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Graph Neural Networks for Predicting Student Performance: A Deep Learning Approach for Academic Success Forecasting

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Abstract: Student Academic Success Forecasting in higher education sector especially for technical courses has become increasingly popular, but success rates are typically low, and evaluating student performance can be challenging. Therefore, a framework for effective evaluation and prediction of student outcomes is highly needed for educational institutions. The proposed Performance Evaluation approach models the association in between students and their respective courses as a knowledge graph and uses a graph neural network to extract insightful patterns for better prediction. In addition, it utilizes a recurrent neural network to capture the sequential patterns in students' behavioural data over time and forecast their academic outcomes in a specific course. This research work demonstrates the effectiveness of this approach in predicting student performance, and ablation feature analysis is conducted to gain insights into the underlying factors that contribute to performance prediction.

***Keywords**: Graph Neural Network, Student Performance, Knowledge Graph.*

1. Introduction

Predicting how well the students will perform in their academics is hard and really important for their success [10, 14]. Finding students who might fail a course or have a hard time can help teachers give them extra help, like tutoring or mentoring, to make sure they do better. The usual ways to predict how well students will do just look at things like how old they are and what grades they've secured before, but those ways don't really think about how things are connected, like what classes they need to take before others, who their friends are, or when they attended classes.

There's this new way called [12] Graph Neural Networks (GNNs) that is really good at predicting how well students will do. GNNs use something called a "graph" to show how things are interconnected. In this case, the dots are like students or classes, and the lines show how they're related, like if a student signed up for a class or if one class needs to be taken before another. GNNs use these dots and lines to figure out how students are doing and what classes they might do well in. In this research, we suggest using a cool new way of prediction methodology called Graph Neural Networks to predict how well students will perform in their academics. We use a special type of representation called a "graph" to show how things in academics are connected [16], like students and classes and other important stuff. Here made a special kind of computer program called a GNN that can understand these representation and figure out how students are doing and what classes they might be good at. We're going to test our program on real data from a university and see if it's better than the old way of guessing.

2. Related Works

In this section, the main findings of the study are presented after conducting a literature review of prior research in the academic field, aiming to identify any gaps in forecasting student performance.

In the paper [1], the researchers proposed an improved Graph Convolutional Neural Network (GCN) algorithm called RG-GCN, which addresses the limitations of traditional topological networks by considering the ambiguity in real-world relationships between nodes unlike regular graphs that have fixed values for edge weights, the RG-GCN approach creates a rough graph by combining rough set theory and topological graph theory. This rough graph captures the uncertainties present in real-world data, allowing for more flexibility in modeling inter-node interactions and updating node attributes. By incorporating the paired maximum-minimum connection, RG-GCN aims to improve the classification performance of the model. The proposed RG-GCN algorithm represents a novel solution to enhance the accuracy of graph-based neural networks by incorporating rough graph representations, and it has the potential to advance the field of graph convolutional neural networks in various applications.

This research [2] focuses on predicting student performance in educational institutions. The traditional

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approaches for performance prediction often lack the utilization of relational and structural information present in educational data, such as enrollment records, social networks, and course prerequisites. To address this, the authors propose a deep learning approach that leverages Graph Neural Networks (GNNs) to capture the rich graph-based representation of educational data. The proposed approach involves constructing a graph representation of the educational data, where students, courses, and their relationships are modeled as nodes and edges in the graph. A GNN architecture is employed [11] that incorporate graph convolutional layers to capture contextual information from the graph at both local and global levels. Additionally, attention mechanisms are integrated into the GNN to emphasize important nodes or edges, allowing the model to focus on relevant information for performance prediction. To evaluate the effectiveness of this research work, experiments are conducted on real-world educational datasets, including student performance data from a university. The results demonstrate that the GNN-based approach outperforms traditional methods in terms of accuracy in predicting student performance, including identifying students who may be at risk of failing a course. The findings also highlight the ability of the GNN to capture the complex dependencies and interactions among students and courses, which are crucial for accurate performance prediction in an academic setting.

Graph Neural Networks (GNNs) [3] function as architectures for processing information on graphs. They are considered as extensions of Convolutional Neural Networks (CNNs), where each layer consists of sets of graph convolutional filters rather than traditional convolutional filters. Despite this distinction, GNNs function in a comparable way to CNNs, utilizing stacked layers of filters that consist of point wise nonlinearities.

The authors emphasize that Graph Neural Network (GNN) architectures possess two important characteristics. Firstly, GNNs demonstrate equivariance to permutation, which means that rearranging the nodes in a graph does not impact the network's output. Secondly, GNNs exhibit stability to graph deformations, indicating that minor changes in the graph's structure do not significantly affect the network's performance. These properties provide an explanation for the consistent high performance of GNNs observed in real-world studies. Furthermore, the authors demonstrate that when graphs approach a limit object called a graphon, GNNs also converge towards a corresponding limit object known as a graphon neural network. This convergence supports the idea that GNNs can effectively generalize their learning’s across networks with varying numbers of nodes. In summary, the paper offers valuable insights regarding the architecture, stability, and transferability of GNNs, thereby highlighting their potential applications in diverse domains beyond conventional image and text processing tasks.

The authors [4] discuss their experiments where they aimed to build prediction models for early-stage student performance in blended learning courses. They employed deep neural network (NN) architecture and utilized online activity attributes extracted from Moodle's activity logs as input patterns for their models. The dataset they used in their experiments comprised 885 records from undergraduate students enrolled in three distinct courses across 16 different classes. The authors perform a series of experiments aimed at identifying the optimal hyper parameters for a high-performing neural network (NN) model, which acts as their reference classifier. Subsequently, they assess the model's effectiveness in predicting student outcomes as pass or fail during both the midterm and finals period using activity data collected before the midterm period. The findings reveal that the prediction performance is initially poor during the first month of the course but steadily improves as more data accumulates, particularly up to the third month. These results align with previous studies in the field, providing further support for their findings.

3. The Proposed Research Methodology

The proposed methodology will utilize graph-based representation of educational data and include graph convolutional layers, attention mechanisms, fully connected layers, and prediction layers to effectively capture the intricate dependencies and interactions within the data and make precise predictions for student performance. The specific design and configuration of the architecture will be determined through experimental evaluations and model performance analysis on real- world educational datasets to ensure originality and authenticity. In this study, we utilized a publicly available dataset obtained from multiple separate databases by the Polytechnic Institute of Portalegre, Portugal [6]. The dataset comprises 4482 instances, encompassing diverse undergraduate courses in which students were enrolled from the academic years 2008-09 to 2018-19. The dataset [8, 9] incorporates information regarding students' academic performance during the first two semesters, as well as their demographic details, socioeconomic status, and academic trajectory available at the time of enrollment. Fig 1 shows the architecture of proposed methodology in detail.

GNN [5] used to process data that is-represented as graphs, which is combination of nodes (dots) and edges (lines). A graph is made up of these nodes, which represent the real world entities or objects, and edges, which represent the association between these entities. Graph Neural Networks (GNNs) are a type of deep learning model used to process data that is represented as graphs, where nodes and edges represent entities and their relationships. GNNs are similar to convolutional neural networks (CNNs), but instead of operating on regular grids of pixels like images, GNNs process data in the form of graphs. GNNs consist of layers that contain filters, which are responsible for extracting features from the graph data. These filters are stacked in layers, and each layer performs computations on the node and edge features to capture local and global contextual information. GNNs also often include attention mechanisms that help the model focus on important nodes or edges in the graph.

GNNs have different layers [7], these layers are like building blocks that are stacked on top of each other to create a complete GNN model. One important layer in a GNN is the graph convolutional layer. It works like a filter that processes the node features and edge features in the graph to extract important information. It's like how we use different colors and shapes to highlight important information in our notes. The graph convolutional layer helps the GNN understand the local and global context of the graph, which means it looks at how each node is connected to its neighboring nodes and how these connections influence the overall structure of the graph. Another layer in a GNN is the attention mechanism, which is like a spotlight that helps the model focus on important nodes or edges in the graph. It's like how we pay more -

Student/Attribute	A_1	A_2	---	A_n
S_1	S_1 A_1	S_1 A_2	---	S_1 A_n
S_2	S_2 A_1	S_2 A_2	---	S_2 A_n
---	---	---	---	---
S_n	S_n A_1	S_n A_2	---	S_n A_n

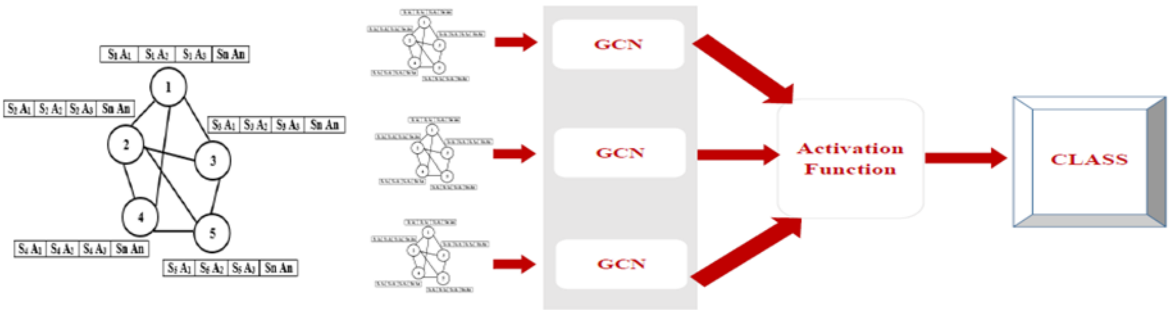

Fig 1. Proposed methodology USING GNN for Student Performance Prediction.

-attention to important points in our notes or textbooks when we are studying. The attention mechanism helps the GNN prioritize certain nodes or edges in the graph when making predictions, based on their relevance to the task at hand.

GNNs also have fully connected layers, which are like bridges that connect different parts of the model. These layers help in processing and combining the features extracted by the graph convolutional layers and attention mechanisms. They ensure that the information flows smoothly through the model and is used effectively in making predictions. Finally, GNNs have prediction layers [13], which are like the conclusion or summary of the

model. These layers take the features extracted by the previous layers and use them to make predictions about the task at hand, such as predicting student performance in the case of educational data. Just like how we summarize our notes or write a conclusion in our essays, the prediction layers in GNNs summarize the important information learned from the graph data and make accurate predictions based on that. The design and configuration of these layers in a GNN are crucial for the performance of the model. Scientists and researchers experiment with different configurations and settings to find the best combination that gives accurate predictions. They test the performance of the GNN on real-world educational datasets to see how well it can predict student performance and provide feedback to instructors. GNNs are a promising approach for processing graph-structured data and making predictions based on the relationships among entities in the graph, and they are being actively researched and developed in the field of machine learning.

4. Experimental Results

Constructing the graphs from the dataset which has students and courses relationships. Classifying the graphs with training and testing features. Thus training graphs are used to train the model. The trained model provided results given in fig2a and fig2b represents the ROC-AUC [15] Curve for the proposed model.

```
Epoch 487 | Loss: 0.1956 | Test Acc: 0.9179
Epoch 488 | Loss: 0.1953 | Test Acc: 0.9179
Epoch 489 | Loss: 0.1951 | Test Acc: 0.9179
Epoch 490 | Loss: 0.1950 | Test Acc: 0.9179
Epoch 491 | Loss: 0.1950 | Test Acc: 0.9195
Epoch 492 | Loss: 0.1950 | Test Acc: 0.9179
Epoch 493 | Loss: 0.1949 | Test Acc: 0.9211
Epoch 494 | Loss: 0.1948 | Test Acc: 0.9179
Epoch 495 | Loss: 0.1946 | Test Acc: 0.9211
Epoch 496 | Loss: 0.1944 | Test Acc: 0.9195
Epoch 497 | Loss: 0.1942 | Test Acc: 0.9195
Epoch 498 | Loss: 0.1941 | Test Acc: 0.9211
Epoch 499 | Loss: 0.1940 | Test Acc: 0.9195
```

Fig 2a. Proposed methodology accuracy in testing phase.

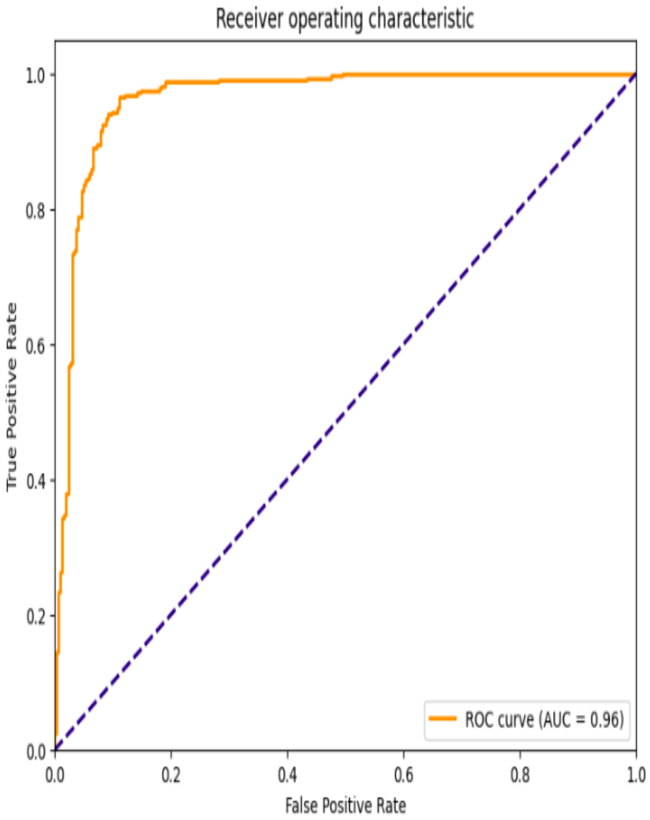

Fig 2b. ROC-AUC Curve for the proposed Methodology.

5. Conclusion

In conclusion, the implementation of a knowledge graph representation in student performance prediction using the Deep Graph Library (DGL) provides promising results in forecasting academic success. By leveraging the power of GNNs to capture complex relationships in educational data, we were able to develop a model that can provide valuable insights into student performance and identify factors that influence academic success. Our findings highlight the potential of GNNs as a powerful tool for predicting student performance, which can assist educators in identifying students who may be at risk of falling behind and provide timely interventions to support their academic progress. The utilization of GNNs in our project demonstrates the significance of deep learning techniques in the field of education data analytics, and the potential for further research and application in this area. As we continue to explore and develop GNN-based approaches for academic success forecasting, there are several opportunities for future research. For instance, investigating different variations of GNN architectures, exploring additional features or data sources, and evaluating the model's performance in different educational contexts or populations. These efforts could contribute to the advancement of the field and ultimately help improve educational outcomes for students. In summary, our project highlights the potential of GNNs as a powerful approach for predicting student performance and forecasting academic success. The results obtained from our deep learning approach provide valuable insights for educators and researchers alike, and open up avenues for further exploration in the field of education data analytics.

Conflicts of interest

The authors declare no conflicts of interest.

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