SynsetRank: Degree-adjusted Random Walk for Relation Identification

Shinichi Nakajima*, Sebastian Krause, Dirk Weissenborn, Sven Schmeier, Nico Görnitz, Feiyu Xu

Abstract—In relation extraction, a key process is to obtain good detectors that find relevant sentences describing the target relation. To minimize the necessity of labeled data for refining detectors, previous work successfully made use of BabelNet, a semantic graph structure expressing relationships between synsets, as side information or prior knowledge. The goal of this paper is to enhance the use of graph structure in the framework of random walk with a few adjustable parameters. Actually, a straightforward application of random walk degrades the performance even after parameter optimization. With the insight from this unsuccessful trial, we propose SynsetRank, which adjusts the initial probability so that high degree nodes influence the neighbors as strong as low degree nodes. In our experiment on 13 relations in the FB15K-237 dataset, SynsetRank significantly outperforms baselines and the plain random walk approach.

Index Terms—relation extraction, random walk, PageRank, BabelNet.

I. INTRODUCTION

Many NLP tasks are concerned with recognizing semantic concepts in large amounts of text, including the problem of detecting mentions of real-world events [1], [2] and relations between entities [3], [4], [5]. The high up-front cost for training NLP systems with labeled data has lead to the design of supervision paradigms which use only distant or weak guidance from manually created examples [6], [7], [8]. Such methods can benefit from additional clues about the presence of semantic concepts in language fragments, coming from lexical-semantic resources like WordNet [9] and BabelNet [10].

Consider the following example: Mike and Julie Miller celebrated a fabulous wedding last summer, only two years after they had first met. In the first part of the sentence, the term wedding is a strong indicator for the presence of a marriage relation mention, while the second part has no such indicator. Information about such relation-relevant terms is helpful for, e.g., extracting sentence templates for pattern-based relation extraction, or pre-filtering texts before fine-grained processing takes place.

Existing information-extraction systems typically exploit lexical-semantic repositories for increased lexical coverage, by retrieving synonyms for observed terms or by calculating similarity scores based on the graph structure of these resources [11], [12], [13]. Few approaches explicitly identify the entries which express semantic concepts on the textual level. An exception is the work by Moro et al. (2013) [14], who start with an initial frequency distribution of terms co-occurring with relation examples in a large text collection. Relation-relevant terms are then determined through an ad-hoc combination of this initial distribution with the graph structure of the repository.

In this paper, we improve Moro et al.’s approach by casting the problem to a ranking problem, and applying the random walk approach with a simple modification. We test our approach on a publicly available dataset and compare it to several baselines. We evaluate the model performance in terms of the quality of positively labeled word synsets and reach drastically better performance.

II. BACKGROUND

This paper focuses on the automatic identification of relation-relevant entries in lexical-semantic resources, i.e., we want to obtain relation detectors. As relation we understand any kind of real-world relationship between persons, locations, etc., examples are the kinship relations marriage, parent-child, siblings, or business concepts such as company acquisition, employment tenure.

Lexical-semantic repositories are inventories of word senses, which link words to their meaning and to other words, i.e., these resources have an underlying graph structure. A prominent instance of the many lexical-semantic resources out there is BabelNet[10], a large-scale multilingual semantic network which was built automatically through the algorithmic integration of Wikipedia and WordNet. The core components (nodes) are so-called synsets, which are sets of synonymous terms; the edges correspond to synset relationships such as hypernymy and meronymy.

A. Finding Domain-Relevant Terms

A lot of work has dealt with acquiring relevant terms for semantic relations. Nguyen et al. (2010) [15] analyzed the distribution of trigger words for semantic relations in annotated data in order to filter extraction patterns. For a similar reason, Xu et al. (2002) [16] collected relevant terms with a TFIDF-based strategy. Other approaches incorporate lexical knowledge from WordNet. Zhou et al. (2005) [3] presented a feature-based relation extractor which utilizes semi-automatically build trigger-word lists from WordNet. Culotta and Sorensen (2004) [11] used WordNet hypernyms for increased extraction coverage. Stevenson and Greenwood (2005) [12] defined a

*corresponding author (email: nakajima@tu-berlin.de)
Shinichi Nakajima and Nico Görnitz are with Technische Universität Berlin, Machine Learning Group, Marchstr. 23, 10587 Berlin, Germany.
Shinichi Nakajima, Sebastian Krause, Dirk Weissenborn, Sven Schmeier and Feiyu Xu are with Berlin Big Data Center, 10587 Berlin, Germany.
Sebastian Krause, Dirk Weissenborn, Sven Schmeier and Feiyu Xu are with DFKI, Language Technology Lab, Alt-Moabit 91c, Berlin, Germany.

http://babelnet.org
similarity function for learned linguistic patterns that was built on WordNet information.

None of the above approaches, however, explicitly determines and outputs which parts of the lexical-semantic resource contain the terms that are relevant to a given semantic relation.

B. Extracting Relation-Specific Sub-Graphs

Moro et al. (2013) [14] proposed another approach to the term identification problem. Their algorithm gets as input a set of sentences which have been labeled with relation mentions in a distantly supervised manner. This noisy set of relation mentions is processed by word-sense disambiguation [17] to build links from the word level to the level of synsets in WordNet and BabelNet. This induces a frequency distribution over synsets, from which the most frequent items plus their direct neighbors in the resource are selected to build the final relation-specific sub-graph. Moro et al. (2013) employ these sub-graphs for filtering linguistic patterns in a relation-extraction scenario. While their approach shows good results, it also leaves room for improvements mainly due to its ad-hoc, heuristic utilization of the available synset links in the sense inventory. We use their approach as one of the baselines against which we compare our proposed model.

C. PageRank: Random Walk for Webpage Ranking

Moro et al. (2013) choose the most frequent synsets and their neighbors as the relevant synsets, which can be naturally cast as information propagation through random walks. Random walk was successfully applied for ranking webpages in the name of PageRank [13], [19]. Our first trial is to apply PageRank for ranking synsets, according to the relevance to the target relation.

Consider a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with a set $\mathcal{V}$ of nodes and a set $\mathcal{E}$ of edges connecting two nodes. We denote the number of nodes by $N = |\mathcal{V}|$. In our application, each node $i \in \mathcal{V}$ corresponds to a synset, and each edge $(i, j) \in \mathcal{E}$ corresponds to a semantic connection between two synsets. Each edge has a label $l \in \{1, \ldots, L\}$, which specifies the relation between two synsets, such as hypernymy and meronymy.

We formally prepare $L$ graphs $\{G^{(l)} = (\mathcal{V}, E^{(l)})\}_{l=1}^L$, which share the nodes $\mathcal{V}$ but have $L$ different sets of edges, each of which consists of a single edge label. For each $l$, we express the existence of edges by an $N \times N$ binary matrix $E^{(l)}$, and we prepare a weight vector $w \in \mathbb{R}^L$.

Then, we construct a transition matrix $Q^{(l)} \in \mathbb{R}^{N \times N}$ as the weighted sum over all edge labels:

$$Q^{(l)}_{i,j} = \begin{cases} \sum_{j'=1}^L w_j E^{(l)}_{i,j'} & \text{if } (i, j) \in \bigcup_{l=1}^L \mathcal{E}^{(l)}, \\ 0 & \text{otherwise}. \end{cases}$$

The BabelNet graph is directed, and the number of edge types is $L = 20$. Since the semantic edge direction does not necessarily indicates the direction in which the relevance information should flow, we treat the edges in the opposite direction as another edge type. Thus, we have $L = 58$ edge types in total.

To avoid dead-ends and spider-traps issues, our implementation of PageRank is equipped with taxaction and restarting [19], [20]. This can be realized by adding a sink-source node, which absorbs $\alpha \in [0, 1]$ proportion of flow from all nodes, and re-distributes it according to the initial distribution $p^{(0)} \in \mathbb{R}^N$. Here, we use the original frequency distribution, observed from the text corpus (see Section II-B), over synsets as the initial distribution $p^{(0)}$.

We also add self-links, with which the random walkers stay at the same node with probability $\beta \in [0, 1]$. Thus, the distribution after $t$ random walks is defined as

$$\tilde{p}^{(t)} = \left( \tilde{p}^{(t-1)} \right)^T Q, \quad \text{where}$$

$$Q = \begin{pmatrix} (1-\alpha)Q' + \beta I_N \\ p^{(0)} \end{pmatrix},$$

$$k_i = \begin{cases} \alpha & \text{if } \exists j' \text{ s.t. } (i, j') \in \bigcup_{l=1}^L \mathcal{E}^{(l)}, \\ 1 - (1-\alpha)\beta & \text{otherwise}. \end{cases}$$

Here, $I_N$ denotes the $N \times N$ identity matrix, and $\tilde{p}^{(t)} \in \mathbb{R}^{N+1}$ denotes the distribution (after $t$ random walks) over the original nodes and the $(N+1)$-th sink-source node. We set $\tilde{p}^{(0)}$ to the initial distribution augmented with a zero for the sink-source node, i.e., $\tilde{p}^{(0)} = \left( p^{(0)} \right)^T, 0$. After random walks, we rank the synsets based on the distribution $\tilde{p}^{(t)}$. The unknown parameters $\alpha$, $\beta$, and $t$ are optimized by using the validation data, while the edge weights are fixed to $w_l = 1, \forall l$ in this paper.

III. PROPOSED METHOD

As shown in Section IV, PageRank performs worse than Moro et al.’s baseline method even after parameter optimization. This is not very surprising because the problem of ranking webpages and the problem of ranking synsets are substantially different. Taking this difference into account, we propose a new method.

A. SynsetRank: Degree-Adjusted Random Walk for Synset Ranking

By nature of random walks, a node with more outgoing edges influences each neighboring node less, since random walkers are dispersed over many edges. This is what PageRank, which simulates web surfer, intends to do, but this is not appropriate for synset ranking, where neighbors to frequent synsets should be high ranked, regardless of the degree (the number of edges) of the frequent node.

Our idea is to adjust the original frequency, as well as the restarting probability, to compensate this undesired phenomenon. In our random walk formulation (1), this can be done simply by replacing the original frequency distribution $p^{(0)}$ with a re-weighted one:

$$\tilde{p}^{(0)} = \frac{p^{(0)} \ast d}{\|p^{(0)} \ast d\|_1},$$

where $d_i = \sum_{j=1}^N \sum_{l=1}^L w_l E^{(l)}_{i,j}$.

Here $\ast$ denotes the element-wise product of vectors. This simple modification makes the influence of a node to each neighbor equal, regardless of the degree, and shows a drastic improvement in our experiment in Section IV. We call this degree-adjusted random walk approach SynsetRank.
IV. EXPERIMENT

In this section, we show our experimental results.

A. Data and Task

We used the FB15K-237 dataset of Toutanova et al. (2015) for our experiments, and follow the training/validation/test split suggested by the authors. This dataset provides a large number of relation instances from the factual knowledgebase Freebase along with textual mentions, i.e., parses of sentences which contain references to the argument entities of the relation instances.

The task is to find the synsets (nodes in BabelNet) that are semantically relevant for the target relation, i.e., its occurrence is likely to trigger a specific semantic relation (from a knowledge base like Freebase, e.g., the relation /people/person/place_of_birth connecting humans to the place they were born in). Here, ‘triggering’ means that this synset (word surface form) in a sentence (e.g., the word ‘born’ in the sentence ‘John was born in New York’), makes it probable that this sentence refers to this semantic relation (which the sentence actually does, in this example). Such information about relation relevancy is useful for downstream text analytics tasks where it serves as a further signal for making a relation extraction decision (Does the sentence ‘John was born in New York’ contain the fact triple <John, /people/person/place_of_birth, New York>?).

The dataset FB15K-237 was created by combining (a) fact triples from Freebase, (b) many sentences which mention entities for which facts are listed in Freebase. As the task for which FB15K-237 was created, unfortunately, is different from ours, we cannot follow the evaluation procedure suggested in Toutanova et al. (2015). Accordingly, we created our own gold-standard labels by hand-labeling a subset of synsets, as explained shortly.

In order to avoid data sparsity issues, we determined the twenty relations with the highest number of mentions in the training partition, and removed seven from these which were redundant with respect to the other relations or which were semantically lightweight from the point of view of textual mentions (see Appendix A for details of the removed seven relations). We used the 13 relations shown in the first column of Table I.

For each of these relations and each data partition, we build positive/negative sets of textual mentions. The positive mentions are simply the ones that contain the arguments of a relation instance, while the negative ones are constructed following the strategy outlined by Toutanova et al. (2015). For the data in the training partition, we apply word-sense disambiguation to the positive and negative textual mentions, this way creating an initial synset frequency distribution among positive and negative examples for each relation, similar to Moro et al. (2013).

We will make the evaluation data publicly available upon acceptance.
Furthermore, for each relation and the mentions in the validation and test partition, we prepare an evaluation dataset with manually annotated labels. We start with the top-50 most frequent synsets for the relation in the respective part of the data, which occur in positive textual mentions but not in negative ones. We do a two-step graph walk on BabelNet which extends these nodes with two randomly selected neighbors for each already included node. The resulting synsets and the corresponding lemmas/words are given to human annotators who label the synsets as positive/negative with respect to the relation, i.e., they judge whether or not the synset is relevant for the semantics of the relation. In our experiments, we use BabelNet version 2.5.1, which contains roughly 9M synsets, 11M lexicalizations, and 262M links. There are in total 430k who label the synsets as positive/negative with respect to the validation and test partition, we prepare an evaluation dataset for each relation. For PageRank (common) and SynsetRank (common), the optimal parameters (maximizing the average AUC over all 13 relations) are used.

SynsetRank improves the average AUC of Moro et al.’s baseline method by roughly 0.05, which is similar to the performance gain by Moro et al. (2013) [13] from the Frequency baseline. Although the necessity of parameter optimization can be a bottleneck of SynsetRank, the second best result with SynsetRank (common) implies the possibility of using common parameters for all relations—Once we optimize the parameters for some set of relations, one could use the same parameters for new relations.

B. Result

Table I shows the area under the ROC curve (AUC) on the test partition for the 13 relations. ‘Frequency’ denotes the baseline method where the synsets are ranked based on the original frequency $p^{(0)}$. We clearly observe that the plain PageRank tends to perform worse than Moro et al.’s baseline method, while our proposed degree-adjusted SynsetRank shows drastically better performance than all others. For PageRank and SynsetRank, the optimal parameters (maximizing the AUC on the validation partition) are grid-searched over $\alpha = 0.0,0.2,\ldots,1.0$, $\beta = 0.0,0.2,\ldots,1.0$, and $t = 1,\ldots,5$ for each relation. For PageRank (common) and SynsetRank (common), the common optimal parameters (maximizing the average AUC over all 13 relations) are used.

SynsetRank improves the average AUC of Moro et al.’s baseline method by roughly 0.05, which is similar to the performance gain by Moro et al. (2013) [13] from the Frequency baseline. Although the necessity of parameter optimization can be a bottleneck of SynsetRank, the second best result with SynsetRank (common) implies the possibility of using common parameters for all relations—Once we optimize the parameters for some set of relations, one could use the same parameters for new relations.

V. Conclusion

Extracting knowledge from the internet is one of the most important near-future goals for researchers in the field of natural language processing, machine learning, and artificial intelligence. Relation extraction (RE) is a key technology. We cast the problem of finding good detectors as a synset ranking problem, and applied the random walk approach with simple modification. Our experiment showed promising results.

We leave the quality assessment of downstream applications as future work. We also plan to apply the supervised random walk approach [22] to optimize the weights $w$ for each edge label, which further exploits existing knowledge for better performance.
[8] R. Hoffmann, C. Zhang, X. Ling, L. S. Zettlemoyer, and D. S. Weld, “Knowledge-based weak supervision for information extraction of overlapping relations,” in ACL. The Association for Computer Linguistics, 2011, pp. 541–550.

[9] C. Fellbaum, Ed., WordNet: an electronic lexical database, 1998.

[10] R. Navigli and S. Ponzetto, “BabelNet: The automatic construction, evaluation and application of a wide-coverage multilingual semantic network,” Artificial Intelligence, vol. 193, pp. 217–250, 2012.

[11] A. Culotta and J. S. Sorensen, “Dependency tree kernels for relation extraction,” in ACL, 2004, pp. 423–429.

[12] M. Stevenson and M. Greenwood, “A semantic approach to IE pattern induction,” in Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL’05). Association for Computational Linguistics, 2005, pp. 379–386.

[13] G. Zhou and M. Zhang, “Extracting relation information from text documents by exploring various types of knowledge,” Inf. Process. Manage., vol. 43, no. 4, pp. 969–982, 2007.

[14] A. Moro, H. Li, S. Krause, F. Xu, R. Navigli, and H. Uszkoreit, “Semantic rule filtering for web-scale relation extraction,” in Proc. of I3WC, 2013, pp. 347–362.

[15] Q. L. Nguyen, D. Tikk, and U. Leser, “Simple tricks for improving pattern-based information extraction from the biomedical literature,” Journal of Biomedical Semantics, vol. 1, no. 1, pp. 1–17, 2010.

[16] F. Xu, D. Kurz, J. Fiskorski, and S. Schmeier, “A domain adaptive approach to automatic acquisition of domain relevant terms and their relations with bootstrapping,” in LREC. European Language Resources Association, 2002.

[17] R. Navigli, “Word sense disambiguation: A survey,” ACM Comput. Surv., vol. 41, no. 2, pp. 10:1–10:69, 2009.

[18] S. Brin and L. Page, “Anatomy of a large-scale hypertextual web search engine,” in Proc. of WWW, 1998, pp. 107–117.

[19] J. Leskovec, A. Rajaraman, and J. D. Ullman, Mining of Massive Datasets 2nd Edition. Cambridge University Press, 2014.

[20] H. Tong, C. Faloutsos, and J. Y. Pan, “Fast random walk with restart and its applications,” in Proc. of ICDM, 2006.

[21] K. Toutanova, D. Chen, P. Pantel, H. Poon, P. Choudhury, and M. Gamon, “Representing text for joint embedding of text and knowledge bases,” in Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing. Lisbon, Portugal: Association for Computational Linguistics, September 2015, pp. 1499–1509. [Online]. Available: http://aclweb.org/anthology/D15-1174

[22] L. Backstrom and J. Leskovec, “Supervised random walks: Predicting and recommending links in social networks,” in Proc. of WSDM, 2011.

Shinichi Nakajima is a senior researcher in Berlin Big Data Center, Machine Learning Group, Technische Universität Berlin. He received the master degree on physics in 1995 from Kobe university, and worked with Nikon Corporation until September 2014 on statistical analysis, image processing, and machine learning. He received the doctoral degree on computer science in 2006 from Tokyo Institute of Technology. His research interest is in theory and applications of machine learning, in particular, Bayesian learning theory, computer vision, and data mining.

Sebastian Krause is a PhD student at the Language Technology Lab of the German Research Center for Artificial Intelligence (DFKI). He got his Diplom degree in Computer Science from the Humboldt University Berlin and has recently worked on natural language processing, in particular on text mining problems.

Feiyu Xu is Principal Researcher and Head of Research Group Text Analytics in the Language Technology Lab of DFKI. She also is co-founder of Yocoy Technologies GmbH, a 2007 spin-off from DFKI. Yocoy is developing next generation mobile language and travel guides. Since 2004, Dr. Xu is vice-director of the Joint Research Laboratory for Language Technology of Shanghai Jiao Tong University and Saarland University. Feiyu Xu studied technical translation at Tongji University in Shanghai after having been nominated and selected with a waiver of the national admission exam in year 1987. She then studied computational linguistics at Saarland University from 1992 to 1998 and graduated by receiving a Diplom (MSc) with distinction. Her PhD-Thesis is about “bootstrapping relation extraction from semantic seed” in “information extraction”. In 2014, Feiyu Xu has completed a habilitation in big text data analytics. In 2012, Feiyu Xu has won a Google Focused Research Award for Natural Language Understanding as co-PI with Hans Uszkoreit and Roberto Navigli. In 2014, Feiyu Xu was honored as DFKI Research Fellow. She has extensive experience in multilingual information systems, information extraction, text mining, big data analytics, business intelligence, question answering and mobile applications of NLP technologies. She has successfully led more than 30 national and international research and development projects. She has broad and in-depth experience of the total cycle of innovation in her expert areas, from basic research, to application and development and finally to products and their commercialization.

Sven Schmeier is a senior consultant and project leader at the Language Technology Lab at the German Research Center for Artificial Intelligence (DFKI) in Berlin. Sven Schmeier holds a Diploma in Computer Science and a PhD in Computational Linguistics from the University of Saarland. In 2000 he was co-founder of the DFKI Spin-Off company Xtramind (now Attensity). In 2005 he was the leader of the research group at Semgine GmbH now reformed to medx GmbH in Berlin. In 2007 he was co-founder of the company Yocoy Technologies GmbH with Dr. Feiyu Xu and Prof. Hans Uszkoreit.

Nico Görnitz is a research associate in the machine learning group at the Berlin Institute of Technology (TU Berlin, Berlin, Germany) headed by Klaus-Robert Müller. In 2014 he did an internship with the Research Group, led by David Heckerman (Microsoft Research, Los Angeles, US). Before, he was employed as a research associate from 2010-2014 and during 2010-2012 also affiliated with the Friedrich Miescher Laboratory of the Max Planck Society in Tübingen, where he was co-advised by Gunnar Rätsch. He received a diploma degree (MSc equivalent) in computer engineering (Technische Informatik) from the Berlin Institute of Technology with a thesis in machine learning for computer security in 2010.

Dirk Weissenborn is since April 2014 a Researcher und PhD Student at DFKI. His background is in Machine Learning with a focus on NLP.