Kyle J. Shaffer. Predicting Speech Acts in MOOC Forum Posts Using Conditional Random Fields. A Master's Paper for the M.S. in I.S degree. April, 2015. 54 pages. Advisor: Jaime Arguello

Massive Open Online Courses (MOOCs) have emerged as a way to reach large numbers of students by providing course materials as free online resources. The popularity of these courses has been reflected in high enrollment numbers, however it is unclear how successful MOOCs are at educating their students given their high attrition rates. One cause for this may be due to instructors' inability to manage the large number of students that enroll. While discussion forums are available for students to seek help, instructors are unable to monitor the large number of posts written in these forums. This study investigates the effectiveness of using machine learning models to classify posts into speech acts as a way to help instructors monitor these discussion forums. Speech acts describe the purpose of a post and may be indicative of common functions such as asking questions or raising issues. A linear classifier is compared against a conditional random field (CRF) classifier, which is able to leverage contextual information about the forum in order to make predictions. The results of this study find that CRFs outperform a simpler linear classifier, and this suggests that casting this prediction problem as a sequence labeling task is fruitful for predicting these speech acts, and automatically identifying posts of interest.

Headings:

Data Mining

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PREDICTING SPEECH ACTS IN MOOC FORUM POSTS
USING CONDITIONAL RANDOM FIELDS

by
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of the School of Information and Library Science
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1. Introduction

1.1 Study Motivation

The increasing intersection of technology and education has changed how both instructors and students view the delivery of courses. Today massive open online courses, or MOOCs, are the primary example of offering free and open course materials to a wide range of people. MOOCs allow for large-scale open enrollment and are typically free of cost, allowing for students from a variety of backgrounds to sign up. Students progress through these courses by watching video lectures and completing tasks such as short quizzes or homework assignments in order to be evaluated. In addition to these course materials that are presented asynchronously, students are able to communicate with one another and with course staff through online discussion forums. Students are free to write whatever they like in these forums, and often use them as a venue to solicit help with course material or to report issues with course management.

The ability to develop course content and offer remote access to these materials has challenged the role of the in-person course offerings in "brick and mortar" institutions, and has allowed for an unparalleled number of students to learn from some of the most highly regarded instructors in the world at little to no cost. This course delivery method has massive potential for increasing equality in education, and is particularly salient given the steeply rising cost of education within the United States.

However, this movement within online education is not without its challenges. Indeed, many have highlighted the extremely high attrition rates compared with in-person course offerings and even the founder of Udacity, one of the largest current MOOC platforms, has publicly called the first iteration of their remote course offerings a "lousy product," when discussing the number of students who do not complete these online courses.[1] The main message from these criticisms seems to be that the sheer volume of students who sign up and have access to these materials provides no indication for how successful students will be in completing the courses. These high attrition rates in MOOCs appear to be a symptom their inability to engage students, and some have suggested that MOOCs be scaled back given the large number of students who do not complete these courses.

Despite widespread disagreement about the effectiveness of MOOCs, there is little disagreement that many students are initially enrolling in these courses. The enrollment for many courses can quickly rise to thousands of students, however these initial enrollment numbers are not necessarily indicative of student success since few students complete these courses. With such large course enrollments, and the threat of many of these students dropping out, there is a unique opportunity to provide MOOC instructors with a tool to alert them to student posts within discussion forums for greater effectiveness in intervention. That is, threads within these forums that contain many students posting about frustration or confusion with course materials could be flagged and brought to the attention of the instructor through an automated application that would classify posts and threads according to their need for intervention.

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[1] *Slate Magazine,* http://www.slate.com/articles/life/education/2013/11/sebastian_thrun_and_udacity_distance_learning_is_unsuccessful_for_most_students.html

1.1 Study Goals

The present study aims to provide an experimental basis for developing such a tool by building machine learning models and evaluating their performance in classifying discussion forum posts into speech act categories. Speech acts are types of sentences or utterances that perform a particular function within a broader discourse or conversation. If these models are able to classify posts into these speech acts with an acceptable degree of precision and recall, then this provides the basis for further developing software accessible by the instructor that would alert her/him to posts within these forums that warrant instructor intervention. This would be far preferable to ignoring struggling students due to an inability to manually identify these posts.

In addition to an assessment of the precision and recall metrics, this study will also test two different types of machine learning models on this classification task. One of the assumptions made by many supervised machine learning models is that there is no relationship between instances to be classified within the dataset. That is, for all practical purposes, instances within the dataset are treated as independent of one another and the features and prediction confidence interval values of one instance have no bearing on the predictions of other instances. However, intuitively it is clear that discussion forums *do* exhibit a structure in which forum users interact with one another and write different types of responses given the previously written posts. This structure violates this independence assumption, and contextual information derived from this structure may be helpful in improving model performance for this task. In an attempt to make use of this structure of the dataset, a type of structured learning model called a conditional random field (CRF) is employed to test whether taking this context into account improves performance over using a linear classifier, which makes simpler assumptions about the underlying structure of the data.

The remainder of the paper will proceed as follows. Related work on MOOC and online discussion forum analyses will be presented next in a literature review (Section 2). Following this, Section 3 will present the methodology of this study including a description of the dataset, a presentation of data collection methods for obtaining labels for use in supervised machine learning experiments, and an overview of the models used in this study. Section 4 will give an experimental overview before presenting results in Section 5. Section 6 will provide a critical discussion of the results obtained before concluding and presenting future work in this area in Section 7.

2. Literature Review

Researchers in various disciplines have utilized quantitative and automated methods to more rigorously study complex social phenomena at a large scale. Many of these analyses have used data mining techniques to collect data from large and complex social networks such as Twitter and Facebook, and MOOCs are an emerging area in which these computational techniques are being used to ask and provide further insight to important questions.

What follows is a survey of the literature that informs the current study. This past work is divided into two sections by theme of the work. The first section (2.1) will cover the broad task of using text mining and machine learning techniques to attempt to classify and detect speech acts in various domains of analysis. The second section (2.2) will focus attention on computational analyses of student engagement and attrition in MOOCs, some of which use linguistic analysis. These areas of the literature will have significant bearing on the proposed study, which seeks to combine aspects of each of these areas into a unique analysis of student behavior within the discussion forums of one particular MOOC.

2.1 Machine Learning Approaches to Speech Act Detection

Many attempts have been made to design classification systems that are able to detect speech acts in various domains of interest. These studies employ speech act theory in order to conceptualize the role of the different messages or other units of analysis being sent in a longer sequence of messages. The goal of these studies is to engineer features and develop models that are effective in classifying messages into one or more speech act categories. Often these speech act categories are highly specific to the domain of analysis, and researchers often provide specific definitions and examples of how they are identified within their dataset.

An early example of such speech act classification appears in Cohen, Carvalho and Mitchell (2004) in which the authors develop classifiers for email messages. This is a unique study in that it is one of the first to investigate speech act classification, and offers results for a fairly rare domain of analysis—email messages. This last point is especially noteworthy given the sparseness of open datasets containing email message data for obvious privacy reasons. The authors define four speech acts that are specific to their dataset of emails from an online graduate course in business offered at Carnegie Mellon University in 2004: (1) requests for information, (2) delivery of information, (3) proposals, and (4) commitments. These speech acts were assigned to each email by two expert annotators and these annotations are used as labels to test four algorithms evaluated for accuracy in predicting the four speech acts within the email messages. After constructing features solely from the text of the emails the authors find, somewhat surprisingly, that combinations of simpler classifiers such as decision trees perform better in terms of accuracy than more complex linear classifiers such as support vector machines.

Following and extending this work, Carvalho and Cohen (2005) likewise focus on classifying these same four speech acts by taking into account features that leverage the context of the email message. That is, it is hypothesized that an email's position within a thread of messages may have a bearing on what type of speech act the message contains since intuitively many types of messages often follow one another, such as requests being followed by deliveries. This is a very similar hypothesis to the one being tested in the current study by utilizing conditional random fields. The authors then conduct three experiments: one in which only linguistic features are used for the model, one in which only contextual features are used, and a final experiment combining both linguistic and contextual features. The authors find that the combined features perform best of any of the models tested, but also note that linguistic features on their own are more predictive than contextual features on their own.

Qadir and Riloff (2011) similarly focus on identifying speech acts within a veterinary medicine message board dataset, but opt to focus on classifying individual sentences within the dataset as opposed to entire messages. This has some advantages in that messages may often contain several speech acts, and increasing the level of granularity to sentences has the benefit of providing a one-to-one correspondence between the unit of analysis within the study and the speech act labels used for the predictive task. Unlike the above studies, the authors focus on four of the classical speech acts from philosopher

John Searle's (1976) taxonomy including *commissives* (utterances that commit the speaker to some future action), *directives* (utterances that command another agent to take an action), *expressives* (utterances that express a speaker's psychological state or mood), and *representatives* (utterances that commit the speaker to a belief about the truth of a proposition). This is noteworthy since these are much more general speech acts and may be much more difficult for models to accurately predict than those that are more specific to a particular domain of analysis. The authors focus on lexical and syntactic features for model building in addition to a dictionary of words that the authors constructed in order to capture semantic characteristics peculiar to the message board dataset they sought to analyze. Given these features, the authors train and test support vector machines on 150 message board posts that consisted of 1,956 individual sentences to be classified and achieve precision scores between 80% and 85% when identifying directives and expressives, but much lower precision scores when attempting to identify commissives and representatives. Perhaps most interestingly, researchers find that when added to other linguistic features, semantic keywords features that are most specific to the veterinary medicine domain significantly boosts precision when added to other linguistic features. However, models that use these semantic features alone perform the worst across all speech acts looking to be detected.

Bhatia et al (2012) also look at message board classification in the domain of a question-answer discussion forum. The authors opt to delimit their own set of speech acts, looking at categories more pertinent to posts that have to do with the question and answer structure of the forum, and thus the speech acts considered for this study have mostly to do with identifying questions, solutions, and similar speech acts that play significant roles within this type of dialog. Seven total classes are considered. This study is useful in terms of the features the authors considered for their models. In most of the studies surveyed above, authors focus on linguistic features with special attention to keywords that may be semantically important to the particular domain of classification. The authors of this study use linguistic *n*-gram features in addition to unique structural features of each post such as absolute position in the thread, cosine similarity between the current post and previous post, as well as the number of times each user has posted in the forum. Additionally, the authors consider sentiment by using keywords of well-established positive and negative sentiment and incorporate these as features. This seems especially useful in these studies since a post that contains higher levels of negative sentiment may be more likely to also be classified as a question or negative acknowledgement of a previous post, and these could therefore be useful clues for the model. However contrary to this intuition, the authors find in their experiments that prediction of these speech acts is not significantly aided by sentiment features, while linguistic features and additional features about users are most helpful for performance.

All of the studies surveyed above follow a method of straightforward supervised learning experiments in which a linear classifier is trained only on labeled data and evaluated on a previously unseen test set of data as to how well it discriminates between several classes or labels. Two important studies are surveyed here that attempt to extend this approach. The first attempts to do so by incorporating unlabeled data into the process of training classifiers, while the second looks to evaluate graphical models that attempt to predict the broader structure of a set of posts as opposed to simpler linear classifiers that predict the category of one post at a time.

These are important extensions to consider since often the classification task entails differentiating between many different classes as opposed to a simple binary classification problem that needs to distinguish between only two, and they highlight the importance of contextual and structural features for increasing classifier performance when looking at sequential data. That is, the very nature of these messages occurring as part of a chain of a greater conversation seems to suggest that there are patterns of where they occur within the thread that could be leveraged by contextual features or different models that are better able to incorporate such features.

Jeong, Lin, and Lee (2009) look at extending speech act recognition within email and forum messages by leveraging unlabeled data during the model training step—a process known as semi-supervised learning. The goal of semi-supervised learning is to increase the size of the training dataset used by the learning algorithm to improve prediction performance, and this can be much more efficient and feasible than obtaining more labeled data which is often an expensive or labor-intensive process. The algorithm in semi-supervised experiments attempts to learn the distribution of the labeled data within the training set and classify the remaining unlabeled training data according to this distribution. The algorithm then uses *all* of this labeled data for a final training step before being evaluated on a test set.

The authors use two smaller labeled dialog datasets consisting of roughly 1,200 labeled instances and one large unlabeled email dataset consisting of roughly 30,000 instances for their training set and attempt to classify held-out instances of the dialog datasets. The authors then run their experiments with primarily linguistic features for models to learn from and demonstrate that their semi-supervised models achieve higher accuracy than baseline classifiers that use only a supervised approach. The authors conclude that utilizing additional unlabeled data can boost performance in classifying speech acts, and make the more ambitious claim that this may work with unlabeled data from disparate domains.

Finally Ji and Bilmes (2005) seek to use graphical models as opposed to linear classifiers in order to classify what they call dialog acts, which are similar to speech acts surveyed in other works here. In addition to focusing on linguistic based features such as unigrams and *n*-grams, the authors also try to incorporate contextual features to classify sentences within message board posts. The model developed by the authors attempts to step through sentences word by word in a sequence in order to use the probabilities of each individual word to identify the dialog act of the entire sentence. However, in addition to the overall distribution of each word in the training set, the model also learns the conditional probability of the word occurring *given* the word that occurred before it. This additional contextual feature is the main extension of their approach compared with the works surveyed above. The authors note an extremely large increase in accuracy between their baseline model which only uses *n*-gram features to predict the dialog act of a sentence (34%) and the extended model which attempts to model dependencies between words when predicting dialog acts for sentences (63%). This suggests that context is a helpful feature when looking at speech or dialog acts, and this provides further motivation for utilizing conditional random fields in this study.

2.2 Computational Approaches to MOOC Analysis

Perhaps the most straightforward and visible issue in research about MOOCs has centered around attrition rates. These issues have been addressed from both qualitative and quantitative perspectives, however the survey that follows will focus mainly on quantitative and computational methods used to analyze these complex social phenomena at a large scale.

Penstein Rosé et al. (2014) focus on analyzing student attrition rates within MOOCs offered through Coursera and the University of Pittsburgh using survival modeling techniques that predict student engagement via their posts within course forums. In addition to this analysis, the authors provide a more interpretive analysis by attempting to cluster students using the discussion forums into emerging groups by using unsupervised clustering algorithms. A dataset of 4,700 forum posts was analyzed with two main groups of features used for predicting whether students would persist through the course or leave—one being a "cohort" feature constructed by identifying which week of the course a student joined, and the other being a sub-community feature identified by the clustering algorithm. Through these methods, the authors find that the most prevalent predictors for attrition were students' membership in the first-week cohort, and students' membership in one sub-group identified by the clustering algorithm. These results suggest that beginning a new course with many other students at the same time and finding a group of students to engage with are helpful in encouraging a student to progress through a MOOC, and these may be factors that are especially important in the online setting.

Chen et al. (2013) likewise attempt to predict student attrition in an online course in human-computer interaction offered through Stanford University. In particular, the authors focus on predicting whether a student will complete a given assignment at each step in a time series of assignments that spans the longevity of the course under analysis. The authors note that while their model was able to predict students who would not complete an assignment three days before it was due with a high degree of accuracy, the amount of data that was available to them decreased drastically throughout the span of the course as the result of students leaving and no longer posting to the discussion forums.

A similar study on predicting MOOC attrition is carried out by Sharkey (2014). In particular, the study looks at using post content to predict attrition in one MOOC, and attempts to apply this model learned from the first MOOC to a second MOOC in order to test generalizability. The authors note that while their model performs with a level of accuracy between 80 and 85%, the majority of this metric is the result of predicting that students will leave the course, which tends to be the majority class. Thus, their model is biased in favor of picking *whatever* the majority class happens to be, which in the case of the present study is not the class of interest.

Several other studies focus on identifying more abstract aspects of MOOC forum posts such as sentiment or subjective point of view. Wen et al. (2014), for instance, attempt to develop classifiers for identifying posts with highly negative sentiment as a way to provide the basis for a tool that would flag these posts for instructor intervention. The researchers analyze MOOC forum datasets from three different courses offered on the Coursera platform in the domains of teaching, science fiction literature, and computer programming totaling roughly 35,000 posts. In addition to classifying these posts according to sentiment, the authors also identify four general topics throughout the forum by using a clustering technique and look to classify sentiment within each of these four topics. While sentiment may seem like an intuitive marker for how well a student is doing in an online course, the authors find through their analysis that sentiment does not aid in predicting whether students will leave a MOOC, and even find that *both* positive and negative sentiment moderately predict student dropouts, though neither of these results is statistically significant.

Finally, Elouazizi (2014) seeks to predict point of view and cognitive presence using the text of the forum posts within MOOCs. It is argued within the study that these subjective aspects of the posts are likely indicative of how engaged a student is in their learning, and this would be useful information for instructors to have when teaching at such a large scale. Another key difference between this study and those above within this section is that the author emphasizes testing the prediction of these aspects of cognitive presence in two different courses: one MOOC with an extremely large enrollment, and another online course with lower enrollment totals. The author defines four classes of cognitive engagement to predict, two of which indicate engagement with course material, while the other two indicate disengagement with course material. While only linguistic features are used for training and testing models, the author focuses on key cognitive verbs that are hypothesized to be stronger indicators of a student's cognitive presence. Through experiments, the author finds lower levels of cognitive engagement in the high-enrollment MOOC data as measured by these linguistic features, and the author suggests that this may point to an adverse effect of such high enrollment numbers within many of the major MOOCs.

3. Method

In the following section, the methodology of the study is presented. First a description of the dataset is presented in Section 3.1. In Section 3.2 the definitions for the speech acts to be predicted are presented. Section 3.3 presents the data collection methodology for obtaining labels for supervised machine learning experiments, and Section 3.4 provides an overview of the models to be tested in this study. The interested reader is referred to Appendix I for a more general overview of the supervised machine learning methods used in this study.

3.1 Description of Dataset

The dataset under analysis is comprised of all published communication within the discussion forums from a MOOC on Metadata offered through the School of Information and Library Science at the University of North Carolina, Chapel Hill on the Coursera[2] platform. The full dataset contains both published and deleted posts, and this study is concerned only with posts that were not deleted by an author. The course was taught over eight weeks from August to November of 2013, and had an initial enrollment of just over 27,000 students in its first week, with an ending enrollment of just under 26,000 in its final week, though not all of these students remained active throughout the duration of the MOOC. Enrolled students need not participate in the MOOC at all to retain enrollment. These two figures depict the difference between students who initially enrolled and those who actively un-enrolled.[3]

Initial enrollments for the course are quite high, however only 1,418[4] of the registered students completed enough course material to earn a statement of accomplishment. While this appears to be an extremely low completion rate, there are important caveats to consider about differences between the MOOC education environment and that of more

[2] https://www.coursera.org
[3] http://jeffrey.pomerantz.name/2013/11/data-about-the-metadata-mooc-part-1
[4] http://jeffrey.pomerantz.name/2013/11/data-about-the-metadata-mooc-part-4

traditional educational settings including marked differences in student motivation and reasons for enrollment Koller *et al* (2013).

Throughout the duration of the MOOC, students were evaluated on eight weekly homework assignments that included short-answer and coding segments, and these along with a final exam made up the evaluation component of the course. Each of these homework assignments followed one of eight learning modules offered throughout the course, ranging from a broad theoretical introduction to metadata and organization schemas to specific domain applications including metadata for the web. The content of each learning module was presented through a set of video lectures recorded by the course instructor along with selected readings that were assigned each week. The instructor and one teaching assistant were responsible for managing the course and responding to students through the discussion forums.

Before presenting summary statistics on the discussion forums, it is helpful to provide some terminology in order to clarify the unit of analysis for the present study. Students communicated with one another and with instructors of the MOOC through written messages or *posts*, and these make up the most granular unit of analysis, and the main focus of the predictive task.[5] This statement/response structure of these messages makes speech act prediction an appropriate and informative task in this domain. A *thread* is a collection of posts and comments that typically make up a distinct topic. Threads vary widely in length throughout the dataset ranging from just over 200 posts to one post in length. Finally, a *forum* is the coarsest unit of analysis, and is comprised of a collection of

[5] Individual messages within the forums consisted of posts, which are top-level messages, and comments, which are structurally tied to a specific post and typically a response to it. These two messages types are modeled as different contextual features for classifiers, but they will be referred to under the umbrella term “posts” hereafter.

threads. The discussion forums are comprised of these threads, which themselves are comprised of individual posts. The dataset consists of 2,943 individual messages (2,166 posts and 777 comments), 425 threads, and 15 forums.

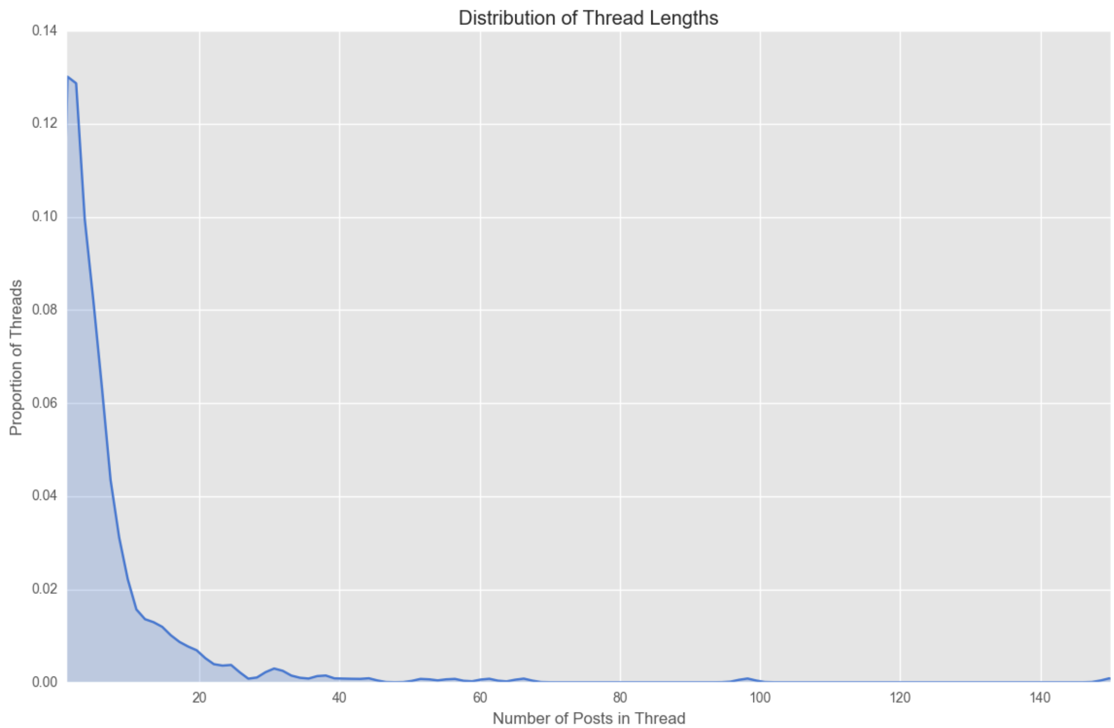

Figure 1: Distribution of thread lengths.

3.2 Speech Act Definitions

In this section, definitions are presented for the speech acts to be predicted. The theory of speech acts arose out of work in philosophy of language and linguistics, and seeks to characterize sentences or utterances in terms of the function they serve within a broader discourse. An early authoritative taxonomy was provided by philosopher John Searle who defined several canonical examples of speech acts including *directives* which compel the listener of an utterance to perform some action, and *expressives* which serve to communicate the psychological or emotional state of the speaker (Searle, 1976). While these have been extremely useful in the fields of pragmatics and discourse analysis, computational approaches to speech act detection often employ speech act definitions specific to a domain of analysis as in Cohen, Carvalho, and Mitchell (2004) above. The present study follows this approach of defining speech acts specific to the domain of analysis.

Seven speech acts were defined for annotation by crowdsourced workers. These speech acts describe several common purposes for writing posts within a MOOC and include **questions**, **answers**, **issues**, **issue resolutions**, **positive acknowledgement**, **negative acknowledgement**, and an **other** category. These definitions are presented below.

Questions are defined as a request for information or clarification about course content, and may appear in interrogative form or as a statement within the post. Common questions revolve around confusion with homework or quiz materials. **Answers** are defined as posts that contain an attempt to provide useful information in direct response to a question post. Answer posts may not successfully fulfill a previously asked question, but must attempt to directly address a previously asked question.

Issues can be viewed somewhat as an analogue to questions, except that issues must be raised in regards to course logistics as opposed to concepts or course content. Common issues are directed at submitting homework assignments or other discrepancies about how material is delivered. A final important distinction between questions and issues is that questions are typically a part of any learning process and would likely not be viewed negatively by an instructor, while issues are typically viewed in a negative light by instructors and may require their direct intervention. Likewise, **issue resolutions** are somewhat analogous to answers in that they (a) must be a direct response to a previously raised issue, and (b) function primarily to resolve an issue raised about the course. An important clue that may help identify issue resolutions is that instructors may be more likely to write them within a thread, however an issue resolution need not definitively resolve an issue.

Positive acknowledgment and **negative acknowledgement** are speech act categories designed to capture sentiment-based posts throughout the forum, and express positive and negative sentiment respectively toward a previously written post. One difficult aspect of finding these speech acts is the requirement that they be written in direct response to a previous post, and this can contribute to confusion between the **negative acknowledgement** and **issue** categories.

Finally, the **other** speech act serves as a category to capture all other speech acts that may be present within the threads. Given that MOOC students are free to write about whatever they choose, much of the writing is quite “noisy” and difficult to place squarely in one speech act category. The **other** category serves as a label for these posts, which may range from general introductions to planning in-person study groups.

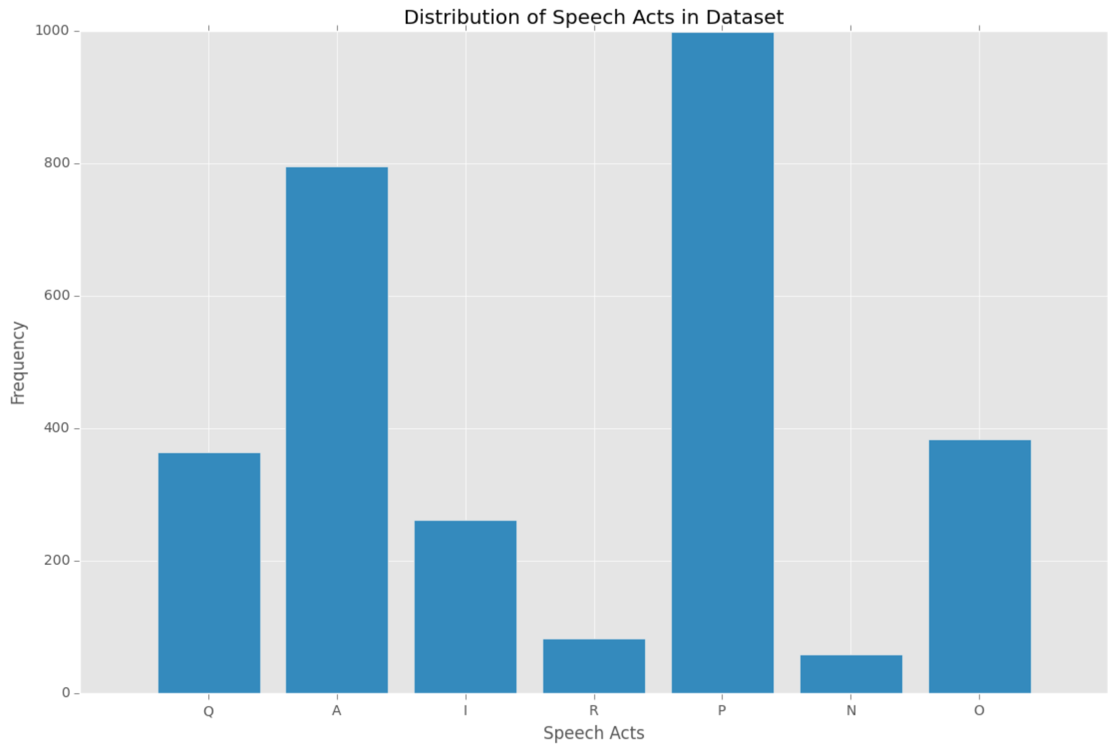

Figure 2: Distribution of labeled speech acts throughout dataset.

3.3 Data Collection

In the following sections, an overview of the data collection methodology is presented. First, Section 3.1.1 presents an overview of crowdsourced data collection methods used for obtaining labels for the machine learning experiments. Section 3.3.2 describes the implementation of an interface for this data collection and the instructions given to non-experts using the Amazon Mechanical Turk web service. Finally, it is important that good labels are used for the machine learning models to learn from. Section 3.3.3 presents results of evaluating the quality of the labels by measuring inter-annotator agreement between the non-expert MTurk workers, and between the MTurk workers and an expert labeler (the author).

3.3.1 Crowdsourced Annotation

In supervised machine learning, the goal is to train a model to identify a set of concepts based on representative features that are "learned" from a set of training data. More technically, supervised learning can be thought of as function approximation. That is, the assumption is that some function $\boldsymbol{f}$ describes the relationship between a set of features $\mathbf{x}$ and a label $\boldsymbol{y}$, and the goal of supervised learning is to train a model to infer this function from a set of training data in order to predict further labels for previously unseen data. This makes aspects such as feature engineering extremely important, but also necessitates a set of good labels that supervised machine learning algorithms will use as their ground truth or "gold standard" to learn from. Often high-quality labels for the concepts to be predicted are not present or ready-made within the dataset, and this necessitates a first step of collecting labels.

In the past, studies have relied on experts to annotate datasets with gold-standard labels, but as the size of these datasets has grown, this process has become prohibitively expensive and time consuming. In recent years crowdsourced options have become widely used among researchers as a way to obtain labeled datasets inexpensively and in a fraction of the time it would take for expert annotation. While there are concerns about the quality of the labels obtained through this method, prior work has shown that aggregating redundant labels for each instance within a dataset can lead to improved quality as opposed to only collecting a single label per instance within the dataset (Sheng *et al,* 2008). Following this insight, labels for this study were collected using the crowdsourcing framework Amazon Mechanical Turk (hereafter MTurk).[6] MTurk allows

[6] https://www.mturk.com/mturk/welcome

anyone with an Internet connection to select Human Intelligence Tasks (HITs) posted by researchers, and complete simple tasks within HITs for a small compensation.

3.3.2 Data Collection Process

MTurk workers were first shown a set of speech act definitions as presented above in Section 3.2, and also provided additional tips and examples to help them differentiate between speech acts that may be easily confused. Some of the posts within the dataset were easily identifiable as belonging to a particular speech act, and MTurk workers were provided with typical examples of these categories (see Table 1 below). While clear definitions were given for these speech acts, these were not exhaustive, and therefore a final category was designated (**other**) to serve as a placeholder for all posts that did not fit into any of the previous categories. This makes the **other** category extremely noisy, containing anything from introductions ("Hi everyone. I'm a web designer and extremely interested in this course!") to sharing tangential material ("sorry, this is not exactly relevant, but I could not stop myself from sharing..."), and this likely contributed to some confusion in the annotation process detailed below. Often these speech acts were informal or conversational in nature, including introductions, organizing in-person study groups based on geographic location, and expressions of excitement about the course. An example of each speech act is presented in Table 1 below.

Speech Act	**Example**
Question	"In Question 8 on the assignment I'm confused about the code formatting. In lectures, the instructor said syntax should be of the form X, but do you have to include Y? Any ideas what I'm doing wrong?"

Answer	“The answer here should follow the form of the practice problems. Hopefully that helps.”
Issue	“The wording for Question 6 was confusing and ambiguous. Please consider revising the wording or giving students the points for this question.”
Issue Resolution	“We are aware of a glitch in our submission form for Homework 2. As a result, the last question has been awarded to each student as a free point.”
Positive Acknowledgement	“I'm glad I'm not the only one stuck on this! That was definitely confusing me too!”
Negative Acknowledgement	“The last question may have been difficult, but part of learning new material is working at it. No sense in complaining.”
Other	“Hi everyone! I'm a web designer and extremely interested in this course!”

Table 1: Speech act examples.

To collect these annotations, an interface was designed presenting MTurk workers with an outlined post to be labeled within a thread. MTurk workers were able to scroll throughout the thread and explore its context before labeling the outlined post with one or more speech acts ranging from none (by labeling the post as **other**) to all seven speech acts. Figure 1 shows an example of this data collection interface. To help ensure worker quality and English-language proficiency, annotations were accepted only from MTurk workers within the U.S. that had an acceptance rate of 95% or greater. In addition, MTurk workers were asked to provide justification for their answer as prior work has shown that users are more likely to submit high-quality work when asked to defend their answers. As a final set of precautions, any given user was only allowed to complete 30 annotations, and five “trap” annotation questions were planted throughout the beginning of the HIT. These trap questions were thought to be trivially simple in the eyes of the author, and users who failed to answer three of these five correctly were removed.

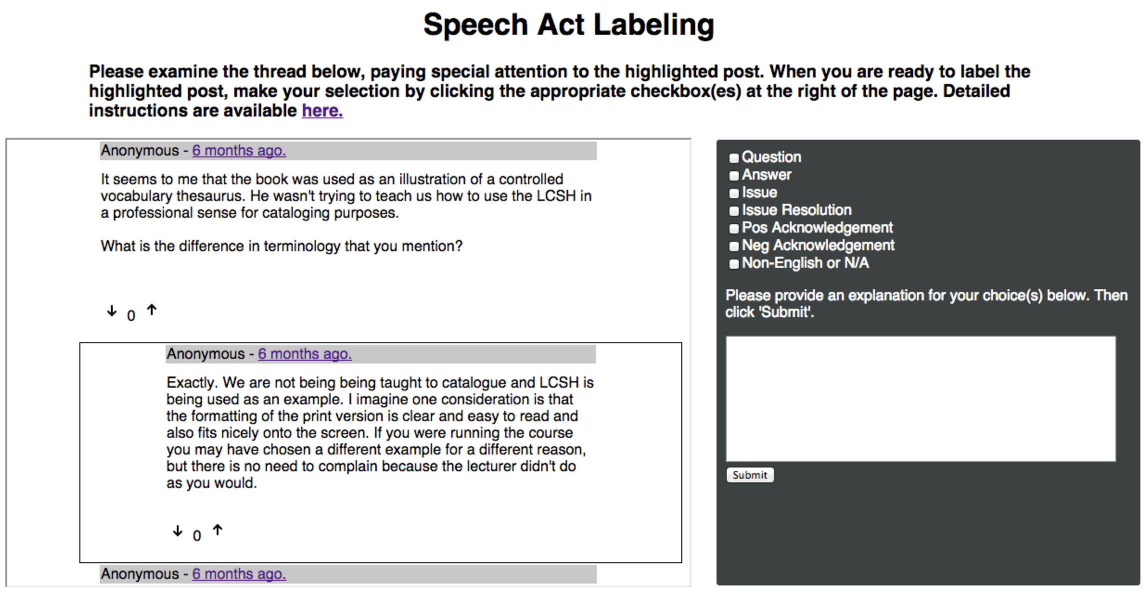

Figure 3: Annotation collection interface.

3.3.3 Evaluating Annotation Quality

Using the above framework, five redundant annotations were collected for each post within the dataset. Inter-annotator agreement was measured with respect to each speech act using Fleiss' Kappa Agreement between the annotators. The author also served as an “expert” annotator, and labeled 30% of the dataset and measured Cohen's Kappa Agreement between the expert annotations and the majority vote annotation from the MTurk workers, where the majority vote was taken to be the speech act that at least three annotators agreed upon for a given post. Cohen's Kappa Agreement scores between the MTurk workers and the expert annotator fell between 0.635 and 0.893, and these scores were found to be satisfactory given the difficulty of the annotation task, however it is acknowledged that agreement could be improved.

Despite providing examples of each speech act and tips for how to differentiate between boundary cases, some speech acts were nonetheless still ambiguous to MTurk workers. Given the informal writing in the majority of the threads, it is perhaps unsurprising that many of the posts were difficult to place cleanly into a speech act category with high agreement among MTurk workers. Speech act pairs that appeared naturally confusable were identified, and one speech act in particular, **positive acknowledgement**, appeared to frequently co-occur in annotations with several other speech acts, most notably **answer** and **other**.

A qualitative look at some of these annotations made it clear why these categories may have been extremely difficult to distinguish between. For example, here is a post that received equal annotations for both **positive acknowledgement** and **other**: "Hi I'm [name] from [location]. I'm currently working part-time as a cataloger, and part-time as a Digital Librarian. I've been a cataloger since 1990, but a digital librarian for only 2 months, so I"m [sic] here to learn all the things I've forgotten about metadata. Nice to meet you all." While the overall tone of this post is positive and friendly, it does not specifically convey positive sentiment or encouragement *directly to a previous post*. Rather it serves as a general introduction and should have been labeled as **other**.

Speech Act	**Fleiss' *Kappa***	**Cohen's *Kappa***
Question	0.569	0.893
Answer	0.414	0.790
Issue	0.421	0.669
Issue Resolution	0.286	0.635
Positive Acknowledgement	0.423	0.768

Negative Acknowledgement	0.232	0.633
Other	0.337	0.625

Table 2: Inter-anotator agreement between MTurk workers (Fleiss' *K*) and between MTurk workers and expert annotators (Cohen's *K*).

3.4 Models

The following section provides an overview of the models used in the study. First, the logistic regression classifier is described. Next, sequential models are briefly introduced before describing conditional random fields, which will be used to compare against logistic regression in terms of precision, recall, and F1 score.

3.4.1 Linear Classification: Logistic Regression

Several popular models are available for linear classification. Logistic Regression was chosen as the model for performing this classification task, and a Python implementation[7] is used to build the models using the Scikit-Learn[8] machine learning library. Logistic regression estimates a conditional probability from the training data using the following equation:

$$P(Y = 1|\, X) = \frac{1}{1 + \exp{(w_0 \sum_{i=1}^{n} w_i X_i)}}$$

where *Y* is the speech act to be predicted conditioned on *X*, which is the set of features used by the classifier. The intuition for classification is the same as prediction of real values with linear regression, however in logistic regression, *Y* is instead the probability of a predicted binary outcome instead of an unbounded real-valued output as in linear

[7] http://scikitlearn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

[8] http://scikit-learn.org/stable

regression. Both models have the advantage of a straightforward interpretation of modeling the outcome variable, or label, as the result of some linear combination of a set of independent variables, or features.

3.4.2 Structured Classification: Conditional Random Fields

While linear classifiers can be effective in many settings, several works surveyed above showed the effectiveness of using structured learning models. These models likewise attempt to infer a function that describes the relationship between features to labels as in the standard binary classification case, but predict a *sequence* of labels to a set of test instances as opposed to assigning predicted labels individually to test instances as in the case of logistic regression. Casting this task as a sequence prediction problem allows for a model to exploit the sequential nature of the posts within these threads, and may help improve model performance.

In particular, conditional random fields are a family of popular sequential models, and will be used for comparison against logistic regression in the speech act prediction task. A structured machine learning library written in Python called PyStruct[9] is used to implement a linear chain conditional random field and test its performance on this classification task (Mueller and Behnke, 2014). While other models exist for sequence prediction, conditional random fields are a good choice here since they estimate a conditional probability distribution over the observed features and labels in a similar fashion to logistic regression, allowing for a fair comparison between the two models. Using conditional probabilities for these estimates as opposed to using joint probabilities

[9] https://pystruct.github.io/

has other theoretical advantages, but these points will not be emphasized here (Lafferty *et al*, 2001).

The most important aspect of conditional random fields (hereafter CRFs) for comparing them against linear classifiers is their ability to model changes in so-called "states." For the purposes of the experiments described here, these states are simply the speech acts that constitute the labels for the posts, and therefore there are seven states. CRFs use a feature function in order to model states that are adjacent to one another, and learn probabilities of changing from one state to another. More formally, a feature function can be defined as $\boldsymbol{f(Z_{n-1}, Z_n, x, n)}$ where $\boldsymbol{Z_{n-1}}$ is the previously observed state, $\boldsymbol{Z_n}$ is the current state, $\boldsymbol{x}$ is the entire input sequence, and $\boldsymbol{n}$ is the index of the current sequence the model is in. For the purposes of forum post classification, the intuition is that this ability to model changes in state may increase performance since many states, or speech acts, within the dataset may regularly follow one another, as in the case of **answers** following **questions** within the discussion thread.

4. Machine Learning Experiments: Predicting Speech Acts

The previous section provided a description of the dataset under analysis, a description of the data collection process, and an introduction to the models that will be tested in this study. In this section, the machine learning experiments are described. These are used to (a) evaluate whether machine learning models are able to classify posts into these speech act categories, and (b) to compare the performance of two different types of model on this task. Section 4.1 describes the features used by the classifiers. The next section (4.2) provides an overview of how all classifiers were evaluated and gives a brief overview of relevant metrics used in the study, including precision, recall and F1 score as well as a brief description of cross validation—a popular method for evaluating classifiers in supervised learning. Finally, Section 4.3 covers the experimental setup.

4.1 Description of Features

Beyond collecting gold-standard labels, perhaps the most important aspect of supervised learning is extracting and constructing high-quality features for the learning algorithm to use in the training stage. Various types of features were constructed for prediction of these speech act categories, and these are presented below. The number of individual features within each feature set is shown in parentheses. In total, 237 features were used for each model.

LIWC Word Count Features

These features were constructed using the Linguistic Inquiry Word Count (LIWC) text analysis software (Tausczik and Pennebaker, 2010). LIWC features are designed to capture a variety of psychological aspects of written text, and these may be useful for predicting speech acts related to aspects of sentiment and cognitive engagement with course material in the forum. These are computed by comparing input text to various word list dictionaries correlated with different psychological and emotional states. Each post within the discussion forums was standardized by down-casing all text and removing punctuation before feeding these threads to the LIWC software, which produced numerical output for these features.

- **Affect (8)** These features capture general positive and negative sentiment within posts, as well as more general emotions such as sadness anxiety, and the presence of emoticons.

- **Cognitive Engagement (9)** These features attempt to measure more abstract aspects of posts including whether the post is comparing and contrasting items, expressing uncertainty, or considering a causal relationship.
- **Personal Concern (9)** These features capture personal aspects of text within posts including personal accomplishments, money, and death.
- **Linguistic (26)** Several more general linguistic aspects of the writing in posts were captured using these features, including relative and absolute word frequency counts, average word counts per sentence, counts for different verb tenses, as well as expressions such as quantification and negation.
- **Perceptual (4)** These features attempt to capture aspects of text directly related to sense perception including hearing, feeling, and seeing.
- **Social (4)** Features referencing social aspects such as other humans, family, or friends were computed for these features.
- **Spoken (3)** Different features were computed to capture typically spoken linguistic features such as non-fluencies ("uh", "hmm") and fillers ("blah", "you know").

Manually Constructed Features

In addition to the features computed using the LIWC software, several features were constructed from other aspects of thread posts.

- **Sentiment features (4)** Sentiment features may be informative for particular speech acts, especially positive and negative acknowledgement. These features were computed by tabulating the raw number and percentage of positive and negative words that occurred in each post using wordlists constructed by Liu et al (2005).

- **Unigram (140)** The terms present in a post are likely predictive of the topic or content therein. To capture these more nuanced aspects of posts, the χ^2 correlation was computed between each stemmed unigram and each speech act independently. The 20 unigrams with the top χ^2 value per speech act category were then taken for these features.
- **Text Similarity (6)** Similarity between post types may be useful in training classifiers. Thus, the cosine similarity[10] metric was used to measure similarity between posts based on TF-IDF[11] weighting scheme of terms in posts. Specifically, similarity between a post and the previous post; similarity with the first post in the thread; and the minimum, maximum, mean, and variance of the similarity with the previous thread post were all computed as similarity features.
- **Temporal Features (3)** Given that students were expected to complete homework assignments and quizzes, features were computed to measure the time in days, hours, and minutes between the time a post was written and the time the nearest homework assignment was due.
- **Author (1)** The type of speech acts contributed in a discussion thread likely varies between instructors and students. To capture this, the author of a thread is

[10] Cosine similarity measures the similarity between two vectors by computing the cosine of the angle between them. The text of each post is represented as such a vector with each feature described here appearing as a numeric value within this vector.

[11] TF-IDF (term frequency-inverse document frequency) is a statistic that attempts to capture terms in a piece of text that occur frequently within that text and also occurs infrequently in other texts.

represented in this binary feature where 1 indicates that the post was written by an instructor and 0 indicates the post was written by a student.

- **Link (1)** Link-sharing may be predictive of answers. Link-sharing is modeled as a binary feature indicating the presence or absence of a hyperlink.
- **Modal Verbs (2)** Modal verbs were shown to be predictive in past work on discussion forum classification (Bhatia *et al,* 2012). These features are computed by calculating the absolute and relative frequencies of common modal verbs in a post.
- **Position (2)** The relative and absolute position of the post within the thread is given by this set of features.
- **Post/Comment (1)** This binary feature indicates whether the post is a “top-level” post or a comment that is structurally tied to a previous post.
- **Punctuation (13)** Punctuation features may be specific to several speech acts, but particularly to identifying questions. To capture this, relative and absolute frequencies of thirteen punctuation types were calculated for each post.
- **Votes (1)** In addition to simply writing the posts, students can communicate with one another in the form of “voting” on posts. Students may “up-vote” a post they found particularly helpful or insightful, and “down-vote” a post they found unhelpful or distracting. These vote counts were included in the dataset and are utilized in the models for this study.

4.2 Evaluation Methodology

Both logistic regression and conditional random field models were evaluated using precision and recall metrics. In the context of this study, precision can be informally defined as the proportion of test instances classified as belonging to speech act *S* that actually belong to speech act *S*. Recall may be informally defined as the proportion of *total* test instances that belong to speech act *S* that were identified by a classifier as belonging to speech act *S*. More formally precision can be formulated as:

$$P = \frac{true\ positives}{true\ positives + false\ positives}$$

where *true positives* are test instances the classifier has correctly predicted as belonging to speech act *S*, and *false positives* are test instances the classifier has incorrectly predicted as belonging to speech act *S*. Similarly, recall can be formulated as:

$$R = \frac{true\ positives}{true\ positives + false\ negatives}$$

where *false negatives* are test instances the classifier has incorrectly predicted as not belonging to class *S.* Finally, the tradeoff between precision and recall is reported in the F1 score, which computes the harmonic mean between precision and recall:

$$F1 = 2\times\frac{Precision \times Recall}{Precision + Recall}$$

Supervised learning experiments use a held-out test set in order to evaluate the performance of classifiers. That is, a classifier is trained on a set of data in order to approximate a function ***f*** that describes a relationship between a set of features **x** and a label ***y*** for each instance within a set of training data. This function ***f*** is then used by the classifier to make predictions on a held-out test set ,which is completely unique from the training set. One approach for evaluation is to split the data into one training set for model learning and one test set for evaluation of model performance. However, this may not give a complete picture of performance since the data could have been split in a number of different ways.

One way to overcome this is to employ a method called *k*-fold cross validation. In this method, the original dataset is randomly split into *k* folds, and *k*-1 of these folds are used for training, while the fold left out of training is used for testing. These steps are then applied iteratively such that each fold is used as the test set, while training on the remainder of folds that are not used in the test set. The final reported metrics using this method are then averaged across the *k* folds to compute the model's average performance. While the value of *k* is arbitrarily chosen, ten is a popular value for *k*, and will be used in the experiments here. This method of evaluation allows for a more realistic picture of model performance to be shown since it is trained and tested on several different partitions of the dataset.

4.3 Experimental Setup

Details of the experiments are presented in this section. Both logistic regression and CRF models were trained and tested using 10-fold cross validation. The same ten folds were used for both models, ensuring a fair comparison between the two when looking at performance. Both logistic regression and the learning algorithm[12] for the CRF have a *C* parameter that can take on different values. This parameter controls the misclassification cost on the training set, and different values may affect performance. For both logistic regression and the CRF learning algorithm, *C* was set to 1 for all experiments.

Logistic regression was trained in a so-called "one vs. rest" fashion for the prediction of these speech acts. That is, one logistic regression classifier was trained for each speech act independently, totaling seven classifiers. In addition to outputting a predicted label, logistic regression outputs a probability of the test instance belonging to a certain label or

[12] The PyStruct implementation of the linear chain CRF uses a structured support vector machine to learn the model from the training data.

speech act. In order to make a single prediction, the label with the highest probability is taken to be the predicted label for a test instance.

Before using the features described in Section 5.1 as input for classifiers, the values of these features were first normalized to a scale between 0 and 1.[13] The raw numerical values for these features may vary widely, and this large range could skew the probability distributions learned by the classifiers being tested. Feature normalization thus attempts to limit the influence of very large or very small feature values that are likely not representative of the overall distribution of the dataset. This feature normalization step was performed in each fold of cross validation, and the same feature scale used for the training set was applied to the test set in each fold.

Finally, the implementation of logistic regression used in these experiments allows for an option to apply weighting schemes to labels within the training set if the distribution of these labels is not uniform. As can be seen in Figure 2 above, the labels throughout the dataset are not uniformly distributed and this presents a challenge when training these classifiers. For training logistic regression, this label weighting option was set to inversely weight labels within the training set, placing greater weight on labels that are seen infrequently in the training set and placing less weight on labels seen frequently within the training set. This re-weighting is performed in each fold of cross validation so as to be tailored to each training set.

[13] This task is often called min-max normalization. It is achieved by using the following equation $Norm(c_i) = \frac{c_i - C_{min}}{C_{max} - C_{min}}$ where c_i is an individual value in column C, C_{min} is the minimum value in column C, and C_{max} is the maximum value in column C.

5. Results

Results from these experiments are shown in Table 3 below. Best results for each speech act by metric are highlighted in bold. Often classification results are presented with the assumption that a model has a 50% random chance of identifying an instance as belonging to the correct class. That is, if a classifier has not learned any meaningful relationship between the features and target labels, we would expect a "random guess" from the classifier as to which label an instance in the dataset belongs to, and this is often taken as an implicit baseline to compare against. However, this assumes (a) that the prediction task is binary where we are interested in predicting either the presence or absence of a label and (b) that the labels in the training and test sets are evenly balanced, with half of the instances consisting of positive examples of the label to be identified and half consisting of negative examples.

These two assumptions do not hold in the present experiments since the goal is to classify posts into one of seven possible labels, and it has been shown that the speech act labels are not uniformly distributed within the dataset, with **answers** and **positive acknowledgment** occurring quite often and **issue resolutions** and **negative acknowledgement** being especially sparse. Thus, along with results from both models tested in this study, precision and F1 score metrics are reported for a baseline heuristic for each speech act label within the test sets.

Each baseline precision metric indicates the proportion of the test set consisting of each speech act, averaged over the ten folds of cross validation. These values are computed as $\frac{1}{N}\sum_{i=1}^{N} P_i$, where N is the number of folds used for cross validation (ten in this case), and P_i is the proportion of the test set taken up by the given speech act at iteration number *i* of cross validation. This can be interpreted as the precision attained for labeling every instance within the test set as speech act *S*. This provides a more realistic measure to compare against when evaluating the performance of both the logistic regression and CRF models.

Finally, F1 scores are computed for these baseline metrics by assuming perfect recall (recall = 1) for each speech act within the test sets, and computing the harmonic mean between these recall metrics and the precision metrics described above. This offers further depth of comparison between the two models tested, and a more naïve baseline approach. The discussion below will focus primarily on precision and F1 score since these are reported across all classification methods, however recall is reported for completeness.

Speech Act	**Logistic Regression**			**CRF**			**Baseline Heuristic**	
	Precision	*Recall*	*F1*	*Precision*	*Recall*	*F1*	*Precision*	*F1*
Question	0.238	0.184	0.208	**0.450**	**0.355**	**0.397**	0.124	0.220
Answer	0.421	0.315	0.360	**0.429**	**0.465**	**0.446**	0.270	0.425
Issue	0.264	**0.285**	0.274	**0.431**	0.264	**0.327**	0.090	0.165
Issue Resolution	0.083	**0.228**	0.122	**0.203**	0.133	**0.161**	0.028	0.055
Pos-Ack	**0.464**	0.39	0.424	0.460	**0.600**	**0.521**	0.339	0.506
Neg-Ack	**0.054**	**0.226**	**0.087**	0.050	0.050	0.050	0.020	0.039
Other	0.361	**0.438**	**0.396**	**0.446**	0.320	0.373	0.131	0.032

Table 3: Results of 10-fold cross validation for Logistic Regression and Conditional Random Field models

6. Discussion

6.1 Model Comparison

Several trends are worth noting in these results. First, both the logistic regression and conditional random field models outperform the F1 scores of the baseline heuristic with respect to every speech act. This is encouraging overall, and indicates that the features that were selected provide a reasonable representation of these posts for the classifiers to learn from. Second, the CRF model makes some impressive gains over both the baseline heuristic and the logistic regression model. For instance, **questions** appear with roughly 12.4% frequency within the test sets on average, and logistic regression identifies these posts with 23.8% precision. This may appear to be quite low performance, but it is important to keep the caveats above in mind. Regardless, the CRF model significantly outperforms both these metrics with 45.0% precision. This provides evidence that modeling this task as a sequence prediction problem has some advantages, and the CRF is able to leverage the structural qualities of these threads to make better predictions, at least with respect to **questions**.

Figure 4 provides a graphical comparison of precision performance for the two models and the baseline heuristic. Overall, we see that the CRF model achieves best performance for all speech acts except two—**positive acknowledgement** and **negative acknowledgement**, where it is slightly outperformed by logistic regression. The gains made by logistic regression in classifying these speech acts are quite small (+0.004 for both **positive** and **negative acknowledgement**), and it is not clear whether these results indicate a true difference in performance between the two models. Overall, the precision performance indicates that both classifiers outperform the baseline and likely learn a reasonable function in order to classify these speech acts, however further work could be conducted to improve performance. Additionally, these results indicate that the CRF model achieves best precision in classifying all but two speech acts.

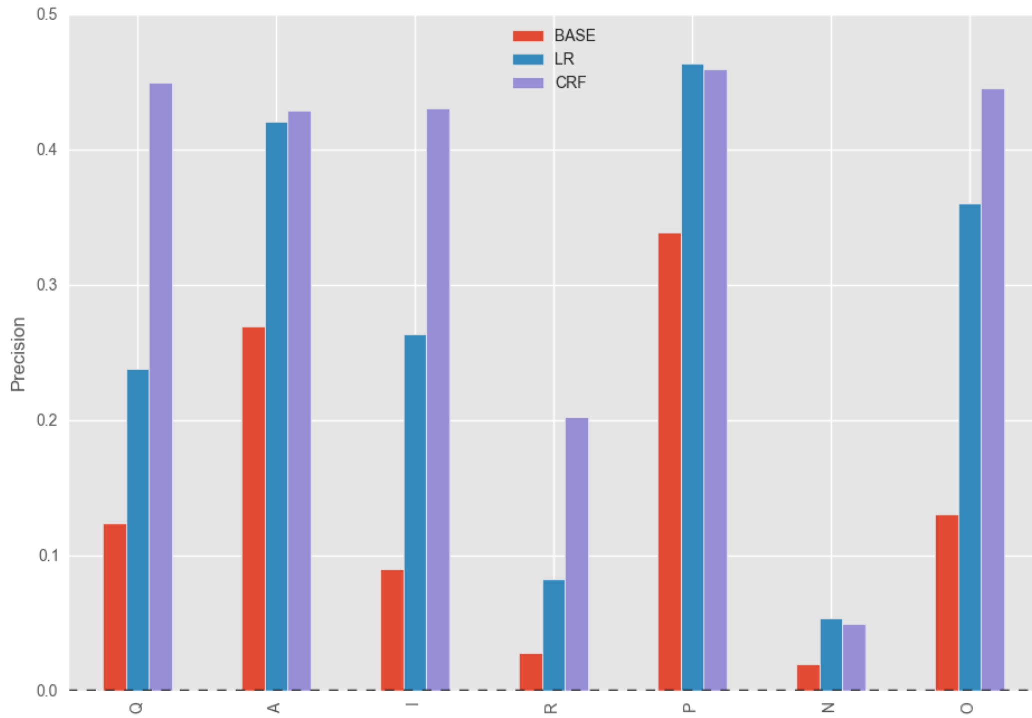

Figure 4: Precision scores for baseline heuristic (BASE), logistic regression (LR), and conditional random field (CRF)

While precision is a useful and popular metric for evaluation, it is important to investigate the performance tradeoffs between precision and recall and this is exactly what the F1 score is used to communicate. Figure 5 presents a graphical depiction of the performance of the two models and the baseline heuristic with respect to the F1 score. Here, a few different trends emerge. While precision scores for the baseline heuristic are quite low, since we are assuming perfect recall this allows for many of the F1 scores for this heuristic to approach the performance of the two classifiers tested in this study. This strong assumption about recall allows the baseline heuristic to outperform the logistic regression model in several cases (**questions**, **answers,** and **positive acknowledgement**). However, the CRF model shows F1 scores that outperform the baseline heuristic in all speech acts. Additionally, the CRF outperforms logistic regression in most cases with the exception of **negative acknowledgement** and **other**. This provides further evidence that the CRF model is able to leverage useful information from modeling these threads in sequence, and this aids in this prediction task.

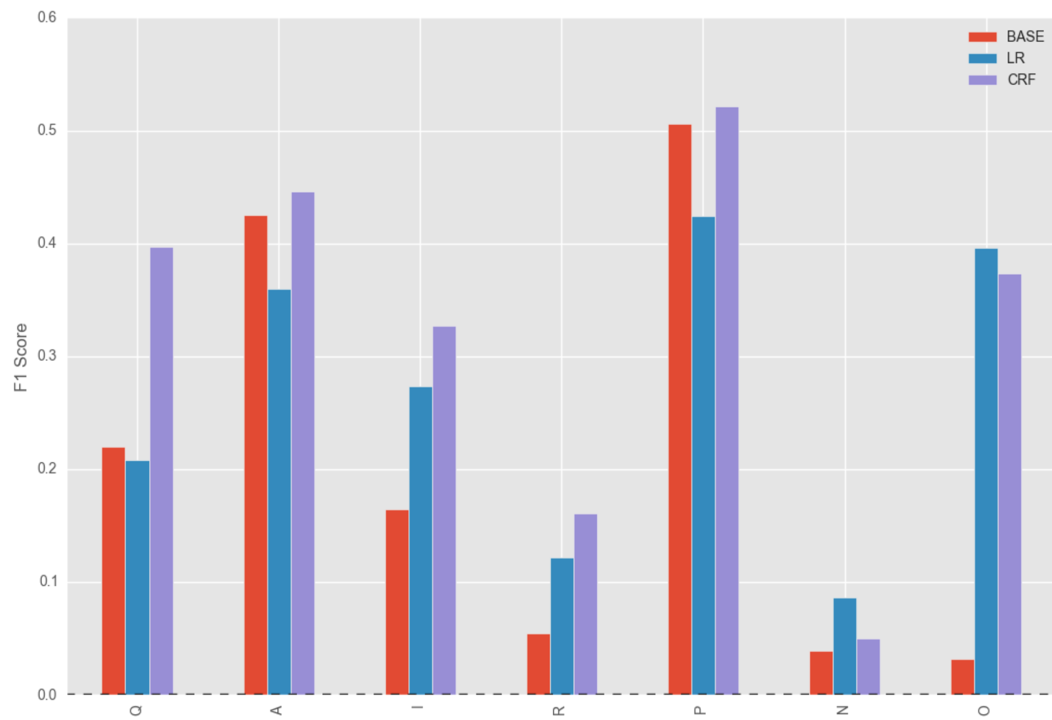

Figure 5: F1 scores for baseline heuristic (BASE), logistic regression (LR), and conditional random field (CRF)

6.2 Error Analysis

Investigating a model's errors is often more informative than presenting its successes. In this section, an error analysis is presented for both logistic regression and CRF models. Confusion matrices are useful visual tools for investigating the performance of classifiers, and one confusion matrix per classifier is presented below. These matrices depict predictions made by the model on the y-axis (left-hand side) and the true labels along the x-axis (top). Thus, if we label any predicted label as *i* and any true label as *j*, the value of a cell at location *i, j* indicates how many instances were predicted to have the label *i*, and whose true label is *j*. A classifier with perfect performance should only have values that occur in the diagonal cells of the matrix, and any values off this diagonal are erroneous predictions made by the model. The confusion matrices below present higher values as red and lower values as blue, with a color bar along the right to aid in interpretation.

The confusion matrix for the logistic regression model is presented in Figure 6. Here we see several prediction patterns for this model. The first two that emerge are the high true-positive rates for **answer** and **positive acknowledgement**. These are the two most prevalent speech act labels within the dataset, so it is not surprising that the model is able to identify these with some degree of ease. However, two prominent mistakes emerge from this model, namely predicting (1) **positive acknowledgement** as **answers** and predicting (2) **other** as **positive acknowledgement**.

A qualitative look at the text within these posts gives some clues as to why these may have been confused by the classifier. For mistake (1) many posts within the forums that provide an **answer** are written with a positive tone and even may contain similar punctuation such as exclamation points and "smiley" emoticons, which occur in posts indicating **positive acknowledgement**. These textual characteristics could have been picked up by the LIWC and other sentiment features, and this would likely have produced similar numerical scores for these features in posts that contained these two speech acts. More qualitatively, these posts likely contain similar kinds of writing style and punctuation, and this contributes to poor performance for this classification task. Similar causes seem to contribute to the confusion between **other** and **positive acknowledgement**.

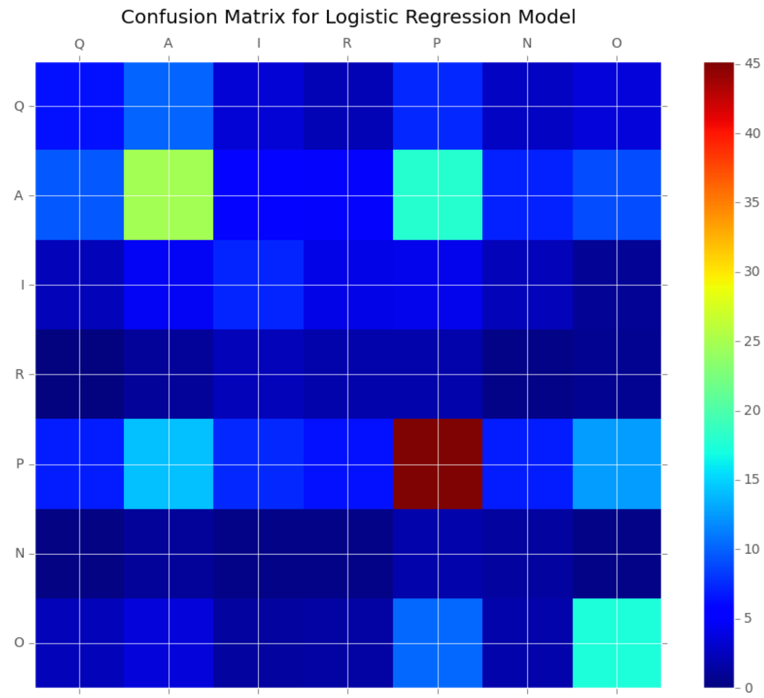

Figure 6: Confusion matrix for logistic regression model

The confusion matrix for the CRF (Figure 7) shows very similar strengths and weaknesses for this classifier. The CRF appears to be slightly better at classifying **answers**, with similar performance in terms of mistakes between predicting **positive acknowledgement** as **answers** and predicting **other** as **positive acknowledgement**. However, the model also appears to make fewer mistakes in identifying other speech acts. For instance, the CRF makes slightly fewer misclassifications of **issue resolutions** as **answers** (a subtle distinction since both these post types are trying to provide help in some way), and is much more conservative in predicting other speech acts as **positive acknowledgement** than logistic regression as shown by the horizontal band in the logistic regression confusion matrix along the "P" row. These mistakes indicate that while the CRF makes similar misclassifications, the ability to take into account transitions between types of posts aids prediction of these speech acts.

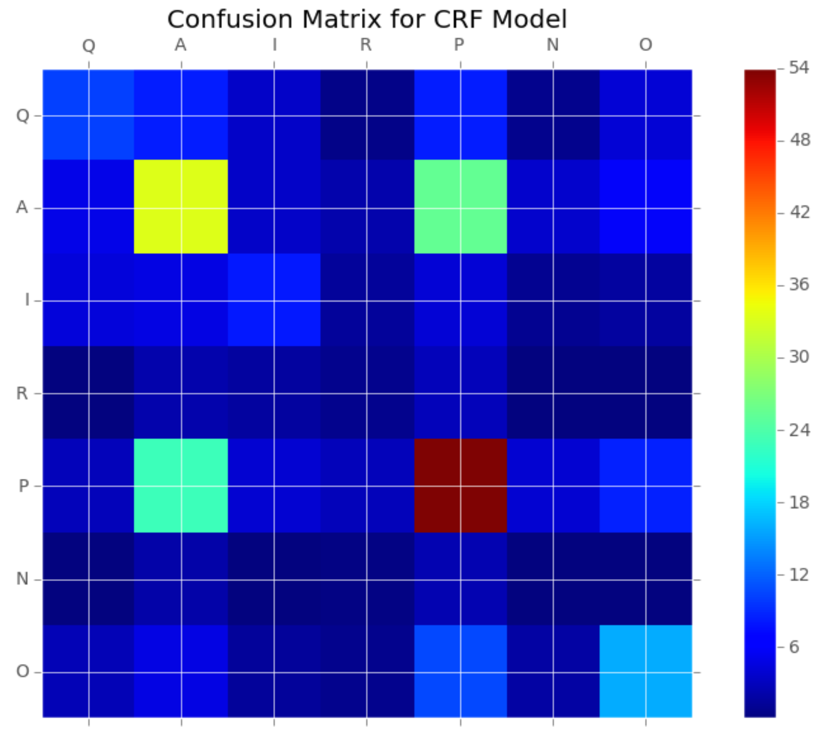

Figure 7: Confusion matrix for CRF model

Perhaps more interesting in terms of analyzing the performance of the CRF is investigating the transition parameters learned by this model shown in Figure 8. In this matrix, the y-axis (left-hand side) indicates a starting state or speech act that the model is in, and the x-axis (top) indicates the next state the model is likely to be in. Values within the cells indicate the probability of the model transitioning from a speech act indicated along the y-axis to a speech act indicated along the x-axis.

Several of these transition state parameters conform to intuition about these forums, and this is an encouraging result. For instance, the cell with the highest transition probability is located in cell (A, Q), indicating that the most likely transition the CRF model learns is from **questions** to **answers**, and this conforms to prior intuition about how students use these forums. Similarly, the CRF learns high probabilities for transitioning from **issues** to **issue resolutions** as shown by cell (R, I), although the model also learns high transition probabilities from **issues** to **answers**, and this is somewhat understandable given the similarity in function between **answers** and **issue resolutions**.

The low probability values in the (Q, Q) cell also helps explain why the CRF performs better than logistic regression in classifying **questions**. That is, the transition matrix shows that the model learns that **questions** are not likely to follow questions, nor are they likely to follow any other speech acts as indicated by the low values throughout the "Q" column. This also conforms to an intuition that **questions** are the most likely speech act to start a thread, and this is something that is clearly inferred by the CRF model.

Finally, the CRF also learns several transitions that appear to be more spurious in nature, and may account for some of the model errors. For instance, the transition matrix shows that **answers** are not only likely to follow **questions**, but are somewhat likely to follow *any* speech act category as indicated by the A column within the matrix. Interestingly, the CRF also learns that **positive acknowledgement** posts are likely to follow all other types of speech act, and this is somewhat surprising. However, as noted earlier, many posts containing **positive acknowledgement**, have similar linguistic characteristics to the **other** speech act, and several threads within the forums contained long sequences of **other** posts that consisted of messages unrelated to course material including organizing study groups or introductions. While many of these posts were positive in tone, they were not in *direct response* to a previous post, and thus should have been labeled as **other**. The CRF model appears to have mistakenly learned these long sequences of **other** posts as sequences of **positive acknowledgement** posts, and this may account for poor performance in classifying the **other** speech act.

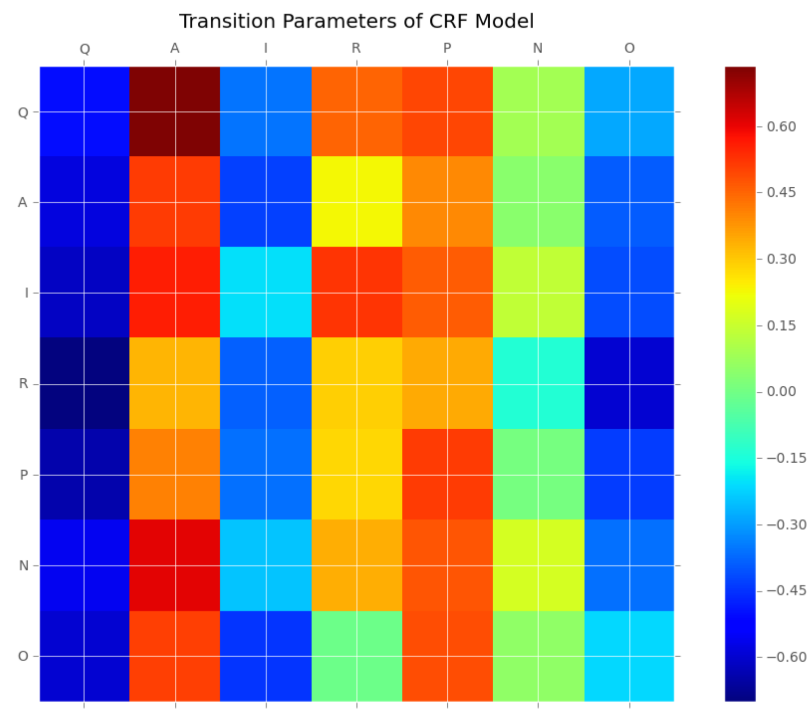

Figure 8: Transition states learned by CRF model

7. Conclusion and Future Work

This study attempted to predict seven pre-defined speech acts within the discussion forums of a MOOC offered through the School of Information & Library Science at the University of North Carolina at Chapel Hill. Two classifiers were tested at this task, and the results were compared against one another as well as being compared against a naïve heuristic approach based on the average proportion of each speech act within the test sets of the machine learning experiments. Another main goal of this work was to test whether casting this task as a sequence prediction problem by using a CRF model is helpful. The results presented above show that the CRF model outperforms a logistic regression classifier in predicting most speech acts, suggesting that a structured learning approach to this problem does improve performance.

Labels for this dataset were collected using the Amazon Mechanical Turk crowdsourcing platform, and the non-expert annotations were shown to have reasonable agreement with an expert when a majority vote label was taken from redundant annotations by non-experts. This justifies using these non-expert labels as well as confirming prior work on this topic.

More broadly, this study has given some insight into how automated methods could be used to identify posts that may be of interest to instructors. Instructors may be particularly interested in posts that are asking questions or raising issues within these forums, and the CRF model tested in this study significantly outperforms a baseline heuristic, as well as a simpler linear classifier in identifying these speech acts. This provides evidence that these speech acts are identifiable by an automated system, and such a system could be helpful for aiding an instructor in identifying posts or threads that require manual intervention on their part.

While this study has shown several encouraging results, there is ample room for future work on these topics. Perhaps most pressing is the need for revision of the speech act definitions in collecting labels for the dataset. While the labels collected had reasonable agreement when aggregated into a majority vote, the performance of both classifiers indicates that some of these speech acts have definitions that are difficult to distinguish between. **Positive acknowledgement** and **other** posts stand out as a prominent example of speech acts that were easily confused, and this may necessitate clearer definitions of these and other speech acts for non-expert annotation.

Secondly, while the results presented here show promise, there is no guarantee that they generalize to other online courses. MOOCs are taught in a variety of different subject areas, and the student participation within the discussion forums may vary widely depending on the course content. If this is the case, it would likely affect the distribution of speech acts throughout the dataset and this would no doubt affect model performance. A wide range of MOOCs should be used for data collection in order to develop classifiers robust enough to perform well across different academic subjects.

Finally, an extensive set of features was explored for this study, however other features may prove helpful for improving classifier performance. For example, unigram features could be expanded to explore the effect of higher order *n*-grams such as bigrams or trigrams. Additionally, while several higher-level features were explored including sentiment and cognitive engagement using the LIWC software, perhaps other linguistic features may aid in predicting certain speech acts. For instance, syntactic features such as part-of-speech may indicate important differences in sentence complexity. This may be a useful feature for detecting answers, which are perhaps likely to be longer in length and more likely to contain complex syntax.

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Appendix I

Overview of Supervised Machine Learning

Given that the goal of this study is to classify discussion forum posts into one of several categories, the interested reader is presented here with a brief background on supervised machine learning methods. MOOCs by their very nature tend to have extremely high enrollments with unmanageable student-to-faculty ratios, and this creates a serious challenge for instructors to manually gauge student behavior from forum posts. Given this conflict between an unmanageable amount of data to sift through and the need for instructors to glean useful feedback from student posts, some form of automated method is needed to aid instructors' efforts, and this is a task especially well-suited for machine learning.

Machine learning is a broad field encompassing many specific tasks, however a common goal is to understand patterns or structure in large amounts of data and to make predictions about this structure. These predictive tasks form a sub-branch of machine learning known as supervised learning in which a researcher or analyst knows the phenomena they are interested in identifying in the data prior to analyzing their data (Witten et al., 2011). An oft-cited example is the task of developing systems to classify email into spam or non-spam categories. This is contrasted with unsupervised learning, or "clustering", which uses algorithms to automatically organize data into groups based on detected features, without the analyst knowing exactly what they are looking for beforehand. Unsupervised methods will not be discussed further as they are not employed in the present study.

Within supervised learning, there are two broad types of tasks that can be employed for different types of problems—regression and classification. A regression task is employed to predict a real-valued numeric output from various features of the dataset as in the case of predicting the price of a house based on features such as square-footage and neighborhood location. On the other hand, classification is the task of predicting discrete-valued outputs based on input features as in the case of the spam classifier mentioned above. Given that this study seeks to predict the discrete category of a student-written post within a discussion forum, classification methods will be used where the input to the classifier will consist of various features of the forum posts and the predicted speech act category will be produced as output.

In order to assess the reliability of classifiers, these models need to be tested on data "previously unseen" data, and this presents an important part about the methodology of running predictive classification experiments. Within these experiments, the data under analysis is partitioned into two sets: a so-called training set in which the model infers the distributions of the given features for each of the classes to be predicted, and a test set which has been withheld from the model and which the model will use to make predictions. This test set provides the basis for evaluation within these experiments, and it is imperative that the model uses absolutely no data from the test set in the training phase of the experiment. That is, the training and test sets must be mutually exclusive in order to have valid results within these experiments.