Detecting Anchors’ Opinion in Hinglish News Delivery

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Abstract. Humans like to express their opinions and crave the opinions of others. Mining and detecting opinions from various sources are beneficial to individuals, organisations, and even governments. One such organisation is news media, where a general norm is not to showcase opinions from their side. Anchors are the face of the digital media, and it is required for them not to be opinionated. However, at times, they diverge from the accepted norm and insert their opinions into otherwise straightforward news reports, either purposefully or unintentionally. This is primarily seen in debates as it requires the anchors to be spontaneous, thus making them vulnerable to add their opinions. The consequence of such mishappenings might lead to biased news or even supporting a certain agenda at the worst. To this end, we propose a novel task of anchors’ opinion detection in debates. We curate code-mixed news debates and develop the ODIN dataset. A total of 2054 anchors’ utterances in the dataset are marked as opinionated or non-opinionated. Lastly, we propose DetONADe – an interactive attention-based framework for classifying anchors’ utterances and obtain the best weighted-F1 score of 0.703. A thorough analysis and evaluation show many interesting patterns in the dataset and predictions.

Keywords: Anchors’ opinion · Opinion Detection · Code-Mixed Conversations.

1 Introduction

News bulletins play a significant role in educating, informing, spreading awareness, and influencing the masses about important current affairs. Recent estimates show that the Indian news channels are broadcast over 161 million TV households, and more than 200 million internet users [5]. This puts a lot of responsibility on the news channels as they are the primary source of the masses’ knowledge about current affairs.

Common citizens expect their news to be free of opinions and only based on facts. However, in recent years, we have seen countless instances where reporters/news anchors either purposefully or unintentionally insert their opinions

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Table 1: An annotated snippet of a dialog (debate) in ODIN. For brevity, we do not show the full conversation. Anchor’s opinion spans are highlighted in blue.

| Utterance                                                                 | Opinion |
|---------------------------------------------------------------------------|---------|
| ![Table content here](https://example.com/table-content.png)              |         |

Table 1: An annotated snippet of a dialog (debate) in ODIN. For brevity, we do not show the full conversation. Anchor’s opinion spans are highlighted in blue. |   |   

| Utterance                                                                 | Opinion |
|---------------------------------------------------------------------------|---------|
| ![Table content here](https://example.com/table-content.png)              |         |

Such utterances should not be presented by an anchor, as the reporter is the face of the news media, and news media is supposed to be unbiased and unopinionated. To help and cater to the news anchors and media in promoting unbiased and unopinionated news, our work aims to help organisations detect opinionated utterances. To this end, we first curate ODIN (Opinion Detection In News) – a dataset developed by transcribing different code-mixed Hinglish
news debates from several mainstream national news channels and annotating the utterances of the debate as opinionated/unopinionated. Then, we propose DetONADe (Detecting Opinion in News Anchor Delivery) to detect utterances as opinionated and benchmark the task. We also present a detailed analysis of the dataset and necessary evaluation of the obtained results.

In summary, we make the following contributions:

1. We explore opinion detection in a code-mixed (Hinglish) dialogue environment, a novel task which, to the best of our knowledge, has never been attempted before.
2. We curate a new dataset, ODIN, by transcribing various Hinglish news debates from three national news channels and annotating these captioned utterances as opinionated/unopinionated.
3. We perform extensive analysis of ODIN and provide interesting insights.
4. We benchmark ODIN using DetONADe and report the necessary results and error analyses.

The source codes and datasets are available at https://github.com/LCS2-IIITD/ODIN-PAKDD.

2 Related Work

Opinion expression is an integral part of opinion mining, and it was first defined as either Direct Subjective Expression (DSEs) or Expressive Subjective Expressions (ESEs) [16]. Following this definition, a fine-grained opinion Mining corpus, namely Multi-Perspective Question Answering (MPQA) was curated for annotating expressions as opinion. Apart from already present datasets, researchers also explored social media, blogs and news articles as opinion mining from heterogeneous information sources can be of great use for individuals, organisations or governments. Ku et al. [8] dealt with the task of opinion extraction, summarisation and tracking on news and blogs corpora, and a lexicon-based feature modelling technique was proposed to extract opinions from documents. Support Vector Machines (SVM) and Decision Trees (C5) were used to predict the results. Breck et al. [2] proposed a Conditional Random Fields (CRF) based model where identifying opinion expression was assumed as a sequence labelling task and achieved expression-level performance within 5% of human inter-annotator agreement. Raina [13] proposed an opinion mining model that leveraged common-sense knowledge from ConceptNet and SenticNet to perform sentiment analysis in news articles, achieving an F1-score of 59% and 66% for positive and negative sentences, respectively. Recently, researchers explored deep learning for opinion detection [6,17].

The scope of this task has always been limited to English language and monolingual settings. There has not been any significant research work on opinion detection in code-mix or Indic languages. But code-mixing is an increasingly common occurrence in today’s multilingual society and poses a considerable challenge in various NLP based downstream tasks. Accordingly, there have been some
helpful developments in the field of code-mix in the form of sentiment analysis task, humour, sarcasm and hate-speech detection. A dual encoder based model for Sentiment Analysis on code-mixed data was proposed wherein the network consisted of two parallel BiLSTMs, namely the collective and the specific encoder [10]. This model particularly generated sub-word level embeddings with the help of Convolutional Neural Networks (CNNs) to capture the grammar of code-mixed words. Recently, pretrained monolingual and cross-lingual deep learning models were also leveraged for detection of hate-speech and sarcasm on code-mixed data [12] wherein they used fine-tuned RoBERTa and ULMFit for English and Hindi data streams, respectively. For cross-lingual setting, XLM-RoBERTa was fine-tuned on transliterated Hindi to Devanagri text.

The works mentioned above do leverage code-mix text for common downstream tasks. However, no research has been done on opinion detection on code-mix text in sequential data streams. Most opinion detection and sentiment analysis studies have focused on news articles, blogs and movie reviews. In online news articles, every piece is reviewed by multiple people, and thus the scope of opinions is limited compared to news coverage on live media sources. Moreover, biased and opinionated live news anchoring can significantly impact our society and go against the essence of free and fair news reporting. Therefore, we aim to detect opinions amongst news anchors. We focus on code-mix news anchoring mainly in live video debates through national news channels that stick to a mix of Hindi and English language (Hinglish) for news distribution. Moreover, our deep learning model not only leverages context but does so in a sequential manner, thus focusing on the text and the utterances before a statement to classify the text as accurately and robustly as possible.

3 Dataset

In this section, we lay out the details of the dataset development process. First, we extract debate videos from three popular Indian Hindi news Youtube’s channels – ABP News, Aaj Tak and Zee News. Subsequently, the collected videos were processed to extract the romanized Hinglish code-mixed utterances. Each utterance is uttered either by the anchor or by the invited speakers. To ensure sanity, we do not identify the utterances with the speaker’s name; instead, we assign ids (A for the anchor, and \{S_1, S_2, \ldots, S_n\} for the invited speakers) to each utterance. Next, we annotate the anchor’s utterances as opinionated or non-opinionated depending upon the dialog conversation. A high-level dataset development process is outlined in Figure 1.

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1 https://www.youtube.com/c/abpnews
2 https://www.youtube.com/c/aajtak
3 https://www.youtube.com/c/zeenews
4 A personal sentiment, which describes the anchor’s feeling on the topic [11].
Table 2: Dataset statistics of ODIN.

| Features                                    | Value       |
|---------------------------------------------|-------------|
| Number of dialog (debate) videos            | 46          |
| Average length of the videos                | 33 mins     |
| Number of utterances                       | 4490        |
| Number of anchor utterances                | 2054        |
| Number of opinionated anchor utterances    | 597         |
| Number of tokens                           | 261811      |
| Number of unique tokens (vocabulary)       | 20023       |
| Average number of utterances per dialog    | 97.6        |
| Maximum number of utterances in a dialog   | 233         |
| Average number of words per utterance      | 58          |
| Maximum number of words in an utterance    | 1192        |

Prepossessing. We collect 46 debate videos for two broad topics as religious and political. Initially, we obtain transcriptions of these videos using the Google Speech Recognition tool. The obtained output had many missing words, possibly due to the background noise or due to the code-mixed nature of the conversation; therefore, we manually add the missing words to complete the utterances. Furthermore, we observe many spelling mistakes in English words – ‘laiv’ for ‘live’, ‘ophis’ for ‘office’, ‘daunalod’ for ‘download’, etc. To fix these spelling mistakes, we try mapping words in the English dictionary to the words in question based on word similarity. We use phonological similarity to achieve this. We employ Libindic’s Soundex library to obtain the correct mapping.

Annotation. Each debate has a series of utterances – some of them were uttered by the anchor and others by the invited speakers. We employ two annotators to annotate the anchor’s utterances as opinionated or non-opinionated. Since the objective of the current work is to identify opinions of anchors, we do not annotate speaker’s utterances. Both annotators read the utterances of the debate and annotate the whole data. To check the inter-rater agreement, we compute Cohen’s $\kappa$ value of 0.88. Subsequently, we perform a consolidated step to include only those annotations where both annotators agree on the opinionated label – we treat disagreement as non-opinionated. Table 1 shows an annotated dialog. For brevity, we show only a snippet of the dialog. There are three speakers and one anchor debating over a topic. Out of all utterances in the dialog, we show the annotated anchor’s utterances as opinionated and non-opinionated.

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5 Henceforth, we will use debate, dialogue, and conversation interchangeably to signify a sequence of utterances.
6 https://pypi.org/project/SpeechRecognition/
7 https://libindic.org/Soundex
Fig. 2: Top 10 most occurring words in opinionated anchor utterances.

Fig. 3: Topic-wise top 10 most occurring words in opinionated anchor utterances.

Statistics. A detailed statistic of ODIN is listed in Table 2. There are total 46 debate videos with an average length of $\sim$33 mins. In total, there are 4490 utterances – 2054 anchor utterances and 2436 other speakers utterances. Out of 2054 anchor utterances, 597 of them are opinionated, accounting for approximately 30% of the utterances.

Dataset Insights. We analyze the dataset to gain insight of the inherent pattern in opinionated utterances. Apart from various topic-related terms such as BJP\(^8\), Congress\(^9\), Islam, etc., corresponding to the political and religious topics, we observe opinionated words like ‘bilkul’ (certainly), ‘matlab’ (means), ‘theek’ (ok), etc., have a significant presence in opinionated utterances. We depict a bar graph of the top-10 most frequent words in opinionated utterances in Figure 2. Moreover, to comprehend whether the frequent words are opinion specific or not, we also plot the ratio to see the distribution of these words in opinionated v/s all the utterances. In Figures 3a and 3b we observe the most frequent words in a topic-wise segregated form.

We observe cases where two or more speakers are involved in a heated exchange without a concrete outcome. In such scenarios, the anchor tries to calm them down, and while doing so, the anchor often slide their own opinions on the

\(^8\) BJP and Congress are two major political parties in India.
subject matter. Cases like these involve the anchor repeatedly calling the name of the speakers – we observe that \(~33\%\) of the opinionated utterances have a single word (or name) spoken multiple times. One such example is shown in the anchor’s second utterance in Table 1. We also find out that anchors tend to ask more questions in an opinionated utterance – on average, 1.45 question words are present in an opinionated utterance, whereas, only 0.9 question words are there in a non-opinionated utterance.

On careful analysis, we observe that an anchor is relatively more likely to express personal opinion at the later stage of the debate rather than at the beginning of the debate. We plot the distribution of the opinionated utterances on the time scale in Figure 4. As we can see that only 78 utterances are opinionated during the first 20\% of the debate duration, which increases to 157 during 20-40\%, 126 during 40-60\%, 99 during 60-80\%, and 137 during 80-100\% of the debate duration. This signifies that an anchor is more conscious about expressing their opinions at the start of the debate and as the debate goes by they get more spontaneous and less conscious.

4 Proposed Benchmark Model

In this section, we describe our proposed benchmark model, DetONADE that we adopt for the anchor opinion detection task. Since the number of the opinionated anchor utterances are significantly few compared to the total number of utterances in the dataset, we adopt an instance-based modeling for the detection. For each anchor’s utterance $u_t$, we create an instance that contains all previous utterances $(u_1, u_2, \ldots, u_{t-1})$ of the dialog as context and the target utterance $u_t$ as the last utterance of an instance. For each instance, we aim to classify the target utterance as opinionated or non-opinionated. We hypothesize that the fixed context will provide appropriate clue about the debate and, at the same time, restrict the model not to overwhelm itself in comprehending the desired context rather than focusing on the opinion discovery. A high-level architecture diagram for the anchor’s opinion detection task is depicted in Figure 5.
We feed each instance one-by-one to DetONADE as input. Since code-mixed texts are susceptible to the spelling variations and various other kinds of noise, representations learned at the sub-word level often counter such variation quite efficiently. Recent literature shows that a wide range of character and sub-word level code-mixed representation models outperform word-level representation models for numerous tasks. Some of them are HIT [14], CS-ELMO [1], CNN\_LSTM [7], etc. We employ HIT (Hierarchically attentive Transformer), the most recent and robust representation learning method for code-mixed text among them, to capture the semantic and syntactical features of the debate. It encodes the code-mixed utterance in the embedding space where the semantic difference among various spelling variations of the same word is minimal.

We obtain representation for each utterance in an instance and feed them through a biLSTM layer for sequence learning. The biLSTM layer captures the cross-sentence relationships across the utterances by exploiting the conversation dynamics of the dialog and subsequently learns latent representations $\hat{h}_i$ for each utterance $u_i$. Next, we apply the multi-headed self-attention mechanism [15] to identify the importance of contextual utterances considering the target utterance $u_t$. To this end, we treat the target utterance $h_t$ as the instance-level context vector $\mu_s$ and compute the interactions between the context vector and every utterance in the dialog through an interactive attention mechanism. The intuition is to obtain an abstract view of the instance that should help in exploiting the dialog dynamics corresponding to the target utterance in a better way. Subsequently, we accumulate the attention weights through a weighted summation and obtain the final vector as $v$.

$$\hat{h}_i = \tanh(h_i); \quad \alpha_i = \frac{\exp(h_i^T \mu_s)}{\sum_j \exp(h_j^T \mu_s)}; \quad v = \sum_i \alpha_i \hat{h}_i$$

Finally, we feed the vector $v$ to the softmax classifier for classifying the target utterance as opinionated or non-opinionated.
Table 3: Experimental results for anchor opinion detection.

| Model      | Opinion        |          |          |          | Non-opinion |          |          |          | Weighted |          |          |          |          |
|------------|----------------|----------|----------|----------|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
|            | F1  | Rec  | Pre  | F1  | Rec  | Pre  | F1  | Rec  | Pre  | F1  | Rec  | Pre  | F1  | Rec  | Pre  |
| ML-BERT    | 0.503| 0.580| 0.447| 0.756| 0.712| 0.806| 0.686| 0.675| 0.707|      |        |        |      |        |        |
| Indic-BERT | 0.500| 0.630| 0.458| 0.609| 0.669| 0.819| 0.657| 0.647| 0.724|      |        |        |      |        |        |
| XLM        | 0.424| 0.468| 0.468| 0.759| 0.758| 0.787| 0.669| 0.675| 0.700|      |        |        |      |        |        |
| DetONADe   | 0.510| 0.555| 0.471| 0.778| 0.752| 0.806| 0.703| 0.692| 0.715|      |        |        |      |        |        |

5 Experiments and Results

In this section, we report our experimental results and error analysis.

**Baselines.** Since opinion mining in code-mixed conversations is relatively unexplored arena, we include various code-mixed representation learning-based system as our baselines. In particular, we employ multi-lingual BERT (mBERT) [4], XLM-RoBERTa [3], and IndicBERT [9] based embedding models to extract the utterance representation. Subsequently, we fine-tune each of these systems through a biLSTM layer followed by a linear layer with softmax classification.

**Experiment Setup.** Since ODIN is skewed towards the non-opinionated anchor’s utterance, we perform oversampling at the instance-level for the opinionated utterances and obtain the equal number of opinionated and non-opinionated instance. For experiments, we perform 3-fold cross-validation and report the average for each case. Note that the oversampling is performed only for the training set in each fold. All experiments are performed on a 12GB K80 Tesla GPU server.

For creating an instance, we vary the size of context from 1 to 7 and observe the best performance with context 5, i.e., \((u_{t-5}, u_{t-4}, u_{t-3}, u_{t-2}, u_{t-1}, u_t)\) as an instance. Furthermore, during experiments, we face a subtle challenge in obtaining the utterance representation for lengthy utterance (number of tokens > 512), since most of the pre-trained language models (PLM) do not comprehend sentences more than 512 tokens. In such cases, a typical solution is to clip the utterance at index 512. However, in this work, we exploit an alternative without omitting the content. We split the lengthier utterances into \(k\) chunks of 512 tokens. Subsequently, we obtain representations for each of these \(k\) chunks and consolidate them by taking an average of the \(k\) representations.

**Results and Comparative Study.** We report the results of DetONADe along with other baselines in Table 3 For each case, we compute the weighted-F1 scores. Moreover, we report the class-wise precision, recall, and F1 for the opinionated and non-opinionated cases as well. We observe that DetONADe records the best weighted F1-score of 0.703 in comparison with 0.686 weighted F1-score of the best baseline, ML-BERT. Among all baselines, Indic-BERT has the least score at 0.657 weighted F1-score.

We further observe the class-wise performance of all systems. For the opinion class, DetONADe yields 0.510 F1-score, whereas, it obtains F1-score of 0.778
Table 4: Token-level confusion matrix. We show performance w.r.t. a few critical words in anchors’ utterances.

| Words         | TP | FN | TN | FP |
|---------------|----|----|----|----|
| congress      | 33 | 19 | 85 | 34 |
| bjp           | 18 | 11 | 46 | 15 |
| modi          | 24 | 16 | 77 | 27 |
| gandhi        | 34 | 18 | 63 | 37 |
| bilkul        | 14 | 15 | 45 | 20 |
| hindu         | 14 | 10 | 50 | 20 |
| muslim        | 6  | 4  | 14 | 6  |
| Question-based |70 | 47 | 235| 102|

for the non-opinionated class. Similar to the weighted case, we obtain inferior results for all baselines in both classes. Another observation is that the performance for the non-opinionated class, irrespective of the model, is better than the opinionated class. We relate this to the complex nature of the anchor opinion detection task, where it is extremely challenging to comprehend the intended opinion especially in a conversational setup.

**Error Analysis.** In this section, we both quantitatively and qualitatively analyse the results obtained from DetONADe. As we observe in Table 3, a relatively lower F1-score for the opinionated class suggests a significant number of false positives and false negatives. Moreover, we also observe a relatively higher false positives than the false negatives, thus reporting an inferior precision score. This could be due to presence of a few words which are highly inclined towards one class of utterance, as depicted in Figure 2.

Therefore, in Table 4, we investigate the words that were prevalent in the dataset, and their distribution in the results we obtained. We observe that utterances with reference to the two major Indian political parties (viz. ‘congress’ and ‘bjp’) caused more false positives than false negatives. On the other hand, question-based utterances (ones that usually start with words like ‘kyu’ (why), ‘kya’ (what), ‘kab’ (when), ‘kaha’ (where), ‘kitne’ (how many), ‘kaise’ (how)) have a very high false negative rate as compared to the false positive. For other words like ‘modi’ and ‘gandhi’ (who are political figures) proportionally have similar false positive and negative values. We also observe similar trends for the words representing two major religions in India, e.g., ‘hindu’, ‘muslim’, etc.

In Table 5, we report two mis-classified instances – one for the false positive, while another for the false negative. We speculate that, in the first case, DetONADe focuses too much on the contextual utterances and due to the presence of allegations in the second utterance of the instance, it classifies the instance as opinionated rather than non-opinionated. On the other hand, in the second example, a small portion of the target utterance (i.e., ‘tabhi yeh haal hai’) suggests an opinion, which the model could not comprehend as the opinionated instance. Moreover, we observe a few mis-classified examples that are at the opposite end of the spectrum – one requires context to get a sense of opinion whereas, for others, context is creating noise in the model. Such observation also signifies the subtleness of the proposed task.
Table 5: Examples of test instances which were wrongly predicted by DetONADe.

| Instance# | Context | Target | Debate Gold Predicted |
|-----------|---------|--------|-----------------------|
| 1         | A: “Aapko kya lagta hai <name1> nah toh <name2>?” (What do you think, if it is not sonia then it is rahul?) | A: “Aapko kya lagta hai <name1> nah toh <name2>?” | No |
|           | S: “jeet haar ek vishe hai aaj jeet ke bhi log haar ja rahe hai kyu aap main wahi bata rahin hun aap ko yeh kar de raha hun jeet ka janvier saa yeh log jeet ke bhi haar jaate has bjp mla kharid leta hai” (Winning and losing is one topic, today, even after winning people are losing. I am answering to your question only. Winning and losing is one topic, today, even after winning people are losing, bjp buys mlas (Member of the Legislative Assembly).) | S: “jeet haar ek vishe hai aaj jeet ke bhi log haar ja rahe hai kyu aap main wahi bata rahin hun aap ko yeh kar de raha hun jeet ka janvier saa yeh log jeet ke bhi haar jaate has bjp mla kharid leta hai” | Yes |
| 2         | A: “Ji Ji toh main supreme court ko argue kar raha hun aapko supreme court pe bharosa nahin aapko air chief marshal par bharosa nahin has thik has <name> thik” (Yes, Yes, I am arguing the supreme court. Don’t you trust the supreme court? Don’t you trust the air chief marshal? Ok <name>) | A: “Ji Ji toh main supreme court ko argue kar raha hun aapko supreme court pe bharosa nahin aapko air chief marshal par bharosa nahin has thik has <name> thik” | Yes |
|           | S: “apna jo opposition hai woh weak hai the congress was weak” (Our opposition is weak. Congress was weak.) | S: “apna jo opposition hai woh weak hai the congress was weak” | No |

6 Conclusion and Future Work

In this work, we proposed a novel task of anchor’s opinion detection in code-mixed conversations. To this end, we curated ODIN, a first of its kind dataset by transcribing various debate videos from mainstream Indian news channels. We performed extensive analyses on ODIN, and reported interesting findings. Furthermore, we benchmark the ODIN dataset using DetONADe – an interactive attention-based framework on top to several pretrained code-mixed representation models. Moreover, we conducted error analysis on the outputs of DetONADe. In future work, we plan to extend the dataset with more opinionated samples as well as other varieties of debates. We also wish to explore the multi-modality for the opinion detection.

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