Honours Year Project Report

Predicting Web 2.0 Thread Updates

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Abstract

In this report, we study a problem and design an efficient algorithm to solve the problem. We implemented the algorithm and evaluated its performance againts previous proposed algorithms that solves the same problem. Our results show that our algorithm runs faster.

Subject Descriptors:
C5 Computer System Implementation
G2.2 Graph Algorithms

Keywords:
Problem, algorithm, implementation

Implementation Software and Hardware:
python, bash

Acknowledgement

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Chapter 1

Introduction

With the advent of Web 2.0, sites with forums, or similar thread-based discussion features are increasingly common. Our goal in this thesis is to create an algorithm that can predict when updates in such threads will occur.

Table **??** shows us that many of the popular Web 2.0 sites have comment features. This suggests that content on the web is increasingly being created by users alongside content providers.

In an increasing number of cases, news travels more quickly through online community discussions than through traditional media. Users also typically discuss purchased products bought online on forums, and companies that want to get timely feedback about their product should turn to data mined from such sites.

Web crawling is largely IO-bound, a large portion of the time spent crawling is waiting for the server to supply a response to the request issued by the crawler. However, for sites with a large number of pages (as in popular forum sites), make this infeasible in practice. On top of the usual requests it has, it then has to deal with repeated requests from such a crawler. Most sites do not mind some additional bandwidth, but if it gets excessive, it may be construed as a Denial-of-Service attack. At best, the site may deny any further requests from the crawler, and at worst the large number of requests may bring down the site.

A simple method to reduce the amount of polling needed is to use the average time differences between previous posts to estimate the arrival of the next one, and to abstain from polling until the estimated time.

	T	FB L	FB S	G +1	L	DL	C	PV	Follows
`http://www.lifehacker.com`	1	1	1				1	1	
`http://digg.com/`	1	1			1	1	1	1	
`http://9gag.com/`	1	1	1	1	1		1	1	
`http://www.flickr.com/`					1		1	1	
`http://news.ycombinator.com/`					1		1		
`http://stackoverflow.com/`					1		1	1	
`http://www.youtube.com/`					1	1	1	1	
`http://www.reddit.com/`					1	1	1		
`http://www.stumbleupon.com/`					1		1	1	
`http://delicious.com/`	1	1					1	1	1

Table 1.1: Features of popular Web 2.0 sites

T = Twitter mentions

FB L = Facebook Likes

FB S = Facebook Shares

G +1 = Google +1

L = Likes (Local)

DL = Dislikes (Local)

C = Comments

PV = Page Views

Follows = Site-local feature for keeping track of user's activities

A key observation in our work is that the contents of the thread may also influence the discussion and hence the rate of commenting. We believe that the content of the thread has information that can give a better estimate of the time interval between the last post and a new one.

For example, a thread in a technical forum about a Linux distribution may start out as a question. Subsequent questions that attempt to either clarify or expand on the original question may then be posted, resulting in a quick flurry of messages. Eventually, a more technically savvy user of the forum may come up with a solution, and the thread may eventually slow down after a series of messages thanking the problem solver.

Let us define all such thread-based discussion styled sites as forums. Ideally, an incremental crawler of such user-generated content should be able to maintain a fresh and complete database of content of the forum that it is monitoring. However, doing so with the previously mentioned naive method would (1) incur excessive costs when downloading un-updated pages, and (2) raise the possibility of the web master blocking the requester's IP address.

Our high level goal: To come up with a suitable algorithm for revisiting user discussion threads, based on the discussion content in the thread. In this project, we focus on forum threads. We demonstrate three different methods for achieving this using regression methods, and also propose a new metric for measuring the timeliness of such a model that balances between the model's timeliness and bandwidth consumption.

Chapter 2

Related Work

In order to devise such an algorithm, we need to predict how often any user may update a page. Some work has been done to try to predict how often page content is updated, with the aim of scheduling download times in order to keep a local database fresh.

2.1 Refresh policies for incremental crawlers

We first discuss the *timeliness* of our crawler to maintain the freshness of the local database, which refers to how new the extracted information is. Web crawlers can be used to crawl sites for user comments for later post-processing. Web crawlers which maintain the freshness of a database of crawled content are known as incremental crawlers. Two trade-offs these crawlers face cited by Yang, Cai, Wang, and Huang (2009) are *completeness* and *timeliness*. *Completeness* refers to the extent which the crawler fetches all the pages, without missing any pages. *Timeliness* refers to the efficiency with which the crawler discovers and downloads newly-created content. We focus mainly on timeliness in this project, as we believe that timely updates of active threads are more important than complete archival of all threads in the forum site.

Many such works have used the Poisson distribution to model page updates. Coffman and Liu (1997) analysed the theoretical aspects of doing this, showing that if the page change process is governed by a Poisson process $\frac{\lambda^k e^{-\lambda\mu}}{k!}$, then accessing the page at intervals proportional to λ

is optimal.

Cho and Garcia-Molina trace the change history of 720,000 web pages collected over four months, and showed empirically that the Poisson process model closely matches the update processes found in web pages (Cho, 1999). They then proposed different revisiting or refresh policies (Cho & Garcia-Molina, 2003; Cho & Garcia-molina, 2003) that attempt to maintain the freshness of the database.

The Poisson distribution were also used in Tan, Zhuang, and Mitra (2007) and Wolf, Squillante, and Yu (2002). However, the Poisson distribution is memoryless, and in experimental results due to Brewington and Cybenko (2000), the behaviour of site updates are not. Moreover, these studies were not performed specifically on online threads, where the behaviour of page updates differs from static pages.

Yang et al. (2009), attempted to resolve this by using the list structure of forum sites to infer a sitemap. With this, they reconstruct the full thread, and then use a linear-regression model to predict when the next update to the thread will arrive.

Forums have a logical, hierarchical structure in their layout, which typically alerts the user to thread updates by putting threads with new replies at the top of the thread index. Yang's work exploits this as well as their linear model to achieve a predicton of when to retrieve the pages. However this design pattern is not applied universally; comments on blog sites or e-commerce sites about products do not conform to this pattern. The lack of such information may result in a poorer estimate, or no estimate at all.

The above works all try to estimate the arrival of the next update (comment), but do not leverage an obvious source of information, which is the content of the posts themselves. Our perspective is that the available thread content can be used to provide a better estimation for predicting page updates.

Next, we look at some of the related work pertaining to thread content.

2.2 Thread content analysis

While there is little existing work using content to predict page updates, we review existing work related to analysing thread-based pages. We think such work will aid our efforts in content-based update prediction.

Wang and McCarthy (2011) find links between forum posts using lexical chaining. They proposed a method to link posts using the tokens in the posts called $Chainer_{SV}$. While they analyse the contents of individual posts, the paper does not make any prediction with regards to newer posts. The methods used to produce a numeric similarities between posts may be used as a feature to describe a thread in its current state, but incorporating this into our model is non-trivial.

With these related work in mind, we next propose our modelling of a thread as a Markov chain, and our approach to solving the problem.

2.3 Evaluation metrics

Yang et al. (2009) proposed a metric for our particular problem of thread update prediction. Known as the T-score, it gives the average time difference between when a post is made and when the post is retrieved by a crawler. The lower the T-score, the better the model. However, the metric does not penalize for visits which retrieve nothing new from the thread. As such, a crawler that repeatedly crawls the site at a frequent rate would do very well.

Broadening our search for more relevant evaluation metrics that take such wasted bandwidth into account, we turn to related work in the evaluation of segmentation algorithms. In Georgescul, Clark, and Armstrong (2009), the authors propose a new scheme for evaluating segmentation algorithms, Pr_{error}. This metric is the weighted sum of two probability counts Pr_{fa} which is the probability that a false alarm segmentation is made, and Pr_{miss} which is the probability that a segmentation is not made when there should be one. Unfortunately for our purposes, the metrics are calculated using the number of ground truths and segmentations given a window. As such, it does not account for the "distance" between the ground truths and the segmentation. It also does not allow for the predictions to appear after the ground truths, all requirements needed for a metric to evaluate timeliness of a model.

The task in this work, was to predict which of three predefined classes a tweet will fall into: no retweets, a low number of retweets and a high number of retweets. Our task is slightly more challenging, since we are trying to minimise the time from which a post is made to when the page is revisited. However, the feature sets used in these works should prove useful in our task.

Chapter 3

Method

We aim to predict the amount of time between the arrival of the next post and the time the last post in the thread was made. The information available to us are the previously made posts that we observe when first visiting the thread. The assumption made here is that the thread is not paginated in any way, and a single visit to the thread gives us the latest posts without having to traverse through the links to the latest page. This is because in practice, we would be able to keep track of where the last visited page of the thread was, and reading the new posts would incur a few more requests to the thread. This, in comparison to constantly hitting the page for updates, would be negligible.

More formally, what we are trying to do is to estimate a function f such that given a feature vector $\mathbf{X}$ representative of a window $\rho_{t-w+1}, \rho_{t-w+2}, \cdots, \rho_t$, where ρ_t represents the t-th post in the thread, we can approximate Δ_t with $f(\mathbf{X})$. In the following sections, we will discuss various methods for estimating f. Various notations will be used, a quick reference is provided in Table 3.1.

In the following sections, we describe the various methods we have to approximate f.

3.1 Baselines

A simple way of estimating the revisit rate would be to use the average time differences given the observed posts, or a training set. In previous work, we have seen that if page updates follow

Notation	Description
ρ	A post
t	Index of a post in a thread
w	Number of posts in a window
ρ_t	The t-th post in the thread
$\mathbf{v}_t$	The frequency count vector of the posts used in the t-th post
Δ_t	Time difference between a post at position t and a post at position $t+1$
$\mathbf{t}_\Delta$	Vector of Δ_ts in a given window
$\mathbf{t}_{\text{ctx}}$	Bit vector representing the day of week, and the hour of day
$\mathbf{X}$	Feature vector extracted from a window
K	The K best features selected from the vocabulary.

Table 3.1: Notation reference

a Poisson distribution, then revisiting at the Poisson mean would be an optimal revisit policy.

In our baseline revisit policy, we took into account the last made post whenever we make a visit to the thread, and calculate our next revisit time based on the average post intervals added to the timestamp of the previous post. This is in contrast to an even simpler revisit policy that just revisits at a constant, fixed rate, independent of the posts being made to the thread.

One other way of predicting using average post intervals would be to use the concept of a *window*. Averaging out the time differences between the posts would intuitively work, because it captures the context of the situation: A series of posts with short intervals should mean that the next post would come at around the same interval as the few that came before.

In terms of using content for prediction, windows also make sense: Forum users view content as paginated posts, so time differences between posts do not affect their decision to post. Rather, reading a number of posts together affect whether or not the user chooses to reply.

An example of a window ($w = 2$) can be seen in Figure 3.1.

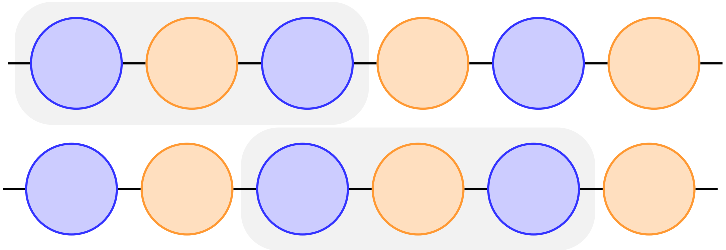


Figure 3.1: A series of events, posts (blue) and visits (orange). The diagram demonstrates the concept of a window of $w = 2$.

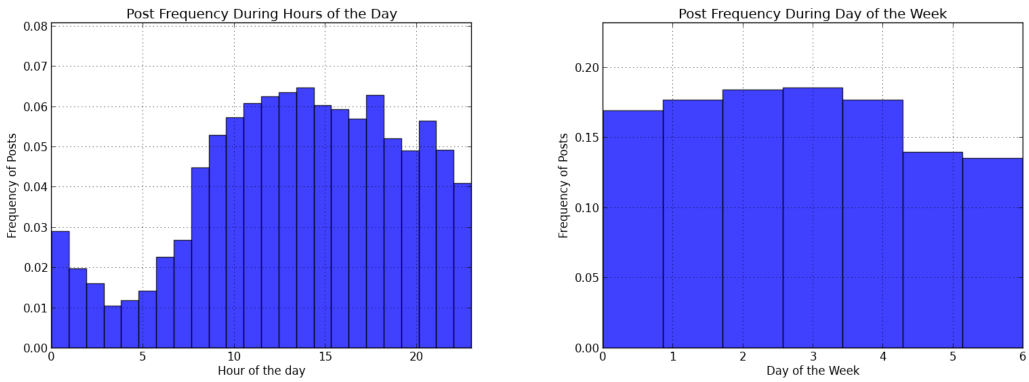
3.2 Performing regression on windows

Previous work has used linear regression on a number of different features extracted from forums (Yang et al., 2009). In their paper, the regressed function was used as a scoring function rather than a predictive function. In site of this, we attempted to implement the same model, but this resulted in evaluations worse than that of the baseline.

We did use some of the features mentioned in the paper: Window posts time differences and time context features (bit-vector representations of the day of the week and hour of the day). In our own statistics we took from the `avsforum.com` threads, we have also found that the time of the day the day of the week matters when dealing with threads. An example of such a thread can be seen in Figure 3.2a and Figure 3.2b, where it can be seen that activity on the board is highest at 2 PM, and drops slightly, suggesting some type of lunch period, and then goes up again during the early evening and at 9 PM, before dropping to its lowest at 3 AM. The weekly graph also shows a pattern, showing lower posting frequencies during the weekends, and its highest during Thursdays.

This suggests that the *time context* of which the posts were made are important when trying to determine the rate of posts. As such, we factor in the day and hour information into our feature sets as well.

However, this time in stead of linear regression, we used a regression method known as Support Vector Regression (SVR), using a radial basis function kernel. This method allows the using of different kernels, allowing for better estimation of the target function.



(a) The hourly post frequency. (b) The daily post frequency. (Monday is 0)

The main focus of study in this report was to see if content helps with predicting thread updates would produce an improvement. Some of the ways that content data were extracted into feature vectors are the following: Word frequency, the tf-idf of these words, and Part-of-Speech tags.

We perform the standard preprocessing steps like removing stopwords and tokens of length less than three. We also use Porter's stemming algorithm as another preprocessing step, before performing a word frequency count. However, the use of the full vocabulary of the thread as a feature vector greatly increases the time needed to train the model. As such, we used a simple univariate regression technique for feature selection, and selected only the K best tokens for consideration. Table 5.1 shows the results of this experiment.

These feature sets are used in different combinations, with different window sizes. The results will be seen in the next chapter.

The methods in this section use features extracted from the current window. A model is then trained using these extracted features in order to make a prediction. We take a look now at a two other novel methods that we developed.

3.3 Discounted sum of previous instances

Posts made further in the history of the thread may have an effect on when the latest posts arrive. The magnitude of this effect, however, may diminish over time.

Instead of having a finite window for which all posts (in said window) are treated equally, why not try to account for all previous posts, but weigh them accordingly: the earlier they were made, the less weightage on the prediction the post should have.

Following this intuition we used a discounted sum over previous posts' word frequency vector:

$$\mathbf{X}'_t = \mathbf{X}_t + \alpha \mathbf{X}'_{t-1}$$

where $\mathbf{X}_t$ is the feature vector at post t. α is the *discount factor* and satisfies $0 \leq \alpha < 1$.

This new feature vector $\mathbf{X}'_t$ will be used in the same way as before, instances of $\mathbf{X}'$ will be regressed with their Δ_t values. As before, we will look at the results for this method in the next chapter.

Up till now, we have looked at methods that treat the model as static – once trained, the model never gets updated during run time. However, this is unrealistic due to the fact that over time, different words are popular as a direct result of different topics in the real world being popular. In this case, these fluctuations may be due to new updates to firmware being released or newer models of, say, a stereo set.

3.4 Stochastic Gradient Descent

We also used stochastic gradient descent to estimate the function f. However, during runtime, instead of using a static function, we continue to allow f to vary whenever new posts and their update times are observed.

Having already attempted using linear regression for this purpose, we have found it unsuitable for f to be estimated by a linear function. Such a linear function has often resulted in making a negative prediction, and sometimes an overly huge one, when given feature vectors that have previously never been observed. The function has to be somehow constrained such that the value returned never drops below 0, and never predicts something too huge such that many posts are missed.

Since $f(\mathbf{X}) > 0$, we used a scaled sigmoid function,

$$f(\mathbf{X}) = \frac{\Lambda - \lambda}{1 + e^{\mathbf{w} \cdot \mathbf{X}}} + \lambda$$

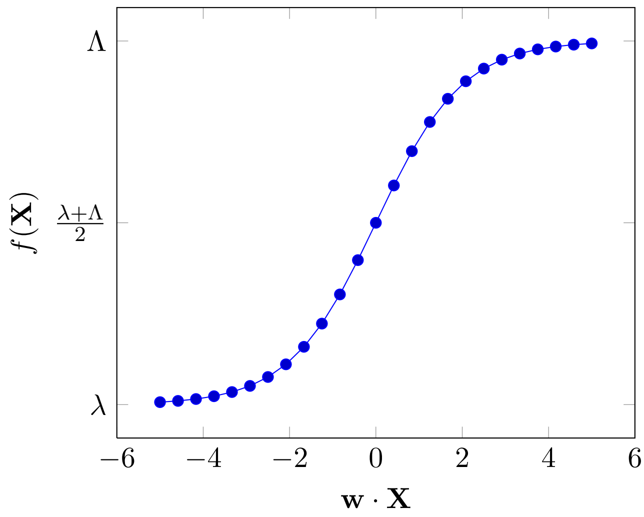


Figure 3.2: Scaled sigmoid curve

where Λ and λ are the scaling factors. This results in $f : \mathbb{R}^{|\mathbf{X}|} \to (\lambda, \Lambda)$. Bounding the estimation function between λ and Λ allows us to restrict the prediction from becoming negative, or, becoming exceedingly huge. For our purposes, we set $\lambda = Q_3 + 2.5(Q_3 - Q_1)$, where Q_n is the value at the n-th quartile. A visual interpretation of such a curve can be seen in Figure 3.2.

The resulting update rule for $\mathbf{w}$ is then given by,

$$\Delta \mathbf{w}_i = \eta \underbrace{\left(\widehat{\Delta_t} - \Delta_t\right)}_{\text{error term}} \underbrace{(f(\mathbf{X})(1 - f(\mathbf{X})))}_{\text{gradient}} \mathbf{X}_i$$

which is similar to the delta update rule found in artificial neural networks. We omit the scaling factor in the gradient as it is a constant and then experiment with various values of η, the learning rate.

In this chapter, we have outlined the specific task we will be attempting, to try and predict the time from the current last post in the thread to the next. We have discussed the types of features we will be using, time context features, with a focus on content features that consists mainly of the tokens present. We have also discussed the concept of a window, and how it could help to make predictions better. Also, two novel methods were discussed, and, in the next chapter, we will look at how these methods stack up against one another.

Chapter 4

Evaluation Metrics

One of the contributions of this project was also to come up with a good metric for measuring the performance of a model that performs predictions.

Our metric has to be different from traditional methods of measuring performance. One example of such a measure is Mean Average Percentage Error (MAPE), which we use to measure the performance of the learnt model. This value is given by

$$\frac{1}{|P|}\sum_{t=1}^{|P|}\left|\frac{f(\mathbf{X}_t)-\Delta_t}{\Delta_t}\right|$$

where A_i is the actual value, and F_i is the forecasted value for the instance i. Realistically, the model would not be able to come into contact with every possible window, since chances are it will make an error that causes it to visit a thread late, causing it to miss two posts or more.

Notation	Description
P	List of posts.
V	List of visits.
T	A thread's T-score.
$T_{\max}$	A thread's maximum T-score.
$t(\rho)$	Timestamp of the post.

Table 4.1: Notation used for evaluation metrics

This value does not reflect how well the model will do in a real-time setting, but gives an idea of how far off the model is given a window.

In such measures, the performance of the model is measured on an instance by instance basis. To give a concrete example, say we are attempting to predict stock prices. Given the feature vector as input, we get an estimate of what the stock prices will be for, say, the next day. We can then measure the absolute difference between what was predicted and the actual amount, and evaluate the model based on that.

In our case, we want to know how long it takes before any post made will be retrieved by the crawler. We also want to ensure that the model does not choose to make too many requests. The rest of the chapter explains in detail how we came up with our metric, its advantages and limitations.

4.1 Potential errors

To be thorough, let us also enumerate the types of errors that a model making predictions could encounter.

The model can potentially make a prediction such that the next visit comes before the arrival of the next post. The predictions being made are the Δ_t between the posts, rather than the visitation times, hence, it is possible for the model to make a prediction that occurs before the current time. An erroneous prediction can also cause the crawler to come in before the next post (two, or more, visits, but nothing new fetched). Errors of this type waste bandwidth, since the crawler will make an unnecessary visit to the page.

Another type of error would have the prediction causing the next visit to come some time after a post. Since most predictions are almost never fully accurate, there will be some time between the post is made and the page is fetched. These errors are still relatively acceptable, but the time difference between the post arriving and the visit should be minimised. The visit could also come more than one post later. Errors of this kind incur a penalty on the freshness of the data, more so than the after one post, especially if the multiple posts are far apart time-wise.

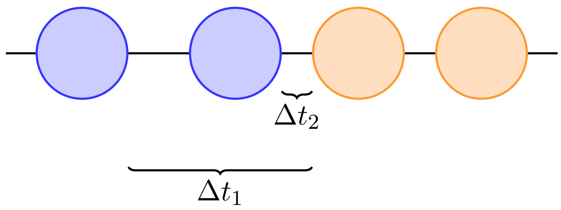


Figure 4.1: An example of a series of events used in our evaluation.

4.2 T-score, and the Visit/Post ratio

We also want to know the *timeliness* of the model's visits. Yang et al. (2009) has a metric for measuring this. Taking Δt_i as the time difference between a post i and it's download time, the timeliness of the algorithm is given by

$$T = \frac{1}{|P|} \sum_{i=1}^{|P|} \Delta t_i$$

A good algorithm would give a low T-score. However, a crawler that hits the site repeatedly performs well according to this metric. The authors account for this by setting a bandwidth (fixed number of pages per day) for each iteration of their testing. In our experimental results, we also take into account the number of page requests made in comparison to the number of posts.

4.3 Normalising the T-score and Visit/Post ratio

We normalise the T-score to get a comparable metric across all the threads. In order to do this, we consider again the thread posts and visits as a sequence of events. We then define the *lifetime*, denoted as l, of the thread as the time between the first post and the last post. Any visits that occur after the last post are ignored.

We then consider the worst case in terms of timeliness, or misses. This would be the case where the visit comes at the end, at the same time as the post. So we get a value $T_{\max}$ and

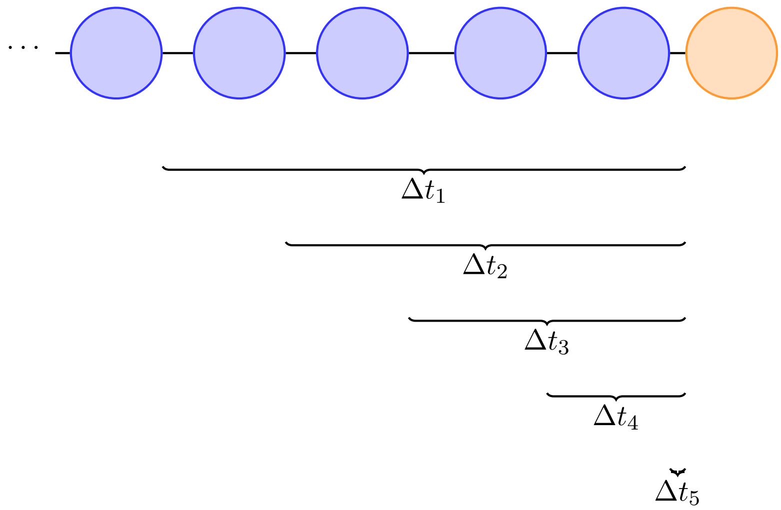


Figure 4.2: An example of calculating $T_{\max}$. A visit is assumed at the same time as the final post made, and the usual T-score metric is calculated

P_{miss} such that

$$\begin{aligned} Pr_{\text{miss}} &= \frac{T}{T_{\max}} \\ &= \frac{T}{\left(\frac{\sum_{\rho}(\max_{\rho'} t(\rho') - t(\rho))}{|P|}\right)} \\ &= \frac{|P| \cdot T}{\sum_{\rho}(\max_{\rho'} t(\rho') - t(\rho))} \end{aligned}$$

An example can be viewed in Figure 4.2. Assuming that there are no posts before ρ_1 here, we simply take the usual T-score value to get $T_{\max}$ It is difficult to consider the worst case in terms of false alarms, or visits that retrieve nothing. There could be an infinite number of visits made if we are to take the extreme case. In order to get around this, we consider discrete time frames in which a visit can occur. Since for this dataset, our time granularity is in terms of minutes, we shall use minutes as our discrete time frame. With this simplified version of our series of events, we can then imagine a worst-case performing revisit policy that visits at every single time frame. Here, we assume all quantities are measured in terms of minutes. This gives us

$$Pr_{\text{FA}} = \frac{|V|}{(\max_{\rho} t(\rho)) - |P|}$$

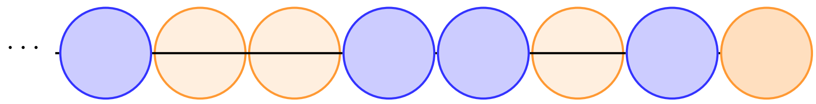


Figure 4.3: An example of calculating the maximum number of visits given a thread. The ratio between the number of visits predicted and the number of visits to the thread, and is used as Pr_{FA}

where l is in units of:our specified discrete time frame. Figure 4.3 shows an example of how Pr_{FA} is calculated.

With these two normalised forms of the original metrics, we can use a weighted mean to give a weighted combined form of the two error rates, Pr_{error}:

$$Pr_{\text{error}} = \alpha Pr_{\text{FA}} + (1 - \alpha) Pr_{\text{error}}$$

In the following sections, we will discuss the results of our experiments with the various algorithms found in the previous chapter, and measure their effectiveness using their T-scores and Visit/Post ratio, and comparing them using the Pr_{error} metric.

Chapter 5

Evaluation

In our project, the dataset we used was crawled from `http://www.avsforum.com/f/`. The forum dealt mainly with Audio-Visual equipment, with discussions mainly about technical details, offers and people showing off their DIY projects.

The forum was chosen from the list which Yang et al. (2009) provided in their paper. The forum users use mainly proper English, which made removing stopwords and stemming simpler.

We crawled 4,158 threads, with a total of 1,002,225 posts. A distribution of how the length of threads are distributed can be seen in Figure 5.1. Threads with 1 to 10 posts already make up half the number of collected threads. The distribution of the time differences are shown in Figure 5.2. In both the figures, the right-hand-side cutoff was set at 1,000 due to the negligible number of items to the right of the cutoff.

5.1 Experiment setup

The first 75% of the thread was used as training data, while the remaining 25% was used as test data. We used Support Vector Regression for this regression task, employing a Radial Basis Function kernel as our learning algorithm.

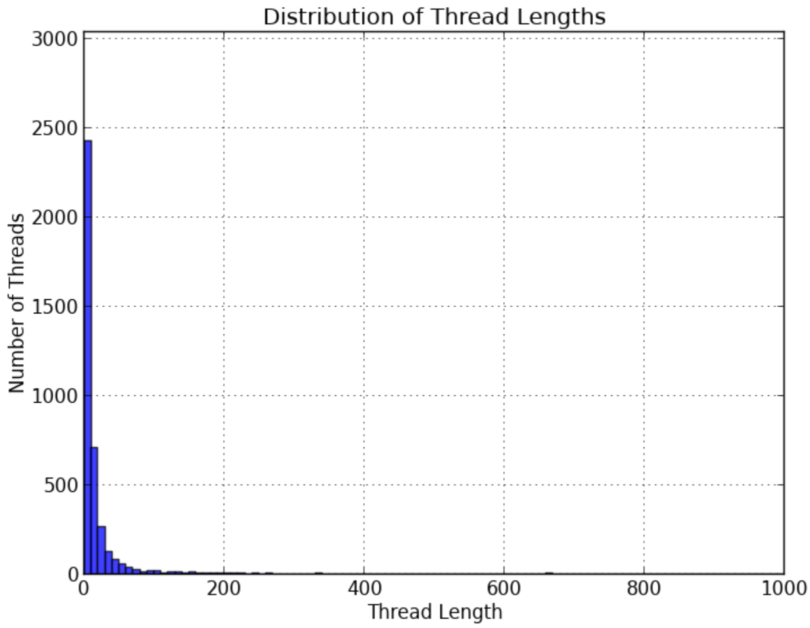


Figure 5.1: Distribution of thread length

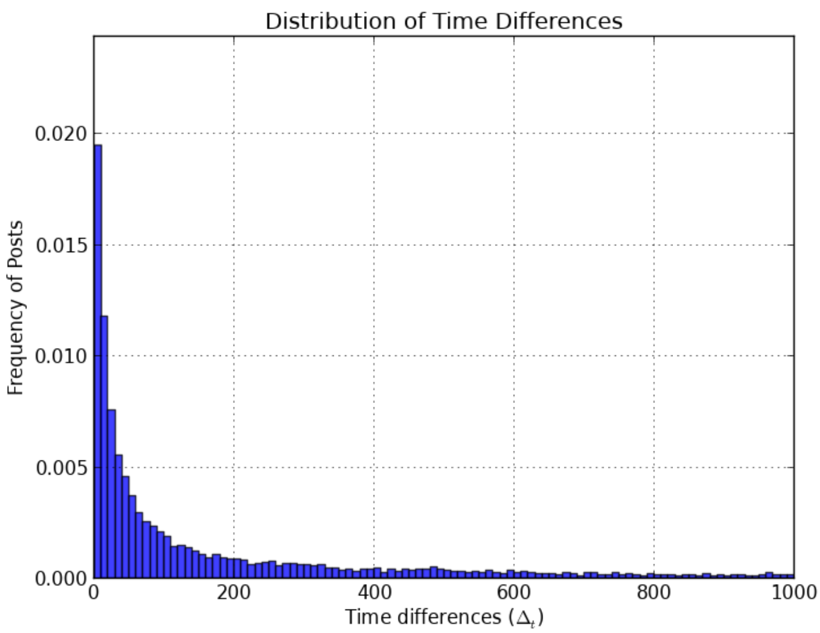


Figure 5.2: Distribution of Δ_t

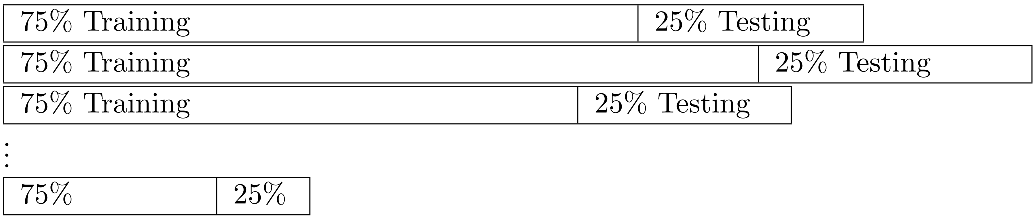


Figure 5.3: Our experiment setup

	T-score	Visit/Post	Pr_{error}
$K = 10$	1590.985 ± 236.131	18.013 ± 7.588	0.019 ± 0.004
$K = 20$	1594.691 ± 237.001	18.005 ± 7.585	0.019 ± 0.004
$K = 30$	1580.981 ± 235.293	18.011 ± 7.587	0.019 ± 0.004
$K = 40$	1579.544 ± 234.802	18.015 ± 7.586	0.018 ± 0.004
$K = 50$	1564.888 ± 235.164	18.024 ± 7.587	0.018 ± 0.004
$K = 60$	1564.759 ± 234.663	18.017 ± 7.588	0.019 ± 0.004

Table 5.1: Experiment results: Varying vocabulary size

5.1.1 Parameter Tuning

Before we begin performing experiments on the full dataset, we first tuned the machine learning algorithms using a sample of the forum threads. In the following experiments, the threads chosen from our extracted dataset are those with a 100 to 1000 posts. This amounted to 97 threads. In each of these experiments, we run the algorithm with different parameters, and use the optimal one in our final evaluation.

Vocabulary size

Window size

Using a combination of feature sets, we experiment with different window sizes, $w = 1, 5, 10, 15$.

Performing the experiment using only the Δ_t values within the window, we obtain the results found in Table 5.2. The results show that $w = 15$ provide the best T-score. We must however, keep in mind that its Visit/Post ratio is the highest, but also has a higher standard error.

Using only the content, we perform the same experiment again. Since the size of the vocab-

	T-score	Visit/Post	Pr_{error}
$w = 5$	1537.682 ± 234.658	18.056 ± 7.585	0.018 ± 0.004
$w = 10$	1485.157 ± 198.664	18.523 ± 8.028	0.019 ± 0.004
$w = 15$	1433.771 ± 185.080	19.396 ± 8.896	0.016 ± 0.003
$w = 20$	1577.639 ± 229.482	19.037 ± 8.690	0.019 ± 0.004

Table 5.2: Some results

	T-score	Visit/Post	Pr_{error}
$w = 5$	1537.682 ± 234.658	18.056 ± 7.585	0.018 ± 0.004
$w = 10$	1485.157 ± 198.664	18.523 ± 8.028	0.019 ± 0.004
$w = 15$	1433.771 ± 185.080	19.396 ± 8.896	0.016 ± 0.003
$w = 20$	1577.639 ± 229.482	19.037 ± 8.690	0.019 ± 0.004

Table 5.3: Some results

ulary is large, we select the $K = 50$ best tokens to consider using Univariate feature selection. This gives us the results in Table 5.3. The best T-score here does not do as well as that in the previous experiment. However, it is interesting to note that, again, $w = 15$ results in the best T-score.

For our final experiment for tuning the window size, we combine the various feature sets together. We also include the time-context in this experiment, and we arrive at the results found in Table 5.4. Again, $w = 15$ has the best T-score, but only with a slight improvement over our first experiment.

In any case, this suggests that $w = 15$ may be the best window size. In the following experiments, this will be our w value.

	T-score	Visit/Post	Pr_{error}
$w = 5$	1537.673 ± 234.657	18.056 ± 7.585	0.018 ± 0.004
$w = 10$	1485.137 ± 198.662	18.523 ± 8.028	0.019 ± 0.004
$w = 15$	1433.762 ± 185.078	19.396 ± 8.896	0.016 ± 0.003
$w = 20$	1577.639 ± 229.482	19.037 ± 8.690	0.019 ± 0.004

Table 5.4: Some results

Decay factor

In our discounted sum method, we have to tune the α parameter. We search through 0.1 to 0.9 (inclusive) with 0.1 increments to find the best possible value for α. We used the combined set of features for this experiment. The results are shown in Table 5.5.

$\alpha = 0.9$ performs the best, but its improvement over the rest of the values for α are not by much. Also, note that the T-scores do not defer much from the previous experiment, although there is a slight improvement.

Learning rate for Stochastic Gradient Descent

Because of the scaling factors applied to the sigmoid function, a small change in the exponent of e results in huge fluctuations. As such, we need to find a small enough learning rate such that the predicted values do not end up at only the extremes, but large enough such that the model is adaptive enough to "react" to changes.

In this experiment, we find that $\eta = 5 \cdot 10^{-8}$ is the best value for the learning rate. Also note that this model produces the best results for the sample dataset.

So at the end of tuning our feature set and parameters, we have the following set of parameters: $K = 50, w = 15, \alpha = 0.9, \eta = 5 \cdot 10^{-8}$. Using these parameters, we run a full evaluation on our dataset.

	T-score	Visit/Post	Pr_{error}
$\alpha = 1$	1433.761 ± 185.078	19.396 ± 8.896	0.016 ± 0.003
$\alpha = 2$	1433.759 ± 185.078	19.396 ± 8.896	0.016 ± 0.003
$\alpha = 3$	1433.757 ± 185.078	19.396 ± 8.896	0.016 ± 0.003
$\alpha = 4$	1433.755 ± 185.077	19.396 ± 8.896	0.016 ± 0.003
$\alpha = 5$	1433.755 ± 185.077	19.396 ± 8.896	0.016 ± 0.003
$\alpha = 6$	1433.755 ± 185.077	19.396 ± 8.896	0.016 ± 0.003
$\alpha = 7$	1433.755 ± 185.077	19.396 ± 8.896	0.016 ± 0.003
$\alpha = 8$	1433.755 ± 185.077	19.396 ± 8.896	0.016 ± 0.003
$\alpha = 9$	1433.746 ± 185.076	19.396 ± 8.896	0.016 ± 0.003

Table 5.5: Some results

	T-score	Visit/Post	Pr_{error}
$\eta = 6$	1527.249 ± 196.277	19.231 ± 8.896	0.019 ± 0.004
$\eta = 8$	1379.733 ± 188.469	19.323 ± 8.893	0.015 ± 0.002
$\eta = 10$	1373.679 ± 176.366	18.670 ± 8.966	0.016 ± 0.003
$\eta = 12$	1466.572 ± 226.819	19.267 ± 8.894	0.016 ± 0.003

Table 5.6: Some results

	T-score	Visit/Post	Pr_{error}
Baseline	2370.09 ± 222.556	18.4430 ± 3.009522	0.0455729 ± 0.00315738
Comb.	1435.96 ± 177.004	21.7333 ± 5.20832	0.0383524 ± 0.00253913
Decay	1435.95 ± 177.004	21.7333 ± 5.20832	0.0383523 ± 0.00253913
SGD	1881.84 ± 416.264	21.0476 ± 5.05733	0.0380083 ± 0.00247992

Table 5.7: Some results

	T-score	Visit/Post	Pr_{error}	
	-938.471 ± 161.545	1.29 ± 5.20697	-0.00728408 ± 0.00327361	$p < 0.05$
	-938.474 ± 161.545	1.29 ± 5.20697	-0.00728413 ± 0.00327361	$p < 0.05$
	-479.093 ± 391.269	1.1346 ± 5.19777	-0.0068692 ± 0.00319584	$p < 0.10$

Table 5.8: Some results

5.2 Experiments

Results of running Stochastic Gradient Descent Results of running SVR Results of running Decay

Analyses of the algo.

	T-score	Visit/Post	Pr_{error}
Comb.	1435.96 ± 177.004	21.7333 ± 5.20832	0.0383524 ± 0.00253913
Decay	1435.95 ± 177.004	21.7333 ± 5.20832	0.0383523 ± 0.00253913
SGD	1881.84 ± 416.264	21.0476 ± 5.05733	0.0380083 ± 0.00247992
Comb.	1554.5 ± 292.206	30.9191 ± 16.996	0.0383057 ± 0.00434776
Decay	1554.5 ± 292.206	30.9191 ± 16.996	0.0383057 ± 0.00434776
SGD	1399.06 ± 254.049	30.6367 ± 16.8814	0.0424276 ± 0.00467794
Comb.	1700.47 ± 300.413	28.7258 ± 17.6231	0.0148638 ± 0.00365225
Decay	1700.44 ± 300.408	28.7258 ± 17.6231	0.0148638 ± 0.00365225
SGD	1676.24 ± 319.828	28.1005 ± 17.2635	0.0131775 ± 0.00266262
Comb.	1527.77 ± 349.794	12.4909 ± 6.69594	0.0151237 ± 0.00453188
Decay	1527.77 ± 349.794	12.4909 ± 6.69594	0.0151237 ± 0.00453188
SGD	1223.58 ± 260.261	11.3483 ± 6.03096	0.0143991 ± 0.00369424
Comb.	708.178 ± 136.94	9.54313 ± 3.14934	0.00642689 ± 0.00124465
Decay	708.175 ± 136.94	9.54316 ± 3.14934	0.00642643 ± 0.00124457
SGD	608.227 ± 109.399	8.45964 ± 2.70039	0.00605408 ± 0.000898222

Table 5.9: Some results

Chapter 6

Conclusion

With the increasing number of sites leveraging user-generated content, a method for predicting the updates of such sites needs to be created in order for an incremental web crawler to effectively crawl the site. Our high level goal: to predict the posting behaviour of users to such sites.

While this primary goal has many challenges, in this report, we have chosen to address challenges specific to forum threads. We want to predict, given content of the current thread, the time at which a user would post to the thread. We evaluate three different machine learning approaches: Two offline algorithms, one that only takes into account only the latest window, and another that accounts for past windows, with decreasing weightage. And an online algorithm, that uses gradient descent to update its weights every time a new post is observed.

Overall, our evaluation shows that our methods work better than the baseline, which was to revisit the thread at the average time interval. These are promising results, and more can be done to improve upon them.

There are, however, limitations with the current methods, such as....

6.1 Contributions

We have made the following contributions with our work:

1. Provide comparable evaluation metrics that can be parameterised, depending on the evaluators' priority: freshness or bandwidth.

2. Three different prediction methods using machine learning.

3. The effectiveness of using content and time differences for post prediction.

6.2 Future Work

With the proposed methods still having many shortcomings when predicting new posts, or providing insight into what causes post arrival times, it leaves much room for future work to be done.

6.2.1 Using Natural Language Processing (NLP) techniques

(Wang, Chen, & Kan, 2012)

6.2.2 Topic modelling

(González, Muñoz, Roque, & García-gonzález, 2005; Hsu & Glass, 2006)

6.2.3 Leveraging context

6.2.4 Using online learning techniques

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Appendix A

Code