Machine Learning in Python - Classification

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Homework 9

CS 4375 Machine Learning with Dr. Mazidi

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1. Read the data

[1]:
```
import pandas as pd

df = pd.read_csv('data/bank-full.csv')
```

2. Some data exploration with code

[2]:
```
print('Data frame shape:', df.shape)
```

```
Data frame shape: (45211, 17)
```

[3]:
```
# print head and tail
df.iloc[:, df.columns != 'y'].head(-20)
```

[3]:
```
       age           job  marital  education default  balance housing loan  \
0       58    management  married   tertiary      no     2143     yes   no
1       44    technician   single  secondary      no       29     yes   no
2       33  entrepreneur  married  secondary      no        2     yes  yes
3       47   blue-collar  married    unknown      no     1506     yes   no
4       33       unknown   single    unknown      no        1      no   no
…     …            …       …          …       …        …       …    …
45186  59       unknown  married    unknown      no     1500      no   no
45187  32      services   single  secondary      no     1168     yes   no
45188  29    management   single  secondary      no      703     yes   no
45189  25      services   single  secondary      no      199      no   no
45190  32   blue-collar  married  secondary      no      136      no   no

        contact  day month  duration  campaign  pdays  previous poutcome
0       unknown    5   may       261         1     -1         0  unknown
1       unknown    5   may       151         1     -1         0  unknown
2       unknown    5   may        76         1     -1         0  unknown
3       unknown    5   may        92         1     -1         0  unknown
4       unknown    5   may       198         1     -1         0  unknown
…          …    …     …        …       …     …        …       …
```

```
45186  cellular   16   nov       280          1    104          2  failure
45187  cellular   16   nov       411          1     -1          0  unknown
45188  cellular   16   nov       236          1    550          2  success
45189  cellular   16   nov       173          1     92          5  failure
45190  cellular   16   nov       206          1    188          3  success

[45191 rows x 16 columns]
```

[4]:
```python
print("Data types:")
print(df.dtypes)
```

```
Data types:
age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
loan         object
contact      object
day           int64
month        object
duration      int64
campaign      int64
pdays         int64
previous      int64
poutcome     object
y            object
dtype: object
```

[5]:
```python
df.describe(include='all')
```

[5]:
```
                 age          job  marital  education default        balance  \
count   45211.000000        45211    45211      45211   45211   45211.000000
unique           NaN           12        3          4       2            NaN
top              NaN  blue-collar  married  secondary      no            NaN
freq             NaN         9732    27214      23202   44396            NaN
mean       40.936210          NaN      NaN        NaN     NaN    1362.272058
std        10.618762          NaN      NaN        NaN     NaN    3044.765829
min        18.000000          NaN      NaN        NaN     NaN   -8019.000000
25%        33.000000          NaN      NaN        NaN     NaN      72.000000
50%        39.000000          NaN      NaN        NaN     NaN     448.000000
75%        48.000000          NaN      NaN        NaN     NaN    1428.000000
max        95.000000          NaN      NaN        NaN     NaN  102127.000000

       housing   loan   contact           day  month      duration  \
count    45211  45211     45211  45211.000000  45211  45211.000000
```

```
unique        2      2         3          NaN     12           NaN
top         yes     no  cellular          NaN    may           NaN
freq      25130  37967     29285          NaN  13766           NaN
mean        NaN    NaN       NaN    15.806419    NaN    258.163080
std         NaN    NaN       NaN     8.322476    NaN    257.527812
min         NaN    NaN       NaN     1.000000    NaN      0.000000
25%         NaN    NaN       NaN     8.000000    NaN    103.000000
50%         NaN    NaN       NaN    16.000000    NaN    180.000000
75%         NaN    NaN       NaN    21.000000    NaN    319.000000
max         NaN    NaN       NaN    31.000000    NaN   4918.000000

            campaign         pdays      previous poutcome      y
count   45211.000000  45211.000000  45211.000000    45211  45211
unique           NaN           NaN           NaN        4      2
top              NaN           NaN           NaN  unknown     no
freq             NaN           NaN           NaN    36959  39922
mean        2.763841     40.197828      0.580323      NaN    NaN
std         3.098021    100.128746      2.303441      NaN    NaN
min         1.000000     -1.000000      0.000000      NaN    NaN
25%         1.000000     -1.000000      0.000000      NaN    NaN
50%         2.000000     -1.000000      0.000000      NaN    NaN
75%         3.000000     -1.000000      0.000000      NaN    NaN
max        63.000000    871.000000    275.000000      NaN    NaN
```

3. Data cleaning

[6]:
```
# one-hot encode the categorical predictors using pandas
df = pd.get_dummies(df, columns=['job', 'marital', 'education', 'default',
                                  'housing', 'loan', 'contact', 'month',␣
 ↪'poutcome'])

# set the target to a numeric category
df['y'] = df.y.astype('category').cat.codes
```

4. More data exploration

[7]:
```
# print new head and tail
df.iloc[:, df.columns != 'y'].head(-20)
```

[7]:
```
       age  balance  day  duration  campaign  pdays  previous  job_admin.  \
0       58     2143    5       261         1     -1         0           0
1       44       29    5       151         1     -1         0           0
2       33        2    5        76         1     -1         0           0
3       47     1506    5        92         1     -1         0           0
4       33        1    5       198         1     -1         0           0
…      …        …  …         …        …      …         …           …
45186   59     1500   16       280         1    104         2           0
45187   32     1168   16       411         1     -1         0           0
```

```
45188   29       703   16        236          1    550          2            0
45189   25       199   16        173          1     92          5            0
45190   32       136   16        206          1    188          3            0

       job_blue-collar  job_entrepreneur  …  month_jun  month_mar  \
0                    0                 0  …          0          0
1                    0                 0  …          0          0
2                    0                 1  …          0          0
3                    1                 0  …          0          0
4                    0                 0  …          0          0
…                  …                …   …        …          …
45186                0                 0  …          0          0
45187                0                 0  …          0          0
45188                0                 0  …          0          0
45189                0                 0  …          0          0
45190                1                 0  …          0          0

       month_may  month_nov  month_oct  month_sep  poutcome_failure  \
0              1          0          0          0                 0
1              1          0          0          0                 0
2              1          0          0          0                 0
3              1          0          0          0                 0
4              1          0          0          0                 0
…            …          …          …          …               …
45186          0          1          0          0                 1
45187          0          1          0          0                 0
45188          0          1          0          0                 0
45189          0          1          0          0                 1
45190          0          1          0          0                 0

       poutcome_other  poutcome_success  poutcome_unknown
0                   0                 0                 1
1                   0                 0                 1
2                   0                 0                 1
3                   0                 0                 1
4                   0                 0                 1
…                 …               …               …
45186               0                 0                 0
45187               0                 0                 1
45188               0                 1                 0
45189               0                 0                 0
45190               0                 1                 0

[45191 rows x 51 columns]
```

[8]:
```python
print("New data types:")
print(df.dtypes)
```

```
New data types:
age                    int64
balance                int64
day                    int64
duration               int64
campaign               int64
pdays                  int64
previous               int64
y                       int8
job_admin.             uint8
job_blue-collar        uint8
job_entrepreneur       uint8
job_housemaid          uint8
job_management         uint8
job_retired            uint8
job_self-employed      uint8
job_services           uint8
job_student            uint8
job_technician         uint8
job_unemployed         uint8
job_unknown            uint8
marital_divorced       uint8
marital_married        uint8
marital_single         uint8
education_primary      uint8
education_secondary    uint8
education_tertiary     uint8
education_unknown      uint8
default_no             uint8
default_yes            uint8
housing_no             uint8
housing_yes            uint8
loan_no                uint8
loan_yes               uint8
contact_cellular       uint8
contact_telephone      uint8
contact_unknown        uint8
month_apr              uint8
month_aug              uint8
month_dec              uint8
month_feb              uint8
month_jan              uint8
month_jul              uint8
month_jun              uint8
month_mar              uint8
month_may              uint8
month_nov              uint8
month_oct              uint8
```

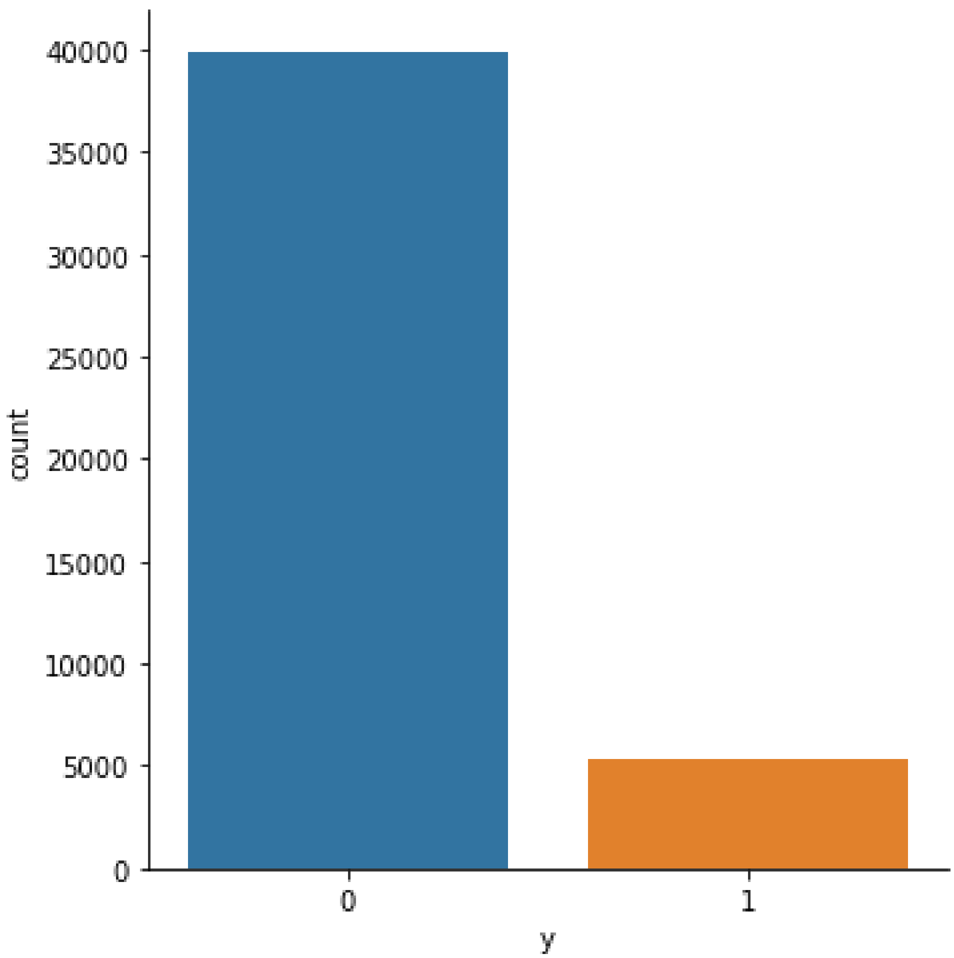
```
month_sep              uint8
poutcome_failure       uint8
poutcome_other         uint8
poutcome_success       uint8
poutcome_unknown       uint8
dtype: object
```

[9]:
```
print('New data frame shape:', df.shape)
```

```
New data frame shape: (45211, 52)
```

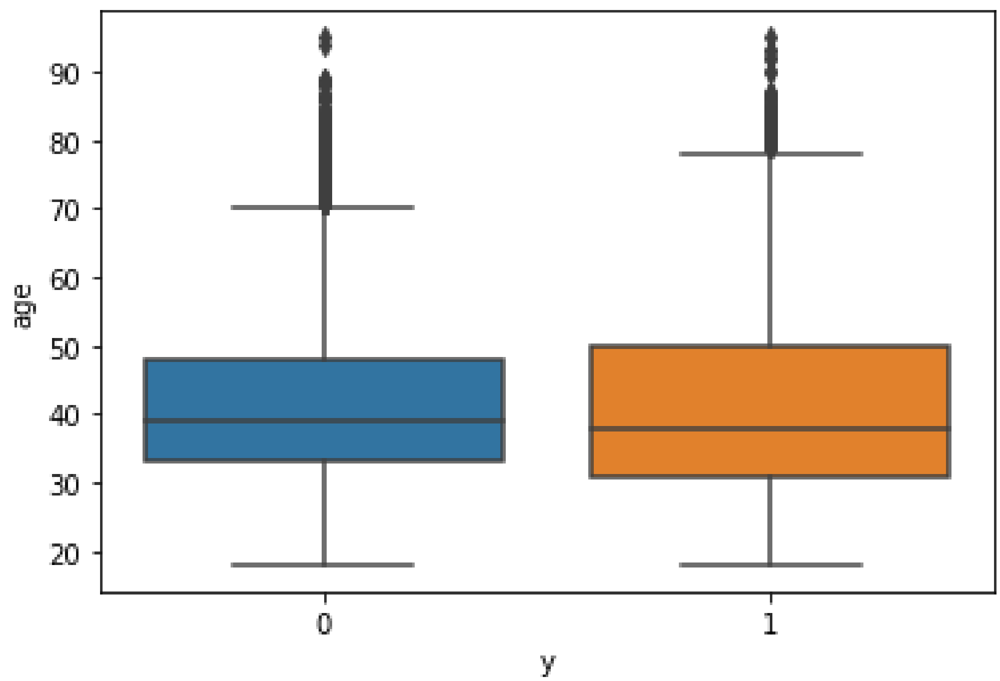
[10]:
```
import seaborn as sb  # for plots

sb.catplot(x="y", kind='count', data=df)
```

[10]:
```
<seaborn.axisgrid.FacetGrid at 0x206017ea5b0>
```



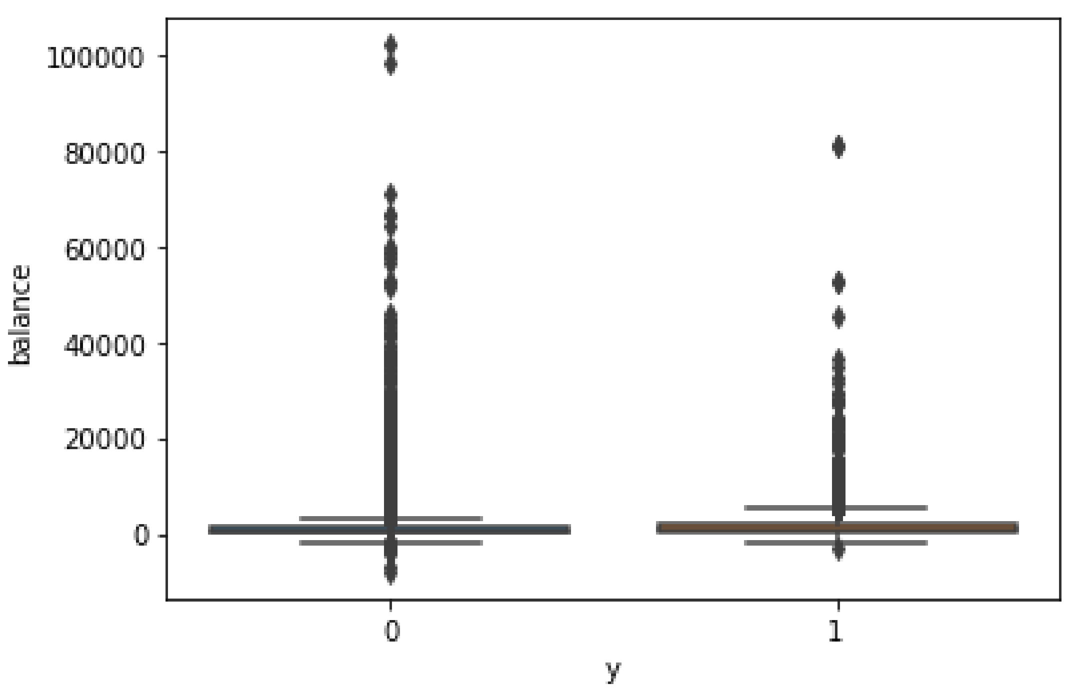
[11]:
```
sb.boxplot(x='y', y='age', data=df)
```

[11]: <AxesSubplot:xlabel='y', ylabel='age'>



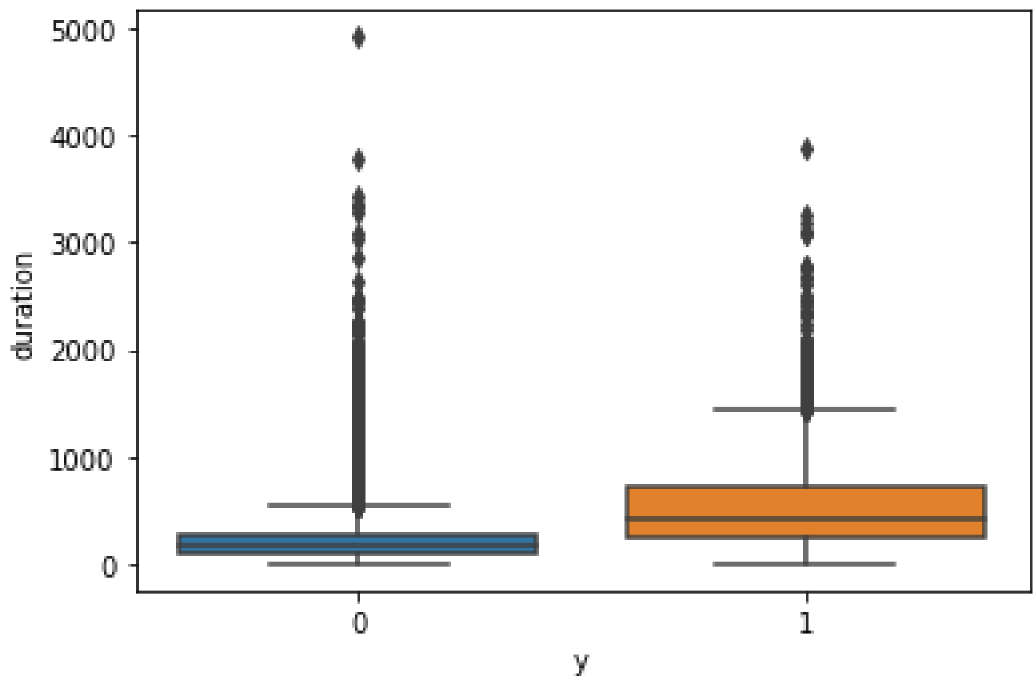
[12]:
```
sb.boxplot(x='y', y='balance', data=df)
```

[12]: <AxesSubplot:xlabel='y', ylabel='balance'>



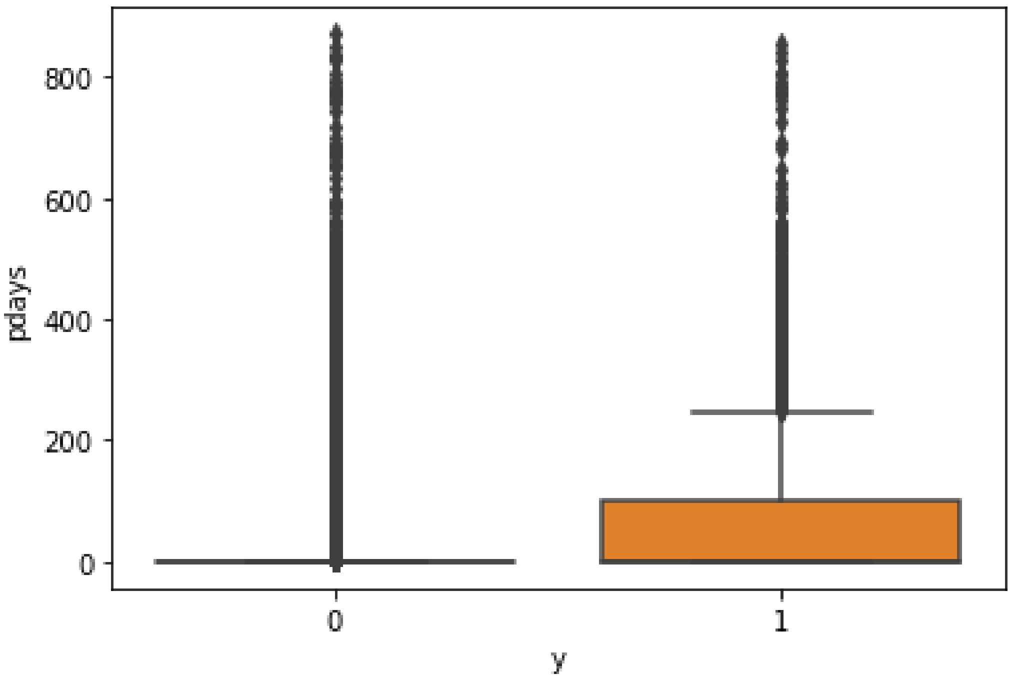
[13]:
```
# boxplot with y on the x axis and duration on the y axis
sb.boxplot(x='y', y='duration', data=df)
```

[13]: <AxesSubplot:xlabel='y', ylabel='duration'>



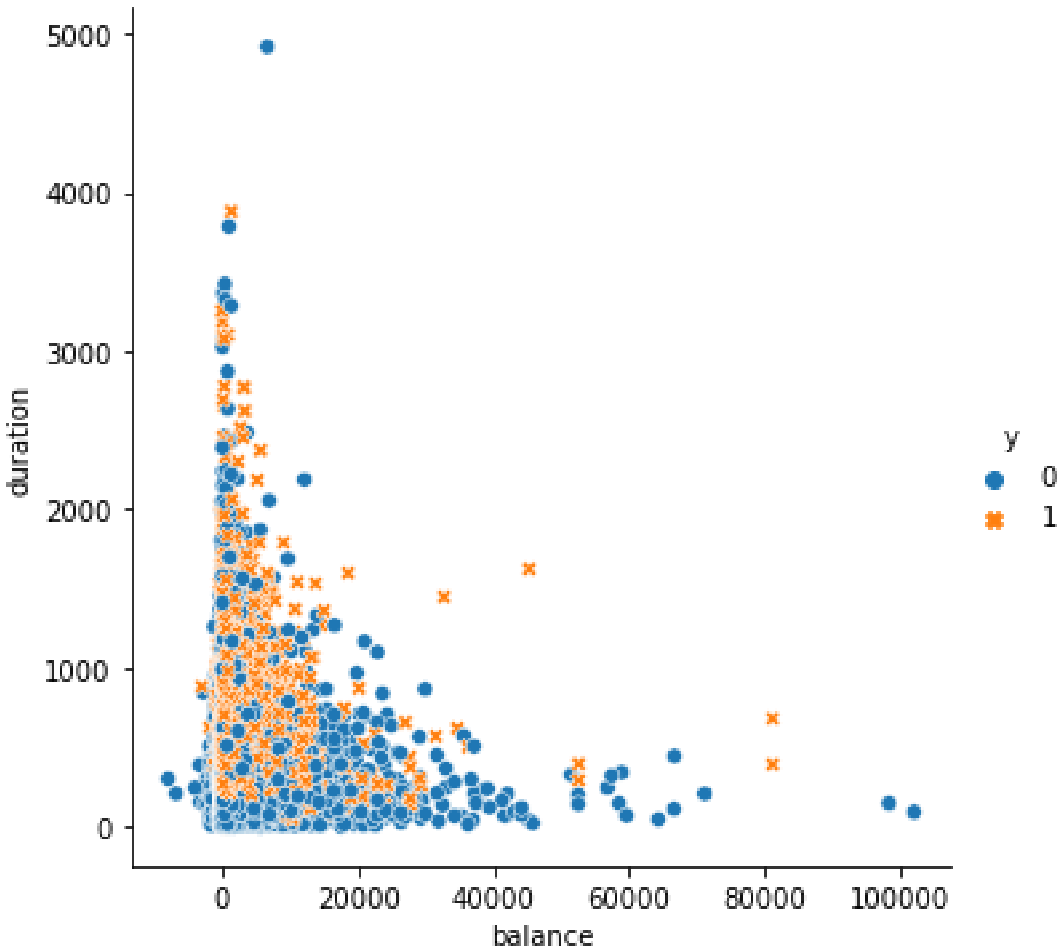
[14]:
```
# boxplot with y on the x axis and pdays on the y axis
sb.boxplot(x='y', y='pdays', data=df)
```

[14]: <AxesSubplot:xlabel='y', ylabel='pdays'>




```
[15]: sb.relplot(x='balance', y='duration', data=df, hue=df.y, style=df.y)
```

```
[15]: <seaborn.axisgrid.FacetGrid at 0x20605475ee0>
```



2. kNN

[16]:
```
# preprocess data
import numpy as np
from sklearn.preprocessing import LabelEncoder

X = df.iloc[:, df.columns != 'y'].values  # predictors
y = df.iloc[:, df.columns == 'y'].values  # target
y = y.ravel()  # convert target array to row vector of size (n, )
y = np.array(y).astype(int)

# ensure inputs are floats and output is an integer label
X = X.astype('float32')
y = LabelEncoder().fit_transform(y.astype('str'))
```

[17]:
```
# define the model
from sklearn.neighbors import KNeighborsClassifier
```

```python
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

pipeline = Pipeline(steps=[('t', StandardScaler()),
                           ('m', KNeighborsClassifier())])
```

[18]:
```python
# evaluate the model
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedKFold

skf = StratifiedKFold(n_splits=10, random_state=1234, shuffle=True)
n_scores = cross_val_score(
    pipeline, X, y, scoring='accuracy', cv=skf, n_jobs=-1, error_score='raise')
```

[19]:
```python
# report performance
from numpy import mean
from numpy import std

print("kNN Accuracy: %0.3f (+/- %0.3f)" % (mean(n_scores), std(n_scores) * 2))
```

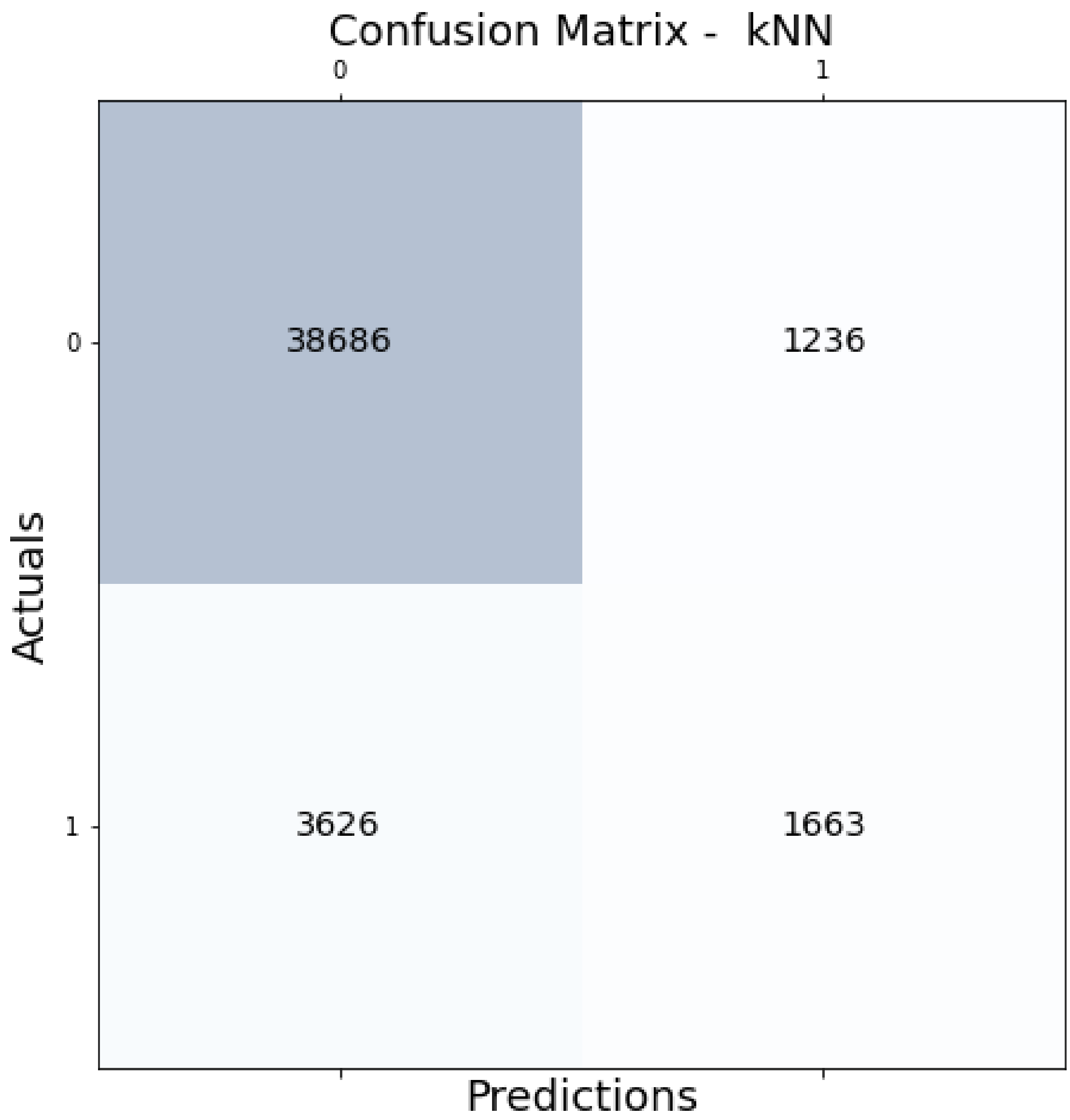
```
kNN Accuracy: 0.892 (+/- 0.004)
```

[20]:
```python
# classification report
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import classification_report

y_pred = cross_val_predict(pipeline, X, y, cv=skf)

print(classification_report(y, y_pred, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.91      0.97      0.94     39922
           1       0.57      0.31      0.41      5289

    accuracy                           0.89     45211
   macro avg       0.74      0.64      0.67     45211
weighted avg       0.87      0.89      0.88     45211
```

[21]:
```python
# confusion matrix
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt

conf_mat = confusion_matrix(y, y_pred)

fig, ax = plt.subplots(figsize=(7.5, 7.5))
ax.matshow(conf_mat, cmap=plt.cm.Blues, alpha=0.3)
```

```
for i in range(conf_mat.shape[0]):
    for j in range(conf_mat.shape[1]):
        ax.text(x=j, y=i, s=conf_mat[i, j],
                va='center', ha='center', size='x-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix -  kNN', fontsize=18)
plt.show()
```



3. Logistic Regression

[22]:
```
# divide into train and test sets
from sklearn.model_selection import train_test_split

# 75% train, 25% test
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.25, random_state=1234)
```

[23]:
```
# perform Logistic Regression
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(solver='liblinear', random_state=1234)
clf.fit(X_train, y_train)
```

[23]:
```
LogisticRegression(random_state=1234, solver='liblinear')
```

[24]:
```
# report performance
print("Log. Regression Accuracy: %0.3f" % clf.score(X_test, y_test))
```

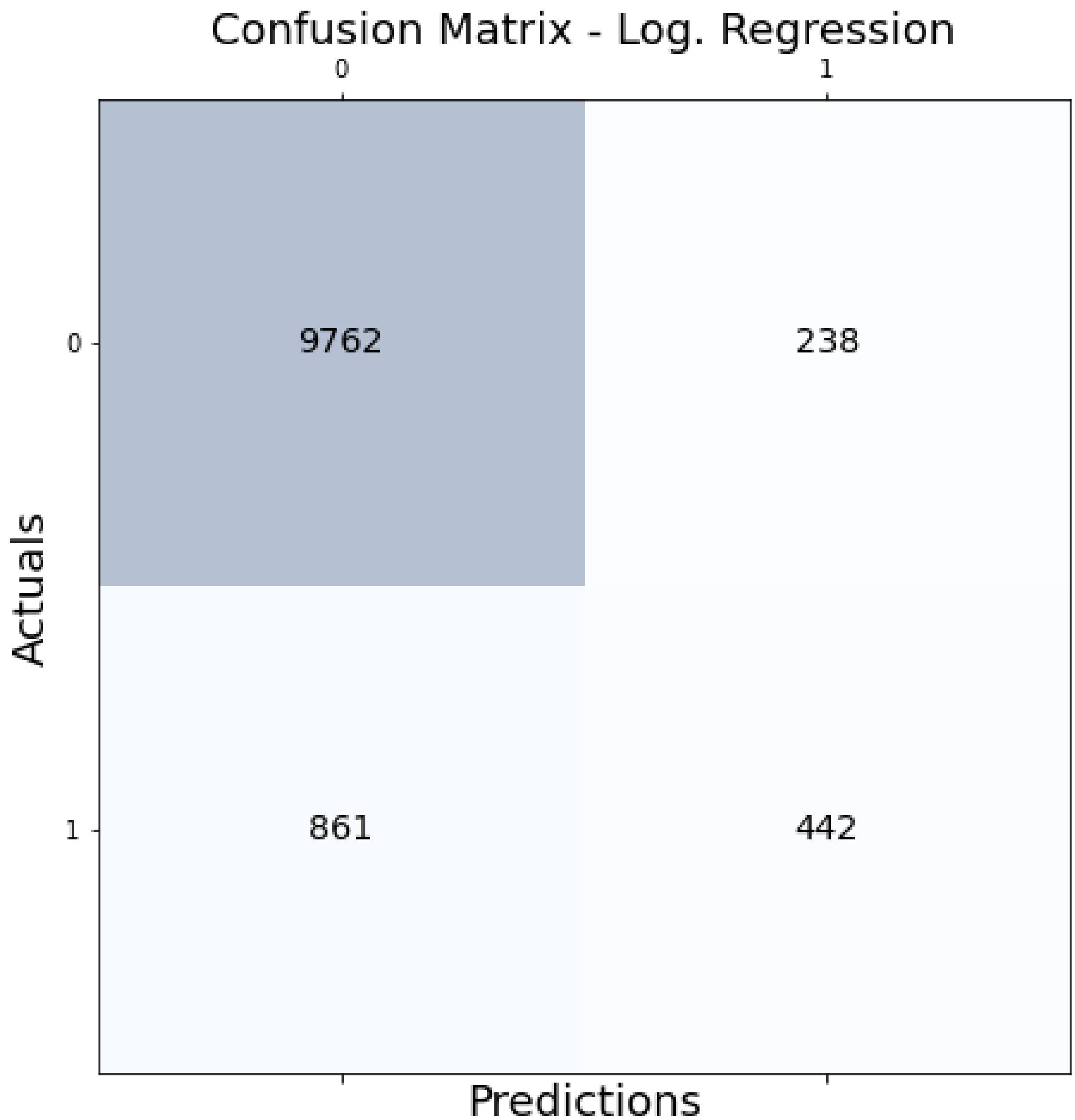
```
Log. Regression Accuracy: 0.903
```

[25]:
```
# classification report
pred = clf.predict(X_test)

print(classification_report(y_test, pred, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     10000
           1       0.65      0.34      0.45      1303

    accuracy                           0.90     11303
   macro avg       0.78      0.66      0.70     11303
weighted avg       0.89      0.90      0.89     11303
```

[26]:
```
# confusion matrix
conf_mat = confusion_matrix(y_test, pred)

fig, ax = plt.subplots(figsize=(7.5, 7.5))
ax.matshow(conf_mat, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_mat.shape[0]):
    for j in range(conf_mat.shape[1]):
        ax.text(x=j, y=i, s=conf_mat[i, j],
                va='center', ha='center', size='x-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix - Log. Regression', fontsize=18)
```

```
plt.show()
```



4. Naive Bayes

[27]:
```
# preprocess data
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.25, random_state=1234, stratify=y)
```

[28]:
```python
# perform Naive Bayes
from sklearn.naive_bayes import GaussianNB

gnb = GaussianNB()
y_pred = gnb.fit(X_train, y_train).predict(X_test)
```

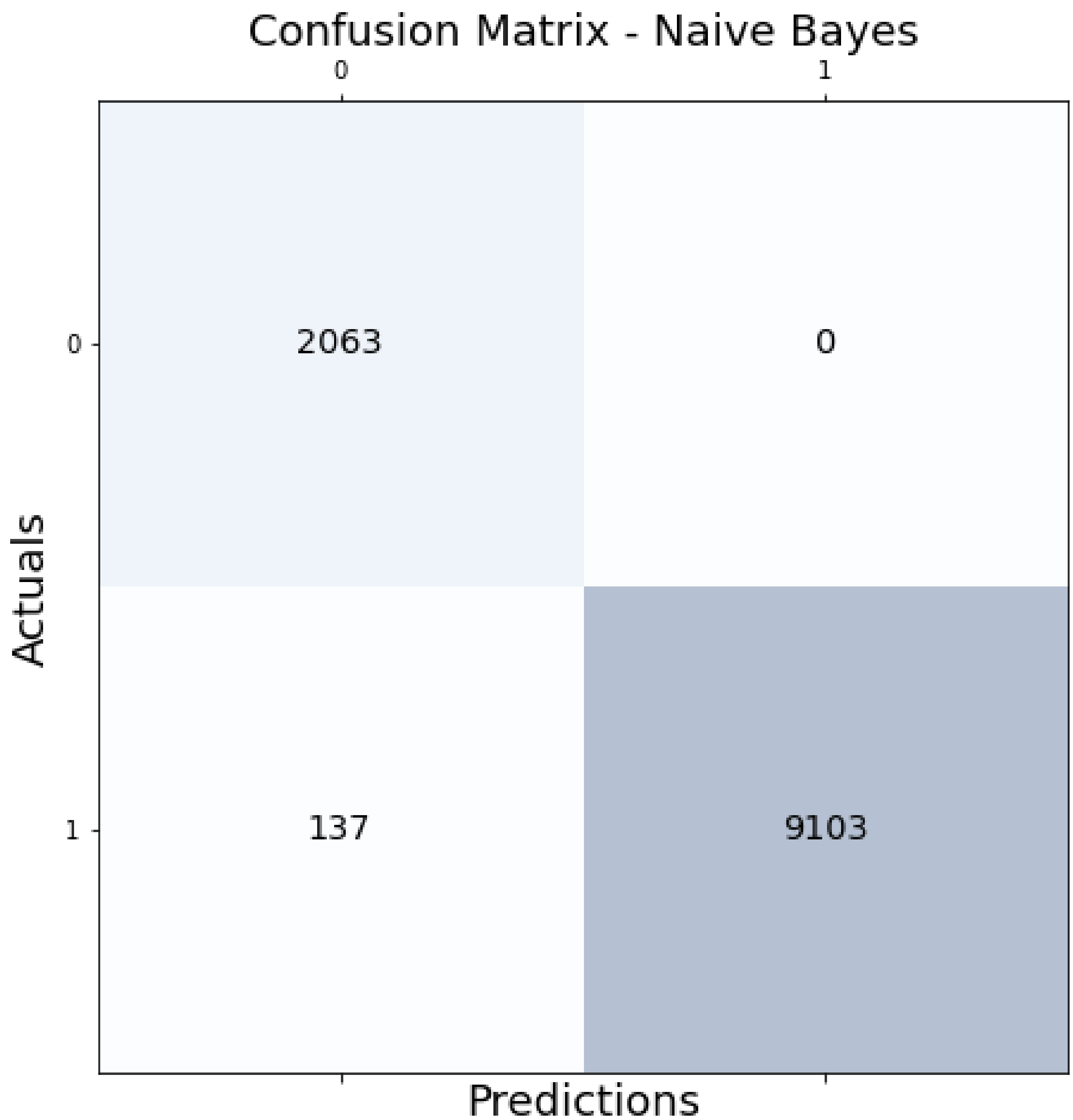
[29]:
```python
# report performance
print("Naive Bayes Accuracy: %0.3f" % ((y_test == y_pred).sum() / y_pred.size))
```

```
Naive Bayes Accuracy: 0.988
```

[30]:
```python
# classification report
print(classification_report(y_test, y_pred, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.94      1.00      0.97      2063
           1       1.00      0.99      0.99      9240

    accuracy                           0.99     11303
   macro avg       0.97      0.99      0.98     11303
weighted avg       0.99      0.99      0.99     11303
```

[31]:
```python
# confusion matrix
conf_mat = confusion_matrix(y_test, y_pred)

fig, ax = plt.subplots(figsize=(7.5, 7.5))
ax.matshow(conf_mat, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_mat.shape[0]):
    for j in range(conf_mat.shape[1]):
        ax.text(x=j, y=i, s=conf_mat[i, j],
                va='center', ha='center', size='x-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix - Naive Bayes', fontsize=18)
plt.show()
```



5. Random Forest

[32]:
```
# instantiate and fit the RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier

forest = RandomForestClassifier(random_state=1234)
forest.fit(X_train, y_train)
```

[32]:
```
RandomForestClassifier(random_state=1234)
```

[33]:
```
# make predictions for the test set
y_pred_test = forest.predict(X_test)
```

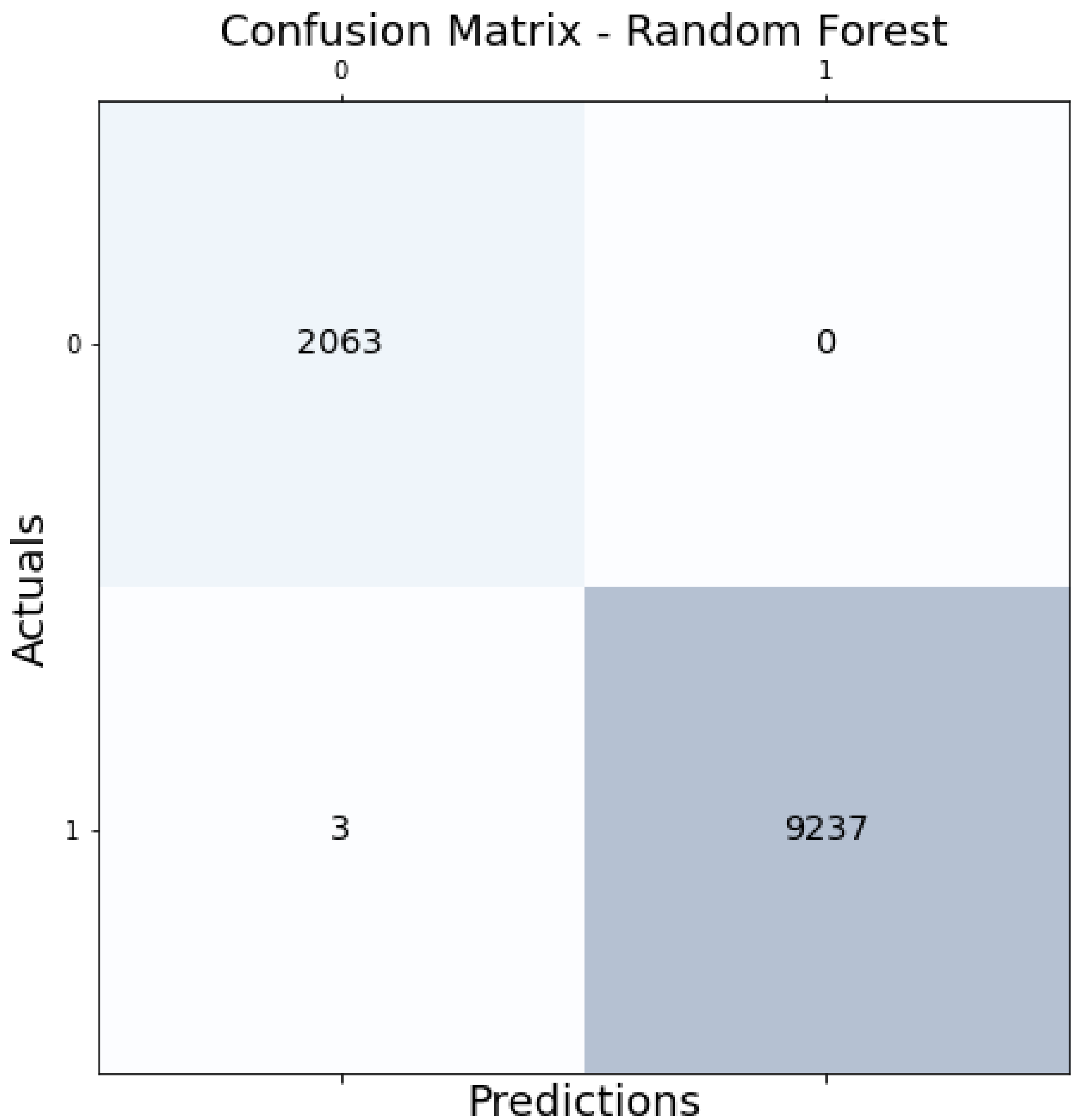
```
[34]: # report performance
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report

print("Random Forest Accuracy: %0.4f" % accuracy_score(y_test, y_pred_test))
```

```
Random Forest Accuracy: 0.9997
```

```
[35]: # classification report
print(classification_report(y_test, y_pred_test, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2063
           1       1.00      1.00      1.00      9240

    accuracy                           1.00     11303
   macro avg       1.00      1.00      1.00     11303
weighted avg       1.00      1.00      1.00     11303
```

```
[36]: # View confusion matrix for test data and predictions
conf_mat = confusion_matrix(y_test, y_pred_test)

fig, ax = plt.subplots(figsize=(7.5, 7.5))
ax.matshow(conf_mat, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_mat.shape[0]):
    for j in range(conf_mat.shape[1]):
        ax.text(x=j, y=i, s=conf_mat[i, j],
                va='center', ha='center', size='x-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix - Random Forest', fontsize=18)
plt.show()
```



6. Analysis

Algorithms ranked by performance:

1. Random Forest: 100% accuracy
2. Naive Bayes: 98%
3. Logistic Regression: 90%
4. kNN: 89%

Random Forest and Naive Bayes achieved very similar accuracy. Naive Bayes was worse in precision for target 0 (91% vs 100% for Random Forest).

The two tree models may have outperformed Linear Regression for the following reasons:

1. Linear separability: The data may not be linearly separable. Logistic Regression assumes that the data is linearly (or curvy linearly) separable in space. Trees are non-linear classifiers; they do not require data to be linearly separable.
2. Skewness: The predictors `displacement`, `horsepower`, and `weight` are moderately/highly skewed. Trees handle skewed predictors nicely if allowed to grow fully. Logistic Regression does not handle skewed predictors well.
3. Outliers: There may be some unhandled outliers influencing the Logistic Regression. Logistic Regression will push the decision boundary towards an outlier. Trees, at the initial stage, won't be affected by an outlier. However, if we let them grow fully, the signal will mote to one side (+ve or -ve), while the outlier will be moved to the other (there will be one leaf for each outlier).

Even with proper scaling provided for fair treatment among features, kNN performed worst of the four.

This script was able to learn that the outcome of a bank's marketing campaigns can be accurately predicted given data on past results. This analyses may be useful to businesses wanting to improve their marketing results. By tailoring their marketing strategy based on past results, businesses can accurately target those with a higher likelihood of success.

R versus Python

I prefer machine learning in R vs. Python by a slim margin. This is mostly due to RStudio. RStudio is the best IDE I have used, and really shines in its ease-of-use. I had some frustration in getting Python for ML working on my PC. I did not have that problem with R.

Python does have a leg up over R in the packages available for ML (e.g. NumPy, pandas, scikit-learn). Python seems to have more community support and is more widely used in industry. This makes learning and troubleshooting easier in Python for me, as there are more online resources available.