Customizing Large Language Models for Legal Consultations

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Abstract. In this paper, we present a novel approach to enhancing the performance of large language models (LLMs) for legal consultation tasks. Our method leverages multi-turn prompt engineering to iteratively refine responses, enabling the model to provide more accurate, legally coherent, and contextually relevant advice. The core of our approach lies in dynamically adjusting the prompt based on previous model outputs, ensuring that the legal reasoning process evolves with each iteration. We evaluate the effectiveness of our method through experiments on a manually curated legal dataset and compare it with multiple baseline approaches. The results demonstrate that our method outperforms existing models across various evaluation metrics, such as legal precision, coherence, and clarity. Additionally, human evaluators consistently rated the outputs generated by our model as more relevant and complete compared to other methods. Our approach shows great potential for real-world legal applications, offering a scalable solution for improving access to legal advice.

Keywords: Large Language Models, Legal Consultation, AI in Law.

1 Introduction

In recent years, large language models (LLMs), particularly those based on transformer architectures such as GPT-3 and GPT-4, have revolutionized a wide range of applications across multiple domains [1]. Among these, the field of legal consultation has seen substantial promise, with LLMs being employed for tasks such as document review, legal research, contract analysis, and decision support [2, 3]. The ability of LLMs to process vast amounts of legal information and generate coherent and contextually appropriate responses has led to significant advancements in automating legal processes, reducing the workload of legal professionals, and providing more accessible legal advice to individuals and businesses. Despite their impressive capabilities, these models still face several challenges when applied to the legal domain, particularly due to the complex, formal, and highly specialized nature of legal language and reasoning [4].

The primary challenge of deploying LLMs in legal consultation is the need for precision and contextual relevance in the generated responses. Legal texts are not only linguistically intricate but also laden with specific jargon, formal structures, and a necessity for exact legal interpretation [5]. General-purpose

models, such as GPT-3, often struggle to meet the stringent requirements of legal applications, leading to issues such as misinterpretation of legal terminology, errors in the application of legal principles, and difficulties in adhering to jurisdictional rules [6]. Furthermore, these models tend to produce responses based on probability distributions from vast training datasets, which may not always align with legal correctness or specific user needs [7]. To address these challenges, it becomes crucial to refine how we interact with and guide these models, particularly through effective prompt engineering.

The motivation for our work is grounded in the recognition that the success of LLMs in legal consultation is significantly influenced by how the queries are presented to the model. A well-crafted prompt can guide the model to better understand the query, providing more relevant and precise answers. Previous studies have shown that prompt design plays a crucial role in controlling the output of language models [8]. Thus, prompt engineering offers a potential solution to enhance the accuracy and reliability of legal consultations performed by LLMs. In this paper, we propose a novel approach to prompt engineering specifically tailored for legal consultation tasks. Our method involves creating dynamic, context-sensitive prompts that adapt based on the legal context of the query and the model's previous outputs. By incorporating domain-specific legal terms, case law references, and contextual information, our approach aims to ensure that LLMs produce responses that are not only linguistically correct but also legally sound.

We further demonstrate the effectiveness of our approach through a series of experiments. We manually curated a dataset of legal queries and tested our prompt engineering strategy using GPT-4, evaluating its performance in various legal consultation scenarios [4]. The results show significant improvements in the relevance and accuracy of the model's responses, particularly in tasks such as contract review and legal reasoning. Our evaluation process also highlights the strengths and limitations of current LLMs in the legal domain, providing valuable insights for future research.

- We propose a dynamic prompt engineering method specifically designed for large language models in legal consultation, which adapts to the context of legal queries.
- We manually collect a dataset of legal queries and apply our method to improve the performance of GPT-4, achieving better results in terms of accuracy and relevance.
- We provide an evaluation of the GPT-4 model, showcasing the effectiveness of our approach and identifying areas for further improvement in legal AI systems.

2 Related Work

2.1 AI for Legal Consultation

The application of artificial intelligence (AI) to the field of legal consultation has garnered increasing attention in recent years due to its potential to streamline

legal processes and improve accessibility to legal services. AI techniques, particularly those based on machine learning and natural language processing (NLP), have been utilized for a variety of legal tasks, including contract analysis, case prediction, and legal research.

Several studies have highlighted the ability of AI systems to enhance the accuracy and efficiency of legal consultations. In particular, AI tools have shown promise in automating repetitive tasks such as document review and case law analysis, providing legal professionals with powerful tools to expedite their work and improve decision-making. For example, some works focus on the use of machine learning models to predict case outcomes based on historical data, allowing for more informed legal advice [9, 10]. Additionally, NLP-based models have been applied to analyze and summarize legal documents, improving the speed of legal research and allowing for more efficient consultations [11].

Furthermore, AI has the potential to democratize access to legal services, especially for underserved populations. Some recent studies explore the role of AI in making legal advice more affordable and accessible by offering automated consultations to individuals who may otherwise be unable to afford traditional legal representation [11]. These advancements are not without challenges, however, as concerns about bias, data privacy, and the ethical implications of AI in legal contexts remain pressing issues [12].

AI-driven systems also face the challenge of navigating complex legal language and ensuring that automated advice adheres to legal standards and norms. Researchers have noted that while AI can provide valuable insights, human oversight is often necessary to ensure the correctness and relevance of the advice generated by AI models [13]. As such, many studies advocate for hybrid systems where AI tools assist legal professionals rather than replace them entirely, facilitating collaboration between human expertise and machine-driven insights.

In addition to these studies, recent works have focused on the limitations of current AI technologies in understanding legal nuances and the need for continuous improvements in model training and fine-tuning to handle the specific demands of the legal domain [14, 15].

2.2 Large Language Models

Large language models (LLMs) have gained significant attention in recent years due to their remarkable success in a variety of natural language processing (NLP) tasks [16, 17]. These models are typically built upon deep learning architectures, with the Transformer and SSM model being dominant frameworks [18]. The foundation of many current LLMs, such as GPT-3, BERT, and Transformer-XL, lies in the Transformer architecture, which has proven to be highly effective in capturing long-range dependencies in text. Notably, [19] introduced the Transformer model, which replaces recurrent networks with self-attention mechanisms and is now the basis for most state-of-the-art language models [20, 21].

BERT [22] and GPT-3 [23] are two seminal works in LLM development. BERT (Bidirectional Encoder Representations from Transformers) utilizes a

bidirectional approach to pre-train language representations, achieving state-of-the-art results across multiple NLP tasks [24, 25]. GPT-3, on the other hand, leverages a massive architecture with 175 billion parameters and showcases impressive performance in few-shot learning, demonstrating the power of large-scale pre-training and fine-tuning.

Moreover, the study of scaling laws for LLMs has provided valuable insights into the trade-offs between model size, data, and computational resources. For instance, [26] demonstrates that the performance of LLMs improves significantly with the increase in model size and dataset, reinforcing the importance of scale in achieving high performance. Additionally, research on specialized architectures, such as Transformer-XL [27], has extended the Transformer model to handle longer sequences, further enhancing the capabilities of LLMs.

The open-source community has also made substantial contributions to the development of LLMs. The EleutherAI group, for example, developed GPT-NeoX, an open-source model designed to replicate the performance of proprietary models like GPT-3 [28]. These efforts aim to make large-scale models more accessible for research and development, enabling broader experimentation and fostering collaboration in the field.

Despite the remarkable success of LLMs, challenges remain in optimizing their performance for specific tasks. While LLMs such as GPT-3 and BERT perform well on a wide range of tasks, they often struggle with domain-specific applications, such as legal consultation, where specialized knowledge and context are crucial. This highlights the need for methods that can fine-tune and adapt LLMs to domain-specific use cases, such as through prompt engineering or further task-specific training.

3 Method

In this section, we introduce a novel approach to improving the performance of large language models (LLMs) in the context of legal consultation through prompt engineering. We propose a multi-turn prompt system designed to iteratively refine the model's responses, addressing the complexity and nuance inherent in legal language. By guiding the model through a series of clarifying questions and responses, our method enables the generation of more accurate, relevant, and legally coherent consultations. The approach is structured around the interactive nature of legal inquiries, where iterative feedback allows the model to refine its responses progressively.

3.1 Multi-Turn Prompt Design

The primary motivation behind the multi-turn prompt design is the need for maintaining context across multiple exchanges in legal consultation tasks. Legal language often contains ambiguities, and single-turn prompts may not capture the necessary context for a precise response. By using multiple rounds of questioning and refinement, we can ensure that the model's response becomes more

focused and accurate as the conversation progresses. Each prompt refines the output step by step, ensuring that the model's reasoning aligns with legal principles and rules.

The multi-turn prompt system begins with an initial query from the user, followed by a response generated by the model. However, the first response might be incomplete, imprecise, or ambiguous, prompting a follow-up question from the system. Subsequent iterations of this dialogue improve the response through incremental refinements. The entire process can be represented mathematically as follows:

$$
\begin{aligned}
P_0 &= \text{Initial User Query},\\
P_1 &= \text{Response from LLM based on initial query,}\\
&\qquad \text{which may be incomplete or ambiguous,}\\
P_2 &= \text{Follow-up prompt designed to clarify or ask for further elaboration,}\\
P_n &= \text{Refined prompts aiming for more accuracy}\\
&\qquad \text{or elaboration based on previous turns.}
\end{aligned}
$$

This iterative refinement continues until the response meets the legal and contextual requirements. The goal of this design is to create a feedback loop in which the model gradually incorporates more details and clarifications, ensuring that the final output reflects both the legal context and the nuances of the query.

3.2 Pipeline Overview

The proposed method operates through a multi-step pipeline, where each stage is crucial for ensuring high-quality legal consultation. The pipeline is composed of the following components:

- **Input Layer**: The system receives an initial legal query, typically phrased as a question concerning legal matters such as case law, statutes, or legal interpretation. This query is encoded into a structured format suitable for processing by the language model.
- **Processing Layer**: At this stage, the language model generates an initial response based on its understanding of the input query. The model uses existing legal knowledge, case law, and relevant precedents to form its response. However, this initial response might not fully address the query due to inherent ambiguities in legal language.
- **Refinement Layer**: The core innovation of our method lies in the iterative refinement process. Here, follow-up prompts are issued to the model, guiding it to elaborate, clarify, and refine its responses. Each prompt is specifically designed to address ambiguities, ensure relevance, and enhance legal accuracy by prompting the model to focus on specific legal aspects that were not sufficiently addressed in the earlier response.

– **Output Layer**: Once the model has iterated through enough refinement steps, the final output is produced. This output contains a detailed, legally sound response, drawing from relevant legal cases, statutes, and established legal principles. It is expected to be both coherent and legally precise, offering the user a robust legal consultation.

The relationship between inputs and outputs at each stage can be formalized as follows:

$$\text{Input} = \text{Initial User Query}, \quad Q_0, \tag{1}$$

$$\text{Intermediate Output} = \text{Legal Reasoning Step}, \quad O_1 = f(Q_0), \tag{2}$$

$$\text{Refined Output} = O_n = g(O_1, P_1, \ldots, P_{n-1}), \tag{3}$$

where f denotes the initial processing by the model, and g represents the iterative refinement based on prior outputs and follow-up prompts.

3.3 Data Collection and GPT-4 as Judge

To evaluate the effectiveness of our approach, we manually curated a specialized dataset comprising a wide range of complex legal queries. The dataset was constructed with input from legal professionals, ensuring the inclusion of various domains such as contract law, intellectual property law, and constitutional law. These queries were selected to test the model's ability to handle diverse legal scenarios and provide contextually appropriate advice.

Instead of relying on traditional evaluation metrics like accuracy or BLEU score, we use GPT-4 as the judge for evaluating the quality of the model's output. Given its advanced natural language understanding and reasoning capabilities, GPT-4 can assess whether the generated responses adhere to legal standards, ensuring correctness and relevance. The evaluation criteria are designed to focus on legal coherence, precision, depth, and iterative improvement, which are critical for legal consultations.

We define four primary evaluation metrics:

– **Legal Coherence**: Measures how well the response adheres to established legal principles and whether the argumentation aligns with legal reasoning. Legal coherence ensures that the model's outputs are logically sound and consistent with the law.
– **Legal Precision**: Assesses whether the generated output correctly applies relevant legal frameworks, including statutes, regulations, and precedents. Precision here refers to the accuracy with which the model incorporates the correct legal details into its response.
– **Reasoning Depth**: Evaluates the depth of legal reasoning in the model's response. Responses that demonstrate deeper reasoning are considered more valuable, as they indicate that the model is engaging with the legal complexities of the query rather than providing superficial answers.

– **Iterative Improvement**: Tracks the improvements in the model's response as it iterates through multiple turns. The goal is to evaluate how well the model improves its output after each feedback step, with a focus on both the richness of the answer and the correction of previous errors.

These metrics are quantified using a scoring function, which combines the various components into a single composite score:

$$S = w_1 L + w_2 P + w_3 D + w_4 I, \tag{4}$$

where L is the legal coherence score, P is the precision score, D is the reasoning depth score, and I is the iterative improvement score. The weights w_1, w_2, w_3, w_4 are determined based on the importance of each criterion in legal consultation tasks.

4 Experiments

In this section, we evaluate the effectiveness of our proposed multi-turn prompt engineering method by comparing it with several state-of-the-art methods in the field of legal consultation. We perform a series of experiments to demonstrate that our approach leads to superior performance, both in terms of traditional evaluation metrics and human judgment.

4.1 Experimental Setup

To assess the effectiveness of our approach, we conduct experiments using the following methods:

– **Baseline 1 (B1)**: A traditional approach using single-turn prompts for legal consultation, without any iterative refinement.
– **Baseline 2 (B2)**: A fine-tuned large language model that uses a pre-defined set of prompts to answer legal questions but without iterative clarification.
– **Baseline 3 (B3)**: A model with limited multi-turn capabilities, where the prompt is refined once based on an initial query, but without further iterations.
– **Our Method (OM)**: The proposed method with multi-turn prompt design and iterative feedback as described earlier.

We evaluate these methods on a manually curated legal query dataset. The dataset includes a diverse set of legal questions from different domains, such as intellectual property law, contract law, and constitutional law. The queries vary in complexity, ensuring that all tested methods are challenged by a broad spectrum of legal scenarios.

4.2 Metrics

We use the following evaluation metrics to compare the performance of the methods:

- **Legal Coherence (LC)**: Measures how well the response adheres to legal principles.
- **Legal Precision (LP)**: Assesses whether the response accurately applies relevant legal details.
- **Reasoning Depth (RD)**: Evaluates the depth of reasoning shown in the response.
- **Iterative Improvement (II)**: Measures the improvements in the model's responses through multiple iterations.

Each of these metrics is scored on a scale from 1 to 5, with higher scores indicating better performance.

4.3 Quantitative Results

The results of our experiments are summarized in Table 1, where we compare our method with the baseline approaches across all evaluation metrics. As shown in the table, our method consistently outperforms the baselines in terms of legal coherence, legal precision, reasoning depth, and iterative improvement.

Method	LC	LP	RD	II
Baseline 1 (B1)	3.1	3.2	3.0	2.5
Baseline 2 (B2)	3.8	3.7	3.5	3.0
Baseline 3 (B3)	4.0	4.1	3.8	3.5
Our Method (OM)	**4.8**	**4.7**	**4.6**	**4.5**

Table 1. Comparison of experimental results across different methods. Our method significantly outperforms the baseline methods in all evaluation metrics.

The quantitative results indicate that our method achieves substantial improvements in all aspects of legal consultation. Notably, the model's ability to refine its responses over multiple iterations leads to a marked increase in both legal coherence and reasoning depth, which are crucial for providing accurate and reliable legal advice.

4.4 Human Evaluation

In addition to the automated evaluation metrics, we also conduct a human evaluation to assess the quality of the generated responses. For this evaluation, we randomly sample 50 queries from our dataset and ask legal professionals to rate the quality of the responses produced by each method. The evaluation is based on the following criteria:

- **Relevance**: How relevant is the response to the legal question?
- **Completeness**: Does the response address all aspects of the query?
- **Clarity**: How clearly is the response written?
- **Legality**: Does the response align with legal standards and principles?

Each criterion is rated on a scale from 1 to 5, with 5 being the best. The average ratings across all criteria are summarized in Table 2.

Method	Relevance	Completeness	Clarity	Legality
Baseline 1 (B1)	3.2	3.0	3.3	3.0
Baseline 2 (B2)	3.7	3.5	3.8	3.6
Baseline 3 (B3)	4.0	3.9	4.1	4.0
Our Method (OM)	**4.7**	**4.6**	**4.8**	**4.7**

Table 2. Human evaluation results for the different methods. Our method is rated significantly higher across all criteria.

The human evaluation results further support the findings from the quantitative experiments, demonstrating that our method provides not only more accurate and relevant legal advice but also more coherent, complete, and legally sound responses. The high ratings in clarity and legality indicate that the iterative refinement process significantly enhances the overall quality of the consultation.

4.5 Iterative Refinement: A Key Strength

One of the most critical advantages of our method is the use of iterative refinement. Traditional single-turn prompt-based models often provide quick answers that may lack the depth needed for complex legal queries. While multi-turn models like Baseline 3 allow for some refinement, they are often limited to a fixed number of iterations, and the prompt refinement is not designed with legal nuances in mind.

In contrast, our method incorporates a dynamic, multi-turn approach that progressively improves the model's understanding of the query. This iterative feedback process is key in refining legal reasoning, enhancing both the precision and legal coherence of responses. Legal consultation often requires complex reasoning, where the initial response may not fully address all legal nuances or may need further clarification. By repeatedly refining the query and response in a controlled manner, our method ensures that the final output is both contextually appropriate and legally sound. This iterative process also aids in addressing ambiguities in user queries, leading to clearer and more accurate legal advice.

4.6 Adaptability to Different Legal Domains

Our approach also stands out for its ability to handle a diverse range of legal domains. Legal consultation can cover a broad spectrum of topics, such as in-

tellectual property law, contract law, family law, and corporate law. Different legal domains require different types of knowledge, reasoning approaches, and contextual understanding.

Our multi-turn prompt method is flexible and adaptable across various domains due to its ability to refine responses based on both the legal context of the question and the iterative feedback process. This makes the model more versatile compared to traditional models, which often need to be fine-tuned on specific legal subdomains to produce accurate responses. Through the iterative process, our model can generate context-aware responses that can easily shift between different areas of law, making it suitable for a wide range of legal consultation tasks.

4.7 Scalability and Efficiency of the Approach

While the iterative nature of our method results in high-quality outputs, it is important to discuss the computational cost of running multiple iterations of the prompt. At first glance, one might assume that our method would be significantly more computationally expensive than single-turn or even traditional multi-turn models due to the repeated query refinement process.

However, the results of our experiments show that the increased computational overhead is minimal in practice, especially when compared to the significant improvements in performance across all metrics. The iterative refinement process can be optimized by limiting the number of iterations required for convergence, thus balancing between performance and computational efficiency. Additionally, given the relatively fast processing power of modern language models like GPT-4, the method remains computationally feasible even when applied to large-scale datasets.

4.8 Human Evaluation and Real-World Applicability

Another key strength of our method is its superior performance in human evaluations. Human raters consistently rated the responses generated by our model as more relevant, complete, clear, and legally sound compared to those produced by baseline models. This is crucial because, in real-world legal consultation, accuracy, clarity, and relevance are of paramount importance. Legal professionals often rely on automated systems for preliminary advice, but the ultimate decision-making process must be based on responses that meet the high standards of the legal profession.

Our method's ability to generate high-quality responses that align with these criteria makes it a promising tool for real-world legal consultation applications. It shows potential not only as a preliminary tool for lawyers and law firms but also as a support system for non-experts seeking legal advice. This is especially important in a world where access to legal counsel may be limited due to cost or geographical constraints. Our method, therefore, has a significant real-world applicability, as it can provide more reliable and accurate legal guidance to a broader audience.

4.9 Limitations and Potential Improvements

Despite the clear advantages, there are still some limitations to our method that warrant consideration. One potential limitation is the inherent reliance on the quality of the initial legal query. If the query itself is ambiguous or poorly framed, the iterative refinement process may struggle to generate the desired level of detail or accuracy in the response. While our method addresses some ambiguities through successive iterations, it is still susceptible to errors introduced by poorly specified queries.

Furthermore, the current setup of our method is based on a fixed sequence of iterative refinements. Although this structure is effective, there may be opportunities for improvement in how we determine when to stop the refinement process. For example, incorporating an adaptive mechanism that evaluates the quality of the response at each iteration and dynamically adjusts the number of required iterations could lead to even better results.

In terms of future work, we could investigate the integration of domain-specific knowledge bases or legal databases that can further enhance the accuracy of the model's legal reasoning. Incorporating these resources could enable the model to make more contextually informed decisions based on specific case law or legal precedents, thus improving its overall legal expertise.

4.10 Broader Impact of Legal AI

The broader impact of our work lies in the potential of large language models to democratize access to legal advice. By improving the quality of AI-generated legal consultations, we can help bridge the gap for people who do not have easy access to legal professionals. This is especially important for individuals in underserved or remote areas where legal services are scarce.

Moreover, as AI becomes increasingly involved in legal decision-making, it is crucial that the technology remains transparent, accountable, and aligned with ethical standards. Our method, by leveraging iterative refinement, ensures that the reasoning process is both more transparent and understandable, which is a step toward building trust in AI-assisted legal systems. Nevertheless, further research is required to address the broader ethical considerations of deploying AI in legal settings, especially concerning privacy and bias.

5 Conclusion

In this work, we introduced an innovative approach to utilizing large language models for legal consultation tasks by employing iterative, multi-turn prompt engineering. Our method enhances the model's ability to generate accurate, relevant, and legally sound responses by refining the prompt iteratively based on previous outputs. Through a comprehensive evaluation, we demonstrated that our method surpasses traditional models, yielding superior results in terms of legal coherence, precision, and relevance. Moreover, human evaluations further

reinforced the effectiveness of our approach, showing that the responses generated by our method were not only legally correct but also clear and contextually appropriate.

Despite the promising results, there are still opportunities for future research. One potential direction is to explore more advanced techniques for dynamically adjusting the number of iterations required, possibly incorporating feedback from external legal databases or case law to enhance model accuracy. Additionally, we aim to explore the integration of ethical guidelines and transparency mechanisms to ensure that our system can be trusted in real-world legal applications. The impact of this work lies in its ability to democratize access to legal advice, particularly for individuals and communities that are underserved by traditional legal services, making legal consultation more accessible and efficient.

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