Classification of URL Bitstreams using Bag of Bytes

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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
- The vector is called as a feature vector
- Designing the model of a 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 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

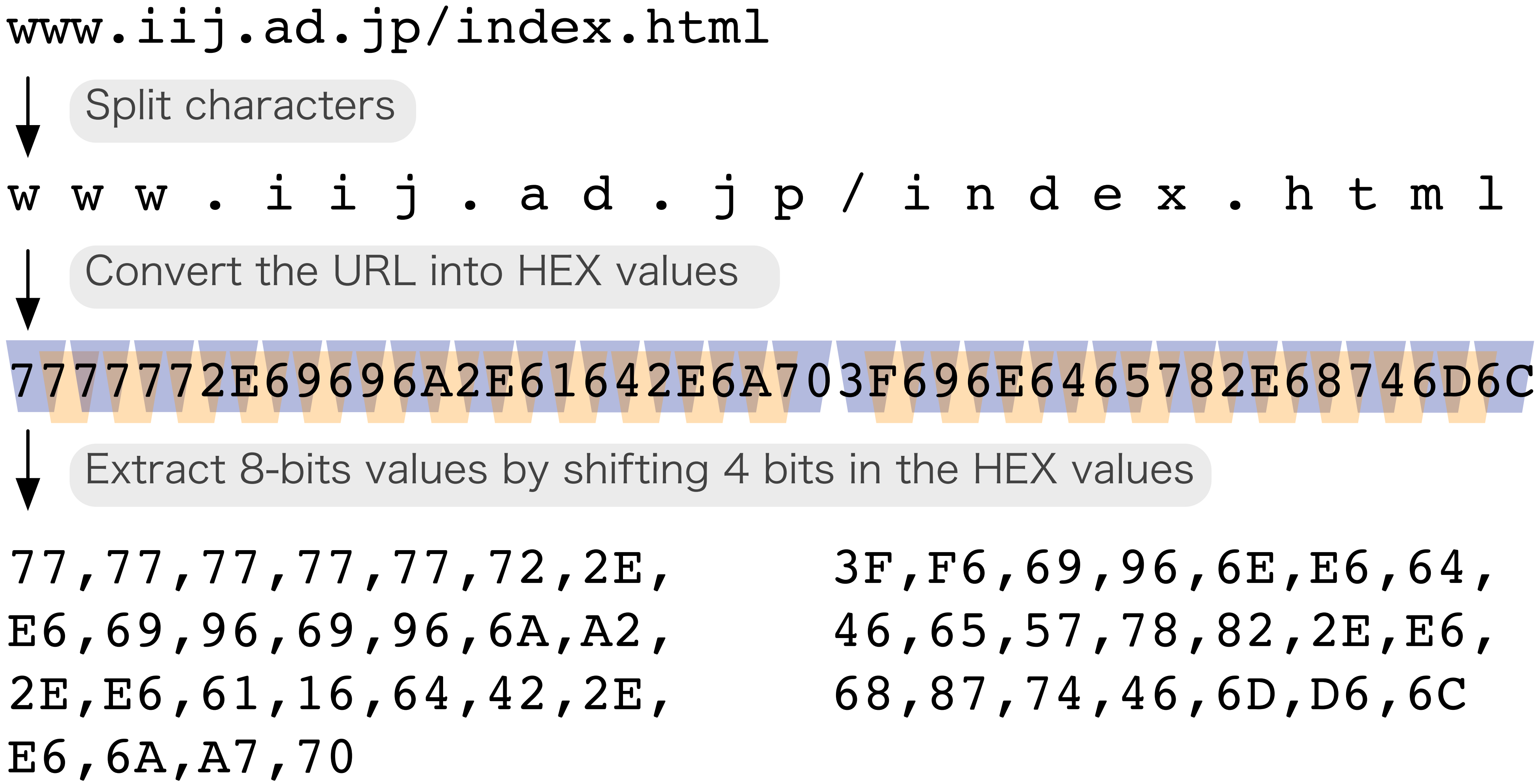
- Phishing is one of the major techniques to steal personal information
    - 1,220,523 attacks were reported in 2016 (*1)
- There exists several services (products) to defend them
    - URL whitelisting
    - Contents investigation

(*1) Anti Phishing WG report: http://docs.apwg.org/reports/apwg_trends_report_q4_2016.pdf

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

```
w w w . i i j . a d . j p / i n d e x . h t m l
```

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?

`www.iij.ad.jp`

16 → 1	2E → 3
42 → 1	61 → 1
64 → 1	69 → 2
6A → 2	70 → 1
72 → 1	77 → 5
96 → 2	A2 → 1
A7 → 1	E6 → 3

256 dimensional sparse vector

`index.html`

2E → 1	46 → 1
57 → 1	65 → 1
68 → 1	6C → 1
6D → 1	74 → 1
78 → 1	82 → 1
87 → 1	D6 → 1
E6 → 1	

256 dimensional sparse vector

512 dimensional sparse vector

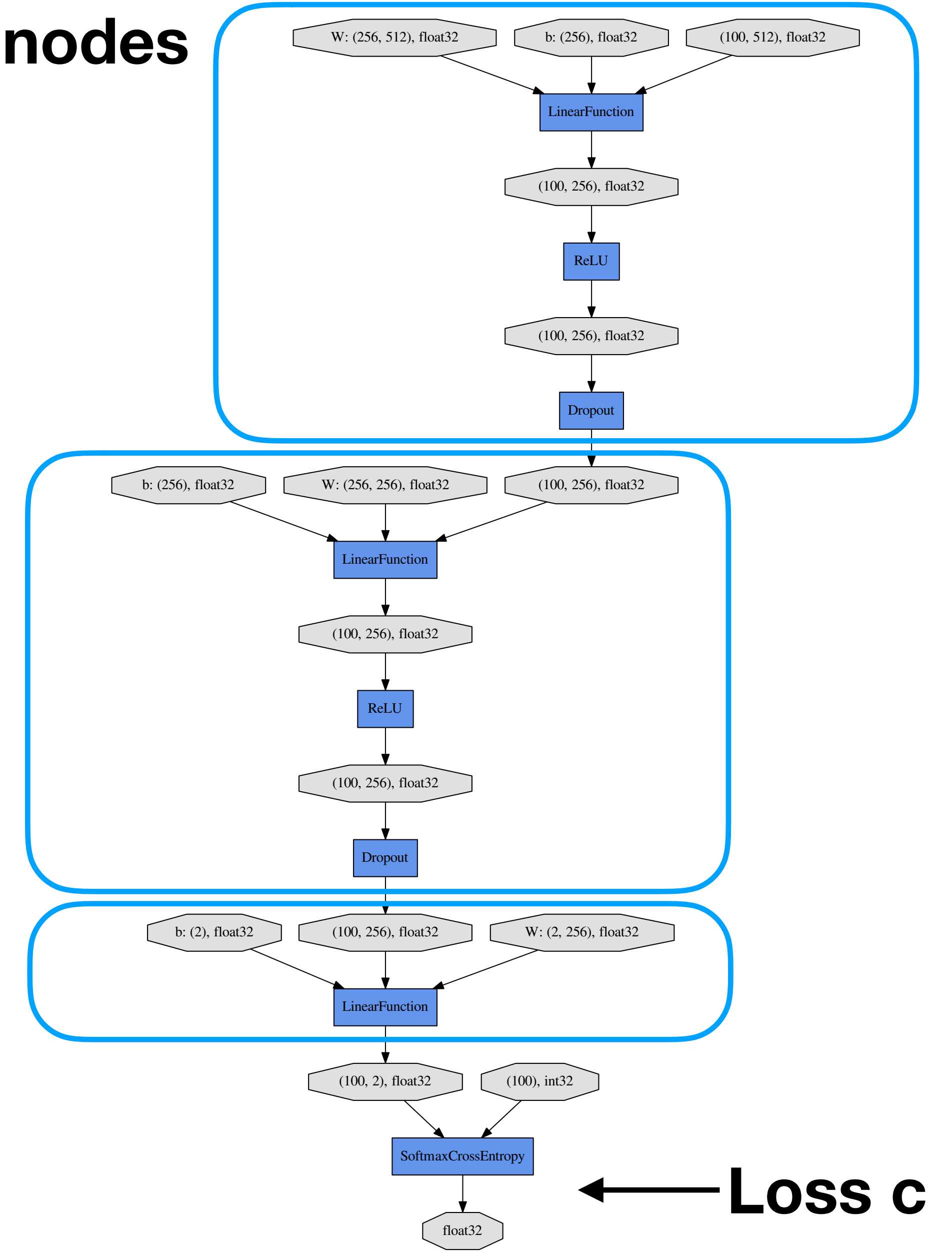
Neural network topology

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

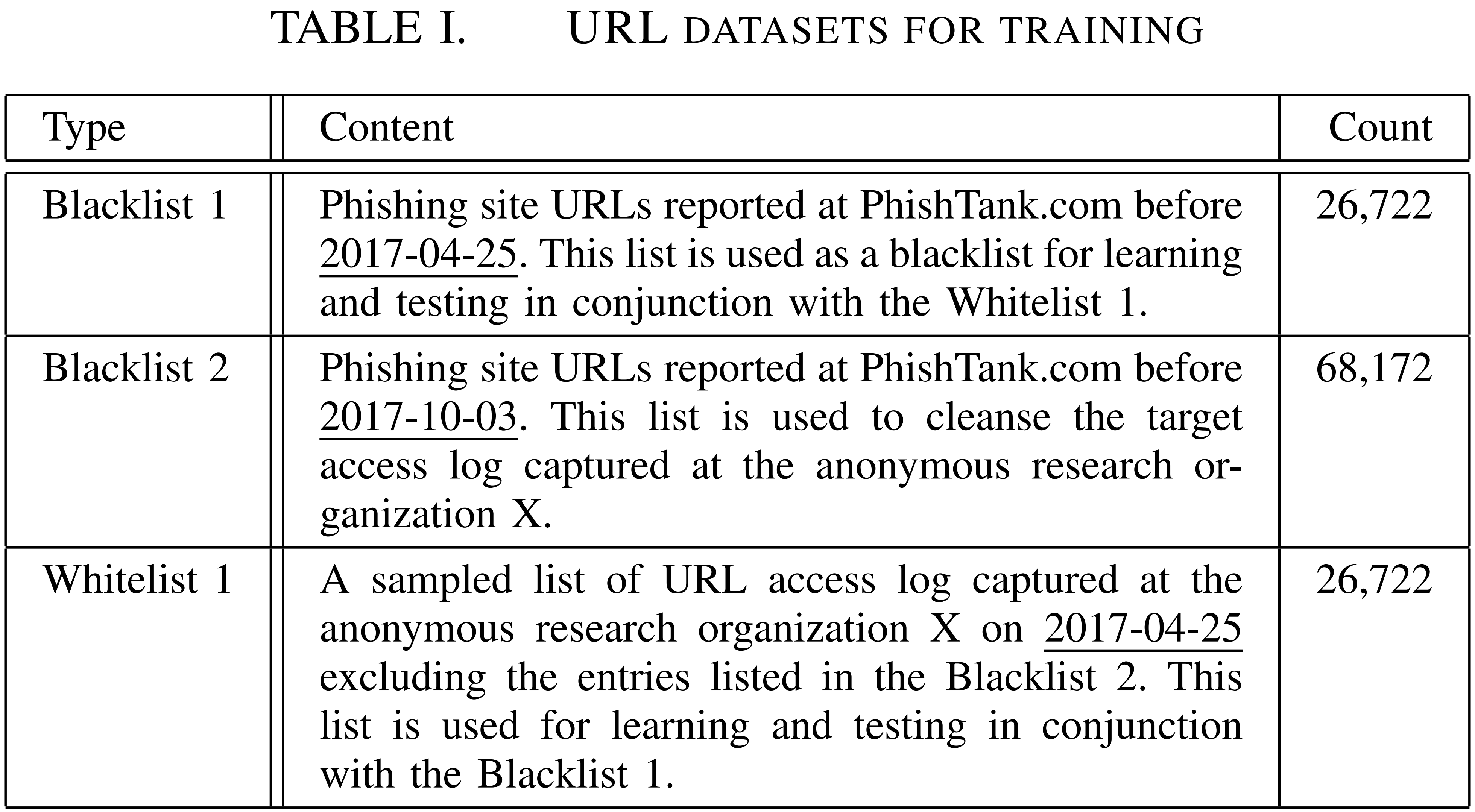
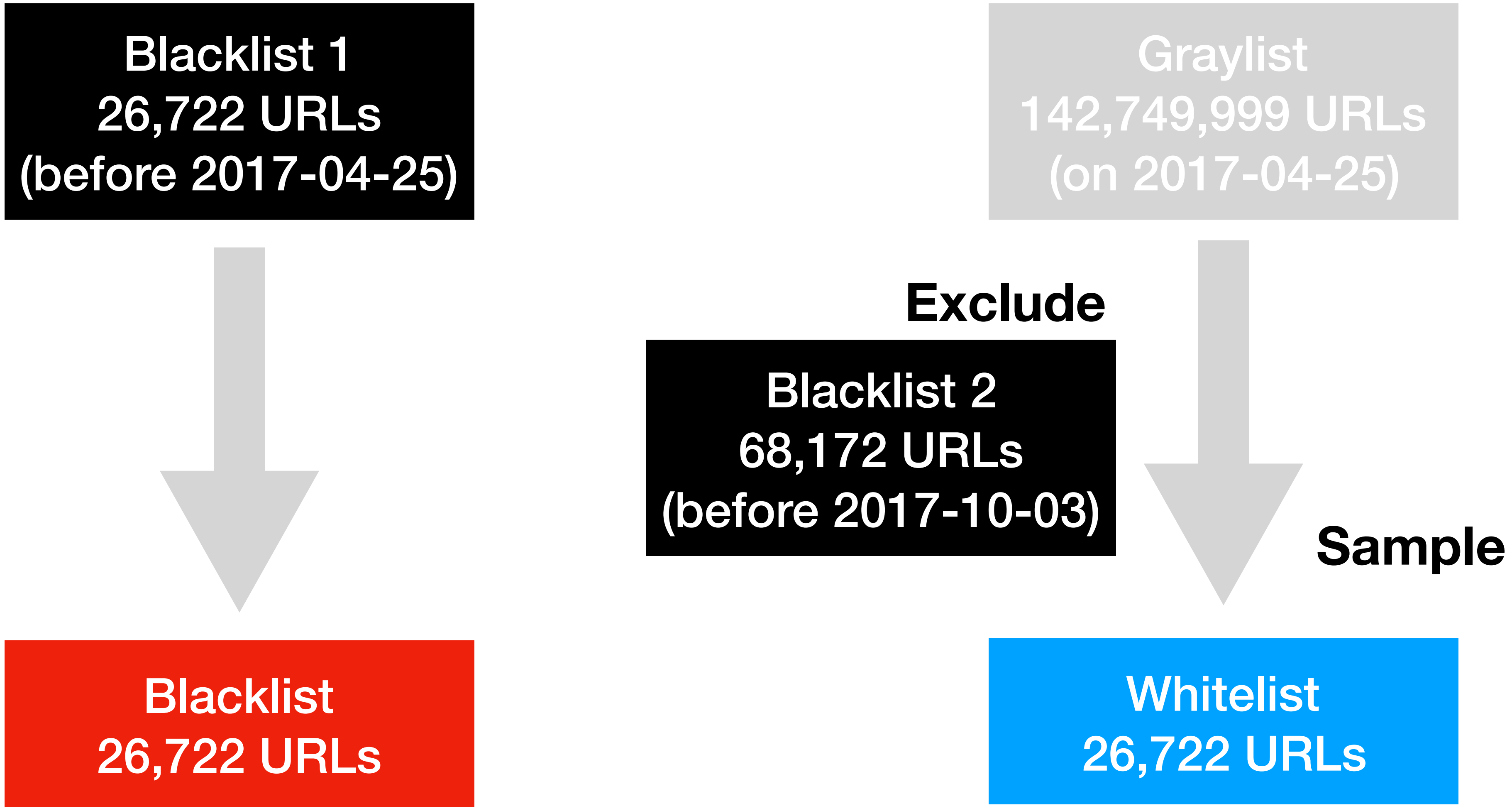


TABLE I. URL DATASETS FOR TRAINING

Type	Content	Count
Blacklist 1	Phishing site URLs reported at PhishTank.com before 2017-04-25. This list is used as a blacklist for learning and testing in conjunction with the Whitelist 1.	26,722
Blacklist 2	Phishing site URLs reported at PhishTank.com before 2017-10-03. This list is used to cleanse the target access log captured at the anonymous research organization X.	68,172
Whitelist 1	A sampled list of URL access log captured at the anonymous research organization X on 2017-04-25 excluding the entries listed in the Blacklist 2. This list is used for learning and testing in conjunction with the Blacklist 1.	26,722

Classify using the neural network



Blacklist 1
26,722 URLs
(before 2017-04-25)

Graylist
142,749,999 URLs
(on 2017-04-25)

Exclude

Blacklist 2
68,172 URLs
(before 2017-10-03)

Sample

Blacklist
26,722 URLs

Whitelist
26,722 URLs

Use 10% of URLs for training, and use the rest for validation

Accuracy and Loss

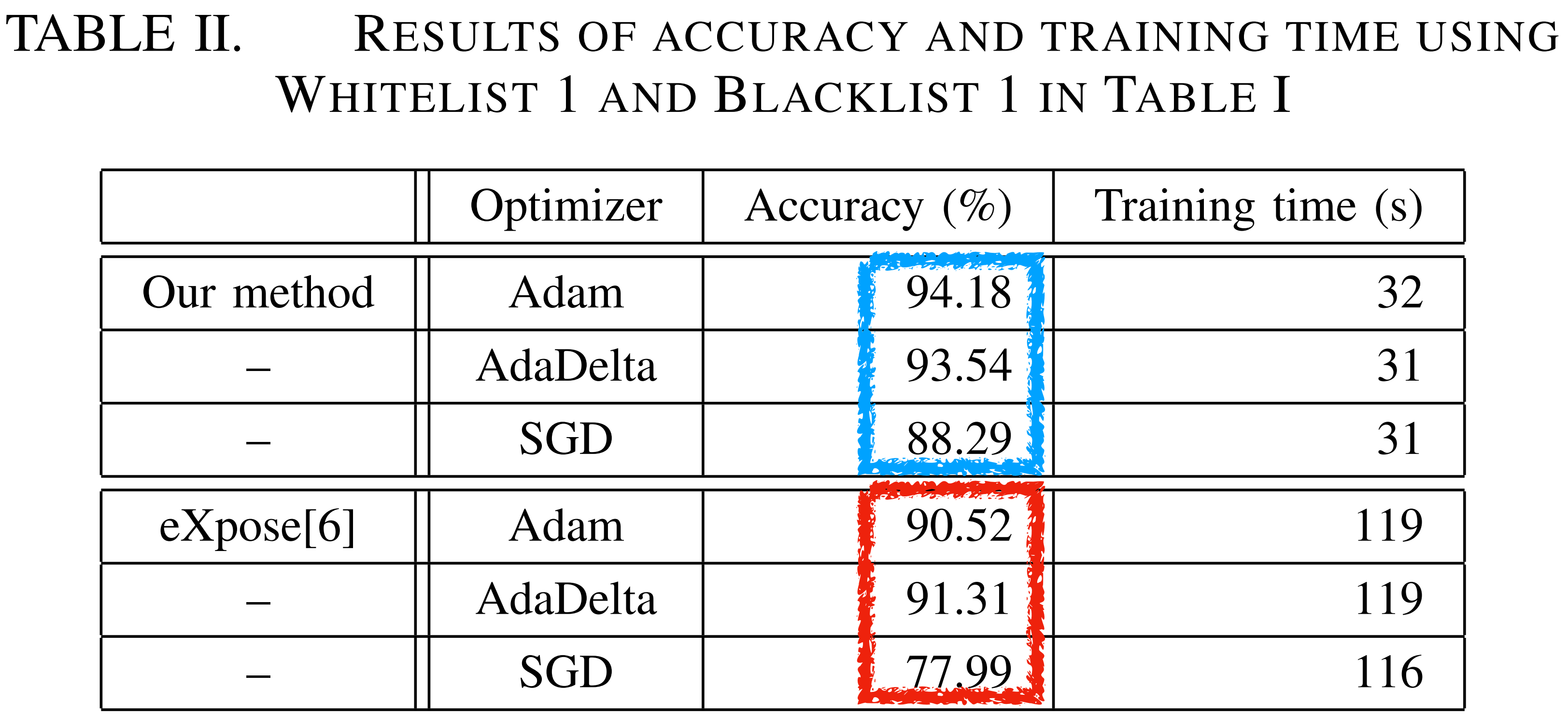


TABLE II. RESULTS OF ACCURACY AND TRAINING TIME USING WHITELIST 1 AND BLACKLIST 1 IN TABLE I

	Optimizer	Accuracy (%)	Training time (s)
Our method	Adam	94.18	32
–	AdaDelta	93.54	31
–	SGD	88.29	31
eXpose[6]	Adam	90.52	119
–	AdaDelta	91.31	119
–	SGD	77.99	116

- Our approach could achieve better accuracy compared to the eXpose(*1) work which uses similar approach using a more complex deep neural network

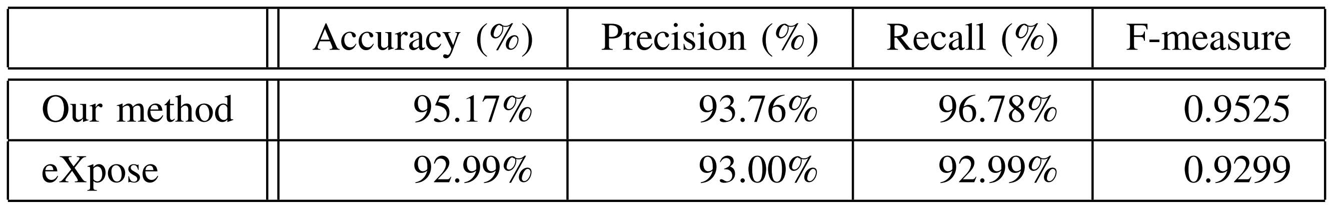
(*1) J. Saxe and K. Berlin, “eXpose: A character-level convolutional neural network with embeddings for detecting malicious URLs, file paths and registry keys,” CoRR, vol. abs/1702.08568, February 2017.

Prediction results

- Try to predict future dataset on 2017-05-25 using the trained model with the dataset of 2017-04-25

- Our approach achieved 95% of accuracy which was also better than the eXpose

TABLE IV. PREDICTION RESULTS OF THE DATASET SHOWN IN TABLE III USING THE TRAINED NEURAL NETWORK MODEL WITH THE DATASET SHOWN IN TABLE I



	Accuracy (%)	Precision (%)	Recall (%)	F-measure
Our method	95.17%	93.76%	96.78%	0.9525
eXpose	92.99%	93.00%	92.99%	0.9299

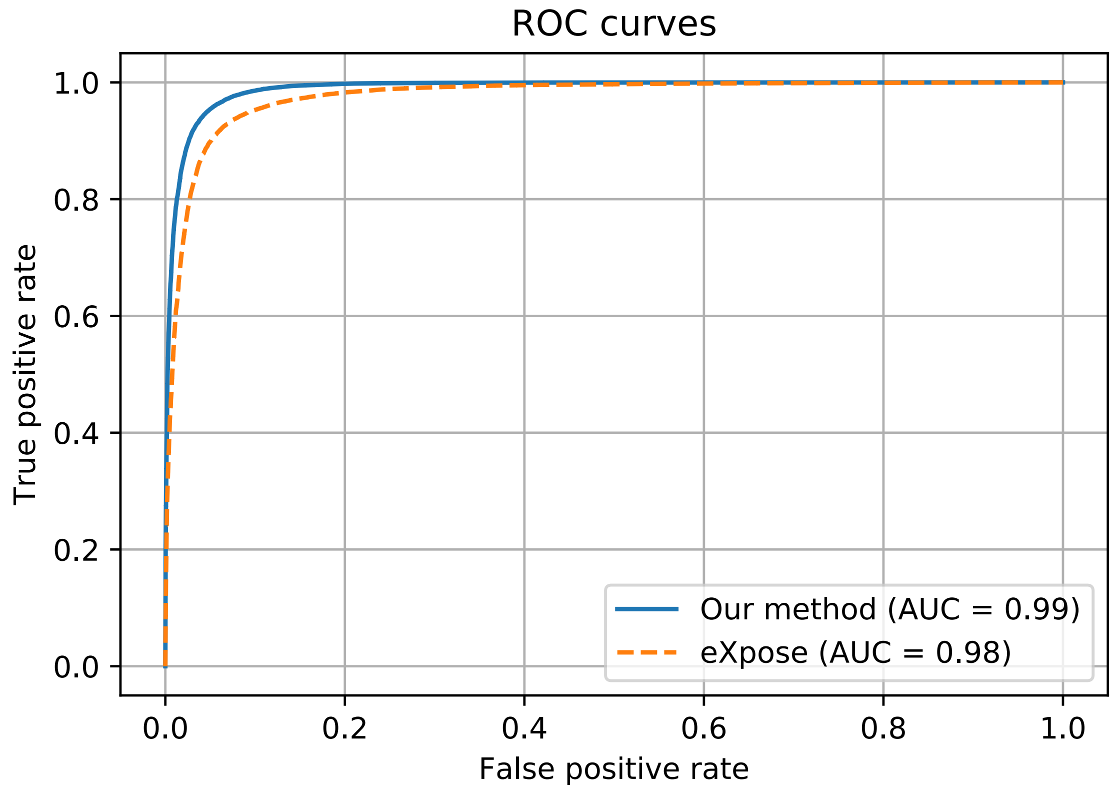


Fig. 5. ROC curves and AUC values measured with the prediction datasets as shown in Table III using our model and eXpose model

Discussion

- Difficulties to create proper datasets
  - It is almost impossible to make a pure white dataset
- Difficulties to compare
  - In most case, the dataset used for the evaluation is not disclosed (same as in our case)
- Need to make efforts to have shared datasets

Related Work

- S. Garera, N. Provos, M. Chew, and A. D. Rubin, “A framework for detection and measurement of phishing attacks,” in Proceedings of the 2007 ACM Workshop on Recurring Malcode, ser. WORM ’07. New York, NY, USA: ACM, November 2007, pp. 1–8.

- J. Ma, L. K. Saul, S. Savage, and G. M. Voelker, “Beyond blacklists: Learning to detect malicious web sites from suspicious URLs,” in Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ser. KDD ’09. New York, NY, USA: ACM, June 2009, pp. 1245–1254.

- P. Prakash, M. Kumar, R. R. Kompella, and M. Gupta, “PhishNet: Predictive blacklisting to detect phishing attacks,” in 2010 Proceedings IEEE INFOCOM, ser. INFOCOM, 2010, pp. 1–5.

- B. Sun, M. Akiyama, T. Yagi, M. Hatada, and T. Mori, “AutoBLG: Automatic URL blacklist generator using search space expansion and filters,” in 2015 IEEE Symposium on Computers and Communication, ser. ISCC, July 2015, pp. 625–631.

- J. Saxe and K. Berlin, “eXpose: A character-level convolutional neural network with embeddings for detecting malicious URLs, file paths and registry keys,” CoRR, vol. abs/1702.08568, February 2017.

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