1 Introduction

Since Knowledge Graph (KG) was announced by Google in 2012, it has been frequently used in many areas, especially in the Semantic Web technologies [14]. KGs serve for representing semantic knowledge, usually in RDF triples (facts), in the form of $<subject, predict, object>$ [13]. The Resource Description Framework (RDF) is a framework to represent information on the Web. Since KGs rapidly developed, the scale of knowledge bases has grown considerably. Generating summaries on lengthy knowledge for quick comprehension of corresponding entities has been an emerging task.

Recently, with the considerable development of information, summarization techniques are becoming some of the main approaches to make the information more concise and recapitulative. It has benefited from work on information retrieval [2] and question answering [3]. Different summarization techniques have been proposed from various communities. Text summarization and sentence summarization [34] [35] are some of examples that perform well in different areas. Meanwhile, with the notion of entity spreading, many researches on it have been implemented, including entity recognition [33], entity disambiguation [12], and others. For quick comprehension of lengthy semantic knowledge, the entity summarization task is also explored in recent years. Existing methods have been proposed for this task, which generates entity summaries that are both brief and informative. Briefness is about selecting a small-scale fact set. Informativeness is about selecting facts with more information to comprehensively represent each entity. The former characteristic can be achieved by ranking or filtering methods. But acquiring informative facts is a tough task, since it is hard to identify facts with more information that people prefer. To some extent, previous approaches of entity summarization have achieved good performance, like RELIN, DIVERSUM, FACES-E, and ES-LDA do, but much improvement still remains to be explored. However, we can hardly find any entity summarization techniques using deep learning algorithms. Recent approaches model summarization as an encoder-decoder architecture, the encoder reads the source input into a list of continuous space representations while the decoder generates results.

In this work, follow the ideas of traditional methods, we ask how to apply deep learning methods into entity summarization task. The intuition of attention can be explained using human biological systems. For instance, we usually selectively focus on parts of the image when we use our visual processing system, while ignoring other unconcerned information. To allocate proper weights for triples according to human preference, we focus on the importance of each triple. A triple with higher weight represents that human more prefer it. Therefore, we propose a model for entity summarization called ESA, which uses supervised attention mechanism with BiLSTM. The ESA allows us to calculate attention weights for facts in each entity, then ranking facts to generate reliable summaries. Experimental results show that our model improves the quality of the entity summaries in both F-measure and MAP.
The remainder sections of this paper is structured as follows. Section 2 introduces the related work for ES task and successful usages of deep learning methods in NLP. Section 3 describes the task of entity summarization. Section 4 presents our ESA model in detail. Section 5 explains the reason why we select transE model to map objects into continuous space. The experimental details are given in Section 6. In the end, we conclude the whole work in Section 7 and give future work we interest in Section 8.

2 Related Work

RELIN [8] is a variant of the random surfer model based on relatedness and informativeness of entities, it emphasizes the most similar and central triples in summarization. The key idea of RELIN is the diversity of summarized triples. DIVERSUM [28] incorporates the notion of diversification into entity summarization to solve the problem of diversified entities. FACES [17] uses a clustering algorithm called Cobweb to balance the centrality and diversity of the selected triples for each entity. Unlike FACES, LinkSUM [29] focuses more on the objects instead of the diversity of properties, it partitions the semantic links of each entity to rank features and is interfaced via the SUMMA entity summarization API. FACES-E [18] extends FACES to generate entity summaries in the way of gleaning and ranking object and datatype properties. While CD [25] formulates entity summarization as a binary quadratic knapsack problem to solve. Interestingly, ES-LDA [24] is a probabilistic topic model based on LDA to generate representative summaries. Most of them focus on specific aspects of entities, which are insufficient to completely describe various relation among entities. Meanwhile, the data supplement technique in this task is limited. For instance, the data supplement method proposed by ES-LDA can only be used for specific facts, which is lack of versatility and probability. KAFCA [20] extracts tokens from objects and convert a KG into a formal concept that considers what tokens predicates can take, it can detect how the knowledge hierarchy reflects the intrinsic relationships between triples. Though rare deep learning methods for ES task has been proposed, there are considerable success using deep learning techniques for many other tasks in NLP. Rush et al. [26] used auto-constructed sentence-headline pairs to train a neural network summarization model for sentence summarization. Instead of using CNN encoder and feed-forward neural network language model decoder, Chopra et al. [10] introduced RNN to optimize the work that Rush et al. did. Inspired by Formal Concept Analysis (FCA), Zhou et al. [34] proposed Att-BLSTM to tackle two problems: one is the dependence of lexical resources, and the other is the randomness of positions in which important information appears.

3 Task Description

RDF is an abstract data model, and an RDF graph consists of a collection of statements. Simple statements generally represent real-world entities, which are usually stored as triples. Each triple \( t \) represents a fact that is in the form of \(<\text{subject}, \text{predicate}, \text{object}>\), abbreviated as \(<s, p, o>\). Since RDF data is encoded by unique identifiers (URIs), an entity in RDF graphs can be regarded as a subject with all predicates and corresponding objects to those predicates.

**Definition 1 (Entity Summarization):** Entity Summarization (ES) is a technique to summarize RDF data for creating concise summaries in KGs. The subject of each entity provides the core for summarizing entities. Therefore, the task of ES is defined as extracting a subset from a lengthy feature set of each entity with the respective subject. Given an entity \( e \) and a positive integer \( k \), the output is top-k features of every entity \( e \) in the ranking list of \( ES(e, k) \).

For example, in Table 1, the triple <\textit{Balanites}, kingdom, Plant> introduces Balanites’s kingdom as Plant. Table 1 presents top-5 summaries for Balanites entity, which are family, order, genus, kingdom, and name.

4 Proposed Model

We model ES as a ranking task similar to existing work, such as RELIN, FACES, and ES-LDA. Unlike the traditional approaches to generate entity sum-
| Predicate                                      | Object                                              | Top5 |
|-----------------------------------------------|-----------------------------------------------------|------|
| http://dbpedia.org/ontology/division         | http://dbpedia.org/resource/Flowering_plant         | ✓    |
| http://xmlns.com/foaf/0.1/name                | "Balanites"SEM                                     |      |
| http://dbpedia.org/ontology/class            | http://dbpedia.org/resource/Eudicots               | ✓    |
| http://dbpedia.org/ontology/family           | http://dbpedia.org/resource/Tribuloideae           | ✓    |
| http://dbpedia.org/ontology/kingdom          | http://dbpedia.org/resource/Plant                  |      |
| http://purl.org/dc/terms/subject              | http://dbpedia.org/resource/Category:Balanites     |      |
| http://dbpedia.org/ontology/genus            | http://dbpedia.org/resource/Balanites              | ✓    |
| http://www.w3.org/1999/02/22-rdf-syntax-ns#type| http://dbpedia.org/ontology/Plant                 |      |
| http://www.w3.org/2000/01/rdf-schema#label   | http://dbpedia.org/resource/2ygophyllales          | ✓    |

Table 1: *Balanites* entity predicates and corresponding objects with the top-5 in ESBM benchmark v1.1

maries in KGs, the ESA is a neural network model using sequence model. Figure 1 describes the architecture of the model.

Similar to most sequence models [9], the ESA has an encoder-decoder structure. The encoder is consisted of knowledge representation and BiLSTM, it maps an input sequence \((t_1, t_2, \ldots, t_n)\) of RDF triples from a certain entity to a continuous representation \(h = (h_1, h_2, \ldots, h_n)\). The decoder is mainly composed of attention model. Given \(h\), the decoder then uses a supervised attention mechanism generates an output vector \((a_1, a_2, \ldots, a_n)\) representing attention vector for each entity, which is then used as evidence for summarizing entities. Higher attention weights are related to more important triples, we finally select triples according to top-k highest weights as our entity summaries.

### 4.1 Knowledge Representation

Entities in large-scale KGs are usually described as RDF triples, while each triple consists of a subject, a predicate, and an object. MPSUM proposed by Wei [31] takes the uniqueness of predicates and the importance of objects into consideration for entity summarization. The experimental results show that the characteristics of predicates and objects are key factors to select entities. In order to make full use of the information contained by RDF triples, we extract predicates and objects from these triples. Let \(n\) be the number of triples with the same subject \(s\), then two lists respectively based on extracted predicates and objects are \(l_1 = (p_1, p_2, \ldots, p_n)\) and \(l_2 = (o_1, o_2, \ldots, o_n)\).

![Figure 1: The Architecture of ESA Model](image)
where $p_i$ and $o_i$ are corresponding predicates and objects from the $i$-th triples. For each entity, we employ different methods to map predicates and objects into continuous vector space respectively [23] [21]. In this way, we can balance the difference of occurrence between predicates and objects, which can impact on word embedding of predicates and objects.

Predicate Embedding Table

We use learned embeddings [1] to convert the predicate input to vectors of dimension $d_p$. We randomly initialize embedding vector for each predicate and tune it in training phase.

Object Embedding Table

Unlike generating representation of predicates based on word embedding technique, we use TransE model [5] to map objects to vectors of dimension $d_o$. We first pretrain transE model based on ESBM benchmark v1.1, and extract the word vectors of objects to construct a lookup table for object vectors. Then we obtain object vectors by looking up the table as input, the object vectors are fixed during training phase.

BiLSTM Network

LSTM units are firstly proposed by Hochreiter and Schmidhuber [15] to overcome gradient vanishing problem, which can keep the previous state and memorize the extracted features of the current data input. Bidirectional LSTM networks [16] extend the unidirectional LSTM networks by introducing a second layer, where the hidden to hidden connections flow in opposite temporal order. The model is therefore able to exploit information both from the past and the future. To estimate the importance of $i$-th triple, we should overall employ the information of former triples from 1 to $i-1$ and later triples from $i+1$ to $n$, where the information respectively propagations forward and backward. Since BiLSTM captures contextual information from two directions by containing two sub-networks for the forward and backward scan respectively, as shown in Figure 1, we use BiLSTM to encode the input vectors of predicates and objects. We denote the $LSTM_L$ and $LSTM_R$ as the forward and backward directional LSTM model, $x_i$ as the input at the time step $i$ for $LSTM_L$ and $LSTM_R$, and $h_{Li}$ is the output at time step $i$ for the $LSTM_L$, $h_{Ri}$ for the $LSTM_R$. $x_i$ is a vector by concatenating the word vectors of predicate $p_i$ in the predicate embedding table, and the translation vector of $o_i$ in the object embedding table. We encode the predicates and objects using Bidirectional LSTM as follows:

$$h_{Li} = LSTM_L (x_i, h_{Li-1}) , \quad h_{Ri} = LSTM_R (x_i, h_{Ri-1}) . \quad (1)$$

Here, we concatenate two kinds of word vectors to combine predicates and corresponding objects as input of LSTM. The final output of BiLSTM are calculated as follows:

$$h_i = concat (h_{Li}, h_{Ri}) . \quad (3)$$

where $h_{Li}$ and $h_{Ri}$ respectively denotes the left and right sequence.

4.2 Supervised Attention

Attention Model (AM) [7] [30] is a mainstream neural network in various tasks such as Natural Language Processing [6] [32]. For instance, in machine translation tasks [23], only certain words in the input sequence may be relevant for predicting the next [7] [32]. AM incorporates this notion by allowing the model to dynamically pay attention to only certain parts of the input that help in performing the task at hand effectively. In entity summarization task, when users observe the facts in each subject, they may pay more attention to certain facts than the rest, which can be modeled based on AM by assigning an attention weight for each fact in the subject. We address this idea into two tasks:

Task 1:

How to use the dataset in entity summarization to construct the gold attention vector in the certain subject, which indicates the different attention users paid to the every facts in this subject.
Task 2:

How to employ AM to calculate machine attention vectors, which have low error with the gold attention vectors in Task 1 [22].

Based on the two task mentioned above, in this section, we first introduce the details of constructing gold attention vectors mentioned in Task 1 and machine attention vectors in Task 2. Then we describe the loss function and training method in our model, which aims at generating machine attention vectors which is similar to the gold attention vectors.

Gold Attention Vectors

In this work, we use ESBM benchmark v1.1 as our dataset. For each subject we need to summarize, ESBM benchmark v1.1 not only provides the whole RDF triples which is related to this subject, but also provides several sets of top-5 and top-10 triples selected by different users according to their preference which we can utilize to construct gold attention vectors. We first initialize an attention vector to zero, whose dimension is the number of RDF triples in the subject. Then, we count the frequency of each triple selected by users to update the vector, the $i$-th value $c_i$ in this vector represents the frequency of triple $t_i$. Since ESBM benchmark v1.1, each subject has five sets of top-5 and top-10 triples selected by five different users, so the frequency of each triple ranges from 0 to 5. Figure 2 illustrates the details, where $\alpha$ is the final gold attention vector after normalization, each value in $\alpha$ is calculated by the following equation, $\alpha_i$ denotes the $i$-th value in vector $\alpha$:

$$\alpha_i = \frac{c_i}{\sum_{i=1}^{n} c_i}.$$  \hspace{1cm} (4)

Machine Attention Vectors

To generate machine attention vectors with AM, we first obtain the output vectors $h = (h_1, h_2, \ldots, h_n)$ that the BiLSTM layer produced. Then, the attention layer can automatically learn attention vector $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_n)$ based on $h$. We use softmax technique to generate final attention vector $\alpha$:

$$\alpha = softmax (h^T \sigma) .$$  \hspace{1cm} (5)

where $h_\sigma$ is concatenated by $h_1^s$ and $h_2^s$, here, $h_1^s$ is the value of hidden state from the final cell of upper LSTM layer, while $h_2^s$ is the value of hidden state from the final cell of lower LSTM layer. We rank final attention weight vector $\alpha$, and pick top-$k$ values. Then we obtain the entity summaries based on corresponding top-$k$ values.

Training

Given the gold attention $\overline{\alpha}$ and the machine attention $\alpha$ produced by our model, we employ cross-entropy loss and define the loss function $L$ of our model as follows:

$$L (\alpha, \overline{\alpha}) = CrossEntropy (\alpha, \overline{\alpha}) .$$  \hspace{1cm} (6)

Finally, we use backpropagation algorithm to jointly train the whole ESA model.
5 Why TransE

In this section, we explain the reason why we employ different embedding techniques for predicates and objects. Following the common used word embedding techniques, we initially use the same word embedding table for both predicates and objects, as shown in Figure 3. Our original embedding method performs unexpectedly poorly, which indicates that simple word embedding technique to represent predicates and objects does not well for entity summarization task. The real-world knowledge datasets have considerable entities, and similar entities should have the similar predicates, e.g., persons may have name and birthPlace as attributes in many knowledge datasets. Herein, the repetitive rate of predicates is usually high, the well-trained word vectors for predicates can be easily acquired in training phase. However, objects in most cases individually appear in knowledge datasets. In addition, the scale of selected datasets in this work is limited. Both flaws greatly impact on training word vectors for objects in our dataset, which is similar to the UNK problem in machine translation task. In testing phase, for the lack of well-trained word vectors for predicates, we can only use well-trained vectors of predicates to compute the values of machine attention vectors, which significantly weakens the performance of our original model. To solve the UNK problem mentioned above, we introduce knowledge graph embedding techniques into our task.

6 Experiment

In this section we introduce the implementation details, and the experimental results on specific datasets. To prove the effectiveness of our model, we take the state-of-the-art approaches to date in entity summarization task for comparison, including RELIN, DIVERSUM, CD, FACES-E, FACES, and LinkSUM.
6.1 Datasets

**DBpedia**

DBpedia [4] is a project aiming to extract structured content from the information created in the Wikipedia project. This structured information is made available on the World Wide Web. DBpedia allows users to semantically query relationships and properties of Wikipedia resources, including links to other related datasets. DBpedia uses the Resource Description Framework (RDF) to represent extracted information and consists of 9.5 billion RDF triples, of which 1.3 billion were extracted from the English edition of Wikipedia and 5.0 billion from other language editions.

**LinkedMDB**

LinkedMDB [11] contains millions of RDF triples with hundreds of thousands of RDF links to existing web data sources that are part of the growing Linking Open Data cloud, as well as to popular movie-related web pages such as IMDb [19]. LinkedMDB uses a novel way of creating and maintaining large quantities of high quality links by employing state-of-the-art approximate join techniques for finding links, and providing additional RDF metadata about the quality of the links and the techniques used for deriving them.

**ESBM Benchmark v1.1**

In this work, experiments are conducted based on ESBM Benchmark v1.1 as ground truth. The ESBM benchmark v1.1 consists of 175 entities including 125 entities are from DBpedia [1] and the rest entities are from LinkedMDB [2] datasets. The datasets and ground truth of the entity summarizers can be obtained from [3]. We employ 5-fold cross validation method for ESBM benchmark v1.1 to construct train sets and test sets.

6.2 Evaluation Metrics

We employ F-measure and MAP as our evaluation metrics. F-measure (so-called F-score or F1-score) is a statistic computed by the harmonic average of the precision and recall, where an F-measure reaches its best at 1 with perfect precision and recall. MAP (Mean Average Precision) is the mean of AP from multiple datasets, where AP represents average precision for each dataset.

6.3 Implementation Details

We apply word embedding technique to map predicates into continuous space and use pretrained translation vectors with transE for objects. During training phase, the word vectors of predicates are jointly trained while the object vectors are fixed. We use thunlp [4] to train the whole ESBM benchmark v1.1. We generate gold attention vectors based on ESBM benchmark v1.1, and calculate machine attention vectors based on our model. Finally, we compare our model in terms of top-5 and top-10 entity summaries with the benchmark results of the entity summarization tools, i.e. RELIN, DIVERSUM, CD, FACES-E, FACES, and LinkSUM, as shown in Table 2 and Table 3.

6.4 Hyper-parameter Setting

Hyper-parameters are tuned on the selected datasets. We set the dimension of predicate embedding to 100, the dimension of transE to 100. The learning rate in our model is set to 0.0001.

6.5 Experimental Results

In this paper, we have carried out several experiments regarding to different metrics based on DBpedia, LinkedMDB, and their combination. The results regarding F-measures are shown in Table 2 and MAPs are shown in Table 3. ESA achieves better results than all other state-of-the-art approaches not only in each dataset, but also perform best in each metric.

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1. https://wiki.dbpedia.org
2. http://linkedmdb.org
3. http://ws.nju.edu.cn/summarization/esbm/
4. https://github.com/thunlp/TensorFlow-TransX
### Table 2: Experimental Results on ESBM benchmark v1.1 of F-measure

| Method    | DBpedia k=5 | DBpedia k=10 | LinkedMDB k=5 | LinkedMDB k=10 | ALL k=5  | ALL k=10 |
|-----------|--------------|--------------|---------------|---------------|---------|---------|
| RELIN [8] | 0.242        | 0.455        | 0.203         | 0.258         | 0.231   | 0.399   |
| DIVERSUM [27] | 0.249        | 0.507        | 0.207         | 0.358         | 0.237   | 0.464   |
| CD [25]   | 0.287        | 0.517        | 0.211         | 0.328         | 0.252   | 0.455   |
| FACES- E [18] | 0.280        | 0.485        | 0.313         | 0.393         | 0.289   | 0.461   |
| FACES [17] | 0.270        | 0.428        | 0.169         | 0.263         | 0.241   | 0.381   |
| LinkSUM [29] | 0.274        | 0.479        | 0.140         | 0.279         | 0.236   | 0.421   |
| ESA       | 0.310        | 0.525        | 0.320         | 0.403         | 0.312   | 0.491   |
| better\(^a\) | 0.023        | 0.008        | 0.007         | 0.010         | 0.023   | 0.027   |

\(^a\) By how much we are better than the best result of all other methods.

### Table 3: Experimental Results on ESBM benchmark v1.1 of MAP

| Method    | DBpedia k=5 | DBpedia k=10 | LinkedMDB k=5 | LinkedMDB k=10 | ALL k=5  | ALL k=10 |
|-----------|--------------|--------------|---------------|---------------|---------|---------|
| RELIN [8] | 0.342        | 0.519        | 0.241         | 0.355         | 0.313   | 0.466   |
| DIVERSUM [27] | 0.310        | 0.499        | 0.266         | 0.390         | 0.298   | 0.468   |
| CD [25]   | -            | -            | -             | -             | -       | -       |
| FACES- E [18] | 0.388        | 0.564        | 0.341         | 0.435         | 0.375   | 0.527   |
| FACES [17] | 0.255        | 0.382        | 0.155         | 0.273         | 0.227   | 0.351   |
| LinkSUM [29] | 0.242        | 0.271        | 0.141         | 0.279         | 0.213   | 0.345   |
| ESA       | 0.392        | 0.582        | 0.367         | 0.465         | 0.386   | 0.549   |
| better\(^a\) | 0.004        | 0.018        | 0.026         | 0.030         | 0.011   | 0.022   |

\(^a\) By how much we are better than the best result of all other methods.
F-measure

As shown in Table 2, the best improvement in single dataset is under top-5 summaries generated from DBpedia, our model gets the highest F-measure with 0.310, which exceeds the previously best result produced by CD. In terms of DBpedia dataset, the total increase of top-5 and top-10 summaries is 0.031. For LinkedMDB dataset, our model obtains the best score both in $k = 5$ and $k = 10$. Meanwhile, we combine two datasets to implement entity summarization, our model has 7.96% and 5.82% increase respectively for the results based on top-5 and top-10 results.

MAP

Our model also gets better scores for MAP metric, as Table 3 shows, where the best increase is 0.030 represented in LinkedMDB for $k = 10$. The improvement of LinkedMDB is more obvious in MAP metric than F-measure, where the total increase is up to 0.056.

ALL

Combine Table 2 and Table 3, it is evident that our ESA model yields better results both for F-measures and MAPs. It is worth mentioning that our model outperforms all other state-of-art approaches in both F-measure and MAP given by EMBS benchmark v1.1, which can significantly prove the effectiveness of our model.

We also visualize the machine attention vector and gold attention vector in both DBpedia and LinkedMDB. We randomly select subject 3WAY_FM in DBpedia and 4106 in LinkedMDB to visualize its machine attention vectors and gold attention vectors, as shown in Figure 5 and Figure 6. We can observe that the machine attention vector in the left is similar to the gold attention vector in the right, which indicates that our model successfully predict the RDF triples people may pay more attention to when they summarize the certain subject. We can find that the machine attention vectors generated by our model is more smooth than the gold attention vectors, which can be explained by the softmax technique we use to normalize the machine attention vectors.

Figure 5: Gold attention vector and machine attention vector generated by ESA of subject 3WAY_FM in DBpedia

7 Conclusion

In this work, based on idea that apply deep learning methods into entity summarization task, we propose a effective neural network model, called ESA (Entity Summarization with attention). Take the human preference into consideration, this model introduces popular notion of attention technique into entity summarization task. Meanwhile, we explore the way to construct gold attention vectors for modelling supervised attention mechanism. The ESA applies extracted predicates and objects as input, in particular, we exploit different but proper knowledge embedding methods respectively for predicates and objects, where the word embedding method is for predicates and TransE is for objects. The final output of ESA is normalized attention weights, which can be used to select representative entities. Our experiments indicate that word embedding technique and graph embedding technique like TransE can be combined together into a single task, which can better represent the fact or knowledge in knowledge graph and provide a more powerful input vectors for neural networks or other models. Moreover, to demonstrate the effectiveness of ESA, we compare our model with the state-of-the-art approaches using ESBM benchmark v1.1. Experimental results show that our work outperforms all other approaches both in F-measure and MAP.
Figure 6: Gold attention vector and machine attention vector generated by ESA of subject 4106 in Linked-MDB

8 Future Work

ESA model shows that similar to other tasks in Knowledge Graph such as entity recognition, relation extraction and ontology matching, deepening learning methods can also be used in entity summarization task. In future work, we expect to try various deep learning methods, and design several more powerful and effective neural networks. Specifically, we may improve our work in the following ways: (1) extend the scale of training set to better train our models; (2) instead of employing transE model to tackle the UNK problem, we plan to analyze RDF triples in more fine-grained aspects.

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A Source Code and Outputs

The link to source code and outputs is as follow:

https://github.com/WeiDongjunGabriel/ESA