this is a heading

```
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving auto.csv to auto (2).csv

```
### load the data
import pandas as pd

df = pd.read_csv('auto.csv')
print(df.head())
print('\nDimensions of data frame:', df.shape)
```

```
    mpg  cylinders  displacement  horsepower  weight  acceleration  year  \
0  18.0          8         307.0         130    3504          12.0  70.0
1  15.0          8         350.0         165    3693          11.5  70.0
2  18.0          8         318.0         150    3436          11.0  70.0
3  16.0          8         304.0         150    3433          12.0  70.0
4  17.0          8         302.0         140    3449           NaN  70.0

   origin                       name
0       1  chevrolet chevelle malibu
1       1          buick skylark 320
2       1         plymouth satellite
3       1              amc rebel sst
4       1                ford torino

Dimensions of data frame: (392, 9)
```

```
df.loc[:, ['mpg', 'weight', 'year']].describe()
#the average of mpg is 23.446, average of weight is 2977.584,
#average of year is 76.010.
```

```
#Range of mpg is 37.6, Range of weight is 3,527, Range of year is 12
```

	mpg	weight	year
count	392.000000	392.000000	390.000000
mean	23.445918	2977.584184	76.010256
std	7.805007	849.402560	3.668093
min	9.000000	1613.000000	70.000000
25%	17.000000	2225.250000	73.000000
50%	22.750000	2803.500000	76.000000
75%	29.000000	3614.750000	79.000000
max	46.600000	5140.000000	82.000000

```
# check data types
print(df.dtypes, "\n")

df.origin = df.origin.astype('category')

# convert cylinders to categorical data type with numeric factor codes
df.cylinders = df.cylinders.astype('category').cat.codes

# convert origin to categorical data type
df.origin = df.origin.astype('category')

print(df.dtypes, "\n")
print(df.head())
```

```
mpg             float64
cylinders         int64
displacement    float64
horsepower        int64
weight            int64
```

```
acceleration    float64
year            float64
origin            int64
name             object
dtype: object

mpg              float64
cylinders          int8
displacement     float64
horsepower         int64
weight             int64
acceleration     float64
year             float64
origin          category
name              object
dtype: object

    mpg  cylinders  displacement  horsepower  weight  acceleration  year  \
0  18.0          4         307.0         130    3504          12.0  70.0
1  15.0          4         350.0         165    3693          11.5  70.0
2  18.0          4         318.0         150    3436          11.0  70.0
3  16.0          4         304.0         150    3433          12.0  70.0
4  17.0          4         302.0         140    3449           NaN  70.0

  origin                       name
0      1  chevrolet chevelle malibu
1      1          buick skylark 320
2      1         plymouth satellite
3      1              amc rebel sst
4      1                ford torino


# check for NAs

print(df.isnull().sum())

# drop remaining rows with NAs

df = df.dropna()
print(df.isnull().sum())
```

```
print('\nDimensions of data frame:', df.shape)
```

```
mpg             0
cylinders       0
displacement    0
horsepower      0
weight          0
acceleration    1
year            2
origin          0
name            0
dtype: int64
mpg             0
cylinders       0
displacement    0
horsepower      0
weight          0
acceleration    0
year            0
origin          0
name            0
dtype: int64
```

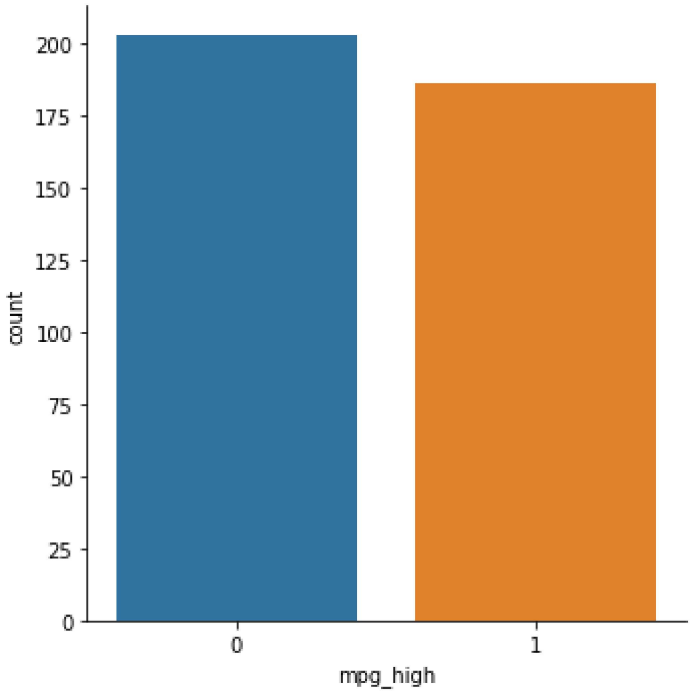
```
import numpy as np

df.loc[df['mpg'] >  df['mpg'].mean(), 'mpg_high'] = '1'
df.loc[df['mpg'] <  df['mpg'].mean(), 'mpg_high'] = '0'
df.mpg_high = df.mpg_high.astype('category')

print(df)
print(df.dtypes, "\n")

##delete cols mpg and name

df = df.drop('mpg',  axis=1)
df = df.drop('name', axis=1)
print(df.head())
```

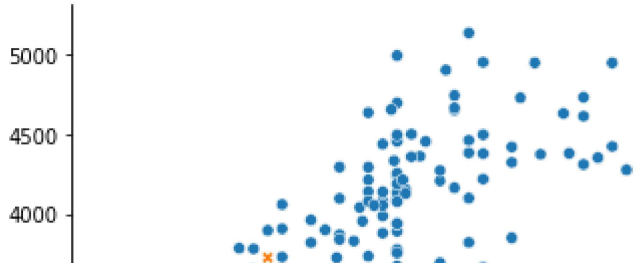
```
      mpg  cylinders  displacement  horsepower  weight  acceleration  year  \
0    18.0          4         307.0         130    3504          12.0  70.0
1    15.0          4         350.0         165    3693          11.5  70.0
2    18.0          4         318.0         150    3436          11.0  70.0
3    16.0          4         304.0         150    3433          12.0  70.0
6    14.0          4         454.0         220    4354           9.0  70.0
..    ...        ...           ...         ...     ...           ...   ...
387  27.0          1         140.0          86    2790          15.6  82.0
388  44.0          1          97.0          52    2130          24.6  82.0
389  32.0          1         135.0          84    2295          11.6  82.0
390  28.0          1         120.0          79    2625          18.6  82.0
391  31.0          1         119.0          82    2720          19.4  82.0

    origin                       name mpg_high
0        1  chevrolet chevelle malibu        0
1        1           buick skylark 320        0
2        1          plymouth satellite        0
3        1               amc rebel sst        0
6        1            chevrolet impala        0
..     ...                         ...      ...
387      1             ford mustang gl        1
388      2                   vw pickup        1
389      1               dodge rampage        1
390      1                 ford ranger        1
391      1                  chevy s-10        1

[389 rows x 10 columns]
mpg              float64
cylinders           int8
displacement     float64
horsepower         int64
weight             int64
acceleration     float64
year             float64
origin          category
name              object
mpg_high        category
dtype: object

   cylinders  displacement  horsepower  weight  acceleration  year origin  \
0          4         307.0         130    3504          12.0  70.0      1
1          4         350.0         165    3693          11.5  70.0      1
```

```
     2          4         318.0         150    3436          11.0  70.0      1
     3          4         304.0         150    3433          12.0  70.0      1
     6          4         454.0         220    4354           9.0  70.0      1

       mpg_high
     0        0
     1        0
     2        0
     3        0
     6        0
```

```
import seaborn as sb
from sklearn import datasets

## catplot,
# from the graph we can tell that there are more 0's than 1's.
# There are 200 '0's and there are around 190 '1's
sb.catplot(x="mpg_high", kind='count', data=df)

## relplot
#  from the relplot we can tell that mpg_high of '0' has a higher weight than
#  mpg_high of '1'.
sb.relplot(x='horsepower', y='weight', data=df, hue="mpg_high",
           style="mpg_high")
```

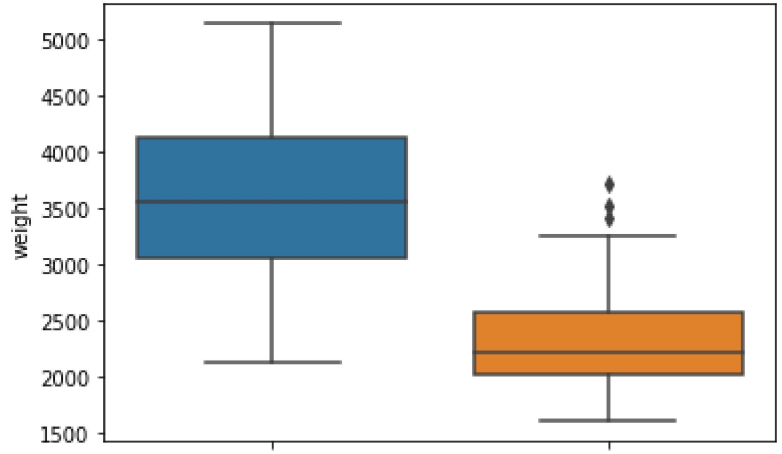
```
<seaborn.axisgrid.FacetGrid at 0x7fea19be6d50>
```






```
## boxplot
#  From the graph we can tell that for '0' median is little above 3500
#  whereas for '1' it is around 2150.  Weight min value of '0' is 2100
#  whereas for '1' it is 1600. Weight max value of '0' is 5250
#  whereas for '1' it is 3250. The outliers of '1' are between 3500 and 4000.

sb.boxplot('mpg_high', y='weight', data=df)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keywo
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fea19c47ad0>
```




```
# train test split
from sklearn.model_selection import train_test_split

X = df.loc[:, ['cylinders', 'displacement', 'horsepower', 'weight',
               'acceleration', 'year', 'origin']]
y = df.mpg_high

X_train, X_test, y_train, y_test = train_test_split(X, y,
    test_size=0.2, random_state=1234)
print('train size:', X_train.shape)
print('test size:', X_test.shape)
```

```
train size: (311, 7)
test size: (78, 7)
```

```
## Logistic Regression

import numpy as np

from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(max_iter=300)
```

```
clf.fit(X_train, y_train)
clf.score(X_train, y_train)


# make predictions
pred = clf.predict(X_test)

# evaluate
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

print('accuracy score: ', accuracy_score(y_test, pred))
print('precision score: ', precision_score(y_test, pred, average="binary",
                                           pos_label="1"))
print('recall score: ', recall_score(y_test, pred, average="binary",
                                     pos_label="1"))
print('f1 score: ', f1_score(y_test, pred, average="binary", pos_label="1"))

# classification report
from sklearn.metrics import classification_report
print(classification_report(y_test, pred, target_names=None))

# confusion matrix
from sklearn.metrics import confusion_matrix

confusion_matrix(y_test, pred)
```

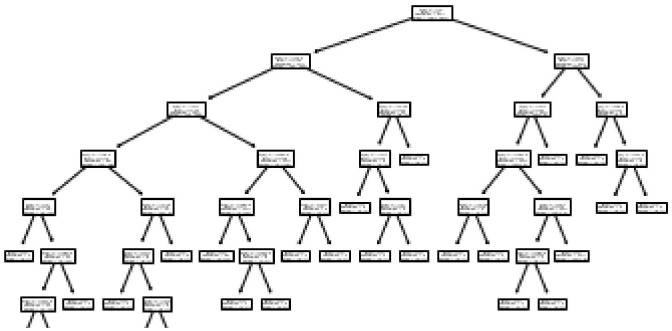
```
accuracy score:  0.8974358974358975
precision score:  0.7777777777777778
recall score:  1.0
f1 score:  0.8750000000000001
              precision    recall  f1-score   support

           0       1.00      0.84      0.91        50
           1       0.78      1.00      0.88        28

    accuracy                           0.90        78
   macro avg       0.89      0.92      0.89        78
```

```
     weighted avg       0.92      0.90      0.90        78

     array([[42,  8],
            [ 0, 28]])
```

```
# Decision Tree

from sklearn.tree import DecisionTreeClassifier
from sklearn import tree

clf2 = DecisionTreeClassifier()
clf2.fit(X_train, y_train)
clf2.score(X_train, y_train)

# make predictions
pred = clf2.predict(X_test)

# evaluate
print('accuracy score: ', accuracy_score(y_test, pred))
print('precision score: ', precision_score(y_test, pred, average="binary",
                                           pos_label="1"))
print('recall score: ', recall_score(y_test, pred, average="binary",
                                     pos_label="1"))
print('f1 score: ', f1_score(y_test, pred, average="binary", pos_label="1"))

# confusion matrix
confusion_matrix(y_test, pred)

#classification report
print(classification_report(y_test, pred, target_names=None))

#plot
tree.plot_tree(clf2)
```

```
accuracy score:  0.9102564102564102
precision score:  0.8387096774193549
recall score:  0.9285714285714286
f1 score:  0.8813559322033899
              precision    recall  f1-score   support

           0       0.96      0.90      0.93        50
           1       0.84      0.93      0.88        28

    accuracy                           0.91        78
   macro avg       0.90      0.91      0.90        78
weighted avg       0.91      0.91      0.91        78

[Text(0.6433823529411765, 0.9444444444444444, 'X[0] <= 2.5\ngini = 0.5\nsamples = 311\nvalue = [153, 158]'),
 Text(0.4338235294117647, 0.8333333333333334, 'X[2] <= 101.0\ngini = 0.239\nsamples = 173\nvalue = [24, 149]'),
 Text(0.27941176470588236, 0.7222222222222222, 'X[5] <= 75.5\ngini = 0.179\nsamples = 161\nvalue = [16, 145]'),
 Text(0.14705882352941177, 0.6111111111111112, 'X[1] <= 119.5\ngini = 0.362\nsamples = 59\nvalue = [14, 45]'),
 Text(0.058823529411764705, 0.5, 'X[0] <= 0.5\ngini = 0.159\nsamples = 46\nvalue = [4, 42]'),
 Text(0.029411764705882353, 0.3888888888888889, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
 Text(0.08823529411764706, 0.3888888888888889, 'X[3] <= 2683.0\ngini = 0.087\nsamples = 44\nvalue = [2, 42]'),
 Text(0.058823529411764705, 0.2777777777777778, 'X[3] <= 2377.0\ngini = 0.045\nsamples = 43\nvalue = [1, 42]'),
 Text(0.029411764705882353, 0.16666666666666666, 'gini = 0.0\nsamples = 38\nvalue = [0, 38]'),
 Text(0.08823529411764706, 0.16666666666666666, 'X[3] <= 2385.0\ngini = 0.32\nsamples = 5\nvalue = [1, 4]'),
 Text(0.058823529411764705, 0.05555555555555555, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.11764705882352941, 0.05555555555555555, 'gini = 0.0\nsamples = 4\nvalue = [0, 4]'),
 Text(0.11764705882352941, 0.2777777777777778, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.23529411764705882, 0.5, 'X[4] <= 17.75\ngini = 0.355\nsamples = 13\nvalue = [10, 3]'),
 Text(0.20588235294117646, 0.3888888888888889, 'X[2] <= 81.5\ngini = 0.469\nsamples = 8\nvalue = [5, 3]'),
 Text(0.17647058823529413, 0.2777777777777778, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
 Text(0.23529411764705882, 0.2777777777777778, 'X[5] <= 71.5\ngini = 0.278\nsamples = 6\nvalue = [5, 1]'),
 Text(0.20588235294117646, 0.16666666666666666, 'X[3] <= 2242.0\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
 Text(0.17647058823529413, 0.05555555555555555, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.23529411764705882, 0.05555555555555555, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(0.2647058823529412, 0.16666666666666666, 'gini = 0.0\nsamples = 4\nvalue = [4, 0]'),
 Text(0.2647058823529412, 0.3888888888888889, 'gini = 0.0\nsamples = 5\nvalue = [5, 0]'),
 Text(0.4117647058823529, 0.6111111111111112, 'X[3] <= 3250.0\ngini = 0.038\nsamples = 102\nvalue = [2, 100]'),
 Text(0.35294117647058826, 0.5, 'X[3] <= 2880.0\ngini = 0.02\nsamples = 100\nvalue = [1, 99]'),
 Text(0.3235294117647059, 0.3888888888888889, 'gini = 0.0\nsamples = 94\nvalue = [0, 94]'),
 Text(0.38235294117647056, 0.3888888888888889, 'X[3] <= 2920.0\ngini = 0.278\nsamples = 6\nvalue = [1, 5]'),
 Text(0.35294117647058826, 0.2777777777777778, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.4117647058823529, 0.2777777777777778, 'gini = 0.0\nsamples = 5\nvalue = [0, 5]'),
 Text(0.47058823529411764, 0.5, 'X[2] <= 82.5\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
```

```
Text(0.4411764705882353, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(0.5, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(0.5882352941176471, 0.7222222222222222, 'X[4] <= 14.45\ngini = 0.444\nsamples = 12\nvalue = [8, 4]'),
Text(0.5588235294117647, 0.6111111111111112, 'X[5] <= 76.0\ngini = 0.444\nsamples = 6\nvalue = [2, 4]'),
Text(0.5294117647058824, 0.5, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
Text(0.5882352941176471, 0.5, 'X[6] <= 1.5\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
Text(0.5588235294117647, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(0.6176470588235294, 0.3888888888888889, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(0.6176470588235294, 0.6111111111111112, 'gini = 0.0\nsamples = 6\nvalue = [6, 0]'),
Text(0.8529411764705882, 0.8333333333333334, 'X[5] <= 79.5\ngini = 0.122\nsamples = 138\nvalue = [129, 9]'),
Text(0.7941176470588235, 0.7222222222222222, 'X[4] <= 21.6\ngini = 0.045\nsamples = 129\nvalue = [126, 3]'),
Text(0.7647058823529411, 0.6111111111111112, 'X[3] <= 2737.0\ngini = 0.031\nsamples = 128\nvalue = [126, 2]'),
Text(0.7058823529411765, 0.5, 'X[4] <= 13.45\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
Text(0.6764705882352942, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(0.7352941176470589, 0.3888888888888889, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(0.8235294117647058, 0.5, 'X[2] <= 83.0\ngini = 0.016\nsamples = 125\nvalue = [124, 1]'),
Text(0.7941176470588235, 0.3888888888888889, 'X[3] <= 3085.0\ngini = 0.375\nsamples = 4\nvalue = [3, 1]'),
Text(0.7647058823529411, 0.2777777777777778, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(0.8235294117647058, 0.2777777777777778, 'gini = 0.0\nsamples = 3\nvalue = [3, 0]'),
Text(0.8529411764705882, 0.3888888888888889, 'gini = 0.0\nsamples = 121\nvalue = [121, 0]'),
Text(0.8235294117647058, 0.6111111111111112, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(0.9117647058823529, 0.7222222222222222, 'X[1] <= 196.5\ngini = 0.444\nsamples = 9\nvalue = [3, 6]'),
Text(0.8823529411764706, 0.6111111111111112, 'gini = 0.0\nsamples = 4\nvalue = [0, 4]'),
Text(0.9411764705882353, 0.6111111111111112, 'X[1] <= 247.0\ngini = 0.48\nsamples = 5\nvalue = [3, 2]'),
Text(0.9117647058823529, 0.5, 'gini = 0.0\nsamples = 3\nvalue = [3, 0]'),
Text(0.9705882352941176, 0.5, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]')]
```



```
# Neural Network
# Using classification
# normalize the data
from sklearn import preprocessing
#from sklearn.metrics import plot_confusion_matrix
```

```
scaler = preprocessing.StandardScaler().fit(X_train)

X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)

# train
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import plot_confusion_matrix


clf = MLPClassifier(solver='lbfgs', hidden_layer_sizes=(5, 2), max_iter=500,
                    random_state=1234)
clf.fit(X_train_scaled, y_train)

# make predictions
pred = clf.predict(X_test_scaled)

# output results

print('accuracy = ', accuracy_score(y_test, pred))

print(confusion_matrix(y_test, pred))

from sklearn.metrics import classification_report
print(classification_report(y_test, pred))

# try different settings

clf = MLPClassifier(solver='sgd', hidden_layer_sizes=(3,), max_iter=1500,
                    random_state=1234)
clf.fit(X_train_scaled, y_train)

# make predictions
pred = clf.predict(X_test_scaled)

print('accuracy = ', accuracy_score(y_test, pred))
```

```
# confusion matrix
print(confusion_matrix(y_test, pred))

print(classification_report(y_test, pred))

"""First neural network using solver lbfgs slighlty performed better
in accuracy and precision compared to the solver sgd. Recall is about the same.
Performance could be different due to number of iterations and more complex
topology"""
```

```
accuracy =  0.8717948717948718
[[43  7]
 [ 3 25]]
              precision    recall  f1-score   support

           0       0.93      0.86      0.90        50
           1       0.78      0.89      0.83        28

    accuracy                           0.87        78
   macro avg       0.86      0.88      0.86        78
weighted avg       0.88      0.87      0.87        78

accuracy =  0.8333333333333334
[[40 10]
 [ 3 25]]
              precision    recall  f1-score   support

           0       0.93      0.80      0.86        50
           1       0.71      0.89      0.79        28

    accuracy                           0.83        78
   macro avg       0.82      0.85      0.83        78
weighted avg       0.85      0.83      0.84        78

'First neural network using solver lbfgs slighlty performed better \nin accuracy and precision compared to the solver
sgd. Recall is about the same.\nPerformance could be different due to number of iterations and more complex
\ntopology'
```

```
"""11.a.
Logistic Regression perform the best because it has the highest accuracy of
0.898.
```

b.
In Logistic Regression, class 0 precision has 1.00, but class 1 precision is 0.78.
And class 0 recall score is 0.84 but class 1 recall score is 1.
And accuracy is 0.898.

In Decision Tree, class 0 precision has 0.92, but class 1 precision is 0.80.
And class 0 recall score is 0.88 but class 1 recall score is 0.86.
And accuracy is 0.871.

In Neural Network Classifier solver lbfgs, class 0 precision has 0.93, but class 1 is 0.78. And class 0 recall score is 0.86 but class 1 recall score is 0.89. And accuracy is 0.871.
In Neural Network Classifier solver sgd, class 0 precision has 0.93, but class 1 is 0.71. And class 0 recall score is 0.80 but class 1 recall score is 0.89. And accuracy is 0.833.

11.c.
Logistic regression might have performed the best because the dataset used is relatively small and there were some NA’s which affects the predictors.

11.d.
I found R to be harder to learn than sklearn, as it was simpler to use the inbuilt libraries. It was also a bit faster than sklearn. For data visualization sklearn uses seaborn where as R use ggplot, and graphs in R is more statistic related. I may have preferred sklearn over R due to fact that I was new to ML when doing R, but I'm now more familiar which might have made it easier to use sklearn.
"""

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