Internship_CodeB_week 2

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1 Phishing Website Detection

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

2 Week 2 Submission

2.1 1. Business Problem Understanding Document

2.1.1 A. Business Problem Summary

- Phishing is a deceptive practice where attackers trick users into revealing sensitive information by mimicking legitimate websites. These malicious websites often appear genuine but are crafted with the intent of stealing personal data such as login credentials, credit card numbers, and banking details.
- With the rapid growth of internet usage and online services, phishing attacks have become more sophisticated and prevalent. Detecting these websites using traditional methods is no longer sufficient. Thus, leveraging machine learning models to identify phishing websites based on URL and site-level features is a crucial step forward.
- **Scope**
- Analyze URLs and website features to detect phishing attempts.
- Build machine learning models that predict whether a website is legitimate or phishing.
- **Importance**
- Enhances cybersecurity by reducing data breaches.
- Helps individuals and organizations identify and block phishing threats.
- Supports the development of real-time phishing detection tools.

2.1.2 B. Key Insights from Literature

- **Common Traits of Phishing Websites:**
- Use of IP addresses instead of domain names.
- Presence of excessive or suspicious characters (e.g., @, -, //, =, &).
- Long and complex URLs to imitate legitimate sources.

- Use of misleading keywords such as “login”, “secure”, “bank”, etc.
- Hosting on domains with short registration durations.
- **Challenges in Detection:**
- High variability in URL patterns.
- Short lifespan of phishing websites (sometimes a few hours).
- Attackers continuously adapt techniques to bypass detection tools.
- **Potential Solutions:**
- Supervised machine learning models trained on labeled datasets.
- Feature engineering from URL structures and domain metadata.
- Ensemble learning and real-time classification to improve prediction accuracy.

[65]:
```
# 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')
```

[66]:
```
# 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)
```

[66]:
```
                                                     url  length_url  \
10710                        http://www.bustybeauties.com/          29
9535                          https://mymsn0.yolasite.com/          28
8518                      https://fifohbibou.blogspot.com/          32
1802   http://encyclopedia2.thefreedictionary.com/Mul…          57
10706             http://totolive.sportstoto.com.my/stoto/          40
…                                                    …         …
9192                      https://www.naturalgasworld.com/          32
3150                                http://www.linea1s.com          22
2950                              http://www.bdmifund.com/          24
2840   https://en.wikipedia.org/wiki/The_Bodyguard_(m…          53
8867   http://support-appleld.com.secureupdate.duilaw…         125

       length_hostname  ip  nb_dots  nb_hyphens  nb_at  nb_qm  nb_and  nb_or  \
```

```
10710              21  0        2           0      0      0       0      0
9535               19  0        2           0      0      0       0      0
8518               23  0        2           0      0      0       0      0
1802               35  0        2           0      0      0       0      0
10706              26  0        3           0      0      0       0      0
…               …  ..       …         …    …    …     …    …
9192               23  0        2           0      0      0       0      0
3150               15  0        2           0      0      0       0      0
2950               16  0        2           0      0      0       0      0
2840               16  0        2           0      0      0       0      0
8867               50  1        4           1      0      1       2      0

       …  domain_in_title  domain_with_copyright  whois_registered_domain  \
10710  …                1                      1                        0
9535   …                1                      0                        0
8518   …                1                      1                        0
1802   …                1                      1                        0
10706  …                1                      1                        1
…    …              …                    …                      …
9192   …                1                      0                        0
3150   …                1                      1                        0
2950   …                1                      1                        0
2840   …                0                      1                        0
8867   …                1                      1                        0

       domain_registration_length  domain_age  web_traffic  dns_record  \
10710                         500        8996      2132314           0
9535                          258        4489            0           0
8518                          374        7295            0           0
1802                         2506        6259          683           0
10706                           0          -1       332453           0
…                           …         …          …         …
9192                          218        1609       291680           0
3150                          208         158            0           0
2950                           79        5034      1372473           0
2840                          902        7133           12           0
8867                           25        3992      5697976           0

       google_index  page_rank      status
10710             0          2  legitimate
9535              0          3    phishing
8518              1          5    phishing
1802              0          6  legitimate
10706             0          4  legitimate
…             …        …         …
9192              0          5  legitimate
3150              1          0    phishing
```

```
2950                0          3  legitimate
2840                0          7  legitimate
8867                1          0    phishing

[11430 rows x 89 columns]
```

3 Dataset Exploration 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.

3.2 Feature Descriptions & Relevance

Here's a list of all 87 features, along with their description and importance:

> Note: Many features represent counts, presence (1), or absence (0) of suspicious patterns in the URL or webpage behavior.

Feature Name	Description	Relevance to Phishing Detection
`url`	Full URL of the website	Used for parsing, may be dropped during modeling
`length_url`	Total length of the URL	Longer URLs are often suspicious
`length_hostname`	Length of the hostname	Abnormally long hostnames may indicate phishing
`ip`	If IP address is used instead of domain name (1 = yes)	Phishers often use IPs instead of domains
`nb_dots`	Number of dots in the URL	Too many dots → suspicious subdomains
`nb_hyphens`	Number of hyphens	Common in phishing URLs to mimic legit domains

Feature Name	Description	Relevance to Phishing Detection
nb_at	Number of ‘@’ characters	‘@’ often used to mask real domain
nb_qm	Number of ‘?’ in URL	Too many parameters can indicate hidden redirection
nb_and	Number of ‘&’ characters	Indicates URL manipulation or hidden tracking
nb_or	Number of ’	’ characters
nb_eq	Number of ‘=’ characters	Common in fake login or redirect pages
nb_underscore	Count of underscores	Can signal obfuscation
nb_tilde	Count of ‘~’ characters	May indicate temporary or unusual pages
nb_percent	Count of ‘%’ characters	Used in encoding redirects or disguising URLs
nb_slash	Count of ‘/’ slashes	Too many = suspicious depth or redirections
nb_star	Count of ’*’ characters	Very rare in legit URLs
nb_colon	Number of colons ‘:’	Used in port specification or data URIs
nb_comma	Number of commas	Rare in legit URLs, may be suspicious
nb_semicolumn	Number of semicolons	Used in injected scripts
nb_dollar	Number of ‘$’ characters	Can indicate obfuscation or script loading
nb_space	Number of whitespaces in the URL	Whitespaces in URL are rare and dangerous
nb_www	Count of “www” keyword	Repeated usage may mimic real sites
nb_com	Count of “.com” string	Overuse can fake legitimacy
nb_dslash	Count of ‘//’ used for redirecting	Excess usage indicates abnormal paths
http_in_path	If “http” is found in the path	Often indicates redirection
https_token	If “https” token is used in URL path (1 = yes)	Fakes legitimacy
ratio_digits_url	Ratio of digits to characters in URL	High ratios = suspicious
ratio_digits_host	Ratio of digits in the hostname	Numeric hostnames = uncommon
punycode	Use of punycode encoding (international domains)	May mask malicious domain names
port	Use of non-standard port numbers	Suspicious ports 80 or 443
tld_in_path	Top-level domain appearing in path	Can mislead users
tld_in_subdomain	TLD used in subdomain	Trick to appear trustworthy
abnormal_subdomain	Abnormal subdomain structure	Eg: login.bank.com.phish.com
nb_subdomains	Number of subdomains	Too many = trickery
prefix_suffix	Hyphen in domain (e.g. bank-login.com)	Fake websites mimic real domains
random_domain	Randomized domain	Non-meaningful or generated domains
shortening_service	Use of services like bit.ly	Used to hide malicious links

Feature Name	Description	Relevance to Phishing Detection
`path_extension`	File extension in path (e.g., .exe, .php)	May indicate downloads
`nb_redirection`	Redirection count	Excessive redirection → phishing
`nb_external_redirection`	External redirects	Leads users to fake sites
`length_words_raw`	Length of raw words in URL	Obfuscation via random text
`char_repeat`	Repeated characters in path	Common in fake or auto-gen links
`shortest_words_raw`	Shortest word in the URL	Random short words = suspicious
`shortest_word_host`	Shortest word in hostname	Useful in domain structure analysis
`shortest_word_path`	Shortest word in path	Detecting disguised segments
`longest_words_raw`	Longest word in the URL	Fake brand names or gibberish
`longest_word_host`	Longest word in hostname	Trick to mimic trusted sites
`longest_word_path`	Longest word in path	Often gibberish or misleading
`avg_words_raw`	Average word length in URL	Helps in pattern detection
`avg_word_host`	Avg. word length in host	Similar to above
`avg_word_path`	Avg. word length in path	Similar to above
`phish_hints`	Count of phishing indicators	Aggregated suspicious signs
`domain_in_brand`	Does domain appear in known brand names?	Fake sites often imitate real brands
`brand_in_subdomain`	Brand name used in subdomain	Fakes legitimacy
`brand_in_path`	Brand name used in path	Can mislead users
`suspecious_tld`	Suspicious top-level domain (e.g. .tk, .ru)	Cheap/free domains used by attackers
`statistical_report`	Appears in blacklist/whitelist or reputation DB	Reliable signal
`nb_hyperlinks`	Number of total hyperlinks	Could include clickbait links
`ratio_intHyperlinks`	Internal hyperlink ratio	Normal for legit sites
`ratio_extHyperlinks`	External link ratio	Phish sites link externally more
`ratio_nullHyperlinks`	Ratio of null or empty links	Dummy links → suspicious
`nb_extCSS`	Number of external CSS files	Excess = suspicious
`ratio_intRedirection`	Internal redirection ratio	Phishers often redirect from own page
`ratio_extRedirection`	External redirect ratio	Leads user out quickly
`ratio_intErrors`	Ratio of internal link errors	Bad design = sign of phishing
`ratio_extErrors`	External errors	External failures = trap
`login_form`	Presence of login form	Major phishing element
`external_favicon`	External favicon used	Stolen favicons mimic legit sites
`links_in_tags`	Links in script/style tags	Trick users via invisible links
`submit_email`	Uses email submission in forms	Unsecure credential theft
`ratio_intMedia`	Ratio of internal media (images, videos)	High = legit
`ratio_extMedia`	External media ratio	External media = phishing risk
`sfh`	Server form handler	Blank/unknown handler = suspicious
`iframe`	Uses iframe tag	Can hide real content
`popup_window`	Popup behavior	Fake prompts to enter info
`safe_anchor`	Safe anchors (linked to real content)	Legit sites have higher safe anchor count
`onmouseover`	Mouseover scripts	Trick users via hover effects

Feature Name	Description	Relevance to Phishing Detection
right_clic	Disabling right-click	Prevents inspection/alerts
empty_title	No page title	Often overlooked by attackers
domain_in_title	Domain appears in title	Good indicator for legit sites
domain_with_copyright	Shows copyright	Adds trust layer
whois_registered_domain	Domain is registered	Whois info missing = suspicious
domain_registration_length	Length of domain registration	Long-term = safe, Short = suspicious
domain_age	Age of domain	New = often phishing
web_traffic	Alexa/Web rank	Low traffic = red flag
dns_record	DNS record exists	No DNS = suspicious
google_index	Is page indexed by Google?	Not indexed = red flag
page_rank	PageRank score from search engines	Low = not trusted

---

[67]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11430 entries, 0 to 11429
Data columns (total 89 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   url                         11430 non-null  object
 1   length_url                  11430 non-null  int64
 2   length_hostname             11430 non-null  int64
 3   ip                          11430 non-null  int64
 4   nb_dots                     11430 non-null  int64
 5   nb_hyphens                  11430 non-null  int64
 6   nb_at                       11430 non-null  int64
 7   nb_qm                       11430 non-null  int64
 8   nb_and                      11430 non-null  int64
 9   nb_or                       11430 non-null  int64
 10  nb_eq                       11430 non-null  int64
 11  nb_underscore               11430 non-null  int64
 12  nb_tilde                    11430 non-null  int64
 13  nb_percent                  11430 non-null  int64
 14  nb_slash                    11430 non-null  int64
 15  nb_star                     11430 non-null  int64
 16  nb_colon                    11430 non-null  int64
 17  nb_comma                    11430 non-null  int64
 18  nb_semicolumn               11430 non-null  int64
 19  nb_dollar                   11430 non-null  int64
 20  nb_space                    11430 non-null  int64
 21  nb_www                      11430 non-null  int64
 22  nb_com                      11430 non-null  int64
 23  nb_dslash                   11430 non-null  int64
```

```
24  http_in_path                11430 non-null  int64
25  https_token                 11430 non-null  int64
26  ratio_digits_url            11430 non-null  float64
27  ratio_digits_host           11430 non-null  float64
28  punycode                    11430 non-null  int64
29  port                        11430 non-null  int64
30  tld_in_path                 11430 non-null  int64
31  tld_in_subdomain            11430 non-null  int64
32  abnormal_subdomain          11430 non-null  int64
33  nb_subdomains               11430 non-null  int64
34  prefix_suffix               11430 non-null  int64
35  random_domain               11430 non-null  int64
36  shortening_service          11430 non-null  int64
37  path_extension              11430 non-null  int64
38  nb_redirection              11430 non-null  int64
39  nb_external_redirection     11430 non-null  int64
40  length_words_raw            11430 non-null  int64
41  char_repeat                 11430 non-null  int64
42  shortest_words_raw          11430 non-null  int64
43  shortest_word_host          11430 non-null  int64
44  shortest_word_path          11430 non-null  int64
45  longest_words_raw           11430 non-null  int64
46  longest_word_host           11430 non-null  int64
47  longest_word_path           11430 non-null  int64
48  avg_words_raw               11430 non-null  float64
49  avg_word_host               11430 non-null  float64
50  avg_word_path               11430 non-null  float64
51  phish_hints                 11430 non-null  int64
52  domain_in_brand             11430 non-null  int64
53  brand_in_subdomain          11430 non-null  int64
54  brand_in_path               11430 non-null  int64
55  suspecious_tld              11430 non-null  int64
56  statistical_report          11430 non-null  int64
57  nb_hyperlinks               11430 non-null  int64
58  ratio_intHyperlinks         11430 non-null  float64
59  ratio_extHyperlinks         11430 non-null  float64
60  ratio_nullHyperlinks        11430 non-null  int64
61  nb_extCSS                   11430 non-null  int64
62  ratio_intRedirection        11430 non-null  int64
63  ratio_extRedirection        11430 non-null  float64
64  ratio_intErrors             11430 non-null  int64
65  ratio_extErrors             11430 non-null  float64
66  login_form                  11430 non-null  int64
67  external_favicon            11430 non-null  int64
68  links_in_tags               11430 non-null  float64
69  submit_email                11430 non-null  int64
70  ratio_intMedia              11430 non-null  float64
71  ratio_extMedia              11430 non-null  float64
```

```
 72  sfh                          11430 non-null  int64
 73  iframe                       11430 non-null  int64
 74  popup_window                 11430 non-null  int64
 75  safe_anchor                  11430 non-null  float64
 76  onmouseover                  11430 non-null  int64
 77  right_clic                   11430 non-null  int64
 78  empty_title                  11430 non-null  int64
 79  domain_in_title              11430 non-null  int64
 80  domain_with_copyright        11430 non-null  int64
 81  whois_registered_domain      11430 non-null  int64
 82  domain_registration_length   11430 non-null  int64
 83  domain_age                   11430 non-null  int64
 84  web_traffic                  11430 non-null  int64
 85  dns_record                   11430 non-null  int64
 86  google_index                 11430 non-null  int64
 87  page_rank                    11430 non-null  int64
 88  status                       11430 non-null  object
dtypes: float64(13), int64(74), object(2)
memory usage: 7.8+ MB
```

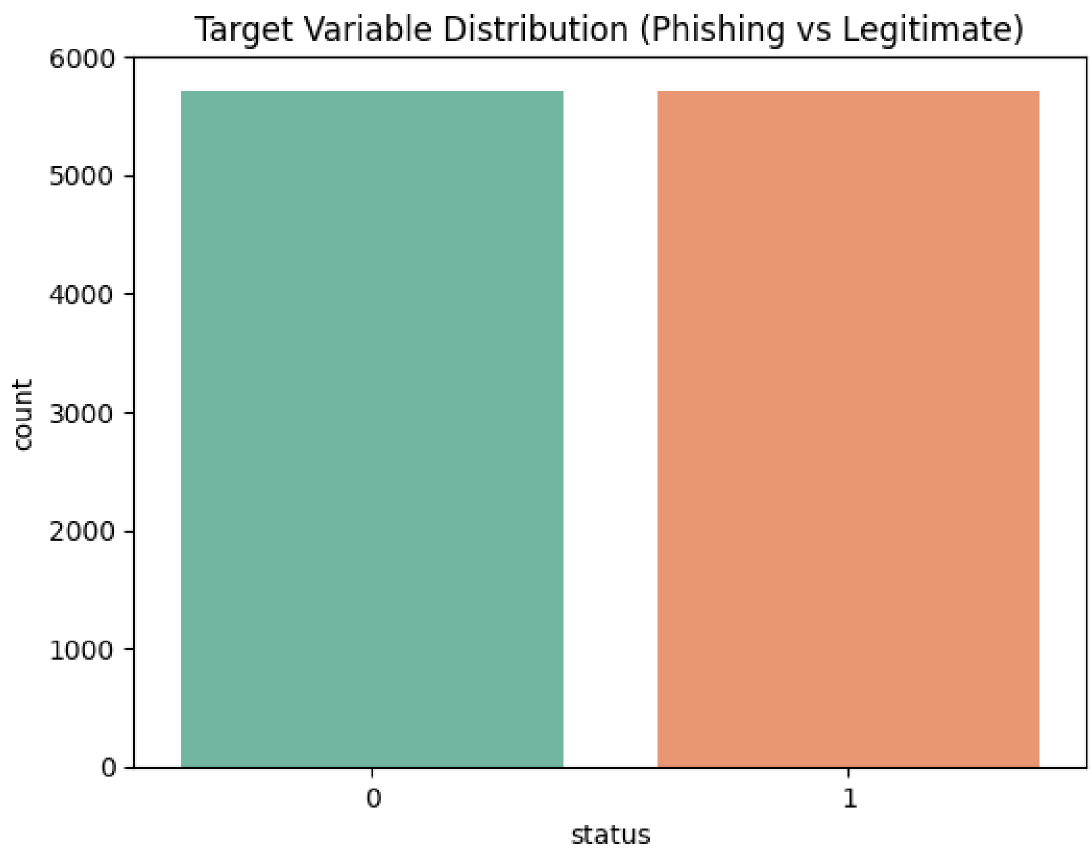
[68]:

```
# 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
```

[83]:

```
# 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
```

[70]:
```
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']
```

[71]:
```python
# Univariate Analysis (Custom Function)

from collections import OrderedDict

stats = []
for i in numeric_features:
    numerical_stats = OrderedDict({
        'Feature': i,
        'Maximum' : df[i].max(),
        'Minimum' : df[i].min(),
        'Mean' : df[i].mean(),
        'Median' : df[i].median(),
        '25%': df[i].quantile(0.25),
        '75%': df[i].quantile(0.75),
        'Standard Deviation': df[i].std(),
        'Variance': df[i].var(),
        'Skewness': df[i].skew(),
        'Kurtosis': df[i].kurt(),
        'IQR' : df[i].quantile(0.75) - df[i].quantile(0.25)
    })
    stats.append(numerical_stats)
report = pd.DataFrame(stats)
report
```

[71]:
```
            Feature     Maximum  Minimum           Mean  Median   25%  \
0        length_url      1641.0     12.0      61.126684    47.0  33.0
1   length_hostname       214.0      4.0      21.090289    19.0  15.0
2                ip         1.0      0.0       0.150569     0.0   0.0
3           nb_dots        24.0      1.0       2.480752     2.0   2.0
4         nb_hyphens       43.0      0.0       0.997550     0.0   0.0
..              …           …        …              …       …     …
83      web_traffic  10767986.0      0.0  856756.643307  1651.0   0.0
84       dns_record         1.0      0.0       0.020122     0.0   0.0
```

```
85     google_index         1.0      0.0        0.533946     1.0    0.0
86        page_rank        10.0      0.0        3.185739     3.0    1.0
87           status         1.0      0.0        0.500000     0.5    0.0

         75%  Standard Deviation      Variance  Skewness    Kurtosis       IQR
0       71.0        5.529732e+01  3.057793e+03  8.085190  144.196391      38.0
1       24.0        1.077717e+01  1.161474e+02  5.160078   69.829931       9.0
2        0.0        3.576436e-01  1.279089e-01  1.954418    1.820067       0.0
3        3.0        1.369686e+00  1.876040e+00  5.718117   66.155843       1.0
4        1.0        2.087087e+00  4.355931e+00  4.695239   40.696686       1.0
..       …                 …             …         …          …        …
83  373845.5        1.995606e+06  3.982443e+12  2.779269    7.306645  373845.5
84       0.0        1.404254e-01  1.971930e-02  6.835821   44.736280       0.0
85       1.0        4.988682e-01  2.488695e-01 -0.136115   -1.981820       1.0
86       5.0        2.536955e+00  6.436143e+00  0.446031   -0.386315       4.0
87       1.0        5.000219e-01  2.500219e-01  0.000000   -2.000350       1.0

[88 rows x 12 columns]
```

[ ]:
```python
# Check for Missing Values
missing_values = df.isnull().sum()
missing_values[missing_values > 0]
```

[ ]:
```
Series([], dtype: int64)
```

[73]:
```python
#Check for Duplicate Rows
duplicate_count = df.duplicated().sum()
print(f"Number of duplicate rows: {duplicate_count}")
```

```
Number of duplicate rows: 0
```

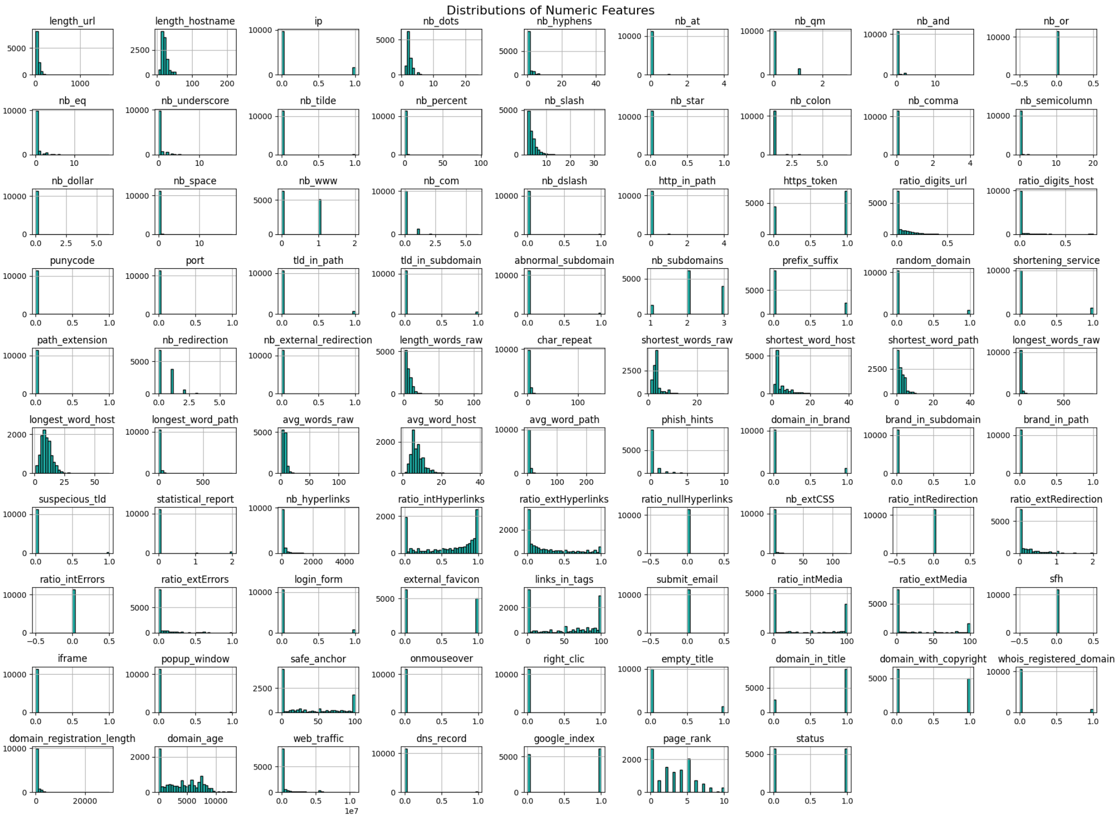
[74]:
```python
# Classify Feature Importance (initial logic-based guess)
for col in df.columns:
    if col != 'status':
        print(f"{col}: {df[col].unique()[:5]} ... ({df[col].nunique()} unique␣
↪values)")
```

```
url: ['http://www.crestonwood.com/router.php'
 'http://shadetreetechnology.com/V4/validation/a111aedc8ae390eabcfa130e041a10a4'
 'https://support-appleld.com.secureupdate.duilawyeryork.com/ap/89e6a3b4b063b8d/
?cmd=_update&dispatch=89e6a3b4b063b8d1b&locale=_'
 'http://rgipt.ac.in'
 'http://www.iracing.com/tracks/gateway-motorsports-park/'] … (11429 unique
values)
length_url: [ 37  77 126  18  55] … (324 unique values)
length_hostname: [19 23 50 11 15] … (83 unique values)
ip: [0 1] … (2 unique values)
nb_dots: [3 1 4 2 5] … (19 unique values)
```

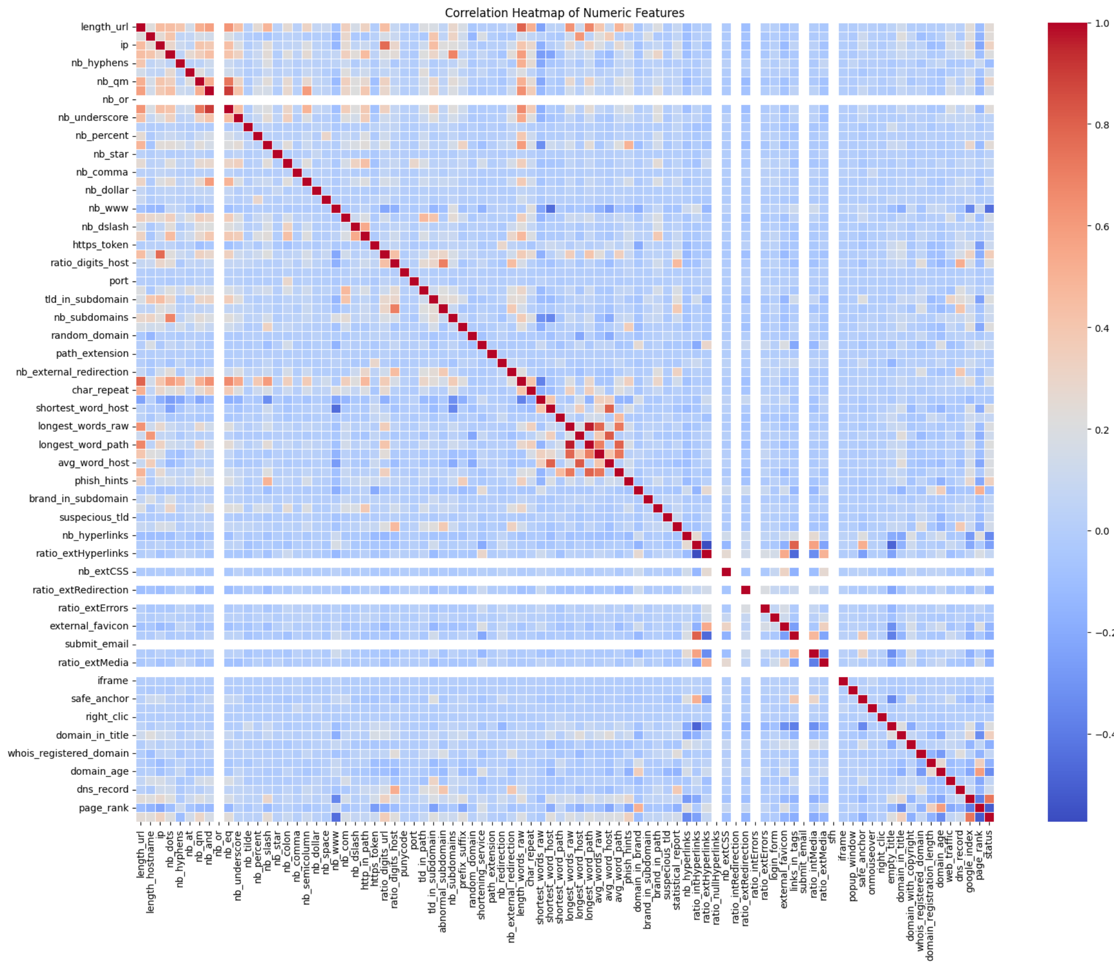
```
nb_hyphens: [ 0  1  2 10  3] … (27 unique values)
nb_at: [0 1 2 3 4] … (5 unique values)
nb_qm: [0 1 2 3] … (4 unique values)
nb_and: [0 2 1 9 5] … (15 unique values)
nb_or: [0] … (1 unique values)
nb_eq: [ 0  3  1  2 10] … (16 unique values)
nb_underscore: [0 2 1 4 3] … (17 unique values)
nb_tilde: [0 1] … (2 unique values)
nb_percent: [0 1 3 8 6] … (25 unique values)
nb_slash: [3 5 2 6 4] … (22 unique values)
nb_star: [0 1] … (2 unique values)
nb_colon: [1 3 5 2 4] … (6 unique values)
nb_comma: [0 1 2 4 3] … (5 unique values)
nb_semicolumn: [0 2 1 9 7] … (15 unique values)
nb_dollar: [0 1 2 3 6] … (5 unique values)
nb_space: [0 1 3 2 5] … (9 unique values)
nb_www: [1 0 2] … (3 unique values)
nb_com: [0 1 2 3 6] … (7 unique values)
nb_dslash: [0 1] … (2 unique values)
http_in_path: [0 1 4 3 2] … (5 unique values)
https_token: [1 0] … (2 unique values)
ratio_digits_url: [0.         0.22077922 0.15079365 0.25925926 0.07692308] …
(1414 unique values)
ratio_digits_host: [0.         0.21052632 0.32142857 0.13636364 0.05714286] …
(241 unique values)
punycode: [0 1] … (2 unique values)
port: [0 1] … (2 unique values)
tld_in_path: [0 1] … (2 unique values)
tld_in_subdomain: [0 1] … (2 unique values)
abnormal_subdomain: [0 1] … (2 unique values)
nb_subdomains: [3 1 2] … (3 unique values)
prefix_suffix: [0 1] … (2 unique values)
random_domain: [0 1] … (2 unique values)
shortening_service: [0 1] … (2 unique values)
path_extension: [0 1] … (2 unique values)
nb_redirection: [0 1 2 4 3] … (7 unique values)
nb_external_redirection: [0 1] … (2 unique values)
length_words_raw: [ 4 12  1  6  2] … (54 unique values)
char_repeat: [4 2 0 3 8] … (55 unique values)
shortest_words_raw: [3 2 5 8 4] … (25 unique values)
shortest_word_host: [ 3 19  5  8  6] … (34 unique values)
shortest_word_path: [3 2 0 4 5] … (33 unique values)
longest_words_raw: [11 32 17  5  7] … (119 unique values)
longest_word_host: [11 19 13  5  7] … (49 unique values)
longest_word_path: [ 6 32 17  0 11] … (120 unique values)
avg_words_raw: [ 5.75       15.75        8.25        5.          6.33333333] …
(896 unique values)
avg_word_host: [ 7.  19.   8.4  5.   4.5] … (174 unique values)
```

```
avg_word_path: [ 4.5        14.66666667  8.14285714  0.          7.        ] …
(757 unique values)
phish_hints: [0 1 4 2 3] … (9 unique values)
domain_in_brand: [0 1] … (2 unique values)
brand_in_subdomain: [0 1] … (2 unique values)
brand_in_path: [0 1] … (2 unique values)
suspecious_tld: [0 1] … (2 unique values)
statistical_report: [0 1 2] … (3 unique values)
nb_hyperlinks: [ 17  30   4 149 102] … (691 unique values)
ratio_intHyperlinks: [0.52941176 0.96666667 1.         0.97315436 0.47058824]
… (3131 unique values)
ratio_extHyperlinks: [0.47058824 0.03333333 0.         0.02684564 0.52941176]
… (3131 unique values)
ratio_nullHyperlinks: [0] … (1 unique values)
nb_extCSS: [ 0 10  3  1  2] … (33 unique values)
ratio_intRedirection: [0] … (1 unique values)
ratio_extRedirection: [0.875      0.         0.25       0.53703704 0.57142857]
… (894 unique values)
ratio_intErrors: [0] … (1 unique values)
ratio_extErrors: [0.5        0.         0.25       0.01851852 0.16666667] …
(635 unique values)
login_form: [0 1] … (2 unique values)
external_favicon: [0 1] … (2 unique values)
links_in_tags: [ 80.         100.          76.47058824   0.
93.10344828] … (473 unique values)
submit_email: [0] … (1 unique values)
ratio_intMedia: [100.          80.           0.          96.42857143  10.
] … (490 unique values)
ratio_extMedia: [  0.          20.           3.57142857 100.          90.
] … (490 unique values)
sfh: [0] … (1 unique values)
iframe: [0 1] … (2 unique values)
popup_window: [0 1] … (2 unique values)
safe_anchor: [  0.         100.          62.5         27.27272727  58.13953488]
… (1083 unique values)
onmouseover: [0 1] … (2 unique values)
right_clic: [0 1] … (2 unique values)
empty_title: [0 1] … (2 unique values)
domain_in_title: [0 1] … (2 unique values)
domain_with_copyright: [1 0] … (2 unique values)
whois_registered_domain: [0 1] … (2 unique values)
domain_registration_length: [ 45  77  14  62 224] … (1659 unique values)
domain_age: [  -1 5767 4004 8175 7529] … (4430 unique values)
web_traffic: [      0 5828815  107721    8725    6774] … (4744 unique values)
dns_record: [1 0] … (2 unique values)
google_index: [1 0] … (2 unique values)
page_rank: [4 2 0 3 6] … (11 unique values)
```

[75]:
```python
# Visualize Numeric Features Distributions

df[numeric_features].hist(bins=30, figsize=(20, 15), color='lightseagreen',␣
    ↪edgecolor='black')
plt.suptitle("Distributions of Numeric Features", fontsize=16)
plt.tight_layout()
plt.show()
```



[77]:
```python
# Correlation Heatmap

plt.figure(figsize=(20, 15))
sns.heatmap(df[numeric_features].corr(), annot=False, cmap='coolwarm',␣
    ↪linewidths=0.5)
plt.title("Correlation Heatmap of Numeric Features")
plt.show()
```



Correlation Heatmap (Feature Redundancy & Selection) **High Correlation Groups (may cause redundancy):**

- longest_words_raw, avg_word_host, shortest_word_host: Highly correlated — consider keeping only one.
- nb_subdomains, tld_in_subdomain, brand_in_subdomain: These also cluster — may contain overlapping information.
- nb_hyperlinks, ratio_extHyperlinks, ratio_extRedirection: Related to link structure — pick wisely.

Independent but Powerful Features:

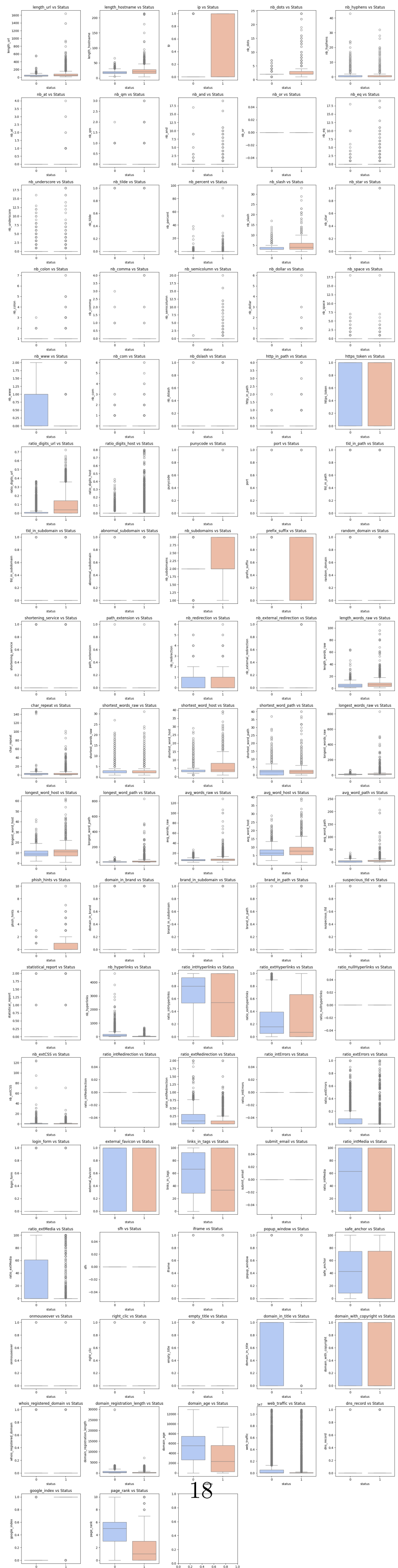
- submit_email, iframe, right_click, phish_hints, https_token, dns_record, domain_age: Appear relatively uncorrelated - — provide unique signals.

Low or No Correlation with Others:

- These might offer unique value and should be retained unless proven noisy.

[88]:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Set up the number of columns
num_cols = 5
# Calculate the number of rows required
num_rows = (len(numeric_features) - 1) // num_cols + 1  # Ensure enough rows to␣
↪fit all features

# Create a figure with subplots arranged in the specified grid
fig, axes = plt.subplots(num_rows, num_cols, figsize=(18, num_rows * 4))

# Flatten the axes array for easier iteration
axes = axes.flatten()

# Loop through each numeric feature and plot
for idx, feature in enumerate(numeric_features):
    if feature != 'status':
        sns.boxplot(data=df, x='status', y=feature, palette='coolwarm',␣
↪ax=axes[idx])
        axes[idx].set_title(f'{feature} vs Status')

# Remove any unused axes if the number of numeric features is not a multiple of␣
↪5
for i in range(idx + 1, len(axes)):
    fig.delaxes(axes[i])

# Adjust layout to prevent overlap
plt.tight_layout()
plt.show()
```


length_url vs Status
length_hostname vs Status
ip vs Status
nb_dots vs Status
nb_hyphens vs Status
nb_at vs Status
nb_qm vs Status
nb_and vs Status
nb_or vs Status
nb_eq vs Status
nb_underscore vs Status
nb_tilde vs Status
nb_percent vs Status
nb_slash vs Status
nb_star vs Status
nb_colon vs Status
nb_comma vs Status
nb_semicolumn vs Status
nb_dollar vs Status
nb_space vs Status
nb_www vs Status
nb_com vs Status
nb_dslash vs Status
http_in_path vs Status
https_token vs Status
ratio_digits_url vs Status
ratio_digits_host vs Status
punycode vs Status
port vs Status
tld_in_path vs Status
tld_in_subdomain vs Status
abnormal_subdomain vs Status
nb_subdomains vs Status
prefix_suffix vs Status
random_domain vs Status
shortening_service vs Status
path_extension vs Status
nb_redirection vs Status
nb_external_redirection vs Status
length_words_raw vs Status
char_repeat vs Status
shortest_words_raw vs Status
shortest_word_host vs Status
shortest_word_path vs Status
longest_words_raw vs Status
longest_word_host vs Status
longest_word_path vs Status
avg_words_raw vs Status
avg_word_host vs Status
avg_word_path vs Status
phish_hints vs Status
domain_in_brand vs Status
brand_in_subdomain vs Status
brand_in_path vs Status
suspecious_tld vs Status
statistical_report vs Status
nb_hyperlinks vs Status
ratio_intHyperlinks vs Status
ratio_extHyperlinks vs Status
ratio_nullHyperlinks vs Status
nb_extCSS vs Status
ratio_intRedirection vs Status
ratio_extRedirection vs Status
ratio_intErrors vs Status
ratio_extErrors vs Status
login_form vs Status
external_favicon vs Status
links_in_tags vs Status
submit_email vs Status
ratio_intMedia vs Status
ratio_extMedia vs Status
sfh vs Status
iframe vs Status
popup_window vs Status
safe_anchor vs Status
onmouseover vs Status
right_clic vs Status
empty_title vs Status
domain_in_title vs Status
domain_with_copyright vs Status
whois_registered_domain vs Status
domain_registration_length vs Status
domain_age vs Status
web_traffic vs Status
dns_record vs Status
google_index vs Status
page_rank vs Status

4 Boxplot Analysis – Key Insights for Phishing Detection

These boxplots compare the distribution of each feature across phishing (`1`) and legitimate (`0`) classes. They provide a clear view of **central tendency**, **spread**, and **outliers**.

4.1 Highly Discriminative Features

These show clear and significant differences between phishing and legitimate classes:

Feature	Observation
`ip`	Phishing URLs frequently use IP addresses instead of domain names.
`https_token`	Often present in phishing; used to deceive users with fake security indicators.
`submit_email`	Strong phishing indicator; almost exclusive to phishing URLs.
`phish_hints`	Typically higher in phishing URLs.
`whois_registered_domain`	Legitimate URLs usually have WHOIS info; phishing lacks it.
`dns_record`	Missing more often in phishing URLs.
`domain_age`	Phishing domains are newer (lower domain age).
`domain_registration_length`	Shorter duration typical in phishing domains.
`external_favicon`	More common in phishing (linking favicons from outside domains).
`ratio_intMedia`, `ratio_extHyperlinks`	Notably different between classes, showing link-based behavioral differences.

4.2 Moderately Discriminative Features

These display differences that are noticeable but might need further feature engineering:

Feature	Observation
`nb_subdomains`	Phishing URLs often use more subdomains.
`ratio_digits_url`	Slightly higher in phishing.
`avg_word_host`, `longest_word_host`	Phishing domains have longer and more complex word structures.
`port`	Non-zero ports appear more in phishing (e.g., custom ports).
`right_click`	Often disabled in phishing.
`iframe`	More frequently used in phishing.

Feature	Observation
`safe_anchor`	Slight variation; phishing may use deceptive anchor links.

4.3 Non-Discriminative / Noisy Features

These features show **minimal variation** across classes and might not contribute much:

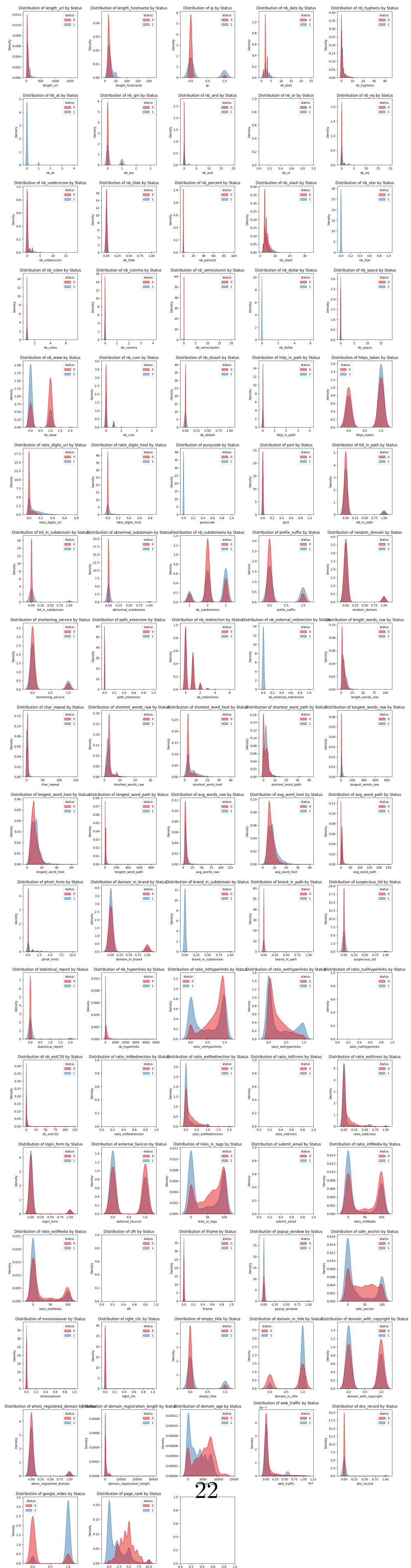
- `nb_star`, `nb_dollar`, `nb_or`, `nb_comma` – These characters don't differ much between phishing and legitimate.
- `domain_with_copyright`, `domain_in_title` – Appear evenly distributed.
- `ratio_redirect`, `path_extension`, `char_repeat` – Less noticeable separation.

4.4 Final Takeaways

- **Strong Predictors**: `ip`, `https_token`, `submit_email`, `phish_hints`, `dns_record`, `domain_age`
- **Useful with Preprocessing**: `nb_subdomains`, `ratio_digits_url`, `longest_word_host`, `right_click`
- **Consider Dropping or Engineering Further**: `nb_star`, `nb_or`, `domain_in_title`, etc.

[90]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

# Set up the number of columns
num_cols = 5
# Calculate the number of rows required
num_rows = (len(numeric_features) - 1) // num_cols + 1  # Ensure enough rows to␣
↪fit all features

# Create a figure with subplots arranged in the specified grid
fig, axes = plt.subplots(num_rows, num_cols, figsize=(18, num_rows * 4))

# Flatten the axes array for easier iteration
axes = axes.flatten()

# Loop through each numeric feature and plot the KDE
for idx, feature in enumerate(numeric_features):
    if feature != 'status':
        sns.kdeplot(data=df, x=feature, hue='status', fill=True,␣
↪palette='Set1', alpha=0.5, ax=axes[idx])
        axes[idx].set_title(f'Distribution of {feature} by Status')

# Remove any unused axes if the number of numeric features is not a multiple of␣
↪5
```

```python
for i in range(idx + 1, len(axes)):
    fig.delaxes(axes[i])

# Adjust layout to prevent overlap
plt.tight_layout()
plt.show()
```


Distribution of length_url by Status
Distribution of length_hostname by Status
Distribution of ip by Status
Distribution of nb_dots by Status
Distribution of nb_hyphens by Status
Distribution of nb_at by Status
Distribution of nb_qm by Status
Distribution of nb_and by Status
Distribution of nb_or by Status
Distribution of nb_eq by Status
Distribution of nb_underscore by Status
Distribution of nb_tilde by Status
Distribution of nb_percent by Status
Distribution of nb_slash by Status
Distribution of nb_star by Status
Distribution of nb_colon by Status
Distribution of nb_comma by Status
Distribution of nb_semicolumn by Status
Distribution of nb_dollar by Status
Distribution of nb_space by Status
Distribution of nb_www by Status
Distribution of nb_com by Status
Distribution of nb_dslash by Status
Distribution of http_in_path by Status
Distribution of https_token by Status
Distribution of ratio_digits_url by Status
Distribution of ratio_digits_host by Status
Distribution of punycode by Status
Distribution of port by Status
Distribution of tld_in_path by Status
Distribution of tld_in_subdomain by Status
Distribution of abnormal_subdomain by Status
Distribution of nb_subdomains by Status
Distribution of prefix_suffix by Status
Distribution of random_domain by Status
Distribution of shortening_service by Status
Distribution of path_extension by Status
Distribution of nb_redirection by Status
Distribution of nb_external_redirection by Status
Distribution of length_words_raw by Status
Distribution of char_repeat by Status
Distribution of shortest_words_raw by Status
Distribution of shortest_word_host by Status
Distribution of shortest_word_path by Status
Distribution of longest_words_raw by Status
Distribution of longest_word_host by Status
Distribution of longest_word_path by Status
Distribution of avg_words_raw by Status
Distribution of avg_word_host by Status
Distribution of avg_word_path by Status
Distribution of phish_hints by Status
Distribution of domain_in_brand by Status
Distribution of brand_in_subdomain by Status
Distribution of brand_in_path by Status
Distribution of suspecious_tld by Status
Distribution of statistical_report by Status
Distribution of nb_hyperlinks by Status
Distribution of ratio_intHyperlinks by Status
Distribution of ratio_extHyperlinks by Status
Distribution of ratio_nullHyperlinks by Status
Distribution of nb_extCSS by Status
Distribution of ratio_intRedirection by Status
Distribution of ratio_extRedirection by Status
Distribution of ratio_intErrors by Status
Distribution of ratio_extErrors by Status
Distribution of login_form by Status
Distribution of external_favicon by Status
Distribution of links_in_tags by Status
Distribution of submit_email by Status
Distribution of ratio_intMedia by Status
Distribution of ratio_extMedia by Status
Distribution of sfh by Status
Distribution of iframe by Status
Distribution of popup_window by Status
Distribution of safe_anchor by Status
Distribution of onmouseover by Status
Distribution of right_clic by Status
Distribution of empty_title by Status
Distribution of domain_in_title by Status
Distribution of domain_with_copyright by Status
Distribution of whois_registered_domain by Status
Distribution of domain_registration_length by Status
Distribution of domain_age by Status
Distribution of web_traffic by Status
Distribution of dns_record by Status
Distribution of google_index by Status
Distribution of page_rank by Status
status

These plots show how various features differ between phishing and legitimate URLs.

Highly Discriminative Features (good for model training): - https_token: Phishing URLs have a significantly higher count of "https" tokens in unexpected parts of the URL.

- phish_hints: Clearly skewed toward phishing; very useful feature.
- submit_email: Almost exclusively found in phishing URLs.
- whois_registered_domain / dns_record / domain_age: Phishing URLs often lack WHOIS records, DNS records, or are newly registered.
- port / ip: Phishing URLs are more likely to use raw IPs and unusual ports.
- external_favicon: Phishing sites often use favicons hosted on external domains.

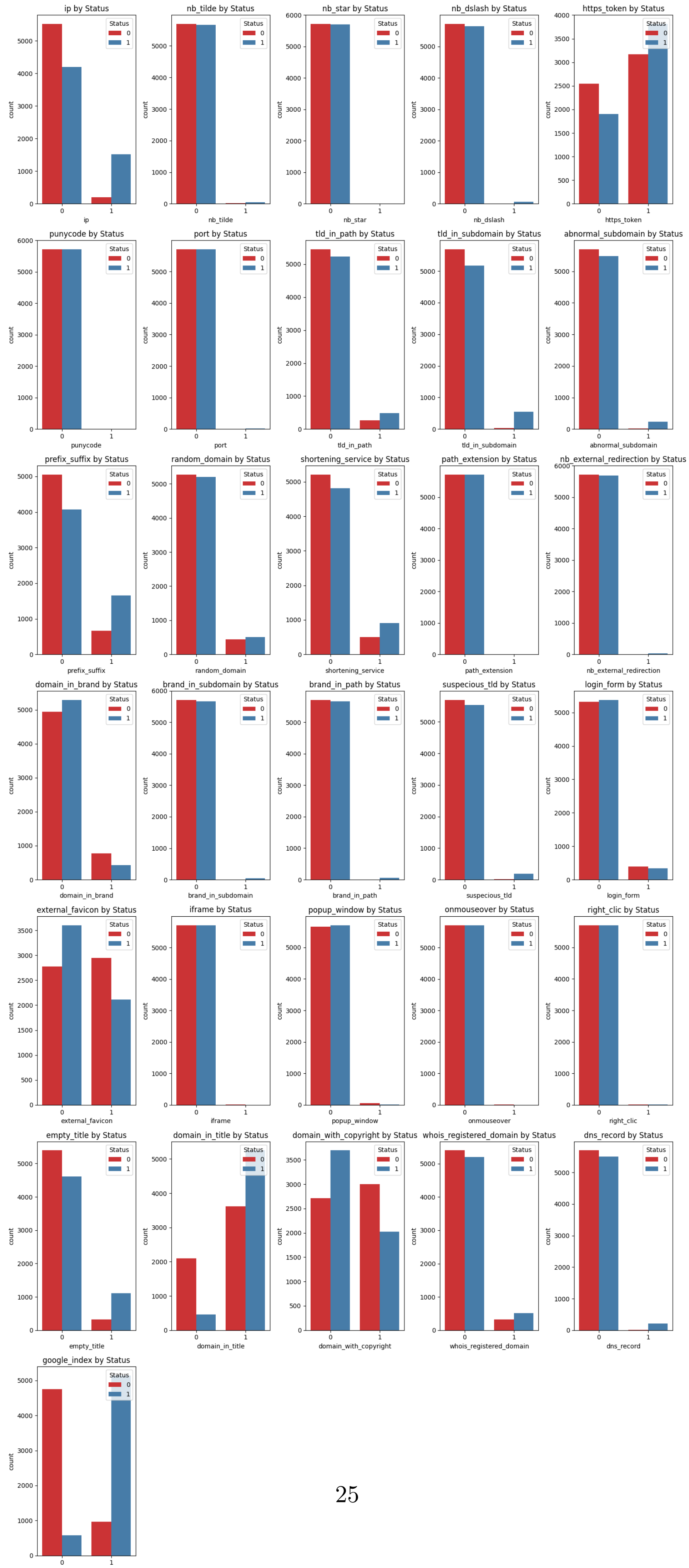
Somewhat Useful Features: - nb_hyphens, nb_dots, length_url, nb_subdomains: Tend to be higher in phishing URLs.

- right_click: Often disabled in phishing sites to avoid copying or inspecting.
- iframe / safe_anchor: These tags are more often misused in phishing.
- domain_in_title: Often absent in phishing URLs.
- path_extension, random_domain, brand_in_subdomain: More frequently manipulated in phishing attempts.

Less Differentiated Features (less useful for models): - Features like nb_star, nb_dollar, nb_or, nb_comma, etc., show little or no difference between phishing and legitimate URLs.

[91]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

# Identify binary features (with 2 unique values)
binary_features = [col for col in df.columns if df[col].nunique() == 2 and col !
 ↪= 'status']

# Define the number of columns for the subplot grid
num_cols = 5
num_rows = (len(binary_features) + num_cols - 1) // num_cols  # Calculate rows␣
 ↪based on number of binary features

# Create a grid of subplots
fig, axes = plt.subplots(num_rows, num_cols, figsize=(15, 5 * num_rows))
axes = axes.flatten()  # Flatten the axes array to make indexing easier

# Loop through the binary features and plot them in the grid
for i, feature in enumerate(binary_features):
    sns.countplot(data=df, x=feature, hue='status', palette='Set1', ax=axes[i])
    axes[i].set_title(f'{feature} by Status')
```

```python
    axes[i].legend(title='Status', loc='upper right')

# Turn off axes for unused subplots
for i in range(len(binary_features), len(axes)):
    axes[i].axis('off')

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


ip by Status
nb_tilde by Status
nb_star by Status
nb_dslash by Status
https_token by Status
punycode by Status
port by Status
tld_in_path by Status
tld_in_subdomain by Status
abnormal_subdomain by Status
prefix_suffix by Status
random_domain by Status
shortening_service by Status
path_extension by Status
nb_external_redirection by Status
domain_in_brand by Status
brand_in_subdomain by Status
brand_in_path by Status
suspecious_tld by Status
login_form by Status
external_favicon by Status
iframe by Status
popup_window by Status
onmouseover by Status
right_clic by Status
empty_title by Status
domain_in_title by Status
domain_with_copyright by Status
whois_registered_domain by Status
dns_record by Status
google_index by Status

[81]:

```

```