Large Scale Question Answering using Tourism Data

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Abstract

Real world question answering can be significantly more complex than what most existing QA datasets reflect. Questions posed by users on websites, such as online travel forums, may consist of multiple sentences and not everything mentioned in a question may be relevant for finding its answer. Such questions typically have a huge candidate answer space and require complex reasoning over large knowledge corpora.

We introduce the novel task of answering entity-seeking recommendation questions using a collection of reviews that describe candidate answer entities. We harvest a QA dataset that contains 48,147 paragraph-sized real user questions from travelers seeking recommendations for hotels, attractions and restaurants. Each candidate answer is associated with a collection of unstructured reviews. This dataset is challenging because commonly used neural architectures for QA are prohibitively expensive for a task of this scale. As a solution, we design a scalable cluster-select-rerank approach. It first clusters text for each entity to identify exemplar sentences describing an entity. It then uses a scalable neural information retrieval (IR) module to subselect a set of potential entities from the large candidate set. A reranker uses a deeper attention-based architecture to pick the best answers from the selected entities. This strategy performs better than a pure IR or a pure attention-based reasoning approach yielding nearly 10% relative improvement in Accuracy@3 over both approaches.

1 Introduction

Recent question answering tasks such as those based on reading comprehension require answers to be generated either based on a single passage, or after reasoning over multiple passages (or small-sized documents) (e.g. SQuAD (Rajpurkar, Jia, and Liang, 2018), HotpotQA (Yang et al., 2018), NewsQA (Trischler et al., 2016)). Answers to questions are assumed to be stated explicitly in the documents (Rajpurkar, Jia, and Liang, 2018) and can be derived with single or multi-hop reasoning over sentences mentioning facts (Yang et al., 2018). Other variants of these tasks add an additional layer of complexity where the document containing the answer may not be known and needs to be retrieved from a large corpus before answers can be extracted/generated (e.g. SearchQA (Dunn et al., 2017), MS MARCO (Nguyen et al., 2016), TriviaQA (Joshi et al., 2017)). While these datasets have been useful in furthering research in comprehension, inference and reasoning, we find that they do not always reflect all the complexities of real-world question answering.

For example, consider the question in Figure 1. Here the user describes who they are, what they are looking for, as well as their preferences for the expected answer. They also mention that they are looking forward to the trip and are going to be first time visitors to the city. Answering such questions requires understanding the relevant parts of the question, reading information about each candidate answer entity in travel articles, blogs or reviews (entity documents), matching relevant question parts with entity documents, and ranking each candidate answer based on the degree of match.

The foremost challenge in building a QA system for this task is model scalability. Typical QA algorithms apply cross-attention between question and candidate answer texts, which will not scale in our case where entities may have long entity documents (see Table 1 for comparison of document sizes across different QA datasets). More-
over, the candidate answer spaces for this problem are very high (e.g., New York has tens of thousands of restaurants to choose from), affecting scalability further. There are other technical challenges as well – the entity documents include reviews written by users, which can be informal and noisy, and may contain subjective contradictory opinions. An entity document may even discuss other entities (e.g., for comparison), making reasoning even harder. Finally, not all aspects of the question are relevant for answering which makes identifying the informational need challenging. It is worth noting that the question in Figure 1 is almost as large as the reading comprehension paragraphs used in tasks such as SQuAD.\footnote{Average size of paragraphs in SQuAD is 140 tokens}

**Contributions:** We introduce the novel task of answering entity-seeking recommendation questions using a collection of reviews describing entities. It is inspired by the recent work on parsing multi-sentence questions (Contractor et al., 2019). Our work differs from theirs, because they do not attempt to solve this QA task end-to-end and, instead, rely on a pipeline of semantic parsing and querying into a Web API. In contrast, we harvest a novel dataset of tourism questions consisting of 48,147 QA pairs collected from online travel forums. Each QA pair consists of a question and an answer entity ID, which corresponds to one of the over 200,000 entity review documents collected from the Web. The entities in our dataset are hotels, restaurants and general attractions of interest in 50 cities across the world. Gold-answer entities are extracted from mentions in full text user responses to the actual forum post. To the best of our knowledge, we are the first to propose and attempt such an end-to-end task using a collection of entity reviews.

We also present our solution that addresses some of the challenges in our task. In addition to a QA task, our task can also be viewed as an instance of information retrieval (IR), since we wish to return entity documents (equivalent to returning entities), except that the query is a long question. IR models are more scalable, as they often have methods aimed at primarily matching and aggregating information (Mitra and Craswell, 2018). Thus, these models typically do not achieve deep reasoning, which QA models do, but as mentioned previously, deeper reasoning in QA models (e.g. using multiple layers of cross attention) makes them less scalable. We propose a Cluster-Select-Rerank (CSRQA) architecture for our task, drawing from strengths of both.

CSRQA’s cluster step clusters sentences of each entity document in embedding space and picks exemplar sentences to create smaller representative documents for each entity. This reduces document sizes by 70% and helps improve scalability. Its select step trains a fast and scalable CNN-based neural IR method, Duet (Mitra and Craswell, 2019), to provide a preliminary ranking of all candidate entities. The top entities returned by Duet are selected for deeper reasoning by the rerank step, which uses cross attention between question and entity documents to provide a final score for each selected entity. Our experiments demonstrate that using CSRQA’s three step architecture results in better performance (over 10% relative improvement in Accuracy@3) than relying only on either retrieval or deeper reasoning.

## 2 Related Work

Recent QA datasets such as those based on reading comprehension require answers to be generated from either a single passage (Trischler et al., 2016; Rajpurkar, Jia, and Liang, 2018) or after reasoning over multiple passages (Yang et al., 2018).
often the answer passages containing the answer may not be known and may need to be fetched from a large collection (Nguyen et al., 2016; Dunn et al., 2017; Joshi et al., 2017). Models for these tasks typically use variants of TF-IDF like BM25 (Robertson and Zaragoza, 2009) to retrieve and sub-select candidate documents (Chen et al., 2017); reasoning is then performed over this reduced space to return answers.

The goal of information retrieval (IR), specifically document retrieval tasks, is to retrieve documents for a given query. Typical queries in these tasks are short, though some IR works have also studied long queries (Agichtein et al., 2015). Documents in such collections tend to be larger than passages and often retain structure – titles, headings, etc. Neural models for IR focus on identifying good representations for queries and documents to maximize mutual relevance in latent space (Mitra and Craswell, 2018). To improve dealing with rare words recent neural models also incorporate lexical matching along with semantic matching (Mitra, Diaz, and Craswell, 2017).

Our task is a QA task that also shares characteristics of IR, because, similar to document retrieval, answers in our task are associated with long entity documents, though they are without any additional structure. However, unlike typical retrieval tasks, the challenge for answering is not merely that of semantic gap – subjective opinions need to be reasoned over and aggregated in order to assess relevance of the entity document. This is similar to other reading comprehension style QA tasks that require deeper reasoning over text. We believe that this setting brings together an interesting mix: (i) a large search space with large documents (like in IR), and that (ii) answering cannot rely only on methods that are purely based on semantic and lexical overlap (it requires reasoning). In response, we present a coarse-to-fine algorithm that sub-selects documents using IR and trains a deep reasoner over the selected subset.

### 3 Task Definition & Data Collection

**Task Definition:** Given an entity seeking recommendation question (q), its target class (t ∈ {hotel, attraction, restaurant}), the city c, a candidate space of entities $E^c_t$ for each corresponding city and entity class, a collection of their reviews $R^c_t$; the goal of this task is to find the correct (gold) answer entity $a \in E^c_t$ using the documents $R^c_t$ describing the candidate answer entities.

**Data Collection:** Our dataset contains QA pairs for 50 cities. We crawled forum posts, reviews for restaurants and attractions for each city from a popular travel forum. Hotel reviews were scraped from a popular hotel booking website. With each question, we also collected the corresponding conversation thread along with its meta-data such as the date and time of posting. Entity meta-data such as the address, ratings, amenities, etc was also collected where available.

It was observed that apart from questions, users also post summaries of trips, feedback about services taken during a vacation, open ended non entity-seeking questions such as queries about the weather and economic climate of a location, etc. Such questions were removed by precision oriented rules which discarded questions that did not contain any one of the phrases in the set ["recommend", "suggest", “where”, “place to” “best”].

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2 https://trec.nist.gov/data/test_coll.html
and “option”). We further removed posts explicitly identified as “Trip Reports” or “Inappropriate” by the forum. Excessively long questions (≥ 1.7X more than average) were also removed.

3.1 Answer Extraction

We create a list of entity names crawled for each city and use it to find entity mentions in user responses to forum posts. A high level entity class (hotel, restaurant, attraction) for each entity is also tagged based on the source of the crawl. Each user response to a question is tagged for part-of-speech, and the nouns identified are fuzzily searched in the entity list (to accommodate for typographical errors). This gives us a noisy set of “silver” answer entities extracted from free text user responses for each question. We now describe a series of steps aimed at improving the precision of extracted silver answers, resulting in our gold QA pairs.

3.2 Filtering of Answer Entities

**Question Parsing:** As a first step, we use the multi-sentence question understanding component developed by Contractor et al. (2019) to identify phrases in the question that could indicate a target entity’s “type” and “attribute”. For instance, in the example in Figure 1 tokens “place to stay” will be identified as an entity.type while “convenient to the majority of first time visitors” will be identified as entity.attribute.

**Type-based filtering:** All entities collected from the online forums are pre-labeled from a list of nearly 210 unique labels indicating the nature of the entity. For instance, restaurants have cuisine types mentioned, attractions are tagged as museums, parks etc. Hotels from the hotel booking website are simply identified as hotels. We manually cluster the unique labels into 11 clusters. For a given question we use the phrase tagged with the entity.type label from the question parse, and determine its closest matching cluster. Similarly, for each silver answer entity extracted we identify the most likely cluster given its tagged attribute list; if the two clusters do not match, we drop the QA pair.

**Peer-based filtering:** Using all silver answers for a question, we determine the frequency counts of each entity type encountered (an entity can be labeled with more than one entity type by the online forum). We then compare each entity with the most frequent type and remove any entity that does not belong to the majority type.

**Filtering entities with generic names:** Some entities are often named after cities, or generic place types – for example “The Cafe” or “The Spa” which can result in spurious matches during answer extraction. We collect a list of entity types from Google Places and remove any answer entity whose name matches any entry in this list.

**Removing entities that are chains and franchises:** Answers to questions can also be names of restaurant or hotel chains without adequate information to identify the actual franchisee referred. In such cases, our answer extraction returns all entities in the city with that name. We thus, discard all such QA pairs.

**Removing spurious candidates:** User answers in forum posts often have multiple entities mentioned not necessarily in the context of an answer but for locative references (e.g. “opposite Starbucks”, or “near Wendys”) or for expressing opinions on entities that are not the answer. We write simple rules to remove candidates extracted in such conditions (e.g.: if more than one entity is extracted from a sentence, we drop them all or if entity mentions are in close proximity to phrases such as “next to”, “opposite” etc. they are dropped). Additionally, we review the set of entities extracted and remove QA pairs with entity names that were common English words or phrases (eg : “August”, “Upstairs”, “Neighborhood” were all names of restaurants that could lead to spurious matches). We remove 322 unique entity names as a result of this exercise. Note that it is the only step that involved human annotation in the data collection pipeline.

3.3 Data Characteristics

For our dataset, the average number of tokens in the questions is approximately 73, which is comparable to the document lengths for some existing QA tasks. Additionally, our entity documents are larger than the documents used in existing QA datasets (See Table 1) – our entity documents contain 3266 tokens on average. Lastly, answering any question requires studying all the possible en-

| Training | Validation | Test |
|----------|------------|------|
| #Ques. | QA Pairs | Tokens per ques. | QA Pairs | QA Pairs | QA Pairs |
| | with Hotels | with Restr. | with Attr. |
| 18,531 | 38,586 | 73.30 | 4,819 | 30,106 | 3.661 |
| 2,307 | 4,831 | 73.29 | 639 | 3,789 | 411 |
| 2,283 | 4,730 | 73.29 | 595 | 3,736 | 399 |

Table 2: QA Pairs in train, validation and test sets

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3 https://developers.google.com/places/web-service/supported_types
entities in a given city – the average number of candidate answer entities per question is more than 5,300 which further highlights the challenges of scale for this task.

The total number of entities in our dataset is 216,033. In almost every city, the most common entity class is restaurants. On average, each question has 2 gold answers extracted. Statistics about the train, test and validation splits as well as details about the knowledge source are summarized in Tables 2 and 3. Samples of review documents of entities and QA pairs, are available for reference in the supplementary material.

3.3.1 Qualitative study

We studied 450 QA pairs, representing approximately 1% of the dataset, for errors in the automated dataset collection. We found that our high precision filtering rules described previously have an answer extraction accuracy of 82%. The errors can be traced to one of four major causes (i) (16%) Entity name was a generic English word (e.g. “The Park”) (ii) (27%) Entity matched another entity in the answer response which was not intended to be the answer entity to the original question. (e.g. Starbucks in “next to Starbucks”) (iii) (31%) Entity matched another entity with a similar name but of a different target class (e.g. hotel with same name instead of restaurant). (iv) (13%) Failing to detect negations/negative sentiment (e.g. an entity mention in a post where the user says “I wouldn’t go there for the food”. (v) The remaining 13% of the errors were due to errors such as invalid questions (non-entity seeking), or incorrect answers provided by the forum users.

4 The Cluster-Select-Rerank Model

We now describe our model that trains on our dataset to answer a new question. Our model uses a cluster-select-rerank approach and combines benefits of both IR and QA architectures. We name it CSRQA. It consists of three major components: (1) a clustering module to generate representative entity documents, (1) a fast scalable retrieval model that selects candidate answers and reduces the search space, and (iii) a QA-style reranker that reasons over the selected answers and scores them to return the final answer.

4.1 Training Objective

Since we formulate the task as a ranking problem, we train the model to score a gold answer higher than an incorrect answer (Rao, He, and Lin, 2016; Lai, Bui, and Li, 2018). Specifically, given an entity document \(d_e\) and a question \(q\), the model generates a score \(s_q^e\) for the entity with respect to \(q\) by computing a weighted dot product \(s_q^e = qWd_e\) and we would like \(s_q^e > s_q^n\) for a correct entity \(p\) and a negative entity \(n\) (sampled). This is easily specified to the model by using max-margin loss
Let \( (\max(0, s_p^q - s_n^q + \delta)) \) as the objective function.

We now describe each of the components in detail.

### 4.2 Cluster: Representative Entity Document Creation

As stated previously, entity documents in our dataset are much larger than documents used by previous QA tasks. Further, in contrast to typical machine reading or multi-hop reasoning tasks, which require reasoning over a few paragraphs, we need to read over 5,000 entities (on average) before selecting each candidate. Existing systems that operate in similar settings (Chen et al., 2017; Wang et al., 2018) prune the search space before running deeper reasoning models. They often employ methods such as those based on BM25 (Robertson and Zaragoza, 2009) ranking to get a small set of precise candidates (usually top-10) (Chen et al., 2017; Wang et al., 2018). As the results in our subsequent section show (see Table 4), these methods perform poorly on our task due to the nature of documents (unstructured entity reviews) – such models just have an accuracy at top 30 of approximately 30%, and thus cannot be used to prune the candidate space effectively.

Thus, we choose neural models for both retrieval and reasoning. In order to make training a sufficiently expressive neural model tractable, CsrQA first constructs smaller representative documents\(^4\) for each entity using the full entity documents (containing all reviews for an entity). It encodes each review sentence using the pre-trained universal sentence encoder (USE) (Cer et al., 2018) to generate sentence embeddings. It then clusters sentences within each document and uses the top-\(k\) (nearest to the cluster centroid) sentences from each cluster to represent the entity.

In our experiments we use \( k = 10 \) and generate 10 clusters per entity, thus reducing our document size to 100 sentences each. This constitutes an approximately 70\% reduction in document size. We note that despite this reduction our problem continues to be large-scale. This is because our documents are still larger than those used in most QA tasks. And, before returning an answer to a question, we still have to explore over 500 times more documents, as compared to most existing QA tasks.

\(^4\)our representative documents are a set of review sentences

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### 4.3 Select: Shortlisting Candidate Answers

In this step, CsrQA trains a neural retrieval model with the question as the query and representative entity documents as the text corpus. As its retrieval model, it uses the recently improved Duet (Mitra and Craswell, 2019) network. Duet is an interaction-based neural network that compares elements of the question with different parts of a document and then aggregates evidence for relevance. It uses both local as well as distributed representations to capture lexical and semantic features. It is quite scalable for our task, since its neural design is primarily based on CNNs (Figure 2 (a)).

Duet is trained over the QA-pair training dataset and randomly sampled negative examples as outlined earlier, but uses cross-entropy loss. Duet can be seen as ranking the full candidate answer space for a given question, since it scores each representative entity document. CsrQA selects the top-50 candidate entities from this ranked list for a deeper reading and reasoning.

### 4.4 Rerank: Answering over Selected Candidates

In this step, our goal is to perform careful reading and reasoning over the shortlisted candidate answers to build the best QA system. We began by trying to adapt traditional reading comprehension QA models such as BiDAF (Seo et al., 2016) for our task, but we found they were infeasible to run – 1 epoch using 10 negative samples per QA pair, and our representative entity documents, took BiDAF over 43 hours to execute on 4 K-80 GPUs. Running just the trained BiDAF model on our test data was projected to require over 220 hours. Similarly, we also tried using models based on BERT fine-tuning, but again, it did not scale for our task.

In the absence of obvious scalable QA baselines, CsrQA implements a simpler model for reranking – a Siamese network with recurrent encoding and attention-based matching.

**Input Layer:** It uses 128-dimensional word2vec embeddings (Mikolov et al., 2013) to encode each word of a question and a representative entity document. It uses a three layer bi-directional GRU (Cho et al., 2014), which is shared between the question and the review sentence encoder.

**Self Attention Layer:** It learns shared self-attention (intra-attention) weights for questions and representative entity documents (Cheng,
Dong, and Lapata, 2016) and generates attended embedding representations for both.

**Question-Entity Attention (QEA) Layer:** In order to generate an entity embedding, it attends over the sentence embeddings\(^5\) of its representative entity document, with respect to the question (Luong, Pham, and Manning, 2015). This helps identify “important” sentences and the sentence embeddings are then combined based on their attention weights to create the entity embedding. Thus, the entity embeddings are question-dependent.

**Scoring Layer:** Finally, given a question and the entity embedding, the model uses a weighted dot product between the two vectors to generate the score that is used to compute the max-margin loss. The model is summarized in Figure 2 (b).

5 Experiments

We ask the following questions in our experiments: (1) What is the performance of the CSRXQA model compared to other baselines for this task? (2) How does the CSRXQA model compare with neural IR and neural QA models? (3) What are the characteristics of questions correctly answered by our system?

**Metrics:** We use Accuracy@N metrics for evaluating a QA system. For a question \(q\), let the set of top ranked \(N\) entities returned by the system be \(E_N\), and let the correct (gold) answer entities for the question be denoted by set \(G\). We give credit to a system for Accuracy@N if the sets \(E_N\) and \(G\) have a non-zero intersection. We also use the standard mean reciprocal rank (MRR) metric. To compute MRR score we only consider the highest ranked gold answer, if multiple gold answers exist for a question.

**Hyper-parameter Settings:** For all experiments we set \(\delta = 1\) in our max-margin criterion. We used Adam Optimizer (Louizos, Welling, and Kingma, 2018) with a learning rate of 0.001 for training. The convolution layers in the Duet model (retriever) used kernel sizes of 1 and 3 for local and distributed interactions respectively. Hidden nodes were initialized with size of input word embeddings, 128 dimensions. The reasoning network (re-ranker) was trained for 5 days on 6 K80 GPUs (approx. 14 epochs models) using 10 negative samples for each QA pair. We used 3-layer 128-dimensional bidirectional GRUs to encode questions and review sentences. Input word embeddings were updated during training and USE embeddings returned 512 dimension embeddings. Training the reasoning network (re-ranker) took 11.5 hours per epoch on 4 K-80 GPUs. The CSRXQA model is trained on negative samples from the Duet model with curriculum learning.

5.1 Models for comparison

As discussed previously, existing neural QA models do not scale for our task. We therefore, compare the performance of CSRXQA with several natural baselines for our task.

**Random Entity Baseline:** Returns a random ranking of the candidate answer space.

**Ratings Baseline:** Returns a global (question-independent) ranking of candidate entities based on user ratings.

**BM25 Retrieval:** We index each entity along with its reviews into Lucene\(^6\). Each question is transformed into a query using the default query parser that removes stop words and creates a disjunctive term query. Entities are scored and ranked using BM25 ranking (Robertson and Zaragoza, 2009). Note that this baseline is considered a strong baseline for information retrieval (IR) and is, in general, better than most neural IR models (McDonald, Brokos, and Androutsopoulos, 2018).

**Review-AVG Model:** This baseline uses averaged vector embeddings of the review sentences to represent each document - we use universal sentence embeddings (USE) (Cer et al., 2018) to pre-compute vector representations for each sentence and average them to create a document representation. Questions are encoded using a self-attended bi-directional GRU (Cheng, Dong, and Lapata, 2016) to generate a question representation. An entity is scored via a weighted dot product between question and document embeddings.

**RSRQA:** This model highlights the value of the clustering step and the creation of representative entity documents. Unfortunately, if we give the full entity document instead of a representative one, the neural select-rerank model cannot be trained due to GPU memory limitations. We also tried to create a model that uses document representations by selecting 100 sentences from an entity document by indexing them in Lucene and then using the question as a query. We found

\(^5\)obtained from the Self Attention Layer

\(^6\)http://lucene.apache.org/
Table 4: Performance of different systems including the CSRQA model on our task. Accuracy report in %.

| Method        | Acc@3 | Acc@5 | Acc@30 | MRR  |
|---------------|-------|-------|--------|------|
| Random        | 0.35  | 0.48  | 3.98   | 0.008|
| Ratings       | 0.39  | 0.83  | 3.46   | 0.007|
| BM25          | 6.78  | 9.97  | 30.58  | 0.073|
| Review-AVG    | 7.97  | 11.91 | 30.9   | 0.084|
| RSRQA         | 11.88 | 17.30 | 52.14  | 0.122|
| CSQA          | 17.03 | 23.65 | 54.90  | 0.168|
| CSRQA         | 18.27 | 23.90 | 53.70  | 0.169|
| CSRQA         | 20.29 | 27.61 | 58.21  | 0.179|

Table 4: Performance of different systems including the CSRQA model on our task. Accuracy report in %.

that this method, understandably, returned very few sentences – the questions (query) are longer than a sentence on average and the lexical gap is too big to overcome with simple expansion techniques. So, in this model, we replace the clustering phase of our CSRQA model and use 100 randomly-selected review-sentences to represent entities.

**CSQA**: This model returns answers by running the neural information retrieval model, Duet, on the clustered representative documents. This model is effectively the CSRQA model but without re-ranking.

**CRQA**: This model returns answers by running the reasoner directly on the clustered representative documents. Thus, this model does not use neural IR to select and reduce the candidate search space.

### 5.2 Results

Table 4 compares CSRQA against other models. We find that all non-neural baselines perform poorly on the task. Even the strong baseline of BM25 retrieval, which is commonly used in retrieval tasks, is not as effective for this dataset. Methods such as BM25 are primarily aimed at addressing challenges of semantic gap while in our task, answers require reasoning over subjective opinions in entity documents. We also observe that the performance of the neural model, Review-AVG, is comparable to that of BM25.

The RSRQA model that runs Duet along with our reasoner, on entity documents containing randomly sampled review-sentences, has a significantly lower Acc@3 of 11.88%. In contrast, both the CSQA and CRQA models, that use the clustered representative entity-documents have higher accuracy than RSRQA. Our final model CSRQA has an Acc@3 of approximately 20.29% (last row).

We also find that the CSRQA model does better than CRQA. We attribute the gain in using CSRQA over CRQA to the fact that training the reasoner is compute intensive, and it is unable to see many hard negative samples for a question even after a long time of training. Due to this it optimizes its loss on the negatives seen during training, but may not perform well when the full candidate set is provided. On the other hand, in the complete CSRQA model, the select module shortlists good candidates a priori and the reasoner’s job is limited to finding the best ones from the small set of good candidates.

Comparing CSRQA and CSQA suggests that, while the scalable matching of Duet is useful enough for filtering candidates, it is not good enough to return the best answer. On the other hand the CSRQA model has a reasoner specifically trained to re-rank a harder set of filtered candidates and hence performs better.

Overall, we find that each component of CSRQA is critical in its contributing towards its performance on the task. Moreover, strong IR only and QA only baselines are not as effective as their combination in CSRQA. Non-neural models including BM25 are also not effective for this task.
5.3 Answering Characteristics

We study the performance of different configurations used in the ablation study. The plots in Figure 3 show the number of times the gold answer was in the top-3 ranks for questions from each entity class\(^7\). The results have been binned based on the size of the candidate space (0-100, 100-1000, 1000+). Questions on restaurants dominate the dataset and also have a larger candidate space with 1,553 questions in the validation set having a search space greater than 1,000 candidates. In this sub-class of questions, we find that the CsQA model, which does not do deep reasoning, answers more questions correctly in the top-3 ranks, as compared to the CRQA model. This observation strengthens our motivation for using a scalable retrieval model to prune the large search space.

We find that in hotels and attractions since the search space in most questions isn’t as large, both the CsQA and CRQA models have comparable performance. However, using the full CSRQA model still shows considerable improvement (30% relative gain). Overall, we find that the reduction of search space is critical for this task and the use of a scalable shallow neural model to reduce the search space is an effective strategy to improve performance.

6 Conclusion

In the spirit of defining a question answering challenge that is closer to a real-world QA setting, we introduce the novel task of identifying the correct entity answer to a given user question based on a collection of unstructured reviews describing entities. We harvest a dataset of over 48,000 QA pairs, which enables end to end training of models.

The biggest challenge in this dataset is that of scalability. Our task requires processing 500 times more documents per question than most existing QA tasks, and individual documents are also much larger in size. In response, we develop a cluster-select-rerank architecture that brings together neural IR and QA models for an overall good performance. The neural models work on smaller but representative documents, which appears to be critical for scaling them to this size. Our best system registers a 10% relative improvement over our baseline models yet picks a correct answer in top-3 for only 20% of the questions, which points to the difficulty of the dataset.

We believe that further research on this task will significantly improve the state of the art in question answering. A natural extension to our model will be to make clustering step question-dependent. An observation is Accuracy@30 is over 58%, but only 20% at 3, suggesting that a better reranker could really improve the performance. A possibility is to use iterative retrieval of sentences from the whole entity document at rerank phase, so that important information is not missed at answering time. We will make resources from this paper available for further research.

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