

# Statistics and Data Analysis

Unit 04 – Lecture 06: VIF, AIC/BIC, Ridge and Lasso (Part 1)

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<https://github.com/tali7c/Statistics-and-Data-Analysis>

# Quick Links

Overview

VIF

Ridge/Lasso

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# Agenda

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# Learning Outcomes

- Compute and interpret VIF (basic)

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- Compute and interpret VIF (basic)
- Explain AIC/BIC as model selection criteria (intuition)
- Write ridge and lasso objectives
- Explain coefficient shrinkage and feature selection idea

# VIF: Key Points

- Definition:  $\text{VIF}_j = 1/(1 - R_j^2)$

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- Rule of thumb thresholds (5/10)

# VIF: Key Formula

$$\text{VIF}_j = \frac{1}{1 - R_j^2}$$

# Ridge/Lasso: Key Points

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- Scale features before regularization

# Ridge/Lasso: Key Formula

$$\min \sum (y - \hat{y})^2 + \lambda \sum \beta_j^2 \quad (\text{ridge})$$

# Exercise 1: Compute VIF

If  $R_j^2 = 0.9$ , compute  $\text{VIF}_j$ .

# Solution 1

- $VIF_j = 1/(1 - 0.9) = 10$  (high).

## Exercise 2: Ridge vs lasso

Which can produce exact zero coefficients?

# Solution 2

- Lasso (L1) can set some coefficients to 0.

## Exercise 3: AIC/BIC meaning

Lower AIC/BIC means what (conceptually)?

# Solution 3

- Better trade-off between fit and complexity (relative).

# Mini Demo (Python)

Run from the lecture folder:

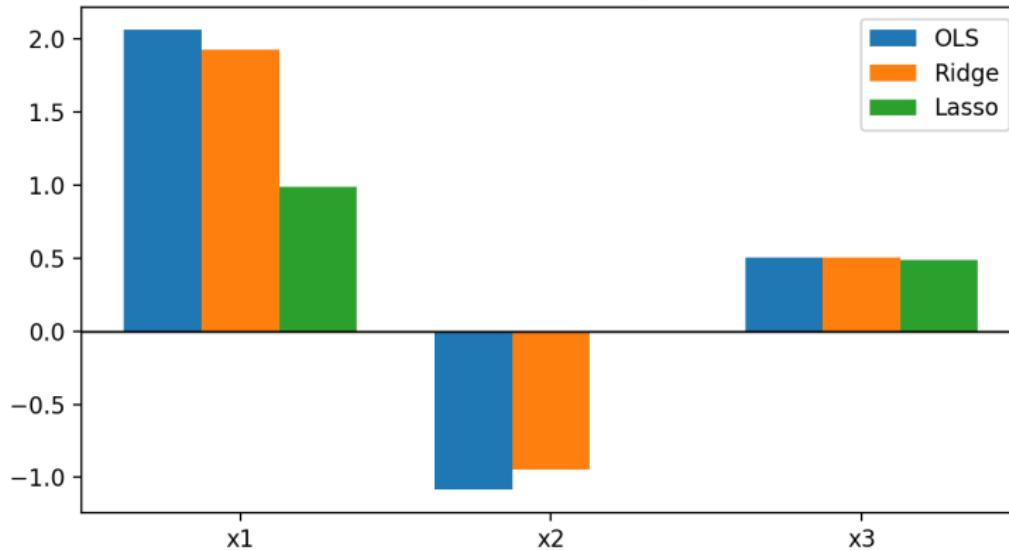
```
python demo/demo.py
```

Outputs:

- images/demo.png
- data/results.txt

# Demo Output (Example)

Coefficients: OLS vs Ridge vs Lasso



# Summary

- Key definitions and the main formula.

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- Key definitions and the main formula.
- How to interpret results in context.
- How the demo connects to the theory.

# Exit Question

Why can ridge help when predictors are highly correlated?