

# best\_splits

March 11, 2024

## 1 Train-Test splits

- In this notebook the approach is changed. Instead of implementing equidistant splits of 1 month or day, the splits are now determined by the percentage length of the training set. Ultimately, a timestamp  $t$  is calculated, designating data before  $t$  as the training set and data at and after  $t$  as the testing set.
- Three splits are computed in total:
  - 50%-50% Training-Test: This setting outlines the minimum amount of training data. The number of appearing families in testing set is the maximum compared to the other following splits.
    1. Once the 50%-50% split  $t$  is found, the number of appearing families in testing set is computed;
    2. Subsequently, the splits after  $t$  are iterated as long as the the number of appearing families remains the same;
    3. The last iterated split is the best one as it ensures a longer training dataset while maintaining the same number of appearing families. The training set is ultimately composed of 51.1% of data points.
  - 70%-30% Training-Test: In this split, a significant percentage of the training set is favored, with less concern about the number of new appearing families in the testing set.
  - 62.33%-37.67% Training-Test: An objective function is constructed to maximize both the train-test balancing (linearly favoring splits as the percentage approaches 70%) and the number of appearing families in the testing set. The identified split represents a trade-off between these two scores.

```
[16]: from utils.best_split_utils import *
```

```
[17]: # Get the merged malware data
df = pd.read_csv("vt_reports/merge.csv")
df.head()
```

```
[17]:
```

	sha256	first_submission_date
0	98f8e26e12b978102fa39c197f300ebe5fe535617737d5...	1630575593 \
1	7b2999ffadbc3b5b5c5e94145ca4e2f8de66ac1e3ddd52...	1629375559
2	e7569d494fe00be04ef6c9fcc5e54720c0df623b08e79d...	1362057319
3	1ed60c04f572b6acb9f64c31db55ef5c6b5465bd4da1eb...	1630624233
4	4c4aaff20a57213d9a786e56ad22f1eaa94694a2f1042b...	1592186154

family

```

0    tnegs
1    quasar
2    pasta
3    cjishu
4    kingsoft

```

```

[18]: fsd = "first_submission_date"
      # Convert the timestamps to datetime format
      df_dt = df.copy()
      df_dt[fsd] = df_dt[fsd].apply(lambda t: pd.to_datetime(t, unit='s'))

```

## 1.1 Choose the Train-Test split by choosing Training set length

Given the length in % of the training set, the dataset is split by the time axis using the bisection method.

```

[19]: def find_balanced_split(timestamps, training_perc):
      low, high = 0, len(timestamps) - 1
      idx = - 1
      while low <= high:
          mid = (low + high) // 2
          mid_value = timestamps[mid]
          perc_train = len(df_dt[df_dt[fsd] < mid_value]) / len(df_dt)
          if perc_train == training_perc:
              idx = mid
              high = mid - 1
          elif perc_train < training_perc:
              # Search in the right half
              low = mid + 1
          else:
              # Search in the left half
              high = mid - 1

      return timestamps[idx]

```

```

[20]: def compute_bs_af(df: pd.DataFrame, ref_df: pd.DataFrame, date_split: pd.
      ↳Timestamp,
      bs_f: Callable = lambda x: 1 - np.abs(x - 0.7) / 0.7):
      # Train-Test balancing: this score increases as the training test length
      # in % is approaching 80% of the samples
      train_prop = len(df[df[fsd] < date_split]) / len(ref_df)
      bs = bs_f(train_prop)

      # % Appearing families in testing set
      df_train_nonzero = split_and_group_nonzero(src_df=df,
      ↳split_condition=df[fsd] < date_split)

```

```

df_test_nonzero = split_and_group_nonzero(src_df=df, split_condition=df[fds]
↳>= date_split)

test_families = df_test_nonzero["family"].unique()
af = ((len(test_families) - len(np.intersect1d(df_train_nonzero["family"].
↳unique(), test_families))) /
      len(ref_df["family"].unique()))

return {"bs": bs, "af": af}

```

```

[21]: def max_train_from_new_f(splits):
    ref_df_dt = df_dt.copy()
    af_f = lambda s: compute_bs_af(df_dt, ref_df_dt, s)["af"]
    ref_af = af_f(splits[0])
    for i in range(1, len(splits)):
        if af_f(splits[i]) < ref_af:
            return splits[i - 1]
    return splits[len(splits) - 1]

```

```

[22]: t_unique = df_dt[fds].sort_values().unique()
t_best_split = find_balanced_split(t_unique, 0.7)
print_statistics(df_dt, t_best_split, f"Split at {t_best_split}")

```

```

-----
Report: Split at 2021-12-09 08:48:58
    Training set length: 46900, (70.0%)
    Testing set length: 20100, (30.0%)
    Num families in training: 663
    Num families in testing: 606
    Common families: 599
    Families in training but not in testing: 64 (9.55%)
    Families in testing but not in training: 7 (1.04%)

```

```

[23]: t_unique = df_dt[fds].sort_values().unique()
t_split = find_balanced_split(t_unique, 0.5)
date_splits = [t for t in t_unique if t >= t_split]
# After computing the 50-50% split, maximize the training set length as the
# number of appearing families in testing set remains the same.
t_min_split = max_train_from_new_f(date_splits)
print_statistics(df_dt, t_min_split, f"Split at {t_min_split}")

```

```

-----
Report: Split at 2021-08-26 12:40:17
    Training set length: 34240, (51.1%)
    Testing set length: 32760, (48.9%)
    Num families in training: 650
    Num families in testing: 650

```

```

Common families: 630
Families in training but not in testing: 20 (2.99%)
Families in testing but not in training: 20 (2.99%)

```

```
[24]: date_splits = [t for t in t_unique if t_min_split <= t <= t_best_split]
```

```
[25]: df_scores, df_ref_scores = df_dt.copy(), df_dt.copy()
js_scores, perc_app_families, balance_scores = [], [], []
for date_split in date_splits:
    scores = compute_bs_af(df=df_scores, ref_df=df_ref_scores,
    ↪date_split=date_split)
    perc_app_families.append(scores["af"])
    balance_scores.append(scores["bs"])
```

```
[26]: # Min-Max normalization
perc_app_families_min_max = ((perc_app_families - np.min(perc_app_families)) /
                             (np.max(perc_app_families) - np.
    ↪min(perc_app_families)))

balance_scores_min_max = ((balance_scores - np.min(balance_scores)) /
                           (np.max(balance_scores) - np.min(balance_scores)))
```

```
[27]: f_objective = perc_app_families_min_max + balance_scores_min_max
t_split_mid = date_splits[np.argmax(f_objective)]
print_statistics(df_dt, t_split_mid)
```

-----  
Report:

```

Training set length: 41763, (62.33%)
Testing set length: 25237, (37.67%)
Num families in training: 654
Num families in testing: 632
Common families: 616
Families in training but not in testing: 38 (5.67%)
Families in testing but not in training: 16 (2.39%)

```

```
[28]: final_splits = [t_min_split, t_split_mid, t_best_split]
```

```
[29]: import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

for split in final_splits:

    df_split = split_and_group(df_dt, df_dt[fsd] < split, df_dt.copy())
    df_split["train_perc"] = df_split["count"] / 100
    df_split["test_perc"] = 1 - df_split["train_perc"]
```

```

df_split = df_split.sort_values(by="train_perc", ascending=False)
split_m = df_split[["train_perc", "test_perc"]].to_numpy()

# Create a heatmap using seaborn
plt.figure(figsize=(6, 10))
sns.heatmap(split_m, annot=True, fmt=".2f",
            xticklabels=["Train %", "Test %"],
            yticklabels=df_split["family"])

plt.xlabel("Family")
plt.ylabel("Split")
plt.title(f"Train-Test % at {split}")
plt.savefig(f"../doc/best_splits_img/split-{split}.png")

# Show the plot
plt.show()

```













