

Helping Metonymy Recognition and Treatment through Named Entity Recognition

H.BURCU KUPELIOGLU

Graduate School of Science and Engineering
Galatasaray University
Ciragan Cad. No: 36 34349 Ortakoy/Istanbul
TURKEY

burcukupelioglu@gmail.com

TANKUT ACARMAN

Graduate School of Science and Engineering
Galatasaray University
Ciragan Cad. No: 36 34349 Ortakoy/Istanbul
TURKEY

acarmant@gmail.com

BERNARD LEVRAT

LERIA

Université d'Angers

Présidence 40, rue de Rennes – BP 73532 49035 – Angers cedex 01
FRANCE

bernard.levrat@gmail.com

TASSADIT AMGHAR

LERIA

Université d'Angers

Présidence 40, rue de Rennes – BP 73532 49035 – Angers cedex 01
FRANCE

amghar@info.univ-angers.fr

Abstract: Metonymy resolution approaches mainly use semantic classifiers, discourse understanding, annotated names lists or unsupervised methods. In our work we propose to expand those approaches that most of the metonymies are caused by a named entity and especially a verb connected with it. Though a well prepared thesaurus and a natural language processing toolkit will be enough for metonymy resolution. The named entity recognition tools are more developed then before therefore use of them for metonymy recognition will help to eliminate human work.

Key-Words: Metonymy; Named Entity; Natural Language Processing; WordNet; Stanford CoreNLP; Dependency Parsing; Figurative Speech, Lesk Algorithm

1 Introduction

Metonymy is a figure of speech in which a concept is replaced by another one connected logically. Although metonymy can be came across often in everyday speeches but also in literature such as poetry.

(1) He read Shakespeare.

It is clear that in (1) Shakespeare is used metonymically. But even by humans metonymy is often confused with metaphor which also is a figure

of speech of designing something by another resembling or sharing with same quality.

Metonymy is often confused with metaphor which also is a figure of speech. Metaphor is a substitution of one concept with another concept similar. This similarity is a relation created by the metaphor itself even though there may be no obvious connection between these two ideas by linking one similar quality.

Metonymy and metaphor differs on a major point; while metaphor creates relations among two ideas by one similar quality for better understanding, generally to emphasize but

metonymy on the other hand draws reference to an existing relation between two concepts. Briefly said a metaphor is a comparison based on the similarities for substitution (2) while a metonymy is a comparison is based on contiguity for association (3).

- (2) The car drank gasoline. [1]
- (3) The car wants his order delivered.

In Natural Language Processing (NLP), metonymy resolution is a subtask of one of its major tasks, Word Sense Disambiguation (WSD). For computational linguistics it is a great challenge even to identify in which sense a polysemous word is used in a given context let alone understanding figure of speeches.

Previous work has been done by the years, with different approaches. Markert and Hahn [2] proposed to analyze metonymies in discourse. To understand if a word is metonymic in a given sentence this method proposes to study other sentences in the same context. This method may be more suitable for metonymies which we call unconventional metonymies as will be seen further. Some works consists of statistical approaches [3] by use of semantic classes, corpus and metonymies themselves.

Most commonly used method is the use of Selectional Restriction Violations (SRVs) [4]. SRV is the semantic content boundary for a predicate of their arguments. If a SRV is detected a possible metonymy is considered and the resolution begins. In our work, we mainly apply the usage of SRVs to recognize metonymies. In example (1), this is a clear Selectional Restriction Violation since reading a human is impossible and reading the artwork of the author is the hidden meaning. In our work, we mainly apply the usage of SRVs to recognize metonymies in usage of named entities. Markert and Nissim [5] tried to resolve metonymies by working with annotated data which contains location names, namely LOCATION type named entities. As there is no language resource for large scale metonymy resolution, the work was more reliable to previous works. There is work on learning algorithms for figurative language [6] which obtained 64.91%. As researches continue it has become more viable to surpass data sparseness for a better metonymy resolution since metonymies are not encountered as much as other literal issues and also it was divided inside [7]. For metonymy detection and resolution, clustering methods are also valid; they can be either by sense differentiation [8] or either by use of contextual SRVs [9].

In our work, we will concentrate on WordNet thesaurus, especially the relations between the mighty metonymic words and the verbs in the same sentences.

2 Metonymy Resolution

Metonymy resolution is a process consisting of two different tasks. In order to detect implied concept we must search for the metonymic word and then extract the metonymic relationship. These detections and classifications are majorly due to Natural Language Processing tools and Word Sense Disambiguation methods. In this section, we define the principle of metonymy resolution, and also define metonymy types of which we are interested as a suite of this project.

Metonymy resolution is a subtask of Word Sense Disambiguation (WSD). Metonymy is a figure of speech in which the name of one thing is used for another with which it is logically associated.

Metonymy resolution presents two main difficulties. First, it is difficult to identify if a word is metonymic. Second, it is more difficult to identify the metonymic relationship.

In the scope of our work, we only try to recognize metonymies. For that, we defined three types of outcomes to tests; Metonymic, Literal and Mixed. Mixed is a situation when we are not capable of telling if it is a metonymy or not.

2.1 Metonymy Types

We define metonymies in two distinct categories; conventional metonymies and unconventional metonymies.

2.1.1 Conventional Metonymy

We define *Conventional Metonymy* as a metonymy detectable by a large scale of humans. It is described by popular proper nouns. In our work, we are interested in metonymies with proper nouns such as country names, company names and organization names which are also named entities.

- (4) Greece begins migrant returns to Turkey.
- (5) Swiss National Bank keeps cards close to chest.

In (4), Greece is used metonymically where it stands for Greece Government. It is a common metonymy with a proper noun, a named-entity. In

(5), Swiss National Bank is used metonymically for its governing board.

2.1.2 Unconventional Metonymy

We define *Unconventional Metonymy* as a metonymy detectable by a group of person, a clique, or in a context-based situation. Or metonymies for common nouns. In the context of our work we are not interested in extracting such metonymies because of the need of other major tasks in Natural Language Processing.

(6) The pen is mightier than the sword.

In example (6) the pen and the sword are used metonymically but understandable by good English speakers.

2.2 Metonymic Relationships

Metonymy is based on a logic association between the predicate and the argument. This logic association can be shown in form of different relations. Seven of these relations are shown in Table 1.

Container for content	Vatican for Pope
A part for a whole	Wheels for vehicle
Author for artwork	Dickens for his books
Consequence for cause	Poison for death
Instrument for agent	Bass for bass player
Producer for product	BMW for its cars
Material for object	Steel for sword

Table 1: Metonymic Relationships

3 Methodology

Using named entities for metonymy detection is an approach slightly used in previous works and thus our main objective. Especially in everyday speeches, journals, articles, etc. metonymies that we encounter are metonymies of the named entities and they can be understood by a large scale of people. In a small scale experiment conducted on BNC [10], it is discovered that approximately 50% of the named entities are used metonymically [2]. Starting from here, we decided that if we analyze the dependency relations of the named entities we can detect metonymies more efficiently. This has lead us especially to look in named entity-verb dependency relations because verbs are the main reason that humans can understand metonymies.

3.1 Pre-processing Text

To look and analyze named entity-verb relations, first we need to prepare the given sentence. The given sentence alongside the given named entity are put to a parsing and tagging process. We use Stanford CoreNLP Natural Language Processing Toolkit [11] for our entire process. First, to find the verb, we use CoreNLP lemma annotator then part-of-speech tagger. The next part is to find the dependencies as well as the named entities and their types. The fully processed text is given in the Fig.1. In our work we focus on named entities such as LOCATION and ORGANIZATION standing for respectively for countries and companies and vice versa.

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Fig.1: Fully Processed Text via Stanford CoreNLP

3.2 Decision Making

Once we find the verb, we must find the sense in which it is used in the given sentence as the verb is possibly polysemous. Therefore we use an adaptation of the Lesk Algorithm [12, 13] for WordNet [14, 15]. We translated the implementation from Python to Java Language for interoperability with Stanford CoreNLP. The adapted Lesk Algorithm outputs a WordNet synset of the given verb by which we determine the verb group. A verb group is a lexicographer file of WordNet.

3.2.1 Named Entities as Agents

The most significant information about the existence of a metonymy is verb groups. Especially when the given named entity is subject so agent of the root verb. In this situation our design mechanism is entirely based on the verb group as for one synset there may be only one verb group corresponding. Human verb groups as shown in Table 2 correspond to verbs who take only human as agent. If our named entity is an agent and our verb group is included in human verb groups we are sure that the named entity in question is used metonymically.

If the verb is a copular verb than its verb group is determined by Lesk Algorithm as stative. These are the case when the outcome for metonymy detection is mixed. When encountered a copular verb, the expected next step is to look at the copula. Copula can be adjectives, adverbs or nouns. With WordNet we have lexicographer files for nouns but not for adjectives and adverbs. This is the reason why continuing to detection is for now quite difficult.

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

Table 2: Some WordNet verb groups

3.2.2 Named Entities as Predicates or Passive Agents

The verb groups are lexicographer files classified by their agents. Therefore they are mostly useless in this case. But some of them can require both parties to be human (verb.communication) or predicates to be non-human (verb.possession). But for verb groups other than described we cannot be sure of the type of the predicate. For this we have to consider verb frames of WordNet. A verb frame is a generic sentence frames in which the verb of the synset can be used, the agent-predicate types is given. The minus here is, a given synset can have multiple verb frames with different agent-predicate types. The same synset may accept also a human and non-human as predicate. If this is the case we cannot tell for sure if given named entity is metonymic or not, instead we decide it is mixed.

3.3.3 Other Cases

Some dependency relations are not suitable for precedent treatments. For example in (7), if we are to examine France is either metonymic or not, the verb isn't interesting but possession relation with the noun success is. The same relation exists with the prepositions. We do not have rules for prepositions but for possession relations it is possible to make a decision based on the possessed

noun by the named entity. As in the same with the verb groups, WordNet has lexicographer files for nouns such as noun groups. In Table 3 the human and mixed noun groups are listed. If the noun with possession relation with named entity belongs to human noun groups than the named entity is metonymic since we are focused only to LOCATIONs and ORGANIZATIONs as named entities. If the noun is in the mixed category we are not able to make a decision which is why the algorithm decides it is mixed. The last option for the noun to be included to none of the lists below. This is the case for literal use.

(7) Britain applauded France's success.

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	
noun.possession	

Table 3: Human and Mixed Noun Groups from WordNet

3.3 Results

To test our method we used SemEval 2007 Task 8 [16] data which is previously annotated by Katja Markert and Malvina Nissim for metonymy resolution [17]. The data is prepared as key and test data in XML. SemEval 2007 Task 8 is a corpora contains approximately 4000 phrases. These sentences are regrouped in two different categories; countries and companies.

The outcomes of our method are evaluated as shown in Table 4. There are four different categories for results; true positive, true negative, false positive and false negative. True positive is when the outcome is metonymic or mixed as well as the annotation. True negative is for situations when the outcome is literal or mixed as well as the annotation. We decided to add mixed in both true conditions because even humans cannot agree every time if it is metonymic or literal. If the annotation is literal and the result is metonymic this means a false positive and vice versa for false negative. False negative is an error state, it means the metonymies that we were unable to catch.

Predicted Condition	Annotation	Result
True Positive	Metonymic, Mixed	Metonymic, Mixed
True Negative	Litteral, Mixed	Litteral, Mixed
False Positive	Litteral	Metonymic
False Negative	Metonymic	Litteral

Table 4: Predicted Condition cases

In Table 5 the numbers of predicted conditions is detailed. As our main goal is to detect metonymies, we cannot eliminate true negative cases from test data which makes recall seem poor. Table 6 shows our method's precision, recall and accuracy. As mentioned earlier, the main goal of this work is metonymy recognition and test results show promise looking at accuracy values.

Predicted Condition	Countries	Companies
True Positive	36	94
True Negative	705	500
False Positive	30	64
False Negative	137	184

Table 5: Test results for countries and companies

	Countries	Companies
Precision	0,545	0,594
Recall	0,208	0,338
Accuracy	0,813	0,705

Table 6: Precision, Recall and Accuracy for countries and companies

4 Conclusion

We have presented a named entity-verb dependency based model for metonymy resolution using the assumption if the named entity dependencies are analyzed it is possible to achieve a slightly eased way to metonymy detections. Having a more detailed thesaurus will help in metonymy resolution. We also figured that both our method and other toolkits which we used in our work suffer from some exceptional cases. For example, part-of-speech tagging a headline does rarely output a reliable data or named entity recognition tool misses some named entities which are very common currently. Such complications interfere with our method's success as we need them. We have to give more attention to these cases and the other ones we missed such as preposition-based dependencies.

It is indisputable that we can improve further our method by considering the points above then the next step is to move to detection of the metonymic relation.

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