# Advanced Machine Learning

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#### What is optimization in deep learning?

The goal of traditional optimization algorithms is to minimize the cost function *J.* 

In deep learning, we care more about some performance measure P, which is measured on some test data. Indirectly, we are trying to optimize P and reduce the cost function  $J^*$  in the hope that it will reduce P.

$$J^*(\boldsymbol{\theta}) = \mathbb{E}_{(\boldsymbol{x}, \mathbf{y}) \sim p_{\text{data}}} L(f(\boldsymbol{x}; \boldsymbol{\theta}), y)$$

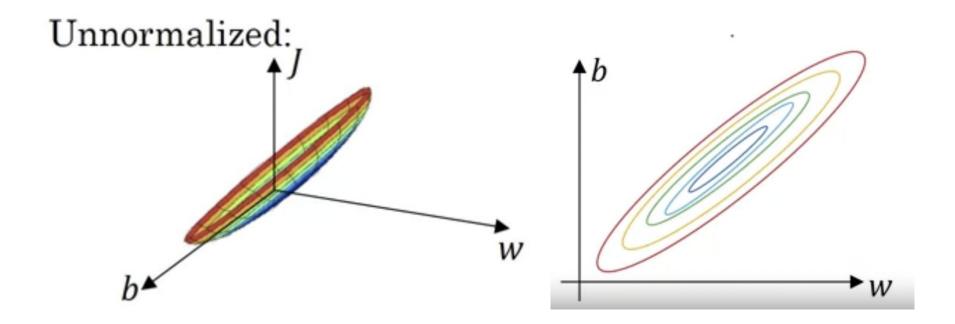
### Empirical risk minimization

When we don't know  $p_{data}$ , we try to minimize the loss over a set of training examples:

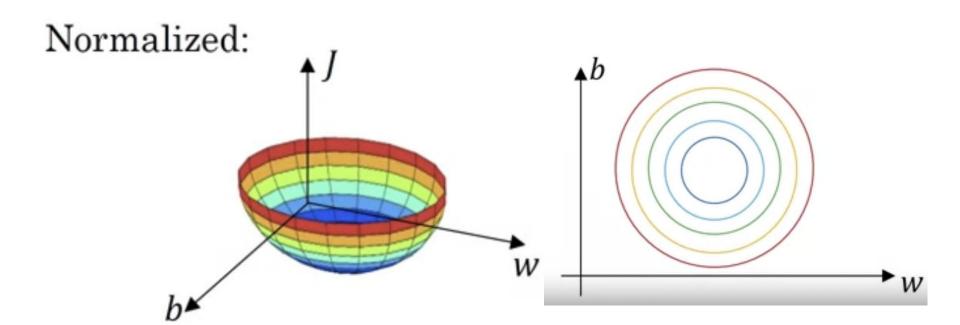
$$\mathbb{E}_{\boldsymbol{x}, \mathbf{y} \sim \hat{p}_{\text{data}}(\boldsymbol{x}, y)}[L(f(\boldsymbol{x}; \boldsymbol{\theta}), y)] = \frac{1}{m} \sum_{i=1}^{m} L(f(\boldsymbol{x}^{(i)}; \boldsymbol{\theta}), y^{(i)})$$

This is called **empirical risk minimization -** works by minimizing the average training error

# Normalizing inputs



# Normalizing inputs



#### Zero-one loss function

One of the simplest loss functions which literally counts the number of mistakes made by the learned function *h*:

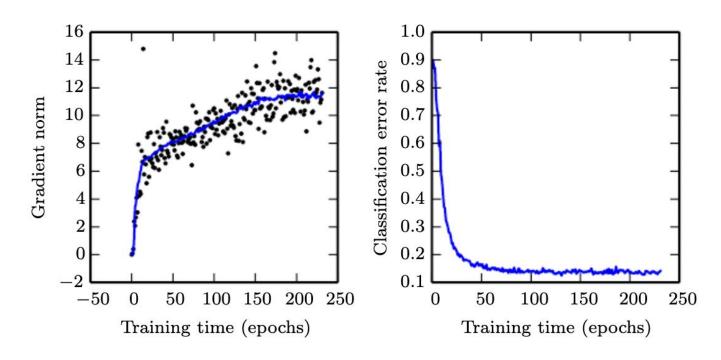
$$\mathcal{L}_{0/1}(h) = rac{1}{n} \sum_{i=1}^n \delta_{h(\mathbf{x}_i) 
eq y_i}, ext{ where } \delta_{h(\mathbf{x}_i) 
eq y_i} = egin{cases} 1, & ext{if } h(\mathbf{x}_i) 
eq y_i \ 0, & ext{o.w.} \end{cases}$$

#### Minibatch Optimization

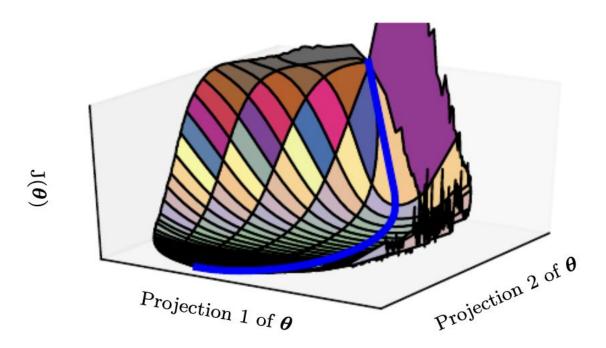
$$J(\boldsymbol{\theta}) = \mathbb{E}_{\mathbf{x}, \mathbf{y} \sim \hat{p}_{\text{data}}} \log p_{\text{model}}(\boldsymbol{x}, y; \boldsymbol{\theta})$$

- 1. Less accurate than full-batch optimization
- 2. Faster than full-batch optimization
- 3. Efficient utilizes multicore architectures
- 4. Regularizing effect

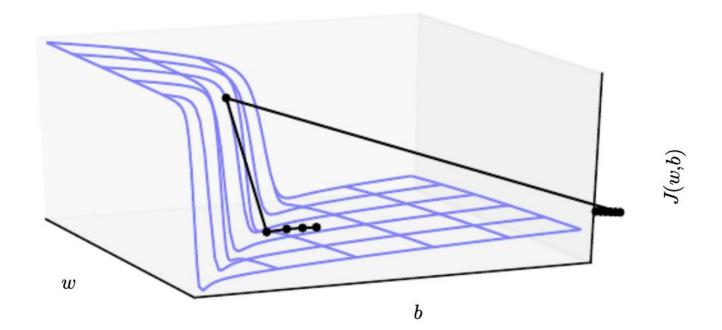
#### 1. III-Conditioning



2. Non-convex optimization



3. Cliffs and exploding gradients



4. Initialization of "descent" algorithms

