

Note: This is the summary note from Udacity Introduction to Deep Learning with PyTorch

Softmax

- Problem: multi-classification
- Solution: satisfy probability, here are two criterias
 - Total sum of the scores need to be one
 - The higher the score the higher the probability
- How?

- Use Softmax function: Turns $\frac{\text{score}}{\text{sum of all scores}}$ to positive number with exponential
- Assume we have linear function score: $z_1 + z_2 + \dots + z_n$
So the Softmax function for probability of class i is

$$P(\text{class } i) = \frac{e^{z_i}}{e^{z_1} + e^{z_2} + \dots + e^{z_n}}$$

One Hot Encoding

- Input data will not always looks like number
- Solution: turn data to number, One Hot Encoding
- How:
 - To avoid dependencies between data we create table of data in which 1 represent correct data input while 0 for the rest of incorrect data

Maximum Likelihood

- Pick the model that give existing labels the highest probability
- The best model more likely be give highest probability to the event that happens to the true label (ground-truth)
- Maximize probability -> get best model
- How:
 - Start with bad model
 - Calculate probability of each point
 - $P = \text{Multiple (Product) the probability of each point}$
 - Find way to maximize P

Maximizing Probabilities

- Probability is important
- Maximize probability --> minimized the error function
- Problem with product
 - Hard when have thousands data point
 - The number is small between 0 to 1
 - If change 1 data point => the whole product change drastically
- Solution
 - Do sum by using log

Cross Entropy

- Resolve product problem above by using log
 $\log(ab) = \log(a) + \log(b)$;

Note: if $\log(x)$ provide negative value, we need to take the

$$\log(1) = \log(0)$$

Products

$$0.6 * 0.2 * 0.1 * 0.7 = 0.0084$$

$$\ln(0.6) + \ln(0.2) + \ln(0.1) + \ln(0.7)$$

$$-0.51 \quad -1.61 \quad -2.3 \quad -0.36$$



$$0.7 * 0.9 * 0.8 * 0.6 = 0.3024$$

$$\ln(0.7) + \ln(0.9) + \ln(0.8) + \ln(0.6)$$

$$-0.36 \quad -0.1 \quad -0.22 \quad -0.51$$

$$-\ln(0.6) - \ln(0.2) - \ln(0.1) - \ln(0.7) = 4.8$$
$$0.51 \quad 1.61 \quad 2.3 \quad 0.36$$

$$-\ln(0.7) - \ln(0.9) - \ln(0.8) - \ln(0.6) = 1.2$$
$$0.36 \quad 0.1 \quad 0.22 \quad 0.51$$

Cross Entropy

- The sum of negative of log of probability -> Cross Entropy
- The bad model give high cross entropy
- The good model give low cross entropy
- Goal is to minimize the cross entropy**
- Connection between probability and error function:
 - Events
 - Probability
 - Cross Entropy

- How often the events happens based on probability
 - if it's likely --> small cross entropy
 - If it's unlikely --> large cross entropy
- Formula :

$$Cross\ Entropy = - \sum_{i=1}^m y_i \ln(p_i) + (1 - y_i) \ln(1 - p_i)$$

Y label

P = probability that event occur

Multi class cross entropy

- Problem: what if we have multiple class?
- $Cross\ Entropy = - \sum_{i=1}^n \sum_{j=1}^m y_{ij} \ln(p_{ij})$
 - m is number of classes

Mini summary:

- Softmax function used for multi-class
- One Hot encoding is used when input data is not numeric
- Maximized probability: pick the model that give existing labels the highest probability
- Cross Entropy is connection between probability and error function.
- How often the events happens based on probability
 - if it's likely --> small cross entropy
 - If it's unlikely --> large cross entropy