

# EXPERIMENT 2

## Implementation of Multiple Linear Regression, Ridge Regression, and Lasso Regression on Insurance Premium Dataset

### 1 Dataset Source

**Dataset Name:** Insurance Premium Prediction Dataset

**Source:** Kaggle

**Link:**

<https://www.kaggle.com/datasets/noordeen/insurance-premium-prediction/data>

The dataset contains medical and demographic information used to predict insurance premium charges.

### 2 Dataset Description

The Insurance dataset contains personal and medical attributes of individuals and their corresponding insurance charges.

#### **Dataset Characteristics**

- Number of Instances: ~1300+ records
- Number of Features: 6 input features + 1 target variable
- Data Type: Mixed (Categorical + Numerical)
- No missing values (in most versions)

## Input Features

Feature	Description
age	Age of the individual
sex	Gender (male/female)
bmi	Body Mass Index
children	Number of dependents
smoker	Whether person is a smoker
region	Residential region

## Target Variable

Variable	Description
Charges	Insurance premium amount (continuous value)

## 3 Mathematical Formulation of the Algorithms

### A. Multiple Linear Regression

Multiple Linear Regression models the relationship between one dependent variable and multiple independent variables.

#### Mathematical Equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \epsilon$$
$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n$$

Where:

- $\hat{y}$  = predicted insurance charge

- $\beta_0$  = intercept
- $\beta_i$  = coefficients
- $x_i$  = independent variables
- $\epsilon$  = error term

The model minimizes the cost function:

- $MSE = \frac{1}{n} \sum (y - \hat{y})^2$
- $x_i$  = independent variables
- $\epsilon$  = error term

The model minimizes:

$$MSE = \frac{1}{n} \sum (y - \hat{y})^2$$

## B. Ridge Regression

Ridge Regression adds a penalty term to reduce overfitting.

### Cost Function:

$$J(\beta) = \sum (y - \hat{y})^2 + \lambda \sum \beta^2$$

$$J(\beta) = \sum (y - \hat{y})^2 + \lambda \sum \beta^2$$

Where:

- $\lambda$  = regularization parameter
- Penalizes large coefficients

Effect:

- Shrinks coefficients
- Reduces variance
- Handles multicollinearity

## C.Lasso Regression

Lasso adds absolute penalty.

Cost Function:

$$J(\beta) = \sum (y - \hat{y})^2 + \lambda \sum |\beta| \quad J(\beta) = \sum (y - \hat{y})^2 + \lambda \sum |\beta|$$

Effect:

- Shrinks coefficients
- Can make some coefficients exactly zero
- Performs feature selection

## 4 Algorithm Limitations

### Multiple Linear Regression Limitations

- Assumes linear relationship
- Sensitive to outliers
- Requires low multicollinearity
- Cannot capture nonlinear relationships

### Ridge Regression Limitations

- Does not perform feature selection
- All features remain in model

- Choosing  $\lambda$  value is critical

## **Lasso Regression Limitations**

- Can remove important features if  $\lambda$  is large
- Unstable when features are highly correlated
- Sensitive to scaling

## **5 Methodology / Workflow**

### **Step 1: Data Loading**

- Dataset uploaded to Google Colab
- Loaded using Pandas

### **Step 2: Data Inspection**

- Checked dataset shape
- Verified missing values
- Identified categorical and numerical features

### **Step 3: Data Preprocessing**

- Applied One-Hot Encoding to categorical variables
- Applied StandardScaler to numerical features
- Created preprocessing pipeline

## Step 4: Train-Test Split

- 80% Training data
- 20% Testing data
- Used random\_state = 42 for reproducibility

## Step 5: Model Training

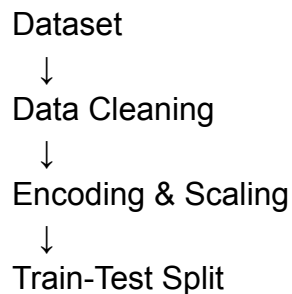
- Trained Multiple Linear Regression
- Trained Ridge Regression
- Trained Lasso Regression

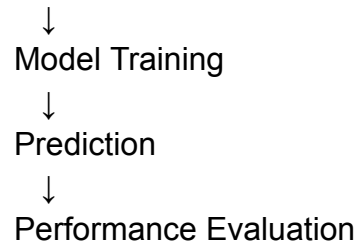
## Step 6: Model Evaluation

Evaluation Metrics Used:

- RMSE (Root Mean Squared Error)
- $R^2$  Score

## Workflow Diagram





## 6 Performance Analysis

### 1) Multiple Linear Regression

Code

```
X = df.drop('expenses', axis=1)
```

```
y = df['expenses']
```

```
cat_cols = X.select_dtypes(include=['object']).columns
```

```
num_cols = X.select_dtypes(exclude=['object']).columns
```

```
numeric_transformer = Pipeline(steps=[
```

```
    ('scaler', StandardScaler())
```

```
])
```

```
categorical_transformer = Pipeline(steps=[
```

```
    ('encoder', OneHotEncoder(drop='first'))
```

```
])
```

```
preprocessor = ColumnTransformer(
```

```
    transformers=[
```

```
        ('num', numeric_transformer, num_cols),
```

```

        ('cat', categorical_transformer, cat_cols)

    ])

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

linear_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
])

linear_model.fit(X_train, y_train)

y_pred_lr = linear_model.predict(X_test)

rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))

r2_lr = r2_score(y_test, y_pred_lr)

print("Multiple Linear Regression")

print("RMSE:", rmse_lr)

print("R2 Score:", r2_lr)

```

```

Multiple Linear Regression
RMSE: 5796.556335884077
R2 Score: 0.7835726930039905

```

## 2) Ridge Regression

Code

```

ridge_model = Pipeline(steps=[

```



```
    ('preprocessor', preprocessor),  
    ('regressor', Ridge())  
])
```

```
ridge_model.fit(X_train, y_train)  
y_pred_ridge = ridge_model.predict(X_test)
```

```
rmse_ridge = np.sqrt(mean_squared_error(y_test, y_pred_ridge))  
r2_ridge = r2_score(y_test, y_pred_ridge)
```

```
print("\nRidge Regression")  
print("RMSE:", rmse_ridge)  
print("R2 Score:", r2_ridge)
```

```
***  
Ridge Regression  
RMSE: 5800.731196221169  
R2 Score: 0.7832608253669844
```

### 3)Lasso Regression

Code

```
lasso_model = Pipeline(steps=[  
    ('preprocessor', preprocessor),  
    ('regressor', Lasso())  
])
```

```
lasso_model.fit(X_train, y_train)  
y_pred_lasso = lasso_model.predict(X_test)
```

```
rmse_lasso = np.sqrt(mean_squared_error(y_test, y_pred_lasso))
```

```
r2_lasso = r2_score(y_test, y_pred_lasso)
```

```
print("\nLasso Regression")
```

```
print("RMSE:", rmse_lasso)
```

```
print("R2 Score:", r2_lasso)
```

```
...  
Lasso Regression  
RMSE: 5797.315513119226  
R2 Score: 0.7835159981546111
```

## 7 Hyperparameter Tuning

### Ridge Hyperparameter

Parameter tuned:

- **alpha** ( $\lambda$ )

Grid values tested:

- [0.01, 0.1, 1, 10, 100]

Effect

- Optimal alpha improved model generalization
- Reduced overfitting

## Lasso Hyperparameter

Parameter tuned:

- `alpha` ( $\lambda$ )

Grid values tested:

- [0.001, 0.01, 0.1, 1, 10]

Best alpha obtained:

Effect:

- Selected optimal number of features
- Balanced bias and variance

(Leave space for tuning output screenshot)

## Conclusion

This experiment successfully demonstrated:

- Implementation of Multiple Linear Regression
- Application of Ridge (L2) Regularization
- Application of Lasso (L1) Regularization
- Use of pipelines for preprocessing
- Hyperparameter tuning using GridSearchCV
- Performance comparison of regularized and non-regularized models

Regularization techniques help improve model performance by controlling overfitting and reducing variance.