Malaysian Journal of Computing, 5 (2): 563-571, 2020
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eISSN: 2600-8238 online

A HYBRID SERENDIPITY SOCIAL RECOMMENDER MODEL

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ABSTRACT

Social support is essential, especially in a working environment, because it can reduce psychological strain. The psychological strain associated with mental health in daily lives could have been gained from mismatched staffing and indirect control of the staffs. In order to meditate the problem, in this study, a hybrid serendipity social recommender model is proposed. This model is a combination of several proposed models encountered during the development process. Firstly, Rough Set Theory (RST) has been used in the early development stage to compute an automated attribute selection. RST is a mathematical tool that is widely used for knowledge discovery and feature selection. At the same time, it minimizes redundancies among variables in classifying objects and extracts rules from the database. In the next stage, the classification model is used to classify the data into subclasses by using a deep learning algorithm. This algorithm aims to define the higher matching suggested attributes and used for processing massive data. Lastly, a reasoning approach is applied by using case-based reasoning from the result produced. The reasoning approach is used to finding the reasons why the attributes are selected. This approach searches the history of the selected attributes or compute a reason by digging back in the database.

Keywords: *Case Base Reasoning, Classification Model, Deep Learning Algorithm, Social Support, Hybrid Serendipity Social Recommender Model, Rough Set Theory.*

Received for review: 04-06-2020; Accepted: 14-07-2020; Published: 08-09-2020

1. Introduction

Social support is the physical and emotional provided to people by those they associate within their daily lives (Gerlach *et al.,* 2013). Meanwhile, Bjornstad *et al.* (2016) and Patil & Raanaas (2016) stated that "overall levels of helpful social interaction at work with both co-workers and supervisors" as social support. To summarize, social support refers to the provision of material and psychological resources by others within one's social network (Li *et al.,* 2017). Social support is necessary because studies show a beneficial impact on reducing psychological strain, increase satisfaction (Drummond *et al.,* 2017) that can be associated with mental and physical health (Rotberg *et al.,* 2016).

Besides, social support is shown to improve depression symptoms consequences and also as an antidepressant medication adherence (Gerlach *et al.,* 2013). Likewise, the scarcity of social support can worsen the experience of work-family conflict, which can result in the increasing of psychological strain and decreasing the satisfaction with both family and job (Drummond *et al.,* 2017). Traditionally, workshop and teamwork are the standard methods employed for promoting social support and increased psychological strain. However, as reported by Miller *et al.* (2018), the workshop session, in general, are useful and well organized,

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but time-consuming. As for the teamwork approach, Chuang (2018) mentioned that teamwork, as the foundation could not assure direct control of employees and in practice, many teams have failed. Moreover, mismatched staffing also could lead to dissatisfaction, time-consuming and capital loss during the process, low of productivity and lead to failure (Parveen *et al.,* 2018).

Accurately, social support can be categorized into informational, emotional and instrumental. Informational support (closely related to self-esteem) helps one to understand, cope and define with problematic events. Emotional support (consolation and comfort) provides through expressions of concern and care and lastly, instrumental support comprises the provision of essential services, financial aids and material resources (Lee *et al.,* 2017). In the working environment, social support that is obtained from supervisors, co-workers and friends usually depend on (1) the time they spent on your problems, (2) the frequency of communication with them and (3) the firm reliance on them (Saijo *et al.,* 2016).

Several factors have shown to influence social support such as team identification, working environment (Galletta *et al.,* 2016) and social connectedness (Lee *et al.,* 2017; Scarf *et al.,* 2017). Social connectedness is a vital ingredient of the acceptance by others (a significant predictor of resilience) and can be fostered through positive interpersonal relationship (Lee *et al.,* 2017). Research in 2015 found a positive relation between social connectedness with the reputation of an employee (Kügler *et al.,* 2015). As social support is essential in working space (research laboratory, office, library, etc.), the workers supposed to know each other to create a supportive environment and also social connectedness. It is challenging to connect colleagues towards the same objective in a working space.

The objective of this study is to develop a hybrid serendipity social recommender model for aware social systems. Specifically, the outlined objectives are (1) to identify attributes for social recommender model, (2) to develop a hybrid serendipitous social recommender model and (3) to evaluate the accuracy of the serendipitous social recommender model. The organization of this paper are as follow; section 1 explains the introduction of the study, section 2 presents the research background, section 3 discusses literature review of this research, section 4 discusses the methodology, section 5 proposes the model and the last section concludes the study.

2. Research Background

Brown (2017) found that co-working practices that associated with co-working spaces had critically challenged the traditional concept of location and workplace of creative works and simultaneously confronting the way in which creative workers related and interact with each other. Co-working spaces are presented and imagined to be as a space of serendipitous encounter, spontaneous exchange and collaboration. However, limited research focusing on how co-working positively supports workers.

Currently, the approach is a serendipity-based recommender system, for example, a system called Auralist, a system that is using serendipity for music recommendation. The beneficial feature of serendipity based recommender system is embedding the unusualness or surprise of recommendation. It will challenge the user to expand their tastes and providing an exciting recommendation of music that can indirectly improve recommendation satisfaction (Zhang & Séaghdha, 2012).

Yamazaki & Nakajima (2017) stated that the necessarily on develop a recommendation system that involving novelty and serendipity for the system to be better in order to build an advantageous recommender system. This element can trigger positive user interest that motivates the user to follow recommendation (Maccatrozzo *et al.,* 2017). Several systems are using or evaluating serendipity as the engine. For example, Serendipity-Oriented Recommender System Considering Product Awareness in Communities (Yamazaki & Nakajima, 2017). This system computes serendipity score by using the purchase log and details subgroup.

However, most of the serendipity element in recommender system was build for user-item interaction. There is limited research focusing on user-user interaction specifically on social recommender system. In addition, most of the systems are using content-based filtering and collaborative filtering, which offer a limitation and the system also only use one or two techniques as the engine of the system. Based on the discussed issues and problems, several research questions are formulated. Firstly, this research is to find the attributed social recommender model. Next, we want to develop a hybrid serendipitous social recommender model and lastly, the hybrid technology will be analyzed on increasing the chances to provide serendipitous recommendation among peers.

3. Literature Review

3.1 Social Connectedness

Social connectedness as described by (van Bel *et al.,* 2009) is "the momentary affective experienced belonging to a social relationship or network" (Visser *et al.,* 2011) that can be caused by an explicit act (by visiting a friend). The usage of telecommunication such as text messaging, online communities, email, instant messaging, telephone and awareness systems has increased significantly the communication horizon resulting to the enhancement feeling of belonging and relatedness (van Bel *et al.,* 2009).

3.2 Social Support

Social support is part of social connectedness and it is defined as the provision of material and psychological resources by others within one's social network (Shi *et al.,* 2017). Social support can be regarded as a protective factor against stress. The social support has been demonstrated to impact several outcomes variables including physical health, psychological well-being and interpersonal satisfaction (Iciaszczyk, 2016) as stated by (Gerlach *et al.,* 2013), the social support involving physical and emotional provided by people who exist in their daily lives. This includes social support through the interaction at working spaces with both superiors and their subordinates (Bjornstad *et al.,* 2016).

3.3 Recommender System

Recommender systems (RS) are the system's using intelligent that typically acquire users' interests, preferences and needs and shape their behaviour by support people in decision-making and personalizing experienced users (Kartoglu & Spratling, 2018). Recommender systems intend to provide users with information of potential interest based on historical data and demographic profiles (Wang *et al.,* 2018). RS has been developed and improved in recent years that make it as an introductory class of systems to push product, services or information based on user expression of interest (Contratres & Alves-souza, 2018). Recommender systems allow people to find products and services and becoming increasingly important in a range of applications. Few products in the market such as Amazon (E-commerce) (Meng *et al.,* 2018), Spotify (Streaming services) and Foursquare (search and discovery services) use RS to suggest services and product to their user (Contratres & Alves-souza, 2018; Kartoglu & Spratling, 2018).

3.4 Serendipity

Currently, many RS is embedding with an element of surprise: Serendipity. As (Möller *et al.,* 2018) stated that serendipity had to become a crucial element of recommender system algorithms. In computer science, there is no agreement on how serendipity should be operationalized and conceptualized other than unexpectedness (Möller *et al.,* 2018). Serendipity represents the element of "surprise" or "unusualness" of recommendations (Rana, 2013; Zhang & Séaghdha, 2012). In past studies, serendipity was defined as "happy accidents" (Magennis *et al.,* 2016), "accidental discovery", or "unintended finding" (Yi *et al.,* 2017). Oxford Dictionary stated that 'serendipity' is "the occurrence and development of events by chance happily or beneficially,' while the origin of the term was "making discoveries, by accidents and sagacity,"(Erdelez *et al.,* 2016). For more than a centuries, the topic of serendipity has been studied in various disciplines (Erdelez *et al.,* 2016) such as medicine, entrepreneurship, organizational sciences and information sciences (Yi *et al.,* 2017). However, in IS research, this concept is still scarce.

3.5 Big Five Factor

Big Five Factor is a factor that will be used in this system. Big Five Factor is an established model that is describing personality (Simha & Parboteeah, 2019). In 2020, Halama *et al.* stated in their study that this approach identified five personality traits (i.e., Extraversion, Neuroticism, Agreeableness, conscientiousness and Openness to experienced). This model is believed to be appropriate as cross-culture psychological factors (Simha & Parboteeah, 2019). User will be matched based on their personality traits to reduce psychological strain.

4. Methodology

The methodology of this proposed work is based on the Design Science Research Process (DSRP) (Dalén & Krämer, 2017; Shrestha *et al.,* 2017). It can be summarized into several stages, i.e.: (1) problem identification and motivation, (2) objectives for the solution, (3) design and development, (4) demonstration, (5) evaluation and lastly (6) communication. Figure 1 shows the DSRP methodology describing all the stages.

The first stage is the problem identification and motivation. In this stage, the problem statement was formulated based on the literature to consolidate the identified problem. Then, the solution for the issues highlighted is to develop a hybrid model that will resolve all the issues. The third stage focuses on designing and developing the model that are divided into three (3) categories (i.e.: profiling, social recommender model and integration). The evaluation will execute after the model development and integration. The evaluation stage is to verify and validate the proposed model that involves two different techniques. The first technique is a deep learning and the second technique is the reasoning. Both techniques will go through verification and validation stages before combining in a sequential hybridization.

The demonstration stage is about prototype development. This stage will embed the social recommender model with robot platform design. After the model is integrated with robotics, it will be validated with human experiment, which is usability test. Lastly, the final stage in this methodology is communication (conclusion in some other research design). This stage introduces all the printed documents for publication in conferences or journal and also the final thesis to complete this research.

5. Proposed Model

The proposed model is a hybrid serendipitous social recommender model. This process starts with an automated attribute selection by rough set theory (RST). RST is a mathematical tool that widely being used for knowledge discovery and feature selection (Anaraki & Eftekhari, 2013). Rough set evaluates important attributes to minimize redundancies among variables in classifying the objects (Azar, 2015). Also, it can be used to extract rules from the database. Next, this model will use multistage classification techniques that involve deep learning algorithms because these algorithms are used for processing massive data and widely applied in many research fields (Rahmat *et al.,* 2019) and combine with reasoning approach to learn about the attribute of the person. This technique is used to compute selected attributes. Deep learning aims to define the higher matching suggested attributes. The reasoning later is used to find the reason why the attributes are chosen. This approach searches the history of the selected attribute (if the attribute is repeatedly used) or computes the reason by digging back in the database to find the reason why that attribute is chosen. In this model, data will be computed in several layers to obtain the preferable matching attributes. Next, this model uses multistage classification techniques that involve deep learning algorithms and reasoning approaches to learning about the attribute of the person and is used to compute the selected attributes.

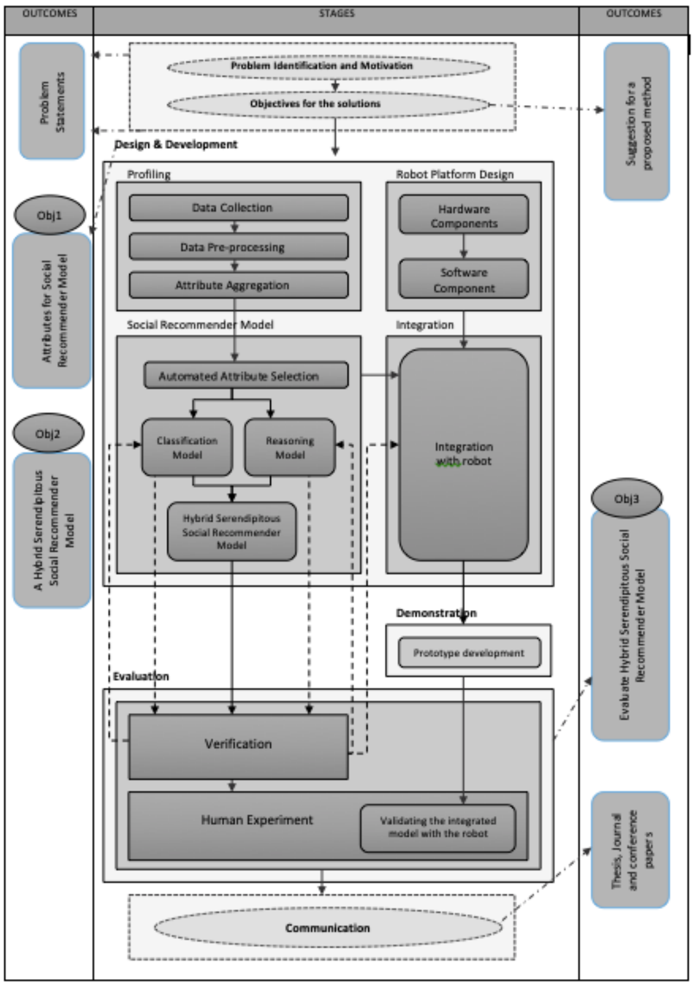

Figure 1. Design Science Research process

Figure 2 shows the proposed hybrid serendipity social recommender model. The processed data will go through the multistage model. The first model is a rough set theory (RST) that will compute data reduction and the raw data is the input. The reduced data after data reduction acted as input for Deep Learning Neural Network (DLNN). This DLNN will then compute the similarities between the data and will output the percentage. This percentage will act as the input for case-based reasoning (CBR) to referring back to its reduced data and will give the reason for the output percentages.

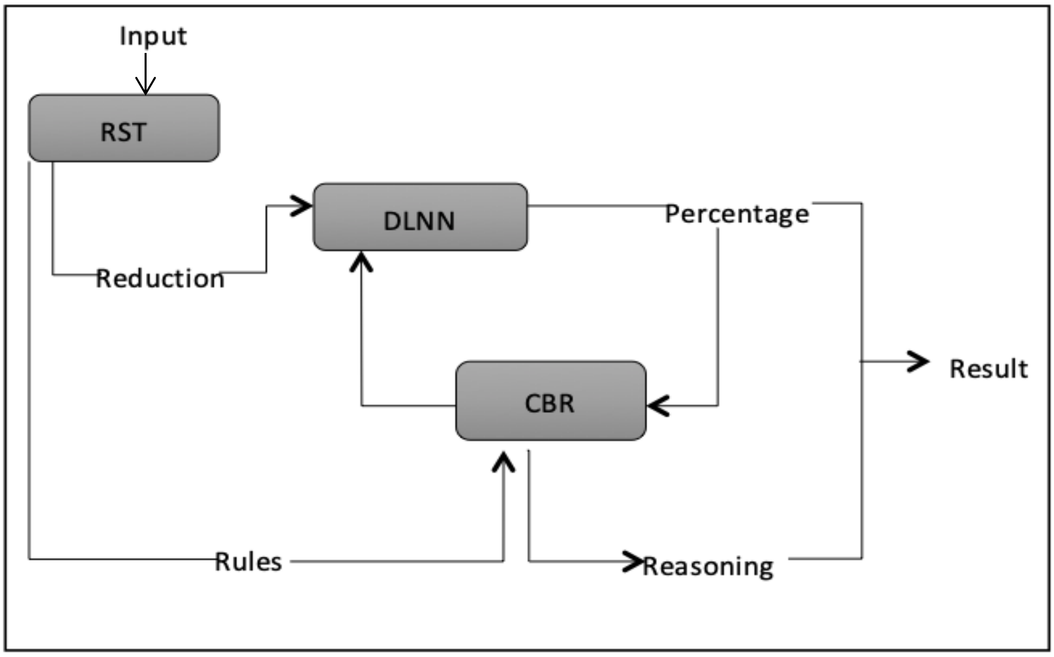

Figure 2: Hybrid serendipity social recommender model.

6. Conclusion

This paper proposed a hybrid serendipity social recommender model that is developed by combining several models. Rough Set Theory is used at the early stage of this model followed by classification model to classifying the data into subclasses and lastly, reasoning model is used to produce reason(s) for the result. The result will be computed in order for measuring the accuracy of the model, whether it could increase the serendipitous accuracy or not.

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