in this notebook we discuss two task: KNN classification task and a regressin task

```
#import necessary libraries
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV,
PredefinedSplit
from sklearn.linear_model import SGDRegressor #for stochastic
regression
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, Lasso, Ridge #batch
from sklearn.metrics import mean_squared_error, mean_absolute_error,
make_scorer, r2_score
import matplotlib.pyplot as plt

# Path to a file in Google Drive
data = pd.read_csv('https://drive.google.com/uc?id=1nqSQ-
M_Ff2TDD2U0syAbFBvJZuXJLWNc')
#data=pd.read_csv('California_Houses.csv')
```

Basic Concepts

#what is regression?

##in a regression problem a model tries to predict the output of some function.

$$f_{w,b}(x) = wx + b$$

- f(x) is the dependent variable we want to predict.
- X is the independent variable we use to make the prediction.
- b is the y-intercept and w is the slope of the line.

these parameteres should minimize some set cost function **J** for linear regression we will use the sum of squared error cost function.

$$J(w,b) = \frac{1}{2m}\sum_{i=0}^{m-1}(f_{w,b}(x^{(i)}) - y^{(i)})^2$$

repeat until convergence: {

$$b := b - \alpha \frac{\partial J(w,b)}{\partial b}$$

$$w := w - \alpha \frac{\partial J(w,b)}{\partial w}$$

}

##Gradient Descent

California Houses Problem

in this problem we use linear regression to predict the median house price given a set of samples and corresponding features.

#split the trainging data into training , test , and validation sets

```
#visiualize the rwa data
# Display the column headers
print(data.columns)
# Inspect the data (this helps verify if there are missing values or
other issues)
print(data.info())
print(data.describe())
```

```
Index(['Median_House_Value', 'Median_Income', 'Median_Age',
'Tot_Rooms',
       'Tot_Bedrooms', 'Population', 'Households', 'Latitude',
'Longitude',
       'Distance_to_coast', 'Distance_to_LA', 'Distance_to_SanDiego',
       'Distance_to_SanJose', 'Distance_to_SanFrancisco'],
      dtype='object')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 14 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Median_House_Value        20640 non-null  float64
 1   Median_Income             20640 non-null  float64
 2   Median_Age                20640 non-null  int64
 3   Tot_Rooms                 20640 non-null  int64
 4   Tot_Bedrooms              20640 non-null  int64
 5   Population                20640 non-null  int64
 6   Households                20640 non-null  int64
 7   Latitude                  20640 non-null  float64
 8   Longitude                 20640 non-null  float64
 9   Distance_to_coast         20640 non-null  float64
 10  Distance_to_LA            20640 non-null  float64
```

```
 11  Distance_to_SanDiego      20640 non-null  float64
 12  Distance_to_SanJose       20640 non-null  float64
 13  Distance_to_SanFrancisco  20640 non-null  float64
dtypes: float64(9), int64(5)
memory usage: 2.2 MB
None
       Median_House_Value  Median_Income    Median_Age
Tot_Rooms  \
count        20640.000000   20640.000000  20640.000000  20640.000000

mean        206855.816909       3.870671     28.639486   2635.763081

std         115395.615874       1.899822     12.585558   2181.615252

min          14999.000000       0.499900      1.000000      2.000000

25%         119600.000000       2.563400     18.000000   1447.750000

50%         179700.000000       3.534800     29.000000   2127.000000

75%         264725.000000       4.743250     37.000000   3148.000000

max         500001.000000      15.000100     52.000000  39320.000000


       Tot_Bedrooms    Population    Households      Latitude
Longitude  \
count  20640.000000  20640.000000  20640.000000  20640.000000
20640.000000
mean     537.898014   1425.476744    499.539680     35.631861   -
119.569704
std      421.247906   1132.462122    382.329753      2.135952
2.003532
min        1.000000      3.000000      1.000000     32.540000   -
124.350000
25%      295.000000    787.000000    280.000000     33.930000   -
121.800000
50%      435.000000   1166.000000    409.000000     34.260000   -
118.490000
75%      647.000000   1725.000000    605.000000     37.710000   -
118.010000
max     6445.000000  35682.000000   6082.000000     41.950000   -
114.310000

       Distance_to_coast  Distance_to_LA  Distance_to_SanDiego  \
count       20640.000000    2.064000e+04          2.064000e+04
mean        40509.264883    2.694220e+05          3.981649e+05
std         49140.039160    2.477324e+05          2.894006e+05
min           120.676447    4.205891e+02          4.849180e+02
25%          9079.756762    3.211125e+04          1.594264e+05
```

```
50%          20522.019101    1.736675e+05          2.147398e+05
75%          49830.414479    5.271562e+05          7.057954e+05
max         333804.686371    1.018260e+06          1.196919e+06

       Distance_to_SanJose  Distance_to_SanFrancisco
count         20640.000000              20640.000000
mean         349187.551219             386688.422291
std          217149.875026             250122.192316
min             569.448118                456.141313
25%          113119.928682             117395.477505
50%          459758.877000             526546.661701
75%          516946.490963             584552.007907
max          836762.678210             903627.663298
```

'Median_House_Value' is the value we want to predict. the rest are feetures.

```python
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Define feature columns
X_features = [
    'Median_Income', 'Median_Age', 'Tot_Rooms', 'Tot_Bedrooms',
    'Population', 'Households', 'Latitude', 'Longitude',
    'Distance_to_coast', 'Distance_to_LA', 'Distance_to_SanDiego',
    'Distance_to_SanJose', 'Distance_to_SanFrancisco'
]

# Arrange data and split
X = data[X_features]  # Feature matrix
y = data['Median_House_Value']  # Target variable

# Transform to numpy arrays
X = X.to_numpy()  # or use X.values
y = np.array(y)

# Normalize the data for comparison later on
scaler = StandardScaler()
X_norm = scaler.fit_transform(X)

# Split the data into 70% training, 15% test, and 15% validation
X_train, X_temp, y_train, y_temp = train_test_split(X, y,
test_size=0.3, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp,
test_size=0.5, random_state=42)

# Split the normalized set as well
Xnorm_train, Xnorm_temp = train_test_split(X_norm, test_size=0.3,
random_state=42)
```

```
Xnorm_val, Xnorm_test = train_test_split(Xnorm_temp, test_size=0.5,
random_state=42)

# Visualize the data
print(f"The features of the first sample are: {X_train[1]}")
print(f"The median price is: {y_train[1]}\n")

print(f"The features of the first sample from the normalized set are:
{Xnorm_train[1]}")
print(f"The median price is: {y_train[1]}")
```

```
The features of the first sample are: [ 2.86310000e+00  2.00000000e+01
2.18300000e+03  5.34000000e+02
  9.99000000e+02  4.96000000e+02  3.27900000e+01 -1.17090000e+02
  1.43449263e+04  1.76528653e+05  1.06011336e+04  6.68041340e+05
  7.36046140e+05]
The median price is: 169700.0

The features of the first sample from the normalized set are: [-
0.53036314 -0.68647699 -0.20754074 -0.00925371 -0.37660163 -0.00925841
 -1.33052136  1.23769666 -0.5324573  -0.3749835  -1.33922748
1.46839372
  1.39678202]
The median price is: 169700.0
```

we are going to use four very similar models: Linear, Ridge, and Lasso the Linear model is the basic Model we discussed earlier where f(x)= wx +b. the ridge and lasso models are derived from this model by adding a regularization term. the SGDR (stochastic)model uses gradient descent iteratively and not as batch.

for the stochastic ghradient descent we will be using the normalized data sets

```
# Initialize models
sgdr = SGDRegressor(max_iter=2000)
linear_model = LinearRegression()
lasso_model = Lasso(alpha=0.1)
ridge_model = Ridge(alpha=1)

# train and evaluate sgdr
sgdr.fit(Xnorm_train, y_train)
y_pred_sgdr=sgdr.predict(Xnorm_val)
```

```
mse_sgdr = mean_squared_error(y_val, y_pred_sgdr)
mae_sgdr = mean_absolute_error(y_val,y_pred_sgdr)

# Train and evaluate Linear Regression
linear_model.fit(Xnorm_train, y_train)
y_pred_linear = linear_model.predict(Xnorm_val)
mse_linear = mean_squared_error(y_val, y_pred_linear)
mae_linear = mean_absolute_error(y_val, y_pred_linear)

# Train and evaluate Lasso Regression
lasso_model.fit(Xnorm_train, y_train)
y_pred_lasso = lasso_model.predict(Xnorm_val)
mse_lasso = mean_squared_error(y_val, y_pred_lasso)
mae_lasso = mean_absolute_error(y_val, y_pred_lasso)

# Train and evaluate Ridge Regression
ridge_model.fit(Xnorm_train, y_train)
y_pred_ridge = ridge_model.predict(Xnorm_val)
mse_ridge = mean_squared_error(y_val, y_pred_ridge)
mae_ridge = mean_absolute_error(y_val, y_pred_ridge)
```

```
a:\pycharm\lib\site-packages\sklearn\linear_model\
_coordinate_descent.py:697: ConvergenceWarning: Objective did not
converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation.
Duality gap: 3.244e+13, tolerance: 1.936e+10
  model = cd_fast.enet_coordinate_descent(
```

```
# Print the results
print("SGDR:")
print("MSE:", mse_sgdr)
print("MAE:", mae_sgdr)

print("\nLinear Regression:")
print("MSE:", mse_linear)
print("MAE:", mae_linear)

print("\nLasso Regression:")
print("MSE:", mse_lasso)
print("MAE:", mae_lasso)
print("Selected features:", sum(lasso_model.coef_ != 0))

print("\nRidge Regression:")
print("MSE:", mse_ridge)
print("MAE:", mae_ridge)
```

```
SGDR:
MSE: 4944486903.294801
MAE: 51321.86075195924

Linear Regression:
```

```
MSE: 4907211997.374781
MAE: 50790.060271050934

Lasso Regression:
MSE: 4907209875.578146
MAE: 50790.1825237019
Selected features: 13

Ridge Regression:
MSE: 4907280799.676526
MAE: 50793.60758762655
```

Behind the code ## what exactly are the regularization factors in the Lasso and Ridge regressions

1 lasso regression #### the lasso regression(also known as the L1 regression) adds a "penalty" term to the cost function so that the cost function becomes :

$$\text{Minimize} \sum_{i=1}(y_i - \hat{y}_i)^2 + \lambda \sum_{j=1} |\beta_j|$$

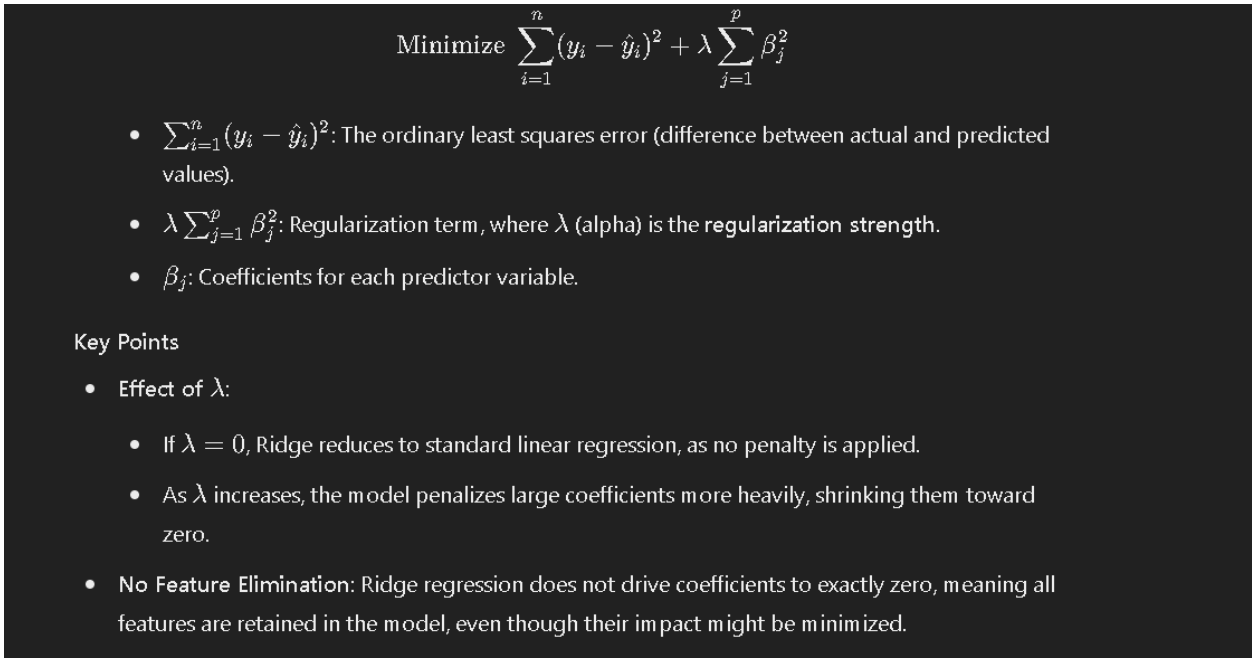
- $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$: Ordinary least squares error.
- $\lambda \sum_{j=1}^{p} |\beta_j|$: Regularization term with absolute values of coefficients.

Key Points

- Effect of λ:
  - When $\lambda = 0$, Lasso reduces to standard linear regression.
  - As λ increases, the Lasso penalty becomes stronger, forcing some coefficients to become exactly zero. This is because the absolute value penalty can make it more favorable for coefficients to be zero, which effectively eliminates them from the model.
- Feature Selection: Lasso can drive coefficients of less important features to zero, effectively performing automatic feature selection. This is especially useful when dealing with high-dimensional data where not all predictors contribute significantly to the output.

2 Ridge Regression

ridge regression(also known as L2 regularization) adds a penalty based on the square of the magnitude of the coeeficients so that the cost function becomes:



###note that the ridge regression minimizes but does not eliminate features unlike the ridge function due to the diffrentiable nature of the ridge cost function.

but why do we need regularization?

- to prevent overfitting
- handling high dimensional data
- simplifying the model as rdge regression can remove some coefficients to zero
- reducing variance hence leading to improved better generalization

#what now?

now we will attempt to tune the lambda parameters so that it gives reduced error

```
import numpy as np
from sklearn.linear_model import ElasticNet, Ridge, Lasso
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, mean_absolute_error,
mean_squared_error
```

```
# Define a range for alpha
alpha_range = np.logspace(-4, 2, 10)

# Create scorers for MAE and MSE
mae_scorer = make_scorer(mean_absolute_error, greater_is_better=False)
# MAE scorer
mse_scorer = make_scorer(mean_squared_error, greater_is_better=False)
# MSE scorer

# Combine the training and validation sets
X_combined = np.concatenate([Xnorm_train, Xnorm_val])
y_combined = np.concatenate([y_train, y_val])

# Define the parameter grid using alpha_range
param_grid = {'alpha': alpha_range}

# Initialize models
model_lasso = Lasso(max_iter=10000)
model_ridge = Ridge(max_iter=10000)

# Initialize GridSearchCV for Ridge and Lasso regression with multiple
scorers
grid_search_ridge = GridSearchCV(model_ridge, param_grid,
scoring={'MSE': mse_scorer, 'MAE': mae_scorer}, cv=5, refit='MSE')
grid_search_lasso = GridSearchCV(model_lasso, param_grid,
scoring={'MSE': mse_scorer, 'MAE': mae_scorer}, cv=5, refit='MSE')

# Fit using the combined dataset
grid_search_ridge.fit(X_combined, y_combined)
grid_search_lasso.fit(X_combined, y_combined)

# Best score and best parameters for Ridge
print("Ridge Regression:")
print("Best score (MSE):", -grid_search_ridge.best_score_)  # Negate
to show as positive
print("Best parameters:", grid_search_ridge.best_params_)
print("Best MAE score:", -
grid_search_ridge.cv_results_['mean_test_MAE']
[grid_search_ridge.best_index_])  # Negate to show as positive

# Best score and best parameters for Lasso
print("\nLasso Regression:")
print("Best score (MSE):", -grid_search_lasso.best_score_)  # Negate
to show as positive
print("Best parameters:", grid_search_lasso.best_params_)
print("Best MAE score:", -
grid_search_lasso.cv_results_['mean_test_MAE']
[grid_search_lasso.best_index_])  # Negate to show as positive
```

```
Ridge Regression:
Best score (MSE): 4781613598.9626045
Best parameters: {'alpha': 1.0}
Best MAE score: 50188.20397156067

Lasso Regression:
Best score (MSE): 4781651958.2599125
Best parameters: {'alpha': 1.0}
Best MAE score: 50185.6559227573
```

note that the results are somewhat different from previuosly manually setting the alpha. and if you set the alpha to 1 you are going to get different MSE and MAE this is due to the different splitting of the data.

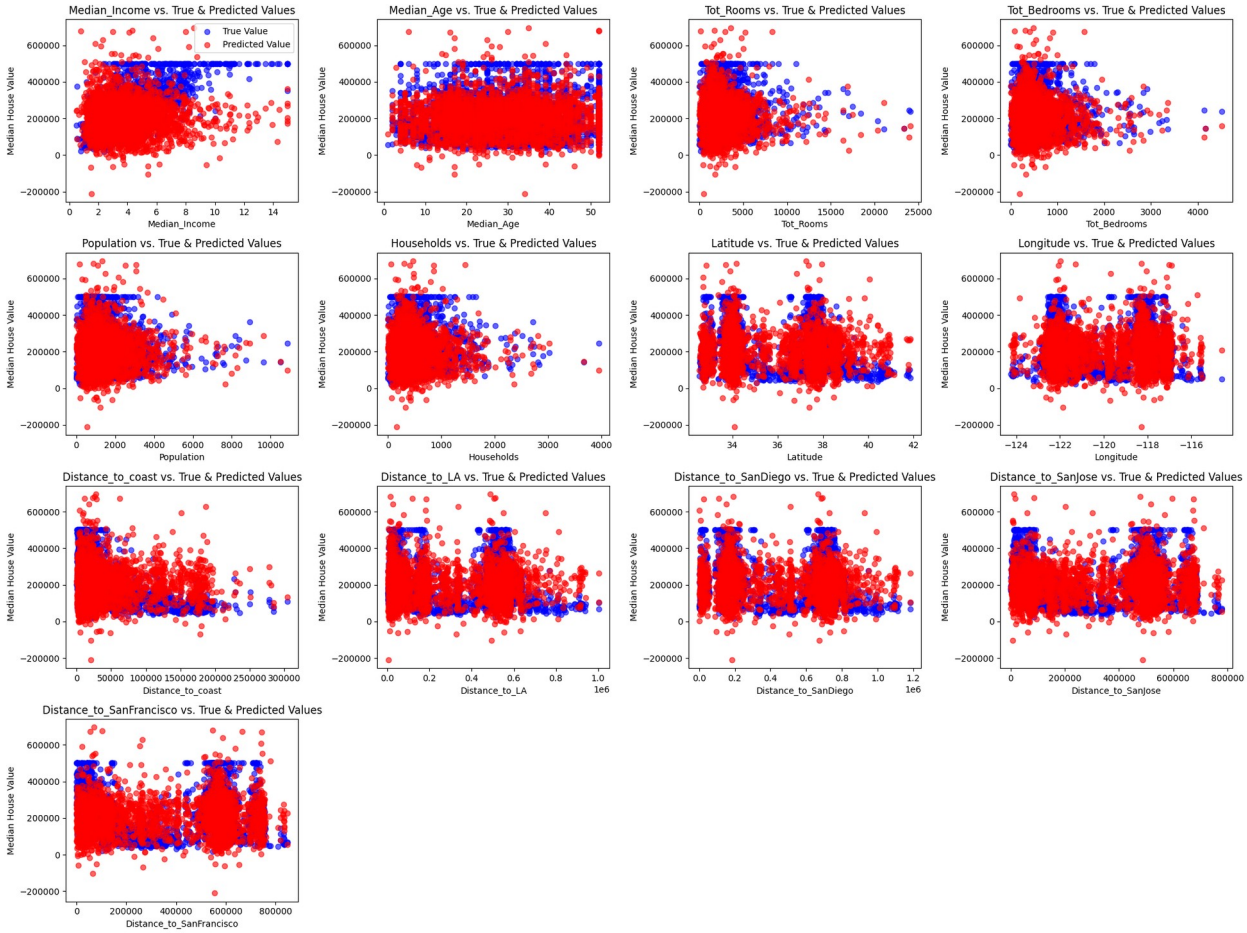
##finally we validate our findings using the reserved test set.

```
#retrain the model with the parametr that scored best
best_ridge_model = grid_search_ridge.best_estimator_
best_lasso_model = grid_search_lasso.best_estimator_

# Make predictions on the test set
y_pred_ridge = best_ridge_model.predict(Xnorm_test)
y_pred_lasso = best_lasso_model.predict(Xnorm_test)

# Evaluate the Ridge model on the test set
print("Ridge Regression Test Set Evaluation:")
print("MAE:", mean_absolute_error(y_test, y_pred_ridge))
print("MSE:", mean_squared_error(y_test, y_pred_ridge))
print("R²:", r2_score(y_test, y_pred_ridge))

# Evaluate the Lasso model on the test set
print("\nLasso Regression Test Set Evaluation:")
print("MAE:", mean_absolute_error(y_test, y_pred_lasso))
print("MSE:", mean_squared_error(y_test, y_pred_lasso))
print("R²:", r2_score(y_test, y_pred_lasso))
```

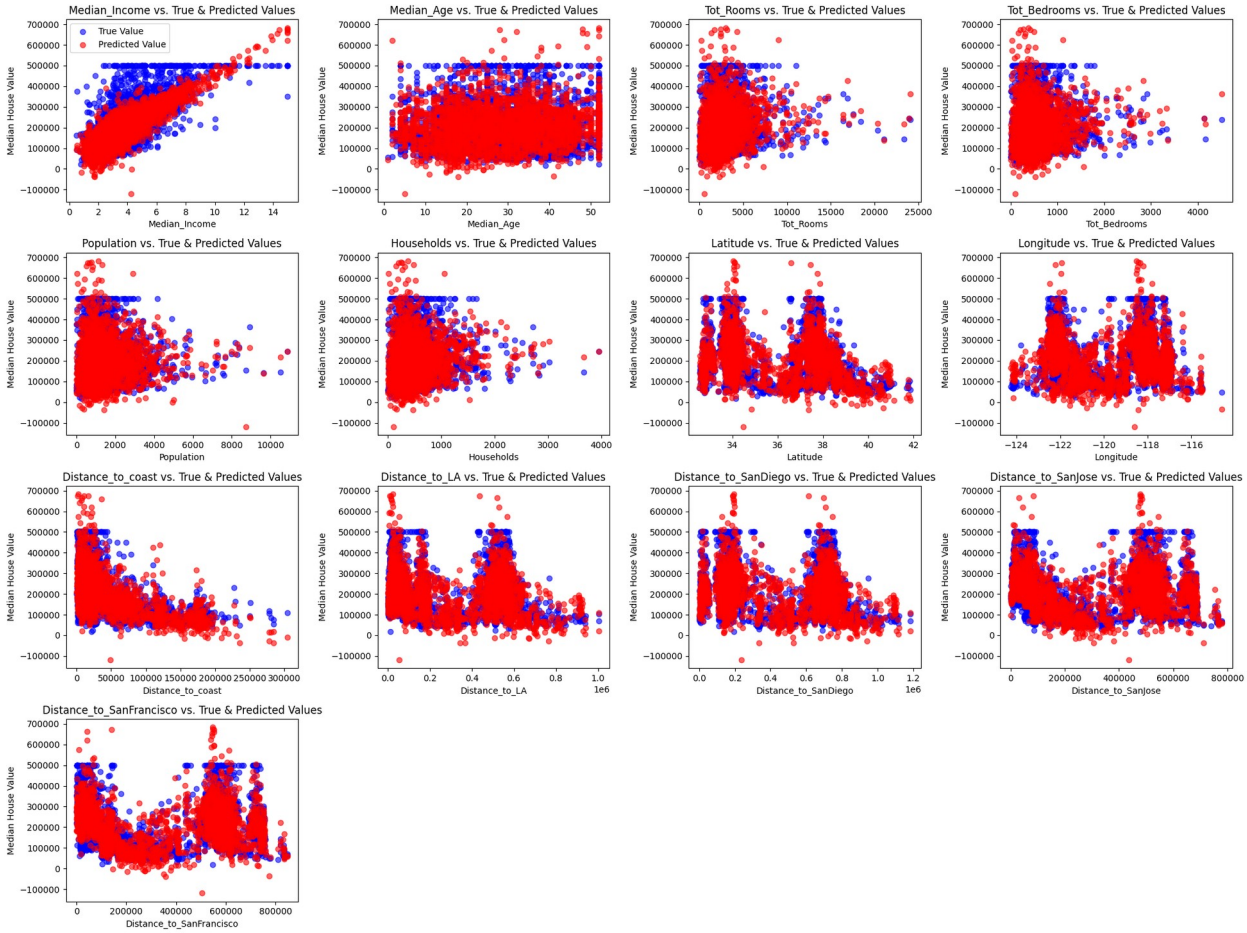
```
Ridge Regression Test Set Evaluation:
MAE: 48843.499421533605
MSE: 4400559506.958959
R²: 0.6672067741176397

Lasso Regression Test Set Evaluation:
MAE: 48842.4855286273
MSE: 4400791925.797452
R²: 0.667189197394749
```

```python
# Scatter plots for each feature
features = X_features  # List of feature names
models = {'Linear Regression': y_pred_linear, 'Lasso Regression':
y_pred_lasso, 'Ridge Regression': y_pred_ridge}

for model_name, y_pred in models.items():
    print(f"Scatter plots for {model_name}")
    plt.figure(figsize=(20, 15))

    for idx, feature in enumerate(features, 1):
        plt.subplot(4, 4, idx)
        plt.scatter(X_test[:, idx-1], y_test, color='blue',
label='True Value', alpha=0.6)
        plt.scatter(X_test[:, idx-1], y_pred, color='red',
label='Predicted Value', alpha=0.6)
        plt.xlabel(feature)
        plt.ylabel('Median House Value')
        plt.title(f"{feature} vs. True & Predicted Values")
        if idx == 1:
            plt.legend()

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

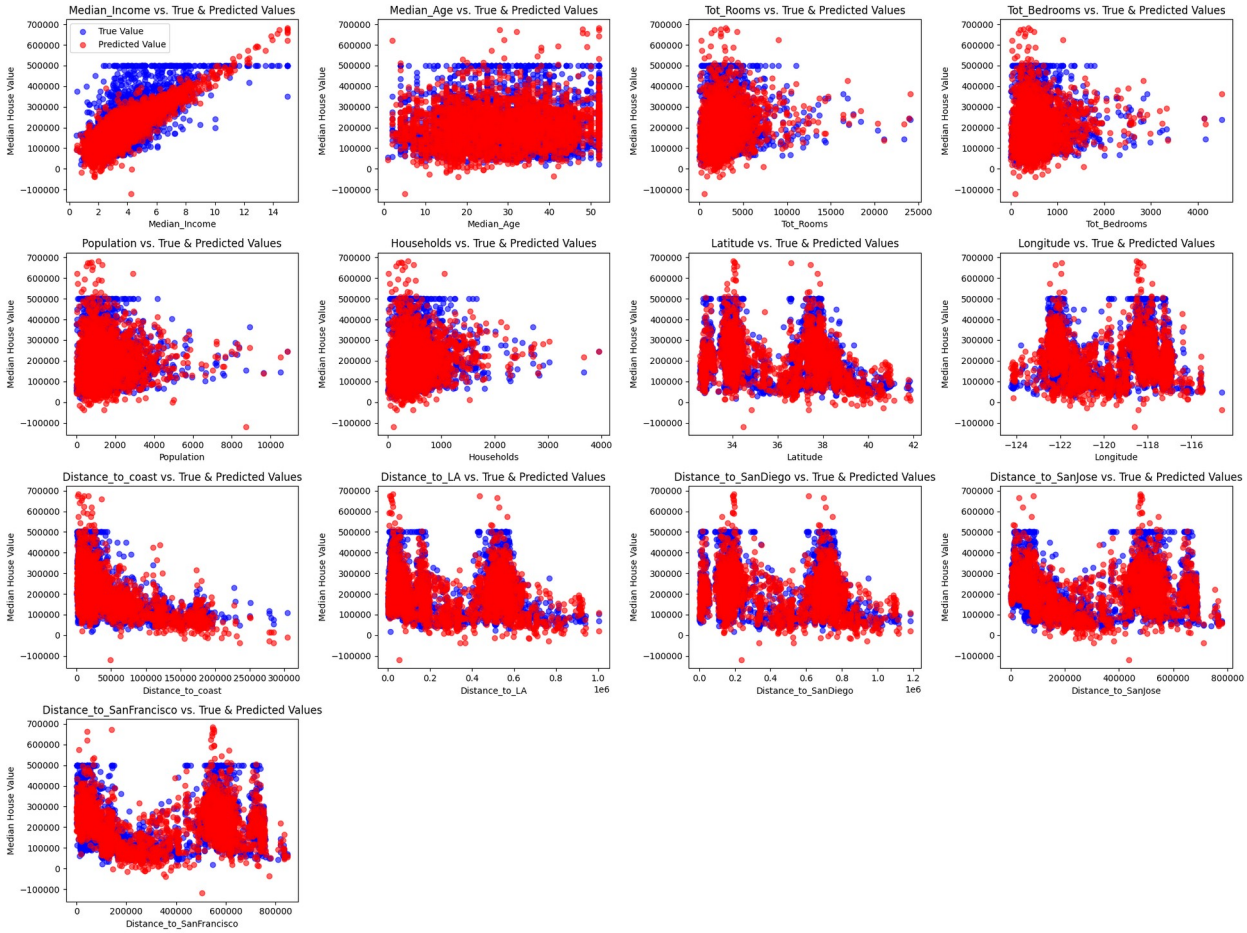
```
Scatter plots for Linear Regression
```



Scatter plots for Lasso Regression



Scatter plots for Ridge Regression



Classification Problem

in this problem we use KNN to differentiate between two classes

```
import numpy as np
import pandas as pd
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score, precision_score, recall_score, f1_score
import matplotlib.pyplot as plt


#initialize variables to hold data#
class_g=[]
class_h=[]
```

we know that the number of samples for both classes is not the same so we have to balance out the number of samples after separating the data.

```
#read the data#
with open('data.txt','r') as file:   #alternatively we can use
np.genfromtxt()...prefered to do it manually for practice
    for line in file:
        values=line.strip().split(',')
        data = list(map(float, values[:-1])) #converting to integers
for later processing
        if values[-1]=='g':
            class_g.append(data + [1]) #class gamma label
        else:
            class_h.append(data + [0]) #class hedron label

#find the imbalance #
len_g=len(class_g)
len_h=len(class_h)
diff=len_g-len_h
print(f"the length of class g is {len_g}")
print(f"the length of class h is {len_h}")
print(f"we need to set aside {diff} random examples from class g to
balance the data")

#fixing the imbalance#
np. random.seed(70) # generate a seed for reproducibility of results
(hn5tar random)
index_of_putaside = np.random.choice(len_g, diff, replace=False)  #
Select 'diff' unique random indices
print(index_of_putaside[0:4])
downsized_g=[item for i,item in enumerate(class_g) if i not in
index_of_putaside] #downsized to elements not in the putaside array
print(len(downsized_g))

#convert to numpy array for proper utilization
gamma=np.array(downsized_g)
hedron=np.array(class_h)
full_data=np.concatenate((gamma,hedron),axis=0)

#visiuallize the data#
print(f"the first three isntances of each matrix gamma features:\
n{gamma[:3]}\n hedron:\n{hedron[:3]}")


the length of class g is 12332
the length of class h is 6688
we need to set aside 5644 random examples from class g to balance the
data
[7198 5785 1665 9586]
6688
the first three isntances of each matrix gamma features:
[[ 7.51362e+01  3.09205e+01  3.16110e+00  3.16800e-01  1.83200e-01
```

```
  -5.52770e+00  2.85525e+01  2.18393e+01  4.64800e+00  3.56462e+02
   1.00000e+00]
 [ 4.82468e+01  1.73565e+01  3.03320e+00  2.52900e-01  1.51500e-01
   8.57300e+00  3.80957e+01  1.05868e+01  4.79200e+00  2.19087e+02
   1.00000e+00]
 [ 1.88562e+01  1.64600e+01  2.43850e+00  5.28200e-01  2.93300e-01
   2.51269e+01 -6.54010e+00 -1.69327e+01  1.14610e+01  1.62848e+02
   1.00000e+00]]
 hedron:
[[ 9.370350e+01  3.794320e+01  3.145400e+00  1.680000e-01  1.011000e-
01
   5.325660e+01  8.905660e+01  1.181750e+01  1.412240e+01
2.319028e+02
   0.000000e+00]
 [ 1.020005e+02  2.200170e+01  3.316100e+00  1.064000e-01  7.240000e-
02
  -5.408620e+01  4.305530e+01 -1.506470e+01  8.846360e+01
2.749392e+02
   0.000000e+00]
 [ 1.002775e+02  2.187840e+01  3.110000e+00  3.120000e-01  1.446000e-
01
  -4.818340e+01  5.765470e+01 -9.634100e+00  2.078480e+01
3.464330e+02
   0.000000e+00]]
```

```python
#split the data into  70% training, 15% test, 15% training
#alternatively np.split()
np.random.shuffle(full_data)

training_set_index=int(0.7*len(full_data))
test_set_index=int(0.15*len(full_data)) +training_set_index

training_set=full_data[0:training_set_index]
test_set=full_data[training_set_index:test_set_index]
validation_set=full_data[test_set_index:]

# Prepare features and labels for training and testing
X_train = training_set[:, :-1]  # Features (all columns except the
last)
y_train = training_set[:, -1]   # Labels (last column)

X_test = test_set[:, :-1]  # Features for test set
y_test = test_set[:, -1]   # Labels for test set

X_validation = validation_set[:, :-1]  # Features (all columns except
the last)
y_validation = validation_set[:, -1]   # Labels (last column)
```

what is a Confusion Matrix

Suppose you're predicting whether a particle is classified as "gamma" (`g`) or "hadron" (`h`) in the MAGIC dataset:

- TP: Number of `g` particles correctly identified as `g`.
- TN: Number of `h` particles correctly identified as `h`.
- FP: Number of `h` particles incorrectly predicted as `g`.
- FN: Number of `g` particles incorrectly predicted as `h`.

Calculating Metrics from a Confusion Matrix

Using the values in the confusion matrix, you can calculate several important metrics:

1. Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$
2. Precision = $\frac{TP}{TP+FP}$: Measures the accuracy of positive predictions.
3. Recall = $\frac{TP}{TP+FN}$: Measures the ability to identify positive cases.
4. F1-Score = $2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision}+\text{Recall}}$: The harmonic mean of precision and recall.

Suppose you're predicting whether a particle is classified as "gamma" (`g`) or "hadron" (`h`) in the MAGIC dataset:

- TP: Number of `g` particles correctly identified as `g`.
- TN: Number of `h` particles correctly identified as `h`.
- FP: Number of `h` particles incorrectly predicted as `g`.
- FN: Number of `g` particles incorrectly predicted as `h`.

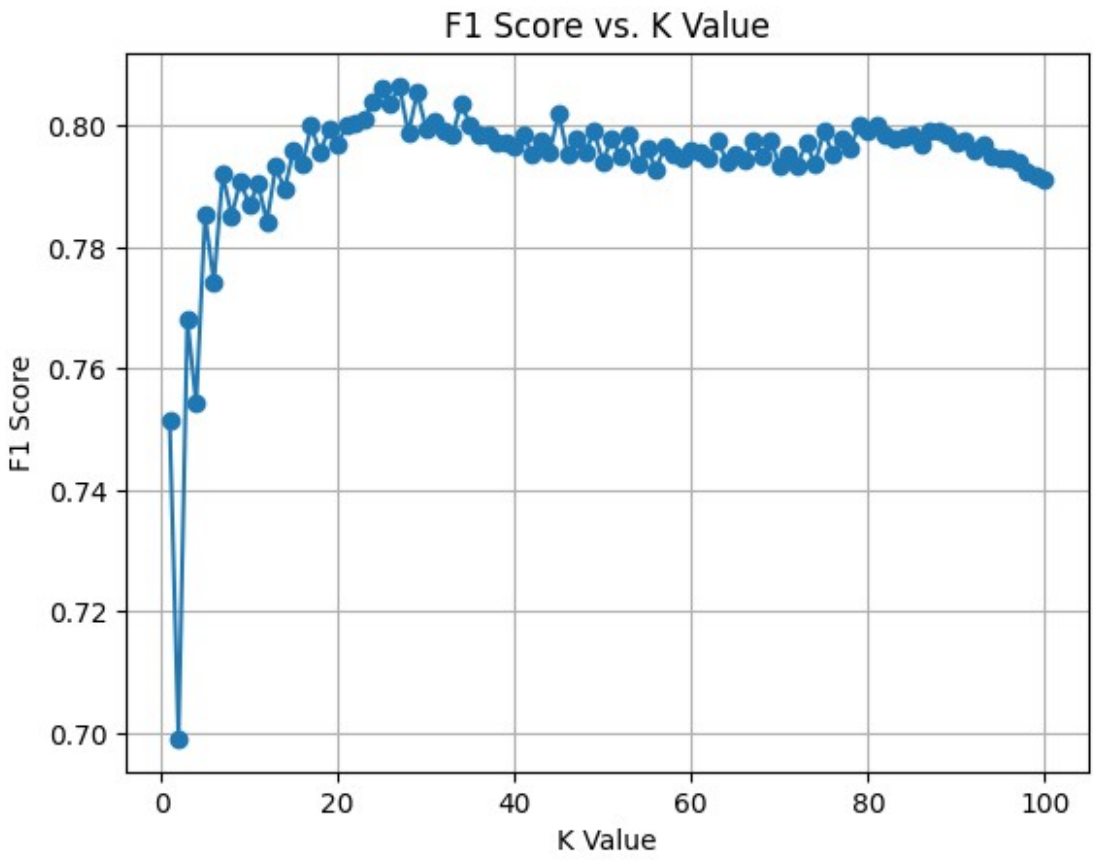
Calculating Metrics from a Confusion Matrix

Using the values in the confusion matrix, you can calculate several important metrics:

1. Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$
2. Precision = $\frac{TP}{TP+FP}$: Measures the accuracy of positive predictions.
3. Recall = $\frac{TP}{TP+FN}$: Measures the ability to identify positive cases.
4. F1-Score = $2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision}+\text{Recall}}$: The harmonic mean of precision and recall.

```
# Apply KNN
f1=[]
for k in range(1,101):
    knn = KNeighborsClassifier(n_neighbors=k)  # You can adjust the
number of neighbors
    knn.fit(X_train, y_train)  # Train the model
    y_pred_val = knn.predict(X_validation)

    # Calculate additional metrics for the validation set
    accuracy = accuracy_score(y_validation, y_pred_val)
    precision = precision_score(y_validation, y_pred_val)
    recall = recall_score(y_validation, y_pred_val)
    cm=confusion_matrix(y_validation,y_pred_val)
    f1.append(f1_score(y_validation, y_pred_val))

best_k_value=f1.index(max(f1))+1
print(f"the best k index is {best_k_value}")

# Visualization of F1 scores
plt.plot(range(1,101), f1, marker='o')
plt.title('F1 Score vs. K Value')
plt.xlabel('K Value')
plt.ylabel('F1 Score')
plt.grid()
plt.show()

# Print out the results
print(f"Test Set Performance Metrics:")
print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 Score: {f1}")
print(f"Confusion Matrix:\n{cm}")
```

```
the best k index is 27
```




```
Test Set Performance Metrics:
Accuracy: 0.7648231190832088
Precision: 0.7217741935483871
Recall: 0.87573385518591
F1 Score: [0.7514285714285714, 0.6990185387131952, 0.7680821278581428,
0.7542457542457542, 0.7852873563218391, 0.7741935483870968,
0.7921245421245421, 0.7851357789423535, 0.7909502262443439,
0.7868852459016393, 0.7904461469130238, 0.7842227378190255,
0.7933363349842414, 0.7894493290143452, 0.7960378208014408,
0.7935779816513762, 0.8, 0.7955801104972375, 0.7994604316546763,
0.7968892955169259, 0.8001792114695341, 0.8005464480874317,
0.8012533572068039, 0.8040018190086403, 0.80625, 0.8037974683544303,
0.8065661047027507, 0.7987364620938628, 0.8054940186087727,
0.7996398018910401, 0.8008869179600887, 0.7992783040144339,
0.7985739750445633, 0.803788903924222, 0.8, 0.7983798379837984,
0.7985803016858918, 0.7973033707865168, 0.797153024911032,
0.7967625899280576, 0.7983978638184246, 0.7954954954954955,
0.7976827094474154, 0.7956795679567957, 0.802134281903068,
0.7953321364452424, 0.7980383415069104, 0.7955056179775281,
0.799109131403118, 0.7940780619111709, 0.7980470483799379,
0.7949753252579632, 0.7985803016858918, 0.7937219730941704,
0.7964444444444444, 0.7928251121076233, 0.7966252220248667,
0.7953425884460367, 0.7948490230905861, 0.7958725886047555,
```

```
0.7955555555555556, 0.7946428571428571, 0.7976980965028774,
0.794104510942385, 0.7953839325343985, 0.7944593386952636,
0.7975133214920072, 0.7951699463327371, 0.7976878612716763,
0.7933810375670841, 0.7953839325343985, 0.7935656836461126,
0.7971593430980914, 0.7937219730941704, 0.7991111111111111,
0.7953529937444147, 0.7978723404255319, 0.7964285714285714,
0.8001776198934281, 0.799109131403118, 0.8, 0.7983942908117752,
0.7978723404255319, 0.7982182628062361, 0.7984049623393886,
0.7967985771453979, 0.7991150442477876, 0.7991111111111111,
0.7984084880636605, 0.7973333333333333, 0.7977082415160864,
0.796107916850951, 0.7968337730870713, 0.7950420540061974,
0.7947252747252748, 0.7946902654867256, 0.7941952506596306,
0.7923860115095175, 0.7919227392449517, 0.7913351016799293]
Confusion Matrix:
[[640 345]
 [127 895]]
```

we finally use the reserved test set.

```
#verify using the test set
knn_final=KNeighborsClassifier(n_neighbors=best_k_value)
knn_final.fit(X_train,y_train)
y_pred_test=knn_final.predict(X_test)

# Calculate metrics for the test set
accuracy_test = accuracy_score(y_test, y_pred_test)
precision_test = precision_score(y_test, y_pred_test,
average='weighted')
recall_test = recall_score(y_test, y_pred_test, average='weighted')
f1_test = f1_score(y_test, y_pred_test, average='weighted')
cm_test = confusion_matrix(y_test, y_pred_test)

# Print out the results
print(f"Test Set Performance Metrics:")
print(f"Accuracy: {accuracy_test:.4f}")
print(f"Precision: {precision_test:.4f}")
print(f"Recall: {recall_test:.4f}")
print(f"F1 Score: {f1_test:.4f}")
print(f"Confusion Matrix:\n{cm_test}")
```

```
Test Set Performance Metrics:
Accuracy: 0.7587
Precision: 0.7645
Recall: 0.7587
F1 Score: 0.7569
Confusion Matrix:
[[666 320]
 [164 856]]
```