# Gradient Descent Analysis Summary

Summary of Gradient Descent Analysis  
  
This analysis explored how gradient descent was applied to a simple linear regression problem using a small dataset:

x = [1, 2, 3, 4, 5] and y = [5, 7, 9, 11, 13].

The objective was to fit a straight line of the form y = mx + b that minimizes the mean squared error (MSE) between the predicted and actual values.

## How the Gradient Descent Works

Gradient descent is an iterative optimization algorithm. At each step (or epoch), the algorithm:  
- Calculates the cost (i.e., the prediction error),

- Computes the gradient (partial derivatives of the cost with respect to m and b),

- Adjusts the parameters m (slope) and b (intercept) against the gradient direction to reduce the cost.

This iterative process continues for a defined number of iterations (e.g., 100) or until the cost reaches a stable low value.

Why the Gradient and Cost Change Over Time

Initially, the model predictions are far from the true values, so:

- The cost is high,

- The gradients are large, which leads to larger updates to m and b.

As the model improves:  
- The error shrinks,

- The gradients get smaller, resulting in smaller updates,

- This stabilizes the values of m and b, indicating that the model is approaching the optimal line.

This change in gradient size is key: large gradients push parameters quickly in the right direction, while smaller gradients fine-tune the model as it gets closer to the solution. This behavior is visible in the convergence plots.

Interpreting the Controls (Hyperparameters)

Two hyperparameters control this behavior:

- Learning rate (α): Controls how much the weights are updated per iteration. A smaller rate leads to slower convergence; a larger one risks overshooting or diverging.

- Number of iterations: Determines how many updates the model will make. Too few and the model underfits; too many may waste computation once the cost plateaus.

- learning\_rate = 0.08 provided a good balance—fast learning without instability,

- iterations = 100 was sufficient to observe convergence, as seen in the cost vs. iteration plot

### What Observed from the Visualizations

1. Cost Curve:

The plot of cost over iterations clearly shows a downward slope, indicating that the model is learning and error is reducing with time.

2. Final Line Fit:

The best-fit line y = 2.00x + 3.00 exactly matches the underlying pattern of the data, proving the effectiveness of the optimization.

3. Convergence of m and b:

These plots show how each parameter evolved over time. Both started at 0 and gradually approached their optimal values. Their curves flattened toward the end, showing the model reached a stable solution.

### Conclusion

Gradient descent is powerful for fitting models by minimizing error step-by-step. This experiment shows how initial errors are corrected through controlled updates to parameters, and how fine-tuning occurs as we get closer to the optimal line.

By monitoring the cost, parameters, and their convergence, we gain insights into how the model learns. The final model performs very well, validating that gradient descent—when properly configured—can produce highly accurate results even with a small dataset.