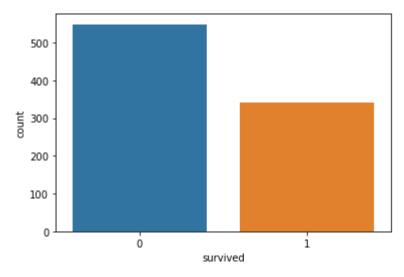
LOGISTIC REGRESSION WITH TITANIC DATASET

```
In [3]:
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
         import numpy as np
         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import classification_report, accuracy_score
         from sklearn.model_selection import train_test_split
In [4]:
         titanic = pd.read_csv('titanic.csv')
In [4]:
         titanic.head()
           survived pclass
                              sex age sibsp parch
                                                       fare embarked class
                                                                              who adult_male deck embark_town alive alone
Out[4]:
         0
                  0
                             male 22.0
                                                     7.2500
                                                                   S Third
                                                                                               NaN
                                                 0
                                                                              man
                                                                                         True
                                                                                                     Southampton
                                                                                                                   no
                                                                                                                       False
         1
                  1
                         1 female 38.0
                                           1
                                                 0 71.2833
                                                                   С
                                                                       First woman
                                                                                         False
                                                                                                 С
                                                                                                       Cherbourg
                                                                                                                  yes
                                                                                                                       False
         2
                  1
                         3 female 26.0
                                                     7.9250
                                                                      Third
                                                                            woman
                                                                                         False
                                                                                               NaN
                                                                                                     Southampton
                                                                                                                        True
                                                                                                                  yes
         3
                  1
                                                   53.1000
                                           1
                                                                                                 С
                         1 female 35.0
                                                 0
                                                                       First woman
                                                                                         False
                                                                                                     Southampton
                                                                                                                  yes
                                                                                                                       False
                  0
                         3
                             male 35.0
                                                     8.0500
                                                                   S Third
                                                                              man
                                                                                         True NaN
                                                                                                     Southampton
                                                                                                                        True
                                                                                                                   no
```

EDA

```
In [5]: sns.countplot(x='survived', data = titanic)
```

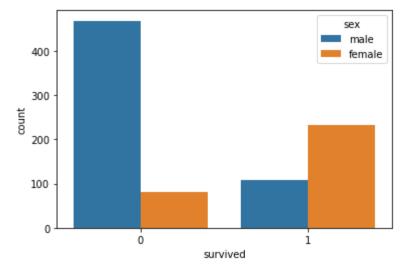
Out[5]: <AxesSubplot:xlabel='survived', ylabel='count'>



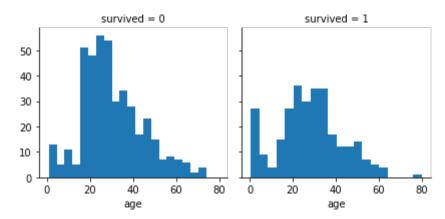
```
import pandas as pd
import seaborn as sns
from pandas_profiling import ProfileReport
#df = pd.read_csv('https://www.kaggle.com/competitions/titanic/data?select=train.csv', )
tips = sns.load_dataset('tips')
#EDA using pandas-profiling
profile = ProfileReport(tips, explorative=True)
#Saving results to a HTML file
profile.to_file("tips-eda.html")
```

```
In [8]: sns.countplot(x='survived', hue = 'sex', data = titanic)
```

Out[8]: <AxesSubplot:xlabel='survived', ylabel='count'>



```
h = sns.FacetGrid(titanic, col = 'survived')
h.map(plt.hist, "age", bins = 20)
```



Data Wrangling

Out[26]:

survived pclass

1

0

sex age sibsp parch

0

1 female 38.0

1 female 35.0

male 54.0

```
In [8]:
          titanic.isnull().any().sum()
 Out[8]: 4
In [18]:
          titanic.dropna(inplace=True)
In [19]:
          titanic.shape[0]
Out[19]: 182
        Pre processings
In [22]:
          sex = pd.get_dummies(titanic['sex'],drop_first=True)
          sex[:5]
Out[22]:
            male
          1
               0
          3
               0
          6
         10
               0
         11
               0
In [23]:
          embark = pd.get_dummies(titanic['embarked'], drop_first=True)
          embark[:5]
Out[23]:
             Q S
          1 0 0
          3 0 1
          6 0 1
         10 0 1
         11 0 1
In [24]:
          cl = pd.get_dummies(titanic['pclass'], drop_first=True)
          cl[:5]
Out[24]:
            2 3
          1 0 0
          3 0 0
          6 0 0
         10 0 1
         11 0 0
In [25]:
          titanic = pd.concat([titanic, sex, cl, embark], axis = 1)
In [26]:
          titanic.head()
```

fare embarked class

S

S

First woman

First woman

man

First

0 71.2833

0 53.1000

0 51.8625

who adult_male deck embark_town alive alone

Cherbourg

Southampton

Southampton

False

False

True

yes

no

С

С

False

False

True

```
Cauthamatan
                                                 16 7000
                                                                         ادانام
                                                                                                         van Falan
In [28]:
          titanic.columns.values
In [29]:
          titanic.drop(['pclass', 'sex','embarked', 'class', 'who', 'adult_male', 'deck', 'embark_town',
                 'alive', 'alone'], axis = 1, inplace=True)
In [30]:
          titanic.head()
Out[30]:
                                       fare male 2 3 Q S
            survived age sibsp parch
                  1 38.0
                                  0 71.2833
                                               0 0 0 0 0
                            1
          3
                  1 35.0
                                  0 53.1000
                                               0 0 0 0 1
          6
                  0 54.0
                            0
                                  0 51.8625
                                               1 0 0 0 1
         10
                     4.0
                            1
                                  1 16.7000
                                              0 0 1 0 1
                  1
         11
                  1 58.0
                            0
                                  0 26.5500
                                               0 0 0 0 1
In [31]:
          X = titanic.drop('survived', axis = 1)
          y = titanic['survived']
In [45]:
          X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.73, random_state=101)
In [46]:
          lr = LogisticRegression()
          lr.fit(X_train,y_train)
         /Users/sumitkumarshukla/opt/anaconda3/lib/python3.8/site-packages/sklearn/linear_model/_logistic.py:763: Con
         vergenceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
           n_iter_i = _check_optimize_result(
Out[46]: LogisticRegression()
In [47]:
          predictions = lr.predict(X_test)
In [48]:
          predictions[:5]
Out[48]: array([1, 0, 0, 1, 0])
In [49]:
          np.array(y[:5])
Out[49]: array([1, 1, 0, 1, 1])
In [50]:
          print(classification_report(y_test, predictions))
                       precision
                                   recall f1-score
                                                     support
                            0.64
                                               0.60
                    0
                                     0.56
                                                           16
                    1
                            0.81
                                     0.85
                                               0.83
                                                           34
                                               0.76
                                                           50
             accuracy
            macro avg
                            0.72
                                     0.71
                                                           50
                                               0.71
         weighted avg
                            0.75
                                               0.76
                                                           50
                                     0.76
In [51]:
          accuracy_score(y_test, predictions)*100
Out[51]: 76.0
In [52]:
          X.columns
Out[52]: Index(['age', 'sibsp', 'parch', 'fare', 'male', 2, 3, 'Q', 'S'], dtype='object')
        prediction
In [56]:
          lr.predict([[87.5, 0, 1, 87.9, 0, 0, 0, 0, 0]])
```

survived pclass

sex

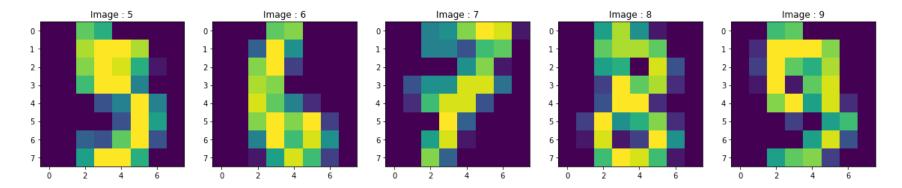
age sibsp parch

fare embarked class

who adult_male deck embark_town alive alone

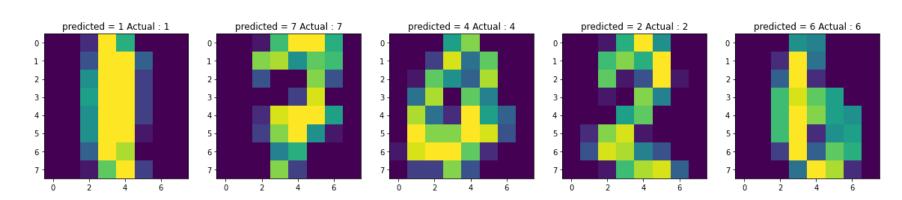
```
Out[56]: array([1])
In [59]:
          titanic.survived.value_counts()/182 * 100
              67.582418
Out[59]: 1
              32.417582
         Name: survived, dtype: float64
        Image Classification
        Predicting the Digits values from images
In [60]:
          from sklearn.datasets import load_digits
In [61]:
          digits = load_digits()
          print(digits.DESCR)
         .. _digits_dataset:
         Optical recognition of handwritten digits dataset
         **Data Set Characteristics:**
             :Number of Instances: 1797
             :Number of Attributes: 64
             :Attribute Information: 8x8 image of integer pixels in the range 0..16.
             :Missing Attribute Values: None
             :Creator: E. Alpaydin (alpaydin '@' boun.edu.tr)
             :Date: July; 1998
         This is a copy of the test set of the UCI ML hand-written digits datasets
         https://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Handwritten+Digits
         The data set contains images of hand-written digits: 10 classes where
         each class refers to a digit.
         Preprocessing programs made available by NIST were used to extract
         normalized bitmaps of handwritten digits from a preprinted form. From a
         total of 43 people, 30 contributed to the training set and different 13
         to the test set. 32x32 bitmaps are divided into nonoverlapping blocks of
         4x4 and the number of on pixels are counted in each block. This generates
         an input matrix of 8x8 where each element is an integer in the range
         0..16. This reduces dimensionality and gives invariance to small
         distortions.
         For info on NIST preprocessing routines, see M. D. Garris, J. L. Blue, G.
         T. Candela, D. L. Dimmick, J. Geist, P. J. Grother, S. A. Janet, and C.
         L. Wilson, NIST Form-Based Handprint Recognition System, NISTIR 5469,
         1994.
         .. topic:: References
           - C. Kaynak (1995) Methods of Combining Multiple Classifiers and Their
             Applications to Handwritten Digit Recognition, MSc Thesis, Institute of
             Graduate Studies in Science and Engineering, Bogazici University.
           - E. Alpaydin, C. Kaynak (1998) Cascading Classifiers, Kybernetika.
           - Ken Tang and Ponnuthurai N. Suganthan and Xi Yao and A. Kai Qin.
             Linear dimensionalityreduction using relevance weighted LDA. School of
             Electrical and Electronic Engineering Nanyang Technological University.
           - Claudio Gentile. A New Approximate Maximal Margin Classification
             Algorithm. NIPS. 2000.
         determine the total number of images and labels
In [62]:
          print('Image Data shape = ',digits.data.shape)
          print('Label data shape = ',digits.target.shape)
         Image Data shape = (1797, 64)
         Label data shape = (1797,)
         Displaying some of the images with their labels
In [67]:
          plt.figure(figsize = (20, 4))
          for index, (image, label) in enumerate(zip(digits.data[5:10], digits.target[5:10])):
              plt.subplot(1, 5, index+1)
```

plt.imshow(np.reshape(image,(8,8)))
plt.title('Image : {}'.format(label))



dataset splitting

```
In [68]:
          X_train, X_test, y_train, y_test = train_test_split(digits.data, digits.target, test_size=0.23, random_state
In [70]:
          print(X_train.shape, X_test.shape)
         (1383, 64) (414, 64)
In [71]:
          ld = LogisticRegression()
          ld.fit(X_train, y_train)
         /Users/sumitkumarshukla/opt/anaconda3/lib/python3.8/site-packages/sklearn/linear_model/_logistic.py:763: Con
         vergenceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
           n_iter_i = _check_optimize_result(
Out[71]: LogisticRegression()
In [73]:
          print(classification_report(y_test, ld.predict(X_test)))
                                                        support
                        precision
                                     recall f1-score
                     0
                             1.00
                                       0.97
                                                 0.99
                                                              39
                                                              37
                             0.92
                                       0.95
                                                 0.93
                     1
                     2
                             0.95
                                       1.00
                                                 0.98
                                                              40
                     3
                                       0.98
                                                 0.99
                                                              43
                             1.00
                             0.98
                                       0.93
                                                 0.95
                                                              44
                             0.98
                                       0.93
                                                 0.95
                                                              44
                     5
                                       1.00
                                                 1.00
                                                              42
                     6
                             1.00
                     7
                                       1.00
                                                 0.99
                                                              42
                             0.98
                     8
                                       0.94
                                                 0.91
                                                              33
                             0.89
                             0.94
                                       0.94
                                                 0.94
                                                              50
                                                 0.96
                                                             414
             accuracy
                             0.96
                                       0.96
                                                 0.96
                                                             414
            macro avg
                             0.96
                                                 0.96
                                                             414
         weighted avg
                                       0.96
In [75]:
          predictions = ld.predict(X_test)
In [76]:
          accuracy_score(y_test, predictions)*100
Out[76]: 96.37681159420289
In [80]:
          print(ld.predict(X_test[0:10]))
         [1 8 4 6 3 5 1 7 4 8]
In [81]:
          print(y_test[0:10])
         [1 8 5 6 3 5 1 7 4 9]
In [82]:
          index = 0
          logre = []
          for Predicted, actual in zip(predictions, y test):
              if Predicted == actual:
                  logre.append(index)
              index += 1
In [91]:
          plt.figure(figsize = (20, 4))
          for image, label in enumerate(logre[5:10]):
              plt.subplot(1, 5, image+1)
              plt.imshow(np.reshape(X_test[label], (8,8)))
              plt.title('predicted = {} Actual : {}'.format(predictions[label], y_test[label]))
```



In []: