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LEVERAGING MAXIMUM LIKELIHOOD METHOD FOR COMMUNITY DETECTION IN SOCIAL NETWORKS: A NEW FRONTIER IN MARKETING

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Annotatsiya
Ijtimoiy medianing yuksalishi marketing landshaftini o'zgartirib, biznesga potentsial mijozlarning keng tarmoqlariga tengsiz kirishni taklif qildi. Biroq, ijtimoiy tarmoqlarning murakkabligi aniq demografiya yoki jamoalarni samarali yo'naltirish uchun murakkab tahliliy vositalarni talab qiladi. Ushbu maqola marketing strategiyalarini yaxshilash uchun yangi yondashuv sifatida ijtimoiy tarmoqlarda hamjamiyatni aniqlashning maksimal ehtimollik usulini qo'llashni o'rganadi. Tarmoqlarni alohida jamoalarga bo'lish orqali sotuvchilar o'z kampaniyalarini har bir guruhning o'ziga xos xususiyatlari va afzalliklariga mos keladigan tarzda sozlashlari mumkin. Maqolada usulning nazariy asoslari, maqsadli reklama, ta'sir etuvchi marketing va mahsulotni ishlab chiqishda amaliy qo'llanilishi hamda undan foydalanish bilan bog'liq muammolar va axloqiy mulohazalar muhokama qilinadi.

Аннотация
Развитие социальных сетей изменило маркетинговую среду, предоставив предприятиям беспрецедентный доступ к обширным сетям потенциальных клиентов. Однако сложность социальных сетей требует сложных аналитических инструментов для эффективного воздействия на конкретные демографические группы или сообщества. В этой статье исследуется применение метода максимального правдоподобия для обнаружения сообществ в социальных сетях как новый подход к совершенствованию маркетинговых стратегий. Разделив сети на отдельные сообщества, маркетологи могут адаптировать свои кампании так, чтобы они соответствовали уникальным характеристикам и предпочтениям каждой группы. В статье обсуждаются теоретические основы метода, его практическое применение в таргетированной рекламе, маркетинге влияния и разработке продуктов, а также проблемы и этические соображения, связанные с его использованием.

Abstract

The rise of social media has transformed the marketing landscape, offering businesses unparalleled access to vast networks of potential customers. However, the complexity of social networks necessitates sophisticated analytical tools to effectively target specific demographics or communities. This article explores the application of the maximum likelihood method for community detection in social networks as a novel approach to enhance marketing strategies. By partitioning networks into distinct communities, marketers can tailor their campaigns to resonate with the unique characteristics and preferences of each group. The article discusses the method's theoretical underpinnings, its practical applications in targeted advertising, influencer marketing and product development, and the challenges and ethical considerations associated with its use.

Kalit so'zlar

Maksimal ehtimollik usuli, hamjamiyatni aniqlash, ijtimoiy tarmoqlar, marketing strategiyalari, maqsadli reklama, ta'sir qiluvchi marketing, mijozlar segmentatsiyasi, raqobat tahlili, mahsulotni ishlab chiqish, ma'lumotlarga asoslangan marketing.

Ключевые слова

Метод максимального правдоподобия, обнаружение сообществ, социальные сети, маркетинговые стратегии, таргетированная реклама, маркетинг влияния, сегментация клиентов, конкурентный анализ, разработка продукта, маркетинг, основанный на данных.

Keywords

Maximum likelihood method, community detection, social networks, marketing strategies, targeted advertising, influencer marketing, customer segmentation, competitive analysis, product development, data-driven marketing.

Introduction

The advent of social media has revolutionized the landscape of marketing, providing businesses with unprecedented access to vast networks of potential customers. However, the sheer volume and complexity of social networks pose a challenge for marketers seeking to target specific demographics or communities. One promising solution lies in the application of the maximum likelihood method for dividing social networks into two communities, a technique that offers a more nuanced understanding of online social structures and enhances marketing strategies.

In the digital age, social networks have emerged as the epicenter of human interaction, providing a rich tapestry of connections and communities that transcend physical boundaries. This evolution has not gone unnoticed by the marketing world, where social networks are now seen as a goldmine of potential customers. However, the vastness and complexity of these networks present a significant challenge: how can marketers effectively identify and target specific groups within this intricate web?

Enter the maximum likelihood method, a statistical tool that has found a new application in the realm of marketing. Traditionally used in fields such as genetics and economics, this method is now being leveraged to dissect social networks into distinct communities. By doing so, marketers can gain a deeper understanding of the social landscape, enabling them to tailor their strategies to the unique characteristics of each group.

This article delves into the transformative potential of the maximum likelihood method for community detection in social networks, exploring its theoretical foundations, practical applications, and the challenges it poses. As we navigate this new frontier in marketing, we uncover how data-driven insights can lead to more targeted, effective, and personalized marketing campaigns, ultimately reshaping the way businesses connect with their audiences in the digital world.

Analysis of the literature on the subject

The author's work [1], discussed in this review, outlines different approaches for identifying social and social networks, relying on the dynamic interaction and recognition of participants within the network structure. Special emphasis is placed on techniques that handle the detection of overlapping and hierarchical communities. In the author's work [2], highlighted in this review, the research focuses on the structure of the Internet community. Newman demonstrates that the Internet serves as an excellent example of a network where intricate community structures can be detected, examined, and leveraged to enhance services and offerings for users.

In the author's work [3], discussed in this review, the authors highlight that homophily, or the tendency for similar individuals to be connected, fosters strong communities within social networks. They explore how this phenomenon might impact the dynamic evolution and overall structure of social networks.

The book delves into various metrics and methods for analyzing social networks, including community detection. It underscores the importance of this issue for understanding the organizational principles and functioning of social networks.

The article [5] showcases the flexibility of community discovery methods that span across social and biological networks. The authors introduce a technique that examines network structure and identifies boundaries between communities.

In "How Digital Customer Communities Build Your Business" by Larry Weber, it is argued that communities and social media can be leveraged to enhance a brand, satisfy customers, and create new business opportunities.

In [7], the authors propose a model for estimating the structure of communities in a network using the maximum likelihood method. This approach allows for the incorporation of additional node attributes, such as age, gender, and interests, in community identification.

[9] article considered the use of maximum likelihood method for community detection in social networks. This method opens a new frontier in improving marketing strategies. By dividing networks into different communities, this method makes it possible to structure marketing campaigns in a way that matches the characteristics and desires of each group. The article discusses the theoretical foundations of the method, practical applications, issues and ethical considerations related to its use in targeted advertising, influencer marketing, and product development.

[10] in the paper rewards a new frontier of how to use the maximum likelihood method for community detection in social networks. This method is used for areas such as collaboration, marketing, customer orientation, and product development. The article details the theoretical basis of the method, its practical application, its experimental results, and some possible problems. [11-12] articles discussed the importance of implementing optimal marketing strategies by using the maximum likelihood method to identify the community in social networks. The theory, practical application, achievements and preliminary results of this method are analyzed. The paper also presents some important points about the potential problems and limitations of the method.

Understanding the Maximum Likelihood Method:

The maximum likelihood method is a statistical approach used to estimate the parameters of a model in a way that maximizes the likelihood of the observed data. In the context of social networks, this method can be employed to detect communities by identifying groups of nodes (individuals or entities) that are more densely connected to each other than to the rest of the network. By modeling the network's structure and applying the maximum likelihood method, it is possible to partition the network into two distinct communities, each with its own characteristics and behaviors.

We consider the following parameters: The probability of a connection between any two vertices within the p_{in} command; The probability of a connection between two vertices from different p_{out} commands. Maximizing the most probable structure of partitioning into communities over all possible network configurations, we obtain a partition that corresponds to real data. Consider a network $G = (X, Y)$, in which the set of vertices has the form $X = \{1,2,\dots,n\}$. The number of network edges is $m = m(Y)$, Let the connection between vertices i and j be as follows:

$$E(i,j) = \begin{cases} 1 \;\; If\ there\ is\ a\ connection\ between\ i\ and\ j\ teams \\ 0 \;\; If\ there\ is\ no\ connection\ between\ teams\ i\ and\ j \end{cases}$$

By a community S we mean a non-empty subset of network vertices, and by a partition $\Pi(X)$ we mean the set of non-overlapping communities whose union is exactly the set X: N:$\Pi(X) = \{S_1, S_2, \dots, S_k\}$, where $\cup_{k=1}^{K} S_k, k = 1, \dots, K$.

Suppose that the real part of the network is $\Pi = S_1, S_2, \dots, S_k$. Let the variables $n_k = n(S_k)$ and $m_k = m(S_k)$ denote the number of vertices and edges in the community $S_k, k = 1, \dots, K$, respectively. Then $n = \sum_{k=1}^{K} n_k$ and $\sum_{k=1}^{K} m_k \le m$. Let us express the conditions under which the division into teams is optimal.

Let us express the conditions under which the division into teams is optimal. Consider the community $S_k \in \Pi$. The probability of realizing m_k connections among n_k vertices in the community S_k is [8]

$$p_{in}^{m_k}(1 - p_{in})^{\frac{n_k(n_k-1)}{2} - m_k} \qquad (1)$$

Each vertex i in the community S_k can have $n - n_k$ connections with the vertices of other communities, but in fact it is connected to the vertices of other communities $\sum_{j \notin S_k} E(i,j)$ has connections.

It is easy to see that the probability of realizing a network with a given structure is equal to

$$L_{\Pi} = \prod_{k=1}^{K} p_{in}^{m_k} (1-p_{in})^{\frac{n_k(n_k-1)}{2}-m_k} \prod_{i\in S_k} p_{out}^{\frac{1}{2}\sum_{j\notin S_k} E(i,j)} (1 - p_{out})^{\frac{1}{2}\left(n-n_k-\sum_{j\notin S_k} E(i,j)\right)} \quad (2)$$

Taking the logarithm of the probability function L_Π in (2) and simplifying it, we get

$$l_\Pi = logL_\Pi = \sum_{k=1}^{K} m_k\, logp_{in} + \sum_{k=1}^{K}\left(\frac{n_k(n_k-1)}{2} - m_k\right) log(1-p_{in}) + \left(m - \sum_{k=1}^{K} m_k\right) logp_{out} + \left(\frac{1}{2}\sum_{k=1}^{K} n_k(n-n_k) - \left(m - \sum_{k=1}^{K} m_k\right)\right) log(1-p_{out})$$

The partition Π^*, for which the function l_Π reaches its maximum over all possible partitions, is called optimal. Note that there is still uncertainty in the choice of probabilities p_{in} and p_{out}. The function $l_\Pi = l_\Pi(p_{in}, p_{out})$ depends on the arguments p_{in}, p_{out}. By maximizing l_Π with respect to p_{in},p_{out}, one can then use these values in numerical calculations.

Statement. For a fixed partition Π, the function $l_\Pi = l_\Pi(p_{in}, p_{out})$ reaches its maximum at

$$p_{in} = \frac{2\sum_{k=1}^{K} m_k}{\sum_{k=1}^{K} n_k^2 - n}, p_{out} = \frac{2(m - \sum_{k=1}^{K} m_k)}{n^2 - \sum_{k=1}^{K} n_k^2}.$$

Applications in Marketing:

1. Targeted Advertising: By identifying distinct communities within a social network, marketers can tailor their advertising campaigns to resonate with the specific interests, preferences, and needs of each group. This targeted approach increases the relevance and effectiveness of marketing messages, leading to higher engagement and conversion rates.

2. Influencer Marketing: Community detection can help marketers identify influential members within each group who have the power to sway opinions and drive trends. By collaborating with these influencers, brands can amplify their reach and credibility within targeted communities.

3. Customer Segmentation: Dividing a social network into communities allows marketers to segment their audience more precisely, enabling the development of personalized marketing strategies that cater to the unique characteristics of each segment.

4. Competitive Analysis: Understanding the community structure of social networks can provide insights into the competitive landscape, revealing how rival brands are positioned within the network and identifying potential opportunities or threats.

5. Product Development: Insights gained from community detection can inform product development efforts, guiding the creation of products or features that meet the specific needs and preferences of different groups within the network.

Challenges and Considerations:

While the application of the maximum likelihood method for community detection in social networks offers significant potential for marketing, it also presents challenges. Ensuring the privacy and security of user data is paramount, as is the need for sophisticated algorithms capable of handling the dynamic and evolving nature of social networks. Additionally, marketers must be mindful of the ethical implications of targeted advertising and influencer marketing, ensuring that their strategies are transparent and respectful of user autonomy.

Practical Example: Fitness App Company Utilizing Community Detection for Marketing

A fitness app company, FitLife, wants to enhance its marketing strategy by targeting two distinct communities within its social network: those interested in weight loss and those focused on muscle building. To achieve this, FitLife employs the maximum likelihood method for community detection.

Data Collection and Analysis: FitLife analyzes user interactions on its social media platforms, including likes, comments, and shares related to their content. By applying the maximum likelihood method, the company identifies patterns in the data that suggest the presence of two primary communities: one group primarily engages with content related to weight loss tips, healthy eating, and cardio exercises, while the other group shows a strong interest in content related to strength training, protein supplements, and muscle gain.

Community Detection and Segmentation: The maximum likelihood method allows FitLife to quantify the strength of connections between users and the probability that they belong to one of the two identified communities. This statistical approach ensures that the division is not arbitrary but based on the underlying structure of the network and the interactions between users.

Targeted Marketing Strategies: With the communities clearly defined, FitLife tailors its marketing campaigns to cater to the specific interests of each group. For the weight loss community, the company promotes features of the app that track calorie intake, offer healthy recipes, and suggest fat-burning workouts. For the muscle-building community, FitLife highlights the app's strength training programs, progress tracking for muscle gain, and partnerships with protein supplement brands.

Outcome and Adjustments: By monitoring the engagement levels and conversion rates from each campaign, FitLife assesses the effectiveness of its targeted marketing efforts. The company uses this feedback to refine its approach, ensuring that the content and promotions resonate with the respective communities and drive app subscriptions and usage.

Fitness app company FitLife tracked 12 participating communities and analyzed the connections between them. We describe the community in the form of a graph below:

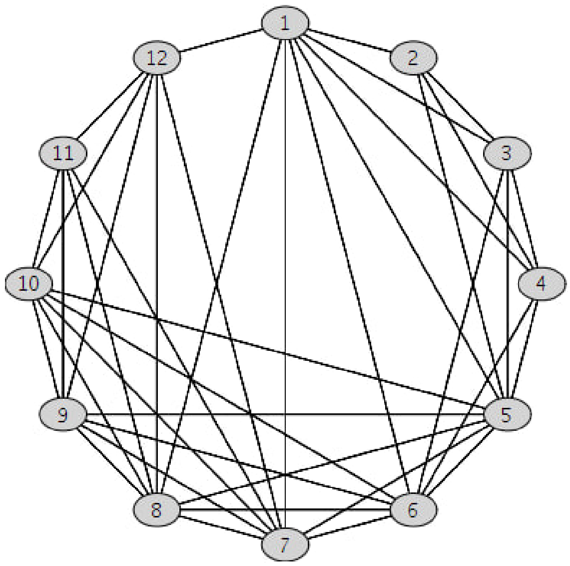


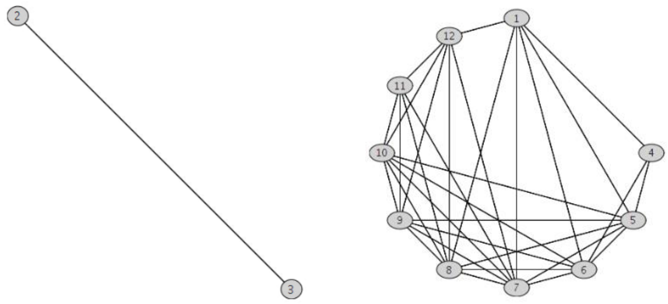
Fig.1. A community with 12 participants and 40 connections between them

If we divide the above community into 2 groups, then 5 types of division will occur. These are:

$$(6;6),(5;7),(4;8),(3;9),(2;10)$$

we calculate the value of the maximum likelihood function for each partition type:

A division of type (2;10) will have l_Π higher in the following case



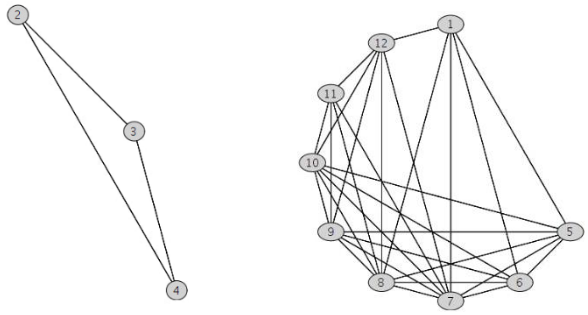
$$l_\Pi = 33\ln p_{in} + 13\ln(1-p_{in}) + 7\ln p_{out} + 13\ln(1-p_{out})$$

We differentiate by p_{in} and p_{out} and set to 0

$$p_{in} = \frac{33}{46}, p_{out} = \frac{7}{20}$$

$$l_\Pi(p_{in};p_{out}) = -40.33734585$$

A division of type (3;9) will have l_Π higher in the following case



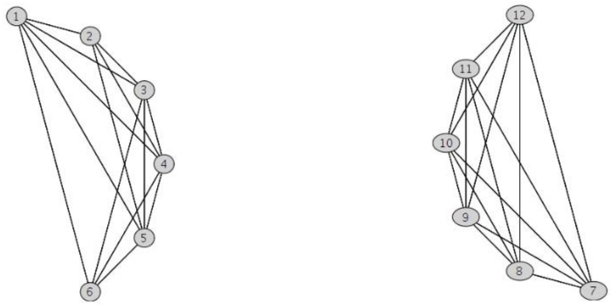
$$l_\Pi = 32\ln p_{in} + 7\ln(1-p_{in}) + 8\ln p_{out} + 19\ln(1-p_{out})$$

We differentiate by p_{in} and p_{out} and set to 0

$$p_{in} = \frac{32}{39}, p_{out} = \frac{8}{27}$$

$$l_\Pi(p_{in}; p_{out}) = -34.76170671$$

A division of type (6;6) will have l_Π higher in the following cas



$$l_\Pi = 29 \ln p_{in} + \ln(1 - p_{in}) + 11 \ln p_{out} + 25 \ln(1 - p_{out})$$

We differentiate by p_{in} and p_{out} and set to 0

$$p_{in} = \frac{29}{30}, p_{out} = \frac{11}{36}$$

$$l_\Pi(p_{in}; p_{out}) = -26.54228055$$

we present the values of the remaining types of partitions in the table below

Table 1. values of division types

№	division type	l_Π	value
1	$(2; 10)$	$l_\Pi = 33 \ln p_{in} + 13 \ln(1 - p_{in}) + 7 \ln p_{out} + 13 \ln(1 - p_{out})$	-40.33734585
2	$(3; 9)$	$l_\Pi = 32 \ln p_{in} + 7 \ln(1 - p_{in}) + 8 \ln p_{out} + 19 \ln(1 - p_{out})$	-34.76170671
3	$(4; 8)$	$l_\Pi = 30 \ln p_{in} + 4 \ln(1 - p_{in}) + 10 \ln p_{out} + 22 \ln(1 - p_{out})$	-32.18992293
4	$(5; 7)$	$l_\Pi = 29 \ln p_{in} + 2 \ln(1 - p_{in}) + 11 \ln p_{out} + 24 \ln(1 - p_{out})$	-29.20277214
5	$(6; 6)$	$l_\Pi = 32 \ln p_{in} + 7 \ln(1 - p_{in}) + 8 \ln p_{out} + 19 \ln(1 - p_{out})$	-26.54228055

As can be seen from Table 1, the value of the l_Π function of the division of the (6;6) type is high

This practical example demonstrates how dividing a social network into distinct communities using the maximum likelihood method can enable a company to implement more targeted and effective marketing strategies, leading to increased engagement and customer satisfaction.

Conclusion

The application of the maximum likelihood method for dividing social networks into two communities represents a powerful tool in the arsenal of modern marketers. By providing a deeper understanding of the complex web of social interactions, this approach enables the development of more targeted, effective, and personalized marketing strategies. As social media continues to evolve, leveraging advanced analytical techniques like community detection will be crucial for businesses seeking to stay ahead in the competitive world of marketing.

The advent of social media has ushered in a new era of marketing, where understanding the intricate web of connections within social networks is paramount. The maximum likelihood method for community detection represents a powerful tool in this context, offering marketers the ability to dissect these networks into distinct communities. By doing so, they can tailor their strategies to the unique preferences and characteristics of each group, resulting in more targeted, relevant, and effective marketing campaigns.

The applications of this method are vast, ranging from targeted advertising and influencer marketing to customer segmentation and product development. By leveraging the insights gained from community detection, businesses can enhance their competitive edge, foster deeper connections with their audience, and drive growth in an increasingly digital marketplace.

However, the journey is not without challenges. Marketers must navigate the ethical considerations of data privacy and the technical complexities of implementing advanced statistical methods. As the landscape of social media continues to evolve, staying ahead will require a commitment to innovation, a deep understanding of the latest analytical tools, and a dedication to ethical marketing practices.

In conclusion, the maximum likelihood method for community detection in social networks opens up a new frontier in marketing, offering a pathway to more personalized, data-driven strategies. As businesses embrace this approach, they unlock the potential to transform their marketing efforts, connect with their audience on a deeper level, and achieve greater success in the digital age.

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