Experiment - 2

Nikhil Kale
D15A/50

Aim - Implement Multi Regression, Lasso, and Ridge Regression on real-world datasets

1. Dataset Source

Dataset Name: Insurance Premium Prediction Dataset
Source: Kaggle
https://www.kaggle.com/datasets/noordeen/insurance-premium-prediction/data

2. Dataset Description

The dataset contains medical insurance information and corresponding charges.

Dataset Size

- 1338 records
- 7 features

Target Variable

- expenses (continuous numeric value)

Features

- age (numeric)
- sex (categorical)
- bmi (numeric)
- children (numeric)
- smoker (categorical)
- region (categorical)

Data Characteristics

- Mixed categorical and numeric data
- Regression problem
- Moderate correlation between smoker and charges

3. Mathematical Formulation

Multiple Linear Regression

$$\hat{y} = \beta_0 + \sum_{i=1}^{n} \beta_i X_i$$

Minimizes:

$$RSS = \sum (y - \hat{y})^2$$

Ridge Regression (L2 Regularization)

$$Loss = RSS + \lambda \sum \beta_i^2$$

Shrinks coefficients to prevent overfitting.

Lasso Regression (L1 Regularization)

$$Loss = RSS + \lambda \sum |\beta_i|$$

Can shrink some coefficients exactly to zero (feature selection).

4. Algorithm Limitations

Multiple Regression

- Sensitive to multicollinearity
- Assumes linearity
- Sensitive to outliers

Ridge

- Does not eliminate features completely
- Requires tuning of lambda

Lasso

- Can eliminate useful features if lambda is large
- Performance depends heavily on alpha value

5. Methodology / Workflow

Step 1: Data Loading

Loaded dataset using Pandas.

Step 2: Data Preprocessing

- One-Hot Encoding for categorical variables
- Train-Test Split (80-20)
- Feature Scaling using StandardScaler

Step 3: Model Training

- Multiple Linear Regression
- Ridge Regression
- Lasso Regression

Step 4: Evaluation

- R^2 Score
- Coefficient comparison

Workflow Diagram

Dataset
↓
Encoding
↓
Train-Test Split
↓
Scaling
↓
MLR / Ridge / Lasso
↓
Prediction
↓
R^2 Evaluation

6. Performance Analysis

Model	R^2 Score
Multiple Linear Regression	0.78357
Ridge Regression	0.78352
Lasso Regression	0.78356

All three models achieved similar R^2 (~78%).

Interpretation:

- 78% of variation in insurance charges is explained.
- Regularization had minimal effect.
- Indicates low multicollinearity in the dataset.

7. Hyperparameter Tuning

Parameter tuned: `alpha`

Used GridSearchCV with:

α∈10−3 to 103\alpha \in 10^{-3} \text{ to } 10^3α∈10−3 to 103

Observation:

- Small alpha → behaves like Linear Regression
- Large alpha → over-regularization
- Optimal alpha improves generalization and reduces overfitting

Code and Output -

```python
# Basic libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Sklearn
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Settings
plt.style.use('seaborn-v0_8')
sns.set_palette("Set2")
```

[2]
✓ 0s

```
df = pd.read_csv('/content/insurance.csv')
df.head()
```

	age	sex	bmi	children	smoker	region	expenses
0	19	female	27.9	0	yes	southwest	16884.92
1	18	male	33.8	1	no	southeast	1725.55
2	28	male	33.0	3	no	southeast	4449.46
3	33	male	22.7	0	no	northwest	21984.47
4	32	male	28.9	0	no	northwest	3866.86

[3]
✓ 0s

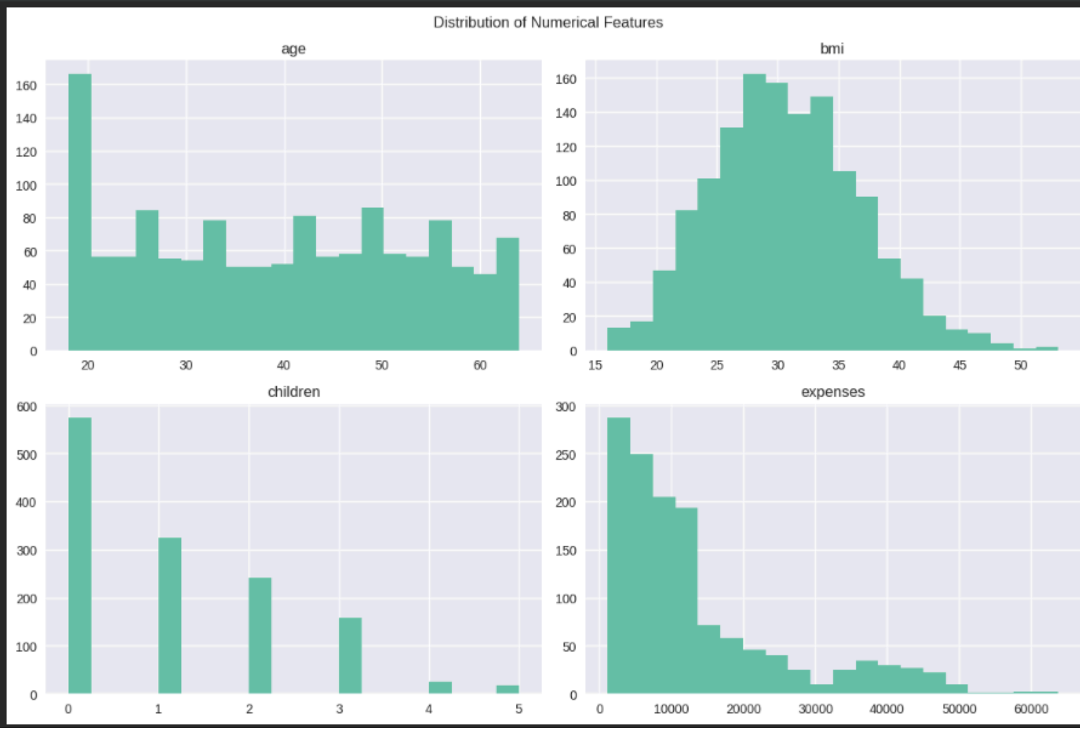
```
df.info()
df.describe()
df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1338 non-null   int64
 1   sex       1338 non-null   object
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64
 4   smoker    1338 non-null   object
 5   region    1338 non-null   object
 6   expenses  1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

	0
age	0
sex	0

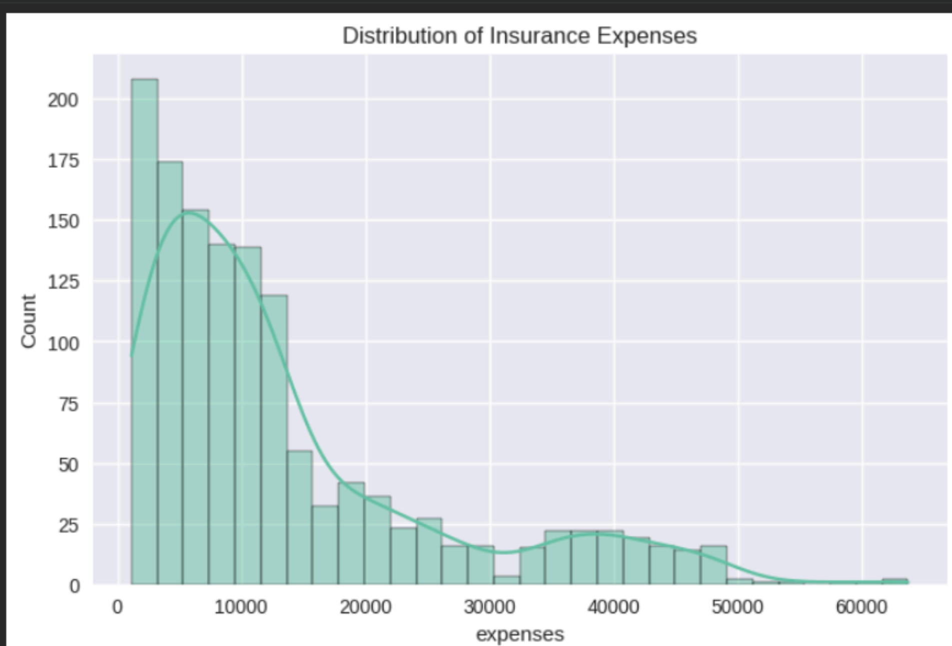
[5]

```
df.hist(figsize=(12,8), bins=20)
plt.suptitle("Distribution of Numerical Features")
plt.tight_layout()
plt.show()
```



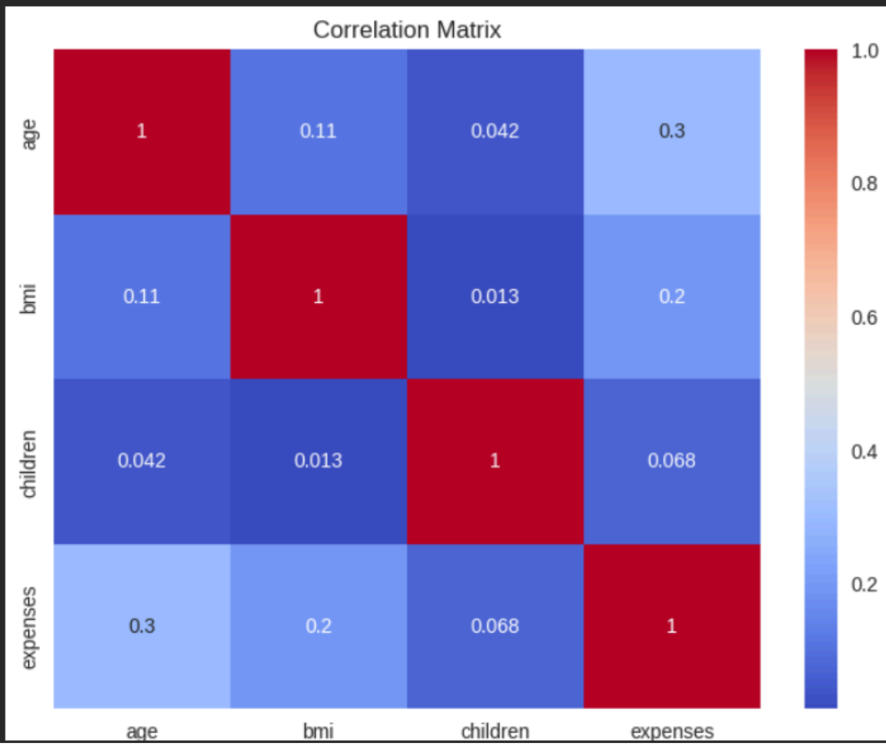
[6]

```
plt.figure(figsize=(8,5))
sns.histplot(df['expenses'], kde=True)
plt.title("Distribution of Insurance Expenses")
plt.show()
```



[7]

```python
plt.figure(figsize=(8,6))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm')
plt.title("Correlation Matrix")
plt.show()
```



[8]

```python
le = LabelEncoder()

df['sex'] = le.fit_transform(df['sex'])
df['smoker'] = le.fit_transform(df['smoker'])
df['region'] = le.fit_transform(df['region'])
```

[9]

```python
X = df.drop('expenses', axis=1)
y = df['expenses']
```

[10]

```python
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)
```

[11]

```python
scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

[12]

```python
lr = LinearRegression()
lr.fit(X_train, y_train)

y_pred_lr = lr.predict(X_test)

print("Linear Regression Performance:")
print("R2 Score:", r2_score(y_test, y_pred_lr))
print("MAE:", mean_absolute_error(y_test, y_pred_lr))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred_lr)))
```

```
Linear Regression Performance:
R2 Score: 0.7833214205203847
MAE: 4186.9401063170135
RMSE: 5799.920265829358
```

[13]

```python
ridge = Ridge()
ridge.fit(X_train, y_train)

y_pred_ridge = ridge.predict(X_test)

print("Ridge Regression Performance:")
print("R2 Score:", r2_score(y_test, y_pred_ridge))
print("MAE:", mean_absolute_error(y_test, y_pred_ridge))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred_ridge)))
```

```
Ridge Regression Performance:
R2 Score: 0.7832789709998405
MAE: 4188.40301104253
```

[14]

```python
lasso = Lasso()
lasso.fit(X_train, y_train)

y_pred_lasso = lasso.predict(X_test)

print("Lasso Regression Performance:")
print("R2 Score:", r2_score(y_test, y_pred_lasso))
print("MAE:", mean_absolute_error(y_test, y_pred_lasso))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred_lasso)))
```

```
Lasso Regression Performance:
R2 Score: 0.7833045151713598
MAE: 4187.054780221619
RMSE: 5800.146517460348
```

[15]

```python
ridge_params = {'alpha': np.logspace(-3, 3, 50)}

ridge_grid = GridSearchCV(Ridge(), ridge_params, cv=5)
ridge_grid.fit(X_train, y_train)

print("Best Alpha for Ridge:", ridge_grid.best_params_)

best_ridge = ridge_grid.best_estimator_
y_pred_ridge_tuned = best_ridge.predict(X_test)

print("Tuned Ridge R2:", r2_score(y_test, y_pred_ridge_tuned))
```

```
Best Alpha for Ridge: {'alpha': np.float64(8.286427728546842)}
Tuned Ridge R2: 0.7829319370377956
```

[16]
✓ 0s

```
lasso_params = {'alpha': np.logspace(-3, 3, 50)}

lasso_grid = GridSearchCV(Lasso(max_iter=10000), lasso_params, cv=5)
lasso_grid.fit(X_train, y_train)

print("Best Alpha for Lasso:", lasso_grid.best_params_)

best_lasso = lasso_grid.best_estimator_
y_pred_lasso_tuned = best_lasso.predict(X_test)

print("Tuned Lasso R2:", r2_score(y_test, y_pred_lasso_tuned))
```

```
Best Alpha for Lasso: {'alpha': np.float64(104.81131341546852)}
Tuned Lasso R2: 0.7815906455716939
```

[17]
✓ 0s

```
models = ['Linear', 'Ridge', 'Lasso']
r2_scores = [
    r2_score(y_test, y_pred_lr),
    r2_score(y_test, y_pred_ridge_tuned),
    r2_score(y_test, y_pred_lasso_tuned)
]

plt.figure(figsize=(6,4))
sns.barplot(x=models, y=r2_scores)
plt.title("Model Comparison (R2 Score)")
```

[17]
✓ 0s

```
plt.figure(figsize=(6,4))
sns.barplot(x=models, y=r2_scores)
plt.title("Model Comparison (R2 Score)")
plt.ylabel("R2 Score")
plt.show()
```