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PROJECT TITLE: The Philadelphia Eagles 2022 Solution at Quarterback

# EXECUTIVE SUMMARY

The Philadelphia Eagles are at a critical decision point with the quarterback position. Jalen Hurts owns the starting role and is approaching the end of his rookie contract while the team is in a window of opportunity to win a championship. This analysis examines NFL quarterback performances from the 1999 season until the current to find suitable predictive models that determine if one is probable to become a Franchise Quarterback based on their individual and team performance. The study also predicts the QB’s average annual value (AAV) in USD and length in years for their first extension beyond their rookie contract.

The consultant sourced data that supports play-by-play, team schedule, draft, and contract analysis. After normalizing stats to reflect each QB’s performance at the same point in their career as Hurts is currently, 15 performance variables entered selection methods to find sparse models with strong predictive performance.

The Lasso variable selection method for logistic regression outperforms other candidate predictive models for Franchise QBs, resulting in a simple model based on Passing TDs per Game and EPA per Play. The Forward-Stepwise variable selection method for linear regression outperforms other models for predicting AAV. The Best Subsets and Forward-Stepwise variable selection methods identify the same model based on two predictors for predicant contract length in years, although there are some concerns with the validity of this model.

After his 26th game as the primary passer on October 16th, the model predicts Hurts to be more probable than not to become a Franchise QB. His performance would earn a contract extension of around $41 million per year over 4 years, which has a similar structure to other notable quarterbacks in the league.

# 1.0 - PROJECT DESCRIPTION

NFL analysts expect the Eagles to have a strong roster in the 2022-2023 season, but there is uncertainty around how the starting quarterback Jalen Hurts should perform. The Eagles personnel department is carefully evaluating Hurts’ performance this year because his current rookie contract extends through 2023. The department will need to determine if he is a “Franchise Quarterback” that has a future with the team and is worth extending. If he is not the long-term solution, then the team will need to consider replacing him. The team engaged the Consultant for an objective assessment of Hurts’ statistics and to predict his potential as the long-term solution.

The Consultant sourced from the nflfastR R library that offers current NFL play-by-play data dating back to the 1999 season. The analysis filtered the data to players who have been the primary passer, or the player that threw the most passes for their team within a game, for at least as many games as Hurts. This analysis only considers NFL games on October 17th, 2022 and prior where Hurts was the primary passer in 26 games to date. The project also required NFL draft data from the nflreadr R library to identify quarterbacks who have started their career in the year 1999 or later. Team-based statistics such as win ratio prior to the QB’s first primary start required schedule data combined between Pro Football Reference and nflreadr. Finally, the Consultant included contract data from nflreadr to support the research questions around Hurts’ potential contract value.

Preparation of the data enabled an observational study of 90 quarterbacks including Hurts. The study considered 16 individual and team-based performance variables, outlined in

**1.2 – VARIABLES OF INTEREST**. The data preparation normalized the variables to reflect each quarterback’s performance as of their 26th game and only included the stats for the primary passer of each game to provide a fair comparison to Hurts at the same point in their career. Several algorithms selected which predictive variables were most significant in predicting three response variables: one categorical variable to label a quarterback as a Franchise QB vs. not, and two continuous variables for contract value and length in years.

# 1.1 - RESEARCH QUESTIONS

Question 1: What is the probability that Jalen Hurts will become a Franchise QB?

Question 2: What would the annual contract value in USD be for a quarterback of Jalen Hurts’ performance if they were to extend?

Question 3: How many years would a contract for a quarterback of Jalen Hurts’ performance extend?

# 1.2 – VARIABLES OF INTEREST

*Table 1. Predictor Variables* includes only the variables that serve as strong predictors of the response variables. The remaining variables considered are available in **Appendix A: Additional Predictor Variables Considered**.

Table . Predictor Variables

|  |  |  |
| --- | --- | --- |
| **Variable Name** | **Category** | **Description** |
| Days to Hurts Game | Individual Performance | The number of calendar days between the quarterback’s first game as primary passer until their 26th game. |
| EPA per Play | Advanced Individual Performance | The mean expected points added (EPA) per play. QB EPA is the difference in the expected points at the start and end of a play. This does not penalize QBs for mistakes they are not at fault for, such as a receiver fumbling. Additional reference material available in **5.0** - **RESOURCES**. |
| Passing Completion Percentage | Individual Performance | The number of passes successfully caught by a receiver on the same team divided by the number of passes the QB attempted. |
| Primary Passing TDs per Game | Individual Performance | The total passing touchdowns divided by the number of games the QB played as primary passer. |
| Primary Rushing TDs per game | Individual Performance | The total rushing touchdowns divided by the number of games the QB played as primary passer. |
| Turnovers per Attempt | Individual Performance | The number of fumbles and interceptions the QB was responsible for divided by the number of snaps the QB played. |

Table . Response Variables

|  |  |  |
| --- | --- | --- |
| **Variable Name** | **Category** | **Description** |
| Franchise QB | Categorical | Labeled as 1 if the QB played at or above the median number of games as primary passer for the 90 QBs considered in this analysis (71 games). Otherwise, 0. |
| Contract Average Annual Value (AAV) | Continuous | The total dollar value (presented in millions of dollars) of the contract adjusted for inflation in 2022 divided by the number of years the contract extends. |
| Contract Years | Continuous | The number of years the contract extends. |

# 2.0 - EXPLORATORY DATA ANALYSIS (EDA)

Table . Numerical Summary of Franchise QB Predictor Variables

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Missing Values** | **Mean** | **Standard Deviation** | **Min** | **Max** | **Range** |
| EPA Per Play | 0 | 0.03 | 0.09 | -0.18 | 0.32 | 0.51 |
| Fumbles Per Attempt | 0 | 0.01 | 0.00 | 0.00 | 0.01 | 0.01 |
| Interceptions Per Attempt | 0 | 0.03 | 0.01 | 0.01 | 0.04 | 0.03 |
| Mean CPOE | **20** | -0.41 | 3.22 | -9.48 | 8.58 | 18.06 |
| Net Point Differential Change | 0 | 52.04 | 144.94 | -386.00 | 365.00 | 751.00 |
| Net Win Percentage Change | 0 | 0.08 | 0.19 | -0.42 | 0.50 | 0.92 |
| Passing Completion Percentage | 0 | 0.60 | 0.03 | 0.53 | 0.67 | 0.14 |
| Passing Yards Per Attempt | 0 | 6.92 | 0.69 | 5.42 | 8.79 | 3.37 |
| Primary Passing Tds Per Game | 0 | 1.31 | 0.36 | 0.65 | 2.69 | 2.04 |
| Primary Rushing Tds Per Game | 0 | 0.15 | 0.15 | 0.00 | 0.73 | 0.73 |
| Rushing Yards Per Attempt | 0 | 3.91 | 1.51 | 1.00 | 6.98 | 5.98 |
| Sacks Per Play | 0 | 0.06 | 0.02 | 0.02 | 0.11 | 0.09 |
| Turnovers Per Attempt | 0 | 0.03 | 0.01 | 0.01 | 0.05 | 0.03 |

The analysis to support Research Question 1 removed 27 quarterbacks who did not play their first season in 2018 or prior because they have not been in the league long enough to play the median 71 games and therefore should not disqualify as a Franchise QB. *Table 3* reflects the numerical summary of the predictor variables. Per the nflfastR documentation, Mean CPOE is only available for the 2006 season and later and causes the 20 missing values for QBs who started their careers prior to 2006. Otherwise, **Appendix C: Histograms of Franchise QB Predictor Variables** shows most variables have an approximately normal distribution. Skewness exists in Primary Rushing TDs per Game and arguably in Net Point Differential Change, but neither are concerning enough to warrant transformation of variables.

Table . Numerical Summary of Contract Predictor Variables

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Missing Values** | **Mean** | **Standard Deviation** | **Min** | **Max** | **Range** |
| Days To Hurts Game | 0 | 860.19 | 547.72 | 407.00 | 2,958.00 | 2,551.00 |

The Contract analyses considered an additional Days To Hurts Game variable not included in the Franchise QB analysis. The study removed quarterbacks who were missing Contract data and Jalen Hurts himself because his data should not influence his own prediction. Numerical summaries for predictor variables shared with the Franchise QB analysis but filtered for the Contract analyses are available in **Appendix D: Predictor Variables for Contract Analyses**. **Appendix E: Histograms of QB Contract Predictor Variables** shows most variables have an approximately normal distribution. Skewness exists in the Days to Hurts Game variable because some veteran QBs have spent many years as a backup. The analysis will remove QBs who took 2,000 days or later to reach their 26th game as primary passer. These excluded veteran QBs might have had several contract extensions and we are only interested in the first extension past the rookie contract.

# 3.0 –STATISTICAL ANALYSIS

3.1 Predicting Franchise QBs

The study first developed a predictive model to determine how likely a quarterback is to become a Franchise Quarterback in their career. The consultant first determined an 80% and 20% split of the data into training and test data respectively. The R script randomly assigned quarterbacks into each dataset. The consultant optimized the Logistic Regression, Random Forest, and XGBoost algorithms against the same training dataset. Within Logistic Regression, the study compared several variable selection techniques including Best Subsets, Lasso, Ridge Regression, and Elastic Net Regression. Each model then captured their predictions from the test dataset into a confusion matrix that separates true positives, false positives, true negatives, and false negatives. The consultant selected the model that had the largest testing overall accuracy, measured as:

The Logistic Regression with Lasso and Elastic Net variable selections both held the highest testing overall accuracy:

Table . Overall Accuracy by Predictive Model in descending order

|  |  |
| --- | --- |
| **Model** | **Overall Accuracy** |
| Logistic Regression with Lasso | 70.6% |
| Logistic Regression with Elastic Net | 70.6% |
| XGBoost | 58.8% |
| Logistic Regression with Ridge Regression | 52.9% |
| Random Forest | 50.0% |

Two selection methods tied for most accurate at 70.6%, but Lasso is the simpler approach of the two and is therefore the preferable method. Lasso is an unbiased method that penalizes the sum of coefficients for predictive variables by reducing some coefficients to zero and eliminating some variables. This elimination results in a simpler and more sparse regression model. This study standardized the variables before applying Lasso, which prevents the algorithm from bias toward selecting those with more variance because of different measurement units.

The user determines the amount of penalty for each predictor’s coefficient with the parameter λ. One can select an optimal parameter by finding the minimal error (in this case, Binomial Deviance for predicting an observation between two classes) over a range of potential λ as shown in *Figure 1. Binomial Deviance by Log of λ in Lasso variable selection*. The dataset is small enough to use Leave-One-Out Cross-Validation (LOOCV), where the prediction function fits on all training data except for one point and then predicts the response for the remaining point for each in the dataset. LOOCV helps minimize the cross-validation error in comparison to other available cross-validation methods and is feasible with this small dataset.

Chart, histogram

Description automatically generated

Figure . Binomial Deviance by Log of λ in Lasso variable selection.

A λ of 0.066 results in the lowest cross-validation error that does not bias the model toward predicting all observations to either be entirely one class. The logistic regression function for predicting the log odds of being a Franchise QB (based on standardized variables) is:

The model then predicts the outcome of the 19 QBs in the test data and collects them into a confusion matrix that compares the predicted values against actual values:

Table . Confusion Matrix for Logistic Regression with Lasso Selection

|  |  |  |  |
| --- | --- | --- | --- |
|  | | **Actual Values** | |
| Not Franchise QB | Franchise QB |
| **Prediction** | Not Franchise QB | 4 | 1 |
| Franchise QB | 4 | 8 |

The results show a low specificity (accuracy in predicting the negative class, Not Franchise QB) of 50%, indicating that the model only accurately predicts Not Franchise QBs in half of observations. However, it has a high sensitivity (accuracy in predicting the positive class, Franchise QB) of 88.89% because it only incorrectly predicts one observation.

3.2 Predicting Contract Average Annual Value (AAV)

The Contract Average Annual Value analysis also evaluated predictive linear regression models with several variable selection methods. The study considers Best Subsets, Forward Stepwise, Backward Stepwise, Lasso, and Ridge Regression variable methods. The analysis found the optimized model for each Adjusted R2, Mallows’ Cp, and BIC information criteria for applicable models. The Consultant randomly assigned the 69 QBs that qualified for the analysis into an 80% vs. 20% split between training test datasets respectively. Each model optimized against the training data and predicted AAV for each QB in the test data. The analysis compares prediction accuracy by finding the lowest Mean Squared Error instead of highest Overall Accuracy because the response variable is continuous and not categorical. Mean Squared Error is calculated as:

The Forward Stepwise Selection Method with BIC information criteria resulted in the best predictions:

Table . MSE of AAV predictions by Variable Selection and Information Criteria

|  |  |  |
| --- | --- | --- |
| **Variable Selection Method** | **Information Criteria** | **MSE** |
| Forward Stepwise | BIC | 116.19 |
| Best Subsets | BIC | 122.77 |
| Best Subsets | BIC | 122.77 |
| Ridge Regression | N/A | 126.74 |
| Lasso | N/A | 137.00 |
| Best Subsets | Adj R^2 | 157.99 |
| Forward Stepwise | Adj R^2 | 157.99 |
| Best Subsets | Adj R^2 | 157.99 |
| Forward Stepwise | Cp | 162.52 |
| Best Subsets | Cp | 172.94 |
| Best Subsets | Cp | 172.94 |

The top predictive model results in an intuitive linear regression with p-values below 0.1 as shown in *Table 8*, indicating this model would be sufficient for 90% confidence in predictions. The model predicts that for every 1 unit increase for Primary Passing TDs and Primary Rushing TDs, the AAV should increase by $9.74M and $28.59M. For a 0.01 increase in Turnovers per Attempt, the AAV should decrease by $5.421M. Finally, for each day it takes from a QB’s first start as a primary passer until their 26th game, the AAV decreases by $10K.

Table . Estimated Coefficients for Model Predicting AAV

|  |  |  |
| --- | --- | --- |
| **Predictor** | **Estimated Coefficient** | **P-Value** |
| (Intercept) | 25.36 | 0.097 |
| Primary Passing TDs per Game | 9.74 | 0.062 |
| Primary Rushing TDs per Game | 28.59 | 0.007 |
| Turnovers per Attempt | -542.10 | 0.069 |
| Days To Hurts Game | -0.01 | 0.024 |

To ensure this is a valid model with reliable predictions, the consultant evaluated the four assumptions for Linear Regression.

1. **Linearity**:The Residuals vs. Fitted plot in *Figure 2* shows no pattern, suggesting we can assume linear relationship.
2. **Independence of Errors**: The data arguably violates this assumption because one QB can impact the performance of another QB within a given game. For example, a rookie QB can begin their career as a backup to a Veteran who removes primary passing game opportunities from the rookie. However, this would be impossible to avoid.
3. **Normality of Errors**: The Normal Q-Q plot in *Figure 2* shows the points fall approximately along the reference line. Therefore, we can assume the errors to be normally distributed.
4. **Equal Variances**: The Scale-Location plot in Figure 2 shows a mostly horizontal line with equally spread points, suggesting the variance is constant through the model.

Chart, scatter chart

Description automatically generated

Figure . Linear Regression Assumption testing for AAV Regression Model

3.3 Predicting Number of Years for Contract

The predictive model selection for the number of years in a QB’s contract used the same dataset referenced and criteria for comparing variable selection methods in Section 3.2, but instead used Contract Years as the response variable. The model comparison available in **Appendix F: Model Comparison for Predicting Contract Years** shows that the Best Subsets and Forward Stepwise variable selection methods with BIC information criteria tied for lowest MSE and strongest prediction accuracy. When observing their estimated coefficients and intercept, they result in the same model.

Table . Estimated Coefficients for Model Predicting Contract Years

|  |  |  |
| --- | --- | --- |
| **Predictor** | **Estimated Coefficient** | **P-Value** |
| (Intercept) | 17.937 | 0.015 |
| Passing Completion Percentage | -25.731 | 0.038 |
| EPA per Play | 15.684 | 0.001 |

The resulting p-values shown in Table 9 are quite strong at <0.05, indicating this model would be sufficient for 95% confidence in predictions. However, one might treat this model with some skepticism because of the large negative coefficient assigned to Passing Completion Percentage. Intuition suggests that a higher Passing Completion Percentage positively reflects a QB’s performance and would yield a longer contract with a positive coefficient. EPA per Play is a more highly significant predictor, and a 0.01 increase would translate to an additional 15.6% of a year being added to the length of the contract.

After evaluating the linear regression assumptions available in **Appendix G: Linear Model Assumptions for Predicting Contract Years**, there is some slight curvature in the Residuals vs. Fitted plot indicating there could be opportunity for a non-linear relationship. However, the remaining plots show no concerns with the assumptions beyond the independence of errors mentioned in Section 3.2.

The resulting prediction will need to round to the nearest whole number because contracts are only measured in integer years.

# 4.0 – RECOMMENDATIONS

Question 1: What is the probability that Jalen Hurts will become a Franchise QB?

According to the Logistic Regression output, the probability that Jalen Hurts will become a Franchise QB is **52.4%**. He is slightly more likely than not to become a Franchise QB.

Question 2: What would the annual contract value be for a quarterback of Jalen Hurts’ ability if they were to extend?

According to the Linear Regression model, we can be 95% confident that Jalen Hurts’ contract would be between $16.3 million and $65.54 million but centered around **$40.9 million per year**. This would place his contract to a similar annual value with Dak Prescott, Matthew Stafford, and Derek Carr.

Question 3: How many years would a contract for a quarterback of Jalen Hurts’ ability extend?

According to the Linear Regression model, we can be 95% confident that Jalen Hurts’ contract length would be between 0 to 7.8 years but centered around 3.8 years. Rounding to **4 years** would be a reasonable contract length.

# 5.0 - RESOURCES

1. nflfastR documentation: <https://www.nflfastr.com/>
2. nflreadr documentation: <https://nflreadr.nflverse.com/>
3. Github repository of project code: <https://github.com/Sweigalytics/STAT581_NFL_Project/tree/main/Code>
4. CPOE Explained: <https://www.the33rdteam.com/breakdowns/cpoe-explained/>
5. EPA Explained: <https://www.nfeloapp.com/analysis/expected-points-added-epa-nfl/>

# 6.0 - CONSIDERATIONS

With only 90 QBs that qualify for the analysis, the size of the data is relatively small. However, if play-by-play data were available prior to 1999 it might not be beneficial to include because of rule changes over time that influence QBs’ ability to perform.

There is a significant amount of missing data from nflfastR and nflreadr that could impact the analysis. The CPOE data is only available for the 2006 season and later, but some active Franchise QBs such as Tom Brady played their first 26 games prior to 2006. Some models that handle missing data like XGBoost found CPOE to be a significant predictor in Franchise QB probability. Although this variable is not included in the chosen models, the personnel department should give it consideration for performance.

The contracts data is also missing contract extensions for 21 QBs. Many of these QBs are from early in the timeline considered in this analysis, such as Daunte Culpepper. Other more recent QBs like Lamar Jackson drop from the dataset because they have yet to have their first extension beyond their rookie contract. The remaining 69 QBs provide enough data for a predictive model, but results in some large prediction intervals. For instance, the 95% prediction interval to Question 3 technically includes a negative value of -0.086, which would be an impossible value.

# 

# Appendix A: Additional Predictor Variables Considered

Table . Additional Predictor Variables considered in selection but not included in final models.

|  |  |  |
| --- | --- | --- |
| **Variable Name** | **Category** | **Description** |
| Fumbles per Attempt | Individual Performance | The number of fumbles the QB was responsible for divided by the number of plays that the quarterback was the passer or rusher. |
| Interceptions per Attempt | Individual Performance | The number of interceptions the QB threw divided by the number of plays that the quarterback was the passer. |
| Mean Completion Percentage Over Expected (CPOE) | Advanced Individual Performance | The Actual Completion Percentage minus the Expected Completion Percentage. Only available for the 2006 season and after. Explanation behind Expected Completion Percentage available in **Error! Not a valid bookmark self-reference.**. Additional reference material available in **5.0 - RESOURCES**. |
| Net Point Differential Change | Team Performance | The mean point differential (a team’s final score minus the opposing team’s final score for a given game) for the QB’s team(s) subtracted by the mean point differential for the 26 games prior to the QB’s first game as a primary passer. |
| Net Win Percentage Change | Team Performance | The number of games the quarterback’s team(s) won divided by 26, subtracted by the number of games the team won in the 26 games prior to the QB’s first game as primary passer divided by 26. |
| Passing Yards per Attempt | Individual Performance | The total passing yards divided by the number of passes the QB attempted. |
| Rushing Yards per Attempt | Individual Performance | The total rushing yards divided by the number of rushes the QB attempted. |
| Sacks per Play | Individual Performance | The number of times the opposing team sacked the QB divided by the number of snaps the QB played. |

# Appendix B: Predictors Included in Expected Completion %

As found in <https://www.the33rdteam.com/breakdowns/cpoe-explained/>:

* Field position
* Down
* Yards to go
* Air yards
* Distance to sticks (air yards – yards to go)
* Whether possession team is at home
* Whether the game is played indoors
* Era, broken down into 2006-2013, 2014-2017, 2018 and beyond
* Pass location (binary: middle or not middle)
* Whether quarterback was hit on the play

# Appendix C: Histograms of Franchise QB Predictor Variables

Diagram

Description automatically generated

Figure . Histograms of Franchise QB Predictor Variables

# Appendix D: Predictor Variables for Contract Analyses

Table . Numerical Summary of Contract Predictor Variables after filtering.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Missing Values** | **Mean** | **Standard Deviation** | **Min** | **Max** | **Range** |
| EPA Per Play | 0 | 0.04 | 0.09 | -0.18 | 0.32 | 0.51 |
| Fumbles Per Attempt | 0 | 0.01 | 0.00 | 0.00 | 0.01 | 0.01 |
| Interceptions Per Attempt | 0 | 0.03 | 0.01 | 0.01 | 0.04 | 0.03 |
| Mean CPOE | 9 | -0.51 | 3.26 | -9.48 | 8.58 | 18.06 |
| Net Point Differential Change | 0 | 69.93 | 142.34 | -300.00 | 365.00 | 665.00 |
| Net Win Percentage Change | 0 | 0.08 | 0.19 | -0.35 | 0.50 | 0.85 |
| Passing Completion Percentage | 0 | 0.60 | 0.03 | 0.53 | 0.67 | 0.14 |
| Passing Yards Per Attempt | 0 | 6.96 | 0.68 | 5.54 | 8.79 | 3.25 |
| Primary Passing Tds Per Game | 0 | 1.33 | 0.35 | 0.65 | 2.69 | 2.04 |
| Primary Rushing Tds Per Game | 0 | 0.15 | 0.15 | 0.00 | 0.73 | 0.73 |
| Rushing Yards Per Attempt | 0 | 3.96 | 1.57 | 1.00 | 6.98 | 5.98 |
| Sacks Per Play | 0 | 0.06 | 0.02 | 0.04 | 0.11 | 0.07 |
| Turnovers Per Attempt | 0 | 0.03 | 0.01 | 0.01 | 0.05 | 0.03 |

# Appendix E: Histograms of QB Contract Predictor Variables

Diagram

Description automatically generated

Figure . Histograms of Contract Predictor Variables

# Appendix F: Model Comparison for Predicting Contract Years

Table . MSE of Contract Years predictions by Variable Selection and Information Criteria

|  |  |  |
| --- | --- | --- |
| **Variable Selection Method** | **Information Criteria** | **MSE** |
| Best Subsets | BIC | 1.58 |
| Forward Stepwise | BIC | 1.58 |
| Forward Stepwise | Adj R^2 | 1.82 |
| Best Subsets | Adj R^2 | 2.07 |
| Backward Stepwise | Adj R^2 | 2.07 |
| Forward Stepwise | Cp | 2.15 |
| Lasso | N/A | 2.96 |
| Ridge Regression | N/A | 3.50 |
| Best Subsets | Cp | 3.58 |
| Backward Stepwise | Cp | 3.58 |
| Backward Stepwise | BIC | 3.58 |

# Appendix G: Linear Model Assumptions for Predicting Contract Years

Chart, line chart, scatter chart

Description automatically generated

Figure . Linear Regression Assumption testing for Contract Years Regression Model