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# EXPLORING ECONOMIC LANDSCAPES: DIVIDING SOCIAL NETWORKS INTO THREE COMMUNITIES USING THE MAXIMUM LIKELIHOOD METHOD

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***Annotatsiya***
*Ushbu maqola ijtimoiy tarmoqlarni uchta alohida jamoaga bo'lishda maksimal ehtimollik usulini qo'llashni o'rganadi va uning iqtisodiy tahlil uchun ta'siriga e'tibor beradi. Ushbu yondashuvdan foydalangan holda, iqtisodchilar ijtimoiy o'zaro munosabatlardagi yashirin naqshlarni ochib berishlari mumkin, bu esa bozorni aniqroq segmentatsiyalash, maqsadli marketing strategiyalari va xabardor siyosatni ishlab chiqish imkonini beradi. Usul, ayniqsa, asosiy ta'sir qiluvchilarni aniqlash va innovatsiyalar tarqalishi dinamikasini, moliyaviy tarmoqlar, mehnat bozorlari va iste'molchilarning xatti-harakatlarini tushunishda foydalidir. Maqolada amaliy misollar orqali ushbu uslub qanday qilib iqtisodiy landshaftlar haqida qimmatli tushunchalar berishi, murakkab iqtisodiy tizimlar haqidagi tushunchamizni kengaytirishi va samaraliroq iqtisodiy strategiyalar haqida ma'lumot berishi mumkinligini ko'rsatadi.*

***Аннотация***
*В этой статье исследуется применение метода максимального правдоподобия для разделения социальных сетей на три отдельных сообщества с акцентом на его последствия для экономического анализа. Используя этот подход, экономисты могут выявить скрытые закономерности в социальных взаимодействиях, что позволит более точно сегментировать рынок, разрабатывать целевые маркетинговые стратегии и принимать обоснованные решения. Этот метод особенно полезен для выявления ключевых факторов влияния и понимания динамики распространения инноваций, финансовых сетей, рынков труда и поведения потребителей. На практических примерах статья демонстрирует, как этот метод может дать ценную информацию об экономических ландшафтах, улучшая наше понимание сложных экономических систем и информируя о более эффективных экономических стратегиях.*

***Abstract***

*This article explores the application of the maximum likelihood method in dividing social networks into three distinct communities, with a focus on its implications for economic analysis. By leveraging this approach, economists can uncover hidden patterns in social interactions, enabling more precise market segmentation, targeted marketing strategies, and informed policy-making. The method is particularly useful in identifying key influencers and understanding the dynamics of innovation diffusion, financial networks, labor markets, and consumer behavior. Through practical examples, the article demonstrates how this technique can provide valuable insights into economic landscapes, enhancing our understanding of complex economic systems and informing more effective economic strategies.*

***Kalit so'zlar***

*Ijtimoiy tarmoqlar, Maksimal ehtimollik usuli, Iqtisodiy, Tahlil, Bozor segmentatsiyasi, Innovatsiyalarning tarqalishi, Moliyaviy tarmoqlar, Mehnat bozorlari, Iste'molchilarning xulq-atvori, Maqsadli marketing, Tarmoq hamjamiyatlari.*

***Ключевые слова***

*Социальные сети, Метод максимального правдоподобия, Экономика, Анализ, Сегментация рынка, Распространение инноваций, Финансовые сети, Рынки труда, Поведение потребителей, Целевой маркетинг, Сетевые сообщества.*

***Keywords***

*Social Networks, Maximum Likelihood Method, Economic, Analysis, Market Segmentation, Innovation Diffusion, Financial Networks, Labor Markets, Consumer Behavior, Targeted Marketing, Network Communities.*

## Introduction

In the intricate tapestry of economics, understanding the nuanced interplay of social interactions is paramount for deciphering the underlying dynamics of markets, consumer behavior, and the propagation of innovations. The advent of social network analysis has equipped researchers with a potent tool to unravel the complexities of economic systems, shedding light on the interconnectedness that governs economic phenomena. Among the various methodologies employed in this domain, the maximum likelihood approach to partitioning social networks into distinct communities stands out as a particularly insightful technique, offering a window into the hidden structures of social and economic interactions [2,3].

This article delves into the application of the maximum likelihood method for dividing social networks into three communities, a process that unveils the latent patterns within social networks and provides a framework for understanding economic behaviors at a granular level. By identifying cohesive groups within larger networks, this approach facilitates a deeper comprehension of market segmentation, enabling targeted marketing strategies and informed policy-making [4,5].

The ensuing sections will explore the theoretical underpinnings of this method, its practical applications in various economic domains, and the challenges and opportunities it presents. Drawing on seminal works in the field [6,7,8], this article aims to provide a comprehensive overview of how the division of social networks into communities using the maximum likelihood method can enhance our understanding of economic landscapes and inform more effective economic strategies. Through a blend of theoretical insights and real-world examples, we will demonstrate the transformative potential of this approach in shaping our understanding of the economic world.

The following sections will explore the theoretical underpinnings of this method, its practical applications in various economic domains, and the challenges and opportunities it presents. Through a blend of theoretical insights and real-world examples, this article aims to provide a comprehensive overview of how dividing social networks into communities using the maximum likelihood method can enhance our understanding of economic landscapes and inform more effective economic policies and strategies.

## Theoretical Background

1. Social Network Analysis: Social network analysis (SNA) is a methodological approach used to understand the relationships and interactions within a network of individuals, groups, or organizations. It involves the mapping and measuring of connections and flows between entities, with the aim of uncovering patterns and dynamics within social structures.

2. Community Detection in Social Networks: Community detection is a key task in social network analysis, which involves identifying clusters or groups within a network where members are more closely connected to each other than to those outside the group. These communities often represent real-world social structures, such as friendship circles, professional networks, or interest groups.

3. Maximum Likelihood Method: The maximum likelihood method is a statistical approach used to estimate the parameters of a model that best fit a given set of data. In the context of community detection, it involves finding the partition of the network into communities that maximizes the likelihood of the observed network structure, given a specific model of how connections are formed within and between communities.

4. Modularity and Likelihood Models: One common approach to community detection is to maximize a measure called modularity, which quantifies the strength of division of a network into communities. However, modularity has limitations, such as a resolution limit that can prevent the detection of smaller communities. The maximum likelihood method can overcome some of these limitations by using more flexible models that can incorporate additional information about the network, such as the expected number of connections within and between communities.

5. Stochastic Block Models: A popular class of models used in the maximum likelihood approach is stochastic block models (SBMs). These models assume that the probability of a connection between two nodes depends on the communities to which they belong. By fitting an SBM to a network, one can infer the most likely community structure. The model can be extended to accommodate different types of networks, such as weighted, directed, or multilayer networks.

6. Computational Challenges: The process of finding the maximum likelihood partition of a network is computationally challenging, especially for large networks. Various algorithms and heuristics have been developed to approximate the solution, including expectation-maximization algorithms, spectral clustering, and variational inference methods.

7. Model Selection and Validation: Determining the number of communities and assessing the quality of the detected community structure are important aspects of the analysis. Techniques such as Bayesian model selection, cross-validation, and comparison with known or benchmark structures can be used to validate the results.

The theoretical background of dividing social networks into communities using the maximum likelihood method involves a blend of social network analysis, statistical modeling, and computational techniques. By leveraging these concepts, researchers can uncover meaningful patterns in social networks, providing insights into the underlying social dynamics and informing various applications in economics and other fields.

## Application to Economics

1. Market Segmentation: By dividing a social network into three communities, economists can identify distinct market segments, each characterized by unique preferences, behaviors, and needs. This granular understanding enables businesses to tailor their products, pricing, and marketing strategies to better align with the specific characteristics of each segment, thereby enhancing market efficiency and customer satisfaction.

2. Innovation Diffusion: Understanding the community structure of social networks is crucial for modeling the spread of new ideas, technologies, or products. By identifying key influencers and bridges between communities, economists can devise more effective strategies for promoting the adoption of innovations, ultimately accelerating their diffusion across markets.

3. Financial Networks: In the realm of finance, dividing social networks into communities can shed light on the interconnectedness of financial institutions and the potential for systemic risk. By identifying closely knit communities within the financial network, policymakers and regulators can better monitor and manage the propagation of financial shocks, enhancing the stability of the financial system.

4. Labor Market Dynamics: The division of social networks into communities can also provide insights into labor market dynamics, such as the flow of information about job opportunities and the formation of professional networks. Understanding these community structures can inform policies aimed at improving labor market efficiency and reducing unemployment.

5. Consumer Behavior Analysis: The segmentation of social networks into distinct communities allows economists to study consumer behavior patterns in greater detail. By analyzing the interactions and influence within and between these communities, businesses can gain a deeper understanding of consumer decision-making processes and develop more targeted marketing strategies.

## Challenges and Future Directions

While the application of the maximum likelihood method to divide social networks into communities offers promising opportunities for economic analysis, it also presents challenges, including data privacy concerns, computational complexity, and the need for robust models that can accommodate the dynamic nature of social networks. Future research in this area may focus on developing more sophisticated algorithms, exploring the implications of community structures for economic resilience, and integrating this approach with other data-driven techniques to enrich economic models.

Practical Examples Across Various Economic Fields:

1. Market Segmentation in Retail Industry: - Example: A retail company uses social network analysis to segment its customer base into three communities:

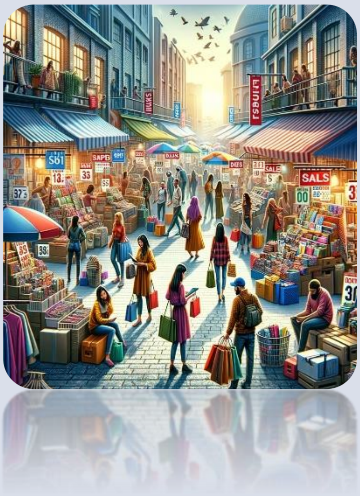
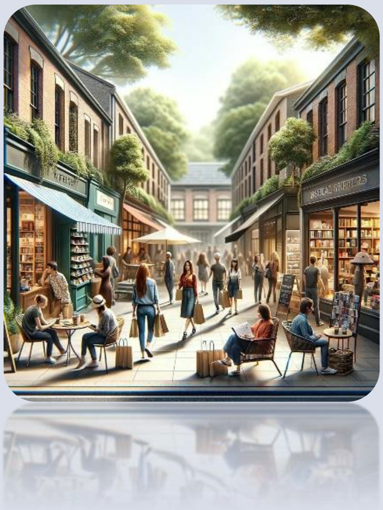
| ***PREMIUM SHOPPERS*** | ***BUDGET-CONSCIOUS CONSUMERS*** | ***OCCASIONAL BUYERS*** |
|---|---|---|
|  |  |  |

**Fig.1. Dividing the customer base into three communities**

Application: By understanding the characteristics and preferences of each community, the company tailors its marketing strategies, product offerings, and promotions to effectively target each segment, leading to increased sales and customer loyalty.

2. Innovation Diffusion in Technology Sector:

Example: A tech startup launching a new app divides its user base into three communities: early adopters, tech enthusiasts, and mainstream users.

Application: By identifying key influencers within each community, the startup focuses its marketing efforts on these individuals to accelerate the adoption of the app across the network, resulting in faster market penetration.

3. Financial Network Analysis in Banking:

Example: A bank analyzes its network of customers and identifies three communities: high-net-worth individuals, middle-income families, and small business owners.

Application: By understanding the financial needs and behaviors of each community, the bank develops tailored financial products and services, such as exclusive investment opportunities for high-net-worth individuals, family savings plans for middle-income families, and loan packages for small business owners.

4. Labor Market Dynamics in Human Resources:

Example: A large corporation divides its employee network into three communities: senior management, mid-level employees, and entry-level staff.

Application: By recognizing the distinct needs and influence patterns of each community, the company designs targeted professional development programs, communication strategies, and team-building activities to enhance collaboration and productivity across all levels of the organization.

5. Consumer Behavior Analysis in E-commerce:

Example: An e-commerce platform segments its user network into three communities: frequent shoppers, occasional buyers, and window shoppers.

Application: By analyzing the purchasing patterns and browsing behaviors of each community, the platform personalizes product recommendations, optimizes user experience, and implements targeted advertising campaigns to convert window shoppers into buyers and increase repeat purchases among frequent shoppers.

These examples demonstrate the practical application of dividing social networks into three communities using the maximum likelihood method across different economic fields. By leveraging this approach, businesses and organizations can gain deeper insights into their networks, enabling them to develop more effective strategies and achieve better outcomes.

## Graphing Social Networks in Economic Analysis

Here's how graphing social networks is integrated into the analysis:

1. Visualization of Network Structure: Graphing social networks allows economists to visually represent the structure of relationships between individuals, organizations, or entities. Nodes in the graph represent the actors within the network, while edges depict the connections or interactions between them. This visual representation helps in identifying patterns, clusters, and key influencers within the network.

2. Identification of Communities: By applying the maximum likelihood method to the graphed social network, economists can identify communities within the network where members are more closely connected to each other than to those outside the group. These communities are often represented by different colors or shapes in the graph, making it easier to distinguish between them.

3. Analysis of Economic Behaviors: Graphing social networks enables the analysis of economic behaviors within and between communities. For example, in market segmentation, the graph can reveal how different communities interact with a brand or product. In innovation diffusion, it can show how a new technology spreads through different segments of the network.

4. Evaluation of Network Metrics: Graphing social networks allows for the calculation of various network metrics, such as degree centrality, betweenness centrality, and modularity. These metrics provide insights into the importance of nodes, the role of connectors or bridges between communities, and the overall strength of community division within the network.

5. Dynamic Analysis: Graphing social networks also enables dynamic analysis, where economists can observe changes in the network structure over time. This is particularly useful in understanding how economic events, such as financial crises or market trends, impact the relationships and behaviors within the network.

6. Communication and Presentation: Graphs provide a clear and intuitive way to communicate complex network structures and findings to stakeholders, policymakers, and the general public. They can be used in reports, presentations, and publications to illustrate the economic insights derived from the analysis of social networks.

We use the maximum likelihood method for clustering given in [1].

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

In the article we consider the division of community S into three communities, then formula (1) looks like this:

$$l_{\Pi} = (m_1+m_2+m_3)logp_{in} + \left(\frac{n_1^2+n_2^2+n_3^2-n}{2} - (m_1+m_2+m_3)\right) log(1-p_{in}) + \left(m-(m_1+m_2+m_3)\right)logp_{out} + \left(n_1n_2n_3 - m + (m_1+m_2+m_3)\right)log(1-p_{out})$$

The appearance of $p_{in}$ and $p_{out}$ looks like this:

$$p_{in} = \frac{2(m_1+m_2+m_3)}{n_1^2+n_2^2+n_3^2-n}, p_{out} = \frac{m-(m_1+m_2+m_3)}{n_1n_2n_3}.$$

let us be given a social network of the following form

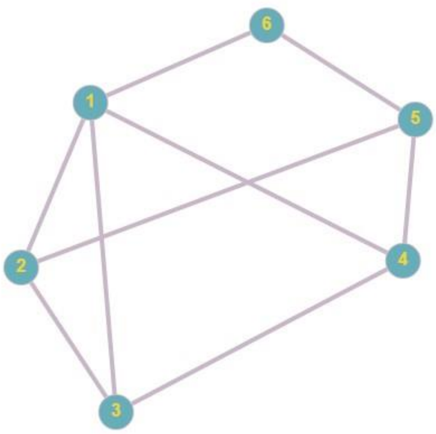



**Fig.2. A social network with 6 vertices and 9 edges**

We will divide the social network given above into 3 groups.

When we divide into 3 teams, each group will have 2 participants, so:

$$n_1 = 2, n_2 = 2, n_3 = 2$$

Since there are 2 participants in each team, there is 1 connection between them, so:

$$m_1 = 1, m_2 = 1, m_3 = 1$$

We calculate $l_\Pi$

$$l_\Pi = 3logp_{in} + 6logp_{out} + 2log(1 - p_{out})$$

We differentiate it by $p_{in}$ and $p_{out}$ and equate it to zero. Having resolved the resulting system of equations, we find probability estimates and the value of the likelihood function, which gives

$$p_{in} = 1, p_{out} = \frac{3}{4}$$

then

$$l_\Pi = 6log\frac{3}{4} + 2log\left(1 - \frac{3}{4}\right) \approx -4.5$$

Graphing social networks is an essential component. It provides a powerful tool for visualizing, analyzing, and communicating the intricate web of relationships that underpin economic systems, thereby enhancing our understanding of economic phenomena and informing decision-making processes.

## Conclusion

The application of the maximum likelihood method to divide social networks into three communities has opened new avenues for economic analysis and strategic decision-making. By unraveling the complex structures of social networks, this approach enables a deeper understanding of market dynamics, consumer behavior, and the diffusion of innovations. The ability to identify and analyze distinct communities within larger networks allows economists and businesses to tailor their strategies more effectively, whether it be in market segmentation, targeted marketing, financial risk management, or policy formulation.

Despite its potential, the method is not without challenges. Computational complexity, data privacy concerns, and the dynamic nature of social networks pose hurdles to its implementation. However, ongoing advancements in computational techniques and data analytics are continuously improving the feasibility and accuracy of this approach.

As we move forward, the integration of the maximum likelihood method with other analytical tools and the exploration of its applications in emerging economic fields hold promise for further enriching our understanding of economic phenomena. The insights gained from dividing social networks into communities will undoubtedly continue to play a pivotal role in shaping economic theories, practices, and policies in an increasingly interconnected world.

In conclusion, the exploration of economic landscapes through the lens of social network communities using the maximum likelihood method represents a significant step forward in our quest to decode the complexities of economic systems. It not only enhances our analytical capabilities but also opens up new possibilities for innovation and growth in the ever-changing economic landscape.

## References


1. Мазалов В. В., Никитина Н. Н. Метод максимального правдоподобия для выделения сообществ в коммуникационных сетях //Вестник Санкт-Петербургского университета. Прикладная математика. Информатика. Процессы управления. – 2018. – №. 3. – С. 200-214.
2. Newman, M. E. J. (2006). Modularity and community structure in networks. Proceedings of the National Academy of Sciences, 103(23), 8577-8582.
3. Fortunato, S. (2010). Community detection in graphs. Physics Reports, 486(3-5), 75-174.
4. Karrer, B., & Newman, M. E. J. (2011). Stochastic blockmodels and community structure in networks. Physical Review E, 83(1), 016107.
5. Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. Journal of Statistical Mechanics: Theory and Experiment, 2008(10), P10008.
6. Airoldi, E. M., Blei, D. M., Fienberg, S. E., & Xing, E. P. (2008). Mixed membership stochastic blockmodels. Journal of Machine Learning Research, 9, 1981-2014.
7. Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., ... & Van Alstyne, M. (2009). Life in the network: the coming age of computational social science. Science, 323(5915), 721-723.
8. Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications. Cambridge University Press.