

Homework 3

Description

We have been looking at the Logistic Model form

$$L(\mathbf{x}_1, \dots, \mathbf{x}_N | \theta) = \log \prod_{i=1}^N \prod_{l=1}^K p(\mathbf{x}_i | \mathbf{w}_l)^{I\{\mathbf{x}_i \in \omega_l\}}$$

Although its power is somewhat limited, we can still have fun with it by going beyond the canonical solution. Take a look at the jupyter notebook provided for you at

- https://github.com/kajuna0amendez/Class_MachineLearning_Jax/tree/main/notebook/Class_05

There you have a Jax canonical logistic implementation.

Homework

1. You need to implement the regularization version of the Logistic Regression

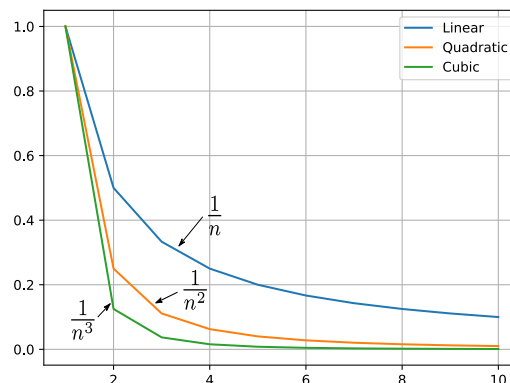
$$L(\mathbf{x}_1, \dots, \mathbf{x}_N | \theta) = \log \prod_{i=1}^N \prod_{l=1}^K p(\mathbf{x}_i | \mathbf{w}_l)^{I\{\mathbf{x}_i \in \omega_l\}} + \lambda \text{trace}(W^T W)$$

$$\text{s.t. } W = \begin{pmatrix} \mathbf{w}_1 & \cdots & \mathbf{w}_k \end{pmatrix}$$

You will implement:

- (a) The search for the λ hyper-parameter.
 - (b) The Quasi-Newton Method described at the notes to accelerate the algorithm.
 - (c) The linear search for the learning rate parameter.
2. Remember the data set
 - https://www.openml.org/search?type=data&sort=nr_of_likes&status=any&id=1590 (Instructions to load it are being provided)

Using accuracy and recall you will compare the classic and Newton algorithms convergency rates as the one show in the figure:



3. In the Robbins-Monro (Stochastic Gradient Descent) proof, we have some stuff that was left to you to do:

(a) Prove that if $Pr[y_n \leq y | \mathbf{w}_n] = H(y | \mathbf{w}_n)$ a distribution then if

$$e_n = E \left[\int_{-\infty}^{\infty} (y - \alpha)^2 dH(y | \mathbf{w}_n) \right]$$

i. Now, assuming that exist C such that (i.e. zero out of the range $[-C, C]$)

$$Pr[|Y(\mathbf{w})| \leq C] = \int_{-C}^C dH(y | \mathbf{w}) = 1 \quad \forall x$$

Then, we have that $0 \leq e_n \leq [C + |\alpha|^2] < \infty$