NeuralQA: A Usable Library for Question Answering (Contextual Query Expansion + BERT) on Large Datasets

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Abstract

Existing tools for Question Answering (QA) have challenges that limit their use in practice. They can be complex to setup or integrate with existing infrastructure, do not offer configurable interactive interfaces, and do not cover the full set of tasks that frequently comprise the QA pipeline (query expansion, retrieval, reading, and explanation/sensemaking). To help address these issues, we introduce NeuralQA - a usable library for QA on large datasets. NeuralQA integrates well with existing infrastructure (e.g. elasticsearch instances and reader models trained with the HuggingFace transformers api). It introduces and implements helpful defaults such as contextual query expansion using a masked language model (MLM), and relevant snippets ($RelSnip$) - a method for condensing large documents into smaller passages that can be speedily processed by a document reader model. Finally, it offers a flexible user interface to support workflows for research explorations (e.g. visualization of gradient-based explanations to support qualitative inspection of model behaviour) and generic search tasks. Code and documentation for NeuralQA is available at https://github.com/victordibia/neuralqa.

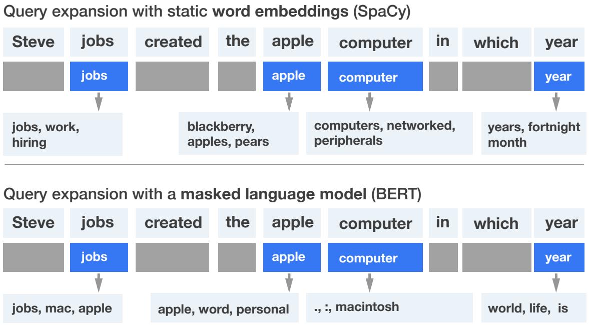


Figure 1: Examples of qualitative results from applying query expansion. (a) Query expansion using SpaCy (Honnibal and Montani, 2017) word embeddings to identify most similar words for each expansion candidate token. This approach yields terms with low relevance. E.g. terms related to work (jobs, hiring) and fruits (apple, blackberry, pears) are not relevant to the current query context (b) Query expansion using a masked language model (BERT): This approach yields terms that are not contained within the original query (e.g. mac, macintosh, personal) but are *in general*, relevant to the current query.

1 Introduction

The capability of providing *exact* answers to queries framed as natural language questions can significantly improve the user experience for many real world applications. As opposed to sifting through lists of retrieved documents, automatic QA (also known as reading comprehension) systems can surface the exact answer, thus reducing the cognitive burden associated with the standard search task. This capability is applicable in extending conventional information retrieval systems (search engines) and also for emergent use cases such as open domain conversational AI systems (Gao et al., 2018; Qu et al., 2019). For enterprises, QA systems that are both fast and precise can help unlock knowledge value from large unstructured document collections.

Across many practical use cases, the QA task is structured as open domain QA where the answer must be extracted from relevant documents which are retrieved from an open corpus (millions of documents). Conventional methods for QA follow a two component implementation - (i) a **retriever** that returns a subset of relevant documents. Retrieval is typically based on sparse vector space models such as BM25 (Robertson and Zaragoza, 2009) and TF-IDF (Chen et al., 2017); (ii) a machine reading comprehension model (**reader**) that identifies spans from each document that contain the answer. While sparse representations are fast

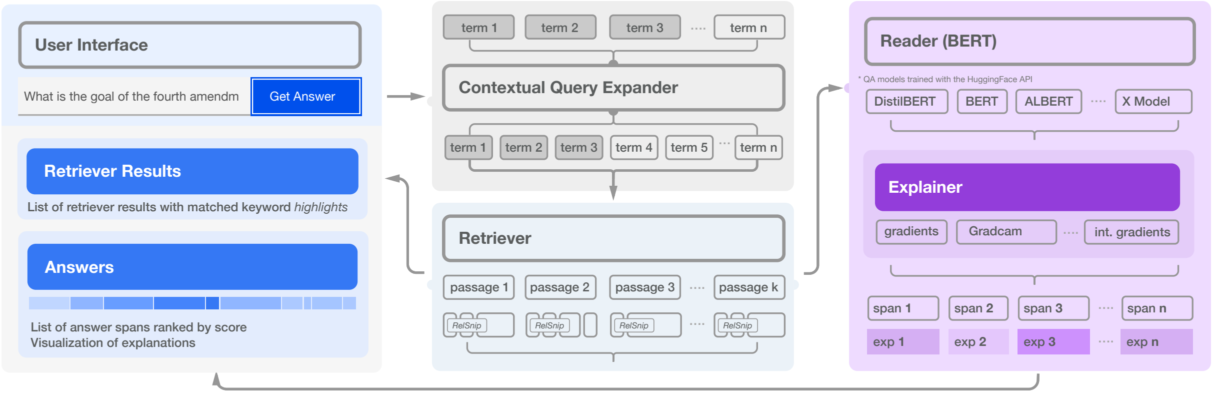


Figure 2: NeuralQA Architecture is comprised of 4 primary modules (a) User interface: enables user queries and visualizes results from the retriever and reader (b) Contextual Query Expander: offers options for generating query expansion terms using an MLM (c) Retriever: leverages the BM25 scoring algorithm in retrieving a list of candidate passages. It also optionally condenses lengthy documents to smaller passages via 3.1 *RelSnip*. (d) Document Reader: Identifies answer spans within documents where available and provides explanations for each prediction.

to compute, they rely on exact keyword match and suffer from the *vocabulary mismatch* problem - scenarios where the vocabulary used to express a query is different from the vocabulary used to express the same content within the documents. To address these issues, recent works have proposed neural ranking (Lee et al., 2018; Kratzwald et al., 2019) and retrieval methods (Karpukhin et al., 2020; Lee et al., 2019; Guu et al., 2020), which rely on dense representations. However, while dense representations show significantly improved results, they introduce additional complexity and latency which limits their practical application. For example, Guu et al. (2020) require a specialized MLM pretraining regime as well as a supervised finetuning step to obtain representations used in a retriever. Similarly Karpukhin et al. (2020) use dual encoders in learning a dense representation for queries and all documents in the target corpus. Each of these methods require additional infrastructure to compute dense representation vectors for all documents in the target as well as implement efficient similarity search at run time. In addition, transformer (Vaswani et al., 2017) based architectures used for dense representations are unable to process long sequences due to their self attention operations which scale quadratically with sequence length. As a result, these models require that documents are indexed/stored in small paragraphs. For many use cases, meeting these requirements (rebuilding retriever indexes, training models to learn corpus specific representations, precomputing representations for all indexed documents) can be cost intensive. These costs are hard to justify given that simpler methods can yield comparable results (Lin, 2019). Furthermore, as reader models are applied to domain specific documents, they fail in unintuitive ways. It is thus valuable to offer visual interfaces that support debugging or sense making of results e.g. explanations for *why* a set of documents were retrieved or *why* an answer span was selected from a document. While several libraries exist for explaining NLP models, they do not integrate interfaces that help users make sense of both the retriever and the reader tasks. Collectively, these limitations can hamper experimentation with QA systems and the integration of QA models into practitioner workflows.

We introduce the NeuralQA library to help address these limitations which are often encountered in practical applications. Our contributions are summarized as follows:

- An easy to use, end to end library for implementing QA systems. It integrates methods for query expansion, document retrieval (elasticsearch[1]), document reading (QA models trained using the HuggingFace API (Wolf et al., 2019)), and offers an interactive user interface for sense-making of results (retriever + reader). NeuralQA is open source and released under the MIT License.
- To address the vocabulary mismatch problem, NeuralQA introduces and implements a method for contextual query expansion (CQE)

[1] Elasticsearch https://www.elastic.co

using a masked language model fine tuned on the target document corpus. Early qualitative results show CQE can surface relevant additional query terms that help improve recall and require minimal changes for integration with existing retrieval infrastructure.

- In addition, we also implement $RelSnip$, a simple method for extracting relevant snippets from retrieved passages before feeding it into a document reader. This in turn reduces the latency required to chunk and read lengthy documents. Importantly, these options offer opportunity to improve latency and recall, with no changes to existing retriever infrastructure.

Overall, this work contributes to a line of end to end applications that improve QA system deployment (Akkalyoncu Yilmaz et al., 2019; Yang et al., 2019)and provide visual interfaces for understanding machine learning models (Wallace et al., 2019; Strobelt et al., 2018).

2 The Question Answering Pipeline

In this section, we focus on a group of sub tasks that frequently comprise the QA pipeline and are implemented in NeuralQA.

2.1 Document Retrieval

The first step in the QA process focuses on retrieving a list of candidate passages which are subsequently processed by a reader. Conventional approaches to QA apply representations from sparse vector space models (BM25, TF-IDF) in identifying the most relevant document candidates. For example, Chen et al. (2017) introduce a end-to-end system combining TFIDF retrieval with a multi layer RNN for document reading. This is further improved upon by Yang et al. (2019) who utilize BM25 for retrieval and a modern BERT transformer reader.

However, sparse representations are keyword dependent and suffer from the *vocabulary mismatch* problem in IR - given a query Q and a relevant document D, a sparse retrieval method may fail to retrieve D if D uses a different vocabulary to refer to the same content in Q. Furthermore, sparse representations lack contextual information often needed to retrieve under-specified queries. To address these issues, a set of related work have focused on methods for re-ranking retrieved documents to improve recall (Kratzwald et al., 2019; Wang et al., 2018). More recently, there have been efforts to learn representations of queries and documents useful for retrieval. Lee et al. (2019) introduce an inverse story close task for pretraining encoders used to create static embeddings that are indexed and used for similarity retrieval during inference). Their work is further expanded by Guu et al. (2020) who introduce non-static representations that are learned simultaneous to reader fine tuning. Finally, Karpukhin et al. (2020) use dual encoders for retrieval - an encoder that learns to map queries to a fixed dimension vector and another that learns to map documents to a similar fixed dimension vector such that representations for similar query and documents are close.

2.2 Query Expansion

In addition to re-ranking and dense representation retrieval, query expansion methods have also been proposed to help address the vocabulary mismatch problem. It serves to identify additional, relevant query terms, using a variety of sources such as the target corpus, external dictionaries (e.g. WordNet), or historical queries. Existing research has explored how implicit information contained in queries can be leveraged in query expansion. For example Lavrenko and Croft (2017); Lv and Zhai (2010) show how relevance model (RM3) can be applied for query expansion and improve retrieval performance. More recently, (Lin, 2019) show that the use of a well tuned relevance model such as RM3 (Lavrenko and Croft, 2017; Abdul-Jaleel et al., 2004) results in performance at par with complex neural retrieval methods.

Word embeddings have also been explored as a potential method for query expansion. In their work Kuzi et al. (2016) train a word2vec (Mikolov et al., 2013) CBOW model on their search copora and use embeddings to identify expansion terms that are semantically related to the query as a whole or its terms. Their results suggest that a combination of word2vec embeddings and a relevance model (RM3) provide good results. While word embeddings trained on a target corpus are useful, they are static and do not take into consideration the context of the words in a specific query.

In this work, we propose an extension on this direction of thought and explore how contextual embeddings produced by an MLM such as BERT (Devlin et al., 2018), can be applied in generating query expansion terms.

2.2.1 Document Reading

Recent advances in pretrained neural language models such as BERT (Vaswani et al., 2017) and GPT (Radford et al., 2019) have enabled robust contextualized representation of natural language which in turn have enabled significant performance increases on the QA task. Each QA model (reader) consists of a base representation and an output feed forward layer which produces 2 sets of scores - (i) scores for each input token indicating the likelihood of an answer span starting at the token offset (ii) scores for each input token indicating the likelihood of an answer span ending at the token offset.

3 NeuralQA System Architecture

In this section, we review the architecture for NeuralQA, design decisions and supported workflows. The core modules for NeuralQA are shown in Figure 2) and consist of a user interface, retriever, expander and a reader. Each of these modules are implemented as extensible python classes to facilitate code reuse and incremental development. Each of these modules are exposed as rest api endpoints that can be consumed by 3rd party applications or interacted with via the NeuralQA user interface.

3.1 Retriever

The retriever supports the execution of queries on an existing Elasticsearch instance, with the industry standard BM25 scoring algorithm. In our implementation, we also configure the elasticsearch instance with an analyzer that implements stop word removal. This step is critical in preventing matches on words which do not contain relevant information.

3.1.1 Condensing Passages with $RelSnip$

In practice, open corpus documents can be of arbitrary length (thousands of tokens) and are frequently indexed for retrieval *as is*. On the other hand, document reader models have limits on the maximum number of tokens they can process in a single pass (e.g. BERT based models can process a maximum of 512 tokens). Thus, retrieving large documents can incur latency costs as a reader will have to first split the document into manageable chunks and then process each chunk. To address this issue, NeuralQA introduces $RelSnip$, a method for constructing smaller documents from lengthy documents. $RelSnip$ is implemented as follows: For each retrieved document, we apply a highlighter (Lucene Unified Highlighter) which breaks the document into fragments of size k_{frag} and uses the BM25 algorithm to score each fragment as if they were individual documents in the corpus. Next, we concatenate the top n fragments as a new document which is processed by the reader. $RelSnip$ relies on the simplifying assumption that fragments with higher match scores contain more relevant information. As an illustrative example, $RelSnip$ can yield a document of 400 tokens (depending on k_{frag} and n) from a document containing 10,000 tokens. In practice, this can translate to 25x speedup.

3.2 Expander

3.2.1 Contextual Query Expansion

Contextual Query Expansion (CQE) relies on the assumption that a masked language model finetuned on the target document corpus contains implicit information on the target corpus that can be exploited in identifying relevant query expansion terms. Ideally, we want to expand tokens such that additional tokens serve to increase recall whilst adding minimal noise or significantly altering the semantics of the original query. We implement CQE as follows: Our first step is to identify a set of expansion candidate tokens. For each token t_i in the query t_{query}, we use the SpaCy (Honnibal and Montani, 2017) library to infer its part of speech tag $t_{i_{pos}}$ and apply a filter f_{rule} to select a subset as candidate for expansion $t_{candidates}$. Next, we construct intermediate versions of the original query where each token in $t_{candidates}$ is masked and a MLM (BERT) predicts the top n tokens that are contextually most likely to complete the query. These predicted tokens $t_{expansion}$ are then added to the original query as expansion terms. To minimize the chance of introducing spurious terms that are unrelated to the original query, we find that two quality control measures are useful. First, we leverage confidence scores returned by the MLM and only accept expansion tokens above a threshold (e.g. $k_{thresh} = 0.5$) where k_{thresh} is a hyperparameter. Secondly, we find that a conservative filter in selecting token expansion candidates can mitigate the introduction of spurious terms. Our filter rule f_{rule} currently only expands tokens that are either nouns or adjectives $t_{i_{pos}} \in (noun, adj)$; other parts of speech tokens are not expanded . Finally, the list of expansion terms are further cleaned - deduplication of terms and removal of punctuation and stop words. Figure 1 shows a qualitative comparison of query expansion terms suggested by a static word embedding and a masked language model for a given query.

3.3 Reader

The reader module implements an interface for predicting answer spans given a query and context documents. Underneath, it loads any QA model trained using the Huggingface Transformers API (Wolf et al., 2019). For documents that exceed the maximum token size for the reader, they are automatically split into chunks with a configurable stride and answer spans provided for each chunk. All answers are then sorted based on an associated confidence score. Finally, each reader model provides a method that generates gradient based explanations.

3.3.1 User Interface

The NeuralQA user interface seek to aid the user in performing queries and in sense making of underlying model behaviour. As a first step, we provide a visualization of retrieved document highlights that indicate what portions of the retrieved document contributed to their relevance ranking. Next, following work done in AllenNLP Interpret(Wallace et al., 2019), we implement gradient based explanations (Simonyan et al., 2013; Erhan et al., 2009; Baehrens et al., 2010) that help the user understand what sections of the input (question and passage) were most relevant to the choice of answer span. We do not use attention weights as they have have been shown to be unfaithful explanations of model behaviour (Jain and Wallace, 2019; Serrano and Smith, 2019) and unintuitive for end user sense making. We also implement a document and answer tagging scheme that indicates the source document from which an answer span is derived.

NeuralQA is scalable as it is built on industry standard OSS tools that are designed for scale (ElasticSearch, HuggingFace Transformers api). We have tested deployments of NeuralQA on docker containers running on CPU machine clusters which rely on Elasticsearch clusters. The UI is responsive and optimized to work on desktop as well as mobile devices.

3.4 Configuration and Workflow

NeuralQA implements a command line interface for instantiating the library and a declarative approach for specifying the parameters for each module. At run time, users can provide a command line argument specifying the location of a configuration yaml file[2]. If no configuration file is found in the provided location and in the current folder, NeuralQA will create a default configuration file that can be subsequently modified. As an illustrative example, users can configure properties of the user interface (views to show or hide, title and description of the page etc), retriever properties (a list of supported retriever indices), and reader properties (a list of supported models that are loaded into memory on application startup).

3.4.1 User Personas

NeuralQA is designed to support use cases and personas at various levels of complexities. Two specific personas are briefly discussed below.

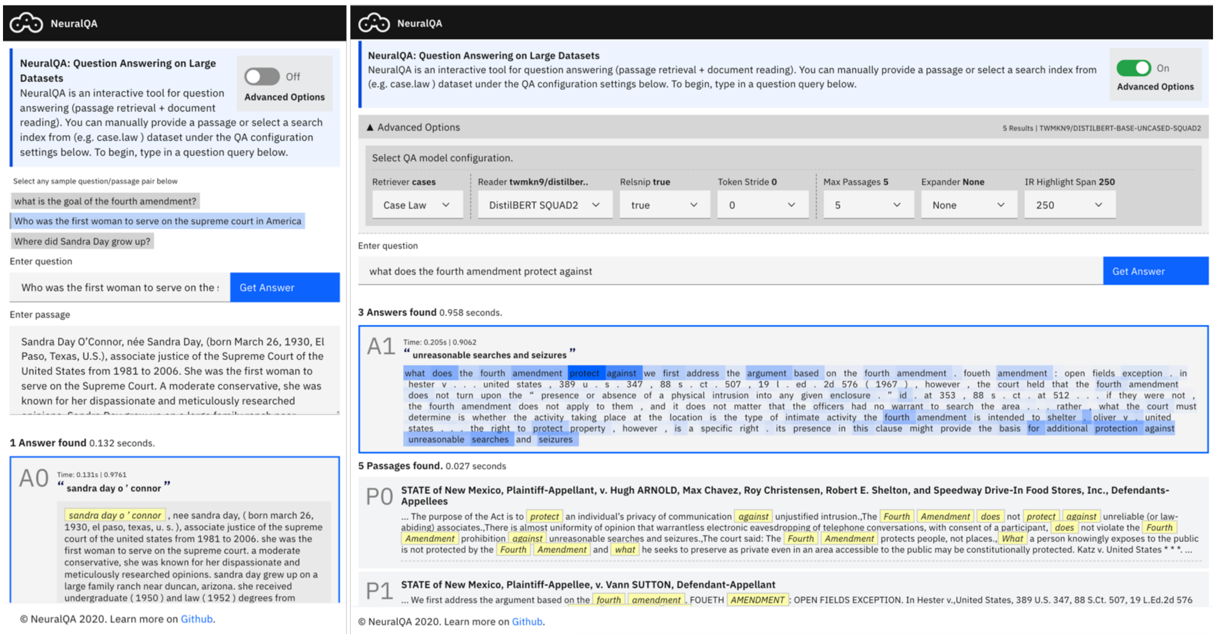
Data Scientist: Janice, a data scientists has extensive experience applying a collection of machine learning models to financial data. More recently, she is starting up a new project where the deliverable includes a QA model skillful at answering factoid questions on financial data. As part this work, Janice has successfully fine tuned a set of transformer models on the QA task but would like to better understand how the model behaves. More importantly, she would like enable visual interaction with the model for her broader team. To achieve this, Janice hosts NeuralQA on an internal server accessible to her team. Via a configuration file, she can specify her set of trained models as well as enable user selection of reader/retriever parameters. This workflow also extends to hobbyists, entry level data scientists or researchers who want an interface for qualitative inspection of custom reader models on custom documents indices.

Engineering Teams: Candice manages the internal knowledge base service for her startup. They have an internal Elasticsearch instance for search but would like to provide additional value via QA capabilities. To achieve this, Candice provisions a set of docker containers running instances for NeuralQA and then modifies their current search frontend application to make requests to the NeuralQA rest api end point and serve answer spans.

3.5 Related Work

QA systems that integrate deep learning models remain an active areas of research and practice. For example, Allennlp Interpret (Wallace et al., 2019)

[2] A sample configuration file can be found on Github.



NeuralQA: Question Answering on Large Datasets
NeuralQA is an interactive tool for question answering (passage retrieval + document reading). You can manually provide a passage or select a search index from (e.g. case.law) dataset under the QA configuration settings below. To begin, type in a question query below.

Select any sample question/passage pair below

what is the goal of the fourth amendment?

Who was the first woman to serve on the supreme court in America

Where did Sandra Day grow up?

Enter question

Who was the first woman to serve on the :

Enter passage

Sandra Day O'Connor, née Sandra Day, (born March 26, 1930, El Paso, Texas, U.S.), associate justice of the Supreme Court of the United States from 1981 to 2006. She was the first woman to serve on the Supreme Court. A moderate conservative, she was known for her dispassionate and meticulously researched

1 Answer found 0.132 seconds.

A0 Time: 0.131s | 0.9761
" **sandra day o ' connor** "

sandra day o ' connor , nee sandra day, (born march 26, 1930, el paso, texas, u. s.), associate justice of the supreme court of the united states from 1981 to 2006. she was the first woman to serve on the supreme court. a moderate conservative, she was known for her dispassionate and meticulously researched opinions. sandra day grew up on a large family ranch near duncan, arizona. she received undergraduate (1950) and law (1952) degrees from

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NeuralQA: Question Answering on Large Datasets
NeuralQA is an interactive tool for question answering (passage retrieval + document reading). You can manually provide a passage or select a search index from (e.g. case.law) dataset under the QA configuration settings below. To begin, type in a question query below.

▲ Advanced Options — 5 Results | TWMKN9/DISTILBERT-BASE-UNCASED-SQUAD2

Select QA model configuration.

Retriever **cases**: Case Law
Reader **twmkn9/distilber..**: DistilBERT SQUAD2
Relsnip **true**: true
Token Stride **0**: 0
Max Passages **5**: 5
Expander **None**: None
IR Highlight Span **250**: 250

Enter question

what does the fourth amendment protect against

3 Answers found 0.958 seconds.

A1 Time: 0.205s | 0.9062
" **unreasonable searches and seizures** "

what does the fourth amendment protect against we first address the argument based on the fourth amendment . foueth amendment : open fields exception . in hester v . . . united states , 389 u . s . 347 , 88 s . ct . 507 , 19 l . ed . 2d 576 (1967) , however , the court held that the fourth amendment does not turn upon the " presence or absence of a physical intrusion into any given enclosure . " id . at 353 , 88 s . ct . at 512 . . . if they were not , the fourth amendment does not apply to them , and it does not matter that the officers had no warrant to search the area . . . rather , what the court must determine is whether the activity taking place at the location is the type of intimate activity the fourth amendment is intended to shelter . oliver v . united states . . . the right to protect property , however , is a specific right . its presence in this clause might provide the basis for additional protection against unreasonable searches and seizures

5 Passages found. 0.027 seconds

P0 **STATE of New Mexico, Plaintiff-Appellant, v. Hugh ARNOLD, Max Chavez, Roy Christensen, Robert E. Shelton, and Speedway Drive-In Food Stores, Inc., Defendants-Appellees**
... The purpose of the Act is to *protect* an individual's privacy of communication *against* unjustified intrusion.,The *Fourth* *Amendment* *does* not *protect* *against* unreliable (or law-abiding) associates.,There is almost uniformity of opinion that warrantless electronic eavesdropping of telephone conversations, with consent of a participant, *does* not violate the *Fourth* *Amendment* prohibition *against* unreasonable searches and seizures.,The court said: The *Fourth* *Amendment* protects people, not places., *What* a person knowingly exposes to the public is not protected by the *Fourth* *Amendment* and *what* he seeks to preserve as private even in an area accessible to the public may be constitutionally protected. Katz v. United States * * *. ...

P1 **STATE of New Mexico, Plaintiff-Appellee, v. Vann SUTTON, Defendant-Appellant**
... We first address the argument based on the *fourth* *amendment* . FOUETH *AMENDMENT* : OPEN FIELDS EXCEPTION. In Hester v.,United States, 389 U.S. 347, 88 S.Ct. 507, 19 L.Ed.2d 576

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Figure 3: The NeuralQA User Interface is optiimzed for web and mobile a) Initial basic view (mobile) with options to provide a question + passage and view model results. b) Advanced options view (desktop) to configure retriever (# of returned documents, toggle $RelSnip$, fragment size) expander and reader parameters (BERT based model, token stride size). View also shows a list of returned passages with highlights that match the query; a gradient based explanation of which tokens impact the selected answer span.

provide a demonstration interface and sample code for interpreting a set of Allennlp models across multiple tasks. Similarly, Chakravarti et al. (2019) provide a grpc based orchestration flow for QA. While these projects provides a GUI, their installation process is complex and requires specialized code to adapt them to existing infrastructure such as retriever instances. Several open source projects also offer a programmatic interface for inference (see Huggingface pipelines[3]) as well as joint retrieval plus reading (see Deepset Haystackc [4]).

NeuralQA makes progress in this line of work by providing an extensible code base, an easy installation process and a visual interface for sense making of results. It can be easily installed locally (via the pip package manager) and scaled via containerization. We believe this ease of use can serve to remove barriers to experimentation for researchers and accelerate the deployment of QA interfaces for experienced teams.

4 Conclusion

In this paper, we presented NeuralQA a usable library for question answering on large datasets. NeuralQA is useful for developers interested in qualitatively exploring QA models for their custom datasets and for enterprise teams seeking a flexible QA interface/api for their customers. NeuralQA is under active development and roadmap features include support for support for a Solr retriever and implementation of additional query expansion methods such as RM3 (Lavrenko and Croft, 2017). Future work will also explore empirical evaluations of our contextual query expansion implementation to better understand its strengths and limitations.

References

Nasreen Abdul-Jaleel, James Allan, W Bruce Croft, Fernando Diaz, Leah Larkey, Xiaoyan Li, Mark D Smucker, and Courtney Wade. 2004. Umass at trec 2004: Novelty and hard. *Computer Science Department Faculty Publication Series*, page 189.

Zeynep Akkalyoncu Yilmaz, Shengjin Wang, Wei Yang, Haotian Zhang, and Jimmy Lin. 2019. Applying BERT to document retrieval with birch. In *Empirical Methods in Natural Language Processing (EMNLP-IJCNLP): System Demonstrations*, pages 19–24, Hong Kong, China. Association for Computational Linguistics.

David Baehrens, Timon Schroeter, Stefan Harmeling, Motoaki Kawanabe, Katja Hansen, and Klaus-Robert MÃŽller. 2010. How to explain individual

[3] Hugginface pipelines `https://huggingface.co/transformers/main_classes/pipelines.html`

[4] Deepset Haystack `https://github.com/deepset-ai/haystack/`

classification decisions. *Journal of Machine Learning Research*, 11(Jun):1803–1831.

Rishav Chakravarti, Cezar Pendus, Andrzej Sakrajda, Anthony Ferritto, Lin Pan, Michael Glass, Vittorio Castelli, J William Murdock, Radu Florian, Salim Roukos, and Avi Sil. 2019. CFO: A framework for building production NLP systems. In *EMNLP-IJCNLP 2019: System Demonstrations*, pages 31–36, Hong Kong, China. Association for Computational Linguistics.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading wikipedia to answer open-domain questions. *arXiv preprint arXiv:1704.00051*.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Dumitru Erhan, Yoshua Bengio, Aaron Courville, and Pascal Vincent. 2009. Visualizing higher-layer features of a deep network. *University of Montreal*, 1341(3):1.

Jianfeng Gao, Michel Galley, and Lihong Li. 2018. Neural approaches to conversational ai. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*, pages 1371–1374.

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

Matthew Honnibal and Ines Montani. 2017. spaCy 2: Natural language understanding with Bloom embeddings, convolutional neural networks and incremental parsing. To appear.

Sarthak Jain and Byron C Wallace. 2019. Attention is not explanation. *NAACL 2019*.

Vladimir Karpukhin, Barlas Oğuz, Sewon Min, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. *arXiv preprint arXiv:2004.04906*.

Bernhard Kratzwald, Anna Eigenmann, and Stefan Feuerriegel. 2019. RankQA: Neural question answering with answer re-ranking. In *ACL*, pages 6076–6085, Florence, Italy. Association for Computational Linguistics.

Saar Kuzi, Anna Shtok, and Oren Kurland. 2016. Query expansion using word embeddings. In *Proceedings of the 25th ACM international on conference on information and knowledge management*, pages 1929–1932.

Victor Lavrenko and W Bruce Croft. 2017. Relevance-based language models. In *ACM SIGIR Forum*, volume 51, pages 260–267. ACM New York, NY, USA.

Jinhyuk Lee, Seongjun Yun, Hyunjae Kim, Miyoung Ko, and Jaewoo Kang. 2018. Ranking paragraphs for improving answer recall in open-domain question answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 565–569, Brussels, Belgium. Association for Computational Linguistics.

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

Jimmy Lin. 2019. The neural hype and comparisons against weak baselines. In *ACM SIGIR Forum*, volume 52, pages 40–51. ACM New York, NY, USA.

Yuanhua Lv and ChengXiang Zhai. 2010. Positional relevance model for pseudo-relevance feedback. In *Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval*, pages 579–586.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119.

Chen Qu, Liu Yang, Minghui Qiu, W Bruce Croft, Yongfeng Zhang, and Mohit Iyyer. 2019. Bert with history answer embedding for conversational question answering. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1133–1136.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. *OpenAI Blog*, 1(8):9.

Stephen Robertson and Hugo Zaragoza. 2009. *The probabilistic relevance framework: BM25 and beyond*. Now Publishers Inc.

Sofia Serrano and Noah A. Smith. 2019. Is attention interpretable? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2931–2951, Florence, Italy. Association for Computational Linguistics.

Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. 2013. Deep inside convolutional networks: Visualising image classification models and saliency maps. *arXiv preprint arXiv:1312.6034*.

H. Strobelt, S. Gehrmann, M. Behrisch, A. Perer, H. Pfister, and A. M. Rush. 2018. Seq2Seq-Vis: A Visual Debugging Tool for Sequence-to-Sequence Models. *ArXiv e-prints*.

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 *Advances in neural information processing systems*, pages 5998–6008.

Eric Wallace, Jens Tuyls, Junlin Wang, Sanjay Subramanian, Matt Gardner, and Sameer Singh. 2019. AllenNLP Interpret: A framework for explaining predictions of NLP models. In *Empirical Methods in Natural Language Processing*.

Shuohang Wang, Mo Yu, Xiaoxiao Guo, Zhiguo Wang, Tim Klinger, Wei Zhang, Shiyu Chang, Gerry Tesauro, Bowen Zhou, and Jing Jiang. 2018. R 3: Reinforced ranker-reader for open-domain question answering. In *Thirty-Second AAAI Conference on Artificial Intelligence*.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, R'emi Louf, Morgan Funtowicz, and Jamie Brew. 2019. Huggingface's transformers: State-of-the-art natural language processing. *ArXiv*, abs/1910.03771.

Wei Yang, Yuqing Xie, Aileen Lin, Xingyu Li, Luchen Tan, Kun Xiong, Ming Li, and Jimmy Lin. 2019. End-to-end open-domain question answering with bertserini. *arXiv preprint arXiv:1902.01718*.