Recognition of Metonymy by Tagging Named Entities

H.BURCU KUPELIOGLU
Galatasaray University
Institute of
Science and Engineering
No:36 Besiktas Istanbul
TURKEY
burcukupelioglu@gmail.com

TANKUT ACARMAN
Galatasaray University
Institute of
Science and Engineering
No:36 Besiktas Istanbul
TURKEY
acarmant@gmail.com

TASSADIT AMGHAR
University of Angers
LERIA
BP 73532 49035 Angers
FRANCE
amghar@info.univ-angers.fr

BERNARD LEVRAT
University of Angers
LERIA
BP 73532 49035 Angers
FRANCE
bernard.levrat@gmail.com

Abstract: Metonymy is referential phenomenon in which one entity is referred by another one on the base of the existence of a relation between the two entities. It occurs very often in texts and so its recognition and resolution is required to be fulfilled for a lot of Natural Language Processing Applications. Among the methodologies and domains implied in the achievement of these tasks we can cite semantic classifiers, discourse understanding methodology, unsupervised and statistical methods. In this paper we propose to expand existing approaches by a preliminary tagging of named entities of the text with the Stanford NER program and using the argument structure of predicates as they figure in the WordNet thesaurus. We show how we can so eliminate a of lot of work which without this should have been made by human.

Key–Words: Metonymy Recognition, Named Entity, Natural Language Processing, Stanford CoreNLP, WordNet

1 Introduction

Metonymy is a figure of speech drawing a reference to an existing logical relation between two concepts. This relation may appear in many different forms for instance, artist for artwork, container for content and so on. Although metonymy detection may be elusive even for humans analytical reasoning, it is also confusing for computers but required to understand human languages.

A pioneering work by Markert and Nissim [1] is focused on metonymy resolution for countries and companies. They annotated a large corpora containing company and country names. But this study is limited to annotations provided by humans but this is a time consuming process. And in this study, we are focused on metonymy resolution by named entity recognition.

Our project is based on metonymy recognition and resolution through named entity recognition. Metonymy is a figure of speech which consists by using a concept b to refer to a concept a, without intending analogy [2]. The existing methods of metonymy resolution depends on supervised and unsupervised learning supported by statistical approaches. The commonly used approaches are catching the Selectional Restriction Violations (SRVs) and deviations from grammatical rules, [3].

Our study has two parts: the first part involves pre-processing the given text. Pre-processing is necessary for further treatment. Pre-processing consists of lemmatization, part-of-speech tagging, NER tagging, dependency tagging and WSD treatment. The second part considers metonymy recognition, namely detections of possible metonymies. Metonymy recognition is achieved via named entities SRVs, and it is a rule based algorithm. The rest of this document is organized as follows: Section 2 presents related work. Section 3 elaborates the proposed method. The data set and the results are given in Section 4 and in Section 5, respectively. Finally, some conclusions are given in Section 6.

2 Related Work

A probabilistic model for logical metonymy is proposed by Lapata [4] and Shutova [5]. In citeasnounroberts2011unsupervised Selectional Restriction Violations (SRVs) and grammatical rule violations are used. A classification task is introduced by Markert and Nissim [6] and occurrence of metonymic readings are used to classify location names. Then, Nissim and Markert [7] proposes a supervised classification method for organization names. The algorithm is trained using a set of key instances of distinct metonymic words of one semantic class to assign outcomes to the new test instances for different metonymic words of the same semantic class.

Markert and Hahn [8] proposes the analysis of metonymies in discourse, and checks other sentences of a context to understand if a word is metonymic.

Birke and Sarkar [9] presents a learning algorithm for figurative language. Bogdanova [10] and Nastase et al. [11] creates clusters based on sense differentiation and the usage of contextual SRVs.

This study is focused on WordNet [12] thesaurus to detect metonymic words and their dependency relations.

3 Named Entity Based Metonymy Recognition - NEBMR

In this section, we present and evaluate an algorithm whether a named entity in a sentence is used metonymically. The algorithm has three stages: the first stage is based on pre-processing the given text using taggers. We use MorphaAnnotator, POS tagger, NER tagger and dependency tagger of Stanford CoreNLP [13]. The pre-processing consists of splitting the given text into sentences and then into tokens to Lemmatize. Then, each lemma is POS, NER and dependency tagged. This tagging process is realized automatically by Sentence class of Stanford CoreNLP. The second stage involves the analysis of processed text by our rule based algorithms. Rule functions have access to WordNet database.

Rule functions use an ordered list of tokenized and tagged sentences subject to an index for the named entity potentially metonymic. The result is either literal, metonymic or mixed as in SemEval 2007 Task 8 [14]. Each rule is processed until an applicable rule is achieved. We mainly use verb or noun groups for metonymy detection. The rule functions depend on the lexicographer files of its dependent verbs or nouns. This information is provided by WordNet synsets. In order to select synset for a verb or noun, we identify its meaning in the given sentence. This identification is realized by an adoption of the Lesk Algorithm [15] [16] [17].

3.1 Named Entities as Agents

The most significant distinction is the lexicographer file of the root verbs synset. If a named entity is an agent of a verb, the first step is to identify the verbs synset. If the verb has multiple senses, in order to identify the synset, the adopted Lesk Algorithm is applied to the verb. Some acts are only related to humans, animals or objects but not suitable for locations or organizations such as cognition verbs or feeling verbs. If the verb belongs to one of these groups, we consider the named entity metonymic.

3.2 Named Entities as Predicates or Passive Agents

If a named entity is a passive agent or a predicate in a sentence, again we check the verb to which the named entity depends. Usually a few groups of verb may be suitable for named entities to be predicates or passive agents. We make decision entirely based on verb groups as same as agent named entities.

3.3 Named Entities Having Compound Dependencies

In some cases named entities are neither agents nor predicates. Also, if a named entity is composed of two words like White House, NER tagger annotator gives the dependency relation as a compound relation. If this is the case, we track the compound dependency until we find a common noun or a verb dependency. For a verb, we check the dependency relation (agents, predicates, etc.) and the metonymy analysis is done accordingly. If the named entity has a dependency to a common noun we have to check the noun group as we check the verb groups. An organization can have a worker, a member or an address like a location can have a room, a lake, etc., but does not have a decision, arm or leg. The decision belongs to the people, and if a named entity does have a compound relation with decision, we consider it as metonymic. Again, we have to identify the synset of the noun at the first stage.

3.4 Dependency Tags

Since we use Stanford CoreNLP POS Tagger, our dependencies are compliant with the Stanford CoreNLP standard [18] shown as in Table1. This standard is also known as Universal Dependencies (http://universaldependencies.org/ language-en).) The motivation of universal dependency creation is to help researchers study multilingual and cross-lingual easier.

3.5 Verb and Noun Groups

WordNets lexicographer files are classified by synset meanings in particular for verbs and nouns. One verb synset can only correspond to a single verb group. Like verbs, nouns also have groups that they belong according to their synsets. In our study, we choose some of these verb and noun groups as follows in Table2 and Table3.

4 Experiment and Data Set

4.1 Evaluation

We predict four conditions for metonymy recognition as seen as in Table4: true positive (TP), false positive (FP), true negative (TN) and false negative (FN). True positives are the cases when our result is either metonymic or mixed and the reading is either metonymic or mixed. It is a true negative if the prediction result is literal or mixed and the reading is literal or mixed. The false positives exist when the result is metonymic but the reading is literal. And finally, when the result is literal but the reading is metonymic it is a false negative. We choose to include mixed results and readings as positive cases because even for humans the mixed cases can not be determined exactly. Namely some mixed cases can be considered as metonymies and some literal readings by other human annotators.

Table 1: Some of the *U*niversal Dependencies.

Dependency	Definiton
nsubj	Nominal subject
nsubjpass	Passive nominal subject
dobj	Direct object
iobj	Indirect object
amod	Adjectival modifier
nmod	Nominal modifier
compound	Compound
conj	Conjunct

Table 2: WordNet verb groups decision lists.

Human Verb Groups	Copular Verb Groups
verb.communication	verb.stative
verb.cognition	(be, become, get,
verb.emotion	remain, seem, etc.)
verb.social	verb.stative
verb.possession	
verb.consumption	
verb.competition	
verb.creation	
verb.body	
verb.perception	
verb.motion	

Table 3: WordNet noun groups decision lists.

Human Noun Groups	Mixed Noun Groups
noun.act	noun.Tops
noun.body	noun.artifact
noun.cognition	noun.attribute
noun.communication	noun.event
noun.feeling	noun.group
noun.motive	noun.process
noun.object	noun.phenomenon
noun.person	

4.2 Data Set

The main challenging aspect of NLP is the need of human annotated corpus. Manual annotation of unstructured data is computationally expensive in the terms of time. Besides linguistics need to study these annotations together with computer scientists. SemEval (Semantic Evaluation) is a continuing series to make automated semantic analysis. SemEval is derived from Senseval [19]. Senseval is a corpus created for WSD. SemEval has semantic evaluation tasks. We use Task 8 of SemEval 2007 that is annotated for metonymy resolution. This task is an organized lexical sample for English and has two particular semantic classes, namely countries and companies. There are 3000 country names and 1000 company names in the existing dataset. Overall, 4000 sentences have been annotated in XML format. The content is provided through British National Corpus Version 1.0 (BNC) [20]. For each potential metonymy four sentences are framed (two sentences before and one sentence after the sentence containing the Potential Metonymy -PM).

4.2.1 Key Data

Key data is divided into two groups: key data for countries and key data for companies. Annotated sentences can be either metonymic, literal or mixed. If the result is metonymic, the metonymic relations are also included in the annotations.

4.2.2 Test Data

The test data is also divided into two groups in a similar manner to the key data: countries and companies. The difference between test and key data is test datas readings are unknown.

Table 4: Predicted Conditions.

Condition	Annotation	Result
TP	Metonymic, Mixed	Metonymic, Mixed
TN	Literal, Mixed	Literal, Mixed
FP	Literal	Metonymic
FN	Metonymic	Literal

5 Results and Discussion

The prediction condition ratio and metrics seen in Table5 illustrate the effectiveness of our rule based algorithm. The accuracy and recall of annotators and thesaurus shown on Table6 attenuate the success. The NER tagger annotator is unable to detect some company names. Also, in some cases the given text is not a full sentence, like headlines. The headlines are difficult for taggers to analyze so the dependency relations are not properly extracted. WordNet does not have detailed lexicographer files for adjectives and adverbs, this also puts us in difficult condition to detect the metonymies. In Fig1, it is possible to visualize the results of predicted conditions.

6 Conclusion

The main goal of this project is to recognize metonymy via named entity tagging. We intended and succeeded to reduce massive human work for feature vector labelling and inconsistency of statistical methods by using our dependency rule-based algorithm.

Table 5: Predicted Conditions for *N*EBMR.

Predicted Condition	Countries	Companies	Total
True Positive	95	168	263
True Negative	614	395	1009
False Positive	78	68	146
False Negative	102	138	240

Table 6: *P*recision, *R*ecall and *A*ccuracy for *N*EBMR.

	Countries	Companies
Precision	0.549	0.643
Recall	0.482	0.522
Accuracy	0.797	0.767

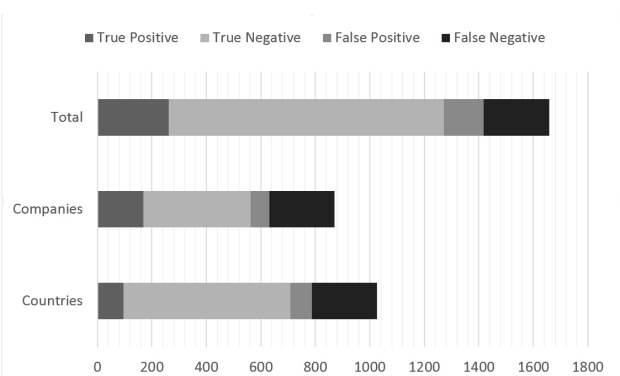

Figure 1: Results for LOCATION and ORGANIZATION.

We have explored the usage of named entity recognition for metonymy resolution. The named entity approach has been rarely used for metonymy recognition task. We use automatic recognition of named entity to reduce time-consuming analysis in order to extract feature vectors or name list. Our approach is platform independent and does not require any tool, the rule functions can be used once taggers and a lexical database is given. Since lexicographer files are prepared according to the languages semantic rules, the presented approach presents the advantages of exploring metonymy independent of language, and it is usable for the languages other than English.

The results we obtained are promising but they point there is still a lot of work with named entities. Through our key and test data we had the opportunity to test our algorithm on two types of named entities such as LOCATION and ORGANIZATION. But for further studies, it will be wise to annotate data containing PERSON typed named entities and test our algorithm on this new data.

References:

[1] Markert, K., Nissim, M. (2007, June). Semeval-2007 task 08: Metonymy resolution at semeval-2007. In Proceedings of the 4th International Workshop on Semantic Evaluations (pp. 36-41). Association for Computational Linguistics.

[2] Amghar, T., Gayral, F., Levrat, B. (1995). Table 10 left without paying the bill! A good reason to treat metonymy with conceptual graphs (pp. 129-143). Springer Berlin Heidelberg.

[3] Roberts, K., Harabagiu, S. M. (2011, July). Unsupervised learning of selectional restrictions and detection of argument coercions. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (pp. 980-990). Association for Computational Linguistics.

[4] Lapata, M. (2003, July). Probabilistic text structuring: Experiments with sentence ordering. In Proceedings of the 41st Annual Meeting on Association for Computational Linguistics-Volume 1 (pp. 545-552). Association for Computational Linguistics.

[5] Shutova, E. (2009, August). Sense-based interpretation of logical metonymy using a statistical method. In Proceedings of the ACL-IJCNLP 2009 Student Research Workshop (pp. 1-9). Association for Computational Linguistics.

[6] Markert, K., Nissim, M. (2002, July). Metonymy resolution as a classification task. In

Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10 (pp. 204-213). Association for Computational Linguistics.

[7] Nissim, M., Markert, K. (2005, January). Learning to buy a Renault and talk to BMW: A supervised approach to conventional metonymy. In Proceedings of the 6th International Workshop on Computational Semantics, Tilburg.

[8] Markert, K., Hahn, U. (2002). Understanding metonymies in discourse. Artificial Intelligence, 135(1), 145-198.

[9] Birke, J., Sarkar, A. (2007, April). Active learning for the identification of nonliteral language. In Proceedings of the Workshop on Computational Approaches to Figurative Language (pp. 21-28). Association for Computational Linguistics.

[10] Bogdanova, D. (2010, July). A framework for figurative language detection based on sense differentiation. In Proceedings of the ACL 2010 Student Research Workshop (pp. 67-72). Association for Computational Linguistics.

[11] Nastase, V., Judea, A., Markert, K., Strube, M. (2012, July). Local and global context for supervised and unsupervised metonymy resolution. In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (pp. 183-193). Association for Computational Linguistics.

[12] Miller, G. A., Beckwith, R., Fellbaum, C., Gross, D., Miller, K. J. (1990). Introduction to wordnet: An on-line lexical database*. International journal of lexicography, 3(4), 235-244.

[13] Manning, C. D., Surdeanu, M., Bauer, J., Finkel, J. R., Bethard, S., McClosky, D. (2014, June). The Stanford CoreNLP Natural Language Processing Toolkit. In ACL (System Demonstrations) (pp. 55-60).

[14] Markert, K., Nissim, M. (2007). Metonymy resolution at semeval i: Guidelines for participants. Rapport technique, SemEval, 252.

[15] Lesk, M. (1986, June). Automatic sense disambiguation using machine readable dictionaries: how to tell a pine cone from an ice cream cone. In Proceedings of the 5th annual international conference on Systems documentation (pp. 24-26). ACM.

[16] Banerjee, S., Pedersen, T. (2002). An adapted Lesk algorithm for word sense disambiguation using WordNet. In Computational linguistics and intelligent text processing (pp. 136-145). Springer Berlin Heidelberg.

[17] Ekedahl, J., Golub, K. (2004). Word sense disambiguation using WordNet and the Lesk algorithm. Projektarbeten 2004, 17.

[18] De Marneffe, M. C., Manning, C. D. (2008). Stanford typed dependencies manual (pp. 338-345). Technical report, Stanford University.

[19] Edmonds, P. (2002). SENSEVAL: The evaluation of word sense disambiguation systems. ELRA newsletter, 7(3), 5-14.

[20] Leech, G. (1992). 100 million words of English: the British National Corpus (BNC). Language Research, 28(1), 1-13.