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RESEARCH ARTICLE

Rethinking Audience Clustering in Sports Market using Gossip Protocol

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Abstract – Analytics and inferences have found their place in all the business domains varying from large-scale businesses with criticality to small scale business with less criticality. Sports are considered to be big business in its aspects like amount of money spent on it but in its other version like number of people associated with it, it is comparatively a small industry. Sports analytics have changed their dimension both in the manner they are thought about and number of participation from scientific society that grew over the years. Contribution from analytics is being looked from by sports management to enhance various industries associated to it. The authors realize that sports industry is a close, strongly connected group that is very similar in its behavior to a social network. The authors propose a graph theoretic model in context of sports analytics that presents preliminary study of using gossip protocol for sharing information among members of sports oriented social network.

Index Terms – Clustering, Gossip Protocol, Sports, Social Network.

1. INTRODUCTION

This Analytics and inferences have found their place in all the business domains varying from large scale businesses with critical impact like health and finances to small scale business with less criticality like online stores and content writing. Sports are considered to be big business in its aspects like amount of money spent on it but in its other version like number of people associated with it is comparatively a small industry [1,2]. In both the versions of game; analytics find an important place to improve the notion of sports. The sports data analysis has been very exotic field for statistics community and has attracted lot of sports professionals across the globe including both the management and players which dates back to 1870s when first boxscore in baseball was recorded [3]. Inclusion of latest technological trends like data mining and machine learning to process data has facilitated draft selection, game-day decision making, and player evaluation in sports analytics to a new level [3,4,6]. The rules of the game are rapidly adapting to new strategies that have direct references to data and ability to analyse that data.

Sports analytics have changed their dimension both in the manner they are thought about and number of participation from scientific society that grew over the years. MIT sponsored leading conference “MIT Solan Sports analytics conference” has seen emergence in participation from mere 175 participants in 2007 inaugural session to 4,000 attendees in year 2016 [7]. Lucey et al, in 2016 attests the increasing popularity of intelligent sports analytics and specialized workshop series in their work published in KDD titled Large Scale Sports Analytics [8]. The amount of data generated in various kinds of sports results in need to address the issues of sports data analysis where machine learning finds its way right deep in the applications. Data from sensors, videos, sports labs, social media, economics, training datasets, historical data etc. all contribute to complexity of analysis [9].

Existence of analytics in all the domains of science has evolved into a whole different group of data science engineers and scientists who find their role in most of modern day industries. They find their place as front office professionals looking to improve and appreciate data trying to enhance performance of sports and team. Various methodologies have been employed from areas of analytics, probabilistic modelling, optimization and choice modelling in application domains of various sports like golf, hockey, football, soccer, motorcycle racing, baseball etc. in context of sports depending on type of sports, data and goal of analysis [5, 6, 10, 64]. Though sports analysis is in its initial stages there already exist diverse set of research application, questions, approaches and data sources. Challenges of standard computation models have been addressed by various scientific communities using methods like deep learning, bayesain networks, neural networks or archetypical analysis methods [64]. However, a vaccum yet needs to be addressed in fields of data preparation, transformation, analysis, visualization and finally gathering inferences from the information.

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Contribution from analytics is being looked for by sports management to enhance various industries associated to it like entertainment, electronics, packaged goods which spend huge amount of money and time to study entities that are more suitable and important for increasing benefits of business eg., purchasing apparel, attending games, watching matches on television and investing time and effort [11].

Analytics in sports has certain stake holders like players, coaches, management, TV channels, healthcare, social media, online fantasy leagues, sponsors and many others [2,11]. Decision making in sports and associated industries is affected by analytics. It has a strong impact on team building, strategy management, injury protection and so forth. As we observe data, analytics, automation, machine learning are brewing in this era of technology but still considerably less number of decision makers rely on technology over their experience and intuitions. Another confounding factor in sports analytics is small team size; hence large investments in technology and analytics are neither appreciated nor desired [2, 11, 14]. Teams prefer to maintain small number employees in front office and high salaried team players over investing in technology.

Analytics has influenced most of business domains and there is a need for effective information sharing. In this paper we discuss various aspect of sports analytics in section 2, Economics of sports market in section 3. This is followed by audience clustering in section 4 and our methodology and analysis in section 5 and 6. The paper is concluded by possible future work in section 7.

2. SPORTS AND ANALYTICS

All Analytics in sports industry finds its place in multiple domains, however, mostly addressed and acknowledged are game analysis, business modelling, healthcare analysis and audience clustering and marketing.

2.1. Game Analysis

Post-match analysis is now a days trending and playing a vital role in team selection [2, 14]. Player performance is keenly studied to select best possible player combination and enhance on the field decisions. Effective use of analytics is highly desired to maintain the team rank in sports ratings [12]. Acceptance of analytics in sports analytics surely enhance the perspective of game strategy and performance. Good coaching and strong skilled players cannot be replaced by analytics team; however, a recipe for team success will certainly be governed. Understanding and analyzing varying and hazy interactions of players on the field are challenging to put into a well-defined generalized model for designing optimal team lineup for winning. Player development can be holistically studied and employed to effectively use the player skills, health statistics and talent on field [2, 13 - 15]. Analysis can play an effective role if adopted by and large, by all the stakeholders of the industry.

2.2. Healthcare Analysis

Injuries are difficult to predict. Player health is one of major goals of analysis due to its direct effect on the game performance [2]. Predicting injuries in advance is quite a difficult as they are caused at any random time and due to random factors often accidental in nature. As team management keenly looks into aspects of nutrition and physical activities to maintain player health [16]. Analysis is done on movement and pattern of play to assess the stress that may lead to physical injuries. Smart biometric devices are used to monitor patterns of player health along with sleep, steps and other health indicating parameters [17]. These help to gauge the fitness of each player for contract decision and predict likelihood of serious health issues and injuries. Biomechanics is also gaining new hype in sports [2, 11]. Rehabilitation and type of rehab required may also be deduced for players to vent out their stress before and after big game days. Rosters can also be scheduled based on player health to effectively use each player.

2.3. Business Modeling

Another class of analysis in sports revolves around business applications. This is mostly concerned with ticket pricing promotions, fan engagements etc. [11, 18, 19]. The field has received more attention lately from team management and professional players. Though more emphasis in sports analytics is on team performance, managing steady rank in field ranking and achieving more wins but business model around sports analytics have also been developed by sports analysts [21]. This does not only talk about investing money and gaining profits from player performance but also about apparel industry and sports goods sector. One of the fascinating applications of this domain is auctioning tickets. There may be a surge in price or ticket rates may fall during various matches depending upon the favorite or most liked team but whole idea is to earn maximum profit by managing rates of tickets over time [2, 21]. This may be simply attributed as dynamic pricing. Sophisticated real time machine learning based analysis could be employed to analyze the situation of match and adjust ticket price overtime with varying team performance and interest of people. This will also enhance sale of products outside sports arena depending upon fan following, importance of game in league and venue of the game [20, 22]. This has a strong impact on food industry that sells products outside the sports event. Sales, promotion and marketing strategies have strongly been influenced by these kinds of analysis and keeping track of customer purchases overtime. This can be well influenced by recommender systems and offers could be customized for customers considering their interests from their browsing and buying history [23, 24]. These deals can make use of online

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advertising on social media to increase number of sales. There is a lot of scope for marketing and optimization that can be redefined into new and modern sports industry over traditional sports industry.

3. ECONOMICS OF SPORTS MARKET

Professional sports adopt economic laws differently and as a different category of business [11]. There are sellers, buyers, investors and products as in any other business model, however, buyers are the audience, the teams or even people who watch sports online or in an arena. The sellers may be clubs, TV channels, product industry, whereas the products may be goods or even the players, brands etc. Sports industry is very similar to entertainment industry and they compete with each other hand-to-hand over a period of time. They have very high revenue during active seasons of play [25 - 27].

A whole different game about analytics is observed by management whereas teams and players exhibit their skills on field [2, 18, 19]. In any other industry the aim of economist is to maximize the profit, which may not be direct goal of sports industry stakeholders. They look for consistent place in respective rankings and maximize the win streak over the years [11]. There is a difference between always winning and winning most of times. A competitive balance is desired to improve the market shares.

Players are the most expensive commodities in sports world and their average salaries vary around $240 million [11]. Media revenue is important in sports industry; whereas a business partnership, sponsorships, advertises, league memberships are other contributors in revenue and economics of sports industry [11, 26]. Players, fans and brands add to the business model. A lot of work has been done in this field of research [26 - 32].

Digital and social media have also a strong impact on sports analytics. This social impact can be utilized effectively particularly from business point of view. Social media by and large affects all the domains of social and scientific knowledge varying from socio-behavior point of view to socio-economic point of view in most of business domains. The intimate and interactive nature of social media with players, clubs, team management, fans, sponsors, broadcaster are emerging as extremely exciting area of study for social network researchers [33, 34, 63].

The authors have looked at this domain from whole different point of view and realize sports industry is a close, strongly connected group that is very similar in its behavior to a social network. Excited about information diffusion in a social network and how this can be treated as a tool to enhance sales, vary business models and marketing strategies, authors treat these sports groups as gossiping graphs and employee gossip protocol for information diffusion that to best of our knowledge has never been used in sports industry.

4. GOSSIP IN SPORTS – CLUSTERING AUDIENCE WITH GOSSIP

In sports network we have information and we want to spread this information in an efficient way so that everybody knows everything about everything. An interesting example about this in our context is that we know about an event and we want to post this information on a social network in such a way that we are able to profit sales and spread it over network. The topologies in social graphs are unstable and dynamic in nature [35, 36]. Big distributed updates keep on changing the structure of a graph. Using spanning tree or contacting all the neighbors is difficult to implement due to changing nature of network. These have lot of communication overhead and are not effective with respect to computation [37]. Idea is to use gossip protocols for sharing and disseminating information and are considered to be convenient for dynamic and changing networks [37 - 39]. They work very similar to spread of infection in biological community so are often referred to as epidemic protocols [40].

The underlying principle of gossip is - a machine selects another machine at some frequent intervals to spread information or rumor. It is periodic, pairwise and bounded size interactions in which at least one of machines changes its state, make it very powerful and robust. The added advantage of using such protocol is that they are inexpensive in terms of computational cost as number of nodes involved is less and random [40 - 48]. These are symmetric, regular, decentralized, periodic and relatively lazy. High degree of symmetry among nodes is one of astonishing features of gossip [42, 50].

Gossip protocol is executed in rounds and in each round an algorithm is followed that allows a node to connect randomly to a neighbor and share its information. In first round a node randomly connects to a neighbor and shares its information, in next round both the nodes again connect to their neighboring nodes (randomly) and share information, so on and so forth. The protocol follows an athematic progression and is convergently consistent. For the protocol to be convergently consistent it must propagate any new information to all nodes that will be affected by the information within time logarithmic in the size of the system (the "information sharing time" must be logarithmic in system size) [37, 49, 50].

Gossip has found its application in databases, networks, coding theory, news spreading and finding aggregates in networks etc, and is now one of addressed topics in social network analysis [37, 39, 50]. Both the limitations and applications of gossip have been studied that bring together

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tools and techniques from optimization, operational research, graph theory and networks [37, 49, 50].

Modern day computing has facilitated high performance reliable communication network that are carefully engineered to provide services based on efficient underlying goals. More recently massive social networks are gaining attention from research and interactions over heterogeneous networks have changed the notion and structure of existing social networks [35 – 37, 39]. This is further facilitated by presence of handheld devices that add to global and ubiquitous presence of social networks and bring along challenges for efficient communication under varying and dynamic environmental conditions. Various algorithms have been designed to support random viral ads on social networks to recommend users, friends and acquaintances, however the biggest challenge in designing such algorithm is dynamic and unpredicted nature of social graphs that vary over period of time. Simple, distributed, robust and efficient nature of gossip is desired in such environments like sports driven social networks [37, 39, 50].

As mentioned in section III, Digital and social media have also a strong impact on sports analytics. This social impact can be utilized effectively particularly from business point of view. The intimate and interactive nature of social media with players, clubs, team management, fans, sponsors, broadcasters are emerging as extremely exciting area of study for social network researchers [33, 34, 63].

Presence of social media in everyday life and its impact on sports media finds a nice place for business models to enhance their sales. These require an efficient algorithm for ads on social networks and the traditional algorithms designed are not built for effective communication over dynamic structures [37, 50-57, 61, 62]. Nodes may be added or removed in any unpredicted manner. Other factors that add to complex nature of these networks are limitation in terms of communication and computation.

In order to address these issues a node should be able to compute locally and should not expect a static infrastructure. There is a need of iterative asynchronous message exchange that is stable with respect to dynamically changing networks. Lightweight data structures can address these issues and utilize minimum communication and computational resources. All these existing issues directly call for use of gossip algorithms, which suit best for these scenarios [39, 50]. Excited about information diffusion in a social network and how this can be treated as a tool to enhance sales, vary business models and marketing strategies, authors treats sports groups as gossiping graphs and employee gossip protocol for information diffusion that to best of our knowledge has never been used in sports industry. This work is highly inspired by Bernhard Haeupler's work discovery through gossip [39].

5. METHODOLOGIES AND CONTRIBUTION

The authors propose a graph theoretic model in context of sports analytics that presents preliminary study of using gossip protocol for sharing information among members of sports oriented social network. This is a form of discovering or identifying members in a group using local gossip operations and sharing information with them [37, 39, 40].

Authors assume an undirected and connected graph wherein communication is synchronous and via nodes only to assume the generality. Assume *G* to be connected social network that shares a common interest about some sport event taking place at a particular place and time. Assume company *C* is interested to share information about a product *X* and increase the sales. The process simply begins with a node randomly choosing its neighbour and shares its information. This is the first round of gossip protocol and information update or exchange at a node is operation at node. The algorithm is how the operation is implemented at a node. In the next round both nodes select their neighbours randomly and share information about the product *X*.

Let $G_t = \{V_t, E_t\}$ be a social graph at time t with n nodes such that $n \in V$ and there exists an edge between two vertices such that $E \subset V*V$. Let topology of graph G be defined as a function of edges and vertices that vary over time which may be mathematically written as $G = f(V,E,t)$. The topology of a graph may change over time as more nodes may be added or removed from the group and edges may be established or revoked. At time t+1, graph may be defined as $G_{(t+1)} = \{V_{t+1}, E_{t+1}\}$ where $V_{t+1} = V_t \cup \varnothing \; or \; Vt \cup (v \notin V_t)$.

Let P_{ij} denote stochastic probability of node i sharing information with node j in a given time period which varies as a function of frequency of sharing. $P_{ij} \in P$ where P_{ij} denotes the stochastic probability of node sharing the information. To simplify we assume that a node i shares its information only with node j in a given round. The algorithm varies as a function of topology of graph G and probability matrix P. Let the degree of node i in graph G be denoted as $d_i = \sum / N(i) /$ where $N(i) = \{ j \in V \,/\, (i,j) \in E \}$.

A node $i \in V$ in graph G must satisfy following to implement gossip operation [39].

1. Information from the neighbor only is computed.

Mathematically $\Psi = f \{ j \in V \,/\, (i,j) \in E \}$ where Ψ is computation at node i. Computation at any node is sharing information hence same for all nodes.

2. Amount of work done at a node is logarithmic in nature which means amount of work done by a node is constant per unit time or per computational unit.

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3. Operation at a node i is not affected by operation being carried out at its neighbor $N(i)$. It does not require synchronization between operations at other nodes.
4. Computation is not much affected if graph is executed in distributed environment.

In natural and local gossip manner, each node randomly shares information with a neighbor. Various push – pull type algorithms have been studied theoretically [58 - 60], however, in this work authors try to look at using gossip based protocols in dynamically changing sports graphs. In a social network people represent nodes and edges are added between people who know each other. People add friends in triangulation manner wherein they get benefited by mutual friends [39]. Other way to handle it is using a neighbor to introduce you to one of his friends and this is a form of 2 hops to spread out [39]. Both these can be thought in terms of a sports market. You have a product and you can use a single stage triangulation process to introduce it to a friend or a sophisticated two-hop process to display products to friend of friend. Both these are well supported by gossip in its natural manner.

5.1. Single Stage Triangulation Process

In this method, we assume a node i in a graph G (say a social network) has information about product X. As we know in gossip protocol a node i randomly selects its neighbor node j and if an edge E_{ij} exists they share information about the product X and one of nodes changes it state. The probability of choosing a neighbor j of node i is governed by $Pij = \frac{N(j)}{\sum_{j+N(i)} N(j)}$. In its advanced form if the edge does not exist, an undirected edge is first established such that $E_{ij} \in E$ and then information is shared. This is a form of pushing information into neighbor. In each round of the protocol, the same process is repeated unless all the nodes have information about the product [39]. This is a kind of viral advertising about the product. The pseudo code for single share triangulation process can be written as shown in Algorithm 1.

Algorithm 1: Single Stage Triangulation Process

1: choose a neighbor $N(i) = \{ j \in V \,/\, (i,j) \in E \}$

2: if edge = true then

3: Compute Ψ such that $\Psi = f \{ j \in V \,/\, (i,j) \in E \}$

4: else

5: establish edge E_{ij} between nodes i and j

where $N(i) = \{ j \in V \,/\, (i,j) \in E \}$

6: Compute Ψ

7: exit

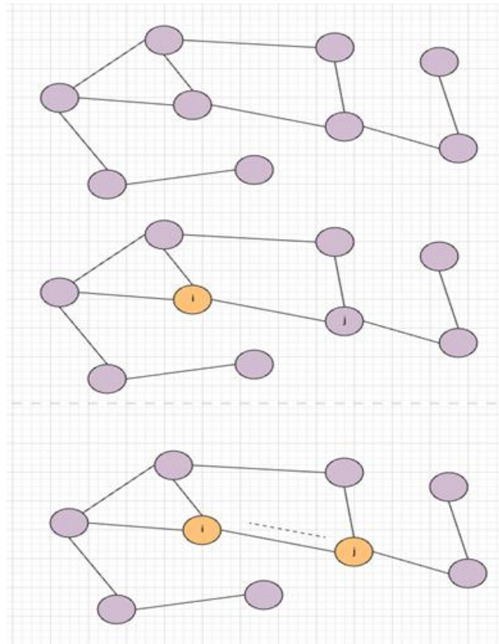

Figure 1 Single Stage Triangulation Process

Figure 1 is the diagrammatic representation of algorithm given above which is single hop process where node i shares its information with node j in a single step.

5.2. Two Stage Information Sharing

This method is a form of two-hop walk where node i in a graph G randomly selects a neighbor node j and node j randomly selects its neighbor k. The node i requests the identifier for node k and establishes an undirected edge E_{ik} such that $E_{ik} \in E$. The newly added neighbors share information about the product X. Figure 2 is the diagrammatic representation of algorithm given as Algorithm 2 which is two hop information sharing process where node i shares its information with node k which is neighbor of node j. This is a simple kind of pull operation where a node pulls information about the neighbors of neighbor and share information between them hence making it a two-stage information sharing method [39].

Algorithm 2: Two Stage Information Sharing

1: choose a neighbor $N(i) = \{ j \in V \,/\, (i,j) \in E \}$

2: if edge = true then

3: choose a neighbor $N(j) = \{ k \in V \,/\, (j,k) \in E \}$

4: Pull the ID neighbor of $N(j)$

5: $\Psi = f \{ k \in V \,/\, (j,k) \in E \}$

6: exit

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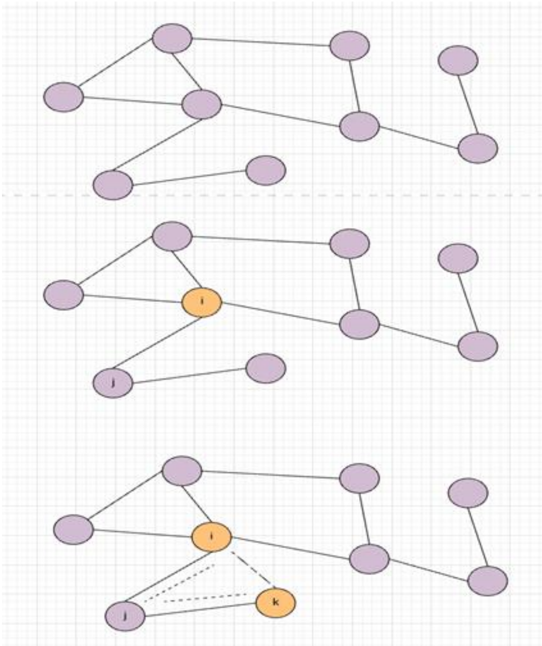

Figure 2 Two Hop Information Sharing

6. ANALYSIS AND CONCLUSIONS

Both the methods bind by the assumption mentioned above and are local in nature because in case of both single stages triangulation and two hop walk, the nodes talk to their direct contact. In either case the process is lightweight i.e., work done is constant [39]. Only single message in a single round is shared between two nodes. This is not highly affected by changing nature and dynamism of graph. In triangulation, a node shares it information with two random nodes and pushes mutual information. If the connection already exists then state of nodes is not changed, however, if edge does not exist, a link is established and information is shared. This is a complete local process and can be thought of as a market strategy to populate information about a product among people in a social network related to a sports event. This is single stage information sharing. Other way to enhance sales is two stage information sharing where a node choses a neighbor and shares its information with neighbor of a neighbor. This is also a local method. It is observed that time taken by a process converges to transitive closure of initial graph unless no more edges are added [39]. The results hold for both undirected and directed graphs and converge in logarithmic factor with high probability [39], however, the directionality of edges can greatly impede the unidirectional identification of neighbor hence affecting the sale of products.

If we have a subset of k nodes and we run a gossip over it, then it converges in logarithmic rounds to complete the sub graph. This is kind of running a gossip in a clique and discovering members using gossip-based methods [39]. Direction of edge also affects the discovery of nodes so it has a certain impact on spreading information and rumor in a group or a subset of a sports network. Since social networks are large, so it is difficult to converge to a complete graph as a whole. It shows good results over smaller sub graphs and cliques [39]. This also helps to predict size of immediate neighborhood. Since dynamic nature of our graphs is constantly changing and introduces non-trivial dependencies hence making it difficult to study the evolution of a network whose growth is usually initiated by a sport event under consideration. The convergence is not monotonic on all sub graphs. Time may vary from sub graph to sub graph. They share a very similar nature as that of a random walk [39]. Probability distribution of graph is hard to specify hence analyzing convergence on regular sports networks is quite difficult.

7. FUTURE

Gossip protocols in sports markets can be utilized to study birth, evolution and death of a community and business models can be developed over it. There is a lot of scope to study sales and markets with varying conditions such that more information is diffused in less number of passed or interactions. This study could be conducted in various probabilities of selecting neighbor; however, the dimension of study will change with selection of node to begin the information sharing. Protocol for information sharing with respect to sports market may be studied in comparison to existing market protocols. Selecting the most influential node of the network for information sharing will certainly increase the computational cost but significantly decrease the information sharing time or number of passes to spread rumor. The authors look forward to contribute in this direction.

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