Joint Spatio-Textual Reasoning for Answering Tourism Questions

Danish Contractor\textsuperscript{1,2,*}  Shashank Goel\textsuperscript{2,†}  Mausam\textsuperscript{2}  Parag Singla\textsuperscript{2}
\textsuperscript{1}IBM Research AI, New Delhi  \textsuperscript{2}Indian Institute of Technology, New Delhi
dcontrac@in.ibm.com, shashankgoel.iitd@gmail.com, 
{mausam,parags}@cse.iitd.ac.in

Abstract

Our goal is to answer real-world tourism questions that seek Points-of-Interest (POI) recommendations. Such questions express various kinds of spatial and non-spatial constraints, necessitating a combination of textual and spatial reasoning. In response, we develop the first joint spatio-textual reasoning model, which combines geo-spatial knowledge with information in textual corpora to answer questions.

We first develop a modular spatial-reasoning network that uses geo-coordinates of location names mentioned in a question, and of candidate answer POIs, to reason over only spatial constraints. We then combine our spatial-reasoner with a textual reasoner in a joint model and present experiments on a real world POI recommendation task. We report substantial improvements over existing models without joint spatio-textual reasoning.

1 Introduction

Users of travel forums often post questions seeking personalized recommendations for their travel needs. Consider the example in Figure 1, which shows a real-world\textsuperscript{1} Points-of-Interest (POI) seeking question. Answering such a recommendation question is a challenging problem as, it not only requires reasoning over a text corpus describing potential restaurants (eg. reviews), but it also requires resolving spatial constraints (“near Hotel Florida”) over the physical location of a restaurant. In addition, the question is also under-specified and ambiguous (eg. “dont have to venture too far”) making the spatial-inference task harder.

Recently, there has been work on QA models that fuse knowledge from multiple sources; for example, by combining data from knowledge bases with textual passages (Xia et al., 2019; Bi et al., 2019), or incorporating multi-modal data sources (Guo et al., 2018; Vo et al., 2019). But, we do not know of systems that fuse geo-spatial knowledge with text. In addition, there exist several geo-spatial IR systems (eg, (Santos and Cabral, 2009; Scheider et al., 2020)), however, to the best of our knowledge, none of them perform joint-reasoning over geo-spatial and textual knowledge sources.

In response, we present our joint spatio-textual QA model for returning answers to questions that require textual as well as spatial reasoning. We first develop a modular spatial-reasoning network that uses geo-coordinates of location names mentioned in a question, and of candidate answer POIs, to reason over only spatial constraints. It learns to associate contextual distance-weights with each location-mention in the question – these weights are combined with their respective spatial-distances from a candidate answer, to generate a ‘spatial relevance’ score for that answer.

We then combine the spatial-reasoner with a textual QA system to develop a joint spatio-textual QA model. We demonstrate the model using a re-

\textbf{Question:} “We’re arriving into Havana from the UK in the late afternoon and are staying at the Hotel Florida. By the time we get there and check in it will be early evening. Can anyone recommend a good restaurant nearby so that we dont have to venture too far on our first night after a long journey? The Hotel is at Calle Obispoesq, a Cuba. Ciudad de La Habana. Any suggestions appreciated.”

\textbf{Answers:}

1. ‘Los Nardos’ (39 R, 2966)
2. ‘La Mina’ (39 R, 2303)

Figure 1: A sample POI recommendation question. The answers correspond to POI IDs of the form <city_id>,<POI type>,<number>. The Tourism QA dataset has three classes of POIs - restaurants (R), attractions (A) and hotels (H).
cently introduced QA task, which contains tourism questions seeking POI (entity) answers (Contractor et al., 2019). It also contains a collection of entity reviews as knowledge source for answering these questions. We provide the geo-spatial knowledge for the task by mapping location-mentions in questions to their geographical coordinates using publicly available APIs. Similarly, candidate answer POIs are also mapped to their geographical coordinates, included as part of the dataset (Contractor et al., 2019). To the best of our knowledge, we are the first to develop a joint QA model that combines reasoning over external geo-spatial knowledge along with textual reasoning.

Contributions: Our paper makes the following contributions:
1. We develop a spatial-reasoner that uses geo-coordinates of locations and POIs to reason over spatial constraints specified in a question.
2. We demonstrate, using a simple toy-dataset, that our spatial-reasoner is not only able to reason over “near”, “far” constraints but is also able to determine location references that are not useful for reasoning (Eg: a location reference mentioning where a user last went on vacation).
3. We develop a spatio-textual QA model, which fuses spatial knowledge (geo-coordinates) with textual knowledge (POI reviews) using sub-networks designed for spatial and textual reasoning.
4. We demonstrate that our joint spatio-textual model performs significantly better than models employing only spatial- or textual-reasoning. It also obtains state-of-the-art results on a real-world tourism questions dataset, with substantial improvement in answering location questions.

2 Related Work

Our work is related to four broad areas of question answering and information retrieval:

Geographical Information Systems: There is significant prior work on Geographical Information systems where standard IR models are augmented with spatial knowledge (Ferrés Domènech, 2017; Purves et al., 2018). Models have been developed to address challenges in adhoc-retrieval tasks with locative references (Gey et al., 2006; Mandl et al., 2008; Santos and Cabral, 2009). However, such models deal primarily with inference problems in toponyms (eg, “Beijing is located in China”), location disambiguation and use of topographical classes (eg, “Union lake is a water-body”). Methods for IR involving locative references use three strategies (i) a pipeline of filtering based on spatial information followed by text-based IR (ii) a pipeline of filtering based on text-based IR followed by ranking based on geo-spatial ranking or coverage, and (iii) a weighted or linear combination of two independent rankings (Leidner et al., 2020). Our work builds on the third strategy by jointly training a model with both geo-spatial and textual components. To the best of our knowledge, joint reasoning over text and geo-spatial data has not been investigated in geographical IR literature.

Geo-Spatial Querying: There has been considerable work in research areas of geo-parsing (toponym discovery and disambiguation) (Kew et al., 2019), geo-spatial query processing over structured or RDF knowledge bases (KB) (Vorona et al., 2019; Scheider et al., 2020), geocoding and geo-tagging documents (De Rassenfosse et al., 2019; Lim et al., 2019; Huang and Carley, 2019) etc. However, such querying methods require KB & task-specific annotations for training and are thus specialized in application and scope (Scheider et al., 2020).

Numerical Reasoning for Question Answering: Spatial reasoning in our task is effectively a form of numerical reasoning over distances between location-mentions in a question and a candidate entity (POI). Recently introduced tasks such as DROP (Dua et al., 2019) and QuaRTz (Tafjord et al., 2019) require reasoning that includes addition, subtraction, counting, etc. for answering reading comprehension style questions. Other tasks such as MathQA (Amini et al., 2019) and Math-SAT (Hopkins et al., 2019) present high school and SAT-level algebraic word problems.

Models developed for numerical reasoning tasks such as NAQANet (Dua et al., 2019) and NumNet (Ran et al., 2019) reason over the explicit mentions of numerical quantities within a question or passage. In contrast, the questions in our task do not explicitly mention geographical coordinates, and also do not contain all the information required for numerical reasoning (since the distances need to be computed with respect to a candidate answer under consideration). Further, in contrast to algebraic word problems and numerical reasoning questions, answers in the POI-recommendation task are also heavily influenced by text-based reasoning on subjective POI-entity reviews.

Points-of-Interest (POI) Recommendation: Existing models for POI recommendation typically
rely on the presence of structured data, including
geo-spatial coordinates. Queries may be structured
or semi-structured and can consist of both spatial
as well as textual arguments. Textual arguments
are usually associated with the structured attributes
or may serve as filters. Approaches include efficient
indexing for ‘spatial’ and ‘preference’ features
along with specialized data-structures as IR-
Trees, (Cong et al., 2009; Zhang et al., 2016; Tsats-
sanifos and Vlachou, 2015; Li et al., 2016), methods based on Matrix Factorization (Yiu et al., 2007)
for user-specific recommendations, click-through
logs used for recommendations from search engines (Zhao et al., 2019)

Our work builds on the recently-released POI
entity-recommendation QA task (Contractor et al.,
2019, 2020). Two approaches have been developed
for this task: semantic parsing of unstructured user
questions to query a semi-structured knowledge
store (Contractor et al., 2020), and an end-to-end
trainable neural model operating over a corpus of
unstructured reviews to represent POIs (Contractor
et al., 2019). Neither of these approaches explicitly
reason on spatial constraints, even though the
questions contain them.

3 Spatio-Textual Reasoning Network

The Spatio-Textual Reasoning Network (Figure 2)
consists of 3 components: (i) Geo-Spatial Reasoner,
(ii) Textual Reasoner, (iii) Joint Scoring Layer.

3.1 Geo-Spatial Reasoner

Our geo-spatial reasoner consists of the follow-
ing components: (1) Distance-aware Question
Encoder - to encode questions along with geo-
spatial distances between location mentions (in
the question) and a candidate entity, (2) Distance
Reasoning layer - to enable reasoning over geo-
spatial distances with respect to the spatial con-
straints mentioned in the question, (3) Spatial Re-
levance Scorer - to score and rank candidates for
spatial-relevance.

Distance-aware Question Encoder: We generate
question representations by using embedding representations of their constituent tokens along
with embedding representations of their location-
mentions. A question token can be represented by
traditional word-vector embeddings, or contextual
embeddings such as BERT (Devlin et al., 2019).
Each token representation is further appended with
a one-hot encoding representing Begin (B), Inter-
termediate (I) or Other (O) labels, indicating the
presence of location tokens. The B-I labels help
the model recognize a single continuous location-
mention. In addition, we concatenate the distance
of the candidate entity c, from a location-mention
to each token-representation Thus, the question
representations are distance-aware and candidate-
dependent.

Formally, let the token embedding representa-
tions in a question be given by \( v_i \)
\( (v_0 \ldots v_i \ldots v_{m-1}) \),where \( m \) is the length of a
question. Let the distance between the \( k \)th location-
mention \( lm_k \) and \( c \) be denoted by \( d_k \). Further, let
\( \phi(lm_k) \) be a function that returns the set of position
indices occupied by location mention \( lm_k \), i.e. it
returns the set of position indices of question tokens
that have been assigned the B or I label from the
B-I encoding for location mention \( lm_k \), \( \phi(lm_k) \) \( \subset \{0, \ldots, m-1 \} \). We create an \( m \)-dimensional
distance vector \( d'_k \) where each element \( d'_k \) of the
vector is given by:

\[
d'_k = \begin{cases} 
  d_k & \text{if } i \in \phi(lm_k) \\
  0 & \text{otherwise} 
\end{cases}
\] (1)

Let the one-hot vector (two dimensional) of the
B-I labels for the \( i \)th position be \( g_i \). The input
question embedding \( t_i \) \( (t_0 \ldots t_i \ldots t_{m-1}) \) is then
given by:

\[
t_i = \text{concat}[v_i, d'_i, g_i]
\] (2)

We encode the question using a bi-directional GRU
(Cho et al., 2014) which results in output states \( q_i \).

Distance-Reasoning Layer (DRL): We first used
a series of down-projecting feed-forward layers ap-
plied to the output state of the GRU, to generate
the final score for each candidate, but we found
this was not effective (Section 4.1.2). We there-
fore include a component designed for distance-
reasoning referred to as the ‘Distance Reasoning
Layer’ which uses the representations generated by
the distance-aware question encoder.

A model could score candidate-entities for rele-
ance if, for each location mentioned in the ques-
tion, it is able to (i) learn whether a location-
mention needs to be considered for answering, and
(ii) learn how a location-mention needs to be used
for answering. Our design of the DRL is motivated
by this insight – it learns a function which, for each
location-mention \( lm_k \), in the question, outputs a

\[\text{Manhattan Distance}\]
Figure 2: Spatio-Textual reasoning network consisting of (i) Geo-Spatial Reasoner (ii) Textual-Reasoning subnetwork (iii) Joint Scoring Layer

distance-weight \( w_k \). Here, \( w_k \) captures the contribution of the spatial-distance between \( l m_k \) and the candidate entity \( c \), under the constraints mentioned in the question. For instance, a question may include location-mentions that could be involved in simple ‘near’ or ‘far’ constraints or other complex constraints such as “within driving distance” or “within walking distance” etc. The DRL layer uses the distance-aware question encoding to understand the nature of the constraint being expressed, as well as, figure out how to compute distance-reasoning weights to express those constraints.

Let the output states of the question encoder be given by \( q_0 \ldots q_i \ldots q_{m-1} \), where \( m \) is the length of the question. To compute distance-weights, we use a series of position-wise feed-forward blocks (Vaswani et al., 2017) that consist of a linear layer with ReLU activation applied at each output position of the Question Encoder:

\[
q^l_i = Block^l(q^{l-1}_i) = \max(0, A^l q^{l-1}_i + b^l)
\]  

(3)

where \( q^l_i \) is the output of the Block layer at layer \( l \), \( A^l \) is a weight matrix and \( b^l \) the bias term.

The initial block input uses the output state of the GRU \( q_i \) concatenated with the final hidden state \( q_L \). Thus, the output \( q^1_i \) from the application of the first block layer, corresponding position \( i \) in the input is given by:

\[
q^1_i = Block^1(\text{concat}[q_i, q_{m-1}])
\]  

(4)

The blocks apply the same linear transformations at each position but we vary the parameters across layers (see appendix). The final layer gives us a single dimension output for each position resulting in an \( m \)-dimensional vector \( r(r_0, r_1, \ldots, r_{m-1}) \).

Let \( B \) be an \( m \)-dimensional one-hot-vector based on the position indices that have been assigned only the \( B \) label\(^3\) from the \( B-I \) encoding used in the input layer. The distance-weight vector \( w \) for a question is given by:

\[
w = \tanh(r \odot B)
\]  

(5)

We use the distance-weights for scoring, as described below.

**Spatial Relevance Scorer:** The final score \( S_L \) of a candidate \( c \) is given by:

\[ S_L = w d' \]  

(6)

Note that since we concatenate the distance values along with token embeddings while encoding locations as part of the Question Encoder (Equation 2), it helps learn distance weights \( w \) which are dependent on the distance value as well as the semantic information present in the question. Thus, the spatial relevance score is not just a simple linear combination of distances and makes the model representationally more powerful (see experiments in 

---

\(^3\)An element of \( B \) is 1 whenever it corresponds to a position index indicating the start of a location mention in a question.
Section 4.2). We refer to the Geo-Spatial Reasoner as SPN\textsuperscript{ET} for brevity in the rest of the paper.

### 3.2 Textual-Reasoning Sub-network:

We use the CRQA (Contractor et al., 2019) model as our textual-reasoning sub-network. It consists of a Siamese-Encoder (Lai et al., 2018) that uses question representations to attend over entity-review sentences and generate question-aware entity-embeddings. These entity embeddings are combined with question representations to generate an overall relevance score. For scalability, instead of using full review documents, the model uses a set of representative sentences from reviews after clustering them in USE-embedding space (Cer et al., 2018). We follow Contractor et al. and use k-means to cluster sentences in USE embedding space. We set $k=10$, and select 10 sentences per cluster, thus creating a $\leq 100$-sentence document to represent an entity. In order to build a model that is capable of joint spatio-textual reasoning, our model learns question-specific combination weights that combine textual and spatial-reasoning scores.

### 3.3 Joint Scoring Layer

Let the score generated by the textual-reasoner be $S_T$ and let the score generated by the spatial-reasoner be $S_L$. Let the rescaling weights for $S_T$ and $S_L$ be $w_T$ and $w_L$ respectively. Then, the overall score $S$ is given by:

$$S = \alpha \sigma(w_T S_T) \cdot \tanh(w_L S_L) + \beta \sigma(w_T S_T),$$

where $\sigma$ is the Sigmoid function and $\alpha, \beta$ are combination weights. The weights are computed by returning a two dimensional output (corresponding to each weight), after a series of feed-forward operations on the self-attended representation (Cheng et al., 2016), of the question using the outputs of a Question Encoder with the same architecture as in SPN\textsuperscript{ET} (see appendix for hyperparameters). Note that the first term of scoring equation uses $S_L$ as a selector – for questions where there are no locations mentioned, the spatial score of a question with no location-mentions will be 0 (due to the equation for $w$). This lets the model rely only on textual scores for these cases.

**Training:** We train the joint model using max-margin loss, teaching the network to score correct-answer entities higher than negative samples.

---

**Figure 3:** Sample questions from the Toy Dataset. The dataset has questions from three categories: (1) close to set X, (2) far from set X (3) Combination.

### 4 Experiments

We first present a detailed study of the spatial-reasoner using a simple artificially generated toy-dataset. This allows us to probe and study different aspects of spatial-reasoning in the absence of textual reasoning. We then present our experiments with the joint spatio-textual model using a real-world POI-recommendation QA dataset (Sec 4.2)

#### 4.1 Detailed Study: Geo-Spatial Reasoner

We conduct this study on a simple toy-dataset generated using linguistically diverse templates specifying spatial constraints and location names chosen at random from a list of 200,000 entities across 50 cities.

#### 4.1.1 Artificial Toy-Dataset

**Template Classes:** We create templates that can be broadly divided into three types of proximity queries based on whether the correct answer entity is expected to be: (1) close to one or more locations (mentioned in the question), (2) far from one or more locations, (3) close to some and far from others (combination). We create different templates for each category with linguistics variations. Figure 3 shows a sample question from each category. See appendix for more details, including the list of templates.

**Use of distractor-locations:** In order to make the task more reflective of real-world challenges we also randomly insert a distractor sentence that contains a location reference which does not need to be reasoned over (e.g the location “Pinati” in Question 2 in Figure 3).

**Gold-entity generation:** The gold answer entity is uniquely determined for each question based on its template. For example, consider a template T, “I am staying at $A$! Please suggest a hotel close to $B$ but far from $K$.” The score of a candidate entity $X$ is given by $\text{dist}_T(X) = -(\text{dist}(X, B) - \text{dist}(X, K))$ (distances from $B$ needs to be reduced, while distance from $K$ needs to be higher). $A$ is a...
distractor. The candidate with the \( \max(\text{dist}_T(X)) \) in the universe is chosen as the gold-answer entity for that question. We use the geo-coordinates of locations to compute the distance.

**Dataset Statistics:** The train, dev and test sets consist of 6000, 1500 and 1500 questions respectively generated using 48 different templates, split equally across all 3 template categories. Each question consists of location-names from only one city and thus the candidate search space for that question is restricted to that city. The average search space for each question is 1250, varying between 10-16200 across cities. The dataset includes questions containing distractor-locations (52.33% of dataset) distributed evenly across all template classes.

### 4.1.2 Results

We study SPNET using the artificial dataset to answer the following questions: (1) What is the model performance across template classes? (2) How does the network compare with baseline models that do not use the DRL? (3) How well does the model deal with distractor-locations, i.e. locations not relevant for the scoring task? For all experiments in this section we use perfectly tagged location-mentions.

**Metrics:** We study the performance of models using \( \text{Acc}@N \) (\( N=3,5,30 \))\(^4\) which requires that any one of the top-N answers be correct. Mean Reciprocal Rank (\( \text{MRR} \)) and the average distance of the top-3 ranked answers from the gold-entity \( \text{Dist}_g \). \( \text{Dist}_g \) is helpful in quantifying the spatial goodness of the returned answers (lower is better).

We use the following models in our experiments: (i) SPNET (ii) SPNET without DRL (iii) BERT-SPNET (iv) BERT-SPNET without DRL. Models without DRL use the final hidden states of the Question Encoder and a series of down-projecting feed-forward layers to generate the final score.

**Performance across template classes:** As can be seen in Table 1, all models perform the worst on the template class that contains a combination of both ‘close-to’ and ‘far’ constraints. Models based on SPNET perform exceeding well on the ‘Far’ templates because the difference between the \( \text{dist}_T(X) \) scores of the best and the second best candidate is almost always large enough for every model to easily separate them.

**Importance of Distance-Reasoning Layer:** As can be seen in Table 1 the performance of each configuration (with and without BERT) suffers a serious degradation in the absence of the DRL. Recall, that all models have access to spatial knowledge in their input layer via the question encoding. This indicates that the DRL is an important component required for reasoning on spatial constraints. To further assess whether our model is able to do distance reasoning, we computed the correlation between ranking-by-distances (appropriate ranking order for each template-class) and SPNET’s ranking on the toy-dataset. We found the rank correlation to be a high 0.97 (\( p < 0.002 \)) suggesting that the model is able to use physical distance to compute the best answer.

**Effect of distractor-locations:** We report results on two splits of the test set: Questions with and without distractor-locations. We report the aggregate performance over all template classes due to space constraints. As can be seen in Table 2, models suffer a degradation of performance in the presence of distractor-locations. We hypothesize that this is because the reasoning task becomes harder; models now need to also account for location-mentions that do not need to be reasoned over.

**Probing Study:** We conduct a probing study (Figure 4) on SPNET to get some insights into the reasoning process employed by the trained network. We use a question that has both ‘near’ and ‘far’ constraints (case 1) and then interchange the constraints (case 2). In both the cases we study the corresponding distance-weights assigned to the location-mentions with respect to two candidates.

---

\(^4\) We report results with \( N=3 \) in the main paper. Please see appendix for full results.

### Table 1: Results of SPNET on the artificial spatial-questions dataset (t-test p-value < \( 10^{-33} \) for \( \text{Acc}@3 \))

| Models               | Close to set X | Far from set X | Combination | Aggregate |
|----------------------|----------------|----------------|-------------|-----------|
|                      | \( \text{Acc}@3 \) | \( \text{MRR} \) | \( \text{Dist}_g \) | \( \text{Acc}@3 \) | \( \text{MRR} \) | \( \text{Dist}_g \) | \( \text{Acc}@3 \) | \( \text{MRR} \) | \( \text{Dist}_g \) |
| SPNET w/o DRL       | 82.58          | 0.820          | 0.881       | 90.80     | 2.88      | 0.975       | 60.40     | 2.88      | 0.975       |
| BERT SPNET w/o DRL  | 81.60          | 0.780          | 0.808       | 89.00     | 2.80      | 0.975       | 60.40     | 2.80      | 0.975       |
| BERT SPNET          | 84.13          | 0.896          | 0.975       | 91.40     | 2.88      | 0.975       | 60.40     | 2.88      | 0.975       |

### Table 2: Performance of spatial-reasoning networks degrades in the presence of location-distractor sentences.

| Models               | Without Distractors | With Distractors |
|----------------------|---------------------|------------------|
|                      | \( \text{Acc}@3 \) | \( \text{MRR} \) | \( \text{Acc}@3 \) | \( \text{MRR} \) |
| SPNET                | 82.58               | 0.820            | 89.00         | 0.808      |
| BERT SPNET          | 84.13               | 0.896            | 91.40         | 0.975      |
Figure 4: Probing study of the Distance Reasoning Layer (DRL) using the question: “I came from Tropicoco today. Any nice ideas for a coffee shop [far from/close to] ‘Be Live Havana’ but [close to/far from] ‘Melia Cohiba’?”

“Santa Isabel” and “Parque Central”. Consider the first case; as can be seen, each candidate entity assigns a higher weight (column-wise comparison) as compared to the other candidate, on the distance property it is most likely to benefit from, with respect to the spatial-constraint. For example, when the spatial-constraint requires an answer to be close to “Melia Cohiba”, the candidate “Parque Central” assigns a higher weight to this location as compared to candidate “Santa Isabel”, since “Parque Central” has a smaller distance value to this location. On the other hand, with respect to the “far” constraint, candidate “Santa Isabel” has a larger distance value from “Be live Havana” as compared to candidate “Parque Central”, thus assigning a higher distance weight for this location-mention. When we interchange the constraints (Case 2) we see the same pattern and the comparative weight trends (at each location-mention) invert due to inversion of spatial-constraints. This suggests, that DRL is learning to transform the inputs and generate weights based on the spatial constraint at hand.

Effect of Candidate Space Size: We analyzed the errors made by the SPNNet model and we find that nearly 40% of the errors were made in questions that have large (> 1000) candidate spaces. Approximately 25% of the test-set contains questions with large candidate spaces.

Effect of the No. of Location-mentions: The complexity of the spatial-reasoning task increases as the number of location-mentions (including distractor-locations) in the question increase. We find that SPNNet makes no errors when spatial-reasoning involves only 1 location-mention but, nearly 57% of the errors are made in questions with 3 location-mentions (See appendix).

4.2 Spatio-Textual Reasoning Network

For the joint model, we investigate the following research questions: (i) Does joint spatio-textual ranking result in improved performance over a model with only spatial-reasoning or only textual-reasoning? (ii) How do pipelined baseline models that use spatial re-ranking perform on the task? (iii) Does distance-aware question encoding help in spatio-textual reasoning? (iv) Is the spatio-textual reasoning model more robust to distractor-locations as compared to baselines? (v) What kind of errors does the model make?

Dataset: We use the recently released data set on Tourism Questions (Contractor et al., 2019) that consists of over 47,000 real-world POI question-answer pairs along with a universe of nearly 200,000 candidate POIs; questions are long and complex, as presented in Figure 1, while the recommendations (answers) are represented by an ID corresponding to each POI. Each POI comes with a collection of reviews and meta-data that includes its geo-coordinates. The training set contains nearly 38,000 QA-pairs and about 4,200 QA-pairs each in the validation and test sets. The average candidate space for each question is 5,300.

Evaluation Challenges: It is infeasible to construct a dataset of POI recommendation QA pairs, which has an exhaustively labeled answer-set for each question, since the candidate space is very large. Hence, this dataset suffers from the problem of false negatives, and $Acc@N$ metrics under-report system performance. Still, they are shown to be correlated with human relevance judgments.

5 https://github.com/dair-iitd/TourismQA
6 CRQA is also not based on BERT due to this reason.
We therefore, use these metrics for all experiments, but additionally present a small human-study on the end-task, verifying the robustness of our results.

**Location Tagging in Questions:** In order to get mentions of locations in questions, we manually label a set of 425 questions from the training set for location mentions. We then use a BERT-based sequence tagger\(^7\) trained on this set to tag locations. The tagger has a macro-F1 of 88.03. This tagger tags all location mentions in a question without considering their utility for spatial-reasoning. It is possible that a question may contain only distractor-locations, i.e., locations-mentions that do not need to be reasoned over the answering task.

Once the location-mentions are tagged, we remove the punctuations and stopwords from the tagged-location span. We then query the Bing Maps Location API\(^8\) using the location-mention along with the city (known from question metadata) to get the geo-tags. To reduce noise in geo-tagging, we ignore the location-mention if the remaining text has a length of less than 4 characters or is identified as a popular acronym, continent, country, city or state (lists from Wikipedia). We further reduce noise by ignoring a location mention: (1) if no results were found from BING, or (2) If the geo-tag is beyond 40km from the city center. We found the location-mention geo-tagging precision on a small set of 83 location-mentions to be 96%.

We label all questions in the full dataset using this tagger, resulting in approximately 49.54% of the QA pairs containing at least one location-mention (see Table 3). In all our experiments, we use the Manhattan distance as our distance value, because it is generally closer to real-world driving/walking distance within a city, as opposed to straight-line distance.

\(^7\)github.com/codedecde/BiLSTM-CCM/tree/allennlp

\(^8\)https://bit.ly/36Vazwo

Table 4: Comparison of the joint Spatio-Textual model with baselines on questions that have location mentions (t-test p-value < 0.009)

**4.2.1 Baselines**

Apart from the textual-reasoning model CRQA we also use the following baselines in our experiments:

- **Sort-by-distance (SD):** Given a set of tagged-locations in a question and their geo-coordinates, rank candidate entities by the minimum distance from the set of tagged locations.

- **SPNET:** Use only the spatial-reasoning network for ranking candidate entities using their geo-coordinates. No textual-reasoning performed.

- **CRQA → SD:** Rank candidates using CRQA and then re-rank the top-30 answers using SD.

- **CRQA → SPNET:** Rank candidates using CRQA and then re-rank the top-30 answers using SPNET.

**Training:** We pretrain SPNET on this dataset by allowing entities within a radius of 100m from the actual gold-entity to be considered as gold (only for pretraining). To train the joint network we initialize model parameters learnt from component-wise pretraining of both SPN\(_T\) as well as CRQA.

**4.2.2 Results**

We present our experiments on two slices of the test-set – questions with tagged location-mentions (called Location-Questions) and those without any location mentions (Non-Location Questions). As can be seen in Table 4 sorting-by-distance (SD) performs very poorly indicating that simple methods for ranking based on entity-distance do not work for such questions. Further, the poor performance of SPNET also indicates that the task cannot be solved just by reasoning on location data.

In addition, pipelined re-ranking using SD or SPNET over the textual reasoning model decreases the average distance (\(Dist_g\)) from the gold-entity but does not result in improved performance in terms of answering (Acc@N) indicating the need for spatio-textual reasoning. Finally, from Tables 4 & 5 we note that the spatio-textual model performs better than its textual counterpart on the Location-
Questions subset, while continuing to perform well on questions without location mentions.

**Effect of distance-aware question encoding:** In order to demonstrate the importance of distance-aware question encoding, we present an experiment where we remove the distance values from the input encoding. Thus, Equation 2 changes to \( t_i = \text{concat}[v_i, g_i] \). As Table 5 shows, the performance of the Spatio-Textual CRQA model in the absence of distance-aware encoding drops (last row), but it still performs better than the text-only CRQA model (first row). This indicates that the distance-aware question encoding helps learn better distance weights for spatio-textual reasoning.

**Effect of distractor-locations:** As mentioned earlier, we use a location-tagger that is oblivious to the reasoning task, to tag locations in the dataset. We manually create a small set of 200 questions, randomly selected from the test-set, but ensuring that half of it contains at least one non-distractor location mentioned in the question while the other half contains questions with only distractor-locations.

**Table 5: Comparison of Spatio-Textual CRQA (with and without (w/o) distance-aware question encoding) and CRQA (t-test p-value < 0.03 for Acc@3)**

| Models                  | Location Questions | Non-location Questions | Full Set |
|-------------------------|--------------------|------------------------|---------|
|                         | Acc@3 | Acc@5 | Acc@30 | MRR  | \(I_{dist} \) | Acc@3 | Acc@5 | Acc@30 | MRR  | \(I_{dist} \) | Acc@3 | Acc@5 | Acc@30 | MRR  |
| CRQA                    | 14.83 | 21.27 | 50.65  | 0.143 | 3.41        | 18.95 | 26.22 | 54.37  | 0.177 | 3.41        | 16.89 | 23.75 | 52.51  | 0.159 |
| Spatio-Textual CRQA     | 18.32 | 25.69 | 56.17  | 0.168 | 2.62        | 20.42 | 26.77 | 56.49  | 0.18  | 2.62        | 19.37 | 26.23 | 56.33  | 0.175 |
| Spatio-textual CRQA (w/o distance-aware QE) | 16.85 | 23.39 | 53.04  | 0.159 | 2.84        | 20.06 | 26.86 | 56.49  | 0.185 | 2.84        | 18.45 | 25.13 | 54.76  | 0.172 |

**Table 6: Experiments on two subsets from the test-set:**

(i) Questions requiring Spatial-reasoning (ii) Questions with distractor-locations only.

As can be seen from Table 6, all models including the spatio-textual model deteriorate in performance if a question only contains distractors; the spatio-textual model however, suffers a less significant drop in performance.

**Table 7: Spatio-Textual CRQA: Classification of Errors**

| Location Questions | Models | Acc@3 | Acc@5 | Acc@30 | MRR  | \(I_{dist} \) |
|--------------------|--------|-------|-------|--------|------|--------------|
| CRQA               | 19.89  | 26.43 | 51.47 | 0.168  | 2.70 |
| Spatio-textual CRQA| 21.36  | 28.36 | 51.47 | 0.183  | 2.27 |
| All Questions      | 21.45  | 28.21 | 52.65 | 0.186  | 2.47 |

**Table 8: Comparison with current state-of-the-art CsrQA on (i) Location Questions (ii) All data**

**Qualitative Study:** We randomly selected 150 QA pairs with location-mentions from the test-set, to conduct a qualitative error analysis of Spatio-textual CRQA (Table 7). We find that nearly 37% of the errors can be traced to the textual-reasoner, 22% of the errors were due to a ‘near’ constraint not being satisfied, while about 13% of the errors were due to the model reasoning on distractor-locations. Lastly 8% of the errors were due to errors made by the location-tagger and incorrect geo-spatial data.

**Effect of Candidate Search Space:** Past work (Contractor et al., 2019) has improved overall task performance by employing a neural IR method to reduce the search space (Mitra and Craswell, 2019), and then using the CRQA textual-reasoner to re-rank only the top 30 selected candidates (pipeline referred to as CsrQA). In line with their work, we create a spatio-textual counterpart to CsrQA, by using spatio-textual reasoning in re-rank step. We find that this final model results in a 1 pt (Acc@3) improvement overall (see Table 16), and a 1.5 pt improvement on location questions (Acc@3), establishing a new state of the art on the task. We note that, because the IR selector is incapable of spatial-
reasoning, it possibly reduces the gains made by the spatio-textual re-ranking. An interesting direction of future work could be to augment general purpose neural IR methods with such spatial-reasoning.

**Effect of False Negatives:** To supplement the automatic evaluation, we additionally conducted a blind human-study using the top-ranked CSRQA and spatio-textual CSRQA models on another subset of 100 questions from the test-set. Two human evaluators (κ=0.81) were presented the top-3 answers from both models in random order and were asked to mark each answer for relevance. As Table 9 shows, the manual annotation resulted in Acc@3 for CSRQA and spatio-textual CSRQA at a much higher, 67% and 78% respectively. On the subset of location questions, the accuracy numbers are 64% and 84%. This underscores the value of joint spatio-textual reasoning for the task, and signifies a substantial improvement in the overall QA performance.

| Location | Non-location | Location | Non-location |
|----------|--------------|----------|--------------|
| 28.00    | 36.00        | 64.00    | 70.00        |
| 32.00    | 32.00        | 84.00    | 72.00        |

Table 9: Acc@3 results on a blind-human study using 100 randomly selected questions from the test-set

5 Conclusion

Our paper presents the first joint spatio-textual QA model that combines spatial and textual reasoning. Experiments on an artificially constructed (spatial-only) toy QA dataset show that our spatial reasoner effectively trains to satisfy spatial constraints. We also presented detailed experiments on the recently released POI recommendation task for tourism questions. Comparing against textual only and spatial only QA models, the joint model obtains significant improvements. Our final model establishes a new state of the art on the task. In future work, we would like to also support reasoning on questions that require directional or topographical inference (e.g. “north of X”, “on the river beach”).

6 Acknowledgements

We would like to thank Krunal Shah, Gaurav Pandey, Biswesh Mohapatra, Azalenah Shah for their helpful suggestions to improve early versions of this paper. We would also like to acknowledge the IBM Research India PhD program that enables the first author to pursue the PhD at IIT Delhi. This work is supported by an IBM AI Horizons Network grant, IBM SUR awards, Visvesvaraya faculty awards by Govt. of India to both Mausam and Parag as well as grants by Google, Bloomberg and 1MG to Mausam.

References

Aida Amini, Saadia Gabriel, Shanchuan Lin, Rik Koncel-Kedziorski, Yejin Choi, and Hannaneh Hajishirzi. 2019. MathQA: Towards interpretable math word problem solving with operation-based formalisms. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 2357–2367, Minneapolis, Minnesota. Association for Computational Linguistics.

Bin Bi, Chen Wu, Ming Yan, Wei Wang, Jiangnan Xia, and Chenliang Li. 2019. Incorporating external knowledge into machine reading for generative question answering. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 2521–2530.

Daniel Cer, Yinfei Yang, Sheng-yi Kong, Nan Hua, Nicole Limtiaco, Rhomni St. John, Noah Constant, Mario Guajardo-Cespedes, Steve Yuan, Chris Tar, Yun-Hsuan Sung, Brian Strope, and Ray Kurzweil. 2018. Universal sentence encoder. CoRR, abs/1803.11175.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to answer open-domain questions. In Association for Computational Linguistics (ACL).

Jianpeng Cheng, Li Dong, and Mirella Lapata. 2016. Long short-term memory-networks for machine reading. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 551–561, Austin, Texas. Association for Computational Linguistics.

Kyunghyun Cho, Bart van Merrienboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning phrase representations using RNN encoder–decoder for statistical machine translation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1724–1734, Doha, Qatar. Association for Computational Linguistics.

Gao Cong, Christian S. Jensen, and Dingming Wu. 2009. Efficient retrieval of the top-k most relevant spatial web objects. Proc. VLDB Endow., 2(1):337–348.
Danish Contractor, Barun Patra, Mausam, and Parag Singla. 2020. Constrained bert bilstm crf for understanding multi-sentence entity-seeking questions. Natural Language Engineering, page 1–23.

Danish Contractor, Krunal Shah, Aditi Partap, Mausam, and Parag Singla. 2019. Large scale question answering using tourism data. CoRR, abs/1909.03527.

Gaëtan De Rassenfosse, Jan Kozak, and Florian Seliger. 2019. Geocoding of worldwide patent data. Scientific data, 6(1):1–15.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Gaëtan De Rassenfosse, Jan Kozak, and Florian Seliger. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. 2019. DROP: A reading comprehension benchmark requiring discrete reasoning over paragraphs. In Proc. of NAACL.

Matthew Dunn, Levent Sagun, Mike Higgins, V. Uğur Güney, Volkan Cirik, and Kyunghyun Cho. 2017. Searchqa: A new q&a dataset augmented with context from a search engine. CoRR, abs/1704.05179.

Daniel Ferrès Domènech. 2017. Knowledge-based and data-driven approaches for geographical information access.

Fredric Gey, Ray Larson, Mark Sanderson, Kerstin Bischoff, Thomas Mandl, Christa Womser-Hacker, Diana Santos, Paulo Rocha, Giorgio M Di Nunzio, and Nicola Ferro. 2006. Geoclef 2006: the clef 2006 cross-language geographic information retrieval track overview. In Workshop of the Cross-Language Evaluation Forum for European Languages, pages 852–876. Springer.

Yangyang Guo, Zhiyong Cheng, Liqiang Nie, Xinhua Xu, and Mohan Kankanhalli. 2018. Multi-modal preference modeling for product search. In Proceedings of the 26th ACM international conference on Multimedia, pages 1865–1873.

Mark Hopkins, Ronan Le Bras, Cristian Petrescu-Prahova, Gabriel Stanovsky, Hannekeh Hajishirzi, and Rik Koncel-Kedziorski. 2019. SemEval-2019 task 10: Math question answering. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 893–899, Minneapolis, Minnesota, USA. Association for Computational Linguistics.

Binxuan Huang and Kathleen Carley. 2019. A hierarchical location prediction neural network for twitter user geolocation. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 4732–4742, Hong Kong, China. Association for Computational Linguistics.

Tannon Kew, Anastassia Shaitarova, Isabel Meraner, Janis Goldzycher, Simon Clematide, and Martin Volk. 2019. Geotagging a diachronic corpus of alpine texts: Comparing distinct approaches to toponym recognition. In Proceedings of the Workshop on Language Technology for Digital Historical Archives, pages 11–18.

Tuan Manh Lai, Trung Bui, and Sheng Li. 2018. A review on deep learning techniques applied to answer selection. In Proceedings of the 27th International Conference on Computational Linguistics, COLING 2018, Santa Fe, New Mexico, USA, August 20-26, 2018, pages 2132–2144.

Jochen L. Leidner, Bruno Martins, Katherine McDonough, and Ross S. Purves. 2020. Text meets space: Geographic content extraction, resolution and information retrieval. In Advances in Information Retrieval, pages 669–673, Cham. Springer International Publishing.

Miao Li, Lisi Chen, Gao Cong, Yu Gu, and Ge Yu. 2016. Efficient processing of location-aware group preference queries. In Proceedings of the 25th ACM International on Conference on Information and Knowledge Management, CIKM ’16, page 559–568, New York, NY, USA. Association for Computing Machinery.

Kwan Hui Lim, Shanika Karunasekera, Aaron Harwood, and Yasmeen George. 2019. Geotagging tweets to landmarks using convolutional neural networks with text and posting time. In Proceedings of the 24th International Conference on Intelligent User Interfaces: Companion, IUI ’19, page 61–62, New York, NY, USA. Association for Computing Machinery.

Thomas Mandl, Paula Carvalho, Giorgio Maria Di Nunzio, Fredric Gey, Ray R Larson, Diana Santos, and Christa Womser-Hacker. 2008. Geoclef 2008: the clef 2008 cross-language geographic information retrieval track overview. In Workshop of the Cross-Language Evaluation Forum for European Languages, pages 808–821. Springer.

Bhaskar Mitra and Nick Craswell. 2019. An updated duet model for passage re-ranking. arXiv preprint arXiv:1903.07666.

R. S. Purves, P. Clough, C. B. Jones, M. H. Hall, and V. Murdock. 2018. Geographic Information Retrieval: Progress and Challenges in Spatial Search of Text.

Qiu Ran, Yankai Lin, Peng Li, Jie Zhou, and Zhiyuan Liu. 2019. NumNet: Machine reading comprehension with numerical reasoning. In Proceedings of
Stephen Robertson and Hugo Zaragoza. 2009. The probabilistic relevance framework: Bm25 and beyond. Found. Trends Inf. Retr., 3(4):333–389.

Diana Santos and Luís Miguel Cabral. 2009. Giki-clef: Expectations and lessons learned. In Workshop of the Cross-Language Evaluation Forum for European Languages, pages 212–222. Springer.

Simon Scheider, Enkhbold Nyamsuren, Han Kruiger, and Haiqi Xu. 2020. Geo-analytical question-answering with gis. International Journal of Digital Earth, 0(0):1–14.

Min Joon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. 2016. Bidirectional attention flow for machine comprehension. CoRR, abs/1611.01603.

Oyvind Tafjord, Matt Gardner, Kevin Lin, and Peter Clark. 2019. Quartz: An open-domain dataset of qualitative relationship questions. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 5940–5945.

George Tsatsanifos and Akrivi Vlachou. 2015. On processing top-k spatio-textual preference queries. In Proceedings of the 18th International Conference on Extending Database Technology, EDBT 2015, Brussels, Belgium, March 23-27, 2015, pages 433–444.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, undedefnedukasz Kaiser, and Ilia Polosukhin. 2017. Attention is all you need. In Proceedings of the 31st International Conference on Neural Information Processing Systems, NIPS’17, page 6000–6010, Red Hook, NY, USA. Curran Associates Inc.

Nam Vo, Lu Jiang, Chen Sun, Kevin Murphy, Li-Jia Li, Li Fei-Fei, and James Hays. 2019. Composing text and image for image retrieval-an empirical odyssey. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6439–6448.

Dimitri Vorona, Andreas Kipf, Thomas Neumann, and Alfons Kemper. 2019. Deepspace: Approximate geospatial query processing with deep learning. In Proceedings of the 27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, pages 500–503.

Jiangnan Xia, Chen Wu, and Ming Yan. 2019. Incorporating relation knowledge into commonsense reading comprehension with multi-task learning. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, CIKM ’19, page 2393–2396, New York, NY, USA. Association for Computing Machinery.

M. L. Yiu, X. Dai, N. Mamoulis, and M. Vaitis. 2007. Top-k spatial preference queries. In 2007 IEEE 23rd International Conference on Data Engineering, pages 1076–1085.

C. Zhang, Y. Zhang, W. Zhang, and X. Lin. 2016. Inverted linear quadtree: Efficient top k spatial keyword search. IEEE Transactions on Knowledge and Data Engineering, 28(7):1706–1721.

Ji Zhao, Meiyu Yu, Huan Chen, Boning Li, Lingyu Zhang, Qi Song, Li Ma, Hua Chai, and Jieping Ye. 2019. POI semantic model with a deep convolutional structure. CoRR, abs/1903.07279.

A Appendix

This appendix is organized as follows.

- Section A.1 provides more details about the Toy Dataset and supplementary experimental information that includes additional tables referred to in the main paper on Spatial Reasoning.
- Section A.2 includes more results of the Location Tagger used in the end-task.
- Section A.3 contains supplementary experiments on Spatio-Textual Reasoning.
- Section A.4 gives details about the model hyper-parameters.

A.1 Toy Dataset

We create a simple toy-dataset that is generated using linguistically diverse templates specifying spatial constraints and locations chosen at random from across 200,000 entities. These entities were sourced from the recently released Points-of-Interest (POI) recommendation task (Contractor et al., 2019). Each POI entity is labeled with its geo-coordinates apart from other meta-data such as its address, timings, etc. Further, each entity in a city has a specific type viz. Restaurant(R), Attraction(A) or Hotel(H). Table 10 shows the list of templates used for generating the dataset. These templates have been to make the toy-dataset reflective of real-world challenges. For instance, templates #41-#48 include the possibility of injecting distractor locations. To generate questions, $LOCATION and $ENTITY values are updated by randomly selecting values from the POI-set for each entity as described in the next section.
A.1.1 Dataset Generation

To generate a question, a city c, type t and a template T are chosen at random. The "ENTITY" token in each template is replaced by a randomly chosen metonym of the type t. Table 11 shows the list of metonyms for each type. Each instance of the "LOCATION" token is replaced by a randomly chosen entity from the city c and type t. The candidate set consists of the entities from the city c and type t. The entities used as location mentions are sampled without replacement and removed from the candidate set.

The gold answer entity is uniquely determined for each question based on its template. For example, consider a template T, "I am staying at $A! Please suggest a hotel close to $B but far from $C." The score of a candidate entity X is given by $dist_T(X) = -(dist(X, B) - dist(X, C))$ (distances from B needs to be reduced, while distance from C needs to be higher). A is a distractor. The candidate with the max($dist_T(X)$) in the universe is chosen as the gold entity for that question.

Each question further consists of 500 negative samples (35% hard, 65% soft). The negative samples are generated as a part of the gold generation process. A hard negative sample has a $dist_T(X)$ value closer to the gold as compared to a soft negative sample. We release the samples used for training along with the dataset for reproducibility.

A.1.2 Template classes

We create templates (Table 10) that can be broadly divided into three different categories based on whether the correct answer entity is expected to be: (1) close to one or more locations [1-16] (2) far from one or more locations [17-32] (3) close to some and far from others (combination) [33-48]. To make the task more reflective of real-world challenges we also randomly insert a distractor location that does not need to be reasoned. The second-half for each category (i.e. [9-16], [25-32], and [41-48]) consists of templates that have a distractor locative reference. Further, for the close (or far) category, the templates could contain one location ([1-4] + [9-12]) or two locations ([5-8] + [13-16]) that need to be reasoned for close (or far).

A.1.3 Results

We use the following models in our experiments: (i) SPNet (ii) SPNet without (w/o) DRL (iii) BERT-SPNet (iv) BERT-SPNet without (w/o) DRL. Models without DRL use the final hidden states of the Question Encoder and a series of down-projecting feed-forward layers to generate the final score.

We study our models’ performance using $Acc@N$ (N=3,5,30) which requires that any one of the top-N answers be correct, Mean Reciprocal Rank ($MRR$), and the average distance of the top-3 ranked answers from the gold-entity $Dist_g$. Table 12 summarizes the results test set.

A.1.4 Error Analysis

Tables 13 and 14 show the effect of candidate search space and the number of location mentions in the question on the performance of the SPNet Model.

A.2 Location Tagger

In order to get mentions of locations in questions, we manually label a set of 425 questions from the training set for location mentions. We then use a BERT-BiLSTM CRF (Contractor et al., 2020) based tagger trained on this set to label locations. Table 15 describes the performance of the tagger on an unseen set of 75 questions.

A.3 Spatio-textual Reasoning Network

The Spatio-Textual Reasoning Network consists of three components (i) Spatial Reasoner (ii) Textual Reasoner (iii) Joint Scoring Layer. Training: We train the joint model using max-margin loss teaching the network to score the
Please advise

Someone please advise

I came from

Any idea of

Suggestions on

Please propose

Do you have any recommendations of

Good Afternoon! Any proposals for

Any ideas for ENTITY close to LOCATION and LOCATION? I would be going to LOCATION. Thanks.

We might be staying around LOCATION. Please advise ENTITY close to LOCATION and not far from LOCATION.

Could anyone suggest ideas for ENTITY close to LOCATION and around LOCATION? We could be going to LOCATION soon.

Any suggestions for ENTITY quite far from the LOCATION? Thank you very much!

Suggest

Hello! Any proposal for ENTITY close to LOCATION and also far from LOCATION?

Does anyone have suggestions for ENTITY far from LOCATION and not around LOCATION?

Any ideas of ENTITY far away from LOCATION and also far from LOCATION?

Could anyone propose ENTITY not close to LOCATION and also far from LOCATION?

Does anyone have any suggestions for ENTITY far from LOCATION and not close to LOCATION?

Any ideas of ENTITY both close to LOCATION and LOCATION? Thank you much!

Hi! I will be staying near the LOCATION. Could anyone propose ENTITY not very close to LOCATION and far from LOCATION?

Does anyone have suggestions for ENTITY far from LOCATION and also far from LOCATION? I will then be visiting LOCATION too.

Any good ideas of ENTITY far from LOCATION but close to LOCATION would be appreciated? Best Regards.

Anyone having ideas of ENTITY close to LOCATION but far from LOCATION?

Could anyone advise ENTITY far from LOCATION but not too far from LOCATION?

Any nice ideas of ENTITY close to LOCATION but not in the neighborhood of LOCATION. Thanks!

Tomorrow I would be coming to stay at LOCATION. Anyone having ideas of ENTITY close to LOCATION but far from LOCATION? I will then be exploring LOCATION.

I came from LOCATION this evening. Any nice ideas for ENTITY far from LOCATION but close to LOCATION would be appreciated?

Suggest ENTITY close to LOCATION but not far from LOCATION. I will then be leaving for LOCATION.

Yesterday I came to stay at LOCATION. Any ideas of ENTITY close to LOCATION but far from LOCATION?

Suggestions of ENTITY far from LOCATION but not very far from LOCATION. I will then be moving to LOCATION.

I came from LOCATION today. Any good ideas for ENTITY far from LOCATION but near to LOCATION would be welcomed?

Advise ENTITY close to LOCATION but not close to LOCATION. I might be leaving for LOCATION soon.

Table 10: Templates used for generating the Toy-dataset

| Id | Description |
|----|-------------|
| 1  | Do you have any recommendations of ENTITY near the LOCATION? |
| 2  | Does anyone have ideas on ENTITY close to LOCATION? Thank you! |
| 3  | Hello! Could anyone please suggest ENTITY in the neighborhood of LOCATION? |
| 4  | Good Morning! Can someone please propose ENTITY not very far from LOCATION? |
| 5  | Suggestions for ENTITY close to both LOCATION and LOCATION? |
| 6  | Some good ideas of ENTITY between LOCATION and LOCATION? I thank much! |
| 7  | Please advise ENTITY close to LOCATION and not very far off the LOCATION. |
| 8  | Any ideas for ENTITY near LOCATION and also close to LOCATION would be welcomed? |
| 9  | I once lived around LOCATION. Does anyone have ideas of ENTITY close to the LOCATION? Thanks! |
| 10 | Any nice suggestions of ENTITY near the LOCATION? I will be going to LOCATION the next day. |
| 11 | I just came from LOCATION. Someone, please recommend ENTITY in the neighborhood of LOCATION. |
| 12 | Could anyone propose ENTITY not far from the LOCATION? I need to leave for LOCATION urgently. |
| 13 | We came from LOCATION this morning. Suggestions for ENTITY close to both LOCATION and LOCATION? |
| 14 | Any ideas of ENTITY between LOCATION and LOCATION? I would be going to LOCATION. Thanks. |
| 15 | We might be staying around LOCATION. Please advise ENTITY close to LOCATION and not far from LOCATION. |
| 16 | Could anyone suggest ideas for ENTITY close to LOCATION and around LOCATION? We could be going to LOCATION soon. |
| 17 | Any suggestions for ENTITY quite far from the LOCATION? Thank you very much! |
| 18 | Somebody please suggest ENTITY cut off from LOCATION. Have a good day! |
| 19 | Does anyone have suggestions for ENTITY away from LOCATION? Thanks a lot! |
| 20 | Good Afternoon! Any proposals for ENTITY not very close to the LOCATION? |
| 21 | Suggestions on ENTITY far from both LOCATION and LOCATION? Thank! |
| 22 | Hi! Any idea of ENTITY far away from LOCATION and LOCATION? |
| 23 | Could anyone please propose ENTITY not close to LOCATION and also far from LOCATION? |
| 24 | Does anyone have any suggestions for ENTITY far from LOCATION and not around LOCATION? |
| 25 | I will be staying at LOCATION. Please suggest ENTITY cut off from LOCATION. |
| 26 | Any pleasant ideas of ENTITY far off the LOCATION? I might then be visiting LOCATION. |
| 27 | I came from LOCATION this afternoon. Any proposal for ENTITY not close to the LOCATION? |
| 28 | Does anyone have a suggestion for ENTITY distant from LOCATION? By the way, I came from LOCATION yesterday. |
| 29 | Suggestions for ENTITY far from both LOCATION and LOCATION? Suggestions for ENTITY far from both LOCATION and LOCATION will be welcomed. |
| 30 | Any idea of ENTITY far away from LOCATION and LOCATION? I would then be visiting LOCATION. |
| 31 | Hi, I will be staying near the LOCATION. Could anyone propose ENTITY not very close to LOCATION and far from LOCATION? |
| 32 | Does anyone have suggestions for ENTITY far from LOCATION and also far from LOCATION? I will then be visiting LOCATION too. |
| 33 | Any good ideas of ENTITY far from LOCATION but close to LOCATION would be appreciated? Best Regards. |
| 34 | Anyone having ideas of ENTITY close to LOCATION but far from LOCATION? |
| 35 | Could anyone advise ENTITY far from LOCATION but not too far from LOCATION? |
| 36 | Suggest ENTITY close to LOCATION but not in the neighborhood of LOCATION. Thank you so much! |
| 37 | Does anyone have good ideas of ENTITY far from LOCATION but near LOCATION? Regards. |
| 38 | Please suggest ideas of ENTITY in the neighborhood of LOCATION but far from LOCATION. |
| 39 | Could anyone advise ENTITY far from LOCATION but not too far from LOCATION? |
| 40 | Any nice ideas of ENTITY close to LOCATION but not in the neighborhood of LOCATION. Thanks! |
| 41 | Tomorrow I would be coming to stay at LOCATION. Anyone having ideas of ENTITY close to LOCATION but far from LOCATION? I will then be exploring LOCATION. |
| 42 | Please propose ENTITY far from LOCATION but not far from LOCATION. I will then be exploring LOCATION. |
| 43 | I came from LOCATION this evening. Any nice ideas for ENTITY far from LOCATION but close to LOCATION would be appreciated? |
| 44 | Suggest ENTITY close to LOCATION but not near LOCATION. Tomorrow, I will be leaving for LOCATION. |
| 45 | Yesterday I came to stay at LOCATION. Any ideas of ENTITY close to LOCATION but far from LOCATION? |
| 46 | Suggestions of ENTITY far from LOCATION but not very far from LOCATION. I will then be moving to LOCATION. |
| 47 | I came from LOCATION today. Any good ideas for ENTITY far from LOCATION but near to LOCATION would be welcomed? |
| 48 | Advise ENTITY close to LOCATION but not close to LOCATION. I might be leaving for LOCATION soon. |

Table 11: List of metonyms for each entity type in the Toy-dataset

| Type | Metonyms |
|------|----------|
| R (Restaurant) | a restaurant, an eatery, an eating joint, a cafeteria, an outlet, a coffee shop, a fast food place, a lunch counter, a lunch room, a snack bar, a chop house, a steak house, a pizzeria, a coffee shop, a tea house, a bar room |
| H (Hotel) | a hotel, an inn, a motel, a guest house, a hostel, a boarding house, a lodge, an auberge, a caravansary, a public house, a tavern, an accommodation, a resort, a youth hostel, a bunk house, a dormitory, a flophouse |
| A (Attraction) | an attraction, a tourist spot, a tourist attraction, a popular wonder, a sightseeing place, a tourist location, a place of tourist interest, a crowd pleaser, a scenic spot, a popular landmark, a monument |
correct-answer higher than a negatively sampled candidate entity. Model parameters are described in the next section.

### A.3.1 Results

Similar to Contractor et al. (2019) we also experiment on this dataset by employing a neural method to reduce the search space (Mitra and Craswell, 2019) before using the CRQA textual-reasoner to re-rank only the top-30 selected candidates (pipeline referred to as CSQA). Unlike CRQA, which uses two levels of attention between question and review sentences to score candidate entities, CSQA does not reason deeply over the text. It compares elements of a question with different parts of a review document to aggregate relevance for scoring. Local and distributed representations are used to capture lexical and semantic features.

We report some experiments using this model referred to as CSQA and compare it with CSQA and spatio-textual CSRQA. As can be seen re-ranking with SD or SPNet does not help the system. An interesting direction of future work could thus, be to augment general-purpose neural-IR methods such as Duet used by CSQA with spatial-reasoning. Another interesting approach could be to extend ideas from existing Graph-neural network based approaches, such as NumNet (Ran et al., 2019). Each entity could be viewed as a node in a graph for reasoning but we note that methods will need to be made more scalable for them to be useful. The entity space (and thus nodes in the graph) would run into thousands of nodes per question making current message-passing based inference methods prohibitively expensive.

### A.4 Model settings

#### A.4.1 Experiments on Toy Dataset

The hyperparameters for the best performing configurations of all models were identified through manual testing on the validation set (Table 17). The models were trained on a 2x NVIDIA K40 (12GB, 2880 CUDA cores) GPU on a shared cluster.

The BERT models were trained with a learning rate of 0.001 whereas the non-BERT models with a learning rate of 0.001.
| Hyperparameter               | Value       |
|-----------------------------|-------------|
| Negative samples            | 40          |
| Batch size                  | 20          |
| Optimizer                   | Adam        |
| Loss                        | MarginRankingLoss |
| Margin                      | 0.5         |
| Max no. of epochs           | 15          |
| GRU Output dimension        | 32          |
| DRL Block Layer 1           | 64 (Input) 64 (Output) |
| DRL Block Layer 2           | 64 (Input) 64 (Output) |
| DRL Block Layer 3           | 64 (Input) 64 (Output) |
| DRL Block Layer 4           | 64 (Input) 1 (Output) |

Table 17: Hyperparameter settings for experiments on the toy-dataset

| Hyperparameter               | Value       |
|-----------------------------|-------------|
| Word embeddings size        | 128         |
| Dropout                     | 0.2         |
| Optimizer                   | Adam        |
| Loss                        | Hinge Loss  |
| Margin                      | 1.0         |
| Batch Size                  | 200         |
| SPN/ET GRU input dimension  | 131         |
| SPN/ET GRU output dimension | 256         |
| Textual GRU input dimension | 128         |
| Textual GRU output dimension| 256         |
| DRL Block Layer 1           | 512 (Input) 256 (Output) |
| DRL Block Layer 2           | 256 (Input) 256 (Output) |
| DRL Block Layer 3           | 256 (Input) 128 (Output) |
| DRL Block Layer 4           | 128 (Input) 50 (Output)  |
| DRL Block Layer 5           | 50 (Input) 10 (Output)  |
| DRL Block Layer 6           | 10 (Input) 1 (Output)  |
| α, β FF Linear Layer 1      | 256 (Input) 50 (Output) |
| α, β FF Linear Layer 2      | 50 (Input) 50 (Output) |
| α, β FF Linear Layer 3      | 50 (Input) 10 (Output) |
| α, β FF Linear Layer 4      | 10 (Input) 10 (Output) |
| α, β FF Linear Layer 5      | 10 (Input) 10 (Output) |
| α, β FF Linear Layer 6      | 10 (Input) 2 (Output)  |

Table 18: Hyperparameters used for experiments on the end-task