Stylometry and Online Underground Markets

Sadia Afroz, Aylin Caliskan Islam
Co-authors: Ariel Stolerman, Rachel Greenstadt, Damon McCoy

Previously at CCC...

- 26c3:
  - Introduced the concept of adversarial stylometry:
    - Authorship recognition algorithms can be evaded by changing writing style.

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  - Introduced the idea of adversarial stylometry
    - Authorship recognition algorithms can be evaded by changing writing style.
- 28c3:
  - Released two tools:
    - JStylo (authorship recognition tool) and
    - Anonymouth (authorship anonymization tool)

This talk

- How stylometric analysis can be used in real world datasets?
  - Identify people based on writing style
  - Identify topic of their discussion
- Real world dataset: online underground markets

Overview

- Online underground markets
- Analysis
- Limitation and Challenges
- Future work
- Anonymouth

Online Underground Markets

- Underground market is a trading place to trade various stolen goods and/or tools such as exploits, malware repackaging kits, phishing kits.

Millions of LinkedIn passwords reportedly leaked online

A hacker says he's posted 6.5 million LinkedIn passwords on the Web -- hot on the heels of security researchers' warnings about privacy issues with LinkedIn's iOS app.

by Lance Whitney | June 6, 2012 6:31 AM PDT

Follow

Update 1:08 p.m. PT: *LinkedIn confirms that passwords were "compromised."*

LinkedIn users could be facing yet another security problem.

A user in a Russian forum says that he has hacked and uploaded almost 6.5 million LinkedIn passwords, according to The Verge. Though his claim has yet to be confirmed, Twitter users are already reporting that they've found their hashed LinkedIn passwords on the list, security expert Per Thorsheim said.

LinkedIn revealed through its own tweet that it's looking into reports of stolen passwords, and it advised users to stay tuned for more information.

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Why is this interesting?

- Cyber-underground ecosystem
- Key information about who controls a given bot
- Who maintains certain tools
- Size and scope of these markets.

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In-depth security news and investigation

11 A Closer Look at Two Bigtime Botmasters

DEC 12

Over the past 18 months, I've published a series of posts that provide clues about the possible real-life identities of the men responsible for building some of the largest and most disruptive spam botnets on the planet. I've since done a bit more digging into the backgrounds of the individuals thought to be responsible for the Rustock and Waledac spam botnets, which has produced some additional fascinating and corroborating details about these two characters.

In March 2011, KrebsOnSecurity featured never-before-published details about the financial accounts and nicknames used by the Rustock botmaster. That story was based on information leaked from **SpamIt**, a cybercrime business that paid spammers to promote rogue Internet pharmacies (think Viagra spam). In a follow-up post, I wrote that the Rustock botmaster's personal email account was tied to a domain name **ger-mes.ru**, which at one time featured a résumé of a young man named **Dmitri A. Sergeev**.


I want to work in

Google

Sergeev Dmitri A.

Summary:

Experience

http://krebsonsecurity.com/2012/12/a-closer-look-at-two-bigtime-botmasters/

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11 A Closer Look at Two Bigtime Botmasters

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93 tweets

retweet

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Online Underground Markets

- Two main markets:
  - Internet Relay Chat (IRC)
  - Web forums

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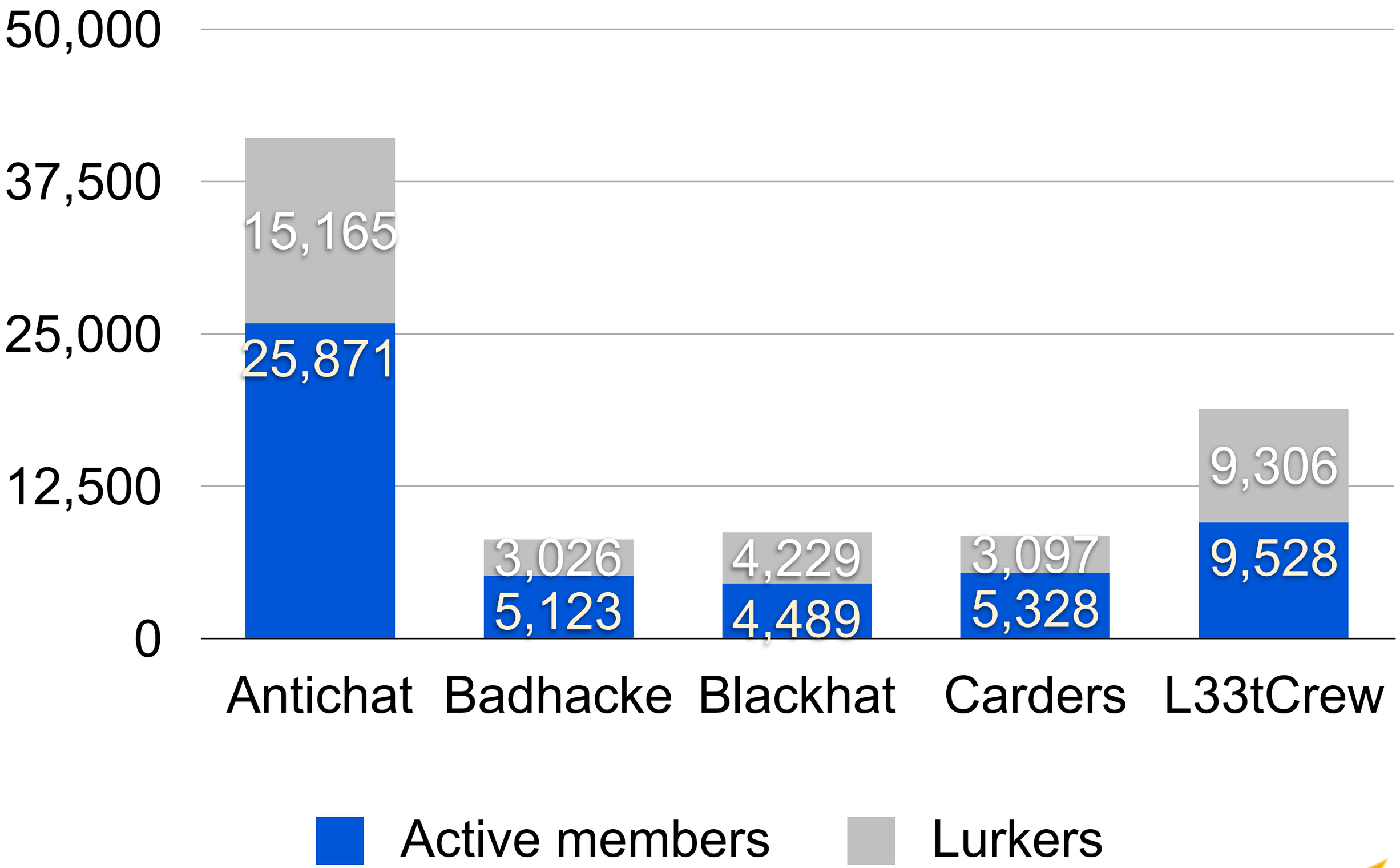
Forums

- Antichat - Russian forum (May 2002-Jun 2010)
- BadHacke - English/Hindi (Nov 2003-May 2008)
- BlackHat - English (Oct 2005-Mar 2008)
- Carders - German (Feb 2009- Dec 2010)
- L33tCrew- German (May 2007-Nov 2009)

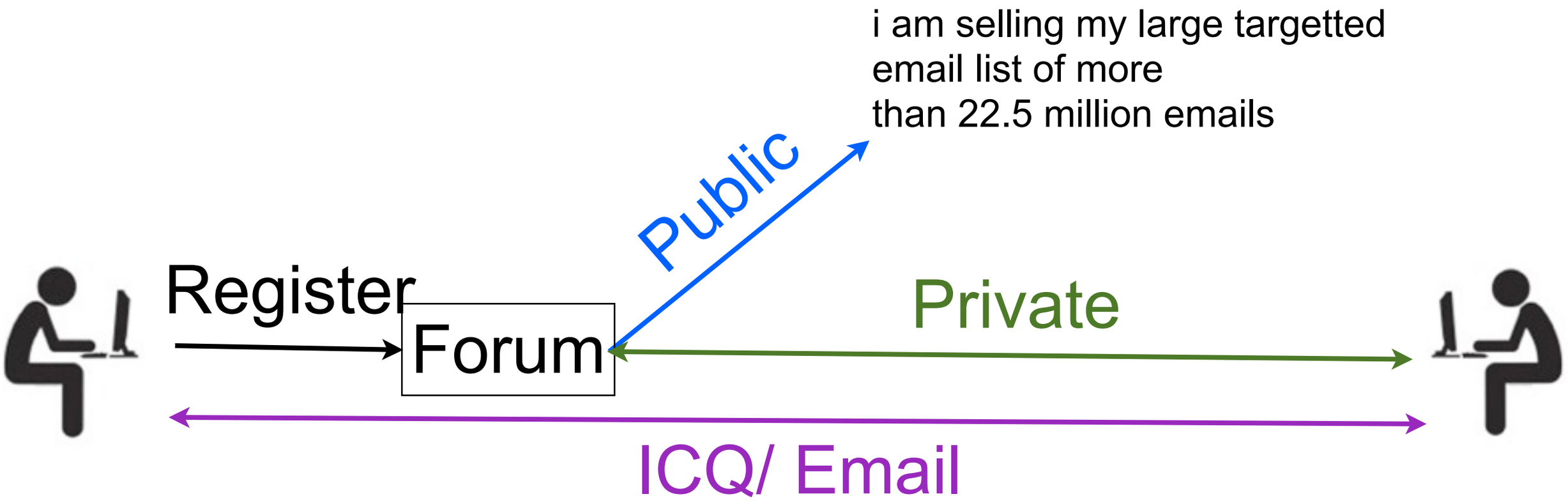
How did we get the data?

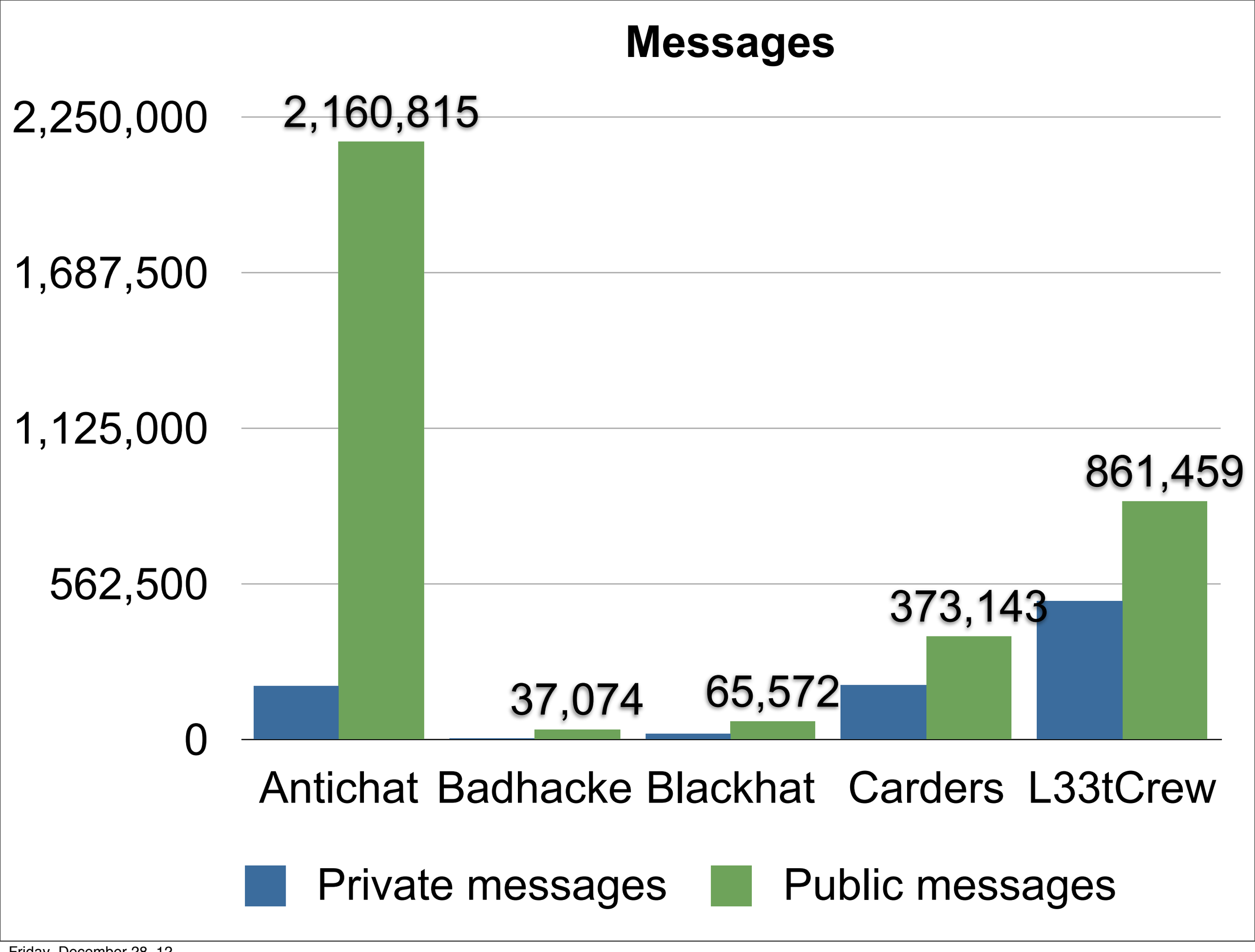
- Leaked by anonymous people
- Publicly available

Members


50,000
37,500
25,000
12,500
0
15,165
25,871
3,026
5,123
4,229
4,489
3,097
5,328
9,306
9,528
Antichat
Badhacke
Blackhat
Carders
L33tCrew
Active members
Lurkers

How Transaction Happens

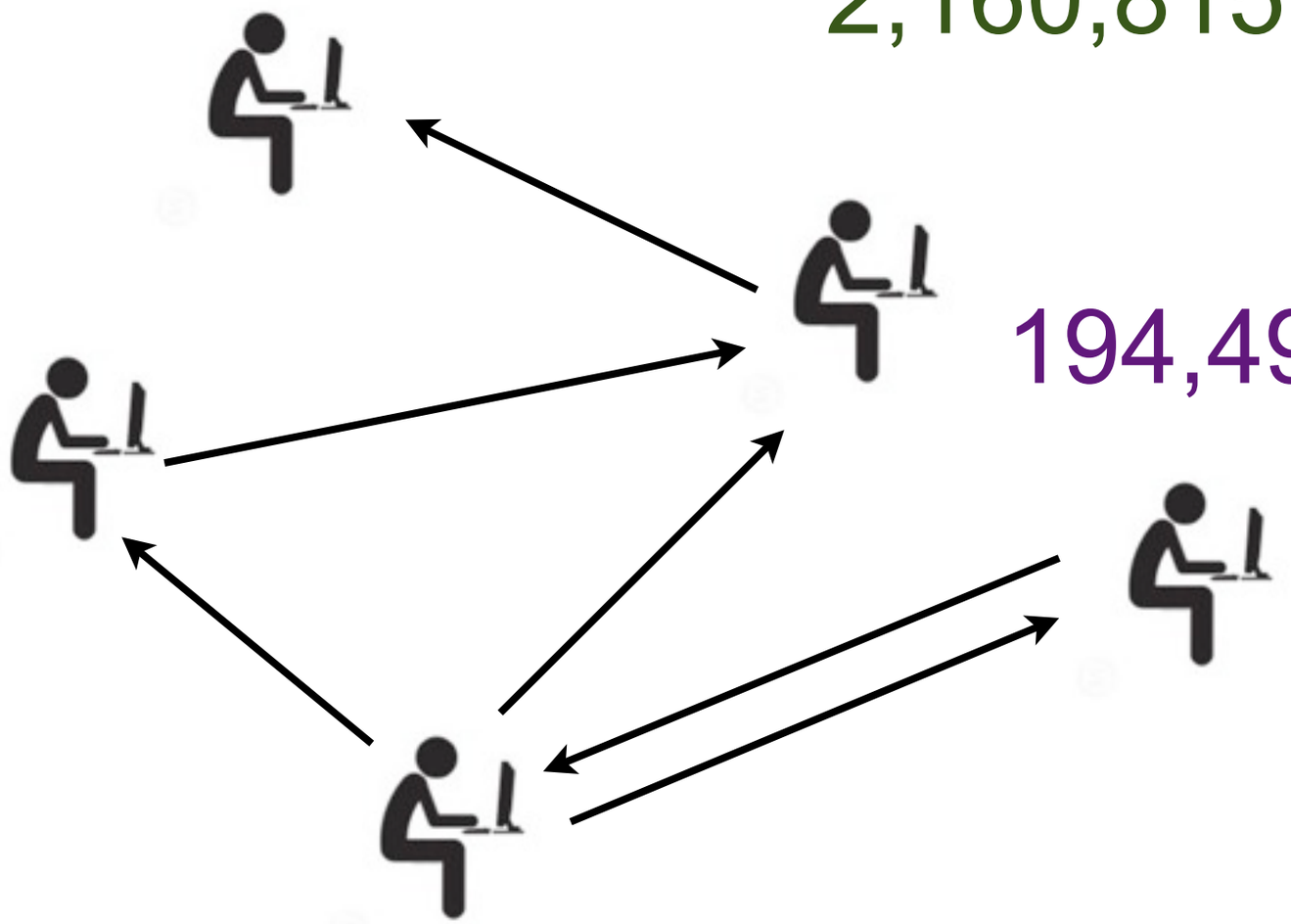



Messages
2,250,000
1,687,500
1,125,000
562,500
0
2,160,815
37,074
65,572
373,143
861,459
Antichat
Badhacke
Blackhat
Carders
L33tCrew
Private messages
Public messages

Challenges

2,160,815 Public posts

41,036
Users



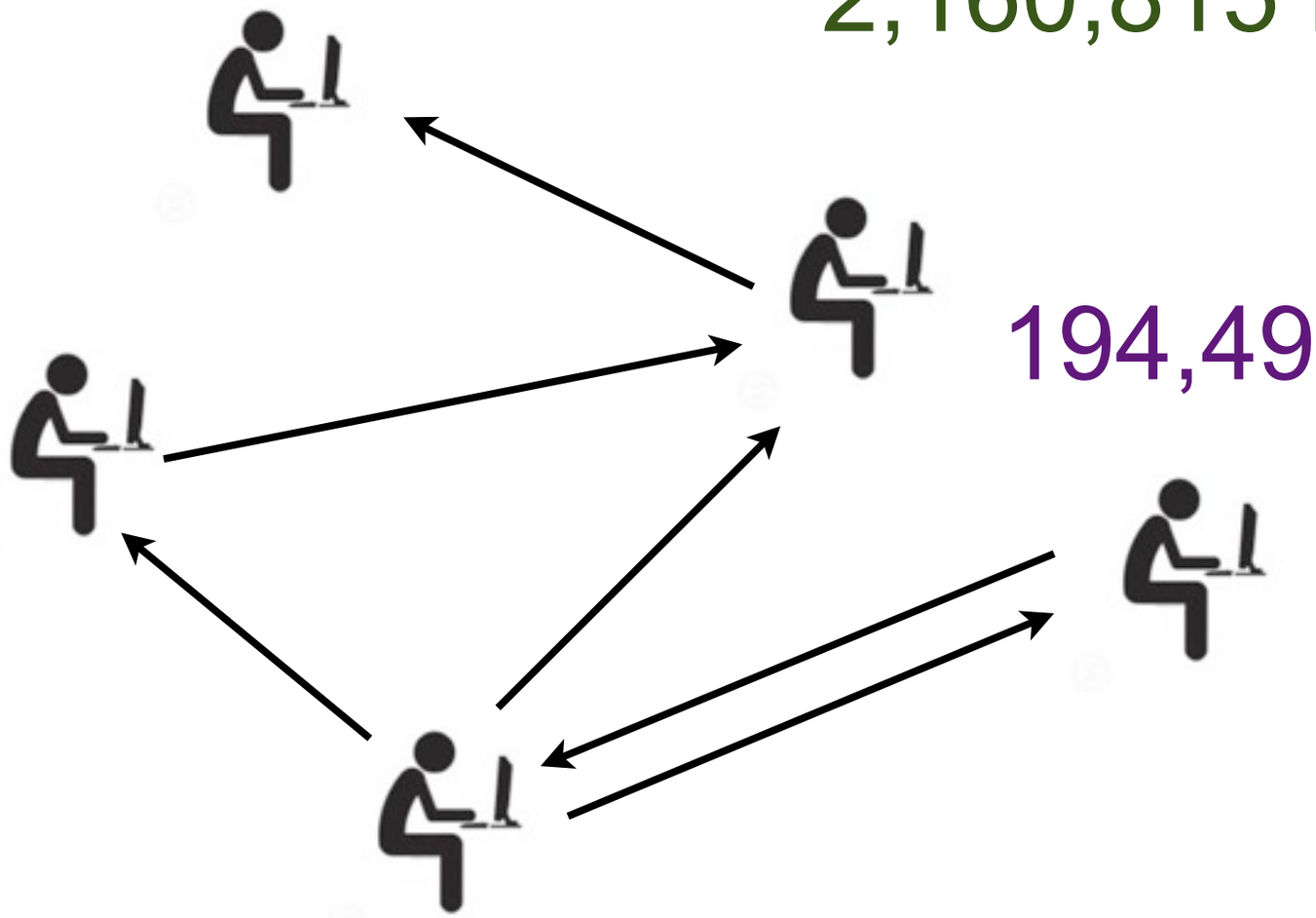
194,498 Private msgs

Challenges

This is just one forum!

2,160,815 Public posts

41,036 Users



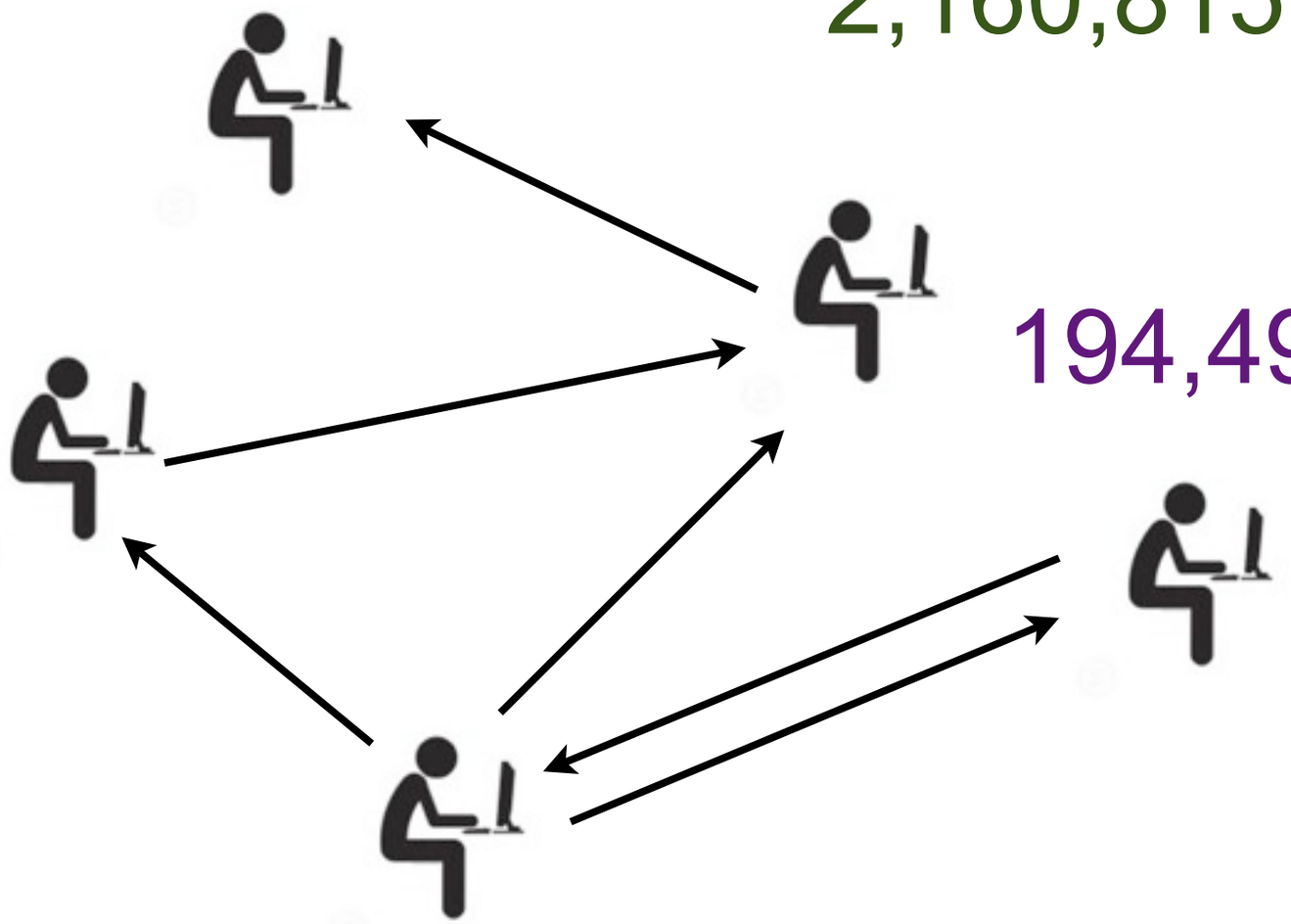
194,498 Private msgs

Challenges

интересует взлом

2,160,815 Public posts

41,036
Users



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Alles läuft vor eurem PC ab

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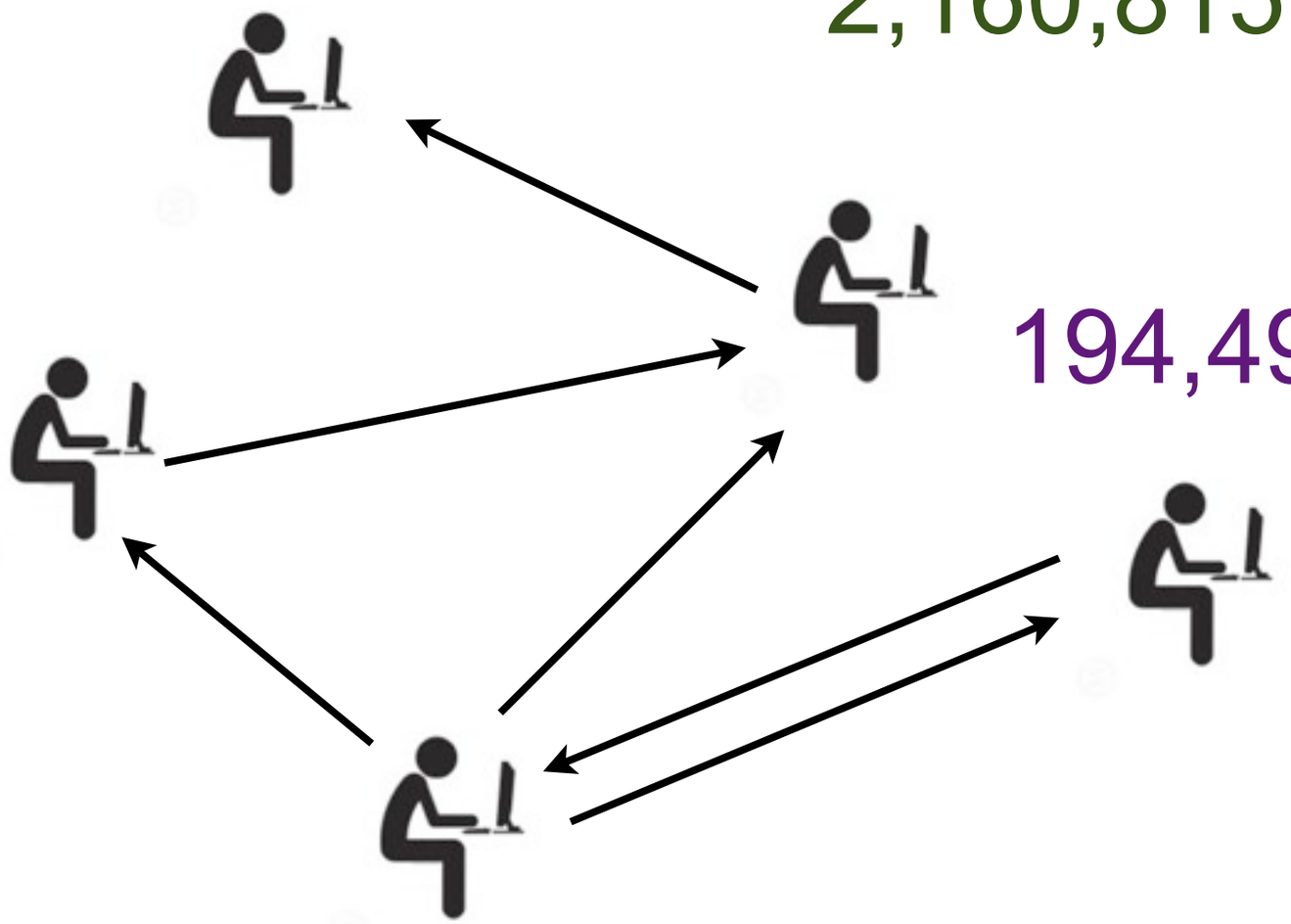

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Challenges

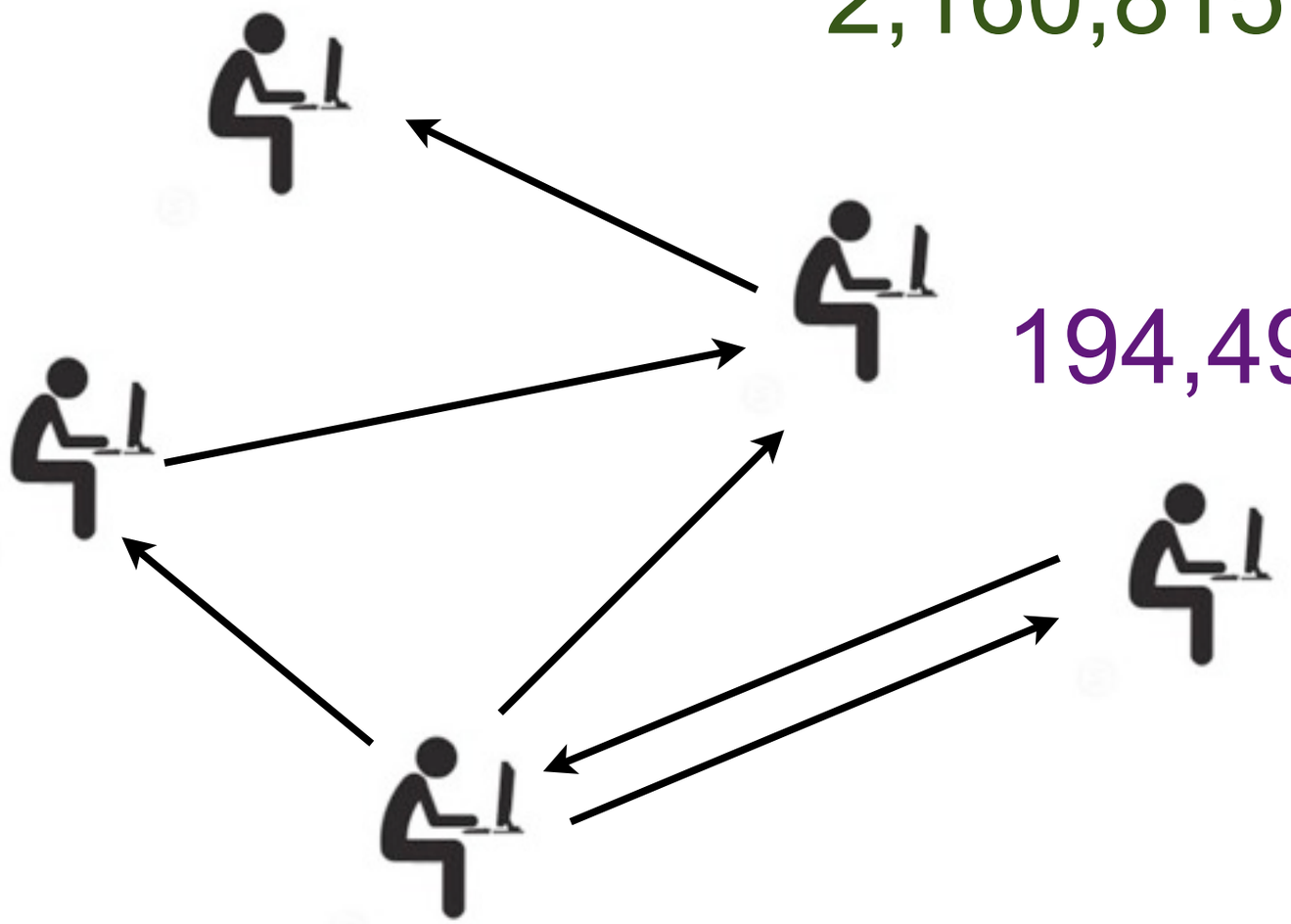
интересует взлом

Alles läuft vor eurem PC ab

I gave 40 bucks and no program what is up man?

2,160,815 Public posts

41,036 Users



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Analysis

- Interaction network analysis
- Member profiling using writing style
- Topic discovery

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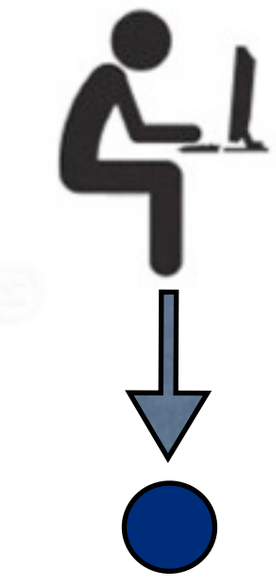
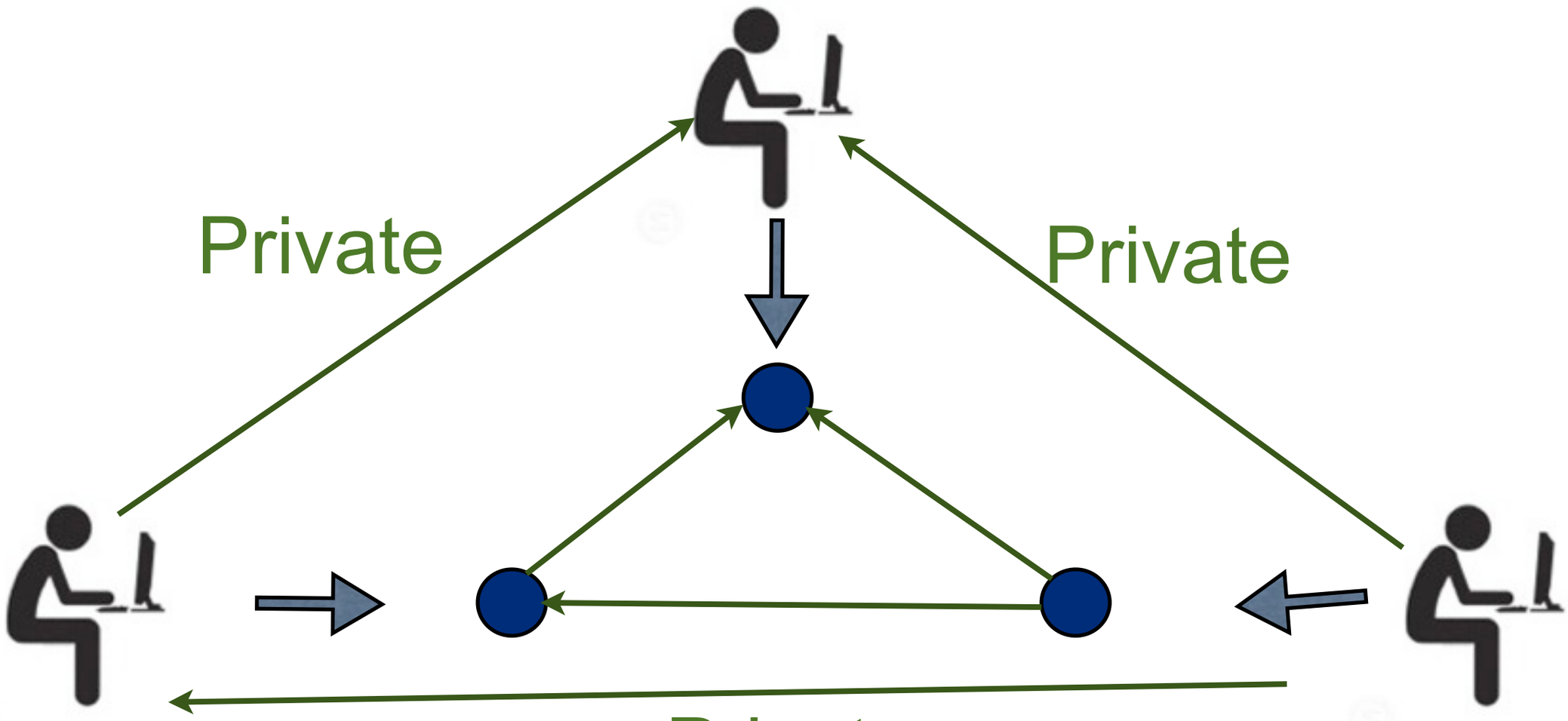
Interaction Network Analysis



Represent a forum with a graph, G=(V, E) where each user is a vertex

Interaction Network Analysis



Represent a forum with a graph, G=(V, E) where
each user is a vertex
each private message is an edge

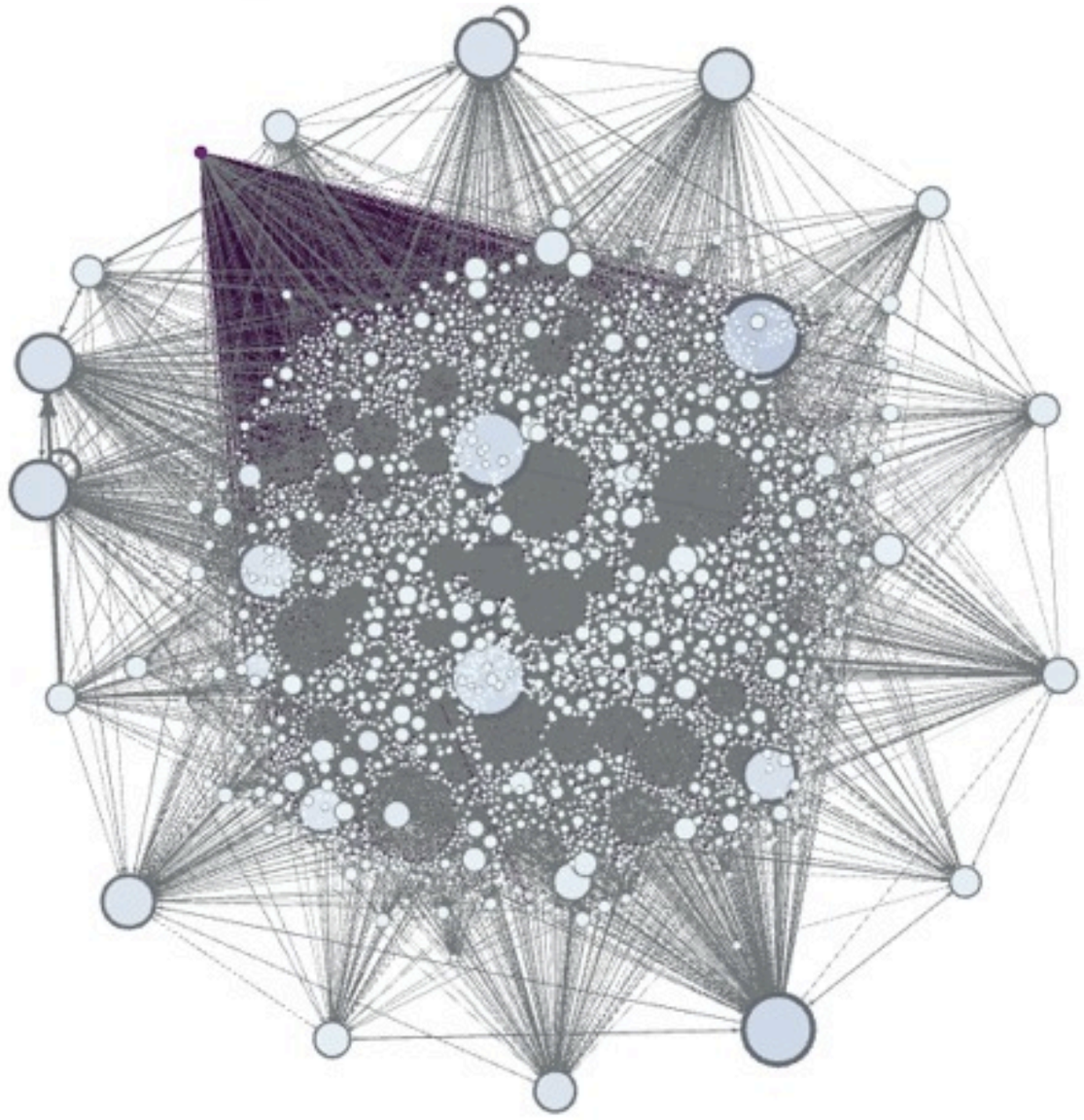
Interaction Network Analysis

- Goal:
  - Structure of interaction
  - Identify central members

Interaction Network Analysis

- Goal:
  - Structure of interaction
  - Identify central members:
    - Eigenvector centrality:
      - It is a measure of the influence of a node in a network.
      - Higher score == More influential member

Interaction Network Analysis: Antichat



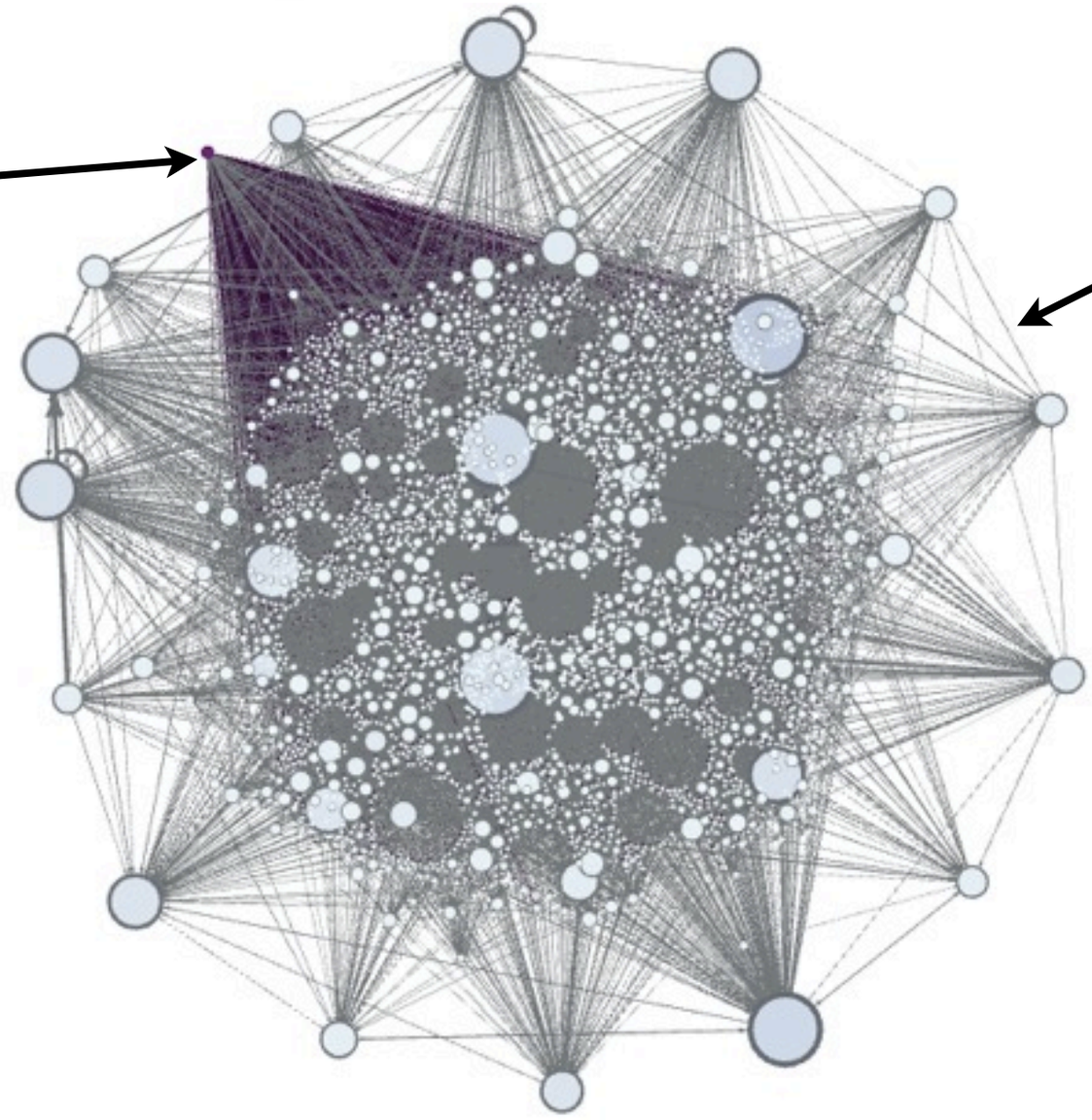
With all users

Drexel UNIVERSITY

GEORGE MASON UNIVERSITY

Interaction Network Analysis: Antichat

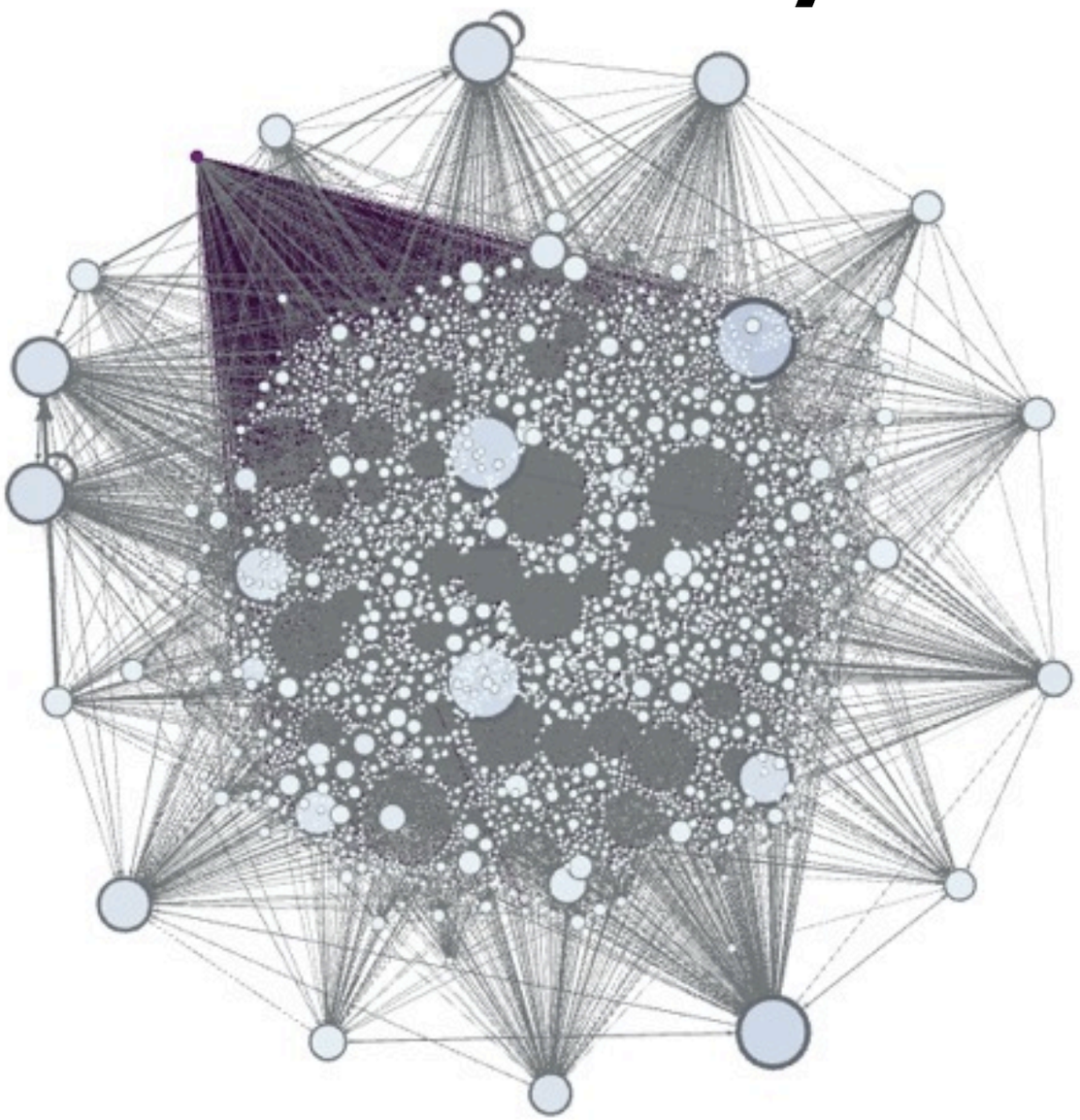
Darker nodes send/receive more msgs



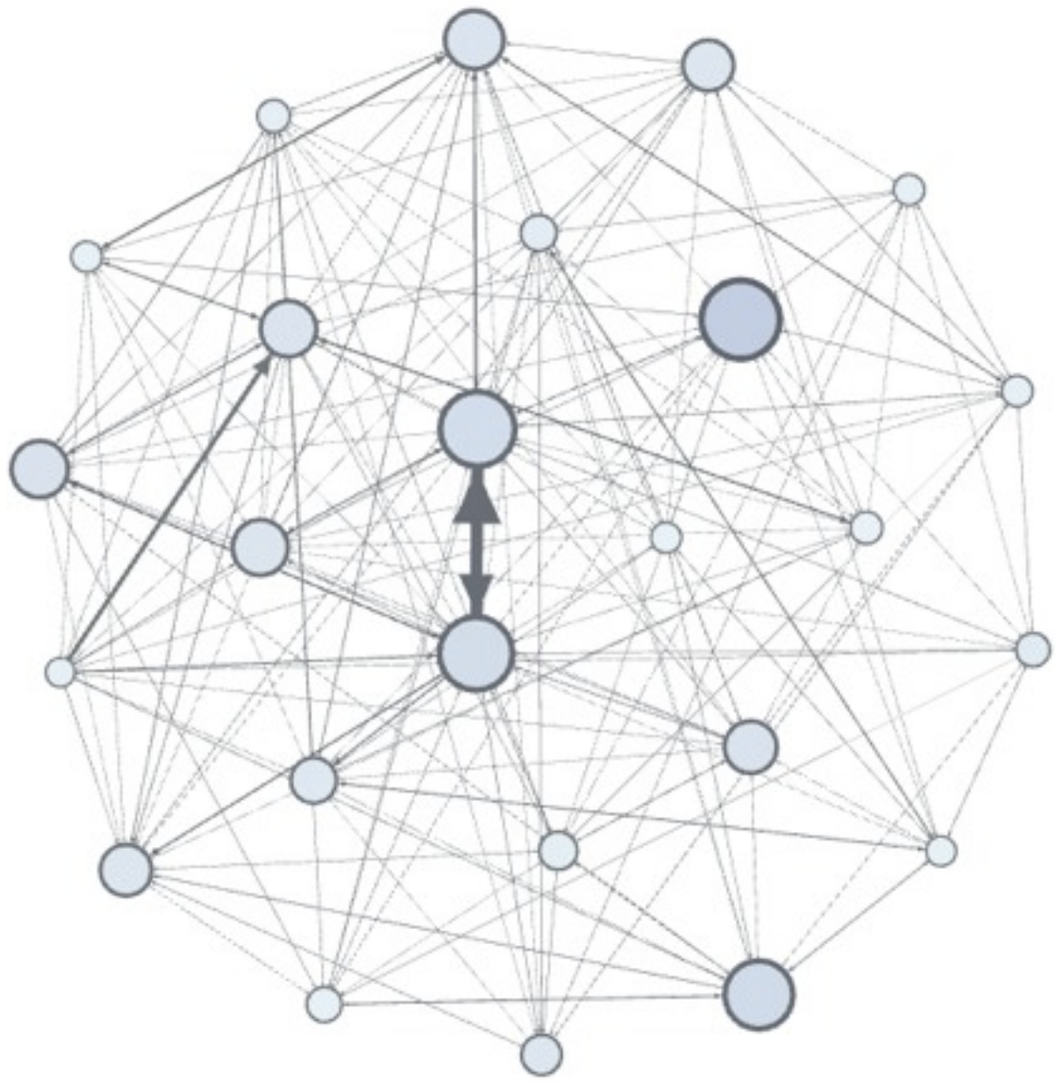
Bigger nodes are more influential

With all users

Interaction Network Analysis: Antichat

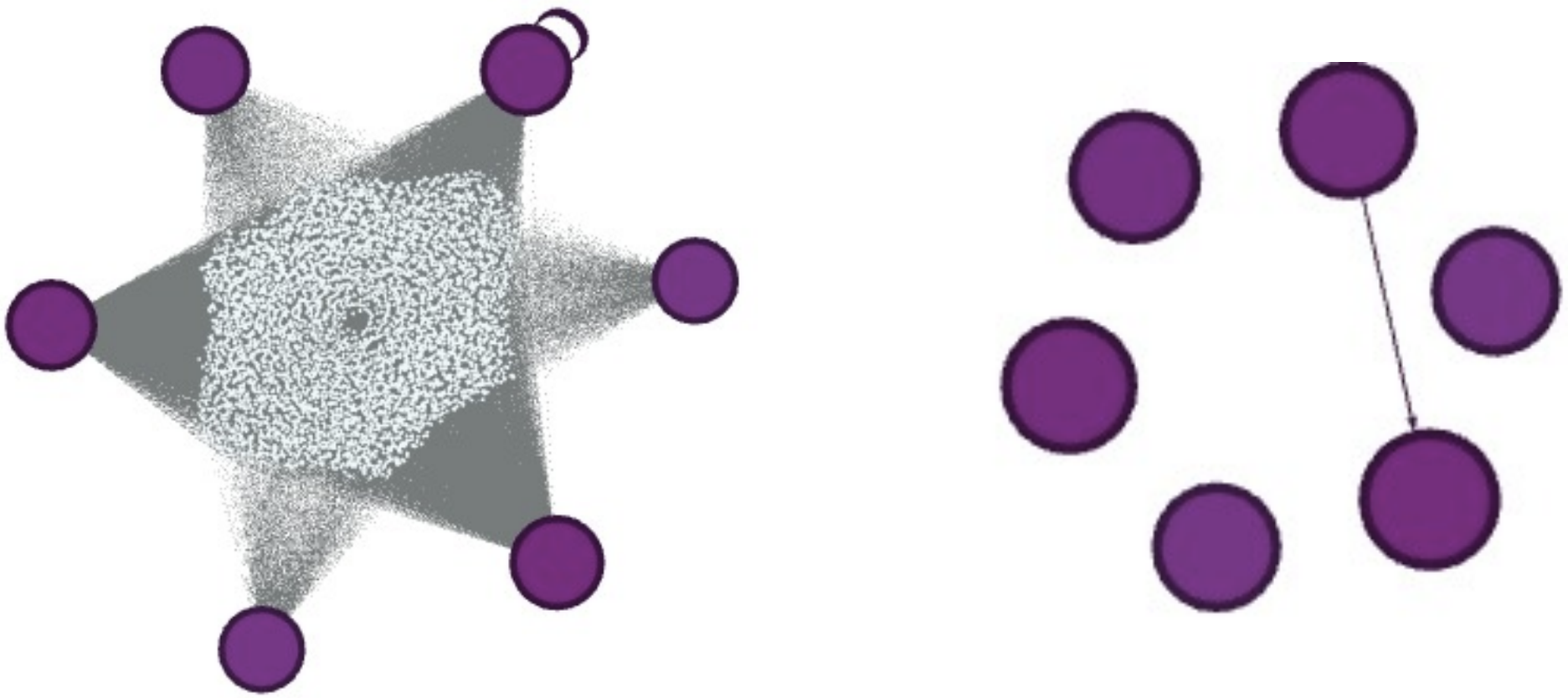


With all users



With top 50 influential users

Interaction Network Analysis: Badhacke



With all members With top influential members

Analysis

- Interaction network analysis
- Member profiling using writing style
- Topic discovery

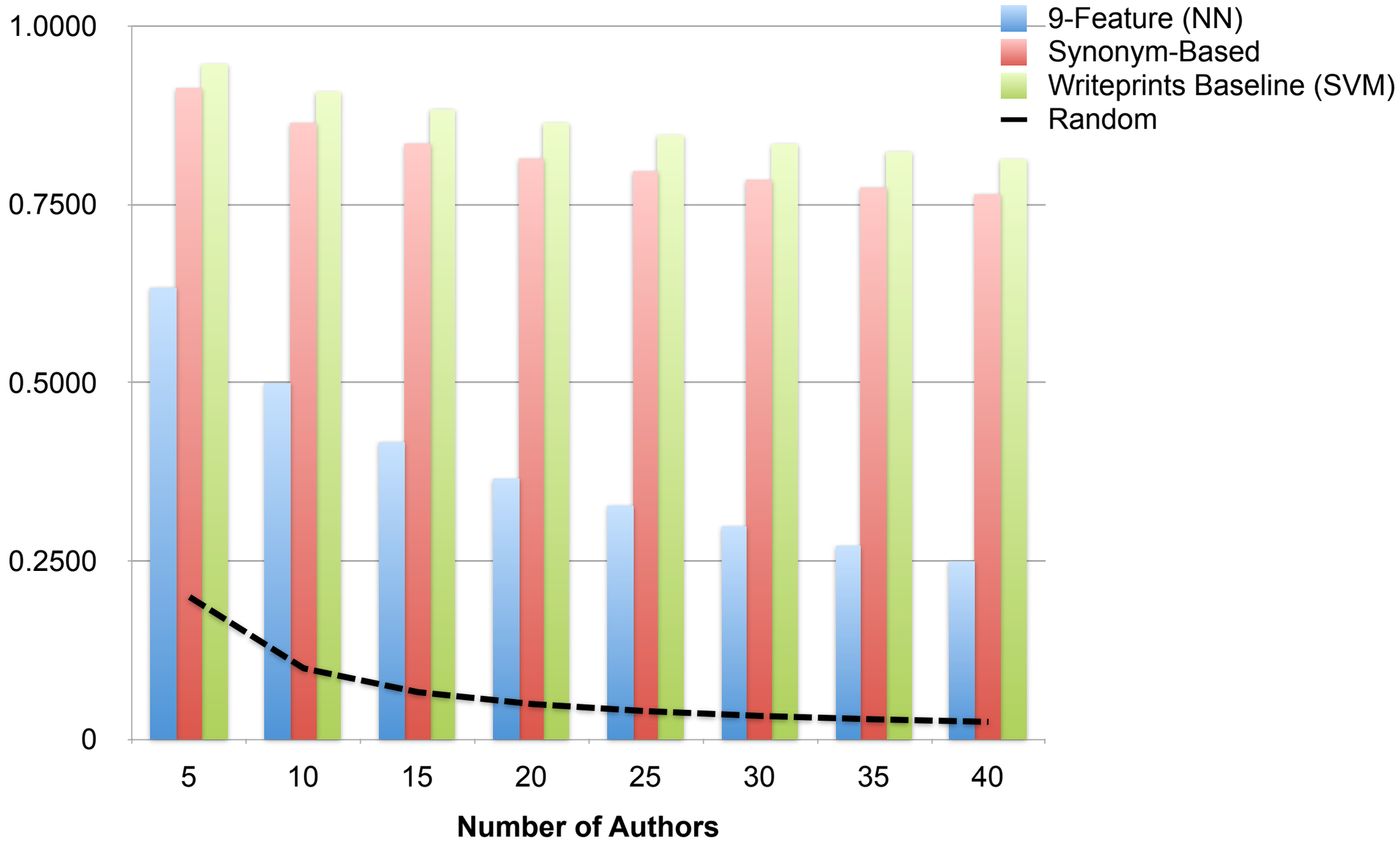
Profiling using writing style

- Everybody has a *unique* writing style.
- Goal:
  - Identify members using their writing style

Try JStylo

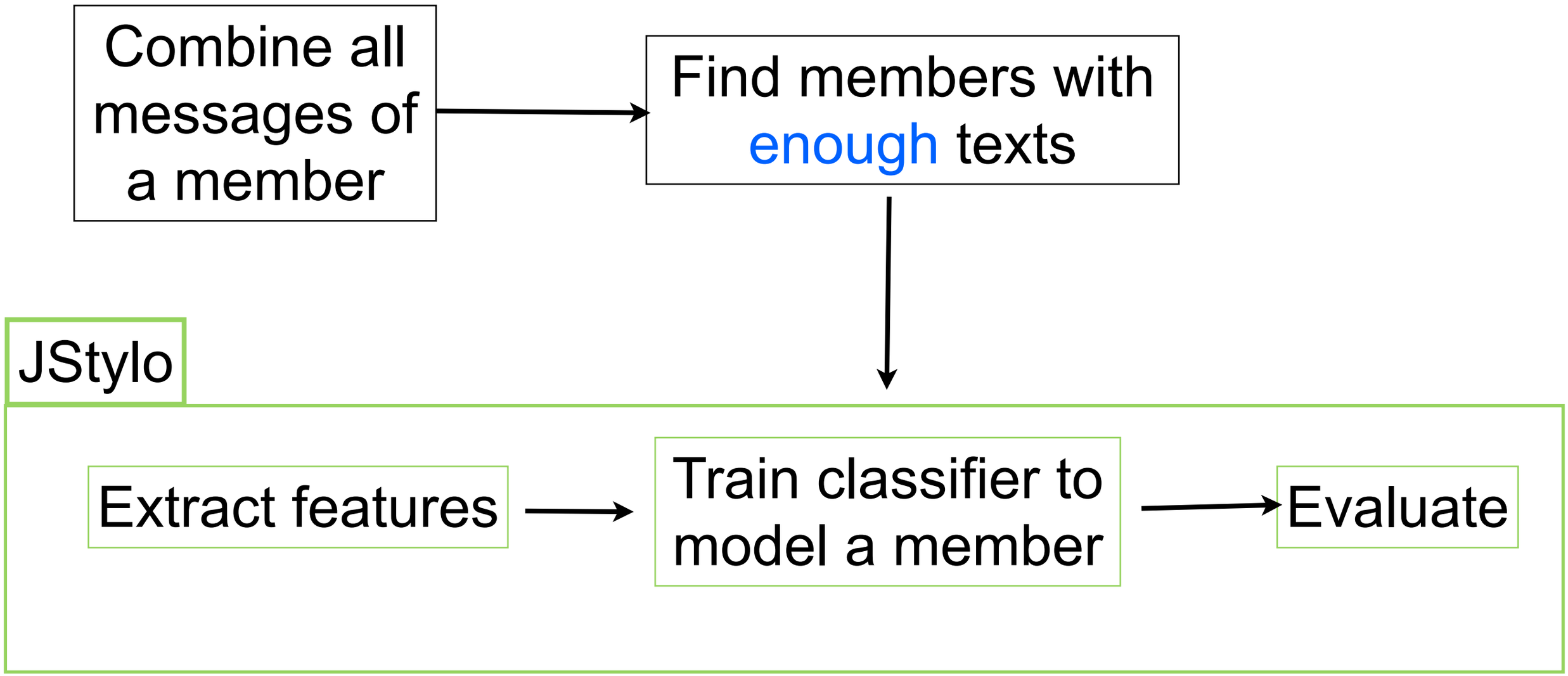
- https://psal.cs.drexel.edu/index.php/JStylo-Anonymouth

Accuracy in detecting authorship of regular documents

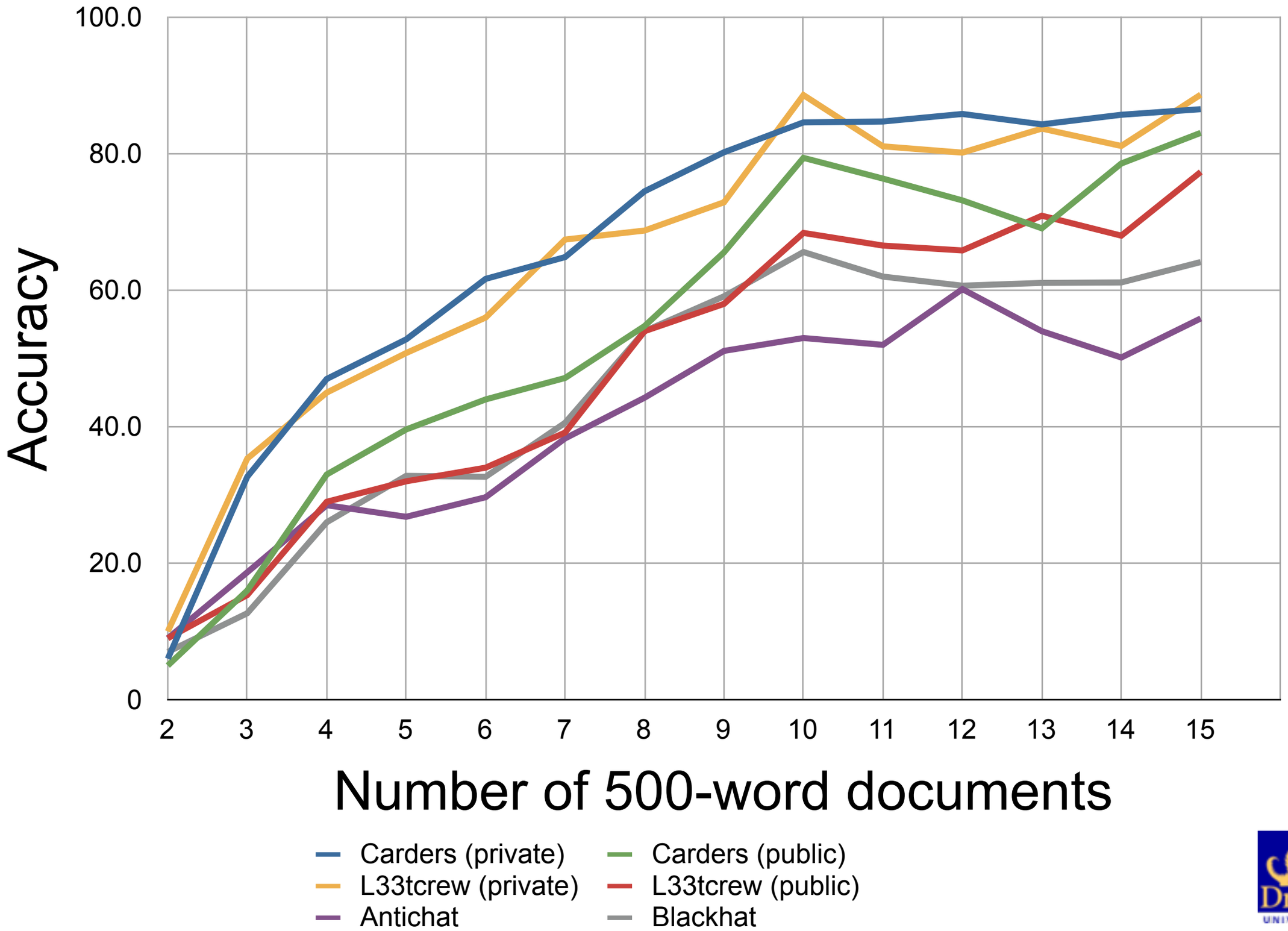


* Thanks to Michael Brennan for the graph

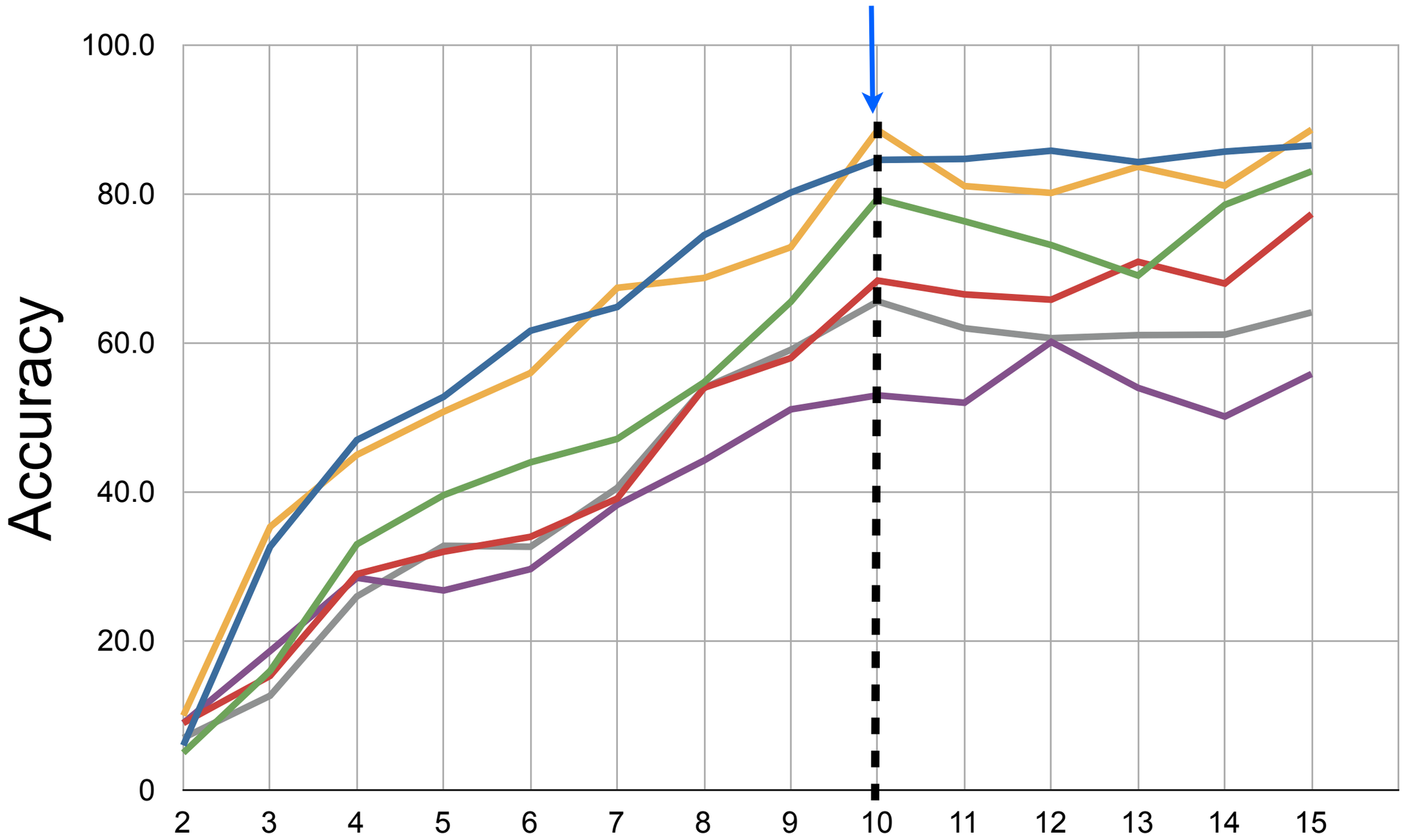
Profiling using writing style



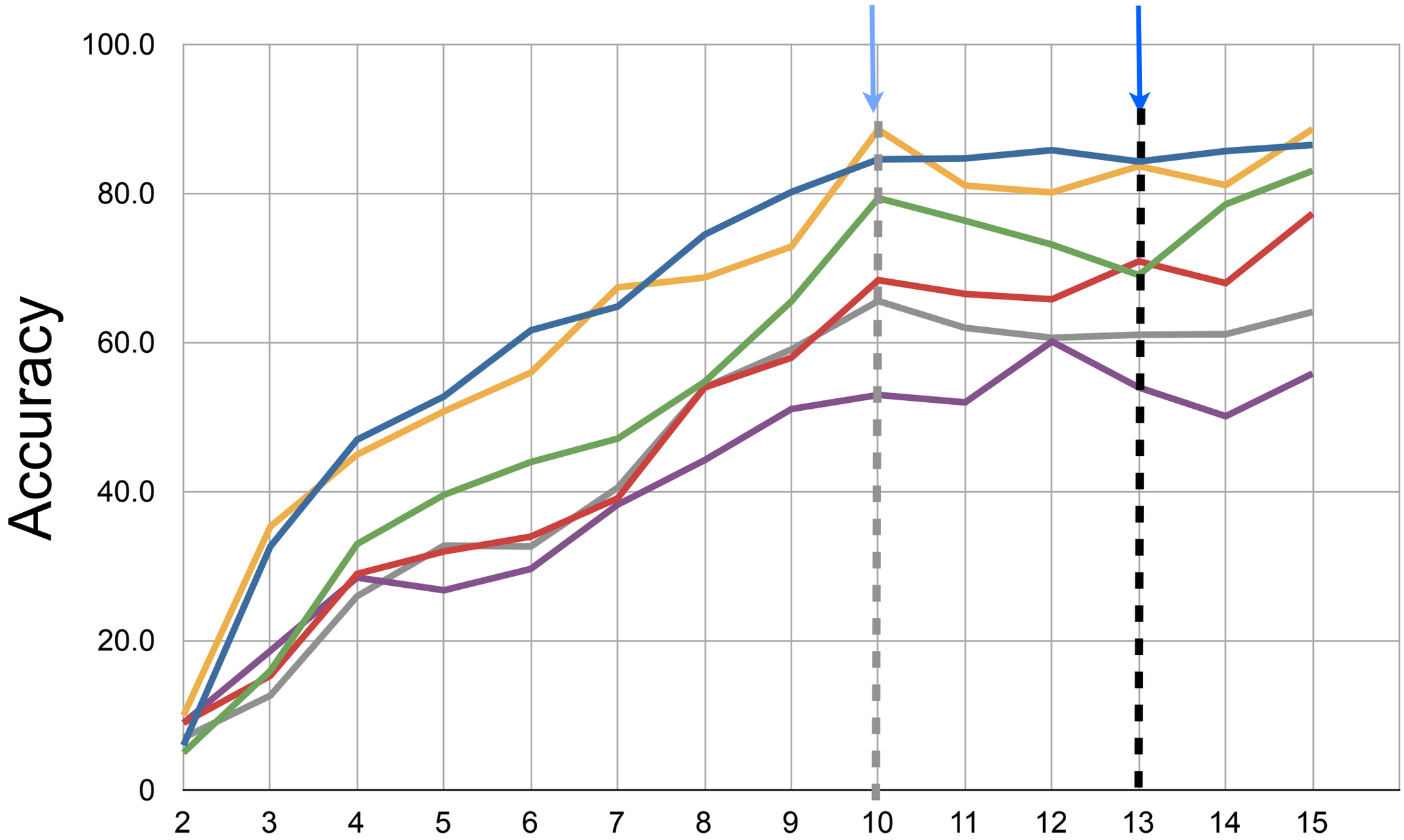
How much text is enough?



How much text is enough?: at least 5000 words



How much text is enough?: we used 6500 words



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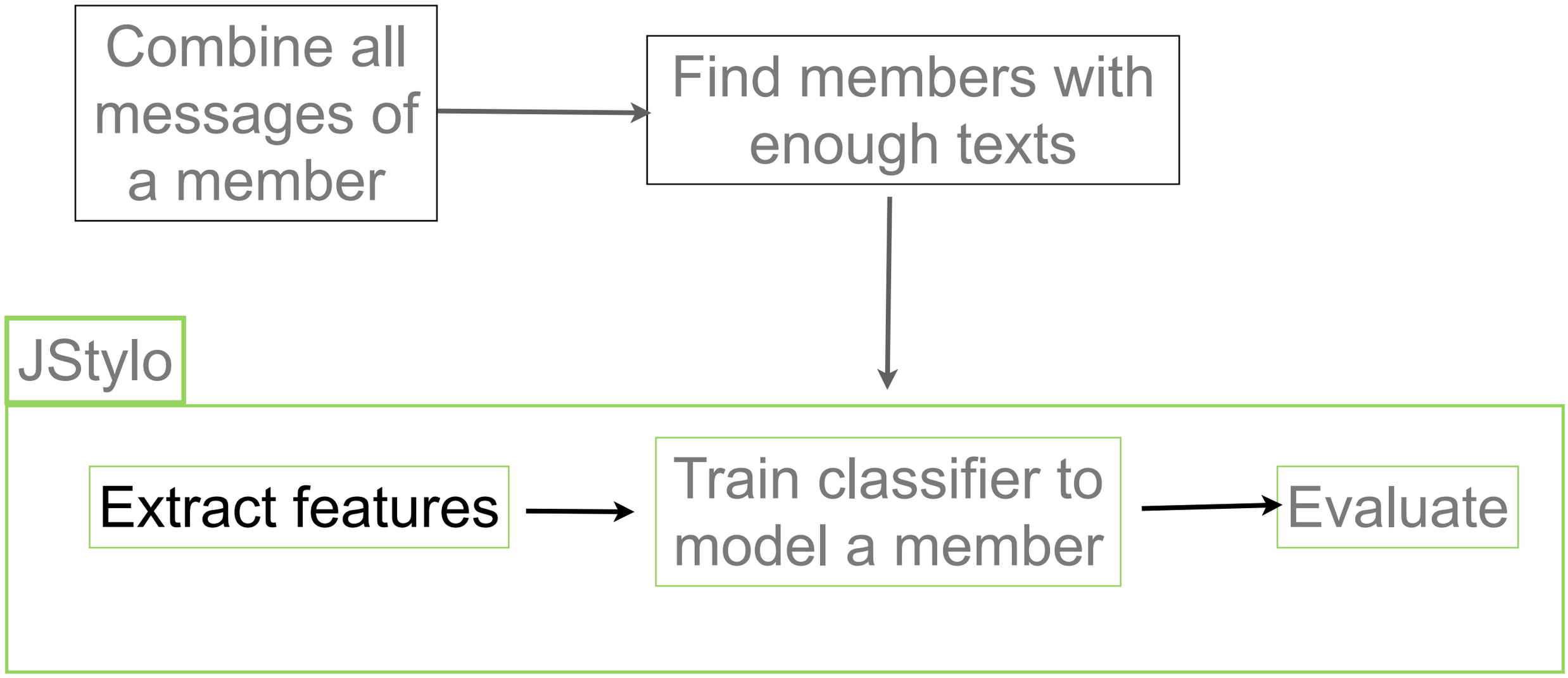
Profiling using writing style



What are these features?

1337 down? **Neh, die Lösung!**
Ne klappt nit, denke mal eher das sie mal wieder DNS probleme haben

Example from Carders

What are these features?

*Translation

1337 down? **Neh, die Lösung!**
Ne klappt nit, denke mal eher das sie mal wieder DNS probleme haben

1337 down? Neh **, the solution! **
Ne nit works, rather guess they have again DNS problems

Example from Carders

*Using Google translator

What are these features?

1337 down? **Neh, die Lösung!**
Ne klappt nit, denke mal eher das sie mal wieder DNS probleme haben

→ Freq. of n-grams

Example from Carders

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Example from Carders

Freq. of n-grams

Freq. of punctuations

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Example from Carders

Freq. of n-grams

Freq. of punctuations

Freq. of special characters

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Example from Carders

Freq. of n-grams

Freq. of punctuations

Freq. of special characters

Language Independent

What are these features?

1337 down? **Neh, die Lösung!**
Ne klappt nit, denke mal eher das sié mal wieder DNS probleme haben

Example from Carders

Parts of speech
Freq. Function words
Freq. of ngrams
Freq. of punctuations
Freq. of special characters

Language specific

Not all conversation

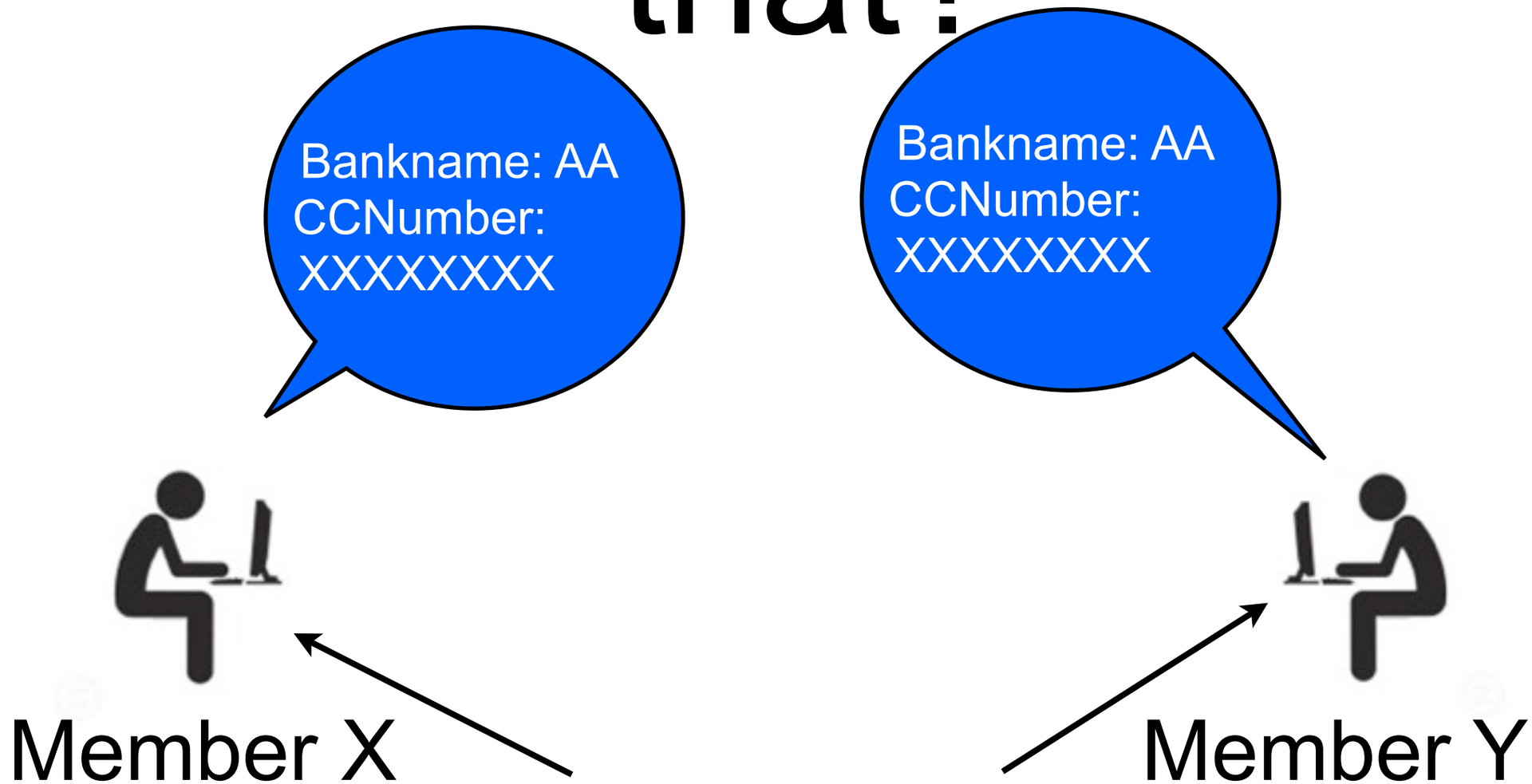
Bankname: XX
CCNumber: XXXXXXXX
CCHolder: XX XXXX
CCExpire: X / XXXX
CVV2: XX
Vorname: XX
Nachame: YY
Addresse: XXXXX
Stadt: XXXX
PLZ: XXXX
Land: XX
Telefon: XXXXX-XXXXX
E-mail: [email]victim@example.com[/email]
Geburtsdatum: XX / XX / XXXX

What's wrong with that?

Member X

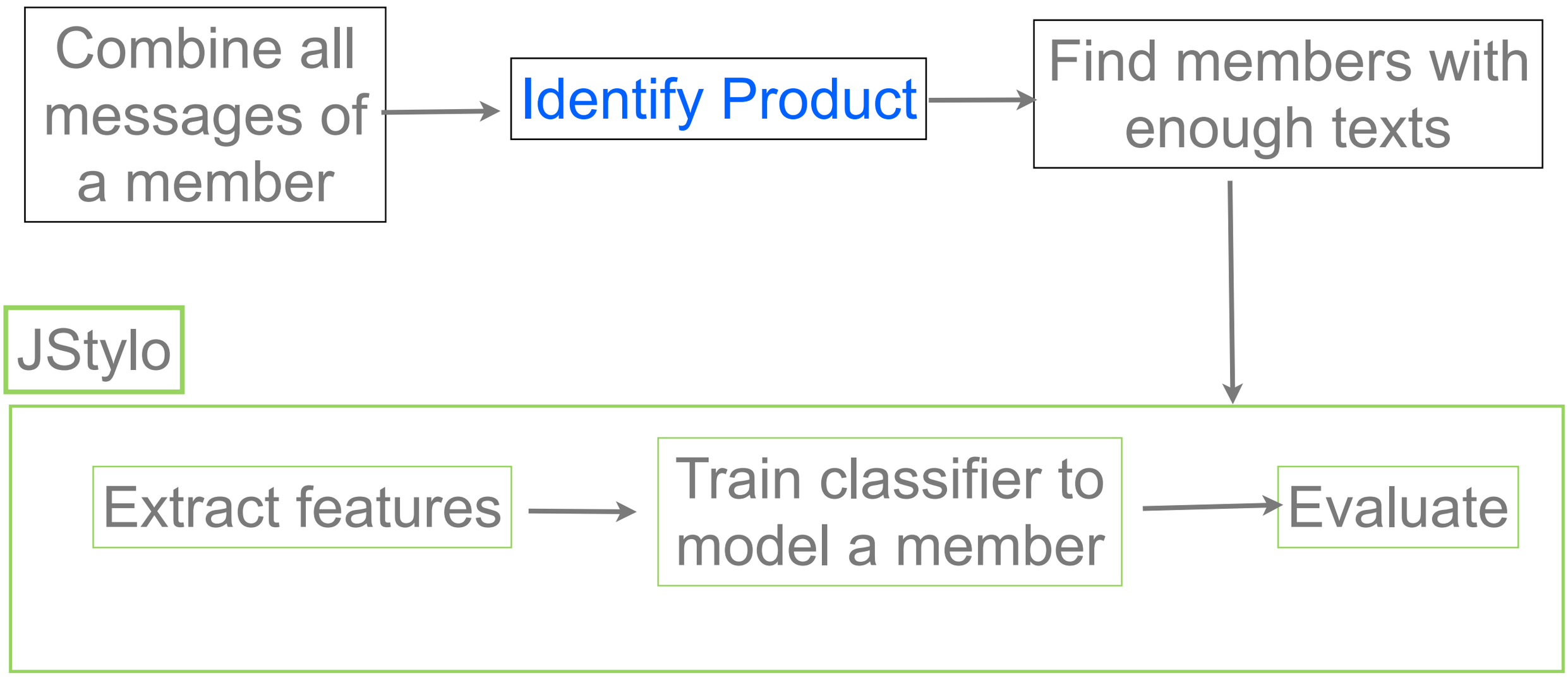
Member Y

What's wrong with that?



Both will look the same to a linguistic classifier

Profiling using writing style



Identify Products

1. Product information has repeated patterns
2. Conversation usually has verb

Bankname: XX
CCNumber: XXXXXXXX
CCHolder: XX XXXX
CCExpire: X / XXXX
CVV2: XX
Vorname: XX
Nachame: YY
Addresse: XXXXX
Stadt: XXXX
PLZ: XXXX
Land: XX
Telefon: XXXXX-XXXXX
E-mail: [email]victim@example.com[/email]
Geburtsdatum: XX / XX / XXXX

Product

1337 down? **Neh, die Lösung!
**
Ne klappt nit, denke mal eher das sie mal wieder DNS probleme haben

Conversation

Identify Products

1. Product information has repeated patterns
2. Conversation usually has verb

Bankname: XX
CCNumber: XXXXXXXX
CCHolder: XX XXXX
CCExpire: X / XXXX
CVV2: XX
Vorname: XX
Nachame: YY
Addresse: XXXXX
Stadt: XXXX
PLZ: XXXX
Land: XX
Telefon: XXXXX-XXXXX
E-mail: [email]victim@example.com[/email]
Geburtsdatum: XX / XX / XXXX

Product

1337 down? **Neh, die Lösung!
**
Ne klappt nit, denke mal eher
das sie mal wieder DNS
probleme haben

Verbs

Conversation

Identify Products

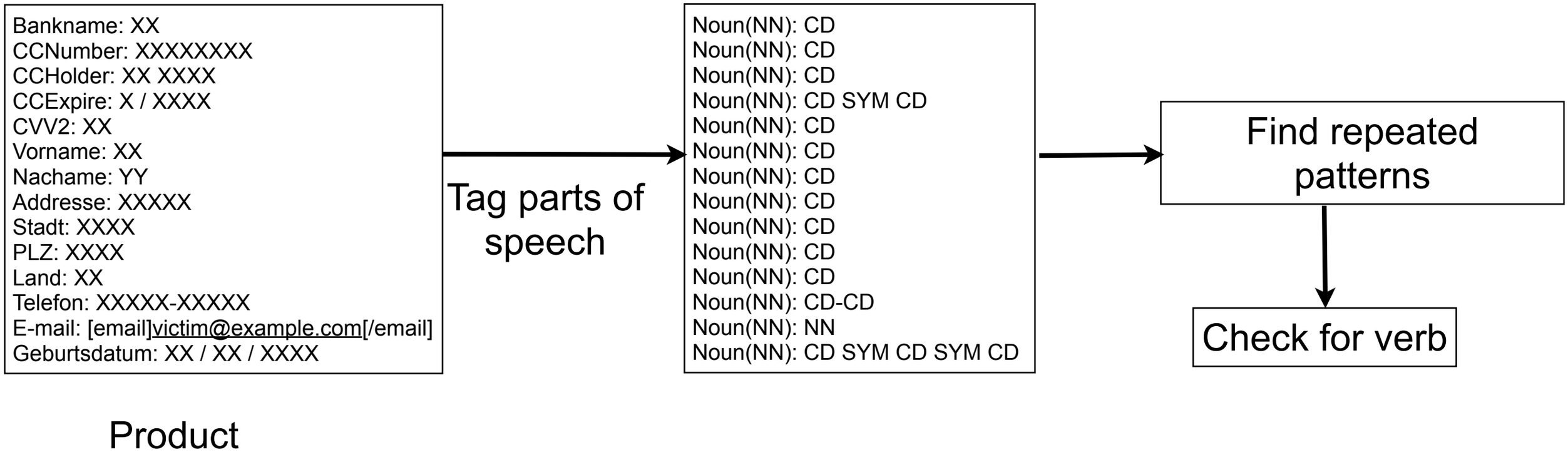
Bankname: XX
CCNumber: XXXXXXXX
CCHolder: XX XXXX
CCExpire: X / XXXX
CVV2: XX
Vorname: XX
Nachame: YY
Addresse: XXXXX
Stadt: XXXX
PLZ: XXXX
Land: XX
Telefon: XXXXX-XXXXX
E-mail: [email]victim@example.com[/email]
Geburtsdatum: XX / XX / XXXX

Tag parts of speech

Noun(NN): CD
Noun(NN): CD
Noun(NN): CD
Noun(NN): CD SYM CD
Noun(NN): CD
Noun(NN): CD
Noun(NN): CD
Noun(NN): CD
Noun(NN): CD
Noun(NN): CD
Noun(NN): CD
Noun(NN): CD
Noun(NN): CD
Noun(NN): CD-CD
Noun(NN): NN
Noun(NN): CD SYM CD SYM CD

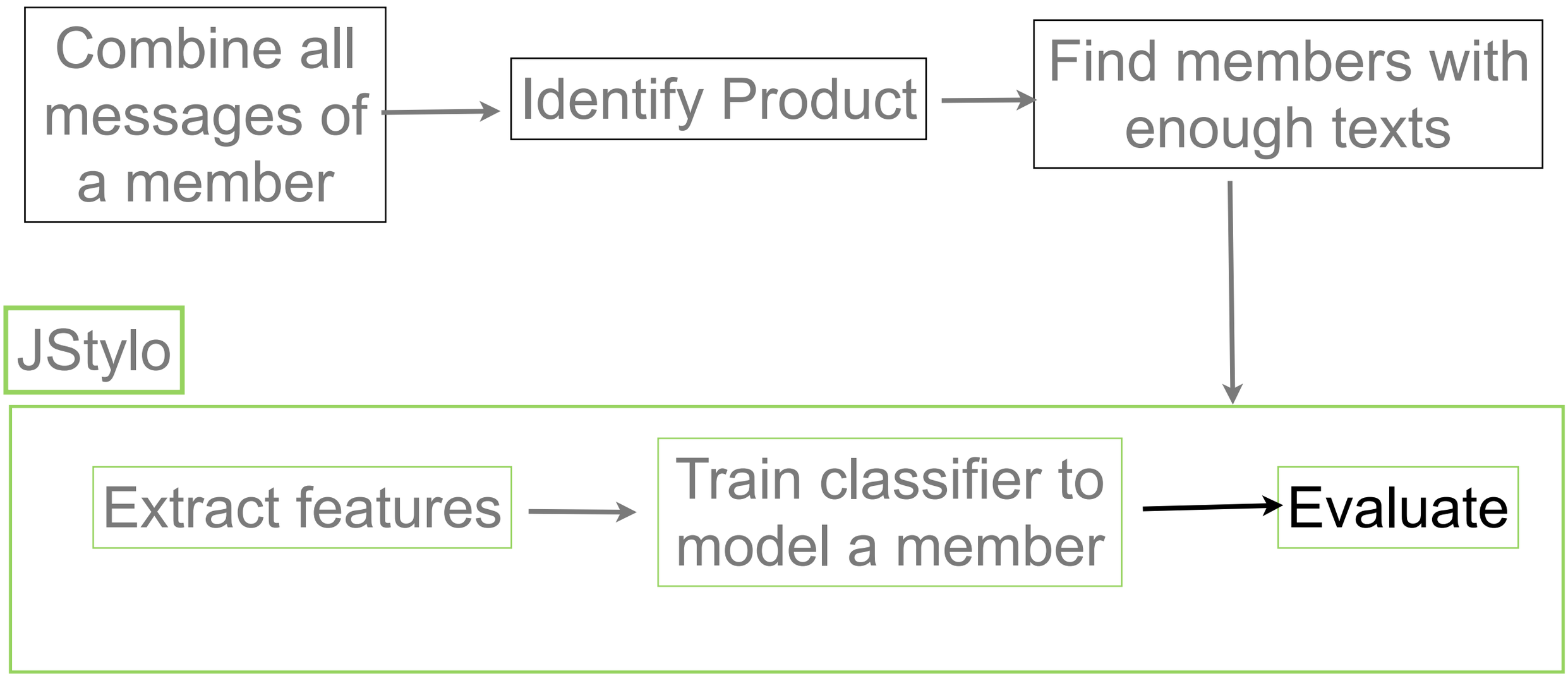
Product

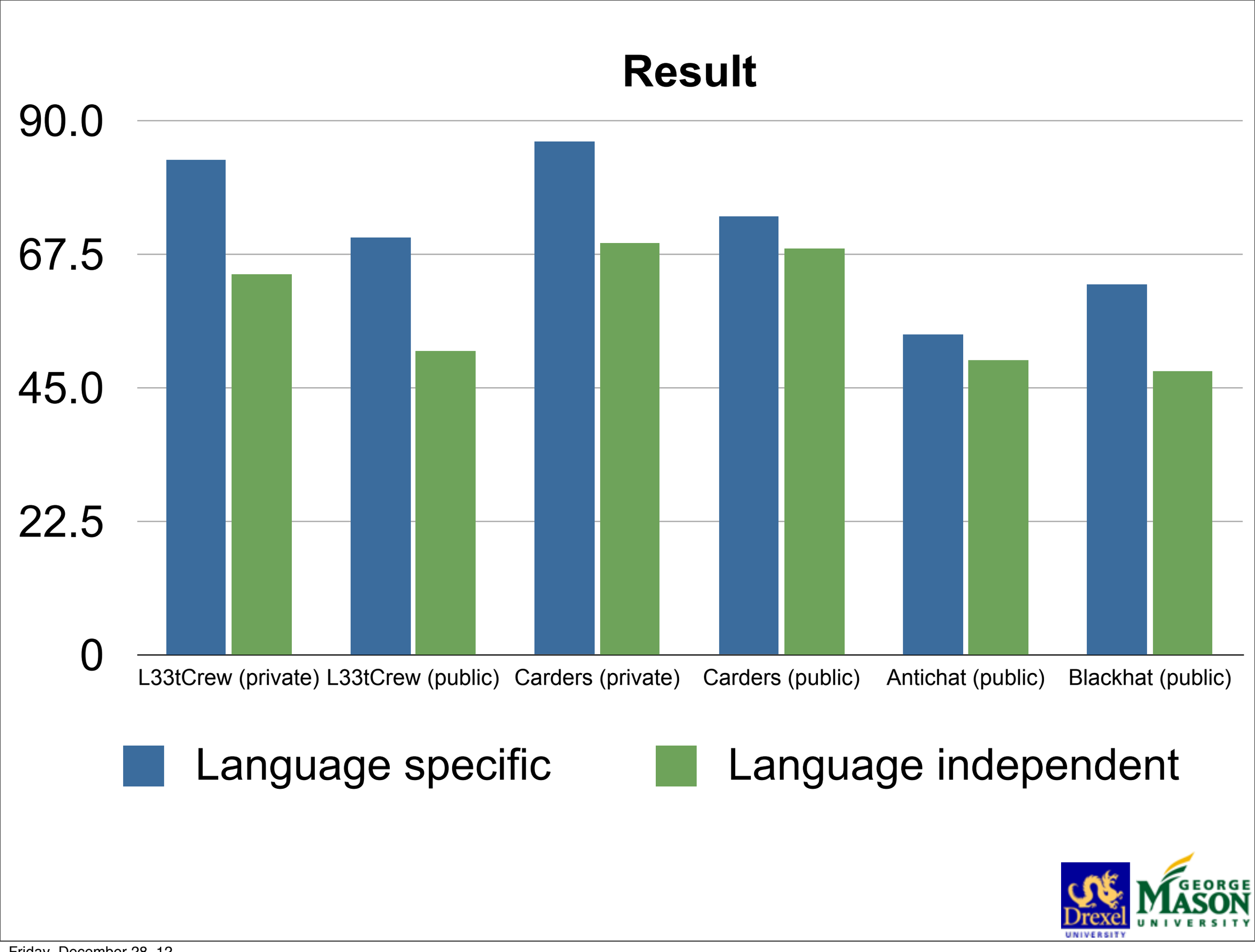
Identify Products

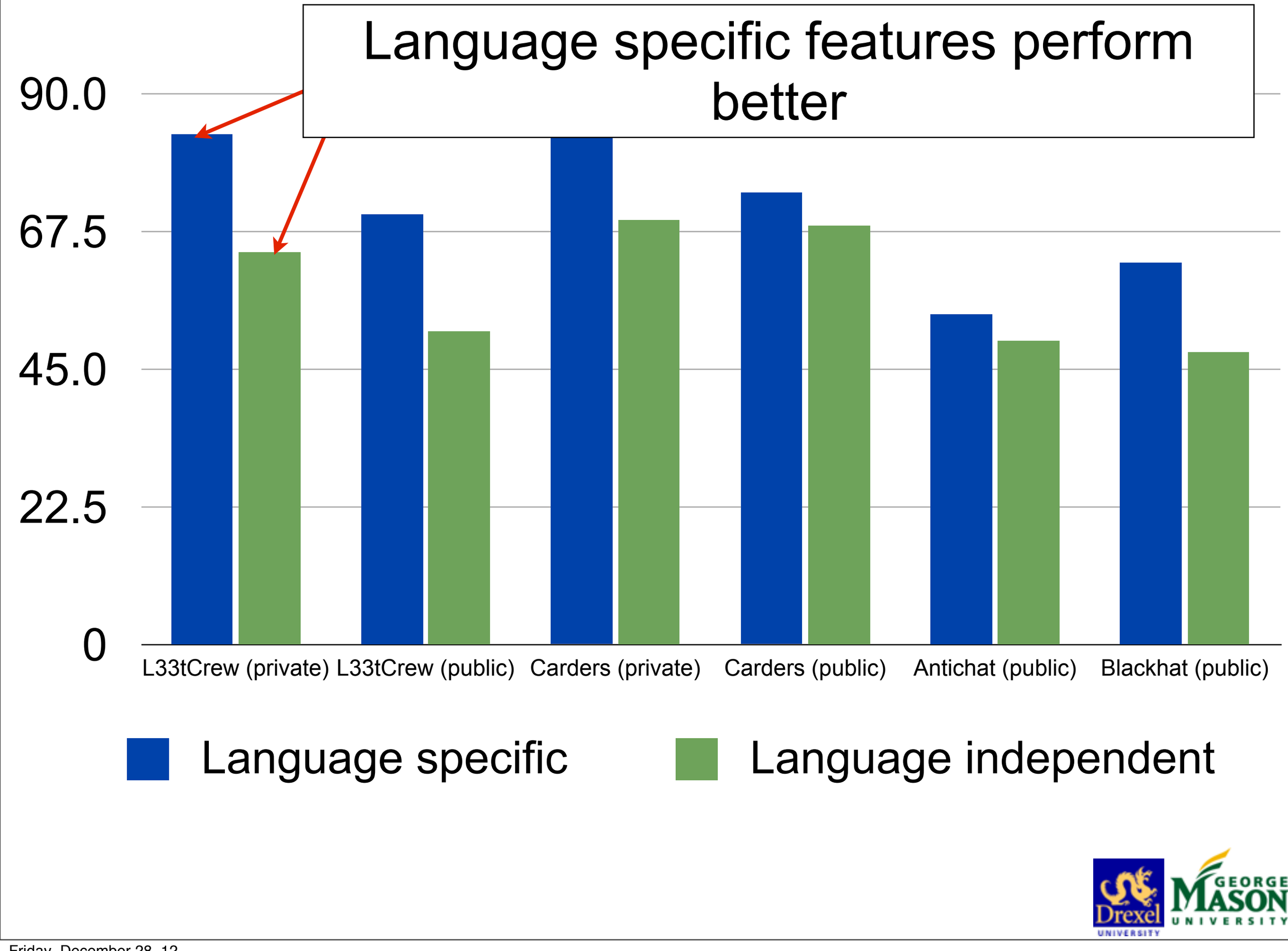


Product

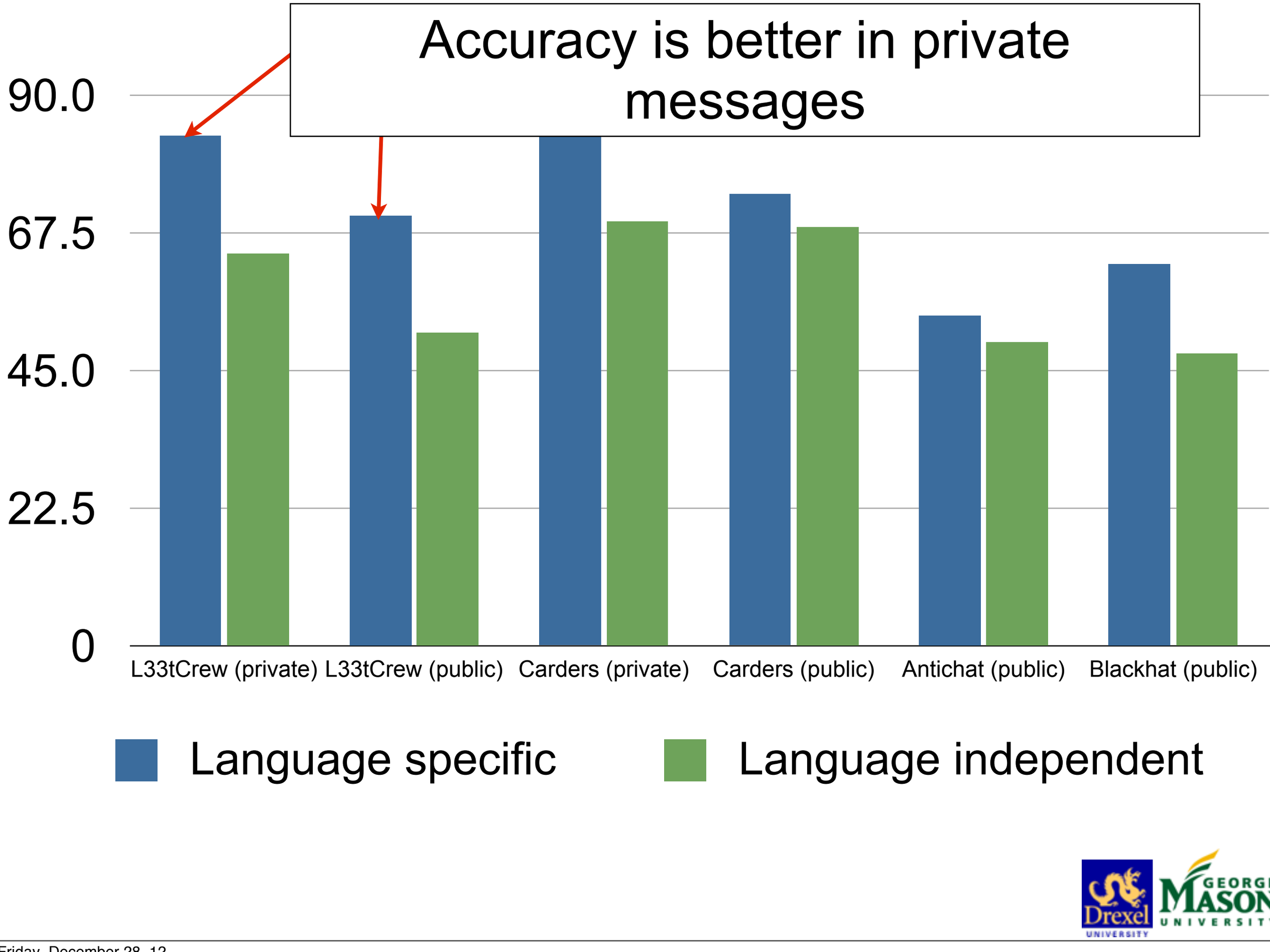
Profiling using writing style




Result
90.0
67.5
45.0
22.5
0
L33tCrew (private)
L33tCrew (public)
Carders (private)
Carders (public)
Antichat (public)
Blackhat (public)
Language specific
Language independent

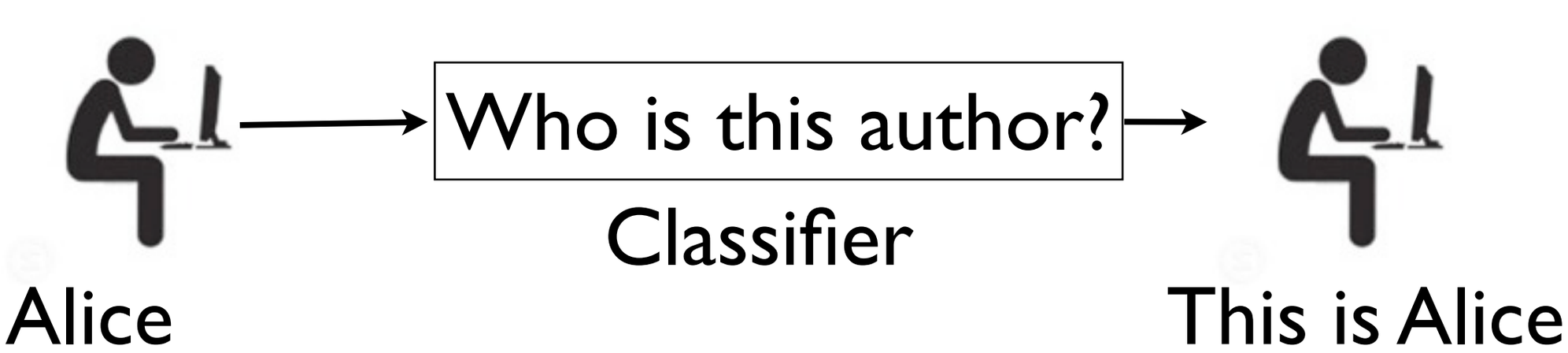

Language specific features perform better
90.0
67.5
45.0
22.5
0
L33tCrew (private)
L33tCrew (public)
Carders (private)
Carders (public)
Antichat (public)
Blackhat (public)
Language specific
Language independent

Accuracy is better in private messages



Relaxed attribution

Exact attribution:



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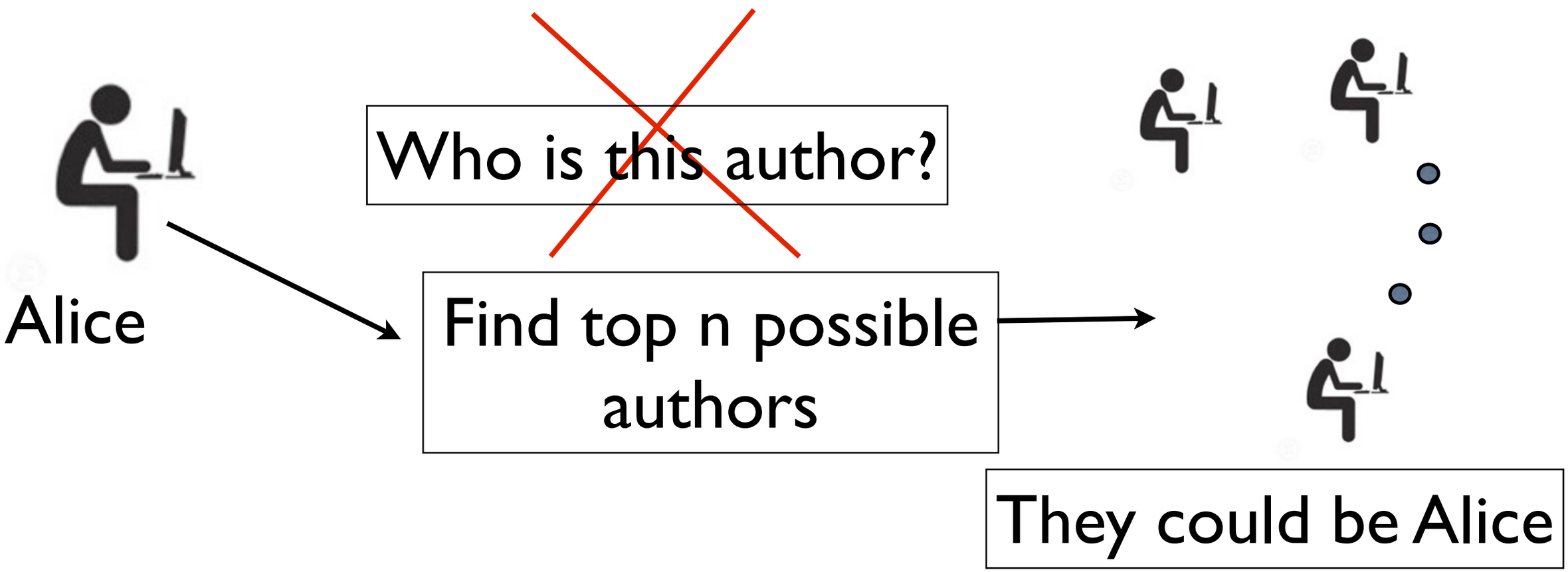
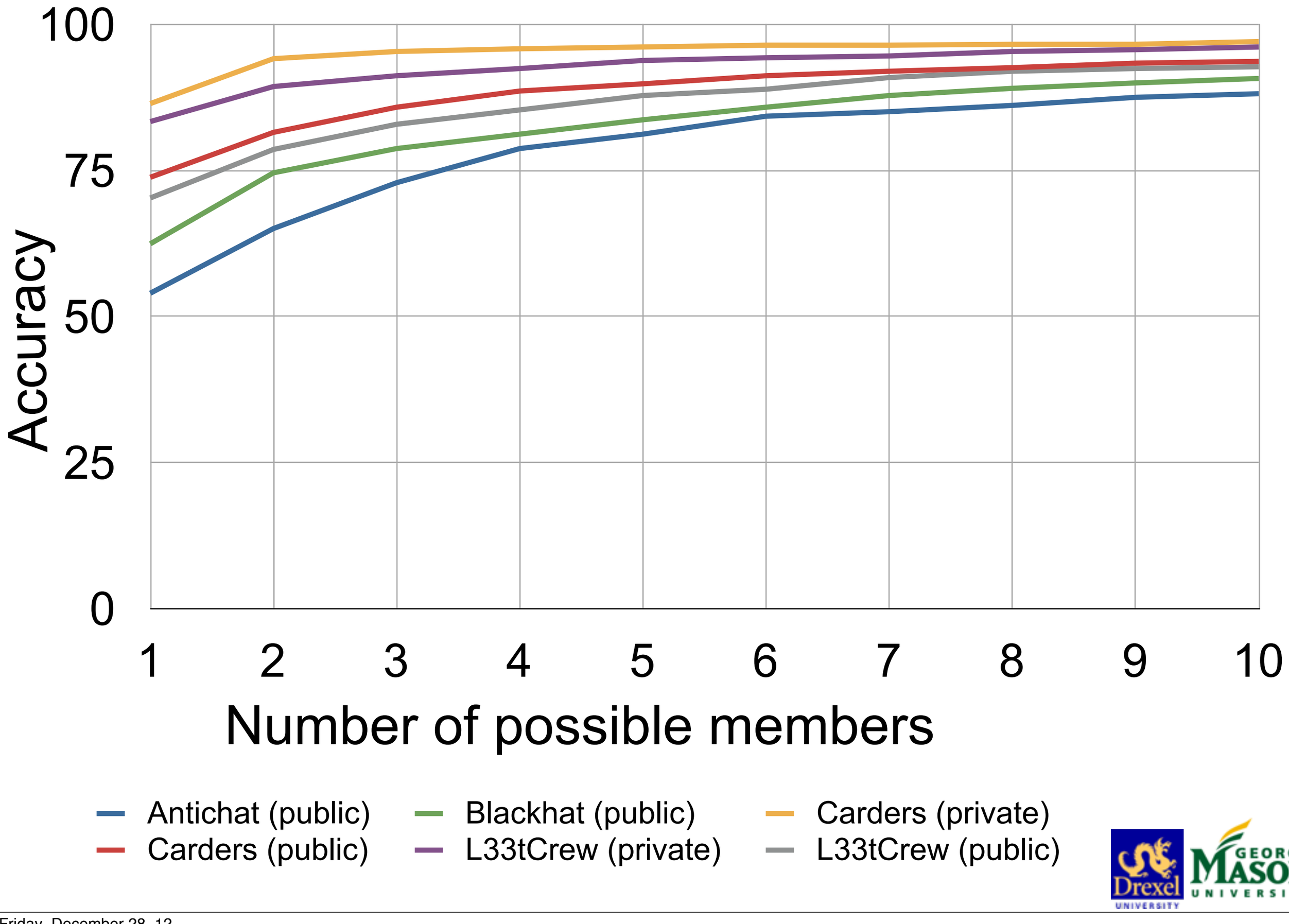
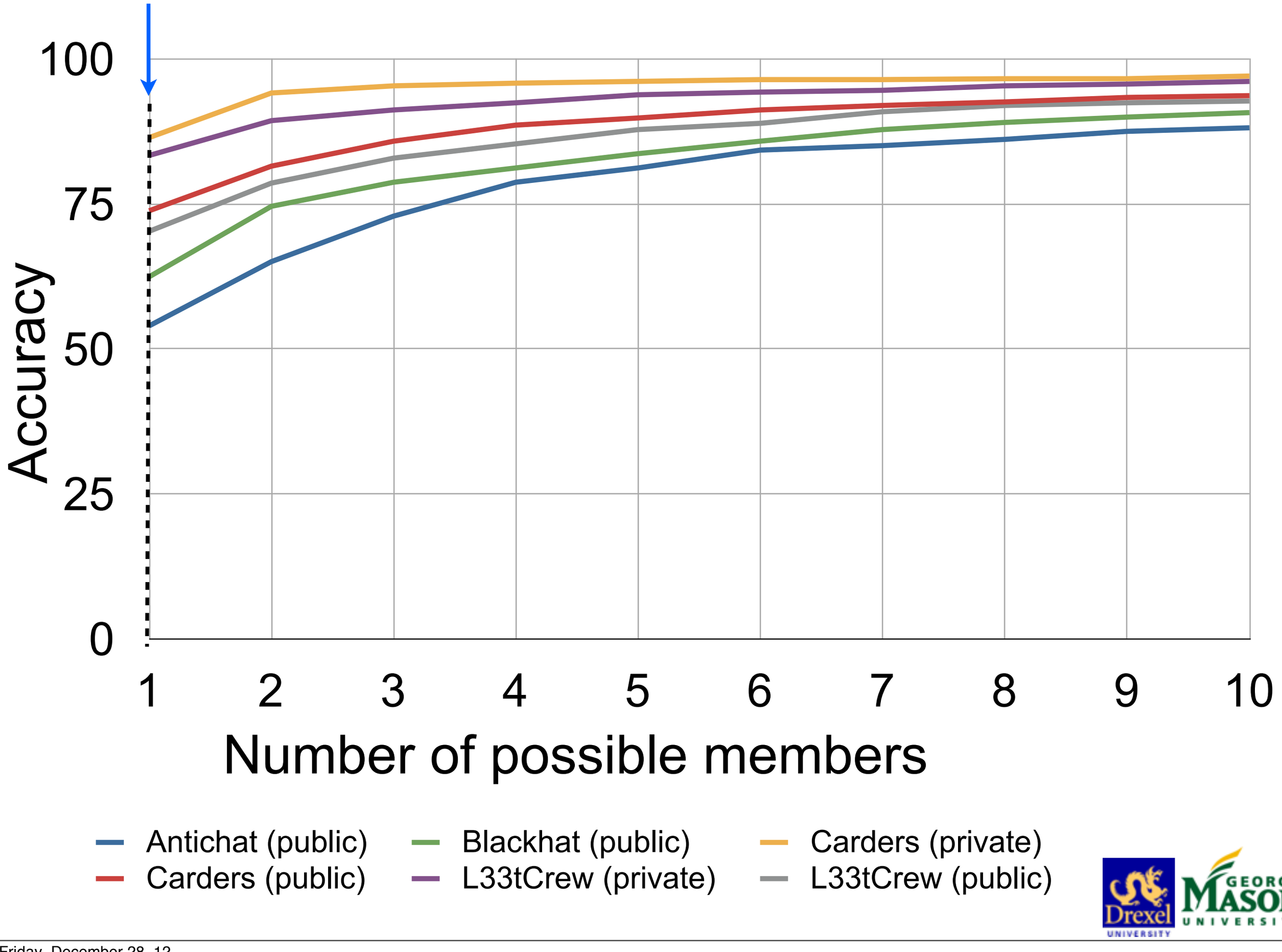
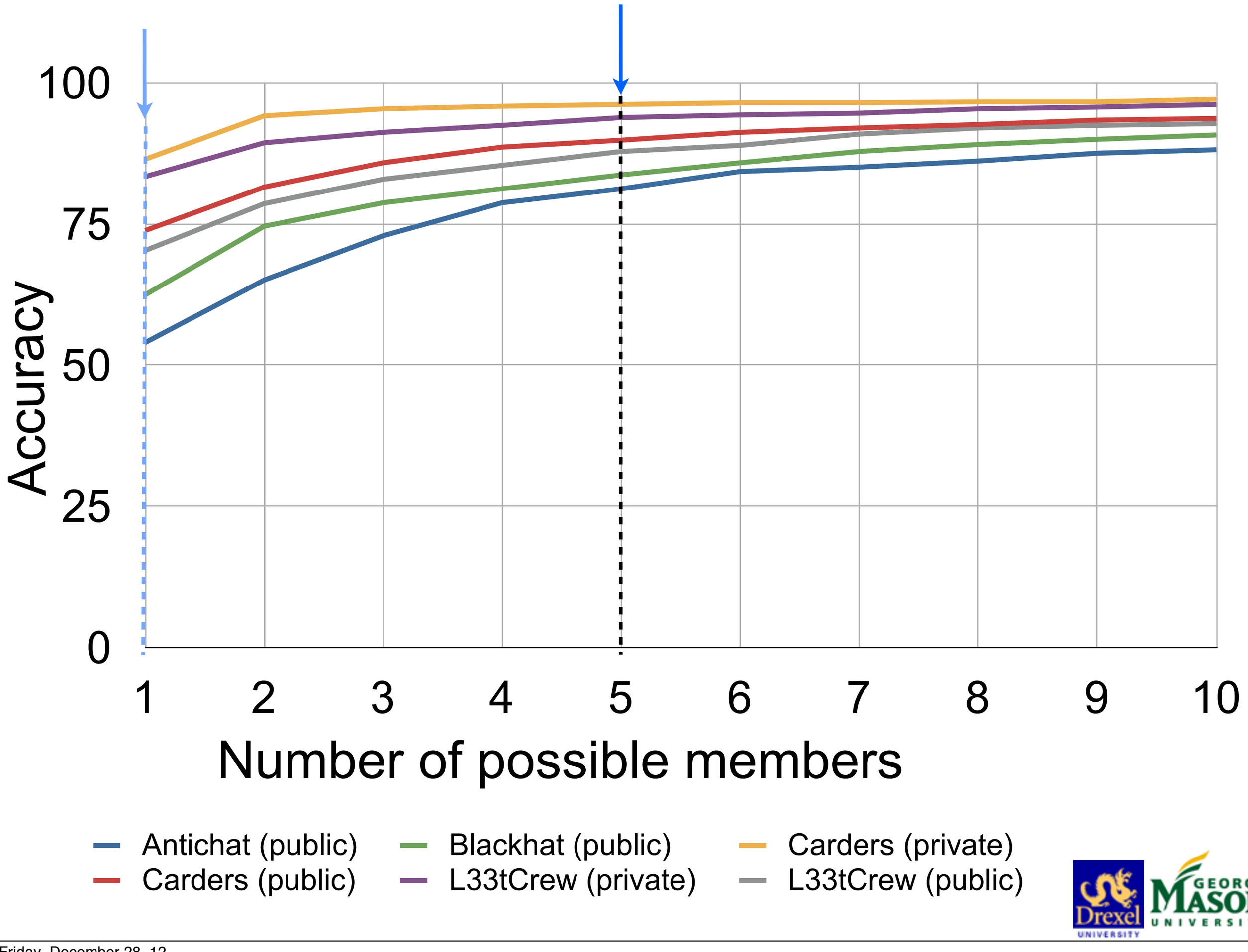



100
75
50
25
0
Accuracy
1
2
3
4
5
6
7
8
9
10
Number of possible members
Antichat (public)
Blackhat (public)
Carders (private)
Carders (public)
L33tCrew (private)
L33tCrew (public)


100
75
50
25
0
Accuracy
1
2
3
4
5
6
7
8
9
10
Number of possible members
Antichat (public)
Blackhat (public)
Carders (private)
Carders (public)
L33tCrew (private)
L33tCrew (public)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L33tCrew (public)
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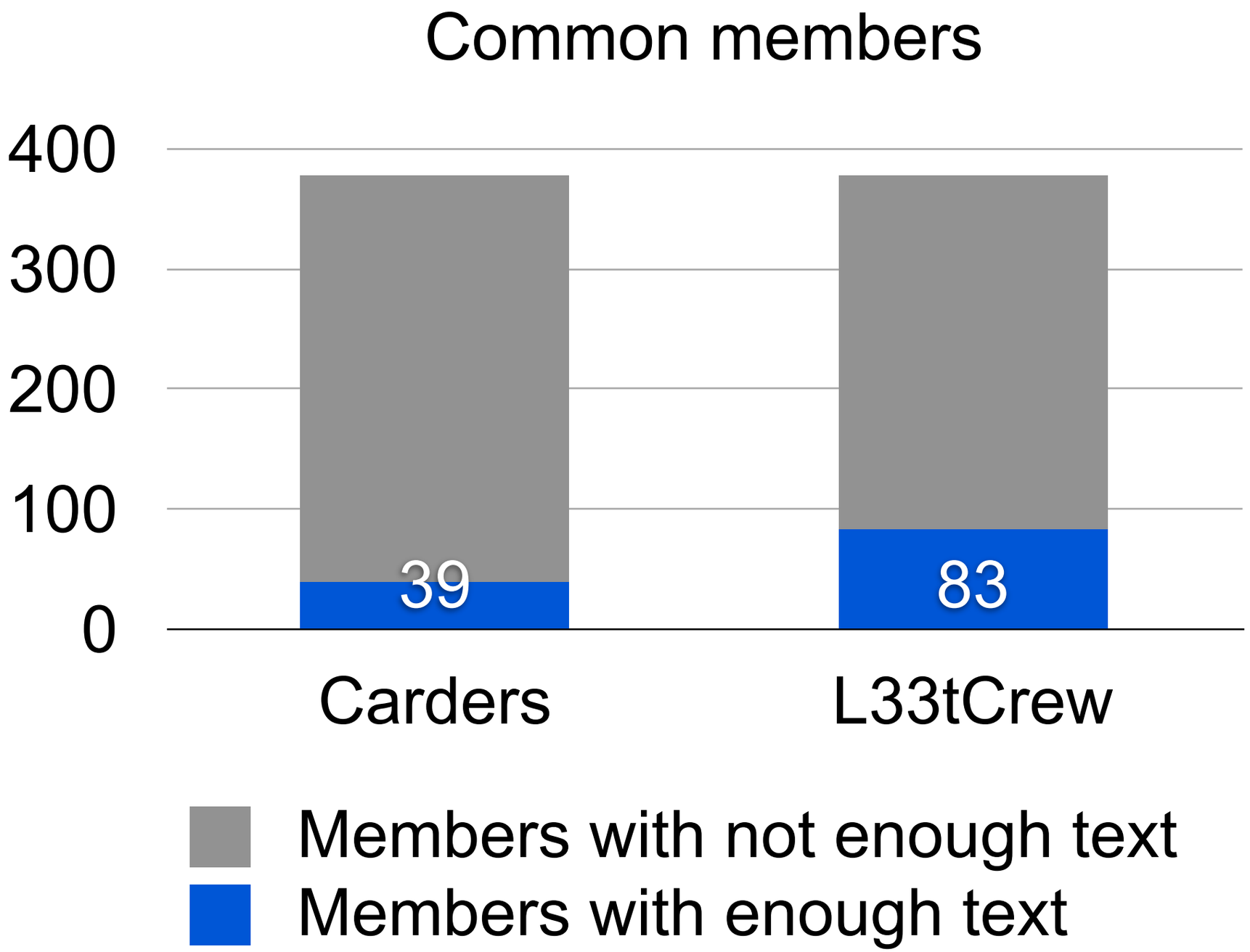
Tracking members across forums

- Can a member's posts on one forum identify him in other forums?

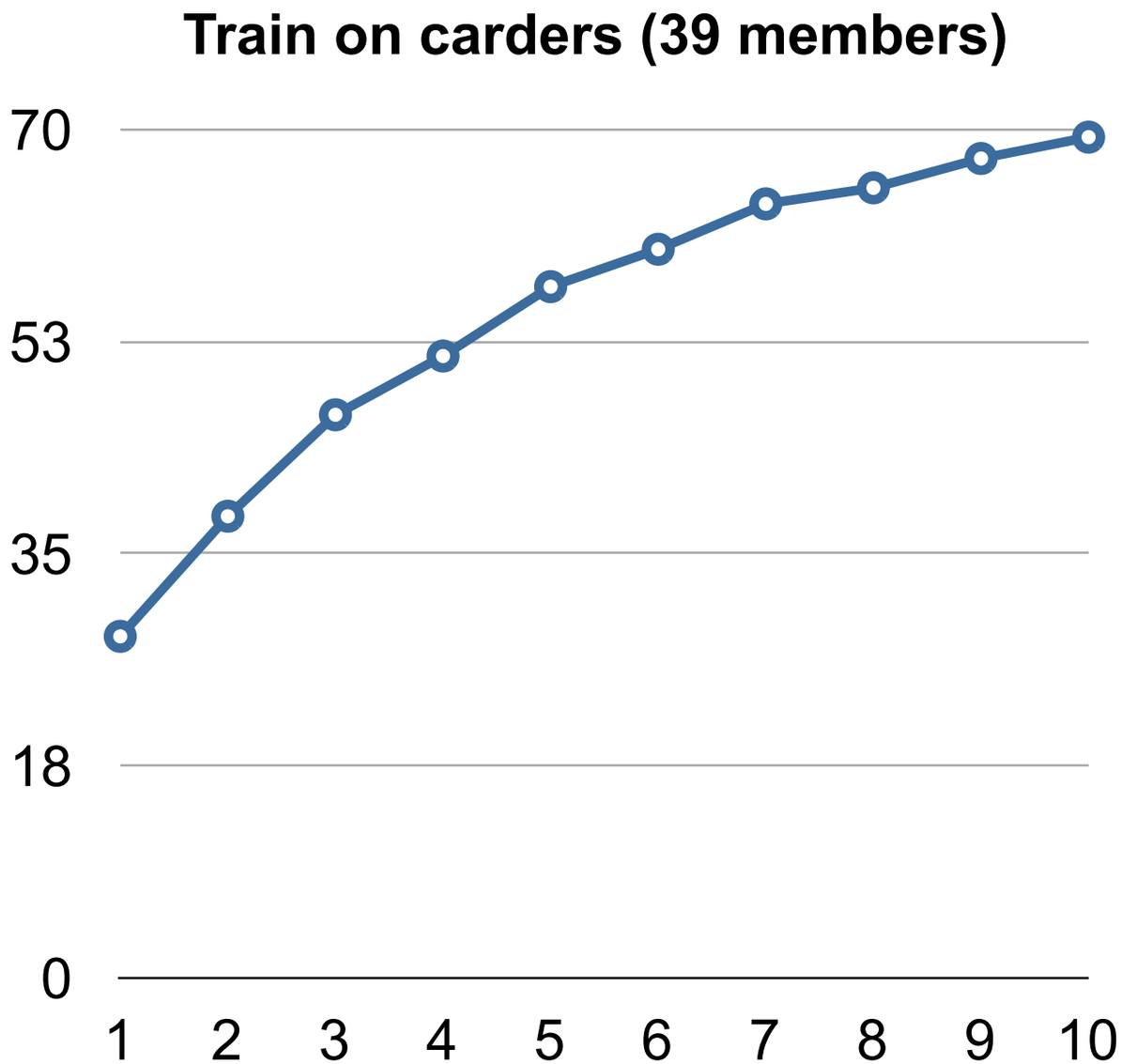
Tracking members across forums

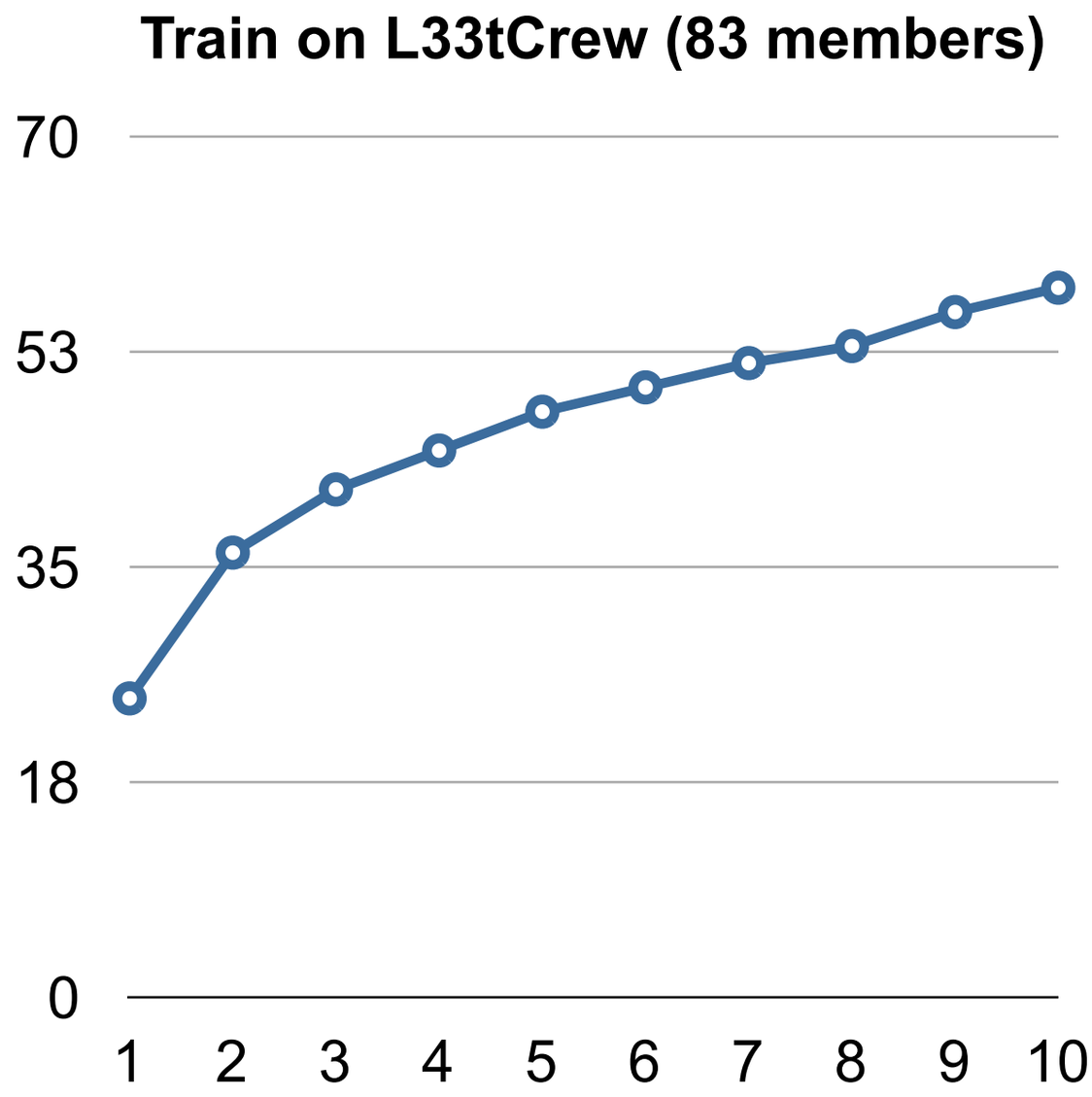
- Approach:
  - Find members using email address
  - Train on one forum's posts and test on another

Tracking members across forums



Cross forum result

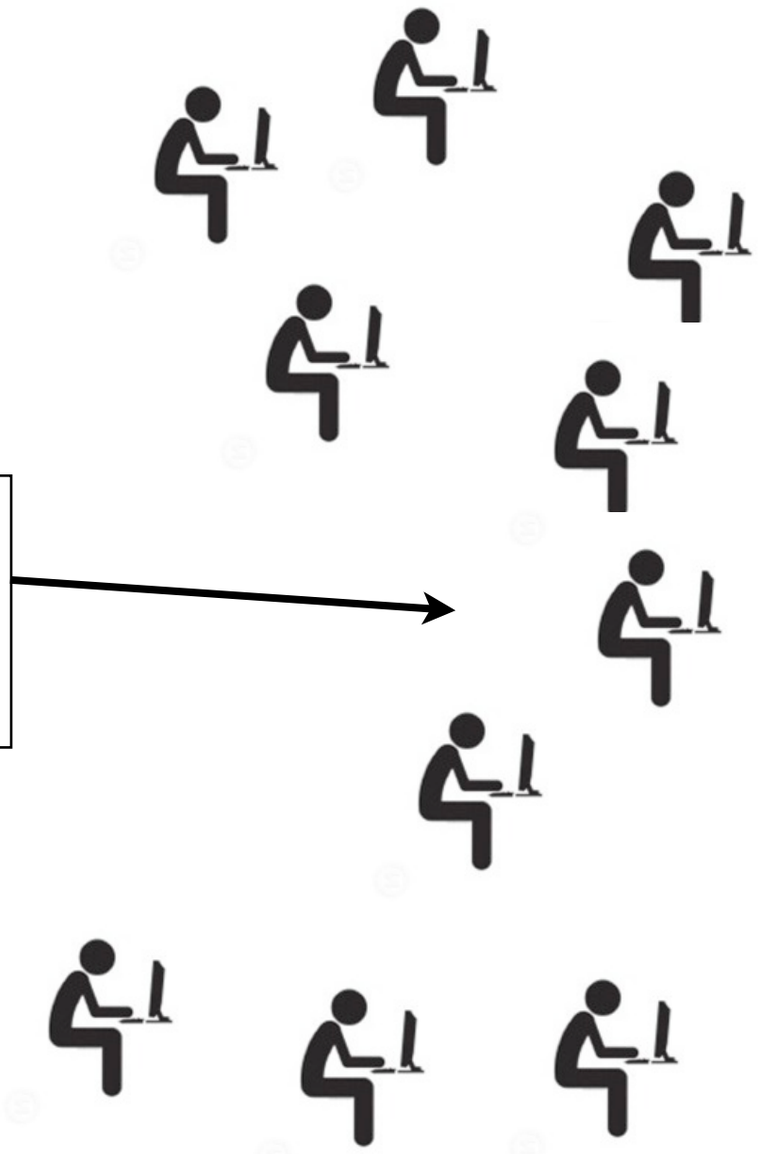




Who are the possible suspects?

Alice

Find top 10 possible identities of Alice

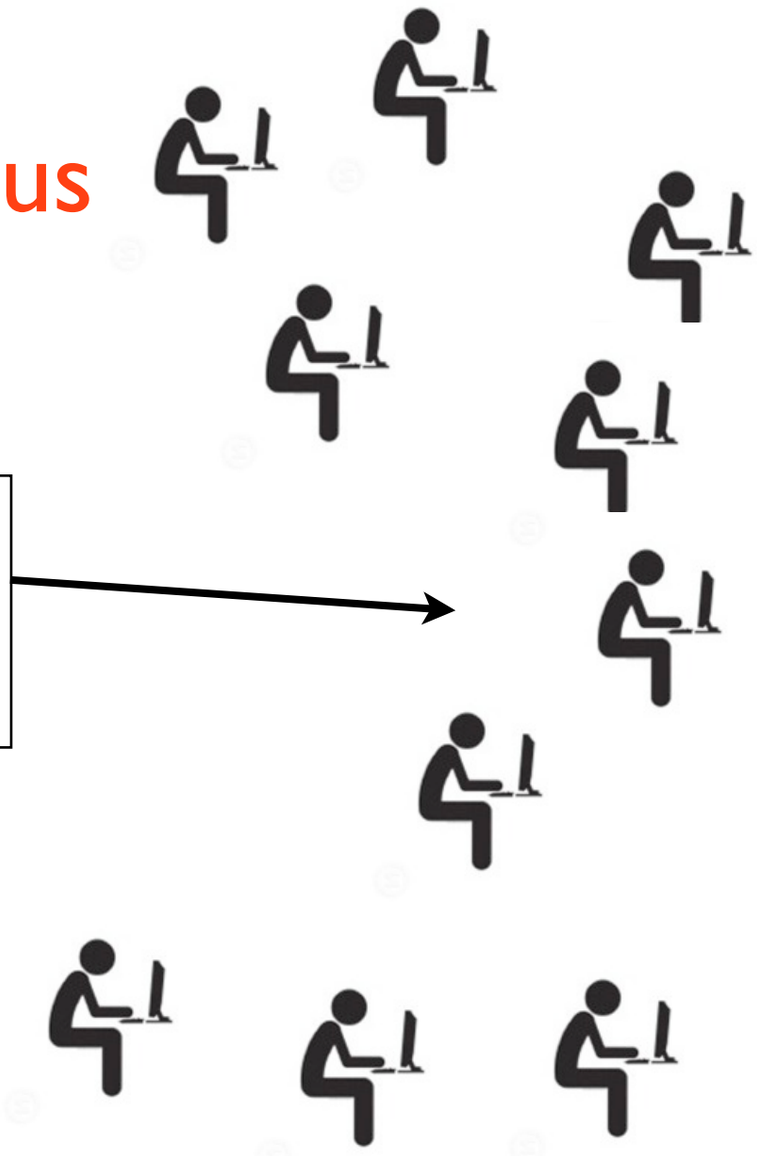


Who are the possible suspects?

What do they tell us about Alice?

Alice

Find top 10 possible identities of Alice



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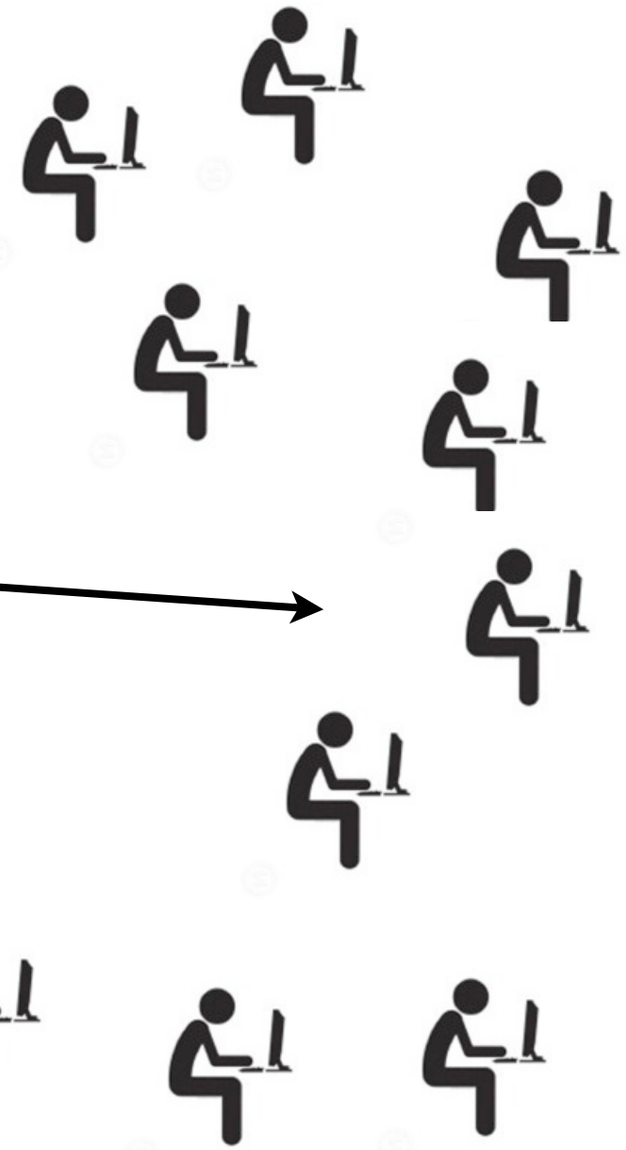


Can we find alternate identities of Alice?

Who are the possible suspects?

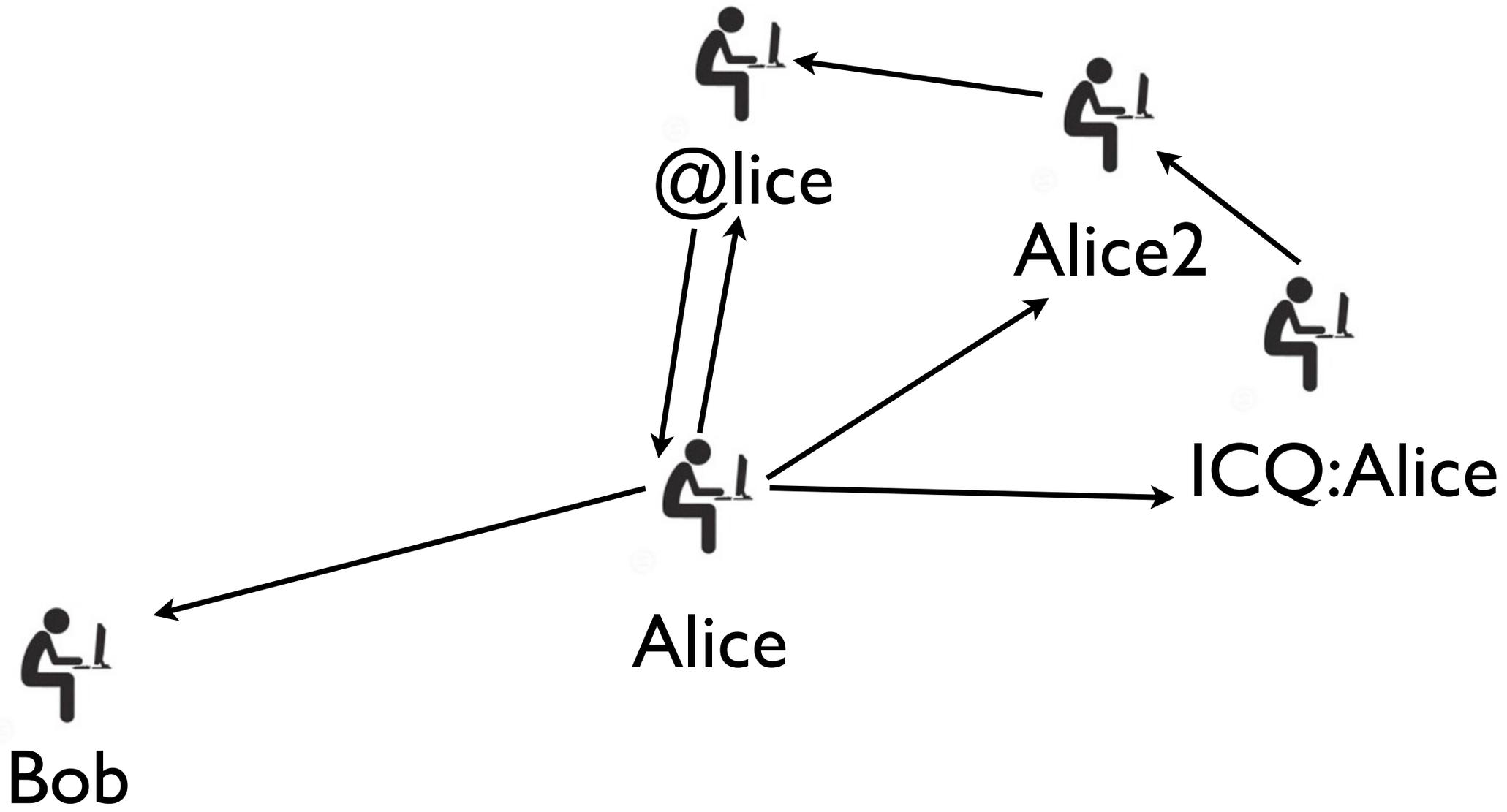
If Bob is
one of the suspects of Alice

Created a graph where
each node= a user
edge a to b if b is one of the suspects of a

Who are the possible suspects?

- Run this analysis of SpamIt forum associates chat conversation
- Because we had ground truth about duplicate accounts

Who are the possible suspects?



Discover Topic

- Topic analysis can identify predominant topic of the forum
- Why is it important?:
  - Automatically identify “interesting” subset of the data
  - Find relevant people
  - Understand trends

Discover Topic

- We used Latent Dirichlet Allocation (LDA) for identifying topic words.

How LDA works

I wonder what kind of products or services you could advertise using bulk mailing. I'm really new to bulk mailing, never tried it before. But I know that you'll get in trouble with your hosting company if you promote stuff that leads to your own server / hosting account. So how does this work???

Example post from Blackhat

How LDA works

Topic 2

Topic 1

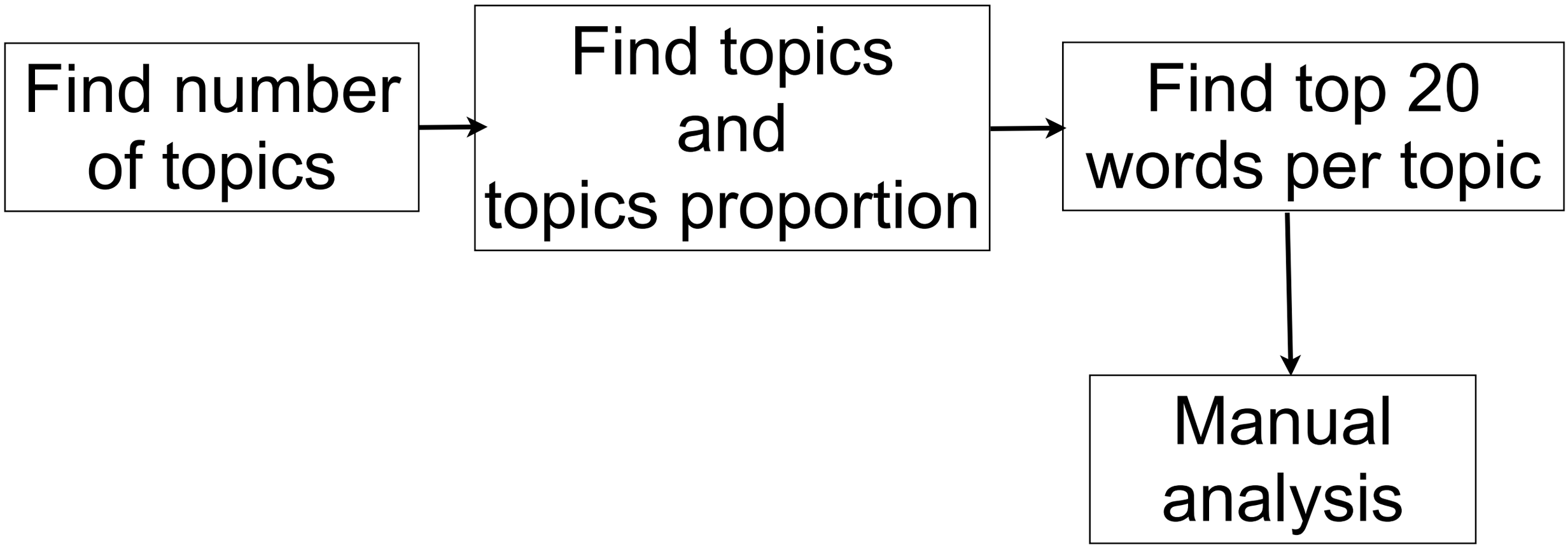
I wonder what kind of products or services you could advertise using bulk mailing. I'm really new to bulk mailing, never tried it before. But I know that you'll get in trouble with your hosting company if you promote stuff that leads to your own server / hosting account. So how does this work???

Topic 2

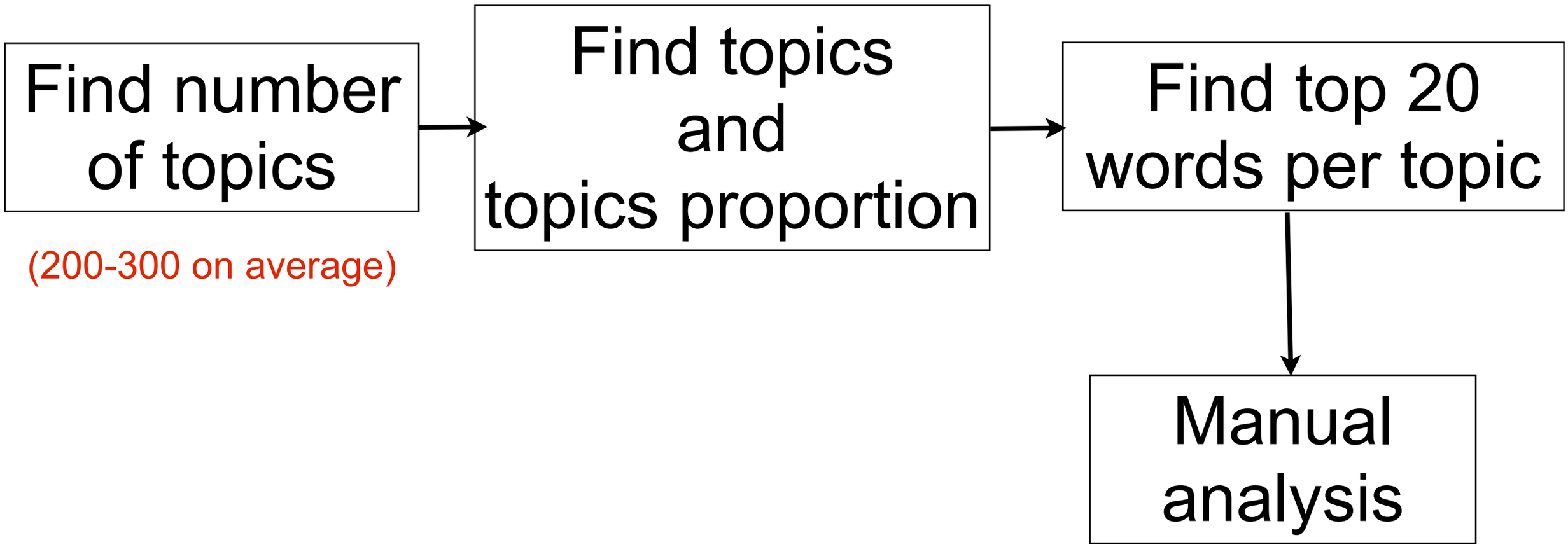
Topic 3

Example post from Blackhat

Discover Topic

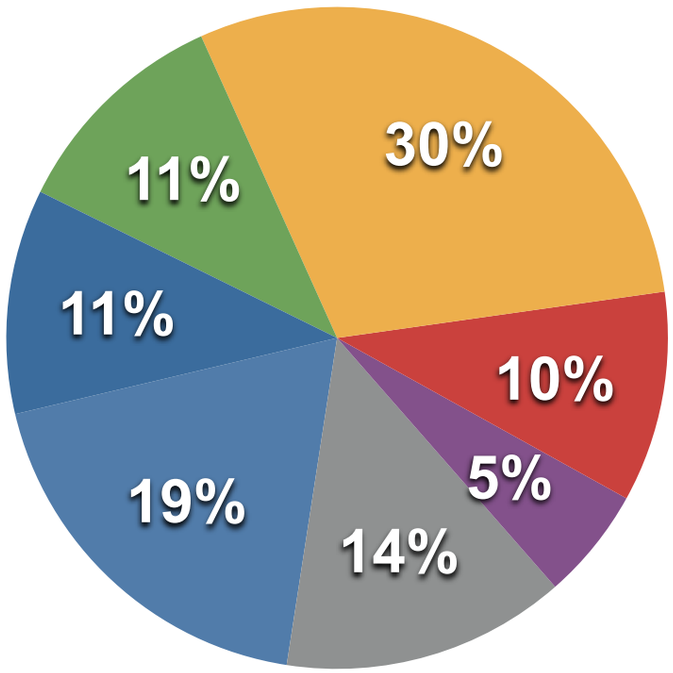


Discover Topic



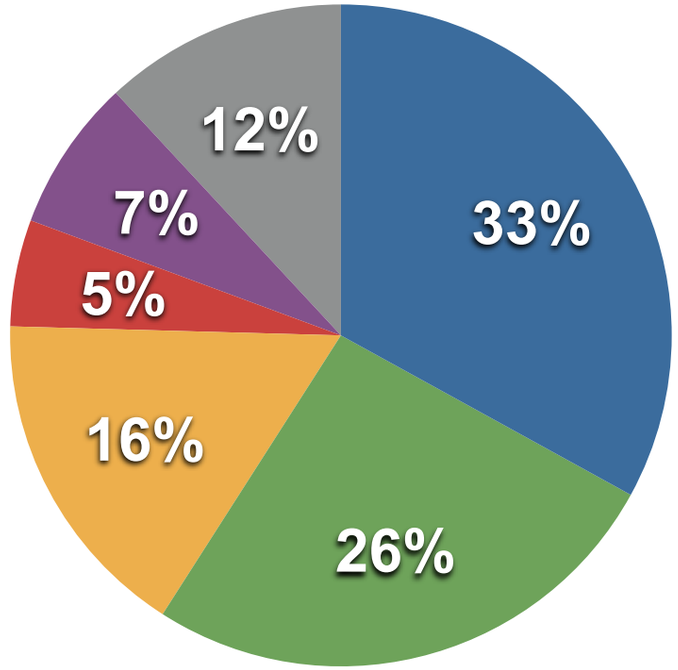
Topics discovered

Carders



- Anonymity services (web and phone)
- Exploits
- Carding and other accounts
- Cardable
- Bankdrop
- Drugs
- Currency: PSC, UKASH, WMZ

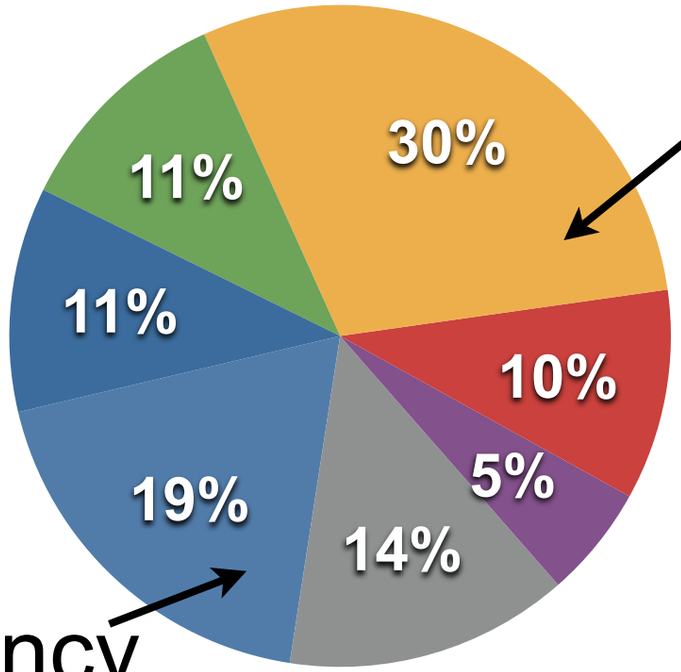
L33tCrew



- Crypting services
- Anonymity services
- Carding
- Other accounts
- Exploits
- Anonymous phone

Topics discovered

Carders



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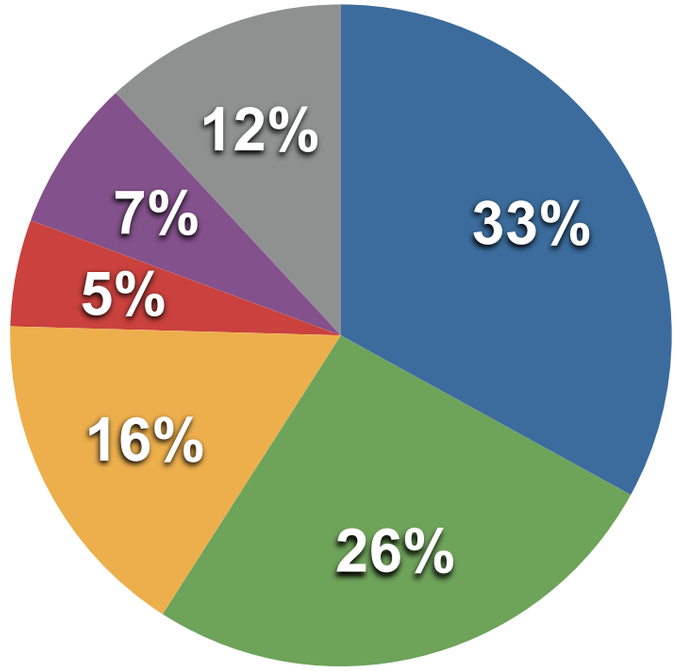

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Topics discovered

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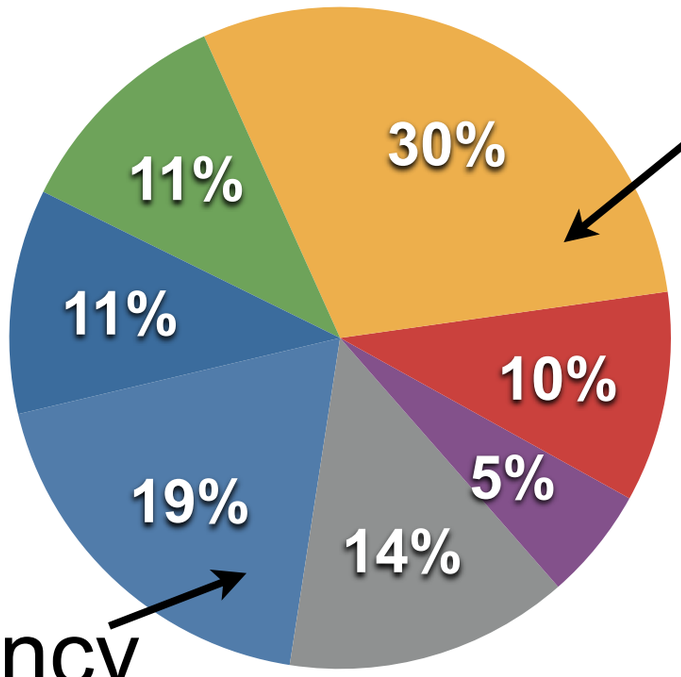

Carding

Currency

- Anonymity services (web and phone)
- Exploits
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- Cardable
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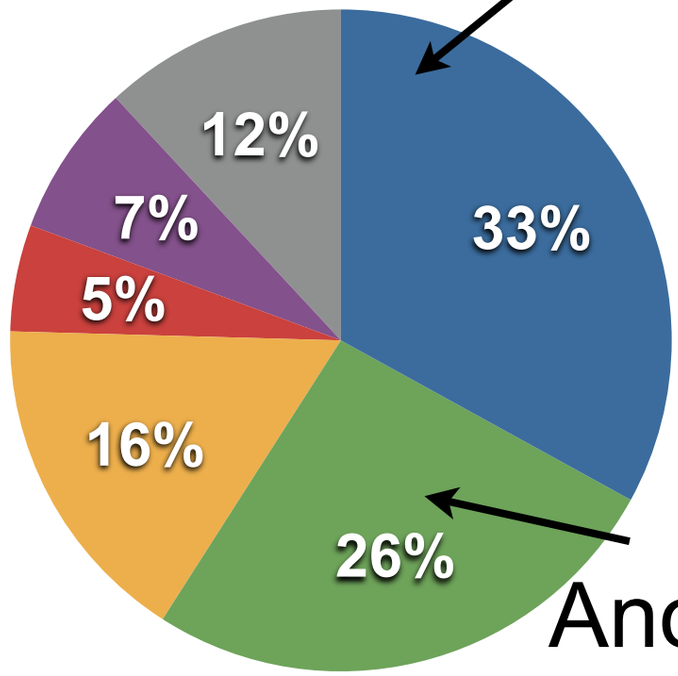
L33tCrew

Crypting service



Anonymity service

- Crypting services
- Anonymity services
- Carding
- Other accounts
- Exploits
- Anonymous phone

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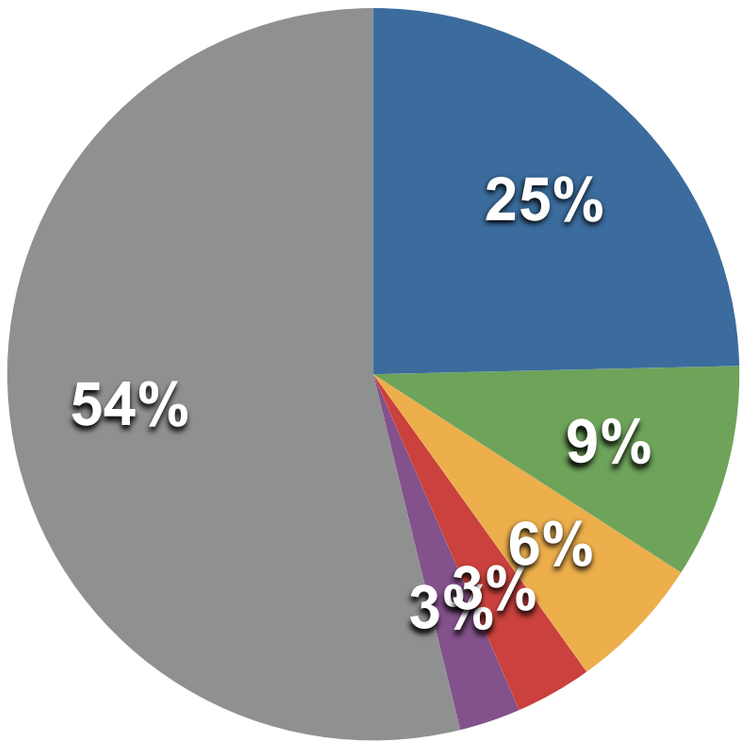
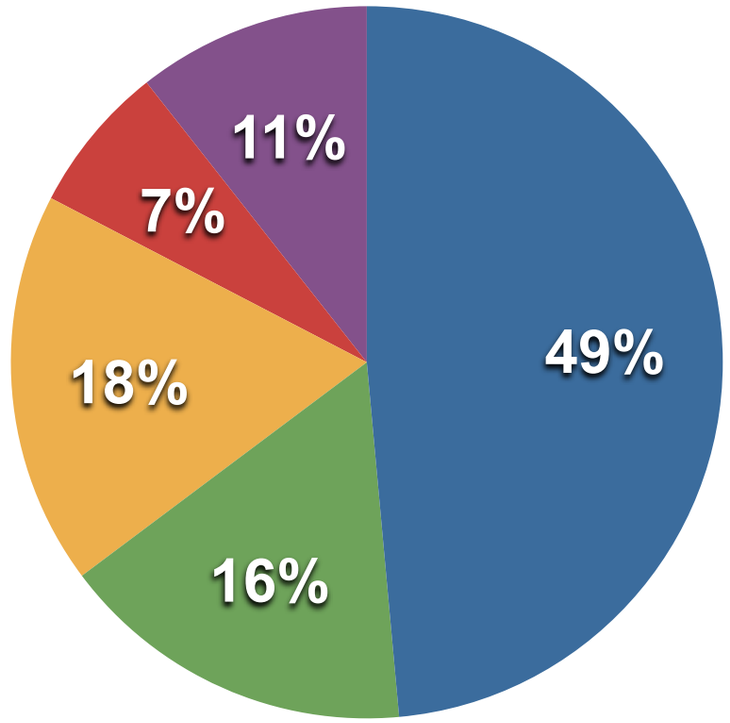
Topics discovered

Antichat



- Web money
- Exploits
- Phone and SMS
- Captcha solving
- SEO blackhat tools
- Password cracking

Blackhat



- SEO blackhat
- SEO for blogs
- SEO for youtube
- Captcha solving
- Buy followers and friends

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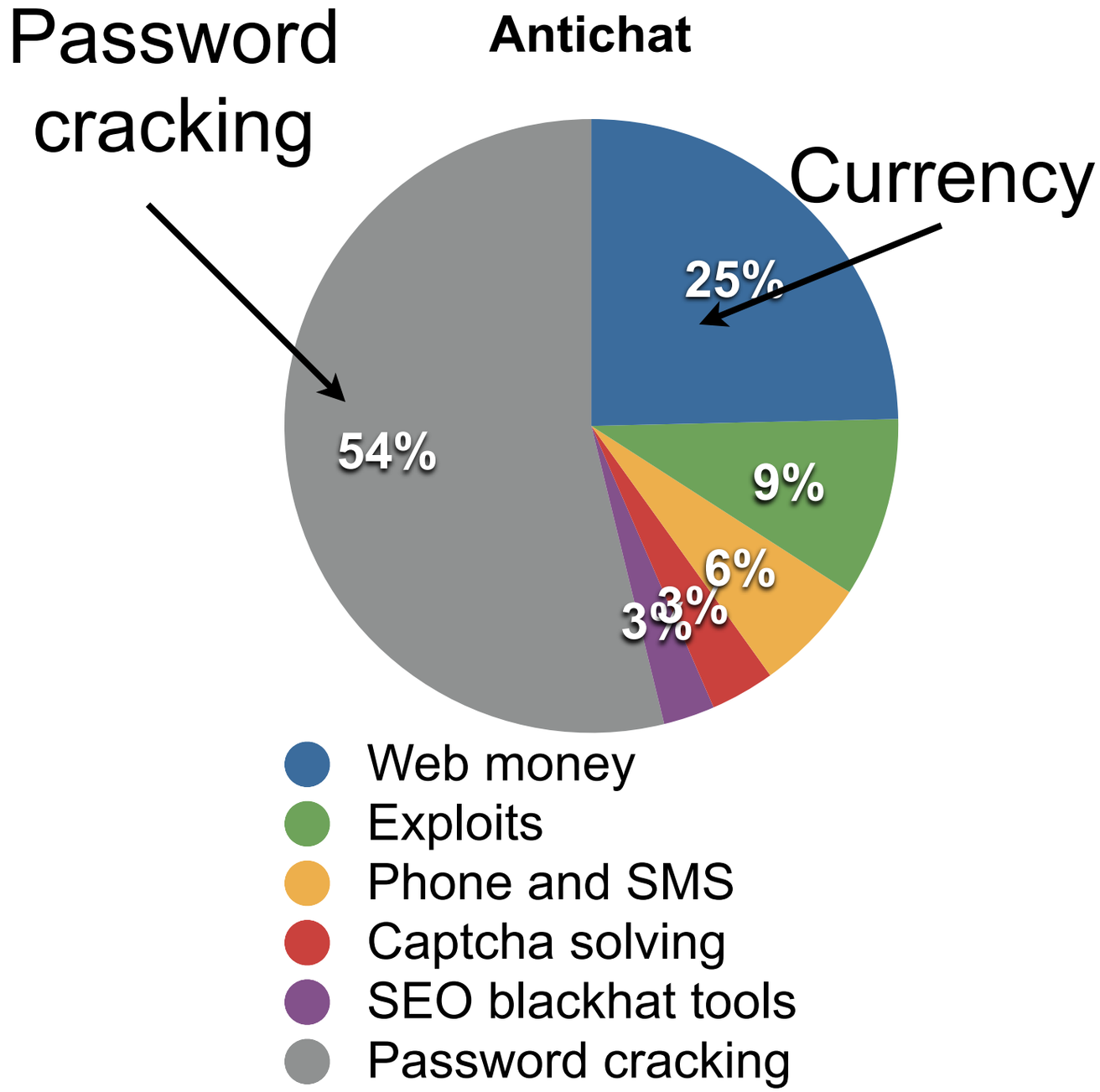
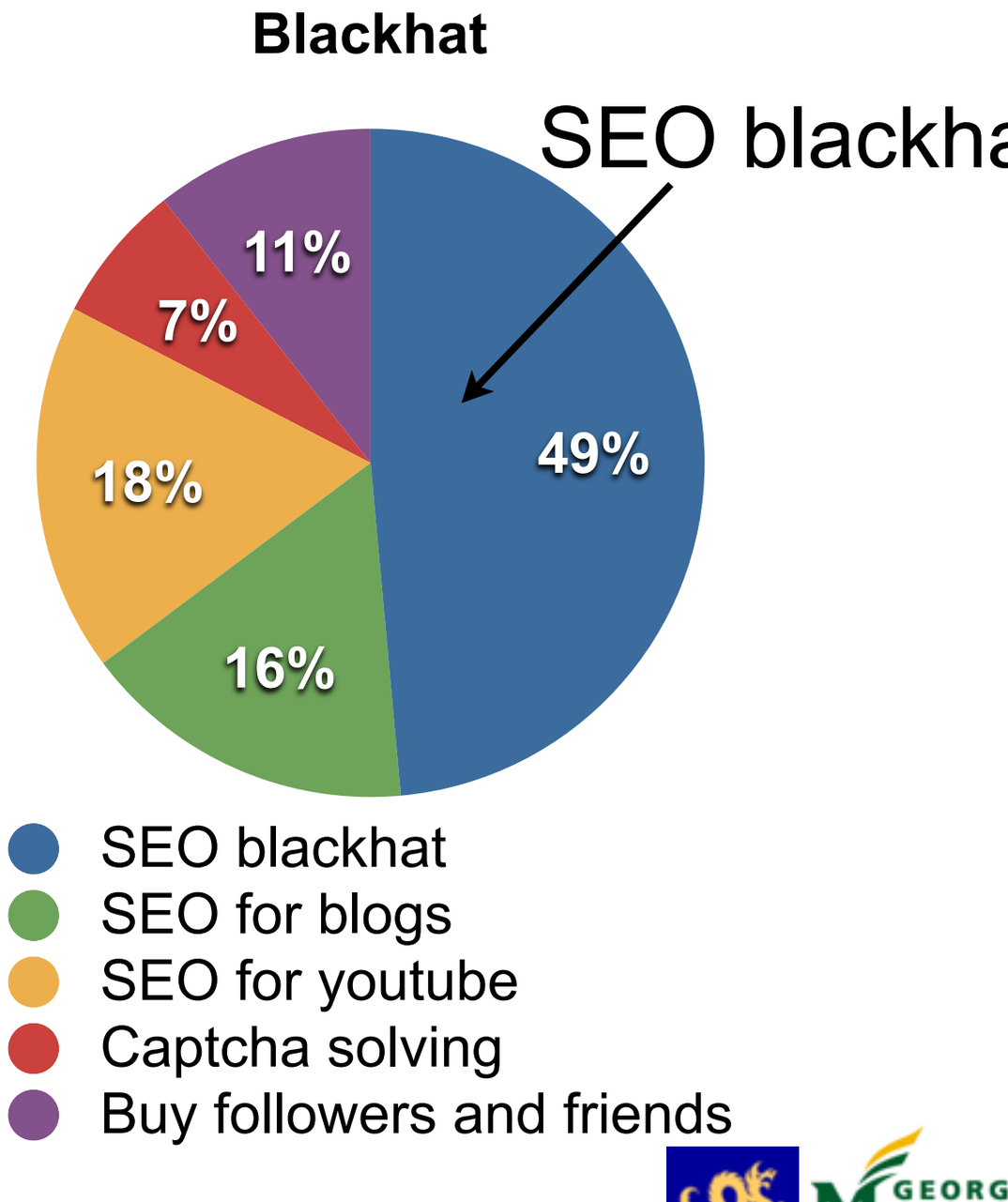
Topics discovered





Next…

- Challenges
- Limitations
- Future work
- Conclusions
- Tools developed in our lab

CHALLENGES

- Microtext
- Multilingual text
- Different types of product information in text
- Users with multiple accounts

Challenges of microtext

- Short writings
  “1x Brazzers heut morgen gings noch”

Challenges of microtext

- Short writings
  “1x Brazzers heut morgen gings noch”

- Informal and conversational style
  “LOL..... nice post”

Challenges of multilingual text

- Require multilingual features in machine learning
  - Language-specific POS tagger
  - Function words

Challenges of multilingual text

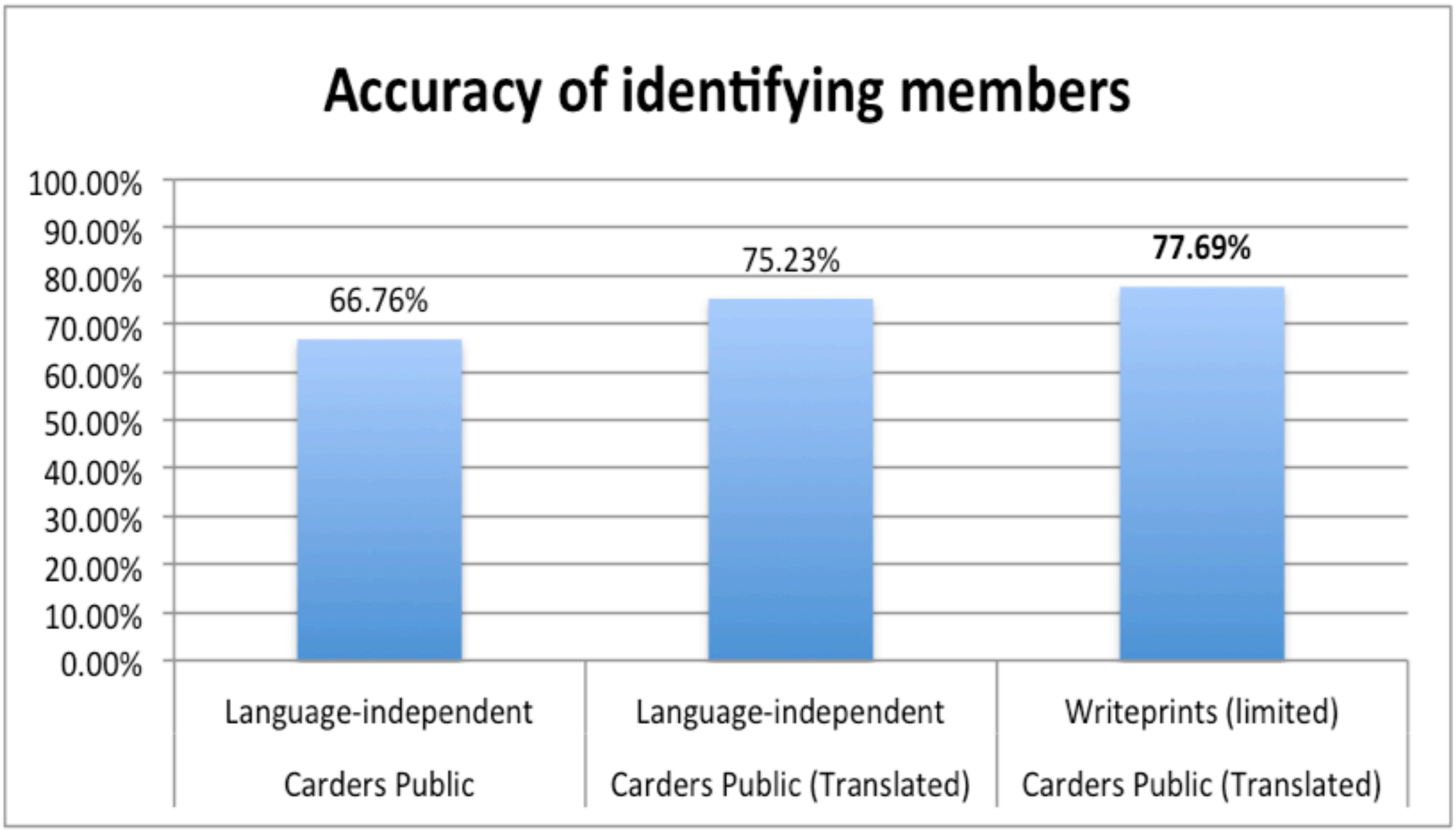
- Many authorship tools are designed for English
- Translated text gives better results in identifying members

Challenges of multilingual text

- We translated Carders public to see how translation affects the accuracy

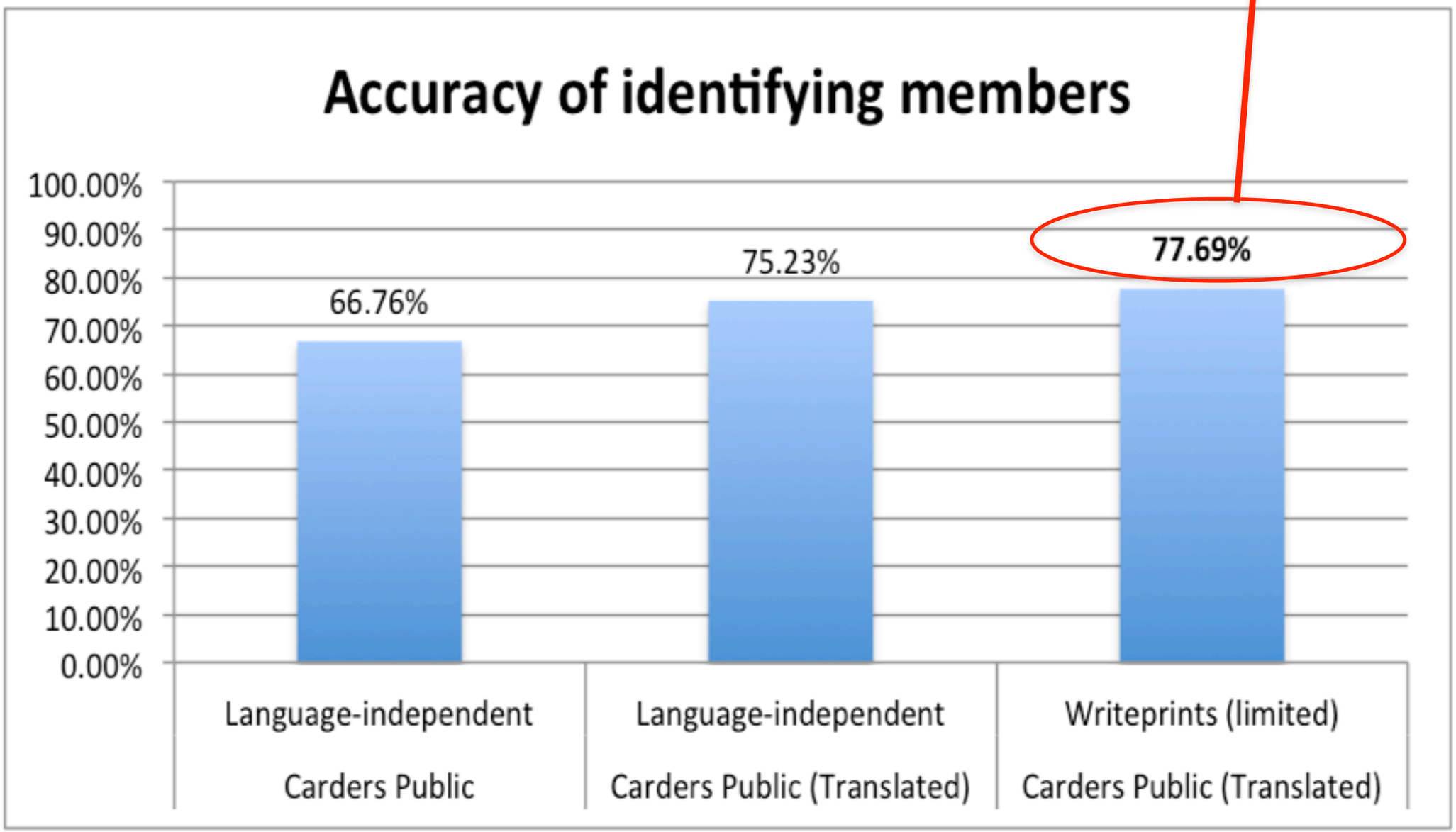
Challenges of multilingual text

- We translated Carders public to see how translation affects the accuracy



Challenges of multilingual text

- Highest accuracy achieved through the translated dataset that used English features



Challenges of translating multilingual text

- Large dataset requires automatic language detection for batch translations
- Low quality translations because of microtext properties

Challenges of multilingual text

- Automatic language detection is hard

Challenges of multilingual text

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Challenges of multilingual text

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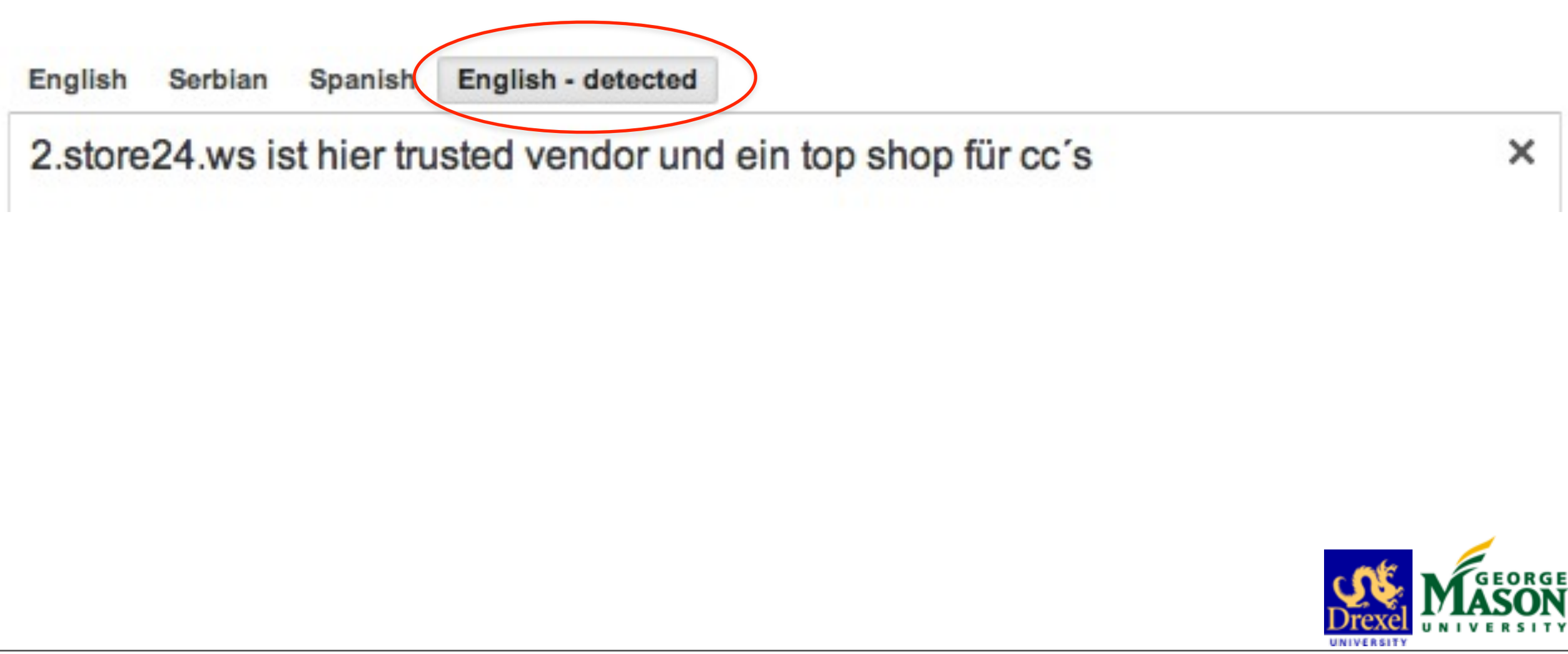

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Challenges of multilingual text

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Challenges of multilingual text

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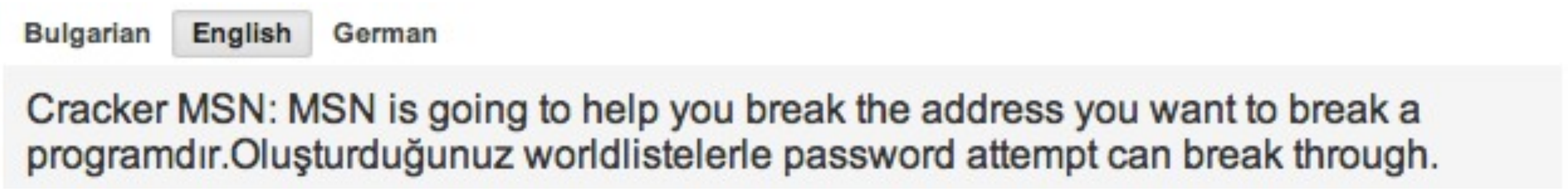
Challenges of multilingual text

- Low quality translations

- Translation:



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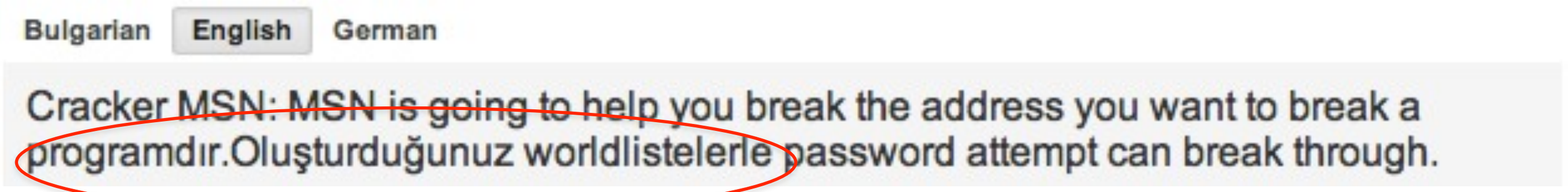
- Translation:



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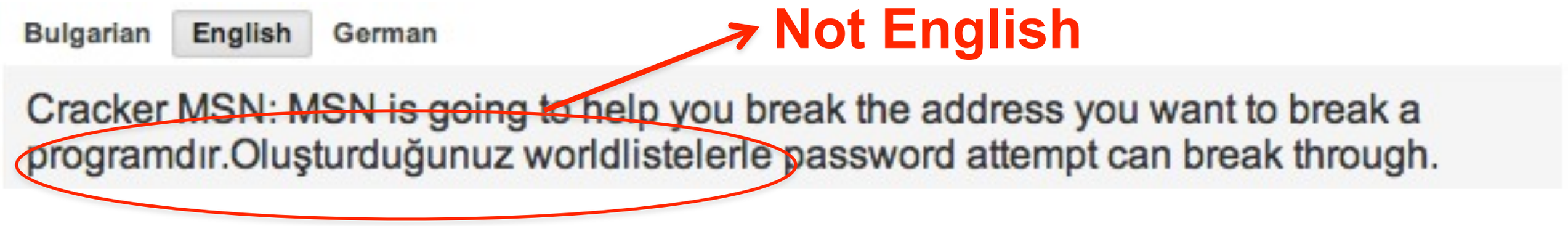

Challenges of product information in text

- Problematic for language independent features such as character n-grams
  - Adds noise to the model for each author
- Messages contain both conversation and product information

Message:
халявщики просыпайтесь..этот раздел не умрет ;) (наверно) :D кто забрал,отпишитесь)
1234;xxxx 1234@rambler.ru
1235;yyyy 1235@rambler.ru
1236;zzzz 1236@rambler.ru

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Conversation

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1236;zzzz 1236@rambler.ru

Conversation

Product information

Challenges of product information in text

- We have this huge dataset

Challenges of product information in text

- We have this huge dataset
- We need to detect products so that we can analyze the conversational text

Challenges of product information in text

- We have this huge dataset
- We need to detect products so that we can analyze the conversational text
- How can you build a method to detect different types of product information

Challenges of product information in text

- We have this huge dataset
- We need to detect products so that we can analyze the conversational text
- How can you build a method to detect different types of product information
- We consider a text pattern that doesn't contain verbs as product information. This is done with a POS-tagger.

Types of products

- Exploits
- Copyright infringement
- Credit cards
- Bank accounts
- E-mail accounts
- Online accounts
- Bankdrops
- Shipping/delivery services
- Drugs

Exploit

```
# Exploit coded by “Alice" and “Bob"
#########################################################
use LWP::UserAgent;
 $ua = new LWP::UserAgent;
 $ua->agent("Mosiac 1.0" . $ua->agent);
if (!$ARGV[0]) {$ARGV[0] = '';}
if (!$ARGV[3]) {$ARGV[3] = '';}
my $path = $ARGV[0] . '/index.php?
act=Login&CODE=autologin';
my $user = $ARGV[1]; # userid to jack
my $iver = $ARGV[2]; # version 1 or 2
....
if (!$ARGV[2])
{print "The type of the file system is NTFS.\n\n";
print "WARNING, ALL DATA ON NON-REMOVABLE DISK\n";
...
```

Copyright infringement

Style: Format: MP3, 160 kbps Size: 50,7 Mb Country: USA

o1. "Flat Line"
o2. "6 6 Sick"
o3. "Addiction" (featuring Zakk Wylde)
o4. "No Regrets"
o5. "My Funeral"
o6. "We Are"
o7. "Dirty World"
o8. "Interlude"
o9. "Violence"
1o. "Best for Me"
11. "Bloodless"
12. "Scorn"
13. "Rebel Yell" (Billy Idol cover)
14. "I Don't Give a..."
15. "Die, Boom, Bang, Burn, F*ck"
16. "Nothing for Me Here"

Download:
http://rapidshare.com/files/123456789/NR-copyrightportal.ru.rar
http://depositfiles.com/files1a2b3c4d5e

Credit Card

DE CCV MasterCard
I Have got here a Master Card Germany checked,
but I can't need it anymore...
*~~*CardholderName:Alice Smith
*~~*FirstName:Alice
*~~*LastName:Smith
*~~*Address:Alice’s Street and number
*~~*ZIP:99999
*~~*City:Alice’s city
*~~*Country:DE
*~~*Phone:12345678900
*~~*Email:alice_smith@xxx.net
*~~*1234123412341234
*~~*012
*~~*0123

Bank Account

Data: Fri Dec 28, 2012 11:11 pm
Login: alice_smith@xxx.net
Parola: Alice’s_password
First Name: Alice
Last Name: Smith
Card Type: Visa
Bank Name: Citigroup Smith Barney
CC Number: 4321432143214321
Month: 01
Year: 2015
CVV2: 215
PIN: 2345

More accounts

==========

Software : Windows Live Messenger
Protocol : MSN Messenger
User : AliceSmith@ggg.de
Password : Alice’s_password

==========

==========

Software : ICQ Lite/2003
Protocol : ICQ
User : 123454321
Password : Alice’s_password

==========

==========

Name : AliceSmith
Application : Hotmail/MSN
Email : AliceSmith@ggg.de
Server :
Type : HTTP
User : AliceSmith
Password : Alice’s_password
Profile :

==========

Online accounts

paypal .....

254/alice_smith1@xxx.net/Alice's_password
253/alice_smith2@xxx.net/Alice's_password
252/alice_smith3@xxx.net/Alice's_password
251/alice_smith4@xxx.net/Alice's_password
250/alice_smith5@xxx.net/Alice's_password
249/alice_smith6@xxx.net/Alice's_password
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241/alice_smith14@xxx.net/Alice's_password
240/alice_smith15@xxx.net/Alice's_password
239/alice_smith16@xxx.net/Alice's_password
238/alice_smith17@xxx.net/Alice's_password
237/alice_smith18@xxx.net/Alice's_password
236/alice_smith19@xxx.net/Alice's_password

Bankdrops

Bankdrop-tutorial

Was wird benötigt?

- Socks/VPN etc.
- 1 Fake Acc (in 2min. erledigt)
- 1 Fake Foto (in 2min. erledigt)
- 1 Fake E-Mail (in 2min. erledigt)
- Briefkastendrop

Shipping/Delivery Services

Once we recieve note of order your selected equipment will be shipped to your indicated address no longer than 2-3 working days you will recieve an email with shipping track and trace.

To place order email below.
Email:alice_smith@xxx.net
ICQ support:123*123*123 or 321*321*321
SKIMMER PACKAGES AND PRICE LIST
SKIMMERS SOLD SEPRATELY

Atm Model:
Diebold / Wincor / Ncr (skimmer only)
Type:USB
Price:$2000

Atm Model:
Diebold / Wincor / Ncr (skimmer only)
Type:Bluetooth
Price:$2500

Skimmer that looks like anti-skimming device

Drugs

Message:
Verified Vendor of **Weed**
Thread: [url]http://www.carders.cc/forum/threads/12345-Alice´s-**Weed**-Store-Verified-Vendor-[/url])
Profil: [url]http://www.carders.cc/forum/members/1234-Alice[/url]

Message:
Intresse an **Drug Store** ?
weed
pep
mdma

Challenges caused by users with multiple accounts

- Same user with different IP and e-mail address opens multiple accounts to avoid being banned

Challenges caused by users with multiple accounts

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- Difficult to identify multiple account holders

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Challenges caused by users with multiple accounts

- Same user with different IP and e-mail address opens multiple accounts to avoid being banned
- Difficult to identify multiple account holders
- In supervised learning, we consider them as different users
- Authorship attribution classification accuracy and social connection graphs suffer due to this lack of ground truth

Limitations

- The required text length is 5000 words

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- Forums with less well known languages anticipated

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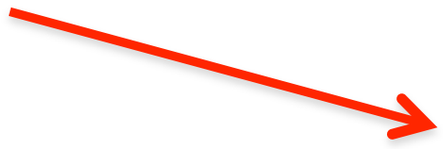
  - False-positive product detection:

Msn Piç : Sinir olduğunuz insanlara ister kendi zevkiniz ister programda bulunan küfürleri yollayabilirsiniz.Sizden fazla hızlı küfür edemez :)

Limitations

- The required text length is 5000 words
- Forums with less well known languages anticipated
- Separate conversational data from product information for better stylometric analysis
  - Our method worked well but needs improvements
- False-positive product detection:

Msn Piç : Sinir olduğunuz insanlara ister kendi zevkiniz ister programda bulunan küfürleri yollayabilirsiniz.Sizden fazla hızlı küfür edemez :)



Not a product

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Future work

- Use more user-specific features and temporal information

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- Completely automate the process of identifying users with sufficient text from the datasets and perform topic and authorship analysis

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JStylo

Our authorship attribution framework,
powered by JGAAP and WEKA

Released in 28C3:

http://events.ccc.de/congress/2011/Fahrplan/events/4781.en.html

Anonymouth

Our authorship anonymization framework, powered by JStylo

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- Assists the user making necessary changes accordingly

https://github.com/psal/JStylo-Anonymouth

JStylo + Anonymouth = JSAN
OPEN SOURCE IN GIT

https://psal.cs.drexel.edu/index.php/JStylo-Anonymouth

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