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MLM based Learning & Boosting Model – Part 2: Matching User Evolutive Interests (MUEI) based on Multi-Engines Learning Match Algorithms (ELMA) using User Created Content and Universal Knowledge Repositories (UKR)

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Abstract: *Various systems have led to the arrival of a massive amounts of contents from multi-sources andvarious MicroMetadata.Hence, the problem of finding which digital resources belong to a specific interestbecomes more important.We proposed a model named LBAM: The Learning & Boosting Architecture Model, who has goals to allow to identify evolving interest of person and potentially to boost their life.The main algorithm is mainly to identify the Matching Evolutive User Interest (MEUI) by an Algorithm of matching from four different levels of User Interests: a) The User Personal Interest using the real timeSwipe Learning Match Interests; b) The Interests of the Personas of the User using Dynamic Personas Learning Match; c) The Bot swipe as a counterpart for Swipe Learning Match Interests using Bot Learning Match – a simulator of automatic matching interests based on a set of user with mainly the same Personas and d) User Created Content allowing to identify interests. The Bot Learning Match is an assisted process (ChatBot) allows to match User Interests for Digital Assets as Events, Photos, Persons, etc. This process uses Multiple Interest-based Models to learn User Interests with the Swipe principle to like (right) or don't like (left)and contextual behavior. Using simulation prototypes, we demonstrate slightly that LBAMmay improves accuracy of the predictability of User Interests in a context of MEUI.This article is the secondpaper of Life Boosterproject using LBAM.*

Keywords: *Learning Resources, Machine LearningModel, MicroMetadata, Event-based social networks, Semantic Shared Knowledge Notice,User Interests.*

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I. INTRODUCTION

Social networks have become very important for networking, communications, and content sharing.However, the large volume of types of content contributed to the difficulty of users to find content that might interest them; a potential solution is the recommendation system (RS) [1, 2][3][4][5][6]appear as a natural solution to overcome such an information overload, as they help users discover relevant information in large data sets. RS are a subclass of information filtering system that seek to predict the "rating" or "preference" that a user would give to an item. RS have become extremely common in recent years, and are applied in a variety of applications. One of the main techniques of a RS is the Collaborative Filtering which recommends products to users based on what other similar people liked in the past. The most popular RS are probably movies, music, news, books, research articles and products in general. In RSs, the semantic information of an item includes the attributes, the relationships among the items, and the relationship between meta-information and items. In recent years, ontologies have been successfully adopted in recommender systems for overcoming the shortcomings of these systems. Some RS models focused on the accuracy improvement of recommender systems by incorporating fuzzy ontology in their approach. Many researchers involve domain ontologies in the recommender systems to in measuring the preferences of users to the items of the content while some researchers develop the semantic recommendation approach using with combining item-based Collaborative Filtering (CF) and item-based semantic similarity techniques. In this work, we will be focused on events, news, knowledges recommendation systems and chatbot as communication interface.

Personal News Recommendation

The newspaper industry has experienced a substantial transformation during the last twenty years. Today, readers can find various sources of news online, e.g., on the web presences of traditional newspaper companies, on digital-only news sites, or on news aggregation platforms provided, for example, by Google or Yahoo!. Additionally, the digital form of information delivery allows publishers to distribute new or updated content in real-time, leading to an increased speed of publication. The availability of the various (often free) online news sources has led to a constant increase of users of such platforms. At the same time, however, the abundance of available information and the constant update cycle make it increasingly challenging for readers to keep track of news that are most relevant to them. Personalized News recommendation systems (NRS) in general represents another application domain in which several of the known techniques for building automated recommendations can be applied. However, news recommendation problems often have certain characteristics that are either not present at all or that are at least less pronounced in other domains. According to literature [7], NRS is still a challenging issue. First, in many news recommendation systems, the user profiles are one-sided, and user modeling from a single perspective cannot reflect the real preferences of users. Second, there is not yet a way to assess the degree of users' preferences for historical news. In reality, users' preferences for news are quite different. Thus, treating these historical records equally to analyze a user's preferences is not reasonable. Third, when building a short-term profile, most research studies abandon the relatively early browsing records, or use only a few recent browsing records. This may cause many contingencies and an incorrect understanding of the user's preferences, or the recommendation results will be too similar to what the user just read. However, some researches propose approaches helping users find interesting articles that match the users' preferences as much as possible.

Events recommendation systems

The increasing popular event-based social networks (EBSNs) [3][8][9][10][11][12][13][14][15][16], such as Allevents, Eventbrite, Meetup and Douban Event, provide online platforms for users to create, discover and share offline social events, such as concerts, exhibitions and parties. Each event published in EBSNs is associated with some metadata including an organizer who creates the event, a location where the event will be held, a timestamp when the event will start and textual content describing the event. Due to the large number of events, it is time-consuming for users to search for events that best match their interests. Indeed, as a large volume of events are published incessantly in EBSNs, it is difficult to find attractive events for users. An important task of managing EBSNs is to arrange proper social events to interested users. Unfortunately, existing approaches usually assume that each user only attends one event or ignore location information. Thus, a more intelligent EBSN platform that provides personalized event planning for each participant is desired; personalized event recommender systems appear as an effective solution to alleviate such an information overload. Event Recommendation Systems (ERS) [1][3][5][6][10][11][12][16][17][18][19][20][21][22]are proposed as a solution for the users' ability to choose the events that best fit their interests due to the sheer volume of events available in EBSNs often undermines and the severe metadata sparsity; but differently from classic recommendation scenarios (e.g. movies, books), ERS problem is arguably more challenging than classic RS approaches, since ERS need to deal with the new item cold-start problem that arises naturally in this setting. Overall, ERS in EBSNs inevitably faces the cold-start problem. Indeed, events published in EBSNs are typically short-lived and, by definition, are always in the future, having little or no trace of historical attendance. Among the various approaches of ERS for filtering information in order to generate recommendations for a user, a technique that has gained prominence by the ease of incorporation with other approaches is the Collaborative Filtering. Collaborative Filtering uses the preferences of the target-user, seeking to recommend products that other users with similar preferences of the target-user have expressed interest for in the past. An important component of Collaborative Filtering is the similarity function that determines how close the target-user is to his similars, and this is a factor that directly influences the generation of a good recommendation. However, the methods to determine similarity between users have presented some problems. The content information of events plays an important role in ERS. However, the content-based approaches in existing ERS cannot fully represent the preference of each user on events since most of them focus on exploiting the content information from events' perspective, and the bag-of-words model, commonly used by them, can only capture word frequency but ignore word orders and sentence structure.

Knowledge Recommendation Systems

A knowledge-recommendation system is based on a combination of information organization, a retrieval system, and knowledge visualization. However, when exploring digital online literature resources, it is difficult to quickly and precisely find what we want because of the problem of information organization and retrieval.

Knowledge reuse is a common means for assisting designers in accomplishing design tasks with high efficiency and quality in a short time. Knowledge retrieval and knowledge recommendation are two main approaches to knowledge reuse. Therefore, knowledge recommendation is gradually replacing knowledge retrieval as the key technology in knowledge reuse. Knowledge recommendation technologies adopt algorithms to search for knowledge that best meets the current needs of the designer and then actively recommend it to the designer. This characteristic requires less experience and is more acceptable to designers. Most researches have been focused on the "what to recommend" problem using similarity computation techniques and the "when to recommend" problem using context matching techniques, but few studies considered all the four problems simultaneously. The "who to recommend" and "how to recommend" problems are also important. These two problems relate to the designers' prior knowledge and experience.

ChatBot System

Automatic conversational agents and dialogue systems such as chatbots, personal assistants and voice control interfaces are becoming ubiquitous in modern society. Examples of these include personal assistants on mobile devices, technical support help over telephone lines, as well as online bots selling anything from fashion clothes and cosmetics to legal advice.

Chatbots are computer programs capable to carry a conversation with human. They can be seen as an artificial agent designed to serve the purpose of conversation with the end user. Chatbots are gaining popularity especially in business and health sector as they have the potential to automate service and reduce human efforts. According to [23], maturation of Artificial Intelligence (AI) technologies and integration of Natural Language Processing (NLP) fuels up the growth of chatbot.

Chatbot conversation capabilities are different with respect to different domain. Some domain requires remembering all the conversation right from the initial point of time to the end. Only then we can make inference on the basis of all sequence of conversation. Whereas in some discussion it is possible to infer on the basis of early few sequence of discussions. The different types of conversational capabilities of chatbots can have divided in three state: (1) stateless that is also described as “memory less” chatbot and where the chatbot handles each message in isolation, without taking previous messages into account; (2) semi stateful which have limited ability to remember previous user input and where the Chabot’s memory capabilities are often confined to the current conversation; (3) stateful chatbot that can remember context and previous conversations, and is able to generate responses based on this knowledge.

The remainder of the paper is organized as follows. Section 2 presents the related work. Section 3 describes the part 2 of MLM based Learning & Boosting Modeland introduces its various algorithms while Section 4 presents the evaluation through a prototype and a number of simulations. Section 5 presents a summary and some suggestions for future work. The other processes and LBAM architecture will be treated in following papers.

II. RELATED WORK

Our literature review will be focused on recommendation system for events, news and knowledges. We will discuss about the use of Chatbots in the context of recommendation system and the Swipe Learning Match Interests (SLMI).

2.1. Recommendation Systems (RS)

Recommender systems (RSs) [1, 2][3][4][5][6][13][24][25][26]are used to help users find new items or services, such as books, music, transportation or even people, based on information about the user, or the recommended item. Recently.In[3], authors provided a systematic review to investigate how ML algorithms used in RSs are studied and used; and what are the trends in ML algorithm research and development. The goals of their study are to (1) identify trends in the use or research of machine learning algorithms in recommender systems; (2) identify open questions in the use or research of machine learning algorithms; and (3) assist new researchers to position new research activity in this domain appropriately. They concluded that there is a trend for collaborative approaches, especially with the use of neighborhood-based methods. Hybrid approaches are still a research opportunity. Clustering algorithms, as well Ensemble, and Support Vector Machines (SVM) are among the ones most used. One may note again the presence of neighborhood-based approaches among the ML algorithms. Finally, authors claim that Mean Absolute Error, Precision, Recall, and F-measure are the most used performance metrics to evaluate ML algorithms in RS development, and Coverage is the most used alternative metric. M. Li*et al.*[1] presented a novel dynamic graph-based embedding (DGE) model which can effectively recommend relevant users and interested items in real-time. Authors proposed to use the distributed representation method for modeling online social networks. Specifically, they constructed a heterogeneous user-item (HUI) network, in which the two types of vertices represent users and various items and the three types of edges respectively characterize the semantic effects, social relationships and user behavior sequential patterns. Then, an incremental learning algorithm is applied to embed the HUI network into low-dimensional vector spaces, in which the proximity information of each vertex is encoded into its learned vector representation. Finally, authors used the learned representations of vertices with some simple search methods or similarity calculations to conduct the task of social recommendation. M. Nilashi*et al.*[4]developed a new hybrid recommendation method based on Collaborative Filtering (CF) approaches to overcome the sparsity and scalability problems in CF algorithms accordingly to improve the performance of recommender systems using ontology and dimensionality reduction techniques. According to authors, using knowledge about items and users help to produce a recommendation based on knowledge and reasoning about which item meet the needs of users. Authors defined two main phases: (i) the recommendation models are constructed, and (ii) the prediction and accordingly recommendations tasks are performed for a given user, called target user. *Unfortunately, their approach is strongly related to a predefined ontology; they do not propose an evolutionary ontology based on machine learning.* As mentioned, this section presents an overview of RSs and focuses on the Chatbots in the context of Semantic Matching Systems (SMS).

Research in the area of Multi-Agent Robot Systems (MARS) [5][27][28][29][30][31][32][33][34][35]has received wide attention among researchers in recent years; however, this research is more focused on the Human-Robot Interaction (HRI) to perforn some of human's physical tasks instead of Social Assistive Robotics (SAR)[31][32][34]such as Amazon's Alexa, Apple's Siri and Microsoft's Cortana. In the both case, trust is critical to the success of multi-agent robot systems (MARS). According to[27][28], trust is a fundamental part of beneficial human interaction and it is natural to foresee that it will soon be important for HRI. S. Rossi*et al.*[31]shown by comparing Social Assistive Robotics (SAR) with Virtual Agents (VA) that are applications on mobile phones. Authors addressed the comparison between these latest two technologies in the context of movie recommendation, where the two considered interfaces are programmed to provide the same contents, but through different communication channels. According to authors, the main result arising from this study is that the SAR is preferred by users although, apparently, it does not change the acceptance rate of the proposed movies. *Unfortunately, use the SAR requires that users move to the cinema.* S. Herse *et al.*[32] conducted a vignette experiment to investigate the persuasiveness of a human, robot, and an information kiosk when offering consumers a restaurant recommendation. They investigated the effect of robot persuasion on decision making when compared against the persuasiveness of non-social machines and humans. Authors found that embodiment type significantly affects the persuasiveness of the agent, but only when using a specific recommendation sentence. These preliminary results suggest that human-like features of an agent may serve to boost persuasion in recommendation systems. However, the extent of the effect is determined by the nature of the given recommendation. *As [31], the main drawback of Social Assistive Robotics (SAR) is the fact that it needs a physical presence.*

2.2. Events Recommendation Systems (ERS)

Event recommendation systems (ERS) [1, 2][3][5][6][8][9][10][11][12][13][14][15][16][17][18][19][20][21][22][36][37], as a main part of EBSNs, play a central role by suggesting relevant events to the user, and at the same time assisting event organizers to predict the overall interest in a particular event. Many approaches have been proposed to recommend different items such a movies or books; however, there are few studies that aim to suggest forthcoming events to users. In literature, different approaches are used in ERS for EBSNs: Context-Aware event matching algorithms, Context-Aware Event Recommendation [16], Content-Venue-Aware Event Recommendation [8], Utility-aware Event Recommendation, Graph based Event Recommendation[14][20], Group events recommendation[8][22][36][37]and Events similarity[19]. Unfortunately, to our knowledge, there is no a model which combines all these approaches. According ti literature, cold-start problem is one of the main issues of ERS in EBSNs. D. Horowitz*et al.*[16] proposed a context-aware tag-based mobile recommender system for events that personalizes the agenda of users attending to a congress, call EventAware (EA). EA has been specifically crafted to assist attending users to a congress by providing them with smart and personalized sessions and exhibitors during the congress. Sessions include conferences, seminars, sponsored events, and other several different programs. Exhibitors are companies who display their products and projects at the event. EA is based on a client-server architecture which consists of two main components: the Event Aware Server and the Event Aware Client. The Event Aware Server, which includes the items tag base (ITB), the user knowledge base (UKB), the Event Aware System for generating recommendations, and the initial profile builder while the Event Aware Client is responsible for gathering both contextual information and user's information, and communicating with the Event Aware Server. *Author claim that their proposal is general enough to be adapted to any event domain; unfortunately their proposal do not outperform existing models for entertainment events. In additional, their EA do not take into account user personas, current emotion and sentiments.* Z. Wang *et al.*[38] proposed a Social Information Augmented Recommender System (SIARS) that included the host-aware, member-aware, time-aware, location-aware and content-aware recommendation model, to calculate the overall recommendation score between any user-event pair. The focus of SIARS is to personalize event recommendation problem in EBSNs in order to recommend the most related events to users. To solve the severe cold-start problem in event recommendation, authors exploited the social influence of event hosts and users' group members together with event contextual information such as location, time and content. Their content-aware recommendation model uses the topic model to find the most similar topic the event belongs to while the location-aware recommendation model integrating location popularity with location distribution for event recommendation. *Unfortunately, author do not consider the users sentiments and emotion for to recommend events.* G. Liao *et al.*[37] proposed two-phase group event recommendation (2PGER) model for EBSNs to deal with the lack of attention to the fact that groups in EBSNs may have potential desires for participating in the unexperienced events, including mining implicit friendships between users, simulating the consulting process between users and their friends outside the groups, and simulating the negotiating process among members inside the groups. For handling the implicit friendships, author utilized the information of users' joining in online social groups and users' participating in offline events to mine implicit friendships and intimacy strengths between friends while the process of consulting with friends is modeled as a random walk process. For handling the negotiating process among members, they aggregated individual preferences based on method of random walk with restarts (RWR), considering the heterogeneous structure of EBSNs, the interaction between users, between events, and between users and events, and the opinions of friends outside groups. *Their proposed ERS cannot by apply for individual recommendation.* L. Tang *et al.*[39]proposed to solve the resulting cold-start problems by introducing a joint representation model to project users and events into the same latent space. They proposed a two-stage processing system by decoupling event semantic model and user profile model from final prediction model. Their method is based on deep Convoluted Neural Networks that take full context into consideration in comparison to bag-of-words-based approaches such as PLSA and LDA. Then, they fed the matching result as a feature, together with other standard features, into a gradient-boosting-decision-trees (GBDT) based combiner model. *Unfortunately, the proposed approach does not consider the users sentiments and emotion for to recommend events. In additional, authors do not take into account the event recommendation for a group.* Y. Lu *et al.*[40] proposed a Bayesian latent factor model, which combines Geographical Information, implicate user ratings and user Behaviors for accurate Friend Recommendation (GIB-FR). For a given user, they defined two low-dimensional latent factor vectors: user personal preference as follower and his personal preference as follower. In order to settle down the implicit feedback challenge, authors used the Bayesian personal ranking (BPR) framework, which emphases on predicting the dyadic ratings and top ranking items with high scores. *Unfortunately, GIB-FR does not take into account the cold-start problems.* S. Liu *et al.*[14]proposed a successive event recommendation based on graph entropy (SERGE) to recommend a list of upcoming events to a user according to his preference. Besides users and events, they first extracted the factors that could indicate users' preferences, including the online groups, tags, hosts as well as various event attributes. After some data preprocessing, they next constructed a primary graph (PG) to capture the characteristics of the extracted entities and their relations. They then applied the random walk with restart (RWR) to compute the similarity scores between the user and upcoming events. Authors also proposed to construct a feedback graph (FG) which contains only users and events to capture such dynamic relations. They then applied the RWR again on FG to obtain a new set of similarity scores. To strike a balance between the two recommendation results, authors proposed to use graph entropy for PG and FG to weight the two sets of similarity scores and to compute the final recommendation similarity scores for each user. *Unfortunately, authors do not take into account the event recommendation for a group.* Z. Wang*et al.*[11] proposed a Deep User Modeling for Event Recommendation (DUMER) to characterize the latent preferences of users by deeply exploiting the contextual information of events that users have attended. Authors exploited the content of events for ERS in EBSNs, and shifted the focus from event's perspective to user's perspective. According to authors, it is more reasonable to exploit the contextual information from the user's perspective to capture the preference of a user on events, than to recommend events based on similarity between new events and historical events. *Their proposal shifts the focus to a user's perspective, and applies CNN on user documents to better capture the user preference considering the unique characteristics of EBSNs; however, extracting events semantic metadata is necessary for more accurate ERS.* W. Fan *et al.*[41] proposed DEXIN (Dynamic EXclusive and INclusive), a fast content-based multi-attribute event matching algorithm for large-scale publish/subscribe systems. Firstly, when processing single-attribute matching, DEXIN uses an exclusive method or an inclusive method dynamically, which have different matching costs over the same attribute. Secondly, the single-attribute matching over each attribute is deployed to a serial pipeline, where the partial result of a next attribute is integrated from the partial result of its previous attribute. Indeed, for an event, DEXIN evaluates the matching rate of the event over each attribute based on the attribute value of the event and the constraints in subscriptions, calculates the matching costs of both exclusive method and inclusive method for each attribute, then determines the sequence and method adopted for each attribute in the pipeline by executing a near-optimal algorithm, which efficiently solves the optimization problem derived by the event matching cost model of DEXIN with small computation cost. *Authors proposal is only to determine the similarity between event that is useful for ERS. In conclusion and according to the literature review, existing ERSs do not combine the context-aware, geolocation-aware, utility-aware, group-aware, content-venue-aware, emotion and sentiment-aware and user persona-aware. In addition, few approaches propose a hybrid machine learning model that combined content-based MLM for events semantic metadata extraction and collaborative filtering MLM for user persona learning.*

2.3. News Recommendation Systems (NRS)

Based on the news content and the user's information, helping users find interesting articles that match the users preferences as much as possible, called Personalized News Recommendation Systems (NRS) [7][42][43][44][45][46][47][48][49][50][51][52], has become one of the main challenges for today's Internet news-portal websites and mobile applications. M. Karimi*et al.*[45] reviewed the state-of-the-art of designing and evaluating news recommender systems (NRS) over the last ten years. One main goal of their work is to analyze which particular challenges of news recommendation (e.g., short item life times and recency aspects) have been well explored and which areas still require more work. Authors focused on the underlying algorithmic approaches used to create the recommendations and on questions related to the empirical evaluation and the user perception of such systems. Their study has shown that news recommendation is an active topic of research and that in recent years significant advances have been made in different directions. They found that content-based methods are quite frequently used in the academic literature. However, in the real world, the observations are that relying solely on content-based techniques can be insufficient. Factors like general article popularity and recency are highly important in the domain and collaborative-content-based hybrid techniques are therefore the method of choice when it comes to optimizing Information Retrieval (IR) accuracy measures or click-through rates. Z. Zhu*et al.*[7] proposed a novel method, called Behavior And the Popularity (BAP) to build the user profile. The method gives each historical news a corresponding weight based on user's reading behavior and the popularity of news, instead of 0, 1, or some fixed value. Furthermore, when dealing with short-term profiles, they proposed a time function to adjust the user's preferences for all historical news rather than some of it. This helps them construct a more objective and comprehensive short-term profile of the user. Their proposal system consists of three main components: news collection and processing, user profiling method, and personalized news recommendation. The user profiling method consists of three stages that are extracted from the user's reading history: (1) representation of some of the news keywords in which the user is interested; (2) representation of the topic distribution of the user's preferences; and (3) representation of the named entities in which the user is interested. For dynamic personalized news recommendation, authors proposed a time-sensitive function to construct the short-term profile by adjusting the long-term profile of the user. Then, they calculated the similarities between each piece of news and the profile of the user. Finally, they adjusted the selection ratio of the two recommended result sets (long-term and short-term) according to the user's historical selection of these two result sets. *Authors proposal is the matching between users' topics of interest and the news topics; for example, the current geolocation of users is not taken into account for news recommendation. In additional, the user agenda needs to be considered to recommend news that match with user daily activities.* M. An*et al.*[42] proposed a neural news recommendation approach with both long- and short-term user representations (LATUR), that contains two major components: (i) a news encoder that aims to learn representations of news articles from their titles and topic categories and (ii) a user encoder that consists of two modules, i.e., a long-term user representation (LTUR) module and a short-term user representation (STUR) module. Authors applied attention mechanism to the news encoder to learn informative news representations by selecting important words. In STUR, they used a GRU network to learn short-term representations of users from their recently browsing news while in LTUR, the long-term representations of users are learnt from the embeddings of their IDs. *Unfortunately, GRU to capture the entire information of very long news browsing history.* M. Ashraf*et al.*[43] have presented a novel multi-agent-based news recommendation system which can process news by making use of user's social media profile. According to authors, their proposed solution performed sentiment analysis on news so that the positive news articles are presented to the user first that aims is to accommodate user's emotional wellbeing along with staying updated about world news and events. They have used a category mapping agent and news source authority agent to rank the news on the basis of user's interests from social media. Indeed, the category map by default has 8 general news categories and it maps all 157 Facebook categories to these 8 general news categories; the user can also add additional category through the user interface in which case the category-mapping agent will map the Facebook categories to the newly added category. The agent selects the news source authority by selecting the news source followed by the user on his/her social media profile. Then that news source is assigned a high score so that the news coming from that particular news source will be processed with high rank for further recommendation. *Authors news recommendation system approach do not take into account user current sentiments; they just focus on the news sentiments analysis.* D. Khattar*et al.*[46] proposed a novel deep learning mode,called Weave&Rec, which utilizes the content of the articles and also takes the users' historical data into account in order to make better recommendations. Weave&Rec consists of two components. The first component of Weave&Rec is based on a 3-dimensional convolutional neural network (CNN) which takes the word embeddings of the articles present in the user reading history as its inputs. The second component of Weave&Rec utilizes 2D CNN and takes the word embeddings of the test article as its input. Then, they modelled the interaction between the outputs obtained from the two components using the Hadamard product. For the word embeddings of the articles, they

combined the title and text of the news articles in our training sample and then learn a word2vec representation for each word. *Unfortunately, authors do not take into account the semantic aspect of word.*
As conclusion, existing news recommendation systems do not *take into account: user daily activities, group news recommendation, sentiments and emotion, semantic topic of news, and geolocation context such as user place of born, residence place of other family members, past residence place and current location place,*

2.4. Knowledge Recommendation Systems (KRS)

The rapid expansion of knowledge makes it increasingly difficult for users to obtain the precise necessary information even on an e-learning platform. Thus, knowledge recommendation [53][54][55][56][57][58][59]has become crucial to support learning. X. Yin*et al.*[53]proposed a knowledge recommendation approach that integrates the degree of correlation between knowledge and tasks, the feedback-based personal experience, the collective experience of designers, and the degree of demand for knowledge based on the forgetting curve. Specifically, authors presented a correlation-experience-demand (CED) integrated knowledge recommendation approach to solve the above four problems: "what to recommend", "when to recommend", "who to recommend" and "how to recommend". Their CED approach uses the workflow engine of the product data management (PDM) system to establish the relationship between the design process and tasks, which solves the "when to recommend" problem while The term frequency inverse document frequency algorithm (TF-IDF) and cosine similarity algorithm are adopted in each workflow node of the design process to compute the similarity between tasks and knowledge to find the knowledge that matches the task, which solves the "what to recommend" problem. Then, according to that individual's access to knowledge information, that individual's degree of demand model for knowledge is constructed based on the forgetting curve, which solves the "who to recommend" problem. Finally, the recommendation list is obtained by ranking the knowledge in assistance score descending order to build personalized and accurate knowledge recommendations, which solves the "how to recommend" problem. *The CED approach is more a correlation system between knowledge and tasks than a recommendation system; indeed, there is not learning process about the recommendation list. In addition, authors evaluated the user need of knowledge using his access to knowledge information based on the forgetting curve function; just the access to knowledge does not allow to know that the user has this knowledge.* L. Wen*et al.*[59] attempted to improve retrieval efficiency by proposing a digital literature resource organization model based on user cognition to improve both the content and presentation of retrieval systems. They focused on (1) resource organizations based on user cognition and (2) new formats on search results based on knowledge recommendations. They will purposefully employ data from users' own information and give knowledge back to users in accordance with the quote "of the people, for the people." Their core concepts and the relationships among the concepts are extracted through natural language processing. The relationships between concepts are either subordination and correlation. A triple consists of two core concepts and their relationship. *Authors just propose a contents classification system that derives a category tree from the contents. And then, recommend a content based on its categories. In addition, the recommendation does not take into account the user daily activities.*

2.5. Recommendation Chatbots (RC)

To overcome to this limit, Chatbots [23][60][61][62][63][64][65][66][67][68][69][70]are good candidates. B. Borah *et al.*[23]presented a overview different models of chatbots along with an architectural overview of computationally intelligent chatbot in context of recent technologies: (1) retrieval-based models that use a repository of predefined responses and pick an appropriat response based on the input and context. These systems don't generate any new text and (2) generative models (also referred as Artificial Intelligence Chatbot) that are based on Machine Translation techniques, but instead of translating from one language to another, translations are made from an input to an output response. Their core emphasis is on analysis of recent development approaches of textbased conversational systems and to identify few challenges in intelligent chatbot development that may be helpful for future research works. Authors have given insights of how the Natural Language Processing (NLP), Natural Language Understanding (NLU) and Decision engine work together with Knowledge Base to achieve Artificial Intelligence (AI) using Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM). In addition, they presented different chatbot platforms and development frameworks of recent times. I. V. Serban*et al.*[66] proposed a socialbot, called MILABOT, that is based on a large-scale ensemble system leveraging deep learning and reinforcement learning. They developed a new set of deep learning models for natural language retrieval and generation (including recurrent neural networks, sequence-to-sequence models and latent variable models), and evaluate them in the context of the competition. In particular, authors proposed a novel reinforcement learning procedure, based on estimating a Markov decision process. Training is carried out on crowdsourced data and on interactions recorded between real-world users and a preliminary version of the system. The trained systems yield substantial improvements in A/B testing experiments with real-world users. Their models are combined into an ensemble, which generates a candidate set of dialogue responses. They applied reinforcement learning (including value function and policy gradient methods) to train the system to select an appropriate response from the models in its ensemble. *Authors do not demonstrate the adaptation of MILABOT for users' well-being in the social context and various contents recommendation from multi-catalogues.* A. Xu*et al.*[67] proposed a new conversational system for customer service on social media based on state-of-the-art deep learning techniques such as long short-term memory (LSTM) networks to generate responses for customer-service requests on social media. The proposed system that was trained on nearly 1M Twitter conversations between users and agents from 60+ brands, takes a request as the input, computes its vector representations, feeds it to LSTM, and then outputs the response. According to authors, the conversation between users and customer service agents on social media can be viewed as mapping one sequence of words representing the request to another sequence of words representing the response. Based on this definition, they applied a deep learning technique to learn the mapping from sequences to sequences. The core of their system consists of two LSTM neural networks: one as an encoder that maps a variable-length input sequence to a fixed-length vector, and the other as a decoder that maps the vector to a variable-length output sequence. *Authors adopted word2vec neural network language model (a word embedding method) to learn distributed representations of words from customer service conversations in an unsupervised fashion. Unfortunately, the context of the conversation and the semantic context are not taken into account.* M. Qiu*et al.*[65] proposed a hybrid approach that integrates both Information Retrieval (IR) and generation models to alleviate the se the problem of long-tail questions in information retrieval models due to the fact that the questions are not close to those in a Question-Answer base. In their approach, authors used an attentive Seq2Seq re-rank model to optimize the joint results. Specifically, for a question, they first used an IR model to retrieve a set of QA pairs and used them as candidate answers, and then re-ranked the candidate answers using an attentive Seq2Seq model: if the top candidate has a score higher than a certain threshold, it will be taken as the answer; otherwise the answer will be offered by a generation based model. *Unfortunately, their approach cannot be considered a chatbot due to the fact that there is not a conversation. It is just an automatic response for Question-Answer system.* G. Cameron*et al.*[70] proposed a chatbot, named iHelpr, that aims to provide guided self-assessment, and tips for the following areas: stress, anxiety, depression, sleep, and self-esteem. iHelpr initially allows the user to complete a self-assessment instrument based on the option they have chosen. Tailored advice with evidence-based contents recommendations (links of website and e-learning programmes) are then presented to the user, based on the results of the self-assessment survey. iHelpr incorporates Microsoft's Language Understanding Intelligent Service to recognise the utterances made by users and to match them to the correct intent. *iHelpr is more a Decision Support Systems (DSS) than a chatbot; many of the questions are yes/no questions or multiplechoices question whose iHelpr uses to perform its recommendation system.* B. R. Ranoliya*et al.*[69] designed and developed an interactive chatbot for University related Frequently Asked Questions (FAQs), which provides an efficient and accurate answer for any query based on the dataset of FAQs using Artificial Intelligence Markup Language (AIML) and Latent Semantic Analysis (LSA). Template based and general questions like welcome/greetings and general questions will be responded using AIML and other service-based questions uses LSA to provide responses at any time that will serve user satisfaction. User inquiries are first taken care by AIML check piece to check whether entered inquiry is AIML script or not. AIML is characterized with general inquiries and welcome which is replied by utilizing AIML formats; first, a processing is done on the users query to match the predefined format by the developer; then, pattern matching is performed between user entered query and knowledge (pattern); finally pattern based answer is presented to the user to answer their query. *As* [70]*, this proposal cannot be consider as ChatBot.* I. Nica*et al.*[68] presented the underlying methods and technologies behind a Chatbot for e-tourism that allows people textually communicate with the purpose of booking hotels, planning trips, and asking for interesting sights worth being visit. Author focused on improving adaptivity of chatbots in the context of recommender systems, where they have identified two issues that arise during and human-computer interaction session. Indeed, in order to make a recommendation, their chatbot has to interact with the user in order to find out preferences and wishes in order to make an appropriate recommendation. *As [69] and*[70]*, this proposal cannot be consider as ChatBot. Their chatbot asks predefined questions and uses the answers to build search criteria whose results list is recommended to the user.*

In conclusion and according to the literature review, existing Chatbots do not personalize the response according to persons and user; indeed, the Chatbot provides the same response to the same question based on the domain. We think that, new generation of Chabot should take into account the user who chats with it. In the context of Semantic Matching Systems with Swipe User Selection (SUS), recommendation algorithm needs to take into account: geolocation, day of the week, hour of the day, MLM-based evolutionary ontology and other users with target user.

III. MATCHING USER EVOLUTIVE INTERESTS (MUEI) BASED ON MULTI-ENGINES LEARNING MATCH ALGORITHMS (ELMA) USING USER CREATED CONTENT AND UNIVERSAL KNOWLEDGE REPOSITORIES (UKR)

In this section, we present the details of the proposed approach. We introduce MLM based Learning & Boosting Model and the details of LBAM algorithms (Part 2).

According to [71], existing literatures on ERS ignore the social aspect of events; indeed, people prefer to attend events with their friends or family rather than alone. In this research work, the proposed ERS model, is being designed to take into account the social aspect of events. MEUI aims is to match users interests with events semantic metadata and hidden characteristics taking into account: (1) context-aware aspect, (2) geolocation-aware approach, (3) utility-aware approach, (4) group-aware approach, (5) content-venue-aware approach and (6) emotion and sentiment-aware approach. MEUI is a Hybrid Machine Learning Model (HMLM) that used content-based MLM for events semantic and hidden metadata extraction and collaborative filtering MLM for user personas learning. The MEUI architecture is divided into three modules: (i) data collection which extracts the unstructured dataset from the several event-based social networks (EBSNs) and social networking site such as Facebook using API's; (ii) data mapping module which is basically used to integrate the common knowledge/data that can be shared between considered different EBSNs. This module integrates and reduces the data into structured events' instances. As the dataset was collected from more than ten different sites, an intersection of all was taken out. This module is carefully designed according to reliability of information that is common between these EBSNs. This two modules are proposed in our previous work [72][73] which are based on [74][75][76][77][78][79][80][79]; and (iii) MEUI algorithm and part of our project [81].

For further understanding about SMESE algorithms and processes to semantically enrich metadata using multiple metadata/data sources, refer to previous papers[72][73]. The LB project proposed to use the SMESE platform to create User Evolutive Interests,portals (Personal Agenda & Channels, Collaborative Learning & Events, Collaborative Digital Resources) and Personal User Space.

3.1 Overview of Life Booster project

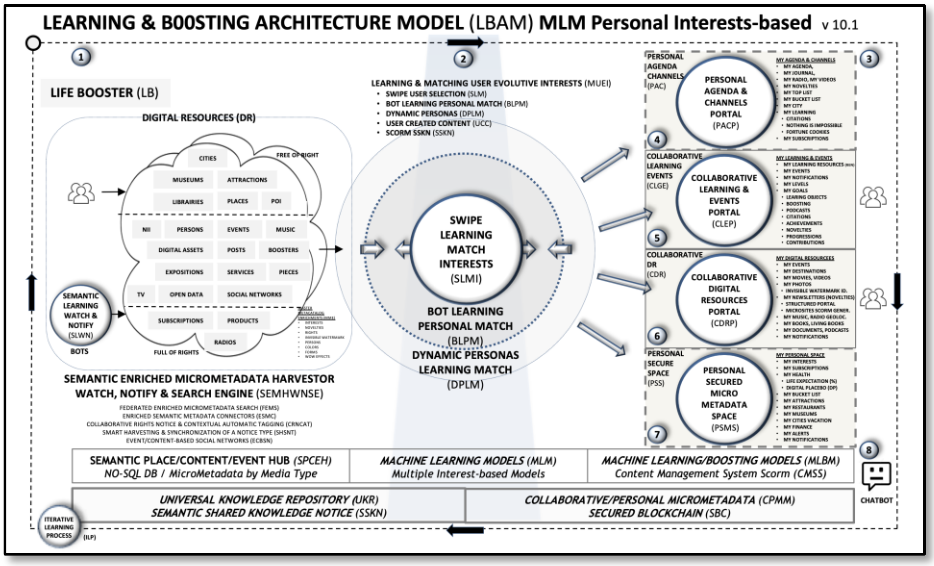

Fig. 1: LBAM Overview Model

The previous Fig. 1represent the Learning & Boosting Architecture Model (LBAM), a Machine Learning Interest-based Model, with the following goals: 1) to identify Matching Evolving User Interest (MEUI) of person and 2) potentially to boost daily their life by providing to them a proposed Daily Smart Agenda (DSA) and a Personal Radio (PR) according to a set of Personal Metrics (PM) and interests who evolve periodically. This LBAM model is built from 3 main process and 4 subprocess: a) Identification of the MM of Digital Resources (DR) including Events and their timeline; b) Matching Evolutive User Interest (MEUI) using a Bot and a swipe action; and c) The Personal Agenda & Channels, DR and UKR.

The **first process** is based on the creation of a hub of secured multiple metadata using the Semantic Enriched MMHarvestor, Watch, Notify & Search Engine linked to Users and Bots (SLWN) and including multiple sources of rights and their aggregation into Multi Sources Semantic Knowledge (SSKN). These Metadata are assembled through a Harvesting process able to catalogue the Rights, the Interests and the Novelties. This section includes many processes to build the Digital Resources. They harvest Free of right and Full of Right Content and manage the MM multi-rights.

The **second process** is mainly to identify the Matching Evolutive User Interest (MEUI) by an Algorithm of matching from four different levels of User Interests: a) The User Personal Interest using the real time Swipe Learning Match Interests (SLMI); b) The Interests of the Personas of the User using Dynamic Personas Learning Match (DPLM) – the Personas of the Users are categorized in 18 different personas in our model; c) The Bot swipe as a counterpart for Swipe Learning Match (SLM) using Bot Learning Match (BLM) – a simulator of automatic matching interests based on a set of user with the 95% of the same Personas and; d) User Created Content (UCC) allowing to extract some behavior from the User. The Bot Learning Match (BLM) is an assisted process (Bot) allows to match User Interests for Digital Assets as Events, Photos, Persons, etc. This process uses Multiple Interest-based Models to learn the User Interests in different situations with the Swipe principle to like (right) or to don't like (left), time of the day and contextual behavior. Using MLM, this process improves the MEUI identification over the learning process.

The **third process** focus on the prediction of the daily evolving interests of each user and context regarding: Personal Agenda & Channels Portal – it is a personal Journal, a personal Radio and a personal TV channel (PACP). Here we build a recommended agenda, journal, radio channel and videos channel to a specific user according to the entire five process of LBAM and his evolving personal interests. This process uses Machine Learning/Boosting Models to: a) improve the cataloguing of the Digital Asset and Events; b) to boost interest of User and c) to improve the identification of the User Interests. This process makes emphasis too on Collaborative Learning & EventsPortal (CLEP) gives games or learning activities to do according to the User's Interest. The Collaborative Digital Resources Portal – Collaborative Digital Resources identifies potential Events and Media who could meet the Evolutive Interests of the User and the last process is Secured Personal MM Space (SPMS) - My Personal Space.

The **fourth process** is the Personal Agenda & Channels Portal (PACP) Process but with an emphasis on Personal Channels process. It allows to propose to User a dedicated Personal Channel according to his interests and available Digital Resources at a specific time. This Personal Agenda & ChannelsPortal is using MLBM evolving with time and all interactions with the User.

The **fifth process** named Collaborative Learning & Events Portal (CLEP) includes the sharing of knowledge and gaming for the benefice of every user. The process includes the ability to create, reference, evaluate and organize content or knowledge in a evolutive learning process at different level.

The **sixth process** is the Collaborative Digital Resources Portal (CDRP). The process includes My Newsletter who fulfill the CDRP to create content and digital resources per different interest categories and learning needs. This process includes too a CMS based Micro-Sites Generator using newsletter smart aggregation to create new content and knowledge.

The **seventh process** is the Secured Personal MM Space (SPMS) but with an emphasis on Personal Metrics (PM) and Digital Placebo (DP). The process includes in My Health, the Life expectation metric and the Digital Placebo (DP).

These seven processes are embedded in a larger MLM allowing to learn at different stages of the macro process and to improve all other learning processes. We will explore more in details the second process of this model in this paper.

3.2The Swipe Learning Match Interests (SLMI)Process

In the Fig. 2we see the process number 2 who is responsible to identify user interests. The two main results of this process are PACP and PSMS.

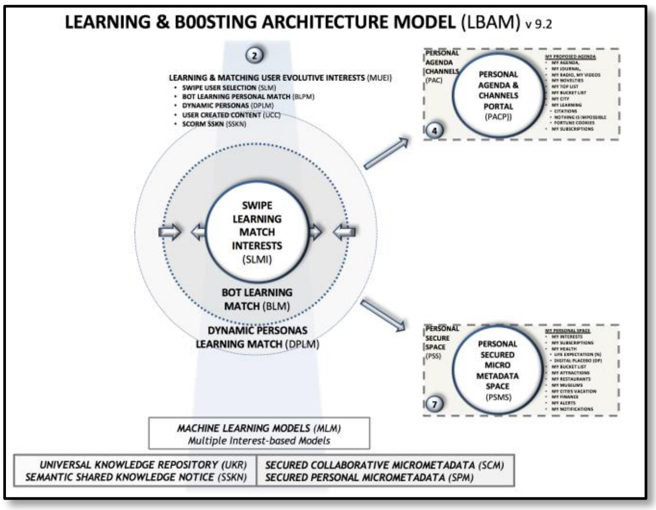

Fig. 2: Swipe Learning Match Interests (SLMI)

3.5 Machine learning model (MLM)
MLM algorithms are used at different levels in LBAM to identify the evolutive interests of users. It uses the same model than SMESE but enhances the process to identify MM sources in the structured environment and unstructured web.

IV. PROTOTYPE APPLICATIONSAND PERFORMANCE EVALUATION

4.1Prototype: Life Booster Application APPS
Life Booster prototype – see Fig. 3, analyses the Swipe Learning Match Interests.

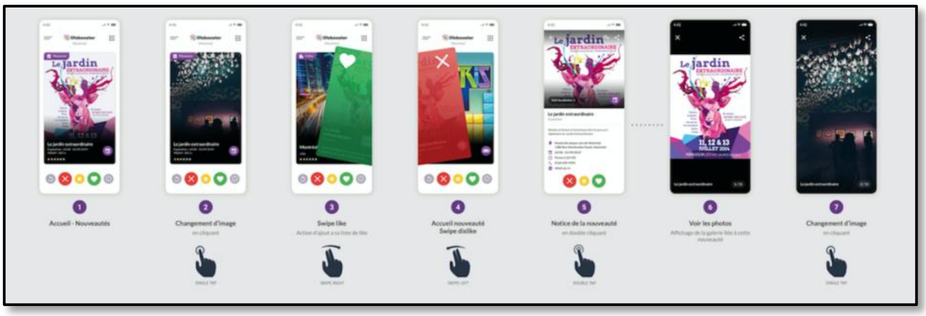

Fig. 3: Mobile APPS – Swipe Prototype

4.3Simulation Setup and DatasetsCharacteristics

To evaluate the proposed method, several types of datasets such as, MovieLens, Yahoo! Webscope R4, and Million Song dataset (MSD). The data were cleaned prior to use in the simulation process.

MovieLens dataset (http://www.movieLens.org) is one of the well-known movie datasets that has been used for the evaluation of machine learning model in recommender systems. The numbers of users and movies in the Movielens dataset are 6,040 and 3,952, respectively. In this dataset, the users have provided ratings on a 5-star scale. We select the users in the dataset who have provided at least 20 ratings. Hence, based on the number of users and movies, this dataset includes 1000,209 anonymous ratings.

Yahoo! Webscope R4 dataset (http://webscope.sandbox.yahoo.com) was provided by the Yahoo! Research Alliance Webscope program. In this dataset, the users have provided ratings on a 5-star scale. This dataset is divided into two sets of data, a training set and a testset. The training set includes 7,642 users, 11,915 movies and 211,231 ratings. The testing set includes 2,309 users, 2,380 movies and 10,136 ratings.

MSD (http://millionsongdataset.com) is one of the largest and free datasets in music domain. It is constructed from about one million songs and users, in which each user plays a small set of songs. MSD was chosen for the evaluation for different reasons: (i) To train our machine learning model in discovering the significant correlation among the Dynamic Personas Learning Match (DPLM) with user's profile. This is done using this dataset because of the need of having a dataset that has implicit information which can be extracted from users' music listening information (music played and listeningtimes for each user) and tagging activities. (ii) To exercise our technique, a dataset with knowledge about song features (artist,year, title, release, song popularity, artist_familiarity, duration, and tags) is needed to compute songs similarities.

4.4Simulation results and discussion

Here, we evaluate via simulations the performance of LBAM-ELMA in terms of accuracy when varying the training data size and precision (the bot's questions and answers) when varying the chat duration.

InFig. 4, we evaluate the average accuracy of users' matching interests when varying the training data of machine learning model. As comparison terms, we use the approaches described in [55], [52], and [53], which are referred to as Algo_1, Algo_2, and Algo_3, respectively. **Error! Reference source not found.** shows that, LBAM-ELMA and Algo_1 average accuracy increases between 5% and 35 % of training data size while Algo_2 and Algo_3 average accuracy increases between 30% and 50 % of training data size; that mains that, LBAM-ELMA and Algo_1 do not need more training data to outperform in contrast to Aolg_2 and Algo_3. **Error! Reference source not found.** also shows that LBAM-ELMA outperforms Algo_1, Algo_2, and Algo_3; for example, LBAM-ELMA provides an average accuracy of 0.812 for 5% of training data, whereas Algo_1 (more efficient than Algo_2 and Algo_3 in this scenario) provides an average of 0.639 for 5% of training data; overall, the average relative improvement of LBAM-ELMA compared with Algo_1 is about 17.30% for 5% of training data. This can be explained by the fact that LBAM- ELMA use a real time Swipe Learning Match (SLM) and a Dynamic Personas Learning Match (DPLM) to improve the User Personal and Personas Interests.

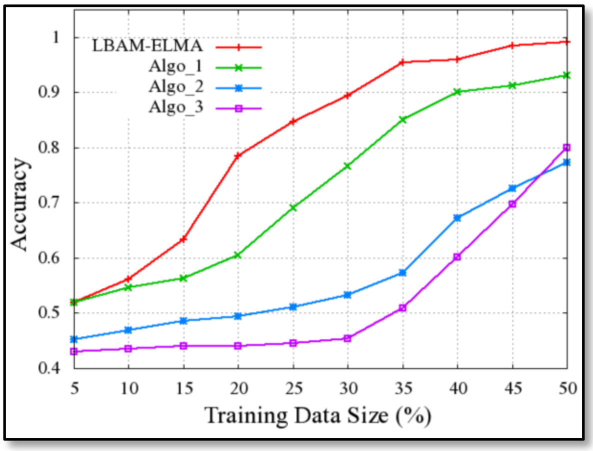

Fig. 4: Accuracy vs Training Data Size

InFig. 5, we evaluate the average precision of conversation with the Bot varying with the chat duration. The precision of conversation with the Bot is defined as the human logic in the bot's questions and answers. As comparison terms, we use the Bots described in [82], [66], and [67], which are referred to as Bot_1, Bot_2, and Bot_3, respectively.

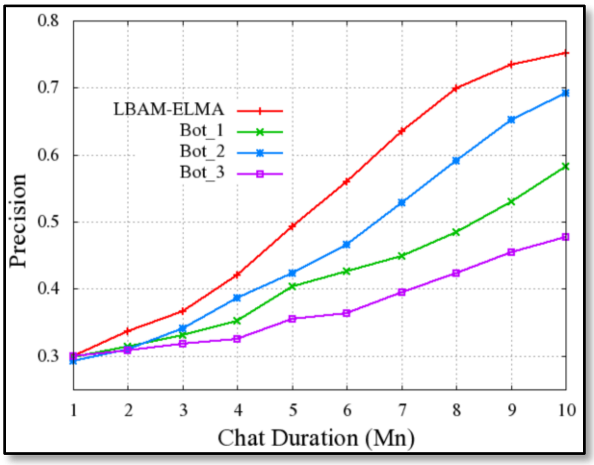

Fig. 5: Precision vs Chat Duration

In our experimentation, we have observed that for LBAM-ELMA and all the comparison Bot, the average precision increases with the duration of the chat; this is expected since when the chat duration increases, the machine learning model training data increases, and thus, the precision accuracy increases. InFig. 5, we observe that, LBAM-ELMA outperforms slightly Bot_1, Bot_2, and Bot_3; indeed, LBAM-ELMA provides an average precision of 0.53 for one minute of chat, whereas Bot_2 (more efficient than Bot_1 and Bot_3 in this scenario) provides an average of 0.47 for one minute of chat; overall, the average relative improvement of LBAM-ELMA compared with Bot_2 is about 06% for one minute of chat.

V. Summary and future work

We have shown that it is possible to identify partly some evolving interests of users by an algorithm using swipe functionality and user interests.Yet, there many improvements that can be added to this model: improvements of the Harvesting Algorithms, refinement of SKU, SSKN, SLM and BLM. Here are some of the future work that we looking to explore furthermore:the Third to Seventh Process of the LBAM model: 4) Personal Agenda & Channels Portal (PACP) Process; 5) Collaborative LearningEvents Portal (CLEP); 6) Collaborative Digital Resources Portal (CDRP); and 7)Personal Secured MM Space (PSMS). Process five, six and seven are the cornerstone to create the process 4 (PACP).

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