Proceedings of Machine Learning Research 122:36–43, 2019 3rd International Workshop on Artificial Intelligence in Affective Computing

Persuasion: What Jane Austin Would Have Written

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Abstract

This paper presents preliminary results for developing an online "persuasion score" that will enable digital marketing content authors to compose and edit materials with better persuasive capability. Inspired by initial insights with digital marketing professionals and research on the foundations of persuasion: pathos, ethos and logos, we extracted features from a data set of over three million consumer reactions to email marketing campaigns covering a three month period. We report on the most significant features of the content, including image position and text readability as well as the most salient customer features such as time since registration and time since last opened email from the same marketing brand.

Keywords: Persuasion Score; Ethos, Logos, Pathos; Enhanced interaction; Digital marketing content;

1. Introduction

Human minds are persuaded by a combination of three modes of communication: (*a*) Ideas that connect to their emotions (*pathos*), (*b*) credibility of the persuader (*ethos*), (*c*) by logical reasoning (*logos*) Kennedy (2008); Ng (2016). Credibility of the persuader can be based on one or more of the three components consisting of goodwill, trust and competence of the person with respect to the subject of persuasion McCroskey and Teven (1999). Trust is one of its most important components and can be built based on 4Ps of communication, namely, Personalization, Positiveness, Plausibility and Plain-spokenness Maslansky et al. (2010).

Persuasion plays an important role in a multitude of areas including digital marketing. This paper introduces an algorithmic approach to developing persuasive digital marketing content for emails with embedded web content (URLS). To get an idea of how various aspects of a marketing email (e.g. images, text and layout design) are related to either of *pathos* or *ethos*, we recruited 15 digital marketing professionals for a semi-ethnographic interview that included a survey. With respect to evoking emotion (*pathos*) 93% considered image memorability to be most important and 64% considered image aesthetics to be most important. With respect to (*ethos*) text readability was considered most important by 79%, text formality by 43% and text sentiment by 50% of those who were surveyed. Layout (top third of page, middle third, or lower third) was considered part of *logos* construct of persuasion.

From these initial findings we developed a framework of an interactive system in an attempt to quantify each of the aspects of pathos, logos and ethos. This system combines these aspects in a real time 'Persuasion Score' that could help authors know if the combination of images, text and layout that they are using to create the content, were likely to have the right balance to be sufficiently persuasive. We envision that this workflow, shown in Figure 1 would be used to develop more appealing content for consumers. The system has two parts to it, the persuasion score and text suggestions, as shown in yellow. These are the two proposed steps which we envision will help create an automated dashboard for authors, with data driven insights.

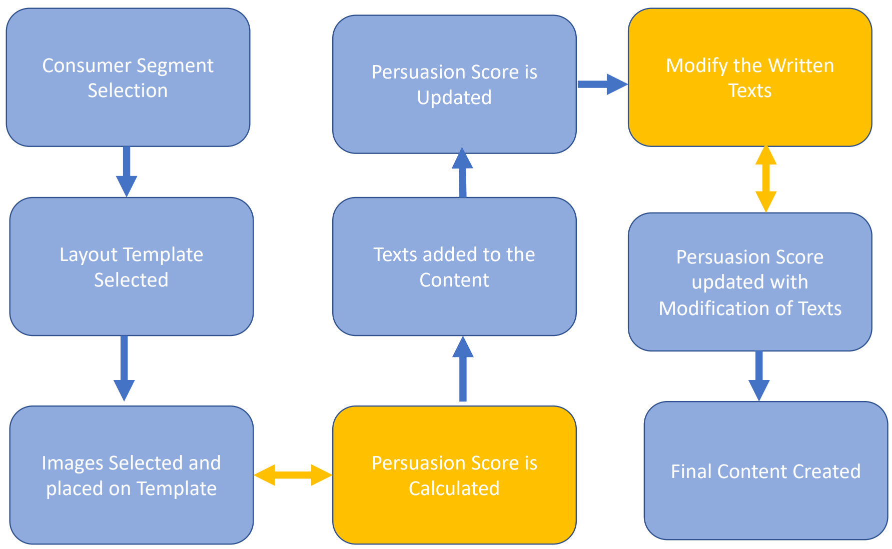

Figure 1: Workflow of the System that helps authors, at the time of Writing: The Yellow boxes are Iterative Calculations

2. Predicting Persuasiveness

2.1. Background

There has been extensive research on the psychology of persuasion, however there does not currently exist a well defined tool that quantifies various aspects of persuasion in real time so that it could be used to assist humans in better authoring of persuasive contents. We bring together a collection of work done in various disciplines and use extensive digital marketing email data to try to develop a quantified persuasion score. In prior work, the concept of persuasion has been applied to the human computer interface with the UI viewed as a social actor Fogg (2002). In other works Smith and Ellsworth (1985), the subjective concept of emotions was made relatively more objective and measurable via cognitive appraisals. Similarly, the memorability of images Khosla et al. (2015) as well as the emotional impact of images Desmet and Hekkert (2007) have been studied. Still other work has related the aesthetics of products and emotions Kumar et al. (2016), all of which we believe to be

Figure 2: A sample email content with 3 URLs, texts on them and specific layout of the URLs (this sample email content is created with open-source images for illustration purposes only)

related to persuasion. The 'credibility' construct of persuasion is quantified by features that relate to plainspokeness, positiveness and personalization Maslansky et al. (2010). It has been shown that helpful wording heuristics like making one's language align to both community norms and one's prior messages help in message propagation by more shares Tan et al. (2014). The authors in Chakraborty et al. (2016) observe that a substantial fraction of clickbait headlines, which also aims for clicking on their content, based on their headers, consists of words having 'Very Positive' sentiments. In the same work, features based on linguistic styles of headers have been successfully used to classify whether a content is clickbait. In Hauser et al. (2009) the authors propose to identify the cognitive styles of consumers, based on their clicking styles and "morph" the look and feel of the website to match her style. Based on this prior art and our initial research with digital marketing professionals, we decided to consider image aesthetics Kong et al. (2016), text readability Kincaid et al. (1975), text formality Li et al. (2013) and text sentiments O'Connor et al. (2010); Thelwall et al. (2010) as quantitative measures of credibility.

2.2. Method

We propose that the persuasiveness of an email is a combination of the persuasiveness of each URL section in the content, where a URL section consists of a combination of image and texts. We calculate the overall 'Persuasion Score' as an average of the persuasion scores over all individuals for an URL and then a weighted sum of the persuasion scores of each URL. The weight used for averaging is the proportion of space taken by each URL in the entire content.

2.2.1. Data

For our experiment we considered about 3 million consumers' data related to permission email marketing over a 3 month period. This consisted of $\sim$ 400 unique images. In our dataset, we observed about 10% of consumers who received an email message, opened the email. Within the email content, each image is associated with a URL, which is clickable, for example, Figure 2 shows a sample email content with 3 URLs. We observed that on an average 5% of consumers, who had opened the email interacted with a URL.

For building our model for URL level 'Persuasion Score', the number of data points used are as follows. During the 3 months period, consider there are K emails that were sent, and the i^{th} email was opened by M_i individuals (say about 3000), and had Q_i URLs (say 6 to 7) within it, which were clicked at least once by one of the M_i consumers. Hence our analysis dataset consists of $N_d = \sum_{i=1}^{K} Q_i M_i$ data points, consisting of rows for each URL and for each individual who opened the email containing that URL. The outcomes in the dataset are labels of 0/1 if an URL has not been clicked or has been clicked respectively. We did not consider those URLs which were not clicked at least once.

From this dataset, we considered, 60% of it as a training set, 20% as test set and 20% as validation set. The training set is for building the model and the test set is for determining a threshold at which the F1 score, a harmonic mean of precision and recall, is highest. The validation set is for testing the performance of the model built, at the chosen threshold, in an independent subset of the data. Among the N_d data points, about 5% is in the positive class, as mentioned earlier and hence there is a class imbalance. We under-sampled the training set to maintain a 1:1 ratio in it. After maintaining the balance in the click rate, we had about $14,000$ data points in the training data. The test and the validation data sets were imbalanced with about $353,000$ data points in each.

2.2.2. Features

We considered the following types of features in our analysis:

- Emotions Features: Image Memorability, and 12 Image Aesthetics features: *Rule of thirds*, *Repetition*, *Depth of field*, *Balancing elements*, *Interesting lighting*, Symmetry, Vivid Color, Motion Blur, *Interesting content*, *Object emphasis*, *Color harmony*, and *Quality*
- Credibility:Text readability, Text Formality, and Text Sentiment
- Logical Reasoning: Proportion of an image within the entire content and Position of an image in the layout.

- Consumer Status: Income, Time since last click. Time since last open and Time since registration

2.2.3. Experiments

We used a generalized linear model with binomial family (logistic regression) to create the statistical model we used to calculate the "Persuasion Score." The features are denoted by X_is and Y denotes whether the URL will be clicked or not in the Persuasion score model below:

$$
\begin{aligned}
\text{Persuasion Score (PS)} &= E(Y|X) = P(Y=1|X) \\
&= \frac{e^{\beta_0 + \sum_i \beta_i x_i}}{1 + e^{\beta_0 + \sum_i \beta_i x_i}}
\end{aligned}
$$

As described in the *Data* section above, the model parameters are estimated using the training data, which is balanced for the two classes, by under sampling. Because of the undersampling, all the parameter estimates in the persuasion score model, except β_0 are statistically consistent, that is, the parameter estimator converges in probability to the true parameter value. So a correction factor is used for β_0 King and Zeng (2001) for a consistent estimate

$$\beta_0^{'} = \beta_0 - ln[(\frac{1-\tau}{\tau})(\frac{\bar{y}}{1-\bar{y}})]$$

Here τ is the fraction of positive class in the population, and $\bar{y}$ is the fraction of the positive class in the training data after under-sampling. In our dataset, τ is approximately equal to 0.05 and because we have undersampled for a balanced training set, $\bar{y}$ is equal to 0.5. We also measured the interaction between the content features and a subset of the consumer features using a statistical model. In the model, we considered each of the listed features individually and all possible pairwise statistical interactions between each of the selected consumer status features and the content features. This model is given as below:

$$E(Y|X) = P(Y=1|X) = \frac{e^{\beta_0 + \sum_i \beta_i x_i + \sum_{j \neq k,} \beta_{jk} x_j x_k}}{1 + e^{\beta_0 + \sum_i \beta_i x_i + \sum_{j \neq k} \beta_{jk} x_j x_k}}$$

where β_i are the parameters related to each of the selected features of the model, β_{jk} are the parameters related to statistical interactions between the j selected consumer level features and k content level features.

2.3. Results

We calculated the Wald statistic to assess the relation between persuasion score and the individual features. Figure 3(a) shows z-values of the statistically significant features from the 'Persuasion Score' model. We can see that, higher the proportion of space taken up by an URL, more likely it will persuade the viewer. We can see that both the middle and bottom positions are significantly different from an image being in the top part of the layout. Since they are negatively correlated, it shows that lower the position of an URL in the layout, less likely will it persuade the viewer. If the readability of the text in a URL is

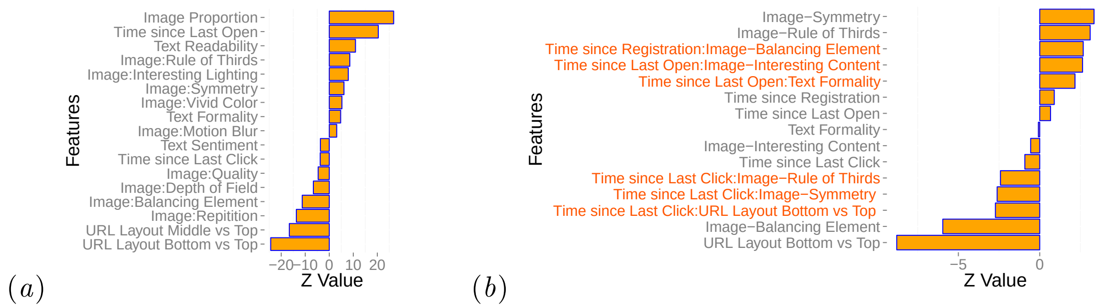

Figure 3: Statistically significant features from Logistic Regression that show relation between the features and persuasion score (a) and statistically significant interaction features (in red texts) show how the consumers' past actions relate to content features that persuade them (b)

high then the persuasion score is higher. Among the image features, higher the amount of interesting lighting, or symmetry, higher the persuasion score.

Additionally, we looked at which type of consumers are persuaded by which type of content, based on the *statistical interaction model* described in the 'Method' section. Figure 3 (b) shows the relation between of each of the statistically significant interaction features, based on the Wald statistic value/z-value. We can see that time since registration and balancing element[1] in an image are positively and negatively related to persuasion respectively. However, their interaction is positively related. This means on an average, consumers like images with lower balancing elements in them. But consumers who are registered for a longer period of time prefer to click those images that have a higher balancing element. Similarly, those consumers who are opening any email from the brand after a long period, that is they have a higher time since last open, are more likely to click a URL with increasing text formality and 'interesting content'. Finally those who have opened and clicked the marketing messages recently, are far less likely to click a URL at the bottom part of the layout than compared to the top part of the layout.

3. Conclusions and Future Work

In this study, we have presented a quantitative approach to determine the predicted interaction between consumers and marketing content. We have considered image aesthetics, image memorability, textual and layout information along with historic consumer behavior to quantify a measure of 'persuasion' of marketing content. Our approach helps to determine, at the time of authoring, whether a given content is persuasive for the consumers being targeted. We find that the larger an image is, and the higher the position of the image in the content, the greater is its persuasive power. For contents with text, higher the text readability and higher the text formality, it helps to persuade consumers. Lower repetition and higher symmetry in images also help in persuasion.

1. Whether the picture has one or more dissimilar/similar elements balanced on each side of a given point

We also explored the effect of content characteristics on certain types of consumers. We observe that consumers interact more with marketing content, if they are opening a message from the same sender after a long time and the content has high text formality. Consumers opening a message after a long time are also likely to be more swayed by the content if the image has interesting content. Those consumers who opened a message recently and did not click or interact with the contents within the message in the past are less likely to be persuaded to interact.

We looked at persuasion of individual URLs that make up a marketing content. We assume that the total effect of the content is a weighted aggregate of all the URLs that comprise the content. The interplay between multiple URLs is not studied, and remains an interesting research question. While most current work is restricted to measurement and reporting of image and textual aspects in a document, through our research, we have tried to take the first steps in the direction of data driven guidance for image, layout and textual suggestions to improve content creation, a field that we believe has immense potential.

References

Abhijnan Chakraborty, Bhargavi Paranjape, Sourya Kakarla, and Niloy Ganguly. Clickbait: Detecting and preventing clickbaits in online news media. 2016.

Pieter Desmet and Paul Hekkert. Framework of product experience. *International journal of design*, 1(1), 2007.

Brian J Fogg. Persuasive technology: using computers to change what we think and do. *Ubiquity*, 2002(December):5, 2002.

John R Hauser, Glen L Urban, Guilherme Liberali, and Michael Braun. Website morphing. volume 28, pages 202–223. INFORMS, 2009.

George Alexander Kennedy. *The Art of Rhetoric in the Roman World: 300 BC-AD 300*, volume 2. Wipf and Stock Publishers, 2008.

Aditya Khosla, Akhil S Raju, Antonio Torralba, and Aude Oliva. Understanding and predicting image memorability at a large scale. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2390–2398, 2015.

J Peter Kincaid, Robert P Fishburne Jr, Richard L Rogers, and Brad S Chissom. Derivation of new readability formulas (automated readability index, fog count and flesch reading ease formula) for navy enlisted personnel. Technical report, DTIC Document, 1975.

Gary King and Langche Zeng. Logistic regression in rare events data. *Political analysis*, 9 (2):137–163, 2001.

Shu Kong, Xiaohui Shen, Zhe Lin, Radomir Mech, and Charless Fowlkes. Photo aesthetics ranking network with attributes and content adaptation. *European Conference on Computer Vision*, 2016.

Minu Kumar, R Batra, C Seifert, and D Brei. Aesthetic principles of product form and cognitive appraisals: Predicting emotional responses to beauty. *The psychology of design: Creating consumer appeal*, pages 234–251, 2016.

Haiying Li, Zhiqiang Cai, and Arthur C Graesser. Comparing two measures for formality. In *FLAIRS Conference*, pages 220–225, 2013.

Michael Maslansky, Scott West, Gary DeMoss, and David Saylor. *The language of trust: Selling ideas in a world of skeptics*. Penguin, 2010.

James C McCroskey and Jason J Teven. Goodwill: A reexamination of the construct and its measurement. volume 66, pages 90–103. Taylor & Francis, 1999.

Derrick Ng. Engaging in persuasive and credible communication: Coursera. Video, 2016. Retrieved August 16, 2016 from http://bit.ly/2bVzwdc.

Brendan O'Connor, Ramnath Balasubramanyan, Bryan R Routledge, and Noah A Smith. From tweets to polls: Linking text sentiment to public opinion time series. *ICWSM*, 11 (122-129):1–2, 2010.

Craig A Smith and Phoebe C Ellsworth. Patterns of cognitive appraisal in emotion. *Journal of personality and social psychology*, 48(4):813, 1985.

Chenhao Tan, Lillian Lee, and Bo Pang. The effect of wording on message propagation: Topic-and author-controlled natural experiments on twitter. *arXiv preprint arXiv:1405.1438*, 2014.

Mike Thelwall, Kevan Buckley, Georgios Paltoglou, Di Cai, and Arvid Kappas. Sentiment strength detection in short informal text. *Journal of the American Society for Information Science and Technology*, 61(12):2544–2558, 2010.