

Methods and Algorithms

MSc Data Science

Spring 2026

By the end of this session, you will be able to:

- ① **Understand** the ordinary least squares (OLS) framework
- ② **Apply** gradient descent for parameter optimization
- ③ **Interpret** regression coefficients in business contexts

Finance Application: House price prediction, factor models

Foundation for all supervised learning methods

Finance Use Case: Predicting House Prices

- Banks need accurate property valuations for mortgages
- Insurance companies assess property risk
- Investors evaluate real estate portfolios

The Question: Given features (size, location, age), what price?

Why Linear Regression?

- Interpretable coefficients (price per square meter)
- Fast, well-understood method
- Strong baseline for comparison

Linear regression: the “hello world” of machine learning

Core Idea: Model the relationship between inputs and a continuous output

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon \quad (1)$$

- y : Target variable (house price)
- x_1, \dots, x_p : Features (size, bedrooms, age)
- β_0, \dots, β_p : Coefficients to learn
- ε : Random error term

Goal: Find coefficients that minimize prediction error

Objective: Minimize the sum of squared errors (SSE)

$$\min_{\beta} \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \min_{\beta} \|y - X\beta\|^2 \quad (2)$$

Why Squared Errors?

- Penalizes large errors more than small errors
- Differentiable (enables gradient-based optimization)
- Leads to closed-form solution

This objective function defines "ordinary least squares" (OLS)

1. Closed-Form (Normal Equation)

$$\hat{\beta} = (X^T X)^{-1} X^T y \quad (3)$$

Pros:

- Exact solution
- One computation

Cons:

- Slow for large p
- Memory intensive

2. Gradient Descent

$$\beta_{t+1} = \beta_t - \alpha \nabla L(\beta_t) \quad (4)$$

Pros:

- Scales to big data
- Memory efficient

Cons:

- Requires tuning α
- Iterative process

Both methods yield the same solution for OLS

Example: House price model

$$\text{Price} = 50,000 + 200 \times \text{Size} + 15,000 \times \text{Bedrooms} - 1,000 \times \text{Age} \quad (5)$$

Interpretation:

- $\beta_0 = 50,000$: Base price (all features = 0)
- $\beta_1 = 200$: Each extra sqm adds \$200
- $\beta_2 = 15,000$: Each bedroom adds \$15,000
- $\beta_3 = -1,000$: Each year of age subtracts \$1,000

Coefficients show marginal effect, holding others constant

Key Metrics:

- **R^2 (Coefficient of Determination):** Variance explained

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (6)$$

- **RMSE (Root Mean Squared Error):** Prediction accuracy

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum(y_i - \hat{y}_i)^2} \quad (7)$$

In Practice: $R^2 = 0.75$ means model explains 75% of price variance

Always evaluate on held-out test data

Use When:

- Target is continuous
- Linear relationships expected
- Interpretability matters
- Fast inference needed

Avoid When:

- Target is categorical
- Strong non-linearities
- High multicollinearity
- Many outliers present

Pros	Cons
Interpretable	Assumes linearity
Fast training	Sensitive to outliers
Well-understood	Limited flexibility

- ① Linear regression models continuous outcomes as weighted sum of features
- ② OLS minimizes sum of squared errors
- ③ Solve via normal equation (small data) or gradient descent (big data)
- ④ Coefficients are directly interpretable as marginal effects
- ⑤ Evaluate using R^2 (variance explained) and RMSE (prediction error)

Next: Deep dive into mathematics and implementation

References:

- ISLR Chapter 3: Linear Regression
- ESL Chapter 3: Linear Methods for Regression