**Abstract**

Inferring semantic types for entity mentions within text documents is an important asset for many downstream NLP tasks, such as Semantic Role Labelling, Entity Disambiguation, Knowledge Base Question Answering, etc. Prior works have mostly focused on supervised solutions that generally operate on relatively small-to-medium-sized type systems. In this work, we describe two systems aimed at predicting type information for the following two tasks, namely 
a) A **TypeSuggest** module, an unsupervised system designed to predict types for a set of user-entered query terms, and  
b) An Answer Type prediction module, that provides a solution for the task of determining the correct type of the answer expected to a given query. Our systems generalize to arbitrary type systems of any sizes, thereby making it a highly appealing solution to extract type information at any granularity.

1 Introduction

Knowledge graphs are generally defined as “a graph of data intended to accumulate and convey knowledge of the real world, whose nodes represent entities of interest and whose edges represent relations between these entities” [5]. Knowledge graphs are designed as directed edge-labelled graphs (also known as multi-relational graphs) where each edge has a direction and a relation type. Most of them use Semantic Web technologies such as RDF(S) and OWL for representing these knowledge graphs with explicit semantics. RDF type or “is-a” relation of relation is one very important relation type that defines the type of each node. For example, if the node is “New York”, it could be typed as a “city” or “populated city”.

Identifying these types can provide vital information in many knowledge graph related tasks such as Knowledge Base Question Answering (KBQA) [4], Table Understanding [12], Table Question Answering (Table QA), etc. For e.g. when a question is asked by the user corresponding to a KBQA or a Table QA task, it is crucial to understand the type of the correct answer pertaining to the question before proceeding to answer search.

In this paper, we introduce two systems for predicting type information, namely 
a) The **TypeSuggest** module, an unsupervised system designed to predict types for a set of user entered seed query terms, and  
b) The Answer Type prediction module, that pulls-in types from the Semantic Web in a distantly supervised fashion, to predict the type of the correct answer for the user provided question. The input to the **TypeSuggest** module is a list of seed query terms, and the output returned by the module is a ranked list of types from some predefined type system. The Answer Type Prediction module takes in question string as input, and returns a ranked list of types for the correct answer. Both of these systems do not require manual annotations, thereby making them highly appealing to be used as it is, in a wide-variety of domains.

2 Related Work

There have been many studies over the years focusing on this problem. In this work, we limit the discussion to those that go beyond predicting a fixed set of coarse-grained answer types.

One of the early works [7] involved using fine-grained and coarse-grained types together in a hierarchical classifier, albeit the types were not overlapping. Other works such as [6, 8] use hand-crafted features or features obtained from pre-existing grammars in conjunction with machine learning models (such as SVMs, Logistic Regression, etc.) to
We rank the Neresa input, our model takes a list of question-answer pairs, i.e. \((q_i, a_i)\), 1 \(\leq i \leq N\), from a large external general-purpose QA dataset. This list of question-answer pairs \(\zeta = (q_i, a_i)\) goes through the following pre-processing steps.

**Type Acquisition:** For each question-answer pair \((q_i, a_i)\), we define the type of the answer \(a_i\) as follows,

\[
\text{TYPE}(a_i) = \begin{cases} 
\text{NER}(a_i), \text{SCORE} & \text{if } \text{NER}(a_i) \in \mathcal{N} \\
\text{TYPESUGGEST}(a_i) & \text{elsewhere}
\end{cases}
\]

where \(\mathcal{N} = \{\text{Date}, \text{Cardinal}, \text{Ordinal}, \text{Quantity}, \text{Money}, \text{Percent}\}\) is a set of coarse named entity types, \(\text{NER}\) denotes an off-the-shelf Named Entity Recognition System and \(\text{SCORE}\) is a fixed numerical value, i.e. a hyper-parameter of our proposed model.

Using this criterion, we obtain a ranked list of types \(T_i\) for each question-answer pair \((q_i, a_i)\), and construct our augmented dataset, \(\zeta^{\text{Aug}} = (q_i, a_i, T_i)\). Note that \(\forall i, 1 \leq i \leq N, T_i\) denotes a ranked list of types.

In comparison, our proposed method utilizes types from the Semantic Web in a distantly-supervised fashion, thereby requiring no manual annotations. In our approach, one can also determine the granularity level of the final types, since these are obtained from open domain ontologies.
Type Prediction: The augmented dataset $\zeta^{AUG}$ built in the previous step is highly likely to yield a large number of unique types because the predefined type systems $TS$ are usually very large in size. In this step, we restrict ourselves to top $k$ (by frequency) unique types and drop the rest. Here, $k$ is a hyper-parameter of our model.

Out of the types that remain, we keep only those whose frequency is less than a pre-set threshold count $c$, thus ensuring that the generic types such as yago:Thing, yago:Abstraction etc. are removed, which allows the learner (to be described later) not to be biased towards these generic types.

Let $T$ denote the union of the left-over types with the set $N$ defined above. This set constitutes our Type Vocabulary, i.e., we build a model (described below) which given a question $q$ as input, returns a ranked list of entries from $T$ as output.

This frequency-based pruning step transforms the augmented dataset $\zeta^{AUG}$ in the following fashion. For each entry $(q_i, a_i, T_i) \in \zeta^{AUG}$, wherein $T_i = (t^i_1, s^i_1), 1 \leq j \leq |T_i|$ denotes the ranked list of types corresponding to answer $a_i$, we have the following update,

$$\tilde{t}^i_j = \begin{cases} t^i_j & \text{if } t^i_j \in T \\ \arg\min_{x^* \in T} \text{DIST}(x, x^*) & \text{if } t^i_j \notin T \end{cases}$$

wherein $\text{DIST}$ between two types $x$ and $x^*$ is defined as the length of the shortest path between types $x$ and $x^*$ within the type system $TS$ encoded as a graph.

Thus, this step outputs a pre-processed dataset $\zeta^{AUG}_{\text{RESTR}} = (q_i, a_i, \tilde{T}_i)$, wherein each instance now contains an updated list of types $\tilde{T}_i = (\tilde{t}^i_1, s^i_1), 1 \leq j \leq |\tilde{T}_i|$ for answer string $a_i$ according to Equation 2.

This pre-processed dataset $\zeta^{AUG}_{\text{RESTR}}$ forms the training dataset for our proposed neural network architecture for the Answer Type Prediction task, which is described in detail in the next section.

Neural Network Architecture: We next describe the detailed architecture of our proposed Answer Type Prediction model. As shown in Figure 1, it consists of three steps:

- Encoding input question $q_i$ to its corresponding question embedding $\tilde{q}_i$.
- Building a simple learning framework that uses $\tilde{q}_i$ and $T$ as inputs, and produces a list of ranked types $T^i_{PRED}$ as output.

The predicted list of types $T^i_{PRED}$ is compared with $\tilde{T}_i$ (from $\zeta^{AUG}_{\text{RESTR}}$) in order to calculate Weighted Cross Entropy loss values, which is minimized during training procedure. We now describe each of these three sections in detail.

Preparing Type Embeddings: We use a pre-trained GLOVE model [1], and encode each entry within the Type vocabulary $T$ to initialize a Type Embedding matrix $S$. Let us illustrate via an example.

- If the type within $T$ is dbo:person or Wikidata:person, we assign it the GLOVE vector for “person”.
- If the type is yago:WikicatAmericanPeople, this type gets assigned the vector $0.5 \ast [v(\text{american}) + v(\text{people})]$, where $v(\text{american})$ and $v(\text{people})$ denote the GLOVE embeddings for the terms “american” and “people” respectively.
  We split WikicatAmericanPeople to Wikicat, American, and People using regular expressions. The term Wikicat is ignored.
- If the type is yago:Person100007846, this type gets assigned the GLOVE vector for “Person”. The numerical part (extracted via regex) is ignored.
- Any term not present in GLOVE gets initialized randomly.

Preparing Question Embedding: As illustrated in Figure 1, given a training instance $(q_i, a_i, \tilde{T}_i) \in \zeta^{AUG}_{\text{RESTR}}$, the question string is tokenized and encoded via a bi-directional LSTM [4]. The vectors from both the unidirectional LSTMs are concatenated together to yield a matrix $Q_i$, of dimensions $|q_i| \times 2D$, where $|q_i|$ denotes the number of tokens in the question string $q_i$ and $D$ is the size of the vectors output by the unidirectional LSTMs.

The Aggregation layer then consists of the following steps,

- Calculate $\psi_i = Q_i \cdot \text{ATT}$ where matrix ATT is of dimensions $2D \times 1$, and $\cdot$ represents matrix multiplication.
• Normalize $\psi_i$ to have unit $l_2$ norm, and calculate $Q_i \otimes \psi_i$, where $\otimes$ denotes element-wise multiplication.

• Calculate $\bar{q}_i = \sum_{j=1}^{q_i} (Q_i \otimes \psi_i)_{[j,:]}$, i.e. sum together all the rows in the matrix obtained in the previous step.

• Here, ATT denotes the model parameters learned during training.

Using these steps, the question string $q_i$ is mapped to its vector representation $\bar{q}_i$. Next, we describe how $\bar{q}_i$ interacts with the Type Embedding matrix $S$.

### Putting it Together:

In this step, our model performs a matrix-vector multiplication $\bar{q}_i^T S$, followed by a sampled softmax operation, in order to obtain a predicted list $P_i$ of scores, one per type. Using this predicted list $P_i$ and the known list of types $\tilde{T}_i$, the loss function (also referred to as Weighted Cross Entropy loss) is calculated as,

$$ J_i = -\sum_{(\tilde{t}_i,s_i) \in \tilde{T}_i} s_i \log P_{i_{\tilde{t}_i}} $$

where $P_{i_{\tilde{t}_i}}$ corresponds to the system predicted score for the type $\tilde{t}_i$.

During inference time, given a query question $q_{\text{QUERY}}$, we use the learned model parameters to build the query embedding $\bar{q}_{\text{QUERY}}$ as well as the embedding matrix $S$. Finally, we perform a matrix-vector multiplication, i.e. $\bar{q}_{\text{QUERY}}^T S$ to obtain a ranked list of predicted scores, which is shown to the user.
5 Conclusion

In this paper, we introduced two systems for predicting type information, namely a) The TYPE SUGGEST module, an unsupervised system designed to predict types for a set of user entered seed query terms, and b) The Answer Type prediction module, that pulls-in types from the Semantic Web in a distantly supervised fashion, to predict the type of the correct answer for the user provided question. We described both of these systems in detail, starting with the data ingestion phase, followed by the pre-processing phase and ended up with a neural network based learner for the Answer Type prediction module. Furthermore, we demonstrated that both these systems do not require manual annotations, thereby making them highly appealing to be used as it is, in a wide-variety of domains.

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