Evaluation

CS 4804: Introduction to AI

Fall 2025

https://tuvllms.github.io/ai-fall-2025/

Tu Vu

VIRGINIA TECH.

Logistics

- We are sending feedback for final project proposals
- Final presentations: 12/4 & 12/9
- Teaching & learning evaluation: 11/4
- Quiz 2 & HW 2: coming this week

Logistics

- Final Project
  - Curating data (optional)
  - Benchmarking models
  - 0-shot/few-shot/chain-of-thought/self-consistency prompting
  - Fine-tuning
  - Test-time scaling
  - LLM-as-a-judge / MLLM-as-a-judge

The rest of the course

- Efficient training and inference
- Compound AI system & Agentic AI

LMArena

- https://lmarena.ai

Elo score

- Models are compared in pairs on the same prompt.
- The winner gains rating points; the loser loses points.
- Expected win probability depends on rating difference.
- The rating change is larger when results are surprising.
- Ratings are relative and stabilize after many comparisons.

LMArena (cont'd)

Image Edit

20 days ago

Rank (UB)	Model	Score	Votes
1	gemini-2.5-flash-image-previ…	1342	8,685,501
2	seedream-4-2k	1311	219,262
3	seedream-4-high-res-fal	1257	87,083
4	reve-v1	1226	2,799
4	seedream-4-fal	1211	150,056
6	flux-1-kontext-max	1194	339,004
7	qwen-image-edit	1182	829,191
7	flux-1-kontext-pro	1180	5,352,306
9	gpt-image-1	1159	2,110,165
9	flux-1-kontext-dev	1158	2,985,649

View all

Search

11 days ago

Rank (UB)	Rank (Style Control)	Model	Score
1	3 ↓	grok-4-fast-search	1164
2	3 ↓	gemini-2.5-pro-grounding	1142
2	1 ↑	o3-search	1142
2	8 ↓	grok-4-search	1140
2	6 ↓	ppl-sonar-pro-high	1138
2	1 ↑	gpt-5-search	1133
6	3 ↑	claude-opus-4-1-search	1128
6	3 ↑	claude-opus-4-search	1128
9	8 ↑	ppl-sonar-reasoning-pro-high	1115
10	10	diffbot-small-xl	1022

View all


OpenAI


Grok

Crowdsourcing platforms

- Upwork.com
- Amazon Mechanical Turk (https://www.mturk.com/)

Human evaluation

- To evaluate a 250-word generation:
  - Crowdworkers take ~10 sec
  - English teachers take ~70 sec
- High variability across runs, low agreement

[The Perils of Using Mechanical Turk to Evaluate Open-Ended Text Generation]

BLUE & ROUGE

- N-gram overlap between the machine output and reference

BLUE & ROUGE

Q. Why are almost all boats white?

A. Why are almost all boats white?

Input copying

Method	ROUGE-L
Input copying (↓)	20.0
RAG (Lewis et al. 2020)	16.1
RT (Krishna et al. 2021)	24.4
Human answers (↑)	21.2

BLEURT: Learning Robust Metrics for Text Generation

Thibault Sellam   Dipanjan Das   Ankur P. Parikh
Google Research
New York, NY
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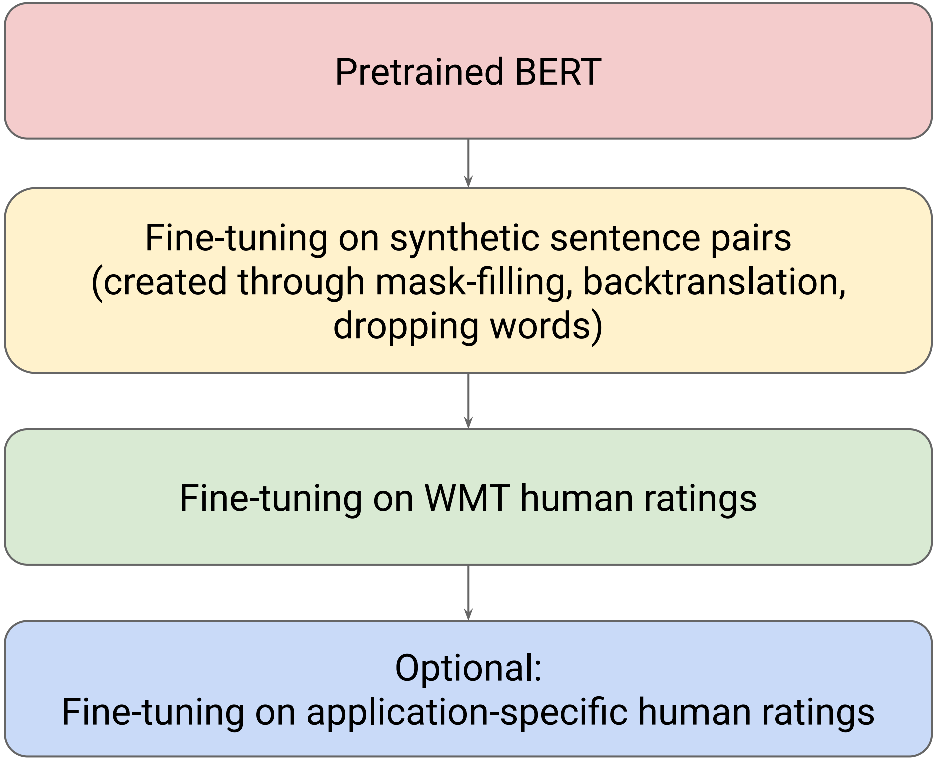
BLEURT (BLUE + BERT)



COMET: A Neural Framework for MT Evaluation

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Unbabel AI
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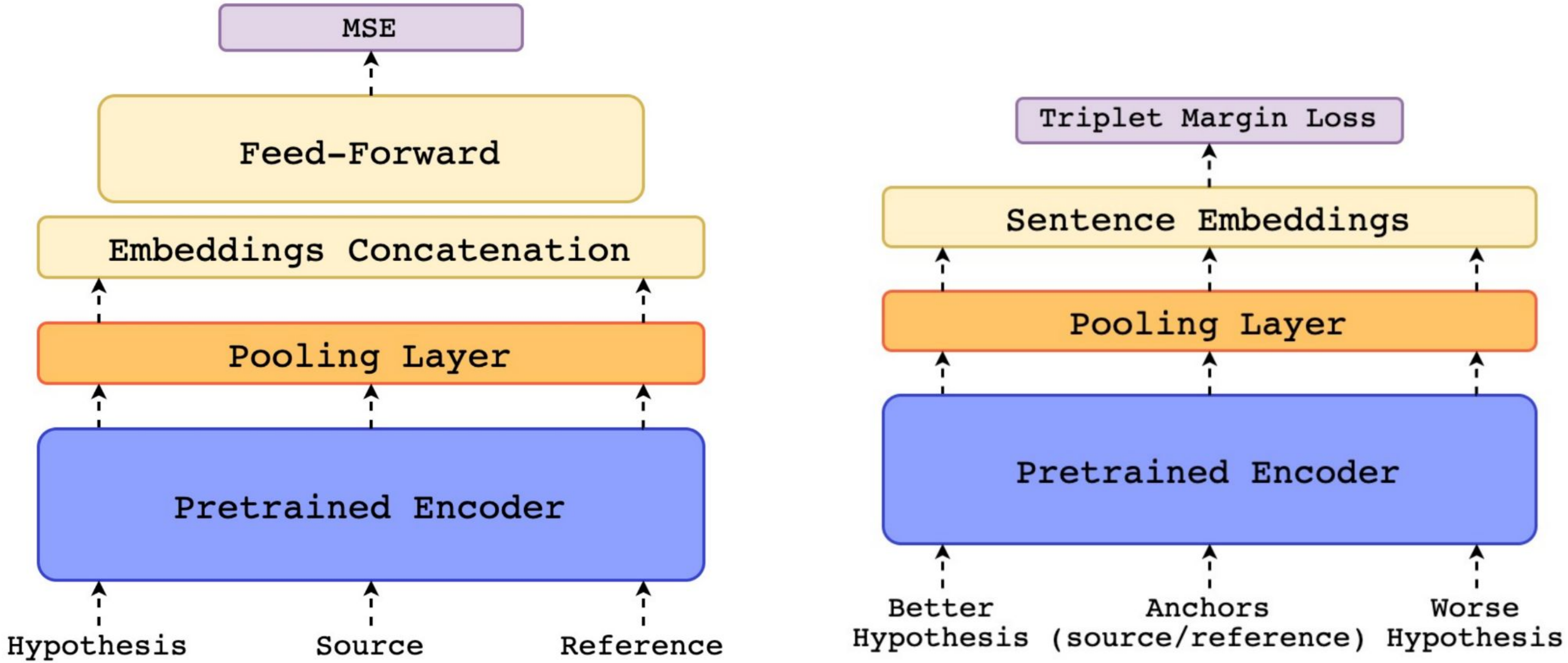
COMET


MSE
Feed-Forward
Embeddings Concatenation
Pooling Layer
Pretrained Encoder
Hypothesis
Source
Reference
Triplet Margin Loss
Sentence Embeddings
Pooling Layer
Pretrained Encoder
Better Hypothesis
Anchors (source/reference)
Worse Hypothesis

FACTSCORE: Fine-grained Atomic Evaluation of Factual Precision in Long Form Text Generation

Sewon Min[†1] **Kalpesh Krishna**[†2] **Xinxi Lyu**[1] **Mike Lewis**[4] **Wen-tau Yih**[4]
Pang Wei Koh[1] **Mohit Iyyer**[2] **Luke Zettlemoyer**[1,4] **Hannaneh Hajishirzi**[1,3]
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FactScore

breaks a generation into a series of atomic facts and computes the percentage of atomic facts supported by a reliable knowledge source.

Chat GPT

Bridget Moynahan is an American actress, model and producer. She is best known for her roles in Grey's Anatomy, I, Robot and Blue Bloods. She studied acting at the American Academy of Dramatic Arts, and ...

Tell me a bio of Bridget Moynahan.

- Bridget Moynahan is American. ✓
- Bridget Moynahan is an actress. ✓
- Bridget Moynahan is a model. ✓
- Bridget Moynahan is a producer. ✗
- She is best known for her roles in Grey's Anatomy. ✗
- She is best known for her roles in I, Robot. ✓
- She is best known for her roles in Blue Bloods. ✓
- She studied acting. ✓
- She studied at the American Academy of Dramatic Arts. ✗
- ...

66.7%

LLM-as-a-Judge / LLM auto-rater

Judging LLM-as-a-Judge with MT-Bench and Chatbot Arena

Lianmin Zheng[1*] **Wei-Lin Chiang**[1*] **Ying Sheng**[4*] **Siyuan Zhuang**[1]

Zhanghao Wu[1] **Yonghao Zhuang**[3] **Zi Lin**[2] **Zhuohan Li**[1] **Dacheng Li**[13]

Eric P. Xing[35] **Hao Zhang**[12] **Joseph E. Gonzalez**[1] **Ion Stoica**[1]

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MLLM-as-a-Judge: Assessing Multimodal LLM-as-a-Judge with Vision-Language Benchmark

Dongping Chen [*1] Ruoxi Chen [*2] Shilin Zhang [*1] Yaochen Wang [*1] Yinuo Liu [*1] Huichi Zhou [*1] Qihui Zhang [*1] Yao Wan [1] Pan Zhou [1] Lichao Sun [3]

Abstract

Multimodal Large Language Models (MLLMs) have gained significant attention recently, showing remarkable potential in artificial general intelligence. However, assessing the utility of MLLMs presents considerable challenges, primarily due to the absence of multimodal benchmarks that align with human preferences. Drawing inspira-

1. Introduction

The advent of Large Language Models (LLMs), such as GPT-3 (OpenAI, 2023) and Llama (Touvron et al., 2023), has achieved substantial progress in content generation, including text generation (OpenAI, 2023), code generation (Roziere et al., 2023), and video synthesis (Wu et al., 2023a). The emergent abilities of LLMs, as demonstrated by the Chain-of-Thought (CoT) framework (Wei et al., 2022), present a promising avenue for their utilization as evalua-

An LLM is given context and tasked with evaluating response quality or selecting the better response among candidates

Question: If the FED buys bonds in the secondary market
(A) the money supply will increase. (B) the money supply will decrease. (C) the money supply will not be affected. (D) the discount rate would be affected. Output the answer only.

Assistant A:

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

Assistant B:

```
(A) the money supply will increase.
```

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

Assistant A:

```
The Federal Reserve buys
bonds in the secondary
market to increase the
money supply. This
affects your daily life
by:
1. Increasing the money
supply.
2. Increasing the money
supply and lowering the
discount rate.
3. Increasing the money
supply and lowering the
discount rate and
increasing the money
supply.
```

Assistant B:

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

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

GPT-4 Judgment:

Assistant A provided an incorrect response to the user's question about how the Federal Reserve buying bonds in the secondary market affects daily life. The answer given is repetitive and lacks clear examples of how the action impacts daily life.
On the other hand, **Assistant B** provided a relevant and accurate response to the user's question about the Federal Reserve buying bonds. The answer includes three clear examples of how the action impacts daily life, such as interest rates, inflation, and employment.

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

Table 1: Sample multi-turn questions in MT-bench.

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

Types of LLM-as-a-Judge

- Pairwise comparison
  - determine which response is better or declare a tie
- Single answer grading (pointwise evaluation)
  - directly assign a score to a single response
- Reference-guided grading
  - a reference solution is provided

Pairwise comparison

```
[System]
Please act as an impartial judge and evaluate the quality of the responses provided by two
AI assistants to the user question displayed below. You should choose the assistant that
follows the user’s instructions and answers the user’s question better. Your evaluation
should consider factors such as the helpfulness, relevance, accuracy, depth, creativity,
and level of detail of their responses. Begin your evaluation by comparing the two
responses and provide a short explanation. Avoid any position biases and ensure that the
order in which the responses were presented does not influence your decision. Do not allow
the length of the responses to influence your evaluation. Do not favor certain names of
the assistants. Be as objective as possible. After providing your explanation, output your
final verdict by strictly following this format: "[[A]]" if assistant A is better, "[[B]]"
if assistant B is better, and "[[C]]" for a tie.

[User Question]
{question}

[The Start of Assistant A’s Answer]
{answer_a}
[The End of Assistant A’s Answer]

[The Start of Assistant B’s Answer]
{answer_b}
[The End of Assistant B’s Answer]
```

Pointwise evaluation

```
[System]
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, please rate the response on a scale of 1 to 10
by strictly following this format: "[[rating]]", for example: "Rating: [[5]]".

[Question]
{question}

[The Start of Assistant's Answer]
{answer}
[The End of Assistant's Answer]
```

Reference-based evaluation

```
[System]
Please act as an impartial judge and evaluate the quality of the responses provided by two
AI assistants to the user question displayed below. Your evaluation should consider
correctness and helpfulness. You will be given a reference answer, assistant A's answer,
and assistant B's answer. Your job is to evaluate which assistant's answer is better.
Begin your evaluation by comparing both assistants' answers with the reference answer.
Identify and correct any mistakes. Avoid any position biases and ensure that the order in
which the responses were presented does not influence your decision. Do not allow the
length of the responses to influence your evaluation. Do not favor certain names of the
assistants. Be as objective as possible. After providing your explanation, output your
final verdict by strictly following this format: "[[A]]" if assistant A is better, "[[B]]"
if assistant B is better, and "[[C]]" for a tie.

[User Question]
{question}

[The Start of Reference Answer]
{answer_ref}
[The End of Reference Answer]

[The Start of Assistant A's Answer]
{answer_a}
[The End of Assistant A's Answer]

[The Start of Assistant B's Answer]
{answer_b}
[The End of Assistant B's Answer]
```

Advantages of LLM-as-a-Judge

Advantages of LLM-as-a-Judge

- Scalability
  - reduces the need for human involvement, enabling scalable benchmarks and fast iterations
- Explainability
  - provides not only scores but also explanations, making its outputs interpretable

Limitations of LLM-as-a-Judge

Position (Order) bias

- The LLM judge favors a particular response position.

Question: What are some business etiquette norms when doing business in Japan?

Assistant A:

Here are some business etiquette norms to keep in mind when doing business in Japan:

1. Bowing: Bowing is a common greeting in Japan. It is a sign of respect and should be reciprocated.
2. Business cards: Business cards are exchanged at the beginning of a meeting. It is important to receive and give business cards with both hands and to take a moment to read the card before putting it away.
3. Punctuality: Being on time is important in Japan. Arrive a few minutes early to show respect for your colleagues.
4. Dress code: Dress conservatively and professionally. Men should wear dark suits and ties, while women should wear conservative business attire.
5. Language: Learn a few basic Japanese phrases to show respect for the culture. It is also important to speak clearly and avoid using slang or idioms.
6. Gift giving: Gift giving is a common practice in Japan. Bring a small gift, such as a box of chocolates or a small souvenir from your home country.
7. Dining etiquette: When dining with colleagues, wait for the host to begin eating before you start. Use chopsticks correctly and avoid leaving food on your plate.

Remember, showing respect for Japanese culture and customs is key to building strong business relationships in Japan.

Assistant B:

When doing business in Japan, it is important to be aware of and respect the country's business etiquette norms. Some of these norms include:

1. Greetings: A handshake and bow is the standard greeting in Japan. It is important to bow deeply and to offer a firm handshake.
2. Business cards: In Japan, business cards are exchanged after the initial greeting. It is important to handle the card with respect and to read it carefully before placing it on the table.
3. Meetings: Meetings in Japan are typically formal and conducted in a hierarchical manner. It is important to address people by their titles and to avoid direct eye contact.
4. Punctuality: Punctuality is highly valued in Japan. It is important to arrive on time for meetings and to be prepared in advance.
5. Gift giving: Gift giving is a common practice in Japan, but it is important to be mindful of the occasion and the relationship. Avoid giving gifts that are considered too personal or extravagant.
6. Dining: Dining is an important part of doing business in Japan. It is important to be aware of the proper table manners and to avoid slurping or making loud noises while eating.
7. Communication: Communication in Japan is typically indirect and reserved. It is important to listen carefully and to avoid confrontational language.

Overall, it is important to be respectful, punctual, and mindful of hierarchy when doing business in Japan.

GPT-4 Judgment (when A is placed in the first position):

Both Assistant A and Assistant B provide helpful and relevant information about business etiquette norms in Japan. However, Assistant A's answer is more detailed and organized, covering a wider range of topics such as dress code and language, which are not mentioned in Assistant B's response. Assistant A also provides more specific advice on how to handle certain situations, such as exchanging business cards and dining etiquette. Therefore, Assistant A's answer is more comprehensive and useful for someone looking to understand Japanese business etiquette.

GPT-4 Judgment (when B is placed in the first position):

Both Assistant A and Assistant B provide helpful and relevant information about business etiquette norms in Japan. However, Assistant B's answer is more detailed and covers a wider range of topics, such as addressing people by their titles, avoiding direct eye contact, and being mindful of communication styles. Assistant A's answer is more concise but lacks some of the depth found in Assistant B's response. Therefore, Assistant B's answer is better in this case.

Table 2: Position bias of different LLM judges. Consistency is the percentage of cases where a judge gives consistent results when swapping the order of two assistants. “Biased toward first” is the percentage of cases when a judge favors the first answer. “Error” indicates wrong output formats. The two largest numbers in each column are in bold.

Judge	Prompt	Consistency	Biased toward first	Biased toward second	Error
Claude-v1	default	23.8%	**75.0%**	0.0%	1.2%
	rename	56.2%	11.2%	**28.7%**	**3.8%**
GPT-3.5	default	46.2%	**50.0%**	1.2%	2.5%
	rename	51.2%	38.8%	6.2%	**3.8%**
GPT-4	default	**65.0%**	30.0%	5.0%	0.0%
	rename	**66.2%**	28.7%	5.0%	0.0%

Verbosity bias

- The LLM judge favors longer, verbose responses, even if they are not as clear, high-quality, or accurate as shorter alternatives.

Question: What is the central dogma of molecular biology? What processes are involved? Who named this?

Assistant A:

```
The central dogma of molecular biology is the
fundamental principle that explains how genetic
information flows within a biological system. It
states that DNA is transcribed into RNA, which is
then translated into proteins. This means that
the genetic information stored in DNA is first
copied into RNA, which then serves as a template
for the synthesis of proteins.

The processes involved in the central dogma are:

1. Transcription rephrased: The act of copying
genetic information from DNA to RNA.
2. Translation rephrased: The act of using
genetic information in RNA to create proteins.
3. Transcription: The process by which the
genetic information in DNA is copied into RNA.
4. Translation: The process by which the genetic
information in RNA is used to synthesize
proteins.

The term "central dogma" was coined by Francis
Crick, one of the co-discoverers of the structure
of DNA, in 1958.
```

Assistant B:

```
The central dogma of molecular biology is the
fundamental principle that explains how genetic
information flows within a biological system. It
states that DNA is transcribed into RNA, which is
then translated into proteins. This means that
the genetic information stored in DNA is first
copied into RNA, which then serves as a template
for the synthesis of proteins.

The processes involved in the central dogma are:

1. Transcription: The process by which the
genetic information in DNA is copied into RNA.
2. Translation: The process by which the genetic
information in RNA is used to synthesize
proteins.

The term "central dogma" was coined by Francis
Crick, one of the co-discoverers of the structure
of DNA, in 1958.
```

GPT-3.5 Judgment:

Assistant A provides a more detailed and accurate response to the user's question. While both assistants correctly state the central dogma of molecular biology and who coined the term, Assistant A provides a more comprehensive explanation of the processes involved in the central dogma, including the rephrased definitions of transcription and translation. Therefore, I choose A as the better assistant.

Claude-v1 Judgment:

Both assistants answer the question by defining the central dogma and detailing the two processes involved, transcription and translation. However, assistant A provides a more in-depth and detailed explanation by briefly rephrasing and elaborating on these processes. Assistant A also mentions who coined the term "central dogma", which provides useful context and shows a more comprehensive understanding of the topic. Overall, assistant A gives a fuller and more insightful response, so I have chosen it as the better assistant for this question.

GPT-4 Judgment:

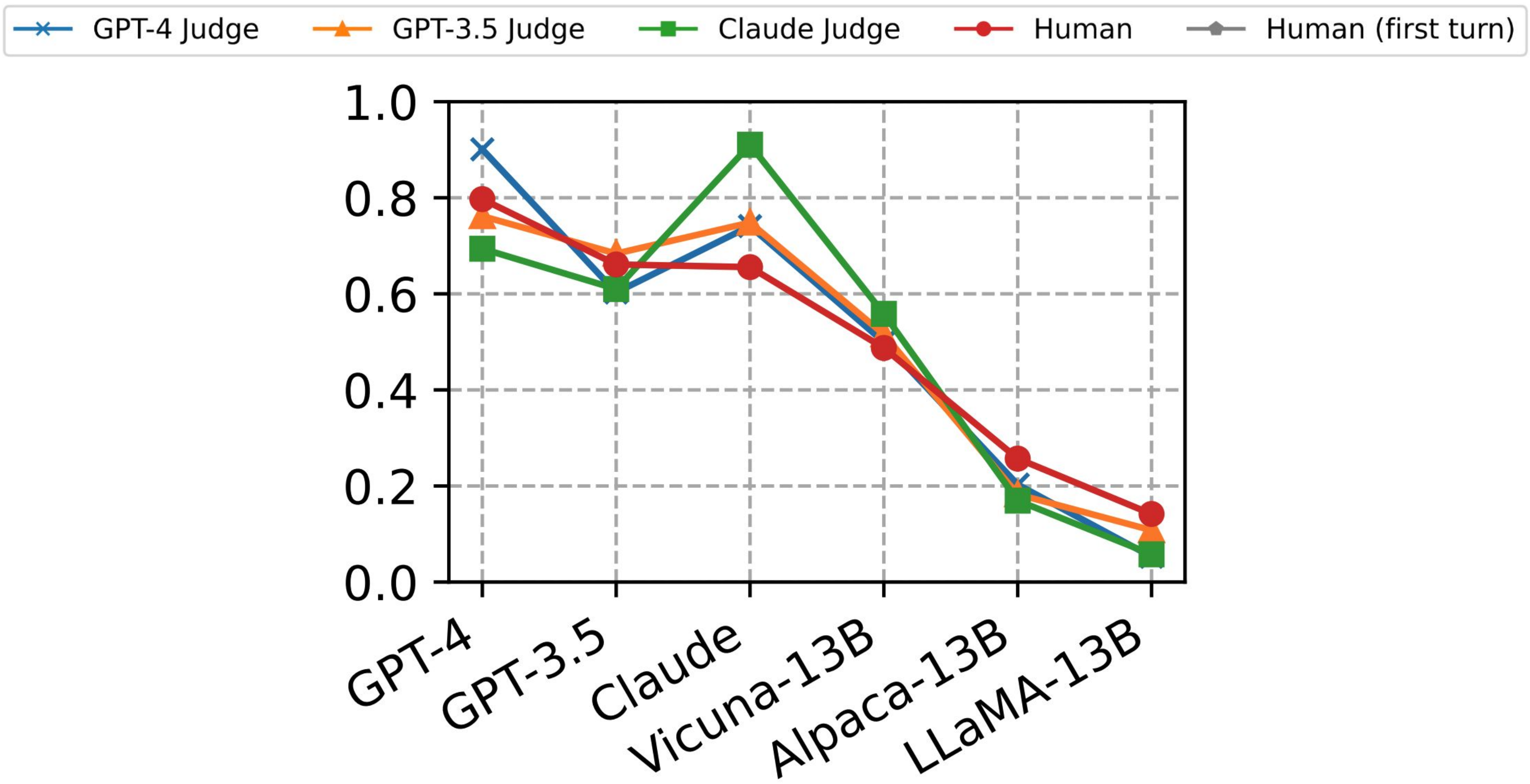
Both Assistant A and Assistant B provide accurate and relevant information about the central dogma of molecular biology, the processes involved, and who named it. However, Assistant A's answer contains a minor redundancy by rephrasing transcription and translation twice. Assistant B's answer is more concise and avoids this redundancy. Therefore, Assistant B's answer is better.

Table 3: Failure rate under "repetitive list" attack for different LLM judges on 23 answers.

Judge	Claude-v1	GPT-3.5	GPT-4
Failure rate	91.3%	91.3%	8.7%

Self-enhancement (egocentric) bias

- The LLM judge favors the responses generated by itself


GPT-4 Judge
GPT-3.5 Judge
Claude Judge
Human
Human (first turn)
1.0
0.8
0.6
0.4
0.2
0.0
GPT-4
GPT-3.5
Claude
Vicuna-13B
Alpaca-13B
LLaMA-13B

Limited capability in grading math and reasoning questions

Question: Benjamin went to a bookstore and purchased a variety of books. He bought 5 copies of a sci-fi novel, each priced at $20, 3 copies of a history book priced at $30 each, and 2 copies of a philosophy book for $45 each. What was the total cost of his purchases?

Assistant A:

```
The total cost of Benjamin’s purchases was $115.
```

Assistant B:

```
The total cost of his purchases is $295.
```

GPT-4 Judgment:

```
Assistant B provided the correct answer to the user’s question. Assistant A’s response was incorrect.
To calculate the total cost of Benjamin’s purchases, we need to multiply the number of books by their
respective prices and then add the results:
5 sci-fi novels * $20 = $100
3 history books * $30 = $90
2 philosophy books * $45 = $90
Total cost = $100 + $90 + $90 = $295
Assistant B’s response is accurate and directly answers the user’s question. Therefore, my final
verdict is: [[B]]
```

GPT-4’s Answer (if asked separately):

```
The cost of the sci-fi novels is 5 * $20 = $<<5*20=100>>100.
The cost of the history books is 3 * $30 = $<<3*30=90>>90.
The cost of the philosophy books is 2 * $45 = $<<2*45=90>>90.
The total cost of his purchases is $100 + $90 + $90 = $<<100+90+90=280>>280. Answer: \boxed{280}.
```

Figure 13: With a default prompt, GPT-4 shows limited capability in grading math questions. Despite being able to answer the question itself, its judgment was influenced by the given answers, leading to arithmetic mistakes highlighted in yellow.

Question: Each problem consists of three statements. Based on the first two statements, the third statement may be true, false, or uncertain.
1. Oranges cost more than apples.
2. Oranges cost less than bananas.
3. Bananas cost more than apples and bananas cost more than orange.
If the first two statements are true, then the third statement is

Assistant A:

```
false.
If oranges cost more than apples (statement 1) and
oranges cost less than bananas (statement 2), then
it is not possible for bananas to cost less than
oranges and also cost more than both apples and
oranges (statement 3). Therefore, statement 3 is
false.
```

Assistant B:

```
False.
If the first two statements are true, then the
third statement is false. The first statement
says that oranges cost more than apples, and the
second statement says that oranges cost less
than bananas. This means that oranges cost less
than bananas, which contradicts the third
statement that bananas cost more than apples and
more than oranges. Therefore, the third
statement must be false.
```

GPT-4 Judgment:

```
Both Assistant A and Assistant B provided accurate and relevant responses to the user's question.
They both concluded that the third statement is false based on the first two statements. However,
Assistant B's response is slightly clearer and more concise in explaining the contradiction between
the statements. Therefore, I choose Assistant B as the better response.

[[B]]
```

GPT-4's Answer (if asked separately):

```
True.

If oranges cost more than apples (statement 1) and oranges cost less than bananas (statement 2), it
logically follows that bananas cost more than apples and bananas cost more than oranges, which is the
third statement. So, if the first two statements are true, the third one is also true.
```

Figure 14: An example of GPT-4's limited capability in grading reasoning question. Despite GPT-4 knows how to solve the question (if asked separately), it made a wrong judgement saying both assistants' wrong answers are correct.

Addressing limitations

Addressing limitations

- Swapping positions
- Few-shot judge
- Chain-of-thought and reference-guided judge
- Fine-tuning a judge model
- Test-time scaling

Table 12: Improvements of the few-shot judge on consistency for position bias.

Model	Prompt	Consistency	Biased toward first	Biased toward second	Error
Claude-v1	zero-shot	23.8%	75.0%	0.0%	1.2%
	few-shot	**63.7%**	21.2%	11.2%	3.8%
GPT-3.5	zero-shot	46.2%	50.0%	1.2%	2.5%
	few-shot	**55.0%**	16.2%	28.7%	0.0%
GPT-4	zero-shot	65.0%	30.0%	5.0%	0.0%
	few-shot	**77.5%**	10.0%	12.5%	0.0%

MLLM-as-a-Judge: Assessing Multimodal LLM-as-a-Judge with Vision-Language Benchmark

Dongping Chen [*1] Ruoxi Chen [*2] Shilin Zhang [*1] Yaochen Wang [*1] Yinuo Liu [*1] Huichi Zhou [*1] Qihui Zhang [*1] Yao Wan [1] Pan Zhou [1] Lichao Sun [3]

Abstract

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1. Introduction

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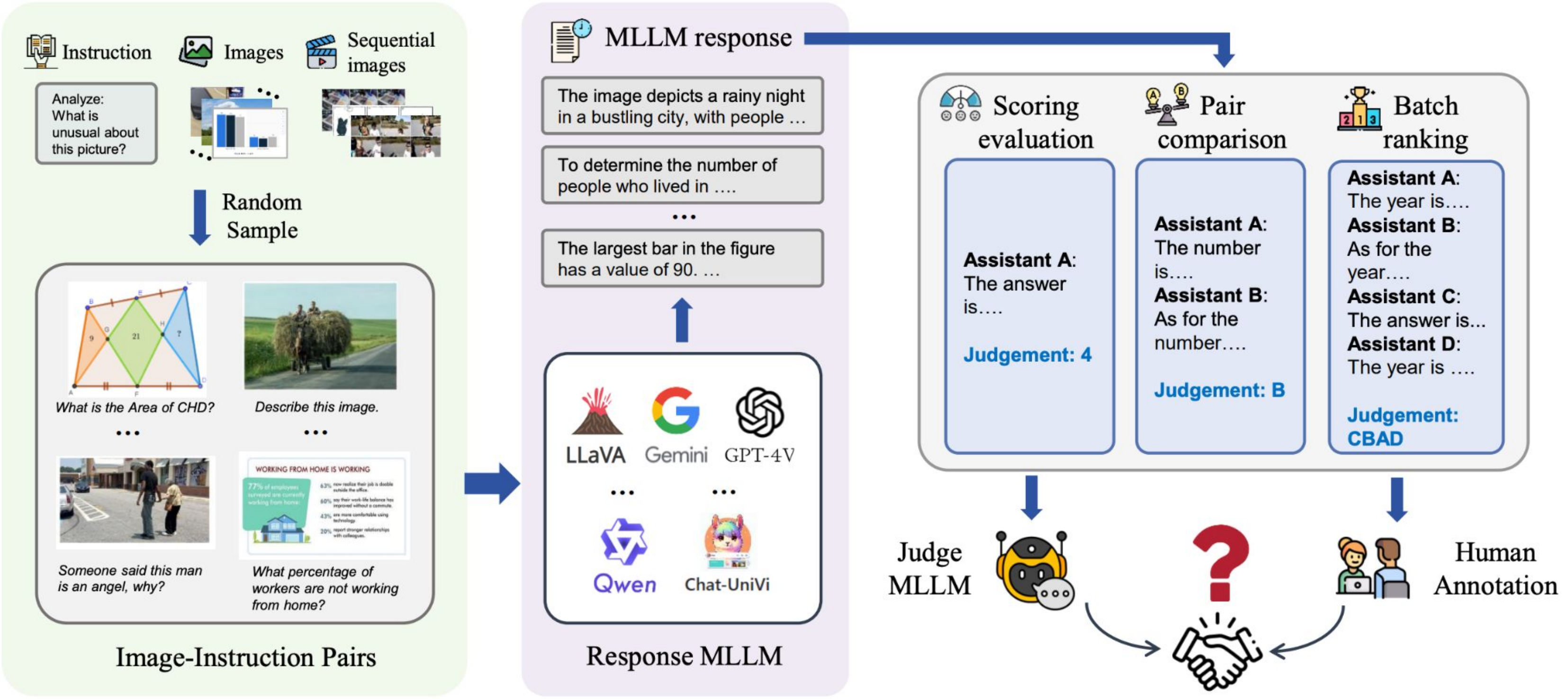
An overview of MLLM-as-a-Judge



Step 1：Image-Instruction Pair Collection

Step 2：MLLM Response Collection

Step 3：MLLM Judge v.s. Human Annotation

Findings

- MLLMs perform quite well at pair comparison: they can relatively reliably pick which of two answers is better, with decent alignment to human judgments
- However, for scoring (assigning a numerical rating) and batch ranking (ordering many responses), the alignment with humans is weaker and there is much more gap.

Findings (cont'd)

The models exhibit biases and issues:

- **Egocentric bias:** tendency to favour their own responses or ones similar to their style.
- **Position bias:** in pair or batch tasks, a preference to choose answers in certain prompt positions due to training artefacts.
- **Length/verbosity bias:** longer responses often get higher scores, even if they aren't qualitatively better.
- **Hallucinations:** especially in batch ranking tasks and longer reasoning chains, the judges make mistakes or generate mis-interpretations

Findings (cont'd)

The models exhibit biases and issues:

- Having vision input does help; and when a model without direct vision is given a detailed text description of the image, performance improves. This suggests that vision perception is beneficial for judging multimodal tasks.
- Surprisingly, adding multi-step chain-of-thought (CoT) reasoning for the judging task did not always help—in some cases it hurt alignment with humans

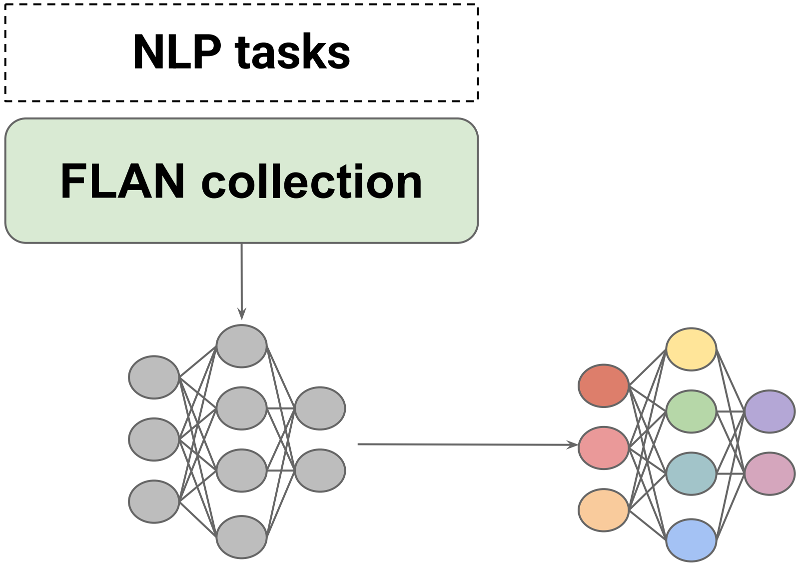
Google DeepMind

2024-07-15

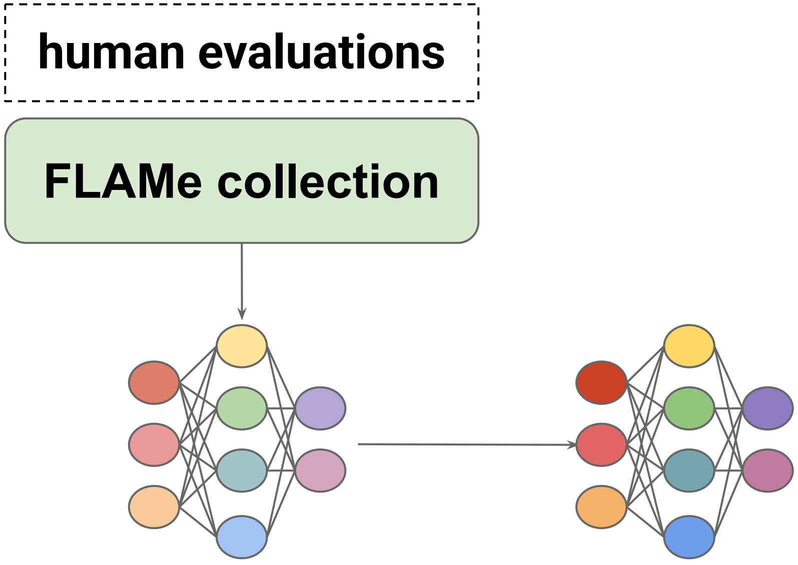
Foundational Autoraters: Taming Large Language Models for Better Automatic Evaluation

Tu Vu[*,1], **Kalpesh Krishna**[*,2],
Salaheddin Alzubi[3], **Chris Tar**[1], **Manaal Faruqui**[2] **and Yun-Hsuan Sung**[1]
[*]Co-lead (equal contribution), [1]Google DeepMind, [2]Google, [3]UMass Amherst

From FLAN to FLAMe



Designing Data and Methods for Effective Instruction Tuning
(Longpre & Hou & Vu et al., **ICML 2022**)



Curating and standardizing existing human evaluations

Source: Gold Miner Adventure

The FLAMe collection

- 102 quality assessment tasks comprising 5M+ total human judgments
- spans a wide variety of task types, from assessing summarization quality to evaluating how well AI assistants follow user instructions
- *all datasets are publicly available and under permissive licenses*

Collecting existing human evaluations is challenging

- Lack of standardization
- Diverse evaluation criteria
- Inadequate documentation
- Data privacy and proprietary concerns
- …

Data preprocessing took 3-4 hours per dataset!

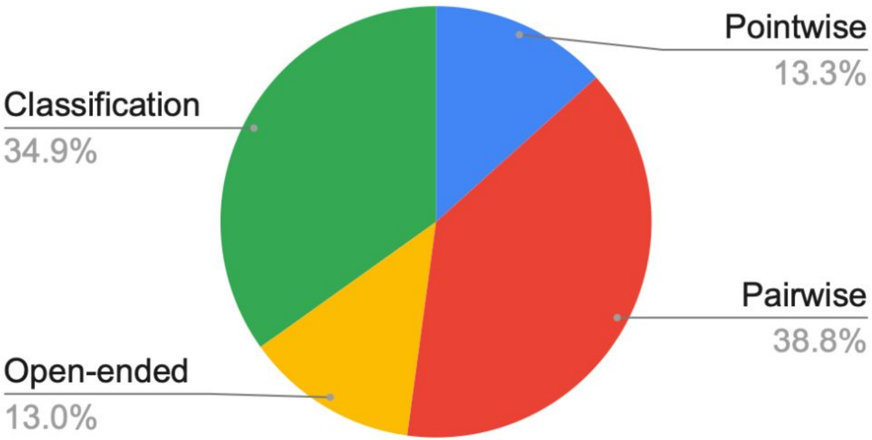
Unified task format

```
"""Input format."""

INSTRUCTIONS:
"""Task definition and evaluation instructions."""
title: Is all of the information in the summary fully attributable to the source article?
description: In this task, you will be shown a summary and a source news article on which the summary is based. Your task is to evaluate whether the summary is attributable to the source article. Answer 'Yes' if all the information in the summary is fully supported by the source article, or 'No' if any information in the summary is not supported by the source article. Provide an explanation for your answer.
output_fields: answer, explanation

CONTEXT:
"""Input fields for context, each starting with a label indicating its type or purpose and is separated by a newline, for example:
'article': <article>
'summary': <summary>
"""
article: Tower Hamlets Council said it would sell Draped Seated Woman after "unprecedented" budget cuts. The work has not yet been valued but a Moore sold for £17m earlier this year. The council said the rising threat of metal theft and vandalism made it too expensive to insure if it was on show. The sculpture was bought by the former London County Council for £6,000 in 1960. The bronze sculpture, nicknamed Old Flo, was installed on the Stifford council estate in 1962 but was vandalised and moved to the Yorkshire Sculpture Park in 1997. A council spokesperson said: "With unprecedented cuts to council budgets, the council finds itself in a difficult situation and being forced to make hard decisions."
summary: A Moore sculpture of a woman sitting on a concrete plinth is to be sold.
```

Unified task format (cont.)

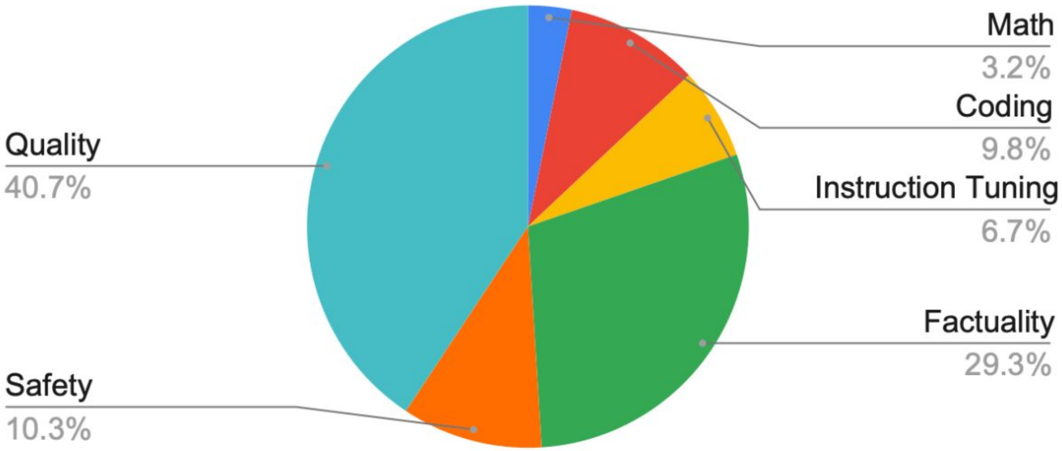
```
"""Target format."""

EVALUATION:
"""Target fields, each starting with a label indicating its type or purpose and is separated by a newline, for example:
'choice': <choice>
'explanation': <explanation>
"""
answer: No
explanation: The detail that the woman is "sitting on a concrete plinth" is not in the article.
```

The FLAMe collection covers diverse task types



FLAMe data collection breakdown by task type, showing the percentage of datapoints (out of 5.3M) for each task type. Over half of FLAMe is dedicated to standard pairwise (*"Which response is better?"*) and pointwise (*"Rate the response on a Likert scale."*) evaluation. The remainder includes classification (e.g., *"Is the summary fully attributable to the source article? (Yes/No)"*) and open-ended evaluation (e.g., *"Explain why response A is better than response B."*).

The FLAMe collection encompasses key LLM capabilities



FLAMe data collection breakdown by LLM capability, showing the percentage of datapoints (out of 5.3M) for each LLM capability. We focus on standard LLM evaluation pillars: general response quality, factuality, safety, coding, and math.

FLAMe models

- **FLAMe**
  - PaLM-2-24B trained on the FLAMe collection (examples-proportional mixing) for 30K steps
- **FLAMe-RM**
  - FLAMe fine-tuned on a balanced mixture of four preference datasets (covering chat, reasoning, and safety) for 50 steps
- **FLAMe-Opt-RM**
  - PaLM-2-24B trained on the FLAMe collection with RewardBench-optimized mixture weights (determined by tail-patch ablations) for 5K steps

FLAMe variants outperform all LLM-as-a-Judge autoraters on 8 out of 12 autorater evaluation benchmarks

Model	Reward Bench	LLM AggreFact	Summ Feedback	Alpaca Farm	Rank Gen	Co Poet	Contr Search	HHH	Dipper	Lit Trans	LFQA Eval	Help Steer
Llama-3-70B-Instruct	76.1	76.1	50.8	53.9	65.6	53.6	53.1	91.9	42.8	60.5	71.1	39.7
Mixtral-8×7B	77.8	73.8	43.8	55.1	63.3	52.9	56.6	90.0	42.2	61.7	71.5	34.0
GPT-3.5-turbo-0125	64.5	70.0	15.6	55.5	58.2	49.0	57.5	85.5	45.0	54.3	69.9	32.0
Claude-3-Opus	80.7	79.2	31.6	49.6	55.1	49.0	45.1	**94.6**	**50.6**	71.1	71.1	41.3
GPT-4-0125	85.9	80.6	46.5	49.6	62.5	56.9	55.8	**94.6**	45.0	67.6	**77.0**	37.9
GPT-4o	84.7	80.2	30.9	50.4	66.0	55.6	57.5	92.3	45.6	**72.7**	75.0	40.1
our models												
PaLM-2-24B	62.9	54.8	13.3	52.3	58.2	54.2	46.0	85.5	48.3	62.5	70.3	20.0
FLAMe-24B	86.0	**81.1**	48.0	**58.2**	62.1	53.6	**69.9**	91.4	48.3	67.2	74.2	**48.4**
FLAMe-RM-24B	**87.8**	80.8	**53.1**	57.8	65.2	**57.5**	57.5	91.0	47.8	67.6	72.7	46.6
FLAMe-Opt-RM-24B	87.0	80.2	52.3	53.1	**69.5**	52.9	48.7	89.1	48.3	69.5	69.5	35.9

Performance of FLAMe compared to popular LLM-as-a-Judge autoraters across various autorater benchmarks.

FLAMe-RM-24B was the top-performing generative model only on permissively licensed data

RewardBench: Evaluating Reward Models

Evaluating the capabilities, safety, and pitfalls of reward models

Code | Eval. Dataset | Prior Test Sets | Results | Paper | Total models: 108 | * Unverified models

rewardbench

🏆 RewardBench Leaderboard | 🔍 RewardBench - Detailed | Prior Test Sets | About | Dataset Viewer

Model Search (delimit with ,)

☐ Seq. Classifiers ☐ DPO ☐ Custom Classifiers ☑ Generative ☐ Prior Sets

	Model	Model Type	Score	Chat	Chat Hard	Safety	Reasoning
1	google/gemini-1.5-pro-0514 *	Generative	88.1	92.3	80.6	87.5	92.0
2	google/flame-1.0-24B-july-2024	Generative	88.1	92.2	75.7	90.7	93.8
3	openai/gpt-4-0125-preview	Generative	85.9	95.3	74.3	87.2	86.9
4	openai/gpt-4-turbo-2024-04-09	Generative	85.1	95.3	75.4	87.1	82.7
5	openai/gpt-4o-2024-05-13	Generative	84.7	96.6	70.4	86.7	84.9
6	Anthropic/claude-3-5-sonnet-20240620	Generative	83.8	96.4	74.0	80.1	84.7
7	google/gemini-1.5-flash-001	Generative	82.1	92.2	63.5	87.7	85.1
8	Anthropic/claude-3-opus-20240229	Generative	80.7	94.7	60.3	89.1	78.7
9	meta-llama/Meta-Llama-3-70B-Instruct	Generative	76.0	97.6	58.9	69.2	78.5
10	Anthropic/claude-3-sonnet-20240229	Generative	75.7	93.4	56.6	83.7	69.1
11	PoLL/gpt-3.5-turbo-0125_claude-3-sonnet-2024022...	Generative	75.6	95.3	54.1	79.5	73.5
12	prometheus-eval/prometheus-8x7b-v2.0	Generative	75.3	93.0	47.1	83.5	77.4

July 15, 2024

FLAMe is significantly less biased than other popular LLM-as-a-Judge models

Autorater	Avg. (↓)	Order (↓)	Compassion (↓)	Length (↓)	Egocentric (↓)	Bandwagon (↓)	Attention (↓)
Random	0.30	0.50	0.50	0.00	0.25	0.25	0.25
baselines reported in Koo et al. (2023)							
Falcon-40B	0.31	0.77	0.27	0.09	**0.05**	0.28	0.40
Cohere-54B	0.41	0.50	0.65	0.10	0.27	0.82	0.14
Llama-2-70B	0.19	0.61	0.26	0.12	0.06	0.04	0.03
InstructGPT	0.45	0.38	0.48	0.16	0.28	0.85	0.54
ChatGPT	0.45	0.41	0.66	0.13	0.58	0.86	0.06
GPT-4	0.31	0.23	0.79	0.06	0.78	**0.00**	**0.00**
our models							
FLAMe-24B	**0.13**	**0.08**	0.09	0.03	0.38	0.18	**0.00**
FLAMe-RM-24B	**0.13**	0.11	**0.08**	0.02	0.40	0.17	**0.00**
FLAMe-Opt-RM-24B	0.15	0.15	0.14	**0.00**	0.41	0.17	**0.00**

Autorater bias analysis on the CoBBLEr bias benchmark from Koo et al. (2023). **Lower values indicate better or less biased autoraters** across all columns. Overall, FLAMe variants exhibit significantly less bias compared to popular LLM-as-a-Judge autoraters like GPT-4. Compared to Table 2 in Koo et al. (2023), we combine first/last numbers for Order/Compassion, report $|\text{bias} - 0.5|$ for Length, and only report the order setup in Egocentric.

Learning to Plan & Reason for Evaluation with Thinking-LLM-as-a-Judge

Swarnadeep Saha, **Xian Li**, **Marjan Ghazvininejad**, **Jason Weston**, **Tianlu Wang**

FAIR at Meta

LLM-as-a-Judge models generate chain-of-thought (CoT) sequences intended to capture the step-by-step reasoning process that underlies the final evaluation of a response. However, due to the lack of human-annotated CoTs for evaluation, the required components and structure of effective reasoning traces remain understudied. Consequently, previous approaches often (1) constrain reasoning traces to hand-designed components, such as a list of criteria, reference answers, or verification questions and (2) structure them such that planning is intertwined with the reasoning for evaluation. In this work, we propose EvalPlanner, a preference optimization algorithm for Thinking-LLM-as-a-Judge that first generates an unconstrained evaluation plan, followed by its execution, and then the final judgment. In a self-training loop, EvalPlanner iteratively optimizes over synthetically constructed evaluation plans and executions, leading to better final verdicts. Our method achieves a new state-of-the-art performance for generative reward models on RewardBench (with a score of 93.9), despite being trained on fewer amount of, and synthetically generated, preference pairs. Additional experiments on other benchmarks like RM-Bench, JudgeBench, and FollowBenchEval further highlight the utility of both planning and reasoning for building robust LLM-as-a-Judge reasoning models.

Thank you!