Evidence Retrieval for Fact Verification using Multi-stage Reranking

Anonymous EMNLP submission

Abstract

In the fact verification domain, the accuracy and efficiency of evidence retrieval are paramount. This paper presents a novel approach to enhance the fact verification process through a Multi-stage ReRanking (M-ReRank) paradigm, which addresses the inherent limitations of single-stage evidence extraction. Our methodology leverages the strengths of advanced reranking techniques, including dense retrieval models and list-aware rerankers, to optimise the retrieval and ranking of evidence of both structured and unstructured type. We demonstrate that our approach significantly outperforms previous state-of-the-art models, achieving a recall rate of 93.63% for Wikipedia pages. The proposed system not only improves the retrieval of relevant sentences and table cells, but also enhances the overall verification accuracy. Through extensive experimentation on the FEVEROUS dataset, we show that our M-ReRank pipeline achieves substantial improvements in evidence extraction, particularly increasing the recall of sentences by 7.85%, tables by 8.29% and cells by 3% compared to the current state-of-the-art on the development set.

1 Introduction

The proliferation of false and misleading information, fuelled by the rapid progress in artificial intelligence (AI), poses a significant societal threat, as highlighted in the World Economic Forum's report (WEF, 2024). For example, the widespread mis/dis-information about COVID-19 vaccines has caused a surge in anti-vaccination sentiment online, leading to low vaccination coverage (Islam et al., 2021). A recent study shows that low-veracity media-induced overconfidence exacerbates the adverse effects of widespread misinformation (i.e., fake news), especially in current global election scenarios (Kartal and Tyran, 2022). To combat this, researchers are focusing on developing automatic fact verification systems to prevent disinformation from spreading online (Guo et al., 2022).

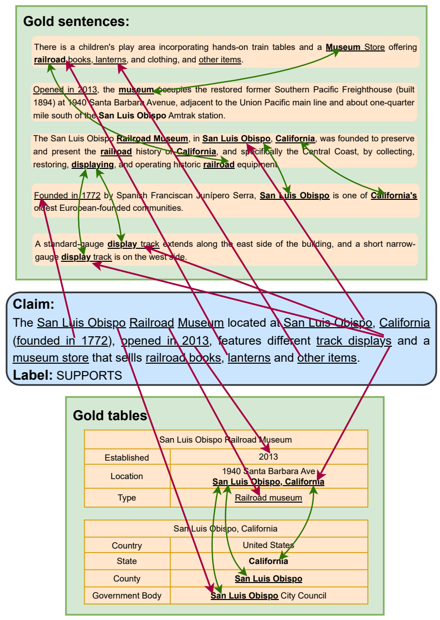

Figure 1: An example in FEVEROUS: The blue, yellow and green rectangle contains claim, sentence evidence, and table evidence, respectively. Arrows depict the interaction between two pieces of text. Keywords are underlined to show claim-evidence overlap and boldly highlighted to indicate intra-evidence interactions.

To answer the increasing demand for such systems, a number of datasets have been released, ranging from claims collected from fact-checking websites, e.g. LIAR (Wang, 2017), to complex collections of claims associated with proof-of-evidences, e.g. FEVER (Thorne et al., 2018), CLEF CheckThat! (Nakov et al., 2021), SemEval (Wang et al., 2021), FEVEROUS (Aly et al., 2021). In this paper, we focus on solving the FEVEROUS task, where the challenge is not only to extract evidence sentences/table cells from millions of passages (Wikipedia), but also combine them to verify a given claim. Unlike other datasets, FEVEROUS proposes a real-world scenario where the evidence could be in both structured (e.g. Tables, lists) or unstructured format (e.g. sentences, paragraphs).

Key advancements on FEVEROUS task are not only on improving the claim verification procedure (Hu et al., 2022), but also focusing on evidence retrieval in various formats (Hu et al., 2023; Wu et al., 2023). The DCUF, a fact-verfication model introduced by (Hu et al., 2022), performs interaction of evidence in each format to improve the final verification accuracy, leaving the evidence extraction within each format separately. Recent works, e.g. UnifEE (Hu et al., 2023), SEE-ST (Wu et al., 2023), give attention to evidence extraction focusing either on individual format or interaction across various format. They mostly look for lexical (word-based) or semantic (meaning-based) overlaps between the claim and evidence pieces. They do not take into account how different pieces of evidence might relate to one another within the same format.

Figure 1 illustrates an example from FEVEROUS, where the goal is to extract both unstructured (e.g., sentences) and structured (e.g., tables or cells) evidence to verify a claim. The figure highlights two types of overlap: between the claim and its associated evidence, and among the evidence pieces themselves. Recognising interactions among evidence is crucial for determining the retrieval score of individual evidence. Critical evidence may not have obvious overlaps with the claim, but their relevance becomes clear when viewed in the context of other evidence. For instance, one piece of evidence might state the "Railroad Museum" is in "San Luis Obispo, California", while another mentions it opened in the year "2013". The underutilisation of interactions among these evidence pieces can lead to the omission of crucial information that could otherwise strengthen the verification process. Therefore, leveraging interactions between candidate evidence in each format is essential for effective evidence extraction.

In this paper, we propose the Multi-stage Reranking (M-ReRank) paradigm, which exploits overlapping among connected evidence candidates as collaborative filtering (Zhang et al., 2022b, 2023) to improve evidence extraction, thereby achieving higher accuracy in veracity prediction. To the best of our knowledge, this has been largely unexplored in the fact-verification domain. We design a novel pipeline, M-ReRank, which comprises a sequence of robust rerankers, e.g. Cross-Encoder (improved recall) (Humeau et al., 2019), HybRank (collaborative assessment) (Zhang et al., 2023), and HLATR (list-aware reranking) (Zhang et al., 2022b). It helps improve the first and second steps in FEVEROUS, i.e. wiki-page retrieval and evidence extraction. Experiments on FEVEROUS show that our M-ReRank model significantly enhances evidence extraction performance and, consequently, boosts final fact verification scores. Detailed ablation experiments exhibit the effectiveness of M-ReRank in evidence extraction, showcasing how each component contributes to the overall improvement. A case study further highlights its role in accurately retrieving and utilising evidence for verification.

The contributions of this work can be summarised as follows: (i) We propose a Multi-stage ReRanking (M-ReRank) pipeline investigating how the retrieval and reranking architectures influence the evidence retrieval process. (ii) We show how evidence extraction can be improved by leveraging the relationships that exist among the evidence through collaborative filtering and list-aware reranking. (iii) Experiments show that our proposed multi-stage reranking significantly outperforms previous works on both the evidence extraction and the final verification accuracy. Detailed analysis reveals that our M-ReRank performs well in retrieving multi-hop evidence and combining evidence in both formats (sentences and tables).

2 Background

2.1 Multi-stage Text Retrieval

Traditionally, information retrieval has relied on lexical methods such as TFIDF and BM25 (Robertson and Zaragoza, 2009), treating queries and documents as sparse bag-of-words vectors and matching them at the token level. Recently, text retrieval systems armed with pre-trained language models have become a dominant paradigm to improve the overall performance where queries and documents are encoded into dense contextualised semantic vectors (Ren et al., 2021; Zhang et al., 2022a), and performing retrieval with optimised vector search algorithms (Johnson et al., 2021).

Recent approaches in reranking concatenate query-passage pairs and input them into a Transformer pre-trained on large corpora, allowing for more nuanced relevance estimation and improved retrieval outcomes through enhanced interaction (Humeau et al., 2019; Nogueira and Cho, 2020). However, these methods typically treat each candidate passage in isolation, neglecting the contextual information in the retrieved passage list. Some learning to rank techniques (Rahimi et al., 2016) and pseudo-relevance feedback approaches (Zhai and Lafferty, 2001; Zamani et al., 2016) leverage the ordinal relationship or list-wise context of retrieved documents for enhanced retrieval, a need corroborated in multi-stage retrieval systems (Liu et al., 2022). HybRank (Zhang et al., 2023) investigates collaboration among the candidate text in the retrieval lists and shows that collaborative filtering improves the precision of retrieval systems by exploiting linguistic aspects of sparse and dense retrieval methods. HLATR (Zhang et al., 2022b) has shown improved performance as a multi-stage text retrieval system by coupling features from both retrieval and reranking stages. We combine HybRank and HLATR in our M-ReRank pipeline.

2.2 Multi-stage Evidence Reranking for Fact-Verification

Multi-stage text retrieval can be highly beneficial for fact verification by enabling a more comprehensive and nuanced approach to rank the evidences and assess the veracity of claims or statements. Evidences in the same format also provide context information to each other. Past works on FEVEROUS mainly rely on using a single-stage evidence extraction (Aly et al., 2021; Bouziane et al., 2021; Saeed et al., 2021; Hu et al., 2022). Some methods propose to fuse evidence in different formats to leverage cross-format dependence but still leave the evidence extraction within each format separate (Hu et al., 2023; Wu et al., 2023). Utilising the collaboration that exists among candidate evidence has largely been unexplored for fact verification. Intuitively, for a specific claim, a set of evidence relevant to the claim tends to describe the same entities, events and relations (Lee et al., 2019), while irrelevant ones address a variety of unrelated topics.

2.3 FEVEROUS Task & Dataset

We use FEVEROUS[1] as the test bed for our approach because it is the only open-domain fact verification benchmark, to our knowledge, that integrates both unstructured and structured evidence. FEVEROUS has two main objectives: first, to extract sentences and table cell evidence from English Wikipedia and second, to predict the veracity of a given claim labelled as SUPPORTS, REFUTES, or NOT ENOUGH INFO (NEI). Each claim in the FEVEROUS dataset can be verified in multiple ways, represented by different evidence sets, each potentially comprising multiple pieces of evidence. For a response to be considered correct, participating systems only need to provide one complete evidence set. Hence, a prediction is considered correct only if at least one complete gold evidence set E is a subset of the predicted evidence $\hat{E}$ and the predicted label is correct. Statistics for the FEVEROUS dataset are provided in Appendix A.

[1] https://fever.ai/dataset/feverous.html

3 Our Approach

The aim of the FEVEROUS open-domain fact verification (Aly et al., 2021) benchmark's task is to verify a claim c based on content from Wikipedia. We follow the widely-adopted three-step pipeline, which involves i) retrieving relevant pages from the Wikipedia dump, ii) extracting sentences and table cells as evidence from these pages, and iii) predicting the veracity label of the given claim based on the compiled evidence set. In this work, we explore improving the first and second steps—wiki-page retrieval and evidence extraction—by employing our multi-stage retrieval pipeline.

In the three-step pipeline, as shown in Figure 2, the Wikipedia pages are *first* retrieved and refined by our M-ReRank approach. The top five pages are then used to extract evidence of both formats in the *second step*. We train the models in the M-ReRank pipeline separately for page, sentence and table retrieval. Combining the first five sentences and five tables, we use SEE-ST's (Wu et al., 2023) cell-retriever to extract potential cell evidence. Finally, at the verification step (*third*), we utilise DCUF (Hu et al., 2022), a method that converts evidence into dual-channel encodings to verify the claim.

3.1 Wikipedia page retrieval

Firstly, given a claim c, a set of relevant Wikipedia pages $\mathcal{P}$=$[p_1, p_2, ..., p_{n_p}]$ are retrieved from TFIDF and BM25-based retrieves to narrow down the search space from millions of pages to a few hundred (Robertson and Zaragoza, 2009). We combine the results of TFIDF and BM25 and keep the top n_p documents. TFIDF is effective at capturing the importance of terms within a document and across the corpus, while BM25 is a probabilistic model that adjusts term weights based on term frequency saturation and document length normalisation. The retrieved pages are further reordered by robust upstream retrievers in the proposed M-ReRank, as depicted in Figure 2 (Step-1).

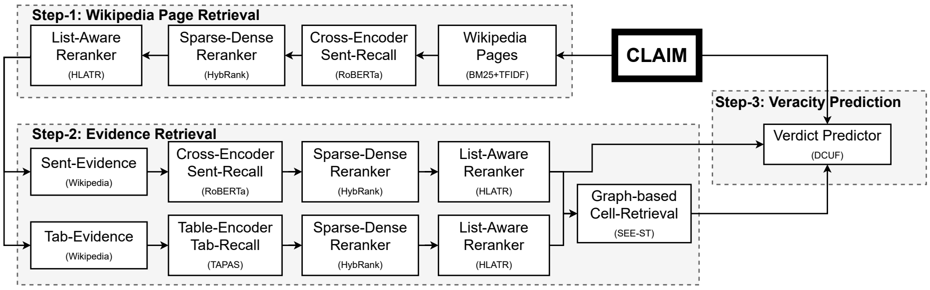

Figure 2: Overview of the pipelined Evidence-Retrieval and Verdict Prediction for a given claim.

3.2 Evidence Retrieval

Top five pages from the previous step are selected to extract the relevant evidence for veracity prediction. We use cross-encoder (Humeau et al., 2019) to extract k sentences $S{=}\{s_i\}_{i=1}^{k}$ and TAPAS[2] based SEE-ST (Wu et al., 2023) model to extract n tables $T{=}\{t_i\}_{i=1}^{n}$. The set of initial sentence and table evidence are then reordered by our M-ReRank (see Figure 2). All the models in the proposed multi-stage pipeline are trained separately using the FEVEROUS dataset's train and dev splits. Based on the extracted sentence/table evidence, we use the Graph-based cell retriever by (Wu et al., 2023), which leverages the row and column semantics of tables to retrieve r cell evidence $C{=}\{c_i\}_{i=1}^{r}$.

3.3 Multi-stage ReRanking (M-ReRank)

Once the initial set of documents, e.g. pages, sentences, tables, are retrieved, the proposed M-ReRank framework reorders them by prioritising their relevance to the given claim based on contextual understanding and semantic similarity. Initially, unstructured candidates like sentences, are reranked using a Cross encoder (Humeau et al., 2019). Subsequently, we utilise advanced rerankers HybRank (Zhang et al., 2023) and HLATR (Zhang et al., 2022b) in the pipeline. HybRank leverages both sparse and dense information to enhance reranking, while HLATR integrates retrieval and reranking features for hybrid list-aware reranking.

For tables, the reranking pipeline starts with the SEE-ST model (Wu et al., 2023), which is effective in capturing the row and column relevance of tables, thereby achieving a more precise extraction of structured candidates. As depicted in Figure 2, the retrieved tables are further reranked sequentially by HybRank and HLATR. Both rerankers take the flattened table as input. After all reranking stages, the retrieved tables and sentences are used to retrieve cells by SEE-ST's cell-retriever.

[2]TAPAS: Table Parser (Herzig et al., 2020)

The proposed pipeline is discussed in detail in the following subsections.

3.3.1 Cross Encoder with Contrastive Learning

(Humeau et al., 2019) showed that cross-encoders typically outperform bi-encoders on sentence scoring tasks by enabling rich interactions between the claim and candidate evidence. In this stage, the claim and evidence are jointly encoded using a transformer architecture into a single vector as E_s=RoBERTa(claim, cand), "cand" represents the candidate evidence. The scoring mechanism involves reducing this embedding through multiple layers including dropout (D), linear layers (L_1, L_2), and activation functions (relu R, sigmoid σ) to obtain a final score $S(\text{claim}, \text{cand}) = \sigma(L_2(R(L_1(D(E_s)))))$. The network is trained using contrastive learning criteria, aiming to minimise a margin ranking loss between pairs of positive x_1 and negative x_2 candidate evidence:

$$\text{MRL}(x_1, x_2, y) = \max(0, -y \cdot (x_1 - x_2)) \quad (1)$$

where x_1 and x_2 are the predicted scores of pos and neg evidence. y is set to 1, indicating a positive candidate ranked higher than the negative.

3.3.2 Table Parser Contrastive Learning

SEE-ST (Wu et al., 2023) showed that leveraging both row and column semantics significantly improves the recall of structured evidence, e.g. tables, table-cells. SEE-ST begins by extracting tables from selected Wikipedia pages targeting the most relevant rows and columns for the given claim, thereby minimising confusion from irrelevant cells. First, the claim and table pair are fed to TAPAS, a pre-trained table model aware of table structures (Herzig et al., 2020), to generate table embedding. Parallely, TAPAS tokenizer also provides row (R_{pool}) and column (C_{pool}) pooling matrix as $E_t, Row_{pool}, Col_{pool}$=TAPAS(claim,table) which are later used for estimating table, row and column losses L_r, L_c, respectively, and final loss L:

$$
\begin{aligned}
L_r &= CrE(R(L(R_{pool}E_t))) \\
L_c &= CrE(R(L(C_{pool}E_t))) \\
Lt &= \sigma(R(L(E_t))) \\
L_t &= \mathrm{MRL}(Lt_{pos}, Lt_{neg}, 1) \\
L &= \alpha_t L_r + \beta_t L_c + \gamma_t L_t
\end{aligned} \tag{2}
$$

Since a cell represents the intersection of a row and a column, its relevance can be determined by analysing both dimensions. During inference, the table score is estimated through various criteria, e.g. $L_r + L_c$, $L_r \times L_c$, L_r or L_c. For the Table retrieval task, $L_r \times L_c$ provides higher retrieval accuracy:

$$S(\text{claim}, \text{table}) = L_r \times L_c \tag{3}$$

3.3.3 HybRank

HybRank (Zhang et al., 2023) utilises the strategy of collaborative filtering (Goldberg et al., 1992) by incorporating lexical and semantic properties of both sparse and dense retrievers in reranking. We utilise BM25 as sparse and RoBERTa as dense retriever to rerank the candidates for a given claim through a 3-stage process:

(a) Retrieval Stage:

Sparse Retrieval: Given the claim c and the candidate d, the BM25 score is obtained by summing the BM25 weights over the terms that co-occurred in c and d. Refer to (Robertson and Zaragoza, 2009) for more details about BM25.

Dense Retrieval: The relevance score is estimated as the dot product of encoded claim c and candidate d, with $S_d(c, d) = E(c)^\top E(d)$, where $E(\cdot)$ denotes the encoder (RoBERTa) which determines the embedding of claim and candidate text.

(b) Collaborative Filtering Stage: The collaborative filtering stage leverages the sparse and dense scores between candidates, distinguishing positive ones in the retrieval list. For each candidate and claim, a sequence of similarity scalars x_{d_i}=$[s_{i1}, s_{i2}, ..., s_{iL}] \in \mathbb{R}$ is estimated with a set of Top-L anchors from both sparse and dense scores. After applying softmax and min-max normalisation, the sparse and dense scores are stacked in a dual channel manner $x_{ij} = [s_{ij}^{\text{sparse}}, s_{ij}^{\text{dense}}] \in \mathbb{R}^2$. Thus, the similarity sequence vector becomes like $X_{d_i} = [x_{i1}, x_{i2}, ..., x_{iL}] \in \mathbb{R}^{L\times 2}$. This dual-channel similarity vector is transformed to D dimensions with a trainable projection layer $e_{ij} = x_{ij}W$, where $W \in \mathbb{R}^{2\times L}$ is a learnable parameter and $e_{ij} \in \mathbb{R}^D$ are embedded similarities. Thereafter, candidate d_i becomes a sequence of similarity embeddings $E_{d_i} = [e_{i1}, e_{i2}, ..., e_{iL}] \in \mathbb{R}^{L\times D}$, which consists of candidate d_i similarity information with anchor list. As a result, we obtain a total of $N_d + 1$ collaborative sequences, where each sequence corresponds to either a candidate or a query and incorporates both lexical and semantic similarity information with respect to L anchors.

(c) Aggregation Reranking Stage: To perform anchor-wise interaction, we gather the j-th similarity embedding e_j^* from the claim sequence and all candidate sequences, refining them using a Transformer encoder as:

$$e'_{cj}, e'_{1j}, \ldots, e'_{N_dj} = \text{Trans}_{\text{inter}}(e_{cj}; e_{1j}; \ldots; e_{N_dj}) \tag{4}$$

where, $e'_{*j} \in \mathbb{R}^D$. This transforms the similarity embedding sequence E_* to E'_*. We transform these sequences into dense vectors by consolidating the refined similarity embeddings. Specifically, we add a [CLS] token at the beginning of the collaborative sequence, process it through another Transformer encoder, and take the output of the [CLS] token as the representation of candidate d_i and claim c as:

$$h_{d_i} = \text{Trans}_{\text{aggr}}([\text{CLS}] \oplus E'_{d_i})[\text{CLS}] \tag{5}$$

$$h_c = \text{Trans}_{\text{aggr}}([\text{CLS}] \oplus E'_c)[\text{CLS}] \tag{6}$$

where $[\text{CLS}] \in \mathbb{R}^{1\times D}$ and $\oplus$ denotes the concatenation operation. Finally, the dot product between encoded vector h_{d_i} of candidate and claim vector h_c determines the similarity score.

3.3.4 HLATR

HLATR (Zhang et al., 2022b) improves text retrieval by combining retrieval and reranking features using a lightweight transformer encoder. As a retrieve-then-reranking architecture, HLATR follows a three-stage pipeline: (a) the *Retrieval Stage* identifies potentially relevant documents, (b) the *Reranking Stage* refines the relevance scores of the retrieved documents, and (c) the *HLATR Stage* consists of a multi-stage feature fusion layer and a transformer encoder to further improve the ranking:

(a) Retrieval Stage: In the Retrieval Stage, we consider the retrieved candidate documents from previous modules in our pipeline, e.g. HybRank, Cross-Encoder/SEE-ST, instead of using a separate dense retrieval model, as the original HLATR algorithm suggests.

(b) Reranking Stage: The Reranking Stage further refines the retrieval scores using an interaction-based model, e.g. Cross-encoder. Each claim-candidate pair (c, d) is rescored as $\text{score}(c, d) = f(E(c, d))$, where, $E(\cdot,\cdot)$ denotes the encoder (RoBERTa), and f is the score function, e.g. σ (sequence classifier). Training involves a contrastive learning objective (L_c), optimising the model with groups of (c, d) pairs consisting of one positive candidate d^+ and multiple negatives as:

$$L_c = -\log \frac{\exp(\text{score}(c, d^+))}{\sum_{p \in G_d} \exp(\text{score}(c, d))} \quad (7)$$

(c) HLATR Stage: The core of this reranking paradigm is the HLATR component, which features a multi-stage fusion layer and a transformer encoder. It enhances the reranking results by combining features from both retrieval and reranking stages, creating a comprehensive representation. The combined features are processed through a lightweight transformer encoder, which models the interactions among all candidates, highlighting mutual relationships. The combined relevance score in HLATR is formulated as: $\text{score}_{\text{HLATR}}(c, D_r) = f_{\text{HLATR}}(E_{\text{HLATR}}(c, D_r))$ where D_r represents a candidates list to be reranked, E_{HLATR} is the encoder that processes the combined features, and f_{HLATR} is the final relevance estimation function. Like the previous stage, this stage is also optimised with a list-wise contrastive loss, as defined by Eq 7.

4 Experimental Evaluation

4.1 Evaluation Metrics

In the FEVEROUS task, two primary official metrics are employed: accuracy (Acc.) and the FEVEROUS score (F.S). Accuracy measures the proportion of instances for which the model correctly predicts the veracity label. The FEVEROUS score evaluates not only the correctness of the final veracity label but also the adequacy of the extracted evidence set. It quantifies the proportion of instances where the extracted evidence set aligns with one of the gold evidence sets, and the predicted veracity label matches the gold standard. Three additional official metrics are utilised to assess the quality of extracted evidence sets in the FEVEROUS task: Evidence Precision (E-P), Evidence Recall (E-R), and Evidence F1 (E-F1). It also provides multiple gold evidence sets for each claim, and a piece of extracted evidence is deemed correct only if it is included in any of the gold evidence sets. For each instance, Evidence Precision represents the proportion of correctly predicted evidence. The overall Evidence Precision is determined by averaging this score across all instances. Evidence Recall measures the proportion of instances with a correctly extracted evidence set, where correctness is defined by covering any of the gold evidence sets. Lastly, Evidence F1 is the harmonic mean of Evidence Precision and Evidence Recall, providing a balanced assessment of precision and recall in evidence extraction.

Models	Page	Sentence	Table	Cell	Evidence
Baseline	63	53	56	29	30
FaBULOUS	63	56.6	-	34.2	40.4
DCUF	85.20	62.54	75.59	58.41	43.22
UnifEE	85.20	75.59	75.36	67.44	55.08
SEE-ST	85.20	75.50	80.86	77.16	61.43
M-ReRank (ours)	**93.63**	**83.35**	**89.15**	**80.16**	**66.69**

Table 1: Recall of different formats of evidence on the development set.

4.2 Implementation Details

Implementation details for all the algorithms used, as well as training hyperparameters, are provided and discussed in Appendix B.

4.3 Main Results

Evidence extraction results: Table 1 presents the evidence extraction results of our M-ReRank pipeline on the development set and compares it with the recent state-of-the-art. Previous methods, such as the official baseline (Aly et al., 2021) and FaBULOUS (Bouziane et al., 2021), employ a weaker document retrieval module, i.e. BM25/TFIDF, leading to error propagation and lower evidence recall. Recent methods, DCUF, UnifEE, SEE-ST, utilise ensemble of cross-encoder[3] and BM25, which improved page recall by 85.20%. However, limited page retrieval limits the overall evidence recall and, consequently, low accuracy in veracity prediction. Our multi-stage reranking improves the page recall by 8.43%. Notably, M-ReRank extracts 36% more gold-standard evidence compared to the official baseline and 5.26% compared to the best model SEE-ST. Through M-ReRank, we obtain substantial recall jump in all formats of evidence retrieval. This is also proved by our ablation study in (§4.4).

Overall Results: Our primary results, summarised in Table 2, demonstrate significant per-

[3]cross-encoder/ms-marco-MiniLM-L-12-v2

Models	Development set					Test set				
	F.S	Acc.	E-P	E-R	E-F1	F.S	Acc.	E-P	E-R	E-F1
Official Baseline	19	53	12	30	17	17.73	48.48	10.17	28.78	15.03
EURECOM	19	53	12	29	17	20.01	47.79	13.73	33.73	19.52
Z team	-	-	-	-	-	22.51	49.01	7.76	42.64	13.12
CARE	26	63	7	37	12	23	53	7	37	11
NCU	29	60	10	42	17	25.14	52.29	9.91	39.07	15.81
Papelo	28	66	-	-	-	25.92	57.57	7.16	34.60	11.87
FaBULOUS	30	65	8	43	14	27.01	56.07	7.73	42.58	13.08
DCUF	35.77	72.91	15.06	43.22	22.34	33.97	63.21	14.79	44.10	22.15
UnifEE	44.86	73.67	**19.04**	55.08	**28.30**	41.50	65.04	**18.35**	53.87	**27.37**
SEE-ST	49.73	74.68	10.60	61.43	18.07	44.75	65.16	9.81	60.01	16.89
M-ReRank (ours)	**60.57**	**87.58**	10.68	**66.69**	18.40	**47.13**	**65.24**	10.35	**63.71**	17.81

Table 2: Model performance on the development set and test set. F.S is FEVEROUS score and Acc. is the accuracy of veracity labels. E-R, E-P and E-F1 are recall, precision and F1 computed based on the evidence set.

Retriever	**T-150**	**T-5**
Baseline TFIDF	91.43	62.71
TFIDF (T)	92.33	69.46
BM25 (B)	90.53	71.40
$\text{Ensemble}_{(T,B)}$ (E)	94.87	73.98
E+Cross-encoder (C)	94.87	87.14
E+HybRank (Hy)	94.87	90.83
E+HLATR (Hl)	94.87	92.90
E+C+Hy	94.87	91.39
E+C+Hy+Hl	94.87	**93.63**

Table 3: Wikipedia page retrieval results with rerankers in our M-ReRank pipeline in Top-150/5 settings.

T-5 Pages	**Retriever**	**T-100**	**T-20**	**T-5**
E	TFIDF	71.56	67.11	54.38
	RoBERTa (R)	88.13	80.35	77.13
	R+HybRank (HyS)	88.13	86.65	78.76
	R+HLATR (HlS)	88.13	86.99	79.09
	R+HyS+HlS	88.13	87.02	80.06
E+C+Hy+Hl	TFIDF	90.03	82.65	67.30
	RoBERTa (R)	92.36	90.15	80.33
	R+HybRank (HyS)	92.36	90.50	81.73
	R+HLATR (HlS)	92.36	89.92	82.49
	R+HyS+HlS	92.36	90.60	**83.35**

Table 4: Sentence retrieval results with various rerankers in our M-ReRank pipeline in Top-100/20/5 settings.

formance improvement in evidence extraction compared to the previous best models, i.e. DCUF, UnifEE, SEE-ST, thereby improving feverous score (F.S) overall. Specifically, our model shows improvements of 5.26%/3.70% in evidence recall on the development/test set, respectively. Adopting the verification approach from (Hu et al., 2022), we achieved accuracy rates of 87.58% on the development set and 65.24% on the test set. These gains indicate that by leveraging context information from other evidence in the candidate list, our multi-stage reranking (M-ReRank) enhances the accuracy of evidence extraction.

Following the constraint on selecting the maximum number of sentences and cells, there are two ways to construct an evidence set. One way is to apply a threshold when selecting evidence with high precision at the expense of slightly lower recall. For example, a former SOTA method, UnifEE, follows the same criteria for high precision, but the label accuracy remains largely unaffected by changes in the evidence set. We employ the maximum number of sentences and cells as constraints, keeping higher evidence recall. Demonstrating the effectiveness of our approach, an example of evidence extraction in both formats is presented in Appendix D.

T-5 Pages	**Retriever**	**T-20**	**T-5**	**T-3**
E	TFIDF	82.17	80.84	76.89
	SEE-ST (S)	88.84	86.27	83.99
	S+HybRank (HyT)	88.84	87.33	84.29
	S+HLATR (HlT)	88.84	87.45	85.23
	S+HyT+HlT	88.84	87.52	85.35
E+C+Hy+Hl	TFIDF	89.30	85.75	79.83
	SEE-ST (S)	93.40	88.44	86.87
	S+HybRank (HyT)	93.40	90.81	88.54
	S+HLATR (HlT)	93.40	90.83	88.65
	S+HyT+HlT	93.40	91.61	**89.15**

Table 5: Tables retrieval results with various rerankers in our M-ReRank pipeline in Top-20/5/3 settings.

The test set accuracy is typically lower than the development set accuracy. This discrepancy is primarily due to the unequal distribution of NEI (Not Enough Information) claims across the different splits. Our analysis of verdict prediction results reveals that DCUF underperforms on NEI instances, which accounts for the accuracy gap between the development and test sets.

4.4 Ablation Study

To evaluate the effectiveness of M-ReRank, we conducted a series of ablation experiments focusing on three aspects: i) Wikipedia page retrieval, ii) sentence extraction, and iii) table extraction.

We first examined the impact of each reranker in M-ReRank by applying them individually. Subsequently, we applied them in a multi-stage manner, prioritising the order based on their individual performance to understand the cumulative effect. Since M-ReRank obtains the maximum number of Wikipedia pages, we also experiment with extracting sentence and table evidence solely from pages retrieved by $\text{Ensemble}_{(T,B)}$, excluding M-ReRank for page retrieval as shown in Table 4 and Table 5. This allows for a fairer comparison of rankers in the M-ReRank pipeline for sentence and table retrieval.

Wikipedia Page Retrieval: Table 3 presents the recall of various methods ranging from FEVEROUS's baseline TFIDF to all rerankers in M-ReRank pipeline. The FEVEROUS baseline achieves a 91.43% recall in the Top-150 setting but is unable to keep relevant in the Top-5. By pre-processing the text to convert Unicode characters to their nearest ASCII equivalents, we observe a 6.75%/8.69% improvement by TFIDF(T) and BM25(B), respectively, in Top-5 recall. Further improvements are seen by applying ensemble reranking (Dwork et al., 2001) on the T and B results, increasing the page recall to 94.87% for Top-150 and 73.98% for Top-5 settings. We see a significant jump in page recall specific to Top-5 retrieval on applying Neural rankers, e.g. Cross-encoder, HybRank, and HLATR, by 13.16%, 16.85%, and 18.92%, respectively. When applied together (E+C+Hy+Hl), they achieve the highest page recall of 93.63% under Top-5.

Sentence Extraction: Table 4 depicts the ablation results on sentence retrieval. To show the effectiveness of M-ReRank based rerankers, we perform ablation with the Top-5 pages retrieved by earlier step via both $\text{Ensemble}_{T,B}$ and E+C+Hy+Hl settings. M-ReRank performs well for sentence retrieval in both scenarios. RoBERTa-based cross-encoder improves sentence recall in both cases by 22.75% and 13.03%. Using the RoBERTa results, the other rankers, HybRank, HLATR, consistently achieve higher recall. In the E+C+Hy+Hl setting, the M-ReRank achieves the highest recall by 83.35% for sentence retrieval, which is 7.85% higher than the previous SOTA method.

Table Extraction: Table 5 display the effectiveness of M-ReRank on table retrieval. Like the ablation experiments of sentence extraction, we again choose the Wikipedia pages retrieved via both $\text{Ensemble}_{T,B}$ and E+C+Hy+Hl settings to fairly compare the rerankers' strength. The retrievers' performance is compared on Top-3/5/20 recall. SEE-ST (Wu et al., 2023) has shown a significant recall improvement of 3-7% compared to the TFIDF baseline by incorporating row and column semantics. M-ReRank retrievers reorder the table candidates in flattened form. For retrieved pages in both $\text{Ensemble}_{T,B}$ and E+C+Hy+Hl setting, M-ReRank consistently improves the table recall, similar to that found in the sentence extraction. We observe a jump of 1.36% and 2.28% table recall in E and E+C+Hy+Hl settings, respectively.

In conclusion, M-ReRank performs well on evidence reranking, which is crucial for fact-checking systems. It demonstrates superior performance in the reranking of unstructured evidence, e.g. sentences and passages, compared to structured evidence. The reason is that structured evidence retrieval requires row and column semantics information, which is crucial for structured evidence retrieval. On the other hand, M-ReRank performs retrieval on the flattened table. However, it is still able to perform collaborative filtering by exploiting interaction among table candidates. Further analysis of the errors of M-ReRank is provided in Appendix C.

5 Conclusion

In this paper, we presented M-ReRank, a multi-stage reranking framework designed to enhance the evidence retrieval process for fact verification tasks. Our experiments on the FEVEROUS dataset demonstrate that M-ReRank significantly improves the recall of evidence extraction, achieving a FEVEROUS-Score jump of 10.84%/2.38% on development/test data compared to previous state-of-the-art methods. M-ReRank pipeline comprised of a sequence rerankers, e.g. Cross-Encoder/SEE-ST, HybRank, HLATR. By leveraging the contextual interactions among multiple evidence pieces and incorporating both lexical and semantic similarities, M-ReRank effectively addresses the challenges of retrieving relevant evidence in both unstructured, e.g. sentences and structured, e.g. tables or cells. The ablation studies further validate the efficacy of each reranking stage, showcasing the robustness and adaptability of our approach. Overall, M-ReRank sets a new benchmark in the domain of fact verification, paving the way for more accurate and reliable verification systems.

6 Limitations

Despite the promising results, our multi-stage reranking approach has several limitations that need addressing in future work. One significant challenge is the computational complexity introduced by the multi-stage process, which can lead to increased processing time and resource consumption, making real-time applications less feasible. Additionally, scalability issues arise when handling large-scale datasets like the extensive Wikipedia corpus, potentially impacting the system's performance. The model's reliance on high-quality data means that incomplete or noisy data can degrade retrieval and verification accuracy.

Another limitation arises from the imbalance in the distribution of the three veracity labels. Specifically, as detailed in Appendix A, the NEI label constitutes only 3% of the training dataset, making it challenging for models to accurately predict this category.

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A FEVEROUS Dataset Statistics

FEVEROUS is based on English Wikipedia, which contains a vast collection of 95.6 million sentences and 11.8 million tables. Within this dataset are 87,026 distinct claims, each with an average length of 25.3 units. On average, verifying each claim requires referencing 1.4 sentences and 3.3 cells (equivalent to 0.8 tables). Notably, evidence for verification is exclusively text-based in 34,963 cases, solely table-based in 28,760 cases, and a combination of both formats in 24,667 instances. Among these claims, 49,115 are classified as SUPPORTS, 33,669 as REFUTES, and the remaining 4,242 are categorised as NEI. Table 6 shows a detailed breakdown of label and evidence distributions across various splits.

	Train	Dev	Test
Supported	41,835(59%)	3,908(50%)	3,372 (43%)
Refuted	27,215(38%)	3,481(44%)	2,973 (38%)
NEI	2,241 (3%)	501 (6%)	1,500 (19%)
Total	71,291	7,890	7,845
Sentences	31,607(41%)	3,745(43%)	3,589 (42%)
Cells	25,020 (32%)	2,738(32%)	2,816 (33%)
Sentence+Cells	20,865 (27%)	2,468 (25%)	2,062 (24%)

Table 6: Details of each split in FEVEROUS. First three rows depicts the distribution of classes across the splits and last three rows presents distribution of claims in each split requiring only sentence evidence, cell evidence, or both, respectively.

B Implementation Details

In the document retrieval step, we retrieve $n_p = 5$ pages from the Wikipedia dump for each claim. As a first step, 150 pages per claim are extracted by TFIDF and BM25 separately and merged together by ensemble reranking (Dwork et al., 2001) to retrieve a final set of 150 pages per claim. We keep the top 5 pages for evidence extraction after Mutlistage reranking. For the evidence retriever, the n_k=5 sentences and n_t=5 tables are extracted from the retrieved pages, and the sentence and table evidence are combined to extract $n_r = 25$ cells.

For Cross-Encoder, we use a RoBERTa-base[4] model, finetune it with contrastive learning criteria where for each positive example, a negative example is selected to determine MarginRanking loss as explained in (§3.3.1). The hyperparameters are set as batch size of 16 and learning rate 10^{-5}.

[4] RoBERTa-base

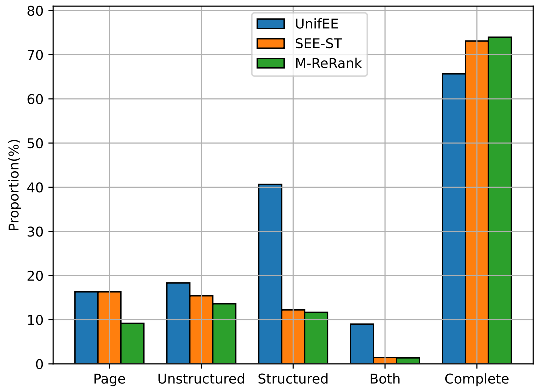


Figure 3: Overall error source analysis.of extracted evidence set for the dev set.

For table extraction, we use SEE-ST (Wu et al., 2023) that encodes the claim-table pair by TAPAS-base[5] model. The hyperparameters are set to default values as mentioned in (Wu et al., 2023), i.e. batch size of 8, learning rate 10^{-7} for TAPAS and 10^{-7} for the classifier, $\alpha_t = 1$ and $\beta_t = 1$.

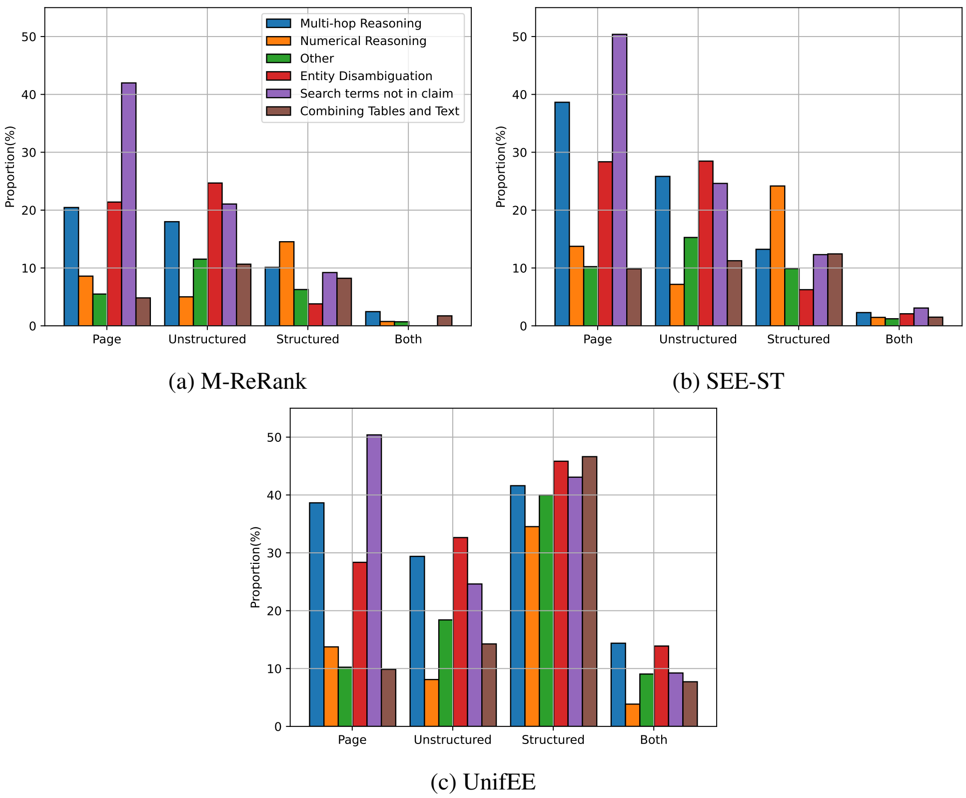
For cell extraction, we use SEE-ST's evidence graph approach which forms a graph of sentences and cell evidence and then score each cell on the basis of row and column semantics. RoBERTa-base and TAPAS-base are used to encode sentence nodes and cell nodes in the graph. The hyperparameters are set as batch size of 4, learning rate 10^{-6}, $\alpha_c = 2$, $\beta_c = 2$, and $\gamma_c = 1$.

In HybRank, the output of earlier step are used to extract sparse features by BM25 and dense features by a fine tuned RoBERTa model[6]. Number of anchors are set to 100 for page/sentence retrieval and 20 during table retrieval. The remaining hyperparameters are set to default as mentioned in (Zhang et al., 2023).

In HLATR, retrieved candidates from the earlier step are used for reranking. We fine tune a transformer model[7] to be used as reranker in the second step. Fine tuning hyperparameters are batch size 4, train group size 16, learning rate 10^{-5}, and number of epochs 5. In HLATR's third step, we fine tune a lightweight RoBERTa-base model with reduced hidden_size as 128, num_attention_heads 2, and num_hidden_layers 4, with a learning rate 10^{-3}, batch size 256, and 30 epochs.

All experiments are done on NVIDIA RTX 4090 24GB type GPUs.

[5] TAPAS-base
[6] sentence-transformers/msmarco-bert-base-dot-v5
[7] CoROM-Reranking



(a) M-ReRank (b) SEE-ST

(c) UnifEE

Figure 4: Error source proportions of claims with different reasoning challenges on dev set.

C Error Analysis

To investigate error propagation within the FEVEROUS pipeline, we conduct a thorough error source analysis for both page and evidence retrieval stages. We also perform the error analysis on the challenge type to show M-ReRank's strength and weakness.

C.1 Error Source Analysis

The candidates not retrieved in any stage leads to error propagation in the pipeline. In the three-step pipeline, the *Page* source error is determined by instances that fail to retrieve all pages containing evidence. Further, error source can also arises when a specific evidence format is not fully extracted. For instances with a complete document set, errors are categorised by the format of evidence that are failed to be retrieved: *Unstructured* (sentences), *Structured* (tables or cells), and *Both*. Figure 3 displays the proportion of instances with failed evidence retrieval. We also show the percentage instances with complete evidence set as *Complete*. Comparing the results with recent models, i.e. UnifEE and SEE-ST, our proposed M-ReRank approach performs well on each evidence type. On page retrieval, M-ReRank decreases the error from 15.8% to 9.2%. The decrement is also observed in proportion of source error on structure and unstructured evidence retrieval. It shows the effectiveness of M-ReRank in evidence retrieval.

C.2 Analysis based on challenge types

In FEVEROUS challenge, the samples are also categorised into various challenge categories. A fact-checker system's strength should also be analysed based on challenge types. These challenges encompass *Multi-hop Reasoning* (MR), performing *Numerical Reasoning* (NR), *Entity Disambiguation* (ED), dealing with *Search terms not present in claim* (ST), and *Combining Tables and Text* (CT). Any challenges outside these five categories are classified as *Other* (OT). We evaluate M-ReRank's performance to demonstrate its capability in retrieving evidence for claims with various challenges. M-ReRank achieves higher performance on almost all challenges with major improvement on *Multi-hop Reasoning* and *Combining Tables and Text* challenges comparing SEE-ST and UnifEE as shown in Figure 4. M-ReRank achieves evidence extraction with a recall rate of 65.43%, 57.89%, 79.66%, 71.52%, 71.05%, 76.75% in MR, NR, OT, ED, ST, and CT, respectively, showing that the collaborative filtering and modelling inter-evidence context can

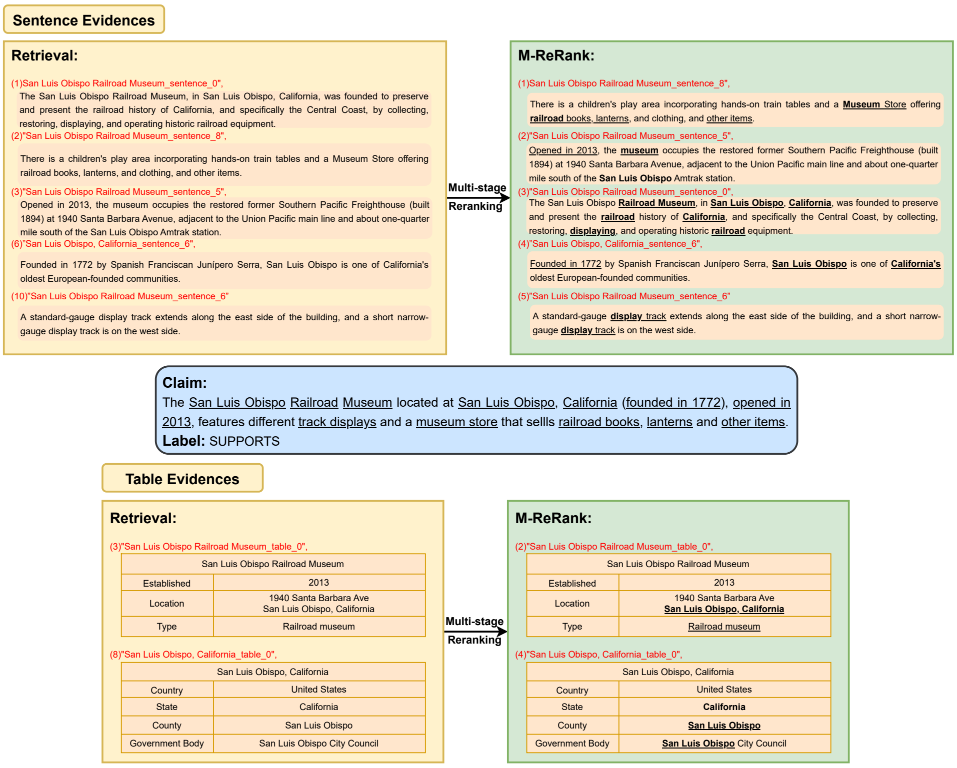


Figure 5: An example in FEVEROUS. The blue rectangle contains the claim. The yellow rectangle highlights the initially retrieved evidence (Retrieval), while the green rectangle depicts the reranked evidence set by our Multi-stage reranking (M-ReRank) paradigm. Text in red color with each evidence show order number (parenthesised) followed by its id in the dataset. To illustrate interactions, brown arrows connect the claim to evidence, and green arrows indicate relationships among evidence pieces. Words and phrases underlined to show interactions between the claim and evidence, while bold highlights indicate inter-evidence interactions in the group, e.g. sentences or tables.

effectively improve the evidence retrieval.

Our multi-stage reranking approach shows enhanced evidence retrieval capabilities, particularly in complex, challenging scenarios. M-ReRank decreases the Unstructured error by 4.71% against UnifEE and 2.92% against SEE-ST. For Unstructured evidence, it reduces the errors significantly by 28.97% against UnifEE, while less margin of 0.54% against SEE-ST as SEE-ST does well in structured evidence retrieval.

D Case Study

A case is shown for evidence extraction of both type sentence and table in Figure 5. For the claim on *San Luis Obispo Railroad Museum*, our M-ReRank successfully retrieves sentences and tables of evidence by reordering them what was provided in initial retrievals. We use RoBERTa (Cross-Encoder) and TAPAS (SEE-ST) retrieval results, respectively, for unstructured and structured evidence extraction. The main challenge for this case is Multi-hop evidence extraction, as the evidence is to be extracted from multiple sources to verify the claim. For sentence extraction, we observe that initial retrieval was only able to retrieve three evidence in Top-5. Through M-ReRank, the evidences are rescored and retrieve those evidences in Top-5. For instance, sentences with evidence id *San Luis Obispo, California_sentence_6* and *San Luis Obispo Railroad Museum_sentence_6*, were earlier ranked six and ten respectively, however, M-ReRank reranks them as four and five. Without them, fact-verification model would not be able to prove when *San Luis Obispo* was founded and what kind *display track* the Railway Museum offers.

In structured evidence, the initial retrieval is unable to retrieve *San Luis Obispo, California_table_0* in Top-5, but M-ReRank reorders it to be included in Top-5 tables. It helps in identifying *San Luis Obispo* as a county in *California* state. This shows the robustness of M-ReRank in utilising the information of interaction among evidence to reorder them, thereby improving overall evidence extraction in each format.