

TECHNISCHE UNIVERSITÄT DRESDEN

FACULTY OF COMPUTER SCIENCE  
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## Master Thesis

Master Computational Logic

# Translating Natural Language to SPARQL

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Dresden, November 19, 2018

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# Selbstständigkeitserklärung

Hiermit erkläre ich, dass ich die von mir am heutigen Tag dem Prüfungsausschuss der Fakultät Informatik eingereichte Arbeit zum Thema:

*Translating Natural Language to SPARQL*

vollkommen selbstständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt sowie Zitate kenntlich gemacht habe.

Dresden, den November 19, 2018

Xiaoyu Yin

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## Abstract

English abstract here

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# 1 Introduction

## 1.1 Motivation

The World Wide Web has been quickly evolving and has now become a huge network containing various kinds of resources for billions of users to interact with. A majority of the documents on the web are formatted texts in Hypertext Markup Language (HTML), serving as the content that can be rendered in computer browsers for humans to read and understand. In order to find a resource satisfying specific needs, a web user normally needs to rely on the help of search engines to retrieve and filter results from innumerable documents on the web. Even so, it takes quite more time for humans to distinguish useful materials from others than machines that can scan a large number of files almost simultaneously. However, finishing such kind of tasks requires the capability of understanding the documents to be scanned and the traditional file format like HTML has made it difficult for machines to do so.

The Semantic Web is the concept of a Web where data and information can be manipulated by machines automatically [SHBL06]. There has been a set of standards for altering the current web to be more machine-readable and processable for automatic machine agents. In order to help achieve the potential of the current web, a series of relevant technologies including mainly Resource Description Framework (RDF) [CWL14] and Web Ontology Language (OWL) have been introduced. With the help of these tools, an increasing number of documents containing uniform organized data have been published conveniently on the web. One notable example of this is cross-domain Linked Datasets such as DBpedia [ABK<sup>+</sup>07]. DBpedia contains RDF documents that represent information extracted from Wikipedia articles, and all the documents with links to other datasets on the web constitute an interlinked ontology model. DBpedia also provides an open API for users to submit complicated queries against those documents.

SPARQL is a language designed for humans to query and manipulate the information sources contained in an RDF store or online RDF graph, and is by far the recommended standard [HS13]. SPARQL has already been widely supported by large open datasets like DBpedia. Though the data queried by SPARQL is made for publicity and openness, the use of it has yet been spread out of a group of experts with prior knowledge specific to some certain domain. For example, if a user wants to ask for a list of

books belonging to some certain category, he or she needs to have prior knowledge about the concepts and relations involved in describing books in RDF. The root of this problem is the gap between the natural language used by non-experts and the query language that consists of unique syntax, semantics and domain-specific vocabulary.

The motivation of this thesis is to bridge this gap between natural language and SPARQL. Since natural language and SPARQL are both able to be represented as sequences of pre-defined tokens, this can be treated as a translation problem. In recent years, the application of neural networks in machine translation has achieved greater improvements in translation results than previously applied statistical and phrase-based methods [MWN17]. Therefore, we want to transfer the success achieved by neural network models in translating from one natural language to another to the task of translating natural language to queries written in SPARQL. We look into the effects of such transfer by conducting several experiments, and comparing between different models with varying network configurations.

## 1.2 Thesis Outline

Chapter 2 presents the notion of Semantic Web and its corresponding technologies, research on the subject of neural machine translation in the area of deep learning, and past work closely related to this thesis.

(TBD) Chapter 3 describes the research method used in this thesis.

Chapter 4 shows the experiments carried out to identify the best performing neural network models on the task of translating natural language to SPARQL. In addition, this chapter discusses used datasets, technical details, and the produced results in textual and tabular form.

Chapter 5 depicts the analysis derived from the experiment results exhibited in chapter 4.

Chapter 6 gives a summary and provides an outlook for the future work.

## 2 Background

This chapter gives an introduction to the background technologies and subfields involved in this thesis. First, Semantic Web technologies are briefly introduced in Section 2.1, including the notion of RDF in Section 2.1.1, Linked Data in Section 2.1.3 and SPARQL in Section 2.1.2. Second, Section 2.2 describes the notion of neural machine translation and involved models and components. Finally, related research is discussed in Section 2.3.

### 2.1 Semantic Web Technologies

The original Web consisted largely of documents made up of hypertexts for rendering in the browsers, the meanings of the web page are not well conveyed, thus being difficult for computers to analyze, or users to make higher-level searches. As Berners-Lee et al. stated in [BLHL01], the Semantic Web is not an individual web separate from the current one but an extension. In the Semantic Web, there is an important functionality that the machines are able to process data and information automatically. The semantics of web pages are well-encoded and displayed to the software agents owned by users or organizations to provide meaningful services. In the Semantic Web, agents from different sources, namely producers and consumers, are able to communicate with each other by exchanging an ontology which typically contains a taxonomy and a set of inference rules. With the ontology, the computers can define classes, subclasses, and relations among entities on the Web and perform automated reasoning as if they "understand" the information [BLHL01].

The World Wide Web has linked more than 10 billion websites, and the useful contents can be delivered almost instantaneously to the users through search engines. Meanwhile, it is evolving from the web of documents for humans to read to a web of data and information derived from shared semantics. There are various types of programs and intelligent agents around the Web handcrafted for particular tasks, however, they usually possess little ability to deal with heterogeneous types of information [SHBL06]. There is also a growing need for the integration of data and information, especially in areas that demand heterogeneous and diverse datasets originating from separate subfields [SHBL06].

A set of technologies are already here to provide a preliminary environment for transforming the current



Web into the Semantic Web. Figure 2.1 shows an illustration of the Semantic Web technology stack, where the language in each layer is dependent on the layers below it. These languages have provided a foundation for allowing shared semantics to be integrated into the current documents on the Web, and data to be connected in a more explicit and standardized way. Resource Description Framework (RDF) [CWL14], a language located at a lower layer, has provided a foundation for the standardization of the formats of common data. SPARQL, on the other end, is a query language that can be utilized to search and manipulate data in RDF format from diverse sources [HS13]. The details of RDF and SPARQL are respectively presented in section 2.1.1 and section 2.1.2.

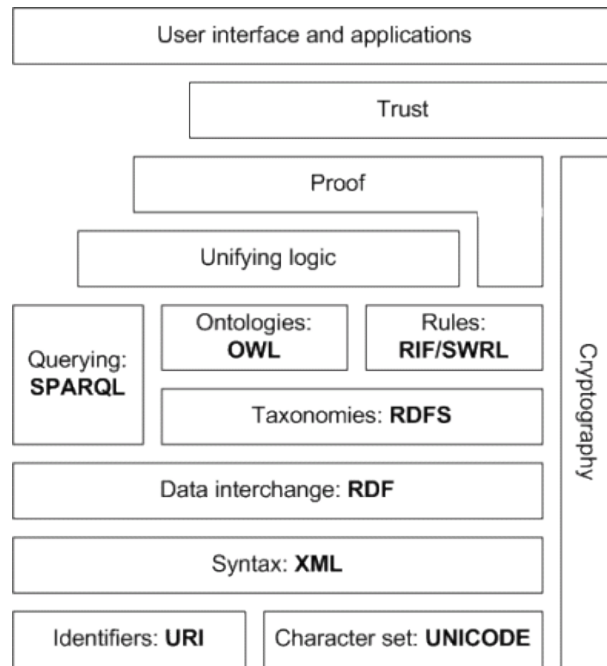


Figure 2.1: Semantic Web technology stack

The development of standardized technologies for the Semantic Web has promoted the integration of semantics into existing documents and linking of common data across different application domains and even regions. This enables a web of data where the data is connected with typed links, known as Linked Data [BHBL09]. It uses RDF to link arbitrary entities in the world by making typed statements, and allows complicated queries to be submitted in SPARQL. The applications of Linked Data are able to work upon a global and unbound data space, whereas the conventional web applications normally operate on top of a fixed set of data sources [BHBL09]. Further information on Linked Data is provided in section 2.1.3.

### 2.1.1 RDF

The Resource Description Framework (RDF) is a representation language for defining information on the Web. The Semantic Web Technology Stack (Figure 2.1) provides the infrastructure to express the meaning of concepts and terms in an organized way that machines can easily process. In 1997, the first RDF specification was defined by the World Wide Web Consortium (W3C) and then it became a W3C recommendation in 1999. Currently, the latest version is RDF 1.1 [CWL14] published in 2014.

In RDF, meanings are expressed in triples. A set of triples constitutes an RDF graph, which can be visualized via a diagram containing nodes and directed arcs. Figure 2.2 demonstrates a simple RDF graph with merely two nodes and one arrow connecting them, which also indicates three components of a triple: subject, predicate, and object. The subject and object represent some resource in the world, and the predicate denotes some relationship. Thus, an RDF triple makes assertions on some relationship of the things it identifies. An RDF graph claims the conjunction of statements encoded by its triples [CWL14].

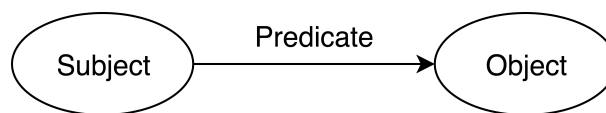


Figure 2.2: An RDF graph with one triple consisting of a subject, a predicate and an object

In the Semantic Web, arbitrary things in the world are denoted as resource and can be referred to by Internationalized Resource Identifier (IRI) or Literals. A datatype is used in addition to the Literal to specify its ranges of value. When no specific resources are identified but implicitly naming some relationship is needed, a blank node is used [CWL14]. In terms of an RDF triple, the following restriction is defined:

- the subject is an IRI or a blank node
- the predicate is an IRI
- the object is an IRI, a literal or a blank node

With the above-introduced notions, we show an example of how RDF can specify the concepts, properties, relations, and corresponding entities existing in the real world. We define the following IRIs<sup>1</sup>: `<http://example.org/bob#me>` referring to a human entity named Bob, `<http://www.w3.org/1999/02/22-rdf-syntax-ns#type>` representing "is a" relation, `<http://xmlns.com/foaf/0.1/Person>` specifying a concept denoting the class of person, `<http://schema.org/birthDate>` as a property representing date of birth, and `<http://www.w3.org/2001/XMLSchema#date>` referring to a data type of date. To express such in-

<sup>1</sup>The IRIs in this example are from <https://www.w3.org/TR/rdf11-primer>

formation: "Bob is a person who is born in 1990-07-04", the following triples are needed:

triple 1	subject	<code>&lt;http://example.org/bob#me&gt;</code>
	predicate	<code>&lt;http://www.w3.org/1999/02/22-rdf-syntax-ns#type&gt;</code>
	object	<code>&lt;http://xmlns.com/foaf/0.1/Person&gt;</code>
triple 2	subject	<code>&lt;http://example.org/bob#me&gt;</code>
	predicate	<code>&lt;http://schema.org/birthDate&gt;</code>
	object	<code>"1990-07-04"^^&lt;http://www.w3.org/2001/XMLSchema#date&gt;</code>

It is noticeable that these IRIs do not share the same prefixes because in an RDF document concepts defined from different sources can be incorporated collaboratively. As a result, the existing knowledge sources are readily combined or extended with new information. Joining the above triples and replacing some IRIs with shorter prefixes we obtain a graph shown in Figure 2.3.

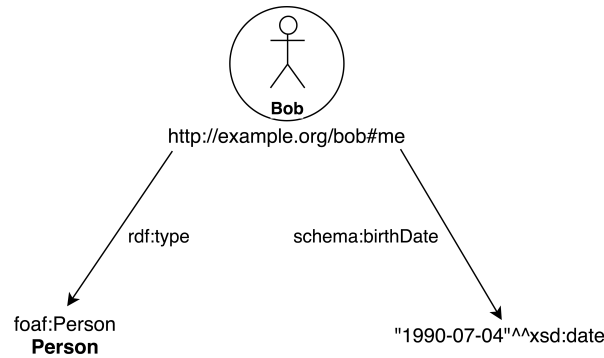


Figure 2.3: An example RDF graph representing "Bob is a person who is born in 1990-07-04". Some absolute IRIs are edited to be relative with prefixes.

RDF graphs provide an abstract representation for the knowledge. To write it down in a document, there exists a variety of serialization formats where each of them are designed for different scenarios and purposes. The most used ones are: Turtle [PC14], JSON-LD [SKL14], RDFa [HASB13], and RDF/XML [GS14]. Referring to the same RDF graph, the documents written in different serialization formats are logically equivalent [SR14]. The data owners can choose from these serialization formats to convert their existing documents into or publish new documents in RDF.

### 2.1.2 SPARQL

SPARQL Protocol and RDF Query Language (SPARQL) is a structured language similar to SQL but for querying and manipulating RDF graphs [HS13]. This thesis primarily focuses on the query capability of SPARQL. A SPARQL query normally consists of a `SELECT` operator followed by queried objects which are usually denoted by variables or their combinations, a `WHERE` block containing graph patterns

for matching the RDF data store, and optionally extensional operators such as filtering and grouping depending on the requirements. A list of prefixes can be provided in the head for shortening the IRIs involved in the matching graph patterns. The results of SPARQL queries are usually result sets or RDF graphs.

For instance, to query the RDF graph exhibited in Figure 2.3, a simple SPARQL query with only one single variable and WHERE block can be formulated as in the Listing 2.1.

Listing 2.1: A SPARQL query asking for "the persons whose birthday is on 1990 July 4th"

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX foaf: <http://xmlns.com/foaf/0.1/>
PREFIX schema: <http://schema.org/>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
SELECT ?person
WHERE
{
  ?person rdf:type foaf:Person .
  ?person schema:birthDate "1990-07-04"^^xsd:date .
}
```

Note that in SPARQL, prefixes are mandatory in the head of the query to make IRIs resolvable into absolute forms if there are any abbreviations in the body. The query in Listing 2.1 simply asks for the persons whose birthday is on 4th of July 1990. Running it on Figure 2.3 leads to a result consisting of a single value which can be displayed in tabular form (see Table 2.1). The query results can also be exhibited in variable standardized formats including XML, JSON, CSV, and TSV for the benefits of exchanging results in miscellaneous environments [HS13].

person
<http://example.org/bob#me>

Table 2.1: Returned result of a SPARQL query on the RDF graph in Figure 2.3

Table 2.1 indicates that <http://example.org/bob#me> is the only entity that matches the conjunction of both triples in the query graph pattern. If it is likely to have multiple values in the result, one can control the sequence size of the result with OFFSET and LIMIT operators, and further specify the ordering by using ORDER BY operator. In addition, SPARQL supports more advanced operators<sup>2</sup> for expressing aggregation, negation, counting, etc. for performing queries with higher complexity against the given RDF data. Some of them are not mentioned here for the reason that it is so far difficult to include all the operators in this thesis. The operators covered in this thesis are listed in Section 4.1.

<sup>2</sup>Full capabilities of SPARQL is available at: <https://www.w3.org/TR/sparql11-query>

### 2.1.3 Linked Data

RDF as a common data format provides a sound foundation for the unification of information on the traditional Web. While a huge amount of data is available in a standard format, to create a Web of Data that is able to provide more meaningful services, the relationships between data are also important. The collection of interrelated datasets that contain links to each other on the Web are referred to as Linked Data [lin18]. Linked Data also refers to a set of best practices to publish, share, and connect the data, information, and knowledge on the Web [BHBL09].

Anyone can create Linked Data and publish it on the Web. There exists a number of ways to do so. One can simply put a static RDF file on a server, or publish relational databases with the help of dedicated tools. A list of tools for editing, publishing, and consuming Linked Data are already publicly available [ldt18]. For large datasets, a SPARQL query service is often needed as well to support broader use cases.

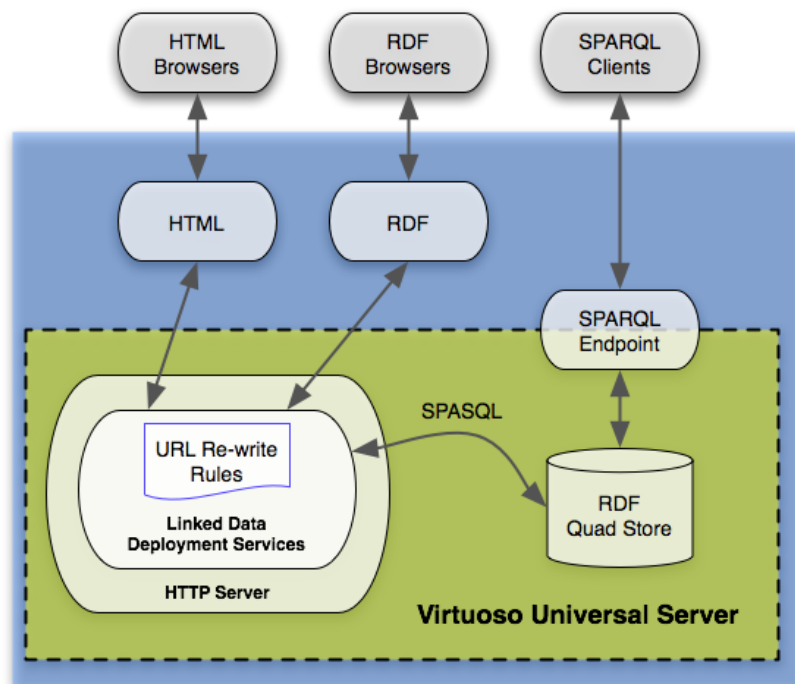


Figure 2.4: Current DBpedia data provision architecture [dbp18]

DBpedia is one of the most popular large-scale Linked Datasets online. It hosts datasets in RDF representing connected knowledge graphs that are generated by essentially parsing the articles of Wikipedia into structured information. The knowledge graphs on DBpedia not only links the described concepts within Wikipedia but also connects the concepts with other external datasets existing on the Web. In addition, DBpedia is serving a public endpoint upon which applications can post queries in SPARQL to retrieve information in RDF triples for different kinds of purposes. Figure 2.4 illustrates the architecture

DBpedia is currently adopting for the provision of its RDF data set. In DBpedia, OpenLink Virtuoso Server<sup>3</sup> is used to provide support for SPARQL endpoint and HTTP hosting.

% Add some DBpedia use cases

## 2.2 Neural Machine Translation

As a global information space, the World Wide Web contains billions of web pages written in languages from various regions of the world. The problem arises when users face the contents they request in a different language from the one they are fluent in. Translation is therefore needed here to lower the language barrier. However, it is evident that human translation does not fit the requirements due to the large quantity of web documents. One alternative solution is Machine Translation (MT). The goal of machine translation is to transform a text from an input language to a target language with the semantic meaning of the text being preserved.

However, due to the complexity of structures, semantics and vocabularies of natural languages, translation is considered a difficulty task for machines. According to [Pop12], the errors occurring in the machine translation output are mainly classified into five base categories: inflectional error, incorrect re-ordering, missing word, extra word, and lexical ambiguity. There is also debate whether fully automated high-quality machine translation systems can be achieved [BH64]. In addition, lack of context, incomplete common sense knowledge, and ineffectiveness in translating rare words have been major issues that affect the quality of the machine translation systems [Okp14] [WSC<sup>+</sup>16].

A large number of approaches have been developed in the area of machine translation over the last years. Currently, the architectures of existing MT systems can be divided into the following categories:

- **Rule-based Machine Translation (RBMT).** RBMT systems usually generate target language text based on an intermediary linguistic representation of the source text and a large set of rules that contain morphological, syntactic, and semantic bilingual mappings. They can be further subdivided into direct, transfer-based, and interlingua-based methods. The performance of RBMT systems, to a certain extent, relies on carefully designed linguistic rules and vast amount of lexicons [MWN17].
- **Statistical Machine Translation (SMT).** SMT systems are developed on the basis of splitting a bilingual text corpus into respective source and translation text pairs. They apply machine learning algorithms that compute a statistical model from the given corpus and the model translates each phrase or word at a time based on a probability distribution [MWN17]. SMT approaches usually

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<sup>3</sup>available at: <https://virtuoso.openlinksw.com/>

require an alignment between source sentence and several target sentences found in each text corpora and vice versa. Such methods suffer in performance when the languages involved have significantly different word orders [Okp14].

- **Example-based Machine Translation (EBMT).** EBMT utilizes bilingual corpora like SMT but they translate the text by example sentences. The major limitation of EBMT systems is translation of unknown words [MWN17].
- **Neural Machine Translation (NMT).** Some argue that NMT is also a statistical approach [MWN17]. NMT systems commonly consist of a model based on deep neural networks to perform end-to-end translation by words or characters in the given sentence [MWN17]. During the training of the model, the system steadily learns a representation of both languages in a continuous vector space and the ability to predict a combination of words with higher probability. The approaches in this category currently set the new state-of-the-art on several benchmark tests. Their relevant models are the primary focus of the investigation of this thesis.
- **Hybrid Machine Translation.** Hybrid approaches essentially leverage the advantages of the methods mentioned above to address their respective limitations and achieve better translation quality. In applications under this category, the hybridization of MT approaches are normally guided by either rule-based or corpus-based statistical systems [CJF15].

Among these categories, we focus primarily on the Neural Machine Translation methods. The development of NMT systems has gained more interests in recent years since deep neural networks have boosted extraordinary advancements in other areas of Artificial Intelligence such as computer vision [KSH12] and speech recognition [DYDA12]. NMT systems are usually superior in not needing hand-engineering of features that are one of the shortcomings of phrase-based systems [BGLL17]. However, some of the current NMT architectures have disadvantages in requiring large amounts of computation and time for training the deep model [BGLL17].

So far, many different architectures have been explored in NMT and new methods are constantly beating previous models in some benchmark datasets and achieving higher efficiency in computing. Among these architectures, primary works are listed here. Sutskever et al. [SVL14] and Cho et al. [CvMG<sup>+</sup>14] proposed and deployed an encoder-decoder architecture that contains two models where Recurrent Neural Networks (RNN) (see section 2.2.2) were used. The encoder encodes the input into a fixed-length vector, the decoder then decodes it into a translation. The two models are jointly trained to maximize the likelihood of a target sequence based on the given source sequence. However, the performance of this architecture drops when the length of the input sentence increases. To address this issue, Bahdanau et al. and Luong et al. presented in [BCB14, LPM15] an attention mechanism which serves as an extension

to align the encoder and decoder. The acceptance of this mechanism increased the quality of translation significantly. Furthermore, there have been other improvement strategies like bi-directional RNN, beam search, etc. Some variants like Long-Short Term Memory (LSTM) [HS97] and Gated Recurrent Unit (GRU) [CvMG<sup>+</sup>14] versions of encoder-decoders have also been investigated. In the mean time, while RNN encoder-decoders consume a lot of computation time on their sequential learning, there are architectures based on Convolutional Neural Networks (CNN) that are able to achieve parallelized computations, thus outperform the former models at a faster speed [GAG<sup>+</sup>17a]. What's more, Vaswani et al. [VSP<sup>+</sup>17] proposed a self-attention model called the Transformer. This model shows both quality and speed advantages and has achieves state-of-the-art results on multiple translation tasks. In the past years, some novel paradigms for NMT have also emerged like the applications of Generative Adversarial Networks (GAN) in [WXZ<sup>+</sup>17, YCWX17].

### 2.2.1 Sequence to Sequence Learning

Sequence to sequence (Seq2Seq) learning [SVL14] [CvMG<sup>+</sup>14] was an emerging area in supervised learning proposed for machine translation, and has been applied to many other sequential problems such as speech recognition, and text summarization. Learning the representation of one sequence and transformation of it into another sequence with different forms effectively and accurately is essentially the goal of Seq2Seq learning. The NMT approaches explored in this thesis belong to the category of sequence-to-sequence learning.

Regarding Seq2Seq learning on automated translation, encoder-decoder is one of the most applied architectures. In the architecture shown in Figure 2.5, the encoder receives the input as a sequence of tokens and turns it into a feature vector representing the input information in higher dimensionality space, the decoder then decodes that information from the vector in a way that enables generating another sequence of tokens as the output. When certain neural networks have been used in both encoder and decoder, this architecture has shown its superiority over the traditional phrase-based models in ease of extracting features, more flexibility with regard to the configuration of models, and better result accuracy [WSC<sup>+</sup>16].

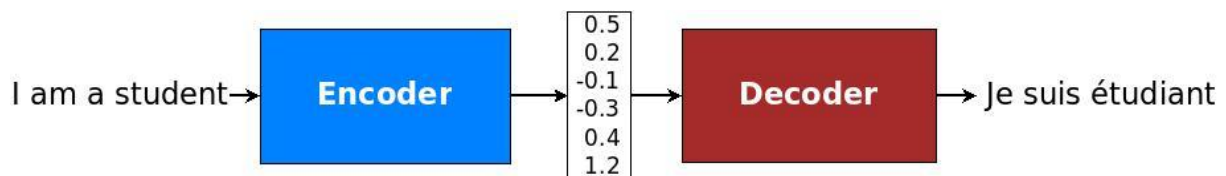


Figure 2.5: A conventional encoder-decoder architecture for machine translation

In the above architecture, different kinds of neural networks in both encoder and decoder can be inte-



grated to make combinations of models suitable for specific tasks. Recurrent Neural Networks are mostly used in problems dealing with texts which normally have variable lengths. In the layers of RNN, various cell types, normally LSTM and GRU, can provide the model with capabilities of maintaining the past information and capturing long-range dependencies in texts. Convolutional Neural Networks are less commonly used in sequence modeling. However, they were appearing in recently proposed models because of their inherent advantage in computation parallelization and effectiveness of building hierarchical representations.

Apart from the already mentioned components, a special attention mechanism is widely applied in Seq2Seq learning and even computer vision tasks that require models to attend to different parts of the input. In machine translation, an attention layer connects the decoder with the encoder hidden states to allow it search for parts of the source sequence instead of merely relying on a global vector. The attention mechanism has further improved the performance of NMT approaches by providing an effective mean to tackle the long-term dependency problem, although it also increases the computation.

### 2.2.2 Recurrent Neural Network

In sequence to sequence learning, Recurrent Neural Networks (RNNs) are the most widely used artificial neural networks. RNNs are specifically effective for processing sequential data. Given a sequence of inputs  $x = (x_1, \dots, x_{T_x})$ , an RNN is able to compute a series of hidden states  $h = (h_1, \dots, h_{T_x})$  step-wise where at each step  $t$  the hidden state  $h_t$  is dependent on the previous hidden state  $h_{t-1}$  and input  $x_t$  by the following equation:

$$h_t = f(h_{t-1}, x_t) \quad (2.1)$$

where  $f$  is a non-linear activation function which may differ in distinct architectures (e.g. GRU and LSTM). Based on this set of hidden states  $h$ , a sequence of outputs  $y = (y_1, \dots, y_{T_y})$  can be generated. Given different configurations of input sequence length  $T_x$  and output sequence length  $T_y$ , RNNs can be adapted to cope with various tasks including image classification (one to one), image captioning (one to many), sentiment analysis (many to one), machine translation (many to many), and video frame labeling (many to many), all of which are shown in Figure 2.6.

In machine translation, the inputs and outputs are normally a sequence of words or characters from the source sentences and the target sentences. Therefore, RNNs suited well in the encoder-decoder architecture (see Section 2.2.1). The RNNs served in the encoder and the decoder have different purposes. Figure 2.7 demonstrates a vanilla RNN encoder-decoder, where the encoder RNN reads the input words and encodes the information into the last hidden state vector, and then the decoder RNN receives this vector as the initial hidden state and samples a sequence word by word beginning from a starting symbol

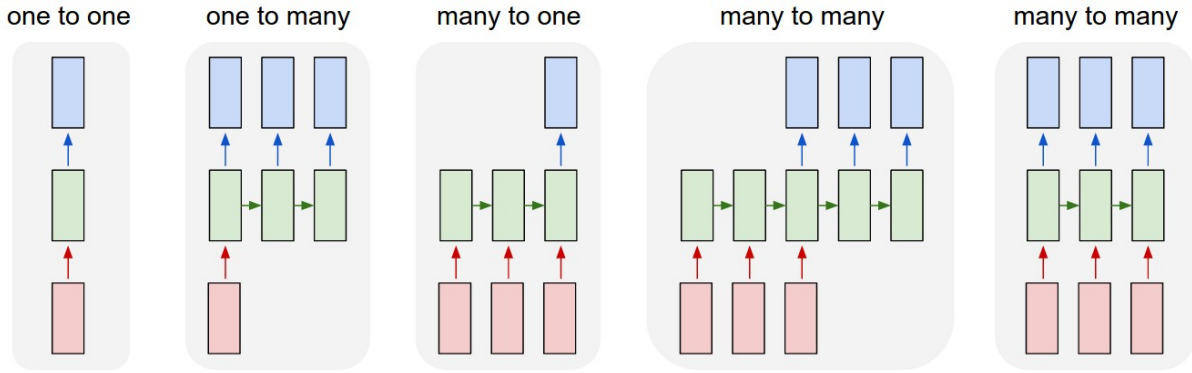


Figure 2.6: A list of RNNs (unfolded) mapping sequences to sequences with variant lengths. Each column of rectangles represents a step, the rectangle at the bottom, middle and top represent the input, hidden state, and output respectively at that step.

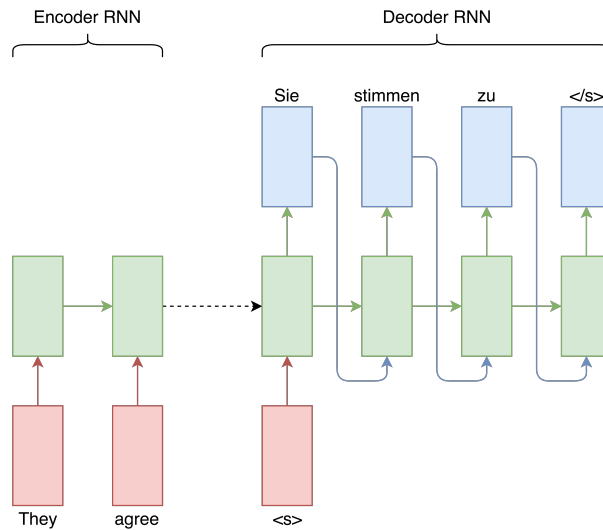


Figure 2.7: A vanilla RNN encoder-decoder

in the input until an ending symbol is produced in the output.

In addition to the primitive structure shown above, there are many techniques optimizing RNNs for various purposes. For example, the layers of hidden units can be stacked together, thus providing deeper representation of the information. Furthermore, residual connections [WSC<sup>+</sup>16] can be applied to deep layered RNNs to improve the gradient flow in terms of training. Bi-directional RNNs [SP97] were used in the encoder to reduce average dependency lengths.

### 2.2.3 Long Short-Term Memory

RNNs usually process information over a long duration. The ability of forgetting the old states once the information has been used becomes an important feature to RNNs. This is achieved by the so called gated

RNNs, where the neural networks are able to gradually learn to decide when to clear the state relying on the use of gated hidden units [GBC16]. Among different kinds of gated RNNs, Long Short-Term Memory (LSTM) [HS97] has been proved to be successful in many applications. LSTM-based models [WSC<sup>+</sup>16, SVL14] have been dominating in the area of machine translation and achieving state-of-the-art results on many benchmark datasets.

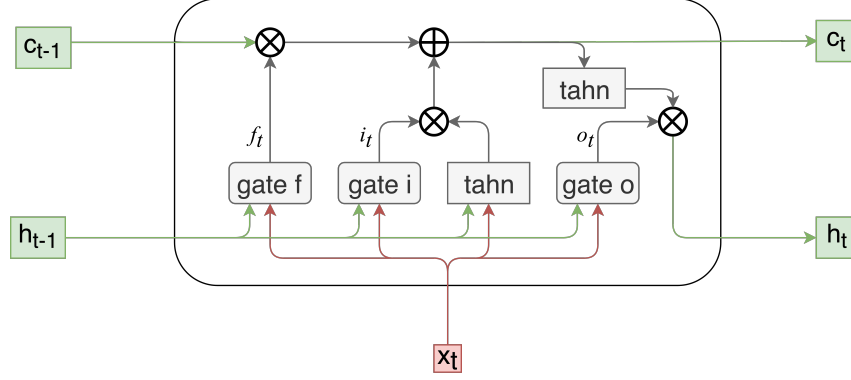


Figure 2.8: The diagram of the LSTM unit

Figure 2.8 reveals the structure of the LSTM unit in an RNN at time step  $t$ . Different from standard RNNs, a new vector which represents the cell state is used. There are also three gates, namely input gate  $i$ , forget gate  $f$ , and output gate  $o$ , each producing an activation vector. Suppose the number of input features is denoted by  $e$  and the number of hidden units is denoted by  $d$ . At step  $t$ , the input  $x_t \in \mathbb{R}^e$ , the previous cell state  $c_{t-1} \in \mathbb{R}^d$ , and the previous hidden state  $h_{t-1} \in \mathbb{R}^d$  are already given information. In order to compute the current cell state  $c_t \in \mathbb{R}^d$  and hidden state  $h_t \in \mathbb{R}^d$ , one needs to firstly compute three activation vectors:

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

, then:

$$c_t = f_t \circ c_{t-1} + i_t \circ \tanh(W_c x_t + U_c h_{t-1} + b_c)$$

$$h_t = o_t \circ \tanh(c_t)$$

where the operator  $\circ$  denotes the element-wise product and  $\sigma$  denotes the sigmoid function.  $W \in \mathbb{R}^{d \times e}$ ,  $U \in \mathbb{R}^{d \times d}$ , and  $b \in \mathbb{R}^d$  denotes the internal weight matrices and bias vectors that are to be continuously updated during training phase.  $f_t \in \mathbb{R}^d$ ,  $i_t \in \mathbb{R}^d$ , and  $o_t \in \mathbb{R}^d$  are the activation vectors from corresponding sigmoid gates that control how much information is accumulated from the old states to the new ones.

## 2.2.4 Convolutional Neural Network

## 2.2.5 Attention Mechanism

Attention mechanism [BCB14] is firstly proposed as an enhancement module for the basic RNN-based encoder-decoder architecture. In general, it gives the model abilities to conduct searching on parts of the source inputs at the time of inference. The conventional encoder-decoder models often perform worse when the length of the processed sentence is long, for the reason that the fixed-length vector produced by the encoder tends to lack some necessary information crucial for the decoder to predict accurate tokens. Attention mechanism addresses this issue by allowing the decoder to, at each decoding step, refer to a context vector calculated from weighted sum of a sequence of annotations to which the encoder maps the input sequence.

We hereby illustrate the concept of attention mechanism with a simplified version of the model proposed by Bahdanau et al. [BCB14] which utilizes GRU-based bi-directional encoder to obtain annotations from the input sequences instead of taking only hidden states along a single direction, which is shown in Figure 2.9.

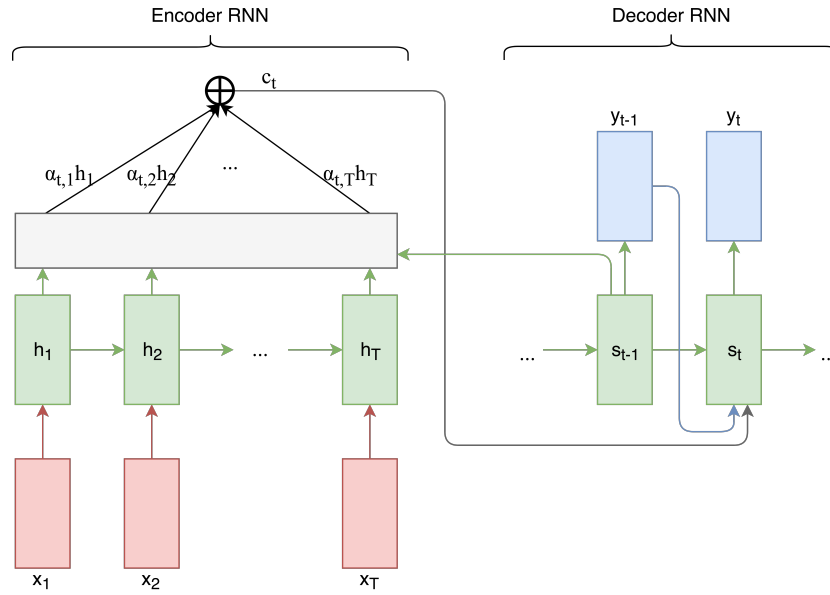


Figure 2.9: The  $t$ -th decoding step of a simplified encoder-decoder model with attention mechanism. The attention layer is placed on top of the hidden layer of the encoder.

Figure 2.9 demonstrates how a encoder-decoder model with attention generates the  $t$ -th target word  $y_t$  given a source sentence  $x = (x_1, \dots, x_T)$ . The encoder maps  $x$  into a sequence of hidden states  $h = (h_1, \dots, h_T)$  by Equation 2.1. For the decoder, the hidden state  $s_t$  for step  $t$  is computed by

$$s_t = f(s_{t-1}, y_{t-1}, c_t)$$

where  $c_t$  is the context vector only for the  $t$ -th target word  $y_t$ .  $c_t$  is computed as a weighted sum of the annotations of the input sequence ( $h$  in this case):

$$c_t = \sum_{i=1}^T \alpha_{t,i} h_i$$

where  $\alpha_{t,i}$  is the weight of each annotation  $h_i$ . It is based on a  $score_{t,i}$  which is dependent on the previous decoder hidden state  $s_{t-1}$  and  $i$ -th annotation  $h_i$ . The equations for computing the score  $e_{t,i}$  and the weight  $\alpha_{t,i}$  is:

$$score_{t,i} = a(s_{t-1}, h_i)$$

$$\alpha_{t,i} = \frac{\exp(score_{t,i})}{\sum_{j=1}^T \exp(score_{t,j})}$$

where  $a$  is an alignment model usually parameterized as a feedforward neural network that can be jointly trained with other parts of the model. The  $score_{t,i}$  is expected to evaluate how important is the input around position  $x_i$  with respect to the previous hidden state  $s_{t-1}$  in determining the next output  $y_t$  being generated. The final attention weights or the alignment model can be visualized into a matrix that reflects the relationships between tokens of input sequence and output sequence as an example is shown in Figure 2.10.

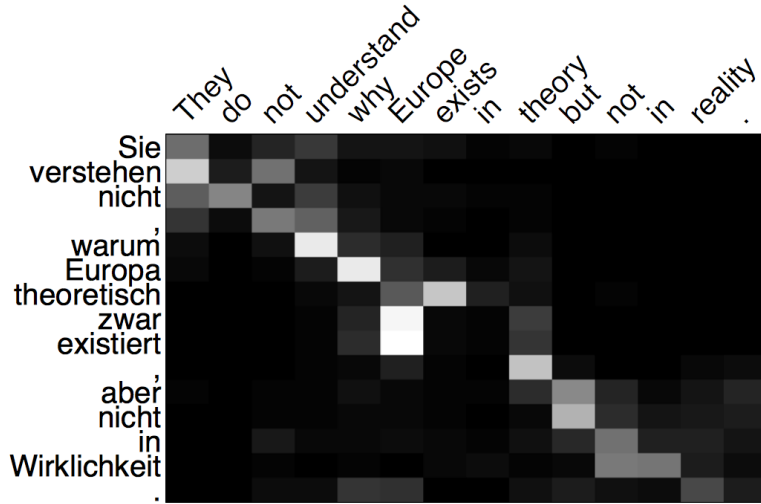


Figure 2.10: Visualization of the attention weights [LPM15]. The color of each block represents the attention weight between the words positioned at the row and the column. Lighter blocks indicate stronger relations.

Although attention mechanism brings more preciseness to the models, it increases the training cost and may cause longer sequences impractical to translate. Therefore, in addition to the one described above

which is referred to as global attention, there is local attention mechanism that in each decoding step only a subset of the whole source sequence is needed [LPM15].

## 2.3 Related Work

The primary focus of the investigation in this thesis is neural network models that can be used to map natural language statements to SPARQL expressions. Regarding the related work, we consider two main categories: the systems that integrate with NMT approaches and the systems not related to NMT. In the first category, we broaden the range on papers which have deployed machine learning methods to map unstructured sequences to structured sequences for the reason that we observe these methodologies sharing similar principles in learning the prediction of structured sequences like SPARQL. In terms of the second category, we narrow down the choices to those which translate natural language to SPARQL using merely non-NMT approaches on account of referencing their employed datasets, evaluation metrics, and experiment results for comparison.

### 2.3.1 Non-NMT Systems

In this section, the systems that did not involve neural computation are discussed. Most of the approaches investigated had similar structure of two-step query composition, where the question provided by the user, either in a controlled natural language or not, needs to be adapted into an intermediary language representation which is lastly translated into a valid SPARQL expression.

*SQUALL2SPARQL* [Fer13] is a translator capable of producing SPARQL from a controlled English called Semantic Query and Update High-Level Language (SQUALL). Despite the limitation in the input side, this system is able to capture nearly full features of SPARQL 1.1. *SQUALL2SPARQL* achieved a high F-measure of 0.90 as well as very good precision and recall on QALD-3 challenge [CCL<sup>+</sup>13].

Pradel et al. [PHH13] presented an approach using an intermediary pivot query to interpret the natural language queries and then formalized into target formal queries like SPARQL. They implemented a system called *Semantic Web Interface using Patterns* (SWIP). The dataset they used primarily for evaluation was QALD-3 targeting the DBpedia knowledge base. An assessment of the system based on the measurements of precision, recall, and F-measure was conducted on it.

Xu et al. [XFZ14] proposed a question answering (QA) system that is able to recognize the intention and map the relevant semantic entities contained in a natural language query, which are used to further instantiate a formal structured query. They firstly extracted phrases from the query and then annotated the

phrases with semantic labels in order to form a Directed Acyclic Graph (DAG) with phrase dependency relations. The DAG was lastly decoded into SPARQL query by mapping the phrases into corresponding entities in KB. They experimented the system on 50 QALD-4 testing questions and achieved F-measure of 0.71, which was a very competitive result at QALD-4 challenge [UFL<sup>+</sup>14].

Dubey et al. [DDS<sup>+</sup>16] proposed a framework called *AskNow*, a QA system targeting at DBpedia. This framework first transforms the questions in English to an intermediary common structure called Normalized Query Structure (NQS), which is later translated into a SPARQL query through a NQS parser and a SPARQL generator. The NQS plays an significant role in carrying the desire, the input information, and their mutual semantic relations in a query. From English query to NQS, they deployed the POS-tagger to retract tags of each tokens in the query and characterized the desire-input dependency relations through semantic analysis based on certain hypotheses. In NQS to SPARQL algorithm, they utilized DBpedia Spotlight [DJHM13] and [Mil95] for query annotation and entity matching, which essentially analyzes the tokens in the query and finds their synonymous entities in the vocabulary of DBpedia. In terms of evaluation, they tested four aspects including syntactic robustness, sensitivity to structural variation, semantic accuracy, and the accuracy of the whole system with precision and recall measurements, and the benchmark data sets QALD-4 and QALD 5 [UFL<sup>+</sup>14, UFL<sup>+</sup>15].

### 2.3.2 NMT Systems

Cai et al. [CXY<sup>+</sup>17] proposed an enhanced encoder-decoder framework for the task of translating natural language to SQL, a similar query language with SPARQL but targeting structured databases instead of knowledge bases. They used not only BLEU [PRWZ02], but also query accuracy, tuple recall, and tuple precision for measuring the quality of output queries, and achieved good results.

Dong et al. [DL16] presented a method based on an encoder-decoder model with attention mechanism aimed at translating the input utterances to their logical forms with minimum domain knowledge. Moreover, they proposed another sequence-to-tree model that has a special decoder better able to capture the hierarchical structure of logical forms. Then, they tested their model on four different datasets and evaluated the results with accuracy as the metric.

Zhong et al. [ZXS17] proposed a framework called *Seq2SQL* for translating natural language questions to SQL. They took LSTM-based encoder-decoder networks as the core model. In order to leverage the structure of the SQL language, they augmented the input question with addition of column names of the queried table and split the decoder into three components, respectively predicting aggregation classifier, column names, and where clause part of a SQL query. As opposed to conventional teacher forcing, they trained the model with reinforcement learning to deal with the problem that queries that execute correct

results but do not have exact string matches would be wrongly penalized. To address this issue in the evaluation, they performed analysis with measuring execution accuracy and logical form accuracy of generated queries.

Luz et al. [LF18] also used an LSTM encoder-decoder model but the purpose is to encode natural language and decode into SPARQL. Furthermore, they employed a neural probabilistic language model to learn a word vector representation for SPARQL, and used the attention mechanism to associate a vocabulary mapping between natural language and SPARQL. For the experiment, they transformed the logical queries in the traditional Geo880 dataset into equivalent SPARQL form. In terms of evaluation, they adopted two metrics: accuracy and syntactical errors. They further compared their method with several other similar approaches [A1A15, KBZ06] and the comparison showed that they obtained better accuracy results. However, they did not deal with the "out of vocabulary" (OOV) problem and the issue of lexical disambiguation.

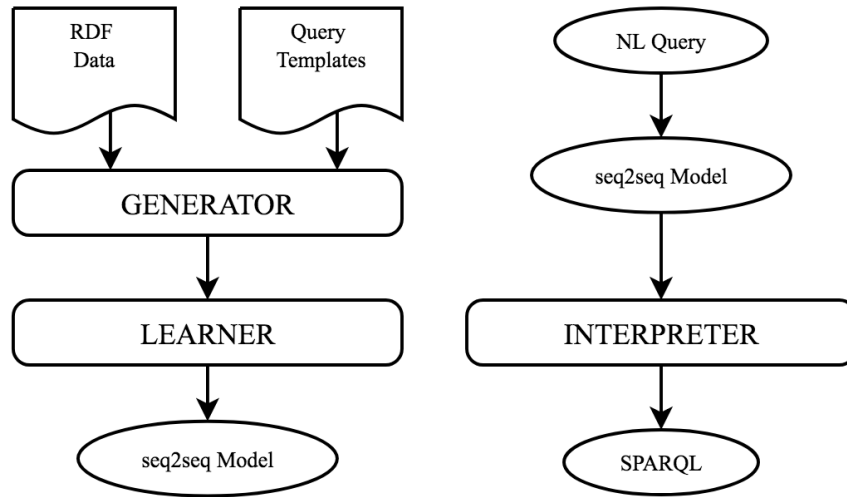


Figure 2.11: The generator-learner-interpreter architecture of *Neural SPARQL Machines* [SMM<sup>+</sup>18]

Soru et al. [SMM<sup>+</sup>18, SMV<sup>+</sup>18] proposed a generator-learner- architecture (see Figure 2.11), namely *Neural SPARQL Machines* to translate any natural language expression to encoded forms of SPARQL queries. They designed templates with variables that can be filled with instances from certain kinds of concepts in the target knowledge base and generated pairs of natural language expression and SPARQL query accordingly. After encoding operators, brackets, and URIs contained in original SPARQL queries, the pairs were fed into a sequence to sequence learner model as the training data. The model was able to generalize to unseen natural language sentence, and generate encoding sequence of SPARQL for the interpreter to decode.



### 3 Methodology

This chapter mainly describes the models and frameworks of neural machine translation involved in this thesis for the task of translating natural language to SPARQL and related preliminaries. Then, a measurement BLEU that is typically utilized in automatic machine translation evaluation is described. We also clarify another metric called query accuracy which suits specifically for our task.

#### 3.1 Preliminary

##### 3.1.1 Input

For the input of the NMT models, a sentence or paragraph can be normally separated into three kinds of sequences: characters, subwords, or words. Different methods of splitting sequences lead to differences in vocabularies that are seen by the model and its effectiveness of dealing with rare words. For the task in this thesis, the texts are fed into the models word-based for the reason that the entities in SPARQL which are normally words in the queries need to be treated as a whole.

English vocabulary	source input	SPARQL vocabulary	target input	output
what	0	select	0	0.1
the	0	...	...	...
...	...	dbr_Monument	1	0.8
are	1	...	...	...
...	...	dbr_Leipzig	0	0.03
deshpande	0			

Figure 3.1:

Each word in the sequences of both source input and target input is represented in an one-hot encoding vector, which is a sparse vector in which one element is set to 1 and all other elements are set to 0. The dimension of the one-hot encoding is equal to the size of the specific vocabulary. An example is shown in Figure 3.1.

Due to the use of one-hot encoding, every word in the vocabulary is orthogonal to each other. This does not reflect the relevance of some similar or distinct words such as man and king, king and queen. Therefore, in NMT models, the one-hot encoding vectors are usually further mapped into a low-dimensional space where each word is represented as a dense vector called word embedding that holds floating-point values in each element. This mapping can be learned along with the training of the whole model or provided with a pre-trained word embedding matrix.

### 3.1.2 Output

The output of NMT model is a sequence of vectors, where the dimension of each vector is the size of the vocabulary for the target language. The sum of the entries in each vector is equal to 1, which means the vector is essentially a probability distribution over all the possible words in the target vocabulary. One can then perform greedy or beam search over this sequence of probability distributions to generate a translation with the highest probabilities.

## 3.2 Models

In this thesis, we mainly focus on investigating three families of deep NMT models, including RNN-based models with an encoder-decoder architecture, the models entirely based on convolutional neural networks, and self-attention models relying on neither RNNs nor CNNs. We consider these three families covering the most advanced research of NMT and best-performing models so far, regardless of any other choices difficult to be classified such as hybrid models. Within each of these categories, one or more representative models are chosen and specified under.

### 3.2.1 RNN-based Models

#### Google's Neural Machine Translation System

Google's Neural Machine Translation (GNMT) system [WSC<sup>+</sup>16]

### 3.2.2 CNN-based Models

#### Convolutional Sequence-to-Sequence

Convolutional Sequence to Sequence (ConvS2S) [GAG<sup>+</sup>17b] is another sequence to sequence modeling architecture that depends on convolutional neural networks instead of traditional RNNs. In machine



Figure 3.2: An RNN-based encoder-decoder architecture with attention mechanism

translation task, CNNs own several advantages over RNNs in the following aspects:

- Faster training speed because the computations of CNNs allow parallelization over every element in a sequence, whereas the computations in RNN are sequentially dependent on each other.
- Long-range dependencies have shorter paths when the inputs are processed in a hierarchical multi-layer CNN compared to the chain structure of RNNs. CNN is able to create representations for  $n$  continuous words in  $\mathcal{O}(\frac{n}{k})$  convolutions with  $k$ -width kernels, while RNN needs  $\mathcal{O}(n)$ .

On the other hand, it also has certain limitations:

- The input needs to be padded before fed into the model for the reason that CNNs can only process sequences of fixed length.
- Additional position encoding is required to provide the model with a sense of ordering in the elements being dealt with.

Figure 3.4 depicts the architecture of ConvS2S model and how it can be trained. In fact, it remains the architecture of encoder-decoder, and the decoding phase is aided by attention mechanism. The encoder (placed at top) and the decoder (placed at bottom left) both consist of several stacked convolutional blocks (only one block is drawn in the figure). The input for the encoder is  $\mathbf{e} = (w_1 + p_1, \dots, w_m + p_m)$  where  $m$  is the length of an input sentence,  $w_i$  and  $p_i$  are the word embedding and the positional embedding of the  $i$ -th input element respectively. Each convolutional block is formed by a one-dimensional convolutional layer that has kernel width  $k$  and a subsequent Gated Linear Unit (GLU) as non-linearity. Note that due to the number of input elements in each block is fixed, the input to each convolutional block needs to be padded with zero vectors. We denote the  $l$ -th block of the encoder output  $\mathbf{z}^l = (z_1^l, \dots, z_m^l)$ , and the decoder output  $\mathbf{h}^l = (h_1^l, \dots, h_n^l)$ . We also assume that the  $l$ -th block is stacked on the  $l-1$ -th block.

After convolution operations, the output of each decoder block and the output of top encoder block are then combined in a multi-step attention. In other words, the model computes  $n$  context vectors

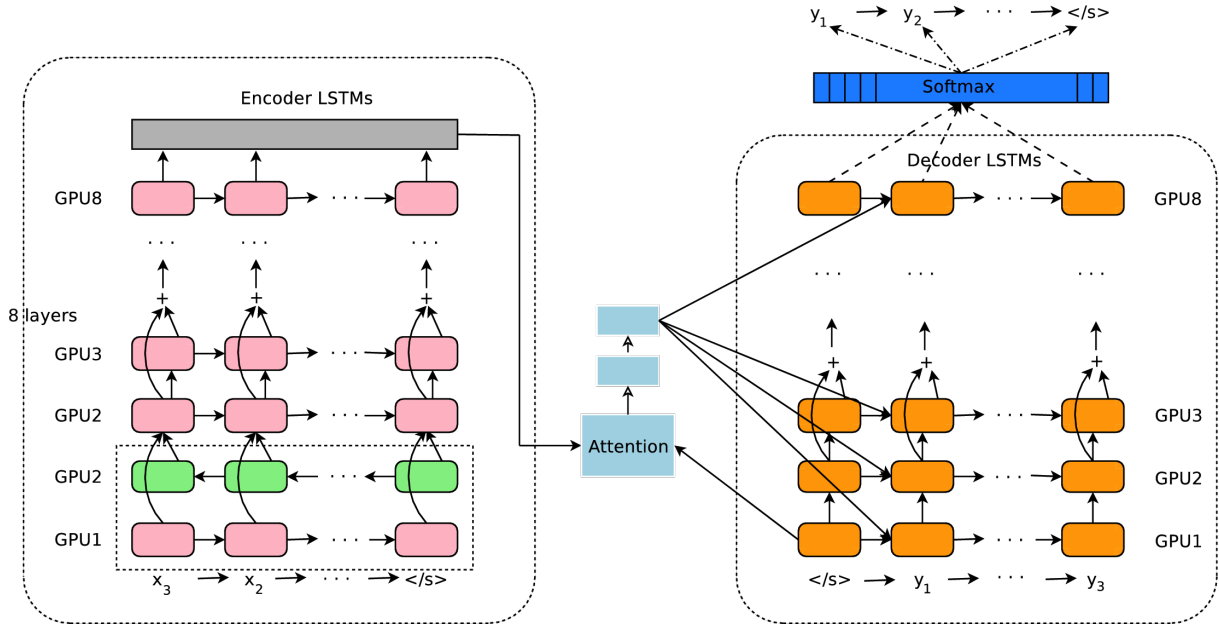


Figure 3.3: The model architecture of GNMT.

$\mathbf{c}^l = (c_1^l, \dots, c_n^l)$  for each decoder convolutional layer (center right in the figure) where  $n$  is a fixed number for the input and the output of decoder. The context vectors  $\mathbf{c}^l$  and  $\mathbf{h}^l$  are simply added together. A softmax layer is placed on  $(\mathbf{c}^l + \mathbf{h}^l)$  for generating the target elements (bottom right).

### 3.2.3 Self-attention Models

#### The Transformer

The Transformer model [VSP<sup>+</sup>17] is another novel neural machine translation model adopting encoder decoder structure, without RNNs or CNNs as the primary units but entirely based on the attention mechanism. The traditional RNN models use attention mechanism to connect the encoder and decoder at some time steps. Differently, the Transformer model uses internal stacked self-attention in both encoder and decoder.

The attention mechanism used in the Transformer model is called Scaled Dot-Product Attention (see Figure 3.5) [VSP<sup>+</sup>17]. The function of it can be described as a mapping from queries  $Q$  and a set of key-value pairs where keys and values can be denoted as  $K, V$  to an output matrix. The queries and keys are of dimension  $d_k$  and the values are of dimension  $d_v$ . The output is computed by:

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

where the dot products of the queries and all keys are computed firstly, scaled by  $\sqrt{d_k}$ , and then applied a softmax function for obtaining the weights on the values.

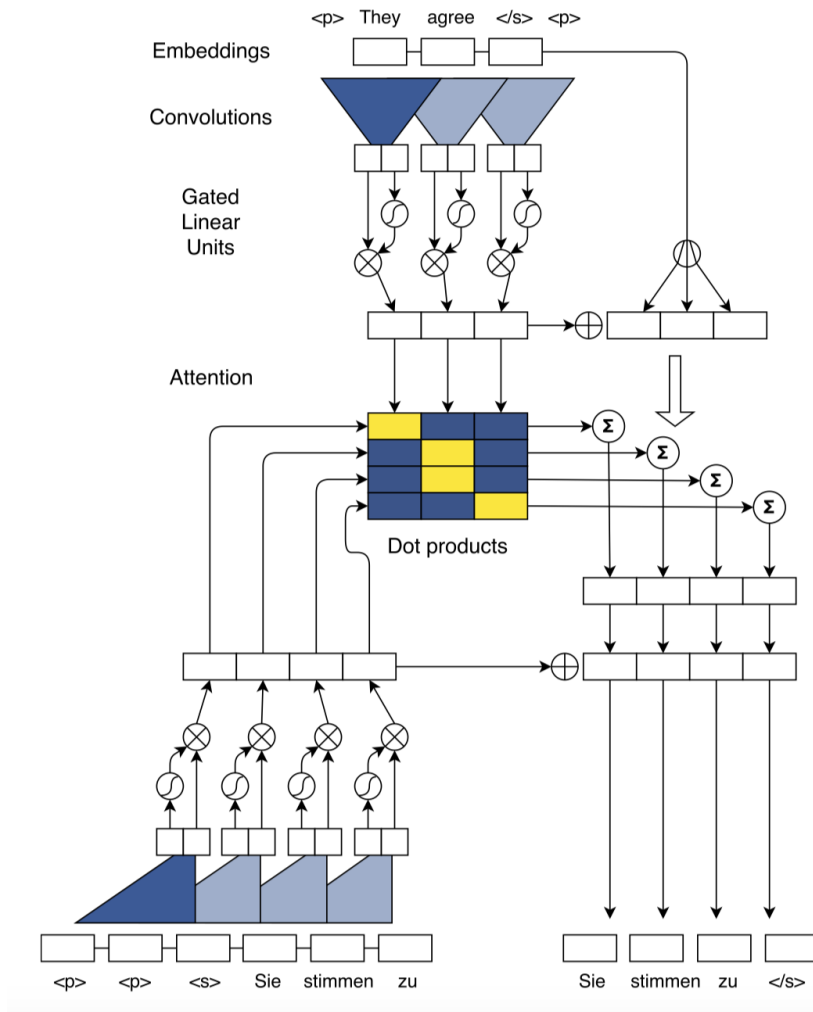


Figure 3.4: The demonstration of training the Convolutional Sequence-to-Sequence model [GAG<sup>+</sup>17b]

Figure 3.6 displays the architecture of the Transformer model, where the left side shows one layer in the encoder and the right half shows one decoder layer.

The encoder consists of two sub-layers. The first is a multi-head attention sub-layer and the second is a point-wise fully connected feed forward sub-layer. Each sub-layer is employed a residual connection, which means the input to the sub-layer is further passed to the tail and added to the output. After that, the addition result is normalized. Therefore, the output of each sub-layer can be specified by  $Norm(x + Sublayer(x))$  where  $x$  is the input and  $Sublayer(x)$  indicates the operation implemented in this sub-layer.

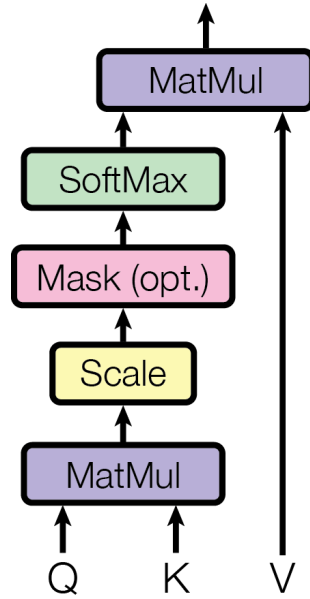


Figure 3.5:

### 3.3 Frameworks

Three frameworks have been used in this thesis, where two of them are based on TensorFlow [AAB<sup>+</sup>15] and the other one based on PyTorch [PGC<sup>+</sup>17].

#### 3.3.1 TensorFlow Neural Machine Translation

[LBZ17]

#### 3.3.2 Facebook AI Research Sequence-to-Sequence Toolkit

[GAG<sup>+</sup>17b]

#### 3.3.3 Tensor2Tensor

[VBB<sup>+</sup>18]

### 3.4 Evaluation Metrics

Automatic machine translation evaluation is crucial for the development of machine translation system, since human evaluations are normally expensive, longer and subjective to some extents. In automatic

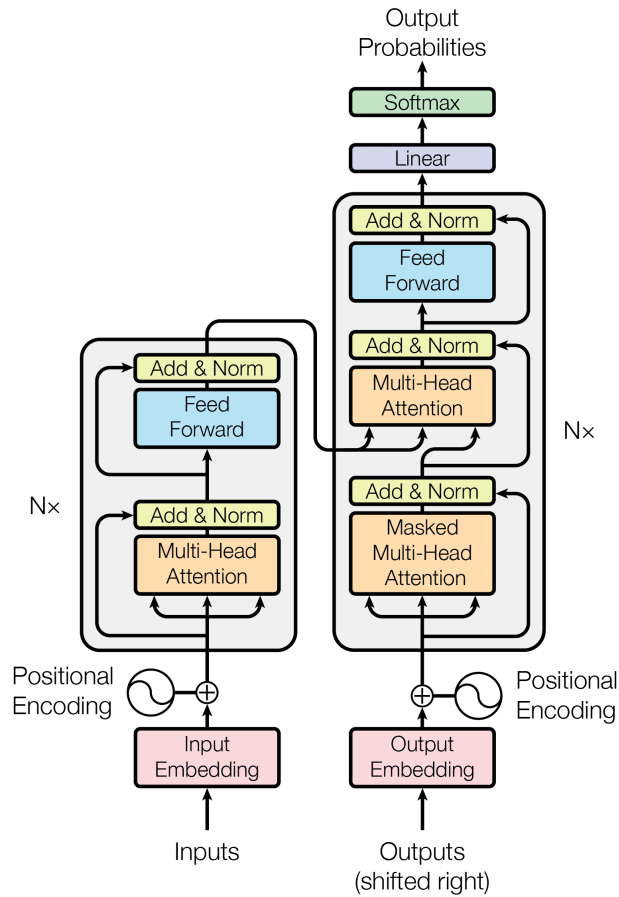


Figure 3.6: The architecture of the Transformer model [VSP<sup>+</sup>17]

MT evaluation, for one candidate translation, a score is usually calculated to assess the closeness of it to one or more reference sentences which were mostly human professional translations.

### 3.4.1 Perplexity

### 3.4.2 BLEU

BLEU is now one of the most popular automated metrics in the evaluation of neural machine translation systems. It is noted for its high correlation with human evaluation and low marginal cost for running [PRWZ02]. We choose BLEU as it is the most dominating metric for translation evaluation at present, which brings the advantage of more straightforward comparisons with other successful models and experiments.

The basis of BLEU is a modified  $n$ -gram precision measure. In a sentence composed of multiple words, an  $n$ -gram refers to a contiguous sequence of  $n$  words within it. To compute the precision of  $n$ -grams, one just counts up the number of the  $n$ -grams which occur in any reference translation, and divide this

number by the total number of n-grams in the candidate sentence. This does not check if the candidate translation contains too many duplicate words which merely exist less times in reference translation. The modified version of precision adopted in BLEU addresses this issue.

In the following example, a candidate translation of poor quality is evaluated with two references. When  $n$  equals 1 (i.e. unigram), with standard precision, the candidate achieves  $7/7$  because every word (unigram) occurs in the first reference, whereas it only achieves  $2/7$  in modified unigram precision.

Candidate: the the the the the the the

Reference 1: The cat is on the mat.

Reference 2: There is a cat on the mat.

### 3.4.3 Query Accuracy



## **4 Experiments**

This chapter describes the details of the experiments conducted in this thesis.

### **4.1 Datasets**

#### **4.1.1 Monument dataset**

#### **4.1.2 LC-QUAD**

#### **4.1.3 DBNQA**

### **4.2 Model Parameters**

### **4.3 Runtime Environment**

#### **4.3.1 High Performance Computing**

### **4.4 Results**

## 5 Analysis

## **6 Conclusion**

### **6.1 Summary**

### **6.2 Outlook**

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