## **Evaluation Techniques for LLMs**









Rajiv Shah @rajistics r.shah@snowflake.com

## **Expectations from Generative Al**



who was the third governor of Illinois



The third governor of Illinois was Ninian Edwards. He served as governor from 1826 to 1830. Edwards played a significant role in the early history of Illinois, including its transition from a territory to a state. He was also involved in various political and legal activities during his lifetime.

how can I sort a dataframe

There are several ways to sort a Pandas DataFrame. Here are a few methods:

'sort\_values()': Sorts the DataFrame by one or more columns. You can specify
either ascending ('ascending=True') or descending ('ascending=False') sorting for
each column.

df = df.sort\_values(by='column\_name', ascending=False)



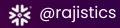
can you summarize my skit in two sentences

Here's a two sentence summary of the key points from the Al industry skit:

The exaggerated banter between AI companies reveals tensions as priorities shift from brute force hardware scaling to data, research, and efficiency gains; an insightful OpenAI emerges above the fray, securing valuable data relationships as competitors remain preoccupied with flexing GPU muscles, underscoring through satire that sustainable AI progress requires strategy beyond just hardware accumulation.

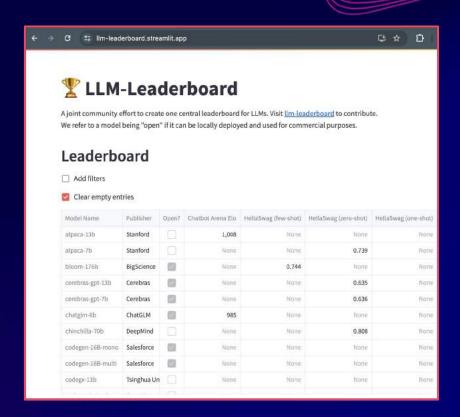






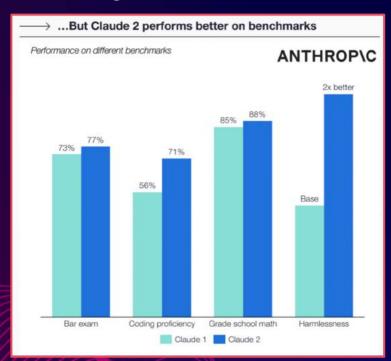
#### So many choices

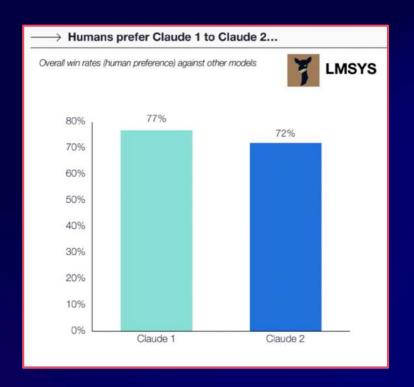






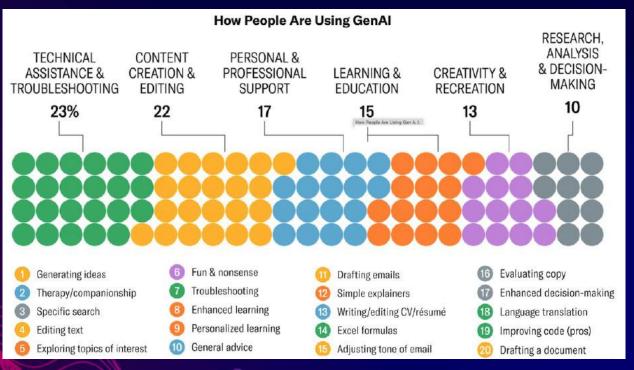
#### Not easy to evaluate



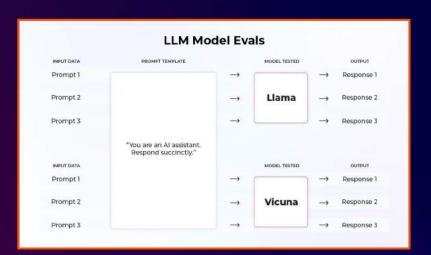


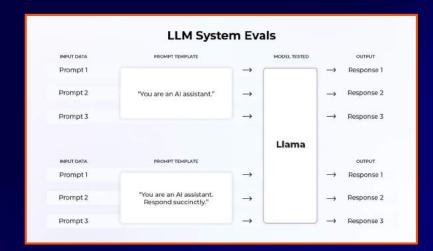


#### Acceptance



#### Recognize: Social Media isn't your friend



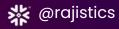


Most approaches focus on selecting from *n* models

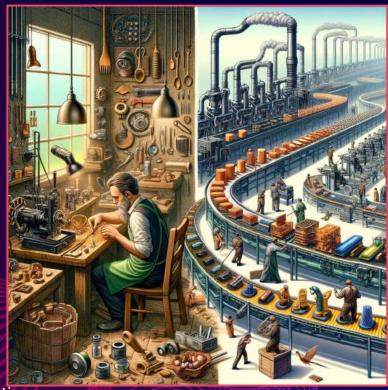
## **Fundamentals: ML Lifecycle**

Evaluation is part of the entire lifecycle!





### Payoff if you do evaluation right!



faster, better, cheaper...



## **Simple Evaluation**

Generative model outputs a multiple choice value:







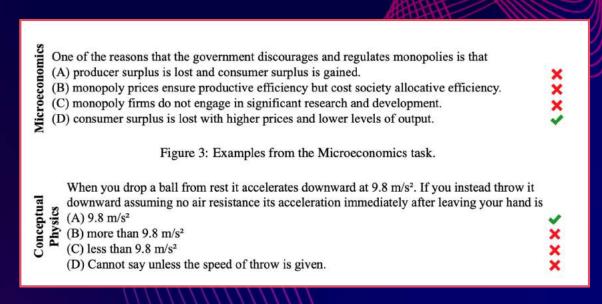
### MMLU: Massive Multitask Language Understanding

Widely used to evaluate the "smarts" of models

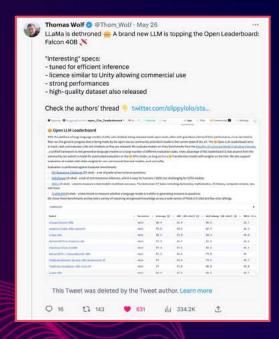
				DATA THEORETICA
1	Gemini Ultra ~1760B	90	×	Gemini: A Family of Highly Capable Multimodal Models
2	Claude 3 Opus	86.8	1	
3	Leeroo (Mix)	86.6	х	Leeroo Orchestrator: Elevating LLMs Performan Through Model Integration
4	GPT-4~1600B	86.5	~	GPT-4 Technical Report
5	GPT-4 (few-shot)	86.4	×	GPT-4 Technical Report
6	Gemini Ultra (5-shot)	83.7	×	
7	Flan-PaLM 2-L	81.2	×	PaLM 2 Technical Report
8	Gemini Pro (CoT@8)	79.1	×	
9	Claude 2 (5-shot)	78.5	×	Model Card and Evaluations for Claude Models
10	PaLM 2-L (5-shot)	78.3	×	PaLM 2 Technical Report
11	Qwen1.5-72B	77.5	×	

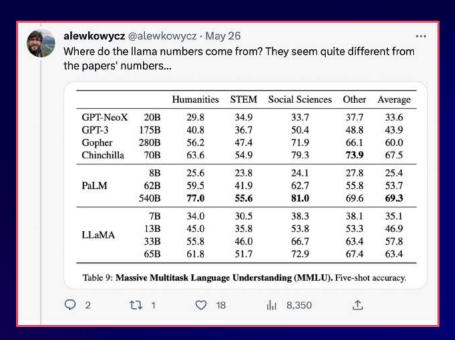
#### MMLU: Massive Multitask Language Understanding

57 tasks: History, Computer science, mathematics



#### **Story Time: MMLU Leaderboards**





#### Why different MMLU scores?

### Differences in prompts

#### **Spot the differences:**

- HELM extra space
- Instructions
- Question prefix? "Choices"

Original implementation Ollmer PR

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:

HELM commit cab5d89

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Ouestion: How did the 2008 financial crisis affect America's international reputation?

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D. It reduced global use of the US dollar

Answer:

AI Harness commit e47e01b

Ouestion: 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

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Answer:

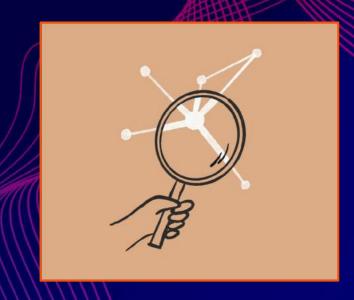


## Why MMLU evaluation differed: Style

#### 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





#### **Prompt Engineering**

#### Chain-of-Thought Prompting

#### Model Input

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

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

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

#### Model Output

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

#### 12 Prompt Engineering Techniques



www.cobusgreyling.com

Identifying the best prompt

#### **Gen Al Prediction Workflow**

Inputs

Tokenization
Prompt Styles
Prompt Engineering
System Prompt

Model

Model selection
Hyperparameters
Nondeterministic inference
Forced "updates"

Outputs



#### **Gen Al Prediction Workflow**

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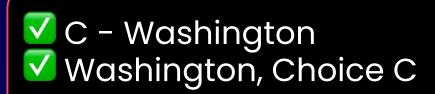
### Generating a Multiple Choice Output



Require one of the choices

First Letter Approach







**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	A	A. It damaged support for the US model	
В		of political economy and capitalism	
С		B. It created anger at the United States	
D		for exaggerating the crisis	
		C. It increased support for American	
		global leadership under President	
		Obama	
		D. It reduced global use of the US dollar	

#### **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





#### **Gen Al Prediction Workflow**

Inputs

Model

**Outputs** 

Tokenization

Prompt Styles

**Prompt Engineering** 

System Prompt

Model selection

Hyperparameters

Nondeterministic inference

Forced "updates"

Output evaluation

PROTER PLAN ON MULTIPLE ITERATIONS WHEN EVALUATING LLMS



# You aren't helping



- Exact matching approach
- approachSimilarity approach
- Unit Tests
- Evaluation Benchmarks
- Human Evaluation
- Human Comparison/Arena
- Model based Approaches
- Red Teaming



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Evaluation for Large Language Models and...

Rajistics - data science, Al, and m... 5.9K views • 4 months ago

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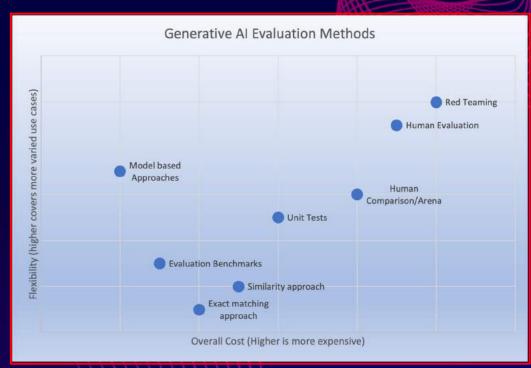
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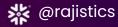
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# You have my attention



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tiiuae/falcon-7b	0.278	0.35	0.254
togethercomputer/RedPajama-INCITE-7B-Base	0.275	0.34	0.269



#### even more benchmarks

Advanced Sommelier (theory

knowledge)

Al2 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

bAbl

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)

**Ouantitative** 

Graduate Record Examination (GRE)

Verbal

Graduate Record Examination (GRE)

Writing GSM8K HaluEval HellaSwaa 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 SocialOA

Synthetic reasoning (abstract symbols)

Synthetic reasoning (natural language)

TfQA TruthfulOA

Uniform Bar Exam (MBE+MEE+MPT)

USABO Semifinal Exam 2020
USNCO Local Section Exam 2022

Webshop WikiFact WinoGender WinoGrande

XSUM



## **Pro tip:** Build your own benchmark / leaderboards

Every organization has multiple use cases

Build a custom benchmark

Examples of Domain specific:

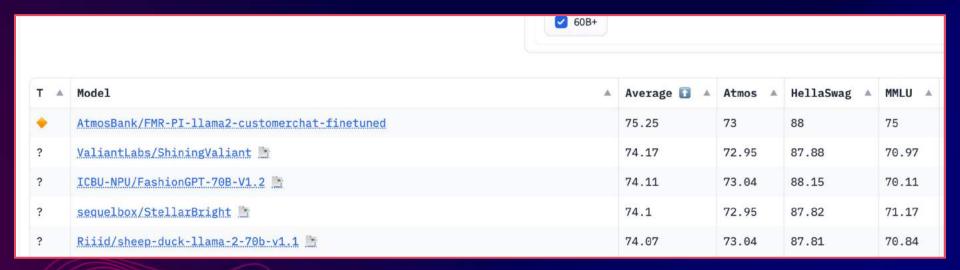
LegalBench

AgentsBench

OWL - IT Operations



## **Pro tip:** Build your own benchmark / leaderboards



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#### **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 1]
```

#### Reference solution:

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

## **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]"""

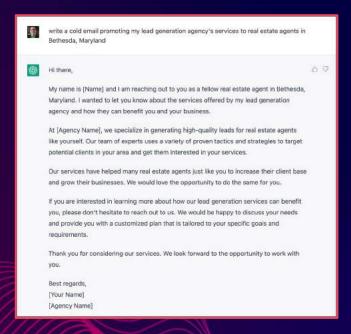
return [(e + 1) for e in l]
```

#### Test Cases:

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

Pass: yes/no

### **Unit Tests Beyond Code**

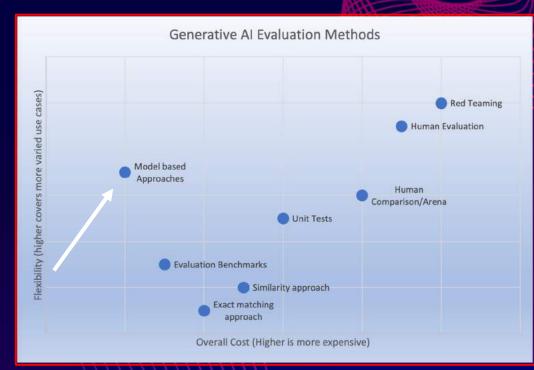


#### Properties of Emails?

- First/Last Name?
- Grammar/spelling
- Concise?
- Verify actions?
- Tone? is it polite

### Methods for evaluating Generative Al

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#### Model based evaluation

#### Task instruction, sample, and question

#### Please rate the story fragment

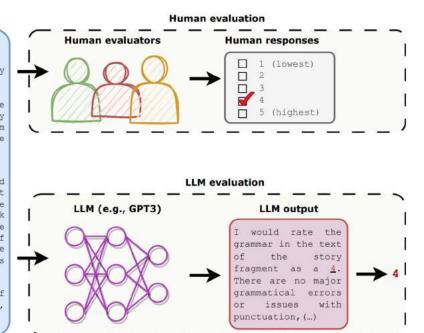
The goal of this task is to rate story fragments.

NOTE: Please take the time to fully read and understand the story fragment. We will reject submissions from workers that are clearly spamming the task.

#### Story fragment

The human ambassador reached down and grasped it's paw. "Humans, cats, is it true that all intelligent beings are omnivorous?" "Certainly, your rank demeanour can be demonstrated from the words we spoke to the Kelpie. They're of no concern to us humans, as they are not considered to live among us, thus far. (...)

How **grammatically correct** is the text of the story fragment? (on a scale of 1-5, with 1 being the lowest?)



### C'mon Man - This isn't going to work

Bharat Saxena · 1st

2d •

Bringing intelligence to Mainframes @ BMC Software | Explainable AI (XAI) | NLP ...

Rajiv Shah From personal experience, I am a big skeptic when it comes to using another model as an evaluator ... Hopefully you will be able to share some details from your presentation as some time in future.



#### It works in Texas

Texas is replacing thousands of human exam graders with Al / Don't call the 'automated scoring engine' Al, though. They don't like that.



# Query: Show me the total population of each state ordered from the most northern one to the most southern one.

#### **Gold Standard**

SELECT SUM(POP10), cbsa.state\_name
FROM county
JOIN cbsa
ON county.geoid = CONCAT(CBSA.fips\_state\_code,CBSA.FIPS\_COUNTY\_CODE)
GROUP BY state\_name
ORDER BY max(INTPTLAT) desc;

Extra Column for Latitude

```
SELECT SUM(POP10), cbsa.state_name, max(INTPTLAT)
FROM county
JOIN cbsa
ON county.geoid = CONCAT(CBSA.fips_state_code,CBSA.FIPS_COUNTY_CODE)
GROUP BY state_name
ORDER BY max(INTPTLAT) desc;
```

- Define Data Quality
- **W** Grading Scale
- Explain Inputs

You are a data analyst quality rater responsible for evaluating the quality of Snowflake SQL statements generated from natural language queries by comparing the candidate SQL statement to the user intent.

You must provide a score on an integer scale of 0 to 3 with the following meanings:

- 3 = perfect match The candidate SQL will produce the same result as the user intent.
- 2 = good match The candidate SQL will produce nearly the same result as the user intent but may suffer from non-deterministic issues such as sorting or grouping.
- 1 = partial match The candidate SQL will produce an output similar to the user intent but may miss some part of the user's desired output
   0 = no match The candidate SQL will not produce anything similar to the user intent.

You will have access to the following elements:

- 1. User Query: The user natural language query enclosed in [{query}].
- 2. Database Schema: Information about the database schema is enclosed in [{db\_formatted}].
- Candidate SQL: The SQL query generated by the system is enclosed in [{candidate\_sql}].

Returned SQL is a bit different:

TX versus TEXAS

User Query	Gold SQL	Candidate SQL
What are the first 100 tract IDs whose total ratio is the highest, except those in Texas?	SELECT tract FROM zip_tract WHERE usps_zip_pr ef_city NOT IN ('TX') ORDER BY tot_ratio DESC limit 100;	SELECT tract FROM zip_tract WHERE usps_zip_pref_cit y NOT IN ('TEXAS') ORDER BY tot_ratio DESC limit 100;



Similarity:

X not a 100% match

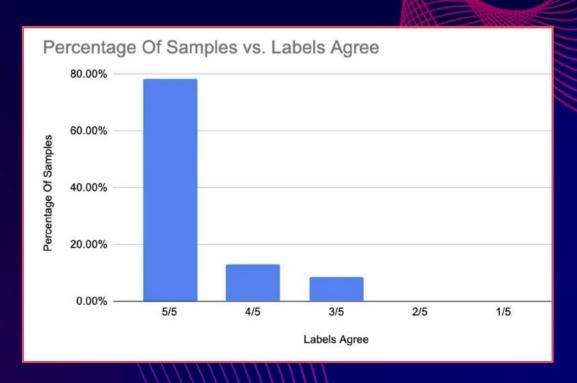
			MPI PET LETT
User Query	Gold SQL	Candidate SQL	Execution Accuracy
What are the first 100 tract IDs whose total ratio is the highest, except those in Texas?	SELECT tract FROM zip_tract WHERE usps_zip_pr ef_city NOT IN ('TX') ORDER BY tot_ratio DESC limit 100;	SELECT tract FROM zip_tract WHERE usps_zip_pref_cit y NOT IN ('TEXAS') ORDER BY tot_ratio DESC limit 100;	No Match

Model:

It's ok, its captures the users intent

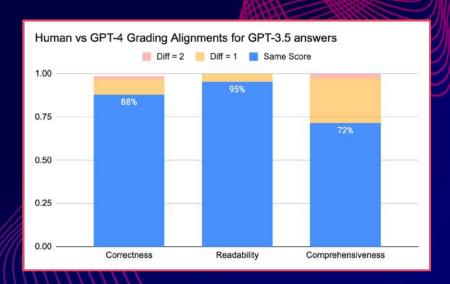
User Query	Gold SQL	Candidate SQL	Execution Accuracy	Execution Score		
What are the first 100 tract IDs whose total ratio is the highest, except those in Texas?	SELECT tract FROM zip_tract WHERE usps_zip_pr ef_city NOT IN ('TX') ORDER BY tot_ratio DESC limit 100;	SELECT tract FROM zip_tract WHERE usps_zip_pref_cit y NOT IN ('TEXAS') ORDER BY tot_ratio DESC limit 100;	No Match	Perfect Match		

Strong correlation to other evaluation approaches

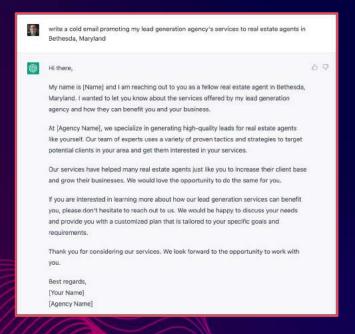


# Model evaluation aligns with humans

Human and GPT-4 judges can reach above 80% agreement on the correctness and readability score.



### **Unit Tests Beyond Code**



#### Properties of Emails?

- First/Last Name?
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- Concise?
- Verify actions?
- Tone? is it polite
- + Explanations

### We can do this!

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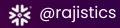




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