LLM LE7 VT2025

Evaluation

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Outline:

- **How to evaluate LLMs?**
- **Evaluating low resource languages**
- **Quality evaluation**
- **EuroEval**

LINKÖPING
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Language modelling

- **Language modelling** is the task of predicting which word comes next in a sequence of words.
- More formally, given a sequence of words $w_1, \ldots, w_t$ we want to know the probability of the next word, w_{t+1}:

$$P(w_{t+1} \mid w_1, \ldots, w_t)$$

- We are assuming that w_{t+1} comes from a finite vocabulary V.

language models = classifiers

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How to Evaluate LLMs?

Four Main Approaches

- **Vibe Check**
- **LLM-as-a-judge**
- **Arena**
- **Benchmark**

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the European Union

Four Main Approaches

Arena

LLM-as-a-judge

Benchmark

Vibe Check

Can evaluate all model types: ✗

Generalises to other tasks: ✗

Objective measure: ✗

Cheap to set up: ✓

Feasible for low-resource language: ✓

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Four Main Approaches

LLM-as-a-judge

Benchmark

Vibe Check

Arena

Can evaluate all model types: ✗

Generalises to other tasks: ✓

Objective measure: ✓*

Cheap to set up: ✗

Feasible for low-resource language: ✗

* Depends on the types of questions and/or users contributing

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Four Main Approaches

Benchmark

Vibe Check

Arena

LLM-as-a-judge

Can evaluate all model types:	✗
Generalises to other tasks:	✓
Objective measure:	✓*
Cheap to set up:	✓
Feasible for low-resource language:	✗

* Can be biased, see Stureborg et al., 2024

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Four Main Approaches

Vibe Check

Arena

LLM-as-a-judge

Benchmark

Can evaluate all model types: ✓

Generalises to other tasks: ✓*

Objective measure: ✓

Cheap to set up: ✗

Feasible for low-resource language: ✓

* Depends on the tasks included in the benchmark

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Four Main Approaches

	Vibe Check	Arena	LLM-as-a-judge	Benchmark
Can evaluate all model types:	✗	✗	✗	✓
Generalises to other tasks:	✗	✓	✓	✓ *
Objective measure:	✗	✓ *	✓ *	✓
Cheap to set up:	✓	✗	✓	✗
Feasible for low-resource language:	✓	✗	✗	✓

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Evaluation challenges for low-resource languages

TrustLLM

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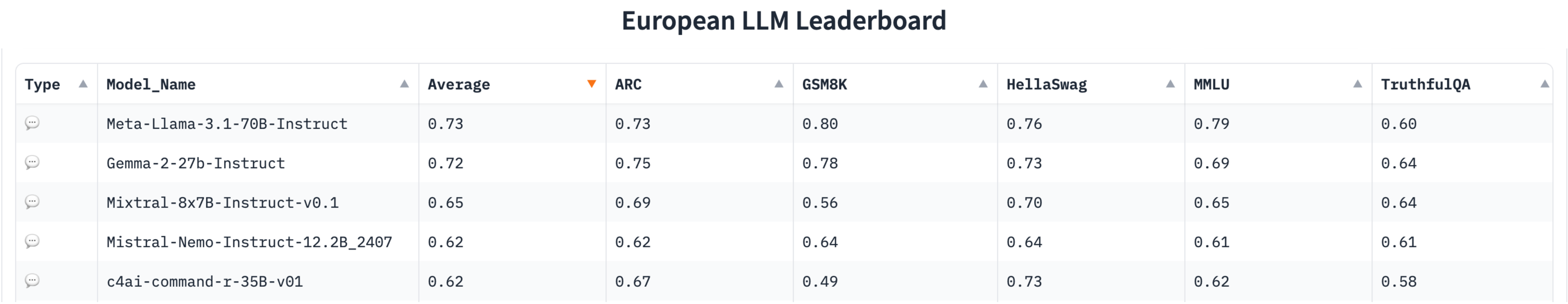
One of several European leaderboards for LLMs



European LLM Leaderboard

Type	Model_Name	Average	ARC	GSM8K	HellaSwag	MMLU	TruthfulQA
💬	Meta-Llama-3.1-70B-Instruct	0.73	0.73	0.80	0.76	0.79	0.60
💬	Gemma-2-27b-Instruct	0.72	0.75	0.78	0.73	0.69	0.64
💬	Mixtral-8x7B-Instruct-v0.1	0.65	0.69	0.56	0.70	0.65	0.64
💬	Mistral-Nemo-Instruct-12.2B_2407	0.62	0.62	0.64	0.64	0.61	0.61
💬	c4ai-command-r-35B-v01	0.62	0.67	0.49	0.73	0.62	0.58

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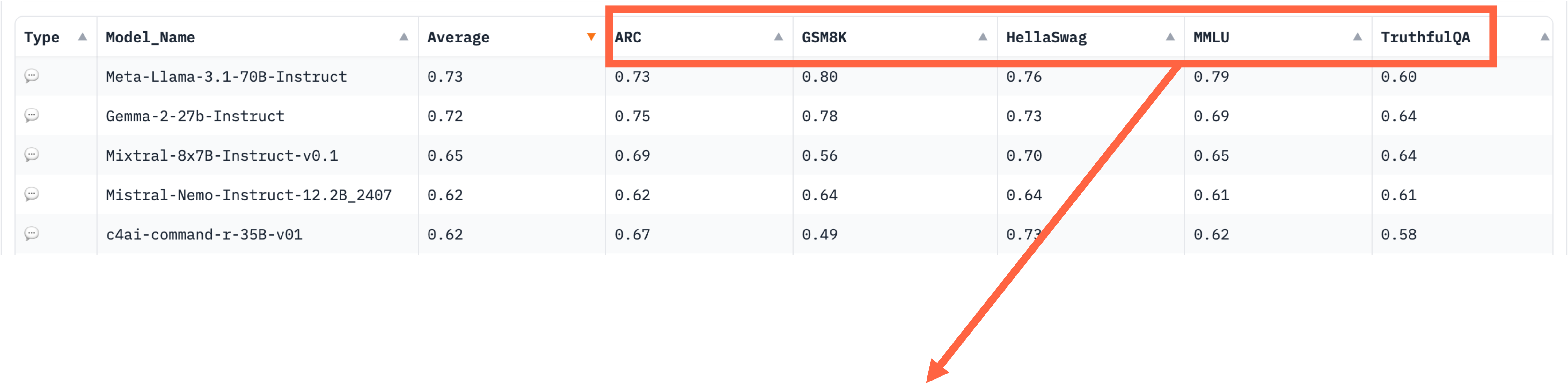
European LLM Leaderboard



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All machine translated from English

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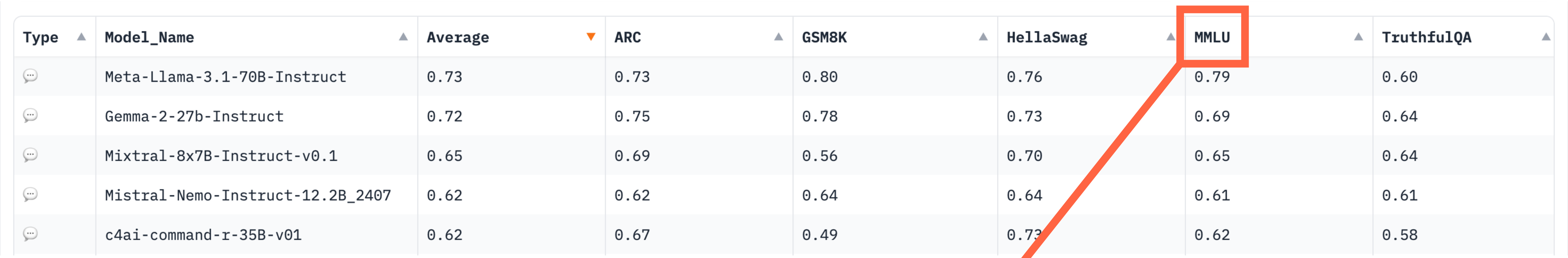

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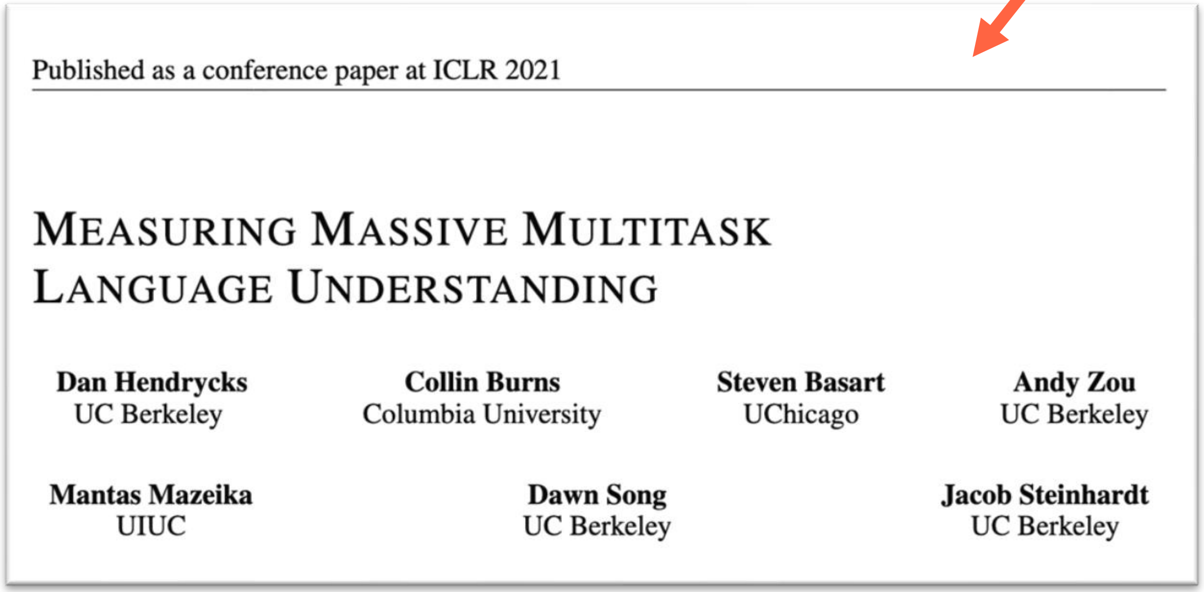

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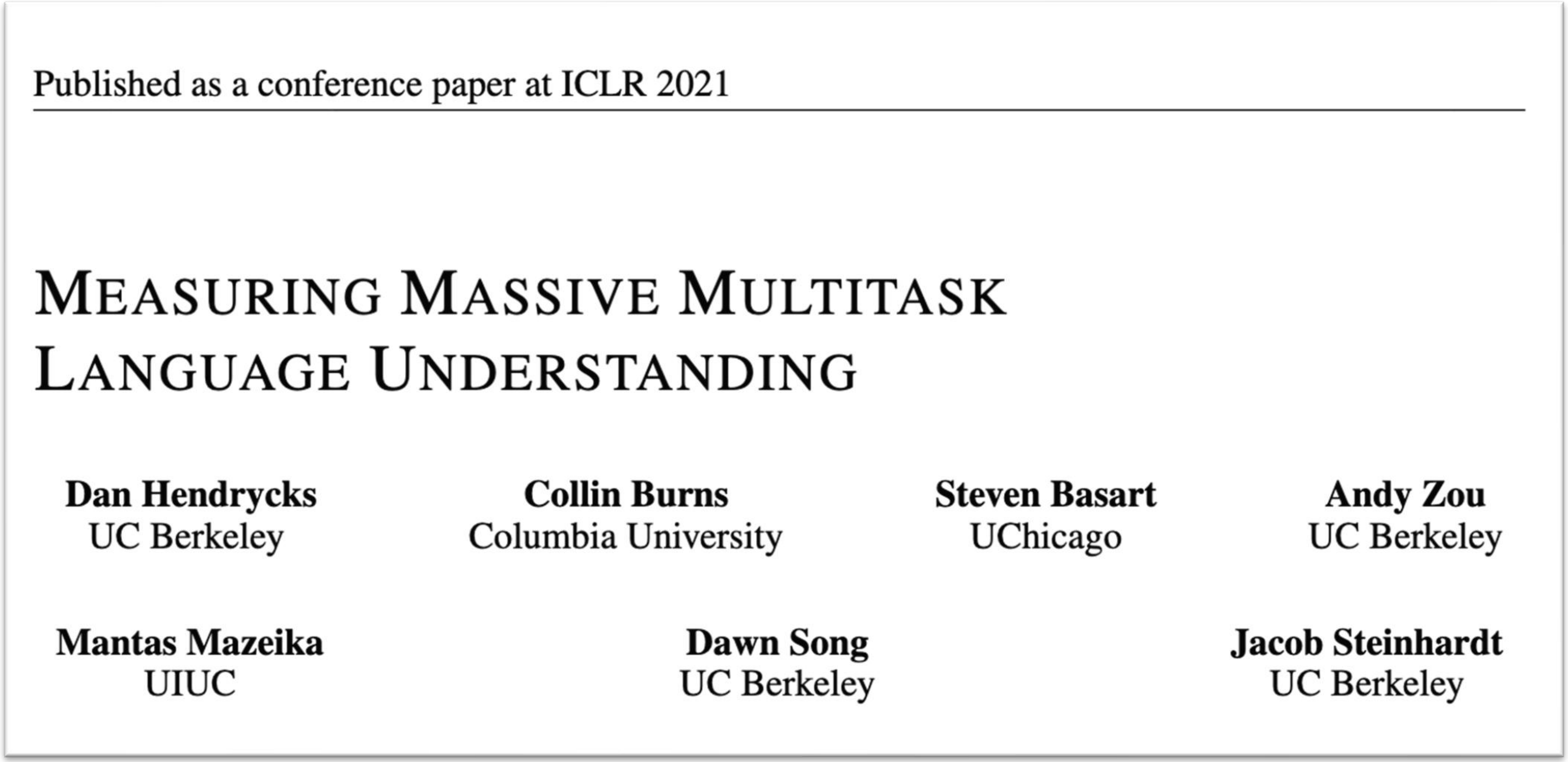

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- Elementary mathematics
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- Electrical engineering
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- Professional law
- Prehistory
- Jurisprudence
- International law
- Logical fallacies
- High school European history
- Moral scenarios
- Formal logic
- Philosophy
- Moral disputes

- College medicine
- Virology
- Anatomy
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- Professional medicine

- Professional accounting
- Business ethics
- Miscellaneous
- Management
- Global facts
- Marketing

- Sociology
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21 questions about the US
7 questions about China
4 questions about India
The remaining 16 countries has 1-2 questions

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Many examples concerns translating logical statements into English

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US foreign policy

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Some questions refer to “Calculus II” classes at high school. Other questions are specific to scholarships in the USA

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Some questions refer to English informal expressions, such as what a “dished face” means

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Focuses on clinical guidelines in the USA. Also questions regarding USA-national statistics, but mentioned in a global sense (e.g., “What was true about informal carers in 2020?”)

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Focuses on laws in the USA

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Focuses on laws in the USA

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Refers to American laws regarding lawsuits

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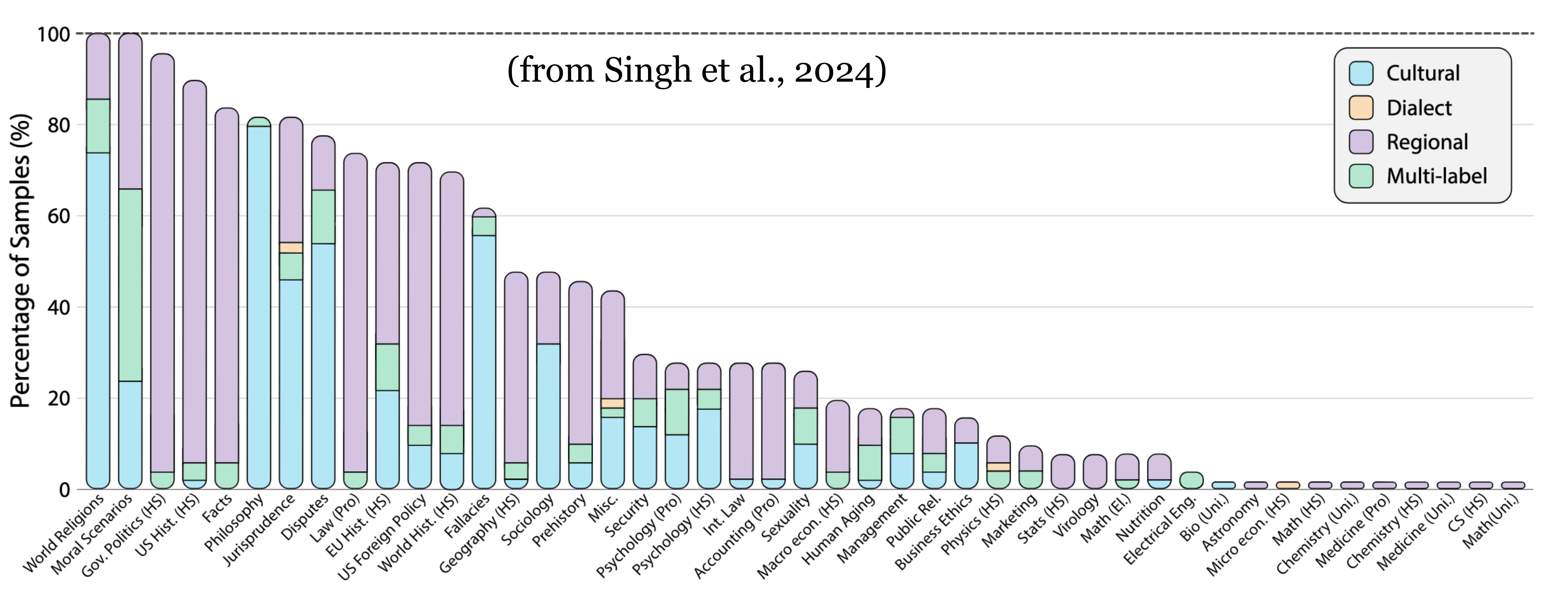

(from Singh et al., 2024)

Figure 3: Proportion of samples containing cultural, regional, or dialect-specific references per subject in the MMLU dataset. Notably, all samples in the *World Religions* and *Moral Scenarios* subjects include at least one such reference. Note that 12 subjects did not contain any Culturally-Sensitive **CS**🗽 samples and have been excluded from the figure.

College

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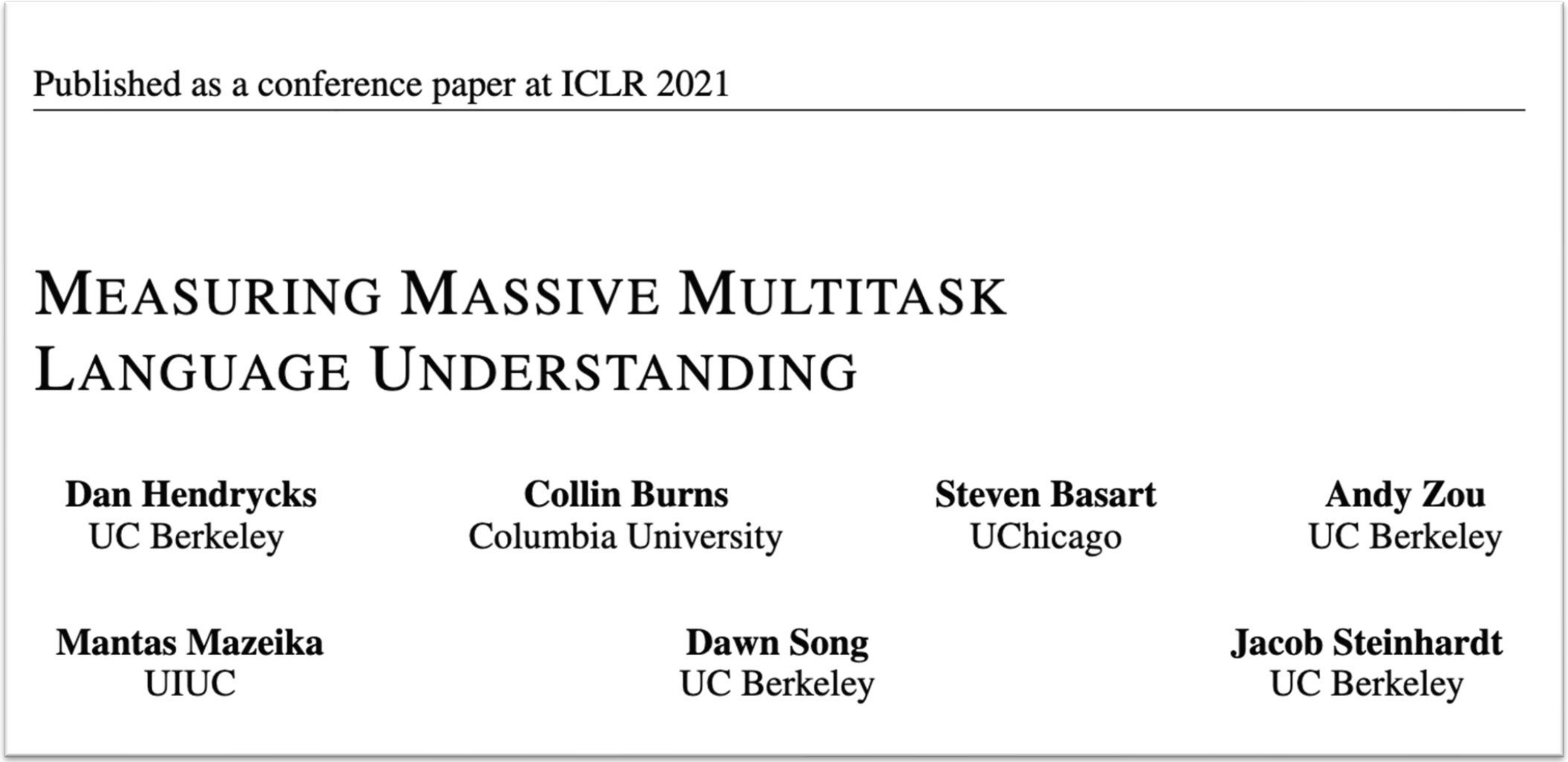

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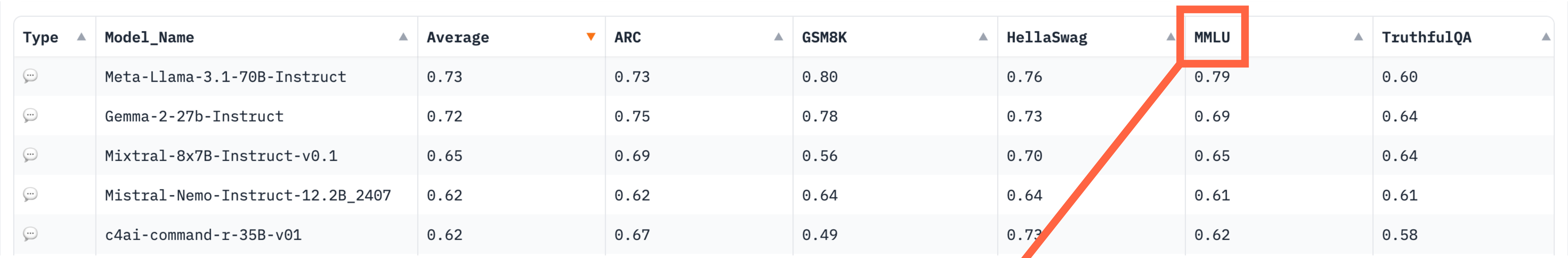

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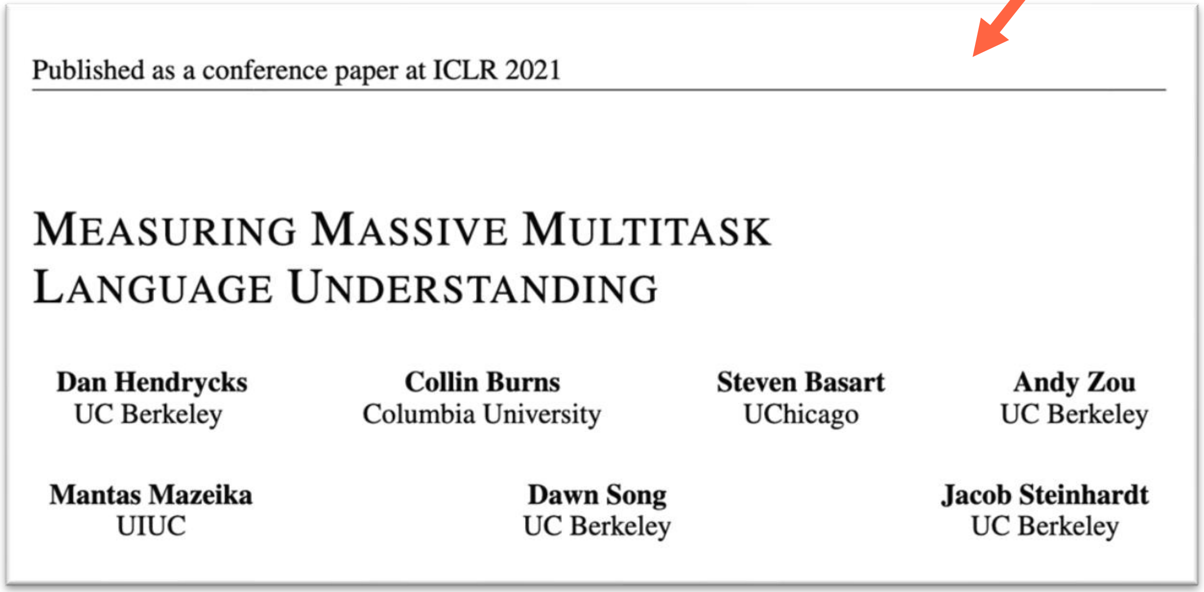

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Evaluation Challenge #1

Many of our evaluation datasets are USA-centric

TrustLLM

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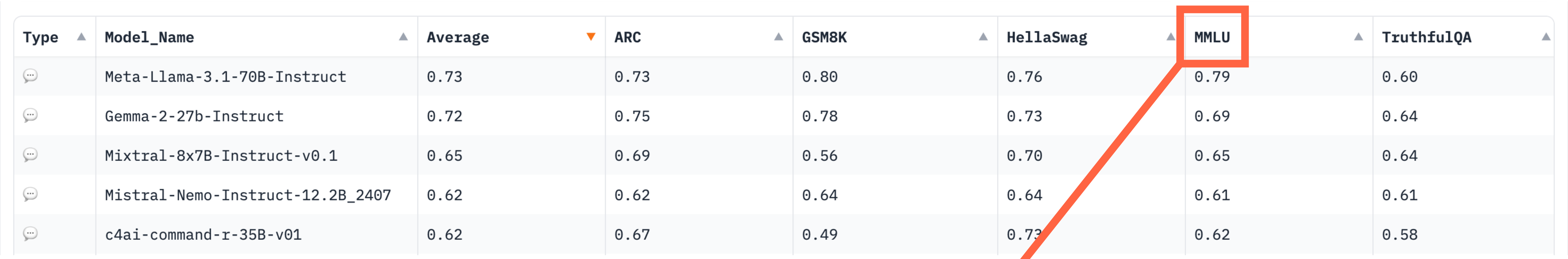
European LLM Leaderboard



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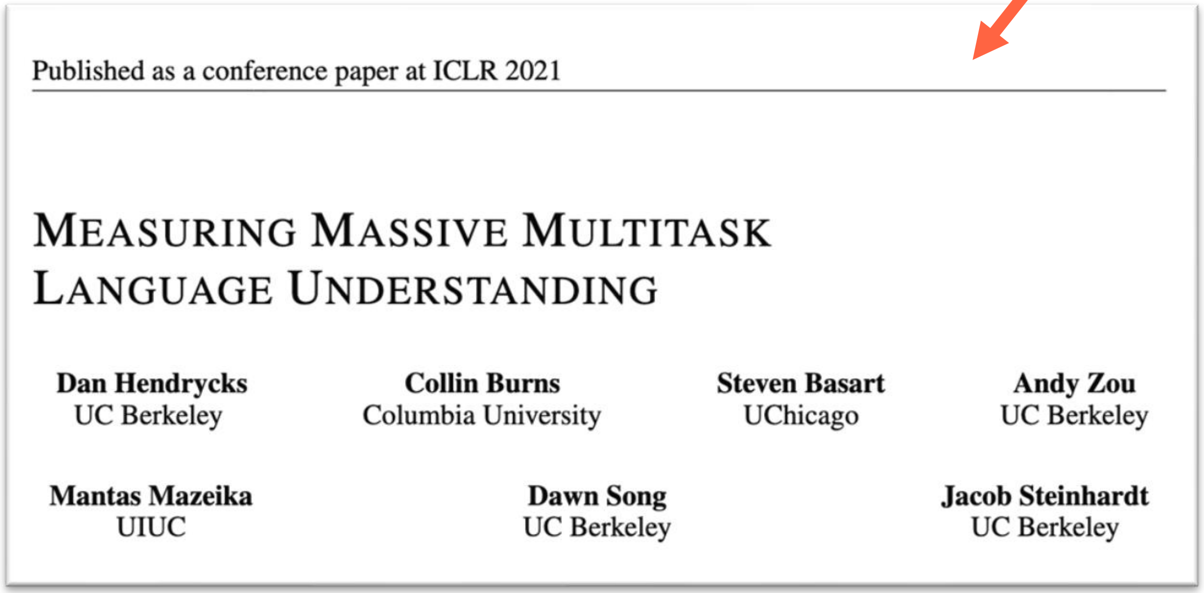

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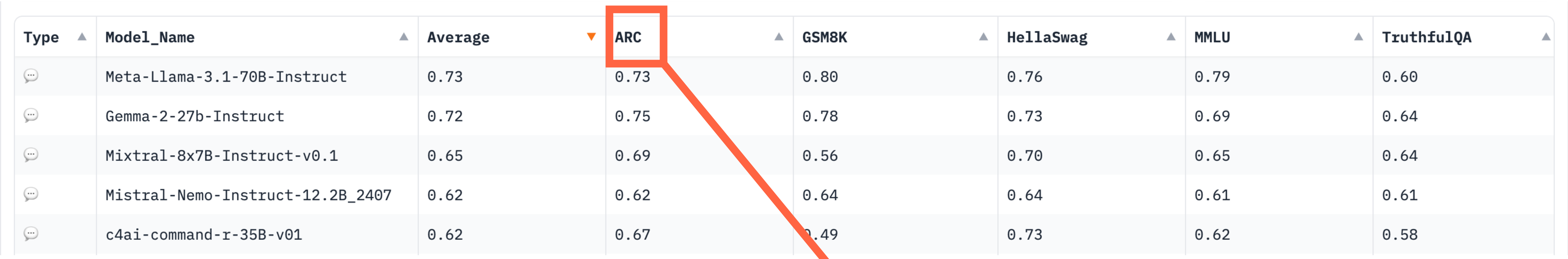

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💬	c4ai-command-r-35B-v01	0.62	0.67	0.49	0.73	0.62	0.58

Science knowledge

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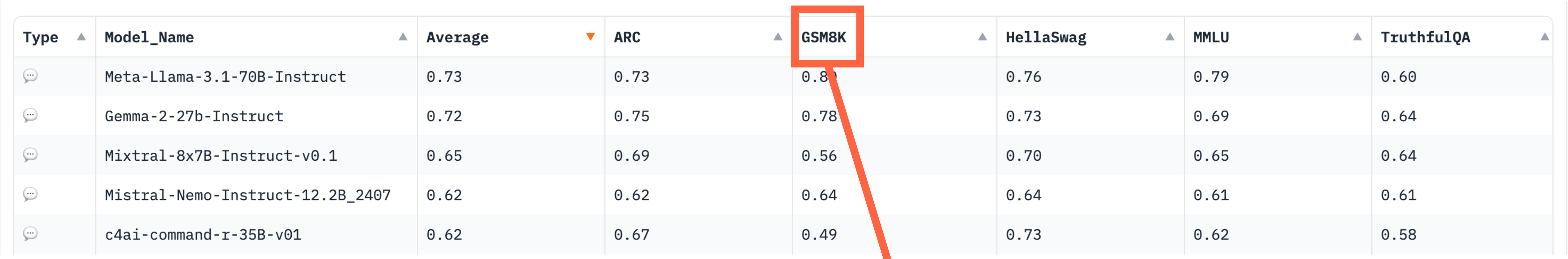
European LLM Leaderboard



Type ▲	Model_Name ▲	Average ▼	ARC ▲	GSM8K ▲	HellaSwag ▲	MMLU ▲	TruthfulQA ▲
💬	Meta-Llama-3.1-70B-Instruct	0.73	0.73	0.80	0.76	0.79	0.60
💬	Gemma-2-27b-Instruct	0.72	0.75	0.78	0.73	0.69	0.64
💬	Mixtral-8x7B-Instruct-v0.1	0.65	0.69	0.56	0.70	0.65	0.64
💬	Mistral-Nemo-Instruct-12.2B_2407	0.62	0.62	0.64	0.64	0.61	0.61
💬	c4ai-command-r-35B-v01	0.62	0.67	0.49	0.73	0.62	0.58

Maths knowledge

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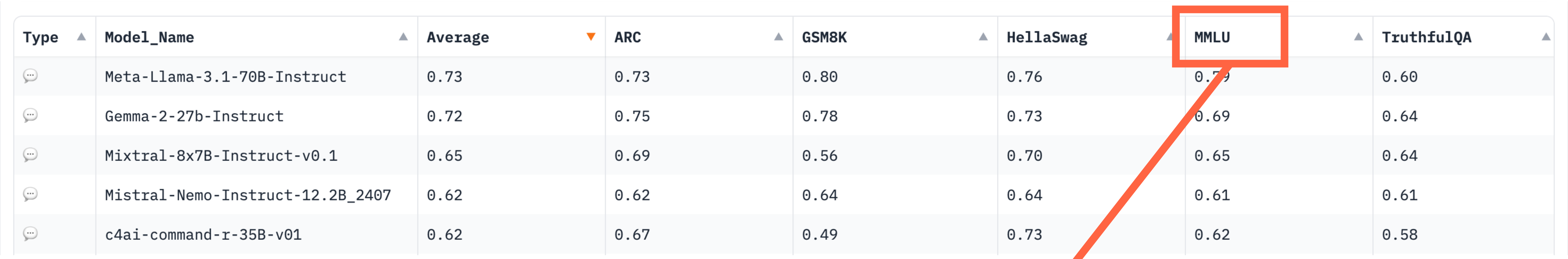
European LLM Leaderboard



Type	Model_Name	Average	ARC	GSM8K	HellaSwag	MMLU	TruthfulQA
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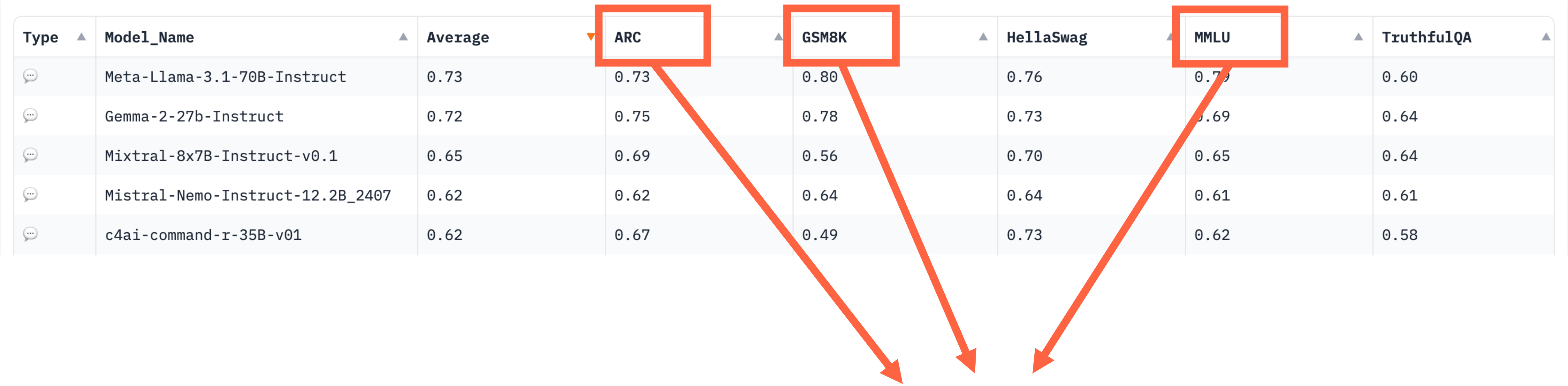
💬	Gemma-2-27b-Instruct	0.72	0.75	0.78	0.73	0.69	0.64
💬	Mixtral-8x7B-Instruct-v0.1	0.65	0.69	0.56	0.70	0.65	0.64
💬	Mistral-Nemo-Instruct-12.2B_2407	0.62	0.62	0.64	0.64	0.61	0.61
💬	c4ai-command-r-35B-v01	0.62	0.67	0.49	0.73	0.62	0.58

A lot of STEM knowledge

European LLM Leaderboard



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💬	Mixtral-8x7B-Instruct-v0.1	0.65	0.69	0.56	0.70	0.65	0.64
💬	Mistral-Nemo-Instruct-12.2B_2407	0.62	0.62	0.64	0.64	0.61	0.61
💬	c4ai-command-r-35B-v01	0.62	0.67	0.49	0.73	0.62	0.58

~50% of the benchmark is testing STEM knowledge

Is that what constitutes a good model?

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Evaluation Challenge #2

We are not clear on what “best” means

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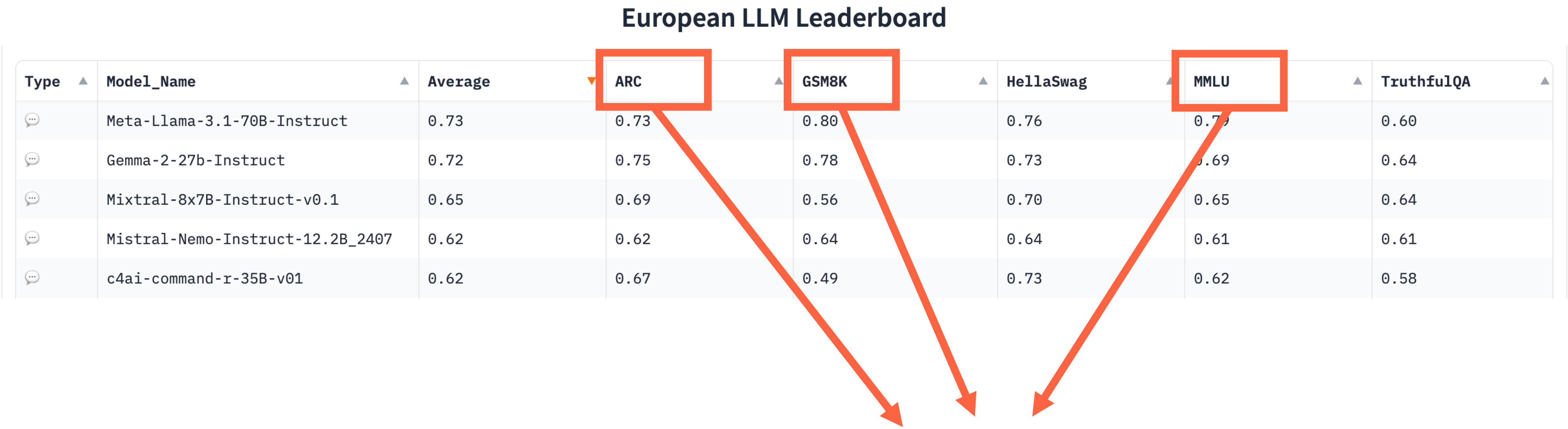

European LLM Leaderboard

Type	Model_Name	Average	ARC	GSM8K	HellaSwag	MMLU	TruthfulQA
💬	Meta-Llama-3.1-70B-Instruct	0.73	0.73	0.80	0.76	0.79	0.60
💬	Gemma-2-27b-Instruct	0.72	0.75	0.78	0.73	0.69	0.64
💬	Mixtral-8x7B-Instruct-v0.1	0.65	0.69	0.56	0.70	0.65	0.64
💬	Mistral-Nemo-Instruct-12.2B_2407	0.62	0.62	0.64	0.64	0.61	0.61
💬	c4ai-command-r-35B-v01	0.62	0.67	0.49	0.73	0.62	0.58

~50% of the benchmark is testing STEM knowledge

Is that what constitutes a good model?

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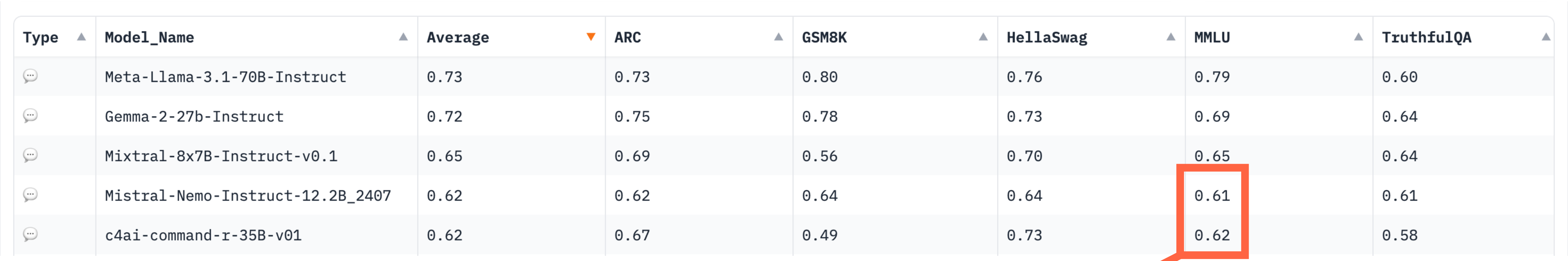
European LLM Leaderboard



Type	Model_Name	Average	ARC	GSM8K	HellaSwag	MMLU	TruthfulQA
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💬	Mistral-Nemo-Instruct-12.2B_2407	0.62	0.62	0.64	0.64	0.61	0.61
💬	c4ai-command-r-35B-v01	0.62	0.67	0.49	0.73	0.62	0.58

Is this significant or by chance?

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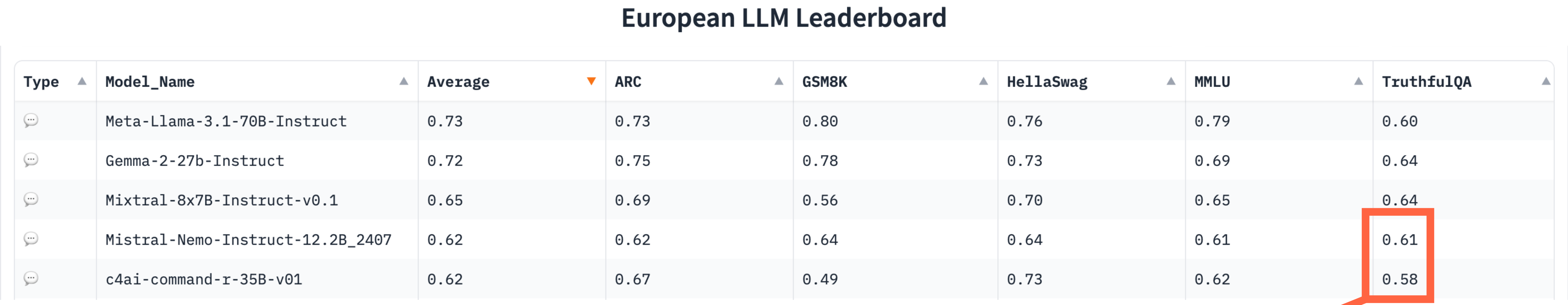

European LLM Leaderboard

Type ▲	Model_Name ▲	Average ▼	ARC ▲	GSM8K ▲	HellaSwag ▲	MMLU ▲	TruthfulQA ▲
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💬	Mistral-Nemo-Instruct-12.2B_2407	0.62	0.62	0.64	0.64	0.61	0.61
💬	c4ai-command-r-35B-v01	0.62	0.67	0.49	0.73	0.62	0.58

How about this?

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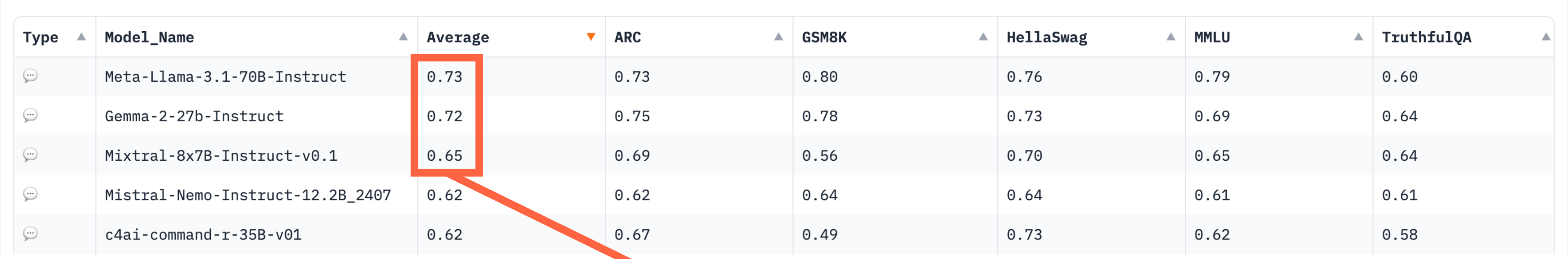
European LLM Leaderboard



Type ▲	Model_Name ▲	Average ▼	ARC ▲	GSM8K ▲	HellaSwag ▲	MMLU ▲	TruthfulQA ▲
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💬	Mistral-Nemo-Instruct-12.2B_2407	0.62	0.62	0.64	0.64	0.61	0.61
💬	c4ai-command-r-35B-v01	0.62	0.67	0.49	0.73	0.62	0.58

Are these models equally good?

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Evaluation Challenge #3

We do not take variance into account

TrustLLM

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Takeaways

- Avoid machine translated evaluation datasets if possible
  - Be careful and transparent about this if not
- Be transparent about *what domain* you are evaluating models on
  - What constitutes a good model according to your benchmark?
- Report error bars!

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Quality Evaluation

Evaluation – Problem Statement

$$F\ (subject,\ criteria) \rightarrow result$$

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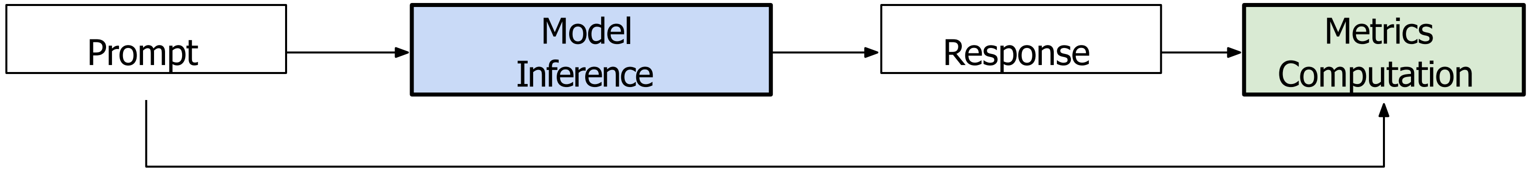
$F\,(\text{subject}, \text{criteria}) \rightarrow \text{result}$

Evaluation – Subject

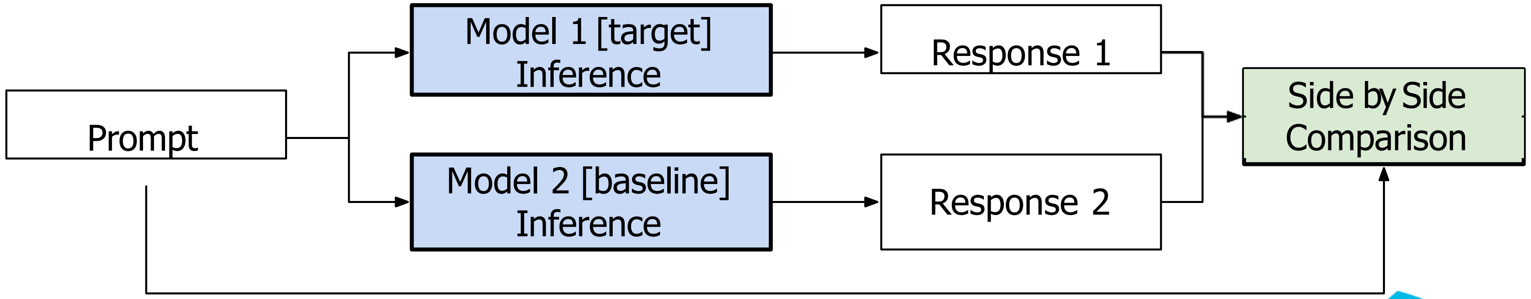
Point-wise:
prompt → response
Result: absolute measures

Point-wise



Pair-wise:
prompt → (response 1, response 2)
Result: relative preference

Pair-wise (Side by Side)



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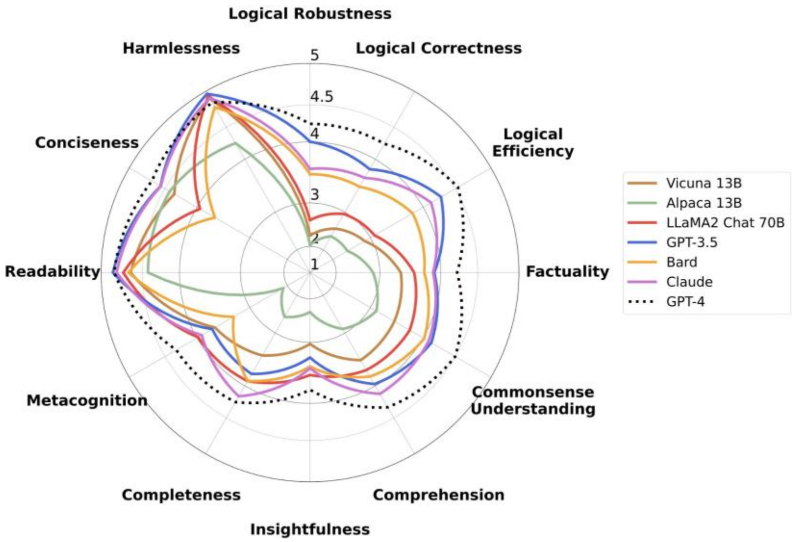
F (subject, criteria) → result

Evaluation – Criteria

Aspect (Dimension):

- General text generation: e.g., fluency, coherence,
- Task related
  - Summary: e.g., Conciseness, Comprehensiveness,
  - Openbook Q/A: Groundedness
  - Code: correctness of execution result
  - Tool use: tool selection accuracy, parameter value correctness
- User specific
  - Entertaining, Engaging, intuitive



Source: FLASK (Ye 2023)

Rubrics

5: (Very good). The summary follows instructions, is grounded, concise, fluent and aligned with reference summary.
4: (Good). The summary follows instructions, is grounded, concise, and fluent but not aligned with reference summary.
3: (Ok). Thg summary mostly follows instructions, is grounded, but is not concise, not fluent, not aligned with reference summary.
2: (Bad). The summary is grounded, but does not follow the instructions.
1: (Very bad). The summary is not grounded.

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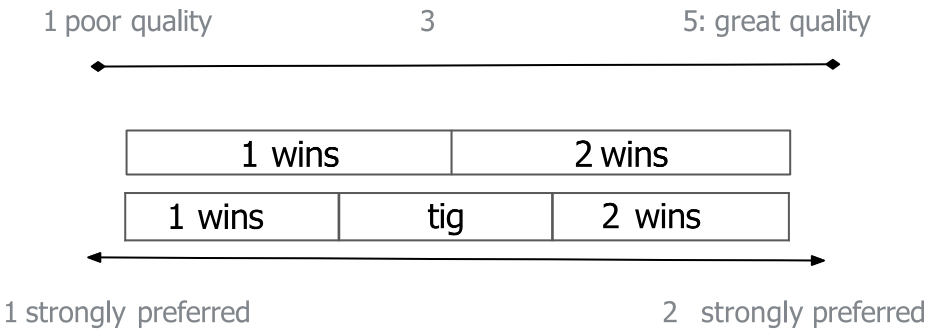
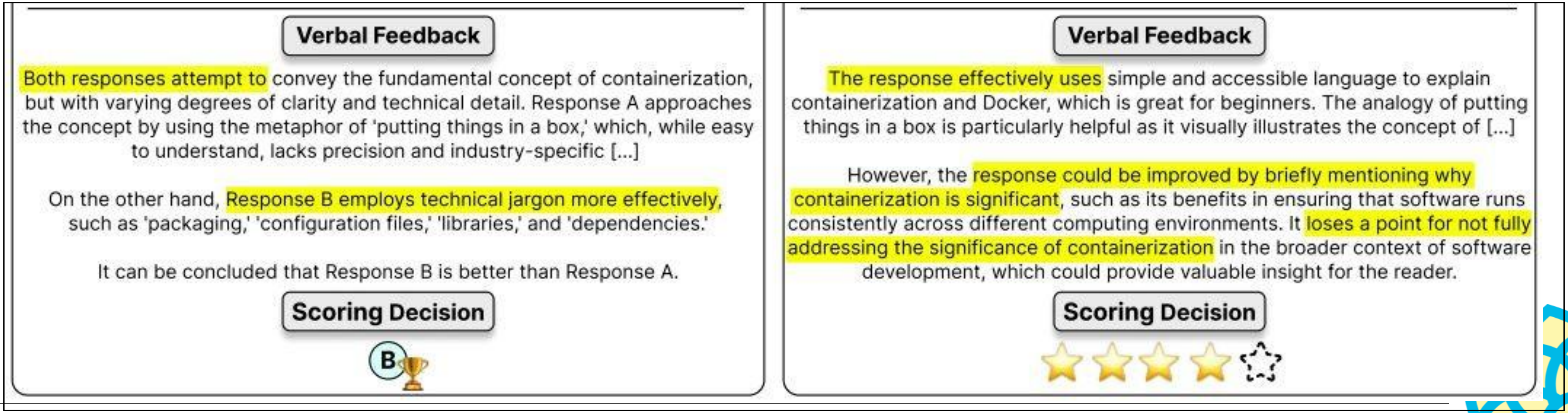
F (subject, criteria) → result

Evaluation – Result

- **Rating**: qualitative measure
  - Point-wise: Absolute measure
  - Pair-wise: Relative preference
- **Rationale**: verbal feedback
  - Explanation to user
  - Captures reasoning thoughts and improves rating quality





Verbal Feedback

Both responses attempt to convey the fundamental concept of containerization, but with varying degrees of clarity and technical detail. Response A approaches the concept by using the metaphor of 'putting things in a box,' which, while easy to understand, lacks precision and industry-specific [...]

On the other hand, Response B employs technical jargon more effectively, such as 'packaging,' 'configuration files,' 'libraries,' and 'dependencies.'

It can be concluded that Response B is better than Response A.

Scoring Decision

Verbal Feedback

The response effectively uses simple and accessible language to explain containerization and Docker, which is great for beginners. The analogy of putting things in a box is particularly helpful as it visually illustrates the concept of [...]

However, the response could be improved by briefly mentioning why containerization is significant, such as its benefits in ensuring that software runs consistently across different computing environments. It loses a point for not fully addressing the significance of containerization in the broader context of software development, which could provide valuable insight for the reader.

Scoring Decision

★★★★☆

Source: Prometheus (Kim 2024)

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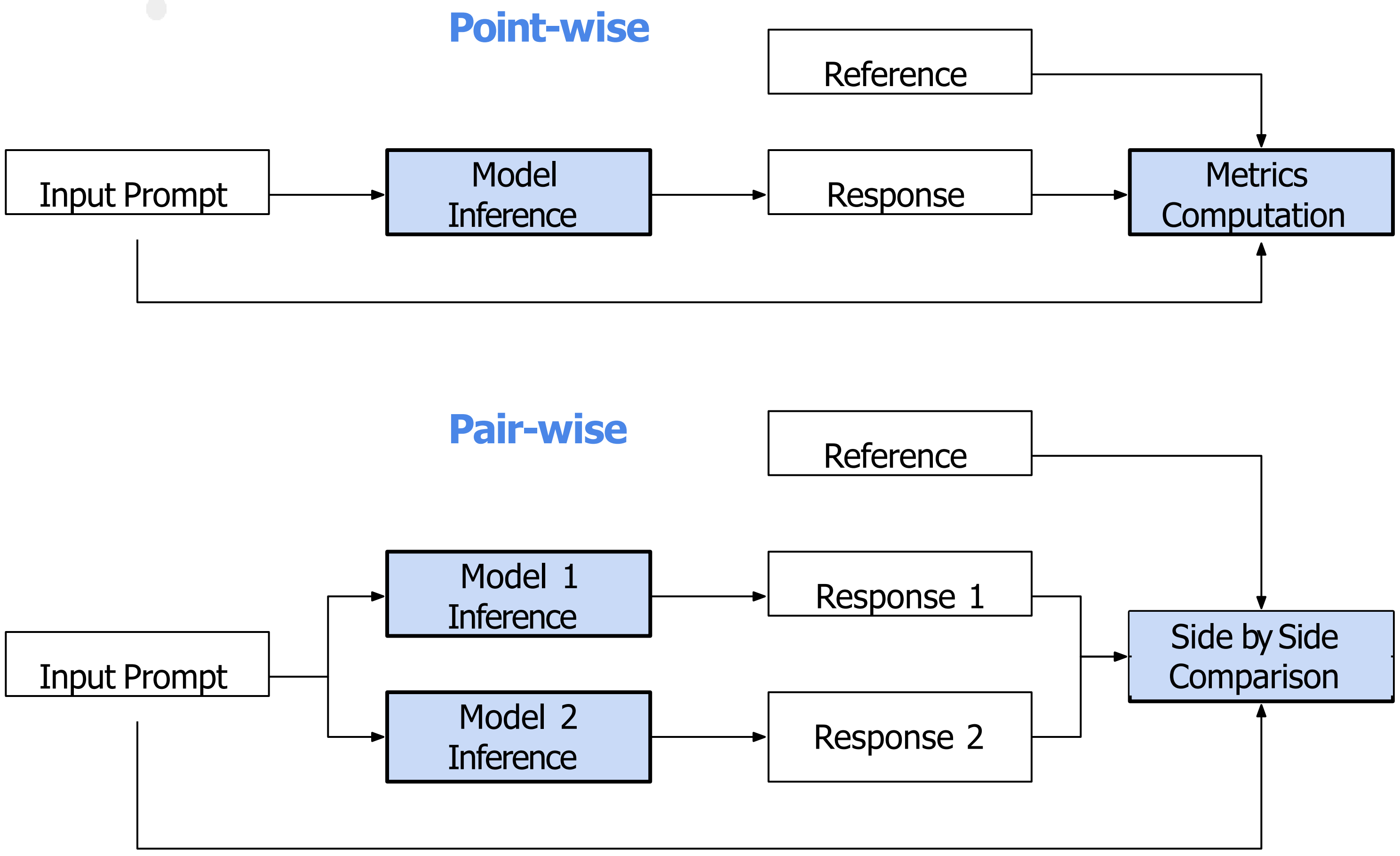
Evaluation – Reference

F (subject, criteria, reference) → result*

- Can be optional
- Evaluation Perspective: Similarity to Reference

- Discriminative task:
    - Ground truth
- Generative task:
    - Representative sample



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F (subject, criteria, reference) ⟶ result*

Evaluation – Method

- Computation
- Human
- LLM (LLM as Judge, as critic, **Autorater**)

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Method – Computation (1)

F (subject, criteria, reference) → result*

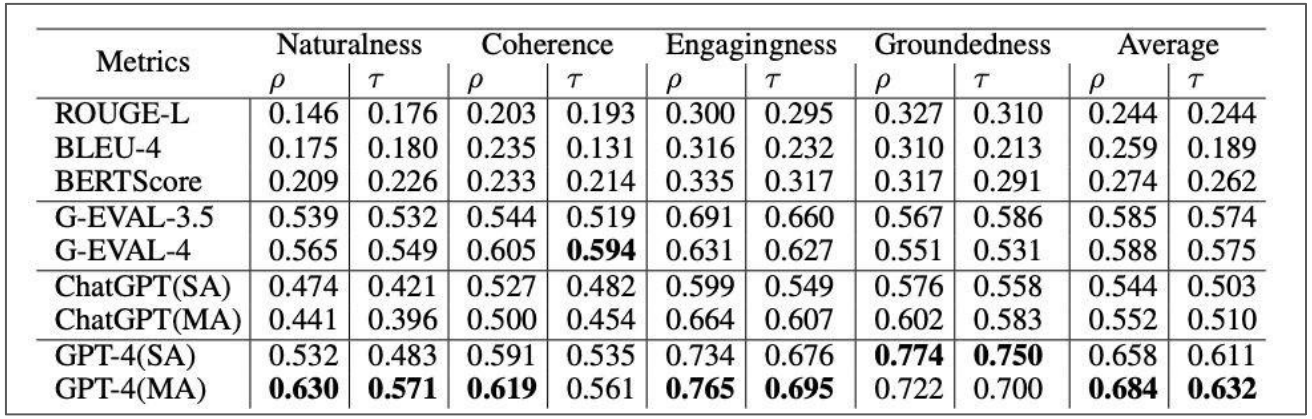
Quantifiy the similarity between response and refierence

- Reference Required
- Support point-wise eval
- Only provide score as result
- Does not support fine-grained criteria specification

*F ((prompt, **response**), **reference**) → score*

Approaches

- Lexicon similarity: E.g., ROUGE, BLEU
- Embedding similarity: E.g. BERTScorg, BARTscorg



Metrics	Naturalness		Coherence		Engagingness		Groundedness		Average	
	ρ	τ	ρ	τ	ρ	τ	ρ	τ	ρ	τ
ROUGE-L	0.146	0.176	0.203	0.193	0.300	0.295	0.327	0.310	0.244	0.244
BLEU-4	0.175	0.180	0.235	0.131	0.316	0.232	0.310	0.213	0.259	0.189
BERTScore	0.209	0.226	0.233	0.214	0.335	0.317	0.317	0.291	0.274	0.262
G-EVAL-3.5	0.539	0.532	0.544	0.519	0.691	0.660	0.567	0.586	0.585	0.574
G-EVAL-4	0.565	0.549	0.605	**0.594**	0.631	0.627	0.551	0.531	0.588	0.575
ChatGPT(SA)	0.474	0.421	0.527	0.482	0.599	0.549	0.576	0.558	0.544	0.503
ChatGPT(MA)	0.441	0.396	0.500	0.454	0.664	0.607	0.602	0.583	0.552	0.510
GPT-4(SA)	0.532	0.483	0.591	0.535	0.734	0.676	**0.774**	**0.750**	0.658	0.611
GPT-4(MA)	**0.630**	**0.571**	**0.619**	0.561	**0.765**	**0.695**	0.722	0.700	**0.684**	**0.632**

On SummEval Spearman (ρ) and Kendall-Tau (τ)

Source: G-Eval (Liu 2023)

Limitation

- Sensitive to the choice of reference.
- Lexicon similarity only measures syntactical matches rather than semantics
- Weak correlation with human judgment in complex, open-ended tasks.

Usage

- Scalable evaluation in simple settings
- Break down big eval tasks into smaller pieces (e.g. in Function Calline evaluation, parameter value comparison)
- Low-cost sanity check and monitoring of tuning progress
- Complement other approaches (human, autorater) to provide an objective assessment

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F((prompt, response), reference) -> score

Method – Computation (2)

Example: **ROUGE** (Recall-Oriented Understudy for Gisting Evaluation)

- The score ranges from 0 (poor similarity) to 1 (strong similarity)
- A set of metrics:
  - ROUGE-n examines word groups (n-grams).

$$RECALL = \frac{Overlapping\ number\ of\ n-grams}{Number\ of\ n-grams\ in\ the\ reference}$$

$$PRECISION = \frac{Overlapping\ number\ of\ n-grams}{Number\ of\ n-grams\ in\ the\ candidate}$$

  - ROUGE-L is based on the longest common subsequence (LCS) appear in the same order.
  - ROUGE-Lsum: based on ROUGE-L at the sentence level; aggregates all the results for the final score; suitable for tasks where sentence level extraction is valuable such as extractive summarization tasks.
- Best Practice: Preprocessing to remove any noise or irrelevant information (e.g., punctuation, stop words) that might interfere with the evaluation process.

```
from rouge_score import rouge_scorer
scorer = rouge_scorer.RougeScorer(['rouge1', 'rouge2', 'rougeL', 'rougeLsum'])

scores = scorer.score('The quick brown fox jumps over the lazy dog',  'The quick brown dog jumps on the log.')
print(scores)

{
'rouge1': Score(precision=0.75, recall=0.67, fmeasure=0.71),
'rouge2': Score(precision=0.29, recall=0.25, fmeasure=0.27),
'rougeL': Score(precision=0.625, recall=0.56, fmeasure=0.59),
'rougeLsum': Score(precision=0.625, recall=0.56, fmeasure=0.59)
}
```

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F (subject, criteria, reference) -> result*

Method – Human

*F ((prompt, **response**), criteria) -> score, rational*
*F ((prompt, **response1, response2**), criteria) -> preference, rational*

Goal: Ensure quality and control cost

Phased Approach:

- Start with Samples: train human evaluators and calibrate their judgments using a clear rubric.
- Proceed to Full Scale: expand evaluation to a larger set; allows for iterative refinement of the evaluation process

Limitations:

- Expensive and time-Consuming
- Human Expertise Matters: The quality of human evaluation depends on the expertise and consistency of the evaluators.
    - Crowdsourcing.
    - Annotator Services: Engage professional annotation services for higher precision.
    - Domain Expertise: For specialized tasks, prioritize evaluators with relevant domain knowledge to ensure meaningful
    - assessments.

Usage:

- Production Release: directly inform decision-making for product readiness, ensuring that quality standards meet production requirements.
- Calibrate and optimize Autorater: Use a small number of human labelled data to assess the quality of autorater, iterate its
- quality as needed, and use autorater for scalable evaluation.

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Method – AutoRater

F (subject, criteria, reference) -> result*

*F ((prompt, **response**), criteria, reference*) -> score, rational*
*F ((prompt, **response1, response2**), criteria, reference*) -> preference, rational*

→ ***Same scope as human evaluation***

- How to use
- How to design
- How to evaluate (meta-evaluation)
- How to align with your needs
- Limitations and mititgations

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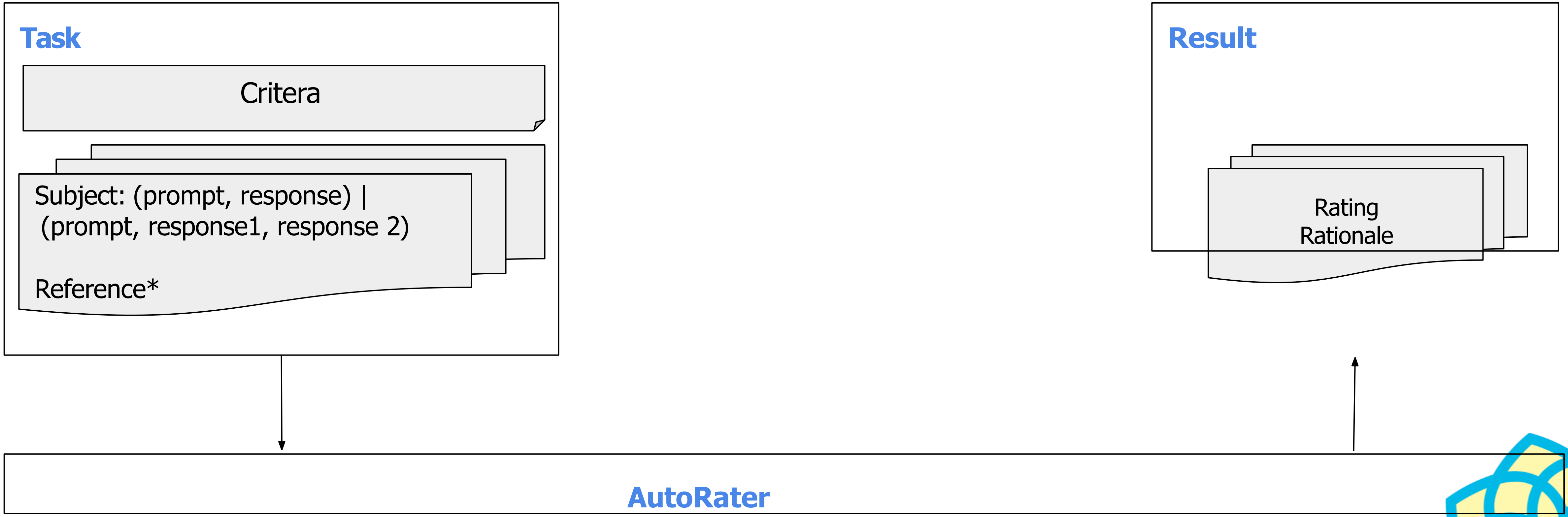
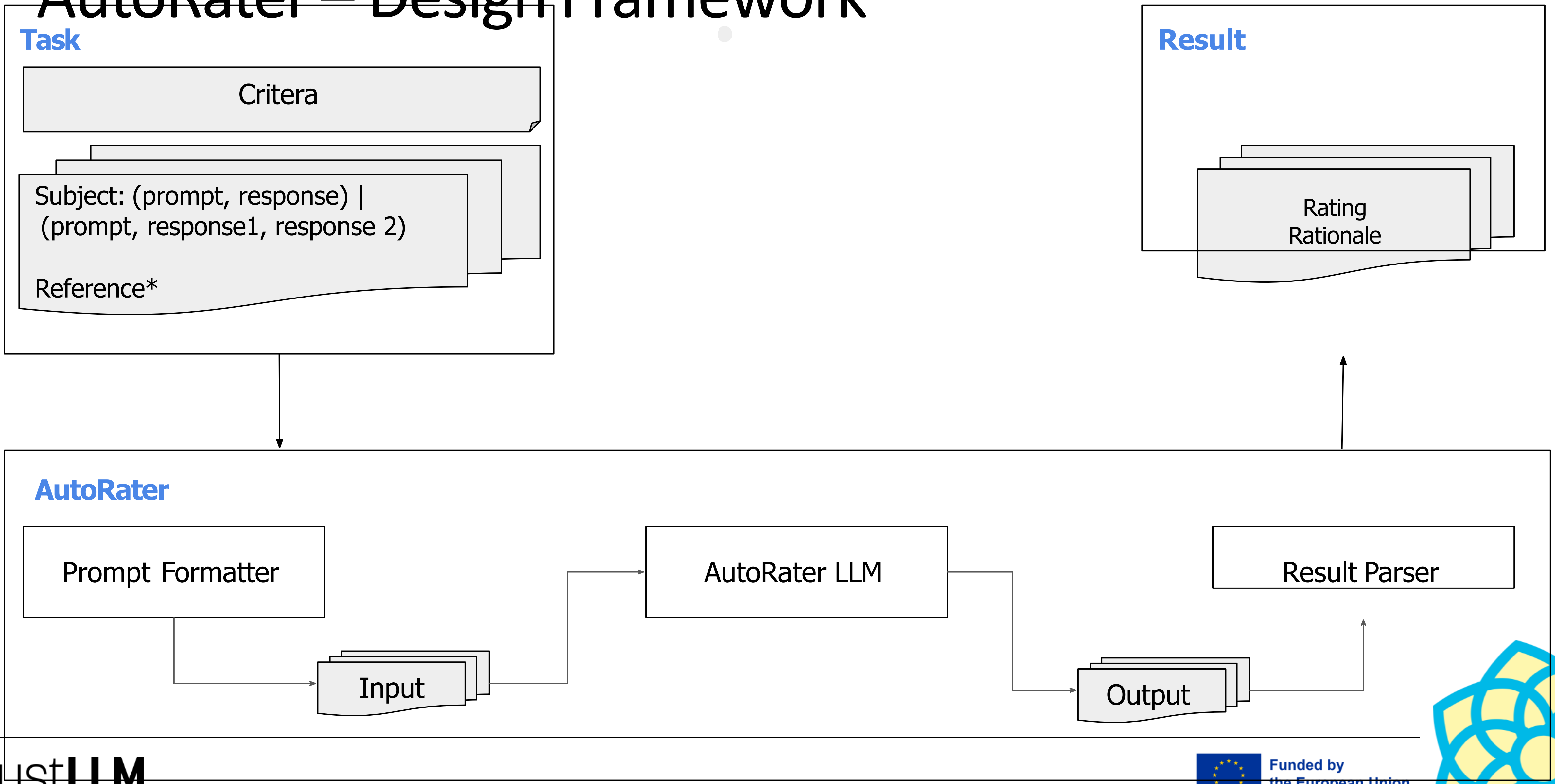
AutoRater – How to Use

F ((prompt, ***response****), criteria, reference*) -> score, rational*
F ((prompt, ***response1, response2****), criteria, reference*) -> preference, rational*



Task
Critera
Subject: (prompt, response) |
(prompt, response1, response 2)
Reference*
Result
Rating
Rationale
AutoRater

AutoRater – Design Framework



Task

Critera

Subject: (prompt, response) |
(prompt, response1, response 2)

Reference*

Result

Rating
Rationale

AutoRater

Prompt Formatter

Input

AutoRater LLM

Output

Result Parser

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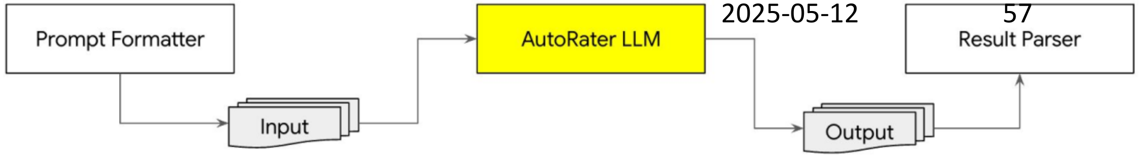
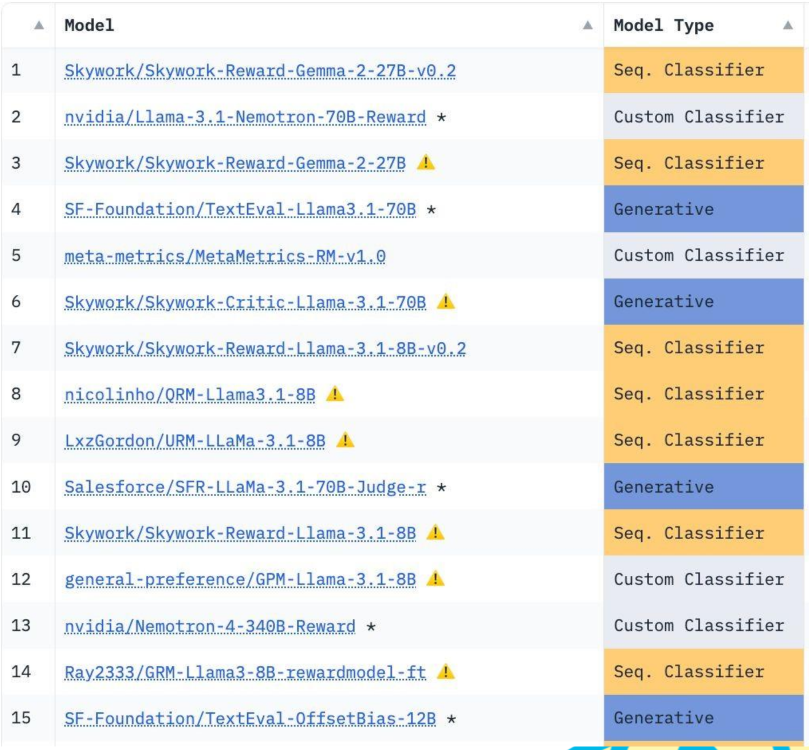
AutoRater – Types of Model



- **Generative Models**
  - Leverage language generation capabilities to deliver both score and detailed rationales (e.g., CoT explanations).
  - General (foundation model) vs fine-tuned specialized autorater model
  - Flexibility in output formatting: Support both pointwise scoring and pairwise comparisons
  - Need a result parser to get the score from the text output, sometimes this may fail due to malformatting.
  - Can directly prompt foundation model without fine-tuning or be fine-tuned for improved accuracy
- **Discriminative Models** (Reward Models).
  - Trained to predict scalar scores
  - Optimized to deliver precise and consistent evaluations based on specified criteria
  - Support both pointwise scoring and pairwise comparisons
  - No support for rationale and nuanced reasoning
- Implicit Reward Models via DPO, Although less common, generally underperform compared to discriminative and generative models and are not the primary focus here.



	Model	Model Type
1	Skywork/Skywork-Reward-Gemma-2-27B-v0.2	Seq. Classifier
2	nvidia/Llama-3.1-Nemotron-70B-Reward *	Custom Classifier
3	Skywork/Skywork-Reward-Gemma-2-27B ⚠	Seq. Classifier
4	SF-Foundation/TextEval-Llama3.1-70B *	Generative
5	meta-metrics/MetaMetrics-RM-v1.0	Custom Classifier
6	Skywork/Skywork-Critic-Llama-3.1-70B ⚠	Generative
7	Skywork/Skywork-Reward-Llama-3.1-8B-v0.2	Seq. Classifier
8	nicolinho/QRM-Llama3.1-8B ⚠	Seq. Classifier
9	LxzGordon/URM-LLaMa-3.1-8B ⚠	Seq. Classifier
10	Salesforce/SFR-LLaMa-3.1-70B-Judge-r *	Generative
11	Skywork/Skywork-Reward-Llama-3.1-8B ⚠	Seq. Classifier
12	general-preference/GPM-Llama-3.1-8B ⚠	Custom Classifier
13	nvidia/Nemotron-4-340B-Reward *	Custom Classifier
14	Ray2333/GRM-Llama3-8B-rewardmodel-ft ⚠	Seq. Classifier
15	SF-Foundation/TextEval-OffsetBias-12B *	Generative

Source: RewardBench

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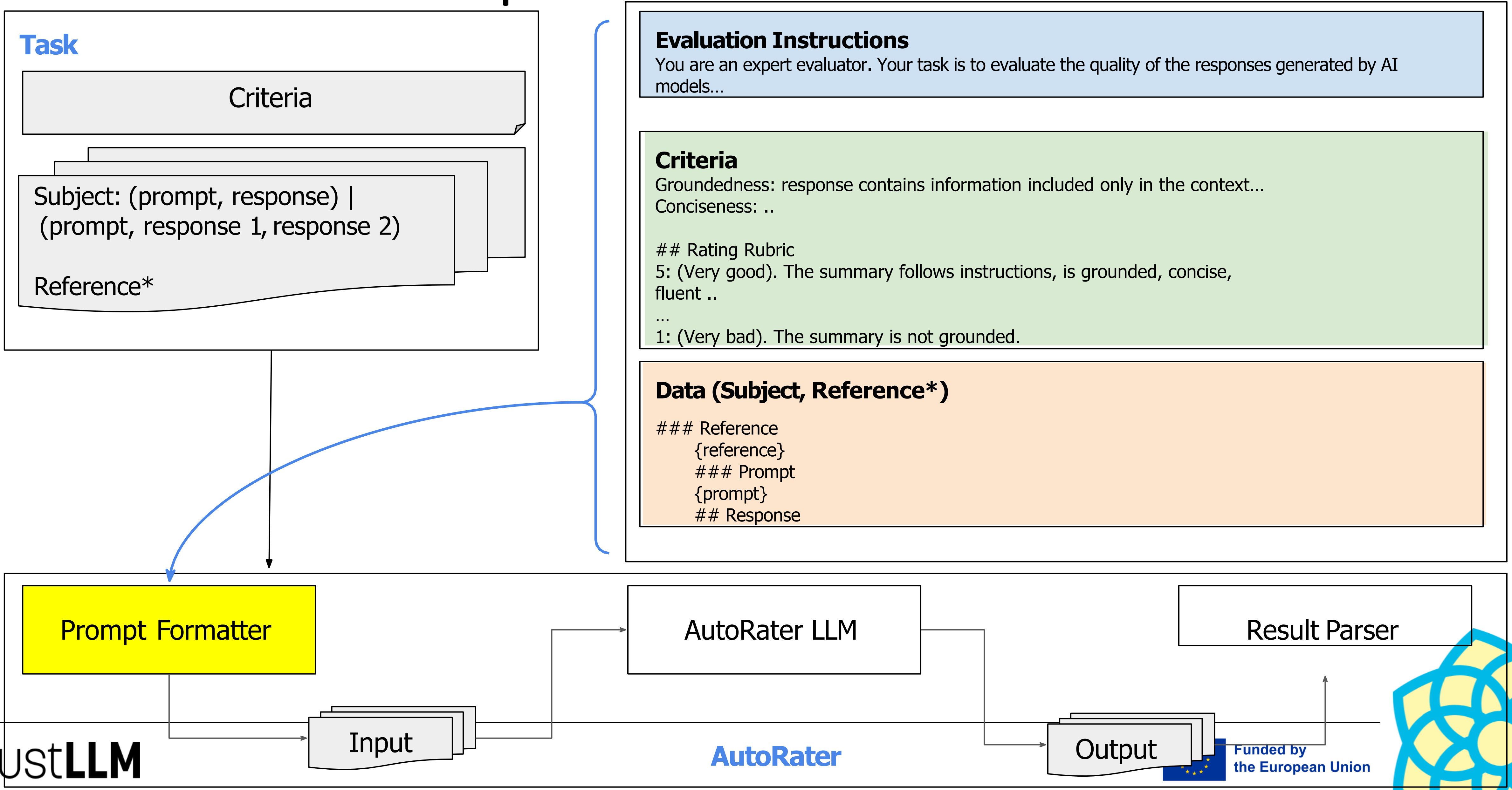
AutoRater – Prompt Formatter



Evaluation Instructions
You are an expert evaluator. Your task is to evaluate the quality of the responses generated by AI models…

Criteria
Groundedness: response contains information included only in the context…
Conciseness: ..

Rating Rubric
5: (Very good). The summary follows instructions, is grounded, concise, fluent ..
…
1: (Very bad). The summary is not grounded.

Data (Subject, Reference*)

```
### Reference
    {reference}
    ### Prompt
    {prompt}
    ## Response
```

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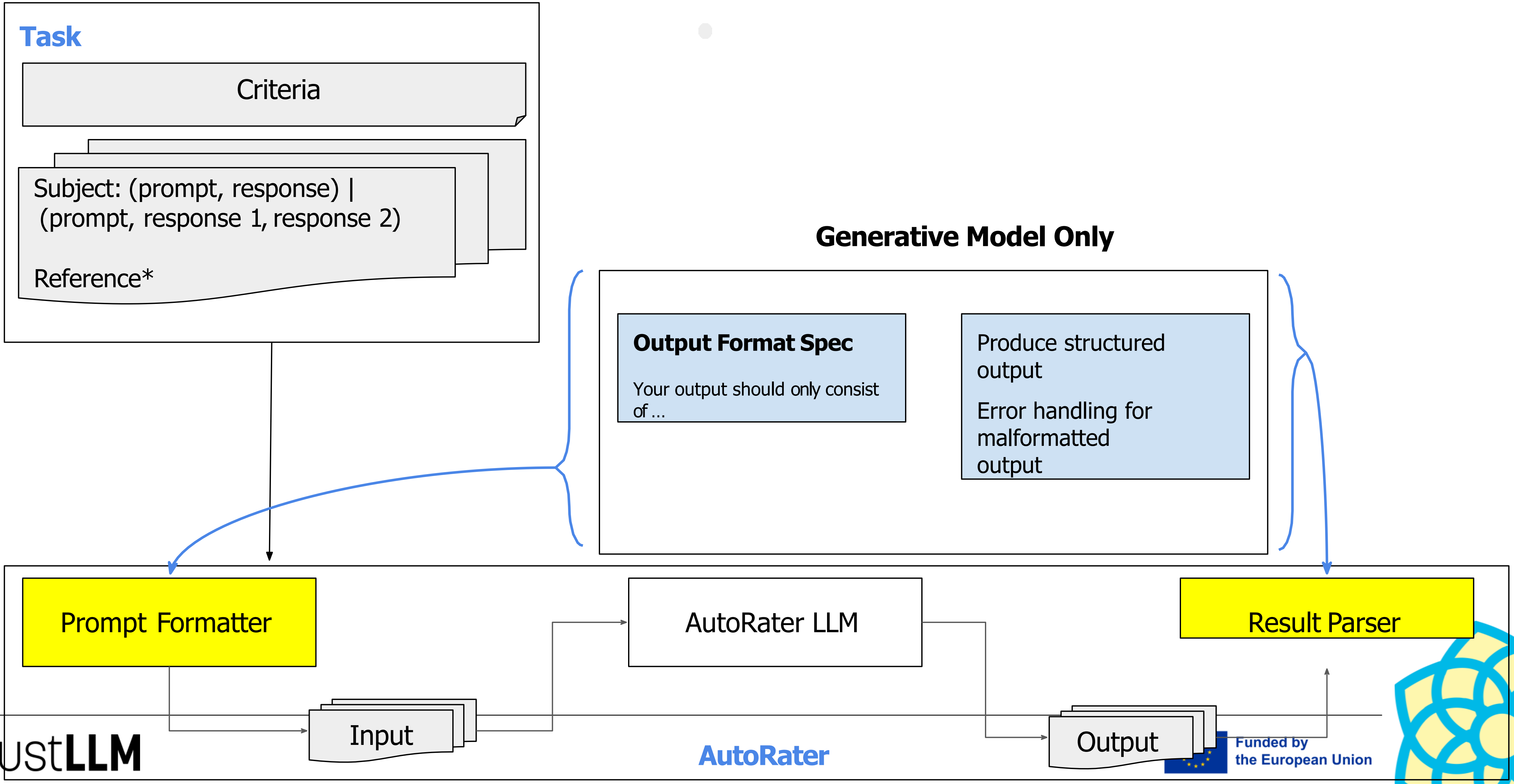
AutoRater – Prompt Formatter



Task

Criteria

Subject: (prompt, response) | (prompt, response 1, response 2)

Reference*

Generative Model Only

Output Format Spec

Your output should only consist of …

Produce structured output

Error handling for malformatted output

Prompt Formatter

AutoRater LLM

Result Parser

Input

Output

AutoRater

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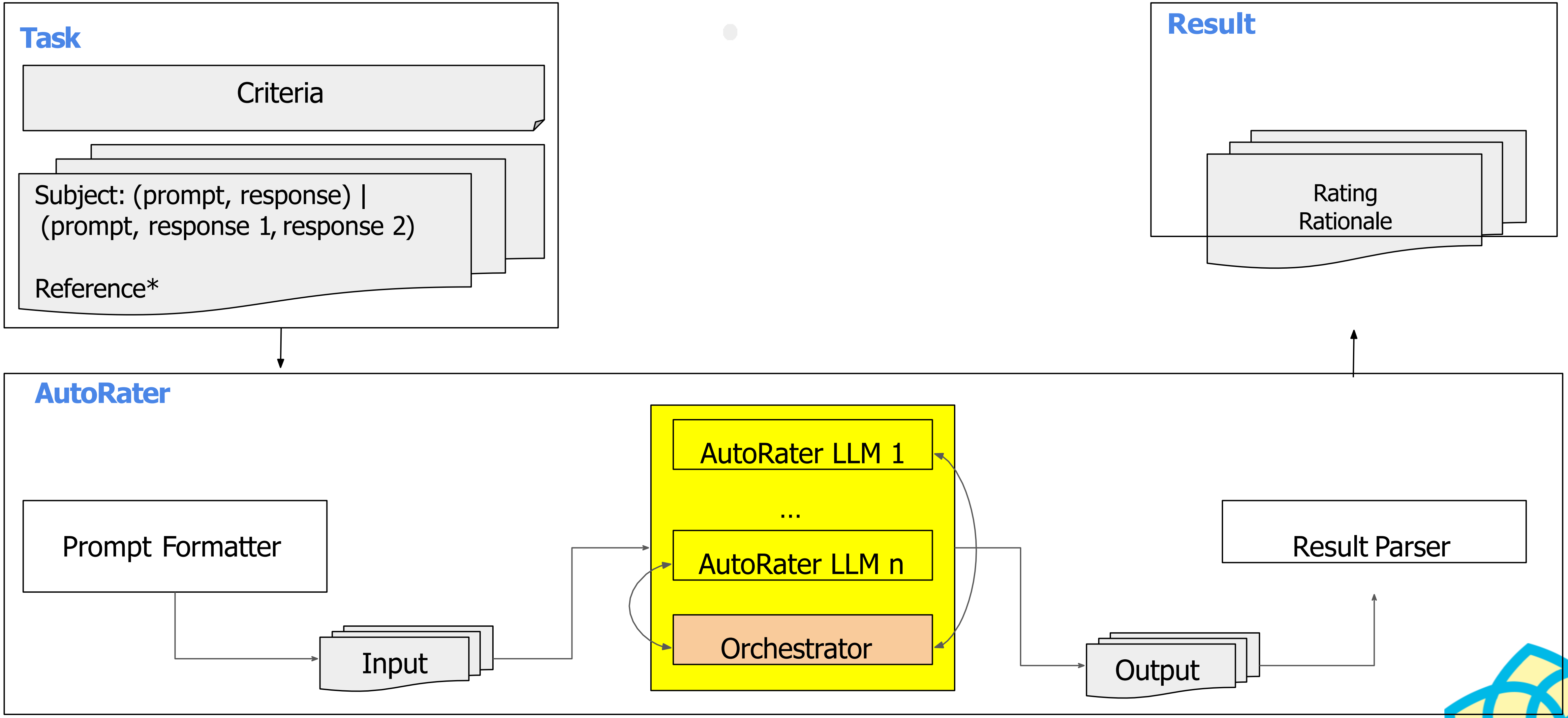
AutoRater – Multiple Rater Orchestration



Reference: Juries (Verga 2024), ChatEval (Chan 2023), Agent-as-Judge (Zhugg 2024), MATEval (Li 2024),

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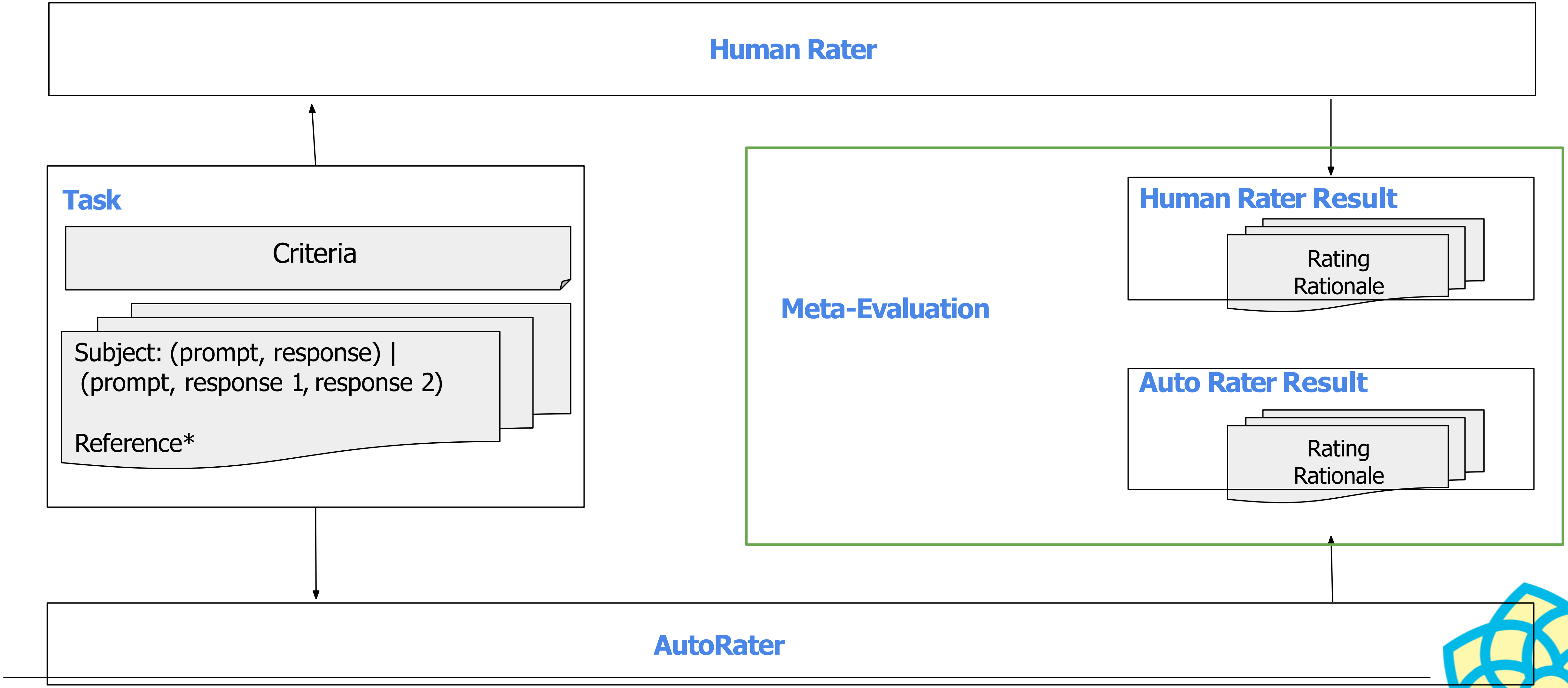
Meta Evaluation - Overview



Human Rater

Task

Criteria

Subject: (prompt, response) |
(prompt, response 1, response 2)

Reference*

Meta-Evaluation

Human Rater Result

Rating
Rationale

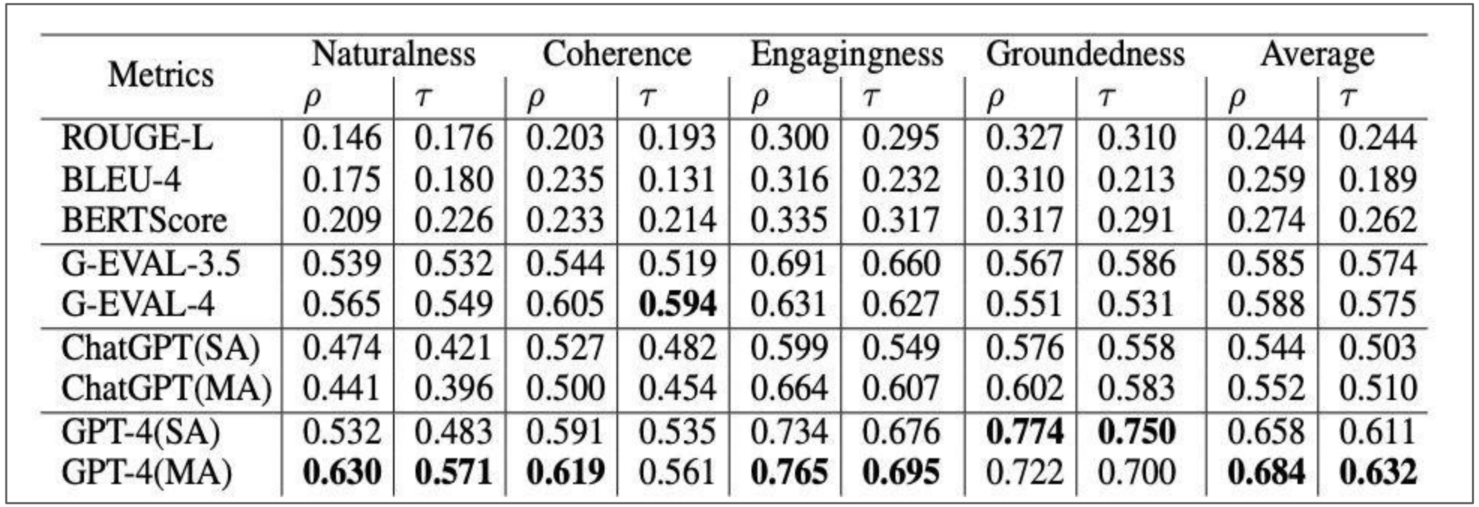
Auto Rater Result

Rating
Rationale

AutoRater

Meta Evaluation - Metrics

- **Correlations** (Point-wise score)
  - **Spearman correlation:** Good for monotonic relationships, less sensitive to outliers.
  - **Kendall's Tau:** Suitable for ranked data and assessing concordance/discordance, handles ties well.
  - **Pearson correlation**: Best for linear relationships with normally distributed data.
- **Agreement** (Pair-wise preference)
  - **Cohen's Kappa**: Measures the agreement between two raters on categorical data, accounting for chance agreement [weight=quadric]
  - Opinions vary on how scores should be interpreted, but in general $\kappa > 0.8$ is considered a strong correlation and $\kappa > 0.6$ is a moderate correlation.
  - Confusion matrix and accuracy



Metrics	Naturalness		Coherence		Engagingness		Groundedness		Average	
	ρ	τ	ρ	τ	ρ	τ	ρ	τ	ρ	τ
ROUGE-L	0.146	0.176	0.203	0.193	0.300	0.295	0.327	0.310	0.244	0.244
BLEU-4	0.175	0.180	0.235	0.131	0.316	0.232	0.310	0.213	0.259	0.189
BERTScore	0.209	0.226	0.233	0.214	0.335	0.317	0.317	0.291	0.274	0.262
G-EVAL-3.5	0.539	0.532	0.544	0.519	0.691	0.660	0.567	0.586	0.585	0.574
G-EVAL-4	0.565	0.549	0.605	**0.594**	0.631	0.627	0.551	0.531	0.588	0.575
ChatGPT(SA)	0.474	0.421	0.527	0.482	0.599	0.549	0.576	0.558	0.544	0.503
ChatGPT(MA)	0.441	0.396	0.500	0.454	0.664	0.607	0.602	0.583	0.552	0.510
GPT-4(SA)	0.532	0.483	0.591	0.535	0.734	0.676	**0.774**	**0.750**	0.658	0.611
GPT-4(MA)	**0.630**	**0.571**	**0.619**	0.561	**0.765**	**0.695**	0.722	0.700	**0.684**	**0.632**

Spearman (ρ) and Kendall-Tau (τ)

Source: G-Eval (Liu 2023)

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Meta-Evaluation – Datasets and Benchmarks

Datasets

- MTBench and Chatbot Arena [pair-wise] Multi-turn conversations, crowdsource preference annotations.
- HelpSteer and HglpSteer2 [pair-wise] helpful, factually correct and coherent, leveraging human annotators.
- LLMBar [pair-wise] manually curated challenging meta-evaluation to assess instruction-following.
- AlpacaEval and AlpacaFarm [pair-wise], chat, low-cost simulation of pairwise feedback from API models.
- Anthropic Helpful and Anthropic HHH [pair-wise]: human alignment capability on helpful, honest, harmless.
- summarize_from_feedback [pair-wise], summary comparison.
- HumanEvalPack [point-wise] coding abilities.
- FLASK [point-wise]: fine-grained scoring with 4 primary abilities divided into 12 fine-grained skills.

Benchmarks

- RewardBench: [5 category with 27 datasets], comprehensive benchmark that covers chat, reasoning, and safety.
- LLM-AggreFact; [11 datasets] fact verification benchmark covering: fact verification, faithfulness of summary, etc.
- JudgeBench: benchmark on challenging response pairs spanning knowledge, reasoning, math, and coding.
- WildBench: WB-Reward and WB-Score with fine-grained outcomes. e.g. for pairwise comparison: much better, slightly better, slightly worse, much worse, or a tie.
- EvalBiasBench: bias benchmark
- CoBBLEr : bias benchmark

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Meta-Evaluation – From Benchmark to Your Task

- **Prompt curation**:
  - **Align** closely with your production usage **distribution**
  - For benchmarks as HelpSteer, crowdsourcing helps cover the diverse range of LLM use cases.
  - Prompts from benchmark datasets may not align with production usage pattern. You need to build your own prompt sets (e.g., initially manually and/or sampling from production traffic).
- **Candidate Responses**:
  - Ensure candidate responses **covers** the specific model candidates you plan to deploy.
  - For benchmarks such as MT-Bench/Chatbot Arena, a wide range of models are selected to produce responses with the goal of comparing all models, which may not be necessary for you.
- **Annotation**:
  - **Quality** is critical
  - Human annotation (pay attention to inter-rater agreement)
  - Use powerful models cautiously (to avoid self-promotion bias).

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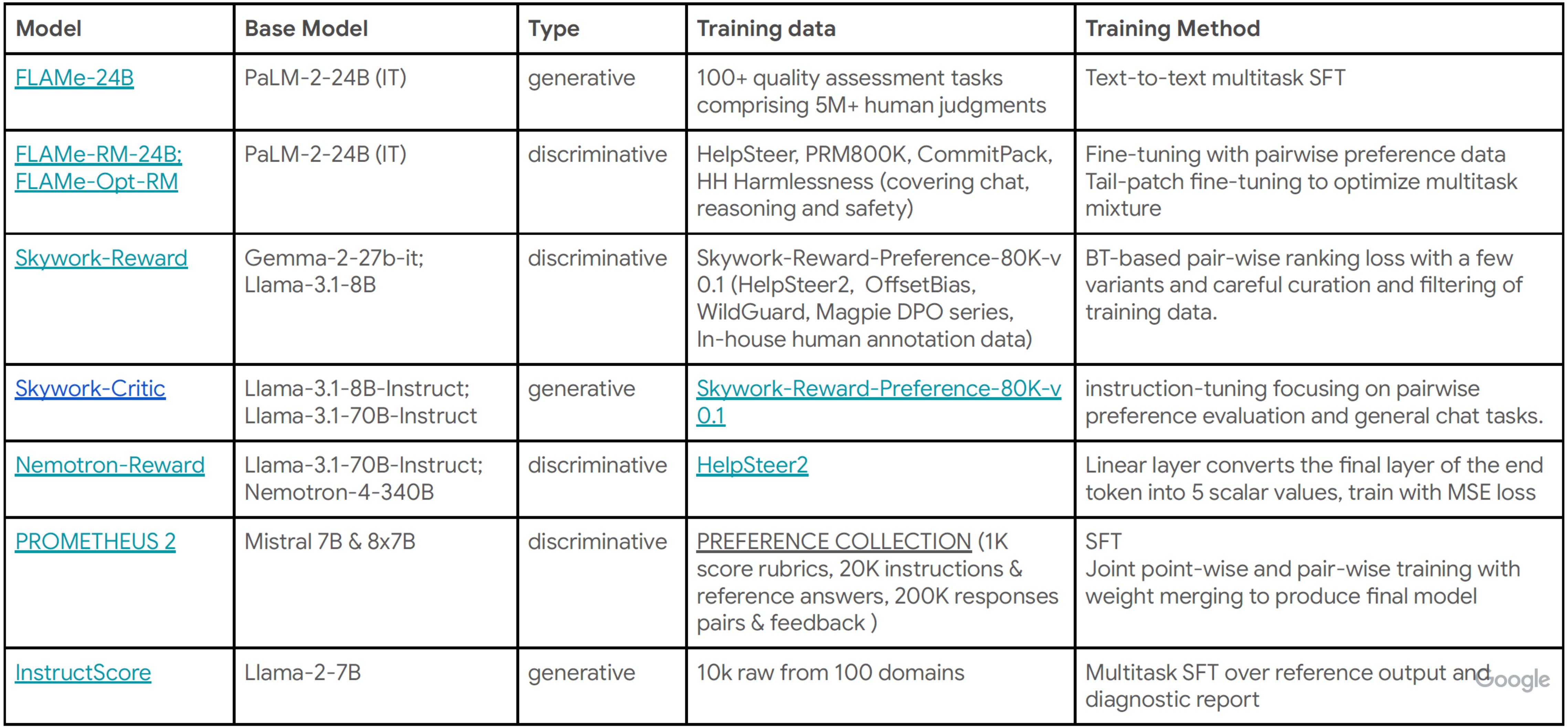
AutoRater – Model Fine-tuning

Representative Models



Model	Base Model	Type	Training data	Training Method
FLAMe-24B	PaLM-2-24B (IT)	generative	100+ quality assessment tasks comprising 5M+ human judgments	Text-to-text multitask SFT
FLAMe-RM-24B; FLAMe-Opt-RM	PaLM-2-24B (IT)	discriminative	HelpSteer, PRM800K, CommitPack, HH Harmlessness (covering chat, reasoning and safety)	Fine-tuning with pairwise preference data Tail-patch fine-tuning to optimize multitask mixture
Skywork-Reward	Gemma-2-27b-it; Llama-3.1-8B	discriminative	Skywork-Reward-Preference-80K-v 0.1 (HelpSteer2, OffsetBias, WildGuard, Magpie DPO series, In-house human annotation data)	BT-based pair-wise ranking loss with a few variants and careful curation and filtering of training data.
Skywork-Critic	Llama-3.1-8B-Instruct; Llama-3.1-70B-Instruct	generative	Skywork-Reward-Preference-80K-v 0.1	instruction-tuning focusing on pairwise preference evaluation and general chat tasks.
Nemotron-Reward	Llama-3.1-70B-Instruct; Nemotron-4-340B	discriminative	HelpSteer2	Linear layer converts the final layer of the end token into 5 scalar values, train with MSE loss
PROMETHEUS 2	Mistral 7B & 8x7B	discriminative	PREFERENCE COLLECTION (1K score rubrics, 20K instructions & reference answers, 200K responses pairs & feedback)	SFT Joint point-wise and pair-wise training with weight merging to produce final model
InstructScore	Llama-2-7B	generative	10k raw from 100 domains	Multitask SFT over reference output and diagnostic report

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AutoRater – Limitation and Mitigation

Biases

- Position bias (favor certain position)
- Verbosity/Length bias (favor longer responses)
- Self-enhancement/EGOCENTRIC bias (prefer self-generated answers)

Lack of consistency

- Prompt sensitivity
- Randomness in autorater output

Mitigation

- Prompt engineering and orchestration
  - Swapping Positions: call the AutoRater LLM twice with the order of options reversed to reduce position bias
  - Self-consistency: call the AutoRater LLM multiple times, analyze the multiple outputs generated and determine a consensus result
  - Panel of Diverse Models: use a LLM jury panel composed of disjoint model families.
  - In-context Learning: Providing a few demonstration examples of good judgments.
- Fine-tuning
  - Fine-tuning model via de-biasing dataset.

[Ref: MT-Bench (Zhgng 2023), OffsetBias (Park 2024), CoBBLEr (Koo 2024), Juries (Vgrga 2024), Length-Controlled AlpacaEval (Dubois 2024), Position Bias (Shi 2024)]

Summary

Three Approaches to LLM Evaluation

- Computation
- Human
- AutoRater

Support Your Application and Task

- **Choose**
  - Trade off between cost and quality
  - Work complementary depending on use cases
- **Customize**
  - Prompt engineering
  - Fine-tuning
- **Calibrate** (Meta Evaluation)
  - Stay truthful to your business needs
  - Fit to your domain and criteria
  - Avoid Bias

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EuroEval

(formerly ScandEval)

TrustLLM

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EuroEval is a robust multilingual benchmarking framework

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EuroEval is a robust multilingual benchmarking framework

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Language Model Benchmarking Framework

- Enables evaluation of implicit language understanding and generation capabilities of language models
- Allows evaluation of *both* encoders through finetuning, and decoders through few-shot evaluation
  - It has been shown that there is a direct correspondence between few-shot evaluation and finetuning [1]
  - This thus allows us to compare encoders with decoders directly

[1] Stureborg et al. arXiv preprint arXiv:2405.01724 (2024)

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Python package

- A large focus of the framework is ease of use
- The framework can simply be installed:

```
$ pip install euroeval[all]
```

- Models can easily be evaluated:

```
$ euroeval --model <model-id> [--language da]
```

- Supports models from:
  - Hugging Face Hub
  - Local models
  - Models from 200+ APIs, including locally hosted APIs via, e.g., Ollama

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EuroEval is a robust multilingual benchmarking framework

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EuroEval is a robust multilingual benchmarking framework

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Evaluation Robustness

- When evaluating models, there are several sources of noise:
  - The choice of training examples
    - When evaluating decoder models, these constitute few-shot examples
  - The choice of test examples
- The training and test examples are bootstrapped 10 times, yielding a more reliable estimation of the true mean
  - Asymptotically correct by the bootstrap theorem

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Natural Language Understanding Tasks in EuroEval

- sentiment classification
- named entity recognition
- linguistic acceptability
- reading comprehension

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Natural Language Generation Tasks in EuroEval

- sentiment classification
- named entity recognition
- linguistic acceptability
- reading comprehension
- world knowledge
- common-sense reasoning
- summarisation

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Evaluation of decoders on NLU tasks

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Evaluation of Decoders on Text Classification

- For each label, identify the first token of the label with the model's tokeniser
    - This could be the entire label, and often is
- If token probabilities are available:
    - Get the generation probabilities for each of these "label first tokens"
    - Return the label whose "label first token" has the highest probability
- Otherwise, generate 5 tokens and return the label whose word edit distance is closest to the generated

sentiment classification

linguistic acceptability

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Evaluation of Decoders on Reading Comprehension

- Simply have the model output at most 32 tokens
- Use the model output as-is

`reading comprehension`

Evaluation of Decoders on Named Entity Recognition

named entity recognition

- Utilise structured generation to have the model output in the following format:

```
{
    “person”: [“<text span 1>”],
    “organization”: [],
    “location”: [“<text span 2>”, ”<text span 3>”],
    “miscellaneous”: []
}
```

  - The list entries must appear in the document
  - Here the keys are in the language we’re evaluating
- We use the Outlines package (Louf & Willard, 2023) for structured generation

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Prompt Design

Prompt template for base decoder models:

```
{{ prefix prompt }}

{% for each few-shot example %}

    {{ document prefix }}: {{ few-shot example document }}
    {{ label prefix }}: {{ few-shot example label }}

{% end for %}

{{ document prefix }}: {{ new document }}
{{ label prefix }}:
```

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Prompt Design

Prompt template for instruction-tuned decoder models:

```
{% for each few-shot example %}

    USER: {{ instruction with few-shot example }}
    ASSISTANT: {{ few-shot example label }}

{% end for %}


USER: {{ instruction with new example }}
ASSISTANT:
```

Here we would use the model’s chat template in the prompt

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Leaderboards

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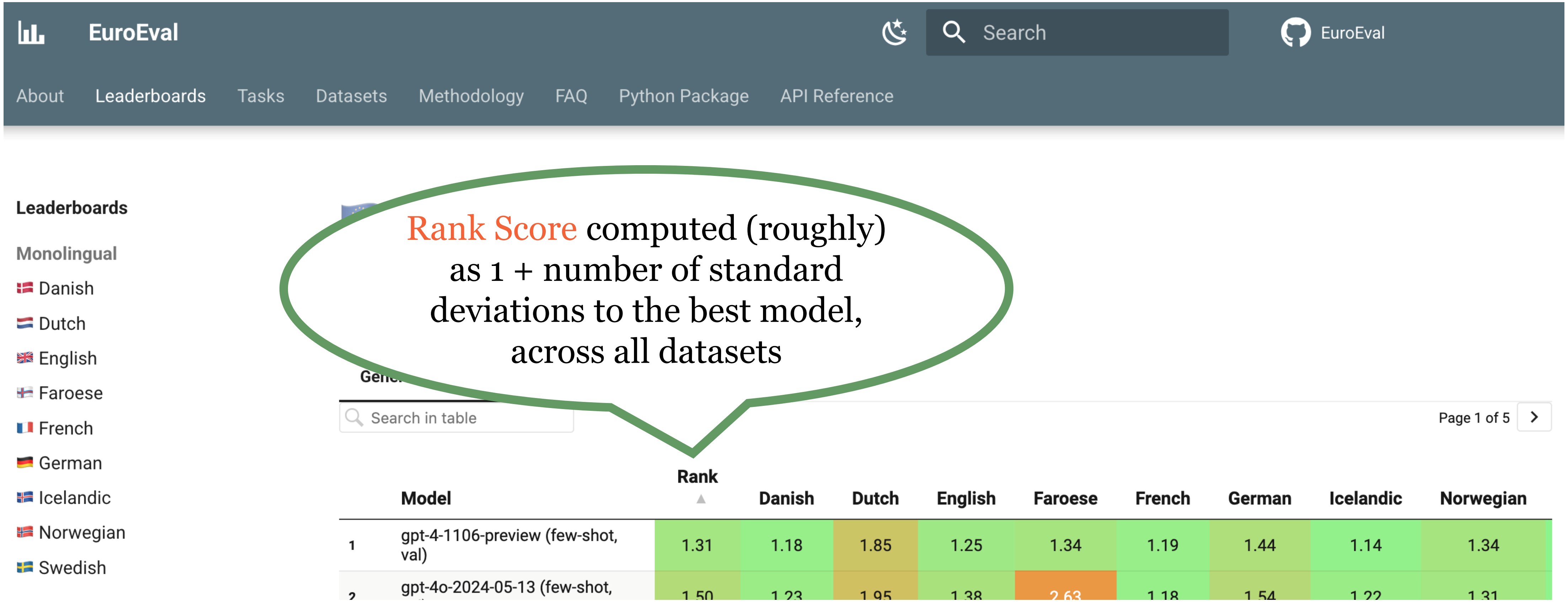
Online Leaderboards

euroeval.com



Leaderboards

Monolingual

- 🇩🇰 Danish
- 🇳🇱 Dutch
- 🇬🇧 English
- 🇫🇴 Faroese
- 🇫🇷 French
- 🇩🇪 German
- 🇮🇸 Icelandic
- 🇳🇴 Norwegian
- 🇸🇪 Swedish

Search in table

Page 1 of 5

	Model	Rank ▲	Danish	Dutch	English	Faroese	French	German	Icelandic	Norwegian
1	gpt-4-1106-preview (few-shot, val)	1.31	1.18	1.85	1.25	1.34	1.19	1.44	1.14	1.34
2	gpt-4o-2024-05-13 (few-shot,	1.50	1.23	1.95	1.38	2.63	1.18	1.54	1.22	1.31

Rank Score computed (roughly) as 1 + number of standard deviations to the best model, across all datasets

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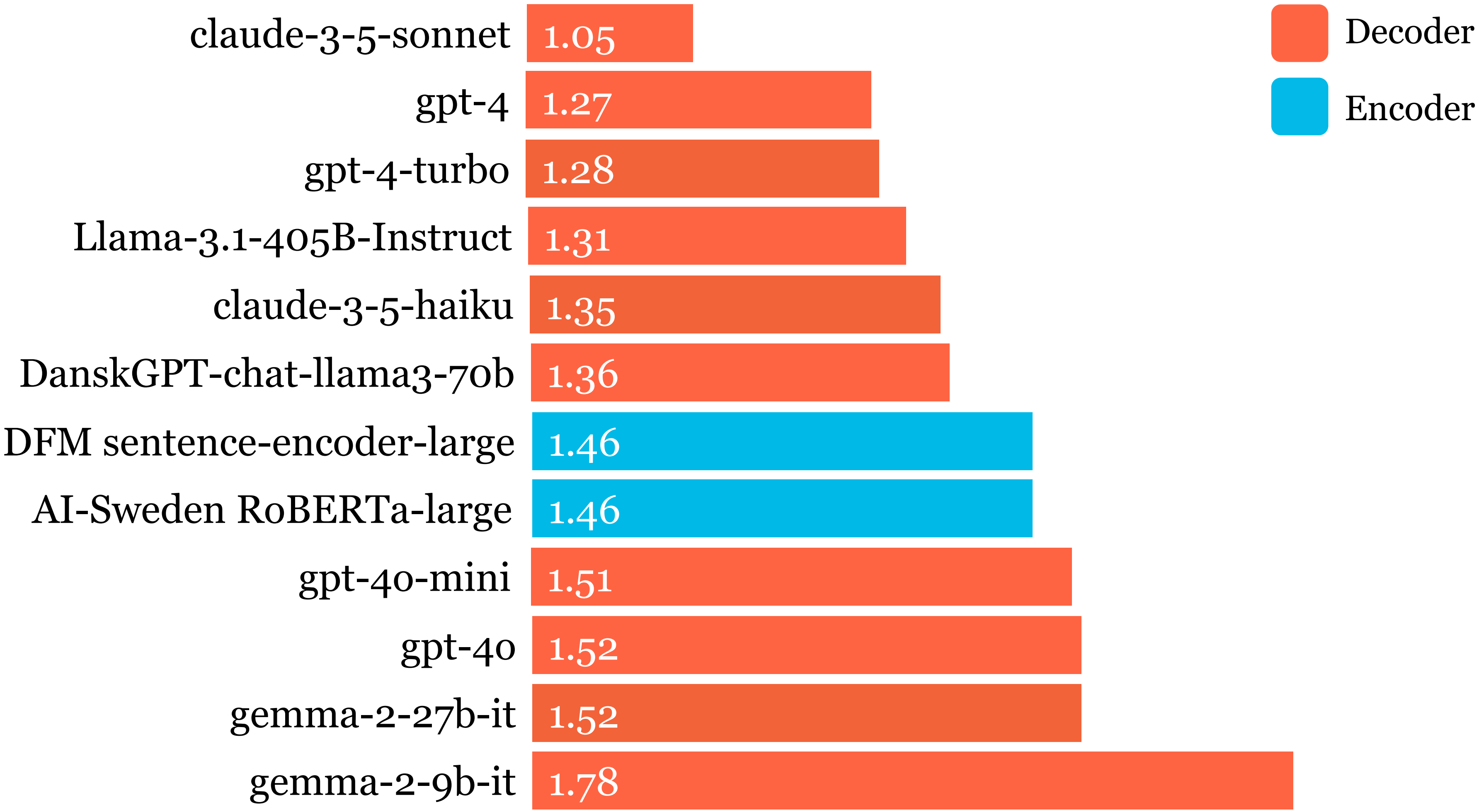
Excerpt of Danish NLU EuroEval Scores

Smaller is better



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What’s next?

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Current Ongoing Work

- Logic reasoning benchmark, based on puzzles
- Bias evaluation benchmark

Want to collaborate?

Future Work

- Hallucination benchmark
- European values benchmark
- Free-form generation benchmark
- Evaluating acoustic models

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- **LAIM LE7 VT2025:**

How to evaluate LLMs?
Evaluating low resource languages
Quality evaluation
EuroEval

www.ida.liu.se/~frehe08/llm

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