# IEEE Bigdata Cup 2022, Osaka, Japan

#### 'Using Generative Adversarial Networks to Simulate System Calls of Malicious Android Processes'

**Challenge:** 'IEEE BigData Cup 2022: GAN-Based Training for Binary Classifier'

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## Outline

- 1. Introduction
- 2. Objective
- 3. Literature Review
- 4. Main Research
- 5. Learnt Distribution Analysis
  - a. Kolmogorov-Smirnov
  - b. PCA
- 6. Further Work



## Introduction

- Issue with Binary Classification
  - Data Imbalances
  - End Result: Bias between majority class and minority class
- Vitally **Essential** to tackle this problem
- **End Goal**: Provide a Benchmark to determine Optimal Model for binary classification



# Objective

- Gathering the training malware traces is restive and can be a nuisance depending on the type of malware.
  - Behavioral polymorphism
- Developing a GAN model to generate a proper training mechanism for binary classification.
- GANs are well suited for these issues because they can generate synthetic data that mimic actual data.

#### **Key Words:-**

Generative Adversarial Networks (GANs), Deep Learning, System Calls, Android Malware Detection



## Literature Review

#### Context of the Problem:

- Cyber services
- Artificial Intelligence (AI) And Machine Learning (ML)

#### Why it Matters:

- Malicious techniques
- Detecting malicious processes

#### **Proposed Solution:-**

- Generating Synthetic Data using GAN



## Main Research

#### Brief GAN Overview

- Deep learning algorithm can generate synthetic data with the same characteristics as the trained data
- Tabular-based and the Pictorial-based GAN models

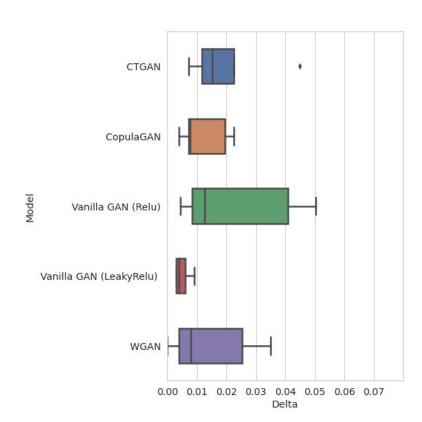
Classifiers	GAN Models			
AdaBoost	CTGAN			
Bagging	CopulaGAN			
Extra-Trees	Vanilla GAN (ReLU)			
Gradient Boosting	Vanilla GAN (Leaky-ReLU)			
Random Forest	WGAN (Leaky-ReLU)			
Stacking	Pictorial GAN (CNNs)			
Voting	2000			
Histogram-Based Gradient Boosting				
Support Vector Machines (SVMs)				
Linear Regression				



## Main Research

## Tabular GAN models (Median of delta values)

- CTGAN = (0.0153)
- CopulaGAN = (0.0076)
- Vanilla GAN (ReLU) = (0.0125)
- Vanilla GAN (LeakyReLU) = (0.004)
- WGAN (LeakyReLU)= (0.0078)





# Results of Machine Learning Algorithms

## Testing parameters:

- 100 epochs
- 10 runs

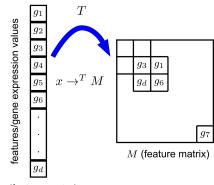
Random Forest		Extra Trees			XGBoost			
Before GAN	After GAN	Delta	Before GAN	After GAN	Delta	Before GAN	After GAN	Delta
13.377 %	13.764 %	0.004	12.978 %	11.698 %	0.013	18.377 %	12.566 %	0.008
17.77 %	18.35 %	0.006	10.26 %	11.239 %	0.01	18.377 %	12.978 %	0.004
13.76%	13.765 %	0	12.978 %	10.761 %	0.022	18.377 %	10.761 %	0.026
16.859 %	17.168 %	0.003	10.26 %	11.698 %	0.14	18.377 %	13.377 %	0
16.859 %	16.543 %	0.003	11.239 %	11.239 %	0	18.377 %	11.239 %	0.021
		0.0032			0.037			0.0118



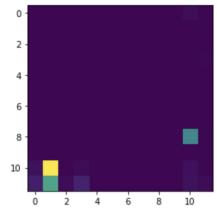
## Main Research, continued

## Pictorial Representation

- Feature extraction is performed by the CNN's hidden layers
- Transforming feature vectors (or tabular data) is done by performing dimensionality reduction techniques, such as t-SNE or kPCA
- Hard problem to fine-tune (number of pixels,channels, etc)
- Tabular representation held better results



*x* (feature vector) Figure taken from [1]



Example of malign synthetic image



## Learnt malicious processes distribution: PCA

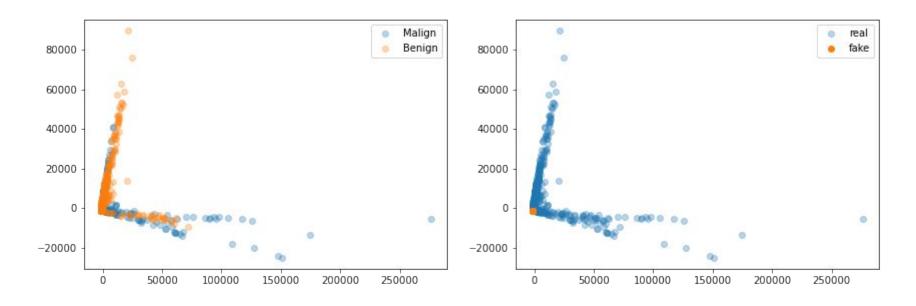


Fig 1: Distribution of labels.

Fig 2: Synthetic data projected onto PCA of real data.



# Learnt malicious processes distribution: Kolmogorov-Smirnov

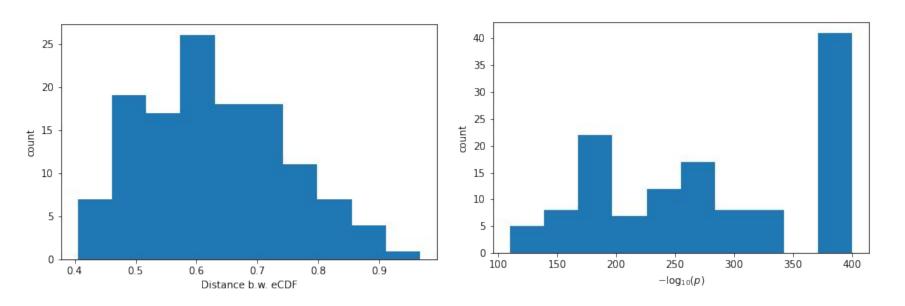


Fig 1: D-statistic i.e. the max distance between eCDFs

Fig 2: Statistical confidence in rejecting the null hypothesis



#### Further work

#### Data and data representation:

- The current data only uses monograms of system calls. Future work could include looking at longer n-grams.
- This work only looks at generation of system calls. However, a more holistic approach would be including things like meta data of processes as well as API calls made by the processes.

#### Model level optimization

- Different GAN architectures
- Further hyperparameter tuning



Thank you for your time