Predictive and Logistic Regression, SVM

Aim: Designing a predictive regression model that forecasts sales based on the "Advertising.csv" dataset, logistic regression and Support Vector Machines (SVM) to predict defaulters using the "Credit.csv" and "Credit-Modified.csv" datasets.

Sales Forecasting Using Linear Regression:

1. Data Exploration:

Begin by exploring the "Advertising.csv" dataset for sales forecasting. This involves importing essential libraries such as pandas, numpy, matplotlib.pyplot, seaborn, and scikit-learn.

- **2.Data Loading and Selection:** Load the "Advertising" dataset into a pandas DataFrame (df). Choose relevant features ('TV', 'radio', 'newspaper') and define the target variable as 'sales'.
- **3.Train-Test Split:** Split the dataset into training and testing sets using the train_test_split function from scikit-learn.
- **4.Linear Regression Modeling:** Create a linear regression model, fitting it to the training data, and subsequently making predictions on the test data.
- **5.Evaluation Metrics:** Evaluate the performance of the linear regression model by calculating and printing key metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).
- **6.Scatter Plot:** Visualize the model's predictions by generating a scatter plot that compares actual sales values to the predicted sales.

Default Prediction Using Logistic Regression and SVM:

1.Data Preprocessing:

For default prediction on the "Credit.csv" and "Credit-Modified.csv" datasets, load both datasets (credit_df and credit_mod_df). Conduct necessary preprocessing steps, including dropping unnecessary columns and creating dummy variables for categorical features.

- **2.Model Creation and Fitting:** Create logistic regression and Support Vector Machines (SVM) models for default prediction. Fit these models to the respective datasets.
- **3.Model Evaluation :** Make predictions using the trained models and assess their accuracy through metrics such as accuracy scores. Visualize predictions through scatter plots.
- **4.Confusion Matrices**: Utilize a function (plot_confusion_matrix) to plot confusion matrices for both logistic regression and SVM models.

Classification Metrics and ANOVA Test:

- **1.Classification Metrics:** Import precision, recall, and F1 score metrics from scikit-learn. Define a function (print_classification_metrics) to print these classification metrics. Print the metrics for both logistic regression and SVM models.
- **2.ANOVA Test:** Conduct an ANOVA test on the features of the "Credit" dataset to analyze the variance between groups. Display the F-statistic, p-value, and a summarized DataFrame of the results.
- **3.Logistic Regression Coefficients:** Print the coefficients of the logistic regression model, providing insights into the impact of each feature on the predicted outcome.

Accuracy of Logistic Regression:

Logistic Regression Accuracy: 0.94166666666666667

Logistic Regression Metrics: Precision: 0.7727 Recall: 0.8947 F1 Score: 0.8293

Accuracy of SVM:

SVM Accuracy: 0.8833333333333333

SVM Metrics: Precision: 0.6923 Recall: 0.4737 F1 Score: 0.5625

Confusion Matrix for SVM:

Confusion Matrix for Loggistic Regreesion:

Confusion Matrix for SVM:
[[97 4]
[10 9]]

Confusion Matrix for Logistic Regression:
[[96 5]
[2 17]]

```
Anova Test Results:
                Feature
                         F-Statistic
                                           P-Value
                 Income
                           78.609099 2.571368e-17
                  Limit
                          252.248530 2.396566e-44
                 Rating
                          259.693257
                                     2.465673e-45
                  Cards
                            4.025334 4.549784e-02
                    Age
                            0.579367
                                      4.470113e-01
              Education
                            0.036607
                                      8.483654e-01
                Balance
                          494.736145
                                      8.163230e-72
            Gender Male
                            0.004563
                                      9.461796e-01
8
            Student_Yes
                           33.242414
                                      1.633990e-08
9
            Married_Yes
                            0.313386
                                      5.759248e-01
10
        Ethnicity_Asian
                            0.036340
                                      8.489131e-01
    Ethnicity_Caucasian
                            0.045334
                                     8.314999e-01
```

Plots:

2000

50

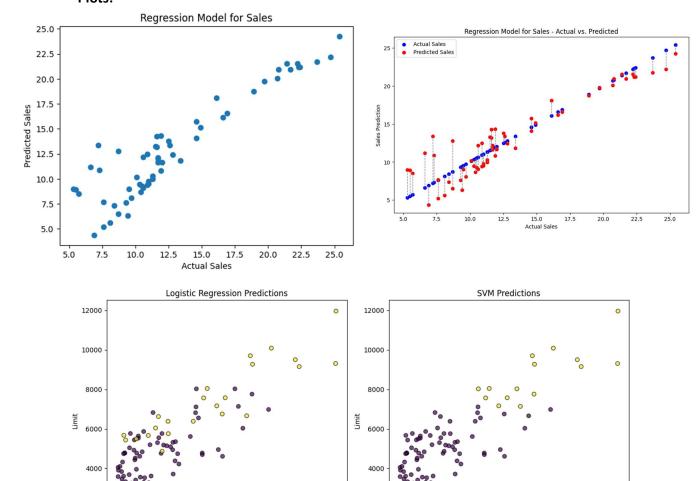
100

Income

125

150

175



2000

25

50

100

Income

125

175

150

