Collective Spammer Detection in Evolving Multi-Relational Social Networks

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Lise Getoor (University of California, Santa Cruz)

Spam in Social Networks

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  - 1 in 200 social messages are spam
  - 5% of all social apps are spammy

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- What's different about social networks?
  - Spammers have more ways to interact with users
    - *Messages, comments on photos, winks,…*
  - They can split spam across multiple messages
  - More available info about users on their profiles!

Spammers are getting smarter!

Traditional Spam:

George

Want some replica luxury watches?
Click here:
http://SpammyLink.com

Shobeir

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(Intelligent) Social Spam:

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Nice profile photo. I live in Bay Area too. Wanna chat?

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Sure! :)

Realistic Looking Conversation ⋮

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I'm logging off here., too many people pinging me!
I really like you, let's chat more here:
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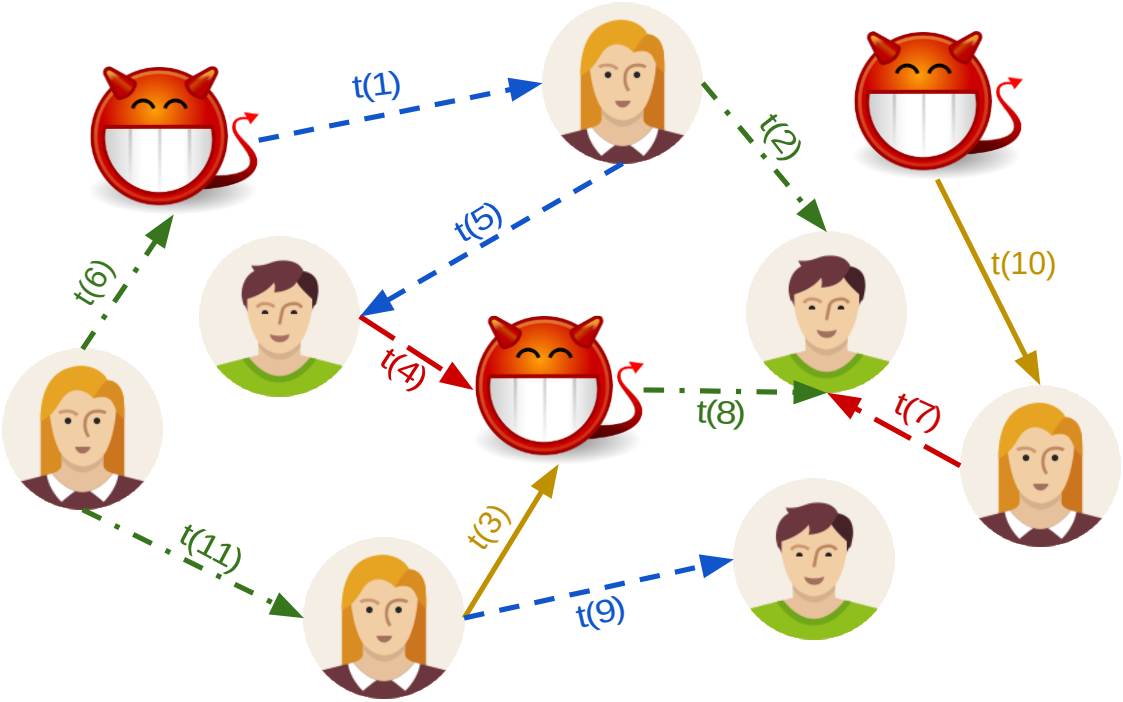
Tagged.com

- Founded in 2004, is a social networking site which connects people through social interactions and games

- Over 300 million registered members

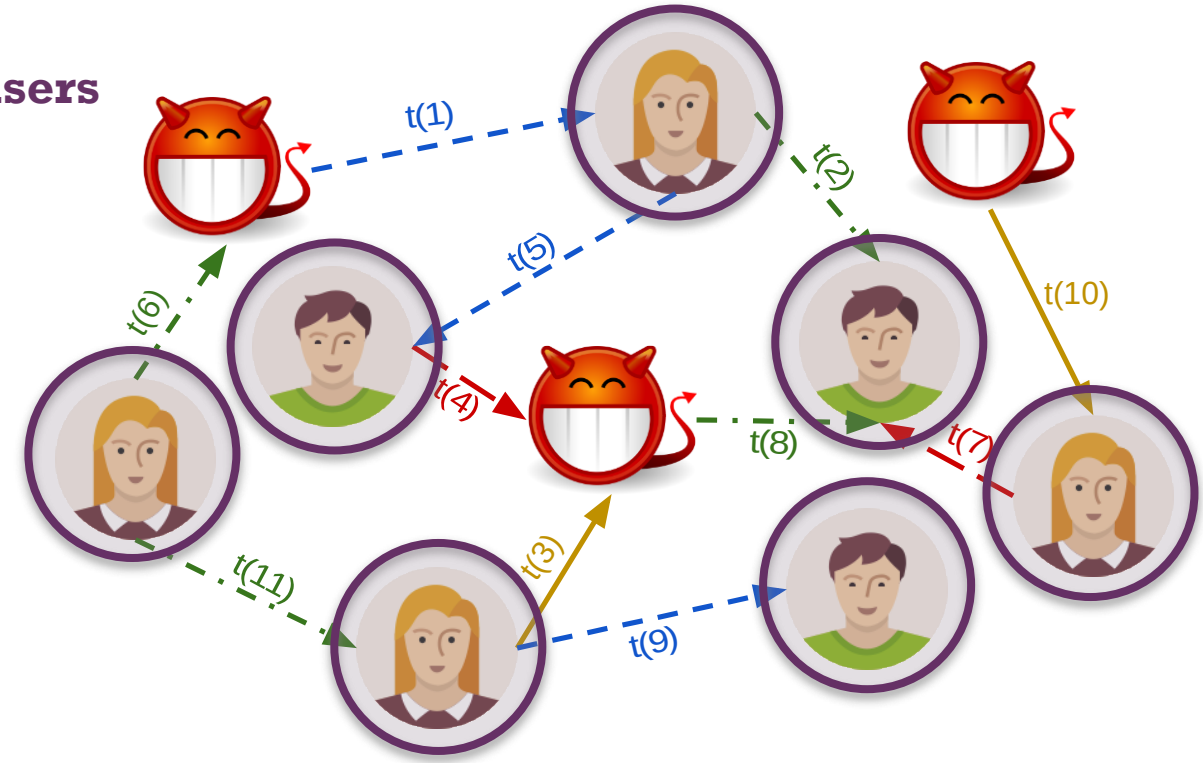
- Data sample for experiments (on a laptop):
  - 5.6 Million users (3.9% Labeled Spammers)
  - 912 Million Links

Social Networks:
Multi-relational and Time-Evolving



Social Networks: Multi-relational and Time-Evolving

Legitimate users



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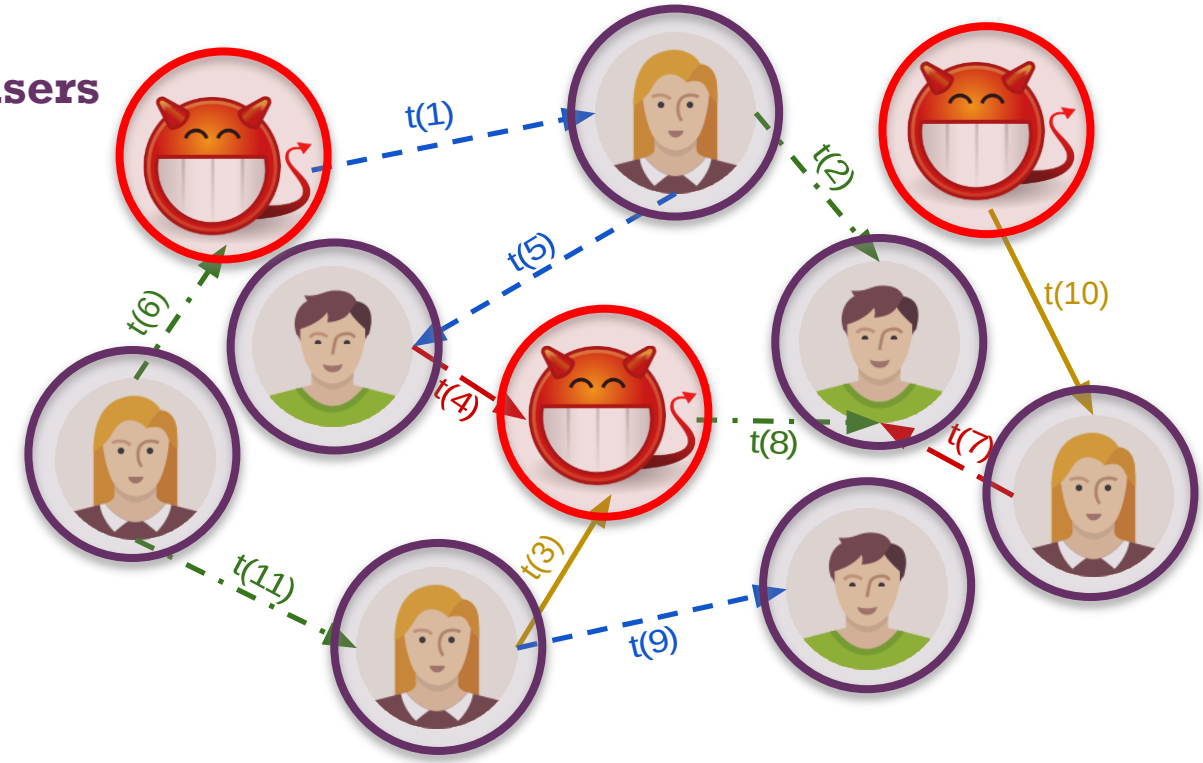

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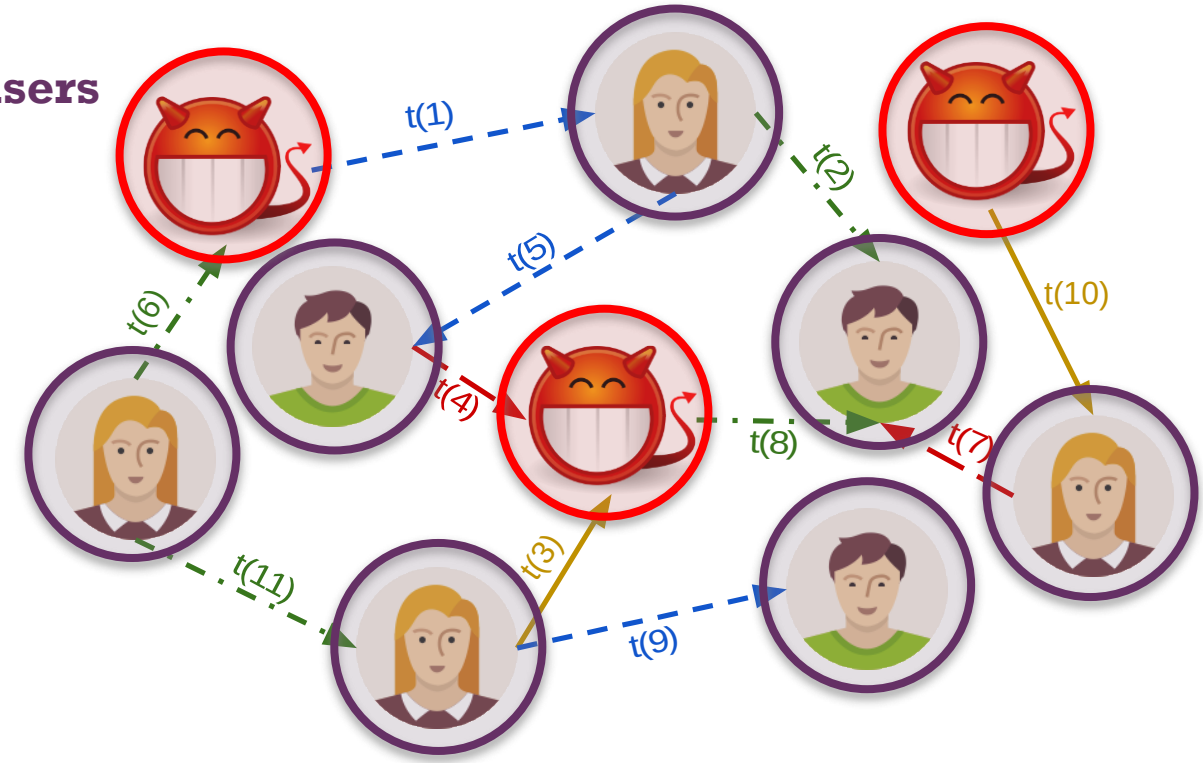

Link = Action at time t

Actions = *Profile view*, *message*, *poke*, *report abuse*, etc

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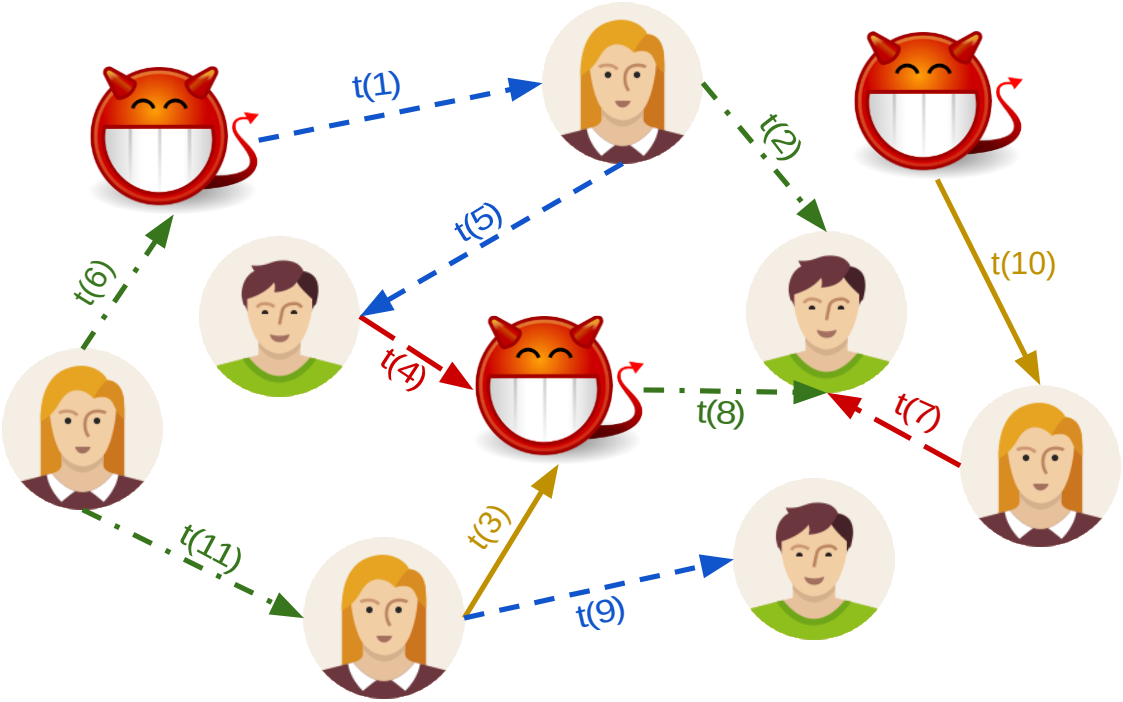

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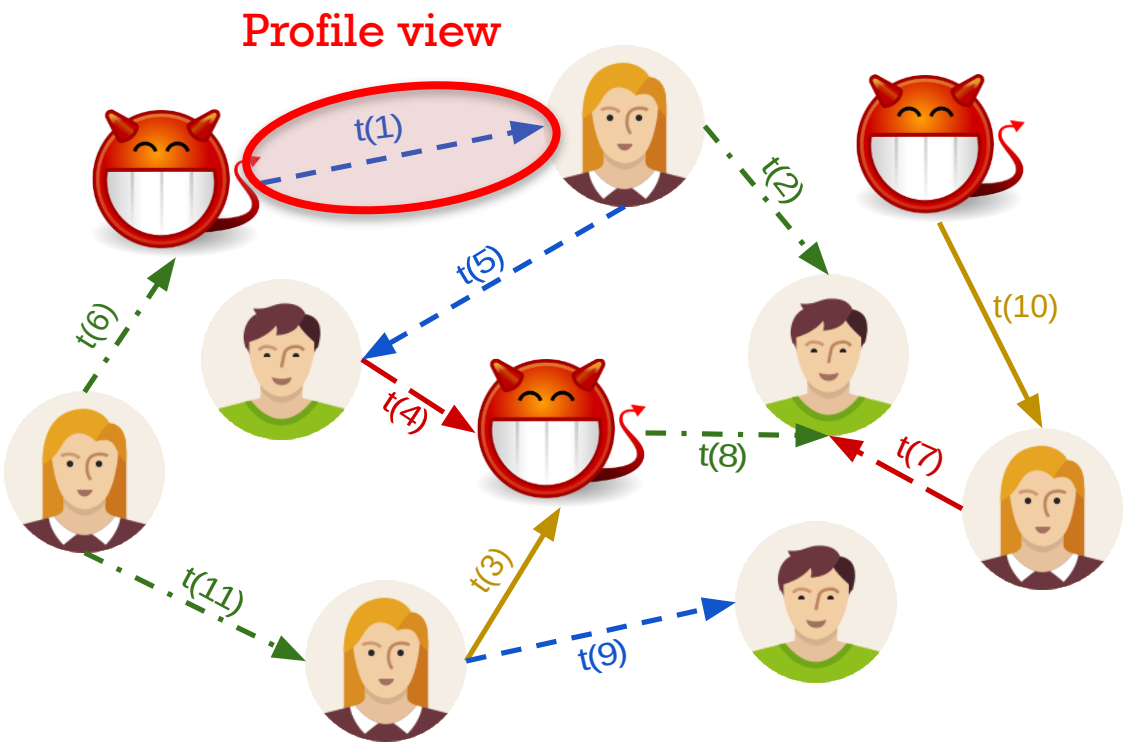

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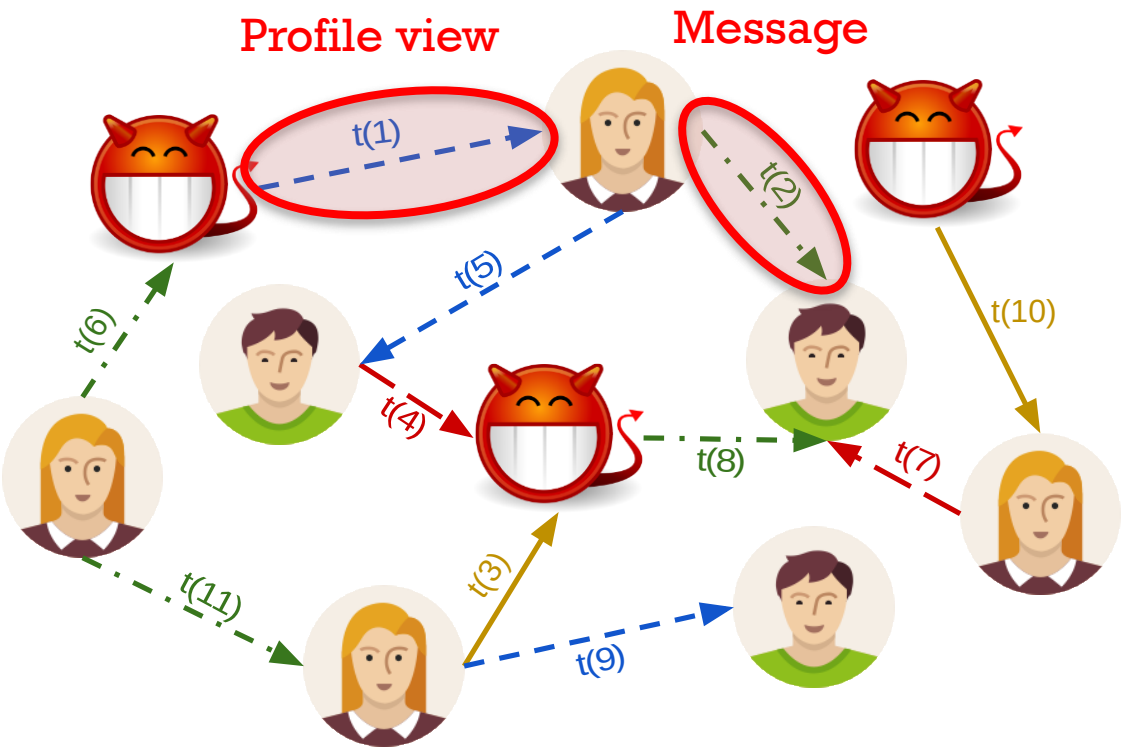

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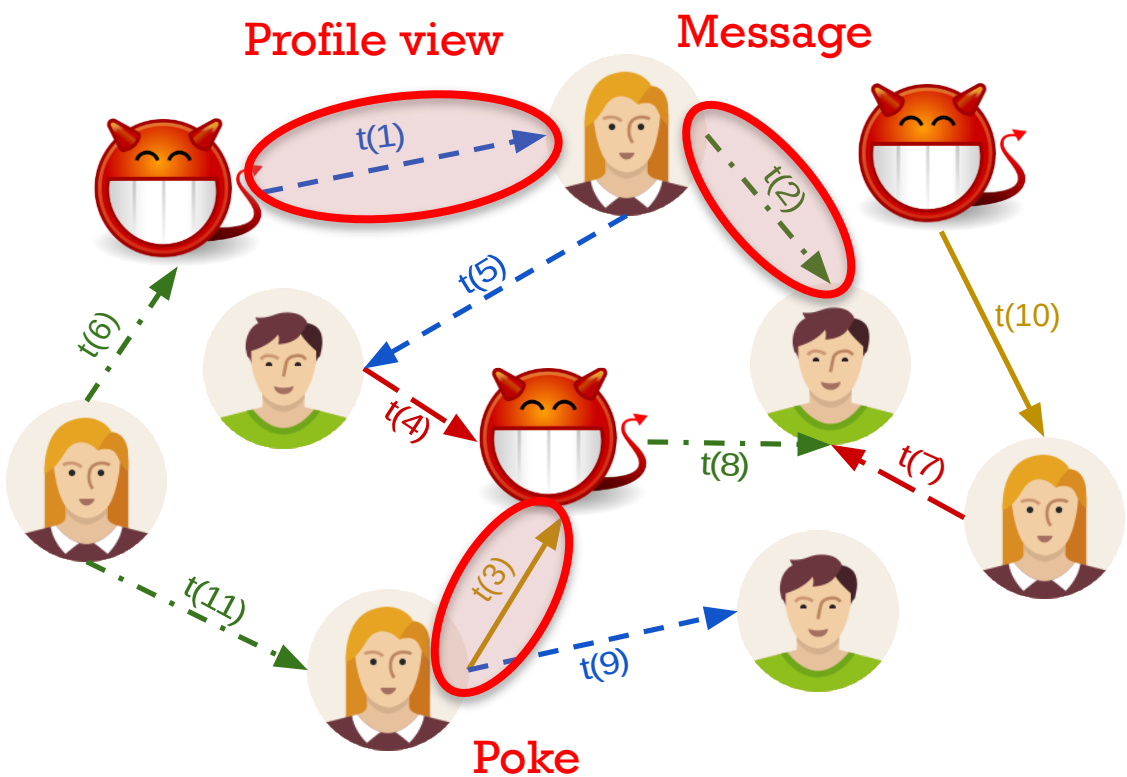

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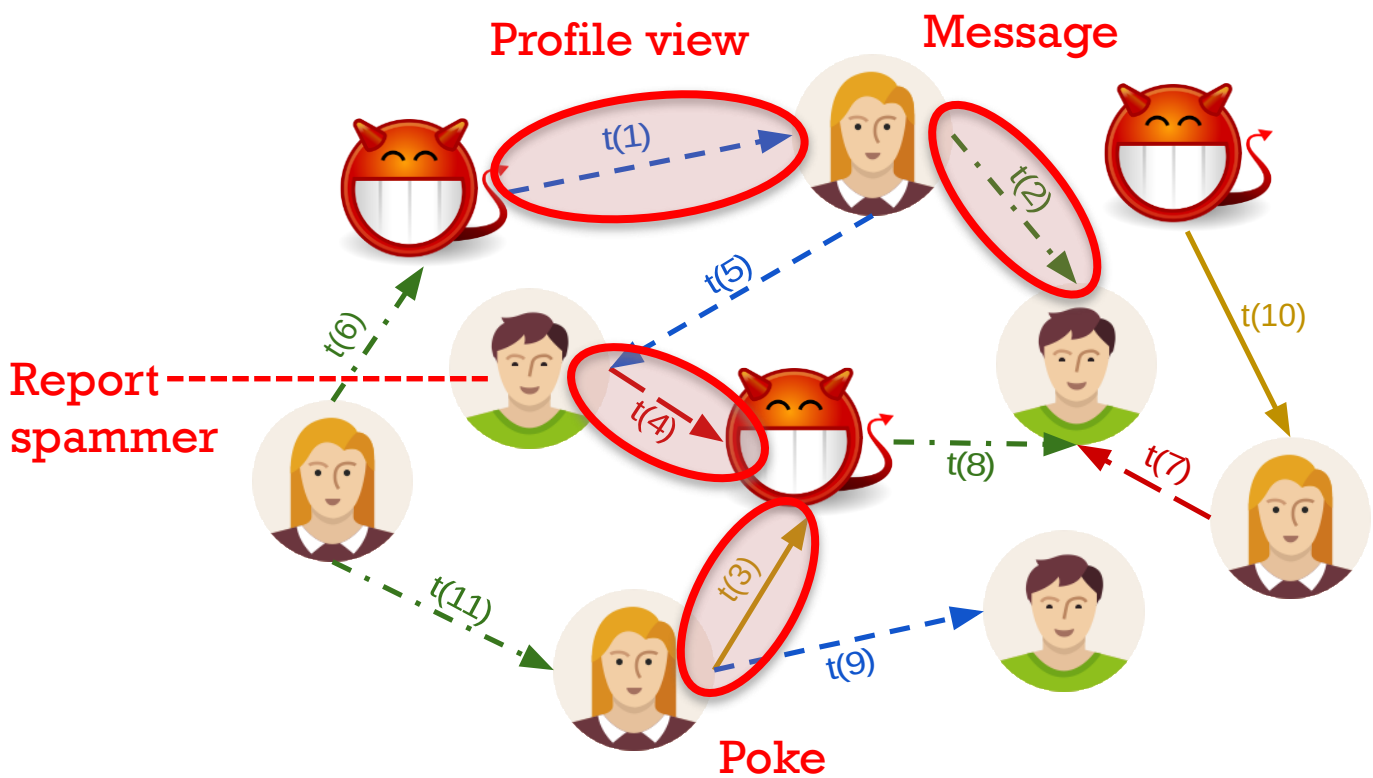

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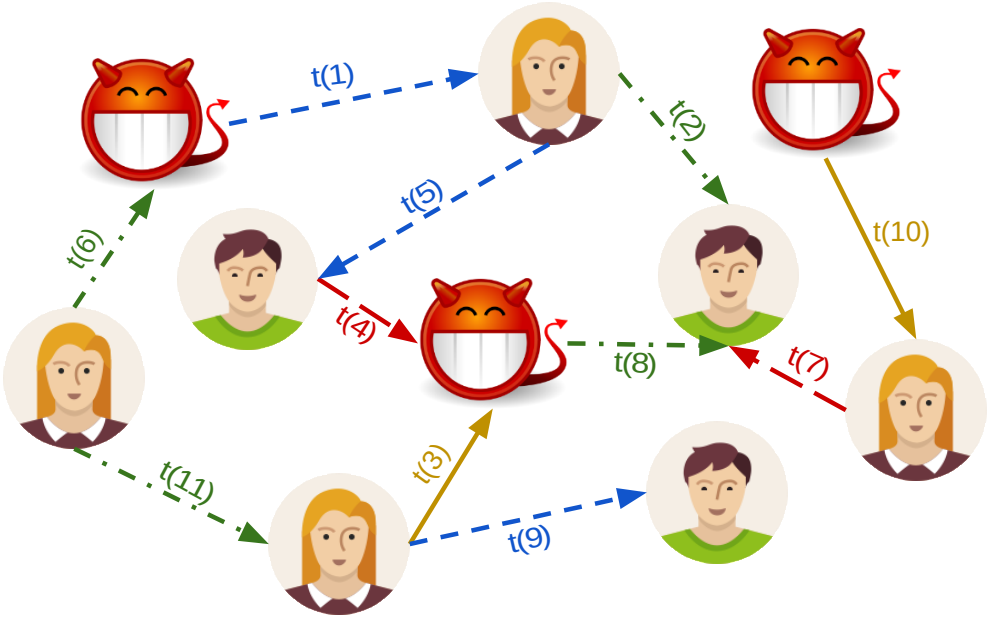
Predict spammers based on:

- Graph structure
- Action sequences
- Reporting behavior



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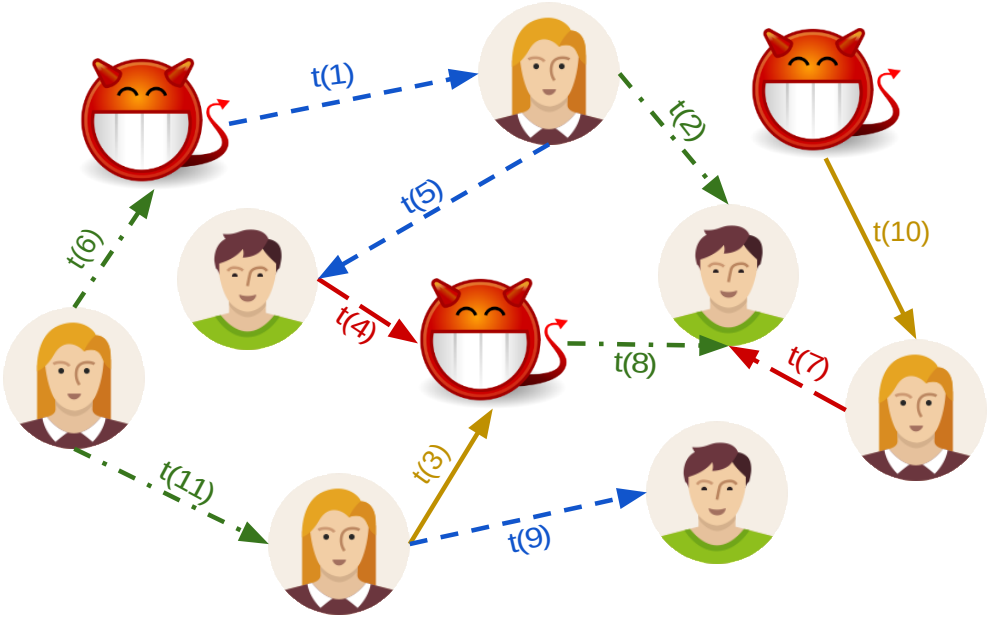
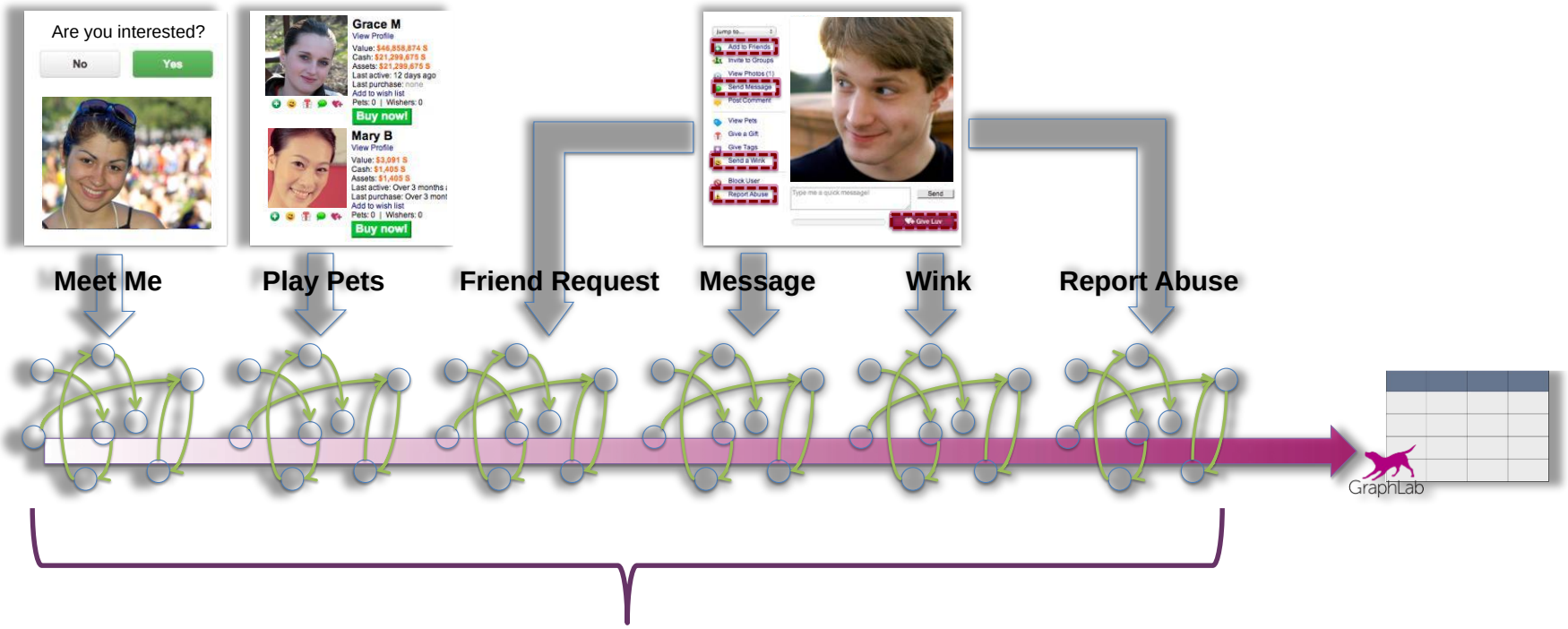
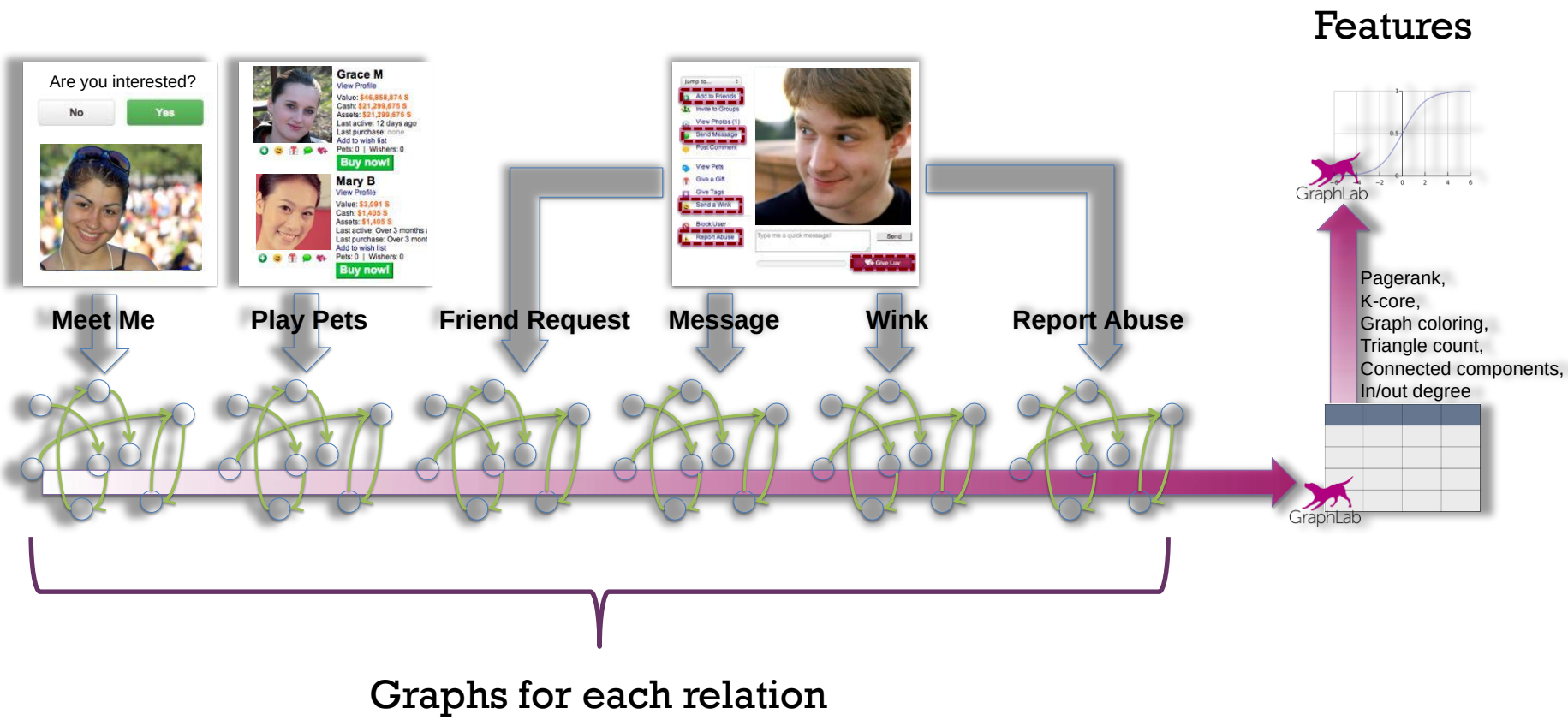


Graph Structure Feature Extraction



Graphs for each relation

Graph Structure Feature Extraction



Graph Structure Features

- Extract features for each relation graph
  - PageRank
  - Degree statistics
    - Total degree
    - In degree
    - Out degree
  - k-Core
  - Graph coloring
  - Connected components
  - Triangle count

(8 features for each of 10 relations)

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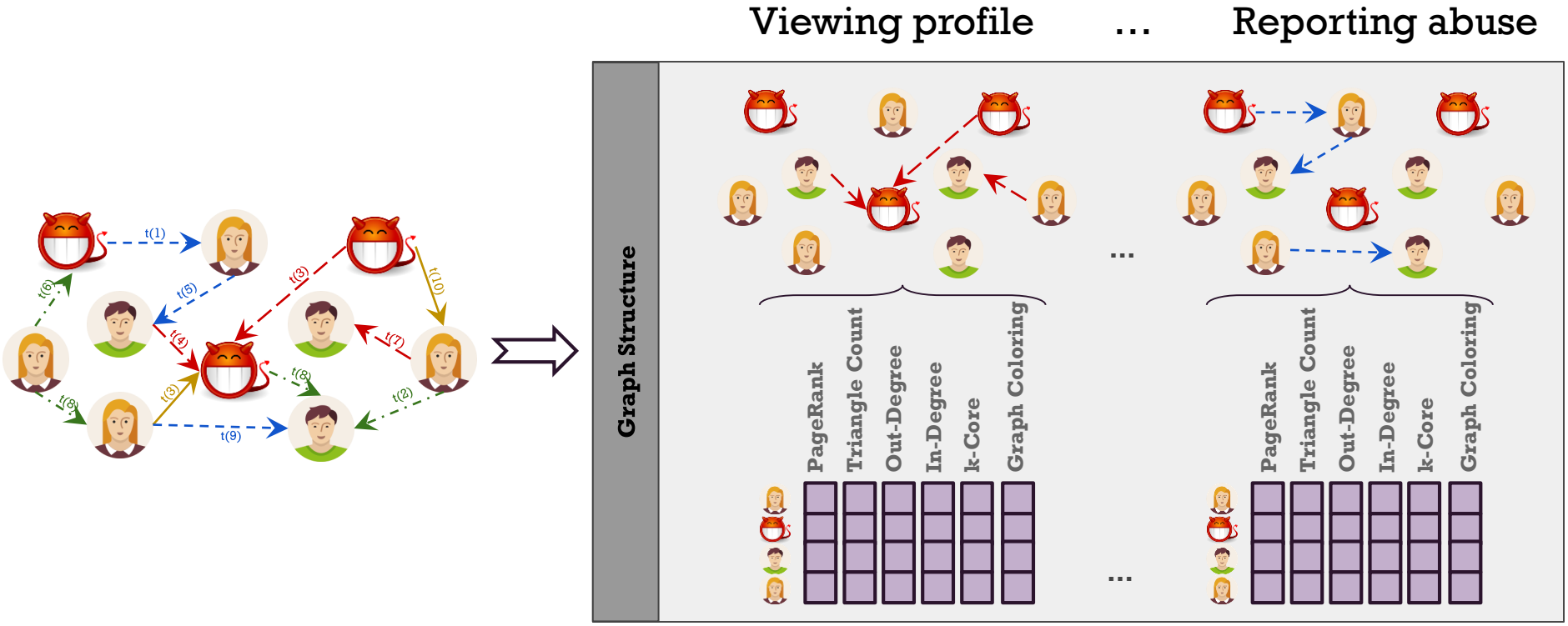
X

- Viewing profile
- Friend requests
- Message
- Luv
- Wink
- Pets game
  - Buying
  - Wishing
- MeetMe game
  - Yes
  - No
- Reporting abuse

(8 features for each of 10 relations)

Graph Structure Features



Classification method: Gradient Boosted Trees

Graph Structure Features

Experiments	AU-PR	AU-ROC
1 Relation, 8 Feature types	0.187 ± 0.004	0.803 ±0.001
10 Relations, 1 Feature type	0.285 ± 0.002	0.809 ± 0.001
10 Relations, 8 Feature types	0.328 ± 0.003	0.817 ± 0.001

Multiple relations/features ⟹ better performance!

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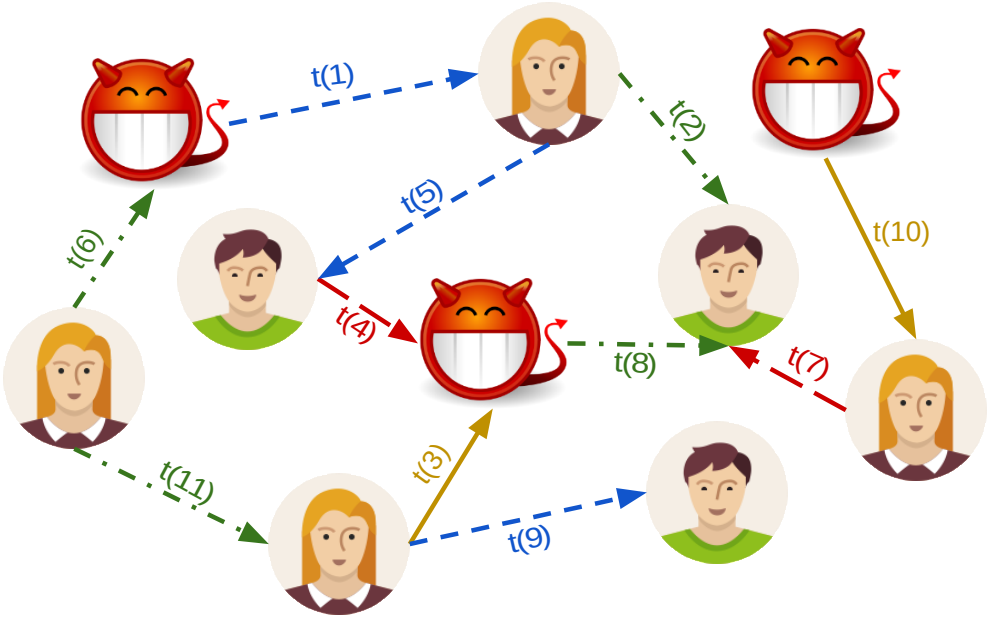


Sequence of Actions

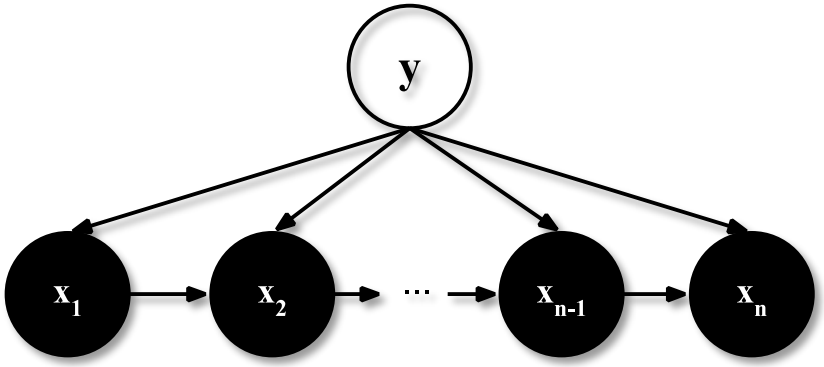
- **Sequential Bigram Features:**
  Short sequence segment of 2 consecutive actions, to capture sequential information

User1 Actions:
Message, Profile_view, Message, Friend_Request, ….

Sequence of Actions

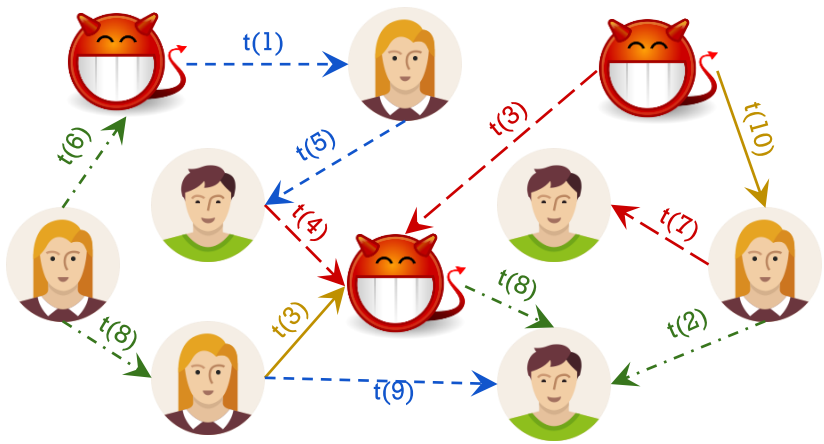
- **Mixture of Markov Models (MMM):**

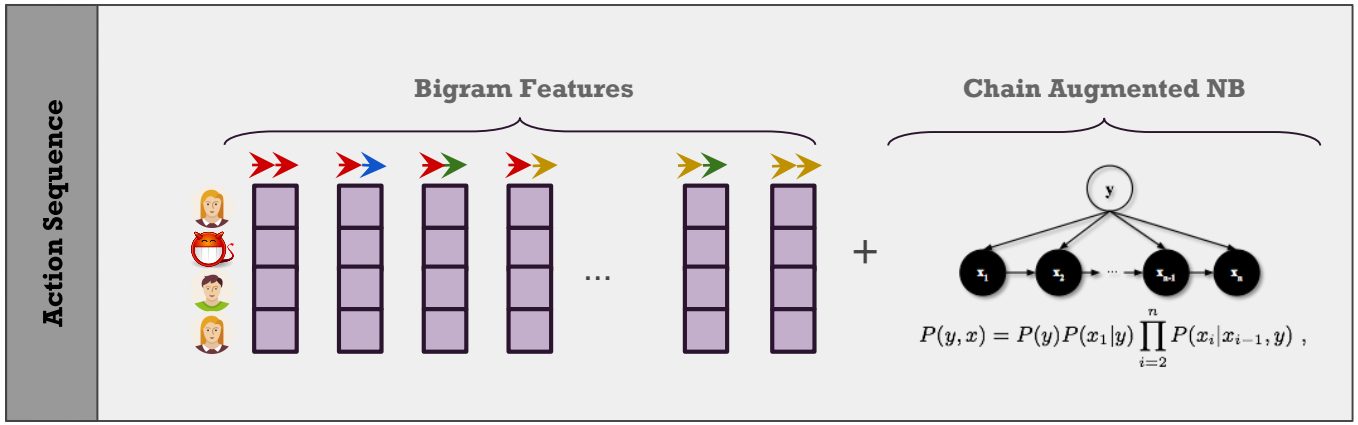
  A.k.a. chain-augmented, tree-augmented naive Bayes



$$P(y,x) = P(y)P(x_1|y)\prod_{i=2}^{n} P(x_i|x_{i-1},y) \ ,$$

Sequence of Actions





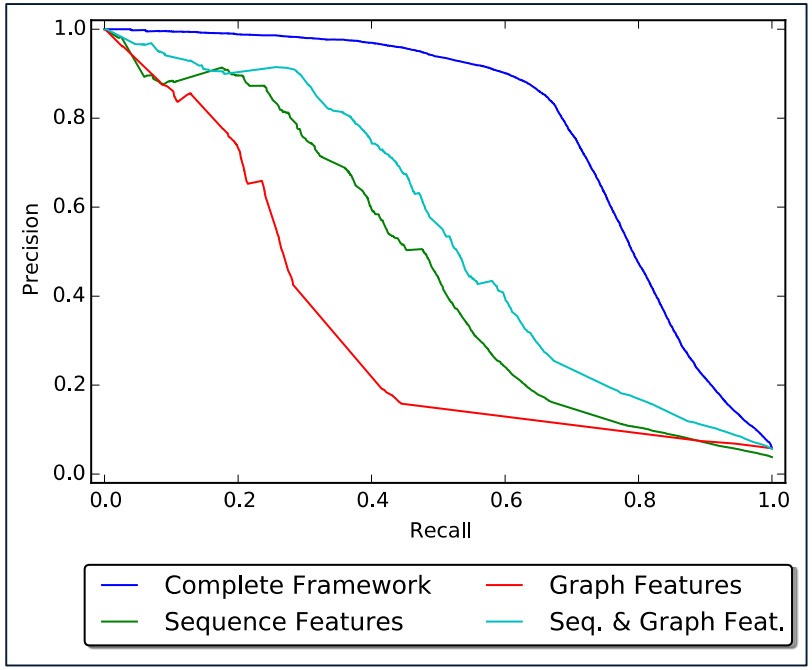
Sequence of Actions

Experiments	AU-PR	AU-ROC
Bigram Features	0.471 ± 0.004	0.859 ± 0.001
MMM	0.246 ± 0.009	0.821 ± 0.003
Bigram + MMM	0.468 ± 0.012	0.860 ± 0.002

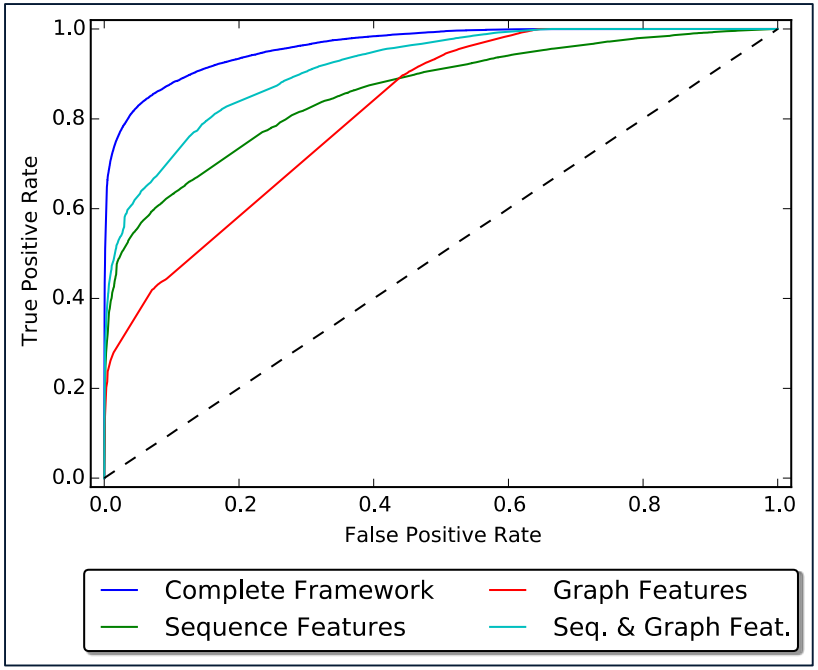
Little benefit from MMM (although little overhead)

Results

Precision-Recall



ROC



We can classify 70% of the spammers that need manual labeling with about 90% accuracy

Deployment and Example Runtimes

- We can:
  - Run the model on short intervals, with new snapshots of the network
  - Update the features as events occur
- Example runtimes with Graphlab Create™ on a Macbook Pro:
  - 5.6 million vertices and 350 million edges:
  - PageRank: 6.25 minutes
  - Triangle counting: 17.98 minutes
  - k-core: 14.3 minutes

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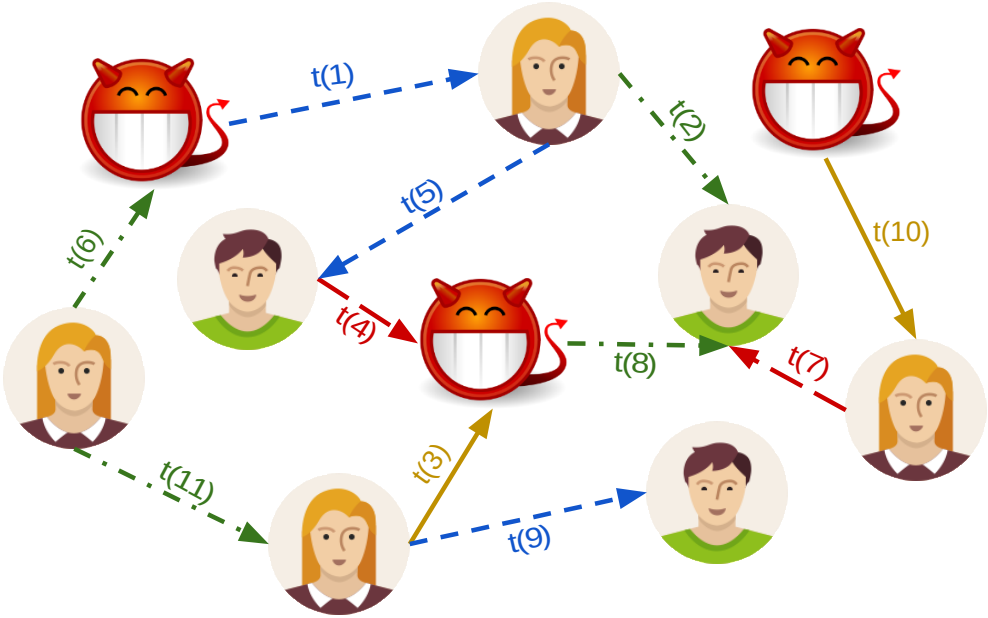
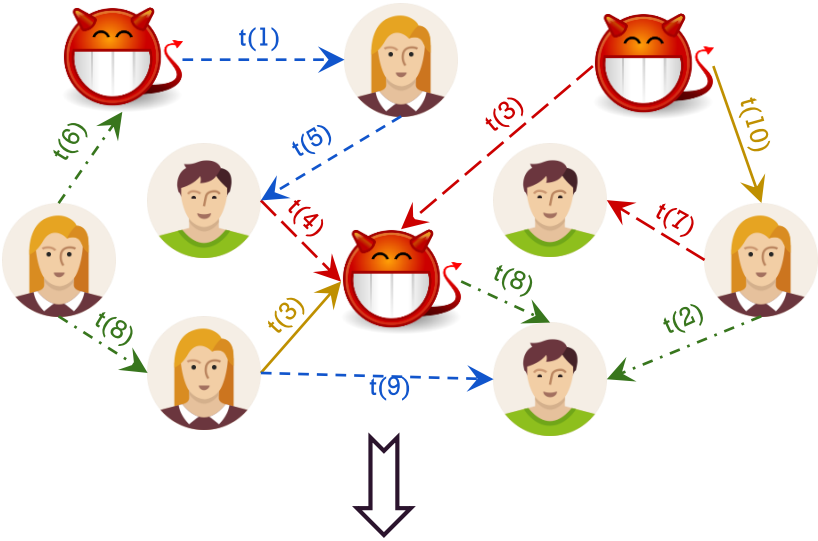
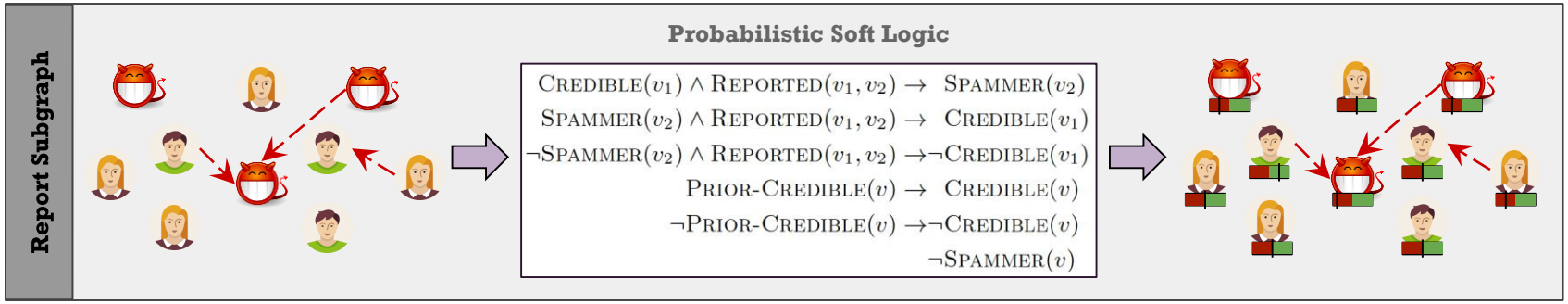


Refining the abuse reporting systems

- Abuse report systems are very noisy
  - People have different standards
  - Spammers report random people to increase noise
  - Personal gain in social games
- Goal is to clean up the system using:
  - Reporters' previous history
  - Collective reasoning over reports

Collective Classification with Reports





HL-MRFs & Probabilistic Soft Logic (PSL)

- Probabilistic Soft Logic (PSL), a declarative modeling language based on first-order logic

- Weighted logical rules define a probabilistic graphical model:

$$\omega : P(A, B) \wedge Q(B, C) \rightarrow R(A, C)$$

- Instantiated rules reduce the probability of any state that does not satisfy the rule, as measured by its *distance to satisfaction*

Collective Classification with Reports

- Model using only reports:

$$REPORTED(v_1, v_2) \rightarrow \quad SPAMMER(v_2)$$
$$\neg SPAMMER(v)$$

Collective Classification with Reports

- Model using reports and credibility of the reporter:

$$
\begin{aligned}
CREDIBLE(v_1) \wedge REPORTED(v_1, v_2) &\rightarrow \quad SPAMMER(v_2) \\
PRIOR\text{-}CREDIBLE(v) &\rightarrow \quad CREDIBLE(v) \\
\neg PRIOR\text{-}CREDIBLE(v) &\rightarrow \neg CREDIBLE(v) \\
&\quad \neg SPAMMER(v)
\end{aligned}
$$

Collective Classification with Reports

- Model using reports, credibility of the reporter, and collective reasoning:

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Results of Classification Using Reports

Experiments	AU-PR	AU-ROC
Reports Only	0.674 ± 0.008	0.611 ± 0.007
Reports & Credibility	0.869 ± 0.006	0.862 ± 0.004
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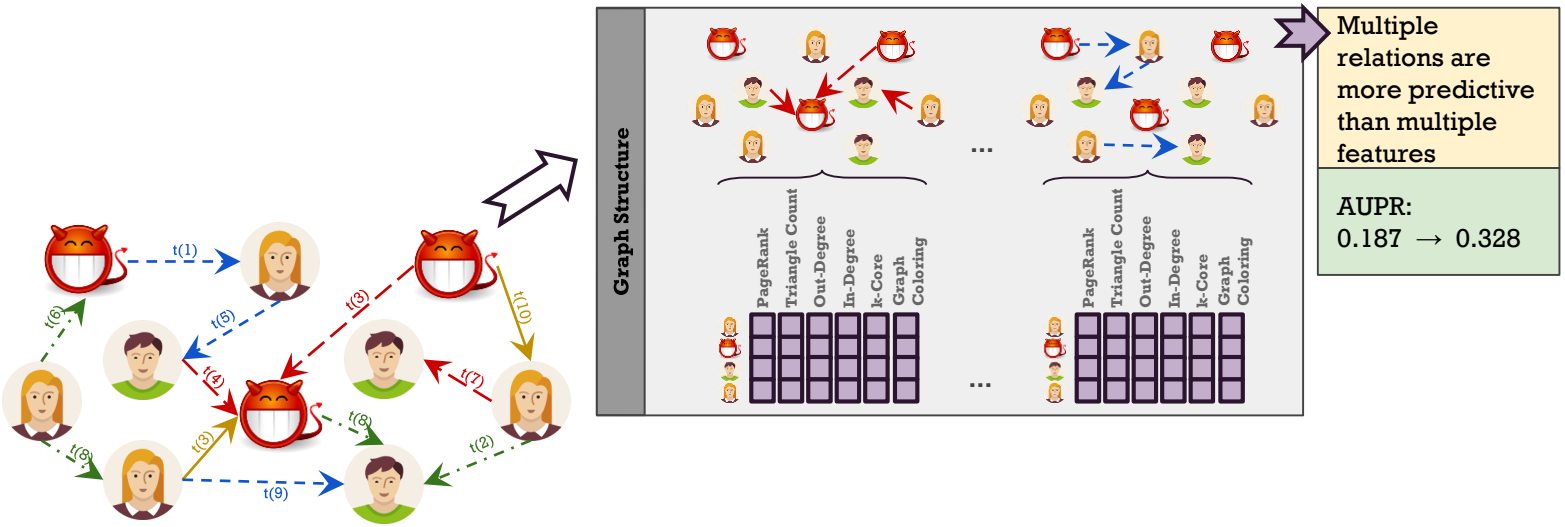
Conclusion



Code and part of the data will be released soon:
https://github.com/shobeir/fakhraei_kdd2015

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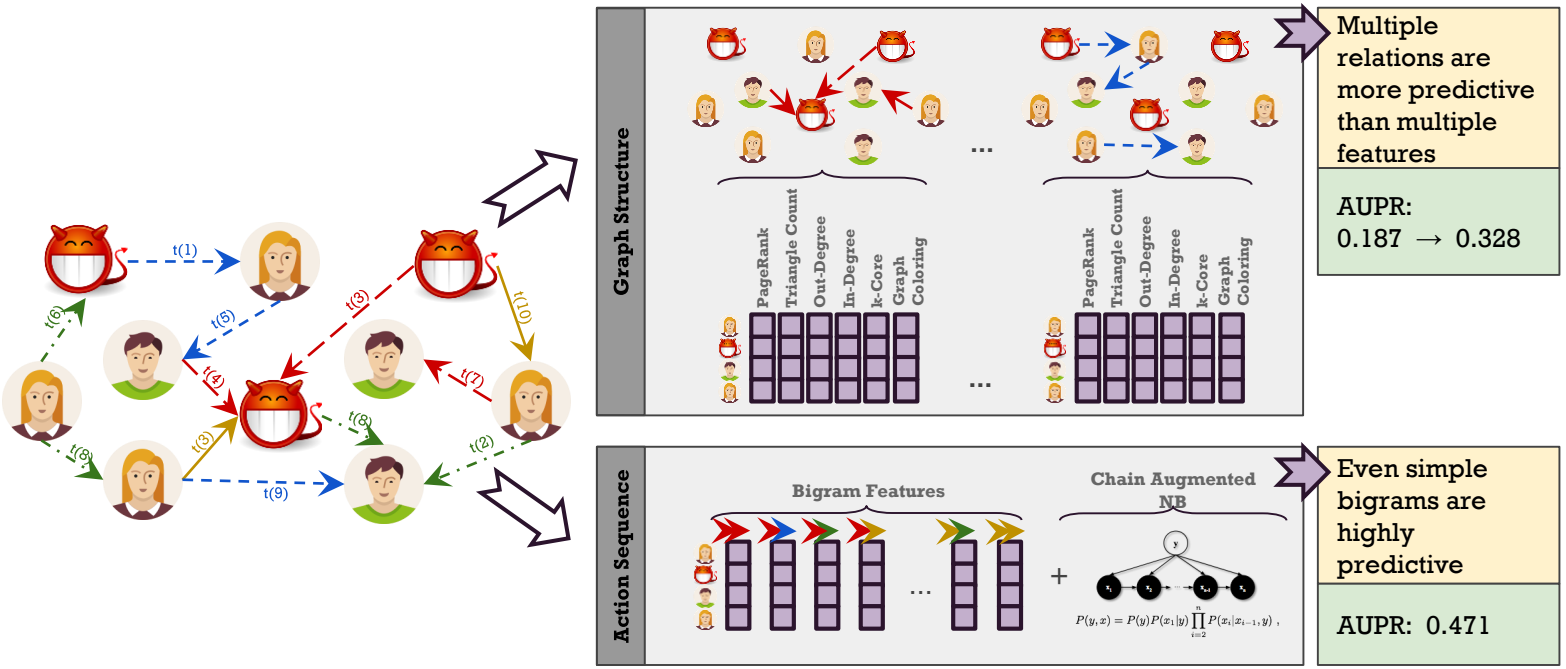

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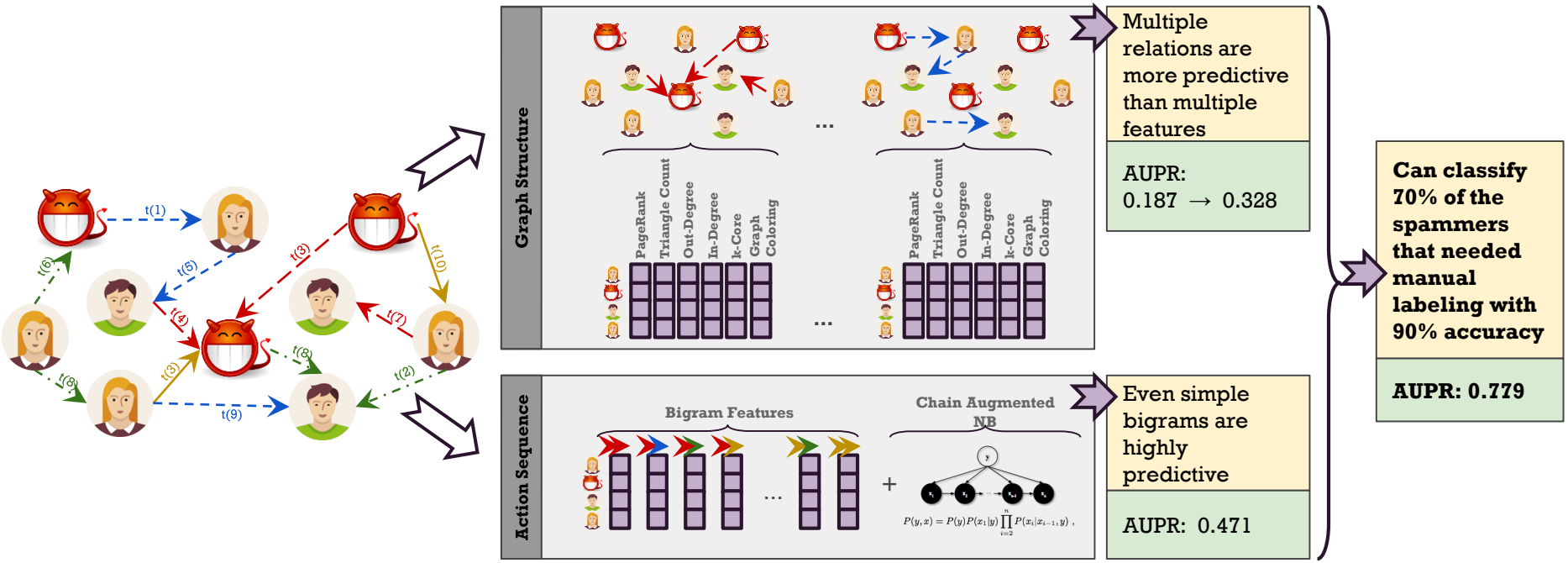

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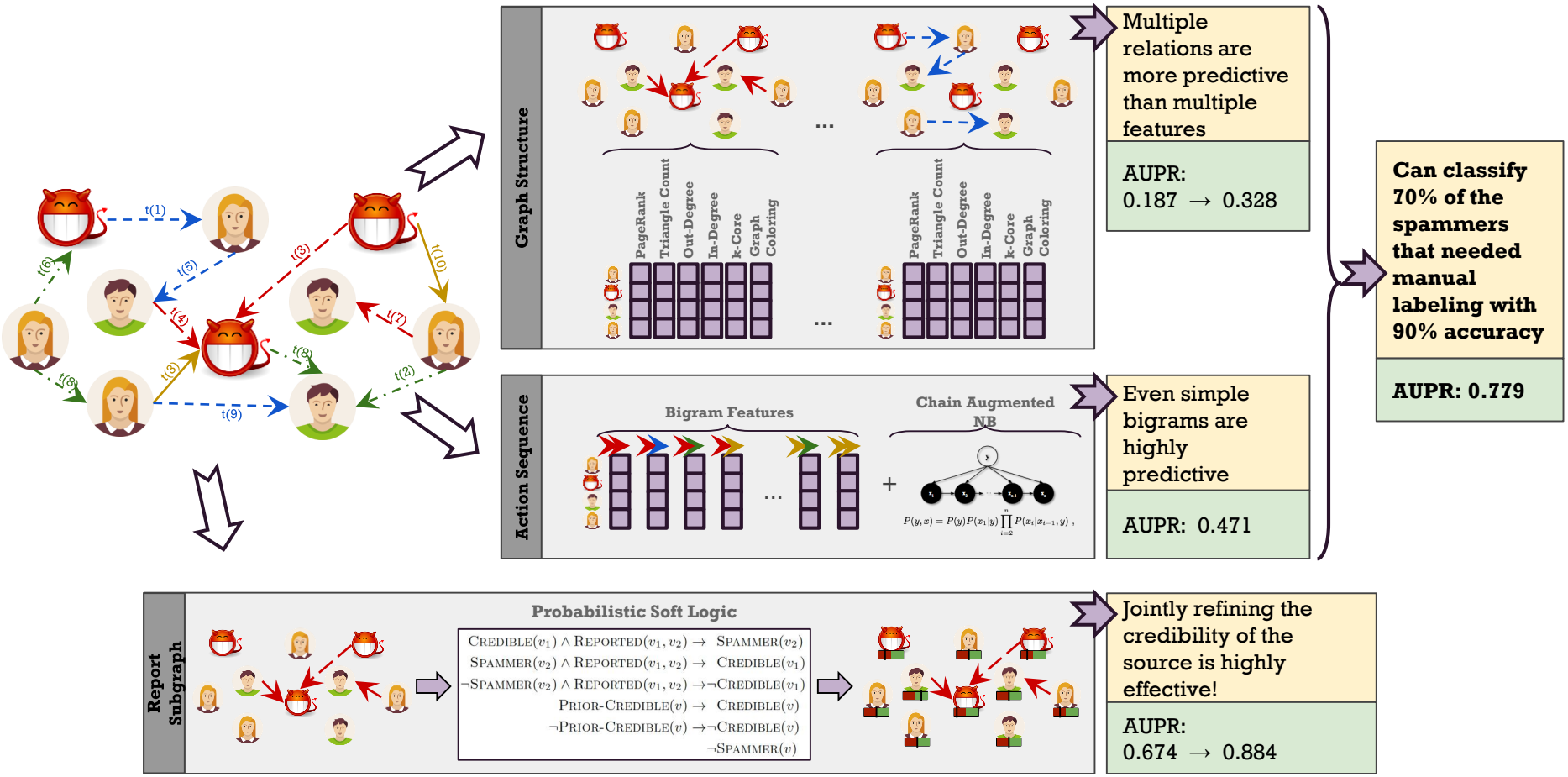

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Shobeir Fakhraei
Univ. of Maryland

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if(we) Inc., currently Niara Inc.

- If(we) Inc. (Formerly Tagged Inc.):

Johann Schleier-Smith, Karl Dawson, Dai Li, Stuart Robinson, Vinit Garg, and Simon Hill

- Dato (Formerly Graphlab):

Danny Bickson, Brian Kent, Srikrishna Sridhar, Rajat Arya, Shawn Scully, and Alice Zheng

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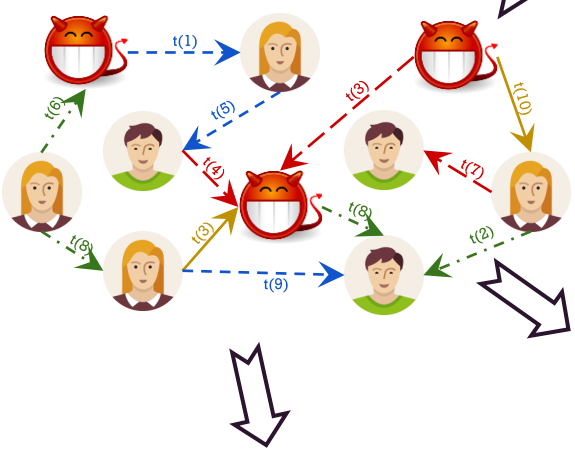
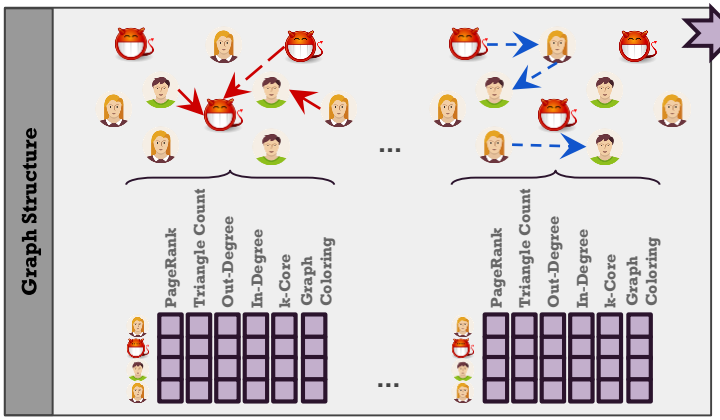
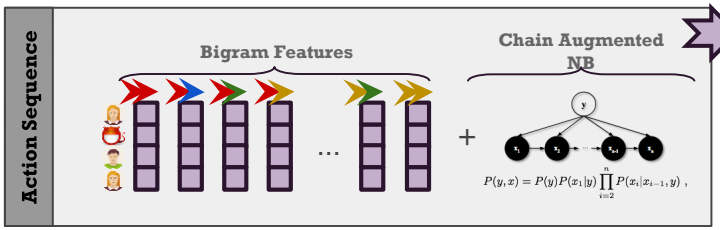




Multiple relations are more predictive than multiple features

AUPR:
0.187 → 0.328

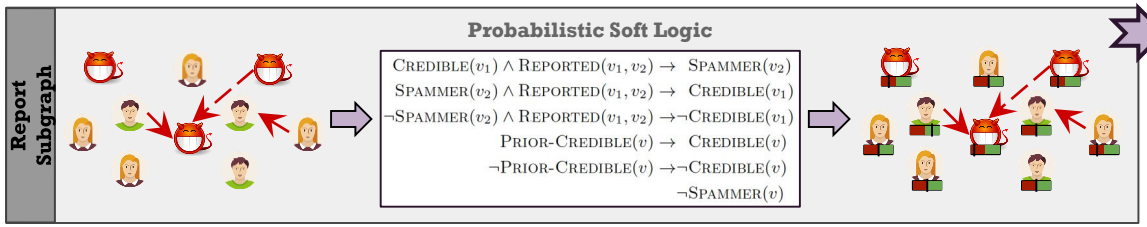


Even simple bigrams are highly predictive

AUPR: 0.471

Can classify 70% of the spammers that needed manual labeling with 90% accuracy

AUPR: 0.779



Jointly refining the credibility of the source is highly effective!

AUPR:
0.674 → 0.884

Code and part of the data will be released soon:
https://github.com/shobeir/fakhraei_kdd2015