# Neural Networks

Deep Neural Network for 3-way Classification

$$h_i^{\text{layer }l} = \phi \left( \sum_j w_{ji}^{(\text{layer }l)} \cdot h_j^{(\text{layer }l-1)} \right)$$

- L := hidden layers -  $h^{(l)} :=$  activations at layer l -  $w^{(l)} :=$  weights taking activations from layer l - 1 to l -  $\phi :=$  nonlinear activation function - Must be nonlinear because otherwise hidden layers are collapsed - Last layer is still just a logistic regression - Prev layers just learn the 'features' of input

## Rectified Linear Unit (ReLU)

$$\phi(z) = \max(0, z)$$

- Type of nonlinear activation function - Commonly used

## Training Neural Networks

• Just like logistic regression:

$$\max_{w} ll(w) = \max_{w} \sum_{i} \log \mathbb{P}(y^{(i)}|x^{(i)};w)$$

- Just w tends to be a much larger vector - Just run gradient ascent and stop when log likelihood of hold-out data starts to decrease - Algorithm: 1. Initialize w 2. Repeat:  $w \leftarrow w + \alpha * \sum_i \nabla \log \mathbb{P}(y^{(i)}|x^{(i)};w) - \alpha := \text{learning rate (generally small)}$ 

#### Computing Derivatives

- Automatic differentiation exists
- Relatively quick with backpropagation

### Neural Network Properties

- Theorem (Universal Function Approximators) := a two-layer neural network with a sufficient number of neurons can approximate any continuous function to any desired accuracy
- Can be seen as learning the features
- Large number of neurons can cause overfitting

### Preventing Overfitting

- - Good because w can grow without constraint
  - Use a constraint hyperparameter  $\lambda$  (typically 0.1 to 0.0001 or smaller)

$$\max_{w} \sum_{i} \log \mathbb{P}(y^{(i)}|x^{(i)};w) - \frac{\lambda}{2} \sum_{j} w_{j}^{2}$$

## Simplicity

- Reduce the hypothesis/model space
  - Assume more
  - Fewer features or neurons
  - Other limits on model structure
- Regularization

- Laplace smoothing
  Weight regularization
  Hypothesis state stays big, but harder to get to outskirts