How Facebook Photo Post's Text Impacts User Engagement in Fashion – A Machine Learning Approach

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Abstract

Fashion industry has become increasingly popular aiming to increase social media users' engagement, brand awareness, and revenues. The aim of this study is to calculate the organic fashion photo posts' text characteristics such as text readability, hashtags number and characters number. Using data mining classification models try to expose whether these characteristics affect organic post user engagement for lifetime post engaged users and lifetime people who have liked your page and engaged with your post. Post text readability score, characters number, and hashtags number are the independent variables. Post's performances were measured by seven Facebook performance metrics, the depended variables. Data, content characteristics, and performance metrics were extracted from a business Facebook page. Finally, user engagement was calculated, and posts' performance classification was represented through decision tree graphs. The findings reveal how post texts content characteristics impact performance metrics helping marketers to better form their Facebook organic image post strategies.

Keywords: Facebook performance metrics, organic post's text content characteristics, fashion post's user engagement

Track: Digital Marketing & Social Media

1. Introduction

Rapid internet growth made companies leverage from using social media marketing to increase profitability and recognition giving marketers the opportunity to extract marketing rules based of customer purchasing patterns (Pancer et al., 2019). It is also estimated that COVID-19 pandemic accelerated shift to e-commerce by 5 years. E-commerce is estimated to show nearly 20% growth in the year of 2020 (World Economic Forum, 2020). From a generic literature review point of view there is an impressive and substantial amount on research projects examining metrics such as impressions, reach, volume of certain keywords and sentiments, social and organic referrals, conversion rates, click through rates and number of users' intentions to purchase based on statistical analysis, predictive analytics text mining, association rules and clustering (Cvijikj et al., 2011). There is empirical evidence suggesting that user behavior depends on several factors such as the nature of the post, the industry sector, the content type and meaning, posting time and day (Cvijikj & Michahelles, 2013). Text readability is also examined as a factor that affects user engagement. Writing skills considered to be the father of thought having the scholars agree on that writing language is by far better than oral expression of thought (Applebee, 1984). Flesch–Kincaid readability test refers to readability measuring formula indicating material that is easy to read. It rates a collection of words on an increasing 100-point scale where the text with the higher score indicates better readability (Kincaid, et al., 1975). Similarly, the Gunning Fog Index calculates the average sentence length and the number of words estimating the years of formal education a person needs to understand the text on the first reading (Du Bay, 2004).

The scope of this research is to help fashion businesses navigate these times of anxiety and uncertainty providing decision makers and retailers information to optimize their social media photo post texts maximizing users' engagement and profits. To succeed that, a machine learning algorithm using decision tree classification will be used to classify the previously mentioned content characteristics and performance metrics.

2. Related Work

There are several research attempts which examine the Facebook performance metrics that affect post user engagements. However, the research about user engagement in fashion posts is scarce. Thus, the most representative studies which study post's text content characteristics and Facebook performance metrics are presented. A significant work using regression on cosmetics data, showed that that five Facebook attributes including “lifetime post total reach”, “lifetime post total impressions”, “lifetime post consumers”, “lifetime post impressions by people who have liked your page” and “lifetime people who have liked your page and engaged with your post” had a causation or predictive significance towards the sum of total “comments”, “likes”, and “shares” of a post called “total interactions” attribute and “total interactions” correlated with attributes such as “lifetime post reach by people who like your page”, “lifetime engaged users”, and “lifetime post total reach” (Mittal, 2020). Facebook engagement metrics such as “comments”, “likes”, “shares”, the type of content, the month, and the day of publication affect “lifetime total organic reach”, “total page likes” of the company’s page performance (Huang et al., 2018). The content type was considered the most relevant input variable for the data-based sensitivity analysis. “Status” posts seemed to double the impact in comparison to other post types. Also, the date of publication proved to affect the engagement (Moro et al., 2016). A more recent research indicated that user engagement is mostly generated by “photo” content than from other post types like “status”, “link”, or “video” (Khan et al., 2019). Another research revealed that “photo” and “link” content generated less engagement than “status” and “videos” content. Users interacted more time with “photo” posts than other post types. More “likes’ came for informative posts while competition posts had the least number of “likes”. (Cvijikj et al., 2011). A similar research indicated “Photo” posts proved to be the most preferred post type by users. Workdays posts have driven to more comments engagement rate while posts made during peak times had the opposite results (Cvijikj & Michahelles, 2013). Another study showed that “photo” posts are more engaging than “text” posts. Engagement rate decreases when users find themselves sharing discounts, contest or offers content (Davidaviciene et al., 2019). Concerning readability performance, a research highlighted the impact of readability on how popular social media messages are in sharing information context. Users’ intention to engage with content can be determined by a few first post vocabulary words and not only the 16 words average long phrases (Pancer et al., 2019).

3. Research Objectives

So far, literature review has indicated that highly engaging posts are those which have maximum number of likes, comments, and shares suggesting “photo” content as the most engaging content type. Also, Facebook has decreased impressions and organic reach for unpaid posts (Bernazzani, 2020). Based on that evidence the authors decided to concentrate their effort examining, apart from the “photo” content characteristics, whether organic “photo” posts’ text affect user engagement. Also, based on that the ideal post contains from 1 to 80 characters gain 86% more engagement, the authors decided to study how engaging are the “photo” posts’ texts based on their readability score (Shleyner, 2020). Finally, whenever users like a page on Facebook they receive more updates or posts from that page in their news feed. This study examines how number of impressions and reach differentiates between total engaged users and those who liked a page and engaged with the post (Stuart, 2020).

4. Research Methodology

4.1. Data Insights

Data extracted from Facebook Page Insights from a retail women fashion store located in Greece selling products through physical and online store. The Facebook page numbers 1800 followers, 1756 “total page likes”, 3690 “total posts likes”, 473 “average organic post reach”, 5985 “average paid post reach”, and 23 “average post reactions”. Data gathered during COVID-19 pandemic from 30th of April 2020 to 25th of October 2020.

4.2. Data features

Facebook metrics can either be exported directly from Facebook manager or computed, and identified by different information type such as identification, content, categorization, and performance (Moro et al., 2016). Identification refers to features like “Post ID” and “Permalink”. Content refers to the post text characteristics “Character Number”, “Hashtag Number”, “Flesch Kincaid Reading Ease” (FKRE), and “Gunning FOG Index” (GFI). Flesch Kincaid Reading Ease ranges text readability score between 1 and 100, while 100 is the highest readability score. The attribute follows the score scale of classified values; “0-30” (very difficult to read), “30-50” (difficult to read), “50-60” (fairly difficult to read), “60-70” (easily understood), “70-80” (fairly easy to read), “80-90” (easy to read), and “90-100” (very easy to read) (Wikipedia, 2020). Gunning Fog Index measures English text readability and generate scores, which indicate the level of education year required to understand a specific text. The attribute follows the score scale of “6” for 6th grade level, “7” for 7th grade level, “8” for 8th grade level, “9” for high school freshman level, “10” for high school sophomore level, “11–12” for high school senior/junior level, “13-15” for college junior/sophomore/freshman level, “16” for college senior level, “17–20” for post-graduate level, and “20+” for post-graduate plus level (Eleyan et al., 2020). Referring to that the ideal post character number contains from 1 to 80 characters, the authors classified the attribute based on the scale of "0-80", "81-160", "161-240", "241-320", "321-400", "400-480", "481-560" (Shleyner, 2020). Referring to hashtags no classification applied, and each hashtag number of occurrences considered as a separate class. To proceeding, it is essential to state that "reach" is the total number of people who see the post, "impressions" refer to the number of times the post is loaded on the news feed, no matter if it was seen or clicked or not, "engagement" defines user actions on the post when at the same time impressions are not able to provide enough evidence for distinguishing whether the user has paid attention to the post or not (Shleyner, 2020). The performance metrics include: "Lifetime Post Total Reach" (LPTR) refers to the number of people who had your Page's post enter their screen. Posts include statuses, photos, links, videos etc.-Unique Users. "Lifetime Post Organic Reach" (LPOR) refers to the number of people who had your Page's post enter their screen through unpaid distribution-Unique Users. "Lifetime Post Total Impressions" (LPTI) refers to the number of times your Page's post entered a person's screen. Posts include statuses, photos, links, videos etc.-Total Count. "Lifetime Post Engaged Users" (LPEU) refers to the number of unique people who engaged in certain ways with your Page post, by commenting on, liking, sharing, or clicking upon elements of the post-Unique Users. "Lifetime Post Impressions by People Who Have Liked the Page" (LPIPLP) refers to the number of impressions of your Page post to people who liked the Page-Total Count. "Lifetime Post Reach by People Who Like the Page" (LPRPLP) refers to the number of people who saw your Page post because they like the Page-Unique Users. "Lifetime People Who Have Liked the Page and Engaged with the Post" (LPLPEP) refers to the number of people who liked your Page and click anywhere in the posts-Unique Users (Ernoult, 2020).

4.3. Data Pre-Processing

Data was pre-processed and WEKA 3 was used for decision tree representation. WebFX was used for post's text assessment, calculating Flesch Kincaid Readding Ease and Gunning Fog Index scores. Table 1 shows classes, their subclasses (labels) and the number of occurrences.

Attribute	Labels (Number of Occurrences)
Character Number	0-80 (28), 81-160 (64), 161-240 (19), 241-320 (18), 321-400 (3), 401-480 (1), 481-560 (2)
Hashtag Number	0 (2), 1 (31), 2 (39), 3 (14), 4 (5), 5 (2), 6 (1), 7 (1), 8 (3), 9 (15), 10 (9), 11 (2), 12(1), 13 (2), 14 (2), 17 (1), 20 (1), 21 (2), 22 (1), 23 (1)
FKRE	Very Difficult, Difficult, Fairly Difficult, Fairly Easy, Easy, Very Easy
GFI	6 (76), 7 (8), 8 (4), 9(18), 10 (8), 11-12 (12), 13-15 (7), 16 (1), 17-20 (1)

Table 1. Nominal Features Labels and Occurrences

4.4. Data mining

Data mining refers to useful information extraction techniques from raw data generating new data connections, data correlations and creating patterns. This study used J48 algorithm to classify the instances among the different labels of nominal features. Decision trees read data dataset’s numeric and nominal attributes and build a model of separated classes from a set of instances and set values to each class. They have nodes for attributes and classes, branches for attributes values, lines, and leaves for subclasses. Data is divided into the training set, the validation set, and the testing set of examples. The hypothesis will occur after training the model with the training set, and the percentage of correctly classified instances of the validations set is calculated after providing each run of the algorithm a different small fraction (folds) of the entire example data which will be selected to validate the results. Testing validates the results of the model using new data. Decision trees trying to be as precise as possible start guess values where they do not exist generating overfitting. Finally, the classified instances are showed in decision trees graphs (Mitchell, 1997).

5. Results and Discussion

Three separate experiments ran each of them using one subset for testing and five for training. Pruned weka.classifiers.trees.J48-C0.25-M 2 with six-fold cross-validation was used.

<table>
<tr><th>LPEU</th><th>LPLPEP</th></tr>
<tr><td>LPEU <= 41
| LPEU <= 35
| | LPEU <= 26: Very Difficult (42.0/12.0)
| | LPEU > 26
| | | LPEU <= 30
| | | | LPTR <= 671
| | | | | LPTI <= 723: Very Difficult (2.0)
| | | | | LPTI > 723: Difficult (5.0)
| | | | LPTR > 671: Very Difficult (4.0)
| | | LPEU > 30: Very Difficult (17.0/1.0)
| LPEU > 35
| | LPTR <= 746
| | | LPTR <= 716: Difficult (4.0/1.0)
| | | LPTR > 716: Fairly Difficult (2.0)
| | LPTR > 746
| | | LPEU <= 39: Very Difficult (12.0/4.0)
| | | LPEU > 39: Difficult (2.0/1.0)
LPEU > 41: Very Difficult (45.0/5.0)
Number of Leaves: 10
Size of the tree: 19
Correctly Classified Instances: 97 - 71.8519%
Incorrectly Classified Instances: 38 - 28.1481%
Mean absolute error: 0.1397</td><td>LPIPLP <= 463
| LPIPLP <= 452: Very Difficult (46.0/15.0)
| LPIPLP > 452: Difficult (6.0/1.0)
LPIPLP > 463: Very Difficult (83.0/14.0)
Number of Leaves: 3
Size of the tree: 5
Correctly Classified Instances: 100 - 74.0741%
Incorrectly Classified Instances: 35 - 25.9259%
Mean absolute error: 0.1396</td></tr>
</table>

Table 2. J48 Classification summary for total engaged users and users who liked the page.

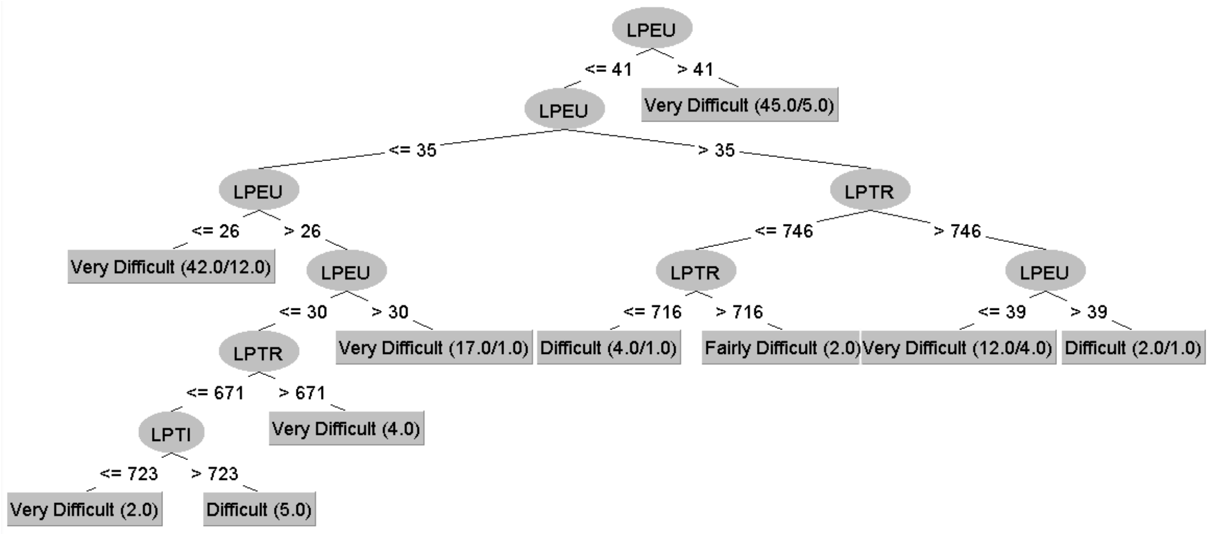

Figure 1. FKRE Classified Instances for LPEU Induced with J48.

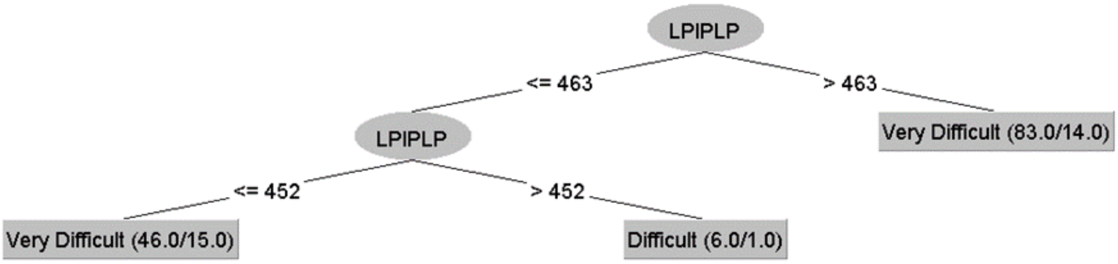

Figure 2. FKRE Classified Instances for LPLPEP Induced with J48.

Figures 1, 2 show the most dominant decision trees with the most correctly classified instances. Both “LPEU” and “LPLPEP” classification accuracies reached 71.8519 % and 74.0741%. From a classification point of view, the decision trees imprint the performance of the actual "photo” posts content based on Facebook performance metrics. However, there is a paradox when it comes to interpret the results. On both the occasions, in most of the cases “photo” posts’ texts with the lowest readability score had higher values of “lifetime total reach” and “lifetime total impressions” along with the most “lifetime post engaged users” than those of the posts’ texts with higher readability scores. Additionally, the “total post user engagement” (1), (2) despite the low readability score and according to the business sector average social media engagement rate levels, the “LPEU" and ”PLPPEP” engagement rates are considered high (Wong, 2020).

$$Total\ "LPEU"\ Engagement = \frac{LPEU}{LPTR} * 100 = 6\% \tag{1}$$

$$Total\ "PLPPEP"\ Engagement = \frac{\mathrm{LPLPEP}}{\mathrm{LPRPLP}} * 100 = 8\% \tag{2}$$

The results confirmed that the “lifetime people who have liked your page and engaged with your post” had a significant higher engagement rate than the “lifetime post engaged users” and this can be explained based on that people who liked or followed a page tend to see displayed in the news feed more post updates than those who did not (Ernoult, 2020). Regarding to the “photo” posts engagement, it seems that in most cases the lifetime post engaged users, and “reach” performance metrics are not affected by the posts’ text readability score for both “lifetime post engaged users” and for “lifetime people who have liked your page and engaged with your post”. “LPEU” and “LPLPEP” engagement must have emerged from the actual “photo” content. Thus, the authors suggest marketers to use high quality image content when it comes to photo promotion. However, Figures 1, 2 indicate a tendency of “impression” performance metrics getting affected by the “photo” post text performance. This tendency comes from the “impression” metrics numbers of “LPTI”>723, “LPIPLP”>452 which classifies “Difficult” over “Very Difficult” text in 2 out of 3 occasions where “impression” metrics participate in classification. Regarding the performance metrics of Gunning Fog Index, number of hashtags, and number of characters the correctly classified instances were below 50% leaving no space for drawing significant classification rules of whether they affect user engagement. Perhaps, a future correlation analysis among metrics could verify this suggestion. Until then, no further assumptions can be made.

6. Conclusions

This study objective is to help brands increase user engagement for organic posts in women fashion. Using decision tree classification on “photo” posts fashion data, this work indicates that “photo” post’s text readability score does not affect “lifetime post engaged users” and overall performance metrics, except from that there is a tendency to affect “impression” performance metrics. Since, biggest numbers of “lifetime post engaged users” and “lifetime post total reach” classified instances contain “Difficult” and “Very Difficult” texts, post’s text readability is not considered performance factor. Since this factor has been excluded as important in shaping users’ engagement, it would be wise to continue the research and examine the actual “photo” post content. A correlation analysis between depended and independent metrics would also answer which content characteristics affect certain performance metrics. However, there are limitations regarding the size of the data and social media platforms that included and further progress needs to be made. It is essential to make publicly known that the current dataset size, compared to other research attempts remains relatively small. Even though the authors have been trying to provide suggestion, they welcome human nature and indifference pointing out that it would be unethical to draw specific rules.

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