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import pandas as pd
         import matplotlib.pyplot as plt
         from sklearn.preprocessing import OneHotEncoder
         from sklearn.model selection import train test split
         from sklearn.linear model import LogisticRegression
         from sklearn.metrics import accuracy score
         from sklearn.preprocessing import StandardScaler
         Split the data in to training and test sets.
 In [ ]: X_all = pd.read_csv('Dataset/train_X.csv')
         y all = pd.read csv('Dataset/train y.csv')
         Here we define the one-hot encoder, which converts the string of sequence of amino acids to a set of values, either one or zero. Each value represents the existance of a certain amino acid on a specific
         position.
 In [3]: def one_hot_encode(df):
              enc = OneHotEncoder(handle_unknown='ignore')
              X = np.array(X all['ConstructedAASeq cln'].apply(lambda x: list(x)).to list())
              enc.fit(X)
              return enc, enc.transform(df['ConstructedAASeq_cln'].apply(lambda x: list(x)).to_list()).toarray()
         We also load all the CSV files in the descriptors. These files describe some properties of each amino acid, and all data are numeric.
 In [4]: # Load descriptors
         dpps = pd.read csv('Dataset/descriptors/DPPS.csv', header=2).drop('AA 3', axis=1)
         df combined = dpps
          for file_name in ['Physical', 'Physical', 'ST-scale', 'T-scale', 'VHSE-scale', 'Z-scale']:
              df = pd.read csv(f'Dataset/descriptors/{file name}.csv', header=2).drop('AA 3', axis=1)
              df_combined = df_combined.merge(df, on='AA_1', how='inner')
         df combined = df combined.set index('AA 1')
         After combining the tables, we can see there are 38 columns.
         df_combined.head()
Out[5]:
                                              D6
                                                    D7
                                                               D9 D10 ... VHSE2 VHSE3 VHSE4 VHSE5 VHSE6 VHSE7 VHSE8 Z(1) Z(2) Z(3)
         AA_1
               -1.02
                     -2.88
                           -0.56
                                 0.36
                                       -6.15 -1.68
                                                   0.04
                                                        -2.51 -1.94 -0.01 ...
                                                                                     -1.35
                                                                                             -0.92
                                                                                                     0.02
                                                                                                           -0.91
                                                                                                                   0.36
                                                                                                                          -0.48 0.07
                                                                                                                                    -1.73
                                                                               -1.11
                                                                                                                                          0.09
                      4.13 -4.41 -1.02 4.78 3.04 -9.06
                                                         6.71 4.41 0.07 ...
                                                                               1.45
                                                                                      1.24
                                                                                             1.27
                                                                                                     1.55
                                                                                                            1.47
                                                                                                                   1.30
                                                                                                                          0.83 2.88 2.52 -3.44
                      1.86 0.38 -0.13 -2.30
                                            1.41 -5.71
                                                       -1.11 1.73 -0.19 ...
                                                                               0.00
                                                                                     -0.37
                                                                                             0.69
                                                                                                    -0.55
                                                                                                            0.85
                                                                                                                   0.73
                                                                                                                          -0.80 3.22 1.45 0.84
                                                        0.14 1.24 -0.15 ...
             D -6.60
                                 0.36 -3.25
                                             1.95 -7.36
                                                                               0.67
                                                                                     -0.41
                                                                                             -0.01
                                                                                                    -2.68
                                                                                                            1.31
                                                                                                                   0.03
                      3.32
                            1.61
                                                                                                                          0.56 3.64
                                                                                                                                     1.13
                                                                                                                                          2.36
                      1.12 3.42 -0.68 -2.27 -1.22 3.11 -2.98 -1.70 1.57 ...
                                                                              -1.67
                                                                                     -0.46
                                                                                             -0.21
                                                                                                     0.00
                                                                                                            1.20
                                                                                                                          -0.19 0.71 -0.97 4.13
                                                                                                                   -1.61
         5 rows × 38 columns
         Then we encode the data, and train a baseline logistic regression model with this encoding. We can see the accuracy is 0.9006, which is good.
 In [ ]: one_hot_encoder, one_hot_encoded = one_hot_encode(X_all)
         brightnesses = y all['Brightness Class']
         X train oh, X test oh, y train, y test = train test split(one hot encoded, brightnesses, test size=0.2, random state=5)
         # Baseline One-Hot Encoding Logistic Regression Model
          # Train the model (~30s)
         logreg = LogisticRegression(max iter=1000, random state=5)
         logreg.fit(X train oh, y train.values)
          # Predict
         y pred = logreg.predict(X test oh)
         # Evaluate
         accuracy = accuracy_score(y_test, y_pred)
         print(f"Accuracy: {accuracy:.4f}")
         Accuracy: 0.9006
         In the following codes, we will create a dataframe to examine the coeficients of the logistic regression model, for each amino acid-posiiton combination.
 In [ ]: variant_nums = []
          for category in one hot encoder.categories :
              variant_nums.append(len(category))
         positions = []
         i = 0
         for n in variant_nums:
              for _ in range(n):
                  positions.append(i)
              i += 1
         one_hot_features = pd.DataFrame()
         one_hot_features['AA'] = [i for s in one_hot_encoder.categories_ for i in s]
         one hot features['Position'] = positions
         one_hot_features['Coef'] = logreg.coef_[0]
         one_hot_features
Out[]:
               AA Position
                                Coef
             0 S
                         0 0.034112
             1 E
                         1 -0.214272
             2 K
                         1 0.331179
             3 M
                         1 0.513529
             4 N
                         1 -0.137291
         1925 H
                       235 -0.265211
          1926 N
                       235 0.165153
          1927 S
                       235 0.370086
         1928 Y
                       235 0.031901
         1929 K
                       236 0.034112
         1930 rows × 3 columns
         We aim to keep only important positions, namely the positions that include some amino acids that has a coeficient greater than 3 or less than -3.
In [17]: important_positions = one_hot_features[abs(one_hot_features['Coef']) > 3]['Position'].values
         unimportant indexs = one hot features[one hot features['Position'].apply(lambda x: x not in important positions)].index
         one hot unimportant = one hot encoded[:, unimportant indexs]
         We will split the original dataset for future use.
In [18]: X_train, X_test, y_train, y_test = train_test_split(X_all, brightnesses, test_size=0.2, random_state=5)
         Using the descriptor files, we take all the features and only on important positions. For each of them, we add 38 features with the value of the given amino acid on that position.
         def create_des_features(df, im_pos):
              matrixs = []
              for p in im_pos:
                  matrix = []
                  for aa in df['ConstructedAASeq_cln'].apply(lambda x: x[p]).to_list():
                      matrix.append(df combined.loc[aa].values)
                  matrixs.append(np.array(matrix))
              return np.hstack(matrixs)
          # ~8s
         X train des = create des features(X train, important positions)
         X_test_des = create_des_features(X_test, important_positions)
         Split the data of all unimportant positions for future use.
In [21]: X_train_oh, X_test_oh, y_train, y_test = train_test_split(one_hot_unimportant, brightnesses, test_size=0.2, random_state=5)
         We combine the two parts we have now: the important positions which replaced by the 38 features in the descriptors, and the unimportant positions which still use the one-hot encoding construction.
In [23]: # Scale and combine the one-hot on unimportant positions and descripters on important positions
          def combine_and_scale(oh, des):
              scaled numeric features = np.hstack((oh, des))
              scaler = StandardScaler()
              return scaler.fit_transform(scaled_numeric_features)
         X_train_oh_des = combine_and_scale(X_train_oh, X_train_des)
         X_test_oh_des = combine and scale(X_test_oh, X_test_des)
         Train the model, which gives 0.8969 accuracy, which is slightly lower, but may be more general for unseen data (which has been proved to be true given the result on Kaggle).
In [24]: # Train the model
         logreg = LogisticRegression(max_iter=1000, random_state=5)
         logreg.fit(X_train_oh_des, y_train.values)
          # Predict
         y_pred = logreg.predict(X_test_oh_des)
          # Evaluate
         accuracy = accuracy score(y_test, y_pred)
         print(f"Accuracy: {accuracy:.4f}")
         Accuracy: 0.8969
         Finally we train the model for prediction.
 In [ ]: # Final model
         X des = create des features(X all, important positions)
         X oh des = combine and scale(one hot encoded, X des)
          final model = LogisticRegression(max_iter=1000, random_state=5)
         final_model.fit(X_oh_des, brightnesses.values)
Out[]:
                            LogisticRegression
         LogisticRegression(max_iter=1000, random_state=5)
         Write the prediction to file.
In [36]: # Make File to Submit
          def write ans(predictions):
              out = pd.read_csv('Dataset/y_sample_submission.csv')
              out['Brightness Class'] = predictions
              out.to_csv('Dataset/predictions.csv', index=False)
         X to predict = pd.read csv('Dataset/test X.csv')
         predictions = final_model.predict(
              combine_and_scale(one_hot_encode(X_to_predict)[1], create_des_features(X_to_predict, important_positions))
```

In [1]: import numpy as np

write_ans(predictions)