The Semantic Web contains large amounts of related information in the form of knowledge graphs (KGs) such as DBpedia or Wikidata. These KGs are typically enormous and are not easily accessible for users as they need specialized knowledge in query languages (such as SPARQL) as well as deep familiarity with the ontologies used by these KGs. To make these KGs more accessible (even for non-experts) several natural language question answering (QA) systems have been developed. Due to the complexity of the task, different methods have been tried including techniques from natural language processing (NLP), information retrieval (IR), machine learning (ML) and the Semantic Web (SW). Most question answering systems over KGs approach the question answering task as a conversion from the natural language question to its corresponding SPARQL query.

This has lead to NLP pipeline architectures that integrate components that solve a specific aspect of the problem and pass on the results to subsequent components for further processing eg: DBpedia Spotlight [1] for named entity recognition, RelMatch for relational mapping, etc. A major drawback of this approach is error propagation through the pipeline. Another approach is to use query templates either manually generated or extracted from existing benchmark datasets to generate the SPARQL queries. These templates are a set of predefined queries with various slots that need to be filled. This approach potentially shifts the question answering problem into a classification task where the system needs to match the input question to the appropriate template (class label).

We propose a neural network-based approach to automatically learn and classify natural language questions into its corresponding template using recursive neural networks. An obvious advantage of using neural networks is the elimination of the need for laborious feature engineering that can be cumbersome and error-prone. The input question is encoded into a vector representation. The model is trained and evaluated on the LC-QuAD dataset (Large-scale Complex Question Answering Dataset). The LC-QuAD queries are annotated based on 38 unique templates that the model attempts to classify. The resulting model is evaluated against both the LC-QuAD dataset and the 7th Question Answering Over Linked Data (QALD-7) dataset. The recursive neural network achieves template classification accuracy of 0.828 on the LC-QuAD dataset and an accuracy of 0.618 on the QALD-7 dataset. When the top-2 most likely templates were considered the model achieves an accuracy of 0.945 on the LC-QuAD dataset and 0.786 on the QALD-7 dataset. After slot filling, the overall system achieves a macro F-score 0.419 on the LC-QuAD dataset and a macro F-score of 0.417 on the QALD-7 dataset.
1 Introduction

Knowledge graphs (KGs) are typically enormous and not easily accessible for users as they need specialized knowledge in query languages (SPARQL), as well as deep familiarity with the underlying ontologies. So, to make these KGs more accessible, several QA systems have been developed over the last decade. At a high level, most QA systems approach the task as a conversion from a natural language question to its corresponding SPARQL query using NLP pipelines. These systems then utilize the query to retrieve the desired entities or literals. Höffner et al. [2] classify the techniques used in QA systems over Linked Data broadly into five tasks:

1. **Question Analysis:** The question of the user is analyzed based on purely syntactic features. QA systems use syntactic features to deduce, for example, the right segmentation of the question, determine the corresponding instance (subject or object), property or class and the dependency between different phrases.

2. **Phrase Mapping:** This step starts with a phrase (one or more words) $s$, and tries to find, in the underlying KG, a set of resources that correspond to $s$ with high probability. $s$ could correspond to an instance, property or a class from the KG.

3. **Disambiguation:** Two ambiguity problems can arise. The first is that from the question analysis step the segmentation and the dependencies between the segments are ambiguous. For example, in the question "Give me all European countries" the segmentation can group or not group the expression "European countries" leading to two possibilities. Next, the phrase mapping step returns multiple possible resources for one phrase. In the example above "European" could map to different meanings of the word "Europe".

4. **Query Construction:** This phase deals with how the QA system constructs the SPARQL query to find the answer to the question. A problem arises during the query construction, that is commonly referred to as the "semantic gap". Assume for example that a user asks the question: "which countries are in the European Union?". Instead of a property $dbo : member$, DBpedia uses the class $dbo: Member_states_of_the_European_Union$ to encode the information. The "semantic gap" refers to the problem that the KG encodes information differently from what one could deduce from the question. This shows that in general, it is difficult to deduce the form of the SPARQL query knowing only the question.

5. **Querying:** The final step is to query the underlying KG to retrieve the answers for the given question. The answer can be from a single KG or depending on the system and the task even from multiple KGs.

Error propagation in such pipelines can lead to crucial ramifications downstream and adversely affect the overall performance of the system. Error propagation becomes especially difficult for complex queries that span multiple triples, where many facts need to be discovered before the question can be answered. Current research follows two paths, namely (1) template-based approaches, that map input questions to either manually or automatically created SPARQL query templates or (2) template-free approaches that try to build SPARQL queries based on the given syntactic structure of the input question. However, template-free approaches require an additional effort of ensuring to cover every possible basic graph pattern, making it a more computationally intensive process [3].

In this paper, we present **template classification as an alternative to the query building** approach or the sub-graph generation (from entities) approach. Furthermore, as the analysis of Singh et al. [4] on QALD subtasks shows, **query building has one of the poorest F-Measures** at 0.48. So, by performing template classification in the beginning, the workflow gets inverted and provides the benefit of restricting the number of resources, entities and ontology classes that need to be considered for a candidate SPARQL query instead of seemingly endless combinations, as is usually done in a non-template approach. In this article and for completeness, we focus on template classification only and use existing methods to fill the slots after the template classification to provide a performance comparison against existing methods. Our contributions are as follows:

- We present a novel QA template classification model using recursive neural networks to replace the traditional query building process.
- Our approach can generalize to different domains/benchmark datasets. We showcase this by training on LC-QuAD only and testing it on the QALD-7 dataset. We emphasize that labeled data or large training data in the form of natural language question-SPARQL pairs is costly to (re-)produce.
- The resulting model was *evaluated* using the FAIR GERBIL QA [5] framework resulting in 0.419 macro f-measure on LC-QuAD and 0.417 macro f-measure on QALD-7.
- The model was implemented using the Pytorch deep learning framework based on a well-known Tree-LSTM based on [6]. Our model was adapted from this source code and is available online at [https://github.com/dasguptar/treelstm.pytorch](https://github.com/dasguptar/treelstm.pytorch) together with supplementary material.

---

1 [https://github.com/dasguptar/treelstm.pytorch](https://github.com/dasguptar/treelstm.pytorch)
2 Related Work

Since the steady growth of the Semantic Web, the necessity for natural language interfaces to ontology-based repositories has become more acute, igniting interest in QA systems [7]. In the last number of years, different complex benchmarks for QA systems over KGs have been developed. Most popular among them in the Semantic Web community is the QALD dataset [9]. QALD is not one benchmark but a series of annual evaluation campaigns for QA systems with 9 iterations of the challenge to date. Another interesting dataset is the LC-QuAD dataset [9] that was developed from the ground up to facilitate machine learning based QA approaches using crowd workers. There is also DBNQA [10] which is an offspring of LC-QuAD and QALD which does not offer new templates but new slots. Since we focus in this paper on template classification, we did not evaluate on DBNQA.

The key QA tasks in non-end-to-end systems comprise of Named Entity Recognition and Disambiguation, Relation Extraction and Query Building. No single system will be perfect for all tasks and across all domains [4]. This has led to the development of QA components that specialize in specific tasks for specific domains which can then be bootstrapped into modular pipelines. The framework by Diefenbach et al. [11], a message-driven and light-weight architecture, leverages linked data technology and particularly vocabularies to create a component-based QA system. Their RDF-based modular approach solves a critical problem in the community, that is, integrating existing components, which is a resource intensive process. The efficiency of these components was studied by training classifiers which take features of a question as input and have the goal of optimizing the selection of components based on those features [4]. Then a greedy algorithm is used to identify the best pipeline that includes the best possible components which can effectively answer the given question. The system was evaluated using the QALD and LC-QuAD benchmarks where they discovered that among the available solutions for the three tasks in QA, Named Entity Recognition ranks the highest (based on Macro Precision, Recall and F-Score) followed by Query Building and finally Relation Linking.

WDAqua [12] is a monolithic rule-based system using a combinatorial approach to generate SPARQL queries from natural language questions, leveraging the semantics encoded in the underlying KG. It can answer questions on both DBpedia (supporting English) and Wikidata (supporting English, French, German and Italian). WDAqua does not require training and was also evaluated on QALD and LC-QuAD previously. Here, we reran the system as a baseline. 

The QA systems mentioned above translate questions into triples which are matched against an existing KG. However, in many cases, such triples do not accurately represent the semantic structure of the natural language question. To circumvent this problem, Unger et al. [14] proposed an approach that relies on a parse tree of the question to produce a SPARQL template that directly mirrors the internal structure of the question. This template contains empty slots which are then instantiated using statistical entity identification and predicate detection. Lopez et al. [15] propose another template based QA system without the need to train a template classifier. The authors use the output of the dependency parse tree to create (linguistic) triples and identify the type of semantic entities. Then they iterate a greedy algorithm for 2 to 3 rounds to determine the most similar template. Abujabal et al. [16] recently introduced an approach which can learn templates from user utterances. The templates are learned by distant supervision from question and Knowledge Graph answer pairs. The authors also employ dependency parse trees, which in turn allow leveraging compositional utterances. The templates are aligned between utterance and query by integer linear programming and learned in an offline step. In the online phase, the authors perform a light-weight template matching, consisting of automatically decomposing the question into constituent clauses and computing answers for each constituent using simple templates which are later combined to fully-fledged SPARQL queries. Unfortunately, none of the template-based approaches are available online as a webservice or working code repository.

By contrast, in this paper recursive neural network would automatically learn the required representations through labeled examples provided in a large dataset, namely LC-QuAD. This methodology is domain independent and can thus be transposed to work with any domain requiring minimal additional modifications to the neural network architecture. Note, we used Tree-LSTMs in the domain of QA over Knowledge Graphs as a first step in this novel research directly and did not consider other baselines. Other baselines have been investigated by other works [6] [17].

3 LC-Quad Dataset

An essential requirement to develop and evaluate question answering systems is the availability of a large dataset comprising of varied questions and their corresponding logical forms. LC-QuAD consists of 5,000 questions along with the intended SPARQL queries required to answer questions over DBpedia. The dataset includes complex questions, i.e. questions in which the intended SPARQL query does not consist of a single triple pattern.
Trivedi et al. [9] generated the dataset by using a list of seed entities, and filtering by a predicate whitelist, generate subgraphs of DBpedia to instantiate SPARQL templates, thereby generating valid SPARQL queries. These SPARQL queries are then used to instantiate Normalized Natural Question Templates (NNQTs) which act as canonical structures and are often grammatically incorrect. These questions are manually corrected and paraphrased by reviewers.

There are two key advantages for using LC-QuAD over similar existing datasets such as SimpleQuestions [18], Free917n [19], or QALD [8]. They are:

1. Higher focus on complex questions unlike SimpleQuestions which focuses entirely on single triple patterns.
2. Larger volume and variety of questions. The Free917 dataset contains only 917 questions and QALD-9 has less than 1000 training and test questions combined.

The LC-QuAD dataset contains 5,000 questions divided into 38 unique SPARQL templates comprising 5042 entities and 615 predicates. The SPARQL queries have been generated based on the 2016 DBpedia release. The dataset broadly contains three types of questions:

1. **Entity Queries**: Questions whose answer is an entity or list of entities with the WHERE clause containing one or more triples.
2. **Boolean Queries**: Questions whose answer is a boolean True or False with the WHERE clause containing exactly one triple.
3. **Count Queries**: Questions whose answer is a cardinal number with the WHERE clause containing one or more triples.

Among the 5000 verbalized SPARQL queries, only 18% are simple questions, and the remaining queries either involve more than one triple, or COUNT/ASK keyword, or both. Moreover, 18.06% queries contain a COUNT based aggregate, and 9.57% are boolean queries. The advantage of using LC-QuAD is that it was tailored specifically for neural network approaches to question answering and has a relatively large variety of questions in the complex, count and boolean categories when compared to existing datasets which is valuable when training models and evaluating approaches. As of now, the dataset does not have queries with OPTIONAL, or UNION keywords. Also, it does not have conditional aggregates in the query head [9].

Table 1 tabulates the frequency distribution of each template in the LC-QuAD dataset along with its corresponding SPARQL template and an example query. Interestingly, the first 14 templates make up over 80% of the dataset and there are 7 templates with under 10 examples. In fact, templates 601, 9 and 906 have only 1 example in the entire dataset.

| ID | Count | Question Type | SPARQL Template | Example Query |
|----|-------|---------------|-----------------|---------------|
| 2  | 748   | Entity        | SELECT DISTINCT ?uri WHERE { <r><p> ?uri . } | Name the mascot of Austin College? |
| 305| 564   | Entity        | SELECT DISTINCT ?uri WHERE { ?x <p><r>. ?x <p2> ?uri . ?x rdf:type <class> . } | What layout can be found in cars similar to the Subaru Outback? |
| 16 | 523   | Entity        | SELECT DISTINCT ?uri WHERE { <r><p> ?uri. <r2><p2> ?uri. } | Which series has an episode called The lost special and also a character named Sherlock Holmes? |
| 308| 334   | Entity        | SELECT DISTINCT ?uri WHERE { ?uri <p><r>. ?uri <p2> ?r2 . ?uri rdf:type <class>} | Name the mountain whose range is Sierra Nevada (U.S.) and parent mountain peak is Nevado de Toluca? |
| 301| 309   | Entity        | SELECT DISTINCT ?uri WHERE { ?uri <p><r>. ?uri rdf:type <class> } | What is the river whose mouth is in deadsea? |
| 3  | 262   | Entity        | SELECT DISTINCT ?uri WHERE { <r><p> ?x . ?x <p2> ?uri . } | What awards did the film director of The Haunted House win? |
| 5  | 213   | Entity        | SELECT DISTINCT ?uri WHERE { ?x <p><r>. ?x <p2> ?uri . } | Starwood operates in which places? |
| Query                                                                                                                                                                                                 | Database Answer                                                                                                                                                                                                 |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| In which part of the world can I find Xynisteri and Mavro?                                                                                                                                               |                                                                                                                                                                                                     |
| Was Ganymede discovered by Galileo Galilei?                                                                                                                                                             |                                                                                                                                                                                                     |
| Does the Toyota Verossa have the front engine design platform?                                                                                                                                          |                                                                                                                                                                                                     |
| Which newspapers are owned by companies which are under Rolv Erik Ryssdal?                                                                                                                            |                                                                                                                                                                                                     |
| How many awards have been given to screenwriters?                                                                                                                                                       |                                                                                                                                                                                                     |
| What are the beverages whose origin is England?                                                                                                                                                        |                                                                                                                                                                                                     |
| What is the region of the ethnic group which speaks the language of Arkansas?                                                                                                                            |                                                                                                                                                                                                     |
| What are some characters of the series produced by Ricky Grevais?                                                                                                                                           |                                                                                                                                                                                                     |
| How many companies have launched their rockets from the Vandenerg Air base?                                                                                                                                |                                                                                                                                                                                                     |
| How many places were ruled by Elizabeth II?                                                                                                                                                            |                                                                                                                                                                                                     |
| Count the number of sports played by schools which play hockey?                                                                                                                                            |                                                                                                                                                                                                     |
| Name all the doctoral student of the scientist who also supervised Mary Ainsworth?                                                                                                                       |                                                                                                                                                                                                     |
| How many TV show has distributor located in Burbank California?                                                                                                                                           |                                                                                                                                                                                                     |
| What is the river that falls into North Sea and Thames Estuary?                                                                                                                                             |                                                                                                                                                                                                     |
| How many movies did Stanley Kubrick direct?                                                                                                                                                             |                                                                                                                                                                                                     |
| Whose former teams are Indianapolis Colts and Carolina Panthers?                                                                                                                                          |                                                                                                                                                                                                     |
| Which colonel consort is Dolley Madison?                                                                                                                                                                |                                                                                                                                                                                                     |
| How many states does the Pioneer corporation operate in?                                                                                                                                                   |                                                                                                                                                                                                     |
| Count all those whose youth club was managed by Luis Enrique.                                                                                                                                             |                                                                                                                                                                                                     |
As shown in Table 1 from the previous section there is great imbalance between the distribution of templates in the dataset. Also, some templates are exact replicas of others with an additional triple. For example, templates below 100 and templates in the 3xx series and templates in the 1xx and 4xx series have only one triple differentiating them:

\[ ?\text{var} \text{ rdf:type } \text{class} \]

With this in mind, during preprocessing all templates which had less than 50 examples in the initial dataset were removed. The rationale here was that each template should have at least a 1% representation in the final dataset. Also, templates below 100 were merged with their corresponding 3xx templates and 1xx templates were merged with 4xx templates by adding additional OPTIONAL queries to the SPARQL template. Also, templates 151 and 152 were merged into each other since they have identical SPARQL templates.
For example template 1 and template 301 were combined into a single template as follows:

Template 1: \[
\text{SELECT DISTINCT ?uri \{ ?uri <p> ?r >. \}}
\]

Template 301: \[
\text{SELECT DISTINCT ?uri \{ ?uri <p> ?r >. ?uri rdf:type <class> \}}
\]

Combined Template: \[
\text{SELECT DISTINCT ?uri \{ ?uri <p> ?r >. OPTIONAL \{ ?uri rdf:type <class> \}}
\]

The removal of sparse templates resulted in only 80 questions being removed and the final dataset had 4,920 questions spread across 15 templates. The frequency distribution and updated templates of the preprocessed dataset are shown in Table 2. It must be noted that this refined dataset was used to train the template classification model. In spite of the manual review process there were several grammatical mistakes and misspellings of proper nouns in the dataset which were corrected as needed and the results of the same is shared with the LC-QuAD team so that they can improve the quality of the dataset for the community.

| ID    | Merged           | Count | Question Type | Original SPARQL Template                                                                 |
|-------|------------------|-------|---------------|-----------------------------------------------------------------------------------------|
| 5     | 5, 305           | 777   | Entity        | \text{SELECT DISTINCT ?uri WHERE \{ ?x <p> ?r >. ?x <p2> ?uri . OPTIONAL \{ ?x rdf:type <class> \}} |
| 2     | 2                | 748   | Entity        | \text{SELECT DISTINCT ?uri WHERE \{ <r> <p> ?uri \}}                                  |
| 16    | 16               | 523   | Entity        | \text{SELECT DISTINCT ?uri WHERE \{ <r> <p> ?uri . OPTIONAL \{ ?r rdf:type <class> \}} |
| 1     | 1, 301           | 468   | Entity        | \text{SELECT DISTINCT ?uri WHERE \{ ?uri <p> ?r >. OPTIONAL \{ ?uri rdf:type <class> \}} |
| 3     | 3, 303           | 377   | Entity        | \text{SELECT DISTINCT ?uri WHERE \{ <r> <p> ?x . ?x <p2> ?uri . OPTIONAL \{ ?x rdf:type <class> \}} |
| 151   | 151, 152         | 368   | Boolean       | \text{ASK WHERE \{ <r> <p> ?r2 >. \}}                                               |
| 8     | 308              | 334   | Entity        | \text{SELECT DISTINCT ?uri WHERE \{ ?uri <p> ?r >. ?uri <p2> ?r2 > , ?uri rdf:type <class> \}} |
| 6     | 6, 306           | 269   | Entity        | \text{SELECT DISTINCT ?uri WHERE \{ ?x <p> ?r >. ?x <p2> ?r2 > , ?uri rdf:type <class> \}} |
| 105   | 105, 405         | 261   | Count         | \text{SELECT (COUNT(DISTINCT ?uri) as ?count) WHERE \{ ?x <p> ?r >. ?x <p2> ?uri . OPTIONAL \{ ?uri rdf:type <class> \}} |
| 15    | 15               | 198   | Entity        | \text{SELECT DISTINCT ?uri WHERE \{ <r> <p> ?uri . OPTIONAL \{ ?r rdf:type <class> \}} |
| 101   | 101, 401         | 144   | Count         | \text{SELECT (COUNT(DISTINCT ?uri) as ?count) WHERE \{ ?uri <p> ?r >. OPTIONAL \{ ?uri rdf:type <class> \}} |
| 7     | 7, 307           | 131   | Entity        | \text{SELECT DISTINCT ?uri WHERE \{ ?uri <p> ?r >. ?uri <p> ?r2 > , OPTIONAL \{ ?uri rdf:type <class> \}} |
| 111   | 111              | 76    | Count         | \text{SELECT (COUNT(DISTINCT ?uri) as ?count) WHERE \{ ?x <p> ?r >. ?x <p> ?uri . OPTIONAL \{ ?uri rdf:type <class> \}} |
| 11    | 311              | 76    | Entity        | \text{SELECT ?uri WHERE \{ ?x <p> ?r >. ?x <p> ?uri . OPTIONAL \{ ?uri rdf:type <class> \}} |
| 106   | 406              | 70    | Count         | \text{SELECT (COUNT(DISTINCT ?uri) as ?count) WHERE \{ ?x <p> ?r >. ?uri <p> ?r2 > , OPTIONAL \{ ?uri rdf:type <class> \}} |

Table 2: Frequency of templates after preprocessing. Templates with 50 examples removed and similar templates merged.

4 Template Classification Approach

Our proposed system follows the steps mentioned below: (i) Question Analysis; (ii) Template Classification (Query Construction); (iii) Slot-Filling (Phrase Mapping and Disambiguation); (iv) Querying. The first two steps are presented in this section and remaining two steps are elaborated in Section 5. This is because the output from step 1 is directly used in step 2 and the same is true for steps 3 and 4.

4.1 Question Analysis

First, the question provided by the user is analyzed based on purely syntactic features. QA systems use syntactic features to deduce, for example, the right segmentation of the question, determine which phrase corresponds to an
instance, property or class and the dependency between the different phrases [2]. For now, we only deal with syntactic parsing of the incoming question in this phase and converting it into a form that can be used for training the Recursive Neural Network.

4.1.1 Part of Speech Tagging

Part-of-Speech (POS) Tagging is the process of annotating a word in a text as corresponding to a particular part of speech, e.g.: noun, verb, adjective, etc. In Natural Language Processing (NLP) applications, POS tagging is usually the first step in a pipeline and the output of POS tagging is typically used by downstream processes such as parsing for instance.

For the model, the English version of the Stanford POS tagger was used [20]. The Stanford POS Tagger is a log-linear POS tagger which utilizes both preceding and following tag contexts through the implementation of a dependency network representation. The tagger uses the Penn Treebank Tagset [21] for tagging the individual parts of speech and the Java implementation (v3.9.1) of the tagger was used.

For example, consider the question "Philadelphia City Council is the governing body of which city?". The corresponding POS tagged question is represented in Figure 1.

![Figure 1: Stanford POS-Tagger Output](image)

4.1.2 Dependency Parsing

Parsing in NLP is the process of determining the syntactic structure of text using a formal grammar. Given a sentence, a parser computes the combination of production rules that generate the sentence according to the underlying grammar. POS tagged information alone is not enough to identify the relationships between the different chunks in a question. But this information can be leveraged by parsers to provide rich meaningful information between constituent words. The Stanford Neural Network dependency parser was used by the system [22]. The input to the parser was the sequence of POS tags generated from the previous step and the output is the corresponding parse tree. The Java implementation (v3.9.1) on the Stanford parser was used by the system.

Figure 2 represents the Stanford Dependency Parser output for the question "Philadelphia City Council is the governing body of which city?".

![Figure 2: Stanford Dependency Parser Output](image)
There are two outputs of interest from Dependency Parsing. The first is the typed dependencies for each word in the input sentence. The typed dependencies representation provide a simple description of the grammatical relationships in a sentence. Its expressed as triples of a relation between pairs of words. For the rest of the paper these relationships are denoted as RELS. The second output is the parse tree.

4.2 Input Preparation

The output from the parse tree needs to be vectorized so that they can be supplied to the neural network model. There are two strategies to vectorize words: 1) One-Hot Encoding or 2) Word Embeddings. Based on the data, five distinct kind of input models were developed for training. These are summarized in Table 3.

4.2.1 One-Hot Encoding

One-Hot encoding is a common strategy in machine learning for converting categorical input into a vector by setting all values as 0 except for 1 bit which has a value 1, hence the name One-Hot. For example the number of POS tags in the LC-QuAD dataset is 43. So each POS tag is represented as a 43 x 1 vector where a single index is 1 and the rest are 0 depending on the index of the POS tag being considered. This conversion from an abstract categorical value to a consistently sized vector enables easier processing and prediction by machine learning models.

4.2.2 Word Embedding

Generally, the goal of word embeddings is mapping the words in unlabeled text data to a continuously-valued low dimensional space, in order to capture the internal semantic and syntactic information. The concept of word embedding was first introduced with the Neural Networks Language Model (NNLM). They are usually unsupervised models and incorporate various architectures such as Restricted Boltzmann Machine (RBM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and Long-Short Term Memory (LSTM) that can be used to build word embeddings. Usually the goal of the NNLM is to maximize or minimize the function of log likelihood, sometimes with additional constraints [23]. A key reason for using word embedding is that, in the past few years it has been shown that pre-trained models produce vastly better performance compared to existing methods such as one-hot vectors.

4.3 Facebook FastText

For word embedding the system uses Facebook’s FastText embedding model [24]. FastText uses an approach based on the skipgram model (taking into account subword information), where each word is represented as a bag of character n-grams. The main advantage of using FastText is its ability to handle out of vocabulary words better. The dataset had over 6000 unique tokens which were compressed into word vectors of dimensions 300 x 1 using the FastText word embedding model.

| Model               | Dimensionality | Description                                           |
|---------------------|----------------|--------------------------------------------------------|
| POS                 | 43 x 1         | Only POS Tags expressed as One-Hot Vector              |
| POS + RELS          | 85 x 1         | One-Hot POS vector concatenated with One-Hot RELS Vector|
| FastText            | 300 x 1        | FastText Word Embedding                                |
| FastText + POS + RELS| 385 x 1       | FastText Word Vector concatenated with One-Hot POS and RELS Vector |
| FastText + POS + RELS + CHARs | 444 x 1 | FastText Word Vector concatenated with One-Hot POS, RELS and CHARs Vector |

Table 3: Dimensionality of different models created for the template classification task

4.4 Recursive Neural Network

A recursive neural network is basically an extension of a recurrent neural network implemented on a graph or tree-based input instead of a sequential input. They are non-linear adaptive models that are able to learn deep structured information. They were introduced as promising machine learning models for processing data from structured domains. They can be employed for both classification and regression problems and are capable of solving both supervised and unsupervised tasks. They provide the flexibility of being able to work with input of arbitrary length compared to other feature based approaches which are constrained to fixed length vectors [25].
Here, the Tree-LSTM was implemented based on the model proposed by Tai et al. [6] and our architecture is based on their implementation. Tree-LSTM is a generalization of LSTMs to tree-structured network topologies. A key distinction between Tree-LSTM and standard LSTM is that, while the standard LSTM composes its hidden state from the input at the current time step and the hidden state of the LSTM unit in the previous time step, the tree-structured LSTM, or Tree-LSTM, composes its state from an input vector and the hidden states of arbitrarily many child units. The standard LSTM can then be considered a special case of the Tree-LSTM where each internal node has exactly one child.

Similar to standard LSTM units, each Tree-LSTM unit (indexed by \( j \)) contains input and output gates \( i_j \) and \( o_j \), a memory cell \( c_j \), hidden state \( h_j \) and input vector \( x_j \) where \( x_j \) is a vector representation of a word in a sentence. The critical difference between the standard LSTM unit and Tree-LSTM units is that gating vectors and memory cell updates for a given node are dependent on the states of its child units. Additionally, instead of a single forget gate, the Tree-LSTM unit contains one forget gate \( f_{jk} \) for each child \( k \). This allows the Tree-LSTM unit to selectively incorporate information from each child. For example, a Tree-LSTM model can learn to emphasize semantic heads in a semantic relatedness task, or it can learn to preserve the representation of sentiment-rich children for sentiment classification [6].

Given a tree, let \( C(j) \) denote the set of children of node \( j \). The Tree-LSTM transition equations are the following:

\[
\tilde{h}_j = \sum_{k \in C(j)} h_k
\]

\[
i_j = \sigma(W^{i}(x_j + U^{i}\tilde{h}_j + b^{i}))
\]

\[
f_{jk} = \sigma(W^{f}(x_j + U^{f}h_k + b^{f}))
\]

\[
o_j = \sigma(W^{o}(x_j + U^{o}\tilde{h}_j + b^{o}))
\]

\[
u_j = \sigma(W^{u}(x_j + U^{u}\tilde{h}_j + b^{u}))
\]

\[
c_j = i_j \odot u_j + \sum_{k \in C(j)} f_{jk} \odot c_k
\]

\[
h_j = o_j \odot \tanh(c_j)
\]

The Tree-LSTM learns a question by passing the sequence of words and the tree structure. Although the tree begins at the root, the model recursively traverses the tree and first learns the hidden states of the leaf nodes. The state of the leaf nodes are used by their corresponding parents to derive their state and so on until the network finally reaches the root node. So learning occurs breadth first from the leaf to the root. Finally, the output from the root node is converted into a \( N_t \) dimensional vector using a softmax classifier where \( N_t \) is the number of templates which in this case is 15.

Formally, to predict template \( \hat{t} \) from the set of templates \( T \) we calculate the softmax at the root node followed by the argmax to classify the template for the given question as shown below:

\[
\hat{p}_\theta(t|x_{root}) = \text{softmax}(W^{t}(h_{root} + b^{t})),
\]

\[
\hat{t} = \text{argmax}_t \hat{p}_\theta(t|x_{root})
\]

The cost function is the negative log-likelihood of the true class label \( y \) and \( \lambda \) is the L2-Regularization hyperparameter as given below:

\[
J(\theta) = -\log \hat{p}_\theta(y|x_{root}) + \frac{\lambda}{2} \| \theta \|_2^2
\]

5 Slot Filling Approach

For a given input question, the template classification algorithm from the previous section determines the top-n (in our case \( n = 2 \) to omit computing overhead) templates that are most likely to answer the question. The template captures the semantic structure of the user’s query, which is then mapped to the underlying knowledge graph, leaving gaps only for the slots that need to be injected as needed. The candidate SPARQL template broadly contains three kinds of slots that need to be filled:
1. **Resources:** are named entities (proper nouns), which can be detected using standard entity recognition tools. For example London, Microsoft, etc.

2. **Predicates:** are nouns, adjectives, or verbs that may modify a resource. For example: born, capital, etc.

3. **Ontology Classes:** Ontology classes that are associated with resources define the type of class a resource might fall under. For example, when considering the resource Barack Obama (dbr:Barack_Obama) a valid ontology class would be Person (dbo:Person). Ontology classes are linked through the `rdf:type` predicate of the target resource.

For example, consider the question "Philadelphia City Council is the governing body of which city?". The underlying candidate template detected for this question form would be:

```
SELECT DISTINCT ?uri { ?uri p r. OPTIONAL { ?uri rdf:type class}}
```

As can be seen, for answering this question, one resource, one predicate and one ontology class need to be detected. It must be noted that the ontology class detection is optional, even though the original candidate SPARQL query from the LC-QuAD dataset does not require an ontology class, the present system requires it since the LC-QuAD templates 1 & 301 were merged during the data preprocessing step, see Section 3. An ensemble of tools was used for the slot filling process. The reason for using multiple tools for a given task was to cover the weaknesses of each while at the same time maximizing their strengths to produce the best possible results. Note, we do not focus on the slot filling part in this paper.

For named entity recognition, DBpedia Spotlight [1] and TagMe [26] were used. DBpedia Spotlight automatically annotates text with DBpedia URIs, aka resources. For the slot filling task, a confidence of 0.4 (default) was used. The specialty of TagMe is that it may annotate texts that are short and poorly composed to underlying Wikipedia pages and their inter-relations. Singh et al. [4] showed that TagMe outperforms other Named Entity Recognition tools on the LC-QuAD dataset and hence it was a natural choice for this task. But TagMe suffers when it comes to the detection of single word entities, such as Geneva (dbr:Geneva) in the question: "Is Esther Alder the mayor of Geneva?". But DBpedia Spotlight has better accuracy in spotting short entities while struggling with multi-word entities, which are detected more efficiently by TagMe. These are hence a good complementary solution. Wherever TagMe detected multi-word entities, these were ranked higher compared to the entities detected by DBpedia Spotlight.

For relation and class linking, Singh et al. [4] state that RNLIWOD [4] has the best overall performance on the LC-QuAD dataset but their results also show that it has poor overall macro performance (0.25 precision, 0.22 recall & 0.23 F-1 score). Thus, we augmented its dictionary of predicates and ontology classes along with their `rdfs:label` used in the DBpedia Chatbot project [27]. This resulted in higher coverage of predicates and classes that could be matched with the input question, thereby leading to better performance. The lexicon is a key-value hashmap with the keys being the various surface forms that can be used to express a particular predicate or class and their value being all possible predicates or classes that match the sequence of words in the given surface form.

After the candidates for each slot are detected, candidate queries are built using the Cartesian product of the possible values in each slot. Each combination is queried against a DBpedia 2016-10 SPARQL endpoint, which was the latest stable release compatible with LC-QuAD and QALD at the time of writing, to determine if they yield any results. This process continues until the first viable combination is discovered that produces results against the endpoint. As Usbeck et al. [28] showed, the problem of SPARQL query generation and pruning of invalid candidate queries is very computationally intensive and very little progress has been made beyond the semantic analysis of the Cartesian product approach to improve both efficiency and performance in this part of the QA process.
6 Experimental Results

In this section, we present the used model parameters and experimental results, followed by a discussion of the findings.

6.1 Model Selection & Hyperparameter Tuning

Among the different models for input that were attempted, the model that produced the best results was the one that used a combination of FastText Word Embedding concatenated with the One-Hot Vectors of the POS tag and word dependency relationship (RELS) derived from the syntactic parse of the sentence combined with the average of the One-Hot character vectors of each character in a given word. Figure 3 shows the accuracy across epochs for each of the model combinations that were considered and clearly shows that the FastText + POS + RELS + CHARS model outperforms all other combinations of input. The preprocessed dataset containing 4920 questions was split into train and test datasets with a split of 80% training and 20% test data. The accuracy of this model was 0.828 on the test dataset. We calculated accuracy as $\text{accuracy}(y, \hat{y}) = \frac{1}{N} \sum_{i=1}^{N} 1(\hat{y}_i = y_i)$, where $\hat{y}_i$ is the predicted value of the $i$th example, $y$ is the corresponding true value and $N$ is the total number of examples.

![Figure 3: Accuracy on the test dataset for different input models](image)

Table 4 tabulates the hyperparameters of the model. The input vector was the concatenated 444-dimensional word vector. The Adam Optimizer [29] was used with a mini batch size of 25 examples. The loss function used was Cross-Entropy Loss, which has been shown to exhibit superior performance for tasks involving multivariate classification [30]. Due to the low number of training examples, the model had to be aggressively regularized and the learning rate periodically curtailed to prevent overfitting while simultaneously improving the model’s generalization performance. Three strategies were employed to achieve this: (1) Weight Decay, (2) Dropout, (3) Adaptive Learning Rate.

6.2 Template Classification

The best model from the template classification task produced an accuracy of 0.828 and 0.945 in the top-2 templates. Table 6 displays template level accuracy. The number of examples does not seem to affect the accuracy at the template level. Rather, based on the confusion matrix from Figure 4 it can be observed that specific templates misclassify each other. For example, templates 3 & 5 are more likely to misclassify each other, and the same can be said for 5 & 6 but 3 & 6 do not misclassify. Also, template 1 misclassifies with template 2 at a much higher rate since they are mirrors of
a single triple pattern. That is, template 1 has the triple pattern ?uri p r while template 2 has the triple pattern r p ?uri. To test how well the model generalizes it was also tested on the QALD-7\cite{31} multilingual dataset without any additional training or optimizations. The model had never seen the dataset before and hence can serve as a good candidate to test the model’s predictive power on never before seen data. The test dataset was not considered due to several issues, e.g., unseen namespaces such as Dublin Core. We were not able to use the entire QALD-7 dataset because we trained the model on LC-QuAD which does not contain examples outside the DBpedia ontology schema. Note, we trained on the whole LC-QuAD dataset as other (unpublished) approaches did, as there is no dedicated development set. The training dataset of QALD-7 [31] contains 215 questions, of which 85 examples were eliminated during pre-processing. The model was tested on a total of 130 examples which is roughly 60% of the dataset and represented 7 templates that were analogous in the LC-QuAD dataset. These 7 templates are a subset of the 15 templates from LC-QuAD. The remaining questions were manually tagged by us based on the similarity of their SPARQL queries to the LC-QuAD dataset. The reasons why questions were eliminated are as follows:

1. **Filter & Union based queries**: As already mentioned, the LC-QuAD dataset currently does not support FILTER, OPTIONAL or UNION queries which do feature in the QALD dataset.

2. **MinMax Queries**: MinMax queries as the name suggests are natural language questions that ask for a variation of minimum or maximum of something eg: highest, lowest, largest, smallest, longest, shortest, etc.

3. **Many Triples**: Some questions require 3 or more triples to answer.

4. **Complex Boolean Questions**: Currently LC-QuAD’s Boolean questions have only a single triple in the where clause. In contrast, the QALD dataset also contains examples of questions with 2 triples and several variations of complex queries for boolean questions which LC-QuAD does not support.

| Template | #Examples | Acc. | Top-2 Acc. |
|----------|-----------|------|------------|
| 2        | 80        | 0.68 | 0.84       |
| 1        | 18        | 0.66 | 0.94       |
| 151      | 12        | 1.0  | 1.0        |
| 3        | 12        | 0.25 | 0.42       |
| 8        | 6         | 0.00 | 0.33       |
| 5        | 1         | 0.00 | 0.00       |
| 11       | 1         | 0.00 | 0.00       |

Table 5: Template Level Model Accuracy on the QALD dataset.

Table 5 shows the template distribution breakdown for accuracy in the QALD dataset. The overall accuracy was 0.618 and the top-2 accuracy was 0.786. The performance varies considerably per dataset. This is because the quality of questions differs across datasets. Quality has various dimensions, such as complexity or expressiveness. Template 2 is over-represented compared to other templates, with some templates such as template 5 and template 11 having only 1

---

https://github.com/AskNowQA/KrantikariQA
example. But the top 3 templates (by number of examples), which comprises 84% of the dataset, have a high top-2 accuracy, which shows reasonable generalization power for the template classification model. Although the original LC-QuAD dataset had 15 different targets while the QALD dataset had only 7, this did not contribute to a significant loss in accuracy since there was sufficient separation between disparate templates / question types, as shown in the confusion matrix in Fig 4. That is, while templates that were very similar to each other, such as template 1 and 2 (simple queries), tended to have a higher chance of misclassification between one another, they did not misclassify with template 151 (boolean query).

An interesting byproduct of the model is its answer type detection capability, i.e., entity, count or boolean questions get efficiently grouped. The results of which are shown in Figure 5.

### 6.3 Slot Filling

Table 7 shows the performance of the system on the LC-QuAD test dataset. Table 8 shows the performance of the system QALD-7 training dataset along with a comparison of the latest QA systems benchmarked on that dataset. We used internal methods of the GERBIL QA framework to assist in testing. Although we do not outperform the state of the art in every case, we wanted to highlight a novel research avenue with this work.
Table 6: Template Level Model Accuracy on LC-QuAD dataset.

| Template | #Examples | Accuracy |
|----------|-----------|----------|
| 2        | 143       | 0.87     |
| 5        | 141       | 0.78     |
| 16       | 103       | 0.83     |
| 151      | 93        | 0.98     |
| 1        | 89        | 0.76     |
| 3        | 79        | 0.75     |
| 8        | 66        | 0.89     |
| 6        | 53        | 0.67     |
| 105      | 51        | 0.94     |
| 15       | 50        | 0.80     |
| 101      | 30        | 0.83     |
| 7        | 21        | 0.66     |
| 111      | 19        | 0.89     |
| 11       | 17        | 0.70     |
| 106      | 9         | 0.66     |

Figure 5: Answer Type Detection visualisation via a confusion matrix.

Table 7: Performance of system on LC-QuAD

| LC-QuAD Test       | Ontology Class | PredicateResource Overall |
|--------------------|----------------|--------------------------|
| Micro Precision    | 0.802          | 0.950                    |
| Micro Recall       | 0.150          | 0.178                    |
| Micro F-1 Measure  | 0.253          | 0.300                    |
| Macro Precision    | 0.218          | 0.266                    |
| Macro Recall       | 0.215          | 0.258                    |
| Macro F-1 Measure  | 0.216          | 0.260                    |

Table 7: Performance of system on LC-QuAD
Reasons for errors in the named entity recognition task were:

1. **Specific instance detection**: Sometimes a specific form of an entity gets detected instead of the generic variety. Consider the question: "How many schools have bison as a mascot?". The entity American Bison (dbr:American_bison) was annotated instead of the generic bison (dbr:Bison).

2. **Disambiguation**: Sometimes it was hard to figure out the right entity to map to the resource when there were partial matches between the sequence of words in the question and the label of the corresponding entity. Consider the question: "Was 2658 Gingerich discovered at Harvard?". Even though Harvard University (dbr:Harvard_University) has a higher PageRank in the DBpedia knowledge graph and would be the correct choice for most questions, in this particular case the correct entity is Harvard College (dbr:Harvard_College).

3. **Accented Characters**: Entities with foreign characters were detected poorly by both entity recognition tools. eg: Étienne Biéler (dbr:Étienne_Biéler).

4. **Colloquialisms**: Colloquial forms referring to well known entities were hard to detect. Consider the question "How many companies were started in the states?" the phrase "the states" refers to USA (dbr:United_States) but instead State (Political) (dbr:State_(polity)) was detected.

| QALD-7 Train | WDAqua | ganswer2 | Proposed System |
|--------------|--------|----------|-----------------|
| Micro Precision | -      | 0.113    | 0.757           |
| Micro Recall  | -      | 0.561    | 0.466           |
| Micro F-1 Measure | -    | 0.189    | 0.577           |
| Macro Precision | 0.490  | 0.557    | 0.416           |
| Macro Recall  | 0.54   | 0.592    | 0.423           |
| Macro F-1 Measure | 0.510  | 0.556    | 0.417           |

Table 8: Performance comparison on QALD-7 [31]

Reasons for errors in the relation extraction task were:

1. **Implicit Predicates**: Sometimes the predicate needed to answer the question cannot be inferred from the question. Consider the question "How many golf players are there in Arizona State Sun Devils?" and its SPARQL query (Template 101): 
   
   SELECT COUNT(?uri) { ?uri dbo:college dbr:Arizona_State_Sun_Devils . ?uri rdf:type dbo:GolfPlayer . } 
   
   To answer the question the predicate college (dbo:college) needs to be detected, but this is impossible to do with existing methods based on just the input question alone.

2. **Abbreviations**: Abbreviations instead of their expanded form were harder for relation linking tools to detect. Eg: PM for Prime Minister (dbo:PrimeMinister).

3. **Disambiguation**: The issue of disambiguation also plagues relation linking. The question, "What is the label of Double Diamond (album)?" refers to a record label (dbo:recordLabel), which was hard for the system to detect.

4. **Subset predicates**: Sometimes specific forms of a predicate needed to be detected e.g., head coach (dbp:headCoach) instead of coach (dbp:coach).

We did not compare ourselves to other works, since they either have a lower overall performance [4], used a non-reproducible subset of LC-QuAD or have significantly changed their codebase since publication [32, 33, 34].

7 Conclusions & Future Work

This paper presents a novel approach for the QA over Linked Data task by converting it into a template classification task followed by a slot filling task. Although earlier template-based approaches have attempted similar solutions, this was the first time (to the best of our knowledge) that recursive neural networks were applied to the template classification task. For completeness, a slot filling approach using an ensemble of the best components for named entity, predicate and class recognition tasks were presented. We answered the following research questions:

1. Can state-of-the-art neural network techniques such as Long Short Term Memory (LSTM), recursive neural networks, and word embeddings be leveraged for the template classification task? Yes, our evaluation showed that the template classification model achieved an accuracy of 0.828 accuracy and 0.945 top-2 accuracy on the LC-QuAD dataset and an accuracy of 0.6183 and 0.786 top-2 accuracy on the QALD-7 dataset. After slot filling the system achieves a macro F-score 0.419 on the LC-QuAD dataset and a macro F-score of 0.417 on the QALD-7 dataset.
2. Can a template classification model serve as a replacement for the query building process that has been shown to be both error-prone and computationally intensive [4, 28, 35]? Yes, our model can address the template classification task without the need for expensive feature engineering.

3. Can the template classification model be developed without any domain specific information/features that can make it easily transferable? Yes, our template classification model was developed without any domain specific information or features as long as it is QALD-formatted. Thus it can easily be transferred across domains using appropriate, KB-agnostic slot filling tools [36].

We are aware that our approach has a coverage issue in terms of being bound to the training templates and look forward to mitigating this issue through a finer-grained training process. While the choice of LSTMs seems arbitrary and does not outperform the state of the art in all respects, we aimed to provide a proof-of-concept for a domain-agnostic QA system. Basing a domain-agnostic QA system on template classification alleviates the need for costly feature engineering that is characteristic of classical machine. We refer to Hakimov et al.’s [17] intuition that until now there is no systematic way to explore neural network architectures for a specific task. Thus, exploring other neural networks is certainly a possible research direction. For instance, we will explore an encoder setting on top of the input words instead of using pretrained embedding.

The new insight we gained about the pairwise misclassification of specific templates points to a potential future research direction where this recursive neural network model can serve as a drop-in. Also, the template classification approach can be extended to predict only certain segments of the final SPARQL query [16]. For domain adoption, the templates can either be reused or will need to be constructed from new training data. We are aware that the existence of particular templates limits the types of the queries a system can handle, and will strive to remedy this issue by template decomposition in upcoming research.

References

[1] Pablo N. Mendes, Max Jakob, Andrés García-Silva, and Christian Bizer. Dbpedia spotlight: shedding light on the web of documents. In Proceedings of the 7th International Conference on Semantic Systems, I-Semantics ’11, pages 1–8, New York, NY, USA, 2011. ACM.
[2] Dennis Diefenbach, Vanessa Lopez, Kamal Singh, and Pierre Maret. Core techniques of question answering systems over knowledge bases: a survey. Knowledge and Information Systems, pages 1–41, 2017.
[3] Konrad Höffner, Sebastian Walter, Edgard Marx, Ricardo Usbeck, Jens Lehmann, and Axel-Cyrille Ngonga Ngomo. Survey on challenges of question answering in the semantic web. Semantic Web, 8(6):895–920, 2017.
[4] Kuldeep Singh, Arun Sethupat Radhakrishna, Andreas Both, Saeedeh Shekarpour, Ioanna Lytra, Ricardo Usbeck, Akhilesh Vyas, Akmal Khikmatullave, Dharmen Punjani, Christoph Lange, et al. Why reinvent the wheel: Let’s build question answering systems together. In WWW, pages 1247–1256. International World Wide Web Conferences Steering Committee, 2018.
[5] Ricardo Usbeck, Michael Röder, Michael Hoffmann, Felix Conrad, Jonathan Huthmann, Axel-Cyrille Ngonga-Ngomo, Christian Demmler, and Christina Unger. Benchmarking question answering systems. Semantic Web Journal, 2018.
[6] Kai Sheng Tai, Richard Socher, and Christopher D Manning. Improved semantic representations from tree-structured long short-term memory networks. arXiv preprint arXiv:1503.00075, 2015.
[7] Esther Kaufmann and Abraham Bernstein. How useful are natural language interfaces to the semantic web for casual end-users? In The Semantic Web, pages 281–294. Springer, 2007.
[8] Ricardo Usbeck, Ria Hari Gusmita, Axel-Cyrille Ngonga Ngomo, and Muhammad Saleem. 9th challenge on question answering over linked data (QALD-9) (invited paper). In Joint proceedings of SemDeep-4 and NLIWOD-4, pages 58–64, 2018.
[9] Priyansh Trivedi, Gaurav Maheshwari, Mohnish Dubey, and Jens Lehmann. Lc-quad: A corpus for complex question answering over knowledge graphs. In International Semantic Web Conference, pages 210–218. Springer, 2017.
[10] Ann-Kathrin Hartmann, Edgard Marx, and Tommaso Soru. Generating a large dataset for neural question answering over the DBpedia knowledge base. 2018.
[11] Dennis Diefenbach, Kuldeep Singh, Andreas Both, Didier Cherix, Christoph Lange, and Sören Auer. The qanary ecosystem: getting new insights by composing question answering pipelines. In International Conference on Web Engineering, pages 171–189. Springer, 2017.

[12] Dennis Diefenbach, Kamal Deep Singh, and Pierre Maret. Wdaqua-core0: A question answering component for the research community. In Semantic Web Challenges - 4th SemWebEval Challenge at ESWC 2017, Portoroz, Slovenia, May 28 - June 1, 2017, Revised Selected Papers, pages 84–89, 2017.

[13] Lei Zou, Ruizhe Huang, Haixun Wang, Jeffrey Xu Yu, Wenqiang He, and Dongyan Zhao. Natural language question answering over rdf: a graph data driven approach. In Proceedings of the 2014 ACM SIGMOD international conference on Management of data, pages 313–324, ACM, 2014.

[14] Christina Unger, Lorenz Bühmann, Jens Lehmann, Axel-Cyrille Ngonga Ngomo, Daniel Gerber, and Philipp Cimiano. Template-based question answering over rdf data. In Proceedings of the 21st international conference on World Wide Web, pages 639–648. ACM, 2012.

[15] Vanessa López, Pierpaolo Tommasi, Spyros Kotoulas, and Jiewen Wu. Queriodali: Question answering over dynamic and linked knowledge graphs. In 15th ISWC, pages 363–382, 2016.

[16] Abdalghani Abujabal, Mohamed Yahya, Mirek Riedewald, and Gerhard Weikum. Automated template generation for question answering over knowledge graphs. In Proceedings of the 26th International Conference on World Wide Web, WWW ’17, pages 1191–1200, Republic and Canton of Geneva, Switzerland, 2017. International World Wide Web Conferences Steering Committee.

[17] Sherzod Hakimov, Soufian Jebbara, and Philipp Cimiano. Evaluating architectural choices for deep learning approaches for question answering over knowledge bases. In 13th IEEE International Conference on Semantic Computing, ICSC 2019, Newport Beach, CA, USA, January 30 - February 1, 2019, pages 110–113, 2019.

[18] Antoine Bordes, Nicolas Usunier, Sumit Chopra, and Jason Weston. Large-scale simple question answering with memory networks. arXiv preprint arXiv:1506.02075, 2015.

[19] Qingqing Cai and Alexander Yates. Large-scale semantic parsing via schema matching and lexicon extension. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics, volume 1, pages 423–433, 2013.

[20] Kristina Toutanova, Dan Klein, Christopher D Manning, and Yoram Singer. Feature-rich part-of-speech tagging with a cyclic dependency network. In Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology-Volume 1, pages 173–180, Association for Computational Linguistics, 2003.

[21] Mitchell P Marcus, Mary Ann Marcinkiewicz, and Beatrice Santorini. Building a large annotated corpus of english: The penn treebank. Computational linguistics, 19(2):313–330, 1993.

[22] Danqi Chen and Christopher Manning. A fast and accurate dependency parser using neural networks. In EMNLP, pages 740–750, 2014.

[23] Yang Li and Tao Yang. Word embedding for understanding natural language: A survey. In Guide to Big Data Applications, pages 83–104. Springer, 2018.

[24] Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. Enriching word vectors with subword information. arXiv preprint arXiv:1607.04606, 2016.

[25] Alejandro Chinea. Understanding the principles of recursive neural networks: A generative approach to tackle model complexity. In International Conference on Artificial Neural Networks, pages 952–963. Springer, 2009.

[26] Paolo Ferragina and Ugo Scaiella. Tagme: on-the-fly annotation of short text fragments (by wikipedia entities). In Proceedings of the 19th ACM international conference on Information and knowledge management, pages 1625–1628. ACM, 2010.

[27] Ram G Athreya, Axel-Cyrille Ngonga Ngomo, and Ricardo Usbeck. Enhancing community interactions with data-driven chatbots—the dbpedia chatbot. In Companion of the The Web Conference 2018 on The Web Conference 2018, pages 143–146. International World Wide Web Conferences Steering Committee, 2018.

[28] Ricardo Usbeck, Axel-Cyrille Ngonga Ngomo, Lorenz Bühmann, and Christina Unger. Hawk–hybrid question answering using linked data. In European Semantic Web Conference, pages 353–368. Springer, 2015.

[29] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.

[30] Katarzyna Janocha and Wojciech Marian Czarnecki. On loss functions for deep neural networks in classification. arXiv preprint arXiv:1702.05659, 2017.
[31] Ricardo Usbeck, Axel-Cyrille Ngonga Ngomo, Bastian Haarmann, Anastasia Krithara, Michael Röder, and Giulio Napolitano. 7th open challenge on question answering over linked data (qald-7). In *Semantic Web Evaluation Challenge*, pages 59–69. Springer, 2017.

[32] Takuto Asakura, Jin-Dong Kim, Yasunori Yamamoto, Yuka Tateisi, and Toshihisa Takagi. A quantitative evaluation of natural language question interpretation for question answering systems. In *Semantic Technology - 8th Joint International Conference, JIST 2018, Awaji, Japan, November 26-28, 2018, Proceedings*, pages 215–231, 2018.

[33] Hamid Zafar, Giulio Napolitano, and Jens Lehmann. Formal query generation for question answering over knowledge bases. In *ESWC*, pages 714–728, Cham, 2018. Springer International Publishing.

[34] Elizaveta Zimina, Jyrki Nummenmaa, Kalervo Järvelin, Jaakko Peltonen, Kostas Stefanidis, and Heikki Hyyrö. GQA: grammatical question answering for RDF data. In *5th SemWebEval Challenge at ESWC 2018*, pages 82–97, 2018.

[35] Muhammad Saleem, Samaneh Nazari Dastjerdi, Ricardo Usbeck, and Axel-Cyrille Ngonga Ngomo. Question answering over linked data: What is difficult to answer? what affects the f scores. In *Joint Proceedings of BLINK2017 and NLIWoD3*, 2017.

[36] Diego Moussallem, Ricardo Usbeck, Michael Röder, and Axel-Cyrille Ngonga Ngomo. Entity linking in 40 languages using MAG. In *ESWC*, pages 176–181, 2018.