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# Sports Data Mining Technology Used in Basketball Outcome Prediction

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I certify that this dissertation which I now submit for examination for the award of MSc in Computing (Knowledge Management), is entirely my own work and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the test of my work.

This dissertation was prepared according to the regulations for postgraduate study of the Dublin Institute of Technology and has not been submitted in whole or part for an award in any other Institute or University.

The work reported on in this dissertation conforms to the principles and requirements of the Institute's guidelines for ethics in research.

***Signed:*** _____

***Date:*** ***31-08-2012***

# ABSTRACT

Driven by the increasing comprehensive data in sports datasets and data mining technique successfully used in different area, sports data mining technique emerges and enables us to find hidden knowledge to impact the sport industry. In many instances, predicting the outcomes of sporting events has always been a challenging and attractive work and is therefore drawing a wide concern to conduct research in this field.

This project focuses on using machine learning algorithms to build a model for predicting the NBA game outcomes and the algorithms involve Simple Logistics Classifier, Artificial Neural Networks, SVM and Naïve Bayes. In order to complete a convincing result, data of 5 regular NBA seasons was collected for model training and data of 1 NBA regular season was used as scoring dataset.

After processes of automated data collection and cloud techniques enabled data management, a data mart containing NBA statistics data is built. Then machine learning models mentioned above is trained and tested by consuming data in the data mart. After applying scoring dataset to evaluate the model accuracy, Simple Logistics Classifier finally yields the best result with an accuracy of 69.67%.

The results obtained are compared to other methods from different source. It was found that results of this project are more persuasive since such a vast quantity of data was applied in this project. Meanwhile, it can be referenced for the future work.



**Key words:** *NBA, data mining, machine learning, prediction, data management*

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I would like to express my sincere thanks …….

*(thank all the people how have assisted you in completing your dissertation. Start with your supervisor, all DIT staff that may have helped, other people can include family and friends, industrial and academic staff from other institution, etc.)*

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# 1 INTRODUCTION

## *1.1 Introduction to Project*

Before the advent of data mining, sports organizations mostly depended on human experience which comes from coaches, scouts, managers, players. It was believed that those experts will convert the history record into useful knowledge. But when the scope of the data they collected more and more consummate, sports organisation looked for more methods to harness those data they already had. Sports data mining techniques can contribute for a better performance by leveraging historical game records and combining game related information and is therefore more and more people devote themselves to this field.

National Basketball Association (NBA) since its origin has over 60 years. During this organisation grow up there are 30 teams formed and divided into Eastern Conference and Western Conference. For the regular season will have 82 games for each team and post season using a best-of-seven series scheme. So a conservative estimate, there will be at least about 12,300 games generated.

A mass of data was generated after each NBA game played; those existed data allow us to discover something invisible valuable knowledge. When people pay attention to their favourite team or players, they definitely will concern about the game outcome. However, predicting the outcomes of competitive sport has always been a challenging and attractive work. This project focus on data mining techniques used to predict the NBA game outcome.

## *1.2 Background*

With the popularity of the Internet, the amount of information is explosive growth. Faced with this boundless stretch of data, more and more people are devoted to exploring the value of data. Although today's database technique can carry data size up to hundreds of millions, there is still not a mature technique can be used to help us

understand data, analyse data, and covert data into useful knowledge. In the past, people used to take the experience from experts to compare, filter, synthesize, and then extract rules and knowledge. However, purely depend on the database knowledge to search and combine data can not satisfy all the requirements from huge business needs. Due to the limitation of the experts and leaders, the reliability of some of gained knowledge will be discounted. When the traditional knowledge acquisition techniques cannot handle the large amount of data, data mining techniques emerge as a practical solution. Data mining is a cross-discipline subject, and its basic objective is to extract hidden, potential and valuable knowledge from large amounts data. Now data mining technique begin to shine in different area, and data mining technique become more and more mature.

Likewise, the data in sports organization also increasing avaliable. In the past, sports organization transformed historical data into useful knowledge mostly depend on the experience from coaches, scouts and managers. However, relying only on the experts' experience and intuition could not discover all the value and potential of collected data. A more science approach was needed to use the data, so sports data mining emerges as the times require.

Currently, sports data mining has been successfully used in many fields, such as baseball, soccer, cricket football, hockey etc. The most famous application is baseball. People are familiar with the movie Moneyball which tells a story about team manager Billy Beane who is The Oakland A's General Manager who used sports data mining knowledge to organise his team and finally win the game. This book subverted traditional sports management ideas. Billy Beane's philosophy is to use very little funds to operate the club, he broke with the conventional method, using historical data and data mining methods to build the evaluation model, and unitized low cost purchased at low cost those undervalued players. Finally, made their team has the ability to fight with the famous New York Yankees.()

Moneyball inspired people to ask the similar question in different types of sports. Dean Oliver was the first data analyst who brought the data mining technique into basketball. Currently, with the standardization and maturity of basketball rule, NBA wave rolled up all over the world. Many data mining tools were born to NBA data mining, such as

Advanced Scout, Synergy Online etc. Meanwhile, those related data sources were also more and more improvable.

When people were concerned about the highlight moments in the game, they also started to think about forecasting the game outcome. It is different from digital lottery which purely focus on lucky or rules, sports prediction has lots of factors to influence the game outcome, and basketball itself is a competitive sport. But while there are contingencies in the game result and also exists a certain level of inevitability. So In this project, collected data will be used to explain the inevitability.

## *1.3 Research problem*

Basketball is a valuable area for sports data mining since it already provides a readily available database. Meanwhile, sports data mining has experienced rapid growth and it begins with those sporting enthusiasts who seek prediction results, tools and related techniques are developed to better measure both player and team performance. Although lots of enthusiasts and experts devoted to research sports data mining in basketball, these include: people used data mining methodology to adjust strategy by coaches; like data mining used in baseball, and it also suit to basketball (e.g. choose their players and control players' salary etc). There is still a broad space for discovering more value. One of the most famous applications of data mining is customer relationship management, especially for customer churn prediction. Data mining gives lots of methods for forecasting.

Thus, data mining technique as a tool for performing NBA game outcome prediction is the key research problem of this dissertation and the results can provide useful insights on its application to data mining tasks and further research direction for this type of resource.

## *1.4 Research objectives*

Having in mind the research problem and intellectual challenges posed in the previous sections, the objectives of this dissertation's research can be outlined as follows:

- Investigate related field of data mining and knowledge discover technique.
- Review research in sports data mining, the state of the applications, tools and limitations for prediction performance.
- Review literature on previous case and algorithms used in predicting sports game outcome.
- Collect dataset and manage data into a state of unity for the preparation of experiment.
- Divide data set into training, cross-validation, and test set; Experiment with predictive algorithms.
- Design the experiment use different techniques and evaluate the result with applying dataset.
- Analyse results and compare results with other research in the literature using the same methodology.

## *1.5 Research methodology*

As part of the dissertation, both primary and secondary research will be used during the creation of this dissertation; the secondary research program will take the form of an extensive literature review on the field of NBA history; machine learning algorithm for predicting; data mining; sports data mining; sports data mining used in NBA and others' similar research or experiment. The following resources were used to perform research.

- Research journals and periodicals (ACM, IEEE, SLAM etc)
- Published paper in the relevant areas.
- Websites and discussion groups associated to relevant research.
- Published dissertation in the related areas.
- Sports Newspaper.

The primary research is an experiment in prediction the results of the NBA games which uses data mining techniques and machine learning algorithms. The experiment is the key in this project and will involve the following process:

- Automated collection of raw data from website publishing NBA statistics data.
- Data management including database and data marts design and implementation
- Design and implementation of predictive model fitting experiment.
- Trained models scoring and evaluation.

## *1.6 Resources*

In this dissertation, the following resources were identified as fundamental requirements:

- Data set was obtained from (basketball-reference.com); (Databasebasketball.com) and the official NBA website (NBA.com). Some benchmark data for evaluating this project is from some major NBA game result prediction website, such as (Team Rankings).
- Regularly contact with supervisor, for review and guidance throughout the preparation of the dissertation.
- Access to other members of DIT research staff as needed, for addressing more technical questions and sharing ideas.
- Personal Computer system or laptop of recent specification for setting up and executing experiment.
- Access to library resources for research in books and periodicals.

- The WEKA data mining tool is chosen as the major tool for model fitting. It is available as a stand-alone application for data analysis and it also provides Java programming interface for deep product integration.
- Ruby programming will be used in this project
- Amazon EC2 cloud service will be rented for experiment due to the capability of my own laptop is limited.
- MySQL will be used for storing NBA game statistics information and game related information and building Data Mart.
- Computer with network access. The availability of a computer with Internet access from DIT and home to remote database, relevant websites and Amazon cloud services.

## *1.7 Scope and Limitations*

This research aims to predict the result of the basketball game using data mining technique with comprehensive statistical data and game related data and finally generates a persuasive model. By taking advantages of machine learning approach, ideally the predictive model would output reasonable prediction accuracy and this model can be used as a reference to make game strategy before games or can be used for sports betting.

The main research of this project is to use machine learning algorithms to predict the result for basketball game, Logistic Regression, Support Vector Machine, Artificial Neural Networks and Naïve Bayes respectively. So the accuracy of the prediction of the result is the important point of this dissertation.

Although data mining technique has been used very commonly, in the field of basketball game outcome prediction is still not mature. Most researches and experiment utilized the statistics method and probability methodology to generate a simple liner formula to forecast the game result, which inspires us to utilize different method to try out. Logistic Regression is the simplest and most commonly used linear classifier to separate linear separable classes. Support Vector Machine (SVM) with non-linear kernels and Artificial Neural Networks are most popular non-linear

classifiers for capturing non-linear relationships among features. Naïve Bayes Classifier is a model based on probability theory with assumption of conditional indecency among features. These four models used in this project is very representative, and they covers most common relationship among features.

Due to the most research in basketball is for coach to combine their team, the research for predicting the game result most used the statistic method, meanwhile a different choice of parameters than ones in this project, so a limited evaluation by experiment.

In another hand, basketball itself is a competitive sport which blends a lot of uncertain factors like injury; competitive state good or bad; players' contract expired or player is traded to other team, etc. The game result also has a close relationship with the players' ability. Many factors influence the game result which is the characters of competitive sports, so the experiment outcomes maybe not fully accurate due to a number of factors.

Because of NBA game in the whole season can be divided into pre-season; regular-season and post season.

For pre-season, the function is to running line-up, test new and old players competitive state; preheat the NBA regular season; promoting the NBA, the expansion of overseas influence. Currently, most famous NBA team did not pay attention to the pre-season, and not all the team joined the pre-season, so the dataset in the pre-season is not representative and in this project, we did not focus on pre-season game prediction.

For post-season, because the rule is different from the regular season and teams always continue fight with the others, so building a model is not suit for post-season.

Based on the consideration of authority and unpredictability, in this project the focus is on predicting basketball game outcome for regular season

## *1.8 Organisation of the dissertation*

The remaining chapters of this dissertation are organised into the review of relevant research, data preparation, experiment design and execution, results evaluation and analysis, conclusion. as follow outline:

Chapter 2 presents a review of research literature. The whole review process is a step by step process from data mining to sports data mining specific used in basketball. It first gives an introduction of data mining from concept to the process, and then goes more detail to sports data mining, which includes the application and tools of data mining in sports. Finally, stressing the sports data mining technique in basketball and popular algorithms for prediction. In order to easily understanding the project for readers and draw more people's interest to the basketball. As an extended review this chapter also generally introduce the NBA origin, history and some basketball terms will be used in this project.

Chapter 3 is the key of this project, in which data for this project is collected and well managed. High quality and comprehensive data is also the premise of successful data mining project, so this chapter will highlight the data collection and management process, which involves data collection, data transformation, data integration, and data marts.

Chapter 4 describes the NBA game prediction experiment: features selection and model training workflow, the setup of the experiment, model fitting and the model evaluation are discussed.

Chapter 5 describes model scoring workflow and the evaluation of the experiment result. It will specifically explain the scoring result comparing with the similar research in this field.

Finally, Chapter 6 concludes this dissertation. It reviews the dissertation's key objectives, the research approach and results obtained. The key contributions to the body of knowledge resulting of this research are presented, along with opportunities for future research. The chapter concludes with final remarks on the overall dissertation project.

The below diagram illustrates the division of Chapters according to its key objectives.

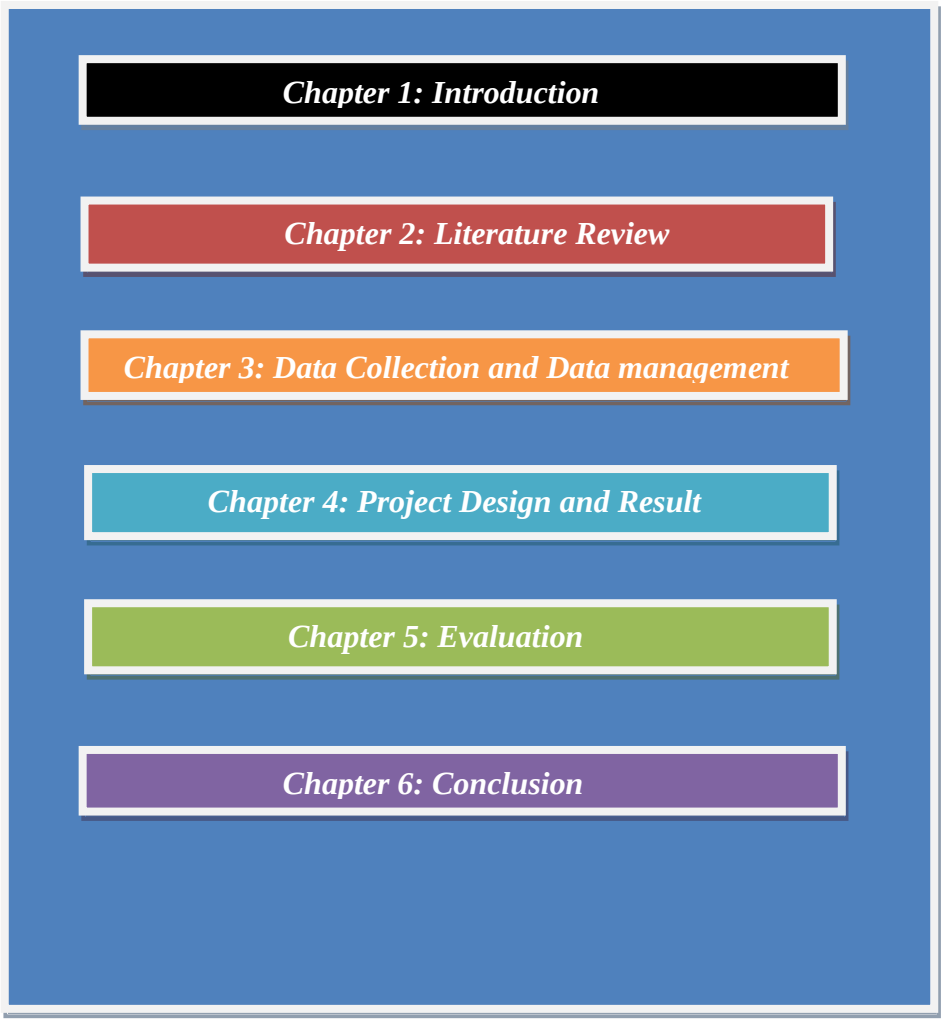



**Figure 1 Organisation of Dissertation**

# 2 LITERATURE REVIEW

## *2.1 Introduction*

This chapter will review the source and document which related to the topic and paves the way for future experiment. The whole review is a step by step process which involves three main parts, from data mining, sports data mining to sports data mining specific in basketball prediction. The following section will explain every part in detail.

## *2.2 Data mining*

In this chapter, research literature focus on the fields of data mining. The discussion involves the concept of data mining, data mining functions, data mining techniques, data mining applications and the data mining process.

### 2.2.1 Data Mining Concept

*"Data mining is extracting or mining knowledge from large amounts of data" – Han and Kamber (2006)*

*"Data mining is the extraction of implicit, previously unknown, and potentially useful information from data"-Lan H.Written*

*"Data mining uses a variety of data analysis tools to discover patterns and relationships in data that can be used to make reasonable accurate predictions. It is a processes not a particular technique or algorithm." – Edelstein (2008)*

*"Data mining is the process that uses statistical, artificial intelligence and machine-learning techniques to extract and identify useful information and subsequently gain knowledge from large databases" (Turban, E., et al., 2007, p.305).*

There are different explanations for data mining, but all of those definitions give a general consensus that data mining is discovering knowledge and information from large amounts of data by identifying and analysing interesting patterns in data to find the potential rules. Han and Kamber define it in terms of extracting information and knowledge from data and the "knowledge" is explained more detail for implicit, previously unknown, and potentially useful information by Lan H.Written. Then Edelstein's definition shows a further clarification that data mining is not a set of algorithms or a technique but a process. In the explanation of Turban, this process is provided a more complete definition which the process involves statistical, artificial intelligence and machine-learning techniques.

Data mining has its origins in lots of disciplines and the most important of them are statistics and machine learning.

As Turban mentioned data mining uses many machine learning models to discover hidden pattern in data. Machine learning is a hot topic in computer science academic and it has its origins much in computer practice. Its goal is to develop a mathematical model which can be reused in to predict future trends, classify unseen data or discover hidden patterns in a data set. Clustering, Classification and Regression are popular machine learning topics. Around these topics, a number of mathematical models have been built and used practically widely.

Statistical method has its root in mathematics and it is also popular in Data mining. Anomaly detection is a popular application using Gaussian statistical model to detect outliers. Many statistical methods are also used to prepare data and evaluate the output models.

There are many other tools such as association rule and decision tree model used in the data mining. Visualization is also a power full way of representing hidden knowledge, especially for business people who do not know data mining techniques well.

Data mining is also known as database knowledge discovery (Knowledge Discovery in Database, of KDD), which is a new emerging database technique along with the database and artificial intelligence. Specifically, data Mining is a technique which focuses on the information hidden in a large number of data which seems chaotic, noisy, fuzzy random data to extract and draw out implicit, previously unknown, but potential useful information and knowledge, in order to find out the inherent laws of the research object.

In recent years, data mining has caused a great concern of the IT industry and is one of the fastest growing fields in the computer industry. Data mining has a greatest strength that data mining is reflected in its wide range of methodologies and techniques that can be applied to a host of problem sets. Due to large amounts of data widely available, and the urgent need to convert these data into useful information and knowledge, obtaining information and knowledge has been widely used in various applications, such as business management, production control, market analysis, engineering design and scientific exploration customer relationship management, bioinformatics, counter-terrorism, business, and other fields.( M Kantardzic , 2011)

As the most important component of the dissertation, a clearly understanding of data mining concept will benefit for the further research. About data mining concept, there are different explanations, so a systematic review of data mining concept is significant not only for researchers but also for public enthusiast

### 2.2.2 Data Mining Tasks and Functions

The data mining functionalities and the variety of knowledge they discover are briefly presented in the following list (Tan et al, 2006):

- Characterisation: Data characterization also called data summary. The purpose of characterisation is summarisation of general features of objects in a target class, and produces what is called characteristic rules. The simplest characterisation is

using statistic methods to calculate the sum, the mean, variance, etc of each item in the database, or using OLAP (0nline Processing Analytical Process) to achieve multi-dimensional query and calculation of data or draw histograms, line charts and other statistical graphics.

- Discrimination: Data discrimination is a comparison of general features of target class data object against the general feature of objects from one or multiple contrasting classes. It produces discriminant rules and is basically the comparison of the general features of objects between two classes referred to as the target class and the contrasting class.( Osmar R. Za ïane, 1999 )
- Association analysis: Association analysis is from the large amounts of data to find interesting associations or relationship between item sets. As the data keeping collection and storage, people are increasingly interested in mining the association rules from their databases. From a large number of business transaction records found interesting relationship can help many business decision making. The main association analysis algorithm involves that Apriori; AprioriTid and FP-growth.
- Classification: Classification analysis also known as supervised classification. In classification, the actual label or category for each piece of the training data is already given. The classification algorithm learns from the training set and builds a model. The model is used to classify new objects.
- Prediction: More and more people pay attention to use the prediction method to forecast business thing. The major idea is to use a large number of past values to predict probable future values. The process is using the previous data to discover the rules and build the model. Forecasting is concerned with the accuracy and uncertainty, often used to predict the variance measure.
- Clustering: It is similar to classification but different from classification, clustering is also called unsupervised classification due to the classification is not dictated by given class labels. The class labels are unknown in clustering, and it is up to the clustering algorithm to discover acceptable classes.
- Outlier analysis: Database may contain some data objects which are not fitted the common behavior, those objects are outliers. They can be easily identified and also be viewed as noise in some applications. However, the exits of outlier has very particular meaning and analysis valuable. For example, in fraud detection, those outliers mean fraud behaviors.
- Evolution and deviation analysis: Evolution and deviation analysis belong to time

series analysis. Evolution analysis models can be used to discover the data trend and search similarity. Deviation analysis considers differences between measured values and expected values, and attempts to find the reason of the deviations from the anticipated values.

After looked the different, we can see that prediction is one of the data mining function which widely used in business and prediction technique also will be utilize in the following experiment, so this plays a supplementary role for the key experiment.

### 2.2.3 Data Mining Techniques

Data mining involves several disciplines and approaches, based on various tasks; data mining can be classified into Association, Classification, Clustering, Predictions, Sequential Patterns, and Similar Time Sequences. Depend on different explore methods; data mining can be generally divided into machine learning, statistics, neutral network and database. In machine learning, it can be divided more detail, such as inductive learning, case-based learning and genetic algorithm, etc. In statics, it can be divided more detail into regression analysis, clustering, discriminant analysis and so on; for the neural network methods, it can be divided into self-organizing neural networks and feed-forward Neural Networks. The main method in database is Multidimensional data analysis and On Line Analytical Processing.

There is no data mining method can cope with all the requirements. For a particular problem, the characteristics of the data itself will affect the choice of tools. The following paragraph will generally introduce several basic methods which involves decision tree and logistic regression.

## Decision tree

Decision tree is a method for classification by modeling a tree structure model with leaves representing class labels and branches representing conjunctions of features. Then method is known as "divide and conquer". The output of the learning process is a classification tree where the split at each node of the tree represents one if -then decision rule and each leaf correspond to one value of the target variable. Given an

example its target could be predicted by starting from the root and going down to a leaf of the decision tree by matching the variables (features) of the example with the splitting conditions at each node. The training algorithm chooses at each step the best variable to split the set of training examples.

The criterion to compare between variables is how well the variable split the set of training examples into homogeneous subsets of examples with respect to the values of the target variables.

Examples of the splitting criterions used to choose a variable are

- the Gini Impurity:
- Information Gain

The popular application of decision tree in CRM domain is customer classification. Decision tree is a very easy model and can be understand by non-professional people. It is such a simple model that it may not perform well on complex classification problems.

## Logistic regression

Logistic regression model is one generalizations of the linear regression model where the target variables are discrete class labels. For the binary classification problem, the linear function $y(X) = W^T X + w_0$ is extended by the logistic function$f(z) = \frac{1}{1+e^{-z}}$ to be $y(X) = F(\theta^T X + w_0) = f(z)$ with $z = \theta^T X + w_0$.

The output $y_x(x)$ has the value in the range (0,1) and is interpreted as the probability that the class (target variable) is 1 given the example X $P(C_1/X)$. Correspondingly the probability that the target variable is 0 given the example X is $P(C_0/X)$.

The example x is classified to class 1 when $y_x(x) \geq 0.5$. The parameter $\theta$ is determined using the maximum likelihood solution, which means for the training set$\{(X_i, y_i)\}, i = 1 \dots m$ is determined as the solution of the minimization problem:

$\min_\theta J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\Big(y_i \log\big(y(X)\big) + (1 - y_i)\log\big(1 - y(X)\big)\Big)$.

Since $J(\theta)$ is a convex function it has a global minimum and its solution could be determined by popular optimization techniques like the gradient descent algorithm. The performance of the determined model can then be measured on the validation set.

Logistic regression is also a classification algorithm and can be used to do customer classification in CRM domain. It is a power full model for complex classification model. But it does not take nonlinear feature into consideration.

There are lots of data mining techniques and for the key model such as Logistic Regression; Artificial Neural Networks; SVM and Naïve Bayes which used for this project will be discuss more detail in the next section.

### 2.2.4 Data Mining Tools

The following section presents and introduces some popular data mining tool, and Weka as the main tool for the experiment will be explain more detail.

**SAS (Enterprise Miner)**

SAS (Enterprise Miner) is very commonly used of integrated tool for data mining which gives a variety of data manipulation and transformation choices. It can run on different platforms such as Windows and UNIX, It enables user to discover data patterns among large sets of data and provide tools to export the graph visualized report via Webpage formatted report. It also provides a rich, easy-to-use set of integrated capabilities for creating and sharing insights that can be used to drive better decisions. However this is not an open-source tool for public, so it mostly commonly used in colleges, originations and companies.

**RapidMiner**

( Ohana, B., 2009) RapidMiner is an open source data mining tool for experimenting with machine learning and data mining algorithms which emerged from the YALE data mining environment. Through this tool users can easily build, execute and validate data mining models; integration with algorithms implemented for the Weka toolkit, making them accessible from inside RapidMiner; it also supports for a wide range of

tasks like SAS on data loading, data transformation, data modelling, data visualization methods, data analysis, prediction and clustering.

**Weka**

Weka is a data mining tool which integrates several machine-learning tools within a common framework and a uniform GUI. Classification and summarization are the main data-mining tasks supported by the Weka system. Users can use GUI or their own Java consuming Weka's API to perform machine learning tasks directly. Weka has the function for data pre-processing, classification, regression, clustering, association rules, and visualization.

Weka with GUI is chosen as the tool for the model fitting process of this project. Because Weka provides all functions required by this project, including data pre-processing, all classification models, and result analysis tool. Weka with GUI also provide KnowledgeFlow tool, which can help user to manage their model fitting workflow. Weka's powerful functionalities and intuitive user interface are the major factor that we choose this tool.

### 2.2.5 Data Mining Process

Data mining can be generally divided into 3 main processes: data preparation, data mining and result expression understanding. Combine with the Crisp-DM steps (Chapman et al, 2000), which are a data mining process model that describes commonly used approaches that expert data miners use to tackle problems. The data mining process can be generally divided into the following phases and the figure below shows the whole process:

- Problem definition

A data mining project starts with a correct understanding of the business problem. Here the understanding can be explained into the project objectives and the requirements from a business perspective. The project objective is then translated into a data mining problem definition and will give a direction for the following work. In the problem definition phase, data mining tools are not yet required.

- Data collection pre-processing

Data collection is to acquire the data; it can be either extremely simple or very complicated (i.e., trying to glean useful data from a large system). Obtain data can be either automatically or manually.

These processes include: data selection, data pre-processing and data conversion.

The purpose of data selection is to determine the related objects involved in data mining tasks, according to the specific requirements of the data mining task, extracted from the relevant data sources and mining related data sets.

The data pre-processing usually consists of the elimination of noisy data; handling missing data; eliminate duplicate data and data type conversion processing.

The main purpose of the data conversion is to reduce the data set and the feature dimension (referred to as dimensionality reduction), Preparing the data for the modelling tool by selecting tables, records, and attributes, are typical tasks in this phase. The meaning of the data is not changed. Filtering the real feature which related to the data mining tasks in order to improve the efficiency of data mining.

- Modelling

There are many data mining functions can be used to solve different type of problems. In this phase, through applying and selected various modelling techniques several times to calibrate parameters into an optimal state until best values are achieved. When the final modelling phase is completed, a model of high quality has been built. (IH Witten, E Frank, MA Hall - 2011)

- Evaluation

Evaluating the model mean to estimate the model whether satisfy the expectations or not. If the model does not fit the original expectations, they go back to the modelling phase and rebuild the model by changing its parameters until optimal values are achieved. When the models are finally satisfied with the targets, they can extract business explanations and evaluate the questions like:

Whether the model fit the business objective or not?

Did all business factors be considered?

Then, how to take advantage of the data mining results?

- Deployment

In this step will involve deploy plan, monitor and maintenance plan, finally express the results and understand the results. Results can be exported into database tables or into other applications, for example, spreadsheets and also can be display by visualization technique.

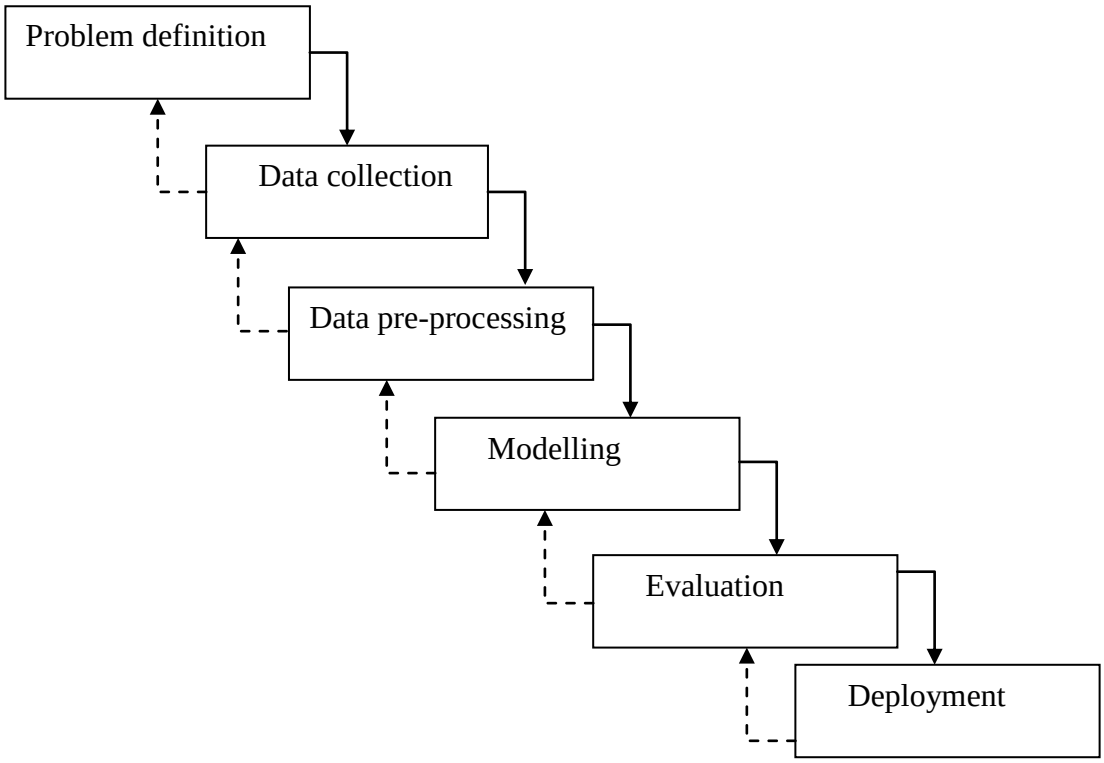



**Figure 2 Data Mining Process**

So follow by this step, the main process will be applied to the experiment which plays as a guidance role for the project.

### 2.2.6 Data mining applications

With the increasing data volume, data mining technique has an ever increasing utilization in different field. The following paragraph will present some famous applications of data mining technique:

**Bank**

Bank has special position in the financial sector, due to the nature of the work, operational characteristics, and the fierce market competition determines it has more requirements about information and electron than other areas. However, for a bank

business, the risk and profit both do coexist, In order to ensure the maximum profit and minimum risk, using scientific way to evaluate and analysis the customer account and do the credit assessment is necessary. Through using data mining technique can help product development department to describe the trend in customer previous demand and then predict the future. It helps bank to prevent fraud cheating and reduce the loan losses. Using data mining technique also help bank to divide their customer into different categories then focus on different group to design different programs to increase profit and keep customers.

**Sales**

The most classics case in sales is the "beer and napkin" which is widely read by industry and business. The story tells a company, which is Wal-Mart used data mining tool to analyse vast amount of data from database and accidentally find that the most frequent item people buy with the napkin, is the beer. The case reminds market sales to adjust the goods layout and put the beer and napkin together to increase the sales. However, data mining function for sales more than that. For example: data mining can help business make sales market strategy; reduce the inventory cost; analysis and predict seasonal, monthly sales trend; better understand customer buying habits and manage customer relationship and discover customer purchasing ability to achieve accurate merchandising, etc.

**Medical science and DNA**

Data mining used in biomedicine will undoubtedly benefit for human. For example, a combination of genes is ever changing, what is the difference between disease genes and normal genes? How to change the difference and turn it to be normal? Those questions will require the support of data mining technology. Data mining also help people to detect the character of one disease then find and treat it before the disease progresses.

**Weather forecasting**

Data mining used in weather forecast is another popular field. Meteorological department has accumulated a lot of meteorological data; take advantage of those data can improve the accuracy of weather prediction and reduce the loss by natural disaster. Climate will influence our daily life, it also has a close relationship with agricultural

production, and meanwhile, agriculture is the key component of country's economy. So weather forecasting domain draws a lot of scientists' attentions. Neural network, classification and clustering has been gotten a widely used in climate prediction.

**Stock market**

Stock market plays an important role in economy， effective stock forecast is very important in financial investment field, however, stock market is influenced by various complicated factors like policy, economy and investors' mentality, etc. Purely depends on personal experience may not accurate enough. So data mining has extraordinary theoretic significance and practical value for stock analyzing and predicting. Currently, lots of algorithms have been used for predict the stock price and help stock investors make the right decision timely. Meanwhile, people combine data mining technique to design software to help those stock investors automated buys and sells which achieves the effective utilize time and make decision more accurately.

### 2.2.7 Summary

This section introduces the basic concept of data mining from data mining tasks, data mining techniques, data mining process to data mining tool and application which give a comprehensive explain of data mining. The aim was to give an understanding of what data mining is used for and what the data mining status quo. Some of the main techniques were discussed briefly such as the decision tree, logistic regression. As data exist everywhere, so data mining has a broad space for development and sports data mining is one of the new rising growth areas.

## *2.3 Data Mining in Sports*

In this section, sports data mining, which is an emerging field in data mining, will be introduced. To begin with we will provide a brief background on the basic knowledge about sports science, including details on sports science concept; origins and research scopes these will be discussed in later sections. In the next section, a short review of

sports data mining applications is given, such as baseball, football and so on. Echo with the above section, some popular sports data mining tool will be discussed in detail.

### 2.3.1 Sports Science and Sports Data Mining Research

Sport Science is a discipline that studies the scientific principles application and techniques with the aim of improving sporting performance. It involves a broad field like medicine, psychology, biochemistry, biomechanics, and other natural sciences, but also includes the field of philosophy and history, economics, sociology, education and other social sciences. (Kent, M., 2006)

Sports concept can be divided into broad and narrow scale:

From the broad view, it refers to use physical exercise as the basic methods, take boosts health, promote human full-scale, rich social and cultural life, promoting the construction of mental civilization as purpose. It is part of the society culture, and its development will be constrained by political and economic, meanwhile it service for political and economic.

From the narrow view, it refers to a technique or a skill that will increase our energy level and it is also a process of training our will. Sports science has been added as our daily module which is an important part of education. With the Olympics game has been got more and more concern, sport science has been viewed as one of important aspect to develop a comprehensive people.

Modern sport should trace back to the 19th century, Arnold who was a British educator was the founder of modern sports. He took sports as a school curriculum in 1828. Then the French bourgeoisie educator Pierre de Coubertin as the founder of the modern Olympic game, put competitive sports into the international scope, and established the foundation for modern competitive sports. Organized to carry out sport science research from the early 20th century began. Japan set up a National Sports Institute in 1924 then the Soviet Union established the Office of Scientific Research at the Moscow Institute of Physical Education and later developed into the Moscow Institute

of Sports Science. After World War II Sports science research truly carried out in the world.

Compared with the discipline like philosophy, history, etc, Sports science is still very young as a subject. It was very incomplete which cannot meet all the requirements of the sports practice. (Stone, M.H., 2004) However, Sports Science is a comprehensive scientific with the rapid development of scientific and technological level and the growing popularity of sports, sports science has developed into a relatively independent of the disciplinary system, and play a significant role in raising the level of competitive sports, the rich people's cultural life. ( Burwitz et al, 1994)

The rapid development of modern science and technology has brought rapid changes to the sports. At present, the sports science research mainly focuses on competitive sports. From the training part to the final competition, each part closely combines with the scientific and technological research work. On the other hand, modern science and technology research has been introduced to the field of sports more than before. For example, the use of the application of computer technology, the application of laser ranging technology, radio-controlled technology, and the plastic track, artificial turf, glass, steel pole, leather bathing suit, etc.

Speaking to the computer technology, we have to mention of the data mining technique. Traditional decision making method which using the intuition or gut instincts has been out of the time, instead of this is digital era embracing into the sports analysis. Sports data mining has a lot of functions, such as matching players to certain situations, measuring individual player contribution, evaluating the tendencies of opposition, uncovering new knowledge and exploiting any weaknesses, etc. However, sports data mining today is still in its infancy and there is a vast of functions awaiting discovery.

### 2.3.2 Sports Data Mining Applications

Sports are ideal for application of data mining tools and techniques due to the vast amounts of statistics are growing and collected for each player, team, game, and

season. Sports organizations use data mining in the form of statistical analysis, pattern discovery, outcome prediction, performance prediction, and scouting, selection of players, coaching and training and for the strategy planning. Currently, Lots of different sports began to utilise data mining technique as their competitive advantage such as football, soccer, greyhound, soccer etc. The following paragraph will review relevant research related to sports applications and give a briefly summary some famous sports data mining applications.

**Soccer**

AC Milan is the Italian professional soccer club, the most famous case by AC Milan is that they uses the prediction model to help predict player injuries through analysing of different channels data. The biomedical tool created by Computer Associates produces predictions from the medical statistics amassed for each player then compared the results against a baseline. When any workout result falls below the baseline expectation, which is a signal either an injury has occurred but the player did not reveal or an existing injury has worsened. (Flinders, 2002) Athletes injury is one of the biggest investments for sport organization, so this predictive software is very successful since it will help organization save millions of dollars. (Schumaker, 2010)

**Baseball**

We all familiar with the book MoneyBall, which published in 2003 by Michael Lewis tells a story about team manager Billy Beane who is The Oakland A's General Manager used sports data mining knowledge to organise his team and finally win the game. This book was adapted into a movie and was released in 2011. Billy is starred by famous movie stars Brad Pitt. This book subverted the traditional sports management ideas. Billy Beane's philosophy is to use very little funds to operate the club, he broke with the conventional method, using historical data and data mining methods to build the evaluation model, and unitised low cost purchased those undervalued players, and finally, made their team have the ability to fight with the famous New York Yankees.（Gerrard, B. & Howard, D., 2007）This is one of the most famous cases which used data mining technique to manage baseball team performance. Therefore Billy Beane became one of pioneers in sports data mining.

**Rugby**

New England Patriots which is a rugby team come from American, this team has been very successful recently because four league games and three victories in the Super Cup. This result contributes to the extensive use of data analysis models, no matter in the field or off the court. Deeply analysis can help this team chose players more effectively and also help this team pay to their player's salary is lower than the upper limit of the industry wage. Unlike the other teams which chose players by scouts, they put some non-traditional feature to consider, such as, intelligence, and willingness to integrate itself into the team and so on.

**Greyhound Racing**

There are many cases that data mining techniques used for predictive purposes; greyhound racing is one of them. Dr. Hsinchun Chen who is a professor of Management Information Systems at the University of Arizona used Machine Learning Approach to predict greyhound racing result successfully. In their experiment, various data components were used to train the system, which involves symbolic Learning, and neural networks algorithms then test the predictive capabilities of machine learning against those of human experts in greyhound racing. (Sicard et al, 1999)This idea also fit to the thoroughbred racing. Undoubtedly, data mining technique support a broad space to discover the sport area.

**Track**

Dr. Gideon Ariel who is the founder and Chief Executive of the Board of Ariel Dynamics, Inc., he founded Computerized Biomechanical Analysis, which is a company to give analysis for athletes' techniques in 1968. Before the Montreal Olympics, he analysed threw technique for Mac Wilkins who is an American athlete, and competed mainly in the discus throw. He found that he did not make full use of his leg power before he threw out of the discus, so he lost part of power to affect his final performance outcome. Through computer simulation calculations, if this error could be corrected, his results can be increased by three meters. Then Wilkins follow Ariel's

proposal to improve its own technology, and finally he improved more than three meters and created a new world record. (Stein, 1999)

### 2.3.3 Sports Data Mining Tools

Currently, sports data mining tools as the derivatives of the data mining technique's has been emerged in a large number, players, coaches and rivals can get a better understanding of their competitive level by using sports data mining tools. So a new industry is rising which takes applying data mining to sports for commercial as purpose. The following session will introduce some popular sports data mining tools:

Advanced Scout

IBM developed Advanced Scout in the mid 1990s as a data mining tool used for National Basketball Association (NBA) data analysis. The application is specifically tailored for NBA coaches and statisticians to discover the hidden patterns or features in basketball data, which provides a new insight by using the business intelligence and data mining technique. (Colet et al, 1997)
There are two data sources for this tool, one came from a courtside collection system include the time stamped events data such as shots, rebounds, three goal, etc. The other source is the game tape includes game footage. This source can be kept by coaches to prepare for upcoming opponents as well as to check mistakes and improve effective. (Schumaker, 2010)

**Digital Scout**

Digital Scout is a software used for collecting and analyzing game-based statistic and tools for baseball, basketball, and football, etc. It also supports the function of producing reports. For instance, baseball hit charts, basketball shots charts and football formation strengths. (Solieman , 2006)

**Synergy Online**

This product has the similar function with Advanced Scout that dedicates to basketball-based multimedia and contains an index of live video broadcasts as searchable media. Coaches, players and fans can query plays in real-time and receive constantly updating player statistics by using this software. ( Schumaker, 2010)

**NHL-ICE**

In recent years, hockey has experienced a data-centric rebirth. The National Hockey League established a technology development joint-stock company with IBM to develop data mining application NHL-ICE. This data mining application is similar to the advanced scout in principle, which is an electronic real-time game scoring and statistics system. The coaches, broadcasters, journalists, and fans can dig the statistics data through this application, when they visit the website of the NHL, fans can use this system to watch the game repeatedly, and meanwhile broadcasters and reporters can discover those data and try to find out the gossip with all sorts of addenda to their reports. (Knorr, 1998)

### 2.3.4 Conclusion

This chapter gives a briefly summary of the data mining technique specific in sports. The motivation is to generally introduce the sports data mining from sports science history, sports data mining application to sports data mining tool. The sports data mining application covers soccer, greyhound racing, tracking and baseball. The sport data mining tools involve that SAS, NHL-ICE, Synergy Online, Advanced Scout and Digital Scout which are popular currently. This section serves as a link between the previous chapter and the following chapter.

## *2.4 Data Mining in National Basketball Association*

Compared with the above paragraphs, which focus on the data mining technique used in sports, the following paragraph will describe the NBA data mining technique in detail.

Corresponding with the sports science development history, the first part describes the background of NBA history, this paragraph will give those basketball fans a better promote knowledge and meanwhile for those people who are not interested in basketball will be a simple introduce and then review the related research of data mining techniques used in basketball. In order to meet the need of the following experiment design, some basis technical term will be explained. NBA game outcome prediction related research and predictive analysis algorithm used in the following experiment will be presented and discussed as well.

### 2.4.1 NBA Introduction

Basketball is one of the most popular sports in the world. It originated on American and it is a team sport, which the target is to shoot a ball through a basket horizontally positioned to score points with a set of rules. Usually, there are two teams of five players play on a marked rectangular court, each width with a basket. (Griffiths, 2010) With the basketball getting more and more attention, there are lots of organizations formed, such as National Collegiate Athletic Association (NAA), National Wheelchair Baskteball Association (NWBA), American Basketball League (ABA), Continental Basketball Association (CBA) and National Basketball Association (NBA), etc.

NBA was started in 1891 by Canadian American Dr. James Naismith who was the physical education professor and instructor of Springfield College in Massachusetts. Due to the restrictions from the weather, Dr. James Naismith started to seek a vigorous indoor game to keep his students occupied and at proper levels of fitness. That is just the original intention of basketball. After fixed some of the idea, Dr. James Naismith wrote some basic rules for basketball and nailed a peach basket onto a 3.05 m elevated track. Different from the modern basketball, the original basketball retained its bottom, and balls had to be retrieved mechanically after each basket was scored; then to improve the efficient, they removed the bottom of the basket to allow the balls to be poked out with a long dowel each time. People used to call it “Naismith ball” and after a long time, James Naismith and his colleagues decided to give it a name: “basketball”.

Naismith invented basketball since he was 30 years old, but basketball was born nearly half a century has always been neglected, basketball get its respects until the 1936 Berlin Olympic Games. Since then, basketball gradually draws more attention and formed Basketball Association of America (BAA) in 1946, then in 1949 this organisation renamed to National Basketball Association and this name is still use today.

Currently, NBA has 30 teams, they are divided into Eastern Conference and Western Conference, the Eastern Conference involves Atlanta Hawks, Boston Celtics, Charlotte Bobcats, Chicago Bulls, Cleveland Cavaliers, Detroit Pistons, Indiana Pacers, Miami Heat, Milwaukee Bucks, New Jersey Nets, New York Knicks, Orlando Magic, Philadelphia 76ers, Toronto Raptors and Washington Wizards respectively. The Western Conference includes Dallas Mavericks, Denver Nuggets, Golden State Warriors, Houston Rockets, Los Angeles Clippers, Los Angeles Lakers, Memphis Grizzlies, Minnesota Timberwolves, New Orleans Hornets, Oklahoma City Thunder, Phoenix Suns, Portland Trail Blazers, Sacramento Kings, San Antonio Spurs and Utah Jazz.

Each team has 5 players in the court; they can be classified into the five positions: point guard, shooting guard, small forward, power forward, and centre. The following figure shows the position of five players.

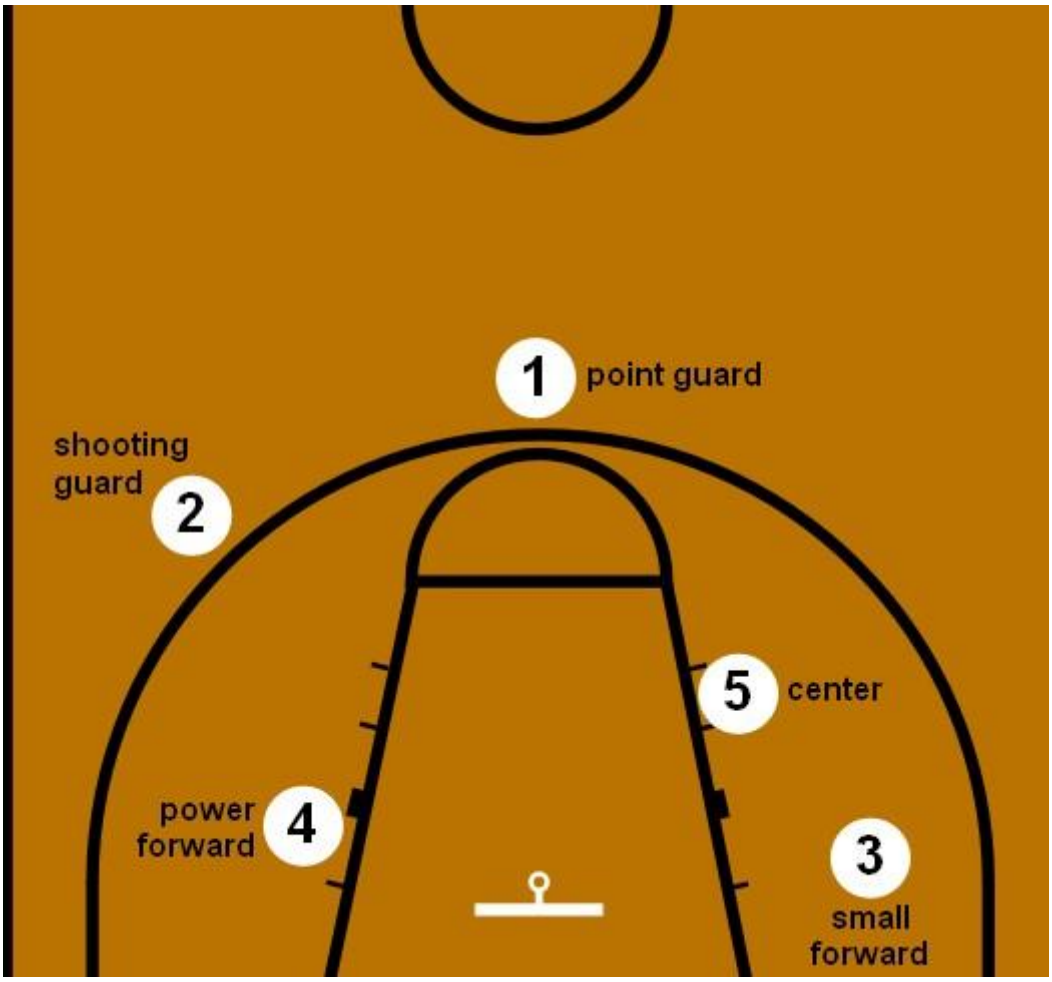



**Figure 3 Basketball Player Position**

Different position has their different functions :

1. Point guard: usually the fastest player on the team and response to organize the team's offense by controlling the ball and insure the ball gets to the right player at the right time. (Trninic, S. & Dizdar, D., 2000)

2. Shooting guard: plays a role to create a high volume of shots on offense and guard the opponent's best perimeter player on defence.

3. Small forward: typically somewhat shorter, quicker, and leaner than power forwards and centers and mainly responsible for scoring points via cuts to the basket and dribble penetration; they are considered to be perhaps the most versatile of the main five basketball positions on defense (WANG, L.,2008)

4. Power forward: plays offensively often with their back to the basket and not allowed the opponents to penetrate and score.

5. Center: often has a great deal of strength and body mass as well, uses height and size to score (on offense), to protect the basket closely (on defense), or to rebound.

The above descriptions just a general description, actually it is more flexible than that. Depend on different situation; three guard offenses can replace one of the forwards or the center with a third guard. The most commonly interchanged positions are point guard and shooting guard when both players have good leadership and ball handling skills. (Miller, S. & Bartlett, R., 1996)

### 2.4.2 Data Mining Techniques Used in Basketball

As the aftershock of Baseball, Dean Oliver does the similar question in basketball during the 1980s and 1990s. He applied statistical analysis techniques to basketball and created ABPRmetrics (Association of Professional Basketball Researchers) used for creating better measurements and statistical yardsticks for comparison purposes. ABPR metrics is similar to sabermetrics which is one of the earliest metrics to evaluate the baseball players' performance but ABPR metrics attempts to view statistics in terms of team rather than individual performance. (Schumaker, 2010)

The same function to evaluate players, Player Efficiency Rating (PER) is another way to evaluate a player effectiveness based on per-minute rating. (Hollinger, 2002). This formula consider many variables like assists, blocked shots, fouls, free throws, made shots, missed shots, rebounds, steals and turnovers among others and tries to quantify player performance in regards to their pace throughout the game and the average performance level of the league. After understanding the contribution of each player, coach can reward positive contribution and punish negative ones. However, PER is still arguable due to it does not take into account all of performance related criteria, such as hustle and desire (Hollinger, 2002). Although, this method is limited on some occasion, it still can identify new insights into offensive capability and provide valuable insight into player execution. (Solieman, 2006)

Another case of data mining technique helps to improve NBA efficiency is Shot Zones. There are 16 areas in the basketball court where a player on offense might be inclined to shoot a basket. Through analyzing the percentage of player success of each zone, defensive adjustments can be made to limit scoring while offensively; coaches may try to maximize these types of shots. (Beech, 2008)

The following figure shows the different shot zone locations.

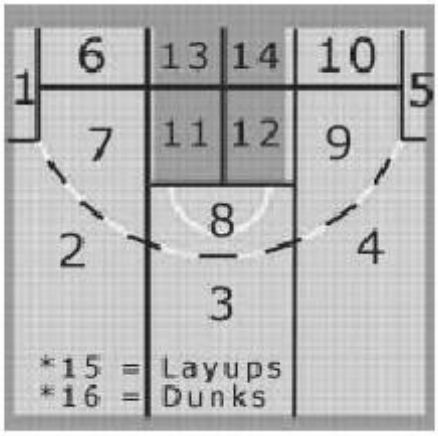



**Figure 4 Shot Zone Layout (82games.com)**

Except the tools which introduced specific for basketball in the above section, such as Advanced Scout software and Synergy Online and the evaluation metric for palyers mentioned above,(Chen, C.Y. & Lin, Y.H., 2006.) Dick and Sack (2003) did a research about effective marketing techniques in the NBA in order to find a more effective way to ensure that advertising messages are received by the right target markets. This technique used by lots of successfully teams, such as Cleveland Cavaliers, the Seattle SuperSonics, the Portland Trail Blazers, and the Miami Heat. The Cleveland Cavaliers created a database, which involves some personal information like customers' names, addresses, telephone numbers, and other detailed information on the products purchased. By analyzing that the relationship of those features to determine whether they were interested in other games or events. (Bonvissuto, 2005). The Portland Trail Blazers use predictive model to analyze their customer database and forecast advertising revenues and spot ticket-sale trends (Whiting, 2001). By using data mining technique ,the overall Miami Heat season-ticket renewal rate increasing about eight-five percent in 2005 than expected. (Lombardo, 2005).

### 2.4.3 Basketball Game Outcome Prediction Research

Although data mining has been successfully used in different fields and the sports organisation is a large business waiting to be discovered, sport data mining is not mature enough, especially for predicting the game outcome. There are lots of uncertain factors to influence the result; however, data mining still has its own value in forecasting the outcome. The following section presents a brief review of data mining technique used for basketball game outcome prediction.

NCAA College Basketball researchers are predicting tournament matchups and victories with impressive accuracy. Jay Coleman and Allen Lynch – a professor of Economics at Mercer University used SAS to develop a formula for predicting the outcomes of the NCAA tournament games called the "Score Card". This system has a 75 percent success rate in predicting winners. However, Score Card has not been made public. (Solieman , 2006)

Bernard Loeffelholz, Earl Bednar, and Kenneth W. Bauer did a research of predicting NBA games by using neural networks. Authors explored subsets obtained from signal-to-noise ratios and expert opinions to identify a subset of features input to the neural nets. Results obtained from these networks were compared to predictions made by numerous experts in the field of basketball. After experiment, their project got 74.33 percent accurate. (Loeffelholz, B., 2009)

David Orendorff and Todd Johnson used the Bayesian Logic (BLOG) and Markov Logic Networks (MLNs) to predict the NBA game outcome. Their project considers the task of predicting the winner of professional basketball games based on historical data.After the prediction accuracy of models implemented in the BLOG and MLN frameworks are compared using cross validation for the 2006-2007 season. MLN method got 64% accuracy and 63% accuracy for the BLOG model respectively. (Orendorff, D., 2007)

Feifang Hu1 and James V Zidek2 forecasted NBA playoff outcome by using the weighted likelihood method. In their experiment, they use all relevant sample

information also consider the reflection of the home game advantage. Finally, we demonstrate the value of the method by showing how it could have been used to predict the 96/97 NBA playoff results which is a high accurate. (Hu, F.,2004)

Matthew Beckler, Hongfei Wang and Michael Papamichael applied machine learning techniques to predict the game outcome for NBA， in their experiment, Logistic Regression get the accuracy of 68.1%, The accuracy achieved by linear regression is 65.4% and Support Vector Machines received an overall classification accuracy of 66.9%.(Beckler, M., 2008)

Neil C. Schwertman; Kathryn L. Schenk and Brett C. Holbrook used National Collegiate Athletic Association (NCAA) regional basketball tournament data to develop simple linear regression and logistic regression models by using seed position to predict the probability of each of the 16 seeds winning the regional tournament. ( Schwertman, NC.,1996)

**Other research related to the competitive sports game outcome prediction**

Except those experiments which focus on basketball game result prediction, the following we will review some similar experiments which used data mining techniques to forecast the game outcome in other competitive sports:

Harville (1980) used data mining regression methods based on historical point spread to develop a method for forecasting the point spread of NFL (National Football League). This research can be also used for predict the game result since these forecasted point spreads can be used to predict NFL game winners.( Loeffelholz, B.,2009)

Purucker (1996) did an experiment which applied back-propagation, self-organizing maps (SOMs) and other neural structures to predict the winner of a football game in the National football League (NFL). After he tried several training methods then he found that backpropagation would be best to develop a model with greater predictive accuracy than various experts in the field of football predictions. The accuracy can

achieved 61% accuracy as compared to the 72% accuracy of the experts. (Purucker, M.C., 1996)

Pardee also use backpropogation for the college football prediction analysis. In his experiment, the 1998 season data was used to train and the subsequent 1999 season data used for testing. Over 100 trials resulted in an average prediction rate of 76.2%.( Loeffelholz, B.,2009)

Kahn applied backpropagation and neural network structure to predict NFL football games. He extended the work of Purucker (1996) and attained 75% accuracy which performed better than Purucker 61% accuracy and also slightly better than the experts in the field. Both of authors used differential statistics from the box scores rather than raw statistics. (Kahn, J.,2003)

### 2.4.4 Popular Predictive Analysis Algorithm

This paragraph will briefly introduce the main algorithms will be used in the following experiment which involves Logistic Regression, Artificial Neural Networks, SVM and Naïve Bayes. At the same time, this section also explains why using those algorithms.

**Logistic Regression**

Logistic regression model is one generalizations of the linear regression model where the target variables are discrete class labels. For the binary classification problem, the linear function $y(X) = W^T X + w_0$ is extended by the logistic function$f(z) = \frac{1}{1+e^{-z}}$ to be $y(X) = F(\theta^T X + w_0) = f(z)$ with $z = \theta^T X + w_0$.

The output $y_x(x)$ has the value in the range (0,1) and is interpreted as the probability that the class (target variable) is 1 given the example X $P(C_1/X)$. Correspondingly the probability that the target variable is 0 given the example X is $P(C_0/X)$.

The example x is classified to class 1 when $y_x(x) \geq 0.5$. The parameter $\theta$ is determined using the maximum likelihood solution, which means for the training set$\{(X_i, y_i)\}, i = 1 \dots m$ is determined as the solution of the minimization problem:

$\min_\theta J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left(y_i \log(\mathrm{y(X)}) + (1 - y_i) log(1 - \mathrm{y(X)})\right)$.

Since $J(\theta)$ is a convex function it has a global minimum and its solution could be determined by popular optimization techniques like the gradient descent algorithm. The performance of the determined model can then be measured on the validation set.

Logistic Regression is also popular classification model in sport data mining domain. It is a power full model for complex classification model. One limitation is that it does not capture non-linear relationships between features. (Hosmer, 2000)

**Naïve Bayes**

The Naïve Bayes Classifier assumes that attributes are conditionally independent of given class label, which implies that the probability of belong to a class is the multiplication of every conditional probabilities of attributes. Naïve Bayes has a great simplicity over other classifiers. Nevertheless, in some cases, it outperforms more sophisticated classification models. (Langley et al., 1992)

The function of computing the likelihood of a sample being a class is given below:

$$prob(C_j|X) = p(C_j)\prod_{k=1}^{d} p(x_k|C_j)$$

where $\mathrm{C_j}$ is the $\mathrm{j^{th}}$ class, X is observed variables $\mathrm{X} = \mathrm{x_1}, \mathrm{x_2}, \dots, \mathrm{x_d}$. The posterior probability of class $\mathrm{prob(C_j|X)}$ is represented by the multiplication of conditional probability $\mathrm{p(x_k|C_j)}$ and $\mathrm{p(C_j)}$, the prior probability of class $\mathrm{C_j}$.

The final prediction of class of a given sample is:

$$classify(C_1, C_2, \dots, C_j) = \underset{j}{\mathrm{argmax}}\, p(C_j)$$

Naïve Bayes Classifier has been widely used in a range of application domains, including text classification, spam-filtering applications, and many predictive analysis applications.

**Support Vector Machine**

Support Vector Machine (SVM) can do a better job with features with non-linear relationships. SVM classification model can be trained by finding a maximal margin hyper-plane.

SVM fits a model by maximizing the geometric margin, which separates positive and negative samples. This introduces a constrained optimization problem, that optimizing the geometric margin and, at the same time, ensuring all samples is separated by the margin. The Karush-Kuhn-Tucker (KKT) condition (Boser et al., 1992) can solve this constrained optimization problem. (Burges, 1998)

And kernel trick can be applied to transform nonlinearly separable features into high dimensional feature space. There are several kernel choices, among which polynomial kernel and Gaussian kernel are commonly used.

**Artificial Neural Network**

Artificial Neural network is mathematical model inspired by biological neural network. It consists of input layer of neurons, hidden layer of neurons and output layer of neurons. It is a non-linear statistical data modelling tool and can model complex relationship between input and output.

The discriminant linear models like the logistic regression model can be extended further by replacing the input variable x by a set of nonlinear fixed basis function $\varphi_j(X), j = 1 \ldots M$ then one has

$$y_x(X) = f\left(\sum_{j=1}^{M} w_j \varphi_j(X)\right)$$

A feedforward neural network is an extension of the above model where the basis functions follow the same form as in the formula above. In feedforward neural networks a basis function (representing by a hidden node in the neural networks) is itself a logistic functions of a linear combination of the inputs where the coefficients (also called weights) of the inputs are adaptive and could be learned. Intuitively, a feedforward neural network can be represented as the input nodes (input variables) connecting through nodes in hidden layers to the output node in the output layer, each node in one hidden layer performs the role of a basis functions for nodes in the next hidden layer.( Zhang, G.P., 2000)

An example of a neural network with one hidden layer is given here, while a feedforward neural network with no hidden layer corresponds to the logistic regression model.

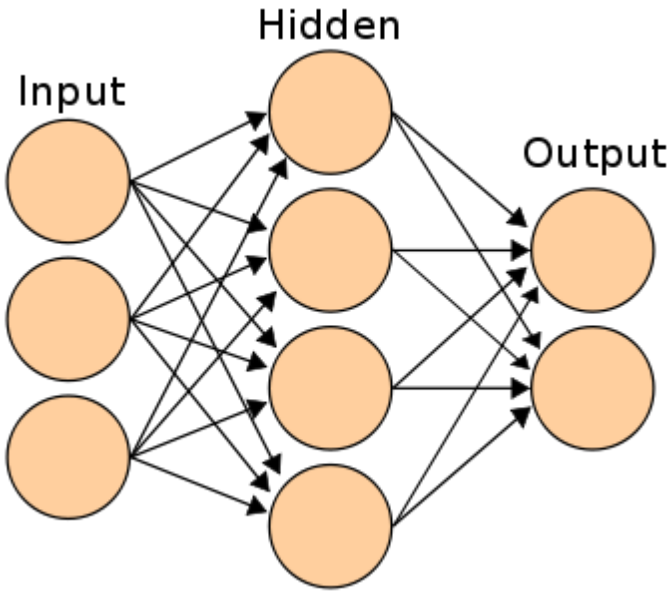



**Figure 5 Neural Network**

If the output of the output units are interpreted as the probability of the target variable to be a specific class given the example x, similarly to the logistic regression the weights connecting all pair of nodes in the neural network could be determined as the ones which maximize the likelihood of the set of training data. The optimization problem for finding the optimum weights could be solved by gradient descent techniques like the back propagation algorithm.

**Boosting**

Boosting is a very powerful learning method that combines many "weak" classifiers to produce a strong classifier committee and provides a solution to the supervised classification learning task. The most familiar weak classifier is decision tree and the simplest decision trees with only a single split node per tree are sufficient. However, simply depend on one of the weak classifier, the result maybe not strong enough, through combining many of weak classifiers will outperforms most “monolithic” strong classifiers such as SVMs and Neural Networks.

The most common boosting algorithm involves that Discrete Adaboost, Real AdaBoost, LogitBoost, and Gentle AdaBoost. However, all of them are very similar in their overall structure and due to in this project we will test the LogitBoost

algorithm used in predict the NBA game result. So the following section will focus on introducing the LogitBoost algorithm.

As the solution of LogitBoost algorithm approaching to the optimal solution of Bayesian and easy to implement, so this is a hot topic in machine learning research.

It is a combination of algorithms with the core algorithm logistic regression. It uses LogitBoost with simple regression function (linear or non-linear functions) as base learners. It support automatic attribute selection and use cross validation to control number of iterations. (Landwehr, N., 2005).

## *2.5 Conclusion*

This chapter reviews the data mining techniques used for basketball. Firstly, the general history of the NBA game development and the basic term of basketball are introduced. Secondly, data mining techniques used in NBA is discussed, which include some metric and method to evaluate players' performance and improve players' skill. Thirdly, we focus on the previous research about basketball game outcome prediction. Finally, two predictive algorithms which will be used in the following experiment are briefly demonstrated.

# 3 DATA COLLECTION AND DATA MANAGEMENT

Data is core of any data mining projects. Collecting sufficient amount of data with high quality is the fundamental and crucial step towards success of the data mining problems.

The NBA league has been around for over 60 years. Game-by-game data has been carefully collected and well organized by NBA analytics and NBA analysis enthusiasts. Some NBA statistics data is available online and freely available to party of interest without any cost. These available data is the foundation for this project, meanwhile vast amount of high quality NBA game data is becoming the ideal test bed for data mining.

This chapter illustrates the process of collecting NBA statistics data from popular non-profit NBA statistics websites, managing MySQL database by Amazon Cloud services, uploading collected data into database, and building a data mart for enabling further data mining. The following graph illustrates major parts involved in this project and main data flow. NBA statistics data is collected from Internet and stored to local personal computer. Local data is then uploaded to MySQL database hosed on Amazon Cloud. Data mart is also built in the Amazon Cloud.

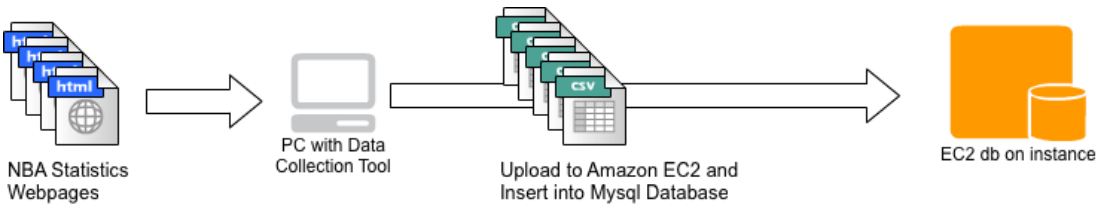



**Figure 6 Data Flow**

## *3.1 Introduction*

This project collects data from some non-profit websites, which publish NBA game statistics data available to public. The following section will introduce sources of data used in this project and data collection tools involved.

## *3.2 Data Sources*

In this project, non-profit websites are the major contributor to data. For data used for model training, testing and scoring, Basketball-reference.com is our major data source. And there are some other sources including (Databasebasketball.com) and the official NBA website (NBA.com). Some benchmark data for evaluating this project is from some major NBA game result prediction website, such as (Team Rankings).

(Basketball-reference.com) is a website used for collecting data especially for basketball and it also collects other sports data such as baseball, football and so on. There are a number of non-profit organisations collecting and calculating NBA statistics data and game related information. Until now, the statistic data about NBA has been over 60 years. Basketball-reference.com is one of the most famous one for those sports data miners, and has been used in many experiments. It was created in 2003 and data requests are comprehensive, relatively well organized, straightforward and easy to navigate and utilize.

For this project about 6 years of NBA game statistics data has been collected, which came from 2005-06 season to 2010-11 season. Due to the new divisional alignment has been used since 2006, so these 6 years of data would have better consistency and applicability to new season predictions. Among data collected, data from 2005-06 season to 2009-10 season year are used for model fitting purpose and data from 2010-11 season is used for scoring purpose.

The statistics data covers a broad spectrum of aspects: for examples, there are per game statistics, starting line-ups statistics, player statistics, opponent statistics, home/road game statistics, injury information and game schedule information. Those features will be illustrated in detail as follow.

The following table shows a fraction of game log statistics of New York Knicks in regular season 2011-2012. It covers statistics data of each game played by New York Knicks against their opponents.

| | | | | | | Team | | | | | | | | | | | | | | Opponent | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rk | G | Date | | Opp | | MP | FG | FGA | 3P | 3PA | FT | FTA | ORB | TRB | AST | STL | BLK | TOV | PF | PTS | FG | FGA | 3P | 3PA | FT | FTA | ORB | TRB | AST | STL | BLK | TOV | PF | PTS |
| 1 | 1 | 2011-12-25 | | BOS | W | 240 | 35 | 74 | 9 | 20 | 27 | 34 | 8 | 31 | 17 | 9 | 11 | 16 | 25 | 106 | 39 | 76 | 2 | 5 | 24 | 31 | 13 | 41 | 28 | 7 | 5 | 18 | 28 | 104 |
| 2 | 2 | 2011-12-28 | @ | GSW | L | 240 | 28 | 70 | 4 | 21 | 18 | 25 | 4 | 31 | 15 | 7 | 0 | 15 | 21 | 78 | 35 | 77 | 6 | 16 | 16 | 24 | 11 | 47 | 20 | 12 | 4 | 14 | 17 | 92 |
| 3 | 3 | 2011-12-29 | @ | LAL | L | 240 | 21 | 67 | 6 | 22 | 34 | 41 | 9 | 32 | 15 | 11 | 6 | 12 | 20 | 82 | 38 | 73 | 9 | 16 | 14 | 22 | 6 | 40 | 23 | 6 | 7 | 14 | 28 | 99 |
| 4 | 4 | 2011-12-31 | @ | SAC | W | 240 | 40 | 89 | 10 | 28 | 24 | 27 | 17 | 43 | 26 | 7 | 6 | 12 | 35 | 114 | 30 | 86 | 6 | 22 | 26 | 41 | 22 | 51 | 15 | 7 | 2 | 12 | 22 | 92 |
| 5 | 5 | 2012-01-02 | | TOR | L | 240 | 28 | 78 | 10 | 35 | 19 | 25 | 6 | 39 | 14 | 8 | 3 | 11 | 24 | 85 | 30 | 68 | 7 | 17 | 23 | 29 | 4 | 44 | 21 | 5 | 5 | 18 | 30 | 90 |
| 6 | 6 | 2012-01-04 | | CHA | L | 240 | 42 | 85 | 11 | 29 | 15 | 20 | 11 | 40 | 19 | 8 | 5 | 17 | 20 | 110 | 47 | 85 | 7 | 11 | 17 | 21 | 7 | 37 | 27 | 9 | 0 | 13 | 16 | 118 |
| 7 | 7 | 2012-01-06 | @ | WAS | W | 240 | 39 | 89 | 6 | 18 | 15 | 21 | 15 | 49 | 22 | 14 | 3 | 19 | 18 | 99 | 41 | 85 | 6 | 14 | 8 | 13 | 10 | 44 | 18 | 11 | 12 | 23 | 26 | 96 |
| 8 | 8 | 2012-01-07 | @ | DET | W | 240 | 39 | 83 | 8 | 28 | 17 | 20 | 12 | 48 | 26 | 12 | 5 | 11 | 20 | 103 | 29 | 78 | 9 | 26 | 13 | 22 | 15 | 41 | 17 | 8 | 5 | 20 | 21 | 80 |
| 9 | 9 | 2012-01-09 | | CHA | W | 240 | 30 | 79 | 1 | 10 | 30 | 40 | 14 | 50 | 16 | 11 | 4 | 12 | 22 | 91 | 34 | 82 | 7 | 19 | 12 | 15 | 10 | 49 | 21 | 4 | 3 | 17 | 24 | 87 |

A fraction of per game statistics of New York Knicks in regular season 2011-2012 (Basketball Reference)

The following table shows a fraction of player statistics of New York Knicks players in regular season 2011-2012. Basketball-reference.com provides a wide range of statistics like PER- Player Efficiency Rating, TS% - True Shooting Percentage and eFG% - Effective Field Goal Percentage etc.

| Rk | Player | Age | G | MP | PER | TS% | eFG% | ORB% | DRB% | TRB% | AST% | STL% | BLK% | TOV% | USG% | ORtg | DRtg | OWS | DWS | WS | WS/48 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Tyson Chandler | 29 | 62 | 2061 | 18.7 | .708 | .679 | 11.8 | 22.7 | 17.2 | 4.3 | 1.4 | 3.4 | 17.1 | 13.0 | 130 | 99 | 5.8 | 3.6 | 9.5 | .220 |
| 2 | Carmelo Anthony | 27 | 55 | 1876 | 21.1 | .525 | .463 | 5.4 | 15.9 | 10.6 | 21.0 | 1.7 | 1.0 | 10.8 | 31.8 | 106 | 102 | 3.7 | 2.6 | 6.2 | .160 |
| 3 | Amare Stoudemire | 29 | 47 | 1543 | 17.7 | .541 | .487 | 7.9 | 19.8 | 13.7 | 6.3 | 1.3 | 2.3 | 12.8 | 25.4 | 104 | 101 | 1.8 | 2.3 | 4.1 | .128 |
| 4 | Steve Novak | 28 | 54 | 1020 | 15.9 | .684 | .675 | 1.0 | 10.9 | 5.9 | 2.0 | 0.8 | 0.7 | 5.7 | 16.2 | 129 | 105 | 2.9 | 0.9 | 3.9 | .181 |
| 5 | Landry Fields | 23 | 66 | 1894 | 12.0 | .506 | .490 | 3.6 | 13.5 | 8.5 | 14.5 | 2.1 | 0.7 | 15.1 | 16.0 | 100 | 102 | 0.8 | 2.6 | 3.4 | .085 |
| 6 | Jeremy Lin | 23 | 35 | 940 | 19.9 | .552 | .478 | 2.2 | 11.1 | 6.6 | 41.0 | 3.0 | 0.8 | 21.4 | 28.1 | 104 | 101 | 1.3 | 1.4 | 2.7 | .140 |
| 7 | J.R. Smith | 26 | 35 | 967 | 15.2 | .508 | .490 | 3.4 | 12.9 | 8.1 | 15.2 | 2.9 | 0.5 | 9.7 | 22.0 | 104 | 100 | 1.0 | 1.5 | 2.5 | .122 |

A fraction of player statistics of New York Knicks players in regular season 2011-12 (Basketball Reference)

The following table shows a fraction of starting lineups information of New York Knicks in regular season 2011-2012. Starting lineups is the starters' combination of a team. It shows who will start the game for the team. Players in the starting lineups are often the key players of a team.

| G | Date | | Opponent | | | Tm | Opp | W | L | Starting Lineup |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Sun, Dec 25, 2011 | | Boston Celtics | W | | 106 | 104 | 1 | 0 | C. Anthony • T. Chandler • T. Douglas • L. Fields • A. Stoudemire |
| 2 | Wed, Dec 28, 2011 | @ | Golden State Warriors | L | | 78 | 92 | 1 | 1 | C. Anthony • T. Chandler • T. Douglas • L. Fields • A. Stoudemire |
| 3 | Thu, Dec 29, 2011 | @ | Los Angeles Lakers | L | | 82 | 99 | 1 | 2 | C. Anthony • T. Chandler • T. Douglas • L. Fields • A. Stoudemire |
| 4 | Sat, Dec 31, 2011 | @ | Sacramento Kings | W | | 114 | 92 | 2 | 2 | C. Anthony • T. Chandler • T. Douglas • L. Fields • J. Harrellson |
| 5 | Mon, Jan 2, 2012 | | Toronto Raptors | L | | 85 | 90 | 2 | 3 | C. Anthony • T. Chandler • T. Douglas • L. Fields • J. Harrellson |
| 6 | Wed, Jan 4, 2012 | | Charlotte Bobcats | L | | 110 | 118 | 2 | 4 | C. Anthony • T. Chandler • T. Douglas • L. Fields • A. Stoudemire |
| 7 | Fri, Jan 6, 2012 | @ | Washington Wizards | W | | 99 | 96 | 3 | 4 | C. Anthony • T. Chandler • T. Douglas • L. Fields • A. Stoudemire |
| 8 | Sat, Jan 7, 2012 | @ | Detroit Pistons | W | | 103 | 80 | 4 | 4 | C. Anthony • T. Chandler • L. Fields • I. Shumpert • A. Stoudemire |
| 9 | Mon, Jan 9, 2012 | | Charlotte Bobcats | W | | 91 | 87 | 5 | 4 | C. Anthony • T. Chandler • L. Fields • I. Shumpert • A. Stoudemire |
| 10 | Wed, Jan 11, 2012 | | Philadelphia 76ers | W | | 85 | 79 | 6 | 4 | C. Anthony • T. Chandler • L. Fields • I. Shumpert • A. Stoudemire |

A fraction of starting lineups information of New York Knicks in regular season 2011-2012 (Basketball Reference)

| G | W | L | W-L% | Starting Lineup |
|---|---|---|---|---|
| 15 | 8 | 7 | .533 | C. Anthony • T. Chandler • L. Fields • J. Lin • A. Stoudemire |
| 14 | 6 | 8 | .429 | C. Anthony • T. Chandler • L. Fields • I. Shumpert • A. Stoudemire |
| 12 | 8 | 4 | .667 | C. Anthony • T. Chandler • B. Davis • L. Fields • I. Shumpert |
| 5 | 2 | 3 | .400 | C. Anthony • T. Chandler • T. Douglas • L. Fields • A. Stoudemire |
| 3 | 3 | 0 | 1.000 | T. Chandler • L. Fields • J. Jeffries • J. Lin • B. Walker |
| 3 | 2 | 1 | .667 | T. Chandler • L. Fields • J. Lin • A. Stoudemire • B. Walker |
| 2 | 1 | 1 | .500 | C. Anthony • T. Chandler • T. Douglas • L. Fields • J. Harrellson |
| 1 | 1 | 0 | 1.000 | C. Anthony • M. Bibby • T. Chandler • L. Fields • I. Shumpert |

A fraction of starting lineup win ratio statistics of New York Knicks in regular season 2011-2012 (Basketball Reference)

Many research shows that team play at home or road has a major impact of the game. In this project, we also add this factor to do the experiment. The following table shows Home vs. Road statistics of New York Knicks in regular season 2011-2012.

| Split | Value | G | W | L | FG | FGA | 3P | 3PA | FT | FTA | ORB | TRB | AST | STL | BLK | TOV | PF | PTS | FG | FGA | 3P | 3PA | FT | FTA | ORB | TRB | AST | STL | BLK | TOV | PF | PTS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Place | Home | 33 | 22 | 11 | 36.2 | 80.2 | 8.2 | 24.3 | 19.2 | 26.1 | 11.5 | 43.0 | 19.9 | 9.8 | 4.1 | 15.5 | 21.1 | 99.8 | 33.8 | 77.9 | 6.8 | 19.1 | 18.1 | 24.5 | 10.1 | 40.6 | 18.1 | 8.3 | 3.8 | 17.0 | 22.7 | 92.5 |
| | Road | 33 | 14 | 19 | 35.4 | 81.4 | 7.5 | 22.3 | 17.5 | 23.5 | 11.1 | 40.5 | 20.3 | 9.0 | 4.3 | 15.0 | 21.0 | 95.9 | 36.4 | 80.8 | 6.6 | 18.4 | 17.4 | 23.7 | 11.7 | 43.1 | 19.7 | 8.0 | 6.4 | 15.4 | 20.9 | 96.8 |

Home vs Road statistics of New York Knicks in regular season 2011-2012 (Basketball Reference)

Opponents' statistics shows the performances of every other 29 teams in the NBA league played against the observed team.

| Split | Value | G | W | L | FG | FGA | 3P | 3PA | FT | FTA | ORB | TRB | AST | STL | BLK | TOV | PF | PTS | FG | FGA | 3P | 3PA | FT | FTA | ORB | TRB | AST | STL | BLK | TOV | PF | PTS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Opponent | Atlanta | 3 | 2 | 1 | 37.3 | 76.3 | 8.7 | 19.3 | 17.3 | 25.7 | 10.3 | 39.0 | 19.0 | 13.0 | 2.7 | 18.7 | 20.3 | 100.7 | 36.7 | 76.7 | 9.0 | 23.7 | 15.7 | 22.3 | 8.7 | 37.7 | 19.0 | 12.7 | 5.0 | 20.0 | 22.0 | 98.0 |
| | Boston | 4 | 2 | 2 | 38.0 | 80.5 | 9.8 | 21.3 | 20.3 | 24.5 | 11.5 | 38.5 | 21.8 | 8.8 | 5.8 | 16.8 | 24.3 | 106.0 | 37.8 | 80.3 | 7.5 | 16.0 | 22.0 | 28.0 | 11.5 | 37.3 | 24.8 | 7.5 | 5.3 | 15.0 | 23.5 | 105.0 |
| | Charlotte | 4 | 3 | 1 | 38.8 | 81.8 | 6.8 | 19.5 | 19.8 | 27.0 | 11.0 | 44.8 | 23.0 | 8.0 | 5.8 | 12.8 | 21.0 | 104.0 | 35.0 | 80.8 | 5.8 | 14.3 | 16.0 | 21.0 | 8.5 | 39.5 | 19.5 | 5.8 | 5.0 | 14.3 | 19.5 | 91.8 |
| | Chicago | 4 | 1 | 3 | 37.8 | 86.3 | 5.5 | 20.5 | 15.8 | 21.5 | 10.8 | 38.8 | 18.5 | 8.3 | 6.5 | 13.0 | 22.3 | 96.8 | 38.3 | 86.5 | 6.8 | 17.0 | 18.3 | 26.0 | 16.8 | 50.8 | 22.0 | 6.8 | 8.5 | 14.3 | 18.8 | 101.5 |
| | Cleveland | 4 | 2 | 2 | 35.0 | 80.0 | 7.5 | 25.3 | 18.0 | 27.3 | 13.3 | 41.3 | 22.0 | 9.5 | 5.0 | 14.8 | 20.3 | 95.5 | 34.0 | 77.8 | 6.5 | 18.0 | 17.3 | 26.8 | 14.0 | 44.3 | 19.3 | 6.0 | 3.3 | 17.3 | 23.0 | 91.8 |
| | Dallas | 2 | 1 | 1 | 36.0 | 85.0 | 9.0 | 26.0 | 13.5 | 20.5 | 14.0 | 45.5 | 20.5 | 11.0 | 3.5 | 16.0 | 18.5 | 94.5 | 33.5 | 80.5 | 9.5 | 29.5 | 19.5 | 23.5 | 12.0 | 43.5 | 19.0 | 10.5 | 4.5 | 16.0 | 20.0 | 96.0 |
| | Denver | 1 | 0 | 1 | 44.0 | 97.0 | 11.0 | 33.0 | 15.0 | 21.0 | 11.0 | 50.0 | 24.0 | 8.0 | 7.0 | 23.0 | 34.0 | 114.0 | 41.0 | 98.0 | 6.0 | 24.0 | 31.0 | 43.0 | 15.0 | 58.0 | 29.0 | 12.0 | 4.0 | 20.0 | 20.0 | 119.0 |
| | Detroit | 3 | 3 | 0 | 39.7 | 77.0 | 7.7 | 22.0 | 18.7 | 25.0 | 11.3 | 44.0 | 23.7 | 12.3 | 5.3 | 15.0 | 20.7 | 105.7 | 29.7 | 75.0 | 6.0 | 18.0 | 16.3 | 23.0 | 11.0 | 35.3 | 14.3 | 8.7 | 3.7 | 18.7 | 20.7 | 81.7 |
| | Golden State | 1 | 0 | 1 | 28.0 | 70.0 | 4.0 | 21.0 | 18.0 | 25.0 | 4.0 | 31.0 | 15.0 | 7.0 | 0.0 | 15.0 | 21.0 | 78.0 | 35.0 | 77.0 | 6.0 | 16.0 | 16.0 | 24.0 | 11.0 | 47.0 | 20.0 | 12.0 | 4.0 | 14.0 | 17.0 | 92.0 |
| | Houston | 1 | 0 | 1 | 34.0 | 89.0 | 5.0 | 26.0 | 11.0 | 15.0 | 15.0 | 40.0 | 17.0 | 10.0 | 3.0 | 16.0 | 16.0 | 84.0 | 38.0 | 77.0 | 4.0 | 12.0 | 17.0 | 22.0 | 9.0 | 47.0 | 19.0 | 9.0 | 5.0 | 16.0 | 20.0 | 97.0 |
| | Indiana | 3 | 2 | 1 | 37.0 | 80.3 | 9.3 | 24.0 | 23.7 | 31.0 | 13.3 | 44.7 | 17.3 | 8.3 | 7.0 | 11.3 | 23.7 | 107.0 | 35.0 | 82.0 | 6.0 | 20.3 | 24.0 | 30.7 | 12.7 | 42.0 | 17.0 | 5.0 | 4.0 | 13.3 | 24.7 | 100.0 |
| | LA Clippers | 1 | 1 | 0 | 36.0 | 77.0 | 9.0 | 24.0 | 18.0 | 24.0 | 8.0 | 36.0 | 18.0 | 9.0 | 2.0 | 8.0 | 18.0 | 99.0 | 34.0 | 70.0 | 11.0 | 25.0 | 14.0 | 25.0 | 9.0 | 40.0 | 19.0 | 6.0 | 3.0 | 13.0 | 20.0 | 93.0 |
| | LA Lakers | 2 | 1 | 1 | 27.0 | 72.0 | 5.5 | 21.5 | 27.5 | 37.5 | 8.5 | 36.5 | 15.5 | 10.0 | 3.5 | 13.0 | 18.5 | 87.0 | 34.0 | 76.5 | 7.5 | 20.0 | 16.5 | 22.5 | 9.0 | 44.0 | 18.0 | 6.0 | 6.0 | 15.5 | 28.5 | 92.0 |
| | Memphis | 1 | 0 | 1 | 31.0 | 83.0 | 11.0 | 26.0 | 10.0 | 11.0 | 8.0 | 41.0 | 19.0 | 8.0 | 3.0 | 18.0 | 23.0 | 83.0 | 34.0 | 75.0 | 6.0 | 12.0 | 20.0 | 30.0 | 8.0 | 48.0 | 20.0 | 9.0 | 6.0 | 16.0 | 11.0 | 94.0 |
| | Miami | 3 | 0 | 3 | 30.7 | 78.7 | 11.3 | 30.0 | 14.7 | 19.7 | 10.0 | 37.7 | 17.7 | 7.7 | 3.0 | 17.3 | 19.7 | 87.3 | 38.3 | 81.0 | 3.3 | 13.7 | 18.0 | 22.0 | 10.3 | 44.3 | 16.7 | 9.3 | 6.7 | 13.7 | 21.0 | 98.0 |

A fraction of opponent statistics of New York Knicks in regular season 2011-2012 (Basketball Reference)

| Player | Date | Type | Note |
|---|---|---|---|
| Chris Bosh | 2012-05-14 | strained lower abdominal | is out indefinitely |

Injury report of Miami Heat in playoff 2011-2012 on 3/6/2012 (Basketball Reference)

This project collected the data from 2006-11 seasons which nearly about 7000 data and those data will be divided into different functions which involves testing set, cross-validation set and scoring set. Different types of data as listed above and saved them

as files in CSV format. The following section introduces the tools created and used for collecting data.

## *3.3 Data Collection*

Our major data source only publishes their data in Webpages. And the statistics data in categorized into teams and further displayed in different types of statistics across thousands of Webpages. In order to collecting data effectively, automated data collection tools have been created.

### 3.3.1 Data Collection Tool

Our goal is to collect all statistics information from our data source website in automated manner. There are several choices available for collecting data from webpages. The following part shows two popular tools as this function:

Python with (Beautiful Soup) library provides powerful functions to collecting data by parsing the HTML of a website.

Ruby is another popular language for web crawling. There are several libraries available for collecting data from webpages:

- (Mechanize) provides abilities to grab webpages, follow interlinks, and filling forms.

- Nokogirli has the outstanding abilities to search documents via XPath or CSS3 selectors. (Nokogirli) It is an ideal tool for parsing HTML based document.

- Watir WebDriver is another outstanding tool. It simulates a human action by interacting with a real browser. It is the perfect tool for dealing with JavaScript heavy webpages or pages getting content dynamically from AJAX. It is also a

popular to for automation testing of websites. It supports all major browsers: including Firefox, Chrome, IE and Safari. (Watir WebDriver)

By assessing our targeting websites which are JavaScript manipulated webpages, Ruby language with Water WebDriver is chosen as the programming language and data collection library in this project.

### 3.3.2 Implementation of Data Collection Tool

The following ruby code files are created to collect NBA statistics data from WebPages.


- get-game-log.rb: collect per game statistics for each NBA team in each NBA season
- get-players.rb: collect player statistics for each NBA team in each NBA season
- get-start-lineups.rb: collect starting lineups statistics for each NBA team in each NBA season
- get-team-detail.rb: collect detailed rosters statistics of each NBA team for each NBA team in each NBA season
- get-team-general.rb: collect general rosters statistics of each NBA team for each NBA team in each NBA season
- get-team-splits.rb: collect team statistics categorized by different criteria. It includes home game vs. road game statistics, rest days statistics and opponent statistics, etc.

The core function of get-game-log.rb is shown below.

```ruby
begin
b = Watir::Browser.new
(2004..2012).each { |year|
 for team in @teams
   # Test if the NBA team exist in the targeting year.
  if !validateTeamYear(team, year)
    next
  end

  # Create URL
  p url = 'http://www.basketball-reference.com/teams/'+ team.to_s + '/' + year.to_s + '/gamelog'

  # Go to the webpage
  b.goto url

  # Test if the targeting HTML element exist
  if b.div(:id => 'page_content').span(:text => 'CSV').exist?
    # Do click action on the targeting HTML element and
    #  triger JavaScript function to translate table in to CSV format text
    b.div(:id => 'page_content').span(:text => 'CSV').click
    dir = "../GameLog/" + team.to_s + "_" + year.to_s + "_game_log.csv"
    aFile = File.new(dir, "w")

    # Save CSV text in to a local CSV file
    csv = b.pre.text

    # Clean up redundant lines in the text
    cnt = 0;
    csv_clean = ''
    csv.each do |line|
      cnt = cnt + 1
      if cnt < 3
        csv_clean = csv_clean + line
        next
      end

      if line =~ /,,,,,,(.*)/ || line =~ /Rk,G,Date,,Opp(.*)/
      else
        csv_clean = csv_clean + line
      end

    end
    aFile.write(csv_clean)
    aFile.close
  end
 end
}
b.close
rescue Exception => e
  print e, "\n"
end
```

**Code Snippet 1 Core function of get-game-log.rb**

The function loop through each targeting NBA season (2006 to 2011) and each NBA team to generate targeting URL and collect CSV format data from HTML content of the generated URL.

### 3.3.3 Data Collection Process and Results

After the data collection scripts have been created, scripts can be run and the result is illustrated below. Take get-game-log.rb for example:

- Command to run the script: ruby get-game-log.rb
- After executing the command, a browser will be automatically started and jump

to the designated URL specified in the code, as shown in Figure below

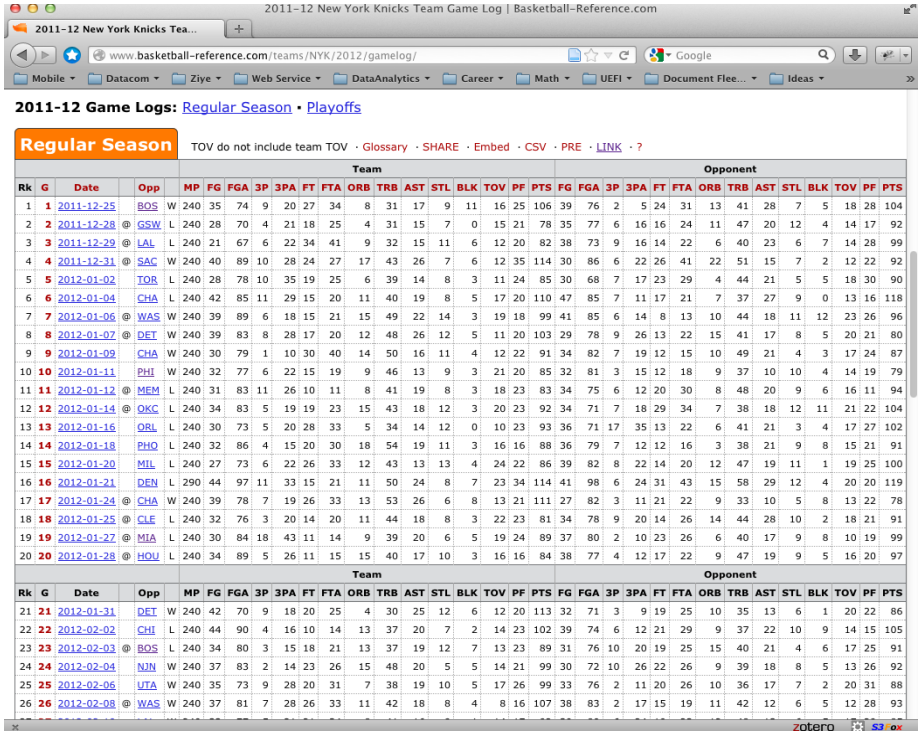



**Figure 7 Webpage of Game Log Data in HTML format**

And the code simulated a click action on the CSV button. This action triggers a JavaScript function to turn the table into a paragraph of CSV format text, as shown below.

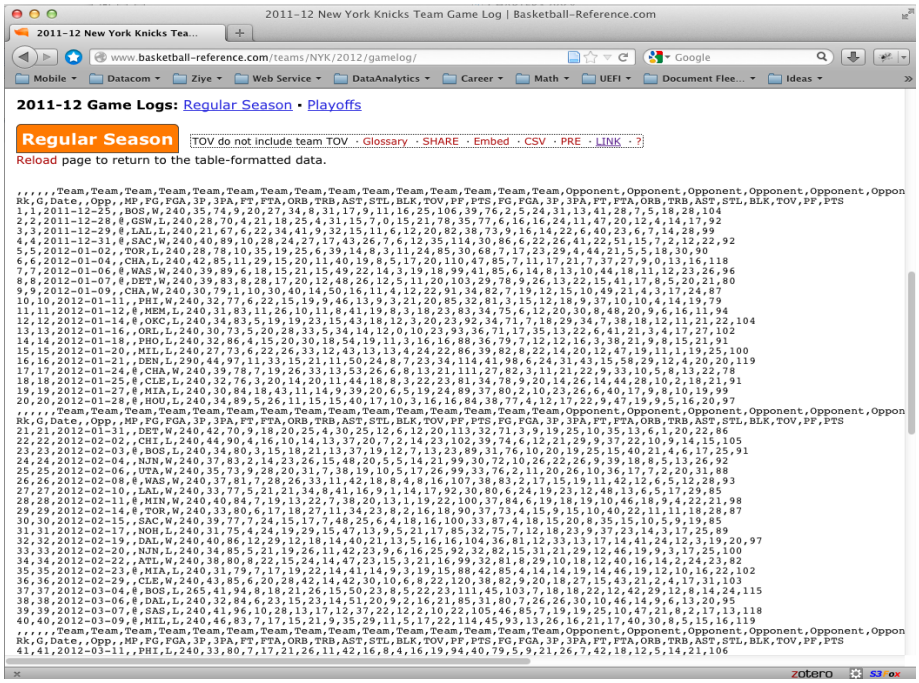



**Figure 8 Webpage of Game Log Data in CSV format text**

- Then the code collected the CSV formatted text and save it into a local CSV file.

These steps were iterated about 180 times (30 NBA teams by 6 seasons), as we collected team log data of all NBA games for 6 NBA seasons and other scripts were executed in similar way. By executing these Ruby scripts, many local CSV files were generated containing comprehensive NBA statistics data, as a result of this data collection process. About 25MB data was collected during this process.

In the Code Snippet 1, there is also a data-cleaning step to strip redundant column names from the CSV text. As data is collected from a managed source, quality of the data is very high. There is seldom of problems of collected raw data has, like missing data, inconsistent format issue and inaccurate data. Data cleaning tasks are not required.

## *3.4 Data management*

Data collected from data sources are mostly stored in CSV formatted files. In order to managing and manipulating effectively, MySQL database is chosen to the data management tool and data in local CSV format is parsed and uploaded to the database.

### 3.4.1 Hosting Environment and Setup

On the era of cloud computing, this project chooses Cloud solution to host the MySQL database. It is an interesting trial to utilizing power full cloud power to facilitate this project and maintain the cost of this project to minimum. Amazon Web Service provides cloud services such as Elastic Compute Cloud and Elastic Block Store, which is ideal for this project. Amazon Elastic Compute Cloud (Amazon EC2) is a web service that provides scalable compute capacity in the cloud with pay-as-you-go billing method (Amazon EC2). Amazon Elastic Block Store (EBS) provides highly available, highly reliable storage volumes for use with Amazon EC2 instances (Amazon EBS).

As this project only requires casual usage of MySQL database, and EC2 with EBS as storage provide a cheap and on demand solution that meet our needs, this project uses Amazon EC2 as the MySQL server and EBS as the storage of the server.

Lunch an EC2 Instance-

One High-CPU medium EC2 instance with 1.7 GB memories and 8GB EBS is used. And Ubuntu is chosen as the Operating System of the database server.

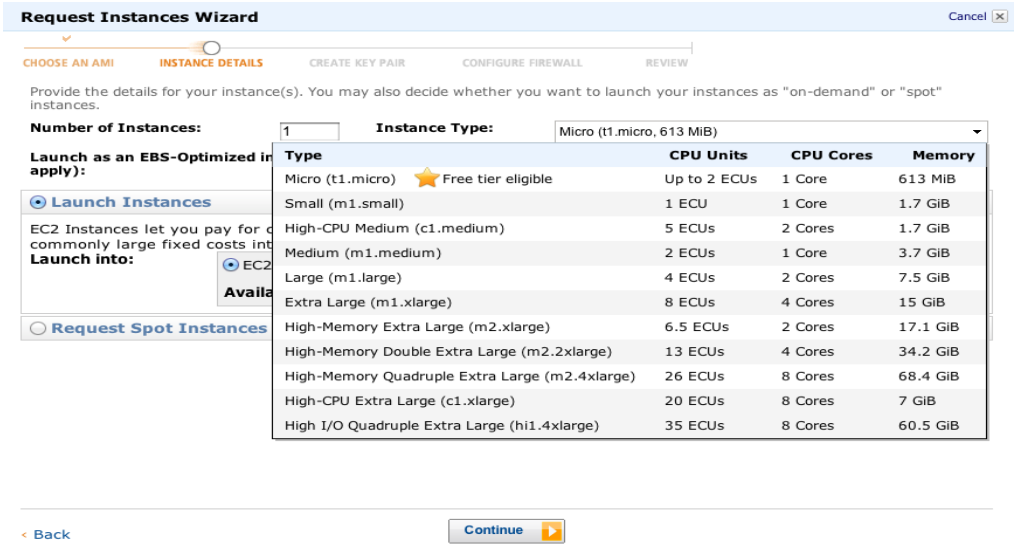



**Figure 9 Screenshot of EC2 instances**

Setup Security Group

When setting up the security group of the EC2 instance, TCP Port 22 and 3306 should be allowed. Port 22 is used for SSH remote command line access and Port 3306 is the default port for accessing MySQL database.

| TCP Port (Service) | Source |
|---|---|
| 22 (SSH) | 0.0.0.0/0 |
| 3306 (MYSQL) | 0.0.0.0/0 |

**Figure 10 EC2 opened Port**

Install and Configure MySQL Database

The following command is used to setup MySQL database in the EC2 Instance:

- Install MySQL Server software
  `sudo apt-get install mysql-server`
- Grand MySQL user permission to access from outside IP
  - Configure my.cnf file: `sudo emacs /etc/mysql/my.cnf`
  - Change bind-address: `bind-address = 0.0.0.0`
  - Grant permission

```
ubuntu@ec2:~$ mysql -u root -p
Enter password: #put your password here

mysql> grant all on *.* to 'root'@'%' IDENTIFIED BY 'securepassword';
```

Access Remote MySQL from Local Computer

In the Mac OS, execute the following command in terminal to setup port forwarding from port 3306 of running EC2 instant to port 33060 at local computer:

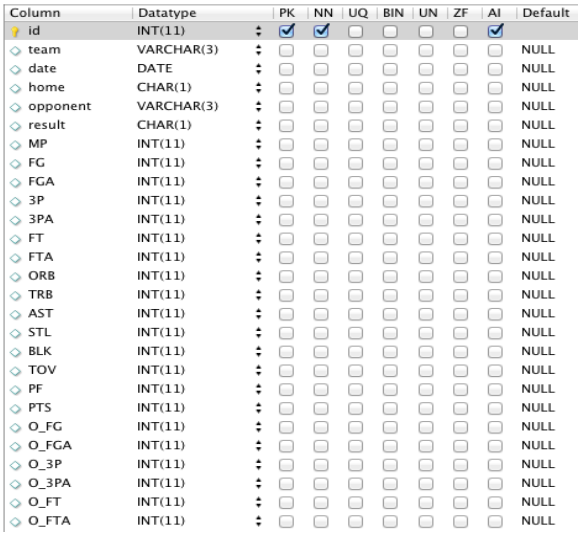
*sudo ssh -i ec2key -L 33060:127.0.0.1:3306 ubuntu@ec2-107-22-157-135.compute-1.amazonaws.com*

where "ec2key" is the secure key file generated from Amazon AWS console and "ec2-107-22-157-135.compute-1.amazonaws.com" is the dynamic IP of the running EC2 instance. By using port forwarding command, remote MySQL database hosted in the cloud can be accessed as a local database.

### 3.4.2 Database Table Design

After setting up the database for managing our data, database tables should be design and created. As data collected is from well designed and report like webpages with different types of statistics of NBA teams and players, table for storing such data should follow the same structure as the collected CSV files.

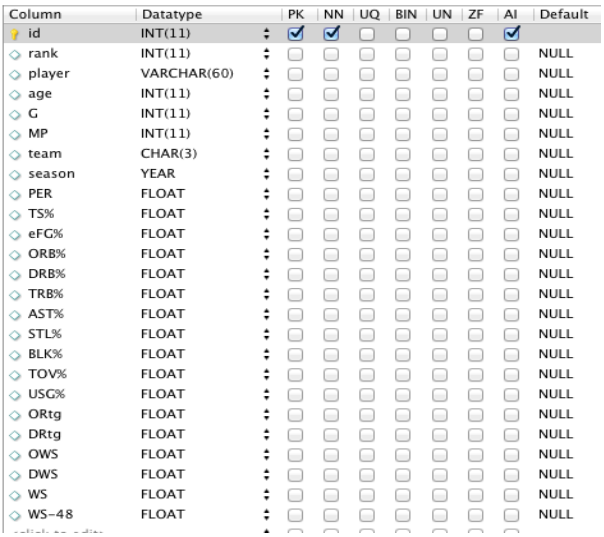
Game log statistics is stored in game_log table. It includes very detailed statistics very single games in each NBA season. The statistics is very comprehensive, which covers statistic data of field goals, 3 points shots, free throws, rebounds, assists, etc. The columns of game_log table is shown below (symbols are explained in Apendix X):



| Column | Datatype | PK | NN | UQ | BIN | UN | ZF | AI | Default |
|---|---|---|---|---|---|---|---|---|---|
| id | INT(11) | ☑ | ☑ | ☐ | ☐ | ☐ | ☐ | ☑ | |
| team | VARCHAR(3) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| date | DATE | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| home | CHAR(1) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| opponent | VARCHAR(3) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| result | CHAR(1) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| MP | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| FG | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| FGA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| 3P | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| 3PA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| FT | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| FTA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| ORB | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| TRB | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| AST | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| STL | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| BLK | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| TOV | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| PF | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| PTS | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_FG | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_FGA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_3P | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_3PA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_FT | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_FTA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |

**Figure 11 Game Log Table Structure**

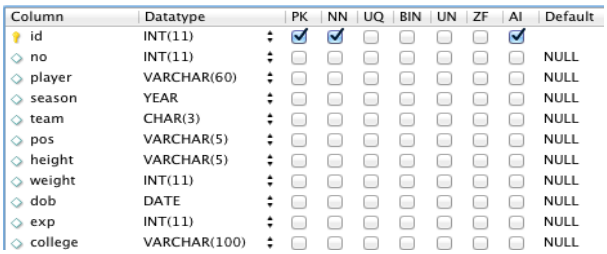
Players statistics data is stored in player related tables, including player_per_game, player_per_36, player_advanced, player_totoal. They record players' seasonal performance metrics. Taking player_advanced table for example, the table covers players turnover percentage, offensive/defensive rating, offensive/defensive win share, etc. (Appendix A) The columns of player_advanced table is shown below:



| Column | Datatype | PK | NN | UQ | BIN | UN | ZF | AI | Default |
|---|---|---|---|---|---|---|---|---|---|
| id | INT(11) | ☑ | ☑ | ☐ | ☐ | ☐ | ☐ | ☑ | |
| rank | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| player | VARCHAR(60) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| age | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| G | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| MP | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| team | CHAR(3) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| season | YEAR | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| PER | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| TS% | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| eFG% | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| ORB% | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| DRB% | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| TRB% | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| AST% | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| STL% | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| BLK% | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| TOV% | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| USG% | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| ORtg | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| DRtg | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| OWS | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| DWS | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| WS | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| WS-48 | FLOAT | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |

**Figure 12 Player Statistics Table Structure**

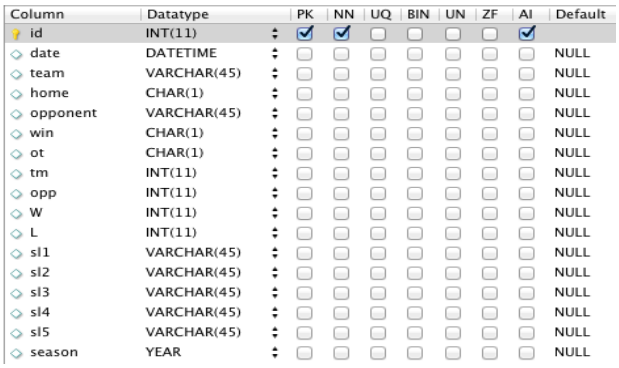
Roster information is stored in roster table, which stores the roster information of each NBA team in every NBA season. The columns of roster table are shown below:



| Column | Datatype | PK | NN | UQ | BIN | UN | ZF | AI | Default |
|---|---|---|---|---|---|---|---|---|---|
| id | INT(11) | ☑ | ☑ | ☐ | ☐ | ☐ | ☐ | ☑ | |
| no | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| player | VARCHAR(60) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| season | YEAR | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| team | CHAR(3) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| pos | VARCHAR(5) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| height | VARCHAR(5) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| weight | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| dob | DATE | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| exp | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| college | VARCHAR(100) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |

**Figure 13 Roster Table Structure**

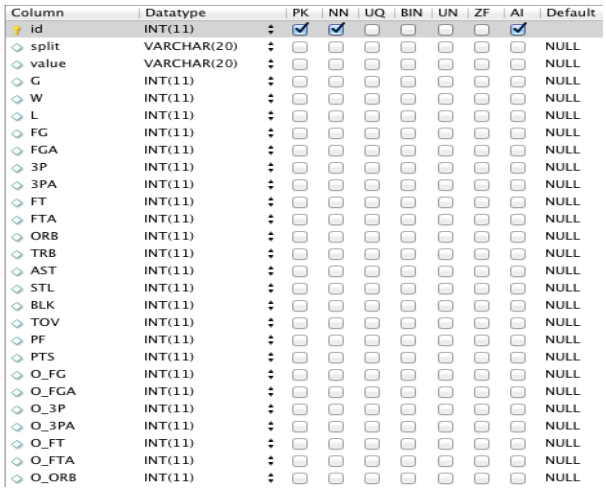
The starting lineups information is stored in starting_lineup table, which records the starting lineups of each game. The columns of starting_lineup table are shown below:



| Column | Datatype | PK | NN | UQ | BIN | UN | ZF | AI | Default |
|---|---|---|---|---|---|---|---|---|---|
| id | INT(11) | ☑ | ☑ | ☐ | ☐ | ☐ | ☐ | ☑ | |
| date | DATETIME | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| team | VARCHAR(45) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| home | CHAR(1) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| opponent | VARCHAR(45) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| win | CHAR(1) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| ot | CHAR(1) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| tm | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| opp | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| W | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| L | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| sl1 | VARCHAR(45) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| sl2 | VARCHAR(45) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| sl3 | VARCHAR(45) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| sl4 | VARCHAR(45) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| sl5 | VARCHAR(45) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| season | YEAR | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |

**Figure 14 Starting Lineups Table Structure**

Comprehensive team related statistics is stored in team_split table. The columns of team_split table are shown below:



| Column | Datatype | PK | NN | UQ | BIN | UN | ZF | AI | Default |
|---|---|---|---|---|---|---|---|---|---|
| id | INT(11) | ☑ | ☑ | ☐ | ☐ | ☐ | ☐ | ☑ | |
| split | VARCHAR(20) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| value | VARCHAR(20) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| G | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| W | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| L | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| FG | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| FGA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| 3P | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| 3PA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| FT | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| FTA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| ORB | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| TRB | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| AST | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| STL | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| BLK | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| TOV | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| PF | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| PTS | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_FG | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_FGA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_3P | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_3PA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_FT | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_FTA | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| O_ORB | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |

**Figure 15 Team Split Table Structure**

Some representative tables have been listed above. They represent different focuses of NBA statistics.

### 3.4.3 Data Upload

Data collected from data sources is mainly stored in CSV files in a local computer. How to parse statistics data out of CSV files and push to remote MySQL database in the cloud is explained in this section.

**Tools**

Ruby and MySQL are the programming languages used for this function. Ruby gem "mysql2" is a library for connecting and querying MySQL database and providing the ability to iterate on results set (Mysql2 Ruby Gem). "fastercsv" (Fastercsv Ruby Gem) Ruby gem is used for parsing CSV file.

Several Ruby scripts have been created for parsing CSV files, filter CSV columns, generating insertion SQL statement and execute the insertion statement. Each script is responsible for the insertion of specific category of the statistics data, which are machine tables created in remote MySQL database. The following screenshot shows automation script for insertion of data in specific tables:

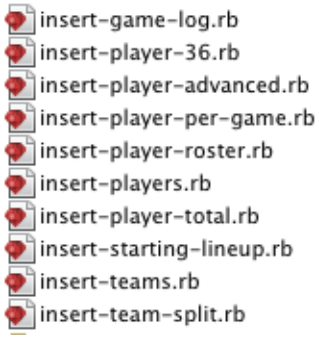



**Figure 16 SQL insertion Automation Script List**

**Connect to Remote MySQL database**

An SqlBroker class which utilizing the mysql2 gem, has been created to facility connecting to MySQL database and executing SQL queries.

```ruby
require 'rubygems'
require 'mysql2'
require 'net/ssh/gateway'
require 'parseconfig'

class SqlBroker
  def initialize()
    p 'initialized()'
    @config = ParseConfig.new('./nba.config')
    @client = Mysql2::Client.new(:host => @config['aws-mysql-host'],
              :username => @config['aws-mysql-user'],
              :password => @config['aws-mysql-pwd'],
              :database => "nba_mart",
              :port => @config['aws-mysql-port'])
 end

  def sqlQuery(sql)
    p 'executing: ' + sql
    return @client.query(sql)
  end

  def closeConnection()
    p 'close()'
    @client.close
  end

end
```

**Code Snippet 2 SqlBroker Class for connecting to remote MySQL client and executing SQL queries.**

## Parsing CSV Files and Generating Insertion SQL

Statistics data stored in CSV files are parsed by using "fastercsv" gem. The following code snippet is the function of batch processing files in GameLog directory and generates SQL insertion statement.

```ruby
def main
  basedir = '../NBA/GameLog/';

  # Get file list of targetting directory
  files = Dir.new(basedir).entries
  sql = ''
  files.each do |file|
    # Loop through the file list
    # and pass file content into insertion sql generation function
    if file != '.' && file != '..' && file != 'Glossary.txt'
      open(basedir + file) do |io|
        sql += generate_insertion_sql(io, file)
      end
    end
  end
  # Execute the sql on remote MySQL server
  insert_records(sql, false)
rescue Exception => e
  puts e.inspect
  puts e.backtrace
end
```

**Code Snippet 3 Get CSV file list in directory containing game log statistics files**

The generate_insertion_sql function parses the CSV text file and then generates insertion SQL statement for each row in the CSV file. It also do some job on filtering empty rows, appending missing information (season of the record in this case) and

transform CSV data into a database friendly format (from using "@" to represent home/road game to using "Y/N" in this case).

```ruby
def generate_insertion_sql(io, file)
  insert_cmd_list = ''
  insert_template = "INSERT INTO `nba_mart`.`game_log_2`(`team`,`date`,`home`,
  `opponent`,`result`,`MP`,`FG`,`FGA`,`3P`,`3PA`,`FT`,`FTA`,`ORB`,`TRB`,`AST`,
  `STL`,`BLK`,`TOV`,`PF`,`PTS`,`O_FG`,`O_FGA`,`O_3P`,`O_3PA`,`O_FT`,`O_FTA`,
  `O_ORB`,`O_TRB`,`O_AST`,`O_STL`,`O_BLK`,`O_TOV`,`O_PF`,`O_PTS`, `season`) VALUES "
  i = 0
  CSVScan.scan(io) do |row|
    c = 0
    # Filter empty rows in CSV file
    row.each do |item|
      if item == nil
        row[c] = 'null'
      end
      c += 1
    end
    # Appending SQL insertion values into the insertion template
    if i != 0 && i != 1
      temp_insert_cmd = insert_template
      temp_insert_cmd += "("
      temp_insert_cmd += "'" + file[0,3] + "',"
      temp_insert_cmd += "'" + row[2] + "',"
      # Home/road symbol @ is translated into Y/N
      if row[3] == '@'
        temp_insert_cmd += "'" + "N" + "',"
      else
        temp_insert_cmd += "'" + "Y" + "',"
      end
      temp_insert_cmd += "'" + row[4] + "',"
      temp_insert_cmd += "'" + row[5] + "',"
      j=0
      row.each do |item|
        if j > 5
          if j != row.count - 1
            temp_insert_cmd += item + ","
          else
            temp_insert_cmd += item + ","
          end

        end
        j += 1
      end
      # Append Season information
      year = file[4,4]
      temp_insert_cmd += year

      temp_insert_cmd += ");"
      insert_cmd_list += temp_insert_cmd
    end
    i += 1
  end
  return insert_cmd_list
end
```

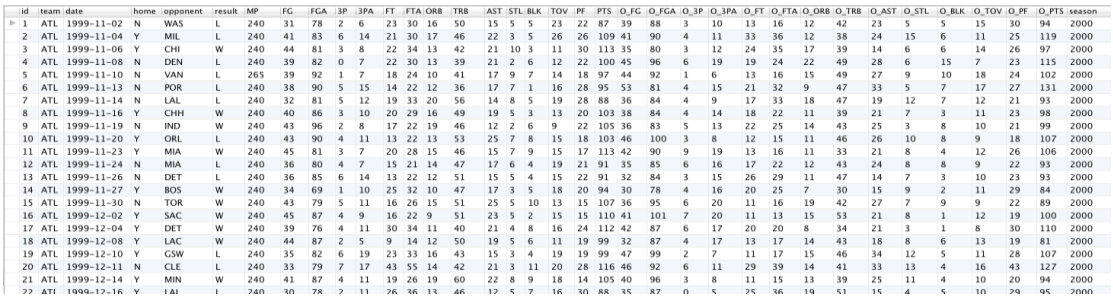
**Code Snippet 4 generate_insertion_sql function for parsing CSV file and generating SQL insertion queries.**

## Executing Insertion Scripts

Taking insert-game-log.rb for example, by executing "ruby insert-game-log.rb", the script is going to run, and data will be parsed out of local CSV files and will be inserted into MySQL server in the Amazon EC2 Cloud.

## Insertion Result

By executing "SELECT * FROM nba_mart.game_log LIMIT 500" in MySQL Workbench, the first 500 rows in game_log table is returned.



| id | team | date | home | opponent | result | MP | FG | FGA | 3P | 3PA | FT | FTA | ORB | TRB | AST | STL | BLK | TOV | PF | PTS | O_FG | O_FGA | O_3P | O_3PA | O_FT | O_FTA | O_ORB | O_TRB | O_AST | O_STL | O_BLK | O_TOV | O_PF | O_PTS | season |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | ATL | 1999-11-02 | N | WAS | L | 240 | 31 | 78 | 2 | 6 | 23 | 30 | 16 | 50 | 15 | 5 | 5 | 23 | 22 | 87 | 39 | 88 | 3 | 10 | 13 | 16 | 12 | 42 | 23 | 5 | 5 | 15 | 30 | 94 | 2000 |
| 2 | ATL | 1999-11-04 | Y | MIL | L | 240 | 41 | 83 | 6 | 14 | 21 | 30 | 17 | 46 | 22 | 3 | 5 | 26 | 26 | 109 | 41 | 90 | 4 | 11 | 33 | 36 | 12 | 38 | 24 | 15 | 6 | 11 | 25 | 119 | 2000 |
| 3 | ATL | 1999-11-06 | Y | CHI | W | 240 | 44 | 81 | 3 | 8 | 22 | 34 | 13 | 42 | 21 | 10 | 3 | 11 | 30 | 113 | 35 | 80 | 3 | 12 | 24 | 35 | 17 | 39 | 14 | 6 | 6 | 14 | 26 | 97 | 2000 |
| 4 | ATL | 1999-11-08 | N | DEN | L | 240 | 39 | 82 | 0 | 7 | 22 | 30 | 13 | 39 | 21 | 2 | 6 | 12 | 22 | 100 | 45 | 96 | 6 | 19 | 19 | 24 | 22 | 49 | 28 | 6 | 15 | 7 | 23 | 115 | 2000 |
| 5 | ATL | 1999-11-10 | N | VAN | L | 265 | 39 | 92 | 1 | 7 | 18 | 24 | 10 | 41 | 17 | 9 | 7 | 14 | 18 | 97 | 44 | 92 | 1 | 6 | 13 | 16 | 15 | 49 | 27 | 9 | 10 | 18 | 24 | 102 | 2000 |
| 6 | ATL | 1999-11-13 | N | POR | L | 240 | 38 | 90 | 5 | 15 | 14 | 22 | 12 | 36 | 17 | 7 | 1 | 16 | 28 | 95 | 53 | 81 | 4 | 15 | 21 | 32 | 9 | 47 | 33 | 5 | 7 | 17 | 27 | 131 | 2000 |
| 7 | ATL | 1999-11-14 | N | LAL | L | 240 | 32 | 81 | 5 | 12 | 19 | 33 | 20 | 56 | 14 | 8 | 5 | 19 | 28 | 88 | 36 | 84 | 4 | 9 | 17 | 33 | 18 | 47 | 19 | 12 | 7 | 12 | 21 | 93 | 2000 |
| 8 | ATL | 1999-11-16 | Y | CHH | W | 240 | 40 | 86 | 3 | 10 | 20 | 29 | 16 | 49 | 19 | 5 | 3 | 13 | 20 | 103 | 38 | 84 | 4 | 14 | 18 | 22 | 11 | 39 | 21 | 7 | 3 | 11 | 23 | 98 | 2000 |
| 9 | ATL | 1999-11-19 | N | IND | W | 240 | 43 | 96 | 2 | 8 | 17 | 22 | 19 | 46 | 12 | 2 | 6 | 9 | 22 | 105 | 36 | 83 | 5 | 13 | 22 | 25 | 14 | 43 | 25 | 3 | 8 | 10 | 21 | 99 | 2000 |
| 10 | ATL | 1999-11-20 | Y | ORL | L | 240 | 43 | 90 | 4 | 11 | 13 | 22 | 13 | 53 | 25 | 7 | 8 | 15 | 18 | 103 | 46 | 100 | 3 | 8 | 12 | 15 | 11 | 46 | 26 | 10 | 8 | 9 | 18 | 107 | 2000 |
| 11 | ATL | 1999-11-23 | Y | MIA | W | 240 | 45 | 81 | 3 | 7 | 20 | 28 | 15 | 46 | 15 | 7 | 9 | 15 | 17 | 113 | 42 | 90 | 9 | 19 | 13 | 16 | 11 | 33 | 21 | 8 | 4 | 12 | 26 | 106 | 2000 |
| 12 | ATL | 1999-11-24 | N | MIA | L | 240 | 36 | 80 | 4 | 7 | 15 | 21 | 14 | 47 | 17 | 6 | 4 | 19 | 21 | 91 | 35 | 85 | 6 | 16 | 17 | 22 | 12 | 43 | 24 | 8 | 8 | 9 | 22 | 93 | 2000 |
| 13 | ATL | 1999-11-26 | N | DET | L | 240 | 36 | 85 | 6 | 14 | 13 | 22 | 12 | 51 | 15 | 5 | 4 | 15 | 22 | 91 | 32 | 84 | 3 | 15 | 26 | 29 | 11 | 47 | 14 | 7 | 3 | 10 | 23 | 93 | 2000 |
| 14 | ATL | 1999-11-27 | Y | BOS | W | 240 | 34 | 69 | 1 | 10 | 25 | 32 | 10 | 47 | 17 | 3 | 5 | 18 | 20 | 94 | 30 | 78 | 4 | 16 | 20 | 25 | 7 | 30 | 15 | 9 | 2 | 11 | 29 | 84 | 2000 |
| 15 | ATL | 1999-11-30 | N | TOR | W | 240 | 43 | 79 | 5 | 11 | 16 | 26 | 15 | 51 | 25 | 5 | 10 | 13 | 15 | 107 | 36 | 95 | 6 | 20 | 11 | 16 | 19 | 42 | 27 | 7 | 9 | 9 | 22 | 89 | 2000 |
| 16 | ATL | 1999-12-02 | Y | SAC | W | 240 | 45 | 87 | 4 | 9 | 16 | 22 | 9 | 51 | 23 | 5 | 2 | 15 | 15 | 110 | 41 | 101 | 7 | 20 | 11 | 13 | 15 | 53 | 21 | 8 | 1 | 12 | 19 | 100 | 2000 |
| 17 | ATL | 1999-12-04 | Y | DET | W | 240 | 39 | 76 | 4 | 11 | 30 | 34 | 11 | 40 | 21 | 4 | 8 | 16 | 24 | 112 | 42 | 87 | 6 | 17 | 20 | 20 | 8 | 34 | 21 | 3 | 1 | 8 | 30 | 110 | 2000 |
| 18 | ATL | 1999-12-08 | Y | LAC | W | 240 | 44 | 87 | 2 | 5 | 9 | 14 | 12 | 50 | 19 | 5 | 6 | 11 | 19 | 99 | 32 | 87 | 4 | 17 | 13 | 17 | 14 | 43 | 18 | 8 | 6 | 13 | 19 | 81 | 2000 |
| 19 | ATL | 1999-12-10 | Y | GSW | L | 240 | 35 | 82 | 6 | 19 | 23 | 33 | 16 | 43 | 15 | 3 | 4 | 19 | 19 | 99 | 47 | 99 | 2 | 7 | 11 | 17 | 15 | 46 | 34 | 12 | 5 | 11 | 28 | 107 | 2000 |
| 20 | ATL | 1999-12-11 | N | CLE | L | 240 | 33 | 79 | 7 | 17 | 43 | 55 | 14 | 42 | 21 | 3 | 11 | 20 | 28 | 116 | 46 | 92 | 6 | 11 | 29 | 39 | 14 | 41 | 33 | 13 | 4 | 16 | 43 | 127 | 2000 |
| 21 | ATL | 1999-12-14 | Y | MIN | W | 240 | 41 | 87 | 4 | 11 | 19 | 26 | 19 | 60 | 22 | 8 | 9 | 18 | 14 | 105 | 40 | 96 | 3 | 8 | 11 | 15 | 13 | 39 | 25 | 11 | 4 | 10 | 20 | 94 | 2000 |
| 22 | ATL | 1999-12-16 | Y | LAL | L | 240 | 30 | 78 | 2 | 11 | 26 | 36 | 13 | 46 | 12 | 5 | 7 | 16 | 30 | 88 | 35 | 87 | 0 | 5 | 25 | 36 | 19 | 51 | 15 | 4 | 5 | 10 | 29 | 95 | 2000 |

**Figure 17 Screenshot of Result of Top 500 Record In game_log Table**

### 3.4.4 Summary

Up to this point, data collected from data sources has been uploaded to remote MySQL database hosed in Amazon EC2 cloud service. MySQL database as data management tools used in this project enables users to access and organize data effectively. For data mining purpose, a data mart can be implemented for preparing and managing data for data mining.

## *3.5 Data Mart*

As data collected is from report like webpages with different types of statistics of NBA teams and players, data collected and managed in MySQL database inherits the feature of reporting data, which is well managed but normalized. But normalized tables stores information in separated related tables, which makes data mining tasks very hard too perform by directly using data from these tables. A Data Mart can be built to connect these tables and demoralise some tables. The data mart can then used for further data mining purpose. A proposed star scheme for the problem is illustrated in Figure 18. The star scheme is centered with a game fact table, which contains the index information for every game. And the fact table is connected with many dimensional tables.

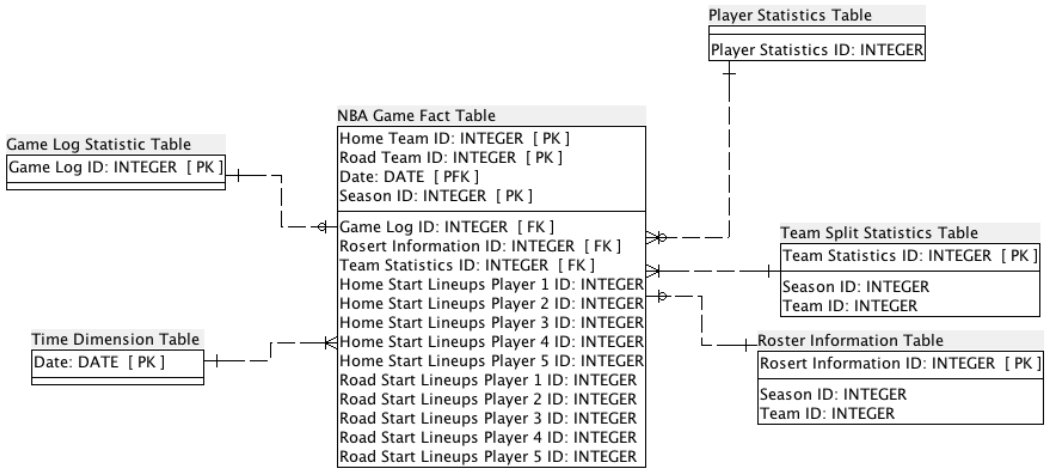



**Figure 18 Proposed Star Scheme Structure**

Time dimension is very important for a data mart. It enables analysts to do time series analysis and it is also the essential table enabling online analytical processing (OLAP). Even though, these are not the focus of this project, it is worth noting that its importance to other data mining projects. By creating the time dimension table, the project preserves the ability to do more work in the future. The columns of time dimension table are listed below:

| Column | Datatype | PK | NN | UQ | BIN | UN | ZF | AI | Default |
|---|---|---|---|---|---|---|---|---|---|
| date_id | INT(11) | ☑ | ☑ | ☐ | ☐ | ☐ | ☐ | ☑ | |
| fulldate | DATE | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| dayofmonth | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| dayofyear | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| dayofweek | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| dayname | VARCHAR(10) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| monthnumber | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| monthname | VARCHAR(10) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| year | INT(11) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |
| quarter | TINYINT(4) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | NULL |

**Figure 19 Time Dimension Table Structure**

## *3.6 Conclusion*

This chapter illustrates the process of management dataset, which involves collecting NBA statistics data from popular non-profit NBA statistics websites, managing MySQL database by Amazon Cloud services, uploading collected into database, and

building a data mart for enabling further data mining. it also provides step-by-step tutorial of the whole process.

This chapter highlights Ruby as a powerful language, which can be used for implementing data collection tool, data processing tool and data transferring tool. This project also makes a brave trial of using Amazon Cloud utilities as the major infrastructure, which is proven to be very effective, powerful and economic.

The whole process from data collection to data uploading is highly automated. It manages to collect about 25MB of data from thousands of WebPages, generates thousands of SQL insertion statement and executing SQL automatically. This chapter illustrated the process of collecting data and managing data and built a solid test bed for further data mining processes.

# 4 EXPERIMENT DESIGN

## *4.1 Introduction*

This chapter focuses on explaining the design of the data mining experiment. The data mart has been built which stores cleaned and well managed NBA statistics data. The feature extraction process, which extracts representative features from data mart, prepares the data samples that can be directly consumed by model training tools. The extracted data samples with selected features go through a data partition process and data samples are further divided into training set, test set and scoring set. The data mining process is conducted using Weka data mining tool. Then 4 distinctive data mining classifiers, Logistic Regression, Naïve Bayes Classifier, Support Vector Machine and Neural Networks, are trained and tested over test sets. Prediction accuracy is provided in the end of this chapter.

## *4.2 Experiment Design*

As illustrated in Chapter 3, data collected from data sources is stored in physically and logically separated files. After being imported into the data management system (MySQL database in this project), data are stored in tables representing different metrics of NBA game statistics. Then these normalized tables are extracted, transformed and loaded in to a data mart with a star scheme structure and a de-normalized fact table.

At this point, an ideal environment has been build for further data mining tasks. Figure 20. Illustrate the conceptual level design of this experiment.

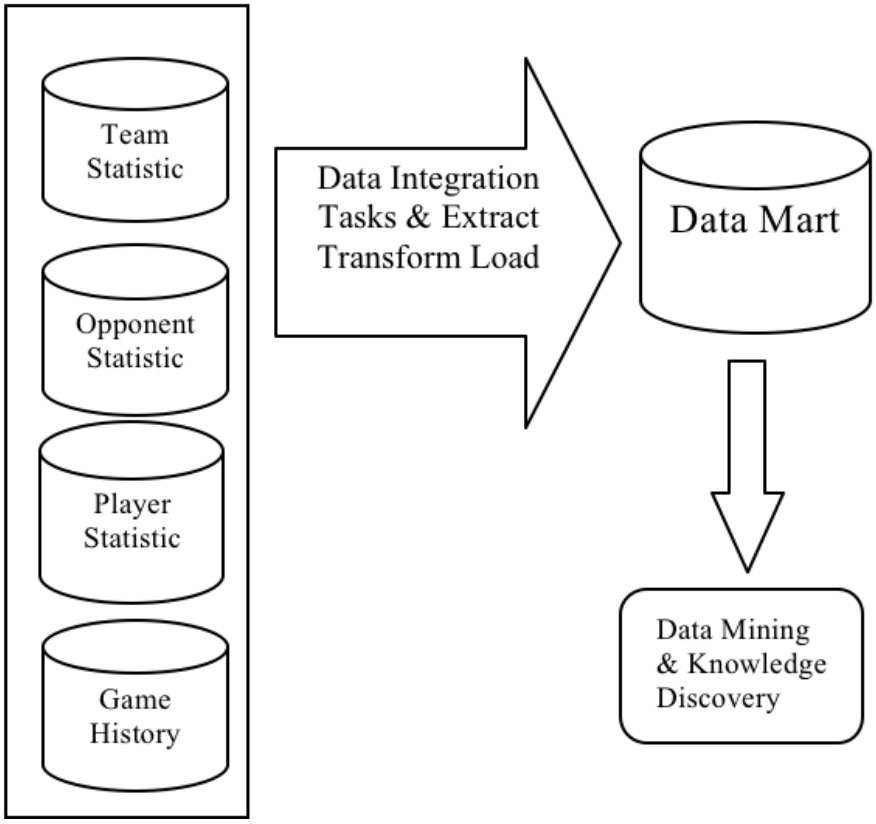



**Figure 20 Data Analytics Architecture**

The goal is to build predictive models, which can assist humans to predict the result of upcoming NBA games. The main idea behind this data-mining project is to build a generalised model, which can take statistics of two teams who are going to play against each other in the next game, using these statistics to predict the result of the game. As the data mart has been built, further data mining experiments directly pull relevant data out of data mart.

## *4.3 Feature Extraction*

Statistics data in the data mart is already well managed, but they cover every detailed and different focus of statistics about games, teams, game schedule and seasonal performance metrics, which is overwhelming for the predictive model fitting tasks. Data stored in data mart are scattered across different tables, which cannot be consumed directly by model training tool. A feature extraction process is required, that selects representative features and transform features into a centralised format.

In NBA game prediction, features selected are required to be comprehensive and representative. The initial idea is combining team statistics, opponent statistics, game schedule, player statistics, and recent team performance statistics (last 3 games or last 7 games) as features. The number of features can reach from 30 to 60 or more.

### 4.3.1 Feature Extracted Explanation

Which features will be extracted from the data mart is decided by employing NBA domain knowledge and expert experience. In this section, the extracted features are explained in details.

In order to make the extracted features easy to understand, this process is explained with a concrete example, which is home team Miami Heat (MIA) play against New York Nicks (NYK) at 2010-12-01 (NBA season 2010-11). The feature extraction process assumes that the game to be predicted is the very next game of two teams in a time line. And all data available is prior to that date. These features will be extracted using SQL queries.

**Statistics of Recent Games of Home Team and Opponent Team**

As a known fact that, playing at home or on road is definitely a core factor affecting the game result, due to fans' supports, travel schedule, weather difference and many other reasons.

The following SQL code is created to obtain statistics of averaging statistics of last 10 home games of the home team (MIA), and statistics of averaging statistics of last 10 road games of road team (NYK).

```sql
# Average statistics of latest 10 game of home team playing home games and road team playing road games
(SELECT team, home, AVG(FG/FGA) AS avg_fgp, AVG(3P/3PA) AS avg_3pp, AVG(FT/FTA) AS avg_ftp,
AVG(ORB) AS avg_orb, AVG(TRB) AS avg_trb, AVG(AST) AS avg_ast, AVG(TOV) AS avg_otv,
AVG(PF) AS avg_pf, AVG(PTS) AS avg_pts,
AVG(O_FG/O_FGA) AS avg_ofgp, AVG(O_3P/O_3PA) AS avg_o3pp, AVG(O_FT/O_FTA) AS avg_oftp,
AVG(O_ORB) AS avg_oorb, AVG(O_TRB) AS avg_otrb, AVG(O_AST) AS avg_oast, AVG(O_TOV) AS avg_ootv,
AVG(O_PF) AS avg_opf, AVG(O_PTS) AS avg_opts
 FROM (SELECT * FROM game_log AS g WHERE g.team = 'MIA' AND
(g.season = '2011' OR g.season = '2011' - 1) AND g.home = 'Y' AND g.date < '2010-12-1'
ORDER BY g.date DESC LIMIT 10 ) as go  GROUP BY go.team )
UNION
(SELECT opponent as team, home, AVG(O_FG/O_FGA) AS avg_fgp, AVG(O_3P/O_3PA) AS avg_3pp, AVG(O_FT/O_FTA) AS avg_ftp,
AVG(O_ORB) AS avg_orb, AVG(O_TRB) AS avg_trb, AVG(O_AST) AS avg_ast, AVG(O_TOV) AS avg_otv,
AVG(O_PF) AS avg_pf, AVG(O_PTS) AS avg_pts,
AVG(FG/FGA) AS avg_ofgp, AVG(3P/3PA) AS avg_o3pp, AVG(FT/FTA) AS avg_oftp,
AVG(ORB) AS avg_oorb, AVG(TRB) AS avg_otrb, AVG(AST) AS avg_oast, AVG(TOV) AS avg_ootv,
AVG(PF) AS avg_opf, AVG(PTS) AS avg_opts
 FROM (SELECT * FROM game_log AS g WHERE g.opponent = 'NYK' AND
(g.season = '2011' OR g.season = '2011' - 1) AND g.home = 'N' AND g.date < '2010-12-1'
ORDER BY g.date DESC LIMIT 10) as ro GROUP BY ro.opponent )
```

**Code Snippet 5 SQL for collecting average statistics of last 10 home games of home team and last 10 road games of road team.**

The query result is shown below:

| team | home | avg_fgp | avg_3pp | avg_ftp | avg_orb | avg_trb | avg_ast | avg_otv | avg_pf | avg_pts | avg_ofgp | avg_o3pp | avg_oftp | avg_oorb | avg_otrb | avg_oast | avg_ootv | avg_opf | avg_opts |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MIA | Y | 0.48 | 0.34 | 0.78 | 9.2 | 42.1 | 20 | 12.9 | 20.8 | 106 | 0.45 | 0.34 | 0.73 | 9.6 | 40.1 | 20.5 | 13.5 | 26 | 97.4 |
| NYK | N | 0.47 | 0.29 | 0.79 | 10.4 | 41.9 | 18.7 | 15.3 | 20.9 | 104 | 0.48 | 0.42 | 0.73 | 10.6 | 40.7 | 20.7 | 14.2 | 22.3 | 104 |

**Table 1 Averaging the last 10 games statistics**

Averaging the last 10 games statistics introduces stability into extracted features. On the other hand, there is very high randomness in the last 10 games, because the team can face teams of different level. Team had games with very strong teams may have a worse performance statistics than facing weak teams. In order to introducing opponents quality in to our feature list and balancing out the randomness of the 10 games, a win/loss contribution score is used by taking the performance of opponents of last 10 games in to our equation. The following SQL query is created to calculate the win/loss contribution score of last 10 games (last 10 home games for home team MIA, and last 10 road games for road team NYK):

```sql
(SELECT home_team, result, SUM(W/G) as win_p  FROM
    (SELECT team AS home_team, date, opponent, result FROM
    game_log AS g WHERE g.team = 'MIA' AND g.season = '2011' and g.home = 'Y' AND g.date < '2010-12-1'
    ORDER BY g.date DESC limit 10) AS gr, team_split AS s
WHERE  gr.opponent = s.team AND s.value = 'Road' AND s.season = 2010 GROUP BY result)
UNION
(SELECT home_team, result, SUM(W/G) as win_p FROM
    (SELECT opponent AS home_team, date, result FROM
    game_log AS g WHERE g.team = 'NYK' AND g.season = '2011' and g.home = 'N' AND g.date < '2010-12-1'
    ORDER BY g.date DESC limit 10) AS gr, team_split AS s
WHERE  gr.home_team = s.team AND s.value = 'Home' AND s.season = 2010  GROUP BY result)
```

**Code Snippet 6 SQL for calculating the Win/Loss score of two teams over last 10 games**

The query result is shown in below:

| Team | Result | Win/Loss Score |
|---|---|---|
| **MIA** | L | 1.36 |
| **MIA** | W | 2.07 |
| **NYK** | L | 2.34 |
| **NYK** | W | 3.15 |

**Table 2 Win/Loss score of last ten games**

The Win score is calculated by summing up the last season's winning percentage of defeated opponents in the last 10 games and the lost score is aggregating the last season's winning percentage of the wining opponents in the last 10 games. As the SQL query result shown, in the last 10 games, MIA has been beaten by a few times by teams who have a sum winning percentage of 1.36, but also won many weak teams who have a aggregated winning percentage of 2.07; NYK has defeated some very strong teams with a aggregated win score of 3.15, but also lost to some teams with a aggregated winning percentage of 2.34.

At the beginning of a NBA regular season, last 10 home/road games of a team contains games from last season. As there usually are significant line-up changes during off-season period, there is no clear consistency between games of current season and games of last seasons. In order to use last 10 home/road games statistics features in this project, a limitation is introduced, that games of first 2 months of a NBA regular season is not considered as prediction candidates. In this way, games after 2 month has the consistent features of last 10 home/road games. As a result, data used for training, testing and scoring will not include data samples from first 2 months of NBA regular seasons.

**Statistics of Recent Game between Home Team and Opponent Team**

The historical confrontation between two teams is also a very good reference for predicting NBA games. If someone counts who won most of the games between two teams, there would be an error that long ago historical games may not reflect the current power line-up of two teams. This project introduces an intuitive score to balancing out this error. If a victory is defined as 1, and loss is defined as -1, the score is calculated by result_num/(current_season – history_game_season + 1). The score is

proportional to the inverse of the season span. The corresponding SQL query is shown below.

```
SELECT team, r.season, SUM(result_num/ (2010 - r.season + 1)) FROM
    (SELECT * FROM game_log_back WHERE date < '2010-12-01' AND ((team = 'MIA' AND opponent = 'NYK')
    OR (team = 'NYK' AND opponent = 'MIA')) AND home = 'Y' ORDER BY date DESC LIMIT 12) AS r
GROUP BY team
```

**Code Snippet 7 SQL for getting statistics of recent games between home team and opponent team**

This query computes the score between MIA and NYK by using their recent 12 history games.

### Number of Games in Last 5 Days

Game schedule is another key factor of game result. Before an upcoming game, tight game schedule affects players' physical energy reserve, which implies players may play a less effective game. The following SQL query calculates the number of games in last 5 days for both MIA and NYK. The Number of games in last 5 days is another feature extracted for data mining purpose.

```
(select count(*) as count from
    nba_mart.game_fact where (team = 'MIA' or opponent = 'MIA') and
    date between (DATE_SUB('2010-12-01', INTERVAL 5 day)) and '2010-12-01' order by date)
union
(select count(*) as count from
    nba_mart.game_fact where (team = 'NYK' or opponent = 'NYK') and
    date between (DATE_SUB('2010-12-01', INTERVAL 5 day)) and '2010-12-01' order by date)
```

**Code Snippet 8 SQL for calculating the number of games in last 5 days for both teams**

### Rest Days before Upcoming Game

Number of rest days before an upcoming game is affecting the game results. The following table is rest day statistics for Atlanta Hawks in season 2000-2001 extracted from our data mart. It shows that number of rest days is a major factor to the Win/Games percentage.

| Rest Days | Games | Win | Lost | Win/Games |
|---|---|---|---|---|
| 0 Days | 24 | 5 | 19 | 0.21 |
| 1 Day | 37 | 12 | 25 | 0.32 |
| 2 Days | 14 | 7 | 7 | 0.50 |
| 3+ Days | 6 | 4 | 2 | 0.67 |

**Table 3 Rest days before upcoming game**

The following SQL query is used for get the date for last game before 2010-12-01. And the rest days can be calculate by get the difference between returned date and 2010-12-01.

```
SELECT date FROM nba_mart.game_fact where  season = 2011 and date < '2010-12-01' and
(team = 'MIA' or opponent = 'MIA') order by date desc limit 1
```

**Code Snippet 9 SQL for getting number of rest days before a up coming game for MIA**

**Statistics of Overall Performance of Last Season**

Last season's statistics is a good indicator of their next season's performance. This can only be taken as references because NBA teams usually trade players between each other or sign new players during off-season period. The following SQL query returns the Win percentage statistics of MIA in the 2009-2010 season. It includes the total win percentage, home/road games win percentage, rest days win percentage, and verses opponent win percentage.

```
SELECT split, value, W/G as win_per
FROM nba_mart.team_split where season = 2010 and team = 'MIA'
```

**Code Snippet 10 SQL for getting the overall performance of MIA in the last NBA season**

There are 46 features (Appendix B) to be extracted after the previous selection phase. And data corresponding to these features are required to be extracted from data mart.

### 4.3.2 Automated Feature Extraction

Data in data mart is stored in de-normalized tabular format, which is not directly usable for model training. In order to transform de-normalized data into model training and model evaluation friendly data format, a feature extraction process is carried out on the data mart.

The goal of this process is to extracted data mining friendly data from data mart, which is storing statistics NBA data. This process requires executing SQL queries to collect data of selected features described in section 4.3.3, and aggregating data returned by these SQL queries into unified datasets.

This process can be automated by calling SQL queries and collecting data using Ruby script.

### Loop Through Each NBA game

Features proposed in section 4.3.1 are statistics information prior to date of an upcoming game in history. To generate training data for every single game between 2004-2011, looping through each game happed in the time period is required. The ruby script does this job is shown below:

```ruby
def getForTeam(team, season)
  # All #team of team in #season
  sql = "SELECT team, date, opponent, result, PTS - O_PTS as 'diff'
          FROM nba_mart.game_fact where (team = '#{team}' or opponent = '#{team}')
          and season = #{season} order by date desc"
  result = @@client.query(sql)
  output = Hash.new
  count = result.count;
  result.each(:as => :hash) do |row|

rescue Exception => e
  puts e.inspect
  puts e.backtrace
end
```

**Code Snippet 11 Ruby script for getting all games of input team at input season**

The Ruby function takes team and season as parameters. By calling this function for each NBA team and providing NBA season information, games information for each team of specific season can be collected. (This function is called in other loop of every NBA team and with specific season.) It retrieves every single game happened in the specific season for the given team and loop through them. In the loop, more feature data retrieving work has been done.

### Retrieve Feature Data

SQL queries have been provided in Section 4.3.1. Automating the SQL queries for each giving game in the NBA history and collecting returned data is required. The Ruby script for collecting statistics of average statistics of latest 10 games for both home team and road team is shown below.

```
# Last 10 games between two team
# Average statistics of latest 10 game of home team playing home games and road team playing road games
  sql = "(SELECT team, home, AVG(FG/FGA) AS avg_fgp, AVG(3P/3PA) AS avg_3pp, AVG(FT/FTA) AS avg_ftp,
AVG(ORB) AS avg_orb, AVG(TRB) AS avg_trb, AVG(AST) AS avg_ast, AVG(TOV) AS avg_otv,
AVG(PF) AS avg_pf, AVG(PTS) AS avg_pts,
AVG(O_FG/O_FGA) AS avg_ofgp, AVG(O_3P/O_3PA) AS avg_o3pp, AVG(O_FT/O_FTA) AS avg_oftp,
AVG(O_ORB) AS avg_oorb, AVG(O_TRB) AS avg_otrb, AVG(O_AST) AS avg_oast, AVG(O_TOV) AS avg_ootv,
AVG(O_PF) AS avg_opf, AVG(O_PTS) AS avg_opts
 FROM (SELECT * FROM game_log AS g WHERE g.team = '#{@@team}' AND
g.season = #{@@season} AND g.home = 'Y' AND g.date < '#{@@date}'
ORDER BY g.date DESC LIMIT 10 ) as go  GROUP BY go.team )
UNION
(SELECT opponent as team, home, AVG(O_FG/O_FGA) AS avg_fgp, AVG(O_3P/O_3PA) AS avg_3pp, AVG(O_FT/O_FTA) AS avg_ftp,
AVG(O_ORB) AS avg_orb, AVG(O_TRB) AS avg_trb, AVG(O_AST) AS avg_ast, AVG(O_TOV) AS avg_otv,
AVG(O_PF) AS avg_pf, AVG(O_PTS) AS avg_pts,
AVG(FG/FGA) AS avg_ofgp, AVG(3P/3PA) AS avg_o3pp, AVG(FT/FTA) AS avg_oftp,
AVG(ORB) AS avg_oorb, AVG(TRB) AS avg_otrb, AVG(AST) AS avg_oast, AVG(TOV) AS avg_ootv,
AVG(PF) AS avg_opf, AVG(PTS) AS avg_opts
 FROM (SELECT * FROM game_log AS g WHERE g.opponent = '#{@@opponent}' AND
g.season = #{@@season} AND g.home = 'N' AND g.date < '#{@@date}'
ORDER BY g.date DESC LIMIT 10) as ro GROUP BY ro.opponent )"
  result = @@client.query(sql)
#  p result.count.to_s
  output = Hash.new
  output = {"avg_pts"=>0 , 'avg_fgp'=>0, 'avg_3pp'=>0, 'avg_ftp'=>0,
    'avg_orb'=>0, 'avg_trb'=>0, 'avg_ast'=>0, 'avg_ootv'=>0, 'avg_ofgp'=>0, 'avg_o3pp'=>0,
    'avg_oftp'=>0, 'avg_oorb'=>0, 'avg_otrb'=>0, 'avg_oast'=>0, 'avg_ootv'=>0, 'avg_opf'=>0, 'avg_opts'=>0}
  output2 = {}

  result.each_with_index do |row, index|
    if index == 0
      output.keys.each do |key|
        output[key] = row[key]
      end
    else
      # get the difference between 2 team statistics
      output.keys.each do |key|
        output2.store(key, row[key])
      end
    end
  end
```

**Code Snippet 12 Ruby script for retrieve features containing statistics about last 10 home games of home teams and last 10 road games of road team**

There is also several Ruby script snippets for retrieving other features discussed in Section 4.3.1. As the code snippet above demonstrates the main techniques and logic already, other snippets are not giving in this project.

### Class Label

Assuming that the home team is our subject, the class label is the ground truth of the result of each game, which is indicated by 'W' for wining of home team and 'L' for losing to opponent team.

### Results and Data Segmentation

After collecting data of proposed features, the data is serialized into CSV files storing data of different NBA seasons.

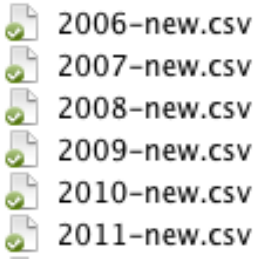



**Figure 21 Files of Collected Sample Data**

Among these files, datasets for 2006-2010 season are used for training and testing purpose. And dataset for 2011 season is preserved as applied dataset for scoring purpose. And how the scoring data is used is explained in Chapter 5.

## *4.4 Model Evaluation Criteria*

The objective of model training is to build a model based on training dataset that captures correctly the charecteristics of Win/Loss games. After building the model, a test set is supplied and passed through the model. It classifies testing sample with same set of features and test against predefined target class labels.

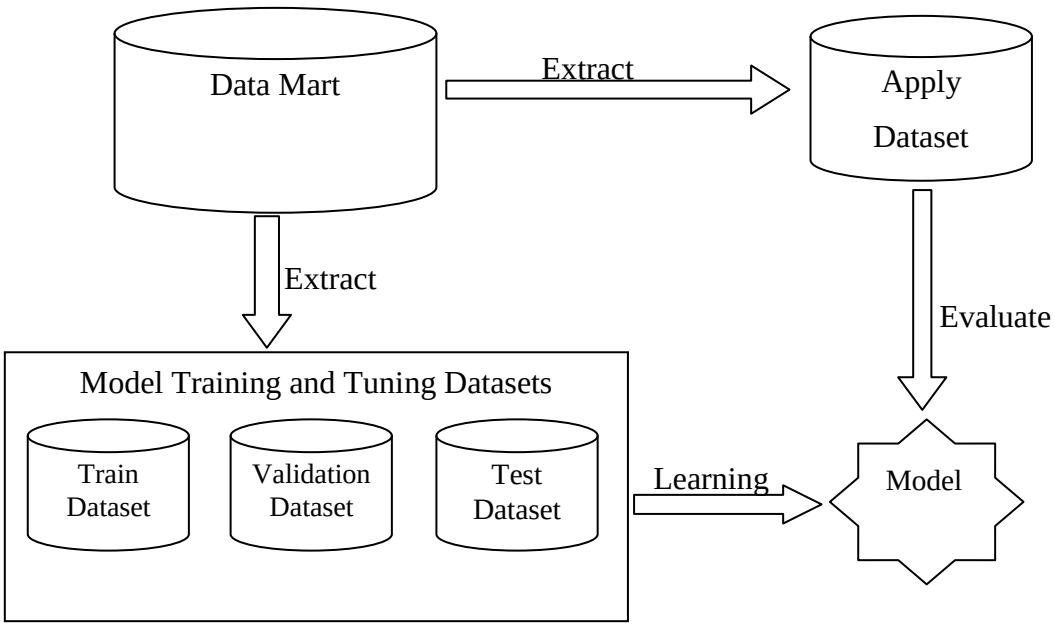



**Figure 22 Training, evaluation and scoring process.**

In order to focus on the accuracy of the prediction model, the accuracy ratio model is used to evaluate the model.

$$Accuracy\ ratio\ of\ the\ model = \frac{\text{corrected prediction games numbers}}{\text{total number of predicted games}}$$

## *4.5 Data Partition*

As data available for building and tuning model is within time range from season 2006 to season 2010, there are about 6,000 data samples. Because the major part of our features are related to last 10 games statistics, games in the first 2 months of a NBA regular season don't have complete last 10 games statistics from the on-going season. So removing data samples from first 2 months in each season from our data samples is required. After filtering the data samples, there are about 4000 data samples available for training and tuning predictive models. Data are then can be partitioned in two ways.

### 4.5.1 Training and Testing (Handout)

The most common approach is handout approach, which divide the data samples into two complementary sets, training set and test set. Training set is used for fitting the data-mining model and the test set is used for compute error estimate. Usually, two thirds of data is used as training set data and the other one third of data is used as testing data.

Cross Validation Training

If 6,000 data samples in this project are not enough to build a complex model using handout data partition approach. This is the scenario of having limited data for building model. Common handout approach may put representative samples with distinctive features into test set. Model built in this case is biased which may not cover the case of representative samples is putted in test set. Cross Validation is a popular technique to compensate bias of handout approach when data samples are limited.

Cross validation involves partitioning data samples into N folds complementary equal size subset, fitting model using N-1 folds of data, and validating the model on the left 1 fold of data. And repeat the process N times and each time leave different fold out for validation. Finally, the N performance metrics is averaged to yield an overall performance metrics. This number N is usually 5, 10 or 20.

### 4.5.2 Experiment Setup

Weka Knowledge Flow Tool is used to demonstrate the experiment process. Firstly, training data and testing data is loaded from a CSV file; Secondly, the game result attribute is chosen as the class label and order of data is randomized with a seed; Thirdly, input data is either divided into training set and test set or organized with cross-validation approach; Fourthly, classifier model is trained and validated; Lastly, error estimate and other performance metrics are outputted in text format and model performance related chart is generated. The process is illustrated below:

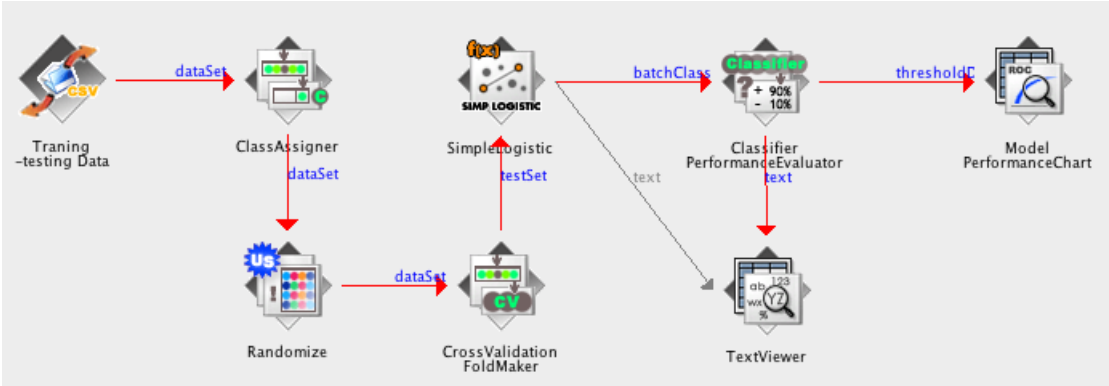



**Figure 23 Experiment Workflow**

The model evaluating in Figure 23 is Simple Logistic classifier. There are a range of classifiers have been tested. And other then replacing the Simple Logistic classifier with other classifiers, experiments for fitting other classifiers follows the exactly same workflow.

## *4.6 Model Training*

There are four models used in this experiment, including Simple Logistics, Naïve Bayes, Support Vector Machine and Artificial Neural Networks. These models have been explained in details in Chapter 2. All these models are trained and tested use Weka data mining tool and parameters used during model fitting process and the final result are presented below.

### Simple Logistics

Simple Logistics is a combination of algorithms with the core algorithm logistic regression. It uses LogitBoost with simple regression function (linear or non-linear functions) as base learners. It support automatic attribute selection and use cross validation to control number of iterations. (Landwehr, N., 2005).

The input parameters of Logistic Regression are listed as bellow:

- Maximum iteration: 500
- Parameter of Heuristic for early stopping of LogitBoost: 805
- Weight Trimming of LogitBoost: 0.02

In this approach algorithm, the model is evaluated with 10-fold cross-validation approach by default. 66% data is divided into training set and 34% data is used for testing purpose.

The output model contains two classifiers, one per each class. The prediction is depending on which classifier output the larger value.

The classification accuracy using the trained Simple Logistics Classifier is about 67.82% over the test set data.

### Naïve Bayes

The Naïve Bayes Classifier assumes that attributes are conditionally independent of given class label, which implies that the probability of belong to a class is the multiplication of every conditional probabilities of attributes. Weka's Naïve Bayes Classifier training tool is used in this process.

The classification accuracy of trained Naïve Bayes Classifier is about 65.82% over the test set data.

### Support Vector Machine

Support Vector Machine (SVM) can do a better job with features with non-linear relationships. SVM classification model can be trained by finding a maximal margin hyper-plane.

In this experiment, parameters for model fitting process are listed below:

- Gamma is $\frac{1}{2\sigma^2}$: 0.002
- Coefficient: 0.5

After tuning the model against the test set, an optimized SVM model is outputted. The classification accuracy of trained SVM model is about 67.22% over the test set data.

### Artificial Neural Networks

An experiment by training Neural Networks to predict the NBA game result is design. Weka provides a feedforward neural networks model named "Multilayer Perceptron" Model. It takes all attributes as input nodes. All hidden nodes and output nodes are all using sigmoid function.

A one hidden layer Neural Networks with two output nodes model is chosen. The output nodes are corresponding to Class label. The input sample is classified according to the output node with larger value.

Parameters used for training Multilayer perceptron model in Weka are assigned as below (Weka.Sourceforge.net, 2012):

- Learning rate back-propagation algorithm: 0.1
- Momentum rate: 0.05
- Number of epochs: 700
- Seed for random initialization weights of nodes: 231
- Percentage of samples in validation set used to terminate training: 30%
- Network training termination condition that the consecutive number of errors allowed for validation testing: 5

The classification accuracy of trained Neural Networks model is about 66.67% using test set.

## *4.7 Model evaluation*

The above 4 experiments are conducted using the same workflow. And trained model are tested over the test set. The testing result is listed in the follow table.

| Model | Simple Logistics | Naïve Bayes | SVM | Neural Networks |
|---|---|---|---|---|
| Accuracy | 67.82% | 65.82% | 67.22% | 66.67% |

**Table 4 Prediction accuracy of different classifiers over testing dataset**

As the result shown, Simple Logistics Classifier yields the best prediction accuracy on test set. Naïve Bayes Classifier yields the lowest prediction accuracy. The testing result of these classifiers over applied dataset and further evaluation is provided in Chapter 5.

## *4.8 Conclusion*

This chapter explained the data mining experiment in details. By using SQL queries with Ruby programming language, the feature extraction process is fully automated. Data samples extracted from data marts covers regular NBA games from 2006 to 2011. The extracted data samples are then partitioned into training set, test set and scoring set. A model training workflow is illustrated and explained for model fitting and testing purpose. By using training set data and test set data, 4 distinctive data mining classifiers, Simple Logistics Classifier, Naïve Bayes Classifier, Support Vector Machine and Neural Networks, are trained and tested. And the prediction accuracy shows that Simple Logistics is a better model for predicting NBA games in this project. Further real world scenario test and evaluation is provided in the next chapter.

# 5 EVALUATION

## *5.1 Introduction*

This chapter explains the concept of model scoring, scoring workflow design for this project and the scoring results. Our trained classifiers are also compared with other researchers' work and a popular NBA game outcome prediction website. Through the scoring process and the comparison with others' work, models built in this project are proven to be effective and generalized at predicting outcomes of real world NBA games.

## *5.2 Model scoring*

In order to test the practicality of our fitted models, a model scoring process is designed and used to evaluate our models. In this section, scoring workflow is introduced and the scoring result is discussed.

### 5.2.1 Introduction

After producing classification models using model training and tuning techniques, these models can be used to predict the upcoming NBA games. So far, out model has only being tested during cross validation or on test sets. In order to simulate how our models are going to perform on "unseen" data, a scoring process is introduced.

"Scoring" is the process of using the model which we built in our experiment to make predictions about behaviour that has yet to happen. The "Score" is the prediction output of the model.

Scoring is monotonous, but data mining is useless without it. So applying a predictive model to a set of data which is referred to as scoring the data is necessary in this project.

Because the project focuses on regular season prediction, in order to keep consistent with the original data, the regular season dataset from 2010-2011 NBA dataset (without first 2 months as last 10 home/road game statistics feature requirement) is taken as the scoring dataset, also known as applied dataset. There are 966 data samples in scoring data. And the classification accuracy is "score" for each model we built.

### 5.2.2 Scoring workflow

Weka is also used for scoring process. The following workflow Figure illustrates the process:

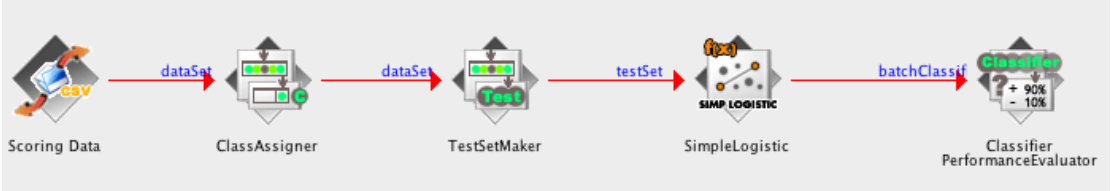



**Figure 24 Model Scoring Workflow**

Firstly, scoring data et is loaded into Weka environment and class label is chosen; Secondly, the whole scoring data is input into the trained classifier; Lastly, the performance metrics of how the classifier performs on scoring dataset is yielded for examination.

### 5.2.3 Scoring result and discussion

Following the workflow proposed in last section, classification models trained in Chapter 4 went through the workflow by using them as trained classifiers.
The scoring result is listed in the table below:

| Model | Simple Logistics | Naïve Bayes | SVM | Neural Networks |
|---|---|---|---|---|
| Accuracy (Score) | 69.67% | 66.25% | 67.70% | 68.01% |

**Table 5 Prediction accuracy of different classifiers over scoring dataset**

By comparing to the test result of trained model over testing dataset, scoring result of each trained model performs better. Models performing better on "unseen data" than on the testing data is not very common. However, as the testing dataset (about 1400 data samples) is much larger than the scoring dataset (966 data samples), and testing data is randomly chosen from dataset of 5 NBA seasons as oppose to scoring dataset from 2010-2011 NBA regular season, scoring data has less variance in its dataset and has high chance to contain data with less noise data (more games follow the common pattern).

The final scores show that simple logistics yield a better result than other models, which near reach 70% of the prediction accuracy.

## *5.3 Comparison to other's work*

There has been comprehensive research work regarding to NBA outcome prediction going on, both from academic researchers and commercial sport betting organizations. In this section, state of art research on prediction outcomes of NBA games is explained below and compared with work of this project. And a commercial sport betting organization teamrankings.com is also discussed and compared with our work.

### 5.3.1 Comparison to State-Of-Art Research

An approach that proposed by (Beckler, M.) used box score statistics similar to this project to predict NBA game outcomes. They built Linear Classifier, Logistics Classifier, SVM Classifier, and Artificial Neural Network Classifier for prediction. The model is trained with data from last season and current up-to-date dataset, for seasons 1992-1993 to 1996-1997. (Beckler, M) And model is evaluated on test set,

which is not clearly explained that where it is collected from and how test data relates to the training data. They built model for each NBA season and tested on test set. The results yield shows that Linear Classifier is most accurate model with an average accuracy rate of 70%; Logistics Regression Classifier comes second with accuracy of 68.76%; SVM yields accuracy of 67.91%; And Artificial Neural Network has the lowest accuracy of 65.36%. Their work took the approach of building specific predictive models for every NBA season. Models from their research use last season's statistics and current season's statistics to predict game of current season. This model training process and their vague explanation of testing dataset make readers suspect there may be co-linearity between training data and testing data that models trained take advantages of unwanted co-linearity when predicting games in test set, so that the result of their research is questionable.
On the other hand, this project is focusing on building a generalized model to predict games of any NBA seasons. And models built in our research project yield similar accuracy in the testing result. This indicates that our generalized model works well on "un-played games".

Bernard Loeffelholz, Earl Bednar, and Kenneth W. Bauer did a research of predicting NBA games by using neural networks. (Loeffelholz, B., 2009). Dataset used in their research is the average box score statistics of first 650 games of the 2007-2008 NBA regular season. In order to minimizing the impact of player transactions and injuries, the first 650 games are used for prediction. And only mid-season average statistics is used as prediction inputs. Among the chosen 650 games, 620 games are used for training and testing, and 30 games for validation. They used fusion techniques to integrate the contribution of different types of neural networks (Loeffelholz, B., 2009) to yield a better result. The final model had 74.33% accuracy. Comparing to the approach in this project, their model has unpleasant limitation and is very unpractical. Because there is not mid-season statistics information until half of a season has been played. As a result of using the average mid-season statistics as features, which covers statistics of the first 650 games, used for training, testing and validation, the trained models has very high variance and cannot yield good prediction results on games of other season or even the rest games of the 2007-2008 NBA season. On the other hand, generalized models trained in this project have been tested and scored on huge datasets and have been proved their wide applicability.

### 5.3.2 Comparison to Popular NBA Game Perdition Website

Popular NBA prediction website Teamrankings.com provides several NBA game prediction models for predicting NBA game results.

| Model | TR Picks | Similar Games | Decision Tree | Power Ratings |
|---|---|---|---|---|
| Accuracy | 69.6% | 65.8% | 69.6% | 68.2% |

**Table 6 Game winner prediction from teamranings.com for 2010-11 NBA regular seasons**

They introduce 4 game prediction models. TR picks performs best among those 4 prediction models. It takes the results of various predictive models and game related trends and statistics and breaking news. (TR picks from teamrankings.com) As shown in the table above, it contains prediction accuracy of various algorithms from teamrankings.com for predicting game results of 2010-2011 NBA regular season without the first 2 months of the season (from Dec 2010 to May 2011). It covers the same sample games as data used in scoring process of this project. Simple Logistics Classifier yield slightly better result comparing to TR picks algorithms. It is worth mentioning that model on teamrankings.com takes latest breaking news and trends into account when predicting games, which enables them using richer information in their prediction process. However, generalized models still yield slightly better results.

### 5.3.3 Summary

By discussing state of art research, there are many concerns regarding to the particularity of other researchers work. Research on predicting outcomes of NBA games by Beckler, M gave readers a vague description of testing process, and this makes their research process questionable. In the research of Loeffelholz, B. for predicting outcomes of NBA games, it uses mid-season statistics to prediction games of first half season. This process is even more questionable because there is clearly

limitation on practicality of their model fitting process. There is no way to predict games from first half season until the half season has been played. Comparing to their result, our models are proved to be effective on both testing data and scoring data. And it is very practical and generalized that it is able to predict most "un-played" games of season.

When comparing our work with prediction result published on a popular NBA game prediction website, teamrankings.com, our work is proven to be as effective as the state-of-art commercial NBA game prediction application, which consume more up-to-date information (breaking news) then our models.

Models built in this project has a high practicality, and they are generalized enough to yield very good accuracy when predicting most games of a given season.

## *5.4 Conclusion*

Models in this project have been evaluated in scoring dataset. Simple Logistics Classifier yields the best result with an accuracy of 69.67%; Artificial Neural Networks yield second best result with an accuracy of 68.01%; SVM comes next with an accuracy of 67.70%; And Naïve Bayes yields the lowest accuracy of 66.25%.

By comparing to other researchers work in predicting NBA game outcomes, models in this project are generalized, which conduct good prediction performance on large number of "un-played games". And our models are proven to be practical and can be used as a real world game prediction application.

# 6 CONCLUSION

This chapter will summarise the work completed in earlier chapters， followed by a discussion on the research objectives and achievements. This chapter also identifies opportunities for further research.

Introduction

This dissertation explores the data mining techniques applied in the field of sports predictive analysis. Driven by the increasing comprehensive of data in digital NBA datasets are collected, and data mining technique successfully used in different area. Sports data mining technique emerge and enable us to find more valuable information to improve the performance and make right decisions in the right time. In many instances, predicting the outcomes of sporting events has always been a challenging and attractive work and is therefore forecasting problem draws a wide concern to conduct experiment in this field.

National Basketball Association (NBA) is a multi-billion dollar industry and its audiences are from all over the world. It is definitely one of the most popular sports league in the world and there is a huge betting market driving predicting analysis. Comprehensive historical statistics data has been collected to assist analysing NBA games and players. As the dataset set grows with the NBA games, it has become the perfect test bed for big data solution and this huge market and well-maintained statistics dataset motivate public, statist and sports enthusiasts to discover implicit knowledge in it.

This dissertation is aiming to achieve predicting NBA game outcome by using big data with modern data warehousing and machine learning techniques. To further understand the challenges of predicting basketball game outcome, a review of the previous research in the above fields has been conducted as part of this research. This project is implemented from the ground up. The relevant work has been done in this dissertation

includes automated data collection, data management and data warehousing, feature selection, model fitting, model scoring and model evaluation.

Not only the whole workflow of practical work performed in this research and its result can be used for future reference in sports predictive analysis, but also the database and data warehouse created in this project can be continuously maintained and reused for further research on a range of interesting topics. In the next sections, research workflow, result and future research opportunities are presented in more details.

## *6.1 Research Definition & Research Overview*

At the beginning stage of this research, a range of topics has been reviewed in order to gaining substantial knowledge to assist the progress of this research. The review covers areas including data management, data mining, sports data mining, basic rules of basketball and predictive model used in sports events. This review was then employed to the design and implementation of an experiment aiming at predicting the NBA game outcome. During this research, the following objectives were achieved.

- Review of the literature in the area of data mining, from the definition, function, techniques, process to the popular data mining tools.
- Review of research in the fields of sports data mining: especially present the sports science history, sports data mining applications, sports data mining tools.
- Review of research literature on data mining technique used in NBA, in which involves the research about NBA history, basic concept for basketball, data mining used in basketball application.
- Review of the previous research literature about data mining technique used for predicting competitive sport outcome especially for basketball and popular predictive machine learning algorithm introduction.
- Preparation for the experiment, which involves automated data collection, data cleaning, data transformation, data integration and data mart design.

- Feature selection and model fitting, which involves extracting features used for building predictive models by employing domain knowledge, and designing workflow of training and testing popular classifiers for predicting NBA game outcomes.
- Evaluation of accuracy and practicality of trained models by using scoring process, comparison with other researchers' work and a popular betting website which public the sports result prediction outcome for betting to prove that this research is an effective, generalized and practical solution.

## *6.2 Contributions to the Body of Knowledge*

As outcomes of this dissertation's research and experiment results, the following findings can be highlighted as contributions to the body of knowledge in the area of sports predictive analysis.

The key part of experiment in this project is to perform machine learning algorithms for NBA game outcome prediction. The output models and the data marts created in this experiment can be used as reference for future research on utilizing machine learning algorithms to predict the NBA game outcome.

The experiment also has shown that the data collection and data management process as an important process before conducting machine learning process also have effect on overall accuracy of the our put models. The experiment also consider some external features, such as home or away, rest of time as factors of influencing the game outcome, which inspires people in the future work to discover more interesting features for sports analysis.

The research has also demonstrated that various algorithms influence the accuracy of prediction. The result finally compare with the similar work from other research to prove the technical feasibility of predicting competitive sports, so in the same way, our experiment can be also used for other experiment comparison.

As the highlight of this dissertation, data from 5 NBA regular seasons was collected for the experiment and data from 1 NBA regular season is collected for model scoring. The fact that models fitted in this project are based on big dataset and have been proven to be very effective on "un-played" games, makes this project more persuasive as a data mining project. This is a meaningful aspect for measuring a data mining prediction work comparing to other researchers work.

## *6.3 Experimentation, Evaluation and Limitation*

### 6.3.1 Experimentation

This dissertation covers the whole process of a data mining project and it is implemented from the ground up. The relevant work has been done in this dissertation includes automated data collection, data management and data warehousing, feature selection, model fitting, model scoring and model evaluation.

Ruby language enabled data collection tool has been created to collect raw NBA statistics data from online data sources. Then collected raw data is organized and uploaded to MySQL database hosted in Amazon EC2. Data collection and uploading data to Cloud technology enabled database process are highly automated by using Ruby programming language and relevant Ruby gems library.

Based on the organized database, a data mart is designed and created to facilitate the data mining experiment. A star scheme with game log as fact table has been designed and implemented.

Features for model training have been carefully designed by incorporating domain knowledge and sample data with these features has been extracted from the data mart. Features are mainly extracted from statistics about teams' performance from last season and recent performance about teams. External features like game schedule and home/road condition are also considered as features.

Extracted data samples are further dived into training set, test set and scoring set. Training set and test set data are used for model fitting. And scoring set data is used for model scoring.

By consuming data samples extracted from the data mart, a number of machine learning predictive classifiers including Simple Logistics Classifier, Naïve Bayes Classifier, Artificial Neural Network Classifier and SVM, have been trained and tested for the purpose of predicting the NBA game outcome.

And finally a scoring process has been performed for testing performance of fitted models on "un-seen" data. The result shows Simple Logistics yields a better result with an accuracy of 69.67%.

### 6.3.2 Evaluation

Models in this project have been evaluated in scoring dataset. Simple Logistics Classifier yields the best result with an accuracy of 69.67%; Artificial Neural Networks yield second best result with an accuracy of 68.01%; SVM comes next with an accuracy of 67.70%; And Naïve Bayes yields the lowest accuracy of 66.25%.
And these results have been compared with the state of art research. There appear to be some significant concerns about other research work on their informal model evaluation method and practicality of their models. On the other hand, models in this project are trained using massive training dataset and have been tested by using data sample representing a whole NBA regular season. Our models are proved to be effective on both testing data and scoring data. And it is very practical and generalized that it is able to predict most "un-played" games of season.
This project is also compared with prediction result published on a popular NBA game prediction website, teamrankings.com. Models fitted in this project are proven to be as effective as the state-of-art commercial NBA game prediction application.
Models built in this project have a high practicality, and they are generalized enough to yield very good accuracy when predicting most games of a given season.

### 6.3.3 Limitation

One limiting factor on our approach is that, due extracted feature is relying on statistics from last 10 home/road games; models trained in this project would not have as high accuracy when predicting NBA games of first 2 months in a regular season as predicting the reset of the season.

Other fact that researchers can work on is that, detailed statistics about players' performance has been managed in our database and data mart, but yet use in the game result prediction. Theoretically, by add more valuable information into the model training process, the output model could perform even better.

## *6.4 Future Work & Research*

Human behaviour, including the game of basketball, is an inexact science with a lot of variance, is inherited a tough problem for machine learning problem. This project takes the approach of using big data solution by collecting massive amount of statistics data about games happen in the last 5 years, with modern data collection, management techniques and popular machine learning models to tackle this problem. And the result of this project is encouraging, that models fitted in this project are proven to be effective, generalized and practical when predicting games in real world scenarios.

The future work involves keep the database up-to-date. Due to the fact that the targeting objects is a live NBA league. Player information will be changed when their contract expire or retire. Meanwhile the upcoming game will happen, so update the database will be beneficial to improve the model accuracy.

In addition, there are some substantial topics that researchers can work on. Using clustering techniques would allow us to group players into clusters, and perhaps learn what position they play, if they are a real standout player, or possibly reveal some other underlying patterns for recurring new players. Another related topic worth investigating is about outlier detection, which can help decision maker to identify

outstanding players or usually team status. Another interesting topic is to investigate the impact of player performance on outcomes of NBA games.

Another interesting area of the future work is to discover the interesting feature based on the arrangement data. There will be a broad space to carry out the hidden knowledge existed in the box score statistics and team statistics through combine features or compare features. Looking at how the features influence the team performance.

## *6.5 Conclusion*

As a research of investigating using data mining techniques for predicting outcomes of NBA games, this project have a certain reference value for the related research work in the future. This project is built from the ground up from collecting raw statistics data to trained model evaluation. And data collection and data management solution is highly automated. A popular Cloud solution is used to maintain the project budgets. The whole process is proven to be successfully designed and implemented. Moreover, the final output models are proven to be very effective, widely applicable and practical. This project also provide an ideal data mining environment, data mart containing comprehensive NBA game information, which can be reused by future research, and a series of methods for keeping data mart up-to-date are also created. In any means, this project can be considered as a successfully exploration of using data mining techniques for sports result prediction, and it leaves a rich legacy for future research, that either reusing techniques created in this project or make reference of this project.

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# APPENDIX A

**NBA statistics explanation**

Source: www.basketball-reference.com

| | |
|---|---|
| Rk | Rank |
| G | Season Game |
| Opp | Opponent |
| MP | Minutes Played |
| FG | Field Goals |
| FGA | Field Goal Attempts |
| 3P | 3-Point Field Goals |
| 3PA | 3-Point Field Goal Attempts |
| FT | Free Throws |
| FTA | Free Throw Attempts |
| ORB | Offensive Rebounds |
| TRB | Total Rebounds |
| AST | Assists |
| STL | Steals |
| BLK | Blocks |
| TOV | Turnovers |
| PF | Personal Fouls |
| PTS | Points |
| FG | Opponent Field Goals |
| FGA | Opponent Field Goal Attempts |
| 3P | Opponent 3-Point Field Goals |
| 3PA | Opponent 3-Point Field Goal |
| AttemptsFT | Opponent Free Throws |
| FTA | Opponent Free Throw Attempts |
| ORB | Opponent Offensive Rebounds |
| TRB | Opponent Total Rebounds |
| AST | Opponent Assists |
| STL | Opponent Steals |
| BLK | Opponent Blocks |
| TOV | Opponent Turnovers |
| PF | Opponent Personal Fouls |
| PTS | Opponent Points |
| PER | Player Efficiency Rating |

| | |
|---|---|
| TS% | True Shooting Percentage; a measure of shooting effeciency that takes into account 2-point field goals, 3-point field goals, and free throws. |
| eFG% | Effective Field Goal Percentage; this statistic adjusts for the fact that a 3-point field goal is worth one more point than a 2-point field goal. |
| ORB% | Offensive Rebound Percentage; an estimate of the percentage of available offensive rebounds a player grabbed while he was on the floor. |
| DRB% | Defensive Rebound Percentage; an estimate of the percentage of available defensive rebounds a player grabbed while he was on the floor. |
| TRB% | Total Rebound Percentage; an estimate of the percentage of available rebounds a player grabbed while he was on the floor. |
| AST% | Assist Percentage; an estimate of the percentage of teammate field goals a player assisted while he was on the floor. |
| STL% | Steal Percentage; an estimate of the percentage of opponent possessions that end with a steal by the player while he was on the floor. |
| BLK% | Block Percentage; an estimate of the percentage of opponent two-point field goal attempts blocked by the player while he was on the floor. |
| TOV% | Turnover Percentage; an estimate of turnovers per 100 plays. |
| USG% | Usage Percentage; an estimate of the percentage of team plays used by a player while he was on the floor. |
| ORtg | Offensive Rating; an estimate of points produced (players) or scored (teams) per 100 possessions. |
| DRtg | Defensive Rating; an estimate of points allowed per 100 possessions. |
| OWS | Offensive Win Shares; an estimate of the number of wins contributed by a player due to his offense. |
| DWS | Defensive Win Shares; an estimate of the number of wins contributed by a player due to his defense. |
| WS | Win Shares; an estimate of the number of wins contributed by a player. |
| WS/48 | Win Shares Per 48 Minutes; an estimate of the number of wins contributed by a player per 48 minutes (league average is approximately .100) league average is 15. |

# APPENDIX B

**Features for Models of This Project**

| No. | Feature |
|---|---|
| 1 | Total wining percentage of home team in last NBA season. |
| 2 | Total wining percentage of road team in last NBA season. |
| 3 | Total wining percentage of home team played home games in last NBA season. |
| 4 | Total wining percentage of road team played road games in last NBA season. |
| 5 | Total wining percentage of games of home teams with specific number of rest days before the game in last NBA season. |
| 6 | Total wining percentage of games of road teams with specific number of rest days before the game in last NBA season. |
| 7 | Total wining percentage of home teams against road teams in last NBA season. |
| 8 | Home team's number of rest days before the game. |
| 9 | Road team's number of rest days before the game. |
| 10 | Average points of home teams played last 10 home games. |
| 11 | Average free throw percentage of home teams played last 10 home games. |
| 12 | Average 3 points shots percentage of home teams played last 10 home games. |
| 13 | Average field goal percentage of home teams played last 10 home games. |
| 14 | Average number of offensive rebounds of home teams played last 10 home games. |
| 15 | Average number of total rebounds of home teams played last 10 home games. |
| 16 | Average number of assists of home teams played last 10 home games. |
| 17 | Average number of turnovers of home teams played last 10 home |

| | |
|---|---|
| | games. |
| 18 | Average points of opponents of home teams played in the in the last 10 home games. |
| 19 | Average free throw percentage of opponents of home teams played in the last 10 home games. |
| 20 | Average 3 points shots percentage of opponents of home teams played in the last 10 home games. |
| 21 | Average field goal percentage of opponents of home teams played in the last 10 home games. |
| 22 | Average number of offensive rebounds of opponents of home teams played in the last 10 home games. |
| 23 | Average number of total rebounds of opponents of home teams played in the last 10 home games. |
| 24 | Average number of assists of opponents of home teams played in the last 10 home games. |
| 25 | Average number of turnovers of opponents of home teams played in the last 10 home games. |
| 26 | Average points of road teams played last 10 home games. |
| 27 | Average free throw percentage of road teams played last 10 home games. |
| 28 | Average 3 points shots percentage of road teams played last 10 home games. |
| 29 | Average field goal percentage of road teams played last 10 home games. |
| 30 | Average number of offensive rebounds of road teams played last 10 home games. |
| 31 | Average number of total rebounds of road teams played last 10 home games. |
| 32 | Average number of assists of road teams played last 10 home games. |
| 33 | Average number of turnovers of road teams played last 10 home games. |
| 34 | Average points of opponents of road teams played in the in the last 10 home games. |

| | |
|---|---|
| 35 | Average free throw percentage of opponents of road teams played in the last 10 home games. |
| 36 | Average 3 points shots percentage of opponents of road teams played in the last 10 home games. |
| 37 | Average field goal percentage of opponents of road teams played in the last 10 home games. |
| 38 | Average number of offensive rebounds of opponents of road teams played in the last 10 home games. |
| 39 | Average number of total rebounds of opponents of road teams played in the last 10 home games. |
| 40 | Average number of assists of opponents of road teams played in the last 10 home games. |
| 41 | Average number of turnovers of opponents of road teams played in the last 10 home games. |
| 42 | The win/loss score of the home team. |
| 43 | The win/loss score of the road team. |
| 44 | Number of games in last 5 days played by home team. |
| 45 | Number of games in last 5 days played by road team. |
| 46 | History performance score of the two teams over last 12 matchups. |