IMPROVING NOISE ROBUSTNESS FOR SPOKEN CONTENT RETRIEVAL USING SEMI-SUPERVISED ASR AND N-BEST TRANSCRIPTS FOR BERT-BASED RANKING MODELS

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ABSTRACT

BERT-based re-ranking and dense retrieval (DR) systems have been shown to improve search effectiveness for spoken content retrieval (SCR). However, both methods can still show a reduction in effectiveness when using ASR transcripts in comparison to accurate manual transcripts. We find that a known-item search task on the How2 dataset of spoken instruction videos shows a reduction in mean reciprocal rank (MRR) scores of 10-14%. As a potential method to reduce this disparity, we investigate the use of semi-supervised ASR transcripts and N-best ASR transcripts to mitigate ASR errors for spoken search using BERT-based ranking. Semisupervised ASR transcripts brought 2-5.5% MRR improvements over standard ASR transcripts and our N-best early fusion methods for BERT DR systems improved MRR by 3-4%. Combining semi-supervised transcripts with N-best early fusion for BERT DR reduced the MRR gap in search effectiveness between manual and ASR transcripts by more than 50% from 14.32% to 6.58%.

Index Terms— spoken content retrieval, BERT reranking, BERT dense retrieval, N-best BERT-based retrieval

1. INTRODUCTION

The growing archives of spoken multimedia content, such as those arising in video streaming services and podcasts, are increasing demands for effective spoken content retrieval (SCR) systems. Unlike textual documents, spoken documents are not directly searchable based on their content. For this reason, spoken multimedia content is often searched only based on user-created summaries and metadata. The effectiveness of this approach relies on availability of meaningful summaries and metadata for the documents. Further, since many spoken content items are long, SCR systems should ideally provide users with more sophisticated, finer granularity search functionalities based on the content itself. Such functionalities can only be provided if transcripts of the spoken contents of the documents are available.

The high cost of creating manual transcripts and the large amounts of content mean that transcripts are generally made using automatic speech recognition (ASR). However, transcription errors from ASR can impact on search effectiveness. While information retrieval (IR) has been shown to generally be robust to moderate word error rates (WERs), Larson and Jones report that WERs greater than about 30% can significantly impact on search reliability [1]. The accuracy of ASR systems continues to improve, with very low WERs reported for some tasks [2, 3]. However, WERs can still though be high when there is domain mismatch between the training of the ASR system and the data to be transcribed [4], speech is informal or acoustic noise is present in audio data [2]. In many settings, there is no control of domains or audio quality of the data, e.g., user-generated data of video streaming services or Podcasts, unlike audio corpora used in laboratory settings. Thus, even a state-of-the-art ASR system can still suffer high transcription WERs. This motivates us to explore development of methods to improve noise robustness of SCR systems.

Transformer-based IR models have recently emerged as a highly effective alternative to traditional models such as BM25 [5]. These new models can largely be classified into two types: re-ranking and dense retrieval (DR). The BERT-based re-ranking model, namely MonoBERT [6] directly takes a query-document pair to compute its relevance score. The drawback of MonoBERT and its successors is that transformer-based inference is very slow and hardware requirements can make them impractical for use in practice [7]. In DR, the transformer-based model is used to encode documents into dense document vectors separately from queries. At search time, only the query needs to be encoded into vector representations. Then, any vector-based similarity measure, such as nearest neighbour (NN), can be used to compute query-document relevance scores. This approach is much faster to run than re-ranking [7].

The contributions of this paper are as follows. (i) We investigate BERT-based re-ranking and DR for a known-item search task of spoken instruction videos. We observe that, despite the use of BERT-based retrieval systems, the gap in search effectiveness between manual and ASR transcripts was around 10-14%. (ii) We augment an ASR system using semi-supervised training for domain adaptation and examine the impact of improved ASR transcripts on the BERT-based rank-

ing systems. The use of semi-supervised ASR transcripts brought 2-5.5% improvement of the MRR score. (iii) We propose the use of N-best ASR transcripts for BERT DR systems and observe that our proposed early fusion approach brought a gain in the MRR score by around 3-4%. Combining these two methods gives an average improvement in MRR of 6.5%.

The reminder of the paper is organised as follows. The next section gives a brief review of BERT-based IR and SCR, followed by details of the models used in this investigation. We then propose our early and late fusion extensions using ASR N-best transcripts for a BERT DR system. Experimental results and analysis of the BERT-based ranking models are then presented, followed by conclusions and future work.

2. RELEVANCE TO PRIOR WORK

Mainstream studies of spoken document retrieval (SDR) began with the Text REtrieval Conference (TREC) [8]. Studies have continued with exploration of SCR in activities such as those at MediaEval [9] and the Podcast retrieval track at TREC 2020 and 2021 [10, 11]. Another line of recent studies on SCR is described in [12, 13], which investigate the use of BERT re-ranking on retrieval of Mandarin news stories.

A number of retrieval models have been introduced over the years, among the most consistently effective is the BM25 probabilistic model [5], which has been applied successfully in many SCR tasks including [9, 10]. Recent years have seen the introduction of neural IR models, including [14]. However, more recently a new class of retrieval models using the pre-trained transformer architecture (BERT) [15] has been introduced [16]. These models have been shown to be better than the classic BM25 model [5] and non-BERT neural models, such as Conv-KNRM [14]. These BERT-based search models can be classified into two categories: BERT-based reranking [6] and dense retrieval (DR) [7, 17]. While BERTbased re-ranking takes as input a query-document pair and directly produces a relevance score, DR encodes documents and queries into dense vectors independently and applies approximate nearest neighbour (ANN) search to these vectors.

N-best ASR hypotheses have been used as input to the BERT model for Spoken Language Understanding as a form of lattices [18], confusion networks [19] and plain texts [20]. Ganesan et al. conclude in [20] that text format input was more suitable for BERT models than alternative formats since BERT models are pre-trained on plain texts. N-best hypotheses have also been explored for ASR error correction [21].

Our paper differs from existing work on BERT-based ranking systems for SCR tasks as follows. (i) We experiment with both BERT re-ranking and BERT DR systems on manual transcripts and ASR transcripts. The TREC Podcasts Tracks [10, 11] have seen the use of BERT reranking and DR models. However, manual transcripts were not available for system evaluation. BERT re-ranking was investigated in [12, 13], while the BERT DR model was not

BERT re-ranking

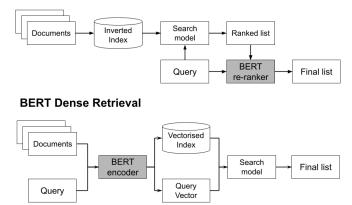


Fig. 1. Schematic diagram of a BERT-based re-ranking system and a BERT-based dense retrieval (DR) system.

applied to their spoken broadcast retrieval. (ii) We employ semi-supervised ASR transcripts to the SCR setting, where a domain-adapted ASR system is not available. Existing literature [1, 8] suggests a near-linear relationship between transcription WERs and search scores. Our investigation into the use of semi-supervised ASR transcripts demonstrates that BERT re-ranking and DR models benefit from improved transcripts using a semi-supervised ASR system. (iii) We propose the use of ASR N-best transcripts for BERT DR systems. To the best of our knowledge, BERT ranking models using ASR N-best for SCR has not been investigated previously. We observe that both early and late fusion approaches for BERT DR mitigate errors in ASR transcripts for the SCR task.

3. BERT-BASED RETRIEVAL MODELS

In this section we provide details of BERT-based re-ranking and DR. We first present the models, and then describe how they are trained.

3.1. BERT for retrieval systems

Figure 1 shows the structure of a BERT re-ranking system and a BERT DR system. The BERT re-ranker takes a ranked document list from an initial search model and re-ranks it using the BERT model, while the DR system uses BERT to transform documents and a query into dense vectors and another search model to obtain the final ranked list of documents.

BERT Re-ranker The BERT model re-ranks a ranked document list retrieved from a document archive using a lightweight search model such as BM25. The first BERT model used for re-ranking was MonoBERT [6]. Suppose a query consists of N tokens and a document M tokens, the input to the BERT model can be expressed as $[CLS]q_1, ..., q_N[SEP]$

 $d_1, ..., d_M[SEP]$, where [CLS] and [SEP] are special tokens of BERT. A relevance score of the query-document pair is computed by feeding an output vector corresponding to the [CLS] token to a fully-connected layer.

BERT Dense Retrieval A BERT model is used to encode a query and documents into vector representations. While two BERT models were used by Karpukhin et al. [17] to encode a query and documents independently, Xiong et al. [7] applied a single BERT model to encode a query and documents (Dual encoder). In this work, we used the dual encoder framework for our DR system. A representation of a query and a document is a vector corresponding to the [CLS] token preceding query tokens or document tokens. In contrast to the re-ranker BERT output which is a relevance score, a dense vector is a representation of a document or a query in a fixed dimensional space, and the final relevance score is computed by taking a similarity score of the query and document vectors.

A similarity score can be computed using a dot product or cosine similarity. This enables an efficient retrieval algorithm, such as approximate nearest neighbour, to be used to create a final list of documents according to query-document similarity scores [22]. In this work, we use a dot product for similarity scoring following [7].

BERT re-ranking vs BERT dense retrieval BERT re-ranking has generally been found to produce better retrieval metrics than the BERT DR [16]. However, Xiong et al. [7] demonstrated that using it can be 100 times slower than DR at search time. Due to its inference speed, BERT re-ranking is often applied to only the k top documents returned by an initial search, while BERT DR needs only to encode a query at search time and can be applied to the whole document collection.

3.2. BERT training for retrieval

BERT Re-ranking The BERT re-ranking model is trained using binary cross-entropy loss [6]. Specifically, given a query and a relevant document pair, the BERT model is trained to produce an output of 1, while it is trained to produce 0 for a query and a non-relevant document. This can be expressed as

$$L = -\log(f(q_i, d_i^+; \theta)) - \sum_{j=1}^{J} \log(1 - f(q_i, d_{ij}^-; \theta)) \quad (1)$$

where $f(q_i, d_i^+; \theta)$ is the score from the BERT model given the *i*th query-document pair and $f(q_i, d_{ij}^-; \theta)$ the score from the BERT model given the *j*th negative query-document pair corresponding to the *i*th train example.

BERT Dense Retrieval The BERT DR model is trained using the negative log likelihood [7, 17]. Specifically, the model is trained to maximise a similarity score of a pair of a query and a relevant document and to minimise a similarity score of a pair of query and a non-relevant document. Formally, this is:

$$s(q, d) = sim(g(q; \theta), g(d; \theta))$$
(2)
$$L = -\log \frac{\exp(s(q_i, d_i^+))}{\exp(s(q_i, d_i^+)) + \sum_{j=1}^{J} \exp(s(q_i, d_{ij}^-))}$$
(3)

where $g(q; \theta)$ is a function to obtain a query dense vector corresponding to the BERT output vector of the [CLS] token and $g(d; \theta)$ its document counterpart. sim() is a function to compute a similarity score of the two vectors. Similar to the cross entropy loss used for the BERT re-ranker, this loss is obtained for the *i*th query-document pair and corresponding *j* negative query-document pairs.

To obtain negative examples for each true query-document pair, the BM25 model is often used to decide the initial negative examples. Xiong et al. [7] proposed an improved algorithm to select negative examples named Approximate nearest neighbour Negative Contrastive Learning (ANCE). This algorithm begins with BERT training on negative examples chosen from the output of BM25 document ranking, and updates negative examples using the BERT model being trained at every specified checkpoint. Xiong et al. [7] provides theoretical grounds for ANCE and empirical results demonstrating that ANCE training produces better search results and faster model convergence. While their original paper proposes asynchronous updates of negative examples where inference for ANCE and model training run in parallel, we stopped model training at the end of every training epoch and ran ANCE updates to resume model training on updated negative examples.

4. N-BEST FUSION FOR BERT DENSE RETRIEVAL

As outlined in Section 2, using ASR N-best transcripts has been effective in SLU and ASR error correction [20, 21]. In this paper, we propose two N-best fusion approaches for BERT DR. The first approach fuses N-best transcripts before feeding text to BERT (early fusion). The second approach creates N indexes for N-best transcripts and combines scores from each of the indexes to compute the final score for each document (late fusion).

4.1. N-best early fusion

The input sequence length of the BERT model is often limited to 512 tokens with tokens exceeding this maximum length being truncated [15]. For the task of SLU, user utterances are generally very short and N-best transcripts can be concatenated with the [SEP] token [20]. However, in case of SCR, document lengths are generally much longer and N-best document representations cannot be simply concatenated with the [SEP] token. This issue can be resolved by the alignment approach introduced in [21], and taking the average of N word

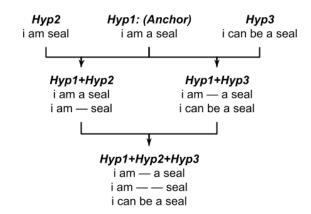


Fig. 2. Example of N-best alignment to create BERT input text.

embeddings for ith token to compress N documents into a single document representation.

Figure 2 shows an example of aligning 3-best transcripts. The 1-best transcript is used as an anchor transcript and aligned with the other two transcripts. The aligned transcripts are further combined to match the length across N-best transcripts. As described in [21], "-" is used as a special token to alleviate a length mismatch between transcripts. This token is added to one of the word embedding vectors. The input of the BERT model is often sub-word tokens [15]. It is important to run alignment of transcripts *after* tokenisation is applied to texts. If this order is reversed, aligned transcripts can create a length mismatch after tokenisation. Once the N-best transcripts have been aligned, the tokens are transformed into word embeddings with the *i*th position of the aligned tokens combined by taking the average. For example, in Figure 2, the first position of the three transcripts are all "i". This results in the averaged embeddings of "i". This could be extended by concatenating embeddings and feeding concatenated embeddings to a linear layer, as in [21], but the concatenated vector size can be large and we did not apply this method in this paper.

4.2. N-best late fusion

Our N-best late fusion approach to BERT DR involved creation of an N index for each of the N-best transcripts. The BERT model encodes a query into a vector and search is carried out for all N indexes. The final result is calculated by summing the scores for each document from each index, and ranking in descending order of summed scores. While a drawback of this approach is creating N indexes, ANN search over N indexes could be run in parallel using N CPUs after computing a query vector to maintain operational speed.

5. EXPERIMENTAL INVESTIGATION

In this section we present our experimental investigation. We first describe our experimental setup. This includes details

of the data used for our experiments, training and hyperparameter details of BERT re-ranking and DR models, and creation of standard ASR transcripts and semi-supervised ASR transcripts. We then present experimental results of a known-item search task using a corpus of spoken instruction videos. The results show search scores of applying BERT ranking systems to different types of transcripts, inference time of BERT re-ranking and DR systems, and the use of an N-best extension for BERT DR systems.

5.1. Experimental Setup

Test Collection and Evaluation Our experimental investigation was carried out using the How2 dataset [23]. How2 consists of 19,770 videos with manual transcripts and metadata including video titles. For our experiments we used How2 video titles as search queries to retrieve the associated video to form a known-item search task where each query has one relevant target document. We randomly selected 500 of the 19,770 video titles as evaluation queries. Experiments used the standard known-item search of mean reciprocal rank (MRR), defined as follows:

$$MRR = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{rank_i} \tag{4}$$

where N is the number of user queries and $rank_i$ is the rank of the relevant document in the retrieval list for the *i*th query. In the How2 corpus, only around 2.5% of the collection used exceeds the length limit of BERT. Thus, our results are unlikely to be affected by the BERT length limit. Examination of any impact of this issue and strategies to address it could form future work.

BERT Retrieval Model Data Setup For the re-ranking BERT model, an additional 500 validation queries were randomly selected. For each validation query, one positive example and one negative example from the top of the BM25 ranked document list were chosen (if the top document is the positive example, the second ranked document was chosen) to compute validation loss using the cross entropy. For the BERT DR model, 500 validation queries were randomly chosen, and for each query, 1 relevant document and 99 irrelevant documents from the BM25 model were ranked by the BERT encoder to compute the mean reciprocal rank of the relevant document.

ASR Transcripts To obtain ASR transcripts of How2 audio data, a Kaldi "chain" system was developed using the LibriSpeech corpus [24, 25]. This is a traditional ASR system integrating an acoustic model with a hidden Markov model. This system, referred to as "standard ASR", trained on LibriSpeech created a domain mismatch scenario to recognise How2 audio and produced an overall WER of 31.1%. We used the "standard ASR" system to generate decode lattices and 1-best transcripts of the How2 train data. Combined with LibriSpeech data, the decode lattices were used to train a

domain-adapted semi-supervised acoustic model, while 1best transcripts were used for training of a semi-supervised N-gram for decoding and a re-scoring recurrent neural network language model [4, 26, 27]. This system, referred to as "semi-supervised ASR" produced an overall WER of 23.95%. Further, we generated lattice oracle transcripts using the "standard ASR" system (i.e., the most correct hypotheses present in lattices with respect to manual transcripts), which produced an overall WER of 11.18%. For the N-best experiments, the "standard ASR" and "semi-supervised ASR" systems were used to generate {2, 5, 10, 20}-best transcripts to develop the N-best version of the BERT DR system.

Retrieval Models The BM25 model used was the Python version of Lucene with k1 1.2 and b 0.75¹. The re-rank system took as input the top 1,000 documents returned for each query. The pre-trained BERT model used was "bert-base-uncased" and its corresponding tokeniser from HuggingFace [28]. For the DR system, after the whole document collection had been encoded by the BERT model, Faiss software [22] was used to run similarity search over a query vector and an index of document vectors.

The hyper-parameter settings for BERT model training were as follows. The re-ranker BERT was trained with 20 epochs and used the model checkpoint which produced the best validation score. Model training was generally converged by epoch 15. The best initial learning rate was empirically selected, and was 3×10^{-7} . The DR BERT was converged by 10 epochs as reported by [7]. The best initial learning rate found was 1×10^{-5} . Both re-ranker BERT and DR BERT used 20 negative examples. Our BERT models were trained using Quadro RTX 6000. The BERT models could potentially be improved by using more negative examples, but the number of negative examples 20 was its memory limit. Increasing the negative examples using a memory queue could form future work. For training of the re-ranker and DR BERT, the AdamW optimizer was used with a weight decay of 5×10^{-5} to avoid overfitting.

5.2. MRR scores using lattice oracle, manual, standard and semi-supervised ASR transcripts

Table 1 presents MRR scores for BM25, BERT re-ranking and BERT DR systems using manual (man), lattice oracle (oracle), semi-supervised ASR (semi ASR) and standard ASR (std ASR) transcripts. We use the paired 2-tailed t-test to compare distributions of MRR scores from BM25 and other BERT-based models.

Comparison of BERT ranking systems The largest MRR gain was obtained using the BERT DR system trained with ANCE. This improved the MRR scores by around 26% over the BM25 model on manual transcripts, and by 23% on standard ASR transcripts, indicating that transcription errors affected the score. The BERT re-ranking system improved

Table 1. MRR results of using different transcripts for How2 known-item search evaluation. All of BERT results are statistically significant over BM25 with p < 0.05 denoted by **

	MRR						
model	eval data						
	man	oracle	semi ASR	std ASR			
BM25	40.27	36.02	30.85	29.37			
rerank	57.32**	52.46**	48.69**	46.37**			
DR	50.61**	45.96**	40.38**	34.81**			
DR-ANCE	66.73**	63.88**	56.22**	52.41**			

the MRR scores by around 16-18% over the BM25 model for all transcript types.

Comparison of searching over different transcripts Despite the improvement in MRR obtained by BERT re-ranking and DR systems, the gap remains between manual and ASR transcript scores. Searching over standard ASR transcripts resulted in around 11% worse MRR scores than manual transcripts with BM25 and BERT re-ranking. BERT DR systems were more affected by transcription errors showing around 15% worse MRR scores when using standard ASR transcripts. Although semi-supervised transcripts had a small impact on the improvement of MRR score by the BM25 model, the BERT re-ranking system improved the MRR score by 2% and the BERT DR systems improved the score by 5.5% without ANCE training and by around 4% with ANCE training. The oracle experiments, however, show that the gap in the MRR scores between manual transcripts and ASR transcripts could potentially be further reduced. In comparison to searching over manual transcripts, all of the models including BM25 produced only 3-4% worse MRR scores when searching over lattice oracle transcripts.

Comparison of search run time Similar to [7], we compare the inference time of 100 documents per query. Search operations of BM25 were measured using a CPU, while inference of BERT re-ranking was performed using a GPU. BERT DR search run time is the total for encoding the query using a GPU and ANN operations using a CPU. For fair comparison, all of the search runs were performed on the same computation node of our high performance computing system. We observe that average run time of BM25 was 40 msecs, BERT reranking 1.84 secs, and BERT DR 18 msecs, respectively. This result agrees with [7], where BERT re-ranking was roughly 100x slower than BERT DR at search time and demonstrates a practical advantage of the BERT DR system.

5.3. MRR scores using ASR N-best for BERT DR

We next present the MRR scores of our proposed ASR Nbest extension for BERT DR. Table 2 summarises the MRR scores of BERT DR using $\{2,5,10,20\}$ -best transcripts either from the standard ASR system or from the semi-supervised ASR system. MRR scores of N-size 1 correspond to the MRR

¹https://lucene.apache.org/

Table 2. MRR results of BERT-DR models with and without ANCE training using the N-best extension over standard ASR and semi-supervised ASR transcripts. % change shows relative improvement/regression of MRR over corresponding 1-best models. Asterisks * and ** denote statistical significance over the baseline 1-best system with p < 0.05 and p < 0.01, respectively.

			MRR			
model	N-size					% change
	1	2	5	10	20	-
standard ASR						
DR-early	34.81	35.42	32.94	- 33.71 -	34.24	+1.75(2-best)
DR-late		35.49	36.94**	37.55**	38.20**	+9.74 (20-best)
DR-ANCE-early	52.41	51.77	52.14	- 52.75 -	54.45	+3.49 (20-best)
DR-ANCE-late		53.29	54.88**	54.86**	55.40**	+5.71(20-best)
semi-sup ASR						
DR-early	40.38	39.40	38.21	37.91	38.72	-2.43 (2-best)
DR-late		40.05	40.21	41.20	40.93	+2.03 (10-best)
DR-ANCE-early	56.22	57.26	57.27	- 57.92 -	60.15**	+6.99 (20-best)
DR-ANCE-late		57.79*	58.19**	58.79**	59.20**	+5.30 (20-best)

scores from row 3 and row 4 and semi ASR and std ASR columns in Table 1. Bold face indicates MRR scores of each BERT DR system which are higher than the baseline 1-best result and highest among other N sizes. A paired 2-tailed t-test was again carried out to compare MRR distributions from the 1-best BERT model and other N-best models.

The 20-best early and late fusion over semi-supervised transcripts using ANCE BERT produced MRR of 60.15% and 59.20%, respectively (row 3 and 4 of *semi-sup ASR* in Table 2). Considering that the 1-best BERT DR over standard ASR transcripts produced MRR of 52.41% and the MRR gap between standard ASR and manual transcripts was 14.32% (66.73 - 52.41), the MRR score gap was reduced to 6.58% (66.73 - 60.15) using the 20-best early fusion approach. This reduction represents a more than 50% relative improvement.

Early vs late fusion While the early fusion approach produced inconsistent improvement of MRR with different N-sizes, the late fusion approach consistently benefited from increase in N sizes. Despite the highest MRR score of 60.15% obtained from early fusion of 20-best transcripts for BERT DR with ANCE training, when the early fusion was applied to BERT DR without ANCE training, the MRR scores did not improve with increase in the value of N. While statistical significance over the 1-best system was observed over semi-supervised ASR transcripts (row 3 semi-sup ASR), the MRR score of 20-best over the standard ASR transcripts did not show statistical significance (row 3 standard ASR). In contrast, the late fusion approach brought consistent improvement over 1best systems. The highest MRR score observed was 59.20 using 20-best semi-supervised ASR transcripts for BERT DR with ANCE training (row 4 semi-sup ASR). Generally, 20best transcripts benefited the late fusion approach the most, except when BERT DR without ANCE training was applied to semi-supervised ASR transcripts (row 2 semi-sup ASR).

In further analysis we examined the average MRR im-

provement and regression per query for the 20-best extension to ANCE BERT DR systems. The early fusion approach brought an average improvement in MRR of 0.32 for 147 out of 500 evaluation queries over the 1-best system, while 123 out of these 500 evaluation queries had a lower MRR score with average 0.22. MRR scores of the other 240 queries were unchanged. The late fusion approach with 20-best ANCE BERT improved the MRR scores of 135 queries with by an average 0.17, while reducing scores of 86 queries by an average of 0.10. MRR scores of the other 279 queries were unchanged by the late fusion approach. These results demonstrate that the early fusion approach introduces more radical changes than late fusion, in computation of document representations over 1-best systems.

6. CONCLUSIONS AND FUTURE WORK

We explored BERT re-ranking and DR systems for a knownitem SCR task. Despite improved search effectiveness using the BERT ranking model, MRR scores from BERT reranking and DR systems were 10-14% lower when using ASR than manual transcripts. We investigated the use of semisupervised ASR transcripts and an N-best extension for BERT DR. Use of semi-supervised transcripts improved MRR by 2-5.5%, while use of 20-best transcripts brought a gain in 3-4%. Combining them gave an average improvement of 6.5%.

Future work includes the use of decode lattices for BERT retrieval. As seen in Table 1, applying BERT ranking models to lattice oracle transcripts further closed the MRR gap in 3-5% MRR to manual transcripts. This motivates development of BERT ranking which can effectively take as input decode lattices to overcome ASR transcription errors.

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