



Ai prompt

Perplexity
Burstiness

“

<https://sspai.com/post/96150>
[DeepSeek “” - \(sspai.com\)](#)

[Claude 3.7 Prompt - \(sspai.com\)](#)

[Prompt Engineering \(for Everyday Tasks\) Doesn't Have to Be So Complicated \(readmedium.com\)](#)

There's a way to restrict it—assign it a role.
有一种方法可以限制它——给它分配一个角色。

Assign a role 分配一个角色

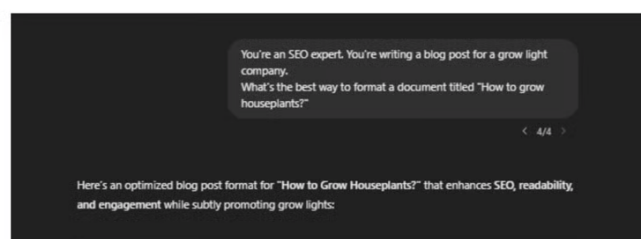
The first and foremost prompt engineering tip is assigning a role. This alone would make tremendous differences in anLLMs response.

提示工程的首要技巧是分配一个角色。仅此一项就能在大型语言模型（LLMs）的响应中产生巨大差异。

Context is the knowledge of your LLM to produce relevant answers.
上下文是你对LLM的了解，以产生相关答案。

Consider this. In the previous section, I asked LLM to write an SEO post about houseplants. What if our post is part of a grow light company's blog? If you're a writer, you'd write a different post with this new contextual information, right? So do an LLM.

考虑这一点。在前一节中，我要求LLM写一篇关于室内植物的 SEO 文章。如果我们的文章是某盏生长灯公司的博客的一部分呢？如果你是一名作家，你会根据这个新的上下文信息写一篇不同的文章，对吧？所以，做一篇LLM。



RAGs | 偷走我的蓝图 --- Steal My Blueprint to Build and Deploy RAGs [In Minutes] | AI Advances (gopubby.com)

Context can be as short as this one, but it can also be an extensive document, a web page, a transcript of a YouTube video, etc. Context sets the stage and provides the required information to produce the correct answer.

上下文可以短到像这样，也可以是广泛的文档、网页、YouTube 视频的转录等。上下文设定了场景并提供所需信息以生成正确答案。

Extended contexts are the basic building blocks of retrieval-augmented generation (RAG), which I have covered in detail in many previous posts.

扩展上下文是检索增强生成（RAG）的基本构建块，我在许多之前的文章中已经详细讨论过。

Steal My Blueprint to Build and Deploy RAGs [In Minutes].

偷走我的蓝图，在几分钟内构建和部署 RAGs。

Most RAGs are built on this stack; why would you redo it every time?

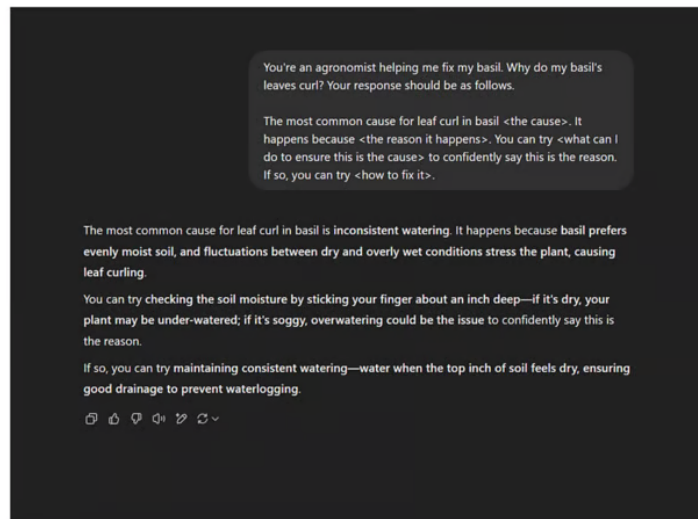
大多数 RAGs 都是基于这个栈构建的；为什么每次都要重新做呢？

Suggest response format

建议回复格式

Here's an example:

这里有一个例子：



In my prompt, I answered the question myself but left placeholders for key information I needed from the LLM.

在我的提示中，我亲自回答了问题，但留下了需要从LLM获取的关键信息占位符。

Provide examples

提供示例

Another popular prompting technique is by providing the LLM with some examples.

另一种流行的提示技术是通过提供一些示例给LLM。

You may have heard terms like zero-shot, one-shot, few-shot, and n-shot learning, which are all related to examples in prompts.

您可能听说过零样本学习、单样本学习、少样本学习和 n 样本学习等术语，这些都和提示中的示例相关。

Zero-shot learning is asking an LLM to answer as it wishes. You don't provide any examples. Giving no examples is okay for open-ended questions like "Why is December colder?". Also, tasks like translation need no examples.

零样本学习是让一个LLM随意回答。你不需要提供任何示例。对于像“为什么十二月更冷？”这样的开放式问题，不提供示例是可以的。像翻译这样的任务也不需要示例。

Other elements of a good prompt (when others would read the response.)

其他良好的提示要素（当其他人阅读回复时。）

Assigning a role, defining a context, and suggesting an output format is always sufficient for me to get a good response. I don't want to complicate things, so I try to stick to these three.

分配一个角色、定义一个上下文以及建议一个输出格式，对我来说总是足够获得良好的回应。我不想让事情变得复杂，所以我尽量坚持这三个步骤。

If you're emailing a customer, the GPT's default response may lack the emotional tone. You might want to convince your customer of a defect on your side, but the GPT might not sound pleasing.

如果您正在给客户发邮件，GPT 的默认回复可能缺乏情感调调。您可能想要说服客户是您这边的缺陷，但 GPT 可能听起来不那么令人愉悦。

Therefore, to ensure a quality response when other people are going to read the responses, I always define the audience, tone, and style.

因此，为确保他人阅读时的响应质量，我总是定义受众、语气和风格。

Audience Specification: Clearly define the audience for the response. This helps tailor the content to their level of understanding, interests, and expectations. Here's how GPT responds when I ask the same question but for a different audience.

受众规范：明确定义响应的受众。这有助于根据他们的理解水平、兴趣和期望来定制内容。以下是我向 GPT 提出相同问题但针对不同受众时，GPT 的响应方式。