Evaluation of Language Models in the Generative Era

Sprogteknologisk Konference 2024

November 28, 2024

Dan Saattrup Nielsen

Senior AI Specialist @Alexandra Institute



ALEXANDRA INST<mark>IT</mark>UTTET



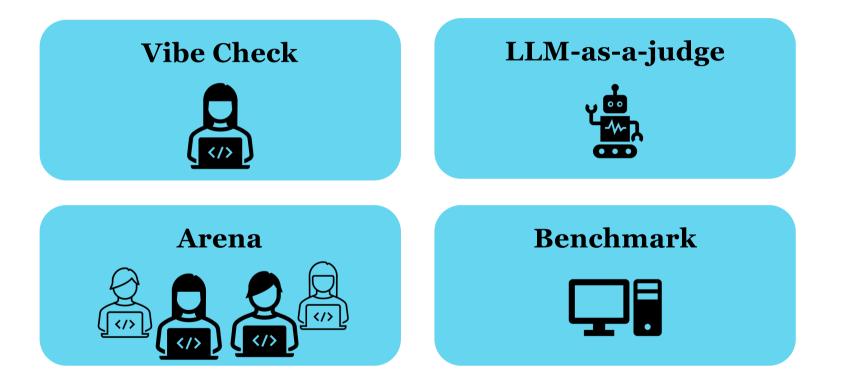


How can we evaluate LLMs?





the European Union





Funded by the European Union







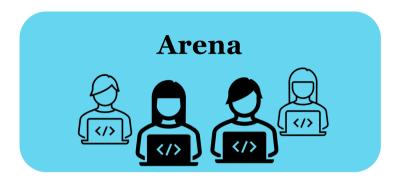
Pros	Cons
Typically gives a good ballpark figure	Can only evaluate instruction-tuned models
Relevant to use cases the user cares about	Does not generalise to other tasks
Very cheap and fast	Not objective, has to be redone for each person





4



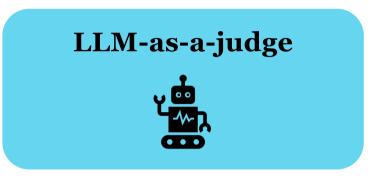


Pros	Cons
Relatively objective measure when a critical mass of volunteers have voted	Can only evaluate instruction-tuned models
More relevant to the user's use cases*	Time-consuming and costly to set up and evaluate
	Requires <i>many</i> volunteers to evaluate

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







Pros	Cons
Allows measuring more complex phenomena	Can only evaluate instruction-tuned models
Cheap to set up and evaluate	The evaluator LLM can be biased [1]
Measure that only has to be done once for each model	Requires the existence of a very good LLM in the given language

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





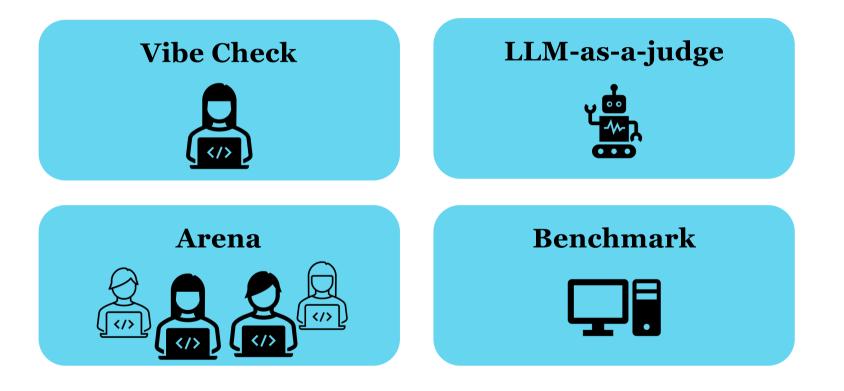




Pros	Cons
Gives a precise measure of performance	Does not necessarily generalise to other types of tasks
Objective measure that only must be done once for each model	Creating evaluation datasets is costly
Can evaluate all types of language models	Models can train on public test sets



Funded by the European Union 7





What is ScandEval?





the European Union

ScandEval is a robust multilingual benchmarking framework



Funded by the European Union

ScandEval is a robust multilingual benchmarking framework



Funded by the European Union



11

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 [2]
 - This thus allows us to compare encoders with decoders directly

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



Language Model Benchmarking Framework

- A large focus of the framework is ease of use
- The framework can simply be installed:
 - \$ pip install scandeval[all]
- Models can easily be evaluated:
 - \$ scandeval --model <model-id> [--language da]
- Supports models on the Hugging Face Hub, local models and OpenAI models



Funded by



ScandEval is a robust multilingual benchmarking framework



Funded by the European Union



14

Evaluation Robustness

- When evaluating models, there are several sources of noise in the evaluation result:
 - The choice of training examples (=few-shot examples when evaluating decoder models)
 - The choice of test examples
 - The stochastic elements (stochastic gradient descent when evaluating encoders, sampling when evaluating decoders)
- The training and test examples are bootstrapped 10 times, yielding a more reliable estimation of the true mean
 - Asymptotically correct by the bootstrap theorem
- We enforce that the stochastic elements are deterministic

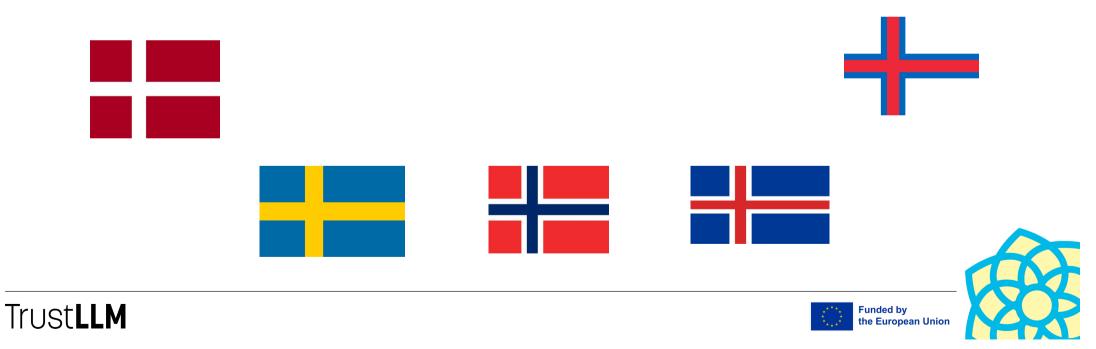


Funded by the European Unio





ScandEval is a robust multilingual benchmarking framework



Which Tasks are Included?





the European Union

Tasks in ScandEval

Natural Language Understanding (NLU) Tasks

- 1. Sentiment classification
- 2. Linguistic acceptability
- 3. Reading comprehension
- 4. Named entity recognition





Tasks in ScandEval

Natural Language Generation (NLU) Tasks

- Sentiment classification 1.
- Linguistic acceptability 2.
- Reading comprehension 3.
- Named entity recognition 4.

- 5. Summarisation
- 6. World knowledge
- Common-sense reasoning 7.



Funded by



Leaderboards





Online Leaderboards scandeval.com

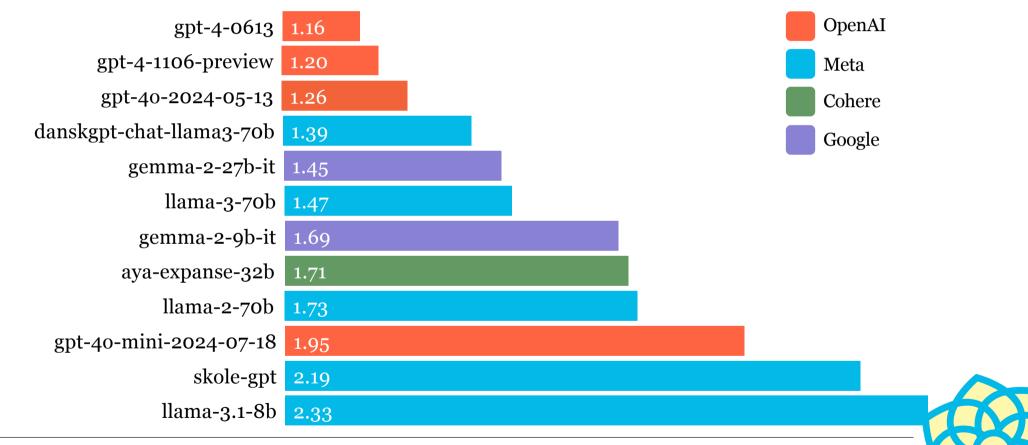
ScandEval ABOUT	DANISH V	SWEDISH V	NORWEGIAN V	ICELANDIC V	FAROESE V	GERMAN		ENGLISH V M
	NLU LEADERBOARD		•			Rank Score com as 1 + numbe	er of s	tandard
□ Include merged models	LEADERBOARD	U		h NL 23/06/2024 10:0		deviations to t across al		,
Model	l ID	Parame	eters Vocabulary	y Size Context	Commercial	Speed	Rank 🕶	DANSK
gpt-4-0613 (fe	èw-shot, val)	unkn	own 100	8192	True	597 ± 197 / 93 ± 33	1.12	64.94 ± 1.96 / 45.76 ±
gpt-4-1106-previe	gpt-4-1106-preview (few-shot, val)		own 100	127999	True	576 ± 221 / 81 ± 28	1.20	66.80 ± 3.01 / 45.69 ±
ont-40-2024-05-	gpt-4o-2024-05-13 (few-shot, val)		own 200) 127999	True	916 ± 329 / 114 ± 38	1.24	71.15 ± 2.89 / 52.24 ±

Download as CSV • Copy embed HTML



Excerpt of Danish ScandEval Scores

Smaller is better



Trust**LLM**

Based on models by:

Funded by the European Union

Encoders vs Decoders





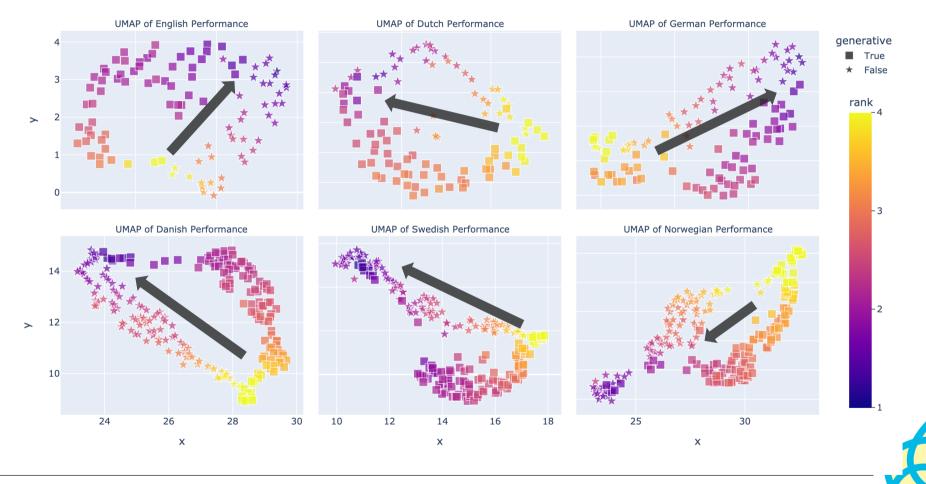
the European Union

Encoders vs Decoders

- Do encoders and decoders "learn" things differently?
- Experiment:
 - Take all raw NLU results from ScandEval leaderboards
 - 4 scores per model and language
 - Mark encoders/decoders as well as their rank
 - UMAP dimensionality reduction to 2 dimensions
 - Visualise



Encoders vs Decoders



Trust**LLM**

Funded by the European Union

Papers

ScandEval NLU benchmark for encoders:

Nielsen, Dan. *Proceedings of the 24th Nordic Conference on Computational Linguistics* (NoDaLiDa). 2023

ScandEval NLU benchmark for decoders:

Nielsen, Dan and Kenneth Enevoldsen and Peter Schneider-Kamp. arXiv preprint arXiv: 2406.13469 (2024).



Funded by



Thanks for your attention!



Trust**LLM**

Code base: github.com/ScandEval/ScandEval

