1_fake_news_prediction

June 7, 2024

1 News Content NLP Analysis - Fake News Detection (Supervised Learning)

This is the python notebook of the news content natural language processing & machine learning project written by Huang Lin, Chun (Wally).

In this notebook, we conducted data cleaning through `pandas` module and used `nltk` module to process the news text data.

We then exploited `TfidfVectorizer` from `sklearn.feature_extraction.text` to transform the tokenized texts into Term Frequency - Inverse Document Frequency (tfidf) vectors as the feature matrix for machine learning model training.

Furthermore, as formal machine learning project procedure, we performed model selections based on four cross validation scores, precision-recall curve, and roc curve. Evaluation metrics adopted include precision, recall, roc_auc, and f1.

Finally, we improved and optimized the selected model by hyper parameter tuning based on `GridSearchCV()` method in sklearn.

- Data source: https://www.kaggle.com/datasets/saurabhshahane/fake-news-classification
- Number of unique rows: 62348
- News contents are from american press media.

Import Module & Dataset

[1]:
```python
import numpy as np
import re
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
sns.set_context('notebook')
sns.set_style('white')

import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize
import string
nltk.download('stopwords')
```

```
nltk.download('punkt')
nltk.download('wordnet')

import sklearn
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_validate, cross_val_score,␣
↪cross_val_predict
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import precision_score, recall_score, accuracy_score,␣
↪f1_score
import time
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/huanglinchun/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     /Users/huanglinchun/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     /Users/huanglinchun/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

[25]:
```
dfraw = pd.read_csv('./WELFake_Dataset.csv')
dfraw.drop('Unnamed: 0', axis = 1, inplace = True)
```

Basic Data Preprocessing

- Remove null value

[26]:
```
print('Before removal of null value:')
for col in dfraw.columns:
    print(f'  number of null value in column {col}= {dfraw[col].isnull().
↪sum()}')
print(f'  Shape of data = {dfraw.shape}')
print('--------------------------------------------')
print('After')
dfraw = dfraw.dropna().reset_index().drop('index', axis = 1)
for col in dfraw.columns:
    print(f'  number of null value in column {col} = {dfraw[col].isnull().
↪sum()}')
print(f'  Shape of data = {dfraw.shape}')
```

```
Before removal of null value:
```

```
  number of null value in column title= 558
  number of null value in column text= 39
  number of null value in column label= 0
  Shape of data = (72134, 3)
-------------------------------------------
After
  number of null value in column title = 0
  number of null value in column text = 0
  number of null value in column label = 0
  Shape of data = (71537, 3)
```

- Remove blank value

[4]:
```
print('Before removal of blank value:')
for col in dfraw.columns:
    print(f'  number of blank value in column {col}= {(dfraw[col] == " ").
 ↪sum()}')
print(f'  Shape of data = {dfraw.shape}')
print('-------------------------------------------')
print('After')
dfraw = dfraw.drop(dfraw[dfraw['text'] == " "].index).reset_index().
 ↪drop('index', axis = 1)
for col in dfraw.columns:
    print(f'  number of blank value in column {col} = {(dfraw[col] == " ").
 ↪sum()}')
print(f'  Shape of data = {dfraw.shape}')
```

```
Before removal of blank value:
  number of blank value in column title= 0
  number of blank value in column text= 738
  number of blank value in column label= 0
  Shape of data = (71537, 3)
-------------------------------------------
After
  number of blank value in column title = 0
  number of blank value in column text = 0
  number of blank value in column label = 0
  Shape of data = (70799, 3)
```

[5]:
```
dfraw.head(10)
```

[5]:
```
                                               title  \
0  LAW ENFORCEMENT ON HIGH ALERT Following Threat…
1  UNBELIEVABLE! OBAMA'S ATTORNEY GENERAL SAYS MO…
2  Bobby Jindal, raised Hindu, uses story of Chri…
3  SATAN 2: Russia unvelis an image of its terrif…
4  About Time! Christian Group Sues Amazon and SP…
5  DR BEN CARSON TARGETED BY THE IRS: "I never ha…
```

```
6  Sports Bar Owner Bans NFL Games…Will Show Only…
7  Latest Pipeline Leak Underscores Dangers Of Da…
8   GOP Senator Just Smacked Down The Most Puncha…
9  May Brexit offer would hurt, cost EU citizens …

                                                text  label
0  No comment is expected from Barack Obama Membe…      1
1   Now, most of the demonstrators gathered last …      1
2  A dozen politically active pastors came here f…      0
3  The RS-28 Sarmat missile, dubbed Satan 2, will…      1
4  All we can say on this one is it s about time …      1
5  DR. BEN CARSON TELLS THE STORY OF WHAT HAPPENE…      1
6  The owner of the Ringling Bar, located south o…      1
7  FILE - In this Sept. 15, 2005 file photo, the …      1
8  The most punchable Alt-Right Nazi on the inter…      1
9  BRUSSELS (Reuters) - British Prime Minister Th…      0
```

- Remove Duplicated Row

[27]:
```python
print('Before removal of duplicated row:')
print(f'  number of duplicated row = {dfraw.duplicated().sum()}')
print(f'  shape = {dfraw.shape}')
print('-------------------------------------------')
print('After')
dfraw = dfraw.drop_duplicates()
print(f'  number of duplicated row = {dfraw.duplicated().sum()}')
print(f'  shape = {dfraw.shape}')
```

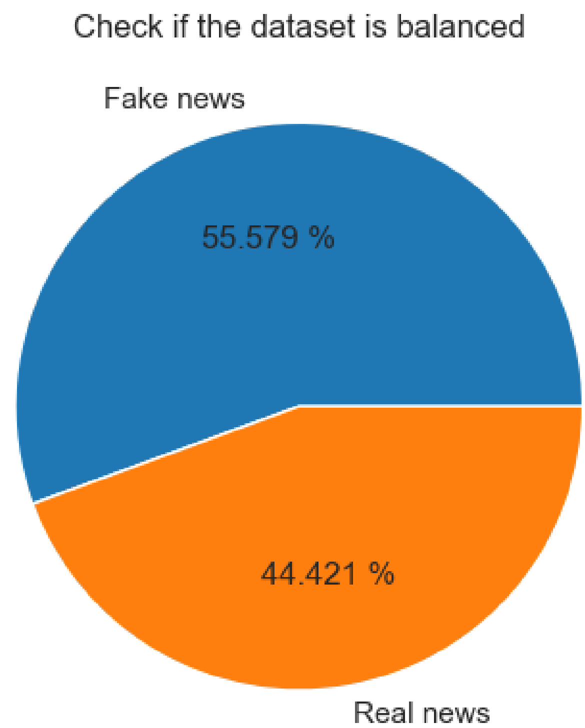
```
Before removal of duplicated row:
  number of duplicated row = 8416
  shape = (71537, 3)
-------------------------------------------
After
  number of duplicated row = 0
  shape = (63121, 3)
```

- Transform label interpretation

[28]:
```python
# in original data: label = 1 -> real
# we want label = 1 -> fake
dfraw['label'] = dfraw['label'].apply(lambda x: 1 - x)
```

- Check if the dataset is balanced

[8]:
```python
pie_label = dfraw.label.value_counts() / dfraw.label.count()
plt.pie(pie_label, labels = ['Fake news', 'Real news'], autopct = lambda x:␣
 ↪f'{round(x, 3)} %');
plt.title('Check if the dataset is balanced');
```



- Sampling: Obtain only a subset of the dataset

Since we lacked the knowledge of the usage of GPU and Cloud Service, we only selected a subset of data to improve the training time and avoid kernel crush.

[9]:
```
fake = dfraw[dfraw['label'] == 1].sample(n = 5000, random_state = 1).
 ↪reset_index()
real = dfraw[dfraw['label'] == 0].sample(n = 5000, random_state = 1).
 ↪reset_index()
data = pd.concat([fake, real]).drop('index', axis = 1)
```

NLP Preprocessing

[13]:
```
# Load stopwords from nltk and add other stopwords
stop_words = stopwords.words('english')
stopwords_to_append = ['said', 'say', 'would', 'mr', 'u']
for stopword in stopwords_to_append:
    stop_words.append(stopword)

# Define nlp function (tokenizer)
def preprocessing(line):
    # remove non-alphabetic characters
    line = re.sub(r"[^a-zA-Z]", " ", line.lower())
```

```
    # tokenize texts
    words = word_tokenize(line)

    # lemmatize texts
    words_lemmed = [WordNetLemmatizer().lemmatize(w) for w in words if w not in␣
 ↪stop_words]

    # remove punctuation
    words_removed_punct = [w for w in words_lemmed if w not in string.
 ↪punctuation]

    return words_removed_punct

# Define the Tfidf Vectorizer and connect the pre-defined tokenizer
tfidf_vectorizer = TfidfVectorizer(tokenizer = preprocessing)
```

[14]:
```
%%time
tfidf = tfidf_vectorizer.fit_transform(data['text']).toarray()
y = data['label']
```

```
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-
packages/sklearn/feature_extraction/text.py:523: UserWarning: The parameter
'token_pattern' will not be used since 'tokenizer' is not None'
  warnings.warn(

CPU times: user 20.6 s, sys: 509 ms, total: 21.1 s
Wall time: 21.5 s
```

[15]:
```
print('Shape of the tfidf-Vectorized features (X)')
print(f'  (sample size, # No. of non-repeating tokens) = {tfidf.shape}')
print("Shape of y")
print(f'  {y.shape}')
```

```
Shape of the tfidf-Vectorized features (X)
  (sample size, # No. of non-repeating tokens) = (10000, 77107)
Shape of y
  (10000,)
```

Model training and selection

[16]:
```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(tfidf, y, test_size = 0.2)
```

- Cross Validation

[17]:
```
# 3 models were selected as candidates
models = [LogisticRegression(max_iter = 2000),
          RandomForestClassifier(),
          MultinomialNB()]
```

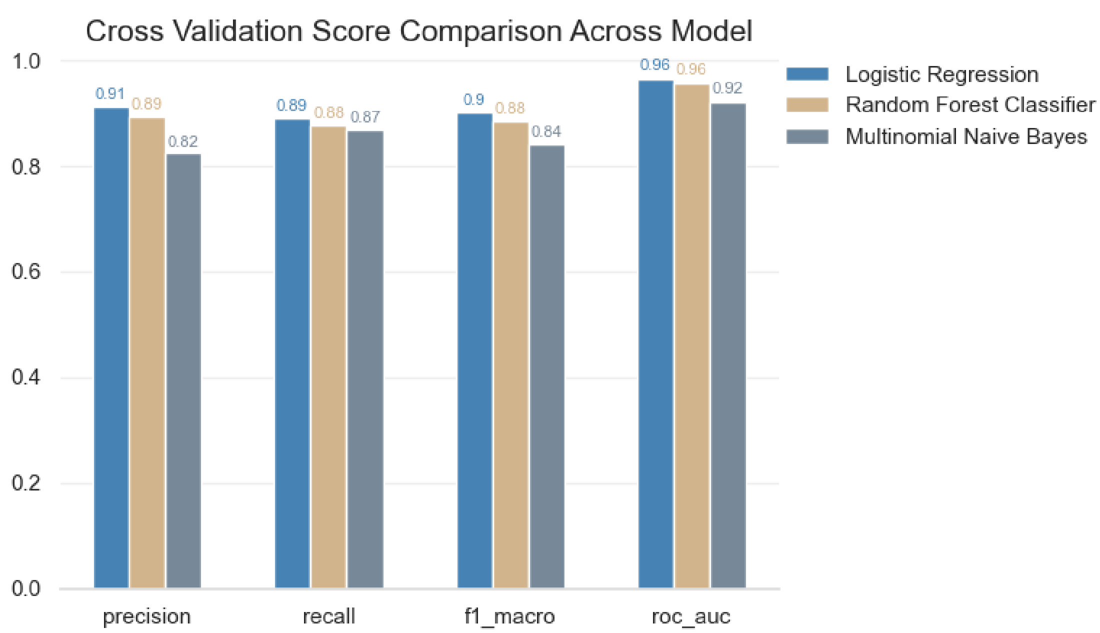
```
model_names = ['Logistic Regression',
               'Random Forest Classifier',
               'Multinomial Naive Bayes']

# define performance evaluation metrices
scoring = ['precision', 'recall', 'f1_macro', 'roc_auc']

# define dataframe for storing cv scores
cross_val_df = pd.DataFrame(columns = scoring)

# train the three models
for model, name in zip(models, model_names):
    start_time = time.time()
    cv_return = cross_validate(estimator = model,
                               X = X_train, y = y_train,
                               scoring = scoring, cv = 3)
    cross_val_df.loc[name, 'precision'] = cv_return['test_precision'].mean()
    cross_val_df.loc[name, 'recall'] = cv_return['test_recall'].mean()
    cross_val_df.loc[name, 'f1_macro'] = cv_return['test_f1_macro'].mean()
    cross_val_df.loc[name, 'roc_auc'] = cv_return['test_roc_auc'].mean()
    stop_time = time.time()
    print(f'{name} trained, {round(stop_time - start_time, 3)} seconds used')
```

```
Logistic Regression trained, 19.726 seconds used
Random Forest Classifier trained, 74.463 seconds used
Multinomial Naive Bayes trained, 11.187 seconds used
```

[18]:

```
## Plot bar plots for Cross Validation Score
barwidth = 0.2
x = np.arange(len(cross_val_df.columns))

fig, ax = plt.subplots(1, 1)
ax.bar(x, cross_val_df.loc['Logistic Regression', :], width = barwidth,
       label = 'Logistic Regression', color = 'steelblue')
ax.bar(x + 1 * barwidth, cross_val_df.loc['Random Forest Classifier', :], width␣
 ↪= barwidth,
       label = 'Random Forest Classifier', color = 'tan')
ax.bar(x + 2 * barwidth, cross_val_df.loc['Multinomial Naive Bayes', :], width␣
 ↪= barwidth,
       label = 'Multinomial Naive Bayes', color = 'lightslategrey')
ax.set_xticks(x + 1 * barwidth)
ax.set_xticklabels(cross_val_df.columns)

ax.legend(frameon = False, bbox_to_anchor=(1.47,0.9), loc = 'right')

def barStyling(bar):
       bar_value = bar.get_height()
```

```
        text = f'{round(bar_value, 2)}'
        text_x = bar.get_x() + bar.get_width() / 2
        text_y = (bar.get_y() + bar_value) * 1.01
        bar_color = bar.get_facecolor()
        ax.text(text_x, text_y, text, ha='center', va='bottom', color=bar_color,␣
 ↪size=8)
for bar in ax.patches:
        barStyling(bar)

def axesStyling(ax):
        ax.spines['top'].set_visible(False)
        ax.spines['right'].set_visible(False)
        ax.spines['left'].set_visible(False)
        ax.spines['bottom'].set_color('#DDDDDD')
        ax.tick_params(bottom=False, left=False)
        ax.set_axisbelow(True)
        ax.yaxis.grid(True, color='#EEEEEE')
        ax.xaxis.grid(False)
axesStyling(ax)

ax.set_title('Cross Validation Score Comparison Across Model', fontsize = 15);
```



- Precision-Recall Curve and ROC

[19]:
```
from sklearn.metrics import precision_recall_curve, roc_curve
def valsPrecisionRecallCurve(model):
```

```
    model.fit(X_train, y_train)
    y_prob = model.predict_proba(X_test)
    precisions, recalls, thresholds = precision_recall_curve(y_test, y_prob[:
 ↪,1])
    return precisions, recalls
def plotPrecisionRecallCurve(precisions, recalls, label, ax, color):
    ax.plot(precisions, recalls, label = f'{label}', color = color)
    ax.set_xlabel('Precision')
    ax.set_ylabel('Recall')
def valsROCCurve(model):
    model.fit(X_train, y_train)
    y_prob = model.predict_proba(X_test)
    fpr, tpr, thresholds = roc_curve(y_test, y_prob[:,1])
    return fpr, tpr
def plotROCCurve(fpr, tpr, label, ax, color):
    ax.plot(fpr, tpr, label = f'{label}', color = color)
    ax.set_xlabel('False Positive Rate')
    ax.set_ylabel('True Positive Rate')
```

[20]:
```
prc_dict = {}
for model, name in zip(models, model_names):
    begin = time.time()
    precisions, recalls = valsPrecisionRecallCurve(model)
    prc_dict[name] = (precisions, recalls)
    end = time.time()

    print(f'''{name} trained and Precision Recall Curve data obtained.
          {round(end-begin,3)} seconds used.''')
```

```
Logistic Regression trained and Precision Recall Curve data obtained.
          24.449 seconds used.
Random Forest Classifier trained and Precision Recall Curve data obtained.
          36.027 seconds used.
Multinomial Naive Bayes trained and Precision Recall Curve data obtained.
          4.057 seconds used.
```

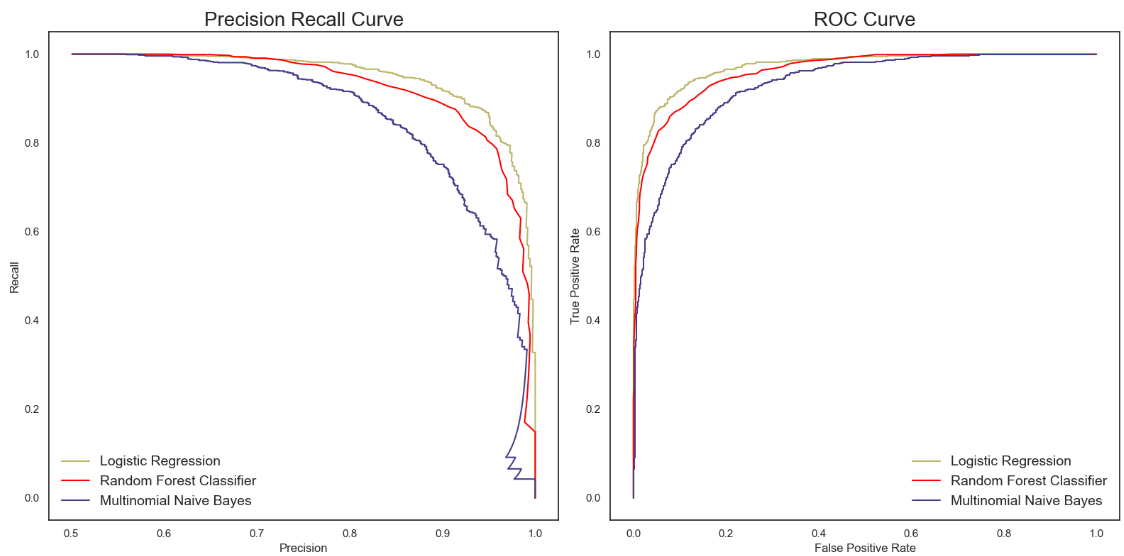
[21]:
```
roc_dict = {}
for model, name in zip(models, model_names):
    begin = time.time()
    fpr, tpr = valsROCCurve(model)
    roc_dict[name] = (fpr, tpr)
    end = time.time()

    print(f'''{name} trained and ROC Curve data obtained.
          {round(end-begin,3)} seconds used.''')
```

```
Logistic Regression trained and ROC Curve data obtained.
          22.399 seconds used.
```

```
Random Forest Classifier trained and ROC Curve data obtained.
          35.623 seconds used.
Multinomial Naive Bayes trained and ROC Curve data obtained.
          4.004 seconds used.
```

[22]:

```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (16, 8))
color_list = ['darkkhaki', 'red', 'darkslateblue', 'darkseagreen']

for model, name, color in zip(models, model_names, color_list):
    plotPrecisionRecallCurve(prc_dict[name][0], prc_dict[name][1], name, ax =␣
 ↪ax1, color = color)
    plotROCCurve(roc_dict[name][0], roc_dict[name][1], name, ax = ax2, color =␣
 ↪color)
ax1.legend(frameon = False, fontsize= 14)
ax1.set_title('Precision Recall Curve', fontsize = 20)
ax2.legend(frameon = False, fontsize= 14)
ax2.set_title('ROC Curve', fontsize = 20)


fig.tight_layout()
```



As indicated in the graph above, `Logistic Regression` surprisingly performed the best among all four different metrices.

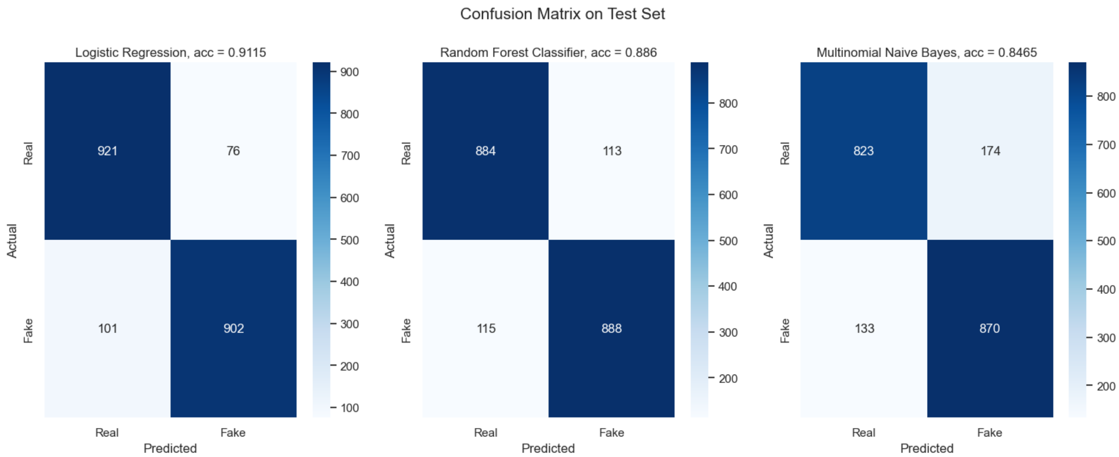
In addition, the precision-recall curve and roc curve also showed that `Logistic Regression` has the most prominent performance.

- Precision Recall curve closest to (1, 1)
- Roc curve closest to (0, 1)

Therefore, we selected logistic regression as the final model to optimize.

Confusion Matrix

[34]:
```
from sklearn.metrics import confusion_matrix
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize = (18, 6))
for name, model, ax in zip(model_names, models, [ax1, ax2, ax3]):
    cm = confusion_matrix(y_test, model.predict(X_test))
    sns.heatmap(cm, annot= True, fmt = 'g', cmap = sns.color_palette("Blues",␣
 ↪as_cmap=True), ax = ax);
    ax.set_xticklabels(['Real', 'Fake']);
    ax.set_yticklabels(['Real', 'Fake']);
    ax.set_xlabel('Predicted')
    ax.set_ylabel('Actual')

    acc = (cm[0, 0] + cm[1, 1])/(cm[0, 0] + cm[0, 1] + cm[1, 0] + cm[1, 1])
    ax.set_title(f'{name}, acc = {acc}');
fig.suptitle('Confusion Matrix on Test Set', y = 1, fontsize = 15);
```



[29]:
```
%%time
# Clean the raw data and save data with tokens to a new file
dfraw['tokens'] = dfraw.text.apply(preprocessing)
dfraw.to_csv('tokenized_data.csv')
```

```
CPU times: user 2min 6s, sys: 1.37 s, total: 2min 8s
Wall time: 2min 9s
```

- Model Optimization and Model Evaluation

[39]:
```
# Hyper parameter tuning for Logistic Regression
from sklearn.model_selection import GridSearchCV
clf = LogisticRegression(max_iter = 2000)
param_grid = {'C': [0.001, 0.01, 0.1, 1, 10]}

begin = time.time()
```

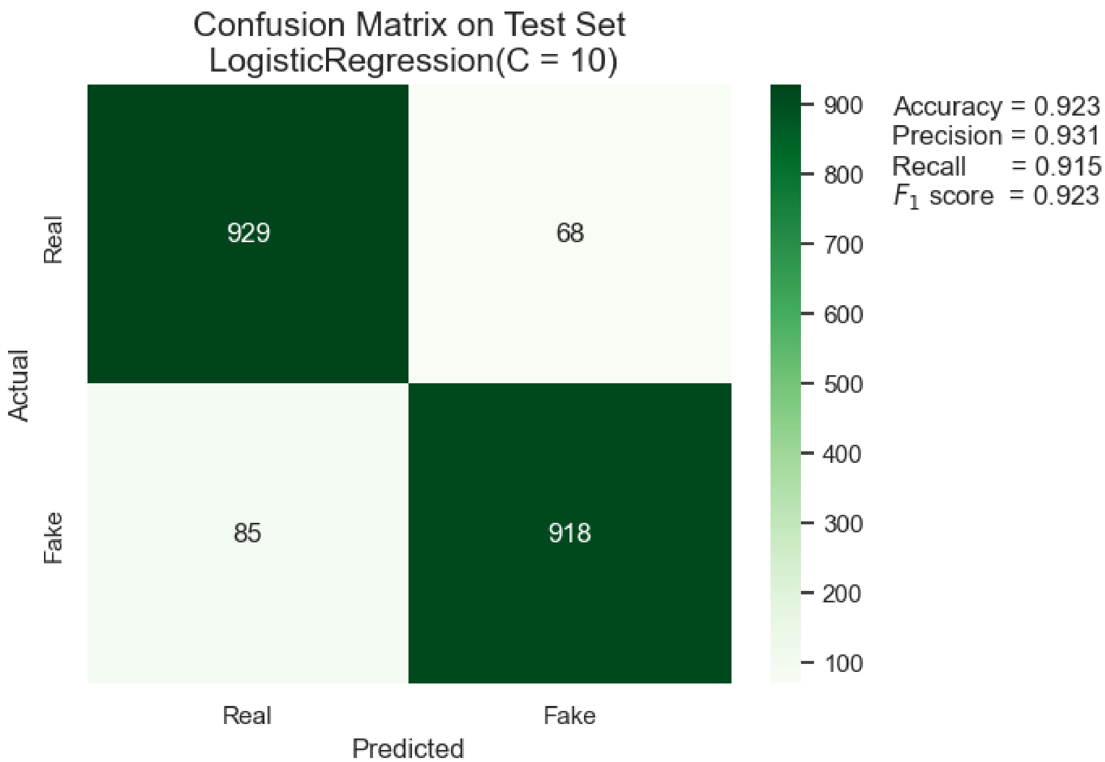
```
GS_logistic = GridSearchCV(estimator = clf, param_grid = param_grid).
 ↪fit(X_train, y_train)
end = time.time()

print(f"Grid Search Hyper parameter tuning is completed. {round(end-begin, 3)}␣
 ↪secs used.")
```

```
Grid Search Hyper parameter tuning is completed. 418.68 secs used.
```

[50]:
```
GS_logistic.best_params_
```

[50]:
```
{'C': 10}
```

[88]:
```
# Plot the confusion matrix and render the performance evaluation metrics by␣
 ↪side

y_pred = GS_logistic.best_estimator_.predict(X_test)
fig, ax = plt.subplots(1, 1)
sns.heatmap(confusion_matrix(y_test, y_pred), annot= True, fmt = 'g', cmap =␣
 ↪sns.color_palette("Greens", as_cmap=True), ax = ax);
ax.set_xticklabels(['Real', 'Fake']);
ax.set_yticklabels(['Real', 'Fake']);
ax.set_xlabel('Predicted');
ax.set_ylabel('Actual');

ax.text(2.5, 0.1, f'Accuracy = {round(accuracy_score(y_test, y_pred),3)}');
ax.text(2.5, 0.2, f'Precision = {round(precision_score(y_test, y_pred),3)}');
ax.text(2.5, 0.3, f'Recall      = {round(recall_score(y_test, y_pred),3)}');
ax.text(2.5, 0.4, f'$F_1$ score  = {round(f1_score(y_test, y_pred),3)}');

ax.set_title("Confusion Matrix on Test Set\n LogisticRegression(C = 10)",
             fontsize = 15);
```



Based on the grid search result, the optimal model parameter for logistic regression is when the regularization term `C` = 10.

The performance scores are all improved after hyper parameter tuning.