housing_regression

July 9, 2025

1 Linear Regression Predictor – Housing Prices

1.0.1 Project Description:

This project demonstrates the implementation of a linear regression model with L2 regularization (Ridge Regression) to predict housing sale prices using a dataset sourced from Kaggle. The workflow includes data exploration, preprocessing, model training from scratch, evaluation through performance metrics like RMSE and R^2, and comparison with a baseline predictor. Visualization techniques are used to understand the distribution of sale prices and assess model performance.

1.0.2 Objectives:

- Load and explore a real-world housing dataset from Kaggle
- Select, inspect, and preprocess relevant features for regression analysis
- Implement a custom Ridge Regression training loop, including feature standardization and loss computation
- Evaluate model performance using test set loss, RMSE, and R^2 score
- Visualize the distribution of sale prices and model predictions
- Benchmark model performance against a simple baseline predictor (mean sale price)

1.0.3 Public dataset source:

Kaggle California Housing Prices The data contains information from the 1990 California census.

[1]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.ticker import FuncFormatter
from sklearn.metrics import r2_score
```

[2]:
```
# Establish file path and import data
path = 'CA_housing.csv'
df = pd.read_csv(path)
df.head()
```

[2]:
```
   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]
```

[ ]:
```
df.describe()
```

[ ]:
```
                Id   MSSubClass  LotFrontage        LotArea  OverallQual  \
count  1460.000000  1460.000000  1201.000000    1460.000000  1460.000000
mean    730.500000    56.897260    70.049958   10516.828082     6.099315
std     421.610009    42.300571    24.284752    9981.264932     1.382997
min       1.000000    20.000000    21.000000    1300.000000     1.000000
25%     365.750000    20.000000    59.000000    7553.500000     5.000000
50%     730.500000    50.000000    69.000000    9478.500000     6.000000
75%    1095.250000    70.000000    80.000000   11601.500000     7.000000
max    1460.000000   190.000000   313.000000  215245.000000    10.000000

       OverallCond    YearBuilt  YearRemodAdd   MasVnrArea   BsmtFinSF1  …  \
count  1460.000000  1460.000000   1460.000000  1452.000000  1460.000000  …
mean      5.575342  1971.267808   1984.865753   103.685262   443.639726  …
std       1.112799    30.202904     20.645407   181.066207   456.098091  …
min       1.000000  1872.000000   1950.000000     0.000000     0.000000  …
25%       5.000000  1954.000000   1967.000000     0.000000     0.000000  …
50%       5.000000  1973.000000   1994.000000     0.000000   383.500000  …
75%       6.000000  2000.000000   2004.000000   166.000000   712.250000  …
max       9.000000  2010.000000   2010.000000  1600.000000  5644.000000  …

        WoodDeckSF  OpenPorchSF  EnclosedPorch    3SsnPorch  ScreenPorch  \
count  1460.000000  1460.000000    1460.000000  1460.000000  1460.000000
mean     94.244521    46.660274      21.954110     3.409589    15.060959
std     125.338794    66.256028      61.119149    29.317331    55.757415
```

```
min       0.000000    0.000000     0.000000    0.000000    0.000000
25%       0.000000    0.000000     0.000000    0.000000    0.000000
50%       0.000000   25.000000     0.000000    0.000000    0.000000
75%     168.000000   68.000000     0.000000    0.000000    0.000000
max     857.000000  547.000000   552.000000  508.000000  480.000000

          PoolArea       MiscVal       MoSold       YrSold      SalePrice
count  1460.000000   1460.000000  1460.000000  1460.000000    1460.000000
mean      2.758904     43.489041     6.321918  2007.815753  180921.195890
std      40.177307    496.123024     2.703626     1.328095   79442.502883
min       0.000000      0.000000     1.000000  2006.000000   34900.000000
25%       0.000000      0.000000     5.000000  2007.000000  129975.000000
50%       0.000000      0.000000     6.000000  2008.000000  163000.000000
75%       0.000000      0.000000     8.000000  2009.000000  214000.000000
max     738.000000  15500.000000    12.000000  2010.000000  755000.000000

[8 rows x 38 columns]
```

[5]:
```
df.dtypes
```

[5]:
```
Id                 int64
MSSubClass         int64
MSZoning          object
LotFrontage      float64
LotArea            int64
                   …
MoSold             int64
YrSold             int64
SaleType          object
SaleCondition     object
SalePrice          int64
Length: 81, dtype: object
```

[16]:
```
# Choose features
cols=['LotArea','OverallQual','OverallCond','YearBuilt','TotalBsmtSF','1stFlrSF','2ndFlrSF','F
print(df[cols].isnull().sum())
print(df['SalePrice'].isnull().sum())
```

```
LotArea         0
OverallQual     0
OverallCond     0
YearBuilt       0
TotalBsmtSF     0
1stFlrSF        0
2ndFlrSF        0
FullBath        0
BedroomAbvGr    0
TotRmsAbvGrd    0
```

```
PoolArea        0
dtype: int64
0
```

[17]:
```
# Feature data types
for item in cols:
  print(f"Item: {item}, Type: {type(item)}")
```

```
Item: LotArea, Type: <class 'str'>
Item: OverallQual, Type: <class 'str'>
Item: OverallCond, Type: <class 'str'>
Item: YearBuilt, Type: <class 'str'>
Item: TotalBsmtSF, Type: <class 'str'>
Item: 1stFlrSF, Type: <class 'str'>
Item: 2ndFlrSF, Type: <class 'str'>
Item: FullBath, Type: <class 'str'>
Item: BedroomAbvGr, Type: <class 'str'>
Item: TotRmsAbvGrd, Type: <class 'str'>
Item: PoolArea, Type: <class 'str'>
```

[18]:
```
# Convert the strings to floats
df_float = df[cols].astype(float)
print(df_float.dtypes)
```

```
LotArea         float64
OverallQual     float64
OverallCond     float64
YearBuilt       float64
TotalBsmtSF     float64
1stFlrSF        float64
2ndFlrSF        float64
FullBath        float64
BedroomAbvGr    float64
TotRmsAbvGrd    float64
PoolArea        float64
dtype: object
```

[20]:
```
# Create a function to split the dataset into train and test
def TrainTestSplit(df, feature_cols, target_col, test_size=0.2, seed=None):
    X = df[feature_cols].values
    y = df[target_col].values

    np.random.seed(seed)
    n = len(X)
    indices = np.random.permutation(n)

    test_size = int(n * test_size)
    test_idx = indices[:test_size]
```

```
    train_idx = indices[test_size:]

    return X[train_idx], X[test_idx], y[train_idx], y[test_idx]
```

[21]:
```
# L2 Regularization Linear Regression function
def model_train_L2(X, y, alpha, n_iterations, reg_lambda, standardize=True):
    # standardize features
    if standardize:
        X = (X - X.mean(axis=0)) / X.std(axis=0)

    # initialize values
    n_samples, n_features = X.shape
    w = np.zeros(n_features)
    b = 0
    loss_history = []

    for i in range(n_iterations):
        # calculate prediction with weights
        y_hat = np.dot(X, w) + b
        # error
        resid = y_hat - y

        # gradient with L2 regularization
        grad_w = (2 / n_samples) * np.dot(X.T, resid) + 2 * reg_lambda * w
        grad_b = (2/n_samples) * np.sum(resid)

        # update weights and bias
        w -= alpha * grad_w
        b -= alpha * grad_b

        # compute loss with regularization
        mse = np.mean(resid ** 2)
        reg_term = reg_lambda * np.sum(w ** 2)
        loss = mse + reg_term
        loss_history.append(loss)

        if i % 100 == 0:
            print(f"Iteration {i}: Loss = {loss:.4f}")
    return mse, loss_history, w, b
```

[22]:
```
# Functions for predict and evaluating utilizing the model
def model_predict(X, w, b, standardize=True, X_mean=None, X_std=None):
    if standardize:
        X = (X - X.mean(axis=0)) / X.std(axis=0)
    return np.dot(X, w) + b

def model_evaluate(y_pred, y_test, w, b, reg_lambda):
```

```
    error = y_pred - y_test
    mse = np.mean(error ** 2)
    reg_term = reg_lambda * np.sum(w ** 2)
    loss = mse + reg_term
    return loss
```

[23]:
```
X_train, X_test, y_train, y_test = TrainTestSplit(df, cols,␣
 ↪target_col='SalePrice')
mse, loss_history, w, b = model_train_L2(X_train, y_train, alpha=0.01,␣
 ↪n_iterations=1000, reg_lambda=0.1, standardize=True)
```

```
Iteration 0: Loss = 39485632301.0421
Iteration 100: Loss = 2315305632.6649
Iteration 200: Loss = 1717553954.7636
Iteration 300: Loss = 1703534185.6004
Iteration 400: Loss = 1702262391.1271
Iteration 500: Loss = 1701856546.3273
Iteration 600: Loss = 1701690472.7704
Iteration 700: Loss = 1701618715.3809
Iteration 800: Loss = 1701586921.7477
Iteration 900: Loss = 1701572589.4160
```

[24]:
```
# Make predictions on test set with predicted weights
y_pred = model_predict(X_test, w, b, standardize=True)

# Evaluate
test_loss = model_evaluate(y_pred, y_test, w, b, reg_lambda=0.1)
print("Test Loss:", test_loss)
```

```
Test Loss: 1240350582.1497772
```

This means that the MSE was about 1.28 billion USD or 1.28e9. Therefore, the RMSE is 3573, meaning the model's predictions of housing price are off by about USD 35,739 on average.

[27]:
```
# To contextualize the MSE, look at the average sale price and the standard␣
 ↪deviation of the target variable for better interpretation
mean_Sale_Price = df['SalePrice'].mean()
print(f"Mean Sale Price: ${mean_Sale_Price:,.2f}")

std_Sale_Price = df['SalePrice'].std()
print(f"Standard Deviation of Sale Price: ${std_Sale_Price:,.2f}")

RMSE_mean_ratio = np.sqrt(test_loss) / mean_Sale_Price * 100
print(f"RMSE / Mean Sale Price: {RMSE_mean_ratio:.0f}%")

RMSE_std_ratio = np.sqrt(test_loss) / std_Sale_Price * 100
print(f"RMSE / Standard Deviation of Sale Price: {RMSE_std_ratio:.0f}%")
```

```
# The scale of the RMSE compared to the mean sale price is small, which is a␣
↪good sign
```

```
Mean Sale Price: $180,921.20
Standard Deviation of Sale Price: $79,442.50
RMSE / Mean Sale Price: 19%
RMSE / Standard Deviation of Sale Price: 44%
```

[28]:

```
# Compare to baseline model
baseline_pred = np.full_like(y_test, y_train.mean())

baseline_rmse = np.sqrt(np.mean((y_test - baseline_pred) ** 2))
print(f"Baseline RMSE: ${baseline_rmse:,.2f}")
rmse = np.sqrt(test_loss)
print(f"Model RMSE: ${rmse:,.2f}")
improvement = (baseline_rmse - rmse) / baseline_rmse * 100
print(f"Improvement: ${baseline_rmse - rmse:,.2f}")
print(f"Improvement: {improvement:.0f}%")
```

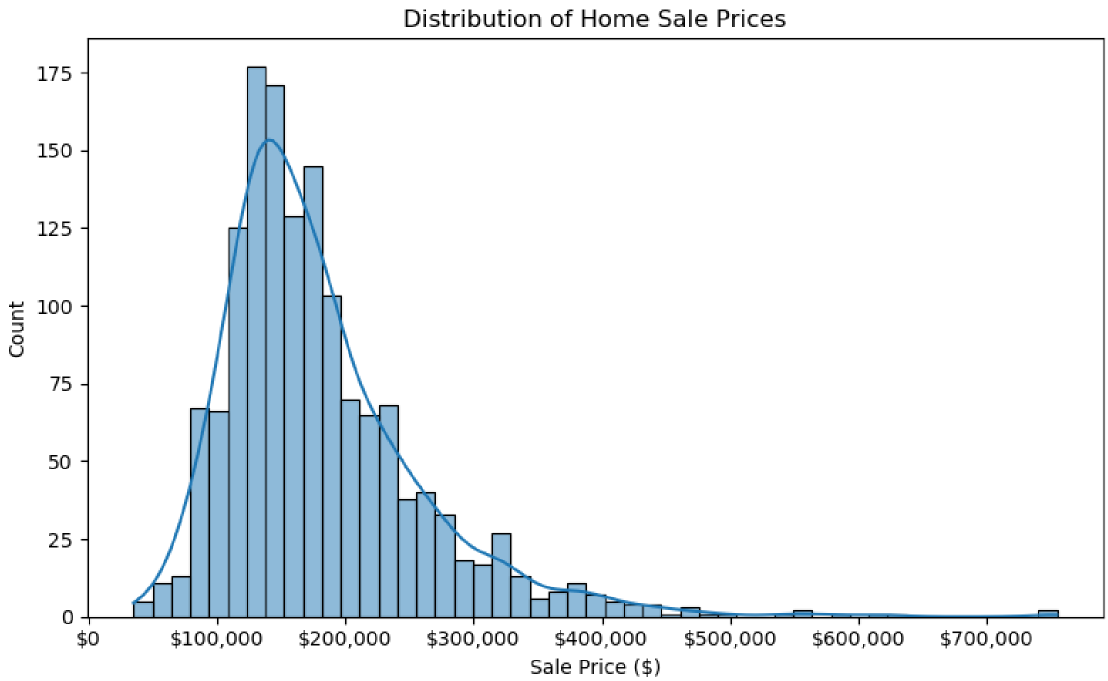
```
Baseline RMSE: $71,592.32
Model RMSE: $35,218.61
Improvement: $36,373.71
Improvement: 51%
```

[32]:

```
# Take a look at distribution of home sale prices
plt.figure(figsize=(8, 5))
sns.histplot(df['SalePrice'], kde=True)

formatter = FuncFormatter(lambda x, _: f'${x:,.0f}')
plt.gca().xaxis.set_major_formatter(formatter)

plt.title("Distribution of Home Sale Prices")
plt.xlabel("Sale Price ($)")
plt.ylabel("Count")
plt.tight_layout()
plt.show()
```



[ ]:
```
# To better understand the R score to see evaluate model performance
r2 = r2_score(y_test, y_pred)
print(f"R² Score: {r2:.4f}")
# Pretty good!
# "Strong" fit
# The model explains ~82.7% of the variance in housing sale prices
```

```
R² Score: 0.7970
```