Enhancing Decision Prediction in Language-Based Persuasion Games with Hybrid Models Integrating LSTM, Attention Mechanisms, and Transformer Architectures

Kinan Ibraheem **Noor Abu El-Hija**
Technion
kinani@campus.technion.ac.il noor.abu@campus.technion.ac.il

Abstract

The increasing complexity of human-agent interaction in language-based persuasion games necessitates advanced predictive models capable of understanding and anticipating human decisions. This paper addresses a key aspect of the hybrid model that consists of Long Short-Term Memory (LSTM) networks, attention mechanisms, and transformer architectures, aimed at enhancing decision prediction in such games, by leveraging the sequential learning capabilities of LSTM, attention mechanisms' context-sensitive strengths, and transformers' parallel processing power.

The research focuses on a comprehensive evaluation of the hybrid model's performance across various language-based persuasion scenarios. Through extensive experimentation and simulation-based training, the model is fine-tuned to predict decisions with higher robustness and reliability. The hybrid approach allows for the simultaneous capture of local and global patterns in the data, providing a more holistic understanding of the decision-making process.

1 Introduction

The increasing complexity of human-agent interaction in language-based persuasion games requires advanced predictive models that are capable of understanding and anticipating human decisions. Language-based persuasion games, where agents aim to influence their partners' decisions through verbal messages, present a unique challenge, because they often involve complex, non-cooperative interactions where the players' objectives are not aligned, making it difficult to model and predict outcomes accurately (Shapira et al., 2024).

Traditional approaches to predicting decisions in language-based persuasion games have typically relied on rule-based methods or basic machine-learning techniques. While these methods have had some success, they often fall short in capturing the complex dependencies and subtle nuances of natural language interactions. Rule-based methods, for instance, struggle with the variability and richness of human language, making them less effective (Apel et al., 2022). Similarly, basic machine-learning models frequently fail to understand long-range dependencies and the contextual importance within sequences of interactions (Ben-Porat et al., 2020).

Recent advancements in Natural Language Processing (NLP) have introduced sophisticated models like Long Short-Term Memory (LSTM) networks (Hochreiter Schmidhuber, 1997), attention mechanisms, and transformer architectures (Vaswani et al., 2017). LSTM networks, known for their ability to remember long sequences, are great for understanding the sequential nature of language interactions. Attention mechanisms enhance performance by allowing models to focus on the most relevant parts of the input, improving their understanding of context and dependencies (Vaswani et al., 2017). Transformer architectures, with their ability to process information in parallel, handle large datasets and complex interactions more efficiently (Vaswani et al., 2017).

Combining these advanced models into a hybrid system offers a promising way to improve decision prediction in language-based persuasion games. By leveraging the strengths of LSTM networks, attention mechanisms, and transformers, this hybrid model aims to overcome the limitations of traditional methods, providing more accurate and robust predictions (Shapira et al., 2024).

This paper explores how advanced Natural Language Processing (NLP) techniques—like Long Short-Term Memory (LSTM) networks, attention mechanisms, and transformer architectures—can be integrated to improve decision prediction in language-based persuasion games. The goal is to create predictive models that better understand the subtleties of human decision-making in complex, non-cooperative interactions, where traditional methods often fall short.

To do this, we plan to design a hybrid model that combines the strengths of LSTM networks, attention mechanisms, and transformer architectures. We'll thoroughly evaluate how well this hybrid model performs in various persuasion scenarios, comparing it to traditional approaches and the individual models on their own. Our aim is to see if the hybrid model offers better prediction accuracy and robustness.

2 Related Work

2.1 Human Choice Prediction in Language-based Persuasion Games

Eilam Shapira and his colleagues conducted research in 2024 and explored an essential aspect of NLP-based agent design: figuring out how humans make decisions in language-based persuasion games using off-policy evaluation (OPE). This research underscores the complex nature of human-agent interactions within non-cooperative, language-based persuasion games, where agents try to influence their partners' decisions through conversation. The goal is to improve the agents' performance by simulating interactions with a variety of artificial agents and decision-makers, making them better at predicting and influencing human behavior.

2.2 Contributions to LSTM Networks, Attention Mechanisms, and Transformer Architectures

Shapira et al. (2024) leverage the strengths of advanced NLP architecture to address the limitations of traditional predictive models. LSTM networks are employed which is crucial for modeling the sequential nature of language-based interactions. The results of the study indicate that integrating LSTM networks significantly enhances the model's ability to capture long-range dependencies and contextual information, leading to improved decision prediction accuracy in language-based persuasion games.

The successful application of the Attention Mechanism motivated Vaswasni et al. (2017) to develop an architecture called the Transformer. The architecture was developed based on the Attention Mechanism. The Transformer uses Multi-Head Attention Mechanisms instead of a single attention head. The model shows better performance in some natural language processing (NLP) tasks.

In addition to Shapira's research, Studies also provide significant insights into the application of hybrid models.(Andayani et al. 2022, Sakatani 2021, Cao et al. 2024) The researches demonstrate the efficacy of combining LSTM networks and transformer architectures for emotion recognition tasks. The hybrid model leverages the benefits of both Lstm and transformer, leading to improved performance in recognizing emotions from speech audio files. This study underscores the versatility and robustness of hybrid models in handling various NLP tasks.

3 Data

In this study, we utilized the exact dataset as described in Shapira et al. (2024), ensuring consistency and comparability with their research findings. The dataset comprises a comprehensive collection of interactions from language-based persuasion games, gathered to capture the nuances of human decision-making in non-cooperative environments.

4 Experiments

4.1 Models:

In our study, we conducted a series of experiments to evaluate the performance of various models in predicting human decisions in language-based persuasion games. The goal was to determine the effectiveness of different model architectures and configurations, ultimately identifying the most robust and accurate predictive model.

1. Logistic Regression: As a starting point, we want to implement a simple model so we implemented a logistic regression model. This model served as a simple baseline to compare the more complex models.

2. Attention Mechanism: Next, we explored the use of Masked attention mechanisms. We used it to enhance performance by allowing models to focus on the most relevant parts of the input, improving their understanding of context and dependencies

3. Transformers: We also implemented transformer models with different parameters. To leverage their parallel processing capabilities and ability to handle large datasets, aiming to enhance the efficiency and accuracy of decision prediction (Vaswani et al., 2017)."

4. LSTM with Shapira's Parameters: To maintain consistency and comparability with Shapira et al. (2024), We used the same LSTM model with the same parameters as they employed.

We developed several hybrid models to leverage the benefits of previous models' combinations:

5. Hybrid Model Containing LSTM and Attention: We developed a hybrid model that integrated Shapira's LSTM networks with attention mechanisms.

6. Hybrid Model Containing LSTM and Transformer: Building on the previous hybrid model, we combined Shapira's LSTM networks with transformer architectures.

7. Hybrid Model Containing Transformer and Attention: In this configuration, we explored the combination of transformer architectures and attention mechanisms.

8. Advanced Hybrid Model with Attention, LSTM, and Transformers Our final and most advanced model was a hybrid architecture that combined attention mechanisms, two LSTM networks, and two transformer architectures using a weighted sum combination where the weights were adaptive.

All the models were experimented with different parameters such as layer depths, number of heads, and learning rate to identify the optimal configuration. Moreover, we used a fully connected layer in each model for the input and the output. After choosing our final model we experimented with different seeds and learning rates.

4.2 Baseline:

Throughout our experiments, we used the results from Shapira et al. (2024) as our baseline. Their findings provided a benchmark that allowed us to evaluate the improvements offered by our hybrid models and parameter optimizations. By comparing our results to their established performance metrics, we were able to quantify the effectiveness of our approaches and identify the most promising model configurations.

5 Results

In this section, we present the results of our experiments, comparing the performance of various models in predicting human decisions in language-based persuasion games. Our primary goal was to identify the most effective model configurations by comparing their performance against the baseline results reported by Shapira et al. (2024).

Logistic Regression: The logistic regression model served as our simplest baseline. While it provided some predictive power, its performance was significantly lower than the more complex models as seen in Figure 1. This was expected due to its inability to capture sequential dependencies and contextual nuances inherent in language-based interactions.

Self-Attention Model: self-attention demonstrated improved performance over logistic regression, as seen in Figure 1.

Transformer with Different Parameters: Transformer models showed substantial improvements over logistic regression and self-attention models (Figure 1). We tested various configurations and got the best performance with 1 layer, and 4 attention heads Transformer. The parallel processing capabilities of transformers allowed for efficient handling of large datasets, resulting in better prediction accuracy.

LSTM with Shapira's Parameters: The LSTM model, implemented with the same parameters as used by Shapira et al. (2024), provided a solid baseline for comparison. This model's ability to retain long-range dependencies and sequential information was evident, resulting in improved performance compared to logistic regression and self-attention models, and got close performance to the transformer model (Figure 1)

Hybrid Model Containing LSTM and Attention: combining LSTM networks with attention mechanisms improved the result in performance gains (Figure 1). The best performance was by the model self-attention and Shapira's Lstm both getting the same input and implementing a fully connected with the average of both models' output as an input.

Hybrid Model Containing LSTM and Transformer: The hybrid model that combined LSTM networks with transformer architectures further enhanced performance (Figure 1). By leveraging the sequence learning strengths of LSTM and the parallel processing capabilities of transformers, this model achieved improvements. The optimal configuration included one Transformer layer with 4 attention heads followed by Shapira's Lstm.

Hybrid Model Containing Transformer and Attention: A model integrating transformers with attention mechanisms also did not demonstrate significant performance improvements (Figure 1). The best-performing configuration involved 2 Transformer Layers with 2 attention Heads and a self-attention model both with the same input vector followed by a fully connected layer with the average of both models' outputs as an input. all previous models' learning rates and dropout values were the same (learning rate = 0.001, dropout = 0).

Advanced Hybrid Model with Attention, LSTM, and Two Transformers: Our most advanced model, which integrated self-attention, two LSTM networks, and two transformers using a weighted sum combination (Appendix A), yielded the best results (Figure 1). This model consists of Shapira's LSTM, one transformer with one layer and 4 attention heads, another transformer with one layer and one attention head, and a self-attention mechanism, all with the same input vector followed by a fully connected layer with the weighted sum of the previous models' outputs as an input followed by LSTM. The hybrid model showed a notable performance improvement, achieving an accuracy of **84.2%** (Figure 2), which is higher than that of our baseline model (Figure 1, Figure 2). In Figure 2 we can see the results of running this hybrid model with different learning rates, the best learning rate was 0.001. In Table 1 we can see the statistics of this model that were calculated from different seed values.

Learning Rate	Mean	std	Best Epoch	CI
0.00001	0.824694	0.002791	last	(0.8229, 0.8263)
0.00004	0.8322	0.002760	23	(0.83069, 0.8337)
0.0001	0.835409	0.002328	23	(0.8340, 0.8368)
0.0004	0.836536	0.002431	15	(0.8350, 0.83784)
0.001	0.835040	0.001669	15	(0.8340, 0.8360)

Table 1: Performance metrics for different learning rates for the chosen model with different seed values.

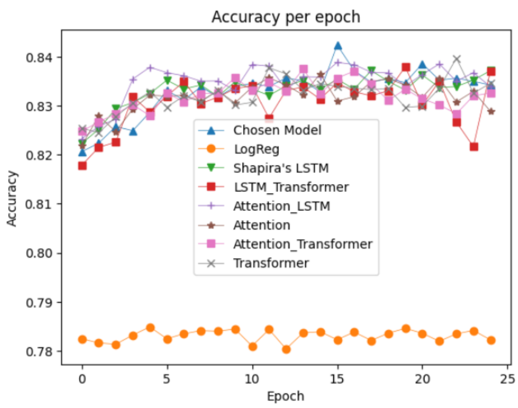

Figure 1: Model performance as a function of the number of epochs, for the various models we experimented.

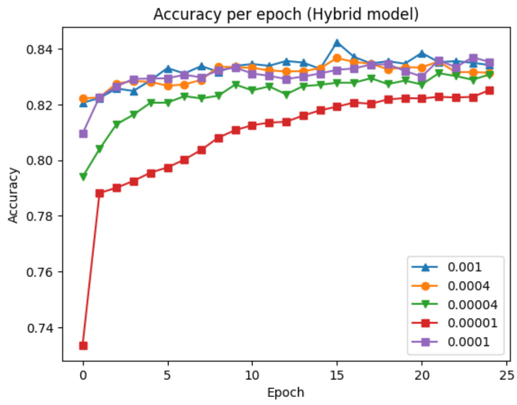

Figure 2: Model performance as a function of the number of epochs, for various values of the learning rate for the chosen model with a fixed seed value = 1

6 Reference

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7 Appendix

A Diagram of the Final Model:

Below is the diagram that describes our final model.

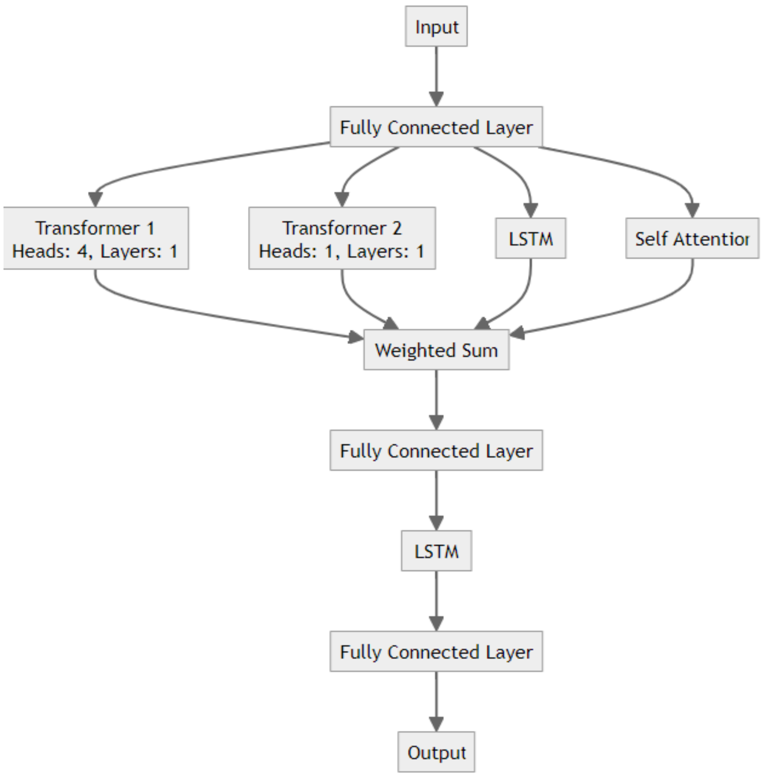

Figure 3: This diagram describes the architecture of our final model. The architecture begins with an input layer that passes through a fully connected layer. Next, the data is processed simultaneously by an LSTM layer, two transformer layers, and a self-attention mechanism, each receiving the output of the fully connected layer as input. The outputs from these components are then combined and passed through another fully connected layer that performs a weighted sum of the previous layer's outputs. Finally, the combined data is processed by an additional LSTM layer, followed by a final fully connected layer to produce the prediction.