
What Makes a Brand Look Expensive?

Jingxian Zhang

University of Illinois at
Urbana-Champaign
Champaign, IL 61820, USA
jzhng144@illinois.edu

Neel Kothari

University of Illinois at
Urbana-Champaign
Champaign, IL 61820, USA
nkothar2@illinois.edu

Asad Imtiaz Butt

University of Illinois at
Urbana-Champaign
Champaign, IL 61820, USA
aibutt2@illinois.edu

Ranjitha Kumar

University of Illinois at
Urbana-Champaign
Champaign, IL 61820, USA
ranjitha@illinois.edu

Abstract

Branding is a powerful tool that companies use to control the perception of their products' quality and price. A company's website is a digital vehicle for conveying this brand information. The look and feel of a website often influence a customer's impression of a brand's price category. To understand what makes a brand look expensive, we evaluate the website designs of two industries — watches and cars. We ran a crowdsourced study to collect ratings of perceived cost based on web page screenshots. By training a random forest regression model over these ratings, we learned which visual features of website design are predictive of perceived cost.

Author Keywords

Web design; perception; brands; price.

ACM Classification Keywords

H.5.2 [Information interfaces and presentation (e.g., HCI)]:
User Interfaces

Introduction

Branding is a powerful tool that companies use to control the perception of their products' quality and price. A company's website is a digital vehicle for conveying this brand information. The look and feel of a website often influence a customer's impression of a brand's price category. Percep-

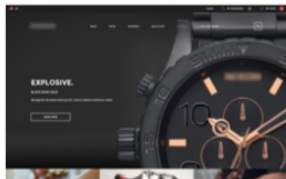
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CHI'16 Extended Abstracts, May 07-12, 2016, San Jose, CA, USA
ACM 978-1-4503-4082-3/16/05.
<http://dx.doi.org/10.1145/2851581.2892467>



(a) Perceived Price: High
Actual Price: High



(b) Perceived Price: Low
Actual Price: High



(c) Perceived Price: High
Actual Price: Low



(d) Perceived Price: Low
Actual Price: Low

Figure 1: Watch brands with their perceived and actual price. The perceived price of (a) and (b) are consistent with their actual price while those of (c) and (d) are not.

tion, however, is not always reality: the branding information communicated by a website can make an economy brand appear like a luxury one, and vice versa 1.

This paper asks the question, “What makes a brand look expensive?” To answer it, we analyze website designs in two industries – watches and cars. We ran a crowdsourced study to collect ratings of perceived cost based on web page screenshots. By training a random forest regression model over these ratings, we learned that visual features such as number of featured products and colors are predictive of perceived cost. Moreover, we found that these predictive features are not necessarily the same across industries.

Related Work

Prior work has studied how low-level visual and structural features of website design influence higher-level aesthetic qualities such as visual complexity and attractiveness [6, 7, 10, 12]. Researchers have developed models that explicitly focus on users’ first impressions of website aesthetics, which are strongly correlated with perceived usability and trustworthiness [5, 9]. Moreover, work in computational advertising has explored how features such as whitespace and logo colors affect brand perceptions [3, 8].

To learn a computational model of perceived price for a brand’s website, we compute visual features similar to those used by prior work. We then use random forest regression with backwards elimination to both predict perceived price ratings and identify the most important features that influence these ratings.

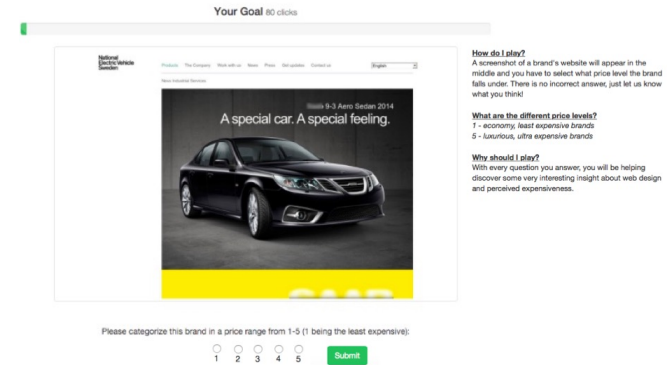


Figure 2: We built a web-based crowdsourcing interface to collect perceived price labels. Based on the website screenshot, users are asked to categorize a brand on a 5-pt price scale, where 1 corresponds to the cheapest brands and 5 corresponds to the most expensive ones.

Data

We scraped the marketing websites of 78 watch and 81 car companies. For each site, we compute and store its screenshot and a set of visual features. To collect perceived price labels for each company, we built a web-based crowdsourcing interface, which presents users with website screenshots in randomized order, and asks them to categorize the brand on a 5-pt price scale, where 1 corresponds to the cheapest brands and 5 corresponds to the most expensive ones (Figure 2). To remove bias around prior brand familiarity, we blur out the company name and logo in the screenshots.

We recruited participants from Facebook and Amazon Mechanical Turk and collected a total of 2000 price labels for watch brands and 681 price labels for car brands. On average, each watch brand received 26 price ratings and each

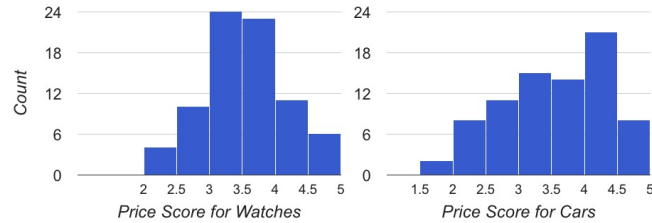


Figure 3: Distribution of perceived price ratings collected for watches (left) and cars (right).

car brand received 8 price ratings. We computed the average price rating for each brand and used it as the target value for regression. The distributions of perceived price ratings for the two datasets are shown in Figure 3.

To measure how closely perception matches reality, we scraped actual price categories for each watch brand from Watchuseek Forums [2]. Figure 4 shows how the perceived price ratings for a subset of watch brands compares with their actual price ratings. Brands above the dashed line are perceived to be less expensive than they actually are, whereas, brands below the line are perceived to be more expensive than they actually are. Therefore, brands in the upper left and lower right of the plot have the greatest disparity between perceived and actual price ratings.

Features

For each watch and car company, we compute a set of 20 features over its screenshot. Given that colors play an important role in determining aesthetic styles and brand perception [3, 9, 12], we compute several color-based features such as mean and standard deviation of a screenshot's HSL and RGB channels. We also compute visual features such as colorfulness and whitespace, similar to prior work

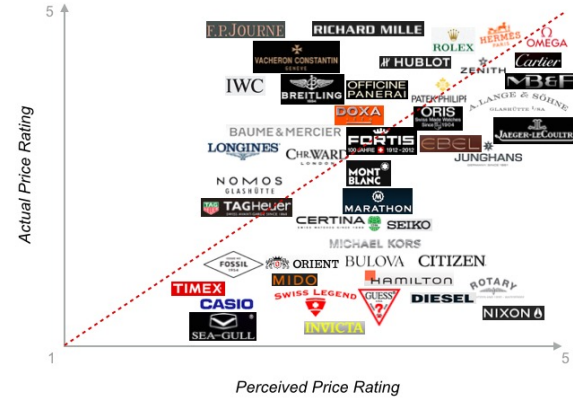


Figure 4: Comparison between the perceived price rating and the actual price rating of watch brands. Brands in the upper left and lower right have the greatest disparity between perceived and actual price ratings.

[8, 9]. While most features are computed automatically, we manually count the number of products found in screenshots as an approximate measure of visual complexity. The features are described in more detail below.

Mean and Standard Deviation of RGB: The mean and standard deviation of a screenshot's RGB channels.

Mean and Standard Deviation of HSL: The mean and standard deviation of a screenshot's HSL channels.

Number of colors: The number of colors in a website. Each channel in RGB is represented with 5 bits.

Dominant color: The percentage of a screenshot covered by its most frequent RGB color.

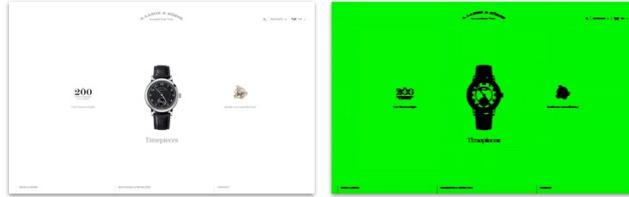


Figure 5: An original screenshot (left) and its computed whitespace in green (right).

Colorfulness: The sum of a screenshot’s mean and standard deviation of saturation [11]. *Whitespace:* The percentage of a screenshot that is whitespace. We iterate over the screenshot with a 5x5 pixel window. If the RGB Manhattan distance between any two pixels in a window is below a threshold, we count the pixels as whitespace.

Number of products: The number of products — watches or cars depending on the dataset — in each website. Three students independently extracted this feature by manually examining screenshots, and discussed to reach consensus for screenshots where different numbers were recorded.

Model

Based on the crowdsourced price ratings and the computed design features, we learn a random forest regression model that predicts the price rating for a brand’s website. Using backward elimination, we iteratively remove features that are not predictive of perceived price [4, 9]. We train two separate regression models for watches and cars using Python scikit-learn [1].

To evaluate the performance of the model, we compute 4-fold cross validation and measure the mean square error (MSE) and the mean absolute error (MAE). During back-

	MSE	MAE
Watches	0.31	0.45
Cars	0.68	0.70

Table 1: Mean squared error (MSE) and mean absolute error (MAE) of predicted price ratings for watches and cars.

ward elimination, we use MSE to determine which features contribute the least to the model’s accuracy, remove them, and retrain. Once the model’s accuracy cannot be improved, we use the *variable importance* measure given by the random forest model to rank features that are most predictive of perceived price rating.

Results

For the watch regression model, the MSE of predicted price ratings is 0.31, and the MAE is 0.45; for the car regression model, the MSE of predicted price ratings is 0.68 and the MAE is 0.70 (Table 1).

The features most predictive of perceived price are shown in Table 2. A watch website design composed of many products, many colors, little whitespace, and a large standard deviation of lightness will be perceived as a cheap brand. Similarly, a car website design composed of many products, a large standard deviation of saturation, a large standard deviation of hue, and many colors will be perceived as a cheap brand. Figure 7 visually illustrates the relationship between perceived price ratings and the predictive features.

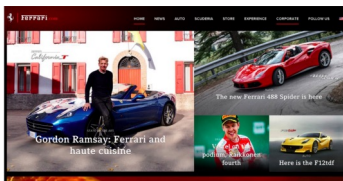


Figure 6: Highly expensive car web designs which are predicted as cheap brands under the current model; however, people correctly label them as expensive brands, most likely because images of sports cars exude luxury.

Top Predictive Features	
Watches	Number of products
	Number of colors
	Whitespace
	SDev of Lightness
Cars	Number of products
	SDev of Saturation
	SDev of Hue
	Number of colors

Table 2: The features that are the most predictive of perceived price for the watches are car datasets.

Discussion and Future Work

While the regression models identify several features predictive of perceived price, there are website designs and brands that the models cannot accurately rate. For example, based on the website design, the car regression model predicts that Ferrari is a relatively cheap brand: the site has little whitespace, many colors, and a large standard deviation of saturation (Figure 6). However, the crowdsourced price rating for this website was high. Although we blur out the brand logo, we suspect that people often associate sports cars with luxury brands. So while people rate these sports car websites correctly, our model currently does not.

To train more robust models for predicting perceived price, we plan to expand the feature set to include content analysis of images and copy. Recognizing objects like sports cars in images, and words like “luxury” in the copy could provide stronger signals about the expensiveness of a brand.

While the watch and car regression models had two predictive features in common, they were not identical. We would like to analyze a broader set of industries to see if the predictive features are similar across industries or vastly different.

References

- [1] 2007. Random Forest Classifier in Python scikit-learn. <http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html>. (2007).
- [2] 2012. Ranking of watch brands (by price), revised. <http://forums.watchuseek.com/f2/ranking-watch-brands-price-revised-755635.html>. (2012). From Watchuseek Forums.
- [3] Paul A Bottomley and John R Doyle. 2006. The interactive effects of colors and products on perceptions of brand logo appropriateness. *Marketing Theory* 6, 1 (2006), 63–83.
- [4] Nesrine Chehata, Li Guo, and Clément Mallet. 2009. Airborne lidar feature selection for urban classification using random forests. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences* 38, Part 3 (2009), W8.
- [5] Gitte Lindgaard, Gary Fernandes, Cathy Dudek, and Judith Brown. 2006. Attention web designers: You have 50 milliseconds to make a good first impression! *Behaviour & information technology* 25, 2 (2006), 115–126.
- [6] Eleni Michailidou, Simon Harper, and Sean Bechhofer. 2008. Visual complexity and aesthetic perception of web pages. In *Proceedings of the 26th annual ACM international conference on Design of communication*. ACM, 215–224.
- [7] Aliaksei Miniukovich and Antonella De Angeli. 2015. Computation of interface aesthetics. In *Proceedings of the 33rd Annual ACM Conference on Human Factors*

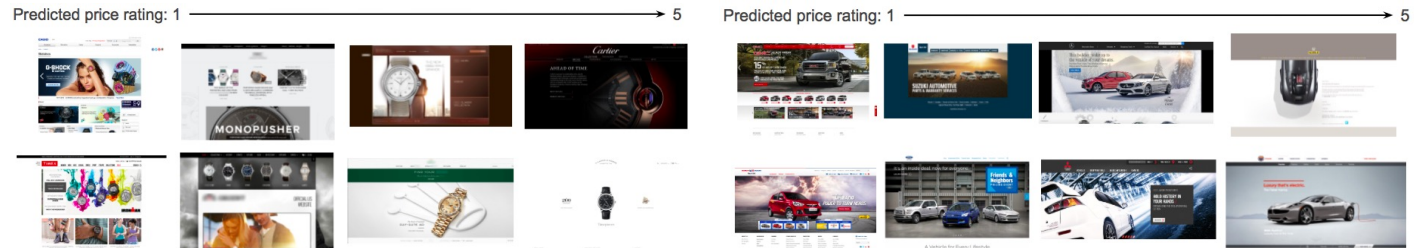


Figure 7: Relationship between predicted price ratings and top predictive features: number of products, number of colors, whitespace, and standard deviation of lightness for watches (left), and number of products, standard deviation of saturation, standard deviation of hue, and number of colors for cars (right).

- in Computing Systems*. ACM, 1163–1172.
- [8] J. W. Pracejus, G. D. Olsen, and T. C. O’Guinn. 2006. How nothing became something: white space, rhetoric, history, and meaning. *Journal of Consumer Research* 33, 1 (2006), 82–90.
- [9] K. Reinecke, T. Yeh, L. Miratrix, R. Mardiko, Y. Zhao, J. Liu, and K. Z. Gajos. 2013. Predicting users’ first impressions of website aesthetics with a quantification of perceived visual complexity and colorfulness. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2049–2058.
- [10] Ou Wu, Weiming Hu, and Lei Shi. 2013. Measuring the visual complexities of Web pages. *ACM Transactions on the Web (TWEB)* 7, 1 (2013), 1.
- [11] SN Yendrikhovskij, FJJ Blommaert, and H De Ridder. 1998. Optimizing color reproduction of natural images. In *Color and Imaging Conference*, Vol. 1998. Society for Imaging Science and Technology, 140–145.
- [12] Xianjun Sam Zheng, Ishani Chakraborty, James Jeng-Wei Lin, and Robert Rauschenberger. 2009. Correlating low-level image statistics with users-rapid aesthetic and affective judgments of web pages. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1–10.