CSE4261: Neural Network and Deep Learning

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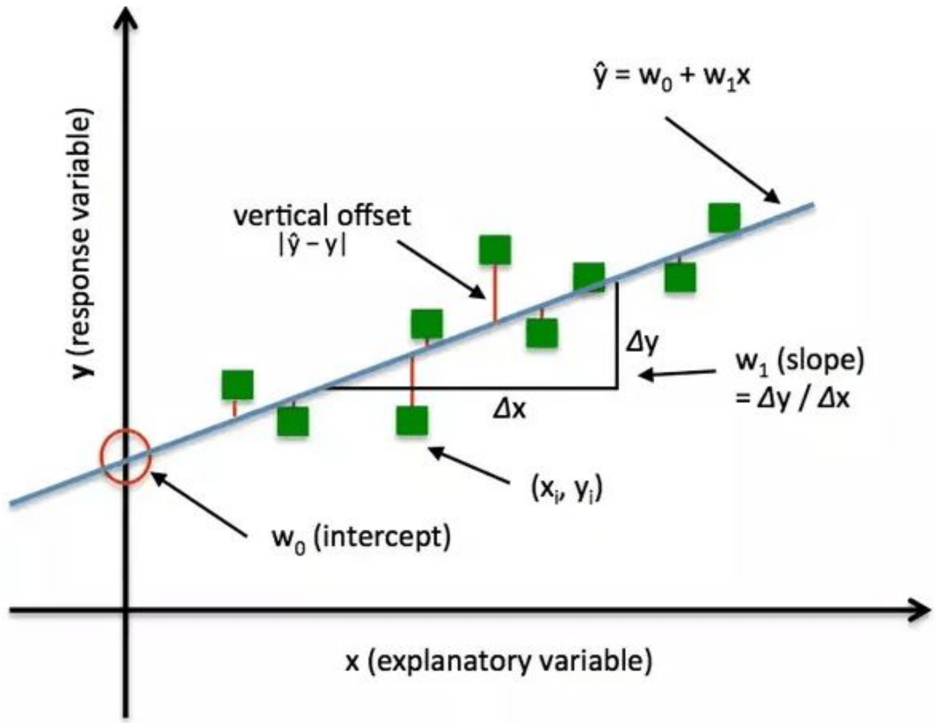
Sangeeta Biswas, Ph.D.
Associate Professor,
University of Rajshahi, Rajshahi-6205, Bangladesh

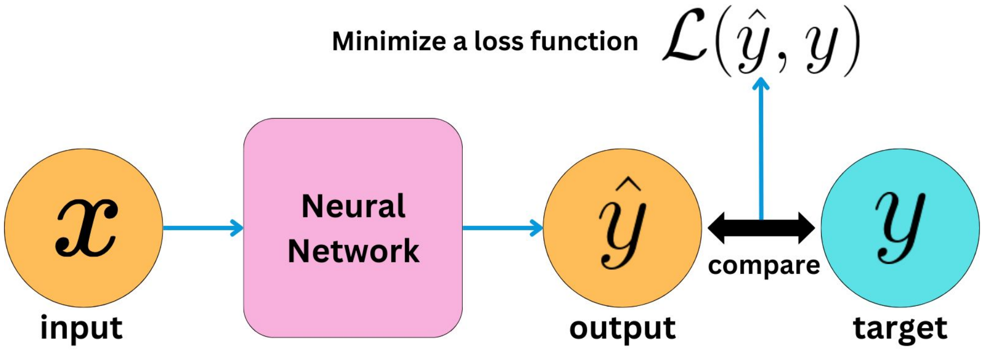
Loss

- Error is a measurement of the difference between the predicted output of the model and the actual output.
- Loss is the weighted error.
- Different types of loss:
  - Absolute loss: $|\hat{y} - y|$
  - Squared loss: $(\hat{y} - y)^2$
  - Log loss: $- y.\log(\hat{y})$



Loss Function

- A loss function is a function which estimates the total loss of all data samples.
- It is used to find optimum values of parameters of a neural network during training.
- It is a function of parameters.
- Different ways of writing:
    - $J(\omega)$; $L(\theta|x)$; $\ell(\omega)$; $\mathcal{L}(\hat{y} - y)$;



Different Loss Functions

Different loss functions penalizes wrong predictions differently

<u>Popular losses:</u>

- Regression:
  - Mean-Squared Error (MSE)
  - Mean Absolute Error (MAE)

- Classification:
  - Binary Cross-Entropy
  - Categorical Cross-Entropy
  - Focal Cross-Entropy
  - Hinge Loss

L1 & L2 Loss

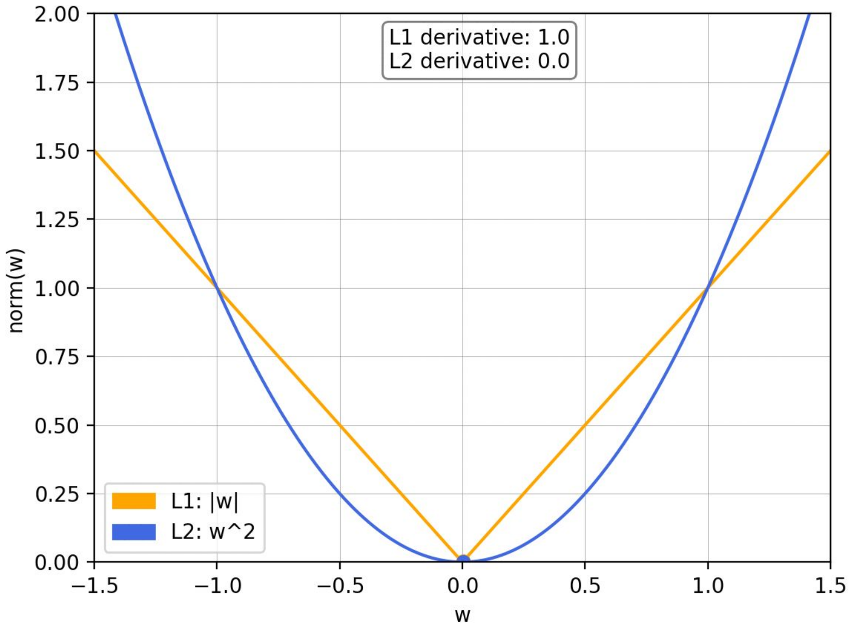
- Absolute Loss is also known as L1 loss
- Squared Error Loss is also known as L2 loss

$$L_1 = \sum_{i=1}^{n} |y_{gt} - y_{pred}|$$

$$L_2 = \sum_{i=1}^{n} (y_{gt} - y_{pred})^2$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_{gt} - y_{pred}|$$

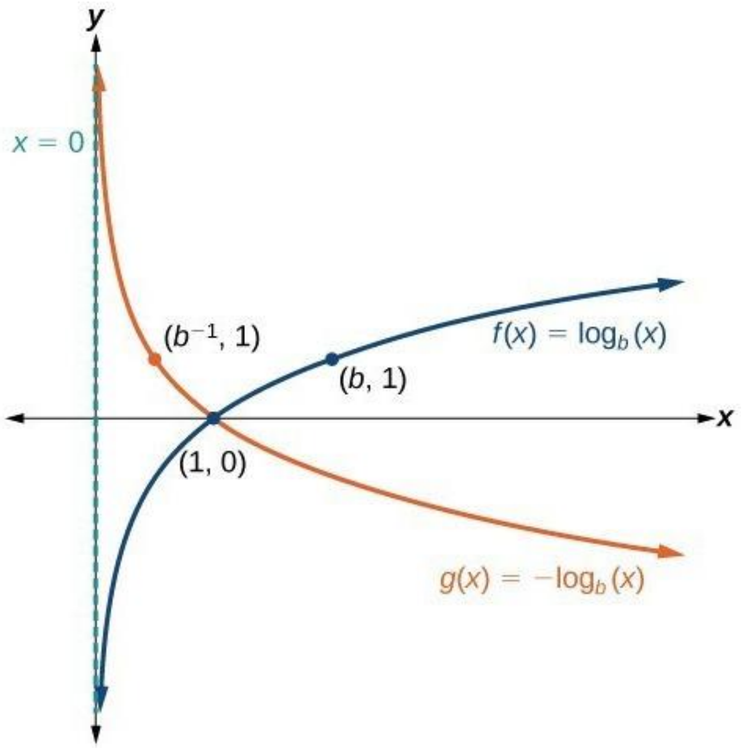
$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_{gt} - y_{pred})^2$$



Negative Log

$g(x) = -\log_b(x)$

- domain $(0,\infty)$
- range, $(-\infty,\infty)$
- vertical asymptote $x = 0$



Entropy

Entropy:

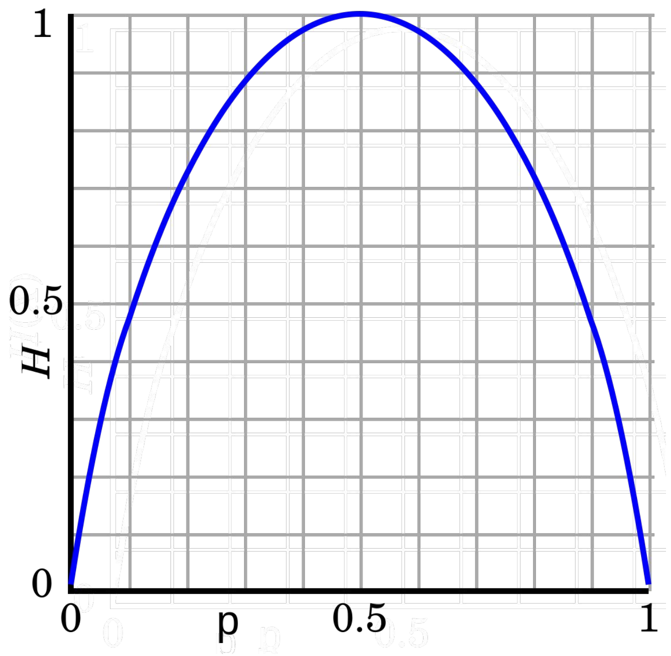
- $H(p) = -\Sigma\ p\_i \times log(p\_i)$
- the average amount of "surprise" or uncertainty associated with a random variable.

Entropy vs Cross-Entropy:

- Entropy measures the inherent uncertainty or randomness of a single distribution
- Cross-entropy measures the difference between two probability distributions.
    - $H(P, Q) = -P \times log(Q)$

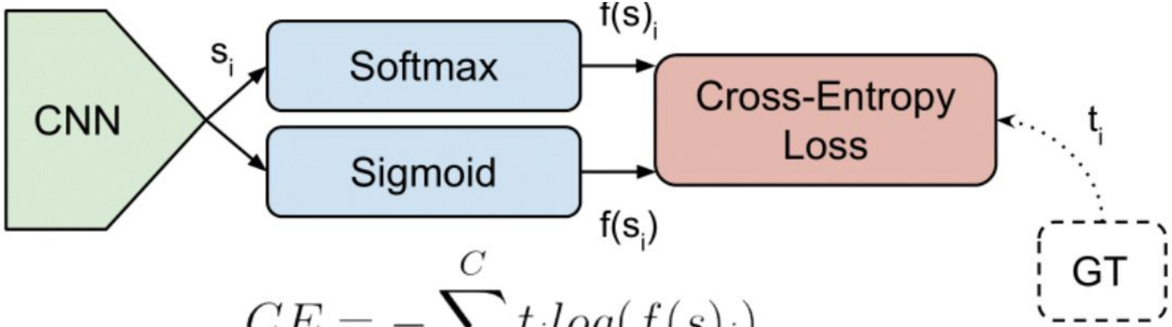
Binary Cross-Entropy:

- $H(p) = -p \times log(p) + (1-p) \times log(1-p)$



Cross-Entropy Loss

- It is also known as Cross-entropy log loss
- It is based on the probability of a model's output

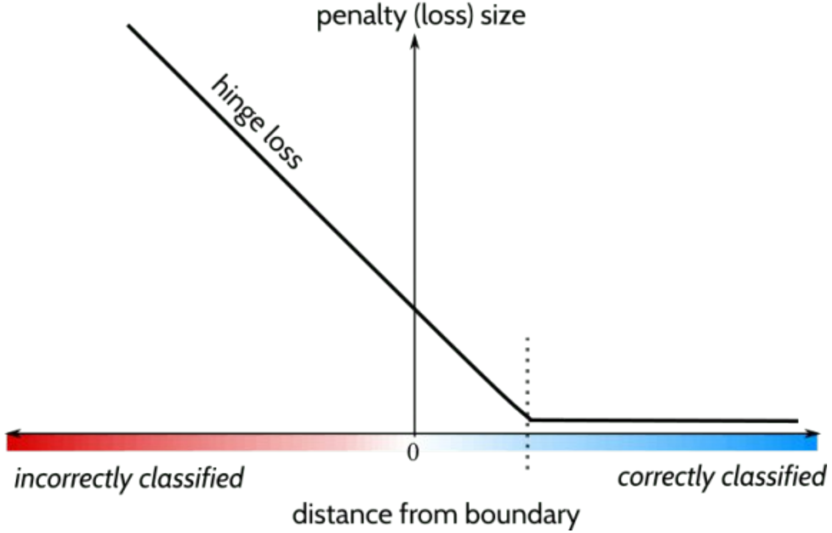


$$CE = -\sum_{i}^{C} t_i log(f(s)_i)$$

$$CE = -\sum_{i=1}^{C'=2} t_i log(f(s_i)) = -t_1 log(f(s_1)) - (1 - t_1) log(1 - f(s_1))$$

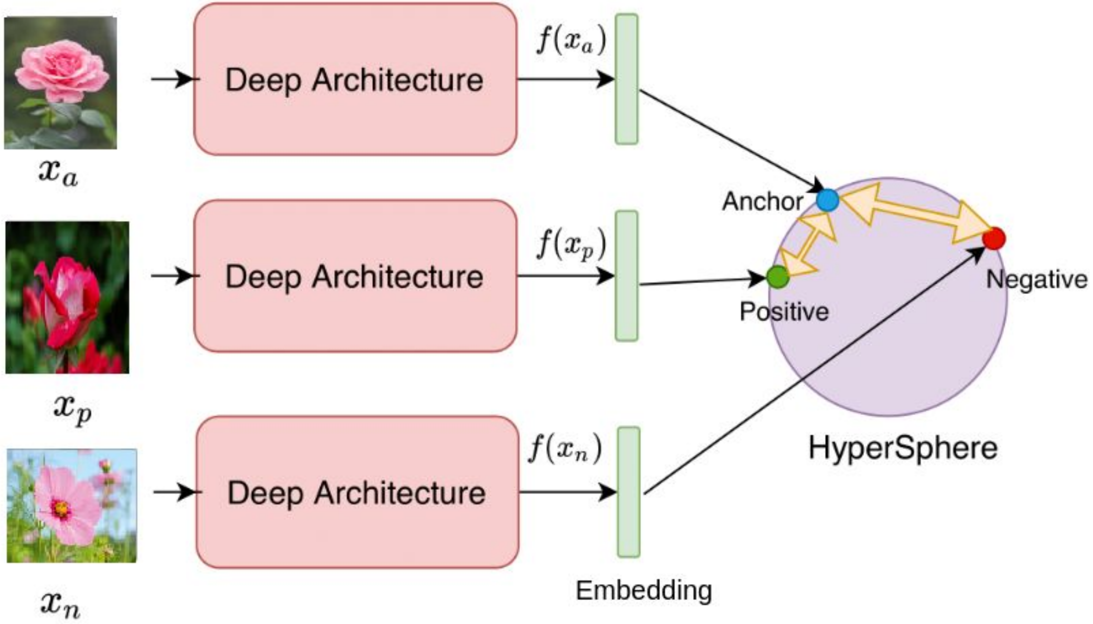
Hinge Loss

- It penalizes misclassified or correctly classified predictions which are too close to the decision boundary in a linear way.
  - Predictions that are far from the decision boundary get more punishments.
- It is generally used in Support Vector Machine based classifier.



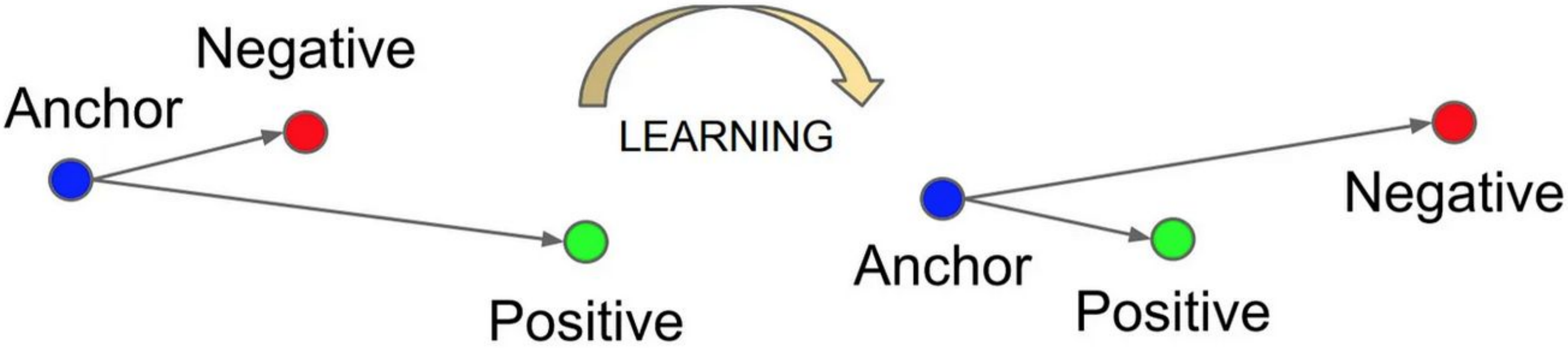
Triplet Loss

In triplet loss, a reference input (called anchor) is compared to a matching input (called positive sample) and a non-matching input (called negative sample)



Triplet Loss

- minimizes the distance between an anchor and a positive
- maximizes the distance between the Anchor and a negative of a different identity.



Triplet Loss

L(a, p, n) = max(d(a, p) - d(a,n) + α, 0)

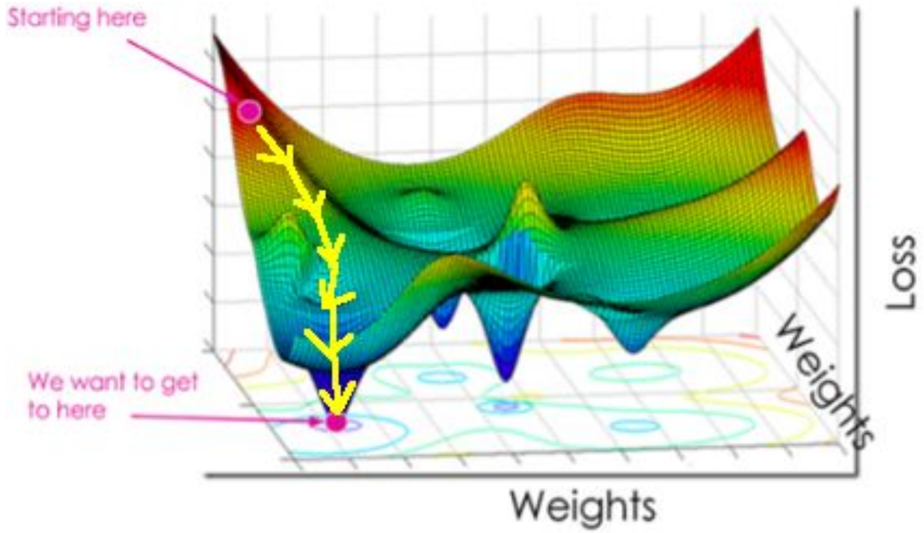
where

- $d(a, p)$: distance between anchor and positive sample
- $d(a,n)$: distance between anchor and negative sample
- α: margin of error

- Lecture: https://www.youtube.com/watch?v=d2XB5-tuCWU

Training Neural Network

During training we try to find the parameter set for which loss is minimum.
Starting at random values, we update parameters by gradient descent algorithm



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