CS298 Proposal

Title: AI-Powered Legal Decision Support System

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Abstract:

This project aims to develop an AI-driven legal case prediction system capable of predicting legal case outcomes, specifically determining which party- plaintiff or defendant more likely to win. Our approach leverages a fine-tuned, pre-trained large language model, DistilBERT, a compact and faster variant of BERT optimized for efficiency while maintaining high accuracy. By using DistilBERT, we capitalize on its ability to process and comprehend legal texts effectively, allowing us to generate informed predictions on case outcomes. For training, we utilize the Supreme Court dataset from Kaggle, a clean and classification-friendly dataset suited to our task. To maximize model performance and resource efficiency, we employ parameter-efficient fine-tuning (PEFT) techniques, including Low-Rank Adaptation (LoRA), Dynamic Low-Rank Adaptation (DoRA), and Quantized Low-Rank Adaptation (QLoRA), which enhance our model's ability to predict legal case outcomes accurately. In addition to DistilBERT, we are experimenting with more advanced LLMs, such as Microsoft's DeBERTa-v3-small-chosen for its manageable parameter size that allows efficient training on our setup as well as traditional machine learning classifiers like XGBoost, to explore alternative classification methods and potentially boost the accuracy of the legal case prediction process. To ensure the system remains interpretable and ethically sound, we integrate Explainable AI tools, including SHAP (Shapley Additive exPlanations). These tools will illuminate the model's decision-making process, helping us understand why specific predictions are made and enhancing transparency in the system's predictions, making it suitable for real-world legal applications.

CS297 Results

- Laid the foundation for understanding supervised fine-tuning of large language models (LLMs) by conducting an experimental study on a simple classification model using LoRA as the fine-tuning technique.
- Developed a legal case classification model leveraging a fine-tuned DistilBERT base model and LoRA for fine-tuning. We utilized the Supreme Court Judgment dataset from Kaggle, preprocessed the data, and trained the model to predict legal outcomes, achieving 68.4% accuracy. This dataset was chosen for its focus on case-specific predictions, making it more suitable for our purpose compared to other available legal case prediction datasets.
- Experimented with various parameter-efficient fine-tuning methods (LoRA, DoRA, QLoRA) to optimize model performance. Using evaluation metrics such as accuracy, F1 score, recall, and precision, we concluded that LoRA outperformed the others due to its ability to fine-tune simple classification models without significant loss of information, ensuring better training efficiency.
- Integrated explainable AI techniques such as SHAP and attention maps to improve model interpretability. By visualizing attention weights, we were able to understand how the model assigns importance to specific words and phrases in making predictions, providing insights into the underlying reasoning behind its outputs.

Proposed Schedule

Week 1: Jan 30 - Feb 6	Experiment with models like DeBERTa-v3-small and XGBoost to evaluate improvements over DistilBERT fine-tuned with LoRA.
Week 2-3: Feb 7 - Feb 20	Select the most effective model based on initial experiments, whether DistilBERT, DeBERTa-v3-small, or a classifier like XGBoost, and apply advanced fine-tuning techniques to further improve accuracy for the legal case prediction system.
Week 4-5: Feb 21 - Mar 5	Develop the user interface for the AI-powered legal prediction software. This interface will allow users to input legal text, select a model from a list of available options, and receive a predicted outcome.
Week 6-7: Mar 9 - Mar 19	Enhance the user interface by incorporating explainable AI features, enabling the system to display insights into why the model generated a particular prediction for the legal case outcome.
Week 7-10: Mar 20 - Apr 09	Test the software with real-world legal case data and validate predictions.
Week 10-12: Apr 10 - Apr 23	Begin writing project report, document results, and finalize deliverables.
Week 13-14: Apr 24 - May 7	Work on CS 298 Report and begin preparation for the Defense.
Week 15: May 7 - May 14	Finish CS 298 Report and Presentation.

Key Deliverables:

- Software
    - **Legal Case Prediction Neural Model Development:** Develop an initial neural model for legal case prediction using DistilBERT fine-tuned on the Supreme Court Judgment Prediction dataset to establish a baseline framework for the project. Evaluate the model's performance using accuracy, F1-score, precision, and recall metrics to identify areas for further optimization.
    - **Legal Case Model Experimentation:** Conduct experiments to compare various models for legal case prediction, including DistilBERT fine-tuned with LoRA, the XGBoost classifier, and Microsoft's DeBERTa-v3-small LLM fine-tuned with LoRA, to identify which model performs best based on different evaluation metrics.
    - **Optimizing Model Fine-Tuning for Legal Case Prediction** Experiment with DistilBERT and Microsoft's DeBERTa-v3-small using fine-tuning techniques like LoRA, DoRA, and QLoRA to identify the best model and tuning method for improving legal case prediction accuracy.
    - **User Interface for Legal Case Prediction:** Develop a user interface that allows users to input legal text, select a model from a list of options, and receive a predicted outcome.
    - **Integrating Explainability into Predictions**: Enhance the user interface by adding explainable AI features, allowing the system to provide insights into why a particular prediction was generated for the legal case outcome.

- Report
    - CS 298 Report
    - CS 298 Presentation

Innovations and Challenges

- We developed a baseline neural model for legal case prediction, tailoring AI to domain-specific legal texts and addressing challenges like imbalanced datasets to establish reliable benchmarks for future enhancements. We also created a scalable framework, enabling the integration of advanced techniques while balancing computational efficiency with interpretability in a complex, high-stakes domain.
- Through experimentation with models like DistilBERT fine-tuned with LoRA, XGBoost, and DeBERTa-v3-small, we compared traditional machine learning methods with advanced LLMs, optimizing for accuracy and efficiency despite limited resources. This effort addresses the scarcity of legal case models and modernizes legal prediction by leveraging AI to process large volumes of legal data, a traditionally human-driven task.
- We fine-tuned DistilBERT and DeBERTa-v3-small using techniques such as LoRA, DoRA, and QLoRA, adapting large models to legal data in a resource-efficient manner. Optimizing hyperparameters to avoid overfitting or underfitting while improving interpretability was a key challenge. This exploration paves the way for accurate AI models that could revolutionize legal processes and automate simpler cases.
- We designed a user-friendly interface that allows users to input legal text, select models, and view predictions. The intuitive design enables experimentation and understanding of result variations while providing a scalable solution for future legal case applications.
- By incorporating explainable AI tools like SHAP or LIME, we enhanced transparency and trust by enabling users to understand the reasoning behind predictions. Simplifying complex explanations for non-technical legal professionals remains a challenge, but this innovation offers clarity and justification, making the system more valuable for legal use.

References:

A. W. Appel, Modern Compiler Implementation in Java, Cambridge University Press, 1998.

R. Hyde, The Art of Assembly Language, No Starch Press, 2004.

K. C. Louden, Compiler Construction: Principles and Practice, Brooks/Cole, 1997.

M. L. Scott, Programming Language Pragmatics, Morgan Kaufmann, 2009.

L. K. Branting et al., "Scalable and explainable legal prediction," Artificial Intelligence and Law, vol. 29, no. 2, pp. 213-238, 2021.

R. Ejjami, "AI-Driven Justice: Evaluating the Impact of Artificial Intelligence on Legal Systems," International Journal for Multidisciplinary Research, vol. 6, no. 3, 2024.

G. A. Tsihrintzis et al., "Advances in Artificial Intelligence-Empowered Decision Support Systems," Springer, 2024.