What *Drives* the Use of Metaphorical Language?
Negative Insights from Abstractness, Affect, Discourse Coherence and Contextualized Word Representations

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Abstract

Given a specific discourse, which discourse properties trigger the use of metaphorical language, rather than using literal alternatives? For example, what drives people to say *grasp the meaning* rather than *understand the meaning* within a specific context? Many NLP approaches to metaphorical language rely on cognitive and (psycho-)linguistic insights and have successfully defined models of discourse coherence, abstractness and affect. In this work, we build five simple models relying on established cognitive and linguistic properties – frequency, abstractness, affect, discourse coherence and contextualized word representations – to predict the use of a metaphorical vs. synonymous literal expression in context. By comparing the models' outputs to human judgments, our study indicates that our selected properties are not sufficient to systematically explain metaphorical vs. literal language choices.

1 Introduction

Metaphors are "not just nice", but represent a "necessary" element of everyday thought and communication (Ortony, 1975; Lakoff and Johnson, 1980; van den Broek, 1981; Schäffner, 2004, i.a.), and are ubiquitous in natural language text corpora (Gedigian et al., 2006; Shutova and Teufel, 2010; Steen et al., 2010, i.a.). From the perspective of natural language processing (NLP), automatic approaches to metaphor processing are therefore important for any task that requires natural language understanding, and NLP has been concerned with the detection (Köper and Schulte im Walde, 2016; Alnafesah et al., 2020; Ehren et al., 2020; Dankers et al., 2020, i.a.), the interpretation (Shutova, 2010; Bizzoni and Lappin, 2018; Mao et al., 2018, i.a.) and, the generation (Stowe et al., 2021; Zhou et al., 2021) of metaphors.[1]

As to our knowledge, however, no study so far has raised the question of WHY a metaphorical expression is used within a specific discourse, rather than an equally plausible literal alternative. For example, consider the discourse in table 1, where both the metaphorical expression *grasp the meaning* and its synonymous literal alternative *understand the meaning* seem equally acceptable (Piccirilli and Schulte im Walde, 2021, 2022). What are the factors priming for one use or the other? Are there cues within the discourse which influence the selection of one usage over the other? To which extent can computational approaches based on discourse properties model human behavior regarding the choice between synonymous metaphorical vs. literal language usage?

According to psycholinguistics and computational linguistics research, the processing of words is a function of their **frequency of occurrence** in the language (van Jaarsveld and Rattink, 1988; Wittmann et al., 2017, i.a.). Is the choice between a metaphorical and a literal expression therefore just an effect of frequency? In contrast, conceptual metaphor theory establishes metaphorical language as a figurative device for transferring knowledge from a concrete domain to a more abstract domain (Lakoff and Johnson, 1980), and the hypothesis that metaphorical usages correlate with the **abstractness of the context** has been supported in numerous NLP studies on automatic metaphor identification (Turney et al., 2011; Tsvetkov et al., 2013; Köper and Schulte im Walde, 2016; Alnafesah et al., 2020; Hall Maudslay et al., 2020). **Affect** has also been explored with regard to metaphoricity. Not only has metaphorical language been found to carry a stronger emotional load than literal language (Blanchette and Dunbar, 2001; Crawford, 2009), but metaphorical words and sentences are also judged to be "more emotionally engaging" than their synonymous literal paraphrases (Citron and Goldberg, 2014; Mohammad et al., 2016), and

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[1] See Tong et al. (2021) for a systematic, comprehensive review and discussion of the most recent metaphor processing systems and datasets.

This wasn't just a play on words, rather it was a demand that they should 'maintain a consistency between their words and their actions'. But I agree, that still does not absolve them from the need to speak truth to power. In our times when people spend so much time with TV and the internet, do they have the interest and time to read poetry? Many people believe that it is difficult to read poetry. Can everyone [*grasp* / *understand the meaning*] of a good poem, or is a skill necessary?

Table 1: Example of a discourse from the dataset introduced by Piccirilli and Schulte im Walde (2021). Both the literal expression *understand* meaning and its metaphorical counterpart *grasp* meaning seem equally acceptable in the discourse.

informing NLP models with **emotion** features has proven useful for metaphor detection (Gargett and Barnden, 2015; Köper and Schulte im Walde, 2018; Dankers et al., 2019). When analyzing metaphorical discourse features (Glucksberg, 1989; Steen, 2004) and the interactions of **discourse coherence** with the contextual salience of metaphorical vs. literal expressions (Inhoff et al., 1984; Gibbs, 1989; Giora, 1997; Giora and Fein, 1999; Gibbs, 2002; Kövecses, 2009), findings are directly connected with the theory of discourse cohesion, i.e., the principle that discourse should be a "group of collocated, structured, and coherent sentences" (Halliday and Hasan, 1976; Jurafsky and Martin, 2019). Models relying on the coherence of lexical semantic discourse structures have therefore been successful in identifying metaphors (Sporleder and Li, 2009; Bogdanova, 2010; Mesgar and Strube, 2016; Dankers et al., 2020). From a yet different perspective, Transformer-based pretrained language models (T-PLMs) (Vaswani et al., 2017), pre-trained on the language modeling task, are able to predict masked items in context and produce **contextual embeddings** accounting for both left and right contexts, and resulting in word representations that are dynamically informed by the surrounding words.

The rich previous interdisciplinary research on figurative language seems to agree on tight interactions between metaphorical language detection and properties of the respective discourses, i.e., **cognitive aspects** (abstractness and affect), **discourse coherence** and **contextual properties**. Do these discourse properties indeed trigger the use of a metaphorical vs. its synonymous counterpart? We address this question by exploring five simple discourse-based models inspired by the above-mentioned properties, namely frequency, abstractness, affect, discourse coherence and contextualized word representations. We approach the question within two studies. First, we explore discourse features of metaphorical usages occurring in natural language by applying the cognitive and linguistically-inspired models to existing discourses from the English corpus *ukWaC* (Baroni

et al., 2009). Then, we zoom into the models' predictions and evaluate them against human preferences (i.e., annotations) for metaphorical vs. literal language within the same discourses. By modeling the prediction for synonymous metaphorical vs. literal expressions motivated by the above discourse perspectives, we gain insight into human behavior for metaphorical vs. literal languages choices.

2 Dataset

Research on figurative language has produced impressive resources on the metaphoricity of lexical items. However, these resources have limitations regarding the specific task we are addressing in this work: (i) the context in which words are metaphorically used is not large enough, providing human judgments only on the *word-level* (Steen et al., 2010) or on the *sentence-level* (Stefanowitsch, 2008; Shutova and Teufel, 2010; Mohammad et al., 2016), (ii) the target words or expressions are *ambiguous*, i.e., they may have both a metaphorical and a literal sense (Tsvetkov et al., 2013; Mohler et al., 2016), (iii) they are *extended* metaphors (Gibbs, 2006; Martin, 2008), (iv) the paraphrases to metaphorically-used words are automatically generated and no manual annotations were provided to evaluate the outputs (Bollegala and Shutova, 2013; Bizzoni and Lappin, 2018, i.a.).

We therefore use our recently released dataset specifically designed to investigate the choice of metaphorical vs. literal expressions in context (Piccirilli and Schulte im Walde, 2021, 2022). It contains a total of 1,000 discourses of five to six sentences (98 words on average), in which the final sentence of each discourse contains either a metaphorical expression or its literal alternative from a pair of synonymous subject–verb (SV) or verb–object (VO) expressions. Table 1 presents an example for the VO pair *grasp/understand meaning*. The overall 50 pairs of English expressions were selected from Shutova (2010) and Mohammad et al. (2016), and for each of the pairs, we extracted 20 discourses from the *ukWaC* (Baroni et al., 2009), 10 of which containing the metaphorical usage (e.g., *grasp*) and

10 of which containing the literal paraphrase (e.g., *understand*). To gain insight into human preferences between the selected pairs of metaphorical vs. literal expressions, we also collected crowdsourced human judgments for these 1,000 discourses, asking annotators to choose which expression they favored given the preceding discourse. This dataset is therefore optimal for the task at hand, as it provides (i) synonymous metaphorical vs. literal expressions, (ii) at the *discourse-level*, (iii) manually annotated. In the present work, we make use of the 1,000 discourses containing the original expressions in the *ukWaC* and the annotators' choices for metaphorical vs. literal usages within a subset of 287 discourses, where 70% or more annotators agreed on the preference (metaphorical or literal).

3 Models and Experimental Setup

3.1 Prediction models

We approach the task of predicting the use of metaphorical vs. literal expressions as a *prompting task*: given an input prompt[2], the models predict whether the missing span should be the metaphorical or the literal expression. We apply five models relying on discourse properties, where each model approaches the task from a different perspective, to give us insight on which discourse features influence the metaphorical vs. literal selection.

Frequency approach When given the choice between a metaphorical expression and its synonymous counterpart, do we tend to favor the most frequent usage? **Baseline (Freq.):** Our baseline relies on the occurrences of the SV and OV tuples in the original *ukWaC* corpus: the model receives the prefix prompt as input, and always outputs the most frequent expression of the pair.

Cognitively-inspired approaches The cognitive interaction between abstractness/affect and metaphorical language raises the question: to which extent (i) a more abstract discourse and (ii) a more emotionally-loaded discourse favor a metaphorical usage? **Abstractness (Abstr.):** We measure the abstractness of a discourse preceding the target expression within four settings, based on the norms from Brysbaert et al. (2014). We assign abstractness scores to *all* words (Abstr.all), only *nouns* (Abstr.n), only *verbs* (Abstr.v) or only *adjectives* (Abstr.adj). We then obtain an overall

rating of abstractness for each discourse by computing the median of the respective lexical items' abstractness scores. For each setting, we use as threshold the abstractness median of the respective part-of-speech class, and the model predicts the metaphorical expression if the overall abstractness score of the discourse is below that threshold (i.e., more abstract/less concrete), and the literal counterpart if above (i.e., less abstract/more concrete). **Emotionality (Emo.):** We build a model predicting the target expression based on the emotionality of the preceding discourse, which we represent using the English emotion lexicon from Buechel et al. (2020). Each lexical item from the preceding discourse is assigned an emotionality score, and the median represents the overall emotionality score of the discourse. Appendix A.1 provides details on the emotionality score.

Discourse coherence approach Is the choice of an expression from a synonymous pair driven by the semantic relatedness between the components of that expression and the lexical items in the surrounding context? We adapt the **Lexical Coherence Graph (LCG)** introduced by Mesgar and Strube (2016) to measure the semantic relatedness between the words in the preceding context and the target expression contained in the final discourse sentence: we compute the cosine scores for the two components in the SV/VO expressions (i.e., the verb and its argument) and each word in the preceding discourse, relying on contextualized BERT embeddings (Devlin et al., 2019). The output is a graph connecting the preceding context to both the metaphorical expression and its synonymous alternative; edge weights are represented by the average of the respecting cosine values. The expression – metaphorical or literal – with the maximum weight (i.e., the largest average cosine score) is selected. Appendix A.2 provides details on the LCG score.

Contextualized discourse properties How do contextualized word representations prime for the use of a metaphorical vs. literal preference? Our question triggers a *cloze-task* style (Taylor, 1953) and applies the **Pre-trained Language Model BERT** (Devlin et al., 2019) in a zero-shot manner. We give a *cloze prompt* as input to the model, as in table 1: we mask the target expression, and the model selects the most probable answer amongst the two candidates (metaphorical or literal). We experiment with both $\text{BERT}_{\text{base}}$ and $\text{BERT}_{\text{large}}$.

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[2]The input prompt is a *prefix prompt* for all models except for BERT, whose input is a *cloze prompt*.

3.2 Experimental Setup

We compare our models' predictions against two gold standards. We first evaluate the models' outputs against the 1,000 discourses collected from *ukWaC*, containing the balanced *originally*-used metaphorical or literal expressions (**Orig. Data**) to investigate which discourse aspects (abstractness, emotionality, coherence, word representations) might have primed the metaphorical vs. literal selection. We expect the model predictions to provide insight into the features that influenced the *original* speakers' preferences. We then zoom into the *annotated* version of the same data (**Anno. Data**), for which participants were asked which expression, metaphorical or literal, they favored in the given 287 discourses (cf. Section 2). We analyze whether (dis-)agreements between humans are also reflected in the models' predictions.

4 Results and Analyses

We first analyze the models' predictions with regard to metaphorical vs. literal usages in the *originally*-extracted data (**Orig. Data**), to address the question: do cognitive and linguistically-inspired models reflect metaphorical language usage encountered in natural language corpora? The first column of figure 1 presents the accuracy score of each model with regard to Orig. Data. All models reach around 50% of accuracy; however, they behave very differently regarding their individual predictions.[3] Figure 1 presents the percentages of overlapping output decisions between our five models, revealing interesting insights: we observe 77% overlapping predictions between the PLMs with the frequency baseline, suggesting that the majority of PLM predictions is frequency-driven, which is not the case for most abstractness settings and emotionality. Emotionality itself correlates with abstractness in all settings but the one where we consider only adjectives, which is surprising as adjectives tend to carry a lot of emotions (Mohammad and Turney, 2010; Bostan and Klinger, 2019). The overlap between LCG and BERT reaches 62%, whereas its correlations with abstractness and emotionality are rather low, suggesting that decisions based on abstractness and emotionality are different to those based on word representations and semantic relatedness. At first sight, our different perspectives seem rather complementary, which is yet to be verified in future studies.
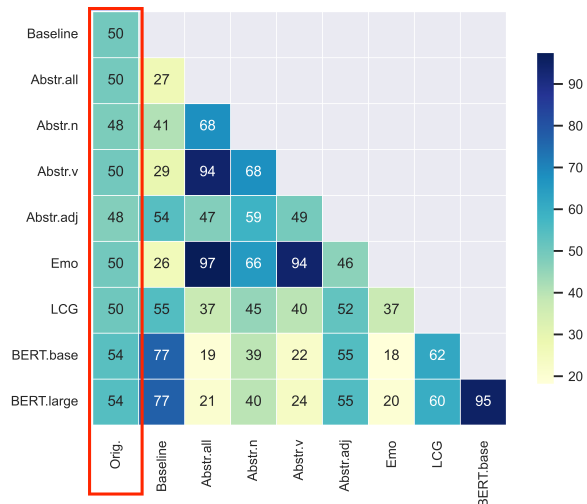

Figure 1: Accuracy scores of each model with regard to the original data (1st column in red) and percentages of overlapping output decisions between models.

Overall, none of our models seems to reliably predict what is observed in natural language data. We thus cannot derive what might have triggered the original speakers to favor a metaphorical or literal expression over the other.

We then compare our models' predictions to human behavior: are the proportions of metaphorical vs. literal predictions from our models similar to human perceptions (**Anno. Data**)? Figure 2 presents the proportions of the metaphorical expressions predicted by four of the models in relation to the proportions of metaphorical usages favored by the human judges.[4] If humans and models were making similar decisions, all data points, each representing the proportion of metaphorical uses for a pair of expressions, would be on the regression line. We make different observations depending on the model in question. As far as frequency is concerned, the model predicts either the metaphorical or the literal expression (100% or 0% respectively, in the graph). Many literal expressions that are favored by participants (low x-axis %) seem to correlate with their higher occurrences in natural language corpora, e.g., *make* vs. *throw remark* (VO). However, humans also favor many metaphorical expressions which are less frequently used, e.g., *stir* vs. *cause excitement* (VO) and inversely, a few metaphorical expressions which are more frequent than their literal counterparts are not necessarily favored by people, e.g., *poison* vs. *corrupt mind* (VO). Thus, frequency does not seem to be a systematic factor for metaphorical/literal choices. Regard-

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[3] Appendix B.1 presents further prediction differences.

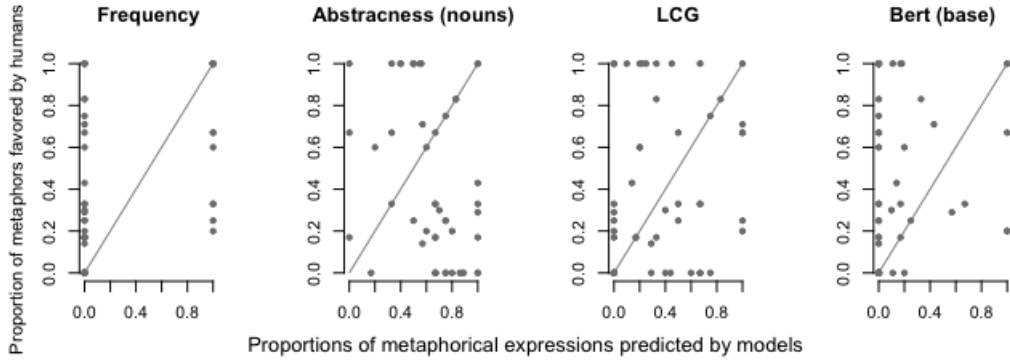[4] Appendix B.2 shows the graphs for all models.

Figure 2: Proportions of predicted metaphorical expressions for each model, with regard to the proportions of these metaphorical expressions favored by annotators. Appendix B.2 shows the graphs for all models.

ing abstractness, many expressions fall perfectly on the regression line, e.g., *twist vs. misinterpret word* (VO), *story grab vs. intrigue* (SV), suggesting at first some interactions between the expression preferences and the abstractness of the respective discourses. However, the numerous metaphorical expressions that are predicted by the model (80%+) but not by humans, e.g., *taste* vs. *experience freedom* (VO), *factor shape* vs. *determine* (SV) do not confirm that hypothesis. Concerning the LCG, the picture is less clear. Many literal expressions are favored by both the model and humans, e.g., *color* vs. *affect judgement* (VO), but many metaphorical usages are preferred by humans when the model predicts the literal ones, e.g., *breathe* vs. *instill life* (VO). Therefore, metaphorical vs. literal coherence does not seem either to be a determining factor for metaphorical vs. literal preference, respectively, which does not support the context-salience hypothesis, where one would expect a metaphorical expression to be favored following a metaphorical discourse, and ditto for a literal expression/literal discourse (Kövecses, 2009). Finally, the overall low metaphorical predictions by the PLM are expressions for which humans provide high metaphorical proportions, such as *abuse* vs. *drink alcohol* (VO). This suggests a potential lack of metaphorical language representation, in line with our observation concerning abstractness and emotionality.

5 Discussion and Future Work

Previous research has provided evidence for interactions between metaphorical language and discourse properties, namely frequency, abstractness, affect, discourse coherence and contextualized word representations, on the *word-* and *sentence-level*. In this work, we took a step further: we looked at the task of predicting the use of a metaphorical vs. synonymous literal expression and built models based on the above-mentioned features on the *discourse-level*. Our findings show that these discourse properties do not seem to be indicative of metaphorical usage.

We propose several directions for future work. First of all, we considered discourses of around five sentences, but the decision on the context window might have an impact on the findings. Further work exploring the optimal size of preceding context would be interesting. Another promising direction might analyze PLMs' attention mechanisms (Tenney et al., 2019; Clark et al., 2019) on the presented task, and also explore the extent to which modifying the attention of such models, i.e., fine-tuning (Peters et al., 2019; Zhao and Bethard, 2020), improves their performance to mimic human preferences for metaphorical vs. literal usages. Finally, we have looked at five features; needless to say that exploring further discourse properties is necessary, such as co-reference, complexity, aptness, creativity, prototypicality, and the influence of genre and specific domains (e.g., religious/scientific texts).

6 Conclusion

We suggested five simple models to investigate WHY humans choose to use a metaphorical expression in a specific discourse. Regardless of the perspectives, our work demonstrates that a range of previously suggested salient discourse properties do not seem to influence preferences on the choice between synonymous metaphorical vs. literal expressions. Our findings thus ask for a more nuanced approach to metaphorical language choices in NLP.

Acknowledgements

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A Models

A.1 Emotionality

Buechel et al. (2020) presented a new methodology to automatically generate lexicons for 91 languages comprising eight emotional variables: *Valence, Arousal, Dominance* (VAD) as well as the five basic emotions *Joy, Anger, Surprise, Fear, Surprise* (BE5) (Ekman, 1992). As a source dataset, they used the English emotion lexicon from Warriner et al. (2013), comprising about 14K entries in VAD format collected via crowdsourcing. They applied the BE5 ratings from Buechel and Hahn (2018a) to convert the VAD ratings. Via their monolingual state-of-the-art multi-task feed-forward network (Buechel and Hahn, 2018b), they projected ratings on these eight variables, resulting in an English lexicon containing 2M word type entries with very high correlation with human judgments (around 90% for each variable).

We are interested in the emotionality of lexical items, i.e., the emotional load that a term conveys, rather than the actual emotion a term refers to. We therefore use the BE5 ratings of the English lexicon for our study. Out of the five scores that a term receives – one for each emotion, we assume that its highest score is reflective of the "emotional load" of that term, i.e., how much emotion it conveys. For example, the lexical item "truth" obtained the scores 2.24, 1.46, 1.4, 1.49, 1.46 for Joy, Anger, Sadness, Fear and Surprise, respectively. In our experiments, the term "truth" is therefore attributed the score of 2.24 as its emotional load.

A.2 Lexical Coherence Graph

Following Mesgar and Strube (2016), we measure the semantic relatedness between words represented by their word embeddings, computing the cosine score between the two words of the expression (SV or VO) with each word of the preceding discourse. Consider v_a, v_b, v_c, the word vectors for word a in the preceding discourse A, word b in the metaphorical expression B_m contained in the last sentence B and word c in the literal expression C_l contained in the last sentence C, respectively. The cosine scores $\cos(v_a, v_b)$ and $\cos(v_a, v_c)$ between the two word vectors is a measure of semantic connectivity of the two words. The range of $\cos(v_a, v_b)$ and $\cos(v_a, v_c)$ is between $[-1, +1]$, showing how well the two words are semantically correlated. Figure 4 shows how relatedness is measured, and figure 5 shows the output of the graph.

B Results

B.1 Evaluation: Predictions vs. Original Data

Figure 3 presents the percentages of metaphorical expressions predicted by each model. As mentioned in section 4, the accuracy scores of all models reach around 50%, but they actually behave very differently with regard to performances for metaphorical vs. literal predictions. Remember that the originally-collected discourses are perfectly balanced (cf. Section 2), where half of the discourses contains metaphorical expressions and the other half contains literal expressions from synonymous pairs. As expected, the frequency baseline therefore reaches 50% of accuracy. We note however that the literal usage of the pairs is the most frequent in the *ukWaC* corpus (37/50 pairs), which leads the model to predict the literal counterpart in 74% of the cases. The abstractness and emotionality models mostly select for the metaphorical usages (up to 100% for Emo.), as the discourses are considered more abstract and more emotionally-loaded based on the respective norms. This suggests that original speakers did not perceive the degree of abstractness and emotionality of the discourse as triggers to favor one usage over the other. This aligns with the findings in Piccirilli and Schulte im Walde (2022), who analyzed the relationship between the abstractness and emotionality of the preceding discourses with human preferences for metaphorical vs. literal expressions. The LCG model favors the literal expressions as well (62%), while both BERT_base and BERT_large predominantly predict the literal expressions (81.80% and 80.10%, respectively.).
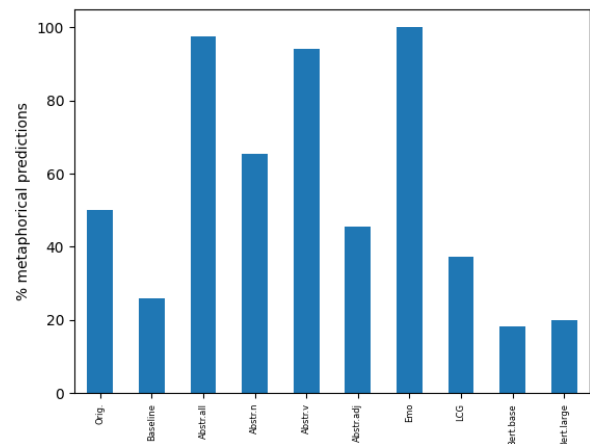

Figure 3: Percentages of metaphorical expressions predicted by each model.
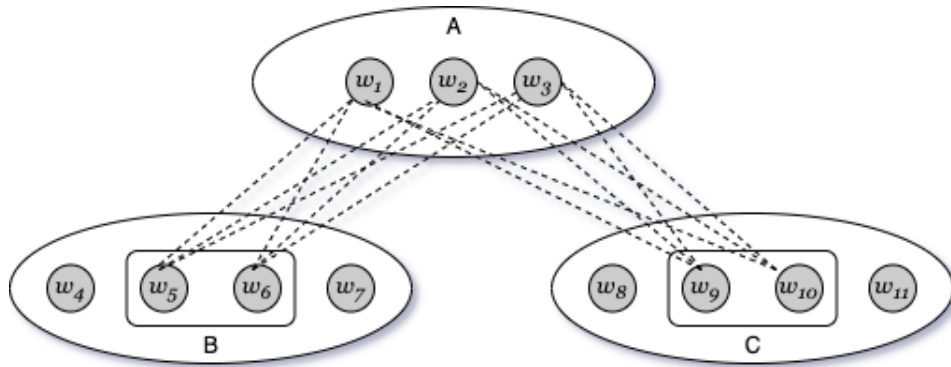
Figure 4: Discourse A with three words $\{w_1, w_2, w_3\}$ and sentences B and C with four words, where $\{w_5, w_6\}$ are the two words composing the metaphorical expression, and $\{w_9, w_{10}\}$ are composing the literal paraphrase. Depending on the expression input (SV or VO), the respective subject or object is identical in $\{w_5, w_6\}$ and $\{w_9, w_{10}\}$, as only the verb is used either as a metaphorical or a literal variant. The semantic relatedness between each word in $\{w_5, w_6\}$ and in $\{w_9, w_{10}\}$ is computed with each word in A.
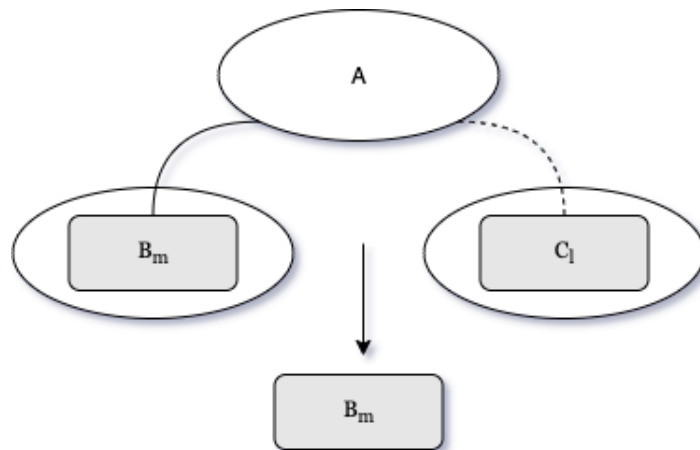

Figure 5: The word relation with the maximum weight (here B_m as indicated by the plain line) represents a stronger connection with the preceding discourse A.

B.2   Evaluation: Predictions vs. Annotated Data

Figure 6 presents an overview of the proportion of expressions that are predicted metaphorically by the models with regard to the preferences of the same expressions by human annotators.
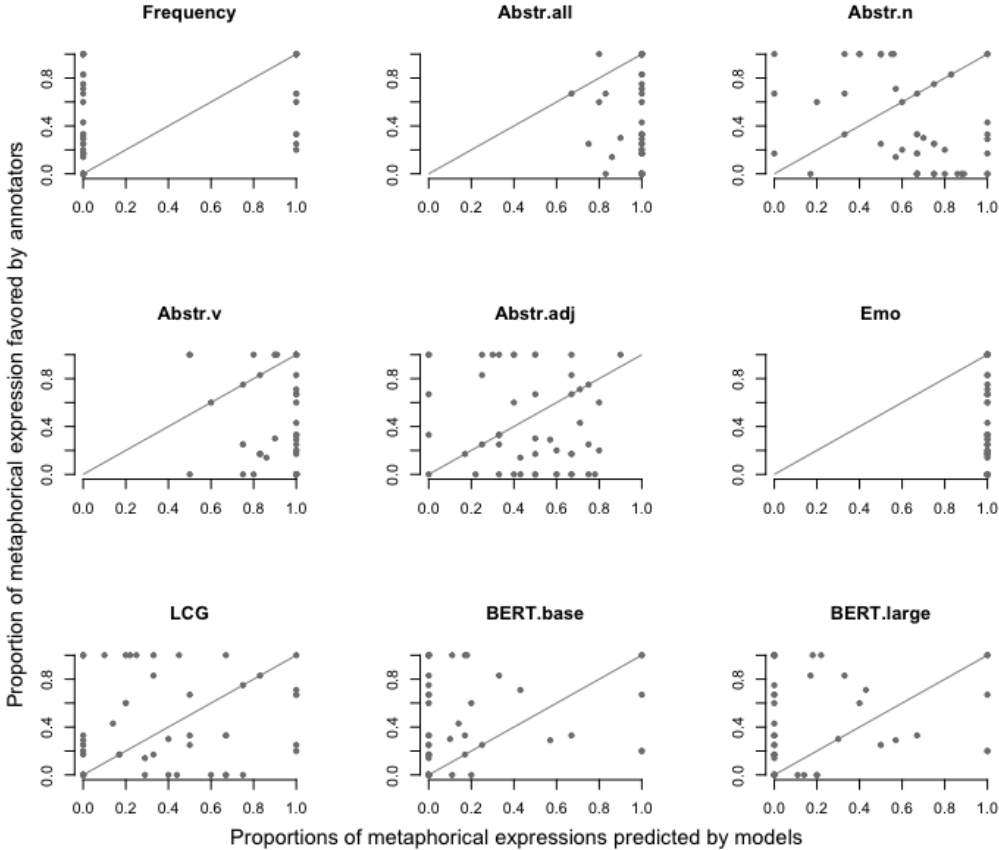

Figure 6: Proportions of the metaphorical expressions predicted by the models with regard to the proportions of these usages to be favored by the participants.