Journal of Engineering and Applied Sciences 12 (Special Issue 12): 9341-9351, 2017
ISSN: 1816-949X

Using Recommender Systems to Support Idea Generation Stage

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Abstract: In order to successfully cope with this era of rapid changes organizations need to develop effective and efficient innovation processes that ensure continuous stream of new valuable ideas that lead to useful innovations. However, generating novel and useful ideas remains a challenging and crucial innovation task. The current study presents a new use of recommendation systems in the first key activity of the front end of innovation and which can assist organizations to improve their ways of generating new ideas. Actually in this study, we investigate the particular use of recommender systems in the idea generation context to encourage actors to contribute their ideas and ensure the good quality of submitted content. We first present the motivation behind this research and define the concept of recommendation. From this, we deduct the different advantages of using recommender systems in idea generation stage. Next, we provide an overview of existing recommendation approaches. From the literature, we draw a synthesis of important learning gathered. Then, we analyze and discuss based on a set of defined characteristics the use of recommendation systems in this initial phase of idea generation. From the results of this analysis, we formulate a concluding remarks aiming to identify the technique which seems the most suitable to meet our qualitative approach in this specific context.

Key words: Idea generation, recommendation systems, creativity, collaboration, quality, innovation

INTRODUCTION

According to recent studies, the Front-End (FE) phase of the innovation process represents the most critical and challenging phase of the whole innovation process and simultaneously the greatest opportunity to improve organization's overall innovation capability. Idea generation is considered as one of the first general key activities in the front-end of the innovation process but often given a limited attention. Studies have shown that companies that are skillful of managing the very first phase of the innovation process are more likely to succeed in the rest of the innovation journey (Kim and Wilemon, 2002). In this respect, the generation stage thus needs to be well-managed and requires well-developed mechanisms for searching and gathering a larger quantity of very high quality ideas.

Theoretical results indicate that application of tools and techniques which help organizations to create more ideas is necessary but not sufficient to reach the expected quality of generation stage outcomes (El-Haiba *et al*., 2017). However, these techniques have to be refined and supported by effective tools that boost creativity and improve the process of ideation. Moreover and to be able to respond more effectively to the emergent challenge which is to connect "the right idea to the right actors in the right context (Elbassiti and Ajhoun, 2014)", organizations should make best use of their knowledge resources. Hence, the idea of integrating recommender systems defined as systems that can provide custom recommendations and guide the user to find interesting resources in a large data space (Burke, 2002).

The central contribution of this study is to analyze how idea generation stage can usefully benefit from recommender systems in order to nourish innovative thinking and principally enhance the quality of generated outcomes. To that end, we will try to answer five main questions:

- What are the main features of a recommender system, in idea generation point of view?
- What is the expected added value of recommender systems from an idea management and generation point of view?
- What are the existing approaches of recommendation known in the literature?
- What are the main techniques involved in recommender systems?
- Which technique seems the most suitable to meet our approach to idea generation?

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Problem statement: When organizations decide to develop a new product, it typically create several hundred of ideas or alternatives then select a few of these for further investigation. So, generating the raw ideas that act as the starting point and feed subsequent development processes plays a critical role in innovation and need to be generated quickly as well as qualitatively. At this stage and on the background of the literature review, there are some weaknesses that need to be considered. These weaknesses concern, especially, the quality of submitted ideas. Actually, most papers in literature focus on the number of ideas generated as opposed to their quality with the tacit assumption that quantity leads to the quality (El-Haiba *et al*., 2017). Also, the few studys that look at the quality of ideas look at the average quality of ideas generated as opposed to the quality of each idea, ignoring what most organizations seek, a few great ideas (El-Haiba *et al*., 2017). This research actually attempts to address a significant need to develop a creativity support within organizations that encourage active participation in the generation of new ideas and improve the quality of submissions. In the study, we discuss and analyze the integration of recommender systems at generation stage in order to meet the various issues and exploit their potential to innovate more effectively. Regarding the current limitations, the theoretical results of the study are highly promising but however should be practically implemented in order to test the impact of this new use on the quantity and the quality of participation. Also, we need to identify a specific application domain for the validation of obtained results. All this of course, fits into the range of our perspectives and future research.

Context of the study: The main purpose of this section is to present the context of the study and discuss how the recommendation concept would be valuable for idea generation quality improvement.

Idea management: Idea generation stage: The research forms a part of a project aimed to manage innovation in organizations with a specific focus on idea management. As first results, a new lifecycle was proposed (El-Bassiti and Ajhoun, 2013). The main aim of this lifecycle is to manage idea from its emergence until it's moving towards the project phase or its abandonment. This lifecycle covers the following stages as shown in Fig. 1.

Generation where new ideas are identified and formulated, interlinking where created ideas are interlinked to other innovation deliverables and actor's profiles, improvement where interlinked schemas of idea profile are transformed into a workable concept through collaboration, validation where current ideas are validated and the most promising one are selected, followed by

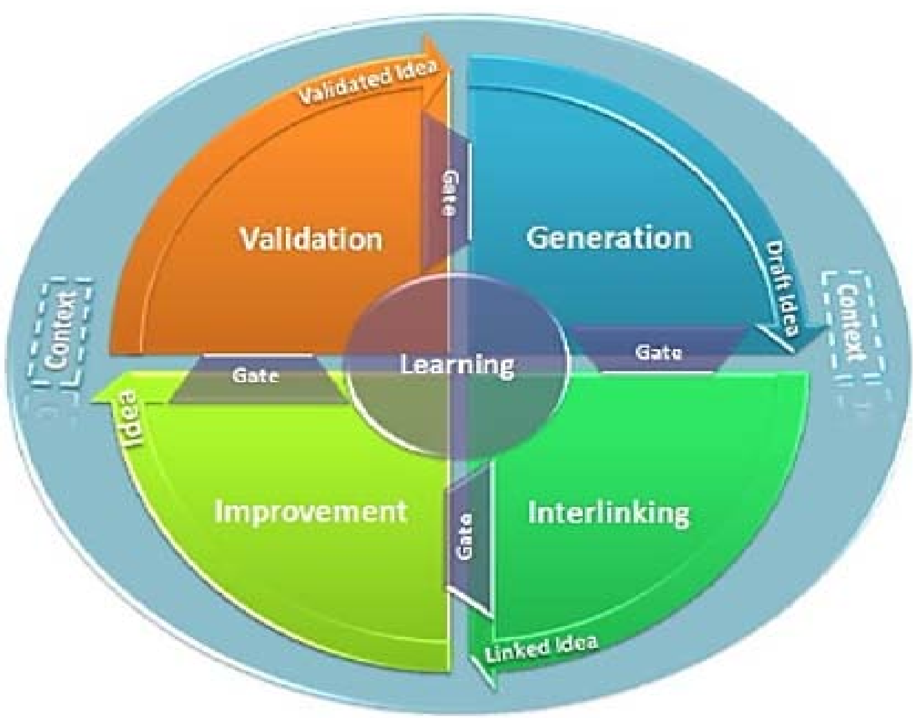

Fig. 1: Idea management life cycle (El-Bassiti and Ajhoun, 2013)

decision points “gates’ that are planned to sift the attractive ideas, knowledge engine that enable learning to occur and flow and contextual factors to keep alignment with organization’s strategy, goals, needs (El-Bassiti and Ajhoun, 2013).

As for us, we focus our study on the generation stage, the first stage which is largely still unstructured in the most organizations (El-Haiba *et al.*, 2017). Idea generation is the creative stage where new ideas are gathered and/or new opportunities identified. Being successful in this phase however involves the ability to generate and collect new promising ideas with potential for future growth. To this end, various methods and techniques that enables teams and groups to contribute to the generation of ideas exist. As stated in the introduction, using only those techniques is not enough. All too often they are used to generate a vast quantity of ideas but this doesn’t seem to translate into real projects. In practice, this generation stage like idea management systems of which it is part, still faces a number of problems usually related to information overflow and recognizing questionable quality of submissions (Westerski, 2013).

A qualitative approach to manage idea generation: In a previous research, we presented an approach with the particular emphasis on the idea generated quality (El-Haiba *et al.*, 2017). The main purpose of this approach is to support the process of gathering ideas from all actors in a structured way with a goal of producing ideas with higher quality. Figure 2 represents the proposed qualitative approach.

The model is centered on quality improvement which is guided and supported at the top by organization structure and processes (including strategy, culture, leadership, climate, …), its human capital (with the personal motivation of sharing, collaboration, contribution, …) as well as information and knowledge (as an important stimulus of new innovative ideas generation) (El-Haiba *et al.*, 2017). This actually implies that all parties should be involved at the same time for the benefit of idea generation stage and of course the innovation process. However, the approach aims to improve the idea generation stage by ensuring better control of the process in terms of time and quality. In this way, we increase the chance of ending up with the most promising idea in the initial stage and thus speed up the innovation process.

Motivation: Taking into account the approach, it’s moreover important for organizations to have a strategic vision of innovation especially the generation of new

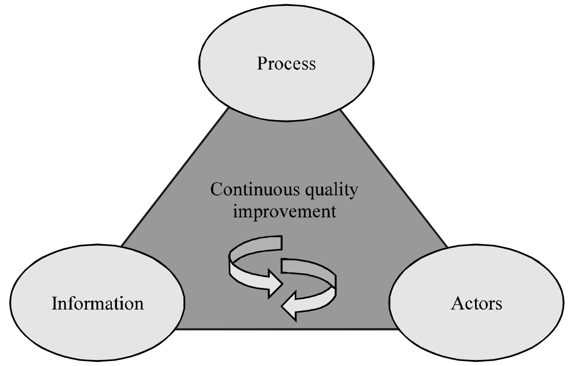

Fig. 2: Model of quality (El-Haiba *et al.*, 2017)

ideas as being the first pillar of the innovation process. In our view, organization should not wait until ideas arrive arbitrarily or a serious problem occurs to start looking for creative ideas in response but rather proactively plan for this. In other words, our aim is to promote the continuous generation of creative ideas and to have an anticipative pool of ideas as a preventive action to decrease problem risks. In fact, more than its traditional definition, the idea generation stage must be an opportunity to both focus and motivate the creation of new ideas and from all areas of the organization, not just specialized departments like R&D. This indeed suggests providing actors the appropriate incentives to generate more ideas and collaborate on the improvement of outcomes. So for this purpose and in order to implement the approach, organizations need to integrate hyper-performing systems to better manage and exploit their resources.

Employees are in general a valuable source of new ideas but sometimes they need inspiration from somewhere. In fact, it’s all about being in the right state of mind and allowing other stimuli into the brain to trigger potential solutions and generate innovative ideas. Viewing other’s ideas is one of important sources of inspiration. Actually, ideas suggested by others aid the activation of problem-relevant knowledge (Nijstad and Stroebe, 2006). Similarly, access to ideas of others can stimulate creativity. Additionally, properly prepared idea outcome data can be used as a motivator in idea generation phase (Westerski, 2013). When employees see the outcome of all of the submitted ideas this increases their enthusiasm for participation in idea generation. It inspires and encourages them to take part in generation of new ideas and/or further development of existing ones. However, being supported by systems which allow access to existing corporate knowledge can certainly help actors to think differently and organizations to innovate efficiently.

Furthermore, most organizations produce a significant number of promising ideas but most of which are often isolated, loosely connected to the business and not exploited. Typically, organizations fail to convert them into valuable outcomes. This in our view is due to the fact that there is still a lack of interlinking between ideas generation outcomes. Indeed, connect idea profile to existing profiles in terms of ideas, actors and innovations facilitate the task of finding entities that can serve as a source of inspiration, learning and future collaboration (El-Bassiti and Ajhoun, 2013). In sum, the key is to go beyond the usual thinking and find interesting resources in a wide range of data. This is where recommender systems have particularly a huge advantage.

MATERIALS AND METHODS

Recommender systems at the front end of innovation

Recommendation systems: Recommender Systems (RS) or recommendation systems are software tools and techniques providing suggestions for items to be of use to a user. The suggestions relate to various decision-making processes such as what items to buy what music to listen to or what online news to read (Ricci *et al*., 2011). They have become fundamental applications in electronic commerce and information access, providing suggestions that effectively prune large information spaces so that users are directed toward those items that best meet their needs and preferences (Burke, 2002). Currently, recommender systems remain an active area of research with a dedicated ACM conference, intersecting several sub-disciplines of statistics, machine learning, data mining and information retrievals. Applications have been pursued in diverse domains ranging from recommending webpages to music, books, movies and other consumer products (Melville and Sindhwani, 2010). A well-known example is the recommendation from Amazon. In the popular web site, Amazon.com, the site employs a RS to personalize the online store for each customer. Amazon can study a customer's profile and analyze the feedback that the customer provides, to recommend books and other items to him or her.

In sum, RSs were created to guide the user in a personalized way to interesting resources and to help users cope with the problem of information overload (Mican *et al*., 2012). Principally, their purpose is to filter information according to the interest of users. Their usefulness is even greater when data space becomes complex. They are usually classified into the following three main categories depends on their approach to recommendation and which will be more detailed later:

Content-based filtering: Recommend items that are similar in content to items the user has liked in the past or matched to attributes of the user (Melville and Sindhwani, 2010).

Collaborative filtering: Items are recommended based on the past ratings of users with similar tastes and preferences (Melville and Sindhwani, 2010).

Hybrid approach: These methods combine both collaborative and content based approaches (Melville and Sindhwani, 2010; Adomavicius and Tuzhilin, 2005).

Other types of recommender systems exist; they are classified as a modern and have been introduced to improve the recommendation accuracies:

Context-aware: Suggest recommendations by including contextual information (such as time, location, weather or accompanying persons) that may influence user decisions (Adomavicius and Tuzhilin, 2015).

Social network-based: Recommend items by utilizing information in social network, especially, that of social influence (He and Chu, 2010).

How idea generation can benefit from RS?: Because we strongly believe that generating creative ideas is essential for survival and success of organizations, our objective is to drive the idea generation process while preserving a creativity margin for actors in order to initially participate by their own ideas and then be guided by recommender systems to further refine them. More specific, our aim is to provide actors the foundations and guidelines to develop the ability to think differently in terms of viewing and stimulate idea generation. In fact, those who wish to achieve any type of innovation must encourage ideas and provide guidance for the scope of ideas. This requires, in particular having right tools which guide actors, push them to generate worthwhileideas and help them, at any moment, to situate themselves in the context where they are requested to act. So, by matching our present needs in idea generation to the manifold definitions of RSs their usefulness appears clearly. Figure 3 shows the matching between our requirements and services provided by RSs.

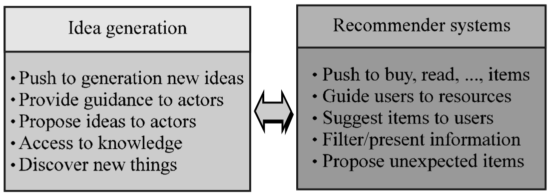

Fig. 3: Matching between IG and RS

By analogy, it will be also possible to define the recommendation more specifically to our research area while illustrating a range of possible roles that a RS can play. However, recommender systems can be:

A personalized way to communicate: Organizations can know more about their employees/actors by providing them a personalized space where to create their profiles, post their ideas, comment on, share their experiences, express their opinions and beliefs, further improve each other's ideas, acquire knowledge, contribute with information and discover something good or useful while not specifically searching for it (Serendipity).

Relevant for the triggering of new ideas: Or even the enrichment of existing ones. They can be considered as a source of inspiration, a new way of thinking by opening mind to new perspectives through recommendations. They operate as catalysts, allowing human brain to externalize its creativity. Thus help organizations to harness the innovative spirit of its employees. Actually by presenting suggestions, some ideas will be mad, some will be bad and some will inspire better ideas. And this is what we are looking for: inspiring ideas.

An opportunity to deal with the information overload: Ultimately a RS addresses this phenomenon by pointing a user towards new, not-yet-experienced items that may be relevant to the user's current task. Upon a user's request, RSs generate recommendations using various types of knowledge and data about users, the available items and previous transactions stored in a structured way in a customized databases.

Used to increase the employees motivation: RS can improve the experience of the user by providing him suggestions-ideas with similar interests to its own where he can create value by participating to further implementation. In fact, working together to solve common problems and develop ideas will certainly help break down the barriers. It's an occasion for employees to become innovation actors.

Table 1: The advantages of using recommender systems

Values for actor	Values for organization
Find things that are interesting	Create personalized space for actors
Help him explore the space of ideas	Gather new ideas
Get inspiration	Increase quantity and quality of
Encourage him to bring fresh ideas	ideas
and enrich existing ones	Obtain more knowledge about actors
Boost and expand creativity	Benefit from the potential of her
Share insights and experiences	creative thinkers

Valuable to improve the quality of generated ideas: By expressing their ideas and receiving recommendations in return, actors can explore the set of ideas previously generated and thus avoid unnecessary duplication of ideas, link the proposed idea to existing ones, learn from prior experiences and ensure development continuity of ideas already expressed. Actually, experience with the guidelines will provide guidance as to how to further refine them. Undoubtedly, this will allow the improvement of ideas quality.

As aforementioned, we investigate the use of recommender systems in idea generation context in order to improve the generation stage and ensure a continuous flow of high quality ideas. This in fact can make recommender systems applicable to an even broader range of applications. So, after these definitions, we can synthesize that through recommendation, idea generation stage can greatly benefit from potential advantages of those systems. Table 1 presents the motivations as to why we want to exploit this technology by listing the main profits whether for actors or organization.

Our vision: This study studied the motivation behind the use of recommender systems at idea generation stage and their impact on the quality of submitted ideas. In what follows, we summarize our study by presenting our vision to idea generation. Figure 4 shows our representation of idea generation process.

This model of process describes in our view, the key steps for an effective idea generation stage while specifying the particular use of recommender systems in this context. The process is designed around best-practice steps to support organizations with a series of clear and purposeful elements for their idea generation stage and innovation program in general.

Nurture idea generation: Involves creating a favourable climate to innovation and changing the prevailing culture that limits the emergence of new ideas. This actually implies preparing the right organization by cultivating a creative environment that encourages people to think in unusual ways and building a workplace where there is a

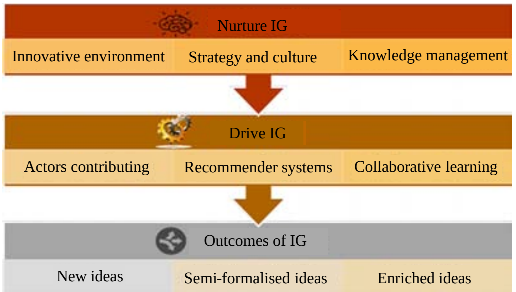

Fig. 4: Idea generation process

constant exchange of ideas. One other key component of this step is knowledge within the organization. Internal communication, based on openness and trust is a key to setting this atmosphere. Indeed, organizations should make effective tools of gathering and sharing knowledge available to all staff.

Drive idea generation: Consists to highlight the central role of the employee in the innovation system. Actually, employees with their competencies, skills and abilities can contribute to innovation by suggesting insights or refining existing ones "best ideas come from employees". Furthermore and through recommendations, actors are exposed to various related ideas submitted by others or projects already implemented. Recommendations actually offer a support and act as a source of inspiration to employees. They also allow them to learn from each other, use prior learning to start new initiatives, boost their creativity in order to make their ideas better and increase team's productivity.

Outcomes of idea generation: Represents the achievement of preceding steps. New submitted ideas, semi-formalized ideas and enriched ideas which occur after recommendation. It's in fact series of new ideas that meets organizations strategic goals with series of individual and group improvements to refine ideas. They can be either a fully developed, ready-to-implement proposal or an incremental contribution to the overall initial idea.

RESULTS AND DISCUSSION

Comparative study of recommender systems: This section presents the techniques most popularly used today for building RSs such as content-based and collaborative filtering which can be characterized as basic types of most modern recommender systems; hybrid methods; context-aware and social network-based. They will be more detailed with the goal of understanding their strengths weaknesses and limitations.

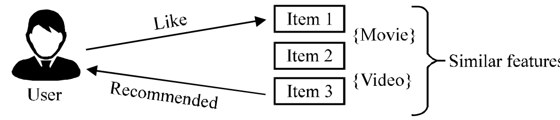

Fig. 5: Content-based filtering

Recommender systems approaches: An overview of main techniques is summarized as.

Content-based: In the recommendation process, the engine compares the items that were already positively rated by the user with the items he didn't rate and looks for similarities. Those items that are mostly similar to the positively rated ones will be recommended to the user. Systems implementing this approach try to analyze a set of documents and/or descriptions of items previously rated by a user and build a model or profile of user interests based on the features of the objects rated by that user (Mladenic, 1999). Figure 5 illustrates the approach.

The approach to recommend in such systems has its roots in the Information Retrieval (IR) and information filtering research (Adomavicius and Tuzhilin, 2005). Besides these methods, other techniques for content-based recommendation have also been used such as bayesian classifiers (Mooney *et al.*, 1998), different algorithms of measuring similarities and various machine learning techniques, including clustering, decision trees and artificial neural networks (Mooney *et al.*, 1998).

Collaborative filtering: CF is the most familiar and most widely implemented. They have been successful in many e-commerce applications. It is a popular technique used to reduce information overload (Herlocker *et al.*, 2004). The idea of collaborative filtering is in finding users in a community that share appreciations (Linden *et al.*, 2003). If two users have same or almost same rated items in common then they have similar tastes. Such users build a group or a so called neighborhood. A user gets recommendations to those items that he/she hasn't rated before but that were already positively rated by users in his/her neighborhood. Figure 6 illustrates the approach.

CF methods can be further sub-divided into two general categories. Both techniques have proven their performances in different contexts.

Memory-based (or user-based): Recommendations are given to user based on evaluation of items by other users form the same group with whom he/she shares

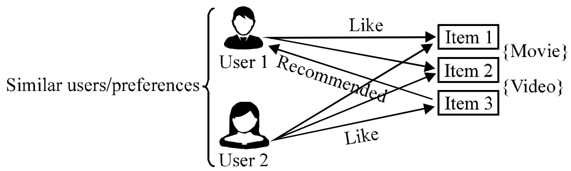

Fig. 6: Collaborative filtering

common preferences. If the item was positively rated by the community, it will be recommended to the user (Zhao and Shang, 2010).

Model-based (or item-based): The fact that the taste of users remains constant or change very slightly similar items build neighborhoods based on appreciations of users. Afterwards the system generates recommendations with items in the neighborhood that a user would prefer (Sarwar *et al*., 2001).

Various methods such as correlation and cosine-based have been used to compute the similarity between users in collaborative recommender systems. Moreover, CF method has been proposed in data mining or machine learning where various machine learning techniques (such as artificial neural networks, Bayesian networks, clustering and latent semantic analysis) coupled with feature extraction techniques can be used (Adomavicius and Tuzhilin, 2005).

Hybrid methods: The hybrid approach has been introduced to avoid the limitations of the content-based and CF approaches. Several recommendation systems combine two or more approaches to gain better performance and eliminate some of the drawbacks of the pure recommendation systems approaches (Alsalama, 2013). Combining CF and content-based approaches is mostly used today in the industry (Fig. 7).

Among the hybridization methods which are employed: Weighted where the scores (or votes) of several recommendation techniques are combined together to produce a single recommendation, switching where the system switches between recommendation techniques depending on the current situation or mixed where recommendations from different recommenders are presented at the same time (Burke, 2002). Another type of personalized recommendation exit:

Demographic: This type of systems recommends items based on the demographic profile of the user only. The demographic types of users include gender, age and knowledge of languages, disabilities, ethnicity, mobility, employment status, home ownership and even location. The system recommends items according to the demographic similarities of the users (Arekar *et al*., 2015).

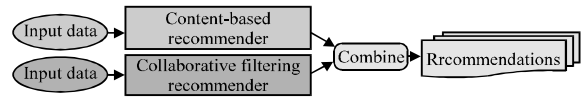

Fig. 7: Hybrid recommendation

Knowledge-based filtering: Attempts to suggest objects based on inferences about a user's needs and preferences (Burke, 2002). Knowledge-based systems recommend items based on specific domain knowledge about how certain item features meet user's needs and preferences and ultimately, how the item is useful for the user (Ricci *et al*., 2011). They are based on the explicit knowledge about item classification, user interest and recommendation standard (which item should be recommend in which feature) (Arekar *et al*., 2015).

Context-aware (CARS): The majority of existing approaches to RS focuses on recommending the most relevant items to individual users and do not take into consideration any contextual information such as time, place and the company of other people (Adomavicius and Tuzhilin, 2015). The recommender systems that pay attention and utilize such information in giving recommendations are called context-aware recommender systems. Context is the information about the environment of a user and the details of situation he/she is in. Such details may play much more significant role in recommendations than ratings of items as the ratings alone don't have detailed information about under which circumstances they were given by users (Fig. 8). Three different algorithmic paradigms of using the contextual information in recommendation process have been introduced: contextual pre-filtering, post-filtering and modeling (Adomavicius and Tuzhilin, 2015).

One of the biggest problems of CARS is obtaining context information. The information can be obtained explicitly by directly interacting with user asking him/her to fill out a form and making a survey. Another way is gathering information implicitly using the sources like GPS to get location or a timestamp on transaction. The last way of information extraction is analyzing users observing their behavior or using data mining techniques (Adomavicius and Tuzhilin, 2015).

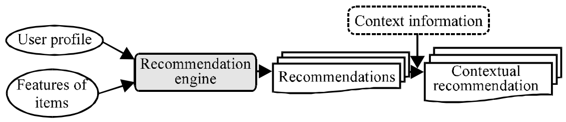

Fig. 8: Context-aware recommender system (post-filtering)

Social Network-Based (SNRS): Social recommendation has been studied, since, Kautz *et al.* (1997) and has attracted increasing attention with the growing popularity of social media (King *et al.*, 2010). Online Social Networks (OSN) present new opportunities as to further improve the accuracy of RSs. In real life, people often resort to friends in their social networks for advice before purchasing a product or consuming a service (Yang *et al.*, 2014). A narrow definition of social recommendation is any recommendation with online social relations as an additional input. Social relations can be trust relations, friendships, memberships or following relations (Tang *et al.*, 2013). In this definition, social recommender systems assume that users are correlated when they establish social relations (Tang *et al.*, 2013). However, social recommendation is still in the early stages of development and there are many challenging issues needing further investigation (Tang *et al.*, 2013) (Fig. 9).

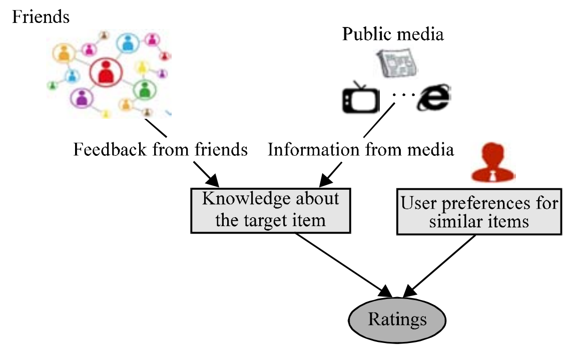

Fig. 9: Factors that influence the user decision in SNRS

Challenges and issues in recommendation systems

Sparsity: Stated simply, most users do not rate most items and hence the user ratings matrix is typically very sparse. It decreases the probability of finding a set of users with similar ratings. This problem often occurs when a system has a very high item-to-user ratio or the system is in the initial stages of use (Melville and Sindhwani, 2010).

Cold-start: Occurs when too little rating data is available in the initial state. The recommendation system then lacks data to produce appropriate recommendations. Two cold start problems are new user problem and new item problem (Arekar *et al.*, 2015).

Stability: The converse of the cold start problem. When consumers have rated so many items their preferences in the established user profiles are difficult to change (Arekar *et al.*, 2015).

Scalability: With the growth of numbers of users and items, the system needs more resources for processing information and forming recommendations. Majority of resources is consumed with the purpose of determining users with similar tastes and goods with similar descriptions.

Gray sheep: Refers to the users whose opinions do not consistently agree or disagree with any group of people and thus recommendations for them are very difficult to find (Arekar *et al.*, 2015).

Over-specialization: When the system can only recommend items that score highly against a user's profile, the user is limited to being recommended items similar to those already rated (Adomavicius and Tuzhilin, 2005).

Privacy: Affect both, the collection of explicit and implicit data. Regarding explicit data, users are not interested to disclose information about themselves and their interests. If questionnaires get too personal, users may give false information in order to protect their privacy (Arekar *et al.*, 2015).

Synthesis: As we have seen there are different approaches to recommendation systems that are used to serve in different contexts based on system needs (Burke, 2002). What is certain is that the design of such recommendation engines depends on the domain and the particular characteristics of the data available. However, it is essential to pick an algorithm that is suitable for the problem being addressed. Therefore, all recommendation approaches have strengths and weaknesses (Table 2).

Which recommendation approach to improve idea generation performance?: As noted before, several techniques of recommendation with different approaches exist. In this study, we will discuss possible extensions of recommendation which make recommender systems applicable to an even broader range of applications especially in our idea generation context.

Table 2: Types of recommendation systems

Approach	Objective	Main techniques	Advantages	Drawbacks	Applications
CB	Provides recommendations based on items already evaluated and liked by user in the past	Stemming Information retrieval TF-IDF Cosine similarity Pearson correlation Bayesian classifiers Clustering Decision trees	User Independence Transparency Recommend new items not yet rated by any user Able to recommend users with unique taste	Have a natural limit in the number and type of features Over specialization Serendipity Not be able to provide recommendations for new user	Letizia Infoscope News dude
CF model based	Recommends items to a particular user based on the similar items that have been rated by some other users with similar preferences	Simple bayesian networks Clustering Latent semantic Sparse factor analysis	Allow an intuitive rationale for recommendation Insensitive to sparsity Well support of the scalability	Lose useful information for dimensionality reduction Expensive model making	Amazon eBay IMDb Elseiver Pandora
CF memory based		Neighbor-based Correlation-based similarity Graph theory Vector cosine correlation KNN co-rated items	Easy implementation Supporting adding new data Need not consider the content of the items being recommended Scale well with when data are sparse	Are dependent on human ratings Cannot recommend for new users and items: Cold start Gray sheep Performance decrease	
Hybrid	Combines content-based and collaborative components	Combining content based and collaborative components using: Weighted Switching Mixed	Overcome limitations of CF and content-based Improve prediction performance Overcome CF problems such as sparsity and gray sheep	Need external information that usually not available Have increased complexity and expense for implementation	Netflix PTV Cinem screen Youtube
CARS	Incorporates contextual information into the recommendation process in order to recommend items to users in certain circumstances	Content based Collaborative filtering	Adapt user's preferences to dynamic situations Improve the quality of recommendations	Privacy and security issues Contextual user preference extraction	COMPASS Booking TripAdvisor
SNRS	Recommends by utilizing information in social network especially that of social influence	Social network analysis SNA Memory based CF Model-based CF	Improve the prediction accuracy of recommendation Remediate data sparsity and cold start issues	Friends may not always have the same interests: especially casual and event friends Noise connections Privacy protection	Facebook LinkedIn Twitter

Evaluation of recommender systems: In order to compare the presented approaches and assess their merits to contribute to the new definition of idea generation we need to specify a set of criteria and then check if each of them satisfies these criteria. Actually we have defined generating ideas in previous research as the process of capturing ideas aligned with the requirements set by the organization and which includes elements related to creativity, knowledge, collaboration, learning and details of the organizational structure to support the process (innovation context) (El-Haiba *et al.*, 2017). However, in what follows we will try to analyze if the different recommendation approaches will permit generating ideas while respecting these elements or criteria. Towards this goal, it's first of all important to describe our own vision and need to idea recommendation in each dimension:

Creativity (C1): Can the approach recommend to an actor, according to his profile and skills, ideas that can interest him and spark his creative imagination to generate innovative new ideas or enrich existing ones?

Knowledge management (C2): Does the approach allows better knowledge management that help actors have quick access in knowledge and experience that are diversified in the whole organization to help them discover and develop new things?

Collaboration (C3): Is there any social interaction which is essential for the forming of new ideas in the approach? Does the approach fosters actor collaboration to improve the gathered ideas?

Learning (C4): Ideally, input and output of the generation stage should be structured to reuse the data for improving the quality of future ideas. Does the approach allows actors to learn from previous experiences and outcomes in order to benefit from it?

Context (C5): Does the approach take into account contextual factor that impacts the innovation process and recommend ideas which are aligned to this context (i.e., time, location, goals, needs, ...)? Relatively to these criteria, recommendation must also take into account:

Pertinence (C6): With reference to both quantity and quality of recommended items and thus of generated outcomes. In fact, we strongly believe that the recommendation quality affects the idea generation quality.

Based on these 6 factors and the detailed description of each approach, we evaluated the recommendation approaches presented above in respect to their purposes and their intended use. Table 3 presents a summary of this evaluation.

As we have seen the bulk of these approaches does not respond completely to the defined criteria and can sometimes overlap. Actually, this overlapping (which is expressed in the table as ×√) in certain case is due to a specific reason and the obtained results for each approach can be explained as follows:

Content-based: This approach in fact presents a limitation in the number and type of recommended items which considerably affects the recommendation quantity and the creative imagination of users. On the other hand, it fully covers learning and knowledge management.

Collaborative filtering: This approach meets the majority of criteria but doesn't take into account any contextual information. The overlapping here is due to the quality of recommendations which depends on the size of the historical rating data set.

Hybrid recommendation: This approach actually responds to the previous shortcomings thus the only missing element is the context dimension.

Context-aware: By considering context this approach seems perfectly adapted to our needs, the only overlapping here depends on the used technique which determines if collaboration will be implemented or not.

Table 3: The comparison of recommendation techniques

Approach/Criterion	C1	C2	C3	C4	C5	C6
Content-based	×	√	×	√	×	×
Collaborative F	√	√	√	√	×	×√
Hybrid	√	√	√	√	×	√
Context-aware	√	√	×√	√	√	√
Social network	×√	√	√	√	√	×√

Social network: All overlapping are due to the type of social relations between users which affects principally the quality of recommended items thus the creativity and relevancy.

However, it's extremely delicate matter to determine which approach is the most suitable to meet our need but rather bring improvement or think to a combination based in particular on the advantages and drawbacks identified in Table 2 previously. What is certain is the integration of recommender systems in the first stage of innovation process as a creativity support and in order to improve organizational ways of generating ideas. Moreover, it is particularly important to draw up the profiles of the idea, actor and context (contextual factors that impact the submitted idea implementation) and consider the relations between them before choosing one approach over another. This also led us to review additional knowledge sources which may be used to incorporate additional information about contextual situations of organizations. In this respect, additional research is in progress in order to identify the proper approach that would further help to enhance idea generation through recommendations.

CONCLUSION

The present study examines whether recommender systems can improve creative ideation output. Actually, our objective is to guarantee a continuous flow of new valuable ideas and ensure their continuous development. However, the integration of recommendation techniques as a creativity support to generation stage aims to provide people with a seamless experience that enhances their creativity in a natural manner. This in fact spurs idea generation. The recommendation concept can effectively help organizations improves their own process for generation new ideas internally.

This study has introduced the context of the idea generation study, presented the recommendation concept and attempted to better understand this concept through the description and the evaluation of its dedicated approaches based on a set of defined characteristics. Furthermore, it should be noted that the goal of integrating recommendation to generation stage is to support creativity and innovation.

RECOMMENDATIONS

Finally, a research initiative for future idea generation support tool was established based on the limitations of current techniques. Further research should be made to identify the most suitable and appropriate approach to adopt as well as possible improvements to bring in order to implement it. Future research will also concentrate on research to further refine profiles, modeling the entire idea generation process and define the architecture of the system.

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