power_prediction

March 12, 2021

[4]:
```
%pip install sklearn
%pip install pandas
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: sklearn in
/home/jdeutsch/.local/lib/python3.6/site-packages (0.0)
Requirement already satisfied: scikit-learn in
/home/jdeutsch/.local/lib/python3.6/site-packages (from sklearn) (0.24.1)
Requirement already satisfied: scipy>=0.19.1 in
/home/jdeutsch/.local/lib/python3.6/site-packages (from scikit-learn->sklearn)
(1.4.1)
Requirement already satisfied: numpy>=1.13.3 in
/home/jdeutsch/.local/lib/python3.6/site-packages (from scikit-learn->sklearn)
(1.16.4)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/home/jdeutsch/.local/lib/python3.6/site-packages (from scikit-learn->sklearn)
(2.1.0)
Requirement already satisfied: joblib>=0.11 in
/home/jdeutsch/.local/lib/python3.6/site-packages (from scikit-learn->sklearn)
(0.15.1)
WARNING: You are using pip version 20.1; however, version 21.0.1 is
available.
You should consider upgrading via the '/usr/bin/python3 -m pip install --upgrade
pip' command.
Note: you may need to restart the kernel to use updated packages.
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: pandas in
/home/jdeutsch/.local/lib/python3.6/site-packages (1.1.5)
Requirement already satisfied: pytz>=2017.2 in
/home/jdeutsch/.local/lib/python3.6/site-packages (from pandas) (2020.1)
Requirement already satisfied: python-dateutil>=2.7.3 in
/home/jdeutsch/.local/lib/python3.6/site-packages (from pandas) (2.8.1)
Requirement already satisfied: numpy>=1.15.4 in
/home/jdeutsch/.local/lib/python3.6/site-packages (from pandas) (1.16.4)
Requirement already satisfied: six>=1.5 in /usr/lib/python3/dist-packages (from
python-dateutil>=2.7.3->pandas) (1.11.0)
```

```
WARNING: You are using pip version 20.1; however, version 21.0.1 is
available.
You should consider upgrading via the '/usr/bin/python3 -m pip install --upgrade
pip' command.
Note: you may need to restart the kernel to use updated packages.
```

[2]:

```
from sklearn.preprocessing import StandardScaler
from sklearn import svm
import pandas as pd
import numpy as np
from sklearn import preprocessing
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.neural_network import MLPClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.model_selection import train_test_split
from sklearn.linear_model import SGDClassifier
from sklearn.model_selection import GridSearchCV
import pickle
import matplotlib.pyplot as plt

#Read in data
raw_train_set = pd.read_csv('xu3_dataset.csv')
raw_bs_test = pd.read_csv('xu3_blackscholes.csv')
raw_bt_test = pd.read_csv('xu3_bodytrack.csv')
label_map = {'idle': 0, 'active': 1}
data = {'train':raw_train_set, 'test_bt':raw_bt_test, 'test_bs':raw_bs_test}
raw_train_set
```

[2]:

	total_watts	w_big	w_little	w_gpu	w_mem	usage_c4	usage_c5	\
0	3.065	0.474810	0.033012	0.096321	0.048800	0.0	0.0	
1	2.706	0.235620	0.032095	0.096515	0.032940	0.0	0.0	
2	2.706	0.235620	0.034846	0.096515	0.032940	0.0	0.0	
3	2.637	0.234685	0.034846	0.096321	0.037758	0.0	0.0	
4	2.637	0.233750	0.033929	0.096321	0.032886	0.0	0.0	
…	…	…	…	…	…	…	…	
5410	3.844	1.157646	0.039474	0.123132	0.035380	0.0	0.0	
5411	3.851	1.157646	0.038514	0.123132	0.036600	0.0	0.0	
5412	3.851	1.156364	0.041310	0.124125	0.036600	0.0	0.0	
5413	3.851	1.158024	0.037638	0.124125	0.036600	0.0	0.0	

```
5414        3.844  1.156364  0.037638  0.123132  0.036600       0.0       0.0

      usage_c6  usage_c7  temp4  temp5  temp6  temp7  temp_gpu  \
0          0.0       0.0     49     53     52     48        47
1          0.0       0.0     48     52     52     48        47
2          0.0       0.0     48     52     52     48        47
3          0.0       0.0     48     51     51     48        47
4          0.0       0.0     48     51     51     48        47
…        …       …    …    …    …    …       …
5410       0.0       0.0     63     67     67     62        60
5411       0.0       0.0     63     67     67     62        60
5412       0.0       0.0     63     67     67     62        60
5413       0.0       0.0     63     67     67     62        60
5414       0.0       0.0     63     67     67     62        60

      freq_big_cluster
0           1000000000
1           1000000000
2           1000000000
3           1000000000
4           1000000000
…                  …
5410        2000000000
5411        2000000000
5412        2000000000
5413        2000000000
5414        2000000000

[5415 rows x 15 columns]
```

[33]:

```
#Parse data
for k, v in data.items():
    data[k]['class'] =\
    data[k]['w_big'].apply((lambda x: 1 if x > 1 else 0))
print(f"bodytrack shape:{data['test_bt'].shape}")
print(f"blackscholes shape:{data['test_bs'].shape}")
```

```
bodytrack shape:(1454, 16)
blackscholes shape:(1653, 16)
```

[3]:

```
# search possible classifiers for good one to optimize
X = data['train'].loc[:,'w_little':'freq_big_cluster'].values
X = StandardScaler().fit_transform(X)
Y = data['train']['class'].values
names = ["Nearest Neighbors", "Linear SVM", "RBF SVM",
         "Decision Tree", "Random Forest", "Neural Net", "AdaBoost",
         "Naive Bayes", "LinearSVC", 'SGD']
```

```python
skip = []
classifiers = [
    KNeighborsClassifier(5),
    SVC(kernel="linear", C=0.025),
    SVC(gamma=2, C=1),
    DecisionTreeClassifier(max_depth=20),
    RandomForestClassifier(max_depth=100, n_estimators=10, max_features=10),
    MLPClassifier(alpha=1, max_iter=10000, hidden_layer_sizes=(100,)),
    AdaBoostClassifier(),
    GaussianNB(),
    LinearSVC(C=10.6),
    SGDClassifier()]
test_sets =  ['test_bt','test_bs']

X_train, X_test, y_train, y_test = \
        train_test_split(X, Y, test_size=.1, random_state=42)

for name, model in zip(names, classifiers):

    print(name)

    model.fit(X_train, y_train)

    for t_set in test_sets:
        t_X = data[t_set].loc[:,'w_little':'freq_big_cluster'].values
        t_Y = data[t_set]['class'].values
        t_X = StandardScaler().fit_transform(t_X)
        score = model.score(X_test, y_test)
        result = model.score(t_X, t_Y)
        print(f'{t_set} score:{result}')

    del model
```

```
Nearest Neighbors
test_bt score:0.905777166437414
test_bs score:0.7985480943738656
Linear SVM
test_bt score:0.8789546079779917
test_bs score:0.7967332123411979
RBF SVM
test_bt score:0.624484181568088
test_bs score:0.6642468239564429
Decision Tree
test_bt score:0.9257221458046767
test_bs score:0.7719298245614035
Random Forest
test_bt score:0.9387895460797799
```

```
test_bs score:0.7737447065940714
Neural Net
test_bt score:0.8253094910591472
test_bs score:0.7743496672716274
AdaBoost
test_bt score:0.9442916093535075
test_bs score:0.7658802177858439
Naive Bayes
test_bt score:0.8535075653370013
test_bs score:0.7737447065940714
LinearSVC
test_bt score:0.9408528198074277
test_bs score:0.8045977011494253
SGD
test_bt score:0.9387895460797799
test_bs score:0.7828191167574108
```

```
/home/jdeutsch/.local/lib/python3.6/site-packages/sklearn/svm/_base.py:986:
ConvergenceWarning: Liblinear failed to converge, increase the number of
iterations.
  "the number of iterations.", ConvergenceWarning)
```

[12]:

```
# we choose the AdaBoost classifier to optimize
# and define the hyperparameter space to conduct our search
param_grid = {"base_estimator__criterion" : ["gini", "entropy"],
              "base_estimator__splitter" :   ["best", "random"],
              "n_estimators": np.arange(1, 20),
              "learning_rate": np.linspace(0.01, 1)
             }
```

[13]:

```
#execute hyperparameter search, saving our best model as we go
top_bs = 0
best_bs = {}
top_bt = 0
best_bt = {}
for i in param_grid['base_estimator__criterion']:
    for j in param_grid['base_estimator__splitter']:
        for k in param_grid["learning_rate"]:
            for l in param_grid['n_estimators']:
                results = [0,0]
                cur = {'c':i, 's':j, 'l':k, 'n': l }
                #DTC =KNeighborsClassifier(i)

                DTC = DecisionTreeClassifier(random_state = 11, max_depth =␣
 ↪None,
                                criterion =i,
                                splitter=j
                )
```

```
                model = AdaBoostClassifier(base_estimator=DTC, learning_rate=k,␣
↪n_estimators=1)
                model.fit(X_train, y_train)
                for t_set in test_sets:
                    t_X = data[t_set].loc[:,'w_little':'freq_big_cluster'].
↪values
                    t_Y = data[t_set]['class'].values
                    t_X = StandardScaler().fit_transform(t_X)
                    score = model.score(X_test, y_test)
                    result = model.score(t_X, t_Y)
                    if t_set == "test_bt":
                        results[0] = result
                    else:
                        results[1] = result
                    if t_set == "test_bt" and result> top_bt:
                        top_bt = result
                        best_bt = cur
                        print(f'{i} {t_set} test_score:{score}, train_score:
↪{result}')
                        print(cur)

                        pickle.dump(model, open("bt_best.pickle", 'wb'))
                    if t_set == "test_bs" and result> top_bs:
                        top_bs = result
                        best_bs = cur
                        print(f'{i} {t_set} test_score:{score}, train_score:
↪{result}')
                        print(cur)

                        pickle.dump(model, open(f"bs_best.pickle", 'wb'))
                worst = int(min(results)*100)
                pickle.dump(model, open(f"best_{worst}.pickle", 'wb'))
```

```
gini test_bt test_score:1.0, train_score:0.9257221458046767
{'c': 'gini', 's': 'best', 'l': 0.01, 'n': 1}
gini test_bs test_score:1.0, train_score:0.7719298245614035
{'c': 'gini', 's': 'best', 'l': 0.01, 'n': 1}
gini test_bt test_score:1.0, train_score:0.9394773039889959
{'c': 'gini', 's': 'best', 'l': 0.01, 'n': 2}
gini test_bs test_score:1.0, train_score:0.7761645493042952
{'c': 'gini', 's': 'best', 'l': 0.01, 'n': 2}
gini test_bt test_score:1.0, train_score:0.9669876203576341
{'c': 'gini', 's': 'random', 'l': 0.01, 'n': 1}
gini test_bs test_score:1.0, train_score:0.7876588021778584
{'c': 'gini', 's': 'random', 'l': 0.01, 'n': 1}
gini test_bs test_score:1.0, train_score:0.7931034482758621
{'c': 'gini', 's': 'random', 'l': 0.01, 'n': 3}
```

```
gini test_bt test_score:1.0, train_score:0.9738651994497937
{'c': 'gini', 's': 'random', 'l': 0.01, 'n': 5}
gini test_bs test_score:1.0, train_score:0.794313369630974
{'c': 'gini', 's': 'random', 'l': 0.01, 'n': 7}
gini test_bt test_score:1.0, train_score:0.982806052269601
{'c': 'gini', 's': 'random', 'l': 0.01, 'n': 9}
gini test_bs test_score:1.0, train_score:0.8160919540229885
{'c': 'gini', 's': 'random', 'l': 0.01, 'n': 9}
gini test_bs test_score:1.0, train_score:0.852994555353902
{'c': 'gini', 's': 'random', 'l': 0.01, 'n': 15}
gini test_bs test_score:1.0, train_score:0.9776164549304295
{'c': 'gini', 's': 'random', 'l': 0.030204081632653063, 'n': 1}
gini test_bt test_score:1.0, train_score:0.9834938101788171
{'c': 'gini', 's': 'random', 'l': 0.2120408163265306, 'n': 12}
entropy test_bs test_score:1.0, train_score:0.9782214156079855
{'c': 'entropy', 's': 'random', 'l': 0.23224489795918368, 'n': 16}
entropy test_bt test_score:1.0, train_score:0.9876203576341128
{'c': 'entropy', 's': 'random', 'l': 0.9595918367346938, 'n': 18}
entropy test_bs test_score:1.0, train_score:0.9806412583182094
{'c': 'entropy', 's': 'random', 'l': 0.9595918367346938, 'n': 18}
```

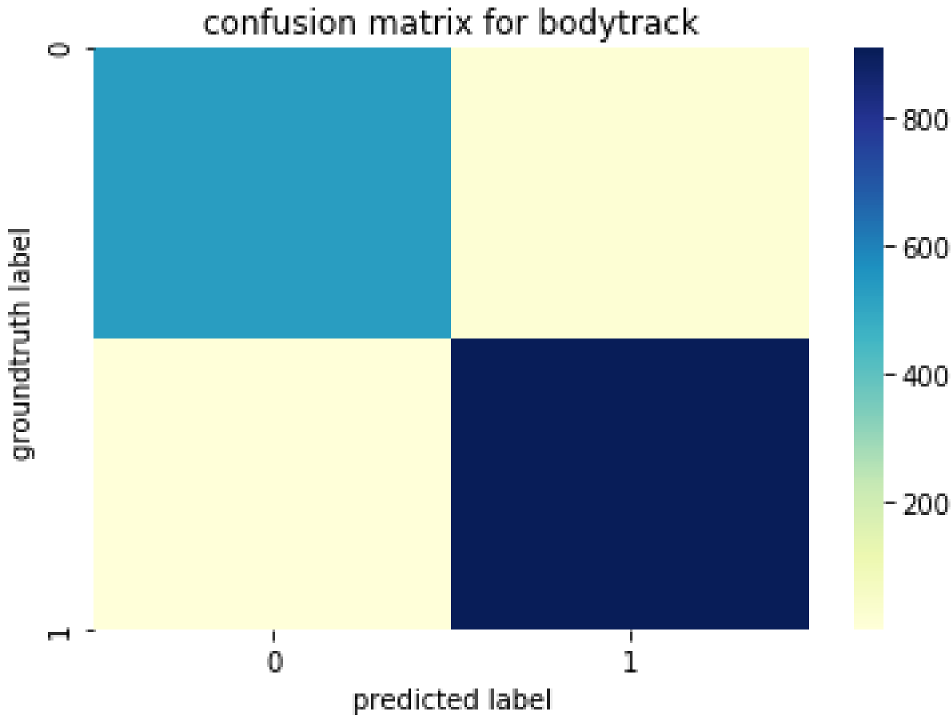
[45]:

```python
import seaborn as sn
# run our best classifiers for each dataset
model = pickle.load(open("bt_best.pickle", 'rb'))
for t_set in test_sets:
    t_X = data[t_set].loc[:,'w_little':'freq_big_cluster'].values
    t_Y = data[t_set]['class'].values
    t_X = StandardScaler().fit_transform(t_X)
    result = model.score(t_X, t_Y)
    y_pred = model.predict(t_X)
    confusion = confusion_matrix(t_Y, y_pred)
    name= "blackscholes" if t_set=="test_bs" else "bodytrack"
    ax = plt.axes()
    print(f'confusion matrix for {name}:\n {confusion}\n')


    print(f'{name} score:{result}')
    akws = {"ha": 'left',"va": 'top'}
    sn.heatmap(confusion, cmap="YlGnBu", ax= ax)
    ax.set_title(f'confusion matrix for {name}')
    ax.set_ylabel(f'groundtruth label')
    ax.set_xlabel('predicted label')
    plt.show()
```

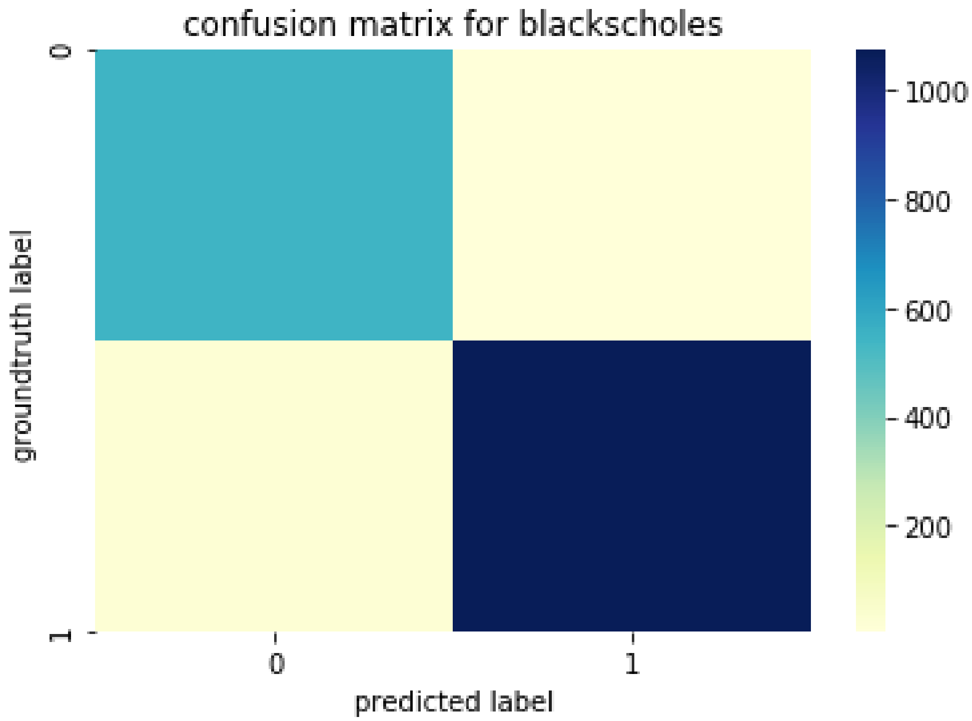
```
confusion matrix for bodytrack:
 [[529  17]
 [  1 907]]
```

```
bodytrack score:0.9876203576341128
```




```
confusion matrix for blackscholes:
 [[ 548    7]
 [  25 1073]]

blackscholes score:0.9806412583182094
```

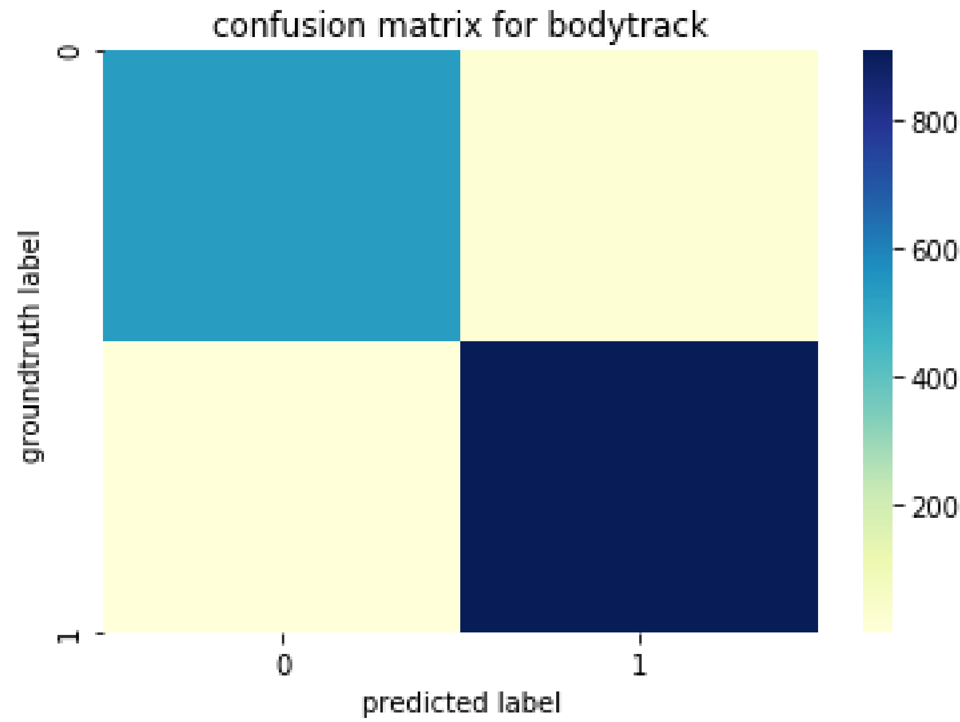


[47]:
```
model = pickle.load(open("bs_best.pickle", 'rb'))
for t_set in test_sets:
    t_X = data[t_set].loc[:,'w_little':'freq_big_cluster'].values
    t_Y = data[t_set]['class'].values
    t_X = StandardScaler().fit_transform(t_X)
    result = model.score(t_X, t_Y)
    y_pred = model.predict(t_X)
    confusion = confusion_matrix(t_Y, y_pred)
    name= "blackscholes" if t_set=="test_bs" else "bodytrack"
    ax = plt.axes()
    print(f'confusion matrix for {name}:\n {confusion}\n')


    print(f'{name} score:{result}')
    akws = {"ha": 'left',"va": 'top'}
    sn.heatmap(confusion, cmap="YlGnBu", ax= ax)
    ax.set_title(f'confusion matrix for {name}')
    ax.set_ylabel(f'groundtruth label')
    ax.set_xlabel('predicted label')
    plt.show()
```

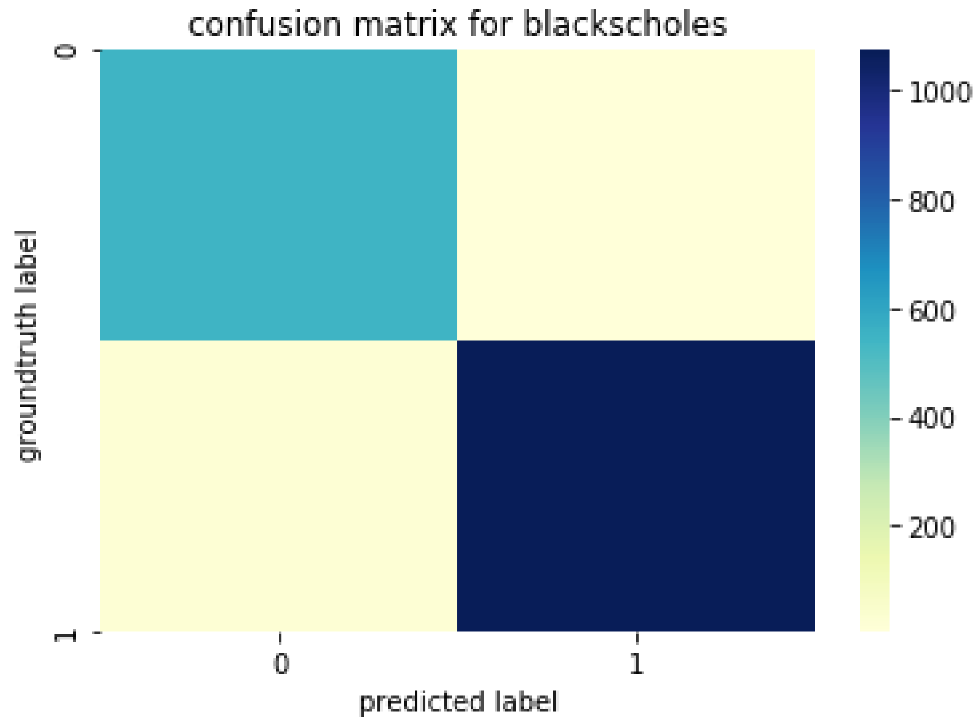
```
confusion matrix for bodytrack:
 [[529  17]
 [  1 907]]
```

```
bodytrack score:0.9876203576341128
```




```
confusion matrix for blackscholes:
 [[ 548    7]
 [  25 1073]]

blackscholes score:0.9806412583182094
```



[15]:
```
# as you can see we achieve 98% accuracy on both test sets!
#the final features of the model were ADABOOST with a DecisionTree base
# estimator, for the DecisionTree the splitter was random and the criterion
# was entropy. for the adaboostclassifier we used 18 estimators &
# a learning rate of 0.95959
```

[34]:
```
from sklearn.ensemble import AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error
# for our regressor we attempt to optimize the adaboostregressor
#Read in data
raw_train_set = pd.read_csv('xu3_dataset.csv')
raw_bs_test = pd.read_csv('xu3_blackscholes.csv')
raw_bt_test = pd.read_csv('xu3_bodytrack.csv')
data = {'train':raw_train_set, 'test_bt':raw_bt_test, 'test_bs':raw_bs_test}


X = data['train'].loc[:,'w_little':'temp_gpu'].values
print(f'training data X shape{X.shape}')
X = StandardScaler().fit_transform(X)
Y = data['train']['w_big'].values
print(f'training data y shape{Y.shape}')
test_sets =  ['test_bt','test_bs']
```

```
print(f"bodytrack shape:{data['test_bt'].shape}")
print(f"blackscholes shape:{data['test_bs'].shape}")

X_train, X_test, y_train, y_test = \
        train_test_split(X, Y, test_size=.1, random_state=42)
```

```
training data X shape(5415, 12)
training data y shape(5415,)
bodytrack shape:(1454, 15)
blackscholes shape:(1653, 15)
```

[31]:
```
param_grid = {"base_estimator__criterion" : ["linear", "square", "exponential"],
              "base_estimator__splitter" :   ["best", "random"],
              "n_estimators": np.arange(1, 4),
              "learning_rate": np.linspace(0.3, 1.5, 100)
             }

top_bs = 10000
best_bs = {}
top_bt = 10000
best_bt = {}
for i in param_grid['base_estimator__criterion']:
    for j in param_grid['base_estimator__splitter']:
        for k in param_grid["learning_rate"]:
            for l in param_grid['n_estimators']:
                results = [0,0]
                cur = {'c':i, 's':j, 'l':k, 'n': l }
                #DTC =KNeighborsClassifier(i)

                DTC = DecisionTreeRegressor(random_state = 11, max_depth = None,
                                criterion ="mse",
                                splitter=j
                )
                model = AdaBoostRegressor(base_estimator=DTC, learning_rate=k,␣
 ↪n_estimators=l, loss=i)
                model.fit(X_train, y_train)
                y_pred = model.predict(X_test)
                score = mean_squared_error(y_test, y_pred)
                for t_set in test_sets:
                    t_X = data[t_set].loc[:,'w_little':'temp_gpu'].values
                    t_Y = data[t_set]['w_big'].values
                    t_X = StandardScaler().fit_transform(t_X)
                    result = mean_squared_error(t_Y, model.predict(t_X))

                    if t_set == "test_bt":
                        results[0] = result
```

```python
                    else:
                        results[1] = result
                    if t_set == "test_bt" and result< top_bt:
                        top_bt = result
                        best_bt = cur
                        print(f'{t_set} train_score:{score}, test_score:
↪{result}')
                        print(cur)

                        pickle.dump(model, open("r_bt_best.pickle", 'wb'))
                    if t_set == "test_bs" and result< top_bs:
                        top_bs = result
                        best_bs = cur
                        print(f'{t_set} train_score:{score}, test_score:
↪{result}')
                        print(cur)

                        pickle.dump(model, open(f"r_bs_best.pickle", 'wb'))
                worst = int(max(results)*100)
                pickle.dump(model, open(f"r_best_{worst}.pickle", 'wb'))
```

```
test_bt train_score:0.004900289112370627, test_score:2.584207579284114
{'c': 'linear', 's': 'best', 'l': 0.3, 'n': 1}
test_bs train_score:0.004900289112370627, test_score:1.394352893448151
{'c': 'linear', 's': 'best', 'l': 0.3, 'n': 1}
test_bt train_score:0.01711428612797359, test_score:1.7095984890638891
{'c': 'linear', 's': 'best', 'l': 0.3, 'n': 2}
test_bs train_score:0.01711428612797359, test_score:0.4185315559772061
{'c': 'linear', 's': 'best', 'l': 0.3, 'n': 2}
test_bt train_score:0.010916495963480155, test_score:1.6699622274529164
{'c': 'linear', 's': 'best', 'l': 0.40909090909090906, 'n': 2}
test_bs train_score:0.004615470595393748, test_score:0.39288942025854995
{'c': 'linear', 's': 'best', 'l': 0.4939393939393939, 'n': 1}
test_bt train_score:0.009609903539511086, test_score:1.4520647397753728
{'c': 'linear', 's': 'best', 'l': 0.5909090909090908, 'n': 2}
test_bs train_score:0.022931043609665445, test_score:0.3837576979769646
{'c': 'linear', 's': 'best', 'l': 0.6878787878787879, 'n': 1}
test_bs train_score:0.0242160388760287, test_score:0.31986877088954846
{'c': 'linear', 's': 'best', 'l': 0.7727272727272727, 'n': 2}
test_bt train_score:0.009993074824939925, test_score:1.448183959030046
{'c': 'linear', 's': 'best', 'l': 1.0393939393939393, 'n': 1}
test_bt train_score:0.010010065803597075, test_score:1.4012181204981515
{'c': 'linear', 's': 'best', 'l': 1.1484848484848484, 'n': 2}
test_bs train_score:0.015092307709194152, test_score:0.2502506104188088
{'c': 'linear', 's': 'best', 'l': 1.1727272727272726, 'n': 2}
test_bt train_score:0.0026582247749359147, test_score:1.3179794707096208
{'c': 'linear', 's': 'random', 'l': 0.3, 'n': 2}
```

```
test_bs train_score:0.0026582247749359147, test_score:0.22948303836175238
{'c': 'linear', 's': 'random', 'l': 0.3, 'n': 2}
test_bt train_score:0.0028986461820559783, test_score:1.3009893856496528
{'c': 'linear', 's': 'random', 'l': 0.31212121212121213, 'n': 2}
test_bt train_score:0.0007211126371050266, test_score:1.2194771054939753
{'c': 'linear', 's': 'random', 'l': 0.33636363636363636, 'n': 2}
test_bs train_score:0.022236623811143903, test_score:0.19067187038564645
{'c': 'linear', 's': 'random', 'l': 0.3727272727272727, 'n': 1}
test_bt train_score:0.0039058486200043503, test_score:1.0063104055998826
{'c': 'linear', 's': 'random', 'l': 0.40909090909090906, 'n': 2}
test_bt train_score:0.009041589242455735, test_score:0.7654716540211469
{'c': 'linear', 's': 'random', 'l': 0.44545454545454544, 'n': 1}
test_bs train_score:0.0008087076766876912, test_score:0.18833846605006563
{'c': 'linear', 's': 'random', 'l': 0.4696969696969697, 'n': 3}
test_bs train_score:0.0014897523295709354, test_score:0.16376555913602783
{'c': 'linear', 's': 'random', 'l': 0.5666666666666667, 'n': 3}
test_bt train_score:0.002847937828964644, test_score:0.7619387671084515
{'c': 'linear', 's': 'random', 'l': 0.6151515151515151, 'n': 2}
test_bs train_score:0.0022387207277982236, test_score:0.1486849719785967
{'c': 'linear', 's': 'random', 'l': 0.6757575757575758, 'n': 1}
test_bs train_score:0.00840020303376718, test_score:0.09412647215356512
{'c': 'linear', 's': 'random', 'l': 0.8212121212121213, 'n': 2}
test_bt train_score:0.027251898005876275, test_score:0.33970840438342215
{'c': 'linear', 's': 'random', 'l': 0.8454545454545455, 'n': 2}
test_bs train_score:0.012825665197564035, test_score:0.057739809032336394
{'c': 'square', 's': 'random', 'l': 0.4818181818181818, 'n': 2}
test_bt train_score:0.00842702410500436, test_score:0.3323279648734418
{'c': 'exponential', 's': 'random', 'l': 1.2212121212121212, 'n': 2}
```

[37]:

```
model = pickle.load(open("r_bt_best.pickle", 'rb'))
for t_set in test_sets:
    name= "blackscholes" if t_set=="test_bs" else "bodytrack"
    t_X = data[t_set].loc[:,'w_little':'temp_gpu'].values
    t_Y = data[t_set]['w_big'].values
    t_X = StandardScaler().fit_transform(t_X)
    y_pred = model.predict(X_test)
    train_mse = mean_squared_error(y_test, y_pred)
    result = mean_squared_error(t_Y, model.predict(t_X))
    print(f"mse for {name}: {result}")
    print(f"train mse for {name}: {train_mse}")
```

```
mse for bodytrack: 0.3323279648734418
train mse for bodytrack: 0.00842702410500436
mse for blackscholes: 0.29794509469723074
train mse for blackscholes: 0.00842702410500436
```

[36]:

```
model = pickle.load(open("r_bs_best.pickle", 'rb'))
for t_set in test_sets:
    name= "blackscholes" if t_set=="test_bs" else "bodytrack"
    t_X = data[t_set].loc[:,'w_little':'temp_gpu'].values
    t_Y = data[t_set]['w_big'].values
    t_X = StandardScaler().fit_transform(t_X)
    y_pred = model.predict(X_test)
    train_mse = mean_squared_error(y_test, y_pred)
    result = mean_squared_error(t_Y, model.predict(t_X))
    print(f"mse for {name}: {result}")
    print(f"train mse for {name}: {train_mse}")
```

```
mse for bodytrack: 0.7540022117383436
train mse for bodytrack: 0.012825665197564035
mse for blackscholes: 0.057739809032336394
train mse for blackscholes: 0.012825665197564035
```

[ ]:

```
# our best results were an mse of 0.75 for bodytrack and 0.058 for blackscholes
# the model was an Adaboostregressor with a decisionTree baseestimator using a␣
↪square loss function,
#random splitter, learning rate of 0.48 and 2 estimators
```