Cognition Aware Multi-modal Sarcasm Detection

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Abstract

Sarcasm is a complex linguistic construct with incongruity at its very core. Detecting sarcasm depends on the actual content spoken and tonality, facial expressions, the context of an utterance, and personal traits like language proficiency and cognitive capabilities. In this paper, we propose the utilization of synthetic gaze data to improve the task performance for multimodal sarcasm detection in a conversational setting. We enrich an existing multimodal conversational dataset, i.e., MUSTARD++ with gaze features. With the help of human participants, we collect gaze features for < 20% of data instances, and we investigate various methods for gaze feature prediction for the rest of the dataset. We perform extrinsic and intrinsic evaluations to assess the quality of the predicted gaze features. We observe a performance gain of up to 6.6% points by adding a new modality, i.e., collected gaze features. When both collected and predicted data are used, we observe a performance gain of 2.3% points on the complete dataset. Interestingly, with only predicted gaze features, too, we observe a gain in performance (1.9% points). We retain and use the feature prediction model, which maximally correlates with collected gaze features. Our model trained on combining collected and synthetic gaze data achieves SoTA performance on the MUSTARD++ dataset. To the best of our knowledge, ours is the first attempt at multi-modal detection of sarcasm using gaze behaviour in a conversational setting. Our primary hypothesis is that there are distinctive eye movement patterns when a human reader is processing sarcasm due to the presence of incongruous words within the utterance or previously spoken sentences (Mishra et al., 2016b).

1 Problem Definition

Sarcasm originates from the Greek word sarkasmós adapted from sarkázein, which means a sneering or cutting remark. Sarcasm depends on “bitter, caustic, and other ironic expressions that are usually directed against an individual.” (Gibbs, 1986). It is a complex linguistic phenomenon that gets expressed with words that mean the opposite of what the speaker intends to say; e.g., I love being ignored expresses the bitterness of the speaker. The roots of sarcasm lie in incongruity (Joshi et al., 2015), which makes computational sarcasm detection a challenging problem; and the NLP community has attempted to tackle this problem using innovative approaches. Sarcasm detection in the text has largely been attempted by focusing on lexical indicators (Bamman and Smith, 2021), sentiment incongruity (Joshi et al., 2015), etc., in both rule-based and learning-based systems (Abulaish and Kamal, 2018). However, sarcasm is also expressed through tonal changes and/or facial expressions. Hence researchers have started investigating modalities other than text, viz., audio and video, to help detect sarcasm (Castro et al., 2019a; Cai et al., 2019; Gupta et al., 2021; Chauhan et al., 2022; Ray et al., 2022). Mishra et al. (2017a) observed that gaze features are helpful in detecting sarcasm within short sentences without context, which is our inspiration. In a conversational setting, sarcasm often results from an earlier utterance, which is the problem we focus on in this work. To the best of our knowledge, ours is the first attempt at multi-modal detection of sarcasm using gaze behaviour in a conversational setting. Our primary hypothesis is that there are distinctive eye movement patterns when a human reader is processing sarcasm due to the presence of incongruous words within the utterance or previously spoken sentences (Mishra et al., 2016b).

1.1 Gaze Terminology

A fixation is a relatively longer stay of gaze on an object (word), and saccades refer to quick shifting of gaze between two positions of rest (Mishra et al., 2017b). An Interest Area (IA) is a part of the screen that is of interest to us. In these areas, the text is displayed and each word is a separate and unique IA. Forward and backward saccades are called progressions and regressions, respectively, while a
scanpath is a line graph that contains fixations as nodes and saccades as edges.

2 Motivation

2.1 Sarcasm: A Challenging Problem

We discussed in the previous section that sarcasm detection is a challenging problem to solve. It is because the sentences in such cases convey a different or opposite meaning for a sentence by using words of opposite meaning. The words cannot be useful mostly in this case to get to the deep meaning of the sentence. This is the reason methods like eye tracking which capture the way of human thinking using the eye movements are useful in such case. The frequency of the eye moving back and forth is often corresponding to the level of complexity in the sentence.

2.2 Gaze: A Useful Resource

Unlike previous studies, we perform the task of sarcasm detection in a conversational setting, exploiting multimodality and gaze features. Figure 1 illustrates gaze fixations (blue circles w/ bigger circles for longer duration) and progressions-regressions for a sarcastic, and a non-sarcastic utterance. From Figure 1, it can be observed that the non-sarcastic utterance has a significantly lower regressive eye movement (yellow lines) as compared to the sarcastic utterance. The number of fixations is also lower in number. In the sarcastic utterance, we see a lot of regression on the part of the text containing “look up at the stars without a roof over your”, we also observe regressive movement towards the previous utterance in the context- towards “PhD in astrophysics”. Such indicators can also be used to explain the origin of sarcasm from a conversational context. However, we observe that the non-sarcastic example (right) also has a few regressive paths leading to previous utterances, which will happen for any reader, given they would like to understand the context in the dialogue fully. We believe capturing these regressions and progressions present in gaze data can help detect sarcasm and generate similar gaze data for new samples, as fixations, movements, and regressions can be learned from them. We also believe the creation of quality synthetic eye-tracking data will be useful in reducing dependency on highly time-consuming human eye-tracking annotations.

2.3 Motivation for Multimodality

The task of sentiment analysis has been in field of research for a long time now and for a lot of years it was being performed only on the text data as the input. Due to recent boom of the internet and digitization in the world, loads and loads of data is getting uploaded every day on the internet. Social media websites like twitter allow users to post text along with images and videos to express their thoughts on the site. This has created an opportunity for collection of huge amounts of Sentiment data which is multi-modal in nature. Text is a very important modality when it comes to understanding of sentiments and opinion s involved in the data, but it is insufficient in many cases. The visual modality can be very useful in providing information about facial gestures. The audio and visual modalities when combined with the text can provide much better information about the opinion present in the input. In case sarcastic data, role of other modalities becomes very crucial, because with only a sarcastic text it is tough to identify the sentiment involved, only when the image and audio features are considered, we can do sentiment analysis for sarcastic data effectively. When it comes to sarcastic data, multimodality becomes very important in order to predict the correct sentiment or emotions for the data.

For Example:

if we have an image of a person speaking "oh wow well done" with a sarcastic expression. Than if we only consider the textual modality, the sentiment which will be predicted is positive but, only when we explore the features of the image we would get to know that the correct sentiment is negative.
2.4 Applications

• Chat bots: Intellect of chat bots can be enhanced if they are able to detect sarcasm in a customers query. The chat bots would be able to give more meaningful and relevant replies to queries having sarcasm.

  For Example: Customer: Thank you so much for your great service, thanks for dropping me in London and my luggage in surrey.
  Reply from bot: Thanks for the appreciation.
  Here the bot was not able to detect the disgust present in the customers comments and could not help too.

• Online Reviews: Many times Customers who are not happy with some product or a service, write negative reviews in sarcastic form. The system if not able to detect the deep meaning of the reviews, would classify such reviews as positive reviews and thus there will be hindrance in betterment of their services.

3 Literature Survey

3.1 Sarcasm Definition

The use of sarcasm to convey disgust is frequently mentioned. The fundamental character of it is, it could be difficult to determine the speaker’s aim when they are "speaking one thing but meaning the other" or when there is incongruity.

Based on (Joshi et al., 2016), sarcasm is considered as a 6-tuple representation:

(u, p, p’, S, H, C)

u = Utterance
p = Literal Proposition
p’ = Intended Proposition
H = Hearer/Listener
C = Context
S = Speaker

Although it is well known that sarcasm is typically used to convey a negative emotion, it is important to analyse the reasons behind this choice of expression.

3.2 Sarcasm types

In the paper (Joshi et al., 2016), four different types of sarcasm are mainly mentioned.

• Propositional: Statements which require context involved to be known in order to understand the sarcasm, otherwise they look as simple prepositions.
  Example: Yeah, right! that looks exactly like ganesh.
  Such statements could be understood only if ganesh’s personality is known.

• Embedded: These statements include incongruity built within the words and phrases themselves.
  Example: Yes, I relish the thought of a stranger covering my body with oil and rubbing it.

• Illocutionary: This type of sarcasm requires other modalities apart from just text, like video and audio in order to be interpreted.
  Example: Oh wow, well done. (Big eyes and clap), this statement would only be understood when visual features are seen.

• Like-Prefixed: In these cases, a Like expression exists that presents an implicit denial of the claim stated in the statement.
  Example: Like you give any importance to me!

3.3 Gaze and NLP

Existing studies demonstrate how cognitive features have been used to improve performance for various NLP tasks. User understandability of sarcasm can be evaluated with the help of gaze behaviour (Mishra et al., 2016a), where incongruity in the text induces gaze behaviour characterized by longer fixation durations, repeated regressions, and also scan path complexity (Mishra et al., 2017b).

Previously, sarcasm detection based on only textual input has shown minor improvements with the help of gaze-based features (Mishra et al., 2016b, 2017a). Gaze behaviour has also been used to identify a reader’s native language (Berzak et al., 2017), as well as to detect grammatical errors in compressed sentences (Klerke et al., 2015a,
Klerke et al. (2015b) also show that gaze behaviour can be used to evaluate the output of Machine Translation systems better than automated metrics. Similarly, gaze-based features have also been shown to help the task of cognate and false friends’ detection (Kanojia et al., 2021). Gaze behaviour has also been used to evaluate how a reader would rate the quality of a piece of text (Mathias et al., 2018). Similarly, Mathias et al. (2020b) also perform the task of essay grading in a zero-shot setting using only gaze-based features and show the efficacy of gaze-based grading for performing NLP tasks (Mathias et al., 2020a). However, existing research does not discuss the correlation of multimodal features (like visual and audio) with gaze-based features, and does not investigate these features for multimodal sarcasm detection in a conversational setting. In the subsection below, we discuss the literature on multimodal studies in NLP. Lack of data has been a common problem in cases of both sarcasm as well as cognitive NLP. Numerous efforts have been made in building gaze feature predictors in order to reduce dependency on gold gaze data by producing high quality synthetic gaze data. Study in Takmaz (2022) utilizes "adapter" in a language model to match the results of a fully fine tuned language model for predicting eye tracking features with a highly efficient network in terms of the number of parameters. Ding et al. (2022) propose a Bi-LSTM-based network that, with the help of a few psycho-linguistic features, predicts eye tracking features. The paper states that the readability of a text reflected in the linguistic features is important to predict eye movement patterns (Scarborough et al., 2009). The creation of synthetic gaze data has also been performed in multilingual settings. In Srivastava (2022), a model trained on a completely different set of languages predicts gaze data for a completely new language.

3.4 Approaches to Sarcasm Detection

Transformers (Vaswani et al., 2017) architecture-based approaches have increased in prevalence within NLP and also within sarcasm detection literature. This is most notably due to their ability to pick up semantic and syntactic relationships within text. Various rule-based and machine learning based approaches to sarcasm detection have been discussed in (Joshi et al., 2017); they also present a linguistic perspective to sarcasm detection. On the dataset released with the SemEval 2018 Shared Task 3 (Van Hee et al., 2018), (Potamias et al., 2020) offered an RCNN-RoBERTa methodology, where a RoBERTa transformer was used with BiLSTM to enhance F1-scores from cutting-edge neural network classifiers for the task of sarcasm detection. This paper also reports that the RCVV-RoBERTa approach achieved an F1-score of 90.0 on the Riloff dataset (Riloff et al., 2013). Several methods for sarcasm detection are discussed by (Shangipour ataei et al., 2020), in their article from 2020. A BERT (Devlin et al., 2019) model without concatenated layers, BERT encodings with a Logistic Regression model, and other language models like IAN (Ma et al., 2017) that are trained and assessed on a Twitter-based sarcastic dataset are among them. With an F1-score of 73.4 in those evaluations, the BERT language model without any additional layers performs the dataset’s best. (Ray et al) proposes a Multimodal approach to sarcasm detection, involving various transformer and neural network-based architectures to extract features from the audio, video and text modalities, they achieved a macro-F1 score of 70.2% on the MUSStARD++ dataset, a sarcasm annotated dataset, with utterances from famous sit-coms. Some existing literature investigates methods for performing sarcasm detection in Arabic (Abu Farha and Magdy, 2021), where an extensive set of experiments are performed on different transformer architectures, that include mBERT, XLM-RoBERTa (Conneau et al., 2020) and language-specific models like MARBERT (Abdul-Mageed et al., 2021). In a low-resource environment, the most effective model in this study achieves an F1-score of 58.4. A weighted average Ensemble of a CNN, LSTM, and Gated Recurrent Unit (GRU) based architectures is trained with GloVe (Pennington et al., 2014) word embeddings to identify sarcasm, as demonstrated in (Goel et al., 2022). The Ensemble outperformed comparative studies by up to 8% on SARC (Khodak et al., 2018), a Reddit comments dataset. (Bouazizi and Otsuki Ohtsuki, 2016) used a pattern-based approach to the task. This study emphasizes the role of four sets of features obtained based on different sarcasm types, the study also analyses the contribution of these features towards the classification task. This pattern-based study achieved 83.1% accuracy and 91.1% precision on the task of sarcasm detection. After transformers came into the picture, the popularity of the machine learning approaches has been declining. Some studies in-
clude (Reyes and Rosso, 2011) and (Barbieri et al., 2014) which used a Naive Bayes and Decision Tree model, respectively, in order to identify sarcasm where both achieve the best F1 scores over 70 on their chosen datasets.

### 3.5 Multimodal NLP

Existing literature on multimodal sentiment classification refers to the MOUD (Pérez-Rosas et al., 2013) and MOSI (Zadeh et al., 2016) datasets and the IEMOCAP dataset (Busso et al., 2008) for the task of multimodal emotion recognition. Poria et al. (2017) propose the use of a bidirectional contextual long short-term memory (bc-LSTM) architecture for both tasks and show improvements over baseline on all three datasets. However, Majumder et al. (2018) later propose context modelling with a hierarchical fusion of multimodal features and achieve improved performance in a monologue setting. In the conversation setting, Hazarika et al. (2018) propose using a Conversational Memory Network (CMN) to leverage contextual information from the conversation history and achieve improved performance. Novel multimodal neural architectures (Wang et al., 2019; Pham et al., 2019) and multimodal fusion approach (Liang et al., 2018; Tsai et al., 2018) have propelled the deployment of computational models. Efficient multimodal Fusion approaches have also been discussed in (Sahay et al., 2020; Tsai et al., 2019; Liu et al., 2018)

For multimodal sarcasm detection, a recent survey discusses the datasets and approaches in detail (Bhat and Chauhan, 2022). The MUSTARD dataset (Castro et al., 2019b) provides clips compiled from popular TV shows, including Friends, The Golden Girls, The Big Bang Theory, and Sarcasmaholics Anonymous, annotated with sarcasm labels. Ray et al. (2022) extend upon this dataset by adding emotion labels and additional clips while also benchmarking for the multimodal sarcasm detection task. They call this extended dataset MUSTARD++ and utilise feature fusion and a feedforward network to predict the sarcasm label. The authors show an F1-score of 70.2% points using audio, text and video modalities.

Our work utilises a similar approach with the additional gaze modality and also reproduces the baseline experiments. With this work, we aim to underpin how gaze-based features perform in a multimodal setting and if they correlate well with feature sets other than textual (visual and audio). We also investigate predicting gaze-based features to save annotation time/cost for multimodal studies.

### 3.6 Test of Significance

In case of human involvement in a project for annotation, it becomes very important to prove the significance of the results generated using those human annotations. This is because, to rely on results produced by some experiments on a dataset one needs to completely trust the authenticity of the annotations i.e. the annotations which were performed were not done casually and have some meaning to it.

Paired Students T-test is one such way of testing significance where the means of two samples are compared and p-value is produced. Hypothesis Tests use samples to infer the properties of an entire population.

There are two kinds of Hypothesis as mentioned below

- **NULL Hypothesis**: The group means are equal(samples represent same population)
- **Alternative Hypothesis**: The groups have unequal means

In case of two sample independent T test: p value is a probability that represents how similar or different the two samples are from each other. We also define a significance level, mostly 0.05. If the p value $< $ Significance level, than the two samples are significantly different.

### 4 Sarcasm Datasets

Some of the important datasets with sarcasm data include MUSTARD, MUSTARD++, ZuCo, MaSaC.

#### 4.1 MUSTARD++

MUSTARD++ is a multimodal dataset that consists of textual utterances with context, audio, and video from a corresponding clip. This data has been acquired from publicly available sources for five television shows: Friends, The Big Bang Theory (seasons 1–8), The Golden Girls, and Burnistoun and The Silicon Valley. Each dialogue is presented as a combination of the main ‘utterance’ and the ‘context’ in which it was uttered. It contains a total of 1,202 instances, out of which 601 are sarcastic, and 601 are non-sarcastic. Along with sarcasm annotation, the dataset also provides additional information like an emotion class, valence, arousal,
and sarcasm type. We chose this dataset for our experiments and performed gaze annotation on 231 samples, where 129 are sarcastic, and 102 are non-sarcastic. To avoid any skew, the sarcastic instances are chosen to encompass all four types of sarcasm with a distribution similar to the one in the source data from MUStARD++. The selected instances include dialogues with short contexts (in the range of 2-5 speaker turns) as well as long contexts (6-13 speaker turns).

Figure 3: Sarcasm-type distribution from D1 (left) and D2 (right) datasets.

4.2 MaSaC

(Bedi et al., 2021) worked on the problem of Multi-modal Sarcasm detection and Humour classification, again in the language of Hindi, but interestingly in Code-Mixed situation along with English. They publicly release their code-mixed dataset for research on github. It contains both English words in Hindi and Hindi words in English as shown below in 4

Figure 4: Examples from MaSaC

Similar to M2H2, MaSaC also contains humour labels for the data, however it also contains sarcasm labels for each utterance. Some other details are as follows

- **Utterances**: 15K utterances
- **Episodes**: 50 episodes (400 scenes)
- **Language**: Hindi+English code-mixed
- **Source**: Sarabhai vs. Sarabhai

4.3 Image+Text Sarcasm Data

While looking for multimodal datasets another commonly faced situation is that, relatively more datasets labelled as multimodal consider images to be their visual modality instead of video as desired by us. Nonetheless, the following dataset created by (Sangwan et al., 2020) contains instances each of which have a text along with an image associated and was built for the task of sarcasm detection. For testing their proposed approach for sarcasm detection they compiled two Instagram based datasets.

- **Silver dataset**
  - Posts: 10K sarcastic and 10K non-sarcastic
  - Annotation method: Hashtag based

- **Gold dataset**
  - Posts: 1600 sarcastic
  - Annotation method: Manual

Since the data is based on Instagram posts, quite often the images themselves contain some text within which could also be a carrier of incongruity and hence the authors take advantage of the transcript extracted from the image and take advantage of that too by treating it as a third modality. The following figures 5 and 6 show the kind of data this dataset holds

Figure 5: Example 1: Text incongruous with image

Figure 6: Example 2: Sarcasm within the transcript in the image

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2https://github.com/LCS2-IIITD/MSH-COMICS.git
4.3.1 Other Multimodal Gaze Datasets

Zuco and Zuco2.0 are two datasets that can be useful resources for gaze and EEG features data. This has 130 Gb of data annotated with gaze features and EEG features.

5 Feature Extraction Techniques: Uni-modal Features

There are techniques to find good quality embedding of feature representations for the separate uni-modal data i.e. for visual, audio, and text data, it is very important to capture useful information in the uni-modal representations of the data so that when these representations are fused, quality information from all modalities are captured. The techniques which are popular for extracting these uni-modal features are mentioned in the following sections.

5.1 Visual Feature Extraction

5.1.1 Facet Library

It is open-source research from google and it is very useful to get an understanding of the data and its structure that is being used. Two tools facets overview and facets dive can be used for this purpose.

5.1.2 Resnet-152 encoder

These are very deep-layered networks with convolution layers, but as in case of standard neural networks with convolution layers, the problem of vanishing/exploding gradients arises. To overcome this skip connections were introduced in the the resnet architecture and the resnet architecture had 152 layers in it. These capture visual features effectively when pre trained on some large image dataset.

![Figure 7: Skip connection in RESNET](image)

5.2 Audio Feature Extraction

Audio features can play an important role in sentiment and emotion analysis, the pitch, tone, and speed of the speech are useful in determining the sentiment of the speaker, for example, if the sentiment involved is anger then most likely the audio will be loud and the tone will not be soft. Some of the Popular tools and techniques used to extract audio features are:

5.2.1 openSMILE

openSMILE (open-source Speech and Music Interpretation by Large-space Extraction) is an open-source software used for audio feature extraction and is also important for the task of classification of music labels.

5.2.2 COVAREP

A COLLABORATIVE VOICE ANALYSIS REPOSITORY which has made access to most of the audio processing and extraction-related algorithms easier. It has made the research more reproducible as reproducing algorithms from original papers was a tougher task. This covarep can be used for extraction of audio features from signal for the task of sentiment and emotion analysis.

5.3 Textual Feature Extraction

Lot of research has been done to generate good quality embedding’s for the text data which capture lots of information in the text for example the Distributional similarity between words or phrases of the text, also semantic information needs to be captured from the text. Some of the Popular word embedding techniques used are:

5.3.1 Glove Pre-trained embedding

GloVe (Pennington et al., 2014) is an algorithm for extracting vector representations for words in a given document. It makes use of the global word-word co-occurrence matrix of a dataset in order to generate the word vectors for the words which is why it captures global semantics or context for the words.

5.3.2 ELMo embedding

Embeddings from Language Models (ELMo) is a technique used for extracting vector representations of words from sentences and these vector representations provide information about the word sense too. The difference between Elmo and the above embedding i.e. glove is that there can be different representations of the same word, when the word is being used in different context’s.
It uses 2 layered Bi-LSTM’s for the generating word embedding’s.

6 Multimodal Fusion

Now after we have the uni-modal representations of all the modalities separately, a task of fusion needs to be performed which is basically combining all the unimodal vectors and generating a single vector for the complete data across all the modalities involved. Some of the techniques for multimodal fusion are mentioned below:

6.1 Gating

(Liu et al., 2020) presents a very detailed work which aims at ensuring good quality representation when videos are involved with other modalities like text, and audio etc., Their main aim is to focus on building a compact representation that finds application in a number of video understanding tasks, such as video retrieval, clustering and summarization. To this extent they propose a multimodal fusion framework, called, ‘Collaborative Gating’ that ensures that video and text that correspond to each other stay similar in representation, as compared to when they are unassociated. They treat the video, audio, and embedded text as three different modalities. Since this methodology internally utilizes attention, we take inspiration from this work to perform multimodal fusion in our project.

6.2 Concatenation

This is the most basic way of fusing uni-modal representations, a concatenation operation is performed among all the vector representations to generate a single fused multimodal vector representation.

6.3 Dynamic Fusion Graph

![Dynamic Fusion Graph](image)

Figure 8: Dynamic Fusion Graph

This Dynamic Fusion Graph explicitly models the n-modal interactions in a hierarchical manner as well as it has the capability of altering its network/structure based on the importance of n-modal dynamics. Dense feed forward neural networks are used to generate representations for all possible combinations of modalities and finally in the last layer concatenation of all these representation is performed to generate the final representation having features from all three modalities.

7 Gaze Annotation

We instructed five annotators to read the ‘textual utterances with its context’ on the screen and ask them to provide annotations for the implied binary sentiment in the dialogue, i.e., positive or negative. These samples are shuffled, and the experiment builder software is allowed to choose a random instance from the 231 samples to be presented next on the screen. We do not instruct the annotators to look for sarcasm to avoid the Priming Effect, i.e., if sarcasm is expected beforehand, it becomes easier to process. It may have resulted in unattentive participation by annotators (Sánchez-Casas et al., 1992). It ensures the ecological validity of our experiment as 1) the participant has no clue which utterance to expect, and no special attention is paid to either class from the instances, and 2) it also ensures attentive participation. Our annotators are graduate students between the ages of 22-27 with good proficiency in the English language. Annotator selection was made after ensuring they had English as the medium of instruction through undergraduate and their ongoing post-graduate degree program. We ensure that they consent to record their eye movement pattern to be used for this research.

We provide two unrecorded samples at the start of the experiment to acquaint them with the annotation process. While annotating for sentiment over 231 samples, we provide our annotators with a short break after every 30 samples to ensure minimal annotator fatigue, and re-calibrate for their eye movements after each break. The head movement was minimised using a chin-rest during the annotation process. The gaze tracking device used is an SR-Research Eyelink-1000 (monocular remote mode with a sampling rate of 500Hz) that captures the eye movement of the reader/annotator.
<table>
<thead>
<tr>
<th><strong>Gaze Feature</strong></th>
<th><strong>Feature Description</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Blink Duration</td>
<td>Mean of all blink duration’s in a Dialogue/trial.</td>
</tr>
<tr>
<td>Avg. Fixation Duration</td>
<td>Average duration(in milliseconds) of all selected fixations in a trial.</td>
</tr>
<tr>
<td>Total Regression Duration</td>
<td>Total time of eye regression in a trial.</td>
</tr>
<tr>
<td>Run Count</td>
<td>Total runs/count of fixations in a trial.</td>
</tr>
<tr>
<td>First Fixation Duration</td>
<td>Time for which the eye fixated first time in a trial.</td>
</tr>
<tr>
<td>Total Duration</td>
<td>Total Duration for a trial.</td>
</tr>
<tr>
<td>Fixation count</td>
<td>Total number of fixations in a trial.</td>
</tr>
<tr>
<td>Max. Fixation Duration time</td>
<td>Maximum time for which eye fixated in a trial.</td>
</tr>
<tr>
<td>Min. Fixation Duration Time</td>
<td>Minimum time for which eye fixated in a trial.</td>
</tr>
<tr>
<td>Interest Area Count</td>
<td>Number of Interest Areas in a trial.</td>
</tr>
<tr>
<td>IP Duration</td>
<td>Duration of Interest Period in milliseconds.</td>
</tr>
<tr>
<td>Out Regression Count</td>
<td>Total number of Regression in a trial.</td>
</tr>
<tr>
<td>Regression In count</td>
<td>Number of times regression happened to a lower id interest area.</td>
</tr>
<tr>
<td>Fixation Duration Median</td>
<td>Mean of fixation durations in a trial.</td>
</tr>
<tr>
<td>Max Pupil Size</td>
<td>Largest size of the pupil in the trial recording.</td>
</tr>
<tr>
<td>Mean Pupil Size</td>
<td>Mean of the pupil sizes in a trial recording.</td>
</tr>
<tr>
<td>Min. Pupil Size</td>
<td>Smallest pupil size in trial recording.</td>
</tr>
<tr>
<td>Min Pupil Size x</td>
<td>X position of the pupil at the time when pupil size is minimum.</td>
</tr>
<tr>
<td>Interest Area Run count</td>
<td>Mean of number of times the interest area was entered and left.</td>
</tr>
<tr>
<td>Saccade count</td>
<td>Total number of saccades in a trial.</td>
</tr>
<tr>
<td>Sample count</td>
<td>Total number of samples in the trial.</td>
</tr>
<tr>
<td>Fixation Duration SD</td>
<td>Standard deviation of all fixation durations.</td>
</tr>
<tr>
<td>Saccade Amplitude SD</td>
<td>Standard deviation of all saccade amplitudes.</td>
</tr>
<tr>
<td>Visited IA count</td>
<td>Total number of times the interest area was visited.</td>
</tr>
<tr>
<td>RT</td>
<td>Reaction time associated with the trial.</td>
</tr>
</tbody>
</table>

Table 1: Gaze features and their description, these are the final set of gaze features that were used in the sarcasm detection experiment.
7.1 Annotation & Feature Validity
We compute inter-annotator agreement using a pair-wise Fleiss’ kappa (Scott, 1955), which resulted in a statistically significant ($p<0.05$) moderate agreement (0.41) among our annotators. To validate features for our experiment, we chose a standard gaze-based feature and a saccadic regression-based feature, i.e., average fixation duration and interest area regression path duration (Table 1), respectively. In Table 2, we show the analysis from a two-sampled t-test over feature data from each participant. We observe that for each participant (P1-P5), the difference between sarcastic and non-sarcastic instances is statistically significant, which further motivates us to use these features for sarcasm detection/classification.

8 Conclusion and Future Work
This paper discussed the use of gaze-based features for the task of sarcasm detection in a multimodal and conversational setting. We propose the use of textual, audio, and video in combination with the gaze modality by showing a substantial improvement in performance with the addition of collected gaze-based features. We collect gaze data over a small number of samples and predict these features for a larger portion of the data, both of which we will release with the code and the best models from our experiments. With predicted gaze-based features, however, we observe a small improvement in the task performance in this case. To the best of our knowledge, our results indicate that adding collected gaze-based features certainly improves task performance in every feature combination, proving the efficacy of gaze-based features. Our qualitative analysis also suggests that better audio and visual features should help improve task performance.

In future, we would like to improve the quality of predicted gaze-based feature further in a multi-task setting of sarcasm detect and gaze prediction.

Limitations
Our work has certain limitations, as gaze data collection is challenging. Multimodal datasets are also scarce, and it’s challenging to benchmark the performance of this approach over multiple datasets. We release the complete gaze data with annotator-provided sentiment labels, but our inter-annotator agreement is only moderate. The subjectivity of sarcasm and cultural contexts present in jokes are the key reasons for the inter-annotator agreement value being low. The understanding of sarcasm varies from person to person depending upon the age, culture, context, familiarity with the characteristics present in the utterance, etc. This makes sarcasm a very hard and cognitively loaded phenomenon for even linguists to annotate. Collection of eye-tracking/gaze data is a tedious and costly process, it requires hours of human participation without any loss of concentration of the annotator. Transformers-based models, in the case of video, audio, as well as text, require large amounts of data to be able to generalise and perform well. Thus, dataset contribution becomes essential to push boundaries and enable more research in the field.

Ethics Statement
MUStARD++ used in our experiments is ethically verified in the previous works that used the dataset (Ray et al., 2022; Castro et al., 2019b). We took consent from all 5 annotators for the gaze annotations, which involved tracking the participant’s eye while they read the text displayed on a screen. We also pay the annotators for their time and efforts in the annotation.
<table>
<thead>
<tr>
<th>Average Fixation Duration</th>
<th>IA Regression Path Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu_{\text{Pos}} \pm \sigma_{\text{Pos}} )</td>
<td>( \mu_{\text{Pos}} \pm \sigma_{\text{Neg}} )</td>
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<td>( \mu_{\text{Neg}} \pm \sigma_{\text{Neg}} )</td>
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<tr>
<td>( p )</td>
<td>( p )</td>
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<tr>
<td>P1</td>
<td>208.0 ± 15.1</td>
</tr>
<tr>
<td>P2</td>
<td>209.6 ± 16.3</td>
</tr>
<tr>
<td>P3</td>
<td>241.6 ± 14.0</td>
</tr>
<tr>
<td>P4</td>
<td>252.1 ± 10.4</td>
</tr>
<tr>
<td>P5</td>
<td>212.6 ± 17.9</td>
</tr>
</tbody>
</table>

Table 2: Two-sampled T-test statistics for average fixation duration and interest area regression path duration for Positive labels (Sarcastic) and Negative labels (Non-sarcastic) for participants P1-P5.

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