summarizing the **theory, visuals, and formulas** behind **Mini-Batch Stochastic Gradient Descent with Momentum**, and how it reduces noise during optimization.

Background: Why We Need Momentum in Mini-Batch SGD

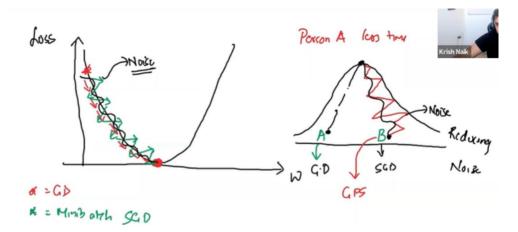
- Mini-Batch SGD introduces noise due to randomness in small batches.
- This leads to **fluctuating updates**, causing instability and slow convergence.

Left Plot (Image 1):

- Red path (α): Gradient Descent (GD) stable but slower.
- Green path (x): Mini-Batch SGD faster but noisy.

Right Plot (Image 1):

- Two persons climbing a hill:
 - o **Person A (GD)** slow, stable path.
 - o Person B (SGD) faster, but noisy.
 - If we give GPS (guidance = momentum), Person B will reach faster and smoother.



SGD with Momentum

Formula:

$$w_t = w_{t-1} - \eta \cdot rac{\partial L}{\partial w_{t-1}}$$

But instead of using raw gradients, we add momentum to smooth the path.

► Concept of Exponential Weighted Average

Key Formula:

$$V_t = eta V_{t-1} + (1-eta)a_t$$

- a_t = current value (e.g., gradient)
- $\beta \in [0,1)$ = smoothing factor (common: 0.9 or 0.95)
- It gives more weight to recent history, smoothing noisy updates.

Example:

$$V_2 = \beta a_1 + (1 - \beta)a_2$$

$$V_3 = \beta V_2 + (1 - \beta)a_3$$

Exponential Weighted Average in SGD

For weights and bias:

$$w_t = w_{t-1} - \eta \cdot V_{dw}$$
 , $b_t = b_{t-1} - \eta \cdot V_{db}$

Where:

$$V_{dw_t} = eta V_{dw_{t-1}} + (1-eta) \cdot rac{\partial L}{\partial w_{t-1}}$$

$$V_{db_t} = eta V_{db_{t-1}} + (1-eta) \cdot rac{\partial L}{\partial b_{t-1}}$$

Implementation Steps

Initialization:

$$ullet$$
 Set $V_{dw}=0$, $V_{db}=0$

On every iteration (inside epoch):

- **1.** Compute gradients: dw, db
- 2. Update:

$$V_{dw} = eta V_{dw} + (1-eta) \cdot dw$$

$$V_{db} = eta V_{db} + (1-eta) \cdot db$$

3. Apply to weights:

$$w = w - \eta \cdot V_{dw}$$
 , $b = b - \eta \cdot V_{db}$

Summary

Concept	Description
Problem	Mini-batch SGD is fast but noisy
Solution	Use momentum to smooth updates
Key Technique	Exponential Weighted Average
Hyperparameter	β=0.9\beta = 0.9 or 0.950.95
Result	Faster and smoother convergence, better minima