Analyzing the language evolution of a science classroom via a topic model

Mohammad Khoshneshin, Mohammad Ahmadi Basir, Padmini Srinivasan, W. Nick Street, and Brian Hand, The University of Iowa

In this paper, we introduce a topic model to analyze the temporal change in the spoken language of a science classroom based on a dataset of conversations among a teacher and students. One of the key goals is discovering the root of the change in the language usage of students. To accomplish this, we defined 4 categories which generate words: 1) back ground (general) 2) activity, 3) session subject, and 4) personal. Our experimental results support the hypothesis that the change in the language of students mainly consists of using more activity-based language which can be interpreted as using more scientific discourse. Such an approach can be used to investigate the effect of teaching methods or to represent an individual's progress.

1. INTRODUCTION

In traditional off-line classrooms, evaluation is mainly based on exams. Other parameters such as attendance or participation are considered but not as much as grades. Considering the fact that learning influences language, we believe that the change in the spoken language of students is a representative of progress. Although a teacher has day-to-day interactions with students, it might be hard to detect the change in spoken discourse of students. Therefore, an automatic tool which analyzes temporal aspects of students' spoken language may yield interesting patterns as feedback to different teaching methodologies. Also, such a tool, besides offering additional educational evaluations, may be used to detect students who are not making progress.

In this work, we use a dataset of dialogues in a science classroom to investigate the changes over time in the language of students. As expected, the language of students becomes more similar to the language of instructor over time. There are two explanations for this change: 1) the personal language usage of students is becoming more similar to the personal language usage of teacher 2) students are learning to use scientific discourse and since the teacher is using scientific discourse as well, their languages are becoming more similar. To identify the main source of change, we designed and implemented a topic model which distinguishes the sources of words. We assume each word may be generated from four different sources: 1) background, 2) activity, 3) session, and 4) personal. Background words are general words such as "I" or "is". Activity words are the words that are related to the scientific discourse. For example if a student is reasoning about a scientific claim, he uses activity-based words. The following conversations are from dialogues in the classroom during a claim and evidence activity:

—Student A: our claim is the more mass you have, the more force you get out of the object

—Teacher: evidence?

—Student B: the more washers you put in the cup, the faster the erasers are going to fall

Author's address: M. Khoshneshin, Department of Management Sciences; email: mohammad-khoshneshin@uiowa.edu, M.A. Basir, Department of Science Education; email: mohammad-ahmadibasir@uiowa.edu, P. Srinivasan, Department of Computer Science; email: padmini-srinivasan@uiowa.edu, W.N. Street, Department of Management Sciences; email: nick-street@uiowa.edu, B. Hand, Department of Science Education; email: brian-hand@uiowa.edu.

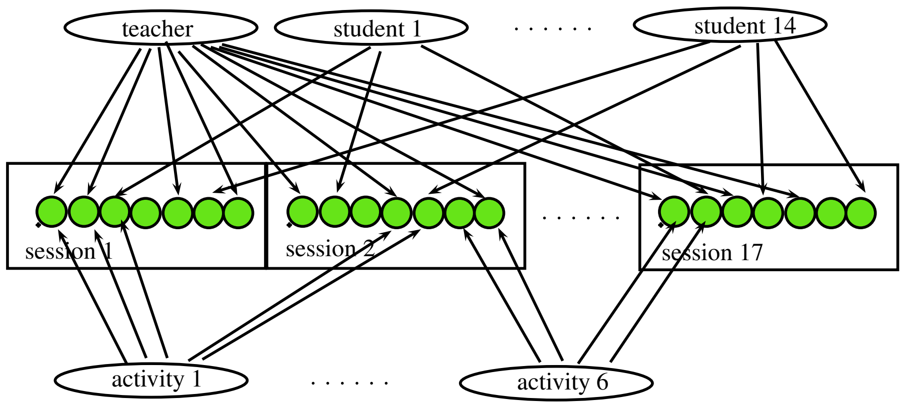

Fig. 1. The structure of the dataset of the classroom conversations. Circles represent utterances in different sessions.

Obviously, words such as "claim" or "evidence" are related to this activity. Session words are related to the subject of the classroom, in the above examples, words such as "mass" or "force" are related to the session subject. Finally, the personal words are related to the specific way to convey concepts such as "actually".

Using the topic model, we show that the change in the language of students is mainly because of an increase in the activity language usage. This means that students are learning to use more terms related to scientific discourse which is a sign of learning. No significant change was observed in personal, session, and background language usage. Although it might seem that growth in session language is a sign of learning, we note that students use session language comparatively more when they are passive and mostly responsive. More precisely, when students comparatively use a lot of words related to the subject of the session, they are mostly responding to the teacher's questions with quick answers.

2. PROBLEM STATEMENT AND DATA DESCRIPTION

The main goal of this paper is extracting useful patterns and knowledge out of classroom conversations. We focus on temporal changes in conversation to investigate the changes in students' language. This may offer key insights into students' learning and also potential feedback on different teaching methods.

Our dataset consists of a snapshot of conversations in a science classroom. Figure 1 shows the structure of the dataset. The parties in the conversation consist of a teacher and 14 students. There are 17 sessions in temporal order over a one-year period and there are a number of utterances in each session (total of 7572 utterances). Each utterance starts when a new person starts talking until the next person starts talking (there were 3 utterances in the example in the previous section). There are 2010 unique words in this dataset. The data was transcribed by human from the videos of the classroom. Note that traditional text analysis preprocessing such as stop-wording or stemming were not performed since some patterns such as the tense of the verb, negative statements, or "wh" words usage are important for us.

Each utterance in the classroom has been assigned manually to an activity. These activities have been identified by human judgment. Table I shows the title of each activity, the number of sessions they appear in and the number of utterances they include. Activity 5 is infrequent and only happens in one session but other activities occur in 4 or more than 4 sessions.

The key question to be addressed is whether the language used by students is changing over time and if yes, how it is changing. Figure 2 shows the cosine similarity between the normalized word vectors of teacher and students (all students treated as one person) over different sessions. Although the linear growth of this similarity is not statistically significant at 0.05, a logarithmic growth in similarity is observed.

Table I. The list of activities in the classroom.

Number	**Activity**	**# utterance**	**# session**
1	categorization	2834	5
2	claim and evidence	1861	8
3	discussing initial ideas before doing experiment	437	4
4	doing experiment	914	4
5	reflection	4	1
6	what experts say	1522	6

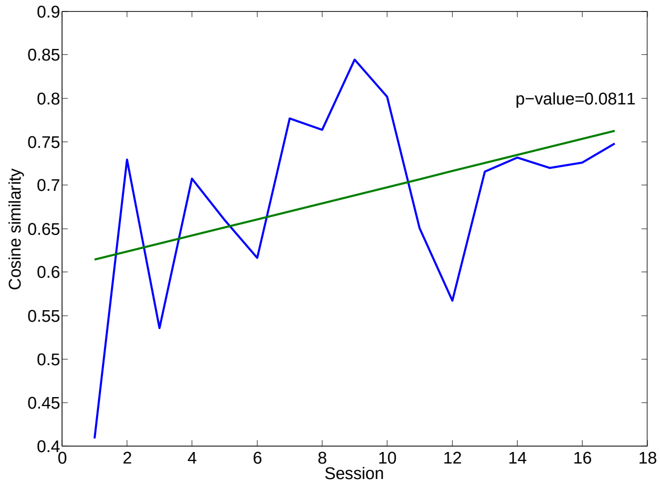

Fig. 2. The cosine similarity between the normalized word vectors of the teacher and students (all students treated as one person) over time.

Table II. Test of linear relationship over time in the cosine similarity between the normalized word vector of the teacher and individual students

	St 1	St 2	St 3	St 4	St 5	St 6	St 7	St 8	St 9	St 10	St 11	St 12	St 13	St 14
slope	0.0104	0.0129	0.0202	0.0118	0.0163	0.0120	0.0054	0.0088	-0.0008	0.0077	0.0014	0.0111	0.0128	0.0124
p-value	0.3561	0.0611	0.0539	0.3846	0.1506	0.2200	0.5439	0.4245	0.9387	0.5057	0.8388	0.4343	0.3219	0.2412

Table II shows the test of linear relationship in the cosine similarity between the normalized word vectors of the teacher and all individual students over time. The word vector of a person is a vector with length of the number of words (here 2010) and each value of the vector depicts the frequency of a word. The language of students (all but one) is becoming more similar to teacher's language but none of them are statistically significant.

Table III represents the words for which the usage has significantly changed (at 0.05 significance). We only considered words that occurred at least in 4 sessions for the students and 8 sessions for the teacher. There are some names such as "tori" or "tanner" in this table. Students' usage of comparison words such as "like" or "kind" is increasing over time. On the other hand, the teacher usage of some key words such as "claim", "evidence", or "why" is less frequent in later sessions. It might be due to the fact that students are able to use these types of discourses more effectively so the teacher needs to mention them less.

In summary, the language model of students is changing over sessions but the essence of the change is not obvious. Is the change because of personal usage of language or is it because of using more terms related to

Table III. The words for which usage is increasing or decreasing at 0.05 significance. For students, we examined the words that occurred in at least 4 sessions and for the teacher in at least 8 sessions.

	Increase in usage	Decrease in usage
Student 1	like, at, blake, need	was
Student 2	no, has, need	and, might
Student 4	you, like, can, them	in
Student 5	go, for	
Student 6	it, like, you, down, first, probably, which, at, called	were, would
Student 7	to	and, might
Student 8	no, kind	or
Student 9	it	
Student 11	in, would	because
Student 12	down, just	is, no
Student 13	you, ok, would, them, see	was
Student 14	says, are, make, sure, ok, pretty, different	too
Teacher	we, would, or, find, need, our, thinking, tori, little, move, her, use, well, listen, over	your, evidence, why, claim, group, good, tanner, questions, fifth, remember, people

scientific discourse? To investigate this question we designed a latent Dirichlet allocation based topic model [Blei et al. 2003] to model the language usage and track changes over time, which is described in the next section.

3. A CUSTOMIZED TOPIC MODEL

We first describe latent Dirichlet allocation [Blei et al. 2003] (LDA) which is the theoretical basis of the proposed topic model. Then we explain the customized topic model to investigate the change in students' language.

LDA is a generative probabilistic model to learn co-occurrence data such as data from text collections. The main model is usually explained via the language model which generates the text content in a collection of documents. In this model, there are a predefined number (K) of topics. The language model of each document is defined by the distribution of the document over the K topics: $\theta_{dz} = P(z|d)$ where z is the topic and d is the document. θ is generated from a symmetric Dirichlet distribution with parameter α ($P(\theta|\alpha) = \frac{\Gamma(K\alpha)}{\Gamma(\alpha)^K} \prod_k \theta_k^{\alpha-1}$). Document d consists of N_d tokens (an instance of a word), and each token comes from a specific topic z. Given that a topic z has generated a token, the probability that word w occurs for that token is $\phi_{wz} = P(w|z)$. ϕ is generated from a symmetric Dirichlet distribution with parameter β. In summary, the process of generating documents of a corpus is as follows:

(1) For each topic z:
  (a) Choose word distribution $\phi_z \sim Dir(\beta)$
(2) For each document d:
  (a) Choose topic distribution $\theta_d \sim Dir(\alpha)$
  (b) For each token t
    i. Choose a topic $z \sim Multinomial(\theta_d)$
    ii. Choose a word $w \sim Multinomial(\phi_z)$

Figure 3 (a) shows the graphical model for LDA using the plate notation. The number in the lower-right corner of each plate depicts the frequency of the contents of that plate. In the corpus, there are D documents and for each document a distribution over topics (θ) is generated. There are K topics and for each topic a distribution over words (ϕ) is generated. Finally, there are N_d tokens in each document and for each token a topic z and a word w is chosen.

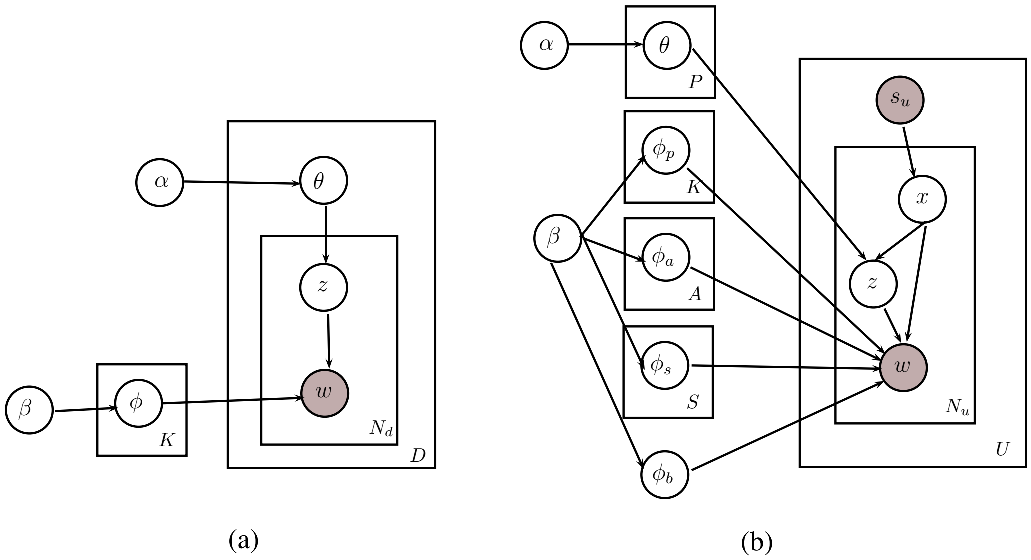

Fig. 3. The graphical model of (a) the latent Dirichlet allocation model and (b) the proposed topic model. Observed variables are shown as gray circles.

In our dataset, instead of documents, there are utterances. However, the size of each utterance is very small and it might consist of only 1 word. As a result, assuming each utterance as a document and generating a specific language model for each utterance causes severe overfitting. Therefore, instead of utterance, we assume a language model for higher level entities. Each utterance is associated with three different higher level entities: an activity, a session, and a person. Here, we can assume that each entity can independently generate words. For example, the activity "claim and evidence" generates words such as "claim", and "support". Each session has a scientific subject such as the cardiovascular system. Then, words such as "heart" or "blood" can be seen as words generated by session language model. A person usually has special ways of conveying concepts which results in specific language. For example, some people use words such as "actually" or "you know" more often.

Additionally, as mentioned in the previous section, we did not perform stemming and stopwording, so the data includes very general words such as "it", and "is". Therefore, we assume another entity is generating general words; we call it the background language representing general English language usage. Such an approach has been used in [Ha-Thuc and Renders 2011]. In summary, each word in an utterance can be generated from one of the following language models:

—Activity language

—Session language

—Personal language

—Background language

For the personal language models, we adapt a a similar strategy as used in the author-topic model [Rosen-Zvi et al. 2004]. In the author-topic model, each author has a distribution over different topics. When a group of scholars writes a paper, for each token, first, an author is chosen from a uniform discrete distribution. Then, a topic is chosen from the selected author language topic distribution, and finally a word is chosen from the topic language model. Here, instead of authors, there are a teacher and a group of students. However, there is no uncertainty about which person said the word as there was in the author-topic model. The uncertainty is about which of the four language models has been used to generate a word.

For the personal language models, we assume a person-topic model. That is, for each person there is probabilistic distribution over K topics ($\theta_{zp} = P(z|p)$). For each topic z, there is a distribution over different words ($\phi^{(p)}_{zw} = P(w|z)$). Note that we used the index (p) to distinguish the language model of personal language (which is of personal topics over words) from other language models.

For the activity language models, each activity a generates words independently from a distribution on words ($\phi_{aw} = P(w|a)$). Similarly for session language models, each session s generates words independently from a distribution on words ($\phi_{sw} = P(w|s)$). Finally, the background language model generates words from a distribution on words ($\phi^{(b)}_{w} = P_b(w)$).

Figure 3 (b) represents the graphical model for the proposed topic model. There are U utterances in the dataset. Each utterance u is associated with a set $S_u = \{a_u, s_u, p_u\}$ which shows which person in which session and over which activity said the utterance. In each utterance, there are N_u tokens. For each token, a latent variable x is chosen from a uniform multinomial distribution which shows which language model (background, session, activity, or personal) has been used to generate the word. Note that the distribution over categories can be learned. However, since we want to explore the temporal changes, it is not useful to fit a static distribution and fitting a dynamic distribution is left for future research. If $x = p$ (personal language generated the word), then a topic z is chosen from a multinomial distribution with parameter θ_{p_u}, and then a word w is chosen from a multinomial distribution with parameter $\phi^{(p)}_{z}$. Similarly, if $x = b$, $x = a$, or $x = s$, a word w is chosen from a multinomial distribution with parameter ϕ_b, ϕ_{a_u}, or ϕ_{s_u} respectively.

Using the topic model proposed here, we will be able to distinguish the type of words students are using and, as a result, better understand the essence of changes. In summary the proposed topic model is as follows:

(1) For each person p:
  (a) Choose $\theta_p \sim Dir(\alpha)$
(2) For each topic z:
  (a) Choose $\phi^{(p)}_{z} \sim Dir(\beta)$
(3) For each activity a:
  (a) Choose $\phi_a \sim Dir(\beta)$
(4) For each session s:
  (a) Choose $\phi_s \sim Dir(\beta)$
(5) Choose $\phi_b \sim Dir(\beta)$
(6) For each utterance u:
  (a) For each token t
    i. Choose $x \sim Multinomial(\{.25, .25, .25, .25\})$
    ii. if $x = b$, then Choose a word $w \sim Multinomial(\phi^{(b)})$
    iii. if $x = a$, then Choose a word $w \sim Multinomial(\phi_{a_u})$
    iv. if $x = s$, then Choose a word $w \sim Multinomial(\phi_{s_u})$
    v. if $x = p$:
      A. Choose a topic $z \sim Multinomial(\theta_{p_u})$
      B. Choose a word $w \sim Multinomial(\phi^{(p)}_{z})$

For inference and learning the parameters, we used the version of Gibbs sampling used in [Griffiths and Steyvers 2004]. Gibbs sampling is a special case of Monte Carlo Markov chain algorithm which is used to sample from the posterior distribution. In Gibbs sampling, the full conditional distribution of a parameter given the rest of the parameters is derived analytically and then samples are drawn iteratively. In Gibbs

Table IV. The test of linear regression of change in activity language model for individual students and all of them as a whole.

	St 1	St 2	St 3	St 4	St 5	St 6	St 7	St 8	St 9	St 10	St 11	St 12	St 13	St 14	All
slope	0.000	0.000	0.003	0.001	**0.006**	-0.002	-0.002	-0.000	-0.001	0.003	-0.002	0.003	**0.006**	**0.004**	**0.001**
P-value	0.974	0.698	0.355	0.623	**0.040**	0.491	0.252	0.944	0.784	0.499	0.650	0.075	**0.003**	**0.003**	**0.043**

sampling for LDA, the topic of tokens is sampled given all other parameters are set. After enough iterations, all parameters can be estimated using the drawn samples. In our model, there are two types of hidden variables: the 4-category usage variable x and the topic z where the latter is in effect when $x = p$ (person is using her personal language). The conditional probability for latent variables of token i is as follows:

$$P(z_i = k, x_i = c | z_{-i}, x_{-i}) = \begin{cases} \frac{n_{w_i k}^{(-i)} + \beta}{n_k^{(-i)} + W\beta} \frac{n_{p_i k}^{(-i)} + \alpha}{n_{p_i}^{(-i)} + K\alpha} & \text{if } c = p \\ \frac{n_{w_i e_i}^{(-i)} + \beta}{n_{e_i}^{(-i)} + W\beta} & \text{if } c = e \neq p \end{cases}$$

where z_i, and x_i are the latent variables for token i, z_{-i}, x_{-i} are the assignment of latent variables for all tokens except for i, and $n_{ab}^{(-i)}$ and $n_a^{(-i)}$ show the count of tokens assigned to entities a and b. After running the Gibbs sampling algorithm, parameters can be estimated via harmonic mean [Griffiths and Steyvers 2004].

4. RESULTS

We ran the proposed topic model on the dataset with parameters: $\alpha = 1$, $\beta = .01$, and $K = 5$. The Gibbs sampling algorithm was run for 3000 iterations and then 200 samples after each 10 iterations were drawn when the algorithm was run for another 2000 iterations.

Table V shows the top words for all language models. In this table, words ranked based on their predictive probability for an entity. That is instead of using the value $P(w|e)$ for entity e to sort words, we used $P(e|w) = \frac{P(w|e)P(e)}{\sum_{e'} P(w|e')P(e')}$ where $P(e)$ are equally probable for all entities. That is we wish to focus on words that are able to distinguish between the entities. The last column of Table V shows the rank of the teacher for each personal language topic based on $\theta_{pz} = P(z|p)$. From this ranking, topic 1 and 4 are related to teacher and topics 2, 3, and 5 are related to students. The first topic includes words to communicate with students while topic 4 includes more lecture-related words. Investigating words associated to activities, sessions or even background reveals that the topic model has separated words appropriately. As an example, the first session was about putting different things inside a bag and distinguishing them from investigating the bag without looking inside. Words such as “sticky”, “pencil”, or “puncher” represent the objects were put inside the bag. Word “feels” is from expression “it feels like” to express a guess about the content of the bag.

To explore the main cause of change in students’ language and the reason that their languages are becoming more similar to the teacher’s, we used 4-category language usage versus personal language topic usage. The 4-category language usage is the probability distribution of using 4 different categories: background, activity, session, and personal. For example, Let assume a person has said 100 words during a session. The Gibbs sampling algorithm has assigned 20 of them to background, 25 to activity, 30 to session, and 25 to personal language. Then the vector for the 4-category usage probability of that person in the session is $\{.20, .25, .30, .25\}$. Furthermore, from the 25 words assigned to personal language, assume the assignment to 5 personal topic is as follows: $\{2, 8, 1, 0, 14\}$ results in a personal topic usage probability vector: $\{2/25, 8/25, 1/25, 0, 14/25\}$. Since such a vector can be identified for each person, the similarity between the teacher and students can be computed from the cosine similarity between these vectors. Figures 4 and 5 present the similarity between teacher’s and students’ 4-category language usage probability and personal topic usage probability respectively. For 4-category language usage probability, the same pattern as general cosine similarity (Figure 2) is observed while for personal topic usage probability no increase or decrease is detected. It means that the change in students’ language is happening at a higher level than in personal

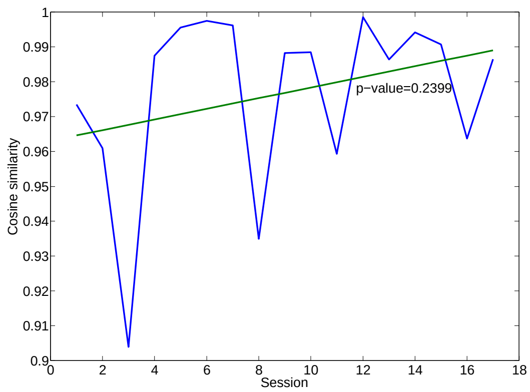

Fig. 4. The cosine similarity between the 4-category language usage probability vector of the teacher and students (all students treated as one person) over time.

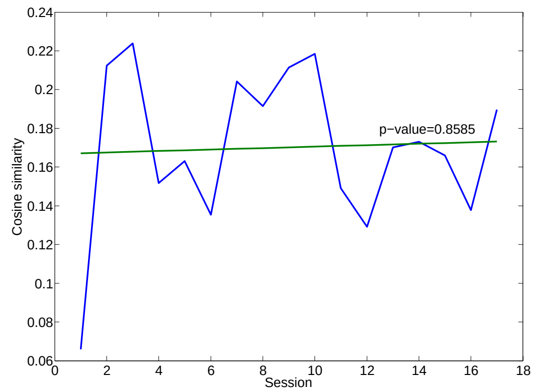

Fig. 5. The cosine similarity between the personal topic usage probability vector of the teacher and students (all students treated as one person) over time.

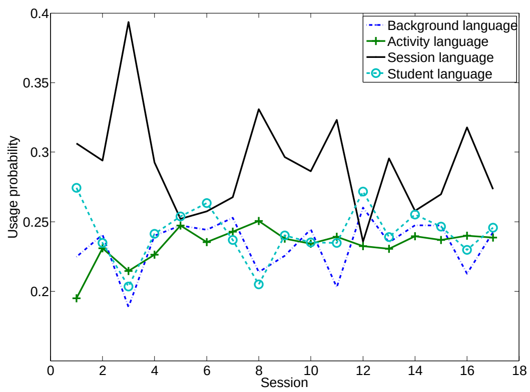

Fig. 6. The 4-category language usage of students (all students treated as one person) over time.

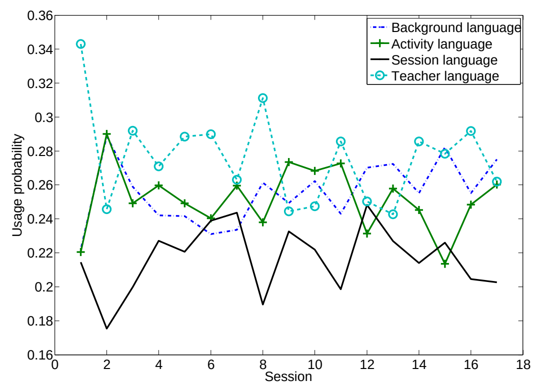

Fig. 7. The 4-category language usage of the teacher.

usage of language. Figures 6 and 7 show the change in 4-category language usage probability over sessions. While no special pattern is observed for teacher, the activity usage probability for students is rising. Table IV shows the linear regression test for the activity-based language usage probability of students and the increasing pattern for 3 of them, and for the whole student group, is significant at .05. No significant pattern was observed for other categories.

Comparing Figures 6 and 7 reveals another key difference between the language usage pattern of the teacher and students. Students tend to use more session based language than the teacher. That may be due to the fact that teacher uses a lecture based language which is based on more frequent usage of personal language while students tend to talk about the course content which is related to the subject of the session. Note that the relative decrease of session language usage does not mean that students are using the related terms less but it means they are using them less frequent compare to other categories. Based on Figure 6, it seems that there is a shift from session based language to activity based language which as discussed in the second section, can be interpreted as a shift from a passive presence to an active presence tied with more usage of scientific discourse.

5. RELATED LITERATURE

There is a limited literature on applying data and text mining tools to classroom spoken language [Romero and Ventura 2010]. Most of the related work applies data mining to extract patterns from discussion forums. As an example, [Dringus and Ellis 2005] summarized the information in an asynchronous discussion forum by applying data mining algorithms to show the quality of discussions. However, none of these types of works attempt to analyze the text data. In another related work, [Singley and Lam 2005] introduce a tool, classroom Sentinel, to mine information related to students on the Web for finding useful patterns about the progress of a classroom. Similarly, this work has not used text information of the classroom.

6. DISCUSSION AND FUTURE DIRECTIONS

In this paper, we introduced a customized topic model to decompose the spoken speech of a science classroom. Our experimental results show that students' usage of activity language increases over time which is a sign of learning. Such an approach can be used to investigate the effect of teaching methods or represent an individual's progress. However, there are many factors that are not controlled in our dataset such as the order of session topics or activities over time. Therefore, the change in the language of students in classroom might have been caused by some other factors rather than learning. For example, students can be forced to use some words by some structured questions. Nevertheless, given the observed unstructured format of the classroom, we conjecture that learning is the strongest factor responsible for change.

In this paper, we used a static topic model, and estimated parameters for different sessions . However, using topic models which incorporate temporal changes in data (e.g. dynamic topic model [Blei and Lafferty 2006]), stronger and more accurate statements can be achieved.

In this work, we used activities labeled by human judgment. However, finding different activities and assigning all utterances to activities are time consuming. Therefore, it is desirable to design an unsupervised algorithm which discovers and assigns activities. Given the sequential nature of activities, a hidden Markov model (HMM) is proper for this purpose. Therefore, a combination of LDA and HMM (similar to [Griffiths et al. 2005]) can be used to simultaneously discover and assign activities while distinguishing words' source.

REFERENCES

Blei, D., Ng, A., and Jordan, M. 2003. Latent Dirichlet allocation. *The Journal of Machine Learning Research 3*, 993–1022.

Blei, D. M. and Lafferty, J. D. 2006. Dynamic topic models. In *Proceedings of the 23rd International Conference on Machine Learning*. ICML '06. ACM, New York, NY, USA, 113–120.

Dringus, L. and Ellis, T. 2005. Using data mining as a strategy for assessing asynchronous discussion forums. *Computers & Education 45,* 1, 141–160.

Griffiths, T. and Steyvers, M. 2004. Finding scientific topics. *Proceedings of the National Academy of Sciences of the United States of America 101,* Suppl 1, 5228.

Griffiths, T., Steyvers, M., Blei, D., and Tenenbaum, J. 2005. Integrating topics and syntax. *Advances in Neural Information Processing Systems 17*, 537–544.

Ha-Thuc, V. and Renders, J.-M. 2011. Large-scale hierarchical text classification without labelled data. In *Proceedings of the Fourth ACM International Conference on Web Search and Data Mining*. WSDM '11. ACM, New York, NY, USA, 685–694.

Romero, C. and Ventura, S. 2010. Educational data mining: a review of the state of the art. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on 40,* 6, 601–618.

Rosen-Zvi, M., Griffiths, T., Steyvers, M., and Smyth, P. 2004. The author-topic model for authors and documents. In *Proceedings of the 20th Conference on Uncertainty in Artificial Intelligence*. UAI '04. AUAI Press, Arlington, Virginia, United States, 487–494.

Singley, M. K. and Lam, R. B. 2005. The classroom sentinel: Supporting data-driven decision-making in the classroom. In *Proceedings of the 14th International Conference on World Wide Web*. WWW '05. ACM, New York, NY, USA, 315–321.

Table V. Top words for different entities. T.R. is the teacher rank for the personal language topics.

#	Top words	T.R.
	Personal language topics	
1	courtney, next, anyone, austin, show, what, blake, so, hearing, whole, happen, tyler, disagree, why, tienna, guys, katie, else,do, tanner	1
2	well, usually, because, nine, yes, little, yeah, really, but, wouldn, goes, ours, moves, too, tiny, nevermind, of, plain, transport, figure	15
3	actually, though, apart, says, pretty, top, except, always, kind, turns, either, another, ones, makes, couldn't, means, place, gets, alive, possible	12
4	again, discussion, talk, ahead, alright, please, brooklyn, scientists, telling, anybody, group, course, question, good, does, tori, talked, writing, me, those	1
5	basically, since, once, saw, started, pulled, tried, somehow, also, day, whatever, quite, larger, almost, we, starts, our, takes, through, later	15
	Background language	
	people, how, not, just, thing, bit, or, make, nothing, be, before, wasn't, very, things, remember, come, anything, but, doesn't, mean	NA
	Activity language	
1	growing, grouped, grouping, vein, plus, girls, smarter, where, are, most, tons, kindergarten, bugs, gotta, categories, divide, hamburger, thinks, these, were	NA
2	used, support, evidence, nose, claim, applause, took, specific, quarter, add, comments, didn't, personally, did, was, for, made, normally, read, better	NA
3	material, measure, cups, mess, supplies, thickness, scary, rulers, might, design, obviously, ideas, write, wrote, share, drinks, clips, gravity, downhill, hill	NA
4	happens, steps, doing, ready, referring, trying, try, representing, see, showed, step, going, gone, pointing, heavily, blows, stick, stretched, are, represents'	NA
5	reflection, fun, liked, experiment, milk, salt, soda, chance, young, puts, my, learned, increase, lab, beginning, idea, calcium, lot, completely, nice	NA
6	raise, discuss, whenever, from, carries, glad, picking, picked, read, card, transports, popped, debate, above, closing, increases, carried, carry, resting, wind	NA
	Session language	
1	sticky, bag, crossed, pencils, puncher, glue, stapler, notes, booth, elephant, list, pens, markers, feels, scissors, marker, squishy, pencil, round, encyclopedia	NA
2	chef, servant, wine, steak, window, kitchen, provide, story, storm, rare, table, cook, mansion, cooks, himself, fence, killed, serve, spilled, balcony	NA
3	nails, bladder, kidney, stomach, bowels, vines, tongue, connections, points, thighs, connected, map, lines, liver, fingers, location, concept, human, relation, intestine	NA
4	cylinder, pounds, layers, shapes, held, layered, shape, triangular, steel, books, layer, duty, femur, triangle, cylinders, wide, stuffed, collapse, wider, potter	NA
5	vinegar, bend, acid, stayed, wrist, slimy, age, strength, yogurt, dissolve, softer, overnight, dissolved, daily, weak, observe, mg, kids, smell, measured	NA
6	bicep, tricep, cardiac, builder, relax, contract, movement, wheaties, fiber, pile, shorten, dk, builders, triceps, joint, anti, shoes, maximus, gluteus, curious	NA
7	balloon, balloons, blow, doh, lung, throat, respiratory, inflate, deflate, expand, straws, straw, chest, inhale, inflates, inflated, technically, expanded, exhaling, experiment	NA
8	universal, clumping, receive, donor, hemoglobin, clear, proteins, emergency, fatal, clumps, receiver, represented, population, receivers, trouble, parents, minus, contain, clot, positive	NA
9	arteries, ventricle, atrium, aorta, circulatory, delivery, pump, pumps, bum, fist, smoking, purplish, boom, bulge, loose, carrying, smoke, rushes, gold, homework	NA
10	block, lifted, teeter, cake, totter, wood, lifting, chunky, mrs, harris, underneath, seesaw, stood, her, close, closer, included, unit, clearer, set	NA
11	accelerated, affecting, agrees, added, christopher, umm, agreement, barely, erasers, tweak, switch, nods, washers, off, slower, differently, represent, less, old, accelerate, repeat	NA
12	stripes, link, tendon, websites, itself, yourself, attached, ninth, myself, hook, attach, muscular, systems, tells, crazy, contracting, relaxing, tendons, stop, involuntary	NA
13	static, invertebrates, vertebrates, invertebrate, fish, vertebrate, blooded, animal, mammal, eggs, warm, yolk, mammals, reptiles, spider, snakes, covered, platypus, insect, sharks	NA
14	carnation, xylem, swollen, coloring, fungus, dots, sucking, apple, talkin, absorbing, rose, turning, fruits, algae, hip, hers, pedals, glossary, dissecting, mold	NA
15	reproduce, sap, reproduction, spores, tubelike, ways, glucose, pollenate, reproductive, xylum, divisions, pollenating, based, bee, pollen, pollenated, vasculars, underground, bats, vascular	NA
16	lever, load, balancing, levers, located, magnifies, machines, magnify, fulcrum, effort, budge, wagon, simple, wheels, class, wheel, cranes, machine, wheelbarrow, amplify	NA
17	clip, drop, tie, gaining, twine, knot, string, falls, acceleration, nowhere, july, accelerate, slow, parachute, washer, desk, twenty, farther, slowing, brave	NA