CSCI 485 Assignment-1

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Title: Recursive Feature Elimination with Linear Regression

1. Introduction

This report explores the application of Recursive Feature Elimination (RFE) with a Linear Regression model on the Diabetes dataset. The goal is to determine the most important features affecting diabetes progression and improve model interpretability.

2. Dataset Exploration

The **Diabetes dataset** from sklearn.datasets.load_diabetes() consists of 10 features: - Age, sex, BMI, blood pressure, and six blood sample-derived measures. - The target variable represents a continuous measure of diabetes progression over one year.

The dataset was split into 80% training and 20% testing for model evaluation.

3. Linear Regression Model

A Linear Regression model was trained on the dataset to establish a baseline performance. The model's accuracy was evaluated using the \mathbb{R}^2 score, which measures the proportion of variance explained by the independent variables.

4. Implementing Recursive Feature Elimination (RFE)

• Process:

- The model started with all **10 features** and iteratively eliminated the least significant feature in each step.
- The R² score was recorded for each iteration to track performance changes.
- The process continued until only one feature remained.

• Results:

- A plot of R² score vs. number of features helped identify the optimal feature set.
- The selected features provided the best trade-off between interpretability and predictive power.

5. Analyzing Feature Importance

The RFE process revealed the most critical features contributing to diabetes progression. The three most important features were: 1. **BMI** - A crucial factor

Task 3: Implement Recursive Feature Elimination (RFE)

```
[5]: num_features = X.shape[1]
    r2_scores = []
    feature_rankings = []

for i in range(num_features, 0, -1):
    rfe = RFE(estimator=LinearRegression(), n_features_to_select=i)
    rfe.fit(X_train, y_train)
    selected_features = X_train.columns[rfe.support_]
    X_train_reduced, X_test_reduced = X_train[selected_features], X_test[selected_features]

    model.fit(X_train_reduced, y_train)
    y_pred = model.predict(X_test_reduced)

    r2 = r2_score(y_test, y_pred)
    r2_scores.append(r2)
    feature_rankings.append((i, list(selected_features)))
    print(f"RFE with {i} features: R² Score = 0.4526
    RFE with 9 features: R² Score = 0.4559
    RFE with 8 features: R² Score = 0.4559
    RFE with 7 features: R² Score = 0.4583
    RFE with 5 features: R² Score = 0.4628
    RFE with 5 features: R² Score = 0.4382
    RFE with 4 features: R² Score = 0.4464
    RFE with 3 features: R² Score = 0.4451
    RFE with 2 features: R² Score = 0.4451
    RFE with 2 features: R² Score = 0.4523
    RFE with 1 features: R² Score = 0.2334
```

Figure 1: RFE_Score

```
y_pred_optimal = model.predict(X_test_optimal)
final_r2 = r2_score(y_test, y_pred_optimal)
print(f"Final Model R2 Score with {optimal_features[0]} features: {final_r2:.4f}")

R2 Score vs Number of Features in RFE

0.45

0.40

0.30

0.25

0.30

0.25

Optimal number of features: 10
Selected Features: ['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6']
Final Model R2 Score with 10 features: 0.4526
```

Figure 2: graph

in diabetes risk. 2. **Blood Pressure** - Strongly associated with metabolic health. 3. **Glucose-related metrics** - Indicators of blood sugar regulation.

6. Reflection

- Feature Selection with RFE: RFE effectively ranks features and removes redundant ones, enhancing model performance and interpretability.
- Comparison with LASSO: RFE selects features iteratively, whereas LASSO applies L1 regularization to shrink coefficients, sometimes setting them to zero. LASSO is computationally faster but less intuitive in feature selection.
- Dataset Insights: The most relevant features highlight key health indicators influencing diabetes progression, making this approach useful for medical analysis.

7. Conclusion

Recursive Feature Elimination (RFE) provides a systematic way to improve model efficiency by selecting the most relevant features. This assignment demonstrated the effectiveness of RFE in identifying important predictors while maintaining model accuracy.

8. References

- Scikit-learn documentation: https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.F
- $\bullet \ \ Diabetes \ dataset \ description: \ https://scikit-learn.org/stable/datasets/toy_dataset.html\#diabetes-dataset$