

機器學習與資訊 安全之應用 期中報告

Here is where your presentation begins

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資料集描述

- 八個 malware family：Android、Bashlite、Mirai、Unknown、Tsunami、Dofloo、Xorddos 與 Hajime
- 不是 API call sequence，而是 system call sequence
- 主要使用 TIMESTAMP 跟 SYSCALL 兩個欄位

```
1 PID,TIMESTAMP,SYSCALL,CATEGORY,SPLIT,ARGC,ARG1,ARG2,ARG3,ARG4,ARG5,ARG6,RESULT,ELAPSED
2 1807,"1565514492.511934","execve",,0,3,"""/aafb16e1""",["""/aafb16e1"""],"0x7fff1c6a23d8 /* 9 vars */",,,,0,"0.002625"
3 1807,"1565514492.523300","ioctl",,0,3,"0","TCGETS","0x7ffddcb70340",,,,,"-1","0.000290"
4 1807,"1565514492.526832","ioctl",,0,3,"1","TCGETS","0x7ffddcb70340",,,,,"-1","0.000225"
5 1807,"1565514492.528700","rt_sigprocmask",,0,4,"SIG_BLOCK","[INT]","NULL","8",,,,0,"0.000389"
6 1807,"1565514492.531051","rt_sigaction",,0,4,"SIGCHLD","{sa_handler=SIG_IGN, sa_mask=[CHLD], sa_flags=SA_RESTORER|SA_RESTART, sa_restorer=0x54349c}","{sa_handler=SIG_DFL, sa_mask=[], sa_flags=0}","8",,,,0,"0.000269"
7 1807,"1565514492.533222","rt_sigaction",,0,4,"SIGTRAP","{sa_handler=0x424b90, sa_mask=[TRAP], sa_flags=SA_RESTORER|SA_RESTART, sa_restorer=0x54349c}","{sa_handler=SIG_DFL, sa_mask=[], sa_flags=0}","8",,,,0,"0.000225"
8 1807,"1565514492.534593","open","IO",0,2,"""/dev/watchdog""","O_RDWR",,,,,"-1","0.000694"
9 1807,"1565514492.538108","open","IO",0,2,"""/dev/misc/watchdog""","O_RDWR",,,,,"-1","0.000378"
10 1807,"1565514492.539324","shmget",,0,3,"IPC_PRIVATE","209","IPC_CREAT|0666",,,,0,"0.002137"
```

Siamese network for few-shot learning

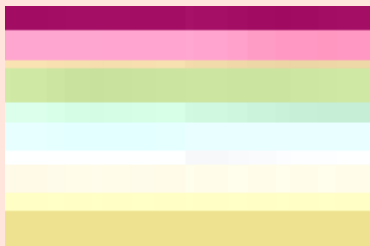
方法一

10種類型

- | | |
|----------------------|-------------------------------|
| 1.File system | 6.Inter Process Communication |
| 2.Network | 7.Non-uniform memory access |
| 3.Time | 8.Linux key management |
| 4.Process management | 9.System-wide |
| 5.Signals | 10.Other |

Siamese network for few-shot learning

方法一



Bashlite



Miral



Unknown

- 2-shot-3-way
- 訓練張數:6張 測試張數:1128張
- train accuracy:0.75 test accuracy:0.5

Siamese network for few -shot learning

方法二

- category 分類改用該 system call 需要引入哪個 header

SYNOPSIS [top](#)

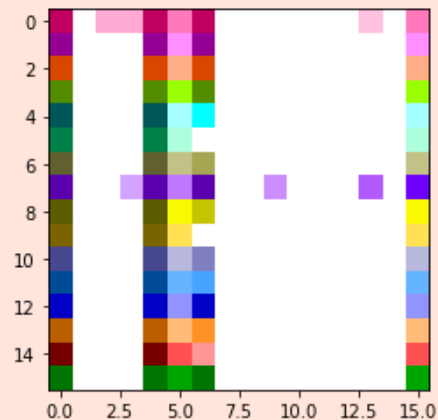
```
#include <unistd.h>
```

```
int execve(const char *pathname, char *const argv[],  
           char *const envp[]);
```

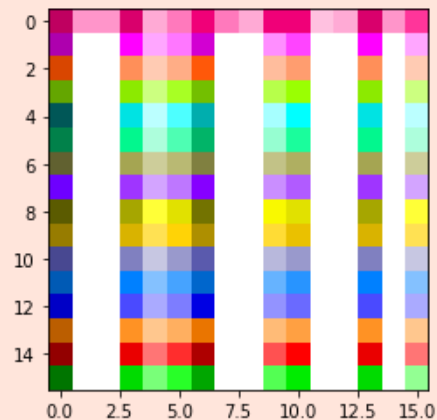
- 轉成 16 * 16 的 image
- 3 way 5 shot
- Train acc: 0.71 Test acc: 0.66

Siamese network for few-shot learning

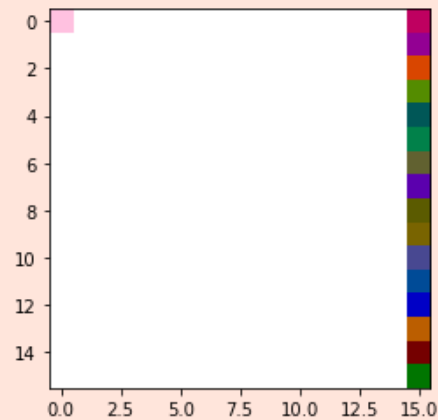
方法二



Mirai



Dofloo

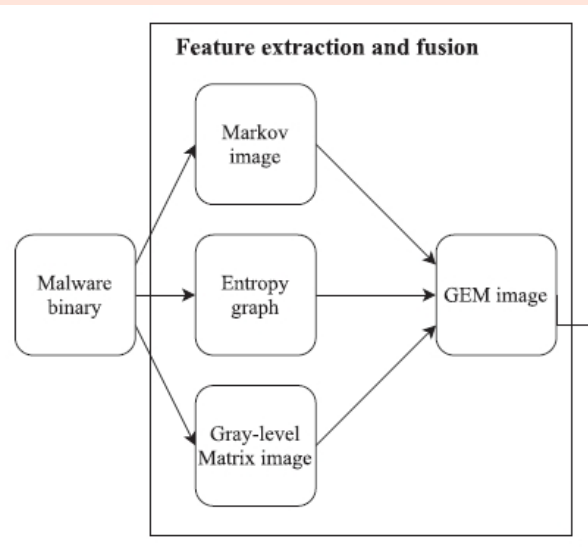


Bashlite

Siamese network for few-shot learning

方法三

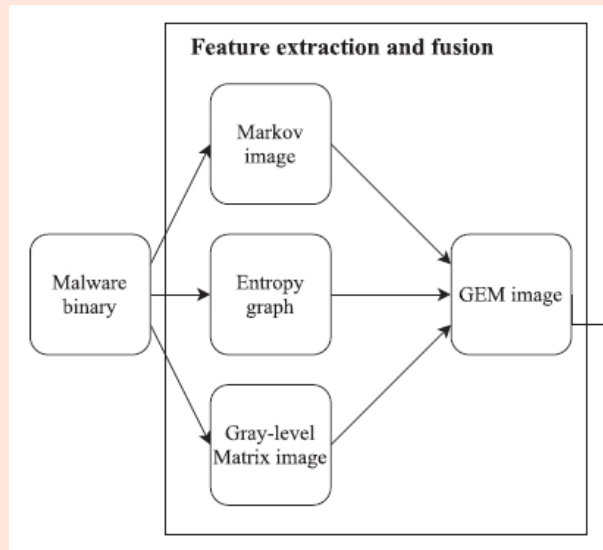
- input 使用 binary file
- 三種方法分別生成 RGB
- Markov image：取 binary 的 2-gram byte 的 frequency matrix 和 probability matrix
- Entropy graph：每 128 bit 切分成一個區塊，計算每個區塊的 Shannon entropy 後繪成圖表，再 resize 成 $256 * 256$



Siamese network for few-shot learning

方法三

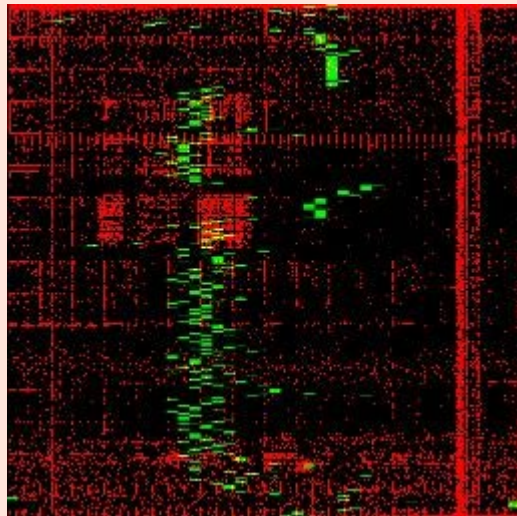
- Gray-level matrix image：將 2-gram byte matrix 的 frequency matrix 的數值降為 0~128，接著分別用 4 個角度 0 度, 45 度, 90 度, 135 度的 Gray-Level Co-occurrence Matrix，Gray-Level Co-occurrence Matrix 是計算圖片中不同角度下相鄰的 pixel 出現的機率，得出 4 個 $128 * 128$ 的 matrix 後，將他們拼在一起，得到第三個 matrix。



Siamese network for few-shot learning

方法三

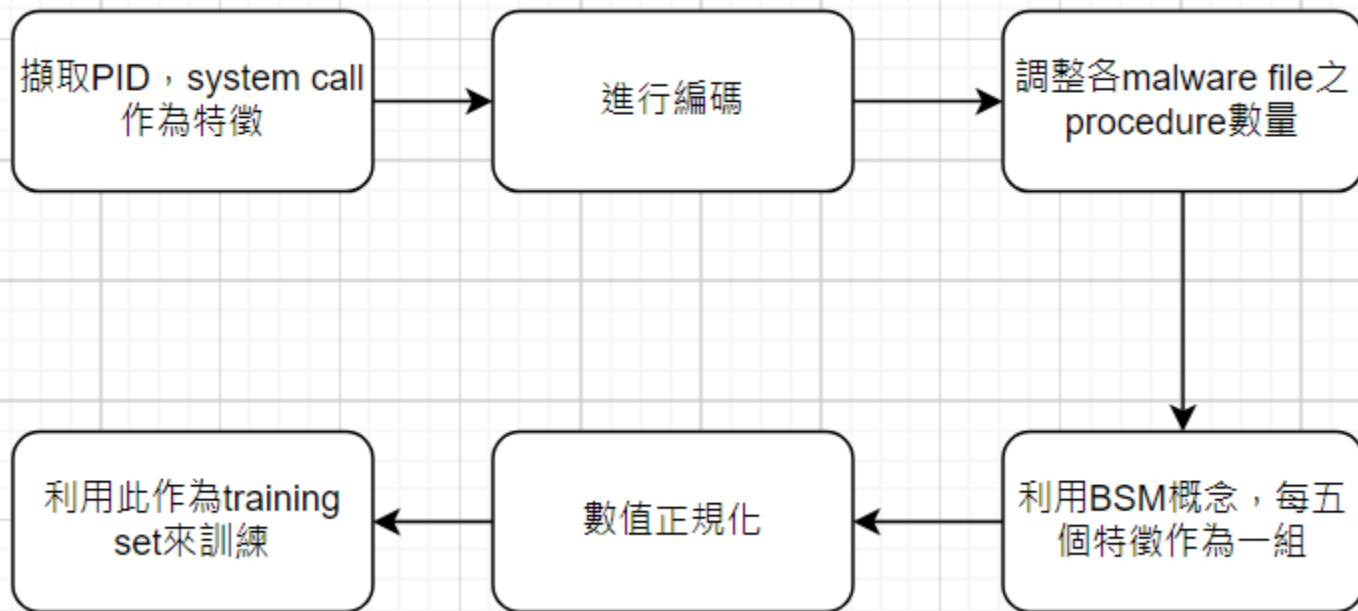
- Result
- 10 training data and 90 test data
- Train loss: 0.3495
- Train accuracy: 0.7500
- Test loss: 0.69
- Test accuracy: 0.53



非few-shot 方法實作比較(BSM方法實作)

PID	TIMESTAMP	SYSCALL	CATEGORY	SPLIT	ARGC
2794	.57E+09	execve			0
2794	.57E+09	rt_sigprocmask			0
2794	.57E+09	rt_sigaction			0
2794	.57E+09	rt_sigaction			0
2794	.57E+09	socket			0
2794	.57E+09	connect			0
2794	.57E+09	getsockname			0
2794	.57E+09	close	IO		0
2794	.57E+09	brk			0

非few-shot 方法實作比較(BSM方法實作)



非few-shot 方法實作比較(BSM方法實作)

Average scores for ten folds:

> Accuracy: 93.15210223197937 (+- 0.6515772298552106)

> Loss: 0.2691150188446045

DecisionTree: 0.9230577153306758

RandomForestClassifier: 0.95229585191617

KNeighborsClassifier: 0.9215201747115549

比較

Dynamic API call sequence visualization for malware classification	Malicious Code Detection: Run Trace Output Analysis by LSTM
image classification	text classification
經特徵提取後，需再轉換為 image	不須進行額外的轉換
惡意程式會將程式碼進行混淆，產生的 image 即有所不同，可能造成模型無法有效判斷	較能不受程式碼混淆技巧的影響
需要惡意程式完整的執行活動行為	擷取特徵時，不一定要有完整的執行行為
使用較少的training data便可得一定的準確率	需要較大量的training data才能有一定的準確率