## Predicting Web 2.0 Thread Updates

Shawn Tan

### Table of Contents

Introduction

Related work

The Dataset

**Evaluation Metrics** 

Evaluation



#### Motivation

- Many sites with thread-based discussion features
- Users post product reviews, feedback

Obtaining such up-to-date information may be vital to companies.



### Table of Contents

Introduction

Related work

The Dataset

**Evaluation Metrics** 

Evaluation



## Refresh policies for incremental crawlers

Many works have used time difference to estimate page updates.

- 1. Coffman et. al. 1997 analysed the theoretical aspects.
- 2. Cho and Garcia-Molina trace the change history of 720,000 web pages collected over 4 months.
  - 2.1 Showed empirically that the Poisson process model estimates the update processes well (Cho et. al. 1999)
  - 2.2 Proposed different revisiting or refresh policies (Cho et. al. 2003, Garcia-molina et. al. 2003)
- 3. Also used in Tan et. al. 2007.

#### Problems with Poisson

The Poisson distribution is memoryless, and in experimental results due to Brewington and Cybenko 2000, the behaviour of site updates are not.

## Using Site-level Knowledge

Yang et. al. 2009, attempted to resolve this by

- 1. Using the list structure of forum sites to infer a sitemap.
- 2. Use a linear-regression model to predict when the next update to the thread will arrive.
- 3. Linear model used together with the sitemap information to prioritise the request queue in the crawler.
- Has the ability to make use of index information to infer changes in threads. Other types of comment systems do not have such indices.



## Summary

- Previous work dealt with Web 1.0 sites.
- ▶ Did not take into account the content in the posts.
- ► Evidence to show that using time, while makes reasonable prediction, does not fully model the behaviour of threads.

### Table of Contents

Introduction

Related work

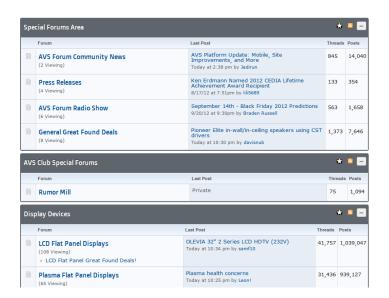
The Dataset

**Evaluation Metrics** 

Evaluation



#### avsforum.com



#### User-centric threads







## Questions

#### What's wrong with my LG LCD?







#### 9/1/12 at 2:20pm THREAD STARTER

post #1



DlacmaD790LL

I noticed this issue today when I powered on my 2011 LG LCD. The set has about 2,100 hrs on and was working fine yesterday. The issue is that the picture looks blurry and low res with distorted text and jagged vertical and diagonal lines in what should be solid sharp and clear text lines, pictures, and other shapes. The issue occurs with all sources/inputs and on the TV menu itself. Is this a panel issue or a main board issue or something else? Anything I can try to resolt this issue? I reset the picture settings and tried various pic modes, but to no avail.

#### 9/1/12 at 2:46pm



Is it a 3D model?

Did you try unplugging it for about 20 minutes in order to make sure it had a complete reboot v

◆ロト ◆御 ト ◆ 恵 ト ◆ 恵 ・ 釣 へ ②

#### **Mentions**

10/1/10 at 6:12pm



Elkhunter ▼

Senior Member

offline

315 Posts. Joined 7/2008

#### rdjam:

Wouldn't a 1.4a AVR with 2 simultaneous HDMI outpu

I have an Yamaha RX-A3000 on order (due next Thu

TIA

10/1/10 at 6:24pm THREAD STARTER |



#### rdjam ▼ New toy The Darblet!

offline

9,716 Posts. Joined 3/2005 Location: Miami. FL

#### Quote:

Originally Posted by Elkhunter 📂

#### rdjam:

Wouldn't a 1.4a AVR with 2 simultaneous HDMI or

I have an Yamaha RX-A3000 on order (due next

ТΤΔ

That should be do-able. Don't have one yet but can't

However, I was planning to have one output for my projectors.

## Table of Contents

Introduction

Related work

The Dataset

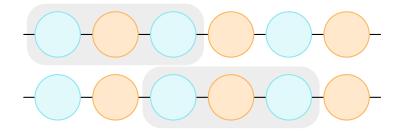
**Evaluation Metrics** 

Evaluation

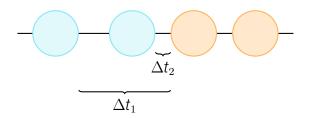
## Requirements

- Balance of freshness and bandwidth usage.
- ► Penalise when using too much bandwidth (visiting the site too much).
- ► Penalise when "database" not fresh (visiting the site too little).

## **Events**



## *T*-score



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

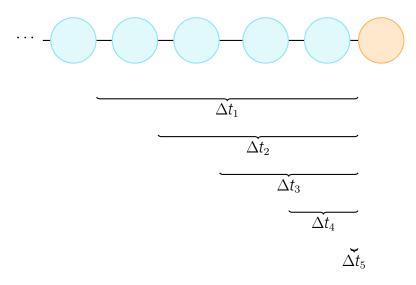
From Yang et. al. 2009

4□ > 4□ > 4□ > 4□ > 4□ > 4□

### Visit/Post ratio

Number of visits per post, keep the *T*-score in check.

## Normalised *T*-score



### Normalised Visit/Post ratio



## Table of Contents

Introduction

Related work

The Dataset

**Evaluation Metrics** 

Evaluation



## **Experiment Setup**

75% Traini	ng	25% Testing
75% Traini	ng	25% Testing
75% Traini	ng	25% Testing
75%	25%	

#### For parameter tuning:

- 1. Threads from 100 to 1000 posts
- 2. 107 Threads in total

#### Baseline

Take the average  $\Delta_t$  from training set, and use that as the revisit time.

	Pr <sub>error</sub>	T-score	Visit/Post
Average	$0.501 \pm 0.001$	$1764.474 \pm 267.227$	$18.117 \pm 7.290$

# Windowing

Use features from windows of posts. Number of posts in window given by w.



# Windowing

Use features from windows of posts. Number of posts in window given by w.



# Windowing

Use features from windows of posts. Number of posts in window given by w.



# Window-based average

Take the average  $\Delta_t$  from training set the previous window, and use that as the revisit time.

	T-score	Visit/Post	<i>Pr</i> <sub>error</sub>
W = 5	$6420 \pm 1000$	$16.6 \pm 7$	$0.028 \pm 0.005$
w = 10	$4580 \pm 700$	$17.4 \pm 8$	$0.028 \pm 0.005$
w = 15	$3830 \pm 600$	$18.5 \pm 9$	$0.021 \pm 0.003$
w = 20	$3340 \pm 400$	$18.3 \pm 9$	$0.022 \pm 0.004$

Performs worse than the simple average baseline.



## Support Vector Regression

Using only the window's  $\Delta_t$  as features.

	T-score	Visit/Post	Prerror
	$1537.682 \pm 234.658$		
w = 10	$1485.157 \pm 198.664$	$18.523 \pm 8.028$	$0.019 \pm 0.004$
	$1433.771 \pm 185.080$		
w = 20	$1577.639 \pm 229.482$	$19.037 \pm 8.690$	$0.019 \pm 0.004$

#### Content-based features

#### Count of individual tokens used:

- 1. Text is stemmed, stopwords removed
- 2. Occurences of usernames are replaced with '#USER#'
- 3. Occurences of tokens with mixtures of alphabets and numbers are replaced with '#MODEL#'
- 4. Univariate regression tests used to select features

#### Time-context

- 1. Hour of the day
- 2. Day of the week

Represented as bit vectors

## Content features only

Using only the content features (stemmed word frequency counts).

	T-score	Visit/Post	<i>Pr</i> <sub>error</sub>
	$1593.380 \pm 237.070$		
w = 10	$1546.839 \pm 198.243$	$18.493 \pm 8.030$	$0.023 \pm 0.006$
w = 15	$1491.695 \pm 187.589$	$19.359 \pm 8.899$	$0.021 \pm 0.005$
w = 20	$1645.177 \pm 232.365$	$19.017 \pm 8.694$	$0.024 \pm 0.005$

Worse than the time difference approach, would using both sets of features help?

## Content features $+\Delta_t$ + time-context

	T-score	Visit/Post	<i>Pr</i> <sub>error</sub>
W = 5	$1537.673 \pm 234.657$	$18.056 \pm 7.585$	$0.018 \pm 0.004$
w = 10	$1485.137 \pm 198.662$	$18.523 \pm 8.028$	$0.019 \pm 0.004$
w  = 15	$1433.762 \pm 185.078$	$19.396 \pm 8.896$	$0.016 \pm 0.003$
w = 20	$1577.639 \pm 229.482$	$19.037 \pm 8.690$	$0.019 \pm 0.004$

### **Discounted Sum**

Discounted sum of feature vectors from previous windows.

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

Where  $0 \ge \gamma > 1$ . Here we use only the word count as before.

	T-score	Visit/Post	$Pr_{\text{error}}$
$\alpha = 1$	$1433.761 \pm 185.078$	$19.396 \pm 8.896$	$0.002 \pm 0.000$
	$1433.759 \pm 185.078$		
$\alpha = 3$	$1433.757 \pm 185.078$	$19.396 \pm 8.896$	$0.002 \pm 0.000$
$\alpha = 4$	$1433.755 \pm 185.077$	$19.396 \pm 8.896$	$0.002 \pm 0.000$
	$1433.755 \pm 185.077$		
$\alpha = 6$	$1433.755 \pm 185.077$	$19.396 \pm 8.896$	$0.002 \pm 0.000$
$\alpha = 7$	$1433.755 \pm 185.077$	$19.396 \pm 8.896$	$0.002 \pm 0.000$
$\alpha = 8$	$1433.755 \pm 185.077$	$19.396 \pm 8.896$	$0.002 \pm 0.000$
$\alpha = 9$	$1433.746 \pm 185.076$	$19.396 \pm 8.896$	$0.002 \pm 0.000$

## Stochastic Gradient Descent

#### Function to be fitted:

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

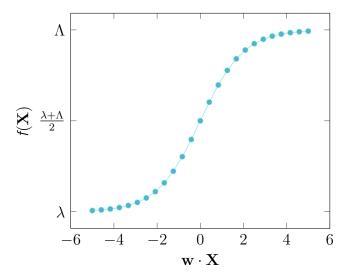
Update rule:

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

Update rule is used everytime a new post and time interval is observed.



# Scaled Sigmoid Function





# SGD results

	T-score	Visit/Post
$\eta = 5 \cdot 10^{-5}$	1595.563	19.097
$\eta = 5 \cdot 10^{-6}$	1525.705	19.122
$\eta = 5 \cdot 10^{-7}$	1440.440	19.121
$\eta = 5 \cdot 10^{-8}$	1407.172	19.108
$\eta = 5 \cdot 10^{-9}$	1416.182	19.110
$\eta = 5 \cdot 10^{-10}$	1451.729	19.106
$\eta = 5 \cdot 10^{-11}$	1482.868	19.104
$\eta = 5 \cdot 10^{-12}$	1487.555	19.104



# Wilcoxon's signed-rank test

Cannot use Student's *t* test, since distribution of *T*-scores is not normal

- Non-parametric statistical hypothesis test
- Data paired, and come from same population
- H<sub>0</sub>: No difference between my model and baseline (average time revisitation)
- $ightharpoonup H_1$ : My model performs better than baseline

#### Results of Paired Tests

*T*-score  $-381.885 \pm 153.673$ 

Visit/Post  $1.053 \pm 1.749$ 

Single-sided test 0.0486



## Analysis of Data

What words are important, and how do they change over time?

How does the number of posts used to train the model affect the result?



#### Limitations

- 1. Experiments only performed on one forum
- 2. (In)Correctness of model
- 3. Stochastic Gradient Descent is slow



### **Future Work**

- 1. Incorporate decay into model
  - SVM with adaptive parameters (Cao & Tay, 2003)
- 2. NLP techniques
  - ▶ Use features from Wang, Chen, and Kan (2012)
- 3. Lexical Chaining
  - Wang and McCarthy (2011)

Questions? Suggestions?