One-Hot Encoding

$$\begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

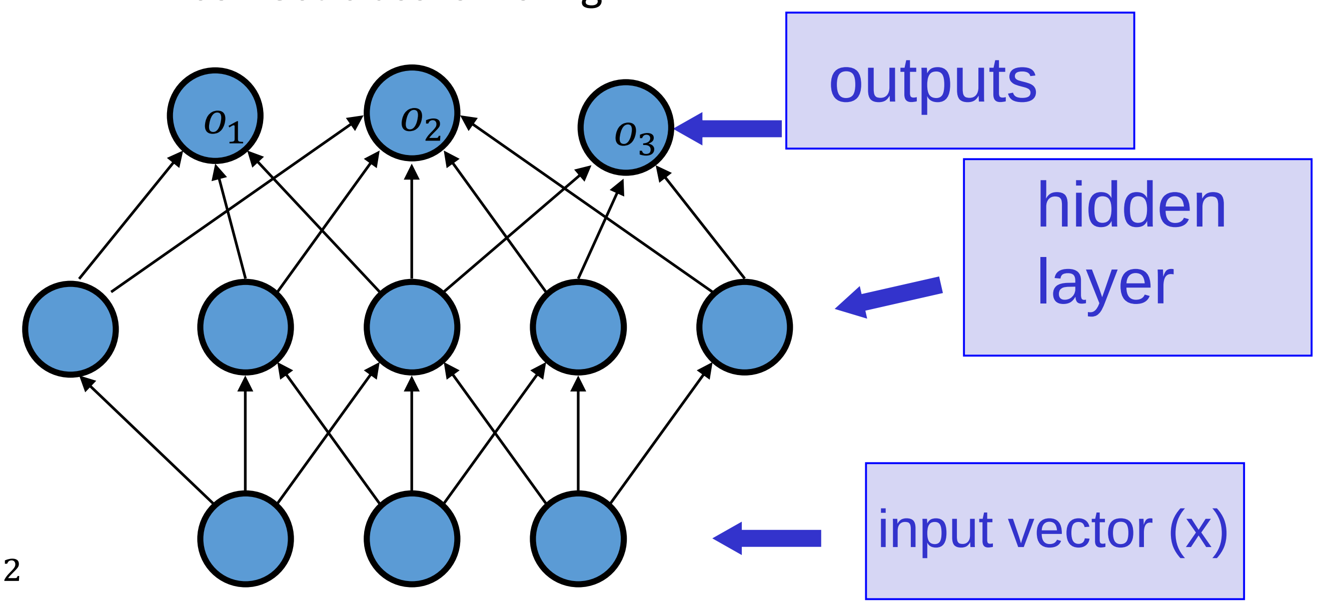
$$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

One-Hot Encoding

- Data: $\left(x^{(1)}, y^{(1)}\right), \left(x^{(2)}, y^{(2)}\right), \dots \left(x^{(n)}, y^{(n)}\right)$
- E.g., $y^{(i)} \in \{\text{"person"}, \text{"hamster"}, \text{"capybara"}\}$
- Encode as $y^{(i)} \in \{1, 2, 3\}$?
  - Shouldn't be running something like linear regression, since "hamster" is not really the average of "person" and "capybara," so things are not likely to work well
    (Explanation on the board)
- Solution: one-hot encoding
  - "person" => [1, 0, 0]
  - "hamster" => [0, 1, 0]
  - "capybara" => [0, 0, 1]

Multilayer Neural Network for Classification

o_i is large if the probability that the correct class is *i* is high



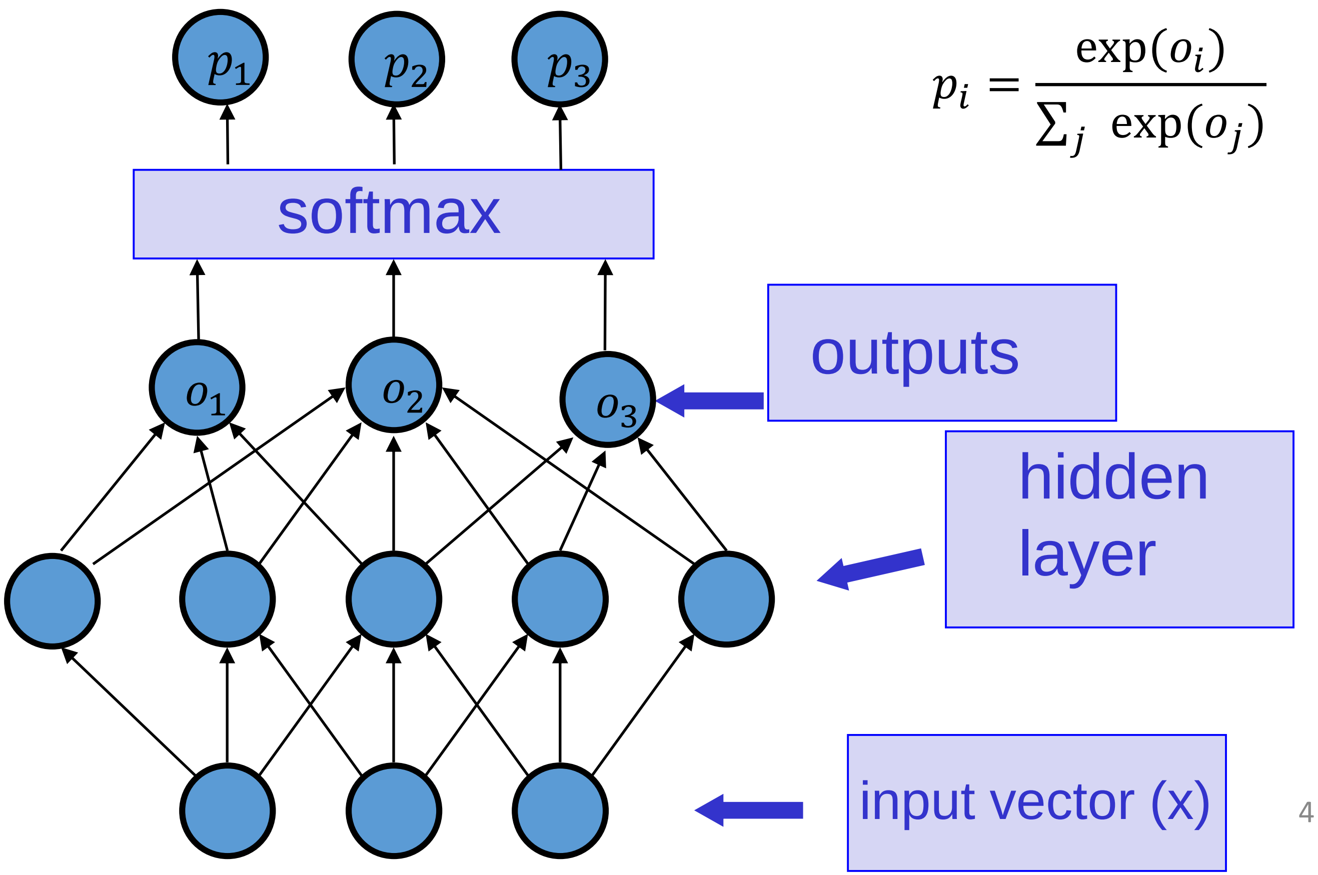
A possible cost function:

$$\sum_{i=1}^{m}\left(o^{(i)} - y^{(i)}\right)^2$$

${y^{(i)}}'s$ encoded using one-hot encoding

Softmax

- Want to estimate the probability $P(y = y' | x, \theta)$
  - θ: network parameters



$$p_i = \frac{\exp(o_i)}{\sum_j \exp(o_j)}$$

Softmax

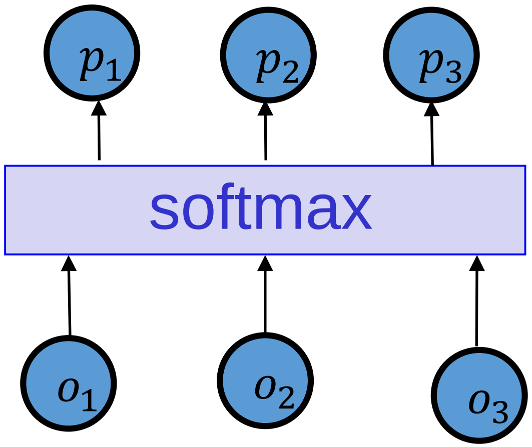
- $p_i = \frac{\exp(o_i)}{\sum_j \exp(o_j)}$ can be thought of as probabilities
  - $0 < p_i < 1$
  - $\sum_j p_j = 1$
  - This is a generalization of logistic regression
    - (For two outputs, $p_1 = \frac{\exp(o_1)}{\exp(o_1)+\exp(o_2)} = \frac{1}{1+\exp(o_2-o_1)}$)

Cost Function: $-\sum_j \ y_j log p_j$

- Likelihood (single training case): $P(y_j = 1; x|w)$
  - The probability for $y_j = 1$ that the network outputs with weights w
- The likelihood of $y = (0, \ldots, 0, 1, 0, 0, \ldots, 0)$ is p_j, where j is the index of the non-zero entry in y
  - Same as $\Pi_j p_j^{y_j}$
- Negative log-likelihood (single training case)
  - $-\sum_j \ y_j log p_j$

Cost Function Gradient

$$p_i = \frac{e^{o_i}}{\sum_j e^{o_j}}$$



$$\frac{\partial p_i}{\partial o_i} = p_i\,(1 - p_i)$$

$$C = -\sum_j y_j \log p_j$$

$$\frac{\partial C}{\partial o_i} = \sum_j \frac{\partial C}{\partial p_j} \frac{\partial p_j}{\partial o_i} = p_i - y_i$$