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Evaluating the Effectiveness of Advertising Campaigns in the Fast-Food Industry Using an Analytical Engine

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Abstract:

Purpose: *The primary objective of this research is to explore the effectiveness of marketing campaigns using an analytics engine capable of processing and interpreting complex data sets. The study focuses on a specific case within the fast-food industry, where traditional marketing strategies are employed to promote new product launches.*
Design/Methodology/Approach: *The methodology employed in this research entails a comprehensive analysis of a dataset titled 'Fast-food Marketing Campaign,' which records sales outcomes from various marketing initiatives across multiple locations. The dataset encompasses market size, location, promotion type, and weekly sales figures, offering a comprehensive view of the campaign's reach and effectiveness. This study utilizes descriptive statistics, predictive modeling through Light GBM (an enhanced decision tree algorithm), and regression analysis to identify key factors that influence the success of traditional marketing campaigns. Moreover, a user-friendly interface was developed using the Dash programming framework, ensuring marketers can easily visualize and interpret the analysis results.*
Findings: *Descriptive analysis highlighted the variability in sales and store characteristics, while predictive analysis showed the model's ability to forecast sales outcomes accurately. Regression analysis further identified the most influential variables affecting campaign success, such as market size and specific promotions. The model's predictions aligned with actual sales data, confirming its effectiveness in capturing underlying data patterns and contributing to strategic marketing decisions.*
Practical Implications: *This research holds substantial practical implications for marketing professionals, particularly in sectors where traditional campaigns continue to be pivotal. The development of an analytical interface enables dynamic data exploration, empowering marketers to make informed decisions based on comprehensive analysis results. This tool can significantly bolster the planning and execution of marketing strategies by providing insights into the factors that most significantly impact campaign success, thereby optimizing marketing investments and strategies.*

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Originality/Value: *This study's originality lies in its focused examination of traditional marketing campaigns within the context of a modern data analytics framework. By integrating advanced analytical techniques with traditional marketing data, this research bridges the gap between conventional marketing approaches and contemporary analytical methodologies.*

Keywords: *Marketing analytics, descriptive analysis, predictive modeling, regression analysis, marketing strategy.*

JEL codes: *C53, C81, L66, M31, D83.*

Paper type: *Research article.*

1. Introduction

Campaign analysis reports play a crucial role in marketing analytics, serving as a fundamental tool for evaluating the effectiveness of marketing activities and refining future strategies (Meinard *et al.*, 2021). These reports help verify if actions align with intentions and budget and if they meet set goals, both online and in public spaces (Mansurali and Jeyanthi, 2022).

In the realm of communication, analyzing media coverage of information campaigns is essential for understanding the impact of messages on the audience and evaluating the success or failure of the campaign (Fox, 2022; Zakharchenko, 2022). Effective reporting in analytics is vital to extracting actionable insights from data, ensuring that the analysis cycle is completed correctly (Tecott and Halterman, 2020).

Analytical models and techniques like clustering methods and regression models play a crucial role in enhancing decision-making processes by offering data-informed insights (Leidecker-Sandmann, 2022). These tools enable marketers to segment customers, predict sales, understand consumer behavior, and evaluate campaigns, showcasing the significance of campaign analysis reports in marketing strategies (Thalassinos and Berezkinova, 2013; Tyagi *et al.*, 2023).

Moreover, the application of analytics in marketing extends from understanding buying patterns to optimizing budget allocations, emphasizing the pivotal role of data-driven decision-making in achieving marketing objectives (Rymarczyk and Kłosowski, 2017; Rymarczyk, Bednarczuk, *et al.*, 2021; Rymarczyk, Golabek, *et al.*, 2021; Anuradha, Sivakumar and Sivaraman, 2023; Havlicek *et al.*, 2013).

Due to the ease of data collection and access, analyzing campaigns conducted on the Internet and social media has become a prevalent issue (Al Adwan *et al.*, 2023; Zolala, Kononova, and Firsov, 2023). With access to data on the number of clicks, advertisement reach, and number of interactions, analysts can proceed to further steps in campaign evaluation to determine its effectiveness (Khandelwal and Arora, 2023). Online marketing tools hold a significant advantage over traditional communication channels in this regard (Szpyrka *et al.*, 2023). Analyzing the outcomes of advertising campaigns requires examining individual channels and then assessing which are the most cost-effective and warrant further investment.

However, it is imprudent to disregard campaigns conducted traditionally entirely. Despite the reduced availability of data, it is worthwhile to exert effort in gathering relevant information and analyzing traditional campaigns as well. For traditional campaigns, metrics primarily revolve around sales figures resulting from the initiatives (Jiménez and Renau, 2022; Zampeta and Chondrokoukis, 2023).

On the other hand, dealing with an internet campaign affords numerous additional indicators, such as the number of advertisement views, clicks, and conversions (Szpyrka *et al.*, 2023). In both scenarios, analytical tools can isolate factors significantly influencing a campaign's success or failure and also predict campaigns' effectiveness with specific characteristics.

In the studies conducted, the scope was intentionally limited to campaigns executed traditionally. This approach was strategically chosen to concentrate on direct sales outcomes and assess the effectiveness of traditional advertising methods in scenarios where digital metrics like clicks and online interactions are not applicable.

This deliberate focus allows a deeper understanding of conventional marketing strategies' enduring relevance and impact, even in an increasingly digital age. The primary objective of this research is to explore the effectiveness of these traditional marketing campaigns through an advanced analytics engine capable of processing and interpreting complex data sets.

2. Materials and Methods

The system's functionality will enable the analysis of the effectiveness of traditional campaigns. Below, the dataset will be described. Based on this data, descriptive analyses will be performed, facilitating a preliminary understanding of the factors influencing campaign effectiveness.

Predictive and regression analyses will be employed to forecast campaign success and identify variables that contribute most significantly to the success or failure of the campaign.

The "Fast-food Marketing Campaign" dataset was selected to analyze traditional marketing campaigns. The campaign's objective under study is defined as follows: a fast-food chain plans to introduce a new item to its menu but has not yet decided among three potential marketing campaigns to promote this new product.

The latest item is launched in several randomly selected markets to determine which promotion significantly impacts sales. In each location, a different promotion is applied, and the weekly sales of the new item are recorded over the first four weeks.

The dataset about the advertising campaign within the fast-food network includes the following columns:

- MarketID: A unique market identifier.
- MarketSize: The size of the market in terms of sales.
- LocationID: A unique identifier for the store's location.
- AgeOfStore: The age of the store in years.
- Promotion: One of the three promotions that were tested.
- Week: One of the four weeks during which the campaigns were conducted.
- SalesInThousands: The sales for the given location, promotion, and week.

The dataset comprises 548 observations. The "Fast-food Marketing Campaign" dataset has no missing data points. Additionally, there are no campaigns for which the sales amount was zero. This completeness and uniformity of data provide a robust basis for analyzing the effectiveness of each promotional strategy employed.

In the realm of descriptive analysis, the following methodologies were employed:

- Analysis of descriptive statistics for numerical variables and the frequency of occurrences for categorical variables,
- Analysis of box plots for numerical variables, bar charts for categorical variables,
- Analysis of plots for the dependent variable across various values of independent variables.

Light GBM (enhanced decision tree algorithm) was used to predict the success or failure of specific advertising campaigns and identify factors affecting the outcome of advertising campaigns. To assess the quality of predictions from the success/failure prediction model, the following methods were utilized:

- Regression model fit metrics - RMSLE (Root Mean Squared Logarithmic Error).
- "Actual vs. Predicted" plots, which display a comparison between actual and predicted values.

For the evaluation of regression models, instead of focusing on model fit metrics, emphasis was placed primarily on the importance of variables (Variable Importance), which denotes the contribution of variables in explaining the dependent variable.

To ensure the accuracy of predictions, datasets were split into training and testing portions. Each model used in this analysis was initially trained on the training set and subsequently tested on a separate testing set. Based on the metrics calculated for the test set, the performance quality of the model and comparisons between models could be assessed.

In the final stage of the ongoing research, an interface was developed using the Dash programming framework in Python to present the analysis results with extensive commentary and interpretation.

3. Research Results

The first research stage was conducting a descriptive analysis of the dataset. All descriptions of the results in the subsequent figures were conducted in Polish, as the case study was prepared for a Polish company.

Figure 1 presents an analysis of basic descriptive statistics for two numerical variables from the Fast-food Marketing Campaign dataset: store age and sales in thousands. The AgeOfStore varies from 1 to 28 years, with an average of approximately eight years and a standard deviation of around 6.4.

The median age of the store is seven years, with the 25th percentile at four years and the 75th percentile at 12 years. The minimum value is one year, and the maximum is 28 years. SalesInThousands range from about 17.3 to nearly 99.7 thousand, with an average sale of roughly 53.5 thousand and a standard deviation of approximately 16.8. The median sales figure is around 50.2 thousand, with the interquartile range extending from 42.5 to 60.5 thousand.

Figure 1. *Basic descriptive statistics of numerical variables*

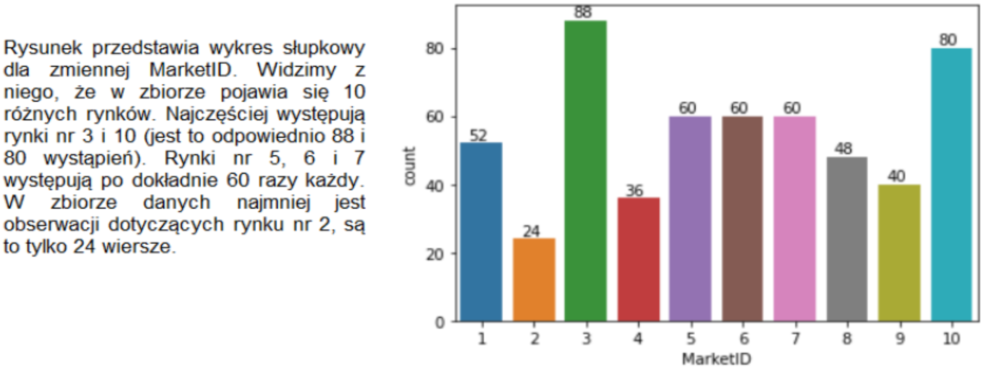
Tabela przedstawia podstawowe statystyki opisowe zmiennych numerycznych ze zbioru Fast-food Marketing Campaign. Są to kolejno: wiek sklepu i sprzedaż w tysiącach.
Wiek sklepu waha się od 1 do 28 lat. Średnia wynosi około osiem i pół roku i jest nieco wyższa od mediany wynoszącej 7 lat. Typowe wartości wieku sklepu zawierają się od 4 do 12 lat.
Wartości sprzedaży w tysiącach mieszczą się w zakresie od 16.75 do 99.65. Średnia wynosi około 53.47 i jest zbliżona do mediany równej 50.2. Zakres typowych wartości to od 42.54 do 60.48.

	AgeOfStore	SalesInThousands
count	548.000000	548.000000
mean	8.503650	53.466204
std	6.638345	16.755216
min	1.000000	17.340000
25%	4.000000	42.545000
50%	7.000000	50.200000
75%	12.000000	60.477500
max	28.000000	99.650000

Source: *Own creation.*

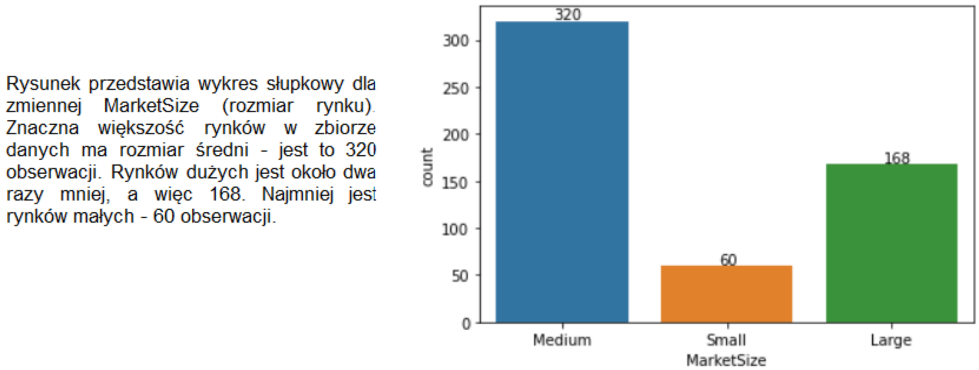
Figures 2 and 3 show bar graphs of the frequency of selected categorical variables (MarketID and MarketSize) from the dataset and commentary on the graphs. Each categorical variable was analyzed. In addition, a box plot analysis was performed for the numerical variables.

Figure 2. *Bar chart for the variable MarketID*



Source: *Own creation.*

Figure 3. *Bar chart for the variable market size*



Source: *Own creation.*

The next stage involved conducting a predictive analysis of the traditional campaign. The LightGBM model was employed and tested for this purpose. During the model training process, k-fold cross-validation with k=5 was utilized. The Root Mean Squared Logarithmic Error (RMSLE) values at various stages of training are presented in Figure 4.

In Figure 5, histograms comparing the distribution of prediction values for both the learning and test sets are presented. The distribution of values exhibits a bimodal nature, with a noticeable gap where no values occur between approximately 65 and 75. Most data points, particularly within the training set, are around 50.

Figures 6 and 7 allow for the evaluation of the model's prediction quality on the test set.

Figure 4. *RMSLE values in successive stages of model learning*

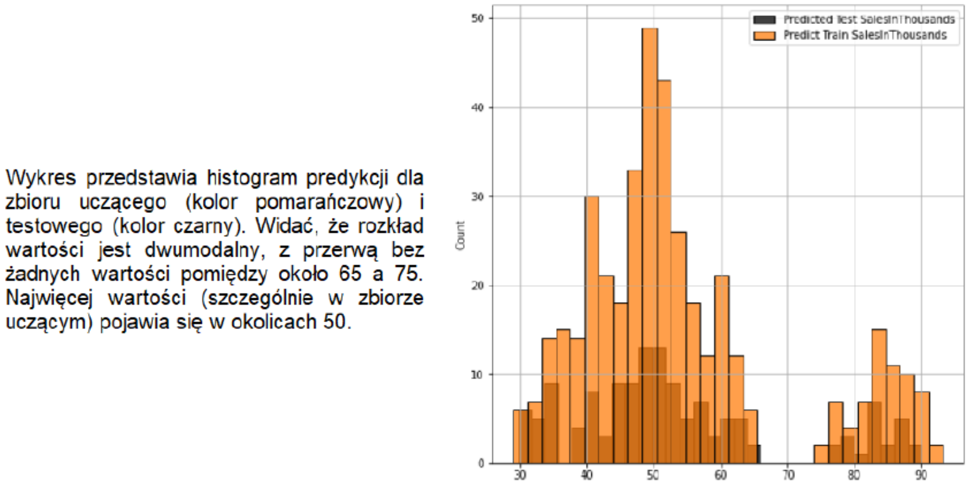
```
fit fold=0  0.065[s]
Fold 0 RMSLE: 5.0163

fit fold=1  0.047[s]
Fold 1 RMSLE: 5.7241

fit fold=2  0.047[s]
Fold 2 RMSLE: 6.0549

fit fold=3  0.039[s]
Fold 3 RMSLE: 5.3990

fit fold=4  0.040[s]
Fold 4 RMSLE: 5.5011

--------------------------------
FINISHED | Whole RMSLE: 5.5486
```

Source: *Own creation.*

Upon examining the Actual vs. Predicted chart for the test dataset, it is observable that the model generally makes accurate predictions, as the points predominantly cluster near the y=x line.

This proximity indicates a high degree of alignment between the predicted values and the actual outcomes, suggesting the model's effectiveness in capturing the underlying pattern of the data.

Figure 5. *Histogram of prediction for the learning and test sets*



Source: *Own creation.*

The subsequent stage of the conducted research involved a regression analysis. Figure 8 presents a plot of essential features from the Light GBM model. Based on

this chart, it is possible to readily ascertain which variables had the most substantial influence on the progression of the traditionally conducted campaign.
It is observable that the most critical variable, significantly more important than others, is MarketId, which denotes the identifier of the market where the campaign is executed.

Figure 6. *Comparison of actual values and those obtained from the model for the first ten observations from the test set*

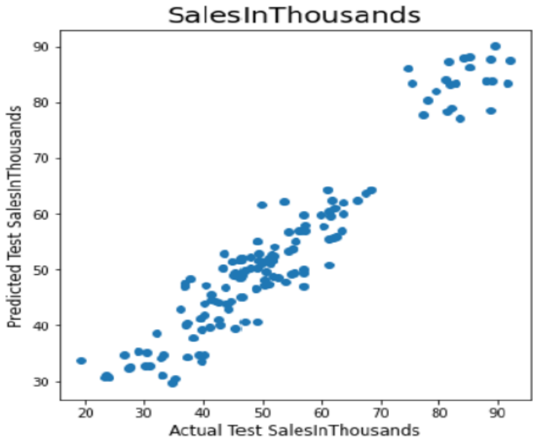
Tabela przedstawia 10 pierwszych obserwacji ze zbioru testowego. W pierwszej kolumnie znajdują się rzeczywiste wartości sprzedaży, a w drugiej przewidywane z modelu. W większości przypadków model myli się o kilka tysięcy. W przypadku ostatniej obserwacji widać pomyłkę o ponad 10 tysięcy.

	Actual	Predicted
0	49.30	52.887965
1	42.59	44.109284
2	39.25	34.825886
3	23.35	30.741834
4	61.59	59.606665
5	51.73	48.808704
6	75.29	83.421741
7	42.15	44.384078
8	43.24	50.294482
9	36.80	47.025706

Source: *Own creation.*

Figure 7. *Actual vs. Predicted chart for the test set*

Rysunek przedstawia wykres "Actual vs Predicted" dla zbioru testowego Fast-food Marketing Campaign. Na osi *x* zaznaczone są prawdziwe wartości sprzedaży, a na osi *y* przewidywane z modelu. Wykres pokazuje, że model dokonuje raczej poprawnych predykcji, ponieważ punkty znajdują się blisko linii *y=x*.

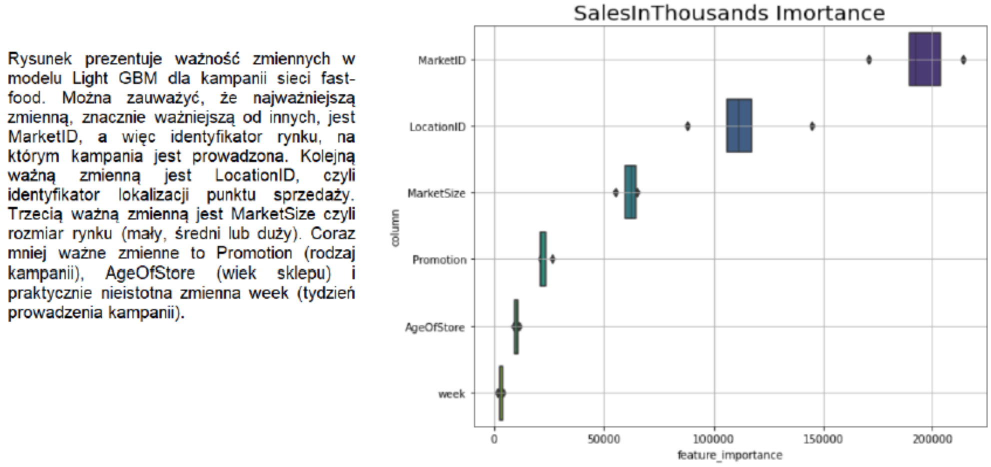


Source: *Own creation.*

The following important variable is LocationId, representing the identifier of the sales point location. The third significant variable is MarketSize, indicating the market size (small, medium, or large).

Variables of diminishing importance include Promotion, referring to the type of campaign, and AgeOfStore, which describes the age of the store. The variable Week, indicating the week of the campaign appears to be nearly insignificant.

Figure 7. *Significance of variables in the Light GBM model*



Source: *Own creation.*

The final stage involved the creation of an interface designed to display the results of analyses, complete with comments and interpretations. On the left side of the interface is a list that allows users to select the type of analysis they wish to review, with results accompanied by comments. Three types of analysis are available for selection: descriptive, predictive, and regression analysis.

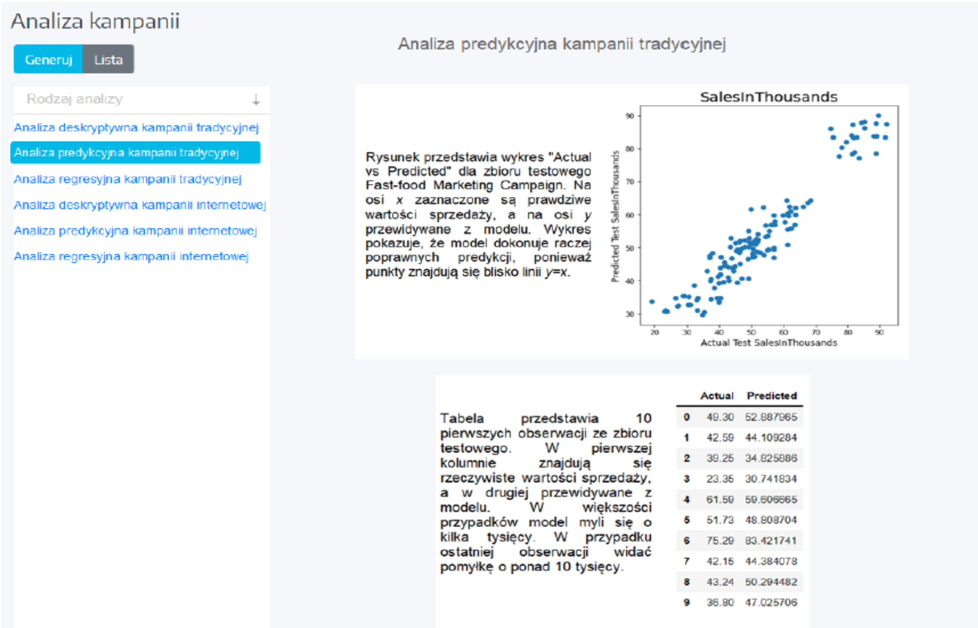
Under the "Descriptive Analysis of Traditional Campaigns" tab, users can choose from a dropdown list of the specific campaign characteristics they wish to analyze. The next tab, "Predictive Analysis of Traditional Campaigns," provides an opportunity to assess the predictive model's performance for a dataset pertaining to a traditionally conducted campaign. This tab includes charts and tables with accompanying comments, as depicted in Figure 8.

In the "Regression Analysis of Traditional Campaigns" tab, users can view a chart displaying the importance of variables, which helps identify factors significantly influencing the outcome of a traditionally conducted campaign. This structured approach facilitates a comprehensive understanding of various aspects of campaign performance, thereby enhancing strategic decision-making based on empirical data.

4. Conclusions

This study underscores the pivotal role of analytical engines in deciphering the complexities of traditional marketing campaign strategies. This research highlights the enduring value of traditional marketing methods, systematically analyzing a dataset from a conventional marketing campaign within the fast-food industry, even in an increasingly digital marketplace. The descriptive, predictive, and regression analyses offer a comprehensive understanding of the factors influencing campaign effectiveness.

Figure 8. *Predictive Analysis of Traditional Campaigns*



Source: *Own creation.*

Significantly, the study demonstrates that despite the constraints associated with traditional campaigns, such as less immediate and granular data, meaningful insights can still be garnered through meticulous analysis. The predictive and regression models employed provide a robust framework for predicting outcomes and assessing variable importance, proving essential for strategic planning and execution in traditional marketing contexts.

Developing a user-friendly interface for displaying analysis results, equipped with detailed comments and interpretations, represents a leap forward in making complex data accessible and actionable. This interface facilitates an in-depth examination of various campaign aspects, enhancing the decision-making process for marketers aiming to optimize campaign strategies.

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