Is a Picture Really Worth a Thousand Words? 
- On the Role of Images in E-commerce

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ABSTRACT
In online peer-to-peer commerce places where physical examination of the goods is infeasible, textual descriptions, images of the products, reputation of the participants, play key roles. Visual image is a powerful channel to convey crucial information towards e-shoppers and influence their choice. In this paper, we investigate a well-known online marketplace where over millions of products change hands and most are described with the help of one or more images. We present a systematic data mining and knowledge discovery approach that aims to quantitatively dissect the role of images in e-commerce in great detail. Our goal is two-fold. First, we aim to get a thorough understanding of impact of images across various dimensions: product categories, user segments, conversion rate. We present quantitative evaluation of the influence of images and show how to leverage different image aspects, such as quantity and quality, to effectively raise sale. Second, we study interaction of image data with other selling dimensions by jointly modeling them with user behavior data. Results suggest that “watch” behavior encodes complex signals combining both attention and hesitation from buyer, in which image still holds an important role when compared to other selling variables, especially for products for which appearance is important. We conclude on how these findings can benefit sellers in a high competitive online e-commerce market.

Categories and Subject Descriptors
G.3 [PROBABILITY AND STATISTICS]: Correlation and regression analysis, Experimental design; H.2.8 [DATABASE APPLICATIONS]: [data mining, image databases]

Keywords
E-commerce, Online shopping, Multimodal data mining, Image, Image Quality, Buyer Behavior, User Engagement

1. INTRODUCTION
Consumers enjoy the convenience and low price offered by online shopping. However, since there is no physical interaction between buyers and sellers, these benefits may be diminished by increased risk due to product uncertainty and seller uncertainty. In online transaction, trust is an essential dimension of success [16]. Online reputation systems can reflect seller credits based on past transaction and crowd wisdom [8, 24]. Yet, each individual product purchase involves understanding the product better. Information and communication with sellers are mostly limited through text, creating a sense of anxiety among online shoppers [28]. Fortunately, product images (or other multimedia format) provide a unique yet profound channel to convey visual information to buyer. It provides buyer, who must put considerable dollars at risk, a way to view and inspect the item before making the decision.

Pictures from online personal albums and social sites are typically used to record events or share visual elements of creativity and beauty. On the other hand, product images are used to provide a clear and attractive picture in a trust-worthy way in order to convey information to consumers about the product and its quality.

With the advent of digital cameras and phone-based cameras, capturing and sharing of images and videos have become prevalent. For instance, according to one source, over 200K images are uploaded to Facebook per minute; 16 billion images have been shared on Instagram; eBay sellers upload above 20 million product images everyday. While most images are for human consumption, on platforms like Amazon, Craigslist and eBay, images form an important component for commerce to happen. While Amazon curates and standardizes the images given its catalog-based commerce, on eBay, given the diversity of the products, product conditions, and the sellers, there are huge variations among images in terms of quantity and quality. In fact, a large portion of inventory images are taken by individual sellers who do not possess professional photography skills, which leads to significant variations in image quality [11].

Studies on selling strategies and trust issues for online shopping are widespread in the literature [6, 28, 16], without focus on role of product images. Previous research on importance of images in an e-commerce scenario can be found in [3, 4, 10, 26, 17, 20, 14, 27]. However, studies related to image quality and quantity are only drawn from small user groups, which may not be extensible to realistic vast online markets. Large scale studies only look at inclusion of images in the success of auctions, without importance to image quality or quantity. Also, we still know little about the effects of image in marketplace where majority of images are taken by individual customers rather being well designed by merchandising standard, and little of to what extent, images influence user’s online shopping choice and behavior.

The goal of this research is to get a thorough understanding of impact of images across various key dimensions. While a successful online transaction is dependent on many factors, such as prod-
uct (price & quality), advertisement (listing title, description, and image), service (shipping & return & communication & security), buyer’s intention and seller’s qualification, we particularly focus on answering the following questions in relation to product images in e-commerce:

- How images of listings differ across categories, sellers, or specific attributes of the item, such as condition?
- Does visual information always help to improve the conversion rate for online shopping by increasing trust and reducing perceived risk, and if it does, in what respect and to what extent?
- How to leverage various image properties (display format, quality or quantity) to raise sale cost-effectively?
- How images impact buyer behavior/experience? For instance, how sensitive are experienced buyers to different quality and quantity of product images?
- How important are images as compared to other selling variables?

Specifically, we choose three important aspects of images: 1) the display format, 2) number of images per product, and 3) image quality. We do a cross study of their relationship with multiple key dimensions in e-commerce, such as conversion rate, seller and buyer, buyer experience and engagement.

We believe that given the significant growth in online shopping, investigation of these issues allows better selling strategies to be designed and better understanding of consumer’s behavior and their preference.

The rest of the paper is organized as follows. In section 2, we review research background, formulate our problem and discuss previous related work in literature. Two major data sets are introduced in section 3. Section 4 presents an overview of the role of images in e-commerce in terms of category, seller and buyer segments, buyer activity and experience, and conversion rate. Also, using product resale (where buyers resell products purchased from other sellers in the same marketplace) as an exemplar, we show improved sell-through and profit by improving image factors. Section 5 studies factors that affect buyer’s behavior of adding items to watch list. We show that the “watch” action is double-faced with complex signals that can be attributed to various factors, including those related to image. Moreover, we propose a binomial action model, and describe the use of logistic regression as a means of combining individual variables and determining significant factors. Section 6 lists some concluding remarks and possible future work.

2. BACKGROUND AND RELATED WORK

Online marketplaces have significantly grown in the past decade affording both local and global online trade. Many of these markets are peer-to-peer in nature and have encouraged useful research on topics like consumer behavior, trust, selling strategy, cross-border languages [6].

Online shopping process consists of five steps similar to those associated with traditional shopping behavior [19], including a) a need for some product or service, b) search online marketplace for need-related information, c) attracted by information about products or services, d) evaluate/compare alternatives, e) make the final decision for purchasing and being provided with post-sale services.

Studies have shown that shopping behavior is significantly influenced by trust and perceived risk, consumer’s attitude, social influence, etc. [21]. Trust and the perceived risk are the very essential issues for online market [28, 16]. This is mainly due to the information asymmetry of online market [2], which causes difficulty for sellers to credibly disclose product information and for buyers to obtain relevant information to evaluate product quality. Risk in each transaction is essentially created by the threats to obtain misleading/incorrect information from the item, thus facing adverse consequences of engaging in e-commerce. With no buildings or staff to evaluate, and no physical items to inspect, consumer decisions rest purely on the the descriptions and pictures provided [13]. Therefore, effective communication between buyer and seller is very important to break up this asymmetry hurdle. Effective product presentation must be visible, clear, and credible [22]. However, text information such as title and listing description can only provide information within the scope of language, while the valuable visual information is lost.

Previous research has shown the use of pictures to be important to buyers when buying on one of the largest e-commerce market - eBay [3, 10, 4, 20, 26]. Study in [5] indicated that product picture is one of the most influential risk-reducing factors. The author found in their particular case that either a real picture of the product actually being sold or a stock picture is a risk-reducing factor that will improve the outcomes of the auction for the seller. The inclusion of the real picture is proved to be effective in increasing auction success, effectiveness, and the value of the final bid. While a stock picture also significantly increases the final bid, the probability of auction success is not enhanced. Study in [18] looks at number of images embedded in item descriptions in eBay motors and draws the conclusion that more images help to boost the selling, especially for old cars. The author also found strong correlation of photo and price for non-dealers, which is possibly because buyers cannot rely on reputation as an alternate source of information about quality.

Moreover, evidence has been presented that clear and detailed pictures of the products also help to reduce perceived risk associated with online purchasing [14, 17, 27]. Based on the study of a smaller user group, the Keynote study in 2005 ([15]) reveals the importance of better quality images as a number of shoppers expressed their preference to see both higher quality photographs and more images in item descriptions.

Recent study showed that certain image features can also help to improve click through rate in product search engine [11, 7]. The authors conducted experiments to show that including image features in a machine learned click based ranking model improves the NDCG (normalized discounted cumulative gain) of the search results. The work in [4] studies the ability to attract customers and likelihood of transaction by including a binary variable indicating whether an image is associated with the listing. They found positive evidence for inexpensive products that providing image can increase number of bidding.

The above mentioned research work address the observed benefit of using images for listing descriptions. However, none of the above work has done a systematic and thorough study on the impact of images on online shopping, either from both the quantity and quality sides of image, or cross various dimensions of online shopping - from seller to buyer, or from user experience to user behavior. Also, these work do not provide the answers to the question that, given known importance of image presence for online transaction, to what extent image affect user’s attention and decision for a product, how does it compare to other key factors such as price or seller reputation, etc.

3. DATA PREPARATION

To avoid bias from studying a smaller user group, in this study, we collect data from real online listing at a large scale. We con-
struct two major data sets from the universe of product listings from a popular online peer-to-peer marketplace. We want to understand, at the highest level, the impact on user engagement and purchase of the number of images; the quality of images; and the way they are laid out (display type). We would also like to know what kind of sellers benefit from these aspects of images. Particularly, the data focuses on three different aspects of a listing image: a) the display type, b) the number of images per listing, and c) the image quality for the dominant image (the one shown up on the product search page).

The first dataset includes randomly chosen product listings from the year 2011-2012. Since displaying type or using multiple images are optional for seller (and costs the sellers), the data may be sparse. It is used to learn the first two aspects of images in relation to conversion rate and seller type. Detailed results are presented in section 4.1 and 4.2. The second data set is mainly used for studying image quality factors. The data covers randomly sampled listings created on several random selected months in the year of 2012. In this dataset, there are in total 4658711 listings. Among them, 889541 are fixed price listings, and others are auctions. This data is used to perform analysis in section 4.3 and 5.2. We further expand this data set with great details to study buyer’s “watch” behavior in section 5.3. Detailed information include title, seller information, item condition, shipping information, gallery type, displaying type, auction type, stock photo indicator, listing duration, image quality and counts, etc..

One additional resale data is also collected as special exemplar case to gain deeper understandings on our major findings. Detailed information can be found in section 4.4.

4. AN OVERVIEW OF IMAGES IN E-COMMERCE

In this section, we study the impact of image display type, the number of images, and the quality of images.

4.1 Photo Display Type

Question 1: What is the effect of custom photos versus original catalog photos on users?

Stock photos are catalog images with high quality. Seller can choose “use stock photo” option without taking and uploading their own photos, but a note stating that the item picture is a stock photo will appear below the photo. We investigate the conversion rate of items using and not using stock photo. Result shows that the conversion rate for items in our dataset using stock photo is only about about half of what it is for items not using stock photo. This result is consistent with previous finding that an actual digital picture of the item being sold will likely increase the probability of success, and the benefit to using a stock source of photos is rather limited [5].

Question 2: Does Size Matter?

The default format for displaying photo is the Standard Show. The platform also provides seller with few other enhanced features with small amount of additional fees. There are features like EPS Picture Show that offers special pricing for multiple pictures (up to 12). Super Size Picture will display images in an enlarged manner. Table 1 shows the conversion rate of few major options. Results indicate that larger photos, which provide more information for buyer to inspect details of the product, increase the chance of success for an online selling.

Table 1: Conversion Rate vs. Photo Display Type, which shows larger picture and pleasing browsing experience increase chance of success in sale. Numbers of sold and listed items are rounded to millions (M).

<table>
<thead>
<tr>
<th>Display Type</th>
<th>Sold</th>
<th>Listing</th>
<th>Conversion rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Show</td>
<td>420.7M</td>
<td>2958.5M</td>
<td>14.2%</td>
</tr>
<tr>
<td>Large Photo Show</td>
<td>4.5M</td>
<td>19.9M</td>
<td>22.9%</td>
</tr>
<tr>
<td>Picture Pack</td>
<td>316.3M</td>
<td>1411.5M</td>
<td>22.4%</td>
</tr>
<tr>
<td>EPS Picture Show</td>
<td>3.4M</td>
<td>9.0M</td>
<td>37.9%</td>
</tr>
<tr>
<td>Super Size Picture</td>
<td>7.7M</td>
<td>26.0M</td>
<td>29.5%</td>
</tr>
</tbody>
</table>

Figure 3: Photo Count distribution vs. Conversion Rate for top sellers and casual sellers. Observed from the curve plots, conversion rate doubled twice when using two images as compared to using one picture. Observed from the bar plots, casual sellers tend to upload more pictures than top sellers as they have low volume to sell and can afford more effort on each item to add more pictures.

4.2 Photo Count

Question 3: More pictures, more information? Better conversion?

Figure 3 shows the normalized distribution of items sold by experienced sellers (green bar) and casual sellers (yellow bar), and the conversion rate (red and blue curves) in terms of number of images per item (photo count). Common to both experienced seller and casual seller, most of the items only have one image. Also, both the conversion rate shows a log-like growth pattern at the beginning. Clearly, by giving buyers more complete information from different views of object, the probability of success is increased, as we can see that conversion rate is almost doubled twice by using two images as compared to using a single one. In our data, more than 3 pictures seem to have a small impact. Further, comparing the normalized distribution of experienced and casual sellers (bar plot), we can see that casual sellers tend to use more images than experienced sellers. One possible explanation is that casual sellers have lower volume of items to be sold, thus can afford more effort for each single item to take or upload more images.

4.3 Image Quality

Quality of product images is important in helping the customer make decisions [14, 27, 17, 15]. Not only they are important to convey the visual information to buyers, also they are viewed as a visual proof of the quality of the real product and even the seller. Buyers expect clear, clean and even visually enjoyable images. A high quality or professionally photographed image may help to draw attentions from buyer or boost buyer’s confidence for the product that they are interested in. On the contrary, poor images may countermand this benefit.
While image quality is a highly content dependent and subjective concept, a proper measurement for this fundamental property is to evaluate whether a listing image is able to convey accurate information about the product effectively. In a peer-to-peer marketplace, where there is huge diversity of content providers, image quality can vary quite a bit even for similar products. Common image quality problems include: bad lighting, cluttered background, blur, specular reflection, and bad composition. Thus, focusing on the preference of product image from e-commerce perspective, we employ quality score that emphasizes on the clarity of the foreground object, high brightness, strong contrast between foreground and background, clean and uniform background, etc.. For each image, scores that represent each of these visual aspects, e.g. brightness or contrast, are computed and used as features to describe the image. A linear regression model is trained based on human rated data, where each annotator rates the image quality to be good, fair or bad. The learned model is then used to aggregate all the features to predict the overall quality of the image. Because some of the these features are computed from RGB values (0-255), as a convention, the range of quality score is also kept in [0, 255], whereas a score of 255 means the best quality. Potential readers are referred to [7, 11] for details.

We study image qualities in relation to seller, buyer and their experience. Sellers are divided into different levels (casual, bronze, silver, gold, platinum, titanium) based on increasing amount of sales made and revenue generated. Buyers are also grouped into several levels (A,B,C,D,E) based on their spend over the last 12 months. A-type buyer spends the most, while E-type buyer spends the least. What we focus here on is the relative grades between sellers and between buyers.

Figures 1 and 2 show the evidences that:

**Question 4:** How do quality of pictures vary with seller levels?

**Question 5:** How do different classes of buyers respond to image quality?

We found that more successful the sellers are, the better quality images they use for their listings. However, limited to professional photograph tools and skills, qualities by casual seller are generally worse than top seller. This also corresponds to our finding that quality of images for *used* items are generally lower than that for *new* items (as casual sellers typically sell *used* products).

On the other hand, Figure 2 shows that, in general, new buyers prefer listings with high quality images which can provide more assurance on the product, whereas frequent buyers show less concern on possible risk for listings with low quality images, with few
exceptions for categories such as Music and Antiques. This confirms the previous findings that perceived risk can be reduced by knowledge, skill, and experience on the Internet ([23, 25, 12]).

4.4 Resale: Profiting from better pictures

To understand how changes in image (quantity & quality) can make a difference, we collect a set of pairs of resale data. The initial sale are listings ended at several randomly selected time windows across 3 months of 2012. Each window covers 15 days. A valid resale is identified if the same buyer re-lists the item within 3 months after he/she bought from the initial sale. We restrict that both listings have the same title and are listed under the same leaf category. We are aware that there are professional sellers who conduct resale at the site by buying lots and then selling individually after modifying titles and other descriptions. However, we found that relaxing the condition to include pairs with similar titles introduces noise and the data become unreliable. We also filter out any items that use stock photos. The final data set consists of 55396 pairs of listings in total.

Figure 4: The most and least profitable leaf categories in resale, and their profit ratio. Electronic categories shows to be more profitable.

Figure 5: Resale profit rate vs. photo count increment rate for top 15 meta-categories. Strong correlation between increment in photo count and profit rate.

To analyze the changes of image factors and profit made from the resale, we compute relative changes in photo count $C$, image quality $Q$ and price $P$ (item price plus shipping & handling fees) by comparing resale (denoted by $b$) with initial sale (denoted by $a$):

\[
\begin{align*}
R_P &= \frac{P_b - P_a}{P_a} \\
R_Q &= \frac{Q_b - Q_a}{Q_a} \\
R_C &= \frac{\alpha + C_b - C_a}{\alpha + C_a}
\end{align*}
\]

where $R_P$ is the profit rate and $R_Q$ is the quality improvement rate. $\alpha$ is a smoothing parameter as some of the initial sale items may not have any image. We choose $\alpha = 0.1$ in the experiments. As shown in Figure 3, increment of conversion rate follows a logarithmic-like growth pattern at the beginning. Hence, we formulate $R_C$ as the incremental rate of photo count, rather than using the absolute photo number.

Figure 4 shows the most profit and least profit leaf categories, along with their average profit rate. One can see that resale of Electronic items tends to be easier to make profit. Figure 5 shows the relationship between average $R_C$, $R_Q$, and $R_P$ for top meta-categories. We found a clear trend that as photo count increases, the probability of making profit also increases. However, image quality shows very small changes between the initial listing and the resale item. We also compute the correlation between $R_C$ and $R_Q$ for top 20 leaf categories, resulting in 0.788, while correlation between $R_Q$ and $R_P$ is only about 0.032. Note that correlation is computed using scores from each item, not from the average profit rate that is shown in Figure 5.

By browsing image pairs in this resale dataset, we notice that reseller may change product images, but in general is able to maintain the quality of picture since the initial sale serves as an example of selling. Some resellers even copy photos from the previous seller, and only make slight modification, such as cropping the image. An example is shown in Figure 6.

5. WATCHING THE WHEELS

Shopping processes can involve various states and stages like "viewing a product", "sharing with friends", "adding to wish list", "adding to watch list", "adding to shopping cart", and finally, "buying". We would like to understand the role of images in these steps in the pipeline of a shopping process.

Among all kinds of buyer behaviors, in this paper, we investigate the buyer’s “add-to-watch-list” behavior. We believe that although “add-to-watch-list” may not necessarily lead to a check out action,
it embeds a more serious shopping attitude and intention than other behaviors, such as click-through, or visiting a page.

Unlike actions such as “add-to-cart”, whereas users have to either confirm their decision for purchase or replace/remove the item from the cart later on, “watch” action comes with lower cost and pressure since no further action is required. It can also be used to reserve an item for a long term purpose. Moreover, “watch” encodes more individual preference, and is less influenced by other buyers in the market. Unlike other actions, the number of watch is always hidden from buyer. For example, at the search result page, the current bidding price and number of bids are often shown to buyers. Study has shown that in competitive situations, online auctions are likely to intensify, as bidders are emotionally involved [1]. Similarly, at the listing page, numbers of actions for “like”, “want”, and “own” are also shown. Buyers may be biased towards items with a higher number of bids or being liked by many people.

However, it would be naive to assume that “watch” only encodes user’s interest and attention for the product. It’s essentially a coin with two sides. As consumers are in the middle stage of a shopping process (browse, compare, decide, checkout), the “watch” behavior should therefore involve buyer’s a) interest/intention for the item which causes them to seriously put the item under check, and b) hesitation as they are putting the item on hold to compare with other similar items, weigh the risk and take time to make the decision.

To understand this behavior, in the following section, we first analyze the relationship between watch and conversion rate. The goal is to see if our assumption that watch action encodes user’s interest in the item is true. Second, we decompose this action by analyzing influential/related selling variables, particularly incorporate image related factors.

5.1 Buying Myself a Chance

The action of watching an item can be attributed to many things. Although we can not directly quantify how much interest the user has for the item through this action, we can assume that higher interest may transfer to higher probability of purchase. To prove this, Figure 7 (a) shows the changes in conversion rate given the watch popularity (in terms of the frequency of watch). It clearly shows that more “watch” indicates the product draws more interest from user, and resulting in higher conversion rate. This phenomenon peaks at about 20 watches, with a slightly down trend afterwards, which is possibly due to the lack of data samples to obtain a stable prediction (items with higher watch numbers are very sparse). It is also possible that a higher watch number indicates more competitive market. To get a sense of how watched item is compared to the overall inventory, Figure 7 (b) shows the averaged conversion rate per meta-category. In general, having more than 10 watches indicates higher market demand, and an above average conversion rate.

Figure 8 shows the percentage of the transactions that is made from watchers (buyers that made the watch action), for the items being watched and successfully sold. It can be seen that nearly one-third of the transactions come from watchers. Especially, percentage is higher for “unique” items, such as categories: music, crafts, and books. This is possibly due to that buyers often have clearer intentions for items in these categories or because items are “unique”, buyers have fewer alternative options and end up going back to purchase the one they bookmarked through watching.

5.2 Better Image = More Watch?

As many variables may affect “watch” behavior, we particularly want to understand the influence of image factors. Does a better image lead to more attention from buyer and how does it compare to other key factors that also influence this action? Also, some products rely more on their visual, e.g. clothing. Other products, e.g. electronics, rely more on their specifications and functionality, since only limited design models are available. Given such intrinsic difference, will it affect the importance of image in presenting the product?

To answer these questions, we collect listing data during the Fall season of 2012. Detailed information of this dataset is given in section 3. We first compare image quality with the number of “watch” per item. As shown in Figure 9, irrespective of the category of the products, data exhibits a strong correlation between image quality and watch count.

In order to understand buyer’s behavior from the product category level, we also look at the performance of four top meta-categories. We divide these four categories into two groups. Type-A-categ, including Clothing, Shoes and Accessories, Consumer Electronics, is more apparel based and popular. On the other hand, type-B-categ is of more unique product, which includes Coins & Paper Money, Books. It can be seen from Figure 11 that type-A-categ shows much stronger response to image quality than type-B-categ. Type-A-categ also has higher average watch action as compared...
5.3 Action Model: A Regression Explanation

Assume each action “watch”(or not) from the buyer is a binary outcome \( W \) from a set of selling variables. It can be modeled by Bernoulli trial as “watch” \( (W_i = 1) \) and “not-watch” \( (W_i = 0) \) for the \( i \)th trial with probability:

\[
Pr(W_i = 1) = \pi_i
\]

where the log value of the odds \( \frac{\pi}{1-\pi} \) of taking action can be approximated by a linear combination of continuous input variables \( x_1 \ldots x_n \), and dichotomous variables \( d_1 \ldots d_m \) with values 0 or 1.

Based on the observations and discussions we had in previous sections, we select several selling dimensions and image related factors as input variables, including item price, shipping price, number of photos per item (photo count), number of word tokens in title (title length), seller condition (new or used), seller feedback positive ratio (percent of positive feedback over all feedback), log of total feedback score, auction duration days (auct-durn-days), bold-title (0 as standard title, 1 as bold title), item category. In the experiment, for each leaf category we choose average token count as the threshold to select the popular keyword set \( \text{Pop}_{kw}(c) \) for each leaf category \( c \).

Keyword Popularity is used to encode the competition especially between popular items. We only use the title information as the product search engine highly depends on title. To compute this popularity score, we first group listings based on their leaf category. Then, we enlarge link. Photo display type include: Standard and Picture Pack which offers special pricing for multiple pictures. We have also discussed these features in section 4.1.

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Figure 9: Overall trend of “watch” per item versus image quality score.

Figure 10: Different “watch” behavior for fixed-price and auction listings (red & blue curves). Yellow and green curves show the distributions of items in relation to image quality for auction and fixed-price items, respectively.

pared to type-B-categ. Differences between categories indicate the different roles of images across various products. It is reasonable to assume that for products that more depend on their looking, image is likely to be a more important channel for communication. Trendy categories also imply that high competition may cause buyer to hold the item and look around for other candidates. This is less likely to happen for type-B-categ. Because items are unique, there are less competition from peers and fewer available alternatives in the market.

Figure 10 also plots the normalized item distribution in terms of image quality for fixed-price (green) and auctions (yellow), respectively. The peak around 170-180 shows that many images have moderate qualities. We also found a similar peak around the same position in the red curve, which is the watch number per item for fixed-price listings. We think this co-occurrence is not random. It’s possibly because intensive competition between similar items holds back buyers from immediate purchase and increases the possibility that buyer adds the item into watch list for further comparison.

5.3 Action Model: A Regression Explanation

As shown in above section, “watch” action as one of the user engagement factor reveals complex signals combining both attention and hesitation from buyer. In order to model this action, we need to consider factors from both sides of the coin.

Assume each action “watch”(or not) from the buyer is a binary outcome \( W \) from a set of selling variables. It can be modeled by Bernoulli trial as “watch” \( (W_i = 1) \) and “not-watch” \( (W_i = 0) \) for the \( i \)th trial with probability:

\[
Pr(W_i = 1) = \pi_i
\]

where the log value of the odds \( \frac{\pi}{1-\pi} \) of taking action can be approximated by a linear combination of continuous input variables \( x_1 \ldots x_n \), and dichotomous variables \( d_1 \ldots d_m \) with values 0 or 1.

Then the amount of “watch” \( Y \) (watch count) that a listing item received can be viewed as a result of a sequence of each these trials. The distribution of this count in the \( N \)th trial is a binomial distribution \( Y \sim \text{Binomial}(N, \pi) \).

Logistic regression models are often used to understand the role of input variables in explaining the outcome \([9]\), where the response variable follows a binomial distribution. It can be formulated as:

\[
\log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n + \delta_1 d_1 + \ldots + \delta_m d_m + \epsilon
\]

where \( \pi \) is the probability of success for a trial.

Figure 11: Examples of several top meta-categories: correlation of “watch” per item versus image quality score.

Figure 12: Examples of several top meta-categories: correlation of “watch” per item versus image quality score.
where \(| S |\) is the cardinality of the set \(S\). \(S_w(t)\) is the set of word tokens for title \(t\). \(f\) is the function to filter out some stop words and punctuation, such as “the”, “of”, “,” etc. We kept some common words such as “new”, “free”, “size”. Although they are commonly seen in titles and do not provide discriminative information to differentiate listings, our goal is instead to highlight the competition. These words are usually top queries and play an important role in product search as many buyers try to search product with certain condition or with free shipping and handling. Taking the leaf category “iPad/Tablet/eBook Accessories” as an example, the popular keyword set \(S_{kw}\) includes: “crystal, protective, touchpad, apple, ereader, portable, magnetic, compatible, dual, camera, bluetooth, slim, amazon, 3gs, 4s”, and many others. While for “Women’s Clothing/Athletic Apparel” category, the popular keyword list instead consists of “yoga, v-neck, seamless, nike, gym, fit, golf, hoodie, cotton, compression, zip, workout, cycling, combat, adidas, shot, stretch”, and so on.

5.4 Regression Results & Discussion

Since market and consumer’s intention change dramatically across different categories, we therefore apply regression model to each meta-category. Variables includes item condition (new or used), seller type (casual, top), gallery types, bold title, and display types. Regression is computed using the first level of each category variable as reference. Others are treated as continuous variables. We also filter out items with watch count over 50, which rarely occur. Then we normalize the count to be within the range of \([0, 1]\). Tables 2 and 3 show the regression results for “Clothing, Shoes & Accessories” and “Consumer Electronics”.

For both categories, common significant factors include photo count, item condition, keyword popularity score and auction duration days. Photo count shows significant positive impact as we expected. Using condition-new as reference, condition(used) shows negative impact on attracting the buyer. With longer listing time, item has more chances to be exposed to consumers, therefore auction duration days is one of the major factors. Keywords help the item to have higher exposure, thus be search-able and accessible to the buyers. A higher keyword popularity score means larger overlap between title and the popular keyword set from the leaf-category that the item belongs to. This also indicates more intensive competition from peers.

Besides photo count, other image related variables, such as image quality and display types show more significant impact on CSA compared to Electronics. We also found similar results for other electronic related categories. This corresponds to our assumption that apparel related category may gain more benefits from providing visual content for consumers. Also, we notice that Electronic category has overall better quality images since it’s easier to obtain standard product image. Sellers also tend to employ good quality images from other sellers. Therefore, the competition between sellers and the focuses from buyers in regards to the product more likely rely on other factors instead of image.

6. CONCLUSIONS AND FUTURE WORK

Given only scattered evidence in literature that inclusion of image or other multimedia information may help improve transaction rate, in this paper, we dive into three major aspects of image: display format, number of views presented per item, and their quality. We focus on understanding not only yes or no question but to what extent images affect online transactions, and how they compare with other selling variables. We analyze conversion rate, seller & buyer segments, consumer experience and interaction behavior in responding to each of the image aspects.

Our results show positive evidence that images help increase buyer’s attention, trust and conversion rate. Among the three properties of images, our study shows that increasing number of images of the product, which is equivalent to providing more complete visual representation of the product, is an effective way to improve sell-through. For marketplaces that cater to used, refurbished, and resale products where most sellers are casual sellers, the impact of image quality is limited to certain extent, since users, especially experienced users, may have developed certain level of tolerance towards poor quality images. However, image quality still serves as an important factor especially for goods where appearance plays a key role. Additionally, one should be aware that the norm of market can dramatically change when comparing this type of market to other markets where only high-quality images are used. In that case, quality of product may become a symbol of the quality of...
the marketplace, and will affect user’s choice on which market to shop online. In other words, cross-market seller should be aware of differences between markets, and adapt their strategy accordingly.

We believe this is the first systematic analysis on this subject that jointly considers key e-commerce dimensions. Our studies provide a deeper understanding of the role of images in the e-commerce flow.

Future studies include developing content based image quality to understand the impact of image aesthetics on attracting buyer’s attention. We will also pursue modeling “watch” action using Graphical model for causal relationship analysis, to discover the transition relationship between “watch” and other behaviors, such as click-through, purchasing and adding-to-cart.

7. REFERENCES


