Internship_CodeB_week 5 & 6

April 23, 2025

1 Phishing Website Detection

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

2 Week 5 & 6 Submission

[ ]:
```
# 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

import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc, confusion_matrix,␣
↪precision_recall_curve, average_precision_score
import seaborn as sns
import numpy as np
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.ensemble import RandomForestClassifier
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[13]:
```
# 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)
```

[13]:
```
                                                    url  length_url  \
5786                            http://www.amlegal.com/          23
766   http://shadetreetechnology.com/V4/validation/9…          77
9131  https://senhasuspensaeviteoblowqueiodefinitivo…          59
7431  http://saigonsportcity.com/wp-content/plugins/…          59
5202  http://mobiliablog.com.au/bin/mySign%20in%20-%…          65
…                                                   …         …
2178  https://www.tripadvisor.ru/AttractionsNear-g58…         100
2782     http://shiflett.org/articles/session-hijacking          46
8869  http://vieuxshack.com/download/adobe/0bbab0b2b…         248
3043        https://thesorrowandthepit64.wordpress.com/          43
1581  https://take5mg.com/wp-content/uploads/2017/03…          75

      length_hostname  ip  nb_dots  nb_hyphens  nb_at  nb_qm  nb_and  nb_or  \
5786               15   0        2           0      0      0       0      0
766                23   1        1           0      0      0       0      0
9131               42   0        2           0      0      0       0      0
7431               19   0        1           1      0      0       0      0
5202               18   0        3           1      0      0       0      0
…                 …  ..        …           …      …      …       …      …
2178               18   1        3           4      0      0       0      0
2782               12   0        1           1      0      0       0      0
8869               14   1        2           0      0      1       2      0
3043               34   0        2           0      0      0       0      0
1581               11   0        2           5      0      0       0      0

      …  domain_in_title  domain_with_copyright  whois_registered_domain  \
5786  …                1                      1                        0
766   …                1                      0                        0
9131  …                1                      0                        0
7431  …                1                      0                        0
5202  …                1                      0                        1
…     …                …                      …                        …
2178  …                1                      1                        0
2782  …                0                      0                        0
8869  …                1                      0                        0
3043  …                1                      0                        0
1581  …                1                      0                        0

      domain_registration_length  domain_age  web_traffic  dns_record  \
5786                        3533        8886       160130           0
766                           76        5767            0           0
9131                         358           7            0           0
7431                          39        1422            0           0
5202                           0          -1            0           0
…                              …           …            …           …
2178                          46        5797         4997           0
```

```
2782                          649         7386      1213116           0
8869                          584         7816            0           0
3043                          586         7448            0           0
1581                          617         1939      8011140           0

      google_index  page_rank      status
5786             0          5  legitimate
766              1          2    phishing
9131             1          0    phishing
7431             1          0    phishing
5202             1          0    phishing
…              …         …          …
2178             1          5  legitimate
2782             0          5  legitimate
8869             1          2    phishing
3043             0          8  legitimate
1581             1          3  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`

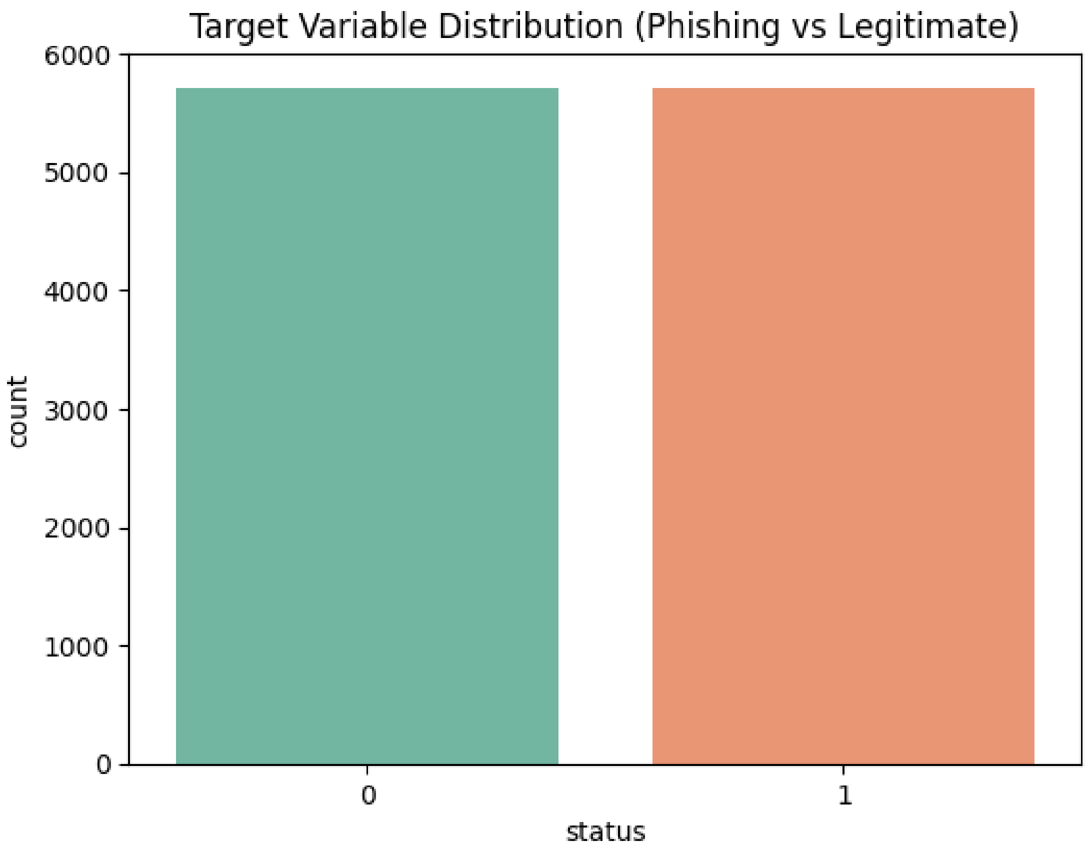
- **Description**: Binary label indicating if the website is phishing (`1`) or legitimate (`0`).
- **Relevance**: This is the variable to be predicted by the classification model.

---

[14]:
```python
# 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
```

[ ]:
```python
# 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
```

[ ]:
```
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']
```

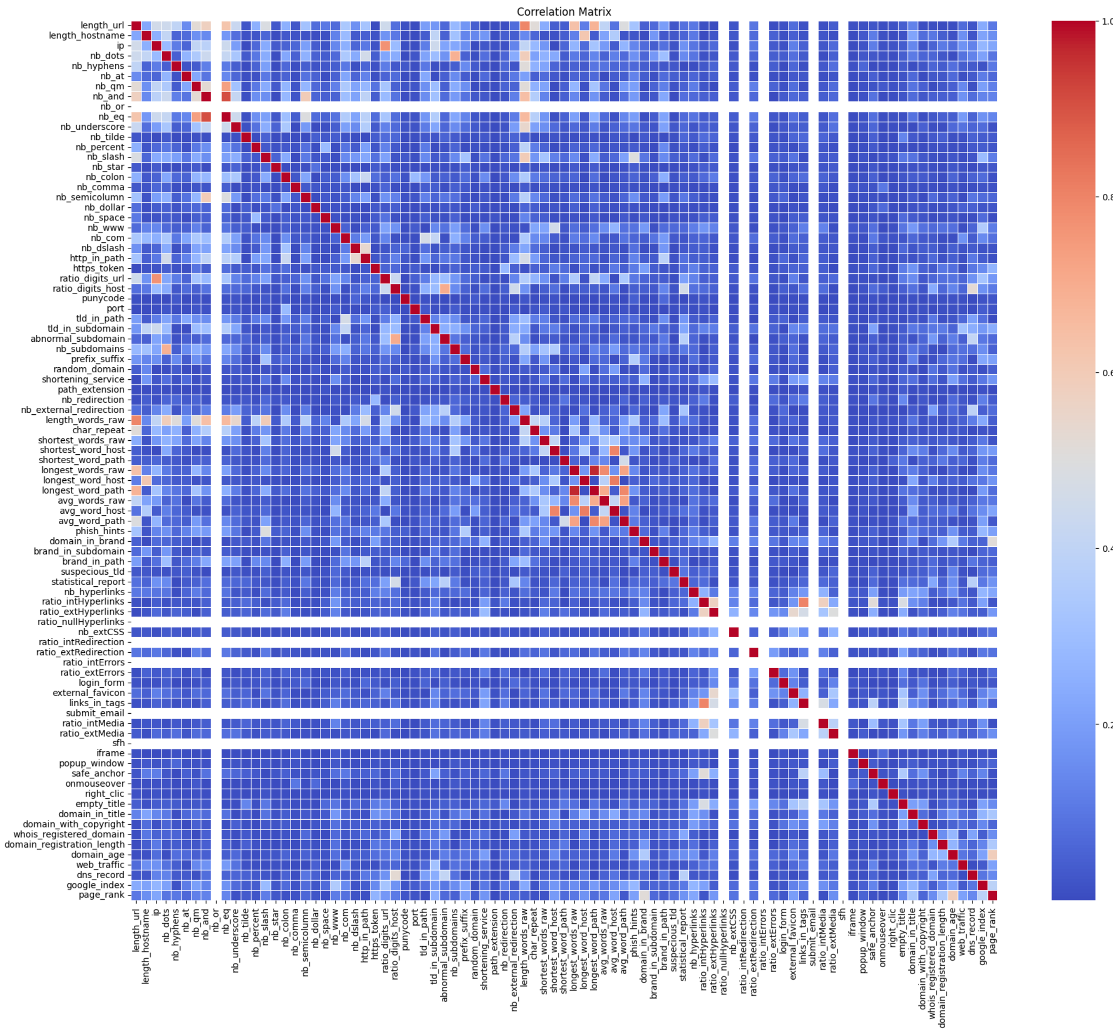
[17]:
```
# Dropping the 'url' column
# The 'url' column is not useful for training the machine learning model.

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.

[ ]:
```
# 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

[19]:
```
# 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.

[20]:
```
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)

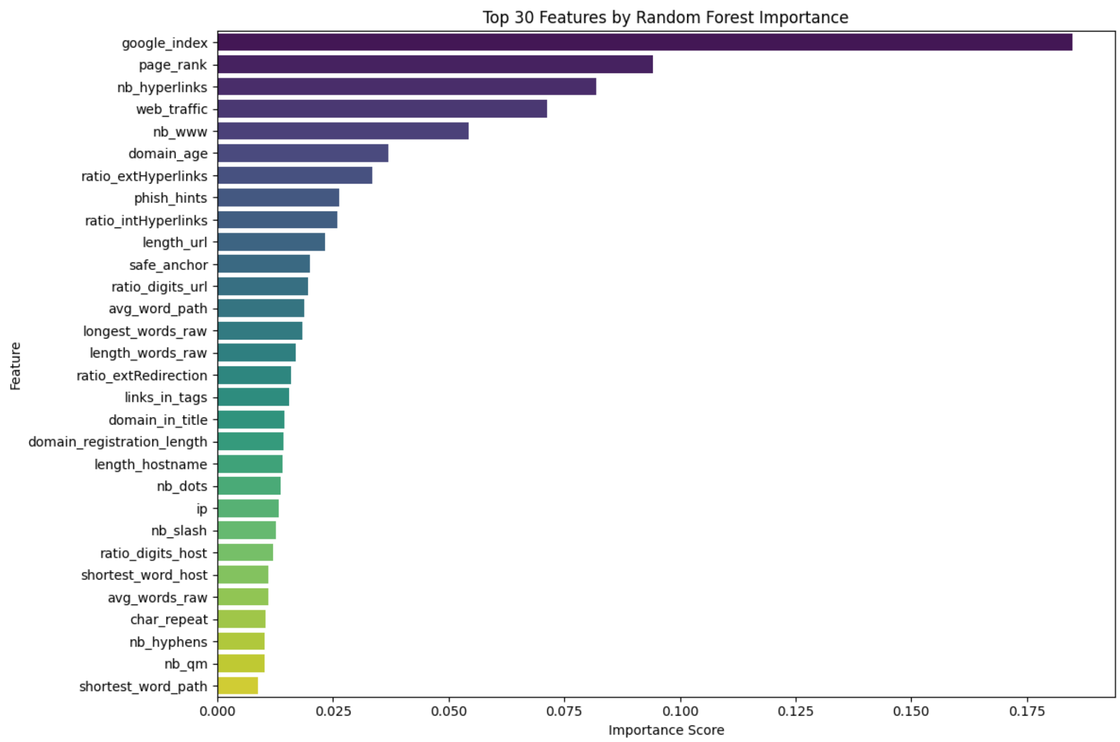
[21]:
```
from sklearn.feature_selection import SelectKBest, f_classif

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

[ ]:
```python
# 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)

[23]:
```python
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

[24]:
```
# 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):
['ratio_digits_url', 'shortest_word_host', 'length_hostname', 'avg_words_raw',
'safe_anchor', 'nb_dots', 'nb_and', 'domain_with_copyright', 'ip',
'google_index', 'avg_word_path', 'shortest_word_path', 'ratio_extRedirection',
'nb_hyphens', 'empty_title', 'domain_registration_length', 'nb_qm',
'ratio_extHyperlinks', 'nb_hyperlinks', 'longest_words_raw', 'domain_in_title',
'domain_age', 'length_url', 'nb_www', 'tld_in_subdomain', 'ratio_intMedia',
'length_words_raw', 'page_rank', 'ratio_intHyperlinks', 'prefix_suffix',
'phish_hints', 'nb_slash', 'links_in_tags', 'ratio_digits_host']
Number of final selected features: 34
```

[ ]:
```
# 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)

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

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

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

[27]:
```python
# 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:
```

[27]:
```
['ratio_digits_url',
 'shortest_word_host',
 'length_hostname',
 'safe_anchor',
 'nb_and',
 'domain_with_copyright',
 'ip',
 'google_index',
 'avg_word_path',
 'empty_title',
 'ratio_extRedirection',
 'nb_hyphens',
 'shortest_word_path',
 'domain_registration_length',
 'nb_qm',
 'ratio_extHyperlinks',
 'nb_hyperlinks',
 'longest_words_raw',
 'domain_in_title',
 'domain_age',
 'nb_www',
 'tld_in_subdomain',
 'ratio_intMedia',
 'page_rank',
 'prefix_suffix',
 'phish_hints',
 'links_in_tags',
 'ratio_digits_host']
```

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

[28]:
```
# 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']
)
```

[ ]:
```
# 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)
```

[30]:
```
# 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']
```

[31]:
```
# 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']
```

[ ]:
```
# 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
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
```

```python
print("Total final features after update:", len(final_features_vif))
final_features_vif
```

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

5.1 ## Feature Engineering and Feature Selection Report

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 as they were used in new feature formations:

- `domain_with_copyright`
- `ratio_intMedia`
- `google_index`
- `page_rank`
- `safe_anchor`

Following features were dropped because of high VIF - `length_words_raw` - `avg_words_raw` - `length_url` - `ratio_intHyperlinks` - `nb_slash` - `nb_dots`

---

6 Split Dataset into Train and Test set

[ ]:
```
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']
```

```python
# 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
```

6.1 Skewness Handling Report

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.

---

[34]:
```
print("\nSkewness of Features:")
X_train.skew()
```

```
Skewness of Features:
```

[34]:
```
ratio_digits_url               2.205006
shortest_word_host             2.296740
length_hostname                4.522406
nb_and                        10.090766
ip                             1.972296
avg_word_path                 12.714639
empty_title                    2.265138
ratio_extRedirection           2.232868
nb_hyphens                     4.034987
shortest_word_path             4.649295
domain_registration_length    10.801880
nb_qm                          2.480994
ratio_extHyperlinks            1.018971
nb_hyperlinks                  7.816814
longest_words_raw             14.463195
domain_in_title               -1.328934
domain_age                     0.168107
nb_www                         0.264874
tld_in_subdomain               4.147150
prefix_suffix                  1.483091
phish_hints                    3.249916
links_in_tags                 -0.148617
ratio_digits_host              5.615369
url_complexity                 4.126829
tag_to_link_ratio              5.024884
domain_numeric_intensity       5.877711
path_word_complexity          32.492235
dtype: float64
```

[ ]:
```
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.

7 Normalization/Scaling Report

7.1 Scaling : RobustScaler()

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

# 1. Store feature names before scaling
original_columns = X_train.columns

# 2. Scale the data
scaler = RobustScaler()
X_train_scaled = scaler.fit_transform(X_train_transformed)
X_test_scaled = scaler.transform(X_test_transformed)
```

```python
# 3. Convert back to DataFrames with correct column names
X_train_scaled_df = pd.DataFrame(X_train_scaled, columns=original_columns)
X_test_scaled_df = pd.DataFrame(X_test_scaled, columns=original_columns)
```

[37]:

```python
X_train_scaled_df.head(10)
```

[37]:

```
   ratio_digits_url  shortest_word_host  length_hostname  nb_and        ip  \
0          1.167672            0.000000        -0.370679 -0.0000  0.104003
1          1.370121            0.000000         1.892424  0.0747  0.104003
2         -0.000000            0.760583        -1.211800 -0.0000 -0.000000
3          1.174977            0.760583        -0.370679  0.0747 -0.000000
4          1.319970           -0.678585        -0.665448 -0.0000  0.104003
5          1.431925            0.000000        -0.370679 -0.0000  0.104003
6          1.389039            1.881667         0.108688 -0.0000  0.104003
7         -0.000000            1.000000        -1.432313 -0.0000 -0.000000
8          1.394908           -0.678585         0.211224 -0.0000 -0.000000
9         -0.000000            0.000000        -0.512428 -0.0000 -0.000000

   avg_word_path  empty_title  ratio_extRedirection  nb_hyphens  \
0       0.185504    -0.000000             -0.000000    1.422259
1       0.213427    -0.000000             -0.000000    1.000000
2       0.036928    -0.000000             -0.000000    1.255627
3      -0.078934    -0.000000              0.213778    1.255627
4      -0.008166    -0.000000              1.437955   -0.000000
5       0.204232     0.087006             -0.000000    1.000000
6       0.265471     0.087006             -0.000000    1.000000
7      -0.180524    -0.000000             -0.000000    1.255627
8      -0.840202    -0.000000             -0.000000   -0.000000
9      -0.206308    -0.000000             -0.000000   -0.000000

   shortest_word_path  …  nb_www  tld_in_subdomain  prefix_suffix  \
0            0.000000  …     1.0         -0.000000         -0.000
1            0.000000  …    -0.0          0.034415          0.145
2            0.000000  …     1.0         -0.000000         -0.000
3           -0.290007  …    -0.0         -0.000000         -0.000
4            0.202838  …    -0.0         -0.000000         -0.000
5            0.202838  …     1.0         -0.000000          0.145
6            0.000000  …    -0.0         -0.000000          0.145
7            0.202838  …    -0.0         -0.000000         -0.000
8           -0.797162  …    -0.0         -0.000000         -0.000
9            0.202838  …     1.0         -0.000000         -0.000

   phish_hints  links_in_tags  ratio_digits_host  url_complexity  \
0    -0.000000       0.215944          -0.000000        0.756403
1    -0.000000       0.215944          -0.000000        0.652849
2     0.182043      -0.784056          -0.000000        0.515310
```

```
3   -0.000000     -0.784056          -0.000000        0.756403
4   -0.000000      0.150889          -0.000000       -0.681264
5   -0.000000     -0.784056          -0.000000        0.515310
6    0.182395      0.215944          -0.000000        0.000000
7   -0.000000     -0.784056          -0.000000        0.318736
8   -0.000000     -0.784056           0.023677       -0.681264
9   -0.000000     -0.461604          -0.000000        0.000000

   tag_to_link_ratio  domain_numeric_intensity  path_word_complexity
0           0.296415                   -0.0000              0.138629
1           1.008329                   -0.0000              0.245673
2          -0.506928                   -0.0000              0.083297
3          -0.506928                   -0.0000              0.199656
4           0.314457                   -0.0000             -0.061817
5          -0.506928                   -0.0000              0.188726
6           1.066808                   -0.0000              0.450126
7          -0.506928                   -0.0000             -0.221424
8          -0.506928                    0.9186             -0.850800
9          -0.076988                   -0.0000             -0.170638

[10 rows x 27 columns]
```

7.2 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.

7.3 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 which the central 50% of data points lie.
- **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**.

---

[38]:
```python
# 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)
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
ratio_digits_url                     0.0         0.724      -0.000       1.486
shortest_word_host                   1.0        39.000      -1.885       2.521
length_hostname                      4.0       214.000      -3.638       4.130
nb_and                               0.0        19.000      -0.000       0.075
ip                                   0.0         1.000      -0.000       0.104
avg_word_path                        0.0       206.000      -0.840       2.999
empty_title                          0.0         1.000      -0.000       0.087
ratio_extRedirection                 0.0         2.000      -0.000       1.465
nb_hyphens                           0.0        32.000      -0.000       1.563
shortest_word_path                   0.0        40.000      -0.797       1.758
domain_registration_length          -1.0     29829.000      -2.223       5.435
nb_qm                                0.0         3.000      -0.000       0.096
ratio_extHyperlinks                  0.0         1.000      -0.432       0.885
nb_hyperlinks                        0.0      4659.000      -1.230       2.729
longest_words_raw                    2.0       829.000      -3.997       3.338
domain_in_title                      0.0         1.000     -10.750       0.000
domain_age                         -12.0     12874.000      -2.338       0.862
nb_www                               0.0         2.000      -0.000       1.342
tld_in_subdomain                     0.0         1.000      -0.000       0.034
prefix_suffix                        0.0         1.000      -0.000       0.145
phish_hints                          0.0        10.000      -0.000       0.182
```

```
links_in_tags                           0.0       100.000       -0.784         0.216
ratio_digits_host                       0.0         0.800       -0.000         0.024
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
```

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

7.3.2 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).

7.3.3 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.

[39]:
```python
# Final split dataset ready for model training
X_test_scaled_df.head(10)
```

[39]:
```
   ratio_digits_url  shortest_word_host  length_hostname  nb_and        ip  \
0         -0.000000            0.000000        -1.432313    -0.0 -0.000000
1          1.380355            0.000000         1.389821    -0.0  0.104003
2          0.354286            1.468276         0.400177    -0.0 -0.000000
3         -0.000000            2.075945         0.308213    -0.0 -0.000000
4         -0.000000            0.000000        -0.370679    -0.0 -0.000000
5         -0.000000            0.000000         0.108688    -0.0 -0.000000
6         -0.000000            1.000000         0.000000    -0.0 -0.000000
7          0.842205            0.000000         2.239898    -0.0 -0.000000
8         -0.000000           -0.678585        -0.370679    -0.0 -0.000000
9          1.461811            0.000000         0.570793    -0.0  0.104003

   avg_word_path  empty_title  ratio_extRedirection  nb_hyphens  \
0       0.200523    -0.000000             -0.000000    1.000000
1       0.564626    -0.000000             -0.000000    1.000000
2       0.016058    -0.000000              0.558900    1.000000
3       0.185504     0.087006             -0.000000   -0.000000
4      -0.840202    -0.000000             -0.000000   -0.000000
5       0.146611    -0.000000              0.243909    1.457444
6      -0.840202    -0.000000              1.315976   -0.000000
7      -0.840202     0.087006             -0.000000   -0.000000
```

```
8       0.210374    -0.000000              1.220511   -0.000000
9       0.545388    -0.000000             -0.000000    1.000000

   shortest_word_path  …  nb_www  tld_in_subdomain  prefix_suffix  \
0            0.000000  …    -0.0              -0.0          0.145
1            0.590573  …     1.0              -0.0          0.145
2            0.000000  …    -0.0              -0.0          0.145
3            0.681775  …    -0.0              -0.0         -0.000
4           -0.797162  …     1.0              -0.0         -0.000
5            0.202838  …     1.0              -0.0          0.145
6           -0.797162  …    -0.0              -0.0         -0.000
7           -0.797162  …    -0.0              -0.0         -0.000
8            0.358520  …    -0.0              -0.0         -0.000
9            0.000000  …     1.0              -0.0          0.145

   phish_hints  links_in_tags  ratio_digits_host  url_complexity  \
0     0.182043      -0.784056          -0.000000        0.318736
1    -0.000000       0.215944          -0.000000        0.318736
2    -0.000000      -0.784056          -0.000000        0.000000
3    -0.000000      -0.784056          -0.000000       -0.681264
4    -0.000000       0.215944          -0.000000        0.000000
5    -0.000000      -0.784056          -0.000000        0.838215
6    -0.000000       0.215944          -0.000000       -0.681264
7    -0.000000      -0.784056           0.022058       -0.681264
8    -0.000000       0.215944          -0.000000       -0.681264
9     0.182395       0.215944          -0.000000        0.515310

   tag_to_link_ratio  domain_numeric_intensity  path_word_complexity
0          -0.506928                 -0.000000              0.146031
1           0.349175                 -0.000000              0.598789
2          -0.506928                 -0.000000             -0.020404
3          -0.506928                 -0.000000              0.247026
4           0.522042                 -0.000000             -0.850800
5          -0.506928                 -0.000000              0.072134
6           0.852320                 -0.000000             -0.850800
7          -0.506928                  0.926473             -0.850800
8          -0.073119                 -0.000000              0.103214
9           0.940470                 -0.000000              0.804899

[10 rows x 27 columns]
```

8 Model Training

[42]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, roc_auc_score, classification_report
import pandas as pd

# Initialize models
models = {
    "Logistic Regression": LogisticRegression(random_state=42),
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "Random Forest": RandomForestClassifier(random_state=42),
    "XGBoost": XGBClassifier(random_state=42, use_label_encoder=False,␣
↪eval_metric='logloss'),
    "SVM": SVC(probability=True, random_state=42),
    "KNN": KNeighborsClassifier()
}

# DataFrame to store results
results = []

# Train and evaluate each model
for name, model in models.items():
    model.fit(X_train_scaled_df, y_train)
    y_pred = model.predict(X_test_scaled_df)
    y_proba = model.predict_proba(X_test_scaled_df)[:, 1] if hasattr(model,␣
↪"predict_proba") else None

    results.append({
        "Model": name,
        "Accuracy": accuracy_score(y_test, y_pred),
        "Precision": precision_score(y_test, y_pred),
        "Recall": recall_score(y_test, y_pred),
        "F1-Score": f1_score(y_test, y_pred),
        "ROC-AUC": roc_auc_score(y_test, y_proba) if y_proba is not None else␣
↪"N/A"
    })

# Display results
results_df = pd.DataFrame(results).sort_values(by="F1-Score", ascending=False)
print("  Model Comparison:")
display(results_df)
```

```
  File "c:\Users\gaura\anaconda3\envs\phishing_env\lib\site-
packages\joblib\externals\loky\backend\context.py", line 257, in
_count_physical_cores
```

```
    cpu_info = subprocess.run(
  File "c:\Users\gaura\anaconda3\envs\phishing_env\lib\subprocess.py", line 503,
in run
    with Popen(*popenargs, **kwargs) as process:
  File "c:\Users\gaura\anaconda3\envs\phishing_env\lib\subprocess.py", line 971,
in __init__
    self._execute_child(args, executable, preexec_fn, close_fds,
  File "c:\Users\gaura\anaconda3\envs\phishing_env\lib\subprocess.py", line
1456, in _execute_child
    hp, ht, pid, tid = _winapi.CreateProcess(executable, args,
```

```
 Model Comparison:

                 Model  Accuracy  Precision    Recall  F1-Score   ROC-AUC
2        Random Forest  0.946632   0.938197  0.956255  0.947140  0.985530
3              XGBoost  0.945757   0.938846  0.953631  0.946181  0.984277
5                  KNN  0.909886   0.908457  0.911636  0.910044  0.957889
4                  SVM  0.899825   0.889267  0.913386  0.901165  0.958717
1        Decision Tree  0.897638   0.886151  0.912511  0.899138  0.897638
0  Logistic Regression  0.887577   0.885217  0.890639  0.887920  0.949259
```

8.0.1 Best Performing Model: Random Forest Classifier

Insights & Justification - Highest Recall (0.956): Effectively identifies phishing websites with minimal false negatives.

- Best ROC-AUC Score (0.986): Demonstrates excellent ability to distinguish between classes.
- Strong F1-Score: Balanced precision and recall, indicating overall robustness.

Random Forest (Best Performer): - Achieved highest overall performance on all key metrics.

- Particularly strong recall (0.9510), which is critical for phishing detection (catching as many phishing sites as possible).
- Robust to overfitting thanks to ensembling.
- Final model selected for deployment.

XGBoost: - Almost tied with Random Forest in F1-score and ROC-AUC.

- Slightly more complex but offers good interpretability with tools like SHAP.
- Suitable for production environments.

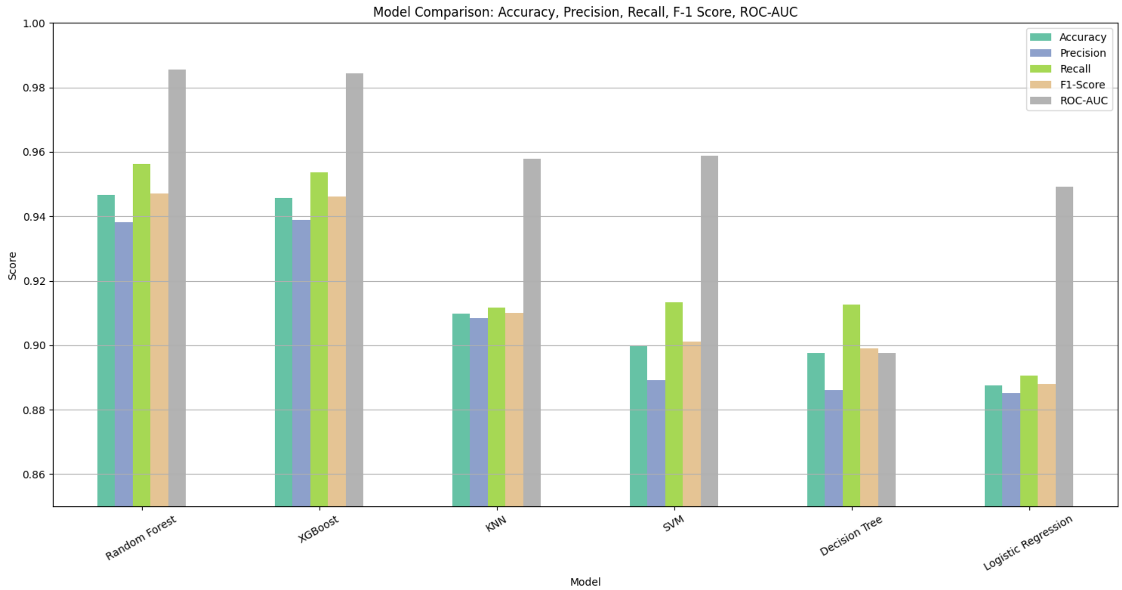
KNN & SVM: - Performed decently with ~0.91 F1-score.

- KNN is computationally expensive at scale and not ideal for real-time systems.
- SVM is powerful but harder to tune and scale with large datasets.

Logistic Regression & Decision Tree: Baseline models.

- Logistic Regression is interpretable but underperformed on non-linear relationships.
- Decision Tree showed slightly better recall but prone to overfitting.

[62]:
```
# Plotting the results

results_df.set_index('Model').plot(kind='bar', figsize=(15, 8), colormap='Set2')
plt.title('Model Comparison: Accuracy, Precision, Recall, F-1 Score, ROC-AUC')
plt.ylabel('Score')
plt.ylim(0.85, 1.0)
plt.grid(axis='y')
plt.xticks(rotation=30)
plt.legend(loc='upper right')
plt.tight_layout()
plt.show()
```



9 Perform Hyperparameter Tuning for Random Forest Classifier

[44]:
```
# Step 1: Import and Set Up the Grid

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Define the base model
rf = RandomForestClassifier(random_state=42)

# Hyperparameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
```

```
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}
```

[45]:
```
# Step 2: Apply GridSearchCV

# Grid search with 5-fold cross-validation
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid,
                           cv=5, n_jobs=-1, verbose=2, scoring='roc_auc')

# Fit on training data
grid_search.fit(X_train_scaled_df, y_train)
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits
```

[45]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=42), n_jobs=-1,
             param_grid={'bootstrap': [True, False],
                         'max_depth': [None, 10, 20, 30],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [100, 200, 300]},
             scoring='roc_auc', verbose=2)
```

[46]:
```
# Step 3: Extract Best Parameters and Model

best_rf = grid_search.best_estimator_
print("Best Parameters:\n", grid_search.best_params_)
```

```
Best Parameters:
 {'bootstrap': False, 'max_depth': 30, 'min_samples_leaf': 1,
'min_samples_split': 5, 'n_estimators': 300}
```

[ ]:
```
# Step 4: Evaluate Tuned Model on Test Set



# Predict on test set
y_pred = best_rf.predict(X_test_scaled_df)
y_prob = best_rf.predict_proba(X_test_scaled_df)[:, 1]

# Evaluation
print("Classification Report:\n", classification_report(y_test, y_pred))
print("ROC-AUC Score:", roc_auc_score(y_test, y_prob))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.96      0.94      0.95      1143
           1       0.94      0.96      0.95      1143
```

```
    accuracy                           0.95      2286
   macro avg       0.95      0.95      0.95      2286
weighted avg       0.95      0.95      0.95      2286

ROC-AUC Score: 0.9868731959686142
```

9.1 Trained Machine Learning Model & Hyperparameter Tuning Report

9.1.1 Model Used

- **Random Forest Classifier**
- Trained multiple machine learning models and chosen RandomForestClassifier for its robustness, ensemble learning capability, and high performance in binary classification.
- Highest Recall (0.956): Effectively identifies phishing websites with minimal false negatives.

9.1.2 Hyperparameter Tuning

- **Technique:** `GridSearchCV`
- **Cross-Validation:** 5-fold
- **Scoring Metric:** ROC-AUC

Parameter Grid:

```python
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}
```

Best Model Configuration (best_estimator_)

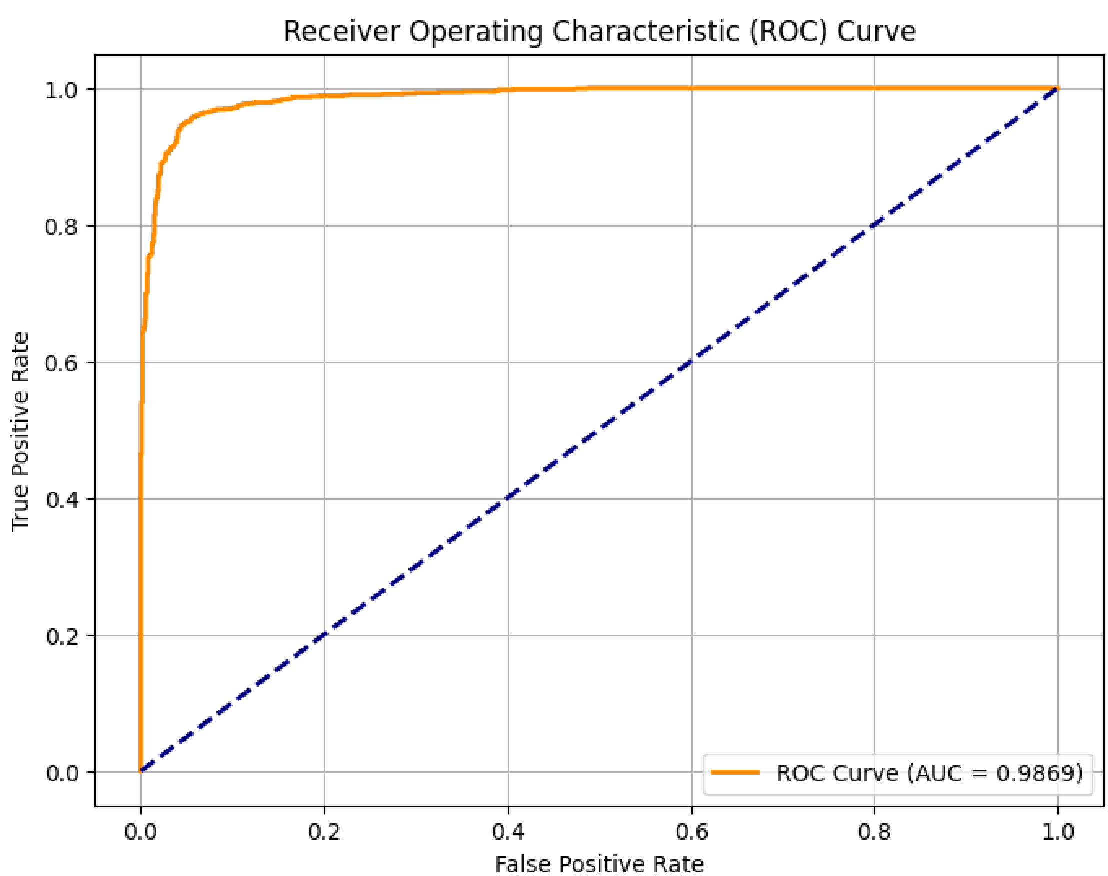
```python
RandomForestClassifier(
    bootstrap=False,
    max_depth=30,
    min_samples_split=5,
    min_samples_leaf=1,
    n_estimators=300,
    random_state=42
)
```

- Best parameters were selected based on highest average ROC-AUC across cross-validation folds.
- The final model was used for evaluation, SHAP/LIME explainability, and deployment pipeline.
- It achieved high performance, making it a reliable model for phishing detection.

9.1.3 Plot the Evaluation Metrics

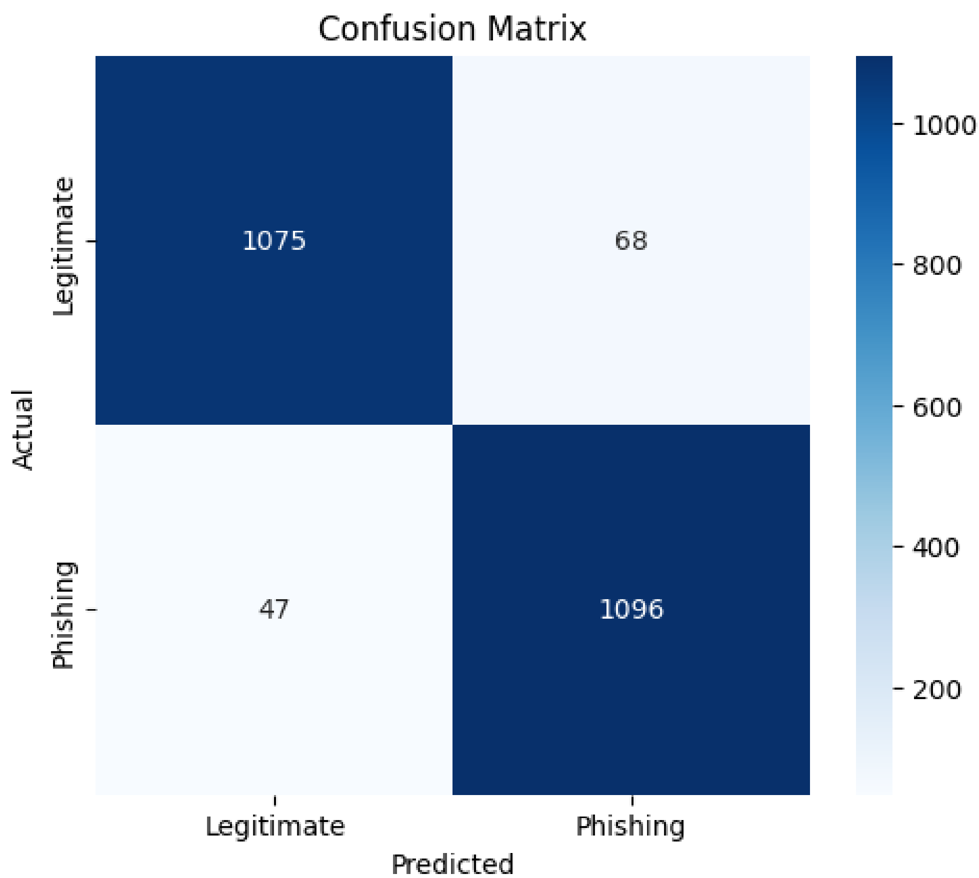
ROC Curve Plot

[49]:
```
# Predict probabilities for ROC
y_probs = best_rf.predict_proba(X_test_scaled_df)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_probs)
roc_auc = auc(fpr, tpr)

# Plot ROC Curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC Curve (AUC = {roc_auc:.
 ↪4f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



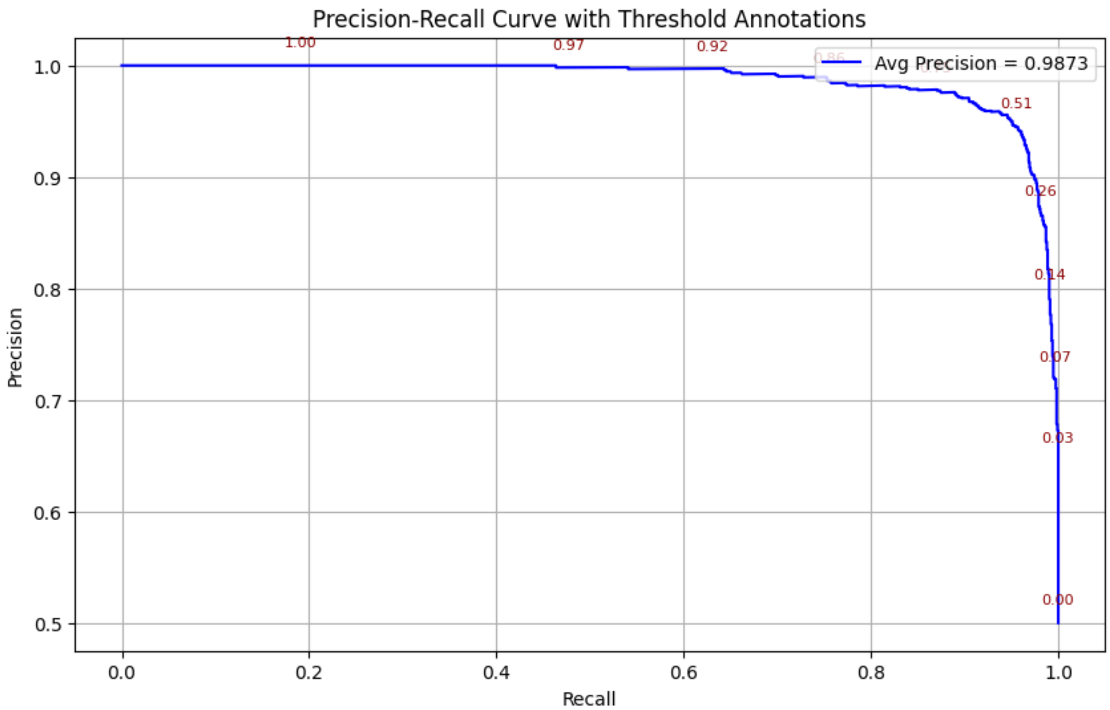
Confusion Matrix Heatmap

[50]:
```
# Predict labels
y_pred = best_rf.predict(X_test_scaled_df)

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred)
labels = ['Legitimate', 'Phishing']

# Plot heatmap
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=labels, yticklabels=labels)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



Plot Precision-Recall Curve

[51]:
```python
# Get predicted probabilities
y_probs = best_rf.predict_proba(X_test_scaled_df)[:, 1]

# Compute precision-recall pairs
precision, recall, thresholds = precision_recall_curve(y_test, y_probs)
avg_precision = average_precision_score(y_test, y_probs)

# Plot Precision-Recall curve
plt.figure(figsize=(10, 6))
plt.plot(recall, precision, label=f'Avg Precision = {avg_precision:.4f}',␣
↪color='blue')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve with Threshold Annotations')
plt.grid(True)

# Annotate some thresholds
for i in range(0, len(thresholds), max(1, len(thresholds) // 10)):
    plt.annotate(f"{thresholds[i]:.2f}",
                 (recall[i], precision[i]),
                 textcoords="offset points",
                 xytext=(0, 10),
                 ha='center',
                 fontsize=8,
                 color='darkred')

plt.legend(loc='upper right')
plt.show()
```



10 LIME Explainer for Random Forest Classifier

Step 1: Import and Create the LIME Explainer

[ ]:
```
import lime
import lime.lime_tabular

# Create the LIME explainer
explainer = lime.lime_tabular.LimeTabularExplainer(
    training_data=np.array(X_train_scaled),
    feature_names=X_train.columns.tolist(),
    class_names=['Legitimate', 'Phishing'],
    mode='classification',
    verbose=True,
    feature_selection='auto'
)
```

Step 2: Explain Multiple Instances

[63]:
```
# Loop through multiple instances for explanation
for i in range(10):
    print(f"\n LIME Explanation for Instance {i} (True Label: {y_test.
 ↪iloc[i]})")
```

```python
    exp = explainer.explain_instance(
        data_row=X_test_scaled[i],
        predict_fn=best_rf.predict_proba,
        num_features=len(X_test.columns)  # Explain all features
    )

    # Display in notebook (visual)
    exp.show_in_notebook(show_table=True)
    # Optional: Save to PNG
    exp.save_to_file(f'lime_explanation_instance_{i}.png')

    # Optional: Save to HTML
    exp.save_to_file(f'lime_explanation_instance_{i}.html')
```

```
 LIME Explanation for Instance 0 (True Label: 1)
Intercept 0.4862108127717426
Prediction_local [0.8825751]
Right: 0.9469444444444444

<IPython.core.display.HTML object>

 LIME Explanation for Instance 1 (True Label: 1)
Intercept 0.7499729148069441
Prediction_local [0.60430553]
Right: 0.9805555555555556

<IPython.core.display.HTML object>

 LIME Explanation for Instance 2 (True Label: 1)
Intercept 0.7233909840055602
Prediction_local [0.55807556]
Right: 0.986388888888889

<IPython.core.display.HTML object>

 LIME Explanation for Instance 3 (True Label: 1)
Intercept 0.6221441463875693
Prediction_local [0.7732483]
Right: 0.9330555555555556

<IPython.core.display.HTML object>

 LIME Explanation for Instance 4 (True Label: 0)
Intercept 0.8564124174373815
Prediction_local [0.3160746]
Right: 0.025555555555555554
```

```
<IPython.core.display.HTML object>

  LIME Explanation for Instance 5 (True Label: 0)
Intercept 0.9719731405695896
Prediction_local [0.1046537]
Right: 0.0475

<IPython.core.display.HTML object>

  LIME Explanation for Instance 6 (True Label: 0)
Intercept 0.7960261476025143
Prediction_local [0.47123998]
Right: 0.009722222222222222

<IPython.core.display.HTML object>

  LIME Explanation for Instance 7 (True Label: 1)
Intercept 0.6984983354979514
Prediction_local [0.60405638]
Right: 0.951111111111111

<IPython.core.display.HTML object>

  LIME Explanation for Instance 8 (True Label: 0)
Intercept 0.8769027744809275
Prediction_local [0.13748132]
Right: 0.0

<IPython.core.display.HTML object>

  LIME Explanation for Instance 9 (True Label: 1)
Intercept 0.44881324938825334
Prediction_local [1.04055762]
Right: 0.9827777777777779

<IPython.core.display.HTML object>
```

10.0.1 LIME Explanation Report (Instance-Level Model Interpretability)

- LIME was applied on multiple test instances to interpret the Random Forest classifier predictions for phishing detection.
- Key features influencing predictions included:

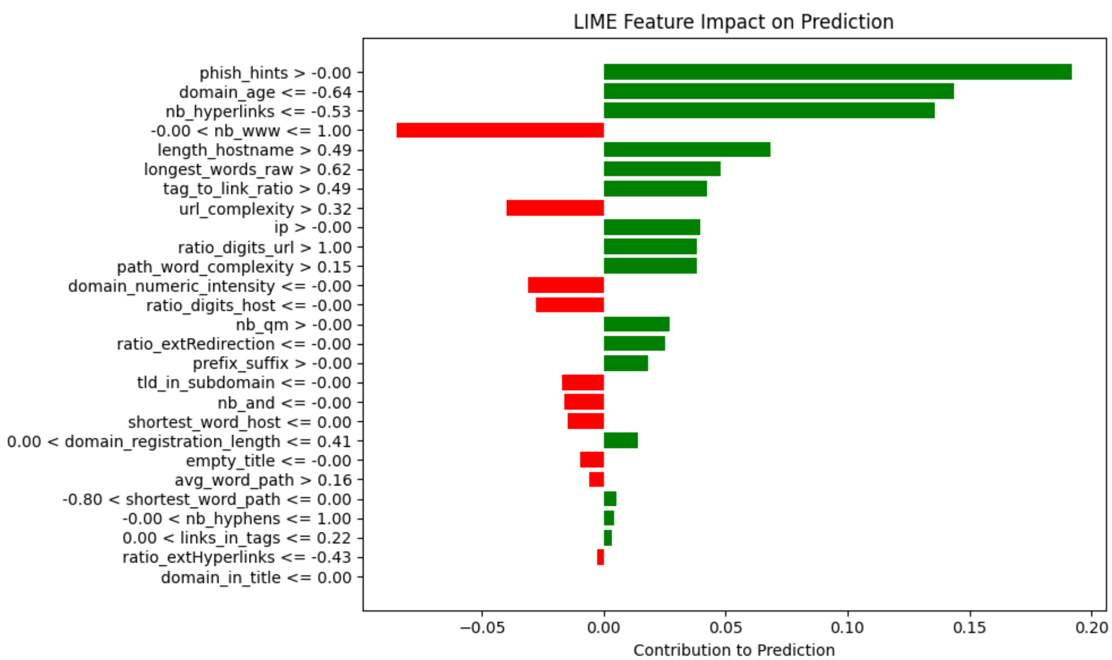
`url_complexity`, `phish_hints`, `nb_www`, `nb_qm`, and `domain_numeric_intensity`

- Engineered features demonstrated strong explanatory power across all instances, validating their inclusion.

- LIME revealed that the same feature (e.g., prefix_suffix, ratio_digits_url) may have positive or negative impact depending on the context.
- Visualizations confirmed that most predictions were driven by a small subset of high-impact features, enhancing transparency and trust in the model.

Step 3: Plot Feature Weights as Bar Plot

[ ]:
```python
# Plot feature impact bar chart (manual)
def plot_lime_weights(exp):
    weights = dict(exp.as_list())
    features = list(weights.keys())
    values = list(weights.values())

    plt.figure(figsize=(10, 6))
    plt.barh(features, values, color=['green' if v > 0 else 'red' for v in␣
 ↪values])
    plt.title("LIME Feature Impact on Prediction")
    plt.xlabel("Contribution to Prediction")
    plt.gca().invert_yaxis()
    plt.tight_layout()
    plt.show()

# Example: Plot for instance 0
plot_lime_weights(exp)
```



10.1 LIME Feature Impact - Phishing Detection

10.1.1 Features Positively Contributing to "Not Phishing"

These features indicate the URL is **likely safe**: - `phish_hints > 0.00` → Absence of phishing-related hints supports legitimacy. - `domain_age > -0.64` → Older domains are usually trustworthy. - `nb_hyperlinks <= -0.53` → Fewer hyperlinks suggest a safe page. - `-0.00 < nb_www <= 1.00` → Moderate use of "www" correlates with legitimate URLs. - `length_hostname > 0.49` → Longer hostnames are often used by real sites. - `longest_words_raw > 0.62` → Longer words in content support legitimacy. - `tag_to_link_ratio > 0.49` → Proper HTML structure suggests trustworthiness. - `url_complexity > 0.32` → Sophisticated URLs (not overly simple) tend to be legitimate. - `ip > -0.00` → Presence of a valid IP can be a positive sign. - `ratio_digits_url > 1.00` → Balanced use of digits is common in real sites. - `path_word_complexity > 0.15` → Complex paths often indicate dynamic, real content.

10.1.2 Features Negatively Impacting Prediction (Pointing to "Phishing")

These features raise suspicion: - `nb_www in range -0.00 < nb_www <= 1.00` (in excess) → May indicate phishing. - `domain_numeric_intensity <= -0.00` → Excessive numbers in the domain = red flag. - `nb_qm > -0.00` → Use of query parameters may imply phishing. - `prefix_suffix > 0.00` → Hyphenated domains often impersonate real brands. - `tld_in_subdomain <= -0.00` → Misuse of top-level domains in subdomains is suspicious. - `domain_registration_length < 0.41` → Recently registered domains are often phishing sites. - `shortest_word_host <= 0.00` → Very short words in host part may be autogenerated.
