Monitoring Social Networks for Event Management: Applicability of MEWMA for Parkrun

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Abstract

Social networks have become a powerful medium for communication and information sharing, influencing various aspects of society, including the organization and participation in community events such as Parkrun. As the popularity of Parkrun events continues to grow, effective monitoring and analysis of network data become crucial for event organizers to understand participant sentiments, engagement, and overall event success. In this paper, we propose the application of the Multivariate Exponentially Weighted Moving Average (MEWMA) chart for social network monitoring of Parkrun events, enabling the detection of anomalies and trends surrounding these events. Implementing the proposed approach with UK Parkrun events data and analyzing the change points highlights how tracking participants' choice of Parkrun site for running can profoundly affect event coordination and enhance the participant experience. Such analysis will assist planners in making more informed decisions regarding event logistics, resource allocation, and safety measures for Parkrun events. This research demonstrates how monitoring methods can improve event management and enhance participant experiences through data-driven insights.

Keywords
Social network monitoring, MEWMA, Change point detection, Parkrun events.

1. Introduction
A network is a collection of interconnected elements or nodes, which represent individual entities, and the connections between them are known as edges or links. A social network is a specific type of network that represents relationships between individuals or entities in a social context. In social networks, nodes represent people or entities (e.g., individuals, organizations), and edges represent relationships between them (e.g., friendship, family ties, professional connections). Social networks can be used to study patterns of social interactions, information flow, influence, and the spread of ideas or behaviors within a social group (Makagon et al., 2012). In today's interconnected world, social networks have become an integral part of our daily lives, revolutionizing the way we communicate, share information, and build relationships. With the massive influx of data generated on these platforms, it has become paramount to ensure the security, privacy, and overall integrity of the information exchanged. However, social networks are not only channels for healthy interactions but also hotbeds for misinformation, cyberbullying, and various illicit activities (Darwish et al., 2023). The demand for robust and effective monitoring systems to identify and mitigate undesirable behaviors on social networks has nevear been more critical. Existing approaches often fall short in handling the dynamic and vast amounts of data generated by users worldwide, leading to delayed or inaccurate identification of potential threats. Therefore, this research aims to address the problem of monitoring social-related data of events, to improve event management.

Social network monitoring offers numerous benefits to businesses and individuals alike. It aids in reputation management by promptly addressing customer feedback and complaints. Additionally, it provides valuable customer insights, facilitates competitor analysis, and supports crisis management efforts. Social network monitoring also helps identify influencers for marketing collaborations, enhances brand awareness and engagement, and fosters product innovation through customer feedback. Furthermore, it enables businesses to spot emerging trends and opportunities, measure campaign effectiveness, and assess potential risks (Bolotaeva & Cata, 2010). Overall, social network monitoring plays a vital role in staying connected, informed, and responsive in today's digital age.

The social network monitoring task holds significant importance in the realm of social networks and online safety. With the ever-increasing prevalence of harmful behaviors on these platforms, the proposed algorithm aims to revolutionize monitoring systems by swiftly identifying and addressing issues such as cyberbullying, hate speech, and misinformation. By integrating statistical process control with generated data of some events, the algorithm ensures real-time detection and response, safeguarding users and fostering a secure online environment. Moreover, this research prioritizes user privacy, employing a privacy-preserving approach during the monitoring process. Beyond its immediate application, the study's implications extend to data analytics and machine learning, opening up new possibilities for cross-domain applications and fostering collaborative efforts between stakeholders to combat social network challenges effectively (Elmaghraby & Losavio, 2014).

Social network monitoring encompasses a variety of methodologies, which can be classified into four distinct types, each offering unique insights and analytical advantages. Firstly, there are control charting and hypothesis testing schemes, enabling analysts to identify significant deviations or anomalies from expected patterns. These techniques provide a structured approach to detecting unusual behaviors or trends within the network data. Secondly, Bayesian approaches offer a probabilistic framework that incorporates prior knowledge and updates beliefs as new data arrives. This flexible method allows for better uncertainty quantification and facilitates more accurate predictions. Thirdly, time series models play a pivotal role in understanding network dynamics over time. By capturing temporal dependencies and trends, these models offer a comprehensive understanding of the network's evolving structure and interactions. Lastly, scan methods are designed to detect localized clusters or hotspots of activity within the network. By focusing on specific regions of interest, scan methods can unearth crucial nodes or communities that might otherwise remain hidden (Woodall et al., 2017). By employing these diverse methodologies, social network monitoring can gain richer insights, make more informed decisions, and unleash the full potential of network analysis in a rapidly evolving digital landscape.

This study aims to address the limitations of traditional change point detection methods in social network monitoring, particularly in learning online and efficiently modeling dynamic social networks by considering network structure and employing multiple variables of network attributes in the monitoring algorithm. Existing approaches for univariate cases, such as control charts and time series models, have shown promise in detecting anomalies and changes in network metrics but fall short in capturing critical network features like sparsity, reciprocity, and network structure in a multivariate manner. Moreover, they lack the generality to handle directed and weighted networks effectively. To overcome these weaknesses, this study proposes a novel statistical process control (SPC) framework infused with a Multivariate Exponentially Weighted Moving Average (MEWMA) method to revolutionize social network monitoring, especially in parkrun events. This research seeks to leverage the dynamic nature of social networks and create an approach capable of capturing the evolving characteristics of the network. By monitoring parameters for each node while considering network features, the MEWMA change point detection algorithm aims to detect anomalies and changes in real-time, providing a more efficient and accurate monitoring solution for social networks.

In summary, the main contributions of this study are: Firstly, it proposes a new and effective tool that revolutionizes event management, specifically for Parkrun events. Secondly, it provides essential network statistics that are crucial for monitoring purposes. And thirdly, it extends a multivariate version of the EWMA method, resulting in a more efficient social network monitoring approach. Moreover, monitoring the flow and network of participants in Parkrun events can have a profound impact on the overall organization and experience. By analyzing participant data, event planners can make well-informed decisions about event logistics, ensuring the efficient allocation of resources and enhancing safety measures. The data also offers valuable insights into route popularity and challenges, facilitating course improvements to create a more enjoyable experience for participants. Understanding participant behavior and engagement patterns fosters a strong sense of community and social interaction among participants. Additionally, the gathered data can be leveraged for targeted marketing efforts, attracting new participants and fostering partnerships with relevant organizations. In addition, the systematic monitoring of participant flow and network dynamics contributes to the continuous improvement and success of Parkrun events, benefiting both organizers and participants.

The remainder of this paper is structured as follows: Section 2 presents a comprehensive literature review on social network monitoring and examines the specific challenges faced in managing Parkrun events, highlighting the need for innovative tools and approaches. In Section 3, we detail the proposed methodology for constructing control charts tailored to network attributes extracted from Parkrun network flow data. This section will outline the steps involved in the analysis and how the control charts can be effectively utilized in event management. Lastly, in Section 4, we conclude with our findings, emphasizing the practical implications of our proposed approach. Furthermore, we identify potential future research directions that can further advance the field of social network monitoring in the context of Parkrun events.

2. Literature Review

Social networks have become an integral part of modern communication, enabling millions of users to connect, interact, and share information. With the exponential growth of social media platforms, there is an increasing need for effective methods to monitor and detect changes and anomalies in these networks. Change point detection is a crucial task in social network analysis, as it facilitates the identification of shifts in network behaviors, the emergence of influential events, and the detection of malicious activities (Stevens et al., 2021a). We present a comprehensive review of existing literature on social network monitoring, and anomaly detection techniques. This section explores the limitations of current methods and highlights the potential benefits of incorporating the MEWMA chart into the context of Parkrun event monitoring.

2.1 Social networks monitoring

Social network monitoring has been a topic of extensive research, and various methods have been proposed to analyze, track, and understand social networks. Here is a literature review highlighting some of the key methods used in social network monitoring:

2.1.1 Control Charting and Hypothesis Testing Schemes

Control charts and hypothesis testing are commonly used to detect anomalies and unusual behavior in social networks. These methods involve setting up statistical control limits based on historical data and comparing the current network attributes against these limits. If a significant deviation is observed, it may indicate potential issues or events that require further investigation. Researchers have applied these techniques to analyze social media data for identifying sudden spikes in activity, fake accounts, or coordinated misinformation campaigns (Stevens et al., 2021b).

Among the well-known approaches in this category are Cumulative Sum (CUSUM) and Exponentially Weighted Moving Average (EWMA) charts. These methods have been successfully employed in monitoring graph measures related to network representation over time and detecting anomalies by applying control charts. CUSUM and EWMA methods are particularly useful for their ability to simultaneously monitor multiple attributes of dynamic networks (Salmasnia et al., 2020). They offer high accuracy in detecting changes in various network metrics, making them popular choices for initial change point detection tasks. However, these classic methods suffer from certain limitations when applied to social networks. They often neglect important network features, such as sparsity, reciprocity, and network structure, which can significantly impact the effectiveness of change point detection. Furthermore, their lack of generality in handling directed and weighted networks poses a challenge when analyzing real-world social networks, which often exhibit diverse and intricate interactions among nodes.

2.1.2 Bayesian Approaches

Bayesian approaches have gained substantial popularity in social network monitoring due to their unique ability to integrate prior knowledge and continuously update beliefs with new data. These methods offer more accurate probabilistic models for assessing network changes and predicting future trends. By leveraging probabilistic models, Bayesian approaches can infer underlying patterns and relationships within the network, enabling more accurate predictions and decision-making (Yang et al., 2011). Additionally, Bayesian methods are particularly beneficial in scenarios where data is limited or noisy, as they can effectively handle uncertainty and continuously update beliefs as new data becomes available. Bayesian networks allow researchers to understand how information propagates and influences individual behaviors and makes changes. Moreover, Bayesian methods shed light on the spread of behaviors or opinions, helping to comprehend the prevalence and decline of specific attributes over time, and contributing to a deeper understanding of social influence and behavioral contagion within networks (Jones & Love, 2011).

2.1.3 Time Series Models

One of the commonly used methods to change point detection in social networks are time series models to fit the temporal evolution of network metrics, effectively monitoring and detecting change points. Time series models are essential in social network monitoring in terms of capturing temporal dependencies and trends in social network data, providing insights into how network attributes evolve, and identifying patterns and seasonal variations, such as dynamics of user engagement, sentiment, and activity on social media platforms (Kendrick et al., 2018). Despite the advantages, time series models may face challenges with increased complexity and computational demands, especially in large-scale social networks with high-dimensional time series data. The selection and calibration of appropriate models for specific network metrics can be challenging, impacting the accuracy of detection (Aminikhanghahi & Cook, 2017). Nevertheless, time series modeling remains a valuable tool for monitoring and understanding social network dynamics, contributing to the advancement of social network analysis and research.

2.1.4 Scan Methods

Scan methods are designed to identify localized clusters or hotspots of activity within a social network, making them particularly useful for detecting communities or groups of users with similar interests or behaviors. Researchers have utilized scan methods to identify influential nodes and detect changes in community structure over time. Scan-based network monitoring provides a different approach compared to control charts and time series models. It operates in real-time and streaming data environments, enabling the detection of changes and anomalies as they occur within the social network. This method utilizes scan statistics to investigate instantiations in network variables, searching for potential local signals over time. By scanning a small window over the data, local statistics, such as the size of k-th order neighborhoods or summary statistics of the network structure, are calculated to identify clusters or hotspots of activity and detect shifts in network behaviors (McCulloh & Carley, 2011). Scan-based methods offer the advantage of real-time detection, enabling the identification of changes and anomalies as they occur. They are particularly useful in dynamic social networks, where shifts in network behaviors may happen more frequently and rapidly. However, selecting the appropriate scan statistics for a specific social network scenario can be challenging, and the method's effectiveness heavily depends on the chosen statistic's sensitivity to detect relevant changes.

2.1.5 Machine Learning and Data Mining Techniques

Machine learning and data mining methods are essential pillars of social network monitoring, contributing significantly to tasks like sentiment analysis, fake account detection, and recommendation systems. With the abundance of data on social networks, these advanced techniques excel at uncovering patterns and correlations that yield more accurate predictions and informed decision-making (Balaji et al., 2021). Applying social network monitoring techniques for sentiment analysis, driven by machine learning algorithms, enables businesses to assess customer satisfaction, track emerging trends, and respond to concerns swiftly, fostering improved customer relationships (Neethu & Rajasree, 2013). In combating fake accounts, machine learning algorithms discern behavior patterns to differentiate between legitimate users and automated bots, safeguarding social platforms from misinformation and fraudulent activities. Moreover, incorporating social-related insights obtained from monitoring procedures in recommendation systems, causes to leverage data mining to tailor personalized content and suggestions, enhancing user engagement and satisfaction. As social networks continue to grow in complexity, the power of machine learning and data mining in social network monitoring is set to expand, empowering users and organizations alike with actionable insights and smarter choices (Baesens et al., 2015).

To sum up, social network monitoring methods have seen significant advancements over the years, driven by the increasing availability of big data, computational power, and the need to understand and manage the complexities of social interactions. The integration of statistical, machine learning and graph-based techniques has enabled researchers and practitioners to gain deeper insights into social networks, making social network monitoring a valuable tool for various applications, including marketing, cybersecurity, public health, and social science research. Each method possesses unique strengths and limitations, with implications for real-world social network analysis. To overcome the limitations of traditional change point detection methods, recent research has focused on advancing network modeling approaches. These efforts aim to present the network's characteristics more accurately in dynamic environments. By considering network features and monitoring obtained parameters, these methods hold promise for improved change point detection in social networks (Amati et al., 2018). In this regard, this research aims to foster important social network attributes such as topological measures of the networks over time, including factors such as density, total weight, weighted degree, weighted closeness, weighted betweenness, clustering coefficient, and the number of triangles. Furthermore, node-specific attributes on network interactions, such as node indegree, node outdegree, and total node connections, are incorporated as explanatory variables for multivariate profile monitoring.

2.2 Parkrun management

The community-based sporting event called "Parkrun" (www.parkrun.com) is a free, five-kilometer run that takes place weekly in 14 countries. Participants register online and receive a personal barcode, which is used to record their time and finishing position each time they participate in a Parkrun event anywhere in the world. There is no minimum skill level or running ability required to take part. After each event, participants receive their run time, overall placing, and ranking within their age group via email. Parkrun is a globally organized event, with over 1,100 locations worldwide. The coordination occurs at various levels, including regional, state, national, and international levels (Grunseit et al., 2018).

Various studies touched upon aspects related to the organization, operations, and community engagement of Parkrun events. For instance, (Quirk et al., 2021) discussed the global reach and impact of Parkrun as a community-based physical activity intervention, providing insights into the management and organization of these events, emphasizing their community-driven nature and the crucial role of volunteers. Additionally, (Westerbeek & Karg, 2022) explored facilitators and barriers to organized physical activity, including events like Parkrun, for individuals with mobility impairments, touching on issues related to event management and accessibility. Ethnographic research (Warhurst & Black, 2022) delved into the social impact of Parkrun events, shedding light on how they are managed and foster a sense of community and social inclusion. While not solely focused on Parkrun, work on sport for social change provides relevant insights that may be applicable to parkrun management given its community-focused approach (Peachey et al., 2019).

Research on Parkrun events in Australia revealed that Australian Parkrun participants generally align with the broader population concerning personal well-being, but they indicated higher satisfaction with their physical health (Grunseit et al., 2018). Women seemed to experience improved mental health benefits from Parkrun, while men appeared to benefit from increased community connectedness. (Grunseit et al., 2018) suggests that Parkrun events may support athletes in expressing their positive identity and maintaining healthy habits, and also offer non-athletes a non-demanding yet health-promoting activity with opportunities for social interaction. (Stevinson et al., 2015) identified two primary themes in Parkrun events: freedom and reciprocity. Freedom encompassed the accessibility and inclusivity of the events, which contributed to sustained participation. Reciprocity highlighted the dual benefits of personal gains and helping others. Initial motivation was rooted in the anticipation of fitness and health benefits, while continued involvement was influenced by the achievement of time or attendance goals, social cohesion, and community contributions. Specific features, such as an accessible and inclusive ethos, opportunities for achievement, social support, outdoor natural settings, and an integrated volunteer system, played a crucial role in encouraging participation. By incorporating these elements into community-based interventions, there is potential to enhance success in promoting and maintaining health-enhancing physical activity.

Wiltshire & Stevinson, (2018) researched to examine the potential of free, community-based initiatives like Parkrun to improve physical activity in low socio-economic groups. Through interviews with previously inactive Parkrun participants, the analysis highlights the role of social capital in initiating and maintaining physical activity. While volunteer-led, community-based initiatives can mobilize resources through social networks, relying solely on existing social capital may limit their impact in addressing socio-economic inequalities in promoting health-enhancing behavior. (Quirk & Haake, 2019) carried out a qualitative study examining Parkrun's PROVE project, targeting people with long-term health conditions in England. Interviews with 15 PROVE Outreach Ambassadors revealed four themes and 13 subthemes. The project enhanced support for participants in a structured manner and aimed to create a safe, inclusive environment for physical activity and volunteering. Challenges included communication, impact demonstration, and reliance on volunteers. The study highlights Parkrun's potential for public health in this context, offering important implications for policymakers and physical activity providers seeking inclusive community opportunities. (Malchrowicz-Mośko et al., 2020) highlights the influence of social-demographic variables, such as gender, age, education, and marital and family status, on the decision to start running. Considering these factors is crucial when promoting mass sports events for improving people's health. Emphasizing safe running for beginners is equally important as encouraging participation. Notably, all participants expressed their aspirations to run a marathon in the future.

A review of related works on Parkrun events indicates a significant research gap in this context, as no studies have utilized monitoring techniques, such as Statistical Process Control (SPC) control charts, for event analysis and improvement. While SPC techniques have been well-established in other fields, their potential application to community-based events like Parkrun remains unexplored. In this article, we present an exciting tool by introducing a monitoring scheme to optimize various aspects of Parkrun events, including participant attendance, volunteer involvement, and overall event performance. By delving into this uncharted territory, researchers and practitioners can provide valuable insights and equip event organizers with data-driven tools to enhance the success and impact of Parkrun events at the community level.

3. Proposed Monitoring Methodology

The MEWMA chart, known for its effectiveness in detecting multivariate anomalies in continuous data streams, is applied to monitor key event-related metrics, such as the number of mentions, sentiment analysis, and user engagement. We demonstrate the step-by-step implementation of the MEWMA chart and discuss the selection of control parameters for optimal performance.

3.1 MEWMA approach

The MEWMA (Multivariate Exponentially Weighted Moving Average) approach is a statistical process control technique used to monitor and detect abnormalities or shifts in multivariate data. It is an extension of the traditional univariate Exponentially Weighted Moving Average (EWMA) method and is particularly effective for monitoring processes where multiple variables are simultaneously measured. The MEWMA approach considers the correlation between variables, making it suitable for applications in various industries, including manufacturing, healthcare, and finance (Niaki et al., 2010).

In the MEWMA approach, data from different variables are combined using weighted averages, with recent observations receiving higher weights than older ones. This weighting scheme allows the MEWMA approach to be sensitive to small shifts or deviations in the multivariate data over time. By continuously updating the control limits based on historical data, the MEWMA approach can quickly identify any unusual patterns or out-of-control conditions, helping organizations maintain process quality and identify potential issues early on (Noor-ul-Amin & Atif Sarwar, 2023).

The model for a multivariate EWMA chart is given by:

$$Z_i = \lambda X_i + (1-\lambda)Z_{i-1}, \qquad i = 1,2,\dots,n \tag{1}$$

Where Z_i is the ith EWMA vector, and X_i is the ith observation vector. In addition, λ is a diagonal matrix with values $\lambda_1, \lambda_2, \dots, \lambda_p$ on the main diagonal, and p is the number of variables in each vector. The control statistics which would be plotted on the control chart are as follows:

$$T_i^2 = Z'_i \Sigma_{Z_i}^{-1} Z_i, \qquad i = 1,2,\dots,n \tag{2}$$

Where Σ is the covariance matrix of the input data. When i becomes large, the covariance matrix may be expressed as:

$$\Sigma_{Z_i} = \frac{\lambda}{2-\lambda}\Sigma, \qquad i = 1,2,\dots,n \tag{3}$$

In addition, the control limits can be obtained by simulations to meet a specified Average Run Length (ARL). In practice, the control limits in the MEWMA approach are usually set based on historical data and the desired level of sensitivity to detect process shifts.

3.2 Network Statistics

Network statistics, also known as network metrics or network measures, are quantitative measures used to analyze and characterize the structure, properties, and behavior of complex networks. A complex network consists of nodes (representing individual entities) and edges (representing connections or relationships between nodes). These networks can be found in various fields, including social networks, biological systems, transportation networks, communication networks, and the Internet (Bloch et al., 2023).

Network statistics provide valuable insights into the structure and behavior of complex networks, where nodes represent entities and edges signify connections between them. Some common network statistics include the degree, which measures the number of connections a node has, indicating its importance and centrality. Centrality measures like Betweenness, Closeness, and Eigenvector centrality help identify influential nodes in the network. The clustering coefficient quantifies how interconnected nodes are in a local neighborhood, reflecting the tendency for nodes to cluster together. Degree distribution aids in understanding the heterogeneity of node connections, while the network diameter gives an idea of how well-connected the network is (Koskinen & Snijders, 2023). These statistics find applications in various fields such as social network analysis, epidemiology, cybersecurity, transportation planning, and information retrieval. They enable researchers to study complex systems, identify critical nodes, detect anomalies, and predict network dynamics under different conditions. By leveraging network statistics, analysts can gain valuable insights to manage and optimize complex networks effectively, contributing to advancements and problem-solving in a wide range of real-world scenarios (Mustapha et al., 2021).

This study aims to enhance our understanding of important social network attributes in Parkrun events by examining topological measures of the networks over time. These measures include factors such as density, total weight, weighted degree, weighted closeness, weighted betweenness, clustering coefficient, and the number of triangles. Additionally, node-specific attributes on network interactions, such as node indegree, node outdegree, and total node connections, are incorporated as explanatory variables for a multivariate profile monitoring approach.

3.3 Parkrun network data

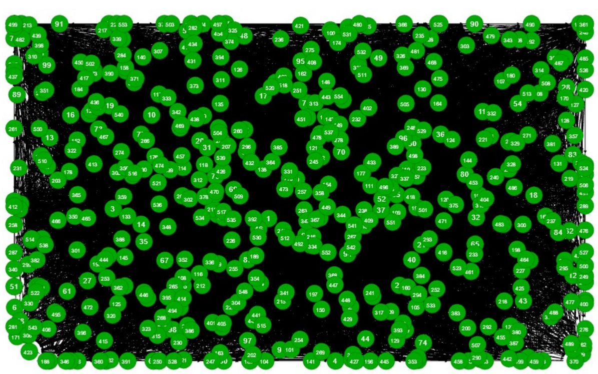
In this section we use the data scraped from the UK's Parkrun website, covering approximately 75% of all the runs completed in UK events in 2022. It consists of more than 4.3 million participations. The following table 1 shows the attributes in the Parkrun dataset.

Table 1. Attributes within the Parkrun dataset.

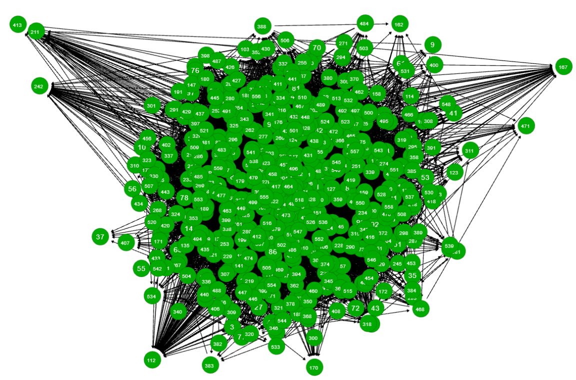
No.	Attribute	Description
1	name	Runner's name
2	time	The time taken to run the 5km course (in minutes)
3	parkrun	The name of the Parkrun event
4	race_num	The event number for that specific location
5	year	Year of event
6	is_male	The gender of the runner is binarised so that 1 is male and 0 is female
7	med_age	The median age of the runner's age group
8	location	where the Parkrun is

In this study, we construct a dynamic network to visualize the flow of participants among various Parkrun sites. In essence, our focus lies in capturing the shifts in participants' behavior when it comes to selecting Parkrun sites. Accordingly, the vertices within the network correspond to individual Parkrun sites, while the weighted edges indicate the count of participants who have transitioned between these running sites over time understudy.

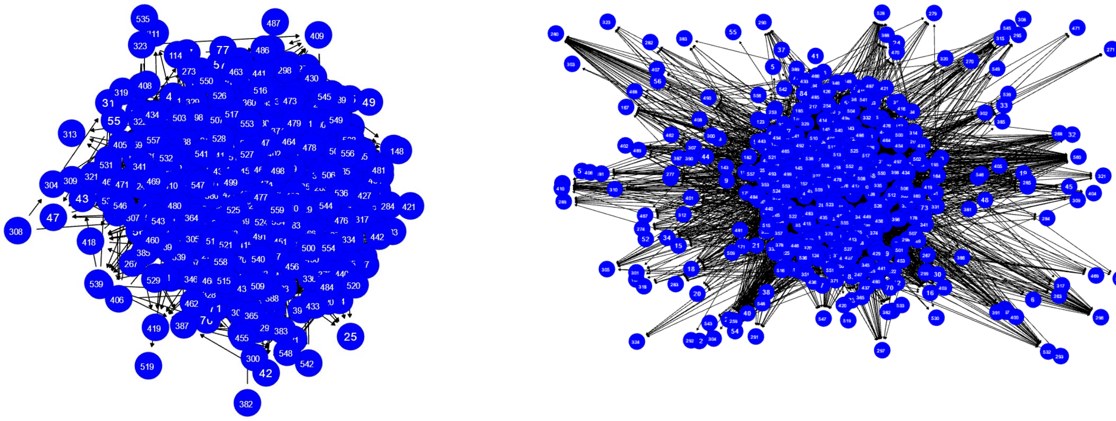
Consequently, the interactional dataset (i, j, t, w) delineates that at a given time t, w participants who were initially using site i at time $t-1$ for their runs have made a switch to site j. This dataset encapsulates the essence of the participants' movement and site preference changes over time.



$t = 20$



$t = 30$



$t = 42$ $t = 45$

Figure 1. Network of participants flow among Parkrun locations

There are 561 Parkrun locations designated for holding Parkrun events in the UK. Additionally, based on the gathered data, 501,824 distinct runners may have opted for various Parkrun locations to participate in the events throughout the year. Furthermore, the dataset encompasses 52 events over the course of the year. Figure 1. provides a snapshot of the network at four-time points.

3.4 Proposed Control Chart

In this section, we introduce a MEWMA control chart specifically designed for monitoring Parkrun events. The objective is to showcase the effectiveness of the MEWMA chart in identifying anomalies and trends within social network data. Our methodology entails leveraging network statistics, which encompass a range of metrics including density, total weight, weighted degree, weighted closeness, weighted betweenness, clustering coefficient, and the number of triangles. All these metrics function as explanatory variables in our analysis. The following figure 2 presents the MEWMA control chart that has been generated for the flow of Parkrun participants among various Parkrun sites during the events that took place in the year 2022.

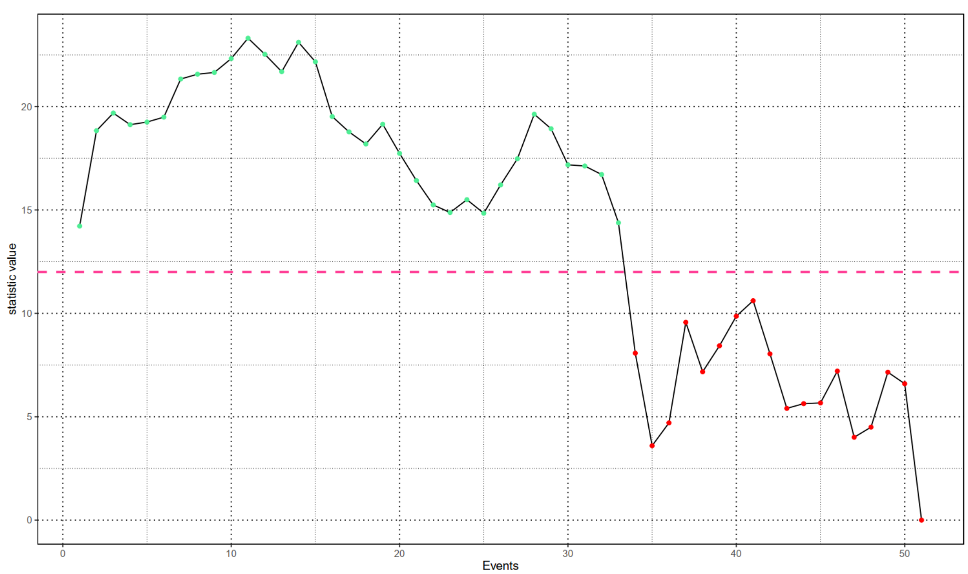


Figure 2. Proposed MEWMA control chart

According to the control limits, event 34 stands out as a pivotal moment in the pattern of participant flows across Parkrun events. Upon deeper investigation, this occurrence took place on August 22, 2022, drawing a total of 101,250 participants across all locations—nearly 14 percent higher than the previous event. Notably, this event marked a significant change by unfolding across 183 previously unutilized locations, indicating that approximately 32% of the locations exert a substantial impact on overall satisfaction and participant attraction to Parkrun events.

The results obtained provide a clear illustration of how event organizers can harness the power of the MEWMA chart to glean insights into participants' behaviors, accentuate impactful activities, and swiftly address potential issues during and post events. The application of the MEWMA approach proves especially advantageous in the context of high-dimensional data like Parkrun data, given its adeptness at effectively analyzing and monitoring intricate systems. This approach finds extensive utility in quality control, fault detection, and anomaly identification, yielding enhanced process performance and diminished variability across a range of practical scenarios.

4. Conclusion

Nowadays, the detection of change points in social networks has emerged as a focal point for researchers. Two primary approaches, model-based and free-model analysis, corresponding to parametric and nonparametric methods, have been extensively studied. While model-based methods have seen significant attention, only a limited number of studies have explored the use of Multivariate Profiles for monitoring network data generated from events. To bridge this gap, this paper highlights the applicability of the MEWMA chart for social network monitoring of Parkrun events, offering event organizers valuable insights to optimize their strategies and create engaging experiences for participants. We outline the potential benefits of using the MEWMA chart for event management, including its ability to facilitate data-driven decision-making, enhance event success, and improve participant experiences. Furthermore, we explore the broader applications of this monitoring technique for various other community events and social campaigns. The implications of this proposed tool extend across various industries, offering potential applications in gaining valuable business insights, conducting marketing analyses, monitoring criminal activities, and tracking the spread of diseases. As future research opportunities unfold, there are several areas for improvement in social network monitoring. The integration of natural language processing techniques for sentiment analysis, and the incorporation of more social media platforms, can significantly enrich the analysis. Additionally, investigating different types of changes can contribute to a better understanding of social network dynamics. Such endeavors have the potential to enhance the efficiency of monitoring techniques in various real-world scenarios.

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