Can Zero-shot LLMs save additional work in machine learning prioritised screening for systematic reviews?

Max Callaghan

October 30, 2024

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	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*
	Ensemb	Unc	**0.35**	0.12	0.54	0.12	0.00	**0.95**
		Cal(0.95)	0.09*	0.94*	**0.75**	**0.38***	0.50*	0.54*
		Cal(1)	0.06	0.99*	0.64	0.32*	0.93*	0.28*
CLEF-2019-dta	Bio BERT	Unc	0.07	0.99	0.58	0.30	0.88	0.18
		Cal(0.95)	0.08	0.89	0.59	0.26	0.50	0.27
		Cal(1)	0.08	0.91	0.59	0.27	0.62	0.25
	7b-ins	Unc	0.09	0.92	0.71	**0.35**	0.62	0.49
		Cal(0.95)	0.10*	0.91*	0.71*	0.34	0.50	0.50
		Cal(1)	0.08*	0.97*	0.66	0.32	0.75	0.34
	13b-ins	Unc	0.19	0.49	0.69	0.32	0.00	0.87
		Cal(0.95)	0.08	0.95	0.56	0.29	0.50*	0.16*
		Cal(1)	0.07	0.99	0.51	0.28	0.88*	0.03*
	Ensemb	Unc	**0.31**	0.21	0.59	0.19	0.00	**0.96**
		Cal(0.95)	0.10	0.91	**0.73**	0.34*	0.50*	0.52*

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Table 2
Performance of GPT 4o mini in screening titles and abstracts against a human reviewer's good truth using different k-value

Data set	k-value	Precision	F1-score	Kappa	PABAK	AUC-ROC	Recall
Hall	0.0	0.575	0.672	0.667	0.662	0.900	0.808
Hall	0.5	0.649	0.670	0.666	0.663	0.844	0.692
Hall	1.0	0.653	0.644	0.640	0.636	0.815	0.635
PTSD	0.0	0.129	0.226	0.216	0.210	0.924	0.895
PTSD	0.5	0.161	0.270	0.260	0.255	0.892	0.816
PTSD	1.0	0.176	0.286	0.277	0.271	0.868	0.763
Virus	0.0	0.339	0.485	0.446	0.417	0.882	0.851
Virus	0.5	0.375	0.508	0.473	0.446	0.861	0.789
Virus	1.0	0.436	0.557	0.527	0.502	0.860	0.772

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- There are a lot of bad papers, which will continue to proliferate, each tweaking some parameters to achieve a high performance that cannot be generalised

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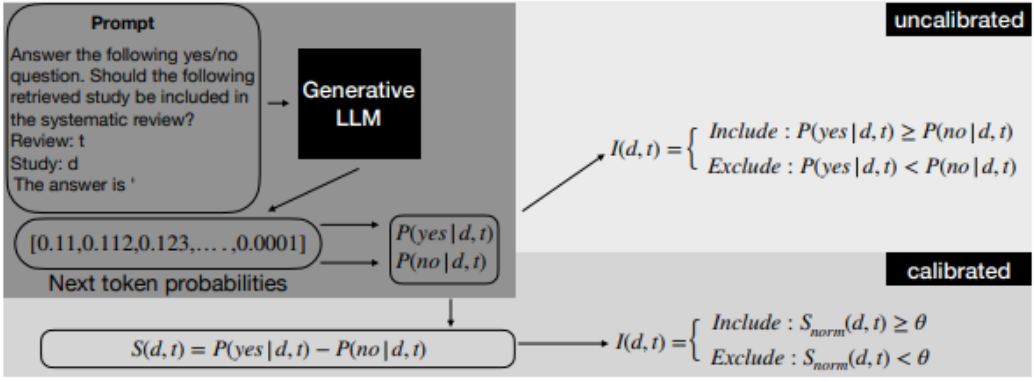
Despite the hype, LLMs might still be helpful, but we need to know

- How do LLMs compare against commonly used (and much cheaper!) baselines?
- How could they safely be used in the real world (Hint: with stopping criteria and prioritised screening)

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



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}),
```

Implementation is relatively straightforward

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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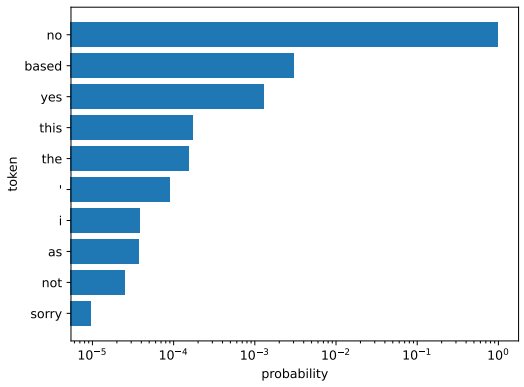

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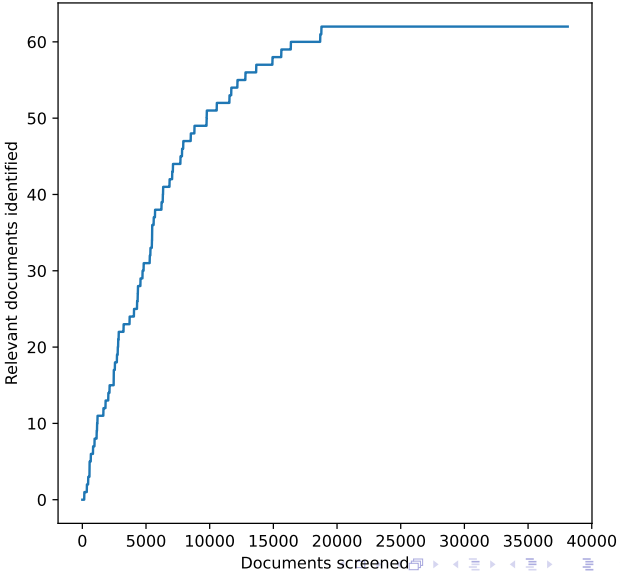
- We also make a prediction for each document with 4 Llama models of different sizes and ages
- We turn these predictions into a prioritised list of documents to be screened

Result #1: It works!

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



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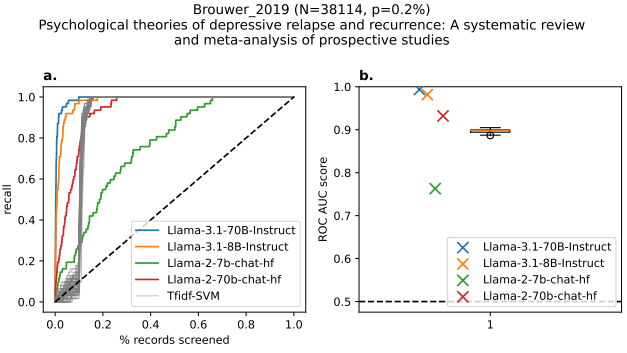

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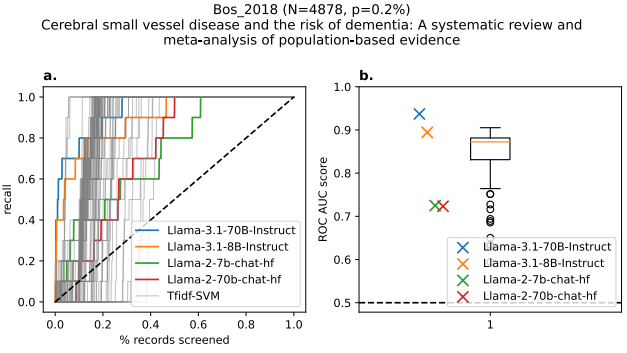

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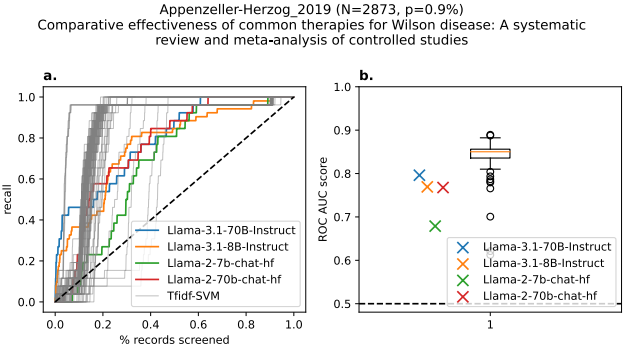

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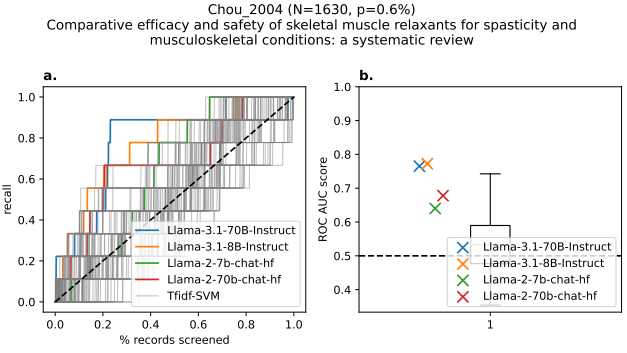

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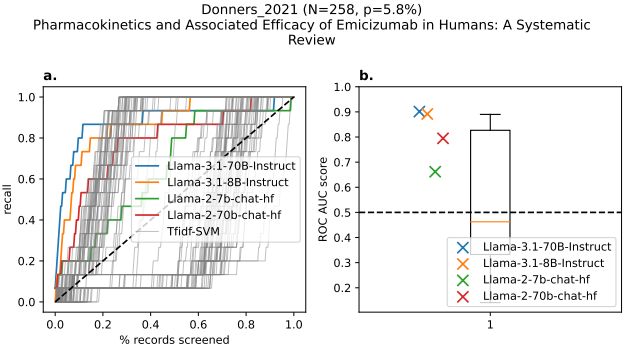

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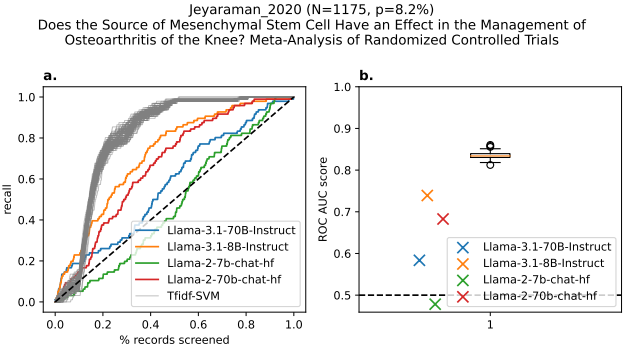

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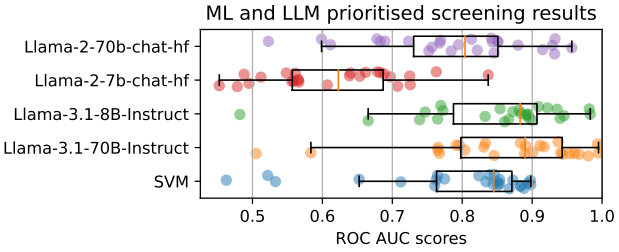

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- Stopping when $p < \alpha$ gives a recall $>$ target in the α^{th} percentile, in 97/100 settings

r target	model confidence	SVM	Llama-2-7b	Llama-2-70b	Llama-3.1-8B	Llama-3.1-70B
0.80	0.50	0.938	**0.758**	0.893	0.911	0.911
	0.80	0.924	**0.797**	0.866	0.845	0.889
	0.90	0.900	0.818	0.872	0.836	0.876
	0.95	0.867	0.806	0.888	0.878	0.878
	0.99	0.811	0.838	0.865	0.876	0.886
0.90	0.50	0.963	0.905	0.936	0.957	0.954
	0.80	0.957	0.900	0.958	0.961	0.933
	0.90	0.947	0.937	0.959	0.953	0.939
	0.95	0.933	0.943	0.944	0.947	0.939
	0.99	0.928	0.941	0.947	0.926	0.958
0.95	0.50	0.979	**0.947**	1.000	0.981	0.987
	0.80	0.974	0.973	0.976	0.975	0.979
	0.90	0.973	0.968	0.981	0.978	0.980
	0.95	0.964	0.973	0.982	0.976	0.968
	0.99	0.973	0.975	0.986	0.983	0.975
0.99	0.50	1.000	1.000	1.000	1.000	1.000
	0.80	0.994	1.000	1.000	1.000	0.991
	0.90	0.993	0.996	1.000	0.999	0.996
	0.95	0.993	0.997	1.000	0.999	0.996
	0.99	0.996	0.992	0.999	0.997	0.996

Stopping criteria

- Next, we calculate scores for our stopping criteria with a range of different recall targets
- Stopping when $p < \alpha$ gives a recall $>$ target in the α^{th} percentile, in 97/100 settings
- In most settings, total work savings were greater for SVMs

r target	model confidence	SVM	Llama-2-7b	Llama-2-70b	Llama-3.1-8B	Llama-3.1-70B
0.80	0.50	126,898	100,248	121,777	127,401	**132,808**
	0.80	113,708	64,568	97,147	111,411	**114,748**
	0.90	105,053	57,678	90,327	101,871	**106,668**
	0.95	98,503	48,608	83,338	94,921	**101,288**
	0.99	**87,803**	37,838	71,397	79,471	85,058
0.90	0.50	114,988	65,778	99,217	112,011	**115,498**
	0.80	93,923	42,768	79,807	83,661	**97,438**
	0.90	**84,658**	34,158	65,007	76,701	82,268
	0.95	**76,483**	28,748	59,447	69,251	73,108
	0.99	**62,350**	23,118	49,790	55,091	59,088
0.95	0.50	98,258	44,408	82,907	94,731	**101,318**
	0.80	**74,098**	27,238	58,587	64,281	68,678
	0.90	**63,245**	21,738	44,470	53,091	57,388
	0.95	**54,860**	18,781	37,370	45,954	48,671
	0.99	**41,676**	13,545	27,171	34,855	35,592
0.99	0.50	**63,573**	22,638	42,897	54,811	55,378
	0.80	**31,323**	11,158	20,597	29,191	30,398
	0.90	**21,160**	5,825	13,480	13,641	18,478
	0.95	**16,229**	4,065	8,837	9,435	11,938
	0.99	**7,980**	1,985	4,355	4,934	6,625

Table: absolute work savings across datasets (N records=169,288)

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Note that although the LLM implementation is simplistic, so is the comparator

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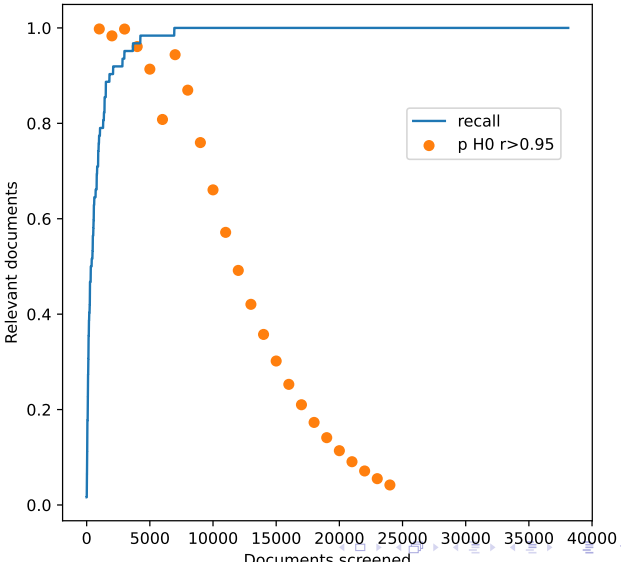
- Do not forget stopping criteria!



Conclusions

- LLMs are neither a quick fix or a silver bullet
- They do not have magic properties that fix problems of traditional ML, they are simply likely to make them worse
- We need to be on our guard!
- Do not forget stopping criteria!
- But they have some advantages, such as the fact that we only need to calculate scores once!

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