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Comparison of Country-Based High And Low Market Valued Transfer Networks

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Keywords
Network science, football transfer market, excess degree, assortativity.

Abstract
Football is a "money game" and this feature of football is evident in the transfer markets. Network science, which has a wide range of applications from the brain to social networks, can also be applied to football transfer markets. In this manuscript, one million Euro has been taken as a threshold and the transfer market and 2019-2020 Winter transfer season of football was divided into two markets such as a low and high valued markets. After obtaining these two networks, their metrics and measures were calculated and compared. In addition, the article focused on "excess degree", "assortativity" concepts of network science and investigated the differences between low and high-valued transfer markets in terms of these concepts. It was found that high market valued transfer network has a low assortativity coefficient (0.562), and low-valued transfer network has a high assortativity coefficient (0.836). This finding can be interpreted as the big transfer values, big money creates big differences in country's transfer connections. The skewness of ingoing-outgoing degree differences distribution is much higher in the one with higher transfer values (0,962), than the one with lower transfer values (0,180). This situation can be attributed to larger deficits in the high-value market. Regarding total number of connections, self-loops and betweenness. In both networks, Brazil is seen as the country that attracts the most attention in winter season of 2019-2020.

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1. Introduction

Network science can be interpreted as a paradigm shift in science. In the two decades of network science, Complex networks have been studied extensively such as biology (e.g. protein interaction networks), information technology (e.g., www, Internet), social sciences (e.g., collaboration, communication, economic, and political networks; the diversity of network science is not only that much, but the theoretical areas on which it is based are also very diverse such as theories and

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methods of graph theory, statistical physics, computer science, statistics, and sociology (Molontay & Nagy, 2019).

In 2019, 18,042 international transfers have been made and the value of international transfers reached USD 7.35 billion. "In 2019, the football transfer market reached unprecedented levels both in terms of the number of transfers and the amount spent on fees (FIFA, 2019). When we look at the transfer markets within the framework of these numbers, it is not possible to say that such an important market has been examined sufficiently. The purpose of our article is to examine the 2019-2020 Winter international transfer market in terms of network science, and to find the differences between low and high valued football transfer markets.

For example, final transfer destinations of some countries are summarized In the network of Figure 1. According to this figure, principal destination of Brazilian, Argentinean and French expatriates are seen as a network, created by transfer market. "*Portugal is by far the chief destination for Brazilians.* On the 1st of October 2017, 219 footballers from Brazil were playing in the three top levels of competition in Portugal (18.1% of all Brazilians abroad)."(Raffaele , Ravenel, & Besson, 2018). And, "*Chile and Mexico are the principal destination for Argentinean expatriates.*"(Raffaele et al., 2018).Besides, "*Almost a quarter of French expatriate footballers play in English or Belgian professional clubs.*"(Raffaele et al., 2018).

Figure 1. Principal destination of Brazilian, Argentinean and French expatriates

Various results have been obtained in the literature with such studies. Using a dataset of transfer records from 2011 to 2015 of 410 professional clubs in 24 world-wide top class leagues it was found that, "Modern professional football is indeed a money game, in which larger investment spent on the acquisition of talented players generally yields better team performance"(Liu, Liu, Lu, Wang, & Wang, 2016). In this study nodes are the elite clubs, and the directed edges connecting the nodes are the player transfers and loans.

In another article, by adopting existing methods for weighted networks, player transfers between European football teams have been analyzed (Lee, Hong, & Jung, 2015). Besides, using 436 transfers that included at least one EPL, La Liga, or Bundesliga team, and these involved 114 teams, "The European football transfer market in the summer of 2014 has been analyzed as a weighted network, in order

to understand the topological and quantitative aspects of the transfer market"(Lee et al., 2015).

In another research article, "the evolution of the football players' transfer network among 21 European first leagues between the seasons 1996/1997 and 2015/2016" has been studied and, "Using a machine learning approach based on Self-Organizing Maps and Principal Component Analysis we confirm that European competitions, such as the UEFA Champions League or UEFA Europa League, are indeed a 'money game' where the clubs with the highest transfer spending achieve better sportive performance"(Matesanz, Holzmayer, Torgler, Schmidt, & Ortega, 2018).

Note that the relationship between sportive performance and transfer spending is addressed in most of these studies. Another article explains the same result as follows:"However, within the 'top cluster' the most important European clubs achieve sportive performance very similarly through transfer spending, which originates mainly from England, Spain, Germany and Italy. As such, club managers might have to reconsider their strategic focus and reevaluate the (financial) resource allocation within their clubs to achieve optimal sportive results"(Matesanz et al., 2018).

Undoubtedly, much more in the framework of network science with such transfer networks can be done by using various calculations, programs and software languages.In our article, countries where transfers were made were taken as nodes and the edges between the nodes were created by the transfers. We obtained two directed transfer networks for 2019-2020 Winter transfers: A transfer network of transfer market values are over 1 million Euros and another transfer network of market values are under 1 million Euros. At the beginning we compared the metrics and the measures of these two networks such as density, diameter, mean degree, betweenness, closeness, clustering coefficient. This comparison was then extended to the differences of ingoing-outgoing degrees and assortativity. Our work has been completed with a conclusion section.

2. Excess Degree and Assortativity

As we know, the distribution of edges of the three types, incoming, outgoing, and undirected (Meyers, Newman, & Pourbohloul, 2006). If we want to compute the expected number of second neighbors excluding the node along which we arrived, we obtain the excess degree distribution(Michael, 2017). M.E.J. Newman explains excess degree such as, "In most case, we are interested in how many edges there are leaving such a vertex other than the one we arrived along, i.e., in the so-called excess degree, which is one less than the total degree of the vertex" (Newman, 2003). "We then define the quantity $e_{j,k}$, which is the joint probability that a randomly chosen edge joins vertices with excess degrees j and k."(Newman & Park, 2003).

And if the properly normalized distribution of the excess degree is q_k, then a correlation coefficient r can be defined with positive or negative degree correlations respectively. These are called "assortative" and "disassortative" mixing by degree.

According to M.E.J. Newman, assortativity can be defined as a correlation function, "in terms of the network's excess degree distribution q(k), and link distribution $e_{j,k}$. The excess degree is the number of remaining links encountered when one reaches a node by traversing a link. The link distribution of the network is the joint probability distribution of the excess degrees of the two nodes at either end of a randomly chosen link."(M Piraveenan, Prokopenko, & Zomaya)

And, this is "the rationale for basing the degree assortativity on the excess degree (= d_i - 1) of node i rather than on the degree of node i, d_i"(Noldus & Van Mieghem, 2015). People prefer to connect with people who have characteristics similar to their own. Similarities in variables such as age, income status, gender, and education cause connections between nodes in networks. "If people prefer to associate with others who are like them, we say that the network shows assortative mixing or assortative matching"(Newman & Park, 2003). Topologies of complex networks have been known to exhibit assortative mixing like heavy-tailed distributions. In assortativity we measure the similarity in terms of the nodes' degrees (Pal, Yu, Novick, Swami, & Bar-Noy, 2019). By way of assortative mixing, networks will tend to break up into separate communities (Newman & Park, 2003). Also quantifying the level of assortativity or disassortativity can shed light on the organization of complex networks (Peel, Delvenne, & Lambiotte, 2018). According to M.E.J. Newman, assortativity can be defined as a correlation function, "in terms of the network's excess degree distribution q(k), and link distribution $e_{j,k}$. The excess degree is the number of remaining links encountered when one reaches a node by traversing a link. The link distribution of the network is the joint probability distribution of the excess degrees of the two nodes at either end of a randomly chosen link." (M Piraveenan et al.) And, "The rationale for basing the degree assortativity on the excess degree (= d_i - 1) of node i rather than on the degree of node i, d_i" (Noldus & Van Mieghem, 2015). It has been shown that local assortativity of a node can be interpreted as a scaled difference between the average excess degree of the node neighbours and the expected excess degree of the network as a whole (Mahendra Piraveenan, Prokopenko, & Zomaya, 2010).

3. Methods

3.1. Comparison of High And Low Valued Transfer Networks

In this section, we will list where the data we use are obtained, with which program the networks are drawn and the differences between the results obtained for both networks.

3.2. Data used & networks

In the application part of our study, firstly, two directed and weighted networks (with low market value and high market value) were drawn using NodeXL program. Our data has been taken from Transfer Markt (www.tranfermarkt.com.tr)While separating the transfer data into two groups (two networks), our threshold value was determined as 1 million Euros. Figure 3 and 4 are drawn in modular form. Modularity coefficients of these two networks are similar (0,135176 and 0,152882). But as seen in Figure 3 and Figure 4, number of countries in first group of low valued transfer network (30) is higher than the other network (19).

Self-loops seen on networks show us transfers from the same country. Ingoing and outgoing degree differences allow us to comment on transfers. For example, if these differences are generally negative, countries sold more than buying players; if positive, they bought more players than they sold.

Figure 3. Low valued transfer network

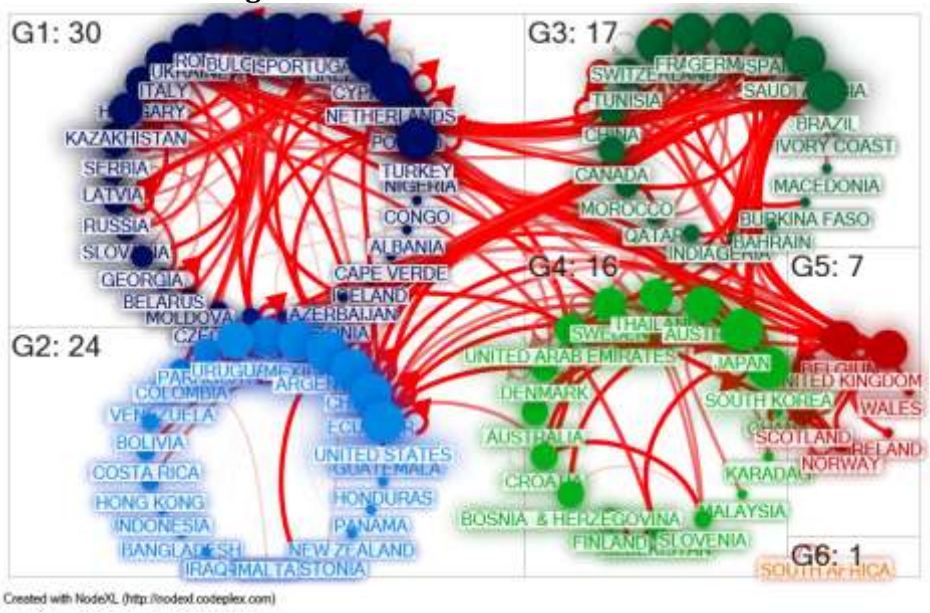
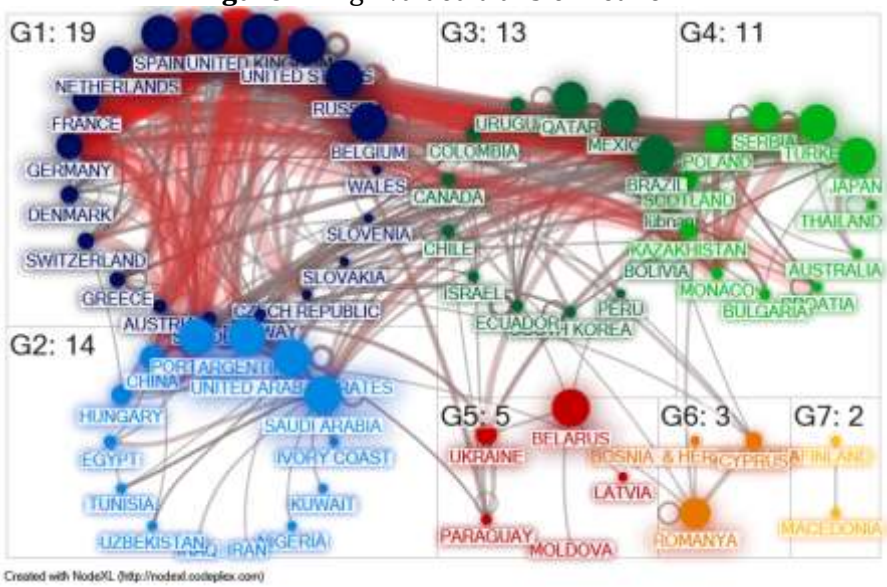


Figure 4. High valued transfer network



In Table 1 first 10 countries were ranked according to the total number of connections. Countries that take place in both networks are scanned in gray in Table 1. As a result: Argentina, Netherlands, Greece and Chile are the countries only take place in low value side, whereas UK, Italy, France and Belgium are the countries only take place in high value side of the Table 1.

Table 1. First 10 countries in two networks according to the total number of connections

Low-valued transfer network	High-valued transfer network
Brazil	United Kingdom
USA	Brazil
Spain	Italy
Turkey	USA
Argentina	Spain
Netherlands	France
Portugal	Belgium
Greece	Portugal
Chile	Turkey
Mexico	Mexico

2.3. Comparison of network metrics

Total self-loops are high (791) in low-valued transfer network. This number means that such countries mostly transfer the players they have trained themselves and they do not transfer players from other countries. On the other hand, countries in high transfer value networks make less transfers from their own countries (429). In Table 2, Brazil, Japan and Columbia are the first, second and the third countries that do self-loops, they transfer football players inside their countries.

Table 2. Number of self-loops in low-valued transfer network

Vertices	Self Loops
Brazil	171
Japan	79
Colombia	43
Spain	37
Italy	34
United Kingdom	32
Ecuador	31
Mexico	27
Argentina	25
Russia	20

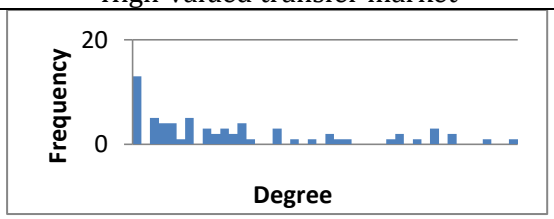
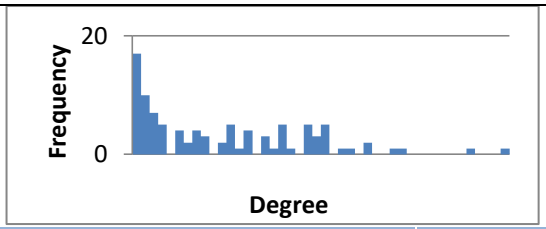
Reciprocated Edge ratio in Table 3 is the percentage of edges that have a reciprocal relationship. Reciprocated Vertex Pair Ratio in Table 3 defines us number of vertex pairs that have edges in both directions divided by the number of vertex pairs that are connected by any edge. This ratio is 0,223 in high value transfer network, 0,138 in low-valued transfer network. So we may say that, Reciprocated Country Pair Ratio, ratio of country pairs that transfers and sends football players reciprocally are high in high-valued transfer network but this ratio is low in low-valued network.

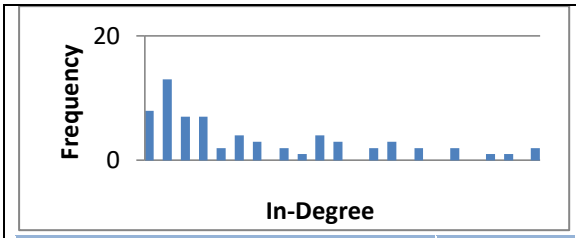
Table 3. Graph metrics

Graph Metric	High-valued Transfer network	Low-valued Transfer network
Graph Type	Directed	Directed
Vertices	67	95
Unique Edges	253	308
Edges With Duplicates	727	984
Total Edges	980	1292
Self-Loops	429	791
Reciprocated Vertex Pair Ratio	0,222614841	0,138138138
Reciprocated Edge Ratio	0,36416185	0,242744063
Connected Components	2	2
Single-Vertex Connected Components	0	1
Maximum Vertices in a Connected Component	65	94
Maximum Edges in a Connected Component	979	1288
Maximum Geodesic Distance (Diameter)	5	5
Average Geodesic Distance	2,296997	2,610162
Graph Density	0,078245138	0,042441209
Modularity	0,135176	0,152882

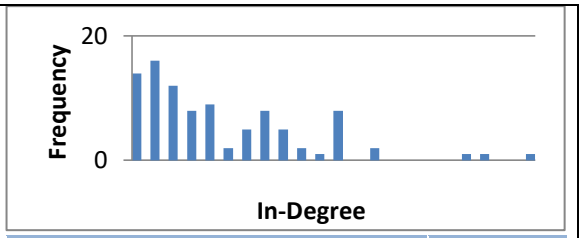
As we know, clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together and average clustering coefficient is the calculated average for all nodes of a graph. In Table 4, average clustering coefficient 0,221 in high-valued transfer market and 0,157 in low-valued transfer market. Thus, it may be said that nodes(countries) of high-valued transfer market tend to cluster together more than the nodes (countries) of low-valued transfer market.

Table 4. Centrality measures

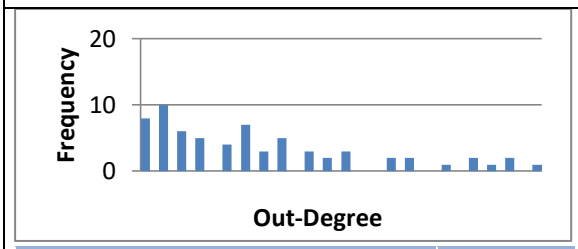
High-valued transfer market		Low-valued transfer market	
			
Minimum Degree	1	Minimum Degree	1
Maximum Degree	38	Maximum Degree	35
Average Degree	11,403	Average Degree	9,179
Median Degree	8,000	Median Degree	7,000



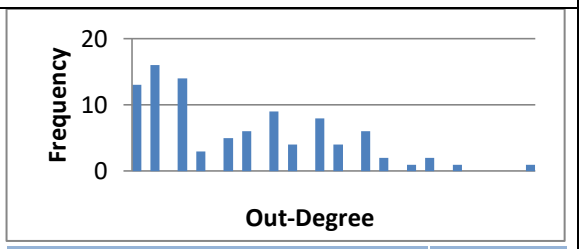
Minimum In-Degree	0
Maximum In-Degree	20
Average In-Degree	5,701
Median In-Degree	3,000



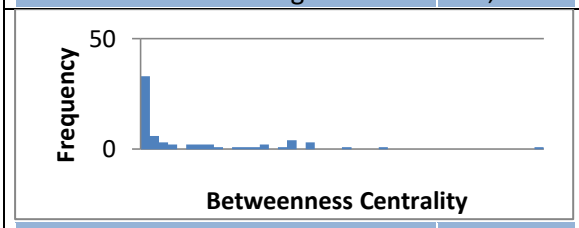
Minimum In-Degree	0
Maximum In-Degree	21
Average In-Degree	4,589
Median In-Degree	3,000



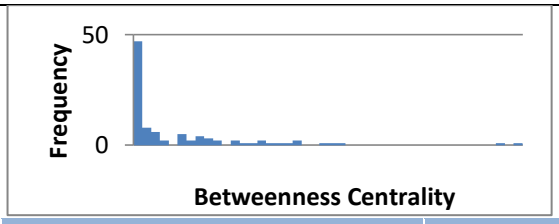
Minimum Out-Degree	0
Maximum Out-Degree	19
Average Out-Degree	5,701
Median Out-Degree	5,000



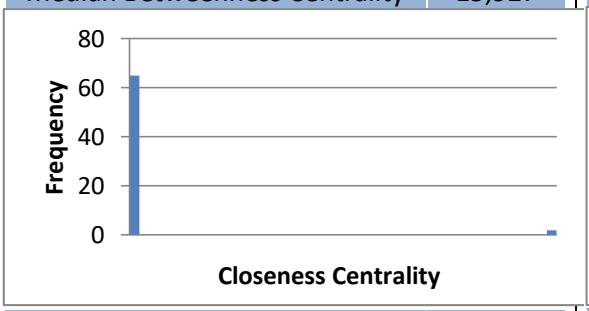
Minimum Out-Degree	0
Maximum Out-Degree	17
Average Out-Degree	4,589
Median Out-Degree	4,000



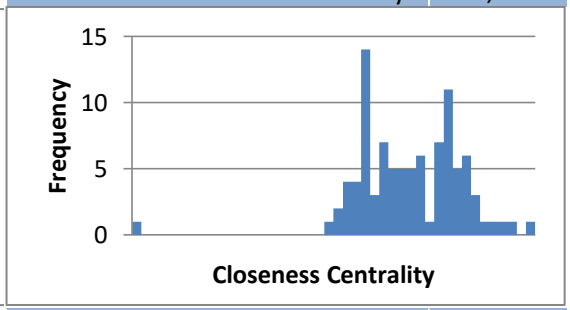
Minimum Betweenness Centrality	0,000
Maximum Betweenness Centrality	649,845
Average Betweenness Centrality	82,866
Median Betweenness Centrality	15,927



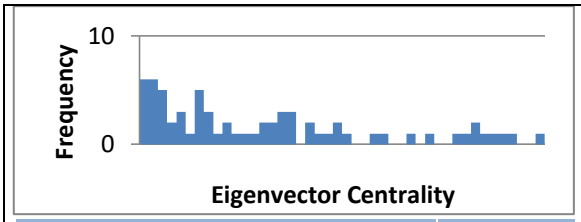
Minimum Betweenness Centrality	0,000
Maximum Betweenness Centrality	1299,171
Average Betweenness Centrality	150,779
Median Betweenness Centrality	31,733



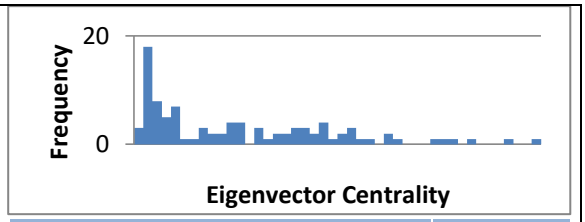
Minimum Closeness Centrality	0,004
Maximum Closeness Centrality	1,000
Average Closeness Centrality	0,037
Median Closeness Centrality	0,007



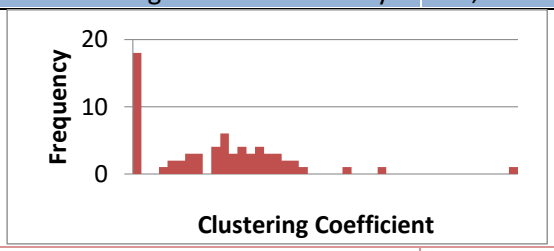
Minimum Closeness Centrality	0,000
Maximum Closeness Centrality	0,006
Average Closeness Centrality	0,004
Median Closeness Centrality	0,004



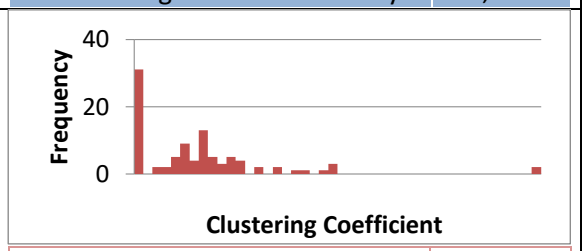
Minimum Eigenvector Centrality	0,000
Maximum Eigenvector Centrality	0,047
Average Eigenvector Centrality	0,015
Median Eigenvector Centrality	0,011



Minimum Eigenvector Centrality	0,000
Maximum Eigenvector Centrality	0,039
Average Eigenvector Centrality	0,011
Median Eigenvector Centrality	0,008



Minimum Clustering Coefficient	0,000
Maximum Clustering Coefficient	1,000
Average Clustering Coefficient	0,221
Median Clustering Coefficient	0,236



Minimum Clustering Coefficient	0,000
Maximum Clustering Coefficient	1,000
Average Clustering Coefficient	0,157
Median Clustering Coefficient	0,136

In Table 4, average betweenness centrality is 82,866 for high valued transfer market, and 150,779 for low -valued transfer market. These coefficients tell us that in low-valued transfer market on the average, countries are on the shortest paths, they serve as a bridge from one part of a graph to another. If we examine the betweenness coefficients of countries in the low-valued transfer network, we see the following order in Table 5.

Table 5. Betweenness coefficients of first 10 countries in low-valued transfer network

Vertices	Betweenness
Brazil	1299,171
USA	1245,315
Spain	565,679
Turkey	675,583
Argentina	710,621
Netherlands	430,507
Portugal	493,882
Greece	294,701
Chile	179,976
Mexico	219,192

Analysis of ingoing-outgoing degrees

When we examine Figure 5 and Figure 6, we see that both of these distributions are skewed to the right. Values in these distributions tend to small values (negative values). Since the ingoing-outgoing degree differences are mostly negative values for the countries, the distributions are observed to be skewed to the right. The skewness is much higher in the one with higher transfer values than the one with

lower transfer values, because the deficits are higher in the one with higher transfer values.

Figure 5. Distribution of ingoing-outgoing degrees for high transfer valued network (Skewness = 0,962)

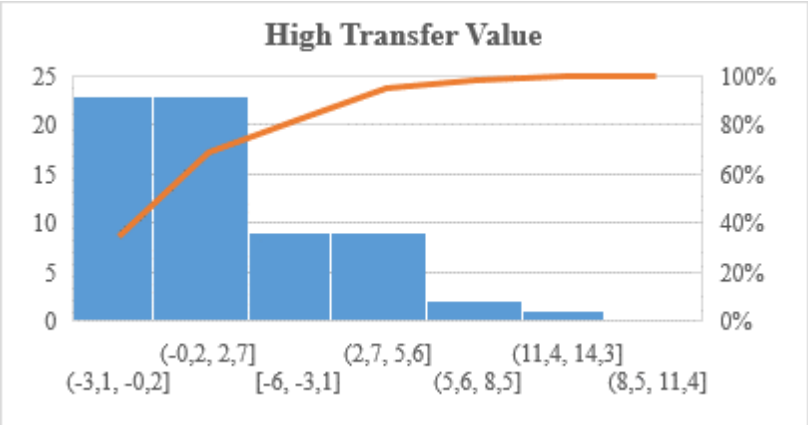
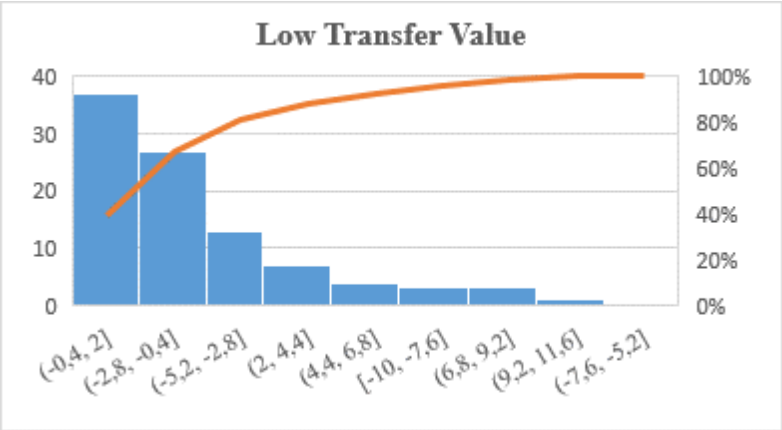


Figure 6. Distribution of ingoing-outgoing degrees for low transfer valued network (Skewness= 0.180)



2.4. Assortativity

It was found that in our low-valued transfer market degree of assortativity is 0.836 and in our high-valued transfer market this coefficient increases to 0.562. This finding can be interpreted as the big transfer values, big money creates big differences in country's transfer connections.

Figure 7. Assortativity degree distrubition for high-valued transfer

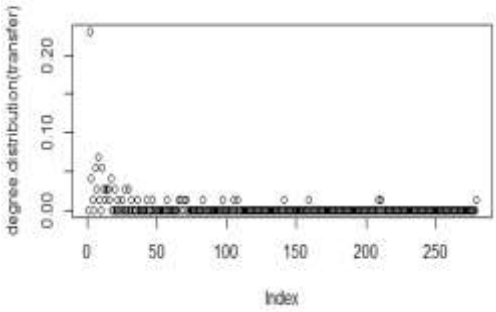
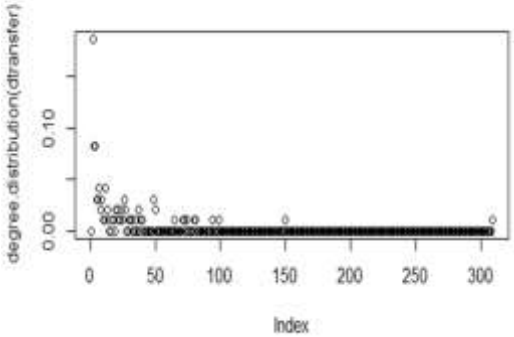


Figure 8. Assortativity degree distrubition for low-valued transfer



3. Conclusion

Ingoing-outgoing degree differences for transfer market networks can be very useful to see the overall condition of a club in a country's transfer market over a period of time. The skewness of ingoing-outgoing degree differences distribution is much higher in the one with higher transfer values (0,962), than the one with lower transfer values (0,180). Hence, it is clear that deficits are higher in high-valued transfer market.

It was found that high market valued transfer network has a low assortativity coefficient (0.836), and low market valued transfer network has a high assortativity coefficient (0.562). This finding can be interpreted as the big transfer values, big money creates big differences in country's transfer connections.

Average betweenness centrality is 82,866 for high valued transfer market, and 150,779 for low-valued transfer market. These coefficients tell us that in low-valued transfer market on the average, countries are on the shortest paths, they serve as a bridge from one part of a graph to another. If we examine the betweenness coefficients of countries in the low-valued transfer network, we see the following order: Brazil, USA, Spain, Turkey and the others.

Average clustering coefficient 0,221 in high-valued transfer market and 0,157 in low-valued transfer market. Thus, it may be said that nodes(countries) of high valued transfer market tend to cluster together more than the nodes (countries) of low-valued transfer market.

Reciprocated Country Pair Ratio, ratio of country pairs that transfers and sends football players reciprocally are high in high-valued transfer network but this ratio is low in low-valued network.

Besides, total self-loops are high (791) in low-valued transfer network. This number means that such countries mostly transfer the players they have trained themselves and not transfer players from other countries. On the other hand, countries in high transfer value networks make less transfers from their own countries (429). Regarding total number of connections, self-loops and

betweenness. In both networks, Brazil is seen as the country that attracts the most attention in winter season of 2019-2020.

In the future researches, it can be analyzed how the assortativity coefficient changes in the network density based on the summer and winter seasons or the next winter transfer period.On the other hand, it can be examined whether the central nodes have a rich club effect.

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