Turning Down the Noise in Classrooms

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ABSTRACT
The use of micro-blogging in classrooms is a recently trending concept in computer-aided education. Micro-blogs offer an effective way of communication in large classrooms, and engage students in meaningful discussions. However, existing micro-blogging systems in education setting suffer from a few drawbacks. First, relevant content might be overwhelmed by irrelevant posts to the lecture which could jeopardize effective learning. Second, students might generate redundant content by posting similar questions to each other and create substantial information overload. Third, posts covering different aspects of the class might be left undiscovered due to real-time characteristics of micro-blogs. To address these issues, we present a principled approach for picking a set of posts that promotes relevant and diverse content while effectively turning down the noise created by redundant posts. We formulate this task as a submodular optimization problem for which we provide an efficient and near-optimal solution. We evaluate our framework on real micro-blog based classroom datasets and our empirical results demonstrate that our framework is effectively able to cover the most important and diverse content that is being discussed in classrooms.

1. INTRODUCTION
The use of micro-blogging in a classroom setting can be useful at engaging students as it provides an effective way of communication, especially in large classes. Using provided tools, students are able to share their questions or comments in real time during the class as well as helping each other by addressing the questions of fellow students. Thus, the use of micro-blogs not only deepens the understanding of the students, but also engages them to the class in real time.

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2. RELATED WORK
Micro-blogging has been increasingly used as a tool for communication between students and instructors in classrooms over the recent years [4, 7, 10, 26]. Some of these works analyze micro-blogging in the context of language learning [4]. Twitter, as one of the most popular micro-blogging service prevalent these days, has also been exten-
Figure 1: Word cloud generated from the lecture material (left) which focuses on keywords like stock, company, growth, price. Word cloud generated from the posts of students (right) which focuses on topics such as stock, company as well as some diverse topics like nyse and nasdaq. Size of the text is positively correlated to frequency of each item.

Table 1: Examples of relevant and irrelevant posts

<table>
<thead>
<tr>
<th>Relevant Posts</th>
<th>Irrelevant Posts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Can you share some examples about disposition effect?</td>
<td>Will there be an extension for homework 3?</td>
</tr>
<tr>
<td>What is the prospect theory?</td>
<td>Is today’s class canceled?</td>
</tr>
<tr>
<td>How much money is usually invested by hedge funds?</td>
<td>Invest in pizza!</td>
</tr>
<tr>
<td>Why having no credit is considered bad?</td>
<td>Will this be on the midterm?</td>
</tr>
</tbody>
</table>

3. DATASET

This study uses the data collected using a tool that is designed as a micro-blogging platform where students can post questions or comments in a real-time setting and interact with the instructor or fellow students during the lectures. The dataset consists of content that is posted during eight semesters of an undergraduate course titled Finance with a total of 20,000 posts.

In addition to obtaining micro-blogging posts, accompanying lecture materials that are prepared by the instructor(s) during the corresponding eight semesters for this course are also collected. Figure 1 shows two word clouds that are generated for a random session of this course. As can be seen from the figure, there is a certain overlap between the content that the instructor is focused on and the content that students emphasized on, such as stock, company, prices. However, one can see that there is also some content that students are focused on even though they are not intensively covered in the lecture, such as nasdaq and nyse. Therefore, the use of a micro-blogging platform allows students not only to extend or enhance the material covered in the lecture, but also enables students to ask and learn additional details about the concepts by asking questions. An important problem of using micro-blogs in education setting is the irrelevant content generated by students. Table 1 lists some examples of relevant and irrelevant questions asked by students.

Therefore, an ideal framework should a) consider the correlation between the lecture material and the content generated by students, b) discard or give low priority to irrelevant content, and c) cover a diverse range of concepts that students are interested in.

4. METHODOLOGY

In this section, we describe the components that comprise our framework. First, we introduce the submodular framework that selects a set of most relevant and diverse content for a given lecture. Then, we discuss the relevancy...
Table 2: An example to illustrate the notion of diminishing returns in our application where \( f \) represents the lecture material, and \( p_1, \ldots, p_3 \) represents the posts submitted by the students.

<table>
<thead>
<tr>
<th>Content</th>
<th>Keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>( l )</td>
<td>stock ( \times 2 ), market ( \times 1 ), company ( \times 1 ), insurance ( \times 3 ), life ( \times 2 )</td>
</tr>
<tr>
<td>( p_1 )</td>
<td>stock ( \times 1 ), market ( \times 1 )</td>
</tr>
<tr>
<td>( p_2 )</td>
<td>life ( \times 1 ), insurance ( \times 1 ), company ( \times 1 )</td>
</tr>
<tr>
<td>( p_3 )</td>
<td>stock ( \times 1 ), company ( \times 1 )</td>
</tr>
</tbody>
</table>

component which expands certain keywords using semantic databases.

4.1 Submodularity

Submodularity is a discrete optimization method that shares similar characteristics with concavity, while resembling convexity. Submodularity appears in a wide range of applications, including social networks, viral marketing [15] and document summarization [16]. Submodular functions exhibit a natural diminishing returns property, i.e., given two sets \( S \) and \( T \), where \( S \subseteq T \subseteq V \setminus v \), the incremental value of an item \( v \) decreases as the context in which \( v \) is considered grows from \( S \) to \( T \).

More formally, submodularity is a property of set functions, i.e., the class of functions \( f : 2^V \rightarrow R \) that maps subsets \( S \subseteq V \) to a value \( f(S) \) where \( V \) is a finite ground set. The function \( f \) maps any given subset to a real number. The function \( f \) is called normalized if \( f(\emptyset) = 0 \), and it is monotone if \( f(S) \leq f(T) \), whenever \( S \subseteq T \). The function \( f \) is called submodular if the following equation holds for any \( S, T \subseteq V \):

\[
f(S \cup T) + f(S \cap T) \leq f(S) + f(T)
\]

(1)

It has been shown that submodular function minimization can be solved in polynomial time [12], while submodular function maximization is an NP-complete optimization problem and intractable. However, it has been shown by [18] that the maximization of a monotone submodular function under a cardinality constraint can be solved near-optimally using a greedy algorithm. In submodular function maximization, we are interested in solving the following optimization problem:

\[
A^* = \arg\max_{A \subseteq V, |A| \leq k} f(A)
\]

subject to a cardinality constraint \( k \). If a function \( f \) is submodular, takes only non-negative values, and is monotone, then even though the maximization is still NP complete, we can use a greedy algorithm (see Algorithm 1) to approximate the optimum solution within a factor of \( (1 - 1/e) \approx 0.63 \) [18].

We formulate our task as a submodular optimization problem for which we also provide an efficient and near-optimal solution. First, let us motivate why we need to consider the notion of diminishing returns with an illustrative example. Table 2 lists an example lecture content, indicated by \( I \) and three example posts, \( p_1, p_2, \) and \( p_3 \). The content of each example is listed by the keywords it contains and the number of times the keywords occur. Let us assume that the task we are interested in is to rank posts in a set \( P = \{p_1, p_2, \) and \( p_3\} \). Let us define the gain as the number of terms a given post contains from the uncovered portion of the lecture material. One can see that selecting \( p_2 \) as the first post yields the highest gain, as it contains three uncovered terms from the lecture material, namely, life, insurance, and company. After selecting \( p_2 \), notice that the gain of selecting \( p_1 \) becomes 2 and that of \( p_3 \) becomes 1. This is simply because \( p_1 \) provides two uncovered terms while \( p_3 \) only provides one uncovered term, since the keyword company is already covered by \( p_2 \). In other words, due to the diminishing returns property, the gain of selecting post \( p_3 \) is reduced. Therefore, we select \( p_1 \) as the second post and \( p_3 \) as the third post. With this intuition in mind, we design a submodular framework that considers the relevancy of a given post to the lecture material as well as ensuring the diversity of the selected content.

Given a lecture \( l \) and a set of posts \( P \), the task we are interested in is to select \( k \) posts as relevant and as diverse as possible. Let us assume that we have a function \( f \) available to us, which simply takes a lecture \( l \) and a set of posts \( P \) and computes the total gain that set \( P \) represents. Then, given a new post \( v \), one can compute the marginal gain of adding \( v \) into a set \( P \) by computing the difference between \( f(l, P + v) - f(l, P) \). In other words, one can compute the benefit of selecting \( v \) as the next post to cover. Next, we discuss the design of such an \( f \) function.

An ideal objective function should take a number of important aspects into account. First, it should promote posts that are relevant to the lecture material since we do not desire students to be distracted by irrelevant content. Second, it should encourage novelty by selecting the most available relevant post to the lecture material as well as ensuring the diversity of the selected content.

An ideal objective function should take a number of important aspects into account. First, it should promote posts that are relevant to the lecture material since we do not desire students to be distracted by irrelevant content. Second, it should encourage novelty by selecting the most available relevant post to the lecture material as well as ensuring the diversity of the selected content.

Algorithm 1 Greedy submodular function maximization with budget constraint

Require: \( V, k \)
Ensure: Selected set of posts \( S \)
1: Initialize \( S \leftarrow \emptyset \)
2: while \( |S| \leq k \) do
3: \( v \leftarrow \arg\max_{v \in V \setminus S} (f(S \cup \{v\}) - f(S)) \)
4: \( S \leftarrow S \cup \{v\} \)
5: end while
6: return \( S \)
Table 3: Examples of augmented keywords with DBpedia.

<table>
<thead>
<tr>
<th>Keywords</th>
<th>Augmented keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>hedge funds</td>
<td>investment, hedge, investors, fund, trade, undertake, markets, regulators, assets, liquid, pension, foundations</td>
</tr>
<tr>
<td>disposition effect</td>
<td>disposition, sell, finance, investors, price, effect, shares, dropped, assets, anomaly, tendency</td>
</tr>
<tr>
<td>prospect theory</td>
<td>decisions, theory, prospect, gains, losses, model, heuristics, alternates, outcomes, involve, economic, risk</td>
</tr>
<tr>
<td>beardstown ladies</td>
<td>beardstown, investment, club, ladies, inception, market, 1983, usa, illinois, stock, business, women, professional</td>
</tr>
<tr>
<td>steve jobs</td>
<td>apple, computer, revolution, executive, charismatic, american, pioneer, chairman, electronics, designer, inventor, influential, businessman</td>
</tr>
</tbody>
</table>

and selects the post with the largest marginal gain. Then, in each iteration, the post that generates the maximum relative increase of the objective function is added to the selected post list $S$. In other words, in each iteration, the relative gain of adding each post $v \in P$ to the set of selected posts $S$ is recomputed and the post with the highest gain is selected. The algorithm terminates when a predefined budget $k$ is reached.

Two important components of our submodular function are $\alpha_i$ and $\beta_p$ values. Given a post $p$, $\beta_p$ simply represents number of times feature $i$ is present in post $p$. Given a lecture $l$ and a post $p$, $\alpha_p$ is computed by taking the dot product between the feature vectors of the lecture, and the post. Next, we discuss how to create feature vectors for the lecture content and the posts.

4.2 Relevancy

Since we would like to promote posts that are most relevant to the course content, we compute the relevancy between each post and the lecture material. However, the length of the lecture material tend to be quite larger than the posts and directly computing a similarity between two texts would yield insufficient results. The intuition behind is that the post is probably only relevant to a portion of the lecture. Therefore, we follow a sliding window approach instead of using the entire lecture content as follows: given a window size $w$, we divide the lecture material into $w$-sized chunks. Then, we compute the similarity between each post and each chunk, and return the average similarity as the relevancy score.

A key component to compute a good relevancy score is to choose an appropriate feature representation. For this purpose, we experimented three traditional approaches, namely, bag of words, n-grams, and topic-modeling approaches.

4.1 Feature representation

For practical purposes. After applying LDA, each lecture and post is represented as a probability distribution over $K$ topics.

In order to further improve the relevancy of our feature representation, we augmented each post by using external resources, following a similar spirit to query expansion. The intuition behind our approach is that, given a keyword that appeared in a question, we can use an external source to augment this piece of information and obtain expanded keywords. We adopted DBpedia [2], which is a crowd-sourced database that extracts structured information from Wikipedia. For a given keyword, we queried DBpedia and obtained a list of possible Wikipedia articles. Each Wikipedia article is ranked by the number of in-links pointing from other Wikipedia articles. Table 3 illustrates a list of keywords that are expanded using DBpedia. As we can see from the table, given a keyword beardstown ladies, we are able to obtain the information that this term is also related to other keywords such as investment, inception, market, illinois.

5. EXPERIMENTS

In this section, we first perform experiments to determine the best feature representation for our application. After that, we use the selected feature representation in our submodular function and compare the efficacy of our framework against other methods.

5.1 Feature representation

In order to determine which feature representation is more appropriate for our application, we compared Precision@k for BOW, n-grams and LDA methods. We used a window size of 200 for all methods, $n = 2$ for n-gram representation, and number of topics $K = 25$ for LDA.

Precision@k represents the fraction of the posts retrieved that are relevant to students at the top $k$ results. In order to obtain a ground truth which is necessary to compute

\footnote{We used Gensim Python Library\cite{22} for the model estimation process, also available at \url{https://pypi.python.org/pypi/gensim}}
Following three methods:

- **Baseline**: Posts are left in their original position as they arrive to the system.
- **Relevancy**: Posts are sorted by their relevancy to the lecture content without considering diversity.
- **Submodular**: Posts are sorted by our submodular framework.

For our data since we do not have hashtags associated with messages or micro-blog questions is a challenging task. Previous efforts mainly focused on tweets where researchers applied methods including aggregating all the tweets of a user into a single document [24] which follows an author-topic model. However, this model fails to capture the fact that each tweet has its own topic assignment. Latest approaches such as Twitter-LDA [28] proposes to overcome this issue; however, it assumes that a single tweet is about a single topic and fails to capture the fact that a post can be about multiple topics. Labeled LDA [20] is another LDA-based approach, however, this model relies on labeled data such as hashtags which makes the model inherently inapplicable for our data since we do not have hashtags associated with posts. Therefore, we decided to use n-gram as our feature representation.

Figure 2 (b) shows the comparison between naïve n-gram approach and augmented n-gram approach. As can be seen from the figure, n-gram with DBpedia significantly improved Precision@k values since it uses an external source to augment the representation of individual words. Therefore, for the rest of our experiments, we use the feature representation with n-grams augmented by DBpedia.

### 5.2 Submodular framework

Our experimental setup is as follows. For each class setting that consists of a list of posts asked by students and a lecture material, we re-rank the questions using each of the following three methods:

- **Baseline**: Posts are left in their original position as they arrive to the system.
- **Relevancy**: Posts are sorted by their relevancy to the lecture content without considering diversity.
- **Submodular**: Posts are sorted by our submodular framework.

We computed Precision@k and Diversity@k values out of $k \in \{1, \ldots, 10\}$ for each class, and report the average value for eight available semesters. Diversity@k metric is computed by counting the number of unique terms at top $k$, which indicates the number of concepts covered by each method.

Figure 2 (c) shows the comparison of methods with Precision@k values. As can be seen from the figure, the Submodular method outperforms the Relevancy method, while both Submodularity and Relevancy significantly outperform the Baseline method.

Figure 2 (d) shows the comparison of methods with Diversity@k values. As can be seen from the figure, Submodular method covers a significantly larger amount of unique terms compared to the Relevancy and Baseline methods. An interesting observation is that the Baseline method is more diverse than the Relevancy method. This is due to the fact that even though the Relevancy method selects posts that are relevant to the lecture material, it ends up selecting posts that are similar to each other and do not provide enough coverage of topics.

### 6. CONCLUSIONS

In this paper, we proposed a novel framework which finds the most relevant and diverse content in educational online discussions. We addressed main problems that occur in these scenarios: a) a large amount of irrelevant content, b) repeated or similar content, and c) content with not enough coverage or diversify. We proposed a submodular framework that ranks questions submitted by students by their relevance and diversity. Our empirical analysis shows the effectiveness of our proposed framework.

Moreover, our framework is not only applicable to micro-blogs in educational setting, but also to micro-blogs and question/answer websites in general.

As future work, we consider the profile of the students into account. In particular, one can rank questions based on how authoritative or active a student is in the class. In addition to enhancing the importance of the questions with student profiles, we also consider designing a personalized ranking for individual students to promote questions on topics that they are interested in.
References


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