# Convolutional Neural Networks for Classification of Malware Assembly Code

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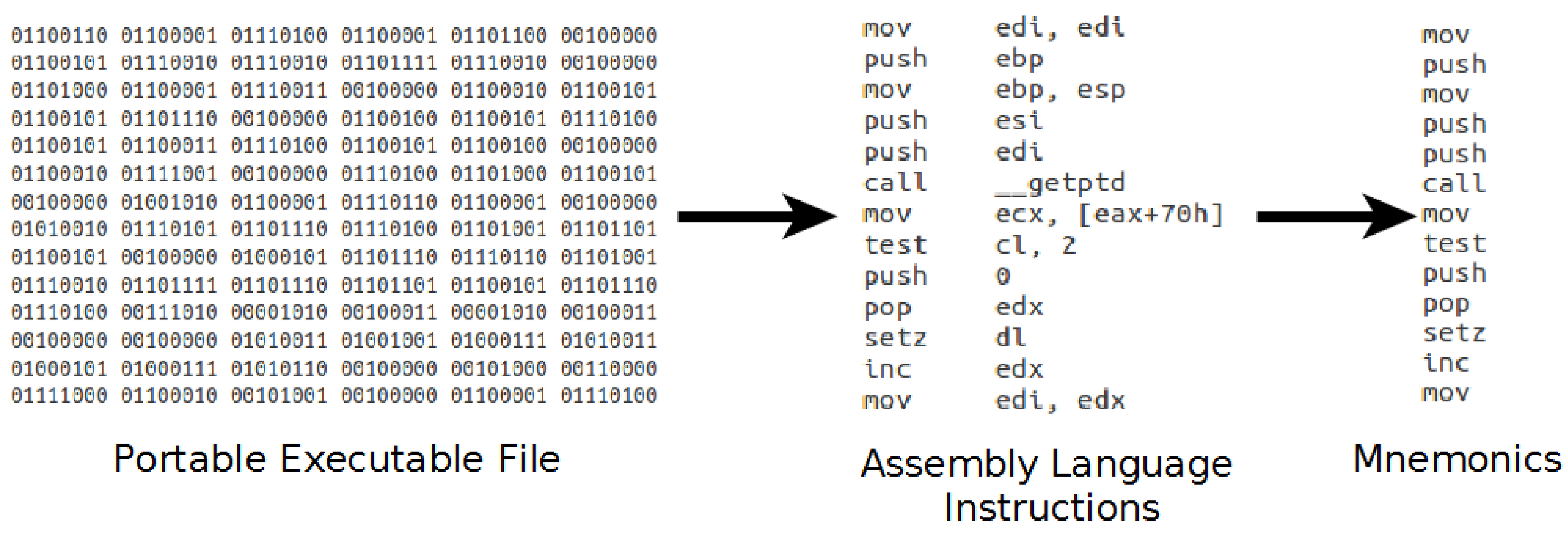
## Objectives

- Build a static classifier without relying on hand-crafted features defined by experts.
- Group malware into families based on their assembly language source code.
- Extract N-Gram like signatures with convolutional neural networks from malware's machine instructions.

## Data Transformation




## CNN Layers Description

- **Input**

  An assembly program is represented as a concatenation of mnemonics

  $$x_{1:n} = x_1 \oplus x_2 \oplus \cdots \oplus x_n$$

  where $n$ is the length of the program and $x_i \in \mathbb{R}^k$ corresponds to the i-th mnemonic in the program.

- **Embedding**

  Every mnemonic is represented as a low-dimensional vector of real values (word embedding).

- **Convolution**

  A convolution operation involves a filter $w \in \mathbb{R}^{hk}$ where $h$ is the number of mnemonics to which is applied and $k$ is the size of the word embedding. In particular, filters are applied to sequences containing from 2 to 7 mnemonics.

  A feature $c_i$ is generated from a window of mnemonics $x_{i:i+h-1}$ (it comprises all mnemonics between position $i$ and $i + h - 1$) and is defined as

  $c_i = f(w \cdot x_{i:i+h-1} + b)$,

  where $f$ is a rectifier linear unit (ReLU) function and $b$ the bias term.

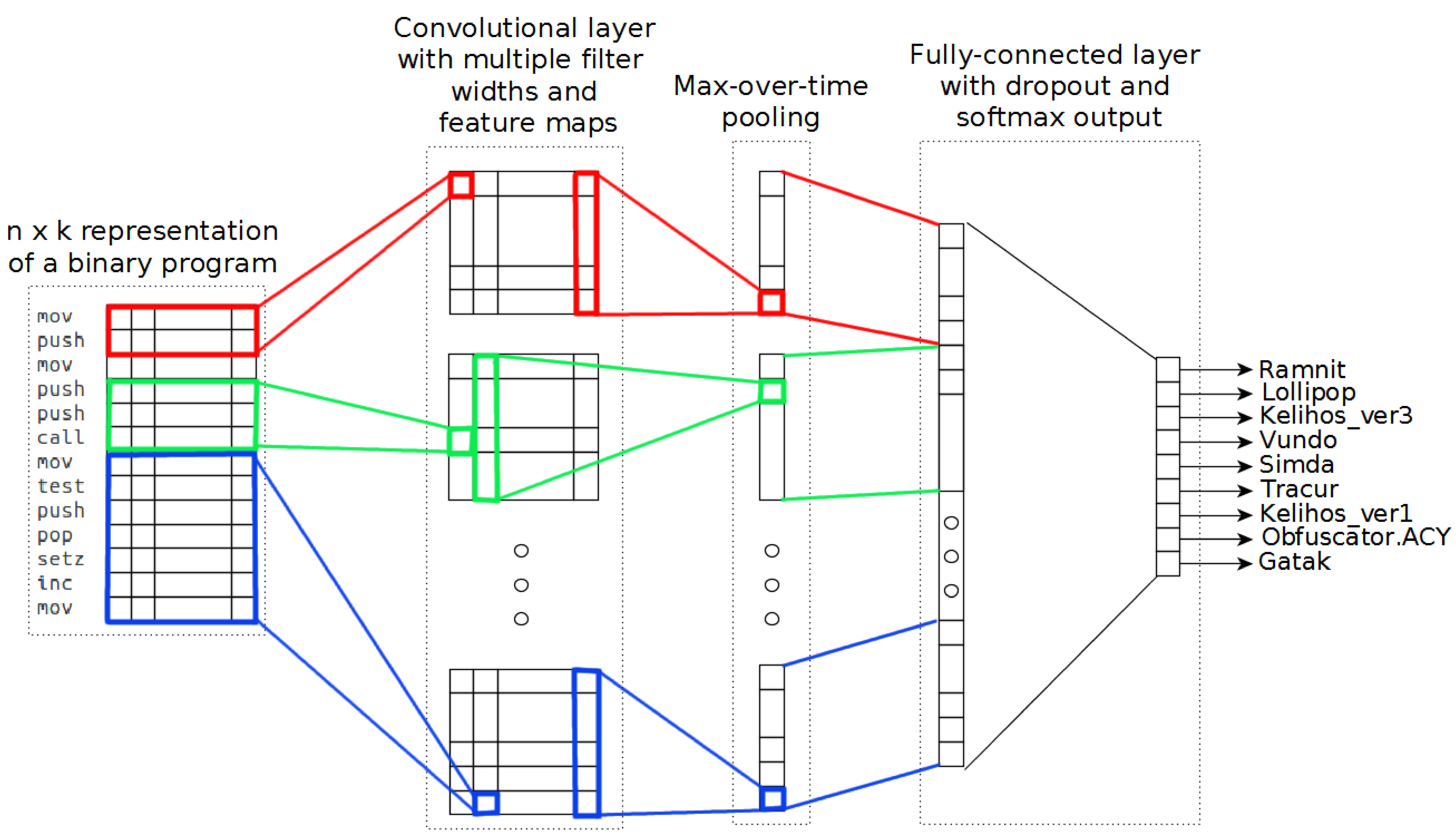
- **Max-Pooling**

  The maximum value $\hat{c} = \max\{c\}$ is taken as the feature corresponding to the filter by applying the max pooling operator over the feature map.

- **Softmax layer**

  The extracted features are passed to a fully-connected softmax layer whose output is the probability distribution over families.

## Architecture




## N-Gram Comparison

- An N-Gram is a contiguous sequence of N items from a given sequence of text.
- N-Gram like signatures have proved useful in classifying malware.
- The main limitation of standard N-Gram based methods is the exponential increase in the number of unique n-grams as n is increased.

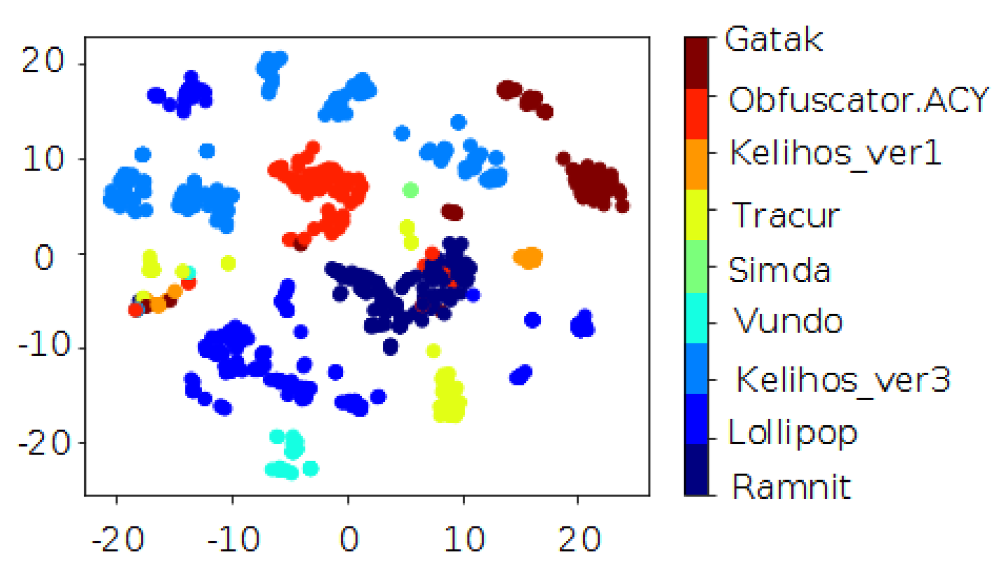
| Method | #features | RAM Usage | Extraction Time (in sec.) | | |
|---|---|---|---|---|---|
| | | (in GB) | Avg | Max | Min |
| 1-Gram | 977 | $1.39 \times 10^{-6}$ | 0.47 | 3.55 | 0.02 |
| 2-Gram | 485809 | $9.72 \times 10^{-4}$ | 0.48 | 3.74 | 0.03 |
| 3-Gram | 338608873 | 0.68 | 23.36 | 31.68 | 9.42 |
| 4-Gram | 236010384481 | 420.02 | - | - | - |
| CNN | 384 | $1.54 \times 10^{-6}$ | 0.49 | 3.57 | 0.04 |

**Table 1:** RAM requirements and feature extraction time considering a subset of 977 mnemonics.

## Conclusion

- End-to-end deep learning framework to automatically extract N-Gram like features and classify malicious software into families based on their assembly language source code.
- Efficient alternative to N-Grams.
- The N-Gram like features learned are highly discriminant and useful for clustering malware into groups.
- Greater predictive power in comparison to opcode-based approaches in the literature.
- Resilient to common obfuscation techniques such as code transposition and function reordering.

## T-SNE Visualization




## Results

| Model | Training accuracy | Test Score |
|---|---|---|
| CNN | 0.9964 | 0.0244 |
| Winner's solution | 0.9986 | 0.0028 |
| NFESF | 1.0000 | 0.0063 |
| SMCMCF (4-Gram+VT) | 0.9980 | 0.0259 |
| SMCMCF (4-Gram) | 0.9930 | 0.0546 |
| STRAND | 0.9859 | 0.0479 |

**Table 2:** Comparison with state-of-the-art methods.

## Acknowledgements

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