In [742...

```
#handle imports
import sys
!{sys.executable} -m pip install numpy
!{sys.executable} -m pip install matplotlib
!{sys.executable} -m pip install sklearn
!{sys.executable} -m pip install pandas
!{sys.executable} -m pip install seaborn
!{sys.executable} -m pip install scipy
!{sys.executable} -m pip install datetime
!{sys.executable} -m pip install arff
%matplotlib inline
%config InlineBackend.figure format = 'retina'
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import arff
from scipy import stats
# use seaborn plotting defaults
import seaborn as sns; sns.set_style('white')
from sklearn.datasets import load digits, make blobs
from sklearn.linear model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy score, plot confusion matrix
from sklearn.model selection import KFold, StratifiedKFold
from sklearn.preprocessing import MinMaxScaler, MaxAbsScaler, StandardScaler, La
from sklearn.preprocessing import RobustScaler, Normalizer, QuantileTransformer,
from sklearn.model selection import GridSearchCV
from sklearn.model selection import train test split, cross val score
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.utils.multiclass import type of target
from sklearn.utils import shuffle
from sklearn.metrics import accuracy score, roc auc score, f1 score
from datetime import datetime
```

```
Requirement already satisfied: numpy in /usr/local/lib/python3.7/site-packages
(1.19.5)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/site-packa
ges (3.3.4)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in /usr/
local/lib/python3.7/site-packages (from matplotlib) (2.4.7)
Requirement already satisfied: numpy>=1.15 in /usr/local/lib/python3.7/site-pack
ages (from matplotlib) (1.19.5)
Requirement already satisfied: python-dateutil>=2.1 in /Users/timothynordahl/Lib
rary/Python/3.7/lib/python/site-packages (from matplotlib) (2.8.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/sit
e-packages (from matplotlib) (1.3.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.7/site-pa
ckages (from matplotlib) (8.1.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/site-pac
kages (from matplotlib) (0.10.0)
Requirement already satisfied: six>=1.5 in /usr/local/Cellar/protobuf/3.7.1/libe
xec/lib/python3.7/site-packages (from python-dateutil>=2.1->matplotlib) (1.12.0)
```

Requirement already satisfied: sklearn in /usr/local/lib/python3.7/site-packages (0.0)Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/site-pac kages (from sklearn) (0.24.1) Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/site-pac kages (from scikit-learn->sklearn) (1.0.0) Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.7/site-pa ckages (from scikit-learn->sklearn) (1.19.5) Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.7/site-pa ckages (from scikit-learn->sklearn) (1.6.0) Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/ site-packages (from scikit-learn->sklearn) (2.1.0) Requirement already satisfied: pandas in /usr/local/lib/python3.7/site-packages (1.2.1)Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/site-pac kages (from pandas) (2020.1) Requirement already satisfied: numpy>=1.16.5 in /usr/local/lib/python3.7/site-pa ckages (from pandas) (1.19.5) Requirement already satisfied: python-dateutil>=2.7.3 in /Users/timothynordahl/L ibrary/Python/3.7/lib/python/site-packages (from pandas) (2.8.0) Requirement already satisfied: six>=1.5 in /usr/local/Cellar/protobuf/3.7.1/libe xec/lib/python3.7/site-packages (from python-dateutil>=2.7.3->pandas) (1.12.0) Requirement already satisfied: seaborn in /usr/local/lib/python3.7/site-packages (0.11.1)Requirement already satisfied: pandas>=0.23 in /usr/local/lib/python3.7/site-pac kages (from seaborn) (1.2.1) Requirement already satisfied: matplotlib>=2.2 in /usr/local/lib/python3.7/sitepackages (from seaborn) (3.3.4) Requirement already satisfied: numpy>=1.15 in /usr/local/lib/python3.7/site-pack ages (from seaborn) (1.19.5) Requirement already satisfied: scipy>=1.0 in /usr/local/lib/python3.7/site-packa ges (from seaborn) (1.6.0) Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/site-pac kages (from pandas>=0.23->seaborn) (2020.1) Requirement already satisfied: python-dateutil>=2.7.3 in /Users/timothynordahl/L ibrary/Python/3.7/lib/python/site-packages (from pandas>=0.23->seaborn) (2.8.0) Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.7/site-pa ckages (from matplotlib>=2.2->seaborn) (8.1.0) Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/sit e-packages (from matplotlib>=2.2->seaborn) (1.3.1) Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in /usr/ local/lib/python3.7/site-packages (from matplotlib>=2.2->seaborn) (2.4.7) Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/site-pac kages (from matplotlib>=2.2->seaborn) (0.10.0) Requirement already satisfied: six>=1.5 in /usr/local/Cellar/protobuf/3.7.1/libe xec/lib/python3.7/site-packages (from python-dateutil>=2.7.3->pandas>=0.23->seab orn) (1.12.0) Requirement already satisfied: scipy in /usr/local/lib/python3.7/site-packages (1.6.0)Requirement already satisfied: numpy>=1.16.5 in /usr/local/lib/python3.7/site-pa ckages (from scipy) (1.19.5) Requirement already satisfied: datetime in /usr/local/lib/python3.7/site-package s(4.3)Requirement already satisfied: pytz in /usr/local/lib/python3.7/site-packages (f rom datetime) (2020.1) Requirement already satisfied: zope.interface in /usr/local/lib/python3.7/site-p ackages (from datetime) (5.2.0) Requirement already satisfied: setuptools in /usr/local/lib/python3.7/site-packa ges (from zope.interface->datetime) (41.0.1) Requirement already satisfied: arff in /usr/local/lib/python3.7/site-packages (0.9)

In [950...

#import letter dataframe

letter_df = pd.read_csv("/Users/timothynordahl/Desktop/COGS118AFinalProject/lett

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final letter_df.head() 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 Out[950... **0** T 2 8 3 5 1 8 13 0 6 6 10 8 0 8 0 8 I 5 12 3 7 2 10 5 5 4 3 2 13 9 8 4 10 **2** D 4 11 6 8 6 10 2 7 3 7 3 9 6 6 10 3 **3** N 7 11 6 6 3 5 9 4 6 4 4 10 6 10 2 8 **4** G 2 6 6 6 5 1 3 1 1 8 6 9 1 7 5 10 In [951... #set A-M as 1 and N-Z as 0 dict = {'A': 1, 'B': 2, 'C': 3, 'D': 4, 'E': 5, 'F': 6, 'G': 7, 'H': 8, 'I': 9, 'J': 10, 'K': 11, 'L': 12, 'M': 13, 'N': 14, 'O': 15, 'P': 16, 'Q': 17, 'R': 18, 'S': 19, 'T': 20, 'U': 21, 'V': 22, 'W': 23, 'X': 24, 'Y': 25, 'Z': 26, } for i in range(letter df[0].size): letter_df[0][i] = dict[letter_df[0][i]] if letter df[0][i] <= 13:</pre> $letter_df[0][i] = 1$ else: letter df[0][i] = 0letter df = letter df.astype('int')

```
letter df.shape
Out[243... (20000, 17)
In [862...
           #Check #positive
          letter_df_pos = letter_df[letter_df[0] == 1]
```

In [243...

```
letter df pos.shape
Out[862... (9940, 17)
In [126...
          #import occupancy data
          occupancy df = pd.read csv("/Users/timothynordahl/Desktop/COGS118AFinalProject/o
In [127...
          #convert datetime data to cyclic seconds past midnight, drop date
          datetime_object = datetime.fromisoformat('2015-02-04 17:51:00')
          pd.options.mode.chained_assignment = None # default='warn'
          for i in range ((occupancy_df['date']).size):
               occupancy_df['date'][i+1] = datetime.fromisoformat(occupancy_df['date'][i+1]
          time_sec = 0
          occupancy_df['sec'] = occupancy_df['CO2']
          for i in range ((occupancy df['date']).size):
               time_sec = occupancy_df['date'][i+1]
               occupancy_df['sec'][i+1] = (time_sec - time_sec.replace(hour=0, minute=0, se
          seconds_in_day = 24*60*60
          occupancy_df['sin_sec'] = np.sin(2*np.pi*occupancy_df.sec/seconds_in_day)
          occupancy_df['cos_sec'] = np.cos(2*np.pi*occupancy_df.sec/seconds_in_day)
          del occupancy_df['date']
          del occupancy df['sec']
          occupancy df.head()
             Temperature Humidity Light
                                          CO2 HumidityRatio Occupancy
                                                                          sin_sec
                                                                                   cos_sec
Out[127...
          1
                   23.18
                          27.2720 426.0 721.25
                                                   0.004793
                                                                     1 -0.999229 -0.039260
          2
                   23.15
                          27.2675 429.5 714.00
                                                   0.004783
                                                                     1 -0.999388 -0.034972
                          27.2450 426.0 713.50
          3
                   23.15
                                                   0.004779
                                                                     1 -0.999534 -0.030539
          4
                   23.15
                          27.2000 426.0 708.25
                                                    0.004772
                                                                     1 -0.999657
                                                                                  -0.026177
          5
                   23.10
                          27.2000 426.0 704.50
                                                    0.004757
                                                                     1 -0.999762
                                                                                  -0.021815
In [128...
          occupancy df.shape
Out[128... (8143, 8)
In [129...
          #set occupancy as first column
          occupancy_df = occupancy_df[['Occupancy','Temperature','Humidity','Light','CO2',
          occupancy df.head()
             Occupancy Temperature Humidity Light
                                                     CO2 HumidityRatio
Out[129...
                                                                          sin_sec
                                                                                    cos_sec
          1
                     1
                                     27.2720 426.0 721.25
                              23.18
                                                              0.004793 -0.999229 -0.039260
          2
                     1
                              23.15
                                     27.2675 429.5 714.00
                                                              0.004783 -0.999388 -0.034972
```

Occupancy Temperature Humidity Light

```
23.15
           3
                       1
                                        27.2450
                                                426.0
                                                       713.50
                                                                   0.004779
                                                                            -0.999534
                                                                                        -0.030539
           4
                       1
                                23.15
                                        27.2000
                                                426.0
                                                      708.25
                                                                   0.004772
                                                                             -0.999657
                                                                                        -0.026177
           5
                       1
                                        27.2000 426.0 704.50
                                23.10
                                                                   0.004757
                                                                             -0.999762
                                                                                        -0.021815
In [860...
           #get positive number for pos rate
           occupancy_df_pos = occupancy_df[occupancy_df['Occupancy']==1]
           occupancy df pos.shape
Out[860... (1729, 8)
In [382...
           #import eeg eye state data
           EEG eye df = pd.read csv("/Users/timothynordahl/Desktop/COGS118AFinalProject/EEG
           EEG eye df.shape
Out[382... (14980, 15)
In [441...
           EEG eye df.dropna()
           EEG_eye_df.head()
                   0
                             1
                                     2
                                              3
                                                      4
                                                               5
                                                                        6
                                                                                 7
                                                                                          8
                                                                                                   9
Out[441...
           0 4329.23
                      4009.23 4289.23 4148.21 4350.26
                                                          4586.15
                                                                  4096.92
                                                                           4641.03 4222.05 4238.46
             4324.62 4004.62 4293.85 4148.72 4342.05
                                                         4586.67
                                                                   4097.44
                                                                           4638.97
                                                                                    4210.77
                                                                                             4226.67
             4327.69 4006.67 4295.38
                                        4156.41 4336.92 4583.59
                                                                  4096.92
                                                                           4630.26
                                                                                    4207.69
                                                                                             4222.05 4
             4328.72
                       4011.79
                               4296.41
                                        4155.90
                                                4343.59
                                                         4582.56
                                                                   4097.44
                                                                           4630.77
                                                                                    4217.44
                                                                                             4235.38
              4326.15
                       4011.79
                               4292.31
                                        4151.28
                                                 4347.69
                                                         4586.67
                                                                  4095.90
                                                                           4627.69
                                                                                    4210.77
                                                                                             4244.10
In [858...
           EEG eye df pos = EEG eye df[EEG eye df[14]==1]
           EEG eye df pos.shape
Out[858... (6723, 15)
In [494...
           #import avila data
           avila df = pd.read csv("/Users/timothynordahl/Desktop/COGS118AFinalProject/avila
           avila df.head()
                     0
                               1
                                          2
                                                                                               7
                                                     3
                                                               4
                                                                          5
                                                                                    6
Out[494...
           0
              0.266074
                        -0.165620
                                   0.320980
                                              0.483299
                                                         0.172340
                                                                   0.273364
                                                                              0.371178
                                                                                        0.929823
                                                                                                   0.25
           1
              0.130292
                        0.870736
                                  -3.210528
                                              0.062493
                                                         0.261718
                                                                   1.436060
                                                                             1.465940
                                                                                        0.636203
                                                                                                  0.28:
           2
              -0.116585
                         0.069915
                                   0.068476
                                             -0.783147
                                                         0.261718
                                                                   0.439463
                                                                             -0.081827
                                                                                       -0.888236
                                                                                                  -0.12:
           3
              0.031541
                        0.297600
                                  -3.210528 -0.583590 -0.721442
                                                                  -0.307984
                                                                             0.710932
                                                                                        1.051693
                                                                                                  0.59
```

CO2 HumidityRatio

sin_sec

cos_sec

```
0
                                       2
                                                3
                                                                    5
          4 0.229043
                      0.807926 -0.052442
                                          0.082634
                                                    0.261718
                                                              0.148790
                                                                       0.635431
                                                                                 0.051062
                                                                                          0.03:
In [495...
          avila df.shape
Out[495... (20867, 11)
In [496...
          avila_df = avila_df.replace('A',1)
          avila_df = avila_df.replace('B',1)
          avila_df = avila_df.replace('C',1)
          avila_df = avila_df.replace('D',1)
          avila_df = avila_df.replace('E',1)
          avila_df = avila_df.replace('F',1)
          avila_df = avila_df.replace('G',0)
          avila_df = avila_df.replace('H',0)
          avila_df = avila_df.replace('I',0)
          avila df = avila df.replace('W',0)
          avila_df = avila_df.replace('X',0)
          avila_df = avila_df.replace('Y',0)
          avila_df[10].unique()
Out[496... array([1, 0])
In [856...
          #get avila pos number
          avila df pos = avila df[avila df[10]==1]
          avila df pos.shape
Out[856... (15606, 11)
In [498...
          # Establish list of dataframes and the associated classification column
          data list = [(avila df,10),(EEG eye df, 14),(occupancy df, 'Occupancy'), (letter
          # Add Name property to dataframes
          occupancy_df.name = "Occupancy"
          EEG eye df.name = "EEG Eye"
          letter_df.name = "Letter"
          avila df.name = "Avila"
          # Create dict of dataframes
          dict = {
               'Occupancy Dataset' : occupancy_df,
               'EEG Eye Dataset' : EEG eye df,
               'Letters Dataset' : letter df,
               'Avila Dataset' : avila df,
          }
In [765...
          # Create pipeline packaging a standard scaler and logistic regression classifier
          pipe = Pipeline([('std', StandardScaler()),
                            ('classifier', LogisticRegression())])
```

```
# Create search space of hyperparameters for logreg model
search space = [{'classifier': [LogisticRegression(max iter=5000)],
                 'classifier__solver': ['saga'],
                 'classifier__penalty': ['l1', 'l2'],
                 'classifier__C': np.logspace(-8, 4, 13),
                 'classifier__random_state':[1000]},
                {'classifier': [LogisticRegression(max_iter=5000)],
                 'classifier solver': ['lbfgs', 'newton-cg', 'sag'],
                 'classifier__penalty': ['none'],
                 'classifier__random_state':[1000]},
                {'classifier': [LogisticRegression(max_iter=5000)],
                 'classifier solver': ['lbfgs', 'newton-cg', 'sag'],
                 'classifier__penalty': ['12'],
                 'classifier__C': np.logspace(-8, 4, 13),
                 'classifier__random_state':[1000]},
                {'classifier': [LogisticRegression(max_iter=5000)],
                 'classifier__solver': ['liblinear'],
                 'classifier__penalty': ['l1','l2'],
                 'classifier C': np.logspace(-8, 4, 13),
                 'classifier__random_state':[1000]}
# instantiate lists to store data from loop
best logreg trials = []
best_logreg_by_data = []
best_logreg_metrics = []
# Loop through each dataframe, collecting the df and Y column
for data_set, target_name in data_list:
    #print line for monitoring purposes
    print("Now working on: ", data_set.name)
    #reset list for later iteration
   best logreg trials = []
    for i in range(5):
        #reset list for later iteration
        best logreg metrics = []
        #Honestly I got frustrated working with gathering params and setting par
        #while unnecessary, it did save time overall as debugging was taking lon
        #for lack of elegance/scalability
        clf = [GridSearchCV(pipe, search space, cv=StratifiedKFold(n splits=5, s
                   scoring=['accuracy'], refit='accuracy', verbose=0,n jobs=-1),
               GridSearchCV(pipe, search space, cv=StratifiedKFold(n splits=5, s
                   scoring=['roc_auc_ovr'], refit='roc_auc_ovr', verbose=0,n_job
               GridSearchCV(pipe, search space, cv=StratifiedKFold(n splits=5, s
                   scoring=['f1_micro'], refit='f1_micro', verbose=0,n_jobs=-1)
        print('Onto trial: ', i + 1)
        # Set X to a sample of 5000 from the current dataset, make Y the relevan
        X = \text{data set.sample}(n = 5000, \text{ random state} = i * 5, \text{ axis} = 0)
        Y = X[target name]
        X = X.drop([target name],axis=1)
        #fit each gridsearch instance and add it to the metric list
        for j in clf:
            best logreg metrics.append(j.fit(X,Y))
```

```
#add the results from each trial to the trial list
best_logreg_trials.append(best_logreg_metrics)

#add the results from each set of trials data list
best_logreg_by_data.append(best_logreg_trials)

print("Finished!")
```

```
Now working on:
               Avila
Onto trial: 1
Onto trial: 2
Onto trial: 3
Onto trial: 4
Onto trial: 5
Now working on:
               EEG Eye
Onto trial: 1
Onto trial: 2
Onto trial: 3
Onto trial: 4
Onto trial: 5
Now working on:
               Occupancy
Onto trial: 1
Onto trial: 2
Onto trial: 3
Onto trial: 4
Onto trial: 5
Now working on:
               Letter
Onto trial: 1
Onto trial: 2
Onto trial: 3
Onto trial: 4
Onto trial: 5
Finished!
```

```
In [930...
```

```
# instantiate standard scaler object
std = StandardScaler()
# establish iteration lists for both the test data and training data
log reg predict metric = []
log reg predict trial = []
log_reg_predict_data = []
log_reg_sample_metric = []
log reg sample trial = []
log reg sample data = []
j = 0
#iterate through the data list again
for data set, target name in data list:
    #print to let me know where the program is running
    print("Now working on: ", data_set.name)
    #reset lists to collect trial data
    log reg predict trial = []
    log_reg_sample_trial = []
    for i in range(5):
        #print to let me know where the program is running
```

print("Onto trial:", i+1)

```
#reset lists to collect trial data
         log reg sample metric = []
         log_reg_predict_metric= []
         for k in range(3):
             # collect the best estimator from the clf collection
             log_reg = best_logreg_by_data[j][i][k].best_estimator_[1]
             # set X and Y to the same data sample as before, this time scaling i
             X = \text{data set.sample}(n = 5000, \text{ random state} = i * 5, \text{ axis} = 0)
             Y = X[target name]
             X = X.drop([target_name], axis=1)
             std.fit(X)
             X = std.transform(X)
             # fit the best model for each metric on the training data
             log reg.fit(X,Y)
             # Predict and score the model on the same training data
             if k % 3 == 0:
                 log_reg_sample_metric.append(accuracy_score(Y,log reg.predict(X))
             elif k % 3 == 1:
                 log_reg_sample_metric.append(roc_auc_score(Y,log_reg.predict(X))
             else:
                 log reg sample metric.append(f1 score(Y,log reg.predict(X)))
             #Set X and Y as the whole dataset, again scaling X
             X = data set.drop([target name], axis=1)
             Y = data set[target name]
             std.fit(X)
             X = std.transform(X)
             # Using the same fit model from above, predict and score it for the
             if k % 3 == 0:
                 log reg predict metric.append(accuracy score(Y,log reg.predict(X))
             elif k % 3 == 1:
                 log reg predict metric.append(roc auc score(Y,log reg.predict(X))
             else:
                 log reg predict metric.append(f1 score(Y,log reg.predict(X)))
         #Record results for the trial
         log reg predict trial.append(log_reg_predict_metric)
         log reg sample trial.append(log reg sample metric)
     #record results for the dataset
     log reg predict data.append(log reg predict trial)
     log reg sample data.append(log reg sample trial)
     i+=1
print("Finished!")
LogisticRegression(C=10.0, max iter=5000, penalty='11', random state=1000,
                   solver='saga')
Now working on: Avila
Onto trial: 1
Onto trial: 2
Onto trial: 3
Onto trial: 4
```

```
Onto trial: 5
         Now working on: EEG Eye
         Onto trial: 1
         Onto trial: 2
         Onto trial: 3
         Onto trial: 4
         Onto trial: 5
         Now working on:
                          Occupancy
         Onto trial: 1
         Onto trial: 2
         Onto trial: 3
         Onto trial: 4
         Onto trial: 5
         Now working on: Letter
         Onto trial: 1
         Onto trial: 2
         Onto trial: 3
         Onto trial: 4
         Onto trial: 5
         Finished!
In [955...
          #instantiate lists to be used for ttests here were working with scores for the w
          log reg avg metric = []
          log_reg_avg_data = []
          log_acc = []
          log_roc = []
          log_f1 = []
          temp = []
          log_data1 = []
          #loop through the score data for the whole datasets
          for i in log reg predict data:
              #scrub lists
              log_reg_avg_metric = []
              temp = []
              #iterate for each trial
              for j in range(5):
                  #Get the error metric values into their respective lists
                  log acc.append(i[j][0])
                  log roc.append(i[j][1])
                  log f1.append(i[j][2])
                  #temp is used to format data1 so the error metrics go in in lists of 3
                  for k in range(3):
                      temp.append(i[j][k])
              #append temp to datal which will hold all of the data for each dataset and t
              log data1.append(temp)
              #gather the means of each metric for all trials
              log reg avg metric.append(np.mean([i[0][0],i[1][0],i[2][0],i[3][0],i[4][0]])
              log_reg_avg_metric.append(np.mean([i[0][1],i[1][1],i[2][1],i[3][1],i[4][1]])
              log_reg_avg_metric.append(np.mean([i[0][2],i[1][2],i[2][2],i[3][2],i[4][2]])
              log reg avg data.append(log reg avg metric)
          print(log data1)
```

[[0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.

9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8 607370489289309, 0.744731689153132, 0.9131084798469083], [0.8607370489289309, 0.744731689153132, 0.9131084798469083], [0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083, 0.8607370489289309, 0.744731689153132, 0.9131084798469083]]

```
In [944...
          #instantiate lists to be used for ttests here were working with scores for the s
          log reg sample avg metric = []
          log_reg_sample_avg_data = []
          log sample acc = []
          log_sample_roc = []
          log_sample_f1 = []
          temp = []
          log data2 = []
          #loop through the score data for the sampled datasets
          for i in log_reg_sample_data:
              #scrub lists
              log_reg_sample_avg_metric = []
              temp = []
              #iterate for each trial
              for j in range(5):
                  #Get the error metric values into their respective lists
                  log sample acc.append(i[j][0])
                  log sample roc.append(i[j][1])
                  log sample f1.append(i[j][2])
                  #temp is used to format data1 so the error metrics go in in lists of 3
                  for k in range(3):
                      temp.append(i[j][k])
              #append temp to datal which will hold all of the data for each dataset and t
              log data2.append(temp)
              #gather the means of each metric for all trials
              log reg sample avg metric.append(np.mean([i[0][0],i[1][0],i[2][0],i[3][0],i[
              log reg sample avg metric.append(np.mean([i[0][1],i[1][1],i[2][1],i[3][1],i[
              log reg sample avg metric.append(np.mean([i[0][2],i[1][2],i[2][2],i[3][2],i[
              log reg sample avg data.append(log reg sample avg metric)
          print(log reg sample avg data)
```

[[0.8612, 0.7510454600786453, 0.9129907934591974], [0.64276, 0.628695333450083, 0.5527368053801064], [0.98864, 0.9870964623764469, 0.9741458661548628], [0.72972 0000000001, 0.7298269699162919, 0.7303042008734786]]

```
# Create decision tree classifier
dec_tree = DecisionTreeClassifier()

# Create search space of hyperparameters for dectree model
search_space = [{
```

```
'criterion': ['gini', 'entropy'],
                  'splitter': ['best', 'random'],
                  'max_depth': [None, 2, 4, 6, 8, 10, 12],
                  'min_samples_split': [2,4,6,8,10],
                  'min_samples_leaf': [2,4,6,8,10],
                  'max_features': ['auto','sqrt','log2',None],
                  'random state':[1000]}
# instantiate lists to store data from loop
best_dectree_trials = []
best dectree by data = []
# Loop through each dataframe, collecting the df and Y column
for data set, target name in data list:
    #print line for monitoring purposes
    print("Now working on: ", data_set.name)
    #reset list for later iteration
    best_dectree_trials = []
    for i in range(5):
        #set up gridsearch instance for three performance metrics
        clf = GridSearchCV(dec_tree, search_space, cv=StratifiedKFold(n_splits=5
                    scoring=['accuracy', 'roc_auc_ovr', 'f1_micro'], refit=False,
                    verbose=0,n_jobs=-1)
        print('Onto trial: ', i + 1)
        # Set X to a sample of 5000 from the current dataset, make Y the relevan
        X = data_set.sample(n = 5000, random_state = i * 5, axis = 0)
        Y = X[target name]
        X = X.drop([target name],axis=1)
        #add the results from each trial to the trial list
        best dectree trials.append(clf.fit(X, Y))
    #add the results from each set of trials data list
    best dectree by data.append(best dectree trials)
print("Finished!")
Now working on: Avila
```

```
Onto trial: 1
Onto trial: 2
Onto trial: 3
Onto trial: 4
Onto trial: 5
Now working on:
               EEG Eye
Onto trial: 1
Onto trial: 2
Onto trial: 3
Onto trial: 4
Onto trial: 5
Now working on:
               Occupancy
Onto trial: 1
Onto trial: 2
Onto trial: 3
Onto trial:
Onto trial: 5
```

```
Now working on: Letter
         Onto trial: 1
         Onto trial: 2
         Onto trial: 3
         Onto trial:
         Onto trial: 5
         Finished!
In [929...
          # establish iteration lists for both the test data and training data
          dec_tree_predict_metric = []
          dec tree predict trial = []
          dec_tree_predict_data = []
          dec_tree_sample_metric = []
          dec tree sample trial = []
          dec_tree_sample_data = []
          i=0
          #iterate through the data list again
          for data_set, target_name in data_list:
              #print to let me know where the program is running
              print("Now Working On: ", data set.name)
              #reset lists to collect trial data
              dec tree predict trial = []
              dec_tree_sample_trial = []
              for j in range(5):
                  #print to let me know where the program is running
                  print("Onto Trial: ", j + 1)
                  temp = best dectree by data[i][j].cv results
                  #gather best params from gridsearch by performance metric
                  error metric = []
                  error metric.append(np.where(temp['rank test accuracy'] == 1))
                  error metric.append(np.where(temp['rank test roc auc ovr'] == 1))
                  error metric.append(np.where(temp['rank test f1 micro'] == 1))
                  #reset lists to collect trial data
                  dec tree predict metric = []
                  dec_tree_sample_metric = []
                  for k in range(3):
                      #make decision tree instance with best params for each error metric
                      error metric[k] = error metric[k][0][0]
                      best temp = temp['params'][error metric[k]]
                      dec_tree = DecisionTreeClassifier(criterion=best temp['criterion'],m
                      # set X and Y to the same data sample as before
                      X = \text{data set.sample}(n = 5000, \text{ random state} = i * 5, \text{ axis} = 0)
                      Y = X[target_name]
                      X = X.drop([target name], axis=1)
                      dec tree.fit(X,Y)
                      # Predict and score the model on the same training data
                      if k % 3 == 0:
                          dec tree sample metric.append(accuracy score(Y, dec tree.predict(
                      elif k % 3 == 1:
```

```
dec tree sample metric.append(roc auc score(Y, dec tree.predict(X)
            else:
                dec tree sample metric.append(f1 score(Y,dec tree.predict(X)))
            #Set X and Y as the whole dataset
            X = data_set.drop([target_name], axis=1)
            Y = data set[target name]
            # Using the same fit model from above, predict and score it for the
            if k % 3 == 0:
                dec tree predict metric.append(accuracy score(Y, dec tree.predict
            elif k % 3 == 1:
                dec_tree_predict_metric.append(roc_auc_score(Y,dec_tree.predict(
            else:
                dec_tree_predict_metric.append(f1_score(Y,dec_tree.predict(X)))
        #Record results for the trial
        dec tree sample trial.append(dec tree sample metric)
        dec_tree_predict_trial.append(dec_tree_predict_metric)
    #record results for the dataset
    dec tree predict data.append(dec tree predict trial)
    dec_tree_sample_data.append(dec_tree_sample_trial)
    i+=1
print("Finished!")
```

```
Now Working On:
                Avila
Onto Trial: 1
Onto Trial: 2
Onto Trial: 3
Onto Trial: 4
Onto Trial: 5
Now Working On:
                EEG Eye
Onto Trial: 1
Onto Trial: 2
Onto Trial: 3
Onto Trial: 4
Onto Trial: 5
Now Working On:
                Occupancy
Onto Trial: 1
Onto Trial: 2
Onto Trial: 3
Onto Trial: 4
Onto Trial: 5
Now Working On:
               Letter
Onto Trial: 1
Onto Trial: 2
Onto Trial: 3
Onto Trial: 4
Onto Trial: 5
Finished!
```

```
In [928...
```

```
print(dec_tree_sample_data)
```

 $\begin{bmatrix} 0.859479305740988, & 0.8224334727613192, & 0.8418363513411976] \end{bmatrix}, & [[0.9960702443816775, & 0.9890084641697068, & 0.9907460960092539], & [0.9927545130787179, & 0.9917418753763592, & 0.9829134086301767], & [0.9939825617094437, & 0.9874468498366878, & 0.9858012170385396], & [0.9942281714355888, & 0.9839238396054899, & 0.9863491141446412], & [0.9958246346555324, & 0.98990964729229709, & 0.9901677270098322]], & [[0.9008, & 0.8634865855170785, & 0.8984335005631207], & [0.8936, & 0.8699036165301951, & 0.8901847455877799], & [0.908, & 0.8699036165301951, & 0.894335005631207], & [0.9045, & 0.8645381233724414, & 0.902937290375038], & [0.9045, & 0.8699036165301951, & 0.902937290375038]]]$

```
In [911...
          #instantiate lists to be used for ttests here were working with scores for the w
          dec_tree_avg_metric = []
          dec tree avg data = []
          dec_acc = []
          dec_roc = []
          dec_f1 = []
          temp = []
          dec_data1 = []
          #loop through the score data for the whole datasets
          for i in dec_tree_predict_data:
              #scrub lists
              temp = []
              #iterate for each trial
              for j in range(5):
                  #Get the error metric values into their respective lists
                  dec acc.append(i[j][0])
                  dec roc.append(i[j][1])
                  dec f1.append(i[j][2])
                  #temp is used to format data1 so the error metrics go in in lists of 3
                  for k in range(3):
                      temp.append(i[j][k])
              #append temp to datal which will hold all of the data for each dataset and t
              dec data1.append(temp)
              #gather the means of each metric for all trials
              dec tree avg metric = []
              dec_tree_avg_metric.append(np.mean([i[0][0],i[1][0],i[2][0],i[3][0],i[4][0]]
              dec_tree_avg_metric.append(np.mean([i[0][1],i[1][1],i[2][1],i[3][1],i[4][1]]
              dec tree avg metric.append(np.mean([i[0][2],i[1][2],i[2][2],i[3][2],i[4][2]]
              dec tree avg data.append(dec tree avg metric)
          print(dec tree avg data)
         [[0.9690995351511956, 0.9169383224515361, 0.979259500773263], [0.84421895861148
```

[[0.9690995351511956, 0.9169383224515361, 0.979259500773263], [0.84421895861148 2, 0.8149624662758704, 0.824458280219112], [0.9945720250521921, 0.98824350038224 3, 0.9871955125664889], [0.90084, 0.8675471116960211, 0.8985852654928195]]

```
#instantiate lists to be used for ttests here were working with scores for the s
dec_tree_sample_avg_metric = []
dec_tree_sample_avg_data = []
dec_sample_acc = []
dec_sample_roc = []
dec_sample_f1 = []
temp = []
dec_data2 = []
```

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```
#loop through the score data for the sampled datasets
          for i in dec tree sample data:
              #scrub lists
              temp = []
              #iterate for each trial
              for j in range(5):
                  #Get the error metric values into their respective lists
                  dec_sample_acc.append(i[j][0])
                  dec sample roc.append(i[j][1])
                  dec_sample_f1.append(i[j][2])
                  #temp is used to format data1 so the error metrics go in in lists of 3
                  for k in range(3):
                      temp.append(i[j][k])
              #append temp to datal which will hold all of the data for each dataset and {\mathsf t}
              dec_data2.append(temp)
              #gather the means of each metric for all trials
              dec tree sample avg metric = []
              dec tree sample_avg_metric.append(np.mean([i[0][0],i[1][0],i[2][0],i[3][0],i
              dec_tree_sample_avg_metric.append(np.mean([i[0][1],i[1][1],i[2][1],i[3][1],i
              dec_tree_sample_avg_metric.append(np.mean([i[0][2],i[1][2],i[2][2],i[3][2],i
              dec_tree_sample_avg_data.append(dec_tree_sample_avg_metric)
          print(dec_tree_sample_avg_data)
         [[0.99448, 0.9388680987639477, 0.9962634087052418], [0.94176, 0.873127518021153
         6, 0.9336664475183228], [0.9963599999999999, 0.9896067697870631, 0.9913051550939
         619], [0.97256, 0.9030489952569335, 0.9717230593093819]]
In [836...
          # Create random forest classifier
          rand forest = RandomForestClassifier()
          # Create search space of hyperparameters for dectree model
          search space = [{
                            'n estimators': [1024],
                           'warm start':[True,False],
                           'criterion': ['gini', 'entropy'],
                           'max features': ['sqrt','log2',None,1,2,4,6,7],
                           'random_state' : [1000]
                          }]
          # instantiate lists to store data from loop
          best rf trials = []
          best rf by data = []
          # Loop through each dataframe, collecting the df and Y column
          for data set, target name in data list:
              #print line for monitoring purposes
              print("Now working on: ", data set.name)
              #reset list for later iteration
              best rf trials = []
              for i in range(5):
```

```
#set up gridsearch instance for three performance metrics
                  clf = GridSearchCV(rand_forest, search_space, cv=StratifiedKFold(n_split
                             scoring=['accuracy', 'roc_auc_ovr', 'f1_micro'], refit=False,
                             verbose=0,n_jobs=-1)
                  print('Onto trial: ', i + 1)
                  # Set X to a sample of 5000 from the current dataset, make Y the relevan
                  X = data_set.sample(n = 5000, random_state = i * 5, axis = 0)
                  Y = X[target name]
                  X = X.drop([target_name],axis=1)
                  #add the results from each trial to the trial list
                  best rf trials.append(clf.fit(X, Y))
              #add the results from each set of trials data list
              best rf by data.append(best rf trials)
          print("Finished!")
         Now working on:
                          Avila
         Onto trial: 1
         Onto trial: 2
         Onto trial: 3
         Onto trial: 4
         Onto trial: 5
         Now working on:
                         EEG Eye
         Onto trial: 1
         Onto trial: 2
         Onto trial: 3
         Onto trial: 4
         Onto trial: 5
         Now working on:
                          Occupancy
         Onto trial: 1
         Onto trial: 2
         Onto trial: 3
         Onto trial: 4
         Onto trial: 5
         Now working on:
                         Letter
         Onto trial: 1
         Onto trial: 2
         Onto trial: 3
         Onto trial: 4
         Onto trial: 5
         Finished!
In [934...
          # establish iteration lists for both the test data and training data
          rf predict metric = []
          rf predict trial = []
          rf predict data = []
          rf sample metric = []
          rf sample trial = []
          rf_sample_data = []
          i=0
          #iterate through the data list again
          for data set, target name in data list:
              #print to let me know where the program is running
              print("Now Working On: ", data set.name)
```

```
#reset lists to collect trial data
rf predict trial = []
rf_sample_trial = []
for j in range(5):
    #print to let me know where the program is running
    print("Onto Trial: ", j + 1)
    temp = best_rf_by_data[i][j].cv_results_
    #gather best params from gridsearch by performance metric
    error metric = []
    error_metric.append(np.where(temp['rank_test_accuracy'] == 1))
    error_metric.append(np.where(temp['rank_test_roc_auc_ovr'] == 1))
    error_metric.append(np.where(temp['rank_test_f1_micro'] == 1))
    #reset lists to collect trial data
    rf predict metric = []
    rf_sample_metric = []
    for k in range(3):
        #make decision tree instance with best params for each error metric
        print("Working on metric: ", k)
        error_metric[k] = error_metric[k][0][0]
        best temp = temp['params'][error_metric[k]]
        rf = RandomForestClassifier(criterion=best temp['criterion'], max fea
        # set X and Y to the same data sample as before
        X = \text{data set.sample}(n = 5000, \text{ random state} = i * 5, \text{ axis} = 0)
        Y = X[target name]
        X = X.drop([target name], axis=1)
        rf.fit(X,Y)
        # Predict and score the model on the same training data
        if k % 3 == 0:
            rf sample metric.append(accuracy score(Y,rf.predict(X)))
        elif k % 3 == 1:
            rf sample metric.append(roc auc score(Y,rf.predict(X)))
        else:
            rf sample metric.append(f1 score(Y,rf.predict(X)))
        #Set X and Y as the whole dataset
        X = data set.drop([target name], axis=1)
        Y = data set[target name]
        # Using the same fit model from above, predict and score it for the
        if k % 3 == 0:
            rf predict metric.append(accuracy score(Y,rf.predict(X)))
        elif k % 3 == 1:
            rf predict metric.append(roc auc score(Y,rf.predict(X)))
        else:
            rf predict metric.append(f1 score(Y,rf.predict(X)))
    #Record results for the trial
    rf predict trial.append(rf predict metric)
    rf sample trial.append(rf sample metric)
#record results for the dataset
rf predict data.append(rf predict trial)
```

```
rf_sample_data.append(rf_sample_trial)
i+=1
print("Finished!")
```

```
Now Working On: Avila
Onto Trial: 1
Working on metric:
Working on metric:
Working on metric:
Onto Trial: 2
Working on metric:
Working on metric:
Working on metric:
Onto Trial: 3
Working on metric:
Working on metric:
Working on metric: 2
Onto Trial: 4
Working on metric:
Working on metric:
Working on metric: 2
Onto Trial: 5
Working on metric: 0
Working on metric:
Working on metric: 2
Now Working On: EEG Eye
Onto Trial: 1
Working on metric:
Working on metric:
Working on metric: 2
Onto Trial: 2
Working on metric:
Working on metric:
Working on metric: 2
Onto Trial: 3
Working on metric: 0
Working on metric: 1
Working on metric: 2
Onto Trial: 4
Working on metric: 0
Working on metric:
Working on metric: 2
Onto Trial: 5
Working on metric:
Working on metric:
Working on metric: 2
Now Working On: Occupancy
Onto Trial: 1
Working on metric: 0
Working on metric:
Working on metric: 2
Onto Trial: 2
Working on metric: 0
Working on metric:
Working on metric: 2
Onto Trial: 3
Working on metric: 0
Working on metric:
Working on metric:
Onto Trial: 4
Working on metric: 0
Working on metric:
Working on metric:
Onto Trial: 5
```

```
Working on metric: 0
         Working on metric:
         Working on metric: 2
         Now Working On: Letter
         Onto Trial: 1
         Working on metric: 0
         Working on metric: 1
         Working on metric: 2
         Onto Trial: 2
         Working on metric: 0
         Working on metric:
         Working on metric: 2
         Onto Trial: 3
         Working on metric: 0
         Working on metric: 1
         Working on metric: 2
         Onto Trial: 4
         Working on metric: 0
         Working on metric:
                            1
         Working on metric: 2
         Onto Trial: 5
         Working on metric: 0
         Working on metric: 1
         Working on metric: 2
         Finished!
In [899...
         rf avg metric = []
         rf_avg_data = []
         rf_acc = []
         rf roc = []
          rf f1 = []
          rf data1 = []
          temp = []
          for i in rf predict data:
```

```
#instantiate lists to be used for ttests here were working with scores for the w
#loop through the score data for the whole datasets
              #scrub lists
             temp = []
              #iterate for each trial
              for j in range(5):
                           #Get the error metric values into their respective lists
                           rf acc.append(i[j][0])
                           rf roc.append(i[j][1])
                           rf f1.append(i[j][2])
                           #temp is used to format datal so the error metrics go in in lists of 3
                           for k in range(3):
                                         temp.append(i[j][k])
              #append temp to datal which will hold all of the data for each dataset and t
             rf data1.append(temp)
              #gather the means of each metric for all trials
             rf avg metric = []
             rf_avg_metric.append(np.mean([i[0][0],i[1][0],i[2][0],i[3][0],i[4][0]]))
             rf_avg_metric.append(np.mean([i[0][1],i[1][1],i[2][1],i[3][1],i[4][1]]))
             \label{lem:rf_avg_metric.append} $$ rf_avg_metric.append(np.mean([i[0][2],i[1][2],i[2][2],i[3][2],i[4][2]])) $$ $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[1][2],i[2][2],i[3][2],i[4][2]])) $$ $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[1][2],i[1][2],i[2][2],i[3][2],i[4][2]])) $$ $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[1][2],i[1][2],i[2][2],i[3][2],i[4][2]])) $$ $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[1][2],i[1][2],i[2][2],i[3][2],i[4][2]])) $$ $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[1][2],i[1][2],i[2]],i[3][2],i[4][2]])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[1][2],i[2],i[2]],i[3][2],i[4][2]])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[1][2],i[2]],i[3][2],i[4][2]])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]],i[3][2],i[4][2]])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]],i[3][2],i[4][2]])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]],i[3][2],i[4][2]])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]],i[3][2])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2]]) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2]) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2])) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2]) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2]) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2]),i[3][2]) $$ $$ rf_avg_metric.append(np.mean([i[0][2],i[2],i[2])) $$
```

```
rf_avg_data.append(rf_avg_metric)
print(len(rf_data1[3]))
```

15

```
In [946...
          #instantiate lists to be used for ttests here were working with scores for the s
          rf sample avg metric = []
          rf_sample_avg_data = []
          rf_sample_acc = []
          rf sample roc = []
          rf_sample_f1 = []
          rf data2 = []
          temp = []
          #loop through the score data for the sampled datasets
          for i in rf sample data:
              #scrub lists
              temp = []
              #iterate for each trial
              for j in range(5):
                  #Get the error metric values into their respective lists
                  rf sample_acc.append(i[j][0])
                  rf_sample_roc.append(i[j][1])
                  rf_sample_f1.append(i[j][2])
                  #temp is used to format datal so the error metrics go in in lists of 3
                  for k in range(3):
                      temp.append(i[j][k])
              #append temp to datal which will hold all of the data for each dataset and t
              rf data2.append(temp)
              #gather the means of each metric for all trials
              rf sample avg metric = []
              rf sample avg metric.append(np.mean([i[0][0],i[1][0],i[2][0],i[3][0],i[4][0]
              rf sample avg metric.append(np.mean([i[0][1],i[1][1],i[2][1],i[3][1],i[4][1]
              rf_sample_avg_metric.append(np.mean([i[0][2],i[1][2],i[2][2],i[3][2],i[4][2]
              rf sample avg data.append(rf sample avg metric)
          print(rf sample avg data)
         [[1.0, 1.0, 1.0], [1.0, 1.0, 1.0], [1.0, 1.0, 1.0], [1.0, 1.0], [1.0, 1.0]]
In [885...
          #Find ttest results for each performance metric - rf outperformed for each one
          log acc p = stats.ttest rel(log acc, rf acc)
          log roc p = stats.ttest rel(log roc, rf roc)
          log f1 p = stats.ttest rel(log f1, rf f1)
          dec acc p = stats.ttest rel(dec acc, rf acc)
          dec roc p = stats.ttest rel(dec roc, rf roc)
          dec f1 p = stats.ttest rel(dec f1, rf f1)
          print(log acc p)
          print(log roc p)
          print(log_f1_p)
          print(dec acc p)
          print(dec roc p)
          print(dec f1 p)
```

```
Ttest relResult(statistic=-5.974231437564191, pvalue=9.484476701867612e-06)
         Ttest relResult(statistic=-6.791101412138696, pvalue=1.7439128162376142e-06)
         Ttest relResult(statistic=-4.300240917781898, pvalue=0.000386165792042603)
         Ttest relResult(statistic=-4.981181411790205, pvalue=8.291283065958167e-05)
         Ttest_relResult(statistic=-7.096573467152287, pvalue=9.47097243970075e-07)
         Ttest relResult(statistic=-4.817784836859598, pvalue=0.00011958662733499019)
In [947...
          log_sample_acc_p = stats.ttest_rel(log_sample_acc, rf_sample_acc)
          log_sample_roc_p = stats.ttest_rel(log_sample_roc, rf_sample_roc)
          log_sample_f1_p = stats.ttest_rel(log_sample_f1, rf_sample_f1)
          dec sample acc p = stats.ttest rel(dec sample acc, rf sample acc)
          dec sample roc p = stats.ttest rel(dec sample roc, rf sample roc)
          dec_sample_f1_p = stats.ttest_rel(dec_sample_f1, rf_sample_f1)
          print(log_sample_acc_p)
          print(log_sample_roc_p)
          print(log sample f1 p)
          print(dec_sample_acc_p)
          print(dec sample roc p)
          print(dec_sample_f1_p)
         Ttest relResult(statistic=-6.456542442933555, pvalue=3.452626386121358e-06)
         Ttest_relResult(statistic=-7.490032681763721, pvalue=4.39511724667642e-07)
         Ttest_relResult(statistic=-5.471867838164947, pvalue=2.8019680512875767e-05)
         Ttest_relResult(statistic=-3.6466024646191233, pvalue=0.0017163635816104868)
         Ttest_relResult(statistic=-7.297293044233187, pvalue=6.385074685333651e-07)
         Ttest_relResult(statistic=-3.6510256040715885, pvalue=0.0016991603325284923)
In [912...
          #Find ttest results for each dataset - rf outperformed for each
          onelog ttest data = []
          dec ttest data = []
          for i in range(4):
              log_ttest_data.append(stats.ttest_rel(log_data1[i], rf_data1[i]))
              dec_ttest_data.append(stats.ttest_rel(dec_data1[i], rf_data1[i]))
          for i in range(4):
              print(log ttest data[i])
          for i in range(4):
              print(dec ttest data[i])
         Ttest relResult(statistic=-8.356011171444266, pvalue=8.219871082473357e-07)
         Ttest relResult(statistic=-13.53271940374474, pvalue=1.9707318517189897e-09)
         Ttest relResult(statistic=-8.710989480811444, pvalue=5.014367108187927e-07)
         Ttest relResult(statistic=-319.43018872840787, pvalue=1.915883757368666e-28)
         Ttest relResult(statistic=-4.458379785191511, pvalue=0.0005406344713840243)
         Ttest_relResult(statistic=-20.494575636540482, pvalue=7.720066362459828e-12)
         Ttest_relResult(statistic=-6.918418666417257, pvalue=7.112154071582886e-06)
         Ttest relResult(statistic=-17.287956340982735, pvalue=7.6757347712904e-11)
In [948...
          #Find ttest results for each dataset FOR SAMPLE SCOREs - rf outperformed for eac
          log sample ttest data = []
          dec sample ttest data = []
          for i in range(4):
              log sample ttest data.append(stats.ttest rel(log data2[i], rf data2[i]))
              dec sample ttest data.append(stats.ttest rel(dec data2[i], rf data2[i]))
          for i in range(4):
              print(log ttest data[i])
          for i in range(4):
              print(dec_ttest_data[i])
         Ttest relResult(statistic=-8.356011171444266, pvalue=8.219871082473357e-07)
```

Ttest relResult(statistic=-13.53271940374474, pvalue=1.9707318517189897e-09)

```
Ttest relResult(statistic=-8.710989480811444, pvalue=5.014367108187927e-07)
         Ttest relResult(statistic=-319.43018872840787, pvalue=1.915883757368666e-28)
         Ttest relResult(statistic=-4.458379785191511, pvalue=0.0005406344713840243)
         Ttest relResult(statistic=-20.494575636540482, pvalue=7.720066362459828e-12)
         Ttest_relResult(statistic=-6.918418666417257, pvalue=7.112154071582886e-06)
         Ttest relResult(statistic=-17.287956340982735, pvalue=7.6757347712904e-11)
In [926...
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         0.9971182092815689,\ 0.9971182092815689,\ 0.9971182092815689,\ 0.9618459264533523,
         0.9618459264533523, 0.9618459264533523, 0.9617908244696808, 0.9617908244696808]
 In [ ]:
 In [ ]:
In [514...
          # there were a lot of hyperparameter sets for DT, just used this to make sure no
          one = [0,0,0]
          two = [0,0,0]
          three = [0,0,0]
          four = [0,0,0]
          five = [0,0,0]
          six = [0,0,0]
          seven = [0,0,0]
          eight = [0,0,0]
          nine = [0,0,0]
          ten = [0,0,0]
          data i = 0
          trial i = 4
          for i in best dectree by data[data i][trial i].cv results ['rank test f1 micro']
              if i == 1:
                  one[1] += 1
              elif i == 2:
                  two[1] += 1
              elif i == 3:
                  three[1] += 1
              elif i == 4:
                  four[1] += 1
              elif i == 5:
                  five[1] += 1
              elif i == 6:
                  six[1] += 1
              elif i == 7:
                  seven[1] += 1
              elif i == 8:
                  eight[1] += 1
              elif i == 9:
                  nine[1] += 1
              elif i == 10:
                  ten[1] += 1
          for i in best dectree by data[data i][trial i].cv results ['rank test roc auc ov
```

```
one[2] += 1
              elif i == 2:
                  two[2] += 1
              elif i == 3:
                  three[2] += 1
              elif i == 4:
                  four[2] += 1
              elif i == 5:
                  five[2] += 1
              elif i == 6:
                  six[2] += 1
              elif i == 7:
                  seven[2] += 1
              elif i == 8:
                  eight[2] += 1
              elif i == 9:
                  nine[2] += 1
              elif i == 10:
                  ten[2] += 1
          for i in best_dectree_by_data[data_i][trial_i].cv_results_['rank_test_accuracy']
              if i == 1:
                  one[0] += 1
              elif i == 2:
                  two[0] += 1
              elif i == 3:
                  three[0] += 1
              elif i == 4:
                  four[0] += 1
              elif i == 5:
                  five[0] += 1
              elif i == 6:
                  six[0] += 1
              elif i == 7:
                  seven[0] += 1
              elif i == 8:
                  eight[0] += 1
              elif i == 9:
                  nine[0] += 1
              elif i == 10:
                  ten[0] += 1
          print("1: ", one, "\n2: ", two, "\n3: ", three, "\n4: ", four, "\n5: ", five, "\n6:
         1: [1, 1, 1]
         2: [1, 1, 1]
         3: [1, 1, 1]
         4: [1, 1, 1]
         5: [1, 1, 1]
         6:
             [1, 1, 1]
         7:
            [1, 1, 1]
         8: [1, 1, 1]
         9: [1, 1, 1]
         10: [1, 1, 1]
In [517...
         best rf by data[1][4].cv results
Out[517... {'mean_fit_time': array([11.46271429, 11.29431119, 11.32947607, 11.39440274, 36.
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```

localhost:8888/lab/workspaces/auto-7/tree/Desktop/COGS118AFinalProject/final.ipynb

```
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        0.0193456 , 0.02551303, 0.0062784 , 0.02571356, 0.01050658,
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```

```
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final

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