Predict Chain

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1 Introduction

Throughout our project, we have built upon, or have related to, the ideas of many other projects and papers. Some of these relations were explicit, such as our work with, and utilization of, various types of neural network. Others were implicit, like the relation that our project has to the many other implementations of blockchain-based predictive projects. It is important to acknowledge the influences that other works have has on our project, and it is equally important to analyze the similarities between our project and the other papers that we have referenced here. Through this, we hope to better understand the perspective of others on similar topics to our project and hopefully improve upon our work and techniques in the future.

2 Related Work

2.1 Recurrent Sequence Modeling

One of the core aspects of our project is our usage of various types of neural network for predictive modeling. Most of our neural networks have some recurrent capability, specifically our RNN, LSTM, and GRU model types. Additionally, the data that we suggest that these models be trained on is sequential data, exactly what these types of model were designed for. One paper that aligns especially closely with this component of our project is *Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling*[1].

Within this paper, the authors aim to evaluate the relative performance of RNNs, LSTM networks, and GRU networks. Similar to our use case, they perform this evaluation using sequential signal data, similar in nature to the stock market dataset that we use in our example. Primarily, they focus on the LSTM and GRU variants of recurrent neural networks, rather than vanilla RNNs themselves. As part of their evaluation, they compare the performance of LSTM unit, GRU unit, and tanh unit RNNs on modeling sequences of polyphonic music and speech signals.

As part of their evaluation, they utilize three publicly available music datasets along with two internal speech datasets from Ubisoft. The design of their experiment is to compare the negative log probabilities of the models after they are given 20 consecutive samples of audio data and are then tasked to predict the next 10 consecutive samples. In the results that they gathered, they concluded that, overall, the GRU unit outperformed the other two evaluated models. These results are amplified in the Ubisoft datasets, where GRU unis significantly outperform the others in one of the test cases and have similar performance to LSTMs in the other. Additionally, in the Ubisoft Dataset B, the negative log-likelihood of the GRU model continues to shrink in a super-linear manner, whereas the other models become asymptotic.

Relation to Our Work

This paper both confirmed some of the initial assumptions that we had about the models and changed some others. In the design of the project, we had initially marked GRU models to be better than all the other models. We denoted this perceived difference in output quality through the constant multiplier we applied to each of their *model_complexity* values. After our analysis of this peper, we decided to update these values to better reflect the experimental performance of these models.

Table 1: *model_complexity* Values of Our Models

Model	Initial Value	Final value
MLP	1	1
RNN	1.5	1.7
LSTM	2	2.2
GRU	2.5	2.4

In our changes, we amplified the values related to all RNN-based networks. We also brought the complexities of the LSTM and GRU networks closer together. This change was made to reflect their relative performances to each other and to more traditional RNNs.

References

[1] Chung, Gulcehre, Cho, and Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *Neural and Evolutionary Computing*, 2014.