Continuous Active Learning Using Pretrained Transformers

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Abstract

Pre-trained and fine-tuned transformer models like BERT and T5 have improved the state of the art in ad-hoc retrieval and question-answering, but not as yet in high-recall information retrieval, where the objective is to retrieve substantially all relevant documents. We investigate whether the use of transformer-based models for reranking and/or featurization can improve the Baseline Model Implementation of the TREC Total Recall Track, which represents the current state of the art for high-recall information retrieval. We also introduce CALBERT, a model that can be used to continuously fine-tune a BERT-based model based on relevance feedback.

1 Introduction

The main objective of High recall information retrieval is to retrieve virtually all relevant documents to an information need, while minimizing the number of non-relevant documents returned. This is particularly useful in high-stake settings. For example, a lawyer might need to find all the relevant information to a specific trademark infringement, or an epidemiologist might need to find all the relevant documents to inner workings of certain protein structures. In such settings, false-positives are merely an inconvenience, but false-positives can be disastrous.

To achieve near perfect recall while minimizing the number of false-positives, there often needs to be some relevance judgment fed back to the model, which often comes in form of a human-in-the-loop. Using the example above, where the lawyer needs the documents relevant to a trademark infringement, the lawyer can start with entering a query such as "Bacardi Trademark Infringement". The system then returns one (or more) documents that it determines to be likely relevant. The user (i.e. the lawyer), would then indicate whether each returned document is relevant or not. This process would continue until the system determines that it is unlikely that there are more relevant documents that has not been shown to the user. The system can then save all the documents labeled as "relevant" and at the end of process show them to the user to read more closely. We note that, the system can also use the feedback from the user to iteratively improve the results being returned.

In fact, many law firms and corporations rely on the method mentioned above to find relevant documents from a large corpus of documents.

2 Related-Work

Technology Assisted Review (TAR) was first introduced by Grossman and Cormack (2011) and it revolutionized how legal e-discovery is being done around the globe. The most successful implementations of TAR is a human-in-the-loop setting where the relevance feedback from user is used to improve the model. This implementation is referred to as Continuous Active Learning (CAL). The current state-of-art is an implementation by Grossman et al. (2016), introduced as part of the High Recall Track in TREC 2015 and 2016. This model was introduced as the baseline implementation (often referred to as BMI), but has not been beaten thus far! The model trains a logistic regression model using BM25 and TF-IDF feature vectors of the documents and the query. This simple, yet effective, model has been able to outperform complex neural network models in a variety of datasets where the goal is achieving high recall.

Yang et al. (2021) is the only attempt we are aware of where a pre-trained large scale language model, such as BERT (Devlin et al., 2019), has been used in the CAL setting. This model initially...
fine-tuned BERT on the target corpus in an unsupervised fashion; then BERT was used to classify each document as relevant or not-relevant to the query, where at each iteration relevance feedback from previous iterations is used to train the model. This model, despite being much more complex than previous models, did not stand a chance when compared to BMI.

3 Experimental Setup

3.1 Data

All of our experiments are ran on a subset of the Jeb Bush Email dataset, released by Roegiest et al. (2015) in High Recall Track of TREC in 2015. A subset of the data we use is known as athome4 and consists of over 290,000 emails sent and received by Jeb Bush during his time as the governor of Florida. There are 34 topics of information need. We use this dataset for a few reasons. First, it is one of the few datasets where for each topic, virtually all the relevant documents are known. Second, we have access to the results for other CAL-like models on this dataset, including BMI, so we can compare our results to other models. Third, the varying lengths of the emails allows us to challenge models with limited input-lengths.

The athome4 dataset was converted into the MSMARCO format, so it can easily be integrated into Pygaggle \(^1\) which made it convenient to use/fine-tune the monoBERT/monoT5 models. Due to input-length limitation of BERT/T5, we had to truncate most of the documents before feeding them in BERT/T5. However, the untruncated documents were still used for BMI.

3.2 Evaluation

First, let us introduce the official metrics that was used to evaluate datasets in the TREC’s Total Recall Track, where the athome4 dataset was first introduced. For a topic \(t\), let \(R_t\) be the number of relevant documents in the corpus. The official metric used in the Total Recall Track was \(Recall@4R_t + 1000\) (i.e. Recall after \(4R_t + 1000\) iterations). We experimented with several resource-intensive models (monoBERT, monoT5, etc.) and different hyperparameters (\(K\): number of first-stage results to rerank; epochs: number of training epochs; etc). Due to time and resource limitations, we use \(P@100\) (i.e. precision after 100 iterations) as our primary metric with the goal of finding a model that can outperform BMI on this metric. If we are able to find a model that can achieve this, we would then use \(Recall@4R_t + 1000\) to further explore the model.

3.3 Model

We primarily used Transformer-based, pre-trained language models, such as BERT (Devlin et al., 2019) and T5 (Raffel et al., 2019). More concretely, we started our experiments with monoBERT (Nogueira et al., 2019) and monoT5 (Pradeep et al., 2021) fine-tuned on the MSMARCO dataset (Nguyen et al., 2016). We also tried fine-tunning monoBERT and monoT5 at each iteration based on the relevance feedback received. We note that in these cases, monoBERT and monoT5 were both utilized to rerank first-stage retrieval results retrieved from BMI. We furthermore, explored creating embeddings of the documents using BERT (Devlin et al., 2019) and sentenceBERT (Reimers and Gurevych, 2019a). These embeddings were then used as an input to CAL in addition to the TF-IDF and BM25 feature vectors.

3.3.1 monoBERT

In monoBERT, given query \(q\) and document \(d\), the relevance score is calculated as follows \(^2\):

\[
\text{input} = "[CLS] q_{64} [SEP] d_{445}[SEP]\"
\]

\[
\text{embedings} = BERT(\text{input})
\]

\[
CLS_{emb} = \text{embedings}[0]
\]

\[
\text{score} = \text{FullyConnected}(CLS_{emb})
\]

Since BERT (and hence monoBERT) is much slower than traditional IR models, we first rank the 290,000 documents with CAL and then rerank the top \(k\) documents with monoBERT. For more details, we refer the reader to Lin et al. (2021).

3.3.2 monoT5

In monoT5, the query \(q\) and document \(d\), the relevance score is determined by computing the logits of next word being “True” or “False” when the following string is fed into T5: “Query: \(q\) Document: \(d\) Relevant: ”. Similar to monoBERT, monoT5 reranks the top \(k\) results from CAL. For more details, we refer the reader to Lin et al. (2021).

\(^2\)For string \(s\), we use \(s_n\) to denote \(s\) truncated to \(n\) tokens. For example, \(q_{64}\) is the query string truncated to 64 tokens.
3.3.3 CALBERT

Just as CAL trains a new logistic regression model for each topic iteratively as it receives relevance feedback, we will fine-tune a BERT model to classify documents as being relevant or non-relevant based on relevance feedback at each iteration. We name this model CALBERT. Note that, the input to CALBERT at each iteration is different documents it needs to rerank. That is, unlike monoBERT, we do not pass in the concatenation of the query and document to CALBERT. This means that we can pass in a longer portion of the document to CALBERT. More precisely, for each topic, CALBERT works as follows:

Algorithm 1 CALBERT

1: initialize CAL
2: initialize BERT
3: for iter = 1, 2, . . . do
4:    top_k ← CAL(docs, query, iter)
5:    for doc in top_k do
6:       inp ← truncate("CLS" + doc, 512)
7:       emb ← BERT(inp)
8:       score_doc ← FullyConnected(emb)
9:    end for
10:   Show argmax_doc {score_doc} to user
11:   Get relevance feedback
12:   Fine Tune BERT
13:   Train CAL based on feedback
14: end for

Moreover, the fine-tuning process itself has some hyper-parameters. Number of epochs trained is an obvious one: after experimenting with different values, we found 5 epochs to be yield reasonably good results. Also, at each iteration we can start with a fresh\(^3\) BERT/T5 model and fine-tune it using all the examples in the previous iterations. This is training from ”scratch”. We also experimented with training models incrementally: that is, we start with a fresh model at iteration 0 and at each iteration we train it on the relevance feedback from that iteration only. This is training ”incrementally”. Obviously training incrementally is much faster than training from scratch; nevertheless, we tried both to see if one has an edge over the other. We also experimented with negative sampling. Although BMI uses 100 random samples as pseudo-negatives, our experiments showed that 100 does not work well with Transformers. Therefore, we used a balancing technique, where at iteration \(i\) we sample \(\min(p_i - n_i, 0)\) pseudo-negatives where \(p_i\) and \(n_i\) are, respectively, the number of positive and negative relevance feedback examples we have received at iteration \(i\).

3.3.4 Embeddings

This approach consisted of using embeddings generated by a Transformer-based model in place or in addition of TF-IDF and BM25 feature vectors, as an input to CAL. In particular, we explored the following inputs as inputs to CAL

E1. TF-IDF/BM25 feature vectors (Baseline)
E2. Using only Transformer embeddings
E3. Concatenating Transformer embeddings with TF-IDF/BM25 feature vectors

\(^\text{3}\)“Fresh” here means a pretrained model that is not fine-tuned on a downstream task/corpus
| Model            | k   | epochs | training | sum negatives | P@100  | R@100  |
|------------------|-----|--------|----------|---------------|--------|--------|
| BMI              | -   | -      | -        | -             | 81.22  | 34.98  |
| monoBERT-large   | 10  | 0      | -        | no            | 72.60  | 28.60  |
| monoBERT-large   | 100 | 0      | -        | no            | 61.07  | 19.15  |
| monoT5-large     | 10  | 0      | -        | no            | 80.26  | 31.80  |
| monoT5-large     | 100 | 0      | -        | yes           | 61.07  | 19.15  |
| monoBERT-large   | 10  | 0      | -        | yes           | 78.86  | 32.59  |
| monoBERT-large   | 100 | 0      | -        | yes           | 64.76  | 19.77  |
| monoT5-large     | 10  | 0      | -        | yes           | 78.51  | 33.02  |
| monoT5-large     | 100 | 0      | -        | yes           | 65.49  | 19.99  |
| CALBERT-large    | 10  | 5      | scratch  | No balanced   | 80.23  | 34.68  |
| CALBERT-large    | 100 | 5      | scratch  | No balanced   | 76.94  | 31.92  |
| CALBERT-large    | 100 | 5      | incrementally | No balanced | 72.10  | 28.66  |
| CALRoBERTa-large | 10  | 5      | incrementally | No balanced | 79.76  | 34.43  |
| E3-TAS           | -   | -      | -        | -             | 76.00  | 33.59  |
| E3-all-mpnet-base-v2 | - | - | - | - | 82.29 | 36.30 |
| E3-contriever    | -   | -      | -        | -             | 58.47  | 25.79  |

Table 1: First k documents returned by BMI, reranked using the respective models trained for the specific number of epochs. For some rows, score from BMI and the reranker is summed to get a final score – this is specified in the “sum” column.

E4. Training two separate CAL models, one based on TF-IDF/BM25 feature vectors, and another based on Transformer embeddings (the final score here was the sum of score from the models)

The Transformer used to generate the embedding consisted mostly of models based on BERT, fine-tuned using different data, loss functions, and techniques. The TAS (Topic Aware Sampling) model (Hofstätter et al., 2021) model is trained on the MSMARCO dataset using a novel batch selection method. The queries are first grouped into k clusters using k-means clustering. Then at training time, a batch of size b is selected by randomly choosing n topics (n ≪ k) and b/n queries than can be used as the basis of the training batch. We omit further details as it is beyond the scope of this work. The all-mpnet-base-v2 model is also part of the sentence-bert library (Reimers and Gurevych, 2019b). It is based on the MPNet model (Song et al., 2020) and is fine-tuned with over 1 billion sentences to generate embedding which are closer to each other in the Euclidean space; that is, embedding of similar sentences is trained to have a cos value close to 1. The Contriever model (Izacard et al., 2021) is trained using a contrastive loss to maximize "agreement" between closely located sentences, while minimizing that for sentences further away from one another. The Contriever model uses a variety techniques for negative sampling to improve its performance; however, these details are beyond the scope of this work.

In these settings, we preprocessed all the documents and queries to generate corresponding embedding. Consequently, there was no additional latency due to BERT inference. Therefore, we did not need to conduct a rank-then-rerank approach; we simply ranked all the candidate documents at each iteration, using CAL and the appropriate embeddings (E1-E4).

4 Results

We report both Average Recall@100 and Average Precision@100 in Table 1. Note that this result is averaged over the 34 topics in the athome4 dataset. We emphasize that all the models reranked the results from BMI in a zero-shot manner. Moreover, only the CALBERT model received relevance feedback; for other models, the relevance feedback was only given to the logistic regression powering BMI. For the BERT embeddings methods, we only report the results for the E3 method (i.e. con-

4“P@100” and “R@100” columns represent average precision and recall for the first 100 iterations. This notation is not to be confused by ones used in ad-hoc information retrieval evaluation, where P@100 and R@100 represent average precision and recall at the 100 cut-off. The use of this notation is justified because, unlike ad-hoc search, at each iteration we only show the user the top scoring document.
Table 2: Recall@4R_t + 1000 results for CAL and E3-all-mpnet-base-v2. This transformer was used since it performed best when compared to other transformer-based models when compared using P@100.

| Topic | CAL   | Transformer |
|-------|-------|-------------|
| 401   | 93.45 | 92.14       |
| 402   | 98.75 | 96.71       |
| 403   | 97.98 | 98.07       |
| 404   | 95.05 | 95.60       |
| 405   | 99.18 | 96.72       |
| 406   | 94.45 | 92.13       |
| 407   | 98.89 | 97.48       |
| 408   | 83.62 | 80.17       |
| 409   | 97.03 | 96.04       |
| 410   | 1.00  | 99.55       |
| 411   | 84.27 | 88.76       |
| 412   | 99.22 | 98.30       |
| 413   | 99.63 | 99.63       |
| 414   | 1.00  | 1.00        |
| 415   | 55.78 | 78.33       |
| 416   | 99.59 | 99.17       |
| 417   | 99.79 | 99.65       |
| 418   | 95.19 | 96.79       |
| 419   | 99.70 | 99.70       |
| 420   | 99.59 | 99.19       |
| 421   | 1.00  | 1.00        |
| 422   | 1.00  | 1.00        |
| 423   | 99.30 | 97.90       |
| 424   | 1.00  | 1.00        |
| 425   | 99.72 | 99.72       |
| 426   | 98.33 | 99.17       |
| 427   | 97.51 | 97.51       |
| 428   | 99.14 | 98.71       |
| 429   | 99.52 | 99.15       |
| 430   | 97.78 | 97.98       |
| 431   | 99.31 | 97.92       |
| 432   | 99.29 | 97.86       |
| 433   | 1.00  | 1.00        |
| 434   | 1.00  | 1.00        |

Average 96.50 96.77

The baseline (BMI) performs better than most the models we explored in this work, with the exception of E3-all-mpnet-base-v2. Even though E3-all-mpnet-base-v2 was able to beat BMI on P@100, the improvement is not statistically significant when measured using a paired T-test.

In general, fusing the first-stage ranker scores with the reranker scores seems to degrade the performance by a few percentage points, with the exception of monoT5large with k = 10. Moreover, to our surprise, using a larger k decrease precision and recall. Also, the result is inconclusive on whether monoT5 perform better than monoBERT for this task. Some embedding models, such as E3-contriever achieved a P@100 of 0% on some topics. We discuss the reasons behind this in the discussion section of this work.

Since E3-all-mpnet-base-v2 was our best model, we will compare it to CAL using Recall@4R_t + 1000. Per topic recall gain curves are included in Appendix A and Recall@4R_t + 1000 for each topic is included in Table 2. Although the transformer appears to achieve superior results, a paired T-test shows that the result is not statistically significant.

5 Discussion

5.1 Cold Start Problem

Since for each topic, BMI initializes an untrained logistic regression model, it may not retrieve relevant documents accurately until it has seen a few relevant results. Parameters of BMI has been tuned so that a relevant document is retrieved in the first few iterations. However, when concatenating the Contriever embeddings with TF-IDF embeddings, the logistic regression model sometimes struggles to find any relevant documents in the first 100 iterations; this happened for 7 of the 34 topics. This problem can be alleviated by feeding in some relevant document to the logistic regression model before starting run for each topic; however, since in a realistic setting this is impractical, we will not utilize this trick.

Another attempt to fix this cold-start problem is to use a model that does not require training (e.g. BM25) until a few relevant documents are retrieved.
Since we wanted to compare our model with BMI, we decided not to utilize this technique, keeping our setting consistent with that of BMI.

5.2 Transformers

We used multiple pretrained transformers to rerank the top $k$ results from BMI. However, increasing $k$ from 10 to 100 degraded the performance of our models significantly. This, we believe, is evidence that current state-of-the-art transformer-based models are not effective in a high-recall setting. Most advances of transformer-based models in information retrieval has been in ad-hoc search, where the goal is to simply return “some” relevant information; that is, they aim to optimize metrics such as $P@10$. This is a vastly different task than finding all relevant documents to a query. Moreover, the datasets used to fine-tune pretrained transformers for retrieval often include sparse labelings: each query has 1-2 documents labeled as relevant; MS-MARCO is an example of such dataset. Therefore, models such as monoBERT and monoT5 find-tuned on MSMARCO are trained to detect a few relevant document from a candidate set of $k$ (e.g. $k = 1,000$) documents. This may be the reason why monoBERT and monoT5 cannot outperform BMI, a simple logistic regression model, when maximizing recall is the objective.

Moreover, we speculate the relevance feedback received at each iteration could be used in a more effective manner to improve the results at the next iteration. Using the relevance feedback as training examples and fine-tuning the model iteratively is effective as evident by superior performance of CALBERT-large when compared to monoBERT-large. Improvements to feeding in relevance feedback to pretrained transformers can pave the path of more effective high-recall transformer-based retrievers.

6 Conclusion

Although pretrained transformer-based models have been making rapid progress in a wide variety of NLP tasks, their advantages in high-recall information retrieval is not yet obvious, when compared to traditional models such as logistic regression with TF-IDF feature vectors. We proposed several ways of utilizing relevance feedback in a variety of transformer-based models (such as BERT, T5, and their descendants). First, we explored with utilizing relevance feedback by fine-tunning a monoBERT/monoT5 model iteratively. Taking inspiration from CAL, we then proposed the CALBERT model, where the pretrained BERT model is fine-tuned for a specific information need; this is in contrast to the monoBERT model where the model is fine-tuned for arbitrary queries. Lastly, we generated representational embedings using a variety of transformer-based models, such as models from the sentence-bert library (e.g. mpnt), the contriver model, and the TAS model. We concatenated these embeddings with the TF-IDF feature vectors as the input to the BMI (recall that in normal BMI only the TF-IDF feature vectors are used). When $P@100$ was compared to BMI, we saw modest (though not statistically significant) improvements in one of the representational models – the mpnt model. We ran a longer experiment with mpnt to calculate $Recall@AR_4+1000$. The gains on this longer experiment was not statistically significant either. In both the monoBERT/monoT5 and the CALBERT approaches, we used transformers to rerank the top $k$ results from BMI. As we discussed, increasing $k$ surprisingly degraded the performance, which suggests using Transformers (at least the variations used in this work) does not yield the same improvements as in the MSMARCO passage retrieval task. This, we suspect, is due to the lack of a large training dataset in the atome4 high-recall retrieval task.

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References

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. ArXiv, abs/1810.04805.

Maura R. Grossman and Gordon V. Cormack. 2011. Technology-assisted review in e-discovery can be more effective and more efficient than exhaustive manual review. 17.

Maura R. Grossman, Gordon V. Cormack, and Adam Roegiest. 2016. Trec 2016 total recall track overview. In TREC.

Sebastian Hofstätter, Sheng-Chieh Lin, Jheng-Hong Yang, Jimmy Lin, and Allan Hanbury. 2021. Efficiently teaching an effective dense retriever with balanced topic aware sampling. Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval.
Gautier Izacard, Mathilde Caron, Lucas Hosseini, Sebastian Riedel, Piotr Bojanowski, Armand Joulin, and Edouard Grave. 2021. Towards unsupervised dense information retrieval with contrastive learning. *ArXiv*, abs/2112.09118.

J. Lin, R. Nogueira, and A. Yates. 2021. *Pretrained Transformers for Text Ranking: BERT and Beyond*. Synthesis Lectures on Human Language Technologies. Morgan & Claypool Publishers.

Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, and Li Deng. 2016. *MS MARCO: A human generated machine reading comprehension dataset*. In *Proceedings of the Workshop on Cognitive Computation: Integrating neural and symbolic approaches 2016 colocated with the 30th Annual Conference on Neural Information Processing Systems (NIPS 2016)*, Barcelona, Spain, December 9, 2016, volume 1773 of *CEUR Workshop Proceedings*. CEUR-WS.org.

Rodrigo Nogueira, Wei Yang, Kyunghyun Cho, and Jimmy Lin. 2019. *Multi-stage document ranking with bert*.

Ronak Pradeep, Rodrigo Nogueira, and Jimmy Lin. 2021. *The expando-mono-duo design pattern for text ranking with pretrained sequence-to-sequence models*.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2019. *Exploring the limits of transfer learning with a unified text-to-text transformer*.

Nils Reimers and Iryna Gurevych. 2019a. *Sentence-bert: Sentence embeddings using siamese bert-networks*. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics.

Nils Reimers and Iryna Gurevych. 2019b. *Sentence-bert: Sentence embeddings using siamese bert-networks*. *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*.

Adam Roegiest, Gordon V. Cormack, Maura R. Grossman, and Charles L.A. Clarke. 2015. Trec 2015 total recall track overview. In *TREC*.

Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. 2020. Mpnet: Masked and permuted pre-training for language understanding. *ArXiv*, abs/2004.09297.

Eugene Yang, Sean MacAvaney, David D. Lewis, and Ophir Frieder. 2021. Goldilocks: Just-right tuning of bert for technology-assisted review.

A Appendices
