California Housing problem

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In [164…

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import chi2_contingency, ttest_ind, zscore, f_oneway
```

Problem Introduction

The California housing prices dataset provides a rich collection of features related to housing districts in California, including median housing prices. This dataset is widely used in machine learning to explore the relationships between various factors and predict the median housing price for different districts. The goal of this problem is to develop a predictive model that can accurately estimate the median housing price based on the given features.

Understanding the dynamics that influence housing prices is crucial for various stakeholders, including real estate investors, policymakers, and homebuyers. A reliable predictive model can assist in making informed decisions about property investments, assessing the impact of socio-economic factors on housing prices, and supporting individuals in their search for affordable housing.

In this context, the task is to analyze the California housing prices dataset, preprocess the data, and build a machine learning model capable of predicting the median housing price for a given district. By developing an accurate predictive model, it is possible to contribute to the broader understanding of housing market trends and provide valuable insights for those interested in the California real estate landscape.

Dataset Description

A link to the dataset used can be found here.

1. **longitude**: A measure of how far west a house is; a higher value is farther west
2. **latitude**: A measure of how far north a house is; a higher value is farther north
3. **housingMedianAge**: Median age of a house within a block; a lower number is a newer building
4. **totalRooms**: Total number of rooms within a block
5. **totalBedrooms**: Total number of bedrooms within a block
6. **population**: Total number of people residing within a block
7. **households**: Total number of households, a group of people residing within a home unit, for a block

8. **medianIncome**: Median income for households within a block of houses (measured in tens of thousands of US Dollars)
9. **medianHouseValue**: Median house value for households within a block (measured in US Dollars)
10. **oceanProximity**: Location of the house w.r.t ocean/sea

In [165…

```
df = pd.read_csv('housing.csv')
```

In [166…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object 
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

Handling of missing or invalid data

In [167…

```
df.isnull().sum()
```

Out[167]:

```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
median_house_value      0
ocean_proximity         0
dtype: int64
```

In [168…

```
df['total_bedrooms'].fillna(df['total_bedrooms'].mean(), inplace=True)
```

In [169…

```
df.isnull().sum()
```

Out[169]:

```
longitude             0
latitude              0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
households            0
median_income         0
median_house_value    0
ocean_proximity       0
dtype: int64
```

In [170…
```
df = df.drop_duplicates()
```

In [171…
```
df.describe()
```

Out[171]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populati
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.0000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.4767
std	2.003532	2.135952	12.585558	2181.615252	419.266592	1132.4621
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.0000
25%	-121.800000	33.930000	18.000000	1447.750000	297.000000	787.0000
50%	-118.490000	34.260000	29.000000	2127.000000	438.000000	1166.0000
75%	-118.010000	37.710000	37.000000	3148.000000	643.250000	1725.0000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.0000

In [172…
```
df["ocean_proximity"].value_counts()
```

Out[172]:
```
ocean_proximity
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: count, dtype: int64
```

In [173…
```
encoded_df = pd.get_dummies(df, columns = ['ocean_proximity'])
encoded_df
```

Out[173]:

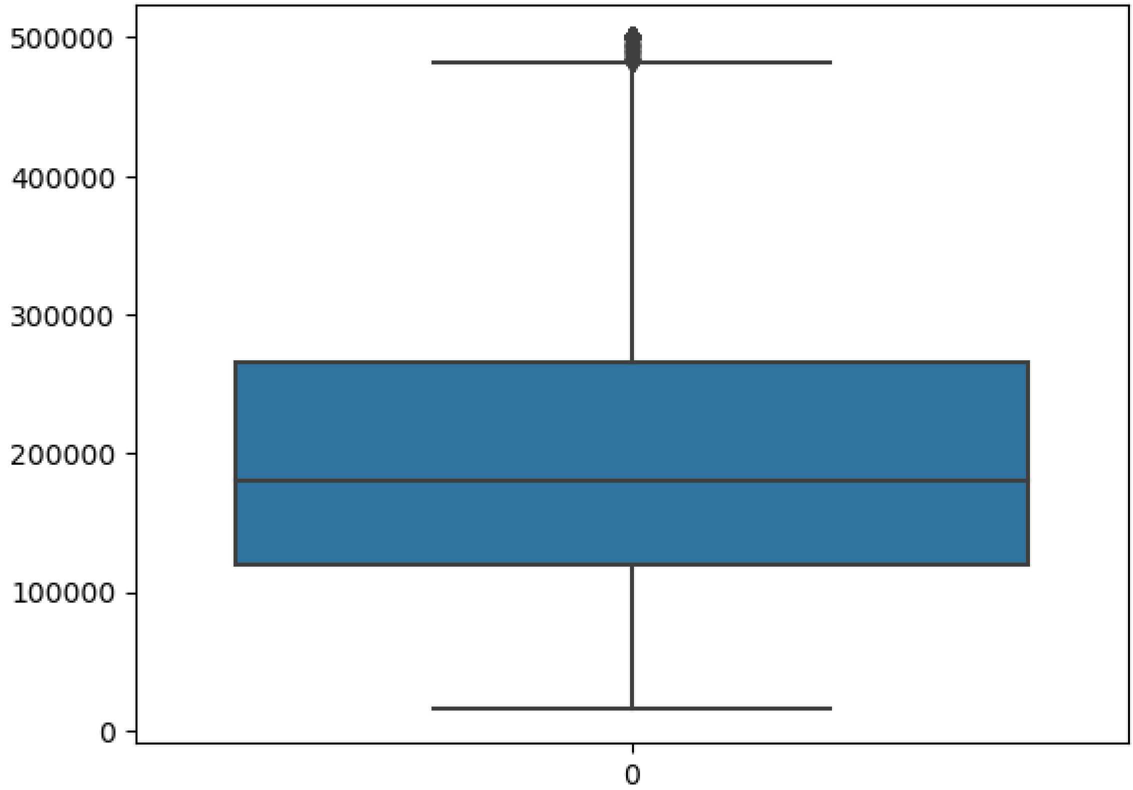
	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	househ
0	-122.23	37.88	41.0	880.0	129.0	322.0	1
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	11
2	-122.24	37.85	52.0	1467.0	190.0	496.0	1
3	-122.25	37.85	52.0	1274.0	235.0	558.0	2
4	-122.25	37.85	52.0	1627.0	280.0	565.0	2
...	...	...	...	...	...	...	
20635	-121.09	39.48	25.0	1665.0	374.0	845.0	3
20636	-121.21	39.49	18.0	697.0	150.0	356.0	1
20637	-121.22	39.43	17.0	2254.0	485.0	1007.0	4
20638	-121.32	39.43	18.0	1860.0	409.0	741.0	3
20639	-121.24	39.37	16.0	2785.0	616.0	1387.0	5

20640 rows × 14 columns

Data Visualization

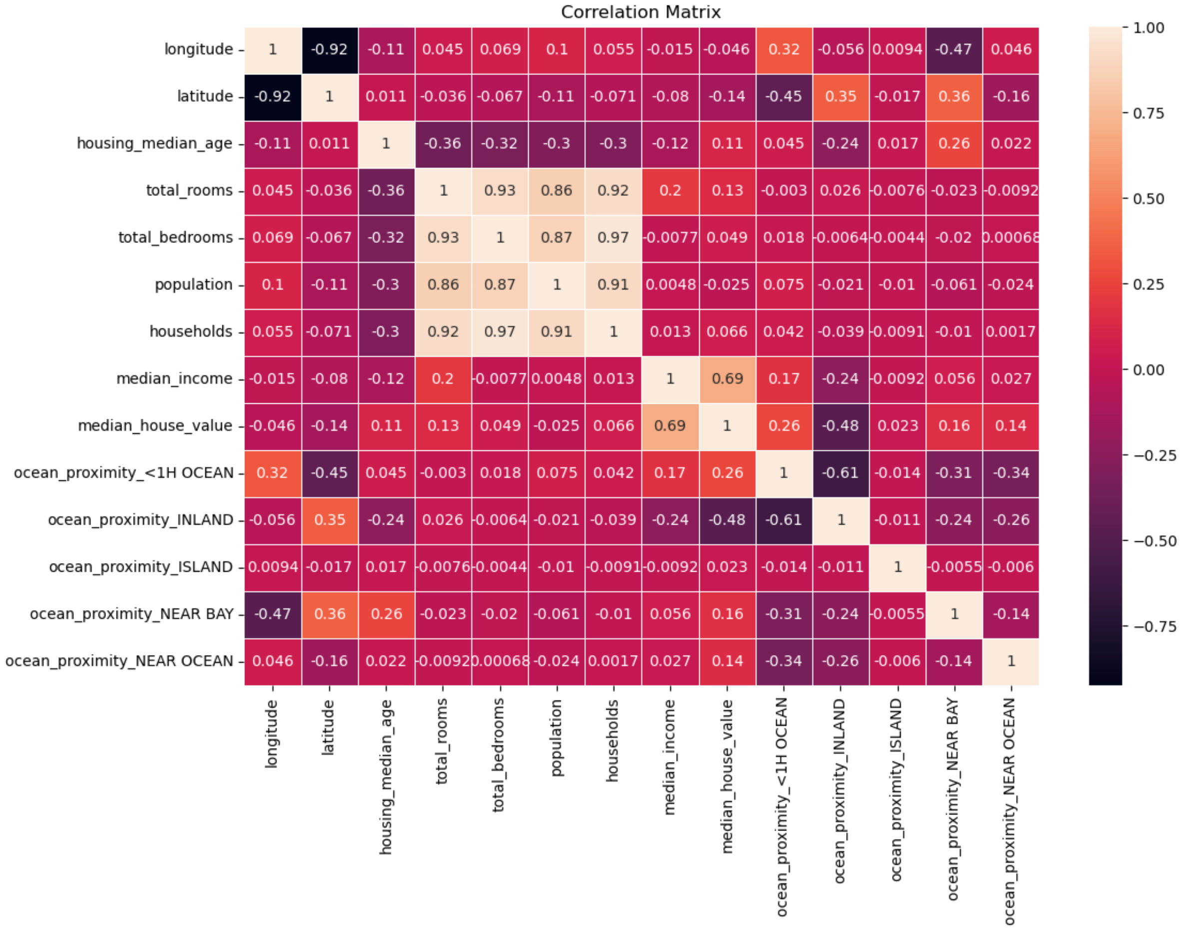
In [174…

```
sns.boxplot(encoded_df['median_house_value'])
plt.show()
```



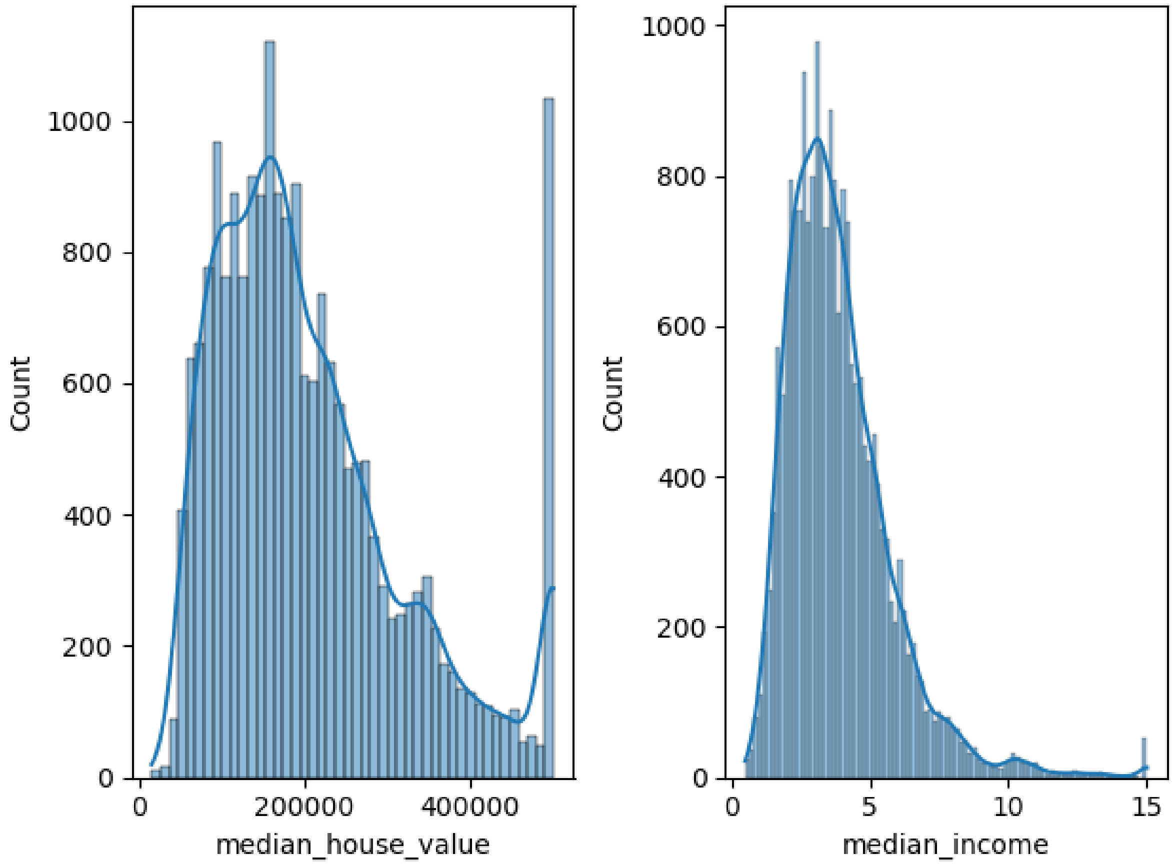
In [175…

```
cov = encoded_df.cov()
cor = encoded_df.corr()


plt.figure(figsize=(12,8))
sns.heatmap(cor, annot=True, linewidths = .5)
plt.title("Correlation Matrix")
plt.show()
```



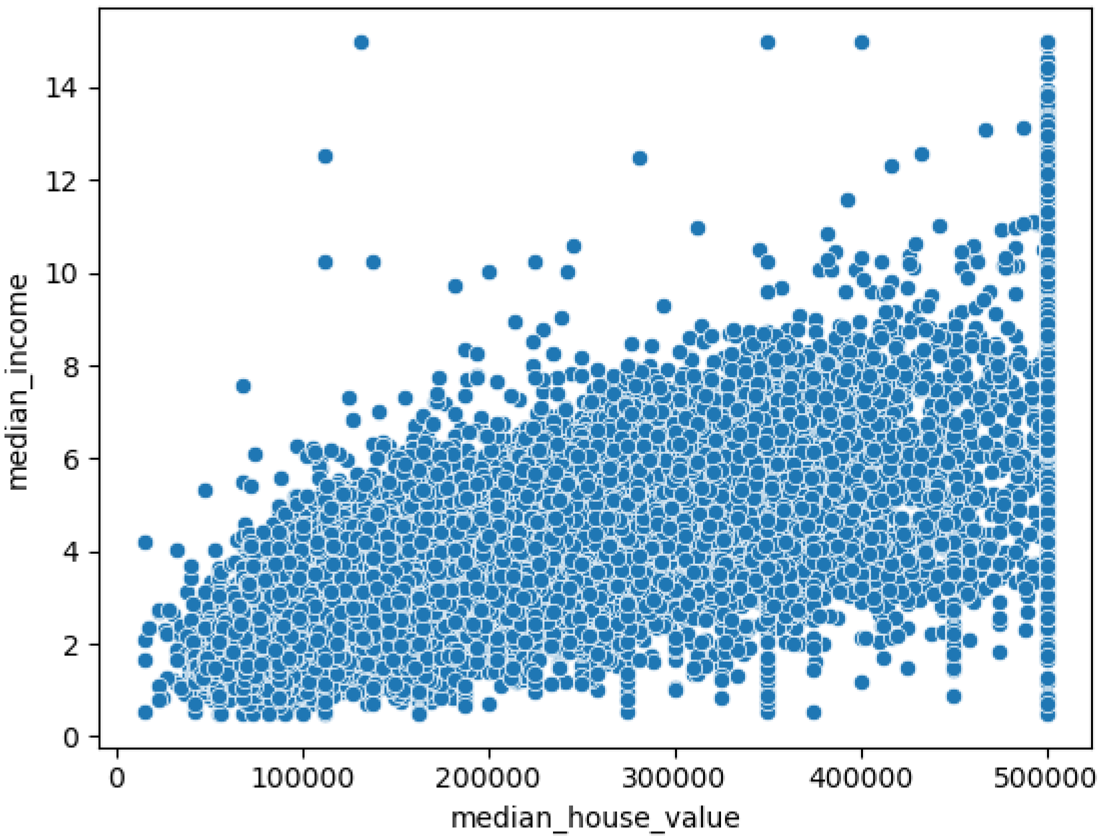
In [176…

```
plt.subplot(1,2,1)
sns.histplot(df['median_house_value'], kde=True)

plt.subplot(1,2,2)
sns.histplot(df['median_income'], kde=True)

plt.tight_layout()
```



In [177…

```
sns.scatterplot(data=encoded_df, x='median_house_value', y='median_income')
plt.show()
```



Data Analysis

In [178…

```
encoded_df.describe().T
```

Out[178]:

	count	mean	std	min	25%	50%
longitude	20640.0	-119.569704	2.003532	-124.3500	-121.8000	-118.4900
latitude	20640.0	35.631861	2.135952	32.5400	33.9300	34.2600
housing_median_age	20640.0	28.639486	12.585558	1.0000	18.0000	29.0000
total_rooms	20640.0	2635.763081	2181.615252	2.0000	1447.7500	2127.0000
total_bedrooms	20640.0	537.870553	419.266592	1.0000	297.0000	438.0000
population	20640.0	1425.476744	1132.462122	3.0000	787.0000	1166.0000
households	20640.0	499.539680	382.329753	1.0000	280.0000	409.0000
median_income	20640.0	3.870671	1.899822	0.4999	2.5634	3.5348
median_house_value	20640.0	206855.816909	115395.615874	14999.0000	119600.0000	179700.0000

In [179…

```
variance = np.var(encoded_df)
skewness = encoded_df.skew()
kurtosis = encoded_df.kurt()
print("Variance: \n{}".format(variance))
print("\nSkewness: \n{}".format(skewness))
print("\nKurtosis: \n{}".format(kurtosis))
```

```
Variance:
longitude                     4.013945e+00
latitude                      4.562072e+00
housing_median_age            1.583886e+02
total_rooms                   4.759215e+06
total_bedrooms                1.757760e+05
population                    1.282408e+06
households                    1.461690e+05
median_income                 3.609148e+00
median_house_value            1.331550e+10
ocean_proximity_<1H OCEAN     2.467093e-01
ocean_proximity_INLAND        2.166548e-01
ocean_proximity_ISLAND        2.421894e-04
ocean_proximity_NEAR BAY      9.863980e-02
ocean_proximity_NEAR OCEAN    1.121950e-01
dtype: float64

Skewness:
longitude                     -0.297801
latitude                       0.465953
housing_median_age             0.060331
total_rooms                    4.147343
total_bedrooms                 3.477023
population                     4.935858
households                     3.410438
median_income                  1.646657
median_house_value             0.977763
ocean_proximity_<1H OCEAN      0.230999
ocean_proximity_INLAND         0.784682
ocean_proximity_ISLAND        64.230833
ocean_proximity_NEAR BAY       2.477658
ocean_proximity_NEAR OCEAN     2.216702
dtype: float64

Kurtosis:
longitude                       -1.330152
latitude                        -1.117760
housing_median_age              -0.800629
total_rooms                     32.630927
total_bedrooms                  22.238643
population                      73.553116
households                      22.057988
median_income                    4.952524
median_house_value               0.327870
ocean_proximity_<1H OCEAN       -1.946828
ocean_proximity_INLAND          -1.384408
ocean_proximity_ISLAND        4123.999496
ocean_proximity_NEAR BAY         4.139189
ocean_proximity_NEAR OCEAN       2.914048
dtype: float64
```

In [180…

```
bins = [0, 50000, 100000, 150000, 200000, 250000, 300000, 350000, 400000, 450000, 5
labels = ['0-50000', '50000-100000', '100000-150000', '150000-200000', '200000-2500
         '350000-400000', '400000-450000', '450000-500000', '500000+']
new_df = encoded_df
new_df['price_range']= pd.cut(encoded_df['median_house_value'], bins=bins, labels=l


from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
le.fit(new_df['price_range'])
LabelEncoder()
labeled = le.transform(encoded_df['price_range'])
```

In [181…
```
import scipy.stats as stats


med_values = encoded_df['median_house_value']

# Sample data for three groups
group1 = med_values.iloc[0:100]
group2 = med_values.iloc[800:900]
group3 = med_values.iloc[1200:1300]
```

ANOVA

In [182…
```
# Performing one-way ANOVA
f_statistic, p_value = stats.f_oneway(group1, group2, group3)

# Displaying results
print("F Statistic:", f_statistic)
print("P-value:", p_value)

# Interpretation
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis. There is a significant difference between th
else:
    print("Fail to reject the null hypothesis. There is no significant difference b
```

```
F Statistic: 66.51311126324842
P-value: 1.3500015100826037e-24
Reject the null hypothesis. There is a significant difference between the means.
```

Z-Test

In [183…
```
alpha = 0.05

sample_mean = group1.mean()
population_mean = med_values.mean()
population_std = med_values.std()
sample_size = group1.count()

z_score = (sample_mean-population_mean)/(population_std/np.sqrt(sample_size))
print('Z-Score :',z_score)

# Approach 1: Using Critical Z-Score

# Critical Z-Score
z_critical = stats.norm.ppf(1-alpha)
print('Critical Z-Score :',z_critical)

# Hypothesis
if z_score > z_critical:
    print("Reject Null Hypothesis")
else:
    print("Fail to Reject Null Hypothesis")

p_value = 1-stats.norm.cdf(z_score)

print('\np-value :',p_value)

# Hypothesis
if p_value < alpha:
    print("Reject Null Hypothesis")
```

```
else:
    print("Fail to Reject Null Hypothesis")
```

```
Z-Score : -4.7752080086721005
Critical Z-Score : 1.6448536269514722
Fail to Reject Null Hypothesis

p-value : 0.9999991023920172
Fail to Reject Null Hypothesis
```

Chi-Square Test

In [184…

```
from scipy.stats import chi2_contingency

contingency_table = pd.crosstab(encoded_df['median_house_value'], df['median_income
res = chi2_contingency(contingency_table)
print("Between Price Range and median Income\nStatistic: {}\nP-Val: {}".format(res.
```

```
Between Price Range and median Income
Statistic: 53276770.92236957
P-Val: 0.0
```

Feature Reduction

In [185…

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.model_selection import train_test_split, cross_val_predict, Stratifiec
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, roc_curve, auc
from sklearn.model_selection import cross_val_predict
```

In [186…

```
X = np.array(encoded_df.drop(['median_house_value', 'price_range'],axis=1), dtype='
y = labeled
```

In [187…

```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [188…

```
# Standardize the features (important for PCA and LDA)
scaler = StandardScaler()
X_train_std = scaler.fit_transform(X_train)
X_test_std = scaler.transform(X_test)
```

In [189…

```
# Function for training and evaluating a classifier
def train_and_evaluate(classifier, X_train, X_test, y_train, y_test):
    """
    Train a classifier, make predictions on the test set, and calculate accuracy.

    Parameters:
    - classifier: The classifier model to be trained and evaluated.
    - X_train: The training data features.
    - X_test: The testing data features.
    - y_train: The training data labels.
    - y_test: The testing data labels.

    Returns:
    - accuracy: The accuracy of the classifier on the test set.
```

```
    """
    classifier.fit(X_train, y_train)
    y_pred = classifier.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    return accuracy
```

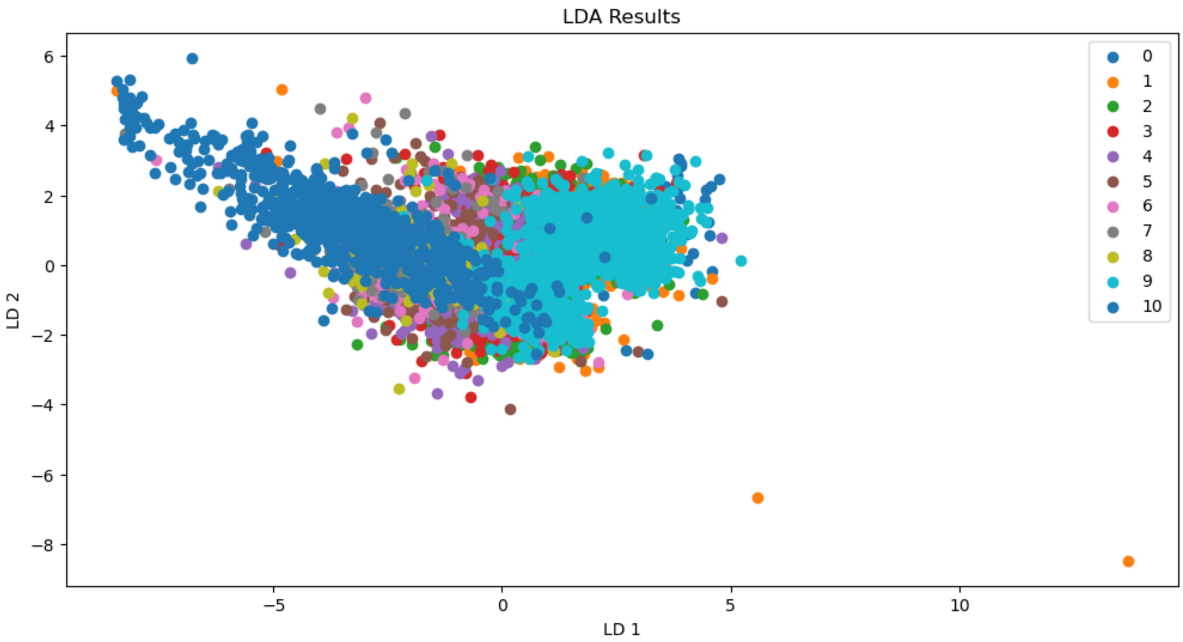
Linear Discriminant Analysis, as a Feature Reduction

In [190…
```
# Linear Discriminant Analysis (LDA)
lda = LinearDiscriminantAnalysis(n_components=2)
X_train_lda = lda.fit_transform(X_train_std, y_train)
X_test_lda = lda.transform(X_test_std)
```

In [191…
```
# Classification using k-Nearest Neighbors (k-NN) with LDA features
knn_lda = KNeighborsClassifier(n_neighbors=3)
```

In [192…
```
# K-fold cross-validation for LDA
cv_lda = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
y_pred_lda = cross_val_predict(knn_lda, X_train_lda, y_train, cv=cv_lda)
fpr_lda, tpr_lda, _ = roc_curve(y_train, y_pred_lda, pos_label=1)
roc_auc_lda = auc(fpr_lda, tpr_lda)
```

In [193…
```
# Visualize the data after LDA
plt.figure(figsize=(12, 6))
for label in np.unique(y_train):
    plt.scatter(X_train_lda[y_train == label, 0], X_train_lda[y_train == label, 1],
plt.title('LDA Results')
plt.xlabel('LD 1')
plt.ylabel('LD 2')
plt.legend()
plt.show()
```



Principle Component Analysis

In [194…
```
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_std)
X_test_pca = pca.transform(X_test_std)
```

In [195…

```
knn_pca = KNeighborsClassifier(n_neighbors=3)
```

In [196…

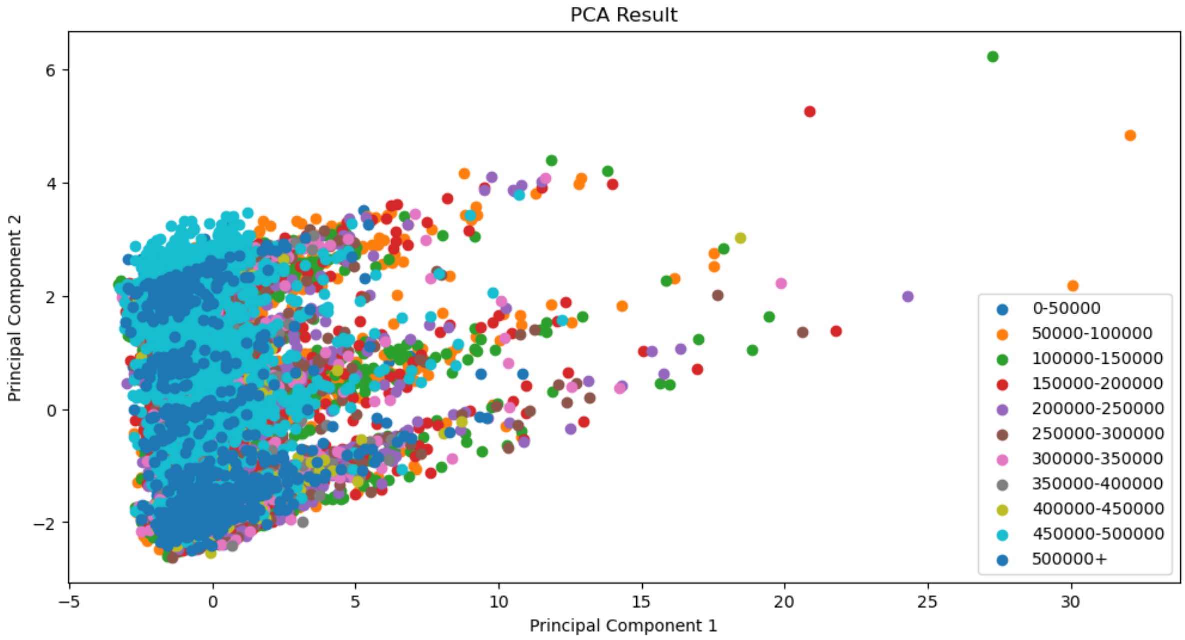
```
cv_pca = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
y_pred_pca = cross_val_predict(knn_pca, X_train_pca, y_train, cv=cv_pca)
fpr_pca, tpr_pca, _ = roc_curve(y_train, y_pred_pca, pos_label=1)
roc_auc_pca = auc(fpr_pca, tpr_pca)
```

In [197…

```
plt.figure(figsize=(12, 6))
for label in np.unique(y_train):
    plt.scatter(X_train_pca[y_train == label, 0], X_train_pca[y_train == label, 1],
plt.title('PCA Result')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
```

Out[197]:

```
<matplotlib.legend.Legend at 0x15955a65a90>
```



Singular Value Decomposition

In [198…

```
U, S, Vh = np.linalg.svd(X_train_std, full_matrices= False)

print('matrix U has {} rows, {} columns\n'.format(*U.shape))
print('here are the first 5 rows.')

print('{}'.format(pd.DataFrame(U).head(5)))
```

```
matrix U has 16512 rows, 13 columns

here are the first 5 rows.
          0         1         2         3         4         5         6  \
0 -0.003299 -0.006799  0.002660 -0.021428  0.002956 -0.001485  0.001668
1 -0.001893 -0.004137 -0.001545 -0.021889  0.005185 -0.001853  0.001624
2  0.001683 -0.000982  0.004005 -0.017356 -0.012693  0.001538 -0.010740
3  0.002489 -0.007512  0.004311 -0.021357  0.006357 -0.002330 -0.000407
4  0.003590  0.004782  0.006283  0.001353  0.003638 -0.000622  0.005939

          7         8         9        10        11        12
0  0.000221 -0.009326 -0.003406 -0.005407  0.003119 -0.002272
1  0.011623  0.010908  0.005723 -0.004137  0.007154 -0.500388
2 -0.014208 -0.002477 -0.000566  0.021760 -0.000978 -0.033879
3 -0.002640 -0.006604 -0.003626 -0.002845  0.000732 -0.000277
4  0.013173  0.004790 -0.001057  0.000073  0.000983  0.029961
```

In [199…

```python
print('matrix Vt has {} rows, {} columns\n'.format(*Vh.shape))

print('{}'.format(pd.DataFrame(Vh).head()))
```

```
matrix Vt has 13 rows, 13 columns

          0         1         2         3         4         5         6  \
0 -0.093074  0.090098  0.220040 -0.479414 -0.486293 -0.469765 -0.487755
1 -0.517710  0.565865 -0.024575  0.094111  0.083621  0.044540  0.078340
2  0.275694 -0.061435 -0.320345 -0.055576 -0.039773 -0.039163 -0.068912
3 -0.054027  0.149936 -0.121124 -0.015017 -0.036442 -0.001486 -0.035145
4  0.099427 -0.091452  0.514649 -0.074697  0.120054  0.126912  0.117284

          7         8         9        10        11        12
0 -0.047018 -0.054524  0.007058  0.004873  0.067770  0.007042
1 -0.085084 -0.434307  0.288156 -0.009048  0.323329 -0.060662
2 -0.306244 -0.306200  0.628079  0.005291 -0.473083  0.027971
3  0.031836  0.437592  0.186315 -0.028164 -0.065997 -0.851338
4 -0.767484  0.025349 -0.023698  0.195640  0.135144 -0.142328
```

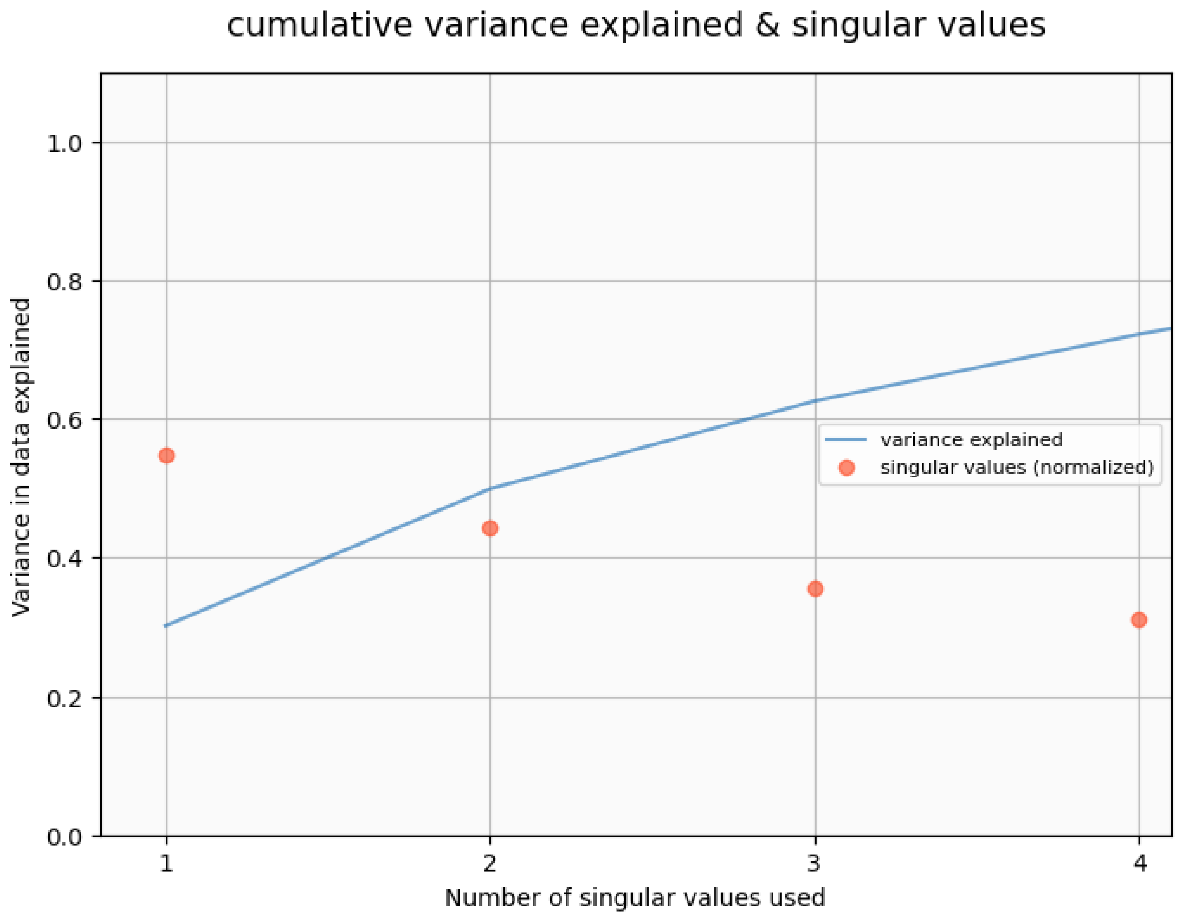
In [200…

```python
num_sv = np.arange(1, S.size+1)

cum_var_explained = [np.sum(np.square(S[0:n])) / np.sum(np.square(S)) for n in num_
```

In [201…

```python
import sklearn
fig = plt.figure(figsize=(7.0,5.5))
ax = fig.add_subplot(111)

plt.plot(num_sv,
         cum_var_explained,
         color='#2171b5',
         label='variance explained',
         alpha=0.65,
         zorder=1000)

plt.scatter(num_sv,
            sklearn.preprocessing.normalize(S.reshape((1,-1))),
            color='#fc4e2a',
            label='singular values (normalized)',
            alpha=0.65,
            zorder=1000)

plt.legend(loc='center right', scatterpoints=1, fontsize=8)

ax.set_xticks(num_sv)
ax.set_xlim(0.8, 4.1)
ax.set_ylim(0.0, 1.1)
```

```python
ax.set_xlabel(r'Number of singular values used')
ax.set_ylabel('Variance in data explained')
ax.set_title('cumulative variance explained & singular values',
             fontsize=14,
             y=1.03)

ax.set_facecolor('0.98')

plt.grid(alpha=0.8, zorder=1)
plt.tight_layout()
```



In [202…

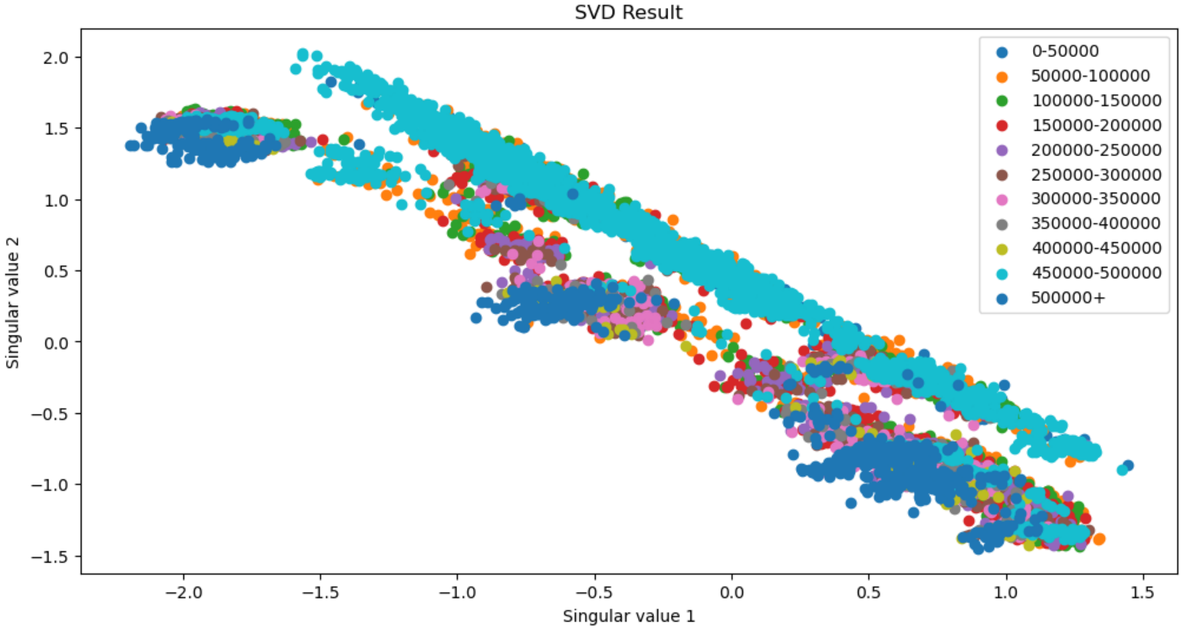
```python
k = 4
U_reduced = U[:, :k]
S_reduced = np.diag(S[:k])
Vh_reduced = Vh[:k, :]
reduced_matrix = np.dot(U_reduced, np.dot(S_reduced, Vh_reduced))
```

In [203…

```python
plt.figure(figsize=(12, 6))
for label in np.unique(y_train):
    plt.scatter(reduced_matrix[y_train == label, 0], reduced_matrix[y_train == labe
plt.title('SVD Result')
plt.xlabel('Singular value 1')
plt.ylabel('Singular value 2')
plt.legend()
```

Out[203]:

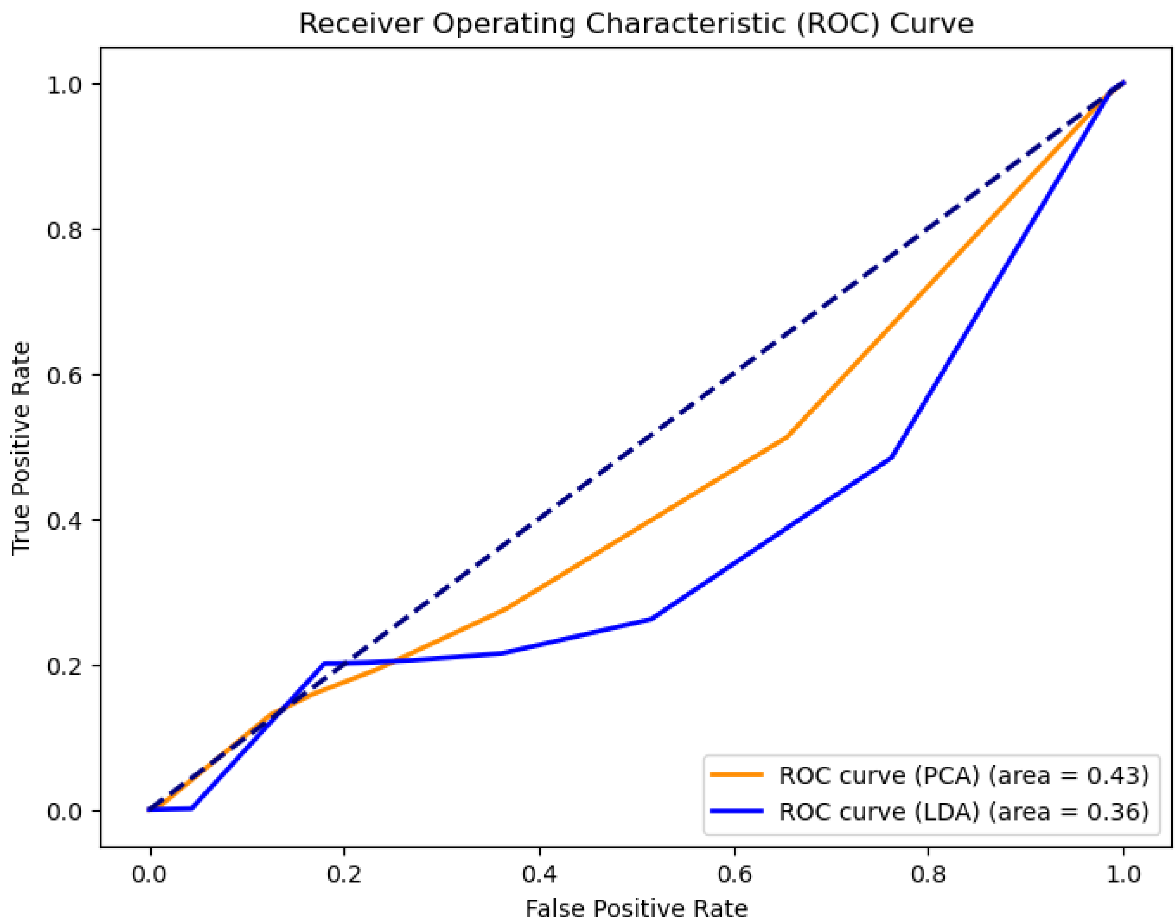
```
<matplotlib.legend.Legend at 0x15953cb7d90>
```



ROC Curve

In [204…

```
# Plot ROC curves
plt.figure(figsize=(8, 6))
plt.plot(fpr_pca, tpr_pca, color='darkorange', lw=2, label=f'ROC curve (PCA) (area
plt.plot(fpr_lda, tpr_lda, color='blue', lw=2, label=f'ROC curve (LDA) (area = {roc
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



In [205…
```
# Evaluate using PCA features
accuracy_pca = train_and_evaluate(knn_pca, X_train_pca, X_test_pca, y_train, y_test
print(f'Accuracy using k-NN with PCA: {accuracy_pca:.2%}')
```

```
Accuracy using k-NN with PCA: 24.90%
```

In [206…
```
# Evaluate using LDA features
accuracy_lda = train_and_evaluate(knn_lda, X_train_lda, X_test_lda, y_train, y_test
print(f'Accuracy using k-NN with LDA: {accuracy_lda:.2%}')
```

```
Accuracy using k-NN with LDA: 35.73%
```

Model Implementations

In [207…
```
from sklearn.naive_bayes import GaussianNB
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
```

Naive Bayesian Classifier

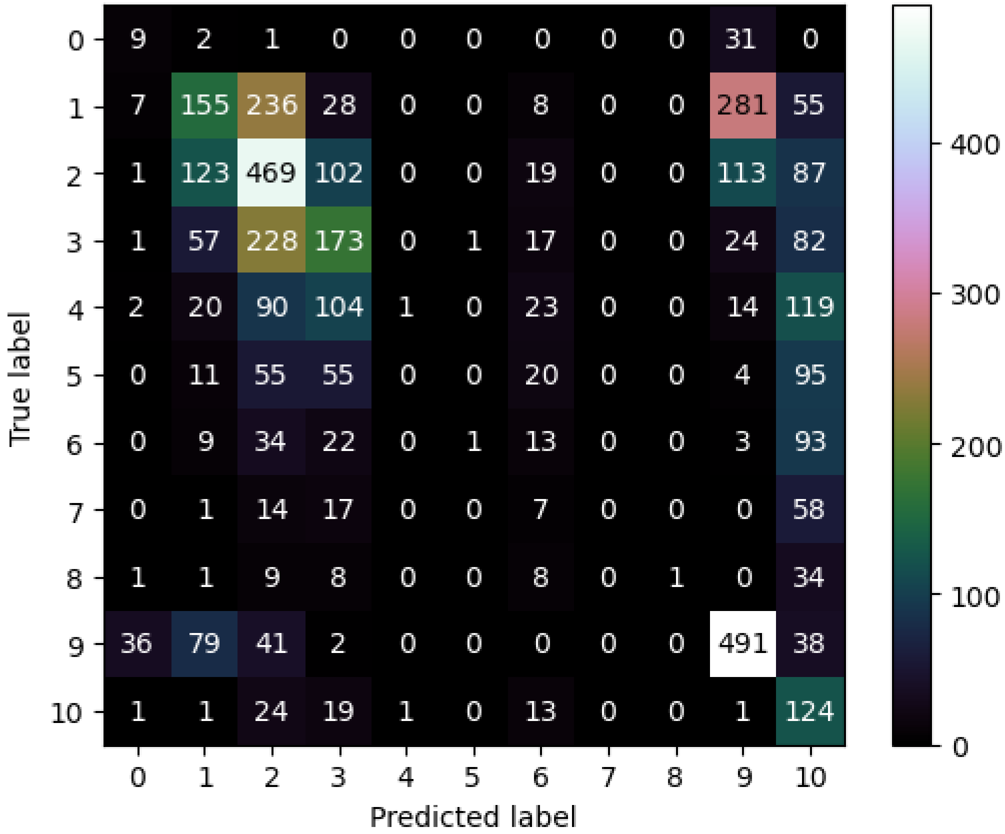
In [208…
```
#implement the classifier
classifier = GaussianNB()
classifier.fit(X_train_std, y_train)
```

Out[208]:
```
▾ GaussianNB
GaussianNB()
```

In [209…
```
#Predict the test set results
#y_pred
predictions= classifier.predict(X_test_std)
#predictions[:10]
```

In [210…
```
Accuracy= print('Accuracy score: ', format(accuracy_score(y_test, predictions)))
print('confusion_matrix: \n', format(confusion_matrix(y_test, predictions)))
from sklearn.metrics import ConfusionMatrixDisplay
ConfusionMatrixDisplay.from_predictions(y_test, predictions, cmap=plt.cm.cubehelix)
plt.show()
from sklearn.metrics import classification_report
Classification =print('Classification report: \n', format(classification_report (y_
```

```
Accuracy score:  0.3478682170542636
confusion_matrix:
 [[  9   2   1   0   0   0   0   0   0  31   0]
 [  7 155 236  28   0   0   8   0   0 281  55]
 [  1 123 469 102   0   0  19   0   0 113  87]
 [  1  57 228 173   0   1  17   0   0  24  82]
 [  2  20  90 104   1   0  23   0   0  14 119]
 [  0  11  55  55   0   0  20   0   0   4  95]
 [  0   9  34  22   0   1  13   0   0   3  93]
 [  0   1  14  17   0   0   7   0   0   0  58]
 [  1   1   9   8   0   0   8   0   1   0  34]
 [ 36  79  41   2   0   0   0   0   0 491  38]
 [  1   1  24  19   1   0  13   0   0   1 124]]
```




```
Classification report:
              precision    recall  f1-score   support

           0       0.16      0.21      0.18        43
           1       0.34      0.20      0.25       770
           2       0.39      0.51      0.44       914
           3       0.33      0.30      0.31       583
           4       0.50      0.00      0.01       373
           5       0.00      0.00      0.00       240
           6       0.10      0.07      0.09       175
           7       0.00      0.00      0.00        97
           8       1.00      0.02      0.03        62
           9       0.51      0.71      0.60       687
          10       0.16      0.67      0.26       184

    accuracy                           0.35      4128
   macro avg       0.32      0.25      0.20      4128
weighted avg       0.35      0.35      0.31      4128
```

```
D:\Anaconda\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Anaconda\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Anaconda\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

KNN Classifier

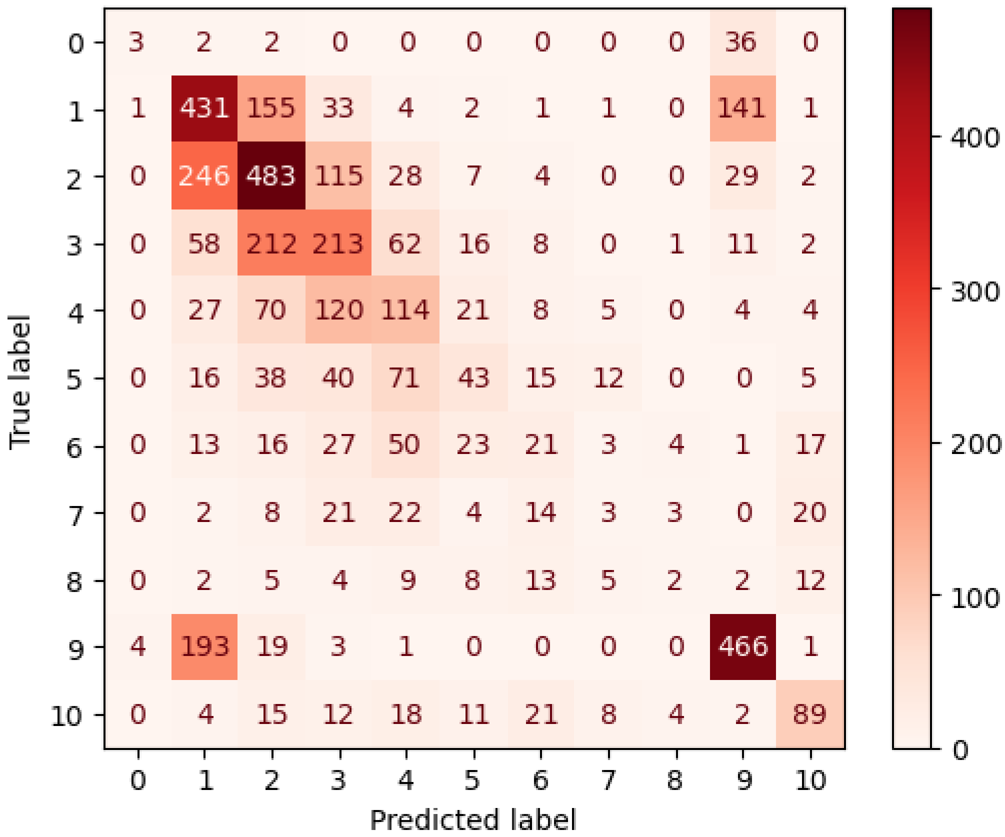
In [211…

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=10)
model = knn.fit(X_train_std,y_train)
predictions = model.predict(X_test_std)
#y_pred[:10]
```

In [212…

```
Accuracy= print('Accuracy score: ', format(accuracy_score(y_test, predictions)))
print('confusion_matrix: \n', format(confusion_matrix(y_test, predictions)))
from sklearn.metrics import ConfusionMatrixDisplay
ConfusionMatrixDisplay.from_predictions(y_test, predictions, cmap=plt.cm.Reds)
plt.show()
from sklearn.metrics import classification_report
Classification =print('Classification report: \n', format(classification_report (y_
```

```
Accuracy score:  0.452519379844961 27
confusion_matrix:
 [[  3   2   2   0   0   0   0   0   0  36   0]
 [  1 431 155  33   4   2   1   1   0 141   1]
 [  0 246 483 115  28   7   4   0   0  29   2]
 [  0  58 212 213  62  16   8   0   1  11   2]
 [  0  27  70 120 114  21   8   5   0   4   4]
 [  0  16  38  40  71  43  15  12   0   0   5]
 [  0  13  16  27  50  23  21   3   4   1  17]
 [  0   2   8  21  22   4  14   3   3   0  20]
 [  0   2   5   4   9   8  13   5   2   2  12]
 [  4 193  19   3   1   0   0   0   0 466   1]
 [  0   4  15  12  18  11  21   8   4   2  89]]
```



```
Classification report:
               precision    recall  f1-score   support

           0       0.38      0.07      0.12        43
           1       0.43      0.56      0.49       770
           2       0.47      0.53      0.50       914
           3       0.36      0.37      0.36       583
           4       0.30      0.31      0.30       373
           5       0.32      0.18      0.23       240
           6       0.20      0.12      0.15       175
           7       0.08      0.03      0.04        97
           8       0.14      0.03      0.05        62
           9       0.67      0.68      0.68       687
          10       0.58      0.48      0.53       184

    accuracy                           0.45      4128
   macro avg       0.36      0.30      0.31      4128
weighted avg       0.44      0.45      0.44      4128
```

ID3 Classifier

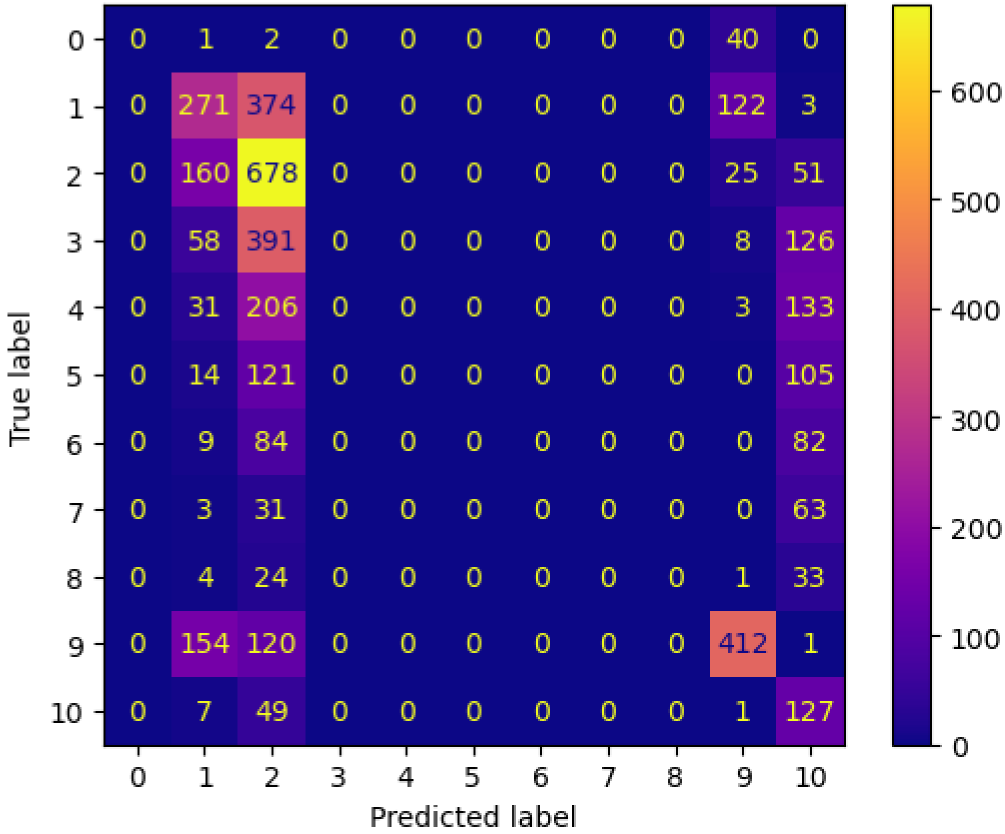
In [213…

```
from sklearn.tree import DecisionTreeClassifier
#Decision Tree using Entropy
dt= DecisionTreeClassifier( criterion='gini', ccp_alpha = 0.015)
dt.fit(X_train_std, y_train)
predictions = dt.predict(X_test_std)
```

In [214…

```
Accuracy= print('Accuracy score: ', format(accuracy_score(y_test, predictions)))
print('confusion_matrix: \n', format(confusion_matrix(y_test, predictions)))
from sklearn.metrics import ConfusionMatrixDisplay
ConfusionMatrixDisplay.from_predictions(y_test, predictions, cmap=plt.cm.plasma)
plt.show()
from sklearn.metrics import classification_report
Classification =print('Classification report: \n', format(classification_report (y_
```

```
Accuracy score:  0.36046511627906974
confusion_matrix: 
 [[  0   1   2   0   0   0   0   0   0  40   0]
 [  0 271 374   0   0   0   0   0   0 122   3]
 [  0 160 678   0   0   0   0   0   0  25  51]
 [  0  58 391   0   0   0   0   0   0   8 126]
 [  0  31 206   0   0   0   0   0   0   3 133]
 [  0  14 121   0   0   0   0   0   0   0 105]
 [  0   9  84   0   0   0   0   0   0   0  82]
 [  0   3  31   0   0   0   0   0   0   0  63]
 [  0   4  24   0   0   0   0   0   0   1  33]
 [  0 154 120   0   0   0   0   0   0 412   1]
 [  0   7  49   0   0   0   0   0   0   1 127]]
```




```
Classification report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        43
           1       0.38      0.35      0.37       770
           2       0.33      0.74      0.45       914
           3       0.00      0.00      0.00       583
           4       0.00      0.00      0.00       373
           5       0.00      0.00      0.00       240
           6       0.00      0.00      0.00       175
           7       0.00      0.00      0.00        97
           8       0.00      0.00      0.00        62
           9       0.67      0.60      0.63       687
          10       0.18      0.69      0.28       184

    accuracy                           0.36      4128
   macro avg       0.14      0.22      0.16      4128
weighted avg       0.26      0.36      0.29      4128
```

```
D:\Anaconda\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Anaconda\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Anaconda\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Linear Discriminant Analysis, as a Classifier

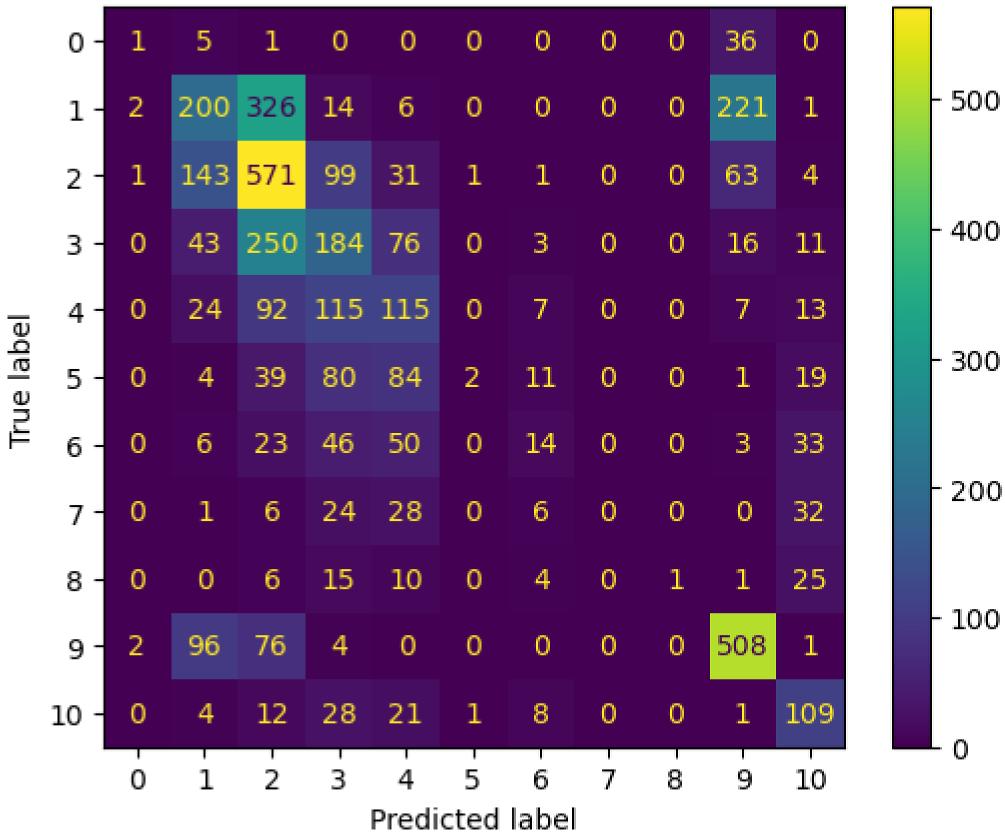
In [215…

```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
lda_model = LinearDiscriminantAnalysis()
X_lda = lda_model.fit(X_train_std,y_train)
predictions=X_lda.predict(X_test_std)
```

In [216…

```
Accuracy= print('Accuracy score: ', format(accuracy_score(y_test, predictions)))
print('confusion_matrix: \n', format(confusion_matrix(y_test, predictions)))
from sklearn.metrics import ConfusionMatrixDisplay
ConfusionMatrixDisplay.from_predictions(y_test, predictions, cmap=plt.cm.viridis)
plt.show()
from sklearn.metrics import classification_report
Classification =print('Classification report: \n', format(classification_report (y_
```

```
Accuracy score:  0.4130329457364341
confusion_matrix:
 [[  1   5   1   0   0   0   0   0   0  36   0]
 [  2 200 326  14   6   0   0   0   0 221   1]
 [  1 143 571  99  31   1   1   0   0  63   4]
 [  0  43 250 184  76   0   3   0   0  16  11]
 [  0  24  92 115 115   0   7   0   0   7  13]
 [  0   4  39  80  84   2  11   0   0   1  19]
 [  0   6  23  46  50   0  14   0   0   3  33]
 [  0   1   6  24  28   0   6   0   0   0  32]
 [  0   0   6  15  10   0   4   0   1   1  25]
 [  2  96  76   4   0   0   0   0   0 508   1]
 [  0   4  12  28  21   1   8   0   0   1 109]]
```



```
Classification report:
              precision    recall  f1-score   support

           0       0.17      0.02      0.04        43
           1       0.38      0.26      0.31       770
           2       0.41      0.62      0.49       914
           3       0.30      0.32      0.31       583
           4       0.27      0.31      0.29       373
           5       0.50      0.01      0.02       240
           6       0.26      0.08      0.12       175
           7       0.00      0.00      0.00        97
           8       1.00      0.02      0.03        62
           9       0.59      0.74      0.66       687
          10       0.44      0.59      0.50       184

    accuracy                           0.41      4128
   macro avg       0.39      0.27      0.25      4128
weighted avg       0.40      0.41      0.38      4128
```

```
D:\Anaconda\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Anaconda\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Anaconda\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

KNN Regressor

In [217…

```
from sklearn.neighbors import KNeighborsRegressor
knn = KNeighborsRegressor()
knn.fit(X_train, y_train)
predictions = knn.predict(X_test)
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, predictions))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, predictions))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, predic
```

```
Mean Absolute Error: 2.5124515503875973
Mean Squared Error: 9.713246124031008
Root Mean Squared Error: 3.1166081120395948
```

Decision Tree Regressor

In [218…

```
from sklearn.tree import DecisionTreeRegressor
Dtree= DecisionTreeRegressor()
Dtree.fit(X_train, y_train)
predictions = Dtree.predict(X_test)
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, predictions))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, predictions))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, predic
```

```
Mean Absolute Error: 1.6632751937984496
Mean Squared Error: 9.136143410852712
Root Mean Squared Error: 3.02260540111552
```

References

Pace, R. Kelley, and Ronald Barry. "Sparse spatial autoregressions." Statistics & Probability Letters 33.3 (1997): 291-297.

Géron, A. (2017). Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow. O'Reilly Media.

In [ ]:

E-JUST University - Computer Science and Information Technology Programs – Artificial Intelligence and Data Science Program (AID)
Subject: Mathematics for Data Science (AID311)

MATH FOR DATA SCEINCE PROJECT (PHASE I& PHASE II COVER SHEET)

Discussions Scheduled for last Week in the fall semester *in your Lab time (From 6-1-2024 to 10-1-2024)*

- Print 1 copy of this cover sheet and attach both to a printed copy of the Project documentation. You must submit a CD including softcopies of all your documents and Project implementation.
- Please write all your name in English.
- Please make sure that your student ID is correct.
- Please attend the discussion on time in your Lab, late students will lose 3 grades. No projects evaluation after this period and no excuses accept. (From 6-1-2024 to 10-1-2024)

Project Name: California Housing Prices prediction

Team Information *(typed not handwritten, except for the attendance signature)*:

	ID [Ordered by ID]	Full Name	Attendance Signature [Handwritten]	Final Grade
1	320210045	علي إيهاب محمد عبدالرازق خليل		

Items		Actual Grade	Notes
Project Documentation **Please follow the style in the document file attached with this phase and be careful with the information. The documentation will check by similarity and plagiarism checker. Each phase has 2 marks.**	16		
Presentation and implementation **Each student has 10 minutes to present the idea, methodology and the interpretation of results.**	4		
Preprocessing			
Data Visualization **Missing Values Treatment** **Binning process** (If exist) **Data Analysis** (Min, Max, Mean, Variance, Standard Deviation, Skewness, Kurtosis). **Data Analysis** (Covariance matrix, Correlation, Heat map, Chi-square Test, Z-test or t-test, ANOVA)	0		
Feature Reduction **Linear Discriminate Analysis (LDA)** **Principle Component Analysis (PCA) and Kernel PCA (if data non-linear)** **Singular Value Decomposition (SVD)**	0		
Model Implementations			

Naive Bayesian	o		
Bayesian Belief Network	o		
Decision Tree (Entropy, and error estimation)	o		
LDA	o		
Neural Network	o		
K-NN (Different distances)	o		
Model evaluations			
Dataset splitting (80% training and 20% testing) and apply all evaluation matrix	o		
K-fold cross validation and avarage accuracy			
Confusion Matrix **Accuracy** **Error rate** **Precision** **Recall** **F-measure** **ROC**			
Inteprete results of confusion matrix and show the model overfitten or underfirren	o		
Comparisons with other related work on the same domain -Table	o		
Refernces (papers used in your domain of work and the studies uses the same data sets)	o		

Teaching-Assistant's Signature: ________________________

20

California Housing Prices

Abstract

The California Housing Prices dataset, derived from the 1990 U.S. census, serves as a pivotal benchmark for regression analysis and predictive modeling in the field of machine learning. The dataset encompasses a diverse array of features characterizing various districts in California, ranging from median housing price and income to demographic factors such as population and housing age. This study aims to employ machine learning techniques to predict median housing prices based on these features and unravel the intricate patterns inherent in the housing market.

The dataset consists of 20,640 instances, each representing a district in California, with 8 features providing essential insights into the district's socioeconomic landscape. The target variable is the median housing price, a critical metric for understanding regional real estate dynamics. Exploratory data analysis reveals a multifaceted interplay between different features, hinting at the complex factors influencing housing prices. The dataset poses a regression problem, challenging researchers to build models capable of accurately predicting the continuous target variable.

Various machine learning algorithms are employed to address this challenge, including linear discriminant analysis, principal component analysis and singular value decomposition. The predictive models undergo rigorous training and validation processes to ensure robust generalization to unseen data. Feature engineering is employed to extract additional insights from the existing variables, enhancing the models' predictive capabilities.

Introduction

The California housing prices dataset provides a rich collection of features related to housing districts in California, including median housing prices. This dataset is widely used in machine learning to explore the relationships between various factors and predict the median housing price for different districts. The goal of this problem is to develop a predictive model that can accurately estimate the median housing price based on the given features.

Understanding the dynamics that influence housing prices is crucial for various stakeholders, including real estate investors, policymakers, and homebuyers. A reliable predictive model can assist in making informed decisions about property investments, assessing the impact of socio-economic factors on housing prices, and supporting individuals in their search for affordable housing.

In this context, the task is to analyze the California housing prices dataset, preprocess the data, and build a machine learning model capable of predicting the median housing price for a given district. By developing an accurate predictive model, it is possible to contribute to the broader understanding of housing market trends and provide valuable insights for those interested in the California real estate landscape.

Related Work

Quigley, John, M., and Steven Raphael. 2005. "Regulation and the High Cost of Housing in California." *American Economic Review*, 95 (2): 323-328**.**

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Wu, Y., Wei, Y. D., & Li, H. (2020). Analyzing spatial heterogeneity of housing prices using large datasets. *Applied Spatial Analysis and Policy*, *13*, 223-256.

Chen, Y. (2023). Analysis and Forecasting of California Housing. *Highlights in Business, Economics and Management*, *3*, 128-135.

Gupta, R., Kabundi, A., & Miller, S. (2011). Using large data sets to forecast house prices: A case study of twenty US states. *Journal of housing research*, *20*(2), 161-190.

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Fekrazad, A. (2019). Earthquake-risk salience and housing prices: Evidence from California. *Journal of behavioral and experimental economics*, *78*, 104-113.

Sunding, D. L., & Swoboda, A. M. (2010). Hedonic analysis with locally weighted regression: An application to the shadow cost of housing regulation in Southern California. *Regional Science and Urban Economics*, *40*(6), 550-573.

Methodology

1. **ANOVA (Analysis of Variance):**
   - ANOVA is a statistical method used to analyze the differences among group means in a sample. It assesses whether the means of different groups are statistically significant. ANOVA is commonly used in experimental studies with multiple groups to determine if there are any significant differences between them.
2. **Encoding:**
   - Encoding is the process of converting data from one form to another, often to facilitate data processing or analysis. In machine learning, encoding is commonly used to convert categorical data into a numerical format that can be fed into models for training.
3. **Binning:**
   - Binning is the process of grouping a set of continuous or numerical data points into a smaller number of discrete "bins" or intervals. Binning is often used to simplify data and discover patterns or trends within specific ranges.
4. **Z-test:**
   - The Z-test is a statistical test used to determine if there is a significant difference between sample and population means, or between the means of two samples. It is based on the standard normal distribution and is commonly used in hypothesis testing.
5. **Chi-Square Test:**
   - The Chi-Square test is a statistical test used to determine the independence of two categorical variables. It compares the expected frequencies of different categories with the observed frequencies to assess if there is a significant association between the variables.
6. **LDA as a Feature Reduction:**
   - Linear Discriminant Analysis (LDA) is not only used for classification but also as a feature reduction technique. It seeks to find the linear combinations of features that best separate different classes, thereby reducing dimensionality while preserving class discrimination.
7. **PCA (Principal Component Analysis):**
   - PCA is a dimensionality reduction technique that transforms high-dimensional data into a lower-dimensional representation, capturing the most significant variance in the data. It is widely used for feature extraction and data visualization.
8. **SVD (Singular Value Decomposition):**
   - SVD is a matrix factorization method used for dimensionality reduction and feature extraction. It decomposes a matrix into three other matrices, capturing the latent structure of the original matrix.
9. **K-Cross Validation:**

- K-Cross Validation is a technique used to assess the performance of a machine learning model. The dataset is divided into k subsets, and the model is trained and evaluated k times, each time using a different subset as the test set and the remaining data for training.

10. **Receiver Operating Characteristic (ROC):**

    - ROC is a graphical representation of a binary classification model's performance across different threshold settings. It plots the true positive rate against the false positive rate, providing insights into the trade-offs between sensitivity and specificity.

11. **Naive-Bayesian Classifier:**

    - The Naive-Bayesian Classifier is a probabilistic classification algorithm based on Bayes' theorem, assuming independence between features. Despite its simplifying assumptions, it often performs well in practice, especially with text classification tasks.

12. **KNN Classifier (K-Nearest Neighbors):**

    - KNN is a simple, instance-based learning algorithm used for classification. It classifies an object based on the majority class of its k nearest neighbors in the feature space.

13. **ID3 Classifier:**

    - Iterative Dichotomiser 3 (ID3) is a decision tree algorithm used for classification. It recursively selects features to split the data and create decision nodes based on information gain.

14. **LDA as a Classifier:**

    - Linear Discriminant Analysis (LDA) is not only used for dimensionality reduction but also as a classifier. It models the distribution of classes and assigns new data points to the class with the highest probability.

15. **KNN Regressor:**

    - Similar to KNN Classifier, KNN Regressor is a variant used for regression tasks. Instead of classifying, it predicts the numerical value of a target variable based on the average of its k nearest neighbors.

16. **Decision Tree Regressor:**

    - Decision Tree Regressor is a tree-based model used for regression tasks. It recursively splits the data based on feature conditions to predict a numerical outcome.

Results and Discussion

The dataset’s columns are split into and described as follows:

1. **longitude**: A measure of how far west a house is; a higher value is farther west
2. **latitude**: A measure of how far north a house is; a higher value is farther north
3. **housingMedianAge**: Median age of a house within a block; a lower number is a newer building
4. **totalRooms**: Total number of rooms within a block
5. **totalBedrooms**: Total number of bedrooms within a block
6. **population**: Total number of people residing within a block
7. **households**: Total number of households, a group of people residing within a home unit, for a block
8. **medianIncome**: Median income for households within a block of houses (measured in tens of thousands of US Dollars)
9. **medianHouseValue**: Median house value for households within a block (measured in US Dollars)
10. **oceanProximity**: Location of the house w.r.t ocean/sea

Conclusion

Results remain inadequate enough to properly make a solid conclusion.

References

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