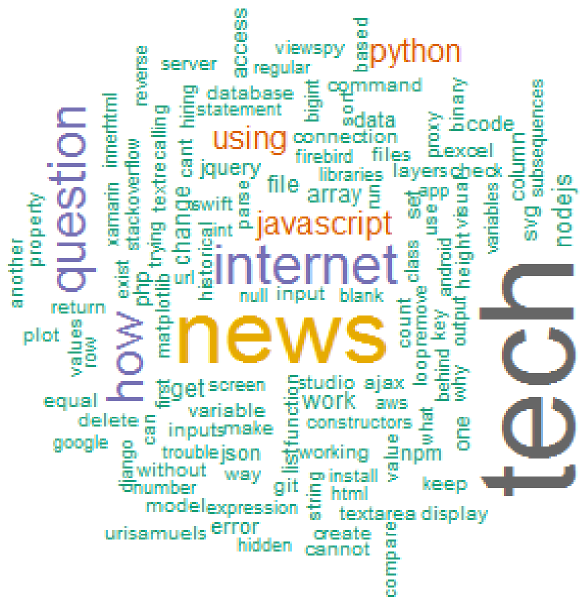
12/10/2016

Predictive Analytics: Analysis of Stack Overflow Data

A report to analyse why coders do what they do on Stack Overflow and predict their actions.



(generated using R word cloud)

<u>Submitted by:</u>

- Alok Satpathy
- Aman Agarwal
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1. Executive Summary

This project involved building classification models to predict characteristics of posts and comments on Stack Overflow, an online platform for discussing programming and software development questions. The primary aim was to identify predictors and construct models which could automate spam detection, suggest the best answer of a question, and gather insights about the posts based on comments.

With over 6.4 million users and approximately 227,000 questions asked per month and answered almost equal number of times, it is imperative to provide best, un-biased suggested answer based on the history of posts and the users involved. Initially, data available from Stack Overflow (on Stack Exchange, see Appendix D) was gathered and analysed. The team tested the viability of the issues and found strong correlations between the components to give interesting results. Proof of concepts were conducted on all the three scenarios and upon getting encouraging results, an approach was designed to handle each issue separately. The prototypes evolved as the study on data progressed and eventually led to a full set of predictors, a lot of them were added while a few were removed. Once the full set of predictors were available, various classification models were applied based on the issue at hand. The report mentions specific technique under each issue. Since there were multiple models which were selected to handle each issue, the best model was chosen based on several factors including the least mis-classification rate.

The results obtained from the study substantiated the motive behind the project. The classification models gave rich results with a capability of predicting best possible answer to a post with almost 95% accuracy. By using Natural Language Processing (NLP), sentiments on the comments were analysed to understand the characteristics of the post on which those comments were posted. As such, the performance of multiple classification models was assessed in the due course of the project. The complete project is checked into GitHub – link here.

2. Introduction

2.1 Problem Statement

Stack Overflow is a collaborative questioning and answering site designed for developers to find answers. As this online community is growing with new users joining every day, it's important to manage the content to avoid irrelevant posts like spams and thus ensure quality of the content. Also, since one question can have multiple answers and only one answer can be marked as the best answer, it would be beneficial to automatically predict and suggest the best answer among the multiple answer. Another aspect of Stack Overflow is the comments which users make on the posts (questions or answer).

The dataset from Stack Overflow can be organized into 5 categories - Posts, Comments, Users, Votes and Badges. The project in addition aims at classify post (question/answer) into spam / non-spam and further evaluate the quality of the answer posts to predict likelihood of it being marked as the best answer. Each post has an option to upvote/downvote. While upvote increases the reputation of the owner by +5, downvote has a negative effect on reputation of both owner (-2) and the user downvoting (-1).

Users accounts	**6.4 Million** (1.1 Million answerers and 1.7 Million askers, respectively)
Questions	**13 Million** (56.76% received best answer, 11.31% no-response questions)
Answers	**20 Million** (33.93% accepted as best answer)
Votes	**61 Million** (89.84% Positive votes, average 2.2 upvotes per post, average 0.25 downvotes per post.)
Comments	**53 Million** (57.25% on answers, 42.75% on questions)
Reputation	Average reputation points (excluding users who have 1 reputation): 317 Average reputation points (containing users who have 1 reputation): 125

Tags	47,000 types of tags
Attributes	188 attributes and 26 tables

Comments often come in the form of clarifications, suggestions, argument, or contradiction. It is often noted that the community members use comments to express the discontent about the post instead of using the downvote. The reason behind this is that downvotes cause a reduction in reputation points. Hence the users tend to provide a negative feedback as a response to a post instead of downvoting it. We would like to apply Natural Language Processing (NLP) on the comments of each of these posts to understand the correlation between downvoting vs. negative comments and predict the likelihood of posts resulting into negative comments.

2.2 Dataset Details

The dataset has been curated from Stack Exchange site available at the link http://data.stackexchange.com/stackoverflow/queries. It is available for sharing and reproduction licensed under Creative Commons by ShareAlike 3.0.

Stack Exchange provides a data dump of all user-contributed content on the Stack Overflow. The dataset available and used in this project was last updated on December 1st 2016. The data was fetched via queries run on Stack Exchange Data Explorer tool. This tool facilitates querying from the huge repository and download the data as .csv file.

The data is ***more than 1TB*** and has ***188 columns*** distributed among ***26 tables***. These tables have data about posts, comments, tags, votes, users and reviews. The whole Stack Overflow model is based on reliability of the posts and comments. This makes it essential for the users to know which comment should be relied upon and which should not. The number of votes on a post determines this reliability. Also, Stack Overflow thrives on the community collaboration and gamification lies at the core of community collaboration. The badges, points on upvotes and privileges thus are essential. This data is also available in the dataset.

For this analysis, however, we have used only part of the whole data. We used joins over relevant tables and fetched the required columns while carefully managing the constraint relationships among the necessary columns. The following table summarizes the tables and their respective columns used in this analysis.

Table	**Column**
Comments	Id
	PostId
	Score
	Text
	UserId
Post	Id
	PostTypeId
	score
	Body
	LastEditDate
	CreationDate
	CommentCount
	ViewCount
	FavoriteCount

Table	**Column**
PostHistory	PostHistoryTypeId
	PostId
PostHistoryTypes	Name
PostTypes	Name
ReviewTasks	ReviewTaskId
	ReviewTaskTypeId
ReviewTaskResults	RejectionReasonId
ReviewRejectionReasons	ReviewRejectionFlag
ReviewTaskResultTypes	Name
	Id
	Description
	Name
	Description
ReviewTaskStates	Name

	AnswerCount
	Title
	Tags
	AcceptedAnswerId
PostFeedback	VoteTypeId
Votes	Id
	VoteTypeId
	PostId
VoteTypes	Id

	Description
User	Reputation
	Location
	WebsiteUrl
	AboutMe
	Views
	UpVotes
	DownVotes

2.3 Methods Employed

Stack Overflow is a state-of-art web application which is highly scalable and responsive. Being extracted from the from the backup of the application data, The Stack Overflow data is quite stable and has very less missing/ corrupt/ data. Yet, for our analysis we diligently followed the principles of ETL to make our data clean. Followed by the this, we employed the following techniques to do our analysis and the application of these methods will be discussed in details later:

In-class methods

- LDA
- QDA
- KNN
- Logistic Regression
- CART
- LASSO
- Ridge Regression
- Dimensionality Reduction
- Random Forest

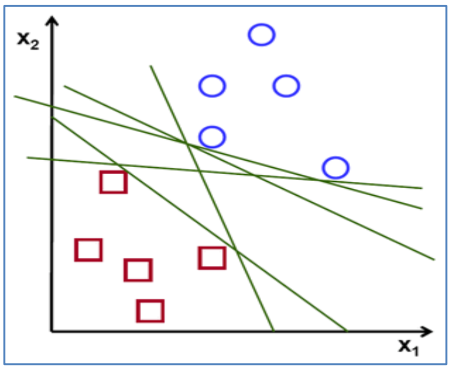
New Methods

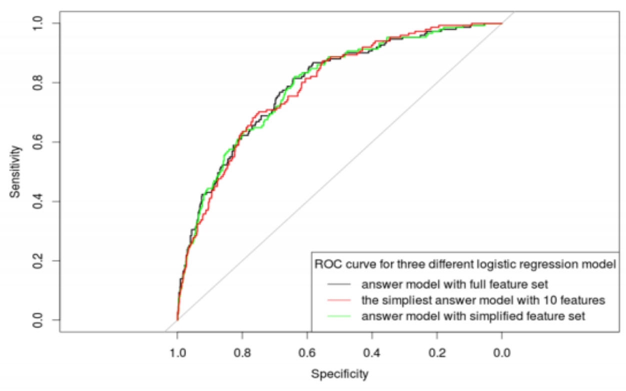
- SVM
- NLP
- C5.0

Description of new technologies:

C5.0 is an extension to C4.5 algorithm, it builds a rule based decision tree which maximizes the information gain. C5.0 can also winnow and remove predictors as required to design an efficient model. This means that initial model can uncover what predictors are to be used for the model and depending on the importance of each predictor the final model is generated only with the most important ones. To achieve this the system breaks training dataset into two equal halves. A ‘winnowing tree’ is created from the first half to evaluate the utilities of numerous predictors. Those predictors which are unimportant for this model are absent in any split of the tree. The other half is used to estimate the error rate of the tree without each predictor and with all the predictors. This helps the system to design the most accurate model while adding and/or removing predictors at each stage.

SVM – Support Vector Machine is a discriminative classifier that is used for separating hyperplane. When a training data is provided the algorithm provides an output in the form of a hyperplane for categorizing the new examples. In terms of machine learning SVMs are used for supervised learning and are associated with learning algorithms that is used for analysis using classification and regression analysis. An SVM is a representation of model of points in space so that the points are divided by a clear gap that is as wide as possible. With new points are mapped into the same space and are





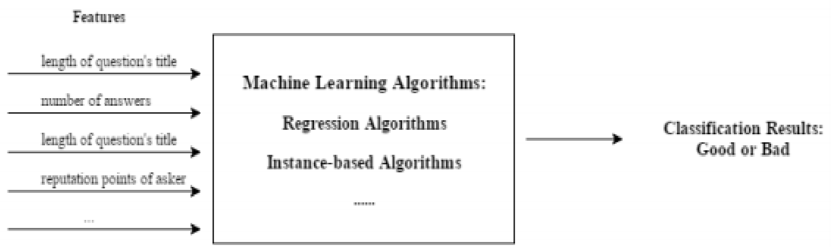
predicted to belong to a category based on the side of the gap it belongs to.
Natural Language Processing (**NLP**) is concerned with analyzing human interaction and understand various behavioral aspects from it. In context of R, it supports computational analysis of speech and language like setting focus on lexicon usage, sentiments and emotions related to it. Tokens are generated from strings through which sentiment tree is constructed according to the pre-designed algorithm and file that defines if the word stands for positive, negative or neutral structure. With usage of token and sentiment analyzing algorithm, successive meaning of the string is generated with each token read.

3. Literature Review

Article 1
Reviewed by: Alok Satpathy
Complete Reference:

1. Daoying Qiu (2015) Evaluation and Prediction of Content Quality in Stack Overflow with Logistic Regression
2. Ahmad, Rizwan, Dmitriy Kunitskiy, and Aleksander Maricq. "Stack Authority: Predicting Stack Overflow Post Helpfulness Using User Social Authoritativeness."

Objective: The paper is addressing the problems that users face in getting quality answers from CQA (Collaborative Questioning and Answering) sites. It is important to address this because there are large-scale of questions and answers on CQA sites, hence it is critical to establish automatic evaluation for content quality. User reputation and voting are not strong enough to evaluate content quality because there are many other influential parameters that can define content quality.
Approach: The authors have tried to address this problem by building a model to measure and evaluate the content quality of the posts in CQA sites. They have used a multi-methodological approach to perform research on the data. Previous researches have used one of the following methods: factoid, definition, list, complex interactive and target. But in this paper the author has used the features approach of questions and answers to evaluate the content quality. They created a model based on the features of questions and answers like length, number of comments, views, up votes, reputation, profile summary, views, etc.


Features
length of question's title
number of answers
length of question's title
reputation points of asker
...
Machine Learning Algorithms:
Regression Algorithms
Instance-based Algorithms
......
Classification Results: Good or Bad

The model's coefficients, p-value, multiple R^2 and adjusted R^2 values are reported and parameters with significance level greater than 0.05 are considered for further analysis. They also took a survey from three people currently working in Information technology field to evaluate the question and answer quality and added this as a human question quality prediction parameter. The result was converted into a binary digit based on the below formula where AE represents average result of an evaluator to a question and Ci denotes evaluator's rating based on one criterion and n denotes number of criteria.

Results: ROC curves technique was implemented to measure the performance of answers model with full feature set, simplified feature set and only 10 features. It was found that all the 3 models are similar. In addition, 10-fold cross validation was performed to check the accuracy which can be verified by the given table.

Summary: The major takeaway is content quality in CQA sites can be evaluated based on features of the content and classification method like logistic regression can be utilized to build the model for prediction. The major features utilized were those of the content and the owner. Other features like comments and badges have not been utilized in this paper.

Article 2
Reviewed By: Aman Agarwal
Complete Reference: Ahmad, Rizwan, Dmitriy Kunitskiy, and Aleksander Maricq. "Stack Authority: Predicting Stack Overflow Post Helpfulness Using User Social Authoritativeness."

Objective:
Question-answer website like Stack Overflow and Quora provide a platform where users can ask questions and community members answer them. However, since these questions are open to the community the answers generally suffer from noises. These noises can be in form of span, slangs, inappropriate use of language or simply unhelpful posts. The authors attempt to create a computer model which would classify a post to be helpful or not based on certain calculation. They also attempt to see the effect of adding social information to the post as a feature to check the effect on the model and the prediction it provides. The primary feature that the paper discussed was the ratio of up votes to the total vote a particular paper received on the post. After applying various regression functions, the authors could build two accurate predictors, a linear ridge regression model and a decision tree regression model. Both these out-performed the trivial base line predictor. However, their attempt to add the social factor failed and did not reveal any significant difference on what was predicted by earlier models.

Approach:
The authors could mine data from the huge Stack Overflow data corpus available publicly. After careful ETL, the data was refined and readied for analysis. They considered five most common tags: Java, JavaScript, C#, PHP and Android. A total of 26.5 million posts with 9.9 million question and 16.5 million answers were analyzed. To successfully add social context, a URL tracking mechanism was adopted to identify the users and their activity and assign points to the post based on the user's posting of questions and the answers. A baseline predictive model was developed initially which was on line with the average user post and average "helpful" posts. Regressions features were analyzed from among the post features like length of post, comments, tags, code, hyperlinks and user features like badges, reputation, views etc. Then beyond this Linear ridge regression and Decision Tree Regression models were developed.

Results:
It was noted that classification accuracy, MSE and R-squared for the Linear ridge and Decision tree were 0.610, 0.217, and 0.069 and 0.675, 0.192 and 0.179 respectively. Overall, the classification was 80% accurate. Most significant feature was number of views for the post followed by the Stack Overflow reputation of the user. Others were owner profile views and badges. No significant effect was found in terms of social features.

Summary:
In summary, the paper highlighted various features of the post and the user and provide a kick start to our project in terms of a focus are. Given that the number of features can be vast, we now understand the factors on which a post can be answered. This can be expanded as per pour needs for the questions that we try to resolve in the project.

Article 3
Reviewed by: Pratik Mrinal
Complete Reference: Correa, Denzil, and Ashish Sureka. "Fit or unfit: analysis and prediction of 'closed questions' on stack overflow." *Proceedings of the first ACM conference on Online social networks*. ACM, 2013.

Objective: The research paper aims at in-depth analysis of closed questions on Stack Overflow detailing their structure, content and trends, to utilize the analysis into predictive modelling for the question closure probability for the identified feature sets from the huge pile of questions present on the website.

The paper is the first ever known focused research on the 'closed' questions section on the Stack Overflow. With a proper analysis into the ever neglected yet most vast aspect of information distribution on the Stack Overflow website, this research aims at developing the predictive models to clearly mark the 'to be closed' questions and give the users a proper feedback about their content style to restrict the size of irrelevant content on this information management portfolio.

2. Approach: The authors analyzed the models based on 19 features sets available. Aside from the self-explanatory feature sets, other important features considered were Badge Score, Post Score, Accepted Answer Score and #Popular Tags. Based on the exhaustive features list, a series of regression methods was used to design the best predictive model. SGBT modeling was finally chosen as it represented the strongest output and hence it was used to form a strong classifier out of series of weak models each handling a separate entity model. A 70-30% ratio was taken for training and testing data. Based on the confusion matrix analysis, three metrics of F1 score, Accuracy and AUC was used to finally predict the effect of feature set obtained by forward selection method.

3. Results: Following were the major results obtained from the research paper:

a. Stack Overflows URLs, Code length, age of account and post score accounts for strongest contribution to prediction of post closures. On the contrary, features like comments score, badge score has a minimal effect on the prediction measure.

b. Feature set analysis represents that new users with a lack of knowledge for stack overflow question formatting process, have highest rate of closure probability.

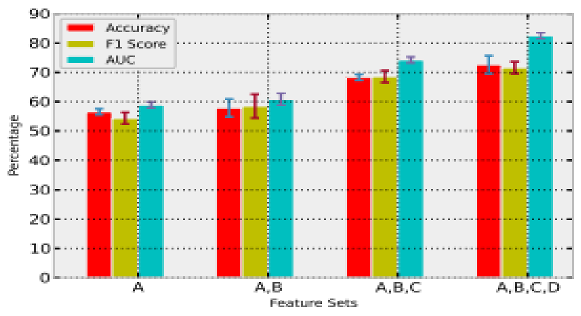


Figure 13: shows classifier performance with Accuracy, F1 and Area Under the ROC curve (AUC) metrics when feature sets are incrementally added. Note the strong performance of our classifier on every feature set addition.

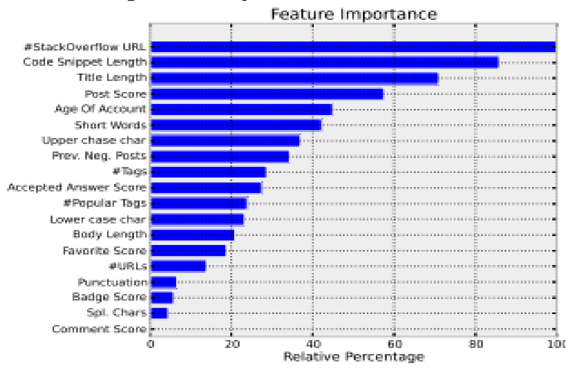


Figure 14: shows the relative feature importance of all 19 fea tures in our predictive model.

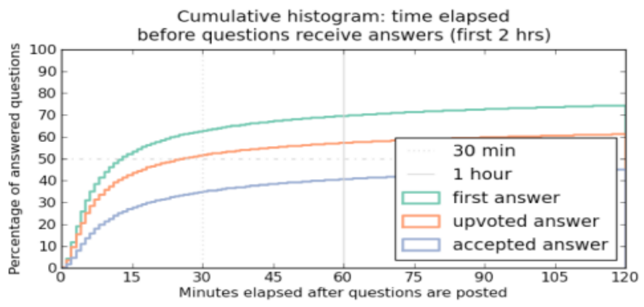
4. Summary: The major takeaway from the paper was implementation of SGBT predictive modeling process using standard parameters and sub-sample sizes. It demonstrates the process of extracting the weak predictive models parameters without the actual requirement for creating the tree, thereby avoiding the overfitting of the model to build a strong classifier.

Article 4
Reviewed By: Aman Agarwal
Complete Reference: Mamykina, Lena, et al. "Design lessons from the fastest q&a site in the west." *Proceedings of the SIGCHI conference on Human factors in computing systems*. ACM, 2011.

Objective: The paper analyzes the user behavior of technical Q&A website Stack Overflow(SO) and tries to find the attributes for such high success rates. The researcher wanted to understand the features which contribute to attract users to SO and make it a favorable site to ask questions and get correct answers quickly. They aimed to emulate these features to other websites, however, limited their study to understanding the features of SO.

Approach:
The authors conducted the research in two phases. First, they conducted quantitative analysis from the data they gathered from the Stack Overflow website. They gathered different metrics like rate of questions being asked, the time it takes for first answer, time it took for first accepted answer, follow up questions (or comment on questions), activity on each question etc. They applied various statistics formula to calculate mean and median times to analyze the user behavior towards a particular event. The second approach was to follow up on the website designers and the users. This was the part of the qualitative approach. The authors selected and contacted the users based on their activity. The interviewed these users over skype, phone or in person for about 1 hour asking them about their interaction patterns on SO, motivation, comparison to other Q&A websites etc.

Results:
The qualitative study revealed that the founders the aim to create a productive environment where searching information is easier. These rewards came in terms of reputation, badges, privileges, and bragging. This was instrumental in understanding what community members needed. Rapidly improving the design of the front end as well as the backend also made Stack Overflow more preferred over other tech blogs and Q&A forums. Another astonishing finding was that the most activity on a question happened in the first hour of the question being posted (Fig. 1). A high success rate of SO was attributed to the finding that a question was answered 92.6% and more than 70% questions were answered multiple times. Other result was that the frequent user of SO were mostly the users who would answer and had high answer ratio.



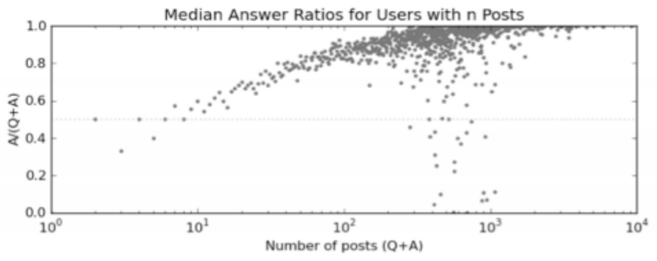


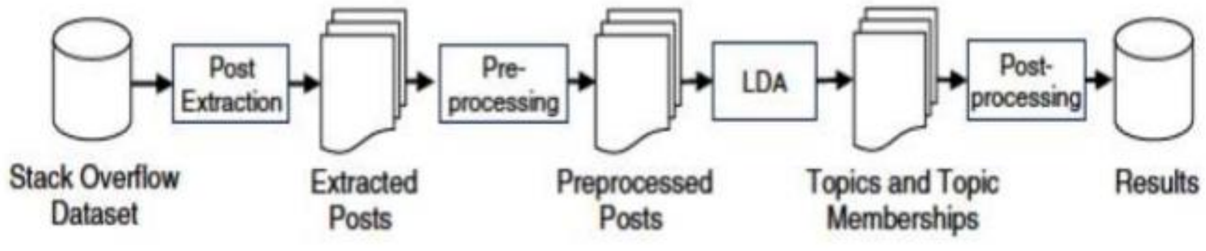
Fig 1: Answers in the 2 hours after questions are posted. **Fig 2: Generally Frequent users post answers.**

Summary: In summary, this paper highlighted various reasons which were responsible for the overall success of Stack Overflow. Moreover, this paper was instrumental in understanding various metrics which will assist us in doing our analysis. We understood the user pattern from the data analysis carried out by the authors. The qualitative analysis highlighted the motivation behind this website. It also highlighted the reasons behind various changes being carried out on the website and the relative implications these changes caused to improve the human interaction with various elements present on the website.

Article 5
Reviewed by: Alok Satpathy
Complete reference: Barua, Anton, Stephen W. Thomas, and Ahmed E. Hassan. "What are developers talking about? an analysis of topics and trends in stack overflow." Empirical Software Engineering 19.3 (2014): 619-654.

Objective: The paper is addressing the cross-cutting areas of concerns for developers that span across multiple domains for different topics. Addressing this problem is important to find if one topic triggers answers in another i.e. if some topics are related to other in terms of questions and answers. This information can be helpful to business analysts to figure out the most used feature of a given software and product developers to assess relative popularity of their products. The objective of the paper is to find the trending topics and the rising interest in certain software or programming language.

Approach: The following diagram shows the various phases of data processing.



The Stack Overflow dataset is organized into five XML documents badges.xml, comments.xml, posts.xml, users.xml and votes.xml. Out of these the dataset used is posts (questions and answers with tags). The entire dataset was divided into 12 partitions covering 3 years with 3 months per partition. The impact of a topic was calculated using the below formula:

$$impact(z_k, m) = \frac{1}{|D(m)|} \sum_{d_i \in D(m)} \theta(d_i, z_k)$$

There are 4 different comparisons that were applied- Programming Languages, Web Technologies, Application development, General Trend. Latent Dirichlet allocation (LDA) was applied for classifying the above comparisons. LDA is one of the most common topic model used and is a generative model that allows sets of observations to be explained by unobserved groups that explain why some parts of data are similar.

Results: The graphs below show the trend of languages and technologies over a 3-year time frame and with 3-month gap between each period.

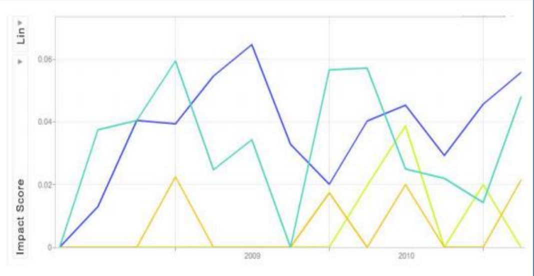


Figure 3 Languages

Java - Green C++ - Blue Orange - Python Light green - PHP

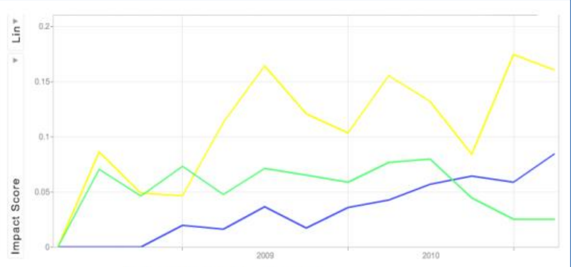


Figure 6 Technology Domains

Yellow - Web Technologies Green - Server Side Technologies
Blue - Mobile Technologies

During this trend analysis there are several peaks as some topics were trending at some particular point of time. The reasons behind this sudden popularity in certain technologies were discovered and were found associated with real time events.

Summary: The above analysis is performed on Stack overflow, a popular Q&A website used by millions of active users. LDA was applied to discover topics from textual content and various metrics were applied to quantify the topics and changes over time. The analysis can help contemporary developers, stack overflow team to better understand the content generated by users and in moderation of website.

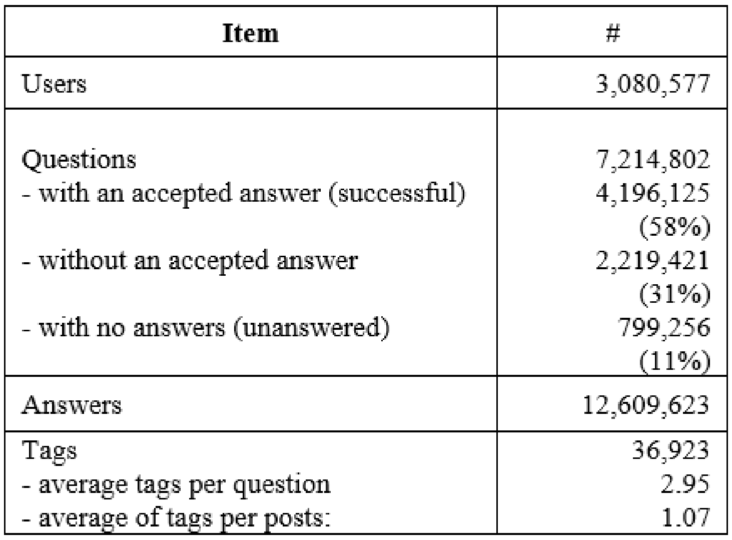
Article 6
Reviewed by: Sankit Gupta
Complete reference: Novielli, Nicole, Fabio Calefato, and Filippo Lanubile. "Towards discovering the role of emotions in stack overflow." Proceedings of the 6th International Workshop on Social Software Engineering. ACM, 2014.

Objective: The research paper tries to analyze through an empirical study to investigate the role of emotions and lexicons used to design a question and their effectiveness on online Question & Answer portals. The paper further investigations are being carried out to analyze the natural language conversation which will help understand user interactions on such portals. Even a very important question might not attract any response because of ineffective usage of words.

The key objective of this paper tries to address the concerns related to understanding user's perception in responding to a question on the Q&A portal apart from analyzing the time to get response based on the usage of lexicons. The research implies that better understanding of user sentiments might lead to future enhancements in enhancing user engagement, experience and online tools with embedded emotional intelligence systems.

Approach: To understand the relation between usage of emotion and user response to it, the team of researchers used various factors that are collected by the Stack Overflow whenever a user posts or responds (to) a question. Factors like date and time of post, code snippet, length of post, topic it related to; responder's details like Q&A score, answers accepted by user, answers provided by user, etc. were used to design a regression model which further predicted a binary result called Success which records if an accepted answer for similar question was provided or not. Per the team of researchers, the key contribution of this research is to support their claim that emotion recognition is a growing and interesting field of software engineering and specifically social computing.

Table 1. Stack Overflow data dump



Item	#
Users	3,080,577
Questions	7,214,802
- with an accepted answer (successful)	4,196,125 (58%)
- without an accepted answer	2,219,421 (31%)
- with no answers (unanswered)	799,256 (11%)
Answers	12,609,623
Tags	36,923
- average tags per question	2.95
- average of tags per posts:	1.07

Results: When the research paper was published, the analyzing process for data was still on-going and hence no concrete evidence has been documented which can be considered the result. But, during the research, authors found that a strong correlation exists between the emotions expressed in the question like how-to, urgency, help, etc. and other factors such as the coding languages for the project, day and time of the week, asker's social status in the Q&A community, etc.

Summary: This research paper provided me with basic understanding of how logistic regression can be applied over set of predictors to understand the success factor of the question to receive the best answer. This paper also helped in understanding what are some critical predictors in the Stack Overflow data that can help design a much efficient and effective model.

Article 7
Reviewed by: Pratik Mrinal
Literature: Analysis of Titles from the Questions of the Stack Overflow Community Using Natural Language Processing (NLP) Techniques

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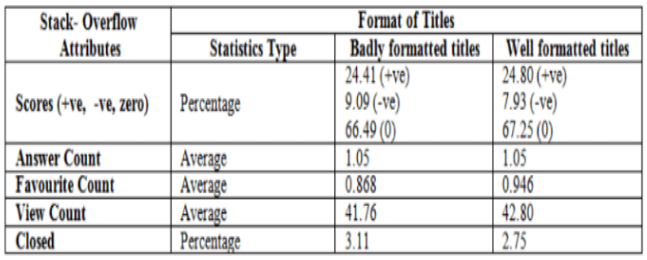
Objective: The research paper aims at evaluating the extent stack overflow posts' title conforms to the guidelines of the Stack Overflow community. Further, it leverages this analysis in sentimental analysis process to check the effect of title format and conformity of rules for a post towards its overall popularity, predicted using the up and down votes for the post. The questions asked in the forum needs to follow a set of rules to help the programmers in their moments of crisis. Many questions which carry considerable potential for the most complex question tend to lose out in the huge pile of the content available on the site. The paper also aims at translating the importance of the tone of the post towards its popularity and meaningfulness. The research implied that format of a question is not a strong contributing factor to the popularity of the question. In other words, a well formatted post may or may not have high upvotes. On the other hand, a question with a positive tone is more likely to get upvotes than a subsequent question with a negative tone. The research showed that it's the quality of the tone that matters to get higher upvotes for a post, rather than its structure which may or may not get upvotes.

2. Approach: Summarize your understanding of how authors address this problem (use equations, flow charts if necessary)? If possible, identify the key contributions they bring.
Response: The authors have broken the research into two parts of titular format checker and sentimental analysis. The extracted data is checked against the pre-defined grouped titles and if found similarity are grouped with the class they are matched with. Similarly, to gather a collection of positive, negative and neutral sentiments, the Bayes classifier is trained against a different data set of movie review which was used to gather positive, negative and neutral sentiment keywords. These classifications were then utilized with the testing data set of Stack Overflow posts to check for the sentimental tone of the posts. The following Naïve Bayes theorem was used in the analysis:

P (label | features) = P(label) * P (features | label) / P(features)

3. Results: Some of the major findings from the research demonstrated that approx. 31% of the titles are ill formatted in the community. However, 24% of these titles gathered positive scores despite their ill format. Further, the research showed that there exists other unthought factors like 'Answercount', 'Viewcount' and 'Favoritecount' that have a huge impact on the popularity of posted questions.



Stack- Overflow Attributes	Format of Titles		
	Statistics Type	Badly formatted titles	Well formatted titles
Scores (+ve, -ve, zero)	Percentage	24.41 (+ve) 9.09 (-ve) 66.49 (0)	24.80 (+ve) 7.93 (-ve) 67.25 (0)
Answer Count	Average	1.05	1.05
Favourite Count	Average	0.868	0.946
View Count	Average	41.76	42.80
Closed	Percentage	3.11	2.75

Table I: Format of titles vs. stack overflow attributes

The outcomes of the research can be summarized below:

a. Sentiment plays a major role in the popularity and hence directly accounts for the number of upvotes received.
b. High Structure + Positive Sentiment = Highest upvotes
c. Low Structure + Positive Sentiment = Fair upvotes.
d. High Structure + Negative Sentiment = Lowest upvotes
e. Low Structure + Negative Sentiment = Fair upvotes

4. Summary: Break and solve model to distinctively handle the sentimental analysis and general classification separately. Training of the Bayes classifier using a different dataset of sentimental data and re analysis of the testing data set based on the classifier gives optimum classification. Exhaustive criteria inclusion to build the model, as many a times most appealing criteria comes out to be a minimal contributor to the model as was the content structure in the given case.

Article 8
Reviewed by: Sankit Gupta
Complete reference: Novielli, Nicole, Fabio Calefato, and Filippo Lanubile. "The challenges of sentiment detection in the social programmer ecosystem." Proceedings of the 7th International Workshop on Social Software Engineering. ACM, 2015.

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1. Objective: The aim of this paper is to understand the probability of an answer to be accepted with the usage of expressive affective states on Stack Overflow. The paper also aims to raise and prove that analyzing just the polarity of the questions or answers isn't an efficient parameter for detecting programmer sentiments. Various researches are being carried out to understand what incites social programmer to seek help or help others with programming issues. To address this problem, the research team analysis top 100 questions along with the asker's comments with highest positive and negative polarity and the best answer to the question. Various state-of-art tools are then used to understand polarity of each lexicon, regression models for analyzing textual occurrences, etc. The resultant dataset helps in supporting the claim made by the research team.

The authors found that analyzing words and their polarity isn't sufficient to justify the positivity or negativity of the question but analysis of whole text structure or huge group of lexicon together makes sense for efficient sentiment analysis. A word as an individual might reflect the negative sentiments but when used in a statement, it might reflect complete opposite of what was predicted from initial research.

2. Approach: The team of researchers first annotated sentiment score in context of the polarity of the statement and its strength. Having done so, they measured the sentiment load in varied threads i.e. questions, answers and comments, to choose cases with highest sentiment score. The team then analyzed the polarity and sentiment strength of the text as an overall lexicon by using the sentiment analysis tool named SentiStrength. To understand the concept properly, they then analyzed top 100 questions from Stack Overflow dump data along with the following threads on the questions like the comments by the asker with highest positive and negative sentiment score. They then use these findings from positive and negative analysis to prove that just analyzing the polarity cannot be an efficient tool to gauge the sentiments of the asker or answerer. Similar thing has been shown in the adjacent figure.

3. Results: The research claims that emotions represent variety of moods and opinions and their resultant dataset confirms this claim that such analysis is more complex a phenomenon than just analyzing the polarity of the lexicon. From the research done by the team, it was clear that the sentiment load cannot be predicted accurately even with the usage of state-of-art sentiment analysis tools. This is because, such tools just consider the polarity of the lexicons to predict the user sentiment. The research tries to set a foundation stone in favor to adopt more efficient and affective state models.

4. Summary: In context of findings based on the affective analysis of text, the researcher shows that the negativity is reflected from the questions posted by the user as it reflects the frustration about the technology or the problem they are not able to solve. Similarly, the negativity in the answers are associated with the empathy of the responder towards the problems faced by the asker and not directly to the asker. This lays a strong foundation and case to justify the research done by this team to reflect that affective analysis of various parameters and lexicons is essential to understand user sentiments rather than just the polarity test.

4. Process, Implementation, and Result

This section deals with the issues that were noticed and believed can be resolved using the predictive analysis techniques. Each issue is introduced, its approach along with the data gathering strategy is elaborated and the methods used for the analysis are discussed. Finally, each issue ends with the results of the study that was carried out and various models used are compared. The flowchart below describes briefly about the whole transition of the project from extracting the data to various models implemented to answer issues on Stack Overflow.

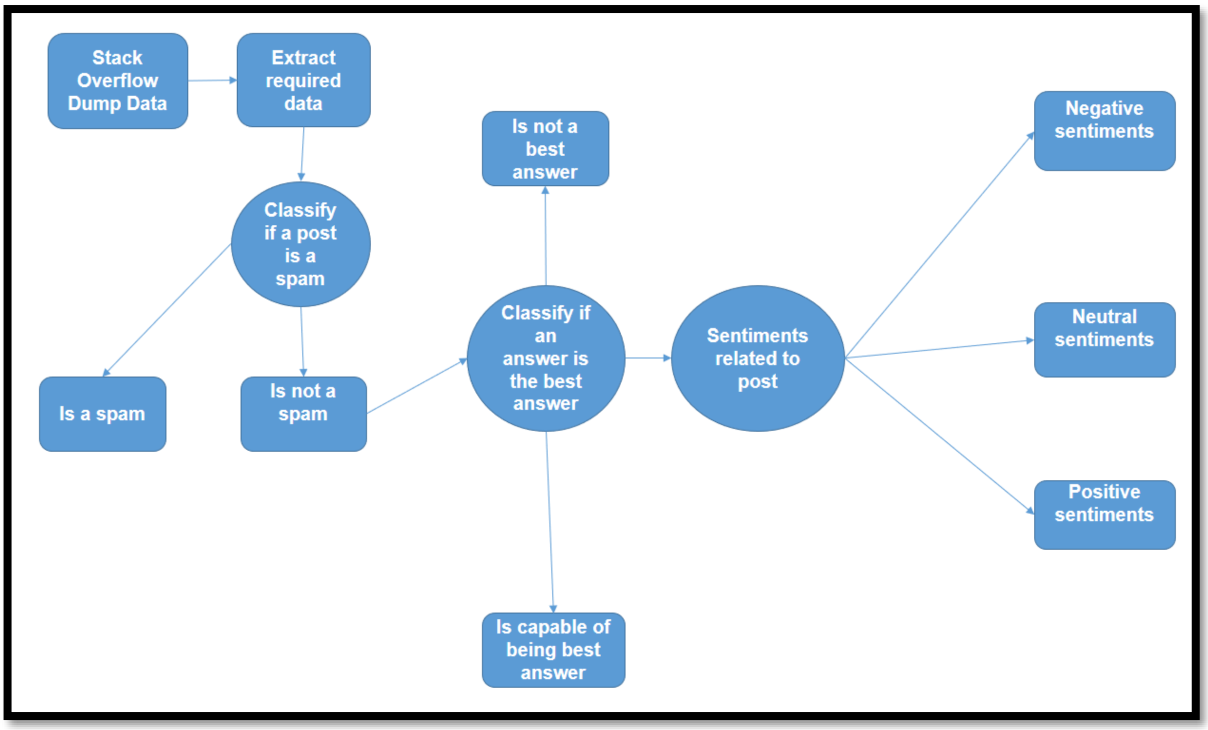


Figure: Flow diagram giving a broad overview of the entire process followed

4.1 Classify data into spam/non-spam

4.1.1 Approach

The approach for the spammer classification can be detailed by the following points:

1. Data Extraction from the stack overflow in accordance to the most important tables that contains the spam alerts for the records. SQL queries were used to extract the required data from the Stack Overflow workbench.
2. The data was then analyzed using classification models that includes logistic regression, LDA, QDA, KNN, CART, Random forest and SVM.
3. Regularization and K-fold Cross Validation method were implemented to avoid over fitting of the model and to check the effectiveness of the obtained model over the different subsets of data.
4. A new technique called C5.0 was implemented to train the model on the previously classified sample dataset utilizing the concept of information entropy, recurring the partitioned data trees on the highest gained attribute and adding next best nodes as the children nodes.
5. Mutual analysis for the misclassification rate between the models gives the model with the best prediction rate and hence the spam modeler for the Stack Overflow data.

4.1.2 Implementation

The implementation of the spam classifier consists mainly of four steps:

a. **Data Extraction:** Stack Overflow provides workbench to extract their processed activity data and related parameters from their backend. A major analysis into the website architecture clearly reveals the huge effort put into the content management portfolio owing to the large number of users working on the website with day in and day out. This calls for a need to classify the data into useful and spammer contents. The backend provides the option for analysis into the spammer content and hence, based on few factors the incoming data traffic can be easily classified to avoid the unintended content. Major tables identified for the related data to the spam content were:

• · ReviewTasks • · ReviewTaskStates	• · PostTypes • · PostFeedback

• · ReviewTaskResults • · ReviewRejectionReasons • · ReviewTaskResultTypes • · Posts • · Users	• · VoteTypes • · Votes • · PostHistory • · PostHistoryTypes

The complex queries created for the data extraction can be referenced in the Appendix section. Because Stack Overflow provides the access to 50,000 records per cycle, the required data were extracted into

b. **Data Cleaning:** The extracted data was cleaned for the description columns and irrelevant columns for the spam identification to obtain a data frame consisting of only of factors that are potential contributors to the spam identification process.

c. **Data Analysis & Modeling:** From the final list of 16 sample features, series of classification models were implemented to check the best model depicting the spammer classifier. Following major factors were identified to be the major contributors in spam detection.

• PostTypeId • PostScore • post_length • owner_reputation • owner_profile_summary • owner_upvotes	• editDurationAfterCreation • q_num_tags • AnswerCount • CommentCount • post_views

Algorithms implemented for checking the best model for the classifier were:

c.1 Logistic Regression:
c.2 LDA:
c.3 QDA:
c.4 KNN:
c.5 CART:
c.6 Random Forest:
c.7 SVM:

Please refer to the Appendix to check for the exact list of steps for the execution.

d. Evaluation:

The models generated were evaluated based on accuracy and misclassification rate using confusion matrix. Correspondingly, ROC area under the curve were also utilized to further validate the strength of classification. Following table shows the results obtained:

Model	Misclassification rate	Accuracy Rate (1-Misclassification Rate)
Logistic Regression	0.3077023	0.70
LDA	0.3075291	0.70
QDA	0.3506516	0.65
KNN	**0.01506082**	0.985
CART	0.2757068	0.73

Random Forest	0.01524007	0.985
SVM	0.28654	0.32
C5.0	0.02281	0.972

PS: Complete output from all the methods can be found in GitHub.

4.1.3 Result

Hence, as is clear from the above table, Random Forest and KNN modelling gives the least misclassification rate of 0.015. However, KNN has a very slight advantage on the Random Forest and hence comes out to be most economic model of the lot. This also falls in very accordance to the most industry standards spam classifiers which uses KNN as the best predictor, also illustrated through the literature reviews. The industry should use the KNN model for this classification using the above mentioned critical parameters that came out to be strongest contributor to the variable IsSpam. On top of providing better accuracy rate for classification rate, KNN model also provides easy interpretation of the model and hence easily manages the bias-variance trade-off thereby providing the optimum model to be used.

4.2 Evaluate quality of answer posts to predict best possible answer

On stack overflow, a user (also called Original Poster or OP) asks questions and other users or the OP, at times, answer the question. The quality of the answer technically depends on two things a) the number of up/ down votes by users on the answer and b) the acceptance of the answer by OP. Generally, OP verifies whether the answer is the solution to the question asked. There can be only one accepted answer to the question. Ever since the inception of Stack Overflow, there have been 12,319,722 questions posted and they have been answered 19,494,601 times. This data does not include deleted or closed questions. Of 12.3 million questions, only 6,717,441 (i.e. 54.5%) questions have an accepted answer.

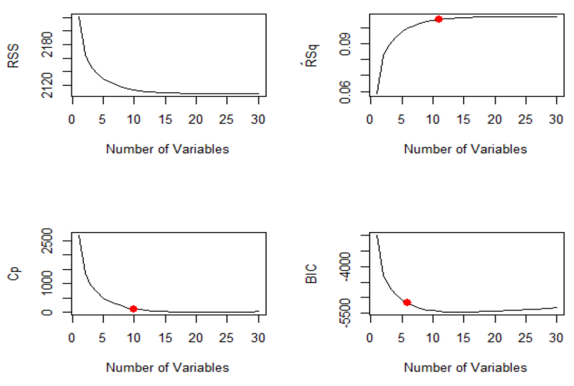
However, as questions are generally answered within 20 minutes, accepted answer is generally the first "working" solution and may or may not be the best solution to the question. It has been noticed that appx. 30% of questions having an accepted answer, however have another answer/s scoring better than the accepted one. Our attempt to evaluate the quality of the answer and predict the best possible answer can help in 2 major instances:

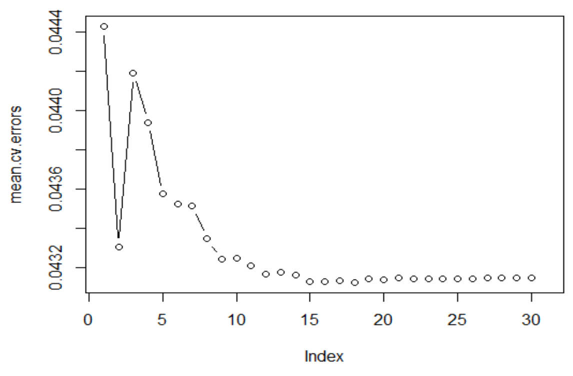
1. Saves time of users who browse for answers to a question without an accepted answer.
2. User can find the best answer to a question which has an accepted answer but may have better answers.

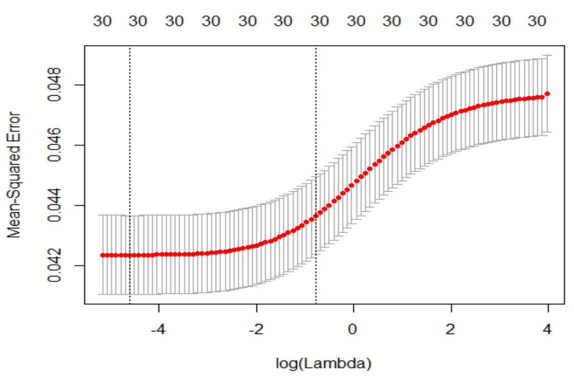
4.2.1 Approach

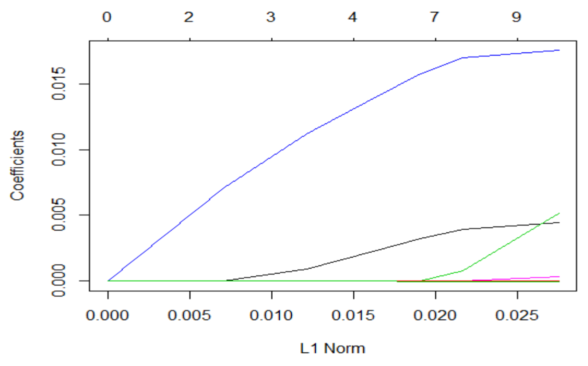
The data was extracted from Posts, Users and Votes table by performing transformations using SQL query as given in the Appendix. A total of 31 features were derived from these tables to prepare a model that can be used to predict the likelihood of it being marked as the best answer. A total of 50,000 answers were extracted dated from January 1, 2016 to December 1, 2016. To increase the quality of the data only questions with more than 4 answers were selected.

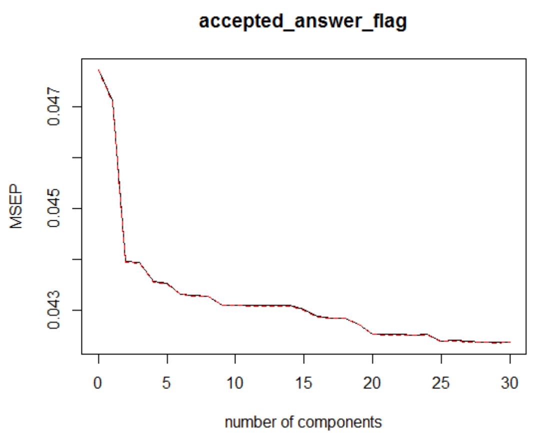
Ridge regression, Lasso and Dimensionality Reduction (PCA) methods were used to find the parameters most contributing towards generating classification model for prediction. The classification models include Logistic Regression, LDA, QDA, KNN, CART, Random Forest and SVM.











4.2.2 Implementation

A total of 31 features were considered for the analysis. Here we want to see other than the Op's bias what other factors could lead to an answer getting accepted. After doing this analysis we will be able to predict which answer is highly likely to get accepted if none of the answers to a question have been accepted yet. We apply a series of techniques and compare the results to finally arrive at the model which gives the best result.

Data Extraction: The data was extracted using SQL Query run against Stack overflow data dumped in Stack Exchange repository. Given below is a sample column mapping used to extract the data:

Required Column	Actual Table	Actual Column	Transformation/Filter	Comments
a_score	Post	score	integer given	how many points did the answer gain
a_body_length	Post	body	length	length of the answer's content

a_body_has_code	Post	body	contains <code> tag	does the answer contain code or not
a_has_edited	Post	LastEditDate, CreationDate	flag if LastEditDate (non-blank) and CreationDate are different	has the answer been edited or not
a_num_comment	Post	CommentCount	integer given	number of comments the question receive
a_owner_reputation	User	Reputation	by joining OwnerUserId with Id User table	reputation points of the answer's owner
a_owner_profile_summary	User	three columns (Location+WebsiteUrl+AboutMe)	sum of non-blank flags of columns	combination value of "Location", "WebsiteUrl", and "AboutMe" from answer's owner

Figure: Sample parameters and the transformation / filter applied to extract from Stack overflow tables

Classification Method:

With 30 predictors to predict "Accepted Answer" probability, Logistic regression was found to be the best model for analysis. On successive elimination of insignificant data, the following model was selected for analysis:

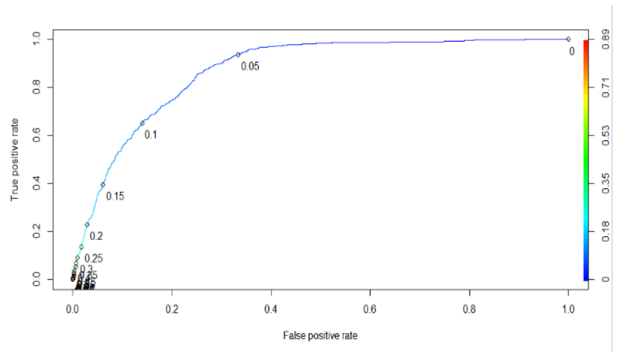
```
glm (accepted_answer_flag ~ a_body_length + a_body_has_code + a_DaysOld + a_has_edited + a_num_comment + a_owner_reputation + a_owner_profile_summary + a_owner_downvotes + q_DaysOld + q_title_length + q_num_answers + q_num_comment + q_owner_profile_summary, data=Q2Train, family="binomial")
```

Of these 13 predictors, 12 were highly significant (***). The definition of the predictors is provided in Appendix A. The code to arrive at the most significant predictor is provided in Appendix C. Cross validation was performed using Leave-one-out cross validation technique and K-fold cross validation. The average mean squared error obtained was 4.16%

The confusion matrix thus obtained with the model is: False Negative rate: 592

A model with lesser False negative rate was instigated further. That means it should predict most acceptable answer. The mis-classification rate obtained from this model is: 0.05296

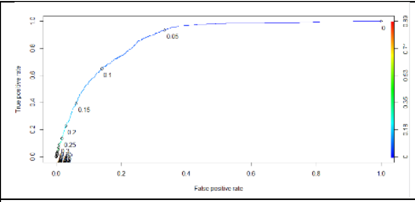
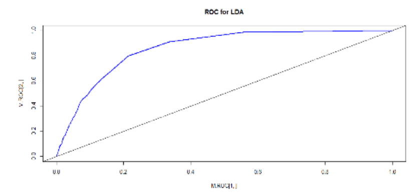
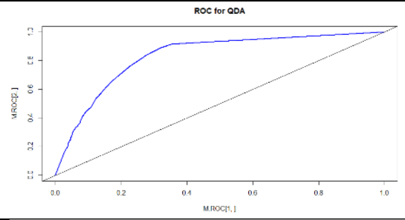
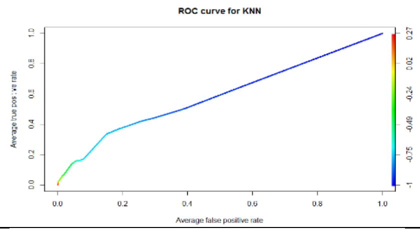
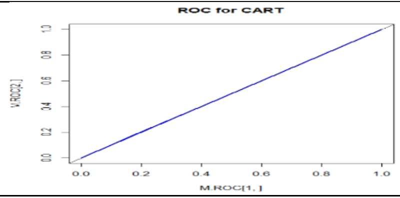
The ROCR curve thus obtained for this model is shown in the below figure.



4.2.3 Result

Out of all the classification techniques we find Logistic regression to be the best classification technique based on its low misclassification rate and ROC curve showing higher area under curve and hence better classification model in predicting the likelihood marking an answer as the best. The following table summarizes the findings obtained after carrying out the analysis.

Parameter	Misclassification Rate	ROC Curve

Logistic Regression	0.052	
LDA	0.063	
QDA	0.083	
KNN	0.052	
CART	0.052	
Random Forest	0.88 (no significance)	

**Complete output from all the methods can be found in GitHub.*

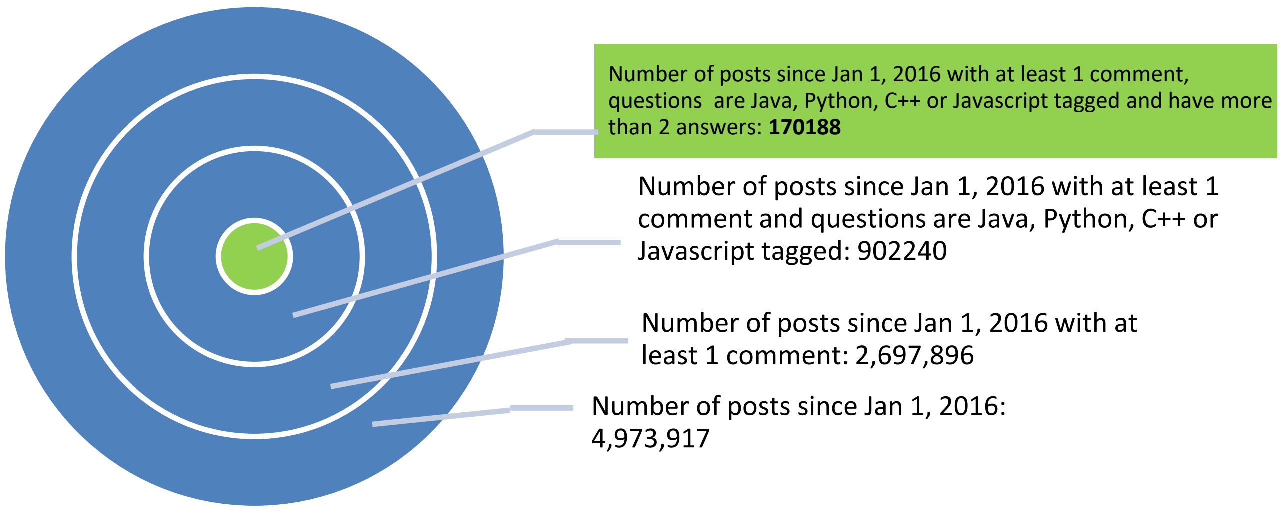
4.3 Predict comment sentiment using NLP and based on Post features

4.3.1 Approach

The data was taken from Posts, Comments and Votes table. The questions which were posted on or after January 1, 2016 till December 1, 2016, have 3 or more answers, and have C++, Python, Java or JavaScript as tags have been considered here. Like the previous issue, this gave us a focused and recent dataset to minimize excessive variability. A total of 50,000 questions and answers were considered for this analysis.

The below figure explains the filters that we applied on the corpus to arrive at the target dataset we used for this analysis. These filters were chosen based on the density of the activity on the posts. While almost 50% of the posts had no comments on them, the number of comments decreased drastically with highest number of comments on a post being 78 and there was only 1 such post. In all 170,188 posts were considered for this study. Users posted 545,413 comments on such posts and all were taken into consideration for the analysis.

Stack overflow data filtered based on date, tags, number of comments and number of answers on the questions. Deleted questions are not included.


Number of posts since Jan 1, 2016 with at least 1 comment, questions are Java, Python, C++ or Javascript tagged and have more than 2 answers: **170188**
Number of posts since Jan 1, 2016 with at least 1 comment and questions are Java, Python, C++ or Javascript tagged: 902240
Number of posts since Jan 1, 2016 with at least 1 comment: 2,697,896
Number of posts since Jan 1, 2016: 4,973,917

4.3.2 Implementation

A total 32 fields were queried and 50,000 records were extracted that consisted comments on posts with answers count > 4 and at least 1 comment. The text field was run through Natural language processing algorithm to analyse positive, neutral or negative sentiment and find correlation between other features of the comment, the post it belongs to, the features of the owner of the post and the comment and its effect on number of upvotes and downvotes of a post. A list of words was downloaded with sentiment scores applied to each of them. This was used to train and predict and analyse the sentiment of each comment.

```
model=glm(SentimentScore~CommentLength+comment_owner_downvotes+num_tags+PostAnswerCount+IsAcceptedAnswer+PostCommentCount,data=Q3Train)
```

4.3.3 Result

As we can see from the above model, the Sentiment of the comments doesn't depend on the Post upvotes and Post downvotes. This goes ahead and proves that there is no correlation between positive/negative comments and upvotes/downvotes of posts. This is evident because whenever a person upvotes a comment the owner gets +5 points, however on downvoting the owner of the post gets -2 and the person downvoting gets -1 reputation points. Hence, people usually tend to leave their agreement/disagreement in the form of comments instead of upvoting/downvoting. Also, the accuracy of the model after considering all possible features related to the comment's sentiment came to only 0.44, hence the comment sentiments can't be predicted based on Posts features and cannot be used to predict upvotes/downvotes of posts.

Sentiment	Number of comments
Positive	20842
Neutral	21688
Negative	7470

5. Conclusion

The major take away from the above analyses can be summarized as below:

a. With huge traffic and regular updates, content management for Stack Overflow is an essential requirement where a best fit Spam Classifier would be dramatically helpful in maintaining the useful content on the website. Of all the major classifiers, KNN model gives the best fit for the spam classifier. This is in accordance to the real world actual implementation technologies used in Google and Yahoo mail spammer.

b. Shrinkage methods of Ridge Regression and LASSO attempts at reducing the critical factors in the model. However, the latter is a better shrinkage method as it attempts to nullify the coefficients for the factors in the ultimate classifier model.

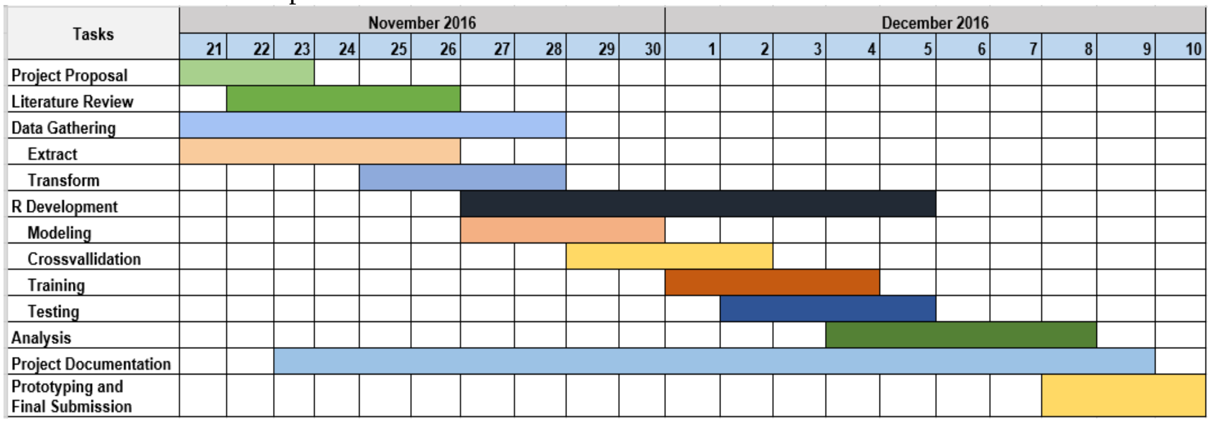
c. Similarly, logistic regression gives the best modeling for the answer quality evaluation. Hence, with all the classifier models in place, different classifiers may give the optimum model based on the data set and context of the model application.

d. Bayes Classifier provides the optimum classification model for the sentimental analysis with model cross trained on multiple sample sets of data through reanalysis and cross training.

e. C5.0 algorithm is the latest development for classification analysis that depicts a large decision tree as a fine-tuned set of objective rules, cross countering the overfitting effect and any associated pruning error.

6. Individual Roles and Responsibilities

As a team, every member was equally responsible to carry out the tasks mentioned in the timeline below. Understanding the data schema and extracting required data from Stack Exchange was found to be very challenging (see Appendix B). Everyone initially worked independently to design models on the problem statements. Once this was done, the team moved forward with the best models and started looking out for new techniques in this analysis. During this time, the team also conducted cross validation and various testing to get the most accurate model from those designed earlier. Additionally, every member individually read and reported the literature in this field, which was then consolidated for a literature review report.



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9. "Understanding the Output of C5.0 Classification Model Using the CARET Package." R - Understanding the Output of C5.0 Classification Model Using the CARET Package - Cross Validated. N.p., n.d. Web. 10 Dec. 2016.
10. "Fitting a Neural Network in R; Neuralnet Package." R-bloggers. N.p., 2015. Web. 10 Dec. 2016.
11. Stack Exchange Website: https://stackexchange.com/about

8. Appendix

Appendix A: Variables

A1. Variables for Question 1 - Spam Classifier

Predictor	Description
PostTypeId	question or answer
PostScore	net of upvote or downvote
post_length	number of characters including spaces in a post
owner_reputation	reputation points of the posts's owner
owner_profile_summary	Owner's profile summary
owner_views	Number of views on owner's profile
owner_upvotes	Number of upvotes owner has received
owner_downvotes	Number of down votes owner has received
editDurationAfterCreation	Time taken between creation and editing of the post
q_num_tags	Number of tags on the post
AnswerCount	Number of answers on the question type post
CommentCount	Number of comments on the posts
has_code	Binary, post has code?
post_views	Number of views the post has received
UserId	Userid who posted the post(OP)

A2. Variables for Question 2 – Evaluate best answer

Predictor	Description
a_score	how many points did the answer gain
a_body_length	length of the answer's content
a_body_has_code	does the answer contain code or not
a_has_edited	has the answer been edited or not
a_num_comment	number of comments the answer receive
a_owner_reputation	reputation points of the answer's owner
a_owner_profile_summary	combination value of "Location", "WebsiteUrl", and "AboutMe" from answer's owner
a_owner_views	number of homepage views of the answer's owner
a_owner_upvotes	number of upvotes the answer's owner

a_owner_downvotes	number of downvotes the answer's owner
q_score	how many points did the answer gain
q_num_views	how many people have read the question
q_body_length	length of the question's body
q_has_edited	has the question been edited or not
q_title_length	length of question's title
q_num_tags	how many tags did the question receive
q_num_answers	number of answers received for a given question
q_num_comment	number of comments for a question
q_num_favorite	how many users have marked the question as favorite
q_owner_reputation	reputation points of the question's owner
q_owner_profile_summary	combination value of "Location", "WebsiteUrl", and "AboutMe" from question's owner
q_owner_views	number of homepage views of the question's owner
q_owner_upvotes	number of upvotes the question's owner
q_owner_downvotes	number of downvotes the question's owner
AcceptedAnswerId	only present if posttypeid=1 i.e. question type
a_DaysOld	Answers
q_DaysOld	Questions
a_num_views	how many people have read the answer
a_PostUpVote	how many points did the answer gain
q_PostDownVote	length of the answer's content

A3. Variables for Question 3 – Sentiment Analysis using NLP on Post comments

Predictors	Description
CommentLength	Number of characters in the comments
comment_owner_downvotes	Number of downvotes comment user has received in the whole life
num_tags	Number of tags in the question post
PostAnswerCount	Number of aswers on the question post
IsAcceptedAnswer	Binary, is any answer marked as Accepted by OP
PostCommentCount	Nummber of comments on the post(question/ answer)

Appendix B: SQL Queries

B1. SQL Query for Question 1 - Spam Classifier

```
select * from
(
select
distinct
P.Id PostId,
case
     when V.VoteTypeId=2 then 'Y'
     else 'N'
end as UpVoted,
case
     when V.VoteTypeId=3 then 'Y'
     else 'N'
end as DownVoted,
P.PostTypeId PostTypeId,
P.Score PostScore,
len(P.Body) post_length,
U.Reputation owner_reputation,
CASE WHEN LTRIM(RTRIM(U.WebsiteURL)) = '' OR U.WebsiteURL IS NULL THEN 0 ELSE 1
END +
CASE WHEN LTRIM(RTRIM(U.Location)) = '' OR U.Location IS NULL THEN 0 ELSE 1 END +
CASE WHEN LTRIM(RTRIM(U.AboutMe)) = '' OR U.AboutMe IS NULL THEN 0 ELSE 1 END
as owner_profile_summary,
U.Views owner_views,
U.Upvotes owner_upvotes,
U.Downvotes owner_downvotes,
U.LastAccessDate owner_lastactivity_days,
DATEDIFF(mi, P.CreationDate, P.LastEditDate) as editDurationAfterCreation,
DATEDIFF(mi, P.CreationDate, P.LastActivityDate) as activityDurationAfterCrea,
P.Title,
LEN(P.Tags)-LEN(REPLACE(P.Tags, '<', '')) as q_num_tags,
P.AnswerCount,
P.CommentCount,
CASE WHEN CHARINDEX('<code>', P.Body)>0
  THEN 1
  ELSE 0 END as has_code,
P.ViewCount post_views,
U.Id UserId,
R.Id ReviewTaskId, R.ReviewTaskTypeId ReviewTaskTypeId,
RR.RejectionReasonId RejectionReasonId, RRT.Name ReviewTaskResultTypes,
RRT.Description, RTS.Name ReviewTaskState, RTS.Description
ReviewTaskStateDescription,
PT.Name PostTypeName, PHT.Name PostHistoryTypeName, VT.Name VoteTypeName,
RRR.Id ReviewRejectionFlag, RRR.Name ReviewRejectionReason, RRR.Description
ReviewRejectionReasonDescription
from ReviewTasks R, ReviewTaskStates RTS, ReviewTaskResults RR,
ReviewRejectionReasons RRR, ReviewTaskResultTypes RRT,
Posts P, Users U, PostTypes PT, PostFeedback PF, VoteTypes VT, Votes V,
PostHistory PH, PostHistoryTypes PHT
where R.Id=RR.ReviewTaskId
and R.ReviewTaskStateId = RTS.Id
and RR.RejectionReasonId = RRR.Id
and RR.ReviewTaskResultTypeId = RRT.Id
and R.PostId=P.Id
and P.OwnerUserId=U.Id
and V.PostId=P.Id
and P.PostTypeId=PT.Id
and PF.PostId=P.Id
and PF.VoteTypeId=VT.Id
and PH.PostHistoryTypeId= PHT.Id
and P.Id=PH.PostId
and upper(RRR.Name) LIKE '%SPAM%'
and RTS.Name='Completed'
and RRT.Name in ('Reject','Delete','Recommend Deletion')
and RR.RejectionReasonId is not null
UNION
select SELECTEDNONREJECTED.*,RRR.Id ReviewRejectionFlag, RRR.Name
ReviewRejectionReason, RRR.Description ReviewRejectionReasonDescription from
(select top 45000 * from
(select
distinct
P.Id PostId,
case
     when V.VoteTypeId=12 then 1
     else 0
end as IsSpam,
case
     when V.VoteTypeId=2 then 'Y'
     else 'N'
end as UpVoted,
case
     when V.VoteTypeId=3 then 'Y'
     else 'N'
end as DownVoted,
P.PostTypeId PostTypeId,
P.Score PostScore,
len(P.Body) post_length,
U.Reputation owner_reputation,
CASE WHEN LTRIM(RTRIM(U.WebsiteURL)) = '' OR U.WebsiteURL IS NULL THEN 0 ELSE 1
END +
CASE WHEN LTRIM(RTRIM(U.Location)) = '' OR U.Location IS NULL THEN 0 ELSE 1 END +
CASE WHEN LTRIM(RTRIM(U.AboutMe)) = '' OR U.AboutMe IS NULL THEN 0 ELSE 1 END
as owner_profile_summary,
U.Views owner_views,
U.Upvotes owner_upvotes,
U.Downvotes owner_downvotes,
U.LastAccessDate owner_lastactivity_days,
DATEDIFF(mi, P.CreationDate, P.LastEditDate) as editDurationAfterCreation,
DATEDIFF(mi, P.CreationDate, P.LastActivityDate) as activityDurationAfterCrea,
P.Title,
LEN(P.Tags)-LEN(REPLACE(P.Tags, '<', '')) as q_num_tags,
P.AnswerCount,
P.CommentCount,
CASE WHEN CHARINDEX('<code>', P.Body)>0
  THEN 1
  ELSE 0 END as has_code,
P.ViewCount post_views,
U.Id UserId,
R.Id ReviewTaskId, R.ReviewTaskTypeId ReviewTaskTypeId,
RR.RejectionReasonId RejectionReasonId, RRT.Name ReviewTaskResultTypes,
RRT.Description, RTS.Name ReviewTaskState, RTS.Description
ReviewTaskStateDescription,
PT.Name PostTypeName, PHT.Name PostHistoryTypeName, VT.Name VoteTypeName
from ReviewTasks R, ReviewTaskStates RTS, ReviewTaskResults RR,
ReviewTaskResultTypes RRT,
Posts P, Users U, PostTypes PT, PostFeedback PF, Votes V, VoteTypes VT,
PostHistory PH, PostHistoryTypes PHT
where R.Id=RR.ReviewTaskId
and R.ReviewTaskStateId = RTS.Id
--and RR.RejectionReasonId = RRR.Id
and RR.ReviewTaskResultTypeId = RRT.Id
and R.PostId=P.Id
and P.OwnerUserId=U.Id
and V.PostId=P.Id
and P.PostTypeId=PT.Id
and PF.PostId=P.Id
and PF.VoteTypeId=VT.Id
and PH.PostHistoryTypeId= PHT.Id
and P.Id=PH.PostId
and RTS.Name='Completed'
and RRT.Name not in ('Reject','Delete','Recommend Deletion')
and RR.RejectionReasonId is  null
) NOTREJECTED
) SELECTEDNONREJECTED
LEFT OUTER JOIN
ReviewRejectionReasons RRR
ON SELECTEDNONREJECTED.RejectionReasonId = RRR.Id
)
DATA
order by PostId
--OFFSET 50000 ROWS
```

B2. SQL Query for Question 2 – Evaluate best answer

```
CREATE TABLE #votesUp(PostId int, VoteTypeIdCnt bigint)
INSERT INTO #votesUp SELECT PostId, Count(*) as VoteTypeIdCnt FROM Votes WHERE
VoteTypeId=2 GROUP BY PostId
```

```
CREATE TABLE #votesDown(PostId int, VoteTypeIdCnt bigint)
INSERT INTO #votesDown SELECT PostId, Count(*) as VoteTypeIdCnt FROM Votes WHERE
VoteTypeId=3 GROUP BY PostId

CREATE TABLE #votesSpam(PostId int, VoteTypeIdCnt bigint)
INSERT INTO #votesSpam SELECT PostId, Count(*) as VoteTypeIdCnt FROM Votes WHERE
VoteTypeId=12 GROUP BY PostId

select top 500
P.PostTypeId as postTypeId,
CASE WHEN P.AcceptedAnswerId IS NOT NULL
 THEN 1
 ELSE 0 END as IsAcceptedAnswer,
P.Score as postScore,
LEN(P.Body) as post_length,
P.CreationDate,
P.LastEditDate,
P.LastActivityDate,
DATEDIFF(mi, P.CreationDate, P.LastEditDate) as editDurationAfterCreation,
DATEDIFF(mi, P.CreationDate, P.LastActivityDate) as activityDurationAfterCreation,
LEN(P.Title) as title_length,
LEN(P.Tags)-LEN(REPLACE(P.Tags, '<', '')) as num_tags,
P.CommentCount as num_comment,
P.FavoriteCount as num_favorite,
CASE WHEN CHARINDEX('<code>', P.Body)>0
 THEN 1
 ELSE 0 END as has_code,
P.ViewCount as post_views,
U.Reputation as owner_reputation,
U.WebsiteURL as owner_WebsiteURL,
U.Location as owner_Location,
U.AboutMe as owner_AboutMe,
CASE WHEN LTRIM(RTRIM(U.WebsiteURL)) = '' OR U.WebsiteURL IS NULL THEN 0 ELSE 1
END +
CASE WHEN LTRIM(RTRIM(U.Location)) = '' OR U.Location IS NULL THEN 0 ELSE 1 END +
CASE WHEN LTRIM(RTRIM(U.AboutMe)) = '' OR U.AboutMe IS NULL THEN 0 ELSE 1 END as
owner_profile_summary,
U.Views as owner_views,
U.UpVotes as owner_upvotes,
U.DownVotes as owner_downvotes,
DATEDIFF(d, U.LastAccessDate, GetDate()) as owner_lastactivity_days,
VU.VoteTypeIdCnt as upVotes,
VD.VoteTypeIdCnt as downVotes,
VS.VoteTypeIdCnt as isSpam

from PostsWithDeleted as P inner join
Users as U on P.OwnerUserId=U.Id left outer join
#votesUp as VU on VU.PostId=P.Id left outer join
#votesDown as VD on VD.PostId=P.Id left outer join
#votesSpam as VS on VS.PostId=P.Id

where (P.PostTypeId=1 OR P.PostTypeId=2)
and VS.VoteTypeIdCnt>0
```

B3. SQL Query for Question 3 – Sentiment Analysis using NLP on Post comments

```
CREATE TABLE #votesUp(PostId int, VoteTypeIdCnt bigint)
INSERT INTO #votesUp SELECT PostId, Count(*) as VoteTypeIdCnt FROM Votes WHERE
VoteTypeId=2 GROUP BY PostId

CREATE TABLE #votesDown(PostId int, VoteTypeIdCnt bigint)
INSERT INTO #votesDown SELECT PostId, Count(*) as VoteTypeIdCnt FROM Votes WHERE
VoteTypeId=3 GROUP BY PostId

select
C.Id as CommentId,
C.Score as CommentScore,
C.Text as CommentText,
DATEDIFF(d, C.CreationDate, GetDate()) as CommentCrDays,
LEN(C.Text) as CommentLength,
C.CreationDate as CommentCrDt,
C.UserId as CommentUserId,
CU.Reputation as comment_owner_reputation,
CASE WHEN LTRIM(RTRIM(CU.WebsiteURL)) = '' OR CU.WebsiteURL IS NULL THEN 0 ELSE 1
END +
CASE WHEN LTRIM(RTRIM(CU.Location)) = '' OR CU.Location IS NULL THEN 0 ELSE 1 END
+
CASE WHEN LTRIM(RTRIM(CU.AboutMe)) = '' OR CU.AboutMe IS NULL THEN 0 ELSE 1 END as
comment_owner_profile_summary,
CU.Views as comment_owner_views,
CU.UpVotes as comment_owner_upvotes,
CU.DownVotes as comment_owner_downvotes,
DATEDIFF(d, CU.LastAccessDate, GetDate()) as comment_owner_lastactivity_days,
P.Id as PostId,
DATEDIFF(d, P.CreationDate, P.LastEditDate) as editDurationAfterCreation,
DATEDIFF(d, P.CreationDate, P.LastActivityDate) as activityDurationAfterCreation,
LEN(P.Title) as title_length,
LEN(P.Tags)-LEN(REPLACE(P.Tags, '<', '')) as num_tags,
P.AnswerCount as PostAnswerCount,
P.FavoriteCount as num_favorite,
CASE WHEN CHARINDEX('<code>', P.Body)>0
 THEN 1
 ELSE 0 END as hascode,
P.ViewCount as post_views,
P.PostTypeId as postTypeId,
P.Id,
P.AcceptedAnswerId,
CASE WHEN QP.AcceptedAnswerId=P.Id THEN 1 ELSE 0 END as IsAcceptedAnswer,
P.Score as postScore,
LEN(P.Body) as post_length,
P.CommentCount as PostCommentCount,
P.CreationDate as PostCrDt,
VU.VoteTypeIdCnt as PostUpVotes,
VD.VoteTypeIdCnt as PostDownVotes
from
Comments as C inner join
Posts as P on C.PostId=P.Id inner join
Users as CU on CU.Id=C.UserId inner join
Users as PU on PU.Id=P.OwnerUserId left outer join
```

```
Posts as QP on P.ParentId=QP.Id left outer join
#votesUp as VU on VU.PostId=P.Id left outer join
#votesDown as VD on VD.PostId=P.Id
where
(P.Tags like '%<python>%' or P.Tags like '%<java>%' or P.Tags like
'%<javascript>%' or P.Tags like '%<c++>%'
or QP.Tags like '%<python>%' or QP.Tags like '%<java>%' or QP.Tags like
'%<javascript>%' or QP.Tags like '%<c++>%')
and P.CreationDate > '2016-01-01 00:00:00' and P.commentCount>0 and
((P.PostTypeId=1 and P.AnswerCount>3) or (P.PostTypeId=2 and QP.AnswerCount>3))
and P.Id>35000000
```

Appendix C : R Code

C1. Classify data into spam/non-spam (*link to complete output*)

```
#reading and transforming the data
df1= read.csv(file="QueryResults1.csv",header=TRUE)
df2<- read.csv(file="QueryResults2.csv",header=TRUE)
StackOverflow<- rbind(df1,df2)
#str(StackOverflow)
#names(StackOverflow)
nrow(StackOverflow)

#replacing NA with 1001
StackOverflow [is.na(StackOverflow)] <- 1001

#removing column that contain text or are unrelated to this question
StackOverflowdata<- StackOverflow[,-c(1,
2,3,12,14,15,22,23,25,26,27,28,29,30,31,32,33,34)]
#str(StackOverflowdata)
nrow(StackOverflowdata)

#to check uniqueness of data
lapply(StackOverflowdata["RejectionReasonId"], unique)
StackOverflowdata$IsSpam= ifelse(StackOverflowdata$RejectionReasonId==101,1,0)
#str(StackOverflowdata)
#names(StackOverflowdata)
StackOverflowdata<- StackOverflowdata[,-c(16)]
lapply(StackOverflowdata["IsSpam"], unique)

#dividing data for training and testing purpose
smp_size<- floor(0.75*nrow(StackOverflowdata))
set.seed(123)
train_ind<- sample(seq_len(nrow(StackOverflowdata)), size=smp_size)
training_data<- StackOverflowdata[train_ind,]
testing_data<- StackOverflowdata[-train_ind,]
testing_y<- testing_data$IsSpam
```

```
nrow(training_data)
nrow(testing_data)
#str(training_data)
#names(training_data)

#GLM
logistics_model<-glm(IsSpam~.,data=training_data,family="binomial")
#to discover better model
#step(logistics_model, direction = "forward")

logistics_model = glm(IsSpam ~ PostTypeId + PostScore + post_length +
   owner_reputation + owner_profile_summary + owner_views +
   owner_upvotes + owner_downvotes + editDurationAfterCreation +
   q_num_tags + AnswerCount + CommentCount + has_code +post_views +
   UserId, family = "binomial", data = training_data)
summary(logistics_model)

#performing trial modelling
#step(logistics_model, direction = "backward")

#final regression model
logistics_model = glm(formula = IsSpam ~ PostTypeId + PostScore + post_length +
   owner_reputation + owner_profile_summary +
   owner_upvotes+ editDurationAfterCreation +
   q_num_tags + AnswerCount + CommentCount+ post_views, family = "binomial", data =
training_data)
summary(logistics_model)

#Bayesian information criterion
BIC(logistics_model)
logistics_probs<-predict(logistics_model,training_data,type="response")
head(logistics_probs)
logistics_pred_y=rep(0,length(testing_y))
logistics_pred_y[logistics_probs>0.55]=1
training_y=training_data$IsSpam
table(logistics_pred_y,training_y)
mean(logistics_pred_y!=training_y,na.rm=TRUE)
logistics_probs<- predict(logistics_model,testing_data, type="response")
head(logistics_probs)
logistics_pred_y=rep(0,length(testing_y))
logistics_pred_y[logistics_probs>0.55]=1
table(logistics_pred_y,testing_y)
mean(logistics_pred_y!=testing_y,na.rm=TRUE)


#kfold for regression
library(boot)
MSE_10_Fold_CV=cv.glm(training_data,logistics_model,K=10)$delta[1]
```

```
MSE_10_Fold_CV
MSE_10_Fold_CV=NULL
for(i in 1:10){
model=glm(IsSpam~poly(PostTypeId + PostScore + post_length +
   owner_reputation + owner_profile_summary +
   owner_upvotes+ editDurationAfterCreation +
   q_num_tags + AnswerCount + CommentCount+ post_views),data=training_data)
MSE_10_Fold_CV[i]=cv.glm(training_data,model,K=10)$delta[1]
}
#summary(model)
MSE_10_Fold_CV

#ROC logistic regression
#install.packagesll.packages("ROCR")
library(ROCR)
ROCRpred=prediction(logistics_probs,testing_y)
ROCRperf=performance(ROCRpred,"tpr","fpr")
#plot(ROCRperf)
#plot(ROCRperf,colorize=TRUE)
#plot(ROCRperf,colorize=TRUE,print.cutoffs.at=seq(0,1,0.05),text.adj=c(-0.2,1.7))
as.numeric(performance(ROCRpred,"auc")@y.values)

#Linear Discriminant Analysis
library(MASS)
lda.model<- lda(IsSpam~PostTypeId + PostScore + post_length +
   owner_reputation + owner_profile_summary +
   owner_upvotes+ editDurationAfterCreation +
   q_num_tags + AnswerCount + CommentCount+ post_views,data=training_data)

#lda.model
#summary(lda.model)
lda_pred<- predict(lda.model,training_data)
lda_class<- lda_pred$class
table(lda_class,training_data$IsSpam)
mean(lda_class!=training_data$IsSpam)

lda_pred<- predict(lda.model,testing_data)
lda_class<- lda_pred$class
table(lda_class,testing_data$IsSpam)
mean(lda_class!=testing_data$IsSpam)

#Cross Validation LDA
library(rpart)
library(ipred)
ip.lda <- function(object, newdata) predict(object, newdata = newdata)$class
errorest(factor(training_data$IsSpam)~ training_data$PostTypeId + training_data$PostScore
+ training_data$post_length +
   training_data$owner_reputation + training_data$owner_profile_summary +
   training_data$owner_upvotes+ training_data$editDurationAfterCreation +
   training_data$q_num_tags + training_data$AnswerCount +
training_data$CommentCount+ training_data$post_views, data=training_data, model=lda,
estimator="cv",est.para=control.errorest(k=10), predict=ip.lda)$err

#ROC LDA
S=lda_pred$posterior[,2]
roc.curve=function(s,print=FALSE){
 Ps=(S>s)*1
 FP=sum((Ps==1)*(testing_data$IsSpam==0))/sum(testing_data$IsSpam==0)
TP=sum((Ps==1)*(testing_data$IsSpam==1))/sum(testing_data$IsSpam==1)
 if(print==TRUE){
    print(table(Observed=testing_data$IsSpam,Predicted=Ps))
  }
 vect=c(FP,TP)
 names(vect)=c("FPR","TPR")
 return(vect)
}
threshold=0.53
roc.curve(threshold,print=TRUE)
ROC.curve=Vectorize(roc.curve)
M.ROC=ROC.curve(seq(0,1,by=.01))
plot(M.ROC[1,],M.ROC[2,],col="blue",lwd=2,type="l",main="ROC for LDA")
abline(0,1)

#Quadratic Discriminant Analysis
qda.model<- qda(IsSpam~PostTypeId + PostScore + post_length +
   owner_reputation + owner_profile_summary +
   owner_upvotes+ editDurationAfterCreation +
   q_num_tags + AnswerCount + CommentCount+ post_views,data=training_data)
#qda.model
qda_pred=predict(qda.model,training_data)
qda_class=qda_pred$class
table(qda_class,training_data$IsSpam)
mean(qda_class!=training_data$IsSpam)
qda_pred1=predict(qda.model,testing_data)
qda_class_n=qda_pred1$class
table(qda_class_n,testing_data$IsSpam)
mean(qda_class_n!=testing_data$IsSpam)

#Cross Validation QDA
ip.qda <- function(object, newdata) predict(object, newdata = newdata)$class
errorest(factor(training_data$IsSpam)~ training_data$PostTypeId + training_data$PostScore
+ training_data$post_length +
   training_data$owner_reputation + training_data$owner_profile_summary +
   training_data$owner_upvotes+ training_data$editDurationAfterCreation +
    training_data$q_num_tags + training_data$AnswerCount +
training_data$CommentCount+ training_data$post_views, data=training_data, model=qda,
estimator="cv",est.para=control.errorest(k=10), predict=ip.qda)$err

#ROC QDA
qda.S=qda_pred1$posterior[,2]
roc.curve=function(s,print=FALSE){
 Ps=(qda.S>s)*1
 FP=sum((Ps==1)*(testing_data$IsSpam==0))/sum(testing_data$IsSpam==0)
 TP=sum((Ps==1)*(testing_data$IsSpam==1))/sum(testing_data$IsSpam==1)
 if(print==TRUE){
    print(table(Observed=testing_data$IsSpam,Predicted=Ps))
    }
 vect=c(FP,TP)
 names(vect)=c("FPR","TPR")
 return(vect)
 }
threshold=0.85
roc.curve(threshold,print=TRUE)
ROC.curve=Vectorize(roc.curve)
M.ROC=ROC.curve(seq(0,1,by=.01))
plot(M.ROC[1,],M.ROC[2,],col="blue",lwd=2,type="l",main="ROC for LDA")
abline(0,1)

#k nearest neighbours
library(class)
#install.packagesll.packages("cars")
#library(cars)
train.x<- cbind(training_data$PostTypeId + training_data$PostScore +
training_data$post_length + training_data$owner_reputation +
training_data$owner_profile_summary + training_data$owner_upvotes +
training_data$editDurationAfterCreation + training_data$q_num_tags +
training_data$AnswerCount + training_data$CommentCount + training_data$post_views)

test.x<- cbind(testing_data$PostTypeId + testing_data$PostScore +
testing_data$post_length + testing_data$owner_reputation +
testing_data$owner_profile_summary + testing_data$owner_upvotes +
testing_data$editDurationAfterCreation + testing_data$q_num_tags +
testing_data$AnswerCount + testing_data$CommentCount + testing_data$post_views)

train1.x=train.x[!duplicated(train.x),drop=FALSE]
test1.x=test.x[!duplicated(test.x), drop=FALSE]
tt<- training_data$IsSpam[duplicated(train.x)=='FALSE']
head(tt)
length(tt)

knn.pred<- knn(data.frame(train1.x),data.frame(test1.x),tt,k=1)
tt1<- testing_data$IsSpam[duplicated(test.x)=='FALSE']
```

```
length(tt1)
table(knn.pred,tt1)
mean(knn.pred!=tt1)

knn.pred<- knn(data.frame(train1.x),data.frame(test1.x),tt,k=2)
table(knn.pred,tt1)
mean(knn.pred!=tt1)



#Classification and Regression Trees
#CART Modeling:
 #install.packagesll.packages("tree")
library(tree)
tree.training_data=tree(as.factor(IsSpam)~PostTypeId + PostScore + post_length +
   owner_reputation + owner_profile_summary +
   owner_upvotes+ editDurationAfterCreation +
   q_num_tags + AnswerCount + CommentCount+ post_views,training_data)
text(tree.training_data,pretty=0)
summary(tree.training_data)
plot(tree.training_data)
text(tree.training_data,pretty=0)
lf<- seq(1,nrow(training_data))
tree.training_data=tree(as.factor(IsSpam)~PostTypeId + PostScore + post_length +
   owner_reputation + owner_profile_summary +
   owner_upvotes+ editDurationAfterCreation +
   q_num_tags + AnswerCount + CommentCount+ post_views,training_data,subset=lf)
tree.pred=predict(tree.training_data,testing_data,type="class")
table(tree.pred,testing_y)
mean(tree.pred!=testing_data$IsSpam)


#Cross Validation and Pruning for the Classification Tree:
cv.training_data=cv.tree(tree.training_data,FUN=prune.misclass)
names(cv.training_data)
#cv.training_data
par(mfrow=c(1,2))
plot(cv.training_data$size,cv.training_data$dev,type="b")
plot(cv.training_data$k,cv.training_data$dev,type="b")

par(mfrow=c(1,1))
prune.training_data=prune.misclass(tree.training_data,best=5)
plot(prune.training_data)
text(prune.training_data,pretty=0)
tree.pred=predict(prune.training_data,testing_data,type="class")
table(tree.pred,testing_y)
mean(tree.pred!=testing_data$IsSpam)
```

```
#ROC for CART:
 tree.pred=predict(tree.training_data,testing_data,type="vector",prob=TRUE)
#tree.pred
tree.S=tree.pred[,2]
roc.curve=function(s,print=FALSE){
Ps=(tree.S>s)*1
FP=sum((Ps==1)*(testing_data$IsSpam==0))/sum(testing_data$IsSpam==0)
TP=sum((Ps==1)*(testing_data$IsSpam==1))/sum(testing_data$IsSpam==1)
if(print==TRUE){
 print(table(Observed=testing_data$IsSpam,Predicted=Ps))
}
vect=c(FP,TP)
names(vect)=c("FPR","TPR")
return(vect)
}
 threshold=0.55
 roc.curve(threshold,print=TRUE)
 ROC.curve=Vectorize(roc.curve)
 M.ROC=ROC.curve(seq(0,1,by=.01))
 plot(M.ROC[1,],M.ROC[2,],col="blue",lwd=2,type="l",main="ROC for CART")
 abline(0,1)

#Random Forest Modeling:
#install.packagesll.packages("randomForest")
library(randomForest)


bag.training_data=randomForest(as.factor(IsSpam)~PostTypeId + PostScore + post_length
+
    owner_reputation + owner_profile_summary +
    owner_upvotes+ editDurationAfterCreation +
    q_num_tags + AnswerCount + CommentCount+
post_views,data=training_data,subset=lf,importance=TRUE)



#bag.training_data
xyz = predict(bag.training_data, newdata = testing_data)
table(testing_y, xyz)
mean(xyz!=testing_y)

 #C5.0
 #install.packagesll.packages("C50")
 library(C50)
c50_model <- C5.0(training_data[-16], as.factor(training_data$IsSpam))
c50_model
#summary(c50_model)
```

```
#testing C50
c50_pred <- predict(c50_model, testing_data)
#install.packagesll.packages("gmodels")
library(gmodels)
CrossTable(testing_data$IsSpam, c50_pred,
          prop.chisq = FALSE, prop.c = FALSE, prop.r = FALSE,
          dnn = c('actual default', 'predicted default'))

#improving C50 with adaptive boosting
c50_boost10 <- C5.0(training_data[-16], as.factor(training_data$IsSpam),
                    trials = 10)
c50_boost10

c50_pred10 <- predict(c50_boost10, testing_data)
CrossTable(testing_data$IsSpam, c50_pred10,
          prop.chisq = FALSE, prop.c = FALSE, prop.r = FALSE,
          dnn = c('actual default', 'predicted default'))

#Dimensional Reduction
#install.packages("ISLR")
library(ISLR)
#fix(StackOverflowdata)
#names(StackOverflowdata)
dim(StackOverflowdata)
sum(is.na(StackOverflowdata$IsSpam))
StackOverflowdata=na.omit(StackOverflowdata)
dim(StackOverflowdata)
sum(is.na(StackOverflowdata))

#install.packages("pls")
library(pls)
set.seed(2)
pcr.fit=pcr(IsSpam~., data=StackOverflowdata,scale=TRUE,validation="CV")
summary(pcr.fit)
validationplot(pcr.fit,val.type="MSEP")
set.seed(1)
pcr.fit=pcr(IsSpam~., data=training_data,scale=TRUE, validation="CV")
validationplot(pcr.fit,val.type="MSEP")
pcr.pred=predict(pcr.fit,testing_data,ncomp=7)
mean((pcr.pred-testing_y)^2)
pcr.fit=pcr(IsSpam~.,data=testing_data, scale=TRUE,ncomp=7)
mean((pcr.pred-testing_y)^2)
summary(pcr.fit)

# Partial Least Squares
set.seed(1)
pls.fit=plsr(IsSpam~., data=StackOverflowdata,scale=TRUE, validation="CV")
```

```
summary(pls.fit)
validationplot(pls.fit,val.type="MSEP")
pls.pred=predict(pls.fit,testing_data,ncomp=2)
mean((pls.pred-testing_y)^2)
pls.fit=plsr(IsSpam~., data=StackOverflowdata,scale=TRUE,ncomp=2)
summary(pls.fit)

# Subset Selection Methods
# Best Subset Selection
#install.packages("ISLR")
library(ISLR)
#sum(is.na(StackOverflow$IsSpam))
lapply(StackOverflowdata["IsSpam"], unique)
#Confirms NO NA data
#install.packages("leaps")
library(leaps)
regfit.full=regsubsets(IsSpam~.,StackOverflowdata)
summary(regfit.full)

regfit.full=regsubsets(IsSpam~.,data=StackOverflowdata,nvmax=19)
reg.summary=summary(regfit.full)
names(reg.summary)

reg.summary$rsq

par(mfrow=c(2,2))
plot(reg.summary$rss,xlab="Number of Variables",ylab="RSS",type="l")
plot(reg.summary$adjr2,xlab="Number of Variables",ylab="Adjusted
RSq",type="l")
which.max(reg.summary$adjr2)
points(11,reg.summary$adjr2[11], col="red",cex=2,pch=20)
plot(reg.summary$cp,xlab="Number of Variables",ylab="Cp",type='l')
which.min(reg.summary$cp)
points(10,reg.summary$cp[10],col="red",cex=2,pch=20)
which.min(reg.summary$bic)
plot(reg.summary$bic,xlab="Number of Variables",ylab="BIC",type='l')
points(6,reg.summary$bic[6],col="red",cex=2,pch=20)
coef(regfit.full,6)

# Forward and Backward Stepwise Selection
regfit.fwd=regsubsets(IsSpam~.,data=StackOverflowdata,nvmax=19,method="forward")
summary(regfit.fwd)
regfit.bwd=regsubsets(IsSpam~.,data=StackOverflowdata,nvmax=19,method="backward"
)
summary(regfit.bwd)
coef(regfit.full,7)
coef(regfit.fwd,7)
coef(regfit.bwd,7)
```

```
# Choosing Among Models
set.seed(1)
train=sample(c(TRUE,FALSE), nrow(StackOverflowdata),rep=TRUE)
test=(!train)
regfit.best=regsubsets(IsSpam~.,data=StackOverflowdata[train,],nvmax=19)
test.mat=model.matrix(IsSpam~.,data=StackOverflowdata[test,])
val.errors=rep(NA,19)
for(i in 1:11){
   coefi=coef(regfit.best,id=i)
   pred=test.mat[,names(coefi)]%*%coefi
   val.errors[i]=mean((StackOverflowdata$IsSpam[test]-pred)^2)
}
val.errors
which.min(val.errors)
coef(regfit.best,10)
predict.regsubsets=function(object,newdata,id,...){
  form=as.formula(object$call[[2]])
  mat=model.matrix(form,newdata)
  coefi=coef(object,id=id)
  xvars=names(coefi)
  mat[,xvars]%*%coefi
  }
regfit.best=regsubsets(IsSpam~.,data=StackOverflowdata,nvmax=19)
coef(regfit.best,10)
k=10
set.seed(1)
folds=sample(1:k,nrow(StackOverflowdata),replace=TRUE)
cv.errors=matrix(NA,k,11, dimnames=list(NULL, paste(1:11)))
for(j in 1:k){
  best.fit=regsubsets(IsSpam~.,data=StackOverflowdata[folds!=j,],nvmax=11)
  for(i in 1:11){
    pred=predict(best.fit,StackOverflowdata[folds==j,],id=i)
    cv.errors[j,i]=mean( (StackOverflowdata$IsSpam[folds==j]-pred)^2)
    }
  }
mean.cv.errors=apply(cv.errors,2,mean)
mean.cv.errors
par(mfrow=c(1,1))
plot(mean.cv.errors,type='b')
reg.best=regsubsets(IsSpam~.,data=StackOverflowdata, nvmax=11)
coef(reg.best,11)

# Ridge Regression and LASSO
#install.packages("ISLR")
library(ISLR)
fix(Hitters)
names(Hitters)
```

```
dim(Hitters)
sum(is.na(Hitters$Salary))
Hitters=na.omit(Hitters)
dim(Hitters)
sum(is.na(Hitters))

#install.packages("glmnet")
library(glmnet)

#the package invokes inputs and outputs separately unlike lm and glm
x=model.matrix(Salary~.,Hitters)[,-1]
y=Hitters$Salary

# set vector of lambda values to study range from 10^10 to 0.01, total length=100
grid=10^seq(10,-2,length=100)
ridge.mod=glmnet(x,y,alpha=0,lambda=grid)
dim(coef(ridge.mod))

# let us look at a few results here

#first lambda=50

ridge.mod$lambda[50]
coef(ridge.mod)[,50]
sqrt(sum(coef(ridge.mod)[-1,50]^2))

#next, lambda=60

ridge.mod$lambda[60]
coef(ridge.mod)[,60]
sqrt(sum(coef(ridge.mod)[-1,60]^2))

#prediction of the coefficients for lambda=50 (play with this)
predict(ridge.mod,s=500,type="coefficients")[1:20,]

#prepare for training and validation set testing

set.seed(1)
train=sample(1:nrow(x), nrow(x)/2)
test=(-train)
y.test=y[test]

ridge.mod=glmnet(x[train,],y[train],alpha=0,lambda=grid, thresh=1e-12)
ridge.pred=predict(ridge.mod,s=4,newx=x[test,])

#evaluate and compare test MSE and the spread of y.test
mean((ridge.pred-y.test)^2)
mean((mean(y[train])-y.test)^2)
```

```
#test wth two other lambdas
ridge.pred=predict(ridge.mod,s=1e10,newx=x[test,])
mean((ridge.pred-y.test)^2)
ridge.pred=predict(ridge.mod,s=0,newx=x[test,],exact=T)
mean((ridge.pred-y.test)^2)


# compare with lm
# The following two are the same
lm(y~x, subset=train)
predict(ridge.mod,s=0,exact=T,type="coefficients")[1:20,]

#Cross validation to get the best lambda
set.seed(1)
cv.out=cv.glmnet(x[train,],y[train],alpha=0)
plot(cv.out)
bestlam=cv.out$lambda.min
bestlam

#now predict with the best lambda
ridge.pred=predict(ridge.mod,s=bestlam,newx=x[test,])
mean((ridge.pred-y.test)^2)
out=glmnet(x,y,alpha=0)
predict(out,type="coefficients",s=bestlam)[1:20,]

# Lasso
#only difference in model building is to use aloha=1
lasso.mod=glmnet(x[train,],y[train],alpha=1,lambda=grid)
plot(lasso.mod)

# use CV to get best lambda
set.seed(1)
cv.out=cv.glmnet(x[train,],y[train],alpha=1)
plot(cv.out)
bestlam=cv.out$lambda.min

#use best lambda for prediction
lasso.pred=predict(lasso.mod,s=bestlam,newx=x[test,])
mean((lasso.pred-y.test)^2)
out=glmnet(x,y,alpha=1,lambda=grid)
lasso.coef=predict(out,type="coefficients",s=bestlam)[1:20,]
lasso.coef
lasso.coef[lasso.coef!=0]
```

```
# Support Vector Classifier
set.seed(1)
install.packages("e1071")
```

```
librarIsSpam(e1071)
svmfit=svm(IsSpam~., data=training_data, kernel="linear", cost=10,scale=FALSE)
plot(svmfit, training_data)

#which ones are support vectors
svmfit$index
summary(svmfit)

svmfit=svm(IsSpam~., data=training_data, kernel="linear", cost=0.1,scale=FALSE)
plot(svmfit, training_data)
svmfit$index

#cross validation
set.seed(1)
tune.out=tune(svm,IsSpam~.,data=training_data,kernel="linear",ranges=list(cost=c(0.001,
0.01, 0.1, 1,5,10,100)))
summary(tune.out)
bestmod=tune.out$best.model
summary(bestmod)


ypred=predict(bestmod,testing_data)
table(predict=ypred, truth=testing_y)

svmfit=svm(IsSpam~., data=training_data, kernel="linear", cost=.01,scale=FALSE)
ypred=predict(svmfit,testing_data)
table(predict=ypred, truth=testing_y)


plot(x, col=(y+5)/2, pch=19)
dat=data.frame(x=x,y=as.factor(IsSpam))
svmfit=svm(IsSpam~., data=dat, kernel="linear", cost=1e5)
summarIsSpam(svmfit)
plot(svmfit, dat)

svmfit=svm(IsSpam~., data=dat, kernel="linear", cost=1)
summarIsSpam(svmfit)
plot(svmfit,dat)

set.seed(1)
svmfit=svm(IsSpam~., data=training_data, kernel="radial",  gamma=1, cost=1)
plot(svmfit, training_data)
summary(svmfit)
svmfit=svm(IsSpam~., data=training_data, kernel="radial",gamma=1,cost=1e5)
plot(svmfit,training_data)
set.seed(1)
tune.out=tune(svm, IsSpam~., data=training_data, kernel="radial",
ranges=list(cost=c(0.1,1,10,100,1000),gamma=c(0.5,1,2,3,4)))
```

```
summary(tune.out)
table(true=testing_data, pred=predict(tune.out$best.model,newx=testing_data))

#ROC
install.packages("ROCR")
library(ROCR)
rocplot=function(pred, truth, ...){
  predob = prediction(pred, truth)
  perf = performance(predob, "tpr", "fpr")
  plot(perf,...)}
svmfit.opt=svm(IsSpam~., data=training_data, kernel="radial",gamma=2,
cost=1,decision.values=T)
fitted=attributes(predict(svmfit.opt,training_data,decision.values=TRUE))$decision.values
par(mfrow=c(1,2))
rocplot(fitted,training_data,main="Training Data")
svmfit.flex=svm(IsSpam~., data=training_data, kernel="radial",gamma=50, cost=1,
decision.values=T)
fitted=attributes(predict(svmfit.flex,training_data,decision.values=T))$decision.values
rocplot(fitted,training_data,add=T,col="red")
fitted=attributes(predict(svmfit.opt,testing_y,decision.values=T))$decision.values
rocplot(fitted,testing_y,main="Test Data")
fitted=attributes(predict(svmfit.flex,testing_data,decision.values=T))$decision.values
rocplot(fitted,testing_y,add=T,col="red")
```

C2. Evaluate best possible answer – (*link to complete output*)

```
getwd()
setwd("C:/Users/Alok Satpathy/Desktop/Fall 2016/EDA/Final Project")

Q2csv=read.csv("Question2Dataset.csv")
attach(Q2csv)

#Selecting columns that would be used for preparing model
Q2df=data.frame(a_score, a_body_length, a_body_has_code, a_DaysOld, a_has_edited,
a_num_comment, a_owner_reputation, a_owner_profile_summary, a_owner_views,
a_owner_upvotes, a_owner_downvotes, q_score, q_num_views, q_body_length,
q_body_has_code, q_DaysOld, q_has_edited, q_title_length, q_num_tags, q_num_answers,
q_num_comment, q_owner_reputation, q_owner_profile_summary, q_owner_views,
q_owner_upvotes, q_owner_downvotes, accepted_answer_flag, a_votes_up,
a_votes_down, q_votes_up, q_votes_down)

str(Q2df)

#Replacing NA with 0
Q2df[is.na(Q2df)]=0
str(Q2df)
```

```
# Subset Selection Methods
# Best Subset Selection
lapply(Q2df["accepted_answer_flag"], unique)

#install.packages("leaps")
library(leaps)
regfit.full=regsubsets(accepted_answer_flag~.,Q2df)
summary(regfit.full)

regfit.full=regsubsets(accepted_answer_flag~.,data=Q2df,nvmax=32)
reg.summary=summary(regfit.full)
names(reg.summary)

reg.summary$rsq
par(mfrow=c(2,2))
plot(reg.summary$rss,xlab="Number of Variables",ylab="RSS",type="l")
plot(reg.summary$adjr2,xlab="Number of Variables",ylab="Adjusted
RSq",type="l")
which.max(reg.summary$adjr2)
points(11,reg.summary$adjr2[11], col="red",cex=2,pch=20)
plot(reg.summary$cp,xlab="Number of Variables",ylab="Cp",type='l')
which.min(reg.summary$cp)
points(10,reg.summary$cp[10],col="red",cex=2,pch=20)
which.min(reg.summary$bic)
plot(reg.summary$bic,xlab="Number of Variables",ylab="BIC",type='l')
points(6,reg.summary$bic[6],col="red",cex=2,pch=20)
coef(regfit.full,6)

# Forward and Backward Stepwise Selection
regfit.fwd=regsubsets(accepted_answer_flag~.,data=Q2df,nvmax=32,method="forward")
summary(regfit.fwd)
regfit.bwd=regsubsets(accepted_answer_flag~.,data=Q2df,nvmax=32,method="backward"
)
summary(regfit.bwd)
coef(regfit.full,7)
coef(regfit.fwd,7)
coef(regfit.bwd,7)

# Choosing Among Models
set.seed(1)
train=sample(c(TRUE,FALSE), nrow(Q2df),rep=TRUE)
test=(!train)
regfit.best=regsubsets(accepted_answer_flag~.,data=Q2df[train,],nvmax=32)
test.mat=model.matrix(accepted_answer_flag~.,data=Q2df[test,])
val.errors=rep(NA,31)
for(i in 1:11){
  coefi=coef(regfit.best,id=i)
  pred=test.mat[,names(coefi)]%*%coefi
```

```
   val.errors[i]=mean((Q2df$accepted_answer_flag[test]-pred)^2)
}
val.errors
which.min(val.errors)
coef(regfit.best,30)
predict.regsubsets=function(object,newdata,id,...){
  form=as.formula(object$call[[2]])
  mat=model.matrix(form,newdata)
  coefi=coef(object,id=id)
  xvars=names(coefi)
  mat[,xvars]%*%coefi
  }
regfit.best=regsubsets(accepted_answer_flag~.,data=Q2df,nvmax=32)
coef(regfit.best,30)
k=30
set.seed(1)
folds=sample(1:k,nrow(Q2df),replace=TRUE)
cv.errors=matrix(NA,k,31, dimnames=list(NULL, paste(1:31)))
for(j in 1:k){
  best.fit=regsubsets(accepted_answer_flag~.,data=Q2df[folds!=j,],nvmax=30)
  for(i in 1:30){
    pred=predict(best.fit,Q2df[folds==j,],id=i)
    cv.errors[j,i]=mean( (Q2df$accepted_answer_flag[folds==j]-pred)^2)
    }
  }
mean.cv.errors=apply(cv.errors,2,mean)
mean.cv.errors
par(mfrow=c(1,1))
plot(mean.cv.errors,type='b')
reg.best=regsubsets(accepted_answer_flag~.,data=Q2df, nvmax=30)
coef(reg.best,3)

# Ridge Regression and LASSO
fix(Q2df)
names(Q2df)
dim(Q2df)
sum(is.na(Q2df$accepted_answer_flag))
Q2df=na.omit(Q2df)
dim(Q2df)
sum(is.na(Q2df))

install.packages("glmnet")
library(glmnet)

#The package invokes inputs and outputs separately unlike lm and glm
x=model.matrix(accepted_answer_flag~.,Q2df)[,-1]
y=Q2df$accepted_answer_flag
```

```
#Set vector of lambda values to study range from 10^10 to 0.01, total length=100
grid=10^seq(10,-2,length=100)
ridge.mod=glmnet(x,y,alpha=0,lambda=grid)
dim(coef(ridge.mod))

#Let us look at a few results here
#first lambda=50
ridge.mod$lambda[50]
coef(ridge.mod)[,50]
sqrt(sum(coef(ridge.mod)[-1,50]^2))

#next, lambda=60
ridge.mod$lambda[60]
coef(ridge.mod)[,60]
sqrt(sum(coef(ridge.mod)[-1,60]^2))

#prediction of the coefficients for lambda=50
predict(ridge.mod,s=500,type="coefficients")[1:31,]

#prepare for training and validation set testing
set.seed(1)
train=sample(1:nrow(x), nrow(x)/2)
test=(-train)
y.test=y[test]

ridge.mod=glmnet(x[train,],y[train],alpha=0,lambda=grid, thresh=1e-12)
ridge.pred=predict(ridge.mod,s=4,newx=x[test,])

#evaluate and compare test MSE and the spread of y.test
mean((ridge.pred-y.test)^2)
mean((mean(y[train])-y.test)^2)

#test wth two other lambdas
ridge.pred=predict(ridge.mod,s=1e10,newx=x[test,])
mean((ridge.pred-y.test)^2)
ridge.pred=predict(ridge.mod,s=0,newx=x[test,],exact=T)
mean((ridge.pred-y.test)^2)

#compare with lm
# The following two are the same
lm(y~x, subset=train)
predict(ridge.mod,s=0,exact=T,type="coefficients")[1:31,]

#Cross validation to get the best lambda
set.seed(1)
cv.out=cv.glmnet(x[train,],y[train],alpha=0)
plot(cv.out)
bestlam=cv.out$lambda.min
```

```
bestlam

#now predict with the best lambda
ridge.pred=predict(ridge.mod,s=bestlam,newx=x[test,])
mean((ridge.pred-y.test)^2)
out=glmnet(x,y,alpha=0)
predict(out,type="coefficients",s=bestlam)[1:31,]

# Lasso
#only difference in model building is to use alpha=1
lasso.mod=glmnet(x[train,],y[train],alpha=1,lambda=grid)
plot(lasso.mod)

# use CV to get best lambda
set.seed(1)
cv.out=cv.glmnet(x[train,],y[train],alpha=1)
plot(cv.out)
bestlam=cv.out$lambda.min

#use best lambda for prediction
lasso.pred=predict(lasso.mod,s=bestlam,newx=x[test,])
mean((lasso.pred-y.test)^2)
out=glmnet(x,y,alpha=1,lambda=grid)
lasso.coef=predict(out,type="coefficients",s=bestlam)[1:31,]
lasso.coef
lasso.coef[lasso.coef!=0]

#Dimensionality Reduction PCA:
install.packages("pls")
library(pls)
set.seed(2)
pcr.fit=pcr(accepted_answer_flag~., data=Q2df,scale=TRUE,validation="CV")
summary(pcr.fit)
validationplot(pcr.fit,val.type="MSEP")
set.seed(1)
pcr.fit=pcr(accepted_answer_flag~., data=Q2df,subset=train,scale=TRUE, validation="CV")
validationplot(pcr.fit,val.type="MSEP")
pcr.pred=predict(pcr.fit,x[test,],ncomp=7)
mean((pcr.pred-y.test)^2)
pcr.fit=pcr(y~x,scale=TRUE,ncomp=7)
summary(pcr.fit)

# Partial Least Squares
set.seed(1)
pls.fit=plsr(accepted_answer_flag~., data=Q2df,subset=train,scale=TRUE, validation="CV")
summary(pls.fit)
validationplot(pls.fit,val.type="MSEP")
pls.pred=predict(pls.fit,x[test,],ncomp=2)
```

```
mean((pls.pred-y.test)^2)
pls.fit=plsr(accepted_answer_flag~., data=Q2df,scale=TRUE,ncomp=2)
summary(pls.fit)

#Dividing dataset 75% for training and 25% for testing
Q2smp_size=floor(0.75*nrow(Q2df))
set.seed(123)
Q2train_ind=sample(seq_len(nrow(Q2df)), size = Q2smp_size)
Q2Train=Q2df[Q2train_ind, ]
Q2Test=Q2df[-Q2train_ind, ]

#Initial logistic regression model with all parameters
Q2lm=glm(accepted_answer_flag~.,data=Q2Train,family="binomial")
summary(Q2lm)

#Checking for significant parameters with forward step
Q2modelstepforward=step(Q2lm, direction="forward")
summary(Q2modelstepforward)

#Checking for significant parameters with backward step
Q2modelstepbackward=step(Q2lm, direction="backward")
summary(Q2modelstepbackward)

#Removing insignificant parameters and remodelling
Q2lm2=glm(accepted_answer_flag~a_body_length+a_body_has_code+a_DaysOld+a_has_
edited+a_num_comment+a_owner_reputation+a_owner_profile_summary+a_owner_downv
otes+q_num_views+q_DaysOld+q_title_length+q_num_answers+q_num_comment+q_owne
r_profile_summary+q_owner_downvotes,data=Q2Train,family="binomial")
summary(Q2lm2)

#Again removing insignificant parameters and remodelling
Q2lm3=glm(accepted_answer_flag~a_body_length+a_body_has_code+a_DaysOld+a_has_
edited+a_num_comment+a_owner_reputation+a_owner_profile_summary+a_owner_downv
otes+q_DaysOld+q_title_length+q_num_answers+q_num_comment+q_owner_profile_sum
mary,data=Q2Train,family="binomial")
summary(Q2lm3)

BIC(Q2lm3)

#Predicting based on the logistic model built
logistic_probs=predict(Q2lm3, Q2Train, type="response")
head(logistic_probs)

testing_y=Q2Test$accepted_answer_flag
logistic_pred_y=rep(0,length(testing_y))
logistic_pred_y[logistic_probs>0.5]=1

training_y=Q2Train$accepted_answer_flag
```

```
table(logistic_pred_y,training_y)

mean(logistic_pred_y!=training_y,na.rm=TRUE)

logistic_probs=predict(Q2lm3, Q2Test, type="response")
head(logistic_probs)

logistic_pred_y=rep(0,length(testing_y))
logistic_pred_y[logistic_probs>0.5]=1
table(logistic_pred_y,testing_y)
mean(logistic_pred_y!=testing_y,na.rm=TRUE)

#Cross Validation for logistic regression
#K-fold
library(boot)
MSE_10_Fold_CV=cv.glm(Q2Train,Q2lm3,K=10)$delta[1]
MSE_10_Fold_CV

MSE_10_Fold_CV=NULL
for(i in 1:10){

model=glm(accepted_answer_flag~a_body_length+a_body_has_code+a_DaysOld+a_has_
edited+a_num_comment+a_owner_reputation+a_owner_profile_summary+a_owner_downv
otes+q_DaysOld+q_title_length+q_num_answers+q_num_comment+q_owner_profile_sum
mary,data=Q2Train)
  MSE_10_Fold_CV[i]=cv.glm(Q2Train,model,K=10)$delta[1]
  }
MSE_10_Fold_CV


#ROC of Logistic Regression
#install.packages("ROCR")
library(ROCR)
ROCRpred<- prediction(logistic_probs,testing_y)
ROCRperf<- performance(ROCRpred,"tpr","fpr")
plot(ROCRperf)
plot(ROCRperf,colorize=TRUE)
plot(ROCRperf, colorize = TRUE, print.cutoffs.at = seq(0,1,0.05), text.adj = c(-0.2,1.7))

as.numeric(performance(ROCRpred,"auc")@y.values)

#install.packages("lda")
library(lda)
library(MASS)

lda.model =
lda(accepted_answer_flag~a_body_length+a_body_has_code+a_DaysOld+a_has_edited+a
_num_comment+a_owner_reputation+a_owner_profile_summary+a_owner_downvotes+q_
```

```
DaysOld+q_title_length+q_num_answers+q_num_comment+q_owner_profile_summary,
data=Q2Train, family = binomial)
lda.model

#predicting the LDA model with training data
lda_pred=predict(lda.model,Q2Train)
lda_class=lda_pred$class

#CONFUSION MATRIX with LDA Training data
table(lda_class,Q2Train$accepted_answer_flag)

#Misclassification Rate with LDA training data
mean(lda_class!=Q2Train$accepted_answer_flag)

#predicting the LDA model with test data
lda_prediction=predict(lda.model,Q2Test)
lda_class_n=lda_prediction$class

#CONFUSION MATRIX with LDA Testing data
table(lda_class_n,Q2Test$accepted_answer_flag)

#Misclassification Rate with LDA testing data
mean(lda_class_n!=Q2Test$accepted_answer_flag)

#CROSS VALIDATION of LDA Model
library(rpart)
library(ipred)
ip.lda <- function(object, newdata) predict(object, newdata = newdata)$class
errorest(factor(Q2Train$accepted_answer_flag)~
Q2Train$a_body_length+Q2Train$a_body_has_code+Q2Train$a_DaysOld+Q2Train$a_has
_edited+Q2Train$a_num_comment+Q2Train$a_owner_reputation+Q2Train$a_owner_profil
e_summary+Q2Train$a_owner_downvotes+Q2Train$q_DaysOld+Q2Train$q_title_length+Q
2Train$q_num_answers+Q2Train$q_num_comment+Q2Train$q_owner_profile_summary,
data=Q2Train, model=lda, estimator="cv",est.para=control.errorest(k=10), predict=ip.lda)$err

#ROC for LDA
S = lda_prediction$posterior[,2]
roc.curve=function(s,print=FALSE){
Ps=(S>s)*1
FP=sum((Ps==1)*(Q2Test$accepted_answer_flag ==
0))/sum(Q2Test$accepted_answer_flag == 0)
TP=sum((Ps==1)*(Q2Test$accepted_answer_flag ==
1))/sum(Q2Test$accepted_answer_flag == 1)
if(print==TRUE){
print(table(Observed=Q2Test$accepted_answer_flag,Predicted=Ps))
}
vect=c(FP,TP)
names(vect)=c("FPR","TPR")
```

```
return(vect)
}
threshold = 0.5
roc.curve(threshold,print=TRUE)

ROC.curve=Vectorize(roc.curve)
M.ROC=ROC.curve(seq(0,1,by=.01))
plot(M.ROC[1,],M.ROC[2,],col="blue",lwd=2,type="l", main = "ROC for LDA")
abline(0,1)

qda_model =
qda(accepted_answer_flag~a_body_length+a_body_has_code+a_DaysOld+a_has_edited+
a_num_comment+a_owner_reputation+a_owner_profile_summary+a_owner_downvotes+q_
DaysOld+q_title_length+q_num_answers+q_num_comment+q_owner_profile_summary,
data=Q2Train, family=binomial)
qda_model

#predicting the model with training data
qda_pred=predict(qda_model, Q2Train)
qda_class=qda_pred$class

#CONFUSION MATRIX for QDA training data
table(qda_class,Q2Train$accepted_answer_flag)

#Misclassification Rate for QDA training data
mean(qda_class!=Q2Train$accepted_answer_flag)

#predicting the model with test data for QDA
qda_pred1=predict(qda_model,Q2Test)
qda_class_n=qda_pred1$class

#CONFUSION MATRIX for QDA test data
table(qda_class_n,Q2Test$accepted_answer_flag)

#Misclassification Rate for QDA test data
mean(qda_class_n!=Q2Test$accepted_answer_flag)

#CROSS VALIDATION for QDA
ip.qda <- function(object, newdata) predict(object, newdata = newdata)$class
errorest(factor(Q2Train$accepted_answer_flag)~
Q2Train$a_body_length+Q2Train$a_body_has_code+Q2Train$a_DaysOld+Q2Train$a_has
_edited+Q2Train$a_num_comment+Q2Train$a_owner_reputation+Q2Train$a_owner_profil
e_summary+Q2Train$a_owner_downvotes+Q2Train$q_DaysOld+Q2Train$q_title_length+Q
2Train$q_num_answers+Q2Train$q_num_comment+Q2Train$q_owner_profile_summary,
data=Q2Train, model=qda, estimator="cv",est.para=control.errorest(k=10),
predict=ip.qda)$err

#ROC for QDA
```

```
qda.S = qda_pred1$posterior[,2]
roc.curve=function(s,print=FALSE){
  Ps=(qda.S>s)*1
  FP=sum((Ps==1)*(Q2Test$accepted_answer_flag ==
0))/sum(Q2Test$accepted_answer_flag == 0)
  TP=sum((Ps==1)*(Q2Test$accepted_answer_flag ==
1))/sum(Q2Test$accepted_answer_flag == 1)
  if(print==TRUE){
    print(table(Observed= Q2Test$accepted_answer_flag, Predicted=Ps))
    }
    vect=c(FP,TP)
    names(vect)=c("FPR","TPR")
    return(vect)
}
threshold = 0.5
roc.curve(threshold,print=TRUE)

ROC.curve=Vectorize(roc.curve)
M.ROC=ROC.curve(seq(0,1,by=.01))

plot(M.ROC[1,],M.ROC[2,],col="blue",lwd=2,type="l", main = "ROC for QDA")
abline(0,1)


library(class)
train.x<-
cbind(Q2Train$a_body_length+Q2Train$a_body_has_code+Q2Train$a_DaysOld+Q2Train$
a_has_edited+Q2Train$a_num_comment+Q2Train$a_owner_reputation+Q2Train$a_owner
_profile_summary+Q2Train$a_owner_downvotes+Q2Train$q_DaysOld+Q2Train$q_title_len
gth+Q2Train$q_num_answers+Q2Train$q_num_comment+Q2Train$q_owner_profile_sum
mary)

test.x<-
cbind(Q2Test$a_body_length+Q2Test$a_body_has_code+Q2Test$a_DaysOld+Q2Test$a_
has_edited+Q2Test$a_num_comment+Q2Test$a_owner_reputation+Q2Test$a_owner_prof
ile_summary+Q2Test$a_owner_downvotes+Q2Test$q_DaysOld+Q2Test$q_title_length+Q2
Test$q_num_answers+Q2Test$q_num_comment+Q2Test$q_owner_profile_summary)
set.seed(123)

#predicting the model with testing data for KNN with k=1
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=1,prob=TRUE)

#CONFUSION matrix for KNN
table(knn.pred,Q2Test$accepted_answer_flag)

#misclassification rate for KNN
mean(knn.pred!=Q2Test$accepted_answer_flag)
```

```
#Trying to predict KNN with different k values to get the lowest misclassification rate
#predicting the KNN model with k=2
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=2,prob=TRUE)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=3
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=3,prob=TRUE)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=4
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=4,prob=TRUE)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=5
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=5,prob=TRUE)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=6
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=6,prob=TRUE)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=7
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=7,prob=TRUE)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=8
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=8,prob=TRUE)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=9
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=9,prob=TRUE)
table(knn.pred,Q2Test$accepted_answer_flag)
```

```
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=10
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=10,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=11
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=11,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=12
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=12,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=13
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=13,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=14
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=14,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=15
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=15,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=17
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=17,prob=TRUE
)
```

```
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=18
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=18,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=19
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=19,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=20
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=20,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=21
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=21,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=22
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=22,prob=TRUE
)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#predicting the KNN model with k=100
knn.pred<-
knn(data.frame(train.x),data.frame(test.x),Q2Train$accepted_answer_flag,k=100,prob=TRU
E)
table(knn.pred,Q2Test$accepted_answer_flag)
mean(knn.pred!=Q2Test$accepted_answer_flag)

#taking the model built using knn=8
#CROSS VALIDATION of KNN
bwpredict.knn <- function(object, newdata) predict.ipredknn(object, newdata, type="class")
```

```
errorest(factor(Q2Train$accepted_answer_flag) ~
Q2Train$a_body_length+Q2Train$a_body_has_code+Q2Train$a_DaysOld+Q2Train$a_has
_edited+Q2Train$a_num_comment+Q2Train$a_owner_reputation+Q2Train$a_owner_profil
e_summary+Q2Train$a_owner_downvotes+Q2Train$q_DaysOld+Q2Train$q_title_length+Q
2Train$q_num_answers+Q2Train$q_num_comment+Q2Train$q_owner_profile_summary,
data=Q2Train, model=ipredknn, estimator="cv", est.para=control.errorest(k=10),
predict=bwpredict.knn, kk=10)$err

#ROC for KNN
library(ROCR)
prob<- attr(knn.pred,"prob")
prob

prob <- (2*(ifelse(knn.pred == "0", 1-prob, prob)) - 1)
knn <- prediction(prob, testing_y)
pred_knn <- prediction(prob, testing_y)
pred_knn <- performance(pred_knn, "tpr", "fpr")
plot(pred_knn, avg= "threshold", colorize=T, lwd=3, main="ROC curve for KNN")
as.numeric(performance(ROCRpred,"auc")@y.values)

#install.packages("tree")
library(tree)

tree.Q2Train =
tree(accepted_answer_flag~a_body_length+a_body_has_code+a_DaysOld+a_has_edited+
a_num_comment+a_owner_reputation+a_owner_profile_summary+a_owner_downvotes+q_
DaysOld+q_title_length+q_num_answers+q_num_comment+q_owner_profile_summary,Q2
Train)
summary(tree.Q2Train)

plot(tree.Q2Train)
text(tree.Q2Train,pretty=0)

#Classification tree
lf=seq(1,nrow(Q2Train))
tree.Q2Train=tree(as.factor(accepted_answer_flag)~a_body_length+a_body_has_code+a_
DaysOld+a_has_edited+a_num_comment+a_owner_reputation+a_owner_profile_summary
+a_owner_downvotes+q_DaysOld+q_title_length+q_num_answers+q_num_comment+q_ow
ner_profile_summary,subset=lf)

summary(tree.Q2Train)

plot(tree.Q2Train)
text(tree.Q2Train,pretty=0)

tree.pred=predict(tree.Q2Train,Q2Test,type="class")

#Confusion matrix for CART
```

```
table(tree.pred,testing_y)

#Misclassification rate for CART
mean(tree.pred!=Q2Test$accepted_answer_flag)

#Pruning and Cross Validation of the Classification Tree
cv.Q2Train=cv.tree(tree.Q2Train,FUN=prune.misclass)
names(cv.Q2Train)

cv.Q2Train

par(mfrow=c(1,2))
plot(cv.Q2Train$size, cv.Q2Train$dev, type="b")
plot(cv.Q2Train$k, cv.Q2Train$dev, type="b")


par(mfrow=c(1,1))
prune.Q2Train=prune.misclass(tree.Q2Train, best=9)

plot(prune.Q2Train)
text(prune.Q2Train,pretty=0)

tree.pred=predict(prune.Q2Train, Q2Test, type="class")
table(tree.pred, testing_y)

mean(tree.pred!=Q2Test$accepted_answer_flag)

library(randomForest)
set.seed(123)

bag.Q2Train=randomForest(accepted_answer_flag~a_body_length+a_body_has_code+a_
DaysOld+a_has_edited+a_num_comment+a_owner_reputation+a_owner_profile_summary
+a_owner_downvotes+q_DaysOld+q_title_length+q_num_answers+q_num_comment+q_ow
ner_profile_summary,data=Q2Train, subset=lf, mtry=4, importance=TRUE)

bag.Q2Train
yhat.bag=predict(bag.Q2Train, Q2Test)

plot(yhat.bag, testing_y)
abline(0,1)

mean((yhat.bag-testing_y)^2)
mean(yhat.bag!=testing_y)

#ROC for CART
tree.pred=predict(tree.Q2Train,Q2Test,type="vector",prob=TRUE)
tree.pred
tree.S = tree.pred[,2]
roc.curve=function(s,print=FALSE){
  Ps=(tree.S>s)*1
  FP=sum((Ps==1)*(Q2Train$accepted_answer_flag ==
0))/sum(Q2Train$accepted_answer_flag == 0)
  TP=sum((Ps==1)*(Q2Train$accepted_answer_flag ==
1))/sum(Q2Train$accepted_answer_flag == 1)
  if(print==TRUE){
    print(table(Observed=Q2Test$accepted_answer_flag,Predicted=Ps))
  }
  vect=c(FP,TP)
  names(vect)=c("FPR","TPR")
  return(vect)
}
threshold = 0.5
roc.curve(threshold,print=TRUE)
ROC.curve=Vectorize(roc.curve)
M.ROC=ROC.curve(seq(0,1,by=.01))
plot(M.ROC[1,],M.ROC[2,],col="blue",lwd=2,type="l", main = "ROC for CART")
abline(0,1)
```

C3. Predict comment sentiment using NLP

```
library(devtools)
library(sentiment)
library(twitteR)
library(plyr)
library(ggplot2)
library(wordcloud)
library(RColorBrewer)
library(devtools)
library(stringr)

getwd()
setwd("C:/Users/Alok Satpathy/Desktop/Fall 2016/EDA/Final Project")

Q3csv=read.csv("Question3Dataset.csv")
attach(Q3csv)
str(Q3csv)

Q3csv[is.na(Q3csv)]=0
str(Q3csv)

Q3csv["SentimentScore"]=NA
str(Q3csv)

#function to clean data
```

```
cleancomments = function(commentstest)
{
  commentstest_cl = gsub("(RT|via)((?:\\b\\W*@\\w+)+)","",commentstest)
  commentstest_cl = gsub("http[^[:blank:]]+", "", commentstest_cl)
  commentstest_cl = gsub("@\\w+", "", commentstest_cl)
  commentstest_cl = gsub("[ \t]{2,}", "", commentstest_cl)
  commentstest_cl = gsub("^\\s+|\\s+$", "", commentstest_cl)
  commentstest_cl = gsub("[[:punct:]]", " ", commentstest_cl)
  commentstest_cl = gsub("[^[:alnum:]]", " ", commentstest_cl)
  commentstest_cl <- gsub('\\d+', '', commentstest_cl)
  return(commentstest_cl)
}

#function to calculate number of words in each category within a sentence
sentimentScore <- function(sentences, vNegTerms, negTerms, posTerms, vPosTerms){
  final_scores <- matrix('', 0, 5)
  scores <- lapply(sentences, function(sentence, vNegTerms, negTerms, posTerms,
vPosTerms){
    initial_sentence <- sentence
    #remove unnecessary characters and split up by word
    sentence = cleancomments(sentence)
    sentence <- tolower(sentence)
    wordList <- strsplit(sentence, '\\s+')
    words <- unlist(wordList)
    #build vector with matches between sentence and each category
    vPosMatches <- match(words, vPosTerms)
    posMatches <- match(words, posTerms)
    vNegMatches <- match(words, vNegTerms)
    negMatches <- match(words, negTerms)
    #sum up number of words in each category
    vPosMatches <- sum(!is.na(vPosMatches))
    posMatches <- sum(!is.na(posMatches))
    vNegMatches <- sum(!is.na(vNegMatches))
    negMatches <- sum(!is.na(negMatches))
    score <- c(vNegMatches, negMatches, posMatches, vPosMatches)
    #add row to scores table
    newrow <- c(initial_sentence, score)
    final_scores <- rbind(final_scores, newrow)
    return(final_scores)
  }, vNegTerms, negTerms, posTerms, vPosTerms)
  return(scores)
}

#load pos,neg statements
afinn_list <- read.delim(file='AFINN-111.txt', header=FALSE, stringsAsFactors=FALSE)
names(afinn_list) <- c('word', 'score')
summary(afinn_list$score)
afinn_list$word <- tolower(afinn_list$word)
```

```
#categorize words as very negative to very positive and add some movie-specific words
vNegTerms <- afinn_list$word[afinn_list$score==-5 | afinn_list$score==-4]
negTerms <- afinn_list$word[afinn_list$score==-2 | afinn_list$score==-1 | afinn_list$score==-
3]
posTerms <- afinn_list$word[afinn_list$score==3 | afinn_list$score==2 | afinn_list$score==1]
vPosTerms <- afinn_list$word[afinn_list$score==5 | afinn_list$score==4]

#Loop through each row in dataframe and calculate the sentiment
for(i in 1:nrow(Q3csv))
{
  rowSenti=as.data.frame(sentimentScore(Q3csv[i,"CommentText"], vNegTerms, negTerms,
posTerms, vPosTerms))
  totalSenti=((as.numeric(as.character(rowSenti[,2])))*(-2)) +
((as.numeric(as.character(rowSenti[,3])))*(-1)) +
((as.numeric(as.character(rowSenti[,4])))*(1)) +
((as.numeric(as.character(rowSenti[,5])))*(2))
  #print(totalSenti)

  if(totalSenti>0)
  {
    totalSenti=1
  }
  else if(totalSenti<0)
  {
    totalSenti=-1
  }

  Q3csv[i,"SentimentScore"]=totalSenti

  if(i%%1000 == 0)
  {
    cat(i, " Sentiments Analyzed\n")
  }
}

attach(Q3csv)

#Selecting columns that would be used for preparing model
Q3df=data.frame(CommentScore, CommentCrDays, CommentLength,
comment_owner_reputation, comment_owner_profile_summary, comment_owner_views,
comment_owner_upvotes, comment_owner_downvotes, comment_owner_lastactivity_days,
editDurationAfterCreation, activityDurationAfterCreation, title_length, num_tags,
PostAnswerCount, num_favorite, hascode, post_views, postTypeId, IsAcceptedAnswer,
postScore, post_length, PostCommentCount, PostUpVotes, PostDownVotes,
SentimentScore)

Q3df$SentimentScore <- as.factor(Q3df$SentimentScore
str(Q3df)
```

```
counts <- ddply(Q3df, .(Q3df$SentimentScore), nrow)
counts

# Subset Selection Methods
# Best Subset Selection
lapply(Q3df["SentimentScore"], unique)

#install.packages("leaps")
library(leaps)
regfit.full=regsubsets(SentimentScore~.,Q3df)
summary(regfit.full)

regfit.full=regsubsets(SentimentScore~.,data=Q3df,nvmax=26)
reg.summary=summary(regfit.full)
names(reg.summary)

reg.summary$rsq
par(mfrow=c(2,2))
plot(reg.summary$rss,xlab="Number of Variables",ylab="RSS",type="l")
plot(reg.summary$adjr2,xlab="Number of Variables",ylab="Adjusted
RSq",type="l")
which.max(reg.summary$adjr2)
points(11,reg.summary$adjr2[11], col="red",cex=2,pch=20)
plot(reg.summary$cp,xlab="Number of Variables",ylab="Cp",type='l')
which.min(reg.summary$cp)
points(10,reg.summary$cp[10],col="red",cex=2,pch=20)
which.min(reg.summary$bic)
plot(reg.summary$bic,xlab="Number of Variables",ylab="BIC",type='l')
points(6,reg.summary$bic[6],col="red",cex=2,pch=20)
coef(regfit.full,6)

# Forward and Backward Stepwise Selection
regfit.fwd=regsubsets(SentimentScore~.,data=Q3df,nvmax=26,method="forward")
summary(regfit.fwd)
regfit.bwd=regsubsets(SentimentScore~.,data=Q3df,nvmax=26,method="backward"
)
summary(regfit.bwd)
coef(regfit.full,7)
coef(regfit.fwd,7)
coef(regfit.bwd,7)

# Choosing Among Models
set.seed(1)
train=sample(c(TRUE,FALSE), nrow(Q3df),rep=TRUE)
test=(!train)
regfit.best=regsubsets(SentimentScore~.,data=Q3df[train,],nvmax=26)
test.mat=model.matrix(SentimentScore~.,data=Q3df[test,])
```

```
val.errors=rep(NA,25)
for(i in 1:11){
   coefi=coef(regfit.best,id=i)
   pred=test.mat[,names(coefi)]%*%coefi
   val.errors[i]=mean((Q2df$accepted_answer_flag[test]-pred)^2)
}
val.errors
which.min(val.errors)
coef(regfit.best,24)
predict.regsubsets=function(object,newdata,id,...){
  form=as.formula(object$call[[2]])
  mat=model.matrix(form,newdata)
  coefi=coef(object,id=id)
  xvars=names(coefi)
  mat[,xvars]%*%coefi
  }
regfit.best=regsubsets(SentimentScore~.,data=Q3df,nvmax=26)
coef(regfit.best,24)
k=24
set.seed(1)
folds=sample(1:k,nrow(Q3df),replace=TRUE)
cv.errors=matrix(NA,k,25, dimnames=list(NULL, paste(1:25)))
for(j in 1:k){
  best.fit=regsubsets(SentimentScore~.,data=Q3df[folds!=j,],nvmax=24)
  for(i in 1:24){
    pred=predict(best.fit,Q3df[folds==j,],id=i)
    cv.errors[j,i]=mean( (Q3df$SentimentScore[folds==j]-pred)^2)
    }
  }
mean.cv.errors=apply(cv.errors,2,mean)
mean.cv.errors
par(mfrow=c(1,1))
plot(mean.cv.errors,type='b')
reg.best=regsubsets(SentimentScore~.,data=Q3df, nvmax=24)
coef(reg.best,3)


# Ridge Regression and LASSO
fix(Q3df)
names(Q3df)
dim(Q3df)
sum(is.na(Q3df$accepted_answer_flag))
Q2df=na.omit(Q3df)
dim(Q3df)
sum(is.na(Q3df))

#install.packages("glmnet")
library(glmnet)
```

```
#the package invokes inputs and outputs separately unlike lm and glm
x=model.matrix(SentimentScore~.,Q3df)[,-1]
y=Q3df$SentimentScore

# set vector of lambda values to study range from 10^10 to 0.01, total length=100
grid=10^seq(10,-2,length=100)
ridge.mod=glmnet(x,y,alpha=0,lambda=grid)
dim(coef(ridge.mod))

# let us look at a few results here
#first lambda=50
ridge.mod$lambda[50]
coef(ridge.mod)[,50]
sqrt(sum(coef(ridge.mod)[-1,50]^2))

#next, lambda=60
ridge.mod$lambda[60]
coef(ridge.mod)[,60]
sqrt(sum(coef(ridge.mod)[-1,60]^2))

#prediction of the coefficients for lambda=50 (play with this)
predict(ridge.mod,s=500,type="coefficients")[1:25,]

#prepare for training and validation set testing
set.seed(1)
train=sample(1:nrow(x), nrow(x)/2)
test=(-train)
y.test=y[test]

ridge.mod=glmnet(x[train,],y[train],alpha=0,lambda=grid, thresh=1e-12)
ridge.pred=predict(ridge.mod,s=4,newx=x[test,])

#evaluate and compare test MSE and the spread of y.test
mean((ridge.pred-y.test)^2)
mean((mean(y[train])-y.test)^2)

#test wth two other lambdas
ridge.pred=predict(ridge.mod,s=1e10,newx=x[test,])
mean((ridge.pred-y.test)^2)
ridge.pred=predict(ridge.mod,s=0,newx=x[test,],exact=T)
mean((ridge.pred-y.test)^2)

#compare with lm
# The following two are the same
lm(y~x, subset=train)
predict(ridge.mod,s=0,exact=T,type="coefficients")[1:25,]
```

```
#Cross validation to get the best lambda
set.seed(1)
cv.out=cv.glmnet(x[train,],y[train],alpha=0)
plot(cv.out)
bestlam=cv.out$lambda.min
bestlam

#now predict with the best lambda
ridge.pred=predict(ridge.mod,s=bestlam,newx=x[test,])
mean((ridge.pred-y.test)^2)
out=glmnet(x,y,alpha=0)
predict(out,type="coefficients",s=bestlam)[1:25,]

# Lasso
#only difference in model building is to use alpha=1
lasso.mod=glmnet(x[train,],y[train],alpha=1,lambda=grid)
plot(lasso.mod)

# use CV to get best lambda
set.seed(1)
cv.out=cv.glmnet(x[train,],y[train],alpha=1)
plot(cv.out)
bestlam=cv.out$lambda.min

#use best lambda for prediction
lasso.pred=predict(lasso.mod,s=bestlam,newx=x[test,])
mean((lasso.pred-y.test)^2)
out=glmnet(x,y,alpha=1,lambda=grid)
lasso.coef=predict(out,type="coefficients",s=bestlam)[1:25,]
lasso.coef
lasso.coef[lasso.coef!=0]

#Dimensionality Reduction PCA:
#install.packages("pls")
library(pls)
set.seed(2)
pcr.fit=pcr(SentimentScore~., data=Q3df,scale=TRUE,validation="CV")
summary(pcr.fit)
validationplot(pcr.fit,val.type="MSEP")
set.seed(1)
pcr.fit=pcr(SentimentScore~., data=Q3df,subset=train,scale=TRUE, validation="CV")
validationplot(pcr.fit,val.type="MSEP")
pcr.pred=predict(pcr.fit,x[test,],ncomp=7)
mean((pcr.pred-y.test)^2)
pcr.fit=pcr(y~x,scale=TRUE,ncomp=7)
summary(pcr.fit)

# Partial Least Squares
```

```
set.seed(1)
pls.fit=plsr(SentimentScore~., data=Q3df,subset=train,scale=TRUE, validation="CV")
summary(pls.fit)
validationplot(pls.fit,val.type="MSEP")
pls.pred=predict(pls.fit,x[test,],ncomp=2)
mean((pls.pred-y.test)^2)
pls.fit=plsr(SentimentScore~., data=Q3df,scale=TRUE,ncomp=2)
summary(pls.fit)

#Dividing dataset 75% for training and 25% for testing
Q3smp_size=floor(0.75*nrow(Q3df))
set.seed(123)
Q3train_ind=sample(seq_len(nrow(Q3df)), size = Q3smp_size)
Q3Train=Q3df[Q3train_ind,]
Q3Test=Q3df[-Q3train_ind,]

nrow(Q3Train)
nrow(Q3Test)

#Initial logistic regression model with all parameters
attach(Q3Train)
Q3lm=glm(as.factor(SentimentScore)~.,data=Q3Train,family="binomial")
summary(Q3lm)

#Checking for significant parameters with forward step
Q3modelstepforward=step(Q3lm, direction="forward")
summary(Q3modelstepforward)

#Checking for significant parameters with backward step
Q3modelstepbackward=step(Q3lm, direction="backward")
summary(Q3modelstepbackward)

#Removing insignificant parameters and remodelling
Q3lm2=glm(as.factor(SentimentScore)~CommentLength+comment_owner_profile_summary
+comment_owner_downvotes+num_tags+
+PostAnswerCount+num_favorite+IsAcceptedAnswer+PostCommentCount,data=Q3Train,fa
mily="binomial")
summary(Q3lm2)

#Again removing insignificant parameters and remodelling
Q3lm3=glm(as.factor(SentimentScore)~CommentLength+comment_owner_downvotes+num
_tags+PostAnswerCount+IsAcceptedAnswer+PostCommentCount,data=Q3Train,family="bi
nomial")
summary(Q3lm3)

BIC(Q3lm3)

#Predicting based on the logistic model built
```

```
logistic_probs=predict(Q3lm3, Q3Train, type="response")
head(logistic_probs)

testing_y=Q3Test$SentimentScore
logistic_pred_y=rep(-1,length(testing_y))
logistic_pred_y[logistic_probs>0.8]=0
logistic_pred_y[logistic_probs>0.9]=1
training_y=Q3Train$SentimentScore
table(logistic_pred_y,training_y)

mean(logistic_pred_y!=training_y,na.rm=TRUE)

logistic_probs=predict(Q3lm3, Q3Test, type="response")
head(logistic_probs)

logistic_pred_y=rep(-1,length(testing_y))
logistic_pred_y[logistic_probs>0.8]=0
logistic_pred_y[logistic_probs>0.9]=1

table(logistic_pred_y,testing_y)
mean(logistic_pred_y!=testing_y,na.rm=TRUE)

#Cross Validation for logistic regression
#K-fold
library(boot)
MSE_10_Fold_CV=cv.glm(Q3Train,Q3lm3,K=10)$delta[1]
MSE_10_Fold_CV

MSE_10_Fold_CV=NULL
for(i in 1:10){
model=glm(SentimentScore~CommentLength+comment_owner_downvotes+num_tags+Pos
tAnswerCount+IsAcceptedAnswer+PostCommentCount,data=Q3Train)
  MSE_10_Fold_CV[i]=cv.glm(Q3Train,model,K=10)$delta[1]
  }
MSE_10_Fold_CV

#ROC of Logistic Regression
#install.packages("ROCR")
library(ROCR)
ROCRpred<- prediction(logistic_probs,testing_y)
ROCRperf<- performance(ROCRpred,"tpr","fpr")
plot(ROCRperf)
plot(ROCRperf,colorize=TRUE)
plot(ROCRperf, colorize = TRUE, print.cutoffs.at = seq(0,1,0.05), text.adj = c(-0.2,1.7))
as.numeric(performance(ROCRpred,"auc")@y.values)
```

Appendix D: Terminology and Abbreviations

Term	**:**	**Meaning**
User	:	Community members who have a registered account to use Stack Overflow, existing or deleted.
Post	:	Question or answer, both are considered posts in context of SO.
OP	:	Original Poster; User who post the question.
SO	:	Abbr. of Stack Overflow.
Comment	:	Messages, observations etc. left by users on posts.
Reputation	:	Points system on SO. Users are awarded or penalised based on the policy of Stack Overflow. (http://stackoverflow.com/help/whats-reputation).
Vote	:	An expression of accepting or rejecting a post. Voting up or down has a direct consequence on the reputation.
Flag	:	An extreme measure taken by user to report failure of adherence to SO standards of posting question, answers or comments. Flagged items are sent to moderators for review.
Privileges	:	Access to various controls as a user. Increases based on reputation.
Moderator	:	A privilege awarded to users with 10000 reputation points.
Stack Exchange	:	Network of 150+ community based Q&A website
Data Explorer	:	Online tool which provides query interface to mine data for the websites which are a part of StackExchange network(http://data.stackexchange.com/)