

Improving Evidence Retrieval for Automated Explainable Fact-Checking

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Abstract

Automated fact-checking on a large-scale is a challenging task that has not been studied systematically until recently. Large noisy document collections like the web or news articles make the task more difficult. We describe a three-stage automated fact-checking system, named Quin+, using evidence retrieval and selection methods. We demonstrate that using dense passage representations leads to much higher evidence recall in a noisy setting. We also propose two sentence selection approaches, an embedding-based selection using a dense retrieval model, and a sequence labeling approach for context-aware selection. Quin+ is able to verify open-domain claims using results from web search engines.

1 Introduction

With the emergence of social media and many individual news sources online, the spread of misinformation has become a major problem with potentially harmful social consequences. Fake news can manipulate the public opinion, create conflicts, elicit unreasonable fear and suspicion. The vast amount of unverified online content stimulated the appearance of the first external post-hoc fact-checking organizations since the early 2000s. Numerous organizations from different countries have dedicated resources to verify claims online, such as PolitiFact, FactCheck.org, Snopes etc. However, manual fact-checking is time consuming and intractable on a large scale. The ability to automatically perform fact-checking is critical to minimize negative social impact.

Automated fact checking is a complex task involving evidence extraction followed by evidence reasoning and entailment. For the retrieval of relevant evidence from a corpus of documents, existing systems typically utilize traditional sparse retrieval which may have poor recall, especially

when the relevant passages have few overlapping words with the facts to be verified. Dense retrieval models have been proven effective in question answering as these models can better capture the latent semantic content of text. The work in (Samarinas et al., 2020) is the first to use dense retrieval in fact checking. The authors constructed a new dataset called Factual-NLI comprised of claim-evidence pairs from the FEVER dataset (Thorne et al., 2018) as well as synthetic examples generated from benchmark Question Answering datasets (Kwiatkowski et al., 2019; Nguyen et al., 2016). They demonstrated that using Factual-NLI to train a dense retriever can improve evidence retrieval significantly.

While the FEVER dataset has enabled the systematic evaluation of automated fact-checking systems, it does not reflect well the noisy nature of real-world data. Motivated by this, we introduce the Factual-NLI+ dataset, an extension of the FEVER dataset with synthetic examples from question answering datasets and noise passages from web search results. We examine how dense representations can improve the first-stage retrieval recall of passages for fact-checking in a noisy setting, and make the retrieval of relevant evidences more tractable on a large scale.

However, the selection of relevant evidence sentences for more accurate fact-checking and explainability remains a challenge. Figure 1 shows an example of a claim and the retrieved passage which has three sentences, of which only the last sentence provides the critical evidence to refute the claim. We propose two ways to select the relevant sentences, an embedding-based selection using a dense retrieval model, and a sequence labeling approach for context-aware selection. We show that the former generalizes better with a high recall, while the latter has higher precision making it suitable for the identification of rele-

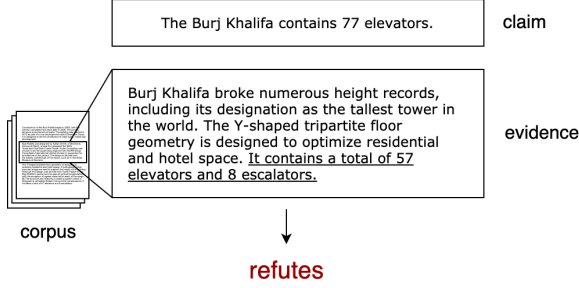


Figure 1: Sample claim and the retrieved passage evidence where only the last sentence is relevant.

vant evidence sentences. Our fact-checking system, Quin+, is able to verify open-domain claims using web search results.

2 Related Work

Automated claim verification using a large corpus has not been studied systematically until the availability of the Fact Extraction and VERification dataset (FEVER) (Thorne et al., 2018). This dataset contains claims that are supported or refuted by specific evidence from Wikipedia articles. Prior to the work in (Samarinas et al., 2020), fact-checking solutions relied on sparse passage retrieval, followed by a claim verification (entailment classification) model (Nie et al., 2019). Other approaches used the mentions of entities in a claim and/or very basic entity linking to retrieve documents and a machine learning model such as logistic regression or an enhanced sequential inference model to decide whether an article most likely contains the evidence (Yoneda et al.; Chen et al., 2017; Hanselowski et al., 2018).

However, retrieval based on sparse representations and exact keyword matching can be rather restrictive for various queries. This restriction can be mitigated by dense representations using BERT-based language models (Devlin et al., 2019). The works in (Lee et al., 2019; Karpukhin et al., 2020; Xiong et al., 2020; Chang et al., 2020) have successfully used such models and its variants for passage retrieval in open-domain question answering. The results can be further improved using passage re-ranking with cross-attention BERT-based models (Nogueira et al., 2019). The work in (Samarinas et al., 2020) is the first to propose a model called QR-BERT to retrieve passages for fact-checking.

Apart from passage retrieval, sentence (evidence) selection is also a critical task in fact-

checking. These evidence sentences provide an explanation why a claim has been assessed to be credible or not. Recent works have proposed a BERT-based model for extracting relevant evidence sentences from multi-sentence passages (Atanasova et al., 2020). The authors observe that joint training on veracity prediction and explanation generation performs better than training separate models. The work in (Stammach and Ash) investigates how the few-shot learning capabilities of the GPT-3 model (Brown et al., 2020) can be used for generating fact-checking explanations.

3 The Quin+ System

The automated claim verification task can be defined as follows: given a textual claim c_m and a corpus $D = \{d_1, d_2, \dots, d_n\}$, where every passage $d_i = \{s_1^i, s_2^i, \dots, s_k^i\}$ is comprised of sentences s_j^i , a system will return a set of evidence sentences $E_m = \{s_1, s_2, \dots, s_k\} \subset \bigcup d_i$ and a label $\hat{y}_m \in \{\text{probably true, probably false, inconclusive}\}$.

We have developed an automated fact-checking system, called Quin+, to perform claim verification in three stages: *passage retrieval* from a corpus, *sentence selection* and *entailment classification* as shown in Figure 2. In our system, the label is determined as follows: we first perform an entailment classification on the set of evidence sentences. When the number of retrieved evidence is low, we label the claim as "inconclusive". If the number of evidence sentences that support the claim exceeds the number of sentences that refute the claim, we assign the label "probably true" to the claim. Otherwise, we assign the label "probably false" to the claim.

3.1 Passage Retrieval

The passage retrieval model in Quin+ is based on a *dense* retrieval model called QR-BERT (Samarinas et al., 2020). This model creates dense vectors for passages by calculating their average token embedding. The relevance of a passage d to a claim c is then given by their dot product:

$$r(c, d) = \phi(c)^T \phi(d) \quad (1)$$

Dot product search can run efficiently using an approximate nearest neighbors index implemented using the FAISS library (Johnson et al., 2017). QR-BERT maximizes the sampled softmax loss:

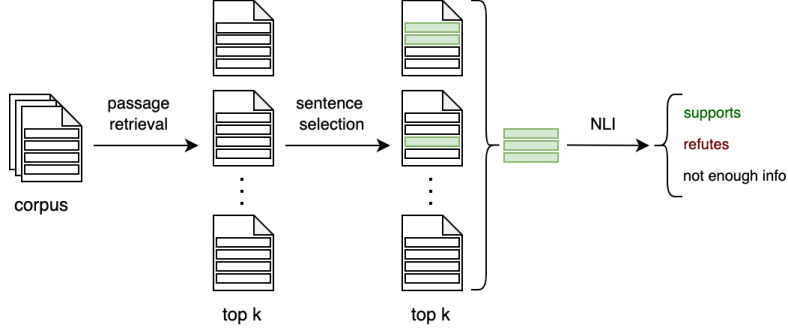


Figure 2: Three stages of claim verification in Quin+.

$$L_{\theta} = \sum_{(c,d) \in D_B^+} r_{\theta}(c,d) - \log \left(\sum_{d_i \in D_B} e^{r_{\theta}(c,d_i)} \right) \quad (2)$$

where D_B is the set of passages in a training batch B , and D_B^+ is the set of positive claim-passage pairs in B .

The work in (Samarinas et al., 2020) introduce Factual-NLI dataset that extends the FEVER dataset (Thorne et al., 2018) with more diverse synthetic examples derived from question answering datasets. There are 359,190 new entailed claims with evidence and additional contradicted claims from a rule-based approach.

To ensure robustness, we compile a new large-scale *noisy* version of Factual-NLI called Factual-NLI+. This dataset includes all the 5 million Wikipedia passages in the FEVER dataset. We add ‘noise’ passages as follows: For every claim c in the FEVER dataset, we retrieve the top 30 web results from the Bing search engine and keep passages with the highest BM25 score that are classified as neutral by the entailment model. For claims generated from MSMARCO queries (Nguyen et al., 2016), we included the irrelevant passages that are found in the MSMARCO dataset for those queries. This results in 418,650 additional passages. The new dataset reflects better the nature of a large-scale corpus that would be used by real-world fact-checking system. We train a dense retrieval model using this extended dataset.

The Quin+ system utilizes a hybrid model that combines the results from the dense retrieval model described above and BM25 sparse retrieval to obtain the final list of retrieved passages. For efficient sparse retrieval, we used the Rust-based Tantivy full text search engine¹.

¹<https://github.com/tantivy-search/tantivy>

3.2 Sentence Selection

We propose and experiment with two sentence selection methods: an embedding-based selection and context-aware sentence selection method.

The embedding-based selection method relies on the dense representations learned by the dense passage retrieval model QR-BERT. For a given claim c , we select the sentences s_j from a given passage $d = \{s_1, s_2, \dots, s_k\}$ such that the relevance score $r(c, d)$ from the QR-BERT model is greater than some threshold λ which is set experimentally.

The context-aware sentence selection method uses a sequence labelling approach. We adopt the BIO tagging format so that all the irrelevant tokens are classified as O , the first token of an evidence sentence classified as B evidence and the rest tokens of an evidence sentence as I evidence (see Figure 3). We train a model based on RoBERTa-large (Liu et al., 2019), minimizing the cross-entropy loss:

$$L_{\theta} = - \sum_{i=1}^N \sum_{j=1}^{l_i} \log(p_{\theta}(y_j^i)) \quad (3)$$

where N is the number of examples in the training batch, l_i the number of non-padding tokens of the i^{th} example and $p_{\theta}(y_j^i)$ is the estimated softmax probability of the correct label for the j^{th} token of the i^{th} example. We train the sentence selection model in Quin+ on Factual-NLI with batch size 64, Adam optimizer and initial learning rate 5×10^{-5} until convergence.

3.3 Entailment Classification

Natural Language Inference (NLI), also known as textual entailment classification, is the task of detecting whether a hypothesis statement is entailed by a premise passage. It is essentially a

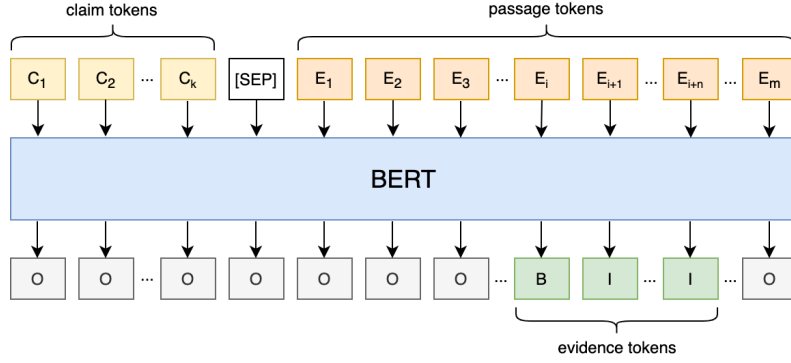


Figure 3: Sequence labeling model for evidence selection from a passage for a given claim.

text classification problem, where the input is a pair of premise-hypothesis (P, H) and the output a label $y \in \{\text{entailment, contradiction, neutral}\}$. An NLI model is often a core component of many automated fact-checking systems. Datasets like the Stanford Natural Language Inference corpus (SNLI) (Bowman et al., 2015), Multi-Genre Natural Language Inference corpus (Multi-NLI) (Williams et al., 2018) and Adversarial-NLI (Nie et al., 2020) have facilitated the development of models for this task.

Even though recent pre-trained NLI models seem to perform very well on the two popular NLI datasets (SNLI and Multi-NLI), they are not as effective in a real-world setting. Recent work has identified bias in these two datasets (Poliak et al., 2018), which has a negative effect in the generalization ability of the trained models. Another weakness of these datasets, is that they are comprised of short, usually single-sentence, premises. As a result, models trained on these datasets usually do not perform well on noisy real-world data with multiple sentences. These issues have led to the development of additional more challenging datasets, such as Adversarial NLI (Nie et al., 2020). In our system, we use an NLI model based on RoBERTa-large with a linear transformation of the [CLS] token embedding:

$$o = \text{softmax}(W \cdot \text{BERT}_{[\text{CLS}]}([P; H]) + b) \quad (4)$$

where $P; H$ is the concatenation of the premise with the hypothesis, $W_{3 \times 1024}$ a linear transformation matrix and $b_{3 \times 1}$ the added bias. We train the entailment model by minimizing the cross-entropy loss on the concatenation of the three popular NLI datasets (SNLI, Multi-NLI and Adversarial-NLI) with batch size 64, Adam optimizer and initial learning rate 5×10^{-5} until convergence.

4 Performance of Quin+

We evaluate the three individual components of Quin+ (retrieval, sentence selection and entailment classification) and finally perform an end-to-end evaluation using various configurations.

Table 1 gives the recall@k and Mean Reciprocal Rank (MRR@100) of the passage retrieval models on the FEVER and Factual-NLI+. We also compare the performance on a noisy extension of the FEVER dataset where additional passages from Bing search engine are included as ‘noise’ passages. We see that when noise passages are added to the FEVER dataset, the gap between the hybrid passage retrieval model in Quin+ and sparse retrieval widens. This demonstrates the limitations of using sparse retrieval, and why it is crucial to have a dense retrieval model to surface relevant passages from a noisy corpus. Overall, the hybrid passage retrieval model in Quin+ gives the best performance compared to BM25 and the dense retrieval model.

(a) FEVER Dataset					
Model	R@5	R@10	R@20	R@100	MRR
BM25	50.53	58.92	67.93	82.93	0.381
Dense	65.47	69.61	72.51	75.71	0.535
Hybrid	71.71	78.60	83.65	91.09	0.556

(b) FEVER with noise passages					
Model	R@5	R@10	R@20	R@100	MRR
BM25	35.17	44.18	53.89	73.95	0.2649
Dense	54.10	62.13	68.09	75.24	0.4053
Hybrid	54.89	64.61	73.33	86.11	0.4074

(c) Factual-NLI+ Dataset					
Model	R@5	R@10	R@20	R@100	MRR
BM25	45.02	53.20	61.56	77.96	0.347
Dense	59.66	67.09	72.23	78.52	0.461
Hybrid	61.29	70.03	77.51	87.90	0.465

Table 1: Performance of passage retrieval models.

(a) Factual-NLI Dataset			
Model	Precision	Recall	F1
Baseline	67.74	91.87	77.98
Sequence labeling	94.78	92.11	93.43
Embedding-based	66.12	90.29	76.34

(b) SciFact Dataset			
Model	Precision	Recall	F1
Baseline	62.21	71.54	66.55
Sequence labeling	69.38	68.45	68.91
Embedding-based	43.30	92.36	58.96

Table 2: Performance of sentence selection methods.

Table 2 shows the token-level precision, recall and F1 score of the proposed sentence selection methods on the Factual-NLI dataset and a domain-specific (medical) claim verification dataset, SciFact (Wadden et al., 2020). We also compare the performance to a baseline sentence-level NLI approach, where we perform entailment classification on each sentence of a passage and select the non-neutral sentences as evidence.

We observe that the sequence labeling model gives the highest precision, recall and F1 score when tested on the Factual-NLI dataset. Further, the precision is significantly higher than the other methods. On the other hand, for the SciFact dataset, we see that sequence labeling method remains the top performer in terms of precision and F1 score after fine-tuning, but its recall is lower than the embedding-based method. This shows that sequence labeling model is able to mitigate the high false positive rate observed with the embedding-based selection method by taking into account the surrounding context.

Recall the Factual-NLI+ dataset contains claims with passages that either support or refute the claims. For these passages, sentences are highlighted as specific evidences to the claims. Table 3 shows the performance of the entailment model to classify the input evidence as supporting or refuting the claims. The input evidence can be in the form of the whole passage or highlighted sentences, or sentences selected by our proposed sequence labeling method. We observe that the entailment classification model performs poorly when whole passages are passed as input evidences. However, when the specific sentences are passed as input, the precision, recall, and F1 measures improve. The reason is that our NLI-based entailment classification model is trained mostly on short premises. As a result, it does

(a) Supporting evidence			
Input	Precision	Recall	F1
Whole passages	63.40	53.93	58.28
Highlighted sentences	82.15	60.05	69.38
Selected sentences	74.40	56.68	64.34

(b) Refuting evidence			
Input	Precision	Recall	F1
Whole passages	33.95	40.65	37.00
Highlighted sentences	77.54	89.32	83.02
Selected sentences	75.27	81.96	78.47

Table 3: Performance of entailment classification model on different forms of input evidence.

Passage retrieval	Sentence selection	F1
BM25, k=5	Embedding-based	52.76
BM25, k=20	Embedding-based	47.65
BM25, k=5	Sequence labeling	49.65
Dense, k=5	Embedding-based	49.03
Dense, k=5	Sequence labeling	52.83
Dense, k=50	Sequence labeling	58.22
Hybrid, k=6	Embedding-based	50.29
Hybrid, k=6	Sequence labeling	57.24
Hybrid, k=50	Sequence labeling	52.60

Table 4: End-to-end claim verification on Factual-NLI+ for different configurations.

better on sentence-level evidence compared to the longer passages.

Finally, we carry out an end-to-end evaluation of our fact-checking system on Factual-NLI+ using various configurations of passage retrieval and evidence selection approaches where k is the number of top- k passages retrieved.. Table 4 shows the macro-average F1 score for the three classes (probably true, probably false, inconclusive). We see that dense or hybrid retrieval with evidence selection using the proposed sequence labeling model gives the best results. Even though hybrid retrieval seems to lead to slightly worse performance, it requires much less passages (6 instead of 50) and makes the system more efficient.

5 System Demonstration

We have created a demo for verifying any open-domain claim using the top 20 results from the Bing search engine. For a given claim, Quin+ returns relevant text passages with highlighted sentences. The passages are grouped into two sets, supporting and refuting. It computes a veracity rating based on the number of supporting and refuting evidences. It returns "Probably True" if there are more supporting evidence, otherwise it returns "Probably False". When the number of re-



Figure 4: The Quin system returning relevant evidence and a veracity rating for a claim.

trieved evidence is low, it returns "Inconclusive". Figure 4 shows a screen dump of the system with a claim that has been assessed to be probably false based on the overwhelming number of refuting sentence evidence (21 refute versus 0 support).

6 Conclusion & Future Work

In this paper, we have investigated how a dense passage retrieval model can lead to higher recall when retrieving passages for a claim. We have proposed a sequence labeling model for selecting relevant sentences to improve the final claim verification accuracy. In order to ensure robustness for verifying real world open domain claims, we have constructed the Factual-NLI+ dataset to train and evaluate a model for passage retrieval. Last but not least, we believe that for the future development of large-scale fact-checking systems, a new benchmark needs to be introduced. The currently available datasets, including Factual-NLI+, are not suitable for evaluating the performance of systems

that have a large number of evidence sources such as news publishers or research papers.

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