Dynamic Data Analysis

We begin by importing all the necessary libraries

In [1]:

```
# For preprocessing
import os
from glob import glob
import statistics
import json

# For visualization
import matplotlib.pyplot as plt
%matplotlib inline

# For training
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
import numpy as np
import time

# For testing
from sklearn.metrics import confusion_matrix

# For exporting
import pickle
```

Analysis

We'll begin our analysis by making a list of all the files that are available to us for analysis

In [2]:

```
malware_dir_1 = "../../Dynamic_Analysis_Data_Part1/Malware"
benign_dir_1 = "../../Dynamic_Analysis_Data_Part1/Benign"
malware_dir_2 = "../../Dynamic_Analysis_Data_Part2/Malware"
benign_dir_2 = "../../Dynamic_Analysis_Data_Part2/Benign"
malwares = []
benigns = []

for malware in glob(os.path.join(malware_dir_1, "*")):
    malwares += glob(os.path.join(malware, "*"))

benigns = glob(os.path.join(benign_dir_1, "*"))

for malware in glob(os.path.join(malware_dir_2, "*")):
    malwares += glob(os.path.join(malware, "*"))

benigns = glob(os.path.join(benign_dir_2, "*"))
```

Now, lets have a look at our features to get a better understand of our data.

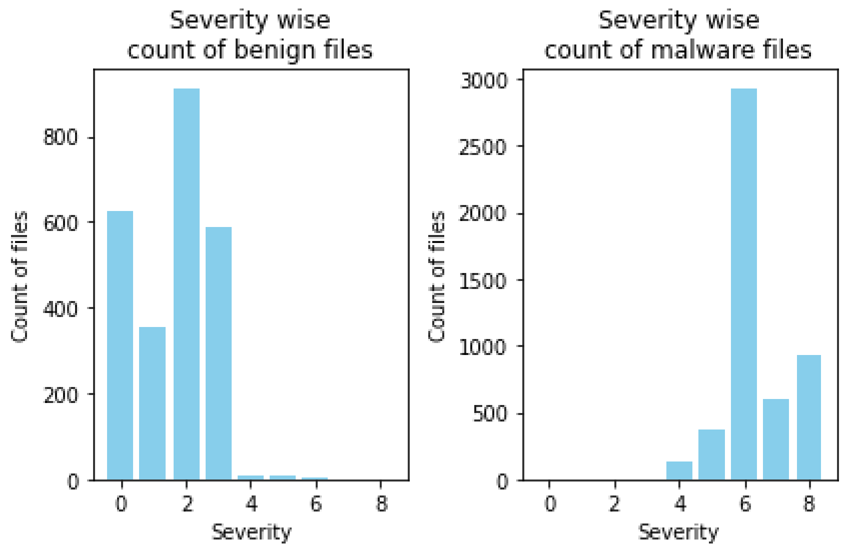
In this case, we were able to get incredible results using just one feature - Severity.

Severity is a measure (on a scale of 8) of how critical the code section that is being executed is.

In general, malwares will try to access more critical code and thus attain a higher severity rate.

In [3]:

```
def max_severity(f_path):
    f = open(f_path, "r", errors="ignore", encoding="utf8")
    f = json.load(f)
    severities = [0]
    for each in f["signatures"]:
        severities.append(each["severity"])
    return max(severities)

benign_vals = []
malware_vals = []

for file in benigns:
    benign_vals.append(max_severity(file))

for file in malwares:
    malware_vals.append(max_severity(file))

# creating the bar plot
plt.subplot(1, 2, 1)
plt.bar(np.arange(9),
        [benign_vals.count(i) for i in range(9)],
        color ='skyblue')
plt.ylabel("Count of files")
plt.xlabel("Severity")
plt.title("Severity wise\ncount of benign files")

plt.subplot(1, 2, 2)
plt.bar(np.arange(9),
        [malware_vals.count(i) for i in range(9)],
        color ='skyblue')
plt.ylabel("Count of files")
plt.xlabel("Severity")
plt.title("Severity wise\ncount of malware files")

plt.tight_layout()
plt.show()
```



Clearly, severity is a great feature to determine whether the given code is malicious or not.

Let's try to see if we can get decent results using just this one particular feature.

Training

We will use the function we defined above to extract features.

For the sake of abstract and future use, we will create a wrapper function that for now, only calls that one function.

In [4]:

```
def extract_features(f_path):
    return [max_severity(f_path)]
```

Next, we write the code to send files from our dataset for feature extraction

In [5]:

```
# Number of samples to take of each type. Set as a negative to use entire dataset
limit = -1

x = []
y = []

i = 0
for file in benigns:
    x.append(extract_features(file))
    y.append(0)
    i += 1
    if i == limit:
        break

i = 0
for file in malwares:
    x.append(extract_features(file))
    y.append(1)
    i += 1
    if i == limit:
        break

x = np.array(x)
y = np.array(y)

x_train, x_test, y_train, y_test = train_test_split(x, y,
                                                    test_size=0.25,
                                                    random_state=42)
```

Now, onto the actual trainning.

We use Random Forest Classifier as the data is highly threshold based. Forest classifiers give good results on such data.

In [6]:

```
cls = RandomForestClassifier()
start = time.time()
cls.fit(x_train, y_train)
stop = time.time()
print(f"Training time: {stop - start} seconds")
```

```
Training time: 0.2561626434326172 seconds
```

Testing

Now that our model is trained, we can test it's accuracy and speed

In [7]:

```
start = time.time()
accuracy = str(cls.score(x_test, y_test))
stop = time.time()

y_pred = cls.predict(x_test)
tp, fp, fn, tn = confusion_matrix(y_test, y_pred).ravel()

precision = tp/(tp + fp)
recall = tp/(tp + fn)
fscore =  2*((precision*recall)/(precision+recall))

print("Accuracy: " + accuracy)
print("Precision: ", precision)
print("Recall: ", recall)
print("F-score: ", fscore)
print(f"Testing time: {(stop - start)} seconds for {len(y_test)} predictions")
```

```
Accuracy: 0.9967811158798283
Precision:  0.9923780487804879
Recall:  0.9984662576687117
F-score:  0.9954128440366974
Testing time: 0.027327775955200195 seconds for 1864 predictions
```

Clearly, our model is able to give us incredible accuracy and speed with just one feature.

This is the most ideal possible case for a ML algorithm.

Export

In [8]:

```
pickle.dump(cls, open("./dynamic_model", 'wb'))
```