Bruno Crémilleux
Sibylle Hess
Siegfried Nijssen (Eds.)

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Editors
Bruno Crémilleux
Université de Caen Normandie
Caen, France

Sibylle Hess
Eindhoven University of Technology
Eindhoven, The Netherlands

Siegfried Nijssen
UCLouvain
Louvain-la-Neuve, Belgium

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According to Table 3, NRI and WavenetNRI outperformed all other baselines, and NRI performed slightly better than WavenetNRI on simulation datasets in both recall and precision of group mitre Δ_{GW}. While on pedestrian datasets, GD-GAN [5] outperformed all other methods in both measures. The proposed WavenetNRI could outperform the original NRI [7] and ATTR [16] as the two classification-based baselines.

Concerning the impact of the population size (comparing *Simulation I* and *Simulation II*), we observed that by increasing the number of particles in simulation datasets, both precision and recall were decreased for all methods, except for NRI [7]. The same behavior was observed regarding the probability of non-group interactions (comparing *Simulation I* and *Simulation III*).

Furthermore, we calculated the average pairwise Euclidean distance between the group and non-group members of the two datasets. Our investigation of the differences between these two types of datasets showed that in the pedestrian datasets, the pairwise average Euclidean distances between group members (0.950 m) were much lower than those from different groups (4.698 m), i.e., the pedestrians were closer to their group members than other groups. While in the group-interaction simulation datasets, the differences between the Euclidean distances of the same groups (1.039 m) and that of different groups (1.725 m) were not significant.

Thus, distinguishing between group members and non-group members is more challenging in the simulation datasets compared with pedestrian datasets. Moreover, the fact that baselines do not generalize to simulation datasets suggests that available research might not be applicable to real-world scenarios where there is a chance for cross-group interactions.

Table 3. Experimental results of recall (R) and precision (P) based on Group Mitre Δ_{GW}. The best average values of recall and precision are highlighted with bold text.

	Simulation I		*Simulation II*		*Simulation III*		*zara01*		*ETH*		*Hotel*	
	R	P	R	P	R	P	R	P	R	P	R	P
ATTR [16]	0.579 ±0.017	0.481 ±0.020	0.512 ±0.009	0.388 ±0.015	0.511 ±0.006	0.386 ±0.005	0.889 ±0.076	0.879 ±0.077	0.745 ±0.067	0.746 ±0.087	0.833 ±0.072	0.841 ±0.068
S-SVM [13]	0.664 ±0.075	0.600 ±0.067	0.529 ±0.039	0.413 ±0.017	0.459 ±0.037	0.382 ±0.030	0.893 ±0.026	0.906 ±0.033	0.887 ±0.027	0.911 ±0.021	0.925 ±0.024	0.927 ±0.030
GD-GAN [5]	0.531 ±0.003	0.430 ±0.004	0.514 ±0.003	0.383 ±0.004	0.512 ±0.003	0.383 ±0.004	**0.949** ±0.046	**0.934** ±0.051	**0.931** ±0.037	**0.950** ±0.028	**0.925** ±0.084	**0.944** ±0.058
NRI [7]	**0.995** ±0.002	**0.994** ±0.003	**0.997** ±0.002	**0.994** ±0.002	**0.998** ±0.001	**0.996** ±0.001	0.801 ±0.096	0.737 ±0.108	0.663 ±0.083	0.669 ±0.080	0.577 ±0.122	0.565 ±0.122
Wavenet-NRI	0.990 ±0.010	0.988 ±0.013	0.985 ±0.005	0.970 ±0.010	0.986 ±0.004	0.972 ±0.007	0.893 ±0.090	0.900 ±0.107	0.793 ±0.078	0.815 ±0.079	0.748 ±0.106	0.790 ±0.086

5.6 Ablation Study

Our proposed approach applied two changes to the original NRI (i.e., adding symmetric edge features and symmetric edge updating process and the GD-RCC block). In this section, we explored the effects of these changes by performing an ablation study. To test the impact of the symmetric edge features and symmetric edge updating process, the same 1D convolutional as the original NRI with the symmetric edge features and the symmetric edge updating process was applied. This model is called "NRI-Symmetric". To test the effects of the GD-RCC block, "Wavenet-GD-RCC" was designed, which used the GD-RCC block with the same edge features and edge updating process as the original NRI. We compared the performance of these two methods with the proposed WavenetNRI and the original NRI on the simulation and pedestrian datasets. The results of both experiments are listed in Table 4. According to the results listed in Table 4, the Wavenet-GD-RCC performed slightly better than NRI, while the performance of NRI-Symmetric was lower than NRI. Therefore, the GD-RCC block could slightly improve the performance of NRI on the group-interaction datasets, and the symmetric edges and symmetric edge updating process negatively affected the original NRI. Additionally, the NRI-Symmetric performed better than the NRI, and Wavenet-GD-RCC performed similarly to NRI on the pedestrian data sets. Therefore, the symmetric edge features with the symmetric edge updating process could improve the performance of NRI on the pedestrian data sets, and the GD-RCC block did not significantly affect NRI's performance. Thus, the results were consistent per dataset type but not overall. We also noticed that either change could add value to one dataset category. As discussed earlier, the complexity of the simulation datasets in the behavior and interactions of the group members and non-group members might explain the inconsistent performance in these two types of datasets.

Table 4. Ablation study results of recall (R) and precision (P) based on Group Mitre Δ_{GW}. The best average values of recall and precision are highlighted with bold text.

	Simulation I		*Simulation II*		*Simulation III*		*zara01*		*ETH*		*Hotel*	
	R	P	R	P	R	P	R	P	R	P	R	P
NRI [7]	0.995 ±0.002	0.994 ±0.003	0.997 ±0.002	0.994 ±0.002	**0.998** ±0.001	0.996 ±0.001	0.801 ±0.096	0.737 ±0.108	0.663 ±0.083	0.669 ±0.080	0.577 ±0.122	0.565 ±0.122
NRI-Symmetric	0.990 ±0.004	0.987 ±0.006	0.981 ±0.007	0.964 ±0.013	0.981 ±0.007	0.961 ±0.009	0.851 ±0.093	0.813 ±0.091	0.679 ±0.094	0.686 ±0.096	0.708 ±0.121	0.739 ±0.115
Wavenet-GD-RCC	**0.998** ±0.002	**0.997** ±0.001	**0.999** ±0.001	**0.997** ±0.002	**0.998** ±0.001	**0.997** ±0.001	0.719 ±0.138	0.625 ±0.165	0.542 ±0.146	0.530 ±0.147	0.566 ±0.169	0.554 ±0.163
Wavenet NRI	0.990 ±0.010	0.988 ±0.013	0.985 ±0.005	0.970 ±0.010	0.986 ±0.004	0.972 ±0.007	**0.893** ±0.090	**0.900** ±0.107	**0.793** ±0.078	**0.815** ±0.079	**0.748** ±0.106	**0.790** ±0.086

6 Discussion and Conclusions

The present study explored the application of GNN by extending the NRI model [7] for group detection in two directions: (1) by applying symmetric edge features with symmetric edge updating processes and (2) by replacing the 1D convolution layer with a GD-RCC block, as proposed by Wavenet [11]. We compared the performance of WavenetNRI with other baselines on the three group-interaction simulation datasets and three pedestrian datasets. NRI and WavenetNRI outperformed all other baselines on the group-interaction simulation datasets. Although the pedestrian datasets were captured in real-world setups, the simulation datasets were better reflecting complex group interactions with larger groups, which stresses the importance of the obtained results. On the pedestrian datasets, although our proposed method did not compete against the clustering-based baselines, i.e., GD-GAN [5] and S-SVM [13], it outperformed classification-based methods, i.e., ATTR [16] and the original NRI [7]. Yet, baseline methods did not generalize very well to the simulation datasets. We further evaluated the effects of our changes to the original NRI in the ablation study. We found that on the group-interaction data sets, the GD-RCC block slightly improved the performance of NRI. Simultaneously, the symmetric edge features with symmetric edge updating processes negatively affected the performance of NRI. On the pedestrian data sets, the symmetric edge features with symmetric edge updating processes improved the performance of NRI, while the GD-RCC block had no significant effect on NRI.

Our analysis demonstrates that WavenetNRI is highly effective at predicting pairwise interactions, which ultimately reflect the group memberships of agents in an interacting environment. One drawback of the proposed method is its dependency on ground truth data. Unsupervised methods such as GD-GAN are preferable if ground truth is not available for a particular study. Many real-world communities, such as sports clubs and schoolyards, can be understood as a dynamic interacting system, where applying a trained WavenetNRI model can be helpful in predicting group memberships within the system.

The current study can be improved by investigating how to adapt the proposed neural network design more efficiently to different datasets using meta-learning. Additionally, it is worth studying how to extend the proposed classification-based method to a supervised clustering task. And finally, designing a fully supervised model by adding a final layer to classify nodes into the group they belong to could be investigated in the future.

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