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Optimal single-path information propagation in gradient-based algorithms

In linear regression problems, the objective is to determine a parameter vector that minimizes the mean squared error between observed and predicted values. Two widely used techniques are the Moore-Penrose pseudoinverse and the Gradient Descent method, which differ in their numerical approach and the way they reach the solution.

The Moore-Penrose pseudoinverse provides an exact solution through the direct computation of $(X^T X)^{-1} X^T y$, offering accurate results when datasets are small or the matrices are well conditioned. However, its application becomes less efficient and more prone to numerical instability as the dataset size increases or when the matrix is nearly singular.

Gradient Descent, on the other hand, is an iterative produce that adjusts the model coefficients in the direction of the negative gradient of the cost function, gradually reducing the error with each iteration. It does not require matrix inversion and is suitable for large-scale datasets or situations where the system's structure prevents a closed from solution. Its performance depends on the learning rate and the number of iterations

Comparative results show that the pseudoinverse provides greater accuracy and stability in small scale problems, while Gradient Descent excels in efficiency and scalability, particularly in large systems or machine learning contexts. In both case, the methods thend to converge to the same optimal solution under proper computational coditions.

Rendimiento de algoritmos de gradiente

Distribuidos en entornos dinamicos

Objetivo

Desarrollar el algoritmo BIS Gradient

- rapides
- Precision
- Reduccion de errores
- Suavidad

RESULTADO

Metodologia

Modelado Matematico
- Simulaciones

Conclusion

BIS Gradiente Entornos

- IoT
- Redes de sensores
- Sistemas Autoorganizados