Modeling Multi-level Context for Informational Bias Detection by Contrastive Learning and Sentential Graph Network

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Abstract

Informational bias is widely present in news articles. It refers to providing one-sided, selective or suggestive information of specific aspects of certain entity to guide a specific interpretation, thereby biasing the reader’s opinion. Sentence-level informational bias detection is a very challenging task in a way that such bias can only be revealed together with the context. For most of us, news articles are the main source of information. Therefore, news articles play a central role in shaping individual and public opinions. However, news reports often show internal bias. The current research is often limited to the lexical bias. This form of bias rarely depends on the context of the sentence. It can be eliminated by deleting or replacing a small number of biased words. Contrarily, researchers [Fan et al., 2019] found that the informational bias is more common and more difficult to detect.

1 Introduction

Informational bias broadly exists in news articles. As a sort of framing bias, it always frames a certain entity by specific aspects using narrow, speculative or indicative information to guide a particular interpretation, thus swaying readers’ opinion.

For most of us, news articles are the main source of information. Therefore, news articles play a central role in shaping individual and public opinions. However, news reports often show internal bias. The current research is often limited to the lexical bias. This form of bias rarely depends on the context of the sentence. It can be eliminated by deleting or replacing a small number of biased words. Contrarily, researchers [Fan et al., 2019] found that the informational bias is more common and more difficult to detect.

Different from other types of bias, the sentence-level informational bias detection largely depends on the context and this fact makes the task very challenging. A sentence alone can be expressed in a neutral manner, but it might be revealed as biased in consideration of the context. Take the second row in Table 1 as example: the sentence “Mr. Mattis, a retired four-star Marine general, was rebuffed.” seems to be a very simple declarative sentence stating a fact. However, if we read the previous sentence “Officials said Mr. Mattis went to the White House with his resignation letter already written, but nonetheless made a last attempt at persuading the president to reverse his decision about Syria, which Mr. Trump announced on Wednesday over the objections of his senior advisers.” (the first row in Table 1), we will know that “a retired four-star Marine general” indicates a negative, even ironic tone towards Mr. Mattis and his last attempt. Therefore, sentence-level informational bias can only be revealed by collecting information from various sources and analyzing the entire article together with its background. Such subtleties of informational bias are more likely to affect unsuspecting readers, which indicates the necessity of research into new detection methods.

In this paper, we propose MultiCTX (Multi-level ConTextX), a model composed of contrastive learning and sentence graph attention networks to encode three different levels of context: 1) Neighborhood-context: adjacent sentences, whole article, and articles from other news outlets describing the same event. 2) Article-context: the whole article containing the target sentence; 3) Event-context: articles from various news media reporting the same event. These three levels encompass the contextual information from the most local to the most global.

In order to make use of the context rather than be overwhelmed by the noise introduced, MultiCTX prioritizes contrastive learning which learns sentence embeddings via discriminating among (target, positive sample, negative sample) triplets to distill the essence of the target sentence. The quality of the learned CSE (Contrastive Sentence Embedding) relies on that of triplets. Other than the traditional brute-force way to select triplets only based on their labels, MultiCTX further considers article-level information which creates higher-quality triplets. Such triplet formulation guarantees that our CSEs infuse the context and reflect sentences’ inherent semantics instead of the shallow lexical features.

MultiCTX then builds a relational sentence graph using CSEs. Edges are connected between two sentences if they are logically related in the same neighborhood or if they are continuous in entities or semantically similar within the same event. Finally we apply a Self-supervised Graph Attention Network (SSGAT) on our sentence graph to make
the final informational bias prediction. The SSGAT structure encodes neighborhood-level and event-level context via edges, making it possible for textually distant but contextually close sentences to connect directly. The flexible graph structure extends beyond the sequential arrangement of traditional LSTMs, which also consider the surrounding context.

Although document graphs are not rare in NLP tasks, they are often short and built by token-wise dependency parsing. It may suffer from high complexity and considerable noise when applied on long texts which is our case with news articles. Our relational sentence graph uses sentence nodes and focuses on inter-sentence relationships. It requires only minimal syntax parsing, takes on less noise and has better interpretability.

Few research studies sentence-level informational bias detection by infusing context. Fan et al. (2019) first published a human-annotated dataset on this task, taking the context into account during annotation. However, sentences are still treated individually in their model. van den Berg and Markert (2020) did a primary research on incorporating different levels of context in the informational bias detection. However, they consider only one kind of context in each model. To our best knowledge, our model is the first to incorporate multi-level contextual information in sentence-level classification task.

In summary, we present the following contributions:

- We are the first to incorporate three different levels of context together in the sentence-level bias detection task. By introducing context, we aim to simulate how people learn new things in real life: widely reading, generally picturing and thoroughly reasoning.
- We propose a novel triplet formation for contrastive learning in bias detection. The methodology can be generalized for other tasks.
- We are the first to use a sentence graph to encode the textual context information in the bias detection task.
- Our model MultiCTX significantly outperforms the current state-of-the-art model by 2 percentage points F1 score. It indicates that contextual information effectively helps sentence-level informational bias detection and our model successfully infuses multi-level context.

## 2 Methodology

Figure 3 illustrates our model MultiCTX (Multi-level Context). First, we carefully construct triplets from the original dataset and then apply supervised contrastive learning on them to obtain sentence embeddings. Second, we build relational sentence graphs by joining sentence nodes according to their discourse relationships and semantic similarity. Finally, we apply a Self-supervised Graph Attention Network (Kim and Oh 2021) to perform the bias detection as a node classification task. In essence, MultiCTX has two modules, Contrastive Learning Embedding (CSE) and Self-supervised Sentence Graph Attention Network (SSGAT). In order to investigate the role of the context and to imitate the way people learn from the news reports, we also apply a more reasonable and challenging cross-event data splitting.

### 2.1 Data splitting

First of all, let’s think about the nature of the news reports and the way people learn about the world in real life. News articles always emerge almost simultaneously in large numbers along with a particular event, over which people reason based on their experience learnt from previous events. Moreover, people usually read an article as a whole instead of randomly picking up several sentences and they are unlikely to encounter a sentence from news events happened before. Additionally, people tend to collect information from more than one article to get a bigger picture of the new event. Therefore, in order to simulate the real human’s learning process, different from the commonly-used data splitting which randomly distributes sentences to one of the three subsets (train/val/test), we use event-wise data splitting mentioned in van den Berg and Markert (2020), Chen et al. (2020). We treat the articles reporting the same event as a unit and keeping sentences from the same event in the same subset. Part of the data is shown in Figure 3 with clear ‘adjacent sentences’, ‘article’ and ‘event’ structure.

Furthermore, splitting by events is more reasonable and more demanding, in terms of model generalizability for identifying informational bias from unseen events. Experiments in van den Berg and Markert (2020) and Chen et al. (2020) also show that common models including BERT-based models all experienced a considerable performance drop when switching from random splitting to event-based splitting.

### 2.2 Sentence Embedding using Contrastive Learning

The idea of contrastive learning is that humans discriminate objects by “comparison”, thus similar objects should be close to each other in the representation space, and different objects should be as far apart as possible. However, news sentences inherently have small differences in terms of pure text. Two sentences with opposite stances might be different in a few words, while two sentences expressing the same idea are likely to be formulated completely differently. To address the problem, we apply supervised contrastive learning with hard negatives described in Gao, Yao, and Chen (2021). The idea is to develop, from the original dataset, the triplets \((x_i, x_i^+, x_i^-)\) each denotes target sentence, positive sample and negative sample respectively. Using the \(h_i, h_i^+, h_i^-\) representations of \(x_i, x_i^+, x_i^-\), the objective function to minimize is InfoNCE Loss.

The difficulty is to mine the positive and negative samples for each target sentence from the original dataset. A good positive sample is supposed to capture the most essential features of the sentence, rather than being influenced by other factors, such as the writing styles of different news media. Therefore, the best positive sample is expected to be significantly different from the target sample in terms of sentence formation, while the best negative sample should be similar to the target sentence in terms of syntactic structure. In short, samples with different labels from the target sentence but with initial embedding in its vicinity are likely to be the most useful, providing significant gradient informa-
Event | Source | Index | Sentence | Label
--- | --- | --- | --- | ---
86 | nyt | 3 | Officials said Mr. Mattis went to the White House with his resignation letter already written, but nonetheless made a last attempt at persuading the president to reverse his decision about Syria, which Mr. Trump announced on Wednesday over the objections of his senior advisers. | 0
86 | nyt | 4 | Mr. Mattis, a retired four-star Marine general, was rebuffed. | 1
86 | nyt | 5 | Returning to the Pentagon, he asked aides to print out 50 copies of his resignation letter and distribute them around the building. | 0
11 | fox | 20 | However, Democrats rejected the plan even before Trump announced it, and a Senate version of the plan failed to get the 60 votes needed on Thursday. | 1
11 | fox | 21 | A second bill, already passed by the Democrat-controlled House to re-open the government, also fell short. | 0
2 | hpo | 10 | There were roughly 520,000 arrests for unauthorized border crossings last year, which is about one-third of the 1.6 million arrests that happened in 2000. | 0
2 | hpo | 11 | Since 2014, a high proportion of those crossing have been Central American children and families seeking to make humanitarian claims such as asylum. | 1

Table 1: BASIL dataset

Inspired by [Baly et al. (2020a)] which applies a triplet loss in training using news media in triplet selection, our final triplet follows article-based criteria and is composed of: $x_i$: target sentence; $x_i^+$: same label and event with $x_i$, but from a different article; $x_i^{-}$: from the same article with $x_i$ but with a different label. Figure 1 illustrates our triplet construction.

Thereby we essentially augment the original 7977-sentence corpus to a much larger dataset of around 300k triplets where sentences are no longer isolated but linked to two others.

More importantly, triplets with the same target sentence provide altogether a microscopic ‘context’ for the target sentence to help its representational learning. This process naturally incorporates article-level context and event-level context information:

- The negative samples are from the same article as the target sentence, thus they provide an article-level context. Written by the same author, these sentences would be similar in writing styles and lexical patterns. Therefore, that article-level context made by negative samples not only informs the necessary background story information, but more importantly, they show a layer of “skin” of the article, forcing the contrastive learning model to uncover the superficial skin of rhetoric and wording and to truly understand the article.

- All samples are from the same event, so they provide event-level contextual information. Therefore, from the perspective of the target sentence, all positive and negative samples provide it with a small but complete world that covers most of the event information, from which the model is allowed to freely and massively draw information and to get a broad and general overview of events. Therefore the target representations can be both comprehensive and fair. Additionally, since the positive samples are from different news media and the negative samples are from the same news media as the target sentence, our model can exclude the influence of different news media writing styles and is encouraged to learn the essential meanings. In summary, our triplet construction process simulates the human learning principle of wide reading.

Figure 1: Triplet construction. Positive sample $x_i^+$ has same label (red) and event with target sentence $x_i$; negative sample $x_i^-$ has different label (blue) but from the same article with $x_i$; note that three sentences must from same event.

2.3 Relational Sentence Graph

Sentences are naturally suitable as nodes when encoding long documents, so we borrowed the idea from extractive text summarization from [Christensen et al. (2013)] and [Zhao et al. (2020a)] to construct graphs. The graphs are formed by connecting the sentences in four different ways illustrated in 2a.

1. Deverbal noun reference: when an action in verb form occurs in the current sentence, it is likely to be mentioned in the noun form in the following sentences. So we attach the current sentence with its downstream sentence when at least one semantically similar deverbal noun is found in the latter.
2. Discourse marker: If the immediately subsequent sentence begins with a discourse marker (e.g., however, meanwhile, furthermore), the two sentences are linked.

3. Entity continuation: We connect two sentences in the same event if they contain the same entity.

4. Sentence similarity: Sentence pairs in the same event with high cosine similarity are joined.

(b) Four types of edges in relational sentence graph. Underline: deverbal noun reference; italic: discourse marker; bold: entity continuation; colored: sentence similarity

Figure 2: Relational sentence graph

The four types of edge formation take different degrees of context into account: Type 1 and Type 2 consider only the subsequent sentences in the same article (neighborhood-context). In particular, Type 2 considers only the immediately following sentence. Type 3 and Type 4 are not limited to adjacent sentences. Rather they consider the whole event (event-context). Note that edges occur only between in-event sentences, which is consistent with our event-based splitting.

Note that our sentence graph doesn’t contain edges between two events, therefore it assures no data leakage while training GAT on the whole graph.

2.4 Graph Attention Network

As one of the representative graph convolutional networks, Graph Attention Networks (GATs) introduces an attention mechanism to achieve better neighbor aggregation. By learning the weights of the neighbors, GAT can learn the representation of the target node by implementing a weighted aggregation of the neighbor node representations. However, it may suffer from graph noise introduced by incorrect node linking. In our study, we use Self-supervised Graph Attention Network [Kim and Oh (2021)] which introduces, on top of the GAT, an edge presence prediction task and thus puts an emphasis on more on distinguishing misconnected neighbors.

The graph structure naturally places each sentence within its context, and as a result, different sentences are no longer isolated. The flexibility of the graph structure also allows it to move beyond the ordered arrangement of traditional LSTM. Therefore two sentences can be directly connected by edges, even if they are far apart in the original article or in different articles.

3 Experiment and Results

We use BASIL (Bias Annotation Spans on the Informational Level) dataset proposed by [Fan et al. (2019)] for the sentence-level informational bias detection task. We experiment with four baselines including the current state-of-the-art model and four variants of MultiCTX in order to fully demonstrate each module’s utility. Our results suggest that MultiCTX greatly outperforms the current SOTA and effectively incorporates the contextual information in sentence-level informational bias detection.

3.1 Data

BASIL dataset provides sentence-by-sentence span-level annotation of informational bias for 300 English news articles grouped in 100 triplets, each discussing on the same event from three news outlets. The articles are selected in order to make a fair coverage in terms of time and ideology: 1) From 2010 to 2019, 10 events are included each year in the
As for the sentence-level informational bias detection task, we use the same data formulation in van den Berg and Markert (2020). In this sentence-wise binary classification task, a sentence is labeled as biased if at least one informational bias span occurs, and seven empty sentences are removed, resulting in a total of 7977 sentences with 1221 annotated bias.

Examples are shown in Table 1.

3.2 Set-up

We use the same 10-fold cross-validation event-split in van den Berg and Markert (2020) to facilitate the comparison.

Each fold has 80/10/10 non-overlapping events for train/val/test partition, and sentences from the same event never appear simultaneously in two different subsets within one fold. There are on average 6400/780/790 sentences in train/val/test set respectively. We use 5 different seeds for each method and the F1 score, precision and recall (‘biased’ is positive class) as the evaluation metrics. For each experiment, a mean value and standard deviation across 5 seeds will be reported if applicable.

Note that in the contrastive learning module, the triplets are constructed only in training set, then the trained model does the sentence-by-sentence inference on the test set (no triplets constructed) to get their sentence embeddings. The CSEs are obtained via inference where no labels are seen during such process.

We use the same hyper-parameters provided in van den Berg and Markert (2020) to reimplement BERT, RoBERTa and WinSSC baselines. However, for EvCIM, We cut the training epochs from 150 to 75 and increase the batch size from 32 to 64 due to the considerable time usage. For Multi-CTX, We trained use a RoBERTa-based contrastive learning following the implementation in Gao, Yao, and Chen (2021). Due to unavoidable non-deterministic atomic operations in implementation of GAT, the result presented below may cannot be exactly reproduced, but we took an average on our experiments to reflect its range. All models are trained and evaluated on a GeForce GTX 1080 Ti GPU with 11G RAM and Intel(R) Xeon(R) CPU E5-2630 with 128G of RAM.

3.3 Baselines

There are few models in sentence-level informational bias detection. Fan et al. (2019) has proposed BASIL dataset and corresponding BERT and RoBERTa benchmarks. Cohan et al. (2019) has proposed several models trying to incorporate context in different ways. We will take two of them, WinSSC and their best and also current SOTA model EvCIM, as our baselines. Few other works used BASIL dataset but with objectives other than sentence-level informational detection. Thus we have four baseline models:

- **BERT** (Devlin et al. 2019) and **RoBERTa** (Liu et al. 2019): we finetune the individual sentence informational bias detection task on BERT base and RoBERTa base.
- **WinSSC** (van den Berg and Markert 2020): WinSSC (windowed Sequential Sentence Classification) is a variant of SSC (Cohan et al. 2019). We include it as one of the baselines because SSC implements the very natural idea that comes to us when we think of using context: directly inputing sequences of consecutive sentences to BERT. SSC feeds the concatenation of sentences from a chunk of document to pretrained language models (PLMs),and then classifies each sentence using the embedding of the separator tokens [SEP] at its end. SSC makes non-overlapping chunks while WinSSC makes chunks by overlapping sentences at both ends, which eretains the contextual information for bookended sentences.
- **EvCIM** : PLM embeddings + BiLSTM

EvCIM (Event Context-Inclusive Model) proposed by Cohan et al. (2019) is the SOTA model on BASIL dataset.
and it also uses the contextual information. It takes the average of the last four layers of fine-tuned RoBERTa as the sentence embedding, and then uses BiLSTM to encode each article from the same event as the target sentence. Finally it concatenates three article representations and the target sentence embedding to make the sentence-level prediction. Besides using the hyper-parameters from the original paper, we generate the result from a separate set of reasonable hyper parameters. We present below results both from the original paper and from our experiments.

3.4 Our Models

- **CSE: Contrastive Sentence Embedding**
  CSE (Contrastive Sentence Embedding), i.e. sentence embeddings obtained directly from contrastive learning. Here we use to refer to the classification model by a logistic regression on CSE.

- **MultiCTX w/o SSGAT: CSE + BiLSTM**
  Similar to EvCIM described in Section 3.3, we utilize BiLSTM-encoded context as the target sentence to perform the sentence-wise classification. However, instead of the average of the last four layers of fine-tuned RoBERTa (RoBERTa embedding, or PLM embedding) in EvCIM, we use CSE in our study. Moreover, we also add news source embeddings before the final fully connected classification layer on top of BiLSTM-encoded in-event article embeddings.

In the original paper (Cohan et al. 2019), adding news source embeddings hurts EvCIM’s performance, but because it is useful for EvCIM w/ CSE according to our experiments, we use this version here. This also indicates that CSE has better captured inherent properties of sentences compared to PLM embeddings. CSE can therefore well incorporate extra news media information rather than be disturbed by it.

- **MultiCTX w/o CSE: RoBERTa embeddings + SSGAT**
  We use the original sentence embedding in EvCIM, which is the average of the last four layers of fine-tuned RoBERTa to build the relational sentence graph. We then apply Self-supervised GAT on the graph (SSGAT, Self-supervised Sentence GAT). In other words, we replace CSE in MultiCTX with EvCIM’s sentence embedding.

- **MultiCTX: our full model (CSE + SSGAT)**
  MultiCTX first performs contrastive learning on carefully composed triplets to obtain CSE. It then builds relational sentence graph according to inter-sentence relationships. Finally, MultiCTX applies Self-supervised GAT above to get the final sentence informational bias prediction.

The results are shown in Table 2. By using different sentence embedding methods and the structure to encode contextual information, we are able to demonstrate the respective utility of the two modules, CSE and SSGAT. The table presents the results (Precision, Recall, F1 score) on the four baseline models, our model MultiCTX and its different variants. The four baselines’ results are our reproduced results, most of which are close to the original work, except for the EvCIM, so we put both in the table. In addition, we used 5 different random seeds, and the table shows their means and standard deviations (if applicable).

From the results, we can draw the following conclusions:

1. **Contrastive learning helps improve sentence embeddings.** While keeping the structure to encode context unchanged, models using CSE as the sentence embedding method are the optimal. We see that when the context is not structurally introduced, the performance of CSE (F1=43.51) purely classified by logistic regression is better than that of BERT (F1=35.49) and RoBERTa (F1=42.13); moreover, with BiLSTM as structure to encode the context, MultiCTX w/o SSGAT (F1=45.01) outperforms EvCIM in its original paper (Cohan et al. 2019). Since EvCIM uses the mean value of the last four layers of the fine-tuned RoBERTa as the sentence embedding, the contrastive learning produces better sentence representations than BERT-based PLMs; the same conclusion can be also drawn from MultiCTX w/o CSE (F1=44.79) vs. MultiCTX (F1=46.08). The reason may be as follows:

- BERT-based PLM tends to encode all sentences into a smaller spatial region, which results in a high similarity score for most of the sentence pairs, even for those that are semantically completely unrelated. Specifically, when the sentence embeddings are computed by averaging the word vectors, they are easily dominated by high-frequency words, making it difficult to reflect their original semantics.

- Instead of individual sentences, CSE considers for each target sentence a context built up by all its positive and negative counterparts in related triplets. Among them, negative samples provide an article-level context and positive samples provide an event-level context. With the goal of contrastive learning to “distill essence”, it learns from its context and naturally suppresses such shallow high-frequency-words features, thus avoiding similar representations of semantically different sentences.

2. **Encoding sequential sentences brutally by PLM may fail.** WinSSC attempts to exploit adjacent sentences by directly feeding sequences of consecutive sentences into the PLM, which is the most failed among all models attempting to incorporate the contextual information. It’s even worse (F1=37.58) than the original RoBERTa (F1=42.13). There are two possible reasons: First, we take sentence chunks instead of individual sentences as input, and doing so may introduce data reduction. Second, BERT-based pretrained language models are not good at processing long text. They simply join neighboring sentences, which may introduce more noise and complexity rather than help integrate the context. Therefore, brute-force concatenation of sequential sentences can rarely make use of the contextual information, and it probably brings in more noise and reduces the data quantity.
3. Context information can effectively improve performance. Except for WinSSC, all other models using some kind of context-introducing structure (BiLSTM or SSGAT) outperform the BERT and RoBERTa baselines. It shows that the introduction of context is indeed helpful for the detection of information bias.

4. SSGAT is the best structure to integrate context. While keeping the sentence embedding method unchanged, the model using SSGAT as the structure to introduce context achieves better results. When both use RoBERTa embeddings, MultiCTX w/o CSE with SSGAT outperforms (F1=44.79) EvCIM with BiLSTM (both F1=44.10 in the original paper and our reproduction F1=42.87); when both use CSE, MultiCTX with SSGAT (F1=46.08) outperforms MultiCTX w/o SSGAT (with BiLSTM, F1=45.01), and CSE without context (F1=43.51). The results prove that our sentence graph structure is more effective in encoding contextual information than sequential models such as BiLSTM.

5. Contrastive learning together with sentence graph achieves the best performance. Our full model MultiCTX achieves F1=46.08 in the sentence-level informational bias detection task, significantly outperforms the current State-of-the-Art model EvCIM (Cohan et al. 2019) (F1=44.10 declared in original paper). Possible reasons are: 1) BiLSTMs are limited to the event context in EvCIM; 2) MultiCTX uses better sentence representations (CSE); 3) MultiCTX incorporates the context in varying degrees explicitly using graph structure and implicitly via contrastive learning.

### Ablation Analysis

We have proved that both CSE and SSGAT are essential for MultiCTX, and in this section, we will further explore roles of different inter-sentence relationships in our model. We keep CSEs fixed and modify our relational sentence graph by removing certain types of edges, and then report the results to see how each part contributes to MultiCTX in our informational bias detection task.

Edge types described in Section 2.3 can be briefly summarized in two categories:
- Type 1, 2 and 3 are discourse relationships
- Type 4 is semantic similarity

Besides, they can also be partitioned by level of context:
- Type 3 and 4 are event-level
- Type 1 and 2 are neighborhood-level and article-level

We will focus on their utility in our ablation study. Table 2 shows the ablation results. Horizontally, the first row represents the comparison between discourse relations and semantic similarity, and the second row represents the comparison between event-level context and neighborhood-level context. Vertically, the three ablation analysis experiments in the first column compare the utility of Type 1, 2 / Type 3 / Type 4 edges. Here we analyze Type 1, 2 together.

In addition to the numerical results, we also want to better analyze the utility of various types of edges through the perspective of plotting, so we take an event in the dataset and connect different types of edges between its sentence perspective of plotting, so we take an event in the dataset and connect different types of edges between its sentence

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Table 2: Results. It shows the sentence embedding method, the structure to encode the context, the Precision, Recall, and F1 score of each model.

| Model                      | Sentence embedding | Structure to encode context | Precision | Recall | F1    |
|----------------------------|--------------------|-----------------------------|-----------|--------|-------|
| baselines                  |                    |                             |           |        |       |
| BERT_base                  | NA                 | No context                  | 40.44 ± 1.07** | 35.49 ± 0.67 |
| RoBERTa_base              | NA                 | No context                  | 38.40 ± 0.64 | 48.53 ± 1.49 | 42.13 ± 1.02 |
| WinSSC                    | [SEP] embed.       | Text chunks                 | 41.47 ± 1.31 | 34.37 ± 0.57 | 37.58 ± 0.77 |
| EvCIM (original paper)    |                    |                             |           |        |       |
| EvCIM (our reproduction)  |                    |                             |           |        |       |
| CSE                       |                    | No context                  | 47.53     | 40.13  | 43.51 |
| MultiCTX w/o SSGAT        | CSE                | BiLSTM                      | 48.53 ± 0.73 | 41.98 ± 0.36 | 45.01 ± 0.26 |
| MultiCTX w/o CSE          | CSE                | SSGAT                       | 47.78 ± 0.94 | 44.50 ± 0.65 | 46.08 ± 0.21*** |

* All results are implemented or reproduced by ourselves except for EvCIM (original paper)
* Mean value and standard deviation across 5 seeds are reported if applicable
*** The best result on a single run obtained in our experiments is F1=46.74
Table 3: Ablation study on different types of edges in SSGAT. Horizontally, the first two rows compare discourse relation vs. semantic similarity and event-context vs. neighborhood-context respectively. Vertically, the first column compares the utility of the Type[1,2] vs. Type 3 vs. Type 4 edges. Mean and standard deviation across 5 seeds are reported.

| Horizontal | Discourse relationship | Semantic similarity |
|------------|------------------------|---------------------|
| Vertical   | Type [1,2]*,3 (w/o Type 4) |
|            | Precision | 47.43 ± 0.96 | 47.16 ± 0.27 |
|            | Recall    | 44.39 ± 0.84 | 43.47 ± 0.38 |
|            | F1        | 45.85 ± 0.35 | 45.24 ± 0.18 |

| Horizontal | Event-context | Neighborhood-context |
|------------|---------------|----------------------|
| Vertical   | Type 3,4 (w/o Type 1,2) |
|            | Precision | 47.07 ± 0.99 | 47.18 ± 1.08 |
|            | Recall    | 44.64 ± 0.37 | 44.01 ± 0.91 |
|            | F1        | 45.81 ± 0.42 | 45.53 ± 0.29 |

| Horizontal | Type [1,2],4 (w/o Type 3) |
|------------|--------------------------|
|            | Precision | 47.56 ± 0.62 |
|            | Recall    | 43.72 ± 0.76 |
|            | F1        | 45.55 ± 0.34 |

* Type 1,2 represent neighborhood-context, so we treat them as a whole.

Table 4: Graphs of ablation studies on different types of edges in SSGAT. They are based on one same event in the dataset. Purple nodes are unbiased sentences and yellow nodes are biased sentences. the nodes of each graph are the same, the only difference is the edge types.
explained by Figure 5, connections are mostly within non-biased nodes while inter-communication between biased/non biased nodes are more frequent in Figure 4.

- Event-level context is more important than neighborhood-level context.

While they are both important according to our results, global event-level context contributes more than local neighborhood-level context. SSGAT with only adjacent sentences (Type 1, 2) obtains F1=45.53 and with only Type 3,4 gets F1=45.81. The result is intuitive because edges of type 3,4 not only include adjacent sentences within article, but also extend to the whole event. We can also see the rare presence of edges of Type 1,2 in Figure 7 compared with the closely linked graph in Figure 6.

- Entity continuation is the most important edge type.

Among three ablation experiments removing respectively edges of Type 4 (F1=45.85), Type 1,2 (F1=45.81) and Type 3 (F1=45.55), the last one without Type 3 (entity continuation) suffers the largest performance drop. It suggests that entity continuation, or, coreference is the most important relation in our setting. We can clearly see that Type 3 edges are the main reason for inter-class communication from Figure 9 and Figure 8.

5 Related Work

Media bias Detection. With the rise of deep learning, neural-based approaches are broadly used in media bias detection. Tyner et al. (2014) used RNNs to aggregate the polarity of each word to predict political ideology on sentence-level. Gangula, Duggenpudi, and Mamidi (2019) made use of headline attention to classify article bias. Li and Goldwasser (2019) captured social information by Graph Convolutional Network to identify political bias in news articles. Fan et al. (2019) used BERT and RoBERTa and van den Berg and Markert (2020) used BiLSTMs as well as BERT-based models to detect sentence-level informational bias.

Contextual information in media bias detection. Contextual information is explored, though primarily, in media bias detection. Baly et al. (2020b) employed an adversarial news media adaptation using triplet loss; Kulkarni et al. (2018) proposed an attention based model to capture views from news articles’ title, content and link structure; Chen et al. (2020) explored the impact of sentence-level bias to article-level bias; Li and Goldwasser (2019) encoded social information using GCN; Baly et al. (2018) made use of news media’s cyber-features in news factuality prediction; Huang et al. (2020) explored cross-media context by a news article graph.

Sentence-level informational bias is under-studied by only a few research and the methods described above are not applicable on this task. In order to infer contextual information, we refer to extractive summarization [Zhao et al. (2020b) and Christensen et al. (2013)] which used sentence graph to encode context.

6 Conclusion

Our work focus on incorporating different levels of context: neighborhood-level, article-level and event-level in sentence-level informational bias detection. We proposed MultiCTX, a model composed of contrastive learning and relational sentence graph attention network to encode such multi-level context at different stages.

Our model (F1=46.08) significantly outperforms the current state-of-the-art model (F1=44.10) by 2 percentage points. Therefore, we conclude that our model successfully learns from contextual information and that multi-level contextual information can effectively improves the identification of sentence-level informational bias.

Moreover, our design aims at simulate the way people learn new things in real life: learn from multiple news reports covering the whole event to form a general picture and then use the past experience to reason about the unknown.

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