Spam Campaign Detection, Analysis, and Investigation

By

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SPAM CAMPAIGN

DETECTION, ANALYSIS AND INVESTIGATION

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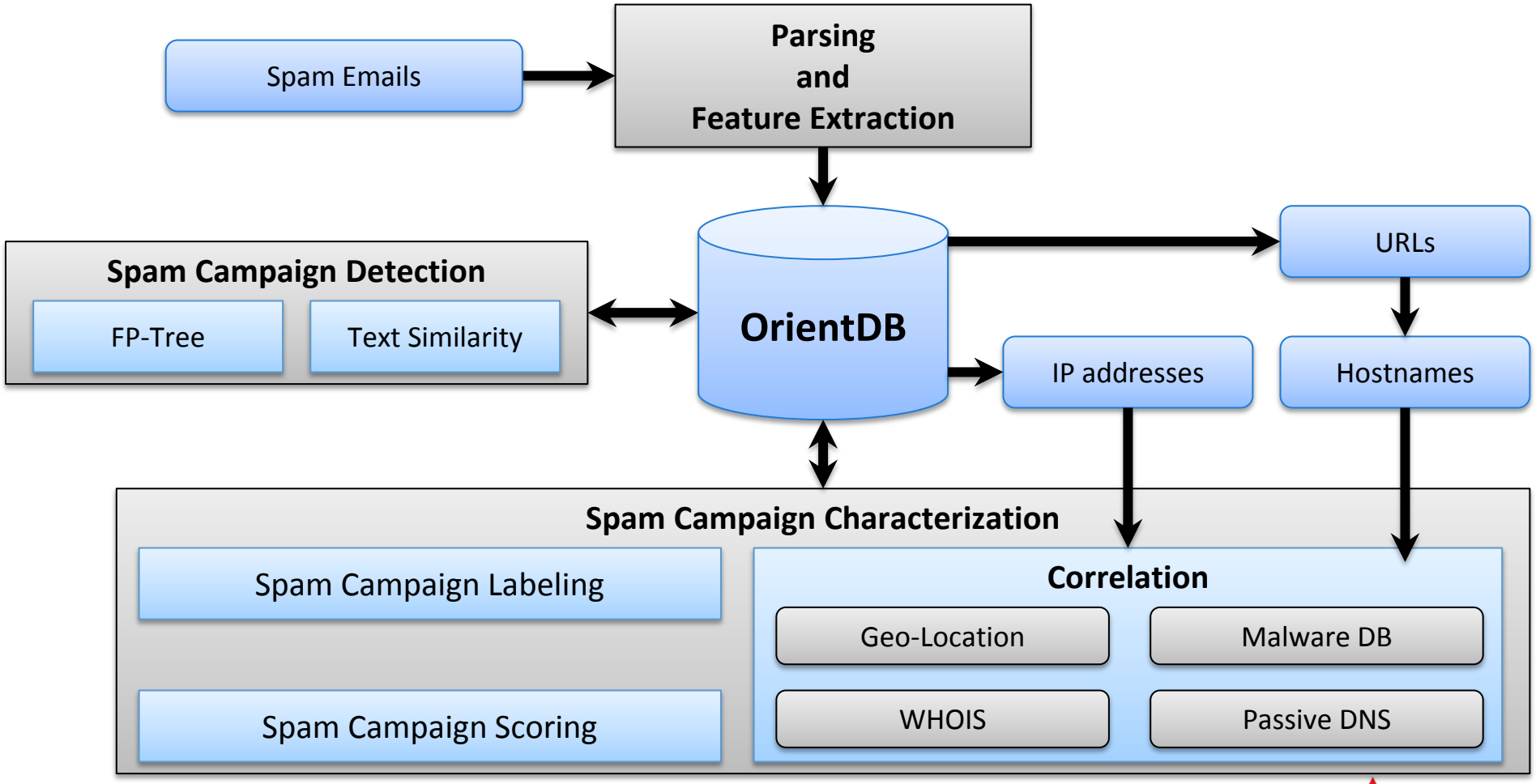
Outline

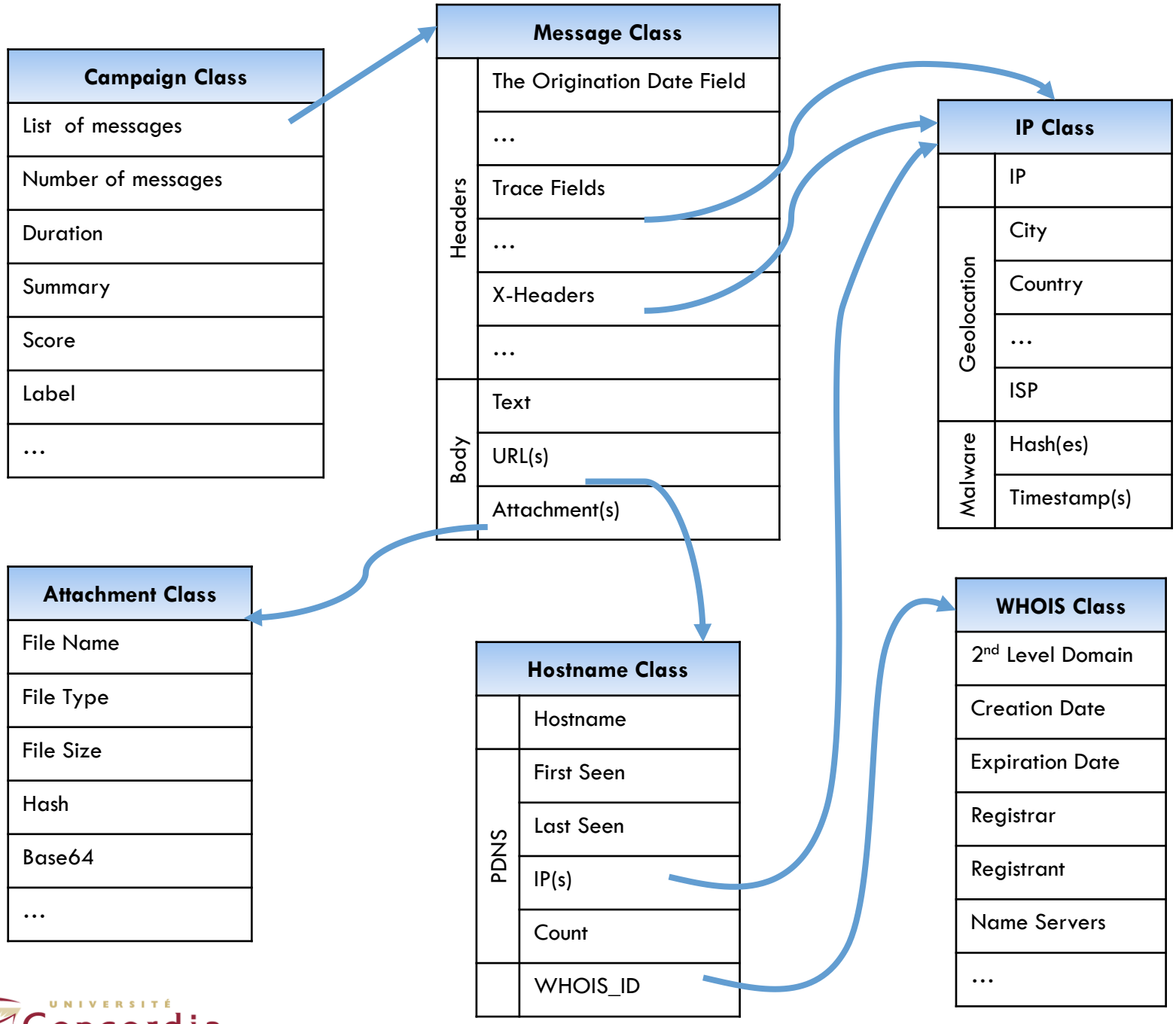
- Architecture
- Central Database
- Parsing and Feature Extraction
- Spam Campaign Detection
- Spam Campaign Characterization
- Results

Architecture



Central Database

- Relational database management system (RDBMS)
- The number of spam emails exceeds 6 *trillion* in Q4 2014
  - McAfee Labs Threats Report (February 2015)
- OrientDB:
  - Flexibility (document database)
  - Interconnectivity (graph database)
  - Scalability
- Documents: spam campaigns, emails, IP addresses, domain names, attachments
- Connections and interconnections between spam campaigns, emails, IP addresses, domain names and attachments



Preprocessing

Parsing and Feature Extraction

- Parser
  - Parse and store standard header fields (RFC5322)
  - Unpack email bodies (single-part or multi-part)
  - Extract embedded URLs
- Feature Extractor
  - Content Type
    - text/*
    - multipart/*
    - image/*
    - application/*
    - etc.
  - Character Set
    - utf-8
    - iso-8859-1
    - windows 1250
    - shift-jis
    - koi8-r
    - etc.
  - Subject
    - Decoded to Unicode
  - URL Tokens
  - Attachment

Parsing and Feature Extraction

- Feature Extractor
  - Email Layout

- text layout
  - T for a paragraph with only text
  - U for a URL
  - N for an empty line
  - For example:

    TNTNUNN

- HTML layout
  - Top levels of the DOM tree
  - For example:

```
<html>
-<head>
-</head>
-<body>
--<p></p>
--<br />
--<div></div>
-</body>
<html>
```

- multipart layout
  - The structure of the multipart email
  - For example:

```
multipart/mixed
-multipart/alternative
--text/plain
--multipart/related
---text/html
---img/jpg
-application/pdf
```

Detection & Characterization

Spam Campaign Detection

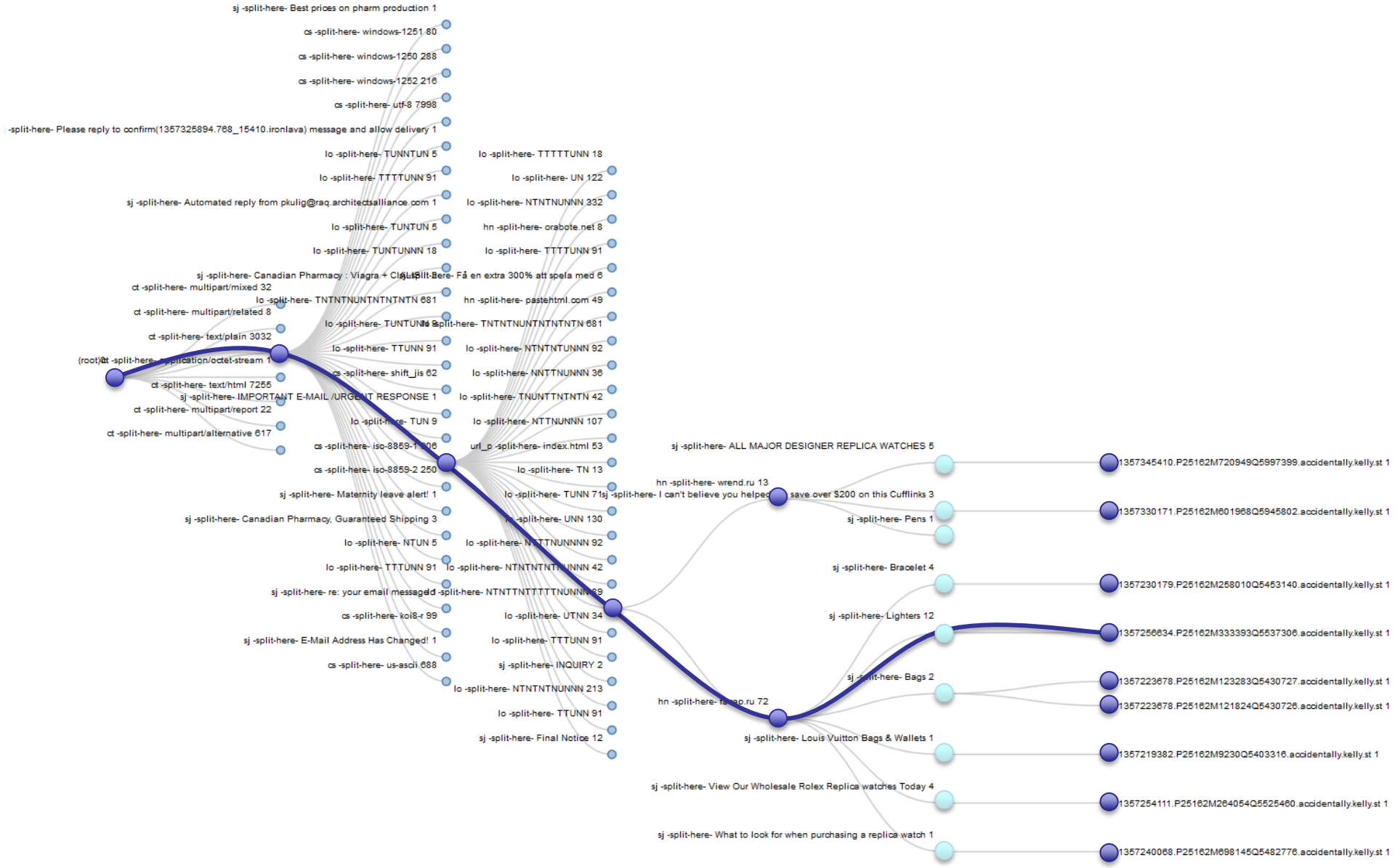
- Distance between two spam emails:
  - w-shingling and the Jaccard coefficient
  - Context Triggered Piecewise Hashing (CTPH)
  - Locality-Sensitive Hashing (LSH)
- Hierarchical, partitional, neural network-based, kernel-based clustering techniques
- Problems:
  - Scalability
  - Obfuscation techniques
    - Spam email templates
    - Randomly picked paragraphs from books or Wikipedia articles
    - Randomly generated subdomains and fast-flux service networks

Spam Campaign Detection

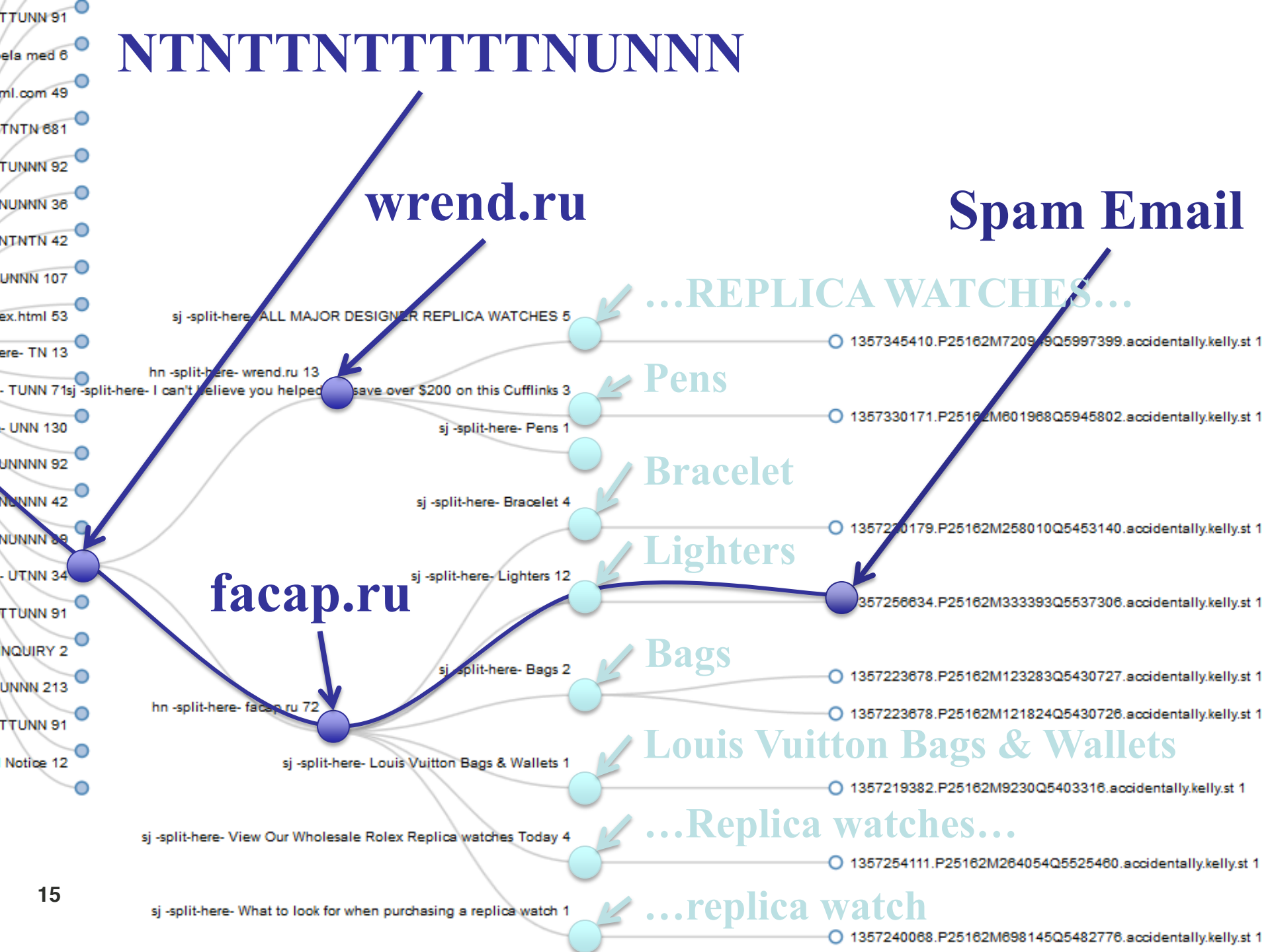
- Frequent-Pattern Tree (FP-Tree)
  - The more frequent a feature is, the more it is shared among spam emails
  - Less frequent features correspond to the obfuscated parts
  - Two scan of the dataset:
    - First scan to compute the number of occurrences for each feature
    - Second scan to insert feature vectors into the tree
  - The cost of inserting a feature vector fv into the FP-Tree is $O(|fv|)$, where $|fv|$ is the number of features in fv.
  - The **Content Type** feature is put at the beginning of each feature vector
  - The unique ID of each email is kept at the end of each feature vector
  - Embedded URLs are split into tokens

Spam Campaign Detection

- Spam Campaign Identification
  - Traverse the tree
  - Conditions:
    - The number of children >= `min_num_children`
    - The average count of children >= `freq_threshold`
    - The path to root must contain **one** feature type not in `n_obf_features`
    - The number of leaves of the sub-tree >= `min_num_messages`
  - If a node satisfies the conditions:
    - The leaves of the sub-tree are spam emails from the same campaign
    - The path from the root to this node contains the common features
    - The sub-tree is then removed from the tree




text/plain
root
iso-8859-1
NTNTTNTTTTTTNUNNN
(root)
ct -split-here- application/octet-stream 1
ct -split-here- multipart/alternative 617
ct -split-here- multipart/mixed 32
ct -split-here- multipart/related 8
ct -split-here- multipart/report 22
ct -split-here- text/html 7255
ct -split-here- text/plain 3032
cs -split-here- iso-8859-1 306
cs -split-here- iso-8859-2 256
cs -split-here- koi8-r 99
cs -split-here- shift_jis 62
hn -split-here- pastehtml.com 49
lo -split-here- NNTTNUNNN 36
lo -split-here- NTNTNTUNNN 42
lo -split-here- NTNTNTUNNN 92
lo -split-here- NTTNUNNN 107
lo -split-here- NTTTNUNNNN 92
lo -split-here- TN 13
lo -split-here- TNUNTTNTNTN 42
lo -split-here- TTTTUNN 91
lo -split-here- TUNN 71sj -sp
lo -split-here- TUNTUNNN 18
lo -split-here- TTTUNN 91
lo -split-here- TNTNTNUNTNTNTNTN 681
lo -split-here- TTUNN 91
lo -split-here- TUNTUNN 8
lo -split-here- TN 9
lo -split-here- UNN 130
lo -split-here- UTNN 34
sj -split-here- Canadian Pharmacy : Viagra + Cialis
sj -split-here- Få en extra 300% att spela med 6
sj -split-here- Maternity leave alert! 1
sj -split-here- Canadian Pharmacy, Guaranteed Shipping 3
sj -split-here- re: your email messageId
id -split-here- NTNTTNTTTTTTNUNNN 89


NTNTTNTTTTTTNUNNN
wrend.ru
Spam Email
facap.ru
TTUNN 91
eela med 6
ml.com 49
TNTN 681
TUNNN 92
NUNNN 36
NTNTN 42
UNNN 107
ex.html 53
ere- TN 13
- TUNN 71
- UNN 130
UNNNN 92
NUNNN 42
NUNNN 89
- UTNN 34
TTUNN 91
NQUIRY 2
UNNN 213
TTUNN 91
Notice 12
sj -split-here- ALL MAJOR DESIGNER REPLICA WATCHES 5
hn -split-here- wrend.ru 13
sj -split-here- I can't believe you helped save over $200 on this Cufflinks 3
sj -split-here- Pens 1
sj -split-here- Bracelet 4
sj -split-here- Lighters 12
sj -split-here- Bags 2
hn -split-here- facap.ru 72
sj -split-here- Louis Vuitton Bags & Wallets 1
sj -split-here- View Our Wholesale Rolex Replica watches Today 4
sj -split-here- What to look for when purchasing a replica watch 1
…REPLICA WATCHES…
Pens
Bracelet
Lighters
Bags
Louis Vuitton Bags & Wallets
…Replica watches…
…replica watch
1357345410.P25162M720949Q5997399.accidentally.kelly.st 1
1357330171.P25162M601968Q5945802.accidentally.kelly.st 1
1357220179.P25162M258010Q5453140.accidentally.kelly.st 1
1357256634.P25162M333393Q5537306.accidentally.kelly.st 1
1357223678.P25162M123283Q5430727.accidentally.kelly.st 1
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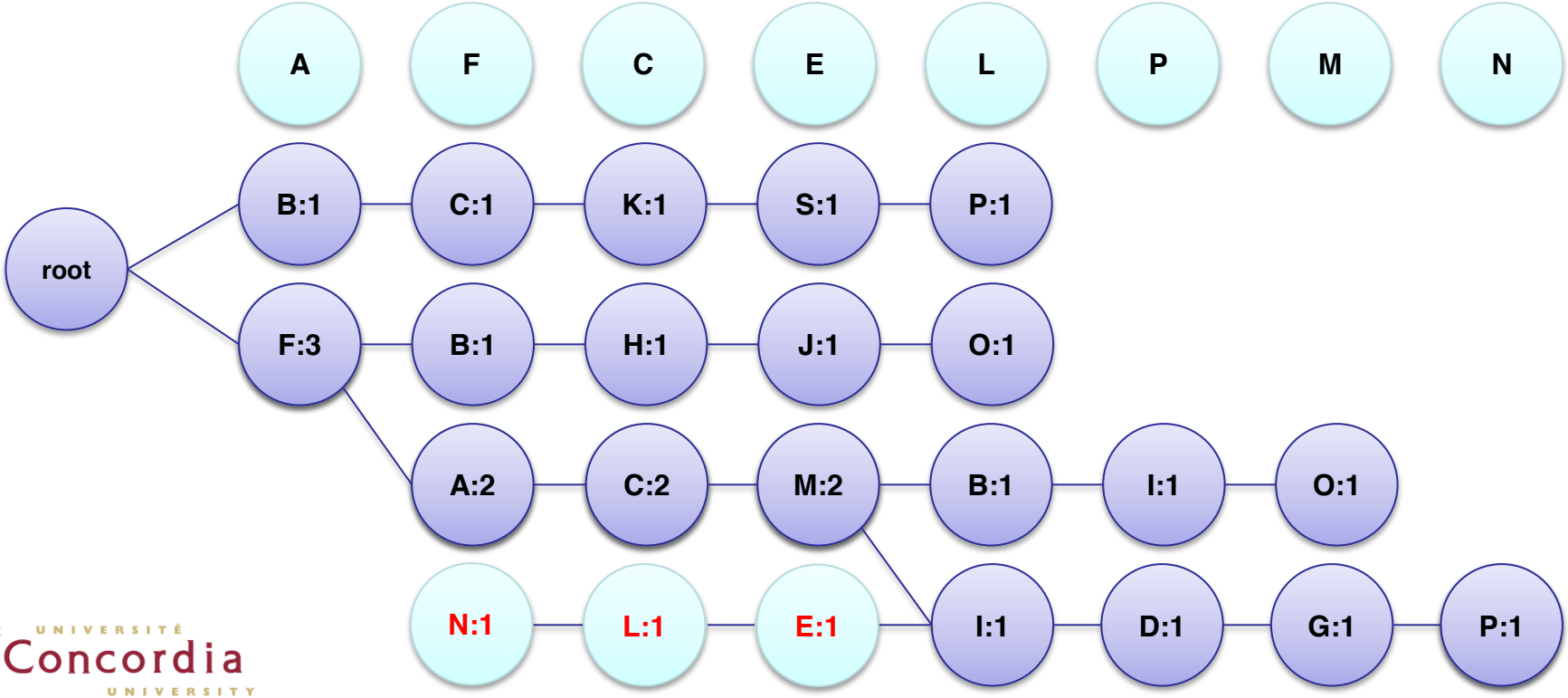
1357219382.P25162M9230Q5403316.accidentally.kelly.st 1
1357254111.P25162M264054Q5525460.accidentally.kelly.st 1
1357240068.P25162M698145Q5482776.accidentally.kelly.st 1

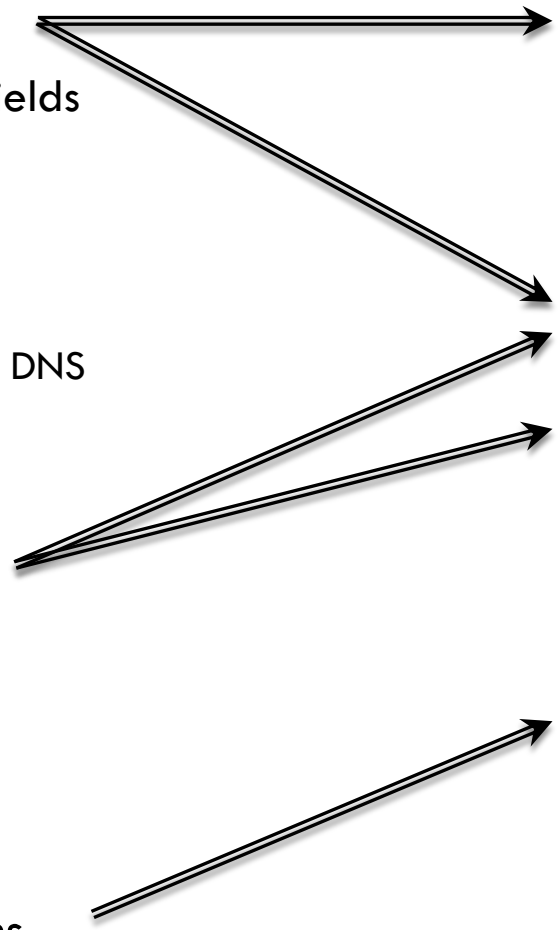
Spam Campaign Detection

- Incremental Frequent-Pattern Tree
  - Spam campaigns may last for a long period of time and therefore should be identified in their early stage
  - Feature vectors are extracted as soon as spam emails arrive and are inserted into the FP-Tree from the root level



Spam Campaign Characterization

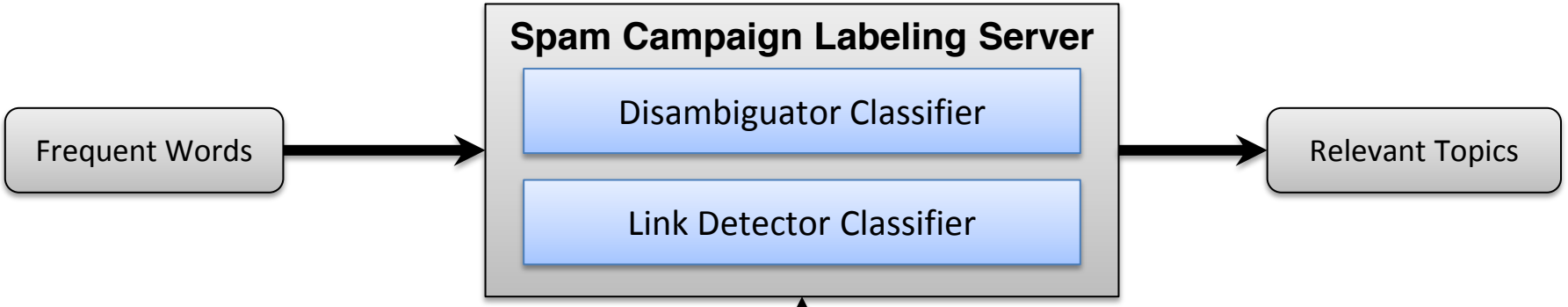
- IP addresses
  - From header fields
    - Received
    - X-*
  - From URLs
    - using passive DNS
- Hostnames
  - From URLs
- 2nd-level domains



- Geo-Location
  - City, Country
  - ISP
  - Organization
- Malware Database
- Passive DNS
  - Timeslot (First/Last seen)
  - IP address(es)
  - Count
- WHOIS
  - Name servers
  - Domain status
  - Creation date
  - Expiration date
  - Registrar & registrant

Spam Campaign Characterization

- Spam Campaign Labeling



Disambiguator Classifier

- Solves the issue of ambiguous terms
- Chooses the most suitable Wikipedia article for each term

Link Detector Classifier

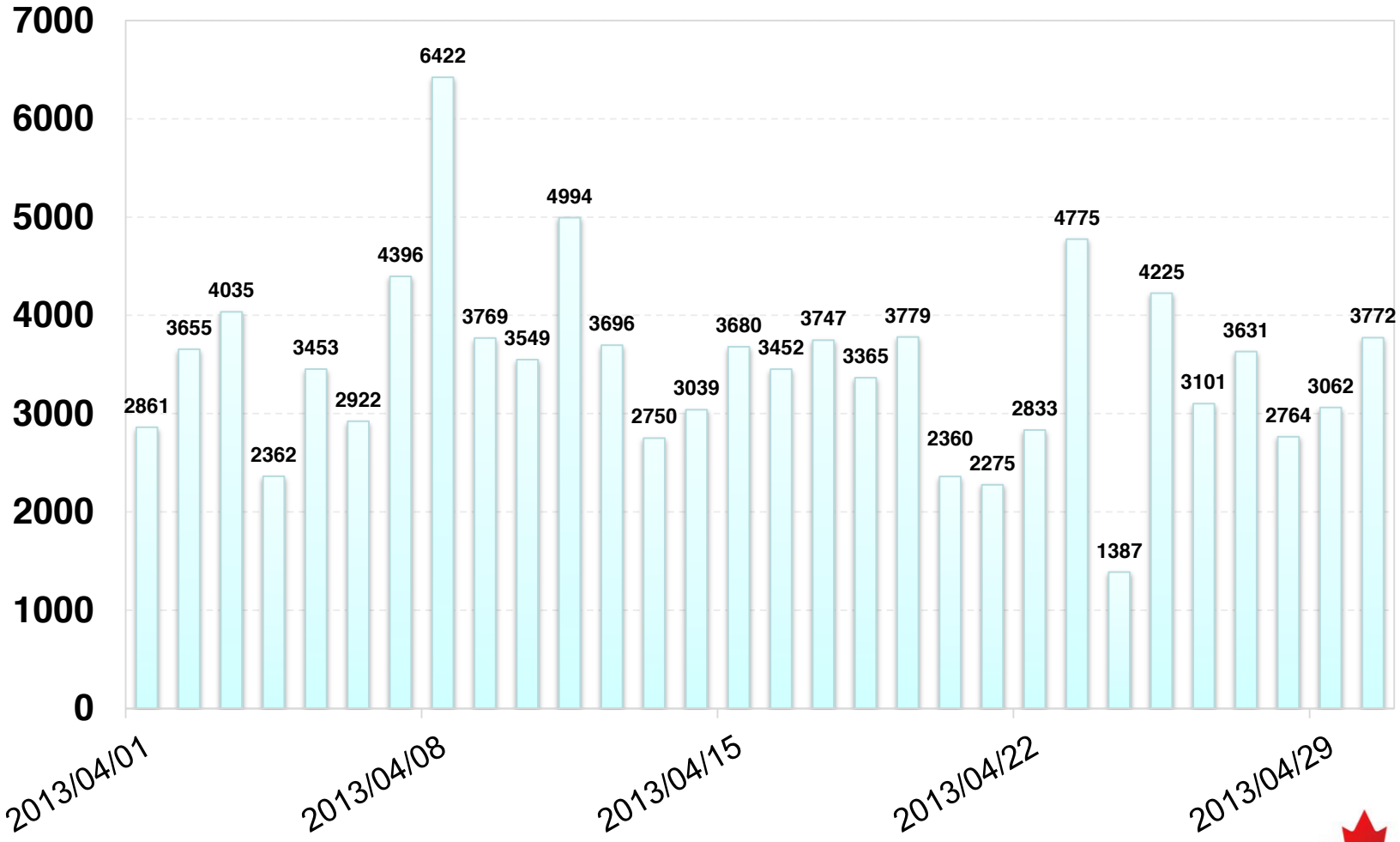
- Selects sufficiently relevant associations between terms and Wikipedia articles to retain

Spam Campaign Characterization

- Spam Campaign Scoring
  - An investigator may only need to pursue a particular objective
  - Each spam campaign is assigned a score computed using:
    - The number of spam emails inside a campaign
    - The number of IP addresses in Canada
    - The number of domain names that are resolved to IP addresses in Canada
    - The number of ".ca" TLDs that appear in the from field
    - The number of ".ca" TLDs that appear in the embedded URLs
    - The number of Canadian city names that appear in the content
    - The number of appearances of the string "Canada" in the content
    - The number of IP addresses that are associated with malware
    - The number of IP addresses that belong to a specific IP range
  - Each criterion has a customizable weight
  - The criteria have been verified by a law enforcement official

Results

Spam Data


7000
6000
5000
4000
3000
2000
1000
0
2861
3655
4035
2362
3453
2922
4396
6422
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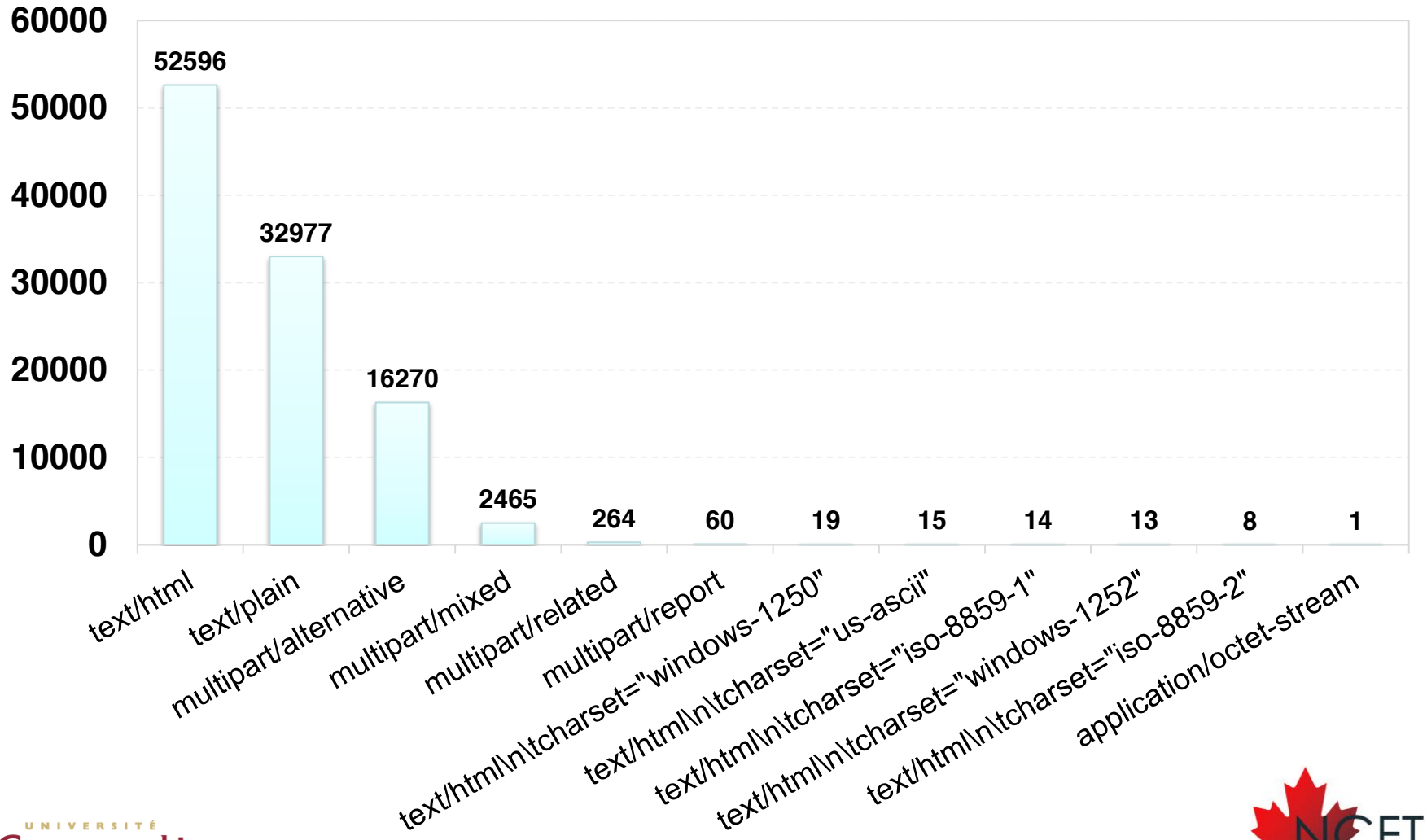
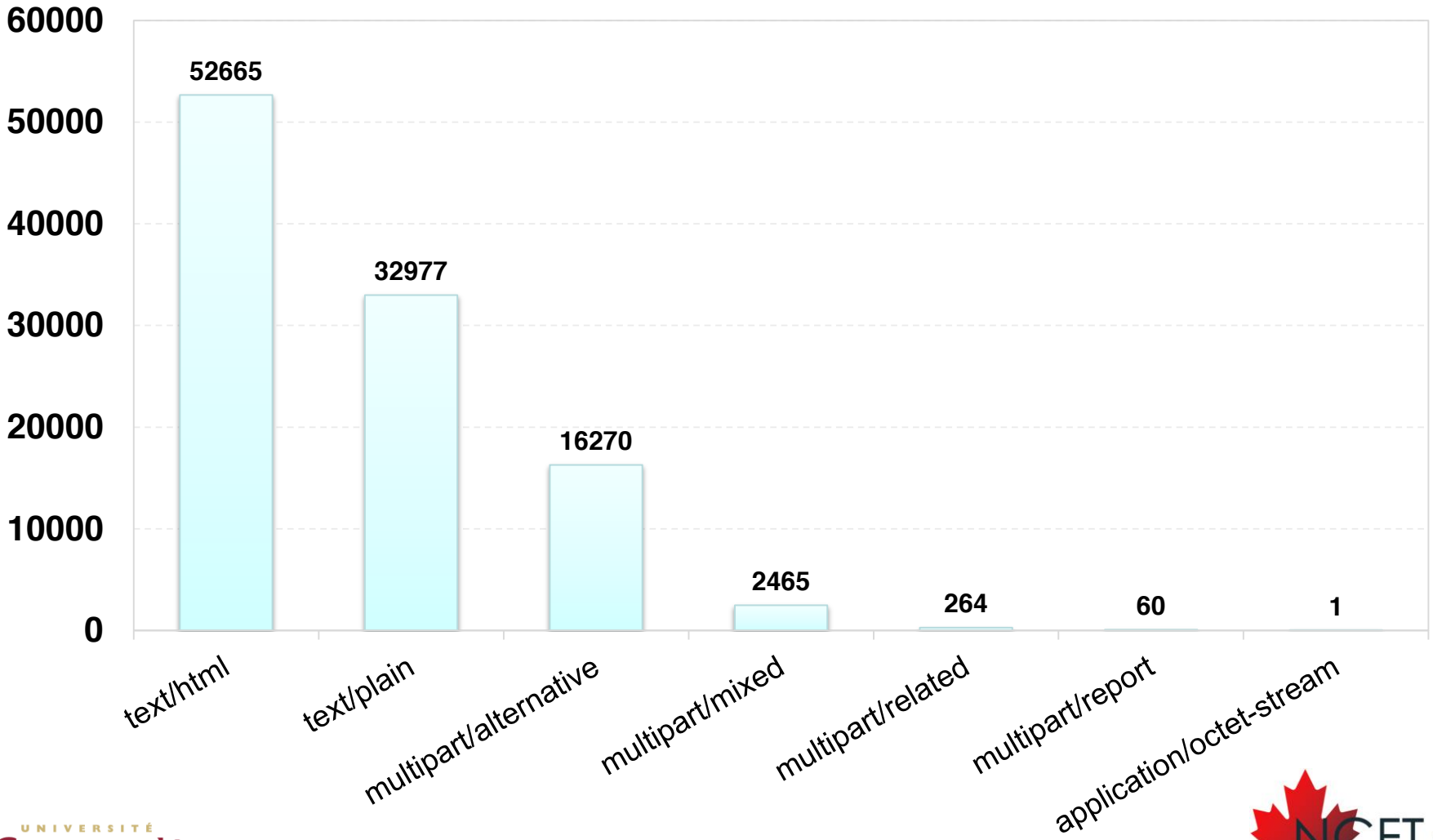
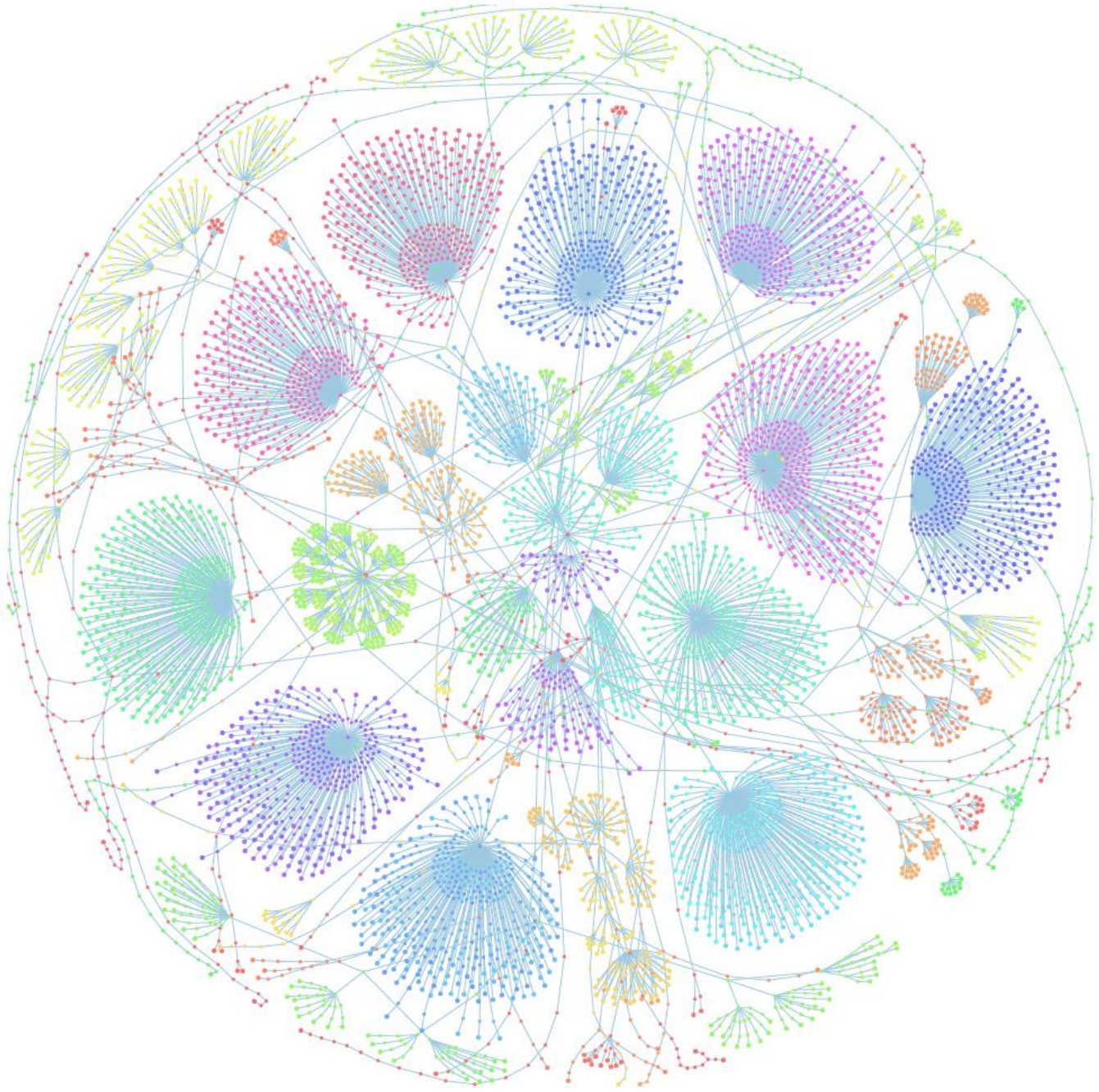
3549
4994
3696
2750
3039
3680
3452
3747
3365
3779
2360
2275
2833
4775
1387
4225
3101
3631
2764
3062
3772
2013/04/01
2013/04/08
2013/04/15
2013/04/22
2013/04/29

Raw MIME Types



Correct MIME Types





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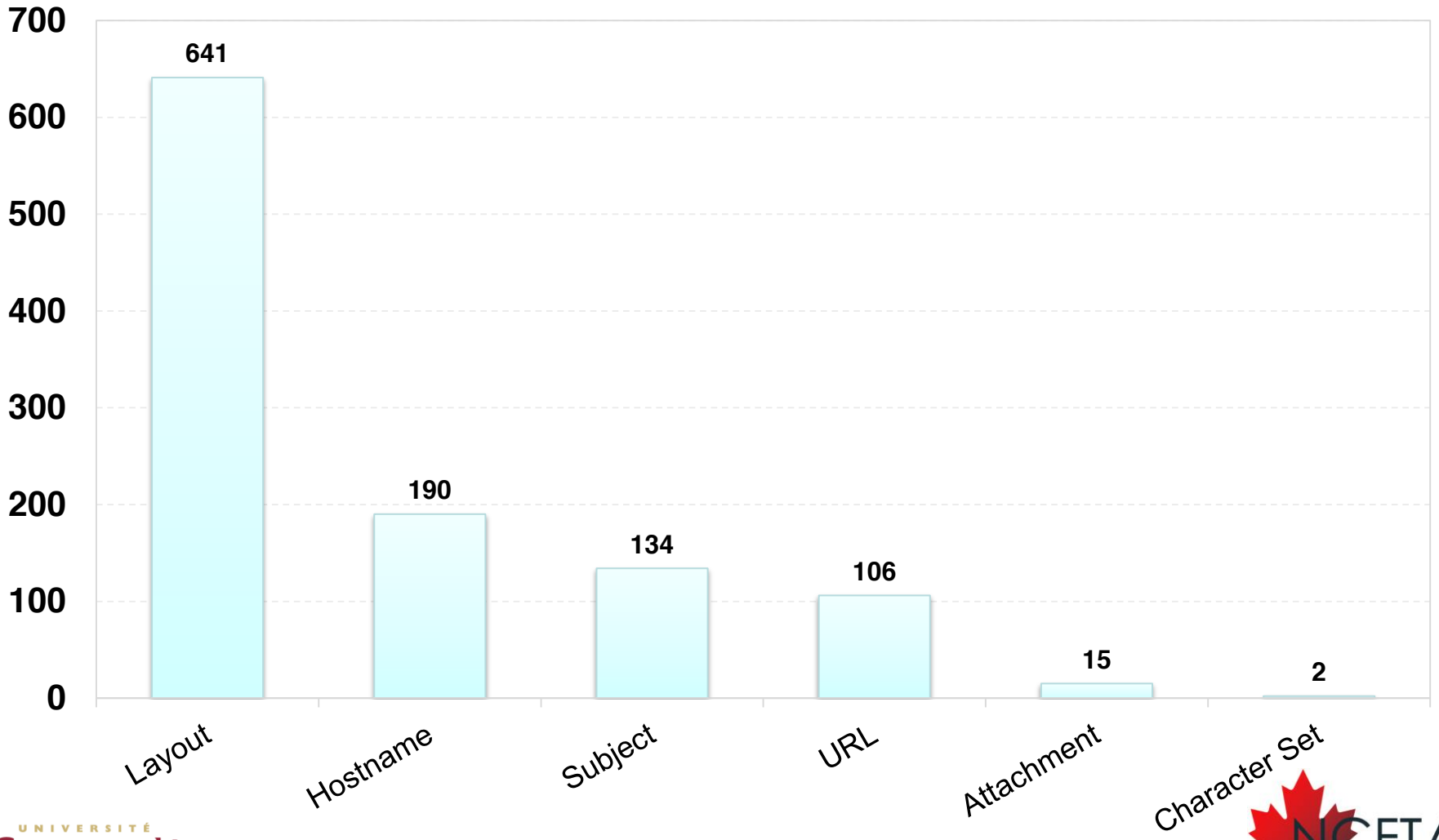
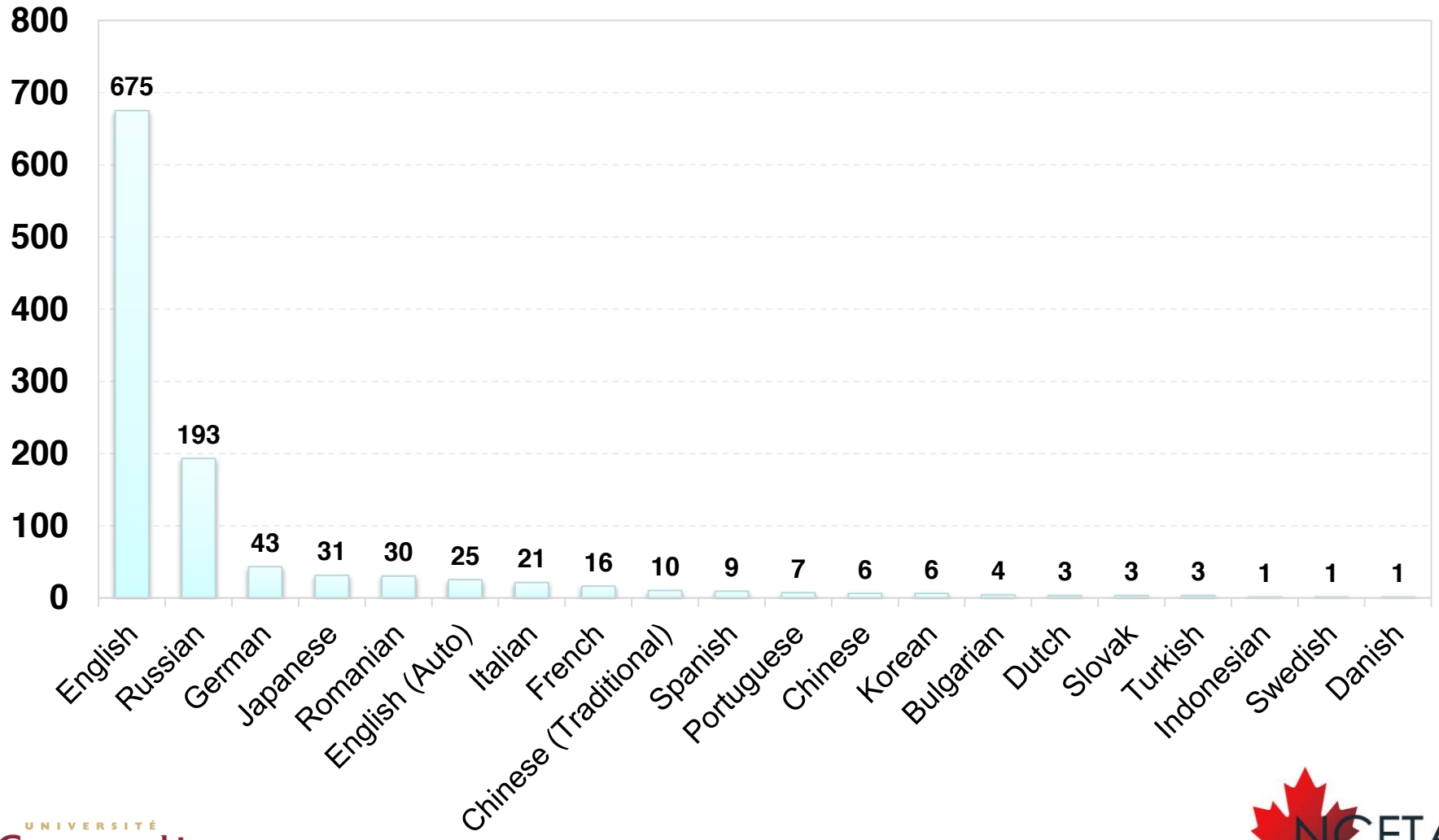
National Cyber-Forensics and Training Alliance CANADA

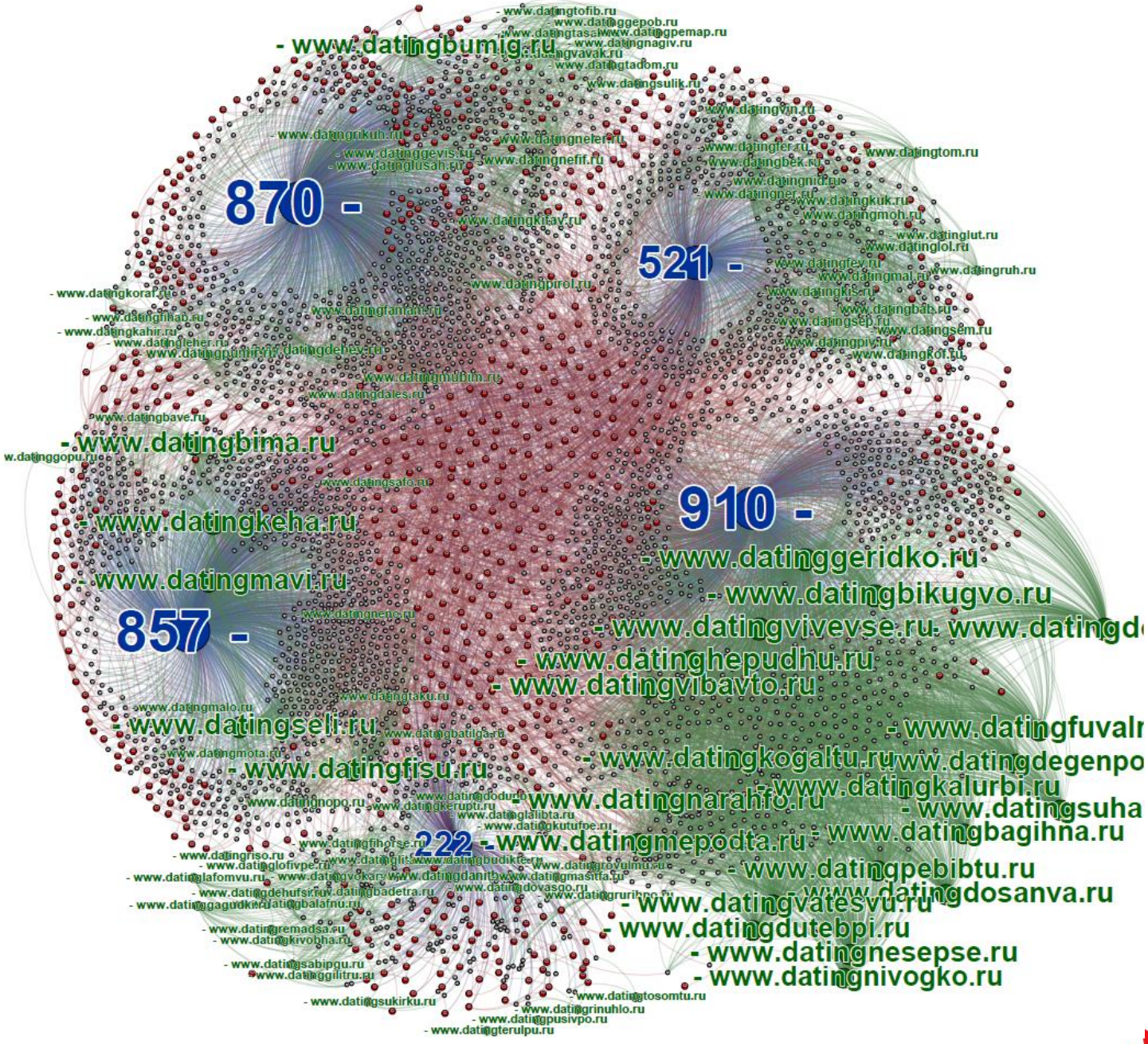
Decisive Features

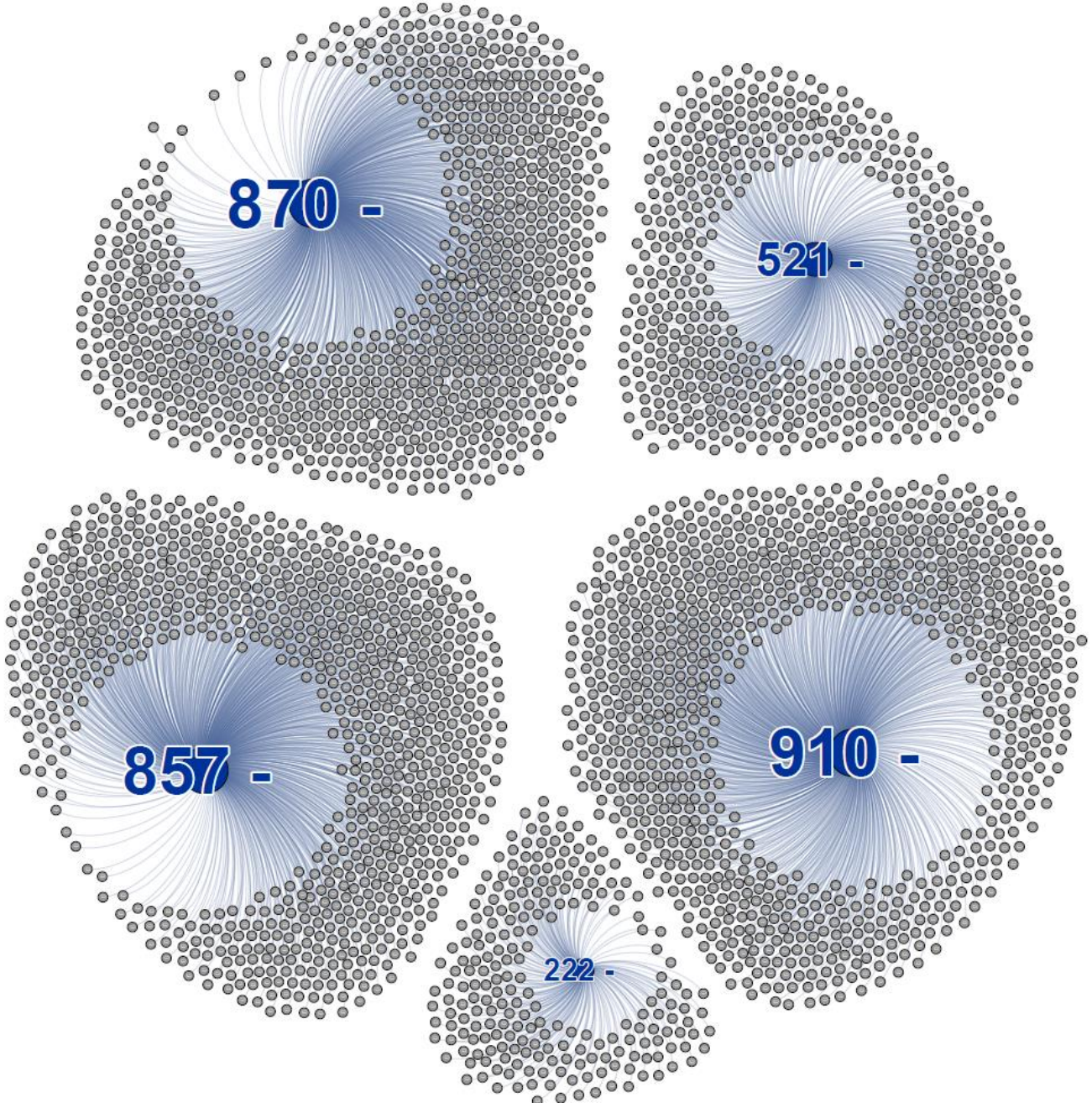


Spam Campaign Languages



Spam Campaign Topics





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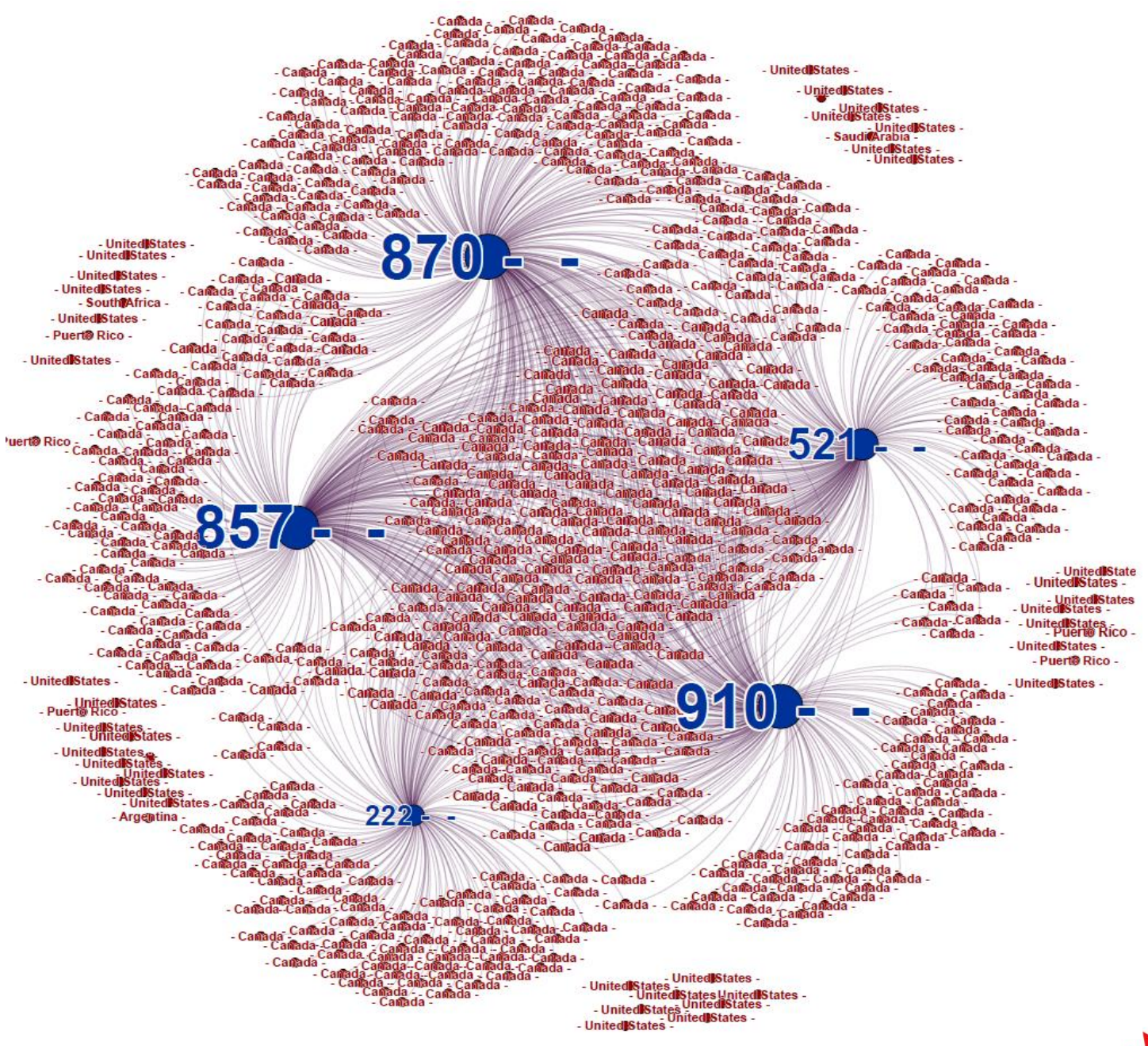
870
857
521
910
222

Conclusions

- Spam:
  - Still a serious threat itself
  - An instrument for other cyber attacks
- A spam campaign detection, analysis and investigation system that:
  - Identifies spam campaigns (on-the-fly)
  - Aggregates different data sources to expose campaign characteristics
  - Labels spam campaigns
  - Scores spam campaigns
- Future work:
  - Improve spam campaign labeling (more suitable for spam contents)
  - Spam campaign categorization (threat-based)

Acknowledgements

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- Canadian Radio-television Telecommunications Commission (CRTC)