Predykcja ataku phishingowego w wiadomości **e-mail** za pomocą ***nadzorowanego nauczania maszynowego***

Dataset:

- ***Phishing Email Curated Datasets***
  - https://zenodo.org/records/8339691

Pobieranie niezbędnych modułów

- pandas - praca z *Data Framami*
- numpy - obliczenia
- matplotlib.pyplot - wizualizacja
- sklearn - wszelakie narzędzia do *Machine Learningu*

In [1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt

from sklearn.model_selection import KFold, train_test_split, cross_val_score, GridS
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler
import sklearn.metrics as skm

import import_ipynb
import re
from unidecode import unidecode
from termcolor import colored
```

Wczytanie uprzednio przygotowanego Data Framu

In [2]:
```
learning_set = pd.read_csv('ML_DataFrame.csv')
print(learning_set.head())
```

```
   Unnamed: 0  label  urls_count  protocol  contains_ip  url_length  \
0           0    1.0         1.0       0.0          0.0        21.0
1           1    1.0         1.0       0.0          0.0        25.0
2           2    1.0         3.0       0.0          0.0       110.0
3           3    0.0         3.0       0.0          0.0        22.0
4           4    1.0         1.0       0.0          0.0       136.0

   TLD_alpha  subdomain_level  slash_count  dots_count  hyphens_count  \
0        1.0              0.0          3.0         1.0            0.0
1        1.0              1.0          2.0         2.0            0.0
2        1.0              1.0          6.0         5.0            0.0
3        0.0              1.0          2.0         2.0            0.0
4        1.0              2.0          4.0         4.0            2.0

   has_non_latin
0            0.0
1            0.0
2            0.0
3            0.0
4            0.0
```

In [3]:
```
print(learning_set.isna().sum())
learning_set.dropna(inplace=True)
```

```
Unnamed: 0          0
label               0
urls_count          0
protocol            0
contains_ip         0
url_length          0
TLD_alpha           0
subdomain_level    84
slash_count         0
dots_count          0
hyphens_count       0
has_non_latin       0
dtype: int64
```

Wybieranie X i y

X:

- urls_count
- protocol
- contains_ip
- url_length
- TLD_alpha
- subdomain_level
- slash_count
- dots_count
- hyphens_count
- has_non_latin

y:

- label

In [22]:
```
X = learning_set.loc[:, 'urls_count':'has_non_latin'].values
y = learning_set.loc[: , 'label'].values
print(X.shape, y.shape)
```

```
<class 'numpy.ndarray'>
(41632, 10) (41632,)
```

Rozdzielanie X, y na treningowe i testowe zestawy

In [5]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

Normalizujemy wartość *X*-ów

In [6]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [7]:
```
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(33305, 10) (8327, 10) (33305,) (8327,)
```

Szukanie najlepszych parametrów dla *KNeighborsClassifier*

In [8]:
```
kf = KFold(n_splits=6, shuffle=True, random_state=42)
params = {
    'n_neighbors': np.arange(1, 15, 1),
    'weights': ['uniform', 'distance'],
    'p': [1, 2]
}
knn = KNeighborsClassifier()
knn_cv = GridSearchCV(knn, param_grid=params, cv=kf)
knn_cv.fit(X_train, y_train)

print('Najlepsze parametry dla KNeighborsClassifier:')
for p, val in knn_cv.best_params_.items():
    print('{}: {}'.format(p, val), end='\n')
print('Uzyskana precyzja: ', knn_cv.best_score_)

best_knn = knn_cv.best_estimator_
test_accuracy = best_knn.score(X_test, y_test)
print("Precyzja zestawu testowego:", test_accuracy)
```

```
Najlepsze parametry dla KNeighborsClassifier:
n_neighbors: 13
p: 1
weights: distance
Uzyskana precyzja:  0.8729022068366331
Precyzja zestawu testowego: 0.8734238020895881
```

Szukanie najlepszych parametrów dla *LogisticRegression*

In [9]:
```
from sklearn.linear_model import LogisticRegression
kf = KFold(n_splits=6, shuffle=True, random_state=42)
params = {
    'penalty': ['l1', 'l2'],
    'C': [0.001, 0.01, 0.1, 1, 10]
}
logreg_forest = LogisticRegression()
logreg_cv = GridSearchCV(logreg_forest, param_grid=params, cv=kf)
logreg_cv.fit(X_train, y_train)

print('Najlepsze parametry dla LogisticRegression:')
for p, val in logreg_cv.best_params_.items():
    print('{}: {}'.format(p, val), end='\n')
print('Uzyskana precyzja: ', logreg_cv.best_score_)

best_logreg = logreg_cv.best_estimator_
test_accuracy = best_logreg.score(X_test, y_test)
print("Precyzja zestawu testowego:", test_accuracy)
```

```
Najlepsze parametry dla LogisticRegression:
C: 10
penalty: l2
Uzyskana precyzja:  0.7300107493550115
Precyzja zestawu testowego: 0.7341179296265161
```

```
C:\Users\Patryk\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kf
ra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\model_selection\_val
idation.py:425: FitFailedWarning:
30 fits failed out of a total of 60.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score
='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
30 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\Patryk\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_
qbz5n2kfra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\model_select
ion\_validation.py", line 729, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\Patryk\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_
qbz5n2kfra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\base.py", li
ne 1152, in wrapper
    return fit_method(estimator, *args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "C:\Users\Patryk\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_
qbz5n2kfra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\linear_model
\_logistic.py", line 1169, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "C:\Users\Patryk\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_
qbz5n2kfra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\linear_model
\_logistic.py", line 56, in _check_solver
    raise ValueError(
ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 penalty.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
C:\Users\Patryk\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kf
ra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\model_selection\_sea
rch.py:979: UserWarning: One or more of the test scores are non-finite: [       nan
0.72688811        nan 0.72853946        nan 0.72974052
        nan 0.72980057        nan 0.73001075]
  warnings.warn(
```

Szukanie najlepszych parametrów dla *DecisionTreeClassifier*

In [10]:

```
kf = KFold(n_splits=6, shuffle=True, random_state=42)
params = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 5, 10, 15],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
tree = DecisionTreeClassifier()
tree_cv = GridSearchCV(tree, param_grid=params, cv=kf)
tree_cv.fit(X_train, y_train)

print('Najlepsze parametry dla DecisionTreeClassifier:')
for p, val in tree_cv.best_params_.items():
```

```
    print('{}: {}'.format(p, val), end='\n')
print('Uzyskana precyzja: ', tree_cv.best_score_)

best_tree = tree_cv.best_estimator_
test_accuracy = best_tree.score(X_test, y_test)
print("Precyzja zestawu testowego:", test_accuracy)
```

```
Najlepsze parametry dla DecisionTreeClassifier:
criterion: gini
max_depth: None
min_samples_leaf: 1
min_samples_split: 2
Uzyskana precyzja:  0.8709505361964377
Precyzja zestawu testowego: 0.8703014290861054
```

Szukanie najlepszych parametrów dla *RandomForestClassifier*

In [11]:
```
from sklearn.ensemble import RandomForestClassifier

kf = KFold(n_splits=6, shuffle=True, random_state=42)
params = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 5, 10, 15],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
rand_forest = RandomForestClassifier()
rand_forest_cv = GridSearchCV(rand_forest, param_grid=params, cv=kf)
rand_forest_cv.fit(X_train, y_train)

print('Najlepsze parametry dla RandomForestClassifier:')
for p, val in rand_forest_cv.best_params_.items():
    print('{}: {}'.format(p, val), end='\n')
print('Uzyskana precyzja: ', rand_forest_cv.best_score_)

best_rand_forest = rand_forest_cv.best_estimator_
test_accuracy = best_rand_forest.score(X_test, y_test)
print("Precyzja zestawu testowego:", test_accuracy)
```

```
Najlepsze parametry dla RandomForestClassifier:
max_depth: None
min_samples_leaf: 1
min_samples_split: 10
n_estimators: 200
Uzyskana precyzja:  0.8760548514646875
Precyzja zestawu testowego: 0.8723429806653056
```

Szukanie najlepszych parametrów dla *SVM Classifier*

In [12]:
```
from sklearn.svm import SVC

kf = KFold(n_splits=6, shuffle=True, random_state=42)
params = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf'],
```

```
    'gamma': ['scale', 'auto', 0.1, 1]
}
svm = SVC()
svm_cv = GridSearchCV(svm, param_grid=params, cv=kf)
svm_cv.fit(X_train, y_train)

print('Najlepsze parametry dla SVM Classifier:')
for p, val in svm_cv.best_params_.items():
    print('{}: {}'.format(p, val), end='\n')
print('Uzyskana precyzja: ', svm_cv.best_score_)

best_svm = svm_cv.best_estimator_
test_accuracy = best_svm.score(X_test, y_test)
print("Precyzja zestawu testowego:", test_accuracy)
```

```
Najlepsze parametry dla SVM Classifier:
C: 10
gamma: 1
kernel: rbf
Uzyskana precyzja:  0.8508033776886236
Precyzja zestawu testowego: 0.8576918458028101
```

Ewaluacja modeli

In [13]:
```
models = {
    'KNeighborsClassifier': KNeighborsClassifier(n_neighbors=13, p=1, weights='dist
    'LogisticRegression': LogisticRegression(C=10, penalty='l2'),
    'DecisionTreeClassifier': DecisionTreeClassifier(criterion='gini', max_depth=No
    'RandomForestClassifier': RandomForestClassifier(max_depth=None, min_samples_le
    'SVM Classifier': SVC(C=10, gamma=1, kernel='rbf')
}

results = []
for model in models.values():
    kf = KFold(n_splits=6, shuffle=True, random_state=10)
    cv_results = cross_val_score(model, X_train, y_train, cv=kf)
    results.append(cv_results)
```

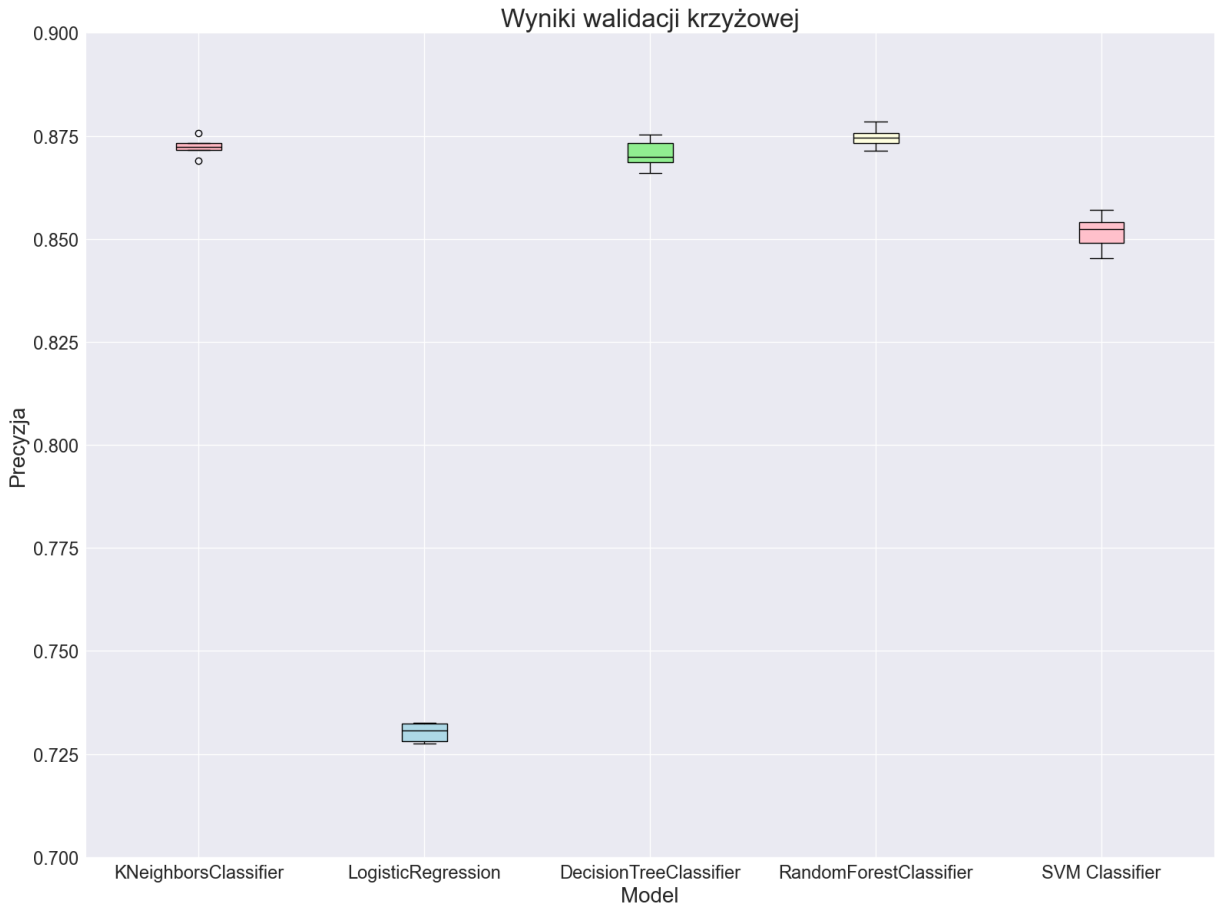
In [14]:
```
plt.style.use('seaborn-v0_8')
fig, ax = plt.subplots(figsize=(16, 12))

boxplot = ax.boxplot(
    results,
    labels=models.keys(),
    patch_artist=True,
    boxprops=dict(edgecolor='black'),
    whiskerprops=dict(linewidth=1),
    capprops=dict(linewidth=1),
    medianprops=dict(color='black', linewidth=1),
    widths=0.2,
)

box_colors = ['#FFB6C1', '#ADD8E6', '#90EE90', '#FFFFE0', '#FFC0CB']
for box, color in zip(boxplot['boxes'], box_colors):
    box.set(facecolor=color)
```

```
ax.set_title('Wyniki walidacji krzyżowej', fontsize=24)
ax.tick_params(axis='both', labelsize=17)
ax.set_xlabel('Model', fontsize=20)
ax.set_ylabel('Precyzja', fontsize=20)
ax.set_ylim(0.70, 0.9)
ax.yaxis.grid(True)

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



Nauczanie najskuteczniejszego modelu

Najlepszy okazał się ***RandomForestClassifier***

In [15]:
```
import sklearn.metrics as skm
random_forest = RandomForestClassifier(max_depth=None,
                                       min_samples_leaf=1,
                                       min_samples_split=10,
                                       n_estimators=50)
rand_forest.fit(X_train, y_train)
y_pred = rand_forest.predict(X_test)
confusion_matrix = skm.confusion_matrix(y_test, y_pred)

target_names = ['safe', 'phishing']
class_report = skm.classification_report(y_test, y_pred, target_names=target_names)
print(class_report)
```

	precision	recall	f1-score	support
safe	0.84	0.82	0.83	3175
phishing	0.89	0.90	0.90	5152
accuracy			0.87	8327
macro avg	0.87	0.86	0.87	8327
weighted avg	0.87	0.87	0.87	8327

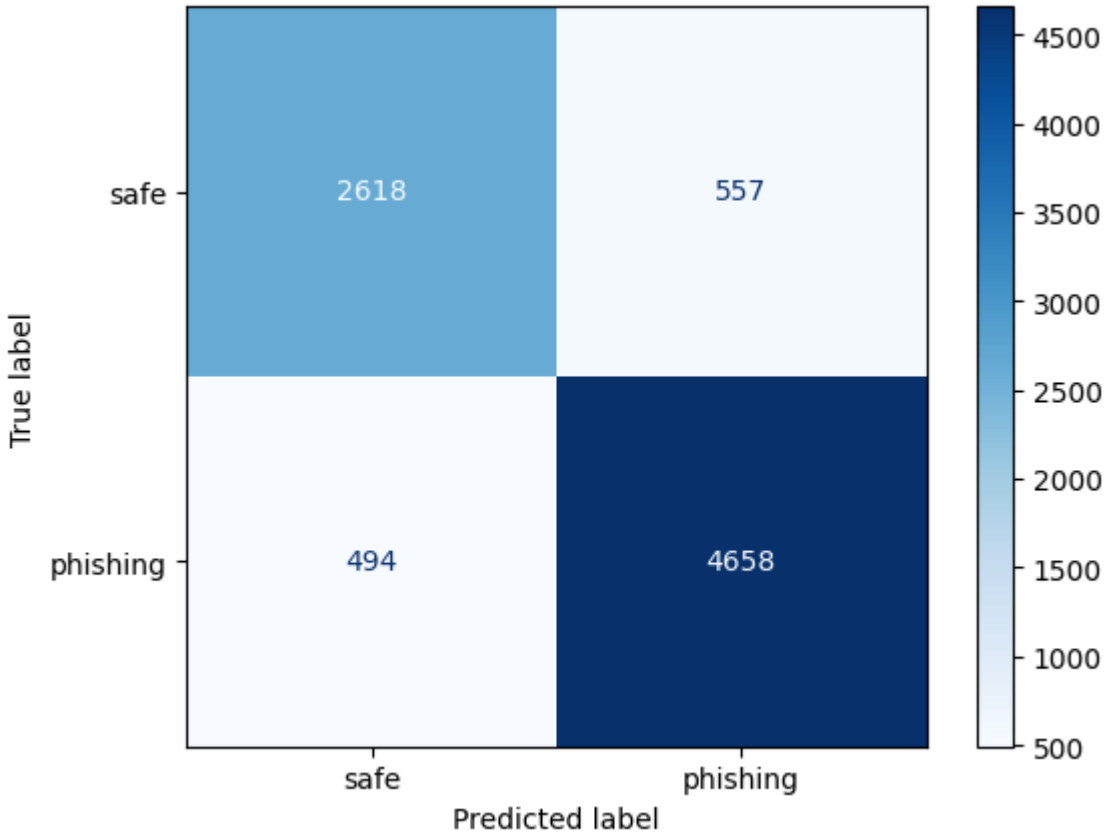
Skuteczność modelu

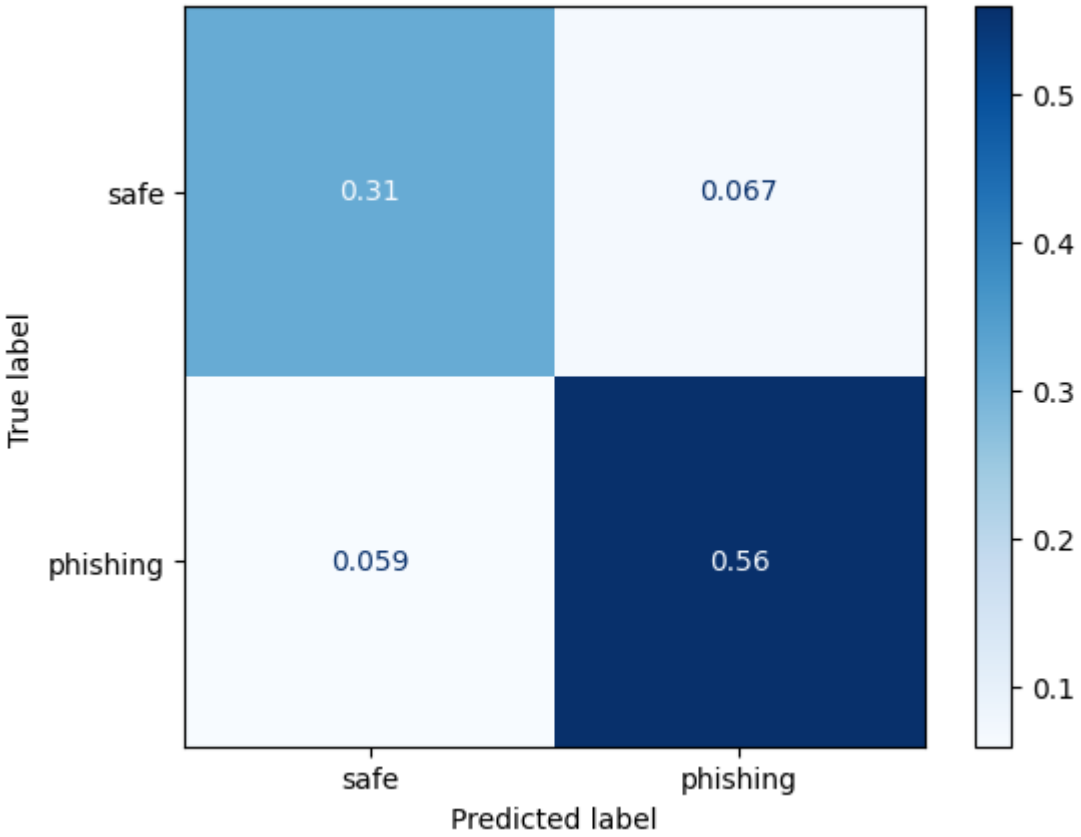
In [16]:
```
plt.style.use('default')
cm_display = skm.ConfusionMatrixDisplay(
    confusion_matrix=confusion_matrix,
    display_labels=['safe', 'phishing'])

cm_display.plot(cmap='Blues')
plt.show()

# Wartości względne
cm_display = skm.ConfusionMatrixDisplay(
    confusion_matrix=confusion_matrix/np.sum(confusion_matrix),
    display_labels=['safe', 'phishing'])

cm_display.plot(cmap='Blues')
plt.show()
```





In [35]:

```python
import re
from unidecode import unidecode


def parse_mail_to_nums(mail: dict):
    body = mail['body']
    url_pattern = re.compile(r'https?://\S+|www\.\S+')
    urls = re.findall(url_pattern, body)
    # urls_count
    urls_count = len(urls)
    url = urls[np.random.randint(0, urls_count)]
    # protocol
    protocol = url[:5].lower()
    protocol = 'https' if protocol == 'https' else 'http'
    # contains_ip
    IP_pattern = re.compile(r'\b(?:\d{1,3}\.){3}\d{1,3}\b|\b(?:[0-9a-fA-F]{1,4}:){7
    IPs = IP_pattern.findall(url)
    contains_ip = 1 if IPs else 0
    # url_length
    url_length = len(url)
    # TLD_alpha
    pattern = re.compile(r'https?://([^/?]+)')
    match = pattern.match(url)
    if match:
        domain = match.group(1)
        if '/' in domain:
            domain = domain.split('/')[0]
    else:
        domain = url
```

```
split_domain = domain.split('.')
n = len(split_domain)
delimiters = ['/', ':', ')', ']', '%', '_', '=', ',', '>', '"', '#', '!']
# Check if not weird ending
after_dot = split_domain[n-1]
if len(after_dot) > 2 and not after_dot.isalpha():
    after_dot = after_dot.split('/')[0]

    if len(after_dot) > 2 and not after_dot.isalpha():
        print(after_dot, 'INSIDE')
        for delimiter in delimiters:
            after_dot = " ".join(after_dot.split(delimiter))

        after_dot = after_dot.split()[0]

TLD = '.'+after_dot.lower()
TLD_alpha = TLD[1:].isalpha()
# subdomain_level
subdomain_level = domain.count('.')-1
# slash_count
slash_count = url.count('/')
# dots_count
dots_count = url.count('.')
# hyphens_count
hyphens_count = url.count('-')
# has_non_latin
ascii = unidecode(url)
has_non_latin = url != ascii

data = {
    'urls_count': urls_count,
    'protocol': protocol,
    'contains_ip': contains_ip,
    'url_length': url_length,
    'TLD_alpha': TLD_alpha,
    'subdomain_level': subdomain_level,
    'slash_count': slash_count,
    'dots_count': dots_count,
    'hyphens_count': hyphens_count,
    'has_non_latin': has_non_latin,
}

for k, v in data.items():
    print('{}: {}'.format(k, v), end='\n')

# numeric values
urls_count_out = urls_count if urls_count <= 2 else 3
protocol_out = 1 if protocol=='https' else 0
contains_ip_out = contains_ip
url_length_out = url_length
TLD_alpha_out = 1 if TLD_alpha is True else 0
subdomain_level_out = subdomain_level if subdomain_level <= 2 else 3
slash_count_out = slash_count if slash_count <= 5 else 6
dots_count_out = dots_count if dots_count <= 4 else 5
hyphens_count_out = hyphens_count if hyphens_count <= 1 else 2
```

```
    has_non_latin_out = has_non_latin

    X_output = np.array(list([
        [urls_count_out],
        [protocol_out],
        [contains_ip_out],
        [url_length_out],
        [TLD_alpha_out],
        [subdomain_level_out],
        [slash_count_out],
        [dots_count_out],
        [hyphens_count_out],
        [has_non_latin_out]
    ]))
    return X_output.reshape(1, -1)
```

```
(41632, 10)
urls_count: 1
protocol: https
contains_ip: 0
url_length: 111
TLD_alpha: True
subdomain_level: 1
slash_count: 6
dots_count: 2
hyphens_count: 0
has_non_latin: False
```

Out[35]:
```
array([[  1,   1,   0, 111,   1,   1,   6,   2,   0,   0]])
```

Test na przykładzie z życka

In [48]:
```
mail_example = {
'sender': 'Marcin Sawiński <Marcin.Sawinski@ue.poznan.pl>',
'subject': 'Projekty zaliczeniowe z PSI',
'body': '''
        Drodzy Studenci,

        Chciałbym Was prosić o zapisanie w arkuszu tematów projektów zaliczeniowych

        https://uniekonpoznan.sharepoint.com/:x:/s/AI_2023_2024/EQ5avb31cRpAliTAmGt

        Pozdrawiam,

        Marcin Sawinski
        --
        Wiadomość wysłana przez system USOS.
        Łączna liczba adresatów tej wiadomości: 117

        Nadawcą korespondencji i jednocześnie administratorem Państwa danych osobow
        al. Niepodległości 10, 61-875 Poznań, z którym można skontaktować się listo
        Państwa dane osobowe przetwarzane będą w celu prowadzenia niniejszej koresp
        Państwu prawo dostępu do danych, ich sprostowania, ograniczenia przetwarzan
        przetwarzania oraz wniesienia skargi do Prezesa Urzędu Ochrony Danych Osobo
        danych osobowych dostępne są w Polityce prywatności.
'''
```

```
}
prediction = rand_forest.predict(
    scaler.transform(parse_mail_to_nums(mail_example))
)

print('-=-=-=-\nResult:\n-=-=-=-')
print(colored('Phishing! :0', 'red')) if prediction == 1 else print(colored('Bezpie
```

```
urls_count: 1
protocol: https
contains_ip: 0
url_length: 111
TLD_alpha: True
subdomain_level: 1
slash_count: 6
dots_count: 2
hyphens_count: 0
has_non_latin: False
-=-=-=-
Result:
-=-=-=-
Bezpiecznie 8)
```

In [58]:
```
mail_example = {
'sender': 'xero <xero@whatever.com>',
'subject': 'Your xero invoice available now.',
'body': '''
        Hi,
        Thanks for working with us. Your bill for $373.75 was due on 28 Aug 2016.
        If you've already paid it, please ignore this email and sorry for bothering
        To view your bill visit http://in.x312412.qwe12/5LQDhRwfvoQfeDtLDMqkk1JWSqC
        If you've got any questions, or want to arrange alternative payment don't h
        Thanks
        NJW Limited
        Download PDF
'''
}
prediction = rand_forest.predict(
    scaler.transform(parse_mail_to_nums(mail_example))
)

print('-=-=-=-\nResult:\n-=-=-=-')
print(colored('Phishing! :0', 'red')) if prediction == 1 else print(colored('Bezpie
```

```
qwe12 INSIDE
urls_count: 1
protocol: http
contains_ip: 0
url_length: 66
TLD_alpha: False
subdomain_level: 1
slash_count: 3
dots_count: 3
hyphens_count: 0
has_non_latin: False
-=-=-=-
Result:
-=-=-=-
Bezpiecznie 8)
```

Rezultat projektu

Przy pomocy ***RandomForestClassifier*** udało się wytrenować model z wynikami:

- (accuracy) ~
- (recall) ~
- (F1) ~

Problemy podczas projektu

- Model bada tylko URLe znajdujące się w e-mailu
  - **WIĘKSZOŚĆ PHISHINGÓW KORZYSTA Z BUTTONÓW, NIE TEKSTU**
- dostęp do API
  - brak sprawdzania domen w blacklistach
  - brak sprawdzania adresów e-mail w blacklistach
  - słabe/brak informacji o szyfrowaniu SSL
  - brak sprawdzania wieku domeny
- Dane zbierane w latach 2008-2022
- Człowiek minimalnie obeznany w internecie poradziłby sobie z klasyfikowaniem ataków phishingowych z datasetu.