Lab 5 Supervised Learning– Regression

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
importfrom sklearn.datasets  fetch_california_housing
```

In [2]:
```
# dataset
housing = fetch_california_housing(as_frame=True)
df = housing.frame
```

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   MedInc       20640 non-null  float64
 1   HouseAge     20640 non-null  float64
 2   AveRooms     20640 non-null  float64
 3   AveBedrms    20640 non-null  float64
 4   Population   20640 non-null  float64
 5   AveOccup     20640 non-null  float64
 6   Latitude     20640 non-null  float64
 7   Longitude    20640 non-null  float64
 8   MedHouseVal  20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
```

In [4]:
```
# print(df.head(5))
```

Exercises

Apply the following regression models to predict charges:

- Simple Linear Regression (using MedInc only)
- Multiple Linear Regression (all features)
- Polynomial Regression (degree 2 and 3, using both single and multiple

features)

- Ridge Regression (with tuning alpha)
- Lasso Regression (with tuning alpha)
- Decision Tree Regressor

For each model:

- Train the model
- Predict on test data
- Evaluate and record:
- MAE
- MSE
- RMSE
- R^2 Score
- Create scatter plot of actual vs predicted value

In [5]:
```
importfrom sklearn.model_selection  train_test_split
importfrom sklearn.metrics  mean_absolute_error, mean_squared_error, r2_score
importfrom sklearn.linear_model  LinearRegression
```

In [6]:
```
# features and target
X = df.drop('MedHouseVal', axis =1)
y = df['MedHouseVal']
```

In [7]:
```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=12)
```

In [8]:
```
# evaluate functions
def evaluate(y_true, y_pred):
    mae = mean_absolute_error(y_true, y_pred)
    mse = mean_squared_error(y_true, y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, y_pred)

    print(f'MAE: {mae:.2f}')
    print(f'MSE: {mse:.2f}')
    print(f'RMSE: {rmse:.2f}')
    print(f'R2 Score: {r2:.2f}')
```

In [9]:
```
# visualise funtion
def visualize(y_test, y_pred):
    plt.scatter(y_test[y_pred > y_test], y_pred[y_pred > y_test], color='red',
label='Predicted > Actual')
    plt.scatter(y_test[y_pred < y_test], y_pred[y_pred < y_test], color='blue',
label='Predicted < Actual')

    # Add a line representing the linear regression fit
    m, b = np.polyfit(y_test, y_pred, 1)
    plt.plot(y_test, m*y_test + b, color='green', label='Linear Fit')
```

```
    plt.xlabel('Actual')
    plt.ylabel('Predicted')
    plt.title('Actual vs Predicted')
    plt.legend()
    plt.show()
```

Simple Linear Regression (using MedInc only)

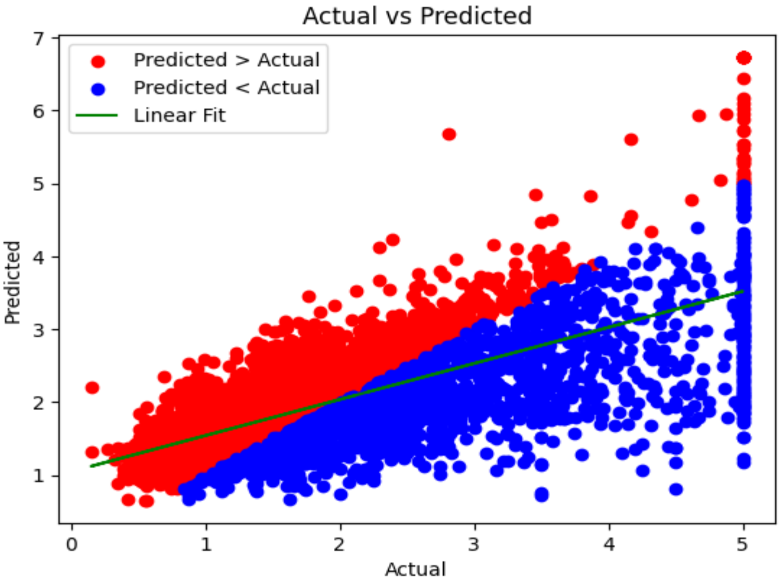
```
In [10]:
# train model - simple liner regression
X_train_inc = X_train[['MedInc']]
X_test_inc = X_test[['MedInc']]

model = LinearRegression()
model.fit(X_train_inc, y_train)
```

```
LinearRegression()
```

```
In [11]:
prediction = model.predict(X_test_inc)
```

```
In [12]:
print("Simple Linear Regression:")
evaluate(y_test, prediction)
visualize(y_test, prediction)
```

```
Simple Linear Regression:
MAE: 0.63
MSE: 0.70
RMSE: 0.84
R2 Score: 0.49
```



Multiple Linear Regression (all features)

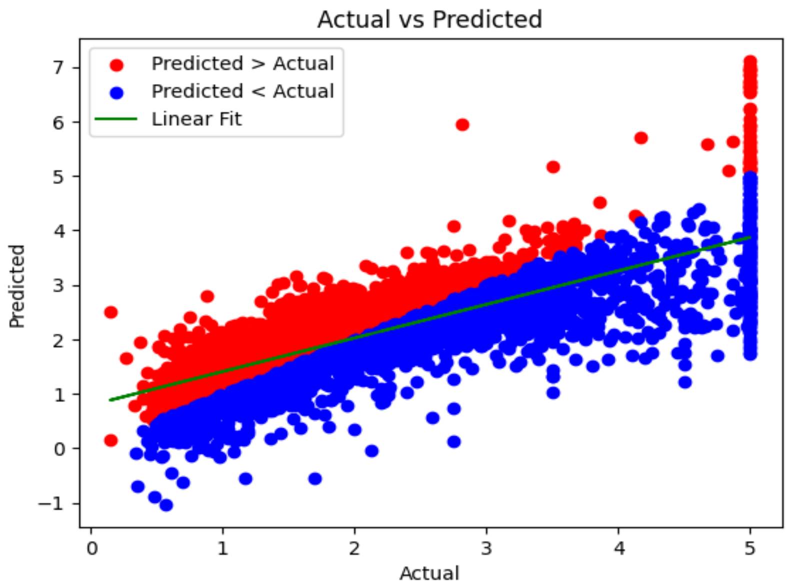
```
In [13]:
# train model - multiple liner regression
X_train_mult = X_train
X_test_mult = X_test

model = LinearRegression()
model.fit(X_train_mult, y_train)
```

```
LinearRegression()
```

```
In [14]:
prediction = model.predict(X_test)
```

```
In [15]:
print("Multiple Linear Regression:")
evaluate(y_test, prediction)
visualize(y_test, prediction)
```

```
Multiple Linear Regression:
MAE: 0.53
MSE: 0.53
RMSE: 0.73
R2 Score: 0.62
```



Polynomial Regression (degree 2 and 3, using both single and multiple features)

```
In [16]:
importfrom sklearn.preprocessing  PolynomialFeatures
importfrom sklearn.pipeline  make_pipeline
```

```
In [17]:
# degree 2 simple regression
model = make_pipeline(PolynomialFeatures(2), LinearRegression())
model.fit(X_train_inc, y_train)
prediction = model.predict(X_test_inc)
```

```
print("Polynomial Regression (degree 2):")
evaluate(y_test, prediction)
# visualize(y_test, prediction)
```

```
Polynomial Regression (degree 2):
MAE: 0.62
MSE: 0.69
RMSE: 0.83
R2 Score: 0.49
```

In [18]:

```
# degree 2 simple regression
model = make_pipeline(PolynomialFeatures(2), LinearRegression())
model.fit(X_train, y_train)
prediction = model.predict(X_test)
print("Polynomial Regression (degree 2):")
evaluate(y_test, prediction)
# visualize(y_test, prediction)
```

```
Polynomial Regression (degree 2):
MAE: 0.46
MSE: 0.44
RMSE: 0.66
R2 Score: 0.68
```

In [19]:

```
# degree 3 simple regression
model = make_pipeline(PolynomialFeatures(3), LinearRegression())
model.fit(X_train_inc, y_train)
prediction = model.predict(X_test_inc)
print("Polynomial Regression (degree 3):")
evaluate(y_test, prediction)
# visualize(y_test, prediction)
```

```
Polynomial Regression (degree 3):
MAE: 0.62
MSE: 0.69
RMSE: 0.83
R2 Score: 0.50
```

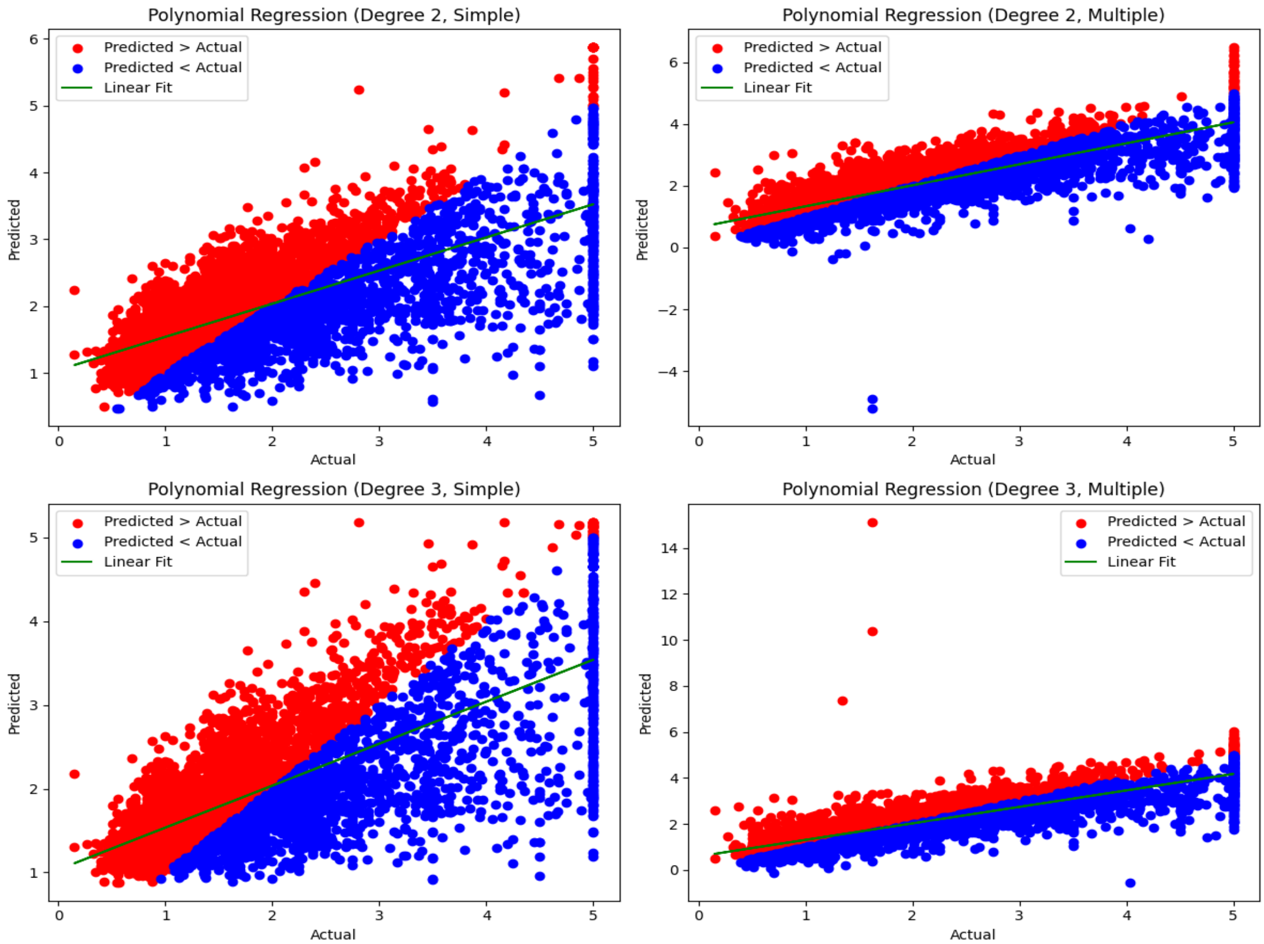
In [20]:

```
# degree 3 multi regression
model = make_pipeline(PolynomialFeatures(3), LinearRegression())
model.fit(X_train, y_train)
prediction = model.predict(X_test)
print("Polynomial Regression (degree 3):")
evaluate(y_test, prediction)
# visualize(y_test, prediction)
```

```
Polynomial Regression (degree 3):
MAE: 0.44
MSE: 0.44
RMSE: 0.66
R2 Score: 0.68
```

In [21]:
```
fig, axes = plt.subplots(2, 2, figsize=(12, 10))

# Degree 2 Simple Regression
model_deg2_simple = make_pipeline(PolynomialFeatures(2), LinearRegression())
model_deg2_simple.fit(X_train_inc, y_train)
prediction_deg2_simple = model_deg2_simple.predict(X_test_inc)
axes[0, 0].scatter(y_test[prediction_deg2_simple > y_test],
prediction_deg2_simple[prediction_deg2_simple > y_test], color='red',
label='Predicted > Actual')
axes[0, 0].scatter(y_test[prediction_deg2_simple < y_test],
prediction_deg2_simple[prediction_deg2_simple < y_test], color='blue',
label='Predicted < Actual')
m, b = np.polyfit(y_test, prediction_deg2_simple, 1)
axes[0, 0].plot(y_test, m*y_test + b, color='green', label='Linear Fit')
axes[0, 0].set_title('Polynomial Regression (Degree 2, Simple)')
axes[0, 0].set_xlabel('Actual')
axes[0, 0].set_ylabel('Predicted')
axes[0, 0].legend()

# Degree 2 Multiple Regression
model_deg2_mult = make_pipeline(PolynomialFeatures(2), LinearRegression())
model_deg2_mult.fit(X_train_mult, y_train)
prediction_deg2_mult = model_deg2_mult.predict(X_test_mult)
axes[0, 1].scatter(y_test[prediction_deg2_mult > y_test],
prediction_deg2_mult[prediction_deg2_mult > y_test], color='red',
label='Predicted > Actual')
axes[0, 1].scatter(y_test[prediction_deg2_mult < y_test],
prediction_deg2_mult[prediction_deg2_mult < y_test], color='blue',
label='Predicted < Actual')
m, b = np.polyfit(y_test, prediction_deg2_mult, 1)
axes[0, 1].plot(y_test, m*y_test + b, color='green', label='Linear Fit')
axes[0, 1].set_title('Polynomial Regression (Degree 2, Multiple)')
axes[0, 1].set_xlabel('Actual')
axes[0, 1].set_ylabel('Predicted')
axes[0, 1].legend()

# Degree 3 Simple Regression
model_deg3_simple = make_pipeline(PolynomialFeatures(3), LinearRegression())
model_deg3_simple.fit(X_train_inc, y_train)
prediction_deg3_simple = model_deg3_simple.predict(X_test_inc)
axes[1, 0].scatter(y_test[prediction_deg3_simple > y_test],
prediction_deg3_simple[prediction_deg3_simple > y_test], color='red',
label='Predicted > Actual')
axes[1, 0].scatter(y_test[prediction_deg3_simple < y_test],
prediction_deg3_simple[prediction_deg3_simple < y_test], color='blue',
label='Predicted < Actual')
m, b = np.polyfit(y_test, prediction_deg3_simple, 1)
axes[1, 0].plot(y_test, m*y_test + b, color='green', label='Linear Fit')
axes[1, 0].set_title('Polynomial Regression (Degree 3, Simple)')
axes[1, 0].set_xlabel('Actual')
axes[1, 0].set_ylabel('Predicted')
axes[1, 0].legend()

# Degree 3 Multiple Regression
model_deg3_mult = make_pipeline(PolynomialFeatures(3), LinearRegression())
model_deg3_mult.fit(X_train_mult, y_train)
prediction_deg3_mult = model_deg3_mult.predict(X_test_mult)
```

```
axes[1, 1].scatter(y_test[prediction_deg3_mult > y_test],
prediction_deg3_mult[prediction_deg3_mult > y_test], color='red',
label='Predicted > Actual')
axes[1, 1].scatter(y_test[prediction_deg3_mult < y_test],
prediction_deg3_mult[prediction_deg3_mult < y_test], color='blue',
label='Predicted < Actual')
m, b = np.polyfit(y_test, prediction_deg3_mult, 1)
axes[1, 1].plot(y_test, m*y_test + b, color='green', label='Linear Fit')
axes[1, 1].set_title('Polynomial Regression (Degree 3, Multiple)')
axes[1, 1].set_xlabel('Actual')
axes[1, 1].set_ylabel('Predicted')
axes[1, 1].legend()

plt.tight_layout()
plt.show()
```

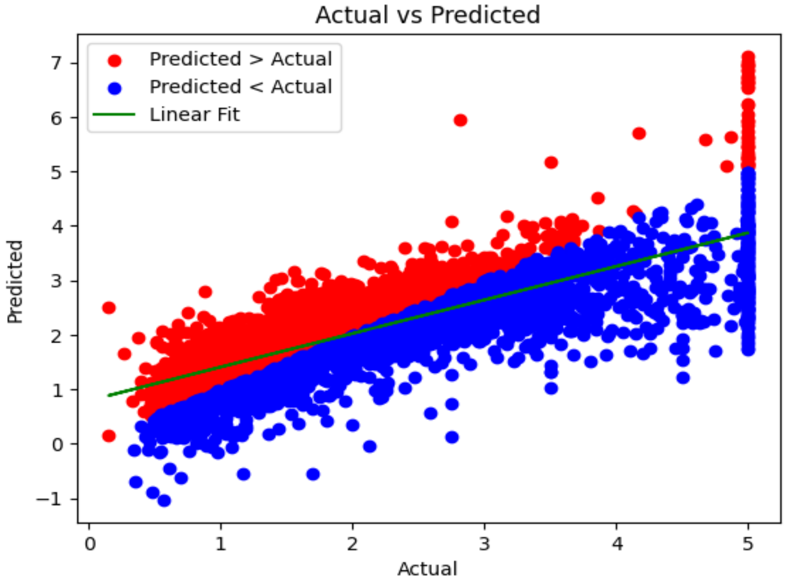


Ridge Regression (with tuning alpha)

```
In [22]:
importfrom sklearn.linear_model  Ridge

model = Ridge()
model.fit(X_train, y_train)

prediction = model.predict(X_test)
```

```
print("Ridge Regression:")
evaluate(y_test, prediction)
visualize(y_test, prediction)
```

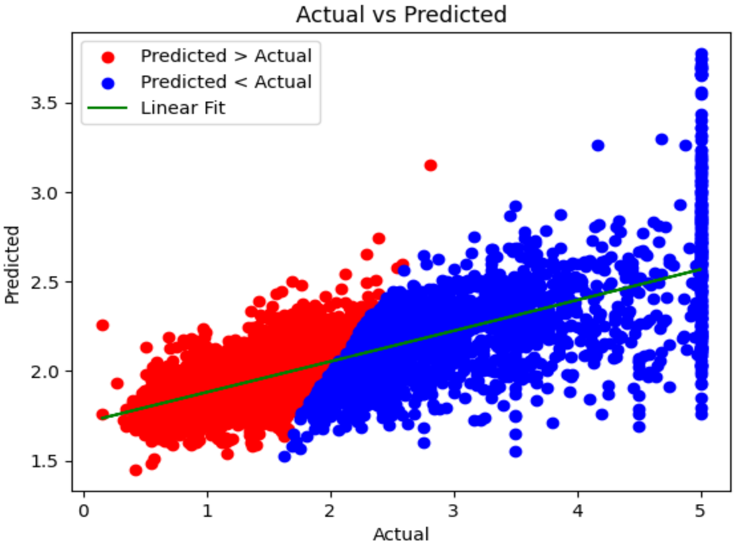
```
Ridge Regression:
MAE: 0.53
MSE: 0.53
RMSE: 0.73
R2 Score: 0.62
```



Lasso Regression (with tuning alpha)

```
In [23]:
importfrom sklearn.linear_model  Lasso

model = Lasso()
model.fit(X_train, y_train)

prediction = model.predict(X_test)

print("Lasso Regression:")
evaluate(y_test, prediction)
visualize(y_test, prediction)
```

```
Lasso Regression:
MAE: 0.78
MSE: 0.98
RMSE: 0.99
R2 Score: 0.29
```



Decision Tree Regressor

```
In [24]:
importfrom sklearn.tree  DecisionTreeRegressor

model = DecisionTreeRegressor()
model.fit(X_train, y_train)

prediction = model.predict(X_test)

print("Decision Tree Regressor:")
evaluate(y_test, prediction)
visualize(y_test, prediction)
```

```
Decision Tree Regressor:
MAE: 0.44
MSE: 0.47
RMSE: 0.68
R2 Score: 0.66
```