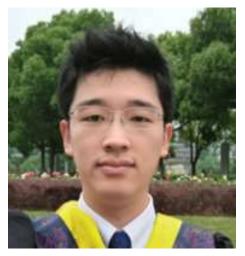


Huajie Xu



Yuchen zeng

Xuanzhu Luo



Yuanxin Liu



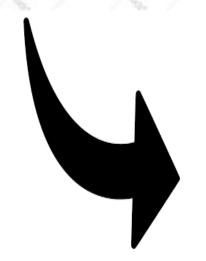
Instructor: Khasha Dehnad







- 1. leave backdoor
- 2. access root permissions
- 3. monitor the network traffic



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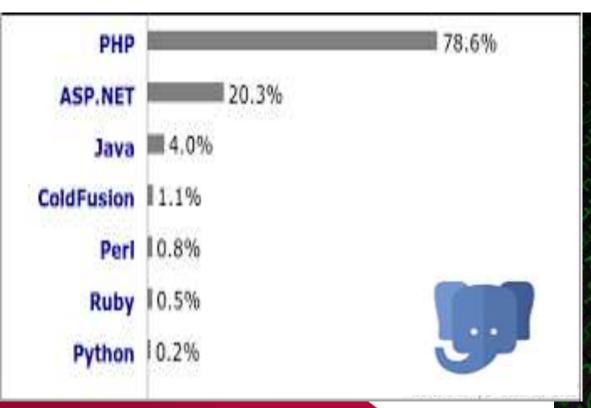


Detect PHP Webshell

PHP is the most common server-side programming language, so a lot of malicious codes are written in PHP language.

Data source:

https://www.kaggle.com/zavadskyy/lots-of-code





Preparation



The dataset we expected...

```
Age, Attrition, BusinessTravel, DistanceFromHome, Education, Employ
NumCompaniesWorked, OverTime, TotalWorkingYears
41, Yes, Travel_Rarely, 1, 2, 1, 2, Female, Single, 5993, 8, Yes, 8
49, No, Travel_Frequently, 8, 1, 2, 3, Male, Married, 5130, 1, No, 10
37, Yes, Travel_Rarely, 2, 2, 4, 4, Male, Single, 2090, 6, Yes, 7
33, No, Travel_Frequently, 3, 4, 5, 4, Female, Married, 2909, 1, Yes, 8
27, No, Travel_Rarely, 2, 1, 7, 1, Male, Married, 3468, 9, No, 6
```

The dataset we have......

```
k?php
/* Autoloader for composer/ca-bundle and its dependencies */
if (!class_exists('Fedora\\Autoloader\\Autoload', false)) {
    require_once '/usr/share/php/Fedora/Autoloader/autoload.php';
}
\Fedora\Autoloader\Autoload::addPsr4('Composer\\CaBundle\\', __DIR__);
```

But HOW?



File Size

Longest String

- Malicious code is often stored as a long string of encoded text within a file. Many popular encoding methods, such as base64 encoding, will produce a long string without space characters.
- Typical text and script files will be composed of relatively short length words; identifying files with uncharacteristically long strings may help to identify files with obfuscated code.

Entropy

- Measuring entropy is useful in locating encrypted shellcode. Encryption can often introduce a large amount of entropy into a text string.

Keywords

eval, shell_exec, fwrite, chr, str_replace......

Example



```
<?php
/* Autoloader for composer/ca-bundle and its dependencies */

if (!class_exists('Fedora\\Autoloader\\Autoload', false)) {
    require_once '/usr/share/php/Fedora/Autoloader/autoload.php';
}

\Fedora\Autoloader\Autoload::addPsr4('Composer\\CaBundle\\', __DIR__);
</pre>
```

CSV generated



275 Webshells, 6000 Ordinary PHP codes.

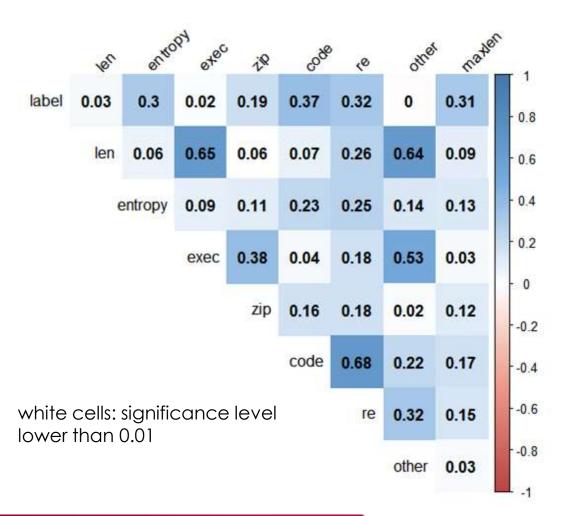
ID,label,len,entropy,exec,zip,code,chr,re,other,maxlen 0,1,1405,5.433242758321368,4,0,0,0,0,0,26 1,1,93545,6.011169553454867,1,1,1,0,0,0,93123 2,1,37391,5.45186781406762,6,0,0,0,17,0,148

ID	
label	1 for webshell, 0 for normal
length	The length of the code file
count_*	Amount of sensitive functions
maxlen	The longest word

correlation analysis



most relevant 3 factors with label: code, re, maxlen



characteristics for malicious code:

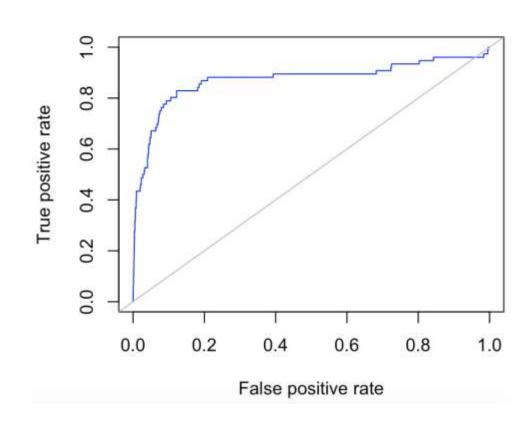
1.frequent calling function: base64_encode/decode, str_replace

2.maxlen higher than normal codes



Model 1 Naive Bayes Results

```
y_pred
         Normal
                 Bad
y_true
  Normal
           1742
                33
  Bad
             43
                  33
> Accuracy(pred, ytest)
[1] 0.9589411
> Precision(ytest, pred)
[1] 0.9759104
> Recall(ytest, pred)
[1] 0.9814085
> F1_Score(ytest, pred)
[1] 0.9786517
```





Model 2 K-Means Results

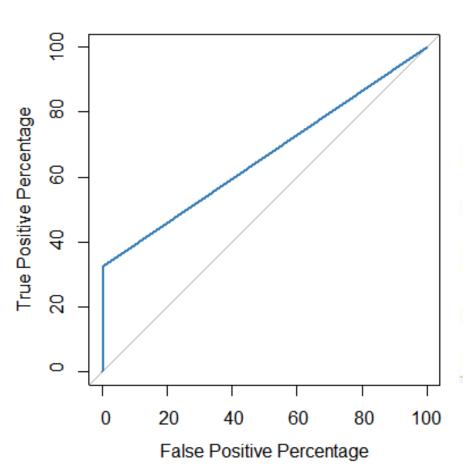
```
TP 47
FP 85
FN 228
TN 5915
Acc 0.9501195219123506
Recall 0.17090909090909
Precision 0.35606060606061
F1 0.23095823095823095
```

This model is not suitable for our condition

Model 3 KNN



Area under the curve: 66.11%



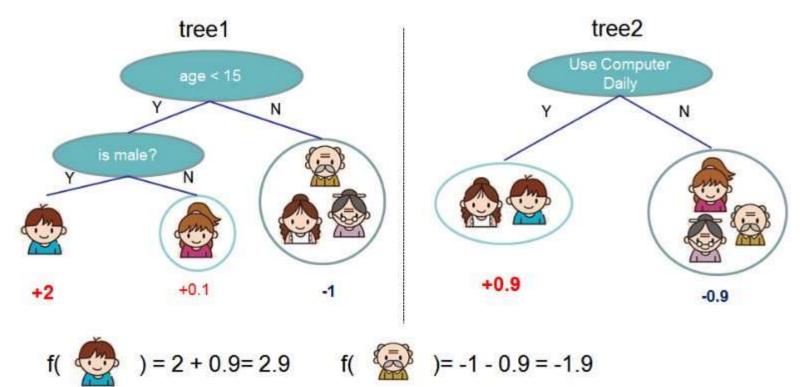
```
y_pred
y_true
     0 1194
         37
              18
> Accuracy(predict_K5, test$label)
[1] 0.9657371
> Precision(test$label, predict_K5)
[1] 0.9699431
> Recall(test$label, predict_K5)
[1] 0.995
> F1_Score(test$label, predict_K5)
[1] 0.9823118
```

Model 4 Gradient Boosted Trees



- Gradient boosting is a supervised learning algorithm, which attempts to accurately predict a target variable by combining the estimates of a set of simpler, weaker models.
- When using gradient boosting for regression, the weak learners are regression trees, and each regression tree maps an input data point to one of its leafs that contains a continuous score.
- XGBoost minimizes a regularized (L1 and L2) objective function that combines a convex loss function (based on the difference between the predicted and target outputs) and a penalty term for model complexity (in other words, the regression tree functions). The training proceeds iteratively, adding new trees that predict the residuals or errors of prior trees that are then combined with previous trees to make the final prediction.



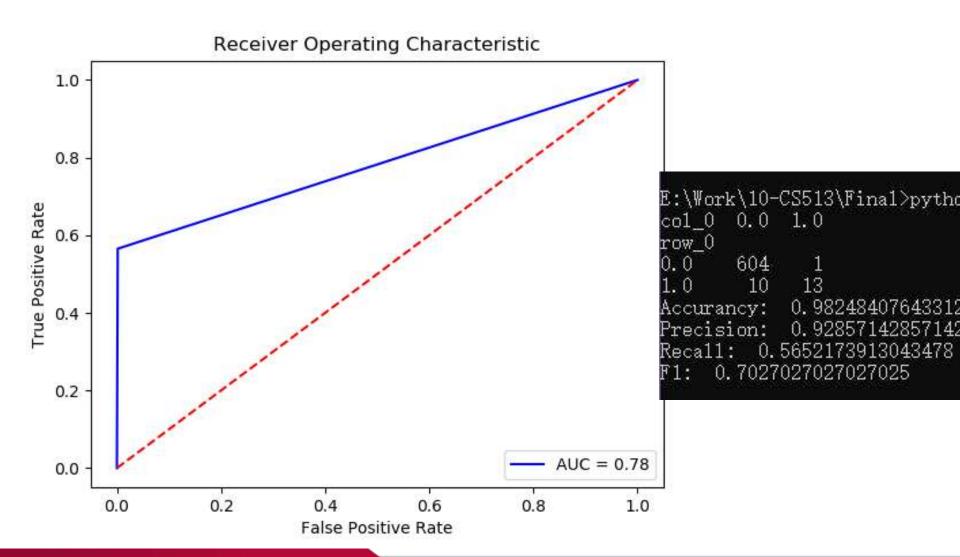


Here is an example of a tree ensemble of two trees. The prediction scores of each individual tree are summed up to get the final score. If you look at the example, an important fact is that the two trees try to complement each other. Mathematically, we can write our model in the form

$$\hat{y}_i = \sum_{i=1}^K f_k(x_i), f_k \in \mathcal{F}$$

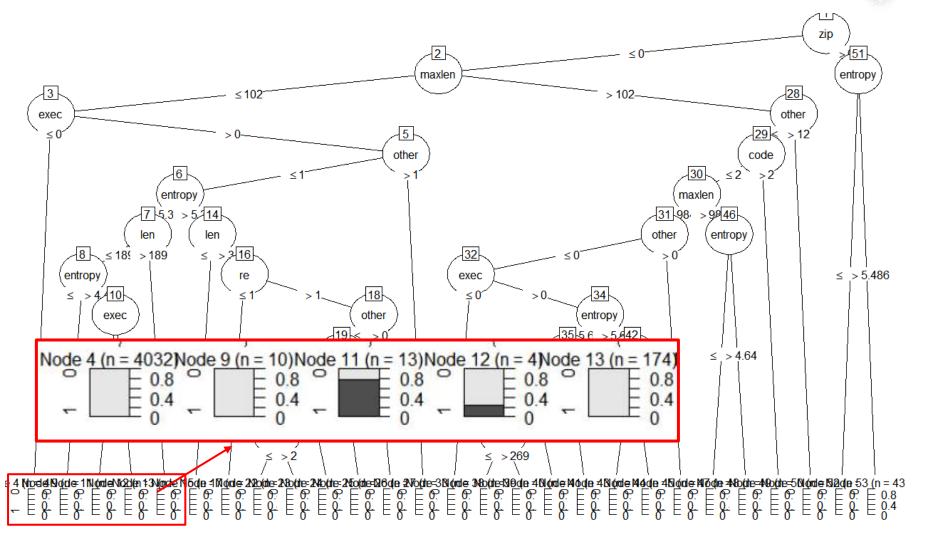


Results



Model 5 C5.0





Model 5 C5.0



Evaluation on training data (4706 cases):

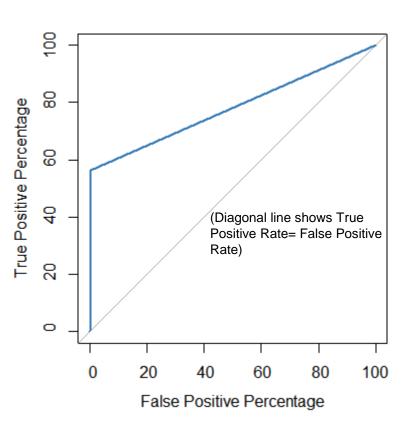
Model 5 C5.0



evaluation using test data

Area under the curve: 0.7786

```
correctRate_c5.0 0.977055449330784
erroRate_c5.0 0.0229445506692161
```

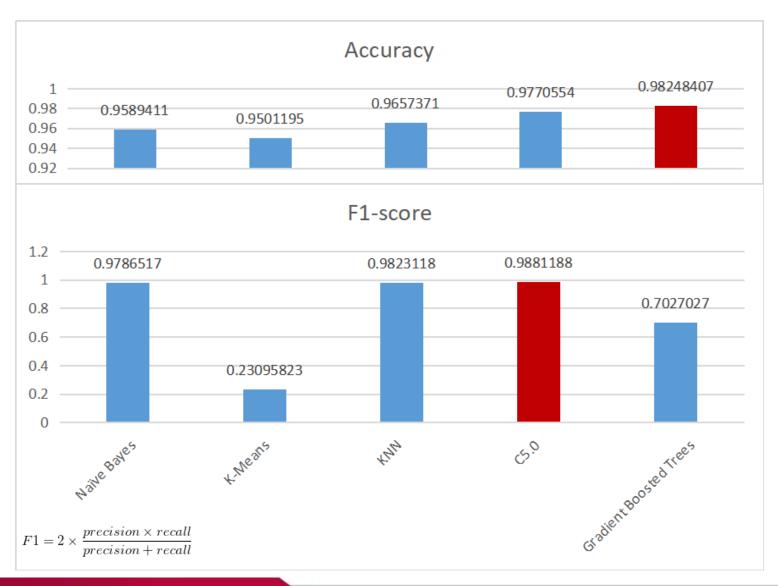


```
prediction
actual 0 1
0 1497 8
1 28 36
```

```
> Accuracy(prediction1, test1)
[1] 0.9770554
> Precision(test1,prediction1)
[1] 0.9816393
> Recall(test1,prediction1)
[1] 0.9946844
> F1_Score(test1,prediction1)
[1] 0.9881188
```

Conclusion







THANK YOU! Q&A

Instructor: Khasha Dehnad **Course:** CS513 Group Project