Importing Libraries

In [1]:

```
import re
import string
import numpy as np
import pandas as pd
import random
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.base import TransformerMixin
from sklearn.metrics import accuracy_score, plot_confusion_matrix, classification_repor
from wordcloud import WordCloud
import spacy
from spacy.lang.en.stop_words import STOP_WORDS
from spacy.lang.en import English
from sklearn.svm import SVC
import warnings
warnings.filterwarnings('ignore')
```

Reading dataset

In [2]:

```
data = pd.read_csv(r'fake_job_postings.csv')
```

In [4]:

```
data.describe()
```

Out[4]:

	job_id	telecommuting	has_company_logo	has_questions	fraudulent
count	17880.000000	17880.000000	17880.000000	17880.000000	17880.000000
mean	8940.500000	0.042897	0.795302	0.491723	0.048434
std	5161.655742	0.202631	0.403492	0.499945	0.214688
min	1.000000	0.000000	0.000000	0.000000	0.000000
25%	4470.750000	0.000000	1.000000	0.000000	0.000000
50%	8940.500000	0.000000	1.000000	0.000000	0.000000
75%	13410.250000	0.000000	1.000000	1.000000	0.000000
max	17880.000000	1.000000	1.000000	1.000000	1.000000

We will check the shape of the dataset and the top five elements of the dataset.

shape of the dataset

In [86]:
```
data.shape
```

Out[86]:
```
(17880, 18)
```

Read of the dataset

In [87]:
```
data.head()
```

Out[87]:

	job_id	title	location	department	salary_range	company_profile	description
0	1	Marketing Intern	US, NY, New York	Marketing	NaN	We're Food52, and we've created a groundbreaki...	Food52, a fast-growing, James Beard Award-winn...
1	2	Customer Service - Cloud Video Production	NZ, , Auckland	Success	NaN	90 Seconds, the worlds Cloud Video Production ...	Organised - Focused - Vibrant - Awesome!Do you...
2	3	Commissioning Machinery Assistant (CMA)	US, IA, Wever	NaN	NaN	Valor Services provides Workforce Solutions th...	Our client, located in Houston, is actively se...
3	4	Account Executive - Washington DC	US, DC, Washington	Sales	NaN	Our passion for improving quality of life thro...	THE COMPANY: ESRI – Environmental Systems Rese...
4	5	Bill Review Manager	US, FL, Fort Worth	NaN	NaN	SpotSource Solutions LLC is a Global Human Cap...	JOB TITLE: Itemization Review ManagerLOCATION:...

In the head of the dataset, we can see that missing values are present as NaN.

We will check all the missing values in the replace them with blank.

In [3]:
```
data.interpolate(inplace=True)
data.isnull().sum()
```

Out[3]:
```
job_id                  0
title                   0
location              346
department          11547
```

```
salary_range           15012
company_profile         3308
description                1
requirements            2695
benefits                7210
telecommuting              0
has_company_logo           0
has_questions              0
employment_type         3471
required_experience     7050
required_education      8105
industry                4903
function                6455
fraudulent                 0
dtype: int64
```

In [4]:

```python
columns=['job_id', 'telecommuting', 'has_company_logo', 'has_questions', 'salary_range'
for col in columns:
    del data[col]
```

Fill NaN values with blank space

In [5]:

```python
data.fillna(' ', inplace=True)
```

In [91]:

```python
data.head()
```

Out[91]:

	title	location	department	company_profile	description	requirements
0	Marketing Intern	US, NY, New York	Marketing	We're Food52, and we've created a groundbreaki...	Food52, a fast-growing, James Beard Award-winn...	Experience with content management systems a m...
1	Customer Service - Cloud Video Production	NZ, , Auckland	Success	90 Seconds, the worlds Cloud Video Production ...	Organised - Focused - Vibrant - Awesome!Do you...	What we expect from you:Your key responsibilit...
2	Commissioning Machinery Assistant (CMA)	US, IA, Wever		Valor Services provides Workforce Solutions th...	Our client, located in Houston, is actively se...	Implement pre-commissioning and commissioning ...
3	Account Executive - Washington DC	US, DC, Washington	Sales	Our passion for improving quality of life thro...	THE COMPANY: ESRI – Environmental Systems Rese...	EDUCATION: Bachelor's or Master's in GIS, busi...
4	Bill Review Manager	US, FL, Fort Worth		SpotSource Solutions LLC is a Global Human Cap...	JOB TITLE: Itemization Review ManagerLOCATION:...	QUALIFICATIONS:RN license in the State of Texa...

The data set is now free from the missing values. Now, we will check the total number of fraudulent postings and real postings.

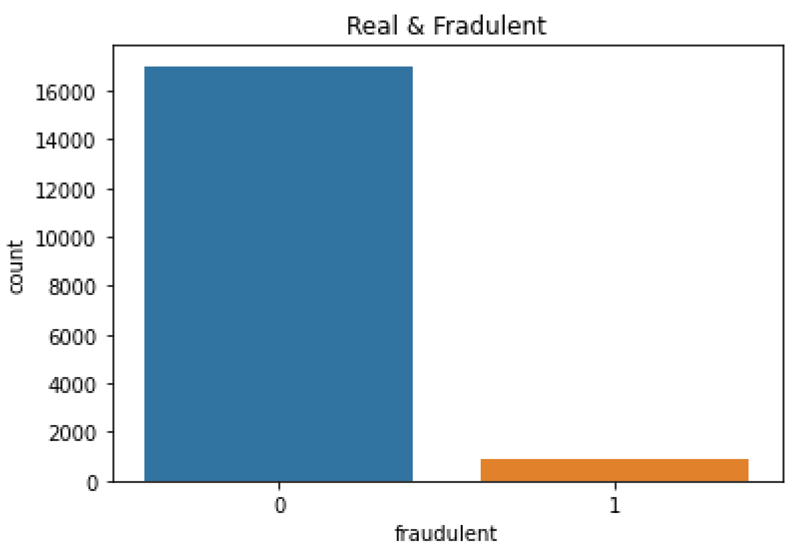
Fraud and Real visualization

In [93]:

```
sns.countplot(data.fraudulent).set_title('Real & Fradulent')
data.groupby('fraudulent').count()['title'].reset_index().sort_values(by='title',ascend
```

Out[93]:

	fraudulent	title
0	0	17014
1	1	866



In the next step, we will visualize the number of job postings by countries and by experience.

Visualize job postings by countries

In [6]:

```
def split(location):
    l = location.split(',')
    return l[0]
```

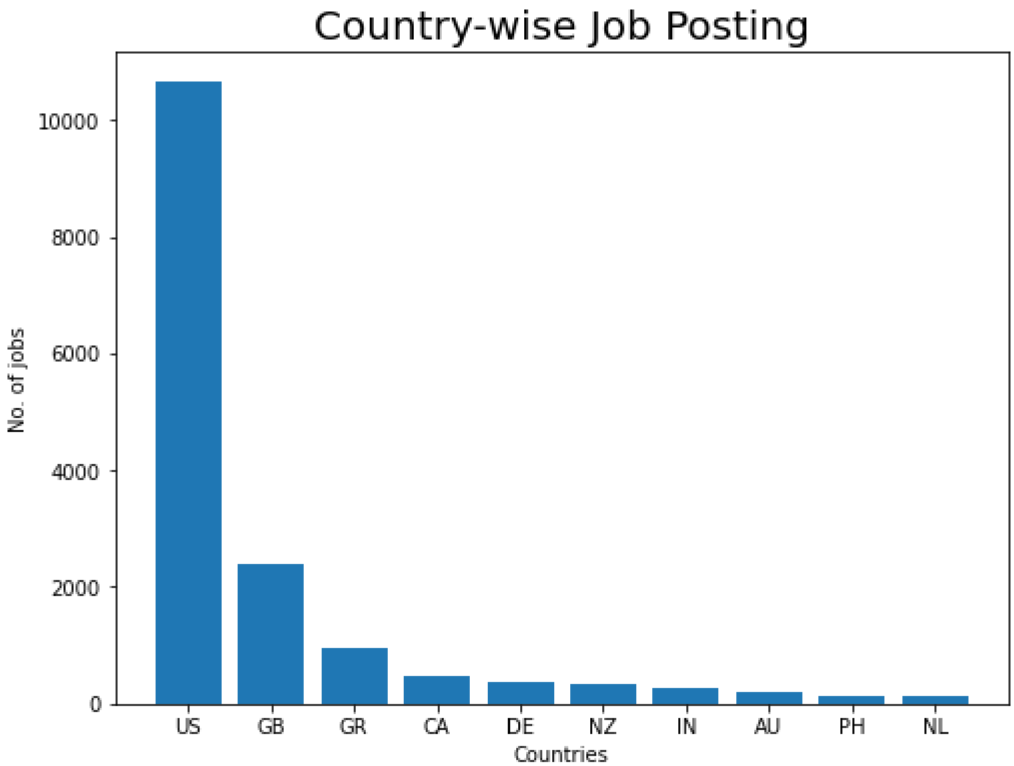
In [7]:

```
data['country'] = data.location.apply(split)
```

In [8]:

```
country = dict(data.country.value_counts()[:11])
del country[' ']
plt.figure(figsize=(8,6))
plt.title('Country-wise Job Posting', size=20)
plt.bar(country.keys(), country.values())
```

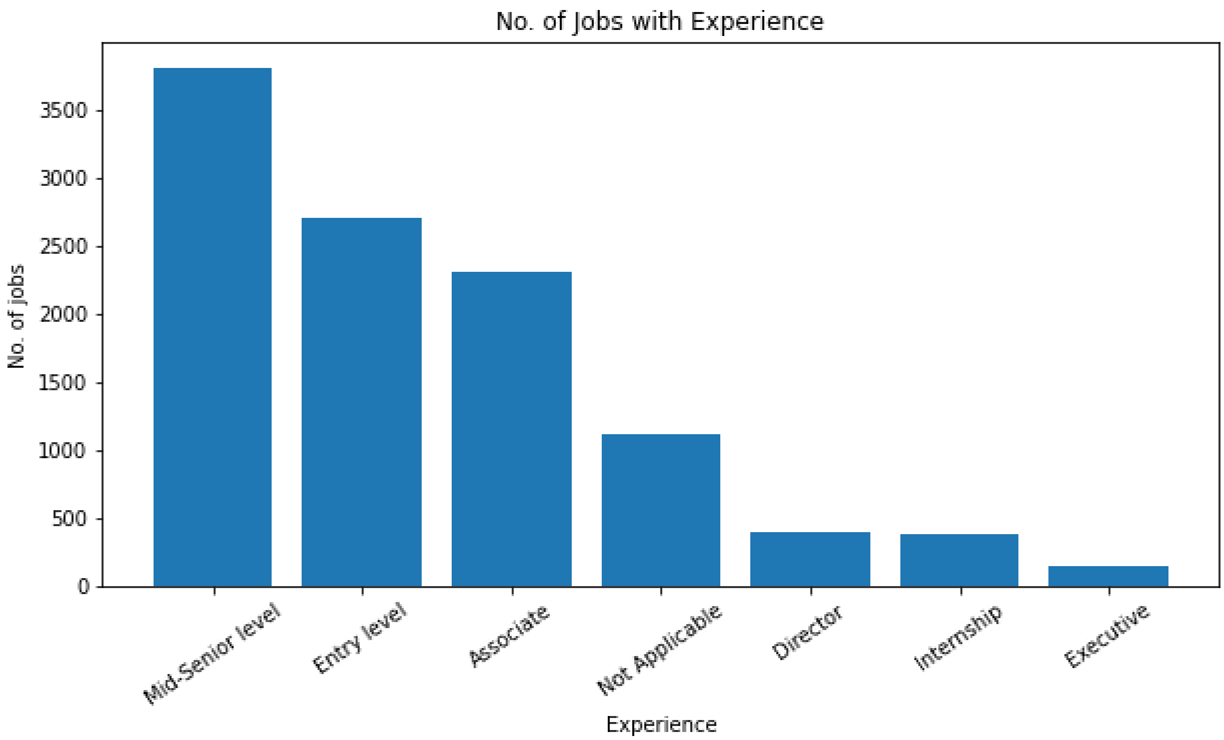
```python
plt.ylabel('No. of jobs', size=10)
plt.xlabel('Countries', size=10)
plt.show()
```



Visualize the required experiences in the jobs

In [9]:

```python
experience = dict(data.required_experience.value_counts())
del experience[' ']
plt.figure(figsize=(10,5))
plt.bar(experience.keys(), experience.values())
plt.title('No. of Jobs with Experience')
plt.xlabel('Experience', size=10)
plt.ylabel('No. of jobs', size=10)
plt.xticks(rotation=35)
plt.show()
```



Here, we will check the count of titles in all job postings, in fraudulent job postings and in real job postings.

In [100…

```
# Most frequent jobs
print(data.title.value_counts()[:10])
```

```
English Teacher Abroad                                311
Customer Service Associate                            146
Graduates: English Teacher Abroad (Conversational)    144
English Teacher Abroad                                 95
Software Engineer                                      86
English Teacher Abroad (Conversational)                83
Customer Service Associate - Part Time                 76
Account Manager                                        75
Web Developer                                          66
Project Manager                                        62
Name: title, dtype: int64
```

In [101…

```
#Titles and count of fraudulent jobs
print(data[data.fraudulent==1].title.value_counts()[:10])
```

```
Home Based Payroll Typist/Data Entry Clerks Positions Available          21
Cruise Staff Wanted *URGENT*                                             21
Data Entry Admin/Clerical Positions - Work From Home                     21
Customer Service Representative                                          17
Administrative Assistant                                                 16
Home Based Payroll Data Entry Clerk Position - Earn $100-$200 Daily      12
Payroll Data Coordinator Positions - Earn $100-$200 Daily                10
Payroll Clerk                                                            10
Account Sales Managers $80-$130,000/yr                                   10
Network Marketing                                                        10
Name: title, dtype: int64
```

In [102…

```
#Titles and count of real jobs
```

```
print(data[data.fraudulent==0].title.value_counts()[:10])
```

```
English Teacher Abroad                                311
Customer Service Associate                            146
Graduates: English Teacher Abroad (Conversational)    144
English Teacher Abroad                                 95
Software Engineer                                      86
English Teacher Abroad (Conversational)                83
Customer Service Associate - Part Time                 76
Account Manager                                        73
Web Developer                                          66
Project Manager                                        62
Name: title, dtype: int64
```

In the next step, the dataset will be preprocessed for training. For this purpose, all the important text data is combined in one column and rest are deleted except the target column.

Combine text in a single column to start cleaning our data

In [10]:

```
data['text']=data['title']+' '+data['location']+' '+data['company_profile']+' '+data['d
del data['title']
del data['location']
del data['department']
del data['company_profile']
del data['description']
del data['requirements']
del data['benefits']
del data['required_experience']
del data['required_education']
del data['industry']
del data['function']
del data['country']
```

In [104…

```
data.head()
```

Out[104…

	fraudulent	text
0	0	Marketing Intern US, NY, New York We're Food52...
1	0	Customer Service - Cloud Video Production NZ, ...
2	0	Commissioning Machinery Assistant (CMA) US, IA...
3	0	Account Executive - Washington DC US, DC, Wash...
4	0	Bill Review Manager US, FL, Fort Worth SpotSou...

To visualize the fraud and real job postings, the WordCloud is used to see the top occurring keywords in the data.

To do so, fraud and real job postings are separated into two text files and WordCloud has plotted accordingly.

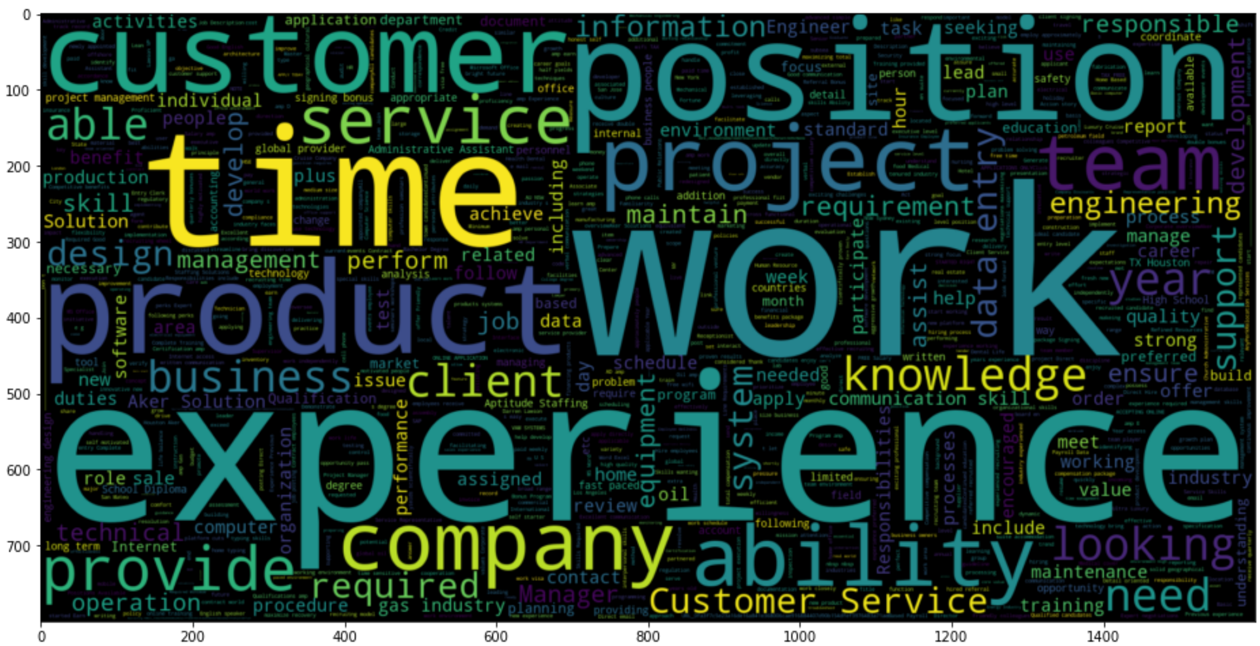
Separate fraud and actual jobs

In [105…

```
fraudjobs_text = data[data.fraudulent==1].text
actualjobs_text = data[data.fraudulent==0].text
```

In [106…

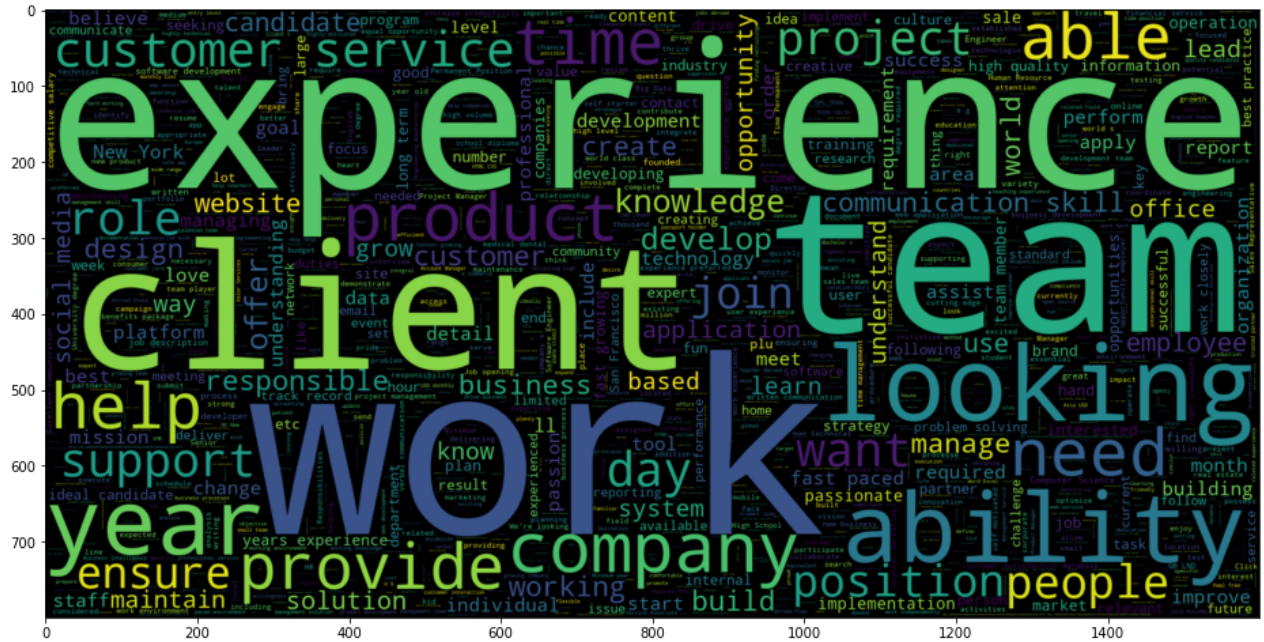
```
# Fraudulent jobs word cloud
STOPWORDS = spacy.lang.en.stop_words.STOP_WORDS
plt.figure(figsize = (16,14))
wc = WordCloud(min_font_size = 3,  max_words = 3000 , width = 1600 , height = 800 , sto
plt.imshow(wc,interpolation = 'bilinear')
plt.show()
```



In [107…

```
# Actual jobs wordcloud
plt.figure(figsize = (16,14))
wc = WordCloud(min_font_size = 3,  max_words = 3000 , width = 1600 , height = 800 , sto
plt.imshow(wc,interpolation = 'bilinear')
```

Out[107… <matplotlib.image.AxesImage at 0x29da628a488>



The dataset is cleaned and preprocessed using the below lines of codes.

leaning and preprocessing

Create our list of punctuation marks

In [11]:

```
punctuations = string.punctuation
```

Create our list of stopwords

In [12]:

```
stop_words = spacy.lang.en.stop_words.STOP_WORDS
```

Load English tokenizer, tagger, parser, NER and word vectors

In [13]:

```
parser = English()
```

Creating our tokenizer function

In [14]:

```
def spacy_tokenizer(sentence):
    # Creating our token object, which is used to create documents with linguistic anno
    mytokens = parser(sentence)

    # Lemmatizing each token and converting each token into lowercase
    mytokens = [ word.lemma_.lower().strip() if word.lemma_ != "-PRON-" else word.lower
```

```
    # Removing stop words
    mytokens = [ word for word in mytokens if word not in stop_words and word not in pu

    # return a preprocessed list of tokens
    return mytokens
```

Custom transformer using spaCy

In [15]:

```
class predictors(TransformerMixin):
    def transform(self, X, **transform_params):
        # Cleaning Text
        return [clean_text(text) for text in X]
    def fit(self, X, y=None, **fit_params):
        return self
    def get_params(self, deep=True):
        return {}
```

Basic function to clean the text

In [16]:

```
def clean_text(text):
    # Removing spaces and converting text into lowercase
    return text.strip().lower()
```

Splitting dataset in train and test

In [17]:

```
X_train, X_test, y_train, y_test = train_test_split(data.text, data.fraudulent, test_si
```

In [18]:

```
# Train-test shape
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(12516,)
(12516,)
(5364,)
(5364,)
```

Once we are ready with the training and test data, we will train the machine learning model to classify the fraudulent and real job postings. In this task, we will use the Support Vector Classifier. The Pipeline is used to bind the cleaning, vectorization and classification works together.

Support Vector Machine Classifier

Create pipeline using Bag of Words

In [19]:

```
pipe = Pipeline([("cleaner", predictors()),
                 ('vectorizer', CountVectorizer(tokenizer = spacy_tokenizer, ngram_rang
                 ('classifier', SVC(C=2, kernel='poly'))])
```

Training the model.

In [20]:

```
pipe.fit(X_train,y_train)
```

Out[20]:

```
Pipeline(steps=[('cleaner', <__main__.predictors object at 0x0000026A38AF5308>),
                ('vectorizer',
                 CountVectorizer(ngram_range=(1, 3),
                                 tokenizer=<function spacy_tokenizer at 0x0000026A3863D1
F8>)),
                ('classifier', SVC(C=2, kernel='poly'))])
```

Fake Job Classification

After successful training of the classifier, we will make predictions through it on the test data and obtain the accuracies by evaluation metrics.

Predicting with a test dataset

In [21]:

```
y_pred = pipe.predict(X_test)
```

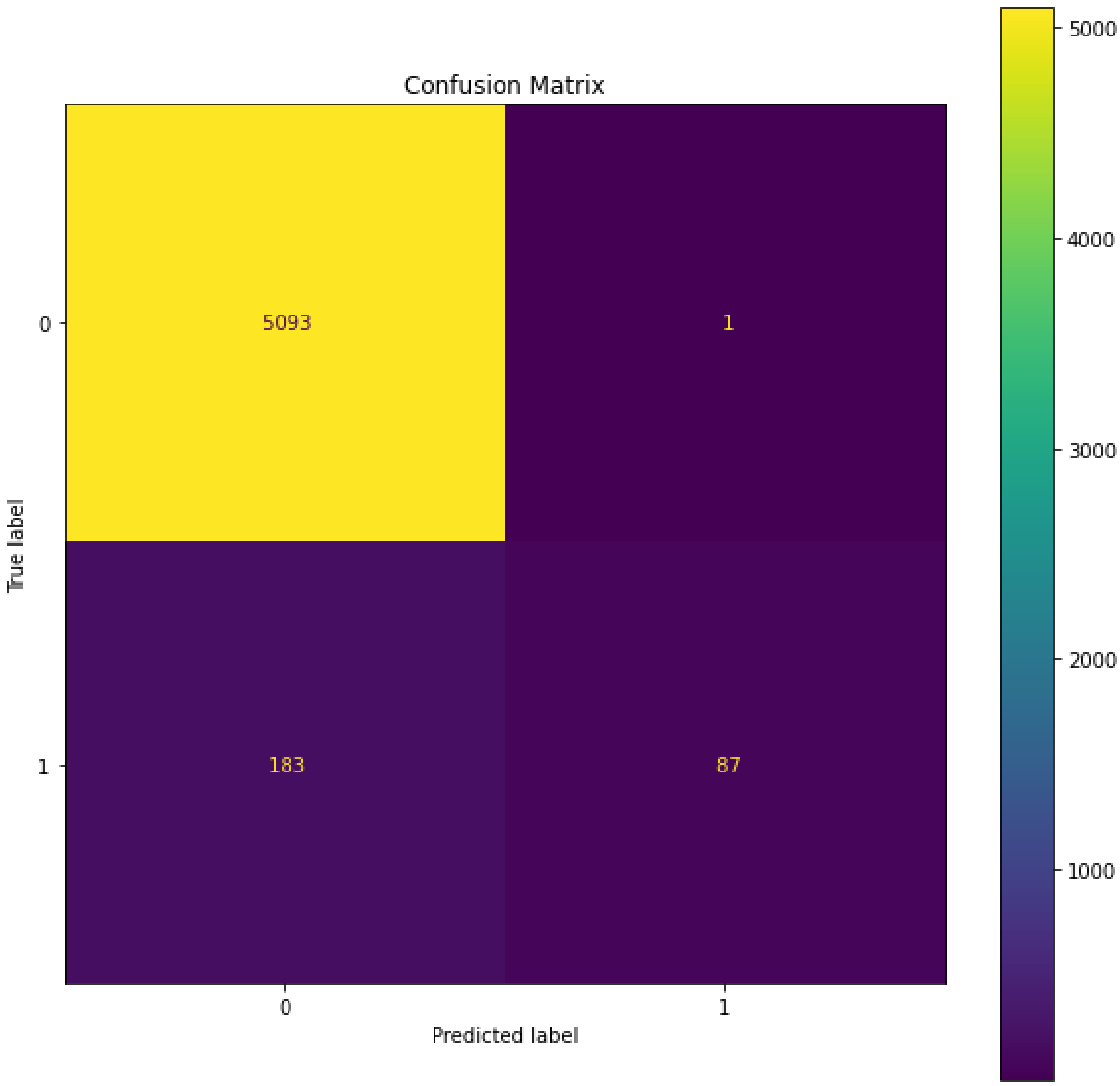
Model Accuracy

In [22]:

```
print("Classification Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report\n")
print(classification_report(y_test, y_pred))
print("Confusion Matrix\n")
print(confusion_matrix(y_test, y_pred))
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(pipe, X_test, y_test, values_format=' ', ax=ax)
plt.title('Confusion Matrix')
plt.show()
```

```
Classification Accuracy: 0.9656972408650261
Classification Report

              precision    recall  f1-score   support

           0       0.97      1.00      0.98      5094
           1       0.99      0.32      0.49       270

    accuracy                           0.97      5364
```

```
   macro avg       0.98      0.66      0.73      5364
weighted avg       0.97      0.97      0.96      5364

Confusion Matrix

[[5093    1]
 [ 183   87]]
```



Save Trained Model Using joblib

In [23]:
```
import joblib
joblib.dump(pipe, 'fyp_model_predict')
```

Out[23]: ['fyp_model_predict']

In [24]:
```
mj = joblib.load('fyp_model_predict')
```

In [124…
```
pred = mj.predict(X_test)
print("Classification Accuracy:", accuracy_score(y_test, pred))
```

```
Classification Accuracy: 0.964951528709918
```

In [25]:
```
p = mj.predict(["PACU RN   US, NV,    Find more jobs at #URL_1efb08d6a6da1c56afb2d0c686
```

In [26]:
```
if p[0]==1:
    predicition='FAKE'
else:
    predicition='REAL'
```

In [27]:
```
predicition
```

Out[27]:
```
'FAKE'
```

In [29]:
```
mj.named_steps
```

Out[29]:
```
{'cleaner': <__main__.predictors at 0x26a278a02c8>,
 'vectorizer': CountVectorizer(ngram_range=(1, 3),
                 tokenizer=<function spacy_tokenizer at 0x0000026A3863D1F8>),
 'classifier': SVC(C=2, kernel='poly')}
```

End here