**GCN Experimentation**

This phase of the project involved enhancing the chatbot system by integrating a Graph Convolutional Network (GCN). The primary goal was to leverage the GCN's capability to process graph-structured data, enriching the chatbot's comprehension and responses. The GCN model was developed to analyse graph data consisting of nodes (representing various entities or concepts) and edges (indicating their relationships). This structure enabled the GCN to extract meaningful feature representations, thereby providing enriched contextual information to the chatbot [4].

Integrating the GCN with the chatbot’s architecture involved processing the graph data through the GCN to extract enhanced features, which were then fed into the chatbot model. This integration aimed at enhancing the chatbot's understanding of both textual and relational context, anticipating more informed and context-aware responses [1]. This strategic enhancement not only aimed to overcome the limitations of traditional chatbot systems but also marked a significant step in conversational AI research, highlighting the potential of AI technique amalgamation for creating more intelligent chatbot systems [7].

The successful integration of the GCN resulted in notably more coherent responses from the chatbot, surpassing the performance of the initial seq2seq encoder-decoder model. This improvement underscored the effectiveness of combining different AI techniques in enhancing conversational AI systems.

**Dataset Experimentation**

In the pursuit of an optimal dataset for our chatbot project, two prominent contenders were considered: the Ubuntu Dialogue Corpus and OpenSubtitles. The Ubuntu Dialogue Corpus, detailed in rkadlec's GitHub (9)​​, was selected as the primary dataset due to its structured conversational format, directly aligning with our project's needs. Given the time constraints, it was deemed the most suitable choice for initial experiments. OpenSubtitles, a diverse and extensive collection of movie subtitles (8)​​, was identified as a secondary option. If time permits, OpenSubtitles could provide a broader linguistic scope, but the focus remains on leveraging the Ubuntu Dialogue Corpus for its immediate relevance and structured nature. Although I couldn’t successfully complete this, with more time I know I could overcome the obstacles presented.

**Conclusion**

This study underscores the complexity and challenges inherent in developing a responsive and coherent chatbot. The use of a GCN to process and interpret graph-structured data has demonstrated considerable potential in enriching the chatbot’s understanding and responses, providing a more nuanced and context-aware interaction experience. Incorporating the GCN with a seq2seq model trained on the CoNLL 2002 movie-corpus dataset has revealed key insights into the dynamic interplay between different AI techniques. The adjustments in hyperparameters, attention mechanisms, and training iterations illuminate the intricate process of balancing computational resources with the aim of achieving more coherent and contextually relevant dialogue generation. This aligns with the findings of [2], which emphasises the importance of feature representation in enhancing AI systems.

The journey from the initial seq2seq model to the integration of the GCN reflects the iterative nature of AI development, as highlighted in [7]. The progression from basic response generation to more informed, relationally contextual responses exemplify the evolution of chatbot capabilities. It also spotlights the challenges in data preprocessing, model optimisation, and computational limitations. Future research could delve deeper into optimising the integration of GCNs with other conversational models, exploring various datasets and graph structures to further improve the chatbot's performance. Additionally, extending training iterations and employing more advanced computational setups, as suggested in the literature, could lead to significant improvements in response quality and coherence.

In conclusion, this study not only contributes to the field of conversational AI by demonstrating the efficacy of GCN integration but also sets the stage for future research. It highlights the potential of combining various AI techniques and the continuous need for adaptation and optimisation in the rapidly evolving landscape of AI-driven conversational systems.

***Please see Appendices(Pages 2-4) for references of graphs, convergence, and chatbot responses.***

**Abstract**

This project develops a conversational AI chatbot using a sequence-to-sequence (seq2seq) model with Luong attention, trained on the CoNLL 2002 movie-corpus dataset. The dataset undergoes preprocessing for vocabulary construction, facilitating word-to-index mapping. The system's design allows experimentation with various hyperparameters, including learning rate and dropout rate, to enhance the chatbot's human-like interaction capabilities. The training process incorporates checkpoint saving for model persistence, and a greedy search decoder is employed for user interactions via a command-line interface [6].

**Development Journey**

In the initial stages of development, I conducted evaluations of the chatbot's responses to establish a performance baseline. This involved adjusting various hyperparameters to assess their impact on the system's performance. After encountering overfitting issues, I made several modifications: reducing the teacher forcing ratio to 0.5, decreasing the hidden layer size to 400, increasing the dropout rate to 0.15, and lowering the batch size to 128. These adjustments, spread over an extended 5000 iterations of training, aimed to balance the model's complexity and its ability to generalise. Despite these changes, the chatbot's responses remained somewhat incoherent, indicating a persistent need for further optimisation. The application of different attention mechanisms – 'dot', 'general', and 'concat' – over 10,000 training iterations improved loss metrics. However, these improvements in quantitative measures did not directly translate into more coherent language generation, suggesting the necessity to reevaluate data preprocessing strategies and consider more advanced modelling techniques, as highlighted in [2] by E. Adamopoulou and L. Moussiades.

The subsequent increase of training iterations to 20,000 and then to 50,000, although computationally demanding, along with adjusting the MAX\_LENGTH to 20, started to show more promising results. This progression suggested a correlation between extended training periods and improved response quality. However, the chatbot still faced challenges in generating contextually relevant dialogue, a common issue in conversational AI as discussed in [6] by J. Brownlee. In addition to these iterations, I experimented with various evaluation methods and different perspectives on analysing the chatbot's outputs. The transition to the GCN development phase presented a challenging but crucial pivot. This phase involved numerous errors and obstacles, but once operational, it led to better model convergence. The responses of the chatbot became more coherent, although they were not yet perfect. This phase of development resonates with the findings of [7] by M. Firdaus et al., who discuss the complexities and potential of using GCNs in enhancing chatbot systems.

Project ChatBot – Executive Summary

Victoria Hektor – Artificial Intelligence MSc - De Montfort University

**Appendices**

**A screenshot of a graph

Description automatically generatedA graph with blue dots

Description automatically generatedA diagram of a network

Description automatically generated**

Figures from L-R, Clockwise: Confusion Matrix, Convergence Scatter Graph, GCN Graph Node Tree

*A screenshot of a computer screen

Description automatically generatedA screenshot of a computer program

Description automatically generatedA screenshot of a computer screen

Description automatically generatedA screenshot of a computer

Description automatically generatedA screenshot of a computer program

Description automatically generatedA screenshot of a computer

Description automatically generatedA screenshot of a computer program

Description automatically generated*

Figures: Chatbot responses, note, these are the poorest responses.

*A screenshot of a computer program

Description automatically generated*

Figure: Best Chatbot response. (10k iters)

**References**

[1]

Q. Yuan *et al.*, ‘An Encoder-decoder Architecture with Graph Convolutional Networks for Abstractive Summarization’, in *2021 IEEE 4th International Conference on Big Data and Artificial Intelligence (BDAI)*, Jul. 2021, pp. 91–97. doi: [10.1109/BDAI52447.2021.9515256](https://doi.org/10.1109/BDAI52447.2021.9515256).

[2]

E. Adamopoulou and L. Moussiades, ‘An Overview of Chatbot Technology’, *Artificial Intelligence Applications and Innovations*, vol. 584, p. 373, 2020, doi: [10.1007/978-3-030-49186-4\_31](https://doi.org/10.1007/978-3-030-49186-4_31).

[3]

‘GCNN Tutorial’. Accessed: Nov. 19, 2023. [Online]. Available: <https://kaggle.com/code/jagdmir/gcnn-tutorial>

[4]

J. Zhou *et al.*, ‘Graph neural networks: A review of methods and applications’, *AI Open*, vol. 1, pp. 57–81, Jan. 2020, doi: [10.1016/j.aiopen.2021.01.001](https://doi.org/10.1016/j.aiopen.2021.01.001).

[5]

K. Xu, L. Wu, Z. Wang, Y. Feng, M. Witbrock, and V. Sheinin, ‘Graph2Seq: Graph to Sequence Learning with Attention-Based Neural Networks’, Sep. 2018, Accessed: Nov. 19, 2023. [Online]. Available: <https://openreview.net/forum?id=SkeXehR9t7>

[6]

J. Brownlee, ‘How to Develop an Encoder-Decoder Model for Sequence-to-Sequence Prediction in Keras’, MachineLearningMastery.com. Accessed: Nov. 19, 2023. [Online]. Available: <https://machinelearningmastery.com/develop-encoder-decoder-model-sequence-sequence-prediction-keras/>

[7]

M. Firdaus, N. Thakur, and A. Ekbal, ‘MultiDM-GCN: Aspect-guided Response Generation in Multi-domain Multi-modal Dialogue System using Graph Convolutional Network’, in *Findings of the Association for Computational Linguistics: EMNLP 2020*, T. Cohn, Y. He, and Y. Liu, Eds., Online: Association for Computational Linguistics, Nov. 2020, pp. 2318–2328. doi: [10.18653/v1/2020.findings-emnlp.210](https://doi.org/10.18653/v1/2020.findings-emnlp.210).

[8]

‘OpenSubtitles’. Accessed: Nov. 20, 2023. [Online]. Available: <https://opus.nlpl.eu/OpenSubtitles.php>

[9]

rkadlec, ‘README -- Ubuntu Dialogue Corpus v2.0’. Nov. 03, 2023. Accessed: Nov. 20, 2023. [Online]. Available: <https://github.com/rkadlec/ubuntu-ranking-dataset-creator>