

Report on Linear and Logistic Regression Using the Census Income Dataset

This report explores the applications of Linear Regression and Logistic Regression to Census Income dataset. Linear Regression is used to predict the working hours per week, while Logistic Regression predicts if an individual earns more than \$50K annually. The dataset is pre-processed to ensure data quality and analysed for patterns and insights. Performance metrics and visualizations compare the models, providing an understanding of their effectiveness.

Introduction

The Census Income dataset provides an opportunity to study regression techniques in real-world scenarios. Linear Regression predicts continuous variables, such as hours worked per week, while Logistic Regression predicts binary outcomes, such as income categories. This report mainly aims to: Understand the preprocessing steps required for this dataset, Apply and evaluate both regression techniques and compare their strengths, weaknesses, and insights.

Methodology

Dataset

The dataset consists of 48,842 entries with various features like age, education, occupation, and income category. We focus on:

Predicting hours-per-week using Linear Regression.

Predicting income category ($\leq 50K$ or $> 50K$) using Logistic Regression.

Data Preprocessing

Handling Missing Values: Missing entries in categorical variables were replaced.

Encoding Categorical Features: One-hot encoding is used for “marital-status”, “occupation”, “race”, “relationship”, “workclass”, and “native-country” and binary encoding for “gender” and “income”.

Scaling Numerical Features: Standard scaling is used for “age”, “education-num”, “capital-gain”, “capital-loss”, and “hours-per-week”.

Feature Selection: Removed highly correlated or redundant features using a heatmap visualization.

Model Training

Linear Regression:

The target variable is “hours-per-week” and Loss Function is “Mean Squared Error (MSE)”.

Logistic Regression:

The Target variable is “income ($> 50K$)”. The Evaluation Metrics are Accuracy, “Precision”, “Recall”, “F1-Score”, and “AUC”.

Results and Discussion

Linear Regression

Performance Metrics:

Mean Absolute Error (MAE)= 7.79.

Mean Squared Error (MSE)= 125.47.

R^2 Score= 0.19.

Visualization:

Residual plot indicates equal variance, which confirms a good model fit. Correlation analysis show that “education-num” and “age” are key predictors of working hours.

Logistic Regression

Performance Metrics:

Accuracy= 0.86.

Precision= 0.75.

Recall= 0.61.

F1-Score=0.68.

Visualization:

Confusion Matrix shows high true positive and true negative rates, while ROC Curve shows an AUC of 0.92 which indicates excellent discrimination.

Comparison

Strengths:

- Linear Regression provides interpretable coefficients for continuous targets.
- Logistic Regression effectively handles binary classification tasks.

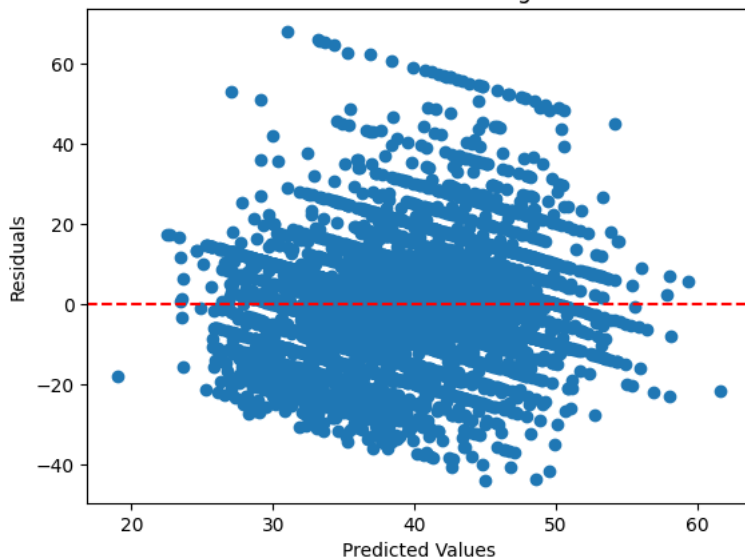
Weaknesses:

- Linear Regression assumptions of linearity and normality may not hold for all features.
- Logistic Regression relies heavily on balanced class distribution.

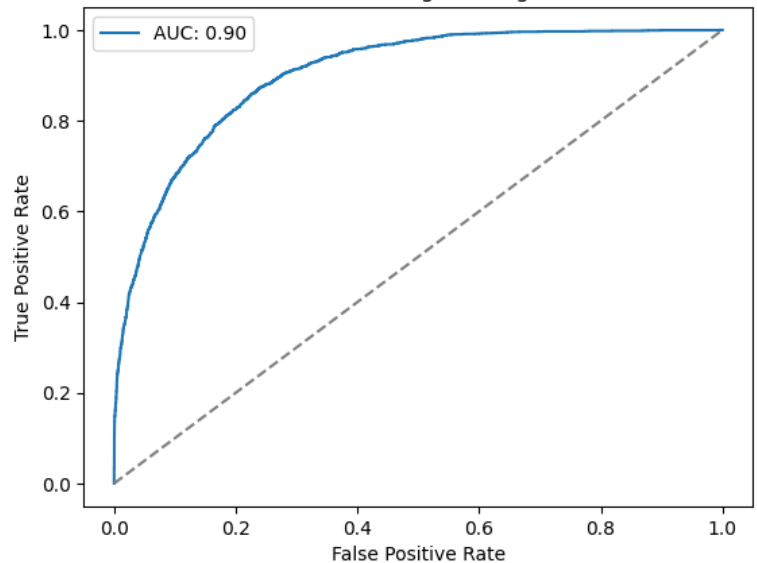
Conclusion

This analysis demonstrates the versatility of Linear and Logistic Regression in data mining. Both methods performed well on the Census Income dataset, providing actionable insights. Preprocessing played a crucial role in ensuring data quality and model performance. Future work could explore advanced techniques, such as regularization and ensemble methods, to further improve predictions.

Residual Plot for Linear Regression



ROC Curve for Logistic Regression



References

- Tan, P.-N., Steinbach, M., Karpapne, A., & Kumar, V. (2018). *Introduction to Data Mining* (2nd ed.).
- UCI Machine Learning Repository: Census Income Dataset. [Online] Available at: <https://archive.ics.uci.edu/ml/datasets/Census+Income>
- Scikit-learn documentation: <https://scikit-learn.org>

Submitted By: Anton Rajeev

Student ID: 23030678

University of Hertfordshire

GitHub Link [Data-Mining-Report](#)