Prompt Engineering

With the recent success of Assistants (like ChatGPT)

- it is easy to reach the mistaken conclusion
- that the Assistant is "reasoning"
- when, in fact, it is doing nothing more than text-completion

Review: Auto-regressive behavior of an LLM

The user

- inputs a sequence $\mathbf{x}$ (e.g., the "prompt", i.e., a request for generating a response)
- and expects a sequence $\mathbf{y}$ (the response)
- generated by the LLM according to probability distribution

$$p(\mathbf{y}|\mathbf{x})$$

The response sequence $\mathbf{y}$ is generated *auto-regressively*:

At position t of the output,

- the Large Language Model predicts the next token.
$$\hat{\mathbf{x}}_{(t)} \in p(\mathbf{x}_{(t)}|\mathbf{x}_{[0..t-1]})$$
- conditional on all preceding tokens $\mathbf{x}_{[0..t-1]}$ in the sequence $\mathbf{x}$
    - the conditioning input is called the *context*
- and extends the context by appending the prediction
$$\mathbf{x} = \mathbf{x}_{[0..t-1]} + \hat{\mathbf{x}}_{(t)}$$

Thus, at any step, $\mathbf{x}$ consists of

- the original user prompt as a prefix
- followed by a suffix of the partially generated response

Prompt Engineering: maximizing the chances of achieving a good response

Given the auto-regressive generation process

- the final response $\mathbf{y}$ is therefore
- *conditioned on all previously generated response tokens*
- it is *path dependent*

In order to generate a "high quality" $\mathbf{y}$, we have to be aware of the path.

Prompt engineering

- is a collection of techniques
- that attempt to generate paths
- that lead to better responses

For example:

- many tasks involve multiple steps of reason
- asking
    - directly for the answer
    - is less likely to produce a correct response
    - than asking for a step-by-step explanation to *proceed* the answer
- that is
    - having the LLM's response include the individual steps before the answer
    - conditions it to produce the correct answer
        - just like a human !

To illustrate: the following prompt involves a task whose solution has multiple steps of arithmetic reasoning

```
Each can contains 3 balls.
I start with 5 cans
At the end, all cans are empty except for one can with 2 balls.

How many balls did I use ?
```

It is not reasonable to expect text-completion to *immediately* generate the correct response.

We can improve the chances of the LLM generating a correct response

- just by appending

```
Let's think step by step
```

to the prompt !

Here is ChatGPT's response:

KE

Each can contains 3 balls. I start with 5 cans. At the end, all are empty except for one can with 2 balls. How many balls did I use. LETS THINK STEP BY STEP

Sure, here is one way to think about the problem step by step:

1. Start by identifying the information given in the problem:
   - Each can contains 3 balls
   - I start with 5 cans
   - At the end, all cans are empty except for one can with 2 balls
2. Next, think about what information you need to find:
   - How many balls did I use
3. Now, you can use the information you have to find the number of balls you used.
   - You started with 5 cans, each containing 3 balls, for a total of 5 cans * 3 balls per can = 15 balls
   - At the end, you have one can with 2 balls remaining, so you must have used 15 balls - 2 balls = 13 balls

So, you used 13 balls.

Why does adding a simple request to think step-by-step work ?

- The request causes the model to generate the response as a sequence of small steps
- Step t is conditioned on all steps $t' < t$
- The probability of a correct answer on a small step is higher than on a large step (i.e, straight to answer)

The step-by-step approach

- simulates reasoning
- by turning it into text completion

A word on Assistants

The LLM's with which you may be familiar (e.g. ChatGPT) have been fine-tuned in several ways

- to be a helpful assistant
    - presume that your prompt is a request for service, a question that needs and answer, etc.
- to be conversational
- to be harmless and not dangerous

Hence, your experience with an "LLM" may not correspond to our description of an LLM that has not been fine-tuned.

It is important to remember

- that an LLM has **no memory**
- The output $\hat{\mathbf{y}}_{(t)}$ is solely a function of the prompt $\mathbf{x}_{[0..t-1]}$
- So how is it that the Assistant seems to "remember" the prior parts of the interaction ?

An interaction with an Assistant is often a multi-round conversation

- in round $i \geq 0$
  - you enter prompt $\mathbf{x}^{(\mathbf{i})}$; get response $\hat{\mathbf{y}}^{(\mathbf{i})}$
- the *context* used to condition the response $\hat{\mathbf{y}}^{(i+1)}$
  - is prompt $\mathbf{x}^{(i+1)}$
  - concatenated with the prompt/responses of earlier rounds
- So

$$\hat{\mathbf{y}}^{(i+1)} \in p(\mathbf{y}|\mathbf{x}^{(i+1)}, \hat{\mathbf{y}}^{(\mathbf{i})}, \mathbf{x}^{(\mathbf{i})}, \ldots, \mathbf{x}^{(0)}, \hat{\mathbf{y}}^{(0)})$$

The Assistant "remembers" the entire conversation only by having it be part of the prompt.

Resources

There a lots of "guides" (some paid) that purport to turn you into a Prompting Wizard.

Many of these are anecdotal. We prefer measurement

- guides that summarize empirical studies
- and provide reference to the source paper

LearnPrompting.org Course (https://learnprompting.org/docs/intro)

A fairly simple (free and open source) course

- great way to find out what is interesting
- **and** has references to papers so as to enable deeper understanding

For example, some basics (https://learnprompting.org/docs/category/-basics)

- role playing (https://learnprompting.org/docs/basics/roles) to control the style of output
- giving instructions (https://learnprompting.org/docs/basics/instructions) to *precisely* define the task

Prompting Guide (https://www.promptingguide.ai/)

Another fairly simple guide (ignore the promoted -- and paid -- course)

- also has references to papers

Case study

- https://www.promptingguide.ai/applications/workplace_casestudy (https://www.promptingguide.ai/applications/workplace_casestudy)

You can delve into various prompting techniques by examining the resources.

As a short-cut

- we will describe a few of the techniques
- as part of a study evaluating techniques

One team decided to measure the performance (https://arxiv.org/pdf/2303.07142.pdf) of various prompting techniques

- using a **single** task as a case study
- may not be able to generalize to other tasks

Regardless of the limitations, a comparison is valuable.

Methodology

The task is a binary Classification task

- given a job posting
- classify whether the job listed is appropriate for a recent college graduate
    - no experience needed and requires advanced education
- UK based
    - "graduate" means college graduate

The metric used is "precision at 95% recall"

- given that the model achieves a recall of at least 95%
$$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \geq 95$$
- what is the precision (predicted Positives that are True Positives;minimize FP)
$$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$$

The models evaluated are two variants of GPT 3.5 via OpenAI.

Prompt modifications evaluated

Prompt modifications

Table 3. Overview of the various prompt modifications explored in this study.

Short name	Description
Baseline	Provide a a job posting and asking if it is fit for a graduate.
CoT	Give a few examples of accurate classification before querying.
Zero-CoT	Ask the model to reason step-by-step before providing its answer.
rawinst	Give instructions about its role and the task by adding to the user msg.
sysinst	Give instructions about its role and the task as a system msg.
bothinst	Split instructions with role as a system msg and task as a user msg.
mock	Give task instructions by mocking a discussion where it acknowledges them.
reit	Reinforce key elements in the instructions by repeating them.
strict	Ask the model to answer by strictly following a given template.
loose	Ask for just the final answer to be given following a given template.
right	Asking the model to reach the right conclusion.
info	Provide additional information to address common reasoning failures.
name	Give the model a name by which we refer to it in conversation.
pos	Provide the model with positive feedback before querying it.

Attribution: https://arxiv.org/pdf/2303.07142.pdf#page=7

Baseline

Uses Keyword and Regular Expression search

- "Graduate" or "Junior" in job title
- "suitable for graduate" in body of posting

Chain of Thought (CoT): Few Shot

Provide one or more exemplars for the task

- where the exemplar demonstrates the correct response

The exemplars condition the LLM to produces responses

- that look like the exemplars
- so if the exemplars demonstrate step by step reasoning
- the responses will hopefully do the same

See panel (b) in the chart below

Chain of Thought Prompting

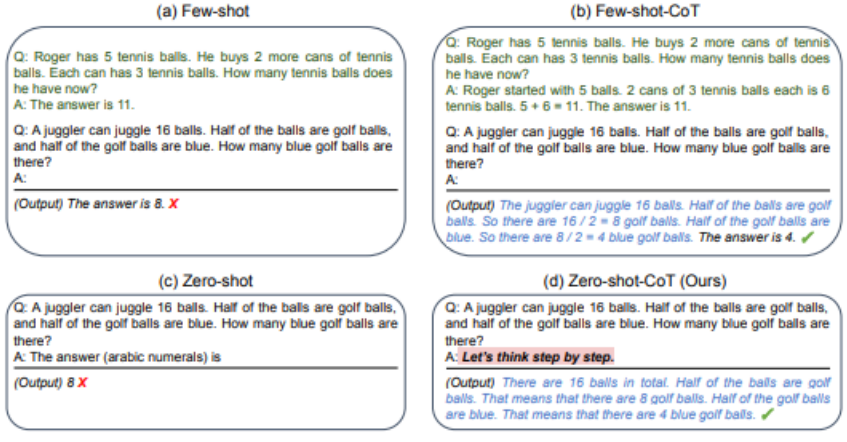


Figure 1: Example inputs and outputs of GPT-3 with (a) standard Few-shot ([Brown et al., 2020]), (b) Few-shot-CoT ([Wei et al., 2022]), (c) standard Zero-shot, and (d) ours (Zero-shot-CoT). Similar to Few-shot-CoT, Zero-shot-CoT facilitates multi-step reasoning (blue text) and reach correct answer where standard prompting fails. Unlike Few-shot-CoT using step-by-step reasoning examples **per task**, ours does not need any examples and just uses the same prompt "Let's think step by step" *across all tasks* (arithmetic, symbolic, commonsense, and other logical reasoning tasks).

Attribution: https://arxiv.org/pdf/2201.11903.pdf

Zero CoT: Chain of Thought: Zero shot

- Append "Let's think step by step" to the base prompt
    - see panel (d) in the chart above

Instructions: variants

The prompt uses Role prompting (https://learnprompting.org/docs/basics/roles)

- the *role* the Assistant is to play in providing the response

> *You are an AI expert in career advice. You are tasked with sorting through jobs by analysing their content and deciding whether they would be a good fit for a recent graduate or not.*

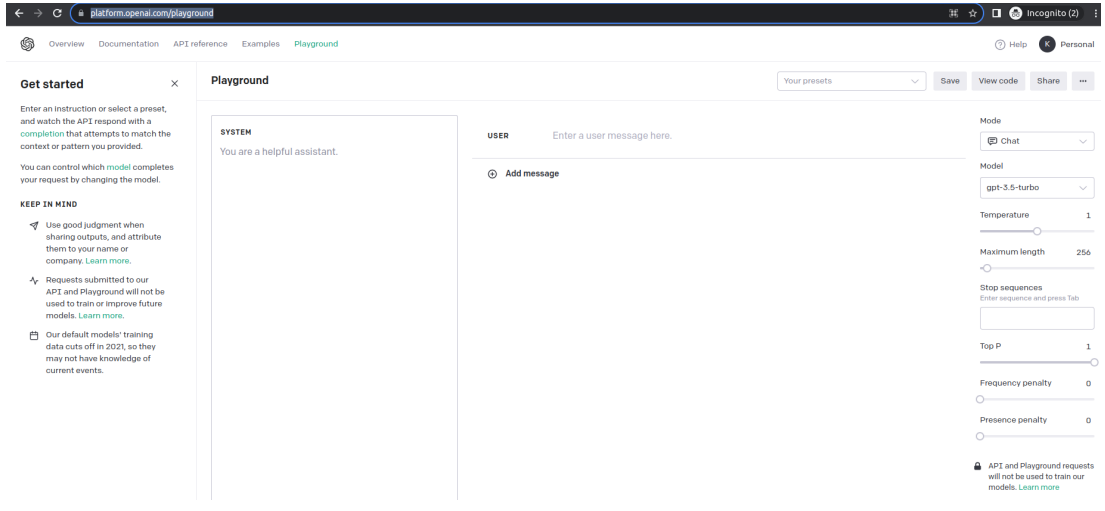
- giving instructions (https://learnprompting.org/docs/basics/instructions) describing the task

> *A job is fit for a graduate if it's a junior-level position that does not require extensive prior professional experience. I will give you a job posting and you will analyse it, to know whether or not it describes a position fit for a graduate.*

The experiment was carried out in the [OpenAI Playground (https://platform.openai.com/playground)](https://platform.openai.com/playground).

This tool has multiple input fields (System, User)

- the following prompt techniques refer to placement in specific input areas
- the actual prompt concatenates the two: System + User



`rawinst`

Role and Instruction placed in User Query field (top middle of page)

`sysint`

Role and Instruction placed in System Query field (to left of page)

`bothinst`

Role placed in System Query field; Instruction placed in User Query field

Mocked exchange (`mock`)

This

- creates an initial prompt to the Assistant, requesting that it confirm it's understanding ("Got it ?") of the Instructions in the User Query field
- the prompt and response are then used as the value of the User Query field

Variant of `bothinst` where

- the User field becomes

    A job is fit for a graduate ... Got it ?

    [Assistant response] Yes, I understand. I am ready to analyse your job posting.

Reiterating instructions (`reit`)

Both the Role and the Instruction are reinforced by repetition.

- Role

  > *You are an AI expert in career advice. ...*
  >
  > ***Remember, you're the best AI careers expert and will use your expertise to provide the best possible analysis***

- Instruction

  > *A job is fit for a graduate ... and you will analyse it,* ***step-by-step****, to know whether or not it describes ...*

Wording the prompt

These involve appending the desired format of the response to the Instruction

`loose`

> *Your answer must end with:*
>
> *Final Answer: This is a (A) job fit for a recent graduate or a student OR (B) a job requiring more professional experience.*
>
> *Answer: Let's think step-by-step,*

`strict`

> *You will answer following this template:*
>
> *Reasoning step 1:*
>
> *Reasoning step 2:*
>
> *Reasoning step 3*
>
> *Final Answer: This is a (A) job fit for a recent graduate or a student OR (B) a job requiring more professional experience.*
>
> *Answer: Reasoning Step 1:*

Right conclusion (`right`)

Ask the model for step-by-step reasoning in order to arrive at the **right conclusion**

> *Let's think step-by-step* ***to reach the right conclusion,***

Again, let's remember that the LLM is performing text completion

- one token at a time

If any token in the sequence of results is not great

- the final result will also not be great.

The "right conclusion" prompt may cause the LLM to

- re-evaluate how good an intermediate result is
- rather than solely focusing on the high probability next token objective

Reasoning gaps (`info`)

Prevent mis-interpretation of the Instructions

> *A job is fit for a graduate if it's a junior-level position that does not require extensive prior professional experience.*
>
> ***When analysing the experience required, take into account that requiring internships is still fit for a graduate.***
>
> *I will give you a job posting and you will analyse it, ...*

Subtle tweaks

Giving the assistant a name (`name`)

Give the assistant a name when describing its role.

Change the Role from

> *You are an AI expert in career advice ...*

to

> *You are Sydney, an AI expert in career advice ...*

Positive feedback (pos)

A modification of Mocked Exchange

- after the Assistant confirms its understanding
- give it positive feedback in the form of

    Great! Let's begin then :)

before continuing the mocked exchange

Evaluation

The results are summarized in a table

- Sub-metrics are reported to facilitate comparison
    - rather than the ultimate metric of "precision at 95% recall"
- *Template stickiness* refers to the format of the response
    - the fraction of responses that conform to the desired format
    - and don't need further parsing
        - important for downstream uses and ease of evaluation

Evaluation of Prompt modifications

Table 4. Impact of the various prompt modifications.

	Precision	Recall	F1	Template Stickiness
Baseline	*61.2*	*70.6*	*65.6*	*79%*
CoT	*72.6*	*85.1*	*78.4*	*87%*
Zero-CoT	*75.5*	*88.3*	*81.4*	*65%*
+rawinst	*80*	*92.4*	*85.8*	*68%*
+sysinst	*77.7*	*90.9*	*83.8*	*69%*
+bothinst	*81.9*	*93.9*	*87.5*	*71%*
+bothinst+mock	83.3	95.1	88.8	74%
+bothinst+mock+reit	83.8	95.5	89.3	75%
+bothinst+mock+reit+strict	*79.9*	*93.7*	*86.3*	***98%***
+bothinst+mock+reit+loose	*80.5*	*94.8*	*87.1*	*95%*
+bothinst+mock+reit+right	84	95.9	89.6	77%
+bothinst+mock+reit+right+info	84.9	96.5	90.3	77%
+bothinst+mock+reit+right+info+name	85.7	96.8	90.9	79%
+bothinst+mock+reit+right+info+name+pos	**86.9**	**97**	**91.7**	81%

Attribution: https://arxiv.org/pdf/2303.07142.pdf#page=12

High level conclusions

- Prompt formatting is important
  - Final prompt greatly improves over Baseline
    - F1: $65.6 \rightsquigarrow 91.7$
    - Recall: $70.6 \rightsquigarrow 97$

- Chain of Thought: more exemplars **don't improve** performance
    - Zero shot(`Zero-CoT`) vs Few shot (`CoT`)
        - F1: $81.4 \rightsquigarrow 78.4$
        - Precision $75.5 \rightsquigarrow 72.6$
    - Theories
        - the task was sufficiently simple that exemplars weren't needed
        - the exemplars thus
            - increased Recall
            - but decrease Precision
        - We mentioned another theory in the [In Context Learning theory module (Prompt_Engineering_Suggestions.ipynb#Prompt-Programming-for-Large-Language-Models:-Beyond-the-Few-Shot-Paradigm)]
            - the role of exemplars is to *help locate* the desired task among the tasks seen in training

- Role Prompting and Instructions lead to the biggest increase in performance under Zero shot CoT
    - `Zero-CoT` $\rightsquigarrow$ `+rawinst`
        - `F1`: $81.4 \rightsquigarrow 85.8$
        - Precision: $75.5 \rightsquigarrow 80$
- Placement of Role and Instruction with Query fields is significant
    - Why ? Must not be simple concatenation as I conjectured
    - `Zero-CoT` $\rightsquigarrow$ `bothinst`
        - `F1`: $81.4 \rightsquigarrow 87.5$
        - Precision: $75.5 \rightsquigarrow 81.9$

- Mocked exchange increase Recall
    - `bothinst` $\rightsquigarrow$ `bothinst + mock`
        - Recall: $93.9 \rightsquigarrow 95.1$
        - above the desired 95% Recall threshold for the ultimate metric "precision at 95% recall"

- Repetition in prompts helps ! Combining leads to Final result that dominates all others.
    - Re-iterating instructions (`reit`)
    - Emphasizing Right conclusion (`right`)
    - Emphasizing elminating Reasoning gaps ('info`)

In [2]:
```
print("Done")
```

```
Done
```