Lesson 22: Regularization

Data Science with Python – BSc Course

45 Minutes

Learning Objectives

The Problem: With many predictors, our model can memorize noise instead of learning patterns. How do we build models that generalize to unseen data?

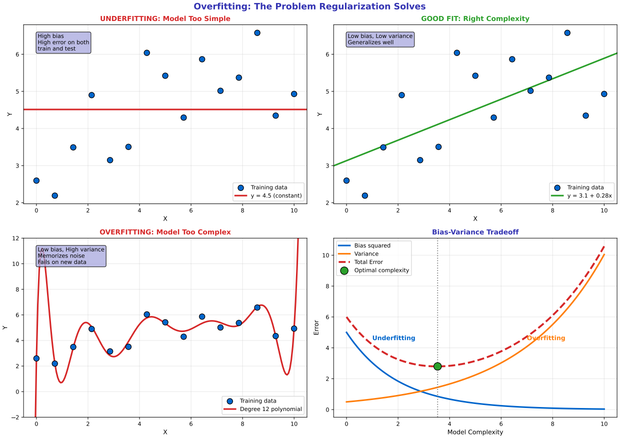
After this lesson, you will be able to:

- Recognize overfitting and its causes
- Apply Ridge (L2) regularization to shrink coefficients
- Apply Lasso (L1) for automatic feature selection
- Tune the regularization strength with cross-validation

Finance Application: Building robust factor models with many correlated predictors

When Models Memorize Instead of Learn

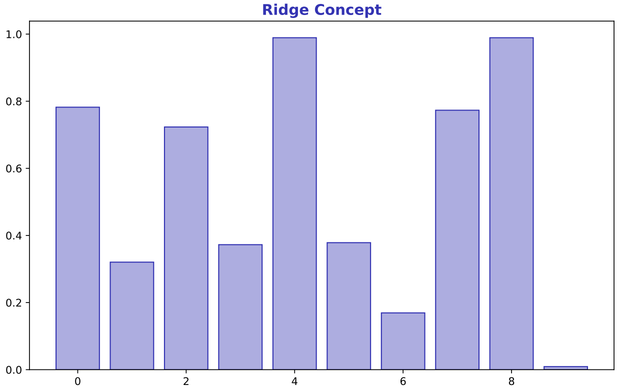
- High training accuracy but poor test performance
- Complex models fit noise in the training data



Red flag: If train error keeps dropping but test error rises, you're overfitting

Shrink All Coefficients Toward Zero

- Add penalty: Loss $= \sum(y - \hat{y})^2 + \lambda \sum \beta_j^2$
- Large λ = stronger shrinkage, simpler model

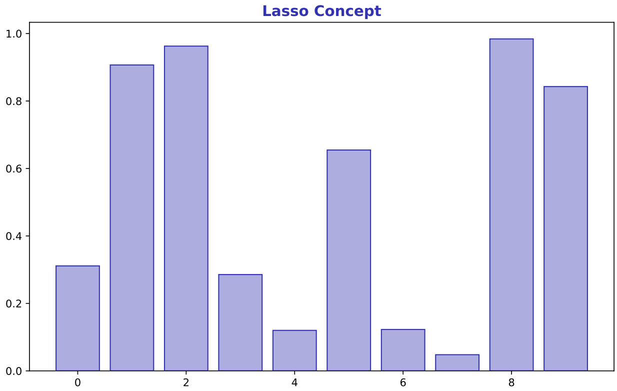


Ridge keeps all features but reduces their influence – good for multicollinearity

Lasso Regression (L1)

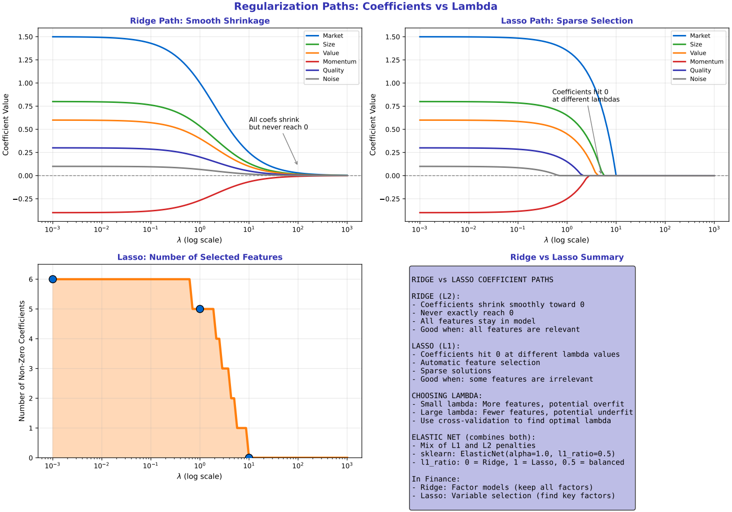
Some Coefficients Go to Exactly Zero

- Add penalty: Loss $= \sum (y - \hat{y})^2 + \lambda \sum |\beta_j|$
- L1 penalty creates sparse solutions (automatic feature selection)



Lasso eliminates irrelevant features – use when you suspect many predictors are useless

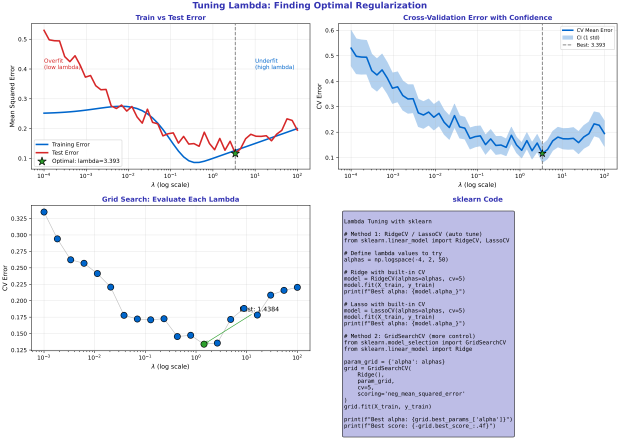
How Coefficients Change with Lambda



As λ increases, coefficients shrink. Lasso drives some to zero; Ridge does not

Finding the Right Penalty Strength

- Too small: overfitting (model too complex)
- Too large: underfitting (model too simple)

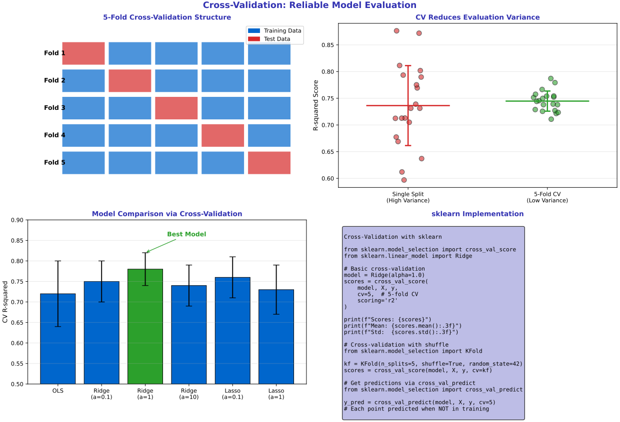


Use cross-validation to find the lambda that minimizes test error

Cross-Validation for Lambda

sklearn Makes It Easy

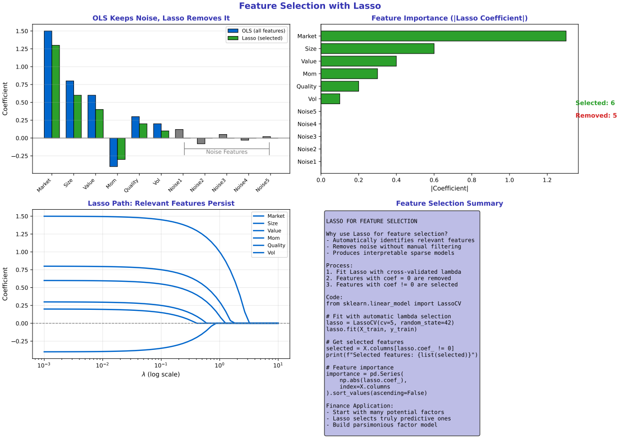
- `RidgeCV` and `LassoCV` automatically search lambda values
- K-fold CV: split data K ways, train on K-1, test on 1, average



Rule: Use `RidgeCV(alphas=[0.1, 1, 10, 100])` to search logarithmically

Which Predictors Actually Matter?

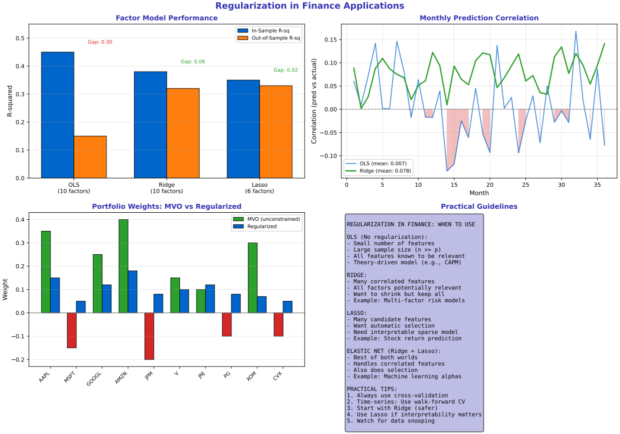
- Non-zero Lasso coefficients = selected features
- Zero coefficients = features eliminated by the model



Finance insight: Lasso often keeps 3-5 factors from a candidate set of 20+

Building Robust Return Predictions

- Many candidate factors are correlated (value, quality, momentum...)
- Regularization prevents unstable, extreme factor weights



Industry practice: Regularized regression for combining alpha signals

Hands-On Exercise (25 min)

Task: Compare Ridge vs Lasso on Multi-Factor Data

1. Create synthetic data with 20 features (only 5 are truly predictive)
2. Fit OLS, Ridge, and Lasso models
3. Compare test set R^2 for each model
4. Plot Lasso coefficients – which features were selected?

Deliverable: Bar chart of coefficients comparing OLS vs Ridge vs Lasso.

Extension: Use LassoCV to find optimal lambda and report selected features

Lesson Summary

Problem Solved: Regularization prevents overfitting when we have many predictors or limited data.

Key Takeaways:

- Ridge (L2) shrinks all coefficients – handles multicollinearity
- Lasso (L1) sets some coefficients to zero – automatic feature selection
- Use cross-validation (RidgeCV, LassoCV) to tune λ

Next Lesson: Regression Metrics (L23) – how do we measure model quality?

Memory: Ridge = Ridge keeps all features. Lasso = Lasso Loses features (L for Lose).