AST-Based Deep Learning for Detecting Malicious PowerShell

Gili Rusak[1], Abdullah Al-Dujaili[2], Una-May O'Reilly[2]
Stanford University[1], ALFA Group, MIT[2]

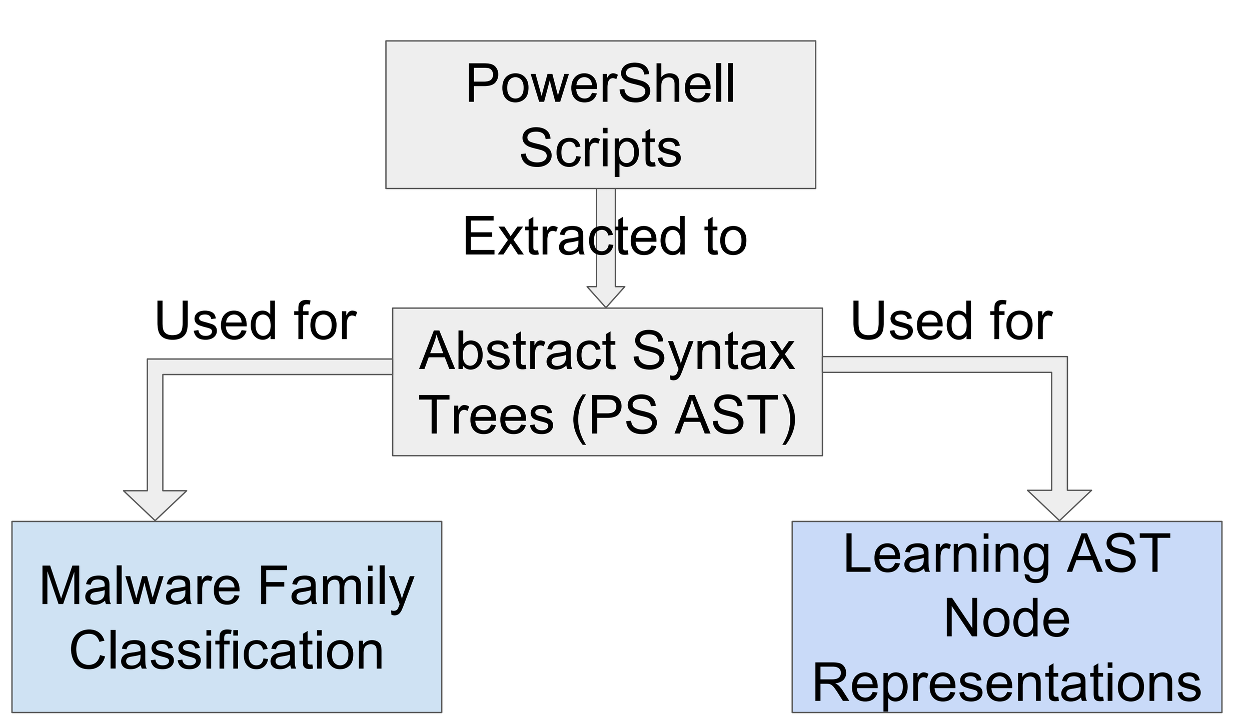
Objective

- Combine static program analysis with deep learning approaches for PowerShell malware detection

Background

- **Introduction**
  - Cyberadversaries use PowerShell (PS) scripts for malicious purposes
  - Previous attempts to use deep learning for PS malware detection used character-level based neural networks [1]
- **Dataset**
  - 4,079 malicious PS scripts annotated and classified based on their family types [2]
  - Example: ShellCode Inject
- **Definitions**
  - Abstract Syntax Tree (AST): tree representation of syntactic structure of script made up of nodes
  - AST Subtree: a non-leaf node and its immediate children

Methods



Acknowledgements

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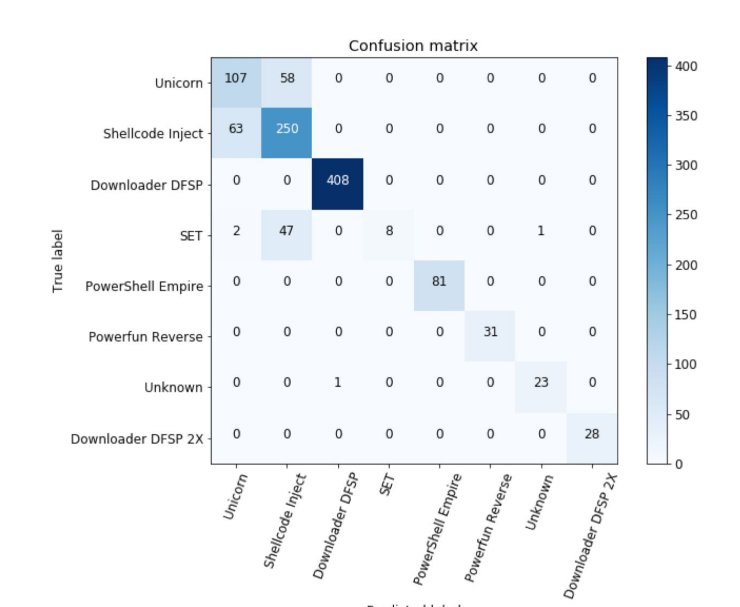
Malware Family Classification

- **Data**
  - Classes: eight different malicious family types
  - Each class has 40 or more examples in dataset
  - Used 70:30 train:test split
- **Experiment**
  - Classify script by family type

> Technique: RandomForestClassifier
> Input Features: (PS AST depth, number of nodes)
> Output: Family Type

  - Weighted classes during training based on number of examples per class due to class imbalance
- **Evaluation**
  - Heatmap for confusion matrix on the held out test set suggests a well-performing model



  - PS script AST representations can be powerful for malware detection

References

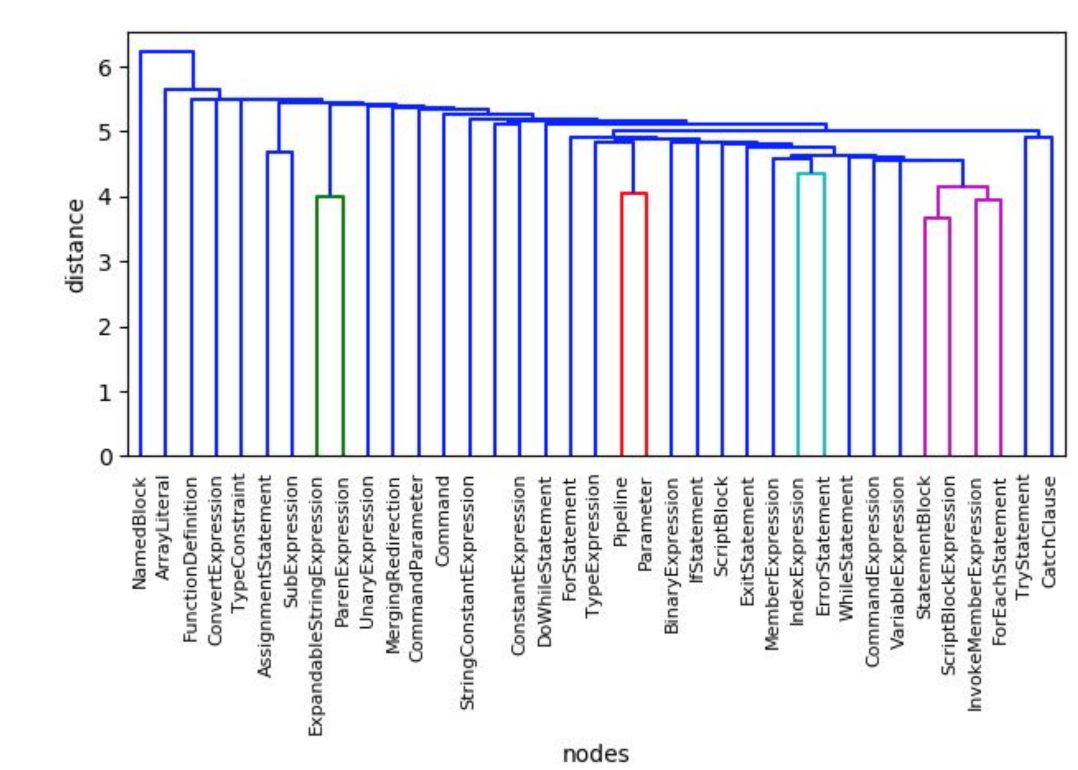
[1] D. Hendler, S. Kels, A. Rubin. Detecting Malicious PowerShell Commands using Deep Neural Networks. *Asia Conference on CCS*. 2018.
[2] J. White. Pulling Back the Curtains on EncodedCommand PowerShell Attacks. https://researchcenter.paloaltonetworks.com/2017/03/unit42-pulling-back-the-curtains-on-encodedcommand-powershell-attacks/. 2017.
[3] H. Peng, L. Mou, G. Li, Y. Liu, L. Zhang, Z. Jin. Building Program Vector Representations for Deep Learning. *International Conference on Knowledge Science, Engineering and Management*. 2015.

AST Node Representations

- **Data**
  - Parsed each of 4,079 PS ASTs to its subtrees
  - 62 different AST node types (i.e. ForStatement)
- **Experiment**
  - Learn embedding vector representations of AST nodes based on PS dataset using [3]'s methods

> Technique: Unsupervised Stochastic Gradient Descent
> Input: AST Subtrees of PS corpus
> Output: Optimized vector representation of AST node types

  - Optimized SGD until loss stabilized and tuned hyperparameters
- **Evaluation**
  - Dendrogram of node types and their relationships



  - Promising preliminary results: (TryStatement, CatchClause) and (ForStatement, DoWhile) node types are neighbors
  - Limitations: ForEachStatement and ForStatement node types are not neighbors

Conclusions and Future Work

- AST-Based Deep learning techniques can be effectively harnessed for malware detection