Screening and coding with LLMs

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Outlook

- Results from the implementation of Wang et al. (2024)

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- Additional results from Santiago's thesis project on coding

We can ask LLMs whether a study should be included in a systematic review

Result: <s>[INST] «SYS» You are a systematic review helper tasked with finding out whether a study is relevant to the review Drug Class Review: Pharmacologic Treatments for Attention Deficit Hyperactivity Disorder

Answer ’yes’ if the study is relevant, or ’no’ if not «/SYS»

Study: Diuretics and beta-blockers do not have adverse effects at 1 year on plasma lipid and lipoprotein profiles in men with hypertension. Department of Veterans Affairs Cooperative Study Group on Antihypertensive Agents.

Concern based on the reported short-term adverse effects of antihypertensive agents on plasma lipid and lipoprotein profiles (PLPPs) has complicated the therapy for hypertension.

Should the study be included? Answer yes or no. [/INST] No, this study should not be included in the drug class review for Pharmacologic Treatments for Attention Deficit Hyperactivity Disorder. The study is focused on the effects of diuretics and beta-blockers on plasma lipid and lipoprotein profiles in men with hypertension, and does not directly relate to the treatment of Attention Deficit Hyperactivity Disorder (ADHD). The review is focused on pharmacologic treatments for ADHD, and the study does not address any of the included drug classes or outcomes of interest for the review.

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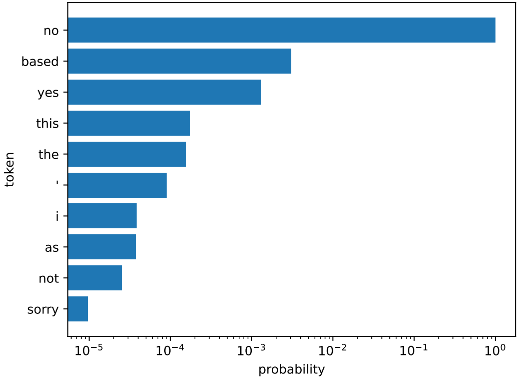
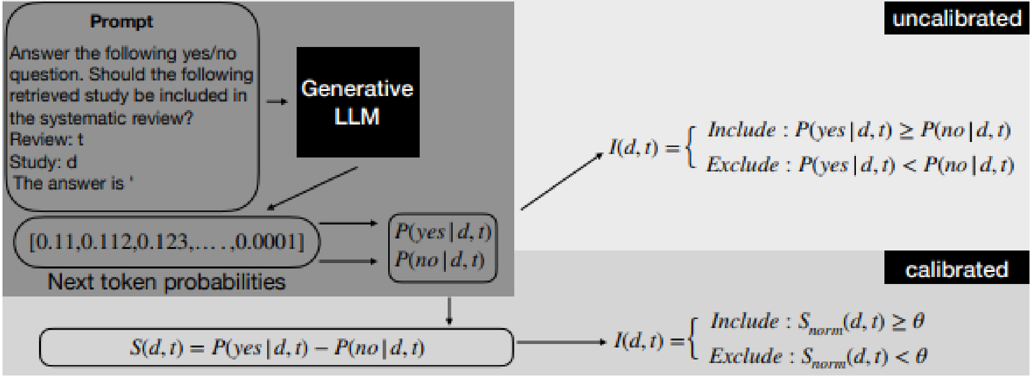
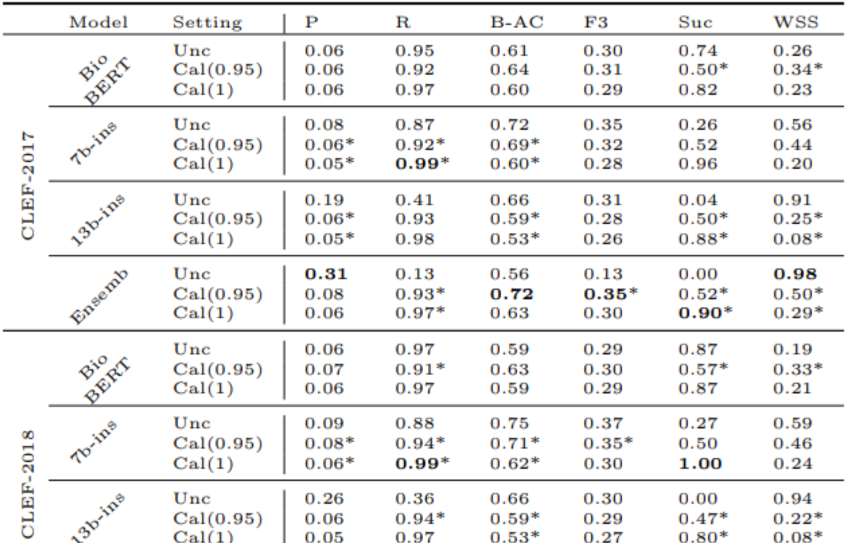


Zero-shot Generative Large Language Models for Systematic Review Screening Automation

Wang et al. (2024) propose a method to extract probability-like scores from LLMs for inclusion/exclusion decisions in a systematic review


Prompt
Answer the following yes/no question. Should the following retrieved study be included in the systematic review?
Review: t
Study: d
The answer is '
Generative LLM
[0.11,0.112,0.123,. . . . ,0.0001]
Next token probabilities
$P(yes|d,t)$
$P(no|d,t)$
uncalibrated
$I(d,t) = \begin{cases} Include : P(yes|d,t) \geq P(no|d,t) \\ Exclude : P(yes|d,t) < P(no|d,t) \end{cases}$
calibrated
$S(d,t) = P(yes|d,t) - P(no|d,t)$
$I(d,t) = \begin{cases} Include : S_{norm}(d,t) \geq \theta \\ Exclude : S_{norm}(d,t) < \theta \end{cases}$

Results are mixed, because the probabilities are poorly calibrated, and their attempts to re-invent stopping criteria do not makes sense



	Model	Setting	P	R	B-AC	F3	Suc	WSS
CLEF-2017	Bio BERT	Unc	0.06	0.95	0.61	0.30	0.74	0.26
		Cal(0.95)	0.06	0.92	0.64	0.31	0.50*	0.34*
		Cal(1)	0.06	0.97	0.60	0.29	0.82	0.23
	7b-ins	Unc	0.08	0.87	0.72	0.35	0.26	0.56
		Cal(0.95)	0.06*	0.92*	0.69*	0.32	0.52	0.44
		Cal(1)	0.05*	**0.99***	0.60*	0.28	0.96	0.20
	13b-ins	Unc	0.19	0.41	0.66	0.31	0.04	0.91
		Cal(0.95)	0.06*	0.93	0.59*	0.28	0.50*	0.25*
		Cal(1)	0.05*	0.98	0.53*	0.26	0.88*	0.08*
	Ensemb	Unc	**0.31**	0.13	0.56	0.13	0.00	**0.98**
		Cal(0.95)	0.08	0.93*	**0.72**	**0.35***	0.52*	0.50*
		Cal(1)	0.06	0.97*	0.63	0.30	**0.90***	0.29*
CLEF-2018	Bio BERT	Unc	0.06	0.97	0.59	0.29	0.87	0.19
		Cal(0.95)	0.07	0.91*	0.63	0.30	0.57*	0.33*
		Cal(1)	0.06	0.97	0.59	0.29	0.87	0.21
	7b-ins	Unc	0.09	0.88	0.75	0.37	0.27	0.59
		Cal(0.95)	0.08*	0.94*	0.71*	0.35*	0.50	0.46
		Cal(1)	0.06*	**0.99***	0.62*	0.30	**1.00**	0.24
	13b-ins	Unc	0.26	0.36	0.66	0.30	0.00	0.94
		Cal(0.95)	0.06	0.94*	0.59*	0.29	0.47*	0.22*
		Cal(1)	0.05	0.97	0.53*	0.27	0.80*	0.08*

Implementation is relatively straightforward

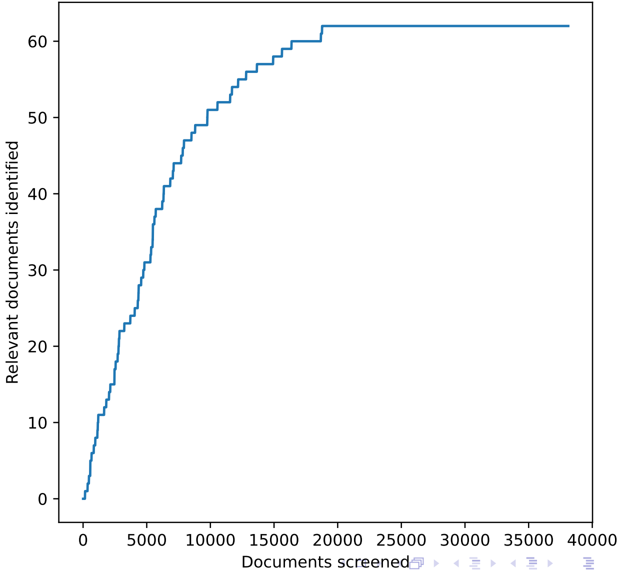
```python
def binary_probs(tokenizer, model, prompt, no_words=[’no’], yes_words=[’yes’], return_all=False):
    device = ’cuda’ if torch.cuda.is_available() else ’cpu’
    encoded_text = tokenizer(prompt, return_tensors="pt").to(device)
    #1. step to get the logits of the next token
    with torch.inference_mode():
        outputs = model(**encoded_text)

    next_token_logits = outputs.logits[0, -1, :]

    # 2. step to convert the logits to probabilities
    next_token_probs = torch.softmax(next_token_logits, -1)

    topk_next_tokens= torch.topk(next_token_probs, 50)
    tokens = [tokenizer.decode(x).strip().lower() for x in topk_next_tokens.indices]
    p = topk_next_tokens.values

    df = pd.DataFrame.from_dict({’t’: tokens,’p’: p.cpu()})
    y = df[df[’t’].isin(yes_words)][’p’].sum()
    n = df[df[’t’].isin(no_words)][’p’].sum()

    if return_all:
        return df.groupby(’t’).sum().reset_index().sort_values(’p’, ascending=False).reset_index(drop=True)
    return y-n, y+n
```

Implementation is relatively straightforward

```
prompt = Template(’’’<s>[INST] <<SYS>>
You are a systematic review helper tasked with finding out whether a study is relevant to the review $t

Answer ’yes’ if the study is relevant, or ’no’ if not
<</SYS>>

Study: $s

Should the study be included? Answer yes or no. [/INST] ’’’)

prompt.substitute({’t’: review, ’s’: study_title}),
```

Result #1: It works!

- The method produces a ranking that identifies all relevant documents before all documents have been screened



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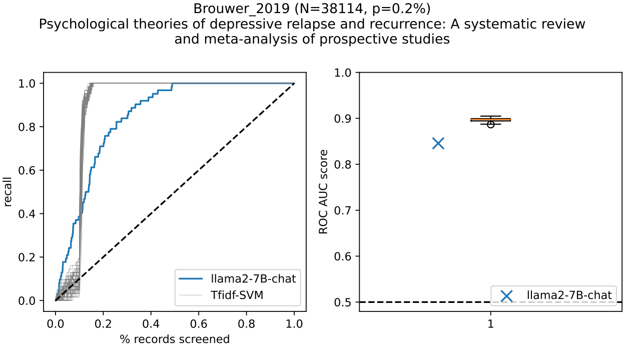

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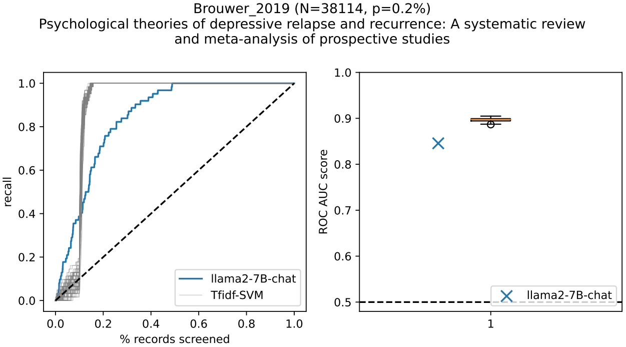
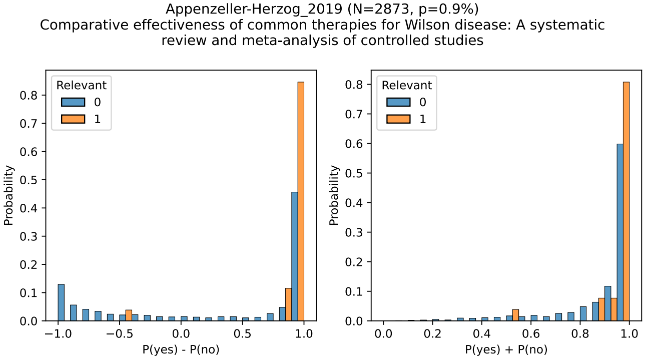
- To compare the quality of rankings, we can use ROC AUC scores



This method simply produces a ranking of documents, but is this ranking better than what we can produce with traditional active learning approaches?



- We generated LLM inclusion scores for each document in a set of reviews in the Synergy dataset

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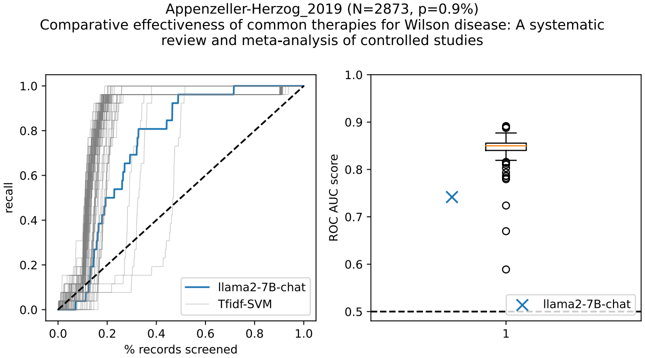

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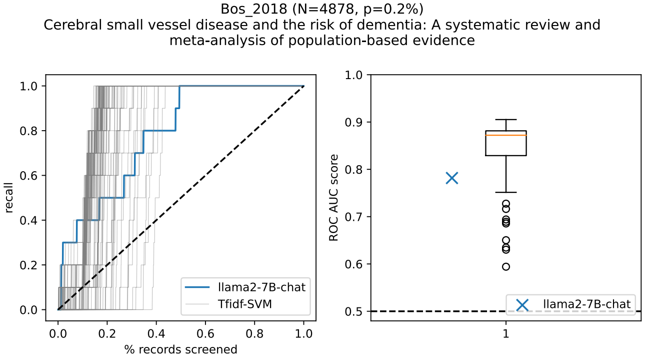

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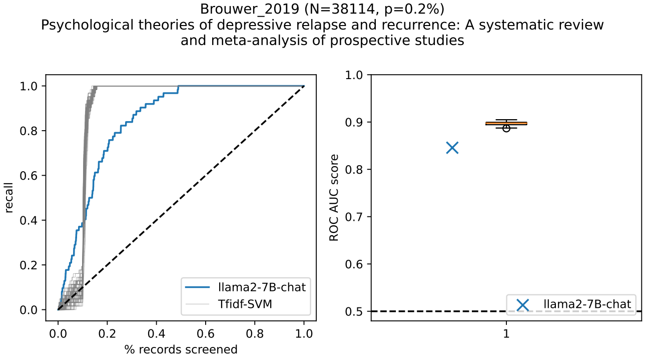

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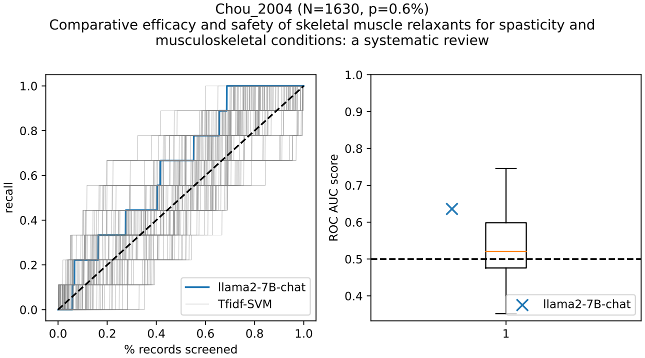

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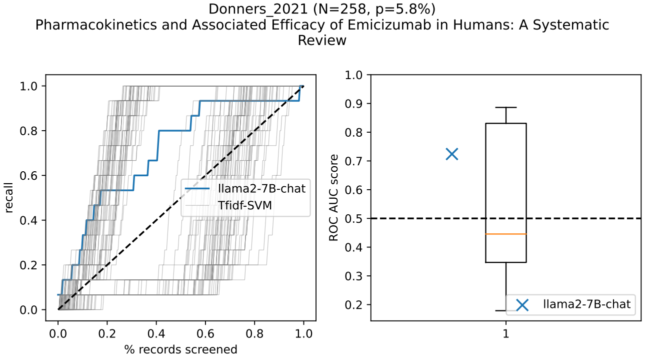

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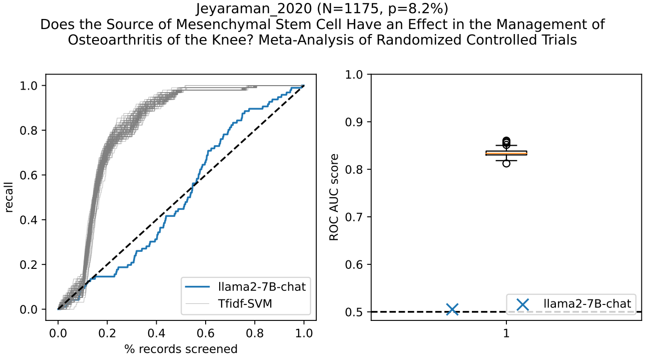

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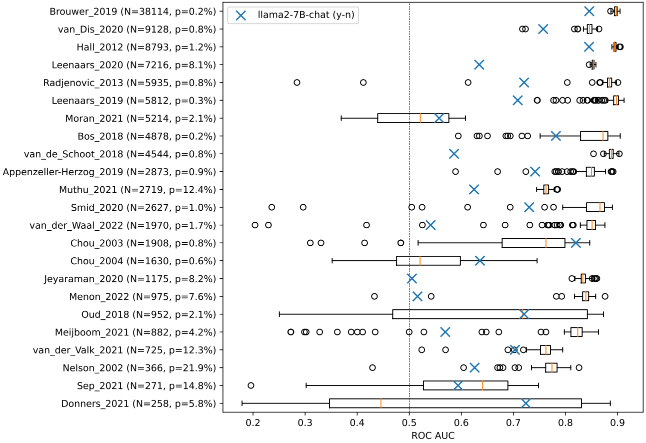
- Initial results are not very promising
- But LLMs can do well where traditional methods struggle
- Sometimes they are no use at all

All results



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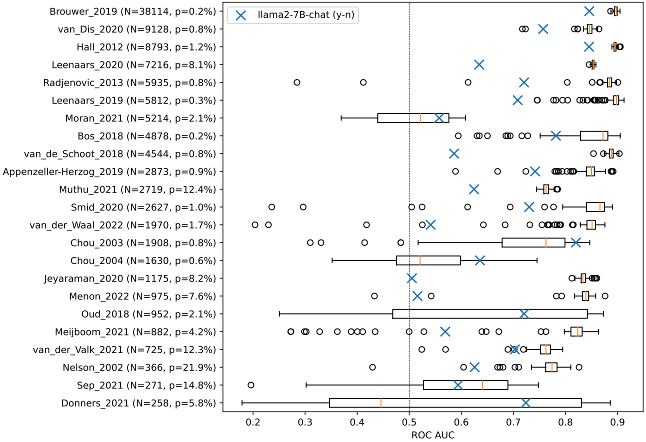

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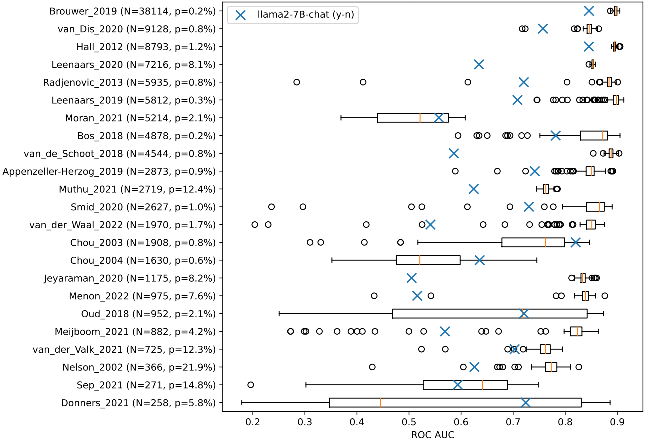

- LLMs and basic active learning pipelines seem to have different weakneses
- Combining both could improve general performance
- LLMs seem most useful for smaller datasets (where active learning has little time to learn)

Some things still to explore

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- Updating prompts based on user feedback

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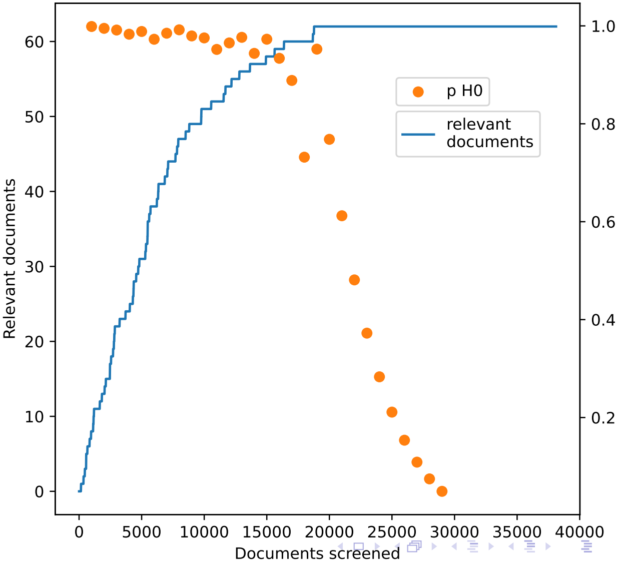
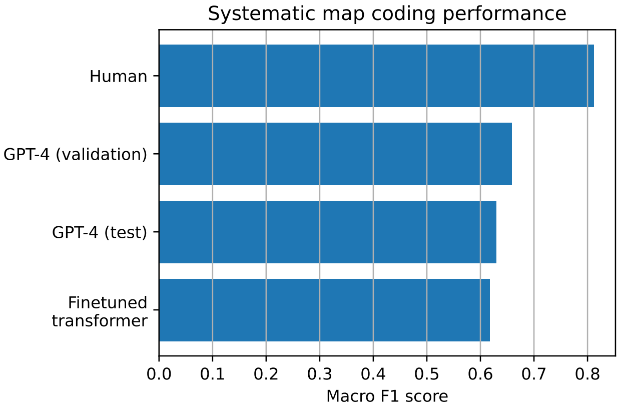
- Evaluation is vital
- We can't forget the need for appropriate stopping criteria Callaghan and Müller-Hansen (2020)



Using LLMs for coding

- Santiago’s thesis showed us that LLMs can achieve comparable performance with BERT-type models



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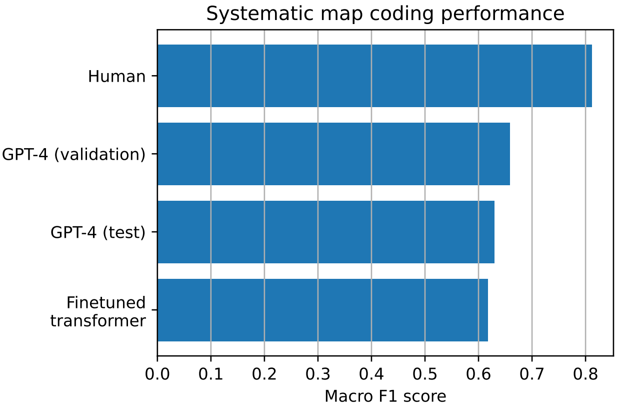

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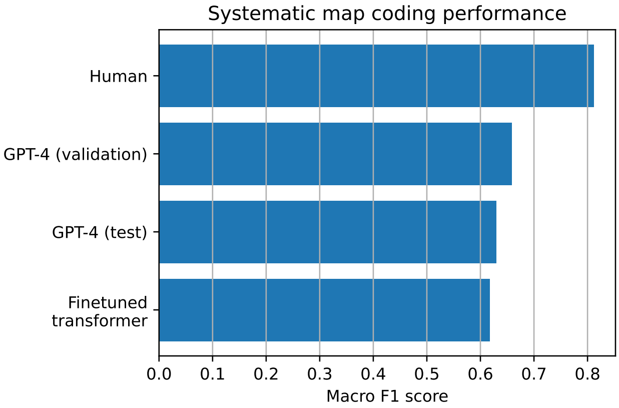
- But we do need annotated data for "prompt engineering" (≈ training?), and for evaluation



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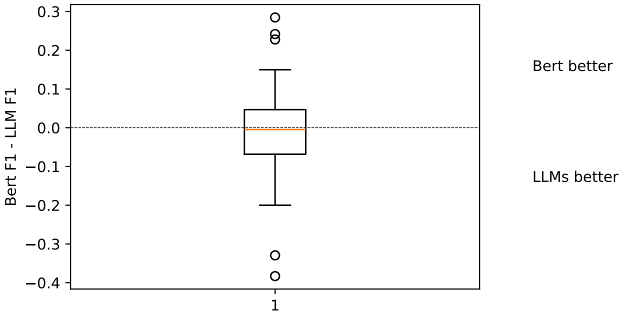

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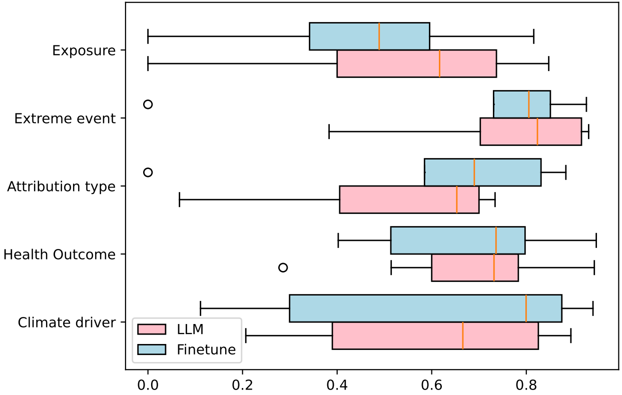

Using LLMs for coding

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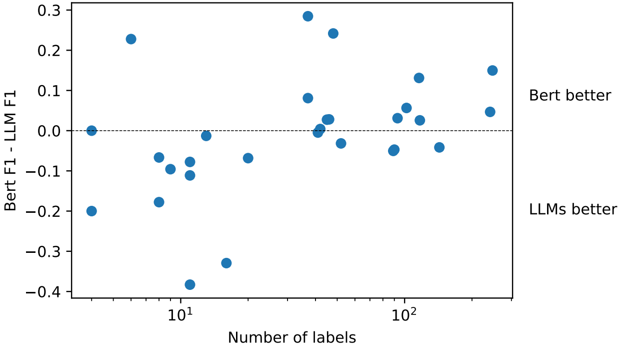
- Aggregate results hide much variation
- This varies across the different coding categories
- And there seems to be a clear correlation with number of labels



Conclusions

Callaghan, M. and Müller-Hansen, F. (2020). Statistical Stopping Criteria for Automated Screening in Systematic Reviews. *Systematic Reviews*.

Wang, S., Scells, H., Zhuang, S., Potthast, M., Koopman, B., and Zuccon, G. (2024). Zero-shot Generative Large Language Models for Systematic Review Screening Automation.