електроенергії, зменшити навантаження на енергомережу та покращити управління ресурсами в умовах нестабільності ринку. Подальший розвиток цієї сфери сприятиме більш ефективному використанню енергії та інтеграції відновлюваних джерел у загальну енергосистему.

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OPTIMIZING GRAPH NEURAL NETWORKS FOR RISK ASSESSMENT IN THE INSURANCE: A COMPREHENSIVE PARAMETER ANALYSIS

ОПТИМІЗАЦІЯ ГРАФОВИХ НЕЙРОННИХ МЕРЕЖ ДЛЯ ОЦІНКИ РИЗИКІВ У СТРАХОВІЙ СФЕРІ: КОМПЛЕКСНИЙ АНАЛІЗ ПАРАМЕТРІВ

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Graph Neural Networks have demonstrated significant potential in capturing complex relationships within interconnected data. The GraphSAGE architecture's ability to aggregate information from a node's local neighborhood makes it particularly suitable for risk assessment, where an individual's insurance risk is influenced by their connections and characteristics [1].

A graph was generated to simulate real-world task of assessing the risk of insuring the individual. The graph comprised nodes representing individuals, with edges denoting 2 types of connections. Each node was assigned a set of features relevant to risk assessment, designed to reflect realistic risk factor with the following node features: health score: a continuous value ranging from 0.1 to 1.0, where lower values indicate poorer health, it is generated using a truncated normal distribution ($\mu = 0.7$, $\sigma = 0.2$, bounded between 0.1 and 1.0) to simulate a realistic health distribution in a population, doesSmoke: a binary feature, assigned using a Bernoulli distribution with $p = 0.2$, reflecting typical smoking rates in many populations.performsRegularCheckups: a binary feature, assigned using a Bernoulli distribution with $p = 0.6$, simulating varying levels of health consciousness.

Two types of edges were created to represent different relationship dynamics: 'Zipcode': these were created with higher probability for nodes with similar health scores, simulating geographical health disparities and 'Family', which were generated randomly, ensuring a minimum edge count of (number of nodes / 2) to maintain graph connectivity.

An expected risk label for each node was computed as a function of its features: Risk = (1 – Health Score) * (1 + 0.2 * Smoking Status – 0.1 * Regular Check-ups).

This formula ensures that lower health scores, smoking, and lack of regular check-ups contribute to higher risk, while better health practices reduce risk.

The resulting graph provided a complex, realistic dataset for evaluating the GraphSAGE model's performance in risk assessment tasks in the insurance area. The controlled nature of this data generation process allowed for a thorough examination of the model's capabilities across various network structures and risk profiles.

An extensive parameter tuning analysis process has been conducted to find the optimal values for the model's performance. The following parameters were checked: number of layers (2, 3, 4): affecting the depth of the neural network, hidden channels (32, 64, 128, 256): determining the feature complexity, learning rate (0.1, 0.01, 0.001): influencing the optimization process, dropout (0.1, 0.3, 0.5): Regulating overfitting through random unit deactivation, weight decay (0, 1e-4, 1e-5): applying L2 regularization to enhance generalization, epochs (200, 300): Controlling the duration of training, loss functions (MSE, L1, Smooth L1): defining the error evaluation method [2].

To represent the best possible options for all the layers, the comparison table may be built:

Layers	**Hidden Channels**	**Learning Rate**	**Dropout**	**Weight Decay**	**Epochs**	**Loss Function**	**Test Loss**	**Conclusion**
2	128	0.1	0.1	1e-05	100	Smooth_l1_loss	0.0001	Achieves excellent performance with higher learning rate.
3	128	0.01	0.1	1e-05	300	Smooth_l1_loss	0.0001	Has lower learning rate and longer potential training time. Early stopping activated.
4	64	0.01	0.5	0.0001	200	Smooth_l1_loss	0.0001	Achieves same performance as simpler models despite higher complexity and stronger regularization. Early stopping activated.

By analyzing the results of training the model using all combinations of these parameters, the following trends can be observed:

1. Performance: All three configurations achieve the same excellent test loss of 0.0001, indicating that they all perform exceptionally well on the given task.
2. Model Complexity: The task is well-solved by models ranging from 2 to 4 layers and 64 to 128 hidden channels, suggesting that the problem doesn't necessarily require a deep or wide architecture to achieve optimal performance.
3. Learning Rate: The 2-layer model uses a higher learning rate (0.1) compared to the 3 and 4-layer models (0.01) but achieves the same

performance. This suggests that the simpler model can afford more aggressive learning steps.

4. Regularization: The 4-layer model uses much stronger regularization (higher dropout and weight decay) compared to the others yet still matches their performance. This might indicate that the task doesn't pose a significant overfitting risk.

5. Training Duration and Early Stopping: The 2-layer model reaches optimal performance in just 100 epochs without mentioned early stopping. The 3-layer model uses early stopping at epoch 220 out of 300. The 4-layer model stops early at epoch 190 out of 200. This suggests that while longer training times are allocated for deeper models, they often don't require the full duration to achieve optimal performance.

Conclusions:

This study provides insights into optimizing GraphSage architecture for risk assessment task of insuring the individuals. The analysis revealed that deeper networks (3-4 layers) with moderate numbers of hidden channels (64-128) generally performed better, capturing more complex graph structures. Lower learning rates (0.001) combined with higher dropout rates (0.5) and moderate weight decay (1e-5) provided the best balance between learning and regularization. However, it is worth noting that the smaller number of layers has also shown good results.

The choice of loss function significantly impacted performance, with Smooth L1 loss showing the best results for all configurations.

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