Analysis of Players Transfers in Esports. The Case of Dota 2

Ekaterina Marchenko
National Research University
Higher School of Economics
Russia
eyumarchenko@edu.hse.ru

Vsevolod Suschevskiy
National Research University
Higher School of Economics
Russia
vvsuschevskiy@edu.hse.ru

ABSTRACT

In this work, we analyze how the esports transfer market is organized with the help of mixed methods. We assume that a combination of Social Network Analysis and Machine Learning can help to achieve deeper understanding and to find patterns which are hidden from the one-side analysis. For the research, we gathered information about transfers of Dota 2 teams made between The Internationals of 2016 and 2017 and built a network based on this data. For the ERGM, we checked the importance of belonging to one region and organization, difference of skills, and participation in TI, and for association rules, on a par with the regions, we added players roles, and a metric of their personal performance – fantasy points. Summing up the results, we found out the importance of homophily within regions, detected presence of vertical mobility, and discover the influence of the specific players roles.

CCS CONCEPTS

• **Networks** → **Network structure**; • **Information systems** → *Association rules*; • **Human-centered computing** → *Social network analysis*;

KEYWORDS

mixed methods, esports, Dota 2, transfers

ACM Reference Format:
Ekaterina Marchenko and **Vsevolod Suschevskiy**. 2018. Analysis of Players Transfers in Esports. The Case of Dota 2. In *Academic Mindtrek 2018 (Mindtrek 2018), October 10–11, 2018, Tampere, Finland*. ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3275116.3275151

1 INTRODUCTION

Transfers of players play important role in sport industry as they determine who will play in the particular team. Even one transfer can greatly affect team strategy and its success[12]. In esports, the vital role of transfer is even more visible than in traditional sports due to frequent changes in the teams line-up. Thus, esports provides us with an opportunity to study connections between individual and team performance, media saliency and market structure based on rich digital data.

Mindtrek 2018, October 10–11, 2018, Tampere, Finland

ACM ISBN 978-1-4503-6589-5/18/10.
https://doi.org/10.1145/3275116.3275151

There is a growing area of social network studies in sports. There are several factors related to players performance and team composition. First, the centrality of the players position and his activity during the game can influence managerial recruitment [4]. Next, teams strength and players talent can be assessed with the help of transfer network analysis [11]. One of the reasons for this is that transfer fees is one of the important instruments for the estimation of players performance [3].

Liu et al. [11] analyzed transfer network of football clubs. They found out there were several clubs which take the most beneficial positions and control the major part of transfer sources. Also, the authors detected a positive correlation between teams performance during matches and their brokerage. On the other hand, for a player, transfer in some cases can significantly increase the risk of injury, compared to old club players [1]. Certainly, the transfer can be considered in terms of capital and mobility [13] being an instrument of either improving or ruining a player's career.

In our research, we investigate the organization of Dota 2 professional the transfer market, focusing on understanding what are the predictors of the transfer from the one team to another.

2 BACKGROUND: DOTA 2, ESPORTS, TRANSFER

Dota 2 is both a free-to-play multiplayer online battle arena (MOBA) video game and a one of the most popular esports disciplines where two teams of 5 players eliminates each other's main buildings. The main goal of teams during the year is to win The International (TI) which is the most prestigious tournament in the game and can be described as world championship in Dota 2. During the year teams can change the roster in order to get successful combination of players and win TI. Each team has a captain who make important strategic decisions, and each player has one of pre-defined in-game roles fulfilling different objectives of the game.

Number of transfers per person or team is not restricted. Consequently, player can freely change several teams during one season. As a result, transfers are always under attention of managers, media, and spectators. Each team has its own audience and own brand which is formed based on current roster, or, in other words, on combination of players. Each transfer drives attention of the media and the fan sources.

3 DATA AND METHOD

In this research, we use Social Network Analysis and Association Rules mining. First, we build a network of transfers and then apply an ERGM (Exponential Random Graph Model)[8, 10] to analyze which variables are important and which structural network characteristics influence tie formation. Second, we use association rules mining[5–7, 14] for reaching deeper understanding of the transfer patterns.

We gathered information from **Liquipedia**[1] about 322 transfers of 118 teams made between The International of 2016 and 2017. These teams were TI-participants, or they were connected with them by transfer. For the ERGM, we use such variables as team region, participation in The International, and Elo rating.

Elo rating [2] is a metric for measuring teams performance which based on its wins, draws, and loses. It is calculated on DOTABUFF[2] data gathered for three months before the start of the observed period with the help of EloRating package in R[9]. If team did not play during that time, it was assigned with the default value equal to 1000.

For the association rules learning (Apriori algorithm), we cut our sample to the transfers which were made only by team-participants of The International 2017 – 201 transfer of 18 teams. All of them were split into two parts according to having or not captains role. For association rules mining, we use players (role (core, offlane, or support), average and total fantasy points earned during TI7) and team (regions of new and old teams) characteristics.

Fantasy points reflect different in-game actions. They are acquired after each match, and they are weighted so that there is no difference in the esportsmen roles. We got data about fantasy points from **Dota 2 Fantasy Tracker**[3]. Both average and total earned fantasy points were split into equal intervals.

Association rules were mined with the following settings (Table 1).

Table 1: Association rules properties

	Captains	Not-captains
support	0.12	0.07
confidence	0.5	0.5
min length of the rule	2	2
number of rules	45	33

Minimal length of the rule – minimal number of items the rule should have to appear.

The rule A ⇒ B is described by[14]: (1) **support** – the proportion of transactions that contain both A and B, and (2) **confidence** – the proportion of transactions containing A that also contain B.

4 ANALYSIS AND RESULTS

With the help of the ERGM, we found out that if it was important for both teams to belong to the one region. Also, it was more likely for transfer to appear if the receiver was TI-participant. Elo rating was not significant factor. Two teams that belong to the same organization are more likely to have transfers. Geometrically weighted edgewise shared partner distribution (GWESP) is used for unsaturated networks when there are few transitions between different parts of the network. Each shared partner of two teams increases the probability of transfer. Outgoing star (ostar) shows the presence of a structure in the network, when from one team there are transfers to the other two. The presence of such structure may be considered as an artefact of network sampling (at this stage we took The International participants and those with whom they had transfers).

Table 2: ERGM summary

	log odds
Edges	-5.852*
Mutual	1.393*
Downward mobility (NODEMIX)	0.304
Upward mobility (NODEMIX)	0.627*
Both TI participants (NODEMIX)	1.132*
North America (NODEMATCH)	2.153*
Europe (NODEMATCH)	2.992*
China (NODEMATCH)	2.136*
CIS (NODEMATCH)	2.594*
South America (NODEMATCH)	2.849*
Southeast Asia (NODEMATCH)	2.481*
ELO rating (ABSDIFF)	0.001
Keen Gaming (NODEFACTOR)	1.022*
Newbee (NODEFACTOR)	-1.206*
Vici Gaming (NODEFACTOR)	0.638*
WarriorsGaming (NODEFACTOR)	0.452*
Transitivity (GWESP)	0.386*
Outstars	0.078*
Akaike Inf. Crit.	1,750.081
Bayesian Inf. Crit.	1,961.001
Note:	*p<0.05

Vertical mobility

As far as the receiver was most likely to be a TI-participant, we can speak mostly about vertical mobility. Well-known teams have two primary channels for recruiting: the same level teams and the freshmen teams. ERGM summary have shown that both of them are actively used. This reflects the paths of esportsman career: when he reaches the top teams, he either moves around or leave the professional arena.

Homophily within regions

Both ERGM and results of association rules mining have shown the importance of belonging to the one region. However, such patterns were detected only on the sample about players who were not captains in their teams. Association rules contain information about following regions: CIS (confidence = 0.57), South-East Asia (confidence = 0.7), and China (confidence = 0.93). The latter case stands out signalizing unique ecosystem: in China, there are esports organizations which unite several teams under one label. For example, PSG.LGD and LGD.Forever Young are united under brand LGD. Moves of players between such teams are one of the easiest way to recruit players. That is why confidence of this rule is so high.

[1] https://liquipedia.net/dota2/Main_Page
[2] https://www.dotabuff.com/
[3] http://fantasy.prizetrac.kr/international2017/players

However, there was no such rules for captains. This may be caused by their higher value. Their responsibility for the match result is higher as they make important decisions. Therefore, good captains are in higher demand, and they are not dependent on the original region.

Effects of role and performance

Distinct subset of rules is connected with captains in the support position. This might be a result of their higher responsibility: they should care about their teammates even during the game as far as duties of their heroes aimed at assistance.

Also, there is a separate set of rules about offlane captains with the worst performance. After checking the data, we found out that these rules were produced because of three players who had changed more than three teams during the season.

Even though there is no detached cluster of rules for players without captains roles, there are patterns connected with the core role. Cores with only the highest and the lowest numbers of fantasy points are more likely to change their teams. This can reflect two main reasons of transfer: kicking the player out and finding the best replacement.

5 DISCUSSION

Our research does not support the vision of esports as a global market, as there is large intra-regional homophily in tranfers.

Also, esports can be characterized by the small distance between professional and amateur teams. It is possible for top teams to invite non-professional players taking into account their skills shown in public games. Besides, unlike traditional sports Dota 2 team is often organized by players themselves, and after achievement of results in tournaments they receive an invitation to become a part of an organization.

6 FUTURE WORK

This research is on its early stages. We are now working on improving sampling and metadata. The work will be developed in two main direction. First, brand formation based on player transfers will be investigated more. Next, even deeper understanding of received patterns is aimed to achieve. For this purpose, may be used qualitative methods as interviews of transferred players or studying such documents as media reports. Also, we plan to distinguish voluntary transitions from forced exclusions which most likely have different reasons. As a result, structure of the transfer market will be fully analyzed and described.

ACKNOWLEDGMENTS

The poster was prepared within the framework of the Academic Fund Program at the National Research University Higher School of Economics (HSE) in 2017-2018 (grant No. 17-05-0024) and by the Russian Academic Excellence Project 5-100.

We thank Ilya Musabirov, Denis Bulygin, Alina Bakhitova, and other teammates from Machine Learning and Social Computing Group for their help.

REFERENCES

[1] Christopher Carling, Alan McCall, Franck Le Gall, and Gregory Dupont. 2018. Injury risk and patterns in newly transferred football players: a case study of 8 seasons from a professional football club. *Science and Medicine in Football* 2, 1 (2018), 47–50. https://doi.org/10.1080/24733938.2017.1370123 arXiv:https://doi.org/10.1080/24733938.2017.1370123

[2] Arpad E Elo. 1978. *The rating of chessplayers, past and present.* Vol. 3. Batsford London.

[3] Jürgen Gerhards and Michael Mutz. 2017. Who wins the championship? Market value and team composition as predictors of success in the top European football leagues. *European Societies* 19, 3 (2017), 223–242.

[4] Oscar Grusky. 1963. The effects of formal structure on managerial recruitment: A study of baseball organization. *Sociometry* (1963), 345–353.

[5] Michael Hahsler, Christian Buchta, Bettina Gruen, and Kurt Hornik. 2018. *arules: Mining Association Rules and Frequent Itemsets.* https://CRAN.R-project.org/package=arules R package version 1.5-5.

[6] Michael Hahsler, Sudheer Chelluboina, Kurt Hornik, and Christian Buchta. 2011. The arules R-Package Ecosystem: Analyzing Interesting Patterns from Large Transaction Datasets. *Journal of Machine Learning Research* 12 (2011), 1977–1981. http://jmlr.csail.mit.edu/papers/v12/hahsler11a.html

[7] Michael Hahsler, Bettina Gruen, and Kurt Hornik. 2005. arules – A Computational Environment for Mining Association Rules and Frequent Item Sets. *Journal of Statistical Software* 14, 15 (October 2005), 1–25. http://dx.doi.org/10.18637/jss.v014.i15

[8] Mark S. Handcock, David R. Hunter, Carter T. Butts, Steven M. Goodreau, Pavel N. Krivitsky, and Martina Morris. 2017. *ergm: Fit, Simulate and Diagnose Exponential-Family Models for Networks.* The Statnet Project (http://www.statnet.org). https://CRAN.R-project.org/package=ergm R package version 3.8.0.

[9] Ethan Heinzen. 2017. *elo: Elo Ratings.* https://CRAN.R-project.org/package=elo R package version 1.0.1.

[10] David R. Hunter, Mark S. Handcock, Carter T. Butts, Steven M. Goodreau, and Martina Morris. 2008. ergm: A Package to Fit, Simulate and Diagnose Exponential-Family Models for Networks. *Journal of Statistical Software* 24, 3 (2008), 1–29.

[11] Xiao Fan Liu, Yu-Liang Liu, Xin-Hang Lu, Qi-Xuan Wang, and Tong-Xing Wang. 2016. The anatomy of the global football player transfer network: Club functionalities versus network properties. *PloS one* 11, 6 (2016), e0156504.

[12] Miohk Ryoo, Namjung Kim, and Kyoungju Park. 2018. Visual analysis of soccer players and a team. *Multimedia Tools and Applications* 77, 12 (01 Jun 2018), 15603–15623. https://doi.org/10.1007/s11042-017-5137-4

[13] Thijs A. Velema. 2018. Upward and downward job mobility and player market values in contemporary European professional football. *Sport Management Review* (2018). https://doi.org/10.1016/j.smr.2018.02.004

[14] Ling Zhou and Stephen Yau. 2007. Efficient association rule mining among both frequent and infrequent items. *Computers & mathematics with applications* 54, 6 (2007), 737–749.