Contents

1 Introduction

1.1 Introduction to the NBA

The National Basketball Association (NBA) is a professional basketball league in North America consisting of 30 teams (also called franchises) where each team has of a squad of players called a roster. The teams are evenly split into two 'conferences' - the Western Conference and the Eastern Conference. Each team plays 82 games throughout the regular season where they are ranked based off of their win-loss (W-L) record. The top 8 from each conference will then compete in the 'playoffs' in an attempt to win the NBA championship. Each franchise is seeded based off of their win-loss record during the regular season and placed in a tournament bracket. Teams with a better win-loss record at the end of the regular season get a higher seeding and are more likely to encounter teams with a lower seeding in the playoffs. In each playoff round, teams play a best-of-seven game series where the first team to win four games moves into the next round of the playoffs whereas the other team is eliminated. The championship series occurs when the final two teams left in the playoffs play one another in a seven game series. The team which wins this series are the champions of the NBA season.

1.2 Project Aim and Motivation

Player statistics are heavily recorded in the NBA as they are a useful indicator of player performance. After every game individual statistics are recorded for every player allowing franchises and basketball enthusiasts to gain an insight about a players contributions throughout the season. Team and individual stats after every game are summarised by a 'box score', an example of which is shown in Table 1. Player perfromances are often evaluated using these stat lines and consequently the individual success of a player's season can be defined by inferring from their statistics. In the NBA there are a multitude of statistics and metrics that are recorded; a few examples of the most popular metrics recorded are: **points scored**, **assists made** and the **total number of rebounds**. Furthermore it is also possible to see a trend of a players career by observing the information provided by stat lines from their previous games. For example, it can be speculated that a player is improving if their points, assists and total rebounds per game are increasing. As the success of a team is heavily dependent on individual performances from their players, there is a large motivation for franchises to find players who will improve their team.

Player	MP	FG	FGA	FG%	3P	3PA	3P%	FT	FTA	FT%	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS	+/-
Jerami Grant	40:24	3	14	.214	0	3	.000	3	4	.750	6	8	14	2	0	1	2	1	9	-5
Paul George	34:50	6	14	.429	3	10	.300	4	7	.571	0	5	5	6	1	0	3	6	19	-4
Russel Westbrook	43:55	16	29	.552	5	10	.500	5	8	.625	2	9	11	6	1	0	9	3	42	-7
Terrance Ferguson	33:16	3	10	.300	2	8	.250	0	0	-	0	1	1	0	1	0	0	3	8	-14
Steven Adams	39:58	2	7	.286	0	0	-	0	0	-	7	0	7	2	1	0	2	3	4	-4

Table 1: An Example of an NBA Box Score showing the stats of the Oklahoma City Thunder players who started the game

This project aims to build on previous studies that explore machine learning models for predicting outcomes in the NBA. Moreover, the focus of this project will be experimenting with different statistical and machine learning algorithms starting with a simple average

model and moving to more complex models such as non-linear multi-feature regression in order to accurately forecast the points scored by players over the course of the 2018-19 season. More specifically this project will aim to answer the following questions:

Can machine learning models accurately forecast the points scored for players for every game during the 2018-19 NBA regular season using trends from previous seasons?

and

Can machine learning models accurately forecasting the average points per game of players for the 2018-19 regular season and thus the general trend of a players career?

The contributions of this paper can be summarised as follows:

- Introducing the range of features available for NBA franchises to use when predicting the **target variable** - points scored
- Selecting the features which best explain points scored, and training machine learning models using these features.
- Outlining, analysing and comparing the different machine learning models that can be used to forecast points scored, and concluding which model achieves the aims in this investigation.

Essentially, the project aims to solve a **time series problem** where outcomes in the future are predicted using information given in the past and present. **Is it possible to accurately predict the points scored in future games based off the trend of past games played?**

The NBA is a multi-billion dollar industry that is growing in popularity at a fast rate with viewership numbers reaching a record level in the 2017-18 season. The average franchise value is $1.9 billion, 13% more compared to the year prior. As a result there is a lot of incentive for franchises to perform well because this would further increase their revenue.

Franchises spend approximately half of their revenue on player salary, and in many ways risk their monetary success on the future of their players when signing them for multi-million dollar long-term contracts. Such monetary risks include team success over multiple seasons, salary cap restrictions, overall franchise value and team marketability. Subsequently the necessity for franchises to accurately forecast future player performance has increased greatly over the recent years in order to acquire players that are most likely to aid their teams success.

The main motivation for this investigation is to help NBA franchises make more informed and well judged decisions when attempting to acquire players. Coaches, scouts and agents can use the models explored to forecast a particular player's future performances and monitor their development before deciding whether or not to acquire the player.

Another motivation for exploring this project is the drastic increase in the sports analytics industry and its role in the sports betting market. The sports analytics market is expected to reach $2.09 billion by 2022, with many more basketball enthusiasts exploring different methods to predict outcomes in basketball games. For example Google Cloud, NCAA and

Kaggle hosted the annual 'March Madness' competition where basketball fans attempt to forecast outcomes of a college basketball tournament in an attempt to win up to $10,000.

Furthermore the sports betting market is so large solely because it is challenging to predict the outcomes of sporting events. As a result, another motivation for exploring this project is to discover a more accurate method of predicting player outcomes to better inform sports betting enthusiasts.

2 Background

2.1 Introduction to Machine Learning Models

This investigation will explore a range of machine learning models in order to find the most accurate when forecasting points per game for players. A machine learning model is a mathematical representation of a real-world process; in the case of this investigation, the machine learning algorithms will attempt to mathematically model points scored in future games. In order to generate a model, necessary features will have to be selected and training data will have to be provided such that the machine learning model can learn.

2.1.1 Features and Feature Selection Methods

Features are measurable properties of the predicted variable. In machine learning, features aid in predicting the target variable. Some models in this investigation will use multiple features in an attempt to forecast points scored and these are stored in a n dimensional vector.

In order to improve the performance of the models when predicting the target variable, the most relevant features need to be selected. Feature selection is the approach of selecting the most relevant features for predicting the target variable. It is important because it removes the features which are irrelevant when predicting the target variable and it aids in avoiding the curse of dimensionality. Additionally feature selection enhances generalisation by reducing overfitting. There are many features present in this investigation (examples can be seen in Table 3), however there are some features which may not be pertinent to forecasting the desired target variable in the investigation - points scored.

2.1.2 Training and Test Data

Machine learning models are initially fit on a training dataset. The training data consists of a set of explanatory variables and the respective target variables. The model essentially learns from this data and fits its parameters to the training data. After the model is trained, its performance is assessed using a test dataset. It is desirable for the model to have similar performance on the training data and testing data.

2.1.3 Overfitting

When attempting to fit a machine learning model to data it is important that overfitting is avoided. Overfitting occurs when the machine learning algorithm attempts to learn the noise within the dataset as well as attempting to learn the signal presented in the dataset. Noise in a dataset refers to the randomness within a dataset and signal refers to the underlying pattern in the dataset that wish to learn. One approach of detecting overfitting when learning is to plot the error of the training data and the test data. If the error begins to increase for the test data while decreasing for the training data then the model has most likely over fitted the training data.

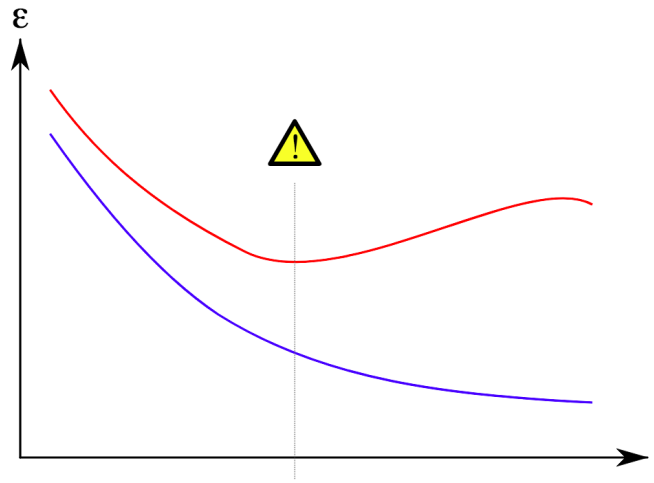


Figure 1: A visualisation of overfitting. The red line represents the error of the testing data whereas the blue line represents the training error. If there is an attempt to completely minimise the training data's error, then the model will become less flexible when attempting to predict future data points, resulting in an increase in the testing data's error.

2.2 The Dataset

This investigation will focus on a specific subset of players, specifically players from the 2014 Draft Class. The dataset consists of 27 players and their box score statistics from every game over the previous three seasons. The players and the references to the statistics are shown below. The incentive for choosing these players was:

- These players are of similar ages and they have had the same number of years of experience in the NBA.
- They are still relatively young, so the possibility of a decline in performance due to aging is low.
- Although these players are still relatively young, they have played 3 seasons in the league and therefore they should be well adjusted to the difficulty of the NBA.

Therefore the assumption made when using this dataset is that it is unlikely that the performance of these players will drastically improve or decline over the course of the 2018/19 season and therefore the points per game for these players may be more predictable.

The data was collected by **scraping** the box scores off of the website **Basketball Reference**. Some box score statistics can be seen as good indicators for predicting the points per game in future games and as a result can be considered as important features. The box score statistics are explained in Table 3.

2.2.1 Overview of the Features

Some of the stats recorded could potentially be used a features for forecasting points per game for future games. The features (and the target variable) provided are summarised

Andrew Wiggins	Jabari Parker	Joel Embiid	Aaron Gordon	Dante Exum
Marcus Smart	Julius Randle	Nik Stauskus	Noah Vonleh	Elfrid Payton
Doug McDermott	Zach LaVine	T.J Warren	Jusuf Nurkic	Gary Harris
Bruno Caboclo	Rodney Hood	Shabazz Napier	Clint Capela	Kyle Anderson
Joe Harris	Spencer Dinwiddie	Jerami Grant	Glenn Robinson	Nikola Jokic
Dwight Powell	Jordan Clarkson			

Table 2: Table consisting of all the players in the dataset

in Table 3.

MP	The number of Minutes Played in the game
FG	The number of field goals (baskets) scored
FGA	The number of field goals (baskets) attempted
FG%	Percentage of field goals scored
3P	Number of 3 point field goals scored
3PA	Number of 3 point field goals attempted
3P%	Percentage of 3 point field goals scored
FT	Number of free throws made
FTA	Number of free throws attempted
FT%	Free throw percentage
ORB	Number of offensive rebounds
DRB	Number of defensive rebounds
TRB	Total number of rebounds
AST	Number of assists made
STL	Number of steals made
BLK	Number of blocks made
TOV	Number of turnovers conceded
PF	Number of personal fouls conceded
PTS	Number of points scored
GmSc	A score which determines how important a player was in a win
+/-	Net number of points scored when on the court

Table 3: Table explaining the box score stats

There are other factors which could determine the number of points scored by a player in a game which are not captured using just box score statistics. One of these factors is **player form**. This can often be hard to quantify, as there is not a statistic in basketball which explains how well a player is performing. However, a potential way to best represent form would be use a rolling-window of points scored from previous games and use this as a feature for predicting the points scored for the upcoming game. Additionally, another main factor not included in box scores is **opponent difficulty**. The motivation for including opponent difficulty is that teams vary in defensive capabilities which could impact how many points a player scores in a game.

In summary, the collection of features explored in this investigation is summarised in Table 2, as well as player form and opponent difficulty. The next chapter explains how

the most relevant features for predicting points per game were selected and also introduces the models used in this investigation.

2.3 Technical Background

The following section outlines the theory of the machine learning models used in this project:

2.3.1 Simple Moving Average

The moving average model is commonly used in time series data. The simple average model essentially uses the previous n data points to forecast future data points by taking the unweighted mean of these n points:

$$\bar{p}_{SMA} = \frac{p_M + p_{M-1} + ... + p_{M-(N-1)}}{n} = \frac{1}{n}\sum_{i=0}^{n-1} p_{M-i} \tag{1}$$

2.3.2 Simple Linear Regression

Ordinary Least Squares (OLS) or Linear Regression is a linear approach to modelling the relationship between an explanatory variable and the target variable. Given explanatory variable x and target variable y, the linear relationship is defined as follows:

$$y(x, w) = w_0 + w_1 x \tag{2}$$

$\mathbf{w}$ (the weight vector) encodes the relationship between the two variables. Simple linear regression attempts to best fit a line to a set of data points by finding values for $\mathbf{w}$ which minimises the sum of the squares of the vertical offsets of the points from the line. Essentially the aim is to minimise the following function:

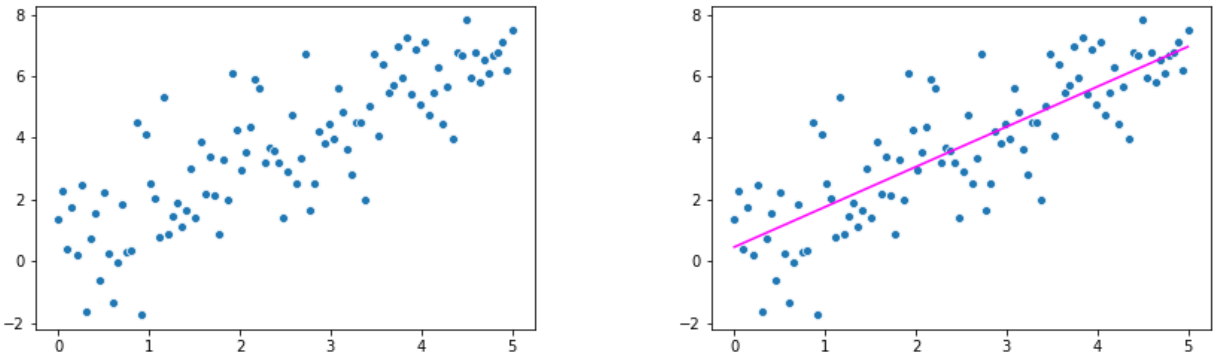
$$L(x) = \sum_{i=0}^{n} (y_i - \mathbf{w}^T x_i)^2 \tag{3}$$

Where $\mathbf{w}^T x_i$ is a point on the line and y_i is the data point that is vertical offset from $\mathbf{w}^T x_i$. In order to minimise this function the partial derivative of L is taken and the following derivative is equated to 0. As a result, the following equations encode the values of w_0 and w_1 which best fit the data points:

$$w_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} \tag{4}$$

$$w_0 = \bar{y} - w_1 \bar{x} \tag{5}$$

where $\bar{y}$ and $\bar{x}$ are the means of the y values and x values.



(a) Data Points Plotted

(b) Linear Relationship calculated

Figure 2: An example of Simple Linear Regression. The magenta line in Figure 1b) visualises the linear relationship between two variables. It can be seen that the two variables have a positive correlation

2.3.3 Bayesian Linear Regression

Bayesian Linear Regression also formulates a linear relationship between the explanatory and target variables, however unlike OLS the relationship is based off a probability distribution rather than point estimates. In other words, the target value is not estimated to be a single value but it is drawn from a specific probability distribution. For this investigation, the weights will be sampled from a Gaussian distribution when computing the target values. The reasoning behind this stems from the Central Limit Theorem. This model uses Bayes Theorem to produce probability distribution for the target values - called the posterior. A probability encoding an existing or prior belief of the weights (also called parameters) is multiplied by the likelihood of the data points. It is then divided by a normalisation constant. The prior belief will be a Gaussian distribution, and due to conjugacy, the posterior will also follow a Gaussian distribution.

$$y \sim N(\mathbf{w}^T\mathbf{X}, \sigma^2\mathbf{I}) \tag{6}$$

$$P(\mathbf{w}|y, \mathbf{X}) = \frac{P(y|\mathbf{X}, \mathbf{w})P(\mathbf{w})}{P(y|\mathbf{X})} \tag{7}$$

2.3.4 Kernel Ridge Regression

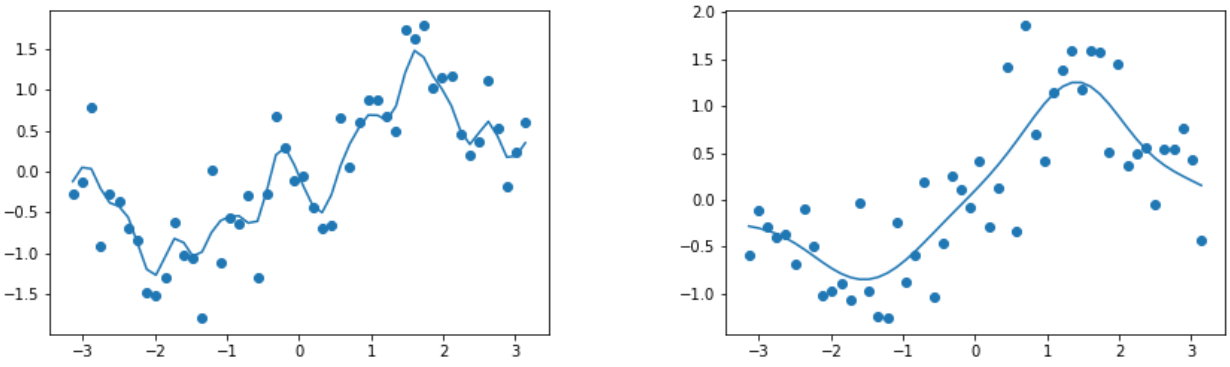
Kernelised Ridge Regression is a nonlinear approach for modelling the relationship between an explanatory variable and a target variable. It combines Ridge Regression with the 'kernel trick'.

Ridge Regression is similar to Least Squares Regression where a curve is best fitted to a set of data points through minimising a loss function specified by Equation (2). However, the major risk when attempting to fit a curve to data is overfitting. One simple method for avoiding overfitting is to include penalty term to $\mathbf{w}$ in the loss function. Subsequently

the loss function becomes:

$$L = \sum_{i=0}^{n} y_i - \mathbf{w}^T x_i + \lambda ||\mathbf{w}||^2 \tag{8}$$

λ is the regularisation parameter. If λ were to be zero, then the loss function function would be the same as the loss function for least squares.



(a) $\lambda = 12$ (b) $\lambda = 1$

Figure 3: Different values of λ has a large impact on the fit of a model. Figure 3a) implies that the model has learnt the training data too well leading to an overfit. Figure 3b) better fits the data points.

In order to achieve a nonlinear curve a kernel function, $k(x, x')$ is applied to all input values. Kernel functions describe the inner product of two input values that are mapped to a different feature space $\mathcal{X} \rightarrow \mathcal{F}$: $k(x_1, x_2) = \phi(x_1)^T \phi(x_2)$. The basis function $\phi(.)$ is unknown however it is not required as long as the mapped feature space is an inner product space; this is known as the kernel trick. The idea behind using kernels is that when the inputs are mapped to a different feature space, they can be classified linearly as seen in Figure 3. Examples of kernel functions include the Radial Basis Function, the Polynomial Kernel and the Fisher Kernel.

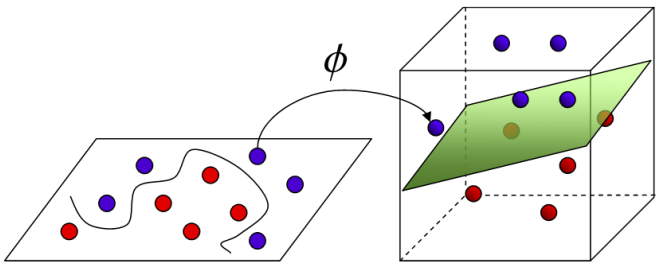


Figure 4: By applying a basis function, the data points are mapped from a 1-dimensional feature space to a 2-dimensional feature space, where it can be linearly separated

2.3.5 Multiple Linear Regression and Multivariable Kernel Ridge Regression

Multiple Linear Regression models a relationship between more than one explanatory variable and a target variable by fitting a linear equation to the observed data:

$$y_i = w_0 + w_1 x_i + w_2 x_i + ... + w_d x_i \tag{9}$$

Given n features, a feature matrix consisting of the explanatory variables $\mathbf{X}$ and a column vectors consisting of the target variable y and weights $\mathbf{w}$ can be represented as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_d \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{d1} & x_{d2} & x_{d3} & \dots & x_{dn} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix}$$

In order to establish a linear relationship between y and $\mathbf{X}$ the weights are calculated using the least squares method akin to simple linear regression. Therefore the following loss function that needs to be minimised is $Xw - y^2$. The formula for finding the weights which minimises the loss function is

$$\mathbf{w} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T y \tag{10}$$

Multi-variable Kernel Ridge Regression can be see as an extension of its single feature counterpart, where instead of training a 1-dimensional vector as the explanatory variable, an n dimensional vector consisting of many independent explanatory variables were trained.

2.4 Root Mean Squared Error

This investigation will use the Root Mean Squared Error (RMSE) quantify the error in each model. RMSE is that standard deviation between the values predicted by a machine learning model and the values observed.

$$RMSE = \sqrt{\frac{\sum_{i=0}^{n}(\hat{y}_i - y_i)}{n}} \tag{11}$$

In order to check whether a model has over fit or underfit the data, the RMSE from the training data and the RMSE of the test data will be compared. If the RMSE is drastically higher for the test data compared to the training data then the model has over fit the data. If the RMSE for both sets are similar then the model has fit the data well.

Additionally, the RMSE can be used to compare the efficacy between models. Models with a lower RMSE compared to others imply that they're better at forecasting the trajectory of player points per game compared to models which score a higher RMSE.

2.5 Existing Literature

2.5.1 ARIMA model Time Series Player Data [?]

DeLay et al. (2016) explores game-by-game data of one player, Derrick Rose, in order to forecast the number of points scored in upcoming games. More specifically this paper

attempts to find the best $ARIMA$ model that fits Derrick Rose's previous statistics in order to accurately predict the points scored in Rose's future games.

The paper uses data from the 2014-15 regular season and as a result the $ARIMA$ models included in this investigation were trained using only 51 games of the season (Rose only played 51 games of the regular season, the other 31 were missed due to injury).

$ARIMA(p, d, q)$ stands for Autoregressive Integrated Moving Average and is commonly used in time series analysis where the data displays non-stationary properties, that is the mean and variance changes over time. This model is a generalisation of the $ARMA(p, q)$ model, which combines the autoregressive model with the moving average model. The autoregressive ($AR(p)$) part of the model learns from the previous p games played and uses them as inputs for a regression model to predict the points scored in future games. The moving average ($MA(q)$) model essentially takes the average of the previous q data points. The 'integrated' part of the $ARIMA(p, d, q)$ model consists of finding the differences between d data points in order to remove the non-stationary element.

The motivation behind using the $ARIMA$ model is that DeLay assumed there would not be a seasonal trend over the course of the year and as a result the mean and variance of points scored over the course of the season would not change. Another assumption made was that the forecasted points scored by Rose in future games would be similar compared to his previous games implying that there would be no drastic improvement or deterioration in points scored by Rose in the near future.

The results produced in this paper suggest that an an integrated moving average of order 1 ($IMA(1, 1)$) best fit Derrick Rose's training data, however the forecasted data was slightly inconclusive. The predicted data points for future games converged to the average of the initial 51 data points. This was potentially due to the fact that the training data set was too small. DeLay believed that over time and given more data the model would predict more fluctuating data points before averaging out at at slower pace.

2.5.2 Weibull-Gamma Statistical Model

Hwang et al. (2012) attempted to forecast the trend of a small subset (7) of player's careers using a different statistical method, namely the Weibull-Gamma model. More specifically, Hwang attempted to forecast the average points per game (PPG) scored by players over the upcoming seasons. The subset of players were all free agents, meaning they were currently not under contract with any particular team in the NBA. This paper aimed to aid NBA franchises such that they could obtain a degree a foresight when deciding whether sign these free agents.

Before Hwang decided to use average PPG over a season as a method for evaluating player performance an array of different features were experimented with to find an accurate metric for player performance. Hwang's reasoning for using the average PPG over the course of a season was because it is a very commonly used statistic. Training data consisted of seven different players, the target variable was the average PPG for a season and the dependent variable was the season number.

The statistical model used was a mixture of the Weibull-Hazard and the Gamma function. The motivation behind using this model is that the assumption of performance over time is included. In other words, Hwang assumes that player performance will begin to decline

as the players partake in more NBA seasons and therefore he is expecting the average points scored per game to decline as more seasons occur.

The results achieved by Hwang after one season of predicting the average PPG for the season upcoming (2010-11) season were fairly encouraging. The difference in points never exceeded more than 2, proving to be a fairly accurate model.

A key difference between Hwang's thesis and the objective in this thesis is that Hwang does not attempt to predict the points scored for individual games throughout a season, only the average points scored per game over the entire season, for multiple seasons in the future. Therefore it can be deduced that this study was focused more on forecasting the general trend of player careers, attempting to decipher the effect of age on a players career rather than attempting to predict the points per game of a player against a particular team.

3 Application to the NBA Dataset

Scatter plots depicting the points scored over games played were created in order to visualise the relationship between these two variables before they were trained by the machine learning models which only consist of one explanatory variable. Certain games were removed in order to avoid the data from being skewed. For example, if a player had played only a small number of minutes of a game due to unforeseen circumstances such as obtaining an injury, it was removed from the dataset. Figure 5 is the scatter plot for one player, Nikola Jokic. The Figure also show the Least Squares Regression plot of the player in the dataset. As visualised in the Figures the variance of points scored over a game-by-game basis is very large, thus potentially making the task of predicting the exact number of points scored by players in a particular game a very challenging task. However a general trend can be deduced from these graphs. There is a weakly positive correlation between number of games played and points and therefore it can hypothesised that for the upcoming season this trend will continue. Some models in this investigation consist of one explanatory variable and a target variable, these include the Simple Moving Average model, Simple Linear Regression, Bayesian Linear Regression and Kernel Ridge Regression.

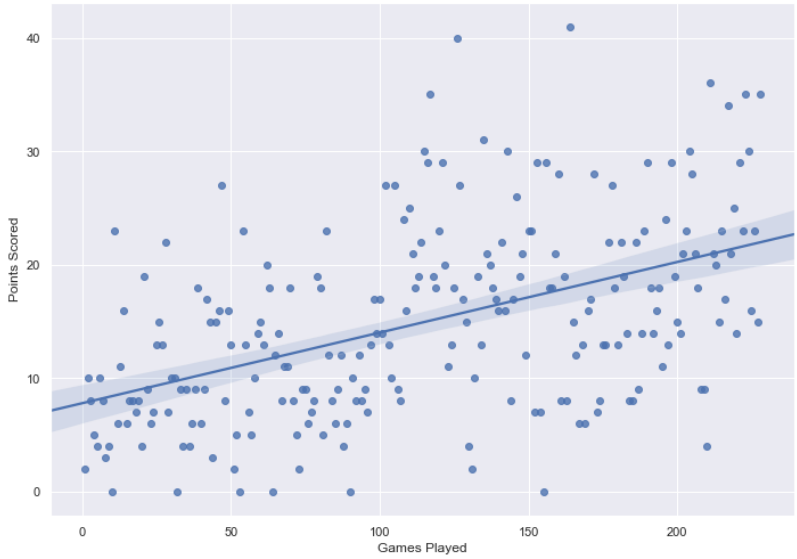


Figure 5: The Figure above visualise the relationship between the points scored of a player in the dataset over the course of their career's so far. The blue line shows the regression represents the linear relationship between the two variables and the shaded blue region represents one standard deviation.

The box scores were also collected for each player and the data was placed in an array for preprocessing. Player form was also added to the array. It was decided that the points scored for the previous n games would best resemble player form. Chapter 4.2 explains how the value of n was chosen. Furthermore opponent difficulty was also added to the array using the defensive rating metric provided by the NBA. Every team in the NBA is

given a defensive rating where the lower the rating implies the better the defence. These features were then subjected to feature selection methods described in Chapters 3.2 and 3.3. A subset of the features which best describe the target variable were selected and trained on the machine learning models. In this investigation, there are two models which will use this subset of features: Multiple Linear Regression and Multi-variable Kernel Ridge Regression.

3.1 Feature Selection

Feature selection is required for the models which use multiple features. Using more than one feature may allow us to explain the target variable better and produce more accurate results when forecasting points per game. Pair plots were produced to see if there was a correlation between a feature and the target variable.

The statistics in box score from the previous game, player form and opponent difficulty summarise the all features that are available in this this investigation. As stated earlier in this chapter, the features which aid in explaining the target variable were selected and the other features were removed.

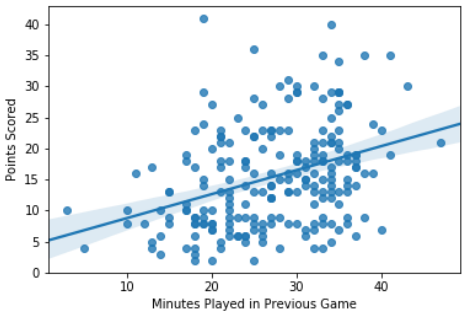
Example pair plots (Figure 6) of some of the features for Nikola Jokic can be seen. The results when visualising the correlation between the features and the target variable show that there is no correlation between the points scored and the opponent difficulty, implying that that the number of points scored for a player is independent of opponent. Additionally the same conclusion can be drawn for the plus-minus (+/-) statistic. However, other features such as field goal attempts (FGA), minutes played (MP) and a players GameScore (GmSc) present weakly positive correlation. This would indicate that these features may aid in forecasting a players points per game.

After visualising the correlation between the features and the target variable, feature selection methods were applied to the dataset. After applying these methods, the final subset of features will consist of those which best aid in forecasting the target variable.

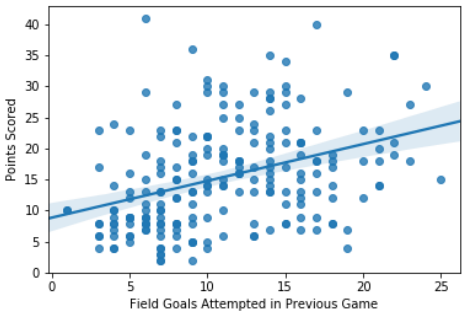
3.2 SelectKBest Algorithm

The 'SelectKBest' algorithm selects a subset of features of size k which have the strongest relationship with the target variable. A wide range of statistical tests can be used to select these features. The statistical test produces a score for each feature, and the top k features which have the highest score the features which have the strongest relationship with the target. A common test used for this algorithm is the chi-squared (χ^2) statistical test.

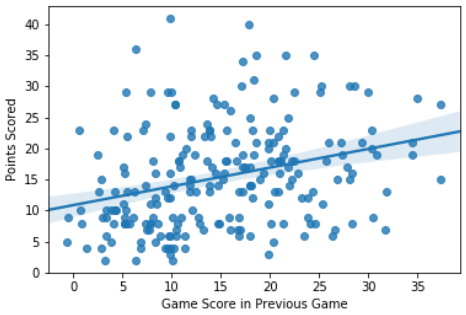
The dataset consisting of every player's statistics were subjected to the SelectKBest algorithm where the k most correlated features with points scored (using the chi-squared test) were selected. The question that arises when using this algorithm is how many features should we select? This is explored more in the upcoming chapters, however the general logic of combatting this issue was increasing the value of k, applying the k number of features to the model and recording the RMSE. If by adding more features, the RMSE for the training and test data increases, then the number of features will be reduced. After applying the SelectKBest algorithm to all player datasets, the most correlated feature was number of **games played**, followed by **points scored from the previous**



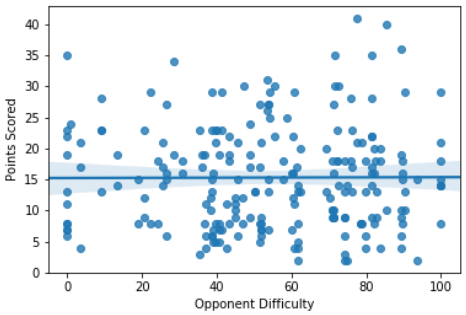
(a) Minutes Played



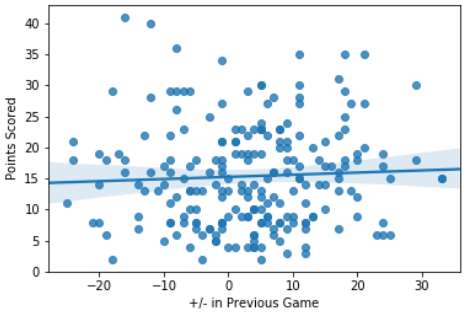
(b) Field Goals Attempted



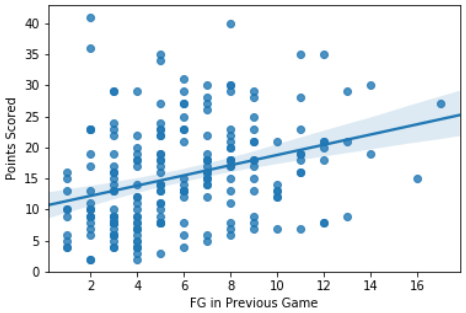
(c) GameScore



(d) Opponent Difficulty



(e) +/- Score



(f) Field Goals Made

Figure 6: The Figures above visualise the relationship between points scored in a game and specific stats from the prior game. This was done to see if there was a positive correlation between these features and the target variable. The Figures shown are taken from one player in the dataset

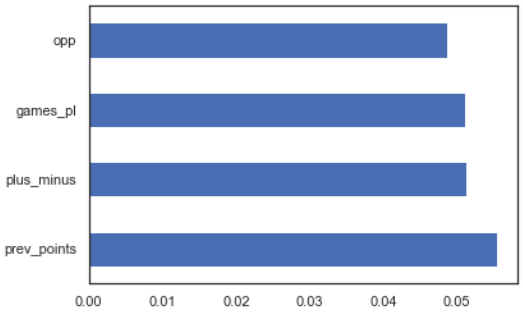
game. The next two features selected was the **game score** and the number of **field goals attempted from the previous game**.

3.3 Feature Importance Using the Extra-Trees Classifier

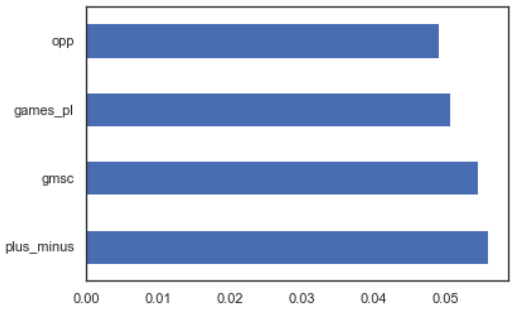
The Extra-Trees Classifier is an algorithm which builds multiple decision trees at random using observations from the training data and the some of the features present in the dataset. This classifier can be used to measure the relative importance of each feature on the target variable. The use that the Extra-Trees Classifier provides is that it can

produce a 'score' for every feature in the dataset, where the higher the score implies the more the correlated that feature is with the predicted variable.

The results obtained when selecting the most relevant features using the Extra-Trees classifier was extremely similar to the features obtained using the SelectKBest algorithm. For most players, the features which were highly correlated with points scored were the **number of games played**, the player's **game score** and the **points scored** from the previous game. However, due to the randomised nature of the extra trees classifier, on a few iterations of the algorithm, one of the highly correlated features for certain players consisted of the players plus-minus (+/-) from the previous game and the opponent they were currently playing. Examples of these are shown in the Figures below. As a result, these features were also experimented with and applied to the machine learning models in order to see whether they yielded more accurate results.



(a) One iteration of Extra-Trees Classifier



(b) Another iteration of Extra-Trees Classifier

Figure 7: The bar charts show two different iterations of the extra-tree classifier for one player. When attempting to choose the 4 most correlated features, some features were selected in one iteration and not selected in another. As a result, the models were applied with both sets of features to see which one resulted in the lowest RMSE

In summary, the most relevant features selected by the SelectKBest algorithm and the Extra-Trees classifier was: the game number, the points scored in the previous game, the player's GameScore and the number of field goals attempted from the previous game.

3.4 Motivation for the Machine Learning Models

The machine learning models were then trained using the features selected from Chapters 3.2 and 3.3. The motivations and assumptions of these models are discussed with regards to why they may be successful in achieving the aim of this project.

3.4.1 Simple Moving Average Model

The Simple Moving Average assumes that the points scored in the previous n games will be sufficient information when forecasting the points scored in the 2018/19 NBA season. For example, if n is chosen to be 20 games, and a player averages 15 points a game over the previous 20 games, the Simple Moving Average model will assume this player will score 15 points a game for every game in the upcoming season. This can be interpreted

as a naive assumption for predicting the number of points for specific games because the number of points scored on a game by game basis varies greatly. However, the Simple Moving Average model may be more accurate at predicting the average number of points scored over the course of the whole season. This is because the model takes into account a players recent form, and assumes this recent form will be extrapolated for future games. On the other hand, this model also implies that the player's performances will plateau, suggesting that there will not be any increase or decrease in player points per game for the entire season.

3.4.2 Simple Linear Regression

For this model the target variable will be points scored per game and the explanatory variable will be the game number. Furthermore, Simple Linear Regression will produce a linear trend between the number of games played in the NBA and the points scored per game. As a result, when attempting to forecast the points scored games in the upcoming 2018/19 season, the model will work under the assumption that the points scored in every following game will follow a linear trajectory resembling the trajectory of the fitted line produced from training data (previous seasons). In other words, the points scored in every game will either continue to increase, decrease or the stay the same without any fluctuations throughout the season. It can be argued that the Simple Linear Regression model better fits the training data compared to the Simple Moving Average model because it encodes the players trajectory and therefore assumes that players will continue to increase or decrease in performance for the upcoming season.

3.4.3 Bayesian Linear Regression

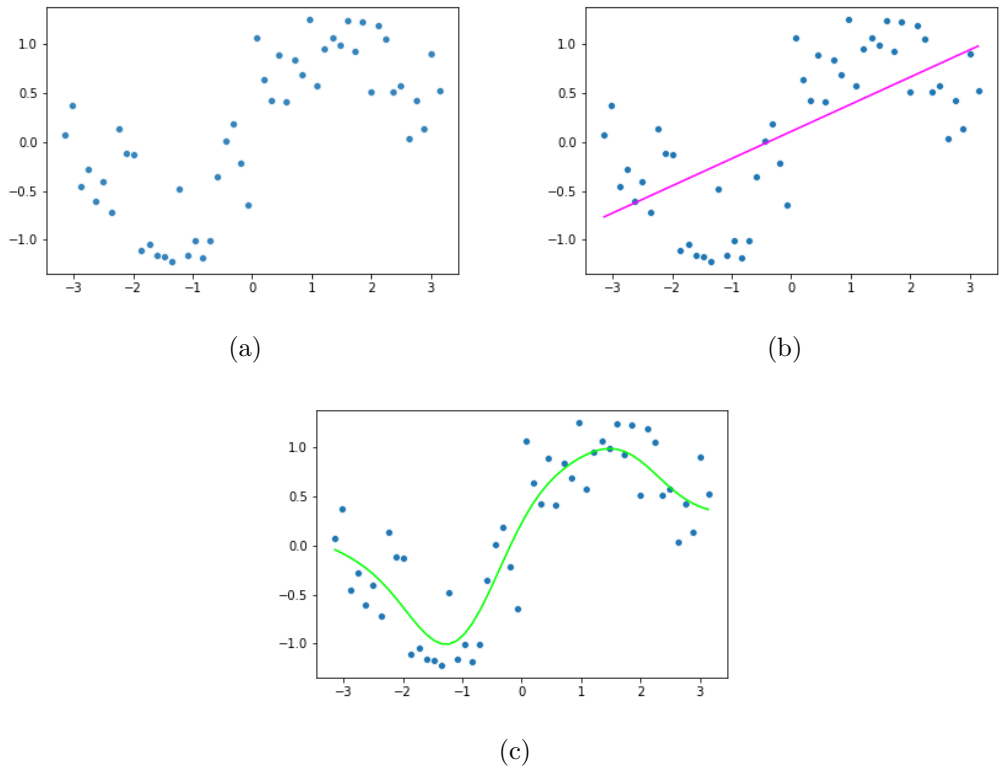
One of the benefits of using Bayesian linear regression is that a prior belief about the model parameters can be specified, rather than assuming that all the information regarding the parameters is included within the data set. Another benefit of Bayesian Linear Regression is that uncertainty is included in our model due to the fact that the posterior is a probability distribution. If the dataset is small the posterior distribution of the parameters will be more spread out. Therefore it can be implied that the model is more uncertain in its belief of parameter values. As more games are observed the posterior probability is 'updated' and the model becomes more certain concerning its parameter values and as a result becomes more certain of the trajectory of the player's points per game for the 2018/19 season. If infinite data points were to be observed, the prior belief would essentially be washed out, and the best fitting line would converge to the OLS best fitting line.

The main motivation for including this model in this investigation is that a prior belief about the trajectory a particular player's upcoming season. If there is a belief that a certain player will definitely perform better for this upcoming season this belief can be encoded into the model.

3.4.4 Kernel Ridge Regression

Kernel Ridge Regression will produce a non-linear fit of the game played and the points scored. The motivation for using this model in this investigation is that the relationship

between the number of games played and the number of points scored may not be linear and therefore a non-linear curve may produce a better fit compared to its linear counterpart. For example a players performances may have improved exponentially over the last 40 games of his career, and therefore the Kernel Ridge Regression model will assume that this trend will continue for the upcoming season. As a result it can be argued that this model will best fit the player's career, allowing for a more accurate forecast of points scored in future games.



(a) (b)

(c)

Figure 8: The relationship between the two variables are not linear, therefore, attempting to use a linear regression would result in a poor fit of the data observed in b). Kernel ridge regression produces a non-linear curve which better fits the relationship between the two variables, seen in c)

3.4.5 Multiple Linear Regression and Multivariable Kernel Ridge Regression

The motivation for using multi-variable regression models such as Multiple Linear Regression and Multi-variable Kernel Ridge Regression is that more than one feature can be used to aid in forecasting the target variable. The other models included in this investigation only use games played to describe points scored. These models will utilise other features which also aid in predicting the number of points scored such as the GameScore (GmSc) and the Field Goals Attempted (FGA) statistics. For example if a player's FGA has been increasing over the past few games, it could indicate that he is getting more opportunity to score more points in those games, therefore these models can utilise this additional information and predict that the number of points that this player will score

in the upcoming game will also increase. Using more features may allow for a more accurate prediction of player points per game. As stated at the end of Chapter 3.3, the features that proved to best explain the target were: the number of games played in the players career, GameScore, Field Goals Attempted and the number of points scored in the previous game.

Multivariable Kernel Ridge Regression is a simple extension of its single feature counterpart. Additionally, like Multiple linear regression there is or than one explanatory variable describing the target variable.

4 Experiments and Results

4.1 Parameter Tuning

4.1.1 Choosing n for the Simple Moving Average Model

To find the value for n which resulted in the lowest testing error different values were experimented with for each player. The n which resulted in the lowest testing error was 20 games. The testing errors for different n is shown below.

Number of Games (n)	**Mean Test RMSE**
1	7.01
2	6.96
5	6.96
10	6.95
20	6.90
25	6.92
30	6.96

Table 4: The different RMSE values when using different number of n for predicting the number of points for every game of the season. As the table shows, using a window of 20 games produces the lowest testing error.

4.1.2 Picking the correct Regularisation parameter

For the kernelised methods, it was vital that the correct regularisation parameter was selected in order to prevent overfitting. When experimenting with different values, it was concluded that higher values of λ resulted in an overfitting of the training data and thus resulted in a poor fit for the test data. However, on the other hand, if the regularisation parameter was too low, the models would under fit the training data and as a result the RMSE for the test data would be high. As a result the regularisation parameter was chosen by looping through different values, and choosing the value which resulted in the lowest RMSE for the training and testing data. The graph below show the testing data's RMSE for single feature kernel regression and multi feature kernel regression with varying values of lambda.

It can be seen in Figure 12 that there is a fall in the test RMSE as the regularisation parameter increases, but as the regularisation parameter rises past a certain value, the test RMSE begins to increase suggesting that the model has overfit the training data.

4.1.3 Choosing Correct window for form

When undergoing feature selection, for player form, only the previous game's points scored was taken into account, however, in order to capture form more accurately, a window of

Figure 9: The RMSE of the testing data for Kernel Ridge Regression with different regularisation values

previous n games was experimented with. Choosing the number of games to use in this window proved to be a challenging task. The method to combat this was to vary the window size when training and testing the models and see which window size would result in the lowest average testing RMSE. The chart below depicts the average RMSE for the multivariable models when different sized windows were used.

Model	**Mean RMSE**
Simple Moving Average	3.80
Simple Linear Regression	3.13
Bayesian Linear Regression	3.73
Kernel Ridge Regression	2.86
Multiple Linear Regression	3.13
Multivariable Kernel Ridge Regression	2.90

Table 5: The different RMSE values when using different window sizes

This approach seemed the most logical as the previous number of games which resulted in the lowest average RMSE would mean that it is more accurate at forecasting the points scored for the next game.

4.2 Results

After the models learned the training data, they were evaluated using the test dataset - the results are shown below. Table 4 shows the average RMSE of each model when predicting points scored per game for every player in the dataset for the 2018/19 season.

Table 5 depicts the models RMSE for predicting for players season average points per

game. In other words, the points predicted for each game of a player is averaged and compared to the observed season average the player scored. This table can be used to see the overall players trajectory for the season, and often determines whether a player had a successful season.

Model	Mean RMSE
Simple Moving Average	6.71
Simple Linear Regression	6.39
Bayesian Linear Regression	6.90
Kernel Ridge Regression	6.27
Multiple Linear Regression	6.60
Multivariable Kernel Ridge Regression	6.27

Table 6: Results when attempting to forecast the points scored for every player on a game by game basis

Model	Mean RMSE
Simple Moving Average	3.80
Simple Linear Regression	3.13
Bayesian Linear Regression	3.73
Kernel Ridge Regression	2.86
Multiple Linear Regression	3.13
Multivariable Kernel Ridge Regression	2.90

Table 7: Results when attempting to forecast season average points per game in the 18/19 season

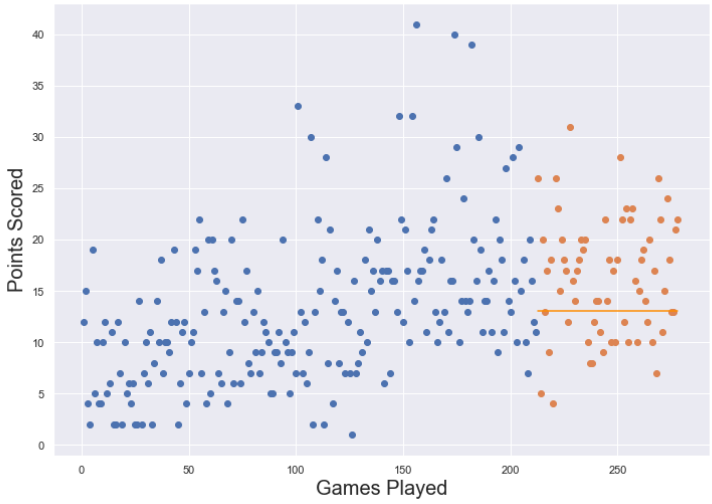
4.2.1 Simple Moving Average

The simple moving average, arguably the most naive method used in this investigation, took the mean of the last n games and assumed that future points scored would be the average produced. Choosing the size of n seemed to be a challenging task. In order to find the value which resulted in the lowest RMSE when predicting the points of every game in the 18/19 season, different values were experimented with. The size of n which resulted in the lowest RMSE was 20, suggesting that the previous 20 games were the most accurate when using this model to forecast future points scored per game. Example plots forecasting the points scored for the 2018/19 can be seen in Figure 9.

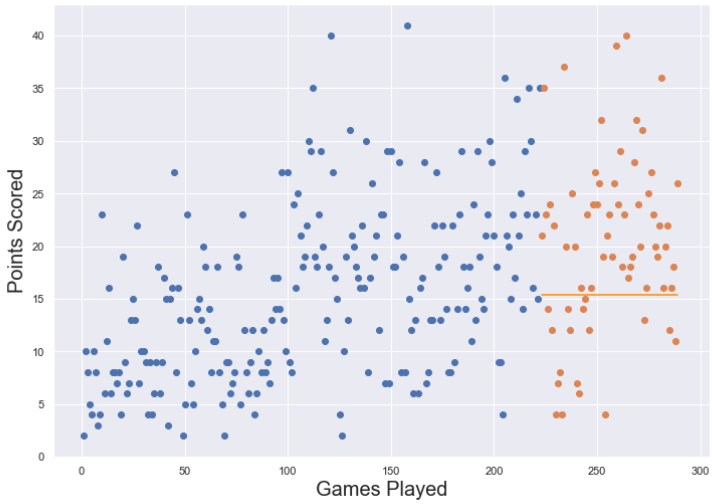
4.2.2 Simple and Bayesian Linear Regression

Simple Linear Regression resulted in a lower RMSE compared to the simple moving average model, implying that this model is a better fit to the data compared the previous model. Example plots of two players are shown in Figure 10.

On the other hand, Bayesian Linear Regression produced the highest RMSE out of all the other models in this investigation.



(a) SMA results for Aaron Gordon

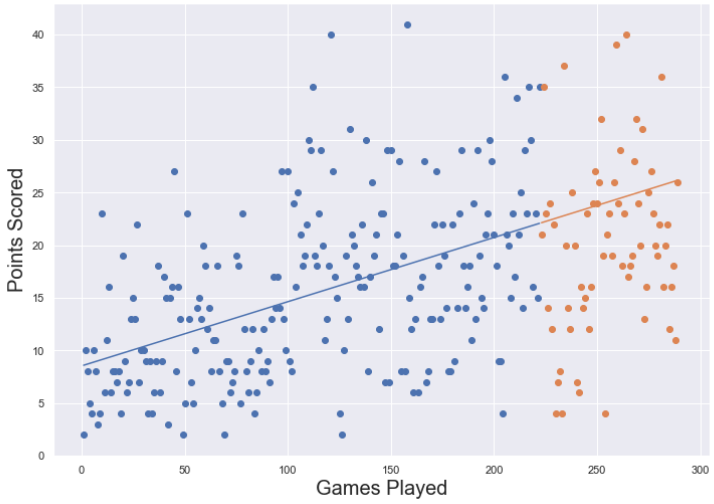


(b) SMA results for Nikola Jokic

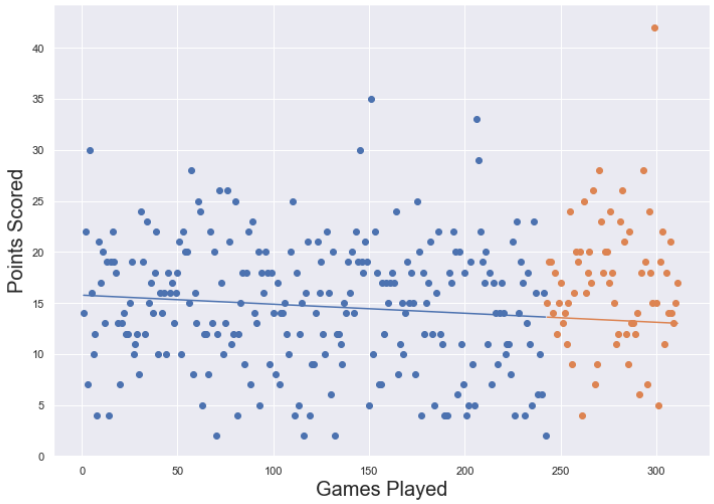
Figure 10: These Figures show the results of the SMA model. The blue data points represents the training data points. The orange line depicts the prediction of the SMA model. The orange data points are the points actually scored by the players in the 18/19 season

4.2.3 Kernel Ridge Regression

Kernel Ridge Regression produced a lower RMSE compared to the other models in the investigation, however choosing the correct regularisation parameter was key in finding the best fitting model whilst also avoiding overfitting of the training data. The results produced suggest that a non-linear curve fits the relationship between the games played and points scored better than a linear fit.



(a) Linear Regression - Nikola Jokic

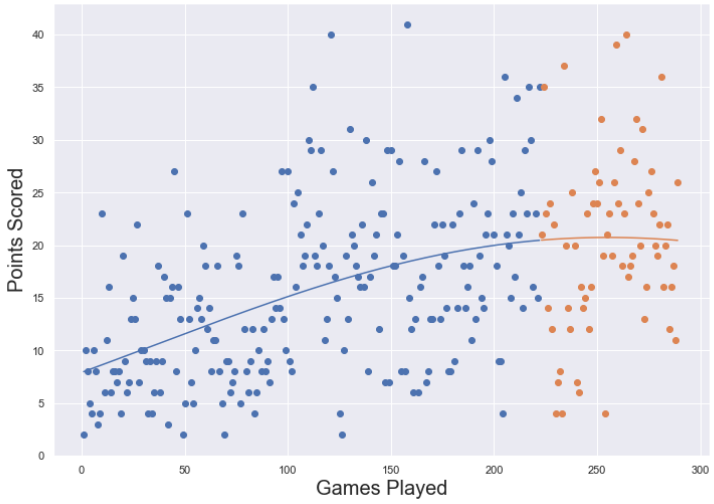


(b) Linear Regression - Jordan Clarkson

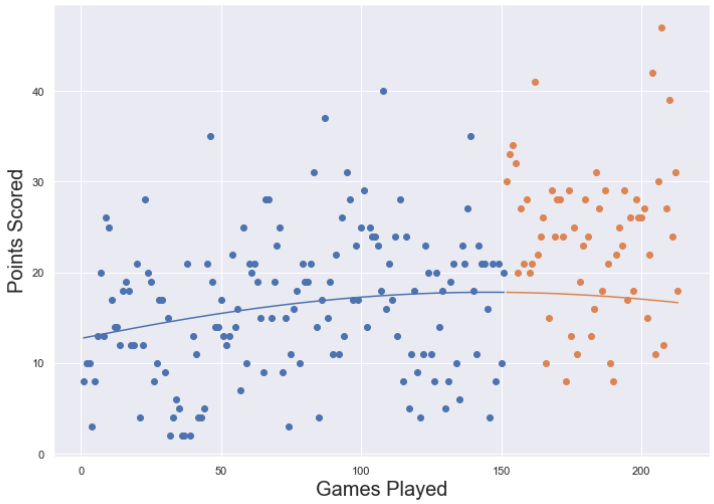
Figure 11: These Figures show the results of the simple linear regression model. The blue data points represents the training data points. The blue line depicts the best fitting line of the training data and the orange line is the predicted points scored for every game in the 2018/19 season. The orange data points are the points actually scored by the players in the 18/19 season

4.2.4 Multivariable Linear Regression and Kernel Ridge Regression

Multivariable linear regression produced a larger error value compared to its simple counterpart, however multivariable Kernel Ridge Regression produced extremely similar results to single feature kernel ridge regression. As stated in the previous section, the features selected were points scored from previous games, as well as the number of FGA attempts



(a) Kernel Ridge Regression - Nikola Jokic



(b) Kernel Ridge Regression - Zach LaVine

Figure 12: These Figures depict the results produced from the Kernel Ridge Regression model for two players in the dataset, Nikola Jokic and Zach Lavine.

and the Game Score from the previous games.

When looking at Table 5, we can see that the models varied in accuracy when compared to one another. We can see that both simple Kernel Ridge Regression and Multivariable Kernel Ridge Regression were the most accurate for forecasting the points scored on a game by game basis - however, the difference in error values are extremely small.

Single feature Kernel Ridge Regression produced the lowest error when forecasting the average points scored of players in the 2018/19 season regarding points scored.

4.3 Discussion and Analysis

4.3.1 Forecasting Player Points Per Game for Every Game

Firstly, the average RMSE for each model ranged from 6.27-6.90 points per game for the players in the dataset. This implies that predicting the exact number of points scored in a game using these models is a challenging task. The number of points scored on a game by game basis can vary and fluctuate by a large amount, and these models were not able to capture these fluctuations. An example of this occurred this season, where Nikola Jokic scored a season high 40 points in the 42nd game of the season, but the models used in this investigation predicted he would only score between 20 to 23 points per game, which is within the range of points that Jokic had scored in the previous 3 games.

4.3.2 Forecasting Season Average Points Per Game

On the other hand predicting the season average of points for the players resulted in a lower RMSE. Thus, it can be argued that the models performed better when attempting to decipher the average of the number of points scored by a player over a season compared to every individual game in a season. These models achieved reasonable success when attempting to give foresight in overall future performance. This can be useful for NBA franchises when they are attempting to forecast a particular player's average points scored for an upcoming season.

The results produced by the regression models for predicting the season average points scored were more accurate for some players compared to other player's, suggesting that the regression models suited some player's careers better than other players. For example, the Kernel Ridge Regression model forecasted that Nikola Jokic would average 20.9 points per game which was close to the 20.1 points per game he achieved. On the other hand, this model predicted Joel Embiid would average 22.3 points per game based off of all of his career games, however he managed to achieve a season average of 27.5 points per game, 5.2 points greater than the prediction and a much larger average compared to his previous seasons. This example shows that these models are not able to anticipate large changes in player form for future seasons.

4.3.3 Comparing the Models

When choosing the model which best fits the data, the results show that single feature kernel ridge regression produced the lowest RMSE when attempting to predict points scored for every game of the 18/19 NBA season as well forecasting the average points scored per game all players included in the dataset.

These results suggest that the trend of player performance over the course of his career is not linear. The plots confirm this assumption and can be seen in Figure 11a) (Nikola Jokic) where this players points scored initially increases at a reasonable rate as the number of games played increases, however the rate of increase of points scored begins to

plateau before the upcoming season. Therefore this model predicts that the number of points scored for the 2018/19 season will follow this trend.

A potential reason why the kernelised models produces a slightly lower testing RMSE compared to the linear models is the assumption that games played closer to the 2018/19 season hold more importance compared to the games played early on in a players career. Linear Regression attempts to find a best fitting linear relationship between the explanatory and target variable using all the data points, however, data points from games which are early in a players career may not be representative for a players career compared to later games.

When comparing the single feature models to the multivariable models, the results display that the single feature methods produce a similar or even a lower RMSE compared to their multivariable counterparts. The results here suggest that the number of games played is sufficient enough to produce the most accurate forecasting of points scored as possible, and that the additional features included do not further improve accuracy of the results.

However, having stated the above, the RMSE for each model are extremely close between one another when predicting game by game results and season average results. All regression models performed similarly to one another, and it can be argued that no model is significantly more accurate than one another.

4.3.4 Limitations in the Models

There were some limitations in the models that were used in this investigation. The main limitation that most of the models encountered were simple regression models. They were not able to forecast the variance of points scored on a game by game basis and they only gave a general trend of the points scored. Particularly for the Linear Regression models and the Simple Moving Average model, a linear relationship could be conceived as a naive assumption after looking the relationship of points scored over time. Therefore, if basketball enthusiasts were to bet on a player scoring a specific number of points in a game, they may not have too much confidence in using these models.

Additionally, the regression models were sensitive to outliers which could have skewed results. For example, if a player had not played well in a prior game due to fatigue,resulting in him scoring fewer points, this would have skewed the models into predicting a slightly lower number of points scored for the next game.

4.3.5 Overfitting Problem

As stated before, avoiding overfitting is key when attempting to forecast future outcomes when using machine learning models. The RMSE of the training data was compared to the test data.

Model	**Mean RMSE of Training Data**	**Mean RMSE of Test Data**
Simple Moving Average	5.91	6.71
Simple Linear Regression	5.69	6.39
Bayesian Linear Regression	6.01	6.90
Kernel Ridge Regression	5.50	6.27
Multiple Linear Regression	5.67	6.60
Multivariable Kernel Ridge Regression	5.47	6.27

Table 8: Comparing the RMSE of the training data and the testing data for every model when attempting to forecast the points scored for players for every game.

Model	**Mean RMSE of Training Data**	**Mean RMSE of Test Data**
Simple Moving Average	2.76	3.80
Simple Linear Regression	2.30	3.13
Bayesian Linear Regression	2.47	3.73
Kernel Ridge Regression	2.19	2.86
Multiple Linear Regression	2.35	3.13
Multivariable Kernel Ridge Regression	2.27	2.90

Table 9: Comparing the RMSE of the training data and the testing data for every model when attempting to forecast the average points scored per game over the course of the season

5 Limitations

There were many limitations involved when attempting to predict the target variable. Firstly, capturing player form as a feature proved to be difficult. As explained before, this investigation used points scored from a specific number of previous games. However, this assumption does not completely capture the form of a player. For example, this assumption would not be able to foresee whether a player has an 'off-game' and doesn't manage to score as many points as usual. Additionally, players often have a busy schedule and can get fatigued or tired when playing multiple games in a short amount of time and thus can affect the number of points scored in a game. This was not taken into account in this investigation. Also, although none of the players in the dataset did suffer from any long term injuries, if NBA franchises were to use these models to forecast player performance , it would not be able to forecast any injuries that players may get.

However, one factor that it is believe did in fact limit the results, is that certain players did change teams for the 2018/19 season. The reason this could affect the results is because the players role may change if he changes team. For example, if the player changes team which has better players compared to his former team, he may not play as much per game and as a result the number of points the player scored may decrease. Additionally, changing team also means changing teammates. As a result, teammate chemistry would have changed and this could have directly affected the point scored by the players. An example of this occurring in the dataset was Julius Randle, where he moved from the Los Angeles Lakers to the New Orleans Pelicans. Resultantly, Randle's average points per game for the season increased dramatically from the previous season (16.1 points per game to 21.4). These models were not able to quantify the effect of a player changing teams and as a result would limit the results for players in this circumstance.

6 Conclusions and Future Work

The aim of this investigation, stated in Chapter 1.2, was to find out whether machine learning would aid in forecasting future player performances. More specifically, this investigation explored whether machine learning models could predict player points per game for every game over the course of the 2018/19 season and whether these models could also forecast the average points scored per game for this season.

With regards to predicting the exact number of points scored every game, the models all performed similarly, however the testing error was relatively high in every model. Therefore, it can be concluded that these models are unable to accurately forecast points scored in specific games accurately. Player performances in the NBA can vary by a lot on a game by game basis due to factors that cannot be captured using the features available such as player mentality and player tiredness.

However, on the other hand the models performed better when attempting to forecasting averaging points per game for the season, the models performed better. As a result it can be concluded that the models explored in this investigation performed better when trying to achieve this aim. The results show that Kernel Ridge Regression was the model which produced the lowest error value - although the testing between each model was fairly close between all the models. It can be concluded that when attempting to accurately predict the average points scored for a player, a non-linear fit of points scored over games played for a players career is enough information to achieve this.

This investigation explored multiple regression models in order to best predict player outcomes for the 2018/19 season. Although the regression models seemed to predict the season averages with a degree of accuracy, forecasting outcomes for specific games proved to be too challenging for these models. As a result, future work in developing a more accurate work would be desirable.