Foundations of Machine Learning Al2000 and Al5000

FoML-21 Logistic Regression - Newton Raphson optimization

> <u>Dr. Konda Reddy Mopuri</u> Department of AI, IIT Hyderabad July-Nov 2025





So far in FoML

- Intro to ML and Probability refresher
- MLE, MAP, and fully Bayesian treatment
- Supervised learning
 - a. Linear Regression with basis functions (regularization, model selection)
 - b. Bias-Variance Decomposition (Bayesian Regression)
 - c. Decision Theory three broad classification strategies
 - Probabilistic Generative Models Continuous & discrete data
 - (Linear) Discriminant Functions least squares solution, Perceptron
 - Probabilistic Discriminative Models Logistic Regression





Logistic Regression - IRLS





Loss function approximation

Taylor series expansion (univariate case)

$$E(w + \Delta w) =$$





Loss function approximation

Taylor series expansion (multivariate case)

$$E(\mathbf{w} + \Delta \mathbf{w}) =$$





Linear (first-order) approximation

$$E(\mathbf{w} + \Delta \mathbf{w}) \approx E(\mathbf{w}) + \Delta \mathbf{w}^T \nabla E(\mathbf{w})$$





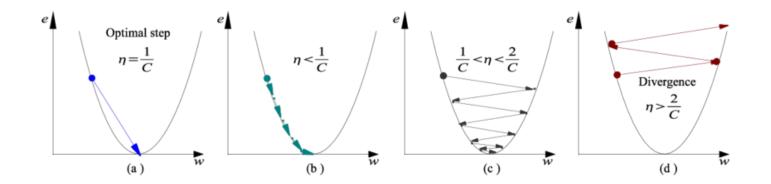
Quadratic (second-order) approximation

$$E(\mathbf{w} + \Delta \mathbf{w}) \approx E(\mathbf{w}) + \Delta \mathbf{w}^T \nabla E(\mathbf{w}) + \frac{1}{2} \Delta \mathbf{w}^T \nabla^2 E(\mathbf{w}) \Delta \mathbf{w}$$





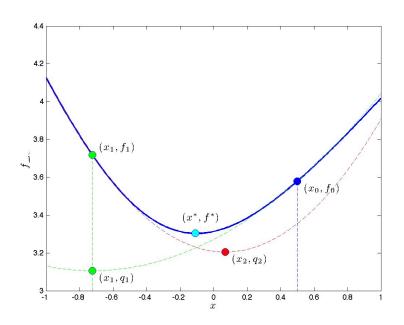
Convergence for Quadratic functions







Generic Convex functions







Newton-Raphson Iterative optimization

$$\mathbf{w}^{t+1} = \mathbf{w}^t - \mathbf{H}^{-1} \nabla E(\mathbf{w}^t)$$

$$\nabla E(\mathbf{w})^T = \sum_{n=1}^N (y_n - t_n)\phi_n =$$





Newton-Raphson Iterative optimization

$$\mathbf{w}^{t+1} = \mathbf{w}^t - \mathbf{H}^{-1} \nabla E(\mathbf{w}^t)$$

$$\mathbf{H}_{ij} = \frac{\partial^2 E(\mathbf{w}^t)}{\partial \mathbf{w}_i \partial \mathbf{w}_j} = \frac{\partial}{\partial \mathbf{w}_i} \sum_{n=1}^{N} (y_n - t_n) \phi_j(\mathbf{x}_n) = 0$$





Newton-Raphson Iterative optimization

$$\mathbf{w}^{t+1} = \mathbf{w}^t - \mathbf{H}^{-1} \nabla E(\mathbf{w}^t)$$

$$\mathbf{w}^{t+1} = \mathbf{w}^t - (\Phi^T R \Phi)^{-1} \Phi^T (\mathbf{y} - \mathbf{t})$$

$$= (\Phi^T R \Phi)^{-1} \Phi^T R \mathbf{z}$$



Next Neural Networks



