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Time Series Modeling of Baseball Performance

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Overview

Motivation: Predicting upcoming player performance is vital to team management and a hot topic in sports media.

Goal: Greater understanding of recent trends impacting future outcomes and increased accuracy of predictions.

Approaches:

I. Use expectation maximization (EM) to identify most predictive past time periods
II. Predict next game performance based on season history using a recurrent neural network (RNN)

Background

Expectation Maximization

- The EM algorithm is a general iterative method to perform maximum likelihood estimation (MLE)
- Find MLE of mixture density parameters via EM

Our Model

Mixture Model

- Future performance as a function of past performance periods:

\[ P_j(x) = w_1 P_{j,1}(x) + w_2 P_{j,2}(x) + w_3 P_{j,3}(x) \]

where

\[ P_{j,1}(x) = (1 - \alpha) \bar{P}_{j,1}(x) + \alpha \delta_j(x) \]  
\[ P_{j,2}(x) = \text{player } j \text{ empirical PMF for period } j \]  
\[ \delta_j - \text{league average PMF for period } j \]  
\[ \alpha - \text{interpolation coefficient of league average PMF, } 0 \leq \alpha \leq 1 \]  
\[ w_j - \text{mixing weight for period } j \]  
\[ 0 \leq w_j \leq 1, \quad w_1 + w_2 + w_3 = 1 \]

Data

- Play-by-play data from Retrosheet.org
- 250+ players per season, years 2008-2013
- 6 statistics: strikeouts (K), walks (BB), singles (1B), doubles (2B), triples (3B), home runs (HR)

Training

- Tune \( \alpha \) to maximize log-likelihood on held out data set
- Use EM to learn appropriate \( w_j \) weights to best predict future outcomes

Experiments

<table>
<thead>
<tr>
<th>Results</th>
<th>Log-Probability of Optimal ( \alpha ) Model vs League Average Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>K</td>
</tr>
<tr>
<td>Optimal ( \alpha )</td>
<td>0.25</td>
</tr>
<tr>
<td>Optimal LogP</td>
<td>-1.016</td>
</tr>
<tr>
<td>( \alpha = 100% )</td>
<td>-1.042</td>
</tr>
</tbody>
</table>

- The optimal \( \alpha \) is highly dependent on the statistic being considered

RNN

- Stats per player, per game, over a season:

\(<\text{start of season up until Recent}>\ |
\text{did not play} | <\text{end of season}>\)

Model

- Train on 60% of data - Tune on 20% - Test on remaining 20%
- Learn optimal \( U, W, V \) matrices
- Trained using backpropagation through time

Results

- To evaluate our methods, we feed held out data to our model in the above form and compute the metrics in the following table

Evolution of model over several games

- Ongoing work: we anticipate more results soon