Part 1: Mutual Information Classification

```python
# Import necessary libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer
from sklearn.feature_selection import SelectKBest, mutual_info_classif

# Load the dataset (replace 'your_dataset.csv' with the actual file
path)
df = pd.read_csv('loan.csv')

# Display the first few rows of the dataset
print("Original Dataset:")
print(df.head())
```

```
Original Dataset:
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0         NaN             360.0
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
```

```python
# Handle null values (replace 'most_frequent' with an appropriate
imputation strategy)
imputer = SimpleImputer(strategy='most_frequent')
df = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)

# Display the dataset after handling null values
print("\nDataset after null value handling:")
print(df.head())
```

```
Dataset after null value handling:
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

  ApplicantIncome CoapplicantIncome LoanAmount Loan_Amount_Term  \
0            5849               0.0      120.0            360.0
1            4583            1508.0      128.0            360.0
2            3000               0.0       66.0            360.0
3            2583            2358.0      120.0            360.0
4            6000               0.0      141.0            360.0

  Credit_History Property_Area Loan_Status
0            1.0         Urban           Y
1            1.0         Rural           N
2            1.0         Urban           Y
3            1.0         Urban           Y
4            1.0         Urban           Y

# Separate features (X) and target variable (y)
X = df.drop('Loan_Status', axis=1)
y = df['Loan_Status']

# Label encoding for categorical variables
label_encoder = LabelEncoder()
X_encoded = X.apply(label_encoder.fit_transform)

# Display the dataset after label encoding
print("\nDataset after label encoding:")
print(X_encoded.head())


Dataset after label encoding:
   Loan_ID  Gender  Married  Dependents  Education  Self_Employed  \
0        0       1        0           0          0              0
1        1       1        1           1          0              0
2        2       1        1           0          0              1
3        3       1        1           0          1              0
4        4       1        0           0          0              0

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0              376                  0          73                 8
1              306                 60          81                 8
2              139                  0          26                 8
3               90                160          73                 8
4              381                  0          94                 8
```

```
   Credit_History  Property_Area
0               1              2
1               1              0
2               1              2
3               1              2
4               1              2

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y,
test_size=0.2, random_state=42)

# Use SelectKBest to select the top K features based on mutual
information scores
k_best_selector = SelectKBest(score_func=mutual_info_classif, k=3)  #
Choose an appropriate value of K
X_train_kbest = k_best_selector.fit_transform(X_train, y_train)

# Get the indices of the selected features
selected_feature_indices = k_best_selector.get_support(indices=True)

# Print the names or indices of the selected features
selected_feature_names = X_train.columns[selected_feature_indices]
print("\nSelected Features:")
print(selected_feature_names)


Selected Features:
Index(['Self_Employed', 'Credit_History', 'Property_Area'],
dtype='object')
```

Part 2: Mutual Information Regression

```
# Import necessary libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer
from sklearn.feature_selection import SelectKBest,
mutual_info_regression
from sklearn.ensemble import RandomForestRegressor

# Load the dataset (replace 'housing_dataset.csv' with the actual file
path)
df = pd.read_csv('housing.csv')

# Display the first few rows of the dataset
print("Original Dataset:")
print(df.head())
```

```
Original Dataset:
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape 
\
0   1          60       RL         65.0     8450   Pave   NaN      Reg   

1   2          20       RL         80.0     9600   Pave   NaN      Reg   

2   3          60       RL         68.0    11250   Pave   NaN      IR1   

3   4          70       RL         60.0     9550   Pave   NaN      IR1   

4   5          60       RL         84.0    14260   Pave   NaN      IR1   


  LandContour Utilities  ... PoolArea PoolQC Fence MiscFeature MiscVal 
MoSold  \
0         Lvl    AllPub  ...        0    NaN   NaN         NaN       0      
2   
1         Lvl    AllPub  ...        0    NaN   NaN         NaN       0      
5   
2         Lvl    AllPub  ...        0    NaN   NaN         NaN       0      
9   
3         Lvl    AllPub  ...        0    NaN   NaN         NaN       0      
2   
4         Lvl    AllPub  ...        0    NaN   NaN         NaN       0     
12   

  YrSold  SaleType  SaleCondition  SalePrice  
0   2008        WD         Normal     208500  
1   2007        WD         Normal     181500  
2   2008        WD         Normal     223500  
3   2006        WD        Abnorml     140000  
4   2008        WD         Normal     250000  

[5 rows x 81 columns]

# Handle null values (replace 'mean' with an appropriate imputation 
strategy)
imputer = SimpleImputer(strategy='most_frequent')
df = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)

# Display the dataset after null value handling
print("\nDataset after null value handling:")
print(df.head())


Dataset after null value handling:
  Id MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape  \
0  1         60       RL        65.0    8450   Pave  Grvl      Reg   
1  2         20       RL        80.0    9600   Pave  Grvl      Reg   
2  3         60       RL        68.0   11250   Pave  Grvl      IR1   
```

```
3  4          70         RL         60.0     9550    Pave   Grvl       IR1
4  5          60         RL         84.0    14260    Pave   Grvl       IR1

  LandContour Utilities  ... PoolArea PoolQC  Fence MiscFeature
MiscVal  \
0         Lvl    AllPub  ...        0     Gd  MnPrv        Shed
0
1         Lvl    AllPub  ...        0     Gd  MnPrv        Shed
0
2         Lvl    AllPub  ...        0     Gd  MnPrv        Shed
0
3         Lvl    AllPub  ...        0     Gd  MnPrv        Shed
0
4         Lvl    AllPub  ...        0     Gd  MnPrv        Shed
0

  MoSold YrSold SaleType SaleCondition SalePrice
0      2   2008       WD        Normal    208500
1      5   2007       WD        Normal    181500
2      9   2008       WD        Normal    223500
3      2   2006       WD       Abnorml    140000
4     12   2008       WD        Normal    250000

[5 rows x 81 columns]

# Separate features (X) and target variable (y)
X = df.drop('SalePrice', axis=1)
y = df['SalePrice']

# Label encoding for categorical variables
label_encoder = LabelEncoder()

# Apply label encoding to each categorical column
for col in X.select_dtypes(include=['object']).columns:
    X[col] = label_encoder.fit_transform(X[col])

# Display the dataset after label encoding
print("\nDataset after label encoding:")
print(X.head())


Dataset after label encoding:
   Id  MSSubClass  MSZoning  LotFrontage  LotArea  Street  Alley
LotShape  \
0   0           5         3           36      327       1      0
3
1   1           0         3           51      498       1      0
3
2   2           5         3           39      702       1      0
0
```

```
3   3           6         3           31      489       1      0
0
4   4           5         3           55      925       1      0
0

   LandContour  Utilities  ...  ScreenPorch  PoolArea  PoolQC
Fence  \
0            3          0  ...            0         0       2       2

1            3          0  ...            0         0       2       2

2            3          0  ...            0         0       2       2

3            3          0  ...            0         0       2       2

4            3          0  ...            0         0       2       2


   MiscFeature  MiscVal  MoSold  YrSold  SaleType  SaleCondition
0            2        0       1       2         8              4
1            2        0       4       1         8              4
2            2        0       8       2         8              4
3            2        0       1       0         8              0
4            2        0      11       2         8              4

[5 rows x 80 columns]

# 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_state=42)

# Use RandomForestRegressor to estimate mutual information scores
rf_regressor = RandomForestRegressor()
rf_regressor.fit(X_train, y_train)
mutual_info_scores = rf_regressor.feature_importances_

# Use SelectKBest to select the top K features based on mutual
information scores
k_best_selector = SelectKBest(score_func=mutual_info_regression, k=3)
# Choose an appropriate value of K
X_train_kbest = k_best_selector.fit_transform(X_train, y_train)

# Get the indices of the selected features
selected_feature_indices = k_best_selector.get_support(indices=True)

# Print the names or indices of the selected features
selected_feature_names = X_train.columns[selected_feature_indices]
print("\nSelected Features:")
print(selected_feature_names)
```

```
Selected Features:
Index(['OverallQual', 'GrLivArea', 'GarageCars'], dtype='object')
```

Part 3 : Linear Regression on the Housing Dataset

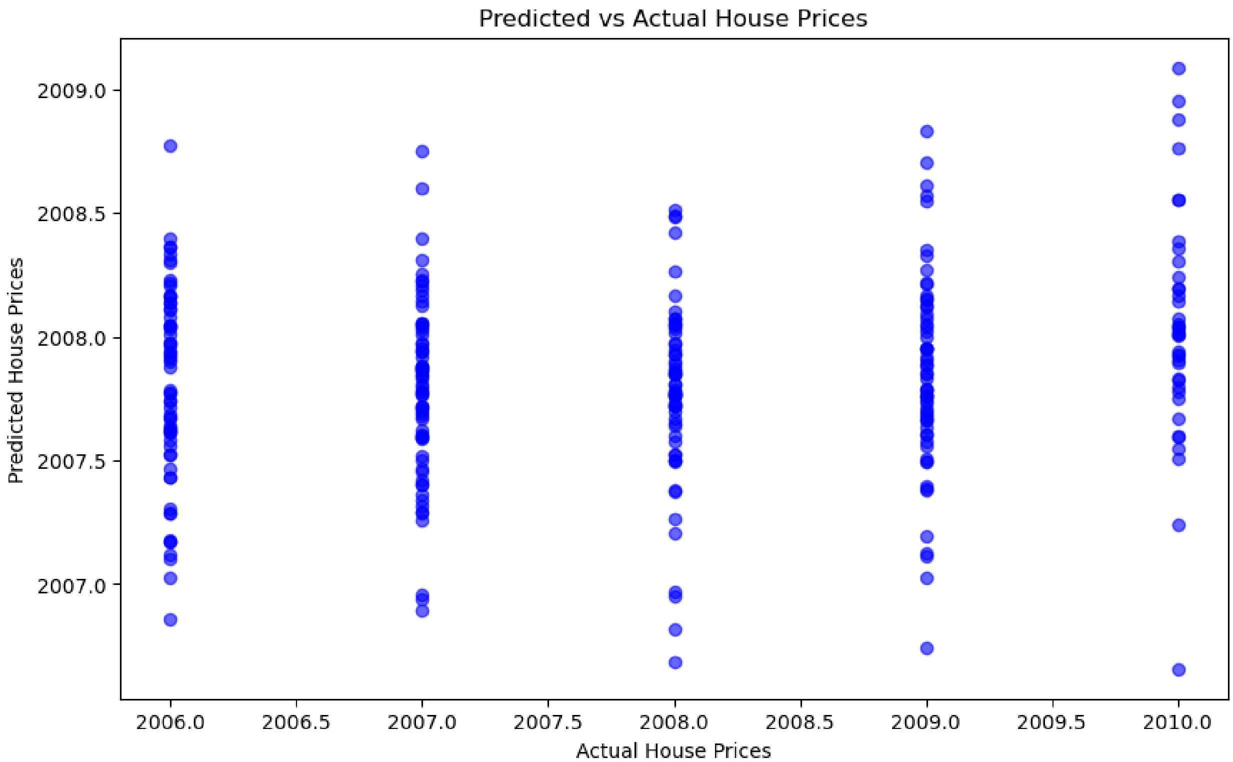
```
# Import necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer

# Load the Housing dataset (replace 'housing_dataset.csv' with the
actual file path)
df = pd.read_csv('housing.csv')

# Display the first few rows of the dataset
print("Original Dataset:")
print(df.head())

Original Dataset:
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape
\
0   1          60       RL         65.0     8450   Pave   NaN      Reg

1   2          20       RL         80.0     9600   Pave   NaN      Reg

2   3          60       RL         68.0    11250   Pave   NaN      IR1

3   4          70       RL         60.0     9550   Pave   NaN      IR1

4   5          60       RL         84.0    14260   Pave   NaN      IR1


  LandContour Utilities  ... PoolArea PoolQC Fence MiscFeature MiscVal
MoSold  \
0         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
2
1         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
5
2         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
9
3         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
2
```

```
4          Lvl    AllPub  ...         0    NaN   NaN         NaN       0
12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

```
# Handle null values (replace 'mean' with an appropriate imputation
strategy)
imputer = SimpleImputer(strategy='most_frequent')
df = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)

# Display the dataset after null value handling
print("\nDataset after null value handling:")
print(df.head())
```

```
Dataset after null value handling:
  Id MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape  \
0  1         60       RL        65.0    8450   Pave  Grvl      Reg
1  2         20       RL        80.0    9600   Pave  Grvl      Reg
2  3         60       RL        68.0   11250   Pave  Grvl      IR1
3  4         70       RL        60.0    9550   Pave  Grvl      IR1
4  5         60       RL        84.0   14260   Pave  Grvl      IR1

  LandContour Utilities  ... PoolArea PoolQC  Fence MiscFeature
MiscVal  \
0          Lvl    AllPub  ...         0     Gd  MnPrv        Shed
0
1          Lvl    AllPub  ...         0     Gd  MnPrv        Shed
0
2          Lvl    AllPub  ...         0     Gd  MnPrv        Shed
0
3          Lvl    AllPub  ...         0     Gd  MnPrv        Shed
0
4          Lvl    AllPub  ...         0     Gd  MnPrv        Shed
0

  MoSold YrSold SaleType SaleCondition SalePrice
0      2   2008       WD        Normal    208500
1      5   2007       WD        Normal    181500
2      9   2008       WD        Normal    223500
3      2   2006       WD       Abnorml    140000
4     12   2008       WD        Normal    250000
```

```
[5 rows x 81 columns]

# Separate features (X) and target variable (y)
X = df.drop('YrSold', axis=1)
y = df['YrSold']

# Label encoding for categorical variables
label_encoder = LabelEncoder()

# Apply label encoding to each categorical column
for col in X.select_dtypes(include=['object']).columns:
    X[col] = label_encoder.fit_transform(X[col])

# Split the dataset into training and testing sets (80:20 ratio)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Scale features using StandardScaler (optional but can improve model
performance)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Fit a linear regression model to the training data
model = LinearRegression()
model.fit(X_train_scaled, y_train)

# Predict house prices for the testing data
y_pred = model.predict(X_test_scaled)

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print the MSE and R^2 values
print(f"\nMean Squared Error (MSE): {mse:.2f}")
print(f"Coefficient of Determination (R^2): {r2:.2f}")


Mean Squared Error (MSE): 1.82
Coefficient of Determination (R^2): 0.00

# Plot a scatter plot between predicted and actual house prices
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, color='blue', alpha=0.6)
plt.title('Predicted vs Actual House Prices')
plt.xlabel('Actual House Prices')
plt.ylabel('Predicted House Prices')
plt.show()
```


Predicted vs Actual House Prices
Predicted House Prices
2009.0
2008.5
2008.0
2007.5
2007.0
2006.0
2006.5
2007.0
2007.5
2008.0
2008.5
2009.0
2009.5
2010.0
Actual House Prices