

A new algorithm for detecting **Web spam** using page features and hyperlinks

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Learning to Find Spam

- Not a typical learning problem:
 - Web page contents are probably generated adversarially, with the intention of fooling the indexer
 - Given a hyperlink graph, BUT it's not clear what purpose each link serves: may be natural, may be used for spam, or may simply be there to confuse the indexer

Which of the Blue Hosts are Bad? 7 ?

One Key Fact

 An extremely useful observation for spam detection:





Methods For Web Spam Detection

Graph Based Detection Methods

- Graph-based methods try to compute the "spamicity" of a given page using only the hyperlink graph.
- Perhaps most well-known is TrustRank, based on the PageRank algorithm.

Content-Based Methods

- Train a classifier based on page features:
 - 1. # words in page
 - 2. Fraction of visible words
 - 3. Fraction of anchor text
 - 4. Average word length
 - 5. Compression rate





Web spam Identification Through Content and Hyperlinks





Key Ingredients

- Support Vector Machine (SVM) type framework
- Additional slack variable per node
- "Semi-directed" graph regularization
- Efficient Newton-like optimization

WITCH Framework 1 Standard SVM: fit your data, but make

sure your classifier isn't too complicated (aka has a large margin)

$$\Omega(\mathbf{w}) \;=\; rac{1}{l} \sum_{i=1}^l [1-y_i \mathbf{w} \cdot \mathbf{x}_i]_+^2 + \lambda \mathbf{w} \cdot \mathbf{w}$$

WITCH Framework 2

 Graph Regularized SVM: fit your data, control complexity, AND make sure your classifier "predicts smoothly along the graph"

$$egin{aligned} \Omega(\mathbf{w}) &= rac{1}{l} \sum_{i=1}^l [1-y_i \mathbf{w} \cdot \mathbf{x}_i]_+ + \lambda \mathbf{w} \cdot \mathbf{w} \ &+ \gamma \sum_{(i,j) \in E} a_{ij} (\mathbf{w} \cdot \mathbf{x}_i - \mathbf{w} \cdot \mathbf{x}_j)^2 \end{aligned}$$

• Graph Regularized SVM with Slack:

 Graph Regularized SVM with Slack: Same as before, but also learn a spam weight for each node.

$$egin{aligned} \Omega(\mathbf{w},\mathbf{z}) &= rac{1}{l} \sum_{i=1}^l [1-y_i (\mathbf{w}\cdot\mathbf{x}_i+z_i)]_+ + \lambda_1 \mathbf{w}\cdot\mathbf{w} + \lambda_2 \mathbf{z}\cdot\mathbf{z} \ &+ \gamma \sum_{(i,j)\in E} a_{ij} ((\mathbf{w}\cdot\mathbf{x}_i+z_i) - (\mathbf{w}\cdot\mathbf{x}_j+z_j))^2 \end{aligned}$$

• When A links to B, penalizing the spam score as $(S_A - S_B)^2$ isn't quite right. This hurts sites that receive links from spam sites.



NOT TRUE!!

Interestingly, the issue is more complex



A *mixture* of the two types of regularization is better!





Semi-Directed Regularization

Seems Strange, BUT...

- Why didn't simple directed regularization work?
- It will fail on certain cases:



Optimization

- Roughly a Newton-method type optimization.
- Hard part is computing the Newton Step
- Can be accomplished using linear conjugate gradient, ~50 passes over data to get one approximate Hessian.
- Requires roughly 10 Newton steps



WITCH Performance Results



Performance Comparison



Web Spam Challenge

- Organized By Researchers at Yahoo!
 Research Barcelona and University Paris 6
- Used a web spam dataset consisting of 10,000 hosts including:
 - 1,000 labelled hosts, roughly 10% spam
 - A Hyperlink graph
 - Content-based features

Web Spam Challenge

- We won the 2nd Track of the Web spam Challenge 2007 (measured by AUC, host-level only)
- Our algorithm outperforms the winner of the Track I competition (we were too late to compete).

Performance Results

Training Algorithm	AUC 10%	AUC 100%
SVM + stacked g.l.	0.919	0.953
Link based (no features)	0.906	0.948
Challenge winner	_	0.956
Only Features	0.859	0.917
Features + GR	0.874	0.917
Slack + GR	0.919	0.954
WITCH (Feat. $+$ Slack $+$ GR)	0.928	0.963



"No Good \rightarrow Bad Links" Assumption?

- Perhaps good sites will link to bad sites occasionally:
 - Blog spam
 - "link swapping"
 - Harpers (thanks to reviewer for pointing this out!)
- How can we deal with this?

Harpers:





Questions?

(and thanks to Alexandra Meliou for the PowerPoint Animations)