Regression

1- Load the libraries:

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

from sklearn.model_selection import train_test_split, KFold
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

2-Load the Dataset:

In [2]:
```
Housing_dataframe = pd.read_csv('California_Houses.csv') # Load data from file
```

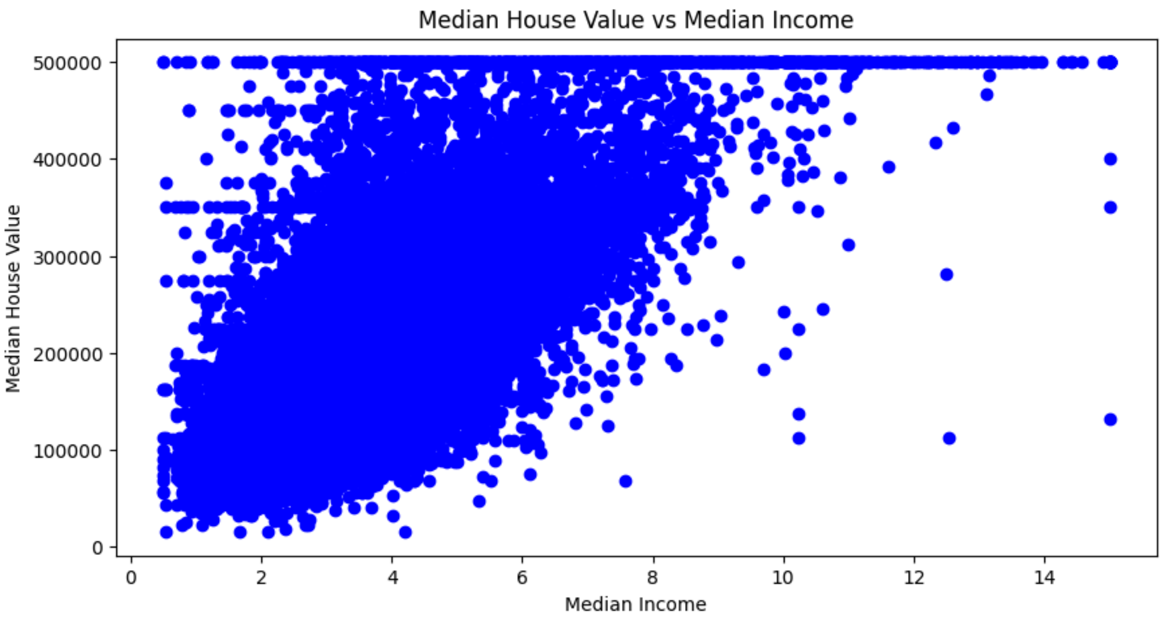
3-Seperate The features and the target:

In [3]:
```
X_housing = Housing_dataframe.drop('Median_House_Value', axis=1) # drop the targ
y_housing = Housing_dataframe['Median_House_Value']# set the target column
print(X_housing.head())
print(y_housing.head())
```

```
   Median_Income  Median_Age  Tot_Rooms  Tot_Bedrooms  Population  Households  \
0         8.3252          41        880           129         322         126
1         8.3014          21       7099          1106        2401        1138
2         7.2574          52       1467           190         496         177
3         5.6431          52       1274           235         558         219
4         3.8462          52       1627           280         565         259

   Latitude  Longitude  Distance_to_coast  Distance_to_LA  \
0     37.88    -122.23        9263.040773   556529.158342
1     37.86    -122.22       10225.733072   554279.850069
2     37.85    -122.24        8259.085109   554610.717069
3     37.85    -122.25        7768.086571   555194.266086
4     37.85    -122.25        7768.086571   555194.266086

   Distance_to_SanDiego  Distance_to_SanJose  Distance_to_SanFrancisco
0         735501.806984         67432.517001              21250.213767
1         733236.884360         65049.908574              20880.600400
2         733525.682937         64867.289833              18811.487450
3         734095.290744         65287.138412              18031.047568
4         734095.290744         65287.138412              18031.047568
0    452600.0
1    358500.0
2    352100.0
3    341300.0
4    342200.0
Name: Median_House_Value, dtype: float64
```

In [4]:
```
plt.figure(figsize=(10, 5))
plt.scatter(X_housing['Median_Income'], y_housing, color='blue')
plt.title('Median House Value vs Median Income')
plt.xlabel('Median Income')
```

```
plt.ylabel('Median House Value')
plt.show()
```



4-Split The Dataset:

In [5]:
```
train_x, test_x, train_y, test_y = train_test_split(X_housing, y_housing, test_s
```

5-Appling K-Fold Cross-Validation:

In [6]:
```
# Step 2: Apply K-Fold with n_splits=6 on 85% Training Data so that training set
kf = KFold(n_splits=6, shuffle=True, random_state=42)
```

6-Standardization:

In [7]:
```
scaler = StandardScaler() # create a StandardScaler object
```

7-Store results:

In [8]:
```
results = {"Linear Regression": {"Mean Square Error": [], "Mean Absolute Error":
           "Lasso Regression": {"Mean Square Error": [], "Mean Absolute Error":
           "Ridge Regression": {"Mean Square Error": [], "Mean Absolute Error":
```

8- Linear Regression

In [9]:
```
def linear_regression(X_train, y_train, X_val, y_val):
    linear = LinearRegression() # create a LinearRegression object
    linear.fit(X_train, y_train) # fit the model
    y_pred_linear = linear.predict(X_val) # make predictions
    mse = mean_squared_error(y_val, y_pred_linear) # calculate the mean squared
    mae = mean_absolute_error(y_val, y_pred_linear) # calculate the mean absolut
    y_pred_linear = linear.predict(X_train)[:10]
    return y_pred_linear ,mse, mae
```

9-Lasso Regression:

In [10]:
```
def lasso_regression(X_train, y_train, X_val, y_val, alpha=0.1):
    lasso = Lasso(alpha=alpha, max_iter=10000) # create a Lasso object with the
```

```
    lasso.fit(X_train, y_train)
    y_pred_lasso = lasso.predict(X_val)
    mse = mean_squared_error(y_val, y_pred_lasso)
    mae = mean_absolute_error(y_val, y_pred_lasso)
    y_pred_lasso = lasso.predict(X_train)[:10]
    return y_pred_lasso ,mse, mae
```

10-Ridge Regression:

In [11]:
```
def ridge_regression(X_train, y_train, X_val, y_val, alpha=0.1):
    ridge = Ridge(alpha=alpha) # create a Ridge object with the specified alpha
    ridge.fit(X_train, y_train)
    y_pred_ridge = ridge.predict(X_val)
    mse = mean_squared_error(y_val, y_pred_ridge)
    mae = mean_absolute_error(y_val, y_pred_ridge)
    y_pred_ridge = ridge.predict(X_train)[:10]
    return y_pred_ridge ,mse, mae
```

11- Plotting the Results:

In [12]:
```
def plot_results(results):
    for model in results:
        mse = results[model]["Mean Square Error"] # get the mean squared error
        mae = results[model]["Mean Absolute Error"] # get the mean absolute erro
        # Plotting Mean Square Error
        plt.figure(figsize=(10, 5))
        plt.subplot(1, 2, 1)
        plt.plot(mse, label='MSE')
        plt.title(f'{model} - Mean Square Error')
        plt.xlabel('Fold')
        plt.ylabel('MSE')
        plt.legend()
        plt.grid(True)

        # Plotting Mean Absolute Error
        plt.subplot(1, 2, 2)
        plt.plot(mae, label='MAE')
        plt.title(f'{model} - Mean Absolute Error')
        plt.xlabel('Fold')
        plt.ylabel('MAE')
        plt.legend()
        plt.grid(True)

        # Display the plots
        plt.tight_layout()
        plt.show()
```

12- K-Fold Cross-Validation on Training Set:

In [13]:
```
for train_index, val_index in kf.split(train_x):
    X_train, X_val = train_x.iloc[train_index], train_x.iloc[val_index] # get th
    y_train, y_val = train_y.iloc[train_index], train_y.iloc[val_index]

    X_train = scaler.fit_transform(X_train) # fit and transform the training set
    X_val = scaler.transform(X_val)

    # Linear Regression
    y_pred_linear, mse, mae = linear_regression(X_train, y_train, X_val, y_val)
```

```
    results["Linear Regression"]["Mean Square Error"].append(mse) # append the m
    results["Linear Regression"]["Mean Absolute Error"].append(mae)

    # Lasso Regression
    y_pred_lasso,mse, mae = lasso_regression(X_train, y_train, X_val, y_val)
    results["Lasso Regression"]["Mean Square Error"].append(mse)
    results["Lasso Regression"]["Mean Absolute Error"].append(mae)

    # Ridge Regression
    y_pred_ridge, mse, mae = ridge_regression(X_train, y_train, X_val, y_val)
    results["Ridge Regression"]["Mean Square Error"].append(mse)
    results["Ridge Regression"]["Mean Absolute Error"].append(mae)

    # Print Predicted Median House Values for Training Set
    print("\nPredicted Median House Values (Training Set):")
    print("Linear Regression:", y_pred_linear)
    print("Lasso Regression:", y_pred_lasso)
    print("Ridge Regression:", y_pred_ridge)
```

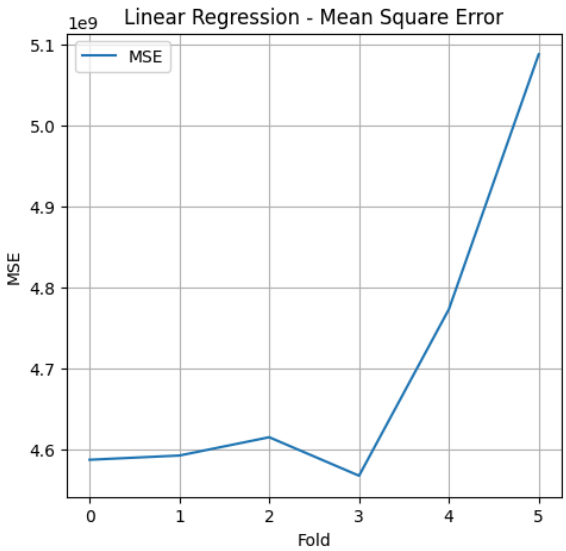
```
Predicted Median House Values (Training Set):
Linear Regression: [104645.39391834 232586.01994387 163983.73109374 151045.202862
47
 180768.21401298 271605.44546516 237972.1189104  210575.28839093
 154821.68687984 258680.70623845]
Lasso Regression: [104642.63499051 232586.09006907 163991.51735802 151046.5147314
4
 180766.63431597 271605.70436294 237968.11392512 210569.28704189
 154821.94794717 258686.23516413]
Ridge Regression: [104638.9672777  232587.81576643 164012.34496609 151051.9142044
7
 180764.31442955 271607.60731267 237946.11256244 210556.6736146
 154822.7813969  258702.10751713]

Predicted Median House Values (Training Set):
Linear Regression: [233875.69104913 163372.11338791 142082.10646333 148876.417678
01
 323490.62325627 182061.7581456  272839.41889865 166827.21261602
 240137.56112176 211465.0937831 ]
Lasso Regression: [233875.73718551 163379.76281417 142086.71295654 148877.8719486
2
 323494.68994353 182060.20520746 272839.60603132 166829.67358844
 240133.66398421 211459.21999472]
Ridge Regression: [233877.80659876 163404.30989914 142091.44919471 148884.8477328
4
 323499.21255696 182057.45310284 272841.44857519 166838.04563067
 240108.16286574 211444.15918147]

Predicted Median House Values (Training Set):
Linear Regression: [103780.36130525 232994.60739344 162779.54731168 146365.196946
8
 150481.32722938 323626.22230971 181254.32053154 271562.05637343
 168486.80861728 239322.55531618]
Lasso Regression: [103777.7486304  232994.66526674 162787.28596509 146369.9729615
6
 150482.74388965 323630.34201889 181252.80525132 271562.32273986
 168489.09662903 239318.5945335 ]
Ridge Regression: [103773.93231511 232996.58523999 162810.32574616 146372.6871017
9
 150489.31354695 323633.66528046 181250.25471874 271564.47726051
 168495.79426611 239293.29767808]

Predicted Median House Values (Training Set):
Linear Regression: [105549.69101469 232770.16678483 162593.43717868 146536.215683
29
 323762.2368673  180282.65607972 272329.09067289 168269.65838237
 240118.07881317 212713.89007844]
Lasso Regression: [105546.89186339 232770.23759607 162601.10154343 146541.0930729
9
 323766.27108484 180281.12525457 272329.29975479 168272.09991534
 240114.01729698 212708.03031364]
Ridge Regression: [105541.72345132 232772.33569223 162625.28521706 146546.1033200
7
 323770.70389819 180278.82422649 272331.03028169 168278.95447959
 240089.15764924 212693.08271508]

Predicted Median House Values (Training Set):
Linear Regression: [104394.82408179 234412.83770645 139645.40712922 137241.778765
07
 325002.32336566 168133.06956453 241255.42385544 211417.16946701
```

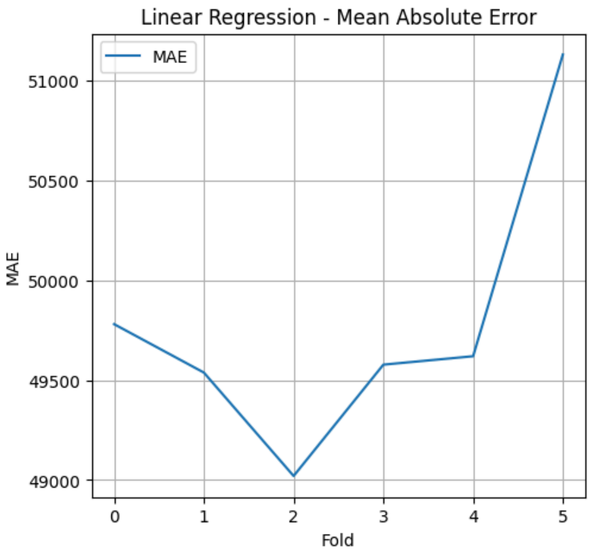
```
 151995.486019   255603.6144342 ]
Lasso Regression: [104392.03394239 234412.89744613 139650.06202484 137243.4030034
6
 325006.39887238 168135.34483399 241251.47480494 211411.27113459
 151995.80340556 255609.0374161 ]
Ridge Regression: [104387.75147082 234414.68789623 139653.76259091 137250.8954276
6
 325009.87757429 168141.74374234 241226.91644208 211397.71043199
 151996.77333056 255627.71101106]

Predicted Median House Values (Training Set):
Linear Regression: [102899.30567984 163322.49667099 144713.26355636 151507.072339
6
 324400.40667593 179910.39997017 271089.54513053 167557.44455454
 211276.0641961  257812.35081055]
Lasso Regression: [102896.586004   163330.21346774 144717.87327292 151508.4992308
8
 324404.45418937 179908.85915442 271089.77977698 167559.80452671
 211270.12141302 257817.90014543]
Ridge Regression: [102892.4672975  163353.09259857 144721.1302067  151514.7696157
 324408.00346465 179906.35908021 271091.87168305 167566.17636688
 211256.25959394 257836.41555069]
```

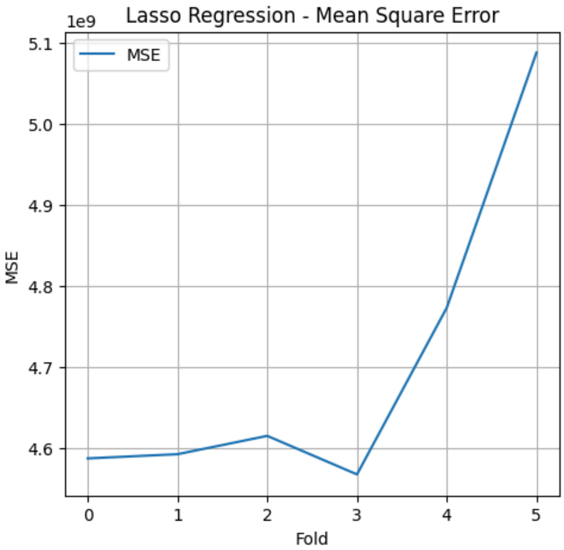
13- Displaying the MSE & MAE Results:

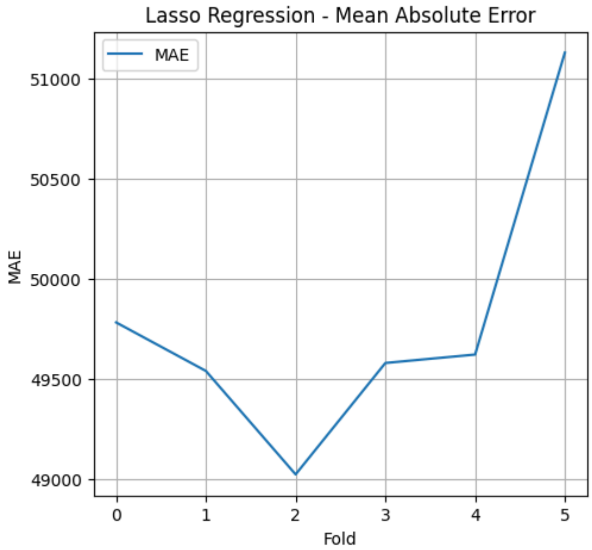
In [14]:
```
for name in results:
    print(f"\n{name}:")
    print(f"Average Mean Square Error: {np.mean(results[name]['Mean Square Error
    print(f"Average Mean Absolute Error: {np.mean(results[name]['Mean Absolute E

plot_results(results)
```

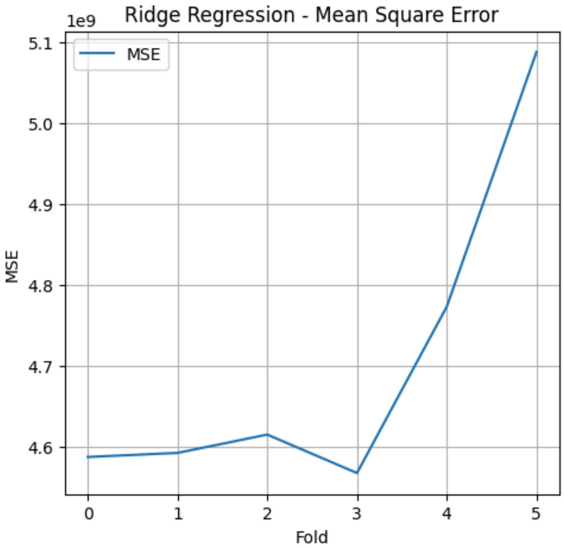
```
Linear Regression:
Average Mean Square Error: 4704039022.857063
Average Mean Absolute Error: 49777.04718315246

Lasso Regression:
Average Mean Square Error: 4704038716.527916
Average Mean Absolute Error: 49777.119757619796

Ridge Regression:
Average Mean Square Error: 4704032521.094236
Average Mean Absolute Error: 49777.38288770585
```

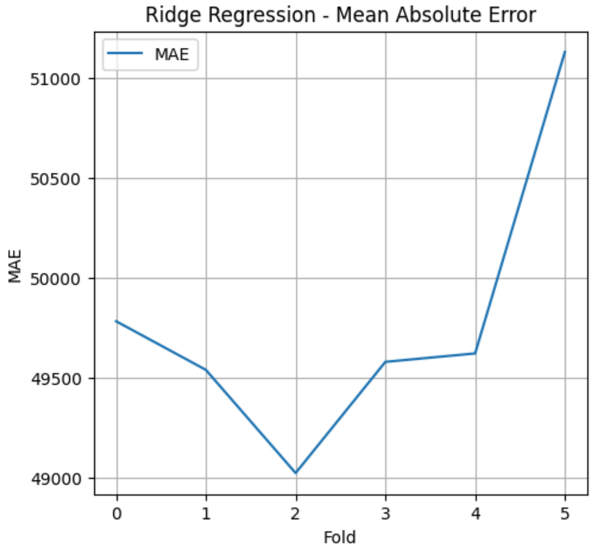












14-Test Set Evaluation:

In [15]:

```
# --- FINAL TEST SET EVALUATION (After K-Fold Cross-Validation) ---
test_x = scaler.transform(test_x)  # Apply same scaling
print("\n--- Evaluating on Final 15% Test Set ---")
final_models = {}
for name, model in zip(["Linear Regression", "Lasso Regression", "Ridge Regressi
                        [linear_regression, lasso_regression, ridge_regression])
    y_pred_test,mse, mae = model(X_train, y_train, test_x, test_y)  # Evaluate c
    final_models[name] = model
    results[name]["Mean Square Error"].append(mse)
    results[name]["Mean Absolute Error"].append(mae)
    print(f"\n{name}:")
    print(f"Mean Square Error: {mse}")
    print(f"Mean Absolute Error: {mae}")
    print(f"Predicted Median House Values (Testing Set): {y_pred_test[:10]}")
```

```
--- Evaluating on Final 15% Test Set ---

Linear Regression:
Mean Square Error: 4859183161.625993
Mean Absolute Error: 50727.67930424335
Predicted Median House Values (Testing Set): [102899.30567984 163322.49667099 144
713.26355636 151507.0723396
 324400.40667593 179910.39997017 271089.54513053 167557.44455454
 211276.0641961  257812.35081055]

Lasso Regression:
Mean Square Error: 4859190771.953638
Mean Absolute Error: 50727.783020306735
Predicted Median House Values (Testing Set): [102896.586004   163330.21346774 144
717.87327292 151508.49923088
 324404.45418937 179908.85915442 271089.77977698 167559.80452671
 211270.12141302 257817.90014543]

Ridge Regression:
Mean Square Error: 4859210931.250007
Mean Absolute Error: 50728.21469793744
Predicted Median House Values (Testing Set): [102892.4672975  163353.09259857 144
721.1302067  151514.7696157
 324408.00346465 179906.35908021 271091.87168305 167566.17636688
 211256.25959394 257836.41555069]
```

15-Training Set Evaluation:

Linear Regression:

- **Average Mean Square Error (MSE)**: 4,704,039,022.857062
- **Average Mean Absolute Error (MAE)**: 49,777.04718315246

Lasso Regression:

- **Average Mean Square Error (MSE)**: 4,704,038,716.527915
- **Average Mean Absolute Error (MAE)**: 49,777.11975761978

Ridge Regression:

- **Average Mean Square Error (MSE)**: 4,704,032,521.0942335
- **Average Mean Absolute Error (MAE)**: 49,777.38288770586

16-Test Set Evaluation:

Linear Regression Final Test Results:

- **Test MSE**: 4,859,183,161.625993
- **Test MAE**: 50,727.679304243354

Lasso Regression Final Test Results:

- **Test MSE**: 4,859,190,771.953638

- **Test MAE**: 50,727.783020306735

Ridge Regression Final Test Results:

- **Test MSE**: 4,859,210,931.250007
- **Test MAE**: 50,728.21469793744

17-Comparison:

1. **Mean Square Error (MSE)**:
   - The MSE values for all three models are very close to each other, both in the training and test sets.
   - Ridge Regression has the lowest average MSE on the training set, indicating slightly better performance in terms of minimizing the squared errors.
   - On the test set, Linear Regression has a slightly lower MSE compared to Lasso and Ridge Regression, but the differences are minimal.
2. **Mean Absolute Error (MAE)**:
   - The MAE values for all three models are also very close to each other, both in the training and test sets.
   - Linear Regression has the lowest average MAE on the training set, indicating slightly better performance in terms of minimizing the absolute errors.
   - On the test set, Linear Regression again has a slightly lower MAE compared to Lasso and Ridge Regression, but the differences are minimal.
3. **Model Performance**:
   - All three models (Linear, Lasso, and Ridge Regression) perform similarly on this dataset.
   - The differences in MSE and MAE are very small, indicating that the choice of regularization (Lasso or Ridge) does not significantly impact the performance for this particular dataset.
4. **Regularization Impact**:
   - Lasso Regression performs feature selection by shrinking some coefficients to zero, which can be useful if there are many irrelevant features. However, in this case, it does not provide a significant advantage over Linear Regression.
   - Ridge Regression helps in dealing with multicollinearity by shrinking the coefficients, but again, it does not provide a significant advantage over Linear Regression in this case.

18-Conclusion:

- **Linear Regression**: Performs slightly better in terms of both MSE and MAE on the test set, but the differences are minimal.
- **Lasso Regression**: Performs similarly to Linear Regression, with no significant advantage in this case.
- **Ridge Regression**: Also performs similarly to Linear Regression, with no significant advantage in this case.

Overall, all three models perform similarly on this dataset, and the choice of model may depend on other factors such as interpretability, computational efficiency, and the presence of irrelevant features or multicollinearity in the dataset.