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COMMON NEIGHBORHOOD-BASED LINK PREDICTION IN SPORTS NETWORKS

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Abstract. Link prediction has been among the popular topics in social network analysis studies in recent years. The prediction of new links that may arise in the future, depending on the analysis of the relations between the entities, has started to be used frequently, especially in recommendation systems. Link prediction methods, especially used in social networks, mostly use the topological features of complex networks in terms of application. This situation has also paved the way for link prediction methods to be preferred in almost all kinds of networks of complex network structures. The increased trend in link prediction studies has also allowed many methods to be proposed and used in this field. The differences in the formation of the network and the link types prevent the developed methods from giving the same performance for every complex network. This situation has increased the importance of choosing the appropriate link prediction method depending on the structure of the complex network. This study applied neighborhood-based link prediction methods in networks created from different sports competitions. Furthermore, The most suitable neighborhood-based link prediction method that could be used in sports networks has been investigated. Link prediction methods were applied to the networks formed with different time periods formed from different sports branches such as tennis tournaments, football competitions, and billiards competitions, and the accuracy performances of the methods were determined. The results obtained from the AUC metric in the experimental studies show that the neighborhood-based link prediction methods successfully predict the new connections that may arise in the future in sports networks.

1. INTRODUCTION

Revealing and analyzing information such as the formation, quality, and continuity of network links created by applying interactions between entities has increased the importance of network science in recent years. In particular, the continuity of interaction between entities causes the formation of large amounts of data. The continuity and diversity of interactions between entities make the network structure

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more complex and allow more information to be analyzed [1]. In recent years, complex network science has become a standard and powerful tool for modeling relationships between entities [2]. The analysis of the information obtained from the networks created by using the tools of complex network science has increased the interest of many disciplines in complex network analysis [3]. The basis of complex network science is determining certain rules and disciplines to extract information from all kinds of direct or indirect links between entities [4]. The basis of this growing interest in complex network science is the increase in applications developed in biological, sociological, technological, and communication fields and the availability of large amounts of real data suitable for complex network analysis are included [5-8]. Revealing the link patterns in the network [9-11] and predicting the possible future links [12-17] have been important areas of study in complex network analysis.

Link prediction in complex networks is the process of detecting invisible links in the network or predicting new links that may occur by using the information obtained from the nodes and the links between the nodes and the general structure of the network [18-19]. In order to reveal non-existent links in a complex network by using link prediction methods, it is necessary to determine the type and direction of relations between nodes and the effect of node structures on the formation of links in the network. The change in the structure of a dynamic network is not just about the emergence of new links. The change in the network may also occur with the addition of new nodes to the network over time or the disappearance of existing relationships. In a dynamic network whose structure changes and continues to change over time, it becomes difficult to predict the connection [20]. The link prediction process is based on analyzing the network structure created based on complex network principles. The most important factors affecting the success of the link prediction process are the correct determination of the relationships in the network and the revealing of the differences between the nodes. Another principal factor in the link prediction process is the selection of link prediction methods to be applied according to the network structure. Considering the formation, type, and weight of the connections in the network and applying the appropriate methods is effective in making a successful connection prediction [12-17].

Link prediction processes are widely applied in many areas, especially in dynamic networks, for different purposes. Link prediction methods are used in different fields, such as the creation of suggestion systems in social networks [24-25], filtering according to users' requests in data analysis [21-22], product recommendation in e-commerce applications [23], and author, reviewer and topic suggestion to increase scientific cooperation [26-27]. However, link prediction applies to dynamic networks that undergo structural changes over time [28]. The fact that link prediction methods can be applied in networks created based on complex network principles and whose structural features can be revealed has paved the way for these methods to be used for different applications in many areas. One of the most important difficulties in applying link prediction methods is the selection of methods suitable for the network's structure.

Unlike the link prediction studies carried out in previous years, this study demonstrated the success of link prediction methods in networks created from sports competitions. By applying traditional common neighborhood-based link prediction methods in sports networks formed from different branches, the most successful methods among link prediction methods have been determined. Neighborhood-based link prediction methods were applied for different time periods by using the networks of World Snooker Championship competitions [29], Australian Open Tennis Tournaments [30], and UEFA Europa League matches [31], which were found to be in accordance with complex network principles by network analysis and the results compared. The AUC metric measures the prediction results' success [32]. The AUC results show that traditional neighborhood-based link prediction methods can be used to predict possible future encounters in networks created from sports competitions.

2. METHODS

Depending on the structure and properties of the complex network, many link prediction methods have been proposed. While the proposed methods give significantly successful results in the networks in which they are used, their success may be adversely affected in different network structures. However, there are also generalized methods that can be applied to many complex networks. These methods reveal the similarities of the node pairs that are not connected to each other in the network. Similarity-based link prediction methods are the easy to implement due to the use of topological properties of the network therefore the most frequently used methods. The basic approach in the application of similarity-based methods is the assumption of probability of link between pairs of nodes that are similar to each other. In similarity-based methods, the node pairs are represented as x and y, while the probability of establishing a link is represented as S_{xy}. The higher the calculated S_{xy} similarity score means that x and y are more likely to link in the future.

Neighborhood-based link prediction methods use local topology information of the network instead of the entire network. In this way, it has low computational complexity and can be implemented faster, especially in dynamic networks. Therefore, neighborhood-based approaches become more applicable in large-scale complex networks [33]. Neighborhood-based link prediction methods are used in this study, which is carried out considering the structural features of the network.

In the similarity score calculations used, $\Gamma(x)$ is the set of neighbors of x and $\Gamma(x)$ is the set of neighbors of y; k_x represents the number of connections of x and k_y represents the number of connections of y.

2.1. **Common Neighbor.** Although common neighbors (CN) is one of the simplest methods developed for link prediction, its prediction success is quite high. Therefore, it is one of the most used methods. The point of view of the common neighbors method in link prediction is as follows; the more common neighbors of two nodes, the higher the connection success [34-35]. The Common Neighbor is calculated as in Eq. 1;

$$S_{xy} = |\Gamma(x) \cap \Gamma(y)|\,. \tag{1}$$

2.2. **Jaccard Index.** The jaccard index, which is mostly used in data mining, is one of the methods with a high success rate applied in similarity-based link prediction. The Jaccard Index (JI) method uses the number of common neighbors while calculating the similarity ratio, and also considers the total number of all neighbors and calculates the probability of two nodes interacting in the future [36-37]. The Jaccard Index is calculated as in Eq. 2;

$$S_{xy} = \frac{|\Gamma(x) \cap \Gamma(y)|}{|\Gamma(x) \cup \Gamma(y)|}. \tag{2}$$

2.3. **Sorenson Index.** The Sorenson Index method calculates the probability that two nodes will interact in the future, taking into account the degrees of all neighbors as well as using the number of common neighbors when calculating the similarity ratio. It aims to show that nodes with low ratings may have high connections in the future[30]. The Sorenson Index is calculated as in Eq. 3;

$$S_{xy} = \frac{2\,|\Gamma(x) \cap \Gamma(y)|}{|\Gamma(x)| + |\Gamma(y)|}. \tag{3}$$

2.4. **Preferential Attachment.** The preferential attachment index, which is preferred in growing networks, suggests that any node newly joining the existing network is more likely to interact with higher order nodes. In other words, according to the approach, it is argued that the higher the current node degree, the more likely it is to increase their future links. According to the preferential attachment index (PAI), the higher the number of neighbors of the nodes in the current network, the higher the probability of link between two nodes [37]. The Preferential Attachment is calculated as in Eq. 4;

$$S_{xy} = \Gamma(x) * \Gamma(y). \tag{4}$$

2.5. **Adamic-Adar Index.** The perspective of the Adamic adar index (AAI) is based on calculating the connection probability by giving importance to the neighbors with low number of links in the current network. For example, in order to find out how many nodes the z node, which has common neighbors (x) and (y), has connections with, the degree of the z node must be taken into account when calculating connection probability[38]. The Adamic-Adar Index is calculated as in Eq. 5;

$$S_{xy} = \sum_{z \in \Gamma(x) \cap \Gamma(y)} \frac{1}{\log(|\Gamma(z)|)}. \tag{5}$$

2.6. **Resource Allocation Index.** Resource allocation index (RAI) measures how strong the connection between pairs of nodes that are not directly connected to each other and is widely used in complex networks. In other words, it is used to calculate the similarity of pairs of nodes that are in communication over common neighbors even though they are not directly connected to each other. The calculation of this similarity ratio is made in accordance with the sources they received from each other [39]. In the formula below, kz represents the number of neighbors of z, which is the common neighbor of (x) and (y). The Resource Allocation Index is calculated as in Eq. 6;

$$S_{xy} = \sum_{z \in \Gamma(x) \cap \Gamma(y)} \frac{1}{k_z}. \tag{6}$$

3. EXPERIMENTAL STUDY

The fact that link prediction applications are generally concentrated on social networks and interaction networks prevents the performance of these methods in different dynamic networks to be adequately evaluated. Therefore, the basis of this study is to evaluate the success of link prediction methods in networks formed from different branches such as sports network. In addition, another aim of the study is to evaluate the usability of neighborhood-based link prediction methods against the difficulties in calculating the probability of future encounters between athletes or teams in sports competitions. The general steps of the experimental study are shown in Figure 1.

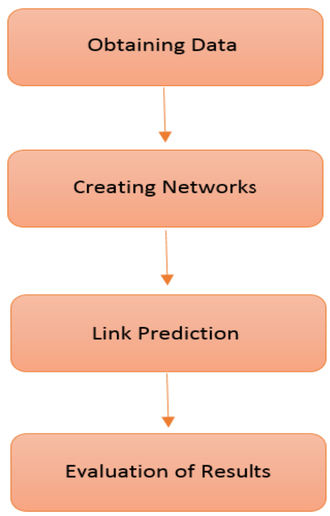

FIGURE 1. Implementation steps of experimental study.

3.1. Data Set.

In the experimental study, networks were created from the World Snooker Championship [29], Australian Open Tennis Tournaments [30] and UEFA Europa League [31]. The reason for using these networks as datasets is their compliance with the basic properties of complex networks supporting the empirical part such as availability of data and critical attributes such as time. The World Snooker Championship dataset [40] is shown in Figure **??**, the complex network of Australian Open Tennis Championships [41] is shown in Figure 2-(a), and the complex network of UEFA Europa League Networks [42] competitions is shown in Figure 2-(b).

As shown in Table 1, in the snooker and tennis networks, the nodes are formed from the athletes, and the links between the nodes are formed from the competitions between the athletes. In the UEFA Europa League networks, the nodes are formed from the teams, and the links between the nodes are formed from the matches between the teams.

TABLE 1. Snooker world championship competitions dataset in [40].

Tournament ID	Stage	Player1_Name	Player2_Name	Score 1	Score 2
772	Final	Alex Higgins	Ray Reardon	18	15
772	Semi-Final	Alex Higgins	Jimmy White	16	15
772	Semi-Final	Ray Reardon	Eddie Charlton	16	11
772	Quarter-Final	Eddie Charlton	Tony Knowles	13	11
772	Quarter-Final	Alex Higgins	Willie Thorne	13	10
772	Quarter-Final	Ray Reardon	Silvino Francisco	13	8
772	Quarter-Final	Jimmy White	Kirk Stevens	13	9
772	Last 16	Eddie Charlton	Bill Werbeniuk	13	5
772	Last 16	Silvino Francisco	Dean Reynolds	13	8
772	Last 16	Alex Higgins	Doug Mountjoy	13	12
772	Last 16	Tony Knowles	Graham Miles	13	7
772	Last 16	Ray Reardon	John Virgo	13	8
772	Last 16	Kirk Stevens	Patsy Fagan	13	7
772	Last 16	Willie Thorne	John Spencer	13	5
772	Last 16	Jimmy White	Perrie Mans	13	6
772	Last 32	Eddie Charlton	Cliff Wilson	10	5
772	Last 32	Patsy Fagan	David Taylor	10	9
772	Last 32	Silvino Francisco	Dennis Taylor	10	7
772	Last 32	Alex Higgins	Jim Meadowcroft	10	5
772	Last 32	Tony Knowles	Steve Davis	10	1
772	Last 32	Perrie Mans	Tony Meo	10	8
772	Last 32	Graham Miles	Dave Martin	10	5
772	Last 32	Doug Mountjoy	Rex Williams	10	3

TABLE 2. Count of nodes and links for the world championship network.

	Snooker World Championship	Australian Open Tennis Championship	UEFA Europa League
Nodes	615	553	154
Edges	3033	2156	388

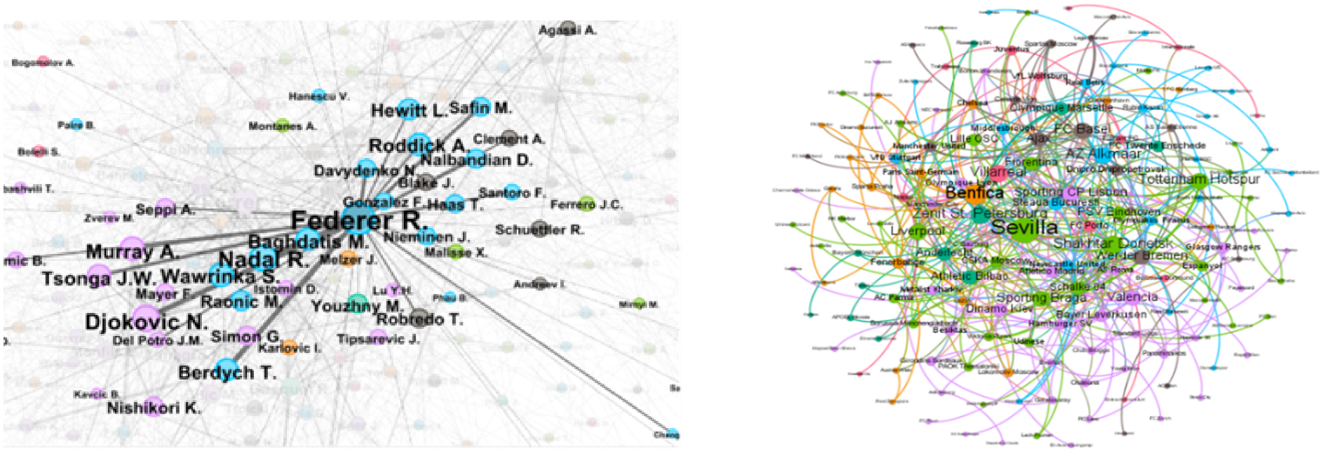

FIGURE 2. a. Network of Australian Open Tennis Championships in [30],
b. Network of UEFA European League in [31].

3.2. **Creating Networks Based on Time Period.** In the experimental study, unweighted and undirected networks were created from the obtained data sets in 2 different time periods.

As shown in Table 2, the importance of the time period in the training network was investigated by choosing time periods at different intervals for training in the networks created. However, to measure the success of the training networks, the 4-years period following the time period forming the training network was used as the test network.

After the training and test networks were created, Common Neighborhoods, Jaccard Index, Preferential Attachment Index, Adamic-Adar Index, Resource Allocation Index and Sorenson Index methods, which are traditional neighborhood-based link prediction methods described in Section 2, were applied.

TABLE 3. Training and test networks created depending on the time period.

Training Network Time Period	**Test Network Time Period**
2004-2007	2008,2009,2010,2011
2004-2013	2014,2015,2016,2017

3.3. **Experiment results.**

3.3.1. *Networks Created Between 2004-2007.* For the data between 2004-2007, the network in the time period between 2004-2007 was used for training, while the years 2008, 2009, 2010 and 2011 were used as tests. Looking at Tables 4 -6, it is seen in the results obtained from the AUC metric that the link prediction methods are not successful at the desired level for all sports networks.

The main reason for this seems to be that the time period used for the training network is short. However, despite the negative effect of the training network, the success of the link prediction methods increased as the time period of the networks created for training increased.

TABLE 4. Link Prediction AUC Results in Snooker Network Created Between 2004-2007.

	2008	2009	2010	2011
Common Neighbour (CN)	0,542	0,780	0,881	0,899
Jaccard Index	0,697	0,947	0,968	0,987
Adamic Adar (AA)	0,560	0,876	0,946	0,965
Preferential Attachment Index	0,776	0,838	0,854	0,871
Sorenson Index	0,465	0,696	0,774	0,790
Resource Allocation Index (RA)	0,576	0,614	0,771	0,787

TABLE 5. Link Prediction AUC Results in Tennis Network Created Between 2004-2007.

	2008	2009	2010	2011
Common Neighbour (CN)	0,516	0,742	0,839	0,856
Jaccard Index	0,664	0,902	0,922	0,940
Adamic Adar (AA)	0,533	0,834	0,901	0,919
Preferential Attachment Index	0,739	0,799	0,814	0,830
Sorenson index	0,443	0,663	0,737	0,753
Resource Allocation Index (RA)	0,549	0,584	0,734	0,749

When the prediction successes at branch level in networks where link prediction methods are applied, it is seen that more successful prediction results are obtained in networks consisting of snooker competitions than in other sports networks, as can be seen in Table 4. It is seen that the lowest prediction success is in the networks created from UEFA Europa League matches.

This is due to the effect of the number of nodes and links in the training and test networks on the prediction success. The high number of nodes and connections used for the training and test network, that is, the quality of the data used in the analysis for the network, increases the link prediction at the right rate.

TABLE 6. Link Prediction AUC Results in UEFA Network Created Between 2004-2007.

	2008	2009	2010	2011
Common Neighbour (CN)	0,304	0,437	0,494	0,504
Jaccard Index	0,391	0,531	0,615	0,627
Adamic Adar (AA)	0,314	0,491	0,53	0,541
Preferential Attachment Index	0,435	0,470	0,603	0,615
Sorenson index	0,261	0,390	0,434	0,443
Resource Allocation Index (RA)	0,323	0,344	0,432	0,441

When the success of the connection prediction methods in the networks created between the years 2004-2007 is compared; in Snooker networks in Table 5, Preferential Attachment Index methods was successful in the 2008 network and Jaccard Index methods were successful in the 2009, 2010 and 2011 networks. In Tennis networks in Table 6, Preferential Attachment Index methods was successful in the 2008 network and Jaccard Index methods were successful in the 2009, 2010 and 2011networks. In UEFA Europa League networks in Table 5, Preferential Attachment Index methods was successful in the 2008 network and Jaccard Index methods were successful in the 2009, 2010 and 2011 networks.

When the success of the link prediction methods for all networks is examined in general, it is seen that the Preferential Attachment Index and Jaccard Index methods are more successful than the other methods in the networks between 2004-2007. It is seen that the Preferential Attachment Index method is more successful than other methods in networks where the test network is formed from a narrow time period, and the Jaccard Index method is more successful than other methods as the time period of the test network increases. The difference in success in link prediction is due to the fact that the applied link prediction methods analyze, the way the nodes in the networks are connected to each other, the number of nodes, the number of connections and the power of the hub nodes in the network differently.

3.3.2. *Networks Created Between 2004-2013.* For the data between 2004-2013, the network in the time period between 2004-2013 was used for training, while the years 2014, 2015, 2016 and 2017 were used as test networks. Looking at the results obtained from the AUC metric in Tables 7-9, it is seen that predictions are made similar to the predictions in the networks created between 2004-2007, as in Tables 4-6. Looking at Tables 7-9, unlike the predicts for the 2004-2007 time period, it is understood that the predictions for the short time intervals used in the training network are more successful than the predictions for the previous time periods. The reason for this is that the network created for training consists of a long time period. Because the time interval of the network created for training is long, it enables the use of more topological information for estimation, and this is a factor that increases the success of prediction in a short time interval. However, the longtime interval of the network used for testing provides a similarly high success as in the previous time periods.

When the success of the link prediction methods in the networks created between 2004 - 2013 is compared, as seen in Tables 7-9, the Preferential Attachment Index predicted more successfully than the

TABLE 7. Link Prediction AUC Results in Snooker Network Created Between 2004-2013.

	2014	2015	2016	2017
Common Neighbour (CN)	0,627	0,7159	0,815	0,930
Jaccard Index	0,724	0,790	0,861	0,938
Adamic Adar (AA)	0,634	0,717	0,809	0,914
Preferential Attachment Index	0,804	0,861	0,912	0,940
Sorenson index	0,524	0,597	0,687	0,796
Resource Allocation Index (RA)	0,610	0,696	0,801	0,841

TABLE 8. Link Prediction AUC Results in Tennis Network Created Between 2004-2013.

	2014	2015	2016	2017
Common Neighbour (CN)	0,615	0,701	0,799	0,912
Jaccard Index	0,710	0,774	0,844	0,920
Adamic Adar (AA)	0,622	0,702	0,793	0,896
Preferential Attachment Index	0,788	0,844	0,894	0,922
Sorenson index	0,514	0,585	0,673	0,780
Resource Allocation Index (RA)	0,598	0,682	0,785	0,825

TABLE 9. Link Prediction AUC Results in UEFA Network Created Between 2004-2013.

	2014	2015	2016	2017
Common Neighbour (CN)	0,609	0,695	0,792	0,903
Jaccard Index	0,703	0,767	0,836	0,911
Adamic Adar (AA)	0,616	0,696	0,786	0,888
Preferential Attachment Index	0,781	0,836	0,886	0,913
Sorenson index	0,509	0,580	0,667	0,773
Resource Allocation Index (RA)	0,593	0,676	0,778	0,817

other methods in all time intervals created for training and in all sports branches. The reason for this is that the Preferential Attachment Index method increases the success of the predictions by calculating more similarity ratios by using the topological information in the network due to the long time period in the networks used for training. However, it is possible to say that the neighborhood-based link prediction methods used in the training and test networks created between 2004-2013 are successful.

4. CONCLUSION

In this study, the success of neighborhood-based link prediction methods used in complex networks in sports networks was investigated. In the study, networks were created in two different time periods from Snooker World Championship tournaments, Australian Open Tennis tournaments and UEFA Europa League competitions and neighborhood-based link prediction methods were applied to these networks. The reason for the creation of networks from different time periods was to determine the success of link prediction methods according to the density of data in sports networks. The success of the results obtained was measured with the AUC metric. The results obtained from the AUC metric show that neighborhood-based link prediction methods are successful for networks created under favorable conditions from sports competitions. The most important factor affecting the success of link prediction methods has been the density of data in the networks created. While the most successful results were observed in the networks created from the Snooker World Championship, it was determined that the lowest success was in the networks formed from the UEFA Europa League competitions. Another result of the study is that the networks created for testing should be created from a large time period, just like the networks created for training. Experimental results show that link prediction methods are more successful in test networks created over a large time period.

REFERENCES

[1] L. Getoor and C. P. Diehl, "Link Mining: A Survey."

[2] A. Kumar, S. Mishra, S. S. Singh, K. Singh, and B. Biswas, "Link prediction in complex networks based on Significance of Higher-Order Path Index (SHOPI)," Physica A: Statistical Mechanics and its Applications, vol. 545, May 2020, doi: 10.1016/j.physa.2019.123790.

[3] P. Srilatha and R. Manjula, "Similarity Index based Link Prediction Algorithms in Social Networks: A Survey," 2016.

[4] S. H. Strogatz, "Exploring complex networks.," Nature, vol. 410, pp. 268–276, 2001.

[5] Newman, M. E. J.:Siam Rev. 45, 167 (2003).

[6] Dorogovtsev ,S. N.,Mendes ,J. F. F.: In Evolution Of Networks, Oxford University Press, Oxford, (2003).

[7] Dodds ,P. S., Muhamad ,R., Watts ,D. J.: Science 301, 827 (2003).

[8] Watts ,D. J., S. Strogatz,H.: Nature (London) 393, 440 (1998).

[9] Watts Dj, Strogatz Sh: Collective Dynamics Of 'Small-World' Networks. Nature. 393 (6684): 440–2, (1998).

[10] Erdos, P., Rényi, A, On Random Graphs. I(Pdf). Publicationes Mathematicae. 6: 290–297, (1959).

[11] Barabasi ,A. -L., Albert ,R.: Emergence Of Scaling In Random Networks, Science, 286, 509 (1999).

[12] Newman M.E.J.: Clustering And Preferential Attachment In Growing Networks, Phys. Rev. E - Stat. Physics, Plasmas, Fluids, Relat. Interdiscip. Top. 64 (2001).

[13] Paul: Etude De La Distribution Florale Dans Une Portion Des Alpes Et Du Jura, Bull. La Soc. Vaudoise Des Sci. Nat. 37, 547–579,(1901)

[14] Barabasi Albert-Laszlo, Albert Reka, Emergence Of Scaling In Random Networks, Science (80-.). 286 (1999) 509–512.

[15] Barabasi ,A. -L., Albert ,R.: Statistical Mechanics Of Complex Networks, Reviews Of Modern Physics. 74 (1): 47–97,(2002)

[16] Zhou,T., Lü, L., Zhang, Y.C.: Predicting Missing Links Via Local Information, Eur. Phys. J. B. 71 623–630, (2009)

[17] Sorensen T.: A Method Of Establishing Groups Of Equal Amplitude In Plant Socio-logy Based On Similarity Of Species Content., Det. Kong. Danske Vidensk, Selesk Biol. Skr. 5,1–34, (1948) .

[18] Liben-Nowell, D., Kleinberg,J.: The Link-Prediction Problem For Social Networks, J. Am. Soc. Inf. Sci. Technol. 58, 1019–1031, (2007).
[19] Linyuan, L.L., Zhou, T.: Link Prediction İn Complex Networks: A Survey, Phys. A Stat. Mech. Its Appl. 390, 1150–1170, (2011)
[20] Huang, Z.: Link Prediction Based On Graph Topology: The Predictive Value Of Gene-ralized Clustering Coefficient, Ssrn. (2010).
[21] Resnick, P., Varian, H.R.: Recommender Systems Mmende Tems, Commun. Acm. 40, 56–58, (1997).
[22] Lü, L., Medo, M., Yeung, C.H., Zhang, Y.-C., Zhang, Z.-K., Zhou, T.: Recommender Systems, Phys. Rep. 519, 1–49, (2012).
[23] Huang, Z., Li, X., Chen, H.: Link Prediction Approach To Collaborative Filtering, Proc. 5th Acm/Ieee-Cs Jt. Conf. Digit. Libr. - Jcdl '05. (2005)
[24] Kleinberg, J.: Analysis Of Large-Scale Social And İnformation Networks Subject Areas , Author For Correspondence, (2013).
[25] Zhang, Q.M., Lü, L., Wang, W.Q., Zhu, Y.X., Zhou, T.: Potential Theory For Directed Networks, Plos One. 8 (2013)
[26] Bürhan, Y., Daş, R.: Akademik Veritabanlarından Yazar-Makale Bağlantı Tahmini, Politeknik Dergisi Journal Of Polytechnic, 787-800, Ankara(2017).
[27] Hanley, J.A., Mcneil, B.J.: The Meaning And Use Of The Area Under A Receiver Operating Characteristic (Roc) Curve., Radiology. 143, 29–36 (1982).
[28] Wang, W.Q., Zhang, Q.M., Zhou, T., Evaluating Network Models: A Likelihood Analysis, Epl. 98, 1–6, (2012)
[29] Joseph D O'Brien, James P Gleeson, A complex networks approach to ranking professional Snooker players, Journal of Complex Networks, Volume 8, Issue 6, 1 December 2020
[30] Fındık ,O., Özkaynak ,E.: Complex Network Analysis Of Players In Tennis Tourna-ments, International Conference On Advanced Technologies, Computer Engineering And Science (Icatces'18), 383-388, Karabük (2018)
[31] Sulak,E.E., Yılmaz,H. Özkaynak,E.: Complex Network Analysis Of Uefa Europe Lea-gue Competitions, International Conference On Advanced Technologies, Computer Engineering And Science (Icatces'18), 389-393, Karabük (2018)
[32] Hanley, J. A. and McNeil, B. J., "The meaning and use of the area under a receiver operating characteristic (ROC) curve.", Radiology, 143 (1): 29–36 (1982).
[33] H. Wang and Z. Le, "Seven-layer model in complex networks link prediction: A survey," Sensors (Switzerland), vol. 20, no. 22. MDPI AG, pp. 1–33, Nov. 02, 2020. doi: 10.3390/s20226560.
[34] Newman M.E.J.: Clustering and Preferential Attachment in Growing Networks, Phys. Rev. E - Stat. Physics, Plasmas, Fluids, Relat. Interdiscip. Top. 64 (2001).
[35] Murata, T. and Moriyasu, S., "Link Prediction of Social Networks Based on Weighted Proximity Measures", IEEE/WIC/ACM International Conference on Web Intelligence (WI'07), Fremont, 85–88 (2007).
[36] Jaccard, P., "Etude de la distribution florale dans une portion des Alpes et du Jura", Bulletin De La Societe Vaudoise Des Sciences Naturelles, 37: 547–579 (1901).
[37] de Sa, H. R. and Prudencio, R. B. C., "Supervised link prediction in weighted networks", The 2011 International Joint Conference on Neural Networks, San Jose, 2281–2288 (2011).
[38] Adamic, L. A. and Adar, E., "Friends and neighbors on the Web", Social Networks, 25 (3): 211–230 (2003).
[39] Zhou, T., Lü, L., Zhang, Y.C.: Predicting missing links via local information. Eur. Phys. J. B 71, 623–630 (2009)
[40] www.figshare.com/articles/dataset/Snooker_datasets/13604480/1
[41] www.tennis-data.co.uk/alldata.php
[42] www.Kassiesa. Ho-me.Xs4all.Nl/Bert/Uefa/Data/Index.Html (2018).