Conducting and Presenting Multiple Linear Regression Analysis Using R

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What is Linear Regression?

Simple Linear Regression:

- Predicts one thing based on another thing
- Example: Predicting house price based on its size
- Draws a straight line through your data that best fits the pattern
- Goal: Find the line that makes the smallest prediction errors

Multiple Linear Regression:

- Predicts one thing based on multiple factors
- Example: Predicting house price using size, number of rooms, age, and location
- Considers all factors together to make better predictions
- Helps you understand which factors matter most
- In R, we use the simple `lm()` function to do this

What is Lasso Regression?

Lasso (Least Absolute Shrinkage and Selection Operator):

- A smarter version of regular regression
- Automatically decides which factors are important and which aren't
- Kicks out the unimportant factors completely (sets them to zero)
- Prevents the model from being too complicated

Key Differences from Standard lm():

- **lm()**: Uses ALL factors you give it, even if some are useless
- **Lasso**: Automatically removes useless factors, keeps only the important ones
- **Lambda ( )**: A dial that controls how aggressive Lasso is in removing factors
- **Benefit**: Gives you a cleaner, simpler model that's easier to understand and explain
- **Best for**: When you have many factors and aren't sure which ones really matter

When to Use Linear Regression

Best For: Continuous outcome variables (numbers on a scale)

- Sales revenue from advertising spend
- House prices based on size and location
- Temperature predictions from weather variables
- Student test scores from study hours

Key Question It Answers: How does one variable respond to changes in others?

Bottom Line: Know your data! Linear regression needs a continuous outcome variable to work properly.

About the Analysis

Packages Used:

- `glmnet` - For Lasso regression
- `lm` - Ordinary least squares regression model
- `MASS` - Contains Boston dataset

Boston Housing Dataset:

- 506 observations
- 14 variables
- Target: `medv` (median home value)
- Predictors: crime rate, room number, age, etc.

Key Concepts

Coefficients: Numerical values that represent the relationship strength between each predictor variable and the target variable. A larger absolute value indicates stronger influence.

R-squared (R^2): R squared is the model's accuracy score, it ranges from 0 to 1.

Penalty (L1): In Lasso, add up all the coefficient values (ignoring positive/negative signs) and "if this total gets too big, we'll add a penalty to the model." This can force some coefficients to become exactly zero, effectively performing feature selection.

Regularization: A technique to prevent overfitting. Without it, models can become too complicated, memorizing training data instead of learning real patterns.

Lambda ( ): Lamda is a hyper parameter, which can use to control how strict and simple a model can be. If the lamda value is more, then it gives more strict penalties and keeps the model simple, and vice-versa.

Step 1: Install & Load Packages

```r
# Install and load packages
if (!require(glmnet)) {
  install.packages("glmnet")
}
if (!require(ggplot2)) {
  install.packages("ggplot2")
}
if (!require(reshape2)) {
  install.packages("reshape2")
}
library(glmnet)
library(MASS)
library(ggplot2)
library(reshape2)
```

Purpose: Set up the required libraries for our analysis

Step 2: Load & Prepare Data

```r
# Load and prepare data
data(Boston)
head(Boston, 3)
```

```
     crim zn indus chas   nox    rm  age    dis rad tax pti
1 0.00632 18  2.31    0 0.538 6.575 65.2 4.0900   1 296
2 0.02731  0  7.07    0 0.469 6.421 78.9 4.9671   2 242
3 0.02729  0  7.07    0 0.469 7.185 61.1 4.9671   2 242
  medv
1 24.0
2 21.6
3 34.7
```

```r
# OR load your own CSV file from computer:
# my_data <- read.csv("path/to/your/file.csv")
# Example: my_data <- read.csv("C:/Users/YourName/Documents

X <- as.matrix(Boston[, -14])
y <- Boston$medv
```

Step 3: Fit Linear Model

```r
# Fit a normal linear model
lm_model <- lm(medv ~ ., data = Boston)
lm_coef <- coef(lm_model)
lm_r_squared <- summary(lm_model)$r.squared

cat("--- Base lm() Coefficients ---\n")
```

```
--- Base lm() Coefficients ---
```

```r
print(lm_coef)
```

```
  (Intercept)          crim            zn         indus
 3.645949e+01 -1.080114e-01  4.642046e-02  2.055863e-
02  2.686734e+00
          nox            rm           age           dis
-1.776661e+01  3.809865e+00  6.922246e-04 -1.475567e+00  3.
01
          tax       ptratio         black         lstat
-1.233459e-02 -9.527472e-01  9.311683e-03 -5.247584e-
```

Step 4: Fit Lasso Model

```r
# Fit a lasso model (with cross-validation)
cv_model <- cv.glmnet(X, y, alpha = 1)
best_lambda <- cv_model$lambda.min

cat("Best lambda from cross-validation:", best_lambda, "\n"
```

```
Best lambda from cross-validation: 0.03373254
```

```r
lasso_model <- glmnet(X, y, alpha = 1, lambda = best_lambda
```

Key Point: Cross-validation automatically selects the optimal lambda value

Step 5: Extract Lasso Results

```
# Extract Lasso coefficients and predictions
lasso_coef <- coef(lasso_model)
lasso_predictions <- predict(lasso_model, newx = X)
lasso_r_squared <- 1 - (sum((y - lasso_predictions)^2) /
                        sum((y - mean(y))^2))

cat("--- Lasso Coefficients ---\n")
```

```
--- Lasso Coefficients ---
```

```
print(lasso_coef)
```

```
14 x 1 sparse Matrix of class "dgCMatrix"
                        s0
(Intercept)  34.160482304
crim         -0.096703363
zn            0.040702395
indus         .
chas          2.674470344
```

Step 6: Compare Results

```
# R-squared Comparison
cat("--- R-squared Comparison ---\n")
```

```
--- R-squared Comparison ---
```

```
cat("Base lm() R-squared:", lm_r_squared, "\n")
```

```
Base lm() R-squared: 0.7406427
```

```
cat("Lasso glmnet R-squared:", lasso_r_squared, "\n")
```

```
Lasso glmnet R-squared: 0.740005
```

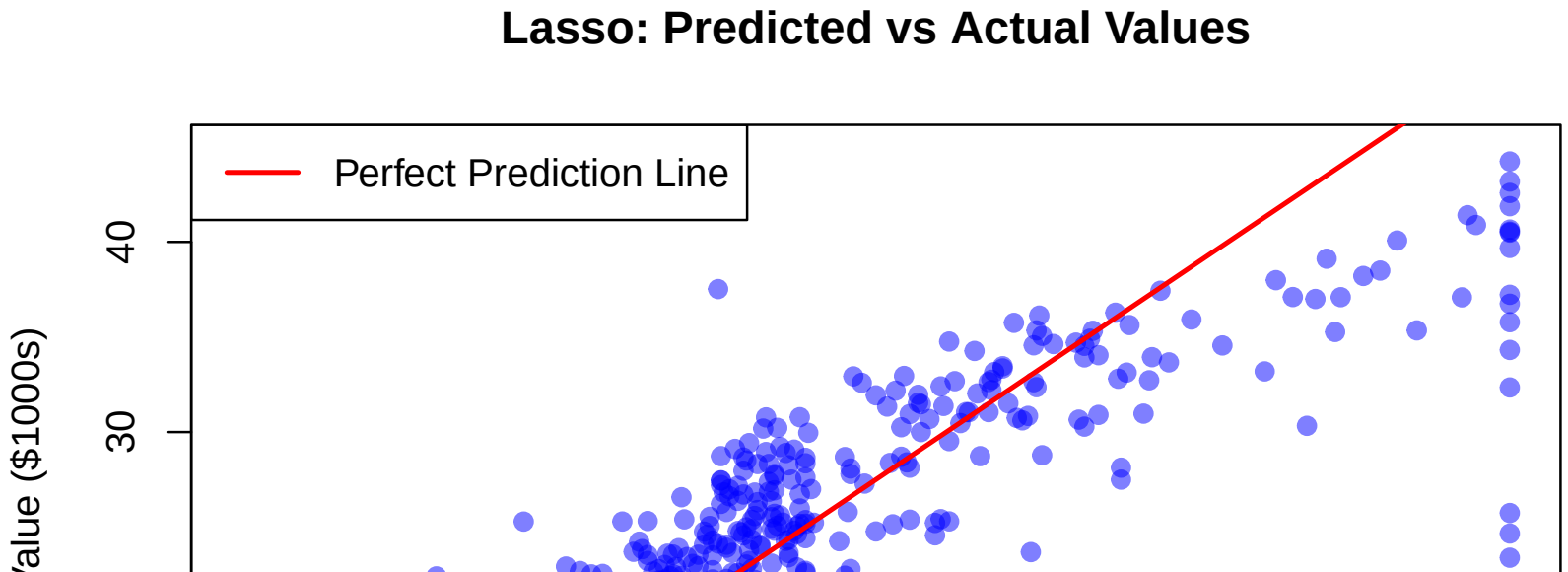
```
cat("\nDifference:", lm_r_squared - lasso_r_squared, "\n")
```

```
Difference: 0.0006376334
```

Observation: Lasso achieves similar performance while potentially simplifying the model by shrinking some coefficients

Plot: Predicted vs Actual

```
# Predicted vs Actual values
plot(y, lasso_predictions,
     main = "Lasso: Predicted vs Actual Values",
     xlab = "Actual Median Value ($1000s)",
     ylab = "Predicted Median Value ($1000s)",
     pch = 19, col = rgb(0, 0, 1, 0.5))
abline(0, 1, col = "red", lwd = 2)
legend("topleft", legend = "Perfect Prediction Line",
       col = "red", lwd = 2)
```



Business Applications

Real-World Uses:

1. **Sales Forecasting**
   Predict future sales based on marketing spend, pricing, and seasonality to plan inventory and budgets.

2. **Customer Churn Prediction**
   Identify which customer behaviors indicate they're likely to leave, so you can take action early.

3. **Marketing Channel Optimization**
   Use Lasso to find which advertising channels (social media, TV, email) actually drive revenue and cut the rest.

4. **Employee Attrition Modeling**
   Predict which employees might quit based on workload, satisfaction scores, and performance reviews.

5. **Demand Forecasting**
   Estimate product demand using weather, promotions, and foot traffic to optimize stock levels.

Exercise: Try With Another Dataset

Task:
Run the same workflow (load $\rightarrow$ prepare $\rightarrow$ fit $\rightarrow$ compare) using a *different dataset* such as `mtcars`, `iris`, or your own CSV.

Steps:

1. Load a dataset: `df <- mtcars`
2. Pick a target variable: `y <- df$mpg`
3. Create predictors: `X <- as.matrix(df[, -1])`
4. Fit linear & Lasso models (same code as earlier)
5. Compare R^2 and identify important predictors.

Goal:
See how model behavior changes with a new dataset.

Thank You!

Questions?