1 Pipeline Overview

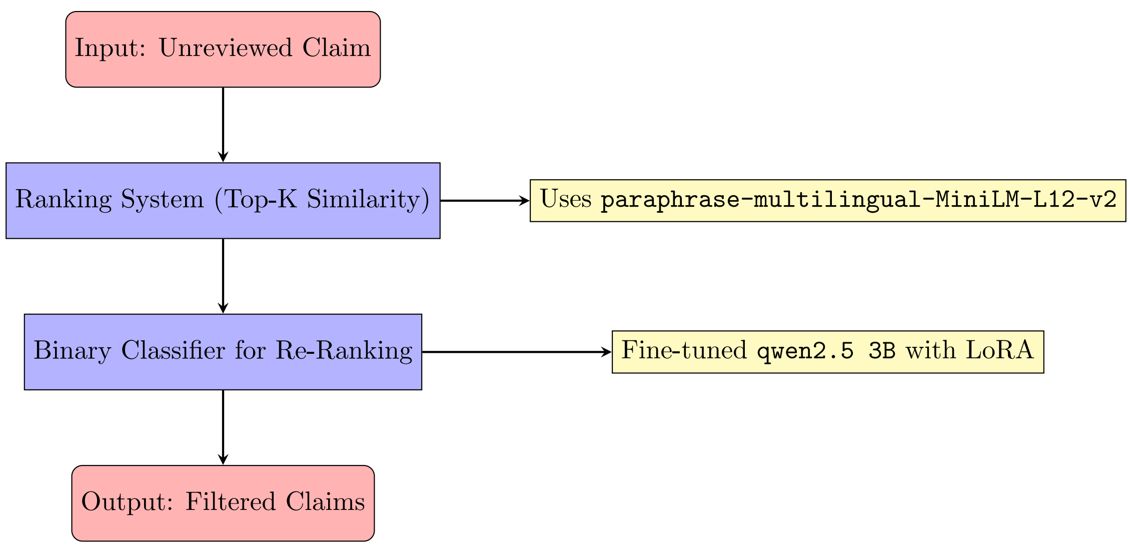
We have a list of unreviewed claims paired with reviewed claims, each labeled with 0 or 1 to indicate whether they are similar or not. Using this dataset, we train a binary classifier with a large language model (LLM) to determine whether an unreviewed claim is similar to another.

The pipeline consists of the following steps:

1. **Ranking System:** The process starts with a ranking system that identifies the top K reviewed claims most similar to the input unreviewed claim. This is achieved by leveraging a transformer model to compute similarities between the unreviewed claim and all reviewed claims, selecting the top K based on similarity scores.

2. **Binary Classification for Re-Ranking:** The top K claims are then passed through a binary classifier that acts as a re-ranking step. This classifier filters out claims from the top K list that are not sufficiently similar, according to the binary classification model.

3. **Final Selection:** After re-ranking, the claims retained by the classifier are presented as the final output. These claims represent the reviewed claims deemed most similar to the input unreviewed claim.



2 Evaluation Metrics

2.1 Accuracy

Accuracy evaluates the proportion of correctly predicted claims compared to the ground truth, where y and $\hat{y}$ are a list of sets of predicted claims and a list of sets of the reviewed claims, respectively:

$$\text{Acc}(y, \hat{y}) = \frac{1}{N} \sum_{i=1}^{N} \text{QA}(y_i, \hat{y}_i) \tag{1}$$

Where N is the total number of queries. A correct prediction for a query means all responses match the ground truth exactly. If not, the accuracy for that query (Query Accuracy, QA) is calculated as:

$$\text{QA}(a, \hat{a}) = \frac{|a \cap \hat{a}|}{|\text{a} \cup \hat{a}|} \tag{2}$$

where a is a set os hypothesis claims and $\hat{a}$ is a set of ground truth claims for a given query.

2.2 Mean Average Precision at K

Mean Average Precision at K (mAP@K) evaluates the average precision of predictions up to K. We define AP as follows, which is a non-standard approach since we do not have an ordered set of relevant claims:

$$\text{AP@K}(a, \hat{a}) = \frac{|\hat{a}_K \cap a_K|}{\min(K, |\hat{a}|)} \tag{3}$$

where a is a set os hypothesis claims and $\hat{a}$ is a set of ground truth claims for a given query. Then, we can calculate mAP@K as follows:

$$\text{mAP@K}(y, \hat{y}) = \frac{1}{N} \sum_{i=1}^{N} \text{AP@K}(y_i, \hat{y}_i) \tag{4}$$

where y and $\hat{y}$ are a list of sets of predicted claims and a list of sets of the reviewed claims, respectively, and K is the cutoff.

2.3 Average Recall at K

Recall at K calculates the fraction of relevant K items retrieved. Then, to calculate the Average Recall (AR) at K, where y and $\hat{y}$ are a list of sets of predicted claims and a list of sets of the reviewed claims, respectively, and K is the cutoff, we follow the next equation:

$$\text{AR@K}(y, \hat{y}) = \frac{1}{N} \sum_{i=1}^{N} \frac{|\hat{y}_{i,K} \cap y_{i,K}|}{\min(K, |y_i|)} \tag{5}$$

Where N is the total number of non-reviewed claims, $y_{i,K}$ is the set of K non-reviewed claims, and $\hat{y}_{i,K}$ represents K reviewed claims, where first we select reviews that are in $y_{i,K}$ and fill the rest with other reviews until K.

2.4 Mean Reciprocal Rank

Mean Reciprocal Rank (MRR) calculates the average reciprocal rank of the first relevant prediction:

$$\mathrm{MRR}(y, \hat{y}) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{r(y_i, \hat{y}_i)} \tag{6}$$

Where $r(a, \hat{a})$ is the position of the first relevant item for query a in $\hat{a}$, and N is the total number of queries. MRR is only computed for $\forall \hat{y}_i \in y, 1 \leq i \leq N$.