Projecting NFL Quarterback Readiness
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Problem
The quarterback is the most important position on an NFL team. Teams often spend first round draft picks to potentially draft a future franchise quarterback. Every now and then some teams find themselves investing in a very promising prospect only to find out later that he is a bust. Our goal is to predict if a quarterback is a bust based on a player’s history, college stats, and the team that drafts him at a certain round and pick.

Labels and feature selection
Labels: We classified a quarterback as “NFL-Ready” if the player was able to record at least 10 total NFL wins as a starter. The reasoning behind this was that if a player was a bust then he would not be starting games let alone winning them. Most of the notable draft busts never reached the 10 win mark, and this also correctly classified players as “NFL-ready” who had poor rookie years due to injury or coaching changes, but eventually found success.

Features:
1. Draft Year
2. Round
3. Pick
4. Age Drafted
5. College Games Played
6. Completions
7. Attempts
8. Passing Yards
9. Touchdowns
10. Rushing Attempts
11. Rushing Yards
12. Rushing Touchdowns
13. College
14. College Conference
15. Team
16. Heisman Winner

Data visualization
Principal Component Analysis
Features such as passing yards, passing completions, and passing attempts are linearly dependent but features like pick number and college are non-linearly dependent or independent, so in order to get a better understanding of our training data PCA was used. 2-dimensional PCA plot shows that data is not easily separable, and there is a lot of overlap between two class labels.

Model selection
Out of 5 different models, the top three performers were logistic regression, SVM with linear kernel, and neural networks. Random forests and SVM (Polynomial Kernel) best classified a majority of the players as busts and had lower recall, precision and f1-scores. To evaluate our models, we used specialized k-fold cross validation where a fold represents a draft year and compared the confusion matrices of each model as well as their evaluation metrics. We also considered the fact that predicting a player as a bust who was actually NFL-ready was a less critical mistake than drafting a bust.

Model input feature selection
After applying the filter feature selection algorithm we were able to conclude that the most important features were selection pick number, passing attempts, rushing attempts, and interceptions. There was almost no statistically significant difference and success correlation when it came to the age a player was drafted, games played in college, rushing touchdowns, and the college they attended.

Neural network structure
During our k-fold cross validation for picking the model, we also experimented with different parameters for our neural network. Our results are based on the top-performing one:

- **NN Structural Parameters:**
  - Hidden layers: 3
  - Units in each layer: 50, 100, 50
  - Optimizer: Proximal Adagrad
  - Hidden Layer activation fn: ReLU
  - Output Layer activation fn: Softmax
  - Regularization Parameter: 0.0001
  - Loss function: Cross Entropy Loss

Results and Analysis
Prediction Results:
<table>
<thead>
<tr>
<th>Player</th>
<th>Prediction</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jameis Winston</td>
<td>NFL-Ready</td>
<td>NFL-Ready</td>
</tr>
<tr>
<td>Johnny Manziel</td>
<td>Bust</td>
<td>Bust</td>
</tr>
<tr>
<td>Teddy Bridgewater</td>
<td>NFL-Ready</td>
<td>NFL-Ready</td>
</tr>
<tr>
<td>Derek Carr</td>
<td>Bust (100%)</td>
<td>NFL-Ready</td>
</tr>
</tbody>
</table>

A large gap between training and test accuracy suggests that model overfits the data and suffers from high variance, it’s not possible to get more data to fix high variance as every year only a handful of quarterbacks make it to NFL. Reduction in feature space results in poor test accuracy.

Future improvements
The biggest improvements we can make are defining better labeling criteria that is more universally accepted and increasing our dataset size as more quarterbacks get drafted. We can also include more features and use better feature selection optimization on coaches and the NFL team’s previous record.
As we mentioned before, it is very difficult for our model to have statistically significant test data as there are only roughly 200 quarterbacks that have ever been drafted. As a fun experiment we assumed the mock draft from Chris Trepasso of CBS Sports was accurate. We applied our model to his draft and got some interesting predictions. This was a fun way of evaluating our model.

It looks like we have a very successful quarterback class in 2018. Despite going to the Cleveland Browns (who have the largest QB turnover in the NFL) the model is very confident that Lamar Jackson will be NFL-ready. Washington should beware that releasing current quarterback Kirk Cousins (who is definitely NFL-ready) in favor of incoming Oklahoma State phenomenon Mason Rudolph might be costly.

<table>
<thead>
<tr>
<th>Quarterback</th>
<th>Pick</th>
<th>Team</th>
<th>Prediction</th>
<th>Confidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lamar Jackson</td>
<td>1</td>
<td>CLE</td>
<td>NFL-Ready</td>
<td>99.9%</td>
</tr>
<tr>
<td>Josh Rosen</td>
<td>2</td>
<td>NYG</td>
<td>NFL-Ready</td>
<td>97.9%</td>
</tr>
<tr>
<td>Sam Darnold</td>
<td>9</td>
<td>CIN</td>
<td>NFL-Ready</td>
<td>99.4%</td>
</tr>
<tr>
<td>Mason Rudolph</td>
<td>12</td>
<td>WAS</td>
<td>Bust</td>
<td>73.4%</td>
</tr>
</tbody>
</table>

Special Thanks to:

[2] Derek Murray
[3] Geo Hsu
[4] Stanford CS 229 course staff

Sources