Detecting Spammers and Content Promoters in Online Video Social Networks

Fabrício Benevenuto, Tiago Rodrigues, Virgílio Almeida,
Jussara Almeida and Marcos Gonçalves

Federal University of Minas Gerais - Brazil

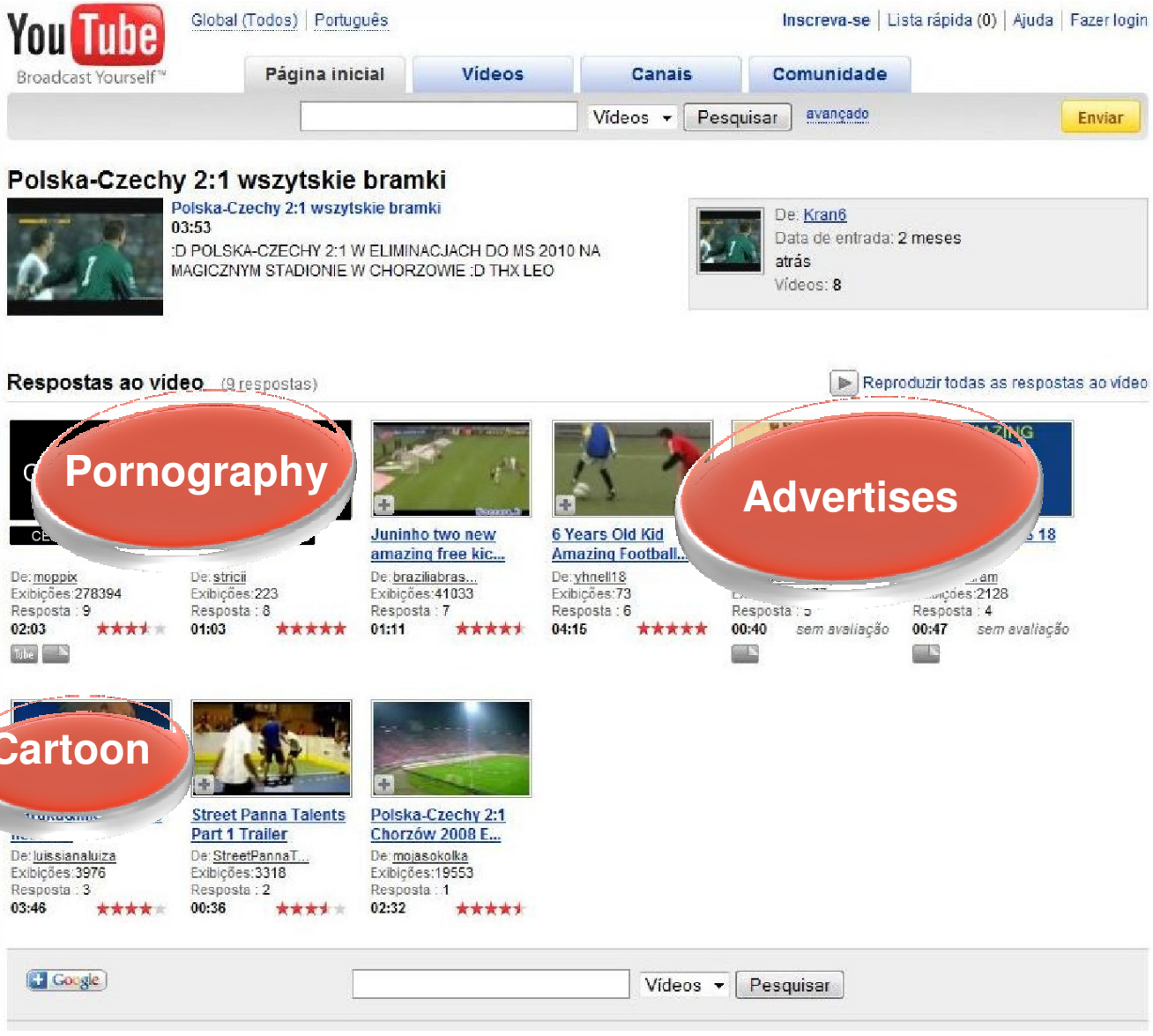
ACM SIGIR Boston, USA July 22, 2009

Motivation

- Video is a trend on the Web
  - video forum, video blog, video advertises, political debates
  - 77% of the U.S. Internet audience viewed online videos
- Explosion of user generated content
  - YouTube has 10 hours of videos uploaded every minute

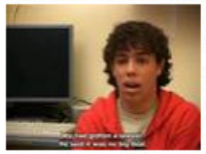
User generated videos are susceptible to various opportunistic user actions

Example of Video Spam



Example of Promotion

Eric and the Army of the Phoenix (1/5)



Èric and the Army of the Phoenix (1/5)
9:48
An incredible but true story: Spanish authorities prosecute child for terrorism when he e-mails companies requesting labelling in Catalan language, using Phoenix monicker from Harry Potter books.
Poli (more)

From: ericielfenix
Joined: 2 years ago
Videos: **6**

Video Responses (8352 Responses)

Play All Video Responses

Torroella de Montgrí (Baix Empordà)
160 views
danimorph

Torrent (Baix Empordà)
22 views
danimorph
no rating

Tallada d'Empordà (Baix Empordà)
27 views
danimorph
no rating

Serra de Daró (Baix Empordà)
36 views
danimorph
no rating

Santa Cristina d'Aro (Baix Empordà)
111 views
danimorph
no rating

Sant Feliu de Guíxols (Baix Empo...
101 views
danimorph

Rupià (Baix Empordà)
67 views
danimorph
no rating

Regencós (Baix Empordà)
63 views
danimorph
no rating

la Pera (Baix Empordà)
27 views
danimorph
no rating

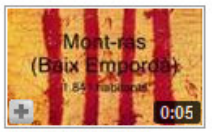
Parlavà (Baix Empordà)
53 views
danimorph
no rating

Pals (Baix Empordà)
40 views
danimorph
no rating

Palau-sator (Baix Empordà)
70 views
danimorph
no rating

Palamós (Baix Empordà)

Palafrugell (Baix Empordà)



Mont-ras (Baix Empordà)

Jafre (Baix Empordà)

Gualta (Baix Empordà)

Garrigoles (Baix Empordà)

Negative Impact of Promotion and Spam

- Challenges for users in identifying video promotion and spam
  - consumes system resources, especially bandwidth
  - compromise user patience and satisfaction with the system
- Pollution in top lists
- Difficulty in ranking and recommendation
  - Promoted or spam videos may be temporarily ranked high

Goal

- Detect video spammers and promoters

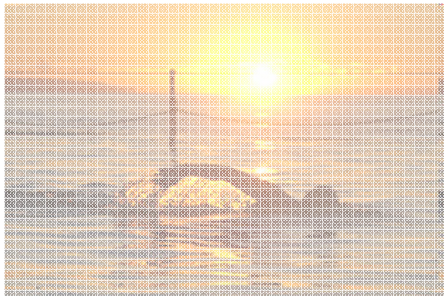
- 4-step approach

  1. Sample YouTube video responses and users

  2. Manually create a user test collection
     (promoters, spammers, and legitimate users)

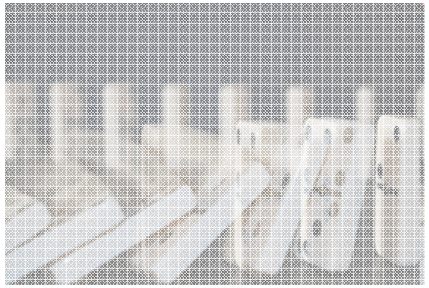
  3. Identify attributes that can distinguish spammers and promoters from legitimate users

  4. Classification approach to detect spammers and promoters



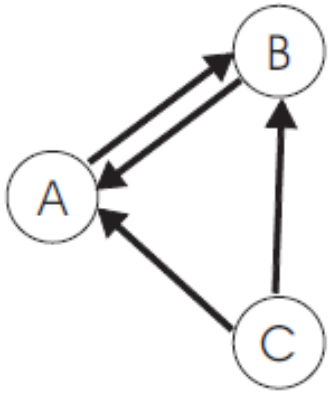
Part1.
Motivation
& Problem

Part2.
4-step
approach



Part3.
Experimental
results

Step1. Sampling video responses



There is an undirected path from
u to v and a directed path from v to u

- Approach: Collect entire weakly connected components
  - Follow both directions: video responses and video responded
  - Collect all videos of each user found
  - This approach allow us to use several social network metrics

- Collected 701,950 video responses and 381,616 video topics, 264,460 users in 7 days in January, 2008

Step2. Create Test Collection

Desired Properties

1) Have a significant number of users in each class

2) Include spammers and promoters which are aggressive in their strategies

3) Include a large number of legitimate users with different behavioral profiles

Step2. Create Test Collection

- Users selected according to three strategies

  1) Manually identified 150 suspect in the top 100 most responded lists

  2) Randomly select 300 users from those who posted video responses to videos in the top 100 most responded lists

  3) Collected 400 users across 4 different levels of interaction

  - sent and received video responses

- Volunteers analyze users and videos

  - Conservative approach -> favor legitimate
  - Agreement in 97% of the analyzed videos

TOTAL: 829 users, 641 legitimate, 157 spammers, 31 promoters

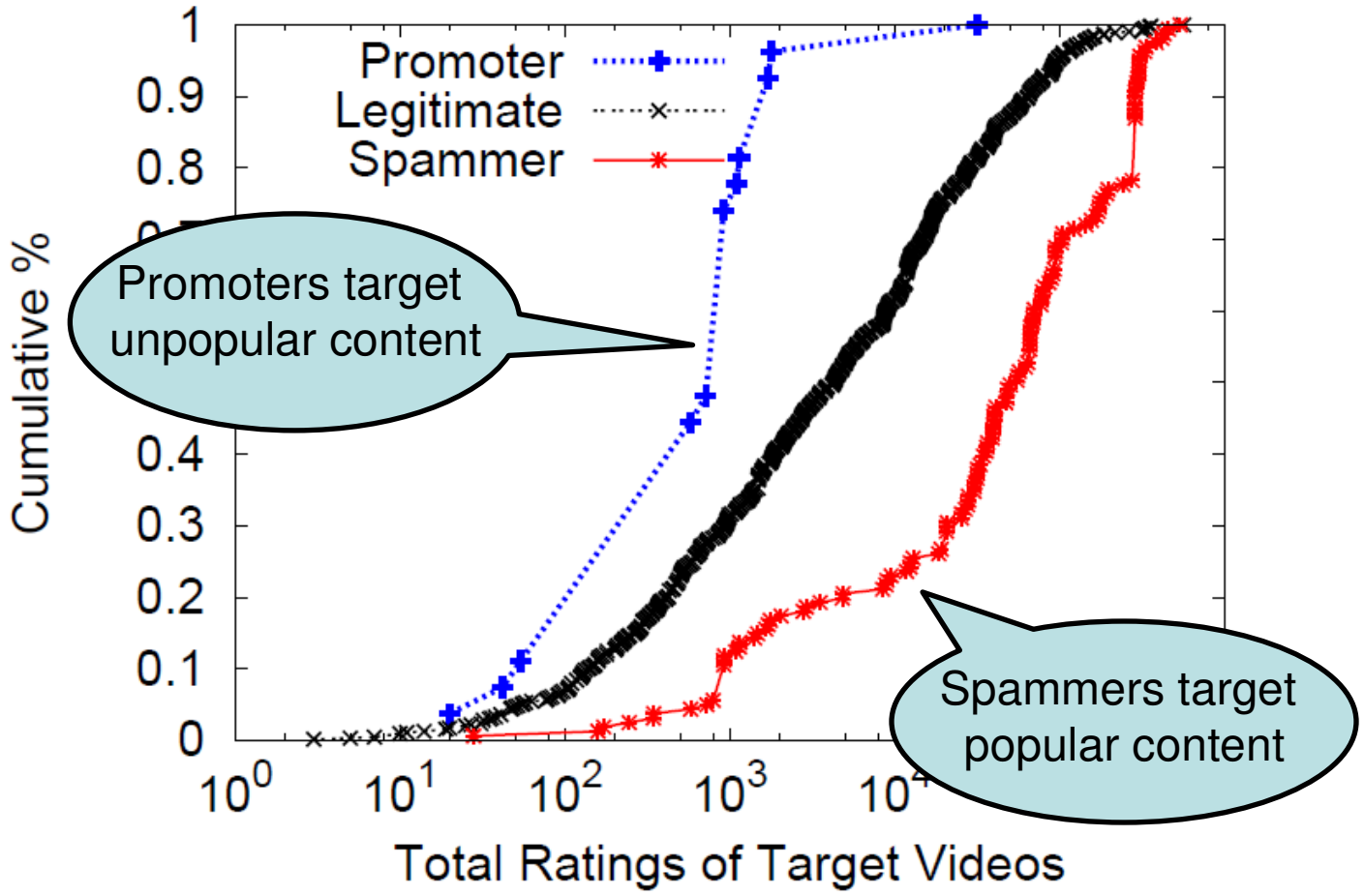
Step3. Attributes

- User-Based:
  - number of friends, number of subscriptions and subscribers, etc
- Video-Based:
  - duration, numbers of views and of comments received, ratings, etc
- Social Network:
  - clustering coefficient, betweenness, reciprocity, UserRank, etc

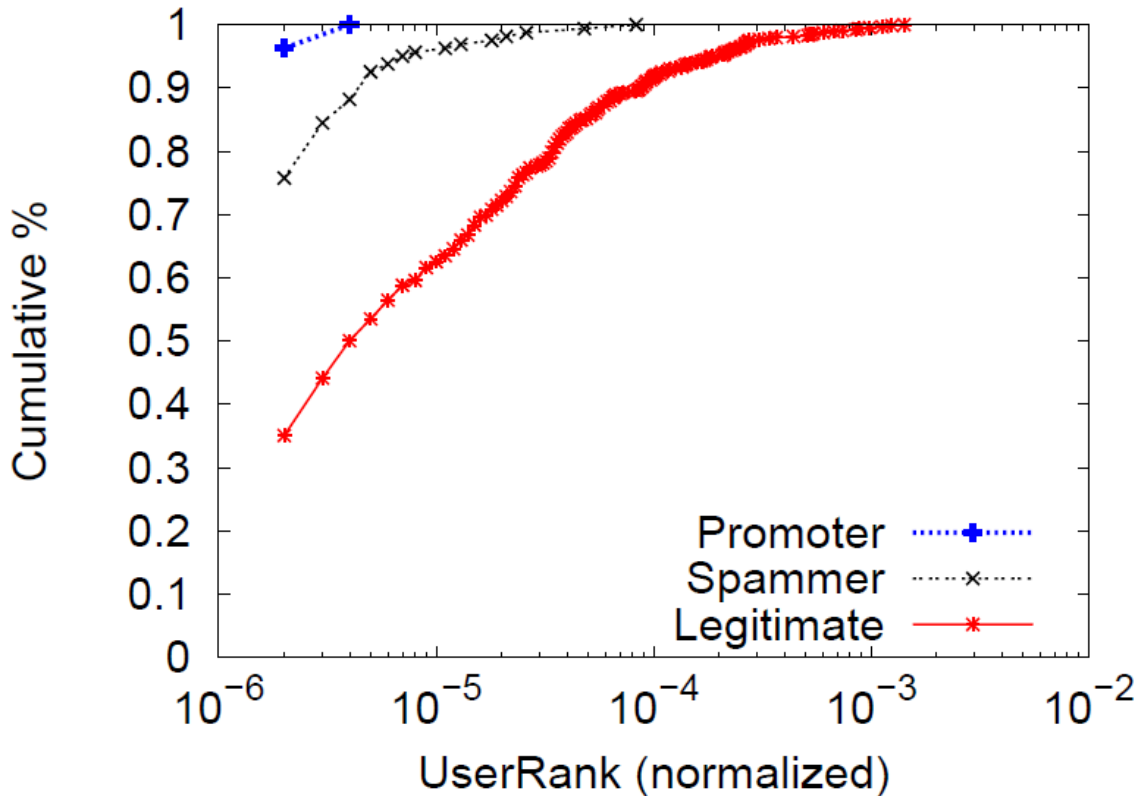
Feature Selection: χ^2 ranking

Attribute Set	Top 10	Top 20	Top 30	Top 40	Top 50
Video	9	18	25	30	36
User	1	2	4	7	9
SN	0	0	1	3	5

Distinguishing classes of users (1)



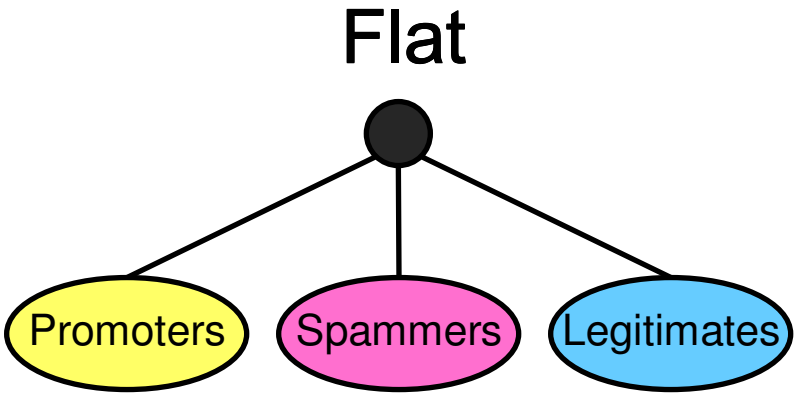
Distinguishing classes of users (2)

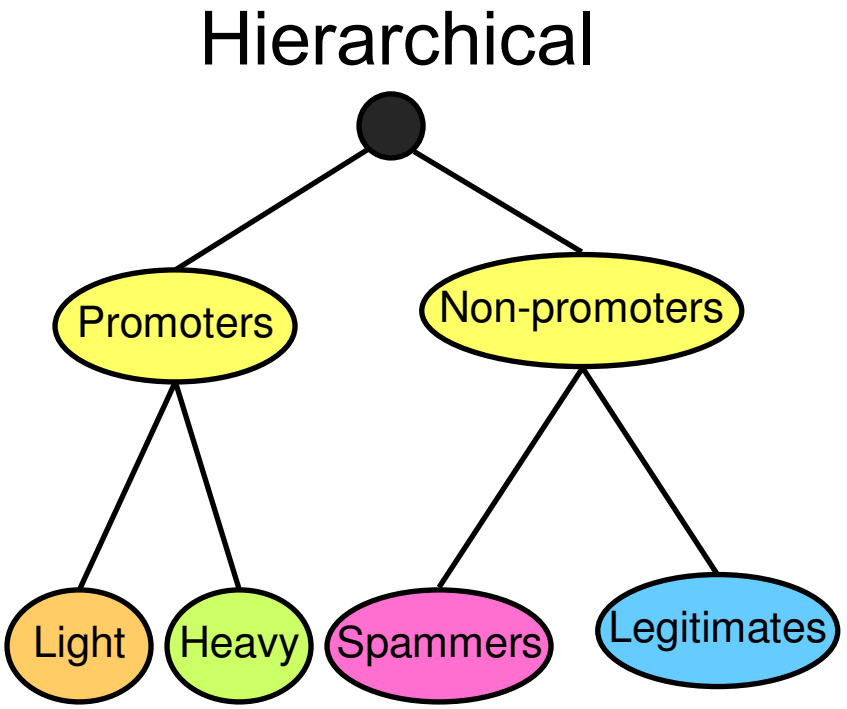


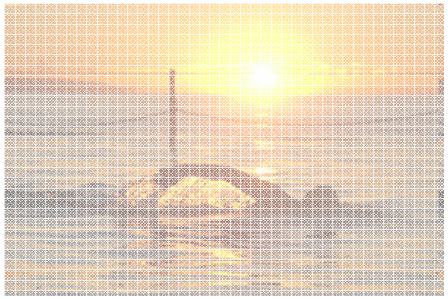
Even low-ranked features have potential
to separate classes apart

Step4. Classification Approach

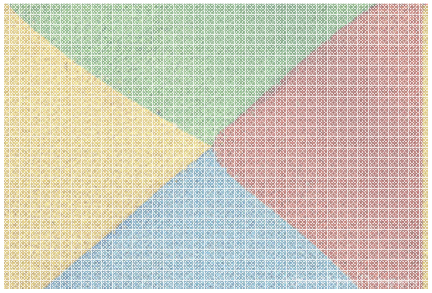
- SVM (Support vector machine) as classifier
  - Use all attributes
  - Two classification approaches







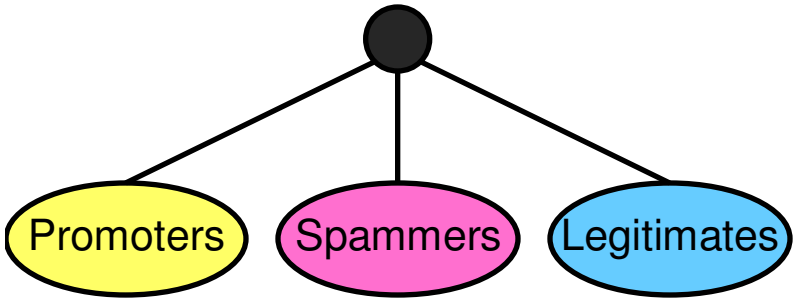
Part1.
Motivation
& Problem



Part2.
4-step
approach

Part3.
Experimental
results

Flat Classification

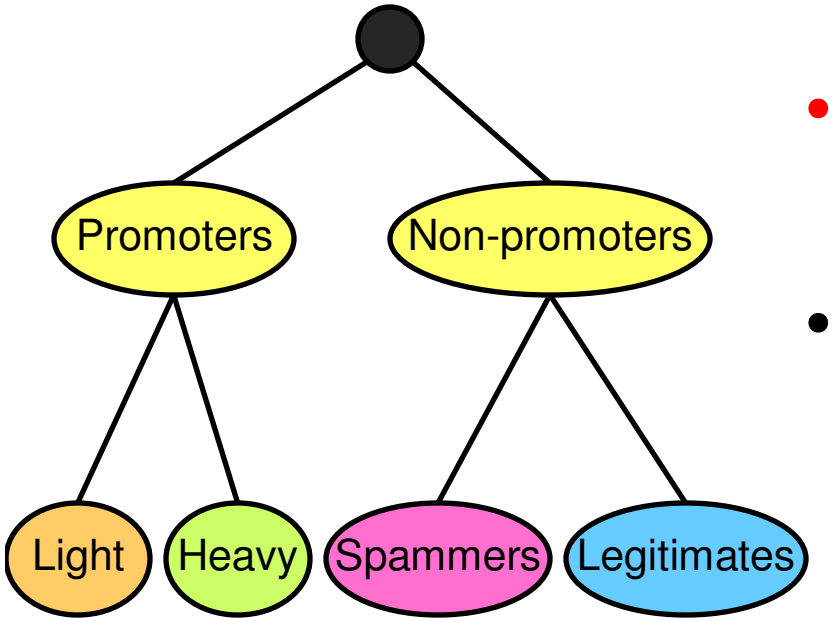


- Correctly identify majority of promoters, misclassifying a small fraction of legitimate users.
- Detect a significant fraction of spammers but they are much harder to distinguish from legitimate users.
  - Dual behavior of some spammers

		Predicted		
		Promoter	Spammer	Legitimate
True	Promoter	**96.13%**	3.87%	0.00%
	Spammer	1.40%	**56.69%**	41.91%
	Legitimate	0.31%	5.02%	**94.66%**

- Micro F1 = 88% (predict the correct class 88% of cases)

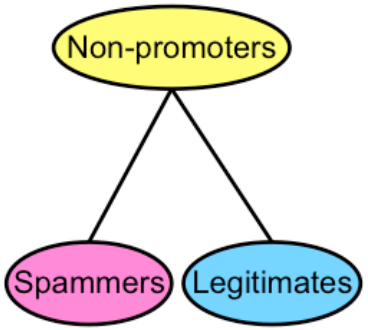
Hierarchical Classification



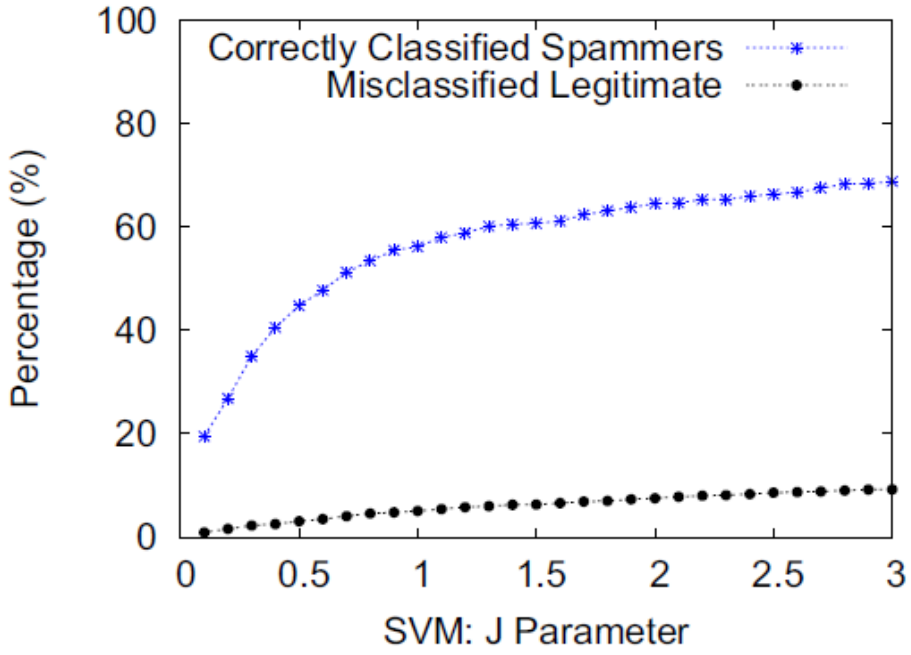
- Goal: provide flexibility in classification accuracy
- First Level:
  - Most promoters are correctly classified
  - Statistically indistinguishable compared with flat strategy

		Predicted	
		Promoter	Non-Promoter
True	Promoter	92.26%	7.74%
	Non-Promoter	0.55%	99.45%

Distinguishing Spammers from Legitimate users



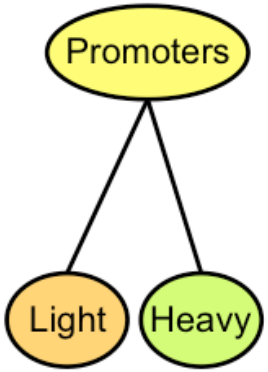
		Predicted	
		Legitimate	Spammer
True	Legitimate	**95.09%**	4.91%
	Spammer	41.27%	**58.73%**



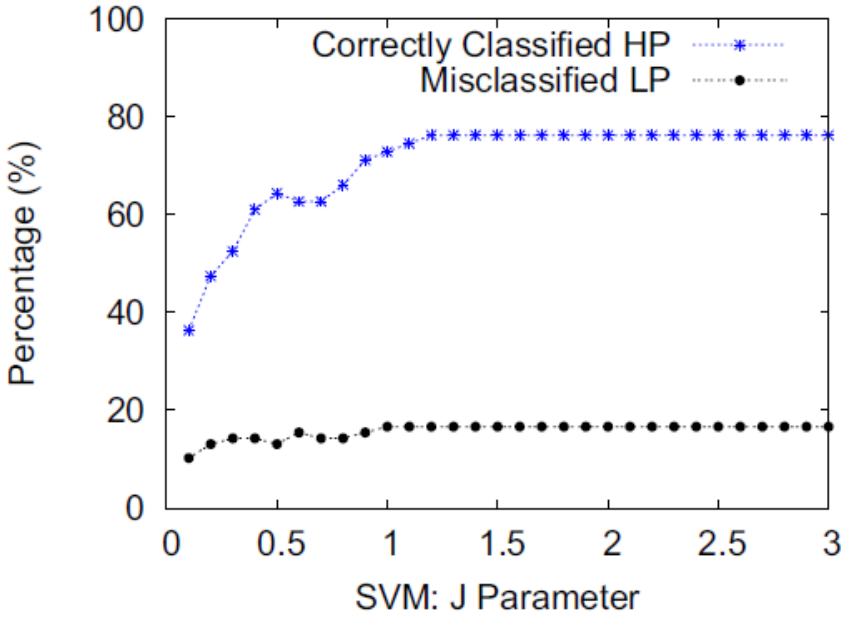
- **J = 0.1:** correctly classify 24% spammers, misclassifying <1% legitimate users
- **J = 3:** correctly classify 71% spammers, paying the cost of misclassifying 9% legitimate users

Distinguishing Promoters

- **Heavy promoters** could reach the top-100 in one day
- **Light promoters** associated with a collusion attack



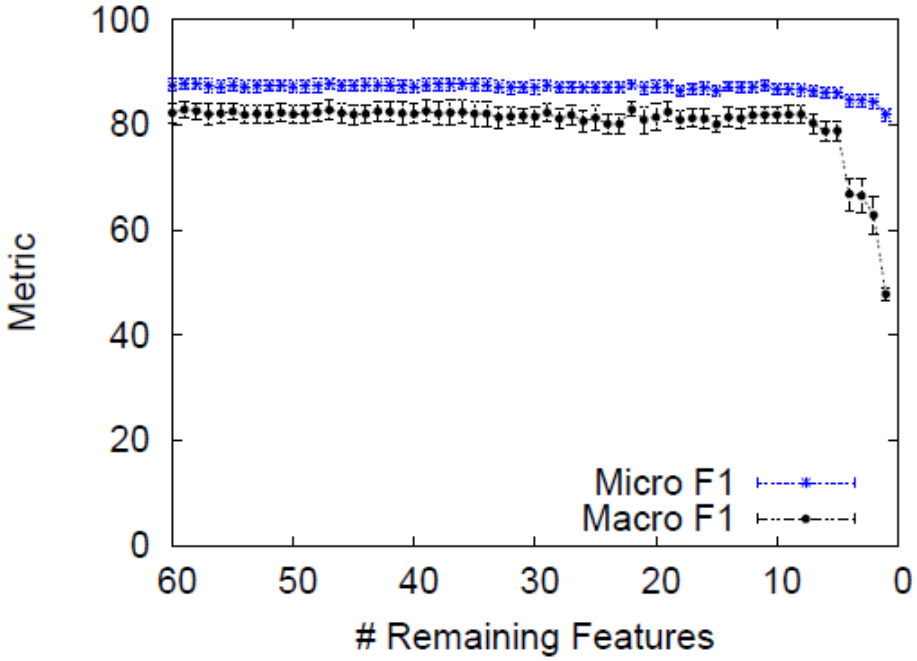
		Predicted	
		Light Promoter	**Heavy Promoter**
	Light Promoter	**83.33%**	16.67%
True	**Heavy Promoter**	27.12%	**72.88%**



- **J = 0.1**: correctly classify 36% of heavy promoters at the cost of misclassifying 10% of light promoters
- **J = 1.2**: correctly classify 76% of heavy promoters at the cost of misclassifying 17% light ones

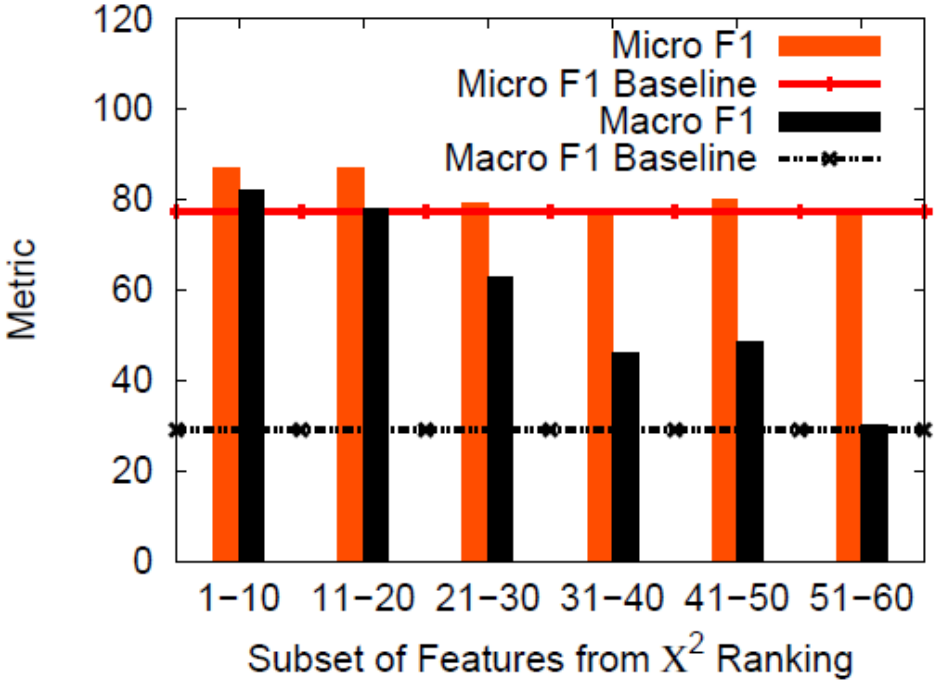
Reducing the Attribute Set

Scenario 1



Classification approach is effective even with a smaller, less expensive set of attributes

Scenario 2



Different subsets of features can obtain competitive results

Conclusions

- First approach to detect spammers and promoters
  - Attribute identification
  - Creation of a test collection
    - available at www.dcc.ufmg.br/~fabricio
  - Classification approach
    - Correctly identify majority of promoters
    - Spammers showed to be much harder to distinguish
      - trade-off between detect more spammers at the cost of misclassifying more legitimate users