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Predicting Community Engagement with Questions in the StackOverflow Online Question-Answer Community

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Acknowledgement

I would like to dedicate this work to my wife Bronwyn. Words cannot describe how much I appreciate your unending love, support and patience over this past year that we have spent together in London.

Summary

Formulating constructive questions and receiving answers to these questions is crucial to how we examine, learn from and critically analyse the world around us. The evolution of the world wide web and the technologies that have emerged with it have given us an unprecedented ability to engage with and learn from individuals around the globe. While substantial attention has been dedicated to finding the right answers (just ask Google), comparatively less has been devoted to how we can improve the constructiveness of our questions. The domain of online question-answer (Q&A) communities is one setting where relevant and well-researched questions are of particular importance, not least because expert resources are scarce in contrast to question volumes. One way to address this problem of "information overload" is to provide questioners with accurate predictions of their question constructiveness, prompting revision of questions before demand is added on expert resources. In light of this goal, this paper builds on predictive modelling and question quality research in online Q&A communities in three ways: 1) I predict community engagement, which I consider a more objective and definitive response than question quality, 2) I accept each questions' community-granted "score" as an informative and comprehensive measurement of community engagement, and 3) I predict a range of community engagement rather than discrete categories. Using only textual question content available when questions are initially submitted, I analyse monthly datasets from the largest online computer programming Q&A community, StackOverflow.com. Contrary to recent research, I find that features derived question content lead to negligible model performance improvement over a low baseline across datasets. While this work shows that accurate prediction of online Q&A community engagement is still an ambitious goal, it serves as a stepping stone in addressing information overload in these platforms and improving their functioning substantially.

1 Introduction

Modern interpersonal communication technologies made possible by the internet have afforded us an exceptional level of connection and engagement with the world. Billions of individuals now interact online instantly, not only with people that they know, but with strangers thousands of miles away. One avenue of online interaction that has become an extremely popular way in which users share knowledge about diverse and nuanced subject matter is question-and-answer (Q&A) websites such as Yahoo! Answers, Quora, the StackExchange family and forums of Massive Online Open Courses (MOOCs). These websites serve as dynamic, engaging platforms where users seek answers to and discussions on complex, technical questions that modern search engines are evidently yet unable to fully address.

Producing relevant, well-researched and high-quality questions in online Q&A fora is especially valuable, not least since these platforms suffer in particular from a low ratio of expert resources to volume of new questions - an example of an increasingly ubiquitous problem known as *information overload*, of which a broader summary can be found in Eppler and Mengis (2004). The overarching hypothesis of this research is that information overload in online Q&A communities would be mitigated if questioners were notified in advance of how well their questions would be received by a community. This would allow them to iterate and increase the "signal" of their questions before exerting demand on community resources. If this were possible, it would not only benefit questioners as they would more effectively garner expert answers to their improved questions, but also entire communities as overall functioning and efficiency is enhanced community-wide.

Predicting the extent to which online communities would react positively to user questions in real time is a non-trivial problem however, since predictions must be made using only the information available when new questions are formulated. This implies that predictive models must learn from features derived from question content alone and not features such user characteristics, final webpage viewing statistics and so on. Ideally, final predictions given to questioners would also be highly granular and direct questioners towards how best to improve their questions as a type of recommendation system, however the aim of this research is only to take one step forward from previous work on questions in online Q&A communities and ascertain if community engagement in online Q&A fora can actually be predicted with some measure of accuracy.

The broad research question for this paper can therefore be summarised as the following:

To what extent can community engagement with questions in online Q&A communities be accurately predicted using only question content?

While there is a substantial amount of literature that has addressed online Q&A communities, curiously the focus has been on identifying expert users and high quality answers rather than on questions, despite questions being the entry point for every interaction in communities. In an attempt to answer the research question above, I build on the small collection of research on *question quality* in online Q&A fora and draw heavily on work done by Ravi *et al.* (2014) with data from the popular computer programming community StackOverflow.

Ravi *et al.* (2014) predicted a binary notion of question quality ("good" versus "bad"), and their classifier significantly beats out a strong baseline with accuracies of 55.5%, 65.8% and 64.2% for a length, textual-content and latent Dirichlet allocation (LDA) latent topic model respectively. I critique, mirror and expand the analysis of Ravi *et al.* (2014) in three core ways: 1) I consider community engagement to be a more objective and definitive metric to predict on than question quality, 2) I use the community-granted question `Score` as a comprehensive measurement of community engagement, and 3) I employ a regression model to allow for predictions to be continuous and informative as opposed to binary.

The `Score` variable is an aggregation of all community *up-votes* and *down-votes* for each question in the StackOverflow community, and I predict this variable in multiple monthly StackOverflow datasets using only the textual content of questions. In line with the analysis of Ravi *et al.* (2014), I engineer length, textual-content and latent topical features from question content for the prediction problem. I use regularised regression for the learning task and evaluate models using root-mean-square error (RMSE).

It should be noted that the goal of this research is quantitative prediction rather than qualitative, causal or inferential analysis. I leave it to further research to address more precisely the *how* and *why* of community engagement in online Q&A communities, rather than just the *if* that is explored here. To my knowledge this research is the first of its kind to test latent topic models on a continuous, objective measurement of online community engagement as well as pertain to a feasible and valuable use-case, which I believe makes it a practical and unique contribution.

The findings from my analysis show that there is still much work to be done to accurately predict community engagement in online Q&A fora. Contrary to the impressive classification accuracies in the results of Ravi *et al.* (2014), I find that models which include textual question content features do not perform any better over a modest baseline of constant mean prediction. Evidently, accurately predicting a continuous measurement of community engagement in a regression setting is an ambitious task, and I recommend that future research employ more sophisticated models and feature engineering, as well as incorporate time-series aspects.

In the following section I discuss the relevant literature in more detail. This is followed by section 3 which discusses the data, explores and validates my choice of the `Score` variable as an objective measurement of community engagement, and describes the predictive model used. Section 4 presents and discusses the results, section 5 explores some recommendations for further research and finally section 6 concludes.

2 Literature Review

My work involves the extraction of textual features from question content submitted to the online Q&A fora, and the training and evaluation of predictive regression models. This section provides brief summaries of previous work related to this research problem. Section 2.1 discusses previous work on online Q&A communities and section 2.2 discusses work on predicting *question quality* in online Q&A communities. Section summarises the approach and results of Ravi *et al.* (2014), and finally section briefly introduces how latent topic models have been applied to questions in online Q&A fora.

2.1 Question-Answer Communities

There is a substantial collection of research that has investigated online Q&A communities. Prior work has addressed answer quality (Jeon *et al.*, 2006; Shah and Pomerantz, 2010; Tian *et al.*, 2013), satisfaction of questioners (Liu *et al.*, 2008) and the behaviour of highly productive, expert community members (Riahi *et al.*, 2012; Sung *et al.*, 2013). Two common frameworks for prior work have been the optimisation of routing questions to experts (Li and King, 2010; Li *et al.*, 2011; Zhou *et al.*, 2012; Shah *et al.*, 2018), and matching questions in accordance with answerer interest in the form of a recommendation system (Wu *et al.*, 2008; Qu *et al.*, 2009; Szpektor *et al.*, 2013).

My research differs from this previous work on Q&A fora in two respects. Firstly, I focus on questions rather than user or answer characteristics, not only because they have received substantially less attention in the literature, but because it has been shown that question quality can substantially impact the quality of answers (Agichtein *et al.*, 2008). Questions in online Q&A fora are also the initial touch point from which all community engagement follows - maximising positive community engagement with questions will thus almost certainly improve the functioning of these communities.

I also deviate from prior research in the framework that I place this research in. I steer clear of the systems-based optimisation of question-answer routing/matching and instead concentrate on how questioners can be nudged to improve the content of their questions before adding demand to community resources. Although there is substantial literature on community engagement in a broad range of fields and disciplines, this literature is either too disparate from the field of research in this paper or focuses on online engagement in other forms. To my knowledge therefore, this work is the first of its kind to characterise and predict community engagement with questions in the context of online Q&A fora. Owing to the fact that the framework I have chosen coincides with a large collection of research on predicting question quality in online Q&A communities, I discuss this literature next.

2.2 Question Quality

Naturally, community engagement and question quality go hand in hand: high quality questions will no doubt lead to positive community feedback in the form of numerous up-votes, answers and discussion promoting comments. I argue in the following section that *community engagement* is a more accurate and thorough definition of what the following literature claims to measure, but for the sake of discussion I will refer to question quality here as well.

A recent line of work has looked at predicting question quality in the large Q&A community Yahoo! Answers (Agichtein *et al.*, 2008; Bian *et al.*, 2009; Li *et al.*, 2012) - a dataset which has metrics for assessing answer quality in the form of answer up-votes, but regrettably lacks a similarly community-attributed and objective metric for question quality. This has resulted in subjective attempts at defining question quality: Agichtein *et al.* (2008) define question quality using questions' semantic features (lexical complexity, punctuation, typos etc.), Bian *et al.* (2009) use manual labels for 250 questions and a semi-supervised coupled mutual reinforcement framework to label a larger number of questions, and Li *et al.* (2012) combine the number of answers, number of tags, time until first answer, author judgement and domain expertise to construct their ground truth.

Fortunately, I analyse data from the StackOverflow Q&A community which is rich in objective community-attributed metrics such as question up- and down-votes, comments, and views, all of which is over and above the textual content of questions and answers themselves. These metrics are objective in the sense that they do not require construction or labelling form the researchers' side, and subsequently allow for large collections of questions to be analysed automatically.

Another aspect of the literature that has evolved substantially are the models employed to predict question quality. Previous work has modelled question quality based on the reputation of the questioner, question categories and lexical characteristics of questions such as length, misspelling, words per sentence etc. (Agichtein *et al.*, 2008; Bian *et al.*, 2009; Anderson *et al.*, 2012; Li *et al.*, 2012). By ignoring the actual textual and topical content of questions and focusing on features of the questioner however, these approaches would perform poorly on questions from new users without a community history.

Since my research goal is centred around predicting community engagement for all community members, and in particular new and inexperienced users who are more likely to receive negative community responses to poorly constructed questions, I use only features available when a question is initially asked and forego features derived from user attributes. The methodology that I have thus far laid out mirrors work done by Ravi *et al.* (2014) to predict question quality for the StackOverflow community. Since I will be closely emulating their methodology, I now demonstrate their contributions.

2.3 Ravi *et al.* (2014)

Ravi *et al.* (2014) analyse a large number of questions from the StackOverflow community to predict a binary notion (i.e. "good" versus "bad") of question quality using features derived from question length, textual-content and latent topics. Their *length* model achieves an accuracy of 55.5%, their *text* model achieves 65.8% accuracy, their global *topic* model achieves 64.2% accuracy, a combined model with all three types of features obtains 70.5% accuracy, all above a modest page-view feature benchmark of 61.1%.

They compare their significant results to a baseline "popularity" model that only includes a variable indicating question webpage views (which achieves 61.1% accuracy), and subsequently claim that their models are able to capture a notion of question quality that extends beyond popularity. Owing to these impressive results and the appeal that these models could be used to successfully predict community engagement, my research closely follows their methodology, but also critiques and extends it in a number of ways.

The first and clearest distinction in my analysis concerns the response variable that is predicted. Ravi *et al.* (2014) decide to construct a composite response variable by dividing the community-attributed question `Score` (the aggregation of all user up-votes and down-votes) by the number of views a question receives, or a questions' `ViewCount` (which is also the independent variable that is used in their benchmark popularity model). While they rightly state that using the `Score` variable alone risks conflating "question quality" and "popularity" since questions that receive higher views are more likely to receive votes, my research objective differs in that I aim to predict community engagement rather than question quality - I thus use only the question `Score` as my response variable. As will be expanded upon later, I believe this metric comprehensively characterises within-community engagement, of which popularity and the ability to attract views is an integral component.

Out of the 410 049 questions that Ravi *et al.* (2014) extract between 2008 and 2009, they further define the "worst" and "best" questions according to a rather arbitrary threshold of 0.001 on their `Score/ViewCount` metric, resulting in only 33 199 "bad" questions being eventually labelled and analysed. On the other hand, my data selection consists of using all questions from five monthly StackOverflow datasets in 2009, which coincides with the time frame of extracted questions in Ravi *et al.* (2014), but not in dataset size. While the reasons for my choice of dataset time-span will be more thoroughly discussed later, I believe it is good practice to include all the questions for a given time-period owing to the aim of providing accurate predictive information to questioners. I therefore do not select a specific subset of questions.

The fact that I predict on the `Score` variable as a continuous measurement of community engagement also has a number of advantages. Firstly, any decisions on potentially arbitrary label boundaries for discrete categories of questions are eliminated, and indeed there is actually no need for categories of questions since each questions' community engagement is represented on a continuous range. Providing predictions of a questions' `Score` to questioners as an indication of how well the StackOverflow community will react to their question is also more informative than a binary good/bad prediction, and has the added benefit of being easily interpreted and understandable. Lastly, predicting on the `Score` variable alone ensures that when I consider the benchmark `ViewCount` model, I am not predicting on a composite variable that incorporates `ViewCount` itself.

More broadly, I believe a framework of community engagement is more robust and methodologically accurate than a rationale of question quality. I am of the opinion that question quality is much more nuanced than the prior research has asserted, not least because the definition of quality itself is highly subjective. As an example, while most communities may universally value certain aspects of questions such as legibility, coherence, relevance and prior-research etc., there are numerous question traits that communities could value to different extents - i.e. closed-end questions being valued in the natural sciences as opposed to discussion-promoting questions in the social sciences.

Beyond differences in inter-community or even intra-community valuation of questions, a community's notion of "quality" could also evolve over time. A framework of community engagement therefore allows for heterogeneity in how questions are valued across communities, subcommunities and over time, yet it still preserves a notion of *positive* or *negative* engagement in metrics that are assumed to measure it.

Although I extend the methodology of Ravi *et al.* (2014) in the key areas discussed above, I will emulate their prediction task to ascertain whether these models are as effective in this new framework and in a regression setting. Since a substantial development in the analysis of Ravi *et al.* (2014) was the use of features derived from latent topics, I briefly introduce this literature next.

2.4 Topic Models

Bayesian inference schemes have recently become prominent in solving a range of structured Natural Language Processing (NLP) prediction problems owing to their ability to allow researchers to include prior knowledge flexibly, as well as to manage uncertainty regarding model parameters (Chiang *et al.*, 2010). One notable application of Bayesian inference is in topic modelling, which has recently been employed in a broad range of NLP and information retrieval tasks, such as query-focused summarisation (Daumé and Marcu, 2006), deriving concept-attribute attachments (Reisinger and Paşca, 2009), co-reference resolution across documents (Haghighi and Klein, 2010), computing selection preferences (Ritter *et al.*, 2010) and name ambiguity resolution (Kozareva and Ravi, 2011).

LDA was originally introduced by David Blei and his co-authors in 2003 (Blei *et al.*, 2003) and it remains a popular topic model used to infer a set of topics inherent in a corpus (collection) of documents. LDA is an unsupervised generative probabilistic model which assumes that each document in a corpus is a mixture of some number of hidden topics, and that each word in a document is generated according to one of these topics. Finer details of LDA will be discussed in section .

LDA has already been applied to the StackOverflow dataset by Allamanis and Sutton (2013), however they did not attempt to predict a measurement of community engagement with their model. In analysing the StackOverflow dataset, Allamanis and Sutton (2013) propose a modelling technique using three LDA models: one over the question body as a whole, another model on the code chunks in each question, and a last model on the question body without noun phrases.

Ravi *et al.* (2014) build on the three-tiered approach of Allamanis and Sutton (2013) and demonstrate that inferred latent topics are significant predictors of their measurement of question quality. The three levels that they choose to capture topical aspects of questions are: a global model to capture topics over each question as a whole (coinciding with the first model in in Allamanis and Sutton (2013)), a local topic model for sentence-level topics, and finally a Mallows model (Fligner and Verducci, 1986) which enforces structural constraints over sentence-level topics to capture a "global topic structure".

I employ only the global topic model implemented in both Allamanis and Sutton (2013) and Ravi *et al.* (2014). With the continuous `Score` variable as my measurement of community engagement, my goal is to ascertain if latent topic models are as effective in the framework I have developed here, as well as if results are consistent over multiple monthly StackOverflow datasets. I begin a thorough discussion of the data and exploration of the `Score` variable in the next section.

3 Methodology

My main work comprises of three parts: data preparation, data processing which includes feature selection, and then learning and evaluation. This section presents the above methodologies in the order stated. The sourcing and selection of data according to specified time ranges are discussed in section 3.1 and 3.2 respectively. Final, section 3.3 motivates the `Score` variable as a measurement of community engagement, as well as discusses the similarities of the `ViewCount` and `Score` variable and corresponding methodological issues.

3.1 Data Sourcing

The StackExchange family of online Q&A fora are a diverse range of over 170 community websites covering topics from vegetarianism to quantum computing to bicycles. Over and above the textual content of questions, answers and comments posted since each community's conception, rich meta-data on an array of community interactions is publicly available in XML files compressed in 7-Zip format at archive.org/download/stackexchange.

At over 11 years of age with 18 million questions, 11 million users and 9.3 million site visits a day, StackOverflow is not only the oldest and largest StackExchange Q&A community, but is arguably the largest dedicated computer programming community on the internet. After launching in July 2008 StackOverflow has averaged 2 million questions posted each year since 2012, now encounters 6 200 new questions every day (StackExchange.com, 2019) and is ranked the 40th most popular website according to Alexa Internet's ranking at the time of writing (Alexa.com, 2019).

Since the StackOverflow dataset is also publicly and freely available for selective querying on Google Big Query, I use this tool to extract my variables of interest from May to September 2009 in JSON files and then convert to Parquet format. The following resulting variables are of interest to my analysis:

- `Score`: An aggregate variable calculated from the difference between registered-user granted up-votes and down-votes for a question
- `ViewCount`: A counter for the number of page views a question receives (from both registered and non-registered users)
- `Title`: The text of the question title

- `Body`: The text of the question body
- `CreationDate`: A datetime variable indicating when the question was initially posted

These additional variables are briefly discussed in section 3.3.1 as alternatives to the `Score` variable as a response variable:

- `AnswerCount`: The number of answers a question has received
- `CommentCount`: The number of comments a question has received
- `FavoriteCount`: The number of times registered-users have favourited a question
- `AcceptedAnswerId`: An indication of which answer the question-asker has selected as accepted
- `LastEditDate`: A datetime variable indicating when the post was last edited
- `ClosedDate`: A datetime variable indicating if a question was closed

3.2 Data Selection

I analyse five monthly StackOverflow question datasets from May 2009 to September 2009. This choice broaches an aspect of the research problem that has yet to be considered in the literature - the temporality of online Q&A data, and the potentially very difficult challenge of predicting *future* community engagement from *past* community engagement. Predicting future community engagement is a particularly ambitious endeavour since there is little doubt that how questioners formulate questions and how communities value questions are subject to change over time. The public and open nature of the StackOverflow community, the dynamically evolving compositions of registered-users comprising the community, and the volatile nature of the computer programming field would all contribute temporal elements to how questions are formulated and received in this community.

By choosing a date range close to the start of the community and by analysing short, monthly snapshots of the StackOverflow community, a number of key issues relating to temporal endogeneity are addressed. Firstly, the choice of 2009 as the year of analysis ensures that I don't include very recent questions (i.e. in the last few years) that have not had enough time to garner votes and views. The use of short time-spans also minimises the possibility of questions evolving over time and being asked by increasingly distinct groups of individuals (questioner and question-specific variation).

In using short time-periods I also mitigate confounding aspects regarding the community itself evolving and changing how it values and engages with questions (community-specific variation), or the formal structure of the community changing (community-structure variation). Examples of the structure of the StackOverflow community changing would include various nudges and guides that have been implemented for users to ask better questions. Lastly, using monthly chronological datasets results in minimal size differences between datasets. Note that my final underlying assumption is that there are no temporal elements or trends in the monthly datasets I analyse - I therefore do not employ time-series models, but treat each isolated monthly dataset as homogeneous.

The five monthly datasets have sizes ranging from 26 026 questions in May 2009, to 33 268 in September 2009, with 153 599 questions in total. I process and analyse the data with PySpark, a Python API for the open-source cluster-computing framework Apache Spark.

3.3 A Notion of Community Engagement

3.3.1 Potential Candidates for Community Engagement

Since there are a number of ways that StackOverflow members engage and interact with each other aside from the fundamental activities of asking/answering questions and up-/down-voting questions and answers, it is worth considering if there are candidates more suited to capturing community engagement and informing questioners rather than the `Score` variable. For example, questioners are able to indicate that an answer has explicitly answered their question, users can "favourite" questions and there are also further privileges for users with enough site *reputation*.

Although questions on StackOverflow are open to the general public, posting a question in the community requires registration with an email address and a username - once registered, users start with a *reputation* level of 1. According to the guidelines of the StackOverflow community, reputation is a "rough measurement of how much the community trusts you; it is earned by convincing your peers that you know what you're talking about" (see meta.stackexchange.com/questions/7237/how-does-reputation-work).

Key reputation levels for this analysis include:

- 1: Users can ask questions and contribute answers
- 15: Users can up-vote questions and answers
- 15: Users can flag posts to bring them to the attention of the community
- 50: Users can comment on questions and answers
- 125: Users can down-vote questions and answers
- 2000: Users can immediately edit any question or answer
- 3000: Users can vote to close questions that are off-topic, unclear, duplicates, too-broad or too opinion-based

Since the `Score` variable is the aggregation of all registered community members' up-votes and down-votes (in accordance with their reputation levels) it is able to register both positive (up-votes), negative (down-votes) and neutral (abstentions) community engagement. This metric also represents a core behaviour of the majority of the community since users can vote regardless of their reputation level. Providing `Score` predictions of new questions to questioners would also be highly valuable because it provides a continuous, granular indication of how likely that will succeed in their request for information from the community (a high score prediction) or essentially be rejected by the community (a low or negative score).

Some metrics are easier to eliminate as alternatives to the `Score` variable than others. `FavouriteCount`, or the number of times a question is favourited by registered users, has no capacity to register negative engagement (i.e. you cannot negatively favourite questions) and it is also not a core functioning of the community. `CommentCount` intuitively feels like a potentially valuable indication of community engagement, yet comments need not be directed at the original questioner (they could be directed at other commenters) and without employing sentiment analysis it would be difficult to ascertain what number of comments constitute positive/negative community engagement.

Using `AnswerCount` as the response variable could indicate to questioners how many answers their question is predicted to receive, but this variable would be biased downwards for more difficult questions. An added advantage of the `Score` variable in this regard, is that users can still up-vote difficult questions and signify that the community appreciates the question.

`EditCount` is another continuous variable which could indicate community engagement in the number of edits a question receives. Unfortunately, there is again uncertainty as to whether a high value for this variable shows that the community has had to go through much effort to get the question into a valuable state, or otherwise indicates that the community deems the question useful enough to spend much energy refining it.

This leaves two variables for consideration, `ClosedDate` and `AcceptedAnswerId`. Indeed, using the `ClosedDate` variable to inform questioners on whether their question is likely to be closed would be very valuable as a measurement of community engagement. `AcceptedAnswerId` on the other hand, would effectively indicate whether a questioner's overarching goal has been satisfied, i.e. whether they indicate their request for information has been completed and therefore be of high utility to questioners. While these variables may be highly relevant for community engagement and valuable to questioners, they can essentially only be represented as binary variables, over which the `Score` variable again has an advantage.

It is thus quite clear that, out of the recorded metrics available in the StackOverflow community data, the `Score` variable is a comprehensive and informative measurement of community engagement. One variable that I haven't been given any attention thus far however, is the `ViewCount` variable. As I will motivate in the next section though, the `Score` and `ViewCount` variables measure very similar underlying attributes, and so I now explore both of these variables.

3.3.2 Conceptualising `Score` and `ViewCount`

While the `Score` and `ViewCount` variables may appear to be measuring different phenomena, in this section I contrast and compare them to motivate that they are two sides of a similar coin. The first evidence of this is the correlations between the both variables, shown in table 1 below. With correlations ranging from 0.71 to 0.86, it is clear that they are both highly positively correlated.

Table 1: **Score and ViewCount Correlations**

Dataset	Correlation
May-09	0.86
Jun-09	0.85
Jul-09	0.81
Aug-09	0.71
Sep-09	0.76

Source: Own calculations in PySpark.

Descriptive statistics for both the `Score` and `ViewCount` variables are now displayed in tables 2 and 3, and density plots are made for both variables in figures 1 and 2. It should be noted that that `Score` variable for each dataset was adjusted upwards by the minimum value across datasets to allow for a log-scaled x-axis.

Table 2: **Score Variable Descriptive Statistics**

Dataset	Count	Mean	SD	Min	Max
May-09	26 026	13.3	142.0	-7	19 640
Jun-09	28 555	13.4	87.2	-9	4 655
Jul-09	32 752	11.3	76.6	-8	6 145
Aug-09	32 998	9.9	70.8	-22	7 133
Sep-09	33 268	8.7	47.1	-10	2 809

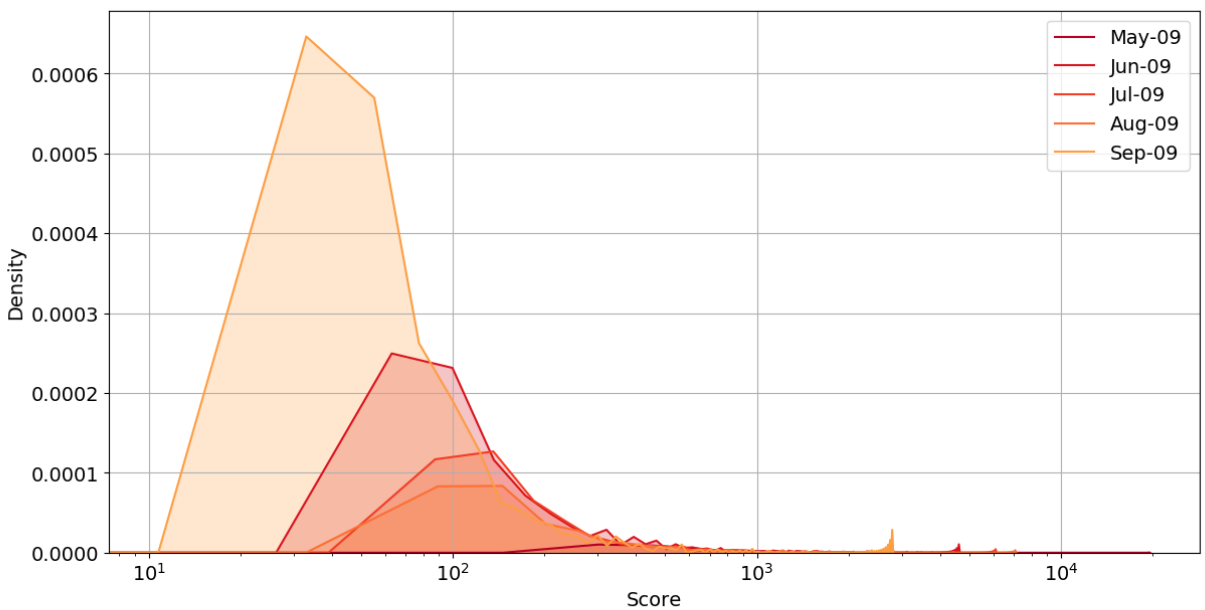
Source: Own calculations in PySpark.

Table 3: **ViewCount Variable Descriptive Statistics**

Dataset	Count	Mean	SD	Min	Max
May-09	26 026	13 817	8 1233	26	7 906 137
Jun-09	28 555	13 948	77 666	26	3 488 812
Jul-09	32 752	11 898	65 538	22	4 170 244
Aug-09	32 998	10 517	48 036	22	2 223 778
Sep-09	33 268	9 555	39 505	23	2 009 096

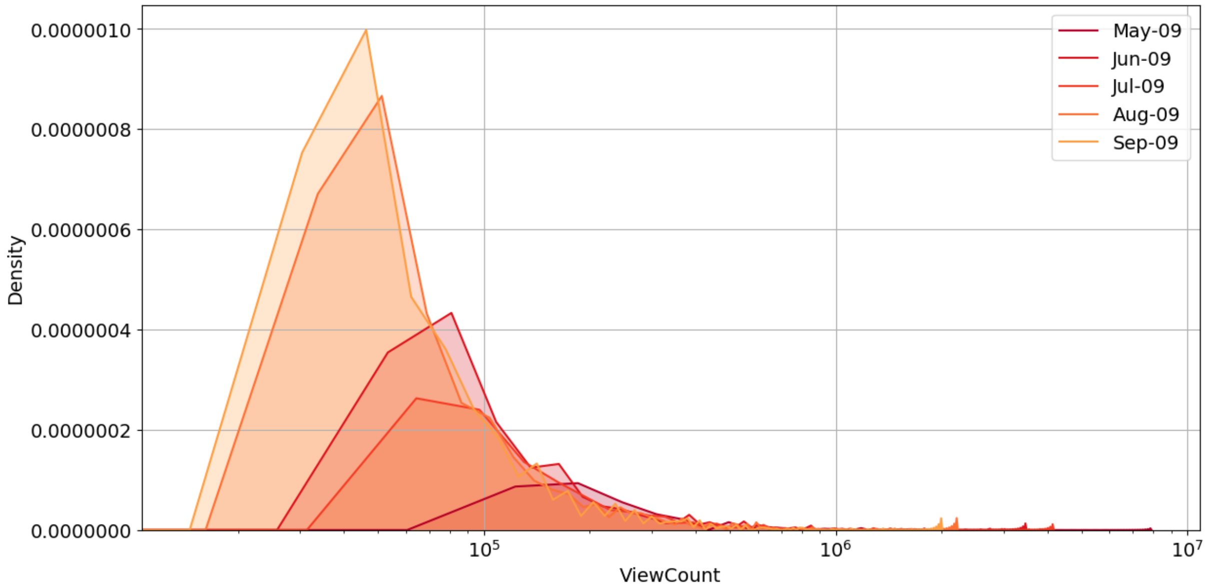
Source: Own calculations in PySpark.

Figure 1: **Score Variable Density Plot**



Source: Own calculations in PySpark.

Figure 2: **ViewCount Variable Density Plot**



Source: Own calculations in PySpark.

In the tables and figures above, we see that the distributions differ across monthly datasets for both the `ViewCount` and `Score` variables, and both variables appear to be highly positively skewed. The dataset for May seems to be particularly distinct from the others, with substantially flatter distributions for both variables. For the `Score` variable, the contrasting reputation levels for up- and down-voting privileges (15 and 125 respectively) discussed in the previous section no doubt are a primary driver of its positive skewness. This is due to the fact that if a question is to receive a vote at all, it is more likely to receive an up-vote.

In light of the positive skewness of both the `ViewCount` and `Score` variables, I opt to take their natural logarithm for the predictive task. In this way, errors in predicting very high scores and very low scores will affect the final evaluation metric in the prediction step equally. The descriptive statistics for the resulting `logScore` and `logViewCount` variables are displayed in tables 4 and 5 below.

Table 4: **logViewCount Variable Descriptive Statistics**

Dataset	Count	Mean	SD	Min	Max
May-09	26 026	7.8	1.7	3.3	15.9
Jun-09	28 555	7.7	1.7	3.3	15.1
Jul-09	32 752	7.6	1.7	3.1	15.2
Aug-09	32 998	7.5	1.7	3.1	14.6
Sep-09	33 268	7.5	1.7	3.1	14.5

Source: Own calculations in PySpark.

Table 5: **logScore Variable Descriptive Statistics**

Dataset	Count	Mean	SD	Min	Max
May-09	26 026	3.4	0.4	2.8	9.9
Jun-09	28 555	3.4	0.4	2.7	8.5
Jul-09	32 752	3.4	0.4	2.8	8.7
Aug-09	32 998	3.4	0.4	0.7	8.9
Sep-09	33 268	3.4	0.4	2.6	7.9

Source: Own calculations in PySpark.

This finally brings us to a discussion of what the distinction between the `Score` and `ViewCount` variables actually is. We now know that more views imply a higher `Score`, owing to the asymmetrical up- and down-voting privileges, but we don't know if there is reverse causality as well. An example of this would be questions with higher `Scores` spurring on more views as these questions rise to the top of popular search engines or "hot question" lists on the StackOverflow site.

Regardless of the intricacies of causality between the variables, it is worth noting that only members that have registered with the community are able to up-vote and down-vote and thus contribute to the `Score`. On the other hand, all questions are open to the public and therefore the `ViewCount` variable registers views from 1) registered users that can vote, 2) registered users that can't vote due to a reputation level below 15, and 3) non-registered members. This leads me on to a discussion on the decision of Ravi *et al.* (2014) to predict on a final response of `Score` divided by `ViewCount`.

Ravi *et al.* (2014) assert that `ViewCount` is a measurement of "popularity" and thus in order to strictly measure question quality, divides `Score` by `ViewCount` to mitigate conflating popularity with question quality. I point out however, that we have no way of knowing what the community-member composition of the `ViewCount` for given question is - i.e. when normalising by `ViewCount`, does this divide by a majority of individuals that can vote, can't vote or a entirely non-registered members in the community? The assumption of Ravi *et al.* (2014) is that the composition is a majority of individuals that can vote, which I believe is not a strong assumption given the popularity of the StackOverflow site with many non-registered members.

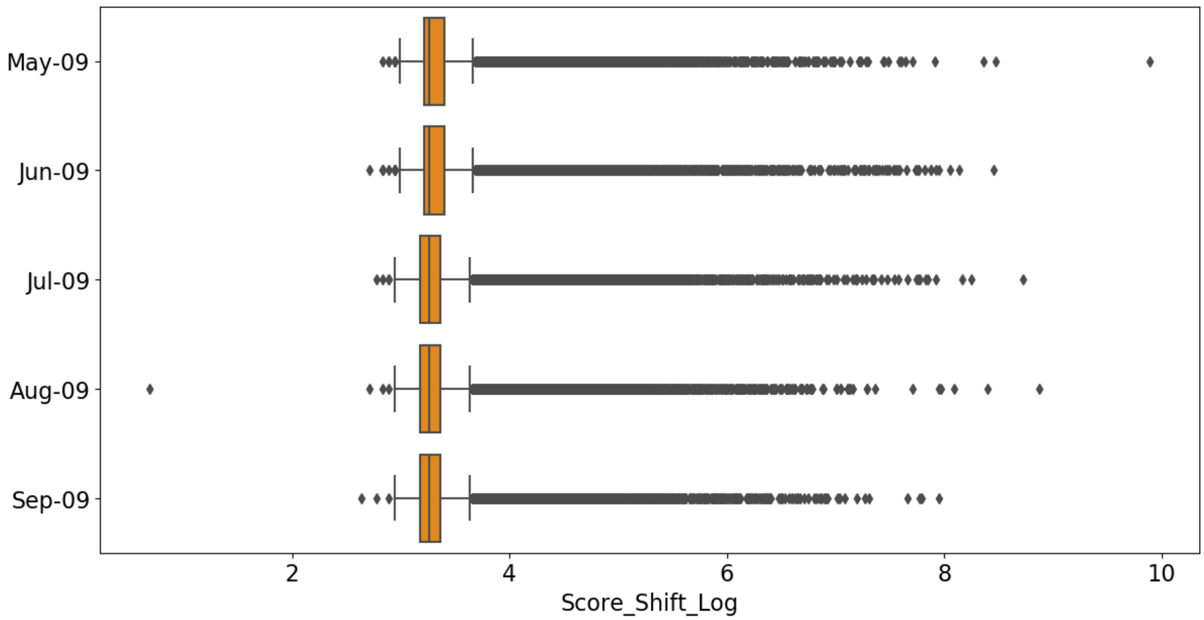
I establish a different framework that I believe is sounder: that of *within-community* engagement versus *outer-community engagement*. With these two definitions in mind, it is plain to see that the `Score` variable is primarily a within-community engagement metric since users are required to commit and register with the StackOverflow community to contribute to this variable by voting. `ViewCount` on the other hand can be seen as both a within- and outer- community engagement variable, because it does not distinguish between voting or non-voting status when registering question views. One obvious difference between the two is that the `Score` variable is a categorical metric in that users can choose between positive, negative and neutral engagement, whereas `ViewCount` only registers one dimension of engagement (i.e. whether a question has been visited or not).

I consequently make the decision to focus solely on within-community engagement and therefore use the `Score` variable as it is rather than normalise by the `ViewCount` variable. While popularity, or outer-community engagement, still may influence this variable to some extent as views drive more registered users to the question who subsequently vote, I take it as given that having the ability to attract views is yet another facet of attracting positive community engagement.

The choice of using a continuous `Score` variable also has two added benefits. Firstly, there is no need to choose a (potentially) arbitrary threshold to label good and bad questions for prediction. This decision in Ravi *et al.* (2014) led to a selection of only 66 388 questions for analysis out of 410 049, or less than 17%. Lastly, I believe providing `Score` predictions over `Score/ViewCount` predictions would be more informative to questioners looking to improve their answers.

The final `logScore` variable is shown in a boxplot across all five monthly datasets in figures 3. One last aspect to note is the significant number of outliers present over the datasets. Note that we do not want to remove these outliers, but aim to extract the features that make them so over- and under-valued in the StackOverflow community.

Figure 3: **logScore Variable Box Plot**



Source: Own calculations in PySpark.

3.3.3 Potential Methodological Issues

Two last potential methodological issues are discussed here. Firstly regarding the `Score` variable, one potential confounding factor is that questions can be edited, not only by the original poster, but by anyone with a reputation of 2 000 or more. General cross-community guidelines for editing include: addressing grammar and spelling issues, clarifying concepts, correcting minor mistakes, and adding related resources and links (https://stackoverflow.com/help/privileges/edit). The concern here is that users could vote, comment and answer on substantially different questions over time as a question is edited further away from its original form. The simplifying assumption that I make here is that most edits, if any at all, happen quickly as moderators and high-reputation users are made aware of offending questions and thus the majority of views and votes would happen on final, edited questions. Consequently, I choose to analyse final edited question content.

A second methodological adjustment that should be considered is the decision by Ravi *et al.* (2014) to only consider questions above a certain `ViewCount` threshold (which they choose to be 1 000). The reasoning they give for this is to increase their confidence that the final dataset contains questions that have been viewed by qualifying users that can vote. Similarly to their decision to normalise their response variable with `ViewCount`, I assert that we can not know if views are contributed by community members that can or can't vote since there is no data on the distribution of qualifying and non-qualifying user contributions to views. One could also just as easily argue that new questions that begin with a low `ViewCount` are more likely to see engagement from proactive community members, especially if these questions don't generate enough webpage activity and views to rise to the top hit for search engines (which incidentally would most likely lead to more non-community member contribution to views). I therefore opt to not disregard any questions below a certain `ViewCount` threshold.

3.4 Feature Selection

The features that I incorporate into the prediction task are extracted from only the textual content of questions. These features reduce variable-length documents to fixed-length vectors of real numbers, essentially numerically summarising documents so that they can be represented as features with the same dimensions. Common feature extraction methods include bag-of-words, term frequency-inverse document frequency (TF-IDF), latent Dirichlet allocation (LDA) and word-embeddings. Since I focus on textual features of questions only, all my features are based on the `Body` and `Title` content of questions. I apply the bag-of-words, TF-IDF and latent Dirichlet allocation feature extraction methods.

3.4.1 Question Length

Length textual features are simple features that can be extracted from the number of characters, the number of words (or tokens) and the number of sentences. I will extract these features for both the `Body` and `Title` of each question, which will be used later in a *length* model in the prediction task.

3.4.2 Bag-of-words

Bag-of-words is a simple textual feature extraction method which maps documents into *term-frequency* vector. This method does not take the order of words within a document into account, and if single words (unigrams) are extracted it does not take into account the co-occurrence of words. To include the co-occurrence of words, one can extract n successive words, or ngrams. Naturally, bag-of-words assumes that the most relevant information in the document is included in the term frequency vector.

The bag-of-words method works by splitting each a document into an array of words or terms (tokenising), and takes their counts as features (with counts of 0 included) - this is the resulting term frequency vector. In order to extract these term frequency vectors from the string `Body` and `Title` of questions, I will parse the HTML content of the `Body` variable and tokenise lower-case terms from both the `Body` and `Title` content, without punctuation. I will also remove English stopwords, which are words that are void of meaning, according to Porter stemming (Porter, 1980).

Once these term frequency vectors have been extracted, each term frequency for a term is considered a feature, with all the term frequencies in a term frequency vector representing a document. In this way, a corpus of documents is represented by a feature matrix with one row per document and one column per word/term.

3.4.3 TF-IDF

Evidently in a large corpus, certain words will occur more often than others. While it is possible to remove many words that have little to no meaning (stopwords), the counts in the term frequency vector from bag-of-words will obviously weight more frequent words, potentially at the expense of words that are rarer, but more meaningful to the analysis. One popular method to address this problem is TF-IDF (Salton and McGill, 1983).

The TF-IDF scheme is a method that re-weights and normalises the term frequencies and compares them to inverse document frequencies, which are also suitably normalised. Formally, let $\mathrm{tf}(t, d)$ denote the term frequency of a term t in a document d. The inverse document frequency for t is then the following:

$$\mathrm{idf}(t) = \log \frac{1 + D}{1 + \mathit{df}(t)} \tag{1}$$

where D denotes the total number of documents in the corpus, and $\mathit{df}(t)$ denotes the number of documents containing term t.

The TF-IDF vectors $\text{tf-idf}(t, d)$ are then given by

$$\text{tf-idf}(t, d) = \mathrm{tf}(t, d) \times \mathrm{idf}(t) \tag{2}$$

and are finally normalised using the Euclidean norm:

$$\text{tf-idf}(t,d)_{norm} = \frac{\text{tf-idf}(t,d)}{\sqrt{\text{tf-idf}(1,d)^2 + ... + \text{tf-idf}(T,d)^2}} \tag{3}$$

where T is the total number of terms in the corpus.

As in bag-of-words, the final result is a term-by-document matrix where columns now contain normalised TF-IDF values for each document and which can be used as features for in a predictive model.

3.4.4 Latent Dirichlet Allocation

LDA (Blei *et al.*, 2003) is an unsupervised, generative, three-level hierarchical Bayesian model that can be used to discover the latent topics in a corpus. LDA assumes that each document is a finite mixture of a certain number of abstract topics, that each topic is a discrete probability distribution over words, and that each word is generated according to one of these topics. In practice, the topics and other structure are hidden, and so we have to infer them from the observable documents.

Topic mixtures across documents share a Dirichlet prior, and all word distributions of topics have another common Dirichlet prior (Blei *et al.*, 2010). The Dirichlet distribution is a multivariate generalization of the beta distribution and is useful in facilitating LDA inference and parameter estimation algorithms because 1) it is in the exponential family, 2) it has finite dimensional sufficient statistics, and 3) it is conjugate to the multinomial distribution. Since Dirichlet distributions are distributions over multinomial parameter vectors (vectors of positive values that sum to one), they are also convenient to qualitatively infer what topics represent by examining the highest probability words per topic.

To formalise notation:

- Let the the number of assumed topics be denoted K
- Let the each of the document d have length N_d, with D questions in the corpus of interest
- Let $\text{Dir}(a)$ denote the Dirichlet distribution with symmetric parameter a

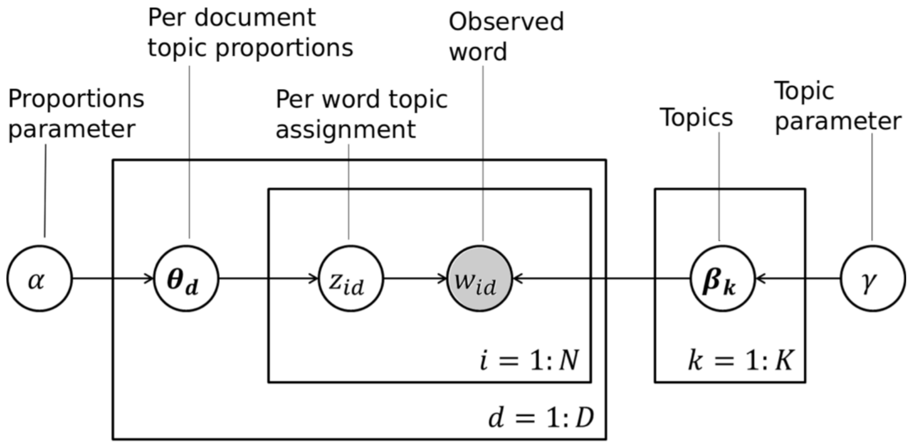
The generative process assumed by LDA is then:

for each topic $k = 1, ..., K$ **do**
  Generate word-distribution $\beta_k \sim \text{Dir}(\gamma)$
end for
for each document $d = 1, ..., D$ **do**
  Generate topic-distribution $\theta_d \sim \text{Dir}(\alpha)$
  for each position $i = 1, ..., N_d$ in document d **do**
    Generate a topic $z_{id} \sim \text{Multinomial}(\theta_d)$.
    Generate a word $w_{id} \sim \text{Multinomial}(\beta_{z_{id}})$.
  end for
end for

Again, the words w_{id} are the only variables that are observed, whereas the topic-document mixtures θ_d and topic-word distributions β_k are latent, or hidden. The Dirichlet priors for the aforementioned multinomial distributions are α and γ respectively, which represent the hyper-parameters of the LDA model.

Since each document has a unique topic mixture, and these topics are distributions over the corpus vocabulary, LDA can also be viewed as a mixed membership model. A graphical model representation of LDA is depicted in figure 4 below, which highlights the hierarchical and multi-level structure of the model.

Figure 4: **A Probabilistic Graphical Model of LDA**



Source: Rasmussen (2015). Nodes are random variables, edges indicate dependence and shaded nodes indicate observed variables. Note that in this figure, all documents are assumed to have fixed length N.

Based on the data generation process above and given the hyperparameters α and γ, the joint distribution of the topic-word distribution, topic mixture, topic assignments and words is given by:

$$\mathrm{P}(\beta_{1:K}, \theta_{1:D}, \{z_{id}\}, \{w_{id}\}|\alpha, \gamma) = \prod_{k=1}^{K} \mathrm{P}(\beta_k|\gamma) \prod_{d=1}^{D} \left[\mathrm{P}(\theta_d|\alpha) \prod_{i=1}^{N_d} [\mathrm{P}(z_{id}|\theta_d)\mathrm{P}(w_{id}|\beta_{1:K}, z_{id})] \right] \tag{4}$$

To analyse a corpus, the assumed data generation can be "reverse engineered" by computing the posterior modes of the latent variables given the words that have been observed. To compute the posterior over the parameters $\beta_{1:K}$ and $\theta_{1:D}$ given the words $\{w_{id}\}$ however, we have to marginalise out the latent topic assignments $\{z_{id}\}$, and this computation is intractable. This leaves researchers to call upon approximate posterior inference.

Algorithms that are now available for this inference task include variational Bayesian (VB) inference proposed in the original paper by Blei *et al.* (2003), maximum a posteriori estimation (Chien and Wu, 2008) and collapsed Gibbs sampling which was derived for LDA in Griffiths and Steyvers (2004). I now move on to a formal discussion of VB inference.

In VB inference, the true posterior is approximated by a simpler distribution, $q(\{z_{id}\}, \eta, \phi)$, which is as close to the posterior as possible. More specifically, a simpler convex distribution is used to ascertain a flexible lower bound on the true posterior. The problematic coupling between θ and β parameters are dropped to make computation tractable. Maximising the lower bound is equivalent to minimising the Kullback-Leibler (KL) divergence between $q(\{z_{id}\}, \eta, \phi)$ and the posterior in 4, where the KL divergence is a measurement of how disparate distributions are and is given by:

$$\mathrm{KL}(f||g) = \sum_{x \in \mathcal{X}} g(x) \log\Big(\frac{f(x)}{g(x)}\Big) \tag{5}$$

for two distributions f and g on a countable set $\mathcal{X}$.

Finally, the variational distribution has the bound given in equation for each document in the corpus 6, with the optimisation equation given in equation 7:

$$q(\theta, \{z_{id}\}|, \eta, \phi) = q(\theta|\eta) \prod_{i=1}^{N_d} q(\{z_{id}\}|\phi_i) \tag{6}$$

$$(\eta^*, \phi^*)) = \underset{(\eta,\phi)}{\mathrm{argmin}} \mathrm{D}(q(\theta, \{z_{id}\}|, \eta, \phi) \quad || \quad \mathrm{P}(\theta, \{z_{id}\}|\{w_{id}\}, \alpha, \gamma)) \tag{7}$$

The size of the datasets I have chosen to analyse necessitate a computationally efficient algorithm, of which two modern approaches stand out: online VB proposed by Hoffman *et al.* (2010), and the expectation maximisation algorithm developed by Asuncion *et al.* (2009), both of which can be implemented with the PySpark `pyspark.sql.ml.clustering.LDA` package. I will employ the online VB implementation in Hoffman *et al.* (2010). This technique is based on online stochastic optimisation, and uses multiple passes to fit the LDA topic model to a dataset, updating the term-topic distribution adaptively. Ravi *et al.* (2014) provide a summary of the algorithm as it relates to this research problem, which is stated below.

Online LDA Inference Algorithm

Until converged:

1) Randomly choose a mini-batch of questions.
2) For each question in the chosen mini-batch:
    a) Estimate the approximate posterior over which topics each word in each question came from
3) Partially update the approximate posterior over the topic distributions in accordance with the words that are believed to come from specific topics.

Online LDA is not only efficient in analysing immense document collections, but also in dealing with streaming data, which would be useful to incorporate future questions incrementally on the StackOverflow site. Having discussed the LDA model and other textual feature extraction methods, this now brings us to the prediction task.

3.5 Predictive model

In this section I describe the approach I take in modelling community engagement in the Stack-Overflow community, represented by the `logScore` variable. Ravi *et al.* (2014) build models with features from the length, textual content and latent topics of questions for their binary classification of questions, and my goal is to investigate whether these models are as effective in predicting `logScore` as a measurement of community engagement in a regression setting.

3.5.1 Regularised Regression

Let q_i represent question i out of all questions Q, which is split into a training set Q_{train} (50%) and testing set Q_{test} (50%). Let s_i denote the `logScore` of each question. Using regularised regression, I predict s_i using only features derived from the raw textual `Body` and `Title` of each question, where these features are denoted $\boldsymbol{x}'_i$. The learning objective therefore, is to find a weight vector $\boldsymbol{w}$ which minimises the residual sum of squares of the training corpus Q_{train}:

$$\underset{\boldsymbol{w}}{\text{minimise}} \quad \sum_{q_i \in Q_{\text{train}}} (s_i - \boldsymbol{w}\boldsymbol{x}'_i)^2 + \lambda \sum_{j=1}^{p} w_j^2 \tag{8}$$

where λ is a regularisation parameter to prevent overfitting.

For the prediction task, I employ a grid search over the λ parameter for a range of 0.001 to 1, and use 2-fold cross validation to select the best performing model on Q_{train}. I choose 2-fold cross validation since increasing the number of folds had no significant effect on predictive performance.

3.5.2 Train/Test Split

One area worth investigating before the prediction task, is potential heterogeneity in the train and test split, with specific focus on heterogeneity with regard to time. After randomly splitting Q into Q_{train} and Q_{test} of equal sizes, descriptive statistics for each set are calculated and depicted in table 6, rounded to two decimal places.

Table 6 demonstrates that the means and standard deviations within datasets are similar, with the largest absolute difference being 0.03 standard deviations in the August dataset. What is interesting however, is that there is a decreasing trend for both variables over time from May to August - however whether this is specific to this data range, or is an indication of downward trends in the mean and standard deviation of the `logScore` (and by implication the `Score`) variable is unknown.

Table 6: **logScore Descriptive Statistics for Random Train/Test Split**

Dataset	**Train Mean**	**Test Mean**	**Train SD**	**Test SD**
May-09	3.4	3.4	0.43	0.42
Jun-09	3.4	3.4	0.43	0.43
Jul-09	3.38	3.38	0.4	0.4
Aug-09	3.36	3.37	0.36	0.39
Sep-09	3.36	3.36	0.35	0.36

Source: Own calculations in PySpark

In the interest of robustness I investigate whether there are substantial differences in means and standard deviations within datasets for a temporal train/test split. The descriptive statistics for a temporal train/test split are displayed in table 7 below, again rounded to two decimal places.

While there appears to be a common trend of slightly smaller means and standard deviations in the test sets for all months, these differences do not appear to be significantly larger than in the random train/test split. This at least provides some evidence for my assumption that the monthly StackOverflow datasets that I have selected are relatively homogeneous with respect to time. I now use the random train/test split for the modelling of the `logScore` variable.

Table 7: **logScore Descriptive Statistics for Temporal Train/Test Split**

Dataset	**Train Mean**	**Test Mean**	**Train SD**	**Test SD**
May-09	3.4	3.4	0.42	0.43
Jun-09	3.4	3.4	0.44	0.42
Jul-09	3.39	3.37	0.42	0.39
Aug-09	3.37	3.37	0.38	0.37
Sep-09	3.36	3.35	0.36	0.35

Source: Own calculations in PySpark

3.5.3 Features

I use the `Body` and `Title` content of questions as separate signals for feature extraction in the StackOverflow community. I extract numerical length features on both the pre-processed `Body` and `Title` variables, employ bag-of-words feature extraction to ascertain term frequency vector features and also translate these into TF-IDF features. I use only unigram features for the bag-of-words and TF-IDF feature extraction, since there were no improvements in performance for higher order ngrams from a held out dataset in the predictive task.

As discussed by Ravi *et al.* (2014), there are a number of aspects that could define a good question, or in the framework presented here, a question that is highly valued by the StackOverflow community. Bag-of-words and TF-IDF may capture certain aspects about questions that are stated particularly clearly or that show prior research through the mentioning of key words, but there are also other more subtler aspects of questions, such as topical relevance, that could signal question constructiveness.

Evidently, a range of overall topics is discussed in the StackOverflow community every day, week, month and so on. Ravi *et al.* (2014) assert that there may be community engagement variation along these topics due to 1) differing behaviour of sub-communities in terms of how up- and down-votes are attributed to questions about specific topics, and 2) questions concerning popular versus unpopular topics receiving varying degrees of community engagement. They use this as a motivation for including features in their prediction task relating to “global” topic information - global here meaning that these topics reflect what entire questions are about. Since these global topics from questions in the StackOverflow community can be extracted in an unsupervised way with latent topic models, they employ LDA to do precisely this.

I employ global the LDA topic model from Ravi *et al.* (2014), and train the online LDA model (Hoffman *et al.*, 2010) over all questions Q. I choose $K = 10$ topics and sparse Dirichlet priors, setting hyperparameters γ and α to a value of 0.01 to encourage the learning of fewer topics per question and sparser topic-word distributions. For each question $q_i \in Q$, I add a feature for topic k with weight $\theta_{q_i k}$ (the inferred topic mixture for question q_i), resulting in 10 features $(\theta_{q_i 1}, \theta_{q_i 2}, ..., \theta_{q_i 10})$ being incorporated for the prediction task per question.

Table 8 shows the top three words per dataset for the 10 sample topics learned in the global LDA model. While these words can help the researcher interpret what the topics concern qualitatively, the true topics will still remain unknown to us. In table 8 we see a range of words that are intuitive, such as *file*, *system*, *twitter* and *socket* etc., as well as words that evidently relate to code extracts in the StackOverflow questions like *div*, *std*, *id*, and *class*. Computer programming languages that the topics appear to be capturing over the monthly datasets include Java, PHP, Ruby, Python and the distributed version-control system Git. All in all, it does appear as if the global LDA model is capturing the “aboutness” of questions to some extent.

Table 8: **Top Words of Global LDA Sample Topics**

Topic	May 2009	June 2009	July 2009	August 2009	September 2009
T1	amp quot lib	imagenam usernam dim	file use system	amp mx twitter	imag menuviewcontrol socket
T2	myclass round treeview	xs width height	helloworld self amp	file user class	lib gem rubi
T3	nhibern station buffer	node neutral publickeytoken	po objnicitem public	char th org	public string xsd
T4	xxx java assembl	countri branch span	amp nbsp me	self std int	sbquo task amp
T5	xsd wsdl anim	div std id	int string std	boost xsl system	java org eclips
T6	control imag public	lib gem rb	java org hibern	div id php	class file id
T7	id div tabl	id select tabl	py date cout	option valu woot	system param dll
T8	file string server	java xsl file	param string thread	width id nbsp	mx unsign hibern
T9	encrypt system http	cach dword age	div text id	xs org schema	id routecount git
T10	java org defaultactioninvoc	int list class	bf xsl xs	java apach org	xsl menuviewcontrol cell

Source: Own calculations in PySpark

3.5.4 Evaluation

A question that still remains is what evaluation metric to use to compare across models and across datasets. Both the mean absolute error (MAE) and the root mean square error (RMSE) are frequently employed as model evaluation metrics in the broad literature, but as statistics that condense and summarise the data into a single value, they characterise model performance error characteristics in decidedly distinct manners.

Criticisms have been laid against RMSE asserting that 1) it does not indicate average model performance well and may be a misleading indicator of average error (Willmott and Matsuura, 2005), and 2) it is ambiguous in interpretation because as a sums-of-squares-based statistic it does not satisfy the triangle inequality for distance metrics (Willmott *et al.*, 2009). Chai and Draxler (2014) demonstrate however that RMSE does satisfy the triangle inequality requirement however, and thus confirm that RMSE is not ambiguous in meaning.

Contrary to the assertion that RMSE does not describe average model performance well, Chai and Draxler (2014) go on further to affirm that RMSE is actually a more appropriate metric over MAE when the error distribution of the model is expected to be Gaussian instead of uniform, and when there are sufficient samples. They note that while RMSE is more sensitive to outliers, the Gaussian distribution describes the existence and probability of outliers well and moreover, since RMSE gives more weight to unfavourable conditions, it may discriminate better between model performance differences.

In light of the findings of Chai and Draxler (2014), I choose to use RMSE to evaluate model performance. Firstly, my sample sizes are not small, ranging from 26 026 to 33 268. Secondly, the large number of outliers identified in the `logScore` variable and depicted in figure 3 in section 3.3.2 are indeed not anomalies in the data, but are highly valuable data points because of the extent to which the StackOverflow community engages positively or negatively with these questions. I therefore believe that a higher weighting for these points is not problematic. Lastly, I assume that the error distributions of models for the `logScore` variable are more likely be Gaussian as opposed to uniform.

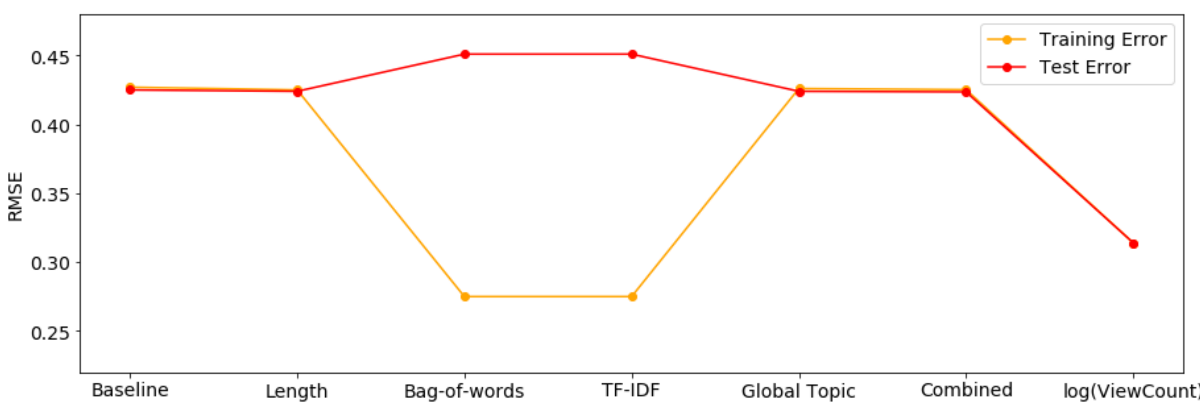
4 Results

In order to be able to draw some comparisons of how well the predictive models are faring, I establish both a low and high benchmark for predictive performance on the `logScore` variable. The low benchmark consists of using the mean of `logScore` in the training set as the prediction for every question in the test set, and the high benchmark uses the `logViewCount` variable alone to predict on `logScore`.

Figures 5 to 9 display the training and test RMSE results for each model employed. The following models are listed from left to right on the x-axis:

- The constant mean baseline
- The length model, which includes features derived from token counts, sentence counts and character counts
- The bag-of-words model (which Ravi *et al.* (2014) refer to as the *text* model)
- The TF-IDF model
- The global LDA topic model, which includes inferred latent topic mixtures
- A final combined model which incorporates features from both the length and topic models (but not bag-of-words or TF-IDF)
- The high benchmark model with `logViewCount` as a single feature (note that this model is vacuous since the `ViewCount` variable is not available for new questions)

Figure 5: **Model Training and Test RMSEs for May 2009**



Source: Own calculations in PySpark.

Figure 6: **Model Training and Test RMSEs for June 2009**

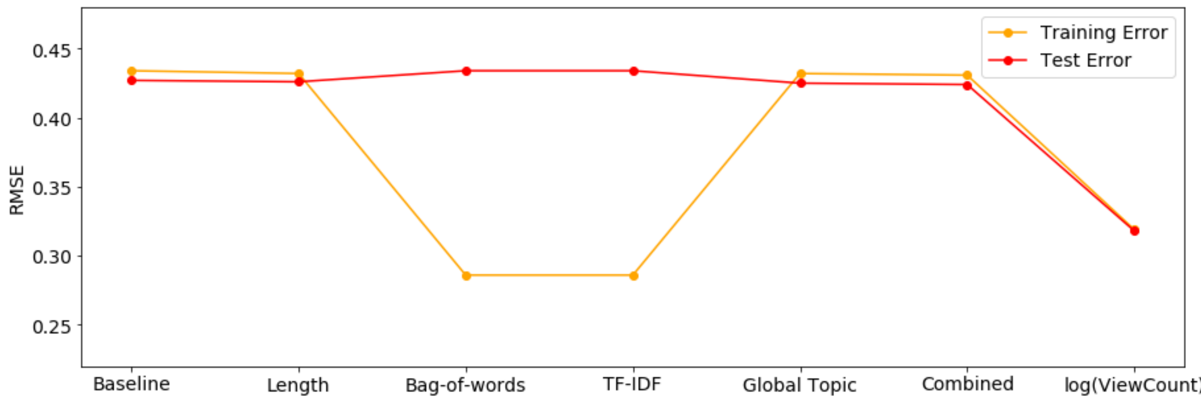


Figure 7: **Model Training and Test RMSEs for July 2009**

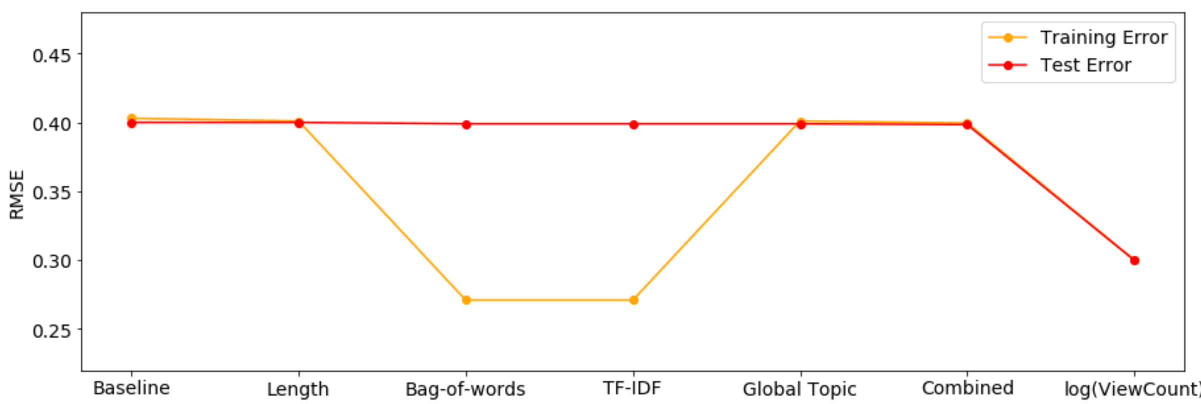
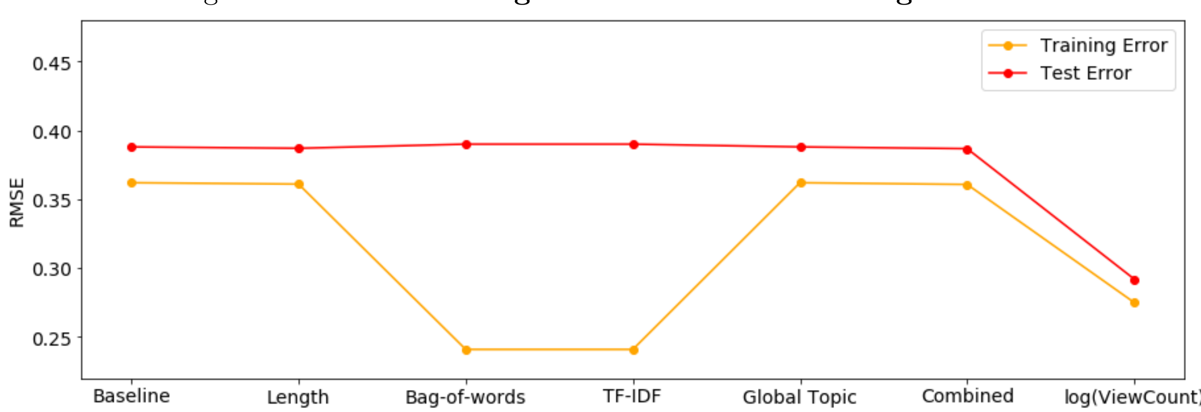
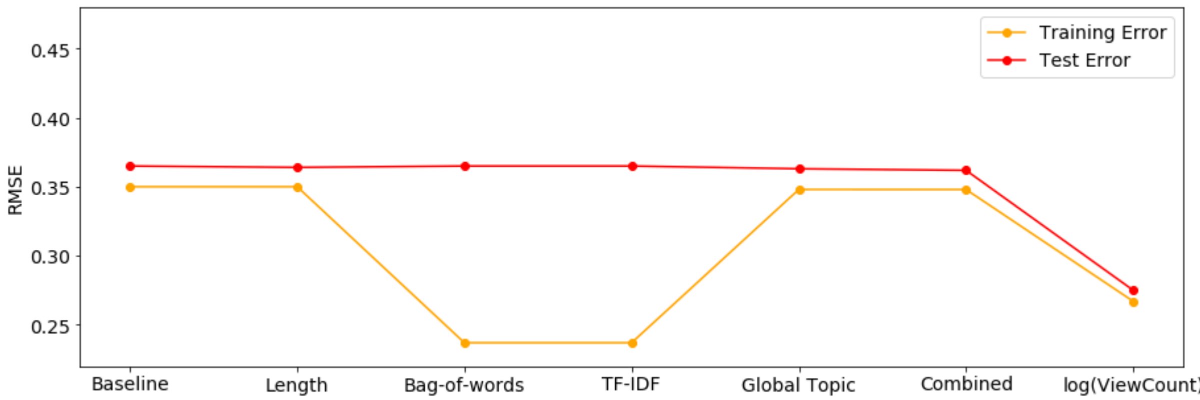


Figure 8: **Model Training and Test RMSEs for August 2009**



Source: Own calculations in PySpark.

Figure 9: **Model Training and Test RMSEs for September 2009**



Source: Own calculations in PySpark.

The most striking result across all monthly datasets is how consistent the results are for the test RMSE on all models except for the `logViewCount` model, which beats out the baseline with a reduction of around 25% in RMSE for all five monthly datasets. This high performance is analogous with the high correlations between `Score` and `ViewCount` seen in table 1 in section 3.3.2. The other models besides the `logViewCount` model show no improvement in test RSME over the baseline, which leads to model test RMSEs mirroring the test set standard deviations seen in table 6, since the models are performing no better than a constant mean prediction on the test set.

For the training error curves, we again see consistent results in the length, global topic and combined model, but significantly lower training errors for the bag-of-words and TF-IDF models. Test RMSE for the bag-of-words and TF-IDF models is marginally higher than the baseline for September and August, but substantially higher in May and June, demonstrating a prevalence of overfitting for these models, since this implies *worse* performance than constant training mean prediction.

Interestingly, we see that the test RMSE coincides or is lower than training RMSE for all models across the May, June and July datasets. If we re-examine table 6 in section 3.5.4 however, we see the reason for the lower test error curves is that the standard deviations of the test set are lower than the training set while the means are almost identical. Thus, by predicting the same mean for both sets but where the test set has less variance, the result will naturally be a lower test RMSE.

Evidently, none of the textual features extracted appear to be good predictors of the `logScore` variable in this regression setting - the models do not appear to be learning specific key words, weighted or otherwise, nor topics identified by the global LDA model that differentiate between positive and negative community engagement. These results thus give us the answer to the research question stated in section 1, namely that with the textual question content features that I extracted in this framework, I am *not* able to predict the `logScore` variable as a measurement of online Q&A community engagement with question content alone.

Recall that Ravi *et al.* (2014) achieved a classification accuracy of 55.5% for their length model, 65.8% in their text model, 64.2% in their global topic model and 70.5% in their combined model with all three types of features obtains (text included), all above a benchmark of 61.1% for their `ViewCount` model. Having extracted questions from the same online Q&A community and time period as Ravi *et al.* (2014), the differences in our methodologies were 1) I predict on the `logScore` variable rather than `Score/ViewCount`, 2) I employ a regression model rather than classification, and 3) I use all the data from monthly time frame, instead of a subset of the data.

While direct comparison to the results of Ravi *et al.* (2014) is limited owing to the aforementioned methodological extensions, my results starkly contrast the same question content models Ravi *et al.* (2014) employed. A particular aspect to point out is that the `ViewCount` model in Ravi *et al.* (2014) was outperformed by the majority of their models, however the results above show that the `logViewCount` model outperforms by a very strong margin.

Ostensibly, accurately predicting a continuous measurement of community engagement from question content alone in a regression setting is an ambitious task, and a task which may not see the success of the likes of the classification model employed in Ravi *et al.* (2014). Nevertheless, I believe it is a useful framework in the interest of providing continuous community engagement predictions to questioners, upon which further research may investigate. This brings me onto how I believe future research can improve upon the results presented here.

5 Recommendations for Further Research

5.1 Improving Methodological Robustness

For recommended areas of further research, I first discuss methodological improvements that I believe would benefit the analysis. In section 3.3.3, I mentioned some potential issues regarding some finer nuances in the functioning of the StackOverflow website. Out of these limitations, the permitted editing of questions stands out as the strongest methodological limitation. As a reminder, questions can be edited not only by the original questioner, but by any community member with 2 000 reputation or more. This means that community members could view and vote on edited questions that are fundamentally different from the original question. While I assumed that this editing was minimal and took place quickly so that very few views and votes were cast on previous versions of questions, suggestions for further research would be investigating 1) how much editing takes place over questions, 2) the time taken until edits versus votes cast and views accumulated, and 3) how evenly editing is distributed over questions.

As discussed in detail in section 3.3.1, there are other options for community engagement besides the `Score` variable, each with their own advantages and disadvantages. While I believe I thoroughly justified and validated my choice of the `Score` variable as an objective and informative response, a thorough exploration of community engagement measurements in different research frameworks may prove fruitful, especially of binary metrics in a classification setting given that prediction in a regression setting here was unsuccessful. Furthermore, Ravi *et al.* (2014) claim that their methods are applicable to other Q&A platforms given that they do not rely on domain-specific knowledge. Consequently, it may well be worthwhile to replicate both Ravi *et al.* (2014) and my analysis on other Q&A communities to gain insight into how our predictive models fare there.

Lastly, although temporal aspects of the data were discussed thoroughly in this paper, I believe this is still a prominent area for further analysis. Further research could investigate the extent to which older questions are biased to have higher `Scores` and `ViewCounts`, and what the main sources of potential bias are (i.e. time, questioner variation, community variation or community-structure variation). I am of the opinion that: the types of questioners asking questions, the way in which questioners ask questions, the composition of the StackOverflow community and overall community engagement behaviour, have all varied substantially over the many years that StackOverflow has been active. This would suggest that any model aiming to predict future community engagement in online Q&A fora must be expanded to include time-series elements (regardless of how short the time span of the data is). This brings me to additional techniques that could improve on the predictive performance in this paper.

5.2 Improving Model Performance

Although the equally poor results of the diverse textual feature models in this paper hint that further feature engineering may not significantly improve model performance, there are a number of more sophisticated feature engineering methods available to employ that may yet yield improvements. Ravi *et al.* (2014) assert that, in addition to global topic models, local topic models may also contain useful information for predicting community engagement. The authors implement two such models that relate to the internal structure of questions such as demonstrating aspects of prior research, a problem statement, reproducible code, and so on.

Ravi *et al.* (2014) follow the work done by Brody and Elhadad (2010) on capturing local document aspects with LDA models over sentences and employ a local sentence-level model to capture certain aspects within questions. For the model with features from local sentence-level topics in Ravi *et al.* (2014), they obtain a classification accuracy 61.4%. The last LDA model employed by Ravi *et al.* (2014) is a generalized Mallows (Fligner and Verducci, 1986) global topic structure model. This model aims to capture discourse-level properties such as adjacent sentences sharing the same topics and related questions with comparable topics in similar orders, however yields only 55.6% accuracy. I believe that the extraction, evaluation and comparison of models with these features to the those in this paper would prove insightful.

Blei *et al.* (2010) note that a key limitation for LDA is that it requires the number of topics to be fixed in advance. Further research can also therefore explore the most prudent choice for the number of topics, K, possibly by examining predictive fits on held out documents, or by selecting the value based on the marginal probability of the corpus.

Other feature engineering techniques that stand out as areas of further research include word-embeddings introduced by Mikolov *et al.* (2013), and even simple dictionary methods that identify sentiment and emotional language. The substantial literature on outliers and outlier detection was also not discussed in this paper, yet owing to the appearance of the numerous outliers in the StackOverflow data, this is seemingly a field ripe for investigation. Lastly, I believe that a major room for improvement concerns the predictive model employed in the regression setting of this paper. I leave it to further research to explore more complex predictive models in both the classification setting of Ravi *et al.* (2014) and the regression setting here, to ascertain if question content can predict a measure of community engagement with some accuracy.

6 Concluding Remarks

The goal of this paper was to build on a relatively unstudied area of research and to test previously successful predictive question content models on a continuous, comprehensive and objective measurement of online community engagement. This objective has a valuable use-case, namely to provide questioners in online Q&A communities with real-time predictions of how positively a community will engage with their question, therefore allowing them to improve their questions before adding demand to expert resources in a community.

In the context of the StackOverflow community, I showed that the `Score` variable is an ideal measure of community engagement for three reasons. First, it is a primary function of the community. Secondly, it is able to register both negative and positive community engagement. Third, it is highly informative. Importantly, the methodology presented here can be implemented on more diverse online community datasets for evaluation: the `Score` variable is available across all of the 174 StackExchange communities, and similar metrics can be found on other Q&A platforms like Quora, MOOCS and so on.

The main extension of the analysis in Ravi *et al.* (2014) that I made was to predict on a continuous measurement for community engagement in a regression setting, rather than classification of binary categories of questions. I also touched on the aspect of temporality in online Q&A communities that has yet to be considered in the literature. I asserted that there are almost certainly temporal trends inherent in online Q&A data extracted from long time periods and thus chose to analyse data over monthly time periods in order to mitigate potential problems relating to temporality. Lastly, I used all question data within my selected time period, compared to Ravi *et al.* (2014) who selected a subset of around 16% from questions extracted over a year.

My results fared poorly for models with features engineered from question content, especially regarding the performance of models in Ravi *et al.* (2014) in their framework, who found that question content models performed substantially better than a strong baseline. I found that question length, textual-content and latent topic models had no better performance in RMSE than a trivial benchmark of constant training mean prediction, and also found that a model including only the `logViewCount` variable outperformed all other models significantly. In light of the poor predictive performance of the models employed in this paper, I recommend future work explore more sophisticated predictive models and textual feature engineering, as well as other binary community engagement variables in a classification setting.

Predicting on a continuous measurement of community engagement using only question content is evidently an ambitious goal. To the best of my knowledge, no prior research has endeavoured to capture and predict community engagement in this regard, and so at the very least this research has taken a humble step forward in predicting online community engagement in real time. I leave it to future research to extend the methodology that I have developed here, with the possibility of significantly enhancing the functioning of all online Q&A communities by accurately predicting online Q&A community engagement.

References

Agichtein, E., Castillo, C., Donato, D., Gionis, A. and Mishne, G. (2008) 'Finding high-quality content in social media', in *Proceedings of the 2008 international conference on web search and data mining*, pp. 183–194. doi: 10.1145/1341531.1341557.

Alexa.com (2019) 'The top 500 sites on the web'. Available at: https://www.alexa.com/topsites.

Allamanis, M. and Sutton, C. (2013) 'Why, when, and what: Analyzing stack overflow questions by topic, type, and code', in *2013 10th working conference on mining software repositories (msr)*. IEEE, pp. 53–56. doi: 10.1109/MSR.2013.6624004.

Anderson, A., Huttenlocher, D., Kleinberg, J. and Leskovec, J. (2012) 'Discovering value from community activity on focused question answering sites: a case study of stack overflow', in *KDD*. ACM, pp. 850–858. Available at: http://dl.acm.org/citation.cfm?id=2339665.

Asuncion, A., Welling, M., Smyth, P. and Teh, Y. W. (2009) 'On smoothing and inference for topic models', in *Proceedings of the 25th conference on uncertainty in artificial intelligence*. AUAI Press, pp. 27–34.

Bian, J., Liu, Y., Zhou, D., Agichtein, E. and Zha, H. (2009) 'Learning to recognize reliable users and content in social media with coupled mutual reinforcement', in *Proceedings of the 18th international conference on world wide web*, pp. 51–60. doi: 10.1145/1526709.1526717.

Blei, D. M., Ng, A. Y. and Jordan, M. I. (2003) 'Latent Dirichlet Allocation', *Journal of Machine Learning Research*, 3, pp. 993–1022.

Blei, D., Carin, L. and Dunson, D. (2010) 'Probabilistic Topic Models: A focus on graphical model design and applications to document and image analysis', *IEEE signal processing magazine*, 27(6), pp. 55–65. doi: 10.1038/jid.2014.371.

Brody, S. and Elhadad, N. (2010) 'An unsupervised aspect-sentiment model for online reviews', in *HLT/naacl*. Association for Computational Linguistics, pp. 804–812.

Chai, T. and Draxler, R. R. (2014) 'Root mean square error (RMSE) or mean absolute error (MAE)? - Arguments against avoiding RMSE in the literature', *Geoscientific Model Development*, 7(3), pp. 1247–1250. doi: 10.5194/gmd-7-1247-2014.

Chiang, D., Graehl, J., Knight, K., Pauls, A. and Ravi, S. (2010) 'Bayesian Inference for Finite-State Transducers', in *HLT/naacl*, pp. 447–455.

Chien, J. T. and Wu, M. S. (2008) 'Adaptive Bayesian latent semantic analysis', *IEEE Transactions on Audio, Speech and Language Processing*, 16(1), pp. 198–207. doi: 10.1109/TASL.2007.909452.

Daumé, H. and Marcu, D. (2006) 'Bayesian query-focused summarization', *ACL*, 1, pp. 305–312.

Eppler, M. J. and Mengis, J. (2004) 'The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines', *Information Society*, 20(5), pp. 325–344. doi: 10.1080/01972240490507974.

Fligner, M. and Verducci, J. S. (1986) 'Distance based ranking models', *Journal of the Royal Statistical Society: Series B (Methodological)*, 48(3), pp. 359–369.

Griffiths, T. L. and Steyvers, M. (2004) 'Finding scientific topics', *Proceedings of the National Academy of Sciences of the United States of America*, 101(SUPPL. 1), pp. 5228–5235. doi: 10.1073/pnas.0307752101.

Haghighi, A. and Klein, D. (2010) 'Coreference Resolution in a Modular, Entity-Centered Model', in *HLT/naacl*, pp. 385–393.

Hoffman, M. D., Blei, D. M. and Bach, F. (2010) 'Online Learning for latent Dirichlet allocation (Supplementary Material)', *Nature*, pp. 1–9. doi: 10.1.1.187.1883.

Jeon, J., Croft, W. B., Lee, J. H. and Park, S. (2006) 'A framework to predict the quality of answers with non-textual features', in *SIGIR*, pp. 228–235. doi: 10.1145/1148170.1148212.

Kozareva, Z. and Ravi, S. (2011) 'Unsupervised name ambiguity resolution using a generative model', in *Proc. 1st workshop on unsupervised learning in nlp*, pp. 105–112. Available at: http://dl.acm.org/citation.cfm?id=2140471.

Li, B. and King, I. (2010) 'Routing questions to appropriate answerers in community question answering services', in *CIKM*, pp. 1585–1588. doi: 10.1145/1871437.1871678.

Li, B., Jin, T., Lyu, M. R., King, I. and Mak, B. (2012) 'Analyzing and predicting question quality in community question answering services', in *WWW companion*, pp. 775–782. doi: 10.1145/2187980.2188200.

Li, B., King, I. and Lyu, M. R. (2011) 'Question routing in community question answering', in *CIKM*, pp. 2041–2044. doi: 10.1145/2063576.2063885.

Liu, Y., Bian, J. and Agichtein, E. (2008) 'Predicting information seeker satisfaction in community question answering', in *SIGIR*, pp. 483–490. doi: 10.1145/1390334.1390417.

Mikolov, T., Chen, K., Corrado, G. and Dean, J. (2013) 'Efficient Estimation of Word Representations in Vector Space', pp. 1–12. Available at: http://arxiv.org/abs/1301.3781.

Porter, M. F. (1980) 'An algorithm for suffix stripping', *Program*, 14(3), pp. 130–137.

Qu, M., Qiu, G., He, X., Zhang, C., Wu, H., Bu, J. and Chen, C. (2009) 'Probabilistic question recommendation for question answering communities', in *WWW*, pp. 1229–1230. doi: 10.1145/1526709.1526942.

Ravi, S., Pang, B., Rastogi, V. and Kumar, R. (2014) 'Great Question! Question Quality in Community Q&A', in *Eighth international aaai conference on weblogs and social media.* (1), pp. 426–435.

Reisinger, J. and Paşca, M. (2009) 'Latent variable models of concept-attribute attachment', in *ACL/ijcnlp*, pp. 620–628. doi: 10.3115/1690219.1690233.

Riahi, F., Zolaktaf, Z., Shafiei, M. and Milios, E. (2012) 'Finding expert users in community question answering', in *WWW companion*, pp. 791–798. doi: 10.1145/2187980.2188202.

Ritter, A., Mausam and Etzioni, O. (2010) 'A latent dirichlet allocation method for selectional preferences', *ACL*, (July), pp. 424–434.

Salton, G. and McGill, M. (1983) *Introduction to modern information retrieval.* Mcgraw-Hill.

Shah, C. and Pomerantz, J. (2010) 'Evaluating and predicting answer quality in community QA', in *SIGIR*, pp. 411–418. doi: 10.1145/1835449.1835518.

Shah, V., Gulikers, L., Massoulié, L. and Vojnović, M. (2018) 'Adaptive matching for expert systems with uncertain task types', in *2017 55th annual allerton conference on communication,* *control, and computing (allerton)*. IEEE, pp. 753–760. doi: 10.1109/ALLERTON.2017.8262814.

StackExchange.com (2019) 'StackExchange Site Details'. Available at: https://stackexchange.com/sites.

Sung, J., Lee, J.-g. and Lee, U. (2013) 'Booming Up the Long Tails: Discovering Potentially Contributive Users in Community-Based Question Answering Services', in *ICWSM*, pp. 602–610.

Szpektor, I., Maarek, Y. and Pelleg, D. (2013) 'When relevance is not enough: promoting diversity and freshness in personalized question recommendation', in *WWW*, pp. 1249–1260.

Tian, Q., Zhang, P. and Li, B. (2013) 'Towards Predicting the Best Answers in Community-Based Question-Answering Services', in *ICWSM*, pp. 725–728.

Willmott, C. and Matsuura, K. (2005) 'Advantages of the Mean Abso- lute Error (MAE) over the Root Mean Square Error (RMSE) in assessing average model performance', *Climate Research*, 30, pp. 79–82. Available at: www.int-res.com.

Willmott, C. J., Matsuura, K. and Robeson, S. M. (2009) 'Ambiguities inherent in sums-of-squares-based error statistics', *Atmospheric Environment*. Elsevier Ltd, 43, pp. 749–752. doi: 10.1016/j.atmosenv.2008.10.005.

Wu, H., Wang, Y. and Cheng, X. (2008) 'Incremental probabilistic latent semantic analysis for automatic question recommendation', in *RecSys*, pp. 99–106. doi: 10.1145/1454008.1454026.

Zhou, T. C., Lyu, M. R. and King, I. (2012) 'A classification-based approach to question routing in community question answering', in *WWW companion*, pp. 783–790.