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EXPLORING ONLINE REVIEWS FOR USER EXPERIENCE MODELING

Yan LIANG, Ying LIU, Han Tong LOH
National University of Singapore, Singapore

ABSTRACT
In the market-driven design paradigm which aims to serve customers with attractive user experience (UX), one of the important stages is to understand customer's feelings about products. Traditional techniques like questionnaire remain important approaches to collect data for UX analysis. However, the data captured are often limited and incremental costs are needed to acquire user's changeable experiences over time. In addition, with the wide use of social software, customers have generated increasing amount of online reviews to share their opinions. In this paper, we aim to investigate whether online reviews are suitable data sources for UX analysis and how useful reviews can be surfaced. Firstly, by considering UX elements and data processing, a faceted-based UX model is proposed. We then measure review content from several aspects, such as richness and diversity, and propose scoring methods to identify useful reviews. Using Amazon reviews as research data, we have reported our experiments on issues like a brief example of useful reviews suggested by the proposed methods, situation-based features concerned by customers and some key product features generated from reviews.

Keywords: experience design, design informatics, conceptual design, user experience modeling, product review

Contact:
Dr. Ying Liu
National University of Singapore
Mechanical Engineering
Singapore
117576
Singapore
mpeliuy@nus.edu.sg

1 INTRODUCTION

As the development of product design and computing technologies, customers not only concern about product usability, they are also willing to have attractive products that can bring them superior experience during their interactions with a product. For example, many Apple product users are attracted by its design of human-product interaction, such as easy to use and friendly user interface. In the market-driven design paradigm, understanding customer's feelings and needs is an important stage. Designers not only need to fulfill functional aspect of products, but also consider UX in the interaction process, such as users' enjoyment, affective aspect and situation aspect of using a product. More and more companies in industries have recognized user experience (UX) as a significant element in product design.

UX is a concept emerging in the field of Human-Computer Interaction. Besides usability, it highlights the non-utilitarian aspects of interactions, and centers on users affect, sensation and satisfaction of using the product in everyday life (Law & van Schaik 2010). In order to support design for UX, studies on UX have received growing attentions, including understanding, modeling and measuring UX. Existing approaches to capture and measure UX are often based on classical survey data and data generated from questionnaires and interviews. While they remain important methods to collect data for UX analysis, limited data are generated and incremental efforts are required to monitor the drifting of UX over time. In addition, questions in the survey are often prescribed from designer's perspectives, while some customers' concerns may be neglected.

There are user narrative data which mention about users' preferences about a product, such customer self-reports and online reviews. Using the online social network platform like Amazone.com, customers can give their comments on products and share their experiences publically. These reviews are written from customers' own angles of interest towards products, such as customer sentiments, comparison between similar product of different brands and usability in different environment. In addition, many online reviews are often generated by different customers over time. Those reviews are often textual and unstructured data. Moreover, existing approaches for online review analysis often focus on mining opinions or gather customer concerns. While online reviews contain useful information for user need and preference analysis, their large volume has challenging organizations on the study of efficient approaches to investigate useful reviews for UX analysis.

Therefore, in this paper, we aim to investigate whether online reviews are suitable data sources for modeling UX and how they can be leveraged towards design for UX. The rest of this paper is organized as follows. In Section 2, relevant topics on UX modeling and online opinion mining are reviewed. Section 3 presents a faceted model for UX analysis. In Section 4, a content-based approach is proposed to investigate and measure the usefulness of product reviews for UX modeling. In Section 5, an example using smartphone reviews is given to illustrate the approach proposed. Section 6 concludes this paper.

2 RELATED WORK

2.1 User experience modeling

In general, UX is the way a user feels about using an artifact, such as a product, system, services and object (Hassenzahl 2008b; Law & van Schaik 2010). UX is commonly considered as subjective, context-dependent and dynamic (Hassenzahl & Tractinsky 2006). Design for UX emphasizes the importance of experiential, affective, valuable aspects of human-product interactions and the fulfillment of user's affective needs. Recently, it is observed that a series of research studies on understanding of the constructs of experience, how to model and measure UX and the evaluation of UX have been conducted (Law & van Schaik 2010).

Considering the nature of UX, one major challenging issue of UX studies is the modeling of UX for understanding and analysis of UX. Based on Hassenzahl (Hassenzahl & Sandweg 2004) and van Schaik and Ling et al. (van Schaik & Ling 2008), the main constructs of UX include hedonic quality, pragmatic quality, beauty (aesthetics) and goodness (overall product quality) (Hassenzahl 2008a). Two types of UX models are identified based on behavioral science, i.e., measurement model and structural model (Edwards & Bagozzi 2000). In measurement model, the constructs are represented as latent variables which are measured using manifest indicators. Data about those indicators are then collected through survey or self-reports, and the model is tested using statistic techniques. Another model, structural model, focuses on the cause-and-effect relations between UX constructs as latent variables and other variables, e.g., usability.

Another main challenging issue is how UX can be measured and quantified for UX analysis based on a UX model defined. Different attempts have been undertaken to elicit and capture UX. Some other research studies user's psychophysiological aspects to measure UX. For example, electromyography (EMG) and tonic electrodermal activity are used to measure users' facial muscle activities during their interactions with a product or a system. While using psychometric instruments are able to acquire more precise data about user physical changes, from the data it is hard to analyze and measure user responses with different aspects of experience.

Some studies focus on user subjective responses to products based on survey or questionnaire. Kujala et al. (Kujala et al. 2011) conducted a qualitative study over 20 mobile phone users using UX Curve method to assist users in retrospectively audio recording how and why their experience with a product has changed over time. The user generated data were then transcribed and assessed based on utility, ease of use and pleasure feelings. Karapanos et al. (Karapanos et al. 2010) attempted to measure the dynamics of UX over time by the elicitation of qualitative user insights from experience narratives and used content-analytical approaches to integrate the narrative data for analysis. They conducted experiments on users' experience with mobile phone changes over the first six months of use. After user data are collected, some statistics techniques like partial least squares and ordinary least squares are used to analyze UX.

2.2 Mining online opinions

In the past decade, it is observed that research topics on online review mining have received much attention. One of the interesting topics is opinion mining, whose research focuses are to identify product features and customer sentiment about products or product features. Ding et al. (Ding, Liu & Zhang 2009) identified the semantic orientation of opinions and discovered product entities and their assignment using linguistic features, such as pronouns, language conventions and comparative sentences. Jin and Ho (Jin & Ho 2009) studied a lexicalized hidden Markov model to integrate linguistic features, such as part-of-speech and surrounding contextual clue words to identify product-specific features. Wang et al. (Wang, Lu & Zhai 2010) analyzed the opinions expressed in each review at the level of topical aspects to discover ratings of various aspects as well as the relative importance weights on different aspects in each review.

Some sentiment analysis attempts to assign product reviews into different groups, such as positive, neutral and negative classes, based on customers' sentiment about product features. Popescu and Etzioni (Popescu & Etzioni 2005) used relaxation labeling method in their proposed OPINE system to find the semantic orientation of words. Pan et al. (Pan et al. 2010) proposed a spectral feature alignment approach to align domain-specific words used in different domains into unified clusters for cross-domain sentiment classification. Gao and Li (Gao & Li 2011) investigated a cross-domain topic indexing using a mixture model for multi-domain sentiment classification.

Some studies focus on gathering or summarizing product reviews to give overall opinions of customers about products or features. Hu and Liu (Hu & Liu 2004) extracted product features commented by customers and identified opinion sentences to form review summarization using part-of-speech and term frequency features. Lu and Zhai (Lu & Zhai 2008) integrated review opinions scattered in various sources at topic level by introducing a semi-supervised topic model. Cruz at al. (Cruz et al. 2010) studied how to improve opinion mining performance by integrating domain knowledge.

In summary, the studies on UX models have made increasing progress recently. However, the approaches of capturing and measuring UX based on classic survey data, questionnaire or interviews are often time consuming. In addition, although online reviews contain information about user shared experience and preference, there lacks an efficient approach to investigate useful online reviews from a large amount of review for UX modelling. It is also observed that in online review analysis studies, few of research attempts to explore online review for UX analysis.

We believe that a new UX modelling from online review is needed to explore how product reviews can be leveraged for UX analysis. In our previous studies, we have reported our efforts on discovering and integrating product reviews for product design, such as gathering customer concerns based on extracting topics from online reviews (Zhan, Loh & Liu 2009) and identifying helpful reviews from a designer's perspective using content-based regression approach (Liu et al. 2013). In this exploration study, we aim to investigate whether online reviews are suitable data sources for modeling UX and how useful user-generated content can be surfaced from a set of product reviews.

3 MODELING FOR USER EXPERIENCE

In order to understand, predict and design the interaction between users and products, a conceptual model should be designed for UX modeling. When designing the UX model in this paper, two main issues are considered. One fundamental issue is the content of UX representation. It is about what kind of elements should be included in UX modeling. It should reflect factors which influence UX or experience information which is concerned by customers. By understanding purposes of UX design and analyzing existing UX representation models, especially the measurement model and the structural model, we notice that several aspects that we can further highlight.

The main UX constructs defined in the measurement model and the structural model are often concerned from users' affective and cognitive perspectives, such as hedonic quality, beauty and goodness. However, how these elements can be represented in a more detailed manner still needs further explored, such as how beauty and goodness can be measured and quantified for UX analysis. In addition, some other factors which influence UX remain implicit in these models. Factors like product information (e.g., product functionality and service) and the situations within which the interaction occurs are considered as influence factors of UX (Hassenzahl & Tractinsky 2006). If entities of a product and situations are not explicitly represented, designers will need significant efforts to identify factors that lead to users' affective states. Studying typical users, situations and their interaction can help designing a product.

Another consideration is the realization of a UX representation model. It relates to how UX data can be captured and structured based on a UX representation. It means that the balance between human involvement and complexity of UX measuring process should be concerned. The existing UX models often rely on using classic survey, questionnaires and interviews to obtain customers' ratings of experiences towards products. They may require much effort to look for customers who are willing to answer questions designed. In addition, some questions are led by designers, while some experience scenarios concerned by customers may be neglected. Moreover, some UX data are documented in the form of self-report and narrative, which are often textual and unstructured data. Manually extracting UX elements from such data are time-consuming. If the UX model includes more elements and relations, much more human effort will be needed to identify relevant UX information. It indicates that we should find a balance between UX representation and measurement approach.

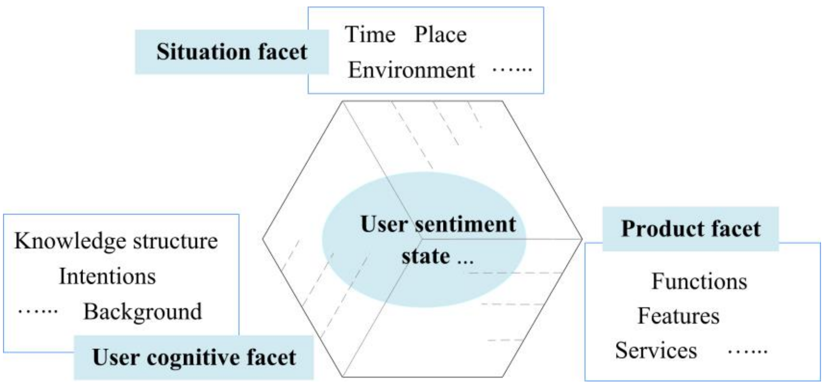


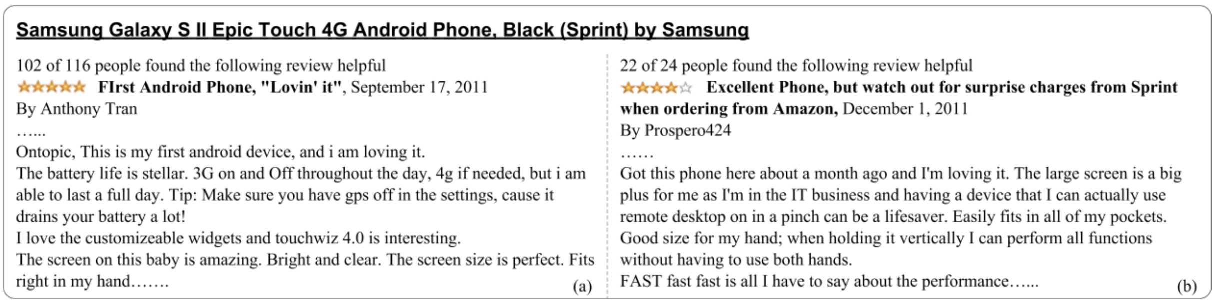
Figure 1. A faceted model for UX

Therefore, based on the considerations of UX factors and its realization, a faceted UX model is introduced to support investigating UX elements from customers' narrative data, such as online product reviews. Basically, the proposed model describes UX as user sentiment state related to combinations of facets including product, interaction situation and user cognitive facets during interactions with a product, as shown in Figure 1. The product facet F of UX refers to product characteristic involved in user experiences. It includes entities of a product, e.g., elements in a product, and product related services, e.g., system upgrades and supports. The situation facet S describes the environmental factors when using a product, e.g., the place and time. The user cognitive facet U refers to user related information, such as user category, e.g., experienced users and novel users, user intentions, e.g., work tasks focused on. The users' sentiment state Y is represented by the corresponding mental states about product facet under certain situation, e.g., positive, neutral and negative opinions. It can be represented by sentiment phrases, e.g., useful and interesting. Generally, using the proposed faceted model, UX can be denoted as Equation (1).

$$\text{UX: } \forall\exists\ (F, S) \cup U \Longrightarrow Y \quad (1)$$

4 INVESTIGATING USEFUL ONLINE REVIEWS FOR UX MODELING

In order to facilitate the data gathering for UX design, we aim to explore whether online product reviews can be used as suitable data source for UX modeling. Figure 2 illustrates some examples of mobile phone reviews from Amazon.com. Based on the data scheme used by Amazon.com, each product has a profile page that contains a set of reviews contributed by different users. Each user can submit one or multiple reviews towards a product. Each review usually consists of a review helpful rating from other reviewers, a numeric rating score for a product, a title and a textual comment.



Samsung Galaxy S II Epic Touch 4G Android Phone, Black (Sprint) by Samsung

102 of 116 people found the following review helpful
FIrst Android Phone, "Lovin' it", September 17, 2011
By Anthony Tran
…...
Ontopic, This is my first android device, and i am loving it.
The battery life is stellar. 3G on and Off throughout the day, 4g if needed, but i am able to last a full day. Tip: Make sure you have gps off in the settings, cause it drains your battery a lot!
I love the customizeable widgets and touchwiz 4.0 is interesting.
The screen on this baby is amazing. Bright and clear. The screen size is perfect. Fits right in my hand……. (a)

22 of 24 people found the following review helpful
Excellent Phone, but watch out for surprise charges from Sprint when ordering from Amazon, December 1, 2011
By Prospero424
……
Got this phone here about a month ago and I'm loving it. The large screen is a big plus for me as I'm in the IT business and having a device that I can actually use remote desktop on in a pinch can be a lifesaver. Easily fits in all of my pockets. Good size for my hand; when holding it vertically I can perform all functions without having to use both hands.
FAST fast fast is all I have to say about the performance…... (b)

Figure 2. Review examples of a mobile phone

From different reviews, we can obtain customers feelings from different angles of interests. For example, if we study the example reviews from the product facet, it indicates that the review Figure 2 (a) focuses on battery life while the review Figure 2 (b) concerns about the speed of the mobile phone. In addition, some reviews may contain sentences about general feelings about a product, while some others give more detailed experiences about interactions with the product under different situations. For example, the review Figure 2 (b) presents the benefit of the large screen in business working. Moreover, some experienced consumers may share their insights for using similar products, e.g., comparisons between similar products of different brands. It suggests that a user characteristic may to some extend indicate the usefulness of a product review. Based on the observation above, a framework is designed to analyze online reviews for UX modeling.

4.1 A framework of review analysis for UX modeling

In order to support design for UX, we aim to design an efficient approach that helps to investigate UX information from a large amount of online reviews using text mining and scoring techniques. Based on the faceted UX model proposed, a content-based approach is proposed to measure the degree of a product review containing UX information. Figure 3 shows its framework.

Given a set of online reviews for a product or similar products, this approach suggests useful product reviews containing rich UX. It consists of three important phases, including pre-processing, review measuring stage and ranking stage. Firstly, given reviews as inputs, the pre-processing module aims to extract and identify language units which are related to UX elements, such as terms or phrases. Based on the faceted model for UX, this process is designed to extract product characteristics, e.g., “battery life”, “screen” and “application”, situation-based features, e.g., “all day long” and “in business working”, and customer’s sentiments about a product, e.g., “amazing”, and “loving it”. These language units indicate UX elements that customers involved.

Using the elements extracted, the review measuring approach is designed to quantitate how richly a review contains UX information. In this approach, score functions are defined based on review content to measure a review from several aspects, including richness, coverage and diversity of a review and user characteristic. In the existing UX analysis approaches, the narrative data of UX are often transferred into numerical data based on human interpretation. It may generate subjective results and much effort is required if the narrative data are in large size. In our strategy, we intend to explore review content and provide a computational approach to suggest useful reviews for UX analysis.

Based on the review measuring data, an aggregated-based approach is then designed to score and rank reviews. By sorting reviews, the ranking stage helps designers to investigate online review data and help them to seek out useful product reviews with rich UX information. In the following sections, the technical approach is reported.

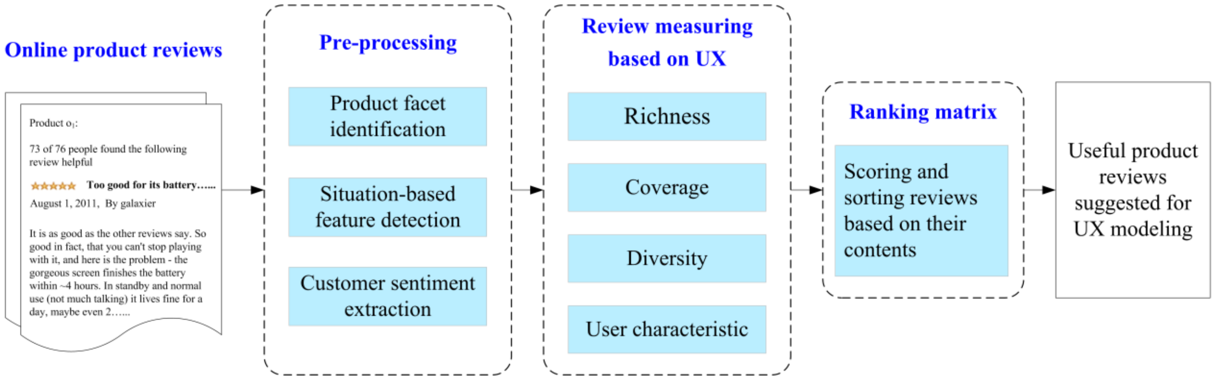


Figure 3. The framework of investigating useful online reviews for UX modeling

4.2 Pre-processing

Based on the faceted UX model, algorithms are designed to extract UX elements from product, situation and customer sentiment aspects. Given a set of product reviews $R = \{r_1, \ldots r_j \ldots r_{|R|}\}$ of n similar products $O = \{o_1, \ldots o_i, \ldots o_n\}$, the pre-processing stage is designed to detect sets of terms and phrases that refer to product facet $F = \{f_1, \ldots f_k \ldots, f_{|F|}\}$, and situation facet $S = \{s_1, \ldots s_l \ldots, s_{|S|}\}$ and customer sentiment $Y = \{y_1, \ldots y_m \ldots, y_{|Y|}\}$ respectively.

Customer sentiment extraction

This process is to extract a set of sentiment terms Y which are used by customers to express their feelings or mental states about products. By analyzing online product reviews, it indicates that customers often use adjectives and verbs to convey their sentiment orientation. Figure 2 illustrates some examples, such as "touchwiz 4.0 is interesting" and "I love the customizable widget". The terms like "interesting" and "love" reflect customers' positive opinions about the product.

In this approach, two subsets of sentiment terms are generated, including the positive word set Y_P and the negative word set Y_N. Y_p includes adjectives and verbs that express a desirable sentiment state, while Y_N consists of adjectives and verbs expressing undesirable states. Firstly, part-of-speech tagging process is used to extract the adjectives and verbs from reviews. Then based on term frequency, we select top k positive and negative terms respectively as seed word lists. Using the WordNet which is a lexical database for English language, the seed word lists are then expanded by adding their synonyms and finally form the sentiment term sets Y_P and Y_N.

Product facet identification

This approach is to identify significant entity set F as product characteristics described by customers in the review set. Each entity f_k is assigned with a weight w_k indicating its frequency of being discussed. Firstly, this process generates frequent candidate terms (ST). A ST is a word or a sequence of words that appears at least μ time in sentences of reviews. The value μ is the threshold for supporting sentences. Usually μ is set with a value not smaller than 2.

$$w_k = tf(f_k) \cdot \log\left(1 + \frac{n(f_k, Y)}{n\left(\overline{f_k}, Y\right) + 1} \frac{n(f_k, Y)}{n\left(f_k, \overline{Y}\right) + 1}\right) \tag{2}$$

Secondly, a weight w_k is given to entity f_k. The basic idea is that if customers give more opinions about a product feature compared with others, it indicates that customers concern this feature more important than others. We thus define the weighting function w_k for entity f_k based on its association with customer sentiment words in set Y. In Equation (2), $tf(f_k)$ represents f_k term frequency. $n(f_k, Y)$ denotes the number of sentences containing both entity f_k and any sentiment word in Y. $n(\overline{f_k}, Y)$ denotes the number of sentiment sentences (containing any word in Y) where f_k does not occur. $n(f_k, \overline{Y})$ denotes the number of non-sentiment sentences where f_k occurs at least once. Finally, based on the term weight w_k, the top k terms are selected as product facet F.

Situation-based feature detection

This process is to detect the phrase set S which describes situation facet of UX. Customers often use preposition phrases to describe usage context about their interactions with a product. As examples shown in Figure 2, the phrases like "as I'm in the IT business", "in all of my pockets" and "when holding it vertically" give a description of when, where and the way the customer uses the product.

This approach starts with segmenting reviews into a set of sentences. Then using the part-of-speech tagging and phrase structure analysis techniques, a sentence is processed and represented by a phrase structure. The phrase structure is generated based on English grammar rules. All the preposition phrases are extracted as candidate phrases.

Secondly, a filtering process is designed to remove phrases which do not mention UX elements. For example, the sentence "So when considering a new Smart Phone, I researched the Galaxy S II." contain a preposition phrase "when…". But it is not a description about a situation of interactions. Based on our observation, it indicates that if a preposition phrase is associated with product facet and customer sentiment, it has high possibility to be the situation information. Therefore, if a preposition phrase co-occurs with any terms in set Y or set F, it is selected as a situation-based feature in S.

4.3 An aspect-based analysis approach for review measurement

In the review measuring approach, four score functions are defined to quantitate a review from its richness, coverage and diversity of UX elements as well as user characteristic aspect.

Richness

A review is considered to be rich with UX if it includes customers' different feelings towards a product feature under different situations. For example, the review in Figure 2 (b) discusses about the phone screen from different aspects, such as how it feels ("big plus"), when it is used ("in the IT business") and where it is put ("my pockets"). These detailed descriptions for a single product feature give rich information about the customer interactions with the phone. A review score function $g_r(r_i)$ is defined to measure the richness of a review r_i, in Equation (3). $|f_{ik}|$ represents the number of times a single product feature appears in r_i. $e(f_{ik}, Y \cup S)$ denotes the number of customer sentiment terms and situation-based features associated with f_{ik} in r_i. Z_r, Z_c, Z_d and Z_u are normalization factors.

$$g_r(r_i) = \frac{1}{Z_r}\left(\sum_{f_{ik} \in F_i} |f_{ik}|\, e(f_{ik}, Y \cup S)\right) \tag{3}$$

Coverage

If a single review r_i mentions about different UX elements, such as product features and situation features with similar length, it suggests that r_i may cover a certain range of information related to UX. A score function $g_c(r_i)$ is thus defined to measure review coverage in Equation (4). The variable X_j represents either product facet set F_j or situation-based feature set S_j in r_i. $|x_{ik}|$ represents the number of x_{ik} appears in r_i. $b(x_{ik},r_i)$ calculates the difference between the number of sentences talking about x_{ik} and the average number of sentences mentioning about different facets in review r_i. $g_c(r_i)$ represents the general deviation of number of product facet and situation discussed in a single review r_i.

$$g_c(r_i) = \frac{1}{Z_c}\left(|F_i| \underset{f_{ik} \in F_i}{Avg} |b(f_{ik}, r_i)| + |S_i| \underset{s_{ik} \in S_i}{Avg} |b(s_{ik}, r_i)|\right), \quad b(x_{ik}, r_i) = |x_{ik}| - \underset{x_{jk} \in X_j}{Avg} |x_{jk}| \tag{4}$$

Diversity

A review which talks about different product facts, situation may contain helpful UX compared with other reviews. General diversity about different elements related to UX is considered to be a possible indicator of a useful review. We thus define a score function $g_d(r_i)$ to measure diversity of a review r_i from overview topics about the same product, as shown in Equation (5). The variable X_i represents either product facet set F_i or situation-based feature set S_i in r_i. $|x_{ik}|$ represents the number of x_{ik} appears in review r_i. $d(x_{ik}, r_i)$ calculates the difference between the number of x_{ik} mentioned in review r_i and its average number among reviews. $g_d(r_i)$ represents the general deviation of number of product facet and situation among whole review set R.

$$g_d\left(r_i\right)=\frac{1}{Z_d}\left(|F_i|\mathop{Avg}_{f_{ik}\in F_i}|d(f_{ik},r_i)|+|S_i|\mathop{Avg}_{s_{ik}\in S_i}|d(s_{ik},r_i)|\right),\quad d(x_{ik},r_i)=|x_{ik}|-\mathop{Avg}_{r_j\in R}|x_{jk}| \tag{5}$$

User characteristic

The three measurements above are analyzed from the review content to reveal UX elements. This user characteristic is designed to consider UX from user perspective. A review of an experienced customer would give more informative and objective knowledge about his experiences with different products. The basic idea is that if a customer generates multiple reviews for a product or products of similar type with different content, it would suggest that reviews submitted by this customer may contain extended experiences compared with others.

$$sim\left(r_j,r_{j'}\right)=\cos\left(r_j,r_{j'}\right),\quad c\left(r_{o_i},u\right)=|r|\mathop{Avg}_{r\ generated\ by\ u,oij<oij'} sim\left(r_{oij},r_{oij'}\right) \tag{6}$$

We define the similarity $sim(r_j, r_{j'})$ between two reviews r_j and $r_{j'}$ as shown in Equation (6). Each review is regarded as a bag-of-word. $\cos(r_j, r_{j'})$ is the cosine similarity between vectors of r_j and $r_{j'}$ using the TFIDF (term frequency and inverse document frequent) as term weight. Then $c(r_{oi}, u)$ is defined to measure the average similarity between reviews generated by user u for a product o_i. Then a score function $\underline{g_u}$ is defined in Equation (7) for user characteristic.

$$g_u=\frac{1}{Z_u}\sum_{o_i\in O}c\left(r_{o_i},u\right) \tag{7}$$

4.4 Ranking matrix

Based on the review measurements from content-based feature and user characteristic, we introduce an aggregated-based method that considers multiple aspects of review measuring functions using a combined score as shown in Equation (8). The weighting scheme for different measuring functions is designed and determined empirically based on the observations from reviews. It gives more emphasis to richness aspect since it reflects more detailed UX information about a single product feature. User characteristic is assigned with less weight because more user information is needed to indicate the experienced customer. The coverage and diversity generally suggest comparable evidence from either a single review or the whole reviews.

$$g(r_i)=\frac{3}{8}g_r(r_i)+\frac{1}{4}g_c(r_i)+\frac{1}{4}g_d(r_i)+\frac{1}{8}g_u \tag{8}$$

5 EXPERIMENT STUDY

In this section, the dataset used is firstly introduced. Then some examples of product review suggested, product facet identified, situation-based features extracted are demonstrated to show the results generated by the proposed approaches. In the experimental study, the online reviews data related to smart phones are downloaded from Amazone.com. Given the queries "Samsung Galaxy sii" and "Samsung Galaxy siii", we have designed a crawler to obtain reviews of 8 relevant products. Totally, 1035 online reviews were downloaded and constructed as the research data.

Examples of product reviews suggested

57 of 63 people found the following review helpful

…...

The video quality was comparable, if not better, than what it is on my computer, which allows me to see my daughter even when I'm not at home in front of my computer. However, if I was forced at gun point to come up with something negative about the video aspect of the S3, I would say, that at 30fps, you may experience some slight lag if the objects/people you are recording move too quickly. I only experienced this lag once, when recording moving cars while running, and it was hardly noticeable……. (a)

2 of 2 people found the following review helpful

……

(Incidentally, the S3 is about the same size as the Samsung Infuse.)As a college student, this phone has been so much more useful then I would have guessed. I have saved PDF files to it so I can read them if I'm waiting somewhere, I have apps to keep track of my assignments and schedule, I even can view MS office documents on the go (was completely impressed when I discovered I could also view PowerPoint slides). Occasionally I will check and post to Facebook, but I use my S3 more for useful things than social networking.…... (b)

Figure 4. Some examples of product reviews suggested

In gathering customer information towards design for UX, the main focus is to understand customers' affective states and interactions with the current products. The first experiment shows some examples of product reviews suggested by the proposed methods. Due to the limitation of the spaces, only parts of the reviews are shown in Figure 4. From the review in Figure 4 (a), it shows that this customer shared about his experiences when using the video function of the phone, such as some slight lag when recording moving car. The review in Figure 4 (b) was from a college student point of view. It shows that he concerns about the applications the phone provided for his reading, checking schedule and social purposes. It may suggest designers to provide suitable screen size or applications that help their daily activities.

Some examples of product facet identified

screen	displai	warranti	button
batteri	Internet	charger	call
camera	softwar	cover	flash
app	pictur	processor	weight
			speaker

Figure 5. Some examples of product facet identified

The second experiment demonstrates some key product facet identified from the product reviews. As shown in Figure 5, it suggests some product features or services that are often concerned by customers when they own the product. Some product features are related to hardware components of the phone, such as screen, battery, processor and button. Some aspects refer to functions that the phone provided, such as camera, call and flash. Some features are relevant to software aspect, such as app and picture.
The third experiment illustrates some examples of situation-based features extracted. We can see there are some situations often concerned by different customers. As shown in Table 1, the context about "time" attracts the most consideration based on customers' experiences expressed. For example, some reviews talk about using phone "at daylight and also at night", some other concerns about the duration of using the phone, such as "all day long for business messages", "in the almost entire week" and "through a day of normal use with GPS turned on". This situation information which is received much attention indicates that customers concern about the battery life of the phone. Some other reviews refer to usage context about where to put the phone, such as "in your pocket" and "in my hands". This may suggest customers also care about the size and shape of the phone.

Table 1. Some examples of situation-feature extracted

ID	Situation-based features extracted
8	at daylight and also at night
10	when you finger a key, all day long for business messages, in your pocket, when making long calls
23	in my hands, into my pocket
92	when it just hit the shelves in few places, when I installed more than 15 apps, within few hours, during calls
103	in terms of contrast and color saturation, in the almost entire week, through a day of normal use even with GPS turned on

6 CONCLUSION

This paper explores a content-based measuring approach to investigate whether user-generated data of online reviews are appropriate data source for UX modeling. Firstly, a faceted UX model is proposed, which model UX as a combination of users' sentiment states, product, situation and user cognitive facets. Based on the proposed UX model, a content-based approach is proposed to measure the degree of a product review containing UX elements from review richness, coverage, diversity and user characteristics. An aggregated UX scoring method is then designed to rank reviews according to the degree they indicate UX information. In the case study, some preliminary experiments are conducted using Amazon dataset containing reviews of mobile phones. They include some examples of product facet and situation facet that concerned by customers, and some useful product reviews suggested using the proposed approach. In the future, we will further explore how the reviews containing rich UX information can be leveraged to support product design.

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