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ORIGINAL PAPER

Social constructivist approach of motivation: social media messages recommendation system

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Abstract Contemporary learning theories and their implementations associated with information and communication technologies increasingly integrate social constructivist approaches in order to assist and facilitate the construction of knowledge. Social constructivism also highlights the important role of culture, learning attitude and behavior in the cognitive process. Modern e-learning systems need to include these psychological aspects in addition to knowledge construction in order to connect with long-standing pedagogical issues such as the decrease and lack of motivation for education. Current Social Networking Services (SNS) provide a platform where peers can express their passion, emotion, and motivation toward learning. Therefore, this research utilizes this platform to recommend motivational contents from peers for learning motivation enhancement (i.e., learners' perception of their goal and purpose for learning). The proposed system consists of an SNS platform for learners to (1) express and evaluate their own goals for learning, (2) observe motivational messages from peers recommended from an LDA-based (latent Dirichlet allocation) model, and (3) evaluate their perceptions on motivational and psychological attributes. The LDA-based model recommends messages expressing diverse purposes for a shared goal by maximizing the topic divergence of Twitter messages. Learners' self-evaluations show the positive and

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significant impact of observing diverse learning purposes from peers on intrinsic motivational attributes such as goal specificity, attainability, and on the confidence to achieve the desired outcome.

Keywords Social constructivism · Learning motivation · Recommendation system · Latent Dirichlet allocation

1 Introduction

Social constructivism designates the concept of people constantly learning, acquiring and building new knowledge in social context, and adopting new behaviors, through observation and external interactions with others (family, school, peers) (Vygotsky 1986). Contemporary learning theories and e-learning implementations increasingly integrate social constructivist approaches in order to promote and facilitate the construction of knowledge.

The key elements of social constructivism originate from Vygotsky's developmental theory of social learning, that is, zone of proximal development (ZPD) and internalization of higher psychological functions (Vygotsky 1978; Luckin and Du Boulay 1999). People assimilate and learn what they observe from others, what is meaningful for them, and behaviors from each actor influence this process (Palincsar 1998). In other words, learners develop and expand their ZPD with the support from experts (teacher, parent, or "More Knowledgeable Other") based on their own understanding of a specific learning object and the sociocultural environment, in order to acquire the skills to understand this object (see Fig. 1).

The essence of social constructivism consists therefore in more than only teaching the surface of learning objects. It requires psychological functions such as a logical way of thinking toward the contents taught, the ability to explain to others, the understanding of culture and environment of learning (passion, emotions and motivation from experts; needs, attitude, and motivation from learners). Figure 1 illustrates this interpretation of Vygotsky's developmental theory with a mutual understanding, enhancing observation and imitation from learners, and support from experts (Ueno 2015). It also highlights the focus of this research on the influence of the psychological functions on different actors of the learning process. For example, one learns differently from a teacher demonstrating enthusiasm and passion, or from someone with little interest in teaching.

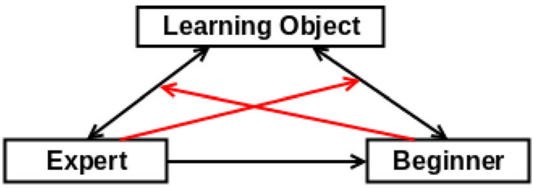

Fig. 1 Vygotsky's development theory

Motivation is a central part of educational psychology (Weiner 1985), and a prominent factor of motivation consists in the strong connection between pedagogical goals and purposes for learning (Eccles et al. 1998; Schunk et al. 2014). Learning goals are efficient when linked with learner's needs and purposes because they want to know the reasons why learning is important for them, to make learning more meaningful (Wigfield and Cambria 2010). Pedagogical institutions provide therefore highly structured education and curricula with syllabus stating specific outcomes. However, learners as individuals have various conceptual perceptions and consequently different purposes for learning. Students are then often unable to relate to goals stated by their formal education, leading to a lack of motivation, the largest cause of education failure (Samuelson 2010). This issue appears even more clearly in informal and self-regulated learning environments where curricula may be absent and where learners monitor their own actions, motivation, and goals (Eraut 2004). The failure to think of a reason to study a given subject or to attain a goal (i.e., to make learning meaningful) results in risks of conflict and discouragement that might harm learner's intrinsic motivation.

The purpose of this research results from the needs for learning motivation enhancement and for diversity in collaborative learning environments. Collaboration with peers creates opportunities for work, positive attitudes, and consequently encourages motivation (Blumenfeld et al. 2006), considering that intrinsic motivation is central in social networks of cognitive discourse (Rienties et al. 2009). Collaborative learning environments require more diverse motivational contents from peers as direct input for contents recommendation.

In particular, Social Networking Services (SNS) consist of an important resource of diverse motivational information and represent an essential and influential factor, including for education (Bandura 2001; Piotrowski 2015). The Internet and SNS having become an essential part of personal life and communication, many research works focus on the use of social media for educational purposes, especially using the two largest platforms: Facebook and Twitter (Tess 2013). Questions related to the effectiveness of using Social Media for pedagogical purposes still remain to be answered authoritatively, whether researchers praise their positive impact on learning behavior, or view them only as a communication tool for socializing rather than for academic work (Madge et al. 2009). However, both opinions agree on the necessity to carefully consider the importance of Social Media for education, and on the "backstage" role in the development of student identity rather than enhancement in formal education per se (Selwyn 2009).

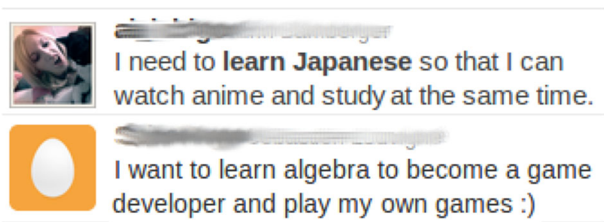

Fig. 2 Example of goal-based messages collected from the social media Twitter

This research proposes an SNS-based platform implemented in an existing e-learning environment to enhance individual motivation and psychological functions. The proposed recommender system considers the diversity of motivation within learning communities and provides diverse purposes for learning expressed by peers (Fig. 2) to enhance learners' intrinsic motivation for achieving a shared goal.

This research proposes a recommendation system based on the following features:

1. **Expression:** Learners express and evaluate their own purpose for achieving a learning goal (e.g., mastering English),
2. **Observation:** LDA-based (latent Dirichlet allocation) model recommends peers messages from SNS containing diverse purposes for learning for a same goal,
3. **Evaluation:** The system analyzes the changes in learners' evaluation of their motivation and purposes for learning after observing similar/diverse messages from peers.

Latent Dirichlet allocation (LDA) is a highly accurate probabilistic model for collections of discrete data that estimates the probabilistic distribution of a fixed number of topics, or themes, on documents, and the word distribution on these topics (Blei et al. 2003). This three-level distinction (document-topic-word) allows the estimation of topic similarity for two documents, even without sharing the same words. In the context of this research where documents consist of Twitter messages expressing various purposes for learning a shared goal, the calculation of word distribution offers limited contribution. Due to the small size of a message (limited to 140 characters), a different word implies an important change in the word distribution with potentially insignificant impact on the topic distribution. LDA offers the best estimation of topic (i.e., purposes for learning) similarity or diversity within a dataset of messages from peers about a similar goal (i.e., mastering English) and was therefore used to focus on topic divergence maximization.

Recommender systems evolve with advanced technology and are notably appealing for Technology-Enhanced Learning systems (Manouselis et al. 2012). Recent implementations use the similarity of item contents, user profiles, and other information to recommend personalized contents to learners with positive results. However, the lack of motivation in education and the difficulty for learners to relate to academic goals call for the recommendation of a larger variety of purposes for learning. LDA has the ability to differentiate topic distribution on documents and is used to recommend motivational messages from peers expressing diverse purposes for achieving a similar goal.

Due to the complexity of motivation, the impact of the goal-based recommendation system is evaluated on a fixed range of motivational attributes related to learners' perceptions of their goal. Previous research works on goal setting and goal orientation mention several attributes related to the goal (*importance*, *attainability*, *difficulty*, *specificity*) or to the learner in regards to this goal (*commitment*, *confidence*, *achievement*, *satisfaction*) (Locke 1996; Locke and Latham 2002).

These attributes are used in addition to the self-evaluation of overall intrinsic motivation in order to analyze the impact of the recommendation of diverse messages from peers.

This paper first describes motivation and goal theories and reviews several motivational attributes necessary for the evaluation of this research. The following section describes the recommendation system using LDA-based model and data previously collected from the Social Media Twitter. The rest of this paper consists of the description of the experiment and the discussion of the evaluations from learners who confirmed the hypothesis that observing the diversity of peers' learning purposes recommended is an important factor positively affecting intrinsic motivational attributes such as goal specificity, attainability, and the confidence to achieve their goal.

2 Collaborative learning environments

Social constructivism forms the roots of recent pedagogical approaches. Collins et al. (1991) believe in the design of learning environments focusing on the concept of cognitive apprenticeship, where learners build their knowledge and acquire new skills through observation, reflection, and exploration. Cognitive apprenticeship makes learning meaningful with communication and engagement within groups of learners and experts working together, also called "Communities of Practice" (Lave and Wenger 1991). Situated learning in communities of practice supports the idea that knowledge is constructed in the real-world context and in situations where it is applied. Derived from communities of practice, "Learning Communities" approach encourages collective knowledge of the community in order to increase individual knowledge.

Scardamalia and Bereiter (1994) claim that a learning community requires (1) diversity of expertise for contributions and support to develop, (2) a shared objective of developing collective knowledge and skills, (3) the focus on learning how to learn, and (4) mechanisms to share what has been learned. In order to develop learning communities, Scardamalia (2004) proposed a Computer-Supported Collaborative Learning (CSCL) approach where knowledge building is achieved through interactions between peers sharing a similar goal, with the help of computers.

Samurai is another example of collaborative intelligent learning management system (LMS) used for numerous e-learning courses (Ueno 2004). It consists of content sessions tailored for 90-min classes that learners can choose and watch from the list of units. Each content session provides instructional text screens, instructional images, instructional videos, and a practice test (Fig. 3). A learning history database stores information related to the completion of sessions from learners (responses, time), which are also analyzed by data mining methods. LMS Samurai also includes a facilitator agent and promotes collaboration between students through discussion and peer assessment (Uto and Ueno 2016).

Contemporary CSCL implementations have demonstrated positive impact in enhancing learning although most implementations limit the diversity aspect

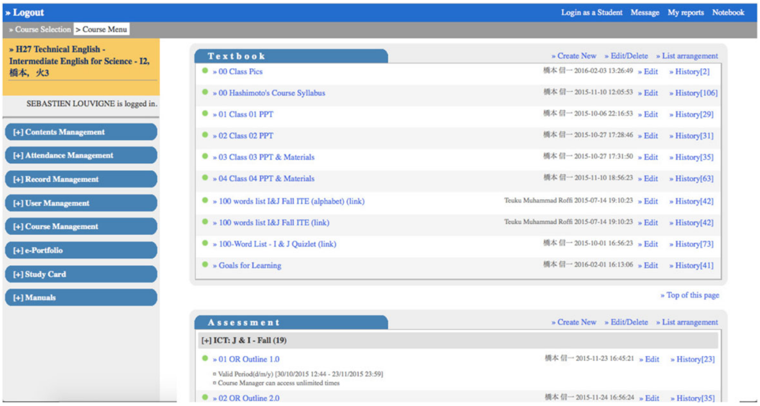

Fig. 3 Learning management system "Samurai"

required in a learning community to learners sharing similar characteristics (e.g., similar age, level of expertise from a same classroom or from a similar background). CSCL systems like Samurai need to integrate a more diverse social presence in order to expand the sharing of learning objectives, methods, outcomes, and motivational contents for learning communities.

3 Motivation, goal, and purpose for learning

Motivation in education is the internal force that generates behaviors for learning and that relates to both expected outcomes and reasons for engaging in learning (Weiner 1985). Pedagogical theorists believe in motivation influence on learning performance, and recent theories insist especially on the relation of expectancy, value, and goals (Eccles and Wigfield 2002). Extensive discussions on theoretical perspectives and empirical works demonstrate the important impact of social settings on motivation (Eccles et al. 1998).

Motivation for learning answers two questions, respectively, about the purposes and the goals for learning: (1) Why do I want to learn? and (2) What do I want to achieve? In other words, it connects on one hand their needs and learning purposes with on the other hand their achievement goals or expected outcomes. This differentiation between "why" and "what" to achieve is similar to what is defined as process (why) and contents (what) of goal pursuit in self-determination theory (Deci and Ryan 2000).

Learners have various goal orientations or purposes for learning, classified as mastery and performance goals based on whether they learn for personal reasons or to satisfy external judgements (Ames 1992; Wigfield and Cambria 2010). Considering the high influence of self-set goals on intrinsic motivation (Locke and Latham 2002), learners need purposes for engaging in a task in order to follow a more intrapersonal and therefore more efficient goal orientation.

3.1 Goal setting

Goal setting is the theory focusing on properties and attributes of learning goals (e.g., importance, difficulty, attainability). In other words, goal attributes define the learning goal and give an estimation of how a learner can relate to it. In his excellent works, Locke (Locke 1996; Locke and Latham 2002) summarizes some goal setting research works and gives a list of different goal attributes. Bekele (2010) also reviews studies about satisfaction and motivation in Internet-supported learning environments.

Among all goal attributes, commitment represents the degree to which a learner is attached to a goal and determined to reach it, and it strengthens the level of performance that can be reached by learners. This central attribute relates to the learner's attitude with regard to the goal and receives direct or indirect influence from several other attributes. For example, individuals who are convinced that a goal is important and attainable, that is within their capacity, demonstrate a high commitment. In addition, goals that are both specific and difficult are critical for commitment and lead to higher performance.

Fulfillment (satisfaction) appears as an important measure of success after goal achievement, especially in internet-supported learning environments (Bekele 2010). Strongly connected to motivation, a high level of satisfaction illustrates a successful learning experience and is considered even more crucial in self-regulated environments that can be less structured than formal education.

Finally, an important component of Bandura's Social Cognitive theory is self-efficacy, which he defines as the confidence or the beliefs in one's capabilities to control a task and reach a goal (Bandura 1986). Self-efficacy (confidence) directly impacts performance, commitment, and the perception of difficulty for the goal to attain (Zimmerman et al. 1992). Research works on cognitive development also show evidence about the influence of social environments (e.g., family, peers, school) on individuals' confidence in achieving goals, mostly through observation of similar peers succeeding in their task performance (Schunk and Pajares 2002).

Goals are more complex than stating an outcome to achieve. Goals also consist of perceptional properties directly related to contents (i.e., importance, attainability, difficulty, specificity) or to learners' behavioral and psychological functions in connection with goals (i.e., commitment, confidence, achievement, satisfaction). These attributes influence each other, eventually leading to performance and

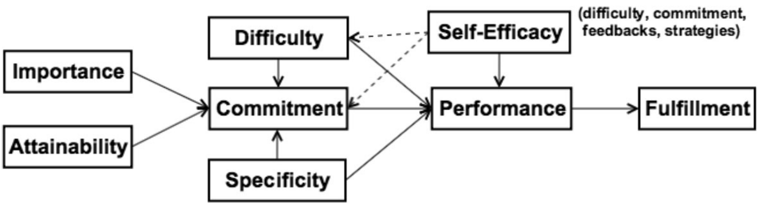

Fig. 4 Goal attributes and their inter-connections

satisfaction (Fig. 4). A perception change in one attribute can affect the entire goal attribution process and the motivation for goal achievement (Sie et al. 2013).

4 Proposed approach: goal-based recommender system

The purpose of this research is to implement a social-constructivist approach utilizing Social Network Services data and design to implement a recommender system in order to enhance peers' motivation for learning. Recommender systems take a major part in the development of advanced technologies (Herlocker et al. 2004). Technology-enhanced learning naturally follows the same direction developing mostly content-based or collaborative recommendation (Manouselis et al. 2012) that showed positive results in enhancing learning by recommending personalized contents to learners. Although the necessity to recommend personalized contents is well admitted, recommended systems also need to consider the diversity factor and to provide outcomes that are different from expectation (Erdt et al. 2015).

Recent pedagogical approaches emphasize the importance of social environments for knowledge building. Several studies have for example described the influence from socioeconomic status and characteristics in neighborhood environments on individuals' expectations and attitudes toward education (Kim et al. 2012; Matsuoka and Maeda 2015). However, modern e-learning approaches and recommender systems for learning need to consider psychological aspects, such as motivation, as part of the scaffolding process (Vygotsky 1978; Luckin and Du Boulay 1999). The purpose of this research is to integrate motivational aspects of learning as a direct and initial factor in collaborative environments, rather than as the measurement of a recommender system's outcomes.

Lack of motivation often occurs when students fail to find learning meaningful and purposeful, to find goals they can relate to. Although learners might know "what" to learn or to achieve, they might still need to know "why" mastering some specific knowledge or achieving a fixed goal is important for them. This calls for a recommender system providing diverse motivational contents such as learning purposes from peers expressing their own reasons for learning, for mastering a same subject (Fig. 5). This process helps learners adopt new purposes or enhance the self-

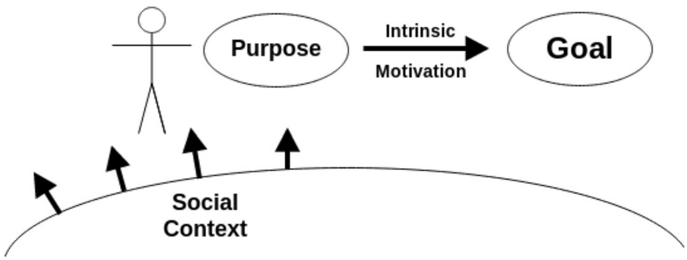

Fig. 5 Utilizing social environment to enhance motivation for goal achievement

perception of their learning purposes in order to improve their intrinsic motivation to achieve the desired goals.

4.1 Goal-based messages from Twitter

Social Networking Services are now one of the most popular tools for exchanging information and social interaction. They provide public access to a very large amount of data where people share their personal sentiments, motivations, and goals. This rapid and massive growth resulted in numerous research works in various domains, including in higher education (Tess 2013; Piotrowski 2015). Although these works and reviews have raised even more questions about the significant implications of social media in education, they have reached agreement on two essential aspects (Madge et al. 2009; Selwyn 2009):

1. The necessity for formal education to recognize and carefully consider Social Media's potential and importance to students,
2. The "backstage" role of Social Media in the development of student identity and in the conflict between students and academic environment.

Twitter has been one of the most visited websites on the internet in the past years and many researchers have studied its usage and influence among its users (Cha et al. 2010). Hughes et al. (2012) found the positive correlation between accessing Twitter for informational purposes and the needs for cognition stimulation and conscientiousness. This research focused on Twitter in order to collect goal-based messages, and later to adopt a familiar design in the implementation.

Figure 6 summarizes the data collection process completed in previous stages on this study in order to create a Goal Database (Louvigné and Rubens 2016). After downloading and filtering Twitter messages from May 2011 until March 2013 using, respectively, the streaming API and keywords related to learning (e.g., learning, study), the learning-based dataset created and containing over 270 million Twitter messages was segmented into several datasets related to various learning

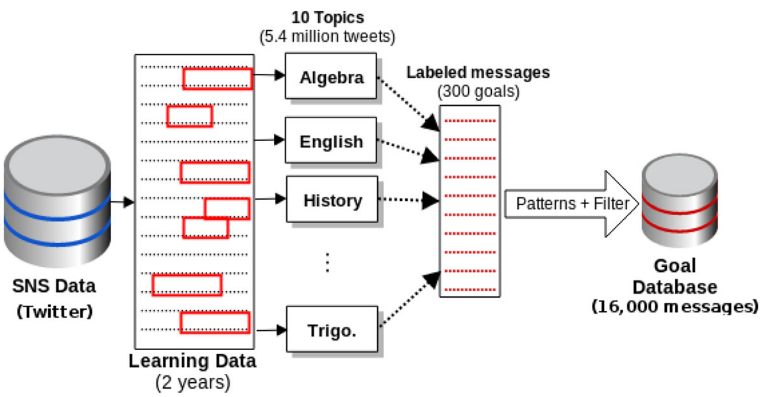

Fig. 6 Goal-based database creation process

subjects (e.g., algebra, chemistry, English, Japanese). After labeling messages expressing goals and purposes within this new dataset, their common linguistic features were applied to the rest of the learning-based dataset to filter out 16,000 goal-based messages in a final dataset.

This process resulted in a significantly small-sized database compared to the initial large-scale dataset (16,000 messages within 270 million in the initial learning-based dataset). The purpose of this initial stage consisted, however, in building a dataset exclusively containing goal-based messages for the recommendation of diverse purposes for learning. The goal-based data extraction process focused, therefore, on precision and fixed some patterns for filtering.

4.2 Latent Dirichlet allocation model

Latent Dirichlet allocation (LDA) is a probabilistic model for collections of discrete data such as text corpora (Blei et al. 2003). It assumes the latent structure of a corpus based on a mixture of topics, also called themes, distributed over documents. Such model is useful when the words observed in the dataset communicate the meaning of the message as a latent structure (Griffiths and Steyvers 2004).

Figure 7 shows the graphical model for LDA. Here, K indicates the number of topics, D is the number of documents, and N signifies the vocabulary size in the documents. Also, W_{dn} represents the n-th word in the d-th document, and Z_{dn} indicates the topic allocation for W_{dn}. The topic distribution $\theta_d = [\theta_{d1}, \ldots, \theta_{dK}]$ is a multinomial distribution over the K topics for the d-th document. Here, $\theta_{dk} \in \theta_d$ represents the occurrence probability of k-th topic in the d-th document. The word distribution $\phi_k = [\phi_{k1}, \ldots, \phi_{kN}]$ is a multinomial distribution over N vocabulary words for the k-th topic. $\phi_{kn} \in \phi_k$ represents the probability of n-th vocabulary word in the k-th topic. α and β are the parameters of the Dirichlet prior distributions.

The parameters of LDA can be estimated from data using a Markov chain Monte Carlo (MCMC) method based on the collapsed Gibbs sampler (Griffiths and Steyvers 2004). Additionally, the number of topics K can also be determined from given data using the perplexity (Blei et al. 2003), marginal likelihood (Griffiths and Steyvers 2004), or a nonparametric extension of LDA (Teh et al. 2006). This study employs the perplexity-based selection method, traditionally used in LDA analysis.

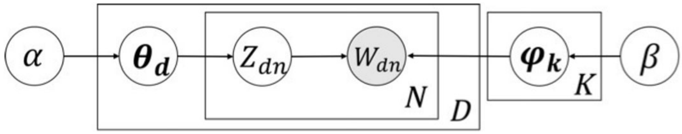

Fig. 7 Graphical model for Latent Dirichlet allocation

4.3 Jensen–Shannon divergence

In the context of this research with a corpus of Twitter messages expressing different purposes for studying the same subject or for engaging in the same achievement task, the different topics estimated by the LDA-based model reflect these diverse purposes. For example, within a corpus of messages expressing purposes for mastering English, the model consequently estimates the topic distributions reflecting learning English for traveling, for business purposes, and so forth. Therefore, we measure the differences of learning purposes as the Jensen–Shannon divergence of the topic distributions (i.e., dissimilarity between distributions).

The Jensen–Shannon divergence D_{JS} between topic distributions θ_d and θ'_d, respectively, for documents d and d' is expressed as

$$D_{\mathrm{JS}}(\theta_d, \theta_{d'}) = \frac{1}{2} D_{KL}(\theta_d \| m_{dd'}) + \frac{1}{2} D_{KL}(\theta_{d'} \| m_{dd'}) \tag{1}$$

where the Kullback–Leibler divergence $D_{KL}(\theta_d \| m_{dd'}) = \sum_{k=1}^{K} \theta_{dk} \log(\theta_{dk}/m_{dd'k})$, with $m_{dd'} = [m_{dd'1}, \ldots, m_{dd'K}]$, and $m_{dd'k} = \frac{1}{2}(\theta_{dk} + \theta_{d'k})$.

This index takes a minimum value of 0 when two topic distributions are consistent. It returns a large positive value that reflects the degree to which the two distributions differ.

In addition to topic distributions, LDA can calculate word distributions. However, Twitter messages are limited to 140 characters. Two messages expressing the same learning purpose using different words may show dissimilar word distributions, but with similar topic distributions. The estimation of dissimilarity based on word probabilistic distribution over topics shows little significance in this context and is omitted for this research.

4.4 Recommender system architecture

Before detailing the recommender system architecture, it is necessary to summarize important terms and their definition in this research, and to avoid any confusion:

- Goal refers to mastering a subject or achieving a final outcome (e.g., becoming fluent in English),
- Purpose is strongly connected with Goal and refers to reasons why one engages in an achievement task (e.g., mastering English to travel around the world),
- Topic is a general term for LDA and refers to the different themes existing in a corpus of documents that are estimated by the LDA-based model,
- Diversity refers to the variety of themes in a corpus of documents. In this case, it refers to the different learning purposes for a same goal.

The three-level distinction between document, topic, and word given by the LDA-based model allows the estimation of topic distribution and word distribution similarities for two documents. An LDA-based model could, therefore, be implemented into a system recommending research articles sharing similar topic distributions and by maximizing word distributions divergence (Uto et al. 2017). The limitation of Twitter messages to 140 characters reduces the probabilistic similarity between word distributions used in different messages. Therefore, the significance of word distribution for similarity estimation between two Twitter messages remains low. On the other hand, two documents (i.e., Twitter messages) might use different words to refer to the same topic (e.g., "work", "job"). The estimation of topic distributions for documents combined with the calculation of topic distributions divergence appears, therefore, as a more effective way to calculate the similarity and dissimilarity between documents in the context of this research.

The complete goal-based recommendation system (Fig. 8) operates following five different steps:

1. **Learner input message:** User expresses in a Twitter message the purpose(s) for engaging in a learning goal *g*,
2. **Goal-based database:** Messages related to goal *g* previously created by other users or collected from the social media Twitter are stored in a Goal Database and used as input for recommendation,
3. **System Input LDA parameters:** Topic and word distributions estimated by the MCMC from the corpus,
4. **Topic distribution dissimilarity:** Dissimilarity estimation between topic distributions of user's input message and messages from peers expressing their learning purposes for the same goal *g*,
5. **Recommendation of diverse purposes:** Messages from different users with the most dissimilar topic distributions sent as output and recommended for observation.

The recommendation process is detailed in Algorithm 1. The algorithm eventually recommends the M most dissimilar messages, with diverse topic distributions and therefore expressing diverse learning purposes for a same goal g.

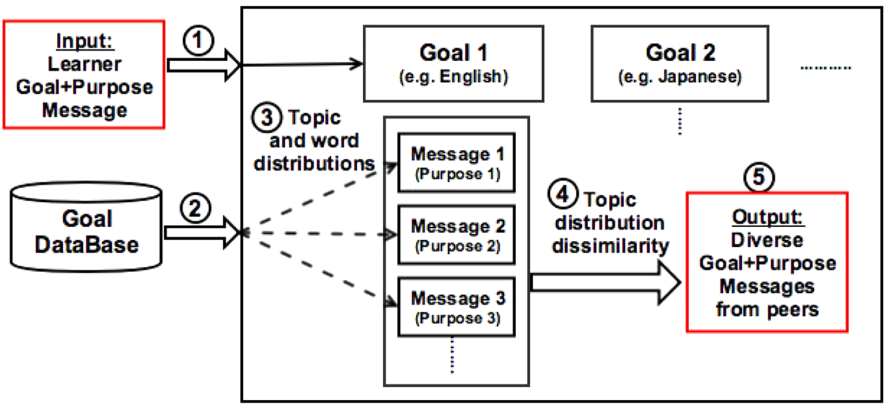

Fig. 8 Illustration of the goal-based messages recommendation process

input : d_u: The user's Twitter message expressing learning purpose for a specific goal g (e.g., "mastering English").
$d^g = [d^g_1, \ldots, d^g_{D_g}]$: Corpus of Twitter messages corresponding to the goal g. Here, D_g represents the number of messages in the corpus.
$\theta^g = [\theta^g_1, \ldots, \theta^g_{D_g}]$: The topic distributions for respective Twitter messages in the corpus d_g. Here, θ^g_i is the topic distribution for the i-th message d^g_i in the corpus.
ϕ^g: The word distributions estimated using the corpus d_g.
output: d_y: M Twitter messages selected from the corpus.

1 *Estimate the topic distribution* θ_u *of the user's message* d_u *using the collapsed Gibbs sampler given the word distribution* ϕ^g.
2 *Create* d_y *by extracting* M *messages from* d^g *with the largest Jensen-Shannon divergence* $D_{JS}(\theta_u \| \theta^g_i)$ *for each* $d^g_i \in d^g$.

Algorithm 1: Recommendation of diverse messages from peers

Recommender systems applied in Technology-Enhanced Learning research have shown positive results by enhancing learning experience. Implementations mostly operate considering similar contents of similar profiles to recommend personalized contents to learners (Manouselis et al. 2012). This research also considered the need for proposing unexpected contents for exploration (Erdt et al. 2015) by recommending messages from peers probabilistically attributed to diverse learning purposes. Participants observe messages from peers containing diverse learning purposes (e.g., "traveling", "business") for the same subject they aim to master (e.g., "English"). The objective is to demonstrate the important and positive impact of observing diverse learning purposes on learners' perception of their own goals.

4.5 System implementation: observing goal-based messages from peers

The goal-based recommender system previously described is implemented as a web application (Louvigné et al. 2015). Considering the source of original goal-based messages, this implementation is based on Twitter design as seen on the homepage (Fig. 9). Participants may use their existing account to access this recommendation system and potentially publish their own messages. For consistency reasons in the recommendation process, users also express their goal and purpose for learning under the format of a Twitter message (i.e., within 140 characters). However, these are the only features kept from Twitter in this implementation.

This system first needs to determine the number of topics as LDA parameter for each learning subject. Figure 10 shows the graphical representation of the perplexity, decreasing for all subjects when the number of topics increases. Considering the decrease in perplexity lower than a fixed value, the number of topics for each subject was set as 8 for Spanish, 7 for French, 6 for English and Japanese, 4 for Chinese, and 3 for chemistry and history. For subjects showing a constant perplexity (algebra, literature, trigonometry), the parameter is fixed as 1 since a variety of goals was not found.

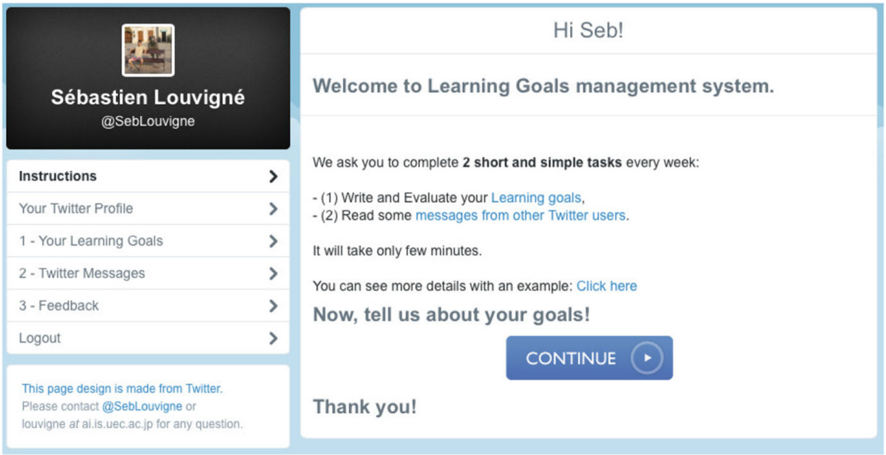

Fig. 9 Goal-based recommendation homepage

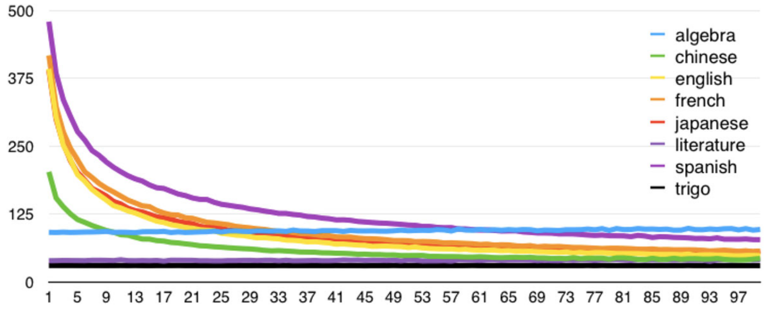

Fig. 10 LDA Perplexity estimation for each subject

The experiment consists into three specific tasks:

1. Creating and updating "Learning Goal Profile(s)",
2. Observing Twitter messages from peers,
3. Repeating the previous two steps over time (starting with observation).

Participants create a "Learning Goal Profile" where they express and evaluate their own purpose for learning a chosen subject (e.g., "English"). Considering the format of messages in the original goal-based database, users write Twitter messages (within 140 characters) to express their learning purpose (e.g., "I want to learn English so I can travel around the world"). In addition, each profile contains evaluations of how participants perceive their own purpose based on motivational attributes: importance, attainability, easiness, specificity, commitment, confidence, achievement, satisfaction, and overall motivation.

After creating a learning goal profile, participants may observe messages from other peers (other participants or Twitter users), recommended by the LDA-based model and expressing diverse purposes.

The last stage consists of reusing the application over time. From the second access, participants first observe recommended messages based on their previously created learning goal profile. After this observation, users are redirected to the same learning goal profile where they have to re-enter learning purpose and self-evaluations. All evaluations are analyzed to recognize the changes in motivational self-perception scores from before the first until after the last observation of peers' messages.

5 Evaluations and discussions

The purpose of this experiment was to evaluate the effect of observing diverse messages from other peers on learners' own perception of their goals. Therefore, participants were randomly classified based on the LDA algorithm recommending:

– Messages with similar topic distribution (i.e., similar learning purpose),
– Messages with dissimilar topic distribution (i.e., diverse learning purposes).

This research proposed and LDA-based recommendation model implemented as a Web application. The model provided results from the dataset of 16,000 goal-based messages mined from Twitter (Louvigné and Rubens 2016).

5.1 Evaluation of learners' perception

Researchers on motivation have used self-reports as the most common method to report people's judgments and assess their motivation. Other assessment methods such as evaluating the time freely spent on studying without extrinsic requirements, or peer evaluations, were considered. However, the self-evaluation of motivational perceptions following the observation of peer messages appeared as the best assessment method in the context of this research.

The initial evaluation completed during the creation of a learning goal profile was used as the basis for the analysis of self-perception score changes after each new observation. Based on their perception, participants rated all goal attributes (Fig. 4) from 0 to 100% (0 = very low, 100 = very high), using radio buttons from 1 to 5, as shown in the questionnaire in Fig. 11.

The questionnaire was used to reflect the perception of overall motivation in addition to attributes related to goal contents and to learners' behavioral and psychological functions in connection with goals, as shown in Fig. 4. The questionnaire started to ask questions in relation to importance, attainability, difficulty, specificity, and commitment. Self-efficacy can be generalized as a cognitive theory and was therefore synthesized in the survey as the evaluation of self-confidence. The performance was asked to be evaluated in relation to what one achieved in the learning process. Finally, learners' satisfaction was evaluated to reflect the feeling of fulfillment.

Undergraduate students in the University of Electro-Communications (Tokyo, Japan) participated in the experiment. In total, 77 students taking English classes

Fig. 11 Questionnaire displayed in learning goal profile where learners can evaluate attributes related to their motivation and their perception on their goal

expressed and evaluated their goals and purposes for mastering English from November 2014 to February 2015. Both groups of participants observing similar or diverse messages from peers, respectively, consisted of 35 and 42 students.

Participants updated their learning goal profiles and re-evaluated their perceptions several times over the semester. The results of this experiment consisted in analyzing the effects of observing recommended messages from peers on learners' perceptions by comparing the average scores from ratings before and after observation. Students could access this web application at their convenience, without fixed time, and completed the tasks a various number of times.

This research considered the hypothesis that students taking optional English class show higher motivation. This caused the distinction between two different types of classes: when students followed English course as part of their *mandatory* curriculum, or when they joined this course as an *optional* class.

Results compare the initial mean values of rating with the latest evaluations. Table 1 shows the changes in rating scores for each attribute, differentiating the two recommendation methods (i.e., similar and diverse messages) and the two types of classes (i.e., mandatory and optional). Evaluations of the difficulty of achieving goals were converted into the complementary level of easiness. Results also include the *t* test significance value for the difference of self-evaluations between pre- and post-observation.

Results appeared more significant for students from mandatory classes due to a larger number of participants. Results also showed in majority an increase in learners' perceptions about their goals, in particular for participants who took mandatory English classes and who were assigned to the recommendation of diverse messages from peers. If the perception of overall motivation generally improved for all participants, most significant changes were observable in the perception of learners' confidence for achievement, goal's attainability, and specificity, when learners observed diverse learning purposes.

Table 1 Self-evaluation changes from before the first to the last observation of recommended peers messages

Observation	Diverse purposes		Similar purposes	
Classes (members)	Mandatory (36)	Optional (6)	Mandatory (27)	Optional (8)
Attributes	Score changes (*p* value)		Score changes (*p* value)	
Importance	– 7.27 (0.129)	– 33. (0.272)	- 3.63 (0.278)	0.00 (0.000)
Attainability	**12.73 (0.038)**	3.33 (0.383)	1.81 (0.380)	5.00 (0.339)
Easiness	1.82 (0.419)	0.00 (0.500)	0.00 (0.500)	– 2.50 (0.447)
Specificity	**12.73 (0.043)**	6.67 (0.334)	– 3.63 (0.296)	2.50 (0.365)
Commitment	3.64 (0.319)	10.00 (0.273)	9.09 (0.134)	– 5.00 (0.268)
Confidence	**14.55 (0.049)**	10.00 (0.230)	0.00 (0.500)	0.00 (0.500)
Achievement	3.64 (0.328)	3.33 (0.272)	3.63 (0.318)	– 2.50 (0.405)
Satisfaction	3.64 (0.371)	13.33 (0.137)	**18.18 (0.015)**	0.00 (0.199)
Motivation	3.64 (0.325)	3.33 (0.153)	1.81 (0.390)	7.50 (0.150)

5.2 Causal mechanisms analysis using DirectLiNGAM model

Figure 4 shows different goal attributes moderating learner's perception in relation to goals and to his/her behavior toward goals. It also illustrates the connections between attributes and how they influence each other based on previous research works.

In addition to self-evaluations, understanding the changes in learners' perceptions on motivational attributes over time called for a method able to discover the causal structure of these attributes based on data. In this regard, Shimizu et al. (2011) and Shimizu (2014) proposed DirectLiNGAM method, a non-Gaussian variant of Structural Equation Models (SEM), to estimate the causal ordering of variables of a dataset with no prior knowledge of the structure.

Tables 2 and 3 show the adjacency matrices with the estimations of connection strength provided by DirectLiNGAM, respectively, for diversity- and similarity-based recommendation methods. Tables show the coefficient of influence from attributes in columns on attributes in rows, confirming the strong and direct impacts of each recommendation method on overall motivation, and more particularly on confidence, specificity, and attainability for diversity, and on satisfaction for similarity.

The network exploration and manipulation software Gephi graphically displays results from Tables 2 and 3, respectively, in Figs. 12 and 13, focusing the goal attributes. Each graphic shows attributes as nodes and only displays estimations higher than 0.2 as edges.

An important finding is the role of commitment that appears as an outcome, influenced by satisfaction in both figures. This observation reveals that, in addition to the sentiment of satisfaction, the efforts and time spent on achieving a goal represent a more efficient way to measure the success of goal setting and the result of increased intrinsic motivation.

Table 2 Adjacency matrix estimated by DirectLiNGAM for evaluations with diversity-based recommendation method

	Attributes	1	2	3	4	5	6	7	8	9	10
1.	Diversity	0	0	0	0	0	0	0	0	0	0
2.	Importance	− 6.667	0	0	0	0	0	0	0	0	0
3.	Achievement	2.899	− 0.165	0	0	0	0	0	0	0	0
4.	Satisfaction	4.226	0.093	0.766	0	0	0	0	0	0	0
5.	Confidence	11.301	− 0.092	0.245	0.265	0	0	0	0	0	0
6.	Commitment	1.841	0.574	0.013	0.385	0.321	0	0	0	0	0
7.	Specificity	10.058	0.401	− 0.355	0.091	0.423	− 0.395	0	0	0	0
8.	Easiness	− 0.143	0.220	− 0.298	0.001	0.876	− 0.591	− 0.527	0	0	0
9.	Motivation	2.367	0.528	0.167	0.104	0.286	0.175	0.102	0.184	0	0
10.	Attainability	4.324	0.088	0.315	− 0.029	0.168	0.494	0.200	0.314	− 0.269	0

Table 3 Adjacency matrix estimated by DirectLiNGAM for evaluations with similarity-based recommendation method

	Attributes	1	2	3	4	5	6	7	8	9	10
1.	Similarity	0	0	0	0	0	0	0	0	0	0
2.	Achievement	2	0	0	0	0	0	0	0	0	0
3.	Specificity	− 2.071	0.036	0	0	0	0	0	0	0	0
4.	Attainability	2.464	0.329	0.228	0	0	0	0	0	0	0
5.	Easiness	− 1.239	− 0.178	0.329	0.595	0	0	0	0	0	0
6.	Confidence	− 0.038	0.356	0.588	0.237	0.193	0	0	0	0	0
7.	Importance	− 2.301	0.077	0.413	0.121	0.026	0.066	0	0	0	0
8.	Motivation	4.735	− 0.118	0.405	0.356	− 0.243	− 0.048	0.550	0	0	0
9.	Satisfaction	8.382	0.576	− 0.356	− 0.636	0.214	0.076	0.122	0.775	0	0
10.	Commitment	− 0.641	− 0.112	0.235	0.401	− 0.203	0.451	− 0.119	0.382	0.363	0

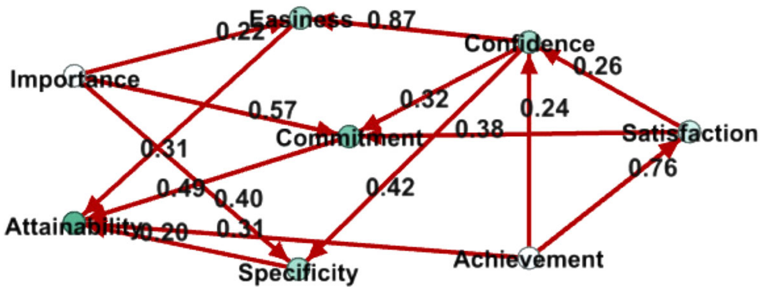

Fig. 12 Graphical representation of DirectLiNGAM adjacency matrix for goal attributes under recommendation by diversity

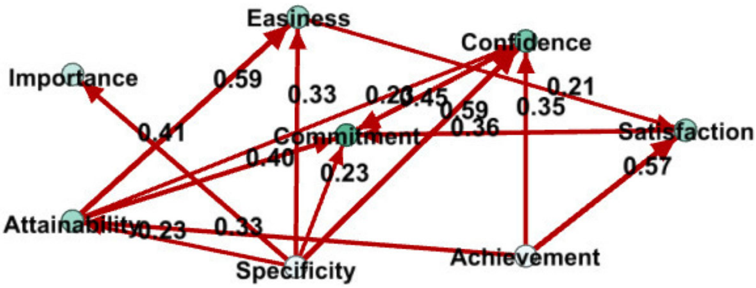

Fig. 13 Graphical representation of DirectLiNGAM adjacency matrix for goal attributes under recommendation by similarity

Figure 12 shows an indirect influence of satisfaction on commitment via confidence, reinforcing the influence of diversity on self-confidence, and eventually on commitment and other attributes related to the goal and purposes for learning (attainability, specificity, easiness). Figure 12 also shows the influence from importance and confidence on specificity, which is in opposite directions in Fig. 13. This observation reflects the differentiation similarity–diversity, and shows a difference with the original theoretical structure in Fig. 4.

6 Conclusion

Contemporary learning approaches and e-learning systems need to include cultural and behavioral aspects with more diversity in addition to knowledge construction in order to connect with long-standing pedagogical issues such as the lack of motivation for education. This research utilized the diversity from Social Networking Services (SNS) to enhance intrinsic motivation by recommending goal-based motivational messages from peers expressing their purposes to achieve a shared goal, to learn a similar subject. The experiment conducted in this research consisted of an SNS platform where 77 undergraduate students expressed their purposes for learning, and evaluated their perceptions on their goals and on their behaviors in relation to these goals.

The SNS platform recommended similar or diverse messages from peers utilizing a latent Dirichlet allocation (LDA) model, estimating topic distributions within a dataset of messages reflecting diverse purposes for engaging in a same achievement goal. The recommendation was implemented by maximizing topic distribution divergence due to the short size of Twitter messages and consequently the low significance in using word distribution divergence.

Participants observed messages from peers at various times over the semester and re-evaluated their perception on goal attributes. The analysis of self-evaluations showed a general increase in overall motivation from participants. More specifically, observing diverse learning purposes showed significant increases in the perception of goal attainability, specificity, and confidence for goal achievement. On the other hand, observing messages from peers expressing similar purpose showed a reinforcement of the satisfaction sentiment. A deeper analysis of causal relationships between goal attributes also revealed that commitment in achieving goal, influenced by confidence and satisfaction, appears as an outcome to measure the success in a goal-setting process. Finally, although observing similar peers succeeding in task performance theoretically facilitates self-efficacy enhancement, this experiment showed a significant increase in self-confidence mostly after observing diverse learning purposes for a similar goal. This finding illustrated the hypothesis that diversity represents an important aspect to be included in collaborative learning environments.

The limited size of Twitter messages calls for a different source of information to be recommended in future experiments, where learners can also express their learning outcomes, methods, and objectives, according to the characteristics of a learning community. The LDA-based recommender model developed and used in this research focused exclusively on textual features made from goal-based messages expressed by participants and collected from the SNS Twitter. Future works should also consider other information from learners profiles related to their interests, outcomes, or relationships. Bayesian networks showed promising results as an approach for collaborative recommendation algorithms (Ueno 2002, 2008; Ueno and Yamazaki 2008) and should be considered with the implementation of learners' portfolios. They might include information such as their interests, outcomes, or relationships, but also their opinions and comments on learning how to learn. They should also reflect the importance of higher psychological functions as described in this study and use them as a resource for learning outcome enhancement.

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