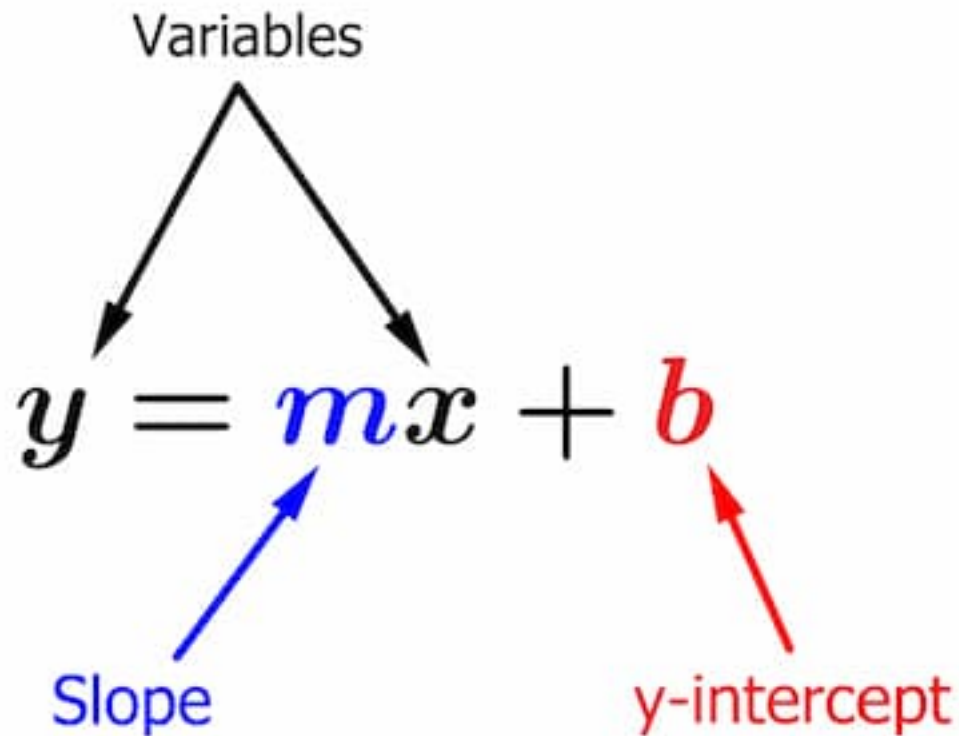


linear-regression

February 11, 2026

```
[77]: import time
import torch
import numpy as np
import matplotlib.pyplot as plt
```



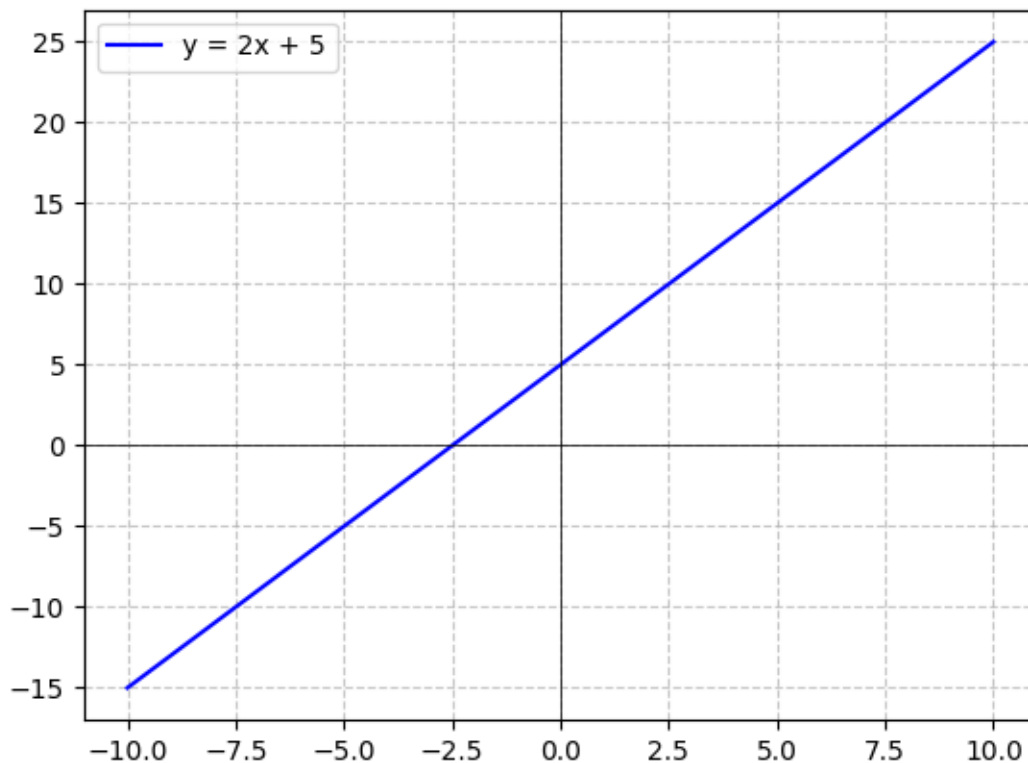
0.0.1 The Line: $y = mx + b$

- y : Dependent variable (The output/prediction).
- x : Independent variable (The input feature).
- m : Slope (Determines the steepness and direction).
- b : y-intercept (Where the line crosses the vertical axis).

```
[78]: # Variables you can control
m = 2
b = 5
```

```
# Data generation
x = np.linspace(-10, 10, 100)
y = m * x + b

# Plotting
_ = plt.plot(x, y, label=f'y = {m}x + {b}', color='blue')
_ = plt.axhline(0, color='black', linewidth=0.5)
_ = plt.axvline(0, color='black', linewidth=0.5)
_ = plt.grid(True, linestyle='--', alpha=0.7)
_ = plt.legend()
```



0.0.2 Adding Noise

To simulate real-world data for regression, we add a random “error” (ϵ) to our perfect line.

- **Equation:** $y = mx + b + \epsilon$
- ϵ (**Epsilon**): Random noise/error.
- **Goal:** Find the original line (m, b) despite the scattered data.

Actual vs. Predicted

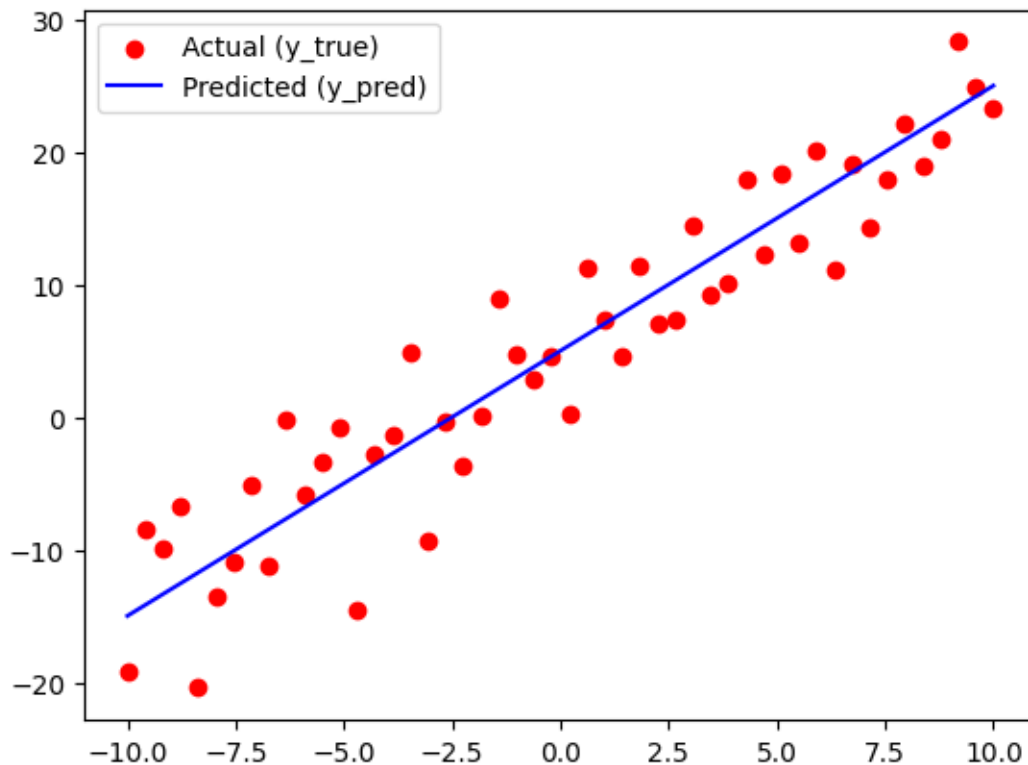
- y_{true} : The noisy data points (Red dots).
- y_{pred} : The line’s output for a given x (Blue line).

```
[79]: # Setup
m, b = 2, 5
x = np.linspace(-10, 10, 50)

# 1. True Values (Noisy Data)
y_true = m * x + b + (np.random.randn(50) * 4)

# 2. Predicted Values (The Line)
y_pred = m * x + b

# Plotting
_ = plt.scatter(x, y_true, color='red', label='Actual (y_true)')
_ = plt.plot(x, y_pred, color='blue', label='Predicted (y_pred)')
_ = plt.legend()
```



0.0.3 Residuals

- **Definition:** $y_{true} - y_{pred}$.
- **Visual:** Vertical lines showing the “error” for each point.

Metrics

- **Mean Error:** Average of residuals. Positive and negative values cancel out.

- **Mean Squared Error (MSE):** Average of squared residuals.
- **Root Mean Squared Error (RMSE):** Square root of MSE. Represents the average error in the same units as y .

```
[80]: m, b = 2, 5
x = np.linspace(-10, 10, 20)
y_true = m * x + b + (np.random.randn(20) * 4)
y_pred = m * x + b

# Metrics
residuals = y_true - y_pred
mse = np.mean(residuals**2)

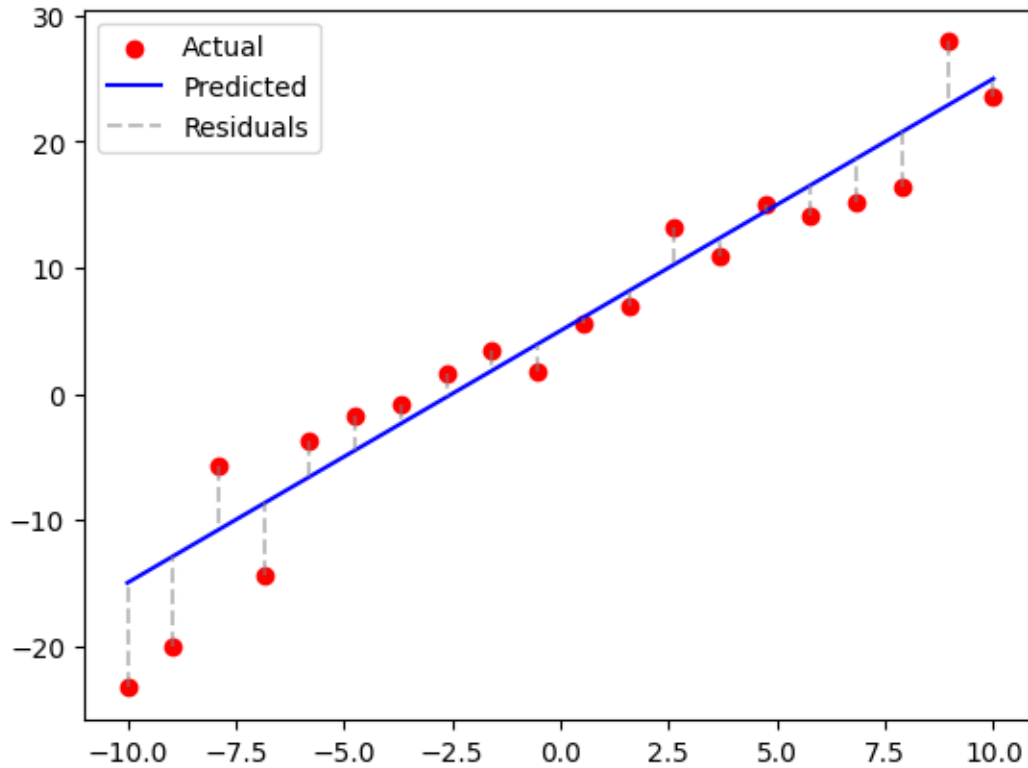
print(f"Mean Error: {np.mean(residuals)}")
print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error (RMSE): {np.sqrt(mse)}")

# Plotting
_ = plt.scatter(x, y_true, color='red', label='Actual')
_ = plt.plot(x, y_pred, color='blue', label='Predicted')
_ = plt.vlines(x, y_true, y_pred, color='gray', linestyle='--', alpha=0.5,
              label='Residuals')
_ = plt.legend()
```

Mean Error: -0.7061731204339597

Mean Squared Error (MSE): 14.390943419052963

Root Mean Squared Error (RMSE): 3.7935396951993217



0.0.4 Scenario: Height Prediction

- **Data:** Age and Height measurements of 20 individuals.
- **Goal:** Build a model to predict Height (y) given Age (x).
- **Model:** Linear Regression (Simplest approach).

Key Parameters

- **Slope (m):** Growth rate (How much height increases per year).
- **Intercept (b):** Base height (Theoretical height at Age 0).

Setup

- **Independent Variable (x):** Age (Years).
- **Target (y):** Height (cm).
- **Goal:** Evaluate 3 manual guesses for slope (m) and intercept (b).
- **Visuals:** 3 subplots showing the guessed lines and their residuals.

```
[81]: # 1. Hardcoded Data (20 samples)
age = np.array([2, 3, 4, 5, 6, 7, 8, 9, 10, 11,
                12, 13, 14, 15, 16, 17, 18, 19, 20, 21])
height = np.array([72, 65, 98, 80, 95, 108, 100, 145, 120, 128,
                  118, 138, 142, 110, 165, 158, 172, 165, 185, 175])
```

```

# 2. Manual Guesses (m, b)
guesses = [(3, 80), (5, 65), (7, 40)] # Guess 1, Guess 2, Guess 3

# 3. Plotting & Metrics
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

for i, (m, b) in enumerate(guesses):
    # Predictions & Residuals
    y_pred = m * age + b
    residuals = height - y_pred

    # Metrics
    mse = np.mean(residuals**2)
    print(f"Guess {i+1} (m={m}, b={b}):")
    print(f"    Mean Error: {np.mean(residuals):.2f}")
    print(f"    MSE: {mse:.2f}")
    print(f"    RMSE: {np.sqrt(mse):.2f}\n")

    # Plot
    _ = axes[i].scatter(age, height, color='red', label='Data')
    _ = axes[i].plot(age, y_pred, color='blue', label=f'Line: {m}x + {b}')
    _ = axes[i].vlines(age, height, y_pred, color='gray', linestyle='--', alpha=0.
↪5)
    _ = axes[i].set_title(f'Guess {i+1}: RMSE = {np.sqrt(mse):.1f}')
    _ = axes[i].legend()

```

Guess 1 (m=3, b=80):

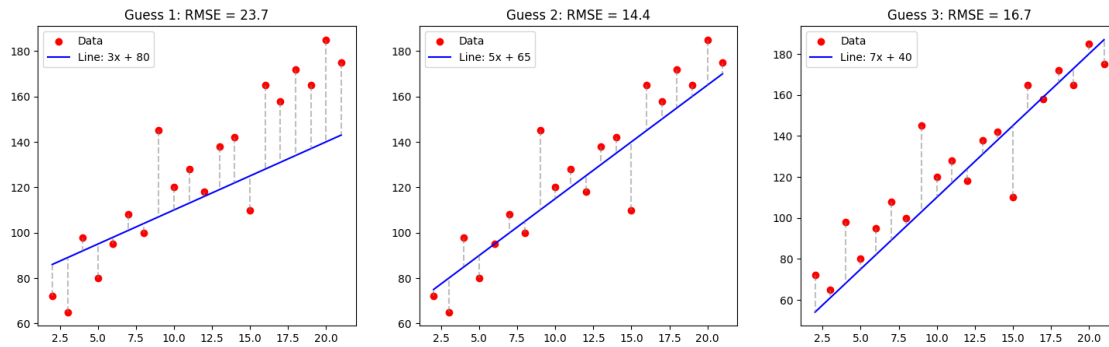
Mean Error: 12.45
MSE: 562.05
RMSE: 23.71

Guess 2 (m=5, b=65):

Mean Error: 4.45
MSE: 208.55
RMSE: 14.44

Guess 3 (m=7, b=40):

Mean Error: 6.45
MSE: 278.05
RMSE: 16.67



0.0.5 Brute Force Approach

Pairwise Iteration

- **Strategy:** Calculate the line connecting every possible pair of points (N^2 iterations).
- **Two-Point Formula:**
 - $m = \frac{y_2 - y_1}{x_2 - x_1}$
 - $b = y_1 - mx_1$
- **Limitations:**
 - **Inefficient:** Checks 400 combinations for just 20 points.
 - **Sub-optimal:** Assumes the “best” line perfectly passes through at least two data points (often false).

```
[82]: best_rmse = float('inf')
best_m, best_b = 0, 0

# Iterate through all unique pairs
for i in range(len(age)):
    for j in range(len(age)):
        if i == j:
            continue

        # 1. Calculate m and b for this pair
        x1, y1 = age[i], height[i]
        x2, y2 = age[j], height[j]

        if x2 - x1 == 0:
            continue # Skip vertical lines

        m = (y2 - y1) / (x2 - x1)
        b = y1 - m * x1

        # 2. Calculate RMSE for this line against ALL points
        y_pred = m * age + b
        rmse = np.sqrt(np.mean((height - y_pred)**2))
```

```

# 3. Store if best
if rmse < best_rmse:
    best_rmse = rmse
    best_m, best_b = m, b

print(f"Best Pairwise Fit:")
print(f"  Slope (m):      {best_m:.4f}")
print(f"  Intercept (b): {best_b:.4f}")
print(f"  RMSE:           {best_rmse:.4f}")

```

```

Best Pairwise Fit:
  Slope (m):      5.7273
  Intercept (b): 60.6364
  RMSE:           13.2483

```

0.0.6 Optimal Solution with Scikit-Learn

Linear Regression

- **Method:** Ordinary Least Squares (OLS).
- **Advantage:** Analytically finds the global minimum error (optimal line).
- **Guarantees:** The best possible m and b for the given data (lowest MSE).

```
[83]: from sklearn.linear_model import LinearRegression
```

```

# Data Reshaping (sklearn requires 2D array for X)
X = age.reshape(-1, 1)
y = height

# Model Training
model = LinearRegression()
model.fit(X, y)

# Parameters
m = model.coef_[0]
b = model.intercept_

# Evaluation
y_pred = model.predict(X)
rmse = np.sqrt(np.mean((y - y_pred)**2))

print(f"Scikit-Learn Optimal Fit:")
print(f"  Slope (m):      {m:.4f}")
print(f"  Intercept (b): {b:.4f}")
print(f"  RMSE:           {rmse:.4f}")

```

```
[83]: LinearRegression()
```



```
Scikit-Learn Optimal Fit:
Slope (m):      5.6414
Intercept (b):  62.0744
RMSE:           13.2314
```

0.0.7 OLS Implementation (From Scratch)

Steps: Ordinary Least Squares (OLS)

1. **Calculate Means:** \bar{x} (mean of age), \bar{y} (mean of height).
2. **Calculate Deviations:**
 - $d_x = x - \bar{x}$
 - $d_y = y - \bar{y}$
3. **Calculate Slope (m):**
 - Formula: $m = \frac{\sum(d_x \cdot d_y)}{\sum(d_x^2)}$
 - Logic: Covariance of x, y divided by Variance of x .
4. **Calculate Intercept (b):**
 - Formula: $b = \bar{y} - m\bar{x}$

```
[84]: x_mean = np.mean(age)
      y_mean = np.mean(height)

      # Calculate terms for slope
      numerator = np.sum((age - x_mean) * (height - y_mean))
      denominator = np.sum((age - x_mean)**2)

      # Calculate parameters
      m = numerator / denominator
      b = y_mean - (m * x_mean)

      # Metrics
      y_pred = m * age + b
      rmse = np.sqrt(np.mean((height - y_pred)**2))

      print(f"Manual OLS Fit:")
      print(f"  Slope (m):      {m:.4f}")
      print(f"  Intercept (b): {b:.4f}")
      print(f"  RMSE:           {rmse:.4f}")
```

```
Manual OLS Fit:
Slope (m):      5.6414
Intercept (b):  62.0744
RMSE:           13.2314
```

0.0.8 How Simple OLS Works

1. The Simple Formula logic

- **Math derivation:** It comes from calculus. We take the MSE equation ($E = \frac{1}{n} \sum (y - (mx + b))^2$), take partial derivatives with respect to m and b , set them to 0, and solve.

- **Intuitive View:**
 - **Numerator:** $\sum(x - \bar{x})(y - \bar{y}) \approx \text{Covariance}$. Measures how much x and y move together.
 - **Denominator:** $\sum(x - \bar{x})^2 \approx \text{Variance}$. Measures how much x spreads out.
 - **Ratio:** We are scaling the “co-movement” by the “spread of x ”.

2. Does it work for 2 or 3 features?

- **Short Answer: No.**
- **Reason:**
 - The simple formula assumes a 2D plane (1 input, 1 output).
 - With 2 features (x_1, x_2), you are fitting a **Plane** in 3D space, not a line.
 - With 3+ features, you are fitting a **Hyperplane**.
 - You cannot use a single scalar division. You must use **Linear Algebra (Matrices)**.

0.0.9 The Normal Equation

To handle 1, 2, or N features, we switch to matrix notation.

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

- X : The input matrix (Design Matrix). Rows are samples, columns are features.
- y : The target vector.
- β : The vector of coefficients (slopes for each feature + intercept).

```
[85]: # --- 1. The Simple Way (One Feature only) ---
# Works ONLY for y = mx + b
def simple_ols(x, y):
    num = np.sum((x - np.mean(x)) * (y - np.mean(y)))
    den = np.sum((x - np.mean(x))**2)
    m = num / den
    b = np.mean(y) - m * np.mean(x)
    return m, b # Returns m, b

# --- 2. The General Way (Any number of features) ---
# Works for y = w1*x1 + w2*x2 + ... + b
def general_ols_matrix(X, y):
    # Add a column of 1s to X for the intercept (bias trick)
    X_b = np.c_[np.ones((len(X), 1)), X]

    # Normal Equation: inv(X.T @ X) @ X.T @ y
    theta = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T).dot(y)
    return theta # Returns [intercept, slope1, slope2, ...]
```

```
[86]: # 1. Synthetic Data (Large)
n_rows = 100
n_cols = 10**4
```

```

X = np.random.randn(n_rows, n_cols)
y = np.random.randn(n_rows)

# 2. Benchmark
print(f"Starting OLS on {n_rows:,} x {n_cols:,} matrix...")
start = time.time()
theta = general_ols_matrix(X, y)
end = time.time()

print(f"Execution Time: {(end - start) * 1000:.4f} ms")
print(f"Coefficients: {theta.shape[0]}")

```

Starting OLS on 100 x 10,000 matrix...
 Execution Time: 27564.7745 ms
 Coefficients: 10001

0.0.10 OLS vs. Gradient Descent

1. Ordinary Least Squares (OLS)

- **Mechanism:** Analytical Solution (Math formula jumps straight to the answer).
- **Pros:** Guarantees exact optimal solution; No tuning required.
- **Cons:** Computationally expensive for large datasets. Inverting matrices is slow ($O(n^3)$).
- **Use Case:** Small to medium data.

2. Gradient Descent (GD)

- **Mechanism:** Iterative Optimization (Steps “downhill” to find the bottom).
- **Pros:** Highly scalable; Memory efficient.
- **Cons:** Approximate (converges to optimal); Requires tuning (Learning Rate).
- **Use Case:** Big Data / Deep Learning.

0.0.11 Gradient Descent Implementation

Gradient Descent (Batch)

- **Logic:** Iteratively adjust weights (w) to minimize error.
- **Update Rule:** $w = w - \alpha \cdot \nabla J(w)$
 - α (Alpha): Learning Rate (Step size).
 - ∇J (Gradient): Direction of steepest increase in error.
- **Formula:** $w_{new} = w_{old} - \alpha \cdot \frac{2}{n} X^T (Xw - y)$

```

[87]: def gradient_descent(X, y, lr=0.01, epochs=100):
    m, n = X.shape
    theta = np.zeros(n) # Initialize weights

    for _ in range(epochs):
        prediction = X.dot(theta)
        error = prediction - y
        gradient = (2/m) * X.T.dot(error)

```

```
theta = theta - lr * gradient

return theta
```

```
[88]: # 1. Synthetic Data
n_rows = 100
n_cols = 10**4

X = np.random.randn(n_rows, n_cols)
y = np.random.randn(n_rows)

# 2. Benchmark
print(f"Starting GD on {n_rows:,} x {n_cols:,} matrix ({100} epochs)...")
start = time.time()
theta = gradient_descent(X, y, lr=0.01, epochs=100)
end = time.time()

print(f"Execution Time: {(end - start) * 1000:.4f} ms")
```

```
Starting GD on 100 x 10,000 matrix (100 epochs)...
Execution Time: 26.8526 ms
```