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BAYESIAN STATISTICS IN MARKETING

Abstract: Every decision in marketing, whether strategic, tactical, or operational in nature, should be based on a previously conducted analysis or research, with collected data processed using appropriate statistical methods. Accordingly, this paper presents two fundamental statistical approaches: the frequentist and the Bayesian approach. While the frequentist approach is based on the measurable frequency of events, Bayesian inference, among other features, enables the incorporation of prior information into the analysis process. Starting from the limitations of frequentist statistics, the focus of the paper is placed on Bayesian inference and its key advantages. Special attention is devoted to the analysis of the application of the Bayesian approach in marketing, through the review of selected studies in which it has been used to address various marketing-related problems.

Keywords: Bayesian Approach, Frequentist Approach, Marketing

1. INTRODUCTION

In contemporary market conditions, where even the smallest change in the environment can cause significant difficulties in business operations, special attention must be paid to the decision-making process. This is particularly evident in the field of marketing, given the increasingly intense competition and the growing demands of consumers, whose behavior is often difficult to predict. Marketing managers are increasingly faced with complex situations that require an analytical approach and consideration of a large number of interrelated factors. In this context, making high-quality decisions should be based on previously conducted detailed analyses, i.e., research. In addition to collecting relevant and reliable data, the quality of decisions largely depends on the choice of an appropriate statistical approach to data processing.

Although it still represents one of the commonly used approaches, frequentist inference has certain limitations that may reduce its applicability in complex marketing problems. As a potential alternative, the Bayesian approach is attracting increasing attention and is already being widely applied in marketing research. In this regard, the paper first explains frequentist inference, highlighting its main shortcomings. It then presents the fundamentals of Bayesian inference and its key advantages. Special attention is devoted to reviewing studies in the field of marketing in which the Bayesian approach has been successfully applied.

2. LIMITATIONS OF THE FREQUENTIST APPROACH

From the perspective of the frequentist approach, probability is interpreted as the long-run frequency of a "repeatable" event, that is, as a measurable frequency of occurrence determined on the basis of repeated experiments (Vallverdú, 2008, p. 5). Since uncertainty regarding parameters is of an epistemic nature, frequentist inference does not yield probabilistic statements about the parameters of a statistical process, which can be illustrated by the example of confidence intervals (Wagenmakers et al., 2008, p. 2). A frequentist 95% confidence interval for the normal mean μ equal to [-0.5, 1.0] does not imply that there is a 95% probability that μ lies within this interval; rather, it means that in a long sequence of repeated applications of the same confidence interval construction procedure on different datasets, in 95% of cases the true value of μ would be captured by the corresponding confidence interval.

In the literature, two main frequentist approaches are typically distinguished – Fisher's approach based on the p-value, and the approach based on the significance level (α-level), formulated by Neyman and Pearson. Although there are important conceptual differences between these approaches, in contemporary research practice they are often combined, so that the p-value is simultaneously interpreted both as a measure of evidence and as a rate of repeatable error (Wagenmakers et al., 2008, pp. 2-3). With regard to Fisher's approach, i.e., significance testing, the general strategy includes the following steps (Kotzen, 2011, p. 5):

- selecting the hypothesis H_0, referred to as the null hypothesis, and examining whether there are grounds for its rejection;
- determining all possible outcomes of the experiment and assigning a likelihood to each outcome under the assumption that H_0 is true;
- after observing the outcome, calculating the probability that this outcome, or one at least as extreme, would occur by summing the probabilities of all outcomes that are at least as extreme as the observed one (including the observed outcome itself);
- using this sum (the p-value) as a guideline for rejecting H_0; in other words, if the p-value $\leq \alpha$, the result is considered statistically significant at level α and H_0 may be rejected at that significance level, whereby a smaller α implies a "stronger" rejection of the null hypothesis.

Both Fisher's procedure and the Neyman–Pearson procedure (which, unlike Fisher's, is strictly frequentist, as it requires knowledge of the procedure's behavior in long-run repeated sampling situations) face numerous theoretical and practical problems; among the most prominent are the following (Wagenmakers et al., 2008, pp. 3-8):

- frequentist inference is generally not based solely on the actually observed data – the procedure is chosen in advance, and the validity of experimental evidence is evaluated according to how that procedure would behave in a long sequence of repeated experiments;
- frequentist inference depends on data that were never observed – the p-value represents the probability, under the assumption that the null hypothesis is true, of obtaining data at least as extreme as those actually observed, meaning that it is partially determined by data that never occurred;
- frequentist inference depends on the intention behind data collection – since p-values are defined relative to the sample space, changes in that space (e.g., experimental design or sample size) can significantly affect the p-value;
- frequentist inference does not prescribe which estimator is the best – as it is not derived from a set of simple axioms describing rational behavior, a single statistical problem may have multiple frequentist solutions, and it is not always clear which one is optimal;
- frequentist inference does not formally quantify statistical evidence – the interpretation of p-values as indicators of the strength of evidence against the null hypothesis, originating from Fisher's tradition and associating specific p-value ranges with levels of evidence (e.g., 0.1, 0.05, and 0.01), relies on informal and heuristic guidelines; additionally, it has been noted that, for equal p-values, studies with small samples may provide stronger evidence against the null hypothesis than studies with large samples (e.g., from a rational perspective, $p = 0.05$ based on only 10 observations may appear more convincing than $p = 0.05$ based on 1000 observations);
- frequentist inference is not applicable to "non-nested" models – since p-values require a clearly defined H_0, they are not suitable for testing non-nested hypotheses (which represent competing theoretical explanations), as they do not allow for their adequate interpretation.

Given the aforementioned limitations of frequentist inference, the Bayesian approach is often highlighted as an alternative. However, despite these limitations, the frequentist approach remains widely used in numerous empirical studies.

3. ADVANTAGES OF THE BAYESIAN APPROACH

In Bayesian statistics, named after the priest Thomas Bayes (whose theorem describes a method for updating probabilities based on data and prior knowledge), unlike in the frequentist framework, parameters and hypotheses are treated as probability distributions, while data are considered fixed (Fornacon-Wood et al., 2022, p. 1077). Probability distributions summarize the current state of knowledge about a parameter or hypothesis and can be updated as new data become available by applying Bayes' theorem, as shown in the following equation (Fornacon-Wood et al., 2022, p. 1077):

$$p(\theta|Data) = \frac{p(Data|\theta) \cdot p(\theta)}{p(Data)} \qquad (1)$$

One of the key differences between frequentist and Bayesian inference is the introduction of the prior, which can be defined based on expert beliefs, historical data, or a combination of both – the prior probability of the parameter θ in the equation is denoted as $p(\theta)$ (Fornacon-Wood et al., 2022, p. 1077). In this context, Data refers to the observed data (sample), $p(Data|\theta)$ represents the likelihood, i.e., the probability of the observed data given parameter θ, while $p(Data)$ denotes the marginal probability of the data and serves as a normalization constant. The goal of Bayesian inference is to determine the posterior distribution $p(\theta|Data)$, i.e., the conditional probability of parameter θ after observing the data (University of Utah, n.d.). The process is carried out in three steps (Gelman et al., 2025, p. 3):

- specifying a full probability model – defining the joint probability distribution for all observed and unobserved quantities within the problem; the model should be consistent with existing knowledge about the underlying scientific problem and the data collection process;
- conditioning on observed data – computing and interpreting the corresponding posterior distribution;
- evaluating model fit and implications of the posterior distribution – assessing how well the model fits the data, whether the main conclusions are reasonable, and the extent to which results depend on the assumptions made in the first step; based on the findings, the model may be modified or extended, after which the process is repeated through all three steps.

The application of Bayesian statistics to parameter estimation and hypothesis testing offers several advantages over the frequentist approach; among the most notable are (Wagenmakers et al., 2008, pp. 11–21):

- coherence – Bayesian inference is prescriptive and does not require ad hoc adjustments to correct procedures; once a model is specified, there is a unique way to obtain the appropriate result;
- automatic parsimony – the Bayesian approach favors models that capture the replicable structure of the data while ignoring idiosyncratic noise; such models, unlike overly complex or overly simple ones, provide the best predictions for new data from the same source;
- applicability to non-nested models – since Bayesian hypothesis testing is based on marginal likelihoods, it does not make a fundamental distinction between nested and non-nested models, allowing for application in a much broader range of situations;
- flexibility – Bayesian inference allows for flexible application of relatively complex statistical techniques, including hierarchical and nonlinear models;
- marginalization – Bayesian statistics enables focusing on relevant quantities by integrating out so-called nuisance parameters, thereby obtaining marginal posterior distributions of parameters of interest;
- validity – Bayesian inference produces results closely aligned with what researchers are actually interested in; by assigning probabilities to hypotheses, it is consistent with intuitive scientific reasoning;
- testable subjectivity – in the Bayesian framework, subjectivity is not hidden; through explicitly specified priors that are open to scrutiny and criticism, it becomes transparent and formally assessable in terms of robustness;
- ability to gather evidence in favor of the null hypothesis – unlike p-values, which can only lead to rejection of the null hypothesis, the Bayesian approach allows for evidence to accumulate in its favor and enables quantitative comparison of competing hypotheses via marginal likelihoods;
- monitoring evidence during data collection – Bayesian inference allows evidence to be tracked as data accumulate, without the need for corrections due to "optional stopping," since stopping rules are irrelevant for result interpretation;
- incorporation of prior knowledge – Bayesian inference enables the inclusion of prior knowledge through priors, which are not only useful but necessary for rational inference; differences in conclusions arising from different priors reflect scientific uncertainty rather than a weakness of the method.

Based on the previously analyzed advantages of Bayesian inference, it can be observed that this approach has wide application across various fields, including economics. In particular, marketing stands out as an area in which the application of the Bayesian approach can make a significant contribution to understanding market phenomena and supporting decision-making.

4. APPLICATION OF THE BAYESIAN APPROACH IN MARKETING

There is a substantial body of research in economics in which the Bayesian approach has been applied. Błażejowski et al. (2016) review some of these studies, focusing on topics related to economic growth. In their own research, the same authors also analyze economic growth using Bayesian methods. The popularity of Bayesian methods in macroeconomic forecasting stems from their ability to efficiently handle a large number of parameters and, through the appropriate specification of prior distributions, to effectively address model uncertainty and specification issues in a macroeconomic context. Similarly, in the field of financial analysis, research objectives related to forecasting and modeling risks associated with financial assets naturally align with the Bayesian framework (Martin et al., 2024).

Bayesian statistical methods represent an important analytical framework in marketing, as they offer an integrated approach to statistical inference and decision-making applicable to both theoretical and empirical analyses (Rossi and Allenby, 2003). Building on this perspective, Rossi et al. (2005) explain the application of Bayesian methods in marketing through the way marketing problems are statistically modeled, highlighting three interrelated components: within-unit behavior, across-unit behavior, and action. The term "unit" refers to the lowest level of aggregation explicitly included in the model, determined by the nature of the problem and data availability (in many cases, this is the consumer, although other levels of aggregation are also possible). The first component refers to the conditional likelihood function describing behavior at the unit level, conditioned on unit-specific parameters that capture heterogeneity across units; the second component concerns the distribution of these parameters across the population of units; the third component represents the decision problem as the ultimate objective of the modeling process, often involving the specification of a profit function, where the optimal action is determined based on the model and the information contained in the data. In this context, the Bayesian approach enables a unified and coherent treatment of all three components of the marketing problem.

In contemporary marketing literature, the Bayesian approach has been applied across a wide range of areas. These include the analysis of consumer choice behavior, demand and customer satisfaction analysis, dynamic pricing, evaluation of advertising effectiveness, and recommendation systems (Martin et al., 2024).

For example, Posch et al. (2022) proposed a novel approach for forecasting menu item sales in restaurants and canteens based on two Bayesian generalized additive models. Their analysis used two datasets obtained from the POS systems of a restaurant and a canteen. The performance of the proposed approach was thoroughly evaluated and compared with other forecasting methods, with results indicating that it provides the most accurate and robust point forecasts overall. In addition, for one of the datasets, the prediction intervals were noticeably more precise than those obtained using competing methods.

By constructing a dynamic game model based on Bayesian updating of information, Fan and Bao (2025) analyzed optimal advertising strategies of retailers in the presence of asymmetric information about product quality. The results showed that the choice of advertising strategy significantly affects the mechanism by which consumers update their beliefs, as well as the efficiency of market transactions. Among the four considered advertising strategies (full disclosure, exaggerated, downplayed, and no disclosure), full disclosure was found to be the optimal strategy for retailers.

Danaher et al. (2020) analyzed data on the exposure of 4,000 consumers to three media channels (email, catalogs, and paid search) and their purchases in both physical and online stores of three apparel retail brands, using a variational Bayesian approach. Their findings suggest that email, and sometimes catalogs, negatively affect competing brands, that paid search affects only the focal brand, and that catalogs often have a positive effect on competing brands, but only among multichannel consumers.

The Bayesian approach can also be applied in the context of A/B testing, primarily due to the ease of interpreting results. In this regard, Kamalbasha and Eugster (2020) presented three experimental scenarios: testing websites where visitors can purchase only a single product, testing websites where visitors can choose among multiple products, and an aggregate scenario. For each scenario, a Bayesian model formulation and corresponding decision-making procedures based on sampling from estimated posterior distributions were presented.

5. CONCLUSION

Faced with numerous market challenges, most often driven by consumer behavior and competitive dynamics, marketing managers frequently find themselves in situations that require making important business decisions on an almost daily basis. In order to improve their effectiveness and ensure a more efficient decision-making process, it is essential, among other things, to pay careful attention to the selection of appropriate statistical data analysis methods, as they form the foundation upon which business decisions are made.

The frequentist approach, as one of the most traditionally used methods in statistical analysis, is based on the frequency of event occurrence. Although widely applied, this approach is characterized by certain limitations. In particular, the issue of interpreting p-values as one of the key indicators of frequentist inference stands out. Since p-values rely on informal and heuristic guidelines, their misuse or uncritical application may call into question the validity of research results and, consequently, the quality of the decisions made. As an alternative to the frequentist approach, Bayesian inference is gaining increasing application, as it enables the incorporation of prior information into the analysis process. The Bayesian approach can substantially overcome the limitations of frequentist methods, offering advantages in terms of coherence, flexibility, and interpretative clarity of results. The application of Bayesian methods facilitates decision-making in marketing, as analytical results are presented in a form that aligns more closely with the way decision-makers think. The growing number of scientific studies applying Bayesian methods to solve marketing-related problems – such as sales forecasting, optimization of advertising strategies, A/B testing, and other relevant challenges – further confirms the importance and applicability of this approach.

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