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Analysing Food-Porn Images for Users' Engagement in the Food Business

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Abstract. This paper presents an approach for analysing *food-porn* images and their related comments published by the cooking school *Getcookingcanada* Instagram account. Our approach processes the published images to extract colour parameters, counts the number of *likes*, and also analyses the comments related to each publication. A dataset containing all these was built, and methods were applied to study correlations among the data: a regression analysis, an ANOVA and a sentiment analysis of the comments on the dataset to explain the relation between the quantity of likes and the sentiment obtained from the food images. Our results show a correlation between the number of *likes* and the sentiment analysis of the comments. Images that evoke a positive sentiment have a higher number of likes and comments. Users' experience on creating posts is also analysed and confirms a positive correlation between the number of *likes* and the publisher's experience.

Keywords. Sentimental analysis, Food-porn, regression, Anova, deep learning.

1. Introduction

Food-porn refers to how people share images of food through social media in order to have an impact on potential consumers. For social media publications (e.g. in Instagram) the number of *likes* associated with them are important since a higher number of *likes* involves a larger number of followers and, therefore, an increased impact. Hence, *food-porn* images is a way for small and medium enterprises (SMEs) to create loyal customers and promote gastronomic tourism.

In the literature, diverse works have also deal with the problem of analysing images and comments appearing in social media [1,2,3,4,5]. According to a study by [1], the emotion of Gastronomic Tourism Experiences on Digital Media Platforms took 25,000 photos of Instagram. The result shows that most gourmet tourism content is positively received across all platforms. And according to [2], Food Brands use social media platforms such as Instagram to market their products to a growing number of consumers, using a high frequency of targeted and curated posts that manipulate consumer emotions rather than present information about their products.

[1] All authors contributed equally to this paper.

2. Methods

This study is based on a dataset of 1523 culinary images published in the Instagram account @*getcookingcanada*[2] by an online cooking school. These images and their associated meta-information were retrieved using the Instagram API. The relevant meta-information includes the textual description of the image, the quantity of *likes* and comments posted by the followers. Among the 1523 images, 958 had comments, with an average of 3.05 comments per image. The average quantity of *likes* for each image was approximately 47.

The *polarity* of the comments was obtained using a model based on DistilBERT [6], a deep learning model based on transformers. The score obtained was discretised converting it into the qualitative labels *Positive*, *Neutral* and *Negative*. Instagrammers' *experience* is measured as years pass by as their uploaded photos become more attractive to their followers progressively.

The *compression factor* of each food image was computed (ratio between the JPEG-compressed image at 100% quality and the full-size uncompressed image) and *colour-related metrics* were also obtained: the 5 predominant colours (obtained by a deep learning model to detect the food within the image [7], and then applying the median cut algorithm to the resulting, cropped image), the *colourfulness* (a linear combination of the mean and standard deviation of the pixel cloud in the colour plane), and the *number of distinct colours* (12-bit-quantised) in the RGB image. A *likelihood ranking for each colour palette* (from 1 to 5) was also computed based on a model obtained by learning from the ColorLovers dataset [8].

3. Results

Figure 1(a) shows how the @*getcookingcanada* account grows as the quantity of *likes* increases (followers reaffirm themselves on Instagram) as years pass by. Moreover, the quantity of comments increases in line with the increasing tendency of *likes*. Negative comments do not increase, but they tend to disappear. Let us indicate that if a food image has not comments then it is tagged as neutral. Figure 1(b) shows that negative items tend to go down, positive ones are increasing, and neutral tones, go down substantially, showing a stronger commitment by the followers to add comments to the posts.

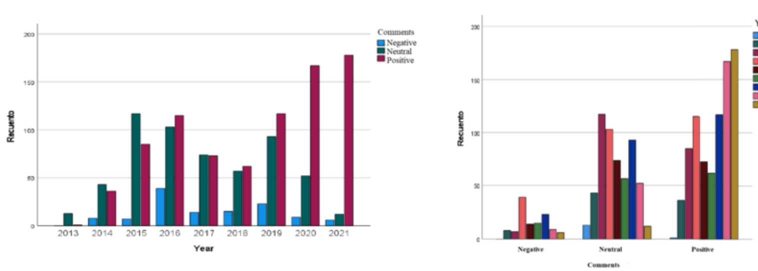

Figure 1. Analysis of followers' comments per year.

[2]Granted their permission to us for processing images. Note also that, our analysis only took into account the food images, other images containing people, such as a chef or student's, were discarded.

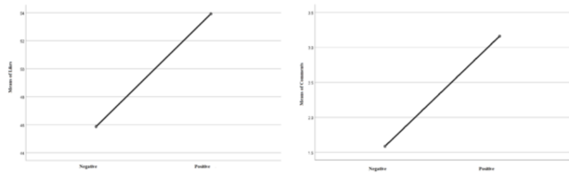

Figure 2. Comparisons of means regarding the likes and the negative/positive sentiments, and (b) Comparisons of means ANOVA regarding the number of comments and the negative/positive sentiments.

Two models are considered in order to find out the relation influencing the quantity of likes in the postings: Model 1 and ANOVA. It is worth noting that the dataset was pre-processed to remove outliers and that images without comments were removed.

Model 1. where the *likes*, denotes by y_i, is the dependent variable and the independent variables are: e_1= experiences, c_2= comments and sa_3= sentimental analysis. That is, the model considered is: $y_i = \beta_0 + \beta_1 e_{i1} + \beta_2 c_{i2} + \beta_3 sa_{i3} + u_i$.

Table 1. (a) Summary of models (b) Coefficients. Dependent Variable: likes

Model	R	R^2	Adjusted R^2	Standard Error
1	.710	.504	.503	15.238
2	.726	.527	.525	14.907

Model	Coefficients no standards β	Desv. Error	standards β	t	p-value
(Constant)	20.650	0.898	- - - - -	22.987	.00
Experiences	0.013	0.001	0.474	24.306	.00
Comments	3.202	0.182	0.385	17.597	.00
Sentimental A.	-0.389	1.275	-0.006	-0.306	.76

Table 1 shows that the experiences and comments are significant but not the results on sentimental analysis (level of significance at 5%). The experience variable is more relevant than the comments variable since its coefficient standard is bigger (.474 > .385). Thus, if the experience and the comments increase, then the likes increase too. The sentimental analysis variable does not provide information to explain the likes. We hypothesised that if the comments are positive, this will result in followers giving a like. However, this is not corroborated in the model. We think that this is due to the fact that the tool for calculating the sentiment score was not able to collect the followers' sentiments. Model 1 explains the $50,4\%$ of the variability of the *likes* of the followers.

ANOVA. Analyzes whether a positive or negative sentiment influence the likes and the number of comments given by the followers. With respect to the likes, Table 2 and Figure 2 (left) show that there is a significant difference between the average of the likes for positive and negative sentiments. When the followers have a favourable impression (positive sentiment) that is demonstrated by the followers participating more positively and contributing a more significant quantity of likes. On the contrary, there are fewer likes if the impression caused by the image is negative (negative sentiment). With respect to the number of comments, Table 3 and Figure 2 (right) show that when the followers have a

Table 2. ANOVA: Dependent variable: likes. Independent variables: + and - sentiments.

Model	Sum of squares	gl	Quadratic Mean	F	Sig.
Regresion	6851.789	1	6851.789	13.807	.000
Residual	469960.091	947	496.262		
Total	476811.880	948			

favourable impression they tend to participate more positively and make a more significant number of comments. On the contrary, there are fewer comments if the impression caused by the image is negative.

Table 3. ANOVA: Dependent variable: number of comments. Independent variables: sentiments Negative and Positive.

Model	Sum of squares	gl	Quadratic Mean	F	Sig.
Regresion	261.503	1	261.503	35.979	.000
Residual	6882.975	947	7.268		
Total	7144.478	948			

4. Conclusion

Culinary photos are crucial to promote the food business, and the images colour and texture are features that could evoke a response that might be positive or negative. According to our results the food images with less complex colours and texture evoked more positive responses or likes. This might be due to the food images are more aesthetic. Finally, the evoked positive emotion may produce a good response for consumers. We intend to carry out a survey in the nearer future in order to test these hypotheses.

We conclude that social networks can be a great promoter of food business and generate followers and loyal consumers to our products. Therefore, the increase in likes and comments from hashtags is suitable for generating greater diffusion of a product, so we see Instagram as a medium for promoting tourist destinations in general, not only for promoting online cooking schools as *@getcookingcanada*.

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