

# Explainable AI- SHAP - Lab

(Machine Learning Security - Fall 2025)

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# Explaining by removing - SHAP

- SHAP - SHapley Additive Explanations

SHAP proposes two approaches for estimating the Shapley values

1. KernelSHAP - kernel-based estimation approach
  - a. Model agnostic
2. **TreeSHAP** - efficient estimation approach for tree-based models
  - a. Not model agnostic

It also proposes to aggregate local explanation to provide global insights

# Explaining by removing - SHAP

Trains a model with and without subsets of features, compares the difference in performance (and then weight features based on all differences observed)

**-> Finds out the marginal contribution of each feature and feature sets**

$$\phi_i(f, x) = \sum_{z' \subseteq x'} \frac{|z'|! (M - |z'| - 1)!}{M!} [f_x(z') - f_x(z' \setminus i)]$$

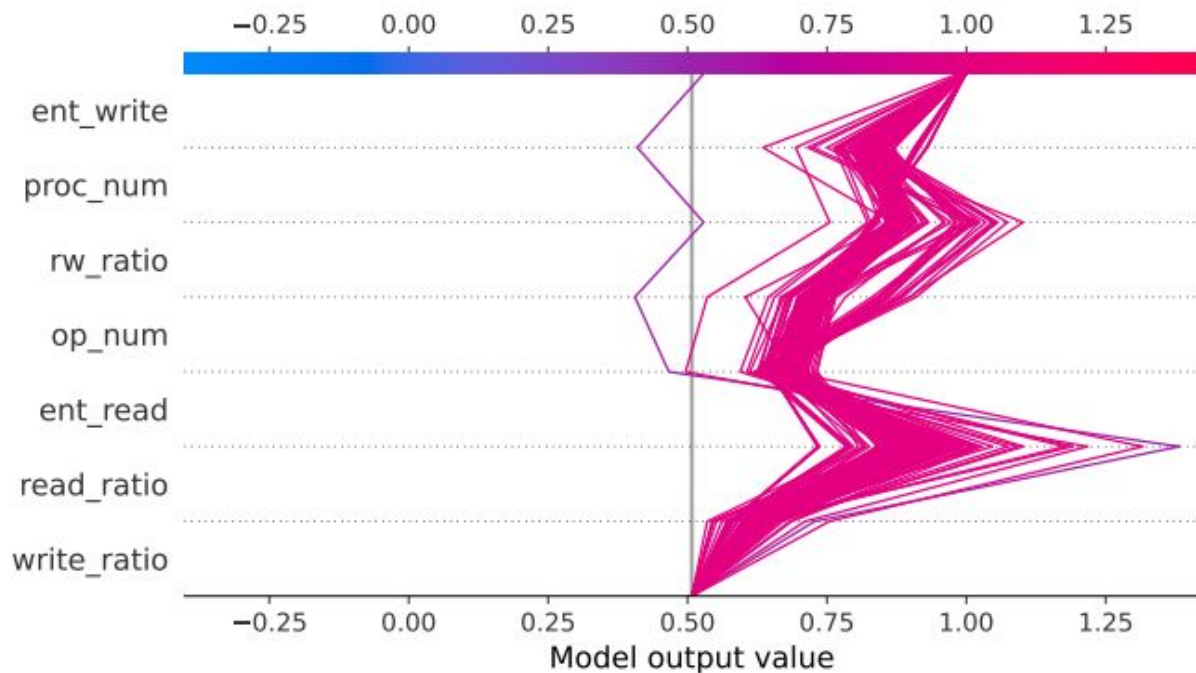
subset of features

weighting term  
(how many features are in the subset)

difference in outcome  
when the subset of  
features is removed

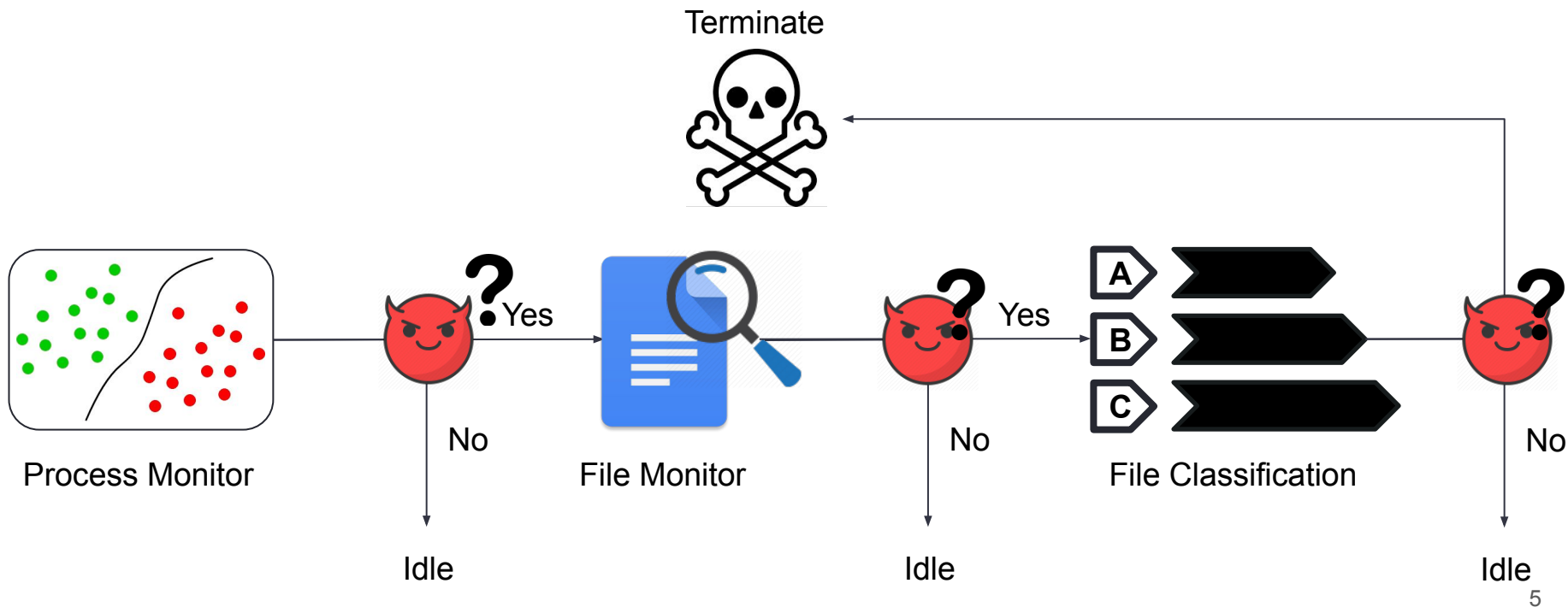
The diagram shows the SHAP formula for 'Explaining by removing'. The summation index  $z' \subseteq x'$  is annotated with 'subset of features'. The fraction  $\frac{|z'|! (M - |z'| - 1)!}{M!}$  is enclosed in a box and annotated with 'weighting term (how many features are in the subset)'. The term in brackets,  $[f_x(z') - f_x(z' \setminus i)]$ , is annotated with 'difference in outcome when the subset of features is removed'.

# Explaining by removing - SHAP



# The Task

- Reimplement the RWGuard Ransomware detector (just the process monitor)



# Dataset

- Dataset.zip
  - **Benign**
    - train/test data already divided into two different .csv files
  - **Ransomware**
    - train/test data already divided into two different .csv files
- Order of features:
  - Read, write, open, close, fast read, fast write, fast close, fast open, label

```
41 35,0,523,505,869,0,0,0,N
42 0,16,197,4,0,0,0,0,N
43 39,34,68,96,10,105,0,0,N
44 4,0,45,55,0,0,0,0,N
45 7,0,46,41,3,0,0,0,N
46 85,0,1242,1172,2071,0,0,0,N
47 0,0,300,5,0,0,0,0,N
48 0,1,2,2,0,0,0,0,N
49 0,0,0,2,0,0,0,0,N
50 0,0,2,2,0,0,0,0,N
51 0,15,297,0,0,0,0,0,N
52 13,22,1,0,4,40,0,0,N
53 1,0,49,40,0,0,0,0,N
54 1,0,10,9,0,0,0,0,N
55 0,7,295,4,0,0,0,0,N
56 16,0,336,320,392,0,0,0,N
```

# Train and evaluate a Random forest classifier on the data

LOAD DATA

Train\_x = ...

Train\_y = ...

```
clf = RandomForestClassifier(n_estimators=100, verbose=1, max_depth=100,  
n_jobs=4)
```

```
clf.fit(train_x, train_y)
```

# Use SHAP library

- [https://shap.readthedocs.io/en/latest/tabular\\_examples.html#tree-based-models](https://shap.readthedocs.io/en/latest/tabular_examples.html#tree-based-models)
- <https://www.kaggle.com/code/vikumsw/explaining-random-forest-model-with-shapely-values>

```
import shap
```

```
explainer = shap.TreeExplainer(random_forest)
```

```
You can do the rest after this :)
```



# Things to discover...

- Find an ordering/ranking of the features
- Understand what different depth models have learned
  - Essentially train different models of varying depth

```
import shap
```

```
explainer = shap.TreeExplainer(random_forest)
```

```
You can do the rest after this :)
```

## Up next...

- Guaranteed robustness towards adversarial examples
- Privacy attacks towards machine learning models