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ME 555 Homework 1

Setup

In [ ]:
```
# We need to import key libraries that we're going to use.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [ ]:
```
# to make this notebook's output stable across runs, we are going to see th
np.random.seed(42)
```

Data For Specific Problems

Problem 3(a): 1-d test scores for pass/fail

In [ ]:
```
# Here is a function that generates data of students taking a test.  It's j
def generate_students_pass_fail(n=300,pass_line=75,random_seed=42):
    def sigmoid(x):
        return 1./(1.+np.exp(-x))
    # Generates noisy data along curved line.
    # The curve is non-linear and the noise/variance is heteroskedastic and
    # pretty much all classical statistical model assumptions.
    np.random.seed(random_seed)
    x = 6*np.random.rand(n, 1)
    x = np.sort(x,axis=0)
    score = 100* sigmoid(-2+x+.4*np.random.randn(n,1))+5*np.random.randn(n,
    y=score>pass_line
    y=y.reshape(-1)
    return x,y
```

In [ ]:
```
x_3a,y_3a=generate_students_pass_fail()
```

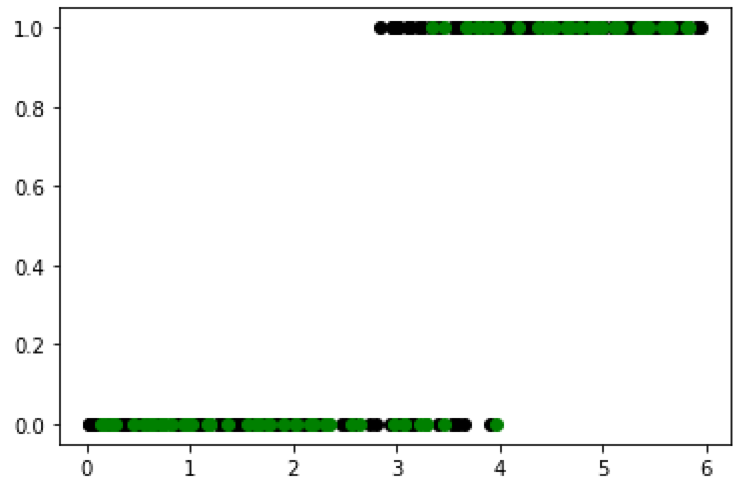
In [ ]:
```
from sklearn.model_selection import train_test_split
```

In [ ]:
```
# # Save to csv if desired
# df=pd.DataFrame(data=np.concatenate((x,y.reshape(-1,1)),axis=1))
# df.columns=['x','y']
# df[:5]
# df.to_csv('3a.csv')
```

In [ ]:
```
xtrain3a, xvalid3a, ytrain3a, yvalid3a = train_test_split(x_3a,y_3a)
```

In [ ]:
```
#Plot, in different colors, the training and validation data sets

fig1 = plt.figure(num=1, clear=True)
ax1 = fig1.add_subplot(1,1,1)
ax1.plot(xtrain3a,ytrain3a, 'ko')
ax1.plot(xvalid3a, yvalid3a, 'go')


#This seems to be a plot of whether or not someone passed based on a number
```

Out[8]:
```
[<matplotlib.lines.Line2D at 0x7efd65f22d90>]
```



In [ ]:
```
from sklearn.linear_model import LogisticRegression
```

In [ ]:
```
def model_learn(k):
  model3a = LogisticRegression(solver = 'liblinear', random_state = 0, C=k)
  model3a.fit(xtrain3a,ytrain3a)
  model3a.classes_
  trainscore = model3a.score(xtrain3a, ytrain3a)
  validscore = model3a.score(xvalid3a, yvalid3a)
  print(f"C Value: {k}\nTraining Score: {trainscore}\nValidation Score: {va
  return trainscore, validscore
```

In [ ]:
```
model_Logistic_Regression_3a_v1 = LogisticRegression(solver = 'liblinear',
model_Logistic_Regression_3a_v1.fit(xtrain3a, ytrain3a)
trainscore = model_Logistic_Regression_3a_v1.score(xtrain3a, ytrain3a)
validscore = model_Logistic_Regression_3a_v1.score(xvalid3a, yvalid3a)

print(f"Training Score: {trainscore}\nValidation Score: {validscore}")
```

```
Training Score: 0.9288888888888889
Validation Score: 0.8933333333333333
```

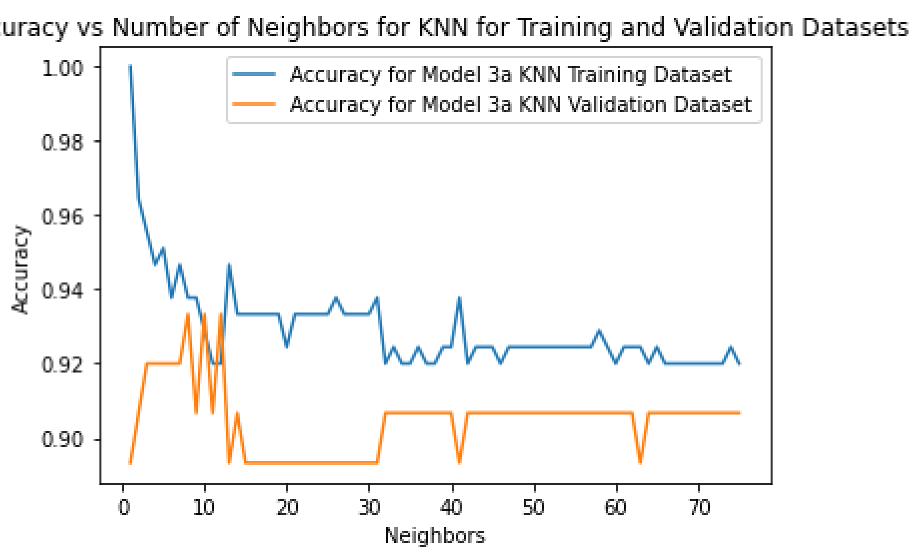
In [ ]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
```

In [ ]:
```
def model_KNN_3_a(number_of_neighbors):
  model_KNN_3_a = KNeighborsClassifier(n_neighbors=number_of_neighbors)
  model_KNN_3_a.fit(xtrain3a, ytrain3a)
  model_KNN_3_a_train_accuracy = accuracy_score(ytrain3a, model_KNN_3_a.pre
  model_KNN_3_a_valid_accuracy = accuracy_score(yvalid3a, model_KNN_3_a.pre
  print(f"k:{number_of_neighbors} Training Accuracy: {model_KNN_3_a_train_a
  return model_KNN_3_a_train_accuracy, model_KNN_3_a_valid_accuracy
```

In [ ]:
```
model_KNN_3_a_accuracy_train = np.zeros(xvalid3a.size)
model_KNN_3_a_accuracy_valid = np.zeros(xvalid3a.size)

for k in range(1, xvalid3a.size + 1):
  model_KNN_3_a_accuracy_train[k-1], model_KNN_3_a_accuracy_valid[k-1] = mo
```

In [ ]:
```
neighbors_3_a = np.linspace(1, 75, 75)

fig3 = plt.figure(num=3, clear=True)
ax3 = fig3.add_subplot(1,1,1)
ax3.plot(neighbors_3_a, model_KNN_3_a_accuracy_train, label = "Accuracy for
ax3.plot(neighbors_3_a, model_KNN_3_a_accuracy_valid, label = "Accuracy for
ax3.set_xlabel("Neighbors")
ax3.set_ylabel("Accuracy")
ax3.set_title("Accuracy vs Number of Neighbors for KNN for Training and Val
ax3.legend()
```

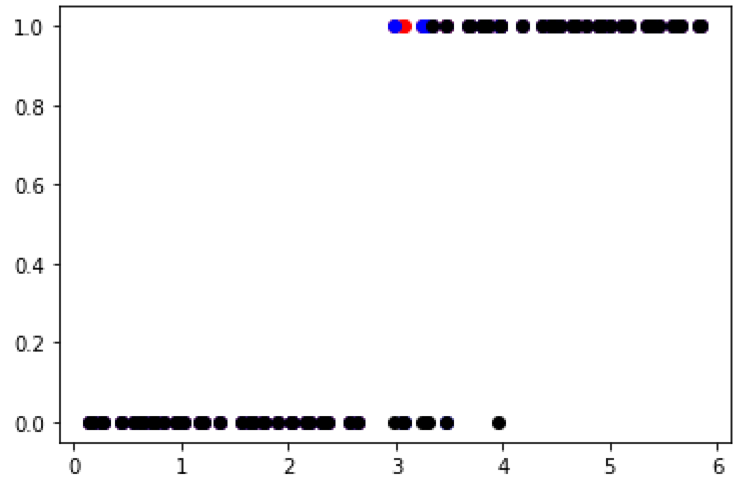
Out[15]:
```
<matplotlib.legend.Legend at 0x7efd65a24650>
```



Let us choose k = 8 since it has the highest accuracy for the validation dataset, given the constraint accuracy of training dataset must be higher than validation dataset, in order to combat over-fitting.

In [ ]:
```
yhat_LogisticRegression_3a = model_Logistic_Regression_3a_v1.predict(xvalid
model_KNN_3_a_v2 = KNeighborsClassifier(n_neighbors = 8)
model_KNN_3_a_v2.fit(xtrain3a, ytrain3a)
yhat_KNN_3a = model_KNN_3_a_v2.predict(xvalid3a.reshape([-1,1]))

fig4 = plt.figure(num=4, clear=True)
ax4 = fig4.add_subplot(1,1,1)
ax4.plot(xvalid3a, yhat_LogisticRegression_3a, 'ro', label = "Logistic Regr
ax4.plot(xvalid3a, yhat_KNN_3a, 'bo', label = "KNN Predictions with N=8")
ax4.plot(xvalid3a, yvalid3a, 'ko', label = "Actual Data")
```

Out[16]:
```
[<matplotlib.lines.Line2D at 0x7efd65427b50>]
```

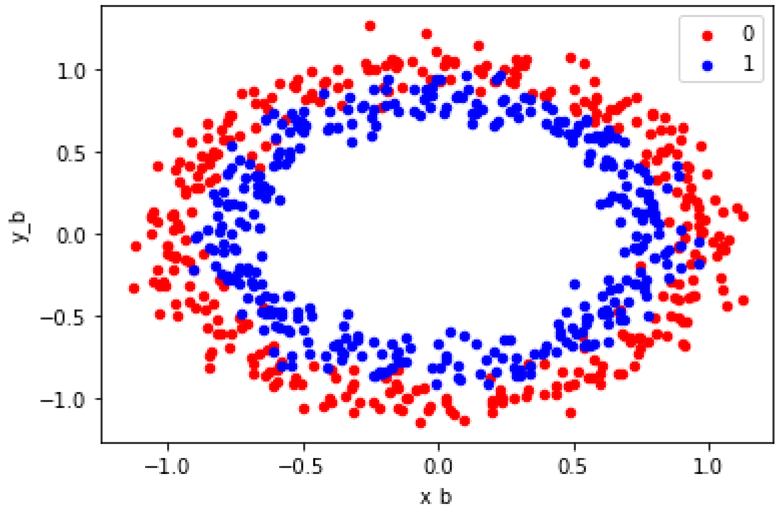


Problem 3(b): 2-d circles

In [ ]:
```
from sklearn.datasets import make_circles
x_3b,y_3b=make_circles(n_samples=700,shuffle=False,noise=.08,random_state=4
```

In [ ]:
```
# # Save to csv if desired
# df=pd.DataFrame(data=np.concatenate((x,y.reshape(-1,1)),axis=1))
# df.columns=['x1','x2','y']
# df[:5]
# df.to_csv('3b.csv')
```

In [ ]:
```
#Plot, in different colors, the training and validation data sets
df = pd.DataFrame(dict(x_b=x_3b[:,0], y_b=x_3b[:,1], label = y_3b))
colors = {0: 'red', 1: 'blue'}
grouped = df.groupby('label')

fig5 = plt.figure(num =5, clear=True)
ax5 = fig5.add_subplot(1,1,1)
for key, group in grouped:
  group.plot(ax=ax5, kind='scatter', x='x_b', y='y_b', label = key, color =

#This is a circle. Points in the outer circle are '0', and points in the in
```



In [ ]:
```
xtrain3b, xvalid3b, ytrain3b, yvalid3b = train_test_split(x_3b,y_3b)
```

In [ ]:
```
model_Logistic_Regression_3b = LogisticRegression(solver = 'liblinear', ran
model_Logistic_Regression_3b.fit(xtrain3b, ytrain3b)
trainscore3b = model_Logistic_Regression_3b.score(xtrain3b, ytrain3b)
validscore3b = model_Logistic_Regression_3b.score(xvalid3b, yvalid3b)

print(f"Training Score: {trainscore3b}\nValidation Score: {validscore3b}")
```

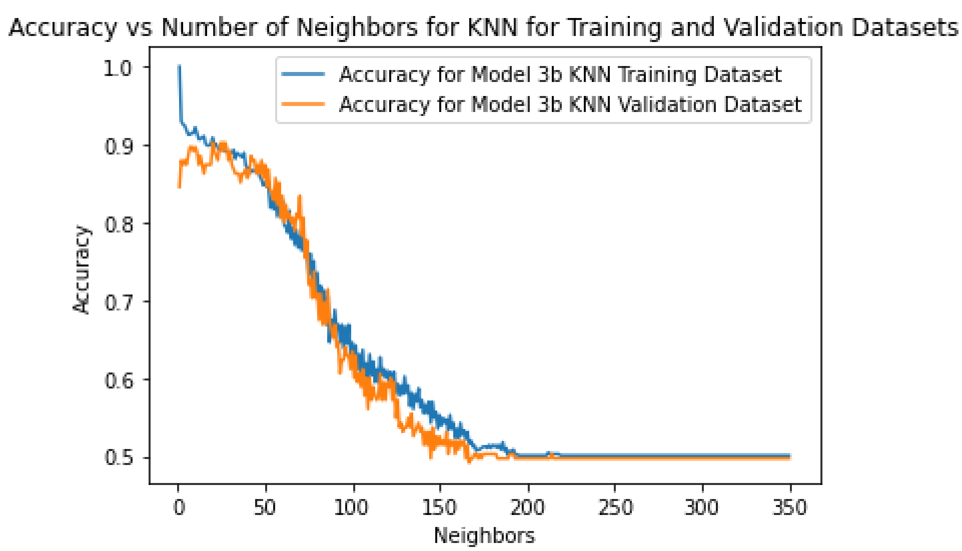
```
Training Score: 0.5028571428571429
Validation Score: 0.4742857142857143
```

In [ ]:
```
def model_KNN_3_b(number_of_neighbors):
  model_KNN_3_b = KNeighborsClassifier(n_neighbors=number_of_neighbors)
  model_KNN_3_b.fit(xtrain3b, ytrain3b)
  model_KNN_3_b_train_accuracy = accuracy_score(ytrain3b, model_KNN_3_b.pre
  model_KNN_3_b_valid_accuracy = accuracy_score(yvalid3b, model_KNN_3_b.pre
  print(f"k:{number_of_neighbors} Training Accuracy: {model_KNN_3_b_train_a
  return model_KNN_3_b_train_accuracy, model_KNN_3_b_valid_accuracy
```

In [ ]:
```
model_KNN_3_b_accuracy_train = np.zeros(xvalid3b.size)
model_KNN_3_b_accuracy_valid = np.zeros(xvalid3b.size)

for k in range(1, xvalid3b.size + 1):
  model_KNN_3_b_accuracy_train[k-1], model_KNN_3_b_accuracy_valid[k-1] = mo
```

In [ ]:
```
neighbors_3_b = np.linspace(1, 350, 350)

fig6 = plt.figure(num=6, clear=True)
ax6 = fig6.add_subplot(1,1,1)
ax6.plot(neighbors_3_b, model_KNN_3_b_accuracy_train, label = "Accuracy for
ax6.plot(neighbors_3_b, model_KNN_3_b_accuracy_valid, label = "Accuracy for
ax6.legend()
ax6.set_xlabel("Neighbors")
ax6.set_ylabel("Accuracy")
ax6.set_title("Accuracy vs Number of Neighbors for KNN for Training and Val
```

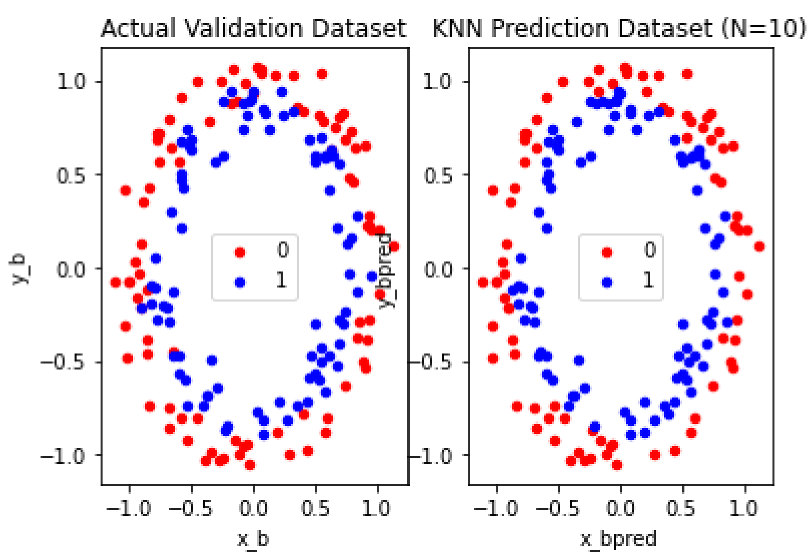
Out[24]:
```
Text(0.5, 1.0, 'Accuracy vs Number of Neighbors for KNN for Training and
Validation Datasets')
```



Let us choose k = 25 since it has the highest accuracy for the validation dataset, given the constraint accuracy of training dataset must be higher than validation dataset, in order to combat over-fitting. This has around a 89.71% accuracy for the validation dataset, and 92.19% accuracy for the training dataset.

In [ ]:
```
model_KNN_3_b_v2 = KNeighborsClassifier(n_neighbors = 10)
model_KNN_3_b_v2.fit(xtrain3b, ytrain3b)
yhat_KNN_3b = model_KNN_3_b_v2.predict(xvalid3b.reshape([-1,2]))

df = pd.DataFrame(dict(x_b=xvalid3b[:,0], y_b=xvalid3b[:,1], label = yvalid
dfpredict = pd.DataFrame(dict(x_bpred=xvalid3b[:,0], y_bpred=xvalid3b[:,1],
colors = {0: 'red', 1: 'blue'}
grouped = df.groupby('label')
groupedpredict = dfpredict.groupby('label')

fig7 = plt.figure(num =77, clear=True)
ax7, ax8 = fig7.subplots(1,2)
for key, group in grouped:
  group.plot(ax=ax7, kind='scatter', x='x_b', y='y_b', label = key, color =

for key, group in groupedpredict:
  group.plot(ax=ax8, kind='scatter', x='x_bpred', y='y_bpred', label = key,

ax7.set_title("Actual Validation Dataset")
ax8.set_title("KNN Prediction Dataset (N=10)")
```

Out[25]:
```
Text(0.5, 1.0, 'KNN Prediction Dataset (N=10)')
```



I prefer the K-Nearest Neighbors Classifier model due its' high accuracy.

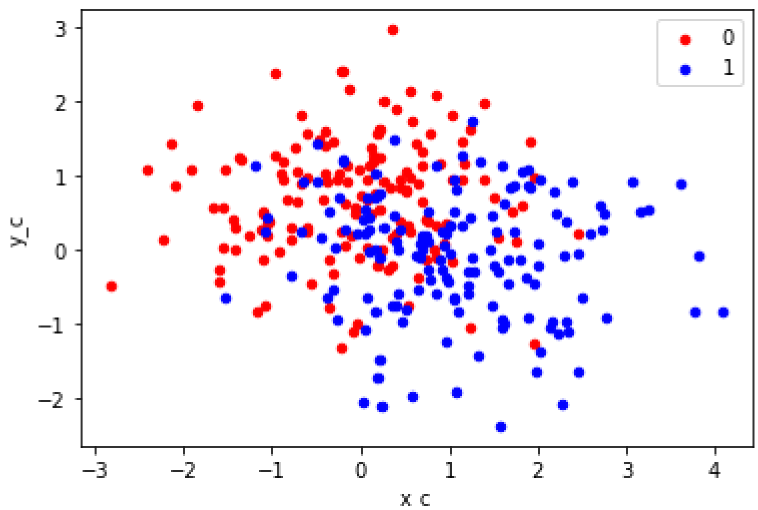
Problem 3(c): 2-d moons

In [ ]:
```
from sklearn.datasets import make_moons
x_3c,y_3c=make_moons(n_samples=300,noise=.75,random_state=42)
```

In [ ]:
```
# # Save to csv if desired
# df=pd.DataFrame(data=np.concatenate((x,y.reshape(-1,1)),axis=1))
# df.columns=['x1','x2','y']
# df[:5]
# df.to_csv('3c.csv')
```

In [ ]:
```
xtrain3c, xvalid3c, ytrain3c, yvalid3c = train_test_split(x_3c,y_3c)
```

In [ ]:
```
#Plot, in different colors, the training and validation data sets
df3c = pd.DataFrame(dict(x_c=x_3c[:,0], y_c=x_3c[:,1], label = y_3c))
colors = {0: 'red', 1: 'blue'}
grouped = df3c.groupby('label')

fig8 = plt.figure(num =8, clear=True)
ax9 = fig8.add_subplot(1,1,1)
for key, group in grouped:
  group.plot(ax=ax9, kind='scatter', x='x_c', y='y_c', label = key, color =

#This is a tough to distinguish. Although we know that this is supposed to
```



In [ ]:
```
model_Logistic_Regression_3c = LogisticRegression(solver = 'liblinear', ran
model_Logistic_Regression_3c.fit(xtrain3c, ytrain3c)
trainscore3c = model_Logistic_Regression_3c.score(xtrain3c, ytrain3c)
validscore3c = model_Logistic_Regression_3c.score(xvalid3c, yvalid3c)

print(f"Training Score: {trainscore3c}\nValidation Score: {validscore3c}")
```

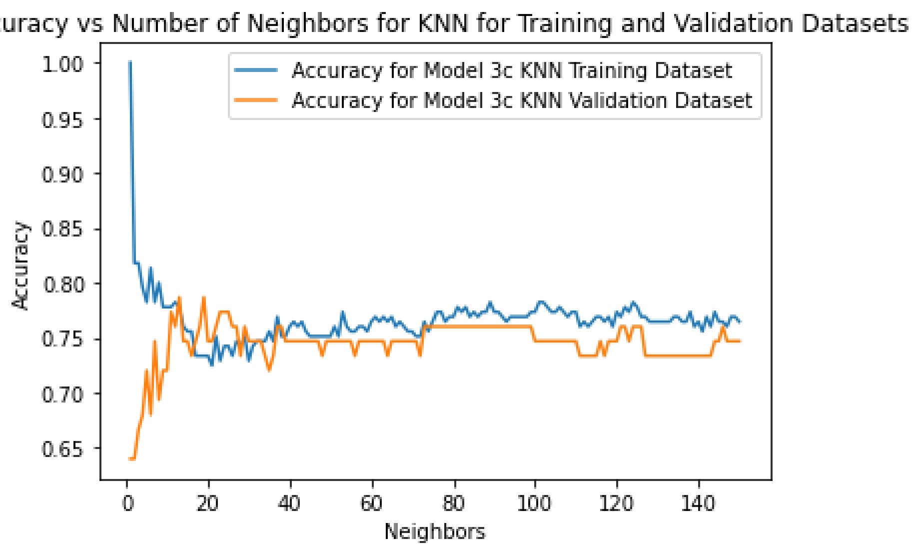
```
Training Score: 0.76
Validation Score: 0.7466666666666667
```

In [ ]:
```
def model_KNN_3_c(number_of_neighbors):
  model_KNN_3_c = KNeighborsClassifier(n_neighbors=number_of_neighbors)
  model_KNN_3_c.fit(xtrain3c, ytrain3c)
  model_KNN_3_c_train_accuracy = accuracy_score(ytrain3c, model_KNN_3_c.pre
  model_KNN_3_c_valid_accuracy = accuracy_score(yvalid3c, model_KNN_3_c.pre
  print(f"k:{number_of_neighbors} Training Accuracy: {model_KNN_3_c_train_a
  return model_KNN_3_c_train_accuracy, model_KNN_3_c_valid_accuracy
```

In [ ]:
```
model_KNN_3_c_accuracy_train = np.zeros(xvalid3c.size)
model_KNN_3_c_accuracy_valid = np.zeros(xvalid3c.size)

for k in range(1, xvalid3c.size + 1):
  model_KNN_3_c_accuracy_train[k-1], model_KNN_3_c_accuracy_valid[k-1] = mo
```

In [ ]:
```
neighbors_3_c = np.linspace(1, 150, 150)

fig9 = plt.figure(num=9, clear=True)
ax10 = fig9.add_subplot(1,1,1)
ax10.plot(neighbors_3_c, model_KNN_3_c_accuracy_train, label = "Accuracy fo
ax10.plot(neighbors_3_c, model_KNN_3_c_accuracy_valid, label = "Accuracy fo
ax10.legend()
ax10.set_xlabel("Neighbors")
ax10.set_ylabel("Accuracy")
ax10.set_title("Accuracy vs Number of Neighbors for KNN for Training and Va
```

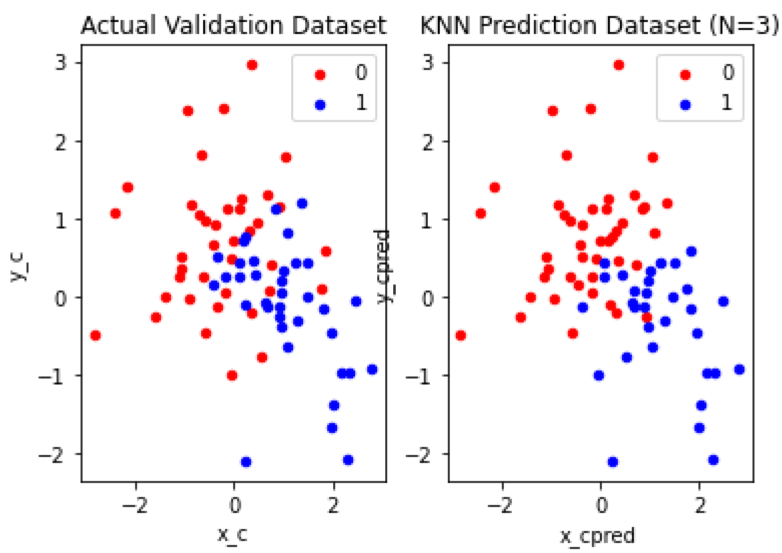
Out[33]:
```
Text(0.5, 1.0, 'Accuracy vs Number of Neighbors for KNN for Training and
Validation Datasets')
```



Let us choose k = 11 since it has the highest accuracy for the validation dataset, given the constraint accuracy of training dataset must be higher than validation dataset, in order to combat over-fitting. This has around a 77.33% accuracy for the validation dataset, and 77.77% accuracy for the training dataset.

In [ ]:
```
model_KNN_3_c_v2 = KNeighborsClassifier(n_neighbors = 11)
model_KNN_3_c_v2.fit(xtrain3c, ytrain3c)
yhat_KNN_3c = model_KNN_3_c_v2.predict(xvalid3c.reshape([-1,2]))

df = pd.DataFrame(dict(x_c=xvalid3c[:,0], y_c=xvalid3c[:,1], label = yvalid
dfpredict3c = pd.DataFrame(dict(x_cpred=xvalid3c[:,0], y_cpred=xvalid3c[:,1
colors = {0: 'red', 1: 'blue'}
grouped = df.groupby('label')
groupedpredict3c = dfpredict3c.groupby('label')

fig10 = plt.figure(num =10, clear=True)
ax11, ax12 = fig10.subplots(1,2)
for key, group in grouped:
  group.plot(ax=ax11, kind='scatter', x='x_c', y='y_c', label = key, color

for key, group in groupedpredict3c:
  group.plot(ax=ax12, kind='scatter', x='x_cpred', y='y_cpred', label = key

ax11.set_title("Actual Validation Dataset")
ax12.set_title("KNN Prediction Dataset (N=3)")
```

Out[34]: Text(0.5, 1.0, 'KNN Prediction Dataset (N=3)')



I prefer the K-Nearest Neighbors model due to its relatively high accuracy and the fact that we can check for over-fitting. In the logistic regression model, if we have over fitted as evidenced by the higher accuracy for the validation / hidden dataset than the training dataset, we couldn't do much to solve it (based on what methods and parameters have been covered).

Problem 3(d): Breast Cancer Dataset

In [ ]:
```
from sklearn.datasets import load_breast_cancer
x,y=load_breast_cancer(return_X_y=True)
```

In [ ]:
```
# # Save to csv if desired
df3d=pd.DataFrame(data=np.concatenate((x,y.reshape(-1,1)),axis=1))
df3d[:5]
df.to_csv('3d.csv')
```

In [ ]:
```
xtrain3d, xvalid3d, ytrain3d, yvalid3d = train_test_split(x, y)
print(xvalid3d.shape)
```

```
(143, 30)
```

In [ ]:
```
model_Logistic_Regression_3d = LogisticRegression(solver = 'liblinear', ran
model_Logistic_Regression_3d.fit(xtrain3d, ytrain3d)
trainscore3d = model_Logistic_Regression_3d.score(xtrain3d, ytrain3d)
validscore3d = model_Logistic_Regression_3d.score(xvalid3d, yvalid3d)

print(f"Training Score: {trainscore3d}\nValidation Score: {validscore3d}")
```

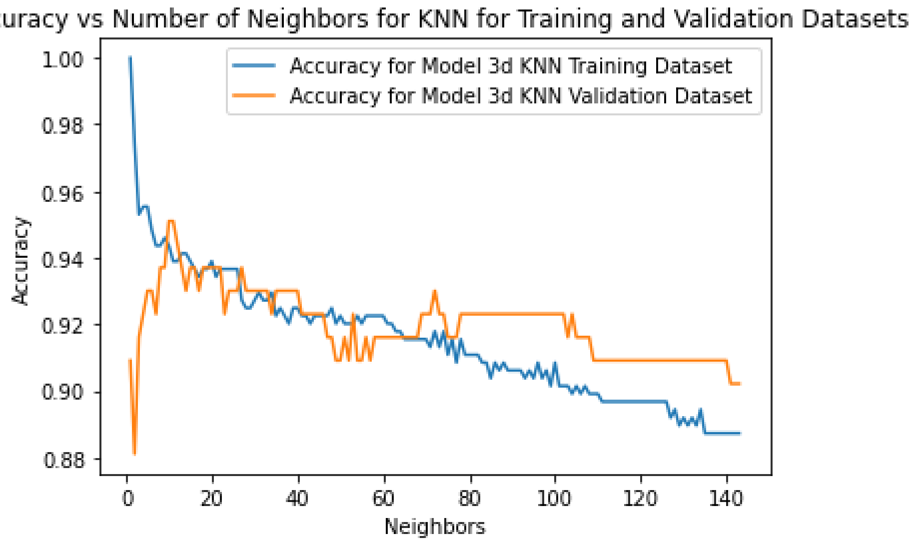
```
Training Score: 0.9694835680751174
Validation Score: 0.951048951048951
```

In [ ]:
```
def model_KNN_3_d(number_of_neighbors):
  model_KNN_3_d = KNeighborsClassifier(n_neighbors=number_of_neighbors)
  model_KNN_3_d.fit(xtrain3d, ytrain3d)
  model_KNN_3_d_train_accuracy = accuracy_score(ytrain3d, model_KNN_3_d.pre
  model_KNN_3_d_valid_accuracy = accuracy_score(yvalid3d, model_KNN_3_d.pre
  print(f"k:{number_of_neighbors} Training Accuracy: {model_KNN_3_d_train_a
  return model_KNN_3_d_train_accuracy, model_KNN_3_d_valid_accuracy
```

In [ ]:
```
model_KNN_3_d_accuracy_train = np.zeros(143)
model_KNN_3_d_accuracy_valid = np.zeros(143)

for k in range(1, 143 + 1):
  model_KNN_3_d_accuracy_train[k-1], model_KNN_3_d_accuracy_valid[k-1] = mo
```

In [ ]:
```
neighbors_3_d = np.linspace(1, 143, 143)

fig11 = plt.figure(num=11, clear=True)
ax13 = fig11.add_subplot(1,1,1)
ax13.plot(neighbors_3_d, model_KNN_3_d_accuracy_train, label = "Accuracy fo
ax13.plot(neighbors_3_d, model_KNN_3_d_accuracy_valid, label = "Accuracy fo
ax13.legend()
ax13.set_xlabel("Neighbors")
ax13.set_ylabel("Accuracy")
ax13.set_title("Accuracy vs Number of Neighbors for KNN for Training and Va
```

Out[41]:
```
Text(0.5, 1.0, 'Accuracy vs Number of Neighbors for KNN for Training and
Validation Datasets')
```



I would prefer the Logistic Regression Model due to its higher accuracy (Validation - 95.8% and Training - 95.3%, compared to Validation - 93.0% and Training - 96.0% for KNN, k=3). However, I would be wary of overfitting, as the validation accuracy for the logistic regression model is higher than the training accuracy. Additionally, we would want to check a matrix of True and False Negatives and True and False Positives, as we would like a higher detection rate of True Positives, despite this possibly increasing the number of False Positives and affecting the overall accuracy, as well as a decreased number of False Negatives, given that we are screening for the presence of cancer.

In [ ]:
```
from sklearn.metrics import confusion_matrix
```

In [ ]:
```
yhat_LogisticRegression_3d = model_Logistic_Regression_3d.predict(xvalid3d)
confusion_matrix(yvalid3d, yhat_LogisticRegression_3d)
```

Out[44]:
```
array([[54,  3],
       [ 4, 82]])
```

In [ ]:
```
model_KNN_3_d_v2 = KNeighborsClassifier(n_neighbors=3)
model_KNN_3_d_v2.fit(xtrain3d, ytrain3d)
yhat_KNN_3d = model_KNN_3_d_v2.predict(xvalid3d)

confusion_matrix(yvalid3d, yhat_KNN_3d)
```

Out[45]:
```
array([[49,  8],
       [ 4, 82]])
```

Comparing the two confusion matrices, KNN with n=3 though less accurate has a higher True Positive count and a lower False Negative count. We would gladly prefer this over the 3-4% accuracy given by the Logistic Regression model.

Problem 4(a): Checking Validation Splits

In [ ]:
```
x_4a,y_4a=make_moons(n_samples=300,noise=.75,random_state=42)
x_4b,y_4b=make_moons(n_samples=300,noise=.75,random_state=24)
x_4c,y_4c=make_moons(n_samples=300,noise=.75,random_state=5)
x_4d,y_4d=make_moons(n_samples=300,noise=.75,random_state=83)
x_4e,y_4e=make_moons(n_samples=300,noise=.75,random_state=63)
```

In [ ]:
```
x_train4a, x_valid4a, y_train4a, y_valid4a = train_test_split(x_4a, y_4a)
x_train4b, x_valid4b, y_train4b, y_valid4b = train_test_split(x_4b, y_4b)
x_train4c, x_valid4c, y_train4c, y_valid4c = train_test_split(x_4c, y_4c)
x_train4d, x_valid4d, y_train4d, y_valid4d = train_test_split(x_4d, y_4d)
x_train4e, x_valid4e, y_train4e, y_valid4e = train_test_split(x_4e, y_4e)
```

In [ ]:
```
def model_KNN_4(number_of_neighbors, xtrain, ytrain, xvalid, yvalid):
  model_KNN_4 = KNeighborsClassifier(n_neighbors=number_of_neighbors)
  model_KNN_4.fit(xtrain, ytrain)
  model_KNN_4_train_accuracy = accuracy_score(ytrain, model_KNN_4.predict(x
  model_KNN_4_valid_accuracy = accuracy_score(yvalid, model_KNN_4.predict(x
  print(f"k:{number_of_neighbors} Training Accuracy: {model_KNN_4_train_acc
  return model_KNN_4_train_accuracy, model_KNN_4_valid_accuracy
```

In [ ]:
```
model_KNN_4_a_accuracy_train = np.zeros(x_valid4a.size)
model_KNN_4_a_accuracy_valid = np.zeros(x_valid4a.size)

for k in range(1, x_valid4a.size + 1):
  model_KNN_4_a_accuracy_train[k-1], model_KNN_4_a_accuracy_valid[k-1] = mo
```

In [ ]:
```
model_KNN_4_b_accuracy_train = np.zeros(x_valid4b.size)
model_KNN_4_b_accuracy_valid = np.zeros(x_valid4b.size)

for k in range(1, x_valid4b.size + 1):
  model_KNN_4_b_accuracy_train[k-1], model_KNN_4_b_accuracy_valid[k-1] = mo
```

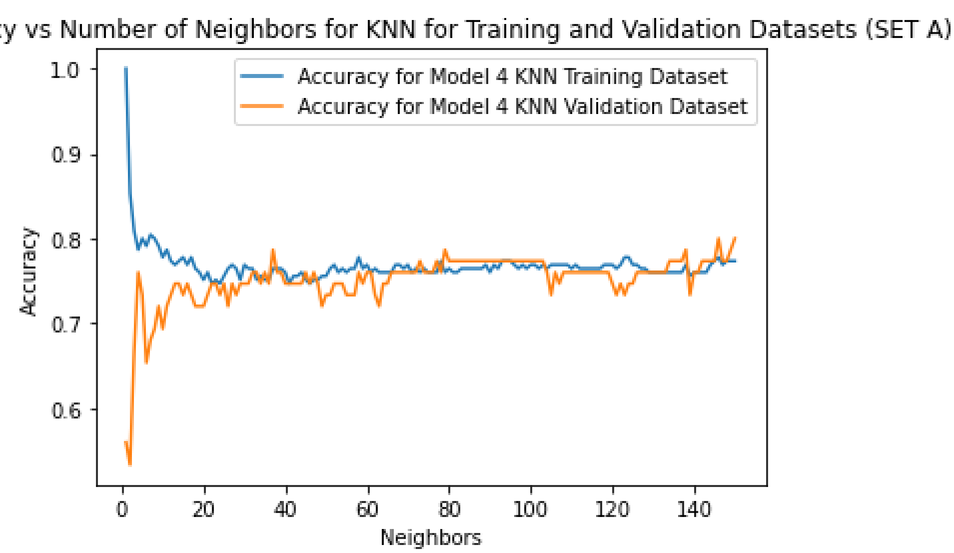
In [ ]:
```
model_KNN_4_c_accuracy_train = np.zeros(x_valid4c.size)
model_KNN_4_c_accuracy_valid = np.zeros(x_valid4c.size)

for k in range(1, x_valid4c.size + 1):
  model_KNN_4_c_accuracy_train[k-1], model_KNN_4_c_accuracy_valid[k-1] = mo
```

In [ ]:
```
model_KNN_4_d_accuracy_train = np.zeros(x_valid4d.size)
model_KNN_4_d_accuracy_valid = np.zeros(x_valid4d.size)

for k in range(1, x_valid4d.size + 1):
  model_KNN_4_d_accuracy_train[k-1], model_KNN_4_d_accuracy_valid[k-1] = mo
```

In [ ]:
```
model_KNN_4_e_accuracy_train = np.zeros(x_valid4e.size)
model_KNN_4_e_accuracy_valid = np.zeros(x_valid4e.size)

for k in range(1, x_valid4e.size + 1):
  model_KNN_4_e_accuracy_train[k-1], model_KNN_4_e_accuracy_valid[k-1] = mo
```

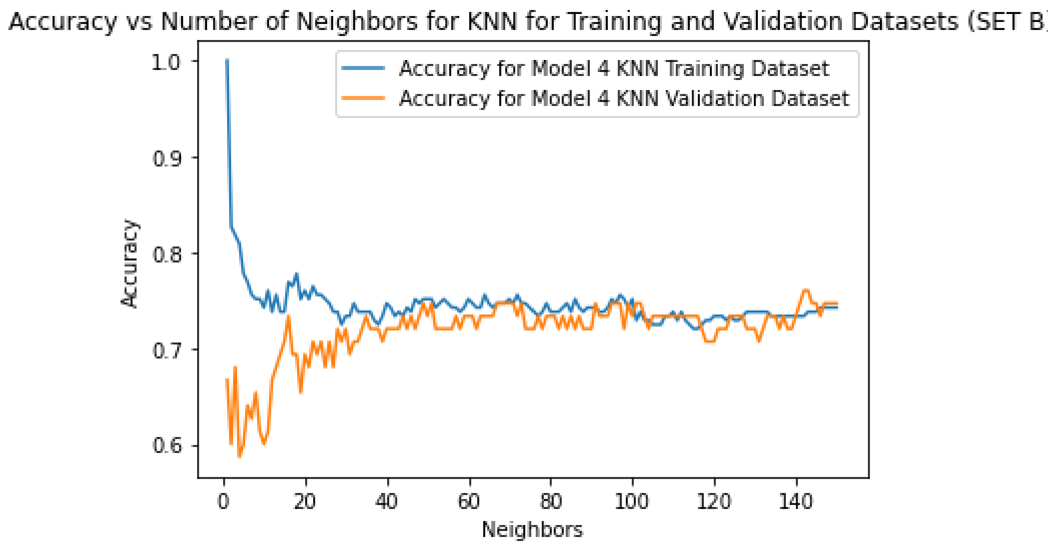
In [ ]:
```
neighbors_4 = np.linspace(1, 150, 150)

fig12 = plt.figure(num=12, clear=True)
ax14 = fig12.add_subplot(1,1,1)
ax14.plot(neighbors_4, model_KNN_4_a_accuracy_train, label = "Accuracy for
ax14.plot(neighbors_4, model_KNN_4_a_accuracy_valid, label = "Accuracy for
ax14.legend()
ax14.set_xlabel("Neighbors")
ax14.set_ylabel("Accuracy")
ax14.set_title("Accuracy vs Number of Neighbors for KNN for Training and Va
```

Out[65]:
```
Text(0.5, 1.0, 'Accuracy vs Number of Neighbors for KNN for Training and
Validation Datasets (SET A)')
```



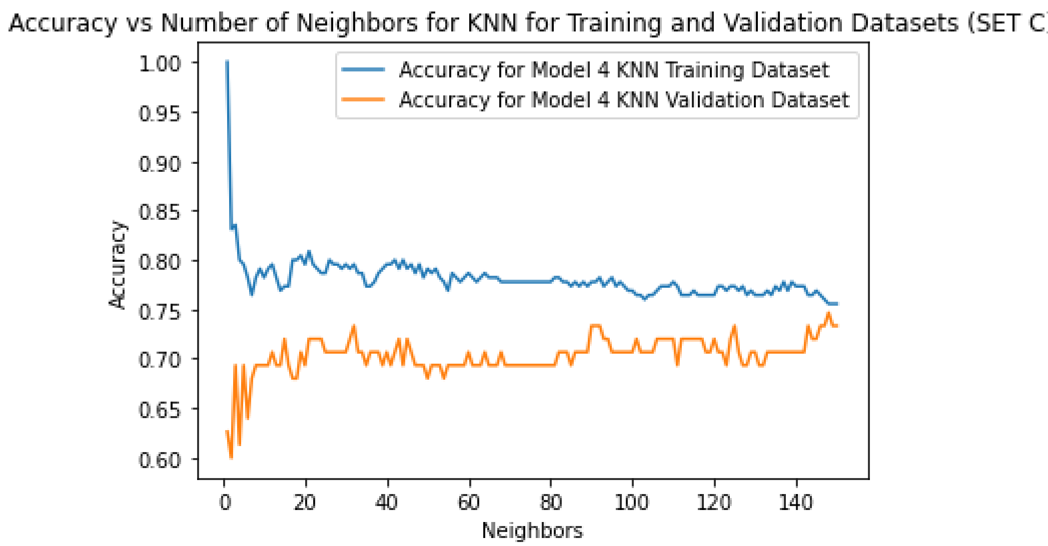
In [ ]:
```
fig13 = plt.figure(num=13, clear=True)
ax15 = fig13.add_subplot(1,1,1)
ax15.plot(neighbors_4, model_KNN_4_b_accuracy_train, label = "Accuracy for
ax15.plot(neighbors_4, model_KNN_4_b_accuracy_valid, label = "Accuracy for
ax15.legend()
ax15.set_xlabel("Neighbors")
ax15.set_ylabel("Accuracy")
ax15.set_title("Accuracy vs Number of Neighbors for KNN for Training and Va
```

Out[63]:
```
Text(0.5, 1.0, 'Accuracy vs Number of Neighbors for KNN for Training and
Validation Datasets (SET B)')
```



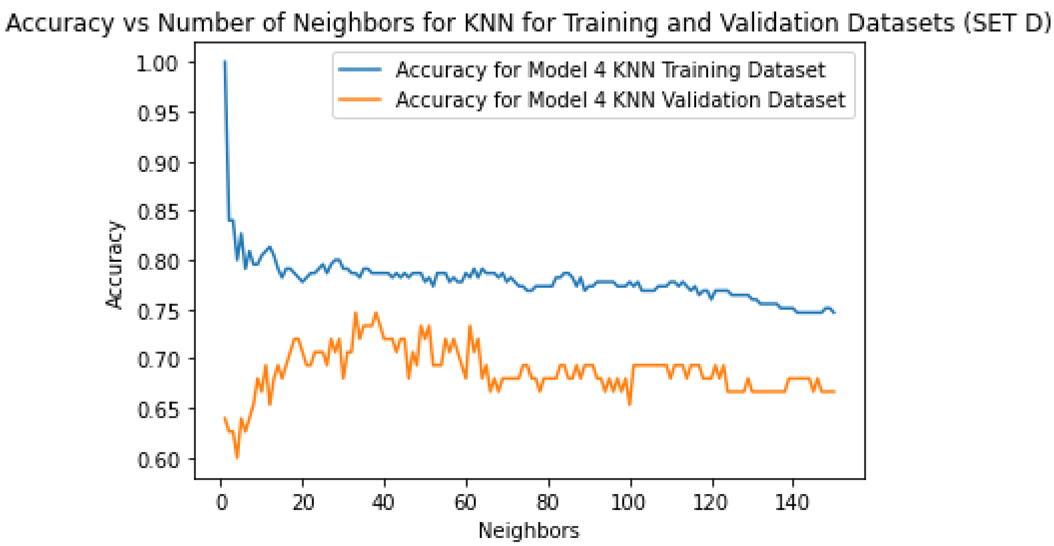
In [ ]:
```
fig14 = plt.figure(num=14, clear=True)
ax16 = fig14.add_subplot(1,1,1)
ax16.plot(neighbors_4, model_KNN_4_c_accuracy_train, label = "Accuracy for
ax16.plot(neighbors_4, model_KNN_4_c_accuracy_valid, label = "Accuracy for
ax16.legend()
ax16.set_xlabel("Neighbors")
ax16.set_ylabel("Accuracy")
ax16.set_title("Accuracy vs Number of Neighbors for KNN for Training and Va
```

Out[62]:
```
Text(0.5, 1.0, 'Accuracy vs Number of Neighbors for KNN for Training and Validation Datasets (SET C)')
```



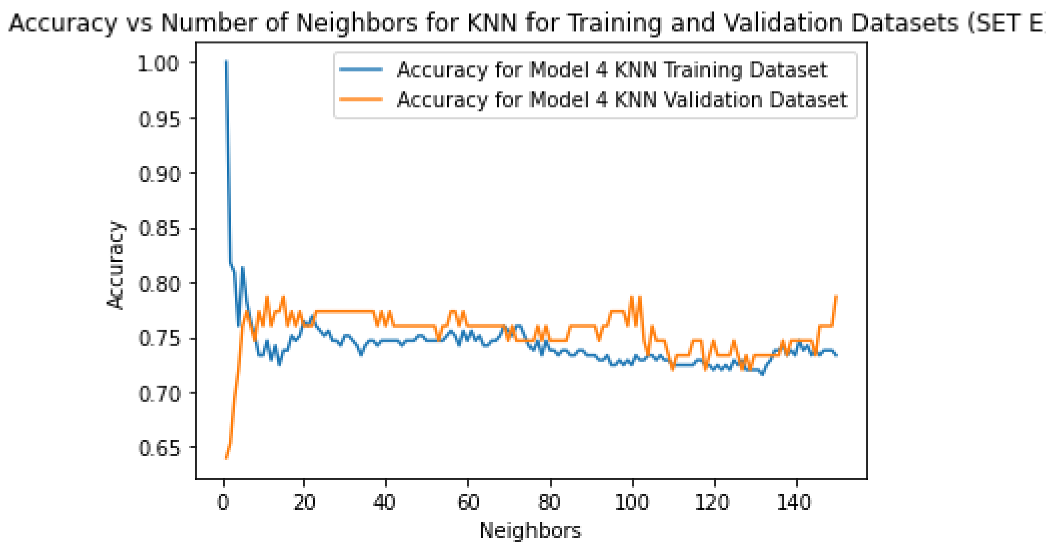
In [ ]:
```
fig15 = plt.figure(num=15, clear=True)
ax17 = fig15.add_subplot(1,1,1)
ax17.plot(neighbors_4, model_KNN_4_d_accuracy_train, label = "Accuracy for
ax17.plot(neighbors_4, model_KNN_4_d_accuracy_valid, label = "Accuracy for
ax17.legend()
ax17.set_xlabel("Neighbors")
ax17.set_ylabel("Accuracy")
ax17.set_title("Accuracy vs Number of Neighbors for KNN for Training and Va
```

Out[61]:
```
Text(0.5, 1.0, 'Accuracy vs Number of Neighbors for KNN for Training and
Validation Datasets (SET D)')
```



In [ ]:
```
fig16 = plt.figure(num=16, clear=True)
ax18 = fig16.add_subplot(1,1,1)
ax18.plot(neighbors_4, model_KNN_4_e_accuracy_train, label = "Accuracy for
ax18.plot(neighbors_4, model_KNN_4_e_accuracy_valid, label = "Accuracy for
ax18.legend()
ax18.set_xlabel("Neighbors")
ax18.set_ylabel("Accuracy")
ax18.set_title("Accuracy vs Number of Neighbors for KNN for Training and Va
```

Out[60]:
```
Text(0.5, 1.0, 'Accuracy vs Number of Neighbors for KNN for Training and
Validation Datasets (SET E)')
```



For Set A, KNN with k = 32 gives the best accuracy pair of 76.44% for Training Dataset and 76% for Validation Dataset.

For Set B, KNN with k = 51 gives the best accuracy pair of 75.11% for Training Dataset and 74.67% for Validation Dataset.

For Set C, KNN with k = 148 gives the best accuracy pair of 75.55% for Training Dataset and 74.67% for Validation Dataset.

For Set D, KNN with k = 33 gives the best accuracy pair of 78.67% for Training Dataset and 74.67% for Validation Dataset.

For Set E, KNN with k = 6 gives the best accuracy pair of 78.22% for Training Dataset and 77.33% for Validation Dataset.

Lastly, for the dataset in Part 3c, k = 11 gives the best accuracy pair of 77.77% for Training Dataset and 77.33% for Validation Dataset.

Problem 4(b): Checking Validation Splits

I expected the varying optimal k-values with the differing splits because the training and validation split of the data using the test_train_split method in the sklearn library splits the data into different sets due to the different values for the random_state argument.

Problem 5

I spent approximately 15-20 hours on this homework. I have adhered to the Duke Community Standard.