Predicting Human Choice in Language-based Persuasion Games

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Abstract

Predicting human decisions is key to enhancing recommendation systems and boosting user engagement. Earlier models that traied to predict human actions such as Transformers and LSTMs have inherent drawbacks; Transformers often falter with sequential data, while LSTMs may tend to overlook broader contextual information needed to mimic human behaviour. Addressing these challenges, we build upon earlier work of (Shapira et al., 2024) to build a hybrid architecture that merges the best of both worlds: the sequential processing strengths of LSTMs with the contextual understanding of Transformers. We present three different implementations, with our best model standing out by achieving an impressive 84.46% accuracy. Our approach holds substantial promise for improving predictive modeling in intricate decision-making scenarios.

1 Introduction

The ability to predict human decisions in different real-life scenarios can be beneficial in many fields such as recommendation systems in order to deliver highly personalized and relevant recommendations, enhancing user satisfaction and engagement. We seek to predict human decisions based on previous decisions, recognizing the importance of leveraging both sequential data processing and contextual understanding we pursue an enhanced predictive model. Existing models such as transformer (Vaswani et al., 2023) and LSTM (Hochreiter and Schmidhuber, 1997) fall short of meeting our requirement, The transformer model has emerged as particularly powerful due to its ability to capture contextual relationships in the data. However, despite its effectiveness, the transformer often struggles with sequential data. While the LSTM model is robust at processing data sequentially, it may not capture the broader context as effectively as a model like Transformer. This can make LSTM less effective for tasks such as human decision prediction, where the ability to consider and integrate broad contextual information from input sequences is crucial for generating accurate predictions. Addressing these limitations, this paper introduces a novel hybrid architecture that synergizes the LSTM's proficiency in sequential data processing with the Transformer's capability to capture contextual relations. By integrating the LSTM with the Transformer's advanced self-attention mechanism, the proposed model not only preserves the contextual strengths of Transformers but also integrates with it sequential data processing capabilities this hybrid approach aims to enhance the performance of the predictive modeling of complex decision-prediction scenarios.In this paper we will be discussing three different architectures: First LSTM-Transformer model that combines an LSTM architecture followed by a Transformer encoder, Second the Transformer-LSTM model that reverses the order of integration, beginning with a Transformer encoder layer followed by an LSTM layer, last model Stacked Transformer-LSTM extends the second model by adding another sequence of Transformer and LSTM layer, resulting in a layered structure: Transformer-LSTM-Transformer-LSTM. In our study, the first model achieved an accuracy of 83.4%, the second model demonstrated superior performance with an accuracy of 84.46%, and the third model also performed well, achieving an accuracy of 84.2%.

2 Related Works

The ability to predict human decisions based on prior decisions is a critical aspect of the broader field of time series prediction, which utilizes historical data to model and forecast future events. Neural network (NN) architectures have gained recognition as strong alternatives to traditional statistical forecasting methods, providing notable enhancements in prediction accuracy and adaptability (Zhang, 1998). The advancement and utilization of diverse NN models for time series forecasting have attracted considerable attention from researchers. Recurrent Neural Network (RNN) architectures, in particular, have captured the attention of the time series forecasting community due to their inherent properties suited for sequential data processing (Zimmermann et al., 2012; Fei and Yeung, 2015; Lipton et al., 2015). In addition, Long Short-Term Memory (LSTM) networks, a specialized form of RNNs, were designed to overcome the limitations of traditional RNNs and have been successfully implemented in a range of time series forecasting tasks, including traffic flow prediction (Tian and Pan, 2015) and travel time estimation (Duan et al., 2016). LSTMs have demonstrated exceptional performance across various sequence learning problems beyond time series forecasting, such as video classification (Ng et al., 2015) and speech recognition (Graves et al., 2013). Their versatility extends to challenging applications like air pollution forecasting (Reeman et al., 2018), medical diagnosis from clinical data (Lipton et al., 2015), and more. These successes underscore the capability of LSTMs to handle complex dependencies in sequence data effectively. Recognizing the strengths of both LSTM and Transformer models, recent research has explored the integration of these two powerful architectures into hybrid models. (Lim and Zohren, 2021) have made significant contributions in this area by developing a hybrid model that combines the sequential data handling capabilities of LSTM with the contextual processing strengths of the Transformer. Their work highlights the potential of hybrid models to substantially enhance predictive performance in time series forecasting by leveraging the best features of both architectures.Their work highlights the potential of hybrid models to substantially enhance predictive performance in time series forecasting by leveraging the best features of both architectures.Inspired by these advancements, our study aims to adopt and expand upon their hybrid model concept.

3 Model Architectures

In this study, we introduce three distinct neural network architectures for human decision prediction. Each model is designed to leverage the strengths of both Long Short-Term Memory (LSTM) networks and Transformer models in different configurations to optimize prediction performance.

1. **LSTM-Transformer Model**: In this architecture, the input data is first fed into an LSTM network. The LSTM processes the sequential data and its output is then passed as input to a Transformer model. This combination aims to capture the dependencies effectively with the LSTM, while the Transformer enhances the model's capability to handle long-range dependencies.

2. **Transformer-LSTM Model**: In contrast to the first model, in this model, the input data is initially processed by a Transformer layer.The Transformer's output is then fed into an LSTM layer.This configuration benefits from the Transformer's ability to capture global dependencies in the data before the LSTM refines these representations by focusing on the sequential order and local dependencies, since the LSTM is more efficient in capturing the local dependencies in short sequences.

3. **Stacked Transformer-LSTM Model**: The third architecture builds upon the second model by incorporating two layers of Transformer and LSTM networks in an alternating sequence.Specifically, the input is first processed by a Transformer layer, followed by an LSTM layer, then another Transformer layer, and finally an LSTM layer. This deeper and more complex model aims to further enhance the learning of both global and local dependencies through multiple layers of processing.

These architectures are designed to test our hypothesis that combining LSTM and Transformer models in various configurations can lead to improved performance in human decision prediction by effectively capturing both short-term and long-term dependencies in the data and leveraging the sequential processing capabilities.

4 Experiments and Results

To validate the effectiveness of the proposed hybrid models we used the same data that has been used in (Shapira et al., 2024). We configured the transformer model with five heads, with each head responsible for capturing the relationships pertaining to a specific feature. The features vector is comprised of the representation of the review and the Strategies feature, which contains five distinct features, along with the Reaction time. Given the number of distinct features, we determined that at least five heads were necessary to effectively capture the complexity of the data, as illustrated in figure 1. This configuration significantly enhanced the model's performance. We set the hidden dimension to 35 for each model.

4.1 Dataset

Building upon the earlier works of (Shapira et al., 2024), we utilized the curated dataset from their study.
This dataset comprises interactions between human decision-makers and rule-based experts in a language-based persuasion game. It includes 87,204 decisions made by 245 players who completed the game. In their experimental setup, the players (humans) competed against a series of six role based experts, with each game consisting of ten rounds. The goal is to predict human actions against the experts.In addition to the simulation data where each instance of the bot-DM interaction simulation, they randomly selected six expert strategies from the strategy space.For each simulated DM-bot interaction, they randomly sampled 10 hotels, one for each of the 10 rounds.

4.2 Hyper-Parameter tuning

To choose the optimal parameters for the models each model has been trained on the train and validation sets to avoid data leakage with 7 learning rates that are represented in Table 1.
The results are displayed in Table 1.As shown in the table the optimal learning rates that achieved the highest accuracy on the validation set for each model are: LSTM-Transformer 0.0007 ,Transformer-LSTM 0.00085,Stacked Transformer-LSTM 0.00075.

4.3 Model selection

Comparing the three models with the parameters chosen after hyper-parameter tuning, as shown in Figure 2, the Transformer-LSTM model clearly outperforms the other models, reaching an accuracy of 84.46% while LSTM-Tansformer and Stacked Transformer-LSTM have reached 83.87% and 83.68%. Additionally, the selected model was trained on five different seeds, with the total number of epochs used as a hyper-parameter in order to choose the best epoch performance for the model, the results indicated that epoch 17 is the optimal epoch. Therefore, the following results are based on training the model for 17 epochs.

4.4 Results

After selecting the ideal model, the Transformer-LSTM, we ran the model with 50 different seeds to ensure the reliability of our findings. The model was trained for 17 epochs as determined in the previous section. To further validate the performance, we calculated the confidence intervals for the accuracy. The calculated mean is 0.8388 , and standard deviation is 0.0025 To quantify the reliability of the model accuracy, we computed the 95% confidence interval. The confidence interval provides an estimated range that is likely to contain the true accuracy of the model
(0.838104, 0.839507).

5 Discussion

The results indicate that the Transformer-LSTM model is highly reliable, with a 95% confidence interval ranging from 83.8104% to 83.9507%, reflecting consistent performance across 50 different seeds to ensure the reliability and consistency of our findings. This level of accuracy and the confidence interval suggests that the model's performance is not due to chance, and it generalizes well across different random initialization.The model achieved an accuracy of 84.46% compared to the LSTM model in the paper (Shapira et al., 2024) that have achieved an accuracy of 83.6%.

Learning rate	LSTM-Trans	Trans-LSTM	Stacked Trans-LSTM
0.0007	**79.85**%	79.80%	79.71%
0.000725	79.38%	80.35%	79.79%
0.00075	79.68%	79.87%	**79.94%**
0.000775	76.71%	79.83%	79.76%
0.0008	76.73%	79.56%	77.86%
0.000825	79.30%	79.94%	77.49%
0.00085	76.84%	**80.63%**	79.57%

Table 1: This table presents the accuracy of the three different models on the validation set across various learning rates.

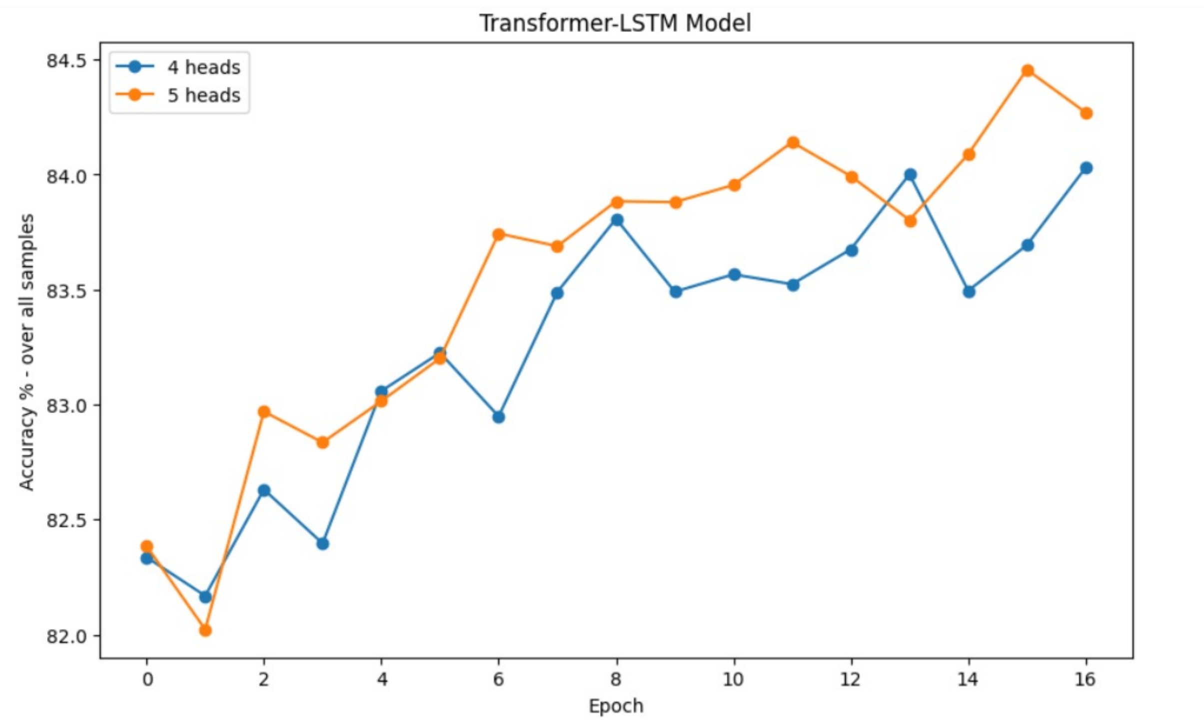

Figure 1: Accuracy of the Transformer-LSTM Model with 4 heads and hidden dimension 32 , 5 heads and hidden dimension 35 on the test set

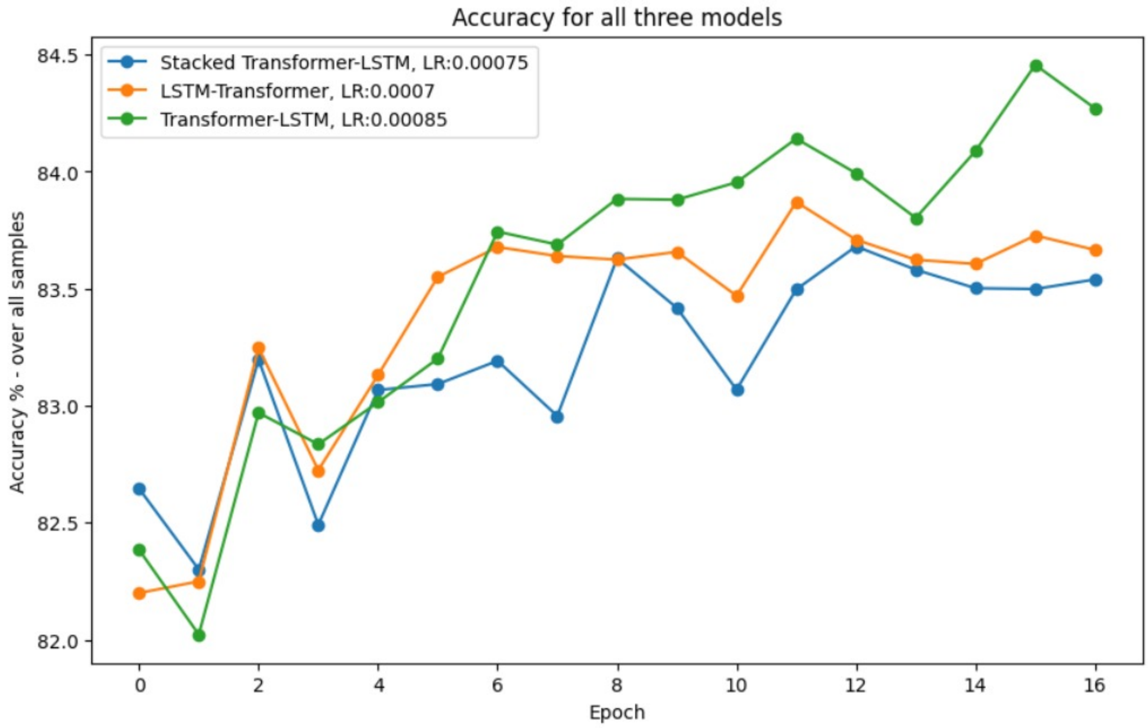

Figure 2: Accuracy of all three models with the optimal learning rates on the test set

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