Dynamic Attention-based LSTM Predictive Model in Language-based Persuasion Games

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Abstract

Recent advances in Large Language Models (LLMs) and deep learning have spurred significant curiosity and provided fertile ground for further research across various tasks. One intriguing application is in language-based human-bot interactions, and particularly being able to predict the outcome of this kind of interactions, as explored in previous research (Shapira et al., 2023) on human-bot interactions in persuasion games. Building on the work presented in the original research, we address the problem and data and propose a sophisticated Attention-based LSTM dynamic model that adapts its architecture based on input values, aiming to produce more accurate predictions. In this paper we interest to contribute to the growing field of deep learning by introducing an innovative and yet simple adaptation that can be implemented on various deep learning architectures, to enhance their capabilities.

1 Introduction

(Shapira et al.'s) study introduced a language-based persuasion game where different atrificial agents aim to influence a human decision-maker's choices through language-based text messages. The researchers gathered a substantial dataset of human decisions in this context, enriched it with simulated data and developed predictive models in order to evaluate these decisions. Surprisingly, their findings revealed that a relatively simple Long Short-Term Memory (LSTM) model (Hochreiter et al., 1997) outperformed more advanced transformer models (Vaswani et al., 2017) in predicting whether a user would decide to go to a hotel based on language-based recommendations presented by the agent.

This conclusion was intriguing, given that transformers are generally considered to be state-of-the-art for many language-based tasks. The LSTM model employed in the study was notably basic, without incorporating an attention mechanism, the core element of transformers. Motivated by this unexpected result, we chose to focus our project on searching for more advanced predictive architectures than the end model used in the original study.

2 Related Work

Our goal was to improve the model's accuracy beyond what was achieved in the original study. Drawing on the work of (Wang et al. 2016), which demonstrated the effectiveness of attention-based LSTM models in sentiment classification, a task somewhat resembles predicting human binary choices in language-based persuasion games.

we started by integrating attention mechanisms into the LSTM model (Hochreiter et al., 1997). During our extensive research on various architectures suitable for our specific problem, we encountered (Han et al., 2021)'s survey on dynamic neural networks, which emphasizes the advantages of adaptive computation and especially sample-wise dynamic behavior of a neural network.

By leveraging recent advances in deep learning and incorporating dynamic architectural adaptations, we sought to create a model that captures the nuances of human decision-making in these contexts much better.

3 Model

Our proposed model is designed to dynamically adapt its architecture based on the characteristics of the input data. This section outlines the key components and mechanisms of our dynamic model.

3.1 The Static Model

As suggested in the survey on dynamic neural networks by (Han et al., 2021), designing and implementing a sample-wise dynamic neural network model should be started with a fine-tuned static model. Thus, we began by creating and fine-tuning a static Attention-based LSTM model. This choice was driven by the fact that a simple LSTM model outperformed all other models, including transformer, that presented in (Shapira et al.'s) original research, and gave the most accurate predictions. The static Attention-based LSTM model was meticulously fine-tuned to serve as the foundation for our dynamic approach.

3.2 Masked Self-Attention Layers

Given the reputation of transformers as the state-of-the-art architecture in many language-based tasks, it was intriguing to find that a less advanced LSTM model outperformed the transformer model in (Shapira et al.'s) original research. This unexpected result prompted us to explore ways to bridge the gap between the high performance of a simple LSTM in the original study and the superior results typically achieved by transformers in various tasks. To achieve this, we combined the LSTM model presented in the original article with an attention mechanism, the core concept behind transformer architectures. Our approach was inspired by the work of (Wang et al., 2016), which demonstrated the effectiveness of attention-based LSTM models in sentiment classification - a task somewhat analogous to predicting human binary choices after language-based persuasion games as presented in the original problem.

We implemented an attention sub-layer after each LSTM sub-layer to create a static attention-based LSTM model. The attention mechanism (Wang et al. 2016), was designed to enhance the model's ability to focus on relevant parts of the input sequence, thereby improving the accuracy.

Upon testing the architecture, we noticed that the attention mechanism, which typically considers future parts of the input sequence, resulted in suspiciously high accuracy predictions. This anomaly led us to investigate potential data leakage. We discovered that the LSTM input sequence in the original problem included all time-steps of a single user-bot interaction, containing information from previous time-steps, including the user's decisions in earlier steps – the same information the model was supposed to predict.

To address this issue, we needed a mechanism that allowed the use of attention without future knowledge. We implemented a masked attention mechanism, where attention scores are calculated only for the current and previous time-steps, excluding any future information. This approach ensured that the model's predictions were based solely on past and present data, thus maintaining the integrity of the prediction task.

3.3 Sample-wise Dynamic Policy

After implementing and fine-tuning a static attention-based LSTM model, we introduced a final adaptation to make it dynamic. This adaptation, inspired by (Han et al.'s) survey involves a single-layer fully connected neural network that acts as a policy maker. This dynamic policy network receives the input values and determines the operation mode for each layer, which consists of LSTM and attention sub-layers. The policy, a list of the size of the number-of-layers, includes one of three actions for each layer, in form of a number in {0, 1, 2}:

1. **Process with both LSTM and Attention (2)**: The policy directs that both the LSTM and attention sub-layers process the hidden state.
2. **Process with LSTM only (1)**: The policy directs that only the LSTM sub-layer processes the hidden state, skipping the attention sub-layer.
3. **Skip the entire layer (0)**: The policy decides to skip both the LSTM and attention sub-layers for that layer.

To optimize the parameters of the architecture, including the dynamic policy layer, we employed a selective gradient update mechanism. During backpropagation, the gradients of all sub-layers and layers that were inactive due to the policy decision for a specific input sequence are zeroed out. This approach ensures that the parameters of inactive components are not updated, focusing the training process on the parts of the model that contribute to the prediction.

In conclusion, our final model comprises a linear FC layer for initial input transformation, a dynamic policy FC layer, multiple layers consist of LSTM and self-masked attention sub-layers, and an output FC layer utilizing softmax for classification. [fig. 1]

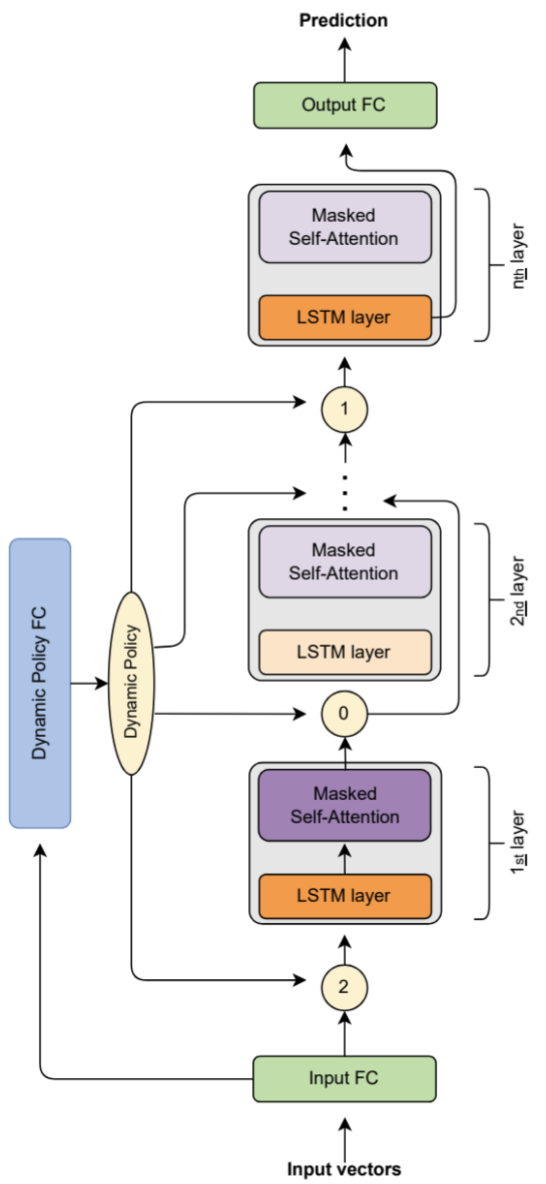

Figure 1: Dynamic Attention-based LSTM model architecture Demonstrating the effect of Dynamic Policy on layer activation.

4 Data

All data and code are available through GitHub.

The dataset used in our study originates from the research conducted by (Shapira et al. 2023) and includes 87,204 decisions made by 245 people engaged in a multi-stage language-based persuasion game with artificial agents. This data was collected through a mobile application, "Travel or Trouble," which simulated a realistic environment where players interacted with various strategy-based expert bots over 10 rounds per game. The game involved presenting the players with textual reviews of hotels, where each bot used a distinct strategy to persuade the player to choose a hotel based on these reviews. Players earned points by making good decisions, such as selecting highly rated hotels or avoiding poorly rated ones. The goal was to accumulate enough points to "defeat" each expert bot, thus advancing through the game.

In effort to enhance their model's accuracy of predicting real human decisions, the researchers incorporated both real human interaction data and simulated data. The simulated data aimed to replicate human decision-making behavior by using predefined strategies that considered both past behaviors and review content. The simulation model involved a series of games where the simulated player interacted with various expert strategies, ensuring that the simulation covered a wide range of possible player-bot interactions. This combined dataset enabled the creation of predictive models that could generalize well to new scenarios and various bot strategies, enhancing the study's overall robustness and applicability.

5 Experiments and Results

5.1 Static Model Hyper-Parameter-Tuning

Following (Han et al.'s) survey on dynamic neural networks, we structured our model training strategy by initially training a static model based on a combined attention-LSTM framework, to later adapt it into a sample-wise dynamic model.
A complete training session of 30 epochs, utilizing both simulated and human data at a 4:1 ratio, as identified as optimal in (Shapira et al.'s) original study for prediction accuracy, required approximately 90 minutes on a virtual machine GPU that was allocated to this work. In contrast, training on the human-only dataset took about 30-40 minutes per session. Given these time constraints, we focused on hyper-parameter tuning using only the human dataset, dividing it to train-set and validation-set. During this phase, the model's "online_simulation_factor" parameter, which dictates the simulation ratio, was set to 0.
To perform hyper-parameter tuning efficiently, we employed Weights and Biases sweeps. We tested various combinations of model parameters configurations, including the number of layers ∈ {2, 4, 6}, the hidden state vector dimensions ∈ {32, 64, 128}, and the optimization

learning rates ∈ {0.01, 0.001, 0.0001} (selected values are highlighted).
Each configuration was trained over 30 epochs with random seeds ranging from 0 to 4 to ensure the accuracy and stability of the results. [Table 1.]

layers	hidden_dim	learning_rate	accuracy	std
2	32	0.0001	0.7710	0.0044
		0.001	0.7743	0.0125
		0.01	0.6333	0.0804
	64	0.0001	0.7740	0.0076
		0.001	0.7702	0.0178
		0.01	0.6424	0.1288
	128	0.0001	0.7735	0.0085
		0.001	0.7633	0.0087
		0.01	0.5240	0.1002
4	32	0.0001	0.7627	0.0108
		0.001	0.7400	0.0107
		0.01	0.5240	0.1002
	64	0.0001	0.7656	0.0131
		0.001	0.7586	0.0194
		0.01	0.5229	0.0992
	128	**0.0001**	**0.7747**	**0.0058**
		0.001	0.7136	0.0755
		0.01	0.5229	0.0992
6	32	0.0001	0.6128	0.0687
		0.001	0.6933	0.0635
		0.01	0.5229	0.0992
	64	0.0001	0.6763	0.0836
		0.001	0.6798	0.0590
		0.01	0.5229	0.0992
	128	0.0001	0.6386	0.0806
		0.001	0.5843	0.0160
		0.01	0.5229	0.0992

Table 1: Static Attention-LSTM Hyper-Parameter-Tuning Results Accuracy and standard deviation (STD) are calculated based on five static model predictions accuracy results tested over $0 \leq seed \leq 4$. Chosen parameters and results are bolded and highlighted.

5.2 Final Dynamic Model's Results

After initializing the static model with the selected hyper-parameters and adapting it to be sample-wise dynamic using a dynamic-policy maker fully connected layer (Han et al. 2021) to determine each layer's behavior for each input (as described in the model section), we trained it on both human-bot interactions and the simulated dataset for 30 epochs. This training was performed over random seeds ranging from 1 to 15, as implemented in the original study (Shapira et al. 2023).

When comparing our results to the original study's simple LSTM model (Hochreiter et al., 1997) trained on the same combined dataset, we found that our dynamic model was consistently less accurate (with mean accuracy ≈ 0.833) than the simple LSTM model presented in the original article (with mean accuracy ≈ 0.837), across all seeds and in the mean accuracy. [fig 2.]
One potential explanation for this outcome is that, due to time constraints, we optimized the hyper-parameters of our static model based solely on human-bot interactions, rather than using the combined human and simulation training set as was done during the hyper-parameter tuning stage in the original study, which might affect our static model's best hyper-parameters configuration. However, when disregarding the model's training conditions and focusing on thetest results only, it appears that in this case, a simpler model might be more effective. The simple LSTM (Hochreiter et al., 1997) outperformed both the advanced transformer model (Vaswani et al., 2017) in the original study and our dynamic attention-based LSTM model.

This finding could be a valuable direction for future research to understand why the simpler model achieved better performance and whether it applies to other similar problems as well.

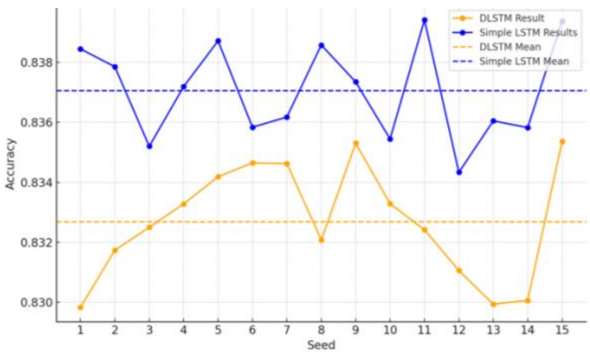

Figure 2: Comparison of Dynamic Attention-based LSTM (Orange) and Original Study's Simple LSTM (Blue), over 15 seed values.

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