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Sarcasm detection using news headlines dataset

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ABSTRACT

Sarcasm has been an elusive concept for humans. Due to interesting linguistic properties, sarcasm detection has gained traction of the Natural Language Processing (NLP) research community in the past few years. However, the task of predicting sarcasm in a text remains a difficult one for machines as well, and there are limited insights into what makes a sentence sarcastic. Past studies in sarcasm detection either use large scale datasets collected using tag-based supervision or small scale manually annotated datasets. The former category of datasets are noisy in terms of labels and language, whereas the latter category of datasets do not have enough instances to train deep learning models reliably despite having high-quality labels. To overcome these shortcomings, we introduce a high-quality and relatively larger-scale dataset which is a collection of news headlines from a sarcastic news website and a real news website. We describe the unique aspects of our dataset and compare its various characteristics with other benchmark datasets in sarcasm detection domain. Furthermore, we produce insights into what constitute as sarcasm in a text using a Hybrid Neural Network architecture. First released in 2019, we dedicate a section on how the NLP research community has extensively relied upon our contributions to push the state of the art further in the sarcasm detection domain. Lastly, we make the dataset as well as framework implementation publicly available to facilitate continued research in this domain.

1. Introduction

There have been many studies on sarcasm detection in the past that have either used a small high-quality labeled dataset or a large noisy labeled dataset. Larger datasets are collected using tag-based supervision like (Bamman and Smith, 2015) collected dataset from Twitter using certain hashtags or Khodak et al. (2018) collected dataset from Reddit using "/s" tag. Smaller datasets with high-quality labels need manual labeling like (Oraby et al., 2017) contributing sarcasm annotated dialogues or Semeval challenge[1] contributing Twitter-based dataset. In each type of scenario, the interpretability of sarcasm can be limited by lack of access to large *and* high-quality datasets due to the following reasons:

- Social media-based datasets are collected using tag-based supervision. As per previous studies by Liebrecht et al. (2013) and Joshi et al. (2017), such datasets can have noisy labels. Furthermore, people use very informal language on social media which introduces sparsity in vocabulary and for many words, pretrained embeddings are not available. Lastly, many posts can be replies to other posts, and detecting sarcasm in such cases requires the availability of contextual information. Thus, deep learning frameworks trained using these types of datasets face challenges in uncovering real sarcastic elements owing to the presence of noise in several aspects.
- Manually labeled datasets usually have a limited number of sarcastic instances due to the high cost associated with obtaining quality labels. This happens because the understanding of sarcasm differs from person to person and there can be a low agreement in many instances. The deep learning frameworks trained using these datasets remain underpowered, thus falling short of uncovering real sarcastic representations.
- Limited qualitative analyses are available from models trained on previously available datasets to showcase what the models are learning and in which cases they can recognize sarcasm accurately.

We understand that detecting sarcasm requires an understanding of common sense knowledge, without which the model might not actually understand what sarcasm is and may just pick up some discriminative lexical cues. This direction has not been addressed in previous studies

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[1] https://competitions.codalab.org/competitions/17468.

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to the best of our knowledge. Due to these limitations, it has been difficult to understand and interpret the elusive concept of sarcasm. To tackle these challenges, we summarize our contributions in this work as follows:

- We first introduce a high-quality and (relatively) large-scale dataset for sarcasm detection and showcase how it is superior in terms of labels and language as compared to previously available benchmark datasets in this domain.
- Next, we use a Hybrid Neural Network with an attention mechanism to showcase how we can reliably train a deep learning model on the newly contributed dataset and produce qualitative analyses to interpret the concept of sarcasm through its attention module.
- Lastly, we survey some of the latest NLP research in the sarcasm detection domain to showcase the impact our work has had since 2019.

The rest of the paper is organized in the following manner: in Section 2, we describe the dataset collected by us to overcome the limitations of previously used benchmark datasets. In Section 3, we describe the Hybrid Neural Network architecture, which we use to showcase quantitative and qualitative results on our dataset. In Section 4 and Section 5, we provide experiment design details, results, and analyses. In Section 6, we cover prominent NLP studies relying on our contributions since 2019. To conclude, we provide a few unexplored future directions in Section 7.

2. News headlines dataset

To overcome the limitations related to label and language noise in social media-based datasets as well as the low-scale nature of other hand-labeled datasets, we present the *News Headlines Dataset*.[2] It is collected from two news websites: *TheOnion*.[3] and *HuffPost*[4] TheOnion produces sarcastic versions of current events and we collect all the headlines from News in Brief and News in Photos categories to construct the sarcastic part of the corpus. We collect real and non-sarcastic news headlines from HuffPost, an American online news media company, using their news archive page. To explore the language of the text collected from two sources, we visualize the word clouds in Fig. 1 to showcase the types of words that occur frequently in each category. We do not notice any immediate distinction of words within each category, which could be because sarcasm is defined in a certain context and does not necessarily have to use specific words. We compare the general statistics of our dataset with some benchmark sarcasm detection datasets in Table 1 and highlight some of the unique characteristics. To summarize, the *News Headlines Dataset* has the following advantages over the existing sarcasm datasets:

- Since news headlines are written by professionals in a formal manner, there are no spelling mistakes or informal usage like in social media-based datasets (Semeval or SARC). This reduces the vocabulary sparsity and also increases the chance of finding pretrained embeddings for improved performance. This is evident from the percentage of words we were able to find word2vec embeddings for in the News Headlines Dataset (∼ 77%) as compared to the Semeval Twitter-based dataset (∼ 64%).
- Since the sole purpose of *TheOnion* is to publish sarcastic news, we get very high quality labels in relatively larger quantity. In that sense, the quality of label is controlled as opposed to self annotated datasets like SARC and at the same time, the scale of the dataset is much larger than manually labeled datasets like IAC or SemEval.
- In social media-based datasets, the sarcastic posts may not be self-contained as the dataset may include posts that reply to other posts which are not part of the dataset. The news headlines we obtained from two news websites are, however, self-contained and do not suffer from this issue. This would ultimately help in teasing apart the real sarcastic elements from the corpus.

3. Hybrid neural network

We take inspiration from a seminal study in sarcasm detection by Amir et al. (2016), which takes in pretrained user embeddings (context) and tweets (content) as input to the CNN-based model and outputs a binary value for the sarcastic nature of the tweet. To draw insights from our newly collected News Headlines Dataset, we tweak this architecture to remove the user-context modeling path since the mention of sarcasm in this dataset is not dependent on authors but rather on current events and common knowledge. In addition to that, we add a new LSTM module to encode the left (and right) context of the words in a sentence at every time step. This LSTM module is supplemented with an Attention module to reweigh the encoded context at every time step.

We hypothesize that the sequential information encoded in the LSTM module would complement the CNN module in the original architecture of Amir et al. (2016) which captures regular n-gram word patterns throughout the entire length of the sentence. We also hypothesize that the attention module can benefit the sarcasm detection task as well as produce useful insights regarding sarcastic cues from our dataset. It can selectively emphasize incongruent co-occurring word phrases (words with contrasting implied sentiments). For example, in the sentence "majority of nations civic engagement centered around oppressing other people", our attentive model can emphasize the occurrence of 'civic engagement' and 'oppressing other people' to classify this sentence as sarcastic. The detailed architecture of our model is illustrated in Fig. 2.

The LSTM module with attention is similar to the one used to jointly align and translate in a Neural Machine Translation task (Bahdanau et al., 2014). A BiLSTM consists of forward and backward LSTMs and they accept a sequence of input embedding vectors x_t. The forward LSTM calculates a sequence of forward hidden states and the backward LSTM reads the sequence in the reverse order to calculate backward hidden states. We obtain an annotation for each word in the input sentence by concatenating the forward hidden state and the backward one $h_w = \left[h_w^{(f)}; h_w^{(b)}\right]$. In this way, the annotation h_w contains the summaries of both the preceding words and the following words. Due to the tendency of LSTMs to better represent recent inputs, the annotation at any time step will be focused on the words around that time step in the input sentence. Each hidden state contains information about the whole input sequence with a strong focus on the parts surrounding the corresponding input word of the input sequence. The context vector $\mathbf{c}$ is, then, computed as a weighted sum of these annotations.

$$\mathbf{c} = \sum_{w=1}^{N} \alpha_w h_w \tag{1}$$

$$\alpha_w = \frac{v^T \mu_w}{\sum_{w' \in s} v^T \mu_{w'}} \tag{2}$$

$$\mu_w = tanh(W_a h_w + b_a) \tag{3}$$

W_a, b_a, and v are all model parameters. The attention α_w of a hidden state h_w calculated by computing softmax over scores of each hidden state. The score of each individual h_w is calculated by forwarding h_w through a multi-layer perceptron with a learnable weight metrics W_a and bias term b_a.

The context vector $\mathbf{c}$ is finally concatenated to the output of the CNN module. Together, this large feature vector is then fed to an MLP which outputs the binary probability distribution of the sentence being sarcastic/non-sarcastic.

[2] https://rishabhmisra.github.io/publications/.
[3] https://www.theonion.com/.
[4] https://www.huffpost.com/.

Table 1
General statistics of datasets.

Statistic/Dataset	Headlines	Semeval	IAC	SARC
# Records	28,619	4792	3260	1,010,826
Domain	News	Twitter	Debate	Reddit
Labeling technique	Source-based	Hand labeled	Hand labeled	Tag-based
Label quality	Controlled	Controlled	Controlled	Not controlled
Language	Formal	Informal	Formal	Informal
% word2vec embeddings found	77	64	–	–

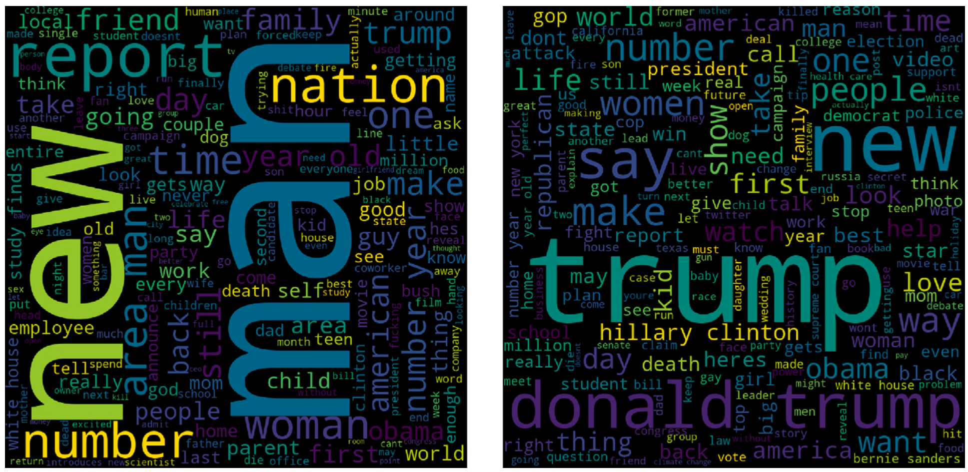

Fig. 1. Wordcloud of sarcastic headlines (left) and non-sarcastic headlines (right).

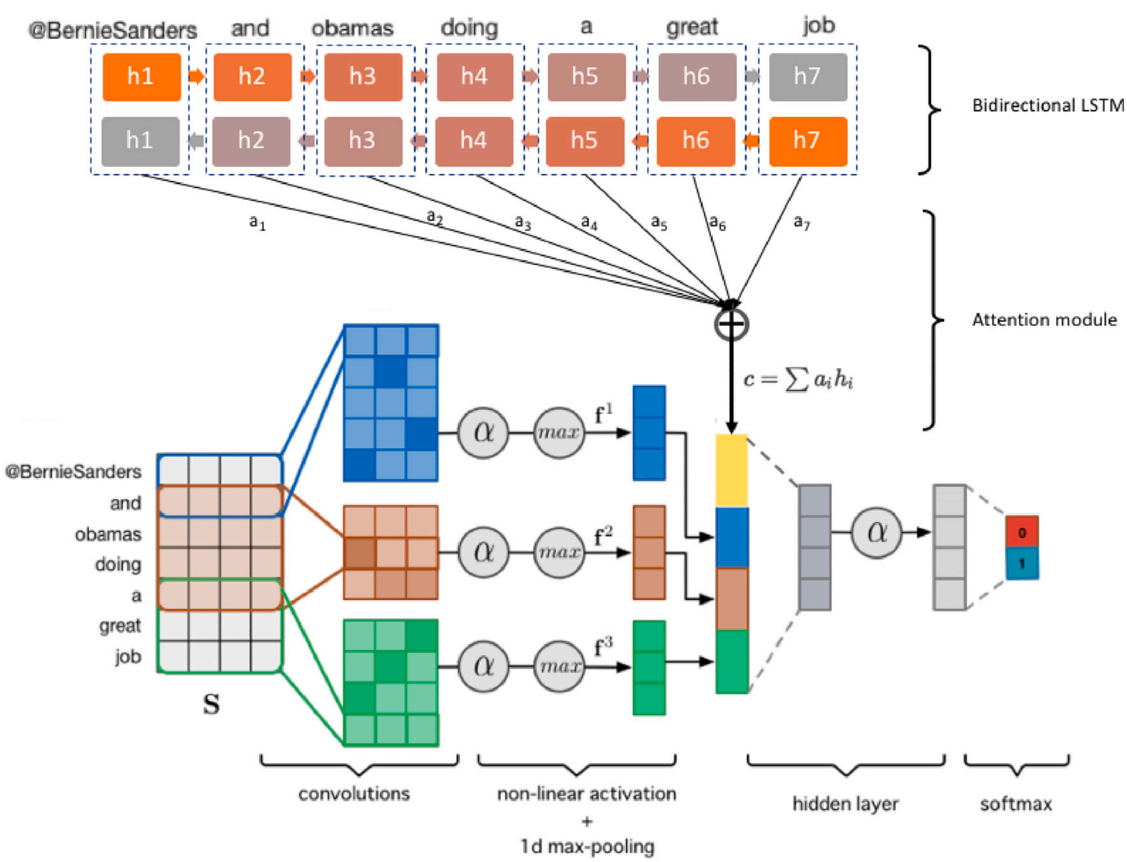

Fig. 2. Attention-based Hybrid Neural Network Architecture.

Table 2
Performance comparison in terms of classification accuracy.

Implementation	Test accuracy
Baseline	84.88%
Hybrid NN	89.7%

4. Experiments

The goal of designing these experiments is to showcase that we can train deep neural networks reliably on our dataset while producing useful insights.

4.1. Baseline

With the new dataset in hand, we tweak the model of Amir et al. (2016) by removing the author embedding component since now the sarcasm is independent of authors (it is based on current events and common knowledge) to form the baseline. We keep the CNN module intact.

4.2. Experimental setup

To represent the words, we use pre-trained embeddings from the word2vec model and initialize the missing words uniformly at random in both models. These are then tuned during the training process. We create a train, validation, and test sets by splitting data randomly in an 80:10:10 ratio. We tune the hyper-parameters like learning rate, regularization constant, output channels, filter width, hidden units, and dropout fraction using grid search. The model is trained by minimizing the cross entropy error between the predictions and true labels, the gradients for the network parameters are computed with backpropagation and the model weights are updated with the AdaDelta rule. Code for both methods is available on GitHub.[5]

5. Results and analysis

5.1. Quantitative results

We report the quantitative results of the baseline and the hybrid neural network in terms of classification accuracy, since the dataset is mostly balanced. The final classification accuracy after hyper-parameter tuning is provided in Table 2. As shown, our model improves upon the baseline by $\sim$ 5% which supports our first hypothesis mentioned in Section 3. The performance trend of our model is shown in Fig. 3 and we can see that the model achieves best performance within 5 epochs. This showcases that we can train a sufficiently complex neural network model reliably on our News Headlines Dataset, while achieving almost $\sim$ 90% accuracy.

5.2. Qualitative results

To gather more insights from our dataset, we visualize the attention over some of the sarcastic sentences in the test set that are correctly classified with high confidence scores. This helps us better understand if our hypotheses are correct and provide better insights into the sarcasm detection process. Fig. 4 shows that the attention module emphasizes the co-occurrence of incongruent word phrases within each sentence, such as ‘civic engagement’ & ‘oppressing other people’ in the left and ‘excited for’ & ‘insane k-pop sh*t during opening ceremony’ in the right.

This incongruency is an important cue for us humans too and supports our second hypothesis mentioned in Section 3. This has been extensively studied in Joshi et al. (2015). Fig. 5 (left) shows that the presence of ‘bald man’ indicates that this news headline is rather insincere probably meant for ridiculing someone. Similarly, ‘stopped paying attention’ in Fig. 5 (right) has more probability to show up in a satirical sentence, rather than a sincere news headline.

6. Notable applications

After our contributions were first released in 2019, there have been quite a few state-of-the-art NLP studies relying on the artifacts discussed in this work (with 50 + citations[6] and wide adoption on Kaggle platform[7]). We cover some prominent applications of our work in this section to showcase the impact.

6.1. Transferring styles between sarcastic and non-sarcastic text

Yang (2022) developed a Natural Language Processing tool that can accurately detect sarcastic parts of a text and reword them in a form that is non-sarcastic without changing the overall meaning of the text. To learn the semantics of sarcastic and non-sarcastic text, the authors sought a data source with high-quality language and sarcasm annotations. They solely relied on our News Headlines Dataset to fine-tune the GPT-2 model to obtain a discriminator that can accurately identify sarcasm. Using SHAP, the authors computed the role of various features for sarcasm detection and made the deletion of certain sarcastic attributes more intuitive and precise. Finally, they used Plug and Play Language Model developed by Dathathri et al. (2019) to generate the deleted part in a non-sarcastic style, thus realizing the style transfer.

6.2. Sarcasm detection using affective cues

The York University lab produced a series of work, Babanejad et al. (2020a,b) and Agrawal et al. (2020), explore the role of affective features (like human emotions of happiness, sadness, surprise, etc.) in computational sarcasm detection. Agrawal et al. (2020) develop an LSTM-based model, Emotrans, that incorporates emotion transitions in texts from our News Headlines Dataset to identify accurately identify sarcastic text. Babanejad et al. (2020a) conduct a comprehensive analysis of the role of preprocessing techniques from NLP in affective tasks (i.e. tasks involving the identification of emotions) based on word vector models. Since one of the affective tasks is sarcasm detection, they utilize our News Headlines Dataset to conclude that the most noticeable improvement in affective tasks (sentiment analysis, sarcasm detection, and emotion classification) is obtained through negation processing (i.e. preprocessing text to remove negations), and that emotion classification benefits most out of all. Babanejad et al. (2020b) train a BERT-based model to learn Affective feature embeddings from our News Headlines Dataset to achieve state-of-the-art performance on the computational sarcasm detection task.

6.3. Corpus for detecting irony and sarcasm in portuguese

Marten and de Freitas (2021) closely study our initial contributions from 2019 and follow a similar approach in building an irony and sarcasm detection corpus in Portuguese, which is generally a low-resource language and there is not much data available from social media platforms. They note that translated corpora from English to Portuguese for sarcasm detection may not work since irony or sarcasm can vary from one language to another, and manual labeling of text can also have errors based on labelers’ understanding of irony. Owing to these reasons, they relied on our approach of collecting sarcastic and non-sarcastic data from different news websites to realize all the benefits we noted in Section 2.

[5] https://github.com/rishabhmisra/Sarcasm-Detection-using-CNN.

[6] https://scholar.google.com/citations?user=EN3OcMsAAAAJ.

[7] https://www.kaggle.com/datasets/rmisra.

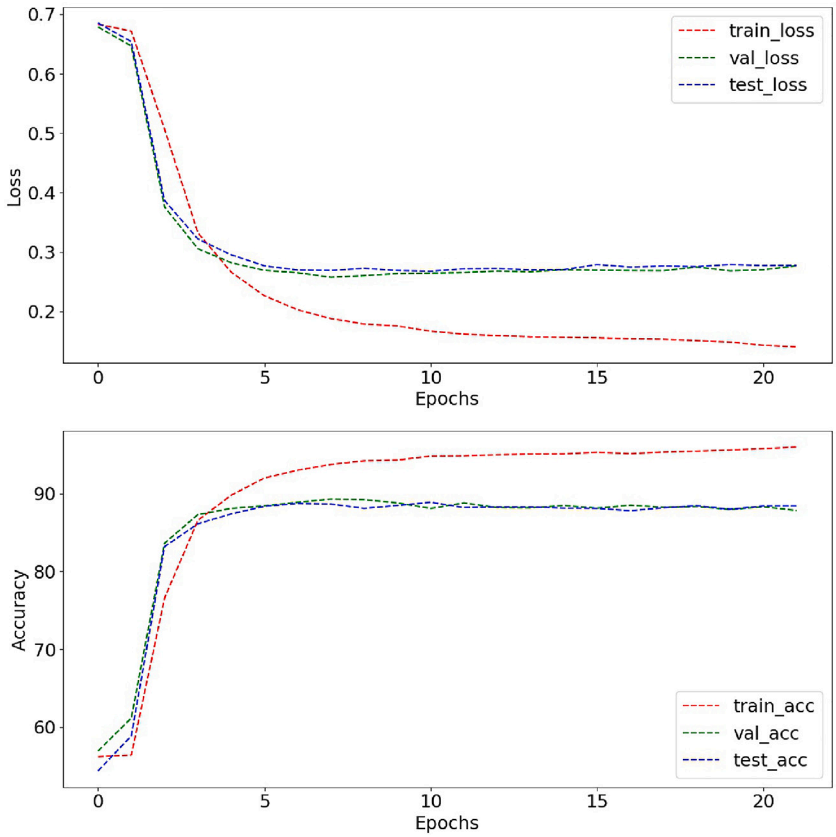

Fig. 3. Loss and accuracy trend of the proposed method.

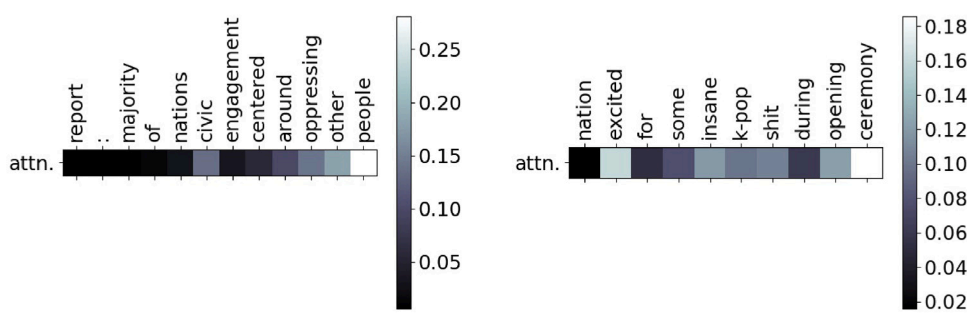

Fig. 4. Attention layer output for co-occurrences of incongruent word phrases.

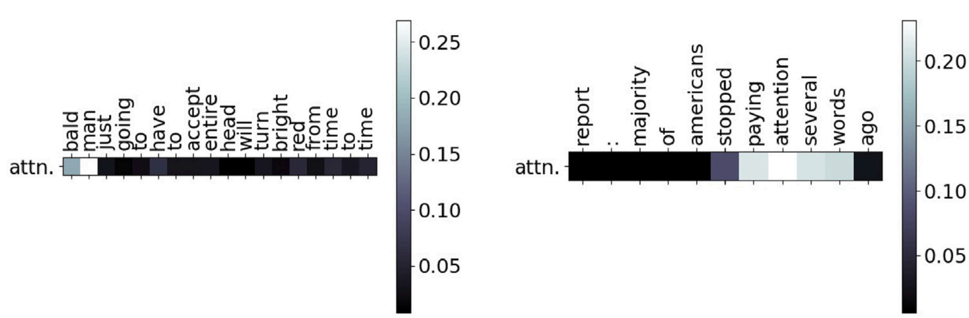

Fig. 5. Attention layer output for insincerity (left) and satirical nature (right).

7. Conclusion and future work

To conclude, we present a relatively large-scale and high-quality dataset for the task of sarcasm detection as well as showcase through training a Hybrid Neural Network with attention mechanism that deep learning models can reliably learn sarcastic cues from the text in expressive manner. Quantitative and qualitative results presented in the paper highlight the strong performance of the proposed framework and we also cover some of the recent NLP research conducted using our contributions in this work. We are left with several open directions that can be explored in future. One direction is using dataset or method proposed in this work as a pre-computation step and tune the parameters on domain-specific datasets for downstream tasks. Our intuition behind this direction is that this pre-computation step would allow us to capture the general cues for sarcasm which would be hard to learn on smaller or domain-specific datasets (given their small size or low-quality labels). This type of transfer learning is shown to be effective when limited data is available (Pan and Yang, 2010). Furthermore, we observe that detection of sarcasm depends a lot on common knowledge (current events and common sense). Thus, another direction would be to integrate this knowledge in modeling efforts so that we are able to detect sarcasm based on which sentences deviate from common knowledge. Young et al. (2017) integrated such knowledge in dialogue systems and the ideas mentioned could be adapted in sarcasm detection setting as well.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Erratum regarding Declaration of Competing Interest statements in previously published articles

Declaration of Competing Interest statements were incorrectly included in the published version of the following articles that appeared in previous issues of AI Open.

The appropriate Declaration of Competing Interest statements, provided by the Authors, are included below.

1. "How to generate popular post headlines on social media?"[AI Open, 2024; 5:1–9] https://doi.org/10.1016/j.aiopen.2023.12.002Declaration of competing interest: The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Min Yu and Xiaoqi Tang are currently employed by Huayun Information and Technology Co. Ltd.
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9. "UPRec: User-aware Pre-training for sequential Recommendation"[AI Open, 2023; 4: 137–144] https://doi.org/10.1016/j.aiopen.2023.08.008Declaration of competing interest: The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Ruobing Xie, Xu Zhang and Leyu Lin are currently employed by Tencent Inc.
10. "Multi-grained hypergraph interest modeling for conversational recommendation"[AI Open, 2023; 4:154–164] https://doi.org/10.1016/j.aiopen.2023.10.001Declaration of competing

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