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Prediction of NBA games based on Machine Learning Methods

The code can be posted on the website

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Introduction

National Basketball Association (NBA) is the men's professional basketball league in North America. The influence of NBA trespass its borders and have countless fans around all the world. As the league involves a lot of money and fans, not surprisingly, a lot of studies have been developed trying to predict its results, to simulate winning teams, to analyze player's performance and to assist coaches.

Through the years a lot of data and statistics have been collected based on NBA and each day the data become more rich and detailed. Although, even with such rich data available, it is still very complex to analyze and try to predict a game. In order to deal with that complexity and to achieve better predictions rate a lot of Machine Learning methods have been implemented over these data. That is exactly the purpose of this project.

The main objective is to achieve a good prediction rate using Machine Learning methods. The prediction will only define the winning team, regardless of the score. As a parameter and as a goal, our prediction rate should be higher than the rate of the very naive majority vote classifier that always looked at all previous games (in the season) between two teams and picked the one with the fewest losses as the winner. Moreover, it would be interesting to discover not only the winner, but also what are the most important features to be one. Finally, as a secondary objective, we will try to classify the position of one player based on his features.

Background (NBA format)

(nfIormation from http://en.wikipedia.org)

The current league organization divides thirty teams into two conferences of three divisions with five teams each.

Eastern Conference			Western Conference		
Atlantic	**Central**	**Southeast**	**Northwest**	**Pacific**	**Southwest**
5 teams	5 teams	5 teams	5 teams	5 teams	5 teams

During the regular season, each team plays 82 games, 41 at home and 41 away. A team faces opponents in its own division four times a year (16 games). Each team plays six of the teams from the other two divisions in its conference four times (24 games), and the remaining four teams three times (12 games). Finally, each team plays all the teams in the other conference twice apiece (30 games).

NBA Playoffs begin in late April, with eight teams in each conference going for the Championship. The three division winners, along with the team with the next best record from the conference are given the top four seeds. The next four teams in terms of record are given the lower four seeds.

The playoffs follow a tournament format. Each team plays an opponent in a best-of-seven series, with the first team to win four games advancing into the next round, while the other team is eliminated from the playoffs. In the next round, the successful team plays against another advancing team of the same conference. All but one team in each conference are eliminated from the playoffs.

The final playoff round, a best-of-seven series between the victors of both conferences, is known as the NBA Finals, and is held annually in June.

Methodology

Firstly, the data-set should be studied, selected and organized. It is important to mention that only the Regular Season data will be used, once not all teams plays in playoffs and also the teams that plays it can changes from one year to another.

Although there are a lot of rich data available, a lot of time it is not ready to be used. Sometimes it is desirable to select the most important features or also to reduce its number using methods as Principal Components Analysis. After the data is prepared some analysis will be done in order to select the best inputs for the methods.

Secondly, the Machine Learning Methods will be implemented. By looking in some articles cited on the references, it seems interesting to start the process with a linear regression, that represents a simple method that has, so far, achieved a good performance. After tried the linear regression and, hopefully, with a good classification rate another method will be explored trying to achieve a better performance. Comparing two methods the results will be more reliable and it will be easier to detect the most important features and to find possible improvements. During the process, probably many modifications will be necessary, so new data analysis may be necessary and also new data preparation.

Obs.: This methodology is a guide, but other methods can be tested and implemented if achieves better results.

Data Preparation

Data Extraction

To decide the data source many websites were visited: Most part of the websites has a wide range of data that goes from the basic box score even to the player's salary. Some points were essential in deciding the data source: first, the easiness of extracting the data from the website; second, the number of seasons provided by the website and finally the basic prerequisites of any data as reliability and utility.

The website http://www.basketball-reference.com presented all these features and was selected as major source. The boxscores in the website is organized in tables as shown below:

Regular Season

Date		Visitor/Neutral	PTS	Home/Neutral	PTS
Tue, Oct 26, 2010	Box Score	Miami Heat	80	Boston Celtics	88
Tue, Oct 26, 2010	Box Score	Houston Rockets	110	Los Angeles Lakers	112
Tue, Oct 26, 2010	Box Score	Phoenix Suns	92	Portland Trail Blazers	106
Wed, Oct 27, 2010	Box Score	Boston Celtics	87	Cleveland Cavaliers	95
Wed, Oct 27, 2010	Box Score	Charlotte Bobcats	86	Dallas Mavericks	101
Wed, Oct 27, 2010	Box Score	Utah Jazz	88	Denver Nuggets	110

To extract the data, the box scores were copied into spreadsheets of the OpenOffice and, using the tool *macro*, all the team names were replaced by numbers, the unnecessary columns were deleted, and .txt files were generated with the data. The .txt files generated were loaded in MatLab and used to generate the feature vectors.

The data extracted was from only regular seasons from the 2006-2007 season to 2012-2013 season. Just for simplicity, now and then the season will only be referred by the year that it started. (so 2012-2013 season will be referred 2012 season). During the data extraction it was observed some irregularities: the regular season 2012-2013 has only 1229 games and the regular season 2011-2012 has only 990 games, also some teams change its names through the period of 2006-2013.

The website, also contains some League Standings as displayed below:

League Standings Standings through November 2, 2010

Eastern Conference	W	L	W-L%	GB	PS/G	PA/G
Atlantic Division						
Boston Celtics*	3	1	.750	—	97.3	90.5
New Jersey Nets	2	1	.667	0.5	95.0	99.7
New York Knicks*	1	2	.333	1.5	98.0	99.3
Toronto Raptors	1	2	.333	1.5	100.7	96.7
Philadelphia 76ers*	0	4	.000	3	97.3	104.0

Western Conference	W	L	W-L%	GB	PS/G	PA/G
Northwest Division						
Portland Trail Blazers*	4	1	.800	—	98.4	92.2
Oklahoma City Thunder*	2	1	.667	1	103.3	106.3
Denver Nuggets*	2	1	.667	1	104.0	94.3
Utah Jazz	1	2	.333	2	100.7	106.3
Minnesota Timberwolves	1	3	.250	2.5	99.5	110.0

Some of the these standings were used during the project, however they were not extracted directly from the website, but, instead, they were derived from the box scores using MatLab scripts. This approach was easier than developing a code as phyton to extract the information from the website. Anyway, the standings of the website were very useful to verify the correctness of the MatLab scripts comparing some standings samples obtained with the website.

Feature Vectors Implementation / Data Anaysis

It is really important to spend some time deciding what are going to be the features vectors (input) of the methods, otherwise the results will be frustrating. This fact is well summarized in the phrase *"Garbage in, garbage out"* , very common in the field of computer science

Initially, the most intuitive features were implemented as the Win-Loss percentage of both teams and point differential per game of both teams. Posteriorly some other features as: Visitor Team win-Loss percentage **as visitor,** Home Team win-Loss percentage **at home** and win-loss percentage in the previous 8 games for both teams. All these features were analyzed through some charts or making some simple predictions.

The table below presents the predictions results obtained using:

A: Win-Loss Percentage of both teams in all previous games of the season and choosing the one with highest percentage as the winning team.

B: point differential per game of both teams in all previous games of the season and choosing the one with highest point differential as the winning team.

C: win-loss percentage of both teams in the previous 8 games and choosing the one with highest percentage as the winning team.

D: Visitor Team win-Loss percentage as visitor and Home Team win-Loss percentage at home in all previous games and chosing the one with highest percentage as the winning team.

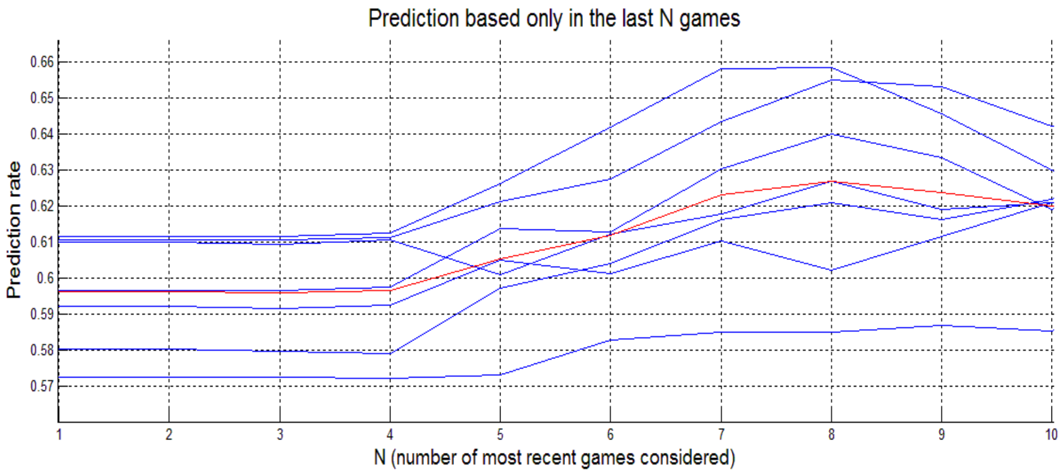
E: Prediction based on the results of previous games between those teams. The team with more wins is predicted as the winner.

	Data Analysis				
Regular Season	A	B	C	D	E
2006	0.6077	0.5972	0.5772	0.6252	0.5358
2007	0.6524	0.6650	0.6411	0.6711	0.5782
2008	0.6524	0.6650	0.6411	0.6711	0.5782
2009	0.6370	0.6398	0.5931	0.6581	0.5835
2010	0.6516	0.6565	0.6285	0.6606	0.5818
2011	0.6308	0.6263	0.6076	0.6434	0.6055
2012	0.6469	0.6603	0.6168	0.6452	0.5921
Mean	0.6398	0.6443	0.6150	0.6536	0.5793

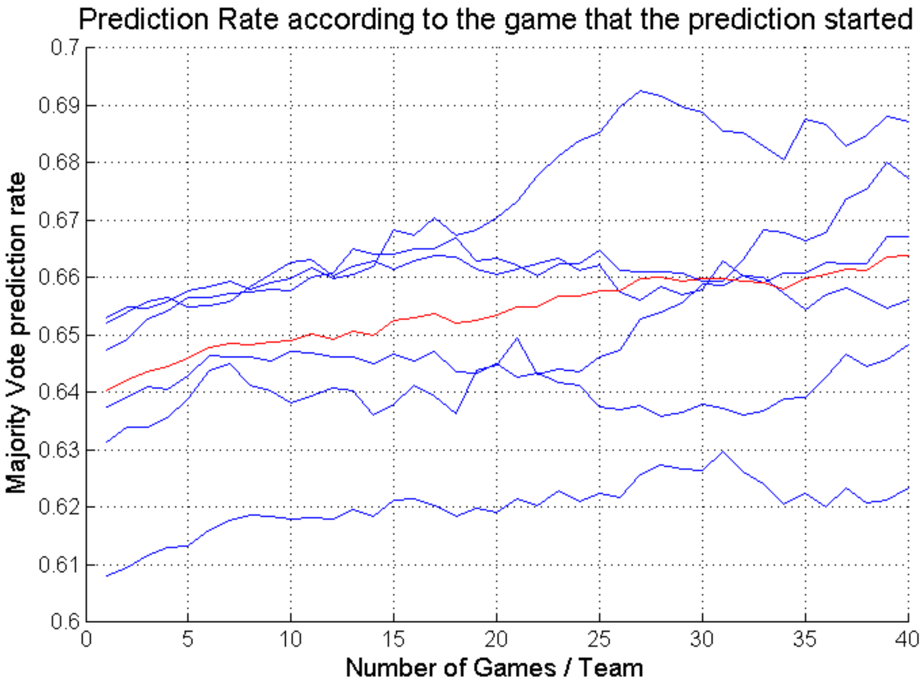
Observations:

- Sometimes, the prediction is impossible because there is no information yet about the teams (very common in the first games of the season) or because the percentages of both teams are equal, or the team have not played 8 games yet. When it occurs, the number of unpredictable games is computed and at the end it is considered that half of them was correctly predicted (according to the probability).

-In the prediction C, it was used the percentage of both teams in the previous 8 games. The aim of this feature is analyze the performance of the team in a short period of time. The number 8 was selected after analyzing the prediction rate for N numbers of previous games for N from 1 to 10. When N=8, it achieved the highest prediction rate.



- Another analysis done was to verify how the prediction rate increases as more data from the season is collected. It can be observed in the graph below that in the first seven games the prediction increases much faster.



-Through the results above it can be observed that all the features are well related with the predction of the game and are good candidates as input for the methods.

- All the features has information of the current season only. None of them uses, for example, the percentage of win-loss of the team in the previous season. It means that the data of previous years are used only to train the methods, but not as a data for the current season.

Methods

Primarily, lets remember our goal: "As a parameter and as a goal, our prediction rate should be higher than the rate of the very naive majority vote classifier that always looked at all previous games (in the season) between two teams and picked the one with the fewest losses as the winner”. Therefore we are going to define our minimum prediction rate. Although, instead of using the the number of losses we are going to use the win-loss percentage, as the number of games played by one team, in a specific day of the season, can differ from the number played by the opponent.

This parameter has already been calculated during the data analysis and corresponds to the data analysis A from the table. So our goal is to have predictions rates better than:

Very naive majority vote classifier	
Regular Season	Prediction Rate
2006	0.6077
2007	0.6524
2008	0.6524
2009	0.6370
2010	0.6516
2011	0.6308
2012	0.6469
Mean	0.6398

Linnear Regression

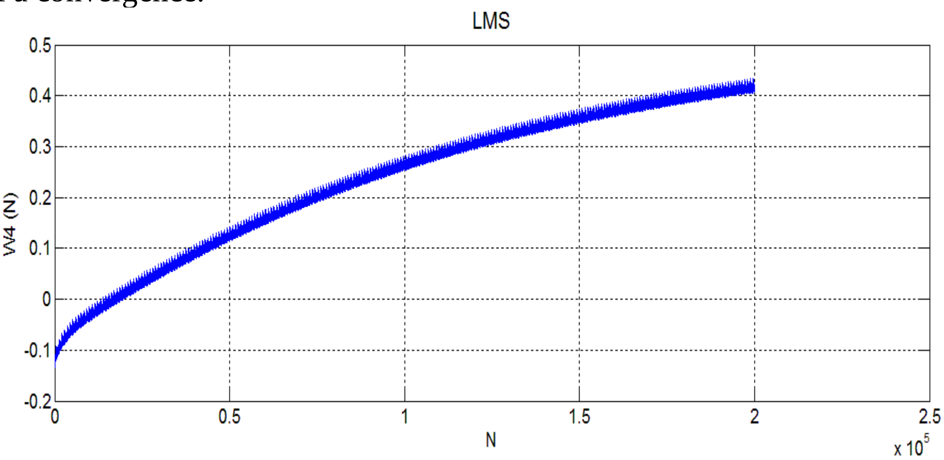
The first method implemented was the linnear regression. The method consists in multiply each feature by a weight, make a summation of all values obtained and a bias, and use this final value to do the classification.

$$Y = w_0 + \sum_{i=1}^{n} w_i * x_i$$

In our case, if Y > 0, the visitor team is considered winner and if Y < 0 the home team is considered winner. Initially all the features obtained were applied as input of the linnear regression:

1. Win-Loss Percentage (Visitor Team)
2. Win-Loss Percentage (Home Team)
3. Point differential per game (Visitor Team)
4. Point differential per game (Home Team)
5. Win-loss percentage previous 8 games (Visitor Team)
6. Win-loss percentage previous 8 games (Home Team)
7. Visitor Team win-Loss percentage as visitor
8. Home Team win-Loss percentage at home

To define the weights of the linear regression the least mean square algorithm was used. The algorithm used has the same structure of the one available in the website of the course. In order to achieve the weights, the parameters of the algorithm (step size and number of iterations) were changed many times but no convergence was achieved. The last attempt was a step size = 0.001 and $2x10^6$ iterations. It was decided to reduce the number of features, that would increase the probability of a convergence.

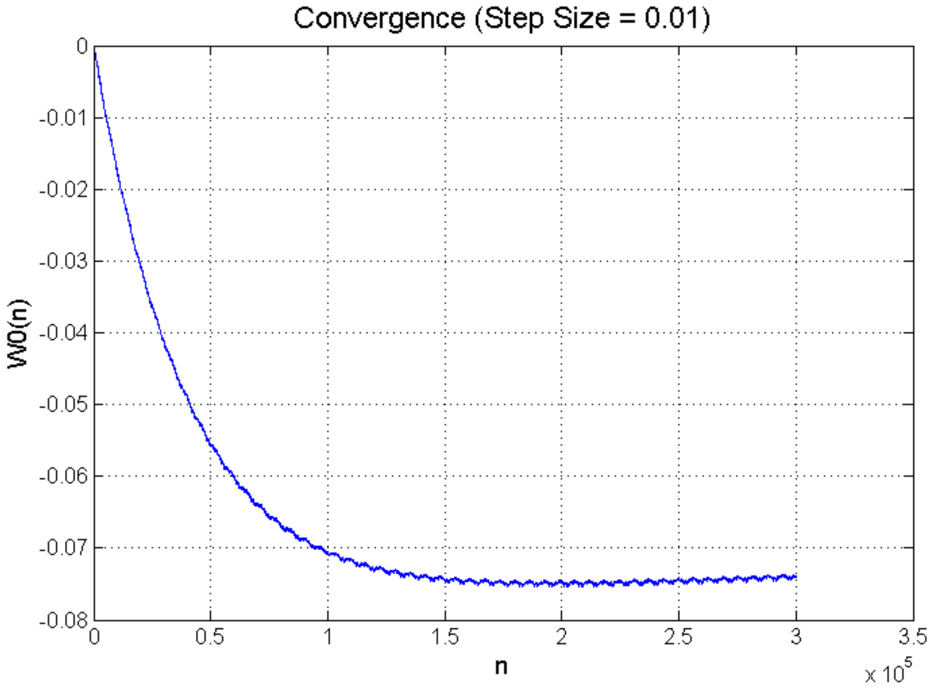


Before doing the principal component analysis it was expected that the features were highly correlated, but ,in order to avoid losing information removing features, the Principal Component Analysis was implemented over the feature vector. The eigen values obtained were:

Eigen Values Matrix							
85267075.244	0	0	0	0	0	0	0
0	24.471589337	0	0	0	0	0	0
0	0	23.728879112	0	0	0	0	0
0	0	0	0.0265259023	0	0	0	0
0	0	0	0	0.0162734088	0	0	0
0	0	0	0	0	0.0121319045	0	0
0	0	0	0	0	0	0.0037955809	0
0	0	0	0	0	0	0	0.0020485835

The first three Eigen Values were used. The next values to these ones becomes really small. This leads to a reduction in a three dimensional space. The principal component analysis was applied in the data of all seasons.

Using the PCA data from 2006-2011 into the LSM algorithm it converged and the following weights for the linear regression were achieved.



LSM weights			
W0	W1	W2	W3
-0.0742	0.0982	0.0754	0.0085

Applying the Linear Regression over the PCA data from 2012, the method has achieved a Prediction Rate of 66.91%, value that is higher than our goal, 63.98%.

Another analysis was made using all the seasons as training vectors and each season separately as testing. This analysis is incorrect from a time perspective as the training data includes future games. Although, as the data is large and the algorithm expects that there is a pattern between seasons, this analysis can be give an idea of the prediction rate of the Linear Regression. The results were:

Linear Prediction Rate	
2006	0.6409
2007	0.6932
2008	0.6932
2009	0.6789
2010	0.6942
2011	0.6541
2012	0.6409
Mean	0.6789

MaximumLikelihood Classifier

The second method implemented was the maximum likelihood. The code used was the one provide in the website of the course. Initially, all the feature vectors were used as input, but ,as the results were lower than the very naive majority vote, a source code was implemented to select the best input features.

Just to select the best input features (and not to really predict results) all the seasons were used as training vector. The code implemented makes an exhaustive search through all possible combinations of the eight features (for any number of features). For each combination the likelihood was trained and if the classification rate was higher than the best combination found before the information of the new best combination was kept.

The best combination achieved includes the following feature vectors:

2. Win-Loss Percentage (Home Team)
4. Point differential per game (Home Team)
5. Win-loss percentage previous 8 games (Visitor Team)
7. Visitor Team win-Loss percentage as visitor
8. Home Team win-Loss percentage at home

After selecting these features, the likelihood was applied for each season using as training data the previous seasons. As a consequence the season 2006 was not computed.

Ex: 2007 >> Training data 2006
20011 >> Training data 2006-2010

The results obtained were:

Likelihood Prediction Rate(%)	
2007	65.8759
2008	68.8869
2009	64.4161
2010	67.8832
2011	60.3972
2012	67.7626
Mean	66.8193

MultiLayer Perceptron – Back Propagation

The last method implemented was the multilayer perceptron using the back propagation code available in the website of the course. The first approach to the method was using all the features, but the best classification rates achieved for many configurations was around 59%, which is lower than our goal and also lower than the previous methods. Trying the method with the data obtained from the Principle Component Analysis the result has increase considerably, aorund 67/68%. In order to try to find the best structure possible the code was adapted to run the back propagation algorithm in different configurations. Each configuration were executed three times, below are the mean prediction rate of them. The training data used was the seasons 2006-2011 and the testing data the season 2012.

1 Hidden Layer Hidden Neurons = 5			
	Momentum		
Alpha	0	0.5	0.8
0.01	66.9084	66.7875	67.0898
0.1	67.1804	66.8178	67.1200
0.4	66.9387	67.3617	67.5128
0.8	67.4524	66.6969	66.7271

1 Hidden Layer Hidden Neurons = 8			
	Momentum		
Alpha	0	0.5	0.8
0.01	66.9084	66.8178	67.1200
0.1	66.8178	66.8782	67.3315
0.4	67.1502	67.5431	67.6035
0.8	67.1502	66.7875	67.0898

1 Hidden Layer Hidden Neurons = 15			
	Momentum		
Alpha	0	0.5	0.8
0.01	66.8782	66.9084	67.1200
0.1	66.7573	66.8178	66.9084
0.4	67.5128	67.3920	67.5733
0.8	65.2161	67.4826	68.9030

This configuration has two hidden layers

1 Hidden Layer Hidden Neurons = [8 3]			
	Momentum		
Alpha	0	0.5	0.8
0.01	63.3726	66.9689	66.8480
0.1	66.8178	66.8178	67.0293
0.4	66.9689	67.6337	66.7271
0.8	64.9743	61.5594	64.9441

The weights of the two best Multilayer Perceptron achieved during this procedure were stored. Applying these MLP to each season the following results were achieved:

MLP 3-8-3-2 (PR[%])	
2006	0.6329
2007	0.6905
2008	0.6905
2009	0.6844
2010	0.6969
2011	0.6844
2012	0.6809
Mean	0.6844

MLP 3-15-2 (PR[%])	
2006	0.6409
2007	0.6932
2008	0.6932
2009	0.6789
2010	0.6942
2011	0.6541
2012	0.6409
Mean	0.6789

It can be observed that those MLP has achieved the best prediction rate, and the prediction rate of the MLP 3-15-2 is the same of the linear regression.

Results

The results obtained in the methods were higher than the goal of the very naive majority vote classifier that was 63.98%. The best prediction rate was achieved using the Multilayer Perceptron Method that achieved 68.44% predction rate. The Linear Regression has achieved a performance of 67.89% which was better than the likelihood method that achived a performance of 66.81%.

The prediction of the season 2011 generally has lower results, maybe it is related with the fact that this season has had less games (990) than the others (1230). Comparing the results of all methods they were very consistent without any big distortion in the results.

Obs.: It is noteworthy that the utilization of the principal component analysis was really important to obtain the MLP results and Linear Regression results.

Discussion of results

We can observe that all the results obtained, including the ones in data analysis, are between 60-70% prediction rate. If we compare the results obtained using the machine learning methods and the ones obtained in data analysis we can verify that the difference of prediction rate is small. This fact leads us to the question: Are these methods really working?

In order to try to answer this question, it is interesting to compare the results obtained in this project with some other people results. The table below is the results obtained by the NBA oracle (link for the article in the references). We can observe that the predictions rates obtained are in the same region and the best result achieved was 0.7009 with the linear regression. Moreover, the prediction rate of experts are also around 70%.

The small difference obtained in the prediction rate actually corresponds to a considerable improvement when considering prediction of basketball games. Sports which involves teams, in general, has many variables associated with the game, for example an injured player. Such variables were not take into account in this project when using the methods, although an expert can take it into account. The point is that a prediction rate near experts prediction is actually good.

However, it would be much more interesting if the prediction was higher than experts. Possible improvements in order to achieve this goal would be to increase the features with some variables as an injured player, also analyze the player individually and also try to improve the methods using new configurations or a mixture of methods for example. Obviously, all these improvements will be hard to be done and, probably, will not represent a very large improvement.

GAME OUTCOME PREDICTION ACCURACY RESULTS

	Linear		Logistic		SVM		ANN	
	P	P+C	P	P+C	P	P+C	P	P+C
1992	0.6945	0.6955	0.6736	0.6800	0.6445	0.6527	0.6473	0.6309
1993	0.7110	0.7070	0.6910	0.7000	0.6680	0.6980	0.6601	0.6620
1994	0.6709	0.6836	0.6527	0.6736	0.6527	0.6655	0.6236	0.6400
1995	0.6882	0.6982	0.6773	0.6891	0.6500	0.6864	0.6415	0.6754
1996	0.7309	0.7200	0.6773	0.6955	0.6827	0.6927	0.6664	0.6595
Mean	0.6991	0.7009	0.6744	0.6876	0.6596	0.6791	0.6478	0.6536

Conclusion

This project was very worthy as it has exhibit the practical part of the machine learning. It has covered the majority part of the steps necessary to use machine learning methods as a important tool in an application: defining a problem (in our case, to predict NBA games); searching for data; studying the data; extracting the data from the source and also the features from the data and finally applying the methods.

Some particular parts as the preparation of data needs a lot of attention as small mistakes can jeopardize all the data and, consequently, the methods. Other steps as implementing the methods needs patience to try many configurations. During this project, it became clear that many times the implementation of the methods is empirical as the math behind methods and the “pattern” behind the problem can be very complex.

Finally, we can assert that the project has achieved the main purpose that was to consolidate and reinforce the concepts studied in class and also is a good look into the possibilities of the machines learning in many applications.

References

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[3] Osama K. Solieman. *Data Mining in Sports:A Research Overview* (http://ai.arizona.edu/mis480/syllabus/6_Osama-DM_in_Sports.pdf)