Assessing the Effectiveness of an Advertising Campaign on Instagram Based on Advertising Cost and Sentiment Analysis: Case of CSR Campaign

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Author Note

The Data and Corresponding Codes of this Research can be Found in the Link Below:
https://github.com/SimplyRamin/bekhatereman_campaign_analysis

Abstract

The growth of social media has changed the face of many aspects of marketing such as online, digital, etc. It also has changed the way modern human communicates and connects with others. Moreover, the behavior on this platform could not and should not be justified with strategies of other marketing channels and media. Due to the nature of social media, they are rich in precise and lean data, but processing these data and extracting knowledge and insights from them are problematic. Evaluating the effectiveness of a marketing endeavor is also a task related to these data. The current research attempts to assess the effectiveness of an advertising campaign on Instagram via advertising cost and sentiment classification of audience opinion regarding the campaign. The methodology used in this research is the standard process of data mining, i.e., CRISP-DM. Furthermore, multiple machine learning models and approaches were studied to train a prediction model based on data. In order to find the most accurate algorithm, grid search was used among the trained models and different algorithms with different combinations of hyper-parameters. The obtained results revealed that although the number of not profitable advertising media was higher than the profitable media, the overall status of the campaign was profitable, both in the cost-effectiveness approach and sentiment analysis approach. The other valued outcome of this research was important general and specific insights which can be used to shape a better-performing and effective advertising campaign on Instagram.

Keywords: Data Science, Advertising Campaign, Effectiveness, Evaluating, Social Media, Digital Marketing, Sentiment Analysis, Instagram, Machine Learning

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1. Introduction

Many experts have evaluated the importance of the current era as the same as the Industrial Revolution. This era is called Digital Transformation. The marketing industry is one of the sections which changed and morphed significantly, so a sub-branch called Digital Marketing emerged. This branch, like any other approach of marketing practices, should be assessed so the effectiveness of withheld efforts can be quantified. This gives managers and marketing strategies insights so that they could make better and more effective efforts. In marketing strategy, goals are defined, and assessing the effectiveness of a campaign is one of the significant sections of an advertising campaign (Patti, Hartley, van Dessel, & Baack, 2017).

The rapid growth of social media has affected and changed the marketing strategies and consumer behaviors who use this media (Bernoff & Li, 2008; Berthon, Pitt, Plangger, & Shapiro, 2012; Constantindes & Fountain, 2008). By shaping the interaction between customers, the social media environment gives customers the value they have not experienced to this day (Baird & Parasnis, 2011). Social media encourage users to use and share content in that environment (Hwang & Kim, 2015).

In a research, Stelzner (2015) found that a marketing specialist in “techniques, engagement, evaluation, audiences, and tools” needs more information (p. 6). 87% of them could not answer questions correctly in this field. However, this research determined that 92% of marketing specialists placed social media in top places of business’ priorities even though they did not fully understand this medium, considering they did not answer questions correctly. In this case, the main challenge for businesses is to use novel and different approaches in order to engage the consumers in this new and adversarial environment (Baird & Parasnis, 2011).

The popularity of social media among the people caused many organizations and businesses to use them without a proper and effective strategy (Larson & Watson, 2011), and many of them found this deed very difficult (Bottles & Sherlock, 2011)! Researchers pointed this problem out by developing effective ways for sample analysis (Effing & Spil, 2016) and sample categorizing (Winer, 2009) in the social media environment.

Social media have drastically altered the decision-making process of consumers (Fulgoni, 2014). Thus, understanding the consumers’ behaviors on this medium is vital for successful marketing (Donthu & Garcia, 1999), because consumers regularly use the online environment to receive information and insights which will help them buy decisions. However, the internet and social media platforms made categorizing consumers and developing an effective topology harder and harder (Barnes, Bauer, Neumann, & Huber, 2007), especially in an environment where the heterogeneous consumer quantity is rising (Thomas, Price, & Schau, 2013). Nowadays, people from all around the world can communicate with each other, and their opinions and information, which can affect their decisions, could be shared easily. This theory, which possibly creates significant problems for marketing specialists by important cultural roles and consumers’ behaviors (Yavas & Green, 1992; Hofstede, 1994), should be discussed.

The final result and statistics of a finished effort in digital marketing modularly produce the delivered campaign's content, and with summation of them, it can be deduced if the aforementioned advertising campaign reached its goals. However, the effectiveness is an exception to this rule, since sometimes a campaign will not reach and fulfill its goals, but in the eyes of experts and specialists, the efforts have been highly effective, and vice versa (Palmatier, Dant, Grewal, & Evans, 2006). Currently, the only measure for companies to analyze the effectiveness of an advertising campaign is the fulfillment situation of specific goals. This measurement cannot provide a clear and completely correct analysis, and the lack of a system being able to assess the "true" effectiveness of the advertising campaign and recommend solutions for improving and increasing the effectiveness is felt.

Generally, to understand the effectiveness of an advertising campaign, its effect on the target audience should be evaluated. Social media is a medium on which the audience shares their opinions regarding the advertisement they see on it (Kryński, 2014). Since social media have a structured nature, their contents are explorable. Gathering target audience comments and opinions regarding the campaign is the first step of understanding the effectiveness of a campaign (Obar & Wildman, 2015). On the other hand, another parameter for assessing the effectiveness is the actual cost of the campaign. Every single effort in marketing, like other fields, has a predefined and sometimes a tight budget, and going over it is a clear sign of ineffectiveness of a campaign.

Current approaches to analyzing the effectiveness of advertising campaigns are all based on audience engagement with content and the cost of the advertising campaign, which is clearly not a good and well-defined approach, since as previously mentioned, many campaigns will not reach the target "performance metric" quantities (i.e., budget is cut from the client, or due to the management change, the campaign is paused and terminated.). In the meantime, however, as the campaign was active, the audience found that excellent, and their opinion regarding the content and context of the campaign were positive. The advertising campaign goal, which is a part of a marketing strategy, is not always to increase the sale quantity. Sometimes a campaign is designed to increase brand awareness or improve the brand image. For that reason, calculating the increase in sales is not a strong and comprehensive measure for analyzing the effectiveness of an advertising campaign.

On the other hand, due to the burst in the usage of smartphones, approaches and strategies in the world have gone through considerable changes. Based on the statistics from Facebook, in 2019's second half, more than seven million active advertisers are present on this social medium (Clement, 2020). The important fact to have in mind here is that the nature of social media is different from each other and should not be categorized together. The target audience on each medium will react differently based on the social medium. For instance, people will not react very nicely to unprofessional content on LinkedIn since this social medium is for professional and serious conversations. Therefore, in order to make this research precise, the focus is on one social medium, which is Instagram.

The main aim of this research is to assess the effectiveness of an advertising campaign on Instagram based on advertising costs and the sentiment of the target audience regarding the campaign content.

2. Methods

2.1. #Bekhatereman Campaign

In order to reach the research goals, a specific campaign called #Bekhatereman (lit. For Me) was studied as a case. This campaign, which was a Cooperate Social Responsibility (CSR) one, was implemented by SISARV Marcom Agency in July – August 2017 for Arian Motor Pouya, the official distributor of Mitsubishi Motors in Iran.

The main message of this campaign was to not use phones while driving. This message was delivered through kids in this campaign due to the stronger intimate bond of adults with kids. Bekhatereman campaign was a full scope and comprehensive campaign, meaning that it used multiple and distinct offline and online approaches with special attention to digital marketing. In this research, the focus was on marketing efforts on Instagram, as the goal was discussed in the Introduction section.

The short-term goals of this campaign were to perform activities regarding the brand's social responsibility and attract public attention. Its long-term goals were to console brand position and increase brand popularity. The target audience was Iranian families with medium to high incomes. The age range for the target audience fit into two categories; 4 to 18 years for future culture building and 18 to 64 years for current culture building. Moreover, the geographic range for the target audience was every city in Iran, with a focus on metropolises.

2.2. Methodology

In the current study, the CRISP-DM[1] methodology was used to achieve the goals. This model was elastic and rotational. Elasticity, along with constant communication, is necessary in each step to keep the project on track. The revision of previous steps might be required in each step of this six-step process in order to make changes. The key feature of this process is to be rotational. Thus, even after finishing, you will have a new understanding of business, and you can reiterate this process after the deployment phase (Shearer, 2000).

2.2.1. Business Understanding

Currently, Instagram or IG is the most popular site/social medium among others in Iran. Therefore, many companies and businesses include this medium as their main channel in marketing strategy. Each post (the main form of content in this social medium) on Instagram achieves specific quantities regarding multiple performance metrics. And with these measurements, we can calculate the performance of each post among other posts in different aspects. Also, the suggestion algorithm of this social medium seems to work on these metrics. For instance, we can point to a number of Likes, Comments, Impressions, etc. as performance metrics. It should be

[1] Cross-Industry Standard Process for Data Mining

noted that these performance metrics play an important role regarding the overall performance of advertising campaigns on Instagram.

To make a post successful on this social medium is like playing a video game called Flappy Bird (Williams, 2014), meaning if a post could achieve a good amount of performance metrics in the early hours of publishing, that post would be flagged as "good" content by suggestion mechanism of Instagram and thus would be featured in the Explore section. Eventually, this situation will exponentially attract views and other types of appreciation for that post publisher's account. This process is not officially documented by Instagram but recorded with trial and error of users on this social medium, especially from advertising agencies whose matter of life and death is related to this fact.

2.2.2. Data Understanding

Based on the discussed goals and available information regarding the matter, the total data of the present research can be categorized into four sections which will be explained briefly:

- Posts: This section of data contains every single post published on the campaign's user account on Instagram as records, and its features are unique links for each post, category of the post, the post's caption, type of post, objects detected in each post which is an output of Instagram's computer vision detection algorithm and used for accessibility purposes, and eventually performance measurements.
- UGC[2]: This section of data is for contents that other users produce and are related to the campaign. Each user who publishes content regarding the campaign is categorized into three categories; users, public pages, and influencers. Other features of these posts are a unique link of each post, the post's caption, user ID, content detected objects as discussed above, and performance measurements.
- Advertisements: This section of data is exclusive to each and every advertising content published regarding the campaign on other accounts. Obviously, this form of resharing is paid. Features of this dataset are the same as other ones.
- Comments: this section of data is for each and every comment written on any campaign's content published by the main user account. For sentiment analysis of the campaign and calculating the overall opinion regarding the context of the campaign, this form of data is required.

In the following section, it will be discussed how these datasets are used to achieve research goals and fit machine learning models.

2.2.3. Analytical Approach

As the main problem and goals of this research were discussed earlier, the researcher faced two types of problems regarding the matter: classification and clustering. Furthermore, a significant part of this research could be answered via exploratory data analysis which will be

[2] User Generated Contents

carried out, and the outcomes will be reported later. Combining that with machine learning approaches, the research goals will be met, and insightful facts will be obtained.

Advertising agencies define a threshold price for each view an advertising post will cost. If a medium cost-per-view would be more than the threshold, it means that particular advertisement was not profitable. On the other hand, if an advertisement cost equal to or less than the threshold price for each view, the advertising agency generates revenue. With this knowledge, a new feature can be made which will be a binary class; 1 value in that feature will mean that a particular advertisement was profitable, and 0 means that the advertisement was not profitable. Also, the difference in prices could be calculated with this approach. Therefore, the overall revenue generated for the campaign can be discussed. With this method, the campaign effectiveness cost-wise can be assessed.

To perform sentiment analysis and eventually calculate the overall sentiment regarding the campaign, first, each comment sentiment must be quantified. Then, with a summation of every sentiment score regarding the comments, the overall sentiment score for the campaign can be calculated. Since this campaign was designed for a Persian-speaking audience, the majority of comments are in Persian. At the time of conducting this research, there is no suitable and bias-less Persian corpus. Available corpora are for niche markets, including comments about the technological products of a famous Iranian marketplace. Although this corpus can be used to train a language model in Persian, the output would be biased, and the results of this language model can be trusted and generalized. In this case, we are obliged to use a knowledge-based natural language processing approach regarding this sentiment analysis (Cambria, Schuller, Xia, & Havasi, 2013). To do this, we prepared a dictionary containing popular and frequently used words and emojis. Each entity in this dictionary has a corresponding score ranging from -1 to 1, indicating the sentiment state and strength. Then, each comment is evaluated according to this dictionary.

In a study conducted by Alom et al in 2019, results showed that in order to benefit from deep learning and artificial neural network methods, a good amount of data is needed. Hence, in situations where we face a low amount of data, using traditional machine learning methods will benefit the cause (Alom et al., 2019). In Figure 1, the graph of the performance in terms of the amount of data is depicted.

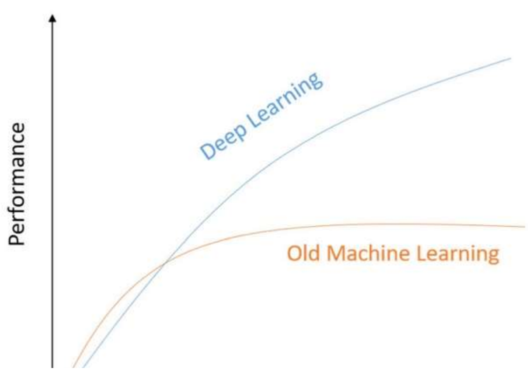

Figure 1. performance vs. the amount of data graph regarding the techniques.

Considering the classification of problems, when we face binary class features, popular methods are logistic regression, k-nearest neighbor, and SVMs. And popular clustering methods are partitioned-based, hierarchal, and density-based. In order to find the best algorithm with the most accurate hyperparameters, we will do a thorough grid search among them since our datasets are not very big, and we can train multiple models almost instantly.

2.2.4. Data requirements

Since the current research was carried out after the completion of the aforementioned campaign, the final report of this campaign was a good and reliable source of raw data. This type of report is usually done by an advertising agency for a client to report the final status of received leads and the overall performance of the campaign. On the other hand, advertising contents are deleted after a defined amount of time by media owners, like other forms of advertisements. Therefore, this report has some data that is no longer available. For instance, the data extracted from this report are the number of performance measurements, such as views, likes, comments, etc., for advertising media. Almost every feature discussed in Section 2.2.2 can be extracted from this report, but not all. Comments and output of the internal object detection algorithm of Instagram are not included in this report. To extract and further use this data, we implemented an Instagram Scraper with Python. After this step, all the data required to achieve goals are available and can be studied.

2.2.5. Data Preparation and Preprocessing

In this step, data cleaning and data enrichment (creating new features based on existing features) are in order. The raw data of this research have three major issues:

- Significant parts of data are missing and/or unavailable.
- The advertising dataset does not have a dependent variable. In other words, they are not labeled.
- To perform the machine learning technique, categorical and discrete variables should be converted to continuous variables.

These issues are addressed in this section. Then, the process of solving them will be discussed.

2.2.5.1 Solving missing and/or unavailable data

There are multiple approaches and techniques to solve this problem, for instance, removing and terminating records in which there are missing features. This technique is the simplest yet dangerous. If missing data are at random and termination does not decrease the size of the dataset, this technique is appropriate. However, if missing data are not at random, this technique will result in biasing the models. Moreover, for classification models, this technique can result in a curse of dimensionality (Bellman, 1957).

Another approach is replacing missing values with the mean, average, or other statistics of a feature. This approach can be implemented very easily, but it does not add additional information to data. Also, if missing values are not at random, especially when there are significant missing values, replacing them with the mean will result in unstable bias. These flaws are the reason why this approach is not welcomed by researchers (Kang, 2013).

The other technique is multiple imputations. This technique is widely accepted and used by the research communities, and with the implementation of every imputation technique for this problem, multiple imputations had the best accuracy among the others. Thus, this technique is used by the researcher to tackle missing and/or unavailable data. There are two possible ways to implement multiple imputations: iterative and k-nearest neighbor (Royston, 2004). To select the most accurate technique, we implemented both of them, then we used Pearson and Spearman's Correlation Coefficients to determine the accuracy of techniques. In Table 1, the accuracy results can be observed.

Table 1. Accuracy of iterative and k-nearest neighbor technique for multiple imputation

Evaluation Criteria	Iterative Score	k-nearest neighbor Score
Pearson Correlation Coefficients	0.99	0.88
Spearman Correlation Coefficient	0.99	0.95

2.2.5.2 Advertising dataset dependent variable issue

Earlier, the approach to solving this issue was briefly defined. To create several new features, and most importantly, the dependent variable, multiply the threshold price to the amount of view each advertising medium was achieved. This number will be the threshold cost of each media based on the achieved view. If the actual cost of that medium is greater than the threshold cost, the medium is not profitable for the agency, and if the actual cost is less than the threshold cost, the medium is profitable for the agency. This fact will result in a feature called Price Difference. The dependent variable, called y, is based on this price difference. If the price difference is a negative number, y will be 0, meaning that medium was not profitable and vice versa. The final product of this process is two new insightful features in one of which there is a dependent variable.

2.2.5.3 Integration and conversion of discrete and categorical values

One of the most important steps in preprocessing data regarding the discrete and categorical values, prior to implementing the "one-hot" concept, is the integration of discrete values (Harris & Harris, 2012). Since the data collection was completely done by the researchers, this step is not required since all the data are integrated. Another duty we have in this step is to convert discrete and categorical variables to continuous variables, so our classifiers could use them. In this research, the "dummying" method is used for this cause (Daly, Dekker, & Hess, 2016). Note that since some features are not useful for classifiers, such as caption, these types of features are omitted in this process.

2.2.6. Data Exploration

In this step of methodology, our data is ready to be examined with statistics. This step will result in interesting results that will lead to insights that will help agencies and businesses reshape their digital marketing strategies. Moreover, the main question of the research, i.e., the effectiveness of advertising based on cost and users' comment sentiment analysis, could be answered in this step and with this technique.

2.2.7. Modeling

As mentioned earlier, there are two types of problems in terms of modeling; classification and clustering. Our approach to finding the most accurate algorithm for each problem is implementing algorithms with possible and appropriate hyperparameters, grid searching, and selecting the algorithm and its hyperparameter combination with the highest accuracy. Since clustering algorithms are unsupervised learning methods, there is no accuracy (Hinton & Sejnowski, 1999). Therefore, we implement every possible approach for algorithms that need a predefined number of clusters. The Elbow (Thorndike, 1953) and Silhouette (Rousseuw, 1987; Lletí, Ortiz, Sarabia, & Sánchez, 2004) methods are used, and the results can be seen in the following section.

2.2.8. Evaluation

In order to evaluate classification algorithms, k-fold cross-validation technique (McLachlan, Do, & Ambroise, 2005) is employed. The number of k is another hyperparameter that will grid search to find the best possible value. Additional evaluation metrics used for classification algorithms are the F1 score, Jaccard score, and for logistic regression is the LogLoss score (Powers, 2020).

2.2.9. Deployment

Due to the nature of the research objective, the deployment of the models is not in order. But the whole process is standardized, and final models can be simply deployed and without additional challenges. Hence, future research can be easily carried out based on this research and relevant models.

3. Results

In this section, the results of withheld works regarding this research can be seen. In the Discussion section, we will elaborate on the results and discuss interesting insights obtained from the results.

29 Out of 45 advertising media in this campaign were overpaid, thus not profitable. And the remaining 16 were profitable (Fig. 2).

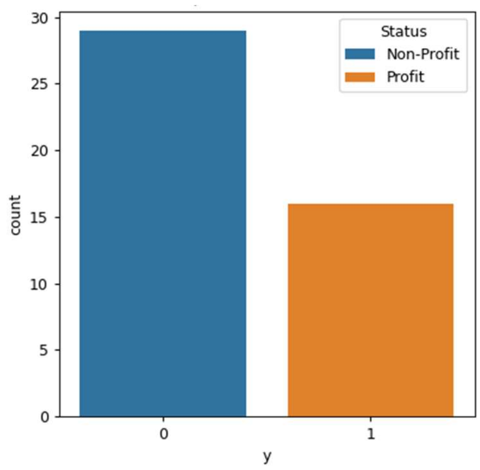

Figure 2. Advertising media status regarding the profit situation.

In Table 2, the mean of performance metrics regarding the status of media can be seen.

Table 2. Mean of advertising media regarding the profit situation.

Status	Followers	View	Like	Comment	Save	Impression	Reach	Engagement	Cost
Non-profit	762,336.7	6,226.9	1,946.3	6.1	58.1	42,473.5	31,779	1,999.7	-226,502.7
Profit	1,199,039	29,984.6	2,999.4	20.8	210.7	79,115.4	66,845.6	3,237.8	500,015.7

Out of 407 total comments received in campaign contents, 171 were positive, 223 were neutral, and 13 were negative. The top 10 and bottom 10 comments sorted by the strength of comment can be seen in Figures 3 and 4. Since the full diverging plot is very long, attached you can find it.

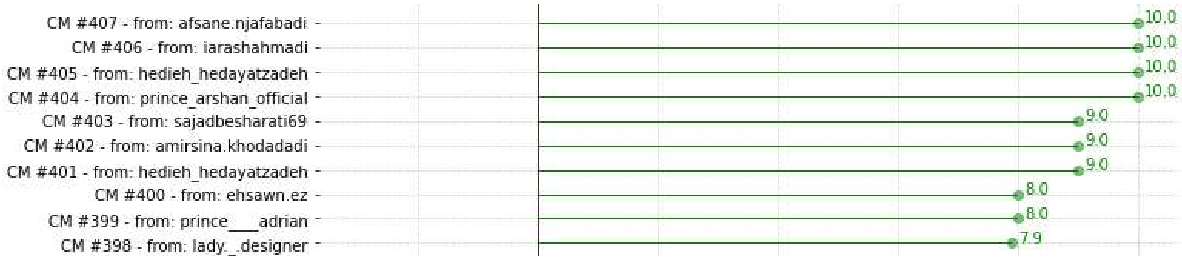

Figure 3. Sentiment analysis' diverging plot of top 10 comments.

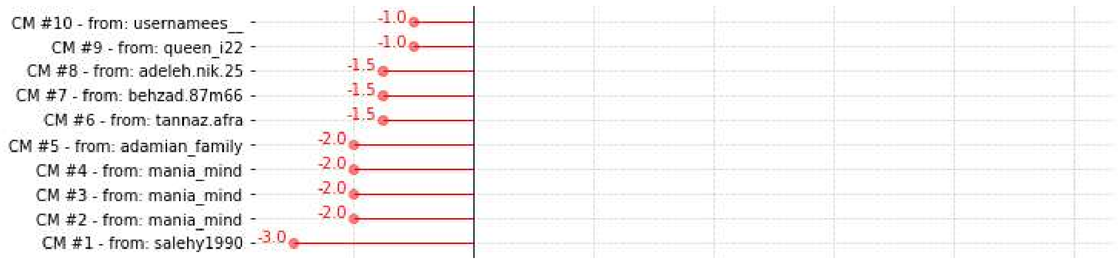

Figure 4. Sentiment analysis' diverging plot of bottom 10 comments.

Performance metrics correlation can be observed in Figure 5. This heatmap is one of the most significant results of this research and will be discussed precisely in the Discussion section.

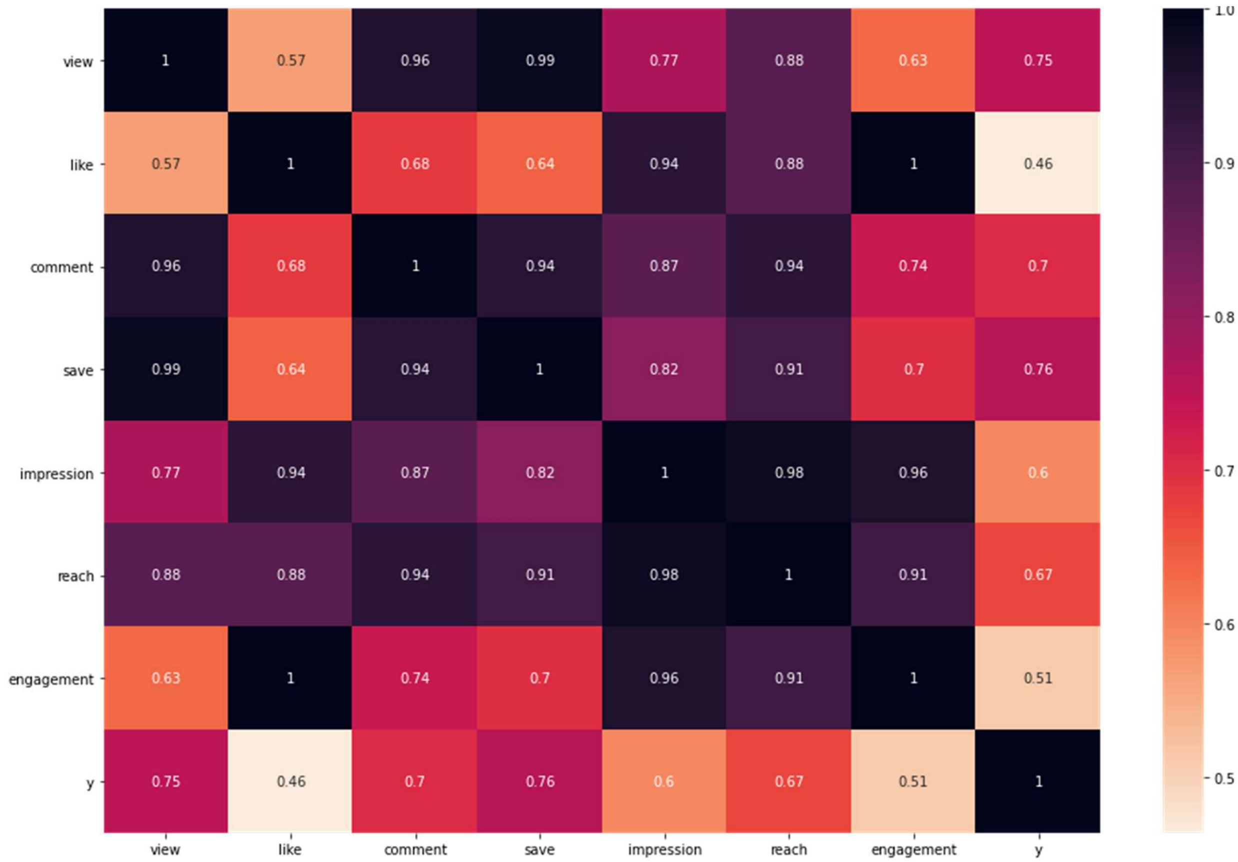

Figure 5. Performance metrics correlation heatmap.

In Table 3, the mean of each performance metric for categories of posts published in the campaign's user account can be seen.

Table 3. The mean of each performance metric for categories of published posts.

Post type	Like	Comment	Save	Reach	Impression	Profile visit
Graphical	140.3	2	0.3	0	0	0
Campaign video	179	11	17	0	0	0
Influencer	184	0.9	1.7	3.1	3.1	0
Logo	90.6	0.8	0.4	0.7	0.8	0
Other ads	59	0.5	0.4	1.7	1.8	0.2
Situational	155.8	1.6	0.9	0.5	0.6	0
Users	201.1	1.5	0.7	0.6	0.6	0
Video	150.6	2.7	4.7	1	1	0.05
Winner announcement	176	18.4	0.4	0	0	0

In Figure 6, the trend of Likes, Comments, and Saves for published posts in the campaign's user account can be seen.

In Figure 7, the scatter plot of main performance metric, i.e., View, regarding other

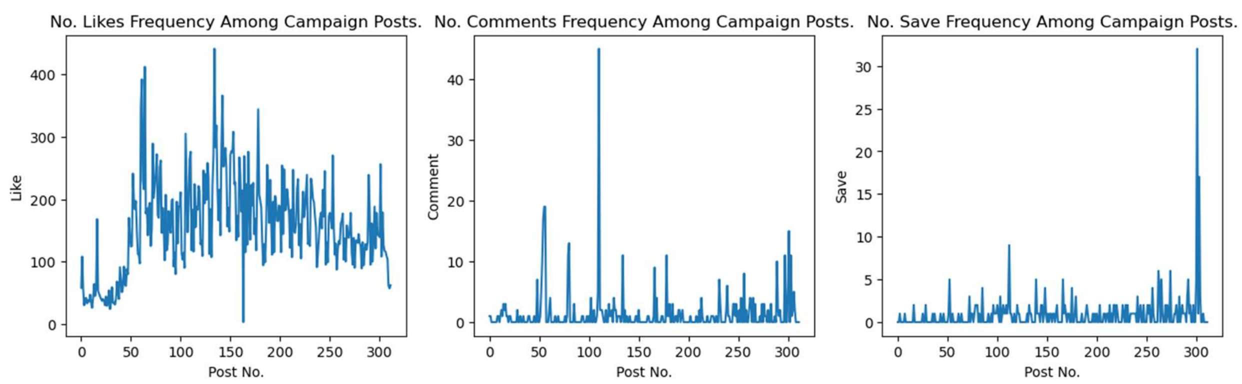

Figure 6. Trend of likes, comments, and saves for published posts in campaign's user account.

performance metrics (i.e., Like, Comment, etc.) with profit status color-coded can be observed.

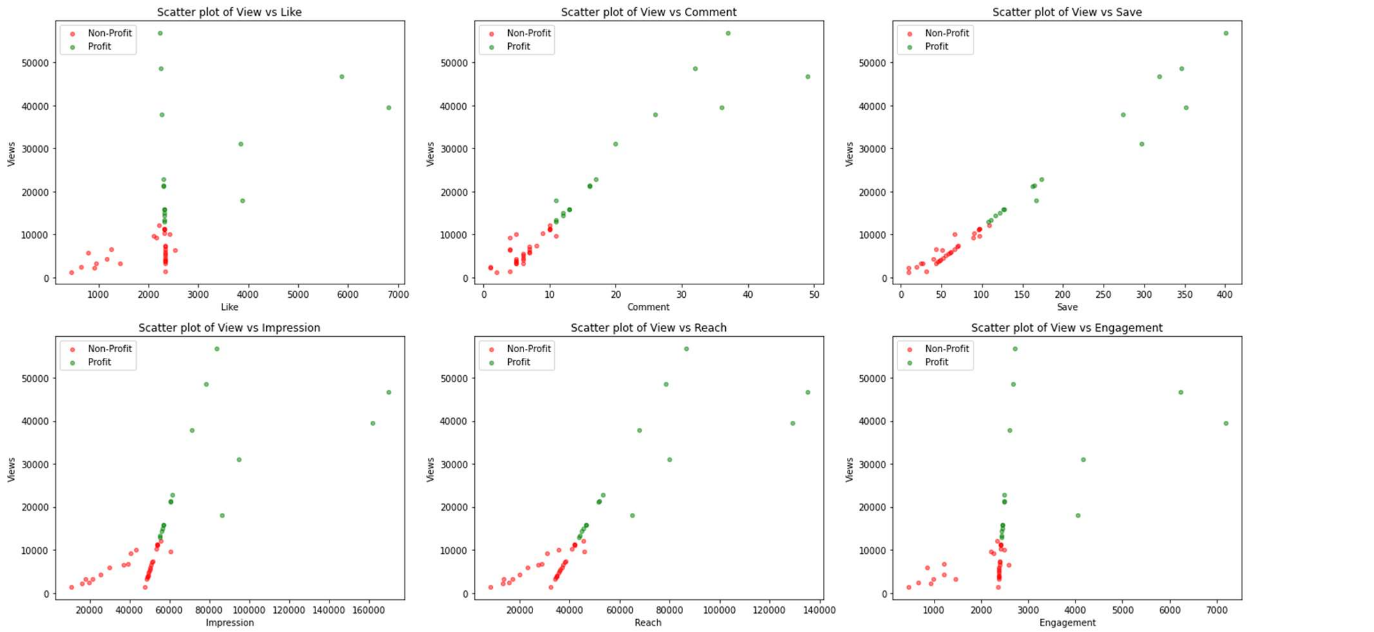

Figure 7. Scatter plot of main performance metric (view) regarding other performance metrics, color-coded via profit status.

In Table 4, the overall number of detected objects in campaign's published content, and in Figure 8, the bar chart of the presented data are accessible.

Table 4. Overall number of detected objects in campaign's published contents.

Object	Quantity	Object	Quantity	Object	Quantity
1 person	82	3 people	1	3 people, text	1
2 people	23	1 person, selfie and close-up	1	1 person, child	1
1 person, close-up	8	9 people	1	1 person, sleeping, baby, close-up	1
1 person, text	4	Shoes	1	1 person sitting and close-up	1
2 people, text	3	Outdoor	1	1 person sitting, eyeglasses and close-up	1
One or more people and text	3	2 people, sunglasses	1	1 person, sunglasses and outdoor	1
1 person, outdoor	3	2 people, close-up	1	Phone	1
One or more people	2	1 person, eyeglasses and close-up	1	2 people, people standing, tree, outdoor and nature	1
1 person, sunglasses	2	1 person, close-up and text	1	1 person, standing and outdoor	1

Object	Quantity	Object	Quantity	Object	Quantity
2 people, sunglasses and text	2	2 people, outdoor	1	1 person, sunglasses and text	1
4 people	2	Indoor	1	One or more people, people sleeping and close-up	1

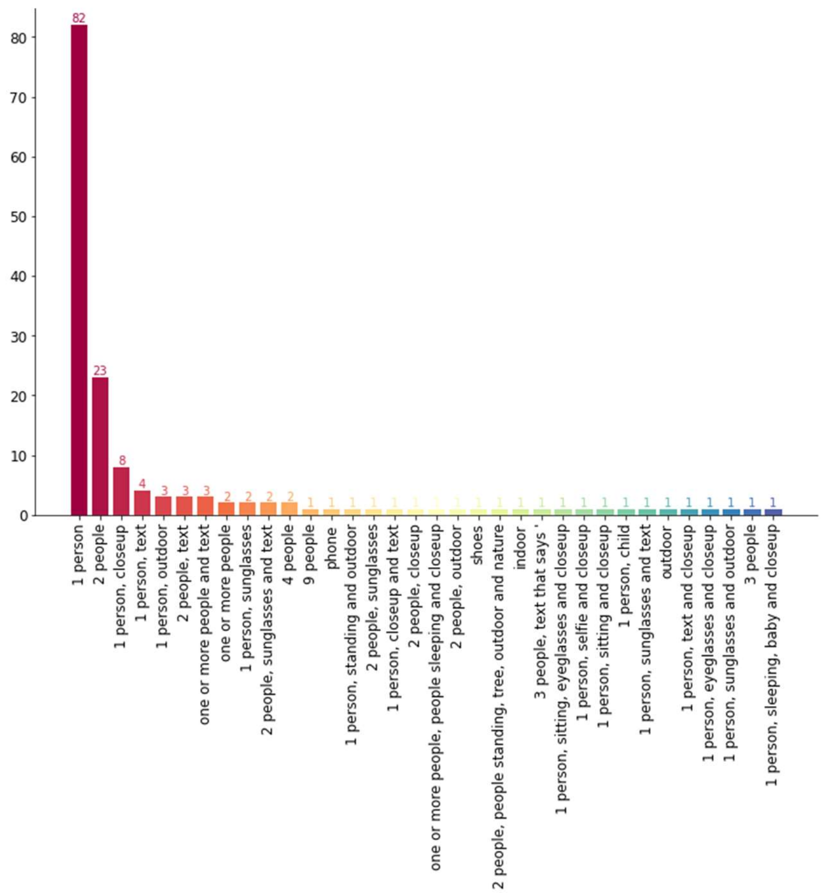

Figure 8. Bar chart of campaign's published contents detected objects.

Out of 49 users who published content regarding the campaign, 22 were influencers, 21 were users, and 6 were public pages. This information and corresponding bar chart can be seen in Table 5 and Figure 9.

Table 5. The quantity of accounts which published content regarding the campaign.

Type of account which published the content	Quantity
Influencers	22
Users	21
Public pages	6

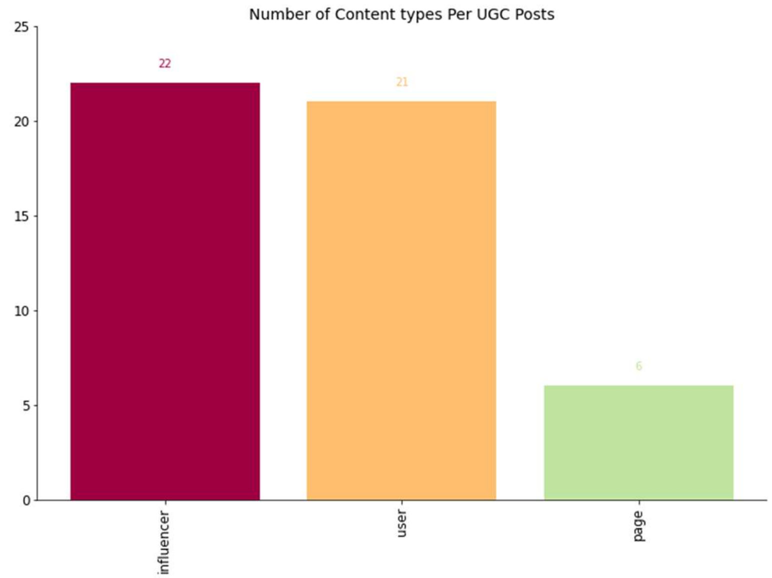

Figure 9. Number of content types per user generated posts.

The quantity of content types per published posts in the campaign's account and corresponding bar chart can be seen in Table 6 and Figure 10.

Table 6. Quantity of content types per published posts in campaign's account.

Content type	Quantity	Content type	Quantity
Users	149	Influencers	16
Logo	79	Graphical posts	4
Video	23	Winner announcement	3
Situational	19	Campaign video	1
Other ads	18		

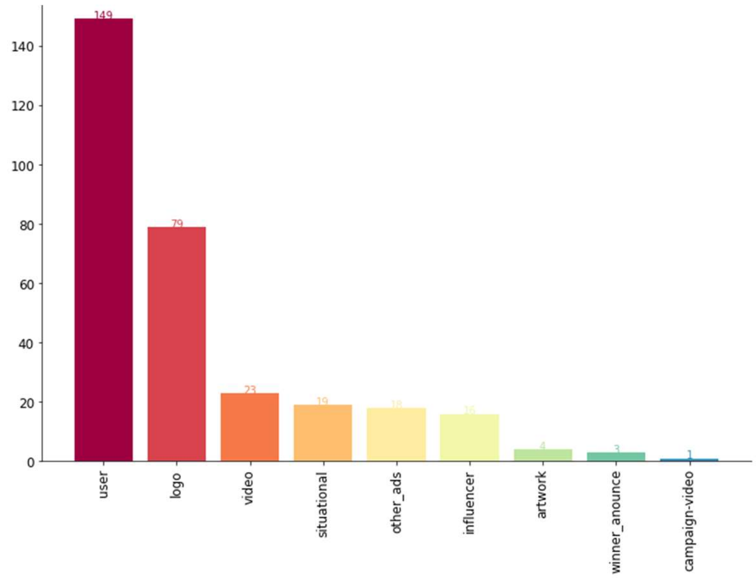

Figure 10. Number of content types per campaign posts.

Regarding the modeling algorithms, the first studied algorithm was logistic regression. As mentioned previously, k-fold cross-validation will be used so the most accurate model on data can be achieved. To find the most accurate model, a grid searching technique is employed. 40 logistic regression models were trained with different combinations of hyperparameters. Table 7 shows the results.

Table 7. Trained logistic regression models hyperparameters combination and evaluation metrics values.

Model index	K	C	Train accuracy	Test accuracy	F1	Jaccard	Logloss
0	2	1	0.9338	0.9348	0.9118	0.85	0.2163
1	2	0.5	0.9111	0.913	0.875	0.8	0.2592
2	2	0.25	0.9111	0.913	0.875	0.8	0.3082
3	2	0.1	0.8893	0.913	0.875	0.8	0.3843
4	2	0.05	0.8893	0.913	0.875	0.8	0.4491
5	2	0.025	0.8893	0.913	0.875	0.8	0.5144
6	2	0.01	0.8893	0.913	0.875	0.8	0.5897
7	2	0.005	0.8893	0.913	0.875	0.8	0.6315
8	2	0.0025	0.9111	0.913	0.875	0.8	0.659
9	2	0.001	0.9111	0.913	0.875	0.8	0.6785
10	3	1	0.9444	0.9333	0.8857	0.8056	0.1974
11	3	0.5	0.9333	0.9333	0.8857	0.8056	0.2375
12	3	0.25	0.9111	0.8889	0.811	0.6944	0.284
13	3	0.1	0.8889	0.8889	0.811	0.6944	0.3567
14	3	0.05	0.8889	0.8667	0.7746	0.6389	0.4202
15	3	0.025	0.8889	0.8667	0.7746	0.6389	0.4868

Model index	K	C	Train accuracy	Test accuracy	F1	Jaccard	Logloss
16	3	0.01	0.9111	0.9111	0.8554	0.75	0.5679
17	3	0.005	0.9222	0.9111	0.8554	0.75	0.6159
18	3	0.0025	0.9222	0.9111	0.8554	0.75	0.6492
19	3	0.001	0.9222	0.9111	0.8554	0.75	0.674
20	4	1	0.9554	0.9337	0.9097	0.85	0.1934
21	4	0.5	0.9332	0.911	0.8819	0.8	0.2336
22	4	0.25	0.9182	0.8902	0.8472	0.75	0.2794
23	4	0.1	0.9035	0.8674	0.8125	0.7	0.3498
24	4	0.05	0.8888	0.8674	0.8125	0.7	0.4113
25	4	0.025	0.8888	0.8674	0.8125	0.7	0.4769
26	4	0.01	0.9037	0.911	0.8819	0.8	0.5589
27	4	0.005	0.9184	0.911	0.8819	0.8	0.6091
28	4	0.0025	0.9258	0.911	0.8819	0.8	0.6447
29	4	0.001	0.9258	0.911	0.8819	0.8	0.6718
30	5	1	0.9556	0.9556	0.92	0.8667	0.183
31	5	0.5	0.9389	0.9333	0.8914	0.8167	0.2218
32	5	0.25	0.9111	0.9333	0.8914	0.8167	0.2678
33	5	0.1	0.8944	0.8889	0.7962	0.6667	0.3393
34	5	0.05	0.8889	0.8889	0.7962	0.6667	0.4021
35	5	0.025	0.8889	0.8889	0.7962	0.6667	0.4694
36	5	0.01	0.9056	0.9111	0.8248	0.7167	0.5539
37	5	0.005	0.9111	0.9111	0.8248	0.7167	0.6057
38	5	0.0025	0.9111	0.9333	0.8914	0.8167	0.6426
39	5	0.001	0.9111	0.9333	0.8914	0.8167	0.6708

The detailed performance result of most accurate logistic regression model can be seen in Table 10. Also, its confusion matrix and ROC curve are illustrated in Figures 11 and 12 respectively.

Table 8. Detailed performance result of most accurate logistic regression model.

	Precision	Recall	F1	Support
0	0.94	1	0.97	29
1	1	0.88	0.93	16
Accuracy			0.96	45
Macro Avg	0.97	0.94	0.95	45
Weighted Avg	0.96	0.96	0.95	45

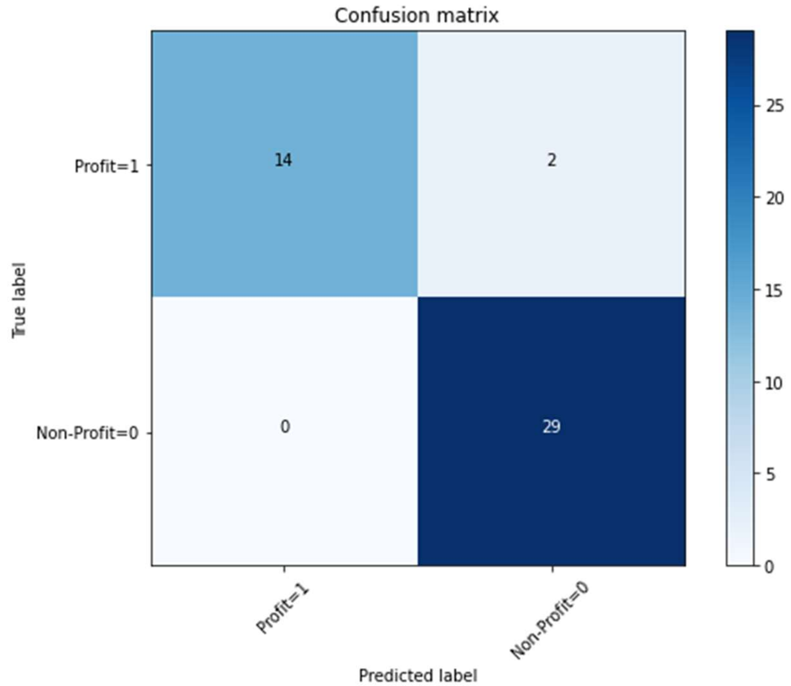

Figure 11. Confusion matrix of most accurate logistic regression model.

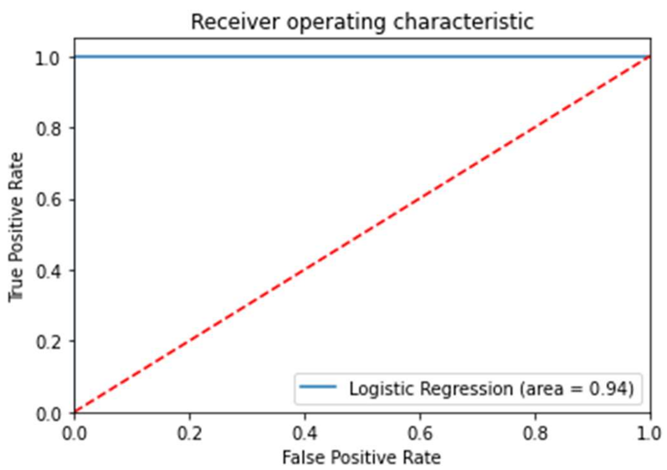

Figure 12. ROC Curve of most accurate logistic regression model.

In Table 9, the intercept of each performance metric in the most accurate logistic regression model can be seen.

Table 9. Intercept of each performance metric based on most accurate logistic regression model.

Performance metric	Intercept
View	1.1901644780020173
Like	0.2663371563656214
Comment	1.0120633096929545
Save	1.0856013601942416

Performance metric	Intercept
Impression	0.47354975087673734
Reach	0.6708793730284395
Engagement	0.35870459756927714

For the support vector machine algorithm, the researcher trained 160 models in total with different hyperparameter combinations. In Table 10, the hyperparameter combination and evaluation metric values of each trained model can be observed.

Table 10. Trained support vector machine models hyperparameters combination and evaluation metrics values.

Model index	K	C	Kernel	Train accuracy	Test accuracy	F1	Jaccard
0	2	1	linear	0.9565	0.9348	0.9118	0.85
1	2	1	poly	0.7796	0.7569	0.4808	0.3167
2	2	1	rbf	0.9328	0.913	0.875	0.8
3	2	1	sigmoid	0.9328	0.913	0.875	0.8
4	2	0.5	linear	0.9565	0.9565	0.9444	0.9
5	2	0.5	poly	0.7796	0.7569	0.4808	0.3167
6	2	0.5	rbf	0.9111	0.913	0.875	0.8
7	2	0.5	sigmoid	0.8676	0.8676	0.775	0.6333
8	2	0.25	linear	0.9545	0.913	0.875	0.8
9	2	0.25	poly	0.7796	0.7342	0.3736	0.2333
10	2	0.25	rbf	0.8221	0.7372	0.4	0.3333
11	2	0.25	sigmoid	0.8231	0.8014	0.619	0.45
12	2	0.1	linear	0.8883	0.8696	0.7857	0.7
13	2	0.1	poly	0.7569	0.7342	0.3736	0.2333
14	2	0.1	rbf	0.6462	0.6462	0	0
15	2	0.1	sigmoid	0.7332	0.7144	0.3333	0.25
16	2	0.05	linear	0.8231	0.8014	0.619	0.45
17	2	0.05	poly	0.7342	0.7125	0.3095	0.1833
18	2	0.05	rbf	0.6462	0.6462	0	0
19	2	0.05	sigmoid	0.6462	0.6462	0	0
20	2	0.025	linear	0.7796	0.7796	0.5641	0.4
21	2	0.025	poly	0.7342	0.6907	0.2338	0.1333
22	2	0.025	rbf	0.6462	0.6462	0	0
23	2	0.025	sigmoid	0.6462	0.6462	0	0
24	2	0.01	linear	0.7342	0.7579	0.5	0.35
25	2	0.01	poly	0.7125	0.6907	0.2338	0.1333
26	2	0.01	rbf	0.6462	0.6462	0	0

Model index	K	C	Kernel	Train accuracy	Test accuracy	F1	Jaccard
27	2	0.01	sigmoid	0.6462	0.6462	0	0
28	2	0.005	linear	0.6897	0.669	0.1429	0.0833
29	2	0.005	poly	0.6907	0.6907	0.2338	0.1333
30	2	0.005	rbf	0.6462	0.6462	0	0
31	2	0.005	sigmoid	0.6462	0.6462	0	0
32	2	0.0025	linear	0.6462	0.6462	0	0
33	2	0.0025	poly	0.6907	0.6907	0.2338	0.1333
34	2	0.0025	rbf	0.6462	0.6462	0	0
35	2	0.0025	sigmoid	0.6462	0.6462	0	0
36	2	0.001	linear	0.6462	0.6462	0	0
37	2	0.001	poly	0.6907	0.6907	0.2338	0.1333
38	2	0.001	rbf	0.6462	0.6462	0	0
39	2	0.001	sigmoid	0.6462	0.6462	0	0
40	3	1	linear	0.9333	0.9333	0.8889	0.8333
41	3	1	poly	0.7889	0.7556	0.4841	0.3333
42	3	1	rbf	0.9333	0.9111	0.8413	0.75
43	3	1	sigmoid	0.9111	0.9111	0.8413	0.75
44	3	0.5	linear	0.9444	0.9556	0.9333	0.8889
45	3	0.5	poly	0.7778	0.7556	0.4841	0.3333
46	3	0.5	rbf	0.9222	0.9111	0.8413	0.75
47	3	0.5	sigmoid	0.8667	0.8667	0.7746	0.6389
48	3	0.25	linear	0.9222	0.8889	0.811	0.6944
49	3	0.25	poly	0.7667	0.7556	0.4841	0.3333
50	3	0.25	rbf	0.8778	0.8667	0.7746	0.6389
51	3	0.25	sigmoid	0.8444	0.8222	0.6746	0.5278
52	3	0.1	linear	0.9	0.8444	0.719	0.5833
53	3	0.1	poly	0.7444	0.7333	0.4127	0.2778
54	3	0.1	rbf	0.6444	0.6444	0	0
55	3	0.1	sigmoid	0.7778	0.8	0.6032	0.4722
56	3	0.05	linear	0.8222	0.8	0.6032	0.4722
57	3	0.05	poly	0.7333	0.7111	0.3238	0.1944
58	3	0.05	rbf	0.6444	0.6444	0	0
59	3	0.05	sigmoid	0.6444	0.6444	0	0
60	3	0.025	linear	0.7889	0.8	0.6032	0.4722
61	3	0.025	poly	0.7333	0.6889	0.1905	0.1111
62	3	0.025	rbf	0.6444	0.6444	0	0
63	3	0.025	sigmoid	0.6444	0.6444	0	0
64	3	0.01	linear	0.7556	0.7556	0.4841	0.3333
65	3	0.01	poly	0.7111	0.6889	0.1905	0.1111

Model index	K	C	Kernel	Train accuracy	Test accuracy	F1	Jaccard
66	3	0.01	rbf	0.6444	0.6444	0	0
67	3	0.01	sigmoid	0.6444	0.6444	0	0
68	3	0.005	linear	0.7	0.7111	0.3238	0.1944
69	3	0.005	poly	0.6889	0.6889	0.1905	0.1111
70	3	0.005	rbf	0.6444	0.6444	0	0
71	3	0.005	sigmoid	0.6444	0.6444	0	0
72	3	0.0025	linear	0.6444	0.6444	0	0
73	3	0.0025	poly	0.6889	0.6889	0.1905	0.1111
74	3	0.0025	rbf	0.6444	0.6444	0	0
75	3	0.0025	sigmoid	0.6444	0.6444	0	0
76	3	0.001	linear	0.6444	0.6444	0	0
77	3	0.001	poly	0.6889	0.6889	0.1905	0.1111
78	3	0.001	rbf	0.6444	0.6444	0	0
79	3	0.001	sigmoid	0.6444	0.6444	0	0
80	4	1	linear	0.9403	0.9129	0.8264	0.725
81	4	1	poly	0.7854	0.7576	0.5595	0.45
82	4	1	rbf	0.9405	0.911	0.8819	0.8
83	4	1	sigmoid	0.9329	0.8902	0.8472	0.75
84	4	0.5	linear	0.9552	0.8883	0.7986	0.675
85	4	0.5	poly	0.7781	0.7576	0.5595	0.45
86	4	0.5	rbf	0.9256	0.8902	0.8472	0.75
87	4	0.5	sigmoid	0.8815	0.8447	0.7679	0.65
88	4	0.25	linear	0.9329	0.8902	0.8472	0.75
89	4	0.25	poly	0.7707	0.7348	0.3095	0.2
90	4	0.25	rbf	0.8815	0.8674	0.8125	0.7
91	4	0.25	sigmoid	0.8445	0.8239	0.7232	0.6
92	4	0.1	linear	0.9033	0.8466	0.7679	0.65
93	4	0.1	poly	0.7558	0.7348	0.3095	0.2
94	4	0.1	rbf	0.652	0.6458	0	0
95	4	0.1	sigmoid	0.8001	0.7803	0.619	0.5
96	4	0.05	linear	0.8298	0.803	0.6637	0.55
97	4	0.05	poly	0.7484	0.7121	0.25	0.15
98	4	0.05	rbf	0.6446	0.6458	0	0
99	4	0.05	sigmoid	0.674	0.6458	0	0
100	4	0.025	linear	0.7854	0.7803	0.619	0.5
101	4	0.025	poly	0.7335	0.6894	0.1667	0.1
102	4	0.025	rbf	0.6446	0.6458	0	0
103	4	0.025	sigmoid	0.6446	0.6458	0	0
104	4	0.01	linear	0.7631	0.7576	0.5595	0.45

Model index	K	C	Kernel	Train accuracy	Test accuracy	F1	Jaccard
105	4	0.01	poly	0.7186	0.6894	0.1667	0.1
106	4	0.01	rbf	0.6446	0.6458	0	0
107	4	0.01	sigmoid	0.6446	0.6458	0	0
108	4	0.005	linear	0.7112	0.7348	0.5	0.4
109	4	0.005	poly	0.6963	0.6894	0.1667	0.1
110	4	0.005	rbf	0.6446	0.6458	0	0
111	4	0.005	sigmoid	0.6446	0.6458	0	0
112	4	0.0025	linear	0.6593	0.6458	0	0
113	4	0.0025	poly	0.6889	0.6894	0.1667	0.1
114	4	0.0025	rbf	0.6446	0.6458	0	0
115	4	0.0025	sigmoid	0.6446	0.6458	0	0
116	4	0.001	linear	0.6446	0.6458	0	0
117	4	0.001	poly	0.6889	0.6894	0.1667	0.1
118	4	0.001	rbf	0.6446	0.6458	0	0
119	4	0.001	sigmoid	0.6446	0.6458	0	0
120	5	1	linear	0.9556	0.9556	0.92	0.8667
121	5	1	poly	0.7889	0.7556	0.4533	0.3333
122	5	1	rbf	0.95	0.9556	0.92	0.8667
123	5	1	sigmoid	0.9111	0.9333	0.8914	0.8167
124	5	0.5	linear	0.9389	0.9556	0.92	0.8667
125	5	0.5	poly	0.7778	0.7556	0.4533	0.3333
126	5	0.5	rbf	0.9167	0.9333	0.8914	0.8167
127	5	0.5	sigmoid	0.8611	0.8667	0.7362	0.6
128	5	0.25	linear	0.9389	0.9333	0.8914	0.8167
129	5	0.25	poly	0.7667	0.7333	0.32	0.2333
130	5	0.25	rbf	0.8667	0.8667	0.7362	0.6
131	5	0.25	sigmoid	0.8389	0.8444	0.6981	0.55
132	5	0.1	linear	0.8944	0.8889	0.8029	0.7
133	5	0.1	poly	0.75	0.7333	0.32	0.2333
134	5	0.1	rbf	0.6444	0.6444	0	0
135	5	0.1	sigmoid	0.8056	0.8222	0.66	0.5
136	5	0.05	linear	0.8278	0.8	0.6067	0.45
137	5	0.05	poly	0.7444	0.7333	0.32	0.2333
138	5	0.05	rbf	0.6444	0.6444	0	0
139	5	0.05	sigmoid	0.6778	0.6444	0	0
140	5	0.025	linear	0.7889	0.7778	0.5067	0.3833
141	5	0.025	poly	0.7333	0.6889	0.16	0.1
142	5	0.025	rbf	0.6444	0.6444	0	0
143	5	0.025	sigmoid	0.6444	0.6444	0	0

Model index	K	C	Kernel	Train accuracy	Test accuracy	F1	Jaccard
144	5	0.01	linear	0.7722	0.7556	0.4533	0.3333
145	5	0.01	poly	0.7167	0.6889	0.16	0.1
146	5	0.01	rbf	0.6444	0.6444	0	0
147	5	0.01	sigmoid	0.6444	0.6444	0	0
148	5	0.005	linear	0.7222	0.7333	0.3933	0.2667
149	5	0.005	poly	0.7	0.6889	0.16	0.1
150	5	0.005	rbf	0.6444	0.6444	0	0
151	5	0.005	sigmoid	0.6444	0.6444	0	0
152	5	0.0025	linear	0.6556	0.6444	0	0
153	5	0.0025	poly	0.6889	0.6889	0.16	0.1
154	5	0.0025	rbf	0.6444	0.6444	0	0
155	5	0.0025	sigmoid	0.6444	0.6444	0	0
156	5	0.001	linear	0.6444	0.6444	0	0
157	5	0.001	poly	0.6889	0.6889	0.16	0.1
158	5	0.001	rbf	0.6444	0.6444	0	0
159	5	0.001	sigmoid	0.6444	0.6444	0	0

The detailed performance result of the most accurate support vector machine model is depicted in Table 11. Also, its confusion matrix can be seen in Figure 13.

Table 11. Detailed performance of most accurate support vector machine model.

	Precision	Recall	F1	Support
0	0.94	1	0.97	29
1	1	0.88	0.93	16
Accuracy			0.96	45
Macro Avg	0.97	0.94	0.95	45
Weighted Avg	0.96	0.96	0.95	45

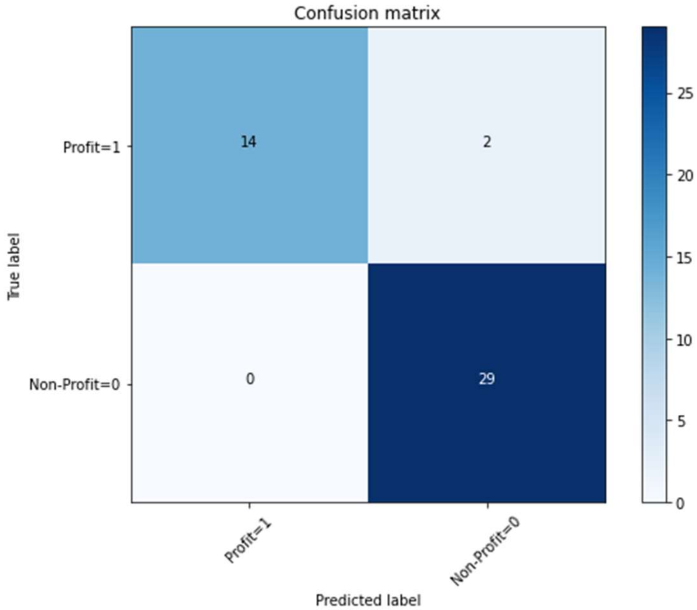

Figure 13. Confusion matrix of the most accurate support vector machine model.

In Table 12, the intercept of each performance metric in the most accurate support vector machine model can be observed.

Table 12. Intercept of each performance metric in the most accurate support vector machine model.

Performance metric	Intercept
View	0.6354777339322173
Like	0.00014963039672058362
Comment	0.5385015130177887
Save	0.5872077697918807
Impression	0.19590618673005702
Reach	0.33328675760233073
Engagement	0.06220372067369484

For k-nearest neighbor algorithm, the researcher trained 72 models with different combination of hyperparameters. In Table 13, every trained k-nearest neighbor model with different hyperparameter combination and their evaluation metric value can be seen.

Table 13. Trained k-nearest neighbors' models hyperparameters combination and evaluation metrics values.

Model index	K	Neighbors	Weight	Train accuracy	Test accuracy	F1	Jaccard
0	2	1	uniform	1	0.9338	0.906	0.8286
1	2	1	distance	1	0.9338	0.906	0.8286
2	2	2	uniform	1	0.9338	0.906	0.8286
3	2	2	distance	1	0.9338	0.906	0.8286
4	2	3	uniform	1	0.9773	0.9615	0.9286
5	2	3	distance	1	0.9773	0.9615	0.9286
6	2	4	uniform	0.9773	0.9348	0.9118	0.85
7	2	4	distance	1	0.9555	0.9352	0.8786
8	2	5	uniform	1	0.9565	0.9444	0.9
9	2	5	distance	1	0.9565	0.9444	0.9
10	2	6	uniform	0.8883	0.8913	0.8333	0.75
11	2	6	distance	1	0.9338	0.906	0.8286
12	2	7	uniform	0.9101	0.8913	0.8333	0.75
13	2	7	distance	1	0.9565	0.9444	0.9
14	2	8	uniform	0.8666	0.8251	0.6853	0.5667
15	2	8	distance	1	0.9338	0.906	0.8286
16	2	9	uniform	0.8883	0.8478	0.7308	0.65
17	2	9	distance	1	0.9348	0.9118	0.85
18	3	1	uniform	1	0.9778	0.9744	0.9524
19	3	1	distance	1	0.9778	0.9744	0.9524
20	3	2	uniform	0.9889	0.9556	0.9441	0.8968
21	3	2	distance	1	0.9778	0.9744	0.9524
22	3	3	uniform	0.9889	0.9778	0.9744	0.9524
23	3	3	distance	1	0.9778	0.9744	0.9524
24	3	4	uniform	0.9889	0.9556	0.9221	0.8611
25	3	4	distance	1	0.9778	0.9744	0.9524
26	3	5	uniform	0.9889	0.9778	0.9697	0.9444
27	3	5	distance	1	1	1	1
28	3	6	uniform	0.9444	0.9111	0.8413	0.75
29	3	6	distance	1	0.9778	0.9744	0.9524
30	3	7	uniform	0.9667	0.9556	0.9333	0.8889
31	3	7	distance	1	1	1	1
32	3	8	uniform	0.9222	0.8667	0.7316	0.6667
33	3	8	distance	1	0.9778	0.9744	0.9524
34	3	9	uniform	0.9	0.9111	0.8333	0.7778
35	3	9	distance	1	1	1	1

Model index	K	Neighbors	Weight	Train accuracy	Test accuracy	F1	Jaccard
36	4	1	uniform	1	0.9773	0.9167	0.875
37	4	1	distance	1	0.9773	0.9167	0.875
38	4	2	uniform	1	0.9318	0.8542	0.775
39	4	2	distance	1	0.9773	0.9167	0.875
40	4	3	uniform	0.9851	0.9773	0.9167	0.875
41	4	3	distance	1	0.9773	0.9167	0.875
42	4	4	uniform	0.9924	0.9773	0.9722	0.95
43	4	4	distance	1	0.9773	0.9167	0.875
44	4	5	uniform	0.9924	1	1	1
45	4	5	distance	1	1	1	1
46	4	6	uniform	0.9628	1	1	1
47	4	6	distance	1	0.9773	0.9167	0.875
48	4	7	uniform	0.9628	1	1	1
49	4	7	distance	1	1	1	1
50	4	8	uniform	0.9329	0.8674	0.8125	0.7
51	4	8	distance	1	1	1	1
52	4	9	uniform	0.9552	0.911	0.8819	0.8
53	4	9	distance	1	1	1	1
54	5	1	uniform	1	0.9778	0.96	0.9333
55	5	1	distance	1	0.9778	0.96	0.9333
56	5	2	uniform	1	0.9778	0.96	0.9333
57	5	2	distance	1	0.9778	0.96	0.9333
58	5	3	uniform	0.9833	0.9778	0.96	0.9333
59	5	3	distance	1	0.9778	0.96	0.9333
60	5	4	uniform	0.9944	0.9778	0.96	0.9333
61	5	4	distance	1	0.9778	0.96	0.9333
62	5	5	uniform	0.9944	0.9778	0.96	0.9333
63	5	5	distance	1	1	1	1
64	5	6	uniform	0.9667	0.9778	0.96	0.9333
65	5	6	distance	1	0.9778	0.96	0.9333
66	5	7	uniform	0.9667	0.9778	0.96	0.9333
67	5	7	distance	1	1	1	1
68	5	8	uniform	0.9611	0.9556	0.92	0.8667
69	5	8	distance	1	0.9778	0.96	0.9333
70	5	9	uniform	0.9889	0.9333	0.88	0.8
71	5	9	distance	1	0.9778	0.96	0.9333

The detailed performance result of the most accurate k-nearest neighbor model can be observed in Table 14.

Table 14. the detailed performance of most accurate k-nearest neighbor model.

	Precision	Recall	F1	Support
0	1	1	1	29
1	1	1	1	16
Accuracy			1	45
Macro Avg	1	1	1	45
Weighted Avg	1	1	1	45

In Figure 14, the scatter plot of major performance metrics (View) in contrast to other performance metrics can be seen. In this graph, data points are color-coded by their profit status, and also areas are marked based on trained k-nearest neighbors' parameters of whether being profit or non-profit.

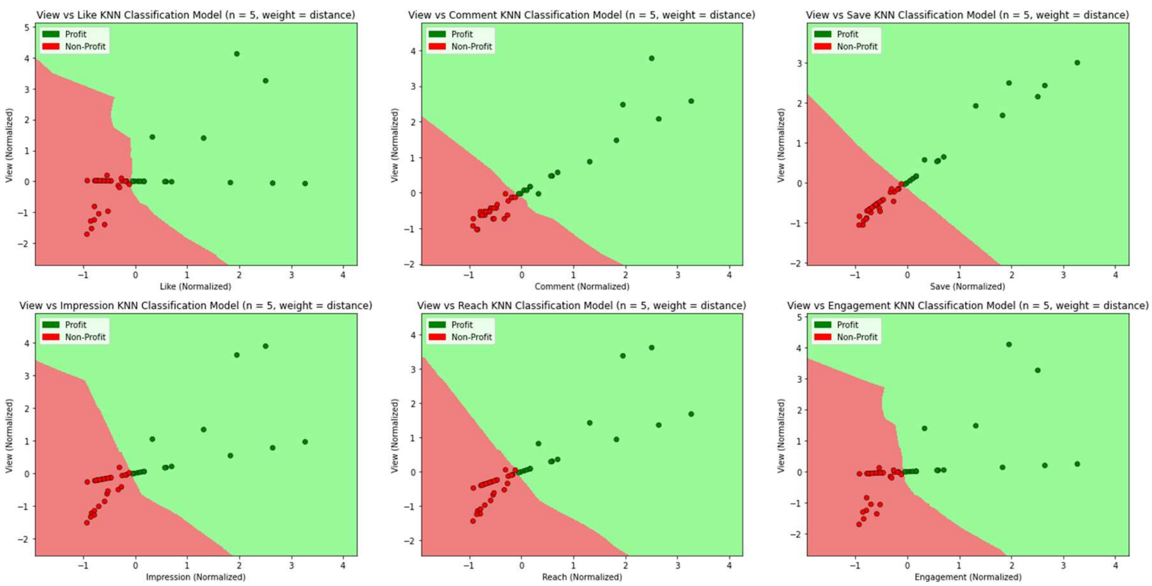

Figure 14. Predicted areas of profit status among performance metrics in k-nearest neighbors' most accurate model.

As pointed out earlier, to find the optimum number of clusters for clustering algorithms, the researcher implemented the Elbow and Silhouette methods. In Figure 15, the results of the Elbow method based on inertia and distortion for the user-generated content and campaign posts can be observed.

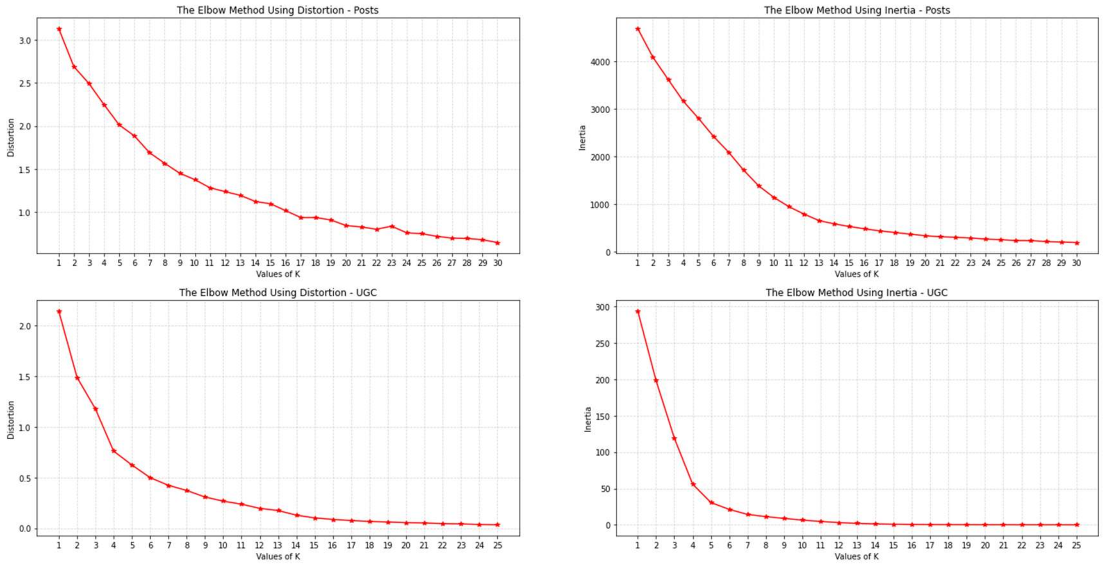

Figure 15. Elbow method results for UGC and Posts dataset based on inertia and distortion.

Moreover, the results of the Silhouette method for the user-generated content and campaign posts datasets are illustrated in Figure 16.

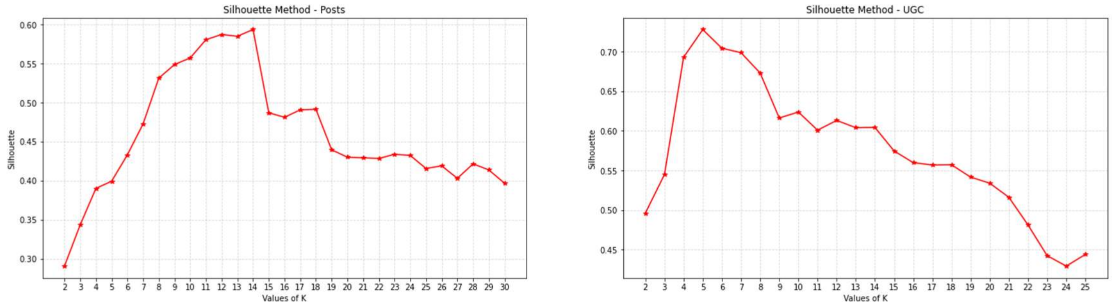

Figure 16. Silhouette method's result for UGC and Posts dataset.

In Table 15, the mean of the optimum k-mean clustering algorithm regarding the clusters in posts dataset can be seen.

Table 15. The mean of most optimum k-mean clustering algorithm regarding the clusters in Posts dataset.

Cluster index	Like	Comment	Save	Reach	Profile visit	Impression	Type-graphic	Type-campaign video	Type-influencer	Type-logo	Type-other ads	Type-situational	Type-users	Type-video	Type-winner announcement
0	200.61	1.10	0.57	0.00	0.0	0.00	0	0	0.00	0.00	0.00	0	1.0	0.00	0
1	90.35	0.65	0.27	0.58	0.0	0.58	0	0	0.00	1.00	0.00	0	0.0	0.00	0
2	155.74	1.53	0.84	0.47	0.0	0.53	0	0	0.00	0.00	0.00	1	0.0	0.00	0
3	49.73	0.33	0.33	1.07	0.0	1.13	0	0	0.00	0.00	1.00	0	0.0	0.00	0
4	151.00	1.75	1.25	6.75	0.0	7.38	0	0	0.63	0.25	0.13	0	0.0	0.00	0
5	176.00	18.33	0.33	0.00	0.0	0.00	0	0	0.00	0.00	0.00	0	0.0	0.00	1
6	185.55	0.64	1.91	1.18	0.0	1.18	0	0	1.00	0.00	0.00	0	0.0	0.00	0
7	179.00	11.00	17.00	0.00	0.0	0.00	0	1	0.00	0.00	0.00	0	0.0	0.00	0
8	200.52	1.15	0.69	1.32	0.0	1.32	0	0	0.00	0.00	0.00	0	1.0	0.00	0
9	266.00	30.00	16.50	0.50	0.0	0.50	0	0	0.00	0.00	0.00	0	0.5	0.50	0
10	140.25	2.00	0.25	0.00	0.0	0.00	1	0	0.00	0.00	0.00	0	0.0	0.00	0
11	84.00	1.00	1.00	3.00	1.3	3.33	0	0	0.00	0.00	0.67	0	0.0	0.33	0
12	150.57	2.24	3.48	0.90	0.0	0.90	0	0	0.00	0.00	0.00	0	0.0	1.00	0

In Table 16, the mean of performance metrics and account type of audience who published content regarding the campaign can be seen.

Table 16. mean of the optimum k-mean clustering algorithm regarding the clusters in UGC dataset.

Cluster index	Like	Comment	Follower	Type-influencer	Type-public page	Type-user
0	0	4213.895	55134.05	1	0	0
1	83.04762	217.381	28614	0	0	1
2	0	70535.5	1057260	1	0	0
3	547	0	59834	0.5	0.5	0
4	37.2	3024.8	78352.6	0	1	0

The results of this clustering are demonstrated in Figures 17 and 18. Figure 17 indicates the scatter plots of main performance metrics (i.e., view) compared to other performance metrics with data points color-coded as their cluster index in the posts dataset. Also, in Figure 18, the same plots for the user-generated content dataset can be observed.

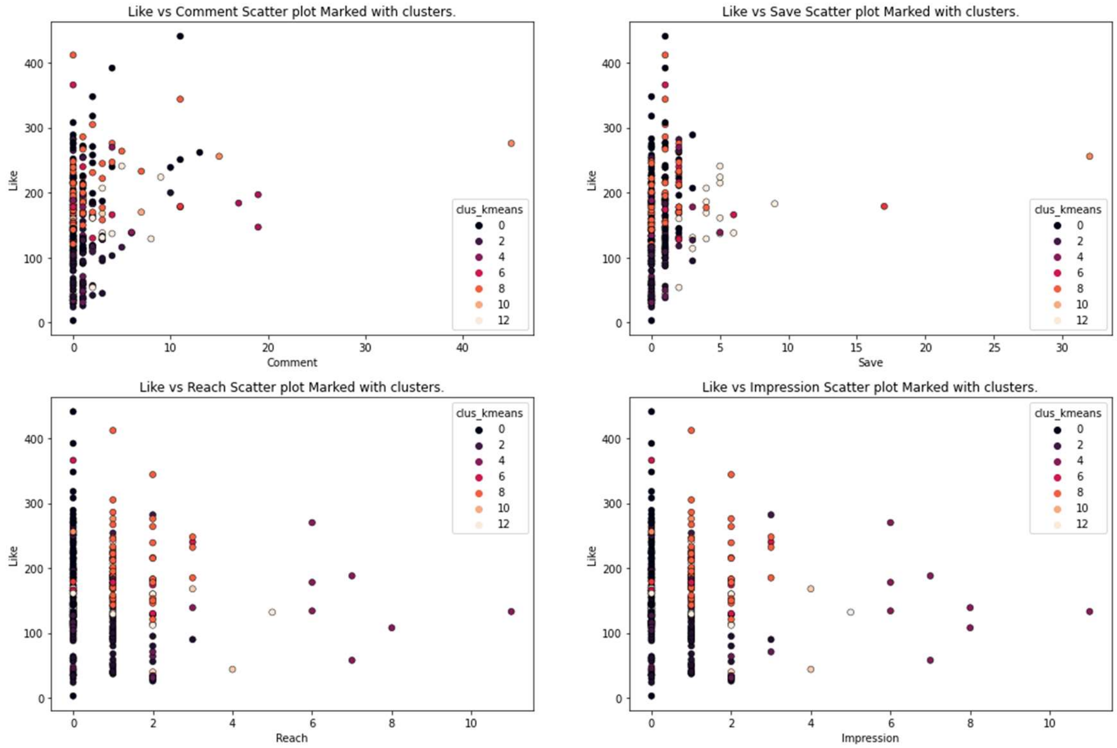

Figure 17. *Scatter plots of View compared to other performance metrics in posts dataset, data points are color-coded as their cluster index.*

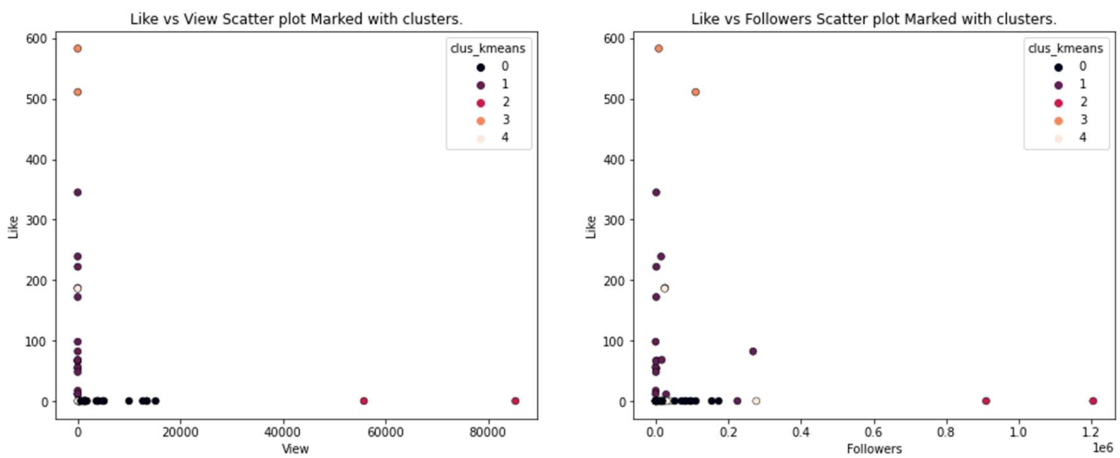

Figure 18. *Scatter plots of View compared to other performance metrics in UGC dataset, data points are color-coded as their cluster index.*

In Figures 19 and 20, the results of the agglomerative hierarchy clustering algorithm for datasets can be seen. In Figure 19, the posts dataset, and in Figure 20, the user-generated content dataset is used.

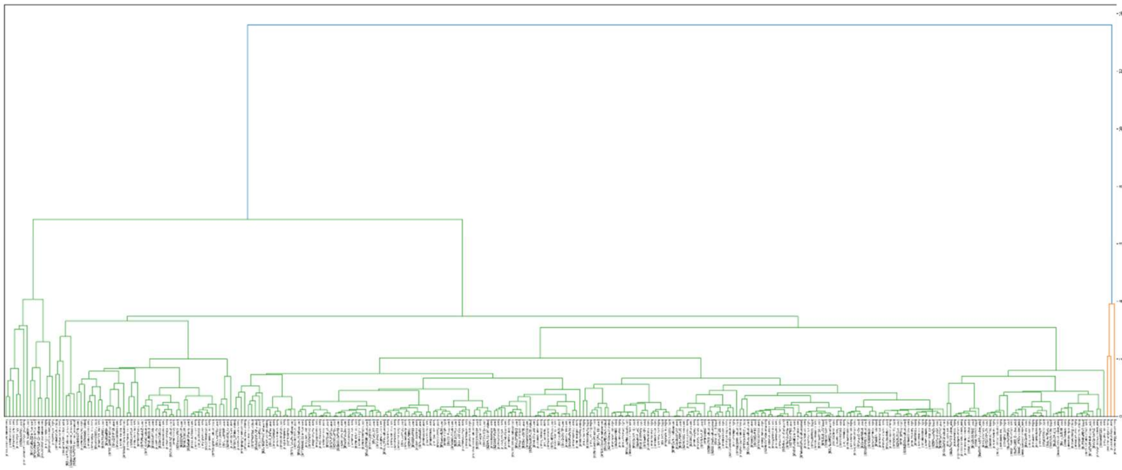

Figure 19. Agglomerative hierarchy clustering algorithm result for posts dataset.

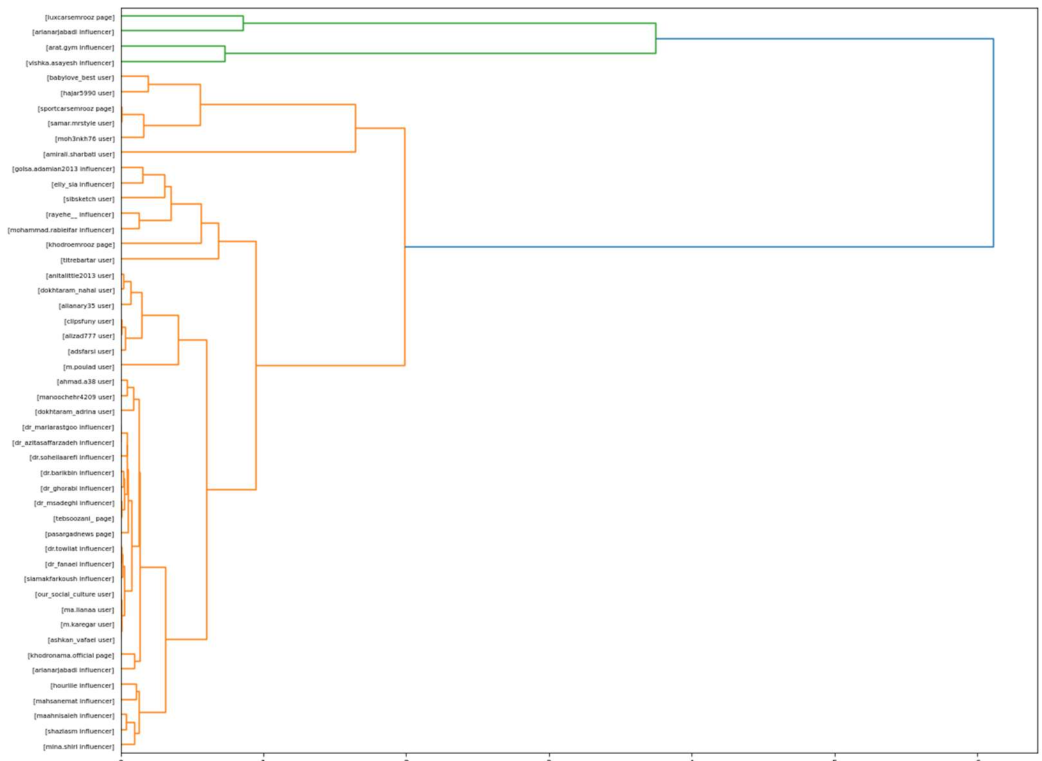

Figure 20. Agglomerative hierarchy clustering algorithm result for UGC dataset.

To implement the DBSCAN, which is a density-based clustering algorithm, we must find the optimum value of the Epsilon hyperparameter that can be done with the Elbow method. In Figure 21, the results of the elbow method are indicated in order to find the optimal value of Epsilon for the user-generated content and posts dataset.

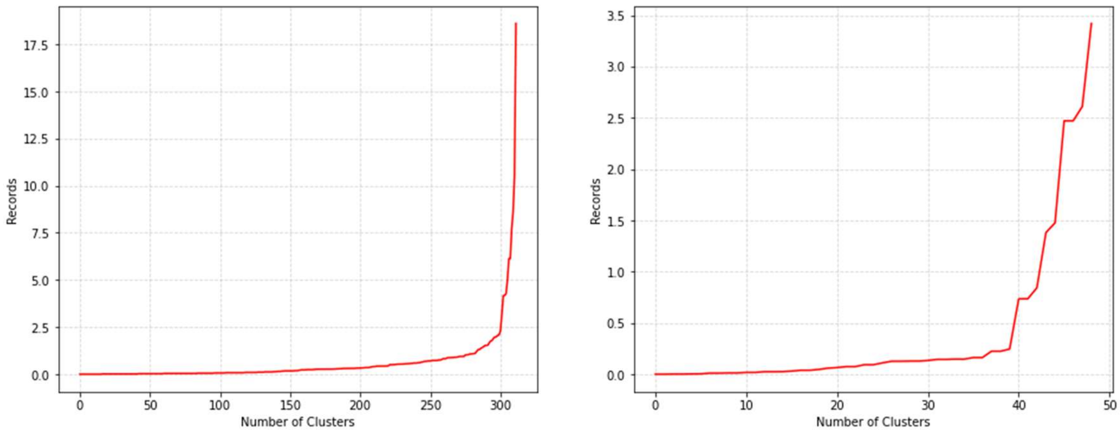

Figure 21. Optimal value of Epsilon hyperparameter for UGC and posts dataset.

In Figures 22 and 23, the result of the DBSCAN algorithm can be seen. Figure 22 demonstrates the scatter plot of view in contrast to Like and Comment in contrast to Like for posts and the user-generated content datasets in which data points are color-coded as their cluster index. In Figure 23, the scatter plot of like in contrast to other performance metrics in posts dataset in which data points are color-coded as their cluster index can be observed.

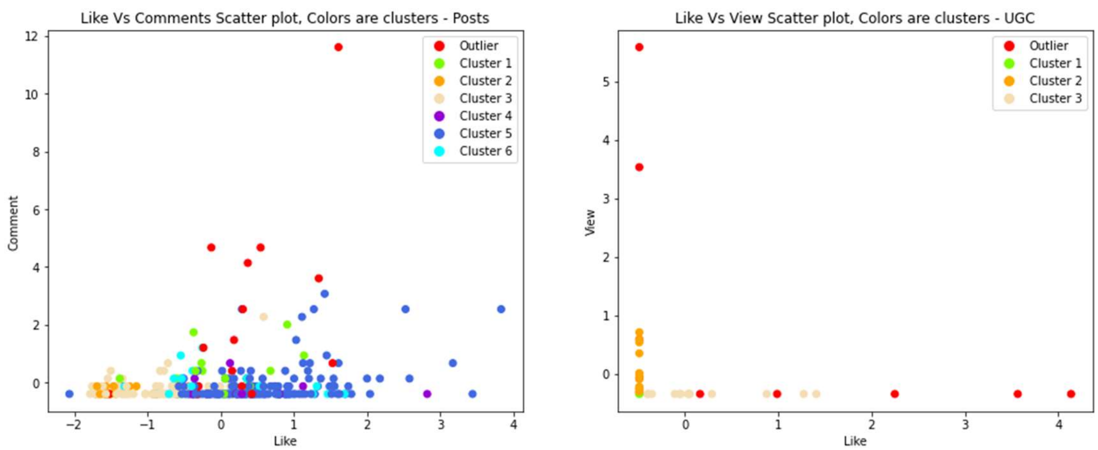

Figure 22. Scatter plots of like vs. comments in posts dataset and like vs view in UGC dataset, membrane clusters are color-coded, result of the DBSCAN clustering algorithm.

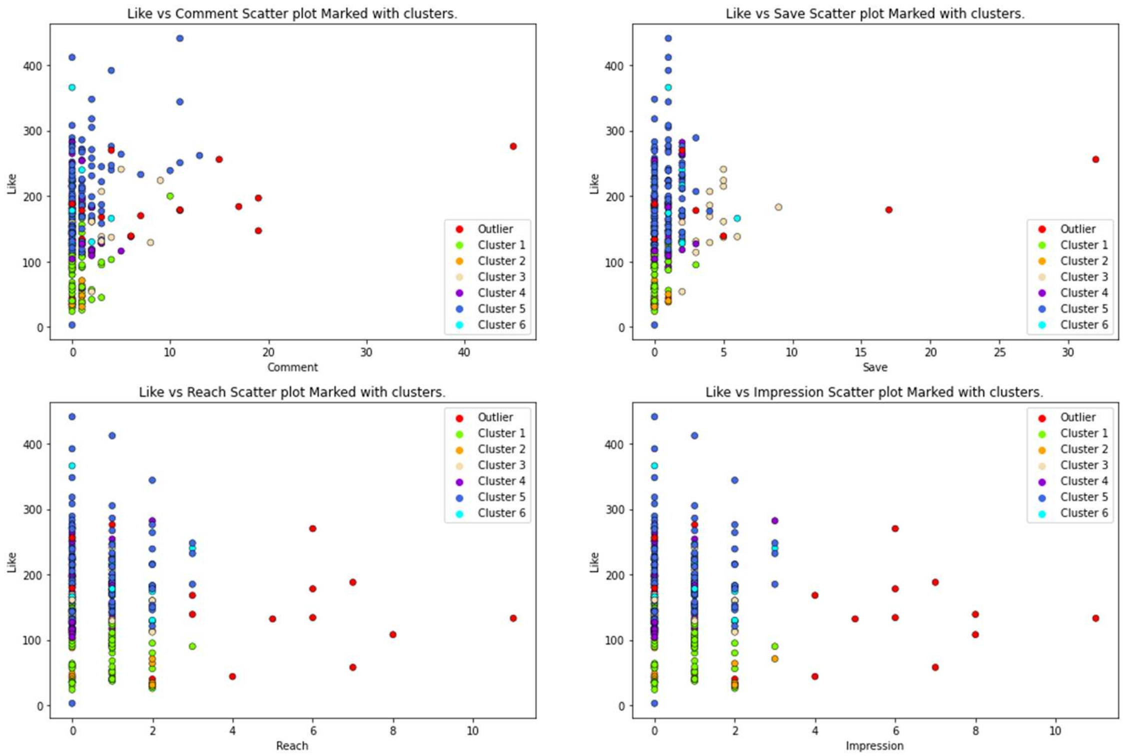

Figure 23. Scatter plot of like in contrast to other performance metrics in posts dataset, data points are color-coded by their clusters, the result of the DBSCAN algorithm.

In Table 17, the mean of performance metrics for each cluster found by the DBSCAN algorithm in posts dataset can be seen.

Table 17. The mean of performance metrics for each cluster found by the DBSCAN algorithm in posts dataset.

Cluster	Like	Comment	Save	Reach	Profile visit	Impression
Cluster 1	90.35	0.65	0.27	0.58	0	0.58
Cluster 2	49.73	0.33	0.33	1.07	0	1.13
Cluster 3	151.50	2.35	3.55	0.70	0	0.70
Cluster 4	155.74	1.53	0.84	0.47	0	0.53
Cluster 5	200.57	1.12	0.62	0.58	0	0.58
Cluster 6	185.55	0.64	1.91	1.18	0	1.18
Outlier	154.18	6.86	3.05	3.14	0.18	3.41

In Table 18, the mean of performance metrics for each cluster found by the DBSCAN algorithm in the user-generated content dataset can be observed.

Table 18. The mean of performance metrics for each cluster found by the DBSCAN algorithm in the UGC dataset.

Cluster	Like	View	Follower
Cluster 1	73.17	30.83	5802.17
Cluster 2	0	4213.89	55134.05
Cluster 3	0	579.67	29644.67
Outlier	189.67	17607.33	337053.22

In the next section, the obtained results and insights will be discussed.

4. Discussion

In this section, the results and insightful information will be explained, interpreted, and discussed. These facts and insights can be useful in terms of the marketing strategy for Instagram advertisement and campaign management.

4.1. Cost-effectiveness insights

Although the majority of advertising media were not profitable, the overall status of the campaign regarding the cost was profitable. This means that there are plenty of low-follower advertising media that were over-priced. However, the high-follower advertising media masked their loss and eventually made this campaign profitable. This is an indicator for marketing strategy and advertising managers to pay special attention to low-follower advertising media and be more careful regarding their price, since they tend to be over-priced than high-follower advertising media. Also, in Table 2, it is visible that profitable advertising media were performing better than not profitable media in every performance metric.

4.2. Sentiment classification insights

As said earlier, out of 407 submitted comments on the campaign's published content, 171 were positive, 223 were neutral, and 13 were negative. The overall sentiment of the campaign was positive. The comparison of the intense negative and positive comments, number-wise and strength-wise, showed minor negativity regarding the campaign. The discovery and analysis of this negativity source require a separate endeavor.

4.3. Exploratory Data Analysis

Performance correlation heatmap is one of the most significant results and insights obtained in this research (Fig. 5). Some of the insightful information of this heatmap is listed below:

- The lowest correlation is between the Like and y (i.e., the status of being profitable or not profitable of an advertising medium). This means that to make a campaign profitable, Like is not a good performance metric to maximize. It is worth mentioning that, currently, Like is a competitive advantage in the opinion of media owners, and their advertising price is based on this parameter.
- The highest correlation is between the Like and Engagement, and this means that the quantity of Like is a subpart of Engagement directly and organically.

- Save and Comment have a strong correlation with the main performance metric, i.e., view. Based on this information, in order to maximize the view parameter for posts, one should focus on these metrics. Currently, strategies to maximize the Save parameter are rarely seen in marketing strategies. Nevertheless, to make the campaign's content more visible and viral organically, the best way is to focus on this parameter.
- There is a strong correlation between Save and Comment which indicates the importance of these performance metrics.
- There is a fair correlation between Reach and Engagement with Impression, indicating a relationship between these parameters and suggesting content on Instagram. There is also a strong correlation between Reach and the main performance metric, i.e., View. It can be deduced that among Engagement, Reach, and Impression, Reach is the most important, and maximizing it will increase View and two other aforementioned performance metrics.
- The correlation between Like and View is one of the weakest. This means that the quantity of Likes for content is not a good measure for advertising media, and this parameter should not be used as an advantage or a unit for assessing media.

In Table 3, the mean of performance metrics for each category of posts in the campaign's user account can be seen. The following insights can be gained from this Table:

- The most-Liked content type was users.
- Most comments were acquired by winner announcement posts and in the second place campaign's video.
- As anticipated, the most-saved interaction was for the campaign's video type.
- Influencer type acquired the most Reach and Impression, possibly because of their high-follower user accounts.
- Other ads type of posts caused the users who had seen those kinds of posts to share them, and also caused other people to visit the campaign's account. This can be interpreted as an effective approach regarding the post-campaign content strategy.

In Figure 6, the frequency of Like, Comment, and Save performance metrics in the campaign life-time can be seen. The number of Likes for each post was growing gradually; obviously, a degree of noise regarding the subject is visible. Moreover, the number of acquired Comments and Saves were almost stable and static for the campaign life-cycle.

It is worth mentioning that analyzing and comparing the performance metrics of advertising media in terms of being profitable or not profitable, shed light on a matter that is vital for advertising agencies: There was some incoherence regarding some advertising media. For instance, although some media did not acquire the highest number of views, they recorded the highest number of Impressions, and their difference was remarkable. Furthermore, this behavior was monitored for that specific media for Reach performance metrics. This is an indicator of possible fraud and data manipulation, which should be investigated further by the advertising agency.

Before implementing the classification algorithms for the advertising media dataset, color coding data points gives a slight hint about the profitable and not profitable prediction area and their linear behavior. This is further investigated in the Modeling section.

In Table 4 and also Figure 8, the state of the detected objects in posts can be seen. Overall, 52.3% of contents contained “1 person”, 14.7% contained “2 people”, and 5.1% were close-ups and contained “1 person”.

In Table 5 and Figure 9, the dispersion of user accounts' types which share content related to the campaign can be observed. Overall, 44.9% were influencers, 42.9% were real users, and 12.2% were public pages.

In Table 6 and Figure 10, the dispersion of content type in the campaign's account can be seen. Overall, the top three types of content were: users (47.8%), logos (25.3%), and videos (7.4%).

4.4. Modeling Analysis

4.4.1. Logistic Regression

In Table 7, there are some records in which the test accuracy is higher than the train accuracy. This might have two reasons: 1) the distribution of the test dataset is different from the training dataset, and 2) the high degree of regularization is applied for that model. In Table 19, the three most accurate, and in Table 20, the three least accurate logistic regression models and their hyperparameter combinations can be seen.

Table 19. The three most accurate logistic regression models and their hyperparameter combinations

Model index	K	C	Train accuracy	Test accuracy	F1	Jaccard	LogLoss
30	5	1	0.9556	0.9556	0.92	0.8667	0.183
0	2	1	0.9338	0.9348	0.9118	0.85	0.2163
20	4	1	0.9554	0.9337	0.9097	0.85	0.1934

Table 20. The three least accurate logistic regression models with their hyperparameter combinations

Model index	K	C	Train accuracy	Test accuracy	F1	Jaccard	LogLoss
14	3	0.05	0.8889	0.8667	0.7746	0.6389	0.4202
15	3	0.025	0.8889	0.8667	0.7746	0.6389	0.4868
33	5	0.1	0.8944	0.8889	0.7962	0.6667	0.3393

As Table 19 demonstrates, the most accurate model with logistic regression algorithm is 5-fold and c=1, and according to Table 20, the least accurate model with logistic regression algorithm is 3-fold and c=0.05.

In Table 9, the intercept of each performance metric based on the most accurate logistic regression model is shown. It is noteworthy that the top three performance metrics with the highest intercept are View, Save, and Comment, in the same order seen in the performance correlation heatmap. In other words, although Save and Comment are not the main performance metrics, they have a significant impact on View, which is the main performance metric. This can clearly help advertising agencies and specialists who are members of the advertising campaign on Instagram increase their campaign's effectiveness. In other words, special attention to Save and Comment on Instagram might increase the effectiveness of the campaign on this social medium.

4.4.2. Support Vector Machine

Table 21 indicates three of the most accurate support vector machine models with their hyperparameter combinations. Moreover, Table 22 shows three of the least accurate support vector machine models with their hyperparameter combinations.

It should be borne in mind that in the worst cases, the F1 score and Jaccard score are set to 0, which means an undefined score. Hence, the classifier is very bad.

Table 21. Top 3 of most accurate support vector machine models with their hyperparameter combination

Model index	K	C	Kernel	Train accuracy	Test accuracy	F1	Jaccard
4	2	0.5	linear	0.9565	0.9565	0.9444	0.9
44	3	0.5	linear	0.9444	0.9556	0.9333	0.8889
120	5	1	linear	0.9556	0.9556	0.92	0.8667

Table 22. Top 3 of least accurate support vector machine models with their hyperparameter combination

Model index	K	C	Kernel	Train accuracy	Test accuracy	F1	Jaccard
14	2	0.1	rbf	0.6462	0.6462	0	0
18	2	0.05	rbf	0.6462	0.6462	0	0
19	2	0.05	sigmoid	0.6462	0.6462	0	0

As can be seen in Table 21, the most accurate support vector machine is 2-fold, c=0.5 and linear kernel. The least accurate support vector machine model is 2-fold and c=0.1 and RBF kernel. In Table 12, the intercept of the most accurate support vector machine algorithm for each performance metric is shown. The same behavior as logistic regression result is visible here that indicates the learning was successful and, in both algorithms, the same concept from the data is trained.

4.4.3. k-nearest neighbor analysis

In Table 23, the three of the most accurate k-nearest neighbor models with their hyperparameter combinations, and in Table 23, the three of the least accurate k-nearest neighbor models with their hyperparameter combinations can be observed.

Table 23. Top 3 of most accurate k-nearest neighbor models with their hyperparameter combinations

Model index	K	Neighbors	Weight	Train accuracy	Test accuracy	F1	Jaccard
27	3	5	distance	1	1	1	1
31	3	7	distance	1	1	1	1
35	3	9	distance	1	1	1	1

Table 24. Top 3 of least accurate k-nearest neighbor models with their hyperparameter combinations.

Model index	K	Neighbors	Weight	Train accuracy	Test accuracy	F1	Jaccard
14	2	8	uniform	0.8666	0.8251	0.6853	0.5667
16	2	9	uniform	0.8883	0.8478	0.7308	0.65
14	2	8	uniform	0.8666	0.8251	0.6853	0.5667

According to Tables 23 and 24, the most accurate k-nearest neighbor is 3-fold with five neighbors and distance weight, and the least accurate k-nearest neighbor algorithm is 2-fold with eight neighbors and uniform weight. It is worth mentioning that with the k-nearest neighbor algorithm, we managed to achieve perfect accuracy, but in logistic regression and support vector machine, this accuracy was not achieved. In Figure 14, the scatter plot of the main performance metric, i.e., view, compared to other performance metrics in the advertising media dataset is visible. The data points and areas are also color-coded as profit and non-profit.

Interestingly, in Figure 14, as seen in measurements correlation heatmaps, Engagement and Like have a strong linear correlation. And this concept was learned by the model. Also, as can be observed, the profit or non-profit areas are the same for these two parameters.

4.4.4. Elbow method analysis

The results of the Elbow method for the user-generated content and posts datasets are presented in Figure 15. As can be seen, there are no concrete and solid elbow points in posts datasets. The reason behind this is the proximity of data points. Therefore, the clustering based on k-means is not a good choice for this problem. Although based on the results of the Elbow method, it is anticipated that 13 is an acceptable number of neighbors in the post dataset, and 5 as the number of neighbors in the user-generated content dataset.

4.4.5. Silhouette method analysis

The results of the Silhouette method for the user-generated content and post dataset are illustrated in Figure 16. As predicted, the results of this method were clearer than the Elbow method regarding the optimum number of clusters. Based on the results of this method, the optimum number of clusters for the posts dataset is 13, and for the user-generated content dataset is 5. Furthermore, the highest approximated score for the Silhouette method in clustering of posts dataset was slightly more than 0.6, and in clustering of the user-generated content dataset was slightly more than 0.7, meaning that the clustering based on k-means is not a suitable approach for these clustering problems, even though this approach was implemented so we could compare its results to other approaches.

4.4.6. Centroid-based clustering (k-means)

In Table 15, the mean of the optimum k-means clustering algorithm regarding the clusters in the posts dataset is presented. Based on that information, these insights can be deduced:

- Three clusters containing the posts with the highest number of Comment and Save.
- The posts with the highest number of Saves are divided into two different categories, which depend on other performance metrics.

- Posts with content types of video, graphical, situational, and winner announcement are placed in exclusive clusters.
- Posts with content types of influencers and logos are divided into two clusters.
- Posts with content types of other ads, users, and videos are divided into three clusters with different ratios.

In Table 16, the mean of the optimum k-means clustering algorithm regarding the clusters in the user-generated content dataset can be seen. Considering this information, the following insights can be achieved:

- The cluster indexed 0 contains the most-followed user accounts, all of which are influencers.
- The cluster indexed 1 contains the user accounts.
- The cluster indexed 2 contains the second part of influencers who have gained the highest number of comments and followers.
- The cluster indexed 3 can be divided into two parts; one part is influencers, and the other one is public pages.
- The cluster indexed 4 completely consists of public pages.

In Figures 17 and 18, each post and the user-generated content, color-coded by their cluster, can be observed.

4.4.7. Hierarchical clustering (agglomerative)

Figures 19 and 20 present the results of hierarchical clustering. The optimal number of clusters found via this method is four, and based on the results of the Silhouette and Elbow methods, they are not optimal. As anticipated, the best method for these clustering problems is clustering based on density with the DBSCAN algorithm.

4.4.8. Clustering based on density (DBSCAN)

As pointed out earlier, to implement the DBSCAN algorithm, we have to find the optimal value for the Epsilon hyperparameter. This issue can be solved via the Elbow method, the results of which can be observed in Figure 21. According to the results, the optimal value of Epsilon for posts datasets is 2.5, and for the user-generated content dataset is 0.75. The result of clustering with the DBSCAN algorithm is presented in Figures 22 and 23. As predicted, the performance of this approach was better than the previous approaches. In post datasets, this algorithm found six clusters, and in the user-generated content dataset, three clusters were found. It should be noted that in the DBSCAN algorithm, automatically a cluster is defined for outliers which is red color-coded in Figures 22 and 23.

In Table 17, the mean of performance metrics for each cluster found by the DBSCAN algorithm in the dataset of posts is presented. Based on that information, these insights can be obtained:

- Outliers: the members of this cluster are not most-Liked, and in fact, are in third place compared to other clusters. Members of this cluster, on average, gained the highest number of Comments, Reach, and Impressions, and second place in the number of Saves. The only cluster which acquired profile visit is in this cluster. The contents which are placed in this cluster are not bad naturally, rather these contents were affected by other parameters which were not recorded by Instagram, and eventually not presented in the dataset. For instance, these parameters can be the time status of the published post, the Instagram trend at the time of publishing, accidents, etc.

- Cluster 1: members of this cluster are posts that, on average, gained the least number of Saves, Reach, and Impressions, and second to the last place in Likes and Comments.
- Cluster 2: members of this cluster are posts that, on average, gained the least number of Likes and Comments, second to the last place in Saves, and fourth place in the number of Reach and Impressions.
- Cluster 3: members of this cluster are posts that, on average, gained the mediocre number of Likes, Impressions, and Reach, but second place in the number of Comments and the highest number of Saves.
- Cluster 4: members of this cluster are posts that, on average, gained third place in the number of Likes and mediocre in other performance metrics.
- Cluster 5: members of this cluster are posts that, on average, gained the highest number of Likes, and mediocre in other performance metrics.
- Cluster 6: members of this cluster are posts that, on average, gained second place in Likes, Reach, and Impressions, also, third place in Saves and mediocre in other performance metrics.

In Table 18, the mean of performance metrics for each cluster found by the DBSCAN algorithm in the user-generated content dataset is presented. Hence, the following insights can be obtained:

- Outliers: members of this cluster, on average, perform better than other clusters. The main reason for this behavior is the presence of celebrities who participated in the campaigns in this cluster. Celebrities' accounts on Instagram, compared to other user accounts, have many more followers and hence perform better than other accounts. Since there are only two celebrities in this campaign, the content created by them is placed in the outlier cluster, which is correct. Although the category of user accounts is omitted in the DBSCAN algorithm, it managed to detect that and distinguished between celebrities' accounts and the others based on other parameters. Thus, bias is terminated. This is one of the reasons why the DBSCAN is a better approach regarding this clustering problem.
- Cluster 1: members of this cluster consist of posts on average since their like-to-view ratio is greater than 1. Also, they are mostly low-follower influencers, because the average of their followers is less than 6000.
- Cluster 2: high-follower influencers are members of this cluster. After celebrities, they are in second place regarding the number of Likes. Since their posts are videos, the number of likes of this cluster, on average, is 0.
- Cluster 3: members of this cluster are influencers with mediocre performance.

5. Conclusion

The current paper attempted to assess the effectiveness of an advertising campaign on Instagram via advertising costs and sentiment classification of audience opinions on the campaign. The standard methodology was utilized for these types of challenges, i.e., CRISP-DM, the features of which were discussed in 2.2. Methodology section. The results of these two approaches are presented comprehensively in 3. Results and interpreted separately in 4.1. Cost-effectiveness insights and 4.2. Sentiment classification insights Another interesting point retrieved from this research was that for the #Bekhatereman campaign, due to the highly effective selection of high-follower advertising media, almost 7.1% of the cost returned as net profit of the additional main performance metric, i.e., View.

Having defined three questions regarding the datasets, one of them was a classification problem for advertising media in which the researcher attempted to predict the effectiveness status of an advertising medium with its performance metrics, and two of them were clustering problems for campaign's posts and the user-generated contents in which we tried to predict the membership status of a post or the user-generated content in the most similar cluster and predict its performance based on that cluster.

To overcome these problems, the researcher implemented multiple algorithms for both classification and clustering and grid-searched among them as well as multiple hyperparameter combinations to find the best possible answer and the most accurate approach regarding the matter. The results of these approaches are comprehensively presented in 3. Results and interpreted separately in 4.4. Modeling Analysis

In this research, multiple insights about the marketing strategy for the campaigns on Instagram were obtained from this campaign. For instance, one of the most important insights was the correlation between the performance metrics on this social medium, presented in 4.3. Exploratory Data Analysis These insights can help marketing specialists and advertising agencies to plan more effective marketing strategies via a better understanding of this medium they want to utilize for their marketing needs. Other types of insights, which are somewhat exclusive to this campaign, are believed to be a good milestone for other campaigns. The analysis of other campaigns based on the approaches presented in this research can organize the analysis process of advertising campaigns on Instagram.

Several suggestions are proposed for further research:

- ✓ Developing and expanding the sentiment score dictionary in Persian, both in words and emojis, with special attention to marketing objectives and other fields.
- ✓ Designing and developing Persian corpora, including various texts, such as news, poems, literature, everyday sentences, etc., so less-biased natural language models can be developed and trained in Persian.
- ✓ Developing models based on machine learning, artificial intelligence, and other heuristic approaches for evaluating effectiveness advertising endeavors in other forms and derivatives of social media.

- ✓ Feasibility study on implementing other forms of computer learning for evaluation and classification of the audience in order to fully deliver customized services.
- ✓ Analyzing the relation of performance metrics in order to reach advertising campaign goals and objectives on other social media.

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