Data Mining in Sports

Implementation and analysis of machine learning prediction models to find potential influential factors in results of matches in the Australian Football League

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Declaration of honour

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Abstract

Despite the large amounts of data produced by the sporting industry every year, there has been relatively little crossover between academic data science and professional sports. On the other hand, Data Mining techniques such as Machine Learning, Neural Networks and Association Methods, have seen rapid increases in their complexity and use over a wide variety of fields and disciplines. This paper aims to address this issue of a lack of data science applications in sports, with regards to the Australian Football League (AFL), by applying Data Mining techniques to improve upon already utilised data analysis techniques present in modern professional sports. In this paper statistics and results from the previous 10 AFL seasons will be assessed to identify key features and possible trends and use them to create more explainable white box prediction models. This will help not only sports professionals and data scientists but also casual viewers to understand the finer statistical details behind sports.

Keywords: Data Analytics, Machine Learning, Sports Prediction, Neural Network

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Introduction

This paper will apply Data Mining techniques on Australian Rules Football data in an attempt to identify any trends that may occur in individual seasons and then further apply this information into a Neural Network to create a prediction model for subsequent games.

The field of Data Mining has seen a rapid increase as we enter the digital age dominated digital information also commonly known as data. While many believe data mining to simply be the extraction of data it is actually a much broader topic. Data extraction is only the first step in data mining, the goal of data mining is to extract 'previously unknown' and unseen patterns from this data [1], much of which would be impossible to uncover without the help of computer systems. Data Mining is most commonly applied in commercial business. There it can be used to 'help identify and predict individual and aggregate behaviour' [2], or more commonly to predict how customers will consume/buy products and their buying habits so that they can more efficiently market their products in specific situations. Data Mining in sports however is much less advanced, despite massive amounts of data being produced by the sporting industry, it is mainly kept behind closed doors, with much of it focusing on player and team performance.

Although it is a quite unrepresented research area, there have been some recent attempts at data mining in sports, which have been used in a variety of areas including, classification [3], action recognition [4] and image recognition [5]. While data mining has also been used to aid in the creation of sports prediction models [6][7][8], none of these models aim to identify trends within the sports apply these as part of their prediction model.

An issue with many prediction models is the lack of transparency in their decision making, a key concept of this is issue is the idea of black box and white box models. Black Box models are in most cases more accurate than white box model but much more difficult to interpret, the internal decisions and processes of the algorithms are much more difficult to extract, resulting in more difficulty when wanting to view how they came to certain decisions. In this paper a combination of exploratory data analysis, data mining and feature extractions will be used in an attempt to overcome this lack of interpretability. Although the final prediction model will still be a black box model, the aforementioned methods will be utilised to extract meaningful interpretable information from the data set regarding which features are likely to have the greatest impact on the prediction model.

The final stage of the practical work will be to input the analysed data into a Neural Network to create a prediction model. Neural Networks are computing systems which aim to 'mimic the way that biological neurons signal to one another'[9]. Neural Networks have a multitude of uses in a variety of fields including medical diagnosis by image classification, targeted marketing and financial predictions through behaviour data analysis and financial data processing, natural language processing and time series analysis. The use of neural networks in sports, like data mining, is very limited in the public domain. Unlike data mining the vast majority of neural networks used in sports deal with prediction models and cover a variety of sports codes. The most common applications are in Football (Soccer)[10], American Football [11] [6] and Basketball [7] [12].

In Australian Football, one of the most data rich sports [13], data is used in many ways. In a professional capacity this includes real time analysis of players and the modelling of games based on Geographical Positioning System (GPS). There also exist some prediction models created in both professional and non-professional settings, however in most cases the full data sets are only available in the professional environments. Most of the data and analysis models are kept internal and utilised only by clubs and a small group of media companies with rights to the data. As a result many prediction models rely on only a small subset of the collected data that is made available to the general public.

As this paper is discussing Australian Football a basic background should be given to understand some of the terms and structure of the game, as well as to understand the structure of the data set.

1. On match day a team is made up of **22 players**, 18 on the field and 4 reserve players
2. The aim is to score more points than the opponent by kicking the ball through either the **goals**, worth 6 points, or **behinds**, worth 1 point.
3. Each team plays **22 games** per season, each season occurs between March and October in the Australian winter.
4. The finals are contested between the top 8 teams from the regular season, the finals series lasts for **4 weeks**
5. There are currently **18 teams** in the competition.
6. 10 teams are based in Victoria. New South Wales, Queensland, South Australia and Western Australia each have 2 teams in the competition.

This paper aims to explore the impacts of external factors on the outcomes of Australian Football matches and generate interpretable results which can be utilised in further analysis and prediction of matches.

2

Background

2.0.1 Research Questions

The area of focus of the paper is the implementation and analysis of machine learning models to find potential influential factors in results of matches in the Australian Football League (AFL). From here I have defined the following research questions which will be explored:

> Can data mining be used to find key features and patterns and explain results in professional sports?
>
> Can these extracted trends and features be used to create an explainable prediction model?
>
> How can the results be utilised in the sporting industry?
>
> If the model can reliably predict outcomes, how many rounds will the model need before it becomes reliable?

2.0.2 Technical Background

The practical section of the paper will follow a basic flow of a Machine Learning process (ML Process) for a classification problem. Which follows the format of Problem Exploration, Data Engineering, Model Engineering, Deployment and Monitoring. Data and Model engineering will be the main areas of the data flow applied in the practical section.

Classification is a technique in which the model tries to predict the discrete class of a given input data. This is also a supervised problem meaning that the

classes are already known to the model and as such no additional methods will be needed to extract the classes from the data set.

The data engineering phase deals with the acquisition, cleaning and exploration of the data set. Data engineering is a very important part of the ML process, as it is critical to have clean and consistent data for a model to function correctly. Without clean data a model cannot be trained efficiently, the model will be unable to extract any meaningful information from the data.

The data acquisition process can vary between projects. In the simplest cases, a data set can be readily and publicly available, needing only to be downloaded before the cleaning and exploration phases can take place. With more complex or industry specific data sets, the data may already exist but be owned by an institution which measured, converted and stored the data set. In these cases the data is normally available via payments or contracts. In the most complex cases the digital data set does not exist at all and must be gathered from physical real-world data and converted into a digital data set by the members working on the project.

Once the data has been acquired Exploratory Data Analysis (EDA) can be performed. EDA is the initial analysis of the data set, it allows for a basic overview of the characteristics of the data to be investigated and identified. Additionally EDA can allow for the easier detection of anomalies and errors within the data set which can be handled in the data cleaning phase. The main method of EDA is data visualisation, which allows for the entire data set or individual features to be viewed in plots. Scatter Plots and Histograms are the most common to implement and will be utilised in the paper, in the initial analysis. Scatter plots are useful in trend identification as they show the relationship between two variables, which would be impossible to see by just viewing the raw data. Histograms are used to separate quantitative values into an interval scale, these interval groups can be used to identify where distributions lie within the data set.

Data cleaning ensures that the incoming data is able to be read and interpreted properly by the computer model. The important steps are ensuring that missing values are handled gracefully, either by removing affected rows and columns, or using imputation to replace null values. The data must also be formatted correctly so that it can be read by the model. As the data is being read by a machine this is

in most cases a numerical input. In this paper two methods will be used to convert text and categorical inputs to numerical values, integer encoding and one hot encoding. Integer encoding involves converting every unique categorical value to a numerical value and replacing the original value in the data set. The issue with integer encoding is that models can also infer false information from the values, one way this occurs is that the model can assume the categorical values have a specific order that applies to them inferred from the order of the numerically encoded values. The solution to these issues is to use One Hot Encoding, this is when a binary value is included for each categorical value. This separates each value into its own feature that the model will interpret individually.

The final phase of the Data Engineering is the feature engineering process. This is the process of extracting features from the raw data set which can be used by the machine learning model to enable it to understand the data. In the case of tabular data, as is being analysed in the paper, a feature is one column of the data. Feature Engineering generally consists of four processes "Feature creation, transformations, Feature extraction and Feature selection" [14]. Feature creation is the creation of features based on domain knowledge and human input or intuition. Transformations deal more with the adjusting of the data to ensure that all of the data is in a similar scale, this can be done via normalisation which converts every value in the data set to a value usually between 0 and 1, or -1 and 1. Min-max normalisation $x' = (x - min)/(max - min)$, is applied to each feature in the data set and normalises the feature values between 0.0 and 1.0 based on the minimum and maximum value present in each feature. Feature extraction "generates new variables by extracting them from the raw data" [14] via detection algorithms, these are also used to combine and reduce the number of variables used in the final model. This will not be utilised in the paper due to the available data set already containing a limited number of features. The final stage is the feature selection, after all of the features have been established, the features that are most useful for the end model in its predictions are identified, and the remaining irrelevant features which have no impact or a negative impact on the results of the model are filtered out from the data set.

Data set splitting also occurs during the data engineering phase. The data set needs to be split into a training set which will be used to train and tune the model and a testing set which will be completely held out from the training phase and used to analyse the final model on unseen data. Additionally a validation set can

be created to aid in the training phase, similar to the testing data set, the validation data is also held out when training the model, but is used to analyse the model during the training and tuning phase. Commonly between 70 percent and 80 percent of the data is used for the training set, with the rest being evenly split between the validation and test sets.

Decision Trees and Random Forests are extremely useful prediction tools, as they can also be used as feature extraction tools. Decision Trees are a "supervised learning method used for classification and regression" [15]. Supervised learning is a machine learning method in which the model is presented with both input and output data so that it can learn the relation between the two and predict the outputs of new input data. The aim of a Decision Tree in classification is to split the data set into subsets called nodes until each node contains only data points of the same class, sometimes called pure leaf nodes. At each node a decision is made by the model which attempts to create a node that is as pure as possible, there are many ways to test for the purity two of the most common are the gini index and entropy. The Gini Index "measures how often a randomly chosen attribute it misclassified", whereas Entropy "measures the impurity of the sample values" [16].

$$GiniIndex = 1 - \sum_{j} p_j^2 \tag{2.1}$$

$$Entropy = -\sum_{j} p_j \cdot \log_2 \cdot p_j \tag{2.2}$$

Both methods are quite similar and have the same aim to minimise the function, have a value as close to 0 as possible. Where Decision Trees become useful in feature engineering is they store the decisions they made and from this can later compute which features had the greatest overall impact in the model. While Decision Trees are useful, they do tend to overfit to the training input data, they become very good at predicting the training data but do not perform as well when introduced to new unseen input data. There are multiple ways to penalise a decision tree, to stop it from over fitting to the training data. Setting a depth level will ensure that the tree will only make a predefined number of splits before stopping. If this is not set the tree will continue to grow until every leaf node is pure, meaning the splits will be too specific to the input data. With a limited number of splits only the more general decisions will be found, which should then be able to explain new unknown data.

A minimum node size can also be set, this stopping criteria will stop the model from splitting a node further once the subset of data in the node reaches a minimum size. A larger minimum node size will result in a smaller tree being made and as such will prevent the model from overfitting to the training data.

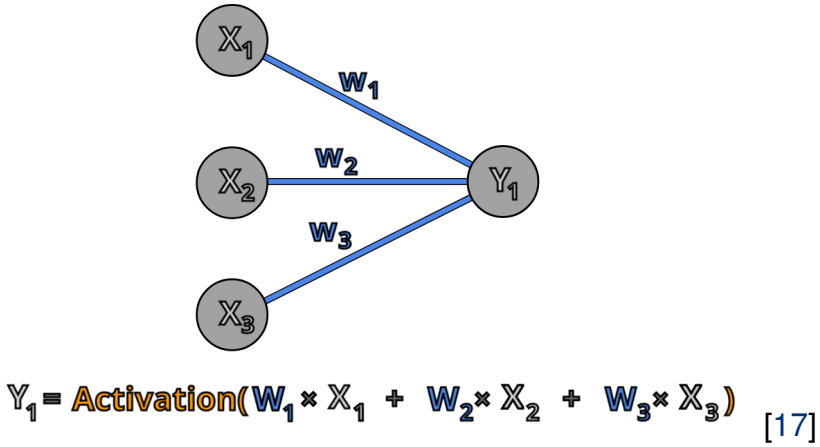
It is also important not to set the stopping criteria too far in the opposite direction and reducing the complexity too much. This would result in the model underfitting and not being able ascertain any valuable information from the data.

Random Forest is an extension of Decision Tree methods that utilises multiple Decision Trees to reach a prediction. Random Forests consist of a collection of Decision Trees that are each trained on a different random subset of the original data set. A random forest has multiple hyper parameters that must be set before training, these include node size, number of trees and number of features to train on. The Random Forest model will create the specified number of trees and then for each tree it will select the random selection of the data set, and then it will randomly select the features based on the number of features defined in the hyper parameters. All of the trees will then be trained on their individual data sets and the results of all the trees will be used to decide on the final result and the most important features present in the data.

For many ML projects using Decision Trees or Random Forests will cover both the feature engineering and the Model Engineering phases. Other models can still be built in the model engineering phase, with the Decision Trees acting as not only a feature engineering tool but also a comparison tool for the final model. In this paper a more complex neural network will be built to further analyse the data in the model engineering phase.

Neural Networks are computer systems designed to replicate the neuron systems in biological brains. They consist of a collection of nodes, also called perceptrons, organised in layers that mimic the way that biological neurons communicate. There are three distinct types of layers in Neural Networks, each contains one input layer, multiple hidden layers and one output layer. All of the nodes are interconnected between layers. Each node takes the input data, either from previous layers or from the input data, and analyses it in a fashion similar to multiple linear regression. The formula for a Neural Network perceptron is shown in figure 2.1. Once the inputs have been computed by the formula the results are passed through an activation function which decides whether the neuron is important and

Figure 2.1: Basic Neural Network Formula



[17]

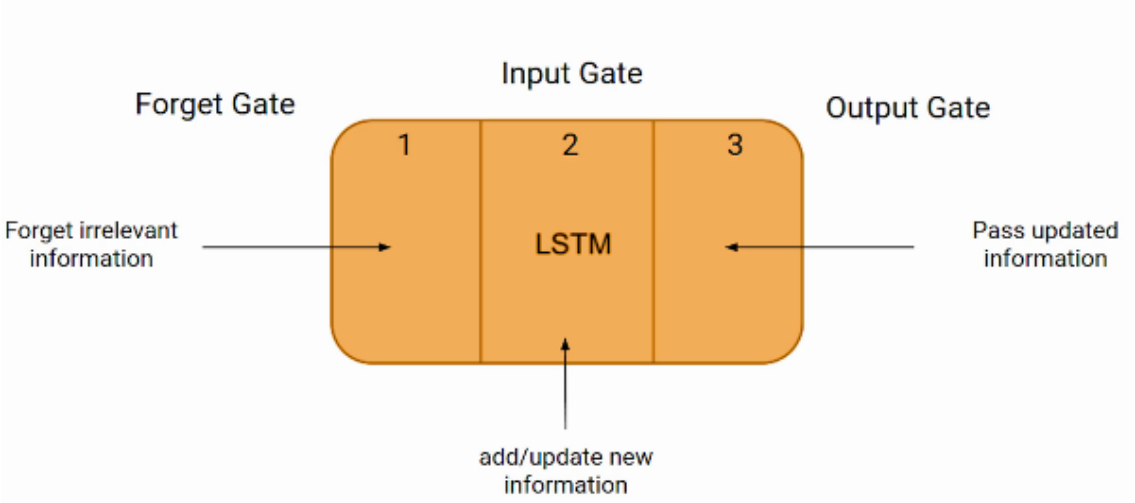
if it should be activated or not. The activation functions also remove the linearity from a neural network. As the basic formula of the neural network follows the linear regression formula, the outputs would also be linear. By using the activation functions to add non linearity to the outputs it allows the Neural networks to find more complex representations of the input data.

$$LinearRegression : y = b_0 + b_1 * x_1 \tag{2.3}$$

$$MultipleLinearRegression : y = b_0 + b_1 * x_1 + b\_2 * x_2 + ... + b_n * x_n \tag{2.4}$$

Traditional Neural Networks also face an issue of handling sequential data, which is partly solved with Recurrent Neural Networks (RNN). RNN add a memory element to traditional Neural Networks, meaning that the output of the previous layers are remembered sequentially. The most common applications of RNN are within time series forecasting and natural language processing. The issue with RNN is that "they cannot learn long term dependencies due to vanishing gradients" [18], this occurs because the weights of the previous layers that are passed through each stage are multiplied which will always result in a smaller number, meaning the loss will decrease towards 0. Long Short Term Memory networks (LSTM) overcome this issue by introducing memory gates (Figure 2.2). The forget gate analyses the information from the previous time step, called the hidden state and decides whether it is important and should be kept of if it should be forgotten. The input gate is used to identify the importance of the current input values. The

Figure 2.2: Long Short Term Memory network gates



[18]

output gate determines the value of the hidden state which will be stored and analysed in the next time step.

After the model has been built and tuned to produce the best result, the Deployment and Monitoring phase can begin.

The first section of this paper will be the exploration of the data set with the aim of identifying trends and important features within the data. Important features are features that have a greater impact on the final result of a prediction model. Trends will be defined as features or feature patterns that occur in multiple seasons. Both known and unknown features and trends will be extracted and from the data set. Known features will be defined as factors that are currently used in analysis of sports games, which stem from less scientific analysis of data. These known features are generally used in predictions of games by both domain experts and casual observers and are widely accepted to be true, but there has been little research to provide evidence to the claims. The unknown features and trends will be discovered during the data exploration and will be represented by the important features, the factors which have the greatest effect on the outcome of the model, extracted during the feature engineering process.

In the analysis of AFL games there are many factors that are said to have an impact on results by domain experts and casual viewers alike, these factors will be analysed as known features in the data set. There are two main ideas behind ex-

ploring these features. Firstly, it is useful to take domain knowledge from experts, even if it second hand as in this case. Having access to expert domain knowledge can provide a solid foundation in data analysis workflows, it allows for the analysis to be applied in a specific area of the data set without the need for pre-analysis and feature extraction. The second reason is to statistically analyse whether there is any truth to these claims and if this analysis can be useful when used as a feature in a computer aided prediction model.

The main points that will be explored from this expert analysis are the effects of weather conditions both during and in subsequent games, the length between games and the impacts of travel on future results. The impact of weather will be analysed in two features, the first being the impact of a previous games rainfall conditions as it is believed that it can negatively affect a team's performance in future weeks, as the game becomes more contested thus requiring a greater physical output. The second will be the impact of rainfall on a current game, rainfall during games generally reduces disposal efficiency making results closer, and also different game plans are impacted more by rainfall thus it can be assumed that rainfall will have some correlation to specific teams (rainfall for the model will be taken as predicted rainfall, connected to teams). While with travel it is suggested that spending long times in planes both before and after games can affect a teams' recovery and preparations. There has been research done on the impact of weather on team performance in the AFL[19], which focuses on the analysis of results as such the findings are not used to aid in any prediction models, which this paper aims to do.

While trends can be extremely useful for prediction they can also be difficult to interpret and extract from data. This is another reason why the expert analysis is being explored. It gives a starting point from which the data can be analysed. Basic visualisation of the data set will be used to asses the expert analysis. Further extraction of trends will be entirely theoretical and based solely on algorithmic interpretation of the data set. This will be very important for the project as it will hopefully enable hidden features to be found, rather than just proving or disproving already voiced opinions. These trends would be much more valuable in the industry as they would give professionals a completely new insight into their analytics.

The final key section will be the implementation of a prediction model. Prediction models are used regularly in sports. However as there are so many unknown factors in these prediction models it is very difficult to explain their predictions and

how they came to these decisions. The aim is to create a prediction model based on the extracted trends and important features, that is more explainable than other models. Assuming that the prediction model does reliably work, one more key piece of information will be extracted, the final research question, what number of rounds/games does the model need before it can reliably predict the outcomes of games? This can be useful not only for this model but for other prediction models for the AFL, as it can give a greater understanding of when results and match data will stabilise and become reliable in defining the characteristics of a season. The general consensus is that after 4 - 6 weeks of matches is when a reliable data set begins to form. There are many algorithms and techniques that can be used in Data Mining and sports, this paper will mainly utilise the following:

Decision Trees: A tree like predictive models that shows where certain decisions were made via nodes.

Random Forest: A collection of decision trees, that uses a random subset of the data in each iteration.

Long Term Short Term Neural Networks (LSTM): A type Neural Network that introduces the concept of memory and feedback connections allowing it to process data sequences.

3

Method

3.1 Description of the Scientific Method

3.1.1 Technical Environment

0.5 pages The project was completed using python as the main programming language, a combination of Jupyter Notebooks and Python files were created to handle different tasks. Jupyter Notebooks were used to sequentially implement workflows of the project and define minor functions. Major functions an more complex code was written in Python files which were accessed in the necessary code blocks within the Jupyter notebooks. There was no traditional database structures used, the data was stored in csv files. There were many libraries used over the different stages of the implementation, in depth explanations of their uses will be given in the individual phases. The pandas library was used throughout the entire project as the main data handling tool. All data was accessed using pandas read csv functions to store the data in Data Frames within the project and the to csv function was used to store the manipulated data sets. Numpy was used for additional data manipulation in combination with pandas. The Selenium library was used in the data acquisition phase to scrape additional data which was not available in the original data set. Scikitlearn, a machine learning library for python, was used in the implementation of the feature engineering and prediction models Treeinterpreter library was used in feature engineering to analyse the Decision Tree and Random Forest models. Tensorflow and Keras were used in the prediction phase to build the prediction models.

3.1.2 Phase 1: Data Acquisition

The main dataset was taken from Kaggle [20]. It is a comprehensive dataset, containing statistics from every AFL game between 2012 and 2021 and is comprised of 3 tables. Games, containing data about the games and environment of the games, it contains 12 columns. Players which contains player basic information in 7 columns. Stats containing individual player statistics for every game has 31 columns. Overall there are over 90000 data points across the three tables.

However there were some values that were not present in the original data set, which were required to enhance the data. The data set did not contain any values that rated player performance, which is a useful data point in sports prediction models. There are two prominent player scoring systems in the AFL, "Supercoach" and "Fantasy", which comprehensively rank every player after each game. To acquire this data I utilised scraping software selenium to scrape and store both sets of player scores from footywire.com.

Additionally some values needed to be manually calculated from the raw data set, these were all handled in the feature engineering phase to construct the final data set.

3.1.3 Phase 2: Data Engineering

Data Engineering is a key process in any data science project. Without good clean data it is nearly impossible to generate clean useful results from a model. At the end of the data acquisition phase I was left with a data set that required considerable cleaning. The acquired data was stored in 4 sets, 'Games', 'Stats', 'Fantasy' and 'Supercoach'. The Players data set identified in the acquisition, only contained basic meta information about the players to it was left out from project. I also decided that the data should be split into individual seasons, firstly to reduce the computation needed to analyse the data final data sets, and also to allow for the analysis of each individual season. The main data engineering was thus divided into three stages, split each data set by year, for each year merge required features into central data set, from here the data could be analysed with basic exploratory data analysis (EDA). The merging of the data set overlaps slightly with the feature engineering as I was only choosing a selected set of data to merge into the final data set. But this was necessary to be able to perform any sort of initial analysis on the data, having the data spread out in different data sets would not yield as

insightful results during EDA. Every feature was calculated for the home and away team separately, to avoid repetition when I will discuss the features as a group and not distinguish between the home and away feature.

Splitting the data set by year was the simplest of the phases. Each csv was read into python as a pandas data frame. From there a script was created to separate each data set by year and create individual data frames for each year, these were then saved into individual csv files.

The largest section of the data engineering was the merging of the data sets into one central group of data. The idea was to build the data around the 'Games' data set, because this already contained the results information from which the final model would be building the prediction. No columns were removed from the data set until the data was being fed into the final model. This was to keep the data set as complete as possible, in case extra features needed to be computed from the existing data then there would be no missing data which would need to be re-acquired.

To identify the team changes and previous results I created a python script entitled team changes. This which counted the number of changes between the selected team and the team the previous week.

The distance travelled by each team was also calculated. Travel can be hard to define so it was calculated based on the teams home location. Each group had up to 6 travel categories based off the distance between their home location and the location of the game.

Ladder positions were taken based off two factors. The first was the historic ladder, so that the model could view where the team had finished in the previous season. For the historic ladder I decided to hard code the final positions and then create a data frame to match each team to the ladder position. This was then used to create the LadderPosition columns. The CurrentLadderPositions required a ladder model to be created. I generated this by creating a set of data frames for each round in the season, they tracked the teams, the points score by the team, the points scored against the team, the teams percentage (points for / points against * 100), and the total points (win = 4, draw = 2, loss = 0). To fill in the data each round was iterated over and each corresponding field was updated, the ladders were then ordered by points and percentage. Once the set was created the fields were added to the main data structure, along with each teams total points for, points against and percentage.

The Fantasy and Supercoach data is used to give an overview of the strength of each team based on the players in the selected sides. I had the option to either include each individual player in the final data set, or to combine the scores from every player and only include this value. I decided on the latter option, as it allowed for the result to stay consistent in its position in the final data set. If I were to include individual player scores as features, it would have required either a column for each individual player, or 22 columns for all selected players but the order of the players would not be consistent. I believed it would be better to have one consistent overall value to describe the teams as opposed to the more inconsistent and changing values.

As the main data set and the supercoach and fantasy data sets were acquired from different sources they required the greatest level of preparation to be able to merge the data sets. The naming conventions between the data sets were slightly different, both player names and team names varied between the data sets. This became an issue when attempting to extract values from the supercoach and fantasy data sets, as I was using these names to search for the corresponding data. The first step taken was to find the inconsistencies in the player names as this was a more difficult process. First I created a script to identify which names were present in either of the data sets that were not present in the other. From here I could view which names were different and which naming conventions were different. After multiple iterations I had discovered and removed the major inconsistencies and was left with only a handful of differing names, in this case I hard coded the name in which I wanted to keep as there were so few names left that it was the quickest option. The same process needed to be repeated for the team names. This was a much quicker process as there were only 18 names to analyse in each data set, meaning I could easily hard code the changes I needed and update the supercoach and fantasy data sets.

The fantasy and supercoach points combined for each player to give an average value between the two as they performed the same function of rating the players, the entire teams average was then used in the final data in 4 features. TeamImportanceDifference, marked the average scores of players who played in the previous match but were not selected in the forthcoming game. TeamImportanceLastGame, calculated the average score of the team in the previous game. TeamImportanceLastFiveGames, calculated the teams average scores over the previous five games to asses a teams recent form line, if 5 games had not been played then the average

was taken from the games that had been played. TeamImportanceSeasonAverage, calculated the average over the whole season for the team.

The final data points added were the break between games for each team. This was done with a simple python script to find the number of days between the previous game that the team played and the upcoming game. To simplify the script it initially only looked at games from the previous round, this needed to be updated to consider games from the previous two rounds because bye rounds resulted in no games being identified in many cases. The break was initialised to 7 days as this was the median value identified.

The final stage of the data preparation was one hot encoding of team and venue data. One Hot Encoding (OHE) is a way to add categorical data into computer models that require a numerical input. Each venue and team are assigned a numerical value which is then added to the data set in place of the text value. In some cases the model will incorrectly assume that the size of the numerical numbers is an important factor, to combat this each category is assigned as its own feature in the data set that is either active (1) or inactive (0). This was only implemented in the final stages of the model and not added to the main data set, because some functions in the EDA and feature engineering sections perform better without OHE as it also creates a large number of empty variables in the data set.

Once the main data set was built EDA was then used to explore relationships within the data. This was mainly implemented on features that had been proposed by domain experts. For the EDA scatter plots and histograms were created to identify any trends and relationships between the data.

3.1.4 Phase 3: Feature Engineering

3 pages Once the final data set had been defined in the data engineering phase, the data was then analysed in the feature engineering phase. The models used for feature engineering were decision trees and random forests. Although the models are traditionally used for prediction and classification, they can also be used in feature engineering as they are able to track which features were most important when creating a decision node, which can then be analysed for the final model. Also as they do provide a prediction model it allowed me to have extra prediction models to compare with the final results of the project.

Before the data could be inputted into the model it needed to go through a final phase of pre processing. Label encoding was used to remove the text values

from the data set and replace them with numeric variables. One Hot Encoding was not utilised during feature engineering, due to the smaller number of variables and the number of features that required OHE being quite large this would have created too many empty data points relative to the size of the data set. After the encoding all unused variables were dropped from the data set, these points comprised of metadata about the games (date, gameID, year, round, startTime), values that had been encoded (teams, venue) and features that described the outcome of the games (homeWin, homeTeamScore, awayTeamScore). Normalisation was then applied to the data set, this was done using a MinMaxScaler

$$MinMaxScaling : X_{std} = (X - X_{min})/(X_{max} - X_{min})) \tag{3.1}$$

Once the values have been defined the model can be built and trained. For testing a new table will be created building on the games table. It will contain a combination of the features: Disposals, Kicks, Handballs, Tackles, Free Kicks, Hit Outs, Contested Possessions, Player Importance, Marks, Contested Marks, Inside 50s, Rebounds, Clangers, Team Name, Travel Distance and Break Between Games for both teams as well as Rainfall. This will try to predict which team won. 20 percent of the data will be held out for testing purposes.

Evaluation in this phase is the feature importance metrics. Random Forests will be used for finding feature importance as they are naturally capable of discerning important features. Ideally 5 features would be identified that consistently are found to have the greatest impact on predicting the result of a model and the 5 features that consistently have the least impact on the result. To realise this outcome a random forest model containing 100 trees and the 5 metrics that were found most and least important on average will be taken as the fitting metrics.

3.1.5 Phase 4: Predictive Model

3 pages The second phase has to do with the building of a prediction model, using the knowledge of important features gained from the previous phase. The prediction model will be created using a LTSM Neural Network. The data acquisition and pre-processing will be much shorter as the majority had been done previously in the first phase of the project. Again a table will be built that is similar to the table used in the random forest model. However, the 5 least important features will be removed (and the corresponding feature for the opposite team). The scores of the

home and away team will be included in the dataset as well as the round number and year. The dataset will then be separated by year and ordered by the round. Because the model will be predicting future events the training and test data split will not be static. The initial tuning phase will hold out only the final round, making the model theoretically as powerful as possible. But in different iterations more or less rounds will be held out, this is crucial to see if there is a certain point where the models begin to see an increase in their predictive powers. Evaluation on the models The main metric I will use to evaluate my model is the Mean Average Percentage Error (MAPE), which is “the proportion of the average absolute difference between projected and true values divided by the true value” [21], and the Weighted Mean Average Percentage Error (WMAPE) will be used if the dataset is too small to calculate the MAPE properly. Previous prediction models utilising machine learning have been able to reach a best accuracy of 68.1 percent and average accuracy of 65.1 percent [22]. Knowing that models are capable of reaching these accuracies, the target accuracy of the prediction model will be greater than those values, ideally above 70 percent.

4

Results and Discussion

4.0.1 EDA Results

4.0.2 Feature Engineering Results

4.0.3 Final Model Results

5

Related Works

5.0.1 Data Mining

Although data mining is not a big subject in sports it is a major influence in many other industries. Data Mining has a very broad use case in both Supervised and Unsupervised learning. Supervised learning is a subcategory of machine learning that deals with data where the input and output is known, as is the case with the data in this paper, it aims to map input data to resulting output data. Supervised learning can be further divided into two categories Classification, where the output is a class or category and Regression where the output is continuous.

There are many state of the art data mining techniques in both Classification and Regression. There have been some Classification Methods already mentioned in the paper, Decision Trees and Neural. Other widely used algorithms include K Nearest Neighbour (KNN), Support Vector Machines (SVM) and Bayesian Methods [23]. The K Nearest Neighbours attempts to classify a data point based on the class of its Nearest Neighbour points, a SVM is a method that aims to define boundaries to separate a space into classes. Bayesian Methods are more complex it is based upon a method that "combines prior information about a population parameter with new evidence from information contained in a sample to guide the statistical inference process" [24], the basis of the inference is gained through an application of Bayes Theorem [24]. The main application of these algorithms is to forecast how a certain input will act based on their characteristics, in the finance industry this can be deciding how likely a customer is to default on their payments based on their previous behaviours, in the medical industry these can be used to predict how likely a patient is to have a certain medical condition.

5.0.2 Long Short Term Memory Networks

The state of the art of Long Short Term Memory networks is very centralised around stock market predictions and natural language processing, with some forays into image and video analysis. Time series forecasting, techniques, similar different Time Series [25]

Stock market predictions, techniques, similarities Indonesia[26] Bitcoin [27] Dividend [28]

Natural language processing, techniques, similarities, Sentence Embedding [29] Spam [30]

5.0.3 Data Mining in Sports

Although there are many state of the art use cases of data mining, they have limited use in the field of sports. As discussed in “Sports Data Mining” by Robert P. Schumaker et al. [31]. This text looks at which data should be collected to properly performing data mining in sports and “how to best make use of it”. It also discusses the issues faced by those entering data mining in sports not only in the initial phases but also the final phases of data mining. One of these difficulties is the relationships between sports organisations and their data, many were unwilling to embrace data mining techniques at the time of the publication of the book. They defined 5 levels of relationships between organisations and the data they produced. Shown below in table 2, taken from Chapter 1, page 2 from the book.

Level	Relationship
One	No relationship
Two	Human domain experts make predictions using instinct and gut feeling
Three	Human domain experts make predictions using historical data
Four	Use of statistics in the decision-making process
Five	Use of data mining in the decision-making process

Table 5.1: Hierarchy of Sport and Sport Data Relationships.

Schumaker claims in the text that at the time of publishing many organisations resided in level 3 or 4 of the hierarchy. The issue is that there is currently no straightforward way to identify if organisations are using data mining and how they are using it. Another issue highlighted in the text is the inconsistencies and misinterpretations of statistical sports data. As is pointed out in the text many long standing statistics are misleading in modern contexts where we now have a better

grasp on these methods and much greater available computing abilities. However, these methods still remain prominent and in use today, as such the book seeks to define new methods to ensure proper algorithms and applications of data analysis and data mining are used. In the book the Data-Information-Knowledge-Wisdom Hierarchy (DIKW) is used to separate techniques and use cases into each of the categories, to identify the best methods and algorithms to be used on each use case.

Moving into the field of academic papers there are only a handful of resources that explore similar issues to this paper. The most common areas of focus are American Football, Basketball and Baseball.

Carson Leung and Kyle Joseph, explore a prediction model for American Football in their paper, "Sports Data Mining: Predicting results for the college football" [6]. They employ an interesting dropout technique for their prediction model, in which they do not explore the results of the two teams that will be predicted, instead focusing on "a set of teams that are the most similar to each of the competing teams" [6], [page 716]. Similarly, they identify statistics on which the final model will be based, but only 4 instead of the larger set as in the model in this paper.

On the more analytical side is the paper "Sports analytics— Evaluation of basketball players and team" by Vangelis Sarlis and corresponding author Christos Tjortjis. This paper looks at and "evaluates the existing performance analytics used in Europe and NBA (in USA) basketball" [7]. They identify two metric types, Player and Team, and four criteria groups; Key Performance Indicators (KPIs), Defensive criteria, Offensive Criteria and Overall Performance Criteria, as well as outlining a Comparison Matrix and Data Mining Techniques used in sports analysis. They also explore if they can optimise existing performance analysis metrics that are used in basketball.

An overall review of the current techniques used in sports prediction (as of 2013) is given in the paper "A review of Data Mining Techniques for Result Prediction in Sports", M. Haghighat et al., [32]. 6 Methods are analysed in the resource of which two, Artificial Neural Networks and Decision Trees are used in this paper. Bayesian Method, Logistic Regression, Support Vector Machines and Fuzzy Methods are the other methods that are analysed. Since nearly 10 years have passed since this resource was published, there has been many improvements to the models that are used in this paper, specifically in the field of Neural Networks.

Very little comprehensive work has been completed regarding Data Science and Australian Football. In 2008 McCabe and Travathan briefly explored the usabil-

ity of neural networks in predicting the outcomes of sports in their conference paper “Artificial Intelligence in Sports Prediction” [22]. Here they reached an average accuracy of 65 percent using 11 performance metrics. Other studies conducted on AFL data include “Using meta-regression data mining to improve predictions of performance based on heart rate dynamics for Australian football” [33], which focuses on individual player performance as opposed to team performance prediction, but does follow a similar scientific method, utilising Random Forest algorithms to extract key features from the dataset, which is more complex featuring GPS data on top of more traditional performance measures. Also utilising GPS data is “The effect of team formation on defensive performance in Australian [34], which analysed a team’s defensive positioning and the effect it had on defensive performance. These both used similar techniques but the dataset differed from what will be used in this paper.

Sports ML [35]

Human Activity Modelling [36]

6

Summary

6.1 Summary

Overall this paper intends to expand the understanding and use of Data Mining in Professional Sports, specifically the Australian Football League. It aims to combine and build upon methods already being used in sports data mining to explore the following research questions:

> Can data mining be used to find key features and patterns and explain results in professional sports?
>
> Can these extracted trends and features be used to create an explainable prediction model?
>
> How can the results be utilised in the sporting industry?
>
> If the model can reliably predict outcomes, how many rounds will the model need before it becomes reliable?

In the paper Decision Trees, Random Forests, Linear Regression Models and LSTM Neural Networks will be utilised to extract important features and trends in the Australian Football League and use them to implement an explainable prediction model.

A two phase approach will be taken to create the final model. The first being feature engineering and trend analysis, using the Decision Tree and Random Forest techniques and Linear Regression. This will be done iteratively until the 5 most important and least important features are identified. The second phase will be the building of the prediction model, utilising the results from the first phase, with the aim of achieving an average accuracy greater than 65.1 percent.

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