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# STOCHASTIC GRADIENT DESCENT

**REPORT** 

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### GitHub Repo Link: arsalmairaj2k/Stochastic-Gradient-Descent-SGD

### Title: Stochastic Gradient Descent for Linear Regression

**Introduction:** Stochastic Gradient Descent (SGD) is a powerful optimization technique used in machine learning to minimize loss functions efficiently. This report summarizes the implementation and key concepts of using SGD for Linear Regression as outlined in the provided Jupyter Notebook in the GitHub Repository.

**Objective:** The primary goal of this notebook is to implement Linear Regression using SGD, demonstrating how it iteratively updates weights to minimize the error between predicted and actual values.

### **Key Concepts:**

- 1. **Linear Regression:** A statistical method for modeling the relationship between a dependent variable and one or more independent variables.
- 2. **Gradient Descent:** An optimization algorithm that updates parameters iteratively to minimize the cost function.
- 3. **Stochastic Gradient Descent:** Unlike Batch Gradient Descent, which updates parameters after computing the gradient for the entire dataset, SGD updates parameters for each training example, making it computationally efficient for large datasets.

#### **Implementation Details:**

- Dataset Preparation: The dataset is loaded and preprocessed for training.
- Hypothesis Function: The linear regression model is defined as:  $y=\theta_0+\theta_1x$
- Loss Function: The Mean Squared Error (MSE) is used to measure the difference between predicted and actual values.
- **Gradient Update Rule:**  $\theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial J / \partial \theta j$  where  $\alpha \setminus \theta j = \theta j \alpha \times \partial$
- **Training Process:** The model iteratively updates parameters using SGD until convergence.

#### **Results and Observations:**

- The model successfully learns optimal parameters through multiple iterations.
- The learning rate impacts convergence speed and accuracy.

• The implementation demonstrates the efficiency of SGD in handling large datasets compared to batch processing.

**Conclusion:** This notebook effectively demonstrates how SGD can be used to train a Linear Regression model. The method provides a scalable solution for large datasets while maintaining good performance. Future enhancements could include tuning hyperparameters like the learning rate and implementing mini-batch gradient descent for improved stability.