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Extracting and Analysing Metaphors in Migration Media Discourse: towards a Metaphor Annotation Scheme

Ana Zwitter Vitez[1], Mojca Brglez[1], Marko Robnik-Šikonja[2], Tadej Škvorc[2], Andreja Vezovnik[3], Senja Pollak[4]
[1]University of Ljubljana, Faculty of Arts,
[2]University of Ljubljana, Faculty of Computer and Information Science
[3] University of Ljubljana, Faculty of Social Sciences
[4] Jožef Stefan Institute
ana.zwittervitez@ff.uni-lj.si, mojca.brglez@ff.uni-lj.si
marko.robnik@fri.uni-lj.si, tadej.skvorc@fri.uni-lj.si
andreja.vezovnik@fdv.uni-lj.si, senja.pollak@ijs.si

Abstract

The study of metaphors in media discourse is an increasingly researched topic as media are an important shaper of social reality and metaphors are an indicator of how we think about certain issues through references to other things. We present a neural transfer learning method for detecting metaphorical sentences in Slovene and evaluate its performance on a gold standard corpus of metaphors (classification accuracy of 0.725), as well as on a sample of a domain specific corpus of migrations (precision of 0.40 for extracting domain metaphors and 0.74 if evaluated only on a set of migration related sentences). Based on empirical results and findings of our analysis, we propose a novel metaphor annotation scheme containing linguistic level, conceptual level, and stance information. The new scheme can be used for future metaphor annotations of other socially relevant topics.

Keywords: metaphor annotation scheme, neural metaphor extraction, linguistic analysis, transfer learning

1. Introduction

The key feature of metaphors is the establishment of parallels between two domains which are not literally connected. Lakoff and Johnson (1980) define the concept of cognitive metaphor (i. e. *wave of migrants*) as a metaphor comparing two domains, the source domain (*wave*) and the target domain (*migrants*). The source domain is used in a non-literal way, and the target domain is the one we try to describe with the non-literal linguistic expressions.

Studying metaphors in media discourse is an increasingly developing field (Koller, 2004: 4) because metaphors indicate the structure of how we perceive, how we think, and what we do (Lakoff and Johnson, 1981: 5). We continually think about things through reference to other things to help us understand various phenomena we face. Consequently, metaphors can have implications not only for how we think about and understand the world, but also for how we act, the institutions we build and how we organize our society (Machin and Myer, 2012: 164).

Since media are an important shaper of social reality, metaphors in media discourse have been widely studied in the fields of media studies, semiotics, critical discourse studies, rhetoric, and critical linguistics which study metaphors in order to disclose unequal relations of power as part of wider ideological operations. Fairclough (1995) claims that metaphors are socially motivated as different metaphors may correspond to different interests and perspectives and may therefore have different ideological loadings. Moreover, perceiving the world through a particular metaphor may form the basis for social action. For instance, the metaphor *wave of migrants*, which metaphorically represents *migrants as flood* (where *wave* is the source domain and *migrant* the target domain), may act as the basis for how we perceive migrants as a danger and how we may take social and political measures such as militarization of borders to assure safety for the majoritarian population.

Media metaphor analysis is therefore an important tool to unmask various types of ideologies, for instance racism (Musolff, 2012), ethnocentrism (Vezovnik, 2017) or dehumanization (Arcimaviciene and Baglama, 2018) to name just a few migration-related qualitative studies. Similarly, corpus linguists have addressed the migration discourse (Horsti, 2012). Recently, advanced automated natural language processing (NLP) methods have been developed for detecting metaphors (Chen et. al., 2020; Gong et al., 2020; Su et al., 2020; Choi et al., 2021), but they were not yet developed for less-resourced languages (in our case Slovene) nor focus on migration discourse.

The main contributions of our paper are as follows. First, we present a neural metaphor extraction method for Slovene, where we build upon the method by Škvorc et al. (2022) for detecting idioms and adapt it to metaphor detection. Next, we evaluate the metaphor extraction on a domain specific corpus of migration news to extract metaphorical sentences, and finally, perform a fine-grained analysis of a set of examples, where we introduce a novel metaphor annotation scheme, which can serve for future metaphor annotation initiatives.

The article is structured as follows. In Section 2, we present the existing research on metaphors in the fields of social sciences, linguistics, and natural language processing. In Section 3, we present our methodology, which consists of dataset preparation, transfer learning from idioms to metaphors, linguistic evaluation, and annotation of the extracted metaphors in migration discourse. In Section 4, we present the results of automatic metaphor extraction, and a fine-grained manual evaluation of the results with a linguistic analysis based on the proposed annotation scheme. In Sections 5 and 6, we explore the contributions and limitations of the study and propose further challenges.

2. Related work

We review the related research in metaphor detection from the perspective of social sciences, linguistics, and natural language processing.

2.1 Social sciences perspective

Conceptual metaphor theory (Lakoff and Johnson, 1981) has been integrated in Critical discourse studies mostly as a response to some earlier criticism that pointed out the lack of attention to cognitive aspects of communication within the approach (Chilton, 2005a; Hart, 2008; Wodak, 2006). This critique was addressed by scholars such as van Dijk (2009), Hart (2008, 2010), Chilton (2005b) and Koller (2004) by creating a sub-approach named Conceptual metaphor-based critical discourse analysis, engaging in the integration of cognitive linguistics and Critical discourse studies. Empirical research integrating Cognitive linguistics and Critical discourse studies have mostly explored the notion of figurative language, especially metaphor (Hart and Lukeš, 2010) in relation to gender and sexual identity discourses (Koller, 2004), racist discourse (Musolff, 2012), migration discourse (Hart, 2010), legal discourse on citizenship (Santa Ana, Waitkuweit and Hernandez, 2017), and neoliberal discourse (Marissa, 2020).

Critical discourse studies approaches have been widely merged with quantitative approaches such as corpus-assisted discourse analysis with the aim of identifying conventionalized discursive devices (such as figurative language) that are repeatedly used in news discourses to construct and perpetuate specific ideologies. However, corpus linguistics is often used for the analysis of frequency (word forms, lemmas, clusters), analysis of keywords/clusters or grammatical/semantic tags, dispersion analysis, and concordances (Bednarek and Caple, 2014).

2.2 Linguistic perspective

The analysis of metaphors usually recognizes two different aspects/parts: linguistic metaphor identification and conceptual metaphor annotation. The most frequently used, widespread procedure for metaphor identification has been proposed by Steen et al. (MIP 2007) and revised by Steen et al (MIPVU, 2013). Here, after reading the entire text-discourse, each linguistic unit is tagged as metaphorical if its contextual meaning (the meaning it has in the discourse) is different from or contrasts with a more concrete, body-related or precise basic contemporary meaning. The meanings are looked up in a contemporary corpus-based dictionary. MIPVU was developed for English; other languages, especially morphologically richer languages and languages without up-to-date corpus-based dictionaries, require specific adjustments to the procedure (Badryzlova et al., 2013; Pavlas et al., 2018; Urbonaitė, 2016; Nacey et al., 2019).

On the other hand, the task of metaphor interpretation (or conceptual metaphor annotation/ identification) is cognitively much more taxing and less systematically delineated. One of the first proposed approaches, the 5-step process by Steen (1999), includes a rigorous propositional analysis. As argued by other researchers (Semino, Heywood and Short, 2004; Deignan, 2016), the process still fails to clarify how to decide for one conceptual metaphor over another and how to decide on the level of specificity; authors remind that the process risks circular analysis (finding the metaphors, one assumes to find from the start).

Shutova and Teufel (2010) introduce an identification and scheme following the MIP procedure, extended by the identification of metaphorical mappings (conceptual metaphor identification) with a limited, pre-defined list of source and target concepts. Kimmel (2012: 15) proposes to limit the annotation and analysis according to the research question, disregarding metaphors not related to the domain in question, as metaphors, apart from framing a topic, often function merely as devices for the organization of text/discourse.

2.3 NLP perspective

In NLP, metaphors have received substantial attention due to their widespread use, e.g., in creative language generation, machine translation, sentiment analysis, and dialogue systems. Several computational approaches have been developed to recognize metaphorical words in a sentence. Shutova et al. (2012) present a review of early statistical approaches to the computational modelling of metaphors. These approaches were superseded by methods using dense embedding. An overview of early neural approaches using word2vec-like vector representation of words (Mikolov et al., 2013) is given by Veale et al. (2016).

Modern approaches exploit contextual nature of metaphors, i.e. to tell the metaphoric use from literal use, one has to know the context a given word expressions appears in. An early approach introducing contextual information into metaphor detection was introduced by McGregor et al. (2019). The authors used the statistical co-occurrence associations between the words and their frequent contexts. A more general approach became possible with the introduction of contextual word embeddings such as ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019). These neural embeddings produce a different vector for each context (typically a sentence) a word appears in. Words in similar contexts are assigned similar vectors which means that different word meanings form clusters in the vector space. This property of contextual embeddings can be exploited also for metaphor detection (Chen et al., 2020; Gong et al., 2020; Su et al., 2020; Choi et al., 2021). The above-mentioned approaches to contextual metaphor detection typically fine-tune a variant of the BERT model. DeepMet (Su et al., 2020) combines the RoBERTa model (Liu et al., 2019) with linguistic features, such as POS features, global, and local text context. IlliniMet (Gong et al., 2020) combines RoBERTa with external linguistic information. Chen et al. (2020) trains BERT using additional tasks of idiom detection and spell-correction before fine-tuning on the metaphor detection task. Finally, Choi et al. (2021) propose MelBERT that explicitly compares the embedding of a standalone metaphor and the embedding of a metaphor within the sentence using a Siamese BERT architecture. All these approaches work on English.

Our approach aims at less-resourced languages, where either cross-lingual transfer or transfer from similar task is necessary due to non-existent or small metaphor detection datasets. As described in Section 3, we use Slovene SloBERTa model (Ulčar and Robnik-Šikonja, 2021) fine-tuned on an idiom detection dataset in Slovene as a baseline (i.e. the MICE system by Škvorc et al., (2022)) and then propose a few-shot transfer to metaphor detection using a small dataset of metaphors.

Compared to the related work, we present the methodology that would allow for quicker extraction and analysis of larger corpora compared to the ones used in qualitative social science studies, and propose a novel annotation scheme, which does not focus only on a single level but on both textual and conceptual levels, as well as on the stance information. Also, compared to other annotation campaigns, we focus on topical corpus of migration news. In terms of NLP, we propose the first metaphor extractor for Slovene, where we use transfer learning with neural language models to first capture the contextual knowledge from idioms and then fine-tune it with a small amount of metaphors.

3. Methodology

We first present the datasets used in our work in Section 3.1. The methodology for extracting metaphoric sentences from the corpus of interest is described in Section 3.2. In Section 3.3, we describe the proposed annotation scheme for the extracted metaphors.

3.1 Datasets

We use two training datasets to extract the metaphors: the corpus of Slovene idiomatic expressions SloIE and the KOMET 1.0 corpus of metaphors. We apply the proposed methodology on the corpus of migration related news, described last. To detect metaphors, we used two datasets. The SloIE dataset (Škvorc et al., 2022, http://hdl.handle.net/11356/1335) contains 29,400 sentences, where each sentence contains a multi-word expression that can occur with a literal or idiomatic meaning. The sentences were manually annotated into three different groups: sentences with a literal meaning, sentences with an idiomatic meaning, and sentences that did not contain enough context to determine the correct meaning. The dataset contains 75 different idiomatic expressions (IEs), with most expressions occurring predominantly in the idiomatic meaning. An overview of the contents of the dataset is presented in Table 1.

Sentences	29,400
Tokens	695,636
Idiomatic sentences	24,349
Literal sentences	5,051
Idiomatic tokens	67,088
Literal tokens	626,707
Different IEs	75

Table 1: An overview of the SloIE idiom dataset.

The KOMET corpus (Antloga, 2020) contains 200,000 words from Slovene journalistic, fiction, and on-line texts. In the corpus, metaphors were manually annotated using the MIPVU protocol (Steen, 2010). Unlike the SloIE dataset, KOMET is not limited to idiomatic multi-word expressions, but contains a variety of metaphors. This could make it suitable for automatic metaphor detection. However, the dataset is difficult to use from a machine-learning perspective, because it has a very broad definition of metaphorical language, and many noisy examples. In terms of metaphor types, the corpus contains direct and indirect metaphors[1], edge-case metaphors which can be interpreted literally or metaphorically depending on the wider (extra-textual) context, and metaphoric signifier information which denotes so called "metaphor flags" - expressions that indicate metaphorical use (such as "*like"* or "*metaphorically speaking"*). For a large number of metaphors, no type is specified. The statistics concerning different metaphor types from KOMET are shown in Table 2. As explained in Section 3.2, we use only direct and indirect metaphors.

SloIE and KOMET both include annotations of idiomatic/metaphorical text, as well as example of literal language use.

The **Migration corpus** was taken from Martinc et al. (2020) and consists of the crawled Slovene news from the period between 2015 and 2019. It contains 11.9 million tokens.

[1] In direct metaphors, a direct comparison is made between a target and source (e.g. *Mike acted like a raging bull)*. In indirect metaphors, we make an implicit comparison, obtaining a contextual meaning different from its original meaning (e.g. *His velvet voice was very soothing).*

Metaphor type	Number of tagged words
Direct metaphor	129
Indirect metaphor	5,767
Edge case	444
Metaphoric signifier	93
No type specified	5,766

Table 2: Different types of metaphors in the KOMET corpus.

3.2 Transfer learning: from idioms to metaphors

To automatically detect metaphors, we propose a two-step approach: we first train the idiom detection system and then fine-tune it to metaphors.

In idiom detection, we follow an approach similar to the one presented in MICE (Škvorc et al., 2022). The model uses neural networks and contextual word embeddings to automatically detect idiomatic text. In our work, we substitute the MICE model architecture with a more powerful CamemBERT architecture (Martin et al., 2020) implemented in the SloBERTa model (Ulčar and Robnik-Šikonja, 2021). We trained the model on two datasets related to metaphorical language: first on the SloIE dataset of Slovene idiomatic expressions, followed by fine-tuning on the KOMET corpus of metaphors.

Metaphors and idioms both deal with figurative language, but while idioms are multi-word expressions and their meaning is not deducible from the individual words (e.g., *To make ends meet*), a metaphor is always conceptualised as an indirect comparison of two different domains (e.g., *To drown in paperwork*, where paperwork is indirectly compared to liquid/flood/water). However, as both deal with highly context-dependent figurative language, we believe it should be possible to transfer knowledge from one task to the other.

The training could use the KOMET corpus alone. However, this corpus is much smaller than the SloIE dataset and given its size and broad definition of metaphorical language, we attempted to improve the performance by using transfer learning from the SloIE dataset. Since the MICE model is capable of detecting idioms that do not appear in the training set (i.e. generalizing to unseen idioms), a similar approach may be capable of generalizing to other types of figurative language, such as metaphors. Therefore, even if idioms are not directly comparable to metaphors, the model may be able to learn information relevant for metaphor detection from the SloIE dataset.

In the first phase, we adapt the SloBERTa model to idiom detection with the SloIE dataset. In the second phase, we use the KOMET corpus to fine-tune the model to the problem of metaphor detection. Given that in KOMET not all metaphor types are aligned with our needs (e.g., edge cases and metaphors without type), we use only a selection of metaphors as follows:

1. As the positive (target class) instances, we select only direct and indirect metaphors, while as negative instances we select non-metaphoric sentences. We further discard metaphors that do not contain either a verb or a noun, as every idiom in the SloIE corpus contained one of those word types. These are also the most interesting word types from the analysis point of view (e.g., majority of linguistic studies mentioned in Section 2.2. focused on those), while metaphorically used prepositions which are a frequent word type in KOMET are not interesting for our needs. Out of all metaphors in the KOMET corpus, 66.8% included one of those word types. However, this approach discards a large amount of the metaphors present in the KOMET corpus, reducing the size of the available training data to 1783 metaphoric instances and 6530 non-metaphoric instances.
2. To increase the number of training instances, we attempted to add additional metaphors using semi-supervised learning. After each epoch, we evaluated the model on each sentence that was left-out of the training set using Monte-Carlo dropout. During the Monte-Carlo dropout, we classified each sentence 20 times, applying dropout to different neurons each time. For each sentence, we calculated its class probabilities as the percentage of the predictions that match the given class. Gal and Ghahramani (2006) show that this can be a more accurate estimate of class probabilities than the probability values returned by a single neural network. We select the sentences where the prediction certainty was either above 95% or below 5% (i.e. sentences where the model was confident in its predictions) and add those to the training set. This gave us a larger dataset, but we still discarded sentences the model was unsure about. The expanded dataset contains 1845 metaphoric instances and 6530 non-metaphoric instances.

The datasets, containing sentences with metaphors (positive class) and without metaphors (negative class) was split into a training, testing, and development set at a ratio of 0.7:0.2:0.1. The training set contained 1783 metaphorical sentences and 6530 literal sentences while the test set contained 1188 literal sentences and 1605 metaphorical sentences. We fine-tuned the models for 3 epochs using the AdamW optimizer with the learning rate set to 0.001 and a batch size of 64. We limited the number of epochs due to the small size of the dataset, as further training led to overfitting.

After training the model, we used it to detect sentences containing metaphors on a corpus of Slovene news articles related to migrations (see Section 3.1). The certainty of the predictions was once again evaluated with the Monte Carlo dropout and we selected the 500 sentences, most reliably classified as containing metaphors.

3.3 Annotation of extracted metaphors

In the analysis, we propose further manual annotation of the automatically acquired metaphoric sentences from the previous step. The annotation scheme follows the main goal of our qualitative discourse analysis, which is to discover migrant-related metaphors. The annotation was conducted in two steps. First, we evaluated whether the extracted example belongs to the topic of migrations (*Yes*) or not (*No*). If the example was sorted into the migrations context, we examined what sort of expression the classifier may have found in the sentence, distinguishing between metaphor, metonymy, idioms or other figures of non-literal language. If the sentence was both related to migration and contained a metaphor, we identified the metaphorically used expression (*Source domain*) and the element in text to which the metaphor refers (*Target domain*), which can be either the explicitly expressed target or the immediate textual context which indicates some sort of semantic tension.

In the second step, we interpreted the metaphors and determined the conceptual, interpretative frames level by assigning *Source Frame* and *Target Frame* information. In addition, we provided information whether the sentence has positive, negative or neutral stance towards the *target frame* to which the metaphor refers (e.g., migration situation, crisis workers, police, etc.), as well as the stance information focusing only on the main topical target in the corpus (*migrants*), where we annotated metaphors as positive, negative or neutral towards migrants (this perspective is more interesting for qualitative analysis in the field of social sciences).

Table 3 shows an example annotated following the proposed scheme (the original example was in Slovene but we provide its English translation):

Example	*Police officers are directing all their efforts into handling the security conditions and ensuring order and peace with the arrival of such a large number of foreigners.*	
Topic of migrations	Yes	
Linguistic annotation	Expression	Metaphor
	Source domain	Handling
	Target domain	Security conditions
Conceptual annotation	Source Frame	Beast/Opponent
	Target frame	Migrant situation
Stance toward	Target Frame	Negative
	Migrations	Negative

Table 3: Linguistic annotation scheme.

To the best of our knowledge, such detailed and systematic annotation has not yet been done in related work, which usually focuses only on source and target information, ignoring the particular scenarios, roles and agents making up these general domains. An exception to that is the PURL corpus (Gordon et al., 2015), which has a somewhat detailed annotation including particular labels for roles and agents, but their domain set was a predefined list of labels, resulting from many years of manual bottom-up analysis and labelling. Additionally, the stance towards the target concept in question was not explicitly laid out. Our annotation scheme, with the goal to acquire metaphorical framings of the topic of migrations and thus intended for further qualitative discourse analysis, makes it possible 1) to alleviate the burden of annotation by only filtering out migration metaphors, 2) to identify lexical triggers of both source and target concepts, 3) to separate the various subjects framed inside the domain (e.g., we differentiate between migration crisis and migrants), 4) to identify attitudes towards the particular concepts mentioned in the text. Moreover, contrary to previous work, it does not limit the annotator to pick just one possible domain but allows for multiple interpretations (as in the case shown above, the annotator chose both BEAST and OPPONENT due to the ambiguous sense of the metaphorically used word “handling”).

4. Results

In this section, we first present results of the automatic extraction methods (Section 4.1), followed by a qualitative linguistic analysis (Section 4.2).

4.1 Evaluation of the automatic metaphor extraction

We performed gold standard evaluation of the automatic metaphor extraction on the test set extracted from the KOMET corpus of metaphors. The results of the different approaches are presented in Table 4.

Method	Classification accuracy	Precision (metaphors)	Recall (metaphors
Default classifier (majority class)	0.575	0	0
Only metaphoric data	0.609	0.743	0.109
Idioms + metaphors	0.725	0.276	0.561
Semi-supervised expansion	0.425	0.425	1

Table 4: Performance of different metaphor extraction approaches on the KOMET test set.

The default classifier always predicts the metaphor and gives 58% classification accuracy. Training on only KOMET data (without transfer from idioms) gives a small 3% improvement. This model only detects a small amount of metaphors in the training set (10.9% recall) but has a precision of 74.3%. The transfer learning using idioms and metaphors improves significantly, giving 72.5% accuracy. Additionally, the recall increases to 56.1%, showing that the model is capable of recognizing more metaphors in the training set at the cost of decreased precision, while expansion of dataset with semi-supervised learning is not successful in this experiment (43% accuracy). This model predicts everything as metaphorical, making it useless for practical applications.

4.2 Fine-grained analysis on the migration texts

The fine-grained linguistic analysis was done on a set of sentences from the migration corpus (see Section 3.1). We first selected 500 sentences most reliably classified as metaphoric (Monte Carlo dropout was used to evaluate certainty of classifier, as described in Section 3.2). From these, we randomly selected 100 sentences for manual analysis.

On 100 examples, we first evaluated the potential of the method for extracting metaphorical sentences from large corpora. In terms of relatedness to the topic, 54% of the sentences belong to the topic of migrations, and out of these in 74% the metaphor classifier correctly tagged the sentence as metaphorical. In terms of direct usability for qualitative analysis of migrations, we consider both topic and metaphorical aspects, and this makes 40% of sentences relevant for our purpose.

In our fine-grained analysis, we followed the proposed annotation scheme (see Section 3.3). The annotated sample is released under the CC-BY-SA licence via https://github.com/TadejSkvorc/metaphor-detection/. We believe that it can serve also other researchers in guiding their analyses or in shaping the NLP annotation campaigns.

Source frame	Freq.	Target frame	Freq.
Liquid	8	Migrants	12
Container	6	Country	9
Natural phenomenon	6	Migration	7
Object	6	Migrant admission	5
Burden	6	Borders	3
Beast	4	Regulation	3
Journey	4	Europe	2
Living being	4	Crisis workers	2
Opponent	3	Society	1
Defender	3		
Contestant	3		
Weapon	2		
Building	2		
Threat	1		

Table 5: List of detected source and target frames.

Table 5 presents a systematic list of all source and target frames in the corpus of 40 relevant sentences (which corresponded to the criteria of the sentence belonging to the topic of migrations and containing a metaphor) and their frequencies. Note that in our annotation, it is possible to attribute more than one source or target frame. The linguistic analysis revealed that the most frequently used metaphorical frames referred to liquid, container, natural phenomenon, object, and burden. The target concepts to which the metaphorical expressions referred were migrants, countries receiving migrants, migrant crisis in general, crisis workers, and borders.

The stance toward migrants in general was predominantly negative (78% negative, 15% positive, 7% neutral), while the stance toward the target concept was a bit more balanced (70% negative, 27% positive, 6% neutral).

Next, we also provide some examples. The most frequently used metaphorical concept in migration discourse is related to *liquid* and *floods* (example 1):

(1)
Države severno od nas začenjajo razmišljati o tem, da bi omejile ***dotok migrantov****.*
Countries Northern of Slovenia are planning to limit ***the inflow of migrants****.*

In most cases, the conceptual domain of liquid is directly related to the target domain of migrants and evokes a negative sentiment towards their situation. In this category, we also find expressions like *wave of migrants*, *rivers of migrants*, and *diffused entering into the country*. However, in some cases (example 2), the concept of liquid is related to the target of crisis workers who are presented as the water source, and triggers a positive sentiment:

(2)
Na notranjem ministrstvu so opozorili na ***izčrpanost aktivnih na terenu****.*
The Ministry of Interior pointed out ***the exhaustion of the staff on the ground****.*

The concept of the container (example 3) was the second most used metaphorical concept:

(3)
Avstrija *na posameznih mejnih prehodih na uro* ***sprejme od 50 do 100 beguncev*** *(…)*
At certain border crossings, ***Austria receives between 50 and 100 refugees*** *per hour (…)*

As we can see from the example (3), this concept is related to the countries and societies that accept migrants and evokes a positive sentiment. In this category, we also sorted expressions like *to integrate into the new environment* and *to enter into a new society*. In some specific cases, a metaphorically used expression could refer to two different concepts, as shown in the example (4):

(4)
***Slovenija namreč nima neomejenih zmogljivosti**.*
***Slovenia does not have unlimited capacities**.*

In this case, we can see that the capacity of a country accepting migrants can be interpreted as limited capacity of a container or limited capability of a person carrying a burden. This is why we annotated both conceptual frames in order to leave both options open for further qualitative analyses.

We present another interesting conceptual pair of beast vs. beast tamer (example 5):

(5)
*Ne glede na vse okoliščine Slovenija z velikimi napori **obvladuje situacijo ob begunski krizi**.*
*Regardless of all the circumstances, Slovenia is making great efforts **to bring the situation under control during the refugee crisis.***

As the example (5) shows, the conceptual frame of a beast tamer refers to the countries accepting the migrants or to the crisis workers, especially the police, and evokes a positive sentiment towards the target and a negative one towards the migrants.
The concept of beast or adversary, sometimes also associated with natural phenomena, refers to the migrant crisis in general (example 6) and elicits a negative sentiment towards the target and towards migrants in general:

(6)
*Mraz se stopnjuje, **begunska kriza pa se ne umirja**.*
*The cold is escalating but the **migrant crisis is not calming down**.*

The linguistic analysis shows that the presented annotation scheme based on automatically extracted examples allows for a systematic set of metaphorically used expressions and a list of target frames to which the metaphors refer which can be used for further discourse analysis.

5. Discussion

The combination of automatic extraction and the linguistic annotation can contribute to Conceptual metaphor-based critical discourse analysis but also exposes some challenges that shall be addressed in the future when further integrating both approaches.
The main limitation of Critical discourse studies is that due to its conception and reliance on qualitative research traditions of social sciences, it cannot process large corpora. The qualitative process of recognizing and analysing metaphors as ideological tools in news media is lengthy and does not allow a throughout identification and analysis of all metaphors appearing in a specific corpus. While corpus linguistics tools can support large scale analysis, they frequently depend on manually predefined metaphorical cues. On the other hand, NLP tools can help qualitative discourse analysis in the phase of automatic metaphor extraction in both synchronic as well as diachronic studies. The results show that the proposed method can significantly shorten the analytical procedure, allows a much bigger set of data to be analysed, and works well on a topical collections. In addition, automated extraction leads towards a more objective sample selection.
In the process of annotating metaphors in the selected examples from the Migrations corpus, we found various types of metaphors (such as migrants as water, migrants as natural force and natural catastrophe, host countries as containers, migrants as object), which matches the most frequently identified metaphorical uses related to migration in qualitative research (Arcimaviciene and Baglama, 2018; Musolff, 2011; Charteris-Black, 2006; O'Brien, 2003; Dervinyte, 2009; Vezovnik, 2018).
Some identified limitations of the proposed methodology are as follows. First, while we automatically extracted many metaphoric sentences, we also omitted many. To better assess the proportion and properties of these, one should compute the recall of the method on a representative sample and therefore annotate the metaphorical (migration-related) sentences in the corpus and not only the ones selected by the system. Next, the linguistic annotation procedure in which source and target domains and especially frames are identified turned out to be challenging mostly because of lack of coherent identification of metaphors and its' components across annotators. In our case, the annotation process was done by two linguists for all the categories but migration related stance, which was annotated by a social scientist with expertise in qualitative analysis of migrations. For this proof of concept study, the two annotators reached consensus on all the examples. When moving to a larger annotation campaign, we will release clear guidelines and use an overlap of annotated examples to assess the inter-annotator agreement. Another limitation of this study is the amount of text (context) taken into consideration when annotating metaphors. A typical segment of text considered in qualitative approaches such as Critical discourse studies is much larger as the context is crucial when investigating the ideological and connotative levels of media texts. This limitation can be addressed by using larger context also in classification and presentation to annotators.

6. Conclusion and future work

We have presented a neural approach to metaphor extraction for Slovene, by building upon the method by Škvorc et al. (2022) for idiom detection. We first adapted the Slovene SloBERTa language model for idiom detection, followed by fine-tuning the model for classification of metaphors. We applied the method to a topical collection of migration news. We have shown that even with a small training corpus of metaphors not belonging to the topic under investigation, we can extract metaphoric sentences with 74% accuracy, getting metaphors on the desired topic of migrations with satisfying precision (40% of the evaluated extracted sentences included metaphors relevant to the migration topics). Next, we proposed an annotation scheme, where we analysed the metaphors on the level of source and target on the textual and conceptual level, as well as provided the stance-related information. The analysis based on this schema showed the most frequently used metaphorical concepts in the migration discourse. The most frequently used metaphorical frames were related to liquid, container, beast, natural phenomenon, object and weight. The target frames to which the metaphorical expressions referred were migrants, countries accepting migrants, migrant crisis in general, crisis workers, and borders.

The presented methodology enables metaphor extraction as an input for larger scale qualitative analyses than the ones currently performed in the field of Conceptual metaphor-based critical discourse analysis. Our annotation scheme contributes to the design of future metaphor annotation initiatives, adding textual and conceptual levels, as well as target and topical stance information.

In future work, we will analyse a sample of target domain texts, to assess the retrieval performance of our method. We plan to organise a much larger annotation campaign. First, based on our pilot study, we will develop detailed guidelines for a larger group of annotators, labelling a larger sample of metaphors, and assessing their inter-annotator agreement. The obtained larger corpus with source and target information on textual and conceptual level shall allow for automatic prediction of these categories, further reducing the manual workload of analysts.

In longer run, we plan to exploit the potential of automated recognition and analysis of metaphors for comparative and diachronic studies. If we managed to establish a reliable procedure of recognizing source and target domains, the two components of a cognitive metaphor, we would be able to create a typology of different metaphors and compare across different media outlets potential differences in metaphorical use (e.g., based on political orientation of the source). Similarly, with the identification of different metaphoric types, we would be able to perform a diachronic analysis of transformations of metaphors related to migration through time, possibly detecting differences in the social perception of migrations. Since many multilingual models, such as multilingual BERT (Devlin et al., 2019) are now available, one could extract and analyse metaphors across several languages. With further improvements in detection of metaphors, one could identify sedimented and new metaphors and analyse the differences in their use across media outlets and countries.

7. Availability

The corpora SloIE and KOMET are already publicly available. The code is accessible under the permissive MIT licence via https://github.com/TadejSkvorc/metaphor-detection/ together with the output of 500 metaphorical sentences, and the fine-grained linguistic annotation of the 100 examples. While we do not have the rights to release the corpus of migration news, it can be obtained by a request to the authors.

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