# Identifying Web Spam With User Behavior Analysis

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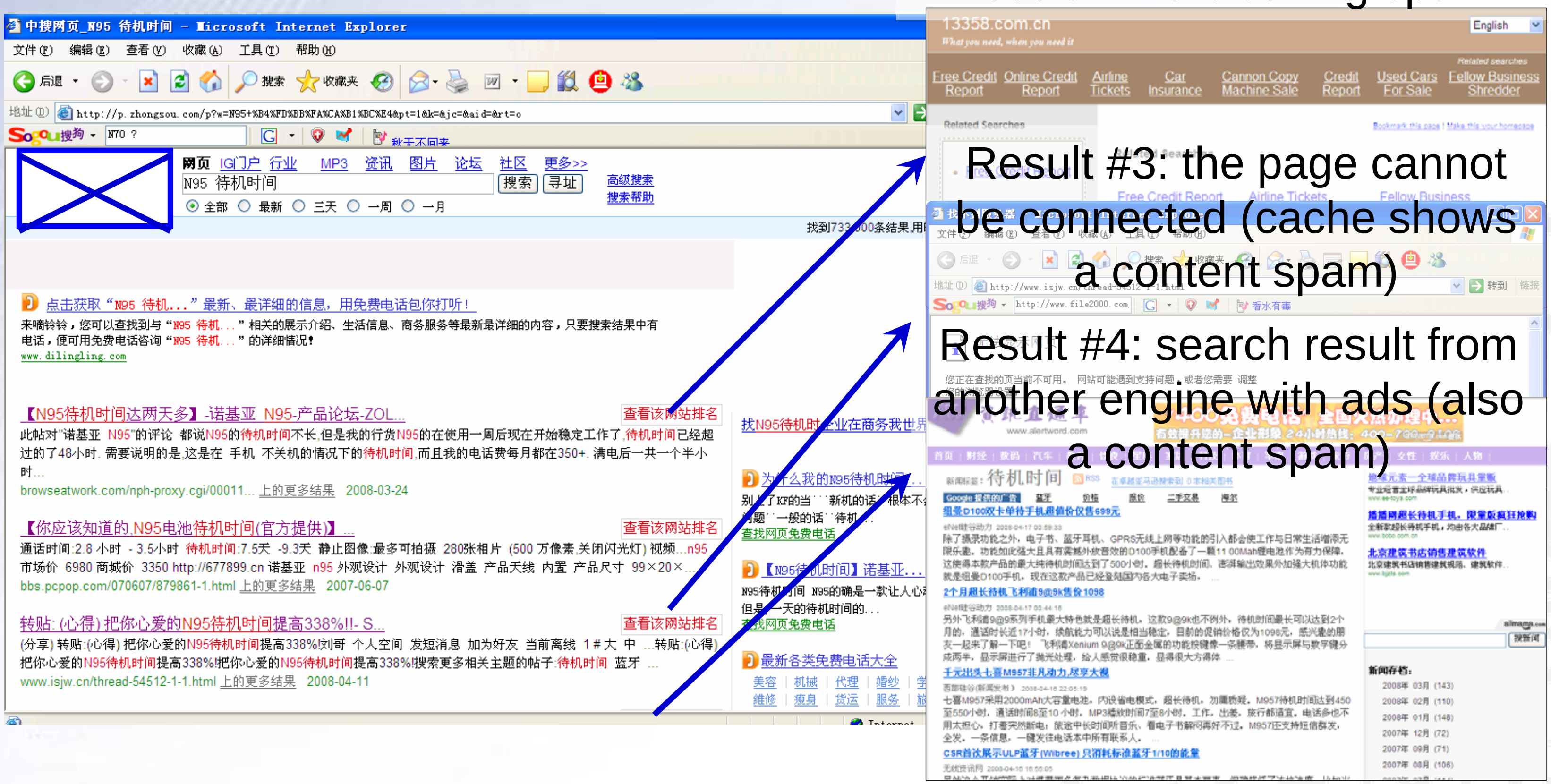
# Introduction – simple math

- How many spam pages are there on the Web?
  - Over 10% (*Fetterly et al.* 2004, *Gyöngyi et al.* 2004)
  - Web has 152 billion pages (How Much Info project 2003)
- How many can a search engine index?
  - Tens of billions (Google: 8 billion@2004, Yahoo: 20 billion@2005)
- #(spam) is equal to/more than search engines' index sizes
- Search index will be filled with useless pages without spam detection.
- We have developed lots of spam detection methods

**However …**

# Introduction

- Search “N95 battery time” with a certain Chinese search engine on 08/04/17



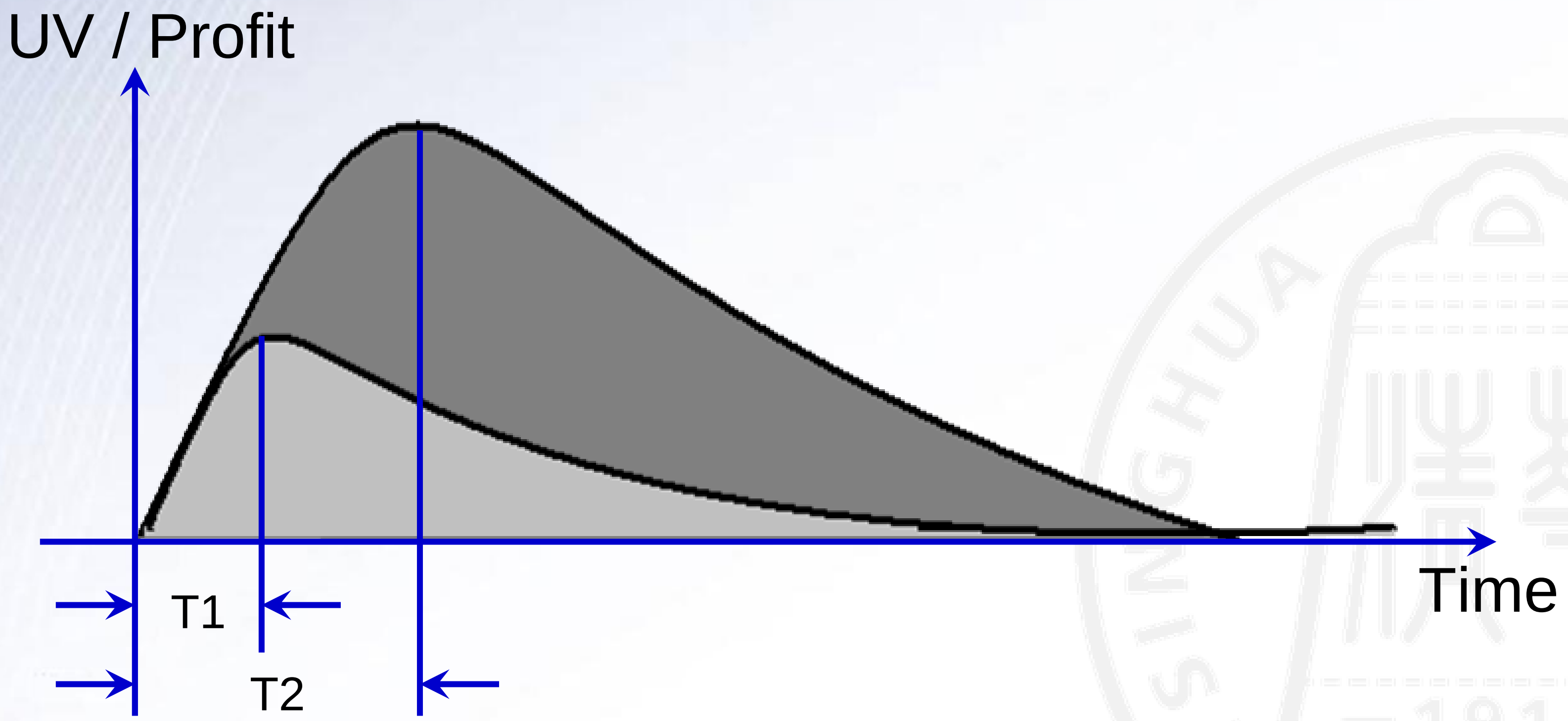
# Introduction

- Problem: spam detection has been an ever-lasting process
  - Good news for anti-spam engineers!
  - Bad news for Web users / search engines
- Are detection methods not effective?
  - No! Lots of works report over 90% detection accuracy (*Ntoulas et al.* 2006, *Saito et al.* 2007, *Lin et al.* 2007, …)
- Are detection methods not timely?
  - Yes! When one kind of spam appears, it takes a long time for anti-spam engineers to realize the appearance.

# Introduction

- How does spam make a profit?

  For a certain kind of Web spam technique



# Introduction

- Important: find new kind of spam as soon as possible

Detect a new kind of Web spam technique timely

↓

Reduce the spam profit

↓

When profit < cost, spam stops

# User-behavior Features

- Users will at first realize the existence of a new spam page
  - How to use the wisdom of crowds to detect spam?
    - Social annotation? (possible noises)
    - Web access log analysis.
  - Web access logs
    - Collected by a commercial search engine
    - July 1st, 2007 to August 26th, 2007
    - 2.74 billion user clicks
      in 800 million Web pages

# User-behavior Features

- The behavior features we propose
  - How many user visits are oriented from search engine?
  - How many users will follow links on the page?
  - How many users will not visit the site in the future?
  - How many user visits are oriented by hot keyword searches?
  - How many pages does a certain user visit in the site?
  - How many users visit the site?
  - …

# User-behavior Features

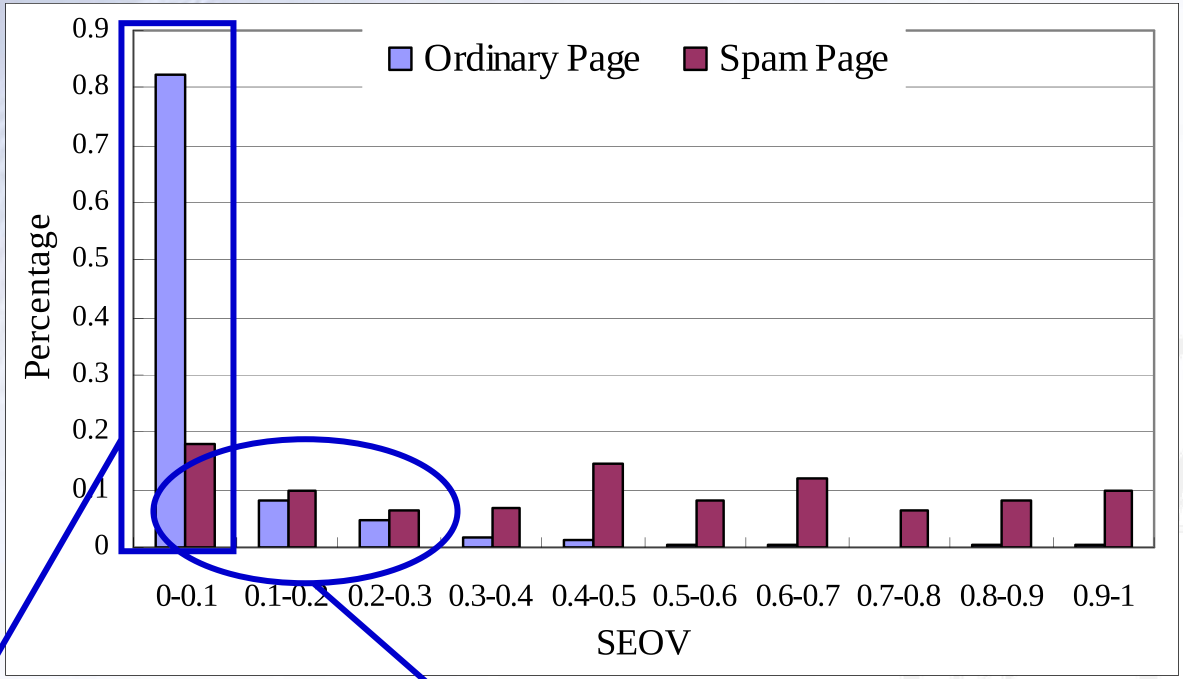
- Search engine oriented visiting rate (*SEOV* rate)
  - Web spam are designed to get “an unjustifiably favorable relevance or importance score” from search engines. (*Gyongyi et. al.* 2005)
  - Assumption:

    Most user visits to Web spam are from search engine result lists
  - Definition:

$$SEOV(p) = \frac{\#(Search\ engine\ oriented\ visits\ of\ \ p)}{\#(Visits\ of\ \ p)}$$

# User-behavior Features

- *SEOV* rate distribution




Some spam don't receive many UV from search engines, either.

Most ordinary pages' user visits are not from search engines

# User-behavior Features

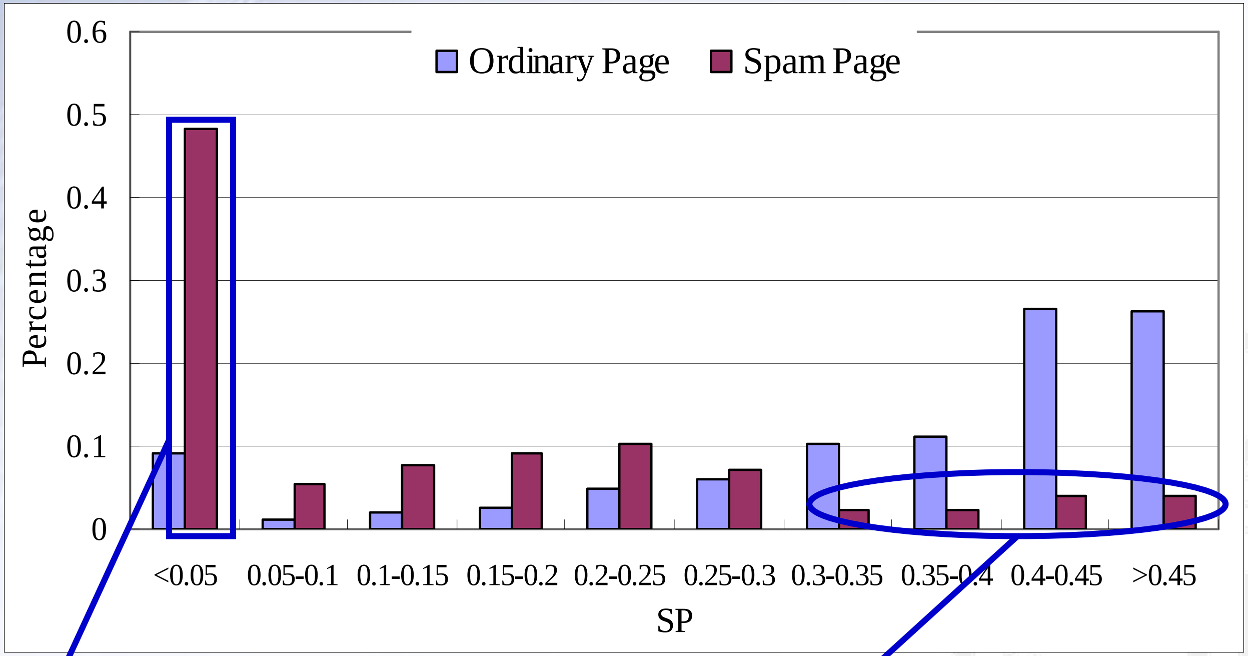
- Source page rate (*SP* rate)
  - Spam pages are usually designed to show users ads/low-quality information at their first look.
  - Users don't trust hyperlinks on spam pages
  - Assumption:

    Most Web users will not follow hyperlinks on spam pages
  - Definition:

$$SP(p) = \frac{\#(p \text{ appears as the source page})}{\#(p \text{ appears in the Web access logs})}$$

# User-behavior Features

- *SP* rate distribution




User clicks hyperlink on some spam page, too. (users may be cheated by anchor texts)

Half of spam pages have very small *SP* values

# User-behavior Features

- Short-time Navigation Rate (*SN* rate)
  - Users cannot be cheated again and again during a small time period
  - Assumption:

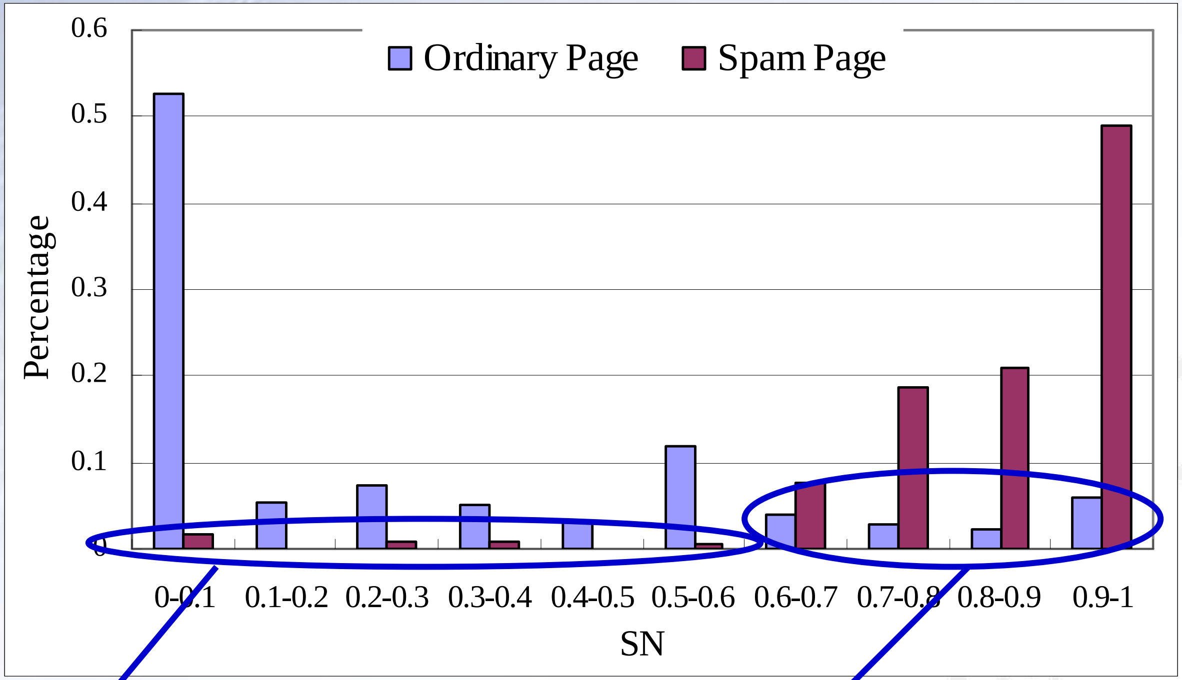
    Most Web users will not visit a spam site many times in a same user session
  - Definition:

$$SN(s) = \frac{\#(Sessions\ in\ which\ users\ visit\ less\ than\ N\ \ pages\ in\ s)}{\#(Sessions\ in\ which\ users\ visit\ s)}$$

*N*: parameter

# User-behavior Features

- *SN* rate distribution (*N* = 3)




A number of ordinary pages also receive few UVs in a session. (redirection sites, low-quality sites, …)

Few spam pages are visited over 2 times in a session

# User-behavior Features

- Correlation values between these features
  - Different assumption
  - Different information sources
  - Relatively low correlation
  - Possible to use Bayes learning methods

| | **SEOV** | **SP** | **SN** |
|---|---|---|---|
| **SEOV** | 1.0000 | 0.1981 | 0.1780 |
| **SP** | 0.1981 | 1.0000 | 0.0460 |
| **SN** | 0.1780 | 0.0460 | 1.0000 |

# Detection algorithm

- Problem:
  - Uniform sampling of negative examples (pages which are not spam) is difficult
- Solution:
  - Learning from positive examples (Web spam) and unlabelled data (Web corpus)
  - Calculate the possibility of a page *p* being Web spam using user behavior features

$$P(p \in Spam \mid SEOV(p), SP(p), SN(p))$$

# Detection algorithm

- For a single feature *A*:

$$P(p \in Spam \mid p\ has\ \ feature\ \ A)$$
$$\propto \frac{\#(p\ has\ \ feature\ \ A \cap p \in Spam\ sample\ set)}{\#(Spam\ sample\ set)} \Bigg/ \frac{\#(p\ has\ \ feature\ \ A)}{\#(CORPUS)}$$

- For three features *SEOV*, *SP* and *SN*:
  - Features are approximately independent as well as conditionally independent given the target value

$$P(p \in Spam \mid p\ has\ \ feature\ \ A_1, A_2, \ldots, A_n)$$
$$\propto \prod_{i=1}^{n} \left( \frac{\#(p\ has\ \ feature\ \ A_i \cap p \in Spam\ sample\ set)}{\#(Spam\ sample\ set)} \Bigg/ \frac{\#(p\ has\ \ feature\ \ A_i)}{\#(CORPUS)} \right)$$

# Detection algorithm

- Algorithm Description

1. Collect Web access log (with information shown in Table1) and construct access log corpus *S*;
2. Calculate *SEOV* and *SP* scores according to Equation (1) and (2) for each Web page in *S*;
3. Calculate *SEOV* and *SP* scores for each Web site in *S* by averaging scores of all pages in the site;
4. Calculate *SN* score for each Web site in *S* according to Equation (3);
5. Calculate *P(Spam | SEOV, SP, SN)* according to Equation (9) for each Web page in *S*.

# Experimental Results

- Experiment setup
  - Training set:
    - 802 spam sites
    - Collected from the hottest search queries' result lists
  - Test set:
    - 1564 Web sites annotated with whether it is spam or not
    - 345 spam, 1060 non-spam, 159 cannot tell
    - Percentage of spam is higher than the estimation given by *Fetterly et. al.* and *Gyöngyi et. al.* . (we only retain the sites which are visited at least 10 times)

# Experimental Results

- How to evaluate the performance
  - Focus: find the recently-appeared spam types (not to detect all possible spam types)

  1: Whether the spam candidates identified by this algorithm are really Web spam. (effectiveness)

  2: Whether this algorithm detect spam types more timely than current search engines. (timeliness)

  3: Which feature is more effective?

# Experimental Results

- Detection performance (effectiveness)
  - Whether the top-ranked candidates are Web spam
  - 300 Pages with the highest *P(Spam)* values
    - Only 6% are not Web spam (low-quality page, SEO page)
    - Many spam types can be identified. (wisdom of crowds)

| Page Type | Percentage |
|---|---|
| Non-spam pages | 6.00% |
| Web spam pages (Content spamming) | 21.67% |
| Web spam pages (Link spamming) | 23.33% |
| Web spam pages (Other spamming) | 10.67% |
| Pages that cannot be accessed | 38.33% |

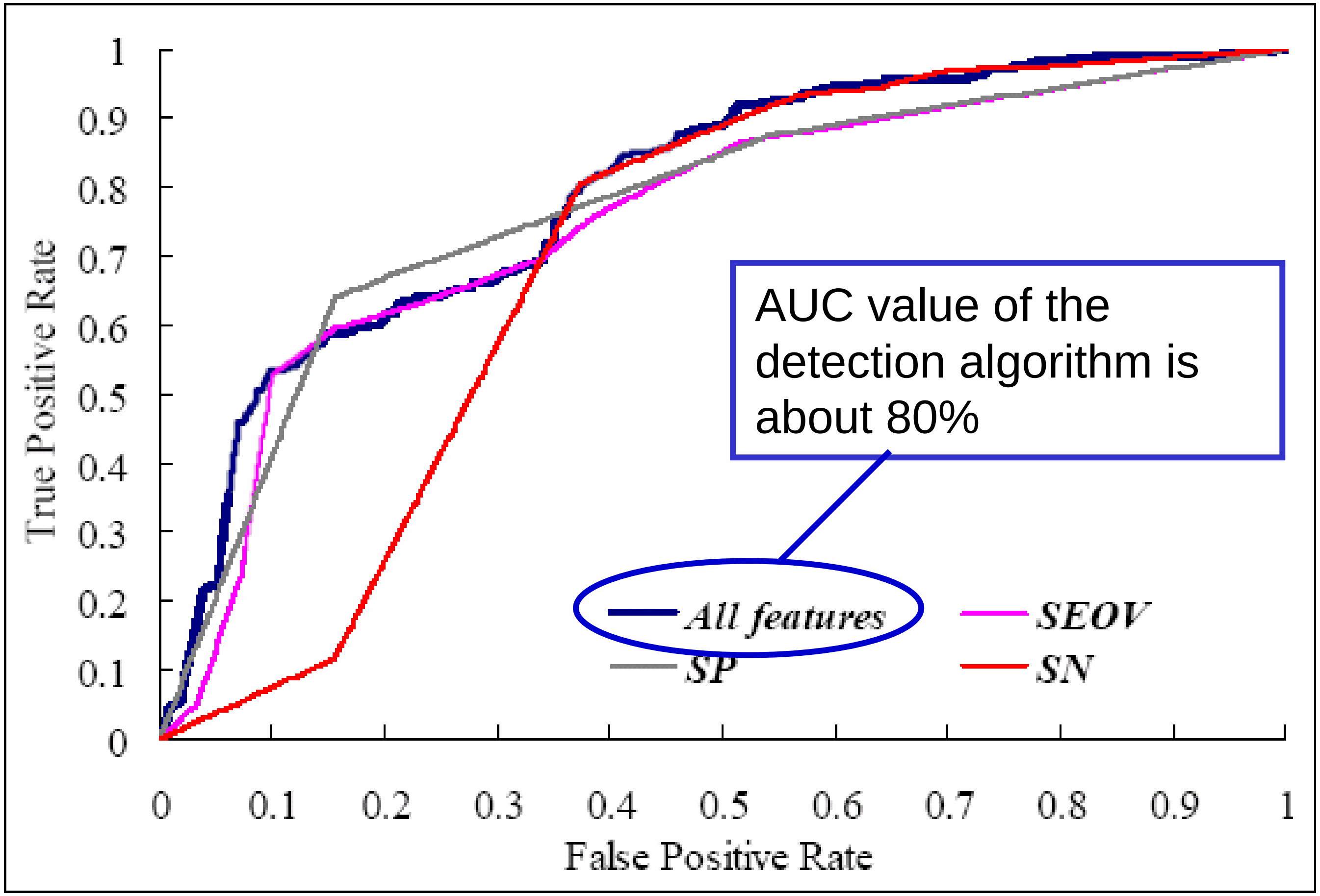
# Experimental Results

- Detection performance (timeliness)
  - Experiments with one of the most frequently-used Chinese search engines (use *X* to represent it)
  - Recent data: Access logs from 08/02/04 to 08/03/02
  - Top-ranked spam candidate sites
    - 723/1000 are spam sites (some failed to be connected)
    - X indexed 34 million pages from these 723 sites in early Mar.
    - 59 million pages were indexed by X at the end of Mar.

These spam are not detected by *X*, *X* spent lots of resources on these useless pages

# Experimental Results

- Detection performance (algorithm & features)



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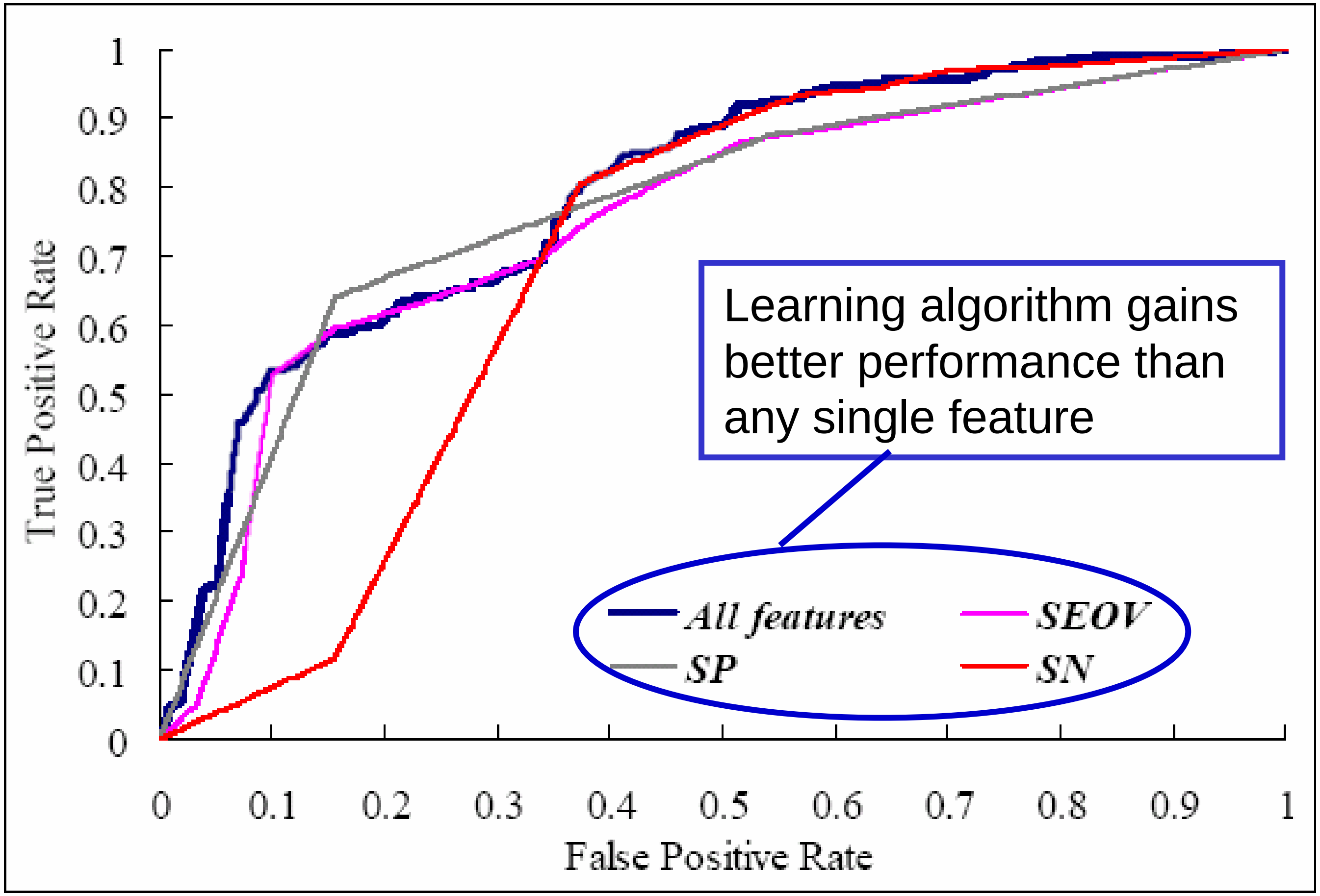
- Detection performance (algorithm & features)



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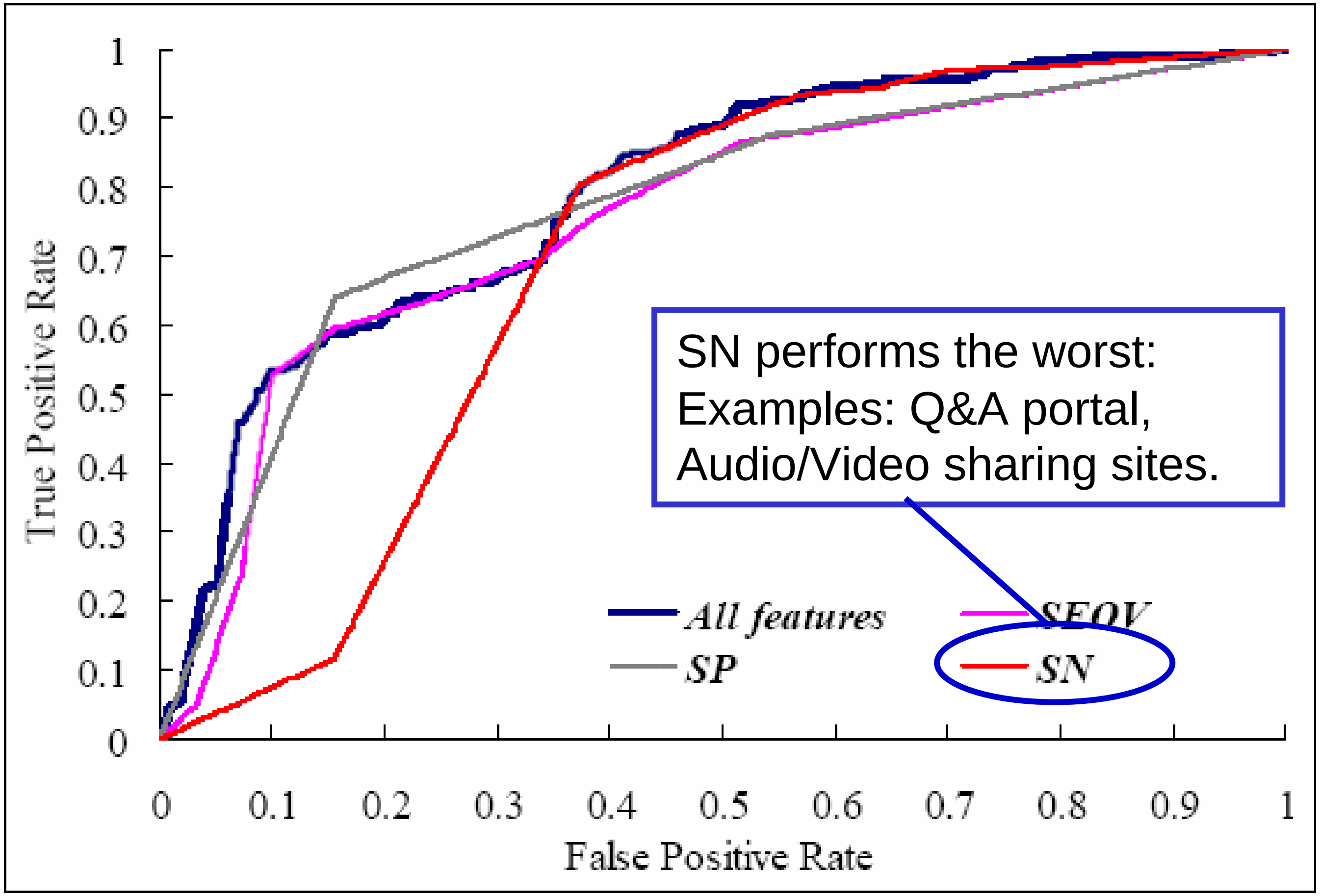

# Conclusions

- The amount of Web spam is perhaps over search engine index size
- Timeliness is as important as effectiveness in spam detection
- User behavior features can be used to find recently-appeared spam types timely and effectively