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Performance Attributes and Risk Taking of Players-Evidence from Lawn Tennis

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ABSTRACT

Lawn tennis is one of the most viewed sports around the world. Different tennis tournaments and grand slams are played round the year. Top tennis players earn huge cash prizes from different tournaments. To achieve a high tennis ranking, specific skills are required. We examined the performance attributes of top 100 single male players of tennis and did a cluster analysis on these performance attributes of the players. One cluster of players is Risk Taker Players and the second cluster is Risk Averter Players.K-Mean clustering technique is utilized to understand the physical attributes of the players in game. Looking into the clusters, it is likely that most of the players are risk averse while playing the game. We found that Double Faults and Aces are important input variables in predicting the risk nature of the Tennis Lawn sports players.

Keywords: *Lawn Tennis, Ranking, specific skills, K means Cluster*

INTRODUCTION

Lawn tennis is one of the most popular and most viewed sports of the world. It is an Olympic sport and played at all levels of society and at all ages. It represents an ideal outdoor sport, promoting alertness, endurance, and self-control, as well as mental and physical health. Professional players across the world take part in various tournaments and based on their performance in those tournaments ranking of tennis players is done by Association of Tennis Players (ATP). Ranking of a player represents achievement or success of the player in lawn tennis.

To achieve and maintain high ranking, any player has to perform consistently throughout his career. The ranking of any player is based on these specific skills. Exercise plays an important role in every sports including lawn tennis.

Investigation of exercise intensity in tennis was examined by T Reilly and Palmer (1995)and found that fluctuations in exercise heart rate were not great. From 1870s, lawn tennis developed a code of behavioral etiquette of court self-restraint, which has a huge influence in the development of playing strokes and styles(Lake, 2011).

Lawn Tennis demands specific skills for achieving a high ranking in the world like serve, and return serve skills. Service is the most important skill in tennis and it is more important in men players and is more successful in doubles(Furlong, 1995). Male players tended to serve more to the corners of the service box, while female players hit more serves to their opponent's body(Hizan et al., 2015).Running speed and stroke quality during intermittent tennis drills are highly dependent on the duration of recovery time(Ferrauti et al., 2001).

There is a relationship between dimensions of social support and performance components in tennis(T. I. M. Rees et al., 1999). In their following study of T. Rees et al. (2000) did confirmatory factor analysis of a performance assessment instrument developed in their previous study. They proved that seven performance factors: Execution of (Flexible) Plan, Loss of Composure, Feeling Flat, Determination, Worry, Flow, and Effective Tactics are the most important in tennis.With the advancement in technology, other factors have also contributed in achieving high performance by the players. Some additional factors may also effect performance of players like racket type, racket grip, shoes, choice of grass species or cultivars etc. Tennis shoe characteristics have effects on performance during sideward cutting movements followed by direction changes(Llana-Belloch et al., 2013). Gender and surface should be accounted for when determining the importance of points in Grand Slam tennis tournaments(O'Donoghue, 2001).

The force during a soft tennis forehand stroke correlates with the grip size(Ohguni et al., 2009). Authors also found correlation of sex and experience with the hitting force.

The choice of grass species and cultivars for use in high quality lawn tennis courts of UK were also determined (Newell, 2014).The influence of scaling court-size and net height on children's tennis performance was examined and optimization of the scaling of net height which may be as critical as other task constraints, such as racquet length or court-size was also determined(Timmerman et al., 2015).

Professional players earn money in different tournaments. Like any other sports such as golf, they are not salaried, but must play and finish highly in tournaments to obtain money. Ranking of any player is associated with the prize money that he has earned in various tournaments. Tennis rankings are underutilized source of information(Reid et al., 2014).

Authors compared the ranking trajectories of male players whom achieved peak professional rankings in the Top 250, 175, 100, 50, 20 and 10.Key points of progression in tennis players' careers were determined with change over time and that evolution was used to inform talent development. It was found that athlete development time has significantly increased between 1985 and 2010(Bane et al., 2014).

The best professional rankings of players born in 1982 or earlier were positively related to the ages at which players earned their first ATP point and then entered the top 100, suggesting that the ages associated with these ranking milestones may have some forecasting potential(Reid & Morris, 2013).

There is a relationship between quantity and level of competition, and cognitive expertise and quantity and level of competition could be of central importance for the development of expertise in tennis players(García-González et al., 2015). Lawn tennis players must possess a wide range of different tennis skills and techniques which includes stroke production, strategy and mental toughness. These skills need to be acquired by the players for achieving success in career. Serve and return skills are considered as main performance skills and are part of fundamental tennis strokes. The tennis serve is the beginning of a point in a tennis game and since the serve begins every point, it's crucial to develop this skill among other tennis skills and techniques.

Different studies found the impact of various factors on performance of tennis players but no study has found the impact of performance attributes of players and this area is ignored in the literature. There is a gap in literature about finding specific attributes of the players and group the players having common attributes. In our best knowledge, this is the first study to find the common attributes of specific group of players. We have taken two categories of performance attributes.

First category consists of attributes relating to serve and second category consists of attributes relating to serve returns. The effect of these performance attributes on ranking of players has never investigated before using cluster analysis. The contribution of this paper lies in finding the most important performance attributes required by the players for achieving high ranking. This paper has a contribution for the tennis player coaches those performances attributes can be improved which have a significant relation with high ranking.

DATA AND METHODOLOGY

Our data consist of top 100 male single players of tennis. Ranking of top 100 male players is collected from Association of Tennis Players (ATP) during February 2016.Skill statistics of each player is also collected from ATP. Skill statistics consist of players for player's whole career played at various surfaces. Cash prize money consist of men singles only as double prize money (men or mixed) would not be a good approximation in our model.

Two categories of performance attributes, one relating to serve and other relating to return have been used for cluster analysis of the payers. First category consists of attributes relating to serve like aces, double faults, first serve won, second serve won, brake points saved, service games won. The second category consists of attributes relating to serve returns like first serve points won, second serve points won, break points converted and return games won. In addition to two categories of performance attributes, physical attributes like age, height and weight are also taken for cluster analysis. In addition, birth place of player and whether the player is right handed or left handed is also taken.

Clustering analysis is done on our data to form cluster having common attributes. Two types of cluster analysis is done:

- K mean clustering
- Two-step clustering

K Mean Clustering

It is first published in 1955, is the most widely used partitioned clustering algorithm(Celebi et al., 2013).In K mean clustering each observation belongs to the cluster with the nearest mean, serving as prototype of the cluster and *k*-means algorithm can be used to partition the input data set into *k* partitions.

Given a set of observations $(X_1, X_2, \ldots, X_n)$, where each observation is a *d*-dimensional real vector, *k*-means clustering aims to partition the *n* observations into k ($\leq n$) sets $\mathbf{S} = \{S_1, S_2, \ldots, S_k\}$ so as to minimize the within-cluster sum of squares (WCSS) (sum of distance functions of each point in the cluster to the K center). In other words, its objective is to find:

$$arg \min_{c} \sum_{i=1}^{k} \sum_{x \in c_i} d(X, \mu_i) =$$

$$arg \min_{c} \sum_{i=1}^{k} \sum_{x \in c_i} \|X - \mu_i\|_2^2$$

Where c_i is the set of points that belong to cluster *i*. The K-means clustering uses the square of the Euclidean distance $d(X, \mu_i) = \|X - \mu_i\|_2^2$

Two-Step Clustering

Two-step cluster technique is a method for identifying and forming homogenous groups of objects called clusters. As the name shows, algorithms are based on two-stage approach. In the first stage, the algorithm undertakes a procedure which is similar to the k-means algorithm.

Based on the results of first stage, second step procedure conducts a hierarchical agglomerative clustering procedure that combines the objects sequentially to form homogenous clusters. Objects in a cluster share many specific common characteristics. The main advantage of two-step clustering is that the procedure itself selects the number of clusters.

Results and Discussion

K Means Cluster Analysis

K means cluster analysis is done to find the cluster of players with similar attributes. Two clusters of players are formed having common performance attributes. First cluster of players may be called Risk Takers and the second cluster of players may be called Risk Averters.

Table1. *K-Mean Cluster*

Final Cluster Centers				
	Cluster			
	1	**2**	**3**	**4**
Ranking	86	32	57	11
Age	28	30	27	28
Tournaments Played	24.47	24.59	25.07	20.20
Z-Score: Aces	-.46884	.59603	-.36401	.55725
Z-Score: Double Faults	-.41945	.58182	-.40310	.55351
Z-Score: 1st Serve	.07717	.22339	-.31996	.08646
Z-Score: 1st Serve Points Won	-.46094	.28883	-.19499	.64668
Z-Score: 2nd Serve Points Won	-.59850	.19066	-.12217	.85905
Z-Score: Break Points Saved	-.40386	.36866	-.34128	.67806
Z-Score: Service Games Won	-.51846	.35758	-.32348	.83723
Z-Score: Total Service Points Won	-.54185	.36540	-.29299	.82102
Z-Score: 1st Serve Return Points Won	-.31964	.10599	-.24670	.70826
Z-Score: 2nd Serve Return Points Won	-.38978	-.20770	.11822	.64764
Z-Score: Break Points Converted	-.30244	-.05170	-.02784	.54950
Z-Score: Return Games Won	-.35326	-.03886	-.08874	.69688
Z-Score: Return points won	-.31803	-.10744	-.07684	.70281

We develop K-mean clustering technique to group our data into serve and serve return attributes such that similarities among the players within the same cluster are maximal. K-mean clustering analysis is computationally efficient, and follows the linear property in data handling. We implement the K-mean clustering based on Z-score ranking. We then perform standardization due to having different scales attributes such as Aces, Double Faults, and Break Points saved *etc*. Four clustered are established in order to check the performance attributes based on ranking of the players.

The mechanism for the clustering analysis is based on its initial mechanism. This mechanism performs the iteration for each variable until the distance among the cluster is minimized. This iteration resolution is performed until the solution attains the stable mechanism.

When analyzing the cluster, we observed that the cluster 1 and 3 contains the similar traits in the first and second category, allowing us to vigilantly look into the serve and serve returns. This shows the traits of the players are not highly professional due to inverse relationship of the tabulated Z-score, which in turn explained the situation in which the adversary serve is broken out during the game. Cluster 1 and cluster 3 are least important argument in understanding the serve and serve returns. Cluster 2 and cluster provides the positive relationship in the first and second category, measuring the professional traits of the top players. This relationship shows that the players are highly connoisseur while playing the game in status quo, which in turn explain the situation for breaking the adversary's serve is indestructible. Cluster 2 and cluster 4 are important in the understanding of serve and serve returns.

Visualizing the game psychology in physical attributes and weights of the player, 1, 2 and 3 clusters are showing the negative relationship with Break Points Converted, Return Games Won, and with Returns Point One and for the 4th cluster the relationship is positive. This relationship to the age aggrandizes the players' traits in maintaining the skills, stamina, strength, speed and spirit. With the passage of time, as a player goes into arena of game, he gets the risk taking strategy for winning the game. First cluster of players are negatively affecting to the game because of their risk taking strategy and these players are vulnerable towards losing the game.

Table2. *ANOVA*

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Ranking	25900.000	3	58.594	96	442.027	.000*
Age	61.308	3	17.821	96	3.440	.020**
Tournaments Played	110.516	3	14.186	96	7.791	.000*
Z-Score: Aces	8.110	3	.778	96	10.427	.000*
Z-Score: Double Faults	7.801	3	.787	96	9.906	.000*
Z-Score: 1st Serve	1.431	3	.987	96	1.450	.233
Z-Score: 1st Serve Points Won	5.879	3	.848	96	6.937	.000*
Z-Score: 2nd Serve Points Won	8.908	3	.753	96	11.831	.000*
Z-Score: Break Points Saved	6.780	3	.819	96	8.274	.000*
Z-Score: Service Games Won	9.275	3	.741	96	12.511	.000*
Z-Score: Total Service Points Won	9.210	3	.743	96	12.389	.000*
Z-Score: 1st Serve Return Points Won	5.016	3	.874	96	5.736	.001*
Z-Score: 2nd Serve Return Points Won	4.762	3	.882	96	5.397	.002*
Z-Score: Break Points Converted	2.955	3	.939	96	3.147	.029**
Z-Score: Return Games Won	4.570	3	.888	96	5.144	.002*
Z-Score: Return points won	4.444	3	.892	96	4.980	.003*
* Shows 1% significant level ** shows 5% significant level						

ANOVA test measures the statistical difference in players attributes using Z-score ranking. Service Games, Second Serve Points and Total Service Points Won are having the largest means square values in the table. These two input variables are valuable in prognosticating the players' performance.

Table 2 also shows the contribution of each variable in the cluster solution. Service game one, total service points, second serve points and aces have the highest F-value.

This indicates the greatest separation among the 4 clusters. From the above table, only 1st serve is the variable which does not contribute in the cluster solution due to its insignificant statistical evaluation. Aces and double faults depicts the moderating evaluation in players' game performance.

Table 3 provides a robust solution for the table 1. Numerous cases are pragmatically assigned to cluster 1 and cluster 3, which unfortunately explains the least performance of the players in serve and serve returns. Cluster 2 and cluster 4 are highly recommended and beneficial in extracting the traits of the game players.

Table3. *No. of Cases in Each Cluster*

Cluster	1	30.000
	2	22.000
	3	28.000
	4	20.000
Valid		100.000
Missing		6.000

Two Step Cluster: Model Summary, Cluster Sizes and Cluster Quality

Model Summery

Algorithm	TwoStep
Inputs	23
Clusters	2

Cluster Quality

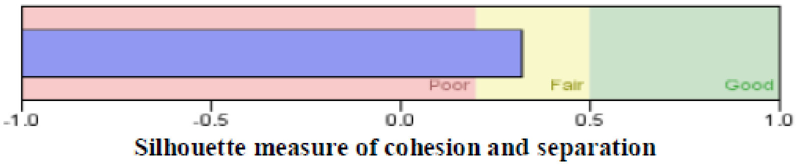

Figure1. *Silhouette Measure of Cohesion and Separation*

Figure 1 shows an intimate compact analysis of the cluster model which includes Silhouette measure of cluster cohesion to illustrate whether the model is poor, fair or good in the shaded portion. This represents the bird eye view to the researchers whether the model is poor or good and it is amended accordingly. If the model is poor, then the iteration of cluster is again submitted to attain the viable results. We have interpreted the results implications on the basis of Kaufman and Rousseeuw (1990) to illustrate the structure of the clusters.

Two clusters have been formed using two-step cluster statistical technique. Cluster 1 consists of 40 players and cluster 2 consists of 58 players. Silhouette measure is based on the tightness and separation of the each cluster defining whether the objects were well-maintained.

Two-steps algorithm along with 23 inputs variables are employed in figure 1. Plotting these clusters in one diagram actually demonstrate the potentials of the clusters in over viewing the data. Silhouette measure of two-step cluster shows the cluster quality as fair. Predictor of input variables show that double faults, aces and total service points won are three most important attributes for male tennis players.

The average Silhouette width is 1.45, explaining the optimal ratio of the serve and serve returns which maximizes the inter-cluster distances among the players' traits and minimizes the intra-clusters distances for the players.

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Figure 2 explains the algorithm used in the model and the input features used to predict the different inputs.

Clusters

Input (Predictor) Importance

1.0 0.8 0.6 0.4 0.2 0.0

Cluster	1	2
Label		
Description		
Size	59.2% (58)	40.8% (40)
Inputs	Double Faults 451.33	Double Faults 1,440.78
	Aces 807.59	Aces 3,758.52
	Total Service Points Won	Total Service Points Won
	Service Games Won 0.75	Service Games Won 0.83
	Break Points Opportunities	Break Points Opportunities
	Break Points Faced 1,111.26	Break Points Faced 3,097.32
	1st Serve Points Won 0.69	1st Serve Points Won 0.74
	2nd Serve Points Won	2nd Serve Points Won
	Break Points Saved 0.59	Break Points Saved 0.63
	Ranking 61.90	Ranking 31.52
	Tournaments Played 27.05	Tournaments Played 23.30
	Career Start 2,006.62	Career Start 2,003.50
	Age (years) 27.36	Age (years) 30.45
	Height (Ft.) 6.08	Height (Ft.) 6.21
	Weight (lbs) 174.21	Weight (lbs) 184.18
	1st Serve 0.60	1st Serve 0.61
	1st Serve Return Points Won	1st Serve Return Points Won
	Left/Right Hand Value	Left/Right Hand Value
	Birth Place Value 47.40	Birth Place Value 51.72
	Return Games Won 0.21	Return Games Won 0.22
	Return Points Won 0.36	Return Points Won 0.37
	Break Points Converted	Break Points Converted
	2nd Serve Return Points Won	2nd Serve Return Points Won

Figure2. *Clusters*

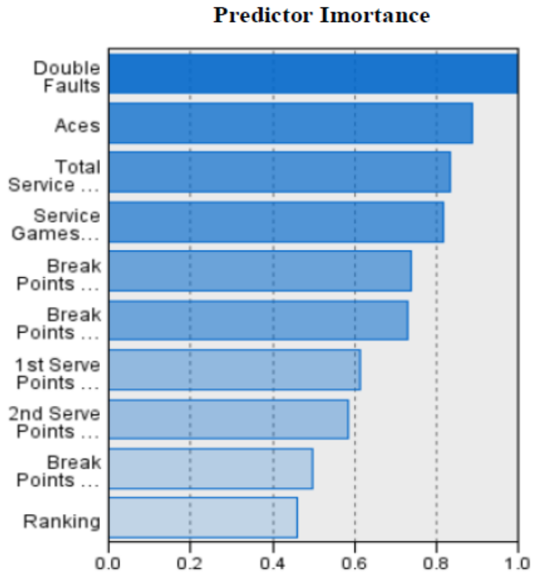
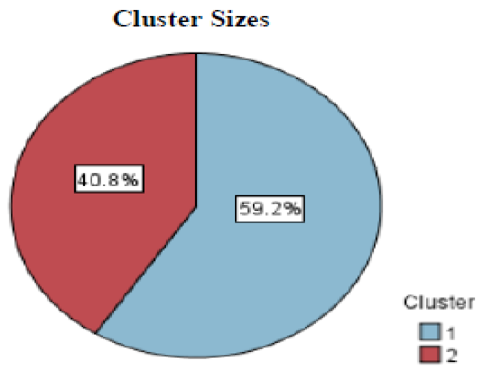


Figure3. *Most Important Predictors*

Figure 3 demonstrates that the Double Faults variable is the most important predictor of Lawn Tennis sport followed by Aces, and Total Serve. The weight age for prediction of Double Faults is high and the other player wins the points. This apparent behavior signifies the importance of Risk Lovers strategy by the player. Aces are highly important as well in predicting the players' performance. It also exhibits the player first serve, with ball strike of maximum force and intuitively concludes the player is adopting the risk loving strategy. Break Points in 1st Serve Points is significant in developing the prediction for Players' strategy. This authoritative behavior manages to conclude that the returner has the advantage in deducing the overall game in order to reduce her risk for losing the game. Break Point in 2nd Serve points is not substantial in anticipating the players' risk attitude.



Size of Smallest Cluster	40 (40.8%)
Size of Largest Cluster	58 (59.2%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	1.45

Figure4. *Cluster Sizes*

Figure 4 explains the sample size needed to obtain the successful statistical power in the behavior of risk for players. We presumably maintained the fixed mean cluster size in calculating the risk attitude for Lawn Tennis players. We produced the cluster analysis and its functional form through iterative process of knowledge discovery subject to trial and error method. We utilized this cluster analysis with the Centroid K-Mean algorithm (also known as Lloyd's Algorithm) to optimally ascertain the nearest neighbor classification for the Risk Averse and Risk Lover players in game.

Conclusion

In this paper, we explore the Lawn tennis which is one of the most viewed sports around the world. Different tennis tournaments and grand slams are played round the year. Top tennis players earn huge cash prizes from different tournaments. To achieve a high tennis ranking, specific skills are required. We examined the performance attributes of top 100 single male players of tennis and did a cluster analysis on these performance attributes of the players. We categorized the first cluster as Risk Taking Player and the other cluster as Risk Averse Player. We implement the K-Mean clustering technique to understand the physical attributes of the players in game. Looking into the clusters, it is likely that most of the players are risk averse while playing the game. We found that Double Faults and Aces are important input variables in predicting the risk nature of the Tennis Lawn sports players.

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