Exploiting User Experience from Online Customer Reviews in Product Design

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Abstract
Understanding user experience (UX) becomes more important in a market-driven design paradigm because it helps designers uncover significant factors, such as user's preference, usage context, product features, as well as their interrelations. Conventional means, such as questionnaire, survey and self-report with predefined questions and prompts, are used to collect information about users' experience during various UX studies. However, such data is often limited and restricted by initial setups, and they won't easily allow designers to identify all critical elements such as user profile, context, related product features, etc. Meanwhile, with widely accessible social media, the volume and velocity of customer-generated data are fast-increasing. While it is generally acknowledged that such data contains important elements in understanding and analyzing UX, extracting them to assist product design remains a challenging issue. In this study, how UX data underlying product design can be isolated and restored from customer online reviews is examined. A faceted conceptual model is proposed to elucidate the crucial factors of UX, which serves as an operational mechanism connecting to product design. A methodology of establishing a UX knowledge base from customer online reviews is then proposed to support UX-centered design activities, which consists of three stages, i.e., UX discovery to extract UX data from a single review, UX data integration to group similar data and UX network formalization to build up the causal dependencies among UX groups. Using a case study on smart mobile phone reviews, examples of UX data discovered are demonstrated and both customers and designers concerned key product features and usage situations are exemplified. This study explores the feasibility to discover valuable UX data as well as their relations automatically for product design and business strategic plan by analyzing a large volume of customer online data.

Keywords: Design Informatics, User Experience, Information Modeling and Management, Opinion Mining, Online Review, Product Design

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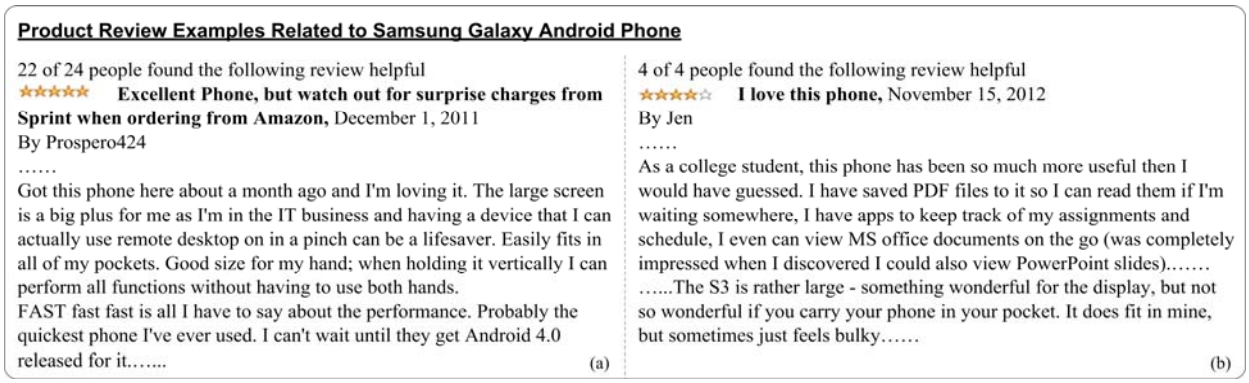
1 Introduction

In a product design and development process, an early identification of product opportunities and attractive conceptual ideas from customer analysis is a crucial issue. With the advances in product development technologies, beyond functionality, customers are willing to have attractive products that can bring them superior experience through interactions with products. More designers and companies increasingly recognize good user experience (UX) as a significant advantage in product design (Pucillo & Cascini, 2014; Lin & Cheng, 2015). In general, UX is the way that a user feels about using an artefact, such as a product, system, service or object (Hassenzahl, 2008b; Law et al., 2009;). According to the ISO definition (ISO 9241-210), factors influencing UX also include user's internal and physical state, product properties, the context of use, etc. Hence, research studies are increasingly conducted to collect and analyze UX information.

Most previous studies use surveys, questionnaire, field studies and lab studies to examine user experience by creating different scenarios, e.g., tasks and usage context, for users to interact with products (Kosmadoudi et al., 2013; Law, van Schaik, & Roto, 2014; Park et al., 2013). They often require labour-intensive efforts in several tasks, such as organizing tests, finding suitable participants, preparing appropriate questionnaires, survey, and products for testing, etc. While they are important methods to collect customer data, such approaches include limited aspects about usage context or product features that will largely affect how customers feel about the product eventually. In the context of product design, few studies have discussed a systematic approach to build up a UX knowledge base and connect UX to any product category for various design tasks.

Meanwhile, with the rise of various social media platforms, user-generated content (UGC) becomes a valuable and significant source for both research and commercial use, e.g., customer concerns summarization (Zhan et al., 2009), sentiment analysis (Chen et al., 2015)

and product purchase suggestion (Ahmad & Laroche, 2017). Their tremendous popularity has reflected a fact that it is feasible to obtain UX information updated from online customer reviews (He, 2013). Consider a typical mobile phone review in Fig. 1 (a). This review discusses multiple factors that influence the user's experience of a smartphone, such as product features, situations, and user's feeling. From the review sentences shown in Fig. 1 (a), two pieces of UX related information can be extracted. The first piece is about using the smartphone in the IT business which appears to be positive. Its UX data (i.e., words or phrases related to facets of UX) include "large screen" related to product feature facet, "in the IT business" related to situation facet and "positive feeling" related to user's state. The second piece of UX is about using the remote desktop through the phone, in which the customer considers the large screen as an advantage of the phone. Its UX data include "large screen", "use remote desktop" and "positive feeling" about a product feature, situation, and user's state facets respectively.


Product Review Examples Related to Samsung Galaxy Android Phone

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. Probably the quickest phone I've ever used. I can't wait until they get Android 4.0 released for it…...
(a)

4 of 4 people found the following review helpful
★★★★☆ **I love this phone,** November 15, 2012
By Jen
……
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)……
…...The S3 is rather large - something wonderful for the display, but not so wonderful if you carry your phone in your pocket. It does fit in mine, but sometimes just feels bulky……
(b)

Fig. 1. Online review examples of the smartphone.

Beside UX from a single user, to obtain UX of other customers on different situations and preferences is important, because customers with different experiences may prefer the same product for diversified reasons. Synthesizing such experiences may give designers an overall view of factors that influence a user's attitude about using a product. For example, one customer may like using the phone to check his business schedule, but another may

prefer the video quality for a regular team meeting. The common element of their experiences is that they both concern product features that can support their daily business activities.

However, the huge body of online reviews often exists in an unstructured form in natural language. How to leverage the user-generated reviews to support product design and innovation? How to build up a feasible approach that can discover UX information from product reviews and integrate useful UX information so as to help designers' to inject insights into generating new design concepts? It is quite challenging for firms and designers to apply advanced analytics and harness such UGC. Although sentiment analysis or online opinion analysis are often used to determine customers' sentiments from online reviews, uncovering UX information from UGC has been very limited in the literature. It has impaired designers' interests in gaining valuable UX insights from such popular resources.

In light of the challenges and the rising needs in UX analysis that have been highlighted, it is desirable to have an automatic and computational approach to manage customer knowledge with different UX factors. Accordingly, this study starts to explore UX modelling from a large number of customer opinions by leveraging text mining capabilities. Specifically, it aims to construct a computational approach that can be utilized to build a UX knowledge base from online reviews for product design. In this approach, UX is represented as a faceted model including product, context, and user cognitive facets. Based on this model, a mutual enhancement approach is designed to extract UX data scattered in reviews. An integration approach is then proposed to synthesize similar UX information in terms of situation and the importance of UX information contributing to customers' feeling, i.e., positive, negative or neutral, is quantified to provide a general view for UX analysis.

The rest of this study is organized as follows. Section 2 presents the relevant studies on online review mining and approaches for UX. Section 3 describes the proposed faceted model for UX modelling. In Section 4, a systematic approach is presented to extract UX data from

online reviews and to build the UX knowledge base. In Section 5, a case study using mobile phone reviews is conducted to demonstrate the approach proposed. Section 6 concludes this study with critical thoughts and discussions.

2 Related Works

2.1 Approaches to User Experience Modelling and Analysis

From the conceptual level, different researchers have different perspectives to interpret what UX is so to suit their research and application purposes. Some researchers argue that UX is considered to be holistic; some suggest to break down the complexity of experience into evaluative constructs, e.g., usability and emotions (Pucillo and Cascini, 2014); while others focus more on the factors influencing UX, e.g., user's state, product properties and usage context (Hassenzahl & Tractinsky, 2006). In relation to our research interests and objectives, we stress the factors influencing UX, where such UX factors are available in our research data, i.e., product online reviews.

In the studies that investigated specific constructs of UX and their interrelations, e.g., hedonic quality and emotion (Hassenzahl, 2008a, Law et al., 2014), user's ratings of these constructs are often obtained and analyzed for UX. One typical approach is to analyze user psychophysiological responses when interacting with products and services. For instance, Hazlett & Benedek (2007) attempted to understand the user's affective responses to software design. Sixteen participants were watching their computer screens to conduct several common everyday tasks, e.g., file search and network share, whilst facial electromyography (EMG) measures were used to record user's affective changes; and self-reports were used to collect their comments about the system, e.g., aspects of the system and features. Their suggested assessment method provided a sensitive measure of the desirability of system features and a measure of emotional tension for interactive tasks. While psychometric

instruments allow for more accurate data about user's physiological changes, it is difficult to analyze other influences on UX, e.g., the context of use, product features, and properties.

Other methods often use survey, questionnaire, and self-report to analyze user's subjective responses to products. Hassenzahl et al. (2010) attempted to understand what constitutes "pleasant experiences", e.g., need fulfilment, pragmatic and hedonic product quality, with an interactive product (e.g., mobile phones and computers) through pre-defined questionnaires. Kujala et al. (2011) conducted a qualitative study over 20 mobile phone users using UX Curve method to assist users in retrospectively audio recording on how and why their experience with a product has changed over time. The user-generated data were transcribed into different UX curves from several viewpoints specific to UX, e.g., general UX, attractiveness, ease of use and utility. Each UX curve includes a user's intensity of UX (i.e., the vertical axis) over time (i.e., the horizontal axis) for a specific UX viewpoint and the reasons for such changes in the curve. Sheng and Teo (2012) studied the role of customer experience in the mobile domain by survey through emails, newsgroups, online forums, etc. Their findings suggested that customer experience plays an important role in mobile brand equity by mediating the effect of perceived usefulness, aesthetics, etc. Karapanos et al. (2010) attempted to measure the dynamics of UX over time by soliciting qualitative user insights into experience narratives and used content-analytical approaches to integrate the narrative data for analysis. Besides, to examine the effects of UX on user resistance to change regarding the voice user interface of an in-vehicle infotainment, UX was measured according to a survey regarding the use frequency of the voice user interface in different devices on a daily basis (Kim and Lee, 2016).

In contrast to the studies of UX constructs, several studies have focused on the factors that influence a user's experience with a product, and the cause-and-effect relations between factors. Tuch et al. (2013) analyzed the content of narratives on structural elements, such as

need fulfilment, technologies involved in the experience and effect. They tried to understand important factors that distinguish positive and negative experiences. In their study, 691 user-generated narratives were analyzed, and the structural elements of each narrative were manually identified. A machine learning approach was then utilized to classify the positive and negative experience based on the textual content. It was argued that it helps to suggest UX elements that influence the positive and negative experience. Zhou et al. (2011) provided a framework for product ecosystem design for UX. In the example of subway station design, they simulated different parameters of factors, such as the number of ticketing machines, the speed and position of escalators, and the position of staircases, to explore how those factors influence user's affective states.

In terms of methodologies, most previous studies utilize classic surveys, questionnaire and interviews to examine UX. Although they can obtain direct UX data of participants under some circumstances, it is time-consuming and often impossible for researchers to identify all of the contexts and the features under such contexts that impose a significant UX impact. To avoid the limitations of these approaches, we aim to take advantage of such online textual customer reviews and exploit them for UX studies, which has received little attention in the literature.

2.2 Online Customer Reviews

Since early 2000s, with the increased use of social media platform, a large amount of user-centric content has been generated by different people all over the world. They are publicly accessible, open and relatively transparent in terms of the underlying rating mechanism. Popular user-generated content (UGC), such as online customer reviews, often has no structural restrictions and is in free form textual format. The content of online reviews includes rich information, for example, purchase experience, vendor information, customer

complaints, user experience, satisfaction and customer ratings regarding products and services (Jin et al., 2018). They have described customer experiences in a more detailed way than traditional rating surveys and thus can reflect customer perceptions more accurately. Scientific research has been conducted to analyze textual reviews so to gain insights for various applications, e.g., sentiment analysis (Chen et al., 2015), product ranking prediction (Li et al., 2010), summarizing customer reviews (Hu and Liu, 2004). Other analysis attempted to support commercial use, e.g., hotel aspect rating prediction (Wang et al., 2010) and service quality measurement (Palese & Usai, 2018).

In the research community of product design, online customer reviews have received much attention as a new source of the voice of the customer to analyze customer preference, user needs and design requirements, e.g., product topic identification for product planning (Jeong et al., 2017) and prioritizing customer concern (Jin, Ji & Liu, 2014). Although online reviews contain rich information about user experience and preference, there are very few studies on investigating a large number of online reviews for UX information modelling and management. It is also observed that in the current studies of product online review analysis, very limited research targets online consumer reviews for UX modelling and analysis. To better harness online textual customer reviews, in our study, we explore a different approach based on the joint efforts of text mining and machine learning for UX study.

2.3 Online Opinion Analysis

One interesting topic in analyzing the big data of UGC is opinion mining, where its research focus is primarily to identify product features and their associated sentiments with respect to products or product features (Dave, Lawrence, & Pennock, 2003; Hu & Liu, 2004b; Liu, 2010; Pang & Lee, 2008). Ding et al. (2009) identified the semantic orientation (i.e., positive, negative or neutral) of opinions and discovered product entities and their assignment using

linguistic features, such as pronouns, language conventions and comparative sentences. To obtain users opinions on product and service (e.g., hotel), Wang et al. (2010) analyzed reviews at the level of topical aspects, e.g., room, location and business service. A probabilistic model was proposed to extract the topical keywords as topical aspects and weights on aspects. Chen et al. (2015) proposed a lifelong learning approach to predict the overall sentiment of a review by retaining the knowledge learned from past tasks and use it to aid future learning.

Some studies attempt to assign product reviews into different groups in the product feature level, such as positive, neutral and negative classes. To identify opinion phrases and their sentiment polarity from reviews, Popescu and Etzioni (2005) used a relaxation labelling method to find the semantic orientation of words. In this method, each word is assumed to be an object and its neighbourhood is defined to include a set of words which influence the choice of its sentiment label. The probability of its label is re-estimated iteratively using an update function based on its previous probability estimate and features of its neighborhood. 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. Turnnry (2002) studied an unsupervised learning approach to classify reviews by the average semantic orientation of phrases in the review that contain adjectives or adverbs. Vilares et al. (2017) designed a rule-based method to update the sentiment orientation of a review sentence using a dependency relationship between words.

Other studies focus on gathering or summarizing product reviews to give overall opinions of customers with respect to products or features. Hu and Liu (2004a) extracted product features and identified opinion sentences to summarize reviews using part-of-speech and term frequency features. Zhan et al., (2009) proposed to use macro- and micro-level information in review summarization, including the salient topics shared among different

documents and sentences which provide complementary details of those salient topics. To integrate opinions scattered in various sources for different product features, Wang et al. (2010) proposed a semi-supervised probabilistic topic model using expert reviews as support information to extract representative opinions to an aspect. According to the extracted features and customer sentiments, online reviews are also utilized in other domains (Gandomi & Haider, 2015), e.g., hospitality and marketing. For instance, a RankSVM based approach was utilized to prioritize customer concerns according to online opinions and an ordinal classification method is proposed to benchmark the proposed approaches with alternatives in terms of different evaluation metrics (Jin, Ji & Liu, 2014). Xu et al. (2017) extracted product features from hotel reviews and analyze feature level customer sentiment. Then, a regression-based approach was employed to examine the effects of travel purposes, hotel types, star level, and editor recommendations on customers' perceptions of attributes of hotel products and services.

In light of the research gap in harnessing the merits of UX and its immense value to product design, this study focuses on how UX centric contents can be automatically identified and extracted from a large set of user online reviews, and how customer UX experience can be organized in a systematic manner to form a knowledge base that is suitable for further UX exploration and integration in product design.

3 A Faceted Conceptual Model for User Experience

To understand, explore and analyze interactions between users and products, a conceptual model should be defined for UX modelling. To define the UX model, two critical issues need to be considered. The first is the content of UX representation, which considers what kind of UX facets should be included in information modelling. The other is that the defined UX model should mirror factors that directly influence UX and customer experience. Based on

the analysis of existing UX representation models, especially the measurement model and the structural model (Edwards & Bagozzi, 2000; Law & van Schaik, 2010), it is noticed that several research aspects can be further highlighted.

In the measurement model and the structural model, UX is defined to include users' affective and cognitive perspectives, such as hedonic quality, beauty, and goodness. However, how these aspects can be represented in a more detailed manner still needs further exploration, such as how 'beauty' and 'goodness' can be measured and quantified for UX analysis. In addition, some other important factors, which also greatly influence UX, remain implicit in these models. For example, product functionality, product service, and the situations within which the interaction occurs are all considered as influence factors of UX (Hassenzahl & Tractinsky, 2006). If the entities of a product and situations are not explicitly represented, designers will require significant efforts to identify factors that lead to users' affective states. Hence, studying typical users, situations and their interactions can be of great help to product design (Boehner, et al., 2007; Chamorro-Koc et al., 2009; Zhou, Xu, & Jiao, 2011).

Another fundamental issue is the realization of the proposed UX model. Essentially, it refers to how each individual case of UX is structured and stored based on a UX representation. It means that how UX is represented, including the specific UX factors involved, the number of UX factors, and their explicit or implicit descriptions, will largely affect the complexity of UX measuring process. Many existing UX models often rely on using classic survey, questionnaires, and interviews to obtain customers' ratings and general inputs of their experiences towards products or services. They require much effort to look for customers who are willing to answer questions designed. In addition, if questions are led by designers, some important experiences concerned by customers can easily be neglected. Moreover, such UX data is documented in the form of self-report and narrative, which are

often unstructured textual data. Manually extracting UX data from such texts are time-consuming. If a UX model includes more factors and relations, much more human efforts will be needed to identify relevant UX information. These two issues strongly suggest that a balance between UX representation, its complexity, and measurement should be reckoned given the present possibilities of soliciting relevant UX information and populating UX models.

Therefore, in considerations of UX factors and its realization, a faceted UX model is proposed to support UX information analysis from customers' narrative data, such as online product reviews. Simply, the proposed model describes UX as a user sentiment state related to the combinations of different facets including product, interaction situation, and user cognitive facets during the interaction with a product or service, which is shown in Fig. 2.

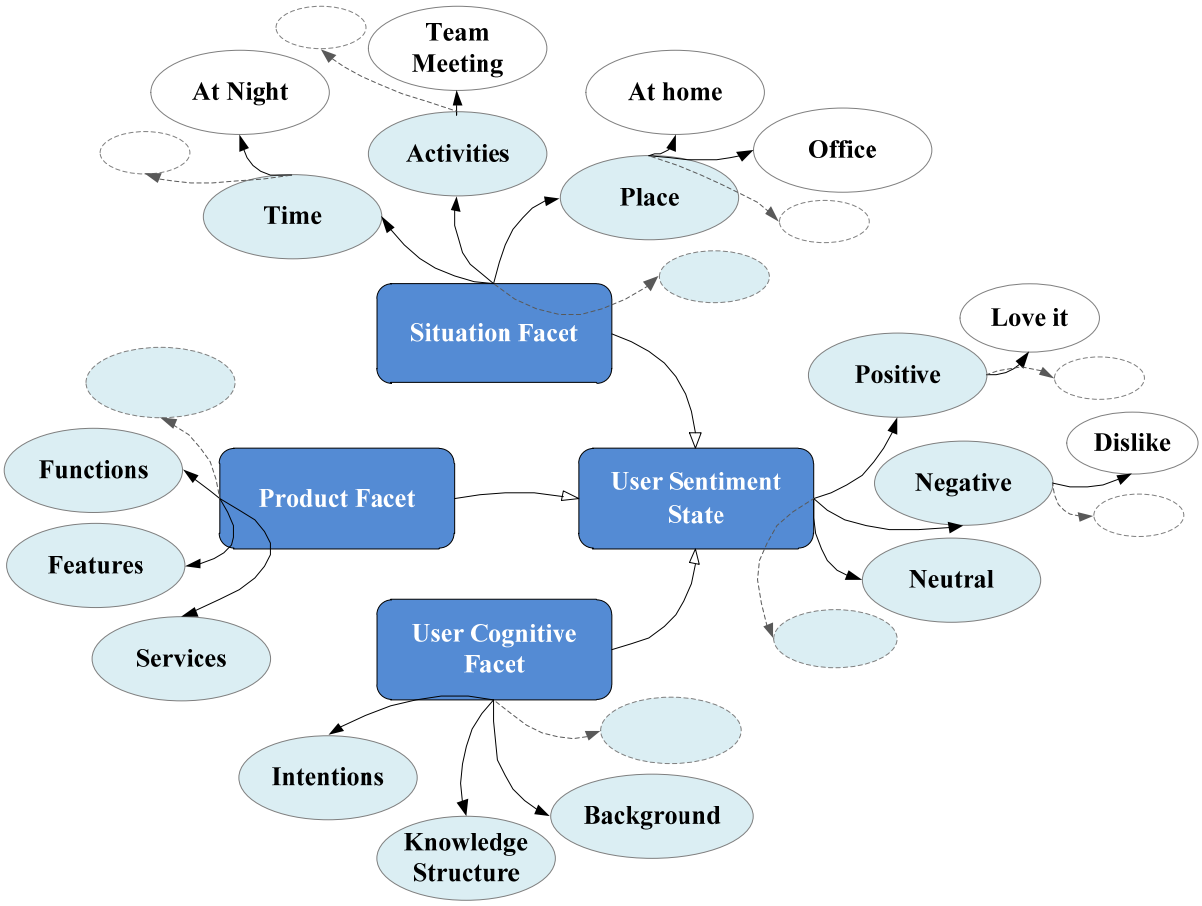


Fig. 2. A faceted model for user experience.

This model is flexible since each facet can be further developed with sub-facets using domain ontology. The product facet *F* of UX refers to the product characteristics involved in UX. It includes entities of a product, e.g., camera and screen of a smartphone, and product-related services, e.g., system upgrade and support. The situation facet *S* describes the contextual factors when using a product, e.g., location, time and activity. The user cognitive facet *U* refers to user related information, such as user category, e.g., experienced users and novices, and user background. The users' sentiment state *Y* is represented by the corresponding mental state about product facet under certain situation, e.g., positive, neutral and negative opinion. It can be represented by sentiment phrases, e.g., useful and interesting. More generically, using the proposed faceted model, UX can be denoted as Equation (1). It indicates that sentiment state *Y* is collectively influenced by product feature *F*, situation feature *S* and user cognitive facet *U*.

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

4 Building User Experience Knowledge Base from Online Reviews

Fig. 1 illustrates two phone reviews from Amazon.com. Customer experience can be obtained from the angles of interests at both a micro and macro level. At the micro level, UX data is observed in the form of words and phrases from review sentences. For example, from the product perspective, review in Fig. 1 (a) focuses on screen size, while Fig. 1 (b) describes the apps for the user activates. In addition, some reviews give more detailed experiences in different situations. For example, a review in Fig. 1 (a) presents the benefit of a large screen "in the IT business. These segments of UX information are useful for designers to understand the details of users' feelings towards product features and the contexts they have experienced.

Moreover, from the design analysis perspective, it is desirable to have a general view of UX for analysis purpose. It is worthwhile to understand what UX aspects are often concerned in customers' daily use. For example, from the situation perspective, it shows that both

reviews Fig. 1 (a) and (b) refer to a specific place where the phone is being carried, i.e., "in the pocket". In the perspective of product facet, it also indicates that "screen size" is an important factor in influencing users' experience. If UX data are investigated that is harvested from the product reviews voiced by hundreds and thousands of consumers, its value in enlightening designers with first-hand UX information is remarkable. Accordingly, in this study, how UX information at both micro and macro levels can be discovered and isolated is investigated in terms of how to form a customer UX knowledge base for product design.

4.1 An Overview of the Proposed UX Modeling Approach

In this study, a content-based approach is investigated to build a UX knowledge base by discovering and integrating each case of UX from product online reviews and a framework of UX modelling from online reviews is presented in Fig. 3.

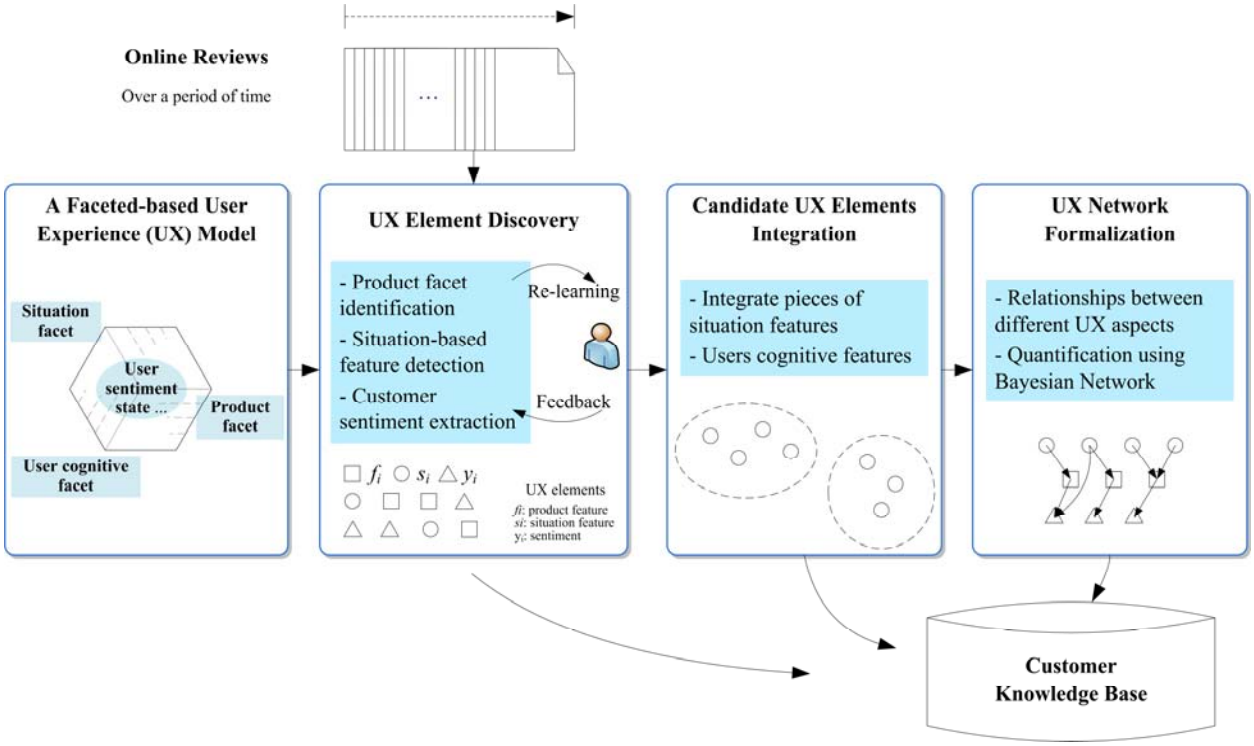


Fig. 3. A framework of user experience modelling from online reviews.

Based on the proposed faceted UX model, this approach includes three important stages to build the UX knowledge base: UX discovery, UX data integration, and UX network

formalization. Firstly, given a set of online reviews as inputs, the UX discovery process aims to identify language units, such as terms or phrases, which are highly relevant to UX.

Using the extracted UX data, the UX integration process is activated to group pieces of UX data with respect to different UX aspects. In this step, several similarity functions are defined to measure the relations between UX data grouped under the same facet. In many existing UX studies, customers' needs and preferences in the narrative data are often interpreted and summarized into structured data manually. Much more effort is required if users' narrative data are lengthy in size or large in quantity. Comparatively, the proposed strategy is to offer a computational approach to suggest experience categories according to review content. The UX data groups then form and represent the UX aspects that are concerned by customers.

Based on the UX groups, a UX network formalization process is proposed to explore the relations between UX aspects using a Bayesian network. By calculating the probability of relationships between UX aspects, the UX network helps designers to analyze UX data and gain more insights concerning different users' experiences. Finally, the identified UX data, UX aspect groups, and UX network collectively form the UX knowledge base. In the following subsections, the details of the proposed technical approaches are described.

4.2 User Experience Data Discovery

Fig. 4 gives the overview of a three-step mutual enhancement approach for UX data discovery. The inputs are reviews of a product. The outputs are the words or phrases about 1) customer's sentiment state about a product feature, i.e., positive or negative; 2) product feature, e.g., "battery life" and "screen"; and 3) situation feature, e.g., "all day long" and "in business working". These language units indicate UX data that customers targeted.

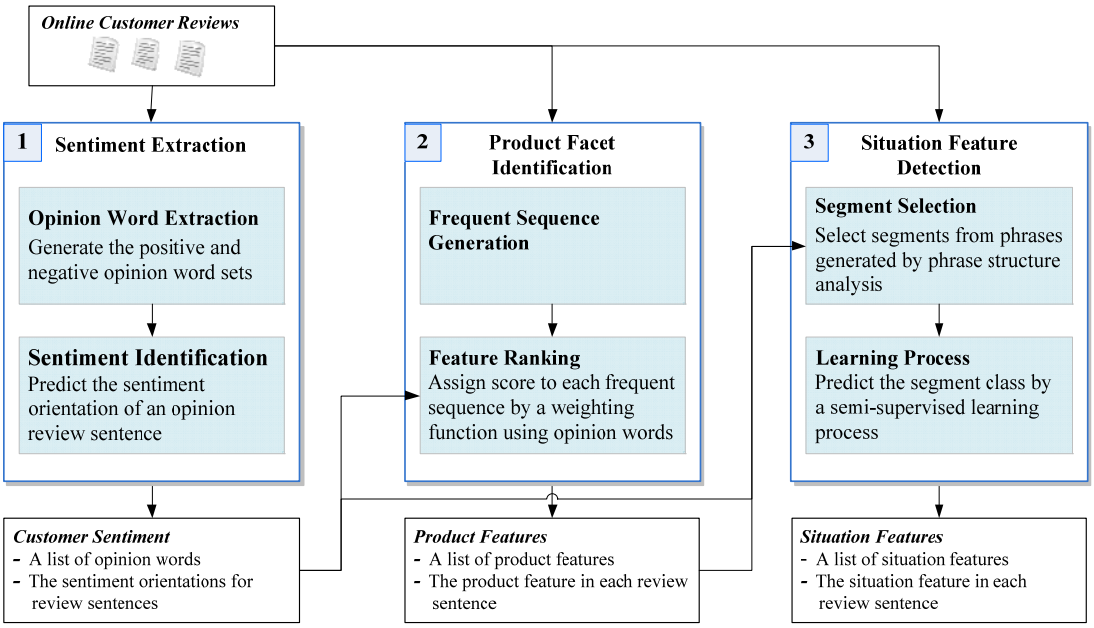


Fig. 4. The mutual enhancement approach for UX data discovery.

Customer sentiment extraction

To identify customer's positive or negative feelings about a product feature, opinion words used to express a subjective opinion are first extracted. Previous work suggests that the presence of adjectives is used for indication of an opinion (Pang & Lee, 2008). In addition, investigation of online reviews shows that verbs are often used to convey customer's sentiment orientations. Thus adjectives and verbs from reviews are extracted as candidate opinion words. Then based on the POS tagging, top k positive and negative terms from reviews are selected respectively as seed word lists. Using the WordNet*, the seed words are expanded by adding their synonyms and finally form the positive and negative word sets. The final opinion words are extracted by checking whether the candidate words are contained in either the positive or negative word sets.

A review sentence with any opinion word is considered as an opinion sentence. Then a sentiment identification method helps to analyze customers' feelings at opinion sentences. Also, the "but" clause and negation words surrounding the opinion words which often

* http://wordnet.princeton.edu/

indicate an opposite sentiment, e.g., “not” and “yet”, are reckoned. More technical details for predicting the orientation of an opinion sentence can be found in (Hu & Liu, 2004b).

Product facet identification

In this step, product features with customers’ feelings are identified. Usually, customers use a limited set of noun/noun phrases to describe product features. Thus the product facet identification first generates frequent word sequences can be generated at first and noun/noun phrases as are assumed to be candidate product features (Lim, Liu, & Lee, 2011).

Then a feature ranking approach with extracted opinion words is employed to find product features from the candidate list. The detailed algorithm is shown in Fig. 5. The fundamental assumption is that if customers present more opinions on a specific product feature than others, it implies that this feature has a higher impact on influencing UX. Accordingly, as shown in Fig. 5, a weighting function w_s for feature s, is defined, which assume that if a word or a phrase is closer to any opinion word, then it stands a higher chance to be a product feature.

Algorithm 1 Feature Weighting Function
Input: Candidate feature set F. Opinion word set Y
Output: Product feature set f
1. **for** each s in F **do**
2. Calculate term frequency in reviews: $tf(s)$
3. Calculate the number of opinion sentences containing no s: $n(\bar{s},Y)$
4. Calculate the number of non-opinion sentences containing s at least once: $n(s,\bar{Y})$
5. Calculate the distance between s and the opinion word at sentence level: $d(s,Y)$
6. Calculate the term weighting of s: $w_s = tf(s)\cdot\log(1+\frac{d(s,Y)}{n(\bar{s},Y)+1}\frac{d(s,Y)}{n(s,\bar{Y})+1})$
7. **end for**
8. Sort items in F based on their term weightings
9. Save the top k of F in product feature set f

Fig. 5. Product feature ranking.

Situation feature detection

In this step, situation features which describe the context information of UX are detected. Situation features are usually preposition phrases, when-phrases, verb phrases or noun phrases in review sentences. To detect their boundary in review sentences, POS tagging (Losee, 2001) and phrase structure analysis (Brill & Marcus, 1992) are crucial. In this study, the Stanford parser* is utilized to generate phrase structure for each review sentence and produce a POS tag for each word. For each review sentence, all possible phrases are extracted as initial candidate segments. Fig. 6 shows a sentence with POS and phrase structure tags.

A review sentence:
I am constantly on my phone for business and for personal use , and it 's perfect for it , but the battery dies so fast .
A preposition phrase with tags:
(PP (PP (IN on) (NP (NP (PRP$ my) (NN phone)) (PP (IN for) (NP (NN business))))) (CC and) (PP (IN for) (NP (JJ personal) (NN use))))
(See http://nlp.stanford.edu/software/lex-parser.shtml for more tag details.)

Fig. 6. Phrase structure of a review sentence.

The next task is to classify the candidate segments into either a feature class or others. At the sentence level, a segment selection process is designed to remove the unlikely items of a sentence, as shown in Fig. 7. The $select_t$ function calculates the score for a segment t by measuring the cohesiveness of its phrase pairs (v_a, v_b) according to the symmetrical conditional probability. Some check rules are then designed to select the segments using the language features in a segment group or between segment groups.

* http://nlp.stanford.edu/software/index.shtml

Algorithm 2 Segment Selection
Input: Sentence set T and phrase segment set i for each sentence t_i
Output: Candidate segment set e

for each t_i **do**
Ignore t_i with no opinion words or product features
while pop a segment s from i and $s \neq null$ **do**
Get the phrase pair (v_a, v_b) in s with the maximum score: $(s, score, v_a, v_b) = \max_{v_a, v_b \in s} score(v_a v_b)$
$score(v_x v_y) = \frac{p(w_1 \ldots w_n)}{\frac{1}{n-1}\sum_{i=1}^{n-1} p(w_1 \ldots w_i)\, p(w_{i+1} \ldots w_n)}$
end while
Check each segment s: if $\lvert s \rvert \leq 2$, remove s
Check segment groups:
Group segments in i with the same phrase pair
In each group, keep s started with prepositions, v_a or v_b, and s with minimum length in e
Check between groups:
If s_j *contains* s_k, remove s_j from e
end for

Fig. 7. Segment selection for situation feature detection.

At the global level, a semi-supervised learning approach is designed to further classify segments using an EM (expectation-maximization) algorithm as shown in Fig.8. Some natural language features, i.e., the segment scores obtained from the segment selection process, are utilized to enrich more seed information for better initialization. By leveraging segments of the whole sentence set, the EM process iteratively learns the parameters using a small labelled set ts, the seeds, and unlabeled data.

Algorithm 3 Learning Process for Situation Feature Detection
Input: Candidate segment set e. Labeled set ts
Output: Feature label c_1 or others c_0 for each s in e

Generate seeds using natural language features:
Initialize $p(c_1\|s)$: scaling $score(s)$ into [0,1]
Initialize $p(c_0\|s)$: $p(c_0\|s) = 1 - p(c_1\|s)$
Initialize $p(w_k\|c_j)$ and $p(c_j)$ using ts and $p(c_j\|s)$
do
//E-Step
for each s in e, calculate $p(c_j\|s)$:
$p(c_j \mid s) = \frac{p(c_j)\prod_{k=1}^{\lvert s \rvert} p(w_k \mid c_j)}{\sum_l^{\lvert C \rvert} p(c_l)\prod_{k=1}^{\lvert s \rvert} p(w_k \mid c_l)}$
//M-Step
update $p(w_k\|c_j)$ and $p(c_j)$ using $p(c_j\|s)$:
$p(w_k \mid c_j) = \frac{1+\sum_{t \in e} n(w_k, s)\, p(c_j \mid s)}{\lvert W \rvert + \sum_{w_m \in W}\sum_{s \in e} n(w_m, s)\, p(c_j \mid s)}$
$p(c_j) = \frac{1+\sum_{s \in e} p(c_j \mid s)}{\lvert C \rvert + \lvert e \rvert}$
until the parameters stabilize

Fig. 8. The learning process for situation feature detection.

4.3 UX Data Integration

The UX data integration process aggregates the extracted UX data into different groups with respect to different UX aspects. In this study, the particular focus is to group the UX data of situation facet. This is largely due to the fact that, among the facets defined in the proposed UX model, the situation data are more dynamic and have more variants than others. Then, this process starts to unveil the key aspects of context information in a holistic view by analyzing a stream of online reviews.

To integrate different types of UX data, a local-based connection and a global-based connection are proposed to measure connections between UX data. Based on the defined correlation, the *k*-Nearest Neighbor approach (Mitchell, 1997) is applied to associate relevant UX data under the same facet. In this study, the local-based connection is proposed based on the content of situation features. The assumption here is that if two situation features s_j and s_k share more common linguistic segments, it suggests a higher possibility that they are associated with each other. For example, the situation phrases "in my hand" and "in my pocket" are closely relevant to a context when consumers use or carry their phones. The local-based connection $M_l(s_j, s_k)$ is stated in Fig. 9.

Algorithm 4 Data Integration

Input: Situation feature set e. Product review set r

Output: The connection matrix M

```
for each s_j in e do
    for each s_k in e do
        Calculate local connection:
        M_l(s_j, s_k) = LocalConnection(s_j, s_k)
        Calculate global connection:
        M_g(s_j, s_k) = GlobalConnection(s_j, s_k)
        Combine local and global connection:
        M(s_j, s_k) = α M_l(s_j, s_k) + β M_g(s_j, s_k)
    end for
end for

Sub function LocalConnection(s_j, s_k)
    Calculate the number of terms shared by s_j and s_k: |s_j ∩ s_k|
    Calculate the total number of terms for both s_j and s_k: |s_j ∪ s_k|
    Calculate local connection: M_l(s_j, s_k) = |s_j ∩ s_k| / |s_j ∪ s_k|
end subfunction

Sub function GlobalConnection(s_j, s_k)
    for each review r_xj containing s_j do
        for each review r_yk containing s_k do
            Calculate the similarity between r_xj and r_yk: sim(r_xj, r_yk)
            M_g(s_j, s_k) += sim(r_xj, r_yk)
        end for
    end for
    Normalize M_g
end subfunction
```

Fig. 9. Calculating the connections between situation features.

Also, their connections to the whole review set are reckoned. The global-based connection is designed based on the content surrounding those situation features. The rationale behind is that if two situation data are often mentioned in a similar linguistic context or verbal context, it is likely that they are referring to a similar aspect. For example, when talking about a specific product feature "screen", situational phrases, such as "in my hand" and "in my pocket", are often noted where "screen" appears. The higher the frequency of occurrence, the higher the possibility these situation data should be categorized into a similar UX aspect group. Accordingly, the global-based connection $M_g(s_j, s_k)$ are defined, which is shown in Fig. 9. Overall, both the local and global connections are balanced to measure the bonding between situation features by a linear combination, as shown in Equation (2). The details for calculating the connections between situation features are presented shown in Fig. 9.

$$M(s_j, s_k) = \alpha M_l(s_j, s_k) + \beta M_g(s_j, s_k) \quad (\alpha, \beta \in [0, 1], \alpha+\beta=1) \tag{2}$$

Based on the situation feature correlation, a key UX data integration process is performed to classify situation data with respect to different UX aspects. Situation data with higher correlation and more shared information are to be included in the same group. The *k*-Nearest Neighbor algorithm (Mitchell, 1997) is applied to integrate relevant situation data for UX analysis.

4.4 User Experience Network Formalization

Based on the extracted UX data and groups, the UX network formalization process aims to explore and establish the relations between UX data. The intention is to understand the factors that influence users' sentiment states and their corresponding probabilities in influencing users' positive or negative feelings. The UX network provides a systematic view of users' needs and preferences towards a product under a wide range of UX contexts. In this study, a computational approach is presented to formulate and represent dependencies among UX data using Bayesian networks.

Firstly, a directed acyclic graph (DAG) is constructed to represent the casual relations between UX data. As discussed in the proposed faceted UX model, UX highlights users' feelings or sentiment states as well as major factors, including product features and contextual factors, which potentially influence users' feelings when they are using the product. Since product features impose direct and significant influences on product usage, users' feelings are collectively influenced by product features and situational features. Therefore, in the UX network, as shown in Fig. 10, there are three types of nodes, i.e., situation group, product feature, and user sentiment state. An edge directed from node x_i to node x_j represents the influence of x_i to be rendered on x_j. In this approach, linkages between nodes are formed automatically based on the textual reviews. If two UX nodes x_i and x_j

appear in the same sentence, then an edge is assigned. Based on the influence of UX facets, the directions of edges include 1) from product feature to situation feature, 2) from product feature to user sentiment, and 3) from situation feature to user sentiment.

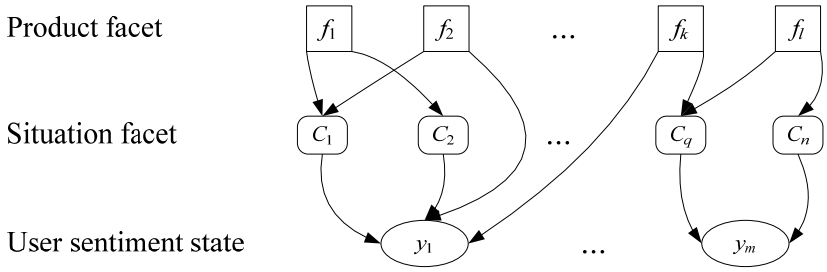


Fig. 10. Relations between UX data.

Secondly, the probabilistic relations between UX data are estimated according to the textual content of online reviews. The edge, which represents the capability of the influence of node x_i imposed on node x_j, are quantified by the conditional probability $p(x_j \mid x_i)$. In existing UX analysis, very limited efforts are paid to automatically leverage user-generated content regarding the quantitative analysis of UX data relations. Comparatively, the rationale of this approach is that the conditional dependency, $p(x_j \mid x_i)$, defined in Equation (3), is measured according to the frequencies of UX data occurrence and appearance in review sentences.

$$p(x_j \mid x_i) = \frac{|sentence(x_j, x_i)|}{|sentence(x_i)| + 1}, \quad p(\overline{x}_j \mid x_i) = 1 - p(x_j \mid x_i) \tag{3}$$

|sentence (x_j, x_i)| represents the number of review sentences that contain both x_j and x_i. |sentence (x_i)| denotes the number of review sentences where x_i appears at least once. By establishing the causal dependency between UX data from reviews, a UX network is formed, where a large amount of UX features are concerned, such as key product features and frequent usage contexts, and their relations.

5 Case Study

In this Section, different categories of experiments were conducted and competitive results are presented to demonstrate the effectiveness of the proposed approach. Also, an illustrative case study for UX modelling from online reviews is presented, including 1) the effectiveness of UX data discovery; and 2) Examples of a UX knowledge base. In order to demonstrate the feasibility of the proposal for UX modelling using customer online reviews, research data was crawled from Amazon.com and all these reviews are o 8 smartphones using the queries "Samsung Galaxy sii" and "Samsung Galaxy siii".

5.1 Experimental Study

The dataset includes 1,145 product reviews, approximately 10,000 review sentences. On average, each review contains about 8.7 sentences or 155 words, and each review sentence contains about 17.7 words. To build up the test dataset, 1130 review sentences from these reviews were randomly selected. Following the methodology of corpus building established in our former study (Liu & Loh, 2007), two annotators, one co-author and a PhD in mechanical engineering, manually read all reviews in a parallel way but independently. For each sentence in the test dataset, product features, situation features and user opinions including whether the opinion is positive or negative (i.e., user's sentiment state) are tagged if any. Only after individual annotation was finished, they started comparing the tagged data. If there was a disagreement, it needed to be discussed until they reached a consensus. In the test dataset, 1130 review sentences were tagged with sentiment polarity. In total, from all review sentences, 81 identical product features and 471 situation features were identified. In the experiment, for each sentence, standard text pre-processing was performed, including converting words into lowercase, removing stop words (Manning & Schütze, 1999), and stemming each word (Jones & Willett, 1997; Lovins, 1968).

Table 1 shows the experiment results of the proposed approach. It shows that about half of product features do not appear or appear only once. If the feature ranking is applied, the performance improves about 17% and 14% respectively in terms of recall and precision and it finally generates about 62% in F_1 score. More details are presented in Fig. 11 and it can be seen that, even if the non-noun terms were not removed, the feature ranking does help to identify more product features and decrease the weightings for non-nouns with higher frequency, such as "love" and "fast". Also, as seen from the results, it indicates that the proposed term weighting scheme has made good use of relevant information, e.g., sentiment terms and term positional information, to suggest product features.

Table 1. Results of UX data discovery.

	Methods	Recall	Precision	F_1 Score
Product Facet Identification	Frequent Sequences	0.506	0.432	0.466
	Feature Ranking	0.679	0.572	**0.621**
Situation Feature Detection	Segment Selection	0.783	0.303	0.437
	Learning Process	0.636	0.682	**0.658**
Sentiment Extraction	Opinion Sentence Extraction	0.846	0.734	0.786
	Sentiment Identification	Accuracy	**0.710**	

Before: before feature ranking. After: after feature ranking procedure.

	Before	After		Before	After		Before	After		Before	After
1	phone	phone	14	devic	dai	27	issu	hand	39	qualiti	data
2	n't	screen	15	batteri life	qualiti	28	set	button	40	amazon	network
3	iphon	iphon	16	look	size	29	feel	voic	41	appl	pictur
4	screen	samsung	17	bui	feel	30	updat	drop	42	hand	actual
5	samsung	app	18	android	look	31	peopl	android phone	43	hour	os
6	time	batteri	19	samsung galaxi	review	32	product	smartphon	44	excel	design
7	app	camera	20	fast	appl	33	charg	light	45	connect	wifi
8	dai	featur	21	galaxi	bui	34	nice	video	46	video	screen size
9	s3	android	22	bought	verizon	35	chang	samsung galaxi	47	abl	speaker
10	batteri	batteri life	23	verizon	set	36	amaz	softwar	48	drop	htc
11	camera	devic	24	review	displai	37	ca n't	run	49	version	connect
12	love	peopl	25	purcha	user	38	easi	updat	50	galaxi s3	option
13	featur	galaxi	26	smartphon	speed						

Fig. 11. Product feature results without removing non-noun terms.

In the situation feature detection, 60 sentences are randomly selected as a small set of training data, including 20 sentences with situation features. For performance evaluation, a

word-based match scheme was used. Since human taggers tend to select long verb phrases as situation features, e.g., “watch a video on YouTube” and “take a video and make still pictures at the same time”, while the proposed approach selects parts of the phrases as candidate features, e.g., “on YouTube” and “make still pictures”. As seen from the result in Table 1, it demonstrates that the proposed approaches are capable to detect an acceptable set of partially matched results.

As shown in Table 1, the segment selection approach keeps about 78% of the situation features, but 70% of segments are irrelevant. One potential reason may be that using all the phrases in review sentences as the initial candidate segment set will cover many difficult cases with overlapping and irrelevant segments. In addition, in the test dataset, only about 20% of the sentences contain situation features. Then, the step of the semi-supervised learning further classifies the candidate segments, achieving about 63% and 68% in terms of recall and precision. It seems that, with this step, a 15% loss is obtained in terms of recall, but 38% of the irrelevant segments are further excluded. It indicates that by using the language features at the sentence level and from the whole segment set, the F_1 score goes up to 65%.

In Table 2, some usage contexts mentioned by different users are presented. It indicates that the general context of “time” attracts more consideration. Other reviews refer to a usage context of carrying the phone, such as “in your pocket” and “in my hands”. This suggests that customers are also concerned about phone size and shape.

Table 2. 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 colour saturation, in the almost entire week, through a day of normal use even with GPS turned on

For the sentiment extraction, in the step of opinion sentence extraction, the recall and precision are about 84% and 73% respectively. It indicates that using the resulting opinion words is an effective way to identify whether a sentence is an opinion sentence. Finally, the step of sentiment identification gave results with 71% accuracy.

In summary, the proposed approach produces acceptable results for UX data extraction by leveraging mutual information between UX data and it can be expected that there are opportunities to improve the overall performance with other state-of-the-art techniques. The current sentiment extraction approach only uses adjectives and verbs as indications and, comparatively, it is found that nouns and adverbs can also be used for this purpose. In addition, in product feature identification, a simple and yet effective weighting function is utilized by utilizing the opinion words at the sentence level. In the future, a semi-supervised learning approach in consideration of context information around segments would be a feasible approach to improve the performance. The proposed learning-based situation feature detection approach also makes good use of opinion words, product features, and local language features. Using a sequential labelling process combined with more term contextual information may be a good try to improve the detection results.

5.2 Examples of UX Knowledge Base

To better illustrate the UX information provided by the UX knowledge base, a scenario is presented regarding designers intend to improve the current smartphone design. Designers may ask some common questions, such as, what reasons lead to typical users possessing such positive/negative experiences, what are common usage context often concerned by users, whether and why different product features involved in different context led to inconsistent feelings, etc. The relevant UX information can be found through three types of components in

the UX knowledge base, i.e., individual cases of UX, UX aspect groups, and UX network. Some examples are illustrated in Fig. 12 - 14.

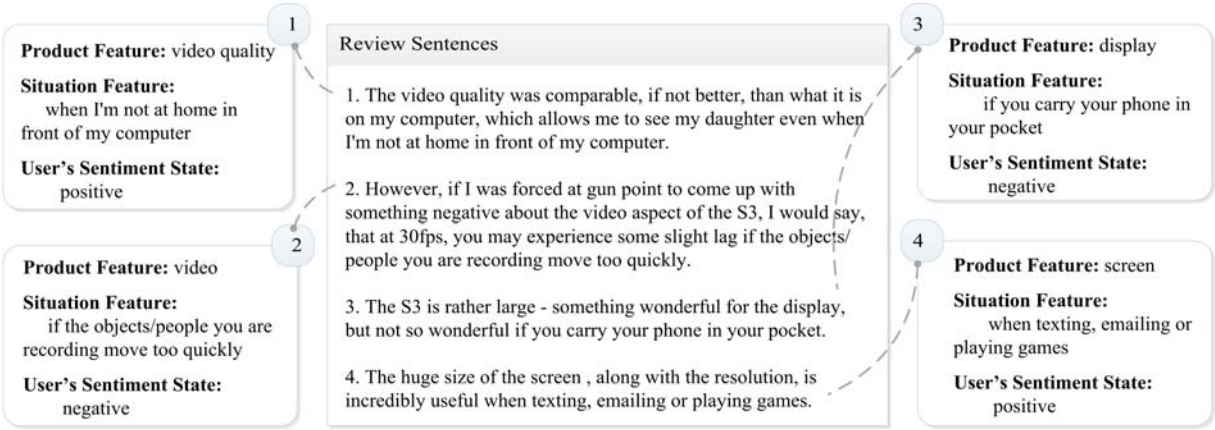


Fig. 12. Individual cases of UX from product review sentences.

In the first case, individual cases of UX from product review sentences are demonstrated. As shown in Fig. 12, each narrative sentence is processed into a structured UX format including product feature, situational feature and user's sentiment state according to the UX modelling approach. For example, sentence No. 2 expresses the user's negative feel about a video of the phone when recording moving objects/people. Reviewer 4 shares his/her user experience on screen for doing some tasks like texting and emailing. These structural organized individual cases of UX are helpful since they provide a more effective and tractable manner for designers to process and catch the useful UX information.

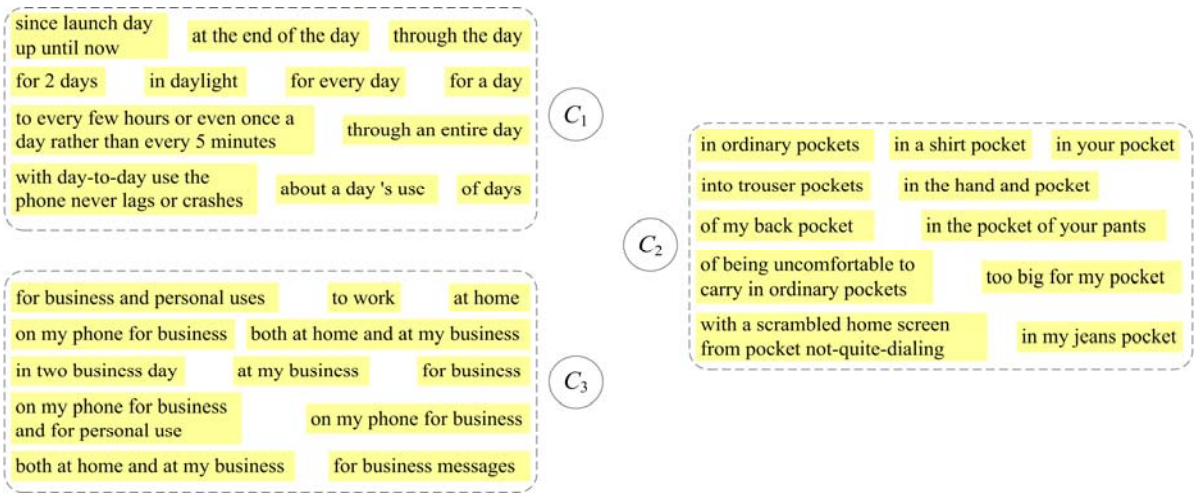


Fig. 13. Some examples of situation feature groups.

The second case shows examples of generated situation feature groups. It is noted that situation features are in different forms, and if they are handled alone, it may jeopardize the understanding of UX context. Accordingly, for analysis purpose, relevant situation features are integrated into different UX aspects. Fig. 13 illustrates three major situation feature groups. Group C_1 is more related to the duration of using a mobile phone, e.g., "through an entire day" and "in daylight". In Group C_2, situation features refer to where exactly the customers tend to carry the phone, e.g., "in ordinary pockets". Interestingly, the majority of feelings associated with such usage features concern phone size and comfortableness in carrying, such as "of being uncomfortable to carry in ordinary pockets" and "too big for my pocket", which collectively suggest that screen size emerges as a major concern for the context of carrying in pockets. Group C_3 clearly includes more usage motivation context, such as "to work" and "for business messages".

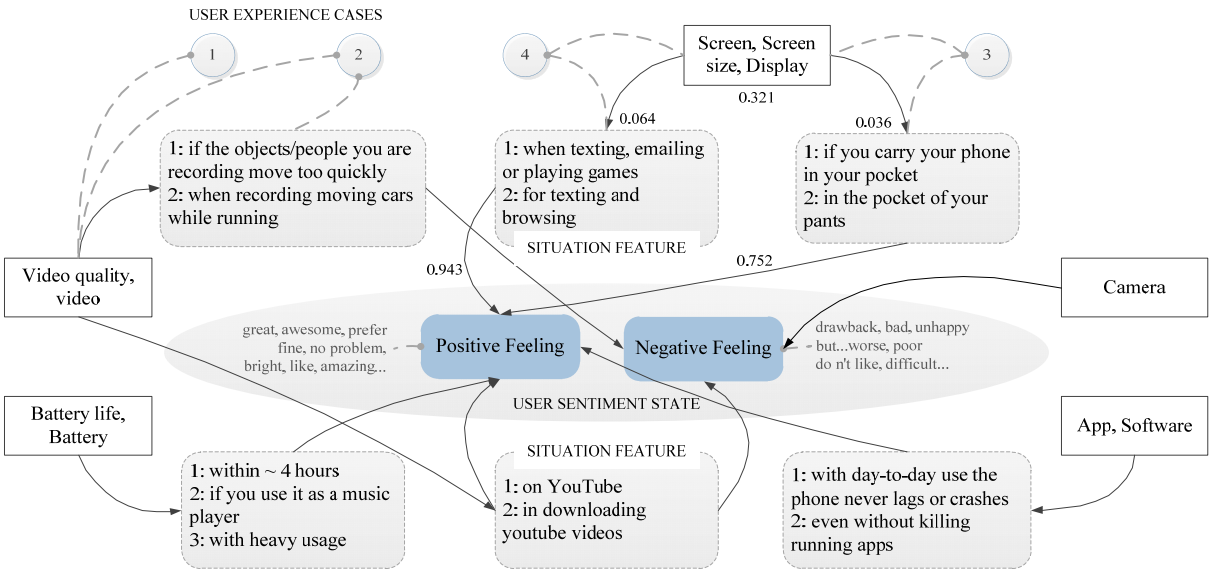


Fig. 14. An example of UX network based on the UX extracted.

Based on the individual cases and situation feature groups, the third case illustrates an example of a UX network formed using the proposed approach. As shown in Fig. 14, there are three node types in` the UX network, i.e., sentiment state, situation group, and product feature. Each node has a linkage to its relevant individual UX cases. For example, the feature screen is related to the individual UX case numbers 3-4 (same cases in Fig. 12). In addition,

directed edges to the node of sentiment state show different factors that influence users' sentiment states. For instance, the product feature screen has more connections to two usage contexts, such as the place for the phone "in the pocket of your pants" and common activities, e.g., "texting" and "emailing". More links from a specific product feature to various situational features indicate that more usage contexts are concerned regarding this feature.

In addition, some examples are included associating with probabilistic relations between UX data. It shows that about 32% of the review sentences in the test dataset refer to the product feature "screen". Among the sentences with "screen", around 6% is about the usage situation information like "texting" and "emailing". Within the sentences with this situation feature, around 94% hold a positive position. From the UX network, it helps designers to understand which usage contexts are often experienced by customers, their profiles and prevailing feelings, either positively or negatively, with respect to certain features under different contexts. It can be seen that automatically parsing such a large amount of UX information will highlight the current status of UX concerning an existing product or its service rendered, competitive advantage or weakness, and more importantly, it provides strong hints on the issues that designers may consider to address particularly in terms of leveraging UX.

6 Discussion and Closing Remarks

In recent years, besides its original domain primarily in human-computer interaction (HCI), the scientific and practical value of integrating UX in engineering design and product design began to gain more attention (Pucillo & Cascini, 2014; Zhou, Xu, & Jiao, 2011). Built upon the strength in user-centred design, human factors, and ergonomics, design research community has started to recognize the merits of studying UX and how a successful offering of pleasant UX can eventually lead to the success of a product or service.

6.1 Theoretical Contributions

Through this study, it marks a few important theoretical contributions. Firstly, different from prevailing possibilities, a machine learning-based computational approach for UX modelling using customer reviews has been proposed and tested. It provides a systematic as well as an automatic approach to model and manages UX information by exploiting a large amount of user-generated online data, e.g., product reviews and consumer opinions, over popular social nets and e-commerce websites. Secondly, beyond targeting customer sentiments or feelings on the product, our study explores a new dimension of UX modelling, i.e., the context of use, and the complex relations within these aspects in UX data. Based on the proposed algorithms, our approach is able to uncover specific language segments as the features intended for UX, e.g., product feature, the context of use and customer feel. Lastly, to further leverage the power of the proposed UX model, an integration process that aggregates similar UX elements has been established. After the UX data has been extracted from reviews, a DAG-based UX network is formed which enables the exploration of complex relations among various UX elements, e.g., what product features and context factors would jointly influence customer feeling positively, which is difficult to be achieved in the past.

In the case study, smartphone reviews are utilized to illustrate how the UX data can be extracted and it presents a good example of key product features and usage context based on the UX integration results. Accordingly, a micro view is suggested by each individual UX of a particular user, and also, a macro view of the collective experiences of different users is provided. On top of these, more interestingly, the proposed UX modelling and analysis approach presents its unique ability to suggest certain UXs with a higher uncertainty (i.e., a lower chance of experiencing). For example, similar product features and functions offered to users that are dramatically different in terms of background and usage context may trigger a

whole different level of affection, surprisingly pleasant or dreadfully disappointed, due to technology readiness and other psychological reasons.

6.2 Implication for Practice

Next, our study also provides important implications for proactive thinking in both strategic and tactical design activities and most helpfully in design concept generation and design for UX. This study is one of the essential research steps towards a novel concept we like to call as "Predictive UX" which aims to help designers to overcome the challenges faced in existing UX studies, where conventional surveys and questionnaires are heavily counted on, so UX-related data quantity, user profile, experience contexts covered, and so on, are inevitably limited, not to mention its time-consuming process of acquiring such data. By tapping into the wealth of user-generated online reviews and opinions, tangible sources of online big data, this study aims to gain more insights of UX from various aspects concerning their intriguing links to product design, which are modeled using a DAG, and in a holistic manner from the word-of-mouth by consumers as they have expressed. For example, when browsing the UX network created, designers would quickly gain a better understanding on products and their features that often yield joyful experiences to users and the connections to users' profiles, e.g. age group and backgrounds, and work contexts. Therefore, for the design and development of subsequent models, if designers wish, they are in the position to maintain these features, boost the collective delivery of such positive experiences, and may incorporate some salient features that would raise a pleasant experience. Simultaneously, valuable understanding can be gathered for competitor's products as long as their corresponding user comments are made available. Such comparative study and insights can offer designers unique angles in branding, product differentiation, and furthermore, intelligence to gain a competitive edge over their market rivals.

Looking forward, a few prominent research tasks can be expected. Arguably, the first one is to provide more guidance to integrate the proposed UX modelling and analysis into a more formalized design methodology and process. Currently, the feasibility of revamping quality function deployment (QFD) and inserting predictive UX analysis into design concept generation and evaluation are being explored in a typical market-driven design process. Although the faceted conceptual UX model is not directly linked to the important UX construct "emotion" (e.g., anger, disgust, fear and happiness), user sentiment (e.g., positive, negative or neutral feeling) in the proposed model also refers to feelings, though not at the detailed level. By further exploiting the linguistic features contained in the reviews, e.g., classifying them based on emotion categories, it offers a possible map from sentiments to emotions.

6.3 Limitations and Opportunities

At the technical level, there is still room to improve the performance of UX discovery, its knowledge construction, and UX analysis and reasoning. One possible route is to append an incremental learning process that extends the existing domain knowledge base. Additionally, although Amazon.com is the world's largest e-commercial website and it provides sufficient product reviews, our results can be further enriched if more relevant reviews from other sites, e.g., eBay or shopping.com, are considered. Thirdly, while our case study has demonstrated that our model is able to uncover UX information directly from customer reviews and form a UX knowledge base based on the novel algorithms proposed, we expect more comparative studies to take this forward in exploring to what extent our approach can help designers in different product design activities, e.g., strategy planning and generation of idea, and what the best way of deployment could be.

On the evaluation of the proposed UX modeling and the impact of predictive UX, a rising trend of bringing digital game and virtual reality (VR) technology is witnessed in the design environment for augmenting and evaluating the UX designed (Engl & Nacke, 2013; Kosmadoudi et al., 2013; Law & Sun, 2012). By taking advantage of digital gaming and VR technology, designers can venture further to assess UX under a higher uncertainty, explore and validate it using digital mockups, and hence, justify whether they should be designed as part of the positive UX to be delivered or to be resolved. This can be accomplished way before product launch, and eventually, it leverages the overall satisfaction of customer in a competitive market.

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