TEAM ID: PNT2022TMID43603

PROJECT NAME: Demand Est - Al powered

FoodDemand Forecaster

Team Leader

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                                                          Model Evaluation
                                                          We're going to use \mathbf{x}_{\underline{t}} train and \mathbf{y}_{\underline{t}} train obtained above in train \underline{t} testion to train our regression model. We're using the fit method and passing the parameters as shown below. Finally we need to check to see how well our model is performing on the test data.
                                                          Regression Evaluation Metrics: RMSE:Root Mean Square Error RMSE is the square root of the averaged squared difference between the target value and the value
                                                          predicted by the model. It is preferred more in some cases because the errors are first squared before averaging which poses a high penalty on large errors. This implies that RMSE is useful when large errors are undesired.
                                                          For testing the model we use the below method,
                                     In [126]: XG = XGBRegressor()
XG.fit(X_train,y_train)y_pred = XG.predict(X_val)y_pred(y_pred < 0) = 0 from sklearn import metrics
                                                             print('RMSLE:', 100*np.sqrt(metrics.mean_squared_log_error(y_val, y_pred))) RMSLE:
                                     In [127]: L = Lasso()
Lfit(X_train, ytrain) y_pred = Lpredict(X_val) y_pred(y_pred<0) = 0 from sklearn import metrics
                                                              print("RMSLE:100" np.sqrt(metrics.mean\_squared\_log\_error(y\_val,y\_pred))) \ RMSLE: \\
                                                             128.9558620089095
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                                     In [128]: EN = ElasticNet()
EN.fit(X_train,y_train)y_pred = EN.predict(X_val)y_pred(y_pred < 0) = 0 from sklearn import metrics
                                                             print('RMSLE:', 100*np.sqrt(metrics.mean_squared_log_error(y_val, y_pred))) RMSLE:
                                                             130.93230794494932
                                      In \ [129]: DT = DecisionTreeRegressor() \\ DT.fit(X\_train, ytrain) y\_pred = DT.predict(X\_val) y\_pred(y\_pred < 0] = 0 \ from \ sklearn \ import \ metrics 
                                                             print('RMSLE:', 100*np.sqrt(metrics.mean_squared_log_error(y_val,y_pred))) RMSLE:
                                                             62 750116693228705
                                     \label{eq:local_local_local_local} $$\ln [130]: KNN = KNeighborsRegressor() \\ KNN.fit(X_train,y_train) y_pred = KNN.predict(X_val) y_pred(y_pred < 0] = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from sklearn import (X_val) y_pred(y_pred < 0) = 0 from 
                                                             print('RMSLE:100*np.sqrt(metrics.mean_squared_log_error(y_val, y_pred))) RMSLE:
                                                              67.27613082623152
                                     In [131]: GB = GradientBoostingRegressor() GB.fit(X_train,
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RMSLE: 130.932307944949932

In [129]: DT = DecisionTreeRegressorQ DT.Fit(X, train, y, train) y, pred = DT.predict(X, val) y, predly_pred < 0] = 0 from sklearn import metrics

print(*RMSLE: 100*np.sqrt(metrics.mean_squared_log_error(y_val_y_predly)) RMSLE: 62.750116693228705

In [130]: KNN = KNeighbonsRegressor(D_wal_y_predly_pred < 0] = 0 from sklearn import metrics

print(*RMSLE: 100*np.sqrt(metrics.mean_squared_log_error(y_val_y_predly)) RMSLE: 67.27613082623152

In [131]: GB = GradientBoostingRegressor(Q GB.Rit(X_train, y, train)) y_pred = GB.predict(X_val) y_predly_pred < 0] = 0 from sklearn import metrics

print(*RMSLE: 100*np.sqrt(metrics.mean_squared_log_error(y_val_y_predly)) RMSLE: 67.27613082623152
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Team Member 1

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Model Evaluation

We're going to use x_train and y_train obtained above in train_test_s pi it section to train our regression model. Were using the fit method and passing the parameters as shown below. Finally, we need to check to see how well our model is performing on the test data.

Regression Evaluation Metrics: RMSE:Root Mean Square Error RMSE is the square root of the averaged squared difference between the target value and the value predicted by the model. It is preferred more in some cases because the errors are first squared before averaging which poses a high penalty on large errors. This implies that RMSE is useful when large errors are undesired.

For testing the model we use the below method,

In [126]: XG - XGBRegressorQ

\text{XG.fit(X_train,y_train)y_pred} = XG.predict(X_val)y_pred[y_pred<0] = 0 from sklearn Import metrics print(\text{?mlx}!\text{E}; \100^np.sqrt(metrics.mean_squared_log_error(y_val,y_pred)))}

RMSLE: 70.06429878638917

In [127]:

 $L = Lasso() \\ Lfit(X_train, ytrain) y_pred = l.predict(X_val) y_pred(y_pred < 0] = 0 from sklearn import metrics print("RMSLE:", 100*np.sqrt(metrics.mean_squared_log_error(y_val, y_pred)))$

RMSLE: 128.9558620089095

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In [128]: EN = ElasticNet()
EN.fit(X_train, y_train) y_pred =
EN.predict(X_val) y_pred[y_pred < 0]
= 0 from sklearn import metrics

 $print('RMSLE:', \\ 100*np.sqrt(metrics.mean_squared_log_error(y_val, \\ y_pred))) \\ RMSLE:$

130.93230794494932

$$\label{eq:decomposition} \begin{split} DT &= DecisionTreeRegressorQDT.fit(X_train, ytrain)y_pred \\ &= DT.predict(X_val)y_pred[y_pred<0] \\ &= 0 \\ from sklearn import metrics \\ print("RMSLE:", 100*np.sqrt(metrics.mean_squared_log_error(y_val,y_pred))) \end{split}$$
In [129]:

RMSLE: 62.750116693228705

 $KNN = KNeighborsRegressor() \\ KNN.fit(X_train,y_train)y_pred = KNN.predict(X_val)y_pred[y_pred < 0] = 0 \text{ from sklearn import } \\ KNN.fit(X_train,y_train)y_pred = KNN.predict(X_val)y_pred[y_pred < 0] = 0 \\ KNN.fit(X_train,y_train)y_pred = KNN.predict(X_val)y_pred = 0 \\ KNN.fit(X_train,y_train)y_pred = 0 \\ KNN.fit(X_train,y_train,y_train,y_train)y_pred = 0 \\ KNN.fit(X_train,y_trai$

metrics print('RMSLE:100*np.sqrt(metrics.mean_squared_log_error(y_val, y_pred)))

RMSLE: 67.27613082623152

In [131]:GB = GradientBoostingRegressor()
GB.fit(X_train),y_train)y_pred =
GB.predict(X_val)y_pred(y_pred<0)
= 0 from sklearn import metrics

print('RMSLE:100*np.sqrt(metrics.mean_squared_log_error(y_val, y_pred))) RMSLE:

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