

NBA Win Percentage Prediction: Comparison of Optimization Methods for Ridge Regression

OBJECTIVE: Minimizing Ridge Regression Loss

The primary objective is to predict NBA win percentages by determining the optimal coefficients β for a Ridge Regression model. This involves minimizing the following loss function.

$$L(\beta) = \|y - X\beta\|^2 + \lambda\|\beta\|^2$$

Data Set

The research utilizes extensive NBA team statistics from the NBA Team Stats dataset (2000–2018) from Kaggle. This comprehensive dataset includes regular season and playoff statistics for NBA teams, featuring wins, losses, points, assists per game, turnovers per game, total rebounds per game, field goal percentage, and three-point percentage.

Methods

1. Ridge Regression Loss Function

$$L(\beta) = \|y - X\beta\|^2 + \lambda\|\beta\|^2$$

2. Steepest Descent Update

$$\beta_{k+1} = \beta_k - \alpha \nabla L(\beta_k)$$

3. Conjugate Gradient Update

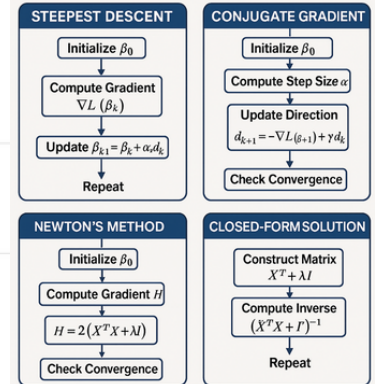
$$d_{k+1} = -\nabla L(\beta_{k+1}) + \gamma_k d_k$$
$$\gamma_k = \frac{\|\nabla L(\beta_{k+1})\|^2}{\|\nabla L(\beta_k)\|^2}$$

4. Newton's Method Update

$$\beta_{k+1} = \beta_k - H^{-1} \nabla L(\beta_k)$$

with Hessian

$$H = 2(X^T X + \lambda I)$$



Results



Conclusion

- All methods converge to the same optimal Ridge Regression objective value (0.26), confirming correctness across approaches.
- Steepest Descent converges slowly (3049 iterations) and does not fully reach the optimum within the iteration limit.
- Newton's Method achieves the fastest convergence (2 iterations) due to quadratic convergence, but requires higher per-iteration computation.
- The Closed-Form solution provides an exact answer in a single step, serving as a useful benchmark but scaling poorly to high dimensions.
- Conjugate Gradient offers the best overall trade-off, reaching the optimal solution in few iterations with low computational cost, making it the most practical method for large datasets.