SNS Messages Recommendation for Learning Motivation

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Abstract. Setting goals for learning enhances motivation and performance. This research shows that observing learning goals from peers on social networks allows learners to specify new learning purposes and to enhance the perception of their own expertise. This study consists of: 1) a model recommending goal-based messages from peers with diverse textual contents (i.e. purpose) for a same goal (e.g. mastering English), and 2) a Web-based implementation using an LDA (Latent Dirichlet Allocation) model, known as a highly accurate text latent topic model. The experiment was conducted by university students who expressed and evaluated their goals before observing similar/diverse messages from other peers. Results showed that observing the diversity of peers' learning purposes is an important factor positively affecting intrinsic motivational attributes such as goal specificity and confidence to achieve the goal.

Keywords: Learning motivation · Social networks · Recommendation · Latent Dirichlet Allocation

1 Introduction

Pedagogical goals and purposes for learning are strongly connected and represent a prominent view of motivation [8,20]. Learning goals are efficient when linked with learner's needs and purposes because learners want to know the reasons why learning is important for them [1,14]. Educational institutions therefore provide highly structured education with syllabus stating specific outcomes.

However learners as individuals have various conceptual perceptions and different purposes for learning. Students are then often unable to relate to the objectives stated by their formal education. This matter 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 [9,19]. This results in risks of conflict and discouragement that might harm learner's intrinsic motivation. Learners need a resource of a larger variety of goals and purposes from peers for better goal orientation and learning motivation.

Vygotsky claimed that individuals learn and build their knowledge in social context, through external relations with others [23]. Other research works later

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developed approaches demonstrating that learners build knowledge by observing others [3], collaborating with others [22], and reflecting new knowledge on new situations [7]. The main interest of this research is therefore about whether the concept of learning from peers can be applied to learning motivation.

Social networks represent an essential and influential factor, including for learning [4]. However, peers also use social media to express and share their motivation. Figure 1 shows examples of Twitter users expressing some goals and purposes for learning.

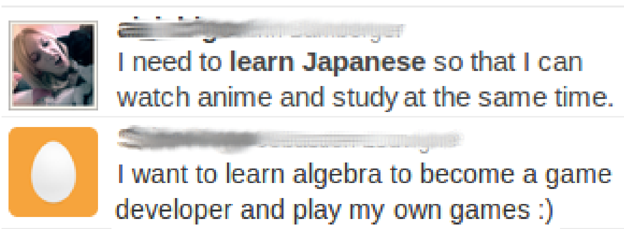

Fig. 1. Example of goal-based messages collected from the social media Twitter. This research consisted in the recommendation of similar/diverse goal-based messages for a same learning subject using LDA.

The purpose of this research consisted in determining how to use social networks in order to enhance motivation for learning, in particular by using the diversity of goal-based motivational messages from peers. Similarity in recommendation e-learning systems showed enhancements and reinforcements in learning performance and behavior (including motivation). However, the difficulty for many learners in following formal education's goals called for a larger and more diverse choice of purposes for learning to be recommended. The purpose of this study was therefore twofold:

1. Design a goal-based recommendation system to let learners observe messages from peers containing diverse purposes for learning a same subject (e.g. English),
2. Web-based implementation using an Latent Dirichlet Allocation (LDA) model in a social environment.

The highly accurate text latent topic model LDA assumes a latent structure based on several topics, also called themes, distributed probabilistically over document [6]. LDA therefore estimated the diversity of topics (i.e. purposes for learning) within a single dataset of goal-based messages from peers. The recommendation model offered then different learning purposes from peers expressed as Twitter messages.

This research viewed the observation and adoption of diverse learning purposes as an important factor to enhance learners' motivation and to positively impact their perception on their goal attributes. This study therefore aimed at (1) designing a model to recommend diverse learning purposes from peers and (2) evaluating the effect on learners' perception of their motivation and the attributes related to the initial goal: *importance*, *attainability*, *easiness*, *specificity*, *commitment*, *confidence*, *achievement*, *satisfaction*, and overall *motivation*.

2 Learning Goals

A general definition for *goal* can be a terminal point towards which actions or behaviors are directed. In learning, goal represents then an outcome that one intends to attain as a result of a cognitive process (e.g. mastering a language). Goals provide the direction to guide learners to act, the force to satisfy a need, to motivate behaviors [20].

2.1 Goal-Setting

Goal-setting focuses on the 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 a learning goal. In his excellent works [12,14] Locke summarized some goal setting research works and gave a list of different goal attributes. Bekele [5] also reviewed studies about satisfaction and motivation in Internet-Supported Learning Environments.

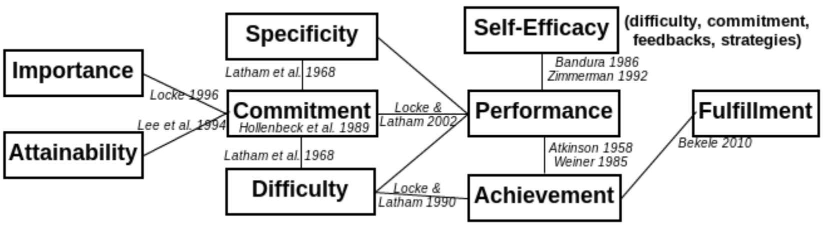

Fig. 2. Goal Attributes. This diagram summarizes the different goal attributes and how they can be connected to each other. It shows that each of these moderators can affect Performance and that Achievement and Fulfillment represent the final outcomes of a learning experience based on a goal.

Among all goal attributes, goal specificity gives a direction to learners and leads to higher performance than ambiguous tasks. Learners with more specific tasks can better control their performance on them. In addition goals both specific and difficult lead to higher performance because they generate higher commitment, in contrast with ambiguous goals (e.g. *"do your best"*). Self-efficacy refers to one's beliefs in the ability to control goals and has a wider influence on motivational moderators (e.g. confidence) and therefore performance [4].

Goal attributes are various and affect each other to lead eventually to achievement and fulfillment (or personal satisfaction). Figure 2 summarizes the connections between those goal attributes and their importance as motivational moderators in a learning experience.

2.2 Goal Orientation

Goal orientation has been in recent years an active research area in educational psychology and achievement motivation. It refers to the purposes and the ways to approach and engage in achievement tasks.

Learners have various goal orientations or purposes for learning, but there are also different types of goal orientations, often referred as mastery and performance goals [1]. The former focuses on mastering tasks according to self-set standards whereas the latter represents the demonstration of a skill based on external judgments [19].

This distinction, like others, is based on whether goals relate to intrapersonal or external aspects. Considering the high influence of self-set goals on intrinsic motivation [13], learners can adopt new purposes for engaging in a task in order to follow a more intrapersonal and therefore more efficient goal orientation.

The diversity of purposes for achieving a similar goal expressed by peers on social media appears as an important factor able to affect motivation for learning and the self-perception of one's goals.

3 Social Networks for Learning and Motivation

Vygotsky claimed that individuals build their consciousness through external relations with others [23]. Behaviors strongly related to needs are learned in social situations and mediation with other persons. Vygotsky's findings and the concept of learning from peers strongly influenced many research works in the past decades.

Several approaches demonstrated that knowledge and behaviors are acquired by observing [3] and collaborating with others [22]. Learners subsequently articulate, reflect their new knowledge, and explore new goals [7].

Eccles et al. extensively discussed theoretical perspectives and empirical works on motivation, and reviewed many social cognitive models [8]. Authors demonstrated the important impact of social settings on motivation and indicated the influence of emotions for future developments.

Therefore, social networks appear to operate naturally as behaviors recommenders [4] influencing learners behaviors, and therefore motivation and purposes for learning [1].

This high potential called for a new recommender model aiming at using the large and diverse amount of motivational contents from peers to influence learners' perceptions of their goals and purposes.

4 Goal-Based Recommendation System

Recommender Systems took a major part in the development of advanced technologies, based on the similarity of item contents, user profiles (Collaborative Filtering) or other information [11]. Previous implementations in education showed positive results in enhancing learning by recommending personalized contents to learners [18].

The main purpose of this research consisted in designing a goal-based recommendation model for learning motivation enhancement. This model aimed at recommending motivational contents from peers (i.e. goal-based Twitter messages containing learning purposes) using social settings. This study focused on the positive effect of observing diverse purposes for learning on learners' perceptions of their own goals.

This goal-based model therefore used LDA, known as a highly accurate text latent topic model, to determine different topics (i.e. learning purposes) within a same dataset of Twitter messages where users expressed why they learn a given subject (e.g. English).

4.1 Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) is a probabilistic model for collections of discrete data such as text corpora [6]. Such model is useful when each document is a mixture of topics and when the words observed in the dataset communicate the meaning of the message as a latent structure [10].

There are different categories of goal-based messages (e.g. "traveling", "business", "manga") for a same subject of study (e.g. "Japanese"). This study used a model based on LDA considering that each document (i.e. Twitter message) contains several topics and that each word is attributable to one of these topics. This model determined several learning purposes as topics in a dataset of goal-based messages for a same learning subject, as done in a preliminary study [15].

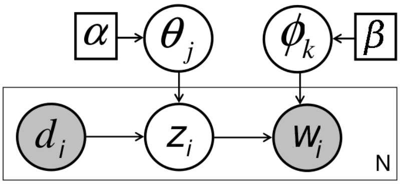

Fig. 3. Graphical model for LDA. Boxes denote the parameters α and β. Shaded and unshadded circles respectively denote observed and hidden variables. [2]

Figure 3 shows the graphical model for LDA used in this study where θ and ϕ respectively represent the estimated distribution of a topic Z for a document d and the distribution of a word W for a topic Z. α and β are the parameters of the Dirichlet prior on respectively the per-document topic distributions and the per-topic word distributions.

This study used the Collapsed Gibbs Sampling method [10] to construct a Monte Carlo Markov chain and to determine the full conditional distribution (1) and the Dirichlet distribution of words per topic (2):

$$P(z_i = j|z_{-i}, w) \propto \frac{n_{-i,j}^{(w_i)} + \beta}{n_{-i,j}^{(\cdot)} + W\beta}(n_{-i,j}^{(d_i)} + \alpha) \tag{1}$$

$$\hat{\phi}_j^{(w)} = \frac{n_j^{(w)} + \beta}{n_j^{(\cdot)} + W\beta} \tag{2}$$

in which W represents all words in all documents. w and z represent respectively the words and the topics. $n_{-i}^{(\cdot)}$ denotes a word count not including the current assignment of z_i.

4.2 Recommendation System Architecture

The LDA-based model aimed at recommending goal-based messages from peers expressing diverse purposes for learning a same subject. Figure 4 illustrates the different steps of the recommendation process as listed below:

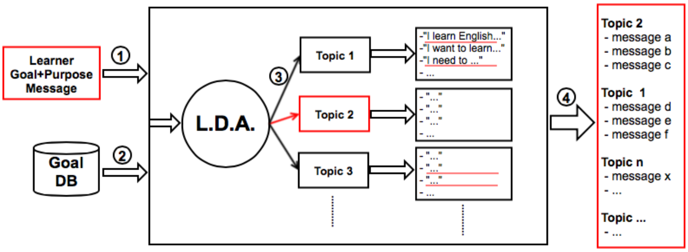

Fig. 4. Illustration of the goal-based messages recommendation process. The model recommends Twitter messages from diverse categories of learning purposes from peers for a same learning subject.

1. **Learner Input:** user's message expressing the reason(s) for engaging in learning a chosen subject,
2. **System Input:** existing dataset containing similar types of messages previously created by other users or collected from the social media Twitter,
3. **Topic distribution:** estimation of topics' probabilistic distribution from the input database, and estimation of the appartenance of user's input message,
4. **Output:** selection of messages from topics others than the one estimated to relate to user's input message.

The recommender model used user's written expression of learning purposes to list goal-based messages from other peers. It required an initial dataset of messages (16,000 Twitter messages) built in previous stages of this research [17,21].

The recommender process utilized the LDA-based model described in Sect. 4.1 during two different situations: offline and online. The former consisted in initially estimating the probabilistic distribution of words and documents (i.e. Twitter messages from the goal-based dataset) over topics corresponding to different learning purposes. In relation to these estimations, the recommender model determines the attribution of a user's goal-based message.

Results from the recommender model showed finally messages belonging to other topics than the one attributed to user's input goal-based message. Most recommender systems focus on similarity with contents or peers. This study considered however the diversity of motivational contents essential for recommendation. Results described in Sect. 5 compared learners' self-evaluation of their goal perception between users who were recommended similar or diverse goal-based messages.

5 Results and Evaluation

The goal-based recommender model was implemented into a Web application [16] in order to create a social environment. Learners could express their learning purposes in the form of a Twitter message and observe messages from other peers.

Undergraduate students in the Tokyo University of Electro-Communications participated in the experiment. Students were randomly assigned into two groups based on the recommendation way: 1) similar messages (attributed to the same topic), 2) diverse messages (attributed to other topics). In total, 77 students taking English classes expressed and evaluated their goals from November 2014 to January 2015.

5.1 Experiment Scenario

The experiment consisted into three specific tasks:

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

Learners managed their learning goals by creating what was called "Goal Profile(s)". In addition to the subject of study (e.g. *"English"*), users were asked to express the reason(s) why they study this subject (e.g. *"I want to learn English so I can travel around the world"*) using a Twitter message format (within 140 characters).

This stage of the experiment also included learner's self-evaluation of the perception of their goals. This feature, essential for the analysis of observing goal-based messages from peers, consisted in rating goal attributes moderating learning performance and fulfillment as shown previously in Fig. 2. Therefore, for each goal profile created, users rated how they think about their goal achievement using the questionnaire shown in Fig. 5.

The recommender model listed then some Twitter messages from other peers based on (1) the messages created in the Goal Profile(s), and (2) the recommendation way (messages from similar/diverse topic(s)).

Fig. 5. List of questions in Goal Profile for learners' self-evaluation

Students were asked to repeat the tasks every week over the school semester in order to analyze of the recommendation system over a long-term period. From the second attempt, however, they first observed peers' messages based what they expressed the first time. After the observation step, students could re-express and re-evaluate their learning goals. This last part was an essential step to analyze the effect of both recommendation ways on learners' perceptions of their goals.

5.2 Evaluation of Learners' Perceptions

77 Japanese undergraduate students taking English classes expressed their goals for studying English. They also rated their perceptions on their goals based on the motivational attributes previously cited. Each attribute was rated from 0 to 100% (0=very low, 100=very high).

Results consisted in comparing both recommendation ways (similar/diverse messages). Table 1 shows in both cases the average ratings from users for each motivational attribute. Results are also summarized for three different times of the experiment: T_0: initially (before any observation of peers' messages); T_1: after the first observation; T_{final}: after the last observation.

"Diff." column of Table 1 shows the change of ratings average from T_0 to T_n, or in other words from the initial evaluation (i.e. before any observation) to the last evaluation (i.e. after observing n times peers' messages).

The results from the evaluations showed that observing diverse goal-based messages from peers generally affected more positively learners' perceptions of their goals, especially for feelings of attainability, goal specificity and confidence for achievement.This utilization of messages from social media also showed an improvement of overall motivation for all users, although slightly superior when observing diverse messages.

Table 1. Self-evaluation: average results of learner's perceptions of their goals

	Similar messages				Diverse messages			
Motivation Attributes	T_0	T_1	T_{final}	Diff.	T_0	T_1	T_{final}	Diff.
Importance	89.23	86.15	86.15	−3.08	91.43	87.14	87.14	−4.29
Attainability	73.85	72.31	78.46	4.62	64.29	71.43	72.86	8.57
Easiness	44.62	42.31	45.38	0.77	44.29	47.14	45.71	1.43
Specificity	81.54	79.23	76.15	−5.38	67.14	77.14	78.57	11.43
Commitment	70.77	72.31	72.31	1.54	67.14	72.86	71.43	4.29
Confidence	66.15	61.54	63.08	−3.08	57.14	62.86	68.57	11.43
Achievement	66.15	66.92	66.92	0.77	62.86	62.86	65.71	2.86
Satisfaction	72.31	78.46	78.46	6.15	61.43	62.86	65.71	4.29
Overall Motivation	78.46	80.77	82.31	3.85	68.57	68.57	74.29	5.71

6 Conclusion

Setting goals that are intrinsically purposeful and meaningful for learners enhances learning motivation and performance. Contemporary social media offer a large variety of motivational contents from peers where they express their goals and purposes for learning. This research interest was based on the influence from peers from social networks on learning motivation. This study regarded the diversity of purposes for learning from peers as an important resource for intrinsic motivation enhancement.

This study consisted in a goal-based recommendation model utilizing social networks to present peers' Twitter messages. The model utilized LDA to estimate the diversity of topics (i.e. learning purposes) within a dataset of Twitter messages expressing the same goal (i.e. mastering a subject). The implementation of this model recommended peers' messages based on the similarity/diversity with learner's purpose.

A total of 77 university students expressed their goals and evaluated their perceptions of their overall motivation. The implemented system recommended similar or diverse Twitter messages to learners. Their self-evaluations showed the positive effect of observing diverse learning purposes from peers on motivation and especially on goal attributes, in particular confidence to achieve the goal, goal specificity and attainability.

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