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LLM Connection Graphs for Global Feature Extraction in Point Cloud Analysis

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ABSTRACT
Graph convolutional networks (GCNs) have effectively utilized local connections for point cloud analysis. How- ever, capturing distant dependencies (i.e., global features) with a single local connection graph, such as the Euclidean k-nearest neighbor graph, remains challenging. To ad- dress this, we introduce the Multi-Space Graph Convolutional Network (PointGCNN), which leverages reinforcement learning to adaptively construct connection graphs in multiple latent spaces, integrating both local and non-local dependencies. Initially, we encode and concatenate low- level local features from Euclidean and Eigenvalue spaces. Convolution layers are then hierarchically built, with each layer forming dynamic connection graphs to guide the propagation of low-level features. [1,2,3,4,11,14,16]These implicitly constructed graphs enable our model to uncover hidden dependencies. The assorted connections from different graphs support the extraction of fine-grained features from various perspectives, enhancing complex scene recognition. Thus, our model can capture multiple global contexts beyond the local scope of a single space, providing strong robustness against perturbations. Experimental results demonstrate that the proposed method achieves state-of-the-art performance on two major public point cloud benchmarks.

Keywords: graphs, cloud analysis, benchmarks

I. INTRODUCTION

The point cloud format, consisting of a set of 3D points, has garnered significant attention due to its wide applications in areas such as autonomous driving [18] and reverse engineering [40]. Despite its simplicity, the sparse and dis- ordered nature of point clouds presents challenges for traditional convolutional neural networks. Specifically, there are three main issues: (1) the permutation invariance of points must be maintained to preserve the geometric structure, (2) models must exhibit robustness to large geometric transformations and deformations [35], and (3) suitable connection graphs are essential for effective feature extraction, capturing local geometric structures and symmetric relationships. Significant progress has been made in point cloud analysis. PointNet [19] introduced shared multi-layer perceptrons and symmetric functions (e.g., point-wise max- pooling) to ensure permutation invariance. However, Point- Net struggles to model local geometric structures. To address this, subsequent works [20, 22, 23] introduced grouping operations (e.g., k-nearest neighbor or ball region groups) to create local connections for hierarchical feature extraction. Despite their success, these methods, based on Euclidean coordinates, fail to capture long-range dependencies, limiting global context extraction.

Dynamic Graph CNN (DGCNN) [30] improved upon this by dynamically updating the connection graph based on features. However, each layer still operates on a single graph, limiting the captured geometric features. More- over, the back-propagation method cannot guide the net- work to construct optimal connection graphs, as neighbor selection in feature space is non-differentiable. GS-Net [35] addressed this by building connections in both Euclidean and Eigenvalue spaces, leveraging local and non-local dependencies. However, it still lacks the ability to implicitly construct connection graphs, limiting its ability to fully capture latent dependencies like symmetry and collinearity (see Figure 1).

To address these limitations, we propose the Multi-Space Graph Convolutional Network (PointGCNN), which employs reinforcement learning to adaptively construct connection graphs in multiple latent spaces, capturing both local and non-local dependencies. Initially, local geometric structures are encoded in Euclidean and Eigenvalue spaces and combined as low-level features. Hierarchical convolution layers then dynamically construct multiple connection graphs, guiding feature propagation. The assorted connections capture diverse dependencies, enhancing complex scene recognition and robustness against perturbations. Experimental results demonstrate PointGCNN's state-of-the- art performance on major point cloud benchmarks.

Our main contributions are three-fold:

- We design a Multi-Space Convolution kernel based on bootstrap [4] and policy gradient [26], which adap- tively explores latent space connections to capture global features.
- We integrate the bootstrap method into deep learning, enabling our model to capture diverse dependencies.
- Our PointGCNN achieves state-of-the-art performance on ModelNet40 and ScanObjectNN datasets, demon- strating its effectiveness, efficiency, and robustness.

II. RELATED WORK

In our comprehensive survey of point cloud analysis, we categorize the research into three main approaches: local feature-based methods, non-local feature-based methods, and methods that do not primarily focus on features.

Local feature-based methods [19, 20, 23, 37, 22, 12, 9, 30, 14, 13, 41, 31, 10, 27, 36, 3, 35, 38 ,57 ,58] often begin with PointNet [19], which addresses the sparse nature and permutation invariance of point clouds using shared MLP and max-pooling. However, PointNet's independent handling of each point can result in the loss of local geo- metric structures. To mitigate this, PointNet++ [20] introduces local connections in Euclidean space for hierarchical feature encoding. Following this, numerous studies [30, 41, 14, 46, 47] have enhanced local information extraction methods. For example, DGCNN [30] links local neighbors with the center point to exploit edge relationships, while PointCNN [12] employs an X-transformation to per- mute and weight the point set. GACNet [29] uses attention mechanisms to address feature isotropy, PointWeb [41] densely connects local points to find interactions, Point- Conv [31] combines MLP with kernel density estimation for convolution kernel construction, and Geo-CNN [10] de- composes edge feature extraction onto multiple orthogonal bases to model local geometric structures explicitly. De- spite these advances, these methods often fail to capture non-local information among distant points [3].

To extract non-local features, Point2Node [3] explores multi-level correlations, including self, local, and non-local correlations, though dense connections can overwhelm important information and increase computational overhead. GS-Net [35] constructs local connection graphs in both Euclidean and Eigenvalue spaces to leverage holistic con- text features. While this approach benefits from explicit eigenvalue-based connections, it still lacks the ability to adaptively build connection graphs in an end-to-end manner, overlooking other dependencies.

Additionally, some works explore non-feature-based approaches. For example, 3DmFV [39] represents points by their deviation from a Gaussian Mixture Model, capturing more details than grids. PointASNL [38] introduces attention mechanisms to reduce noise. Other significant contributions include [8, 11, 34, 1, 42, 33, 17].

III. METHODOLOGY

Our neural architecture is depicted in Figure A point cloud is represented as a set.

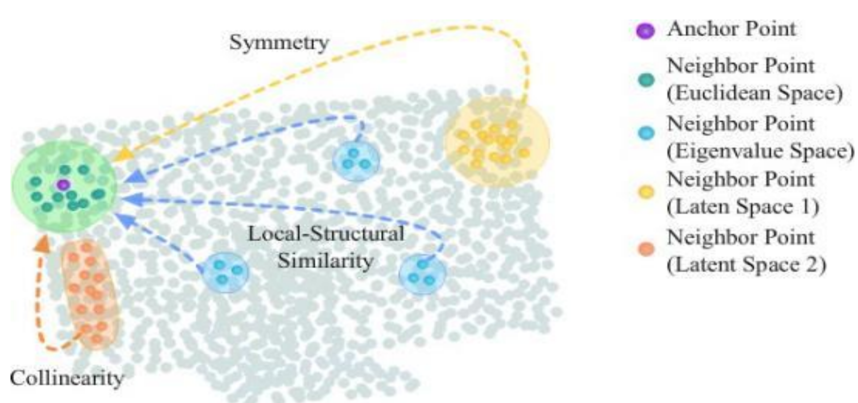

Figure 1: Neighbors from different latent spaces (A real-world Ex- ample on ModelNet40). (Best viewed in color and zoom in)

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The purple point is the anchor point. Different colored clusters indicate the neighbors of the anchor point in various spaces, serving as examples to extract different local/global features. The range of neighbors in Euclidean space is circled, with dependencies marked along the edges. For example, the green/blue points are local neighbors in Euclidean/Eigenvalue space [35], providing local geometric and structural similarity features. The yellow/orange clusters offer symmetric property/collinearity features relative to the anchor point. By bridging local connections in different spaces, various dependencies can be captured.

Where P represents all point coordinates, pi denotes the 3D coordinate of the i-th point, and N is the total number of points.

Initially, we encode low-level local features in two prior spaces (Euclidean and Eigenvalue spaces [35]) using the Prior Space Encoding Module (PSEM). The model then stacks Multi-Space Convolution (MSConv) layers to hierarchically propagate and gather features across diverse graphs. High-level representations are generated using point-wise shared multi-layer perceptrons (MLP). Finally, both low-level and high-level features are utilized for down- stream tasks.

The architecture consists of four main parts (Figure ??):

1. Prior Space Processing. The Eigen-Graph [35] calculates eigenvalue features we concatenate these eigenvalue features with the Euclidean coordinates and use T-Net [19] to align the point cloud in Euclidean space. This results in adjusted 3D coordinates

$$edge_i^{Nei_i}(Set) = \oplus(s_j, s_j - s_i, \|s_j - s_i\|), j \in Nei_i \quad (1)$$

$$conv_i^{Nei_i}(Set) = \sigma(Max(MLP(edge_i^{Nei_i}(Set)))) \quad (2)$$

$$x_i^0 = \sigma(FC(\oplus(conv_i^{EUC_i}(P'), conv_i^{EIG_i}(E)))) \quad (3)$$

2. High-level Dependency Extraction. We propose MSConv layers to extract and fuse multiple geometric features. Each layer uses policy gradients [26] to select weighted input feature channels, inspired by bootstrap

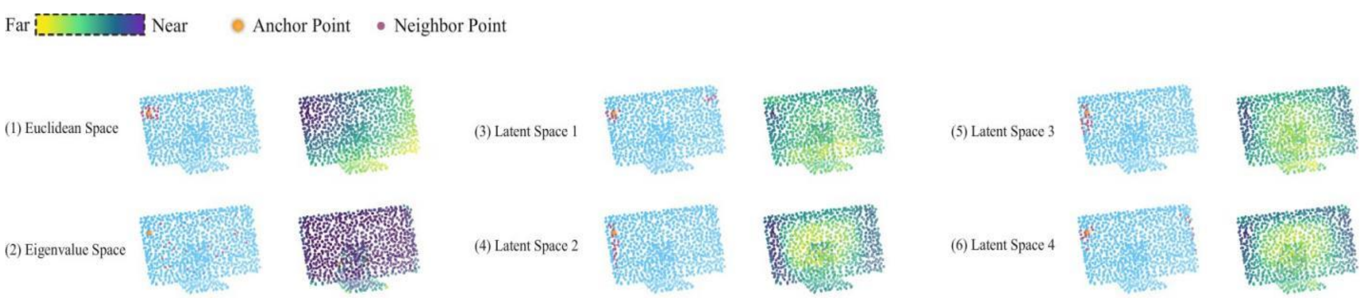

Figure 2: Visualization of the local connections in different spaces (Best viewed in color and zoom in)

We visualize the local neighbors of the same anchor point (a.k.a., the original point) in different spaces. Each point is colored based on its distance from the anchor point in the specific space, with shorter distances shown in darker colors.

Method	OBJ_ONLY	PB_T50_RS
PointNet[19]	79.2	68.2
PointNet++[20]	84.3	77.9
3DmFV[39]	73.8	63.0
SpiderCNN[37]	79.5	73.7
PointCNN[12]	85.5	78.5
DGCNN†[30]	86.2	78.1
GS-Net[35]	84.7	78.1
PointGCNN (ours)	**87.6**	**81.5**

Table 3: Overall accuracy(%) on the ScanObjectNN benchmark. This comparison includes only supervised models trained exclusively on ScanObjectNN.

Method	Model Size(M)	Forward Time(ms)	Accuracy (%)
PointNet[19]	13.4	30	89.2
PointNet++[20]	7.0	603	91.9
DGCNN[30]	7.2	73	92.2
GS-Net[35]	6.0	126	92.9
PointGCNN (ours)	20.8	36	93.7

Table 4: Efficiency analysis of PointGCNN in classification.

k	S	Channel Weight	Voting	Accuracy (%)	Model Size(M)
12	0	√		93.0	10.4
12	4	√		93.5	20.8
12	2	√		93.2	19.2
12	4	√		93.7	20.8
12	6	√		93.4	22.6
16	4	√		93.1	20.8
20	4	√		93.6	20.8
12	4		√	93.8	20.8

Table 5: Ablation Study for PointGCNN. “k” represents the number of neighbors in each space. “S” indicates the number of latent spaces. “Channel Weight” means the latent spaces are weighted feature spaces rather than raw feature subsets. “Voting” denotes the use of the voting technique

Performance Comparison. Results on ScanObjectNN [28] show the effectiveness of our model in point cloud understanding. PointGCNN achieves significant improve- ments on PB T50 RS (3.0%) and OBJECT ONLY (1.4%), demonstrating its robustness to large geometric transfor- mations through inherent dependencies like symmetry and connectivity.

1.1 ShapeNet: Point Cloud Part Segmentation

Dataset and Metric. The ShapeNet Part dataset [2] con- sists of 16, 880 models from 16 categories and 50 parts.

There are 14, 006 models for training and 2, 874 for test- ing. We concatenate a one-hot category vector to the last point representation and use mean IoU (mIoU) to evaluate segmentation performance.

Performance Comparison. While our PointGCNN is designed for global dependencies rather than discriminative local features, it still achieves comparable results (85.2%) in segmentation tasks.

1.2 Ablation Study

Table 5 shows the effectiveness of learned latent spaces and hyper-parameter impacts. Generated latent space connections provide significant improvements (0.8%), indicating the presence of latent semantic dependencies. Visualization of distance figures (Figure 2) illustrates these dependencies.

1.3 Efficiency Analysis

We evaluate time efficiency on the ModelNet40 [32] dataset, comparing forward propagation speed. All codes are based on PyTorch [16], and ”forward time” represents the mean time to process a batch of 8 samples on a sin- gle GTX1080 GPU. Our PointGCNN, designed for parallel computing, achieves the best performance with minimal time. [4], creating multiple latent spaces for each sample. Features are propagated along these connections, and a fully connected layer transforms outputs into final layer features.

3. Downstream Task Docking. For point classification, we concatenate low-level (PSEM output) and high- level features (MSConv outputs). A fully connected layer and two pooling layers (max and mean) produce global representations. An MLP with dropout [25] evaluates category distribution. For segmentation, a fully connected layer concatenates multi-level features for each point, and an MLP with dropout performs point-wise segmentation.

IV. CONCLUSION

To analyze point clouds more comprehensively, we pro- pose a novel neural architecture, PointGCNN, inspired by Prior Space Encoding Module (PSEM). The PSEM extracts local geometric features from Euclidean and Eigenvalue spaces, producing a N 64 low- level feature matrix from the input N 3 Euclidean coordinate matrix and N 3 eigenvalue feature matrix.

Formally, given adjusted spatial coordinates and bootstrap and optimized by policy gradient. PointGCNN adaptively organizes latent spaces to capture hidden distant dependencies. These rich dependencies enhance robust- ness and enable the model to achieve state-of-the-art performance on benchmark datasets.

REFERENCES

1. Yang, R. (2024). *CaseGPT: A case reasoning framework based on language models and retrieval-augmented generation*. arXiv preprint arXiv:2407.07913.
2. Gao, H., Li, Y., Long, K., Yang, M., & Shen, Y. (2024). *A survey for foundation models in autonomous driving*. arXiv preprint arXiv:2402.01105.
3. Tao Y. (2023). SQBA: Sequential query-based blackbox attack, *Fifth International Conference on Artificial Intelligence and Computer Science (AICS 2023), 12803*, pp. 721-729.
4. Wantlin, Kathryn, et al. (2023). *Benchmd: A benchmark for modality-agnostic learning on medical images and sensors*. arXiv preprint arXiv:2304.08486.
5. Tao Y. (2023). Meta learning enabled adversarial defense. *IEEE International Conference on Sensors, Electronics and Computer Engineering (ICSECE)*, pp. 1326-1330.
6. Tan, K., Li, P., & Beckers, T. (2024). *Physics-constrained learning for PDE systems with uncertainty quantified port-hamiltonian models*. arXiv preprint arXiv:2406.11809.
7. Chen, Y., Shi, H., Liu, X., Shi, T., Zhang, R., Liu, D., ... & Wu, F. (2024). *TokenUnify: Scalable autoregressive visual pre-training with mixture token prediction*. arXiv preprint arXiv:2405.16847.
8. Zhan, Donglin, et al. (2019). *Adaptive transfer learning of multi-view time series classification*. arXiv preprint arXiv:1910.07632.
9. Tan, K., Wang, J., & Kantaros, Y. (2023, June). Targeted adversarial attacks against neural network trajectory predictors. In: *Learning for Dynamics and Control Conference*, pp. 431-444. PMLR.
10. Liu, Y., Yang, H., & Wu, C. (2023). Unveiling patterns: A study on semi-supervised classification of strip surface defects. *IEEE Access*, *11*, 119933-119946.
11. Jiang, L., Yu, C., Wu, Z., & Wang, Y. (2024). *Advanced AI framework for enhanced detection and assessment of abdominal trauma: Integrating 3D segmentation with 2D CNN and RNN models*. arXiv preprint arXiv:2407.16165.
12. Yan, H., Wang, Z., Xu, Z., Wang, Z., Wu, Z., & Lyu, R. (2024). *Research on image super-resolution reconstruction mechanism based on convolutional neural network*. arXiv preprint arXiv:2407.13211.
13. Jiang, L., Yu, C., Wu, Z., & Wang, Y. (2024). *Advanced AI framework for enhanced detection and assessment of abdominal trauma: Integrating 3D segmentation with 2D CNN and RNN models*. arXiv preprint arXiv:2407.16165.
14. Gao, Z., Wang, Q., Mei, T., Cheng, X., Zi, Y., & Yang, H. (2024). *An enhanced encoder-decoder network architecture for reducing information loss in image semantic segmentation*. arXiv preprint arXiv:2406.01605.
15. Jiang, L., Yu, C., Wu, Z., & Wang, Y. (2024). *Advanced AI framework for enhanced detection and assessment of abdominal trauma: Integrating 3D segmentation with 2D CNN and RNN models*. arXiv preprint arXiv:2407.16165.
16. Yao, J., Lai, Y., Kou, H., Wu, T., & Liu, R. (2024). QE-BEV: Query evolution for bird's eye view object detection in varied contexts. In: *ACM Multimedia*.
17. Song, X., Wu, D., Zhang, B., Peng, Z., Dang, B., Pan, F., & Wu, Z. (2023). *Zeroprompt: streaming acoustic encoders are zero-shot masked lms*. arXiv preprint arXiv:2305.10649.
18. Guan, B., Cao, J., Huang, B., Wang, Z., Wang, X., & Wang, Z. (2024). *Integrated method of deep learning and large language model in speech recognition*.
19. Liu, C., Ouyang, C., Chen, Y., Quilodrán-Casas, C. C., Ma, L., Fu, J., ... & Arcucci, R. (2023). *T3d: Towards 3d medical image understanding through vision-language pre-training*. arXiv preprint arXiv:2312.01529.
20. Wu, J., Hobbs, J., & Hovakimyan, N. (2023). Hallucination improves the performance of unsupervised visual representation learning. in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 16132-16143.
21. Dang, B., Zhao, W., Li, Y., Ma, D., Yu, Q., & Zhu, E. Y. (2024). *Real-time pill identification for the visually impaired using deep learning*. arXiv [Cs.CV]. Retrieved from: http://arxiv.org/abs/2405.05983.
22. Yao, J., Li, C., Sun, K., Cai, Y., Li, H., Ouyang, W., & Li, H. (2023, October). Ndc-scene: Boost monocular 3d semantic scene completion in normalized device coordinates space. in *IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 9421-9431. IEEE Computer Society.
23. Dang, B., Ma, D., Li, S., Qi, Z., & Zhu, E. (07 2024). Deep learning-based snore sound analysis for the detection of night-time breathing disorders. *Applied and Computational Engineering*, *76*, 109–114. doi:10.54254/2755-2721/76/20240574.

24. Pan, Xiaochao, et al. (2023). HarmonicNeRF: Geometry-informed synthetic view augmentation for 3D scene reconstruction in driving scenarios. *ACM Multimedia*.
25. Li, S., Dong, X., Ma, D., Dang, B., Zang, H., & Gong, Y. (2024). Utilizing the LightGBM algorithm for operator user credit assessment research. *Applied and Computational Engineering*, *75*(1), 36–47. doi:10.54254/2755-2721/75/20240503.
26. Yang, R. (2024). CaseGPT: *A case reasoning framework based on language models and retrieval-augmented generation*. arXiv preprint arXiv:2407.07913.
27. Wang, J., Hong, S., Dong, Y., Li, Z., & Hu, J. (2024). Predicting stock market trends using lstm networks: overcoming RNN limitations for improved financial forecasting. *Journal of Computer Science and Software Applications, 4*(3), 1-7.
28. Sun, M., Feng, Z., Li, Z., Gu, W., & Gu, X. (2024). Enhancing financial risk management through lstm and extreme value theory: A high-frequency trading volume approach. *Journal of Computer Technology and Software, 3*(3).
29. Xu, Q., Feng, Z., Gong, C., Wu, X., Zhao, H., Ye, Z., Li, Z. and Wei, C. (2024). Applications of explainable AI in natural language processing. *Global Academic Frontiers, 2*(3), 51-64.
30. Xiao, Minheng, Shi Bo, & Zhizhong Wu. (2024). *Multiple greedy quasi-newton methods for saddle point problems*. arXiv preprint arXiv:2408.00241.
31. Qi, Zongqing, et al. (2024). *Improved YOLOv5 based on attention mechanism and FasterNet for foreign object detection on railway and airway tracks*. arXiv preprint arXiv:2403.08499.
32. Xiang, Ao, et al. (2024). *A neural matrix decomposition recommender system model based on the multimodal large language model*. arXiv preprint arXiv:2407.08942.
33. Mo, Yuhong, et al. (2024). *Large Language Model (LLM) AI text generation detection based on transformer deep learning algorithm*. *International Journal of Engineering and Management Research 14*(2), 154-159.
34. Ma, Danqing, et al. (2024). *Transformer-based classification outcome prediction for multimodal stroke treatment*. arXiv preprint arXiv:2404.12634.
35. Xiang, Ao, et al. (2024). *A multimodal fusion network for student emotion recognition based on transformer and tensor product*. arXiv preprint arXiv:2403.08511.
36. Ao Xiang, Jingyu Zhang, Qin Yang, Liyang Wang, & Yu Cheng. (2024). Research on splicing image detection algorithms based on natural image statistical characteristics. *Journal of Image Processing Theory and Applications, 7*, 43-52. http://dx.doi.org/10.23977/jipta.2024.070106.
37. Li, Zhenglin, et al. (2023). Stock market analysis and prediction using LSTM: A case study on technology stocks. *Innovations in Applied Engineering and Technology*, 1-6.
38. Li, Shaojie, Yuhong Mo, & Zhenglin Li. (2022). Automated pneumonia detection in chest x-ray images using deep learning model. *Innovations in Applied Engineering and Technology*, 1-6.
39. Mo, Yuhong, et al. (2024). Password complexity prediction based on roberta algorithm. *Applied Science and Engineering Journal for Advanced Research, 3*(3), 1-5.
40. Song, Jintong, et al. (2024). A comprehensive evaluation and comparison of enhanced learning methods. *Academic Journal of Science and Technology, 10*(3), 167-171.
41. Liu, Tianrui, et al. (2024). Spam detection and classification based on distilbert deep learning algorithm. *Applied Science and Engineering Journal for Advanced Research, 3*(3), 6-10.
42. Dai, Shuying, et al. (2024). The cloud-based design of unmanned constant temperature food delivery trolley in the context of artificial intelligence. *Journal of Computer Technology and Applied Mathematics, 1*(1), 6-12.
43. Mo, Yuhong, et al. (2024). Make scale invariant feature transform “Fly” with CUDA. *International Journal of Engineering and Management Research, 14*(3), 38-45.
44. He, Shuyao, et al. (2024). Lidar and monocular sensor fusion depth estimation. *Applied Science and Engineering Journal for Advanced Research, 3*(3), 20-26.
45. Liu, Jihang, et al. (2024). Unraveling large language models: From evolution to ethical implications-introduction to large language models. *World Scientific Research Journal, 10*(5), 97-102.
46. Mo, Yuhong & Zhang, Yuchen & Li, Hanzhe & Wang, Han & Yan, Xu. (2024). Prediction of heart failure patients based on multiple machine learning algorithms. *Applied and Computational Engineering, 75*, 1-7. doi:10.54254/2755-2721/75/20240498.
47. Zhu, Armando, et al. (2024). Cross-task multi-branch vision transformer for facial expression and mask wearing classification. *Journal of Computer Technology and Applied Mathematics, 1*(1), 46-53.
48. Li, Keqin, et al. (2024). Utilizing deep learning to optimize software development processes. *Journal of Computer Technology and Applied Mathematics, 1*(1), 70-76.
49. Li, Keqin, et al. (2024). The application of augmented reality (AR) in remote work and education. *Journal of Computer Technology and Applied Mathematics, 1*(1), 33-39.

50. Hong, Bo, et al. (2024). The application of artificial intelligence technology in assembly techniques within the industrial sector. *Journal of Artificial Intelligence General Science (JAIGS)*, *5*(1), 1-12.
51. Dai, Shuying, et al. (2024). AI-based NLP section discusses the application and effect of bag-of-words models and TF-IDF in NLP tasks. *Journal of Artificial Intelligence General Science (JAIGS)*, *5*(1), 13-21.
52. Zhao, Peng, et al. (2024). Task allocation planning based on hierarchical task network for national economic mobilization. *Journal of Artificial Intelligence General Science (JAIGS)*, *5*(1), 22-31.
53. Hu, X., Sun, Z., Nian, Y., Wang, Y., Dang, Y., Li, F., ... & Tao, C. (2024). Self-explainable graph neural network for alzheimer disease and related dementias risk prediction: Algorithm development and validation study. *JMIR Aging*, *7*(1), e54748.
54. Li, F., Rasmy, L., Xiang, Y., Feng, J., Abdelhameed, A., Hu, X., ... & Tao, C. (2024). Dynamic prognosis prediction for patients on DAPT after drug-eluting stent implantation: Model development and validation. *Journal of the American Heart Association*, *13*(3), e029900.
55. He, J., Li, F., Hu, X., Li, J., Nian, Y., Wang, J., ... & Tao, C. (2022, June). Chemical-protein relation extraction with pre-trained prompt tuning. in *IEEE 10th International Conference on Healthcare Informatics (ICHI)*, pp. 608-609. IEEE.
56. He, J., Li, F., Li, J., Hu, X., Nian, Y., Xiang, Y., ... & Tao, C. (2024). Prompt tuning in biomedical relation extraction. *Journal of Healthcare Informatics Research*, *8*(2), 206-224.
57. Bo, S., & Xiao, M. (2022). *Dynamic risk measurement by EVT based on stochastic volatility models via MCMC*. arXiv preprint arXiv:2201.09434.
58. Xiao, M., Bo, S., & Wu, Z. (2024). *Multiple greedy quasi-newton methods for saddle point problems*. arXiv preprint arXiv:2408.00241.