01 - Supervised Learning - Classification - Gradient Boosting(Solution) st122097 thantham

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1 Programming for Data Science and Artificial Intelligence

- 1.1 Classification Gradient Boosting
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- 1.3.1 = = Task = = =

Modify the above scratch code such that: - Notice that we are still using max_depth = 1. Attempt to tweak min_samples_split, max_depth for the regression and see whether we can achieve better mse on our boston data - Notice that we only write scratch code for gradient boosting for regression, add some code so that it also works for binary classification. Load the breast cancer data from sklearn and see that it works. - Further change the code so that it works for multiclass classification. Load the digits data from sklearn and see that it works - Put everything into class

1.3.2 TASK 4 Making Gradient Boosting Class

```
# init model list
       self.models = ___
→ [DummyRegressor(strategy='mean')]+[estimator(**model_params) for _ in__
→range(self.n_estimators)]
       self.learning rate = learning rate # alpha
       self.is_regression = is_regression # to check if it is regression or_
\hookrightarrow classification
   def fit(self, X, y):
       self.models[0].fit(X, y) # fit first dummy regressor
       current_model = 1 # init first boosting idx
       while current_model != len(self.models): # while not all boosters ->_
\rightarrow keep fit them
           # predict model i and keep not result output class
           h_x = self.predict(X, self.models[:current_model],__
→argmax_output=False)
           residual = self.residual(y, h_x) # find residual (gradient)
           self.models[current_model].fit(X, residual) # try to fit X to_{\sqcup}
\rightarrow residual prediction
           current_model += 1 # next model
   def residual(self, y, h_x):
       return y - h_x # simple y - h(x)
   def predict(self, X, estimators=None, argmax_output=True):
       if estimators == None: # if predict was used from outside
           estimators = self.models # define all models to be predictors
       # predict H(x) by addition of first dummy with other regressor
\rightarrowpredictions * alpha
       H_X = self.models[0].predict(X) + sum(self.learning_rate * self.
→models[i].predict(X) for i in range(1, len(estimators)))
```

```
if not self.is_regression: # if this boosting is classification

H_X = np.exp(H_X) / np.sum(np.exp(H_X), axis=1, keepdims=True) #__

→implement softmax (works with binary and multiclass)

if argmax_output: # if predict method was used from outside

H_X = np.argmax(H_X, axis=1) # return class of predicted

return H_X
```

```
[2]: from sklearn.model_selection import train_test_split
from sklearn.ensemble import

GradientBoostingRegressor,GradientBoostingClassifier

from sklearn.datasets import load_boston
from sklearn.metrics import mean_squared_error

from sklearn.datasets import load_breast_cancer
from sklearn.metrics import accuracy_score

from sklearn.datasets import load_digits
from sklearn.metrics import classification_report
```

1.3.3 TASK 1 Implementing Regression Gradient Boosting on Boston Data

```
[3]: X, y = load_boston(return_X_y=True)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, □

→random_state=48)
```

After loading Boston, lets apply out gradient boosting model

Our model Mean square error: 10.917610709239431

However, we have tried on max depth 1 or 3 before, lets change some to max depth 5 and min split to 4

```
[5]: model_boston = GradientBoosting(n_estimators=200, learning_rate=0.1, 

→model_params={'max_depth':5, 'min_samples_split':4}, is_regression=True)

model_boston.fit(X_train, y_train)
```

```
ypred_boston = model_boston.predict(X_test)
print("Our model Mean square error: ", mean_squared_error(y_test, ypred_boston))
```

Our model Mean square error: 11.767735935158402

We found that there was some lower MSE after increasing max depth and min sample split. This tells us that there was some change if we try on different hyperparameter of regressors inside models.

However, to reach better result, we cannot exactly find what hyperparameters can do, we need **Cross-Validation** to automatically do that.

```
[6]: sklearn_boston = GradientBoostingRegressor(n_estimators=200,learning_rate = 0.

→1,max_depth=3, loss='ls')

sklearn_boston.fit(X_train, y_train)

ypred_sk_boston = sklearn_boston.predict(X_test)

print("Sklean Mean square error: ", mean_squared_error(y_test, ypred_sk_boston))
```

Sklean Mean square error: 12.35891581425541

1.3.4 TASK 2 Implementing Binary Classification Gradient Boosting on Breast Cancer Data

```
[7]: X, y = load_breast_cancer(return_X_y=True)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, u)

random_state=48)
```

For The binary classification, we can directly implement softmax because softmax can do any binary or muiticlass classification.

To address this, we need to encode by onehot method for y_train

Simply implement onehot function to y_train

```
[9]: y_train_onehot = onehot(y_train)
    print('Convert binary class to One hot', set(y_train))
    print('y train as :', y_train_onehot[:10])

Convert binary class to One hot {0, 1}
    y train as : [[1. 0.]
       [1. 0.]
       [0. 1.]
       [0. 1.]
       [0. 1.]
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       [0.]
```

However, we don't need to convert y_test because predictions will be integer directly, and we can examine result via integer class

Our classification report:

```
precision
                              recall f1-score
                                                   support
           0
                    0.87
                              0.95
                                         0.91
                                                      76
           1
                    0.95
                              0.88
                                         0.92
                                                      95
                                         0.91
                                                     171
    accuracy
   macro avg
                    0.91
                              0.92
                                         0.91
                                                     171
weighted avg
                    0.92
                                         0.91
                              0.91
                                                     171
```

Sklearn classification report:

	precision	recall	f1-score	support
0	0.94	0.95	0.94	76
1	0.96	0.95	0.95	95
accuracy			0.95	171
macro avg	0.95	0.95	0.95	171
weighted avg	0.95	0.95	0.95	171

1.3.5 TASK 3 Implementing Multiclass Gradient Boosting on Digits Data

```
[12]: X, y = load_digits(return_X_y=True)
      X_train, X_test, y_train, y_test = \
              train_test_split(X, y, test_size=0.3, random_state=48)
      y_train_onehot = onehot(y_train)
      print('Convert binary class to One hot', set(y_train))
      print('y train as :', y_train_onehot[:10])
     Convert binary class to One hot {0, 1, 2, 3, 4, 5, 6, 7, 8, 9}
     y train as : [[0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
      [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
      [0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
      [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
      [0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
      [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
      [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
      [0. 0. 0. 0. 0. 0. 1. 0. 0.]
      [0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
      [0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]]
     One hot was performed the same as binary
[13]: model_digit = GradientBoosting(n_estimators=200, learning_rate=0.1,__
      →is_regression=False)
      model_digit.fit(X_train, y_train_onehot)
```

Our classification report:

```
precision recall f1-score support
0 0.96 0.95 0.95 56
```

```
0.97
                              0.91
                                        0.94
                                                     69
           1
           2
                   0.98
                              0.96
                                        0.97
                                                     52
           3
                   0.98
                              0.94
                                        0.96
                                                     47
           4
                   0.97
                              0.95
                                        0.96
                                                     63
           5
                              0.93
                                        0.90
                   0.88
                                                     40
           6
                   0.97
                              0.98
                                        0.98
                                                     64
           7
                              0.98
                   0.94
                                        0.96
                                                     52
                   0.87
                              0.82
           8
                                        0.84
                                                     55
                   0.80
                              0.93
                                        0.86
                                                     42
                                        0.94
                                                    540
   accuracy
   macro avg
                   0.93
                              0.93
                                        0.93
                                                    540
weighted avg
                   0.94
                              0.94
                                        0.94
                                                    540
```

Sklearn classification report:

	precision	recall	f1-score	support
0	1.00	0.98	0.99	56
1	0.93	0.96	0.94	69
2	1.00	1.00	1.00	52
3	0.98	0.98	0.98	47
4	0.97	0.97	0.97	63
5	0.90	0.90	0.90	40
6	0.98	0.94	0.96	64
7	0.98	0.98	0.98	52
8	0.93	0.93	0.93	55
9	0.91	0.95	0.93	42
accuracy			0.96	540
macro avg	0.96	0.96	0.96	540
weighted avg	0.96	0.96	0.96	540

[]: