OPERATIONALIZING EMOTIONS BASED ON CLICK STREAM DATA IN SOCIAL AND DIGITAL MEDIA PLATFORMS

by

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A Thesis

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Master of Science

Department of Computer Graphics Technology

West Lafayette, Indiana

May 2017

THE PURDUE UNIVERSITY GRADUATE SCHOOL
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ABSTRACT

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Degree Received: May 2017
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Emotions play an important role in the decisions made in our day-to-day lives. Consequently, due to the increasing dependency on technology, expression of emotions over the digital media and technology platforms has become a common phenomenon. Additionally, there has been several research to accurately predict and understand human emotions in digital media platform using the least amount of available resources. This study will explore the influence of emotions on the behavior of users in such digital media platforms based on the click stream and scroll data. The proposed experimental study will include the participants, who are familiar with social media style websites. Further, the participants will be induced with intended emotions psychologically to understand the resulting behaviors based on the click stream and scroll data.

CHAPTER 1. INTRODUCTION

This chapter provides an overview and background for the research and further describes the significance and purpose of this research. It also provides an overview of limitations and boundaries of the research.

1.1. Background

As technology is evolving, human interaction with technology is evolving and the focus is shifting more towards personalization and adaptability. Adaptive systems adapt their behavior to an individual, based on information collected from the user. Such systems may predict the user behavior to adjust and act (Mareels & Polderman, 1996). Recommender systems have played a significant role in making technology more adaptive. To personalize and adapt to the user's tastes, recommender systems make recommendations based on the user's and others' preferences and behaviors (Chaney, Blei, & Eliassi-Rad, 2015). Multiple factors such as culture, gender, education, age-group, behavior, attitude, information, and emotion play a role in adapting to human behavior (Baylor & Kim, 2004; Dai, Han, Dai, & Xu, 2015).

In a study to explore the framing effects of emotion, Nabi (2003) found that emotions such as fear and anger can differentially affect information accessibility. Further, Sears and Jacko (2009) discussed the emotion's influence on judgement and decision making. They also mention that the user's previous emotional state can affect subsequent emotions.

Accordingly, affective computing tries to model human like behavior, such as emotions. The word "affective" was mostly used by psychologists and lately, it has been of great interest to artificial intelligence researchers (Tao & Tan, 2005). At the dawn of intelligence modelling, Pfeifer (1988) stated that there are several issues about emotional modelling. He discussed the issues related to emotional processes, emotion generation, the influence of emotion, the goal-oriented nature of emotions, interaction between different subsystems, emotions as heuristics and the representation of emotions. Since then, several attempts have been made to try and model the emotions in various contexts.

Consequently, Schwark (2015) conducted an elaborate study on some previous work and provided his inputs about affective computing. Affective computing taxonomy has been a result of his discussions, which tries to arrive at a unified theory to model emotions.

Nevertheless, the emotions in social and digital media platforms are not particularly considered in these models, and a general model isn't sufficient to apply to the social media context. Therefore, this research tries to understand and operationalize human emotions based on their behavior on the digital media platforms.

1.2. Significance

Social media platforms are different from conventional websites and involve numerous interactions. Designing great experiences in such websites can be challenging. From the business point of view, a social media platform's (such as Facebook, Twitter) objective is to have people use the platform recurrently, for longer durations. Correspondingly, recommender system plays a vital role in keeping the existing users intact and attracting new users, by feeding them topics of their interest (Chaney, Blei, & Eliassi-Rad, 2015; Graus & Willemsen, 2015). Popular algorithms in recommender systems are based on collaborative filtering, where recommendations are made by collecting preferences or taste information from the users (Chaney, Blei, & Eliassi-Rad, 2015; Charlin, Ranganath, McInerney, & Blei, 2015; Graus & Willemsen, 2015).

With a high-level goal to refine recommender systems and a low-level goal to understand the implications of intelligent systems in social and digital media platforms in the matter of satisfaction and trust, a qualitative study was conducted (Kumarswamy, 2016). The study involved multiple data sources; an online focus group with 13 participants, a traditional focus group with five participants and data mining of online discussion groups with representation from about 30 nations. It was found that current recommender systems do not satisfactorily gauge the emotions and moods of the users. The participants talked about popular social media platforms such as YouTube, Twitter, Verge, Quora, and Facebook. They often indicated their dislike to spoon-feed the platform by answering questions about their choice of topics. Additionally, they preferred social media to accurately understand their emotions and moods.

Correspondingly, in a study conducted by Sugiyama, Hatano, and Yoshikawa (2004), the users believed that the method of collecting feedback and ratings can be time consuming and instead, they preferred easier methods (Sugiyama, Hatano, & Yoshikawa, 2004). Therefore, it may be useful to try and capture the human emotions without seeking feedback from them. But the potential challenge is, how?

If the users do not provide feedback explicitly, it may be possible to gather the data implicitly. Moe and Fader (2004) suggest that clickstream data such as number of clicks, mouse travel distance, number of page views, characteristics of the items viewed are rich with information related to human behavior. This implies that, it may be possible to predict the emotional state of the user by understanding the clickstream data generated by the user.

Imagine a user on a busy day, frustrated by his work, logging in to a social media website to take a break. Moments after he logs in, the website adaptively provides posts and newsfeeds to lighten up the user based on their current emotonal state. Further, the system displays a message to cheer up the user, trying to make their day better. Such eventful predictivity constitutes the intention of this research. Improving such experiences needs intelligent systems to understand humans better. Assisting intelligent systems to understand moods and emotions without seeking explicit feedback can help intelligent systems to work collaboratively with human users to arrive at a better solution (Carminati, Ferrari, & Viviani, 2013; Ferguson & Allen, 2007).

1.3. Statement of Problem

As intelligent systems are evolving, their application in numerous tasks and processes are evolving as well. With this evolution, or “The fourth industrial revolution” (Schwab, 2016), human life is rapidly changing. Daily chores are being influenced by intelligent systems, and humans are working with the intelligent systems to finish their tasks. As the dependency on technology is swelling, expectations of technology to sense, understand and serve humans are increasing as well (Cambria, 2016). However, unlike humans, machines need to quantify human emotions (Tang et al., 2012). To quantify human emotions and model them, predictive algorithms seek input from users. Sugiyama, Hatano, and Yoshikawa (2004) mention that users dislike the fact that machines seek feedback from users and view them as intrusive and time-consuming. Additionally, such intrusiveness from technology itself is not desired by users (Grint & Woolgar, 1997). Therefore, the current research tries to capture the emotions of social and digital media platform users without seeking explicit feedback from them.

1.4. Research Question

The central question of the research is:

- Do emotions (happiness and sadness) influence the clickstream data while using a social media website?

1.5. Assumptions

The assumptions inherent in this study are as follows:

- The participants will honestly go through the process of psychological induction and take the experiment seriously
- The participants will have normal (or corrected to normal) vision.
- The websites chosen for experiment will have good usability and will not account for an unintended frustration variable
- The participants will not be in a hurry and will patiently go through the process
- The clickstream data and screen capture data collected during the study are accurate
- Human emotions, expressions, and complex interactions can be viewed as complex interactions and statistical models

1.6. Limitations

The limitations associated with the study are as follows:

- Due to the feasibility of the study, the participants in the study will most likely be students of Purdue University
- The users' behavior will be analyzed in laboratory conditions, and not in their natural settings

1.7. Delimitations

The delimitations of this study include the following:

- The study considers participants who are familiar with social-media websites and comfortable using the Windows™ environment
- The study will account only for desktop settings and not for the tablet or mobile settings
- The study does not categorize the participants based on their ethnic background
- The study accounts only for click stream data and the amount of time spent on the posts. Further, it does not take the facial expressions of the participants into account

1.8. Definitions of Key Terms

Adaptive user interfaces– "An adaptive user interface is an interface which can change its behavior to suit an individual or group of individuals" (Browne, Totterdell, & Norman, 1990, p. 2).

Affective computing– "It is computing that relates to, arises from, or deliberately influences emotion or other affective phenomena" (Picard, 1997, p. 3).

Agents or Intelligent agents– "Intelligent agents represent software programs that independently perform requests on behalf of a user in a networked and digital world, for example, the search for information" (Brenner, Zarnekow, & Wittig, 1998, p. 18).

Clickstream data– When the user clicks anywhere on the screen while using the application or a website, the data such as a number of clicks are collected for analysis. This is referred as clickstream data in the current context (Bucklin & Sismeiro, 2003).

Emotional intelligence– "Emotional intelligence is the capacity of individuals to recognize their own, other people's emotions, to discriminate between different feelings and label them appropriately, to use emotional information to guide thinking and behavior and to manage and/or adjust emotions to adapt environments or achieve one's goals (s)" (Colman, 2015, p. 244).

Framing– "Framing theory posits that the way in which information is presented, or the perspective taken in a message, influences the responses individuals will have to the issue at hand" (Nabi, 2003, p. 225).

Heuristics– In psychology, heuristics are simple, efficient rules which people often use to form judgments and make decisions. They are mental shortcuts that usually involve focusing on one aspect of a complex problem and ignoring others (Lewis, 2008, p. 43;)

Mixed initiative systems– "Mixed initiatives refers broadly to methods that explicitly support an efficient, natural interleaving of contributions by users and automated services aimed at converging on solutions to problems" (Horvitz, 1999, p. 2). According to Ferguson and Allen (2007, p. 23), "Mixed-initiative system is one that allows the participants to separately contribute what they can to the group's overall success. In collaborative problem solving, this means coming up with solutions to problems, with initiative varying depending on who can solve which problems"

Recommender systems– "It is a system where, people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients. In some cases, the primary transformation is in the aggregation; in others, the system's value lies in its ability to make good matches between the recommenders and those seeking recommendations" (Resnick & Varian, 1997, p. 56).

1.9. Summary

This chapter provided an overview of the research and constitutes a brief foundation. The discussion included background, significance of the research, statement of the problem, the definition of important terms, limitations, assumptions, and delimitations. The next chapter explores the previously conducted research pertaining to the current research via literature study.

CHAPTER 2. REVIEW OF RELEVANT LITERATURE

Social media websites have evolved beyond networking, by enabling a platform for entertainment, education, and knowledge (Moran, Seaman, & Tinti-Kane, 2011). The emergence of the recommender systems in news websites, social media websites, advertisements, and e-commerce websites have facilitated more personalized and relevant suggestions to users. The emotions of human users play an important role in such websites, and operationalizing the emotions can make websites more personalized, and provide a better user experience (Baylor & Kim, 2004; Dai, Han, Dai, & Xu, 2015). This idea of personalization invites adaptive behaviors in websites. One way to make the system adaptive is by improving the collaboration between the software agent and the user (Vale, Faria, Ramos, Fernandez, & Marques, 1996). Agents can assist in accomplishing the user's task by predicting the emotions. Affective computing field opens the door to the myriad possibilities of understanding the emotions and operationalizing the same for the benefit of users.

The high-level goal of this research is to make the recommender systems in social and digital media platforms more adaptive and affective. To lay a groundwork for the research, first, intelligent systems and adaptive systems are discussed. The recommender systems may use mixed initiative transactions to collaboratively finish a certain task by sensing users and behave adaptively. Further, the need for sensing emotions and its implications in finishing the tasks are explored. Consequently, affective computing plays an important role in modeling such emotions. Therefore, some of the previous attempts in understanding and modelling emotions are discussed. Finally, some of the methods to capture emotions without seeking explicit feedback are deliberated.

2.1. Adaptive Systems, Mixed Initiative Systems and Recommender Systems

This research is set within the framework of intelligent technologies. The definition of intelligent technologies varies based on the context. In some cases, technology that undertakes a significant amount of cognitive activity is considered as intelligent technology (Salomon, Perkins, & Globerson, 1991). For example, a simple calculator in the Windows operating system is an intelligent technology. In other cases, intelligent technologies are referred as technologies with artificial intelligence (Pollack, 2005). For example, recommender systems in social and digital media platforms make suggestions based on user's likes and dislikes. Recommender systems in social media can have machine learning components, and therefore, it is an intelligent technology. Henceforth, when intelligence, intelligent technology or intelligent systems are referenced, they encompass both artificial intelligence (AI) and non-artificial intelligence components as discussed above. The social and digital media platform utilizes several intelligent technologies to operate. Some systems that are important in the current context are adaptive systems and recommender systems.

According to Browne, Totterdell, and Norman (1990), "An adaptive user interface is an interface which can change its behavior to suit an individual or group of individuals" (p. 2).

Implementation of adaptive user interfaces in the social media and digital media platforms has resulted in aiding search and discovery mechanisms, and to identify relevant posts, tags, and people (Leung, Chan, Milani, Liu, & Li, 2012). Adaptive systems understand the behavior of users, by creating a statistical model of user behavior (Vora & Bojewar, 2011). The adaptation to user in adaptive interfaces, albeit based on the user behavior is, automatic in nature (Browne, Totterdell & Norman, 1990). Reinecke and Bernstein (2011) discuss the performance improvement, perceived usability, and aesthetics with adaptive user interfaces on the cultural platform. Further, Vora and Bojewar (2011) mention that web interfaces with personalization, based on the user needs has a positive impact on usability and user experience. Perugini and Ramakrishnan (2003) claim that personalizing user interaction is one of the best ways to establish collaboration between humans and intelligent technologies. This implies that adaptive interfaces work on the principle of creating a more personalized interaction with users. One of the ways to achieve this personalization is by sensing the user finishing a task. Such collaborative sensing can be achieved by using mixed initiative systems.

Mixed initiative systems in social and digital media platform form a partnership with users to sense their activities and help them with their tasks (Carminati, Ferrari, & Viviani, 2013). Mixed-initiative systems exhibit true collaborative behavior, which requires a software agent to have several capabilities such as reasoning, communication, planning, execution, and learning (Ferguson & Allen, 2007). Mixed initiative systems depend on the distribution of cognition and joint cognitive systems to form an intellectual partnership. The partnership here does not imply computer technologies that aid in cognitive processing and support intellectual performance to enrich individuals' minds (Salomon, Perkins, & Globerson, 1991). Instead, the two systems (human and computer) work together by sensing (accurately predicting) each other to finish the task. This principle of predicting the user behavior to suggest and enable personalization forms a basis for recommender systems.

Resnick and Varian (1997) defined recommender systems as follows:

> Recommender system is a system where, people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients. In some cases, the primary transformation is in the aggregation; in others, the system's value lies in its ability to make a good match between the recommenders and those seeking recommendations (p. 56).

Recommender systems help the users to make better choices from mammoth content catalogs and entertainment-related items, such as movies, jokes, news, and even insurance policies (Resnick & Varian, 1997; Xiao & Benbasat, 2007). These recommendations are based on the algorithms that derive the user's preferences from implicit or explicit feedback (Pommeranz, Broekens, Wiggers, Brinkman, & Jonker, 2012).

Therefore, recommender systems can be viewed as adaptive systems which leverage the partnership between software agent and user to predict and personalize websites. Many recommender systems try to model user behavior, based on the user's feedback. For example, in the Google Now cards ("Learn more about the Google app", 2016), the recommendations are based on both the user's behavior of reading articles and providing feedback on the same. Facebook follows a similar pattern of understanding user behavior where it typically seeks feedback from the user. This implies that, to personalize and adapt to the user's tastes, the recommender systems gather information based on their tastes and preferences. Further, they also gather information from other users similar to the user in question to have a more accurate model (Chaney, Blei, &

Eliassi-Rad, 2015). Multiple factors such as culture, gender, education, age-group, behavior, attitude, information, and emotion play a role in adapting to human behavior and make relevant suggestions (Baylor & Kim, 2004; Dai, Han, Dai, & Xu, 2015). Klein, Moon, and Picard (2002) also discuss the implications emotions on a digital media platform. They found that the computer can undo some of the negative feelings it may cause by helping the user to manage their emotional state.

Nevertheless, it is important to note that emotions play a significant role while users are using social and digital media platform. The next section discusses emotions in relation to digital media platform and how they are used to make the recommender systems more collaborative. Then, some of the existing research in creating emotional models is discussed through the lens of affective computing.

2.2. Emotions and Affective Computing

In the previous section, the importance of emotions in making recommender systems more adaptive was discussed. Correspondingly, emotional aspects of intelligent systems such as recommender systems not only encompass cognitive aspects, but other behavioral and expressive aspects as well (Pfeifer, 1988, pp. 287 - 320). He further asserts and discusses the issues in emotion modeling as the following:

- Emotion as process
- Influence of emotion
- The goal-oriented nature of emotions
- Interaction between subsystems
- Emotions as heuristics and
- Representation of emotions

The issues of interest in the current research are emotions as models (heuristics), which help to make predictions and representations of emotions. As per Pfeifer (1988), emotions as heuristics can allow the software agent to solve problems and make decisions while considering the current emotion of the users. This notion of predicting user's emotions is explored in affective computing paradigm.

According to Schwark (2015), “Affective computing is the field of designing machines that can recognize, express, communicate, and respond to humans using emotions” (p. 761).

Affective understanding is a notion, where the system tries to model the user’s mood, emotional aspect, and patterns, by understanding the user behavior (Tao & Tan, 2005). A configurable model can store the user’s preferences and patterns, to affectively predict logistics that are required to provide a recommendation.

Attempts to understand human emotions have been made several times. To understand the basic emotions (e.g., anger, disgust, sadness) through the lens of affective computing, D'Mello and Calvo (2013) discussed the importance of non-basic emotions, such as frustration and boredom. However, they refrained from discussing the methods to understand the emotions based on the user behavior. Cambria (2016) discussed sentiment analysis through methods such as knowledge-based techniques, statistical methods, and hybrid approaches.

Furthermore, there are discussions on the ideological discourse between artificial intelligence and the HCI field (Winograd, 2006). Winograd (2006) discussed the rationalistic approach of modeling where, actions, behaviors, and emotions can be modelled into statistical equations and symbolic representations. Consequently, all human emotions, expressions, and complex interactions can be viewed as complex algorithms and statistical models. The current research aims to provide an actionable model for emotions which can be used to refine the recommender systems.

First recommender systems were discussed through the lens of mixed initiative and adaptive interfaces. Then, the role of emotions in enhancing recommender systems to collaboratively perform tasks and suggestions was discussed. This sensing and collaboration involved human emotions as a factor. One possible way to model emotions is by using statistical methods. In the next section, emotion is formally defined and previous attempts to model them are discussed. Further, a way to model emotions relevant to the current research is deliberated.

2.3. Affective Model of Emotions

According to Scherer (2001), emotion is defined as, “An episode of interrelated, synchronized changes in the states of all or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism” (p. 93).

To find the dimension of emotions, Ekman (1955) uses a similarity analysis. His main purpose was to isolate the factors of emotions, which are generally considered as primary emotions. With this experiment, he identified different aliases and words used for the same emotion. However, in the world of the internet, relying upon the usage of words alone might be implausible as the internet has become more of a community, and people express behaviors in various ways (Derks, Bos, & Grumbkow, 2007).

According to studies in neuroscience, sub-neocortical limbic circuitries handle the neocortical processing essential for the recognition of emotions in humans and other mammals (Damasio et al., 2000; Liotti and Panksepp, 2004; Panksepp, 1998). However, computers lack such limbic circuitries to understand human emotions. “Probabilistic neural networks” (Specht, 1990, p. 108) tries to address this lack of biological signatures in computers.

Scherer (2005) defined emotions and attempted to distinguish them from other affective traits or states. He discussed various issues associated with the measurement of emotions and provided a certain list of design characteristics to understand emotions. However, this attempt tried to characterize emotions qualitatively, while the focus of the current research is to model the emotions quantitatively.

Hu, Zeng, and Shang (2016) discussed various algorithms for the recommendation that were tested against popular websites such as Netflix for performance. The topic of discussion was more on the performance side rather than bettering the algorithm from the functional perspective.

Winoto and Tang (2010) discussed the implications of digital media platform users’ moods and emotions while rating or recommending a movie. This implied a relationship between the user's emotional state, and their behavior while using such platforms. Here, the focus is towards the affective capabilities of recommender systems.

Several algorithms and approaches have been presented and implemented over the years (Katarya & Verma, 2016), which are listed as follows:

- Data mining and information fusion, where various data mining algorithms are implemented to suggest recommendations
- Content-based filtering, where the recommendations are based on the user's feedback, such as likes and dislikes
- Collaborative filtering, where the recommendations are based on similar tastes of the public while using a website
- Context-based filtering, where the recommendations are based on the contextual information, such as time of the day and weather conditions
- Semantic-based recommendation system, where the suggestions are based on the ontological aspects of the web usage
- The group is filtering, where suggestions are triggered by a group of people with similar likes
- Tagged filtering, where the suggestions are based on the actions connected to the keyword associated with photos, videos and pictures online
- Sentiment analysis, where recommendation is given by understanding the responses and remarks of the users
- Other methods involve Latent Dirichlet allocation, Fuzzy, Support vector machine, Feature selection, Gaussian process and Naïve Bayes to provide a recommendation

However, the above approaches involved some sort of explicit feedback from the user to get accurate and appropriate recommendations.

As per a qualitative study conducted by Kumarswamy (2016), social media users are often bothered when recommender systems seek repeated feedback from the users. Participants in the research preferred the intelligent system to understand their emotions, likes, and dislikes automatically, rather than seeking explicit feedback from the users. Similarly, in a study conducted by Sugiyama, Hatano, and Yoshikawa (2004), users of digital media platform believed that collecting explicit feedback and ratings can be time consuming and instead preferred easier methods. Additionally, Hu et al. (2013)

mentioned that to provide a personalized recommendation, explicit feedback data (e.g., text feedback, ratings, etc.) are sometimes hardly available in the real-world scenario.

Furthermore, Schwark (2015) asserted the need to interpret emotional states of users through available resources, to accurately model the emotional aspects in intelligent systems. If the users do not provide feedback explicitly, it may be possible to gather the data implicitly. To find high-quality content in social media from users, Agichtein, Castillo, Donato, Gionis, and Mishne (2008) used clickstream data. This method was particularly used to capture data without relying on explicit feedback. Hu et al. (2013) also focused on using implicit feedback generated by clickstream and other behavioral data to provide personalized recommendations to the users.

The current research attempts to understand the emotions of users using implicit feedback. Therefore, creating a model based on click patterns and scroll times may be beneficial. This does not mean that other standpoints where, the user's emotions can be gauged should not be used (e.g., explicit feedback, video inputs, heart-rate monitoring etc.). Instead, implicit feedback along with other methods may increase the accuracy to predict the emotions. This research focuses on using clickstream data to predict emotions. Consequently, some of the previous research using clickstream data relevant to this research is discussed in the next section..

2.4. Clickstream data

According to Moe and Fader (2004), “Clickstream data is rich with behavioral information such as duration of visits, a number of page views, characteristics of items viewed, and so on” (p. 7).

Further, Gündüz and Özsu (2003) propose a model that considers both the time spent on the order and the order information themselves. They delineate detailed steps to collect and understand clickstream data, which is listed as follows:

1. The clickstream data might contain other irrelevant data for analysis. Therefore, it is important to clean them and prepare to understand the usage patterns
2. The second step is to extract the data that was mined and make sense out of the usage patterns

3. The third step is to build a predictive model based on the extracted usage patterns (p. 535).

They further assert that knowing the clickstream data is not enough to predict and understand the user behaviors. The time spent on the pages and posts can also play an important role in providing the user interests.

Ting, Kimble, and Kudenko (2005) propose an interesting model to understand and extract the clickstream data. They introduce a technique called as Unexpected Browsing Behavior (UBB). According to them:

> Unexpected Browsing Behavior mining is useful for website designers to understand how a user browses their website, especially for those website designers who want to redesign their website. The concept behind this method of web usage mining is that the designer of the site ought to be able to define patterns of expected browsing behavior, and then by using this as a template, we should be able to discover any unexpected deviations from these routes in the clickstream data (p. 1).

A similar method can be implemented in this study as well. A model can be derived based on the user behavior by understanding the clickstream data, and a prediction for the outcome in a subsequent instance can be provided based on the emergent model.

In this research, two datatypes in the clickstream data will be considered:

1. Number of clicks while the user is using the given website
2. Amount of time spent on happiness related posts and sadness related posts on the website

To find the amount of time spent on happiness related posts and sadness related posts, the system must be able to interpret emotional valence of the content. However, there are many research where the intelligent systems identified emotions by analyzing the contents (Alm, Roth, & Sproat, 2005; Calvo & Mac Kim, 2012; Strapparava & Mihalcea, 2008). Moreover, there are several APIs available to analyze emotions in social and digital media contents ("ML Analyzer API Documentation", 2016; "Repustate: text analytics for businesses", 2016; "TweetSentiments", 2016).

To capture and analyze the emotions, the emotions need to be used as a control variable. One way to do so is by psychologically inducing emotions to human subjects. Therefore, this research makes use of psychological induction of emotions, where participants are induced with intended emotions and further, their behavior will be analyzed using clickstream and scroll data. These methods will be discussed in detail, in the next two sections.

2.7. Psychological Induction of Emotions

To understand the user behavior due to emotions, current research takes the approach of psychological induction of emotions. Certain emotions may be induced to the users and have them use certain websites to capture the clickstream data. For the sake of this research, only happiness and sadness will be operationalized, because it is comparatively easier to induce and differentiate.

There are several ways to induce emotions to users. Yan and Dillard (2010) discuss usage of the Life Inventory Task to induce emotions. In this method, users are asked to recall an event in their lives, which evoked an emotion. Further, they were asked to write the description of an event, as much as possible (Schwarz & Clore, 1983).

In another study, the participants were induced with emotions (happiness and sadness) by using a guided imagery procedure (Bakic, De Raedt, Jepma, & Pourtois, 2015). The participants were asked to vividly recollect a happy (or sad) moment in their life. Such episodic memories were further asked to report in a descriptive way to the researchers. While recollecting, the participants were asked to close their eyes and visualize the memory in detailed specificity.

In another study, emotions were induced by using music. This was referred as psychophysiological effects of music (Balteş, Avram, Miclea, & Miu, 2011). In the study, the users were made to listen to certain music, which potentially induces happiness or sadness and positive or negative effects. Later, subjective changes were measured through a specific set of questionnaires. Consequently, knowing the sad plot still induced positive emotions, such as peace, and joyfulness among the participants.

Ohrt, Foster, Hutchinson, and Ieva (2009) discuss the two research standpoints in music's role in inducing emotions:

1. Scientists believe that emotions can indeed be induced by the music
2. Music can only express emotions, but not induce it.

However, in the research they use music videos to evoke emotions among the participants and study the effects. Teixeira, Wedel, and Pieters (2012) also induced emotions by means of video, where they explored the implications of videos in the advertisements to induce emotion. Additionally, Philippot (1993) suggested that film segments can be considered as a rich source of controlled stimuli for inducing emotion. Consequently, in the current research, either a combination of guided memory and music video, or either of these methods can be used to induce emotions.

2.8. Summary

This chapter discussed the implications of mixed-initiatives and their role in making the recommender systems more efficient and personalized. Further, the role of affective computing in understanding human emotions, and operationalizing them is significant. For intelligent systems to behave instinctively, it is of importance to make them more affective. Machines are not like humans, and they lack certain biological signature that humans possess. However, this does not stop us from making the intelligent systems intuitive. At the same time, understanding the human emotions has always been a challenge to the scientific community. Each of us is different and behave differently, however, our actions, reactions, and responses can be similar than we imagine (de Rivera & Grinkis, 1986; Schimmack & Reisenzein, 1997). There are several types of research which focus on operationalizing the human emotions to predict mood and behaviors of human beings (Moridis & Economides, 2009; Siegert, Böck, & Wendemuth, 2012). However, predicting the emotions without seeking feedback, remains a challenge. We can use methods for psychological induction of emotions and thereupon, use the ensuing clickstream data to model an algorithm, or an equation to predict the emotions. However, this is contingent upon the dependency of emotions and clickstream data generated by users, while using a website. Correspondingly, this is yet to be determined by the research.

CHAPTER 3. FRAMEWORK AND METHODOLOGY

In the previous sections, the need for current research was discussed by exploring existing research. Consequently, several gaps were identified as well. Further, methods to induce emotions were deliberated, which will consequently act as an independent variable for the current research. This section provides a brief overview of the research design and the statistical tools that will be used in the research. A list of hypotheses which needs to be tested is presented, followed by, the methods to test the hypotheses.

The study will involve an experiment with completely randomized design (Giesbrecht & Gumpertz, 2005). In this design, the participants are randomly assigned to the treatments. A psychological induction method will be used to induce emotions to participants. There will be three groups, one with induced happiness, another with induced sadness and the third group without induction. Therefore, emotions act as a control variable in the study. The participants will be provided with website and clickstream data is collected using the screen recorder and a clickstream data register. For this experiment, the clickstream data that will be collected are:

- The average value of the number of mouse clicks and mouse travel distance
- Average scroll speed per post

These data form the basis for the hypothesis which is discussed in the next section.

3.1. Hypothesis

$N_C = N_{MC}/D$

Where, N_{MC}= number of mouse clicks per person and D = average distance travelled by the mouse per person.

H_{O1}: The average N_C value for happiness is not different from the average N_C for sadness

H_{A1}: The average N_C for happiness is different from the average N_C for sadness

H_{O2}: Among happiness-induced participants, the average scroll speed for happiness related posts is not different from average scroll speed for sadness related posts

H_{A2}: Among happiness-induced participants, the average scroll speed for happiness related posts is different from average scroll speed for sadness related posts

H_{O3}: Among sadness-induced participants, the average scroll speed for happiness related posts is not different from average scroll speed for sadness related posts

H_{A3}: Among sadness-induced participants, the average scroll speed for happiness related posts is different from average scroll speed for sadness related posts

If there is a significant relationship between the clickstream data and the emotions (happiness and sadness), the slope (B_1) will not equal zero.

H_{O4}: $B_1 = 0$

H_{A4}: $B_1 \neq 0$

3.2. Variables and Level of Data

Basic emotions (Weiner & Graham, 1984) such as happiness and sadness (nominal) will be used as independent variables (ratio) for the experiment. Correspondingly, the dependent variables are clickstream data (ratio) and scroll speed (ratio). The intervening variable can be scroll time per post. Additionally, other demographic data such as age, gender, and social media usage frequency will be collected.

3.3. Population of Inference

The frequent users of social media are the potential population of inference and a qualifying survey will be used to determine the frequency of usage. Accordingly, the users who login to least one social media website, at least once a day, are defined as frequent users.

3.4. Sample

The samples for the experimental design will be selected by using probabilistic sampling. Here all the participants are randomly assigned to treatments. However, a certain level systemization may be introduced such as making sure that each group has an equivalent gender ratio.

The samples are selected by using probabilistic sampling to accurately represent the population of inference. Sufficient samples will be drawn with 95% confidence level and sufficient standard deviation (SD = 0.5). The power is will be 0.8 with the required alpha of 0.05. With F-test and One-Way ANOVA, this corresponds to a minimum of 14 participants in each group. From the samples, three independent groups will be created. Two of the groups will be subjected to different tests (for happiness and sadness) and one group will act as a placebo.

3.5. Data Source

The experiment consists of three groups and each group will be having the same sets of websites to browse. Consequently, one group will be induced with happiness and the other group will be induced with sadness. The psychological methods for induction of emotions, such as a video with happiness will be introduced to the participants. However, the third group will not be induced with any emotions, which will act as a placebo. Each group will be given respective websites, to collect the corresponding click stream and scroll speed data. Furthermore, the data will be collected using click stream and scroll data collection software such as Morae.

3.6. Statistical Tools

The analysis of results involves the determination of statistical significant difference between the means of three independent groups. Therefore, one-way Analysis of Variance (Cohen & Cohen, 2008) with F-test (Harper, 1984) as test statistic will be used. To determine which specific groups differed from each other, a post-hoc such as Bonferroni method will be used.

3.7. Analytical Procedure

There will be three groups for comparison; the first group with induced happiness, the second group with induced sadness and a placebo group. A one-way ANOVA (Analysis of variance) is the appropriate analytical procedure to analyze the data from the experiment. Using an ANOVA, the comparison between the groups will be determined.

Emotions (happiness and sadness) are the independent variables, which will be used to control the resulting clickstream data. To understand the relationship between the emotions and clickstream data/scroll data, a regression analysis will be conducted. Consequently, this will provide the direction of the relationship between the variables.

3.7.1. Self-report measures

In a psychological research of mood induction, Kučera and Haviger (2012) used several methods. To verify the induced emotions, the participants were asked to report their emotional state. Similarly, an emotional scale can be given to participants after the induction process to verify their emotional state.

3.8. Threats to Validity

The independent variable in the experiment, which is emotions, can also be a result of frustration due to the social media experience. Therefore, the usability of the social media is taken into consideration. During the experiment, popular websites like Facebook, Twitter, and Google-plus will be used to nullify the effects of bad usability.

Another threat to validity is; the subjects will be induced with the emotions before the experiment. There may be no reliable way to accurately verify if the participants were induced with the intended emotions other than depending on participant's self-report. However, the proven methods in psychology and other related sciences will be implemented to induce the emotions.

3.9. Summary

This chapter provided an overview of the research methodology. Several hypotheses were stated, followed by variables, sample size, population, experiment setting and initial threats to validity were identified.

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