ABSTRACT

This study presents a new approach to metaphorical paraphrase generation by masking literal tokens of literal sentences and unmasking them with metaphorical language models. Unlike similar studies, the proposed algorithm is not limited to the replacement of verbs, but also of nouns and adjectives. Despite the fact that the transfer rate for the former is the highest (56%), the transfer of the latter is feasible (24% and 31%). Human evaluation showed that our system-generated metaphors are considered more creative and metaphorical than human-generated ones. Additionally, when using our transferred metaphors for data augmentation we show that state of the art metaphorical sentence classification improves by 3% in F1.

1 Introduction

Figurative language is ambiguous and often contains mapping of concepts from one domain to another. In “The wheels of Stalin’s regime were well-oiled and already turning”, for example, a political system is viewed through the lens of conceptual metaphor theory [Lakoff and Johnson [1980] as a mechanism which can function, break, and have wheels. Due to its challenging nature, even Transformers struggle to model figurative language Chakrabarty et al. [2022]. This, however, is not only hindering the progress of computational metaphor detection, but also that of Natural Processing tasks, such as sentiment analysis Liu et al. [2020], or other ones, such as cybersecurity Hilton et al. [2022].

Computational approaches related to metaphors that can be found in literature mostly focus on detection and generation. Metaphor detection comprises the identification of metaphor-related words in the text Fass [1997], Birke and Sarkar [2006], Shutova et al. [2010], Steen et al. [2010] and interpretation, which is mostly based on paraphrasing Tong et al. [2021]. Metaphor generation concerns the task of creating novel metaphorical sentences, for example by taking literal ones and transforming them in a way that makes them acquire a figurative meaning, which can be useful to poetry generation Van de Cruys [2020]. No study in literature, to the best of the authors’ knowledge, however, has tried to simultaneously address metaphor detection and generation in the same setting. Furthermore, all existing metaphor generators Chakrabarty et al. [2021], Yu and Wan [2019], Tong et al. [2021], Brooks and Youssef [2020], Stowe et al. [2021] depend on custom and external systems that go beyond standard fine-tuning procedures.

With this work we present a new metaphorical language generation perspective by transferring literal to metaphorical texts. The transfer concerns the replacement of tokens of different parts of speech, not only the common verb type Stowe et al. [2021], Chakrabarty et al. [2021], Yu and Wan [2019], but also nouns and adjectives (examples shown in Fig.1]). Human evaluation showed that a randomly selected sample of our system-generated metaphors were more creative and metaphorical than respective human-generated ones. Our method is open-source and can be exploited to generate an infinite number of new metaphors, assisting tasks such as metaphor detection through data augmentation. Experimenting with this hypothesis, we show that when we used our system-generated metaphors to augment the training data, the performance of a state of the art metaphor detector improves by 3%.
2 Related Work

Metaphor identification is often treated as a sequence labelling task, creating an output that consists of a sequence of labels (metaphorical or not) for a sentence or a sequence of input words [Bizzoni and Ghanimifard, 2018; Chen et al., 2020; Dankers et al., 2020; Gao et al., 2018; Gong et al., 2020; Mao et al., 2019; Mykowiecka et al., 2018; Pramanick et al., 2018; Su et al., 2020; Wu et al., 2018]. Di-LSTM Contrast [Swaroop and Singh, 2018] encoded the left and right side context of a target word through forward and backward LSTMs. Mao et al., 2019 combined GloVe [Pennington et al., 2014] and BiLSTM hidden states for sequence labelling. Despite their efficiency, the static nature of embeddings such as GloVe makes it difficult to cope with polysemy, which is crucial when dealing with metaphors since the meaning of a polysemous word depends on its context [Wang et al., 2020]. Fine-tuning pre-trained contextual language models, however, do not suffer from this problem [Chen et al., 2020; Dankers et al., 2020; Gong et al., 2020].

![Figure 1: Literal sentence (on the left) transferred to a metaphorical one (right) with the automated substitution of a single term.](image)

### Table 1: Metaphor generation studies that comprise masked language modeling (MLM), metaphor reconstruction (MR), and/or recognition of the metaphor’s location within the text (MLR).

| Study                              | MLM | MR | MLR |
|------------------------------------|-----|----|-----|
| [Chakrabarty et al., 2021]         | X   | X  |     |
| [Yu and Wan, 2019]                 | X   | X  |     |
| [Brooks and Youssef, 2020]         | X   |    |     |
| [Stowe et al., 2021]               | X   |    |     |
| **Ours**                           | X   | X  | X   |

Metaphor generation is usually based on obtaining novel figurative sentences either by replacing verbs contained in literal phrases [Chakrabarty et al., 2021; Yu and Wan, 2019; Stowe et al., 2021], or by exploiting syntactic patterns that discriminate between creative metaphorical expressions and non-metaphorical ones [Brooks and Youssef, 2020]. Information regarding recent advances in metaphor detection, processing and generation, can be found in [Tong et al., 2021] while Table 1 presents the main studies. Chakrabarty et al., 2021 fine-tuned BART [Lewis et al., 2020] on a parallel corpus of metaphorical and literal sentences, which they created by replacing relevant verbs from literal expressions and by applying masked language modeling (MLM) [Song et al., 2019] on metaphorical sentences from the Gutenberg Poetry corpus [Jacobs, 2018]. We also address the lack of resources by employing MLM and reconstruction, but our approach does not need a parallel corpus while it can recognise the metaphor’s location and hence it is not limited to verbs.

Yu and Wan, 2019 employed a neural approach to extract the metaphorical verbs from the sentences along with their metaphorical senses in an unsupervised way. Then, the same neural approach is exploited to train a neural language model from a Wikipedia corpus. The novel metaphors are obtained by conveying the assigned metaphorical senses through a decoding algorithm. Stowe et al., 2021 obtained new metaphorical sentences by replacing relevant verbs in literal expressions and encoding conceptual mappings (FrameNet-based embeddings - CM-LEX, and a custom seq-to-seq model - CM-BART) between cognitive domains. Brooks and Youssef, 2020 trained an unsupervised LSTM model and used an inherent inference engine to create new metaphors. The novelty of these new metaphors is ensured by checking that none of the generated sentences match the training data, and that the identified syntactic patterns of metaphors were not present in the non-metaphorical data. Besides focusing on more than verbs and disregarding language-specific syntactic patterns, our approach does not depend on external or custom systems.
3 Literal to Metaphor Transferring

The proposed literal to metaphor generation approach is described with Algorithm 1.

The concept of reconstructing metaphors is not new, and it was first used in Sullivan [2007]. Algorithm 1’s input consists of a corpus $C$ of unlabelled texts, a dataset $I^{M/L}$ of texts labelled as literal or metaphorical, and a classification threshold $h$. We refer to “M|L” as the sentence’s label being either metaphorical or literal. True positives based on $MC^{M/L}$ are used to fine-tune a masked metaphor model (MMM).

Metaphorical text classification is a binary classification task (Algorithm 1, line 2), where a sentence is considered metaphorical if the returned score is higher than a threshold (e.g., in line 7) and literal otherwise (e.g., line 4). A classifier can be trained on a dataset with a binary label per text, such as $I^{M/L}$.

Masked metaphor modeling concerns the restoration of masked metaphors (line 1). This is a task similar to masked language modeling but the masked tokens are tagged metaphors. Fine-tuning a pre-trained model requires a limited number of texts classified as metaphorical and with the metaphor tagged within the text. The algorithm assumes that $I^{M/L}$ comprises such tags.

Generation of new metaphors requires sentences from a corpus $C$ which $MC^{M/L}$ has classified as literal (line 4). A random token is masked and the masked metaphor model replaces the masked token, effectively trying to create a metaphorical text. There is no guarantee that the masked token of the literal sentence will be replaceable by one that would turn the text into metaphorical. Hence, we employ again $MC^{M/L}$ now to keep only truly transferred texts (line 7).

The overall process is also depicted in Figure 2. A classifier, named $MC^{M/L}$, is trained on $I^{M/L}$. True positives based on $MC^{M/L}$ are used to fine-tune a masked metaphor model (MMM). MMM is then used to replace masked tokens of sentences from $C$, originally classified by $MC^{M/L}$ as literal. Reconstructed sentences, which are also classified as metaphorical by $MC^{M/L}$, are finally returned by the algorithm.

4 Empirical analysis

We undertook an empirical analysis on the most common datasets employed for metaphor-related tasks and experimented with several baselines.

4.1 Datasets

Table 2 presents the three datasets we experimented on: MOH-X, TroFi, and TroFi-X.
Algorithm 1 Literal To Metaphor

Input: : A corpus \( C \) of unlabelled texts, a dataset \( I^M|L \) of texts labelled as literal or metaphorical, and a classification threshold \( h \).

Output: A set of metaphorical sentences.

1: \( MR \leftarrow \text{finetune}(I^M|L, \text{reconstruction}) \)
2: \( MC^M|L \leftarrow \text{finetune}(I^M|L, \text{classification}) \)
3: while \( N \neq 0 \) do
   4:   if \( MC^M|L(t \in C) < h \) then
      5:     \( t^\text{mask} \leftarrow \text{mask}(t) \)
      6:     \( t^\text{met} \leftarrow MR(t^\text{mask}) \) ▷ Random mask
      7:   if \( MC^M|L(t^\text{met}) > h \) then
         8:     yield \( t^\text{met} \) ▷ Reconstruct
   9:   end if
10: end while

Table 2: Statistics of all the datasets employed in this work. All datasets comprise English sentences. Size is measured in sentences and POS shows the part(s) of speech of the metaphors.

| Name     | Size | POS               |
|----------|------|-------------------|
| MOH-X    | 646  | Noun/Verb         |
| TroFi    | 3,737| Verb              |
| TroFi-X  | 1,444| Noun/Verb/Adjective |

MOH-X [Mohammad et al., 2016] is derived from the subset of the MOH dataset that was used by [Shutova et al., 2016]. Mohammad et al. [2016] annotated different verbs for metaphoricity. They extracted verbs that had between three and ten senses in WordNet [Mao et al., 2018] along with their glosses. The verbs were annotated for metaphoricity with the help of crowd-sourcing. Ten annotators were recruited to assess each sentence, and only those verbs that were annotated as positive for metaphoricity by at least 70% of the annotators were selected in the end. The final dataset consisted of 647 verb-noun pairs: 316 metaphorical, and 331 literal.

TroFi contains feature lists consisting of the stemmed nouns and verbs in a sentence, with target or seed words. It is named after TroFi (Trope Finder), a nearly unsupervised clustering method for separating literal and non-literal usages of verbs [Birke and Sarkar, 2006]. For example, given the target verb \( \text{pour} \), TroFi is able to cluster the sentence \( \text{Custom demands that cognac be poured from a freshly opened bottle} \) as literal, and the sentence \( \text{Salsavand rap music pour out of the windows} \) as nonliteral. The target set is built using the ’88–’89 Wall Street Journal Corpus \(^1\) tagged using the Ratnaparkhi [2002] tagger and the Bangalore and Joshi [1999] SuperTagger. The final dataset consisted of 3,737 sentences.

TroFi-X is an alternative version of TroFi. It contains 1,444 sentences annotated not only with metaphorical verbs, but also with metaphorical nouns, pronouns and adjectives.

4.2 Evaluation measures

For the classification task, we employed Accuracy (i.e. the fraction of instances that were correctly classified), Precision (i.e., the number of instances that were correctly predicted as metaphorical to the number of instances that were predicted as metaphorical), Recall (i.e., the number of instances correctly predicted as metaphorical to the number of instances that should have been predicted as metaphorical) and F1 (i.e., the harmonic mean of Precision and Recall). For the reconstruction task, we employed Accuracy (i.e., the ratio of sentences that are correctly reconstructed/generated).

4.3 Methods

For metaphorical sentence classification, we employed Naive Bayes [Rish, 2001], Random Forests [Fratello and Tagliaferri, 2019], KNN [Guo et al., 2003], SVM [Evgeniou and Pontil, 2001], Logistic Regression [Peng et al., 2002], MLP [Marius et al., 2009], BERT [Devlin et al., 2019], and XLM-R [Conneau et al., 2020].

\(^1\)https://catalog.ldc.upenn.edu/LDC2000T43
Table 3: All tested Classifiers and their respective results for the three metaphorical data sources. \( P, R, F1 \) and \( Ac \) stand respectively for Precision, Recall, F1 Score and Accuracy. Along with BERT and XLM-R (base and fine-tuned), we have, in order: NB - Naive Bayes; RF - Random Forest; KNN - K-nearest Neighbours; SVM - Support Vector Machine; LR - Logistic Regression; MLP - Multi-Layer Perceptron Neural Network.

Table 4: Accuracy of T5, BART, and two MMMs (BERT, XLM-R) used to reconstruct metaphorical tokens on three datasets. Only sentences correctly classified as metaphorical (by BERT and XLM-R sentence classifiers) are used. Noun (N) and verb (V) accuracy scores indicate the percentage of correctly reconstructed metaphorical nouns and verbs, respectively. TroFi-X sentences comprise three metaphorical tokens each. The first two, \( T1 \) and \( T2 \), can be of any part-of-speech while \( V \) is always a verb. The best one per column is shown in bold.

4.4 Experimental Results

Table 5 provides the results of the metaphorical sentence classifiers (see Section 4.3) on the three metaphorical data sources (see Section 4.1). XLM-R (fine-tuned) has the best Precision in all datasets. BERT (fine-tuned) achieves the best Recall on MOH-X, leading also to the best Accuracy and F1. Overall, BERT and XLM-R (fine-tuned) yield the best results. Naive Bayes, Random Forests, KNN, SVM and MLP performed much lower. However, it is worth noting that Logistic Regression, despite its simple nature, performed surprisingly well.

Table 6 presents the accuracy in metaphor reconstruction on the metaphorical sentences that have been correctly classified as metaphorical (the green box in the middle, in Fig. 2) by the best-performing fine-tuned BERT and XLM-R (see Table 5). We employed T5 and BART, as well as two masked language models, BERT and XLM-R [Alfarò et al. 2019, Goyal et al. 2021], which have been fine-tuned by masking (known) metaphorical tokens of the metaphorical sentences. We refer to this process as Masked Metaphor Modeling (MMM; the red box on the right of Fig. 2). MMM with BERT was applied only on sentences correctly classified as metaphorical by BERT while MMM with XLM-R was applied on sentences correctly classified by XLM-R. T5 and BART were applied on both and results are shown in respective columns (see Table 5). In MOH-X, the accuracy scores for nouns and verbs show the percentage of correctly reconstructed metaphorical tokens (respectively nouns or verbs) inside the sentences, by the different reconstruction models. TroFi sentences comprise only verb metaphors while TroFi-X sentences comprise three metaphorical tokens each; the first two, \( T1 \) and \( T2 \), can be any part-of-speech tokens, while \( V \) can only be verb metaphors.

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**The following sentence taken from TroFi-X is given as an example: Beyond that, conditions on board were so vile that “the sailor was at greater risk eating his meals abroad than fighting.” Here, risk is “token 1” (in this case, it is a noun), meals is “token 2” (in this case, also a noun), and eating is the verb token of the sentence (one of the three metaphorical tokens in each TroFi-X sentence is always a verb).**
Table 5: Ratio of literal sentences that were classified as metaphorical, after applying MMM on a verb, noun, or adjective per sentence. XLM-R used in both tasks.

|            | Nouns | Verbs | Adj. |
|------------|-------|-------|------|
| Wikipedia - Music | 0.22  | 0.43  | 0.31 |
| Wikipedia - technology | 0.08  | 0.29  | 0.07 |
| Gutenberg Poetry Corpus | **0.24** | **0.56** | **0.27** |

MMM with XLM-R is consistently better than that with BERT. This is also true for MOH-X, where BERT outperforms XLM-R for metaphorical sentence classification (see Table 3), which means that XLM-R is better in reconstruction. BART and T5 are also overall better when metaphorical sentence classification has been performed with XLM-R. When focusing on results obtained using XLM-R as the metaphorical sentence classifier, nouns are more accurately reconstructed by BART on MOH-X and TroFi-X (for T2). T5, which achieves a high accuracy in all datasets as far as verb reconstruction is concerned, is better than BART in TroFi and TroFi-X and only slightly worse in MOH-X. When comparing MMM with T5 and BART, the latter two seem to work better across MOH-X and TroFi sentences. MMM models, however, perform better on the first tokens (T1) of TroFi-X sentences.

5 Building synthetic metaphors

The proposed algorithm required two training steps. First, a text classifier learns to classify metaphorical from literal sentences. Second, metaphorical sentences, which were correctly classified by our classifier as metaphorical, were passed to a reconstruction step, where metaphorical tokens were masked and then recovered through extraction (T5, BART) and masked language modeling (BERT, XLM-R). The algorithm then receives a corpus of literal sentences, masks a random token (Algorithm 1, line 5), and replaces it with a metaphorical one, inferring new metaphorical sentences created from originally literal ones. Our experimentation with this inference part is described next.

As literal sentences we used: 2,000 sentences scraped from Wikipedia, related respectively to music (1,000 sentences) and technology (1,000 sentences) topics; 1,000 sentences scraped from the Gutenberg Poetry Corpus [Jacobs 2018], which comprises 3,085,117 lines of poetry extracted from hundreds of books. We applied our fine-tuned XLM-R classifier (Table 3) on these sentences, and the ones classified as literal (Algorithm 1, line 4) were fed into our XLM-R-based MMM (Table 4). Filtering out incorrectly transferred sentences (line 7), the algorithm yields new metaphorical sentences (line 8).

Table 5 presents the ratio of originally literal sentences that have been (automatically) classified as metaphorical, after replacing a randomly selected (literal) noun, verb or adjective with a metaphorical token. Higher ratios are preferred, because they indicate a successful transfer based on the employed classifier. When the token to be replaced by the MMM was a verb, more than 50% of the literal sentences from the Gutenberg Poetry Corpus and 43% of the Wikipedia sentences related to music were turned into metaphorical ones. When the token was an adjective, the ratios dropped to 27% and 31% respectively. The lowest ratios were obtained for nouns, where 24% of the Gutenberg and 22% of the Wikipedia (related to music) sentences were transferred. Wikipedia sentences related to technology had the lowest ratios of all, achieving 29% for verbs but 8% for nouns and 7% for adjectives.

Following the work of Chakrabarty et al. [2021], we performed human evaluation of the newly constructed metaphorical sentences, by comparing them against human-generated ones. Two hundred metaphorical sentences were selected, 100 that were built with our algorithm, starting from sentences that originally came from both Wikipedia and Gutenberg Poetry Corpus data sources, and 100 from our employed metaphorical datasets. Two graduates of English literature were then asked to evaluate each sentence. We asked the annotators to assess How metaphoric are the generated utterances and named this dimension metaphoricity. Tokens that were supposedly being used in a figurative way inside the sentences were shown in bold and sentences were shuffled. For each sentence, then, four different dimensions were evaluated, vis. fluency, meaning, creativity, and metaphoricity.

1. **Fluency (Flu)** - “How fluent, grammatical, well formed and easy to understand are the generated utterances?”
2. **Meaning (Mea)** - “Are the input and the output referring or meaning the same thing?”
3. **Creativity (Cre)** - “How creative are the generated utterances?”
4. **Metaphoricity (Met)** - “How metaphoric are the generated utterances?”

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3 The location of the metaphor is assumed known.

4 We note that in principle, any number of new metaphorical sentences can be generated given any positive ratio. For example, the proposed algorithm can be applied on more literal sentences to counter-balance a low ratio.
For each one of these dimensions, a score ranging from 1 (very low) to 5 (very high) had to be assigned based on the evaluator’s personal judgement. Example sentences that were taken from [Chakrabarty et al., 2021] were provided to the annotators, in order to clarify the assignment further. Two are shown below:

1. The scream pierced the night. Fluency: 4, Meaning: 5, Creativity: 4, Metaphoricity: 4;

2. The wildfire swept through the forest at an amazing speed. Fluency: 4, Meaning: 3, Creativity: 5, Metaphoricity: 4

Table 6: Human evaluation for metaphorical sentences that were generated by our algorithm (top) or by humans (low). Scores are averaged across the sentences regarding fluency (Fl), meaning (Mn), creativity (Cr) and metaphoricity (Mt).

|       | Fl  | Mn  | Cr  | Mt  |
|-------|-----|-----|-----|-----|
| A1    | Ours| 4.00| 3.65| 3.11| 3.41|
|       | Hum.| 3.89| 4.27| 2.82| 3.21|
| A2    | Ours| 4.39| 4.25| 3.18| 3.06|
|       | Hum.| 4.69| 4.41| 2.69| 2.97|
| Avg   | Ours| 4.20| 3.95| 3.15| 3.24|
|       | Hum.| 4.29| 4.34| 2.76| 3.09|

Table 6 shows the human evaluation for the system- and human-generated metaphorical sentences, regarding fluency, meaning, creativity and metaphoricity. The scores, averaged per creation source and dimension for each annotator, show that the first evaluator (A1) finds that the system-generated metaphors are better in three out of four dimensions. The second evaluator (A2) scored the human-generated metaphors higher in terms of fluency, but also scored the system-generated ones higher in terms of creativity and metaphoricity. The macro-averaged scores across the two annotators in the last two rows reflect this finding, showing that our system-generated metaphors are better in creativity and metaphoricity but lack in meaning preservation.

6 Discussion

A quality assessment is presented in Table 7 which shows three system-generated sentences that obtained the highest-score (ranking based on A1) and the respective three highest-scored human-generated ones, along with their four assigned scores. Although all the six sentences, human and system-generated, got an excellent score in fluency and meaning, our algorithm creates better metaphors with regards to creativity and metaphoricity. Two system-generated sentences out of three got an excellent creativity score with the third one obtaining a score equal to 4, while all

Table 7: The three highest-scored human (H) and system (S)-generated metaphors. The latter outperform human-generated ones on average. We show the scores in a 1-5 scale, with 1 denoting the worst and 5 the best, that were assigned to each sentence for Fluency (Fl), Meaning (Mn), Creativity (Cr) and Metaphoricity (Mt). The tokens highlighted in bold are the words that are supposedly being used in a figurative way inside the sentences.

| Metaphorical sentence (metaphor in bold) | Original literal word | Fl  | Mn  | Cr  | Mt  |
|------------------------------------------|-----------------------|-----|-----|-----|-----|
| S Day by day his heart within him grew more saturated with love and longing | was | 5   | 5   | 5   | 5   |
| S Through the green lanes of the country, where the tangled barberry-bushes fluttered their tufts of crimson berries | tangled | 5   | 5   | 5   | 5   |
| S Love the wind among the branches, and the rain-shower and the snow-storm, and the roaring of great rivers | rushing | 5   | 5   | 4   | 5   |
| H Headlines scream of pollution and dwindling natural resources | – | 5   | 5   | 4   | 5   |
| H Musical creativity really flowed inside that family | – | 5   | 5   | 4   | 4   |
| H This one scandal could very well sink his candidacy | – | 5   | 5   | 4   | 4   |
human-generated sentences got a creativity score of 4. All three system-generated sentences got a metaphoricity score of 5, while only one of the top human-generated sentences reached this score.

We believe that creativity is a very important dimension, which can facilitate human tasks, e.g., by providing inspiration. This is why it is worth noting that our approach not only shows promising results based on human evaluation, but also generates more creative metaphoric sentences than its human competitor.

The standard error of mean per dimension (Fl, Me, Cr, Mt) is respectively 0.09, 0.11, 0.16, 0.15 for the first annotator and 0.06, 0.10, 0.08, 0.08 for the second. The ones based on our system were only slightly higher. The mean absolute error between the annotations of the two annotators, per dimension, is respectively 1.04, 0.92, 1.35 and 1.24, reflecting the subjectiveness of the task: in fact, these differences are not statistically significant.

As far as the qualitative analysis of the results is concerned, the following are a few examples showing where the pipeline failed. In particular, we report examples from the Wikipedia music, Wikipedia technology and Gutenberg poetry corpus reconstructed sentences, whose newly generated verbs were mistakenly still identified as literal by our system in the final process' step. In fact, it is clear that these reconstructed words were characterized by a more metaphorical meaning compared to their original counterparts (thus, accomplishing the algorithm's purpose).

Wikipedia music:

1. "Music drawn solely from electronic generators was first produced in Germany in 1953" - Reconstructed sentence: drawn was still classified as literal
2. "Music produced solely from electronic generators was first produced in Germany in 1953" - Original literal sentence

Wikipedia technology - Example I:

1. "The prehistoric invention of shaped stone tools inspired by the discovery of how to control fire increased sources of food..." - Reconstructed sentence: inspired was still classified as literal
2. "The prehistoric invention of shaped stone tools followed by the discovery of how to control fire increased sources of food..." - Original literal sentence

Wikipedia technology - Example II:

1. "The invention of the wheel encouraged humans to travel in and control their environment" - Reconstructed sentence: encouraged was still classified as literal
2. "The invention of the wheel helped humans to travel in and control their environment" - Original literal sentence

Gutenberg poetry corpus:

1. "Finally, my mother used to rock me to sleep..." - Reconstructed sentence: rock was still classified as literal
2. "'Finally, my mother used to put me to sleep..." - Original literal sentence

Improving metaphorical text classification

Motivated by the promising human evaluation of our system-generated metaphors, we hypothesise that they might be beneficial as training material for metaphor-related tasks. To experiment with this hypothesis, a random sample of our new system-generated metaphorical sentences has been attached to the TroFi-X training set that we used to train the metaphorical sentence XLM-R classifier. We also attached the same number of randomly sampled literal sentences, leading to 428 more training sentences in total (an increase of 37%). Both the artificial metaphorical sentences and the literal ones have been extracted from Wikipedia and the Gutenberg Poetry Corpus. By fine-tuning the XLM-R metaphorical/literal sentence classifier on the increased training set, a percentage increase of all four classification metrics has been registered across TroFi-X over the respective scores of Table 3: 3% up in F1 (96.12%), Precision

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5 The similarity between the initial literal and the new metaphorical sentences that are constructed was computed with BERTScore [Zhang et al., 2020] and was found to be very high (0.99) for all topics, probably due to the fact that only a single word had to change per sentence.

6 We employed TroFi-X for this experiment, since this dataset comprises nouns, verbs and adjectives, similarly to the new artificial data.
Table 8: Accuracy of BERT and XLM-R for metaphor location detection across the datasets

|               | MOH-X | TROFI | TROFI-X |
|---------------|-------|-------|---------|
| BERT          | 70.97 | 47.62 | 56.67   |
| XLM-R         | 77.42 | 57.41 | 63.33   |

(96.88%) and Recall (95.38%); 2.8% in Accuracy (96.55%). Simpler augmentation strategies, such as random instance duplication, yielded no improvement. 7

**Metaphorical token recognition**

BERT and XLM-R can be used to successfully classify metaphorical sentences (Table 3) and to reconstruct a metaphor through Masked Metaphor Modeling (MMM), with XLM-R achieving even the best reconstruction accuracy in one case (see T1 of TroFi-X in Table 4). Although reconstruction is based on the fact that the information of the location of the metaphor is already known (Section 4.3), we also assessed the ability of the BERT and XLM-R metaphorical sentence classifiers to recognize the exact location of the metaphor. Automated metaphor recognition could potentially allow the use of a dataset \( I^{M/L} \) that will only comprise text level annotations without any token-level tags, such as the much larger TroFi dataset (Table 2).

We filtered the metaphorical sentences that were correctly classified (true positives) respectively by the fine-tuned BERT and XLM-R sentence classifiers and then we used the attention of the CLS token, in order to detect the location of the metaphor. In this study, we employed the fifth attention layer and the second to last (eleventh) head, since this combination yielded the best results in preliminary experiments, but we note that there are 144 possible layer-head combinations that could have also been investigated [Clark et al., 2019; Voita et al., 2019; Rogers et al., 2020]. The location of the metaphor, then, is simply considered to be the token of the sentence that received the maximum attention. Table 8 provides the accuracy for this metaphor location detection task, which is the fraction of metaphorical sentences whose metaphor location was correctly detected. XLM-R is consistently better than BERT, while both models perform best in MOH-X and worse in TroFi.

Three example MOH-X sentences are shown below with metaphorical tokens in bold and italics, and with XLM-R’s attention heatmap in gray shade. In the first sentence, most of the attention was on the gold metaphorical verb. In the second one, it was on a part of the gold verb while in the third one it was on the gold noun (‘soup’) and the (not gold) adjective on the left (‘hot’).

1. He **marched** into the classroom and announced the exam.
2. I **wrestled** with this **decision** for years.
3. A **hot soup** will **revive** me.

We note that only metaphorical words were ablated here, rather than any word as in the MLM’s objective. We consider this use of Masked Language Modeling novel due to this explicit focus, which would have made word control and selection far more challenging. The usefulness of metaphorical location recognition is indicated by the high accuracy (see Table 8; it reaches up to 77.42%), as it can unlock the development of larger training datasets in future work.

**Ethical Considerations**

The following ethical considerations are worth our attention and perhaps further investigation in future work:

- The proposed approach could in principle be used to create toxic (e.g., sarcastic or heavily ironic) text alternations about people. To avoid such misuse, the employed models were fine-tuned on data obtained from Wikipedia, which do not comprise abusive language or ironic speech.
- By implementing the proposed algorithm on data collected from the wild, one could end up sharing explicit details leaking information. One of the authors undertook a manual investigation of the data to verify that this was not the case in this study. Furthermore, we suggest that future use of the algorithm shall validate that the data will not contain sensitive user information that is not shared with the world. Examples of such information comprise health or negative financial status, racial or ethnic origin, religious or philosophical affiliation or beliefs, sexual orientation, trade union membership, alleged or actual commission of crime.

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7 We used the same number of added instances and the results showed that the same number of true positives is achieved for literal texts but less for metaphorical ones.
• In this study we opted for language models that are trained on data collected from the Web. These models may carry bias and have issues with abusive language [Sheng et al. [2019], Wallace et al. [2019]]. We expect that the inductive bias of our models will limit inadvertent negative impacts. For example, BART is a conditional language model, which provides more control of the generated output. In any case, however, updating Algorithm [1] with the addition of a text toxicity classifier [Kiritchenko et al. [2021]] could limit any unwanted outcomes.

• We note that ethical issues that go beyond the authors’ knowledge may exist. Hence, and in order to allow future studies of possible weaknesses and vulnerabilities, along with the artificial data we release the source code and released trained model.  

7 Conclusion

This study presented an algorithm for transferring literal to metaphorical language, by employing metaphorical sentence classification and metaphor reconstruction. The obtained results showed that 24%, 31% and 56% of the originally literal sentences get classified as metaphorical after masking and then reconstructing a noun, an adjective or a verb, respectively. Human evaluation on a mixed test set of system- and human-generated metaphorical sentences showed that we are able to generate synthetic metaphors that are considered on average as more creative and metaphorical than ones created by a human competitor. By using our synthetic metaphors to augment a metaphorical sentence classification dataset, we registered an F1 improvement of 3% for an XLM-R metaphorical sentence classification baseline that was fine-tuned on the augmented dataset. The potential benefit of using a larger-scale version of our synthetic dataset, in order to improve metaphorical sentence classification further, will be studied in future work. External reviewers have provided us with very useful feedback, which has improved this paper. Our extensive experiments concern a challenging natural language generation task that deserves more work, which we hope to facilitate with our shared resources. Finally, we consider that our intuitive suggested approach can inspire other researchers in this field and beyond, as in text simplification.

Limitations

• The proposed approach receives (likely) literal texts, that are ablated (masking) and then reconstructed as metaphorical ones. Human evaluation showed that the system-generated metaphors follow behind human-generated ones when assessing “meaning”. However, we did not investigate the reasons behind this assessment, which could lead to suggestions for future improvements.

• We used artificial data, generated by employing our algorithm, in order to improve metaphorical text classification with data augmentation. The benefit was more clearly shown compared to simple oversampling techniques. We note, however, that several augmentation strategies could have been tested, such as using large pre-trained language models to generate text [Bayer et al. [2021]]. Such a study could reveal the potential of the proposed approach as an augmentation strategy.

• Extrinsic evaluation of this approach, which could improve downstream tasks, has not been explored in detail yet and will be studied in future work.

• Although label leaking could happen in our experiments, we note that this is a valid concern with any augmentation application. Nevertheless, all our data and code will be shared to allow further analysis and validation.

References

George Lakoff and Mark Johnson. *Metaphors we Live by*. University of Chicago Press, Chicago, 1980. ISBN 978-0-226-46800-6.

Tuhin Chakrabarty, Yejin Choi, and Vered Shwartz. It’s not rocket science: Interpreting figurative language in narratives. *Transactions of the Association for Computational Linguistics*, 10:589–606, 2022.

Jerry Liu, Nathan O’Hara, Alexander Rubin, Rachel Draelos, and Cynthia Rudin. Metaphor detection using contextual word embeddings from transformers. In *Proceedings of the Second Workshop on Figurative Language Processing*, pages 250–255, 2020.

Kelsey Hilton, Akbar Siami Namin, and Keith S Jones. Metaphor identification in cybersecurity texts: a lightweight linguistic approach. *SN Applied Sciences*, 4(2):1–22, 2022.

*The URL remains hidden to preserve the anonymity of the authors during the review process. The synthetic data and other material are now shared as supplementary material.*
D. Fass. Processing metonymy and metaphor. In A. Lesgold and V. Patel, editors, Contemporary Studies in Cognitive Science and Technology, volume 1. Ablex Publishing Corporation, Greenwich, 1997.

Julia Birke and Anoop Sarkar. A clustering approach for nearly unsupervised recognition of nonliteral language. In 11th Conference of the European Chapter of the Association for Computational Linguistics, pages 329–336, Trento, Italy, April 2006. Association for Computational Linguistics. URL https://aclanthology.org/E06-1842

Ekaterina Shutova, Lin Sun, and Anna Korhonen. Metaphor identification using verb and noun clustering. In Proceedings of the 23rd International Conference on Computational Linguistics (Coling 2010), pages 1002–1010, Beijing, China, August 2010. Coling 2010 Organizing Committee. URL https://aclanthology.org/C10-1113

G.J. Steen, A.G. Dorst, J.B. Herrmann, A.A. Kaal, T. Krennmayr, and T. Pasma. A method for linguistic metaphor identification. From MIP to MIPVU. Number 14 in Converging Evidence in Language and Communication Research. John Benjamins, 2010. ISBN 9789027239037.

Xiaoyu Tong, Ekaterina Shutova, and Martha Lewis. Recent advances in neural metaphor processing: A linguistic, cognitive and social perspective. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 4673–4686, Online, June 2021. Association for Computational Linguistics. doi:10.18653/v1/2021.naacl-main.372 URL https://aclanthology.org/2021.naacl-main.372

Tim Van de Cruys. Automatic poetry generation from prosaic text. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2471–2480, Online, July 2020. Association for Computational Linguistics. doi:10.18653/v1/2020.acl-main.223 URL https://aclanthology.org/2020.acl-main.223

Tuhin Chakrabarty, Xurui Zhang, Smaranda Muresan, and Nanyun Peng. MERMAID: Metaphor generation with symbolism and discriminative decoding. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 4250–4261, Online, June 2021. Association for Computational Linguistics. doi:10.18653/v1/2021.naacl-main.336 URL https://aclanthology.org/2021.naacl-main.336

Zhifei Yu and Xiaojun Wan. How to avoid sentences spelling boring? towards a neural approach to unsupervised metaphor generation. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 861–871, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi:10.18653/v1/N19-1092 URL https://aclanthology.org/N19-1092

Jennifer Brooks and Abdou Youssef. Discriminative pattern mining for natural language metaphor generation. In 2020 IEEE International Conference on Big Data (Big Data), pages 4276–4283, 2020. doi:10.1109/BigData50022.2020.9378442

Kevin Stowe, Tuhin Chakrabarty, Nanyun Peng, Smaranda Muresan, and Iryna Gurevych. Metaphor generation with conceptual mappings. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 6724–6736, Online, August 2021. Association for Computational Linguistics. doi:10.18653/v1/2021.acl-long.524 URL https://aclanthology.org/2021.acl-long.524

Yuri Bizzoni and Mehdi Ghanimifard. Bigrams and BiLSTMs two neural networks for sequential metaphor detection. In Proceedings of the Workshop on Figurative Language Processing, pages 91–101, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi:10.18653/v1/W18-0911 URL https://aclanthology.org/W18-0911

Xianyang Chen, Chee Wee (Ben) Leong, Michael Flor, and Beata Beigman Klebanov. Go figure! multi-task transformer-based architecture for metaphor detection using idioms: ETS team in 2020 metaphor shared task. In Proceedings of the Second Workshop on Figurative Language Processing, pages 235–243, Online, July 2020. Association for Computational Linguistics. doi:10.18653/v1/2020.figlang-1.32 URL https://aclanthology.org/2020.figlang-1.32

Verna Dankers, Karan Malhotra, Gaurav Kudva, Volodymyr Medentsiy, and Ekaterina Shutova. Being neighbourly: Neural metaphor identification in discourse. In Proceedings of the Second Workshop on Figurative Language Processing, pages 227–234, Online, July 2020. Association for Computational Linguistics. doi:10.18653/v1/2020.figlang-1.31 URL https://aclanthology.org/2020.figlang-1.31

Ge Gao, Eunsol Choi, Yejin Choi, and Luke Zettlemoyer. Neural metaphor detection in context. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 607–613, Brussels, Belgium, October-November 2018. Association for Computational Linguistics. doi:10.18653/v1/D18-1060 URL https://aclanthology.org/D18-1060
Hongyu Gong, Kshitij Gupta, Akriti Jain, and Suma Bhat. IlliniMet: Illinois system for metaphor detection with contextual and linguistic information. In Proceedings of the Second Workshop on Figurative Language Processing, pages 146–153, Online, July 2020. Association for Computational Linguistics. doi:10.18653/v1/2020.figlang-1.21 URL https://aclanthology.org/2020.figlang-1.21

Rui Mao, Chenghua Lin, and Frank Guerin. End-to-end sequential metaphor identification inspired by linguistic theories. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3888–3898, Florence, Italy, July 2019. Association for Computational Linguistics. doi:10.18653/v1/P19-1378 URL https://aclanthology.org/P19-1378

Agnieszka Mykowiecka, Aleksander Wawer, and Malgorzata Marciniak. Detecting figurative word occurrences using recurrent neural networks. In Proceedings of the Workshop on Figurative Language Processing, pages 124–127, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi:10.18653/v1/W18-0916 URL https://aclanthology.org/W18-0916

Malay Pramanick, Ashim Gupta, and Pabitra Mitra. An LSTM-CRF based approach to token-level metaphor detection. In Proceedings of the Workshop on Figurative Language Processing, pages 67–75, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi:10.18653/v1/W18-0908 URL https://aclanthology.org/W18-0908

Chuandong Su, Fumiyo Fukumoto, Xiaoxi Huang, Jiyi Li, Rongbo Wang, and Zhiqun Chen. DeepMet: A reading comprehension paradigm for token-level metaphor detection. In Proceedings of the Second Workshop on Figurative Language Processing, pages 30–39, Online, July 2020. Association for Computational Linguistics. doi:10.18653/v1/2020.figlang-1.4 URL https://aclanthology.org/2020.figlang-1.4

Chuhan Wu, Fangzhao Wu, Yubo Chen, Sixing Wu, Zhigang Yuan, and Yongfeng Huang. Neural metaphor detecting with CNN-LSTM model. In Proceedings of the Workshop on Figurative Language Processing, pages 110–114, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi:10.18653/v1/W18-0913 URL https://aclanthology.org/W18-0913

Krishnkant Swarnkar and Anil Kumar Singh. Di-LSTM contrast: A deep neural network for metaphor detection. In Proceedings of the Workshop on Figurative Language Processing, pages 115–120, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi:10.18653/v1/W18-0914 URL https://aclanthology.org/W18-0914

Jeffrey Pennington, Richard Socher, and Christopher Manning. GloVe: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, Doha, Qatar, October 2014. Association for Computational Linguistics. doi:10.3115/v1/D14-1162 URL https://aclanthology.org/D14-1162

Yuxuan Wang, Yutai Hou, Wanxiang Che, and Ting Liu. From static to dynamic word representations: a survey. International Journal of Machine Learning and Cybernetics, 11:1611—1630, 07 2020. doi:10.1007/s13042-020-01069-8

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. pages 7871–7880, 01 2020. doi:10.18653/v1/2020.acl-main.703

Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. Mass: Masked sequence to sequence pre-training for language generation. In International Conference on Machine Learning, pages 5926–5936, 2019.

Arthur Jacobs. The gutenberg english poetry corpus: Exemplary quantitative narrative analyses. Frontiers in Digital Humanities, 5:5, 04 2018. doi:10.3389/fdigh.2018.00005

Karen Sullivan. Grammar in metaphor: A construction grammar account of metaphorical language. 2007.

Saif Mohammad, Ekaterina Shutova, and Peter Turney. Metaphor as a medium for emotion: An empirical study. In Proceedings of the Fifth Joint Conference on Lexical and Computational Semantics, pages 23–33, Berlin, Germany, August 2016. Association for Computational Linguistics. doi:10.18653/v1/S16-2003 URL https://aclanthology.org/S16-2003

Ekaterina Shutova, Douwe Kiela, and Jean Maillard. Black holes and white rabbits: Metaphor identification with visual features. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 160–170, San Diego, California, June 2016. Association for Computational Linguistics. doi:10.18653/v1/N16-1020 URL https://aclanthology.org/N16-1020

Rui Mao, Chenghua Lin, and Frank Guerin. Word embedding and WordNet based metaphor identification and interpretation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1222–1231, Melbourne, Australia, July 2018. Association for Computational Linguistics. doi:10.18653/v1/P18-1113 URL https://aclanthology.org/P18-1113
Adwait Ratnaparkhi. A maximum entropy model for part-of-speech tagging. *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 133–142, 12 2002.

Srinivas Bangalore and Aravind Joshi. Supertagging: An approach to almost parsing. *Computational Linguistics*, 25:237–265, 06 1999.

Irina Rish. An empirical study of the naïve bayes classifier. *IJCAI 2001 Work Empir Methods Artif Intell*, 3:6, 01 2001.

Michele Fratello and Roberto Tagliaferri. Decision trees and random forests. In *Encyclopedia of Bioinformatics and Computational Biology*, 2019.

Gongde Guo, Hui Wang, David A. Bell, Yaxin Bi, and Kieran R. C. Greer. Knn model-based approach in classification. In *OTM*, 2003.

Theodoros Evgeniou and Massimiliano Pontil. Support vector machines: Theory and applications. In *Machine Learning and Its Applications*, 2001.

Joanne Peng, Kuk Lee, and Gary Ingersoll. An introduction to logistic regression analysis and reporting. *Journal of Educational Research - J EDUC RES*, 96:3–14, 09 2002. doi:10.1080/00220670209598786

Popescu Marius, Valentina Balas, Liliana Perescu-Popescu, and Nikos Mastorakis. Multilayer perceptron and neural networks. *WSEAS Transactions on Circuits and Systems*, 8:579–588, 07 2009.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding, 2019.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Eduard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451, Online, July 2020. Association for Computational Linguistics. doi:10.18653/v1/2020.acl-main.747 URL https://aclanthology.org/2020.acl-main.747

Felipe Alfaro, Marta R. Costa-jussà, and José A. R. Fonollola. BERT masked language modeling for co-reference resolution. In *Proceedings of the First Workshop on Gender Bias in Natural Language Processing*, pages 76–81, Florence, Italy, August 2019. Association for Computational Linguistics. doi:10.18653/v1/W19-3811 URL https://aclanthology.org/W19-3811

Naman Goyal, Jingfei Du, Myle Ott, Giri Anantharaman, and Alexis Conneau. Larger-scale transformers for multilingual masked language modeling. In *Proceedings of the 6th Workshop on Representation Learning for NLP (RepL4NLP-2021)*, pages 29–33, Online, August 2021. Association for Computational Linguistics. doi:10.18653/v1/2021.repl4nlp-1.4 URL https://aclanthology.org/2021.repl4nlp-1.4

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilián Q. Weinberger, and Yoav Artzi. Bertscore: Evaluating text generation with bert. *ArXiv*, abs/1904.09675, 2020.

Kevin Clark, Urvashi Khandelwal, Omer Levy, and Christopher D. Manning. What does BERT look at? an analysis of BERT’s attention. In *Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 276–286, Florence, Italy, August 2019. Association for Computational Linguistics. doi:10.18653/v1/W19-4828 URL https://aclanthology.org/W19-4828

Elena Voita, David Talbot, Fedor Moiseev, Rico Sennrich, and Ivan Titov. Analyzing multi-head self-attention: Specialized heads do the heavy lifting, the rest can be pruned. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5797–5808, Florence, Italy, July 2019. Association for Computational Linguistics. doi:10.18653/v1/P19-1580 URL https://aclanthology.org/P19-1580

Anna Rogers, Olga Kovaleva, and Anna Rumphisy. A primer in bertology: What we know about how bert works. *Transactions of the Association for Computational Linguistics*, 8:842–866, 12 2020. doi:10.1162/tacl_a_00349

Emily Sheng, Kai-Wei Chang, Premkumar Natarajan, and Nanyun Peng. The woman worked as a babysitter: On biases in language generation. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3407–3412, Hong Kong, China, November 2019. Association for Computational Linguistics. doi:10.18653/v1/D19-1339 URL https://aclanthology.org/D19-1339

Eric Wallace, Shi Feng, Nikhil Kandpal, Matt Gardner, and Sameer Singh. Universal adversarial triggers for attacking and analyzing NLP. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2153–2162, Hong Kong, China, November 2019. Association for Computational Linguistics. doi:10.18653/v1/D19-1221 URL https://aclanthology.org/D19-1221
A Appendix

A.1 Shared Software and Data

All the exploited models, software and Python code have been shared and run using Google Colaboratory’s GPUs. The characteristics and the hyperparameter configurations for the best-performing model, the fine-tuned XLM-R metaphor classifier, are the following:

- Model: fine-tuned XLMRobertaForSequenceClassification model from Transformers
- Tokenizer: XLMRobertaTokenizer from Transformers
- batch size = 32
- number of labels = 2
- optimizer = AdamW
- learning rate = 2e-5 (default value = 5e-5)
- adam_epsilon = 1e-8 (default value)
- epochs = 10
- seed value = 42

Additional details such as the models’ runtime (training, inference, etc.), validation performances and number of training and evaluation runs, depend on the datasets being used and can be found in comments inside the shared code for all experiments/approaches.

All the datasets that were used and/or obtained during the experiments have been shared. The datasets are in English language and in .csv, .txt or .xlsx formats. Sentences from MOH-X, TroFi and TroFi-X are either labelled as metaphorical (label = 1) or literal (label = 0), and the datasets’ structure is the following:

- MOH-X: arg1, arg2, verb, sentence, verb_idx, label
- TroFi: verb, sentence, verb_idx, label
- TroFi-X: arg1, arg2, verb, sentence, verb_stem, label

Each original and custom dataset’s number of sentences can be found in the paper, along with an explanation of any data that were excluded, and all pre-processing steps. Data initially scraped from Wikipedia and Gutenberg poetry corpus (then processed with masked metaphor modeling), as well as data obtained through augmentation techniques described in the paper, were kept in the following format:

- sentence: scraped sentences with original or masked tokens
- label: 1 = metaphorical or 0 = literal, for the metaphor classifiers

Additional details such as those regarding train/validation/test splits ratios can be found in comments inside the shared code for all experiments/approaches.