost of less than $0.20!



OpenAI: https://arxiv.org/abs/2310.03693
Llama: https://arxiv.org/abs/2310.20624

How to: Red Teaming with a Model

Use a locally hosted model like Llama-2 to assess the riskiness of a query

You can then log this to track which queries are risky

https://arxiv.org/abs/2307.09288

How to: Red Teaming from Meta

Proactive risk identification

Bring people with different backgrounds, look at different risk categories (such as criminal planning, human trafficking, regulated or controlled substances, sexually explicit content, unqualified health or financial advice, privacy violations, and more), as well as different attack vectors (such as hypothetical questions, malformed/misspelled inputs, or extended dialogues).

Conduct specific tests to determine the capabilities of our models to facilitate the production of weapons (e.g. nuclear, biological, chemical, and cyber); findings on these topics were marginal and were mitigated

Meta held back Llama 2 33b model because it didn't pass red team

https://arxiv.org/abs/2307.0928
https://arxiv.org/abs/2306.09442

How to: Red Teaming

Prompts in English and non-English

After creating each dialogue, the red team participant would annotate various attributes, including risk areas and degree of risk, as captured by a 5-point Likert scale.

Learners were used for model safety training, and specifically took data from these exercises for model fine-tuning, model feedback training, and as a signal for other safety model training.

https://arxiv.org/abs/2307.09288

Methods for evaluating Generative AI

- Exact matching approach
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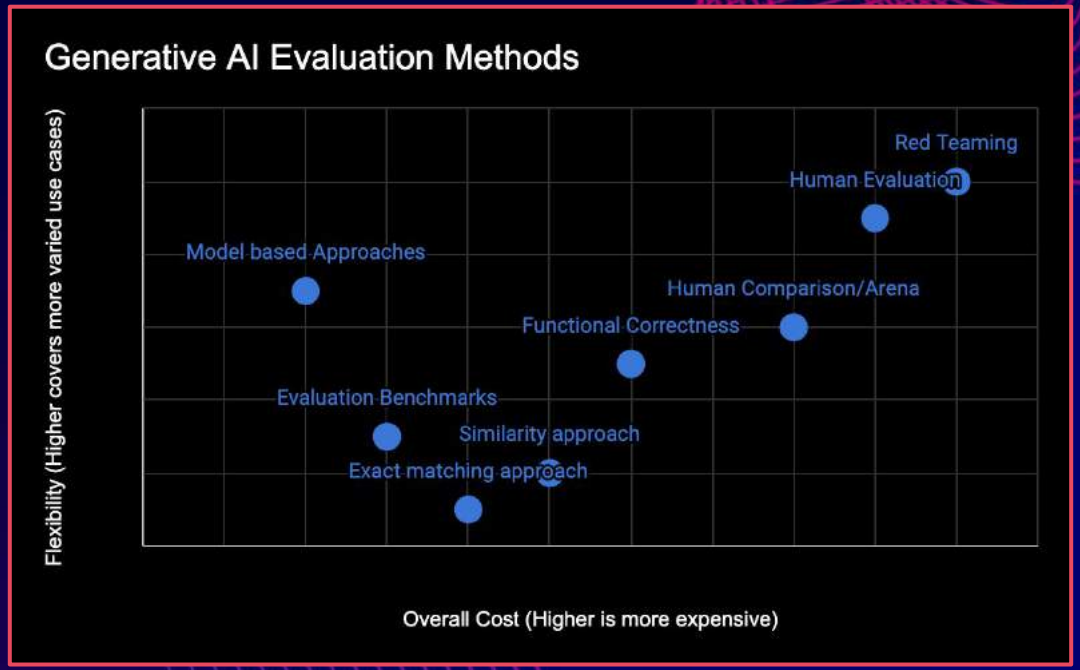


Evaluate Generative AI

Technical (F1)

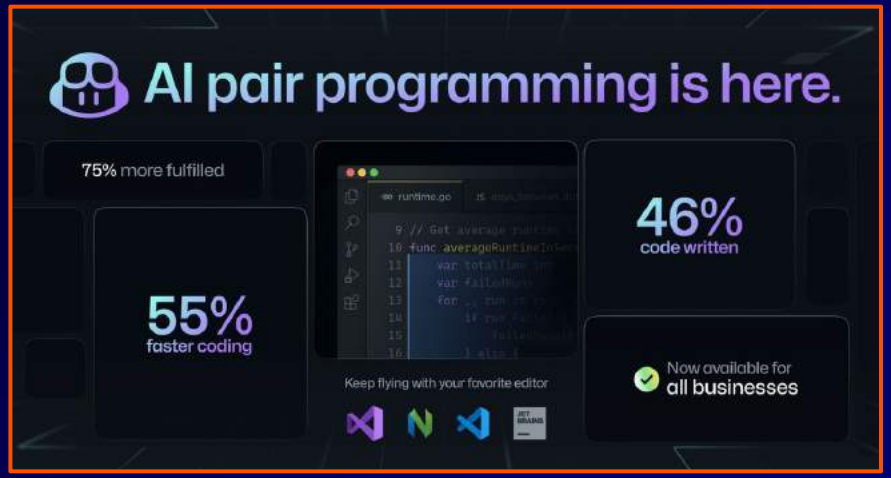
Business ($$)

Operational (TCO)

Story: Costs for your application

Github CoPilot:

- Individuals pay $10 a month
- Losing more than $20 a month per user
- Some cost $80 a month.



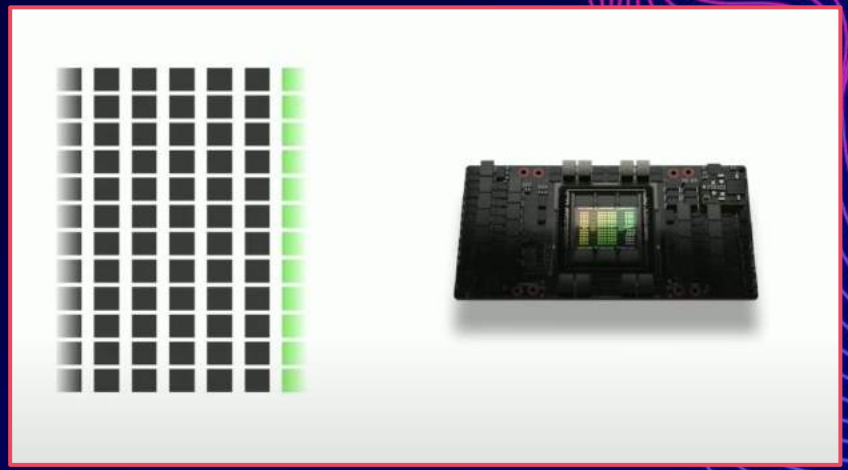
Epidemic of *cloud laundering* in AI

https://www.theregister.com/2023/10/11/github_ai_copilot_microsoft/

Monitoring - Sibling of Evaluate

Monitoring LLMs

1. Functional Monitoring
   a. number of requests
   b. response time
   c. error rates
   d. KV Cache + Batch
2. Monitoring Prompt Drift
3. Monitoring Responses



Alerting and Thresholds

The Monitoring UI

https://youtu.be/PeKMEXUrlq4?si=TcVTZLcqLhbXRRib

Monitoring: Metrics

GPU Utilization

1. Number of 429 error response
2. Total tokens
3. Prompt tokens
4. Completion tokens
5. Wasted utilization
6. Tokens with truncated responses

Responsible AI

1. % Prompts with HTTP 400 errors
2. % Responses with “finish_reason”: “content_filter”

https://www.microsoft.com/en-us/research/group/experimentation-platform-exp/articles/how-to-evaluate-llms-a-complete-metric-framework/

Monitoring: Metrics

Performance Metrics

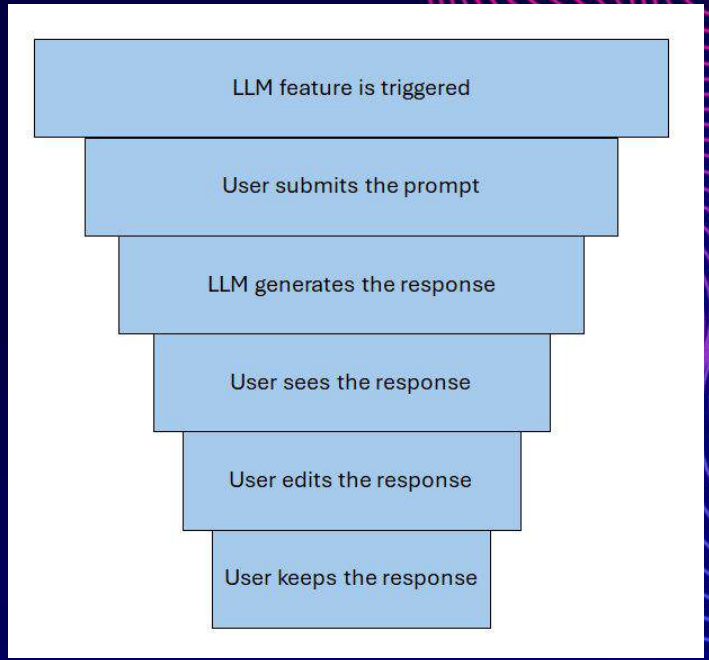
1. Time to first token render from submission of the user prompt, measured at multiple percentiles.
2. Requests Per Second (RPS) for the LLM.
3. Tokens rendered per second when streaming(opens in new tab) the LLM response.

https://www.microsoft.com/en-us/research/group/experimentation-platform-exp/articles/how-to-evaluate-llms-a-complete-metric-framework/

Monitoring: Metrics

User Engagement

How often the user engages with the LLM features, the quality of those interactions and how likely they are to use it in the future.



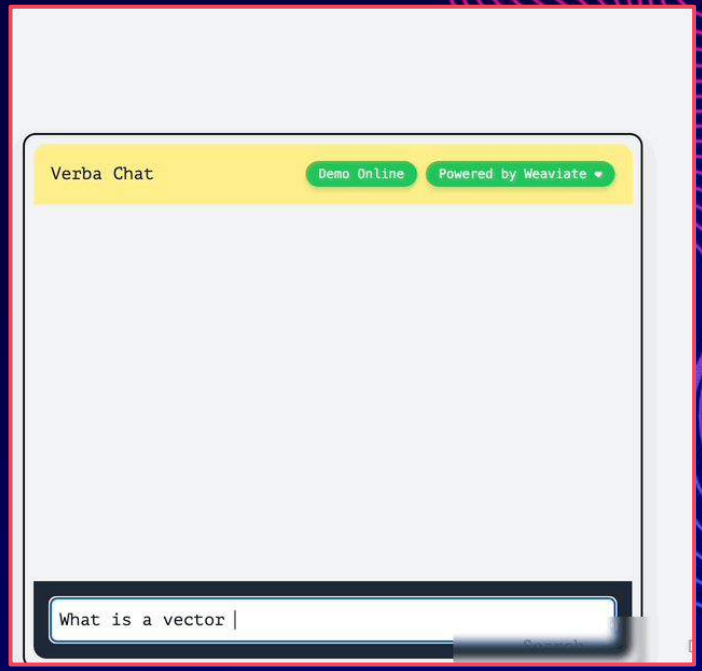
https://www.microsoft.com/en-us/research/group/experimentation-platform-exp/articles/how-to-evaluate-llms-a-complete-metric-framework/

APPLICATION TO RAG

If you need facts - bring them yourself

Combines classical
information retrieval
+
LLMs for summarization

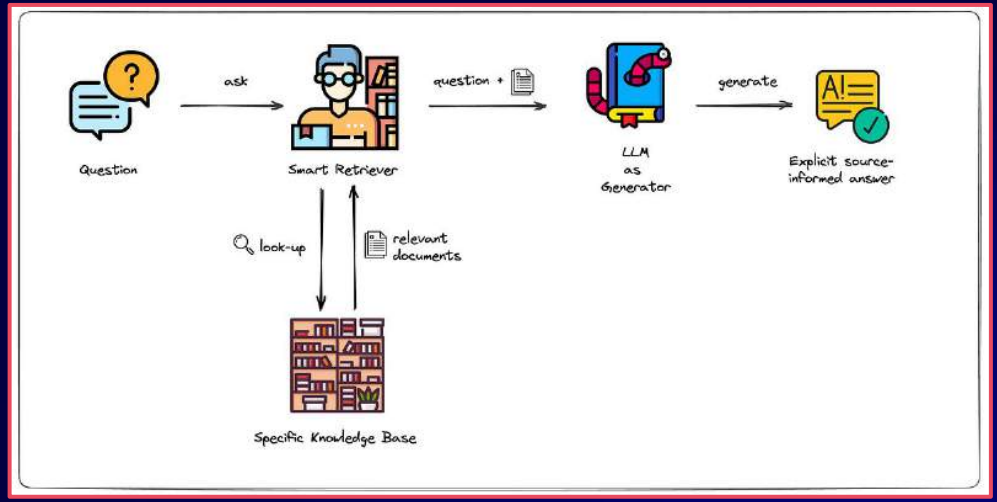
Retrieval Augmented Generation



What is RAG?

Retriever Augmented Generation

Improving the quality of LLM-generated responses by grounding the model on external sources of knowledge to supplement the LLM's internal representation of information



Fun Fact: A better term is RALM (Retriever Augmented Language Modeling) after In-Context Retrieval-Augmented Language Models but RAG took off in popularity.

Evaluating RAG

Model based evaluation on factuality:

Focus on precision

Factuity about 95%

What's wrong with this?

Video that asks meaningless details on RAG to make it clear they are missing the larger point of view

Evaluate Generative AI?

Technical (F1)

Business ($$)

Operational (TCO)

Still the same principles!

Business Metric for RAG

What is the value of your RAG system?

What is the value of correct answer?

What are the consequences if you get it wrong?

	Actual +	Actual -
Predicted +	Correctly Predict Active **$0**	Falsely Predict Active **$0**
Predicted -	Falsely Predict Churn **-$150**	Correctly Predict Churn **$175**

Operational Metrics for RAG

How much to label data?

How much time will this take?

Cost of running these models?

How much will this change over time?

How hard will it be internally to move this project to production?

(Just a handful of the important questions)

Evaluate Generative AI?

Technical (F1)

Business ($$)

Operational (TCO)

Still the same principles!

Evaluate Generative AI

Technical (F1)

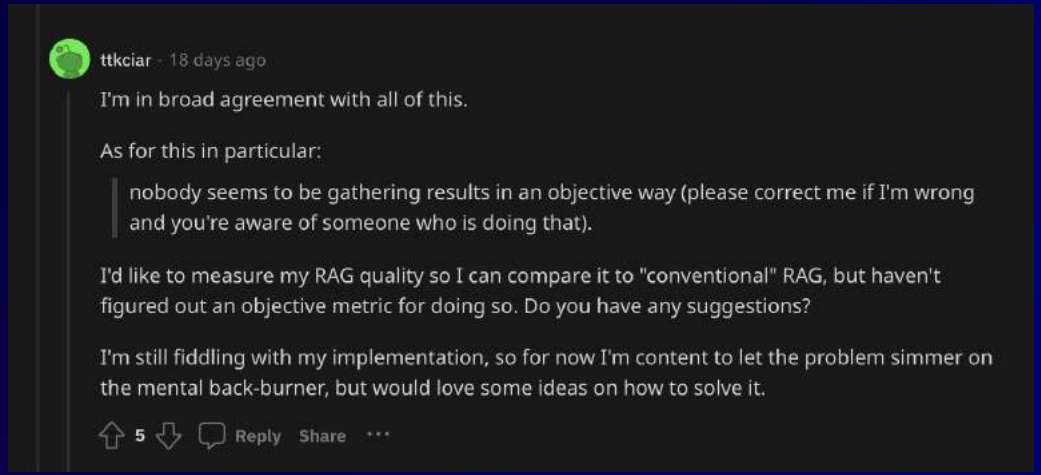
Business ($$)

Operational (TCO)

Current Approaches for Evaluation

People are building these systems, but evaluation is pretty haphazard

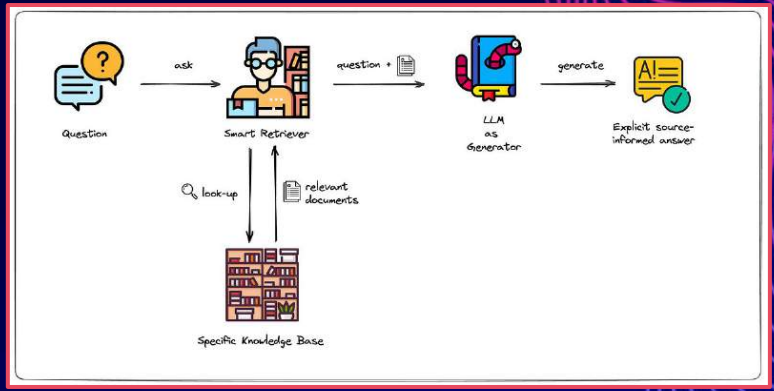
It's usually just eyeballing a few examples, let's use our evaluations learnings to build a better evaluations system



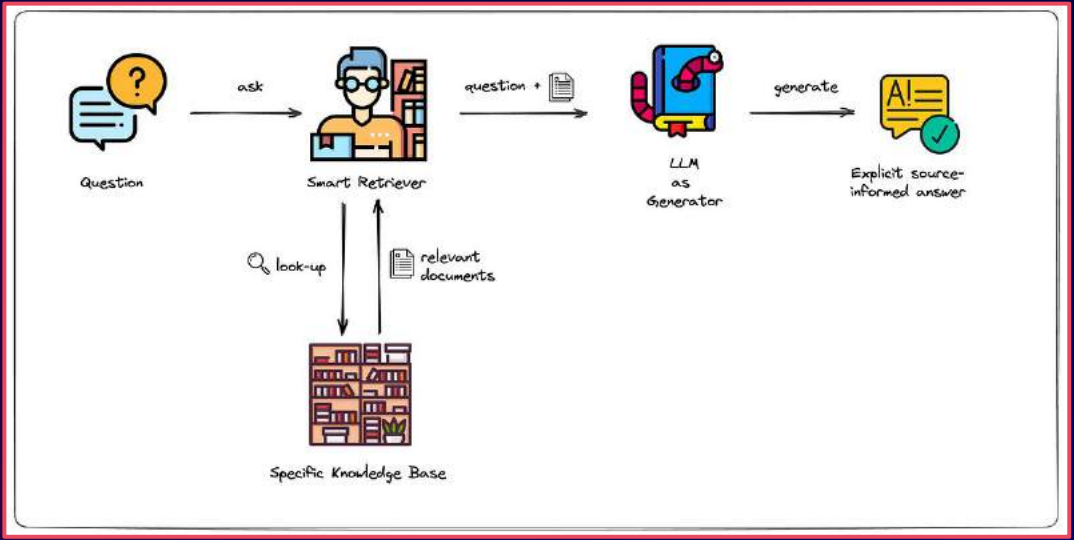
Evaluate LLM System

When I asked a question was the answer accurate?

- Was it factual?
- Did it include the proper references?
- Was it easy to understand?
- What was the query time?



RAG System



1. Retrieval
2. Augmented Generation

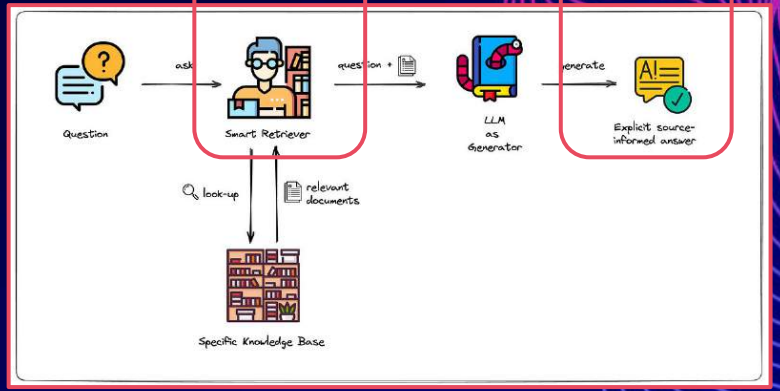
Evaluate LLM System: Components

Retrieval:

- Low Precision: Not all chunks in retrieved set are relevant
- Low Recall: Not all relevant chunks are retrieved.
  - Were they in the proper order?
  - Were they outdated
- What was the latency?

Augmentation:

- How can we ensure the answer were factually correct?
- How can we measure the answers were understandable?
- Toxicity/Bias issues
- How can we measure latency?



WHENEVER POSSIBLE HAVE INTERMEDIATE MEASUREMENTS TO IDENTIFY WEAK AREAS

Analyze retrieval

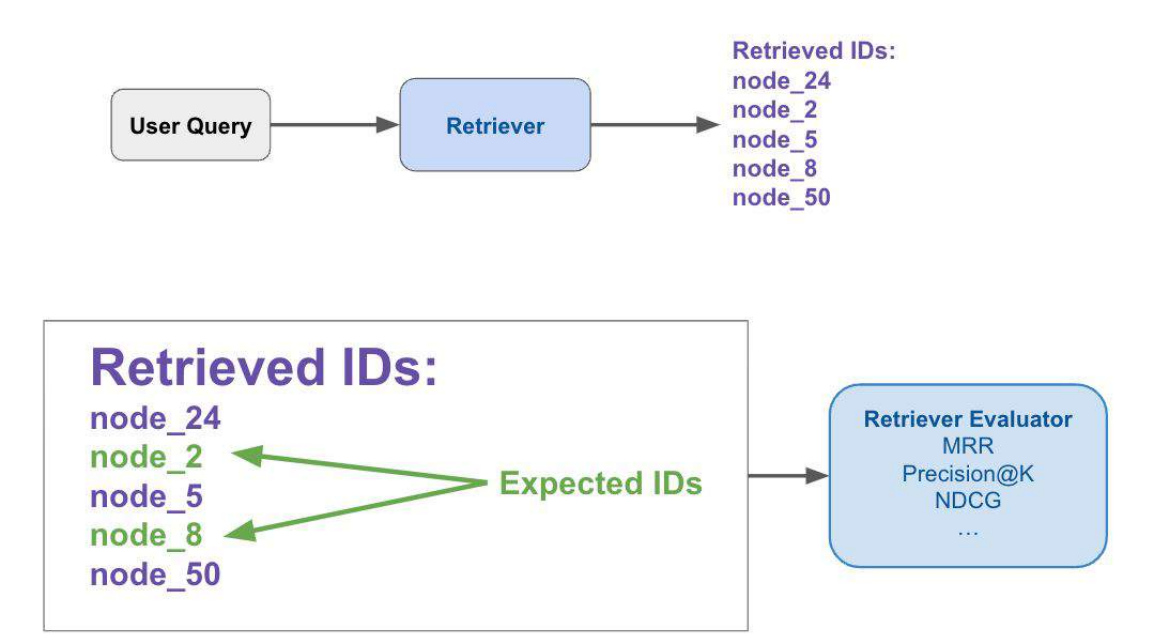
Evaluate quality of retrieved chunks given user query

Collect dataset

Input: query

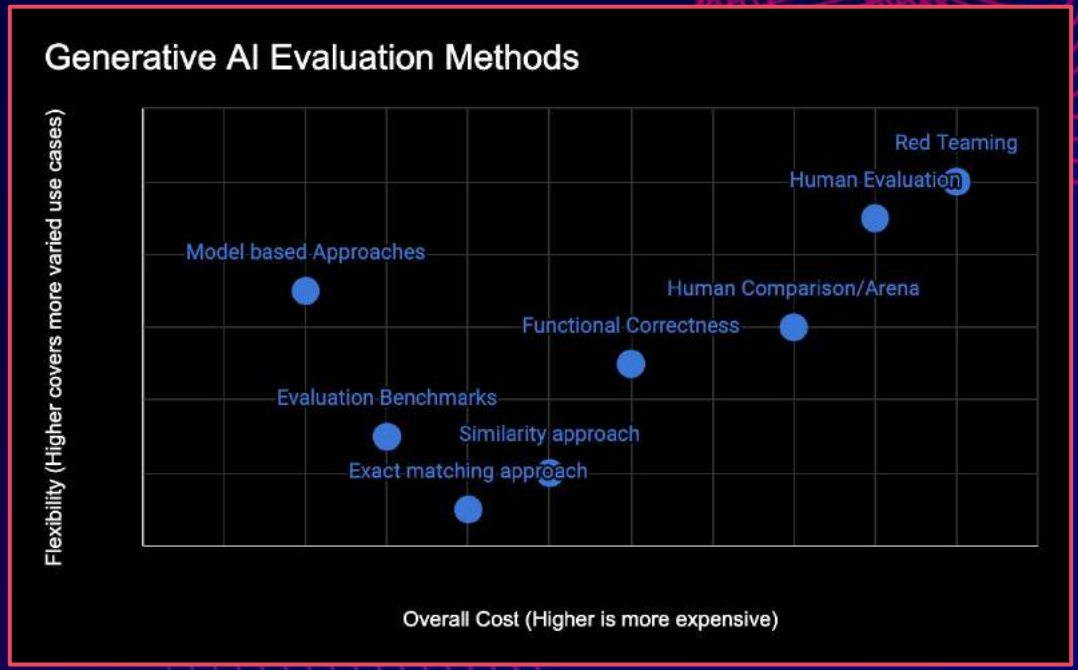
Output: the “ground-truth” documents relevant to the query

Run retriever over dataset



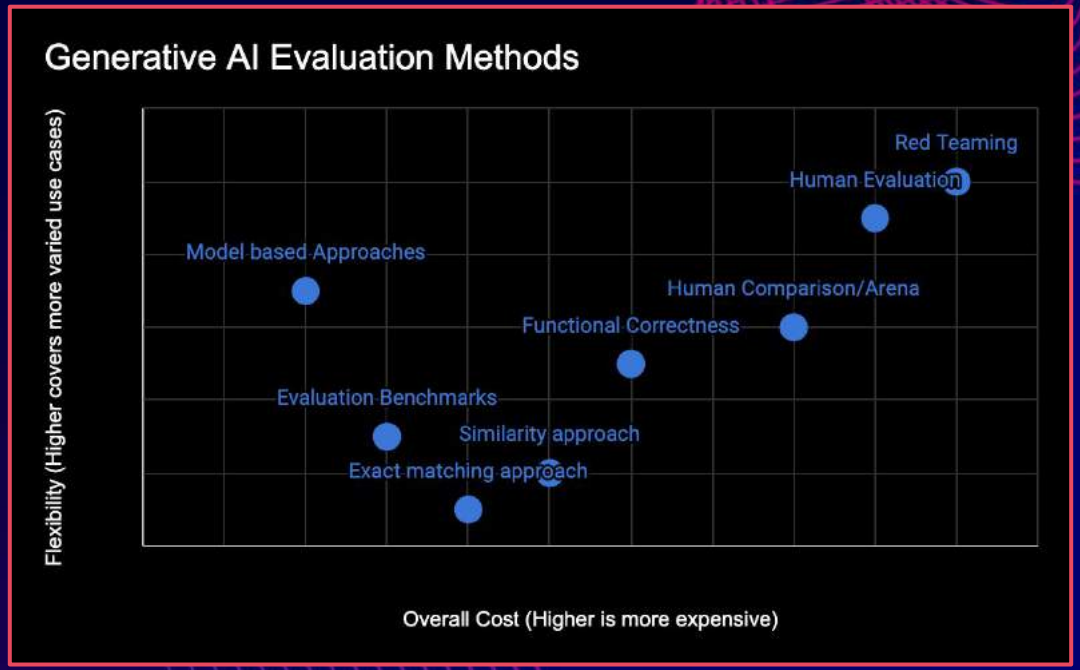
Methods for evaluating retrieval

- Exact matching approach
- Similarity approach
- Functional Correctness
- Evaluation Benchmarks
- Human Evaluation
- Human Comparison/Arena
- Model based Approaches
- Red Teaming



Methods for evaluating retrieval

- Exact matching approach
- Metrics:
  - Success rate / hit-rate
  - Mean reciprocal rank
  - Hit-rate



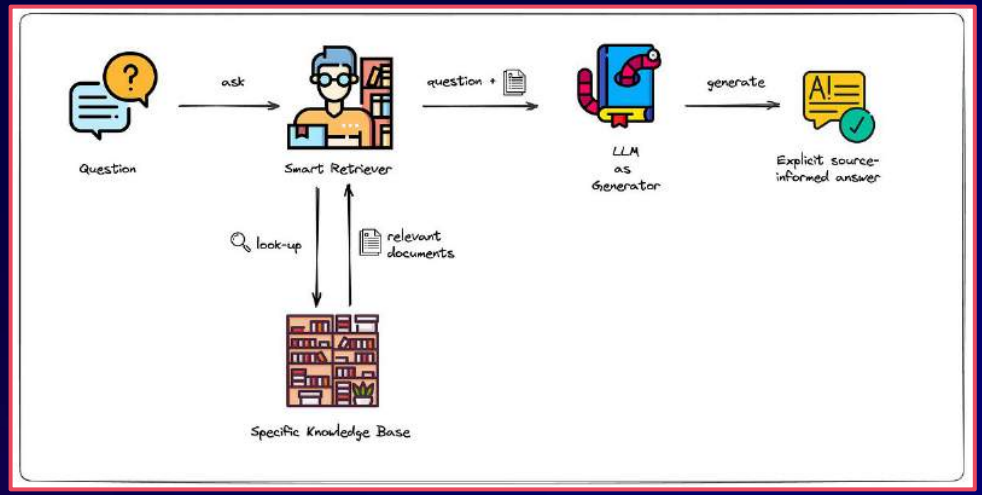
Jerry Liu:
Evaluating and Optimizing your RAG App

Analyze augmentation

Evaluate quality of augmentation

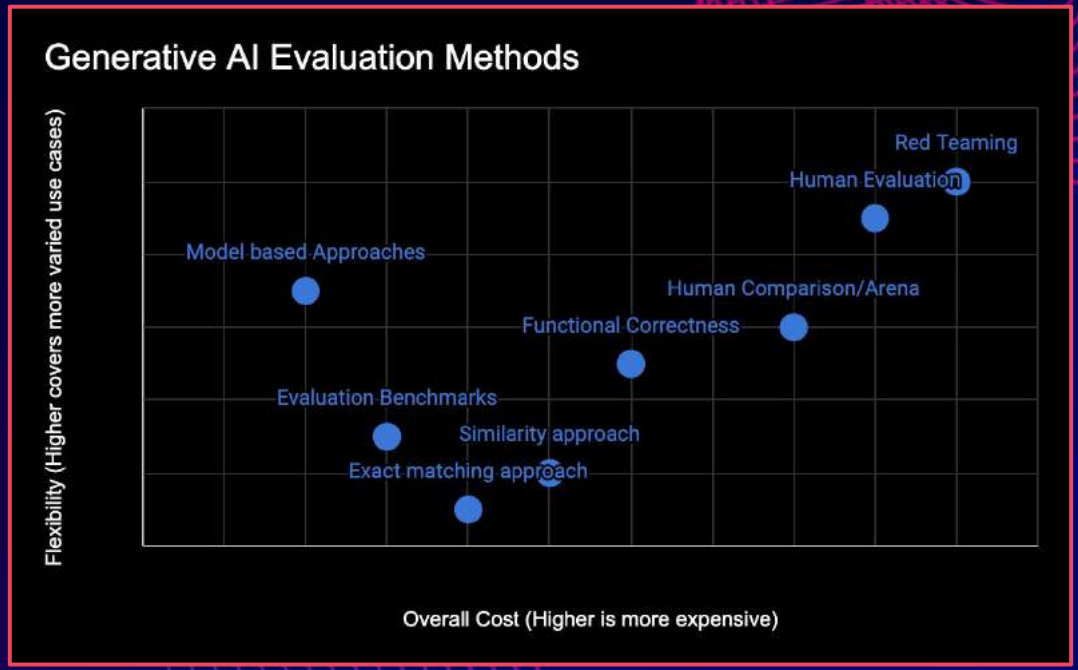
Collect dataset:

- Context
- Generated Response
- “Ground-truth” Response



Methods for evaluating augmentation

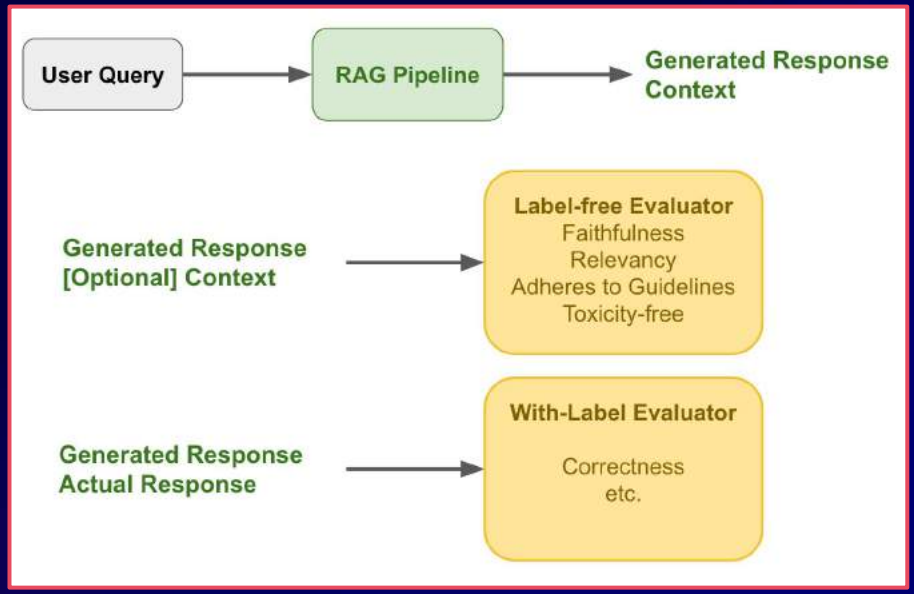
- Exact matching approach
- Similarity approach
- Functional Correctness
- Evaluation Benchmarks
- Human Evaluation
- Human Comparison/Arena
- Model based Approaches
- Red Teaming



Methods for evaluating augmentation

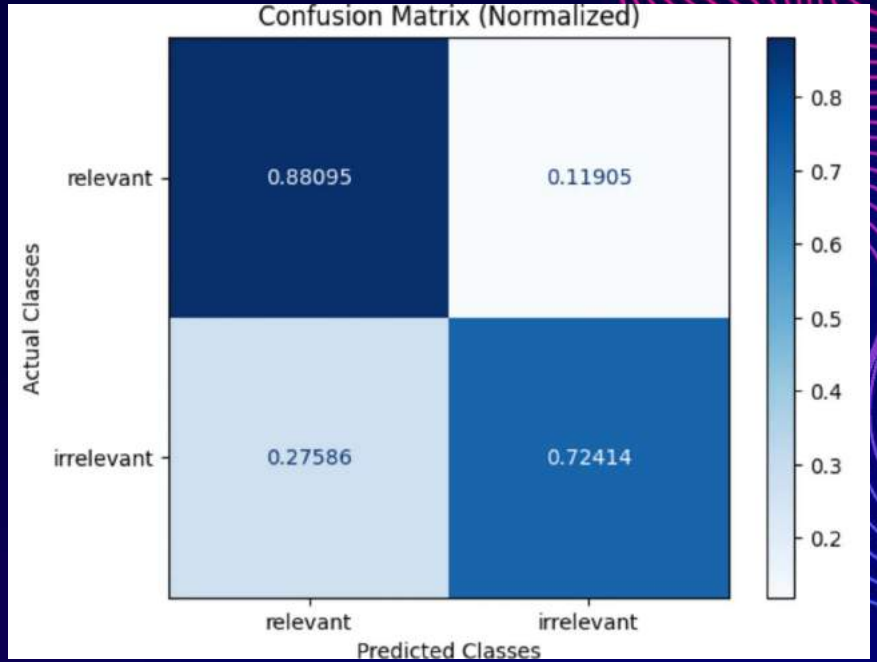
- **Human Evaluation**
- **Human Comparison/Arena**
- **Model based Approaches**

- Label-free Modules
  - Faithfulness: whether response matches retrieved context
  - Relevancy: whether response matches query
  - Guidelines: whether response matches guidelines
- With-Labels
  - Correctness: whether response matches “golden” answer



Pro Tip: Evaluating augmentation - Imbalance

- Many relevance questions may be unbalanced
- Need to look at precision and recall



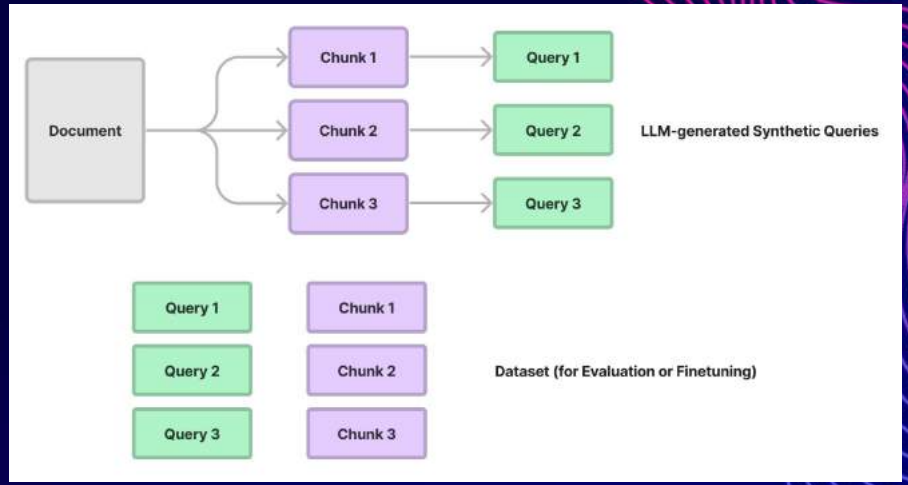
https://towardsdatascience.com/llm-evals-setup-and-the-metrics-that-matter-2cc27e8e35f3

Pro Tip: Generate an synthetic evaluation dataset

You can use a LLM to help create synthetic evaluation datasets

Anthropic:
https://github.com/anthropics/anthropic-cookbook/blob/main/long_context/mc_qa.ipynb

Llama-Index:
https://gpt-index.readthedocs.io/en/v0.8.30/examples/low_level/evaluation.html



https://www.databricks.com/blog/LLM-auto-eval-best-practices-RAG
Jerry Liu: Evaluating and Optimizing your RAG App

Notebooks used

Summary of the notebook tutorials:

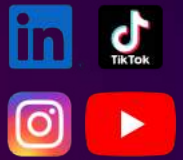
1. Prompting a chatbot
2. Testing properties of a system (Guidance AI)
3. Eleuther AI harness
4. langtest (John Snow Labs)
5. Ragas (Confident AI)

Other good stuff:

Josh Tobin's Evaluating LLM-based Application:
https://youtu.be/r-HUnht-Gns?si=5vU3RzXf7Jkprwn1

Evaluating LLMs

Repo: https://github.com/rajshah4/LLM-Evaluation



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raj@huggingface.co

Nov 2023