MPSUM: Entity Summarization with Predicate-based Matching

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Abstract
With the development of Semantic Web, entity summarization has become an emerging task to generate concrete summaries for real world entities. To solve this problem, we propose an approach named MPSUM that extends a probabilistic topic model by integrating the idea of predicate-uniqueness and object-importance for ranking triples. The approach aims at generating brief but representative summaries for entities. We compare our approach with the state-of-the-art methods using DBpedia and LinkedMDB datasets. The experimental results show that our work improves the quality of entity summarization. The source code and outputs are available at https://github.com/WeiDongjunGabriel/MPSUM

1 Introduction
Linked Open Data (LOD) can describe entities on the Semantic Web using Uniform Resource Identifiers (URIs) or Resource Description Framework (RDF). Therefore, LOD is regarded as a collection of entity descriptions and has formed many public datasets, such as DBpedia² and LinkedMDB⁵. An RDF triple is in the form of <subject,predicate,object>. However, lengthy descriptions will take much time for users to comprehend and identify the underlying entities. To solve this problem, entity summarization has been proposed to generate a set of descriptions that are brief but effective to acquire enough information for quick comprehension. In this paper, we propose a method called MPSUM based on LDA model to identify the top − k representative triples as summaries for entities. Apart from ranking triples based on their probability distributions, we propose a novel method for triples ranking with consideration of the importance of objects and uniqueness of predicates in RDF data.

2 Related Work
RELIN⁴ is a variant of the random surfer model for ranking features mainly based on relatedness and informativeness for quick identification of entities. DIVERSUM¹¹ solves the problem of diversified entity summarization in RDF-like knowledge graphs by incorporating the notion of diversification into the summarizing algorithm. FACES-E⁶ is able to match a suitable class from existing ontology classes set, which extends FACES to generate entity summaries in the way of gleaning and ranking object and datatype properties. CD¹⁴ formulates entity summarization as a binary quadratic knapsack problem to solve. FACES⁷ improves the quality of entity summaries by taking the diversification of the relation types into consideration, introduces the concept of Cobweb clustering algorithm to partition features and rank them. LinkSUM¹² partitions the semantic links of each entity to rank features and is interfaced via the SUMMA entity summarization API. ES-LDA⁹ is
a probabilistic topic model based on LDA to generate representative summaries for entities and outperforms LinkSUM and FACES.

3 Preliminaries

3.1 Resource Description Framework (RDF)

RDF is a data modeling language of Semantic Web and is widely used to describe entities or resources. An RDF data graph is a set of entities (nodes) and relations (edges) between them, which is referred to a collection of triples where each triple \( t \) consists of a subject \( s \), predicate \( p \), object \( o \), in the form of \(<s,p,o>\).

**Document** A document \( d \) is defined as a collection of triples, \( d = \{t_1, t_2, ..., t_n\} \), that describes a single entity \( e \). Therefore, all triples of a document \( d \) have the same subject.

**Entity summarization** Given an entity \( e \) and a positive integer \( k \), a summary of the entity \( e \) is \( ES(e,k) \), is the top \(-k\) subset of all predicates and corresponding objects that are most relevant to that entity.

3.2 Latent Dirichlet Allocation (LDA)

The Latent Dirichlet Allocation (LDA)\[13\] is an unsupervised machine learning technique that can be used to identify latent topics from a collection of documents. It uses a "bag of words" approach that regards each document as a word frequency vector, transforming the text information into digital information for modeling. LDA generates the words in a two-stage process: words are generated from topics and topics are generated from documents.

4 Problem Statement

4.1 Problem Definition

An RDF document is in the form of a set of triples consisting of a subject with all predicates and corresponding objects related to a specific entity. In this paper, given an RDF dataset, entities are described by sets of their properties and correspond-
document can be deemed as "a bag of objects" because it owns the same subjects as mentioned above in Definition 3.1. Therefore, a method called MP (match up objects and RDF triples based on predicates) has been proposed to rank the RDF triples via taking the predicate-uniqueness and object-importance into consideration.

Algorithm 1 MP

1: Retrieve topic words words and RDF triples triples in document d from trained model
2: Initialize predicates’ list predicates in d
3: for topic word tw in words do
4:   if tw is in d then
5:     for RDF triple rp in triples do
6:       predicate p ← extractor(rp)
7:       if tw matches rp and p is not in predicates then
8:         Add p into predicates
9:         Output rp and remove it from triples
10:      end if
11:   end if
12: end for
13: for RDF triple rp in triples do
14:   predicate p ← extractor(rp)
15:   if p is not in predicates then
16:     Add p to predicates
17:     Output rp and remove it from triples
18: end if
19: end for
20: for RDF triple rp in triples do
21:   Output rp and remove it from triples
22: end for

Our model repeats the following process of MP for each document.

Step 1: Initialize the predicate set and enumerate all the RDF triples of an entity to identify the triples of which the objects are ranked based on probabilities. Then extract the corresponding predicate and add it into the aforementioned predicate set and output the triple when the predicate is not in the collection.

Step 2: Select the next triple from the remaining ones until all the objects complete the matching work, extract their predicates to compare with the predicate set generated from Step 1. If the predicate is not in the collection, add it into the current predicate set and output the related triple.

Step 3: Output the rest triples in order.

For example, after applying LDA method for training, top-10 predicates are selected according to the probability of each object within the subject which has the highest probability and corresponding triples of a given subject, including broadcastArea, broadcastArea, callsignMeaning, programmeFormat, type, type, label, name, type and homepage. However, apart from the probabilities of objects, MP method takes the information of subjects which is based on predicates into consideration, and generates better training effects, since the top-10 predicates are broadcastArea, callsignMeaning, programmeFormat, label, name, type, subject, homepage, slogan and type. The generative process of MP is shown in Algorithm 1.

4.4 Estimating Posterior Inference

Since it's difficult to acquire the posterior inference of the LDA, it needs to find an algorithm for estimating the posterior inference. There are many existing methods including variational EM[3] and Gibbs sampling[10]. EM[3] is a maximum likelihood estimation method including probabilistic model parameters of latent variables. Gibbs sampling[10] is a Markov Chain Monte Carlo algorithm, which constructs a Markov chain over the latent variables in the model and converges to the posterior distribution, after a number of iterations. However, TF-IDF[8] is a statistical method to assess the importance of a word for a file set or one of the files in a corpus. In our case, we evaluated our model using EM, Gibbs sampling and Gibbs sampling with TF-IDF to estimate posterior inference and the results demonstrate that the Gibbs sampling shows the best performance.

5 Experiments and Results

Data Preprocessing: Excessive work on RDF triples would introduce more corresponding triples to the topics that have higher probabilities and reduce the precision of MP method. Then we apply a concise extraction algorithm for objects to adapt to the algorithm for estimating the posterior inference. The extraction algorithm first acquires RDF triples which conclude the selected objects, then intercepts the part from the last ‘#’ or
Table 1: MAP values on different configurations

|       | dbpedia: |       |       |
|-------|----------|-------|-------|
|       | top5     | top10 |       |
| config.1: | 0.389 | 0.463 |       |
| config.2: | 0.396 | 0.568 |       |
| config.3: | 0.379 | 0.554 |       |
|       | lmdb:    |       |       |
|       | top5     |       |       |
| config.1: | 0.370 | 0.474 |       |
| config.2: | 0.370 | 0.476 |       |
| config.3: | 0.371 | 0.576 |       |

'/' of RDF to the end. For example, we extract "broadcaster" after lowering the capital letters from http://dbpedia.org/ontology/Broadcaster.

Corpus Enlarging: As mentioned in section 4.2, we supplement the RDF data via adding categories of objects and repeating the topics in each document to deal with common RDF data problems including sparseness, lack of context, etc. Compared with the methods of supplementing RDF data in ES-LDA model, the results of our model outperforms better.

Inference Algorithm: In section 4.4, we have introduced three algorithms to estimate the posterior inference including EM, Gibbs sampling and Gibbs sampling with TF-IDF. All of the above methods have been used in our experiments respectively, and the Gibbs sampling shows the best results.

Model Training: In the training process, it’s essential to set proper hyperparameters, $\alpha$ and $\beta$. We conduct experiments and finally find that when $\alpha = (E/20)/R$, , we can get a satisfying result. $E$ is the total number of unique entities and $R$ is the total number of unique predicates. We test 3 configurations as table 1. As the results show, taking the total number of entities into account can optimize training effects. When the value of $\beta$ is set to 0.01, DBpedia has the best result since it contains enrich corpus. However, for LinkedMDB, its corpus is insufficient, when $\beta = 50/R$, the result is better.

The DBpedia and LinkedMDB datasets are chosen for our experiments. We evaluate the F-measures (the harmonic average of the precision and recall) and MAP (Mean Average Precision) to compare our MPSUM model with other state-of-the-art approaches including RELIN, DIVERSUM, FACES-E, CD, FACES and LinkSUM, and the results are in Table 2 and Table 3 respectively. From the results, we can observe that MPSUM performs best on all cases except the top-10 in DBpedia.As the results show, RELIN and LinkSUM could not meet the diversity requirement in the summarization process. FACES discount literals in entity summarization while FACES-E and RELIN take literals into account. Our approach maintains both diversity and relevancy, while representing each entity through $top - k$ predicates. Above all, MPSUM outperforms the selected approaches on overall datasets.

6 Conclusion
In this paper, we put forward an LDA-based model MPSUM for entity summarization. In our method, we propose to increase the frequency of words by adding categories of the objects to supplement RDF data, which is an improvement of ES-LDA[9]. Besides, a novel method called MP has been proposed to rank triples with consideration of the importance of objects and uniqueness of predicates in RDF data. We utilize three algorithms (EM, Gibbs sampling, Gibbs sampling with TF-IDF) to estimate posterior inference and finally take advantage of Gibbs sampling for experiments and comparisons. The experimental results of our approach for entity summarization are quite promising. It performs better than 5 state-of-the-art techniques to generate summaries.

7 Future Work
In this paper, we select the topic with the maximum probability. For further work, the selection of topics can be implemented by proportion to apply more topics for ranking RDF triples. Moreover, other proper methods to enlarge RDF data remain to be explored to improve the quality of representative triples for entity summarization.
Table 2: F-measure of selected entity summarizers under their best parameter settings

|           | DBpedia | LinkedMDB | All       |
|-----------|---------|-----------|-----------|
| RELIN     | $0.250_{\lambda=1.00}$ | $0.468_{\lambda=1.00}$ | $0.210_{\lambda=1.00}$ | $0.260_{\lambda=1.00}$ | $0.239_{\lambda=1.00}$ | $0.409_{\lambda=1.00}$ |
| DIVERSUM  | $0.260$ | $0.522$ | $0.222$ | $0.365$ | $0.239$ | $0.477$ |
| CD        | $0.299_{\gamma=0.47}$ | $0.531_{\gamma=0.23}$ | $0.215_{\gamma=1.00}$ | $0.326_{\gamma=1.00}$ | $0.207_{\gamma=0.52}$ | $0.467_{\gamma=0.16}$ |
| FACES-E   | $0.285$ | $0.527$ | $0.252$ | $0.348$ | $0.276$ | $0.476$ |
| FACES     | $0.272$ | $0.439$ | $0.160$ | $0.259$ | $0.240$ | $0.388$ |
| LinkSUM   | $0.290_{\alpha=0.01}$ | $0.498_{\alpha=0.04}$ | $0.117_{\alpha=1.00}$ | $0.255_{\alpha=1.00}$ | $0.240_{\alpha=0.01}$ | $0.428_{\alpha=0.04}$ |
| MPSUM     | $0.313$ | $0.522$ | $0.270$ | $0.440$ | $0.300$ | $0.499$ |
| Better$^a$| $0.014$ | -         | $0.018$ | $0.075$ | $0.024$ | $0.022$ |

*By how much we are better than the best result of all other methods.

Table 3: MAP of selected entity summarizers under their best parameter settings

|           | DBpedia | LinkedMDB | All       |
|-----------|---------|-----------|-----------|
| RELIN     | $0.348_{\lambda=1.00}$ | $0.532_{\lambda=1.00}$ | $0.243_{\lambda=1.00}$ | $0.337_{\lambda=1.00}$ | $0.318_{\lambda=1.00}$ | $0.476_{\lambda=1.00}$ |
| DIVERSUM  | $0.316$ | $0.511$ | $0.269$ | $0.388$ | $0.302$ | $0.476$ |
| CD        | -       | -         | -         | -         | -         | -         |
| FACES-E   | $0.354$ | $0.529$ | $0.258$ | $0.361$ | $0.326$ | $0.481$ |
| FACES     | $0.247$ | $0.386$ | $0.140$ | $0.261$ | $0.261$ | $0.351$ |
| LinkSUM   | $0.240_{\alpha=0.25}$ | $0.366_{\alpha=0.03}$ | $0.120_{\alpha=1.00}$ | $0.254_{\alpha=1.00}$ | $0.210_{\alpha=0.25}$ | $0.348_{\alpha=0.03}$ |
| MPSUM     | $0.396$ | $0.568$ | $0.371$ | $0.476$ | $0.389$ | $0.542$ |
| Better$^a$| $0.042$ | $0.036$ | $0.102$ | $0.088$ | $0.063$ | $0.061$ |

*By how much we are better than the best result of all other methods.

Acknowledgements

This research is supported in part by the National Natural Science Foundation of China under Grant No. 61702500.

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