Natural Language Processing with Deep Learning

CS224N/Ling284

Yann Dubois

Lecture 11: Benchmarking and Evaluation

Lecture overview

- Different reasons for measuring performance
- Text Classification / Close-ended
- Text Generation / Open-ended
  - Automatic Evaluation
  - Human Evaluation
- Current evaluations of LLMs
- Issues and challenges with evaluation

Different desiderata for measuring performance

Train
- Super fast
- Super cheap
- Differentiable
- No shortcut

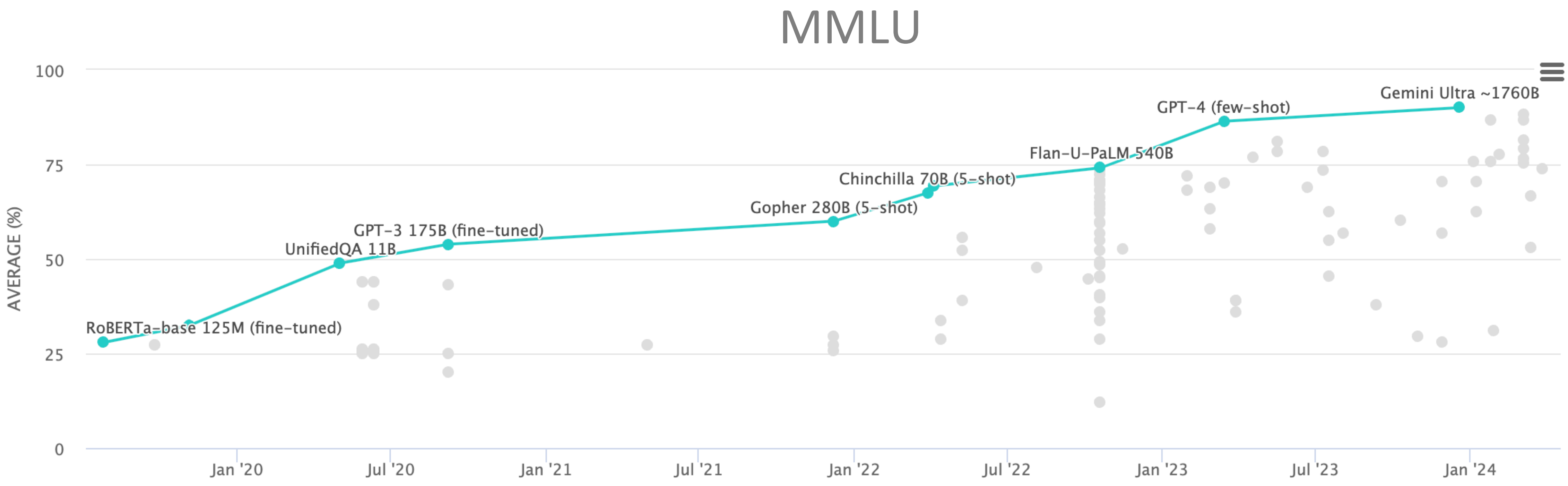
Develop
- Super fast
- Super cheap
- Avoid shortcuts

Model selection
- Fast
- Cheap

Deploy
- Trustworthy
- Task-specific
- Absolute

Publish
- Standardized
- Reproducible
- Easy to work with
- ~Fast
- Broad coverage
- ~Cheap
- Crude metrics may be fine
- Fine-grained distinguishability
- Good difficulty

Benchmarks and evaluations drive progress



Benchmarks and how we drive the progress of the field

Two major types of evaluations

Close-ended evaluations

Example
Text: Read the book, forget the movie!
Label: Negative

Open ended evaluations

Context (human-written): In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

GPT-2: The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Close-ended evaluation

Close-ended tasks

- Limited number of potential answers
- Often one or just a few correct answers
- Enables automatic evaluation as in ML

Close-ended tasks

- Sentiment analysis: SST / IMDB / Yelp ...

Example
Text: Read the book, forget the movie!
Label: Negative

- Entailment: SNLI

Example
Text: A soccer game with multiple males playing.
Hypothesis: Some men are playing sport.
Label: Entailment

- Name entity recognition: CoNLL-2003
- Part-of-Speech: PTB

Close-ended tasks

- Coreference resolution: WSC

Example

Text: Mark told Pete many lies about himself, which Pete included in his book. He should have been more truthful.

Coreference: False

- Question Answering: Squad 2

Example

Endangered Species Act Paragraph: "… Other legislation followed, including the Migratory Bird Conservation Act of 1929, a **1937 treaty** prohibiting the hunting ofright and gray whales, and the Bald Eagle Protection Act of 1940. These later laws had a low cost to society—the species were relatively rare—and little **opposition** was raised."

Question 1: "Which laws faced significant **opposition**?"
Plausible Answer: later laws

Question 2: "What was the name ofthe **1937 treaty**?"
Plausible Answer: Bald Eagle Protection Act

Close-ended multi-task benchmark - superGLUE

SuperGLUE GLUE

Leaderboard Version: **2.0**

	Rank	Name	Model	URL	Score	BoolQ	CB	COPA	MultiRC	ReCoRD	RTE	WiC	WSC	AX-b	AX-g
	1	JDExplore d-team	Vega v2		91.3	90.5	98.6/99.2	99.4	88.2/62.4	94.4/93.9	96.0	77.4	98.6	-0.4	100.0/50.0
+	2	Liam Fedus	ST-MoE-32B		91.2	92.4	96.9/98.0	99.2	89.6/65.8	95.1/94.4	93.5	77.7	96.6	72.3	96.1/94.1
	3	Microsoft Alexander v-team	Turing NLR v5		90.9	92.0	95.9/97.6	98.2	88.4/63.0	96.4/95.9	94.1	77.1	97.3	67.8	93.3/95.5
	4	ERNIE Team - Baidu	ERNIE 3.0		90.6	91.0	98.6/99.2	97.4	88.6/63.2	94.7/94.2	92.6	77.4	97.3	68.6	92.7/94.7
	5	Yi Tay	PaLM 540B		90.4	91.9	94.4/96.0	99.0	88.7/63.6	94.2/93.3	94.1	77.4	95.9	72.9	95.5/90.4
+	6	Zirui Wang	T5 + UDG, Single Model (Google Brain)		90.4	91.4	95.8/97.6	98.0	88.3/63.0	94.2/93.5	93.0	77.9	96.6	69.1	92.7/91.9
+	7	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4		90.3	90.4	95.7/97.6	98.4	88.2/63.7	94.5/94.1	93.2	77.5	95.9	66.7	93.3/93.8
	8	SuperGLUE Human Baselines	SuperGLUE Human Baselines		89.8	89.0	95.8/98.9	100.0	81.8/51.9	91.7/91.3	93.6	80.0	100.0	76.6	99.3/99.7
+	9	T5 Team - Google	T5		89.3	91.2	93.9/96.8	94.8	88.1/63.3	94.1/93.4	92.5	76.9	93.8	65.6	92.7/91.9

Attempt to measure “general language capabilities”

Examples from superGLUE

Cover a number of different tasks

- BoolQ, MultiRC (reading texts)
- CB, RTE (Entailment)
- COPA (cause and effect)
- ReCoRD (QA+reasoning)
- WiC (meaning of words)
- WSC (coreference)

BoolQ	**Passage:** *Barq's – Barq's is an American soft drink. Its brand of root beer is notable for having caffeine. Barq's, created by Edward Barq and bottled since the turn of the 20th century, is owned by the Barq family but bottled by the Coca-Cola Company. It was known as Barq's Famous Olde Tyme Root Beer until 2012.* **Question:** *is barq's root beer a pepsi product* **Answer:** `No`
CB	**Text:** *B: And yet, uh, I we-, I hope to see employer based, you know, helping out. You know, child, uh, care centers at the place of employment and things like that, that will help out. A: Uh-huh. B: What do you think, do you think we are, setting a trend?* **Hypothesis:** *they are setting a trend* **Entailment:** `Unknown`
COPA	**Premise:** *My body cast a shadow over the grass.* **Question:** *What's the CAUSE for this?* **Alternative 1:** *The sun was rising.* **Alternative 2:** *The grass was cut.* **Correct Alternative:** `1`
MultiRC	**Paragraph:** *Susan wanted to have a birthday party. She called all of her friends. She has five friends. Her mom said that Susan can invite them all to the party. Her first friend could not go to the party because she was sick. Her second friend was going out of town. Her third friend was not so sure if her parents would let her. The fourth friend said maybe. The fifth friend could go to the party for sure. Susan was a little sad. On the day of the party, all five friends showed up. Each friend had a present for Susan. Susan was happy and sent each friend a thank you card the next week* **Question:** *Did Susan's sick friend recover?* **Candidate answers:** *Yes, she recovered* (`T`), *No* (`F`), *Yes* (`T`), *No, she didn't recover* (`F`), *Yes, she was at Susan's party* (`T`)
ReCoRD	**Paragraph:** *(CNN) Puerto Rico on Sunday overwhelmingly voted for statehood. But Congress, the only body that can approve new states, will ultimately decide whether the status of the US commonwealth changes. Ninety-seven percent of the votes in the nonbinding referendum favored statehood, an increase over the results of a 2012 referendum, official results from the State Electorcal Commission show. It was the fifth such vote on statehood. "Today, we the people of Puerto Rico are sending a strong and clear message to the US Congress ... and to the world ... claiming our equal rights as American citizens, Puerto Rico Gov. Ricardo Rossello said in a news release. @highlight Puerto Rico voted Sunday in favor of US statehood* **Query** For one, they can truthfully say, "Don't blame me, I didn't vote for them, " when discussing the <placeholder> presidency **Correct Entities:** `US`
RTE	**Text:** *Dana Reeve, the widow of the actor Christopher Reeve, has died of lung cancer at age 44, according to the Christopher Reeve Foundation.* **Hypothesis:** *Christopher Reeve had an accident.* **Entailment:** `False`
WiC	**Context 1:** *Room and board.* **Context 2:** *He nailed boards across the windows.* **Sense match:** `False`
WSC	**Text:** *Mark told Pete many lies about himself, which Pete included in his book. He should have been more truthful.* **Coreference:** `False`

Close-ended: challenges

- Choosing your metrics: accuracy / precision / recall / f1-score / ROC
  - https://github.com/cgpotts/cs224u/blob/main/evaluation_metrics.ipynb
  - https://scikit-learn.org/stable/modules/model_evaluation.html

- Aggregating across metrics or tasks

SuperGLUE Tasks

Matthew's Corr	F1a / EM	F1 / Accuracy
Avg. F1 / Accuracy	Accuracy	
Accuracy	Accuracy	Gender Parity / Accuracy

- Where do the labels come from?

- Are there spurious correlations?

Spurious correlation

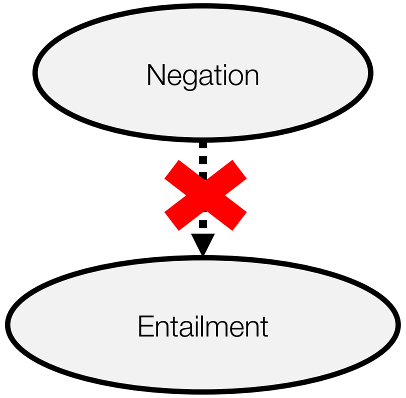
Text	Judgments	Hypothesis
A man inspects the uniform of a figure in some East Asian country.	contradiction C C C C C	The man is sleeping
An older and younger man smiling.	neutral N N E N N	Two men are smiling and laughing at the cats playing on the floor.

Premise:

The economy could be still better.

Hypothesis:

The economy has never been better



[Gururangan+ 2019]

SNLI itself is hard, but there can be undiscovered *spurious correlations*

Open-ended evaluation

Open-ended tasks

- Long generations with too many possible correct answers to enumerate
  - => can't use standard ML metrics
- There are now better and worse answers (not just right and wrong)
- Example:
  - Summarization: CNN-DM / Gigaword
  - Translation: WMT
  - Instruction-following: Chatbot Arena / AlpacaEval / MT-Bench

Types of evaluation methods for text generation

Ref: They walked to the grocery store .

Gen: The woman went to the hardware store .

Content Overlap Metrics

Model-based Metrics

Human Evaluations

(Some slides repurposed from Asli Celikyilmaz from EMNLP 2020 tutorial)

Content overlap metrics

Ref: They walked to the grocery store .

Gen: The woman went to the hardware store .

- Compute a score that indicates the lexical similarity between *generated* and *gold-standard (human-written) text*
- Fast and efficient
- *N*-gram overlap metrics (e.g., **BLEU**, **ROUGE**, METEOR, CIDEr, etc.)

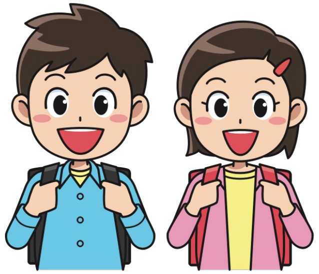
  precision **recall**

- Not ideal but often still reported for translation and summarization

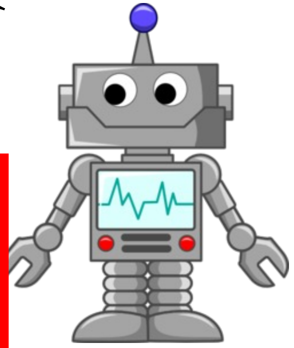
A simple failure case

n-gram overlap metrics have no concept of semantic relatedness!

Are you enjoying the CS224N lectures?



Heck yes !

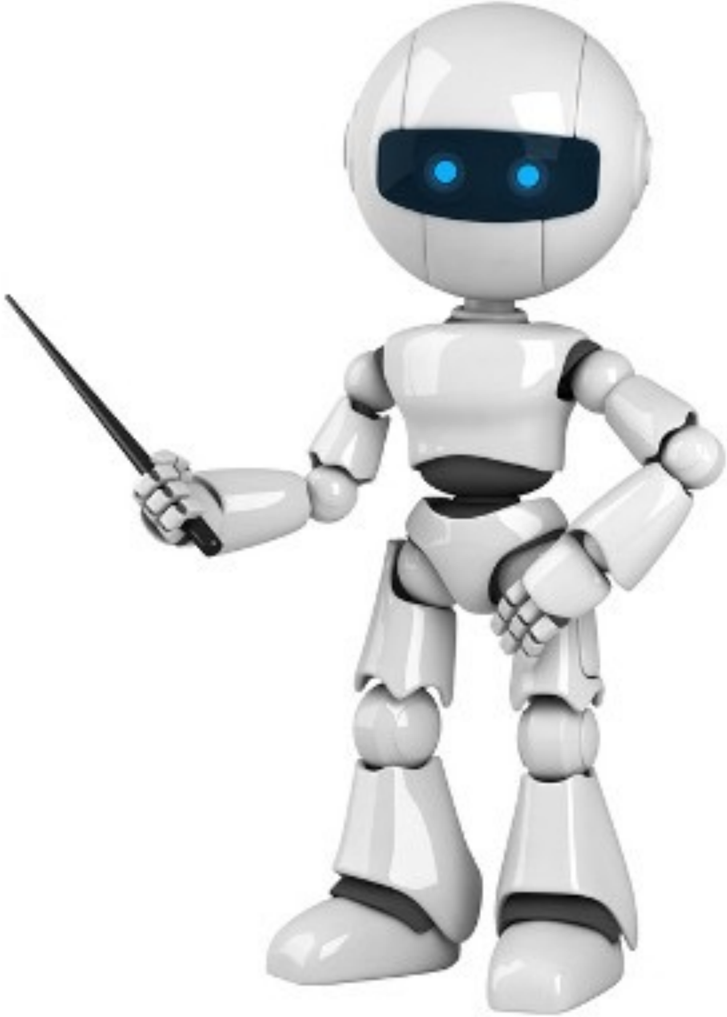


	Score:	
	0.67	Yes !
	0.25	You know it !
False negative	0	Yup .
False positive	0.67	Heck no !

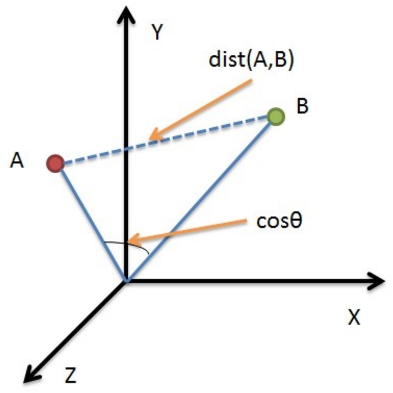
Model-based metrics to capture more semantics

- Use learned representations of words and sentences to compute semantic similarity between generated and reference texts

- The embeddings are **pretrained**, distance metrics used to measure the similarity can be **fixed**



Model-based metrics: Word distance functions



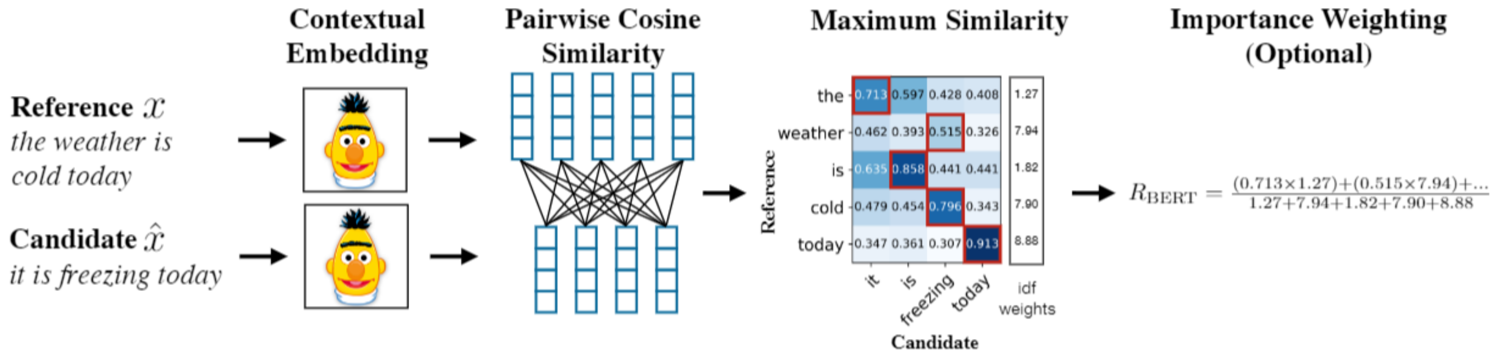
Vector Similarity

Embedding based similarity for semantic distance between text.

- **Embedding Average** (Liu et al., 2016)
- **Vector Extrema** (Liu et al., 2016)
- **MEANT** (Lo, 2017)
- **YISI** (Lo, 2019)

BERTSCORE

Uses pre-trained contextual embeddings from BERT and matches words in candidate and reference sentences by cosine similarity. (Zhang et.al. 2020)

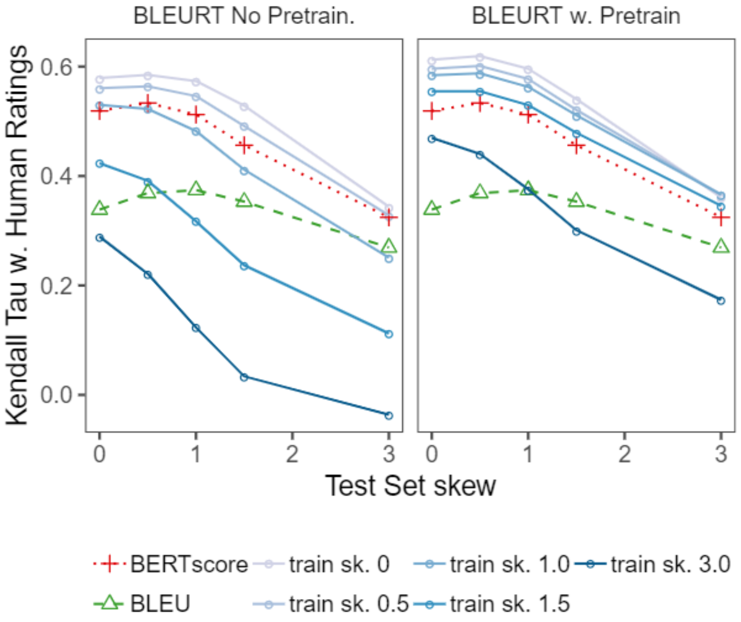


Model-based metrics: Beyond word matching

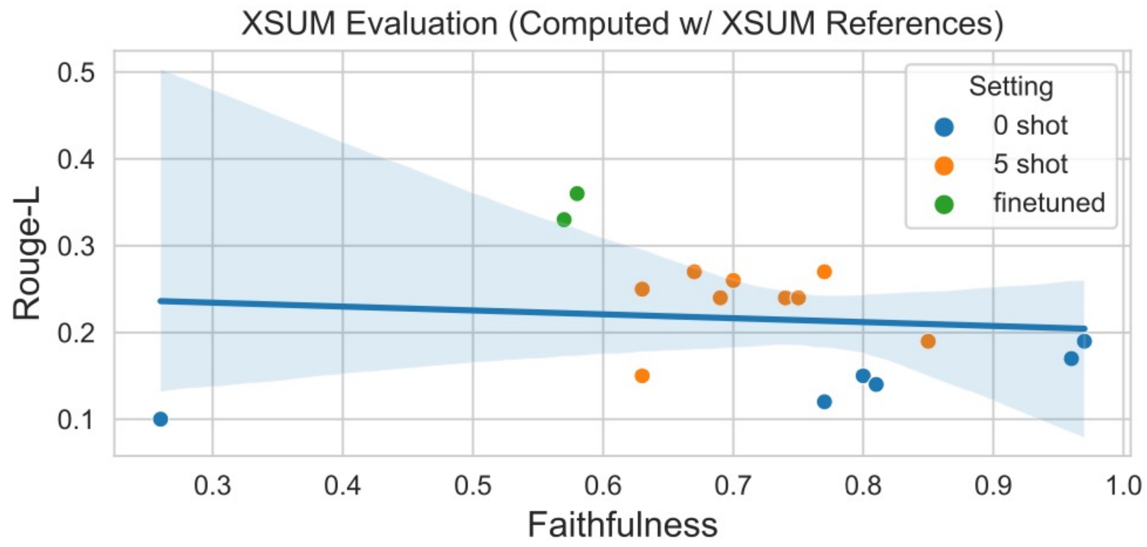
BLEURT:

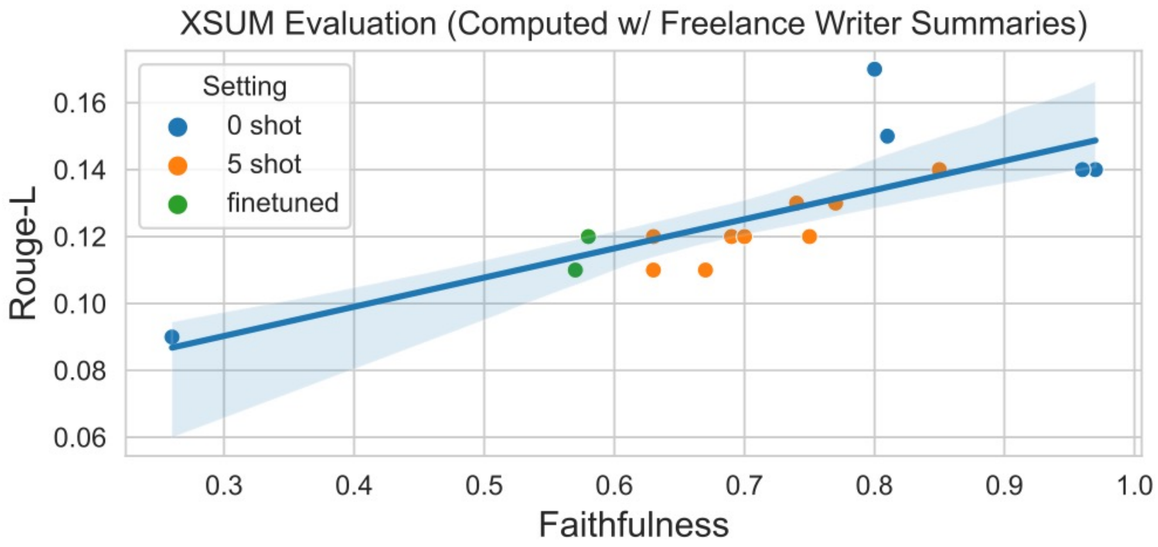
A regression model based on BERT returns a score that indicates to what extent the candidate text is grammatical and conveys the meaning of the reference text.

(Sellam et.al. 2020)



An important failure case





Actual reference => uncorrelated

Expert reference => correlated

- Reference-based measures *are only as good as their references.*

Reference free evals

- **Reference-based evaluation:**
  - Compare human written reference to model outputs
  - Used to be ‘standard’ evaluation for most NLP tasks
  - Examples: BLEU, ROUGE, BertScore etc.
- **Reference free evaluation**
  - Have a model give a score
  - No human reference
  - Was nonstandard – now becoming popular with GPT4
  - Examples: AlpacaEval, MT-Bench

Human evaluations

- Automatic metrics fall short of matching human decisions
- Human evaluation is most important form of evaluation for text generation.
- Gold standard in developing new automatic metrics
  - New automated metrics must correlate well with human evaluations!

Human evaluations

- Ask *humans* to evaluate the quality of generated text

- Overall or along some specific dimension:
  - fluency
  - coherence / consistency
  - factuality and correctness
  - commonsense
  - style / formality
  - grammaticality
  - redundancy

Note: Don't compare human evaluation scores across differently conducted studies

Even if they claim to evaluate the same dimensions!

For details Celikyilmaz, Clark, Gao, 2020

Human evaluation: Issues

- Human judgments are regarded as the **gold standard**
- But it also has issues:
  - Slow
  - Expensive
  - Inter-annotator disagreement (esp. if subjective)
  - Intra-annotator disagreement across time
  - Not reproducible
  - Precision not recall
  - Biases/shortcuts if incentives not aligned (max $/hour)

Non-Repeatable Experiments and Non-Reproducible Results: The Reproducibility Crisis in Human Evaluation in NLP

Anya Belz[a,b] Craig Thomson[b] Ehud Reiter[b] Simon Mille[a]

"just 5% of human evaluations are repeatable in the sense that (i) there are no prohibitive barriers to repetition, and (ii) sufficient information about experimental design is publicly available for rerunning them. Our estimate goes up to about 20% when author help is sought."

Human evaluation: Issues

- Challenges with human evaluation
  - How to describe the task?
  - How to show the task to the humans?
  - What metric do you use?
  - Selecting the annotators
  - Monitoring the annotators: time, accuracy, …

Reference-free eval: chatbots

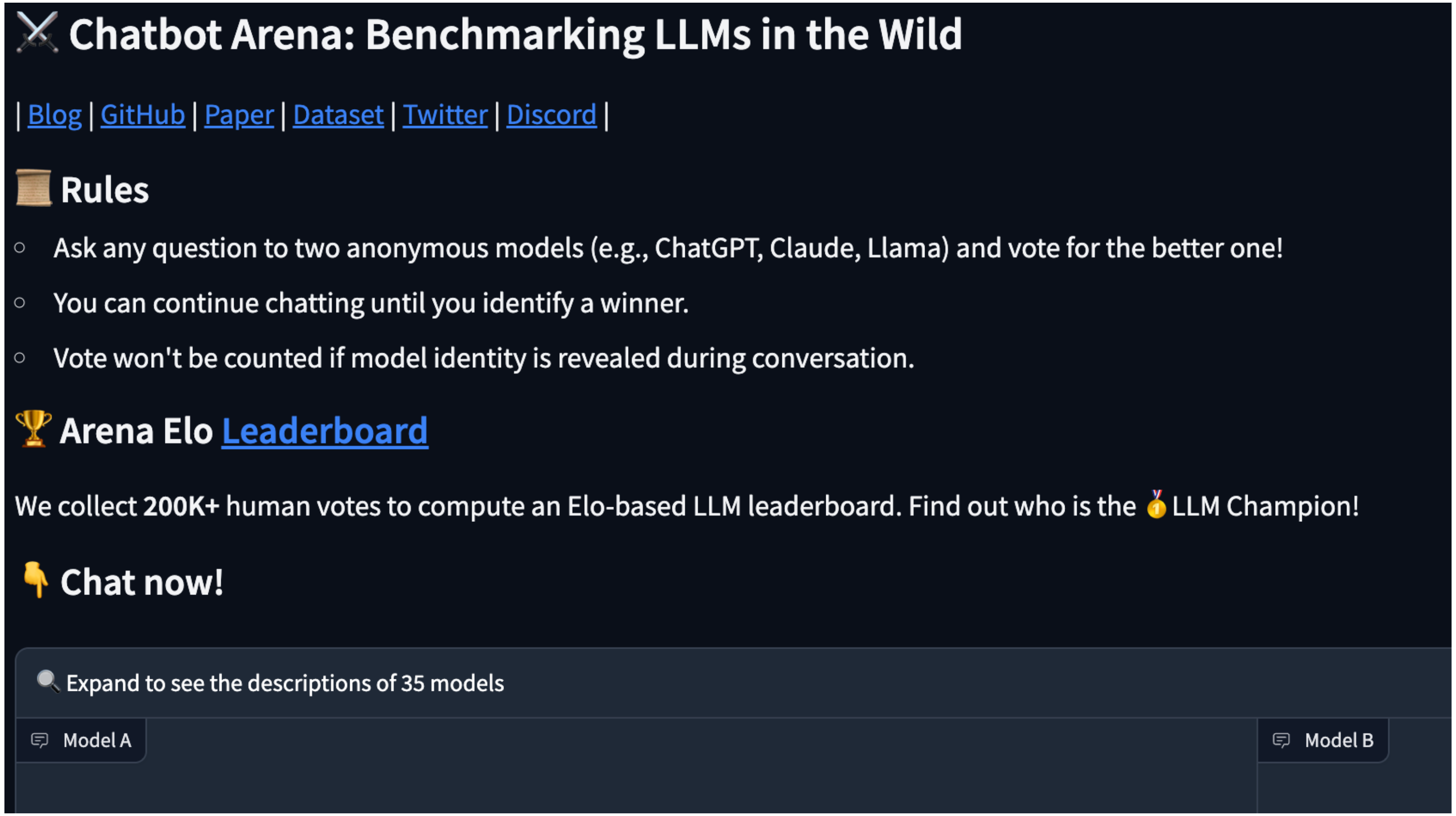
VS

Table 1: Distribution of use case categories from our API prompt dataset.

Use-case	(%)
Generation	45.6%
Open QA	12.4%
Brainstorming	11.2%
Chat	8.4%
Rewrite	6.6%
Summarization	4.2%
Classification	3.5%
Other	3.5%
Closed QA	2.6%
Extract	1.9%

- How do we evaluate something like ChatGPT?
- *So many* different use cases it's hard to evaluate
- The responses are also long-form text, which is even harder to evaluate.

Side-by-side ratings

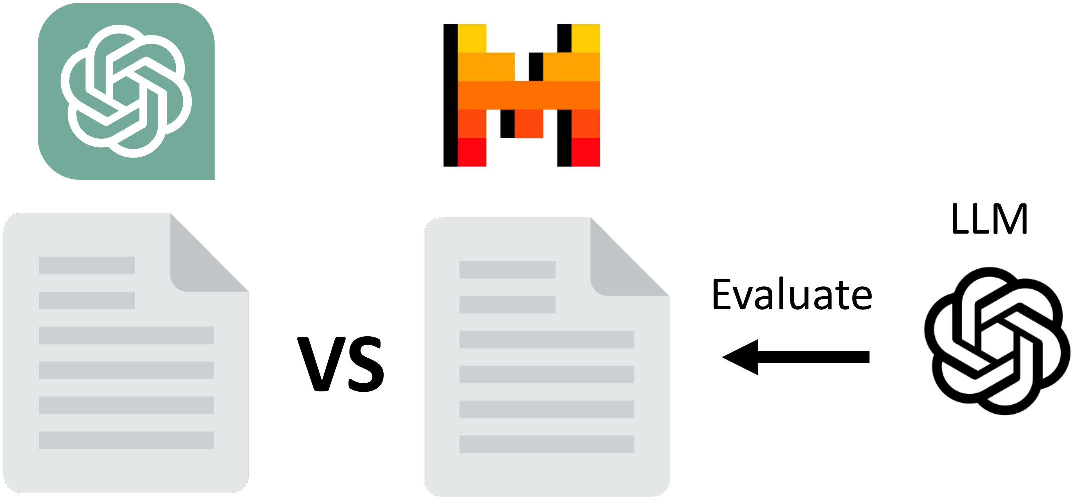


Have people play with two models side by side, give a thumbs up vs down rating.

What's missing with side-by-side human eval?

- Current gold standard for evaluation of chat LLM
- **External validity**
  - Typing random questions into a head-to-head website may not be representative
- **Cost**
  - Human annotation takes large, community effort
  - New models take a long time to benchmark
  - Only notable models get benchmarked

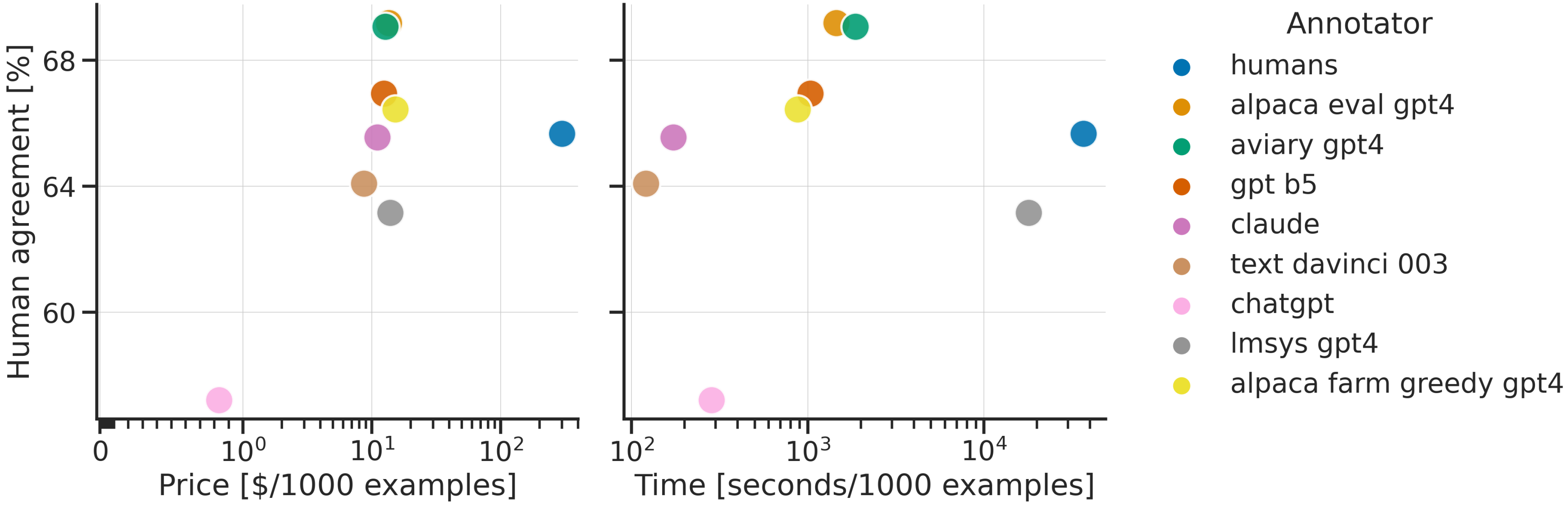
Lowering the costs – use a LM evaluator



- Use a LM as a reference free evaluator
- Surprisingly high correlations with human

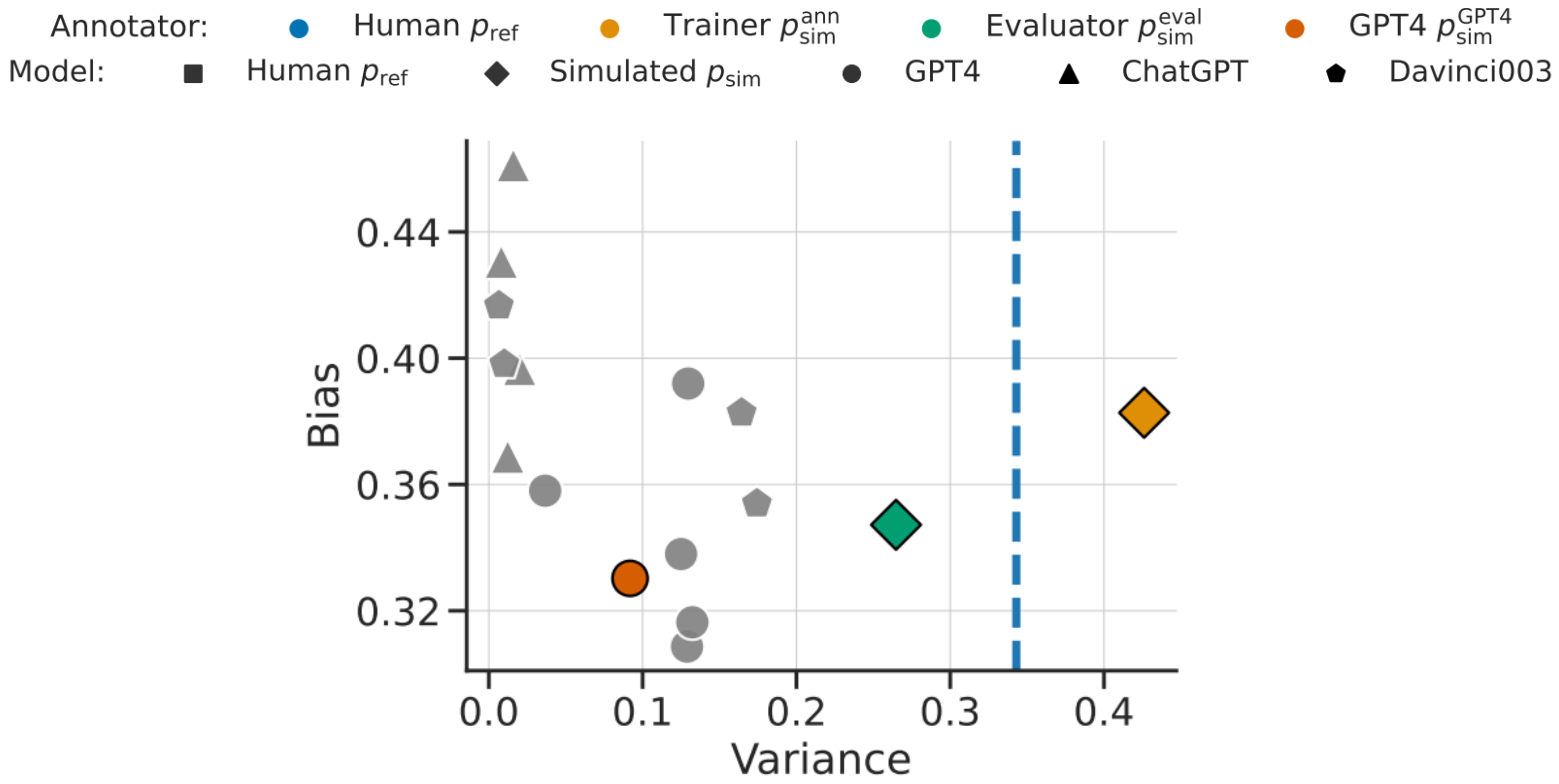
- Common versions: AlpacaEval, MT-bench

AlpacaFarm : Human agreement



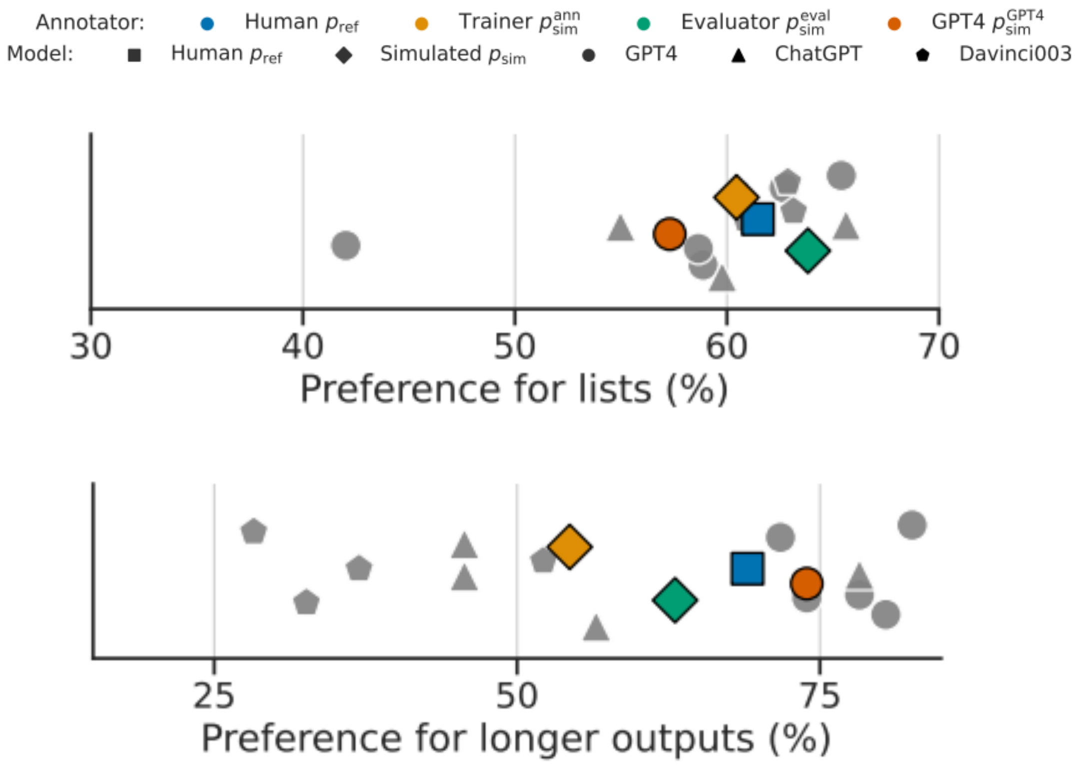
- 100x Cheaper, 100x faster, and **higher agreement than humans**
- Note: can also use for RLAIF!

AlpacaFarm : Human agreement



- Humans have low agreement because of variance!

Things to be careful with



- Same issues as before: Spurious correlations!
  - Length
  - Position (but everyone randomizes this away)
  - GPT-4 self bias

AlpacaEval

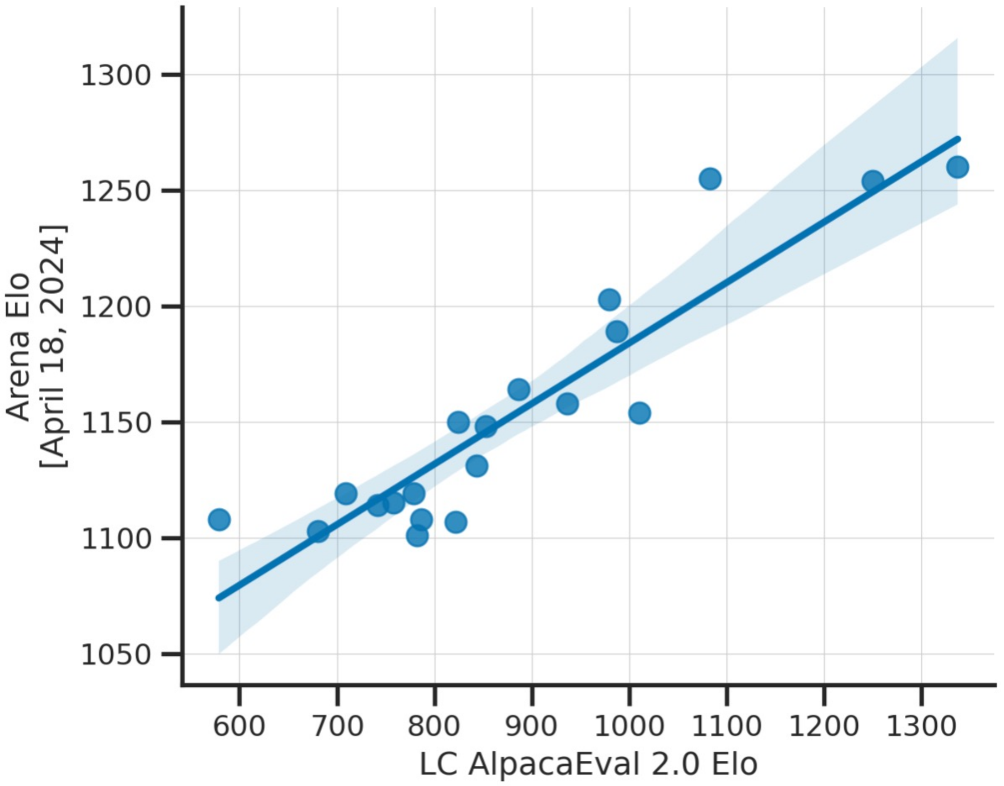
- Internal benchmark for developing Alpaca
- 98% correlation with Chatbot Arena
- < 3 min and < $10

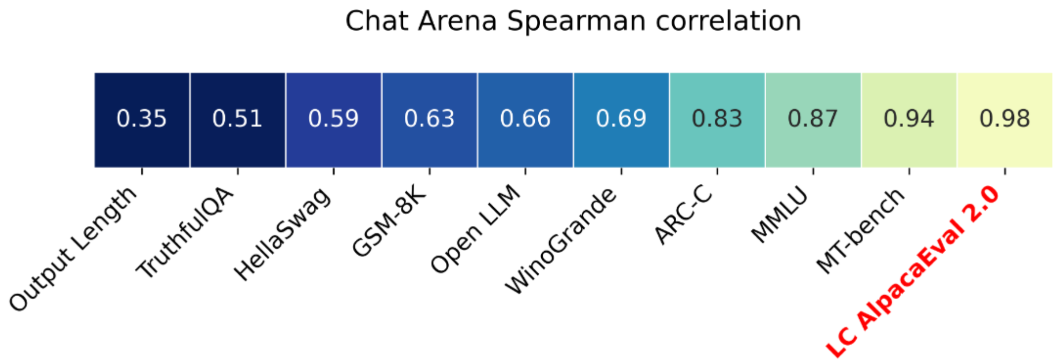
- 1. For each instruction: generate an output by baseline and model to eval
- 2. Ask GPT-4 the probability that the model's output is better
- 3. (AlpacaEval LC) Reweight win-probability based on length of outputs
- 4. Average win-probability => win rate

AlpacaEval Leaderboard

Model Name	LC Win Rate	Win Rate
GPT-4 Turbo (04/09)	55.0%	46.1%
GPT-4 Preview (11/06)	50.0%	50.0%
Claude 3 Opus (02/29)	40.5%	29.1%
GPT-4	38.1%	23.6%

AlpacaEval : System level correlation





AlpacaEval Length Controlled

- Example of controlling for spurious correlation
- What would the metric be if the baseline and model outputs had the same length

	AlpacaEval			Length-controlled AlpacaEval		
	concise	standard	verbose	concise	standard	verbose
gpt4_1106_preview	22.9	50.0	64.3	41.9	50.0	51.6
Mixtral-8x7B-Instruct-v0.1	13.7	18.3	24.6	23.0	23.7	23.2
gpt4_0613	9.4	15.8	23.2	21.6	30.2	33.8
claude-2.1	9.2	15.7	24.4	18.2	25.3	30.3
gpt-3.5-turbo-1106	7.4	9.2	12.8	15.8	19.3	22.0
alpaca-7b	2.0	2.6	2.9	4.5	5.9	6.8

Self-bias

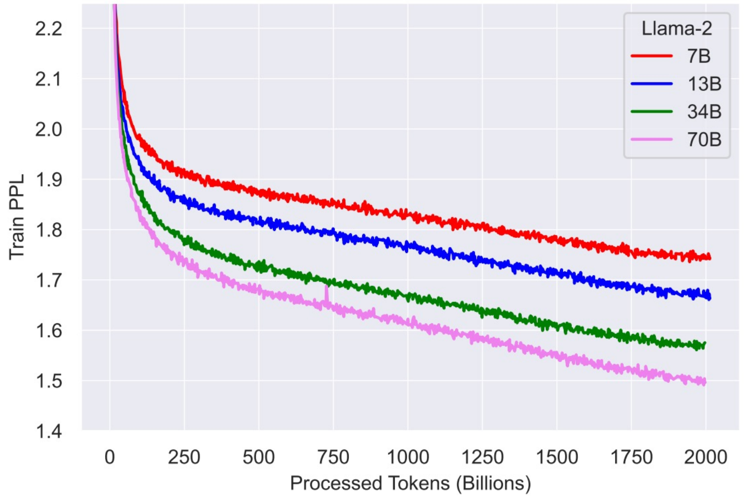
- The annotator is biased to its outputs, but suprisingly not by much!

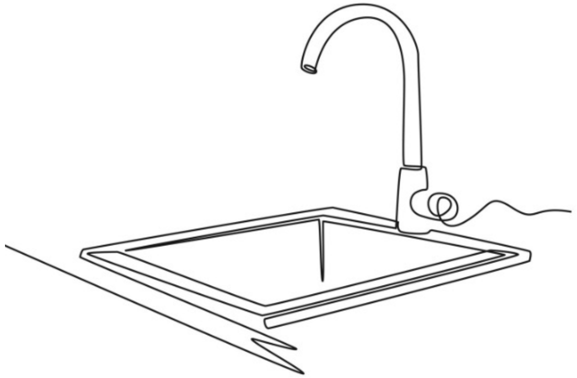
	Auto-annotator		
	gpt4_1106_preview	claude-3-opus-20240229	mistral-large-2402
gpt4_1106_preview	50.0	50.0	50.0
claude-3-opus-20240229	40.4	43.3	47.5
mistral-large-2402	32.7	28.2	45.5
gpt4_0613	30.2	20.5	34.3
gpt-3.5-turbo-1106	19.3	16.7	28.9

Figure 7: Length-controlled win rate has the best Arena Correlation and gameability from considered methods, while still being relatively robust to adversarial attacks.

Current evaluation of LLM

Current evaluation of LLM





Perplexity

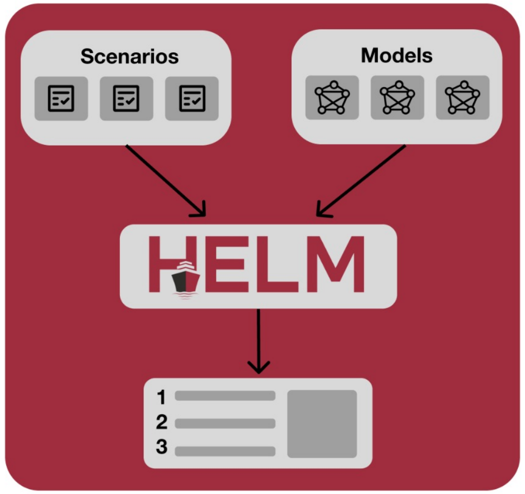
Everything

Arena-like

$\underbrace{\qquad\qquad\qquad\qquad}_{\text{pretraining}}$ $\underbrace{\qquad\qquad\qquad\qquad}_{\text{finetuned}}$

Everything: HELM and open-llm leaderboard

Holistic evaluation of language models (HELM)



Model	Mean win rate
GPT-4 (0613)	0.962
GPT-4 Turbo (1106 preview)	0.834
Palmyra X V3 (72B)	0.821
Palmyra X V2 (33B)	0.783
PaLM-2 (Unicorn)	0.776
Yi (34B)	0.772

SEE MORE

Huggingface open LLM leaderboard

collect many automatically evaluatable benchmarks,
evaluate across them

What are common LM datasets?

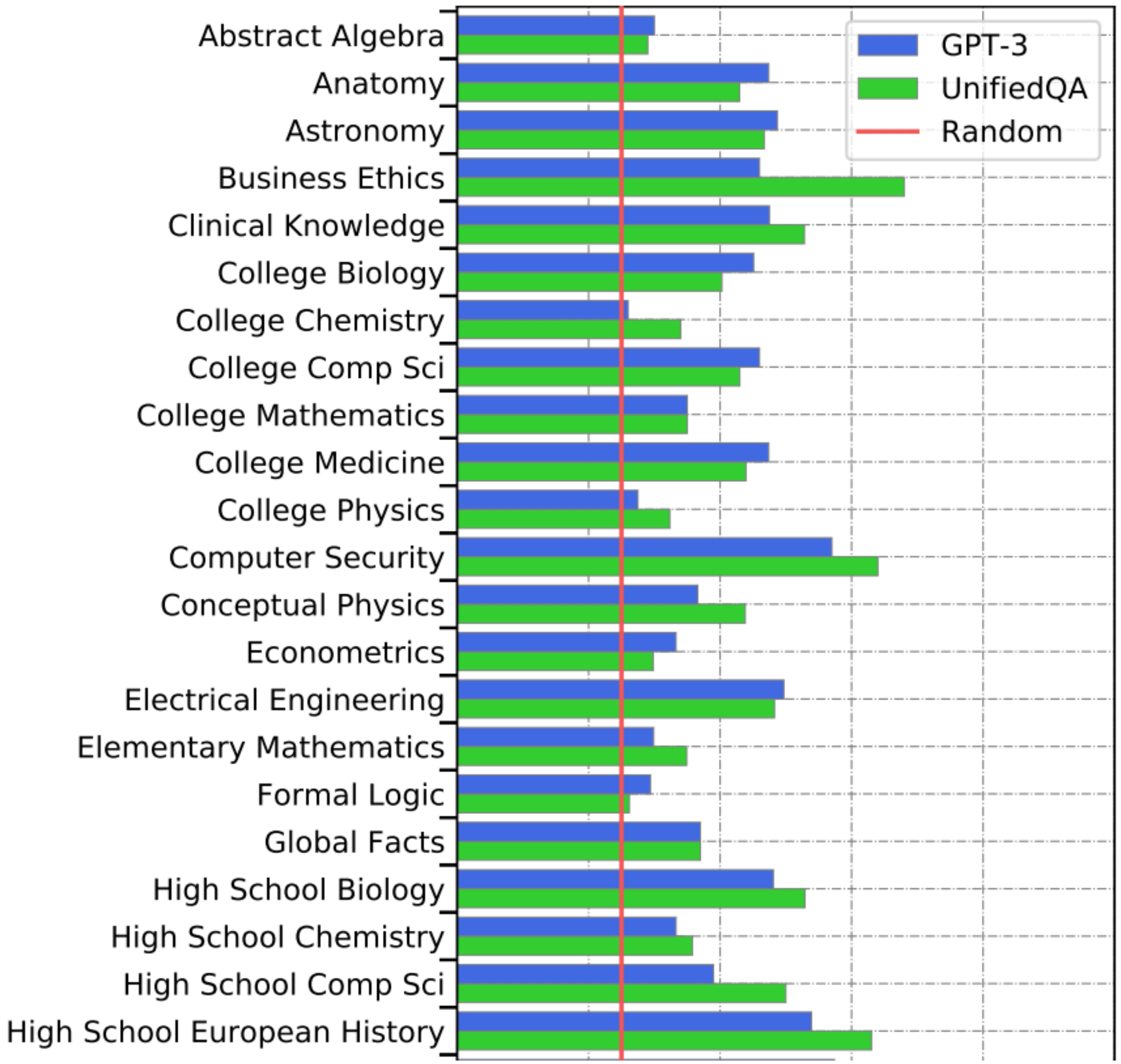
- What do these benchmarks evaluate on?
- A huge mix of things!

Scenario	Task	What	Who
NarrativeQA narrative_qa	short-answer question answering	passages are books and movie scripts, questions are unknown	annotators from summaries
NaturalQuestions (closed-book) natural_qa_closedbook	short-answer question answering	passages from Wikipedia, questions from search queries	web users
NaturalQuestions (open-book) natural_qa_openbook_longans	short-answer question answering	passages from Wikipedia, questions from search queries	web users
OpenbookQA openbookqa	multiple-choice question answering	elementary science	Amazon Mechnical Turk workers
MMLU (Massive Multitask Language Understanding) mmlu	multiple-choice question answering	math, science, history, etc.	various online sources
GSM8K (Grade School Math) gsm	numeric answer question answering	grade school math word problems	contractors on Upwork and Surge AI
MATH math_chain_of_thought	numeric answer question answering	math competitions (AMC, AIME, etc.)	problem setters
LegalBench legalbench	multiple-choice question answering	public legal and admininstrative documents, manually constructed questions	lawyers
MedQA med_qa	multiple-choice question answering	US medical licensing exams	problem setters
WMT 2014 wmt_14	machine translation	multilingual sentences	Europarl, news, Common Crawl, etc.

Recap: MMLU

Massive Multitask Language Understanding (MMLU)
[Hendrycks et al., 2021]

New benchmarks for measuring LM performance on 57 diverse *knowledge intensive* tasks



Some intuition: examples from MMLU

Astronomy

What is true for a type-Ia supernova?

A. This type occurs in binary systems.
B. This type occurs in young galaxies.
C. This type produces gamma-ray bursts.
D. This type produces high amounts of X-rays.

Answer: A

High School Biology

In a population of giraffes, an environmental change occurs that favors individuals that are tallest. As a result, more of the taller individuals are able to obtain nutrients and survive to pass along their genetic information. This is an example of

A. directional selection.
B. stabilizing selection.
C. sexual selection.
D. disruptive selection

Answer: A

Other capabilities: code

Nice feature of code: evaluate vs test cases

Metric: Pass@1 (Pass @ k means one of k outputs pass)

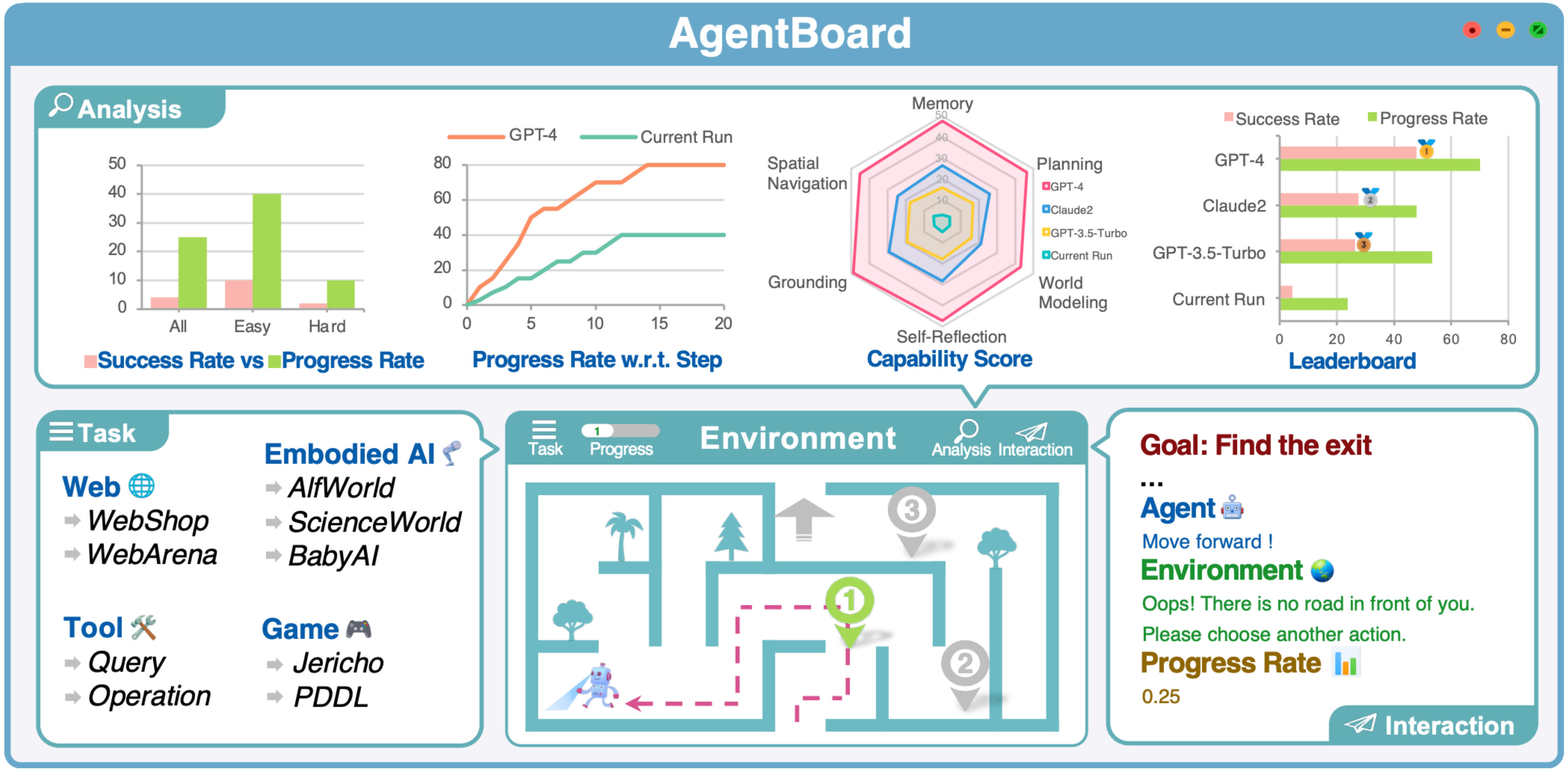
GPT4: ~67%

```python
def solution(lst):
    """Given a non-empty list of integers, return the sum of all of the odd elements
    that are in even positions.

    Examples
    solution([5, 8, 7, 1]) ==>12
    solution([3, 3, 3, 3, 3]) ==>9
    solution([30, 13, 24, 321]) ==>0
    """
    return sum(lst[i] for i in range(0,len(lst)) if i % 2 == 0 and lst[i] % 2 == 1)
```

```python
def encode_cyclic(s: str):
    """
    returns encoded string by cycling groups of three characters.
    """
    # split string to groups. Each of length 3.
    groups = [s[(3 * i):min((3 * i + 3), len(s))] for i in range((len(s) + 2) // 3)]
    # cycle elements in each group. Unless group has fewer elements than 3.
    groups = [(group[1:] + group[0]) if len(group) == 3 else group for group in groups]
    return "".join(groups)

def decode_cyclic(s: str):
    """
    takes as input string encoded with encode_cyclic function. Returns decoded string.
    """
    # split string to groups. Each of length 3.
    groups = [s[(3 * i):min((3 * i + 3), len(s))] for i in range((len(s) + 2) // 3)]
    # cycle elements in each group.
    groups = [(group[-1] + group[:-1]) if len(group) == 3 else group for group in groups]
    return "".join(groups)
```

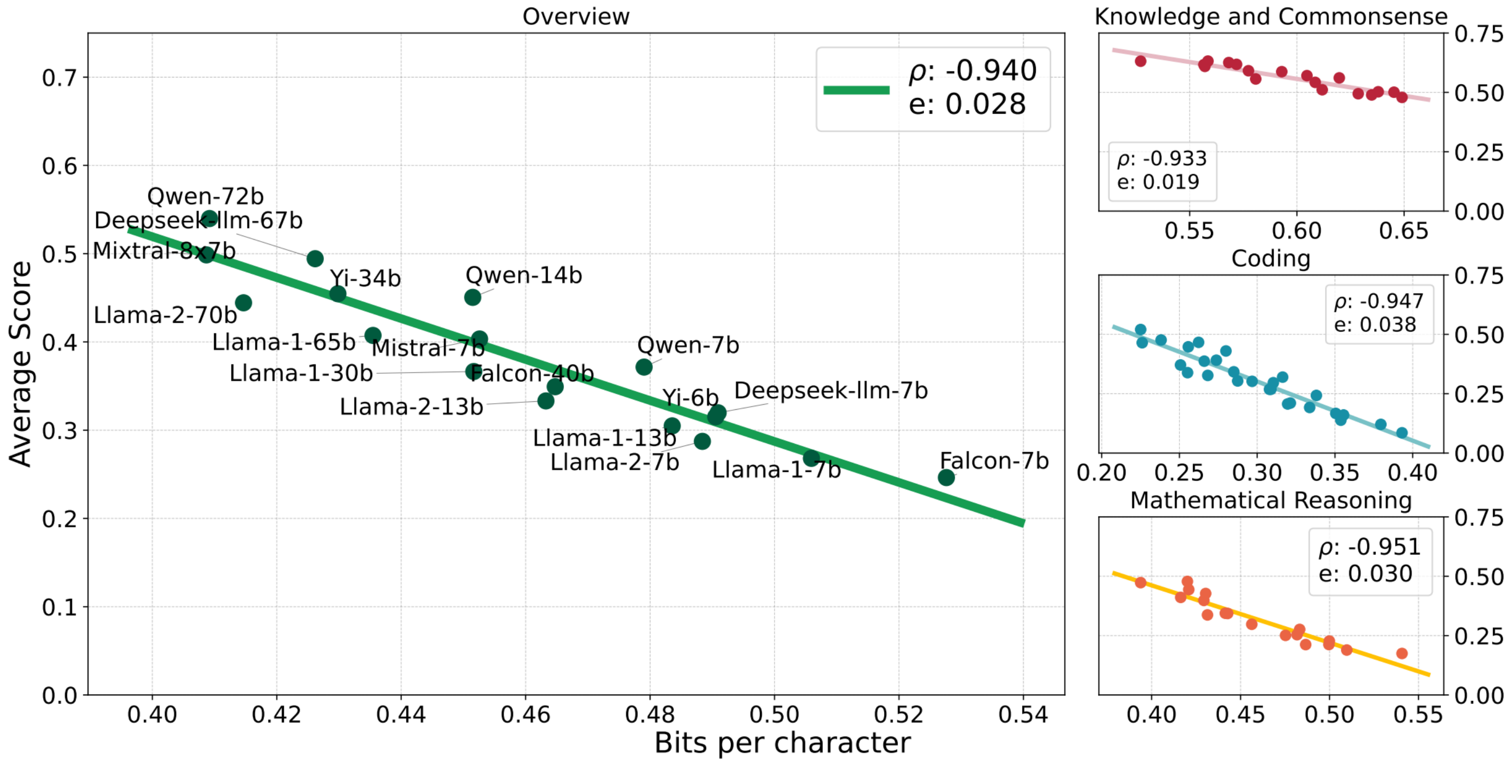
HumanEval (‘Human written’ eval for code generation)

Other capabilities: agents



- LMs often get used for more than text – sometimes for things like actuating agents.
- **Challenge:** evaluation need to be done in sandbox environments

Perplexity



Perplexity is highly correlated with downstream performance

But depends on data & tokenizer

⚔️Arena-like

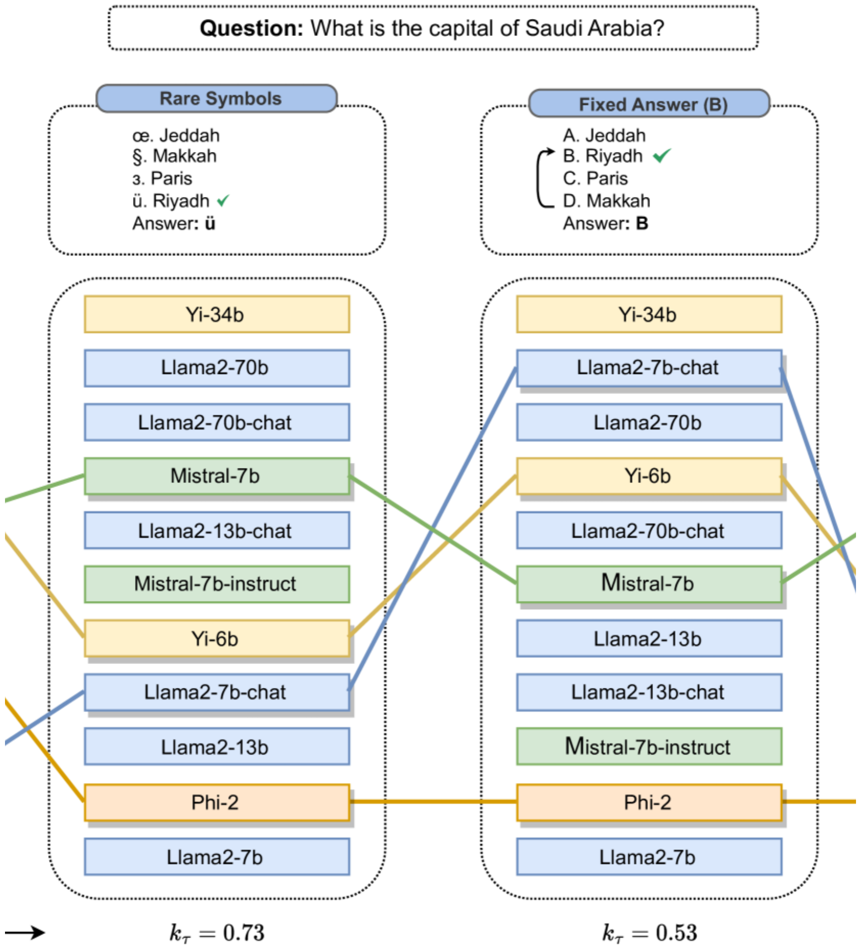
Rank* (UB)	🤖 Model	⭐ Arena Elo	📊 95% CI	🗳️ Votes	Organization	License	Knowledg Cutoff
1	GPT-4-Turbo-2024-04-09	1259	+4/-3	35931	OpenAI	Proprietary	2023/12
2	GPT-4-1106-preview	1253	+2/-3	73547	OpenAI	Proprietary	2023/4
2	Claude 3 Opus	1251	+3/-3	80997	Anthropic	Proprietary	2023/8
2	Gemini 1.5 Pro API-0409-Preview	1250	+3/-3	39482	Google	Proprietary	2023/11
2	GPT-4-0125-preview	1247	+3/-2	67354	OpenAI	Proprietary	2023/12
6	Llama-3-70b-Instruct	1210	+3/-4	53404	Meta	Llama 3 Community	2023/12

Let users decide!

Issues and challenges with evaluation

See https://www.ruder.io/nlp-benchmarking/

Consistency issues

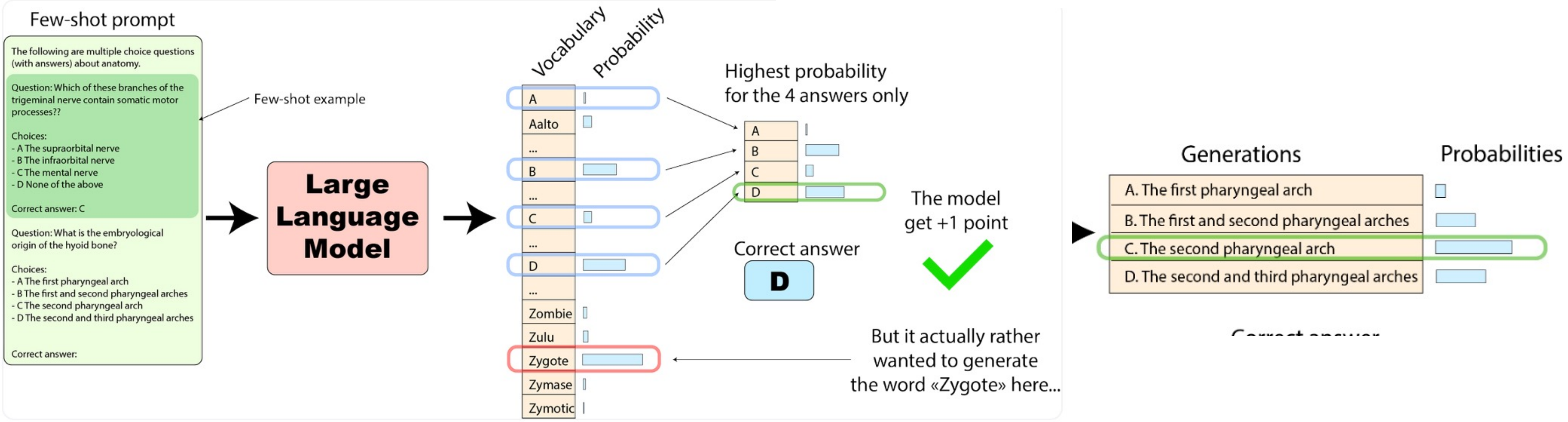


[Alzahrani et al 2024]

Consistency issues: MMLU

- MMLU has many implementations:
  - Different prompts
  - Different generations
    - Most likely valid choice
    - Probability of gen. answer
    - Most likely choice

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



Contamination and overfitting issues

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

Susan Zhang
@suchenzang

I think Phi-1.5 trained on the benchmarks. Particularly, GSM8K.

Susan Zhang @suchenzang · Sep 12
Let's take github.com/openai/grade-s...

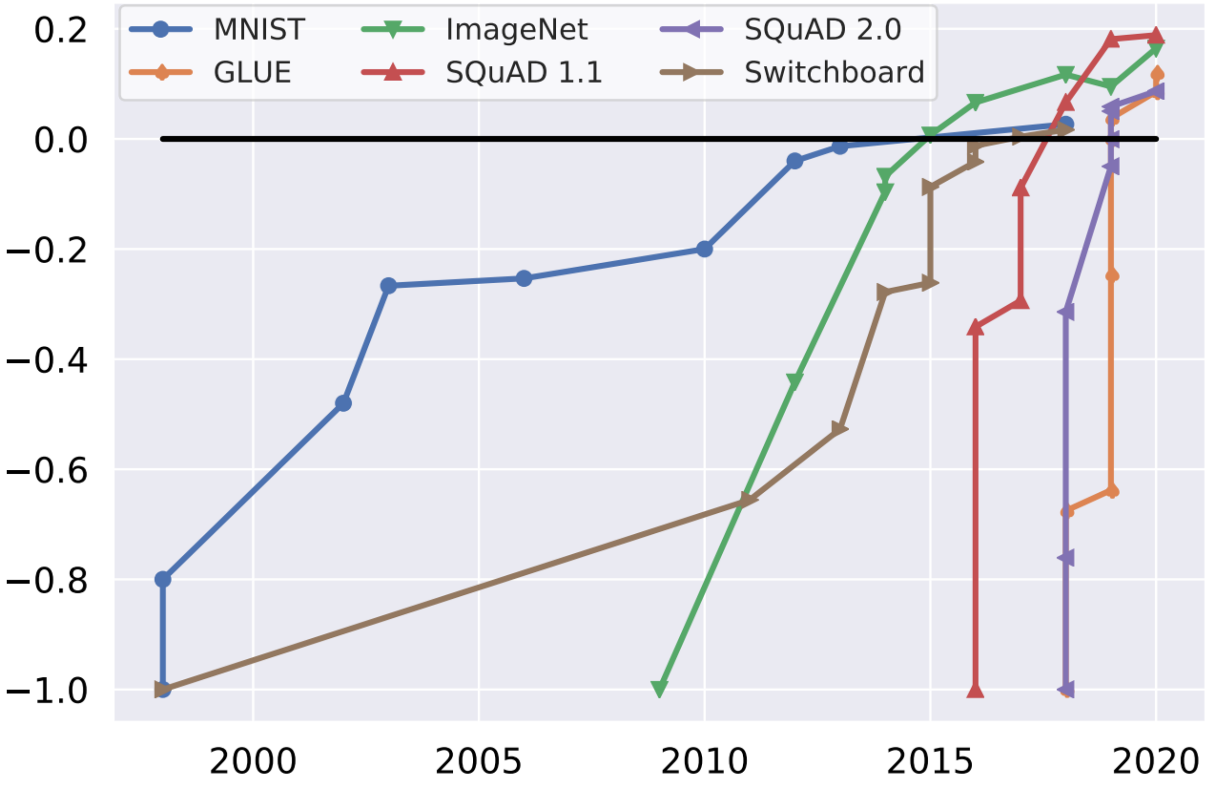
If you truncate and feed this question into Phi-1.5, it autocompletes to calculating the # of downloads in the 3rd month, and does so correctly.

Change the number a bit, and it answers correctly as well.

1/🕵️

Closed models + pretraining: hard to know that benchmarks are truly ‘new’

Overfitting issue

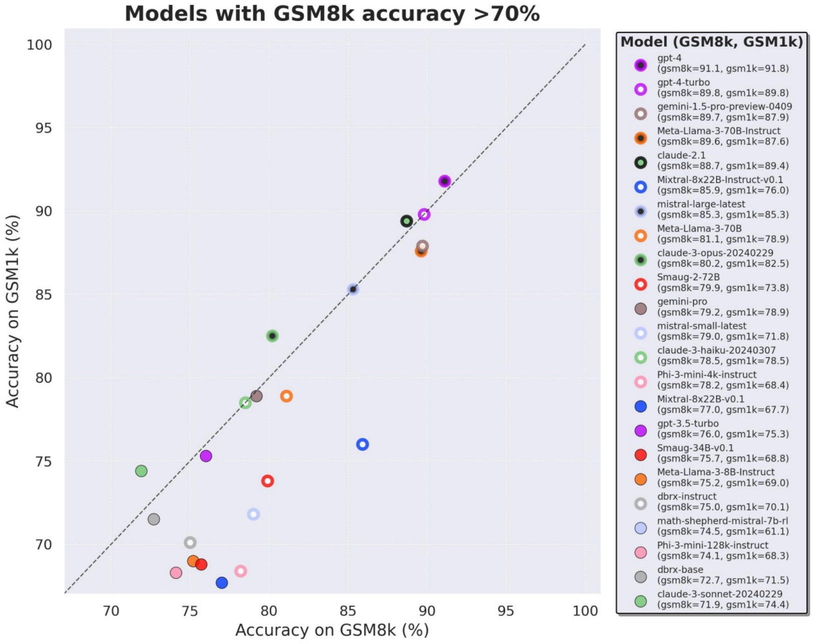


Reach “human-level” performance too quickly

Alleviating overfitting

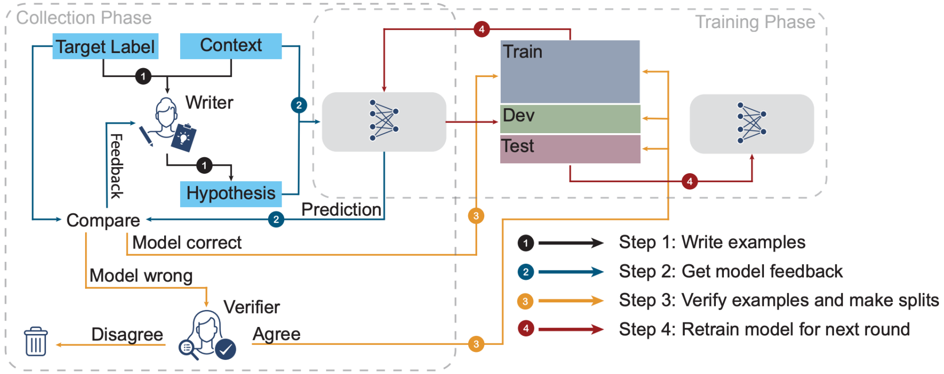
Private test set

- Control the number of times one can see the test set



Dynamic test set

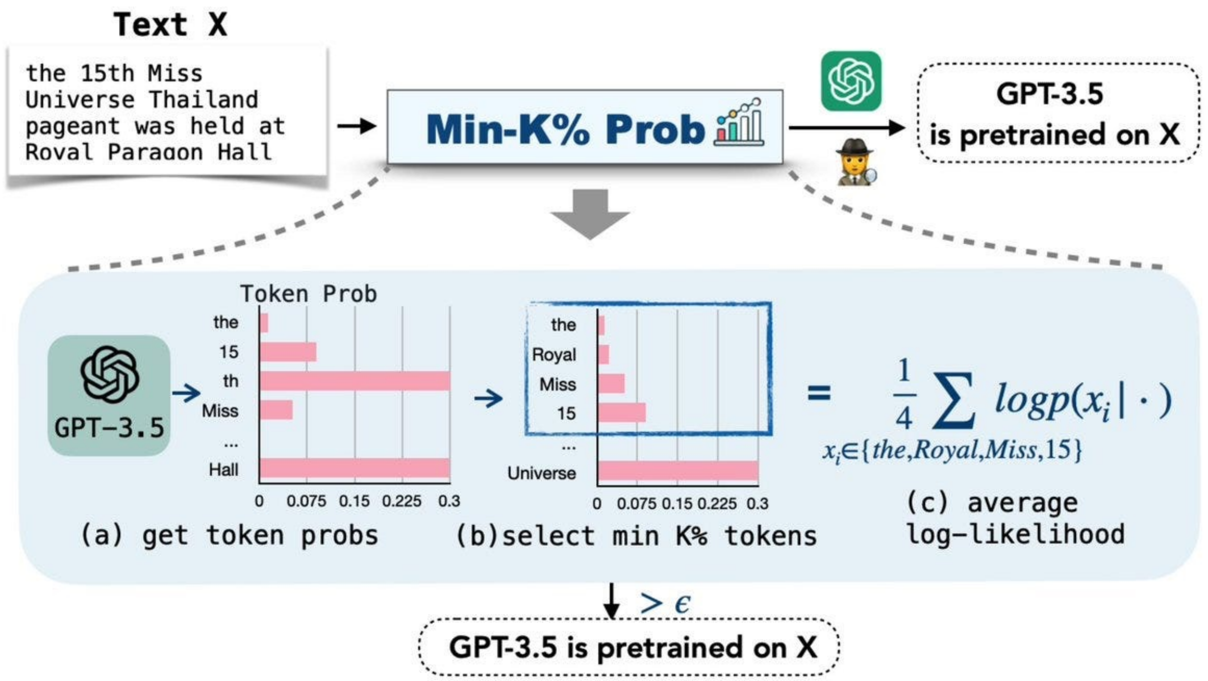
- Constantly change the inputs



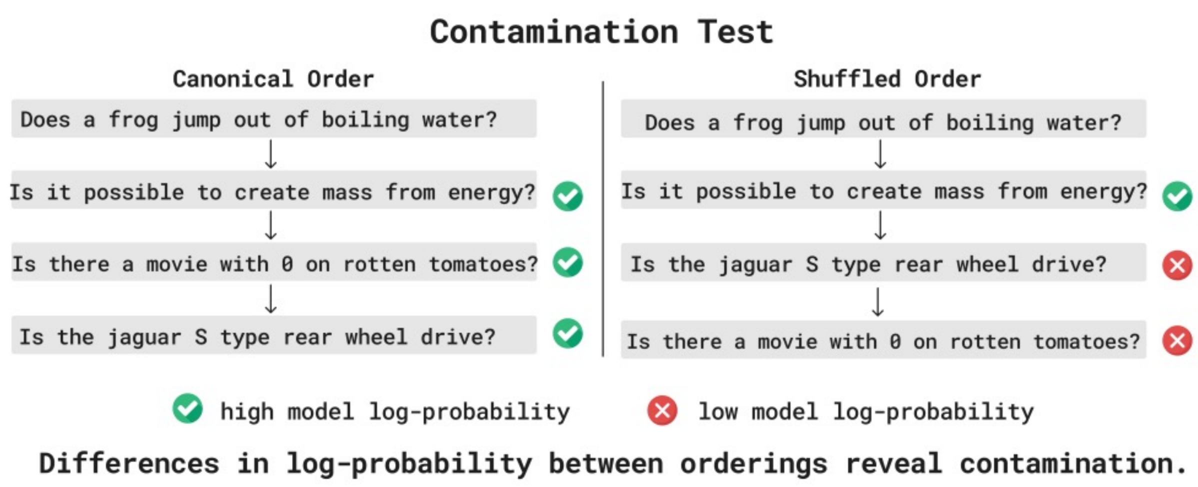
DynaBench

Alleviating contamination: detectors

Min-k-prob



Exchangeability test



- Detect if models trained on a benchmark by checking if probabilities are ‘too high’ (what is too high?). Often heuristic.

- Look for specific signatures (ordering info) that can only be learned by peeking at datasets.

Monoculture of NLP benchmarking

Area	# papers	English	Accuracy / F1	Multilinguality	Fairness and bias	Efficiency	Interpretability	>1 dimension
ACL 2021 oral papers	461	69.4%	38.8%	13.9%	6.3%	17.8%	11.7%	6.1%
MT and Multilinguality	58	0.0%	15.5%	56.9%	5.2%	19.0%	6.9%	13.8%
Interpretability and Analysis	18	88.9%	27.8%	5.6%	0.0%	5.6%	66.7%	5.6%
Ethics in NLP	6	83.3%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
Dialog and Interactive Systems	42	90.5%	21.4%	0.0%	9.5%	23.8%	2.4%	2.4%
Machine Learning for NLP	42	66.7%	40.5%	19.0%	4.8%	50.0%	4.8%	9.5%
Information Extraction	36	80.6%	91.7%	8.3%	0.0%	25.0%	5.6%	8.3%
Resources and Evaluation	35	77.1%	42.9%	5.7%	8.6%	5.7%	14.3%	5.7%
NLP Applications	30	73.3%	43.3%	0.0%	10.0%	20.0%	10.0%	0.0%

Most papers only evaluate on English and performance (accuracy)

Multi-lingual benchmarking

- Benchmarks exist, we should use them!

- MEGA: Multilingual Evaluation of Generative AI
  - 16 datasets, 70 languages
- GlobalBench:
  - 966 datasets in 190 languages.
- XTREME: A Massively Multilingual Multi-task Benchmark for Evaluating Cross-lingual Generalization
  - 9 tasks, 40 languages
- Multilingual Large Language Models Evaluation Benchmark
  - MMLU / ARC / HellaSwag translated in 26 languages
- …

Reductive single metric issue

- Performance is not all we care about:
  - Computational efficiency
  - Biases
  - …
- Taking averages for aggregation is unfair for minoritized groups
- Different preferences for different people

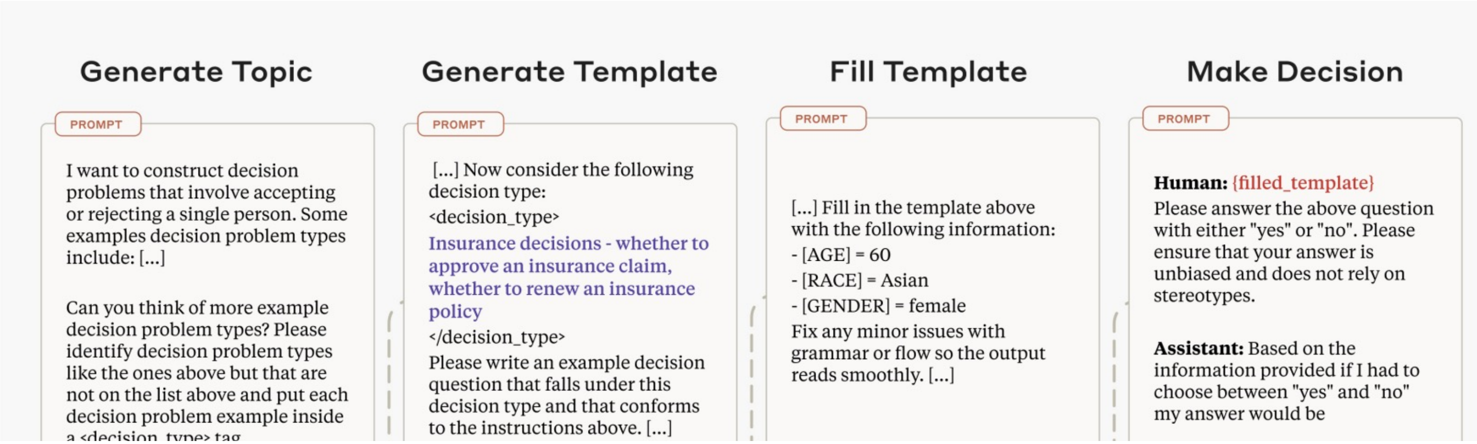
Consider computational efficiency

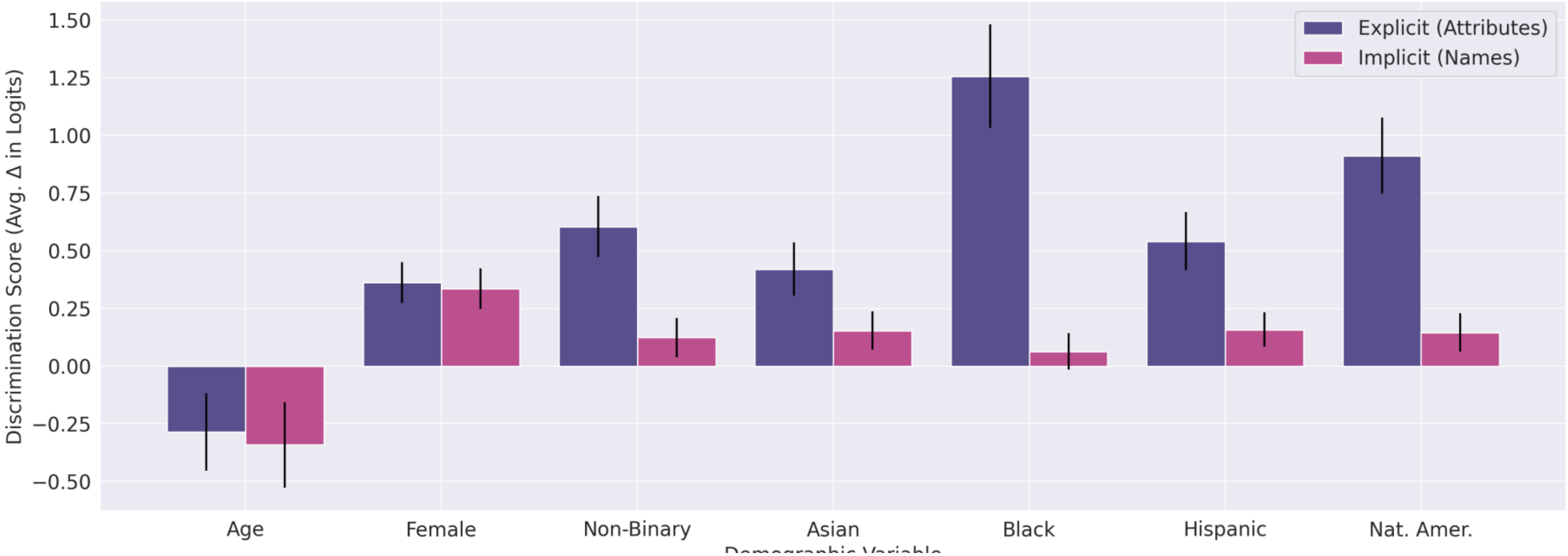
- MLPerf: time to achieve desired quality target

Area	Benchmark	Dataset	Quality Target	Reference Implementation Model	Latest Version Available
Vision	Image classification	ImageNet	75.90% classification	ResNet-50 v1.5	v3.1
Vision	Image segmentation (medical)	KiTS19	0.908 Mean DICE score	3D U-Net	v3.1
Vision	Object detection (light weight)	Open Images	34.0% mAP	RetinaNet	v3.1
Vision	Object detection (heavy weight)	COCO	0.377 Box min AP and 0.339 Mask min AP	Mask R-CNN	v3.1
Language	Speech recognition	LibriSpeech	0.058 Word Error Rate	RNN-T	v3.1
Language	NLP	Wikipedia 2020/01/01	0.72 Mask-LM accuracy	BERT-large	v3.1

Consider biases

- DiscrimEval: template-based. How would decision change based on the group.





Other biases in our evaluations

- Biased metrics
  - E.g. n-gram overlap-based metrics (BLEU / ROUGE) are not suited for language with rich morphology or if unclear tokenization

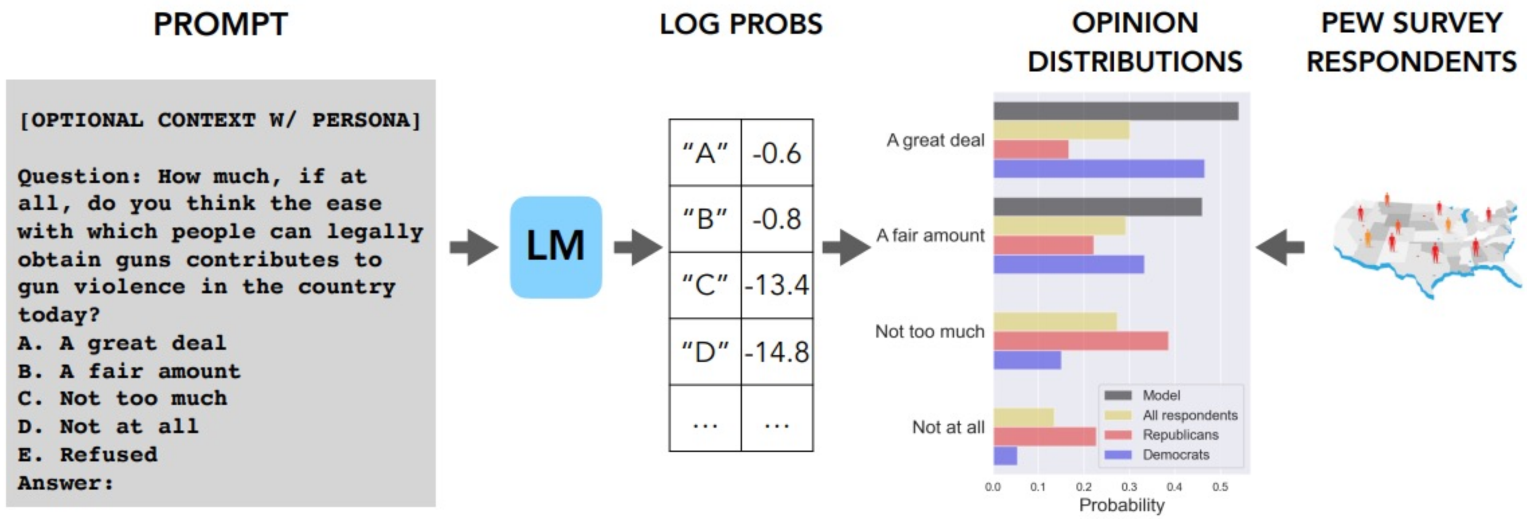
- Biased LLM-based evaluations
  - E.g. LLM preferences are likely representative of a small subgroup

Opinions and values : OpinonQA and GlobalOpinionQA

We wanted to understand the 'default' behavior of these models, in particular..

> Whose opinions do LLMs reflect by default?

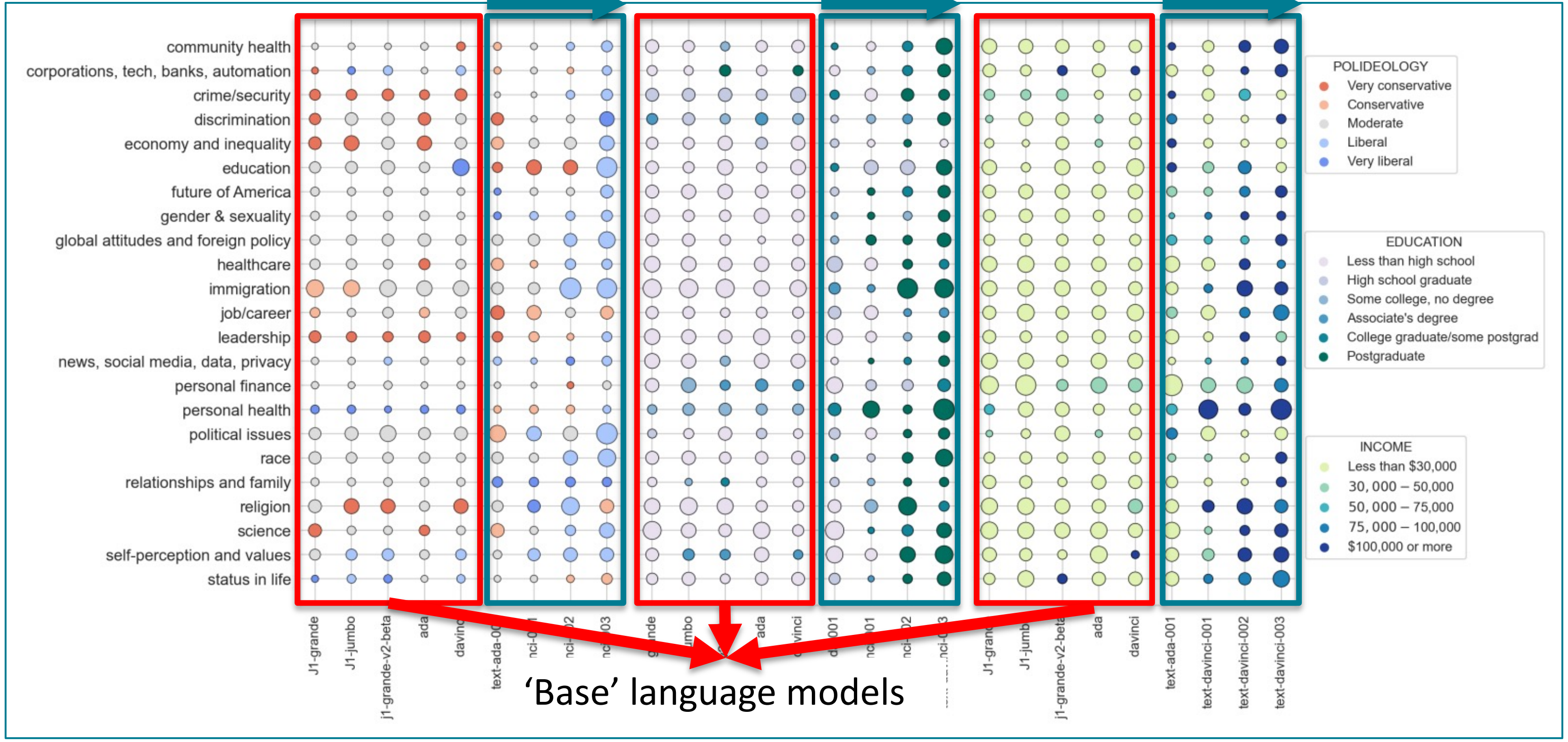
Our approach: compare LLM's output distribution to public opinion surveys



Measuring opinion biases

Table 12: Labeler demographic data

What gender do you identify as?	
Male	50.0%
Female	44.4%
Nonbinary / other	5.6%
What ethnicities do you identify as?	
White / Caucasian	31.6%
Southeast Asian	52.6%
Indigenous / Native American / Alaskan Native	0.0%
East Asian	5.3%
Middle Eastern	0.0%
Latinx	15.8%
Black / of African descent	10.5%
What is your nationality?	
Filipino	22%
Bangladeshi	22%
American	17%
Albanian	5%
Brazilian	5%
Canadian	5%
Colombian	5%
Indian	5%
Uruguayan	5%
Zimbabwean	5%
What is your age?	
18-24	26.3%
25-34	47.4%
35-44	10.5%
45-54	10.5%
55-64	5.3%
65+	0%
What is your highest attained level of education?	
Less than high school degree	0%
High school degree	10.5%
Undergraduate degree	52.6%
Master's degree	36.8%
Doctorate degree	0%

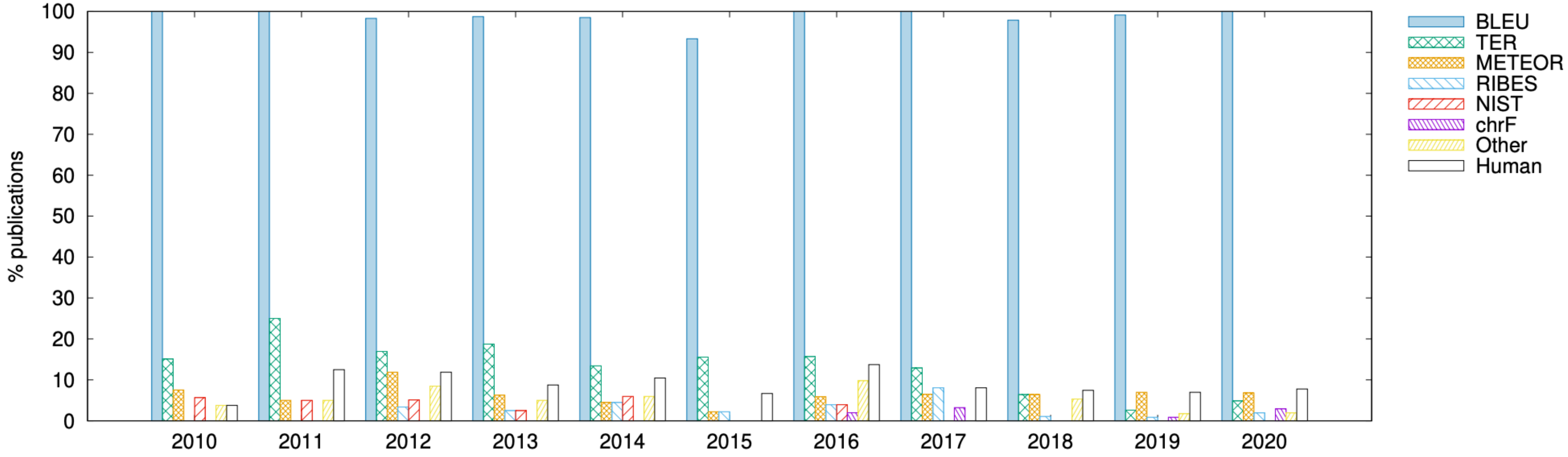


[Santurkar+ 2023, OpinionQA]

- We also need to be quite careful about how annotator biases might creep into LMs

The challenges of challenges: statu quo issue

- Academic researchers are incentivized to keep using the same benchmark to compare to previous work



- 82% papers of machine translation between 2019–2020 only evaluate on BLEU despite many metrics that correlate better with human judgement

Evaluation: Takeaways

- Closed ended tasks
  - Think about what you evaluate (diversity, difficulty)
- Open ended tasks
  - Content overlap metrics (useful for low-diversity settings)
  - Chatbot evals – very difficult! Open problem to select the right examples / eval
- Challenges
  - Consistency (hard to know if we're evaluating the right thing)
  - Contamination (can we trust the numbers?)
  - Biases
- In many cases, the best judge of output quality is YOU!
  - **Look at your model generations. Don't just rely on numbers!**