

Linear Regression

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Example 1 - Travel time vs. Distance dataset

| Time (X, hours) | Distance (Y, km) |
|-----------------|------------------|
| 1 | 2 |
| 2 | 4 |
| 3 | 6 |
| 4 | 8 |
| 5 | 10 |
| 6 | |
| 8 | |
| 12 | |

- X = Time (in hours)
- Y = Distance covered (in km)

The relationship is:

$$Y = 2X$$

Example 2 - Advertisement vs. Sales dataset

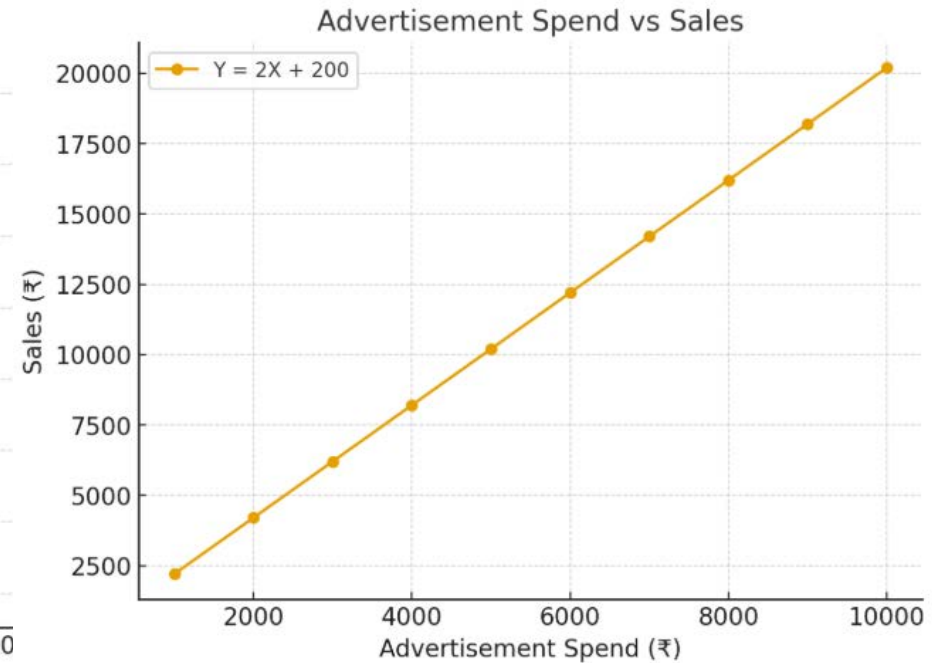
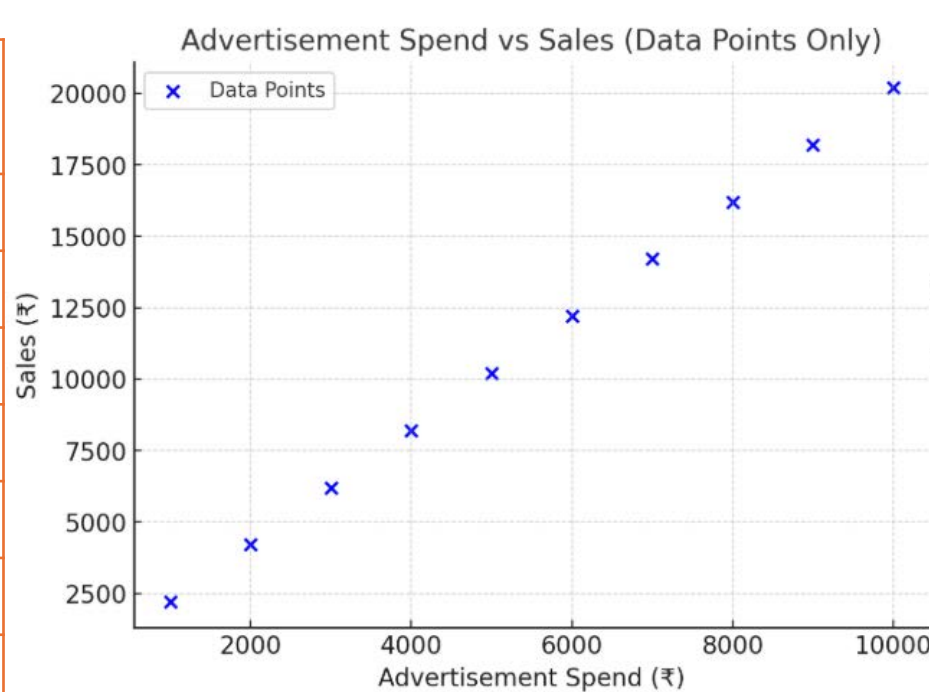
| Advertisement Spend (XX, ₹) | Sales (YY, ₹) |
|--------------------------------|---------------|
| 1000 | 2000 |
| 2000 | 4000 |
| 3000 | 6000 |
| 4000 | 8000 |
| 5000 | 10000 |
| 6000 | 12000 |
| 7000 | |
| 8000 | |
| 9000 | |
| 10000 | |

$$Y = 2X$$

- X = Advertisement spend (₹)
 - Y = Sales revenue (₹)
-

Example 3 - Advertisement vs. Sales dataset

| Advertisement Spend (X, ₹) | Sales (Y, ₹) |
|----------------------------|--------------|
| 1000 | 2200 |
| 2000 | 4200 |
| 3000 | 6200 |
| 4000 | 8200 |
| 5000 | 10200 |
| 6000 | 12200 |
| 7000 | 14200 |
| 8000 | 16200 |
| 9000 | 18200 |
| 10000 | 20200 |



Let's use the **two-point form of a line equation**:

$$y - y_1 = \frac{y_2 - y_1}{x_2 - x_1} (x - x_1)$$

$$(x_1, y_1) = (2000, 4200),$$

$$(x_2, y_2) = (5000, 10200)$$

$$y - 4200 = \frac{10200 - 4200}{5000 - 2000} (x - 2000)$$

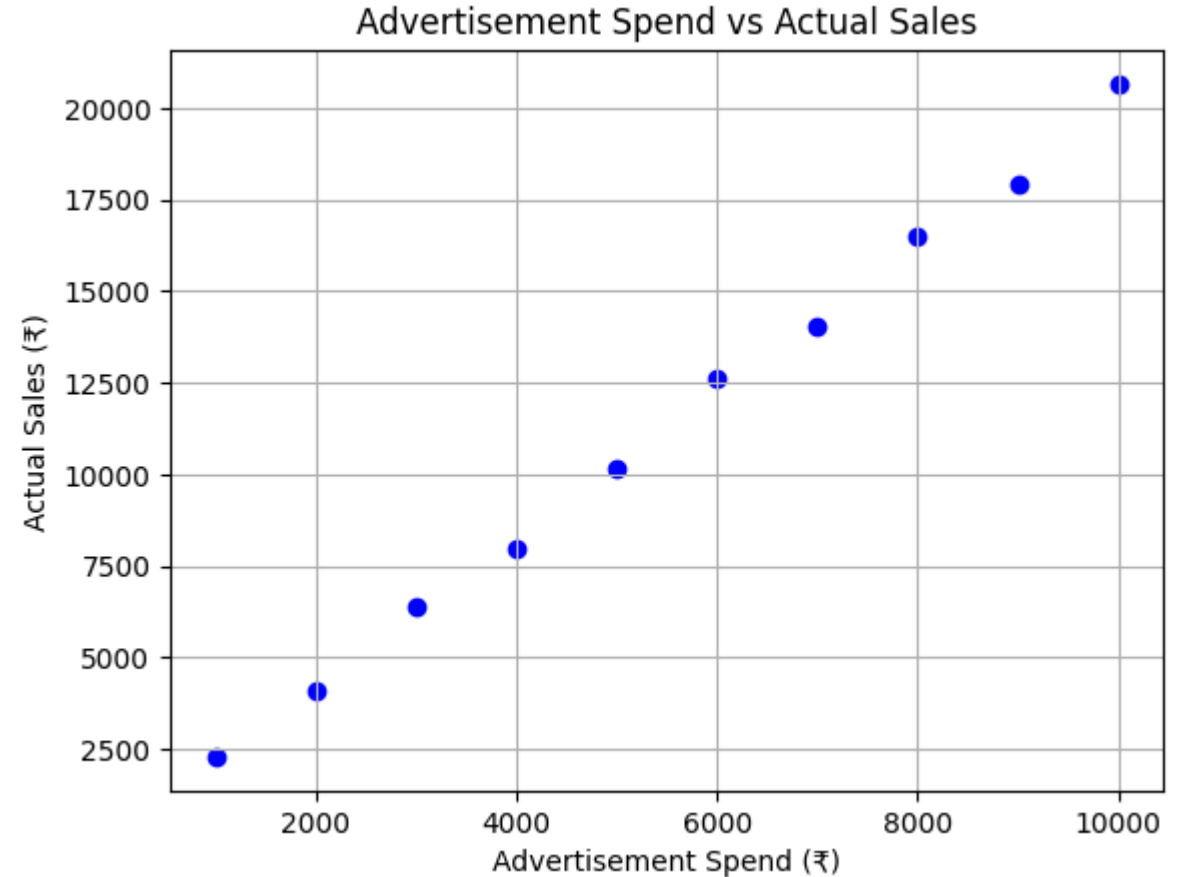
$$y - 4200 = \frac{6000}{3000} (x - 2000)$$

$$y - 4200 = 2(x - 2000)$$

$$y = 2x + 200$$

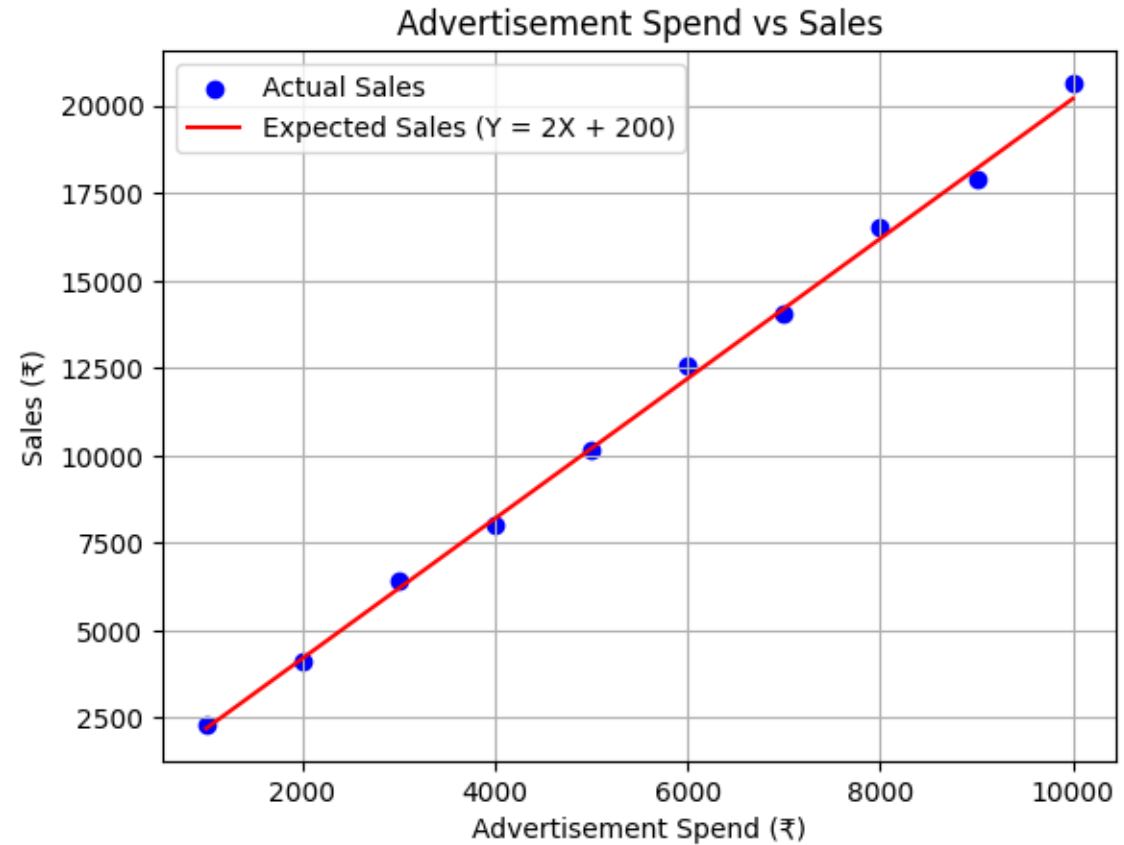
Example 4 - Advertisement vs. Sales dataset

| Advertisement Spend (X, ₹) | Actual Sales (Y, ₹) |
|----------------------------|---------------------|
| 1000 | 2300 |
| 2000 | 4100 |
| 3000 | 6400 |
| 4000 | 8000 |
| 5000 | 10150 |
| 6000 | 12600 |
| 7000 | 14050 |
| 8000 | 16500 |
| 9000 | 17900 |
| 10000 | 20650 |
| 11000 | |
| 120000 | |



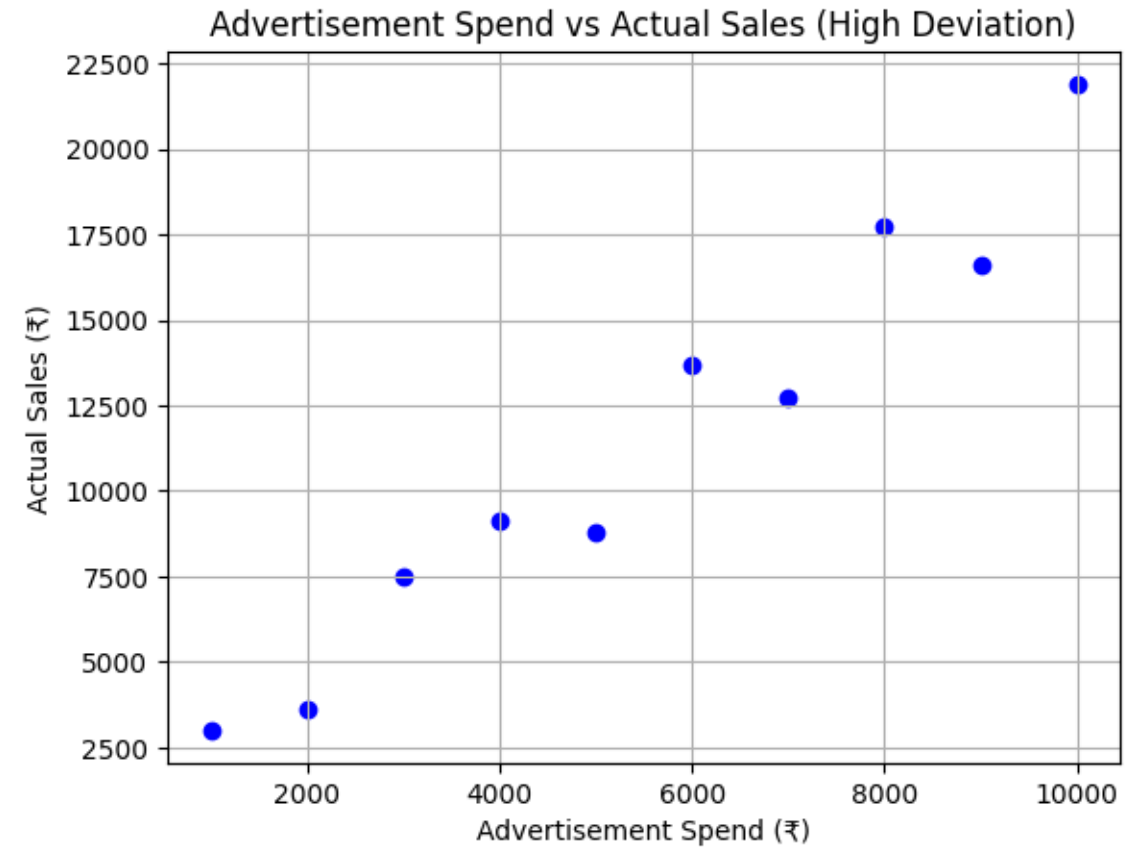
Example 4 - Advertisement vs. Sales dataset

| Advertisement Spend (X, ₹) | Actual Sales (Y, ₹) |
|----------------------------|---------------------|
| 1000 | 2300 |
| 2000 | 4100 |
| 3000 | 6400 |
| 4000 | 8000 |
| 5000 | 10150 |
| 6000 | 12600 |
| 7000 | 14050 |
| 8000 | 16500 |
| 9000 | 17900 |
| 10000 | 20650 |



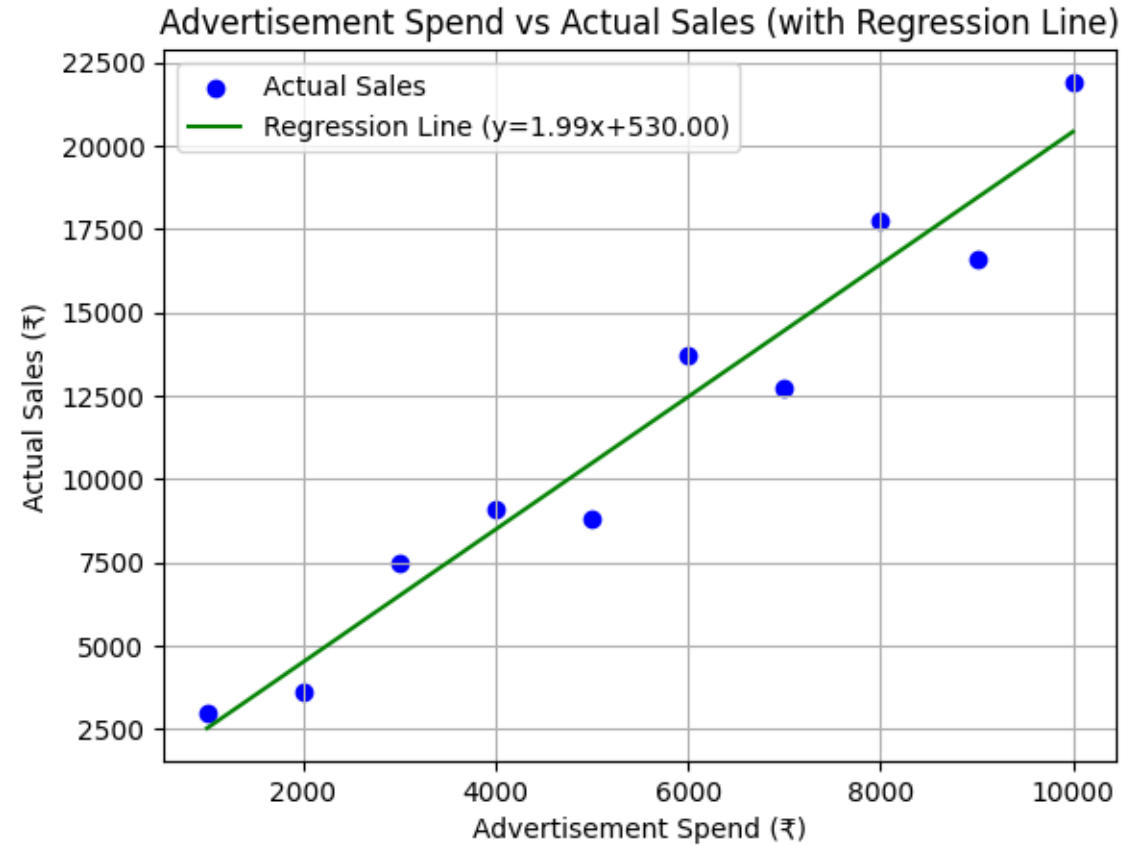
Example 5 - Advertisement vs. Sales dataset

| Advertisement Spend (X, ₹) | Actual Sales (Y, ₹) |
|----------------------------|---------------------|
| 1000 | 3000 |
| 2000 | 3600 |
| 3000 | 7500 |
| 4000 | 9100 |
| 5000 | 8800 |
| 6000 | 13700 |
| 7000 | 12700 |
| 8000 | 17750 |
| 9000 | 16600 |
| 10000 | 21900 |
| 11000 | |
| 12000 | |



Example 5 - Advertisement vs. Sales dataset

| Advertisement Spend (X, ₹) | Actual Sales (Y, ₹) |
|----------------------------|---------------------|
| 1000 | 3000 |
| 2000 | 3600 |
| 3000 | 7500 |
| 4000 | 9100 |
| 5000 | 8800 |
| 6000 | 13700 |
| 7000 | 12700 |
| 8000 | 17750 |
| 9000 | 16600 |
| 10000 | 21900 |
| 11000 | |
| 12000 | |

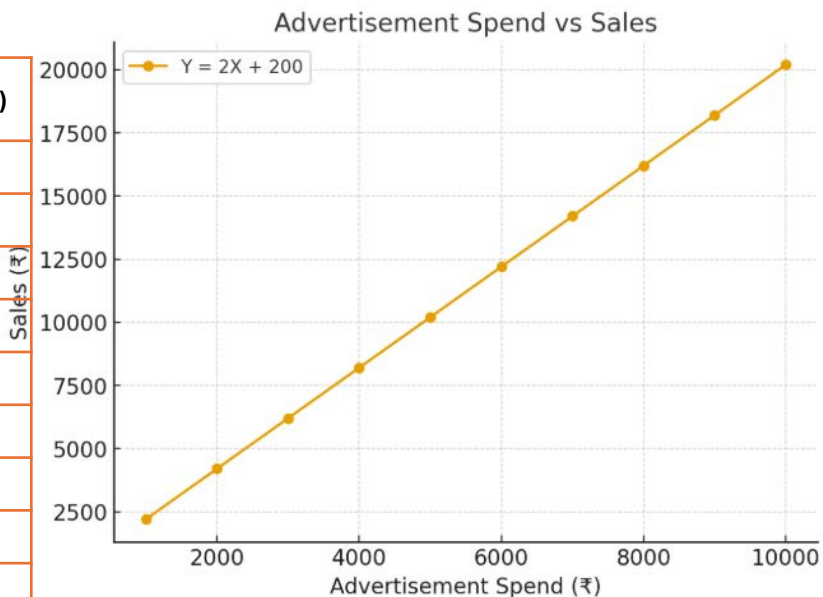


Linear Regression

- When your data points don't lie exactly on a straight line (because of noise, measurement errors, or natural variability), linear regression finds the **best-fit line** that minimizes the error.

Consider these two cases

| Advertisement Spend (X, ₹) | Sales (Y, ₹) |
|----------------------------|--------------|
| 1000 | 2200 |
| 2000 | 4200 |
| 3000 | 6200 |
| 4000 | 8200 |
| 5000 | 10200 |
| 6000 | 12200 |
| 7000 | 14200 |
| 8000 | 16200 |
| 9000 | 18200 |
| 10000 | 20200 |



$$y = 2x + 200$$

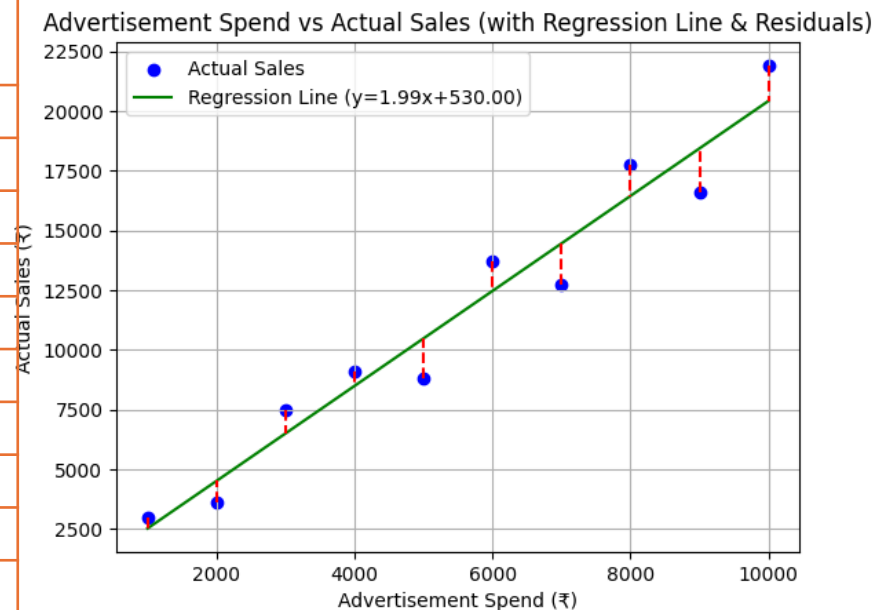
For $X = 4000$:

$$Y = 2(4000) + 200 = 8000 + 200 = 8200$$

For $X = 6000$:

$$Y = 2(6000) + 200 = 12000 + 200 = 12200$$

| Advertisement Spend (X, ₹) | Actual Sales (Y, ₹) |
|----------------------------|---------------------|
| 1000 | 3000 |
| 2000 | 3600 |
| 3000 | 7500 |
| 4000 | 9100 |
| 5000 | 8800 |
| 6000 | 13700 |
| 7000 | 12700 |
| 8000 | 17750 |
| 9000 | 16600 |
| 10000 | 21900 |



$$Y = 1.99X + 530$$

For $X = 4000$:

$$Y = 1.99(4000) + 530 = 7960 + 530 = 8490$$

For $X = 6000$:

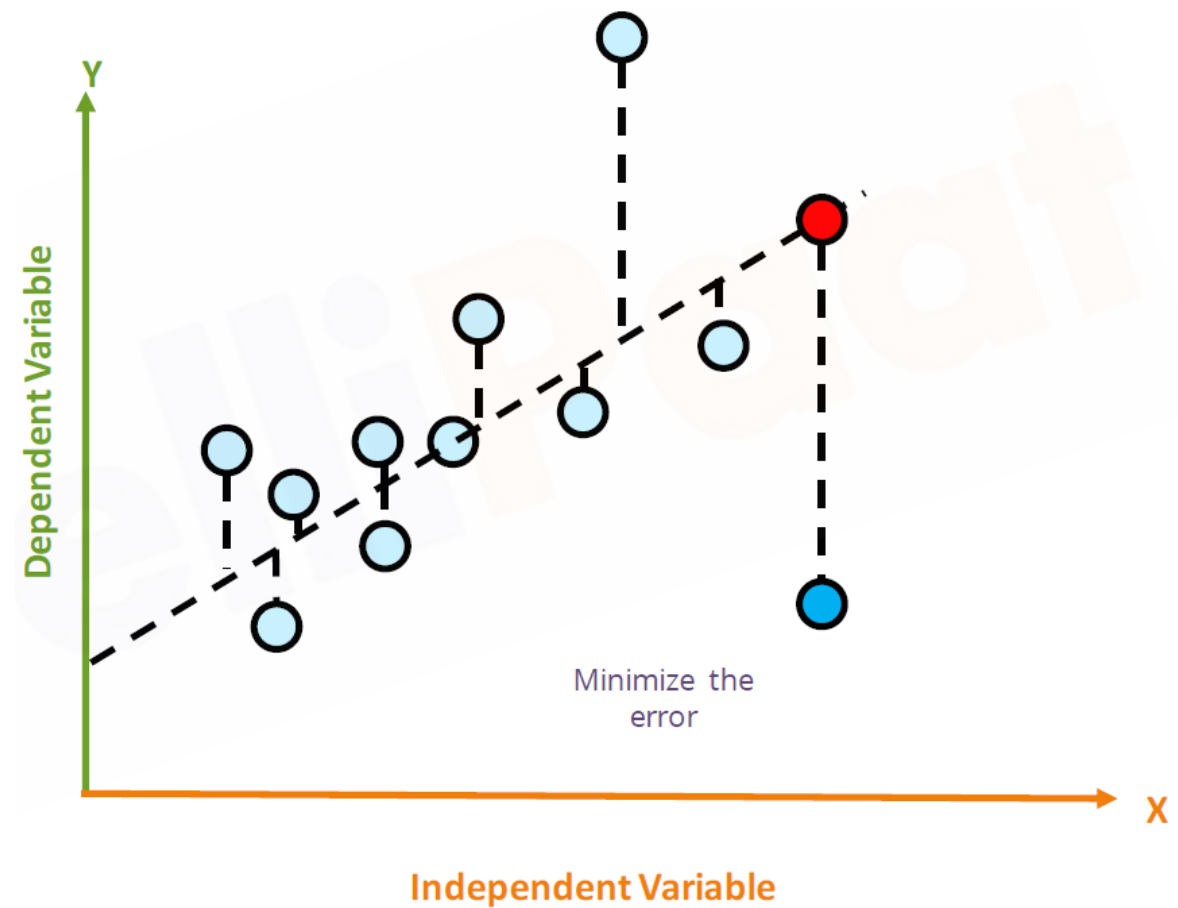
$$Y = 1.99(6000) + 530 = 11940 + 530 = 12470$$

Least Square Fitting

Best Fit Line Equation:

$$\hat{y} = mx + c$$





Error Function (Mean Squared Error):

$$\text{Error} = \frac{1}{n} \sum_{i=1}^n (mx_i + c - y_i)^2$$

Closed form solution for 2-D case

Error Function (Mean Squared Error):

$$\text{Error} = \frac{1}{n} \sum_{i=1}^n (mx_i + c - y_i)^2$$

Set partial derivatives to zero

$$\frac{\partial E}{\partial m} = \frac{2}{n} \sum_{i=1}^n x_i (mx_i + c - y_i) = 0, \quad \frac{\partial E}{\partial c} = \frac{2}{n} \sum_{i=1}^n (mx_i + c - y_i) = 0$$

This gives the normal equations:

$$m \sum x_i^2 + c \sum x_i = \sum x_i y_i$$

$$m \sum x_i + nc = \sum y_i.$$

Solve the 2×2 linear system

Slope ***m*** and intercept ***c*** that minimize the Mean Squared Error

$$m = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2}, \quad c = \bar{y} - m\bar{x}$$

Gradients for Gradient Descent:

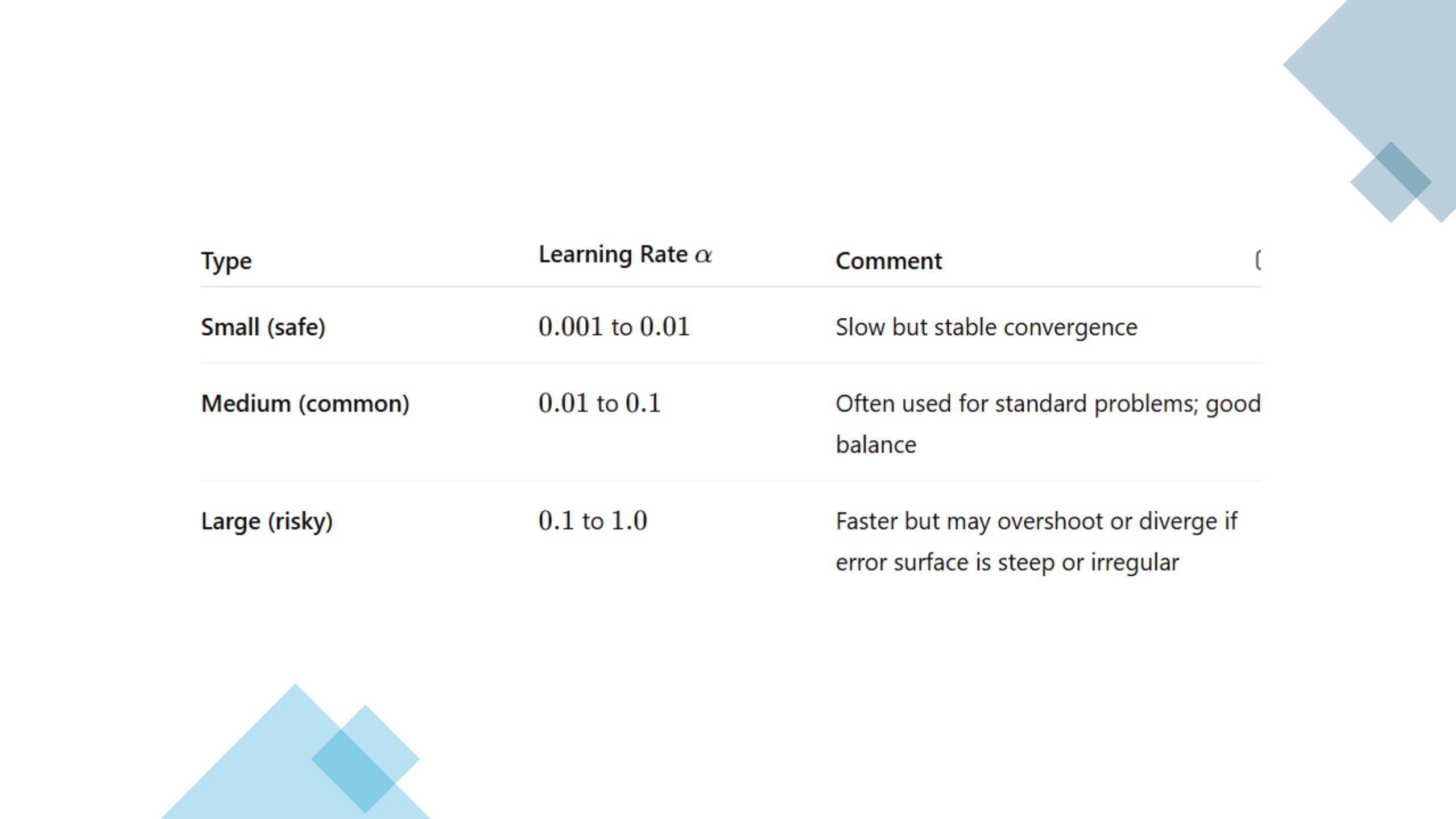
$$\frac{\partial \text{Error}}{\partial m} = \frac{2}{n} \sum_{i=1}^n x_i (mx_i + c - y_i)$$

$$\frac{\partial \text{Error}}{\partial c} = \frac{2}{n} \sum_{i=1}^n (mx_i + c - y_i)$$

Gradient Descent Update Rules:

$$m \leftarrow m - \alpha \cdot \frac{\partial \text{Error}}{\partial m}$$

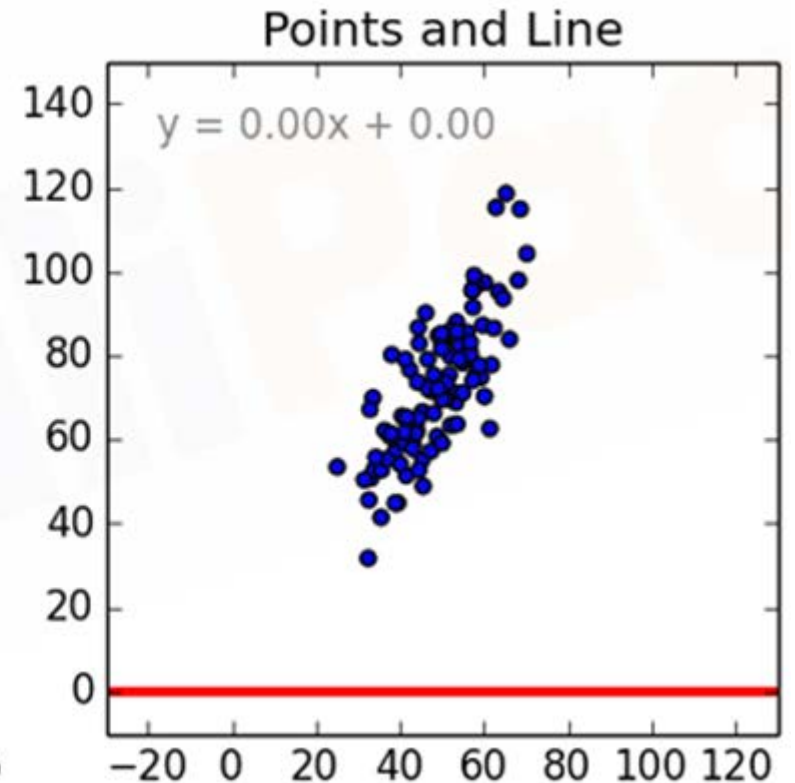
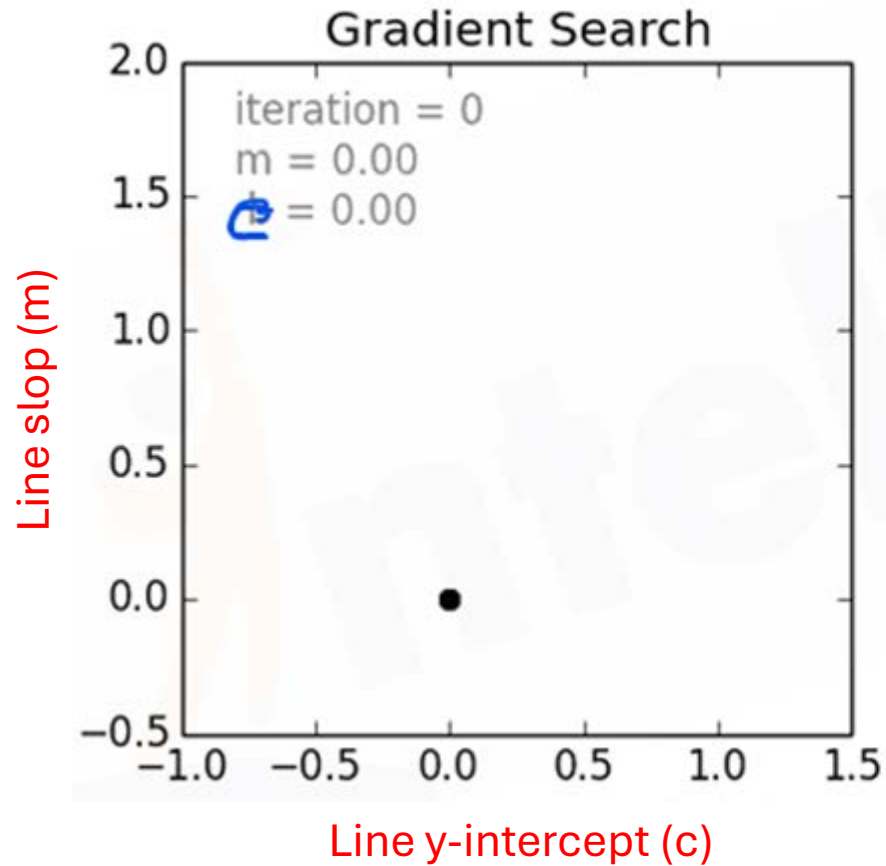
$$c \leftarrow c - \alpha \cdot \frac{\partial \text{Error}}{\partial c}$$



| Type | Learning Rate α | Comment |
|-----------------|------------------------|--|
| Small (safe) | 0.001 to 0.01 | Slow but stable convergence |
| Medium (common) | 0.01 to 0.1 | Often used for standard problems; good balance |
| Large (risky) | 0.1 to 1.0 | Faster but may overshoot or diverge if error surface is steep or irregular |

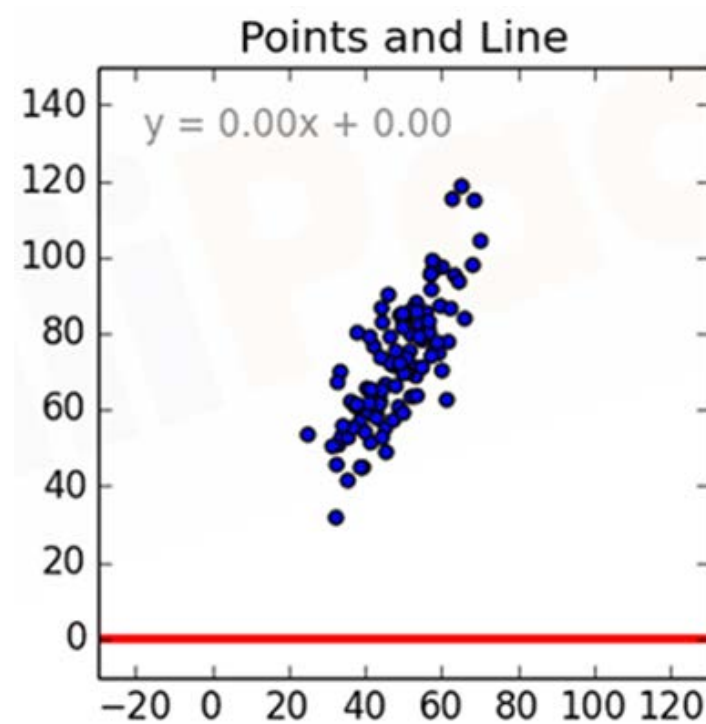
$$m \leftarrow m - \alpha \cdot \frac{\partial \text{Error}}{\partial m}$$

$$c \leftarrow c - \alpha \cdot \frac{\partial \text{Error}}{\partial c}$$

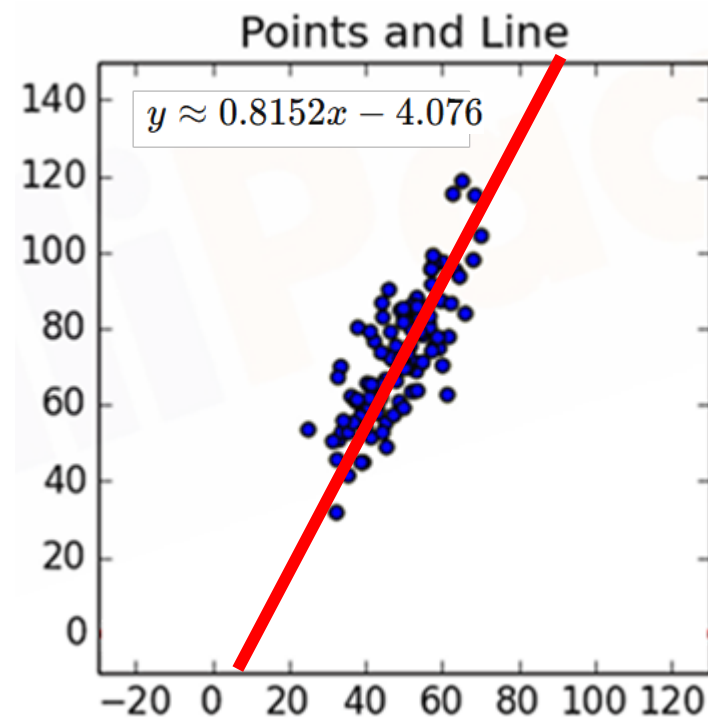


$$m \leftarrow m - \alpha \cdot \frac{\partial \text{Error}}{\partial m}$$

$$c \leftarrow c - \alpha \cdot \frac{\partial \text{Error}}{\partial c}$$



Initial



Final