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Goal-based messages Recommendation utilizing Latent Dirichlet Allocation

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Abstract—Observing various learning goals from peers allows learners to specify new objectives and sub-goals to improve their personal experience. Setting goals for learning enhances motivation and performance. However an unrelated goal might lead to poor outcome. Hence learners have divergent objectives for a same learning experience. Latent Dirichlet Allocation (LDA) is a model considering documents as a mixture of topics. This study then proposed a recommendation model based on LDA, able to determine distinct categories of goals within a single dataset. Results focused on a dataset of 10 learning subjects and over 16,000 goal-based Twitter messages. It showed (1) different goal categories and (2) the correlation between the LDA parameter for the number of topics and the type of subject. Evaluations of goal attributes also showed an increase of goal specificity, commitment and self-confidence after observing different types of goals from peers.

I. INTRODUCTION

Pedagogical goals affect learning performance by providing a sense of direction, effort and an aim to attain specific standards [1]. They guide learners in their experience to satisfy their needs for learning, personal or shared with others. In particular, cognitive theories of motivation consider goals to be critical motivators, in interaction with personal emotions and belief [2].

Although numerous motivation theories and approaches demonstrated their effective influence on achievement and performance, a lack of motivation for learning is still nowadays a large cause of education failure [3]. Hence, Goal-Setting appears clearly to be an essential approach to adapt and enhance learner's commitment, motivation for learning, and eventually performance and the sentiment of fulfillment.

Academic curricula propose well defined syllabuses with fixed objectives. However learners with various profiles, backgrounds and abilities might not relate to the proposed goals, whether they previously had their own fixed goals or not. This matter appears even more clearly in self-regulated learning environment where learners construct, control and monitor their own actions, motivation, and goals [4]. Learners need a larger variety of suggested goals from teachers or peers to find one they can relate to, or to set multiple goal levels for an even better orientation [5].

There are different types of goal orientations, often divided into mastery and performance goals [6]. The former based on the learner's personal standards and skills showed

interesting influence on intrinsic motivation and seems more likely to fit in self-regulated learning environment. However such goal setting should be done properly and selectively in order to avoid discouragement or conflict [7].

This research consists in the recommendation of goal-based messages created from Social Media in order to let learners (1) observe learning goals from peers as shown in Figure 1, and (2) set their own goals for their personal experience. Observational Goal Setting approach designates this combination of Goal-Setting theory with Observational Learning approach [8]. However in order to assist learners in setting different or new goals, diversity of the collected information is an important factor.

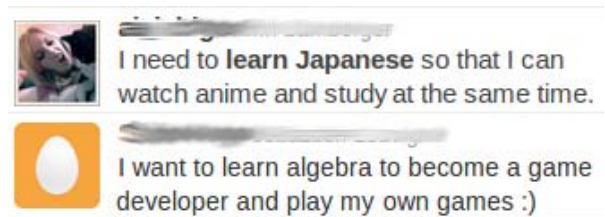


Figure 1. Example of goal-based messages found on social media. This research proposes to determine different categories of goal-based messages within a single dataset using LDA.

The study presented in this paper used a model for documents based on Latent Dirichlet Allocation (LDA). This model determined a latent structure based on several topics, also called themes, distributed probabilistically over documents (Section III). The dataset used in this study consisted of 10 different learning subjects (e.g. algebra, history, French) with over 16,000 goal-based messages previously collected from the social media Twitter [8] [9].

The model determined several sub-categories for a same set of goal-based messages about one subject. For example, one could have the objective to learn a language for traveling, for business purpose, or for some cultural interest. Hence, a diversity of goals for a same subject can be recommended to learners.

Learning subjects have different specificities. Based on the original dataset they provided an unequal number of groups of goal-based messages. The second purpose of this study was then to determine, for each subject, the optimum

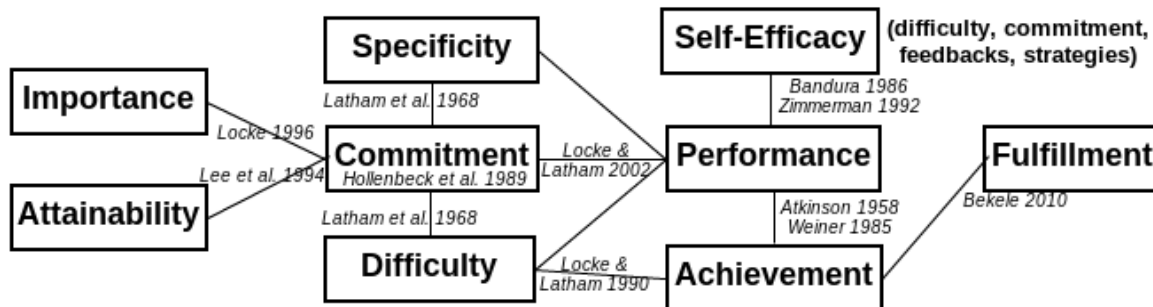


Figure 2. Goal Attributes. This diagram summarizes the different goal attributes and how they can be connected to each other. It shows that each of these moderators can affect Performance and that Achievement and Fulfillment represent the final outcomes of a learning experience based on a goal. In other words, learning should be considered successful when learner is satisfied.

parameter for the LDA model related to the number of topics (the number of groups of goals).

Learners participated in an experiment where they could rate the attributes of their own goals, before and after observing recommended messages from peers. Results showed learners, especially when they observed different types of goals, rated their goal specificity, commitment and self-confidence higher than before observation.

II. 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. Goals provide the direction to guide learners to act, the force to satisfy a need, to motivate behaviors [2].

This section reviews two different aspects of goal theories: goal orientation (Section II-A) and goal-setting (Section II-B).

A. 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 [6]. The former focuses on mastering tasks according to self-set standards whereas the latter represents the demonstration of a skill based on external judgments [4].

B. Goal-Setting

Unlike goal orientation which refers to the purpose for learning, 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 [1] [7] Locke summarizes some

goal setting research works and gives a list of different goal attributes. Bekele [10] also summarizes studies about satisfaction and motivation in Internet-Supported Learning Environments.

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 [11]. 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"). Persistence and commitment are also important goal setting factors as they complement effort required to complete the task and the time given affects the importance of these two mechanisms [12].

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

III. GOAL-BASED MESSAGES RECOMMENDATION

Pintrich's self-regulated learning theory assumes that learners actively manage their own goals (*orientation* and *setting*) [4]. This phase is an essential prerequisite of the learning process but goal-setting can also occur at any point. In fact goals can be monitored and adjusted at any time during a task.

The purpose of this research is (1) to determine different categories of goal-based messages for a same learning subject and (2) to recommend a diversity of learning goals to learners. They can afterwards observe and adopt new learning goals to improve their motivation and personal experience. Learners have indeed different goals and motivational orientations for learning and want to know the reasons why learning is important for them [13].

A. Goal-based Dataset

The dataset used in this study consisted of over 16,000 messages collected from the social media Twitter [8]. Orig-

inal data was initially filtered based on learning concepts before focusing on 10 different learning subjects: *algebra, chemistry, Chinese, English, French, history, Japanese, literature, Spanish, and trigonometry*.

Linguistic methods used in previous works [9] allowed to mine the final dataset used in this study. The next phase consisted in determining categories of goals within all collected goal-based messages for a same learning study.

B. Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) is a probabilistic model for collections of discrete data such as text corpora [14]. 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 [15].

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 which considers that each document (i.e. Twitter message) contains several topics and that each word is attributable to one of these topics.

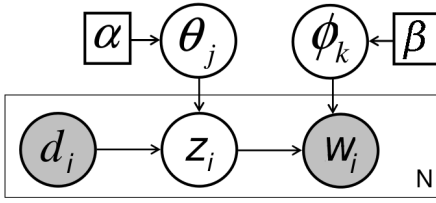


Figure 3. Graphical model for LDA. Boxes denote the parameters α and β . Shaded and unshaded circles respectively denote observed and hidden variables. [16]

Figure 3 shows the graphical model for LDA used in this study where θ_j and ϕ_k are respectively the topic distribution for document j and the word distribution for topic k . 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 [15] to construct a Monte Carlo Markov chain and to determine the full conditional distribution (Eq. (1)) and the Dirichlet distribution of words per topic (Eq. (2)):

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

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

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 .

C. System Architecture

After the collection and categorization phases, the next stage of this study was to let learners observe goal-based messages from peers. Figure 4 describes the architecture of the system used to recommend goal-based messages from peers to learners.

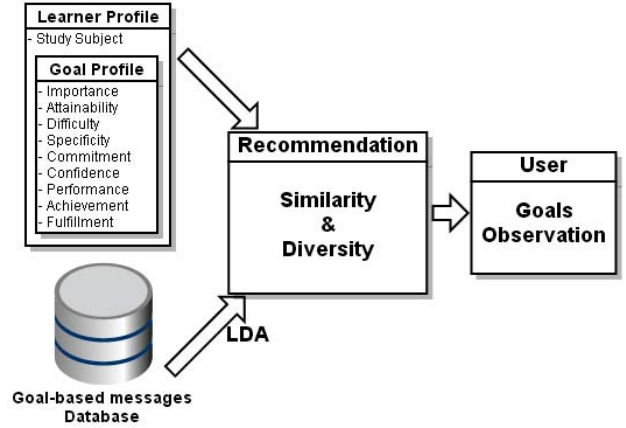


Figure 4. Goal-based messages Recommendation System.

The recommendation system needs as input (1) the learner profile including the subject of study and the goal content and attributes, and (2) the database of goal-based messages from peers. Recommending goals consisted in collecting messages related to the subject of study and the goal of the learner, via the previously presented LDA algorithm.

The model based on LDA determined the categories where learners goals belonged. In addition, goals recommendation also consisted in providing messages belonging to different categories of goals. Diversity of goal-based messages was an important aspect of this recommendation system.

IV. EVALUATIONS

This study proposed a peer goal recommendation model based on LDA to provide a variety of goal-based messages to learners. The results provided an estimation of topics for each selected subject of study and an evaluation of the optimum parameter for the number of topics to estimate (Section IV-A). Learners were then asked to evaluate the attributes of their goals, and the potential changes after observing different categories of goal-based messages from peers (Section IV-B).

A. LDA results

The proposed model provided interesting results based on a dataset of 10 learning subjects and over 16,000 messages mined from Twitter during previous studies [8] [9] (Section III-A). Results consisted for each subject of study of several estimated topics with the list of words and their probabilistic distribution according to the topic. Table I

below shows a sample of estimation of topic with the 10 words most likely to be associated to this topic and their distribution.

Word	Distribution
topic: 6	
french	0.1202725671
learn	0.0669345561
learning	0.0463266883
speak	0.0145663272
paris	0.0140814362
move	0.0140814362
going	0.0109296446
talk	0.0104447536
day	0.0102023081
start	0.0099598626

Table I
LDA RESULTS SAMPLE

This study measured next the perplexity related to the LDA parameter for the number of topics, for each learning subject included in the dataset. For example, the dataset contained much more messages for subjects such as English, French or Japanese, than some more specific and possibly less popular to learners such as algebra or trigonometry. Hence the model required an analysis of the optimum parameters for the number of topics. Measures were conducted using the number of topics $k = \{1, 2, \dots, 100\}$. Figure 5 shows results for all learning subjects and with $k = \{1, \dots, 15\}$.

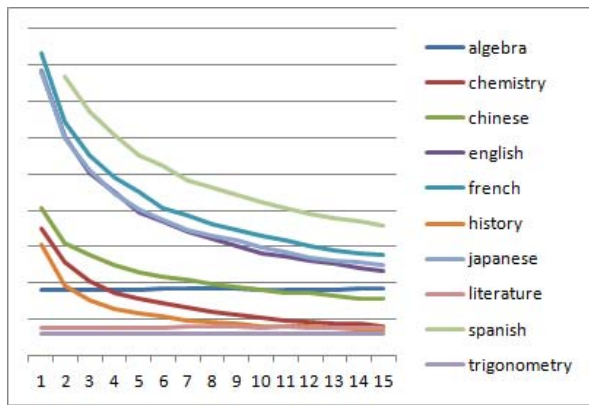


Figure 5. LDA Perplexity estimation. This graph shows the results for the ten different learning subject used in this study.

Figure 5 clearly shows a decrease of perplexity for most of learning subjects when the parameter for the number of topics k increases. Twitter messages being limited to 140 characters per message and the dataset containing various messages written in different ways, the LDA model estimated a high number of topics to be more accurate. This assumption however was considered superfluous. Hence the model needed to consider a condition which, when met, fixed the number of topics considered the most accurate for the given topic. Considering the decrease of perplexity lower

than a fixed value, this model estimated the best number of topics at 9 for Spanish, 8 for French, 7 for English and Japanese, 5 for Chinese, 4 for chemistry and history.

Subjects such as algebra, literature and trigonometry, showed a nearly constant perplexity. Hence the entire group was already an accurate goal categorization based on the learning subject. This was explained by the low number of goal-based messages compared to other subjects. Hence a variety of goals for learning such subjects was unnecessary.

B. Learners Evaluations

The recommendation model presented in this paper resulted in displaying different types of goal-based messages from peers to learners. In order to analyze the effect of this observation on self-set goals and personal motivation, this study proposed an experiment based on self-report, goal recommendation and observation.

A group of 30 learners first filled a questionnaire where they expressed their current studies with the respective objectives. The survey asked participants to rate from 1 (*not at all*) to 5 (*very much*) the attributes of their own objectives previously showed in Figure 2. The results in Figure 6 showed that learners evaluated a high importance for their objectives in contrast with a lower level of other attributes (i.e. commitment, confidence, performance and satisfaction).

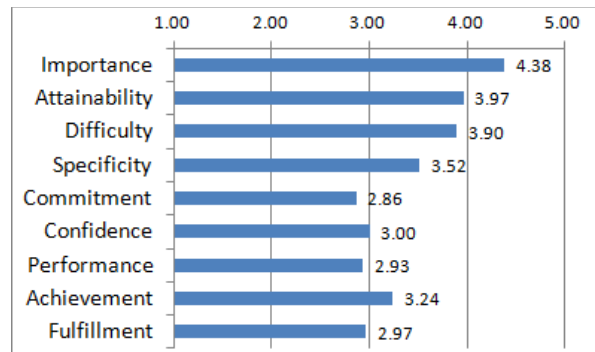


Figure 6. Goal attributes evaluation from learners. Learners rated the attributes of their own goals (1 = not at all; 5 = very much). They expressed a high importance in contrast with lower levels of commitment, performance and fulfillment.

Series of goal-based messages were sent afterwards to participants related to their learning subjects. Based on their originally expressed objectives, participants either received similar goals of different types of goals from peers. At last they filled a second questionnaire asking to evaluate the changes of attitude regarding their own objectives for learning. Table II lists the average values for (1) all participants, (2) participants who observed messages similar to their goals, and (3) participants who received messages from diverse goal categories. Participants chose between "negative change" (negative values), "no change" (0) and "positive change" (positive values).

Goal attributes	Variations after Observations		
	1) Total	2) Similar	3) Diverse
Importance	0.34	0.33	0.44
Attainability	0.50	0.33	0.67
Difficulty	-0.21	0.17	-0.33
Specificity	0.71	0.17	1.00
Commitment	0.50	0.33	0.56
Confidence	0.29	0.17	0.33
Performance	0.36	0.00	0.67
Achievement	0.43	0.17	0.56
Fulfillment	0.29	-0.17	0.67

Table II
VARIATIONS OF GOAL ATTRIBUTES EVALUATIONS

The first notable change showed in Table II was the global increase of the goal specificity evaluation for all participants. Observing peer goals allowed them to have a more precise idea about their own goal. In addition, participants observing goals similar to their own one showed minimal changes. It confirmed however the evaluations preceding the observation stage. Finally, participants observing goals from diverse categories expressed higher rates of specificity and a general increase of other attribute rates, except difficulty. This confirmed the importance of observing a diversity of recommended peer goals.

V. CONCLUSION & FUTURE WORKS

Setting pedagogical goals enhances motivation for learning and performance. Observing various learning goals from peers allows learners to specify new objectives and sub-goals for their personal experience. Therefore the purpose of this study was to design a recommendation model able to (1) determine various groups of learning goals within a dataset and (2) provide a list of goal-based messages from peers.

The proposed goal recommendation model used LDA because goal-based messages from peers contained different topics for different goals (Section III). Perplexity measurements of the parameter for the number of topics showed different optimum values depending on the selected study subject (Section IV-A).

Self-reports of goal attributes from learners expressed first a high rate of the importance of personal objectives for learning (Section IV-B). This was in contrast with lower rates for commitment, self-confidence, and performance. After observation of different goals from peers, learners evaluated an increase of the goal specificity and their commitment for learning. Results showed that this change was due to learners who observed diverse goals, hence not only similar to their own goal initially expressed. This confirmed the importance of diversity when recommending different types of goals to learners.

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