

# URLNet : Learning a URL Representation with Deep Learning for Malicious URL Detection

## Summary

### Previous Methods

#### *blacklist, whitelist*

- cannot be exhaustive, cannot detect newly generated malicious URLs

#### *by machine learning*

- Bag-of-Words like features, with SVM
- unable to capture semantic and sequential patterns
- require substantial manual feature engineering
- unable to handle unseen features and generalize to test data

### Our method

- Deep learning with CNN
  - learn to classify
  - learn word/char embedding jointly
  - advanced word-embedding to solve too many rare words problem

## Malicious URL detection

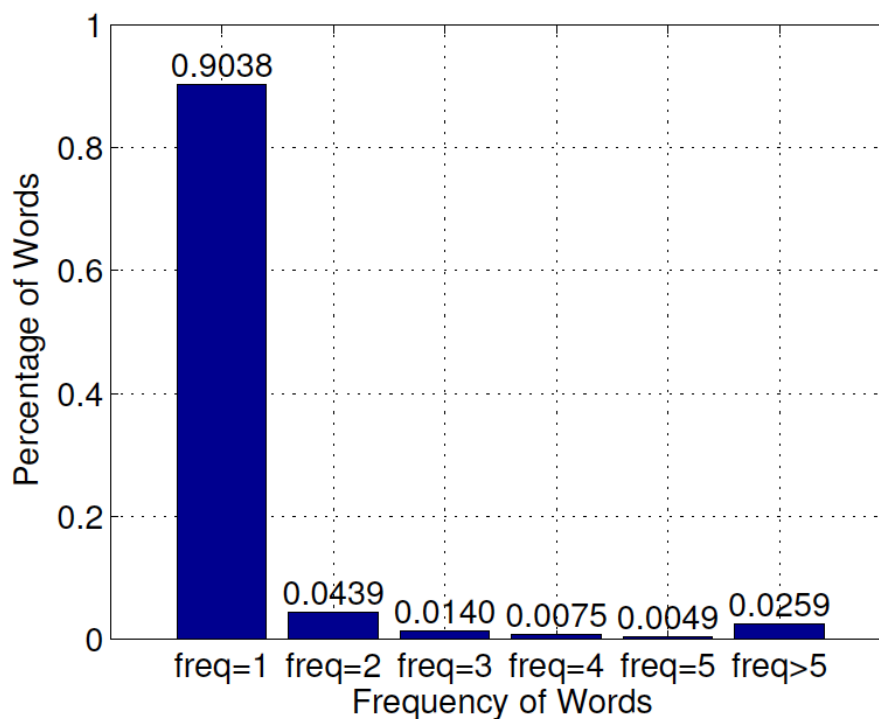
### Problem setting

Consider a set of  $T$  URLs,  $\{(\mathbf{u}_1, y_1), \dots, (\mathbf{u}_T, y_T)\}$ , where  $\mathbf{u}_t$  for  $t = 1, \dots, T$  represents a URL, and  $y_t \in \{-1, +1\}$  denotes the label of the URL, with  $y = +1$  being a malicious URL, and  $y_t = -1$  being a benign URL. The first step in the classification procedure is to obtain a feature representation  $\mathbf{u}_t \rightarrow \mathbf{x}_t$  where  $\mathbf{x}_t \in \mathbb{R}^n$  is the  $n$ -dimensional feature vector representing URL  $\mathbf{u}_t$ . The next step is to learn a prediction function  $\mathbf{f} : \mathbb{R}^n \rightarrow \mathbb{R}$  which is the score predicting the class assignment for a URL instance  $\mathbf{x}$ . The

### Lexical Features

- URL splitted into words which are delimited by special characters
- dictionary constructed by unique words in training set
- features

- Bag-of-Words features : occurrence in dictionary list
- length of URL, lengths of different segments in URL, number of dots
- lack of sequential info => create a separate dict for every segments of the URL



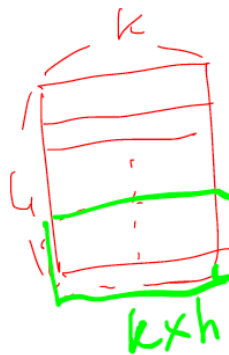
- unable to obtain information from rare words
  - most of words appears only once
  - in training => become unknown
  - in test => become unknown

## URLNet

### embedding

A URL  $\mathbf{u}$  is essentially a sequence of characters or words (delimited by special characters). We aim to obtain its matrix representation  $\mathbf{u} \rightarrow \mathbf{x} \in \mathbb{R}^{L \times k}$ , such that the instance  $\mathbf{x}$  comprises a set of contiguous components  $x_i, i = 1, \dots, L$  in a sequence, where the component can be a character or a word of the URL. Each such component is represented by an embedding such that  $x_i \in \mathbb{R}^k$ , is a  $k$ -dimensional vector.

### CNN convolution



padding, usually all sequences are padded or truncated to the same length  $L$ .

A CNN would convolve over this instance  $\mathbf{x} \in \mathbb{R}^{L \times k}$  using a convolutional operator. A convolution operation  $\otimes$  of length  $h$  consists of convolving a filter  $\mathbf{W} \in \mathbb{R}^{k \times h}$  followed by a non-linear activation  $f$  to produce a new feature:

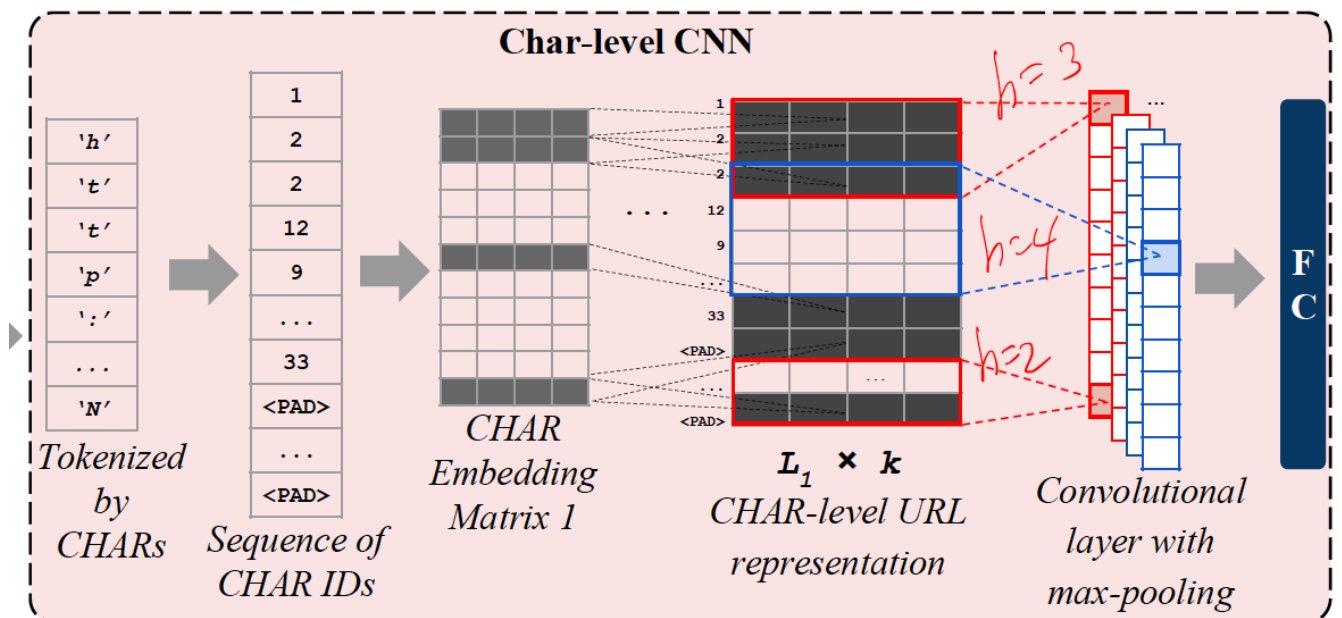
$$c_i = f(\mathbf{W} \otimes \mathbf{x}_{i:i+h-1} + b_i)$$

where  $b_i$  is the bias. This convolution layer's output applies a filter  $\mathbf{W}$  with a nonlinear activation to every  $h$ -length segment of its input, each of which is separated by a pre-defined stride value. These outputs are then concatenated to produce output  $\mathbf{c}$  such that:

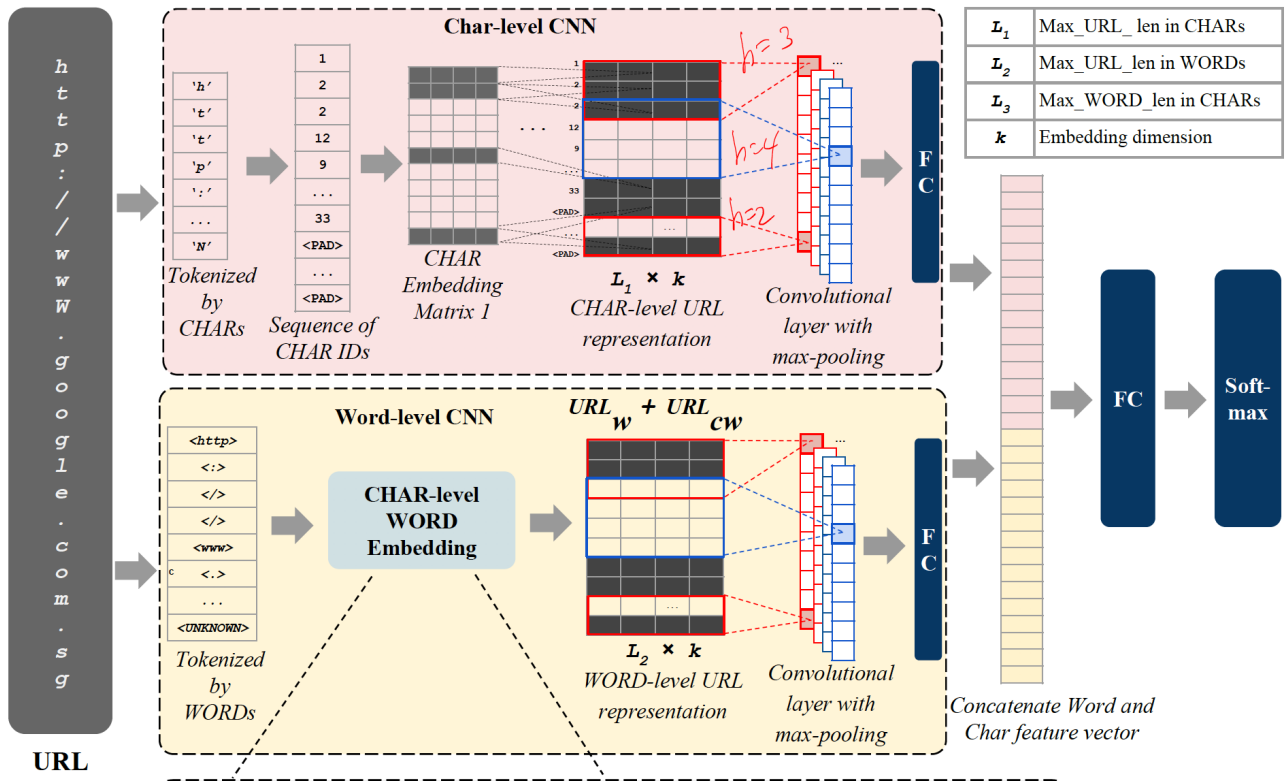
이걸 W에 곱하고  
출력 2.  $\mathbf{c} = [c_1, c_2, \dots, c_{L-h+1}]$  이런것이 W에 곱해서  
출력 2. After the convolution, a pooling step (either max or average pooling) is applied to reduce the feature dimension and to identify the most important features.

## CHAR embedding and Detection

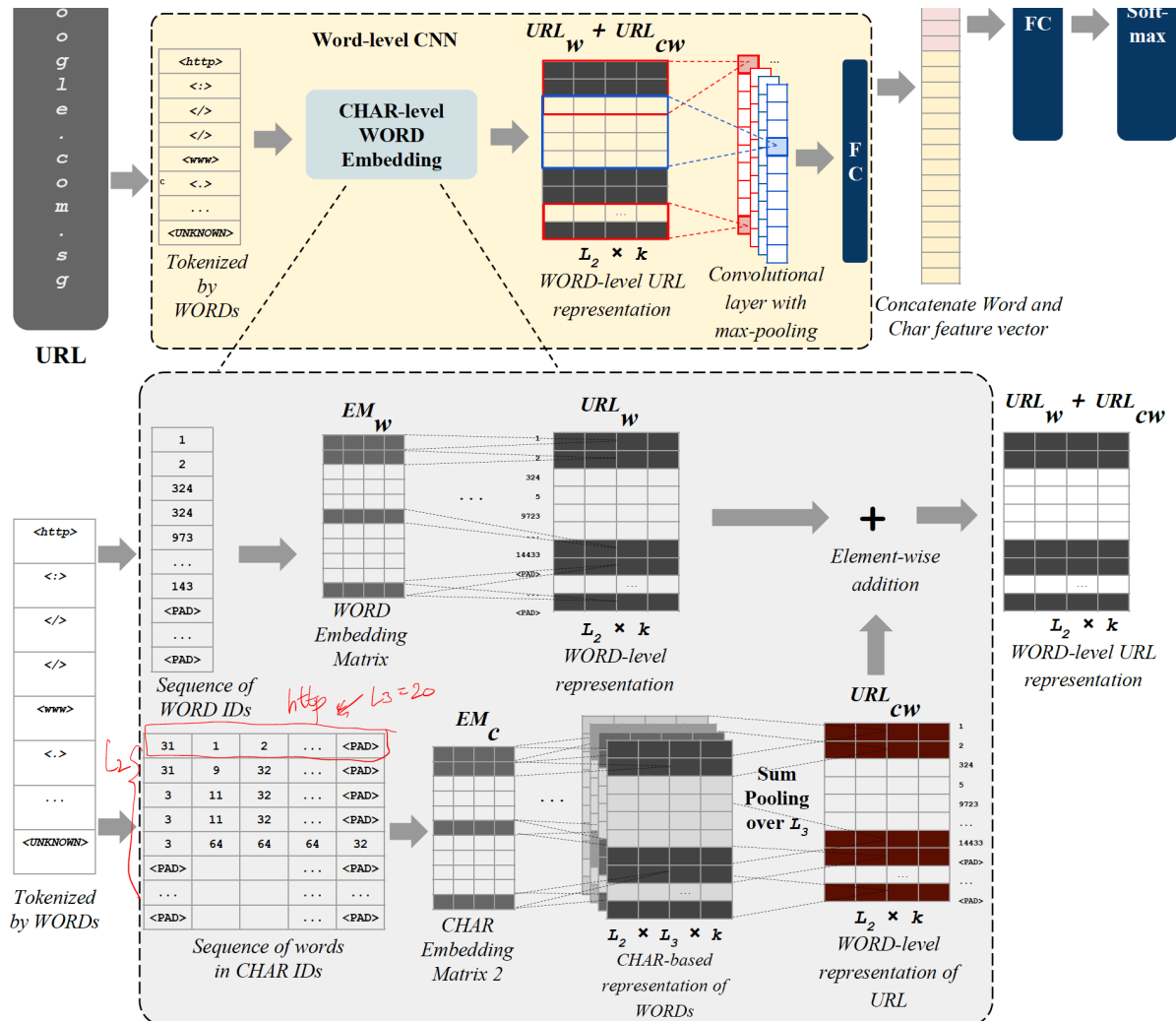
- but limitations : ignore word boundary, weak to attack of minor modification



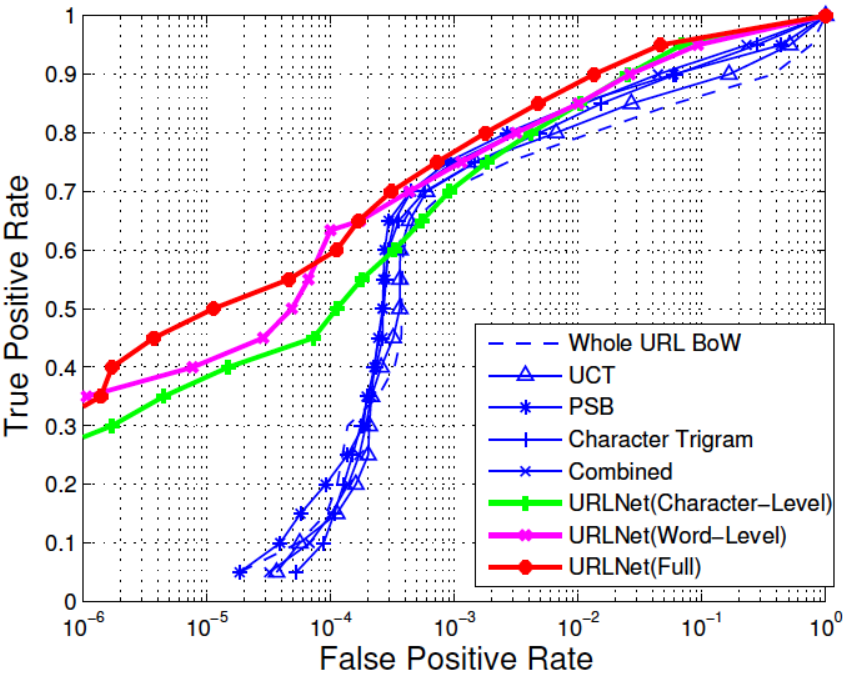
## Word-level embedding and Detection



### Improved Word Embedding Using Character-level Word Embedding\



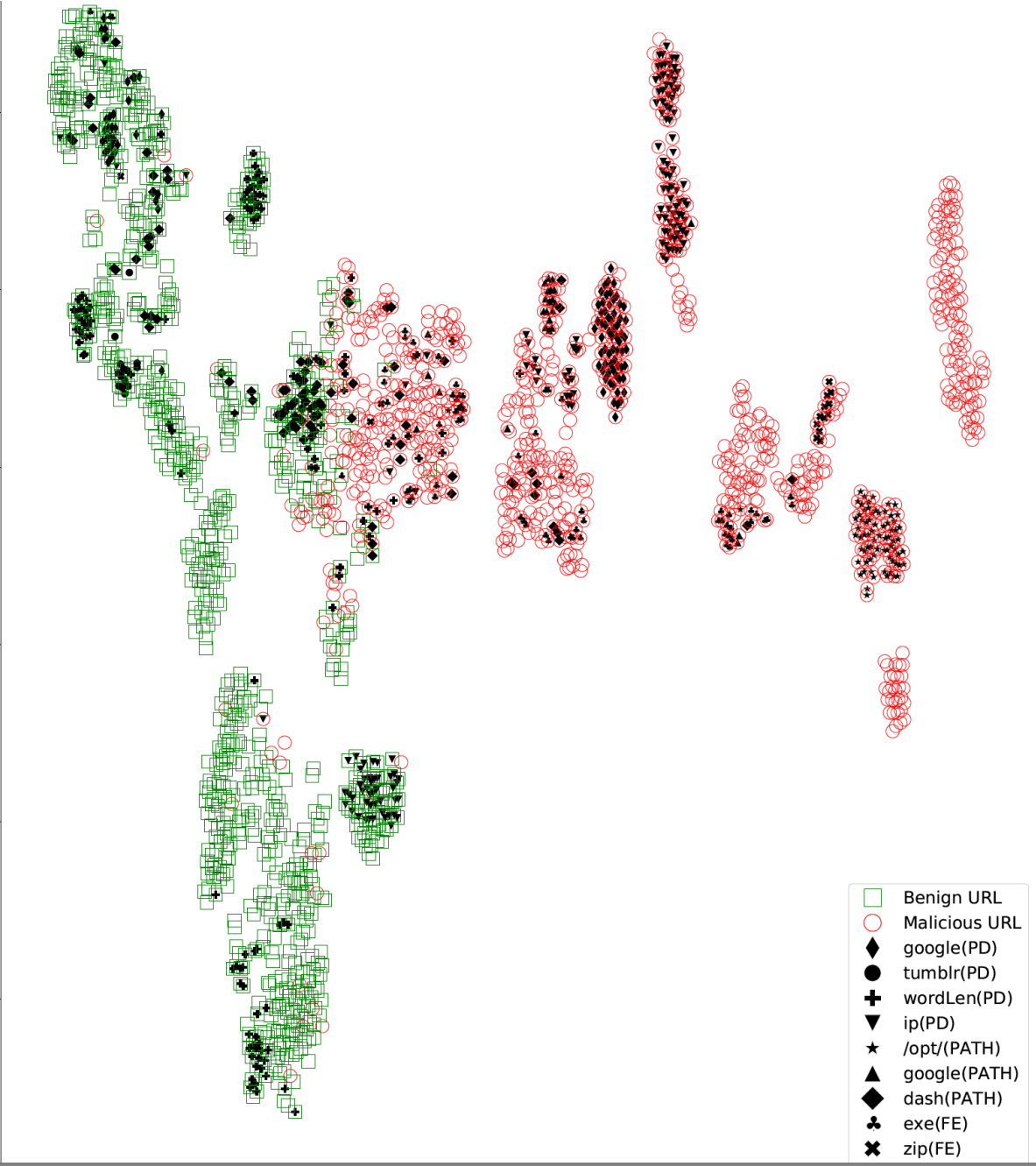
## Experiments



**Figure 4: Area Under ROC Curve (Trained on 1m, Tested on 10m). URLNet(Full) is slightly worse than URLNet(Word-level) at  $FPR = 10^{-4}$ , but better otherwise. URLNet(Full) is consistently better than URLNet(Character-level). All URL-Net variants outperform baselines.**

**Table 5: Examples of lexical patterns in URLs and example URLs. The lexical patterns are extracted at different parts of the URL string: primary domain, URL path, and file extension.**

URL Component	Lexical Pattern	Example URL
Primary Domain	contains 'tumblr'	http://exampledomain.tumblr.com/
	contains 'google'	http://www.google.com/urlpath/... http://abcd123googlexyz456.com/urlpath/...
	contains IP	http://192.168.0.1/ http://192.168.0.1/urlpath/...
	has average word length >10	http://a1ds2dce0b33fdgd425d8fsgg9836c4234d0.exampledomain.net/
Path	contains 'google'	http://www.exampledomain.com/filename?f=GOOGLEEARTH... http://exampledomain.net/urlpath/googledrive/sub_dir/...
	contains '/opt/'	http://www.exampledomain.com/opt/...
	contains the <i>dash</i> pattern in the last path token	http://exampledomain.com/urlpath/abc-123-fff-456-...
File Extension	Includes a file with extension 'exe'	http://exampledomain.net/urlpath/filename.exe
	Includes a file with extension 'zip'	http://exampledomain.com/urlpath/filename.zip



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