Web Spam Challenge 2008

Data Analysis School, Moscow, Russia

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The Data Used

- Web graph
  - Host graph (114K hosts)
  - The full Web graph (105M URLs) wasn’t used
- Sample pages – up to 400 (first crawled) pages per host, in WARC format (12M)
- Spam judgments – for ~3.75% of hosts
- Features provided by organizers
The Host Graph

- **114529** hosts
  - **453** hosts labeled as spam (by 2006 and 2007 judgments)
  - **4995** hosts labeled as normal

- **Weight of an edge is the number of inter-host links**
Pre-computed Feature Vectors

- **Two obvious direct features:**
  - Number of pages in host
  - Host name length (in bytes)

- **Features, proposed in the articles:**
  - L. Becchetti, C. Castillo, D. Donato, S. Leonardi, R. Baeza-Yates:
    - "Using Rank Propagation and Probabilistic Counting for Link-Based Spam Detection"
  - C. Castillo, D. Donato, A. Gionis, V. Murdock, F. Silvestri:
    - "Know your Neighbors: Web Spam Detection using the Web Topology"

- **Link-based features (the list on the next slide)**
  - For the front page and the page with the maximal PageRank

- **Content-based features (the list on the second slide)**
  - For the front page and the page with the maximal PageRank – plus averages and standard deviations over all host pages
Link-based Features

- Assortativity coefficient (degree / average degree of neighbors)
  - “degree” here is undirected (in-degree+out-degree)
- Average in-degree of out-neighbor pages
- Average out-degree of in-neighbor pages
- Number of in-neighbor pages at distances 1 to 4 (4 features)
- Out-degree
- PageRank
  - in the doc graph with no self-loops, with a damping factor of 0.85, with 50 iterations
- Standard deviation of the PageRank of in-neighbors
- Fraction of out-links that are also in-links
  - a page with no out-links has a value of 0
- Number (approx.) of in-neighbor hosts at distances 1 to 4 (4 features)
- TruncatedPageRank using truncation distances 1 to 4 (4 features)
- TrustRank (obtained using 3,800 hosts from ODP as trusted set)
Content-based Features

- Number of words in the page
- Number of words in the title
- Average word length
- Fraction of anchor text
- Fraction of visible text
- Compression rate of the page
- Top 100, 200, 500, 1000 corpus terms precision (4 features)
- Top 100, 200, 500, 1000 corpus terms recall (4 features)
- Top 100, 200, 500, 1000 query terms precision (4 features)
- Top 100, 200, 500, 1000 query terms recall (4 features)
- Entropy of trigrams
- Independent trigram likelihood
The Challenge Submission Overview

- A boosted vote of few large margin classifiers
  - There were 13 partial classifiers combined
- Voters built by separate groups of features
- Two overall classifiers were built
  - using different training procedures and data
Groups of Features Used

- Host graph analysis (scores extension)
- Distribution of host pages compression rate
- Content features (word frequencies)
- Features readily provided by organizers
Host Graph Analysis

- The features were an elaboration of those in:
    - Extension and Propagation of manual Spam scores
- They were extensively reworked due to
  - 10-fold increase of this year’s host graph size
  - Relatively low amount of spam scores available
Compression Rate Features

- GZIP compression rates for every page of a host:
  - Were put into bins: [0, 0.5), [0.5, 1), [1, 1.5) ... [9.5, 10), [10, +)
  - Makes 63 features – three per each of 21 bins:
    - The bin’s page count, average compression rate and standard deviation
  - Normalization of the features:
    - for the mean=0, std=1 on our training set
Compression Rate Results

- SVMLight with linear kernel was used
  - The features were normalized (mean = 0, std=1)

- Classification results:
  - $F1 = 27.99\% \ (R = 35.38\%, \ P = 23.15\%)$

<table>
<thead>
<tr>
<th></th>
<th>Normal</th>
<th>Spam</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted Normal</td>
<td>3495</td>
<td>137</td>
</tr>
<tr>
<td>Predicted Spam</td>
<td>249</td>
<td>75</td>
</tr>
</tbody>
</table>

- Just 8.63\% of non-labeled hosts classified as spam with these settings
Word Frequency Features

- Words* in <title>, <meta> (keywords, description), <anchor> and <body>
  - Computed the average of $\frac{\log(1 + wc)}{\log(1 + pl)}$
    - where $wc$ – word count, and $pl$ – page length
  - Separately for each word and each tag
  - Also used query log frequencies in word counting for pages
- Feature selection
  - Should be present with at least 10% of either spam or normal hosts
  - A threshold of 75% discriminating power between classes by Student test
- SVMLight with linear kernel used for classification

- * a ‘word’ is any sequence of letters, numbers and some special symbols
  - lowercased
  - Numbers excluded
  - Examples: seed, foo, 123f, $100$, бабай
Classification by Word Frequencies

Max F1 = 22.35% (R = 39.07%, P = 15.65%)
Classification by Pre-computed Features

- Total of 276 features provided
- The training data were made by extending host labels from ones given
  - Total of 9700 hosts
- Three different ways of data normalization were used:
  - 1) normalizing features to (mean=0, std=1)
  - 2) normalizing data vectors to |x|=1
  - 3) the combination of 1) followed by 2)
- One classifier set has been built using Gaussian kernel SVMLight
  - The weight –j was set to 1/40
    - That was the ratio of spam to normal within the training set
- The training set was divided into three equal parts
  - The first one used for SVM training, the other one for kernel gamma parameter tuning, the third one for cross-evaluation
  - The best achieved F1 (for normalization 3) was 0.39 (R=0.6, P=0.29)
Classification by Pre-computed Features

- The other classifier used weighted Linear kernel SVMLight
  - with feature selection
  - with weight of normal class = 0.2
- Feature selection
  - The features correlated at level >0.95 were considered connected
  - Then 276 features yielded 188 connected components
    - Of each connected component a single feature has been taken as a representative
    - The one most correlated with spam judgments is taken
- That set of 188 features achieved F1=22.4 (R=0.23, P=0.22)
Results with Pre-computed Features

Max F1 = 24.66% (R = 28.46%, P = 21.75%)
Host Graph Structure (an Illustration)

Labeled graph nodes (connected by >100 links) are distributed on plane using “spring” model and the spam ends up together ("Know your Neighbors: Web Spam Detection using the Web Topology")
Host Graph Data

- The original training set:
  - Spam – 229 nodes
  - Normal – 3714 nodes

- The set, extended by last year’s judgments:
  - Spam – 453 nodes
  - Normal – 13504 nodes
Scores Extension

- Additional scores taken
  - At least two judges gave the same score
  - Or, hosts that were in “trusted” domain:
    ac.uk, sch.uk, gov.uk, nhs.uk, police.co.uk
Normal Nodes Labeling

- The nodes classified a priori as normal:
  - Those judged as normal
  - Those linked by normal... – the idea was:
    - Spam refers to spam frequently, normal hosts don’t
Spam Labeling (1)

- The nodes classified a priori as spam:
  - Those judged as spam
  - Those linking spam… – the idea was:
    - Spam refers to spam frequently, normal hosts don’t
Two features computed for each node:

- **Overlap:**
  - The ratio of bidirectional links to sum of in- and out-links
  - The idea is of link farms detection

- **Variance:**
  - Standard deviation in number of out-links with in-neighbors
  - The idea: if it’s small, the graph might be automatically generated

Thresholds for Overlap и Variance were learned

- The node is classified as spam by either one
Scores Initialization

Node $x$ is assigned a pair $(\text{Bad Score}(x), \text{Good Score}(x))$:

- 1) If a node was marked normal, $\text{Good Score}(x) = 1$
- 2) If a node was marked spam, $\text{Bad Score}(x) = -1$

Make iterations on scores – and consider the pair:

- $(\text{Old Bad Score}(x), \text{Old good score}(x))$
  - the values on previous iteration
Scores Propagation

Then next iteration scores are computed as:

Bad Score(\(x\)) = Old Bad Score(\(x\)) + \(\alpha \sum \frac{\text{Old Bad Score}(\(y\))}{|\text{in neighbors}|}\)  

Good Score(\(x\)) = Old Good Score(\(x\)) + \(\alpha \sum \frac{\text{Old Good Score}(\(y\))}{|\text{out neighbors}|}\)

\(\alpha\) is a free parameter here
- we set it to 0.2
The Final Node Classification

After fixed number of iterations we get final values of Bad Score and Good Score, and use it for classification:

\[ \beta \times \text{Bad Score} + (1 - \beta) \times \text{Good Score} < 0 \Rightarrow \text{spam} \]
\[ \beta \times \text{Bad Score} + (1 - \beta) \times \text{Good Score} > 0 \Rightarrow \text{normal} \]

The value of parameter \( \beta \) is set to \( = 0.95 \)
Algorithm Parameters were Chosen

- Overlap
  - 0.5
- Threshold on link weight for spam labeling
  - 5000
- Threshold on variance
  - 0.05
- $\alpha = 0.2$
- $\beta = 0.95$
Choosing the Parameters

Two approaches were used:
1. The gradient optimization
2. The mesh search

Starting point:
1. Overlap = 0.1, step = 0.1
2. Link weight threshold = 4000, step = 1000
3. Variance threshold = 0.01, step = 0.01
4. \( \alpha = 0.1 \), step = 0.1
5. \( \beta = 0.9 \), step = 0.01
The target functions in parameter choice

- Specificity = 
  - Spam correctly classified / Total spam

- Sensitivity = 
  - Normal correctly classified / Total normal

- The threshold on specificity was set
  - It was set to 0.4
    - Values in (0.4 – 0.6) were originally tried
  - The sensitivity was maximized
Results for Host Graph 2006

- Results with no cross-validation (on a training set)
  - F1 = 89.93% (R = 100%, P = 81.7%)

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<tr>
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<td>0</td>
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<tr>
<td>Predicted Spam</td>
<td>151</td>
<td>674</td>
</tr>
</tbody>
</table>

- Results with cross-validation (2-fold)
  - F1 = 52.8% (R = 50.08%, P = 55.83 %)

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<tbody>
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<tr>
<td>Predicted Spam</td>
<td>265</td>
<td>335</td>
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</table>
Results for Host Graph 2007

- Results with no cross-validation (on a training set)
  - F1 = 99.67% (R = 100%, P = 99.34%)

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<tbody>
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<tr>
<td>Predicted Spam</td>
<td>3</td>
<td>453</td>
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</tbody>
</table>

- Results with cross-validation (2-fold)
  - F1 = 21.47% (R = 30.82%, P = 16.47%)

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<td>12559</td>
<td>312</td>
</tr>
<tr>
<td>Predicted Spam</td>
<td>705</td>
<td>139</td>
</tr>
</tbody>
</table>
Results for Host Graph 2007 (no cross-validation)

- Max F1 = 99.67% (R = 100%, P = 99.34%)
Results for Host Graph 2007 (cross-validation)

Max F1 = 21.47% (R = 30.82%, P = 16.47%)
The Final Classifier Training

- The classifier was created by combining weak learners
  - Weak learners obtained by separate groups of features
- Combination was done with the TreeNet software
  - In classification mode, with unit weights
- The partial classifiers were created using:
  - SVM with Linear and Gaussian kernels, Naïve Bayes
    - four SVM and three Naïve Bayes classifiers were built on word frequencies
- There also was a direct graph-based rule
- Discriminant functions were weak learners for TreeNet model
- The F1 measure of stand-alone classifiers did not exceed 39%
  - The combined F1 for spam detection estimated as 67.5% (at R=68.3%, P=66.7%)
The Second Final Classifier Training

- With the first submission
  - the TreeNet classifier trained on overall spam judgments
    - Obtained with judgments by all judges taken together

- With the second submission
  - 34 separate classifiers were built for judgments of each judge
  - Judges that made more than 100 judgments (we took 34 of them)
  - For four judgment types (borderline, nonspam, spam, unknown)

- The probabilities of each class were computed for each judge

- Weighted sum of 34 probabilities for each of first three classes taken
  - The weights equal to (1-prob(“unknown”))

- Then the final spam probability was calculated as
  - \((s + 0.5\times b)/(s + n + b)\)
    - Where s, n, b were weighted sums of computed probabilities from all judges
    - For the classes of “spam”, “nonspam” and “borderline”, respectively
“Borderline” as 0.5 Spam (training)

- First Version: Max F1 = 58.9% (R = 49.2%, P = 73.3%)
- 2nd Version: Max F1 = 76.3% (R = 96.3%, P = 63.3%)
“Borderline” as 0.75 Spam (training)

- First Version: Max F1 = 53.5% (R = 45%, P = 65.9%)
- 2nd Version: Max F1 = 83.8% (R = 95.3%, P = 74.8%)
“Borderline” Judgments Ignored (training)

- First Version: Max F1 = 76% (R = 77.9%, P = 74.2%)
- 2nd Version: Max F1 = 87.2% (R = 98.2%, P = 78.4%)
The authors are grateful to several people who have made this work possible…

- … and especially to:
  - Alexander Melkov
  - Alexei Pyalling
  - Sergey Pevtsov
- … for their invaluable help and contributions