Internship_CodeB_week 4

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1 Phishing Website Detection

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- github : [https://github.com/jadhavgaurav/CodeB_Internship_Project]

2 Week 4 Submission

[25]:

```
# Import Necessary Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

[26]:

```
# import dataset

data_url = 'https://raw.githubusercontent.com/jadhavgaurav/
↪CodeB_Internship_Project/refs/heads/main/dataset_phishing.csv'

df = pd.read_csv(data_url)

df.sample(frac = 1)
```

[26]:

```
                                                    url  length_url  \
9990                               https://beta.znipe.tv/          22
10367                        https://www.armeriaegara.com/          29
7134   http://www.techsupportalert.com/content/best-f…          74
7535                  http://www.forlocations.com/savealot          36
3676   http://www.howdesign.com/editors-picks/10-eye-…          80
…                                                   …           …
3545        http://houseoftiresbcs.com/Adobe/css/XML/PDF/          45
9653                             http://www.yilport.n.nu/          24
1533                   http://smsenligne.myfreesites.net/          34
```

```
11223                        http://www.waymarking.com          25
5677   https://www.osapublishing.org/abstract.cfm?URI…          61

       length_hostname  ip  nb_dots  nb_hyphens  nb_at  nb_qm  nb_and  nb_or  \
9990                13   0        2           0      0      0       0      0
10367               20   0        2           0      0      0       0      0
7134                24   0        3           4      0      0       0      0
7535                20   0        2           0      0      0       0      0
3676                17   0        2           6      0      0       0      0
…                  …  ..      …         …    …    …      …    …
3545                19   0        1           0      0      0       0      0
9653                16   0        3           0      0      0       0      0
1533                26   0        2           0      0      0       0      0
11223               18   0        2           0      0      0       0      0
5677                21   0        3           3      0      1       0      0

       …  domain_in_title  domain_with_copyright  whois_registered_domain  \
9990   …                0                      0                        0
10367  …                1                      1                        0
7134   …                1                      1                        0
7535   …                1                      0                        0
3676   …                1                      0                        0
…    …               …                     …                       …
3545   …                1                      0                        0
9653   …                0                      0                        0
1533   …                1                      0                        0
11223  …                0                      1                        0
5677   …                1                      1                        0

       domain_registration_length  domain_age  web_traffic  dns_record  \
9990                          173        1654      4127669           0
10367                         171        4578            0           0
7134                           79        7226        52982           0
7535                           14        3639       246250           0
3676                          218        8915       566894           0
…                            …         …          …          …
3545                           53        1407            0           0
9653                         2692          -1            0           0
1533                          242        1950       341948           0
11223                          67        5776       197005           0
5677                         1697        2320        35081           0

       google_index  page_rank      status
9990              0          3  legitimate
10367             0          2  legitimate
7134              0          5  legitimate
7535              0          3  legitimate
```

```
3676               1          5  legitimate
…             …        …         …
3545               1          0    phishing
9653               0          3  legitimate
1533               1          1    phishing
11223              0          5  legitimate
5677               0          5  legitimate

[11430 rows x 89 columns]
```

3 Data Cleaning Report Phishing Website Detection

3.1 Dataset Overview

- **Total Records:** 11,430
- **Total Features (excluding target):** 87
- **Target Variable:** `status`
  - `0`: Legitimate
  - `1`: Phishing
- **Data Types:**
  - **Numerical (int64/float64):** 87
  - **Categorical/Object:** 1 (`url`)

3.1.1 Target Column

3.1.2 `status`

- **Description**: Binary label indicating if the website is phishing (`1`) or legitimate (`0`).
- **Relevance**: This is the variable to be predicted by the classification model.

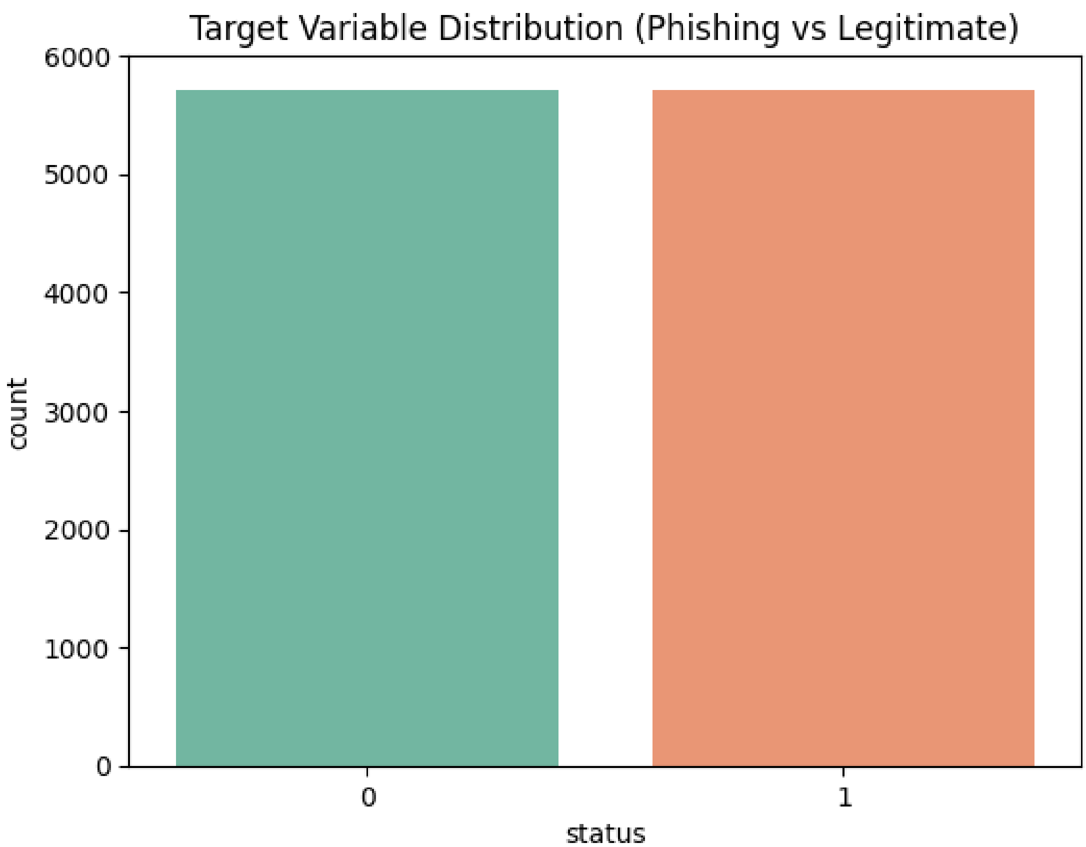
---

[29]:
```
# Replace 'Legitimate' with 0 and 'Phishing' with 1 in the 'status' column
df['status'] = df['status'].map({'legitimate':0, 'phishing':1})

print(df['status'].value_counts())
```

```
status
0    5715
1    5715
Name: count, dtype: int64
```

[30]:
```
# Basic Info About Target Column and Visualize Target Distribution (Bar Plot)

# Check class distribution

sns.countplot(data=df, x='status', palette='Set2')
plt.title("Target Variable Distribution (Phishing vs Legitimate)")
```

```
plt.show()

print(df['status'].value_counts())
```




```
status
0    5715
1    5715
Name: count, dtype: int64
```

[31]:
```
numeric_features = df.select_dtypes(include=['int64', 'float64']).columns.
↪tolist()
categorical_features = df.select_dtypes(include='object').columns.tolist()

print("Numeric Features:", numeric_features)
print("Categorical Features:", categorical_features)
```

```
Numeric Features: ['length_url', 'length_hostname', 'ip', 'nb_dots',
'nb_hyphens', 'nb_at', 'nb_qm', 'nb_and', 'nb_or', 'nb_eq', 'nb_underscore',
'nb_tilde', 'nb_percent', 'nb_slash', 'nb_star', 'nb_colon', 'nb_comma',
'nb_semicolumn', 'nb_dollar', 'nb_space', 'nb_www', 'nb_com', 'nb_dslash',
'http_in_path', 'https_token', 'ratio_digits_url', 'ratio_digits_host',
```

```
'punycode', 'port', 'tld_in_path', 'tld_in_subdomain', 'abnormal_subdomain',
'nb_subdomains', 'prefix_suffix', 'random_domain', 'shortening_service',
'path_extension', 'nb_redirection', 'nb_external_redirection',
'length_words_raw', 'char_repeat', 'shortest_words_raw', 'shortest_word_host',
'shortest_word_path', 'longest_words_raw', 'longest_word_host',
'longest_word_path', 'avg_words_raw', 'avg_word_host', 'avg_word_path',
'phish_hints', 'domain_in_brand', 'brand_in_subdomain', 'brand_in_path',
'suspecious_tld', 'statistical_report', 'nb_hyperlinks', 'ratio_intHyperlinks',
'ratio_extHyperlinks', 'ratio_nullHyperlinks', 'nb_extCSS',
'ratio_intRedirection', 'ratio_extRedirection', 'ratio_intErrors',
'ratio_extErrors', 'login_form', 'external_favicon', 'links_in_tags',
'submit_email', 'ratio_intMedia', 'ratio_extMedia', 'sfh', 'iframe',
'popup_window', 'safe_anchor', 'onmouseover', 'right_clic', 'empty_title',
'domain_in_title', 'domain_with_copyright', 'whois_registered_domain',
'domain_registration_length', 'domain_age', 'web_traffic', 'dns_record',
'google_index', 'page_rank', 'status']
Categorical Features: ['url']
```

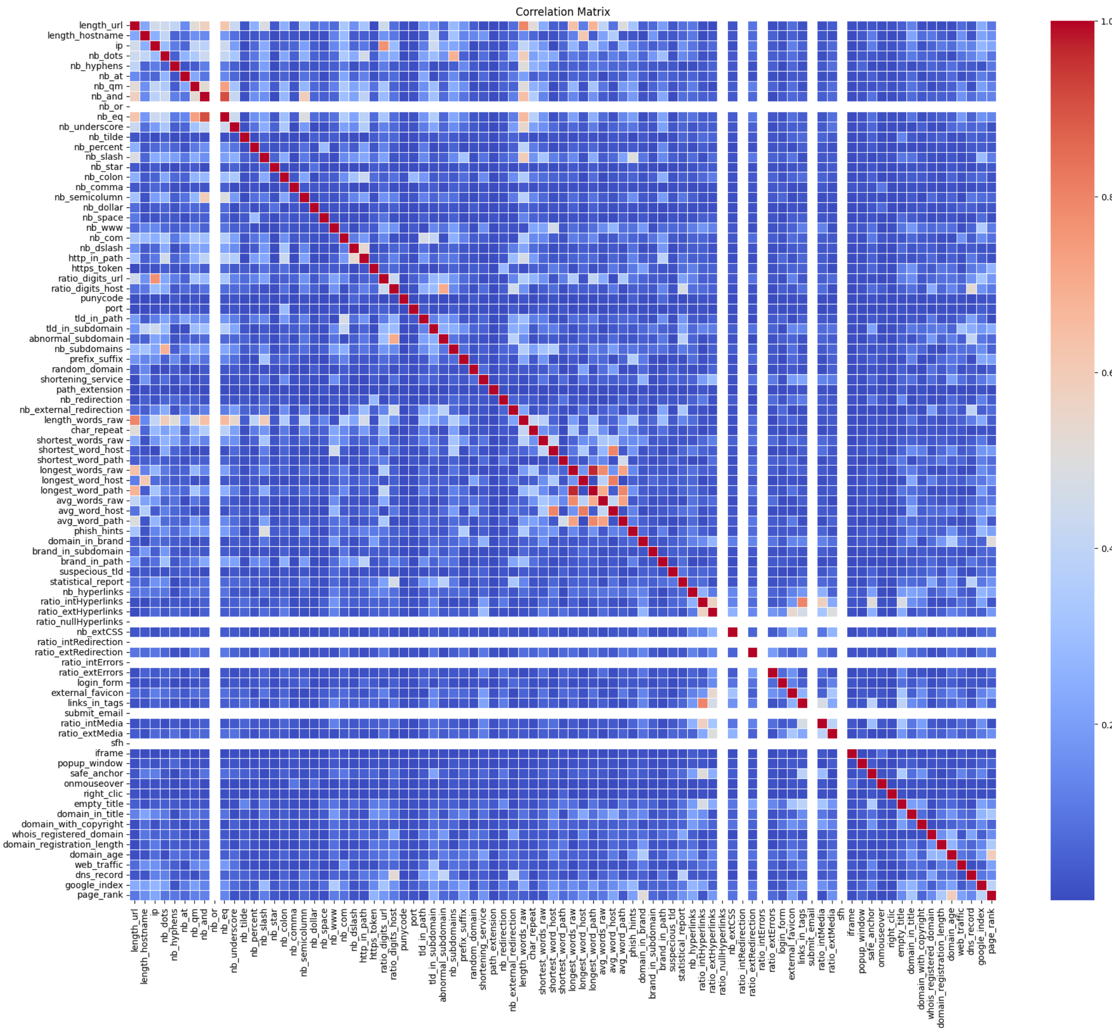
[32]:
```
# Dropping the 'url' column
# The 'url' column is not useful for training the machine learning model.

df.drop(columns=['url'], inplace=True)
```

4 Feature Selection Report

Step 1: Correlation Analysis

Remove features that are highly correlated with each other (e.g., correlation > 0.9 or < -0.9) to reduce multicollinearity.

[33]:
```
# Step 1: Compute correlation matrix
corr_matrix = df.drop('status', axis=1).corr().abs()  # Exclude target column
plt.figure(figsize=(22, 18))
sns.heatmap(corr_matrix, annot=False, cmap='coolwarm', linewidths=0.5)
plt.title("Correlation Matrix")
plt.show()
```



- The correlation heatmap was generated to visually inspect multicollinearity between features.
- Correlation threshold used: `0.90`

Heatmap legend:

`Red diagonal` = perfect correlation (with itself)

`Light blue` = weak or no correlation

`Orange/red`= strong correlation

[34]:
```
# Step 2: Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))

# Step 3: Find features with correlation > 0.9
to_drop = [column for column in upper.columns if any(upper[column] > 0.9)]
print(f"Highly correlated features to drop (corr > 0.9):\n{to_drop}")
```

```
# Step 4: Drop the features from the dataset
df_reduced = df.drop(columns=to_drop)
print(f"\nShape before dropping: {df.shape}")
print(f"Shape after dropping: {df_reduced.shape}")
```

```
Highly correlated features to drop (corr > 0.9):
['nb_eq', 'longest_word_path']

Shape before dropping: (11430, 88)
Shape after dropping: (11430, 86)
```

- Computed the correlation matrix (Pearson correlation).
- Identified pairs of features with absolute correlation > 0.90.
- From each such pair, one feature was dropped to reduce redundancy.

Dropped Features:

- Based on correlation > 0.90, the following features were removed:

'nb_eq'

'longest_word_path'

- These features were highly correlated with other features carrying similar information.

[35]:
```
df_reduced.drop(columns=['avg_word_host'], inplace=True)  # Drop avg_word_host␣
↪column as per VIF analysis
```

4.0.1 2: Feature Selection using ANOVA F-test (f_classif)

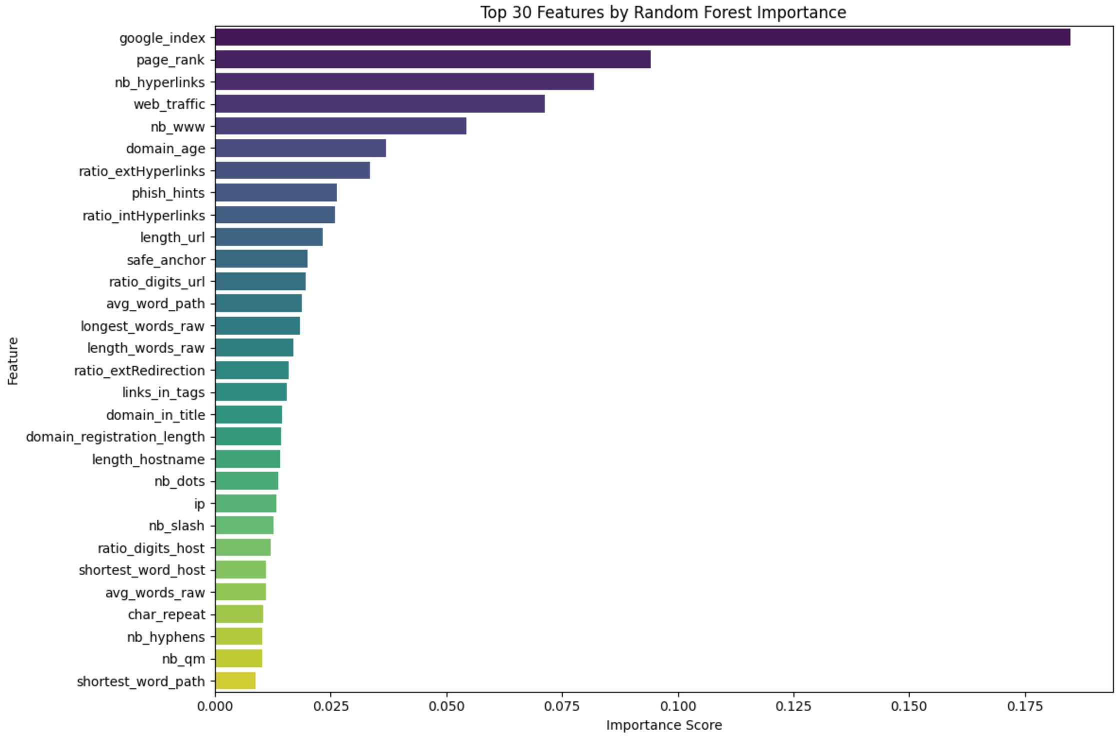
[36]:
```
from sklearn.feature_selection import SelectKBest, f_classif

X = df_reduced.drop(columns=['status'])
y = df_reduced['status']

# Apply ANOVA F-test
selector = SelectKBest(score_func=f_classif, k=30)  # Select top 20 features
X_kbest = selector.fit_transform(X, y)

# Get selected feature names
selected_features_f_classif = X.columns[selector.get_support()]
print("Top 30 Features selected using f_classif:")
print(selected_features_f_classif)
```

```
Top 30 Features selected using f_classif:
Index(['length_url', 'length_hostname', 'ip', 'nb_dots', 'nb_qm', 'nb_and',
       'nb_slash', 'nb_www', 'ratio_digits_url', 'ratio_digits_host',
       'tld_in_subdomain', 'prefix_suffix', 'length_words_raw',
       'shortest_word_host', 'longest_words_raw', 'avg_words_raw',
```

```
 'avg_word_path', 'phish_hints', 'nb_hyperlinks', 'ratio_intHyperlinks',
 'links_in_tags', 'ratio_intMedia', 'safe_anchor', 'empty_title',
 'domain_in_title', 'domain_with_copyright',
 'domain_registration_length', 'domain_age', 'google_index',
 'page_rank'],
dtype='object')
```

4.0.2 3: Random Forest Feature Importance

[37]:
```python
from sklearn.ensemble import RandomForestClassifier
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load dataset (assuming df is already preprocessed and target is separated)
X = df_reduced.drop('status', axis=1)
y = df_reduced['status']

# Train Random Forest
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X, y)

# Get feature importances
importances = pd.Series(rf.feature_importances_, index=X.columns)
top_30_features = importances.sort_values(ascending=False).head(30)

# Plot
plt.figure(figsize=(12, 8))
sns.barplot(x=top_30_features.values, y=top_30_features.index,
 ↪palette='viridis')
plt.title('Top 30 Features by Random Forest Importance')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```



4.0.3 4: Apply RFE (Recursive Feature Elimination)

[38]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE

# Use top 40 features for RFE
X_top30 = X[top_30_features.index]

# Apply RFE with Logistic Regression
lr = LogisticRegression(solver='liblinear', random_state=42)
rfe = RFE(estimator=lr, n_features_to_select=20)
rfe.fit(X_top30, y)

# Get selected feature names
selected_features_rfe = X_top30.columns[rfe.support_]
print("Top 20 features selected by RFE:\n")
print(selected_features_rfe)
```

```
Top 20 features selected by RFE:

Index(['google_index', 'page_rank', 'nb_www', 'ratio_extHyperlinks',
       'phish_hints', 'ratio_intHyperlinks', 'ratio_digits_url',
       'avg_word_path', 'longest_words_raw', 'length_words_raw',
       'ratio_extRedirection', 'domain_in_title', 'nb_dots', 'ip',
```

```
 'ratio_digits_host', 'shortest_word_host', 'avg_words_raw',
 'nb_hyphens', 'nb_qm', 'shortest_word_path'],
dtype='object')
```

4.0.4 Final Selected Features from

`selected_features_rfe` → top 20 features from RFE on top 30 RF features

`selected_features_f_classif` → top 30 features from f_classif

[39]:
```
# Convert both to sets
rfe_features_set = set(selected_features_rfe)
f_classif_features_set = set(selected_features_f_classif)

# Take intersection
final_selected_features = list(rfe_features_set.union(f_classif_features_set))

print("Final Selected Features (Intersection of RFE and f_classif):")
print(final_selected_features)
print(f"Number of final selected features: {len(final_selected_features)}")
```

```
Final Selected Features (Intersection of RFE and f_classif):
['prefix_suffix', 'nb_hyphens', 'domain_registration_length',
'ratio_digits_host', 'ratio_intHyperlinks', 'avg_word_path', 'ratio_intMedia',
'ip', 'length_hostname', 'length_words_raw', 'nb_www', 'empty_title',
'ratio_extRedirection', 'nb_dots', 'nb_slash', 'tld_in_subdomain',
'nb_hyperlinks', 'google_index', 'nb_and', 'length_url', 'domain_in_title',
'shortest_word_path', 'longest_words_raw', 'ratio_digits_url',
'shortest_word_host', 'links_in_tags', 'safe_anchor', 'page_rank', 'domain_age',
'phish_hints', 'domain_with_copyright', 'avg_words_raw', 'ratio_extHyperlinks',
'nb_qm']
Number of final selected features: 34
```

[40]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
import pandas as pd

# Subset the dataframe to final selected features
X_vif = df_reduced[final_selected_features]

# X_vif = X_vif.drop(columns=['avg_word_host'])

# Compute VIF
vif_data = pd.DataFrame()
vif_data["Feature"] = X_vif.columns
vif_data["VIF"] = [variance_inflation_factor(X_vif.values, i) for i in␣
↪range(X_vif.shape[1])]

# Sort VIF descending
vif_data = vif_data.sort_values(by="VIF", ascending=False)
```

```python
print("VIF for Final Selected Features:")
print(vif_data)
```

```
VIF for Final Selected Features:
                       Feature        VIF
9              length_words_raw  26.646784
31                avg_words_raw  22.677655
19                   length_url  21.356093
4           ratio_intHyperlinks  17.695732
14                     nb_slash  16.004551
13                      nb_dots  11.074524
8               length_hostname  10.018208
22            longest_words_raw   8.455121
5                 avg_word_path   8.351384
25                links_in_tags   7.433357
20              domain_in_title   5.553849
27                    page_rank   5.356246
24            shortest_word_host   4.893766
23             ratio_digits_url   4.508979
28                   domain_age   4.483027
32          ratio_extHyperlinks   4.213635
7                            ip   3.718532
17                 google_index   3.634672
18                       nb_and   2.981160
6               ratio_intMedia   2.974564
1                    nb_hyphens   2.916684
21           shortest_word_path   2.902547
26                  safe_anchor   2.861841
10                       nb_www   2.772176
11                  empty_title   2.450279
33                        nb_qm   2.128720
30        domain_with_copyright   2.101064
15             tld_in_subdomain   1.972449
29                  phish_hints   1.833878
3             ratio_digits_host   1.726988
0                 prefix_suffix   1.718168
2    domain_registration_length   1.603927
16                 nb_hyperlinks   1.593017
12         ratio_extRedirection   1.540672
```

[41]:
```python
features_to_drop_vif = [
    'length_words_raw',
    'avg_words_raw',
    'length_url',
    'ratio_intHyperlinks',
    'nb_slash',
```

```
    'nb_dots',
]
```

[42]:
```
# Final Set of Features After VIF Cleaning

final_features_vif = list(set(final_selected_features) -
 ↪set(features_to_drop_vif))
print(f"Number of final features after VIF cleaning: {len(final_features_vif)}")
print("Final Features After VIF Cleaning:")
final_features_vif
```

```
Number of final features after VIF cleaning: 28
Final Features After VIF Cleaning:
```

[42]:
```
['prefix_suffix',
 'nb_hyphens',
 'domain_registration_length',
 'ratio_digits_host',
 'avg_word_path',
 'ratio_intMedia',
 'ip',
 'length_hostname',
 'nb_www',
 'empty_title',
 'ratio_extRedirection',
 'tld_in_subdomain',
 'nb_hyperlinks',
 'google_index',
 'nb_and',
 'domain_in_title',
 'shortest_word_path',
 'longest_words_raw',
 'ratio_digits_url',
 'shortest_word_host',
 'links_in_tags',
 'safe_anchor',
 'page_rank',
 'domain_age',
 'phish_hints',
 'ratio_extHyperlinks',
 'domain_with_copyright',
 'nb_qm']
```

4.1 Applied Steps for Feature Selection Process:

4.1.1 1. Correlation Analysis

- Removed highly correlated features (`corr > 0.9`)
- **Dropped:** `'nb_eq'`, `'longest_word_path'`
- **Reduced from 88 to 86 features**

4.1.2 2. ANOVA (f_classif)

- Selected **top 30 features** based on **univariate F-test**
- Suitable for **numerical features** with **categorical target**

4.1.3 3. Random Forest Feature Importance

- Trained a **Random Forest Classifier**
- Retrieved **top 30 features** using `feature_importances_`

4.1.4 4. Recursive Feature Elimination (RFE)

- Applied **RFE** with Random Forest as estimator
- Selected another **top 30 important features**

4.1.5 5. Feature Union

- Took **intersection** of `f_classif_features_set` & `rfe_features_set`
- Created a **robust final feature set** using two strong methods

---

4.1.6 6. Variance Inflation Factor (VIF)

- Evaluated multicollinearity in final selected features

- Dropped 6 features with VIF > 10 to avoid redundancy

5 Feature Engineering

[43]:
```
# 1. URL Complexity Score
# Combines counts of common "suspicious" tokens into a single indicator.
# Phishing URLs often cram many special characters (www, -, ?, &) to obfuscate␣
 ↪their true destination.

df_reduced['url_complexity'] = (
      df_reduced['nb_www']
    + df_reduced['nb_hyphens']
```

```
    + df_reduced['nb_qm']
    + df_reduced['nb_and']
)
```

[44]:
```
# 2. Tag-to-Link Ratio
# Measures the density of "hidden" tags relative to visible hyperlinks.
# Fake pages load script/link tags disproportionately to real hyperlinks-high␣
↪ratios indicate suspicious embedding.

df_reduced['tag_to_link_ratio'] = df_reduced['links_in_tags'] /␣
↪(df_reduced['nb_hyperlinks'] + 1)
```

[45]:
```
# 3. Domain Numeric Intensity
# Scales the digit-density in the hostname by domain age (older domains with␣
↪many digits are rarer).
# Young domains with a high digit ratio are more likely auto-generated by␣
↪attackers; multiplying by domain_age highlights this risk.

df_reduced['domain_numeric_intensity'] = df_reduced['ratio_digits_host'] *␣
↪df_reduced['domain_age']
```

[46]:
```
# 4. Path Word Complexity
# Captures both the average word length and the longest word in the URL path.
# Extremely long or complex path segments often appear in phishing payload URLs-
this combines average and maximum word length in the path.

df_reduced['path_word_complexity'] = df_reduced['avg_word_path'] *␣
↪df_reduced['longest_words_raw']
```

[47]:
```
# Drop 5 low-importance/redundant features
features_to_drop = [
    'domain_with_copyright',
    'ratio_intMedia',
    'google_index',
    'page_rank',
    'safe_anchor'
]

# Drop from X_train and X_test
df_reduced = df_reduced.drop(columns=features_to_drop)

# Update the final_features_vif list
final_features_vif = [feature for feature in final_features_vif if feature not␣
↪in features_to_drop]

# Add the newly engineered features
```

```python
new_engineered_features = ['url_complexity', 'tag_to_link_ratio',␣
↪'domain_numeric_intensity', 'path_word_complexity']
final_features_vif.extend(new_engineered_features)

#  Check final feature count
print("Total final features after update:", len(final_features_vif))
print("Updated Features:\n", final_features_vif)
```

```
Total final features after update: 27
Updated Features:
 ['prefix_suffix', 'nb_hyphens', 'domain_registration_length',
'ratio_digits_host', 'avg_word_path', 'ip', 'length_hostname', 'nb_www',
'empty_title', 'ratio_extRedirection', 'tld_in_subdomain', 'nb_hyperlinks',
'nb_and', 'domain_in_title', 'shortest_word_path', 'longest_words_raw',
'ratio_digits_url', 'shortest_word_host', 'links_in_tags', 'domain_age',
'phish_hints', 'ratio_extHyperlinks', 'nb_qm', 'url_complexity',
'tag_to_link_ratio', 'domain_numeric_intensity', 'path_word_complexity']
```

5.1 Insights and Recommendations

5.1.1 Key Insights from Feature Selection Process

The feature selection pipeline combined statistical rigor and machine learning techniques to ensure an optimal set of predictive variables:

1. **Correlation Analysis**
   - Identified and removed highly correlated features (`corr > 0.9`) to reduce redundancy.
   - **Dropped:** `'nb_eq'`, `'longest_word_path'`
   - Reduced feature count from **88 to 86**.

2. **ANOVA F-Test (f_classif)**
   - Used to select the **top 30 features** based on **univariate analysis**.
   - Suitable for identifying strong relationships between **numerical features** and the **categorical target**.

3. **Random Forest Feature Importance**
   - Leveraged `feature_importances_` from a **trained Random Forest** to extract **top 30 influential features**.

4. **Recursive Feature Elimination (RFE)**
   - Applied **RFE with Random Forest** as the estimator.
   - Selected another **top 30 features**, enhancing robustness.

5. **Feature Intersection (Union Strategy)**
   - Took the **intersection** of features selected by both **f_classif** and **RFE**.
   - Resulted in a **robust and refined feature set** based on two complementary methods.

6. **Variance Inflation Factor (VIF)**
   - Dropped **6 features** with **VIF > 10** to mitigate multicollinearity issues:
     - `length_words_raw`, `avg_words_raw`, `length_url`, `ratio_intHyperlinks`, `nb_slash`, `nb_dots`

5.1.2 Engineered Features That Add High Predictive Value

The following features were engineered to capture phishing-specific patterns:

Feature Name	Insight
`url_complexity`	Measures obfuscation via special characters in the URL. High values are often seen in phishing.
`tag_to_link_ratio`	Captures disproportionate script embedding relative to visible hyperlinks.
`domain_numeric_intensity`	Reflects digit-heavy domains with short registration times—typical of fraudulent domains.
`path_word_complexity`	Combines average and maximum path word lengths—phishing URLs often embed deep, confusing paths.

5.1.3 Dropped Redundant / Low-Predictive Features (Post-VIF)

The following features were removed to reduce redundancy or due to weak contribution:

- `domain_with_copyright`
- `ratio_intMedia`
- `google_index`
- `page_rank`
- `safe_anchor`
- *(+6 VIF drops)*: `length_words_raw`, `avg_words_raw`, `length_url`, `ratio_intHyperlinks`, `nb_slash`, `nb_dots`

5.1.4 Final Recommendations

- Continue including engineered features in future model pipelines for domain-specific performance gains.

- Reapply VIF and correlation checks for each new dataset to ensure stability.
- Leverage tree-based models like **XGBoost** or **Random Forest** for feature importance validation.
- Normalize highly skewed features using **PowerTransformer** with `method='yeo-johnson'` to maintain model interpretability and performance.
- Consider permutation importance and SHAP values for model explainability.

5.2 Split Dataset into Train and Test set

[48]:
```python
from sklearn.model_selection import train_test_split

# Define final feature set and target
X_final = df_reduced[final_features_vif]
y_final = df_reduced['status']

# Perform stratified train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X_final, y_final,
    test_size=0.2,
    random_state=42,
    stratify=y_final  # maintain class distribution
)

# Generate report
train_size = X_train.shape[0]
test_size = X_test.shape[0]
total_size = len(y_final)

train_percent = round((train_size / total_size) * 100, 2)
test_percent = round((test_size / total_size) * 100, 2)

print("  Data Splitting Report:")
print(f"  Total records: {total_size}")
print(f"  Training set: {train_size} records ({train_percent}%)")
print(f"  Testing set: {test_size} records ({test_percent}%)")

print("\n  Target Distribution Check:")
print("Train set distribution:")
print(y_train.value_counts(normalize=True).map(lambda x: f"{x:.2%}"))

print("\nTest set distribution:")
print(y_test.value_counts(normalize=True).map(lambda x: f"{x:.2%}"))
```

```
Data Splitting Report:
Total records: 11430
Training set: 9144 records (80.0%)
Testing set: 2286 records (20.0%)
```

```
 Target Distribution Check:
Train set distribution:
status
0    50.00%
1    50.00%
Name: proportion, dtype: object

Test set distribution:
status
1    50.00%
0    50.00%
Name: proportion, dtype: object
```

[49]:
```
print("\nSkewness of Features:")
X_train.skew()
```

```
Skewness of Features:
```

[49]:
```
prefix_suffix                 1.483091
nb_hyphens                    4.034987
domain_registration_length   10.801880
ratio_digits_host             5.615369
avg_word_path                12.714639
ip                            1.972296
length_hostname               4.522406
nb_www                        0.264874
empty_title                   2.265138
ratio_extRedirection          2.232868
tld_in_subdomain              4.147150
nb_hyperlinks                 7.816814
nb_and                       10.090766
domain_in_title              -1.328934
shortest_word_path            4.649295
longest_words_raw            14.463195
ratio_digits_url              2.205006
shortest_word_host            2.296740
links_in_tags                -0.148617
domain_age                    0.168107
phish_hints                   3.249916
ratio_extHyperlinks           1.018971
nb_qm                         2.480994
url_complexity                4.126829
tag_to_link_ratio             5.024884
domain_numeric_intensity      5.877711
path_word_complexity         32.492235
dtype: float64
```

5.2.1 Handle Skewness

5.3 Skewness Handling Report

5.3.1 Technique Applied

- **Transformer:** Yeo–Johnson PowerTransformer
- **Library:** `sklearn.preprocessing.PowerTransformer(method='yeo-johnson', standardize=False)`
- **Reason:** Handles both positive and negative values and reduces skewness without removing outliers.

---

[50]:
```python
from sklearn.preprocessing import PowerTransformer

# Initialize the Yeo-Johnson transformer
pt = PowerTransformer(method='yeo-johnson', standardize=False)

# Fit the transformer on the training data and transform the training data
X_train_transformed = pt.fit_transform(X_train)

# Use the fitted transformer to transform the test data
X_test_transformed = pt.transform(X_test)

# Optional: Check skewness on transformed data
print("Skewness after Yeo-Johnson transform (Train):\n", pd.
 ↪DataFrame(X_train_transformed, columns=X_train.columns).skew().
 ↪sort_values(ascending=False))
print("Skewness after Yeo-Johnson transform (Test):\n", pd.
 ↪DataFrame(X_test_transformed, columns=X_test.columns).skew().
 ↪sort_values(ascending=False))
```

```
Skewness after Yeo-Johnson transform (Train):
 tld_in_subdomain             4.147150
nb_and                       3.512775
empty_title                  2.265138
ratio_digits_host            2.199596
nb_qm                        2.130345
ip                           1.972296
phish_hints                  1.701765
prefix_suffix                1.483091
ratio_digits_url             0.720100
domain_numeric_intensity     0.656725
ratio_extRedirection         0.650762
nb_hyphens                   0.563168
tag_to_link_ratio            0.364356
ratio_extHyperlinks          0.319543
```

```
nb_www                        0.219986
url_complexity                0.070897
shortest_word_host            0.018237
shortest_word_path            0.005782
avg_word_path                -0.013200
path_word_complexity         -0.015818
length_hostname              -0.031823
nb_hyperlinks                -0.040903
domain_registration_length   -0.071173
longest_words_raw            -0.097140
links_in_tags                -0.491997
domain_age                   -0.765253
domain_in_title              -1.328934
dtype: float64
Skewness after Yeo-Johnson transform (Test):
 tld_in_subdomain             4.035637
nb_and                        3.346951
empty_title                   2.298328
ratio_digits_host             2.277310
nb_qm                         2.097703
ip                            1.886440
phish_hints                   1.594152
prefix_suffix                 1.474563
domain_numeric_intensity      0.676689
ratio_digits_url              0.643409
nb_hyphens                    0.635152
ratio_extRedirection          0.630630
tag_to_link_ratio             0.355226
ratio_extHyperlinks           0.295872
nb_www                        0.222480
length_hostname               0.205641
url_complexity                0.125121
avg_word_path                 0.053828
path_word_complexity          0.034095
longest_words_raw             0.014290
shortest_word_path            0.004271
shortest_word_host           -0.036910
nb_hyperlinks                -0.082770
domain_registration_length   -0.107386
links_in_tags                -0.507143
domain_age                   -0.760209
domain_in_title              -1.301086
dtype: float64
```

- After Yeo–Johnson transformation, **most features' skewness** is reduced **close to zero**, indicating more symmetric distributions.
- This makes subsequent **scaling** (`RobustScaler`) and **model training** more stable and effective.

5.4 Scaling : RobustScaler()

[51]:
```
from sklearn.preprocessing import RobustScaler

scaler = RobustScaler()
X_train_scaled = scaler.fit_transform(X_train_transformed)
X_test_scaled = scaler.transform(X_test_transformed)
```

6 Normalization/Scaling Report

6.1 Techniques Used:

- **Scaling Method Applied: RobustScaler**
- **Reason for Selection:**
  - **RobustScaler** was chosen because it is robust to outliers. Unlike **StandardScaler** or **MinMaxScaler**, it scales features using **median** and **IQR (Interquartile Range)**, making it suitable for datasets with outliers, which is common in real-world data.
  - It helps ensure that features are on a similar scale, which is important for machine learning models like **SVM**, **Logistic Regression**, and **KNN**, which are sensitive to the scale of data.

6.2 Description of RobustScaler:

- **Scaler Formula:**

$$\text{scaled} = \frac{X - \text{median}(X)}{\text{IQR}(X)}$$

```
- **Median:** The middle value, less affected by outliers.
- **IQR:** The difference between the 75th and 25th percentiles, representing the range within
```

- **Impact of RobustScaler:**
  - **Prevents Outlier Influence:** The scaling technique is **not influenced by extreme values**.
  - **Preserves Distribution:** Data is centered and scaled based on the distribution within the interquartile range, making it **robust to skewed distributions**.

---

[52]:
```
# Calculate original distribution (min, max)
original_stats = X_train.agg(['min', 'max']).T
original_stats.columns = ['Original Min', 'Original Max']


X_train_scaled_df = pd.DataFrame(X_train_scaled, columns=X_train.columns)

# Calculate scaled distribution (min, max)
```

```python
scaled_stats = X_train_scaled_df.agg(['min', 'max']).T
scaled_stats.columns = ['Scaled Min', 'Scaled Max']

# Combine both into a single table for comparison
comparison_df = pd.concat([original_stats, scaled_stats], axis=1)

# Print results
print("Before-and-After Feature Scaling (RobustScaler):\n")
print(comparison_df.round(3))
```

```
Before-and-After Feature Scaling (RobustScaler):

                            Original Min  Original Max  Scaled Min  Scaled Max
prefix_suffix                        0.0         1.000      -0.000       0.145
nb_hyphens                           0.0        32.000      -0.000       1.563
domain_registration_length          -1.0     29829.000      -2.223       5.435
ratio_digits_host                    0.0         0.800      -0.000       0.024
avg_word_path                        0.0       206.000      -0.840       2.999
ip                                   0.0         1.000      -0.000       0.104
length_hostname                      4.0       214.000      -3.638       4.130
nb_www                               0.0         2.000      -0.000       1.342
empty_title                          0.0         1.000      -0.000       0.087
ratio_extRedirection                 0.0         2.000      -0.000       1.465
tld_in_subdomain                     0.0         1.000      -0.000       0.034
nb_hyperlinks                        0.0      4659.000      -1.230       2.729
nb_and                               0.0        19.000      -0.000       0.075
domain_in_title                      0.0         1.000     -10.750       0.000
shortest_word_path                   0.0        40.000      -0.797       1.758
longest_words_raw                    2.0       829.000      -3.997       3.338
ratio_digits_url                     0.0         0.724      -0.000       1.486
shortest_word_host                   1.0        39.000      -1.885       2.521
links_in_tags                        0.0       100.000      -0.784       0.216
domain_age                         -12.0     12874.000      -2.338       0.862
phish_hints                          0.0        10.000      -0.000       0.182
ratio_extHyperlinks                  0.0         1.000      -0.432       0.885
nb_qm                                0.0         3.000      -0.000       0.096
url_complexity                       0.0        34.000      -0.681       1.447
tag_to_link_ratio                    0.0        50.000      -0.507       1.067
domain_numeric_intensity            -0.8      3828.649      -1.659       0.927
path_word_complexity                 0.0     83636.000      -0.851       2.596
```

6.3 Before-and-After Comparison of Numerical Feature Distributions:

6.3.1 Before Scaling:

- Features can have **different ranges** (e.g., one feature ranges from 0 to 10, while another ranges from 100 to 1000).
- Outliers could heavily influence the distributions (e.g., extremely large values may shift the

mean).

6.3.2 After Scaling (RobustScaler):

- Features are scaled within a similar range but **without the influence of outliers**.
- The **central tendency** (median) and **spread** (IQR) are preserved and adjusted for each feature, so all features are on a comparable scale for model training.

All feature values are now on a similar scale centered around 0, making the model training more stable and faster.

[53]:
```
# Final split dataset ready for model training
X_train_scaled
X_test_scaled
```

[53]:
```
array([[ 0.1450004 ,  1.        , -1.97451712, …, -0.50692832,
        -0.        ,  0.14603119],
       [ 0.1450004 ,  1.        , -0.17208061, …,  0.349175  ,
        -0.        ,  0.59878878],
       [ 0.1450004 ,  1.        , -0.03154315, …, -0.50692832,
        -0.        , -0.02040373],
       …,
       [-0.        , -0.        ,  2.09673827, …, -0.20355885,
        -0.        , -0.85079951],
       [-0.        ,  1.50903381,  0.09939827, …,  0.35561974,
        -0.        , -0.00963592],
       [ 0.1450004 ,  1.        , -1.97451712, …, -0.42727707,
        -0.        , -0.85079951]], shape=(2286, 27))
```

[ ]: