The Web Is Your Oyster - Knowledge-Intensive NLP against a Very Large Web Corpus

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Abstract

In order to address the increasing demands of real-world applications, the research for knowledge-intensive NLP (KI-NLP) should advance by capturing the challenges of a truly open-domain environment: web-scale knowledge, lack of structure, inconsistent quality, and noise. To this end, we propose a new setup for evaluating existing KI-NLP tasks in which we generalize the background corpus to a universal web snapshot. We repurpose KILT, a standard KI-NLP benchmark initially developed for Wikipedia, and ask systems to use a subset of CCNet—the SPHERE corpus—as a knowledge source. In contrast to Wikipedia, SPHERE is orders of magnitude larger and better reflects the full diversity of knowledge on the Internet. We find that despite potential gaps of coverage, challenges of scale, lack of structure and lower quality, retrieval from SPHERE enables a state-of-the-art retrieve-and-read system to match and even outperform Wikipedia-based models on several KILT tasks—even if we aggressively filter content that looks like Wikipedia. We also observe that while a single dense passage index over Wikipedia can outperform a sparse BM25 version, on SPHERE this is not yet possible. To facilitate further research into this area, and minimise the community’s reliance on proprietary black box search engines, we will share our indices, evaluation metrics and infrastructure.

1 Introduction

When language models are applied to knowledge-intensive NLP tasks such as fact checking, open-domain question answering (ODQA) or knowledge base population, it is useful to augment their input with extra context retrieved from a knowledge source (Izacard and Grave, 2020; Guu et al., 2020; Lewis et al., 2020b). Often, this source is Wikipedia (Dinan et al., 2019; Christodoulopoulos et al., 2020; Kwiatkowski et al., 2019), for obvious reasons: it tends to be highly accurate (at least when compared to the general web content), it is well structured and formatted and small enough to test computationally demanding architectures. Still, there are at least two reasons to look beyond Wikipedia. First, it covers a lot of ground, but certainly not everything, and in practice many information needs cannot be fulfilled based on Wikipedia alone (Redi et al., 2021). Second, even for topics it does cover, there might be biases that cannot be resolved without looking at a broader context (Wagner et al., 2016; Graells-Garrido et al., 2015).

By virtue of its sheer scale, the web promises access to both broader and more specific knowledge, covering more topics and containing more in-depth information on the topics already present in

| QUERY | Who is Joëlle Sambi Nzeba? |
|-------|---------------------------|
| WIKIPEDIA | No results found for Joëlle Sambi Nzeba. |
| SPHERE | [...] Joëlle Sambi. She was born in Belgium and grew up partly in Kinshasa (Congo). She currently lives in Brussels. She is a writer and slammer, alongside her activism in a feminist movement. She is an award-winning author of fiction with Le Monde est gueule de chèvre (novel, 2007) and Je ne sais pas rêver (short-stories, 2002). Joëlle Sambi questions situations of powerlessness in social matters and raises questions about identity. [...] |
| URL | https://www.buala.org/en/mukanda/musala-worf |

Table 1: Web knowledge coverage goes beyond Wikipedia. We propose a synthetic question about one of the women listed in the Women in Red project - an initiative mobilizing the community to fill out gender-biased gaps in Wikipedia, and the top BM25 retrieval result from SPHERE. At the time of writing, Joëlle Sambi Nzeba does not have a Wikipedia page.

1We will update the link as soon as the release is ready.
Wikipedia. However, along with the benefits come new challenges—inconsistent document quality, lack of structure and noisy or harmful content on one hand, and increasing infrastructural demands on the other. Today it is unclear what the impact of these challenges is on knowledge-intensive tasks. While work exists that investigates the use of web content in KI-NLP, it usually relies on proprietary, black-box search engines to find documents relevant to the input queries and focuses on individual tasks (primarily ODQA) (Joshi et al., 2017; Bajaj et al., 2018; Talmor and Berant, 2019), or only uses general web content at pre-training time (Guu et al., 2020; Borgeaud et al., 2021; Lewis et al., 2020a).

By contrast, we propose to use a web corpus as a universal, uncurated and unstructured source of knowledge for multiple tasks at once, leveraging current state-of-the-art retrieval methods for KI-NLP instead of commercial solutions. This exposes retrievers and retrieval augmented models to important real-world challenges discussed above, facilitates open and reproducible research and opens up a path for future studies comparing search engines optimised for human information seeking with retrieval solutions optimised for neural networks.

In this work we therefore aim to answer the following question: what impact does replacing Wikipedia with a large-scale web corpus have on the performance of knowledge-intensive systems? More precisely, should we expect the performance to improve, because for a given fact, there is potentially more evidence on the web, or degrade, due to the uncurated nature of the data? We use KILT (Petroni et al., 2021), a standard KI-NLP benchmark, as an evaluation platform for our work. Instead of the default Wikipedia with almost 6M articles yielding 22 M passages, we use a web corpus as a knowledge source—we choose a subset of CCNet (Wenzek et al., 2020) covering 134M documents split into close to a billion passages—we will refer to it as SPHERE. Though far from the full web-scale, SPHERE is orders of magnitude larger than previously researched KI-NLP knowledge sources (cf. Table 2). To enable experiments with dense retrieval for a corpus this large, we build and open-source SPHERE—a CCNet-based corpus of 134M web documents split into 906M passages—using distributed-faiss implementation, allowing for building and querying of large-scale dense indices.

We investigate two retrieval architectures—DPR (Karpukhin et al., 2020) and BM25 (Robertson, 2009), to search through SPHERE, and combine them with a FiD reader component (Izacard and Grave, 2020). Despite the aforementioned challenges of web-based knowledge sources and the fact that KILT was specifically designed to query knowledge from Wikipedia, we find that SPHERE-based models can match or outperform Wikipedia-based baselines on a subset of KILT tasks and in some cases this holds even when we aggressively filter SPHERE by removing not just Wikipedia itself but also content that looks like it. To dig deeper, we carry out an in-depth analysis of our results focusing on phenomena such as the knowledge coverage of our web corpus and Wikipedia text dissemination on the web. We also find ample room for future work: while dense retrieval outperforms sparse methods in most prior work, in our case the opposite is true. How to develop large scale and universal dense indices that support a multitude of tasks hence remains an open research question.

To summarize, we make the following contributions in this paper:

• We evaluate the performance of a strong end-to-end system on KILT with Wikipedia replaced by SPHERE as the knowledge source, achieving state-of-the-art results on 2 tasks;
• We identify potential reasons explaining the drop in end-to-end performance on other tasks, and study the dissemination of Wikipedia text on the web and its impact on our results;
• We release sparse and dense indices of SPHERE—a CCNet-based corpus of 134M web documents split into 906M passages;
• We propose a distributed-faiss implementation, allowing for building and querying of large-scale dense indices.

2 Background

2.1 Knowledge-intensive NLP Tasks

We refer to an NLP task as knowledge-intensive if a human would not be reasonably expected to solve it without access to an external knowledge source. KI-NLP tasks are typically solved with retriever-reader systems: first, a retriever component surfaces a small set of relevant documents from a knowledge source, then the reader model consumes the query with the retrieved documents and returns an answer (Chen et al., 2017; Lewis et al., 2020b; Izacard and Grave, 2020).
Table 2: Sizes of large scale unstructured web corpora for KI-NLP tasks.

| Name                        | Reference                        | Corpus source         | Task     | #passages | #documents |
|-----------------------------|----------------------------------|-----------------------|----------|-----------|------------|
| KILT                        | Petroni et al. (2021)            | Wikipedia snapshot    | Multitask| 22M       | 5.9M       |
| TriviaQA                    | Joshi et al. (2017)              | Bing search results  | ODQA     | -         | 662K       |
| MSMarco                     | Bajaj et al. (2018)              | Bing search results  | ODQA     | 8.8M      | 3.2M       |
| ComplexWQ                   | Talmor and Berant (2018)         | Web search snippets  | ODQA     | 12.7M     | -          |
| Eli5                        | Fan et al. (2019a)               | Common Crawl search   | ODQA     | -         | 27.2M      |
| Internet Augmented Dialog  | Komeili et al. (2021)            | CCNet snapshot       | Dialog   | 250M      | 109M       |
| SPHERE                      | ours                             | CCNet snapshot       | Multitask| 906M      | 134M       |

2.2 Retrieval models

We consider two baseline retrieval models: BM25 (Robertson, 2009) and DPR (Karpukhin et al., 2020). BM25 is a popular *sparse* model, which represents queries and documents as high-dimensional, *sparse* vectors, with dimensions corresponding to vocabulary terms and weights indicating their importance. In contrast, the Dense Passage Retriever (DPR) belongs to the category of *dense* models, which embed queries and documents into a latent, real-valued vector space of a much lower dimensionality, originating from the Latent Semantic Analysis (Deerwester et al., 1990). DPR is based on a neural bi-encoder architecture where passages and queries are embedded with separate text encoders. The dot product of the embeddings is interpreted as the relevance measure between the query and the passage. DPR is trained with a contrastive loss which aims to maximize the similarity of a query to a relevant, positive passage, while pushing it away from a set of irrelevant, negative passages. To speed up training, DPR makes use of *in-batch* negatives, where positive passages are used as negatives for other samples in a batch. Additionally, *hard* negatives (passages which have high lexical overlap with the query but don’t satisfy the information need of the sample) have been found useful. Although both sparse and dense models use the distance in the vector space as the relevance function, they need different indexing schemes to support efficient retrieval.

2.3 Indexing

An index is a data structure which stores representations of corpus documents, built with the objective of optimizing the retrieval efficiency. For sparse methods, this goal is typically achieved with an inverted index — a well researched technique entertaining the support of multiple robust libraries and toolkits such as Lucene.\(^2\) Efficient dense retrieval is made possible by maximum inner product search algorithms (Shrivastava and Li, 2014; Guo et al., 2015) leveraged by tools like FAISS (Johnson et al., 2017), a robust, open-source library for similarity search and clustering of dense vectors.

2.4 Reader models

Reader models operate by consuming a set of context documents retrieved from a knowledge source and the task input, and returning the output — either a class label or text. In the latter case, we typically distinguish between extractive and abstractive readers. Extractive readers return pointers to spans in provided context documents, while abstractive ones generate the output text. In this work, we use an abstractive Fusion-in-Decoder model from Izacard and Grave (2020) — an encoder-decoder architecture, where each context document is concatenated with the input and embedded by the encoder. Resulting embeddings are then passed to the decoder where attention is performed over encoded passages before generating the output.

3 Search Infrastructure

Incorporating web search components into KI-NLP research comes with significant scale-related challenges. In this section, we describe tools and resources we develop and open-source with the hope of simplifying and speeding up future research in this direction.\(^3\)

3.1 Distributed FAISS

FAISS is an efficient similarity search library, which provides APIs for building and querying indices of vectors. However, as the size of the corpus grows, the index may exceed typical single-server hardware limits for both GPU and RAM. Two main

\(^2\)https://lucene.apache.org/
\(^3\)We will provide relevant links as soon as the release is ready.
approaches for handling large scale emerge: compression of the document embeddings and distribution of the index over multiple servers. Good compression results can be achieved with quantizers available in FAISS out-of-the-box or with more sophisticated bi-encoder training pipelines (Yamada et al., 2021; Zhan et al., 2021). This usually helps to reduce the index size by a few times factor but does not solve the core scaling issue.

The ability to distribute a FAISS index over multiple server nodes is what we address with our open-source release of distributed-faiss. At indexing time the distributed-faiss client receives batches of embeddings to be indexed and routes them to the index server nodes in a round-robin fashion, guaranteeing a balanced data distribution. At retrieval time, the client queries all servers and aggregates the results. The service is model-independent and operates with supplied embeddings and metadata.

### 3.2 The Sphere Library

We will release indices of Sphere both for the sparse retrieval baseline, compatible with Pyserini (Lin et al., 2021) and our best dense model compatible with distributed-faiss.

### 4 Experimental setup

The goal of our work is to establish whether KILNLP tasks can be solved effectively when using a web snapshot as knowledge source rather than Wikipedia. The answer will depend on how well the retrievers handle the web-scale corpus and how much knowledge is covered by the web snapshot we consider. In this section we discuss how we approach the problem.

#### 4.1 Evaluation

We use the KILT benchmark (Petroni et al., 2021) as an evaluation suite for our work. KILT consists of 11 knowledge-intensive tasks, grouped into 5 categories: fact checking, entity linking, slot filling, open domain question answering and dialog. Given that entity linking tasks are intrinsically tied to the underlying Wikipedia snapshot, as entity labels come from Wikipedia titles of respective entities, we choose to omit those in our experiments. See Table 3 for the full list of datasets we consider and the shortcuts we use to refer to them.

We focus on downstream evaluation to compare different architectures. As for retrieval evaluation, when switching from Wikipedia to Sphere, we lose the notion of a gold retrieval passage defined by KILT. Instead, we track retrieval performance using the following proxy metrics:

- **answer-in-context@k**, indicating the fraction of examples for which there exists a passage containing the gold answer among the top-\(k\) retrieved ones,
- **answer+entity-in-context@k**, indicating the fraction of examples for which among top-\(k\) passages there exists one containing both the gold answer and the main entity of the data-point. We use the Wikipedia title of the gold retrieval passage as the search term for the main entity—a choice which is not generalizable beyond Wikipedia-based datasets.

See Table 4 for examples of metrics usage. Note that we can only obtain results on these metrics for the dev sets as KILT test sets are hidden.

#### 4.2 Corpora

We experiment with two knowledge sources. First, we consider the KILT knowledge source based on the 2019/08/01 Wikipedia dump, comprising 5.9M Wikipedia articles split into 22.2M passages of 100 tokens. Hereon when mentioning Wikipedia, we refer to the KILT knowledge source.

Second, we use CCNet (Wenzek et al., 2020) to create our web corpus. CCNet processes Common Crawl by performing deduplication, language identification and quality filtering (articles are split into three quality tiers: head, middle and tail based on perplexity under a Wikipedia-based language model). In our experiments, we use the head tier of a single CCNet snapshot in English. Additionally, we exclude all articles which contain wikipedia.org in their URL. We pick the CCNet snapshot corresponding to the August 2019 Common Crawl snapshot\(^4\) as it is temporally the closest

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*Table 3: KILT tasks we consider.*

| Shortcut | Dataset   | Reference                        |
|---------|-----------|----------------------------------|
| FEV     | FEVER     | Thorne et al. (2018)             |
| T-REx   | T-REx     | Elsahar et al. (2018)            |
| zsRE    | Zero Shot RE | Levy et al. (2017)           |
| NQ      | Natural Questions | Kwiatkowski et al. (2019) |
| HoPo    | HotpotQA  | Yang et al. (2018)               |
| TQA     | TriviaQA  | Joshi et al. (2017)              |
| ELI5    | ELI5      | Fan et al. (2019b)               |
| WoW     | Wizard of Wikipedia | Dinan et al. (2019)  |

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*https://commoncrawl.org/2019/08/august-2019-crawl-archive-now-available/
Where was the world economic forum held this year?

Davos

Who is playing the halftime show at super bowl 2016?

Coldplay

Table 4: Two example passages from NQ dev set with corresponding answer-in-context@1 and answer-entity-in-context@1 values. We use the gold Wikipedia provenance title as the main entity for metrics calculation.
We follow the finetuning setup proposed by the authors, using T5-base (Raffel et al., 2019) as initialization. Unless otherwise stated, we train FtD with the top 100 retrieved passages.

5 Results

We present our main results in Table 5. In total, our models achieve state-of-the-art (SOTA) results\(^3\) on 5 out of 8 tasks we consider. The FtD+BM25 architecture with SPHERE as knowledge source sets a new SOTA on FEV and TQA (see Table 11 in Appendix for examples). A web-trained FtD+DPR\(_{\text{WEB}}\) model achieves SOTA on zsRE, NQ and HoPo with Wikipedia as knowledge source. We follow with a more granular analysis of the results, focusing on the impact of three aspects of our system: the reader model, the retrieval architecture and the corpus.

5.1 Impact of using FtD

FtD has emerged as a strong reader baseline which, at the time of its publication, established new SOTAs on core ODQA benchmarks such as the standard (non-KILT) variants of NQ and TQA. Ours is the first paper to report official results of applying FtD to KILT - and with great outcomes. When using Wikipedia as the knowledge source, our baseline FtD+DPR\(_{\text{MULTI}}\) model outperforms similar DPR-based architectures (such as BART+DPR and RAG from Petroni et al. (2021)) across the board, achieving SOTA results for FEV, HoPo and NQ (which we further improve with DPR finetuning). In order to factor out the impact of moving to a stronger reader baseline, we mainly focus on comparing our SPHERE-based architectures to our FtD and Wikipedia-based baselines.

5.2 Web knowledge coverage

Next, we study the impact of replacing the KILT knowledge source with SPHERE. It is important to remember that the KILT benchmark was designed with a specific Wikipedia snapshot in mind and examples for which no evidence was found were removed. Thus, there is a strong bias towards this particular knowledge source, and the performance of systems using it can be considered topline.

First, we note that slot-filling tasks suffer the biggest drop in downstream performance when moving from Wikipedia to SPHERE, which we investigate further by exploring their per-predicate accuracy (Table 13 in Appendix). We observe a high variance in accuracy for the most common predicates, with those referring to more general concepts (e.g. crosses, country) scoring higher than more specific ones (e.g. occupant, performer). We further note that, unlike T-REx and zsRE, which were sourced from unfiltered WikiData snapshots, all non-slot filling tasks incorporate a notion of input popularity in the data collection process. This suggests the knowledge coverage on the web is not balanced, with popular topics receiving more representation than rare ones. In the environment where building a full web index is infeasible and one needs to rely on incomplete snapshots, this will result in inconsistent knowledge coverage of rare topics, as evidenced by a significant drop in performance for the slot-filling tasks.

Subsequently, we observe that for the remaining tasks, SPHERE-based results are competitive with Wikipedia. Our most salient result is the SOTA performance that FtD+BM25 architecture achieves on TQA, outperforming our best Wikipedia-based model by over 6 points. We test a hypothesis that the SPHERE advantage might result from the fact that it contains trivia websites with questions from the dataset. We find this not to be the case though: filtering out passages which contain input questions verbatim from the result sets of respective samples does not meaningfully impact downstream performance (see Table 12 in Appendix for more context). Instead, we note that TQA is an outlier among other datasets and it can be considered one of the least Wikipedia-dependent of all KILT tasks. Questions and answers in TQA were created independently by trivia enthusiasts and only distant supervision was applied to collect Wikipedia evidence. We see this as an encouraging evidence that web knowledge may be particularly useful in satisfying diverse information needs, especially those going beyond Wikipedia.

Finally, in Table 6, we report results on KILT dev sets for the best systems using Wikipedia and SPHERE respectively. We also consider a hypothetical hybrid oracle system which is correct if either of the aforementioned systems is correct. We observe that the oracle outperforms both baselines, suggesting that evidence provided by SPHERE adds value on top of Wikipedia. For example, on NQ, we see a 10+ points improvement with respect to the

\(^3\)We consider current results (November 2021) from KILT downstream performance leaderboard at kiltbenchmark.com, which were published on arxiv.org.
Table 5: Downstream evaluation results on the test set as per KILT leaderboard. We present results for published baselines (top section), our Wikipedia-based models (middle section) and SPHERE-based models (bottom section). SOTAs in bold, previous SOTAs underlined.

| Model                | FEV  | T-REx | zsRE | NQ   | HoPo | TQA  | ELI5 | WoW |
|----------------------|------|-------|------|------|------|------|------|-----|
| (Glass et al., 2021) | -    | 84.36 | 72.55| -    | -    | -    | -    | -   |
| (Petroni et al., 2021) BART+DPR | 86.74 | 59.16 | 30.43| 41.27| 25.18| 58.55| 17.41| 15.19 |
| (Petroni et al., 2021) RAG | 86.31 | 59.2  | 44.74| 44.39| 26.97| 71.27| 14.05| 13.11 |
| (Maillard et al., 2021) | 86.32 | -    | 57.95| 39.75| 31.77| 59.60| -    | 15.33 |
| (Krishna et al., 2021) | -    | -    | -    | -    | -    | 23.4 | -    | -   |
| (Paranjape et al., 2021) | -    | -    | -    | -    | -    | 19.19| -    | -   |
| FID+DPR\textsubscript{MULTI} | 88.99 | 82.52 | 71.72| 49.86| 36.90| 71.43| 17.88| 16.11 |
| FID+DPR\textsubscript{WEB} | 89.03 | 81.66 | 74.18| 51.59| 38.27| 72.73| 15.91| 15.45 |

Table 6: Downstream evaluation results on the dev set on our best systems for Wikipedia and SPHERE. At the bottom we estimate an upper bound performance of a hybrid oracle system by running inference on both of the aforementioned architectures and choosing the better one with respect to the gold answer.

| Model                | FEV  | T-REx | zsRE | NQ   | HoPo | TQA  | ELI5 | WoW |
|----------------------|------|-------|------|------|------|------|------|-----|
| Wikipedia (FID+DPR\textsubscript{WEB}) | 90.93 | 80.94 | 72.39| 54.98| 38.04| 71.43| 17.88| 16.11 |
| SPHERE (FID+BM25) | 90.71 | 59.66 | 38.61| 46.28| 34.12| 78.43| 17.13| 17.82 |
| ORACLE               | 94.52| 85.40 | 77.58| 65.10| 47.84| 86.58| 20.60| 22.59 |

5.3 Impact of fine-tuning DPR

Next, we investigate the effect of finetuning DPR on web data. When using SPHERE as the knowledge source, switching to DPR\textsubscript{WEB} has a clear impact, outperforming the DPR\textsubscript{MULTI} baseline on all datasets but ELI5. We observe significant downstream improvements, with +8 points on zsRE, +6 points on TQA or +5 points on T-REx. Interestingly, we also see improvements when using DPR\textsubscript{WEB} with Wikipedia as the knowledge source for all tasks that were used as training data, except for T-REx, leading to SOTAs on zsRE, NQ and HoPo. On the other hand, for the tasks that were not included in finetuning, the behavior is not consistent. Unlike with FEV, where applying DPR\textsubscript{WEB} yields SOTA results both against Wikipedia and SPHERE, we do not observe downstream gains for the long-form and dialog tasks (WoW and ELI5), which highlights the challenge in zero-shot transfer from short-form to long-form retrieval.

5.4 Sparse vs. Dense retrieval for web

We now focus on the comparison between dense and sparse retrieval architectures for SPHERE. First, we note that answer-in-context gains we observe when moving from DPR\textsubscript{MULTI} to DPR\textsubscript{WEB} (Figure 1a) correlate well with downstream performance. However, we don’t observe a similarly strong dependency when comparing DPR\textsubscript{WEB} with the performance of BM25 (Figure 1c) - even though the former often achieves better answer-in-context retrieval scores, it still lags on downstream metrics for all but one dataset (NQ being the exception).

To explain this, we ablate on the number of retrieved passages (see results in Figure 2). We note...
that the fewer contexts we consider, the smaller the BM25 advantage. For models trained with top-1 context, the DPR\textsubscript{WEB}-based model is better across the board, correlating well with the answer-in-context\textsubscript{@1} metric. This suggests that as much as the DPR\textsubscript{WEB} retriever is able to find a good top document, the quality of a larger result set is worse than that retrieved by BM25. We hypothesize that this is because using answer-in-context as retrieval supervision will inadvertently introduce false positives, and some of the gains in answer-in-context\textsubscript{@k} for larger \(k\)’s will result from those.

We explore the concept of result set quality further by looking at the answer+entity-in-context metric (Figure 1b). In this refined version of answer-in-context, BM25 achieves the best results for all datasets except NQ (Figure 1c), correlating better with downstream performance. We measure how often the main entity is present in the input itself. It turns out that NQ is an outlier in this regard, with the lowest number of datapoints containing the main entity (Table 7). It has been shown previously (Chen et al., 2021) that BM25 is better at lexical exact-match on the salient spans in the query. In our experiments the BM25 retriever can leverage this advantage - however, if the queries are more challenging in this regard as it is in the case of NQ, DPR becomes competitive.

We conclude that fine-tuning a retriever by using answer-in-context as retrieval supervision is able to improve DPR’s ability to retrieve relevant passages, while also introducing false positives. Gains obtained by the retriever translate well to downstream improvements. At the same time, we can’t use the metric for direct comparison of different retrieval architectures, in our case DPR and BM25. Answer+entity-in-context metric emerges as a potential better source of retrieval supervision, which we aim to explore in future work.

### 5.5 Wikipedia dissemination on the web

Excluding Wikipedia URLs from SPHERE was an early design decision. However, Wikipedia text dissemination on the web goes beyond Wikipedia itself. We apply a simple ngram filtering heuristic testing if a web passage has at least one 8-gram overlap with a Wikipedia passage to establish if it was based on Wikipedia (a method inspired by Radford et al. (2019)). We will refer to such a passage as wiki-based.

First, we note that as much as 5% of passages in our web corpus are wiki-based, adding up to almost 46M passages in total while the original Wikipedia corpus contains only 22M passages. This surprisingly high number can be partly explained by how SPHERE was constructed - the head CCNet tier we used contains the documents with the lowest perplexity under a Wikipedia-based language model, favoring the inclusion of wiki-based passages into the corpus. We further note that almost 47% of the passages present in the KILT knowledge source inspire at least one web passage in SPHERE, suggest-
We then look at the median number of wiki-based passages retrieved from SPHERE for respective datasets in Table 8. It turns out that all retrieval methods have a bias towards Wikipedia - the average median number of wiki-based results retrieved by the BM25 retriever is 12.1 and it increases sharply for the DPR-based methods, with 22.6 for DPR\textsubscript{MULTI} and 24.2 for DPR\textsubscript{WEB}. DPR\textsubscript{MULTI} is a Wikipedia retriever so it is not surprising that it is biased towards wiki-based passages. However, it is unexpected that fine-tuning leads to a retriever yielding even more wiki-based results than the original. The analysis from the previous paragraph may shed some light here: we estimate that as many as 34% of DPR-based and 22% of the BM25-based web training samples include wiki-based passages, so the fine-tuning process will reinforce the Wikipedia bias present in the baseline retrievers.

Table 8: Median number of wiki-based passages among top-100 results retrieved from SPHERE for respective datasets and models followed by Wikipedia—SPHERE overlap statistics. We consider passages to be overlapping if they share an 8-gram.

| Model     | FEV | T-REx | zsRE | NQ  | HoPo | TQA  | ELI5 | WoW | Avg. |
|-----------|-----|-------|------|-----|------|------|------|-----|------|
| DPR\textsubscript{MULTI} | 32  | 21    | 21   | 20  | 30   | 19   | 10   | 18  | 22.62 |
| DPR\textsubscript{WEB}   | 29  | 20    | 29   | 23  | 26   | 24   | 18   | 25  | 24.25 |
| BM25      | 15  | 9     | 10   | 8   | 17   | 16   | 2    | 4   | 12.12 |

Wikipedia passages with an overlapping passage in SPHERE: 46.9%

Wikipedia passages in SPHERE: 5.07%

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Finally, we seek to establish how much of the SPHERE performance is thanks to the wiki-based passages contained in the corpus. In Table 9, we present the relative change in downstream results for SPHERE-based models if we use the more aggressive ngram filtering strategy. We generally see worse downstream results, however, the drop is not as dramatic as we would have expected. In particular on TQA, even though suffering a small drop, the BM25-based architecture still obtains a SOTA performance with 77.46 points of exact match. These observations leave us optimistic about usefulness of the web as a knowledge source for KI-NLP tasks.

Table 9: The relative change in the downstream performance when moving from the default, URL-based Wikipedia filtering strategy (see results in Table 5) to a more aggressive ngram filtering strategy, expressed in percents.

| Model          | FEV T-REx zsRE NQ HoPo TQA ELI5 WoW |
|----------------|-------------------------------------|
| FI\textsubscript{D}+DPR\textsubscript{WEB} | -2.01 -1.47 -5.20 -7.96 -11.47 -0.45 +0.76 -4.71 |
| FI\textsubscript{D}+BM25                  | -1.84 -3.57 -10.42 -6.17 -12.26 -0.96 -2.50 -8.04 |

5.6 Risks associated with using web content

In our current work we focus on scale and knowledge coverage as key challenges in moving from Wikipedia to the web. Another crucial problem which needs to be addressed regards the quality of retrieved information. Using Wikipedia as a knowledge source allows researchers to make assumptions about the high quality of the documents (where quality could mean truthfulness, objectivity, lack of harmful content, source reliability, etc.). When transitioning to a web corpus, we no longer have the certainty that any document is good, truthful or unique, or that a certain “gold document” containing all the necessary information even exists. Future work should focus on the ability of the
models to assess the quality of the retrieved documents, handle duplicates, detect potential false claims and contradictions, prioritize more trustworthy sources and refrain from providing the answer if no sufficiently good evidence exists in the corpus.

6 Discussion

6.1 The web corpus

Given that we apply SPHERE without any explicit alignment to the considered datasets, the question of whether the corpus actually contains the information needed to solve the tasks at hand becomes of major importance. First, we note that SPHERE contains a surprisingly large amount of wiki-based content, with 47% of Wikipedia passages having an equivalent in our web corpus. At the same time, the web is a source of knowledge which goes beyond Wikipedia - exploring the Wikipedia knowledge gap studies and projects (e.g. Women in Red) provides examples of such concepts (e.g. Table 1). That said, the popularity of the topic impacts how much coverage it gets on the web. When working with incomplete snapshots rather than an exhaustive index of the web, this will result in limited knowledge coverage of rare topics. In the future, extra care should be taken to include rare, underrepresented topics, which might mean moving away from randomly crawled snapshots to more targeted, coverage oriented data collection strategies.

6.2 DPR fine-tuning for web

Even though neural retrievers such as DPR beat BM25 by a large margin on Wikipedia, we haven’t been able to apply DPR to the web with similar success. It has been previously suggested that bi-encoders may be inherently not expressive enough for the purposes of large scale retrieval (Luan et al., 2021). Still, we do see avenues for improvement of our current models. We hypothesize that answer-in-context may be too weak of a signal for retrieval supervision, with answer+entity-in-context emerging as a potential alternative. Additionally, our current DPR models display a strong bias towards retrieving Wikipedia and wiki-based results which could be mitigated with picking better positive samples for finetuning from the web. In line with previous research (Maillard et al., 2021; Oğuz et al., 2021), we also note that zero shot transfer of DPR models (in our case from short form to long form KI-NLP tasks) doesn’t yield good results, leaving the challenge of building universal, neural retrievers open.

6.3 KILT benchmark

Finally, our experiments provide useful insights into the KILT benchmark itself. First we observe that slot-filling tasks emerge as an outlier in terms of the type of knowledge required to solve them - all remaining tasks are biased towards popular topics, while slot-filling tasks pull samples uniformly from all of Wikipedia. Additionally, KILT tasks vary in terms of how much respective tasks’ input reveals about the entities they refer to - tasks which contain the main entity in the input more often will give an advantage to sparse retrieval methods such as BM25, and Wikipedia-based models.

7 Related Works

Most existing research in KI-NLP uses Wikipedia as the source of knowledge (Kwiatkowski et al., 2019; Joshi et al., 2017; Thorne et al., 2018; Yang et al., 2018; Dinan et al., 2019; Petroni et al., 2021). In this paper, we instead study the ability to solve KI-NLP tasks with web as the background corpus. Previous works that operate on web (Joshi et al., 2017; Bajaj et al., 2018; Talmor and Berant, 2018) typically rely on results from black-box search engines to create a corpus. A CCNet snapshot has been considered as a knowledge source in dialog research by Komeili et al. (2021), where authors use it together with a Wikipedia snapshot. As far as we know, our work is the first to consider an uncurated snapshot of the web without Wikipedia as a knowledge source for multiple KI-NLP tasks at once. Moreover, our scale is significantly larger than previously attempted (see Table 2).

There are other large scale resources that could be considered to tackle KI tasks, such as large collections of question-answer pairs (Lewis et al., 2021a; Huber et al., 2021), structured knowledge sources (Berant et al., 2013; Levy et al., 2017; Elsayar et al., 2018) or domain specific collections (Tsatsaronis et al., 2015; Saikh et al., 2021).

8 Conclusions

Harnessing the vast textual resources available online today through white-box retrieval may be the source of the next big break in NLP. In our current work we propose to use a web snapshot as a universal, unstructured knowledge source for multiple KI-NLP tasks. We see encouraging results even in the experimental setup with a strong pro-Wikipedia bias, which suggests that SPHERE is a competitive knowledge source with a potential of
achieving state of the art results especially for tasks with diverse information needs. At the same time, while remaining closer to the needs of real-world applications, our setup exposes limitations of existing retrievers, providing a challenging test bed for future innovations. We release SPHERE indices and infrastructure for large-scale web retrieval with the hope of encouraging the research in this direction.

Figure 2: Dev set downstream evaluation results for FiD models with $k \in 1, 5, 20, 100$ context passages. We plot accuracy for T-REx and zsRE and exact match for the remaining tasks.

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| k     | 1   | 20  | 100 | 1   | 20  | 100 | 1   | 20  | 100 | 1   | 20  | 100 |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| T-REx| 76.36 | 94.54 | 96.74 | 57.87 | 90.82 | 96.08 | 56.47 | 88.09 | 93.76 | 30.64 | 64.70 | 76.52 | 69.75 | 94.61 | 98.10 |
| zsRE | 84.28 | 96.34 | 97.62 | 75.54 | 96.62 | 98.74 | 58.48 | 90.27 | 95.31 | 35.48 | 70.23 | 81.00 | 73.13 | 96.12 | 98.64 |
| NQ   | 76.36 | 94.54 | 96.74 | 57.87 | 90.82 | 96.08 | 56.47 | 88.09 | 93.76 | 30.64 | 64.70 | 76.52 | 69.75 | 94.61 | 98.10 |
| HoPo | 84.28 | 96.34 | 97.62 | 75.54 | 96.62 | 98.74 | 58.48 | 90.27 | 95.31 | 35.48 | 70.23 | 81.00 | 73.13 | 96.12 | 98.64 |
| TQA  | 76.36 | 94.54 | 96.74 | 57.87 | 90.82 | 96.08 | 56.47 | 88.09 | 93.76 | 30.64 | 64.70 | 76.52 | 69.75 | 94.61 | 98.10 |

Table 10: Answer-in-context@k (top) and answer+entity-in-context@k (bottom) for Wikipedia and SPHERE indices.
**Input:** What is the title of the film considered to be the debut of cartoon character Mickey Mouse?

**Gold answer:** Steamboat Willy, Timeless River, steamboat willie, Steamboat Willie, timeless river, steamboat willy, steam boat willie, Steam boat Willie

**Web answer:** steamboat willie

**Wiki answer:** plane crazy

**Web prov.** [http://www.worldlibrary.org/articles/eng/Mickey_Mouse](http://www.worldlibrary.org/articles/eng/Mickey_Mouse) ...in the world. Mickey first was seen in a single test screening (Plane Crazy). Mickey officially debuted in the short film Steamboat Willie (1928), one of the first sound cartoons. He went on to appear in over 130 films, including The Band Concert (1935), Brave Little Tailor (1938), and Fantasia (1940). Mickey appeared primarily in short films, but also occasionally in feature-length films. Ten of Mickey’s cartoons were nominated for the Academy Award for Best Animated Short Film, one of which, Lend a Paw, won the award in 1942. In 1978, Mickey became the first cartoon character to have a...  

**Wiki prov.** Mickey Mouse … The Pointer” (1939) - “The Nifty Nineties” (1941) - "Lend a Paw" (1941) - "Symphony Hour" (1942) - "Squatter’s Rights" (1946) - "Mickey and the Seal" (1948) - "The Simple Things" (1953) - "Mickey’s Christmas Carol" (1983) - "Runaway Brain" (1995) - “Get a Horse!” (2013) Filmography Full-...

**Wiki gold** Mickey Mouse … Mickey Mouse is a funny animal cartoon character and the mascot of The Walt Disney Company. He was created by Walt Disney and Ub Iwerks at the Walt Disney Studios in 1928. An anthropomorphic mouse who typically wears red shorts, large yellow shoes, and white gloves, Mickey is one of the world’s most recognizable characters. Created as a replacement for a prior Disney character, Oswald the Lucky Rabbit, Mickey first appeared in the short "Plane Crazy", debuting publicly in the short film "Steamboat" ...

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**Input:** Michelin Guides have been published for more than a decade.

**Gold answer** SUPPORTS

**Web answer** SUPPORTS

**Wiki answer** REFUTES

**Web prov.** [https://guide.michelin.com/it/en/about-us](https://guide.michelin.com/it/en/about-us) ...diners - or restaurant inspectors, as we better know them today - to visit and review restaurants anonymously. In 1926, the guide began to award stars for fine dining establishments, initially marking them only with a single star. Five years later, a hierarchy of zero, one, two, and three stars was introduced, and in 1936, the criteria for the starred rankings were published. During the rest of 20th century, thanks to its serious and unique approach, the MICHELIN Guides became best-sellers without equals: the guide now rates over 30,000 establishments in over 30 territories across three continents, and more than ...  

**Wiki prov. / Wiki gold** Michelin Guide … Michelin Guide Michelin Guides () are a series of guide books published by the French tire company for more than a century. The term normally refers to the annually published Michelin "Red Guide", the oldest European hotel and restaurant reference guide, which awards up to three "Michelin stars" for excellence to a select few establishments. The acquisition or loss of a star can have dramatic effects on the success of a restaurant. Michelin also publishes a series of general guides to cities, regions, and countries, the ...
After he had directed "Australia", it was reported that Baz Luhrmann’s next project was a film based on which book by F Scott Fitzgerald?

Gold answer: The Great Gatsby

Top web

Although Australia sadly ended up as one of this year’s biggest flops (currently at $39 million), filmmaker Baz Luhrmann has already started work on his next project - F. Scott Fitzgerald’s The Great Gatsby. Nikki Finke of Deadline Hollywood confirms that this is Luhrmann’s next gig and that he’s already actively searching for a young actress to portray Daisy in the film. This isn’t the first time Fitzgerald’s book has been adapted - there was a 1974 film directed by Jack Clayton as well as a 1949 film directed by Elliott Nugent...

Top trivia

The publication of which book by Salman Rushdie led to threats on his life by Ayatollah Khomeini? On the last day of his life Bhagat Singh was reading a book about the Ideology of which revolutionary? Who wrote the book "Life of Pi"? After he had directed "Australia", Baz Luhrmann’s next project was a film based on which book by F Scott Fitzgerald? Who advocated that a free market economy is more productive and more benevolent to society, in his famous book? Who is the author of the book titled "A Kingdom For His Love"? The publication of which book by Salman Rushdie led to threats on his life by Ayatollah Khomeini?

Gold Wiki

The publication of which book by Salman Rushdie led to threats on his life by Ayatollah Khomeini? On the last day of his life Bhagat Singh was reading a book about the Ideology of which revolutionary? Who wrote the book "Life of Pi"? After he had directed "Australia", Baz Luhrmann’s next project was a film based on which book by F Scott Fitzgerald? Who advocated that a free market economy is more productive and more benevolent to society, in his famous book? Who is the author of the book titled "A Kingdom For His Love"? The publication of which book by Salman Rushdie led to threats on his life by Ayatollah Khomeini? posted Jan 17...

Table 12: The SPHERE corpus contains passages from trivia-devoted web pages featuring questions from the TQA dataset, however, these passages typically don’t provide any context information and often don’t contain answers. Filtering them out doesn’t significantly impact downstream performance.

| predicate               | count | accuracy | predicate               | count | accuracy |
|-------------------------|-------|----------|-------------------------|-------|----------|
| mouth of the watercourse| 692   | 25.43    | country                 | 617   | 88.17    |
| employer                | 650   | 50.77    | located in the administrative territorial entity | 470 | 35.96 |
| production company      | 459   | 28.54    | instance of            | 464   | 68.32    |
| spouse                  | 357   | 41.46    | country of citizenship  | 344   | 85.17    |
| from fictional universe | 340   | 16.18    | taxon rank              | 325   | 99.08    |
| crosses                 | 327   | 70.95    | occupation              | 311   | 74.28    |
| time of spacecraft launch|295   | 33.9     | sport                   | 278   | 84.89    |
| drafted by              | 287   | 68.64    | place of birth          | 215   | 37.21    |
| date of official opening| 117   | 36.75    | performer               | 147   | 27.89    |
| occupant                | 112   | 4.46     | parent taxon            | 140   | 54.29    |

Table 13: Top ten predicates in our slot-filling tasks, with per-predicate accuracy in the dev set.