

Project Proposal: The Practicality of Prompt Engineering

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Abstract

This paper examines the practicality of prompt engineering in improving the performance of Large Language Models (LLMs). Through empirical analysis, we evaluate the trade-offs between costs and benefits of prompting using novel metrics. Different prompting methods are assessed using standardized tasks and both modern and older models.

Introduction

Prompt engineering, the practice of developing specialized prompts and queries to improve the accuracy of Large Language Models after training, is a prominent topic of interest in the NLP community, and among the general public. The practice is believed to allow for improvements in LLM performance a variety of domains without investment in underlying training (Martineau, 2021). It is not, however, without its critics. Some commentators believe that the practice will become irrelevant as models grow larger and more powerful, becoming more capable of directly interpreting a user's intent. (Ethan Mollick [@emollick], 2023). Others question the need for specialized professionals or training to attain minimal improvements which are often not repeatable across domain types and contexts (Shackell, 2023; Acar, 2023).

Despite such controversy, it is difficult to find empirical and quantitative analyses of the trade-off between costs and accuracy benefits associated with advanced prompting. Papers introducing new prompting techniques often only include performance benchmarks concerning the techniques' efficacy, typically within a limited question domain. Some authors briefly mention problems associated with human-tailored problems, such as the increased complexity induced by prompt-chaining and limitations on creativity and randomness (Wu et al., 2022), and others suggest the automation of prompting (Diao et al., 2023). Online marketplaces

such as Promptbase (noa) provide input token costs for prompt texts sold on the platform, but do not provide any other information.

This paper uses several metrics to evaluate the costs of prompt engineering methods systematically, and analyzes the tradeoffs inherent in their application to standardized data. Such an assessment is valuable on several dimensions. Beyond quantifiably testing the practicality of prompt engineering as a whole, it can be used to compare the performance of different approaches, useful in a world where so many competing techniques are available. I also offer a new look at these methods in a period long after ideas were introduced and in an environment with greater capabilities in underlying models. Finally, I survey and introduce some useful measures of costs and complexity such as the ratio of interaction length with prompting to the length of an accepted human-generated answer.

Data

To evaluate the LLMs, I attempt to use tasks that are both general-purpose and close to practical, real-world applications. In this spirit, I use GRE General Test questions (likely from a purchased prep book/or practice exams recently published online to minimize contamination), as well as HumanEval coding problems. For multiple choice questions, I add formatting to the prompt to indicate what should be done to represent a final answer "When you are ready, please put your final, letter answer in the form of a single capital letter, enclosed in parentheses. For example, if you think the answer is A, please write (A)." HumanEval uses the pass at k metric to automatically assess the probability a solution is correct given a set of unit tests. (Chen et al., 2021)

I perform the analysis on one cutting-edge model, to get the current state of things, and one older model, closer to the time that these techniques were introduced. This will allow one picture of the

changing costs and benefits of advanced prompting, a trend that may even be extrapolated into the future if current LLM scaling laws continue to hold. As the most widely used models and the ones behind much original work in the field, I select two models from the OpenAI series: GPT-4 and text-davinci-003 on OpenAI playground. Should text-davinci-003 (a legacy model) become unavailable during the course of the project, or should I encounter other difficulties, I will use the simplest/smallest model available, likely GPT-3.5 (something to note is that models older than GPT-3.5 have, in the past, scored 0% for accuracy on coding problems - I will need to test all of my evaluations quickly to get a sense of their feasibility before scaling up). All of these models are available both via the OpenAI API and in web interfaces - where possible I will use web interfaces to limit resources required.

To the extent possible, I will report accuracy scores on the domain dataset as they are in the original paper. It may also be possible to use any prompts, LLM responses, and correct responses provided along with original papers to calculate other simple metrics such as response lengths and complexity. However, some metrics (time taken, human assessments of complexity) will require my own evaluations.

Metrics

Accuracy

Improved accuracy can be a benefit of prompt engineering. I report:

- Correct/Incorrect accuracy at the point a technique has been fully implemented (the end of the chain of thought, etc., modelling the real world)

Length

The length of responses and interactions can effect the practicality of prompting. It could indicate that a model is carefully and correctly solving through the steps of a problem. It can also impose time and financial costs to users, or become an indicator of degraded performance as models sometimes tend to go off on tangents or repeat themselves (to the extent some platforms have imposed length limitations) (Mann). I report:

- Length of the entire interaction in tokens
- Financial cost of the entire interaction in tokens

- Length of the entire interaction in tokens relative to the length of the baseline task + a human/solved out/generally accepted as correct answer. How much is the engineering stretching the interaction out? Is this stretching adding value/improving accuracy?
- Length of the entire interaction in time (seconds). This can include time writing a response, waiting for a response, or reviewing a response - this level of granular data may be hard to collect, but it might be possible to look at human assessments of time spent on these activities. Attempts will be made to have queries to models made during off-peak hours to minimize confounding due to server load, connectivity issues, etc.

Complexity

Similarly to length, complexity could be an indicator of high accuracy. However, it has substantial costs in potentially making review more difficult. I report:

- Vocabulary - share of words on the Academic Vocabulary List (AWL). (Gardner and Davies, 2014)
- Sentence length and Flesch reading ease (implemented via the textstat Python package) for natural language and non-code components of responses. (Flesch, 2016; Aggarwal)
- Cyclomatic complexity for code responses (implemented via the radon Python package). (Lacchia)
- Ratio or difference of these scores in prompts vs. responses, responses vs. accepted/outside correct answer
- Human assessment of need for specialized knowledge/difficulty of implementation of the technique. This could be task specific (done for some novel real world example questions/prompting scenarios), or it could be done overall based on a pre-existing description of the technique. Perhaps a balance of both is best. The actual metric will be a numerical score and a qualitative description.
- Human assessment of output complexity (ease of evaluating results). This could be task specific (done for some novel real world example

174	questions/prompting scenarios), or it could be	consistently useful technique. (Brown et al.,	221
175	done overall based on a pre-existing examples	2020) Second, earlier research has found that	222
176	of the technique. Perhaps a balance of both	the formatting and input/label space distribu-	223
177	is best. The actual metric will be a numerical	tion is more important than example correct-	224
178	score and a qualitative description.	ness, meaning this method is somewhat robust	225
		to human error. (Min et al., 2022)	226
179	Prompting Methods Assessed		
180	This list is subject to change, pending further as-	Analyses	227
181	essment of implementation difficulty and potential	I provide summary statistics of the metrics for each	228
182	accuracy gains for each method. Higher accuracy	prompting method by model. In cases where hu-	229
183	methods are likely to be more interesting.	man/textual assessment and comments have been	230
184	Below items are listed in order of increasing	provided, it might be interesting to use NLP meth-	231
185	complexity/human intervention:	ods to evaluate responses (ex: for sentiment).	232
186	• Zero-Shot Control Baseline: Providing the	Responsibilities	233
187	question/task directly. (Sometimes called "Di-	I am the sole author of this proposal, but I am	234
188	rect Prompting")	open to working with others with similar interests.	235
189	• Zero-Shot Chain of Thought Prompting: Ex-	Expanding the group would be helpful in order to	236
190	isting literature mentions several examples of	improve the project.	237
191	this: a simple one to append to every initial		
192	question/task, found to be optimal through au-	Limitations	238
193	tomated testing is "Let's work this out in a	It was difficult to select prompt engineering meth-	239
194	step by step way to be sure we have the right	ods to try for this paper, and there is potential for	240
195	answer." (Hebenstreit et al., 2023; Zhou et al.,	my choice of methods to be somewhat biased. I	241
196	2022)	mostly picked methods based my perception of	242
197	• Tree of Thought Prompting: This prepends the	their popularity and on their ease of implementa-	243
198	following to the task/question: "Imagine three	tion. If anything, this may lead to an underestima-	244
199	different experts are answering this question.	of costs.	245
200	All experts will write down 1 step of their	Just as my evaluation comes at a time with signif-	246
201	thinking, then share it with the group. Then	icantly more capable LLMs relative to that where	247
202	all experts will go on to the next step, etc. If	much work began on prompting, I expect the under-	248
203	any expert realises they're wrong at any point	lying calculus concerning prompting to continue to	249
204	then they leave. The question is..." (Hulbert,	change in the future. However, I again only expect	250
205	2023)	relative costs of complex engineering to increase	251
206	• Chain of Verification Prompting: The LLM	as models get better.	252
207	is prompted a series of times to produce an	Another potential problem is the extent that	253
208	initial baseline response, write its own veri-	prompting techniques have been absorbed into de-	254
209	fication questions, answer those verification	fault LLM behavior, likely through reinforcement	255
210	questions, and write a final, verified response.	learning. GPT-4 in particular does seem to im-	256
211	(Dhuliawala et al., 2023)	plement chain-of-thought methods when prompted	257
212	• Few-Shot Prompting: The prompter provides	with a sufficiently complex problem. In this envi-	258
213	a few examples of successfully/answered	ronment, this paper become less of an evaluation	259
214	questions or tasks before the main ques-	of prompting techniques themselves, but more of	260
215	tion/task. Despite the work involved in im-	an evaluation of their manual implementation.	261
216	plementing this method, I believe it has po-	Finally, though I have taken steps to limit it,	262
217	tential to be effective for two reasons. First,	data contamination remains a real concern. The	263
218	prior evidence indicates that larger and more	evaluations I use may have been used to train the	264
219	modern language models benefit more from	LLMs, or the questions/tasks from them may have	265
220	few-shot learning, potentially making this a	been introduced through reinforcement learning	266
		based on other evaluations. On the other hand,	267
		this seems unlikely to bias the results for any one	268

particular prompting method relative to the others
- comparisons between them are still likely to be
useful.

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