COMP90042 Report

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Abstract

In this project, we developed an automated fact-checking system to address the challenges of manual fact-checking. Our system includes two main components: evidence retrieval and claim classification. For evidence retrieval, we used a Siamese network architecture with a listwise loss function and leveraged TF-IDF, Word2Vec, and BM25 for initial retrieval and negative sample generation. For claim classification, we employed GRU and Transformer models, with GRUs enhanced by an attention mechanism performing best. Despite not using pretrained models, our system demonstrated effective performance in handling long sequences and focusing on relevant text, providing valuable insights into automated fact-checking capabilities and limitations.

1 Introduction

Automated fact-checking is crucial in today's media ecosystem due to the rapid spread of information and misinformation, especially for complex climate-related claims (Guo et al., 2022). Manual fact-checking cannot keep up with the volume of new information, prompting interest in automated systems. These systems have two main components: evidence retrieval, which finds relevant information to support or refute claims, and claim verification, which assesses the truthfulness of claims based on the retrieved evidence.

Evidence retrieval is challenging due to the need for high precision and recall from diverse datasets. Traditional methods like commercial search APIs, Lucene indices, and TF-IDF vectors are effective for initial retrieval but often lack the precision needed for identifying relevant evidence (Thorne et al., 2018). To improve this, we adopted dense retrievers with learned representations and dot-product similarities (Karpukhin et al., 2020). Inspired by the Deep Relevance Matching Model (DRMM) (Guo et al., 2016), our Siamese network encodes claims and evidence into a shared vector space, enhancing precision and recall by maximizing the similarity between relevant pairs and minimizing it for irrelevant ones.

Claim verification can be seen as a form of Recognizing Textual Entailment, predicting whether the evidence supports or refutes the claim (Bowman et al., 2015). We experimented with two strategies: evidence-level and direct claim-level classification. The evidence-level approach classifies each piece individually before aggregation, providing detailed insights (Thorne et al., 2018). However, it underperformed due to the often insufficient quality of retrieved evidence. In contrast, the direct claim-level classification treats the claim and evidence as a single sequence, capturing their holistic context (Nie et al., 2019). This approach yielded better performance by leveraging the integrated context crucial for accurate verification in complex domains like climate science.

Through our experiments, we compared a GRU-based model with attention mechanisms and a Transformer-based model for fact-checking tasks. The GRU model outperformed the Transformer, likely due to its ability to focus on relevant text parts through attention, which is crucial without pretrained embeddings and limited data (Vaswani et al., 2017). The Transformer model struggled without pretrained embeddings and sufficient data to effectively capture underlying patterns. Our GRU model ranked 14th in the in-class competition, demonstrating competitive performance and providing valuable insights into the strengths and weaknesses of different sequence models for these tasks.

2 Approach

2.1 Evidence Retrieval

For the evidence retrieval task, our goal is to encode a given claim c_i and a list of evidence documents

$\{e_1, e_2, \ldots, e_N\}$ such that the relevant evidence e_j^+ is closer to the claim c_i than the irrelevant evidence e_k^- in the vector space. We achieve this using a Siamese network architecture (Mitra and Craswell, 2018), which consists of two encoders, f and g, to encode the claims and evidence documents, respectively, and compute their similarity.

Specifically, we use the Siamese network to obtain the vector representations of the claim and the evidence documents. Let $f(c_i)$ denote the vector representation of the claim c_i encoded by the model, and let $g(e_j)$ denote the vector representation of the evidence document e_j encoded by the model. The similarity $\text{sim}(c_i, e_j)$ between the claim c_i and the evidence document e_j is computed as the dot product of their vector representations:

$$\text{sim}(c_i, e_j) = f(c_i) \cdot g(e_j)$$

The objective of the neural ranking model is to maximize the similarity score $\text{sim}(c_i, e_j^+)$ for relevant evidence documents e_j^+ and minimize the similarity score $\text{sim}(c_i, e_k^-)$ for irrelevant evidence documents e_k^-. This is achieved by optimizing the negative log-likelihood of the positive passage(Karpukhin et al., 2020). The loss function used is defined as:

$$\mathcal{L}(c_i, e_j^+, e_{i,1}^-, \ldots, e_{i,n}^-) = -\log \frac{e^{\text{sim}(c_i, e_j^+)}}{e^{\text{sim}(c_i, e_j^+)} + \sum_{k=1}^{n} e^{\text{sim}(c_i, e_{i,k}^-)}} \quad (1)$$

To utilize the defined loss function, we use the ground truth evidences for each claim c_i as positive samples. For negative samples, we include both in-batch negatives and top negatives from initial filtering. In-batch negatives are other claims' positive evidences, providing $B - 1$ in-batch negatives for each claim, where B is the batch size. For top negatives, we evaluate the effectiveness of TF-IDF (Thorne et al., 2018), Word2Vec (Mikolov et al., 2013) (using cosine similarity), and BM25 (Zhan et al., 2021) algorithms. We manually implemented BM25 with an inverted index in Python to compute similarity scores and rerank evidences for each claim.

We also explore different sequence models for encoding the text in the Siamese network. Our baseline model uses a simple GRU, followed by an advanced GRU with attention mechanism, and finally a Transformer model. This allows us to compare the performance and effectiveness of these models in encoding and retrieving relevant evidence documents.

2.2 Claim Verification

For the claim verification task, our objective is to classify a given claim c_i into one of four categories: `SUPPORTS`, `REFUTES`, `NOT ENOUGH INFO`, or `DISPUTED`. We explored two different strategies to achieve this classification: the evidence-level aggregation approach and the direct claim-level classification approach. Both strategies employ the same underlying model architectures but differ in how the evidence is aggregated and utilized to make the final prediction.

Evidence-Level Classification: In the evidence-level aggregation approach, each piece of evidence related to a claim is individually classified into one of three categories: `SUPPORTS`, `REFUTES`, or `NOT ENOUGH INFO`. These individual classifications are then aggregated to produce the final claim label. The aggregation method involves tallying the individual evidence predictions. If both `SUPPORTS` and `REFUTES` evidence are present, the claim is classified as `DISPUTED`. If only `SUPPORTS` or only `REFUTES` evidence is present, the claim is classified accordingly. If neither `SUPPORTS` nor `REFUTES` evidence is found, the claim is classified as `NOT ENOUGH INFO`.

Direct Claim-Level Classification: The direct claim-level classification approach treats the claim and its related evidence as a single combined sequence. This combined text is input to the model, which then directly classifies the claim into one of the four categories. By processing the combined sequence of the claim and all related evidence documents as a single text input, the model can capture the semantic relationships between the claim and the evidence, allowing for a more informed prediction based on the integrated context of all the evidence provided for the claim.

2.3 Model Architectures

We employed two primary model architectures: a GRU-based model with attention and a Transformer-based model. Both architectures were used in the context of the two tasks mentioned above: evidence retrieval and claim verification.

The **Bi-Directional GRU** (Tang et al., 2015) model with attention uses a Gated Recurrent Unit (GRU) to encode the sequence of words in both the claim and the evidence documents. An attention mechanism is applied to the GRU outputs to enhance the model's focus on the most relevant parts of the text. The encoded representations from the GRU are then used differently depending on the task. For evidence retrieval, the dot product is computed in a Siamese network setting to measure similarity between claims and evidence. For claim verification, the encoded representations are passed through fully connected layers to produce the final classification logits. The attention mechanism computes attention weights that highlight important parts of the evidence when making a decision about the claim. This helps the model to focus on the most relevant information, improving the accuracy of the classification.

The **Transformer-based** (Vaswani et al., 2017) model leverages self-attention mechanisms to capture long-range dependencies within the text. Both the claim and evidence documents are processed using multiple layers of self-attention and feedforward networks. Positional encodings are added to the word embeddings to retain the order of the tokens. The encoded representations from the Transformer are used differently depending on the task. For evidence retrieval, the similarity is computed in a Siamese network setting. For claim verification, the encoded representations are combined to make the final classification. The self-attention mechanisms in the Transformer allow the model to better understand the relationships between different parts of the text, making it well-suited for tasks that require deep semantic understanding.

3 Experiments

3.1 Evaluation method

Evidence Retrieval Recall at k: This metric evaluates the proportion of relevant evidence passages retrieved in the top k predictions compared to the ground truth. It measures the system's recall in retrieving the correct evidence passages. We use this metric to evaluate the initial retrieval models—TF-IDF, Word2Vec, and BM25. The goal is to achieve high recall to narrow the search space from over 1 million evidence passages and provide negative samples for efficient training of the neural ranking model.

$$\text{Recall@}k = \frac{\text{Relevant Passages Retrieved@}k}{\text{Total Relevant Passages}}$$

Evidence Retrieval F-score at k: This metric evaluates how well the system retrieves evidence passages compared to the ground truth, considering the top k predictions. By setting k to 5, we focus on the most confident predictions, balancing precision and recall to measure both completeness and relevance. This metric is used to assess the effectiveness of our neural retrieval model, which aims for high F1 scores given that the average number of evidence for a claim in the training data is between 3 and 4.

$$\text{F1@}k = 2 \times \frac{\text{Precision@}k \times \text{Recall@}k}{\text{Precision@}k + \text{Recall@}k}$$

Claim Classification Accuracy: quantitatively computes the accuracy of claim label predictions with an ignorance of the evidence passages that system retrieves. This metric evaluates the effectiveness of the system's ability to classify claims, which reflects the overall performance of the claim verification models.

$$\text{A} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

Harmonic Mean of F and A: measures the harmonic mean of the evidence retrieval F-score and claim classification accuracy, which evaluates both the retrieval and classification tasks. This metric is utlized in the final evaluation on the test set.

$$\text{Harmonic Mean} = \frac{2 \cdot \text{F}_{\text{retrieval}} \cdot \text{A}_{\text{classification}}}{\text{F}_{\text{retrieval}} + \text{A}_{\text{classification}}}$$

3.2 Experimental details

3.2.1 Preprocessing

In the preprocessing process of evidence retrieval, we refine the text by tokenizing, removing stop words and special characters, and applying the Porter Stemmer to reduce words to their root forms, aiding in effective matching. For claim verification, we tokenize the text while retaining stop words, special characters, and numbers, and use lemmatization to convert words to their base forms, preserving context for accurate claim verification.

3.2.2 Model Configuration

The model parameters were tuned through testing with different settings to identify the configurations that produced the best results.

For the **GRU-based model**, we use an embedding layer initialized with random weights, mapping input tokens to 256-dimensional dense vectors. The core of the model is a bidirectional GRU with 512 hidden units, which captures dependencies in both forward and backward directions. An attention mechanism computes attention scores over the GRU hidden states, allowing the model to focus on the most relevant parts of the sequences. A dropout rate of 0.7 is applied for regularization, preventing overfitting by randomly dropping units during training.

For the **Transformer-based model**, the embedding layer maps input tokens to 256-dimensional dense vectors, initialized with random weights. Positional encoding is added to retain the order of the tokens. The Transformer encoder consists of 6 layers, each with multi-head attention comprising 8 heads, a feedforward network with a hidden size of 1024, ReLU activation, a dropout rate of 0.8 for regularization, and layer normalization. This configuration captures complex dependencies and stabilizes the training process by maintaining a consistent representation of the input data.

3.2.3 Training Details

Loss Function: For evidence retrieval, we utilized the Negative Log-Likelihood of the positive passage discussed in Equation 1. For claim verification, we used Weighted Cross-Entropy Loss, which is appropriate for multiclass classification as it effectively handles multiple classes by comparing the predicted probability distribution across all classes to the actual class labels, ensuring accurate and stable training.

Optimizer: The Adam optimizer is used for training with a learning rate of 0.001. We also applied gradient clipping to prevent exploding gradients. Additionally, we used a learning rate scheduler, `torch.optim.lr_scheduler.ReduceLROnPlateau`, to adjust the learning rate, reducing it by a factor of 0.5 if the validation loss did not improve for 3 consecutive epochs

Epochs: Our experiments used 15 epochs for the GRU-based model and 30 epochs for the Transformer-based model. The model state was saved when it reached the best F1 score on the evaluation set for retrieval and the best accuracy for classification.

Batch Size: A batch size of 32 is used to train the model, which is chosen to ensure efficient use of computational resources while maintaining sufficient data variability within each batch.

3.2.4 Data Sampling

For the evidence retrieval part, we experimented with different negative sampling strategies to evaluate their effectiveness:

Random: Randomly samples negatives from the top filtered set provided by the initial retriever. This baseline introduces diverse negative examples but may include easily distinguishable negatives.

In Batch: Uses positive evidence from other claims within the same batch as negatives. Each claim has one positive sample and $B - 1$ in-batch negatives, improving the model's ability to distinguish between similar evidence.

In-Batch + Gold Negatives: For each claim, this strategy uses one positive sample, $B - 1$ in-batch negatives, and one top negative from the top 50 reranked non-ground truth evidence as the gold negative. All claims in the same batch share these top negatives. This approach combines the challenge of in-batch negatives with the relevance-based difficulty of top negatives, improving precision and recall (Karpukhin et al., 2020).

4 Result

4.1 Initial Retrieval Model

Model	Recall @ 100
BM25	0.5128
TF-IDF	0.4104
Word2Vec	0.4203

Table 1: Comparison of Recall @ k = 100 for different models

The results of the initial retrievers, as shown in Table 1, indicate that BM25 outperforms both TF-IDF and Word2Vec in terms of recall at k = 100. BM25's superior performance can be attributed to its advanced handling of term frequency saturation and document length normalization, which allows it to better manage variations in term frequency and document length (Robertson and Zaragoza, 2009). TF-IDF, while useful, does not normalize for document length and can favor longer documents, leading to less effective retrieval results (Mitra and Craswell, 2018). Word2Vec captures semantic relationships between words but lacks the term frequency and document relevance considerations that are crucial for precise information retrieval (Mikolov et al., 2013). Therefore, BM25's design makes it more suitable for initial retrieval tasks, resulting in higher recall compared to TF-IDF and Word2Vec.

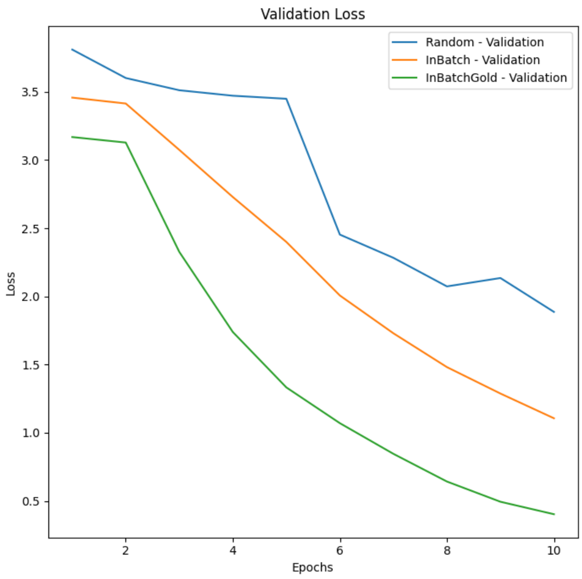

Figure 1: Validation Loss for Different Sampling Strategies

4.2 Negative Sampling Strategies

Figure 1 shows that InBatchGold yields the lowest validation loss, followed by InBatch and Random sampling. InBatchGold, which selects top negatives from the top 50 reranked non-ground truth evidence, provides challenging samples, helping the model develop precise decision boundaries. Random sampling results in the highest loss due to insufficiently challenging negatives, causing overfitting. InBatch offers intermediate performance with moderately challenging negatives. These results highlight that using more informative and challenging negatives, as in InBatchGold, improves the model's ability to distinguish between relevant and irrelevant evidence.

4.3 Neural Retrievers

Model	Precision @ k=5	Recall @ k=5	F1 @ k=5
GRU (Baseline)	0.1211	0.0714	0.0841
GRU + Attention	0.1727	0.0922	0.1122
Transformer	0.1633	0.0896	0.1068

Table 2: Performance of Neural Retrievers (Precision, Recall, and F1 @ k=5)

The results in Table 2 show that the GRU with attention outperforms both the GRU baseline and the Transformer model in precision, recall, and F1 score at $k = 5$. The attention mechanism in the GRU enhances its ability to focus on relevant parts of the input, capturing key patterns and relationships more effectively. The Transformer's performance, while competitive, is limited by the lack of extensive pre-training, which is essential for fully leveraging its complex architecture. This highlights the effectiveness of attention mechanisms in GRUs for precise feature extraction and relevance determination in evidence retrieval.

4.4 Claim Verification

Performance Comparison of Different Models and Approaches			
Model	Approach	Macro Avg F1	Accuracy
Bi-Directional GRU	Evidence Level	0.40	0.48
	Claim Level	0.42	0.49
Transformer	Evidence Level	0.34	0.25
	Claim Level	0.39	0.41

Table 3: Performance Comparison of Different Models and Approaches

The results in Table 3 indicate that the Bi-Directional GRU outperforms the Transformer model in both evidence-level and claim-level approaches. This is likely due to the lack of pre-training, which is crucial for Transformer models to capture complex language patterns. The claim-level approach yields better results than the evidence-level approach because it allows the model to learn decision boundaries for the 'DISPUTED' class more effectively, whereas the evidence-level approach's majority voting can struggle with ambiguous or conflicting evidence. This demonstrates the importance of holistic context in claim verification.

5 Conclusion

In this project, we developed an automated fact-checking system focusing on evidence retrieval and claim verification for climate-related claims. Our findings show that the GRU-based model with attention outperformed both the GRU baseline and Transformer models, highlighting the importance of attention mechanisms for precise feature extraction. The InBatchGold sampling strategy provided the best results, emphasizing the need for challenging negative samples. The claim-level classification approach yielded better results than the evidence-level approach, demonstrating the value of holistic context. The primary limitation was the absence of pre-trained models, which are crucial for fully leveraging Transformer architectures. Future work should explore joint learning approaches to better utilize patterns learned during retrieval and improve overall system performance.

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