URL Classification using Bag of Features (BoF) of URL bitstream

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Outstanding AI works

• In recent years, AI, more specifically, Deep Learning (DL), is getting notable attention.

• Especially in media recognition fields, such as image, voice recognition, etc.

• Some researchers are also trying to apply DL in different fields (e.g. factory robots, games, etc).

• Back to our works, are we getting a benefit from AI technologies?
Difficulties

- DL (or Machine Learning (ML) also) requires information to be converted into vectors
- We call it as a feature vector
- Designing the model of the feature vector requires deep knowledge of the target information domains
Why is DL so hot?

- Because recent DL applications don’t require to extract features manually
- A neural network learns which parts of information are important from a lot of examples
- For example, we can just throw the binary photo data into a neural network and that’s it
- Well, it is not that simple, anyway :)}
What we are

We are not good at feature extraction

We have computers

Don’t think. Just try

We’ve established the Muscle Learning (ML) team in WIDE
What we try to achieve

• We are thinking if we can apply the similar approach used for image recognition to network information

• Just put (almost) raw data and let the machines extract features

• No need to achieve domain specific deep knowledge before analyzing
Back to URLs

- Phishing is one of the major techniques to steal personal information
  - 1,220,523 attacks were reported in 2016 (*1)

- There are several services to defend
  - URL whitelisting
  - Contents investigation

URL features?

• Challenges

  • Is there any hidden features in the URL strings used for phishing sites?

  • Is it possible to distinguish “white” URLs and “black” URLs by just looking at the URL strings?

• We try to vectorize URLs to use as input information of ML methods without any specific domain knowledge
How to vectorize?

www.iij.ad.jp/index.html

[Split characters]

www.iij.ad.jp/index.html

[Convert the URL into HEX values]

7777772E69696A2E61642E6A703F696E6465782E68746D6C

[Extract 8-bits values by shifting 4 bits in the HEX values]

77,77,77,77,77,72,2E, 3F,F6,69,96,6E,E6,64, E6,69,96,69,96,6A,A2, 46,65,57,78,82,2E,E6, 2E,E6,61,16,64,42,2E, 68,87,74,46,6D,D6,6C E6,6A,A7,70

Count the number of unique values for the host part and the URL path part respectively (Bag of features)
How to vectorize?

<table>
<thead>
<tr>
<th>256 dimensional sparse vector</th>
</tr>
</thead>
<tbody>
<tr>
<td><a href="http://www.iij.ad.jp">www.iij.ad.jp</a></td>
</tr>
<tr>
<td>16 → 1 2E → 3</td>
</tr>
<tr>
<td>42 → 1 61 → 1</td>
</tr>
<tr>
<td>64 → 1 69 → 2</td>
</tr>
<tr>
<td>6A → 2 70 → 1</td>
</tr>
<tr>
<td>72 → 1 77 → 5</td>
</tr>
<tr>
<td>96 → 2 A2 → 1</td>
</tr>
<tr>
<td>A7 → 1 E6 → 3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>index.html</th>
</tr>
</thead>
<tbody>
<tr>
<td>2E → 1 46 → 1</td>
</tr>
<tr>
<td>57 → 1 65 → 1</td>
</tr>
<tr>
<td>68 → 1 6C → 1</td>
</tr>
<tr>
<td>6D → 1 74 → 1</td>
</tr>
<tr>
<td>78 → 1 82 → 1</td>
</tr>
<tr>
<td>87 → 1 D6 → 1</td>
</tr>
<tr>
<td>E6 → 1</td>
</tr>
</tbody>
</table>

| 512 dimensional sparse vector |

www.iij.ad.jp and index.html both produce 256 dimensional sparse vectors, while the combination of both produces a 512 dimensional sparse vector.
Neural network topology

A 512 dimensional vector generated from a URL string

Linear mapping to 256 nodes

Linear mapping to 256 nodes

Reduction to 2 nodes

Loss calculation
Classify using the neural network

- Datasets
  - 26722 “black” URLs downloaded from www.phishtank.com which are active phishing site URLs as of 2017-4-24
  - 175290 “white” URLs captured at a research network

- Method
  - Convert all the URLs into vectors and shuffle them
  - 10% of them were used for the DNN training and the rest were used for validation
Accuracy and Loss

(a) Our method (optimizer = Adam)
Related Work


The neural network topology of eXpose
The neural network topology of eXpose

A URL string (200 characters at max)

Convert each character into a 32 dimensional vector
The neural network topology of eXpose

Convolution using 4 different sizes to make 256 nodes for each (1024 nodes in total)
The neural network topology of eXpose

Perform 1024 to 1024 linear mapping 3 times
The neural network topology of eXpose

Finally reduce the node into 2 nodes

OK, great
Comparison with the same dataset

(a) Our method (optimizer = Adam)

(b) eXpose (optimizer = Adam)
Summary

- We are trying to utilize Deep Learning technologies for network information

- The goal is to provide better vectorization mechanisms for network data that don’t require any domain specific knowledge

- The proposed URL vectorization works with some limited sets of data, but can be improved more

- We will explore further