

APPLICATION OF MAXIMUM LIKELIHOOD METHOD FOR DIVIDING COMMUNITIES INTO THREE IN ECONOMICS

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Annotation: *This informative article explores the novel application of the Maximum Likelihood Estimation (MLE) method in the context of social networks from an economic perspective. It discusses the problem of classifying users of a social network into three distinct economic groups. It explains how MLE facilitates the identification of these groups by maximizing the likelihood of the observed data given certain parameters. By iterating and modifying group assignments and parameter estimates, MLE effectively segments markets and facilitates detailed investigations and targeted interventions. The article provides a practical problem and solution approach with numerical examples furthering the understanding of MLE's application in economic community segmentation.*

Keywords: *Maximum Likelihood Estimation, Social Networks, Economic Classifications, Market Segmentation, Gaussian Mixture Model, Probabilistic Model, User Classification, Economic Communities, Network Graph, Optimization Process, Community Membership.*

INTRODUCTION

The Maximum Likelihood Estimation (MLE) is the cornerstone of theoretical perspectives in applied statistics, often acting as the basis for many standard statistical methodologies, including linear regression, logistic regression, and survival analysis, amongst others. The method revolves around the determination of the 'most likely' parameters for a given statistical model, deriving its principles from complex probability theory formulas. However, beyond its dense theoretical matrix, MLE finds its roots in real-world applications across various disciplines, one of which is economics.

The MLE fundamentally represents an approach used to estimate the parameters of a statistical model. It achieves this feat by maximizing a likelihood function to achieve the parameter values, consequently making the observed data most probable under the model dynamics. Given a sample dataset, the method strives to find the parameter values that render the sample outcome likeliest. In essence, the MLE method seeks to answer the question: what values upon substitution into the statistical model will make the data

observed the most likely outcome? Hence, it involves working 'backwards', as it seeks to find the parameter values that generate the likeliest dataset.

While the Maximum Likelihood Estimation may find its basis in mathematics and probability theory, it offers practical applications in the realm of economics. When it comes to partitioning communities—be it geographical, social, or economic—into distinct clusters, the MLE plays a pivotal role. By invoking this method, economists can divide large communities into three segments, allowing for precise analyses of each segment's behavior, their influence on the economic cycle, and how they respond to specific policy adaptations.

Accordingly, understanding the Maximum Likelihood estimation method's role in economics requires delving into the principal aspects of community structures in economic analysis. Economists must analyze a multitude of variables, from income distribution and resource allocation to impact assessment of government policies, pricing strategies, and more. The larger the community, the more complex such analyses become. Herein lies the MLE method's essence, as it affords economists with an effective tool for dividing an extensive community into three smaller, manageable, and cohesive subgroups, thereby facilitating the implementation of effective and context-specific economic strategies and policies.

UNDERSTANDING THE MAXIMUM LIKELIHOOD METHOD

The Maximum Likelihood Estimation (MLE) is a statistical technique utilized for estimating the parameters of a statistical model, given a dataset. At its core, it is founded on the notion of 'likelihood', which in simple terms refers to the compatibility of observed data with a statistical model. Essentially, the likelihood of a parameter value given observed data is the probability of obtaining that dataset, assuming the particular parameter value is the correct one.

The goal of MLE is to find the set of values for the model parameters that maximize this likelihood function. In other words, it identifies the parameter values that would make the observed data the most probable occurrence. It is crucial to note that while probability typically predicts outcomes before they happen, the likelihood, on the other hand, is used after the data has been obtained to measure the compatibility of different parameter values with the observed data.

Let's consider an everyday example to better understand the process. Suppose you flip a coin ten times, and it lands on heads eight times. If you are trying to determine the probability of the coin landing on heads, you could assign different parameter values to the probability of getting heads (For instance, 0.1, 0.5, or 0.8). Using the likelihood concept, you can then ask: given the parameters, what is the likelihood of observing a dataset with eight heads out of ten tosses? In this case, the MLE would suggest 0.8 to be the most likely parameter value.

The application of MLE typically follows a systematic four-step process: first, one has to specify the statistical model (probabilistic function) and the parameters that need to be

estimated. Second, construct and express the likelihood function in terms of unknown parameters for the given data. Third, find parameter values that maximize the likelihood function. Lastly, one has to justify and interpret the estimates.

By maximizing the likelihood function, one determines the most probable set of parameters that best explains the variability in the dataset and thus derive the maximum likelihood estimates. The MLE approach assumes that the data follows a specific probability distribution, such as normal distribution, binomial distribution, etc., and it is this set of assumptions that are specified in the statistical model used in MLE calculations. These MLE parameters shape the description of our population and explain trends and patterns within the analyzed data.

In conclusion, the Maximum Likelihood Method is a powerful statistical tool that aids us in parameter estimation. By understanding the concept of likelihood and maximizing this likelihood given a certain dataset, we can derive a statistical model with parameters that make our observed data the most probable occurrence.

APPLICATION IN ECONOMICS

Expanded Application in Economics: The Maximum Likelihood Estimation (MLE) has found extensive use in the field of economics, providing pragmatic solutions to some of the discipline's most pressing challenges. Specifically, this estimation method has proven invaluable in dividing communities into manageable segments for more nuanced and accurate economic analysis.

Macro and Microeconomic Analysis: In macroeconomic analysis, the MLE method comes into play in the strategic division of large economic communities. Economists could, for instance, divide a single community into three segments such as capital providers (investors, banks, etc.), goods/service producers (companies, industries), and consumers. By creating these distinct groups, economists can achieve a better understanding of how resources, wealth, and goods/services flow within an economy.

Capital providers are essential for the investment in businesses, which in turn produce goods/services. The consumers are those that spend their resources (money) on these goods/services, thus fulfilling the cycle. With these distinct segments, one can then delve deeper into each group's economic behaviors, predict future trends, analyze government policies on each cluster and so forth.

In microeconomics, where the focus is on individual and group behavior in response to particular economic variables, the MLE method holds equal relevance. The overall community could be divided into three income-based segments, namely low income, middle income, and high income. These divisions allow economists to specifically analyze different strata of society.

By analyzing the spending habits, savings, investment behaviors of each income class, it is possible to tailor economic policies that cater to the needs of each group. For example, different tax policies might be suitable for different income levels, and thus the division into these categories is crucial.

MLE and Economic Forecasting: Economic forecasting also reaps the benefits of the MLE method. By understanding the parameters that maximize the likelihood of a specific economic model, economists can forecast future trends, resources allocation, economic growth rate, etc., using historical data accurately.

MLE assists in understanding the probability distributions that govern the behaviors of economic variables such as income, consumption, inflation, unemployment, etc., thereby enabling economists to construct models and make predictions about future states of the economy.

MLE tools can capture the dynamic relations between different groups, allowing policymakers to devise strategies that adapt to changes within an economy. For example, by understanding what parameters influence the spending habits of a middle-income class, policies can be devised that exploit these parameters to stimulate economic growth.

In conclusion, the Maximum Likelihood Estimation method is an instrumental tool in economics. Its ability to determine the most probable parameters for observed data facilitates the division of communities into meaningful segments, enriching the overall economic analysis, and improving the efficiency of policy design and implementation.

ADVANTAGES OF MLE USE IN ECONOMICS

The Maximum Likelihood Estimation (MLE) method offers an array of substantive benefits to the discipline of economics, making it integral to both micro and macroeconomic analysis. Here are some of the key advantages.

1. Enhanced Accuracy and Precision: MLE provides an exacting approach to estimating economic parameters. By characterizing the parameters that render observed results the most likely, MLE reduces the margin of error in economic projections and forecasts.

2. Comprehensive Economic Analysis: By breaking down broad economic cohorts into manageable and coherent subgroups, MLE enriches the breadth and depth of economic investigation. Such stratification enables economists to tailor unique analyses for each group, thereby gleaning a finer understanding of their specific economic behaviors and responses.

3. Predictive Power: MLE shines in predictive modeling, which is vital in economics. Economists can use MLE to build models that optimally predict future outcomes based on historical data. These models help plan economic strategies and deliver insights into future economic situations.

4. Maximizing Economies of Scale: The partitioning of communities facilitated by MLE steers toward more efficient resource allocation, allowing economies to better achieve economies of scale. Identifying the parameters that maximize likelihoods can help gauge how to distribute resources within and among communities for optimal economic impact.

5. Robust Statistical Framework: The MLE method sits atop a robust statistical foundation, drawing on probability theory and statistical analysis. This rigor enables MLE to

address many complex, real-world economic problems and relay statistically sound solutions.

6. Policy Effectiveness: The application of MLE in economics contributes to the creation and implementation of effective economic policies. With MLE, policy makers can better understand the probable impacts of their policies on different community segments and adjust strategies accordingly.

7. Flexibility and Generality: MLE is a versatile method that can handle different types of distributional assumptions and data types, making it applicable to a wide array of economic questions, models, and scenarios.

Overall, the Maximum Likelihood Estimation method offers invaluable advantages in economic theory and practice. By maximizing the likelihood of observing given economic data, MLE promotes more accurate, efficient, and context-specific economic analyses and policies, thereby enhancing the overall discipline of economics.

Suppose we have an anonymized dataset from Facebook.



We've decided to use two key user metrics: post frequency per day (pf) and daily active usage time (au). The data is shown in the table below for four users:

User	pf (posts/day)	au (hours/day)
1	10	5
2	20	7
3	5	2
4	30	8

We hypothesize these metrics can infer user income levels.

High-income users are assumed to post less and use less active usage time due to their busy lifestyle.

Middle income are moderate in both metrics, and low-income users have high post frequency and active usage time due to more free time.

We use MLE to estimate the parameters (means and variances of a Gaussian distribution in this case) of the three



income groups. We initialize by randomly assigning users to each group and computing the means and variances.

Let's say Users 1 and 2 fall in the low-income category, User 3 in middle-income, and User 4 in the high-income.

Low-Income

$$[Mean(pf, au) = (15, 6);$$

$$Variance(pf, au) = \left(\frac{(10^2 + 20^2)}{2}, \frac{(5^2 + 7^2)}{2} \right) = (250, 37)]$$

$$\textbf{Middle-Income} [Mean(pf, au) = (5, 2); Variance(pf, au) = (0, 0)]$$

$$\textbf{High-Income} [Mean(pf, au) = (30, 8); Variance(pf, au) = (0, 0)]$$

We then evaluate the likelihood that the data for each user was produced by the three distributions. If a user's data has a higher likelihood under a different group than current, we switch the user to that group.

This process is repeated until the group mean and variance are relatively stable - signifying we've found the grouping that maximizes the likelihood of the observed data.

The final result might yield something like:

$$\text{Low-Income} [Mean(pf, au) = (20, 7), Variance(pf, au) = (50, 1)]$$

$$\text{Middle-Income} [Mean(pf, au) = (10, 5), Variance(pf, au) = (0, 0)]$$

$$\text{High-Income} [Mean(pf, au) = (5, 2), Variance(pf, au) = (0, 0)]$$

Based on this classification, Facebook can develop more targeted advertising strategies for its users.

In conclusion, the Maximum Likelihood Estimation presents a potentially transformative tool for economic analyses, aiding both micro and macro-economic studies' accuracy and precision. By bridging the realm of statistics with the practical world of economics, the MLE method symbolizes a valuable resource, particularly for partitioning broader communities into smaller, manageable segments. This affords policymakers and economists alike, the opportunity to craft more encompassing and effective economic policies and strategies.

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