Determining Community Interest in Text-Only Posts on Reddit

Project Proposal

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ABSTRACT

This paper proposes a term project for the EECS 498 Information Retrieval course at the University of Michigan which seeks to analyze content on Reddit[1] to determine community interest in certain topics, keywords, and questions.

The project involves collecting a set of data from a number of subreddits (individual forums on Reddit) including textual content of each post, number of votes that the post received, number of comments on the post, and other information. This information will be used to estimate the community's interest in each post. These estimates will be compiled and indexed by keyword, allowing a user to query the system to determine the expected interest in a new post and whether a new post is very similar to previous posts.

Categories and Subject Descriptors

H.3.1 [**Information Storage and Retrieval**]: Content Analysis and Indexing; H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval

Keywords

Data analysis, Reddit, community interest

1. PROBLEM

We sought to explore whether it was possible to predict whether a post would be popular (community interest) or not on `www.reddit.com`, specifically text-only posts on subreddits sucht as `/r/AskReddit` or `/r/ELI5`. `Reddit` is a platform where users upvote and downvote posts based on various criteria. The users also have the option of posting a comment on a particular post. The overall motivation was to research different machine learning and information retrieval process in order to figure out which would prove to be helpful in determining community interest on `Reddit`.

[1] `http://www.reddit.com/`

There are various applicaitons in which this work would benefit. This could help indicate when it might be a useful time to repost something. The community of Reddit has a strong aversion to things that are posted often. These are often refered to "reposts". However, there is some benefit to reposts. Users that are recently new will find the content new and relevant to them. In addition, there is benefits to bringing up a topic again as it will generate close to the same community interest as it did when it was initially posted. Our work could provide a way of detecting when might be the best possible time to repost something for it to be meaningful and relevant to the community.

An alternative application could be for buisness marketting. Knowing how a particular community will respond to your post can help buisness tailor their marketing strategies to a particular subreddit. There is also the possibility that future work on some of the proposed solutions/methods that we researched could help indicate things that a marketer could change in order to make their content generate more interest.

2. PREVIOUS WORK

<NEED TO ADD TO THIS>

There are a number of websites dedicated to detecting "reposts" on Reddit, which are exact duplicates of previously posted content. One such website is KarmaDecay[2]. However, these websites only detect exact duplicates of hyperlinks and images, which make up the majority of posts in many subreddits. The textual content of posts in text-only subreddits such as `/r/AskReddit` or `/r/ELI5` is not analyzed. This gives these websites limited usefulness in text-only subreddits, where no images or external links are generally allowed.

Furthermore, existing systems are designed mostly to help users avoid reposting exact duplicates of existing material, and do not match based on a similarity measure. This means that related or very similar posts will not be matched, only exactly identical ones. By using a text-matching system based on similarity scores, our project will allow text-only topics to be analyzed not to detect exact duplicates (as these are rare in text posts due to the diversity inherently present in language), but to find similar posts from the past based on matching keywords, topics, phrases, and other content. These similar posts can then be used to judge or estimate

[2] `http://karmadecay.com/`

potential interest in the new post and to predict useful information such as whether a post will be popular or successful or which subreddits it may be most successful in by analyzing the interest in the previous posts. In addition, the uniqness of the post will also contribute to determing how popular a post might be.

Therre has been work done analyzing news content, not based on the article but upon the responses of the general public [**?**]. This paper describes a way of what they describe as "comment centric tagging" as a means to identify which articles were highly interesting and important. They use these comments within a post to alter and adapt the interest weighting on an article.

While this work is not the main focus of the paper, it does highlight how important the comments of a post can be. The study they performed showed that the comments of a post greatly impacted the community interest within that specific topic. This will help us direct or findings towards the comments found on Reddit, weighing them higher, than the actual post itself.

Some work has also been done by researchers to determine characteristics of articles that have been ranked by crowdsourced feedback from users [**?**]. The results of this study point out that while crowdsourced feedback mechanisms "can be relatively effective for ... promoting content of high quality, they do not perform well for ordinal objectives such as finding the best articles." In other words, while interesting topics and general themes are often highlighted as outstanding by user feedback, the best specific articles are not always at the very top of the list. Rankings which are based on user feedback will likely tend to positively identify good topics, but perhaps not the absolute best topics. This means that we should not use a post's score as an absolute ranking; that is, we should not conclude that one post is definitively better than another simply because it has a higher score. For our purposes, this means that all posts with a reasonably high score could be determined to be interesting to the community, but that comparing levels of interest (or ranking the level of interest) between two interesting topics will likely be very difficult.

The article also has some interesting discussion about crowdsourced scores over time, indicating that posts tend to take a while to gain momentum, but then explode rapidly if they are determined to be interesting. This means that some posts which are not "discovered" by users (they may be posted at the wrong time of day or when few users are online, so they are not identified by interested users) may fail to gain traction and perform as they should. This may mean that the same post, created at different times, may be extremely popular one time and not at all another time. In fact, the post may go unnoticed several times and only be discovered once. Our scoring algorithms will have to take this into account, likely by giving the positive feedback of posts which are determined to be interesting much more weight than the negative feedback of posts which are determined to be uninteresting (because a post that scores highly is almost certainly an indicator of community interest, while a post that scores poorly may have many different reasons for receiving that score).

Work has been done in this area before by another Michigan student, targeting Digg instead of Reddit. His website[3] analyzed all of the most recently-posted links on Digg, and used various heuristics to predict which articles would make it to the front page. Various differences between the algorithms used by the two sites make it impossible to use the exact same approach here–the code relied on being able to see which users voted on which articles, while on Reddit this information is made private by default. In addition, Digg weighted the votes of some users above others instead of treating everyone equally. The fundamental concept of extrapolating early votes to predict eventual popularity will still be an important concept for us to investigate.

In addition to using upvotes and downvotes to rank content, reddit keeps track of the total score of all of a user's comments. Power users of reddit have a strong incentive to identify posts that will eventually reach the front page, since commenting early on these threads provides the maximum return of points for the time spent. To this end, the subreddit `/r/risingthreads` tries to identify these threads within minutes of when they are posted, but how it does this is not known. The submissions to this subreddit are submitted by a bot, that presumably flags posts with lots of early upvotes. In the sidebar of the subreddit, `/r/askreddit` is specifically named as a subreddit for which the bot's algorithm performs poorly. Our project, by analyzing the text content of the post and its comments, may be able to improve upon this performance. This subreddit also shows a way to get user feedback on our project's effectiveness. If our project works well enough, we could set up our own subreddit to share and test its results.

3. APPROACH

Our approach for this project involves three major areas: data collection, processing, and retrieval.

First, data must be collected from Reddit. This will involve collecting and indexing a number of past posts in text-only subreddits. The posts and their comments will be analyzed, looking for common keywords, themes, or topics which seem relevant to the post in order to match the post with other submissions that have similar topics.

We focused on the upvotes of a redit post. When implementing our various different systems, we focused on the score as our measure of community interest. We thought of using the comments instead of the score, or inconjunction with the score, but we did not experiment and analyze that within our research and implementations.

There were three different implementations that we approached: cosine similarity between topics, naive bayseian on the words found within the posts, and a boolean classifier machine learning approach. We believed that each method had benefits and disadvantages and wanted to experiment with the various different methods to see which method, if any, peformed better than the baseline.

3.1 Cosine similarity-weighted scoring

[3]http://gigaom.com/2010/08/24/hey-digg-this-17-year-old-knows-what-you-are-thinking/

The premise of this method is our expectation that the scores of new submissions will correspond approximately with the scores of past submissions that are very similar, which we can judge by the similarity of their titles. All of the indexed submissions are therefore tokenized with a regular-expression based tokenizer that separates words, and then passed through a standard Porter stemmer[4]. Once tokenized and stemmed, the tokens are placed into an index using the tfc-nfx[**?**] algorithm.

To determine the expected score of a submission, the index is then queried using the tokens from the new submission's title, matching by cosine-similarity. For this method, the "score" of each similar topic is calculated using the formula $upvotes - downvotes + comments * 2.5$, where *comments* represents the number of comments that the post received. The values used were all takes after the post had existed for one full day.

Other methods of scoring were also tested, including only using upvotes, or only number of comments. The stated method of scoring appears to work best for this algorithm, although some others produced similar results. The score returned is not intended to correspond with any score available from Reddit or any other source; it is an arbitrary number only comparable to other scores returned by the algorithm.

A weighted average was then taken of the scores of each post returned by the index, using the square of the cosine-similarity result. The similarity is squared to minimize the effects of the "long tail" of posts that have relatively low similarity, but which would otherwise dominate the average because of their large quantity.

By analyzing the posts returned from the index, we can see that this method does fairly accurately recognize similar and related questions as we would expect, since it works very much like a search engine looking through old posts. However, the method has a number of downsides that would prevent it from working properly under certain conditions.

First, questions which contain unique words and tokens will match fewer submissions from the index, despite the fact that they are probably more interesting than the average question because of their uniqueness. This will result in a lower score being predicted for those posts, which will lead to lower accuracy for these types of posts.

Second, questions which contain many common words will likely match other submissions with very common words, and therefore their scores will be lowered. The use of the tfc-nfx algorithm reduces the effect of this by decreasing the weight of the common words, but for a question whose title consists *only* of common words, tfc-nfx will not be able to correctly match similar posts.

Because some words appear on AskReddit with fairly high frequency, such as the words "Reddit" and "Redditors", a stopword eliminator was implemented and these words were added to the filter. This further reduces the impact of this problem, but also leads to an increased occurrence of the third problem: posts which do not match any previously existing posts cannot be scored at all. This could happen because the post contains only unique words (words that do not appear in any other submissions) after stopword removal.

[4]http://tartarus.org/ martin/PorterStemmer/

3.2 Naive Bayes - Bag of Words Classifier

The goal of this method was to be able to create something that would categorize a post as being popular or unpopular based on the words and the frequency of those words that appear in unpopular and popular posts. The idea behind this is that would mark something that has been reposted many times as being unpopular and something that is unique would be marked as being popular.

In order to accomplish this the posts were split into two categories, popular and unpopular. The weights of these categories was determined by how many posts in the data set were marked as popular versus how many posts in the data set were marked as popular. The weights for each specific dataset were determined by the formula:

$$\frac{Number\_of\_posts\_that\_fit\_category}{total\_number\_of\_posts}$$

After each categoryies weights were determined, all the posts in the training set were split into two major categories.

A total vocabulary was created out of each of those categories. The vocabulary also contained the number of times that specific word appeared. The vocabulary was build upon the titles of the posts pertaining to that category. The titles went through a standard tokenizer that removed punctation. In addition, a stop word remover to further filter the title data. However, unlike within the cosine method, there were no specific considerations made due to the posts coming from Reddit. The hope was that these words might fit into one category more than another and could further provide useful information on which category a post pertained to. This vocabulary served as a weighting in the classification step.

Weights for the relavency of each word to the category were created by taking the frequency of a specific word and dividing it by the total amount of words in that category. These weights were later used in order the classification step by weighting the scores associated with that word.

A score vocabulary was also created in order to help the classification step. For every word that occured in each category, the words score was added to a seperate score vocabulary. The score vocabulary consisted of the list of unique words in specific category, and the upvotes minus downvotes (the Reddit score) of the post that the word appeared in.

$$\frac{\sum_{posts\_in\_category} upvotes - downvotes}{Frequency\_of\_word}$$

This allowed us to map specific word to their score in order to generate a score of a new post given to the system. While this new score was never revealed from the system, it helped improve the quality of the classification from the system.

The classification step took a new post, which could be

unique or from a test set, and classified it into either unpopular or popular. The classification step would take each word that occured in the new topic, multiply the word score by the weight, and multiply the summation of words in that category by the category probability.

$$(category\_probability) \sum_{word\_in\_query} (Weight * Word\_Score)$$

This operation would occur per category. The results would then be compared and the system would return which category is pertained to. In the evaluation step, the resulting category would be compared to the category it is supposed to belong two, and if they matched up then the system would increase the number it got correct. This would end with being able to decide how well it did compared to the baseline of the system.

3.3 Machine Learning - Boolean Classifier

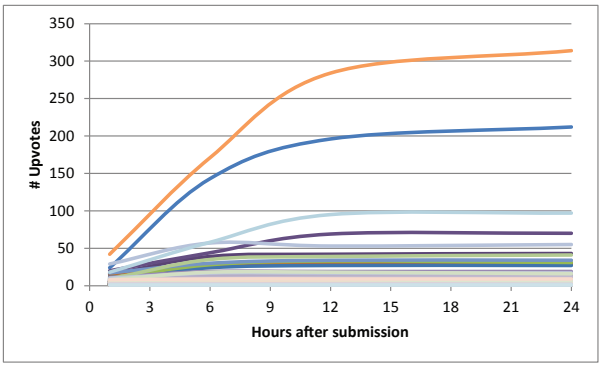
<machine learning approach>

Next, the popularity or interest of the post will then be measured through various statistics including number of comments, number of upvotes/downvotes received (through Reddit's voting system), number of distinct users who commented on the post, average length of the comments, average depth of comment trees[5], number of upvotes/downvotes on comments and their distribution among the comments, time of day that the post was made, and how long the post has been on Reddit.[6]

Finally, the keywords, and posts matching those keywords, will then be used to create a database which can be used to judge popularity of a post based on which keywords appear in the post title or text body. This database can then be queried to determine expected popularity of a new post given its text. This database will also be designed in such a way that new posts on Reddit will be automatically incoporated into the corpus. The query system may also be able to suggest similar keywords (words which are frequently used with the ones in the given text), topics, or information to include in the post which may increase the post's popularity score (and thus hopefully lead to a more interesting post on Reddit). [7]

4. EVALUATION

Initially, we experimentally determined what would a good threshold be to determine whether something was popular or not (whether it generated sufficient community interest). To do this, we randomly sampled the data five different times to look for correlations in the posts. We looked at the spread of posts to help figure out what our threshold should be. The graphic below shows this data from a random 240 posts. For the purposes of our evaluation, we determined that a score of 20 or above would be deemed as popular by the community, and anything less than that would be unpopular. [8]



(random sample of 240 posts)

We initially used a data set cultivated from a week of posts. This data set included 20,000 posts to `/r/AskReddit` but was later cut down to 17000 posts once all the deleted posts were removed (by the user or by a moderator). This dataset consisted largely of posts that did not make it to the front page and we not seen by users. These post generated little to no community interest. Out of the 17000 posts, about 270 generated community interest. We initially supplied each implementation with this dataset for training and evaluation.

We built an additional, balanced data set as well. This dataset contains an equal amount of popular versus unpopular posts. This dataset was used to make sure that there was no bias in the data that was skewiing our results. This dataset contains 1,977 posts above a 20 upvote threshold and 1,977 below a 20 upvote threshold.

We additionally built a third dataset to that incorporates the balanced dataset with a time weighting. Time of day plays a major factor into whether a post will be successful or not on Reddit. We wanted to utilize a dataset that helps incooperate this time factor into account.

To generate this dataset, we counted the number of submissions that scored above the threshold of 20 upvotes in each two-hour period (based on the submission's creation time). The average number of submissions above the thershold in each two-hour period was 164.75. For each of the two-hour periods, the actual number of threshold-reaching submissions in that period was divided by the average to determine a ratio, which roughly corresponds to how well submissions in that two-hour period are expected to perform. The results of this process can be seen in the table below.

Once the ratios were determined, each submission's scores were divided by the ratio (multiplied by the reciprocal, which is shown in the table) for their creation time period. That is, posts between midnight and 2:00 AM UTC had their scores multiplied by 1.19, because they tended to perform slightly worse than average.

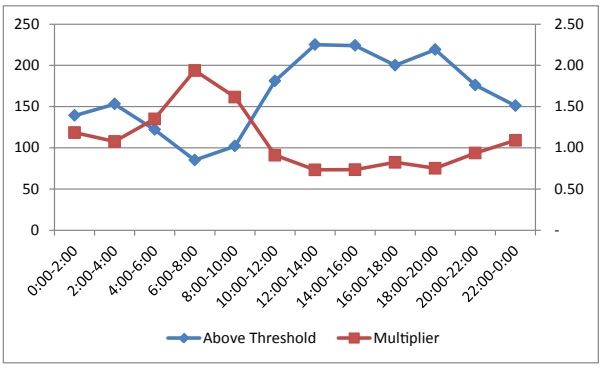
[5]On Reddit, users can comment on other comments, forming a tree-like structure of comments.

[6]Reddit's algorithm works in such a way that posts that have been on Reddit a long period of time have a lower "score". We may have to inflate the score given to older posts as their ranking has decayed over time.

[7]This is a possible extension of the project and will need to be explored further.

[8]20 or above represents the top 5% of Reddit posts

Time (UTC)	Submissions	Above Thresh.	%	Mult.
0:00-2:00	3762	139	3.69	1.19
2:00-4:00	3796	153	4.03	1.08
4:00-6:00	3544	122	3.44	1.35
6:00-8:00	2526	85	3.37	1.94
8:00-10:00	1927	102	5.29	1.62
10:00-12:00	2155	181	8.40	0.91
12:00-14:00	3145	225	7.15	0.73
14:00-16:00	3880	224	5.77	0.74
16:00-18:00	3862	200	5.18	0.82
18:00-20:00	3823	219	5.73	0.75
20:00-22:00	3804	176	4.63	0.94
22:00-0:00	3640	151	4.15	1.09



This has the result of scaling up the scores of posts made during off-peak hours, and scaling down the scores of posts made during peak hours, so that by using the scaled scores, posts have a more-or-less even score distribution throughout the day.

When evaluating the systems with each dataset, we tested on how well it worked on a subset of that dataset. For example, we might use 80% of a given dataset as training and the reamining portion of the dataset for testing. We would go through and mark posts as being popular or unpopular based on our threshold. Then, we would use each of our implementations to go through the dataset and classify the posts. We would then compare how the specific implementation did by using the formula $\frac{NumberClassifiedCorrectly}{TotalClassified}$. This would give us a percentage how well it classified the posts.

In all of the implementations we compared against marking every post as unpopular. Over 95% of the posts on Reddit are unpopular, so for our systems to be successful we had to achive better than marking everything as unpopular.

5. RESULTS

5.1 Cosine similarity-weighted scoring

Unlike the other two implementations, the cosine similarity-weighted scoring algorithm does not produce a binary response as to whether the post will be interesting or not. It instead produces a continuous score from zero to (potentially) infinity. This leads to a slightly more complicated problem of evaluating this system.

Two methods of interpreting the results are used here. The first attempts to determine whether the cosine-similarity method is statistically recognizing "interesting" posts and scoring them above the average posts. The second attempts to define a threshold score returned by the algorithm that can be used to convert the resulting scores into a binary response for comparison with the other implementations and with marking every post as unpopular.

For the first scoring method, a sample of posts taken from AskReddit's "top posts" and front page were scored using the cosine-similarity scoring algorithm. Then, a random sample of other posts was taken. None of the posts used for this analysis were available in the query system's index.

The scores of the posts from each category were averaged and compared using a standard statistical Z-test. Using the original data set (non-time-weighted) the average score for random posts was 114.44 with a standard deviation of 33.29. The average score for the top posts was 156.40 with a standard deviation of 103.48. This leads to a Z-score of 1.2605, corresponding to a confidence level of roughly 89.626%.

Using the time-weighted data, the algorithm actually performed very slightly worse. The average score for randomly selected posts was 110.82 with a standard deviation of 31.65, while the average score for top posts was 149.36 with a standard deviation of 95.56. This gives a Z-score of 1.2180, which corresponds to 88.839% confidence level.

Unfortunately, both of these tests fail to reach a significance level of 90%, because of the wide range (high standard deviation) of the returned scores. We cannot, therefore, conclude that this algorithm effectively predicts higher scores for top posts than for random posts (on average).

However, our confidence levels are fairly close to a 90%, indicating that it may be possible to improve upon the scoring algorithm or increase the size of the index in order to reduce the deviations in the results and gain a statistically significant result. Furthermore, the returned scores are fairly normally distributed, but are skewed somewhat left toward lower scores, so the Z-test (which relies on a normally distributed data set) will not produce a completely accurate result for determining whether this algorithm is reliable. (It is used here because the data is close enough to normal that even with a more sophisticated and specific statistical test, we would still not reach significance).

For the second scoring method, a cutoff must be found to determine which posts are "interesting" which we define by being in the top 5% of posts. To find this cutoff, all of the posts currently in the index were scored using the same scoring formula as is used in the cosine similarity scoring algorithm (described above). Then, a value for the cutoff score was chosen such that 95% of posts fall below the cutoff score, and only 5% of posts exceed the cutoff score.

The value we found was 135.5 for the original (non-time-weighted) data set and 149.320 for the time-weighted data set. However, this does not account for the squaring of the similarity score which is used for weighting the results. To take this into account, the average scores of returned posts using squaring of the similarity score was divided by the av-

erage scores of the returned posts without squaring, in order to find a score multiplier that corresponds to the expected artificial increase in score because of the squaring. The multiplier that was applied to the cutoffs was 0.870058, giving the new cutoffs 117.893 and 129.917 for non-weighted and time-weighted data sets respectively.

To find the accuracy of the algorithm, the number of actually-interesting posts (above 20 upvotes) that reached the cutoff score was divided by the number of posts classified, using posts that were not indexed by the similarity-scoring method. This yielded an accuracy of 78% for the non-time-weighted data set but only 44% for the time-weighted data set. This may indicate that the success of a post does not depend as much on its creation time as on other factors, but it is unclear.

The accuracy for non-time-weighted data is fairly reasonable, indicating that (as above) the algorithm is incapable of clearly distinguishing interesting posts from uninteresting posts more often than an algorithm which marks every post as uninteresting (for which we would expect to see an accuracy of 95%). Again, this is likely due to the extremely high variance found in the scores returned by the algorithm.

5.2 Naive Bayes - Bag of Words Classifier

The evaluation of the classifier measured the number of correct classifications that the system got divided by the number of total test posts.

$$\frac{correct\_classifications}{total\_test\_posts}$$

This measurment was compared to a baseline of marking everything as in the unpopular category.

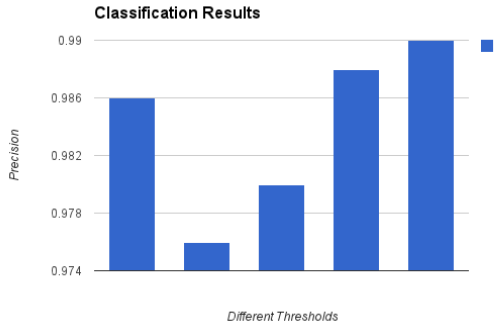
First the system ran with a strict baseline of marking everything as unpopular. This resulted in a baseline of 98.6% accuracy. Thus, the further evaluations would have to perform better than this baseline in order for the results to be relevant.

The subsequent test were conducted on the first dataset. In these tests the post score threshold was manipulated. The post scores that were tested were 20, 40, 100, and 200. A post must have equal to or over the score in order to be considered as popular.

The results are shown in the table below:

Method	Precision
Baseline	0.986
20	0.976
40	0.98
100	0.988
200	0.99

As is shown by the precision raitings, the higher the score threshold, the higher the precision. The reason, we believe, why the 20 and 40 score thresholds are below the baseline is due to the fact that those thresholds, while they may mark things as being popular, acutally incorrectly mark unpopular posts. The higher thresholds do better than baseline due to the fact that they are being more strict on what the



(left to right: Baseline, 20, 40, 100, 200)

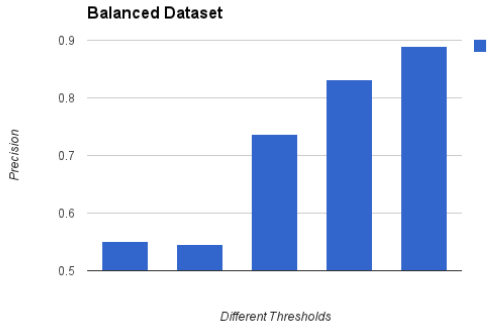
threshold should be, and mark only the most popular posts as being popular. Thus, it benefits from the nature of the dataset that most things are considered unpopular, and that only a few posts within the dataset are actually popular.

The system was also later tested on the balanced dataset and the timeweighted balanced dataset. The same tests were performed on each of these datasets. However, the altering of the threshold also affects the balanced nature of the dataset. The thresholds alter what category each post will fall into. For example, if the balanced_postdata dataset was used with a threshold of 40, then now there would be more unpopular vs popular posts when the system goes to split the posts into the categories for the bag of words operations on the posts.

The following is the results for each other dataset:

Balanced Dataset

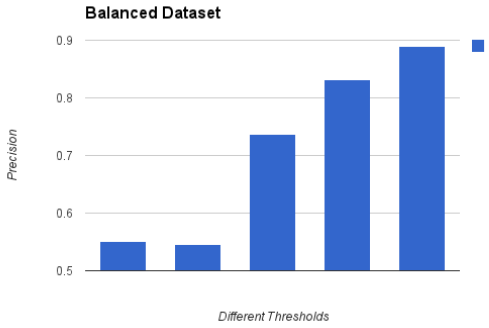
Method	Precision
Baseline	0.551
20	0.546
40	0.736
100	0.832
200	0.889



(left to right: Baseline, 20, 40, 100, 200)

Time-Balanced Dataset

Method	Precision
Baseline	0.562
20	0.54
40	0.734
100	0.836
200	0.896



(left to right: Baseline, 20, 40, 100, 200)

What was surprising about these results is that even baseline did better than 50% even though the dataset was completely split in half. The reasoning for this, we believe, is due to the weightings that the words are given and the scores that they recieved.

The balanced dataset actually inhibits the results of the naive bayes classifier because it relies upon the category weighting. With the category weighting set at 50% (for Baseline and 20 thresholds), the system struggled to correctly classify the documents. This is why as the threshold gets higher and higer for the balanced datasets, and as the balanced datasets become more unbalanced, the systems performance increases.

5.3 Machine Learning - Boolean Classifier

<machine learning approach>

5.4 Discussion

6. CONCLUSION

<Nathan will fill this in>