Lecture Notes for **Machine Learning in Python**

Logistic Regression

Optimization

Agenda

- Lab 1 general feedback
- Numerical Optimization Techniques
 - Types of Optimization
 - Programming the Optimization

Whirlwind Lecture Alert

- Entire classes cover these concepts in expanded form
- But we can cover them in one lecture to get a good intuition!
- And then you can look over this even more for better understanding.
- If you feel confused after this lecture, that's okay.
 These are not easy the first time you see them. Keep going, you got this.

Last time

$$p(y^{(i)} = 1 \mid x^{(i)}, w) = \frac{1}{1 + \exp(w^T x^{(i)})}$$

$$l(w) = \sum_{i} \left(y^{(i)} \ln[g(w^{T} x^{(i)})] + (1 - y^{(i)}) (\ln[1 - g(w^{T} x^{(i)})]) \right)$$

$$\underbrace{w_j}_{\text{new value}} \leftarrow \underbrace{w_j}_{\text{old value}} + \eta \underbrace{\sum_{i=1}^{m} (y^{(i)} - g(x^{(i)})) x_j^{(i)}}_{\text{gradient}}$$

$$w \leftarrow w + \eta \sum_{i=1}^{M} (y^{(i)} - g(x^{(i)}))x^{(i)}$$

$$w \leftarrow w + \eta \left[\underbrace{\nabla l(w)_{old} - C \cdot 2w}_{\text{old gradient}} \right]$$

def _get_gradient(self,X,y):
 # programming \sum_i (yi-g(xi))xi
 gradient = np.zeros(self.w_.shape) # set
 for (xi,yi) in zip(X,y):
 # the actual update inside of sum
 gradi = (yi - self.predict_proba(xi,
 # reshape to be column vector and ad
 gradient += gradi.reshape(self.w_.sh
return gradient/float(len(y))

Professor Eric C. Larson

Demo Lecture

06. Optimization

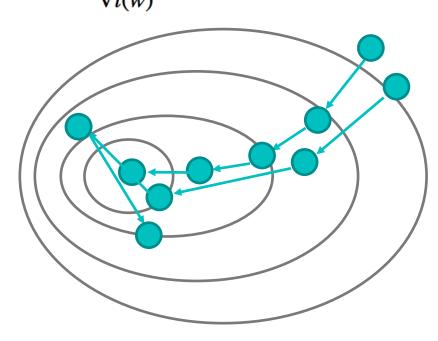


Optimization: gradient descent

What we know thus far:

$$\underbrace{w_j}_{\text{new value}} \leftarrow \underbrace{w_j}_{\text{old value}} + \eta \underbrace{\left[\left(\sum_{i=1}^{M} (y^{(i)} - g(x^{(i)}))x_j^{(i)}\right) - C \cdot 2w_j\right]}_{\nabla l(w)}$$

$$w \leftarrow w + \eta \nabla l(w)$$



Line Search: a better method

Line search in direction of gradient:

$$w \leftarrow w + \eta \nabla l(w)$$

$$w \leftarrow w + \underbrace{\eta}_{\text{best step?}} \nabla l(w)$$

Stochastic Methods

How much computation is required (for gradient)?

$$\sum_{i=1}^{M} (y^{(i)} - \hat{y}^{(i)}) x^{(i)} - 2C \cdot w$$

$$w \leftarrow w + \eta \underbrace{\left((y^{(i)} - \hat{y}^{(i)}) x^{(i)} - 2C \cdot w \right)}_{\text{approx. gradient}},$$

i chosen at random

