Looking into the Past to Better Classify Web Spam

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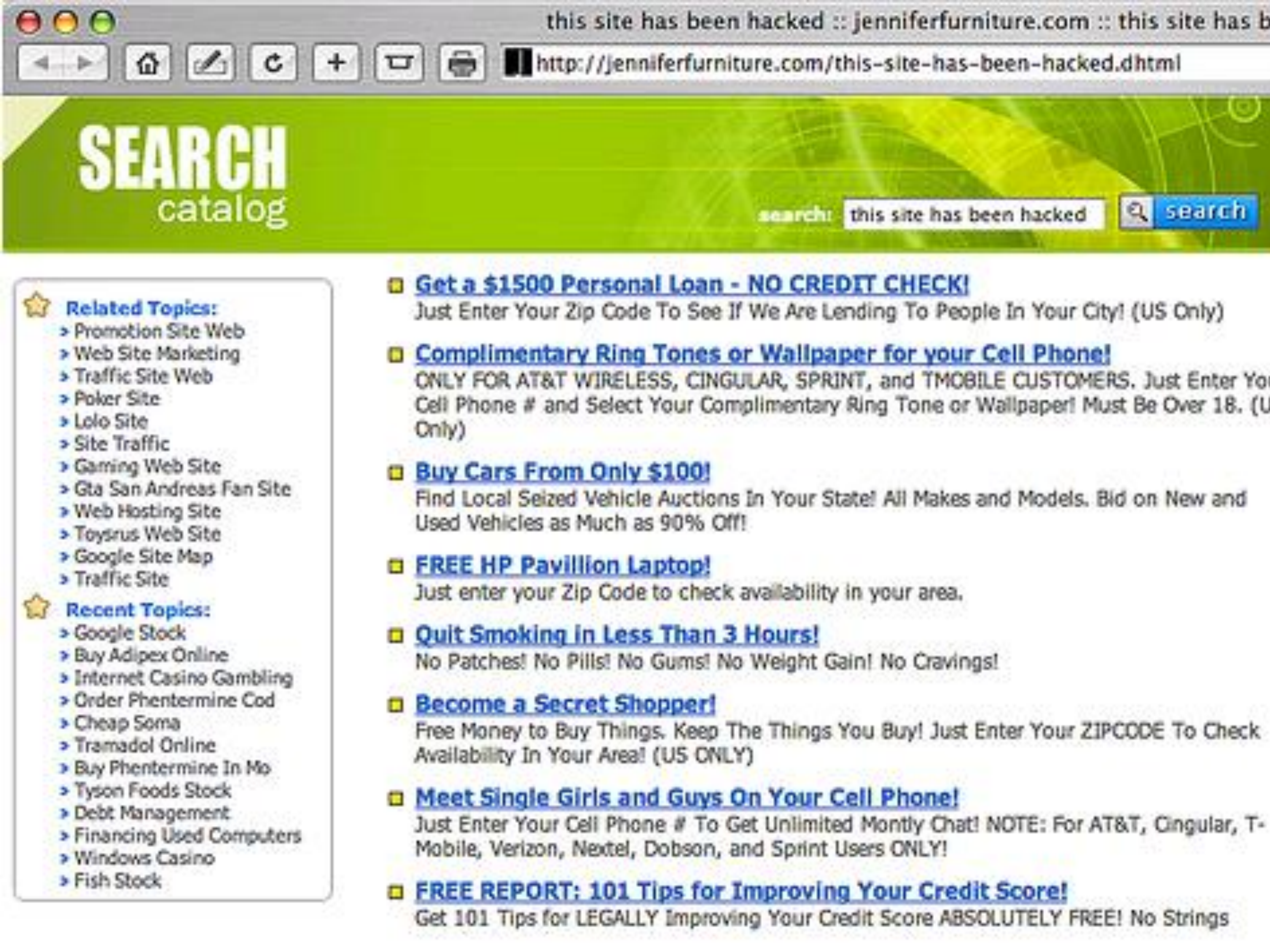
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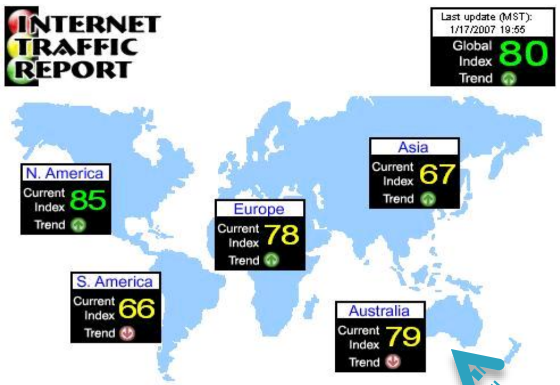
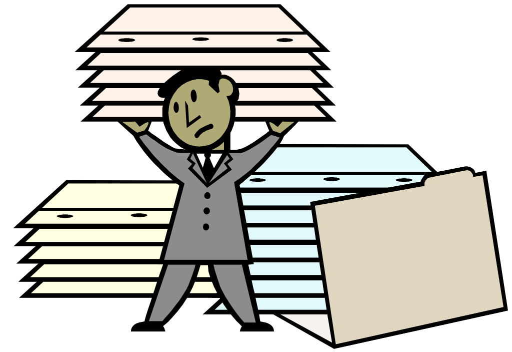
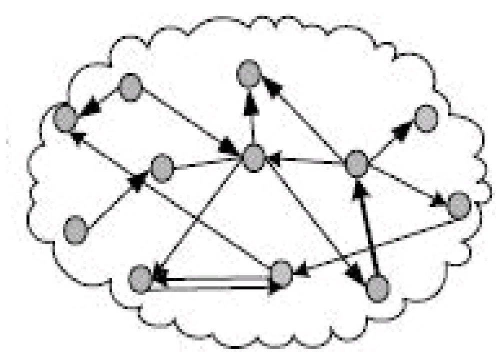
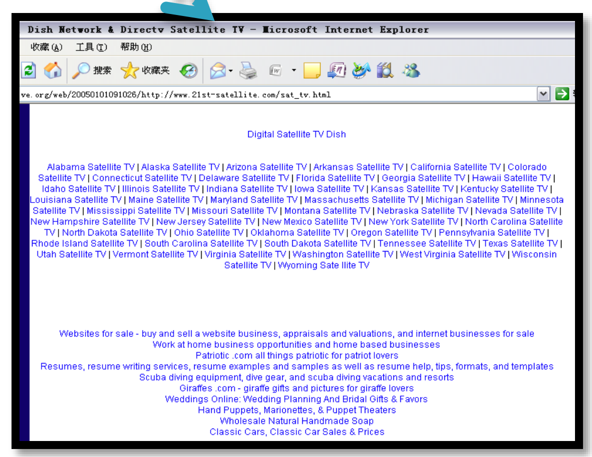




Detect Spam

Historical information about the page itself?





Introduction

- The characteristics of web pages have their own evolution patterns
- Spam pages may have distinguishable evolution patterns from normal pages

Main Questions

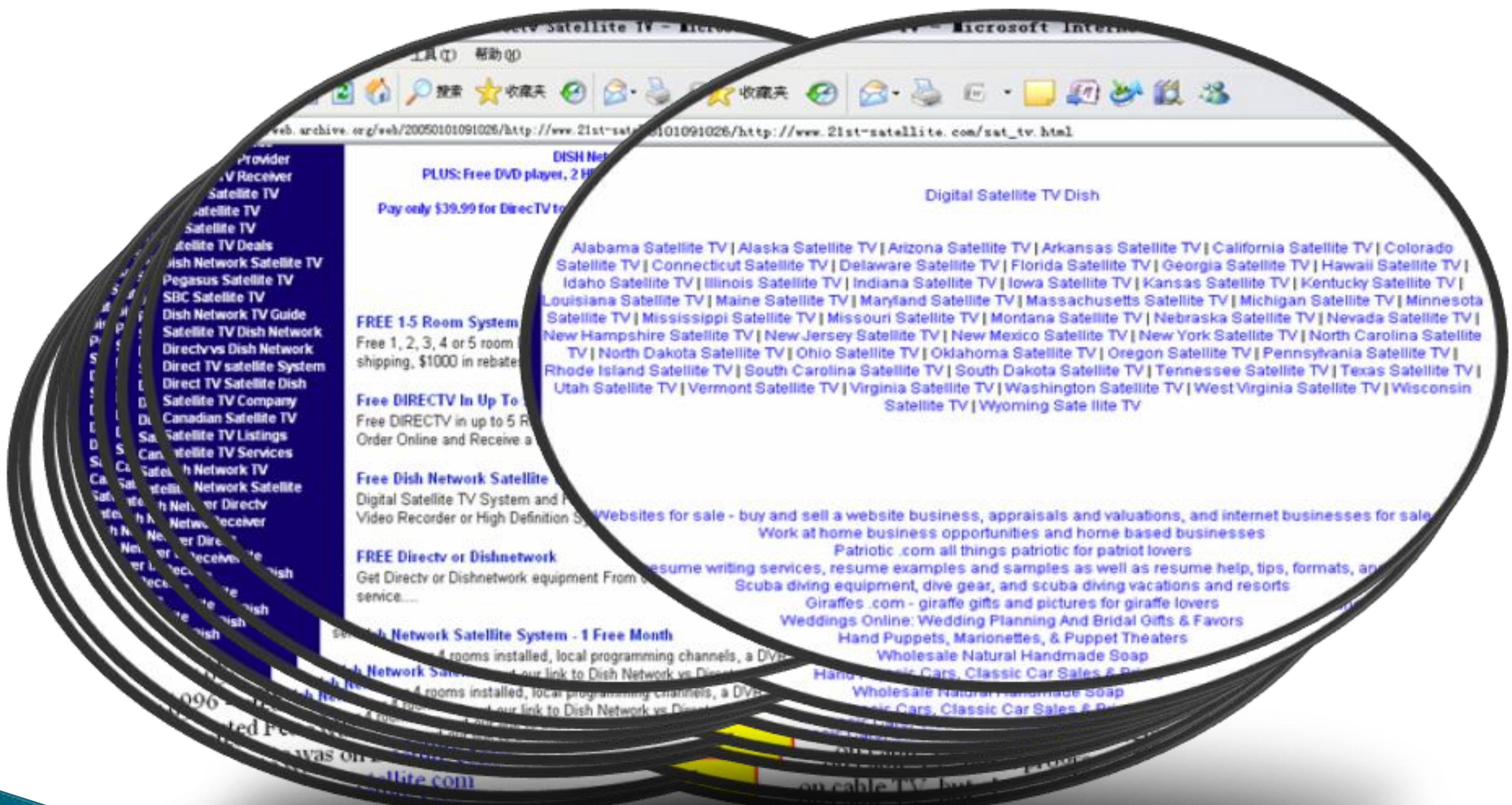
- Can we use different evolution patterns to help Web spam detection?
- Which evolution patterns will make Web pages more likely to become spam pages?
- How long should these patterns influence the decision on spam detection?

Introduction

- Our investigated characteristics
  - Variation of terms contained in web pages
  - Variation of page ownership

- Assumptions
  - Characteristics of spam pages are more likely to have some sudden changes in a previous time interval.

http://www.21st-satellite.com/sat_tv.html from 2004 to 2006



Introduction

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  - Variation of page ownership
- Assumptions
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http://www.emrguide.com/ in 2003 and 2005

Introduction

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- Assumptions
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Principle Introduction

- Our proposed approach
  - Train separate classifiers based on multiple groups of temporal features
  - Combine the classification results to achieve the final decision on spam classification

- In our experiment, this approach can boost spam classification F-measure by 30%.

Related Work

- Google filed a patent (2005) on using historical information for scoring and spam detection.
- Lin et al. (2007) showed blog temporal characteristics with respect to splog detection.
- Shen et al. (2006) extracted temporal link features from two historical snapshots to help identify link spam.

Related Work

- Ntoulas et al. (2006) detected spam pages by combining multiple heuristics based on page content analysis.
- Gyongyi et al. (2006) proposed a concept called spam mass and successfully utilize it for link spamming detection.
- Wu and Davison (2006) detected semantic cloaking by comparing the consistency of two copies retrieved from a browser's perspective and a crawler's perspective.

Approach

- Tracking variance of term importance
  - Bucketize the time interval, and extract one snapshot in each time bucket
  - Quantify term importance and make it comparable among different snapshots (BM scores)
  - Quantify term importance change over time
    - Ave (T) – average term weight vector among the selected snapshots
    - Ave (S) – average difference (slope) between two temporally successive snapshots

Approach (Cont.)

- Dev(T) – deviation of term weight vector among the selected snapshots
- Dev(S) – deviation of difference (slope) between two temporally successive snapshots
- Decay (T) – the decayed version of accumulated term weight vectors among the selected snapshots

$$\text{Decay}(T)_i = \Sigma_j \lambda e^{\lambda(N-j)}\, t_{ij}$$

An example

	T_1	T_2	T_3			…			T_m
H_9	t_{91}	t_{92}	t_{93}			…			t_{9m}
…									
H_1	t_{11}	t_{12}	t_{13}			…			t_{1m}
C	t_{01}	t_{02}	t_{03}			…			t_{0m}

$Ave(T)_1 = 1/10 * (t_{01}+t_{11}+\ldots+t_{91})$
$Dev(T)_1 = 1/9 * ((t_{01}-Ave(T)_1)^2+(t_{11}-Ave(T)_1)^2+\ldots+(t_{91}-Ave(T)_1)^2)$
$Ave(S)_1 = 1/9 * (\|t_{01}-t_{11}\|+\|t_{11}-t_{12}\|+\ldots+\|t_{81}-t_{91}\|)$
$Dev(S)_1 = 1/8 * ((\|t_{01}-t_{11}\|-Ave(S)_1)^2+(\|t_{01}-t_{11}\|-Ave(S)_1)^2+\ldots+(\|t_{01}-t_{11}\|-Ave(S)_1)^2)$
$Decay(T)_1 = 1/10 * (\lambda t_{01}+\lambda e^{\lambda} t_{11}+\ldots+\lambda e^{9\lambda} t_{91})$

Approach (Cont.)

- Classification of page ownership change
  - Problem statement: Given a time interval, determine whether a given page has changed its ownership.
  - Extract page-level temporal features (different emphasis from previous feature groups)

Approach (Cont.)

Content-based feature group(s)
➢ Features based on title information;
➢ Features based on meta information;
➢ Features based on content;
➢ Features based on time measures;
➢ Features based on the organization responsible for the target page;
➢ Features based on global bi-gram and tri-gram lists;
Category-based feature group(s)
➢ Features based on topic distribution;
Link-based feature group(s)
➢ Features based on outgoing links and anchor text;
➢ Features based on links in framesets

Approach (Cont.)

- The number of repeated terms in C(d)_i and C(d)_j
- The difference of probability of terms on a predefined list occurring in two snapshots

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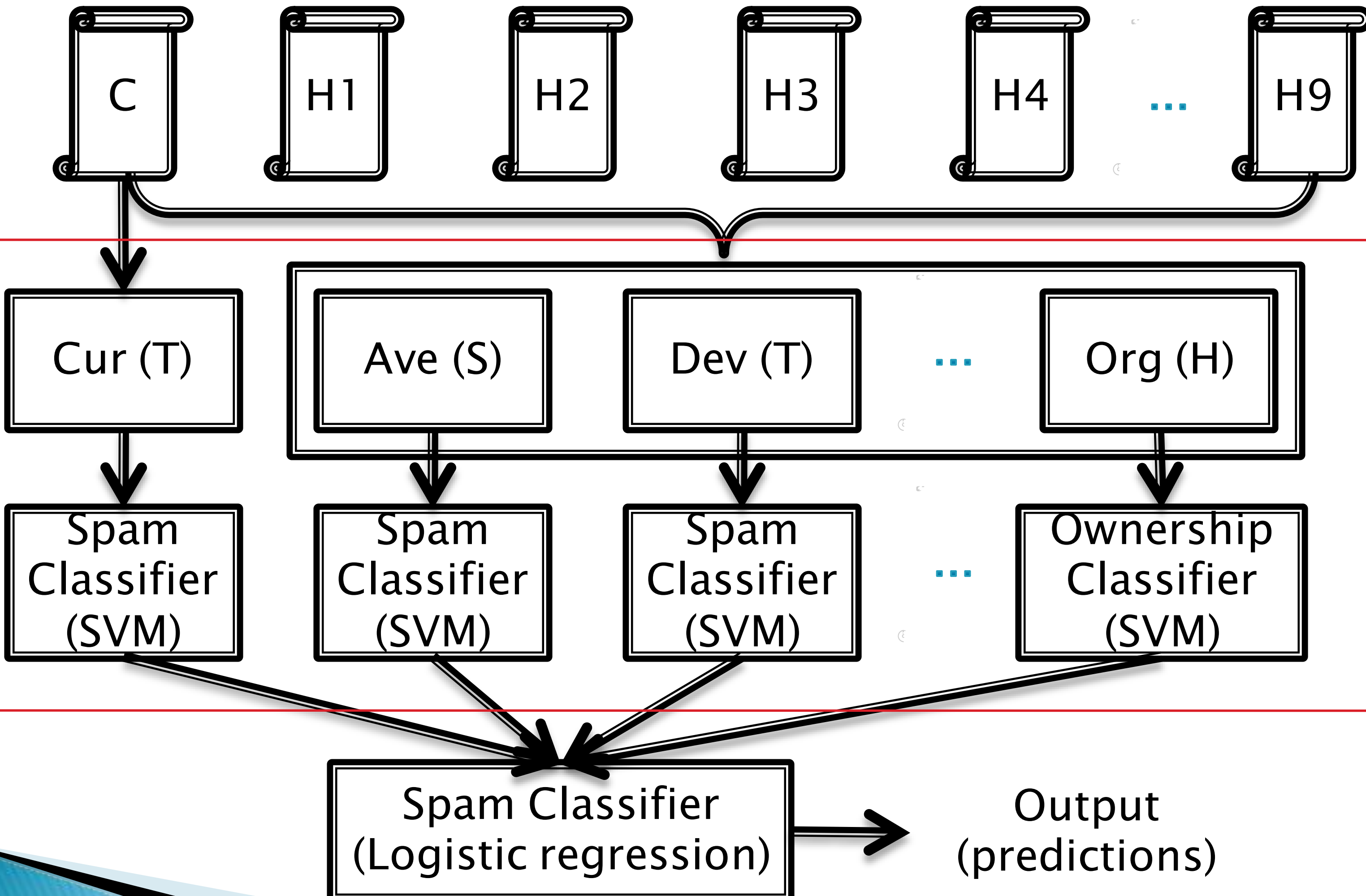
Classification architecture



Experiments

- Features' sensitivity on classification performance with respect to time-span

- The spam classification performance comparison before and after we use temporal features

Datasets

- WEBSPAM-UK2007
  - 6479 sites are labeled with about 6% spam sites
  - We select 3926 sites with 201 spam sites (5.12%).
  - Term based temporal features: 10 snapshots ranging from 2005 to 2007.
  - Use the site home page and up to 400 out-linked pages within the same site to represent the sites' content .
- ODP external pages
  - Training set for determining page ownership change.
  - Manually labeled 247 external pages within the time interval from 2005 to 2007.
  - 100 examples are labeled as positive.

Metrics

- Precision
- Recall
- F-Measure
- Confusion matrix

Features’ sensitivity on F-Measure(1)

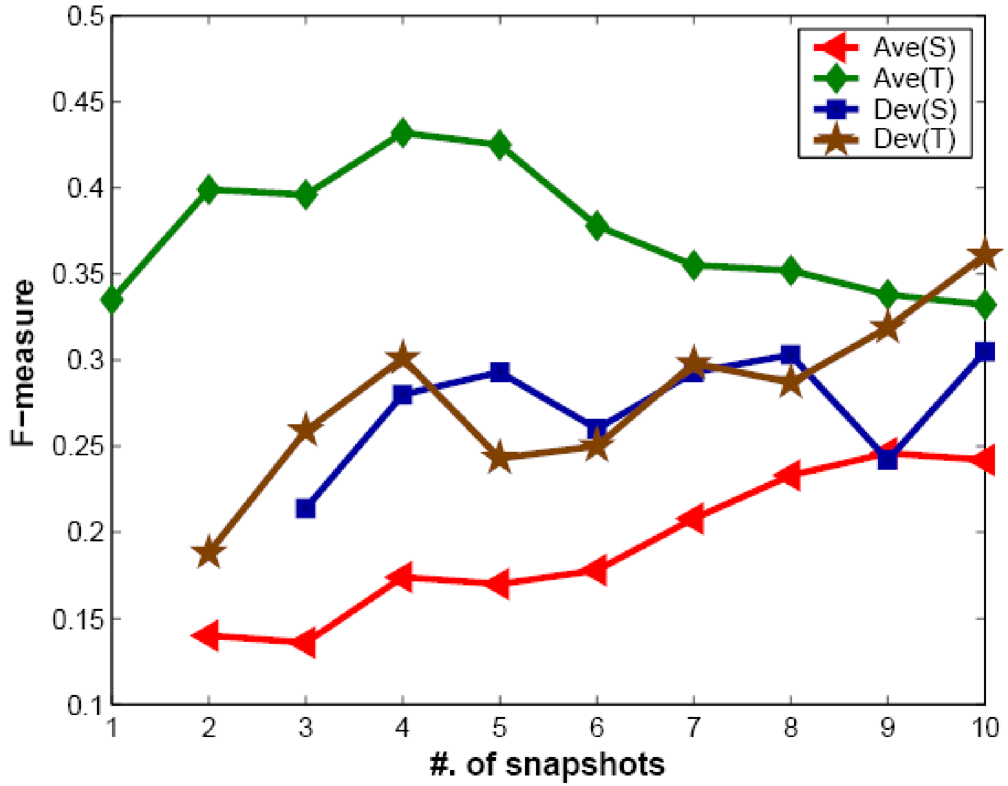


Figure 2: Features’ sensitivity on F-measure performance with respect to time-span.

Features' sensitivity on F-Measure(2)

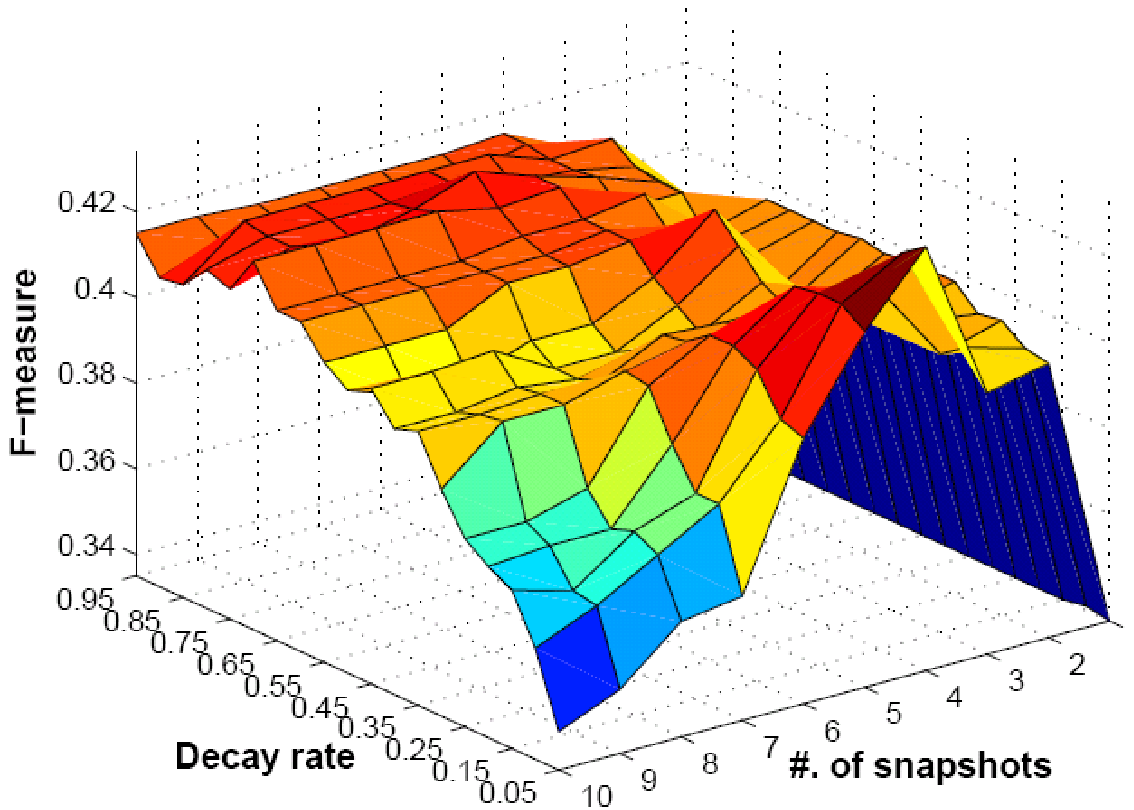


Figure 3: Feature Decay(T)'s sensitivity on F-measure performance with respect to time-span and decay rate.

Individual classification results

Combination	Precision	Recall	F-Measure
BM (baseline)	**0.674**	**0.289**	**0.404**
Dev(S)	0.530	0.214	0.304
Dev(T)	0.529	0.274	0.361
Ave(S)	**0.744**	0.144	0.242
Ave(T)	0.573	0.234	0.332
Decay(T)	0.656	0.303	**0.415**
ORG	0.120	**0.373**	0.181

Combined classification results

Combination	Precision	Recall	F-Measure
BM (baseline)	0.674	0.289	**0.404**
BM+Dev(S)+Dev(T)+ORG	0.650	0.443	**0.527**

Possible Extensions

- Tuning the number of snapshots in classification models
- Combining other temporal features
- The proposed features can be potentially used in other applications.

Conclusion

- Historical information can be a useful resource to help spam classification.
- We demonstrate its capability for spam detection in WEBSPAM-UK2007 data set, and outperform the textual baseline by 30%.

Thank you!

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- Questions?

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