Abstract
Recognizing sarcasm often requires a deep understanding of multiple sources of information, including the utterance, the conversational context, and real world facts. Most of the current sarcasm detection systems consider only the utterance in isolation. There are some limited attempts toward taking into account the conversational context. In this paper, we propose an interpretable end-to-end model that combines information from both the utterance and the conversational context to detect sarcasm, and demonstrate its effectiveness through empirical evaluations. We also study the behavior of the proposed model to provide explanations for the model’s decisions. Importantly, our model is capable of determining the impact of utterance and conversational context on the model’s decisions. Finally, we provide an ablation study to illustrate the impact of different components of the proposed model.

1 Introduction
Recently, dialogue systems have received a lot of attention from researchers. Unfortunately, existing approaches often fail to detect sarcastic user comments in order to provide proper responses.

Sarcasm detection is an important and challenging task for natural language understanding. The goal of sarcasm detection is to determine whether a sentence is sarcastic or non-sarcastic. Sarcasm is a type of phenomenon with specific perlocutionary effects on the hearer (Haverkate, 1990), such as to break their pattern of expectation. Consequently, correct understanding of sarcasm often requires a deep understanding of multiple sources of information, including the utterance, the conversational context, and, frequently some real world facts. Table 1 shows three different sarcastic samples from the SARC dataset (Khodak et al., 2018), each of which requires a different source of information for disambiguation.

| Type | Sample |
|------|--------|
| U.S. | just don’t, if you are telling anyone else what they can and can’t put on their bodies, just don’t |
| R    | we’re on Reddit, don’t you know we control everything people do? |
| C.D. | who else thinks that javascript alert is an annoying, lazy, and ugly way to notify me of something on your site. |
|     | it’s a useful debugging tool |
| C.D. | till that some cattle ranchers in south dakota lost between 20% - 50% of their livestock in winter storm atlas, and may not be eligible for insurance due to the expiration of the farm bill and federal government shutdown. |
| E.K.D. | this is clearly barrack hussein obama’s fault, since he refuses to modify the aca and obamacare. |

Table 1: Different types of sarcastic examples from the SARC dataset. Each data sample contains a comment and response. Important and influential tokens are shown in blue.

Existing approaches for sarcasm detection primarily focus on lexical, pragmatic cues (e.g. interjections, punctuations, sentimental shift etc.) found in utterance (Kreuz and Caucci, 2007; Joshi et al., 2017). In contrast, the natural language understanding aspect of sarcasm detection could be more robust, interesting and challenging. Moreover, most sarcasm detection systems have considered utterances in isolation (Davidov et al., 2010; González-Ibáñez et al., 2011; Liebrecht et al., 2013; Riloff et al., 2013; Maynard and Greenwood, 2014; Joshi et al., 2015; Ghosh et al., 2015; Joshi et al., 2016; Ghosh and Veale, 2016; Poria et al., 2016; Amir et al., 2016; Hazarika et al., 2018). However, even humans have difficulty in recognizing sarcastic intent when considering
There are some limited attempts toward taking the conversational context into account (Ghosh et al., 2017) by using a variety of LSTMs (Hochreiter and Schmidhuber, 1997) to encode both context and reply sentences. Still such approaches only focuses on the conversation dependent samples. In this work, we propose an end-to-end model that combines information from both the utterance and the conversational context to detect sarcasm. Considering the utterance beside the conversational context enables the model to (1) properly handle utterance-sufficient samples, (2) automatically extract lexical and grammatical features from the utterance. First, We demonstrate the effectiveness of our model through empirical evaluations on the SARC dataset (Khodak et al., 2018), the largest available dataset for sarcasm detection. Next, we illustrate the impact of different aspects of the proposed model through an ablation study. Finally, we present an extensive data analysis to (1) provide explanations regarding our model’s decisions and behavior by visualizing attention and attention saliency (Ghaeini et al., 2018b); (2) study the impact and effect of utterance and the conversational context on our model’s final prediction. In summary, our contributions are as follows:

- Proposing a novel end-to-end and interpretable deep learning model that combines information from both the utterance and conversational context in parallel.
- Illustrating the impact of the proposed model’s component through an extensive ablation study.
- Explaining the model’s behavior and predictions by visualization of the attention and attention saliency.
- Examining the impact of utterance and conversational context on the model’s final predictions.

2 Related Work

Automatic sarcasm detection is a relatively recent field of research. Early studies use small datasets and leverage lexical and syntactic features for sarcasm detection (Joshi et al., 2017). Here we classify the previous works into three categories, isolate-utterance based, contextual-feature based, and conversation based sarcasm detection models.

- **Isolate-utterance based:** Most existing sarcasm detection systems consider the utterances in isolation (Davidov et al., 2010; González-Ibáñez et al., 2011; Liebrecht et al., 2013; Riloff et al., 2013; Maynard and Greenwood, 2014; Joshi et al., 2015; Ghosh et al., 2015; Joshi et al., 2016; Ghosh and Veale, 2016). Methods in this category commonly rely on hand-designed features, syntactic patterns, and lexical cues.

- **Contextual-feature based:** Wallace et al. (2014) illustrates the necessity of using contextual information in sarcasm detection by showing how traditional classifiers fail in instances where humans also require additional context. Consequently, researchers recently started to exploit contextual information for sarcasm detection. In particular, contextual information about authors, topics or conversational context have been considered (Khatta et al., 2015; Bamman and Smith, 2015; Wallace et al., 2015; Rajadesingan et al., 2015; Poria et al., 2016; Zhang et al., 2016; Amir et al., 2016; Hazarika et al., 2018). Such techniques rely on either feature engineering or embedding-based representation via deep learning.

These approaches benefit from contextual information in a pipelined and feature based manner. We should note that user profiling has been shown to have noticeable impact on sarcasm detection (Hazarika et al., 2018). However, user profiling is not always possible. In this work, we are primarily interested in the language side of the sarcasm detection and aim to provide an end-to-end user/author independent system that could be used in a variety of applications, especially dialogue systems and chat boxes.

- **Conversation-based:** The last category of methods aims to detect sarcasm based on the understanding of the conversation (other than simply extracting features from the context). To the best of our knowledge, there is just one conversation dependent sarcasm detection system (Ghosh et al., 2017), which focuses on modeling conversational context using a variety of LSTMs to help sarcasm detection. They effectively demonstrated the importance and impact of considering con-
versational context for sarcasm detection.

Among all previous works, Ghosh et al. (2017) and our system share similar intuition and motivation. However, we utilize a different deep learning architecture to address sarcasm detection. Furthermore, we consider the utterance in both isolation and conversation dependent settings. Such a strategy allows the model to (1) extract lexical and grammatical features from the utterance, and (2) selectively attend to the proper source of information. Finally, we evaluate our system with a much larger and broader dataset that could lead to more robust and unbiased evaluation.

3 Model

The inputs to our model are \( u = [u_1, \cdots, u_n] \) and \( v = [v_1, \cdots, v_m] \), which are the given comment (length \( n \)) and response (length \( m \)) respectively. Here \( u_i, v_j \in \mathbb{R}^r \) are \( r \)-dimensional word embedding vectors. The goal is to predict a label \( y \) that indicates whether the response \( v \) is sarcastic or non-sarcastic.

Our proposed model (Attentional Multi-Reading system; AMR) consists of an utterance-only (left side) part and a conversation-dependent (right side) part, formulated with the following major components: input encoding, attention, re-reading, and classification. Figure 1 demonstrates a high-level view of our proposed AMR framework.

3.1 Input Encoding

RNNs provide a natural solution for modeling variable length sequences and have shown to be successful in various NLP tasks (Ghaeini et al., 2018a,c; Bahdanau et al., 2014; Ghaeini et al., 2016). Consequently, we utilize a bidirectional LSTM (BiLSTM) (Hochreiter and Schmidhuber, 1997) for encoding the given comment and response. Here we simply read and encode the comment and response using a BiLSTM. Equations 1 and 2 formally represent this component.

\[
\bar{u} = \text{BiLSTM}(u) \tag{1}
\]

\[
\bar{v} = \text{BiLSTM}(v) \tag{2}
\]

where \( \bar{u} \in \mathbb{R}^{n \times 2d} \) and \( \bar{v} \in \mathbb{R}^{m \times 2d} \) are the BiLSTM reading sequences of \( u \) and \( v \) respectively.

3.2 Attention

Here we employ a soft alignment method to associate the relevant sub-components between the given comment and response. The unnormalized attention weights are computed as the similarity of the hidden states of the comment and response as shown in Equation 3 (energy function).

\[
e_{ij} = \bar{u}_i \bar{v}_j^T, \quad i \in [1, n], j \in [1, m] \tag{3}
\]

where \( \bar{u}_i \) and \( \bar{v}_j \) are the hidden representations of \( u \) and \( v \) respectively which are computed earlier in Equations 1 and 2 respectively. Next, for each word in either comment or response, the relevant semantics in the other sentence is extracted and composed according to \( e_{ij} \) as shown in Equations 4 and 5.

\[
\bar{u}_i = \sum_{j=1}^{m} \frac{\exp(e_{ij})}{\sum_{k=1}^{m} \exp(e_{ik})} \bar{v}_j, \quad i \in [1, n] \tag{4}
\]
\[ \hat{v}_j = \sum_{i=1}^{n} \frac{\exp(e_{ij})}{\sum_{k=1}^{n} \exp(e_{kj})} \hat{u}_i, \quad j \in [1, m] \]  

where \( \hat{u}_i \) represents the extracted relevant information of \( \hat{v} \) by attending to \( \hat{u}_i \) while \( \hat{v}_j \) represents the extracted relevant information of \( \hat{u} \) by attending to \( \hat{v}_j \).

### 3.2.1 Attention Augmentation and Projection

To utilize the collected attentional information \( \hat{u}_i \) and \( \hat{v}_j \), a trivial next step would be to concatenate them with \( \tilde{u}_i \) and \( \tilde{v}_j \) respectively. More over, it is often interesting to compare and contrast the information from the comment and the response in order to detect sarcasm. Hence, we calculate the element-wise difference and element-wise and include these vectors for further consideration. We concatenate all the vectors and represent the comment and response as [\( [\hat{u}_i, \hat{v}_j, \tilde{u}_i - \hat{u}_i, \tilde{v}_j - \hat{v}_j, \hat{u}_i \odot \hat{v}_j] \) with \( i = 1, \ldots, n \) and \( j = 1, \ldots, m \) respectively. Finally, a feed-forward neural layer with the ReLU activation function projects the concatenated vectors from the \( d \)-dimensional vector space into a \( 2d \)-dimensional vector space (Equations 6 and 7). This projection layer serves the dual purpose of both helping the model to capture deeper dependencies between the comment and response and lowering the complexity of vector representations.

\[
p_i = \text{ReLU}(W_c([\hat{u}_i, \hat{v}_j, \tilde{u}_i - \hat{u}_i, \tilde{v}_j - \hat{v}_j, \hat{u}_i \odot \hat{v}_j]) + b_c) \quad (6)
\]

\[
q_j = \text{ReLU}(W_c([\tilde{u}_i, \tilde{v}_j, \hat{u}_i - \tilde{u}_i, \hat{v}_j - \tilde{v}_j, \tilde{u}_i \odot \tilde{v}_j]) + b_c) \quad (7)
\]

Here \( \odot \) stands for element-wise product while \( W_c \in \mathbb{R}^{8d \times d} \) and \( b_c \in \mathbb{R}^d \) are the trainable weights and biases of the projector layers respectively.

### 3.3 Re-Reading

During this phase, two BiLSTMs are used. First, we use a shared BiLSTM (\( \text{BiLSTM}_c \)) to aggragate the sequences of computed matching vectors, \( p \) and \( q \) from the Attention stage. This aggregation is performed in a sequential manner to ensure that sequential information in the latent variables is retained. Second, We use another BiLSTM to re-read and re-encode the previous encoding of the response from the Input Encoding section (\( \bar{v} \)). Such a re-reading process is helpful toward achieving a deeper and more meaningful representation for the response when considered in isolation. The Re-Reading procedure is done through Equations 8, 9, and 10.

\[
\hat{p} = \text{BiLSTM}_c(p) \quad (8)
\]

\[
\hat{q} = \text{BiLSTM}_c(q) \quad (9)
\]

\[
\bar{x} = \text{BiLSTM}_u(\bar{v}) \quad (10)
\]

Finally, we convert \( \hat{p} \in \mathbb{R}^{n \times 2d} \), \( \hat{q} \in \mathbb{R}^{m \times 2d} \) and \( \bar{x} \in \mathbb{R}^{m \times 2d} \) to fixed-length vectors using a max pooling layer (Equations 11, 12, and 13).

\[
\hat{p} = \text{MaxPooling}(\hat{p}) \quad (11)
\]

\[
\hat{q} = \text{MaxPooling}(\hat{q}) \quad (12)
\]

\[
\bar{x} = \text{MaxPooling}(\bar{x}) \quad (13)
\]

where \( \hat{p} \in \mathbb{R}^{2d} \), \( \hat{q} \in \mathbb{R}^{2d} \) are the final and fixed representations of the comment and the response produced via conversation-dependent reading (the right part of the model), and \( \bar{x} \in \mathbb{R}^{2d} \) is a separate representation of the response produced by the utterance-only reading (the left portion of the model).

### 3.4 Classification

To make final prediction, we consider both the utterance-only representation as well as the conversation dependent representations. Equation 14 represents a feed-forward layer that computes the utterance-only prediction from \( \bar{x} \). For the conversation-dependent layer, we enrich the extracted information from the comment and response by incorporating the difference and element-wise product of \( \hat{p} \) and \( \hat{q} \) respectively. Equation 15 formally describes the prediction procedure for the conversation-dependent part.

\[
o_u = U_u \bar{x} + a_u \quad (14)
\]

\[
o_c = U_c([\hat{p}, \hat{q}, \hat{p} - \hat{q}, \hat{p} \odot \hat{q}]) + a_c \quad (15)
\]

where \( U_u \in \mathbb{R}^{2d \times 2} \), \( U_c \in \mathbb{R}^{8d \times 2} \), \( a_u \in \mathbb{R}^2 \) and \( a_c \in \mathbb{R}^2 \) are the trainable weights and biases of the prediction layers respectively. Finally, we combine both predictions (i.e. \( o_u \) and \( o_c \)) using a trainable weight \( \alpha \) (Equation 16).

\[
\text{output} = \text{Softmax}(o_u + \alpha o_c) \quad (16)
\]

The model is trained in an end-to-end manner. More detailed information about the architecture and training can be found in the following section.
4 Experiments and Evaluation

4.1 Dataset

SARC\(^1\) (Khodak et al., 2018) is a self-annotated corpus for sarcasm detection. SARC is the largest available sarcasm detection dataset for this task and contains more than a million of sarcastic/non-sarcastic samples extracted from Reddit\(^2\). Every instance in SARC is a response to a set of comments. The response is annotated by its author as either sarcastic or non-sarcastic. In this work, we concatenate all of the available comments for each response in chronological order into a single comment.

We evaluate our system on the latest version of the balanced SARC (SARC V2.0, Main balanced). Due to the lack of a pre-defined validation set, we randomly hold out 10% of the training set data as our validation set. All hyper-parameters are tuned based on the performance on the validation set. Table 2 shows the SARC (V2.0) dataset statistics.

|        | non-sarcastic | sarcastic |
|--------|---------------|-----------|
| Train  | Data Size     | 128,541   | 128,541   |
|        | # Avg. Comment| 60.9      | 60.9      |
|        | # Avg. Response| 55.0      | 54.5      |
| Test   | Data Size     | 32,333    | 32,333    |
|        | # Avg. Comment| 60.8      | 60.8      |
|        | # Avg. Response| 55.8      | 54.7      |
| Vocabulary |          | 95,043    |           |

Table 2: SARC main balanced V2.0 statistics.

4.2 Experimental Setup

We use the pre-trained 300-D Glove 840B vectors (Pennington et al., 2014) to initialize our word embedding vectors. All hidden states of BiLSTMs for both input encoding and re-reading have 300 dimensions \((r = 300 \text{ and } d = 300)\). The weights are learned by minimizing the log-loss (Equation 17) on the training data via the Adam optimizer (Kingma and Ba, 2014). The initial learning rate is 0.0001. To avoid overfitting, we use dropout (Srivastava et al., 2014) with the rate of 0.5 for regularization, which is applied to all feed-forward connections. During training, the word embeddings are updated to learn effective representations for the sarcasm detection task. We use a fairly small batch size of 32 to provide more exploration power to the model. We consider 200 and 100 as the maximum acceptable length of the comment and response respectively \((n \leq 200 \text{ and } m \leq 100)\). In other words, only 200 and 100 words of the given comment and response is processed and the rest (in case of existence) are thrown away.

\[
y^*_i = \arg\max_i (output_i)
\]

\[
l = -\frac{1}{N} \sum_{i=0}^N (y_i \log(y^*_i) + (1 - y_i) \log(1 - y^*_i))
\]

4.3 Results

Here we evaluate our model based on two versions of SARC. (1) Hazarika et al. (2018) is the most recent work that use SARC dataset for evaluation. It is not clear which version of SARC is used, but they have released their train and test sets\(^3\). We refer to this dataset as SARC\(_{csd}\) in the rest of this paper. In this sub-section (Results), we use SARC\(_{csd}\) to compare our system with the reported performances in Hazarika et al. (2018). (2) We use the SARC V2.0 in next section (Ablation and Configuration Study) to report standard results on SARC V2.0 and compare the performance of different configurations of our model.

Table 3 shows the F1-measures and accuracies of models on the test set of SARC\(_{csd}\). The first row shows the results of a baseline classifier using the bag-of-words method. All other listed models are deep learning based. The second model is a simple

\(^1\)http://nlp.cs.princeton.edu/SARC/
\(^2\)https://www.reddit.com/
\(^3\)https://github.com/SenticNet/CASCADE–Contextual-Sarcasm-Detection
| Model                  | Test Set | F1  | Acc* |
|-----------------------|----------|-----|------|
| (1) Bag of Words      |          | 64% | 63%  |
| (2) CNN               |          | 66% | 65%  |
| (3) CASCADE − Pf      |          | 66% | 68%  |
| (4) CNN-SVM (Poria et al., 2016) | | 68% | 68%  |
| (5) CUE-CNN (Amir et al., 2016) | | 69% | 70%  |
| (6) CASCADE (Hazarika et al., 2018) | | 77% | 77%  |
| (7) Ours (AMR)        |          | 68% | 70%  |

Table 3: F1-measures and Accuracies of models on the test set of SARCcsd. The second three (4, 5, and 6) models benefit from personality feature (their results are shown in blue). Whereas the first three models (1, 2, and 3), similar to our model; only rely on response or response and comment. Our models (AMR) achieves the F1-measure and accuracy of 68% and 70% respectively, the best results observed on SARCcsd among similar methods which does not use personality features.

Comparing methods that benefit from personality features and user profiling (4, 5, and 6) with the ones that do not (1, 2, and 3), it is clear that such features are very helpful for sarcasm detection. However, user profiling helps a model primarily by providing information about the user’s behavior or how the user forms sarcastic sentences. In other words, it does not really enrich the model’s capability to understand what constructs sarcasm in general. More over, user history and information may not always be available for extracting such features. Importantly, one of the main goals of this work is to move toward solving the sarcasm understanding issue in a dialog system. In particular, we are mainly interested in the language understanding aspect of sarcasm detection. As such, we aim to build an end-to-end system that does not depend on any additional information or assumption (user profiling, topic modeling, etc.) other than the sequence of the sentences (the conversation). Due to these considerations, the fair comparison would be comparing the results of our system with the first three models in Table 3, which demonstrates the effectiveness of our models.

From Table 3 we can see that AMR achieves an F1-measure and accuracy of 68% and 70% respectively on the test set of SARCcsd, which are the best reported results among the existing comparable baselines for sarcasm detection. Here we obtain 2% improvement on both F1-measure and accuracy on the test data of SARCcsd in comparison with the previous state-of-the-art system: CASCADE without personality feature (row 3 in the Table 3). It is interesting to note that although we do not employ user profiling, our performance is similar and competitive with several baselines that use user profiling (CNN-SVM (Poria et al., 2016) and CUE-CNN (Amir et al., 2016)).

4.4 Ablation and Configuration Study

In this section, we conduct an ablation and configuration study of our model to examine the importance and effect of each major component. We report the performance (Precision, Recall, F1-Measure, and Accuracy) of different variants of our model on the test set of SARC V2.0 in Table 4.

The first row shows the performance of the proposed model, AMR. Rows 2 and 3 study the impact of the conversation-dependent and utterance-only parts of the models. Rows 4-6 examine the impact of attention and re-reading stages by removing either one (rows 4 and 5) or both components (row 6). Rows 7-10 investigate the effect of data augmentation in attention and classification of conversation-dependent part of the proposed model. Specifically, we consider removing the different data augmentations shown in Equation 6, 7, and 15. Finally, row 11 shows the result of our model without fine-tuning the word embedding during the training procedure.

First, we compare the models based on their F1-Measure and Accuracy. The results show that removing any part of our model leads to reduced test set performance both in terms of F1-Measure and accuracy (expect for row 9 where accuracy remained the same), indicating the usefulness of
| Models                                      | SARC V2.0 Test Set                                      |
|---------------------------------------------|--------------------------------------------------------|
| (01) AMR                                    | Precision 69.33% Recall 69.64% F1-Measure 69.48% Accuracy 69.45% |
| (02) Conversation-dependent                 | Precision 70.23% Recall 66.36% F1-Measure 68.24% Accuracy 69.11% |
| (03) Utterance-only                         | Precision 70.86% Recall 64.66% F1-Measure 67.62% Accuracy 69.04% |
| (04) AMR — Attention                        | Precision 69.39% Recall 68.79% F1-Measure 69.09% Accuracy 69.22% |
| (05) AMR — Re-Reading                      | Precision 72.93% Recall 60.20% F1-Measure 65.96% Accuracy 68.93% |
| (06) AMR — Re-Reading — Attention           | Precision 74.76% Recall 55.31% F1-Measure 63.58% Accuracy 68.32% |
| (07) AMR — difference                       | Precision 70.07% Recall 67.53% F1-Measure 68.78% Accuracy 69.34% |
| (08) AMR — element-wise product             | Precision 70.41% Recall 67.01% F1-Measure 68.67% Accuracy 69.42% |
| (09) AMR — element-wise product — difference| Precision 71.19% Recall 65.50% F1-Measure 68.23% Accuracy 69.45% |
| (10) AMR with only element-wise product      | Precision 70.75% Recall 65.05% F1-Measure 67.78% Accuracy 69.07% |
| (11) AMR — train embedding                  | Precision 67.22% Recall 69.68% F1-Measure 68.43% Accuracy 67.85% |

Table 4: Ablation study results. Precision, Recall, F1-Measure, and Accuracy of different models on the test set of SARC V2.0.

We observe that AMR performs noticeably better than both Utterance-only and Conversation-dependent configurations, validating the intuition of our design. It is noteworthy that Conversation-dependent model performs better than the other one, suggesting the importance of considering the conversation and context for this task. Comparison of rows 4, 5, and 6 suggests that although both of Attention and Re-Reading are important, but Re-Reading has a more significant impact on the performance of AMR.

A closer look into the precisions and recalls of the different models suggests an interesting trend — removing different components of the model typically leads to improved precision in sarcasm detection but suffers from significantly reduced recall. This is evidenced by the results of the first 10 rows. Comparing the first three rows, it is interesting to note that either part of the model (conversation-dependent or utterance-only) individually achieves slightly higher precision but significantly lower recall. The fact that by combining the two our model was able to achieve significantly improved recall suggests that the two parts were able to detect different types of sarcasms, which is consistent with our intuition.

Removing fine-tuning of the word embedding during the training has an opposite effect with reduced precision but little or no impact on the recall. This suggests that by fine tuning the word embeddings for the sarcasm detection task, we were able to increase the specificity of the sarcasm detector without sacrificing the sensitivity.

5 Analysis

In this section, we first show visualization of the energy functions (i.e. attention) in the attention stage (Equation 3) and its saliency for an instance from the SARC V2.0 test set. Next, we study the performance of our system (Utterance-only, Conversation-dependent and AMR) against the length of comment and response.

5.1 Attention Study

Here we show a visualization of the normalized attention (Equation 3) and normalized attention saliency in Figure 2.

We show a comment and response pair, where the comment is “man accidentally shoots himself when concealed weapon goes off in movie theater.”, and the response is “just another responsible gun owner exercising his rights under the 2nd amendment.” which is a sarcastic response and AMR identifies it as sarcastic response as well. Attention visualization in Figure 2 indicates that the model could successfully attend to relevant pairs of words like <gun, shoots>, <gun, concealed>, <gun, weapon>, <his, himself>, etc. However, still we cannot clearly explain the model’s prediction. Thus we use the attention saliency to visualize the impact of each word pair toward the model’s prediction. Attention saliency is the absolute value of the partial derivative of the model prediction respect to the attention. Larger saliency indicates stronger impact on the model’s prediction. According to the attention saliency visualization in Figure 2 (b), the phrase pair of <another responsible gun, man accidentally shoots> has the highest impact toward

4For more details refer to (Ghaeini et al., 2018b)
identifying the aforementioned example as sarcastic, which is consistent with human intuition. This demonstrates and verifies the model’s ability in understanding comment and response and then utilizing the crucial relationships between the comment and response for identifying sarcastic responses. The word “responsible” in the response appears to be the key phrase that deliver the sarcastic intent of the response — when paired with the phrase “man accidentally shoots” we see the highest saliency, suggesting the most significant impact toward the final prediction.

5.2 Length Study

One of the advantage of our model is its prediction interpretability. AMR contains two major parts: Utterance-only and Conversation-dependent. Each part makes its own prediction. Then AMR combines utterance-only and conversation-dependent predictions using a trainable variable $\alpha$ to obtains its final prediction. Consequently, the impact of each part toward the final prediction can be computed. In other words, we can determine which part affects the final prediction the most.

Figure 2: Normalized attention (a, top) and normalized attention saliency (b, bottom) visualization for a sarcastic instance from the test set of SARC V2.0.

Figure 3: Test accuracy of AMR and its sub-parts (Utterance-only and Conversation-dependent) against the length of the comment (A) and response (B).

According to Figure 3, the utterance-only part provides more accurate predictions for short comments ($n \leq 50$). We believe that the utterance-only part of AMR is capable of automatically extracting useful lexical and grammatical cues from utterance which could be beneficial for detecting sarcastic utterances/responses. Consequently, among samples with short comment; thus less contextual information, the utterance-only part shows better performance. It is noteworthy that the performance of AMR is almost always higher than both utterance-only and conversation-dependent parts. However, the conversation-dependent part performs better for longer comments ($50 < n \leq 200$). This observation is consistent with our expectation because long comments are more likely to have relevant and crucial information for determining the sarcastic intent of the response. Such an analysis verifies the intuition behind the design our model.
Despite of the plot A in Figure 3, plot B does not reflect a very coherent behavior and trend among the reported settings. Interestingly, for the very short responses category ($m \leq 10$) which is also the most frequent response category, the conversation-dependent part performs better than the utterance-only part. Due to lack of information in very short responses, disambiguation of such samples are usually reliant on the comment. If we ignore the aforementioned category ($m \leq 10$), plot B illustrates similar behavior and trend for utterance-only and conversation-dependent parts. The utterance-only part perform better for short responses ($10 < m \leq 50$) and the conversation-dependent part beats the utterance-only part for long responses ($50 < m \leq 100$).

Overall, Figure 3 suggests that the conversation-dependent part performs better when (1) we do not have enough information in the response ($m \leq 10$) or (2) the response or the comment is too long ($n, m > 50$). We believe that in case of dealing with long comment or response, we require some guidance for attending to the important and influential sub-parts of the comment or response. Such a goal can be achieved by utilizing an attention mechanism on both comment and response.

6 Conclusion

We propose a novel interpretable end-to-end sarcasm detection model that benefits from both the utterance and the conversational context in parallel. Our evaluations successfully demonstrate the effectiveness of the proposed model. We provide an extensive oblation study that illustrates and justifies the importance and impact of different components of the proposed model. Moreover, we study the model’s behavior by visualizing attention and attention saliency. Finally, we present an interesting data analysis to examine the impact of utterance and conversational context on the model’s predictions. Our future work will extend our study to include the world fact information in the disambiguation procedure to produce more robust and accurate predictions.

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