Knowledge-driven Answer Generation for Conversational Search *

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Abstract

The conversational search paradigm introduces a step change over the traditional search paradigm by allowing users to interact with search agents in a multi-turn and natural fashion. The conversation flows naturally and is usually centered around a target field of knowledge. In this work, we propose a knowledge-driven answer generation approach for open-domain conversational search, where a conversation-wide entities’ knowledge graph is used to bias search-answer generation. First, a conversation-specific knowledge graph is extracted from the top passages retrieved with a Transformer-based re-ranker. The entities knowledge-graph is then used to bias a search-answer generator Transformer towards information rich and concise answers. This conversation specific bias is computed by identifying the most relevant passages according to the most salient entities of that particular conversation. Experiments show that the proposed approach successfully exploits entities knowledge along the conversation, and outperforms a set of baselines on the search-answer generation task.

1. Introduction

In conversational search systems, users can interact in a natural manner with search systems. These go beyond the traditional search task where, on a multi-turn session, users query the system until the information need is met, thus resembling the way humans interact with each other. Supporting this paradigm shift are the observations made in [Vtyurina et al., 2017], which revealed that users are receptive to conversational systems, provided that they meet users’ expectations with respect to information seeking. To this extent, two main challenges must be addressed [Huang et al., 2020; Vtyurina et al., 2017]: a) keep track of the dialog context and b) generate informative yet concise search-answers. To address a), conversational search systems adopt a query rewriting-based approach [Lin et al., 2020; Voskarides et al., 2020], which rewrites a conversational query in order to make it context-independent. Then, retrieval and re-ranking are performed to retrieve a set of relevant passages. Addressing b) requires going beyond passage retrieval, and generate a short search-answer, similar to what is accomplished in chit-chat dialogue systems [Song et al., 2018; Wang et al., 2020; Zhuang et al., 2017]. We argue that knowledge from current and previous turns is still crucial to provide the user with the most informative answer, and should be used seamlessly in addressing challenges a) and b). Knowledge about entities has proved to be important for search tasks [Dalton et al., 2014; Kato et al., 2020; Xiong et al., 2018]. Over the conversation, the interactions between different entities are expected to implicitly encode the conversational context. Therefore, whether the query re-writer perfectly manages to do coreference resolution or not, the entities that are not mentioned in the current query, but from previous turns, also shape the conversation context.

In this paper we propose a knowledge-driven answer generation system for conversational search that is aware of the context of the conversation to generate abstractive
and knowledge-driven responses. Specifically, the knowledge about entities’ interactions across a conversation will be modelled and used to condition the generation of a single and short search-answer, based on the information comprised in top-retrieved passages. Hence, the core research hypothesis of this paper is that a conversational agent’s most informative answer can be generated by considering the intersection of the rank of passages and its graph of entities. In particular, we take a knowledge-driven approach to guide the generation of the answer. First, the framework is built on top of a solid conversational response-retrieval method that is on par with state-of-the-art results on conversational search [Dalton et al. (2020a)]. Second, the answer generation is leveraged by a conversation-wide entities knowledge graph, and biased according to the relations with the entities present on the query and top passages. Therefore, combining an entities knowledge-base with a strong conversational passage ranking baseline, allows scoring already highly relevant individual passages, according to their entities relations. These can then be fed to an answer-generation Transformer [Vaswani et al. (2017)], that will produce a knowledge-enriched agent response, biased by the knowledge-base. This enables the creation of richer answers covering a wider range of information, i.e., more comprehensive answers.

Next, we discuss the related work. Section 2 details the state-of-the-art conversational response retrieval method. Section 4 proposes a knowledge-driven answer-generator. Evaluation and results discussion is presented in sections 5, 6 and 7 and concluding remarks in section 8.

2. Related Work

Open-domain conversational assistant. Research on interactive search systems started a long time ago, with the goal of developing artificial intelligent conversation search agents to aid users in a variety of search tasks in a natural manner [Belkin (1980); Croft and Thompson (1987); Oddy (1977)]. With recent developments on machine learning and deep neural networks, together with improvements on computational infrastructures, the field is once again highly active. Namely, very recently the TREC CAsT (Conversational Assistant Track) [Dalton et al. (2020a)] task introduced a multi-turn passage retrieval dataset, supporting research on conversational search systems. Current state-of-the-art approaches [Dinan et al. (2018); Lin et al. (2020); Qu et al. (2020); Voskarides et al. (2020)] overcome the need for abundant labelled data, by training self-supervised neural models on large and wide (w.r.t. topic coverage) collections such as Wikipedia [Devlin et al. (2018); Li and et al. (2019); Yang et al. (2019)]. This results in rich language models that can be applied to the several components of a conversational search agent pipeline, including addressing conversational context and passage re-ranking in each turn. Transformer models, pre-trained on large collections, have been used lately for both the task of query rewriting [Lin et al. (2020); Voskarides et al. (2020)] and passage re-ranking [Han et al. (2020); Nogueira and Cho (2019); Nogueira et al. (2019)]. In the former, the current query and previous utterances are provided as input to generate the rewritten query, and in the latter, transformer-based models are fine-tuned on a relevance classification task to then score candidate passages.

Knowledge-guided conversation response-generation. The dialogue context can be captured by tracking the conversation knowledge over the different turns. Then, given the previous utterances’ context and the current query, a natural language search-answer needs to be generated. In chit-chat dialogue generation agents, most approaches use encoder-decoder neural architectures that first encode utterances, and then the decoder generates a response [Li et al. (2016, 2017); Song et al. (2018); Wang et al. (2020); Zhuang et al. (2017)]. For knowledge-guided generation, it is necessary to bias the generator such that it attends to knowledge-specific aspects, such as entities, that convey the conversation context. In a standard setting, models are trained end-to-end and the type of answers generated is entirely dependent on the training data. An interesting approach to bias answer generation, is retrieval-based dialogue generation, in which the generator takes as input retrieved candidate documents to improve the comprehensiveness of the generated answer [Song et al. (2018); Zhuang et al. (2017)]. In Ishigaki et al. (2020) a different approach is used to bias the generator, in which to obtain query-biased responses using a recurrent neural network, a copy mechanism is used to pay special attention to overlapping terms between the document and query. In end-to-end dialog systems that incorporate external knowledge to generate answers, a common approach is
to fuse information from a knowledge-base in encoder-decoder models Qin et al. (2019); Wang et al. (2020). All these end-to-end approaches require a large dataset with annotated dialogues. In an open-domain conversational search setting, this is not feasible, as collections can be comprised by millions of passages. An alternative is to leverage on transfer-learning and use Transformer-based models pre-trained on large corpora, that have proved to be effective at abstractive summarization Raffel et al. (2019). We depart from previous work by leveraging on pre-trained transformer models for a knowledge-guided answer-generation. Given the knowledge encoded in entities relations over queries and passages, with demonstrated usefulness on search settings Dalton et al. (2014); Kato et al. (2020); Xiong et al. (2018), we propose to use the entities conversation graph to select a set of top passages that are fed to the generator, towards enforcing entity knowledge-graph bias in the generated answers.

3. Conversation-aware Passage Retrieval

In Dalton et al. (2020a) the conversational search task is defined as, given a sequence of natural language conversational query turns $T = q_1, ... q_i, ... q_n$, the conversational search task aims to find the relevance passages that fit the current conversational context.

We implemented a three-stage conversation-aware passage retrieval pipeline composed of a context tracker, a first-stage retrieval and a re-ranker. Because of the conversational characteristics of this task, the current query may not include all of the information needed to be answered. To solve this, we use as the context tracking component, a query rewriting method based on the T5 model Raffel et al. (2019). This model requires an input sequence and a target sequence given as strings. Following Lin et al. (2020), we fine-tune a T5-BASE model by providing as input the sequence of conversational queries and passages, and as target the rewritten query. In particular the input is defined as

$$ q_i [CTX] q_1 p_1 [TURN] q_2 p_2 [TURN] \ldots [TURN] q_{i-1} $$

where $i$ is the current turn, $q$ is a query, $p$ is a passage retrieved from the index by the retrieval model, and $[CTX]$ and $[TURN]$ are special tokens. $[CTX]$ is used to separate the current query from the context (previous queries and passages) and $[TURN]$ is used to separate the historical turns (query-answer pair).

The first-stage retrieval component uses a query likelihood retrieval model Zhai and Lafferty (2001) to recover a small set of passages. After the first-stage retrieval step, we re-rank the top-$n$ retrieved passages to obtain a better rank using a BERT model Devlin et al. (2018). This model generates contextual embeddings for a sentence and each of its tokens. We used a model fine-tuned on the passage ranking task Nogueira and Cho (2019) through a binary relevance classification task, where positive examples are relevant passages, and negative examples are non-relevant passages. To obtain the embeddings for a passage $p$ and a query $q$, BERT is fed with the following sequence of size $N$ tokens

$$ \text{emb} = \text{BERT}("[CLS] q [SEP] p"), $$

where $\text{emb} \in \mathbb{R}^{H \times N}$ ($H$ is BERT embedding’s size), represents the embeddings of all tokens, and $[CLS]$ and $[SEP]$ are special tokens in BERT’s vocabulary, representing the classification and separation tokens, respectively. We then extract from $\text{emb}$ the embedding of the first token, which corresponds to the embedding of the $[CLS]$ token, $\text{emb}_{[CLS]} \in \mathbb{R}^H$. This embedding is then used as input to a single layer feed-forward neural network (FFNN), followed by a softmax, to obtain the probability of the passage being relevant to the query:

$$ P(p|q) = \text{softmax}(\text{FFNN}(\text{emb}_{[CLS]})). $$

With $P(p|q)$ calculated for each passage $p$ given a query $q$, the final rank is obtained by re-ranking according to the probability of being relevant.

4. Knowledge-aware Answer Generation

In this section we address the key research hypothesis of this paper and propose a method to generate search-answers while considering the intersection between the entities in the top retrieved passages and the entities in the conversation turns.

The graph of entities is built from the top retrieved passages and queries from previous turns. Figure [1] illustrates the rationale of the proposed approach. We extract the entities from passages and queries, and then propose two
methods to explore this information: one based on the relation of entities in the query and in the passage; and one that adapts the PageRank algorithm to a graph of entities. The answer is then generated with the passages that exhibit a stronger relation with the most salient entities of the conversation until a given turn.

4.1. Entity Linking

To build the conversation-specific knowledge graph, we start by performing Entity Linking (EL) over both conversation queries and passages. Entity linking tackled the two main existing classes of entities Balog (2018): named entities and concepts. The named entities class include specific locations, people and organisations. Concepts are abstract objects that include, but are not limited to, mathematical, physical and social concepts such as, “distance”, “gravity” and “authority”. We examined several entity linkers which are focused only on named entities (e.g. AIDA Hoffart et al. (2011) and FOX Speck and Ngonga Ngomo (2014)), and on both named entities and concepts (e.g. WAT Piccinno and Ferragina (2014) and DBpedia Spotlight Daiber et al. (2013)).

4.2. Selection of the best Passages

Each passage is scored according to the entity graph of the conversation. The relation between a query \( q_i \), on turn \( i \), and a candidate passage \( p_k \), is computed as the average,

\[
\text{PassageScore}(p_k|q_i) = \sum_{e_j \in E_{p_k}} \frac{\text{EntityRank}(e_j)}{|e_j|},
\]

where the target passage \( p_k \) is scored as the sum of the \( \text{EntityRank}() \) scores of all entities \( e_j \) present in that passage. When \( E_q = \emptyset \), it is equivalent to \( \gamma = 0 \) on equation 4.

4.3. Entities with Strong Pairwise-Relations

Given that EL provides us with meaningful DBpedia identifiers for the mentions detected in text, we can obtain the relationship between two given entities, by exploiting their connections on DBpedia. This knowledge can be used to rearrange the order of the top passages provided by the previous step of our conversational system.

We can obtain a measure of entity relatedness between \( e_1 \) and \( e_2 \), two entities of interest, following the measure proposed by Milne et al. Milne and Witten (2008):

\[
\text{EntRel}(e_1, e_2|KB) = \frac{\log(\max(|E_1|,|E_2|) - \log(|E_1 \cap E_2|))}{\log(|D|) - \log(\min(|E_1|,|E_2|))},
\]

where \( E_1 \) and \( E_2 \) are the sets of all entities that link to \( e_1 \) and \( e_2 \) in the KB, respectively, and \( D \) is the set of all the entities in the KB. We use DBpedia Bizer et al. (2009) as our KB.

Using the relatedness measure, for every turn \( i \), we rearrange the top passages by considering the relatedness between the set of entities of top passages, \( E_p \), and the set of query entities from the current and past turns, \( E_q = \bigcup_{j=0}^{i-1} E_{qj} \), where \( E_{qj} \) denotes the entities of query \( q \) on turn \( j \). By considering both the current and previous
queries of the same conversation topic, we cover possible topic shifts in the conversation. The score of a passage according to the DBpedia entity relatedness, is computed as the average entity relatedness between a query \( q \), on turn \( i \), and each candidate passage \( p^k \),

\[
\text{PassageScore}(p^k|KB,q_i) = \frac{1}{|E_q||E_{p^k}|} \sum_{e_1 \in E_q} \sum_{e_2 \in E_{p^k}} \text{EntRel}(e_1, e_2|KB),
\]

where each current passage entity \( e_1 \in E_{p^k} \), is measured against every query-entity \( e_2 \in E_q \), from previous and current turns. When \( E_q = \emptyset \), we select the top-3 passages.

4.4. Conversation Knowledge Graph

In this section, we propose to look at the entire graph of entity relations that are in the top passages and query. This introduces a step change in relation to the above approach where we only looked at the relations between entities in the query and entities in each individual passage.

To represent the conversation specific knowledge, we collect all the linked entities that occur in the queries and the top passages. This results in the concatenation of the query entities vector and the matrix with the entities in the passages,

\[
\text{Map}_E = \begin{bmatrix}
\gamma & [q_{e_1}] & \cdots & [p^1_{e_1}] & \cdots & [p^N_{e_1}] \\
\vdots & \ddots & \cdots & \vdots & \cdots & \vdots \\
[q_{e_m}] & \cdots & [p^1_{e_m}] & \cdots & [p^N_{e_m}]
\end{bmatrix}
\]

where each element of the matrix is a boolean indicator of entity presence, and the \( \gamma \) variable adjusts the importance of the entities in the queries vs passages. Moreover, to allow soft context shifts within the conversation, we consider the entities present in both the current and previous queries.

The graph of entities of a given conversation is computed as

\[
\text{Graph}_E = \text{Map}_E \cdot \text{Map}_E^T.
\]

This results in the covariance matrix between different entities. We control the sparsity of the graph by cancelling entity relations below a given threshold. This allows us to compute the centrality of each entity \( e_i \) in the conversation by applying the PageRank algorithm to the conversation entity-graph:

\[
\text{EntityRank}(e_i) = \frac{1}{N} + \alpha \cdot \sum_{e_j \in \text{neighbors}(e_i, \text{Graph}_E)} \frac{\text{EntityRank}(e_j)}{|e_j|},
\]

where \( e_i \) is the target entity, \( e_j \) correspond to a neighboring entity of \( e_i \), \( \text{Graph}_E \) is the conversation’s entity graph, and the damping factor \( \alpha \) was set to 0.99. The rationale for using PageRank, is that in the top passages there will be a stronger focus on the entities that are central to the conversation, while the entities that lie outside the conversation topic will be sparsely connected to the other entities in the graph.

4.5. Answer Generation with Entity Relatedness

Having identified a set of candidate passages according to the retrieval model (eq. 3) and the entities knowledge, the goal is to generate a natural language response that combines the information comprised in each of the passages. To address this problem, we follow an abstractive summarisation approach, which unlike extractive summarisation that just selects existing sentences, can portray both reading comprehension and writing abilities, thus allowing the generation of a concise and comprehensive digest of multiple input passages. Therefore, we select the passages that maximise the expression:

\[
\arg\max_{p^k} \text{PassageScore}(p^k,q_i)
\]

and generate the agent response with the sequence of the top \( N = 3 \) passages, “\( p^1 \ p^2 \ldots \ p^N \)”. With this strategy, we implicitly bias the answer generation by asking the model to summarise the passages that are not only deemed as more relevant according to the retrieval system, but also that maximise the relatedness measure from eq. 6 or eq. 4.

This task has been commonly addressed by seq2seq models that learn to map input sequences to output sequences, but the Transformer architecture [Vaswani et al. 2017] has led to groundbreaking results, due to its high effectiveness at modelling large dependency windows of textual sequences. Thus, in this work we consider the Text-to-Text Transfer Transformer (T5) [Raffel et al. 2019] based on the encoder-decoder Transformer architecture. This model is pre-trained on the large C4 cor-
pus, which was derived from Common Crawl\footnote{https://commoncrawl.org/}. A masked language modelling objective is used, where the model is trained to predict corrupted randomly sampled tokens of varying sizes.

5. Evaluation

5.1. Datasets and Protocol

5.1.1. TREC CAS\textsc{T} Dataset

The TREC CAS\textsc{T} dataset, Dalton et al. (2020\textsc{b}), was used to evaluate both the conversational retrieval and the knowledge-aware answer generation components. There are 20 labelled conversational topics each with about 10 turns. The evaluation process uses a graded relevance that ranges from 0 (not relevant) to 4 (highly relevant). The passage collection is composed by MS MARCO Nguyen et al. (2016), TREC CAR Dietz et al. (2018), and WaPo NIST (2019) datasets, which creates a complete pool of close to 47 million passages.

5.1.2. Experimental Protocols

To evaluate the passage retrieval component we used the TREC CAS\textsc{T} setup and the official metrics, nDCG@3 (normalised Discounted Cumulative Gain at 3), MAP (Mean Average Precision), and MRR (Mean Reciprocal Rank).

In the answer generation experiment, we used METEOR and the ROUGE variant ROUGE-L. The reference passages correspond to all the passages with a relevance judgement of 3 and 4. Hence, the goal is to generate answers that cover, as much as possible, the information contained in all relevant passages, in one concise and summarised answer.

5.2. Implementation

5.2.1. Passage Retrieval

To index and search we used Pyserini\footnote{https://github.com/castorini/pyserini/} and in specific the Language Model Dirichlet (LMD) Zhai and LaF\textsc{f}erty (2001) retrieval model with the stemming algorithm Kstem\footnote{http://lexicalresearch.com/kstem-doc.txt}. To perform re-ranking, we used a BERT LARGE model fine-tuned on a binary relevance classification task on the MS MARCO dataset Nguyen et al. (2016) following Nogueira and Cho (2019). The query-rewriting component uses a T5-BASE model Raffel et al. (2019) fine-tuned on the conversational query-rewriting task using the CANARD dataset Elgohary et al. (2019), following Lin et al. (2020).

5.2.2. Entity Linking

For Entity Linking, we use DBpedia Spotlight Daiber et al. (2013) (DBS) to link general concepts and Named Entities, and the Federated Knowledge Extraction Framework Speck and Ngonga Ngomo (2014) (FOX) to link only Named Entities.

5.2.3. Transformer based answer generation

To generate the answers that summarise the entity-focused passages, we employed the T5-BASE (T5) summariser Raffel et al. (2019)\footnote{https://huggingface.co/models} fine-tuned on the summarisation task with the CNN/Daily Mail dataset Hermann et al. (2015). To generate the summary, we use 4 beams, restrict the n-grams of size 3 to only occur once, and allow for beam search early stopping when at least 4 sentences are generated. We fix the maximum length of the summary to be of the same length of the input given to the models (3 passages) and vary the minimum length from 20 to 100 words.

5.2.4. Parameters

We observed that the value of the min\_length parameter is not directly proportional to the number of words in the created summary. We can see in Figure\textsuperscript{2} an example showcasing this phenomena. For this example, the original top-3 passages are fed to the models. We select on the first graph the points corresponding to summaries of length 50, 60 and 70. We see that the different models, in order to create summaries of the same length between them, need different values for the min\_length parameter. Moreover, we can observe that summaries created with a similar number of words by the different models hold really different contents, as we can see in the graphs of the showcased metrics.
Figure 2: Showcase of how the min_length parameter can influence the number of words of a summary and its metrics values.

We can also see that the METEOR metric, much like the other applied metrics, follows the tendency established by the first graph. The ROUGE and BLEU metrics show to reach a peak in performance when setting the min_length parameter to around 80, whose value is probably related to the average length of the reference summaries used in the evaluation procedure.

In order to properly compare the different annotators we then fix the number of words of our liking and extract the min_length value that each different model requires to allow the creation of a summary with that attribute.

It is obvious that, in order to obtain the maximum possible value in METEOR, for instance, a big value for the min_length parameter has to be chosen, and to obtain a better value in ROUGE and BLEU, the min_length should be set to around 80 tokens, as easily seen in the Figure. However, by doing so, we argue that the goal of studying the generation of short and informative answers, essential for a conversational search setting, is completely missed. We believe that answers which possess the fewer words possible without losing information are the most desirable. With a quick analysis on the results yet to be presented we observed that 1) PEGASUS is the model which can present the shorter summaries out of the three models in all settings and that 2) the least number of words that all models can generate collectively applying all the proposed methods is on average 50. Because of this, we will fix the number of the summaries generated to have on average 50 words in order to better compare the different summarizers in this a setting where the least number of words possible is used to answer to a query.

6. Results and Discussion

6.1. Quantitative Results

For all experiments we report the F1 scores for ROUGE-1, ROUGE-2 and ROUGE-L, because both precision and recall are important for the setting at hands. Precision shows to be important regarding the concise nature of the created summaries and Recall captures how much of the reference summary is captured in the created summaries. We find important to report ROUGE-2 scores in conjunction with ROUGE-1 to show the fluency of the created summaries, with the intuition that the more closely the words ordering of the reference summary is followed, the more fluent the summary can be considered.

6.1.1. Answer Generation Baselines

In order to assess the performance of the proposed models, we firstly measured the various summaries pro-
duced by varying the min_length parameter from 0 to 160 tokens.

In order to study the performance of the summarizers, we established different baselines, targeting both the original rank of documents and the proposed methods to complement and aid a comparison between the results achieved by the different models. From this point forward, we will refer the proposed methods Entity Relatedness and Entity Graph Passage Scoring by their initials: ER and EG, respectively. We will refer from now on the ranked passages given by the model described in Section 3 as “O”, which stands for Original passages rank.

The baselines present in Table 1 are composed by the top-3 text passages. We can clearly see that the baseline which shows better metric values has neither the biggest or smallest number of words. It is also relevant to point out that these baselines have at least the double of words than their Top-1 counterparts but not always present better metric values.

Before showing our main experiments results, we reaffirm that the usage of full text passages as references brings an unfair comparison between the created summaries and the above baselines. The baselines shown bring forward the evidence that having the biggest number of words does not lead to better metrics and, ignoring the different number of input words, the baselines with best performance are achieved by following the proposed EG method. A more complete evaluation would use ground truth, however, this is the only feasible way regarding the dataset at hands. To compensate for this we also elaborated a human evaluation experiment whose results will be explored further ahead.

6.1.2. Answer Generation with Original Rank

We will now report the results of our first experiment, following the original ranked passages, feeding the top-3 to the different models and fixing the min_length parameter as needed to create summaries with 50 and 70 words on average.

In Figure 3 we analyze the retrieval and the answer generation performance over conversation turns by making usage of two axis showcasing different metrics. We see that peak retrieval performance is achieved on the first turn, which was expected given that the first turn is the one that establishes the topic. As the conversation progresses, retrieval performance decreases, but surprisingly, answer generation performance is overall stable. When asked to perform summaries with 70 words as average, the METEOR values displayed become less dense. We also observed that the decreases in performance are linked to sub-topic shifts within the same conversation topic and BART is the model which tends to follow more closely the trend established by the retrieval performance. We suspect this is because of his extractive behavior.

Finally, in Table 2 we illustrate the answer generation with all the three Transformers. This Table further confirms the abstractive versus extractive summarization behaviors of the different Transformers. In this example we see that T5-BASE tries to generate new sentences by combining different sentences and PEGASUS makes use of verb synonyms not seen in text in order to convey the same message but with fewer words.

6.1.3. Answer Generation with Entity Graph Rank

In the third experiment, we focus on the proposed Entity Graph Passage Scoring (Section 4.4), i.e. EG, and investigate the impact of γ on the summary quality. Figure 4 shows the summary generation quality results. On a quick glance it may appear as the scores are directly related to the number of words in the input, but with a more attentive inspection we can see that it is not quite right, as γ = 0 and γ = 0.75 have approximately the same number of words but induce different metrics performance. We observe that the best results are obtained with γ = 0.25, meaning that more weight was given to entities from top-10 retrieved passages, but entities from current and previ-
Table 1: Averaged metric values for different baselines with top-3 passages.

| Baseline       | # Words | ROUGE-1 | ROUGE-2 | ROUGE-L | BLEU-1 | BLEU-4 | METEOR |
|----------------|---------|---------|---------|---------|--------|--------|--------|
| Top-3 O        | 237.21  | 31.95   | 23.42   | 28.19   | 20.83  | 15.26  | 42.62  |
| Top-3 ED       | 205.50  | 28.88   | 17.28   | 23.54   | 18.62  | 10.97  | 34.82  |
| Top-3 ER       | 292.68  | 30.76   | 23.23   | 27.39   | 19.83  | 15.07  | 42.85  |
| Top-3 EG $\gamma = 0$ | 319.75 | 30.24   | 23.52   | 27.34   | 19.44  | 15.31  | 43.14  |
| Top-3 EG $\gamma = .25$ | 282.72 | 31.66   | 24.64   | 28.74   | 20.49  | 16.17  | 44.07  |
| Top-3 EG $\gamma = .5$   | 287.73  | 32.23   | 25.47   | 29.37   | 20.88  | 16.69  | 45.35  |
| Top-3 EG $\gamma = .75$ | 325.30 | 29.91   | 22.99   | 26.79   | 19.08  | 14.83  | 42.75  |
| Top-3 EG $\gamma = 1$    | 237.41  | 31.85   | 23.27   | 28.06   | 20.74  | 15.15  | 42.44  |

This supports our initial intuition that all entities contribute to the context of the conversation. While the conversation-aware query rewriting solves coreferences on the current query, it is still important to consider entity relations between passages, and current and all previous queries. This is further evidenced by the results with $\gamma = 1.0$ (passage entities are ignored), where it was the second best. When $\gamma = 0.0$ (query entities are ignored) performance drops, as only knowledge from passage entities is used.

For entity graph passage scoring, we selected $\gamma = 0.25$ based on the previous experiment. We observe that BART-EG overall achieves the best results although PEGASUS-EG shows to have better metric scores regarding BLEU and METEOR with summaries of 50 words. Also we notice that with this approach the addition of the query to the top-3 documents does not lead to a better performance.

Looking at the Top-1 O Trim baseline results (appended at the end of Table[3]), we can easily notice that, for summaries with 50 words, the EG approach leads to better ROUGE-1 and ROUGE-2 scores from all models. BART and PEGASUS also show to have better ROUGE-L scores than this baseline. Regarding the original Top-1 O baseline and looking at the results achieved with #W = 70 we can also notice that PEGASUS and BART far surpass this baseline regarding ROUGE-1 and ROUGE-2. As for the other metrics, these models present really close results.

To show how the performance evolves through the different turns of the conversation, we can see in Figure[5] that the “ER” approach maintains a stable performance (although it is noticeable that the “peaks” achieved by “ER” bring an overall better performance). As it was observed with the “O” method, the different models performance is evidenced by creating summaries with more words. Interestingly, we can see that “ER” follows more closely the trend established by the retrieval performance, specially with summaries with size 70.

6.2. Human Evaluation

To better assess how the different proposed methods and baseline impact the information quality, conciseness and naturalness of the answers given in the conversations, we conducted a human evaluation experiment on Amazon Mechanical Turk. In this experiment we asked that each Worker would evaluate a conversation by rating each conversation turn on two 1-5 Likert scales, with higher being better, each targeting, for each turn:

- Information Quality (IQ) - which aims to evaluate how well a answer addressed the query of the present turn, taking into account the context of the conversation.
- Naturalness and Conciseness (NC) - which aims to evaluate if the answers can be though as being created by human beings and don’t include too much extraneous information.

Each task comprised one random conversation created with a combination of model (baseline, T5-BASE, BART, PEGASUS), method (O, ER, EG) and length (50, 70). For the baseline the method is fixed as the O one and the length is not controlled. The user, of course, didn’t know...
Table 2: Answer generation example for the turn "What was the first artificial satellite?". The summaries have on average 50 words. Green sentences illustrate abstractive and blue sentences illustrate extractive summaries.

| Method     | Answer                                                                                                                                 |
|------------|---------------------------------------------------------------------------------------------------------------------------------------|
| Retrieval  | The first artificial Earth satellite was Sputnik 1. Put into orbit by the Soviet Union on October 4, 1957, it was equipped with an on-board radio-transmitter that worked on two frequencies: 20.005 and 40.002 MHz. Sputnik 1 was launched as a step in the exploration of space and rocket development. While incredibly important it was not placed in orbit for the purpose of sending data from one point on earth to another. And it was the first artificial satellite in the steps leading to today’s satellite communications. |
| Passage 1  | The first artificial satellite was Sputnik 1. It was the size of a basketball and was made by the USSR (Union of Soviet Socialist Republics) or Russia. It was launched on October 4, 1957.                                                                                       |
| Retrieval  | The first artificial satellite was Sputnik 1, launched by the Soviet Union on October 4, 1957, and initiating the Soviet Sputnik program, with Sergei Korolev as chief designer (there is a crater on the lunar far side which bears his name). This in turn triggered the Space Race between the Soviet Union and the United States. |
| Passage 2  | the first artificial satellite was launched by the ussr or Russia. it was the size of a basketball and launched on October 4, 1957. it was equipped with an on-board radio-transmitter that worked on two frequencies.it was not placed in orbit for the purpose of sending data from one point on earth to another. |
| Retrieval  | The first artificial satellite was Sputnik 1, launched by the Soviet Union on October 4, 1957. It was equipped with an on-board radio-transmitter that worked on two frequencies: 20.005 and 40.002 MHz. This in turn triggered the Space Race between the Soviet Union and the United States. |
| Passage 3  | Sputnik 1 was launched by the Soviet Union on October 4, 1957. It was the first artificial satellite in the steps leading to today’s satellite communications. It was not used to send data from one point on earth to another. Sputnik 1 triggered the Space Race between the Soviet Union and the United States. |

which combination was being asked to be evaluated in a given task. We chose to study only these combinations since encompassing all of them would result in the rise of the experiments’ complexity.

Each task was independently done by 4 different Workers which, to be able to partake in the task, had to present a minimum approval rate of 95% and had to at least have completed 100 Human Intelligence Tasks (HITs) already. Additionally, all HITs were inspected to the best of our ability and when, for a single user, a continuous session of HITs submission took place, the first and last submissions time and number of HITs performed was taken to calculate the average time spent per HIT. Users that showed an average value of less than 20 seconds had their submissions rejected and those HITs were re-submitted by other users. On total, this experiment was performed by 136 people.

In a perfect situation, we argue that the number of HITs per Worker should have been more or less the same for all Workers, to take into account extreme Workers that consistently evaluate highly/low all HITs received. However, this feature is not accessible via the Amazon Mechanical Turk platform and we did verify that the results didn’t drastically change when the top performing users were not pictured in the experiment results.

In Figure 6 we can see the obtained evaluation of Information Quality and Naturalness and Conciseness that were averaged per row. Each row comprises 20 different conversations that were evaluated each by 4 different Workers, totaling in 80 evaluations per row.

First off, we can observe that overall the Information Quality of the answers were rated higher than the Naturalness and Conciseness, as we can see in the range used in both axis. We must also be aware that the range in each
Figure 4: Input size and answer generation performance results under different $\gamma$ values for summaries of length 50.

Figure 5: Answer generation versus retrieval performance per conversation turn applying the EG method. The minimum length is 50 and 70 in the top and bottom graphs respectively.

axis is focused on portraying the differences between each score. If the axis would start at 0, the differences wouldn’t be so striking, but nonetheless would still be there.

We can easily see that the Baseline shows the worst value in terms of IQ and the best result, both in terms of IQ and NC is presented with the combination of the BART model with answers of 70 words generated with the EG method. The EG method seems to synergize well with T5-BASE with the combination of also Length 70 in terms of IQ. In terms of NC, the results suggest that the method EG coupled with PEGASUS and with Length 70 also achieves better results than other combinations.

On the other hand, the summaries of 50 words created using PEGASUS and the ER method show, on both evaluation types, low results, suggesting that this combination should not be used to this conversational search setting.

In order to better understand the final conclusions we can gather from this experiment and check if the results obtained reveal statistical significance, we performed ANOVA and paired t-tests with $\alpha = 0.05$.

With all the information gathered, these experiment results suggest the following:

- **Summaries created with 70 words on average have better Information Quality.**

In order to determine if there is an interaction effect between our three independent variables (Model, Length and Method) on our continuous dependent variables (Information Quality and Naturalness and Conciseness) we performed a three-way ANOVA test. The results targeting both dependent variables only show statistical significance when the dependent variable studied was the Information Quality. We observe that that indeed summaries
Table 3: Averaged metric values for summaries created with the top-3 documents following the Entity Graph method as input (top) plus query (bot).

| Model       | # W | ROUGE-1 | ROUGE-2 | ROUGE-L | BLEU-1 | BLEU-4 | METEOR |
|-------------|-----|---------|---------|---------|--------|--------|--------|
| T5-BASE-ER  | 31.97 | 15.07  | 24.43  | 19.97  | 8.23  | 21.13  |
| BART-ER     | 32.15 | 15.86  | 25.14  | 21.18  | 10.41 | 21.54  |
| PEGASUS-ER  | 33.35 | 16.09  | 24.89  | 23.50  | 10.13 | 24.64  |
| T5-BASE-EG  | 35.09 | 18.43  | 26.76  | 25.93  | 13.63 | 26.76  |
| BART-EG     | 35.90 | 20.08  | 28.50  | 22.19  | 11.34 | 24.37  |
| PEGASUS-EG  | 36.89 | 21.36  | 29.18  | 24.63  | 14.64 | 25.52  |
| T5-BASE-EG  | 37.08 | 20.47  | 28.19  | 25.77  | 12.76 | 27.88  |
| BART-EG     | 39.50 | 23.80  | 30.76  | 29.52  | 17.90 | 30.89  |

created with more words (70) were preferable in comparison with summaries created with fewer words (50).

This goes against our initial hypothesis that a Conversational Search answer should be short and informative but nonetheless this can make sense if our initial setting of 50 words is too short to convey the information that is required to met the conversation goal. This can also be connected with the type of questions that are asked, since there are questions that can be more straightforward answered than others. An other explanation can be that users of these systems want to know the most possible about the discussed topic, without it being overwhelming, of course.

This test also suggests that there was a statistically significant three-way interaction between Model, Length and Method, \(F(4, 342) = 2.437, p = .047\).

- **The best combinations to improve our Conversational Search system Information Quality wise are:**
  - EG method with summaries of length 70 created by BART.
  - EG method with summaries of length 70 created by T5-BASE.
  - ER method with summaries of length 70 created by PEGASUS.

We targeted the comparison of each combination of Model/Length/Method with the Baseline in order to better understand if the combinations indeed lead to a better system performance and were not achieved by mere chance. A paired-samples t-test was conducted to compare the IQ and NC (averaged per topic) separately, in the conditions where the combination of Model/Length/Method were and were not applied.

Focusing the dependent variable IQ, there was a significant difference in the scores for the BART/70/EG (\(M = 4.05, SD = .33\)) and the Baseline (\(M = 3.74, SD = .31\)) conditions, \(t(19) = -3.25, p = 0.004\). There was also a significant difference in the scores for the T5-BASE/70/EG (\(M = 4, SD = .32\)) and the Baseline conditions, \(t(19) = -2.68, p = 0.015\). Additionally, a significant difference in the scores for the PEGASUS/70/ER (\(M = 3.93, SD = .3\)) and the Baseline conditions was found, \(t(19) = -2.22, p = 0.039\).

These results suggest that these combinations really do have an impact on the IQ perceived in the conversations. Specifically, our results suggest that when these combinations are applied, the systems performance in terms of Informational Quality increases.

In order to better understand if any of these combinations were indeed superior to the other two, we performed a second paired-samples t-test, but didn’t find statistical relevant results both in terms of IQ and NC.

It’s interesting to notice that the best performing combinations make usage of the proposed methods. We can see in the Table 4 the results of the human evaluation in the
Figure 6: Averaged values of the human evaluation in terms of Information Quality, Naturalness and Conciseness per combination of Length, Model and Method. Each table pane shows a vertical gray line which represents the average of each Model with the different Lengths set.

| IQ | Model | Length | Method | T5-BASE | BART | PEGASUS |
|----|-------|--------|--------|---------|------|---------|
|    |       | 50     | O      | 77.5 (+2.6) | 78.0 (+3.1) | 76.3 (+1.5) |
|    |       | 50     | ER     | 78.9 (+4.0) | 78.3 (+3.4) | 75.0 (+0.1) |
|    |       | 50     | EG     | 76.0 (+1.1) | 75.5 (+0.7) | 78.7 (+3.9) |
|    |       | 70     | O      | 78.9 (+4.0) | 77.9 (+3.0) | 77.8 (+2.9) |
|    |       | 70     | ER     | 76.5 (+1.6) | 78.7 (+3.8) | 78.7 (+3.8) |
|    |       | 70     | EG     | **80.2 (+5.3)** | **81.2 (+6.3)** | 77.8 (+2.9) |

| NC | Model | Length | Method | T5-BASE | BART | PEGASUS |
|----|-------|--------|--------|---------|------|---------|
|    |       | 50     | O      | 73.6 (+2.6) | 73.2 (+2.2) | 70.5 (+0.5) |
|    |       | 50     | ER     | 72.0 (+1.0) | 72.1 (+1.1) | 70.7 (+0.3) |
|    |       | 50     | EG     | 72.15 (+1.2) | 71.2 (+0.2) | 72.3 (+1.4) |
|    |       | 70     | O      | 74.1 (+3.1) | 72.9 (+1.9) | 71.81 (+0.8) |
|    |       | 70     | ER     | 70.5 (+0.5) | 70.85 (+0.1) | 72.2 (+1.2) |
|    |       | 70     | EG     | 72.6 (+1.6) | 75.7 (+4.8) | 75.0 (+4.9) |

Table 4: Human evaluation side-by-side results on a 1-100 scale. Baseline reports the mean value of 74.85 in terms of IQ and 70.97 in terms of NC. Bold values are statistically significant, difference between baseline is shown between parenthesis in percentage and underlined values show the best score achieved by each model.

scale of 0-100 in order to better visualize the differences between each combination. Regarding the BART/70/EG combination, we can see an improvement of over 6%.

7. Discussion

We deem useful to use automatic metrics (ROUGE, BLEU, METEOR) as proxies for measuring quantitatively the results achieved by the different models with the different proposed methods. However, these only provide limited information and don’t give forward information regarding fluency and information needs met.

To this regard, options which were shown to not improve metric scores can still be considered for a further analysis since they can contribute for more natural and informative answers.

7.1. Analysis of the Conversational Answers created with Added Query

When using the query jointly with the top-3 passages, interesting cases arose in which the query was “woven” into the summary, producing a much natural and desirable answer. We can see an example of this phenomena in Table 5.

There are cases in which the addition of the query 1) does not lead to any different in the creation of the summary, 2) makes the summary use the same words but with a different ordering (usually starting with the words seen
Table 5: Different answers given by the different model approaches for the question “What is the largest shark ever to have lived on Earth?”

| Model Approach | Description |
|----------------|-------------|
| PEGASUS-O      | The megalodon is an extinct species of shark that roamed the waters of Earth over 1.5 million years ago. Although now extinct, it is still listed in the Guinness World Records as the largest shark (…)|
| PEGASUS-O•wQ  | The largest shark to have ever lived on Earth is thought to have been the megalodon. Although now extinct, it is still listed in the Guinness World Records as the largest shark (…)|

in the query) and 3) changes completely the summary created, with no similarity between the original and added query approaches.

7.2. Analysis of the Conversational Answers with the Entity Density filter

As with other methods, the application of the Entity Density filter does not automatically imply a different answer generation. Looking at the overall filtered passages, it is noticeable cases in which the filter acts as expected, as demonstrated in Table 5.

However we observed cases in which the filter removed phrases which could bring relevant information forward. It was also noticeable that some top-3 texts gather a lot of irrelevant information forward but the ED method could not be applied, since the confidence parameter of Entity Linkers set could lead to the identification of relevant concepts amidst the text. We believe that for texts with a bigger number of words this confidence parameter should be set higher in order to better curate information by being more critical about the contents to be selected.

We invite the reader to visit our Conversation Interactive Explorer and check the differences in quality that each available parameter can have in the showcased conversations.

7.3. Analysis of a Conversation Knowledge Graph

Figure 7 depicts the entity graph of the top-10 passages, from a conversation turn focused on the entity “The Avengers”. The top-3 passages and corresponding answer summary made by T5-BASE can be seen in Table 7. From the graph we can identify top entities (dark blue), the most salient entities for the current turn of the present topic, and bottom entities (light blue), which are connected to top entities but are not so central. As such, passages that have a better coverage of those entities (according to eq. 4), are expected to be ranked higher. We can see that the 3 passages in Table 7 gather both top and bottom entities. Using these passages as targets to the answer generation component, we can see that the produced answer ends up accounting for all this information and successfully answers the given query.

8. Conclusions

In this paper we proposed a knowledge-aware answer generation method that considered the conversation specific graph of entities. The key findings of this paper are as follows:

1. Knowledge-aware Search-Answer Generation. The proposed method was able to abstract the information contained in multiple passages to generate a single, yet informative, search-answer. This reduces the burden on the user that now only needs to read a snippet long answer containing links to multiple passages.

2. Conversation-specific Knowledge-Graph. The quality Knowledge-graph creation process is directly influenced by the quality of the retrieved passages. A fundamental step in the creation of Conversation Knowledge-graphs was a state-of-the-art conversational search baseline that we used to select the seeds for the graph creation process.

3. Conversation-specific Rank of Entities. The final critical element in the proposed method, concerns the ranking of entities by their importance during the conversation. We applied a modified PageRank algorithm to detect the salient entities along the con-

https://knowledge-answer-generation.herokuapp.com
Table 6: Different processed text passages to give answer to a question about blood.

| BART-EG                      | BART-EG-ED                              |
|------------------------------|----------------------------------------|
| Confidence votes 133. Red blood cells are produced in the bone marrow. Red blood cells are also known as erythrocytes (...) | Red blood cells are produced in the bone marrow. Red blood cells are also known as erythrocytes (...) |

Figure 7: Conversation entity graph for the topic “The Avengers”. The graph considers the most salient entities of the top-10 passages.

The results presented in this paper support the initial hypothesis and opened other questions that we plan to investigate in the future. The first one being related to the quality of entity-linkers, which may be further improved. The second concerns the research of models that can seamlessly combine the Transformer architecture advantages with the conversation knowledge-graphs.

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Table 7: Answer generation example. The summary minimum length is set to 90. The top and bottom entities are highlighted in blue and light blue respectively.

| Query Turn: | Who are The Avengers? |
|---|---|
| **Passage 1** | The Avengers (2012 film) Marvel’s The Avengers (classified under the name Marvel Avengers Assemble in the United Kingdom and Ireland), or simply The Avengers, is a 2012 American superhero film based on the Marvel Comics superhero team of the same name, produced by Marvel Studios and distributed by Walt Disney Studios Motion Pictures. |
| **Passage 2** | Marvel’s The Avengers (Marvel Avengers Assemble in the UK and Ireland) more commonly known as The Avengers, is a 2012 American superhero film, scripted and directed by Joss Whedon, based on the Marvel Comics superhero team of the same name. The film stars an ensemble cast consisting of Robert Downey, Jr., Chris Evans, Mark Ruffalo, Chris Hemsworth, Scarlett Johansson, Jeremy Renner, Tom Hiddleston, Clark Gregg, Cobie Smulders, Stellan Skarsgård and Samuel L. Jackson. In The Avengers, Nick Fury (Jackson), director of the peacekeeping organization S.H.I.E.L.D., recruits Iron Man (Downey), Captain America (Evans), the Hulk (Ruffalo), and Thor (Hemsworth) to form a team that must stop Thor’s adoptive brother Loki (Hiddleston) from subjugating Earth. |
| **Passage 3** | The Avengers (also known as Marvel’s The Avengers and classified in the UK and Ireland under the title Marvel Avengers Assemble) is a 2012 American superhero film produced by Marvel Studios and distributed by Walt Disney Studios Motion Pictures, based on the Marvel Comics superhero team of the same name. |
| **TS-BASE Answer** | The Avengers is a 2012 american superhero film based on the Marvel comics superhero team of the same name. the film stars an ensemble cast consisting of Robert Downey, Jr., Chris Evans, Mark Ruffalo, Chris Hemsworth, Scarlett Johansson and Jeremy Renner. In the film, Nick Fury recruits Iron man, Captain America, the Hulk and Thor to form a team that must stop Loki from subjugating earth. |
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