# LawLLM: Law Large Language Model for the US Legal System

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### 1 Introduction

The development of Large Language Models (LLMs) has led to significant progress in computational linguistics, particularly impacting fields like legal analytics. Given the nature of legal language, which includes complex terminologies and context-specific logical frameworks, LLMs offer unprecedented capabilities in this domain [21]. The integration of LLMs into the legal field significantly boosts the efficiency of legal practitioners, such as lawyers and judges, by accurately interpreting their natural language input and generating most relevant responses. This reduces the need for extensive manual review of huge legal texts. Moreover, LLMs can provide lawyers with novel insights, revealing overlooked details and perspectives that can be critical in complex cases. Recent developments in legal domain have demonstrated the potential of LLMs in enhancing legal judgment predictions and handling various legal tasks effectively. For example, studies such as LM-CompEval-Legal [26] have systematically evaluated the effectiveness of LLMs, other projects like PLJP [33] and LoT [11] have focused on integrating domain-specific models and advancing LLMs' understanding of legal reasoning.

Although these models have shown promise, there remain research challenges. First, these models generally address single-task challenges. In contrast, LawLLM innovatively supports multiple legal tasks simultaneously, providing a more nuanced analysis of complex legal datasets and filling a critical void in the field. Second, another controversial area in the legal domain is the difference between precedent cases and similar cases [22]. Various models have been developed for precedent case recommendation, ranging from expert knowledge-based models to models based on natural language processing [2, 16, 18, 20]. These approaches typically convert legal text into embeddings and calculate similarity at the embedding level, which aids in precedent selection. However, we believe that this approach is more on identifying similar cases with textual and contextual similarities, not precedent cases.

In our study, we emphasize the key differences between the two. Firstly, a precedent case must have been closed before the input legal case, ensuring its relevance and applicability to the current case under consideration. Secondly, precedent cases are those that

# Abstract In the rapid

In the rapidly evolving field of legal analytics, finding relevant cases and accurately predicting judicial outcomes are challenging because of the complexity of legal language, which often includes specialized terminology, complex syntax, and historical context. Moreover, the subtle distinctions between similar and precedent cases require a deep understanding of legal knowledge. Researchers often conflate these concepts, making it difficult to develop specialized techniques to effectively address these nuanced tasks. In this paper, we introduce the Law Large Language Model (LawLLM), a multi-task model specifically designed for the US legal domain to address these challenges. LawLLM excels at Similar Case Retrieval (SCR), Precedent Case Recommendation (PCR), and Legal Judgment Prediction (LJP). By clearly distinguishing between precedent and similar cases, we provide essential clarity, guiding future research in developing specialized strategies for these tasks. We propose customized data preprocessing techniques for each task that transform raw legal data into a trainable format. Furthermore, we also use techniques such as in-context learning (ICL) and advanced information retrieval methods in LawLLM. The evaluation results demonstrate that LawLLM consistently outperforms existing baselines in both zero-shot and few-shot scenarios, offering unparalleled multi-task capabilities and filling critical gaps in the legal domain. Code and data are available at https://github.com/Tizzzzy/Law LLM.

## **CCS** Concepts

• Applied computing  $\rightarrow$  Law; • Computing methodologies  $\rightarrow$  Natural language processing; Multi-task learning; • Information systems  $\rightarrow$  Top-k retrieval in databases.

### Keywords

Large Language Models, Multitask Learning, Legal System, Natural Language Processing

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Figure 1: LawLLM supports three tasks: Similar Case Retrieval, Precedent Case Recommendation, and Legal Judgment Prediction.

were actually considered by judges in making their decisions, unlike similar cases which might not have been taken into account. Thirdly, similar cases share textual and thematic similarities in the case narrative or might fall into similar case categories, while precedent cases might seem unrelated at face value. It is also worth noting that while a legal case's precedent case can sometimes be the same as a similar case, this is not always the case.

In this paper, we introduce the Law Large Language Model (LawLLM), a multi-task LLM capable of Similar Case Retrieval (SCR), Precedent Case Recommendation (PCR) and Legal Judgment Prediction (LJP). To build LawLLM, we finetune Gemma-7B [29] using instruction tuning on United State real-life legal datasets and can perform LJP, PCR, and SCR tasks. The instructions for all three tasks fall under the classification category. By doing so, we can effectively minimize irrelevant and noisy options for the model, thereby improving its performance. We show the overall idea of LawLLM in Figure 1. The development of LawLLM also includes three innovative preprocessing approaches for transforming unstructured legal data into a trainable format. More specifically, for LJP, we summarize and extract verdicts from raw datasets and apply zero and few shot In-context learning (ICL) [13, 36] technique to enhance the model performance. In PCR, LawLLM connects ground truth legal cases' precedent relationships as a Knowledge Graph (KG), treating each case as a unique entity linked by precedential connections [25]. Additionally, the SCR task creates a legal case vector database and integrates advanced Information Retrieval (IR) techniques [8, 12].

Our study presents LawLLM as a pioneering model in the realm of legal LLMs. Our key contributions are given as follows:

- We propose LawLLM, which is adept at handling a range of legal tasks, including LJP, PCR, and SCR. This multi-task functionality is important in addressing the diverse requirements of the legal domain.
- LawLLM distinguishes between precedent cases and similar cases, providing clarity on the objectives of each task. This clarification enables the future research to develop tailored strategies for those tasks.

• Experimental results indicate that LawLLM outperformed all baseline models, including the GPT-4 model, across all three tasks. These results highlight LawLLM's robust capabilities in the legal domain.

### 2 Related Work

Legal AI is significantly increasing the efficiency and effectiveness of the legal community. AI technologies, specifically Large Language Models (LLMs), are leading the way in automating complex tasks like document analysis, case prediction, and legal research [34, 38]. LLMs utilize advanced algorithms and data analytics to process and generate legal texts, which leads to significant improvements in speed and accuracy [39]. In this section, we introduce the various applications of Legal AI and LLMs in legal practices.

### 2.1 Precedent Case Recommendation

The recommendation of precedent cases is a fundamental aspect of legal practice, as previous verdicts significantly affect current legal decisions. The field has evolved from early keyword-based searches and manual annotations to more complicated AI-driven models that improve retrieval efficiency and contextuality. Wu et al. [34] proposed the Precedent-Enhanced Legal Judgment Prediction framework, which combines LLMs with domain-specific expertise to improve legal prediction accuracy significantly. Ma et al. [17] developed the Structured Legal Case Retrieval system, which uses structural information from legal documents to improve case search precision and contextual relevance. Moreover, Su et al. [27] proposed the Caseformer. This innovative pre-training framework learns from a vast corpus of legal texts to refine case retrieval and contextualization across multiple languages.

### 2.2 Similar Case Retrieval

Besides precedent recommendation, retrieving similar cases, those sharing analogous facts or legal issues, is crucial for comprehensive legal analysis and strategy formulation. Traditionally, this process required extensive manual labor, with professionals needing to dig through large case databases [17, 19]. Today advances in NLP and machine learning have transformed this task, allowing semantic content extraction and comparison across documents. Kang et al. [14] enhanced similarity-based retrieval by incorporating associative knowledge. This approach refines retrieval outcomes by leveraging similarity and associative analyses, a technique also proven effective in other fields such as medical diagnosis and IT service management. Mandal et al. [19] analyzed textual similarity techniques on an Indian Supreme Court dataset and discovered that traditional methods like TF-IDF outperform modern contextaware models like BERT. Wu et al. [32] studied semantic retrieval in the Chinese judicial system and developed a model that generates knowledge graphs for cases to improve trial accuracy and fairness. These technological advances have greatly simplified legal research, making it more effective and comprehensive.

### 2.3 Legal Judgment Prediction

Predicting legal judgments involves estimating potential verdicts based on a deep analysis of historical data and established legal standards. Initial models in this field were relatively simple, mainly



Figure 2: An overview of our LawLLM: Data Preprocessing is in the upper left in green, Similar Case Retrieval Processing is in the upper right in yellow, Precedent Case Recommendation is in the lower left in red, and Legal Judgment Prediction is in the lower right in blue.

depending on linear algorithms incapable of capturing the various aspects of legal reasoning. Wang and Jin [31] CNN-BiGRU multi-task learning model improves prediction accuracy through the utilization of shared information from related legal subtasks. Chalkidis et al. [3] used European Court of Human Rights data to establish robust performance benchmarks for long legal texts using hierarchical BERT. Rusnachenko et al. [23] showed attentionbased methods could improve system performance by optimizing document preprocessing and attention mechanisms in competition contexts. These models predict outcomes and are constantly learning from new cases to improve their accuracy, demonstrating the adaptability of LLMs in legal judgment prediction.

### 2.4 LLMs in the Legal Domain

Prior to the development of large language models (LLMs), pretrained language models (PLMs) for specific domains were explored, such as Lawformer, which is to process lengthy Chinese legal documents using a Longformer-based architecture [35]. Researchers discovered that models like GPT-4 could successfully pass bar exams as LLMs gained attention, demonstrating profound abilities in legal reasoning and text generation [15]. This success resulted in the growth of legal domain-specific LLMs, such as Chatlaw, which utilizes conversational AI to improve user interactions with legal systems [5]. In this vein, SaulLM-7B was introduced as the first LLM explicitly designed for comprehending and generating legal texts, leveraging a substantial legal corpus to achieve state-of-the-art performance [4]. LLMs' influence extends beyond specific tasks to broader legal operations. These applications range from document automation, where LLMs assist in drafting and reviewing legal documents, to compliance monitoring, which ensures adherence to regulatory standards [28]. LLMs simplify complex legal processes

for non-specialists and lower barriers to legal advice [9]. This broad application of LLMs demonstrates their broad application and the potential for continued innovation in the legal sector.

Despite the success of those contemporary works, these models primarily focus on utilizing LLMs' understanding and capabilities to perform general legal question answering. However, LawLLM is designed to leverage the LLMs' comprehension and learned abilities to predict and perform specific tasks within the legal domain.

## 3 Methodology

In this study, we propose the Law Large Language Model (LawLLM) to address three critical tasks within the legal domain: Similar Case Retrieval (SCR), Precedent Case Recommendation (PCR), and Legal Judgment Prediction (LJP). Our methodological framework, illustrated in Figure 2, is divided into four distinct parts: Data Preprocessing, SCR Processing, PCR Processing, and LJP Processing.

### 3.1 Data Preprocessing

Our approach begins with the systematic collection of case data from legal databases, denoted as  $\mathcal{D}$ . We make sure all collected raw case data,  $d_i \in \mathcal{D}$ , encompasses a variety of information as below:

$$d_i = \{\text{Title, Date, Judge, Plaintiff(s), Plaintiff's Attorney(s), Defendant(s), Defendant's Attorney(s), Case Detail, (1) Precedent Relationship}.$$

As depicted in the upper left of Figure 2, data preprocessing consists of three primary steps:

**Step 1.** Given the voluminous nature of the textual content within case detail and their often implicit verdicts, we utilize a GPT-4 [1]

model to extract core information and summarize each case. This step reduces information overload and ensures the adaptability of our dataset to the constraints of Gemma, particularly with token size limitations. The GPT-4 preprocess instruction is shown here:

*I have a legal case description and require two distinct pieces of information:* 

1. Summary: Please provide a detailed summary of the case, focusing on the facts and events. Exclude any information about the verdict.

2. Verdict: State the verdict of the case, consider the following categories:

- Plaintiff win

- Defendant win

- Settlement

- Case dismissal

- Unsure

If the verdict is mentioned, respond exclusively with the chosen categories ONLY. If the outcome is not explicitly mentioned or cannot be inferred from the information given, please respond with 'unsure' only. Format your responses as follows: # - For the summary, begin with 'Answer 1:' # - For the verdict, start with 'Answer 2:' Here is the description of the case: [Case Description...]

The output of this step includes a summarized case and a labeled verdict, formatted as follows:

Case Summary, Verdict = LLM(Case Detail, Maximum Token  $| d_i$ ). (2)

For each legal case  $d_i$ , we reorganize the data into a new format  $d'_i$ , defined as:

$$d'_i = \{\text{Title, Date, Judge, Plaintiff(s), Plaintiff's Attorney(s),}\}$$

Defendant(s), Defendant's Attorney(s), Case Summary}.

$$D' = \left\{ \left( d'_1, v'_1 \right), \left( d'_2, v'_2 \right), \dots, \left( d'_n, v'_n \right) \right\}.$$
(4)

(3)

There are some constraints when we separate the D' into training and testing data. We make sure that all legal cases have at least five precedent relationships. To ensure a balance training, the training dataset has 25% from each of the following categories: plaintiff wins, defendant wins, settlements, and case dismissals. We also make sure that all testing legal cases have at least five precedent relationships connect to the training dataset, further explanation is given in Section 4.1 Data Splits.

**Step 2.** After Step 1, all training legal cases  $d'_i$  are transformed into high-dimensional vectors using the OpenAI Embedding model. This vector database is later used to retrieve the top-*k* similar cases based on semantic and contextual similarities.

**Step 3.** This step involves converting the precedent case relationships from our training dataset into a knowledge graph (KG). Defined as KG = (E, R, L), where *E* represents entities, *R* represents binary relationships (indicative of precedent relations), and

 $L \subseteq E \times R \times E$  represents the set of triples forming the graph's edges. Each triple  $(e_s, r, e_t) \in L$  indicates a directed edge from source entity  $e_s$  to target entity  $e_t$  via relationship r. The KG data structure simplifies the complex task of identifying relevant precedent cases, turning it into a entity prediction problem, i.e., given a query of

We further customize data processing for SCR, PCR, and LJP tasks, ensuring a robust and effective implementation of LawLLM.

 $(e_s, r, ?)$ , the model will predict the missing entity.

### 3.2 Similar Case Retrieval

As depicted in the upper right of Figure 2, the SCR process is divided into two phases: training (Steps 1-2) and testing (Steps 3-4).

**Training Phase.** During training, each training case  $d'_i$  is inputted into the vector database, which generates the top 10 candidate cases. These cases are then randomized in order and formulated into the SCR training instruction. Here is an example SCR model input:

#### ### Instruction:

You are a legal expert who specializes in comparing usersupplied legal cases to a list of candidate legal cases, which includes titles and content. Your main function is to identify and output the title of the most similar case from the list based on the description provided. You should only output the case title and not any other information. Consider the following choices: Choice 1: [Case 1...] Choice 2: ... Choice 10: [Case 10...] ### Input: [Input Case...]

In this scenario, the SCR task instruction will fall into the classification category, which provides the model with 10 cases to choose the most similar one. It is important to note that the top-0 similar case is the case  $d'_i$  itself, so in practice, we retrieve the top-1 to top-10 similar cases from the vector database, and the top-1 case from this selection serves as the ground truth for this training task.

**Testing Phase.** The testing phase mirrors the training process as we initially retrieve the top 10 similar cases from the vector database. However, during testing, we retrieve cases ranked from top-0 to top-9, as the test case itself is not included in the vector database. The model's expected response depends on the evaluation metrics we use: top-1, top-3, and top-5. For the top-1 metric, we expect LawLLM to identify the most similar case as the top result. The top-3 metric evaluates whether the model's answer falls within the top three retrieved candidates, while the top-5 metric extends this evaluation to include the top five candidates.

### 3.3 Precedent Case Recommendation

The Precedent Case Recommendation (PCR) within LawLLM utilizes a unique approach by employing a precedent case knowledge graph (KG), which differentiates itself from conventional PCR methods LawLLM: Law Large Language Model for the US Legal System

that often speculate on potential precedent relationships. Our system instead relies on confirmed precedent pairs, as illustrated in the lower left of Figure 2, where Steps 1 and 2 constitute the training phase and Steps 3-5 are the testing phase.

**Training Phase.** From the previously established KG, for each confirmed triple  $(e_s, r, e_t)$ , we utilize BERT embeddings [7] to evaluate the similarity between various case features (e.g., Judge, Case Detail, Plaintiff, or Defendant), denoted as  $\{F_1, F_2, ..., F_j\}$ . We calculate the similarity score  $S_i$  for each feature pair  $F1_i$  and  $F2_i$ , as follows:

$$S_i = \sin(BERT(F1_i), BERT(F2_i)),$$
  
$$i \in \{1 - j\}$$
(5)

The highest similarity score across all features determines the primary factor underlying their precedent relationship:

Primary Factor = 
$$\max(S_1, S_2, ..., S_j)$$
. (6)

During the training input creation, we present a total of 10 choices for the model. The ground truth precedent case  $e_t$  is randomly placed among these choices, with the other 9 selections filled with similar, yet non-precedent, cases from the vector database. This setup aims to teach the model that textual similarity does not necessarily imply a precedent relationship. The model's expected output includes the correct precedent case  $e_t$  and the reasoning for its selection (i.e, which primary factor caused this precedent relationship). An example of the model input is:

### Instruction:

You are a legal expert who specializes in comparing usersupplied legal cases to a list of candidate legal cases, which includes titles and content. Your main function is to identify and output the precedent case from the list based on the description provided. You should only output the reasoning process and case title. Consider the following choices: Choice 1: [Case 1...] Choice 2: Choice 10: [Case 10...] ### Input: [Input Case...] Testing Phase. For each test case, since we made sure there are at

least five precedent cases in the training dataset, we can identify k precedent cases from the KG (which structured by the training dataset) as ground truths, where k aligns with the top-k evaluation metrics. For the top-1 metric, a single ground truth precedent case is selected, while for top-3 and top-5 metrics, 3 and 5 ground truths are selected, respectively. The remaining slots of 10 - k are filled with similar cases. The model is then tasked with selecting one of k precedent cases and explaining the reasoning behind its choice.

## 3.4 Legal Judgment Prediction

The Legal Judgment Prediction (LJP) processing utilizes the dataset D' constructed during the data preprocessing stage. This dataset

pairs each processed legal case  $d'_i$  with its corresponding verdict  $v'_i$ . As illustrated in the lower right of Figure 2, the training phase involves step 1 and the testing phase involves rest of steps.

**Training Phase.** We use  $(d'_i, v'_i)$  to establish a four-category classification training input, Plaintiff wins, Defendant wins, Settlement, or Case Dismissal. Each case's corresponding verdict  $v'_i$  serves as the label for training. Here is an example of the model input:

#### ### Instruction:

You are a legal expert who specializes in predicting outcomes for legal cases. Utilize your internal knowledge base to predict verdict. Your main function is to anticipate the likely verdict of the legal case presented by the user. You should only output the verdict and not any other information. Consider the following choices: 1. Defendant Wins 2. Plaintiff Wins 3. Settlement 4. Case Dismissal ### Input: [Input Case...]

**Testing Phase.** During the testing phase, we evaluate LawLLM with both zero-shot and few-shot in-context learning (ICL) scenario. In few-shot ICL, we enhance each test case  $d'_i$  with additional contextual information, one similar case and one precedent case. Its precedent cases is sourced from our KG, and one is randomly selected to be included in the test input. Simultaneously, a most similar case is retrieved from the vector database. This approach ensures that the model's predictions are influenced by relevant legal precedents and similar case facts, thereby improving the accuracy and reliability of the judgment predictions.

### 3.5 Unified Model Fine-Tuning

Our methodology involves a unified fine-tuning strategy for the LawLLM, leveraging a combined dataset with three tasks. This dataset, denoted as Dataset<sub>combined</sub> = LJP $\oplus$ PCR $\oplus$ SCR. We employ a cutting-edge 4-bit quantized Low-Rank Adaptation (LoRA) technique to instruction fine-tune the Gemma model. We use the cross-entropy loss function *L* during the LoRA. It calculates the difference between the model's predicted token probabilities and the actual token probabilities in the expected output sequence. In the following equation, *n* represents the length of the expected output sequence, *x* represents the input instruction, and *y<sub>i</sub>* denotes the i-th token in the expected output sequence.

$$L = -\sum_{i=1}^{n} \log P(y_i | x, y_1, y_2, ..., y_{i-1}).$$
<sup>(7)</sup>

## 4 Experiments

In this section, we conduct experiments to evaluate the performance of LawLLM on three tasks: Similar Case Retrieval (SCR), Precedent Case Recommendation (PCR), and Legal Judgment Prediction (LJP).

#### 4.1 Experimental Setup

**Datasets.** We conduct our experiments on the CaseLaw dataset, initiated by Harvard Law School's Library Innovation Lab as part of the CaseLaw Project [10]. This database encompasses a wide range of court cases from both state and federal in the United States. The project primarily focuses on democratizing access to American legal information, particularly through its Case Access Project (CAP), which is aimed at providing free and public access. The statistics of the CaseLaw dataset used in our experiments are shown in Table 1.

Table	1:	Datasets	Statistics
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DATASETS	CaseLaw
Language	English
# State and Federal Totals	6,930,777
# Train case	1,00,000
# Test case	200,000
Avg. length per case (words)	2695.38

**Evaluation Metrics.** As previously mentioned, we employ top-*k* metrics to evaluate the performance of the SCR and PCR tasks. Specifically, we use top-1, top-3, and top-5 metrics. These metrics measure the model's precision in identifying the correct response from a pool of 10 choices. For example, the top-1 metric requires the model to return the top choice as the answer. The top-3 and top-5 metrics provide more flexibility, allowing the correct answer to be anywhere within the top three or top five choices, respectively.

In addition to top-*k* metrics, we evaluate the hallucination rate of models using a 'not-found' metric. This metric tracks the proportion of responses that are entirely fabricated and do not match any of the 10 given choices. By measuring the 'not-found' rate, we aim to understand how often models produce answers unrelated to the provided options, offering insight into their reliability.

For the LJP task, we employ accuracy and F1-score [24] metrics to gauge the model's performance. Accuracy calculates the proportion of correctly predicted verdicts across all cases, providing a direct measure of overall prediction performance. The F1 score ranging from 0 to 1, combines precision and recall into a single harmonic mean, offering a balanced evaluation of the model's effectiveness.

**Data Splits.** As previously noted, our data are split according to three constraints.

- **Constraint 1:** For PCR, we employ top-*k* evaluation metrics, which means each case has to have a minimum of five precedent cases, allowing us to identify *k* ground truths.
- **Constraint 2:** We must ensure that when a test case is evaluated, its ground truth precedent case can be located within the knowledge graph formed by the training cases. Therefore, each test case must have at least five precedent cases present in the training data.
- **Constraint 3:** To ensure balanced model training for Legal Judgment Prediction (LJP), the training data's verdict distribution should consist of 25% for each possible outcome: plaintiff wins, defendant wins, settlements, and dismissals.

These approaches result in a total of 1,000,000 cases for training and 200,000 cases for testing.

**Comparing Baselines.** Our model is evaluated against advanced baselines including LLaMa2-7b [30], Gemma-7b [29], Vicuna-13b [37] and Guanaco-13b [6], alongside the larger and more advanced GPT-3.5 and GPT-4 models [1]. Each model undergoes the same testing phase to ensure a consistent and fair comparison of their multi-task capabilities within the legal domain.

**Implementation Details.** We conducted the training of our model over 10 epochs using an A40 GPU. To ensure compatibility, we monitored the input token size, capping it at 4096 tokens to align with Gemma's maximum token capacity. Additionally, we configured the model's dropout rate at 0.1 and set the learning rate to  $2e^{-4}$ .

### 4.2 Similar Case Retrieval Results

According to Table 2, LawLLM outperformed the baseline models in all categories. Specifically, it achieved the highest accuracy in top-1, top-3, and top-5 retrieval rates, with scores of 29.8%, 63.2%, and 81.6% respectively. Remarkably, it also demonstrated minimal hallucination, as indicated by the not-found rate of 0.1%.

**Table 2: SCR Test Results** 

Method	top-1↑	top-3↑	top-5↑	Not Found $\downarrow$
llama2-7b	0.083	0.197	0.309	0.406
gemma-7b	0.181	0.428	0.536	0.121
vicuna-13b	0.185	0.372	0.564	0.187
guanaco-13b	0.077	0.214	0.375	0.372
gpt3.5	0.219	0.579	0.691	0.148
gpt4	0.274	0.526	0.708	0.005
LawLLM	0.298	0.632	0.816	0.001

Comparatively, GPT-4 showed strong performance with top-1, top-3, and top-5 accuracies of 27.5%, 52.5%, and 70.5%, and a low not-found rate of 0.5%. GPT-3.5 also performed well, especially in the top-3 and top-5 metrics. On the other hand, models like LLaMa2-7b and Guanaco-13b displayed higher not-found rates, indicating a tendency towards hallucination.

The results underscore the effectiveness of our LawLLM model in accurately retrieving similar cases while minimizing the risk of generating irrelevant or nonexistent cases.

#### 4.3 Precedent Case Recommendation Results

According to Table 3, the LawLLM model again outperformed other baseline methods. It achieved the best results with a top-1 rate of 31.8%, top-3 rate of 59.7%, and top-5 rate of 83.2%. Additionally, the LawLLM model exhibited an low not-found rate of 0.1%.

Among the baseline models, GPT-4 was a strong performer, with high accuracy in top-1, top-3, and top-5 metrics, alongside a very low not-found rate, suggesting reliable and accurate recommendations. In contrast, models like LLaMa2-7b and Guanaco-13b showed higher not-found rates, highlighting challenges in providing relevant case recommendations. The overall results demonstrate the effectiveness of the LawLLM model in PCR task, outstripping baseline models in both accuracy and reliability. LawLLM: Law Large Language Model for the US Legal System

Table 3: PCR Test Results

Method	top-1↑	top-3↑	top-5↑	Not Found $\downarrow$
llama2-7b	0.069	0.148	0.343	0.479
gemma-7b	0.187	0.386	0.519	0.124
vicuna-13b	0.175	0.352	0.506	0.203
guanaco-13b	0.073	0.198	0.357	0.383
gpt3.5	0.154	0.325	0.504	0.165
gpt4	0.262	0.514	0.697	0.007
LawLLM	0.318	0.597	0.832	0.001

One notable insight from comparing SCR and PCR results is that most baseline models exhibited a performance drop in the PCR task compared to SCR. For instance, the GPT-4 model achieved scores of 27.4%, 52.6%, 70.8%, 0.5% in SCR top-k and "Not Found" metrics, while in the PCR task, its scores dropped to 26.2%, 51.4%, 69.7% and 0.7%. This decline underscores the greater difficulty of identifying precedent cases compared to similar cases, as models cannot rely solely on textual similarity when determining precedent relationships. Instead, they must consider nuanced factors such as legal relevance. This performance difference reinforces the our previous assertion that precedent cases are distinct from similar cases, emphasizing the importance of distinguishing between the two concepts in the legal domain.

We conducted an analysis to identify the factors that are predominantly considered by LawLLM when determining a precedent relationship under the top-1, top-3, and top-5 settings. This analysis involves comparing the frequency with which each factor is chosen as the primary determinant in our model against the ground truth (GT) distribution. As shown in Table 4, the GT distribution is heavily weighted towards the 'Case Detail' factor, with some toward other factors. In the top-1 scenario, where there is only one correct precedent case among nine similar cases, our model strongly focuses on the 'Case Detail' factor. This bias likely stems from the GT distribution's heavy emphasis on 'Case Detail,' leading our model to prioritize this factor, especially when faced with numerous similar cases that serve as potential distractions. However, as the pool of correct answers expands to three and five in the top-3 and top-5 scenarios respectively, LawLLM begins to diversify its focus slightly to include other factors, although 'Case Detail' continues to dominate. This trend indicates a move towards a more balanced approach in factor consideration as the number of correct choices increases, suggesting that LawLLM adjusts its focus based on the availability of correct answers, while still reflecting the main emphasis observed in the ground truth data.

### 4.4 Legal Judgment Prediction Results

As shown in Table 5, the LawLLM surpasses all baseline methods in both zero-shot and few-shot scenarios for the LJP task. In the zeroshot scenario, LawLLM achieves an accuracy of 0.636 and an F1 score of 0.591, significantly outperforming the second best model, GPT-4, which scores 0.573 and 0.563 in accuracy and F1, respectively. In the few-shot scenario, LawLLM maintains its superior performance, reaching an accuracy of 0.794 and an F1 score of 0.758. CIKM '24, October 21-25, 2024, Boise, ID, USA

**Table 4: Primary Factor Percentage Comparison** 

Factor	LawLLM top-1	LawLLM top-3	LawLLM top-5	GT
Title	0.000	0.000	0.000	0.000
Date	0.000	0.000	0.000	0.000
Judge	0.027	0.054	0.116	0.149
Plantiff(s)	0.002	0.009	0.013	0.027
Defendent(s)	0.004	0.012	0.025	0.041
Case Detail	0.967	0.925	0.846	0.783

These results show a considerable improvement over GPT-4, the closest competitor, which scores 0.732 in accuracy and 0.712 in F1.

Additionally, all models demonstrate higher performance in the few-shot in-context learning (ICL) scenario compared to the zeroshot setting. For instance, LLaMA2-7b shows an increase from 0.235 to 0.473 in accuracy, and from 0.239 to 0.455 in F1 score. This pattern indicates that all models benefit from incorporating a few ICL examples, which helps them better understand the task.

**Table 5: LJP Test Results** 

Method	Accuracy ↑ (Zero-shot)	F1 ↑ (Zero-shot)	Accuracy ↑ (Few-shot)	F1 ↑ (Few-shot)
llama2-7b	0.235	0.239	0.473	0.455
gemma-7b	0.317	0.287	0.568	0.527
vicuna-13b	0.503	0.432	0.645	0.594
guanaco-13b	0.281	0.247	0.491	0.463
gpt3.5	0.558	0.546	0.679	0.647
gpt4	0.573	0.563	0.732	0.712
LawLLM	0.636	0.591	0.794	0.758

#### 5 Conclusions and Future Work

In this study, we introduced the Law Large Language Model (LawLLM), a multi-task LLM specifically designed for the US legal domain. By leveraging unique data processing techniques tailored for each task, LawLLM effectively handles Similar Case Retrieval (SCR), Precedent Case Recommendation (PCR), and Legal Judgment Prediction (LJP). Furthermore, we emphasized the crucial distinctions between precedent relationships and textual similarity, providing insights that can inform future research in developing task-specific models. Our results consistently demonstrated that LawLLM outperforms existing baseline models, showcasing its superior multi-task capabilities.

In the future, we aim to expand the scope of LawLLM by incorporating additional legal tasks to further enhance its versatility and practical applicability. This will involve exploring emerging challenges in legal analytics and integrating new datasets that reflect diverse legal contexts. Moreover, we plan to refine our data processing techniques and in-context learning methodologies to improve the model's understanding of legal nuances and precedents. CIKM '24, October 21-25, 2024, Boise, ID, USA

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LawLLM: Law Large Language Model for the US Legal System

# A Appendix

# A.1 The Choice of 10

According to Table 6, we have several reasons for giving 10 choices to the model in the Similar Case Retrieval (SCR) and Precedent Case Recommendation (PCR) tasks:

- Given that we utilize top-*k* evaluation metrics where *k* is 1, 3, and 5, the number of choices must be greater than 5.
- Our exploration revealed that when the number of choices exceeds 11, some inputs surpass the maximum token length of the Gemma model. Thus, the appropriate range for the number of choices lies between 6 and 11.
- We randomly selected 1,000 test cases to evaluate the performance of LawLLM. From Table 6, we observe that with 6 or 7 choices, the model's performance in top-5 metric approaches 100% due to the limited challenge of smaller sets. Therefore, 6 or 7 choices are not the optimal option. Also, "Not Found" cases only emerge when the choice size reaches 9 in PCR tasks and 10 in SCR tasks. Ultimately, we chose 10 as the optimal size, as the model perform similarly, and it provides more challenge to the model.

CIKM '24, October 21-25, 2024, Boise, ID, USA

Table 6: Choice Size Results

Method	top-1	top-3	top-5	Not Found
6 Choices (SCR)	0.493	0.857	0.998	0.000
7 Choices (SCR)	0.461	0.814	0.982	0.000
8 Choices (SCR)	0.427	0.779	0.916	0.000
9 Choices (SCR)	0.354	0.625	0.873	0.000
10 Choices (SCR)	0.329	0.602	0.848	0.001
11 Choices (SCR)	0.305	0.571	0.814	0.001
6 Choices (PCR)	0.478	0.831	0.994	0.000
7 Choices (PCR)	0.431	0.807	0.973	0.000
8 Choices (PCR)	0.417	0.742	0.906	0.000
9 Choices (PCR)	0.362	0.665	0.878	0.001
10 Choices (PCR)	0.323	0.609	0.839	0.001
11 Choices (PCR)	0.296	0.584	0.812	0.001

# A.2 Examples

To help readers better understand our tasks, we have included example inputs and outputs for each task. Please refer to Table 7-18.

# Table 7: SCR Example

Input	Output
<pre>### Instruction: You are a legal expert who specializes in comparing user-supplied legal cases to a list of candidate legal cases, which includes titles and content. Your main function is to identify and output the title of the most similar case from the list based on the description provided. You should only output the case title and not any other information. Consider the following choices: Choice 1:</pre>	### Response: BISHOP v. STEWART.
 Choice 2:	
 Choice 3:	
 Choice 4: Case Title: BISHOP v. STEWART Date: Nov 12, 1940 Court: District Court, E.D. Pennsylvania Judge: Hopkinson Plaintiffs: Bishop Priest, alias Lewis Johnson Defendants: Commodore Charles Stewart Case detail: This case involved a habeas corpus petition addressed to Commodore Stewart, requiring him to produce the body of Bishop Priest, alias Lewis Johnson, who was alleged to be a minor improperly enlisted in the navy. The case focused on the legality of enlisting minors in the U.S. Navy without parental consent. The court's decision hinged on the interpretation of various acts of Congress regarding naval enlistment and the common law regarding contracts made by minors. The primary legal question was whether the enlistment of minors without parental consent was valid. Ultimately, the court found that the proof of the petitioner's minority status failed, and he was remanded. The case cited previous decisions and acts of Congress, emphasizing the importance and necessity of minors in naval service and the constitutional powers granted to Congress to raise and support a navy. Choice 5:	
Choice 6:	
Choice 7:	
Choice 8:	
Choice 9:	
Choice 10:	
### Input: Case Title: UNITED STATES v. Anderson Date: Jan 1, 1869 Court: United States Circuit Court for the District of Tennessee Judge: McNAIRY, District Judge Plaintiffs: George Bigby Defendants: Colonel Anderson	
Case Detail: This case involves a writ of habeas corpus directed to Colonel Anderson to bring up the body of Zebedee Bigby, who was allegedly enlisted in the army without the necessary consent from his father. The main legal questions addressed were whether the court had the right to discharge a soldier before an application to the Secretary of War proved fruitless, and whether the soldier could be discharged when the application was made not by him but by his father. The court ruled that minors enlisted without parental consent could be discharged on habeas corpus, regardless of any application to other government departments.	

# Table 8: SCR Example

Input	Output
### Instruction: You are a legal expert who specializes in comparing user-supplied legal cases to a list of candidate legal cases, which includes titles and content. Your main function is to identify and output the title of the most similar case from the list based on the description provided. You should only output the case title and not any other information. Consider the following choices: Choice 1:	### Response: Robinson v. Campbell.
 Choice 2:	
 Choice 3:	
 Choice 4:	
 Choice 5:	
 Choice 6:	
 Choice 7:	
Case Title: Robinson v. Campbell Date: Jan 1, 1818 Court: United States Circuit Court Judge: Mr. Justice Todd Plaintiffs: The lessor of Robinson	
Defendants: Campbell Case Detail: This case involves a dispute over land titles derived from grants issued by the state of Virginia, with the land falling within the boundaries of Tennessee following a boundary settlement between Virginia and Tennessee. The central legal issue was whether an equitable title (settlement rights) could be asserted as a valid claim in an action of ejectment in the circuit courts of the United States, as opposed to being a matter exclusively for equity courts. The plaintiff's title was based on a grant to John Jones dated 1787, part of which was conveyed to the plaintiff's lessor. The defendant, Campbell, claimed the land through a subsequent grant dated 1788, which was based on a settlement right previously established by a settler in 1778 and transferred to Joseph Martin. The defendant attempted to introduce evidence supporting this claim and a deed of conveyance during the pendency of the lawsuit, which could potentially impact the plaintiff's title. However, the court rejected this evidence on the basis that it was more suitable for consideration in a court of equity rather than a law court.s Choice 8:	
 Choice 9:	
Choice 10:	
 ### Input: Case Title: RULE S LESSEE v. PARKER Date: Feb 18, 1815 Court: Federal Circuit Court, Nashville Plaintiffs: Rule S Lessee Defendants: Parker	
Case Detail: This case involves an ejectment proceeding where the title to land was contested. The land in question was originally owned by someone named Grant, who then conveyed it to the plaintiff. The property was sold for direct taxes as belonging to Grant and was purchased by Smith and Bradford. They subsequently sold it to Parker, and the collector issued a deed to Parker. A significant legal issue in this case was the adequacy of the public notices required by law before the sale. The court focused on whether all statutory requirements for the sale were met to guard against fraud and imposition, particularly the proper advertisements preceding the sale. The court found that certain procedural safeguards, such as proper advertisement and identification of Grant as the owner in the collector's book, were not sufficiently demonstrated. This was deemed fatal to the defense's case, leading to a verdict for the plaintiff.	

# Table 9: SCR Example

Input	Output
### Instruction: You are a legal expert who specializes in comparing user-supplied legal cases to a list of candidate legal cases, which includes titles and content. Your main function is to identify and output the title of the most similar case from the list based on the description provided. You should only output the case title and not any other information. Consider the following choices: Choice 1:	### Response: The Philadelphia and Tren- ton Railroad Company vs. James Stimpson.
 Choice 2:	
 Choice 3: Case Title: The Philadelphia and Trenton Railroad Company vs. James Stimpson Date: Jan 1, 1840 Court: Circuit Court for the Eastern District of Pennsylvania Plaintiffs: The Philadelphia and Trenton Railroad Company Defendants: James Stimpson Case Detail: This case involves James Stimpson, the defendant in error, who brought an action against the Philadelphia and Trenton Railroad Company, the plaintiffs in error, for infringing his patent right. The patent, initially granted in 1831 and renewed in 1835 after the first was cancelled due to a defective specification, covered a new and useful improvement for turning short curves on railroads. At trial, significant legal discussions focused on the admissibility and validity of the renewed patent, which lacked specific recitals required by the patent act of 1832. The court ruled that the issuance of the patent under the great seal by high-ranking officials created a presumption of regularity and compliance with legal prerequisites, effectively making the patent prima facie evidence of its validity. Additionally, objections regarding prior art and the admission of evidence were addressed, with the court reinforcing strict adherence to procedural rules in patent litigation. Ultimately, the court affirmed the lower court's judgment in favor of Stimpson, emphasizing the discretion courts hold in managing procedural aspects of trials. Choice 4:	
 Choice 5:	
 Choice 6:	
Choice 7:	
Choice 8:	
Choice 9:	
Choice 10:	
<ul> <li>### Input:</li> <li>Case Title: Pennock v. Dialogue</li> <li>Date: Oct 24, 1984</li> <li>Court: United States Supreme Court</li> <li>Judge: Mr. Justice Story</li> <li>Plaintiffs: Abraham L. Pennock &amp; James Sellers</li> <li>Defendants: Adam Dialogue</li> </ul>	
Case Detail: This case involves a dispute over a patent related to an improvement in the art of making leather tubes or hose for conveying various fluids. The plaintiffs, Pennock and Sellers, who held the patent, alleged that Dialogue violated this patent. However, the original trial resulted in a verdict for Dialogue, which was upheld by the Supreme Court. The Court's decision centered on the principle that public use of an invention without the patent holder's objection signifies an abandonment of the exclusive rights later claimed through a patent. The plaintiffs' failure to secure a patent while allowing the invention to be used publicly, essentially forfeited their right to claim exclusive rights later. This case underscores the importance of timely patent protection and the implications of public use prior to patent approval.	

# Table 10: PCR Example

Input	Output
### Instruction: You are a legal expert who specializes in comparing user-supplied legal cases to a list of candidate legal cases, which includes titles and content. Your main function is to identify and output the precedent case from the list based on the description provided. You should only output the reasoning process and case title. Consider the following choices: Chains 1.	### Response: Clark v. Arnold. They have precedent rela- tion is due to their similar case details.
 Choice 1: Case Title: Clark v. Arnold Date: Oct 1, 1803 Court: Superior Court of North Carolina, Hillsborough Judge: HALL, J. Plaintiffs: Trustees of the University (Clark) Defendants: Arnold Case Detail: In "Clark v. Arnold", the dispute centered on the validity of land conveyance practices and the impact of deed registration. The case involved the trustees of the University, who claimed land under confiscation acts, arguing that the land had belonged to Henry Eustace McCulloch, an absentee during the war. The key issue was whether the deed to the defendant, Arnold, which was delivered but initially taken back by the vendor (McCulloch's attorney) to secure the payment of purchase money, effectively transferred title upon its eventual registration. The court ruled that the registration of the deed related back to the time of its initial delivery, thereby confirming Arnold's title before the land could have been confiscated. This verdict upheld the principle that a registered deed, even if initially delivered conditionally, ultimately confirms the transfer of title from the delivery date, thus rejecting the plaintiffs' claims based on the confiscation acts. Choice 3:	
 Choice 4:  Choice 5:	
 Choice 6:	
 Choice 7:	
Choice 8:	
Choice 9:	
Choice 10:	
### Input: Case Title: PATTON et al. v. REILY Date: Jan 1, 1812 Court: Circuit Court, D. Tennessee Judge: M'NAIRY, District Judge Plaintiffs: PATTON et al. Defendants: REILY	
Case Detail: In the case of PATTON et al. v. REILY, the court was faced with the legal intricacies of land conveyance through registration. The plaintiffs presented a deed that had not been registered at the time of the trial, arguing for its validity based on earlier proofs and registrations. The defendants challenged the legality of the deed's evidence due to its lack of proper registration as mandated by the legislative act of 1715, which clearly required registration for the conveyance of legal estates in lands. This act substituted the common law requirement of livery of seizin with registration. The court ruled that the deed could not be admitted as evidence since it failed to meet the requisite registration requirements set by the legislation, which emphasized that a legal estate could only be passed through properly registered deeds. This decision underscored the strict adherence to legislative requirements for land conveyance, reflecting the court's stance that no	
statutory framework of property law.	

# Table 11: PCR Example

Input	Output
### Instruction: You are a legal expert who specializes in comparing user-supplied legal cases to a list of candidate legal cases, which includes titles and content. Your main function is to identify and output the precedent case from the list based on the description provided. You should only output the reasoning process and case title. Consider the following choices: Choice 1:	### Response: Miller v. White They have precedent rela- tion is because they are un- der the same court.
 Choice 2:	
 Choice 3:	
Choice 4:	
Choice 5:	
Choice 6:	
Choice 7: 	
Choice 8: 	
Choice 9: Case Title: Miller v. White Date: March 29, 1934 Court: Supreme Court of South Carolina Judge: Justice Carter	
Plaintiffs: Thomas E. Miller, Jr. Defendants: Benjamin White Case Detail: This case concerns an action for specific performance of a written contract wherein the plaintiff, Thomas E. Miller, Jr., agreed to sell a lot in Charleston, SC, to the defendant, Benjamin White, for \$1,800, payable partly in cash and partly secured by a mortgage. Miller alleged that he tendered a deed to the property as per the contract, but White refused to comply with the contract terms. White's defense involved alleged defects in Miller's title, originating from prior foreclosure proceedings against other parties, which were not correctly served, potentially affecting the validity	
of the title Miller offered. The trial court sustained a demurrer against White's defense, leading to this appeal. The Supreme Court found that proper service in the prior foreclosure was crucial for establishing a clear title, disagreed with the trial court's dismissal of this defense, and remanded the case for further proceedings, allowing White to prove his defense related to service defects. Choice 10:	
"" ### Input: Case Title: Ex Parte S.C. Dept. of Social Services Date: April 6, 1976 Court: Supreme Court of South Carolina Judge: Justice Littlejohn	
Plaintiffs: South Carolina Department of Social Services Defendants: Not explicitly mentioned, relates to the order concerning Terry Carter Case Detail: The case arose from an order by the Richland County Family Court, which directed the South Carolina Department of Social Services (D.S.S.) to fund the enrollment and maintenance of Terry Carter, a minor, at Devereaux School in Pennsylvania. Terry Carter had previously been identified as a runaway and an emotionally disturbed child requiring long-term residential treatment. The Family Court's decision aimed to provide necessary treatment for Terry at the Devereaux Schools, with expenses estimated at \$18,000 annually, which the County Department of Social Services argued was beyond their financial capacity. The South Carolina Supreme Court reversed the lower court's order, concluding that the Family Court lacked the authority to compel the State Department of Social Services to allocate funds for Terry's treatment outside the state, thus invalidating the directive.	

# Table 12: PCR Example

Input	Output
### Instruction: You are a legal expert who specializes in comparing user-supplied legal cases to a list of candidate legal cases, which includes titles and content. Your main function is to identify and output the precedent case from the list based on the description provided. You should only output the reasoning process and case title. Consider the following choices: Choice 1:	### Response: Simms's Lessee v. Baker They have precedent rela- tion is due to their similar case details.
 Choice 2:	
 Choice 3:	
 Choice 4:	
"." Choice 5: Case Title: Simms's Lessee v. Baker Date: January 1, 1812 Court: Circuit Court of the United States, Nashville Judge: M'Nairy, J. Plaintiffs: Simms's Lessee Defendants: Baker Case Detail: The case involved an action of ejectment brought by Simms's Lessee to recover possession of a tract of land granted by North Carolina. The dispute centered on the interpretation of boundary descriptions in the land grant, specifically whether the described boundaries could extend beyond explicitly stated distances to reach a natural boundary, in this case, Duck River. The plaintiff's grant started from a point where the lower line of a survey crossed Duck River, but the actual line fell short by one mile and eight poles. The court held that natural boundaries mentioned in the grant take precedence over the specified distances. Therefore, even though the physical survey fell short, the grant could extend to the river as intended, validating the plaintiff's claim up to that boundary. The decision underscored the principle that when a land grant includes a call for a natural boundary, that boundary governs, even if it contradicts specific measurements cited in the grant. Choice 6:	
Choice 7: 	
Choice 8:	
Choice 9: 	
Choice 10:  ### Input: Case Title: Doss v. Tenn. Prod. Chem. Corp.	
Date: December 9, 1960 Court: Court of Appeals of Tennessee, Middle Section Judge: Humphreys, J. Plaintiffs: Leonard Doss and Blanche Lee Doss	
Defendants: Tennessee Products Chemical Corporation Case Detail: The case involved Leonard Doss and Blanche Lee Doss filing a lawsuit against the Tennessee Products Chemical Corporation for trespassing and damaging their property through tree cutting and strip mining coal. The plaintiffs claimed ownership and actual possession of the land, supported by a deed and continuous occupation over several years, sufficient to establish their claim under the relevant statutes of limitation. The defendant contested the boundaries of the property, claiming a different boundary line that would exclude their activities from the plaintiffs' land. The court found in favor of the plaintiffs, determining that the boundary line supported by longstanding recognition and actual possession was as the plaintiffs contended, not as the defendant claimed. The court held that the plaintiffs did not need to establish a valid legal title as their actual possession and the absence of valid legal title in the defendant were sufficient. The court affirmed the lower court's decision, granting an injunction against further trespass and unmediant devented from the property is presented.	

# Table 13: LJP Example (Zero-Shot)

Input	Output
### Instruction:	### Response:
You are a legal expert who specializes in predicting outcomes for legal cases. Utilize your internal	Plaintiff Wins
knowledge base to predict verdict. Your main function is to anticipate the likely verdict of the	
legal case presented by the user.	
You should only output the verdict and not any other information.	
Consider the following choices:	
1. Defendant Wins	
2. Plaintiff Wins	
3. Settlement	
4. Case Dismissal	
### Input:	
Case Title: Newsom v. Newsom	
Date: Decided February 13, 1956	
Court: Supreme Court of Mississippi	
Judge: Arrington, J.	
Plaintiffs: Mamie Newsom	
Defendants: Other heirs of Mrs. M.J. Newsom	
Case Detail: The case "Newsom v. Newsom" involved a dispute over the validity of a deed from	
1922 purportedly given by Mrs. M.J. Newsom to Mamie Newsom. The primary issue was whether	
the deed had been validly delivered, which is critical for its effectiveness. The appellant, Mamie	
Newsom, argued that the deed was a valid instrument and had been properly delivered, citing a	
statement in a cross-bill that indicated the deed had been altered after its execution and delivery.	
The respondents, other heirs of Mrs. M.J. Newsom, contested the validity of the deed, arguing it	
had not been delivered and had been altered after execution, thereby nullifying it. They also raised	
issues of estoppel and laches to argue that Mamie Newsom was barred from claiming under the	
deed. The case included several legal debates over the interpretation of these claims and whether	
they could be properly introduced at different stages of the appeal process.	

# Table 14: LJP Example (Zero-Shot)

Input	Output
### Instruction:	### Response:
You are a legal expert who specializes in predicting outcomes for legal cases. Utilize your internal	Plaintiff Wins
knowledge base to predict verdict. Your main function is to anticipate the likely verdict of the	
legal case presented by the user.	
You should only output the verdict and not any other information.	
Consider the following choices:	
1. Defendant Wins	
2. Plaintiff Wins	
3. Settlement	
4. Case Dismissal	
### Input	
Case Title: NY.S. Rifle & Pistol Ass'n. Inc. v. Bruen	
Date: June 23, 2022	
Court: Supreme Court of the United States	
Judge: Justice Thomas	
Plaintiffs: New York State Rifle & Pistol Association, Inc., et al.	
Defendants: Kevin P. Bruen, in his official capacity as Superintendent of New York State Police, et	
al.	
Case Detail: The case challenged New York's licensing regime for carrying concealed handguns,	
which required applicants to demonstrate a special need for self-protection distinguishable from	
the general community, known as the "proper cause" requirement. The petitioners argued that	
this standard infringed upon their Second and Fourteenth Amendment rights to bear arms, as it	
restricted their ability to carry handguns publicly for self-defense. This case arose in the context of	
New York's long-standing regulatory approach to the public carry of handguns, starting from	
the early 20th century Sullivan Law to contemporary requirements that a license applicant	
demonstrate "good moral character" and "no good cause exists for the denial of the license." The	
regulation was contested on the grounds that it was not aligned with the historical tradition of	
firearm regulation in the United States.	

# Table 15: LJP Example (Zero-Shot)

Input	Output
### Instruction:	### Response:
You are a legal expert who specializes in predicting outcomes for legal cases. Utilize your internal	Case Dismissal
knowledge base to predict verdict. Your main function is to anticipate the likely verdict of the	
legal case presented by the user.	
You should only output the verdict and not any other information.	
Consider the following choices:	
1. Defendant Wins	
2. Plaintiff Wins	
3. Settlement	
4. Case Dismissal	
### Input:	
Case Title: Freeman v. South Carolina	
Date: October 6, 2008	
Court: Supreme Court of the United States	
Plaintiffs: Fred Freeman	
Defendants: South Carolina, et al.	
Case Detail: The case involves Fred Freeman, who petitioned the United States Supreme Court	
seeking a writ of certiorari to review a decision from the United States Court of Appeals for the	
Fourth Circuit. The specifics of the underlying case or the issues on appeal are not detailed in the	
available excerpt. Generally, a petition for a writ of certiorari is requested to appeal a lower court's	
decision to the Supreme Court, indicating that significant legal questions or matters of federal law	
were likely involved.	

# Table 16: LJP Example (Few-Shot)

Input	Output
### Similar Case Example: Case Title: L Aron & Co x SemCrude L P	### Response: Defendant Wins
Date: June 28, 2013	Detendunt Wins
Court: United States Bankruptcy Court, D. Delaware	
Judge: Brendan Linehan Shannon Plaintiffs: L Aron & Company, BP Oil Supply Company, et al	
Defendants: SemCrude, L.P., et al.	
Case Detail: This case arose from SemCrude L.P.'s bankruptcy proceedings, where J. Aron & Co.	
and other downstream purchasers filed against SemCrude and associated companies, seeking a	
Prior to bankruptcy, SemCrude engaged in substantial trading and midstream oil and gas services,	
which faltered due to massive trading losses and a subsequent liquidity crisis. The litigation	
addresses whether downstream purchasers, who bought oil and gas from SemCrude, did so free from claims by unstream producers who originally sumplied the cil and gas. The control legal	
question was the applicability of liens and security interests under the U.C.C. and other state laws	
to the transactions made by SemCrude with the plaintiffs.	
Verdict: Case Dismissal	
### Precedent Case Example:	
Case Title: Walker v. Turner	
Date: March 19, 1824	
Court: Supreme Court of the United States	
Plaintiffs: Walker	
Defendants: Turner	
case Detail: The case involved a land dispute where Walker, the plaintiff, sought to recover a lot in Nashville from Turner, the defendant, Walker based his claim on a deed from 1790. Turner	
defended his claim with a series of legal and administrative moves starting from 1804, including a	
sheriff's sale of the property due to a judgment for a small debt against Walker, which resulted	
in Turner's predecessor in title acquiring the property. This led to a series of property transfers culminating in Turner's acquisition and development of the land. Key issues revolved around the	
validity of the sheriff's deed and the application of Tennessee's statute of limitations regarding	
possession under such deeds.	
verdict: Defendant wins	
### Instruction:	
You are a legal expert who specializes in predicting outcomes for legal cases. Utilize your internal	
legal case presented by the user.	
You should only output the verdict and not any other information.	
Consider the following choices:	
2. Plaintiff Wins	
3. Settlement	
4. Case Dismissal	
### Input:	
Case Title: MOORE v. BROWN ET AL	
Date: January 1, 1850	
Plaintiffs: Joshua J. Moore	
Defendants: James Brown, Alfred Brown, Harmon Hogan, and Joseph Froward	
Case Detail: The case centered around a deed issued by the Illinois Auditor of Public Accounts,	
on the basis that it violated statutory requirements, notably because the sale occurred earlier than	
permitted by law. The plaintiffs argued that the deed, showing a sale date that did not comply with	
the mandatory notice period, was void and could not confer title to the defendants. This raised	
void on its face due to procedural defects could support a defense of adverse possession under a	
color of title.	

# Table 17: LJP Example (Few-Shot)

Input	Output
### Similar Case Example:	### Response:
Case Title: M'Donald's Heirs v. Smalley	Plaintiff Wins
Date: January 1, 1832	
Court: Supreme Court of the United States	
Judge: Chief Justice Marshall	
Plaintiffs: M'Donald's Heirs	
Detendants: Smalley	
Case Detail: The case involved a dispute over land ownership in Ohio, where M Donald's Heirs	
sought to secure failed that was here by Smalley under a senior patent. The plainting claimed the	
the entry. This prior entry was crucial as it formed the foundation of the plaintiffs' claim. The case	
centered on whether an entry made in the name of a deceased person could be valid, a point that	
had previously been addressed in another case, Galt et al. v. Galloway.	
Verdict: Case Dismissal	
### Precedent Case Example:	
Case Title: De La Vergne Refrigerating Machine Co. v. Featherstone	
Date: Decided January 9, 1893	
Court: United States Supreme Court	
Judge: Chief Justice Fuller	
Plaintiffs: De La Vergne Refrigerating Machine Co.	
Defendants: Featnerstone et al.	
Lames Boyle The patent was issued to Boyle "his heirs or assigne" which raised questions about	
its validity since Boyle had died before the patent was granted. This led to a discussion on whether	
the patent could be validly issued to his legal representatives or heirs under existing patent laws.	
The case delved into whether the administrative process followed by Boyle's legal representatives,	
including filing amendments and maintaining the application posthumously, adhered to patent	
laws and whether such actions could legitimately sustain the patent's validity.	
Verdict: Plaintiff Wins	
### Instruction:	
You are a legal expert who specializes in predicting outcomes for legal cases. Utilize your internal	
knowledge base to predict verdict. Your main function is to anticipate the likely verdict of the	
You should only output the verdict and not any other information	
Consider the following choices:	
1. Defendant Wins	
2. Plaintiff Wins	
3. Settlement	
4. Case Dismissal	
UUU Toorst	
### input:	
Lase Line, Ands I. W. Mullels V. McCallulli Date January 23, 1020	
Court: Supreme Court of Texas	
Judge: Justice Speer	
Plaintiffs: Atlas Trailers Water Mufflers, Inc.	
Defendants: Mrs. McCallum, Secretary of State	
Case Detail: This case involved Atlas Trailers Water Mufflers, Inc., seeking a writ of mandamus	
to compel the Secretary of State, Mrs. McCallum, to file the company's amended charter, which	
included patents valued at \$50,000 as capital stock. The Secretary of State had denied the filing	
based on a long-standing departmental policy that did not recognize patents as tangible property	
suitable for capitalizing a corporation. The company argued that patents, being property capable	
of assignment and possessing an ascertainable value, should be recognized as valid contributions	
towards the capital stock under the relevant Texas constitutional and statutory provisions.	

# Table 18: LJP Example (Few-Shot)

Input	Output
### Similar Case Example:	### Response:
Case Title: Stewart v. Griffith	Defendant Wins
Date: April 25, 1910	
Court: Supreme Court of the United States	
Judge: Justice Holmes	
Plaintiffs: The executor of one Ball (Stewart)	
Detendants: Griffith	
Case Detail: This case centers on a dispute over a contract for the sale of real estate, where the	
executor of a deceased s estate seeks specific performance of a contract made by the appellant to	
purchase land. The contract had provisions that were to result in fortenture and make the contract	
allowed the appellant to withdraw from the contract or obligated him to complete the purchase	
as per the initial agreement. The executor argued that despite the death of the property owner	
just before the finalization of the sale, the contractual obligations still stood, entitling the estate	
to enforce the contract. The complexities of the case involve interpretations of Maryland real	
estate law, the powers of an executor under a will, and the legal implications of contract terms	
that stipulate conditions for forfeiture and nullification.	
Verdict: Defendant Wins	
### Precedent Case Example:	
Case Title: Willis v. First Real Estate Investment Co.	
Date: January 24, 1934	
Court: Circuit Court of Appeals, Fifth Circuit	
Judge: Hutcheson, Circuit Judge	
Plaintiffs: Henry B. Willis	
Defendants: First Real Estate investment Company and others	
Land titles hald by the First Real Fetate Investment Company and others based on historical claims	
The conflict arises from a Mexican title originating in 1927 and a Texas title from 1861 Willis's	
claim is grounded in the assertion that changes in the river's course–specifically the avulsive	
changes referenced in boundary treaties—affected the jurisdiction over the land, which was	
located along the Texas bank of the Rio Grande. The case examines intricate historical and legal	
arguments surrounding land ownership, jurisdictional changes due to natural river movements,	
and the implications of international treaties between the U.S. and Mexico.	
Verdict: Defendant Wins	
### Instruction:	
You are a legal expert who specializes in predicting outcomes for legal cases. Utilize your internal	
knowledge base to predict verdict. Your main function is to anticipate the likely verdict of the	
legal case presented by the user.	
Consider the following choice:	
1 Defendant Wins	
2. Plaintiff Wins	
3. Settlement	
4. Case Dismissal	
### Input:	
Case Title: San Lorenzo T. I. Co. v. City Mortgage Co.	
Date: June 30, 1934	
Court: Supreme Court of Texas	
Judge: Justice Pierson	
Prantins: San Lorenzo Title and Improvement Company	
Case Detail: The case involves a trespass to try title suit regarding land along the Pio Grande	
designated as a "banco" under treaties between the USA and Mexico. The San Lorenzo Title and	
Improvement Company claimed title to the land, arguing it derived from Mexican governmental	
and court actions before the International Boundary Commission declared the land a banco in	
1930 and stated it belonged to the USA. The core of the dispute rested on the effect of the 1905	
treaty which aimed to resolve the issues of bancos along the Rio Grande by stipulating those on	
the north bank would pass to the USA. The company contended that prior Mexican claims to the	
land should be recognized despite the treaty's provisions.	