1. Code

1.1. **Summary.**

The idea of this code is to provide a foundation for a streamline research into temporal network modelling. To that end it is planned to be compatible with popular Julia packages such as Graphs, the SciML ecosystem, and Ecological-Networks.

The core of the code developed for this project is the TemporalNetworkEmbedding (TNE) structure. This structure was developed not only for me to be able to interface with data quickly and easily, but also so the SciML ecosystem could interface with it during training of the NN. In particular, the ability to index the TNE with a float was essential for the continuous time evolution of the UDEs and NNDEs to function.

1.2. **Statement of Need.**

Throughout this thesis, we have demonstrated that temporal networks are found in many different areas, that, on small networks, temporal progression of embedded nodes can be modelled with NNDEs, and that there are still problems to be overcome.

With this in mind, the code has been developed to:

1: Allow for interface with popular packages

2: Allow for further exploration of optimal network structures for deep learning

3: Provide opportunities for collaboration of experts from other fields

1.3. **Package Methods.**

In the package [1], I created code for constructing: The TemporalNetworkEmbedding structure. This structure stores the temporal network as tensors of the $\hat{L}, \hat{R}$ matrices. This structure has many methods for streamlining interactions with the TemporalNetworkEmbedding. These include indexing with integers and floats, where the floats will linearly interpolate between time steps. Other methods include viewing and or removing specific nodes from the network.

As well as constructRDPG, which takes a temporal network embedding and optionally the time steps of interest, and outputs the RDPG from the embedding.

I also added the nearestNeighbours method which takes a vector point in the dimension of the embedding, the time step, a TemporalNetworkEmbedding and the number of nearest neighbours required. The method then outputs the indices of the nearest nodes of the network to the vector in descending order.

1.4. **Future Work.** The current TNE structure is not yet GPU compatible. We plan to remedy this as well as include support for constructing a TNE from Graph.jl and MetaGraph.jl objects.

2. Conclusion

In this thesis, we proposed a novel framework for modelling temporal networks. We then tested this framework on three types of small, synthetic network sequences. Throughout these tests we showed that an NNDE model can be used to approximate the movement of points in the embedded space of some temporal networks. We also demonstrated that a functional expression generated using symbolic regression can increase the accuracy of prediction on unseen data. This has been a proof of concept for this framework; we believe future work can dramatically improve the understanding and modelling of this framework.

References

[1] Smith C Dalla Riva G. *DotProductGraphs.jl*. https://github.com/gvdr/DotProductGraphs.jl. 2023.