Impact of Target Word and Context on End-to-End Metonymy Detection

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Abstract

Metonymy is a figure of speech in which an entity is referred to by another related entity. The task of metonymy detection aims to distinguish metonymic tokens from literal ones. Until now, metonymy detection methods attempt to disambiguate only a single noun phrase in a sentence, typically location names or organization names. In this paper, we disambiguate every word in a sentence by reformulating metonymy detection as a sequence labeling task. We also investigate the impact of target word and context on metonymy detection. We show that the target word is less useful for detecting metonymy in our dataset. On the other hand, the entity types that are associated with domain-specific words in their context are easier to solve. This shows that the context words are much more relevant for detecting metonymy.

1 Introduction

Metonymy is a figure of speech in which an entity is referred to by another related entity (Lakoff and Johnson, 1980; Littlemore, 2015). Note how the word Barcelona is interpreted in the following two snippets of text:

(1) Toral was born in Barcelona, in the Province of Tarragona, Catalonia. He began playing football as a child with his local club, UE Barri Santes Creus.

(2) Modrić started in Real Madrid’s home match against rivals Barcelona. From a corner kick, he assisted Sergio Ramos to score the winning goal, giving Real a victory in El Clásico.

In the former, Barcelona refers to the city of Barcelona located in the country of Spain. However, in the latter, the same word does not refer to the city of Barcelona, but to a sports team as is evident from the context words such as match, rivals, goal and victory. The likely hidden entity here is the football club FC Barcelona based in the city of Barcelona. The linguistic phenomenon in action here is metonymy. Although the word Barcelona refers to the city in its general (or literal) sense, the same word refers to the football team, a different but related entity, in its metonymic sense.

Metonymy is frequent in verbal as well as written communication. According to Gritta et al. (2017), the natural distribution of literal and metonymic usage is 80% and 20% respectively based on location names sampled from Wikipedia. Resolving metonymy in text aids natural language processing (NLP) tasks such as entity linking (Ling et al., 2015), coreference resolution (Recasens et al., 2010), geoparsing (Gritta et al., 2018), and may also aid machine translation (Markert and Hahn, 2002). In spite of this, metonymy, as opposed to metaphor (Mao et al., 2019) or sarcasm (Khodak et al., 2018), has not received much attention in the NLP community.

The task of metonymy detection aims to identify metonymy in text. In this paper, we present and compare different models for metonymy detection. In the task as performed in previous work (Li et al., 2020; Gritta et al., 2017; Nastase et al., 2012), a specific noun phrase in a sentence is designated for disambiguation. The target, known as the potentially metonymic word (PMW), is typically a mention such as a location name or an organization name. However, such target words are not highlighted in real-world texts. In addition, if the PMW is labeled in advance, the models perform very well. For instance, the BERT-based metonymy detection system, proposed by Li et al. (2020), reports an accuracy of 95.9 on the WiM-COR (Mathews and Strube, 2020) data.
In this paper, we consider every word to be potentially metonymic and disambiguate every word in a sentence. As a result, metonymy detection can readily be applied to different downstream tasks without any fine-tuning. For this purpose, we reformulate metonymy detection as a sequence labeling task. This setting realizes end-to-end metonymy detection. Formally we define the task of metonymy detection as follows: given a sequence of tokens \((t_1, t_2, t_3, \ldots, t_n)\), predict a sequence of labels \((\ell_1, \ell_2, \ell_3, \ldots, \ell_n)\) to indicate whether a word is metonymic or not.

In addition, Li et al. (2020) observes that the interpretation of a target word relies more on the context than the word itself. To test this claim for end-to-end metonymy detection, we compare two variants: one variant relies primarily on the target word, and the other variant relies primarily on the context. Our results show that masking the target word improves end-to-end metonymy detection, especially in the fine-grained experimental setting.

Note that Li et al. (2020) use their proposed BERT-based model for end-to-end metonymy resolution. However they use BERT named entity recogniser to detect locations and then these location names are checked for metonymy. Our method does not use any such external resource.

In short, our contributions are as follows: (1) formulate metonymy detection as a sequence labeling task (end-to-end metonymy detection), (2) adapt an existing dataset for sequence labeling, and (3) compare the impact of target word and context words.

### 2 Related Work

#### 2.1 Metonymy Resolution

Several studies have explored different hand-crafted features for metonymy detection such as co-occurrence, collocation and grammatical features (Markert and Hahn, 2002; Markert and Nissim, 2002; Nissim and Markert, 2003), associative information (Teraoka et al., 2011; Teraoka, 2016), and selectional preference features (Nastase and Strube, 2009; Nastase et al., 2012).

Gritta et al. (2017) employ a neural-network-based model that uses the context words of the PMW to identify whether the PMW is literal or metonymic. Mathews and Strube (2020) propose WIMCOR, a larger and richer dataset of location metonymy, extracted using Wikipedia. They construct benchmarks for metonymy detection using GLOVE and BERT embeddings. Li et al. (2020) propose target word masking to use BERT for metonymy detection. For this purpose, they mask target words during training and testing. This model outperforms the model that sees the target word during detection.

#### 2.2 Word Sense Disambiguation

Both metonymy resolution and word sense disambiguation (Navigli, 2009) deal with lexical ambiguity. The principal difference is that the candidate interpretations of a potentially metonymic word are strongly related to each other. For instance, Barcelona and FC Barcelona form a metonymic pair of candidates because the football club is based in the city and both entities can be referred to by the same word Barcelona.

On the other hand, word sense disambiguation primarily deals with other linguistic phenomena such as polysemy or homonymy. While polysemy pertains to a textual item having multiple fine-grained related senses, homonymy pertains to two (or more) textual items that are accidentally similar in surface form. The city of Paris in France and Paris, the mythological character, fail to form a metonymic pair of candidates because of the lack of any strong relationship between the two entities, although both can be referred to by the same word Paris through their association via homonymy.

According to Cruse (2000), metonymy, along with metaphor, is a type of non-linear polysemy due to the non-linear (non-taxonomic) relationship between the literal (most-common) interpretation and the figurative interpretation.

According to Kilgarriff (2006), it is difficult to generate a inventory of word senses due to the various policies to make such as which senses to be merged, which senses to be considered distinct or how to address issues such as metaphor, metonymy. Lexicographers rely on corpus to identify different word senses and thus typically new word senses originate slowly.

According to the ICM view of metonymy, anything that is related can be a potential candidate; even new entities. So the candidate senses of metonymy resolution are more open-ended (Nunberg, 1978).

Metonymy resolution has been influenced
by advances in word sense disambiguation in the selection of hand-crafted features (Markert and Nissim, 2002) and techniques (Nastase and Strube, 2009). The fine-grained evaluation discussed in this paper is closely related to word sense disambiguation where the candidate senses are different entity types.

3 Methodology

Pretrained language models based on transformers (Vaswani et al., 2017) are successfully used in various natural language understanding tasks (Wu et al., 2020; Baldini Soares et al., 2019). We deploy a pretrained language model and then fine-tune the model for metonymy detection. To fine-tune the model, we add a recurrent layer, and a fully-connected layer on top of the final encoder layer.

We create two variants by feeding different input to the recurrent layer, as described below:

1. In the first variant, the vector representation of the current token is given as input at each timestep. We refer to this model as NO MASK (Figure 1).

2. In the second variant, the vector representations of the context words of the current token are given as input to predict the label of the current token. We refer to this model as MASK_n (Figure 2), where n refers to the length of the context window.

The performance of the former is highly tied to the vector representation of the target word. The latter relies more on the context to detect metonymy. Having these two variants makes it possible to compare the impact of presence of the target word and context on end-to-end metonymy detection.

The model architecture of MASK_n is inspired by Gritta et al. (2017), whose model performed well on the metonymy datasets SEM-EVAL (Markert and Nissim, 2007) and RELOCAR (Gritta et al., 2017). Their model used a predicate window of context words, which is a small and focused context formed using the grammatical head of the target word. However, in this work, we use the adjacent words as context in order to avoid the overhead necessary to compute the predicate window of every token.

In our experiments, we use the pretrained base, uncased version of BERT (Devlin et al., 2019). We add the representations from the last four hidden layers of the BERT transformer to compute subword embeddings. According to Devlin et al. (2019), the only other method that outperforms summation is concatenation of last four hidden layers. However concatenation creates longer vectors and thus increases memory requirements. These subword embeddings are then combined through summation to generate the word embeddings. In this way, we ensure that the feature length of a sequence matches its label length. The gradients are not backpropagated into BERT.
4 Experimental Setup

4.1 Experimental Data

We conduct our experiments\(^1\) on WiMCOR (Mathews and Strube, 2020)\(^2\). The other metonymy datasets, namely SEM-EVAL (Markert and Nissim, 2007) and RELOCAR (Gritta et al., 2017), are small in size and hence inadequate for large-scale machine learning and statistical analyses. WiMCOR is much larger in size and has richer annotation, which leads to empirically more reliable and linguistically more meaningful results. The data is extracted automatically using Wikipedia data.

Every WiMCOR sample is composed of a piece of text and two labels of varying granularity for the word designated as the PMW. The coarse-grained label classifies the word into LITERAL and METONYMIC. The fine-grained label classifies the metonymy word further into entity types such as INSTITUTION, ARTIFACT, TEAM and EVENT. Note that while metonymy operates on different entity types such as locations, organizations or persons, all the the positive instances in WiMCOR are location names. For example, the literal reading of the token Barcelona comprises the geographical and locative interpretations of the city of Barcelona in Spain. The token is assigned the label LITERAL (see Example (1)). If the same token is used to denote the football team based in the city of Barcelona then the token is metonymic. The token is assigned the coarse-grained label METONYMIC, and the fine-grained label TEAM (see Example (2)).

We modify the labels of WiMCOR to fit the new task formulation. We consider unannotated words to be literal. Gao et al. (2018) follow a similar approach in metaphor detection. However this assumption introduces noise in the data because some words that are not PMW in the original version might be metonymic in reality. Such words are incorrectly labeled LITERAL in the modified version.

A statistical breakdown of the dataset after relabeling is shown in Table 1 and Table 2. Note that the dataset is in English. The corpus is split into train, validation and test partitions in the ratio 60:20:20 respectively. The metonymic mentions in each partition are pairwise disjoint with each other to ensure that the models treat metonymic and literal tokens alike.

As we can observe from Figure 1 and Figure 2, while NoMASK model parses the whole input at once, Mask\(_n\) parses the input token by token. However the literal tokens far outnumber the metonymic tokens with a a ratio of 1:377 (see Table 2). So in the case of Mask\(_n\), we randomly downsample the majority class during the training phase to ensure that the classes are balanced. If the percentage of the majority class decreases, then recall increases but precision decreases (Zhang and Mani, 2003). The best balance between precision and recall is achieved when about 15% of the majority class is sampled.

4.2 Evaluation Settings

The objective of our experiments is to analyze how well the models distinguish metonymic usage of tokens from literal usage of tokens. We designed two different settings for evaluation: coarse-grained and fine-grained. The objective of the former is to identify the metonymic tokens. The valid output label here is either LITERAL or METONYMIC. The objective of the latter is to identify the specific entity type referred to by a metonymic token. Hence the valid output label is either LITERAL for literal reading, or INSTITUTE, ARTIFACT, TEAM or EVENT for metonymic reading.

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\(^1\)The code will be made publicly available upon publication.

\(^2\)https://github.com/nlpAThits/WiMCOR

| Item | Train | Val/Test |
|------|-------|----------|
| # samples | 123.6K | 41.2K |
| # sentences | 478K | 159K |
| # avg. sample length | 80 | 80 |
| # tokens | 12M | 4.1M |
| # unique tokens | 338K | 189K |

Table 1: Basic statistics of WiMCOR after relabeling the data to fit sequence labeling.

| Coarse | Fine | Train | Val/Test |
|--------|------|-------|----------|
| LITERAL | LITERAL | 11.7M | 4.08M |
| METONYMIC | INSTITUTE | 18K | 5.9K |
| | ARTIFACT | 6K | 2.0K |
| | TEAM | 6K | 1.9K |
| | EVENT | 1K | 0.4K |

Table 2: The labels of tokens in WiMCOR after relabeling the data to fit sequence labeling.
4.3 Evaluation Metrics

We evaluate each model using the following classification metrics: precision, recall and F1-score. As the class distribution in the dataset is imbalanced (see Table 2), we report micro-averaged and macro-averaged metrics. While macro-averaging treats all classes alike, micro-averaging takes into account the proportion of each class in the data. Since we are interested in evaluating how well the models detect metonymic readings as opposed to literal readings, we consider the set of metonymic instances as the positive class. All the metrics reported in Section 5 pertain to the positive class only.

4.4 Baselines

We use two baseline systems for comparison.

4.4.1 Probabilistic Modeling

In this paper, we choose CRF owing to its robust performance in various sequence labeling tasks such as entity analysis (Durrett and Klein, 2014), part-of-speech tagging (Silfverberg et al., 2014), parsing (Finkel et al., 2008), and language modeling (Roark et al., 2004). CRFs jointly predict the labels of the entire sequence by taking into account the transition probabilities of labels.

We use four sets of hand-crafted features to train this model:

1. surface-level features — whether the token has only alphabetic characters, whether the token has only digits, whether the token is punctuation, whether the token has only uppercase characters, and whether the token starts with an uppercase character,
2. syntactic features — part-of-speech (POS) tag of a token,
3. n-gram features — token in lemmatized form, and
4. grammatical features — dependency role of a token, and the 2-tuple (dependency role, dependency head).

We compile this feature set from previous work on metonymy resolution and commonly used features in other sequence labeling tasks. Markert and Nissim (2002) conclude that generalized collocation features, as opposed to co-occurrence features, are useful for metonymy resolution. More recent work such as Nastase and Strube (2009) and Nastase et al. (2012) focus on selectional preference features. Some of the features proposed in the metonymy literature do not fit our experimental settings. For instance, we do not use the features number of grammatical roles and number of words proposed by Nissim and Markert (2003) because the former characterizes only mixed readings and the latter is rendered irrelevant as we assume every word to be potentially metonymic.

4.4.2 Context-insensitive Embeddings

We also use context-insensitive embeddings for comparison. For this purpose, we use 50-dimensional GLOVE (Pennington et al., 2014) trained on six billions tokens in Wikipedia 2014 and English Gigaword (fifth edition) corpus.

5 Results and Discussion

The results of each model are reported in Table 3. We experiment with different context windows. All the models exhibit better performance in coarse-grained setting as compared to fine-grained setting due to fewer number of classes and thus lesser dependence on the context for disambiguation.

The feature set of CRF consists of surface-level, syntactic and grammatical features of the current token, and the surface-level, syntactic, grammatical features and lemmatized forms of the context words. We classify the top 1000 informative features on the basis of the group to which they belong. We observe that grammatical features (92.5%) are the most informative, followed by n-gram (5.6%), surface (0.8%) and syntactic (0.9%) features respectively.

As mentioned in Section 1, while previous work treats metonymy detection as a token-level classification task, in this paper, we reformulate metonymy detection as a sequence labeling task. In coarse-grained evaluation, Li et al. (2020) reports an accuracy of 95.9. On the other hand, even the best performing model in Table 3 achieves an F1-score of 0.71 only.

5.1 Impact of Target Word

In the context of metonymy detection, the target word can be used in different ways. Nastase et al. (2012) and Nastase and Strube (2009) compute selectional preferences of the target word for the words in its context. The model proposed by Gritta et al. (2017) does not take into consideration the surface form of the target word. Li et al. (2020) mask the target word during training and evaluation.
Table 3: Performance of different models on WiMCOR data. The MASK<sub>_5</sub> models outperform the NoMASK model by a significant margin as shown by the macro-averaged metrics of the fine-grained evaluation setting.

| Model              | Coarse-grained | Fine-grained |
|--------------------|----------------|--------------|
|                    | Micro-average  | Macro-average|
|                    | P   R   F1     | P   R   F1   |
| CRF                | .59 .27 .37    | .39 .17 .23  |
| NoMASK<sub>GLOVE</sub> | .12 .03 .04    | .07 .01 .02  |
| MASK<sub>5, GLOVE</sub> | .38 .45 .41    | .26 .14 .14  |
| MASK<sub>10, GLOVE</sub> | .36 .53 .43    | .25 .26 .25  |
| MASK<sub>50, GLOVE</sub> | .32 .51 .39    | .22 .33 .25  |
| NoMASK<sub>BERT</sub> | .83 .62 .71    | .66 .36 .43  |
| MASK<sub>5, BERT</sub> | .58 .85 .69    | .57 .68 .61  |
| MASK<sub>10, BERT</sub> | .58 .83 .69    | .59 .64 .60  |
| MASK<sub>50, BERT</sub> | .54 .84 .66    | .57 .48 .49  |

As shown in Table 3, the performances of NoMASK and MASK<sub>5</sub> are similar to each other (0.71 and 0.69 F1-scores respectively) in the coarse-grained setting. This is because coarse-grained setting considers all fine-grained entity types as METONYMIC and thus takes into account the proportion of each entity type in the dataset. For the same reason, in the fine-grained setting, the micro-averaged metrics of NoMASK and MASK<sub>5</sub> exhibit a similar behavior (0.66 and 0.69 F1-scores respectively). On the other hand, the macro-averaged metrics, which disregards the proportion of labels in the dataset, in the fine-grained evaluation setting clearly demonstrate the difference between the two models. For instance, while the macro-averaged F1-score of the NoMASK model is 0.43, the MASK<sub>5</sub> model exhibits a much higher F1-score of 0.61.

The results discussed above indicate that the target word is less useful for end-to-end metonymy detection, since the masked variants outperform the unmasked variant. In addition, NoMASK<sub>GLOVE</sub>, which relies on the target word and nothing else, is the worst performing of all the models. The irrelevance of the target word can be attributed to two factors. First, all the metonymic mentions in the dataset are location names, which, in turn, are proper nouns. Even if we replace the metonymic mention Barcelona in Example (2) with any other location, the sentence will retain its figurative nature. So the surface form of the mention is less relevant here. On the other hand, the target word might be more useful for detecting metonymy in other word categories such as common nouns, For instance, consider the sentence “The ham sandwich is waiting for his cheque.” (Lakoff and Johnson, 1980). Here the noun phrase the ham sandwich is metonymic because it refers to the customer who placed the order. If this phrase is replaced with the word customer, then the sentence is no longer figurative.

Second, in this paper, we study the impact of target word in metonymy detection, which only predicts whether the target word is metonymic or literal. The next phase in metonymy resolution is metonymy interpretation (Teraoka, 2016; Markert and Nissim, 2002), which identifies the hidden entity represented by the target word. We believe the surface form of the target word to be more useful in the interpretation phase as compared to the detection phase.

5.2 Impact of Context Words

The per-class performance of the best variant of each model is shown in Table 4. The F1-scores of the entity types TEAM and INSTITUTE are much higher compared to that of ARTIFACT and EVENT. We hypothesize that context words have high impact on the classification, and might throw light on the disparity in performance on different entity types. It has previously been noted that context words in the form of collocation and cooccurrences are relevant to metonymy detection (Markert and Nissim, 2002).

To better understand the impact of context, we analyze the data using the context words of mentions belonging to each class. For this purpose, we measure the association between context words
Table 4: Per-class performance of different models. Only the models based on BERT are shown here for comparison. All the models exhibit better performance on TEAM and INSTITUTE, compared to ARTIFACT and EVENT.

| Class     | NoMask | Mask5 | Mask10 | Mask50 |
|-----------|--------|-------|--------|--------|
|           | P   | R   | F1   | P   | R   | F1   | P   | R   | F1   |
| TEAM      | .89 | .49 | .63  | .65 | .89 | .75  | .69 | .88 | .77  |
| INSTITUTE | .84 | .77 | .80  | .69 | .91 | .78  | .71 | .89 | .79  |
| ARTIFACT  | .33 | .08 | .13  | .31 | .41 | .36  | .29 | .37 | .32  |
| EVENT     | .58 | .10 | .17  | .64 | .51 | .57  | .70 | .40 | .51  |

Table 5: Top 10 words (taken from context window of 5 tokens each from either side) associated with the mentions of each class in descending order of normalized PMI scores. While the context words associated with TEAM and INSTITUTE are domain-specific in nature, the context words associated with ARTIFACT and EVENT are more general in nature.

| Type       | TEAM | INSTITUTE | ARTIFACT | EVENT |
|------------|------|-----------|----------|-------|
| Top 10 context words | club | university | squadron | battle |
|              | fc   | college    | cathedral | tokugawa |
|              | match| professor  | airport   | clan   |
|              | league| degree    | flight    | ieyasu |
|              | goal | teach      | prix      | domain |
|              | season| science   | fly       | province |
|              | cup  | institute  | aircraft  | norman |
|              | loan | school     | length    | festival |
|              | score| study      | bury      | fight   |
|              | uefa | honorary   | stakes    | regiment |

Table 5: Top 10 words (taken from context window of 5 tokens each from either side) associated with the mentions of each class in descending order of normalized PMI scores. While the context words associated with TEAM and INSTITUTE are domain-specific in nature, the context words associated with ARTIFACT and EVENT are more general in nature.

and classes using normalized pointwise mutual information (PMI) ([Church and Hanks, 1989]). Normalized PMI handles the bias of PMI towards low frequency data ([Bouma, 2009]). First we parse the train partition of our data to extract the immediate context words of all positive mentions. We convert the words into their lemmatized form and filter out words whose count falls below a threshold of 2. Normalized PMI is then computed as follows:

$$PMI(w, c) = \log \frac{p(w, c)}{p(w)p(c)};$$

$$NPMI(w, c) = \frac{PMI(w, c)}{-\log(w, c)};$$

where $w$ and $c$ correspond to context word and class respectively.

Table 5 shows the top 10 words (taken from context window of 5 tokens each from either side) associated with each class in descending order of normalized PMI scores. While the context words associated with TEAM and INSTITUTE are domain-specific in nature, the context words associated with ARTIFACT and EVENT are more general in nature.

We also report the average cosine similarity between the context words of each entity type. We use the 50-dimensional GloVe embeddings to compute the similarity between each pair of context words. The similarity scores are then aggregated through simple averaging to compute the average cosine similarity of each entity type. As shown in Table 5, the average cosine similarities of INSTITUTE and TEAM are significantly higher compared to that of EVENT and ARTIFACT. For instance, the top context words associated with INSTITUTE such as university, college, professor and degree are highly representative of educational institutions and thus have a high average cosine similarity of 0.69. On the other hand, the top context words associated with ARTIFACT as RAF (which stands for Royal Air Force stations),
squadron, cathedral and airport exhibit more diversity and thus have a low average cosine similarity of 0.33.

These results demonstrate that the models fail to perform well when the mention is flanked by domain-agnostic context words. This observation reaffirms the significance of context for detecting metonymy in text.

5.3 Impact of Window Size

Following Gritta et al. (2018), we experiment with contexts of different sizes: 5, 10 and 50. In case of the GLOVE embeddings, short context maximises precision but lowers recall because the model misses out on important words lying outside the context window. Long context maximises recall but lowers precision because the model encounters irrelevant words. For instance, as shown in Table 3, the macro-averaged precision drops from 0.26 to 0.22 as the window size is increased from 5 to 50, and the macro-averaged recall rises from 0.14 to 0.33 as the window size is increased from 5 to 50.

On the other hand, since the BERT embeddings are context-sensitive, increasing the context window has a negative impact on performance. However, as shown in Table 4, MASK5 outperforms both MASK10 and MASK50 for the minority class EVENT suggesting that shorter window size facilitates faster learning.

5.4 Error Analysis

To further understand the difference between NO-MASK and MASKn models, we conduct a manual error analysis. We compiled four examples (see Table 6) representing the manner in which the models treat the samples in the dataset. In this subsection, we discuss each example in detail.

1. Both NO-MASK and MASKn models solve this example correctly. The predicate 'sign with' is a strong indicator of the metonymic sense of the target word Lorca.

2. NO-MASK fails to solve this example because the metonymic mention Compostela is metonymic in ARTIFACT, INSTITUTE, and LOCATION train partitions. The model prediction is highly tied to the current string thus and however the MASKn models rely on context for disambiguation. For instance, the name Heidelberg can refer to, among others, the Heidelberg Castle (ARTIFACT), the Heidelberg University (INSTITUTE) or the city Heidelberg (LOCATION).

A metonymy detection system should be able to distinguish these interpretations from the context.

3. While MASK10 misclassifies the metonymic mention Santiago as ARTIFACT and MASK50 fails to detect the mention as metonymic, MASK5 correctly identifies the mention as an EVENT.

4. All the models fail to even detect the metonymic mention. This example is difficult to resolve due to a lack of any domain-specific word in the neighbourhood of the metonymic mention.

6 Conclusions

Previous work treats metonymy detection as a token-level classification task, which disambiguates only a single pre-specified mention in the input. In this paper, we reformulate metonymy detection as a sequence labeling task by disambiguating every word in the input. We show that the new setting is computationally harder compared to token-level classification.

We also investigate the impact of target word and context on metonymy detection. The model that relies primarily on context outperforms the model that has access to both context and the target word in the fine-grained classification task. This shows that the target word is less useful for detecting metonymy in WiMCOR. On the other hand, the entity types that are associated with domain-specific words in their context are easier to solve. This shows that the context words are much more relevant for detecting metonymy.

In order to fully resolve metonymy, it is necessary to identify the specific hidden entity referred to by the metonymic mention. This interpretation task can be formulated as entity linking, which attempts to link named entity mentions in text to entities in a knowledge base. WiMCOR, unlike the other metonymy datasets RELOCAR and SEMEVAL, is suitable for this task because the metonymic mentions in WiMCOR are linked to Wikipedia.

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In January 2018, Brown signed with Lorca in Spain.

He was Born in Vigo, Galicia, Spain on 16 February 1958. In 1982 Virgós graduated from Compostela with a degree in psychology. His training and professional activity were mainly in the field of community intervention and social services.

Blanco believed it better to fight than surrender to the Americans. He ordered Pascual Cervera y Topete to break the American blockade, leading to Santiago.

Lawrence has also worked on Reading’s educational website Romans Revealed, creating stories about Roman Britain closely based on archaeological finds.

| No. | Example                                                                 | Label       | NOMASK | MASK5 | MASK10 | MASK50 |
|-----|--------------------------------------------------------------------------|-------------|--------|-------|--------|--------|
| (1) | In January 2018, Brown signed with Lorca in Spain.                      | TEAM        | ✓      | ✓     | ✓      | ✓      |
| (2) | He was Born in Vigo, Galicia, Spain on 16 February 1958. In 1982 Virgós graduated from Compostela with a degree in psychology. His training and professional activity were mainly in the field of community intervention and social services. | INSTITUTE   | ×      | ✓     | ✓      | ✓      |
| (3) | Blanco believed it better to fight than surrender to the Americans. He ordered Pascual Cervera y Topete to break the American blockade, leading to Santiago. | EVENT       | ×      | ✓     | ×      | ×      |
| (4) | Lawrence has also worked on Reading’s educational website Romans Revealed, creating stories about Roman Britain closely based on archaeological finds. | INSTITUTE   | ×      | ×     | ×      | ×      |

Table 6: Error analysis. The metonymic mention is shown in boldface. Only the models based on BERT are shown here for comparison.

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