Fact Checker Law Based for Bangladesh
Project Report

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Problem Statement

Many people find it difficult to understand whether a legal statement is true or false. There is a need for a system that can help classify such statements in a simple and automatic way.

But most traditional NLP models struggle in this domain due to the specificity of legal language and lack of generalizability across different subdomains (e.g., labor law, traffic violations, international student regulations).

So, the problem addressed in this project is to accurately classify simple input statements using NLP techniques, and transformer-based model BERT to overcome these challenges.

Objective

Key goals include:

1. **Multiple domain Integration**: Merging claims from various areas like labor laws, traffic rules and student visa issues into a unified dataset for training and evaluation.

2. **Text Preprocessing with Legal Context**: Implement domain-sensitive preprocessing that retains meaningful legal abbreviations and expands critical terms to ensure semantic clarity.

3. **Model Development**: Fine-tuning BERT for optimal performance.

4. **Performance Optimization**: Handle class imbalance, optimize hyperparameters, and use evaluation metrics such as F1-score, Precision, and Recall for performance tuning.

5. **Scalability and Real-world Applicability**: Create a pipeline that can be extended to new legal domains or integrated into larger legal tech systems like document triage platforms.

Literature Review

Selection of Papers Using the PRISMA Method

We systematically selected 10 relevant papers for this literature review on the fact-checking domain. We used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology for our selection process.
Firstly, we began by searching different online sites like Google Scholar, PubMed, ResearchGate etc. To search we used terms like "Law based fact-checking," “nlp fact checker,” “text classification” and "claim verification." Initially, we listed 29 papers.
As these initial papers were listed by all three of the team members, we had some duplicate papers. After removing duplicates, 18 unique papers remained. Then we removed another 8 papers by analyzing the Introduction and Abstract part of the papers.
Ultimately, 10 papers were selected for this review. These papers provide a comprehensive overview of our project.

Interconnection of Papers: Differences and Similarities

Similarities Across Papers

1. Core Frameworks:
    - Most papers describe a three-stage pipeline for fact-checking: claim detection, evidence retrieval, and claim verification. This is useful to make efficient and accurate claim assessment.
2. Use of Models:
    - Most of the papers discuss machine learning (ML) and deep learning (DL) methods using models like BERT, RoBERTa, and GPT, to verify facts. Some deal with legal texts, like MEL and LEGAL-BERT, which are trained to understand complex legal documents.
3. Common Challenges in Fact-Checking:
    - Most of the papers mention problems like data bias, lack of reliable sources, difficulty in handling long documents, and need of human involvement to make the system more effective.

Differences Across Papers

1. Datasets:
    - Some papers rely on well-known datasets like FEVER or Fact Extraction and VERification (FEVEROUS). One paper uses FEVER but acknowledges its limitations for non-English languages.

2. Focus Areas:
    - Certain papers focus on textual claims, while others explore multimedia verification.
    - Another paper delves into legal entailment tasks, which are directly relevant to integrating legal frameworks into fact-checking systems.
3. Legal Integration:
    - Few papers discuss integrating fact-checking systems with legal frameworks. One focuses on NLP applications in law but does not address misinformation specifically.
4. Real-Time Fact-Checking:
    - Real-time capabilities are explored in some works but are not optimized for low-resource settings or social media platforms prevalent in Bangladesh.

Summary of Shortcomings

Despite significant advancements, several limitations persist across the reviewed literature:

1. Lack of Bangladesh-Specific Solutions:
    - None of these works is based on Bangladesh-specific domains.
2. Dependence on External Sources:
    - Some fact-checking models rely on Google Search, Wikipedia, or fact-checking websites, which might not always be reliable.
3. Explainability vs. Accuracy Trade-Off:
    - While explainable AI is prioritized, many models sacrifice accuracy or scalability for interpretability.
4. Scalability Issues:
    - Real-time fact-checking at scale remains a challenge due to computational constraints and data bottlenecks.

Network Description

At the core of this project lies a fine-tuned **BERT (Bidirectional Encoder Representations from Transformers)** model, a state-of-the-art transformer architecture developed by Google. Unlike traditional models that read text in a single direction, BERT reads text bidirectionally, allowing it to understand context in a much richer way.

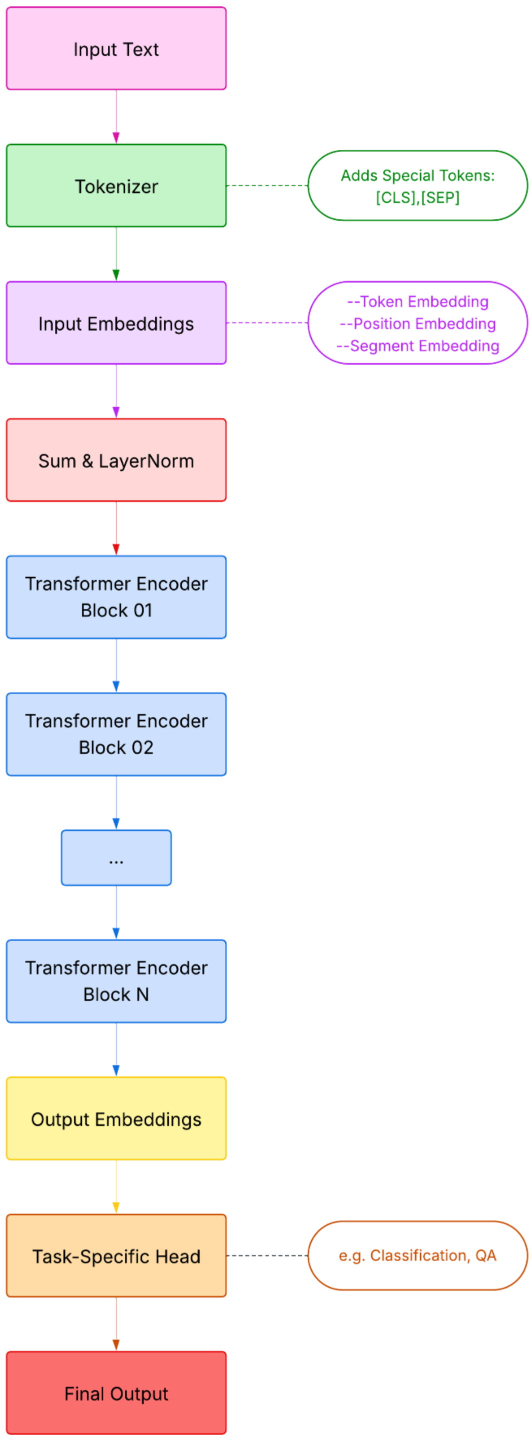
Data Pipeline:

- **Dataset Aggregation**: Four datasets were used, each representing a specific legal domain—Labour, Traffic, USA Student, and UK Student.
- **Data Cleaning**: Duplicates were removed and null values handled. Legal claims were normalized while preserving legal abbreviations and domain-specific semantics.
- **Label Encoding**: Labels were mapped into binary values for classification.
- **Train/Test Split**: The dataset was divided into training and testing sets with stratified sampling to maintain label distribution.

Model Architecture:

- **Base Model**: bert-base-uncased from HuggingFace Transformers.
- **Fine-Tuning Layers**: A classification head consisting of a dense layer with ReLU activation followed by a softmax layer for binary classification.
- **Optimizer**: AdamW optimizer with linear learning rate warmup.
- **Loss Function**: Binary Cross-Entropy Loss, weighted to handle class imbalance.

This architecture enabled the model to learn legal context effectively, even across domains, while maintaining generalization through careful preprocessing and domain balancing.



Bert Network Model that has been used shown in a Block Diagram

Challenges

1. **Data Imbalance**: There was initially a lot more True label data. This imbalance often biased the model, requiring techniques like SMOTE or loss function weighting to stabilize performance.

2. **Legal Jargon Variance**: Legal documents contain a plethora of abbreviations, symbols, and region-specific terminologies. Standard NLP preprocessing would strip these out, leading to semantic loss. A custom normalization function had to be crafted with care.

3. **Overfitting on Small Domains**: Smaller datasets (e.g., UK student legal cases) often led to overfitting. Techniques such as early stopping, dropout, and data augmentation through synonym replacement were explored to mitigate this.

4. **Compute Resources**: Training transformer models is resource-intensive. Experiments had to be carefully optimized for runtime and memory, and some iterations were conducted on cloud GPUs.

5. **Domain Shifts**: Claims across different countries (e.g., UK vs. USA) sometimes introduced domain shifts—where the language patterns were too different for the model to generalize well without domain tagging.

Conclusion

This work shows the promising prospects of transformer-based NLP models in the challenging domain of legal text classification. By domain-aware preprocessing, careful treatment of the domain bias and BERT's capacity, we were able to construct a model that generalizes well to various legal domains.

Not only does it have academic value, but this system also scales to other applications in the real world such as, automated legal advice systems, and legal research assistants. As future work, we would like to add more domains and apply multi-label text classification on the model.

By combining law and technology together, the project not only automates a historically manual domain, but also helps increase the availability and effectiveness of legal services.