Projecting NFL Quarterback Readiness

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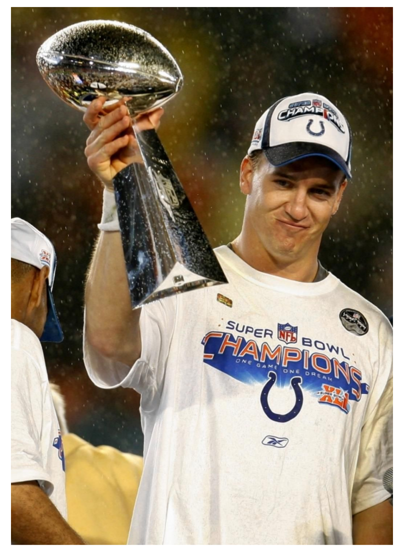
Problem

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.

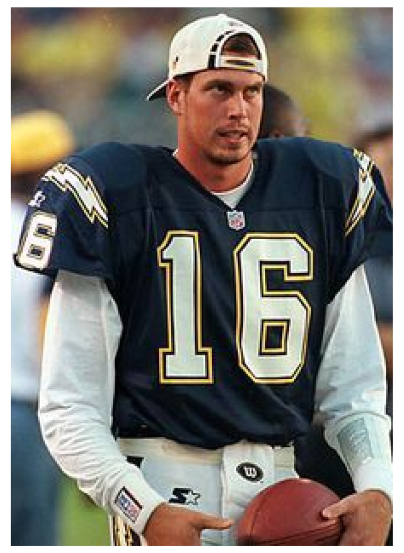


Peyton Manning

- 1998 #1 Pick
- 2 Time SuperBowl Champion

Ryan Leaf

- 1998 #2 Pick
- Cut after 3 losing seasons



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.

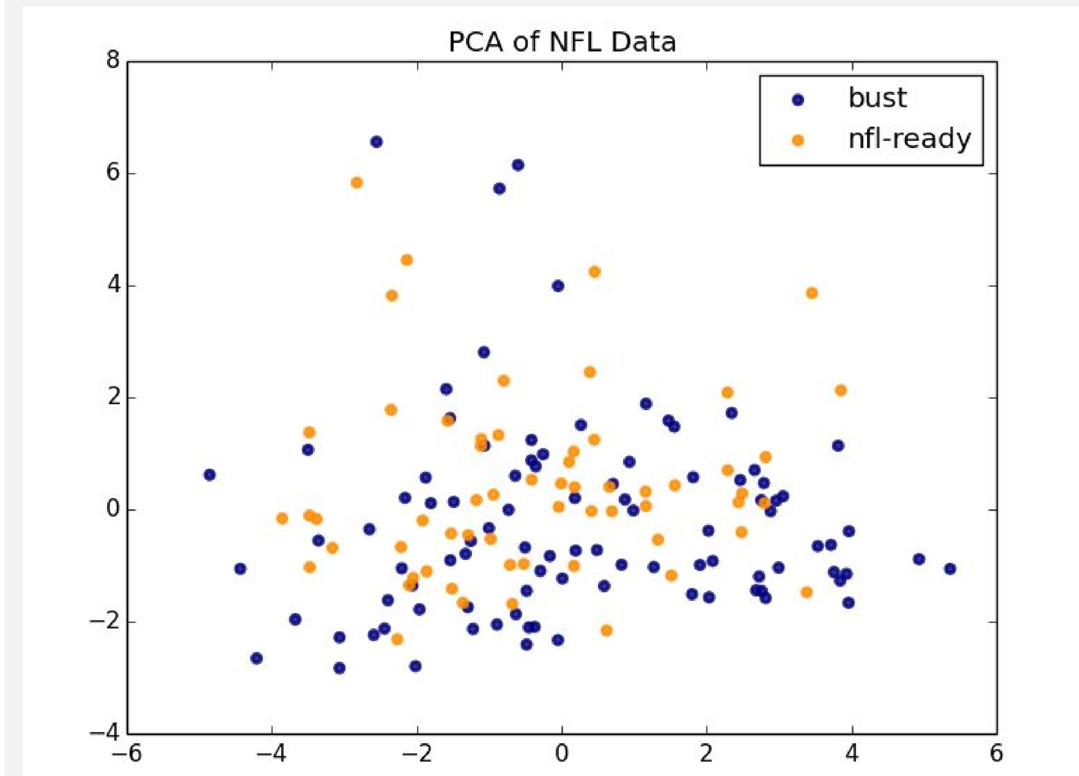
Features:

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**

Los Angeles Rams → [1, 0, 0, 0… 0]
New England Patriots → [0, 1, 0, 0 … 0]
Green Bay Packers → [0, 0, 1, 0 … 0]
Baltimore Ravens → [0, 0, 0, 1 … 0]

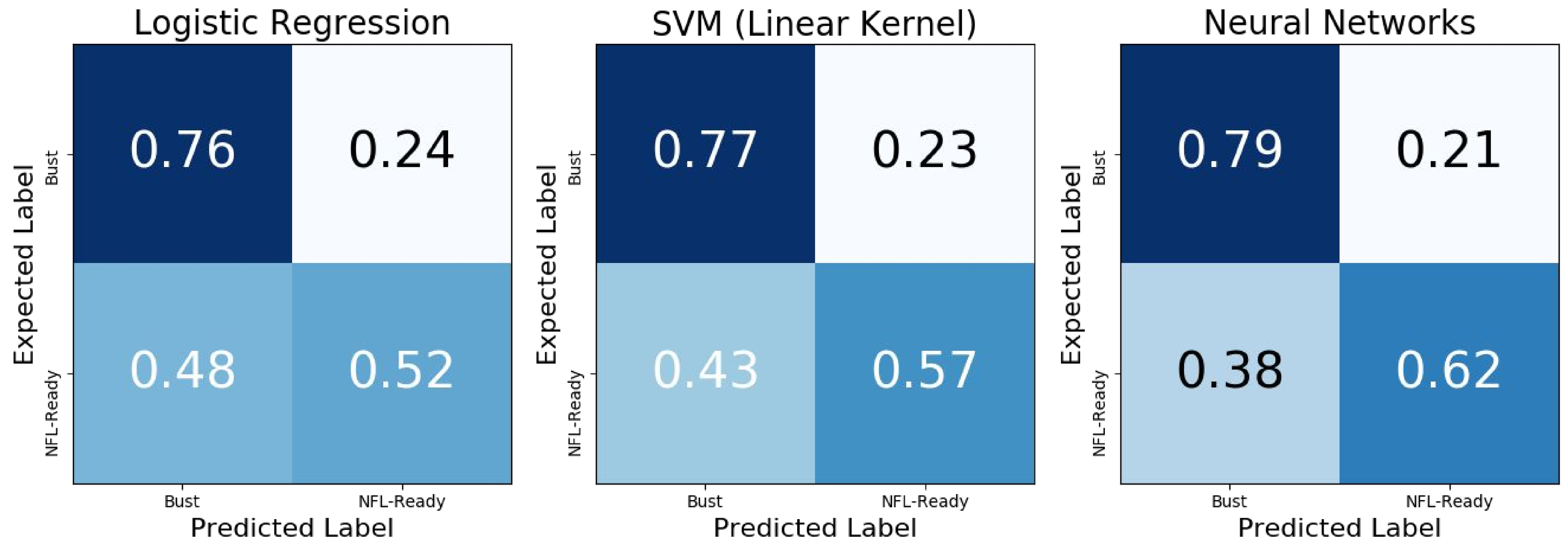
Text Embedding:
Colleges, conferences, and the team drafted are represented as text data. We used an embedding feature column wrapped around a categorical vocabulary column to map text data from a finite set into a numeric vector space.

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



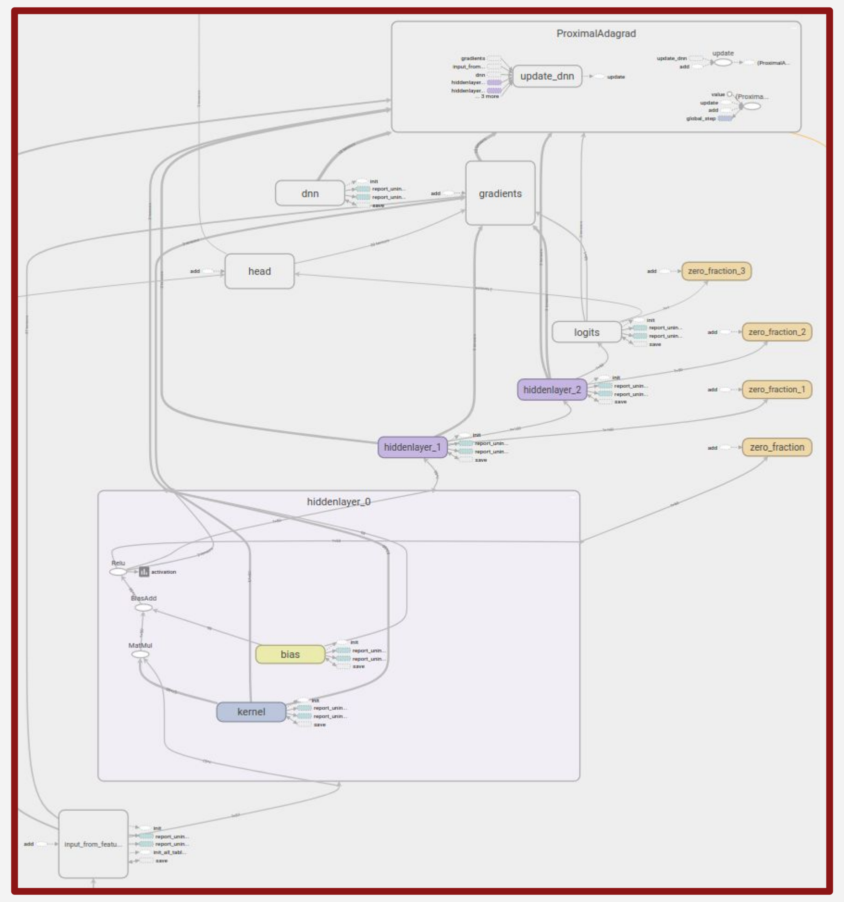
Out of 5 different models, the top three performers were logistic regression, SVM with linear kernel, and neural networks. Random forests and SVM (Polynomial Kernel) would classify a majority of the players as busts and had lower recall, precision and f1-scores. To evaluate our models, we used specialized 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

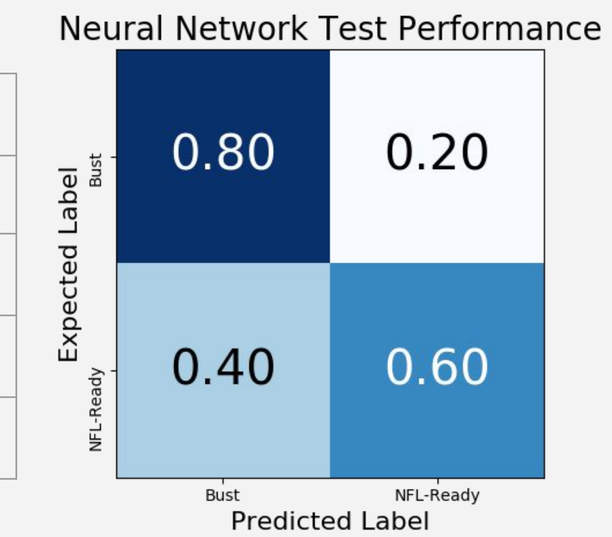
Prediction Results:

Training Accuracy	Test Accuracy
96.4%	73.3%

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.

Player	Prediction	Actual
Jameis Winston	NFL-Ready (52.7%)	NFL-Ready
Johnny Manziel	Bust (99.8%)	Bust
Teddy Bridgewater	NFL-Ready (91.8%)	NFL-Ready
Derek Carr	Bust (100%)	NFL-Ready

Here are some interesting predictions from our model's test set data.



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.

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2018 Draft Experiment

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.

Quarterback	Pick	Team	Prediction	Confidence
Lamar Jackson	1	CLE	NFL-Ready	99.9%
Josh Rosen	2	NYG	NFL-Ready	97.9%
Sam Darnold	9	CIN	NFL-Ready	99.4%
Mason Rudolph	12	WAS	Bust	73.4%

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.

Special Thanks to:

[1] TensorFlow open-source community
[2] Derek Murray
[3] Geo Hsu
[4] Stanford CS 229 course staff

Sources

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