A Study on the Impact of Product Images on User Clicks for Online Shopping

Anjan Goswami
eBay Search
angoswami@ebay.com

Naren Chittar
eBay Search
nchittar@ebay.com

Chung H. Sung
eBay Search
suchung@ebay.com

ABSTRACT

In this paper we study the importance of image based features on the click-through rate (CTR) in the context of a large scale product search engine. Typically product search engines use text based features in their ranking function. We present a novel idea of using image based features, common in the photography literature, in addition to text based features. We used a stochastic gradient boosting based regression model to learn relationships between features and CTR. Our results indicate statistically significant correlations between the image features and CTR. We also see improvements to NDCG and mean standard regression.

Categories and Subject Descriptors: H.4 [Information Systems Applications]:Miscellaneous

General Terms: Experimentation, Human Factors

Keywords: product images, online shopping, shopping search

1. INTRODUCTION

Online shopping constitutes a significant portion of commerce. Convenience is the biggest advantage of online shopping, but the inability to touch and feel the product is a big drawback. Therefore, images play an important role in online shopping. Good quality images provide better user experience by providing a better idea of the product features and condition.

Product search engines are the main gateways for of online shopping sites. Typically users use the search engines to look for products that they are interested in. The search results page (SRP) contains a list of products, with each entry containing the product image, the product title, product summary and various attributes like price, condition, seller name etc. The users browse images and the text and then decide which ones to click to navigate into the details page.

Many product search engines are small in scale and there is editorial review of product images to control the quality of an image. So usually only high quality images are displayed. However, in a large scale social online market like eBay, there is no central quality control over the images is not feasible, the variance in the quality of product images is large. In such cases, it might be important to incorporate image features in the ranking models so that relevant results with good images ranked higher compared with relevant results with bad images. Additionally, this can act as an incentive for the sellers to make an effort to make their images better, resulting in a higher number of better quality images, thereby improving the brand value of the product search engine. Hence there might be a long term value in incorporating image based features in ranking.

In this paper, we first discuss what kind of image features may be important for online product images and then we present a study on how we can use these feature to improve regression CTR ranking models.

2. IMAGE QUALITY FEATURES

We divide the image features into two classes.

Global features: These features are global statistics computed over the whole image.

Brightness: Brightness is an important factor since it represents the amount of illumination. We used the following normalized average gray scale intensity from the RGB space as brightness. $0.3R + 0.6G + 0.1B$.

Contrast: This quantity represents the variation in brightness that makes an object appear more clear. There are different kinds of contrast measures in the image processing literature based on various studies of human perception. We used root mean square contrast [4] that is computed as follows: $\sqrt{\frac{1}{MN}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(I_{ij}-\overline{I})}$ where $M \times N$ is the size of the image and I is the gray scale intensity and $\overline{I}$ is the average intensity.

Regional features: A typical product image consists of a product (foreground) which is placed on a background. The regional features are statistics similar to the global statistics but are computed separately for the background and the foreground. Important information can be derived by looking at the foreground and background individually and also in comparison with each other. We use a Graphcut [3] based approach to segment the image into a background and foreground. The basic Graphcut algorithm requires some manual input. We modified Graphcut using some heuristics to achieve fully automated segmentation. We compute the following features.

Lightness of background: We observe that a good product image typically has a light colored background. We computed the standard deviation and mean of the background pixels and then measured the L2 distance from the white color in the RGB color space(R=255,B=255,G=255). We then take a linear combination of the mean and the stdev as follows $\alpha\mu + \beta\sigma$ where μ is the mean and σ is the standard deviation. α and β are two constants. We used $\alpha = 1$ and $\beta = 0.3$.

Colorfulness of foreground: Colorfulness is a quantity that is related to the human perception of color. There is extensive research available on perceptual quality of color and there are many different empirical expressions for colorfulness. We use an expression that appeared in a paper by Hasler [2] based on sRGB color space.

Ratio of background and foreground In this feature, we compute the ratio of the area of the foreground and the background. A larger ratio indicates a larger product image in the image frame.

3. EXPERIMENTS AND RESULTS

Our datasets were derived from eBay's actual query logs. They consist of tuples of the form (query, product-id, CTR). A tuple consists of a query that users typed, a product-id that they clicked on and the CTR for that product-id. The CTR for a product is defined as number of clicks per impression for an item. We used 150,000 query-product pairs chosen randomly. We used Salford systems's TreeNet [1], which is a boosted tree based regression model, to predict CTR. We used a 10 fold crossvalidation method for testing.

We trained two versions of the model - one with just text based features and the one with text as well as image features. We observed that the mean standard error for regression is reduced if we add image features into the model. We also observed an improvement in NDCG (where NDCG is computed using human judgment data). The table 1 summarizes the results . The results a slight improvement in NDCG at 5th and 10th position and also and also a slight improvement in reducing the mean standard error for the regression.

Our current dataset includes data from all eBay categories ranging from fashion to tickets. Categories like fashion have a greater visual component to it than a category like tickets. The result that we report is the average increase across all these diverse categories. We think that the DCG improvement will be larger for categories like fashion where images are more important. We plan to investigate these questions in future work.

TreeNet also provides a significance rank for each feature and we observed that a large number of the image features were in the top 25 features, out of a total of 100+ features used. Also note that the colorfulness of foreground and the rms contrast turn out to be the two most important image features for ranking.

The above experiment answers the question that image features have the power to predict CTR. It however does not answer the question whether better images means better CTR. This is because a tree based model are non linear and can have different correlations in different regions of the feature subspace.

In another experiment, we wanted to measure the correlation of CTR with image based features. To keep other factors like price, type etc, we created a dataset of about 4000 items from the fashion category. This included jeans which are new in a certain narrow price range. We conducted a correlation study with image features with CTR. The tables 2 and 3 show the result of the study. We report ρ , which is the Spearman's rank coefficient in the table and also the "p-value" for the experiments. It shows that these image features are correlated with CTR and the correlations are statistically significant. We see that the lightness of the background is most correlated with CTR and this conforms with the anecdotal marketing wisdom that a product picture in a lighter background better emphasizes the actual object in the image. Although, it is evident that the correlations are not very strong since we think there is an effect of relevance in this correlation study. It is important to notice that the importance of the features as ranked by TreeNet (regression) can be different than the importance of the features based on correlation study.

Models	MSE	NDCG 5	NDCG 10
No image factors	.0209	.8092	0.8719
With image factors	.0207	.8151	0.8761

Table 1: Regression study with image features

Global features	Contrast	Brightness
ρ	.14	0.10
p value	10^{-6}	10^{-8}

Table 2: Correlation study with image features

Reg features	BG light.	FG Color.	FG BG Area
ρ	.21	.15	.10
p value	10^{-16}	10^{-4}	10^{-6}

Table 3: Correlation study with image features

4. CONCLUSION

In this paper, we find that the product image features can have an impact on user search behavior. We find that some image features have correlation with CTR in a product search engine and that that these features can help in modeling click through rate for shopping search applications. This study can provide sellers with an incentive to submit better images for products that they sell. This has a potential to improve the brand value for the shopping site and thus have long term positive impact. In our future work, we plan to study more image features and their impact, particularly on visually characterized products such as fashion items.

5. REFERENCES

[1] J. H. Friedman and O. K. (y X)-values. Stochastic gradient boosting. *Computational Statistics and Data Analysis*, 38:367–378, 1999.

[2] D. Hasler and S. E. Suesstrunk. Measuring colorfulness in natural images. *Proceeding of SPIE Electron. Imag.: Human Vision and Electron. Imag. VIII*, 5007:87–95, 2003.

[3] M. Marsh, S. Bangay, and A. Lobb. Implementing the grabcut segmentation technique as a plugin for the gimp. In *Proceedings of the 4th international conference on Computer graphics, virtual reality, visualisation and interaction in Africa*, pages 171–175. ACM, 2006.

[4] E. Peli. Contrast in complex images. *Journal of Optical Society of America*, 7(10):2032–2040, 1990.