Zero-shot Neural Retrieval via
Domain-targeted Synthetic Query Generation

Ji Ma  Ivan Korotkov  Yinfei Yang  Keith Hall  Ryan McDonald
{maji, ivankr, yinfeiy, kbhall, ryanmcd}@google.com

Abstract

Deep neural scoring models have recently been shown to improve ranking quality on a number of benchmarks (Guo et al., 2016; Dai et al., 2018; MacAvaney et al., 2019; Yang et al., 2019a). However, these methods rely on underlying ad-hoc retrieval systems to generate candidates for scoring, which are rarely neural themselves (Zamani et al., 2018). Recent work has shown that the performance of ad-hoc neural retrieval systems can be competitive with a number of baselines (Zamani et al., 2018), potentially leading the way to full end-to-end neural retrieval. A major road-block to the adoption of ad-hoc retrieval models is that they require large supervised training sets to surpass classic term-based techniques, which can be developed from raw corpora. Previous work shows weakly supervised data can yield competitive results, e.g., click data (Dehghani et al., 2017; Borisov et al., 2016). Unfortunately for many domains, even weakly supervised data can be scarce. In this paper, we propose an approach to zero-shot learning (Xian et al., 2018) for ad-hoc retrieval models that relies on synthetic query generation. Crucially, the query generation system is trained on general domain data, but is applied to documents in the targeted domain. This allows us to create arbitrarily large, yet noisy, query-document relevance pairs that are domain targeted. On a number of benchmarks, we show that this is an effective strategy for building neural retrieval models for specialized domains.

1 Introduction

Thanks to the rapid development in deep-learning techniques, there has been a surge of interest in investigating neural information retrieval models (Guo et al., 2016; Borisov et al., 2016; Dehghani et al., 2017; Dai et al., 2018; MacAvaney et al., 2019; Yang et al., 2019a; Zamani et al., 2018). Neural retrieval models not only reduce the burden of feature engineering, but more importantly they are capable of capturing relations between entities and topics that are implicitly conveyed in the training data, e.g., “Theresa May” and “Prime Minister” (Cohen et al., 2018). As a result, neural retrieval models achieve new state-of-the-art performance on several information retrieval (IR) benchmarks (Guo et al., 2016; Pang et al., 2016; Hui et al., 2017; Dai et al., 2018; MacAvaney et al., 2019; Yang et al., 2019a; Gillick et al., 2018; Yang et al., 2019b).

The most effective neural models are usually deep and wide – many layers with large hidden representations. This results in models with a huge number of parameters, which are prone to overfitting. Thus, a key factor in training high quality models is the availability of large training sets. Such data can be prohibitively expensive to create. Previous work attempts to alleviate this issue by pre-training deep retrieval models on weakly supervised data such as user clicks, search results from traditional IR systems, or anchor texts (Borisov et al., 2016; Dehghani et al., 2017). Unfortunately, large weakly supervised data is not always available in some domains. E.g., enterprise or personal search environments (Hawking, 2004; Chirita et al., 2005).

On the other side, the public domain question answer pairs can be acquired from community question/answer platforms such as Yahoo Answers and Stack Overflow\textsuperscript{1} or high quality human annotated question/answer datasets that are publicly available (Kwiatkowski et al., 2019). However, as we will show in later experiments, neural retrieval models trained on the public domain data can be barely transferred to a particular domain, especially for specialized domains like biomedical, legal.

In order to solve the problem to train deep

\textsuperscript{1}https://answers.yahoo.com/, https://stackoverflow.com/
retrieval models in the zero resource scenario – where no (weakly-) supervised data is available, we propose a data augmentation approach (Wong et al., 2016) to leverage naturally occurring question/answering pairs to train a generative model that synthesis queries given a text. Once the model is trained, we can apply this model to documents in the target domain, resulting in unlimited pairs of synthetically generated queries and target-domain documents. This data then can be used to train a neural retrieval model. Synthetic query generation for zero-shot neural IR training is outlined in Figure 1. Question generation has also been employed to augment QA training sets (Alberti et al., 2019; Lewis et al., 2019), but has never been tested for ad-hoc retrieval nor the zero-shot setting. Nogueira et al. (2019) employed query generation in the context of information retrieval. In that study, the generated queries were used to augment documents to improve BM25 keyword search. Here we focus on using synthetic queries to train neural retrieval models, which is an complementary approach. Experiments on four different dataset show that our approach compares favorably with other zero-shot alternatives. Though outside the scope of this study, our method can also be combined with alternative domain adaptation techniques (Cohen et al., 2018; Tran et al., 2019).

2 Neural Retrieval Model

Our retrieval model belongs to the family of Dual Encoders (DE)\(^2\) (Gillick et al., 2018; Palangi et al., 2016) that encodes pairs of items in a shared space. Formally, a DE model consists of two encoders, \(\{f_q(), f_d()\}\) and a similarity function, \(sim()\). An encoder is a function \(f\) that takes an item \(x\) as input and outputs a real valued vector as the encoding, \(e_x = f(x)\). The similarity function, \(sim()\), takes two encodings, \(e_x\) and \(e_y\), and calculates a real valued score, \(s = sim(e_x, e_y)\). For retrieval, the two encoders are responsible for computing vector representation of queries (query encoder) and documents (document encoder). In this work, both encoders are implemented using deep neural networks with identical architecture. In particular, we adopt the Transformer (Vaswani et al., 2017) with the same configuration as BERT-base, e.g. 12 layers with hidden size 768 and 12 attention heads. We initialize parameters with pre-trained BERT checkpoints (Devlin et al., 2019). Early works (MacAvaney et al., 2019; Yang et al., 2019a) show such pre-trained models can lead to large performance gains across a number of tasks, including document ranking. In addition, we share parameters between the query and document encoder – so called Siamese networks – as we found this greatly increased performance while reducing parameters.

To encode a query \(q\) of \(k\) tokens \(q = (q_1, q_2, ..., q_k)\), we first expand \(q\) with two boundary tokens, i.e., \((CLS, q_1, q_2, ..., q_k, SEP)\) and then feed the expanded query to the BERT encoder. Let \(e_{cls}\) denote the final representation of the “CLS” token. Query encoding \(h_q\) is computed by applying a linear projection on \(e_{cls}\), i.e., \(h_q = W * e_{cls}\), where \(W\) is 768 by 768 weight matrix. To encode a document, we concatenate its title \(t = (t_1, ..., t_m)\) with its content \(c = (c_1, ..., c_n)\) as \((CLS, t_1, ..., t_m, SEP, c_1, ..., c_n, SEP)\). The expanded sequence is feed to the BERT encoder, and document encoding \(h_d\) is obtained by project the corresponding “CLS” token representation with the same weight matrix \(W\). The final similarity function is chosen from cosine and dot-product similarity based on development set performance for each dataset. All dual-encoder models in the experiments are trained with in-batch softmax objective, we did a small grad-search on learning rate \([1e-6, 2e-6, 5e-6, 1e-5]\) and batch size \([1024, 2048, 4096, 8192]\), and choose the best setting according

---
\(^2\)Also called two-tower or relevance-based ranking.

Figure 1: Synthetic query generation for neural IR.
to development set accuracy. At inference time, we first pre-encode all documents in a collection, and then for a given query we retrieve the nearest documents using brute-force search.

3 Synthetic Query Generation

In this work, we investigate a zero-shot scenario where there exists neither user issued queries nor domain specific data except the document collection itself. We propose to address the training data scarcity by generating syntactic queries, where a query generation model is first trained using question-answering data mined from the web. The document collection of a new domain is then fed into this generator to create pairs of noisy question-document training examples, which are used to train a retrieval model (see Figure 1).

Our question generator is based on encoder-decoder model with Transformer (Vaswani et al., 2017) layers, which is a common model for generation tasks such as translation and summarization (Vaswani et al., 2017; Rothe et al., 2019). The encoder is trained to build a representation for a text and the decoder generates a question for which that text answers. One advantage of our approach is that there are large question-answer data sources that can be freely obtained from the web. In this work, we mine English question-answer pairs from community question-answering resources, primarily StackExchange and Yahoo! Answers. To ensure data quality, we further filter the data by only keeping question-answer pairs that were positively rated by at least one user on these sites. In total, the final dataset contains 2 millions pairs, and the average length of question and answer are 12 tokens and 155 tokens respectively. This dataset is general domain in that it contains question-answer pairs from a wide variety of topics. Most of these though are general knowledge questions and do not represent questions that a specialist might ask. Our approach is flexible in dealing with domain shift as the generator is learned to create questions targeting entities and concepts occurred in the given text.

In our implementation, both the encoder and decoder share the same network structure. Parameter weights are also shared and are initialized from a pretrained RoBERTa (Liu et al., 2019) checkpoints. We truncate answer and question to 512 sentence-piece (Kudo and Richardson, 2018) tokens, and limit decoding to at most 64 steps. The model is trained with a batch size of 128, and the training objective is the standard cross entropy. Our implementation is based on that of Rothe et al. (2019). Fast approximate nearest neighbour search is possible for dense vectors through techniques described in Liu et al. (2011).

4 Experimental Setup

We evaluate our approach against other zero-shot baselines on three different datasets accounting for four domains.

4.1 Datasets

**BIOASQ** dataset contains English biomedical questions collected from the document ranking task of BIOASQ competition (Tsatsaronis et al., 2015). We use BIOASQ 7B test data to evaluate performance of our retrieval model. This test set contains 500 expert questions with relevant judgments from trained biomedical practitioners. For supervised experiments, we use the last 200 queries of BIOASQ 7B training data as development set and use the rest 2573 queries for training. This yields a training set of 29K query-document pairs. The document collection contains roughly 28M articles from MEDLINE. We discard about 10M articles that only contains a title. For each of rest article, we concatenate title and abstract, and truncate at 200 wordpiece tokens with BERT tokenization.

**Forum** consists of threads from two online user forum domains: Ubuntu technical help and TripAdvisor topics for New York City (Bhatia and Mitra, 2010). For each domain the document collection consists of 100,000 threads and the test data contains 25 queries with relevant marked threads. For each thread, we concatenate the title and initial post and truncate at 350 wordpiece tokens. Unlike the BIOASQ data, this data generally does not contain specialist knowledge queries. Thus, compared to the collection of question-answer pairs mined from the web, there is less of a domain shift. Since this forum data does not contain training set, we do not perform supervised experiments.

**NaturalQuestions** consists of aggregated queries issued to Google Search (Kwiatkowski et al., 2019). We convert the original format to a retrieval task, where the goal is to retrieval the long answer among all wiki paragraphs (Ahmad et al., 2019). We discard questions whose long answer is either a table or a list. This yields 74097 queries in the original training set which is used for supervised experiment, and 1772 queries in original development set which we
Table 1: Zero-shot ad-hoc retrieval. Unsupervised∗; Out-of-domain†; Synthetic‡. Bold=Best; Underline=Best non-hybrid.

| Models          | Average | BioAsq | NaturalQuestions | Forum Travel | Forum Ubuntu |
|-----------------|---------|--------|------------------|--------------|--------------|
|                 | MAP @10 | nDCG@10| MAP @10 | nDCG@10 | MAP @10 | nDCG@10 | MAP @10 | nDCG@10 | MAP @10 | nDCG@10 |
| BM25            | 0.148   | 0.087  | 0.105  | 0.406    | 0.175  | 0.455   | 0.066  | 0.018   | 0.088  | 0.140  | 0.116  | 0.149  |
| ICT∗            | 0.058   | 0.098  | 0.130  | 0.070    | 0.023  | 0.076   | 0.047  | 0.016   | 0.057  | 0.036  | 0.174  | 0.214  |
| QA†             | 0.131   | 0.168  | 0.239  | 0.180    | 0.028  | 0.154   | 0.126  | 0.051   | 0.183  | 0.063  | 0.288  | 0.341  |
| QGen‡           | 0.168   | 0.192  | 0.290  | 0.333    | 0.150  | 0.183   | 0.101  | 0.316   | 0.318  | 0.130  | 0.320  | 0.352  |
| BM25 + QGen‡    | 0.188   | 0.111  | 0.247  | 0.422    | 0.182  | 0.476   | 0.167  | 0.060   | 0.215  | 0.025  | 0.048  | 0.208  |

Figure 2: Retrieval performance on BioAsq (y-axis) w.r.t. the % of documents used for synthesizing queries (x-axis).

use to evaluate our models. The target collection contains paragraphs from 2016-12-21 dump of Wikipedia (Chen et al., 2017). Each paragraph is also concatenated with title and then truncated at 350 wordpiece tokens. The yields a collection of size 29.5M. This data is different from the previous data in two regards. First, there is a single annotated relevant paragraph per query. This is due to the nature in which the data was curated. Second, this data is entirely “general domain”.

4.2 Zero Shot Systems

BM25: Term-matching systems such as BM25 (Robertson et al., 2004) are themselves zero-shot, since they require no training resources except the document collection itself. We train a standard BM25 retrieval model on the document collection for each target domain.

QA: The dataset mined from community question-answer forums (Sec. 3) itself can be used directly to train a neural retrieval model since it comes of the form query and relevant text (document) pair. This data is naturally occurring and not systematically noisy, which is an advantage. However, the data is not domain-targeted in that it comes from general knowledge questions. We call the dual-encoder model trained on this dataset as QA.

ICT: The Inverse Cloze Task (ICT) (Lee et al., 2019b) is an unsupervised pre-training objective which randomly masks out a sentence from a document and creates synthetic sentence-document pairs representing membership of the sentence in the document. These masked examples can then used to train or pre-train a retrieval model. Lee et. al. (Lee et al., 2019b) showed that masking a sentence with a certain probability, p, can both mimic the performance of term-based retrieval systems (p = 0) or semantic matching (p > 0). In this work, we set p to 0.9 and select at most 5 sentences from each document, this setting has been shown perform well on multiple dataset in Lee et. al. (Lee et al., 2019b). The total number of query-document pairs for BIOASQ, NQ, Forum-Travel and Forum-Ubuntu are about 75M, 72M, 294K and 430K respectively. ICT is domain-targeted since examples for training are created directly from the relevant document collection.

QGen: The QGen retrieval model is the one described in Section 3, where we use the community mined question-answer data to train a synthetic query generator that is applied to the target domain. Thus, while this model can contain systematic noise from the generator, it is domain-targeted. We filter questions that only contain stop words, and the number of query-document pairs for BIOASQ, NQ, Forum-Travel and Forum-Ubuntu are roughly 89M, 60M, 152K and 319K.

BM25+QGen: Term-matching and neural retrieval models have complementary characteristics. Neural retrieval models naturally generalize, match synonyms and paraphrases without any special handling. Term-matching is highly precise and can be preferred from some queries where specific terms must match. We present a hybrid zero-shot retrieval model that linearly interpolates BM25 and QGen scores with a parameter tuned via grid search.

All QA, ICT and QGen models are trained using the neural architecture from Section 2. For BIOASQ experiments, query and document encoder are initialized with BioBERT base v-1.1 (Lee...
et al., 2019a). On NaturalQuestions and Forum data, we use uncased BERT base (Devlin et al., 2019).

5 Results and Discussion

Our main results are shown in Table 1. We report Mean Average Precision over the first 100 results (MAP), Precision@10 and nDCG@10. For NaturalQuestions we report Precision@1 since there is a single relevant document annotation. Here we compare the zero-shot systems on three data sets across four domains. First, on average, QGen is the best neural retrieval model. This suggests that synthetic query generation is a viable option for zero-shot retrieval, often outperforming using gold out-of-domain data and unsupervised neural models. However, the efficacy of the model depends on the specific domain. The more specialize the domain, the better the relative performance of QGen, specifically when compared to QA because QA contains general knowledge question-answer pairs, we would expect it to do well on datasets like NaturalQuestions, which also covers general knowledge questions. However, on highly specialized data like BioAsq, QGen is by far the best superior system.

When comparing zero-shot neural models to traditional term-based methods, again it depends on the domain. For instance, BM25 does exceptionally well on BIOASQ, but very poorly on most other sets. For BIOASQ this is likely an artifact of the data, where the experts who created the questions also annotated relevant judgements. This leads to a high overlap in query terms and document terms favoring methods like BM25 – an artifact that has been observed for other datasets (Lee et al., 2019b). However, once the hybrid model is considered, adding neural signals still improves results.

For BIOASQ and NQ we have corresponding in-domain training sets, though they are significantly smaller than weakly supervised sets used for QA and QGen. The last row of Table 1 shows the performance of a neural retrieval model when trained only on this supervised data. For BIOASQ, the supervised results are worse than the zero-shot models, however, for NQ, the supervised results are significantly better. Note NQ has a much larger supervised training set than BIOASQ, especially in terms of unique queries (70K vs 2.5K). The result suggests that even in domains with small supervised training sets, synthetic query generation is a powerful alternative.

Since our approach allows generate queries on every document of the target corpus, one question to answer is that whether retrieval system trained this way simply memorizes the target corpus or it also generalize on unseen documents. Furthermore, from an efficiency standpoint, how much synthetic training examples are required to achieve maximum performance. To answer this question, we conduct experiments where we uniformly sample a subset of documents and then generate synthetic queries only on that subset. Results on BIOASQ are shown in Figure 2, where x-axis denotes the percentage of sampled documents. We can see that retrieval accuracy improves as document coverage increases. The peak is achieved when using a 20% subset, which covers 21% of the reference documents. This is not surprising because the number of frequently discussed entities/topics are typically limited, and a subset of the documents covers most of them. The result is encouraging as it indicates that the learned system does generalize.

Another interesting question is how important is the quality of the query generator relative to retrieval performance. What is more important, large domain specific data sets or higher quality pairs. Below we measured generation quality (via Rouge-based metrics (Lin and Hovy, 2002)) versus retrieval quality for three systems. The base generator contains 12 transformer layers, the lite version only uses the first 3 layer. The large one contains 24 transformer layers and each layer with larger hidden layer size, 4096, and more attention heads, 16. Retrieval quality was measured on BIOASQ and generation quality with a held out set of the community question-answer data set.

| Models   | Rouge-1 | Rouge-1 | MAP | Prec@10 | nDCG@10 |
|----------|---------|---------|-----|---------|---------|
| Lite     | 0.2355  | 0.2190  | 0.290 | 0.112   | 0.333   |
| Base     | 0.2620  | 0.2423  | 0.286 | 0.116   | 0.333   |
| Large    | 0.2681  | 0.2490  | 0.286 | 0.114   | 0.331   |

We can see that larger generation models lead to improved generators, at least with respect to automatic evaluations. However, there is little difference in retrieval metrics, suggesting that large domain targeted data is more important than high quality generations.

6 Conclusion

We address data scarcity in zero-shot neural retrieval by generating synthetic queries. We show our approach outperforms several alternatives and yields robust neural retrieval system that also generalizes on unseen documents.
References

Amin Ahmad, Noah Constant, Yinfei Yang, and Daniel Cer. 2019. ReQA: An evaluation for end-to-end answer retrieval models. CoRR, abs/1907.04780.

Chris Alberti, Daniel Andor, Emily Pitler, Jacob Devlin, and Michael Collins. 2019. Synthetic qa corpora generation with roundtrip consistency. arXiv preprint arXiv:1906.05416.

Sumit Bhatia and Prasenjit Mitra. 2010. Adopting inference networks for online thread retrieval. In Twenty-Fourth AAAI Conference on Artificial Intelligence.

Alexey Borisov, Ilya Markov, Maarten Rijke, and Pavel Serdyukov. 2016. A neural click model for web search. pages 531–541.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to answer open-domain questions. In Proc. ACL, pages 1870–1879.

Paul Alexandru Chirita, Wolfgang Nejdl, Raluca Paiu, Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2015. Using odp metadata to personalize search. In Proc. SigIR.

Daniel Cohen, Bhaskar Mitra, Katja Hofmann, and W. Bruce Croft. 2018. Cross domain regularization for neural ranking models using adversarial learning. CoRR, abs/1805.03403.

Zhuyun Dai, Chenyan Xiong, Jamie Callan, and Zhiyuan Liu. 2018. Convolutional neural networks for soft-matching n-grams in ad-hoc search. In Proc. WSDM.

Mostafa Dehghani, Hamed Zamani, Aliaksei Severyn, Jaap Kamps, and W. Bruce Croft. 2017. Neural ranking models with weak supervision. In Proc. SigIR.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019a. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proc. NAACL.

Daniel Gillick, Alessandro Presta, and Gaurav Singh Tomar. 2018. End-to-end retrieval in continuous space. CoRR, abs/1811.08008.

Jiafeng Guo, Yixing Fan, Qingyao Ai, and W. Bruce Croft. 2016. A deep relevance matching model for ad-hoc retrieval. In CIKM ’16.

David Hawking. 2004. Challenges in enterprise search. In ADC, volume 4, pages 15–24. Citeseer.

Kai Hui, Andrew Yates, Klaus Berberich, and Gerard de Melo. 2017. PACRR: A position-aware neural ir model for relevance matching. arXiv preprint arXiv:1704.03940.

Taku Kudo and John Richardson. 2018. Sentencepiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. CoRR, abs/1808.06226.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Matthew Kelcey, Jacob Devlin, Kenton Lee, Kristina N. Toutanova, Llion Jones, Ming-Wei Chang, Andrew Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: a benchmark for question answering research. Transactions of the Association of Computational Linguistics.

Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. 2019a. BioBERT: a pre-trained biomedical language representation model for biomedical text mining. Bioinformatics.

Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019b. Latent retrieval for weakly supervised open domain question answering. arXiv preprint arXiv:1906.00300.

Patrick Lewis, Ludovic Denoyer, and Sebastian Riedel. 2019. Unsupervised question answering by cloze translation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4896–4910, Florence, Italy. Association for Computational Linguistics.

Chin-Yew Lin and Eduard Hovy. 2002. Manual and automatic evaluation of summaries. In Proc. Workshop on Automatic Summarization.

Wei Liu, Jun Wang, Sanjiv Kumar, and Shih-Fu Chang. 2011. Hashing with graphs. In Proc. ICML.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. CoRR, abs/1907.11692.

Sean MacAvaney, Andrew Yates, Arman Cohan, and Nazli Goharian. 2019. CEDR: Contextualized embeddings for document ranking. In Proc. SigIR.

Rogério Nogueira, Wei Yang, Jimmy Lin, and Kyunghyun Cho. 2019. Document expansion by query prediction. arXiv preprint arXiv:1904.08375.

Hamid Palangi, Li Deng, Yelong Shen, Jianfeng Gao, Xiaodong He, Jiashen Chen, Xinying Song, and Rabab Ward. 2016. Deep sentence embedding using long short-term memory networks: Analysis and application to information retrieval. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 24(4):694–707.

Liang Pang, Yanyan Lan, Jiafeng Guo, Jun Xu, Shengxian Wan, and Xueqi Cheng. 2016. Text matching as image recognition. In Thirtieth AAAI Conference on Artificial Intelligence.

Stephen Robertson, Hugo Zaragoza, and Michael Taylor. 2004. Simple bm25 extension to multiple weighted fields. In Proc. CIKM.
Sascha Rothe, Shashi Narayan, and Aliaksei Severyn. 2019. Leveraging pre-trained checkpoints for sequence generation tasks. CoRR, abs/1907.12461.

Brandon Tran, Maryam Karimzadehgan, Rama Kumar Pasumarthi, Mike Bendersky, and Don Metzler. 2019. Domain adaptation for enterprise email search. In Proc. SigIR.

George Tsatsaronis, Georgios Balikas, Prodromos Malakasiotis, Ioannis Partalas, Matthias Zschunke, Michael R Alvers, Dirk Weissenborn, Anastasia Krithara, Sergios Petridis, Dimitris Polychronopoulos, Yannis Almirantis, John Pavlopoulos, Nicolas Baskiotis, Patrick Gallinari, Thierry Artières, Axel-Cyrille Ngonga Ngomo, Norman Heino, Eric Gaussier, Liliana Barrio-Alvers, Michael Schroeder, Ion Androustopoulos, and Georgios Paliouras. 2015. An overview of the bioasq large-scale biomedical semantic indexing and question answering competition. BMC bioinformatics, 16:138.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Proc. NeurIPS. Curran Associates, Inc.

Sebastien C Wong, Adam Gatt, Victor Stamatescu, and Mark D McDonnell. 2016. Understanding data augmentation for classification: when to warp? In Proc. DICTA. IEEE.

Yongqin Xian, Christoph H Lampert, Bernt Schiele, and Zeynep Akata. 2018. Zero-shot learning: a comprehensive evaluation of the good, the bad and the ugly. IEEE transactions on pattern analysis and machine intelligence, 41(9):2251–2265.

Wei Yang, Haotian Zhang, and Jimmy Lin. 2019a. Simple applications of bert for ad hoc document retrieval. arXiv preprint arXiv:1903.10972.

Yinfei Yang, Daniel Cer, Amin Ahmad, Mandy Guo, Jax Law, Noah Constant, Gustavo Hernández Abrego, Steve Yuan, Chris Tar, Yun-Hsuan Sung, Brian Strope, and Ray Kurzweil. 2019b. Multilingual universal sentence encoder for semantic retrieval. CoRR, abs/1907.04307.

Hamed Zamani, Mostafa Dehghani, W Bruce Croft, Erik Learned-Miller, and Jaap Kamps. 2018. From neural re-ranking to neural ranking: Learning a sparse representation for inverted indexing. In Proc. CIKM.