Predicting Lung Cancer with Machine Learning

October 9, 2022

[ ]:
```
import pandas as pd
%config Completer.use_jedi = False
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, log_loss, hinge_loss
from sklearn.model_selection import train_test_split, KFold
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.svm import SVC
```

[ ]:
```
# Read in the data stored in the file 'survey lung cancer.csv'
df = pd.read_csv('survey lung cancer.csv')
df.head(5)
```

[ ]:
```
  GENDER  AGE  SMOKING  YELLOW_FINGERS  ANXIETY  PEER_PRESSURE  \
0      M   69        1               2        2              1
1      M   74        2               1        1              1
2      F   59        1               1        1              2
3      M   63        2               2        2              1
4      F   63        1               2        1              1

   CHRONIC DISEASE  FATIGUE   ALLERGY   WHEEZING  ALCOHOL CONSUMING  COUGHING  \
0                1         2         1         2                  2         2
1                2         2         2         1                  1         1
2                1         2         1         2                  1         2
3                1         1         1         1                  2         1
4                1         1         1         2                  1         2

   SHORTNESS OF BREATH  SWALLOWING DIFFICULTY  CHEST PAIN LUNG_CANCER
0                    2                      2           2         YES
1                    2                      2           2         YES
2                    2                      1           2          NO
3                    1                      2           2          NO
4                    2                      1           1          NO
```

```
[ ]: # replace all M/F with 1/0
     df.GENDER.replace(['M', 'F'], [1, 0], inplace=True)

     # replace all YES/NO with 1/0
     df.LUNG_CANCER.replace(['YES', 'NO'], [1, 0], inplace=True)
```

1 Data analysis

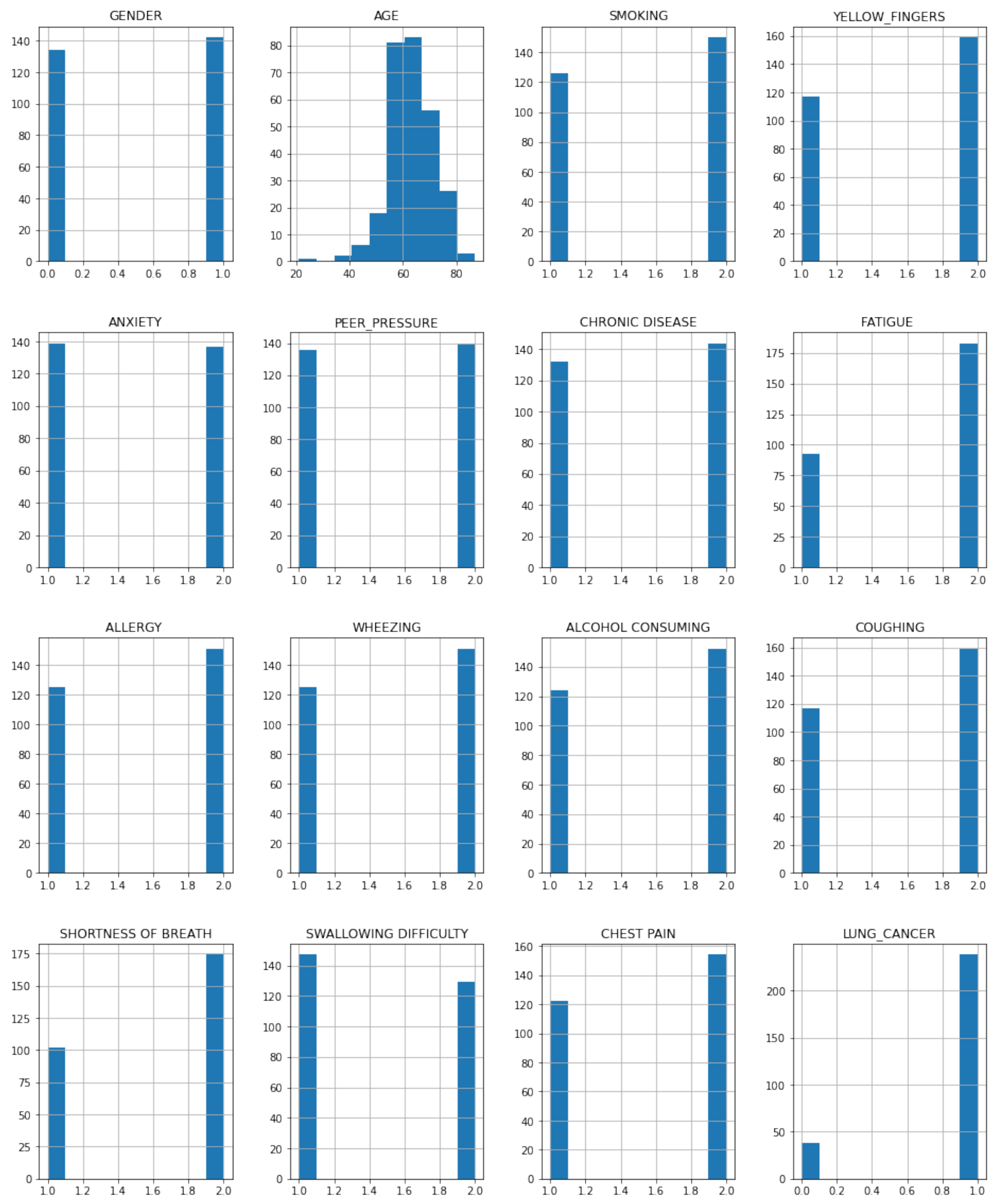
```
[ ]: print("Number of duplicates: ", df.duplicated().sum())
     df = df.drop_duplicates()
     print("Number of duplcates after drop ", df.duplicated().sum())
```

```
Number of duplicates:  33
Number of duplcates after drop  0
```

1.1 Histrogram

```
[ ]: # Data histogram
     df.hist(figsize=(16,20))
```

```
[ ]: array([[<AxesSubplot:title={'center':'GENDER'}>,
             <AxesSubplot:title={'center':'AGE'}>,
             <AxesSubplot:title={'center':'SMOKING'}>,
             <AxesSubplot:title={'center':'YELLOW_FINGERS'}>],
            [<AxesSubplot:title={'center':'ANXIETY'}>,
             <AxesSubplot:title={'center':'PEER_PRESSURE'}>,
             <AxesSubplot:title={'center':'CHRONIC DISEASE'}>,
             <AxesSubplot:title={'center':'FATIGUE '}>],
            [<AxesSubplot:title={'center':'ALLERGY '}>,
             <AxesSubplot:title={'center':'WHEEZING'}>,
             <AxesSubplot:title={'center':'ALCOHOL CONSUMING'}>,
             <AxesSubplot:title={'center':'COUGHING'}>],
            [<AxesSubplot:title={'center':'SHORTNESS OF BREATH'}>,
             <AxesSubplot:title={'center':'SWALLOWING DIFFICULTY'}>,
             <AxesSubplot:title={'center':'CHEST PAIN'}>,
             <AxesSubplot:title={'center':'LUNG_CANCER'}>]], dtype=object)
```

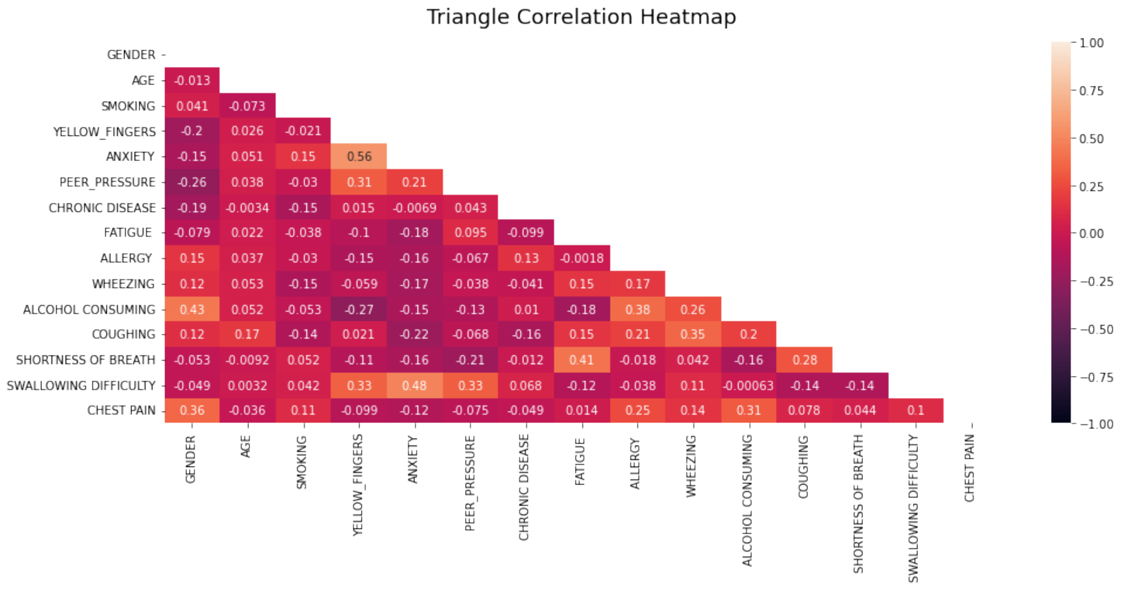


1.2 Heatmap

```
[ ]: # create X and y sets
X = df.drop(columns="LUNG_CANCER").to_numpy()
X_ht = df.drop(columns="LUNG_CANCER", axis= 1)
y = df['LUNG_CANCER'].to_numpy().reshape(-1,)
```

```
[ ]: # Heatmap of dataframe
     plt.figure(figsize=(16, 6))
     mask = np.triu(np.ones_like(X_ht.corr()))
     htmap = sns.heatmap(X_ht.corr(),vmin= -1, vmax= 1,  annot= True , mask = mask)
     htmap.set_title('Triangle Correlation Heatmap', fontdict={'fontsize':18},␣
      ↪pad=16);

     #https://medium.com/@szabo.bibor/
      ↪how-to-create-a-seaborn-correlation-heatmap-in-python-834c0686b88e
```



1.3 Virtual Inflation Factor VIF

Was just used for some manual testing

```
[ ]: X_t = df.drop(columns="LUNG_CANCER", axis=1)
     vif_data = pd.DataFrame()
     vif_data["feature"] = X_t.columns
     vif_data["VIF"] = [variance_inflation_factor(X_t.values, i) for i in␣
      ↪range(len(X_t.columns))]
     print(vif_data.sort_values(by = ["VIF"]))

     #https://www.geeksforgeeks.org/detecting-multicollinearity-with-vif-python/
```

```
                  feature        VIF
0                  GENDER   3.012213
2                 SMOKING  10.738372
6         CHRONIC DISEASE  10.896006
8                 ALLERGY  13.490502
```

```
5          PEER_PRESSURE  13.564503
9               WHEEZING  13.986291
14            CHEST PAIN  14.003207
13  SWALLOWING DIFFICULTY  15.218347
11              COUGHING  17.344194
10      ALCOHOL CONSUMING  17.545363
12    SHORTNESS OF BREATH  17.666498
7               FATIGUE   17.770848
3          YELLOW_FINGERS  19.138132
4                ANXIETY  19.508213
1                    AGE  41.961929
```

2 Machine Learning part

2.1 Data splitting

[ ]:
```
# splitting out the test set, to be used later in comparing models
X_reduced, X_test, y_reduced, y_test = train_test_split(X, y, test_size=0.2,␣
↪shuffle=True)
```

2.2 Logistic Regression

[ ]:
```
# Spitting the data in 5 sets
kf = KFold(n_splits=5, shuffle=True, random_state=69)

#results for train error
train_res_acc = []
train_res_err = []

# results for validation set
val_res_acc = []
val_res_err = []

# results for test set
test_res_acc = []
test_res_err = []

# iteration for k-fold
for train_index, val_index in kf.split(X_reduced):
    X_train, X_val= X_reduced[train_index], X_reduced[val_index]
    y_train, y_val= y_reduced[train_index], y_reduced[val_index]

    # make logistic regression model
    linreg = LogisticRegression(max_iter=100000)
    linreg.fit(X_train, y_train)
    # predict training set
    # calculate accuracy and logistic loss
    y_pred_train = linreg.predict(X_train)
    train_acc = accuracy_score(y_train, y_pred_train)
    train_err = log_loss(y_train, y_pred_train)

    # predict validation set
    # calculate accuracy and logistic loss
    y_pred_val = linreg.predict(X_val)
    val_acc = accuracy_score(y_val, y_pred_val)
    val_error = log_loss(y_val, y_pred_val)

    # predict test set
    # calculate accuracy and logistic loss
    y_pred_test = linreg.predict(X_test)
    test_acc = accuracy_score(y_test, y_pred_test)
    test_error = log_loss(y_test, y_pred_test)


    # append train results for later
    train_res_acc.append(train_acc)
    train_res_err.append(train_err)

    # append validation results for later
    val_res_acc.append(val_acc)
    val_res_err.append(val_error)

    # append test results for later
    test_res_acc.append(test_acc)
    test_res_err.append(test_error)




# print results
print("Logistic Regression")
print("Training accuracy: ", np.mean(train_res_acc))
print("Training error: ", np.mean(train_res_err))
print("Validation accuracy: ", np.mean(val_res_acc))
print("Validation error: ", np.mean(val_res_err))
print("Test accuracy: ", np.mean(test_res_acc))
print("Test error: ", np.mean(test_res_err))
```

```
Logistic Regression
Training accuracy:  0.9295454545454545
Training error:  2.433456497231457
```

```
Validation accuracy:  0.8954545454545455
Validation error:  3.610937499257678
Test accuracy:  0.9035714285714287
Test error:  3.3305734136389353
```

2.3 SVC

```
[ ]: # Spitting the data in 5 sets
kf = KFold(n_splits=5, shuffle=True, random_state=69)

#results for train error
train_res_acc2 = []
train_res_err2 = []

# results for validation set
val_res_acc2 = []
val_res_err2 = []

# results for test set
test_res_acc = []
test_res_err = []

# iteration for k-fold
for train_index, val_index in kf.split(X_reduced):
    X_train, X_val= X_reduced[train_index], X_reduced[val_index]
    y_train, y_val= y_reduced[train_index], y_reduced[val_index]


    #make SVC model
    svc = SVC(gamma='auto',kernel='linear')
    svc.fit(X_train,y_train)

    # predict training set
    # calculate accuracy and logistic loss
    y_pred_train2 = svc.predict(X_train)
    train_acc2 = accuracy_score(y_train, y_pred_train2)
    train_err2 = hinge_loss(y_train, y_pred_train2)

    # predict validation set
    # calculate accuracy and logistic loss
    y_pred_val2 = svc.predict(X_val)
    val_acc2 = accuracy_score(y_val, y_pred_val2)
    val_error2 = hinge_loss(y_val, y_pred_val2)

    # predict test set
    # calculate accuracy and logistic loss
    y_pred_test = svc.predict(X_test)
    test_acc = accuracy_score(y_test, y_pred_test)
    test_error = hinge_loss(y_test, y_pred_test)



    # append train results for later
    train_res_acc.append(train_acc2)
    train_res_err.append(train_err2)

    # append validation results for later
    val_res_acc.append(val_acc2)
    val_res_err.append(val_error2)

    # append test results for later
    test_res_acc.append(test_acc)
    test_res_err.append(test_error)

# print results
print("SVC")
print("Training accuracy: ", np.mean(train_res_acc))
print("Training error: ", np.mean(train_res_err))
print("Validation accuracy: ", np.mean(val_res_acc))
print("Validation error: ", np.mean(val_res_err))
print("Test accuracy: ", np.mean(test_res_acc))
print("Test error: ", np.mean(test_res_err))
```

```
SVC
Training accuracy:  0.9363636363636363
Training error:  1.3155918849793649
Validation accuracy:  0.9
Validation error:  1.923650567810657
Test accuracy:  0.9214285714285715
Test error:  0.20357142857142857
```

[ ]:

```

```