# lab03\_partB

September 23, 2024

```
[88]: import pandas as pd
housing = pd.read_csv('housing.csv')
```

## 0.1 Question 1

```
[89]: ## 1. split data to get train and test set
      from sklearn.model_selection import train_test_split
      train_set, test_set = train_test_split(housing, test_size=0.2, random_state=10)
      ## 2. clean the missing values
      train_set_clean = train_set.dropna(subset=["total_bedrooms"])
      train_set_clean
      ## 3. derive training features and training labels
      train_labels = train_set_clean["median_house_value"].copy() # get labels for_
       \hookrightarrow output label Y
      train_features = train_set_clean.drop("median_house_value", axis=1) # drop_
       → labels to get features X for training set
      ## 4. scale the numeric features in training set
      from sklearn.preprocessing import MinMaxScaler
      scaler = MinMaxScaler() ## define the transformer
      scaler.fit(train_features) ## call .fit() method to calculate the min and max__
       →value for each column in dataset
      train_features_normalized = scaler.transform(train_features)
      train_features_normalized
[89]: array([[0.77988048, 0.1360255, 0.39215686, ..., 0.10146024, 0.28498602,
              0.13939808],
```

```
0.13939808],
[0.14043825, 0.63336876, 0.88235294, ..., 0.02253426, 0.06002302, 0.14701177],
[0.18525896, 0.54091392, 0.58823529, ..., 0.04117268, 0.10146358, 0.32103695],
...,
[0.25498008, 0.50797024, 0.09803922, ..., 0.06045573, 0.09537905,
```

```
[0.60956175, 0.15302869, 0.66666667, ..., 0.06045573, 0.08156553,
              0.11765355],
             [0.24601594, 0.50584485, 0.29411765, ..., 0.04683427, 0.11182371,
              0.15009448]])
[90]: ## 1. split data to get train and test set
      from sklearn.model_selection import train_test_split
      train_set, test_set = train_test_split(housing, test_size=0.2, random_state=10)
[91]: ## 2. clean the missing values
      test_set_clean = test_set.dropna(subset=["total_bedrooms"])
      test_set_clean
[91]:
             longitude latitude housing_median_age total_rooms total_bedrooms \
      20303
               -119.18
                           34.16
                                                 12.0
                                                              460.0
                                                                               101.0
               -122.31
                           37.55
      16966
                                                 27.0
                                                             3931.0
                                                                              933.0
      10623
                                                 12.0
               -117.77
                           33.67
                                                             4329.0
                                                                             1068.0
      6146
               -117.95
                           34.11
                                                 29.0
                                                             1986.0
                                                                              448.0
      2208
               -119.87
                           36.81
                                                  6.0
                                                             1891.0
                                                                              341.0
               -122.88
                           39.14
                                                 20.0
                                                             1125.0
                                                                              231.0
      3263
      11694
               -117.98
                           33.89
                                                 18.0
                                                             2939.0
                                                                              437.0
      1729
               -122.34
                           37.98
                                                 33.0
                                                             2014.0
                                                                              410.0
      5087
                           33.98
                                                 45.0
               -118.28
                                                             1720.0
                                                                              416.0
                           34.21
                                                 40.0
      6581
               -118.20
                                                             1477.0
                                                                              228.0
             population households median_income median_house_value
      20303
                  405.0
                               103.0
                                             5.2783
                                                                167400.0
      16966
                                             3.9722
                 1877.0
                               851.0
                                                                354100.0
      10623
                 1913.0
                              978.0
                                             4.5094
                                                                160200.0
      6146
                 2013.0
                              432.0
                                             3.1034
                                                                140800.0
      2208
                  969.0
                               330.0
                                             4.6726
                                                                107800.0
      3263
                  521.0
                               196.0
                                             2.2188
                                                                106300.0
      11694
                 1278.0
                               435.0
                                             7.1425
                                                                393700.0
      1729
                 1354.0
                               427.0
                                             3.9773
                                                                131300.0
      5087
                 1382.0
                               365.0
                                             0.9337
                                                                92300.0
      6581
                  609.0
                               224.0
                                             7.8375
                                                                500001.0
      [4087 rows x 9 columns]
[92]: ## 3. derive training features and training labels
      test_labels = test_set_clean["median_house_value"].copy() # get labels for_
       \hookrightarrow output label Y
      test_features = test_set_clean.drop("median_house_value", axis=1) # drop labels_
       →to get features X for training set
```

0.34714694],

```
[93]: ## 4. scale the numeric features in training set
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler() ## define the transformer
scaler.fit(test_features) ## call .fit() method to calculate the min and max_u
value for each column in dataset

test_features_normalized = scaler.transform(test_features) ## call .transform()_u
method to scale the features
```

### 0.2 Question 2

#### 0.2.1 Step 10b

```
[94]: from sklearn.neighbors import KNeighborsRegressor
```

```
[95]: import time
start_time = time.time()

KNN_Regeressor = KNeighborsRegressor(n_neighbors=10, metric='euclidean')
KNN_Regeressor.fit(test_features_normalized, test_labels)

end_time = time.time()
elapsed_time = end_time - start_time
print("Training time: ", elapsed_time)
```

Training time: 0.0034983158111572266

#### 0.3 Question 3

#### 0.3.1 Step 10c

```
[96]: training_predicttions = KNN_Regeressor.predict(test_features_normalized)
    shape=training_predicttions.shape
    print("Shape of testing_predictions: ", shape)
    label_shape=test_labels.shape
    print("Shape of test_labels: ", label_shape)
```

Shape of testing\_predictions: (4087,) Shape of test\_labels: (4087,)

## 0.4 Question 4

### 0.4.1 Step 10d

#### task 1

```
[97]: prediction_summary = pd.DataFrame({'Actual': train_labels, 'Predicted':⊔

→training_predicttions})

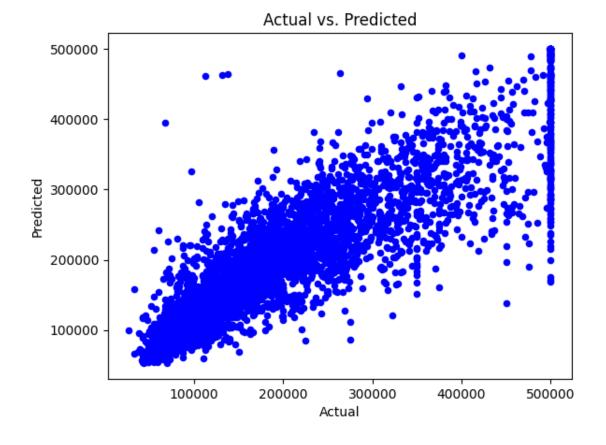
print(prediction_summary)
```

```
ValueError
                                           Traceback (most recent call last)
Cell In[97], line 1
----> 1 prediction_summary =
 apd.DataFrame({'Actual': train_labels, 'Predicted': training_predicttions})
      2 print(prediction_summary)
File c:
 →\Users\Julian\AppData\Local\Programs\Python\Python311\Lib\site-packages\panda \core\frame.
 py:778, in DataFrame. init (self, data, index, columns, dtype, copy)
            mgr = self. init mgr(
                data, axes={"index": index, "columns": columns}, dtype=dtype,__
    773
 774
    776 elif isinstance(data, dict):
            # GH#38939 de facto copy defaults to False only in non-dict cases
    777
--> 778
 dict_to_mgr(data, index, columns, dtype=dtype, copy=copy, typ=manager)
    779 elif isinstance(data, ma.MaskedArray):
    780
            from numpy.ma import mrecords
File c:
 →\Users\Julian\AppData\Local\Programs\Python\Python311\Lib\site-packages\panda;\core\internation

¬py:503, in dict_to_mgr(data, index, columns, dtype, typ, copy)
    499
            else:
    500
                # dtype check to exclude e.g. range objects, scalars
                arrays = [x.copy() if hasattr(x, "dtype") else x for x in array ]
    501
--> 503 return
 arrays_to_mgr(arrays, columns, index, dtype=dtype, typ=typ, consolidate=copy)
File c:
 →\Users\Julian\AppData\Local\Programs\Python\Python311\Lib\site-packages\panda;\core\international
 py:114, in arrays to mgr(arrays, columns, index, dtype, verify integrity, type,
 ⇔consolidate)
    111 if verify_integrity:
            # figure out the index, if necessary
    113
            if index is None:
--> 114
                index = _extract_index(arrays)
    115
            else:
                index = ensure index(index)
    116
File c:
 →\Users\Julian\AppData\Local\Programs\Python\Python311\Lib\site-packages\panda;\core\internation
 →py:690, in _extract_index(data)
            if lengths[0] != len(index):
    685
    686
                msg = (
    687
                    f"array length {lengths[0]} does not match index "
                    f"length {len(index)}"
    688
```

```
689 )
--> 690 raise ValueError(msg)
691 else:
692 index = default_index(lengths[0])

ValueError: array length 4087 does not match index length 16346
```



task 2

```
[52]: import numpy as np
      np.corrcoef(train_labels, training_predicttions)
[52]: array([[1.
                       , 0.86191378],
             [0.86191378, 1.
                                    ]])
     0.5 Question 5
     0.5.1 Step 10e
[53]: prediction_summary['error'] = prediction_summary['Actual'] -__
       →prediction_summary['Predicted']
[54]: from sklearn.metrics import mean_squared_error
      lin_mse = mean_squared_error(train_labels, training_predicttions)
      lin rmse = np.sqrt(lin mse)
      lin rmse
[54]: 59804.04517062825
     0.6 Question 6
     0.6.1 Step 10f
     0.7 task 2
[55]: # practice 10f.1: Define one KNN model
      from sklearn.neighbors import KNeighborsRegressor
      KNN regressor = KNeighborsRegressor(n_neighbors=7, metric = 'euclidean') # pick_
       ⇔one configuration K=7
[56]: | ## practice 10f.2: Evaluate the KNN model using cross-validation on the
      ⇔training set
      # KNN will take ~3min set using 10-fold cross-validation
      from sklearn.model selection import cross val score
      CV_mse_scores = cross_val_score(estimator = KNN_regressor, X = __
       strain_features_normalized, y = train_labels, cv = 10, scoring =_u

¬'neg_mean_squared_error')
      print("CV_mse_scores: ", CV_mse_scores)
     CV mse scores: [-3.91841608e+09 -4.10790086e+09 -3.59604082e+09 -3.81505352e+09
      -4.08762578e+09 -3.83463385e+09 -4.10664865e+09 -3.77413013e+09
      -3.73180413e+09 -4.15740833e+091
     Task 3
[57]: # display CV scores
      def display_scores(scores):
          print("CV_scores: ", scores)
          print("CV Mean: ", scores.mean())
```

```
print("CV Standard deviation: ", scores.std())
[58]: display_scores(CV_mse_scores)
     CV_scores: [-3.91841608e+09 -4.10790086e+09 -3.59604082e+09 -3.81505352e+09
      -4.08762578e+09 -3.83463385e+09 -4.10664865e+09 -3.77413013e+09
      -3.73180413e+09 -4.15740833e+091
     CV Mean: -3912966215.784583
     CV Standard deviation: 182773010.66517955
     Task 4
[59]: from sklearn.model_selection import cross_val_score
      CV_r2_scores = cross_val_score(estimator = KNN_regressor, X = __
       strain_features_normalized, y = train_labels, cv = 10, scoring = 'r2')
      print("CV_r2_scores: ", CV_r2_scores)
     CV_r2_scores: [0.69080821 0.70565108 0.71749391 0.69946592 0.69684798
     0.71756461
      0.69251691 0.71558565 0.72019134 0.68628121]
     0.8 Question 7
 []:
[66]: def evaluate_knn(k_values):
          results = []
          for k in k_values:
              knn_regressor = KNeighborsRegressor(n_neighbors=k)
              knn regressor fit(train features normalized, train labels)
              # Training MSE
              training_predictions = knn_regressor.predict(train_features_normalized)
              training_mse = mean_squared_error(train_labels, training_predictions)
              # Training Correlation
              training_corr = np.corrcoef(train_labels, training_predictions)[0, 1]
              # Cross-validation MSE (10-fold CV)
              cv_mse_scores = cross_val_score(knn_regressor,_

¬train_features_normalized, train_labels, cv=10,

□

¬scoring='neg_mean_squared_error')
              mean cv mse = -cv mse scores.mean()
              std_cv_mse = cv_mse_scores.std()
              # Cross-validation R<sup>2</sup> (10-fold CV)
              cv_r2_scores = cross_val_score(knn_regressor,__
       strain_features_normalized, train_labels, cv=10, scoring='r2')
```

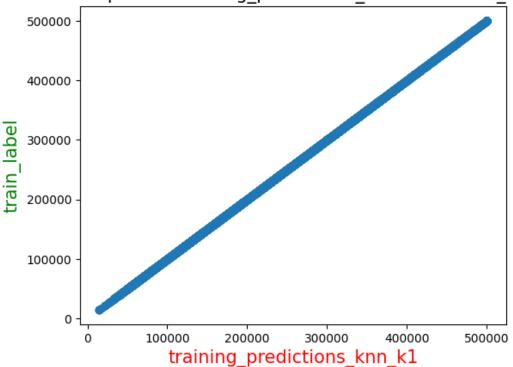
```
mean_cv_r2 = cv_r2_scores.mean()
              std_cv_r2 = cv_r2_scores.std()
              # Append the results for this K value
             results.append({
                  'K': k,
                  'Training MSE': training_mse,
                  'Training Correlation': training_corr,
                  'Mean CV MSE': mean cv mse,
                  'Std CV MSE': std_cv_mse,
                  'Mean CV R2': mean_cv_r2,
                  'Std CV R2': std_cv_r2
             })
         return pd.DataFrame(results)
[67]: k_values = [1, 3, 5, 7, 9]
     knn_results = evaluate_knn(k_values)
[68]: print(knn_results)
        K Training MSE Training Correlation
                                              Mean CV MSE
                                                              Std CV MSE \
     0
       1 0.000000e+00
                                     1.000000 5.785628e+09
                                                            2.825489e+08
     1 3 2.017961e+09
                                     0.920965 4.248065e+09 1.789400e+08
     2 5 2.559006e+09
                                     0.898736 4.013255e+09 2.132148e+08
     3 7 2.856855e+09
                                     0.886280 3.912966e+09 1.827730e+08
       9 3.027968e+09
                                     0.879043 3.905838e+09 1.614103e+08
        Mean CV R2 Std CV R2
     0
          0.562436
                   0.023991
     1
          0.678839 0.013231
     2
          0.696624 0.015209
     3
          0.704241 0.012067
          0.704746
                    0.011111
     0.9
          Question 8
[61]: from sklearn.neighbors import KNeighborsRegressor
     KNN regressor k1 = KNeighborsRegressor(n neighbors=1) # pick one configuration_
     KNN_regressor_k1.fit(train_features_normalized, train_labels)
[61]: KNeighborsRegressor(n_neighbors=1)
[62]: training_predictions_knn_k1 = KNN_regressor_k1.

¬predict(train_features_normalized)
     training_predictions_knn_k1
```

```
[62]: array([145200., 117000., 263900., ..., 241900., 150000., 191100.])
```

```
[63]: import matplotlib.pyplot as plt
plt.scatter(training_predictions_knn_k1, train_labels)
plt.xlabel('training_predictions_knn_k1', fontsize=15, color="red")
plt.ylabel('train_label', fontsize=15,color="green")
plt.title('Scatter plot for training_predictions_trees and train_label', u
fontsize=15)
plt.show()
```

# Scatter plot for training\_predictions\_trees and train\_label



```
[65]: from sklearn.metrics import mean_squared_error knn_k1_mse = mean_squared_error(train_labels, training_predictions_knn_k1) print("Training MSE of model: ",knn_k1_mse)
```

Training MSE of model: 0.0

## 0.10 Question 10

```
[69]: # Practice 13.1: define a ML model to finetune the hyper-parameters from sklearn.neighbors import KNeighborsRegressor

KNN_regressor = KNeighborsRegressor()
# leave the hyper-parameters empty inside the method classs
```

```
[72]: # parameter 1: n_neighbors
      n_{\text{neighbors\_list}} = [1, 3, 5, 7, 9]
[73]: # parameter 2: weighting strategies
      metrics_list = ["uniform", "distance"]
[74]: # Practice 13.2: Define the hyper-parameter combination
      KNN param grid = {
      'n_neighbors': n_neighbors_list,
      'weights': metrics list
[75]: # Practice 13.3: define grid_search
      from sklearn.model_selection import GridSearchCV
      grid_search = GridSearchCV(estimator = KNN_regressor, param_grid = __
      KNN param grid, cv = 10, scoring = 'r2', return_train_score = True)
      ## we use 'r2' as evaluation metrics for this example
      ## check what does return train score = True mean
[76]: # Practice 13.4: fit grid-searchev on training data
      grid_search.fit(X = train_features_normalized, y = train_labels)
[76]: GridSearchCV(cv=10, estimator=KNeighborsRegressor(),
                   param_grid={'n_neighbors': [1, 3, 5, 7, 9],
                               'weights': ['uniform', 'distance']},
                   return_train_score=True, scoring='r2')
     0.11 Question 11
[77]: # practice 13c.1: get best parameters
      grid search best params
[77]: {'n_neighbors': 9, 'weights': 'distance'}
[78]: # practice 13c.2: get best estimator
      best_knn_model = grid_search.best_estimator_
      best_knn_model
[78]: KNeighborsRegressor(n_neighbors=9, weights='distance')
[79]: # Create a df from the cv_resutls
      df_cv = pd.DataFrame(grid_search.cv_results_)
      df_cv.head()
[79]:
        mean_fit_time std_fit_time mean_score_time std_score_time \
      0
              0.009519
                            0.000231
                                             0.008628
                                                             0.000473
              0.009242
                            0.000225
                                             0.008370
                                                             0.000327
      1
      2
              0.009432
                            0.000270
                                             0.011961
                                                             0.001824
```

```
3
        0.009071
                       0.000268
                                         0.011555
                                                          0.000535
4
        0.009189
                       0.000249
                                         0.013176
                                                          0.000828
   param_n_neighbors param_weights
                                                                           params
0
                    1
                            uniform
                                       {'n_neighbors': 1, 'weights': 'uniform'}
                    1
                                      {'n_neighbors': 1, 'weights': 'distance'}
1
                           distance
                                       {'n_neighbors': 3, 'weights': 'uniform'}
2
                    3
                            uniform
                                     {'n_neighbors': 3, 'weights': 'distance'}
3
                    3
                           distance
                                       {'n neighbors': 5, 'weights': 'uniform'}
4
                    5
                            uniform
                       split1 test score
                                          split2 test score
   split0 test score
0
            0.519702
                                 0.603715
                                                     0.573019
1
            0.519702
                                 0.603715
                                                     0.573019
2
            0.665652
                                 0.689578
                                                     0.684602
3
            0.669229
                                 0.697347
                                                     0.692106
4
            0.684007
                                 0.699685
                                                     0.705688
   split2_train_score
                        split3_train_score
                                             split4_train_score
             1.000000
0
                                   1.000000
                                                        1.000000
             1.000000
                                   1.000000
                                                        1.000000
1
2
             0.845155
                                   0.845877
                                                        0.847110
3
             1.000000
                                   1.000000
                                                        1.000000
4
             0.803992
                                   0.804432
                                                        0.805589
   split5_train_score
                        split6_train_score
                                             split7_train_score
0
             1.000000
                                   1.000000
                                                        1.000000
             1.000000
                                   1.000000
                                                        1.000000
1
2
             0.845713
                                   0.845675
                                                        0.843759
3
             1.000000
                                   1.000000
                                                        1.000000
4
             0.804018
                                   0.805180
                                                        0.802353
   split8_train_score
                        split9_train_score
                                                                 std_train_score
                                             mean_train_score
0
             1.000000
                                   1.000000
                                                      1.000000
                                                                        0.000000
             1.000000
                                   1.000000
                                                      1.000000
1
                                                                        0.00000
2
             0.845161
                                   0.846836
                                                      0.845660
                                                                        0.001091
3
             1.000000
                                   1.000000
                                                      1.000000
                                                                        0.00000
             0.802877
                                   0.806684
                                                      0.804357
                                                                        0.001389
[5 rows x 32 columns]
```

## 0.12 Question 12

```
[80]: ## 1. clean the missing values in test set
test_set_clean = test_set.dropna(subset=["total_bedrooms"])
test_set_clean
```

```
## 2. derive test features and test labels. In this case, test labels are only.
       ⇔used for evaluation
      test_labels = test_set_clean["median_house_value"].copy() # get labels for_
       \hookrightarrowoutput label Y
      test_features = test_set_clean.drop("median_house_value", axis=1) # drop labels__
       ⇒to get features X for training set
      ## 4. scale the numeric features in test set. The scaler is derived from Step 10
      ## important note: do not apply fit function on the test set, using same scalar
       ⇔from training set
      test_features_normalized = scaler.transform(test_features)
      test_features_normalized
[80]: array([[0.52191641, 0.17241379, 0.21568627, ..., 0.02481851, 0.01928268,
              0.32954028],
             [0.20285423, 0.53771552, 0.50980392, ..., 0.11615065, 0.16351716,
             [0.6656473, 0.11961207, 0.21568627, ..., 0.11838431, 0.18800617,
              0.27651343],
             [0.19979613, 0.58405172, 0.62745098, ..., 0.08370044, 0.08175858,
              0.23981738],
             [0.61365953, 0.15301724, 0.8627451, ..., 0.08543774, 0.06980332,
              0.02991683],
             [0.62181448, 0.17780172, 0.76470588, ..., 0.03747596, 0.04261473,
              0.5060344 11)
[81]: ### Step 5: make a prediction using the best model from the hyper-parameter.
       \hookrightarrow tuning
      # practice 13c.2: get best estimator
      best knn model = grid search.best estimator
      test_predictions_knn = best_knn_model.predict(test_features_normalized)
      test predictions knn
[81]: array([322741.00801447, 250409.67942524, 191558.03474468, ...,
             260163.42618696, 129864.63337078, 467212.33086968])
[82]: from sklearn.metrics import mean squared error
      from sklearn.metrics import r2_score
      test_knn_mse = mean_squared_error(test_labels, test_predictions_knn)
      test_knn_correlation = np.corrcoef(test_labels, test_predictions_knn)
      test_knn_R2 = r2_score(test_labels, test_predictions_knn)
      print("MSE: ", test_knn_mse)
      print("Correlation: ", test_knn_correlation)
      print("R2-score: ", test_knn_R2)
```

MSE: 4364782631.990618

```
Correlation: [[1.
                                0.83272273]
      [0.83272273 1.
                            ]]
     R2-score: 0.6803241320815888
[83]: from joblib import dump, load
      dump(scaler, 'scaler.joblib')
[83]: ['scaler.joblib']
[84]: dump(best_knn_model, 'best_knn_model.joblib')
[84]: ['best_knn_model.joblib']
[85]: scaler_reload = load('scaler.joblib')
[86]: print("Scaler Min: ",scaler_reload.data_min_)
      print("Scaler Max: ",scaler_reload.data_max_)
                               32.56
                                                              3.
                                                                        5.
                                                                                  3.
     Scaler Min: [-124.3
                                          1.
                                                   16.
         0.4999]
     Scaler Max: [-1.14490e+02 4.18400e+01 5.20000e+01 3.79370e+04 5.47100e+03
       1.61220e+04 5.18900e+03 1.50001e+01]
[87]: KNN_model_reload = load('best_knn_model.joblib')
      KNN_model_reload
[87]: KNeighborsRegressor(n_neighbors=9, weights='distance')
```