Improved Regularization of Event-based Learning by Reversing and Drifting

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Abstract

Event camera has an enormous potential in challenging scenes for its advantages of high temporal resolution, high dynamic range, low power consumption, and no motion blur. However, event-based learning is hindered by insufficient generalization ability. In this paper, we first analyze the influence of different brightness variations on event data. Then we propose two novel augmentation methods: EventReverse and EventDrift. By reversing and drifting events to their corresponding positions in the spatiotemporal or polarity domain, the proposed methods generate samples affected by different brightness variations, which improves the robustness of event-based learning and results in a better generalization. Extensive experiments on N-CARS, N-Caltech101 and CIFAR10-DVS datasets demonstrate that our method is general and remarkably effective.

1 Introduction

Event cameras [15][10] are bio-inspired vision sensors that operate in a completely different way from traditional cameras [3]. Instead of capturing images at a fixed rate, the cameras asynchronously measure per-pixel brightness changes and output a stream of events that encode the time, location, and sign of the brightness changes. Event cameras have great potential in challenging robotics
and computer vision scenes due to their appealing properties, including high dynamic range, high temporal resolution, low power consumption, and no motion blur [3]. Modern neural network models provide powerful representational capabilities to unlock the potential of event data. However, excessively complex models, such as ones with too many parameters relative to the number of training samples, may easily overfit and weaken the generalization ability of models [24]. This situation is even more pronounced in the event data.

In order to generalize better, several different regularization techniques have been proposed, such as data augmentation [18, 17, 24], weight decay [12], or batch normalization [5]. In the domain of computer vision, data augmentation is almost ubiquitous due to its ease of implementation and effectiveness [2]. Nevertheless, most existing data augmentation methods perform unsatisfactorily on event-based learning. Therefore, we rethink the principle of event generation [3] and find that the brightness variation problem hinders the generalization performance of event-based learning.

Specifically, unlike traditional pixel values, events record the position, time, and polarity of the brightness variation when the change reaches a threshold. Consequently, even a slight variation in scene brightness can affect the time, polarity, or position of events, leading to cascading changes in subsequent events. When scene brightness varies, a well learned model should draw conclusions from the overall condition. However, the collected training samples usually exhibit limited variations in brightness. In extreme cases, models trained under the same brightness conditions can rapidly degrade when predicting data for scenes with different brightness. Moreover, adding training data with multiple brightness variations is theoretically possible but costly in practice.

To address the problem of poor generalization caused by brightness variations, we propose two novel data augmentation methods, EventReverse and EventDrift. The proposed methods can simulate the effects of brightness variations in the spatial, temporal, and polar domains of events. In detail, EventReverse can move events to opposite positions in time, space, and polarity, as shown in Figure [a]. EventDrift drifts events in time or space by a certain distance, and the part beyond the event stream is discarded, as shown in Figure [b]. The proposed methods generate samples affected by different brightness variations, which significantly improve the generalization ability of the model.

The closest work to the proposed methods are flipping and translation, but with three important differences. First of all, flipping and translation are frame-based, while EventReverse and EventDrift deal with four-dimensional asynchronous event data. More importantly, while flipping and translation only transform in space, our method can also reverse and drift events in the temporal and polar domain. Furthermore, flip and translation consider mirroring and offset factors, while the proposed methods reflect the influence of brightness variations on event data.

Our main contributions are summarized as follows:

- We propose the EventReverse data augmentation method. By reversing the space, time, and polarity of events, EventReverse simulates samples generated by opposite brightness and thus improves the robustness of models against brightness variations.
• We propose the EventDrift data augmentation method. EventDrift simulates the influence of untimed brightness on events by moving them across the spatiotemporal domain, resulting in better generalization.

• The proposed methods are evaluated on N-CARS, N-Caltech101, and CIFAR10-DVS datasets. Extensive experiments demonstrate that our methods are remarkably effective and general for various event representations and network architectures.

2 Related Work

2.1 Event-based Learning

Event-based learning is gaining momentum due to the advantages of event cameras [15, 10, 3]. It can be roughly divided into two categories: one is to take full advantage of powerful convolutional neural networks (CNNs) by representing events as frames. Nevertheless, the time or polarity information is compressed in common event representations, such as EventFrame [16], EventCount [13], VoxelGrid [25], EST [4].

The other is to feed the events into the spiking neural networks (SNNs). SNNs are attractive because they are more biologically plausible, known as third-generation neural networks. Intuitively, they can directly learn asynchronous event data without information loss, including event-driven and clock-driven. Event-driven SNNs handle individual events directly, while clock-driven SNNs typically handle events at the same time point, called TimeSteps. However, SNNs currently only have competitive performances on small networks due to their inability to backpropagate directly.

2.2 Regularization

Regularization is a critical component in improving generalization in neural network training. Various regularization methods have been proposed [12, 7, 1, 22, 5]. Weight Decay [12] prevents models from overfitting by adding a term to the loss function that penalizes model weights, such as L1 and L2 regularization. Dropout [7] refers to randomly setting the output of each hidden neuron to zero during the training process, thereby improving the robustness of the model. Adaptive dropout [1] further optimizes the dropout probability of each hidden neuron, which estimates this probability through a binary belief network. Stochastic pooling [22] randomly selects activations from a multinomial distribution to prevent overfitting. BatchNormal [5] improves generalization by adjusting the distribution of input.

2.3 Data Augmentation

The most straightforward way to alleviate overfitting is training with more data. However, it is costly to obtain and label training data. Data augmentation can effectively enrich the diversity of data, which is widely used in neural network training. For example, random flipping [18] flips the input image horizontally or vertically to obtain a mirror image. Random cropping [7] extracts sub-blocks from the input image to avoid the network overfitting a particular block. Translation [17] moves the image around to avoid positional biases in the data. Cutout [2] artificially impedes a rectangular block in the image to simulate the impact of occlusion on the image. Random erasing [24] further optimizes the erased pixel value by adding noise. Mixup [23] uses the weighted sum of two images as training samples to smooth the transition line between classes. Unfortunately, none of these frame-based methods can be used directly on event data due to the fundamental difference between event data and frame-like data.

3 Method

3.1 Event Generation Model

Each pixel of the event camera responds to changes in its logarithmic photocurrent $L = \log(I)$. Specifically, in a noise-free scenario, an event $e_k = (x_k, y_k, t_k, p_k)$ is triggered at pixel $(y_k, x_k)$ and at time $t_k$ as soon as the brightness variation $|\Delta L|$ reaches a temporal contrast threshold $C$ since the
last event at the pixel, as shown in Figure 2(a). The event generation model can be expressed by the following formula:

$$\Delta L(x_k, y_k, t_k) = L(x_k, y_k, t_k) - L(x_k, y_k, t_k - \Delta t_k) = p_k C$$

(1)

where $C > 0$, $\Delta t_k$ is the time elapsed since the last event at the same pixel, and the polarity $p_k \in \{+1, -1\}$ is the sign of the brightness change. During a period, the event camera triggers events stream $E$:

$$E = \{e_k\}_{k=1}^N = \{(x_k, y_k, t_k, p_k)\}_{k=1}^N$$

(2)

where $N$ represents the number of events in the set $E$. Further, inspired by previous work [4], an event field is used to represent the discrete $E$ by replacing each event of the spatiotemporal flow with a Dirac spike, resulting in a continuous representation of events. For convenience, we define the complete set of transformation domains as $D = \{x, y, p, t\}$, and map the polarity $p$ from $\{-1, +1\}$ to $\{0, 1\}$. The continuous event filed $S$ can be expressed as the following formula:

$$S(x, y, p, t) = \sum_{e_k \in E} \delta(x - x_k)\delta(y - y_k)\delta(t - t_k)\delta(p - p_k) = \sum_{e_k \in E} \prod_{i \in D} \delta(i - i_k)$$

(3)

Due to the asynchronous nature, novel methods are required to learn from these spatiotemporal event data. The proposed EventDrift and EventReverse methods are introduced to simulate the samples generated by brightness variations. Moreover, the event representations transform the events into a grid-like form, which is progressed by CNNs or SNNs to build learning models.

3.2 Motivation

This work stems from the observation of uncommon generalizability on event data, as shown in Figure 3. The EST representation method [4] is reproduced with the resnet9 network on three datasets, where accuracy on training samples is close to 100% but may be less than 60% on test data. Therefore, we revisit the event generation model to find the key factors affecting generalization. The influence of brightness variations catches our attention. As can be seen...
from Figure 2(b) and Figure 2(c), the polarity or time of events can be reversed when the brightness variations are opposite in time or direction. In addition, the time of the event may drift due to the untimed brightness. When the brightness is delayed or advanced, the time of the event will also drift forward or backward. The delayed case is shown in the figure 2(d). These observations inspire us to simulate the effects of scenes such as opposite brightness or untimed brightness by generating reversed or drifted samples, thereby improving the generalization performance of event-based learning.

3.3 EventReverse

EventReverse refers to reversing certain events $E_s$ on a specific domain $d$, and the transformed event field $S_{er}$ can be represented as:

$$S_{er}(x, y, p, t) = \sum_{e_k \in E_s} \delta \left( d - (R_d - d_k) \right) \prod_{i \in \mathcal{C}d} \delta \left( i - i_k \right), \quad d \in D$$

where $R_d$ represents the resolution of the domain $d$. When $d$ is the time domain $t$, $R_d$ represents the largest timestamp, and when $d$ is the polarity $p$, $R_d$ represents the largest polarity. $\mathcal{C}d$ is the complement of $d$ with respect to $D$.

EventReverse move events from $d_k$ to their symmetrical positions $R_d - d_k$ in the event stream. As shown in Figure 1(a), EventReverse can reverse the selected events in the time domain, spatial domain, and polarity domain, thus greatly enriching the diversity of events. When reversed in the spatial domain, it is similar to the effect of flipping frame-based images. Moreover, when reversed in the temporal or polar domains, the generated samples reflect the influences of opposite brightness variations on events. The pseudocode of EventReverse can be found in the supplementary material.

3.4 EventDrift

EventDrift moves events a certain distance on a specified domain, which can be represented as a convolution kernel $k_{ed}$:

$$k_{ed}(x, y, p, t) = \delta \left( d - r_d \right) \prod_{i \in \mathcal{C}d} \delta \left( i \right), \quad d \in \{x, y, t\}$$

where $r_d$ represents the moving distance in the domain $d$. The transformed event field $S_{ed}$ can be obtained by convolving $k_{ed}$ with the event field $S$:

$$S_{ed}(x, y, p, t) = (k_{ed} * S)(x, y, p, t) = \sum_{e_k \in E_s} k_{ed}(x - x_k, y - y_k, p - p_k, t - t_k)$$

$$= \sum_{e_k \in E_s} \left( \delta \left( d - d_k - r_d \right) \prod_{i \in \mathcal{C}d} \delta \left( i - i_k \right) \right), \quad d \in \{x, y, t\}$$

where $E_s$ represents the events to be moved.

EventDrift moves the events a distance $r$ in the domain $d$, and the part beyond borders will be discarded, as shown in Figure 1(b). When the spatial coordinates are drifted, the effect of EventDrift is similar to traditional translation. Furthermore, drifting the time of events is similar to the scenario of advancing or delaying lighting conditions, as shown in Figure 2(d). Note that samples of different drift scales are generated by different drift distances $r$, which obey a specific distribution specified by the hyperparameter. The pseudocode of EventDrift can be found in the supplementary material.

In addition, the event field $S_{rd}$ that applies both EventReverse and EventDrift can be obtained by convolving $k_{ed}$ and $S_{er}$:

$$S_{rd}(x, y, p, t) = (k_{ed} * S_{er})(x, y, p, t)$$

3.5 Event Representations

Both CNNs and SNNs have great potential for processing event data streams. Therefore, EventFrame [16], EventCount [13], VoxelGrid [25], EST [4], and TimeSteps [21] representations are
introduced since asynchronous event streams cannot be directly processed by neural networks, as shown in Figure 4.

EventFrame \cite{16} representation uses the histogram size of pixel to aggregate the four-dimensional events into two-dimensional images:

\[ V_{EF}(x, y) = \sum_p \sum_t S(x, y, p, t) = \sum_{e_k \in E} \delta(x - x_k)\delta(y - y_k) \]  

(8)

EventCount \cite{13} representation further retains the polarity information and the channel \( c \) represents the polarity of events:

\[ V_{EC}(x, y, c) = \sum_t \delta(c - p)S(x, y, p, t) = \sum_{e_k \in E} \delta(x - x_k)\delta(y - y_k)\delta(c - p_k) \]  

(9)

Different from EventFrame and EventCount, VoxelGrid \cite{25} representation explicitly considers the influence of the time domain through the grids. As expressed by the following formula:

\[ V_{VG}(x, y, c) = \sum_p \delta(c - \left\lfloor \frac{t - t_0}{n} \right\rfloor)S(x, y, p, t) = \sum_{e_k \in E} \delta(x - x_k, y - y_k)\delta(c - \left\lfloor \frac{t_k - t_0}{n} \right\rfloor) \]  

(10)

where the grid of VoxelGrid is treated as channel \( c \), \( t_0 \) is the smallest timestamp, and \( n \) represents the grid number of the VoxelGrid.

EST \cite{4} representation is also a grid-like representation, which retains the polarity of events. It treats both the grid and the polarity as channels:

\[ V_{EST}(x, y, c) = k_{est} * (\delta(c - 2 \cdot \left\lfloor \frac{t - t_0}{n} \right\rfloor - p)S(x, y, p, t)) \]  

(11)

where \( k_{est} \) is a quantized convolution kernel. The kernel is replaced with a multilayer perceptron, which initialized by a trilinear voting kernel \( k(x, y, p, t) = \delta(x, y, p) \max (0, 1 - \frac{|t|}{T}) \), thus EST is an end-to-end learned representation.

Above representations are all applicable to CNNs. For SNNs, the TimeSteps representation \cite{21} simply normalizes the timestamps to \( T \) time steps. As expressed by the following formula:

\[ V_{TS}(x, y, p, ||t||) = \delta(||t|| - \left\lfloor \frac{t - t_0}{T} \right\rfloor) \cdot S = \sum_{e_k \in E} \delta(x - x_k, y - y_k, p - p_k)\delta(||t|| - \left\lfloor \frac{t_k - t_0}{T} \right\rfloor) \]  

(12)

where \( ||t|| \) is the normalized time.

4 Experiments

The EventReverse and EventDrift methods are evaluated with EventFrame, EventCount, VoxelGrid, EST, and TimeSteps representations on N-CARS, N-Caltech101, CIFAR10-DVS datasets.
4.1 Datasets

N-CARS dataset [19] is recorded by an ATIS camera mounted behind the windshield. It is a large real-world event-based car classification dataset extracted from various driving courses, comprising 12,336 car samples and 11,693 non-car samples (background). Training samples include 7940 cars and 7482 backgrounds, while test samples contain 4396 cars and 4211 backgrounds, each lasting around 100 ms.

CIFAR10-DVS dataset [9] consists of 10,000 samples from CIFAR10. The recordings contain noise and blur caused by stationary DVS cameras capturing moving raw images. CIFAR10-DVS is a challenging recognition dataset due to the complexity of the samples. We follow previous work [21] and randomly select 90% of the images as training samples, and the rest are test samples for each class.

N-Caltech101 dataset [14] is a spiking version of the original frame-based Caltech101 dataset. The Faces class has been removed from N-Caltech101 to avoid confusion, leaving 100 object classes plus a background class. The N-Caltech101 dataset is captured by mounting the ATIS sensor on a motorized pan-tilt unit and having the sensor move while it views Caltech101 examples on an LCD monitor. Similarly, the ratio of training sets is 0.9.

4.2 Implementation

Various representations and architectures [8] are used for each dataset. For the convenience of comparison, previous works [21, 4] are reproduced as the baseline. For example, the accumulated spiking flow work [21] is regarded as the baseline of TimeSteps representation. The configurations of other experiments are the same, including a batch size of 40, an initial learning rate of $1 \times 10^{-4}$, and an Adam [6] optimizer. The cross-entropy loss function is used to train the CNNs for 120 epochs, while the MSE loss function is used to train the SNNs for 50 epochs. The details of the network architectures and the detailed configurations of the experiments can be found in the supplementary material.

4.3 Overall Performance

The proposed methods are evaluated on three datasets with five representations. EventRD refers to that EventReverse and EventDrift are simultaneously applied, while the same experiments without EventRD are considered as baseline.

| Structure | Method | Average Accuracy (Std) (%) | TimeSteps | EventFrame | EventCount | VoxelGrid | EST |
|-----------|--------|---------------------------|-----------|------------|------------|-----------|-----|
| VGG7      | Baseline | 62.10(0.93) 62.81(0.82) 64.23(0.50) 60.58(0.78) 63.45(0.59) | 62.10(0.93) 62.81(0.82) 64.23(0.50) 60.58(0.78) 63.45(0.59) | 62.81(0.82) 64.23(0.50) 60.58(0.78) 63.45(0.59) |
|           | EventRD | 76.07(0.66) 74.11(0.33) 75.53(0.61) 72.72(0.79) 73.37(0.73) | 76.07(0.66) 74.11(0.33) 75.53(0.61) 72.72(0.79) 73.37(0.73) | 74.11(0.33) 75.53(0.61) 72.72(0.79) 73.37(0.73) |
| Resnet9   | Baseline | 61.33(0.87) 57.00(0.49) 57.66(0.93) 55.20(0.95) 53.40(0.25) | 61.33(0.87) 57.00(0.49) 57.66(0.93) 55.20(0.95) 53.40(0.25) | 57.00(0.49) 57.66(0.93) 55.20(0.95) 53.40(0.25) |
|           | EventRD | 76.05(0.33) 78.49(0.16) 78.24(0.47) 76.71(0.54) 78.12(0.58) | 76.05(0.33) 78.49(0.16) 78.24(0.47) 76.71(0.54) 78.12(0.58) | 78.49(0.16) 78.24(0.47) 76.71(0.54) 78.12(0.58) |

CIFAR10-DVS  Extensive experiments are performed on CIFAR10-DVS datasets to evaluate the proposed method. As shown in Table 1, EventRD significantly improves the performance of all models with different representations and architectures, which powerfully demonstrates that the EventRD method is remarkably effective and broadly applicable. It is worth noting that when represented as EST on the Resnet9 network, the improvement can reach up to 24.72%.

N-Caltech101  EventRD achieves significant improvements on N-Caltech101 dataset, as shown in Table 2. The improvement can reach 11.01% when events are represented as TimeSteps on the Resnet9 network. Furthermore, the performance on the Resnet9 network is better than that on the VGG7 network. Because the deep residual network can be seen as an ensemble of shallow neural networks of different depths, randomly removing a layer will not degrade the performance drastically [20], thus leading to a better generalization.
Table 2: Performance of various representations on N-Caltech101 dataset.

| Structure | Method   | TimeSteps | EventFrame | EventCount | VoxelGrid | EST       |
|-----------|----------|-----------|------------|------------|-----------|-----------|
| VGG7      | Baseline | 61.20(1.25)| 64.08(0.82)| 64.18(0.70)| 62.41(0.07)| 65.06(0.24)|
|           | EventRD  | 69.06(0.73)| 69.26(0.59)| 68.29(0.94)| 66.58(0.72)| 71.07(0.50)|
| Resnet9   | Baseline | 60.27(0.52)| 68.52(0.35)| 67.78(0.12)| 71.93(0.41)| 72.87(0.30)|
|           | EventRD  | 71.28(0.47)| 72.50(0.59)| 73.38(0.22)| 76.87(0.15)| 78.31(0.07)|

Table 3: Performance of various representations on N-CARS dataset.

| Structure | Method   | TimeSteps | EventFrame | EventCount | VoxelGrid | EST       |
|-----------|----------|-----------|------------|------------|-----------|-----------|
| VGG7      | Baseline | 90.88(0.31)| 91.63(0.11)| 91.91(0.14)| 91.93(0.34)| 92.03(0.03)|
|           | EventRD  | 92.19(0.35)| 94.04(0.20)| 93.34(0.09)| 93.03(0.30)| 92.52(0.05)|
| Resnet9   | Baseline | 86.63(0.26)| 91.12(0.44)| 91.76(0.47)| 88.71(0.26)| 90.47(0.09)|
|           | EventRD  | 88.21(0.15)| 94.04(0.29)| 94.53(0.19)| 93.75(0.13)| 94.91(0.07)|

N-CARS EventRD is still quite effective on the N-CARS dataset, as shown in Table 3. When events are represented as VoxelGrid on the Resnet9 network, the error rate is nearly halved from 11.27% to 6.25%. It is worth noting that as a binary classification dataset, N-CARS is relatively simple, with more than 7,000 samples per class. Therefore, the performance of the EventRD method on the N-CARS dataset is also remarkable.

4.4 Effects of EventReverse and EventDrift

Table 4: Performance on CIFAR10-DVS dataset with Resnet9 network.

| Representations | Baseline | EventReverse | EventDrift | EventRD |
|-----------------|----------|--------------|------------|---------|
| TimeSteps       | 61.33(0.87)| 65.67(0.45)  | 71.37(1.40) | 76.03(0.33)|
| EventFrame      | 57.00(0.49)| 63.69(0.31)  | 77.35(0.63) | 78.49(0.16)|
| EventCount      | 57.88(0.93)| 63.68(0.79)  | 76.96(0.71) | 78.24(0.47)|
| VoxelGrid       | 55.20(0.95)| 59.49(0.30)  | 74.19(0.09) | 76.71(0.54)|
| EST             | 53.40(0.25)| 58.74(0.43)  | 75.44(0.24) | 78.12(0.58)|

We further demonstrate the effectiveness of EventReverse and EventDrift on the CIFAR10-DVS dataset with various representations, as shown in Table 4. The performances of EventReverse and EventDrift are consistently significant across all representations. Compared with baseline, EventReverse can reach up to 6.94% improvement, while EventDrift can achieve 22.04% improvement. When they are used together, the effect is even better. It is worth noting that in many vision tasks, the untimed brightness scenes are more frequent than opposite brightness scenes, and EventDrift improves the robustness to untimed brightness, thus leading to greater advancements.

4.5 Effects of Transformations in Different Domain

To demonstrate the performance of event variations across different domains, we evaluate the EventReverse method on the N-CARS dataset with EST representation method and Resnet9 network. As shown in Figure 5, EventReverse is effective in both spatiotemporal and polar domains. It should be noted that EventReverse performs better in the polar and temporal domains, indicating that brightness variations are an essential factor in the poor generalization of models.
Figure 5: Performance of EventReverse method in different domains.

Figure 6: Generalization performance with the EventRD method.

Figure 7: Performance using different proportions of the CIFAR10-DVS dataset.

Figure 8: Performance under different levels of brightness variations.

4.6 Analysis of the Effects

As shown in Figure 6, the poor generalization shown in Figure 3 is significantly improved with EventRD method. To better understand the effect of EventRD method, we analyze the influence of training data volume on it with EST representation and Resnet9 network. As shown in Figure 7, the improvement of the model with EventRD is consistently significant at all scales. In particular, the model with EventRD improves more as the number of data increases, which indicates that EventRD improves the robustness of models against a certain interference factor by simulating the brightness variations. Figuratively, EventRD is like a defog glasses for models, which reduces distractions by improving robustness to make decisions clearly. When the same amount of training data is added, the model with EventRD can learn a new classification boundary under interference, while the baseline model cannot directly and clearly see the boundary, leading to less improvement.

In order to further verify that the interference factor is brightness variations, we evaluate the same model by adding various untimed brightness interference to the test set. The interference is achieved by drifting the time of events, and the ratio of drifted time ranges from 0 to 0.5. As shown in figure 8, the models with EventRD perform significantly better on brightness variation data.

Both experiments strongly demonstrate that EventRD improves the robustness of models against brightness variations and consequently results in a better generalization.

5 Conclusion

In this work, we propose two novel event data augmentation methods: EventReverse and EventDrift. Both methods take into account the effect of brightness variations on events. EventReverse and EventDrift reverse and drift events in the event stream to simulate samples under brightness variation scenes, thus improving the generalization performance of event-based learning. Extensive experiments demonstrate the effectiveness and generality of proposed methods. In future work, we will delve into the reasons for the unusual generalization of event data and apply our methods to other vision tasks.
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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes] We propose EventReverse and EventDrift data augmentation methods to improve the regularization ability of event-based learning.
   (b) Did you describe the limitations of your work? [Yes] The limitations of my work are described in the supplementary material.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] The potential negative societal impacts of my work are discussed in the supplementary material.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes] I have read the ethics review guidelines and our paper conforms to these guidelines.

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes] We state the full set of assumptions for all theoretical results.
   (b) Did you include complete proofs of all theoretical results? [Yes] We include full proofs of all theoretical results.

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] We will attach the code, data, instructions of our experiments in the supplementary material.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 4.2, and the rest details are specified in the supplementary material.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] We conduct multiple experiments with random seeds randomly generated and calculate the standard deviation.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] We will explain the total amount of compute and the type of resources in the supplementary material.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] We cite the creators of these assets.
   (b) Did you mention the license of the assets? [Yes] They are open source using license such as Creative Commons Attribution 4.0.
   (c) Did you include any new assets either in the supplemental material or as a URL? [No]
   (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [Yes] The data we are using is all open source.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] The data we are using does not contain personally identifiable information.

5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [No]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [No]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [No]