Detecting Tip Spam in Location-based Social Networks

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LOCATION-BASED SOCIAL NETWORK (LBSN)

- What?
  - Systems that allow the users to share their geographic location with their social network
- How?
  - Check-in through a smartphone with GPS
  - Recommendations

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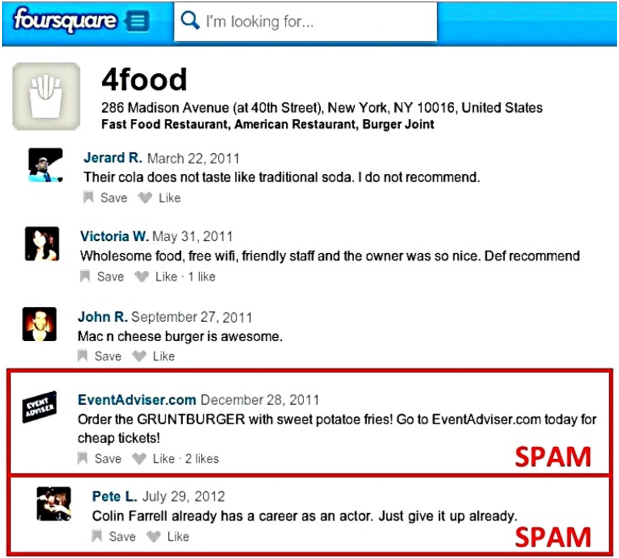
MOTIVATION

- The most interesting function: post tips
- New form of spam
  - Unsolicited message
  - Spread advertise
  - Disseminate pornography
  - Fake tips

TIP SPAM IN LBSN



NEGATIVE IMPACT OF TIP SPAM

- Jeopardize the trust of users on the existing tips
- Waste human attention

Goal and methodology

- **Goal**: Detect tip spam in LBSN
- 3-step approach
  1. Obtain tips labeled as spam or non-spam and crawler additional information
  2. Identify attributes able to distinguish spam from non-spam tips
  3. Classification approach to detect tip spam

STEP1. LABELED DATASET AND CRAWLED INFORMATION

- Apontador
  - Brazilian LBSN
  - Provided us tips labeled as spam or non-spam by their moderators

STEP1. LABELED DATASET AND CRAWLED INFORMATION

- Labeled dataset
  - Week period
  - **1,260** tips classified as spam and the **1,260** tips classified as non-spam
  - Each tip contains the following information
    - tip content
    - tip ID
    - user ID
    - place ID
    - etc.

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STEP1. LABELED DATASET AND CRAWLED INFORMATION

- Crawled information
  - Information not available in the provided data:
    - Geographical location of places
    - User information
    - Social graph
  - In total our labeled dataset contains
    - **2,520** tips
    - **1,984** unique users
    - **2,216** different places
    - social graph with **137,464** users

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VERIFYING LABELING ACCURACY

- Volunteers from our research group manually verify 100 randomly selected spam tips
- Volunteers classified 2 tips as non-spam and **98** as spam
  - **65** were local advertises
  - **29** pollution (i.e., unrelated or irrelevant text)
  - **4** were aggressive comments about the places

STEP2. ATTRIBUTES

- **Content attributes** (total=16)
  - number of words
  - number of numeric characters
  - number of URLs
  - etc.
- **User attribute** (total=8)
  - number of tips posted by the user
  - average distance among all places reviewed by the user
  - etc.
- **Place attributes** (Total=5):
  - number of tips on the place
  - place rating
  - etc.
- **Social attribute** (Total=12)
  - number of followers
  - number of followees
  - clustering coefficient
  - etc.

IMPORTANCE OF THE ATTRIBUTES

category	χ^2 ranking	description
place	**1**	Number of tips on the place
place	**2**	Place rating
content	**3**	Number of contact information on the text
content	**4**	Number of numeric characters
content	**5**	Number of phone numbers on the text
content	**6**	Number of email addresses on the text
content	**7**	Number of words
social	**8**	Number of followers (in-degree)
user	**9**	Maximum distance among all places reviewed by the user
user	**10**	Standard deviation of distance among all places reviewed by the user

It was important to investigate each attribute set

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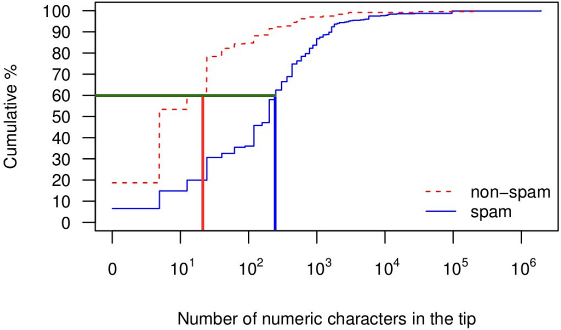
DISTINGUISHING CLASSES OF TIPS



Spam tips tend to have phone numbers, and thus, more numerical characters

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STEP3. CLASSIFICATION APPROACH

- *RandomForest* implemented in the Weka tool as classifier
- Use all **41 attributes**
- 5-fold cross validation (repeated 10 times with different seeds)
- Results are average of **50 runs**

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CLASSIFICATION RESULTS

		Predicted Label	
		Non-spam	**Spam**
True Label	**Non-spam**	**0.918**	0.082
	Spam	0.160	**0.840**

- **84%** of the spam tips were correctly classified as spam
- For the non-spam tips, **92%** were classified correctly
- **88%** of accuracy

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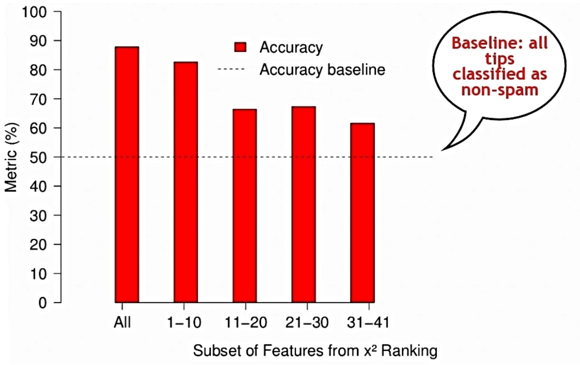
Reducing the attribute set



Different subsets of attributes can obtain competitive results

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Conclusions and Future Work

- We propose a mechanism to detect tip spam in LBSN
  - Apontador dataset and labeled collection
    - Publicly available (soon) at `homepages.dcc.ufmg.br/~fabricio/`
  - Attribute identification
  - Classification approach
    - Correctly identified majority of spam tips
    - Different subsets of attributes can obtain competitive results
- Future work
  - Identify subclasses of tip spam

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Questions

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