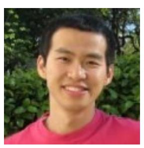
Who will **RT** this?

Automatically Identifying and Engaging Strangers on Twitter to Spread Information

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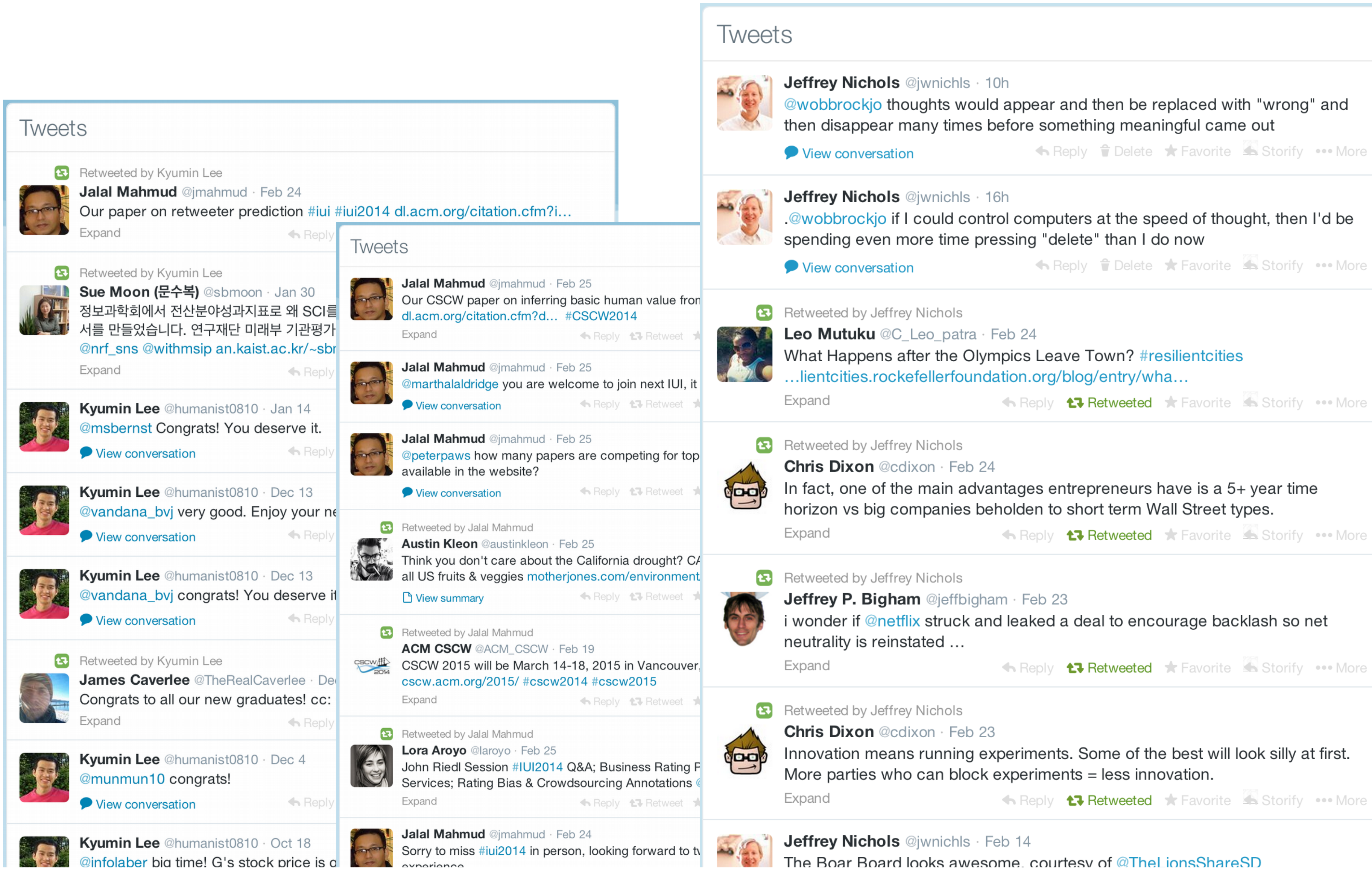
Public Social Media Contains a Wealth of Information about Individuals…



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Public Social Media Contains a Wealth of Information about Individuals…

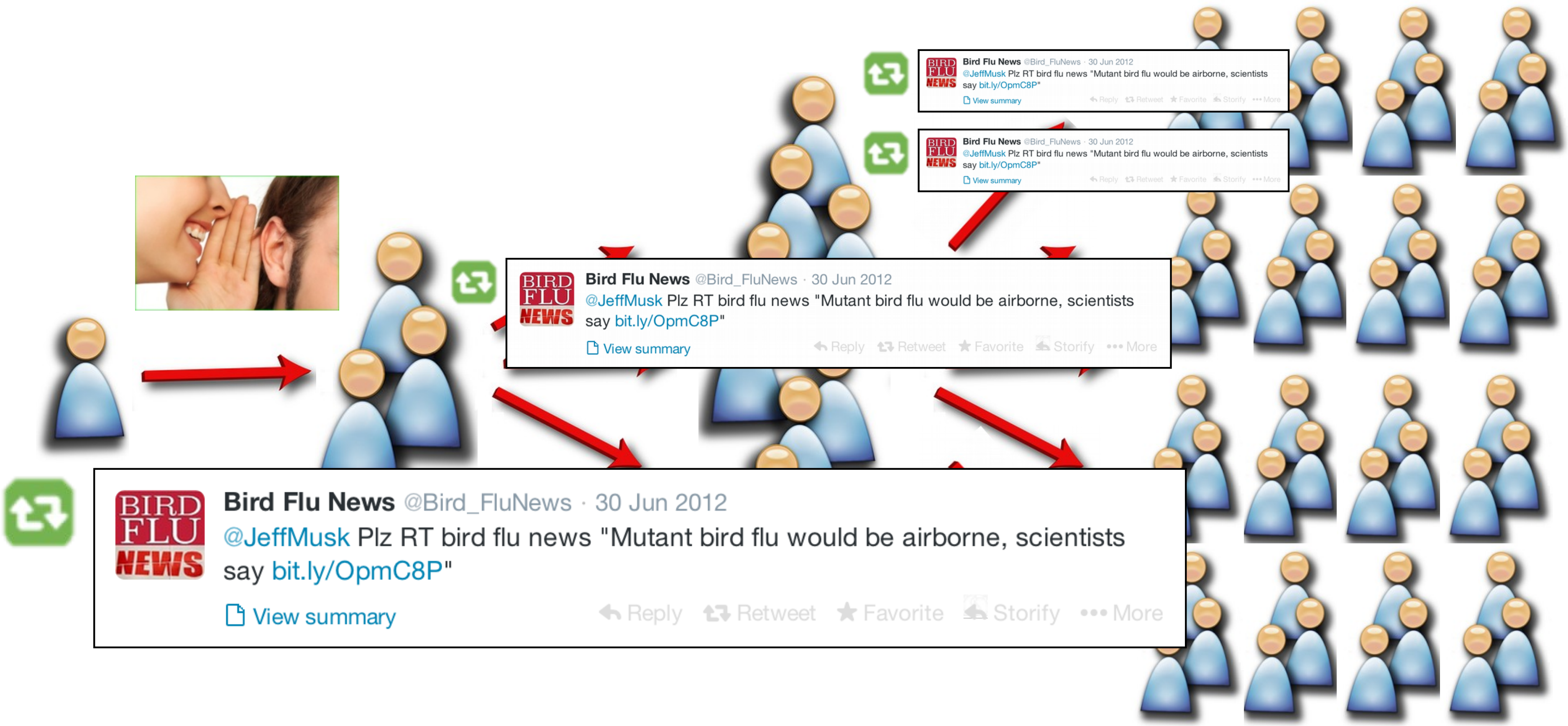
Can we harness this information for something useful?

- Identify people to recruit to do various tasks
- Collect Information
- Spread Information

Today: Information Spreading

- Relevant marketing campaign messages
- Alerts and SOS messages in an emergency
- Etc.

Today: Information Spreading



Challenge: Low percentage of people respond to this task

- Can we predict who will retweet and direct requests only to them?
- Can we predict who will retweet more quickly?

Our Process

1. Data Collection
2. Feature Extraction
3. Feature Selection
4. Model Building
5. Evaluation

Ground-Truth Data Collection

Public Safety (location-based)

- Randomly selected users who tweeted from the San Francisco bay area (via geo-tags)
- Contacted 1,902 users
- 52 (2.8%) retweeted our message
- Message reached a total of 18,670 followers

Bird Flu (topic-based)

- Randomly selected users who posted one of the following words in at least one tweet: *"bird flu"*, *"H5N1"* and *"avian influenza"*
- Contacted 1,859 users
- 155 (8.4%) retweeted our message
- Message reached a total of 184,325 followers

Resulting Data

In total:

- Contacted 3,761 strangers
- 207 positive examples, 3554 negative examples

For each user we contacted, we collected:

- Twitter profile (screen name, tweet count, etc.)
- People they followed, followers,
- Up to 200 recent messages
- Ground truth ("**retweeter**" or "**non-retweeter**")

Feature Extraction

Feature Categories

- Profile Features
- Social Network Features
- Personality Features
- Activity Features
- Past Retweeting Features
- Readiness Features

Feature Extraction

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Profile Features

- longevity (age) of an account
- length of screen name
- whether the user profile has a description
- length of the description
- whether the user profile has a URL

Social Network Features

- number of users following (friends)
- number of followers
- and the ratio of number of friends to number of followers

Feature Extraction

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- Readiness Features

Users' word usage has been found to predict their personality

•Linguistic Inquiry and Word Count (LIWC) dictionary

•Personality features derived from LIWC categories [Yarkoni 2010, Mahmud 2013]

Personality Features	Total Number	Examples
LIWC	68	Sadness, 1st Person Plural, Anxiety
Big Five	5	Agreeableness, Conscientiousness
Big Five Sub-Facets	30	Friendliness, Anxiety

Feature Extraction

Feature Categories

- Profile Features
- Social Network Features
- Personality Features
- Activity Features
- Past Retweeting Features
- Readiness Features

- Number of status messages
- Number of direct mentions (e.g., @johny) per status message
- Number of URLs per status message
- Number of hashtags per status message
- Number of status messages per day during her entire
- Account life (= total number of posted status messages / longevity)
- Number of status messages per day during last one month
- Number of direct mentions per day during last one month
- Number of URLs per day during last one month
- Number of hashtags per day during last one month

Feature Extraction

Feature Categories

- Profile Features
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Past Retweeting Behavior

- Number of retweets per status message: R/N
- Average number of retweets per day
- Fraction of retweets for which original messages are posted by strangers who are not in her social network

Readiness Based on Previous Activity

- Tweeting Likelihood (Day)
- Tweeting Likelihood (Hour)
- Entropy of Tweeting Likelihood (Day)
- Entropy of Tweeting Likelihood (Hour)
- Tweeting Steadiness
- Tweeting Inactivity

Predicting Retweeters

Training and Test Sets:

- Each dataset (public safety and bird flu) was randomly split to training set (2/3 data) and testing set (1/3 data)

5 Predictive Models

- Random Forest, Naïve Bayes, Logistic Regression, SMO (SVM) and AdaboostM1

Handing Class Imbalance

- Used both over-sampling (SMOTE) and weighting approaches (cost-sensitive approach)

Feature Selection

Computed χ^2 value for each feature in training

Feature Group	Significant Features (bolded is common to both data sets)
Profile	the longevity of the account
Social-network	|following| ratio of number of friends to number of followers
Activity	**|URLs| per day** **|direct mentions| per day** **|hashtags| per day** |status messages| |status messages| per day during entire account life |status messages| per day during last one month
Past Retweeting	**|retweets| per status message** **|retweets| per day**
Readiness	Tweeting Likelihood of the Day Tweeting Likelihood of the Day (Entropy)
Personality	7 LIWC features: **Inclusive**, Achievement, Humans, Time, Sadness, Articles, Nonfluencies 1 Facet feature: Modesty

21 Features Selected by χ^2 in Publish Safety Dataset

Feature Group	Significant Features (bolded is common to both data sets)
Profile	the length of description has description in profile
Activity	**|URLs| per day** **|direct mentions| per day** **|hashtags| per day** |URLs| per status message |direct mentions| per status message |hashtags| per status message
Past Retweeting	**|retweets| per status message** **|retweets| per day** |URLs| per retweet message
Readiness	Tweeting Likelihood of the Hour (Entropy)
Personality	34 LIWC features: **Inclusive**, Total Pronouns, 1st Person Plural, 2nd Person, 3rd Person, Social Processes, Positive Emotions, Numbers, Other References, Occupation, Affect, School, Anxiety, Hearing, Certainty, SZensory Processes, Death, Body States, Positive Feelings, Leisure, Optimism, Negation, Physical States, Communication 8 Facet features: Liberalism, Assertiveness, Achievement Striving, Self-Discipline, Gregariousness, Cheerfulness, Activity Level, Intellect 2 Big5 features: Conscientiousness, Openness

46 Features Selected by χ^2 in Bird Flu Dataset

Activity, personality, readiness and past retweeting feature groups have more significant power.
Six significant features (bolded names) are common to both sets.

Evaluating Retweeter Prediction

Only the significant features are used for prediction

Classifier	AUC	F1	F1 of Retweeter
Basic			
Random Forest	0.638	0.958	0
Naïve Bayes	0.619	0.939	0.172
Logistic	0.640	0.958	0
SMO	0.500	0.96	0
AdaBoostM1	0.548	0.962	0.1
SMOTE			
Random Forest	0.606	0.916	0.119
Naïve Bayes	0.637	0.923	0.132
Logistic	0.664	0.833	0.091
SMO	0.626	0.813	0.091
AdaBoostM1	0.633	0.933	0.129
Cost-Sensitive (Weighting, showing the best results in each model)			
Random Forest	**0.692**	0.954	0.125
Naïve Bayes	0.619	0.93	0.147
Logistic	0.623	0.938	0.042
SMO	0.633	0.892	0.123
AdaBoostM1	0.678	0.956	0.133

Prediction accuracy (Public Safety)

Classifier	AUC	F1	F1 of Retweeter
Basic			
Random Forest	0.707	0.877	0.066
Naïve Bayes	0.670	0.834	0.222
Logistic	0.751	0.878	0.067
SMO	0.500	0.876	0
AdaBoostM1	0.627	0.878	0.067
SMOTE			
Random Forest	0.707	0.819	0.236
Naïve Bayes	0.679	0.724	0.231
Logistic	0.76	0.733	0.258
SMO	0.729	0.712	0.278
AdaBoostM1	0.709	0.837	0.292
Cost-Sensitive (Weighting, showing the best results in each model)			
Random Forest	**0.785**	0.815	0.296
Naïve Bayes	0.670	0.767	0.24
Logistic	0.735	0.742	0.243
SMO	0.676	0.738	0.256
AdaBoostM1	0.669	0.87	0.031

Prediction accuracy (Bird Flu)

We use Random Forest for all following experiments.

Comparison with Two Baselines

Baselines

Random people contact

- Randomly select and ask a sub-set of qualified candidates

Popular people contact

- Sort candidates in our test set by their follower count in the descending order

Approach	Retweeting Rate in Testing Set	
	Public Safety	Bird flu
Random People Contact	2.6%	8.3%
Popular People Contact	3.1%	8.5%
Our Prediction Approach	**13.3%**	**19.7%**

Comparison of retweeting rates

Live Experiment

- To validate the effectiveness of our approach in a live setting, we used our recommender system to test our approach against the two baselines
- Randomly selected 426 candidates who had recently tweeted about “bird flu” in July 2013
- Each approach selected top 100 candidates based on its criteria

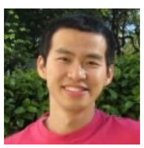
Approach	**Retweeting Rate**
Random People Contact	4%
Popular People Contact	9%
Our Prediction Approach	**19%**

Comparison of retweeting rates in live experiment

To wrap up…

- We have presented a feature-based prediction model that can automatically identify the right individuals at the right time on Twitter
- We have also described a time estimation model
- In the experiments, our approaches **doubled** the retweeting rates over the two baselines
- With our time estimation model, our approach outperformed other approaches significantly
- Overall, our approach effectively identifies qualified candidates for retweeting a message within a given time window

Thanks!

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Why Retweet a Stranger's Request?

We randomly selected 50 people who retweeted and asked them why they chose to retweet (33 replied)

Main reasons to retweet our requested message

- Trustworthiness of the content

  "Because it contained a link to a significant report from a reputable media news source"

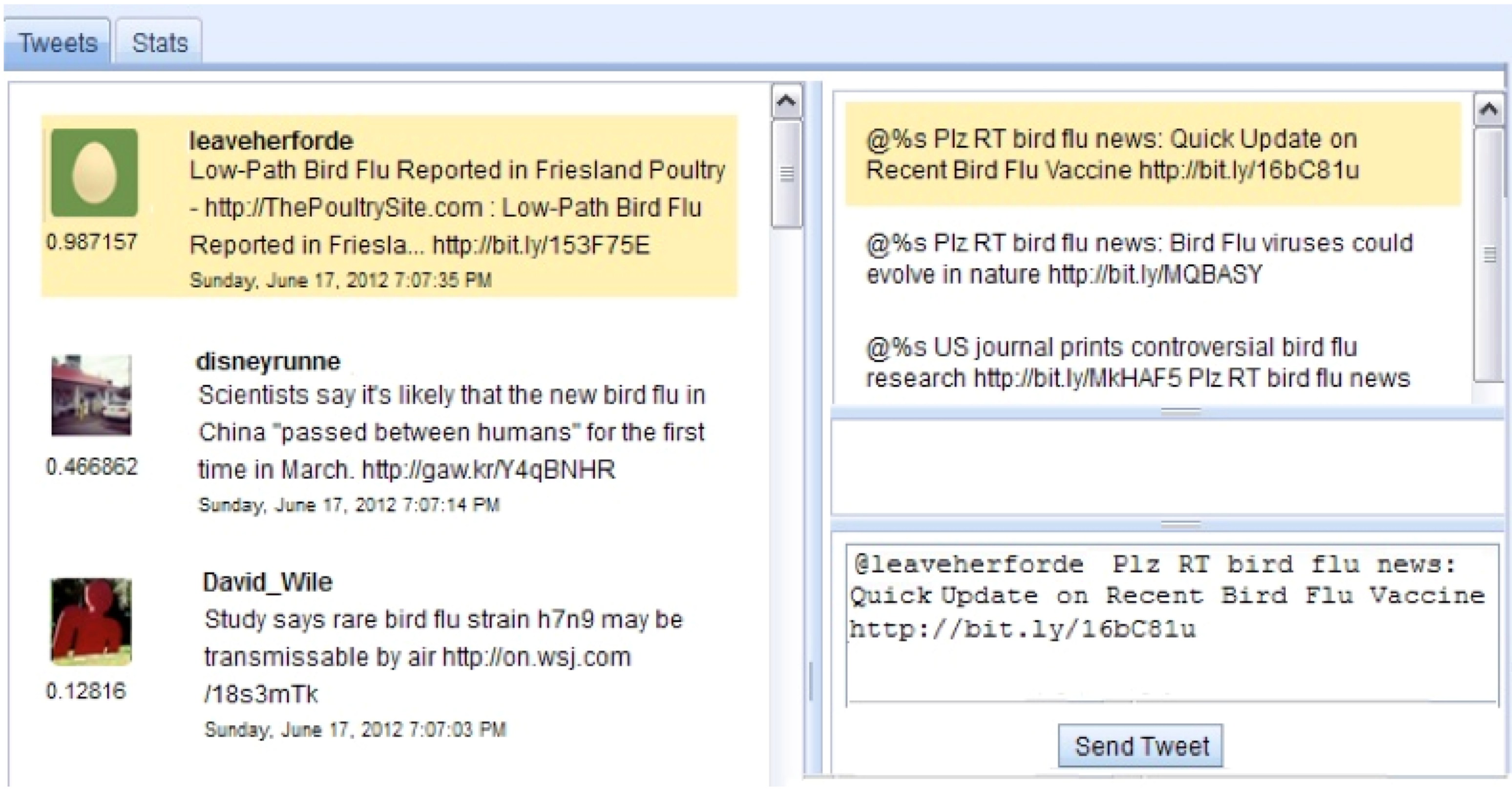
- Content relevance

  "Because it happened in my neighborhood"

- Content value

  "my followers should know this or they may think this info is valuable"

Real-Time Retweeter Recommendation



The interface of our retweeter recommendation system: (a) left panel: system-recommended candidates, and (b) right panel: a user can edit and compose a retweeting request.