ZERO-SHOT SLOT FILLING WITH DPR AND RAG

A PREPRINT

Michael Glass, Gaetano Rossiello, Alfio Gliozzo
IBM Research AI
mrglass@us.ibm.com, gaetano.rossiello@ibm.com, gliozzo@us.ibm.com

April 20, 2021

ABSTRACT

The ability to automatically extract Knowledge Graphs (KG) from a given collection of documents is a long-standing problem in Artificial Intelligence. One way to assess this capability is through the task of slot filling. Given an entity query in form of [ENTITY, SLOT, ?], a system is asked to ‘fill’ the slot by generating or extracting the missing value from a relevant passage or passages. This capability is crucial to create systems for automatic knowledge base population, which is becoming in ever-increasing demand, especially in enterprise applications. Recently, there has been a promising direction in evaluating language models in the same way we would evaluate knowledge bases, and the task of slot filling is the most suitable to this intent. The recent advancements in the field try to solve this task in an end-to-end fashion using retrieval-based language models. Models like Retrieval Augmented Generation (RAG) show surprisingly good performance without involving complex information extraction pipelines. However, the results achieved by these models on the two slot filling tasks in the KILT benchmark are still not at the level required by real-world information extraction systems. In this paper, we describe several strategies we adopted to improve the retriever and the generator of RAG in order to make it a better slot filler. Our KGI₀ system reached the top-1 position on the KILT leaderboard on both T-REx and zsRE dataset with a large margin.

1 Introduction

A main barrier for adoption of KG technology for enterprise is the effort required to define the schema and populate enterprise specific relational data sources, such as KGs. In this work, we address this problem by exploring the use of zero-shot learning approaches for slot filling.

In the task of slot filling the goal is to identify a pre-determined set of relations for a given entity, and use them to populate infobox like structures. This can be done by exploring the occurrences of the input entity in the corpus and gathering information about its slot fillers from the context in which it it located. Figure 1 illustrates the slot filling task. A slot filling system processes and indexes a corpus of documents, then when prompted with an entity and a number of relations, fills out an infobox and provides the evidence passages which explain the predictions.

Over the past years, the proposed slot filling systems commonly involve complex pipelines for named entity recognition, entity co-reference resolution and relation extraction [Ellis et al., 2015]. In particular, the task of extracting relations between entities from text has been shown to be the weakest component of the chain. The community proposed different solutions to improve relation extraction performance, such as rule-based [Angeli et al., 2015], supervised [Zhang et al., 2017], or distantly supervised [Glass et al., 2018]. However, all these approaches require a considerable human effort in creating hand-craft rules, annotating training data, or building well-curated datasets for bootstrapping relation classifiers.

The use of language models as sources of knowledge [Petroni et al., 2019, Roberts et al., 2020, Wang et al., 2020, Petroni et al., 2020a], has opened tasks such as zero-shot slot filling to pre-trained transformers. The introduction of retrieval augmented language models such as RAG [Lewis et al., 2020b] and REALM (Guu et al., 2020) also permit providing textual provenance for the generated slot fillers.

1Our source code is available at: https://github.com/IBM/retrieve-write-slot-filling
A recently introduced suite of benchmarks, KILT (Knowledge Intensive Language Tasks) [Petroni et al., 2020b], standardizes two zero-shot slot filling tasks: zsRE [Levy et al., 2017] and T-REx [Elsahar et al., 2018]. These tasks provide a competitive benchmark to drive advancements in slot filling.

One of the most interesting aspects of using pre-trained language models for zero-shot slot filling is the lower effort required for production deployment, which is a key feature for fast adaptation to new domains. However, the best performance achieved by the current retrieval-based models on the two slot filling tasks in KILT are still not satisfactory. This is mainly due to the lack of retrieval performance that affects the generation of the filler as well.

In this work, we propose a new slot filling specific training for both DPR and RAG. Furthermore, we observed that the RAG strategy of multiple sequence-to-sequence works better than the three passage concatenation in Multi-DPR BART. We implemented these ideas in our KGI system, showing large gains on both T-REx (+24% KILT-F1) and zsRE (+18% KILT-F1) datasets.

2 Related Work

KILT was introduced with a number of baseline approaches. The best performing of these is RAG [Lewis et al., 2020b]. The model incorporates Dense Passage Retrieval (DPR) [Karpukhin et al., 2020] to first gather evidence passages for the query, then uses a model initialized from BART [Lewis et al., 2020a] to do sequence-to-sequence generation from each evidence passage concatenated with the query to generate the answer. In the baseline RAG approach only the query encoder and generation component are fine-tuned on the task. The passage encoder, trained on Natural Questions [Kwiatkowski et al., 2019] is held fixed. Interestingly, while it gives the best performance of the baselines tested on the task of producing slot fillers, its performance on the retrieval metrics is worse than BM25. This suggests that fine-tuning the entire retrieval component could be beneficial.

In an effort to improve the retrieval performance, Multi-task DPR [Maillard et al., 2021] used the multi-task training of the KILT suite of benchmarks to train the DPR passage and query encoder. The top-3 passages returned by the resulting passage index were then combined into a single sequence with the query and a BART model was used to produce the answer. This resulted in large gains in retrieval performance.

DensePhrases [Lee et al., 2020] is a different approach to knowledge intensive tasks with a short answer. Rather than index passages which are then consumed by a reader or generator component, DensePhrases indexes the phrases in the corpus that can be potential answers to questions, or fillers for slots. Each phrase is represented by the pair of its start and end token vectors from the final layer of a transformer initialized from SpanBERT-base-cased [Joshi et al., 2020]. Question vectors come from the [CLS] token of two other transformers: one to be matched with the slot filler’s start vector and one for the end vector. The start and end token vectors are indexed separately for maximum inner product search. Then at inference time the top-k start tokens are found for the question’s start vector and the top-k end tokens...
are found for the question’s end vector. These results are merged to find the top scoring phrase, which is then predicted as the slot filler.

GENRE [De Cao et al., 2020] addresses the retrieval task in KILT slot filling by using a sequence-to-sequence transformer to generate the title of the Wikipedia page where the answer can be found. This method can produce excellent scores for retrieval but does not address the problem of producing the slot filler. It is trained on BLINK [Wu et al., 2020] and all KILT tasks jointly.

3 Knowledge Graph Induction

Figure 2 shows Knowledge Graph Induction (KGI), our approach to zero-shot slot filling, combining a DPR model and RAG model, both trained for slot filling. Due to the close connection between slot filling and open factoid question answering, we initialize our models from the Natural Questions [Kwiatkowski et al., 2019] trained models for DPR and RAG available from Hugging Face. We then use a two phase training procedure: first we train the DPR model, i.e. both the query and context encoder, using the KILT provenance ground truth. Then we train the sequence-to-sequence generation and further train the query encoder using only the target tail entity as the objective.

Since the transformers for passage encoding and generation can accept a limited sequence length, we segment the documents of the KILT knowledge source (2019/08/01 Wikipedia snapshot) into passages. The ground truth provenance for the slot filling tasks is at the granularity of paragraphs, so we align our passage segmentation on paragraph boundaries when possible. If two or more paragraphs are short enough to be combined, we combine them into a single passage and if a single paragraph is too long, we truncate it.

Our approach to DPR training for slot filling is a straightforward adaptation of the question answering training in the original DPR work [Karpukhin et al., 2020]. We first index the passages using a traditional keyword search engine, Anserini. The head entity and the relation are used as a keyword query to find the top-k passages by BM25. Passages with overlapping paragraphs to the ground truth are excluded as well as passages that contain a correct answer. The remaining top ranked result is used as a hard negative for DPR training.

After locating a hard negative for each query, the DPR training data is a set of triples: query, positive passage (given by the KILT ground truth provenance) and our BM25 hard negative passage. Figure 3 shows the training process for DPR.

For each batch of training triples, we encode the queries and passages independently. The passage and query encoders are BERT [Devlin et al., 2019] models. Then we find the inner product of all queries with all passages. After applying a softmax to the score vector for each query, the loss is the negative log-likelihood for the positive passages.

2 https://github.com/huggingface/transformers
3 https://github.com/castorini/anserini

Figure 2: KGI Architecture
Using the trained DPR passage encoder we generate vectors for the approximately 32 million passages in our segmentation of the KILT knowledge source. Though this is a computationally expensive step, it is easily parallelized. The passage-vectors are then indexed with an ANN (Approximate Nearest Neighbors) data structure, in this case HNSW (Hierarchical Navigable Small World) [Malkov and Yashunin, 2018] using the open source FAISS [Johnson et al., 2017] library. We use scalar quantization down to 8 bits to reduce the memory footprint.

The query encoder is also trained for slot filling alongside the passage encoder. We inject the trained query encoder into the RAG model for Natural Questions. Due to the loose coupling between the query encoder and the sequence-to-sequence generation of RAG, we can update the pre-trained model’s query encoder without disrupting the quality of the generation.

Figure 4 illustrates the architecture of RAG. The RAG model is trained to predict the ground truth tail entity from the head and relation query. First the query is encoded to a vector and relevant passages are retrieved from the ANN index. The query is concatenated to each passage and the generator predicts a probability distribution over the possible next tokens for each sequence. These predictions are weighted according to the score between the query and passage - the inner product of the query vector and passage vector. The weighted probability distributions are then combined to give a single probability distribution for the next token. Beam search is used to select the overall most likely tail entity.

Because the provenance used is at the level of passages but the evaluation is on page level retrieval, we retrieve up to twenty passages so that we typically get at least five documents for the Recall@5 metric.
We have not done hyperparameter tuning, instead using hyperparameters similar to the original works on training DPR and RAG. Table 1 shows the hyperparameters used in our experiments.

### 4 Experiments

Table 2 gives statistics on the two zero-shot slot filling datasets. While the T-REx dataset is larger by far in the number of instances, the training sets have a similar number of distinct relations. We use only 500 thousand training instances of T-REx in our experiments to increase the speed of experimentation.

As an initial experiment we tried RAG with its default index of Wikipedia, distributed through Hugging Face. We refer to this as RAG-KKS, or RAG without the KILT Knowledge Source. Since the passages returned are not aligned to the KILT provenance ground truth, we do not report retrieval metrics for this experiment. Motivated by the low retrieval performance reported for the RAG baseline by Petroni et al. [2020b], we also experimented with replacing the DPR retrieval with simple BM25 (RAG+BM25). We provide the raw BM25 scores for the passages to the RAG model, to weight their impact in generation. This provides a significant boost in performance. Finally, we use the approach explained in Section 3 to train both the DPR and RAG models. We call this system $KGI_0$, an initial knowledge graph induction system.

The metrics we report include accuracy and F1 on the slot filler, where F1 is based on the recall and precision of the tokens in the answer - allowing for partial credit on slot fillers. Our systems (except for RAG-KKS) also provide provenance information for the top answer. R-Precision and Recall@5 measure the quality of this provenance against the KILT ground truth provenance. Finally, KILT-Accuracy and KILT-F1 are combined metrics that measure the accuracy and F1 of the slot filler only when the correct provenance is provided. Table 3 gives our development set results.

---

### Table 1: $KGI_0$ hyperparameters

| Hyperparameter     | DPR | RAG |
|--------------------|-----|-----|
| learn rate         | 5e-5 | 3e-5 |
| batch size         | 128 | 128 |
| epochs             | 2   | 1*  |
| warmup instances   | 0   | 10000 |
| learning schedule  | linear | triangular |
| max grad norm      | 1   | 1   |
| weight decay       | 0   | 0   |
| Adam epsilon       | 1e-8 | 1e-8 |

* Since the training set for T-REx is so large, we take only 500k instances.

### Table 2: Zero-shot Slot Filling Dataset Sizes

| Dataset | Instances | Relations |
|---------|-----------|-----------|
|         | Train     | Dev       | Test     | Train | Dev | Test |
| zsRE    | 147909    | 3724      | 4966     | 84    | 12  | 24   |
| T-REx   | 2284168   | 5000      | 5000     | 106   | 104 | 104  |

### Table 3: Dev. Set Performance for Various Retrieval Methods

| Method      | R-Prec | Recall@5 | Accuracy | F1   | KILT-AC | KILT-F1 |
|-------------|--------|----------|----------|------|---------|---------|
| RAG-KKS     |        |          | 38.72%   | 46.94% |         |         |
| RAG+BM25    | 58.86% | 80.24%   | 45.73%   | 55.18% | 36.14%  | 41.85%  |
| $KGI_0$     | 77.27% | 96.37%   | 69.55%   | 97.66% | 69.31%  | 76.83%  |
| T-REx       |        |          |          |      |         |         |
| RAG         |        |          | 63.28%   | 67.67% |         |         |
| RAG+BM25    | 46.40% | 67.31%   | 69.10%   | 73.11% | 39.98%  | 41.21%  |
| $KGI_0$     | 61.30% | 71.18%   | 76.58%   | 80.27% | 56.40%  | 57.70%  |
Table 4 gives the test set performance of the top systems on the KILT leaderboard. KGI0 is our system, while DensePhrases, GENRE, Multi-DPR and RAG for KILT are explained briefly in Section 2. KGI0 gains dramatically in slot filling accuracy over the previous best systems, with gains of over 10 percentage points in zsRE and even more in T-REx. The combined metrics of KILT-AC and KILT-F1 show even larger gains, suggesting that the KGI0 approach is effective at providing justifying evidence when generating the correct answer. We achieve gains of 17 to 27 percentage points in KILT-AC.

| Method                  | R-Prec | Recall@5 | Accuracy | F1      | KILT-AC | KILT-F1 |
|-------------------------|--------|----------|----------|---------|---------|---------|
| KGI0                    | 94.18% | 95.19%   | 68.97%   | 74.47%  | 68.32%  | 73.45%  |
| DensePhrases            | 57.43% | 60.47%   | 47.42%   | 54.75%  | 41.34%  | 46.79%  |
| GENRE                   | 95.81% | 97.83%   | 0.02%    | 2.10%   | 0.00%   | 1.85%   |
| Multi-DPR               | 80.91% | 93.05%   | 57.95%   | 63.75%  | 50.64%  | 55.44%  |
| RAG (KILT organizers)   | 53.73% | 59.52%   | 44.74%   | 49.95%  | 36.83%  | 39.91%  |

| Method                  | R-Prec | Recall@5 | Accuracy | F1      | KILT-AC | KILT-F1 |
|-------------------------|--------|----------|----------|---------|---------|---------|
| KGI0                    | 59.70% | 70.38%   | 77.90%   | 81.31%  | 55.54%  | 56.79%  |
| DensePhrases            | 37.62% | 40.07%   | 53.90%   | 61.74%  | 27.84%  | 32.34%  |
| GENRE                   | 79.42% | 85.33%   | 0.10%    | 7.67%   | 0.04%   | 6.66%   |
| Multi-DPR               | 69.46% | 83.88%   | 0.00%    | 0.00%   | 0.00%   | 0.00%   |
| RAG (KILT organizers)   | 28.68% | 33.04%   | 59.20%   | 62.96%  | 23.12%  | 23.94%  |

Table 4: KILT Leaderboard Top Systems

5 Conclusion

The KGI0 system, combining slot filling specific training for both its DPR and RAG components, produces large gains in zero-shot slot-filling. Our early experiments suggested the effectiveness of fine-tuning the retrieval component for the task, and highlighted the loose coupling of RAG’s retrieval with its generation. We find that DPR can be customized to the slot filling task and inserted into a pre-trained QA model for generation, to then be fine-tuned on the task. Relative to Multi-DPR, we see the benefit of weighting passage importance by retrieval score and marginalizing over multiple generations, compared to the strategy of concatenating the top three passages and running a single sequence-to-sequence generation. GENRE is still best in retrieval, suggesting that at least for a corpus such as Wikipedia, generating the title of the page can be very effective.

References

Gabor Angeli, Melvin Jose Johnson Premkumar, and Christopher D. Manning. Leveraging linguistic structure for open domain information extraction. In ACL (1), pages 344–354. The Association for Computer Linguistics, 2015.

Nicola De Cao, Gautier Izacard, Sebastian Riedel, and Fabio Petroni. Autoregressive entity retrieval. arXiv preprint arXiv:2010.00904, 2020.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, 2019.

Joe Ellis, Jeremy Getman, Dana Fore, Neil Kuster, Zhiyi Song, Ann Bies, and Stephanie M. Strassel. Overview of linguistic resources for the TAC KBP 2015 evaluations: Methodologies and results. In TAC. NIST, 2015.

Hady Elsahar, Pavlos Vougiouklis, Arslen Remaci, Christophe Gravier, Jonathon Hare, Frederique Laforest, and Elena Simperl. T-rex: A large scale alignment of natural language with knowledge base triples. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018), 2018.

Michael R. Glass, Alfonso Giuseppe, Oktie Hassan-zadeh, Nandana Mihindukulasooriya, and Gaetano Rossiello. Inducing implicit relations from text using distantly supervised deep nets. In International Semantic Web Conference (1), volume 11136 of Lecture Notes in Computer Science, pages 38–55. Springer, 2018.

Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Ming-Wei Chang. Realm: Retrieval-augmented language model pre-training. arXiv preprint arXiv:2002.08909, 2020.

Jeff Johnson, Matthijs Douze, and Hervé Jégou. Billion-scale similarity search with gpus. arXiv preprint arXiv:1702.08734, 2017.
Mandar Joshi, Danqi Chen, Yinhan Liu, Daniel S Weld, Luke Zettlemoyer, and Omer Levy. Spanbert: Improving pre-training by representing and predicting spans. Transactions of the Association for Computational Linguistics, 8: 64–77, 2020.

Vladimir Karpuhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. Dense passage retrieval for open-domain question answering. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6769–6781, 2020.

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, Lilian Jones, Ming-Wei Chang, Andrew Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. Natural questions: a benchmark for question answering research. Transactions of the Association of Computational Linguistics, 2019.

Jinhyuk Lee, Mujeen Sung, Jaewoo Kang, and Danqi Chen. Learning dense representations of phrases at scale. arXiv preprint arXiv:2012.12624, 2020.

Omer Levy, Minjoon Seo, Eunsol Choi, and Luke Zettlemoyer. Zero-shot relation extraction via reading comprehension. In Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017), pages 333–342, 2017.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880, 2020a.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpuhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. arXiv preprint arXiv:2005.11401, 2020b.

Jean Maillard, Vladimir Karpuhin, Fabio Petroni, Wen-tau Yih, Barlas Oğuz, Veselin Stoyanov, and Gargi Ghosh. Multi-task retrieval for knowledge-intensive tasks. arXiv preprint arXiv:2101.00117, 2021.

Yu A Malkov and Dmitry A Yashunin. Efficient and robust approximate nearest neighbor search using hierarchical navigable small world graphs. IEEE transactions on pattern analysis and machine intelligence, 42(4):824–836, 2018.

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick S. H. Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander H. Miller. Language models as knowledge bases? In EMNLP/IJCNLP (1), pages 2463–2473. Association for Computational Linguistics, 2019.

Fabio Petroni, Patrick S. H. Lewis, Aleksandra Piktus, Tim Rocktäschel, Yuxiang Wu, Alexander H. Miller, and Sebastian Riedel. How context affects language models’ factual predictions. In AKBC, 2020a.

Fabio Petroni, Aleksandra Piktus, Angela Fan, Patrick Lewis, Majid Yazdani, Nicola De Cao, James Thorne, Yacine Jernite, Vassilis Plachouras, Tim Rocktäschel, et al. Kilt: a benchmark for knowledge intensive language tasks. arXiv preprint arXiv:2009.02252, 2020b.

Adam Roberts, Colin Raffel, and Noam Shazeer. How much knowledge can you pack into the parameters of a language model? In EMNLP (1), pages 5418–5426. Association for Computational Linguistics, 2020.

Chenguang Wang, Xiao Liu, and Dawn Song. Language models are open knowledge graphs. CoRR, abs/2010.11967, 2020.

Ledell Wu, Fabio Petroni, Martin Josifoski, Sebastian Riedel, and Luke Zettlemoyer. Scalable zero-shot entity linking with dense entity retrieval. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6397–6407, 2020.

Yuhao Zhang, Victor Zhong, Danqi Chen, Gabor Angeli, and Christopher D. Manning. Position-aware attention and supervised data improve slot filling. In EMNLP, pages 35–45. Association for Computational Linguistics, 2017.