DeepTennis: Mid-Match Tennis Predictions

Dipika Badri, 1 Sven Lerner, 1 Kevin Monogue 1,2

1 Electrical Engineering, Stanford University
2,3 ICME, Stanford University

Motivation / Summary

We built a recurrent neural network utilizing the Long Short-Term Memory (LSTM) model to compute ‘live’ win probabilities for tennis matches mid-game. Using a detailed point-by-point dataset [1] for the four Grand Slam tennis tournaments, our model is designed to learn deep relationships behind the sequential data and to predict the probability of winning the match for each player after every point.

Results and Experiments

<table>
<thead>
<tr>
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<th>DeepTennis</th>
<th>K-M Logit Elo (Gollub)</th>
<th>Logistic Regression</th>
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<tbody>
<tr>
<td>Accuracy (points correctly predicted)</td>
<td>79.5%</td>
<td>76.5%</td>
<td>73.4%</td>
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Model Calibration

We utilized an architecture consisting of stacked LSTM units followed by a single linear output layer with sigmoid activation.

Data

We used the point-by-point dataset for the tennis Grand Slams (Wimbledon, US Open, French Open, and Australian Open) provided by Jeff Sackman [1] along with derived data such as minimum sets to win. We also incorporated pre-match win probabilities for each player from a paper on pre-match tennis win predictions (Gollub).

Model Accuracy over Match

Our model assigned high win probability for Gulbis for the majority of the match - he was a heavy favorite over Thiem, who was participating in his first ever Grand Slam. Thiem only became favored when being mere points away from pulling off the upset.

The 2014 Wimbledon final exhibits our models ability to detect momentum well, especially when the match involves similar level players. Federer first set win was a crucial head start, before Djokovic nearly put the match away until a back-and-forth final set.

DeepTennis Prediction Accuracy

By definition, after set 4, the match is tied and has become a best of one series. Our model exhibits a 9 percent accuracy boost over the prematch win probability when predicting this decisive set, illustrating that it has learned important features over the course of the match.

Conclusion / Future Directions

The implementation of a two-layer, 50 hidden node LSTM model appears to have improved performance over existing methodologies for mid-match tennis prediction. We believe our model’s performance could be further improved with the incorporation of more data or more detailed features, and future work should involve the collection of that data.

References
