Hyperparameter Tuning, Regularization, Optimization

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Tuning Process

- Choose parameter combinations (points) at random in a space
- 2 parameters - grid
- 3 parameters - cube
- Coarse to fine sampling
  - Sample densely within a region with better parameter combinations
  - Coarse sample of all combinations

Scale to pick hyperparameters

- Use a log scale to range α for example
  - Set $r \in [a.b]$
  - Then $\alpha \in [10^a, 10^b]$ satisfying the range
- Hyperparameters for exponentially weighted averages
  - Set $r \in [a, b]$
  - $1 - \beta = 10^r$
  - $\beta = 1 - 10^r$
  - Sampling regime important, as small changes change the values in Adam optimization largely

Pandas vs. Caviar

- Babysitting one model
  - Adjust hyperparameters one day at a time while observing performance
  - Can't train many models at once
  - Panda approach
- Train many models in parameter with different hyperparameter settings
  - Caviar approach

Normalizing Activations

- $\mu = \frac{1}{M} \sum_i x^{(i)}$
- $x = x - \mu$
- $\sigma^2 = \frac{1}{m} \sum_i x^{2(i)}$
- $x = x / \sigma$
- Makes contours more circular, beneficial for gradient descent
- Batch normalization $\rightarrow$ normalize $a^{[2]}$ to train $w^{[3]}, b^{[3]}$ faster

- Normalize the values of $z^{[2]}$ instead of $a^{[2]}$
- Implementing Batch Norm
  - Given intermediate NN values $z^{(1)}, \ldots, z^{(i)}$

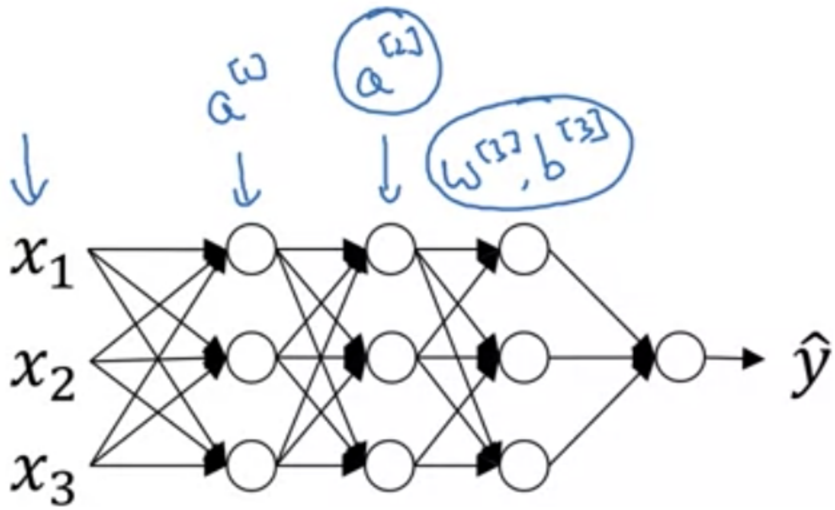

Figure 1: Batch norm

        * $\mu = \frac{1}{M}\sum_i x^{(i)}$
        * $\sigma^2 = \frac{1}{m}\sum_i (z_i - \mu)^2$
        * $z^{(i)}_{\text{norm}} = \frac{z^{(i)} - \mu}{\sqrt{\sigma^2 + \epsilon}}$
    - $\tilde{z}^{(i)} = \gamma z^{(i)}_{\text{norm}} + \beta$
        * These are hyperparameters which allow for adjustment of $z^{(i)}_{\text{norm}}$
    - Use $\tilde{z}^{[l](i)}$ instead of $z^{[l](i)}$

Fitting Batch Norm into network

- Example computation for first layer

$$x \overset{w^{[1]},b^{[1]}}{\rightarrow} z^{[1]} \overset{\beta^{[1]},\gamma^{[1]}}{\rightarrow} \tilde{z}^{[1]} \rightarrow a^{[1]} = g^{[1]}(\tilde{z}^{[1]})$$

- Repeat for each layer
- Parameters are $W^{[k]}, b^{[k]}, \beta^{[k]}, \gamma^{[k]}$ for $k \in [1, L]$ are the parameters
- Working with mini-batches
    - Conduct batch norm for each minibatch (i.e. starting with $X^{\{1\}}$)
    - Batch norm only uses examples from the current minibatch
- $b^{[l]}$ gets subtracted out in the mean subtraction step, so **eliminate this parameter, is redundant**
    - Simply remove from the subtraction
- Implementing gradient descent
    - For $t \in [1, \text{numMiniBatch}]$
        * Compute forward prop on $X^{\{t\}}$
            · In each hidden layer, use batch norm
        * Use backprop to calculate $dw^{[l]}, d\beta^{[l]}, d\gamma^{[l]}$ and update parameters

Batch norm reasoning

- Conducts input normalization but for hidden units
- Makes deeper weights robust to changes in weights of earlier layers
- Learning on shifting input distribution → covariant shift

  - If X distribution changes, must retrain for $X \to Y$ mapping, so values input to a hidden layer change
  - Batch norm reduces this effect, layers are more independent
- Batch norm as regularization
  - Each minibatch scaled by mean/variance of the examples in it
  - Adds noise to $z^{[l]}$, so adds noise to hidden layer activations similar to dropout
  - Has slight regularization effect, but with a larger minibatch size this is reduced

Batch Norm at Test Time

- Need to estimate μ, σ^2 at test time using weighted average across minibatches
- Calculate $\mu^{\{1\}l}, \ldots, \mu^{\{n\}l}$, using a moving average, same for σ^2