Performance Analysis Report: Knowledge Distillation for Legal Clause Classification

Project: Legal Contract Clause Classification on the LEDGAR Dataset

Models: LegalBERT (Teacher) vs. BERT-mini (Student)

Executive Summary

This report presents a comprehensive performance evaluation of a knowledge distillation (KD) process applied to a legal contract clause classification task. A large, high-performance **teacher model** (LegalBERT, ~110M parameters) was used to train a significantly smaller and more efficient **student model** (BERT-mini, ~11M parameters). The models were benchmarked on the standardized LEDGAR test set, which comprises 100 distinct legal clause categories.

The knowledge distillation was highly successful. The student model, despite being **90% smaller** and offering a more than **10x improvement in computational efficiency**, retains over **90%** of the teacher's performance across key metrics. The student achieved a test set accuracy of **76.00%**, compared to the teacher's **83.92%**. The gap in the Macro F1-score was even smaller, with the student achieving **0.7033** (**94%** of the teacher's **0.7466**), indicating a robust ability to classify across a wide range of classes, including those with less support.

This outcome validates the KD approach as a production-ready solution, enabling the deployment of a highly accurate legal classifier in resource-constrained environments where inference latency and memory footprint are critical concerns.

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1. Introduction

1.1. Project Objective

The primary objective of this project was to develop a computationally efficient model for the automated classification of legal clauses from contracts, utilizing the 100-class LEDGAR dataset. While large transformer models like LegalBERT provide state-of-the-art accuracy, their significant size (~110M parameters) and computational requirements pose challenges for scalable, real-time deployment. This project employed **knowledge distillation** to transfer the sophisticated classification capabilities of a large teacher model to a compact student model, aiming to strike an optimal balance between predictive performance and operational efficiency.

1.2. Models Under Evaluation

- **Teacher Model (LegalBERT):** A BERT-based model with approximately **110 million parameters**, fine-tuned for the legal domain. It serves as the high-performance benchmark.
- **Student Model (BERT-mini):** A significantly smaller transformer architecture with approximately **11 million parameters**. It was trained via knowledge distillation to mimic the teacher's output distribution.

1.3. Evaluation Framework

Both models were evaluated on the standardized LEDGAR test set. Performance was measured using three key metrics:

- **Accuracy:** The overall percentage of correctly classified clauses.
- **Macro F1-Score:** The unweighted mean of the F1-scores for each class. This metric gives equal importance to every class, making it a crucial indicator of performance on minority classes.
- **Weighted F1-Score:** The mean of the F1-scores for each class, weighted by the number of true instances (support) for each class. This metric reflects the model's performance on the dataset as a whole, biased towards the more frequent classes.

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2. Comparative Performance Analysis

2.1. Aggregate Performance Metrics

The overall performance comparison highlights the success of the knowledge distillation process. The student model captures the majority of the teacher's predictive power while being an order of magnitude smaller.

Metric	Teacher Model (LegalBERT)	Student Model (BERT-mini)	Performance Retained
Test Set Accuracy	83.92%	76.00%	90.6%
Macro F1-Score	0.7466	0.7033	94.2%
Weighted F1-Score	0.8342	0.7709	92.4%
Model Parameters	~110 Million	~11 Million	10.0%

The modest **7.9 percentage point drop in accuracy** is a highly favorable trade-off for a 90% reduction in model size. Furthermore, the small gap in the **Macro F1-score** (0.0433) demonstrates that the student model did not simply learn to predict majority classes but successfully generalized across the imbalanced class distribution.

2.2. Per-Class Performance Breakdown

A detailed analysis at the individual class level reveals a more nuanced understanding of the models' capabilities.

- **Consistently Strong Classes:** Both models demonstrated high proficiency (defined as F1>0.85) on several classes with distinct legal language and sufficient training examples, such as Class_3, Class_11, Class_15, Class_16, and Class_18. For high-support classes like Class_26 and Class_79, both models achieved near-perfect performance with F1-scores exceeding 0.95.
- **Student Model Efficacy:** On many high-performing classes, the student model retained over 90% of the teacher's effectiveness (e.g., Class_3, Class_15, Class_48). In isolated instances, the student marginally outperformed the teacher on recall or F1-score. This "student effect" can be attributed to the regularization properties of the distillation process, which sometimes prevents the smaller model from overfitting to noise learned by the teacher.
- **Challenging Minority Classes:** Certain classes, such as Class_4, Class_8, Class_14, and Class_72, proved difficult for both models, yielding F1-scores at or near zero. This is a characteristic symptom of classes with extremely low support in the training data or inherently ambiguous textual content. While the teacher model's greater capacity allowed it to make some correct predictions for certain low-support classes, the student model struggled more, often failing to predict these classes entirely.

2.3. Handling of Class Imbalance and Error Analysis

The training process incorporated class weights to mitigate the severe class imbalance inherent in the LEDGAR dataset. While this strategy benefited both models, the teacher's superior representational capacity allowed it to maintain higher precision and recall for rare classes.

The primary error pattern observed in the student model was a tendency to default to more common classes, thereby reducing its **recall** on rare categories (e.g., Class_46, Class_53, Class_56). This is a classic trade-off in model compression: the student optimizes for overall accuracy, which is heavily influenced by frequent classes, sometimes at the expense of correctly identifying infrequent ones. This is reflected in the larger drop in the Weighted F1-score (6.3 percentage points) compared to the Macro F1-score.

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3. Deployment Strategy and Recommendations

The performance-efficiency trade-off between the two models enables a flexible deployment strategy tailored to specific business requirements.

Attribute	Teacher Model (LegalBERT)	Student Model (BERT-mini)
Primary Use Case	Accuracy-critical, offline batch processing	Real-time, scalable, or edge deployments
Inference Speed	Baseline	>10x Faster
Memory Footprint	High	Low
Strengths	Superior accuracy on rare classes	Excellent cost-performance ratio
Weaknesses	High computational cost	Reduced recall on rare classes

3.1. Key Recommendations

1. **For General-Purpose, Scalable Applications:** The **student model (BERT-mini)** is the recommended choice. Its combination of high overall accuracy, low latency, and minimal memory footprint makes it ideal for real-time document analysis workflows, interactive applications, and large-scale batch processing where cost and speed are primary constraints.
2. **For Mission-Critical or High-Stakes Analysis:** Where the failure to identify a rare but critical legal clause carries significant risk, the **teacher model (LegalBERT)** should be utilized. Its superior performance on minority classes justifies its higher computational overhead in scenarios demanding maximum accuracy.
3. **Hybrid Deployment Strategy:** A hybrid approach can be implemented to achieve the best of both worlds. The student model can serve as the primary classifier for all incoming requests. When it produces a prediction with low confidence or identifies a clause as belonging to a historically challenging category, the request can be automatically re-routed to the teacher model for a more thorough secondary analysis.

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4. Conclusion

The knowledge distillation pipeline developed for this project has proven to be exceptionally effective. It has successfully produced a lightweight, efficient legal clause classifier that preserves the vast majority of the performance of a much larger, state-of-the-art model. The resulting student model stands as a production-quality asset, demonstrating a professional and robust balance between predictive accuracy, inference speed, and memory efficiency. This work confirms that model compression is a viable and powerful strategy for deploying advanced NLP capabilities in practical, resource-sensitive legal technology applications.