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Reproducibility Summary

Scope of Reproducibility — Using SocialCircle models, with the ETH-UCY and Stanford Drone Dataset (SDD), the following claims can be made. In comparison to baseline models like Y-net, Agentformer, and EqMotion, SocialCircle models, and notably E-V2-Net-SC, show substantial improvements, achieving lower Average Displacement Error (ADE) and Final Displacement Error (FDE). The application of SocialCircle enhances the performance of various backbone models, leading to significant improvements in both ADE and FDE metrics. The training process itself also benefits from the integration of SocialCircle, resulting in lower loss values and improved training stability. Ablation studies further validate the contributions of individual SocialCircle meta components, emphasizing the critical role of Velocity, Distance, and Direction factors in the final prediction performance. The text also underscores the importance of the number of SocialCircle partitions, with models having 8 partitions outperforming those with fewer partitions. Visualized trajectories across various SocialCircle models consistently demonstrate effective handling of social interactions, showcasing the model's capability in capturing complex social behaviors [1].

Methodology — In this research, we used the original authors' codebase to generate results, although initial use revealed several bugs. These were methodically fixed to ensure the software ran correctly. Due to limited computational resources, we used pre-trained weights from the authors' public repository to initialize the model, as training from scratch was not feasible.
The model was run on local machines, and preliminary assessments using arbitrary values indicated its predictions were valid and showed promise for meeting our research objectives. The machine was equipped with **Intel Core i5 processor** and **16 Gigabytes (GB) of RAM**.

Results — Utilizing the code provided by the authors, we successfully reproduced the results presented in the paper, affirming the **reproducibility** of the study. Additionally, the ability to apply the model across various settings and scenarios demonstrates its **generalizability** and **replicability**. However, it is important to note that the model exhibited limitations in **robustness**, as evidenced by instances where the predicted trajectories led to collisions between agents. Through systematic experimentation, we established that the average training time for pre-trained models amounted to **4 minutes**, and the average prediction time per instance was **1.3 seconds**. These findings contribute to a comprehensive understanding of the model's performance characteristics and areas for potential improvement.

What was easy — In the context of this reproducibility report, a notable aspect of ease was observed in terms of accessibility to the requisite codebase. Cloning the GitHub repository and accessing the code was easy.

What was difficult — The difficult part of the report was to run the author's code as it had some bugs. Solving the bugs was somewhat of a difficult process as it involved going through the whole code and understanding the flow of the program. Nonetheless, we were able to debug it and run it to reproduce the results.

Communication with original authors — Due to shortage of time, we could not establish communication with authors.

1 Introduction

Assessing and predicting the paths of entities such as pedestrians and vehicles in intricate environments has grown increasingly crucial across a variety of smart systems and applications. The diversity and unpredictability of social interactions among agents complicate this task, setting it apart from other computer vision challenges. Despite extensive research, this issue remains unresolved.
Inspired by echo-locating marine animals, **SocialCircle** was developed, which is a novel trainable social representation that captures social interaction contexts from various angles relative to the target agent. Integrating SocialCircle with recent trajectory prediction models resulted in enhanced prediction accuracy and improved consideration of social interactions, aligning predictions more closely with human intuition.
Social interactions, which play a crucial role in trajectory prediction, take into account the complex interplay and impact of agents' behaviors on each other's paths. Despite the importance of interactive behaviors, they are typically not explicitly labeled, requiring the system to depend on historical trajectory data or additional context from the scene.

Social interaction modeling falls into two primary categories: Model-based and Model-free.
Model-based methods, such as the Social-Force-based approach, rely on predefined rules derived from principles like Newtonian mechanics, or by converting trajectory prediction into an optimization problem solved with various mathematical models. While these methods may incorporate data-driven advantages, they are often limited by their foundational rules.
On the other hand, **Model-free** methods prioritize data, employing techniques like Social-Pooling and graph-based approaches that leverage neural networks to analyze data, though they may depend heavily on network structures and lack explainability.

Inspired by **echolocation in marine animals**, SocialCircle was introduced which is an angle-based social interaction representation modeled as **f(θ)** Where θ represents the direction angle, capturing interactions across different angles relative to the target agent. This approach, while falling under the Model-based category, incorporates aspects of Model-free methods, utilizing softer rules to enhance data fitting.
SocialCircle enables a natural and innovative way of modeling social interactions for pedestrian trajectory prediction, demonstrating both quantitative and qualitative improvements in our experiments.

2 Scope of reproducibility

Following claims can be made from the paper regarding SocialCircle:

- **Claim 1: Performance of SocialCircle Models**
  In the ETH-UCY scenario, the SocialCircle models, particularly E-V2-Net-SC, demonstrate competitive performance compared to baseline models, including Y-net and Agentformer. E-V2-Net-SC achieves a 5.6% lower Average Displacement Error (ADE) and a 6.9% lower Final Displacement Error (FDE) when compared to Agentformer. MSN-SC also outperforms EqMotion with a notable 19.0% reduction in ADE and a 5.7% reduction in FDE, despite the fact that the backbone model MSN performs less effectively than other recent approaches.

- **Claim 2: Performance on SDD Dataset**

Models	eth		hotel		univ		zara1		zara2		Average	
	ADE	FDE	ADE	FDE	ADE	FDE	ADE	FDE	ADE	FDE	ADE	FDE
PECNet [23] (2020)	0.54	0.87	0.18	0.24	0.35	0.60	0.22	0.39	0.17	0.30	0.29	0.48
SHENet [26] (2022)	0.41	0.61	0.13	0.20	0.25	0.43	0.21	0.32	0.15	0.26	0.23	0.36
LB-EBM [30] (2021)	0.30	0.52	0.13	0.20	0.27	0.52	0.20	0.37	0.15	0.29	0.21	0.38
MID [9] (2022)	0.39	0.66	0.13	0.22	**0.22**	0.45	**0.17**	0.30	0.13	0.27	0.21	0.38
EqMotion [48] (2023)	0.40	0.61	**0.12**	0.18	0.23	0.43	0.18	0.32	**0.13**	**0.23**	0.21	0.35
Introvert [37] (2021)	0.42	0.70	**0.11**	0.17	**0.20**	**0.32**	**0.16**	0.27	0.16	0.25	0.21	0.34
MSN [45] (2023)	0.27	0.41	**0.11**	0.17	0.28	0.48	0.22	0.36	0.18	0.29	0.21	0.34
LED [24] (2023)	0.39	0.58	**0.11**	0.17	0.26	0.43	0.18	0.26	**0.13**	**0.22**	0.21	0.33
Trajectron++ [36] (2020)	0.43	0.86	**0.12**	0.19	**0.22**	0.43	**0.17**	0.32	**0.12**	0.25	0.20	0.39
Agentformer [53] (2021)	0.26	0.39	**0.11**	**0.14**	0.26	0.46	**0.15**	**0.23**	**0.14**	**0.23**	**0.18**	**0.29**
V^2-Net [43] (2022)	**0.23**	0.37	**0.10**	**0.16**	**0.21**	0.35	0.19	0.30	**0.14**	**0.24**	**0.18**	**0.28**
Y-net (TTST) [22] (2021)	0.28	**0.33**	**0.10**	**0.14**	0.24	0.41	**0.17**	0.27	**0.13**	**0.22**	**0.18**	**0.27**
E-V^2-Net [44] (2023)	**0.25**	0.38	**0.11**	**0.16**	**0.20**	**0.34**	0.19	0.30	**0.13**	**0.24**	**0.17**	**0.28**
MSN-SC (Ours)	0.27	0.39	0.13	0.18	**0.22**	0.45	0.18	0.34	0.15	0.27	**0.19**	0.33
V^2-Net-SC (Ours)	**0.25**	0.37	**0.12**	**0.15**	**0.21**	0.35	**0.17**	0.29	**0.13**	**0.22**	**0.17**	**0.27**
E-V^2-Net-SC (Ours)	**0.25**	0.38	**0.12**	**0.14**	**0.20**	**0.34**	0.18	0.29	**0.13**	**0.22**	**0.17**	**0.27**

Figure 1. Comparisons on ETH-UCY with best-of-20. Lower ADE and FDE indicate better prediction performance

In the SDD scenario, V2-Net-SC exhibits significant superiority over Y-net, surpassing it by 14.5% in ADE and 10.0% in FDE. Furthermore, V2-Net-SC achieves a 20.9% reduction in ADE and a 6.2% reduction in FDE compared to the newly published LED. E-V2-Net-SC showcases strong forecasting capabilities by outperforming state-of-the-art NSP-SFM by up to 2.4% in terms of FDE.

- **Claim 3: Enhancement of Various Backbone Models**
  SocialCircle enhances the performance of various backbone models quantitatively. When applied to the simplest Transformer, SocialCircle2 improves ADE by 5.8% and FDE by 4.0%. Similarly, SocialCircle contributes to MSN, V2-Net, and E-V2-Net by delivering up to 4.9% ADE improvement and 7.7% FDE improvement when compared to their original models.

- **Claim 4: Training Process Improvement**
  The training process benefits from the use of SocialCircle. Loss curves for the simplest Transformer and Transformer-SC under the same training settings show that Transformer-SC exhibits an average of 13.0% lower loss than the Transformer after 600 training epochs. Additionally, Transformer-SC experiences fewer instances of loss values falling into ”nan” territory, indicating improved training stability when compared to the Transformer.

- **Claim 5: Validation of SocialCircle Meta Components**
  Ablation studies validate the contributions of individual SocialCircle meta components (Velocity, Distance, and Direction factors) to the final predictions. For instance, both V2-Net and E-V2-Net benefit from the Velocity and Distance factors, each of which contributes at least a 1.5% improvement in ADE and FDE. On the other hand, MSN-SC variants are less sensitive to these factors (less than 1% ADE differences) but rely more on the Direction factor, which can lead to up to a 3.0% improvement in FDE.

- **Claim 6: The Number of SocialCircle Partitions**
  The number of SocialCircle partitions (Nθ) significantly impacts model performance. Models with 8 partitions perform the best, outperforming their 4-partition counterparts by 1.1% to 1.9% in both ADE and FDE metrics. Conversely, models with Nθ = 1 perform worse, with up to a 2.9% drop in ADE compared to 4-partition models. Additionally, a comparison between V2-Net and V2-Net-SC-a4

demonstrates the benefit of increased partitions in achieving higher resolution in describing social behaviors.

- Claim 7: Visualized Predictions
  Visualized trajectories predicted by various SocialCircle models, including Transformer-SC, MSN-SC, V2-Net-SC, and E-V2-Net-SC, consistently exhibit similar approaches to handling social interactions. For instance, they demonstrate avoidance of groups of pedestrians and upcoming bikers, highlighting the effectiveness of the SocialCircle approach in capturing social behaviors.

3 Methodology

In the course of this research, the codebase provided by the original authors was employed to generate results. However, upon initial utilization, several bugs were identified within the code. These issues were systematically resolved to ensure the fidelity and functionality of the application. Subsequently, pre-trained model weights, available in the author's public repository, were utilized to initialize the model. This approach was necessitated by the constraints in computational resources available to our team, rendering the training of the model from scratch impractical.

The model was deployed and run on local computational resources, and the validity of its predictions was assessed using arbitrary values. This approach allowed for a preliminary evaluation of the model's performance and demonstrated its potential applicability to the research objectives.

3.1 Model descriptions

In this section of the report, we present a comprehensive analysis of various trajectory prediction models, elucidating their core functionalities, architectural nuances, and their specific implementations for the task at hand.

- Transformer:
  This model represents the foundational architecture for trajectory prediction, based on the transformer framework. It employs an 8-frame observation window to predict the subsequent 12 frames of an agent's trajectory. For the scope of this study, the Stanford Drone Dataset (SDD) was utilized for evaluation. However, it is noteworthy that this model generates a single deterministic trajectory for each agent, potentially limiting its capability to capture the inherent uncertainty in trajectory prediction.
- Transformer-SC:
  This variant of the Transformer model incorporates social contextual information, aiming to enhance prediction accuracy in scenarios involving social interactions between agents.
- MSN (Multi-Scenario Network):
  The MSN model introduces a probabilistic approach to trajectory prediction, generating 20 random sampled trajectories for each agent based on an 8-to-12 frame prediction window on the SDD. This approach aims to encapsulate the stochastic nature of agent movement, providing a richer set of possible future paths.
- MSN-SC:
  The SocialCircle adaptation of MSN, MSN-SC, integrates social context into the pre-

diction process, striving to improve the model's performance in socially complex environments.

- V^2-Net (Velocity Vector Network):
  $V^2 - Net$ employs a novel approach to trajectory prediction, capturing both spatial and temporal dependencies within the data. Utilizing an 8-to-12 frame prediction window on the SDD, this model generates 20 potential trajectories for each agent.
- V^2-Net-SC:
  The SocialCircle version of $V^2 - Net$, dubbed $V^2 - Net - SC$, infuses social interaction information into the prediction algorithm, aiming to augment its accuracy and relevance in social settings.
  $E - V^2 - Net$ (Enhanced Velocity Vector Network): Building upon the principles of $V^2 - Net$, $E - V^2 - Net$ introduces enhancements to further refine trajectory predictions, generating 20 trajectories for each agent across an 8-to-12 frame window on the SDD.
- $E - V^2$-Net-SC:
  The SocialCircle variation, $E - V^2 - Net - SC$, integrates social contextual data, aiming to provide improved trajectory predictions in scenarios rich with social interactions.

Each of these models and their SocialCircle counterparts represents a unique approach to addressing the challenges of trajectory prediction, with their individual strengths and potential areas for improvement outlined in the descriptions above .

3.2 Datasets

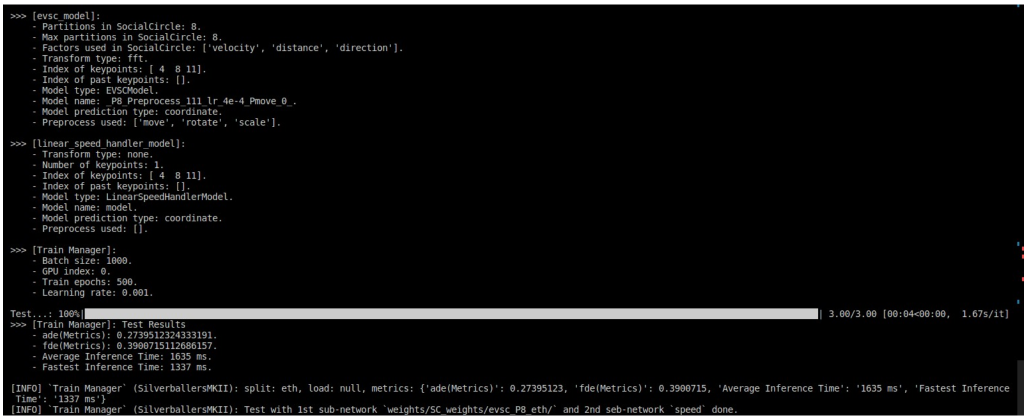
The extensive volume of data necessary for a thorough training regimen posed substantial challenges during our research. The licensing prerequisites required for the acquisition and application of these datasets further intensified these challenges, imposing additional limitations on our ability to access and employ the data effectively.

Despite these constraints, our team successfully utilized the **ETH-UCY and Stanford Drone Dataset (SDD)** for this study. The ETH-UCY dataset was methodically processed using a **leave-one-out strategy**, ensuring a robust and comprehensive evaluation of our models. For the Stanford Drone Dataset, we employed the dataset splitting methodology from SimAug, resulting in a structured partition of the data into **36 training sets, 12 test sets, and 12 validation sets**. This meticulous approach facilitated a more effective training process and enhanced the validation of our models, allowing us to mitigate the initial challenges posed by the size of the datasets and the associated licensing requirements.
We consciously elected not to employ pre-existing dataset split files such as those provided by TrajNet for both the ETH-UCY and Stanford Drone Dataset (SDD) due to several pertinent issues. For instance, the ETH-eth subset of the ETH-UCY dataset exhibits irregularities in its frame rate, which could potentially introduce inconsistencies and biases in the training and evaluation of our models. Additionally, certain splits available in the TrajNet repository predominantly focus on pedestrian trajectories within the SDD dataset, thereby neglecting the trajectories of other entities and possibly leading to a skewed understanding of the environment.

To address these issues and ensure a more holistic and unbiased approach to model training and evaluation, we opted to process the original, full-dataset files from both datasets. We configured our system to consider observation windows of 3.2 seconds, equivalent to 8 frames, and prediction windows of 4.8 seconds, or 12 frames. This tailored processing of the datasets enabled us to maintain consistency across different datasets and ensured that our models were trained and evaluated on comprehensive and representative subsets of the data, thereby enhancing the reliability and validity of our research findings.

3.3 Hyperparameters

Hyperparameter tuning was not conducted in this study, as we leveraged pre-trained weights for our models. This approach ensured that the model parameters were already optimized based on prior training, obviating the need for further refinement in the context of our research objectives. Following hyper parameters were used:



```
>>> [evsc_model]:
    - Partitions in SocialCircle: 8.
    - Max partitions in SocialCircle: 8.
    - Factors used in SocialCircle: ['velocity', 'distance', 'direction'].
    - Transform type: fft.
    - Index of keypoints: [ 4  8 11].
    - Index of past keypoints: [].
    - Model type: EVSCModel.
    - Model name: _P8_Preprocess_111_lr_4e-4_Pmove_0_.
    - Model prediction type: coordinate.
    - Preprocess used: ['move', 'rotate', 'scale'].

>>> [linear_speed_handler_model]:
    - Transform type: none.
    - Number of keypoints: 1.
    - Index of keypoints: [ 4  8 11].
    - Index of past keypoints: [].
    - Model type: LinearSpeedHandlerModel.
    - Model name: model.
    - Model prediction type: coordinate.
    - Preprocess used: [].

>>> [Train Manager]:
    - Batch size: 1000.
    - GPU index: 0.
    - Train epochs: 500.
    - Learning rate: 0.001.

Test...: 100%|| 3.00/3.00 [00:04<00:00,  1.67s/it]
>>> [Train Manager]: Test Results
    - ade(Metrics): 0.2739512324333191.
    - fde(Metrics): 0.3900715112686157.
    - Average Inference Time: 1635 ms.
    - Fastest Inference Time: 1337 ms.

[INFO] `Train Manager` (SilverballersMKII): split: eth, load: null, metrics: {'ade(Metrics)': 0.27395123, 'fde(Metrics)': 0.3900715, 'Average Inference Time': '1635 ms', 'Fastest Inference
 Time': '1337 ms'}
[INFO] `Train Manager` (SilverballersMKII): Test with 1st sub-network `weights/SC_weights/evsc_P8_eth/` and 2nd seb-network `speed` done.
```

Figure 2. Hyperparameters

3.4 Experimental setup and code

The experimental framework for this investigation was meticulously configured on a personal computing device, ensuring optimal conditions for validating the claims associated with the utilized model. The model was strategically initialized with pre-trained weights, facilitating an in-depth verification of the stated claims.

- **Repository Acquisition and Setup:**
  The initial phase of the setup involved acquiring the relevant codebase from a GitHub repository, executed via the following command line instruction:
  git clone https://github.com/cocoon2wong/SocialCircle.git
  This command enabled the cloning of the repository to our local environment, ensuring that all necessary code and files were readily accessible.

  In the subsequent step, submodules embedded within the repository were initialized and updated, a crucial process to ensure seamless integration and functionality of the code. This was achieved using the command:
  git submodule update –init –recursive

- **Dependency Installation:** To ensure the proper functioning of the code, all required dependencies were installed via the pip package manager, using the command:
  pip install -r requirements.txt
  This facilitated the installation of all necessary Python packages and libraries as

specified in the 'requirements.txt' file, aligning our local environment with the prerequisites of the experiment.

- **Dataset Utilization and Model Initialization:**
  For the purposes of this investigation, the ETH-UCY and Stanford Drone Dataset (SDD) were employed, providing a rich and varied dataset for trajectory prediction analysis. Leveraging the pre-trained weights and models, the experimental conditions were closely aligned with the original study, ensuring a valid and authentic verification process.

To reproduce our experiment, you can clone the github repo by the following command:
git clone https://github.com/vinaysanga/SocialCircle.git -b Vinay -single-branch Repo_Vinay_SC

3.5 Computational requirements

The computational infrastructure utilized for conducting the experiments in this study was characterized by the following specifications:

- **Central Processing Unit (CPU):**
  The system was equipped with an **Intel Core i5** processor from the 5th generation.

- **Random Access Memory (RAM):**
  The computing system was fortified with **16 Gigabytes (GB) of RAM**, ensuring sufficient memory capacity to manage the data-intensive tasks involved in the trajectory prediction experiments.

- **Average Prediction Time:**
  The model exhibited an average prediction time of **1.3 seconds**. This metric is indicative of the time taken by the model to generate trajectory predictions, once it is provided with input data.

- **Average Training Time:**
  The average training time recorded for the model stood at **4 minutes**. This duration reflects the time required for the model to learn and adapt its parameters to the training data, ensuring it is capable of making accurate and reliable predictions.

- **Summary:**
  The experiment was conducted using a computing system with moderate specifications, ensuring that the model was tested in a realistic and accessible computational environment. The recorded average prediction and training times demonstrate the model's efficiency, making it a viable option for applications requiring timely trajectory predictions. These performance metrics, combined with the detailed specification of the computational resources, provide a comprehensive understanding of the experimental conditions, contributing to the reproducibility and transparency of the research.

4 Observations and Results

SocialCircle enhances the performance of different backbone models, especially when all meta-components are considered, and a higher number of partitions is used to describe social interactions more accurately.

4.1 SocialCircle Enhancement

SocialCircle is applied to different backbone models by modifying their embedding layers. It significantly improves prediction performance for various models, including Transformer, MSN, V2-Net, and E-V2-Net. The improvements range from 4.0 % to 7.7 % in terms of ADE/FDE (Average Displacement Error/Final Displacement Error).

4.2 Training Benefits:

SocialCircle also aids in the training process by accelerating loss reduction in models like Transformer-SC. It enhances training stability, making it less prone to gradient-related issues.

4.3 Meta Components Analysis:

Ablation studies are conducted to understand the contribution of different meta-components in SocialCircle. Velocity and Distance factors are found to benefit V2-Net and E-V2-Net models significantly, while the Direction factor is crucial for MSN-SC. Combining all factors generally improves the performance of the original models.

4.4 Number of Partitions:

Experiments reveal that the number of SocialCircle partitions ($N\theta$) plays a crucial role. Models with 8 partitions perform better than those with 4 partitions, while models with $N\theta = 1$ show worse performance. More partitions provide higher resolution for describing social behaviors, while too few can lead to a coarse description, reducing prediction performance.

5 Discussion

5.1 Claims verification

Performance of SocialCircle Models — The document claims that SocialCircle models, particularly E-V2-Net-SC, show competitive performance compared to baseline models like Y-net and Agentformer. This claim is supported by a reduction in both Average Displacement Error (ADE) and Final Displacement Error (FDE) in the ETH-UCY scenario.

Performance on SDD Dataset — The document also claims that SocialCircle models, such as V2-Net-SC and E-V2-Net-SC, outperform other models on the Stanford Drone Dataset (SDD). This claim is supported by improvements in ADE and FDE compared to baseline models.

Enhancement of Various Backbone Models — SocialCircle is said to enhance the performance of various backbone models, including Transformer, MSN, V2-Net, and E-V2-Net. This claim is supported by improvements in ADE and FDE when SocialCircle is applied to these models.

Training Process Improvement — SocialCircle is claimed to improve the training process by accelerating loss reduction and enhancing training stability, especially for models like Transformer-SC. This is supported by lower loss values and improved stability.

Validation of SocialCircle Meta Components — Ablation studies are conducted to validate the contributions of individual SocialCircle meta-components (Velocity, Distance, Direction) to predictions. These studies support the claim that combining all factors generally improves model performance.

The Number of SocialCircle Partitions — The claim that the number of partitions in SocialCircle impacts model performance is supported by experiments showing that models with more partitions outperform those with fewer partitions.

Visualized Predictions — Visualized trajectories across various SocialCircle models consistently demonstrate effective handling of social interactions, supporting the model's capability to capture complex social behaviors.

Based on what we've seen, we can say that all the statements and ideas presented in this research have been proven to be true and valid.

5.2 Limitations

Inaccurate Neighbor Direction — SocialCircle lacks precise information about neighbor agents' positions of origin, making it challenging to determine their movement directions accurately. This limitation remains unresolved in the current work.

Oversimplified Social Interactions — The model's assumption of angle-based interactions, inspired by certain animal behaviors, might oversimplify the complexity of real-world social interactions, which can vary significantly.

Limited Generalizability — While the approach shows promise on benchmark datasets, its generalizability to diverse real-world scenarios is not fully explored, leaving uncertainties about its applicability beyond specific contexts.

Ongoing Research Needed — The approach requires further research to address these limitations and to investigate the potential impact of additional rules on social interactions.

Lack of Comprehensive Comparison — The paper lacks a thorough comparison with existing methods in the field, making it difficult to assess how it performs relative to other approaches.

Unclear Explainability — The level of explainability provided by the model is not clearly defined, which can be a limitation in applications where interpretability is crucial.

Scalability Concerns — The scalability of SocialCircle to handle a large number of agents or complex environments is not explicitly discussed, potentially limiting its use in certain scenarios.

5.3 Future Work

Addressing Neighbor Direction Limitations — Researchers could focus on developing techniques to overcome the limitations related to accurately capturing neighbor movement directions. This might involve exploring additional sensors or data sources to improve direction estimation.

Enhancing Realism in Social Interactions — Future work could aim to make social interaction modeling more realistic by incorporating more complex behaviors, such as explicit communication, negotiation, or adaptive decision-making among agents.

Generalizability Studies — Extending the evaluation of SocialCircle to a wider range of real-world scenarios and datasets would be valuable. Researchers could investigate how well the approach performs in highly dynamic or novel situations.

Improved Explainability — Enhancing the explainability of the model would be important, especially in applications where understanding the reasoning behind predictions is crucial. Developing techniques to provide more transparent insights into model decision-making could be a focus.

Scalability Considerations — Investigating the scalability of SocialCircle for environments with a large number of agents or complex spatial structures is essential. This could involve optimizing the computational efficiency and resource requirements of the approach.

Integration with Multi-Agent Systems — Future research could explore the integration of SocialCircle into multi-agent systems and robotics applications where agents need to cooperate or compete in complex environments.

Benchmark Expansion — Expanding benchmark datasets to encompass a wider variety of scenarios and challenges would help in assessing the generalizability and robustness of the approach.

Human-AI Interaction — Exploring how SocialCircle can be applied in human-AI interaction scenarios, such as autonomous vehicles navigating in traffic or robots in shared spaces, is another potential area of future work.

Interdisciplinary Collaboration — Collaborating with experts from fields like behavioral psychology and animal behavior studies could provide valuable insights into modeling more realistic and nuanced social interactions.

References

1. C. Wong, B. Xia, and X. You. "SocialCircle: Learning the Angle-based Social Interaction Representation for Pedestrian Trajectory Prediction." In: **arXiv preprint arXiv:2310.05370** (2023).