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USING THE TOPIC OF DIVIDING SOCIAL NETWORKS INTO COMMUNITIES IN TEACHING THE TOPIC OF MATHEMATICAL STATISTICS TO STUDENTS OF THE ECONOMICS DEPARTMENT

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Annotation: This article explores the concept of dividing social networks into communities as a teaching method for the topic of mathematical statistics to students in the economics department. By incorporating real-world examples and applications, educators can enhance students' understanding of statistical concepts and their relevance in analyzing social network data. This approach helps students bridge the gap between theory and practical implementation, fostering a deeper appreciation for the role of statistics in economics.

Keywords: *social networks, communities, mathematical statistics, teaching, economics department, real-world examples, practical applications, statistical concepts, data analysis, theory, implementation.*

In the age of digitalization, social networks have become an integral part of our lives, serving as platforms for communication, information exchange, and community building. As these networks grow in size and complexity, the need to understand and analyze their structure becomes increasingly important. This is where the field of mathematical statistics comes into play, offering powerful tools and techniques for dissecting the intricate web of connections that make up social networks. In this article, we explore the innovative approach of using the topic of dividing social networks into communities as a teaching tool for students of the economics department, aiming to enhance their understanding of mathematical statistics and its real-world applications.

The Relevance of Social Network Analysis in Economics

Social network analysis (SNA) is a multidisciplinary approach that examines the structure and dynamics of social networks. It has found applications in various fields, including economics, where it is used to study market dynamics, consumer behavior, and the diffusion of information and innovation. By understanding the communities within social networks, economists can gain insights into how individuals and groups interact, make decisions, and influence each other.

Integrating SNA into Mathematical Statistics Curriculum

To effectively teach mathematical statistics to economics students, it is essential to demonstrate the practical relevance of statistical methods. By incorporating SNA into the curriculum, educators can provide students with a tangible context in which to apply statistical concepts. For example, students can learn about clustering algorithms, such as k-means or hierarchical clustering, by applying them to divide social networks into communities. This hands-on approach not only reinforces their understanding of statistical techniques but also illustrates their applicability in analyzing real-world economic phenomena[1,2,4].

Case Study: Community Detection in Social Networks

Objective: The goal of this case study is to demonstrate the application of community detection algorithms to identify distinct groups within a social network. By analyzing the structure of these communities, students can gain insights into the behavior and interactions of individuals within the network.

Dataset: The dataset used for this case study consists of a social network represented as a graph, where nodes correspond to individuals and edges represent relationships or interactions between them. The dataset can be a real-world social network, such as a network of friends on a social media platform, or a simulated network designed to exhibit certain characteristics.

Methodology:

1. Data Preparation: Load the social network dataset and represent it as a graph. Ensure that the data is clean and formatted appropriately for analysis.

2. Exploratory Analysis: Perform initial exploration of the network to understand its basic properties, such as the number of nodes (individuals), the number of edges (relationships), and the distribution of node degrees (number of connections per individual).

3. Community Detection: Apply community detection algorithms to partition the network into communities. Common algorithms used for this purpose include:

- Modularity-Based Methods: These methods, such as the Louvain algorithm, aim to maximize modularity, a measure that quantifies the strength of division of a network into communities.

- Spectral Clustering: This approach uses the eigenvalues and eigenvectors of the network's adjacency matrix to identify communities.

- Hierarchical Clustering: This method builds a hierarchy of communities by iteratively merging or splitting groups based on their similarity.

4. Analysis of Communities: Analyze the resulting communities to understand their characteristics and significance. Key questions to address include:

- How many communities were detected?

- What are the sizes of the communities?

- Are there any notable patterns or structures within the communities, such as densely connected subgroups or central nodes?

5. Interpretation and Implications: Discuss the implications of the community structure for understanding the behavior and dynamics of the social network. For example, communities might represent groups of individuals with similar interests, social circles, or organizational structures.

The case study of community detection in social networks provides a practical application of mathematical statistics and graph theory in analyzing complex social structures. By identifying and studying the communities within a network, students can develop a deeper understanding of the underlying patterns and dynamics that govern social interactions. This exercise not only enhances their analytical skills but also prepares them for tackling real-world problems in economics and other social sciences. Enhancing Critical Thinking and Data Analysis Skills[3,5,6]

By tackling real-world problems such as community detection in social networks, students are encouraged to think critically about the data and the methods they use. They learn to question assumptions, interpret results, and consider the limitations of their analysis. This not only strengthens their statistical reasoning skills but also prepares them for the challenges of data-driven decision-making in the economic realm.

Practical Example: Analysis of a University Social Network

Background:

A university wants to understand the social dynamics among its students to improve campus life and student engagement. The university has collected anonymized data from its social media platform, which includes information on friendships and interactions among students.

Objective:

The objective is to use community detection algorithms to divide the university's social network into communities and analyze the characteristics of these communities to gain insights into student social dynamics.

Step 1: Data Preparation

The dataset consists of a list of pairs of student IDs, representing friendships between students. The data is loaded into a graph structure, where nodes represent students and edges represent friendships.

Step 2: Exploratory Analysis

Basic properties of the network are analyzed:

- Number of students (nodes): 1,000

- Number of friendships (edges): 4,500

- Average number of friends per student (average degree): 9

Step 3: Community Detection

The Louvain algorithm is applied to detect communities within the network. The algorithm identifies 6 distinct communities, varying in size from 50 to 300 students.

Step 4: Analysis of Communities

Key characteristics of the communities are analyzed:

- Community Sizes: The sizes of the communities are examined to understand the distribution of social groups within the university.

- Inter-Community Connections: The number of friendships between members of different communities is analyzed to assess the level of social integration across the campus.

- Intra-Community Connections: The density of friendships within each community is studied to gauge the cohesiveness of social groups.

Step 5: Interpretation and Implications

The analysis reveals interesting insights into the university's social dynamics:

- Diverse Social Groups: The presence of multiple communities indicates a diverse range of social groups among students.

- Social Integration: The number of inter-community connections suggests a moderate level of social integration across different groups.

- Cohesive Communities: The high density of intra-community connections indicates that the communities are cohesive and likely represent close-knit social circles or interest groups.

The practical example of analyzing a university social network demonstrates the application of community detection algorithms in understanding social dynamics. By dividing the network into communities and analyzing their characteristics, valuable insights can be gained into student interactions and social cohesion. This exercise not only provides a real-world context for teaching mathematical statistics to economics students but also highlights the relevance of statistical methods in addressing practical problems in social sciences.

Conclusion

Incorporating the topic of dividing social networks into communities into the teaching of mathematical statistics for economics students offers a unique opportunity to bridge theory and practice. By providing a concrete application of statistical methods, educators can enhance students' understanding of the subject matter, foster critical thinking, and equip them with valuable skills for analyzing complex economic systems. As social networks continue to play a pivotal role in our economy, the ability to analyze and interpret their structure will become an increasingly valuable asset for the next generation of economists.

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