



# **DAY 4: LOSS FUNCTIONS**

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# TOPICS

- Cross Entropy Loss
- Negative log likelihood loss
- Hinge loss
- Custom loss implementation: Focal loss

# CROSS ENTROPY

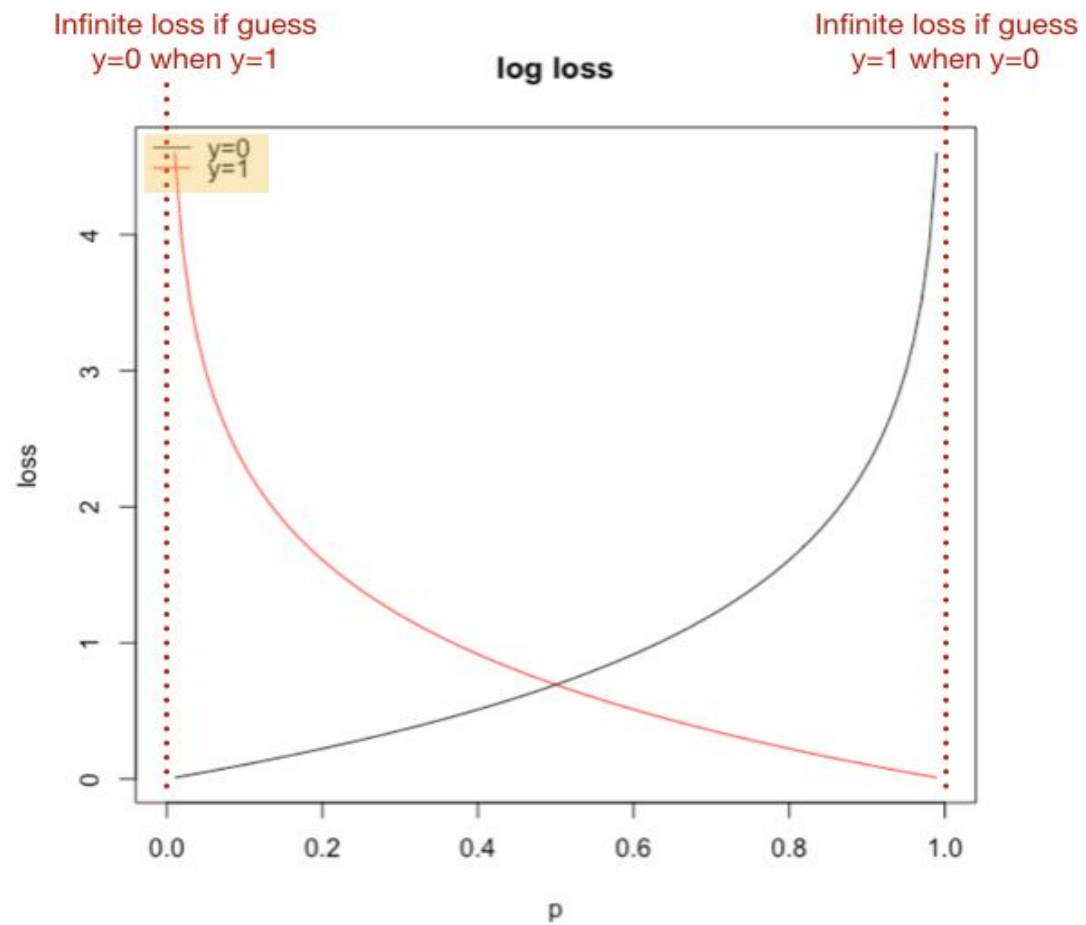
**Cross-Entropy** is used for classification problems. It minimizes the distance between the predicted and the actual probability distribution.

The Equation of Cross-Entropy loss:

$$L = -\frac{1}{m} \sum_{i=1}^m y_i \cdot \log(\hat{y}_i)$$

So, it's used for Classification problems.

# CROSS ENTROPY



Source: <https://wandb.ai/site/tutorial/multilayer-perceptrons>

## NEGATIVE LOG LIKELIHOOD

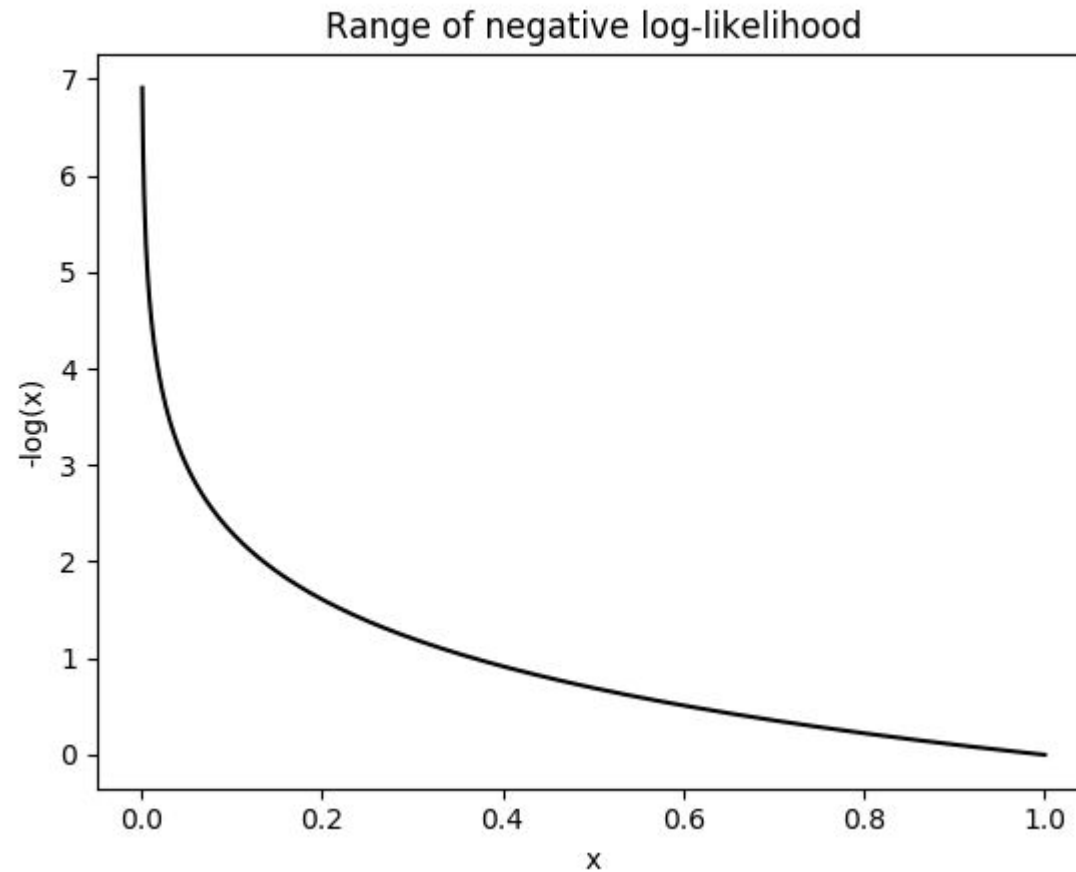
**Negative Log Likelihood** is also used for classification problems telling us how bad it's performing, the lower the better. Where most machine learning frameworks only have minimization optimizations, here we want to maximize the probability of choosing the correct category. We can **maximize by minimizing** the **negative** log likelihood.

The equation of the loss function:  $L(y) = -\log(y)$

$$\min_{w. r. t \theta} -l(\theta)$$

$$\min_{w. r. t \theta} \left( - \sum_{i=1}^m \left( y^{(i)} \times \log(h_{\theta}(x^{(i)})) + (1 - y^{(i)}) \times \log(1 - h_{\theta}(x^{(i)})) \right) \right)$$

# NEGATIVE LOG LIKELIHOOD



Source: <https://lvmiranda921.github.io/notebook/2017/08/13/softmax-and-the-negative-log-likelihood/>

# HINGE LOSS

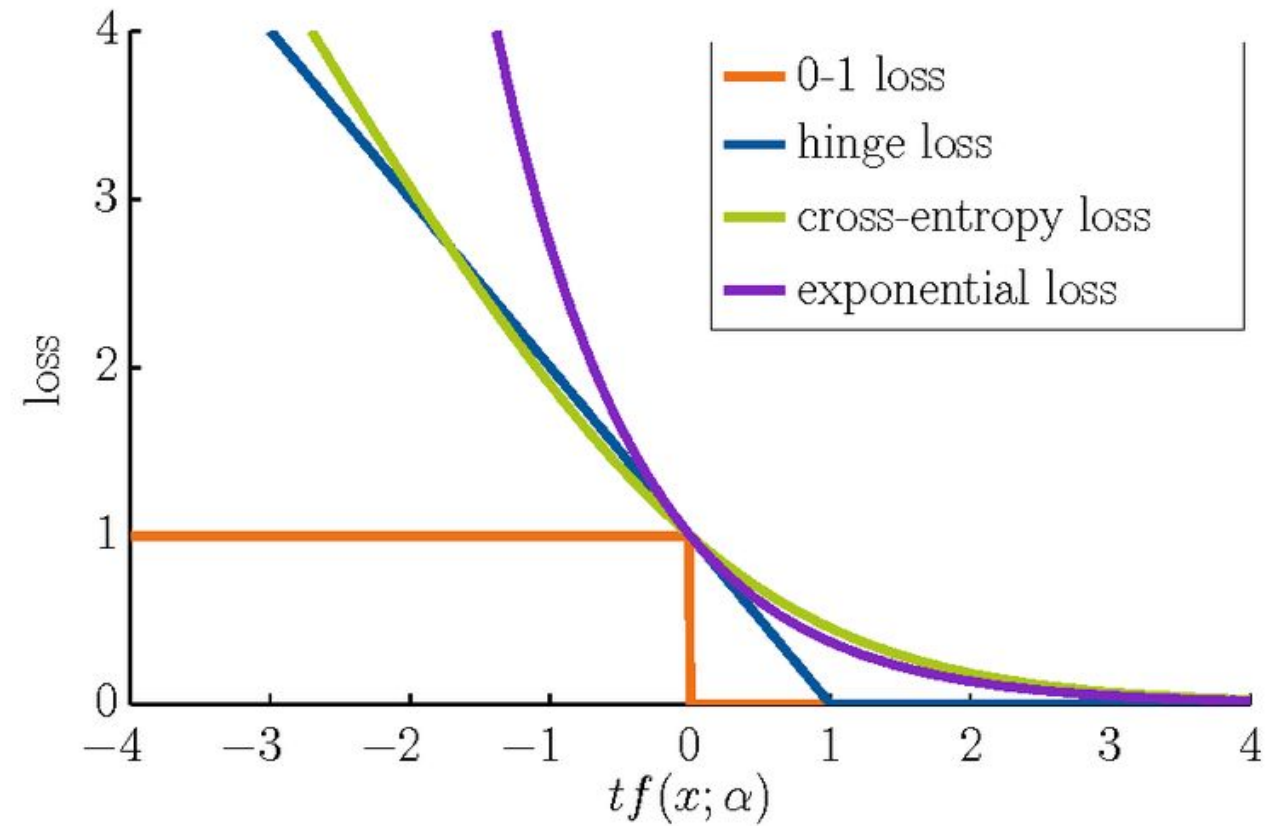
The **hinge loss** is used for "maximum-margin" classification, most notably for support vector machines (SVMs). SVM uses a hinge loss, which conceptually **puts the emphasis on the boundary points**.

The formula for Hinge Loss:

$$L = \max(0, 1 - y * f(x))$$



# HINGE LOSS



Source: [https://www.researchgate.net/figure/Loss-functions-for-commonly-used-classifier-hinge-loss-SVM-cross-entropy-loss\\_fig5\\_236150927](https://www.researchgate.net/figure/Loss-functions-for-commonly-used-classifier-hinge-loss-SVM-cross-entropy-loss_fig5_236150927)



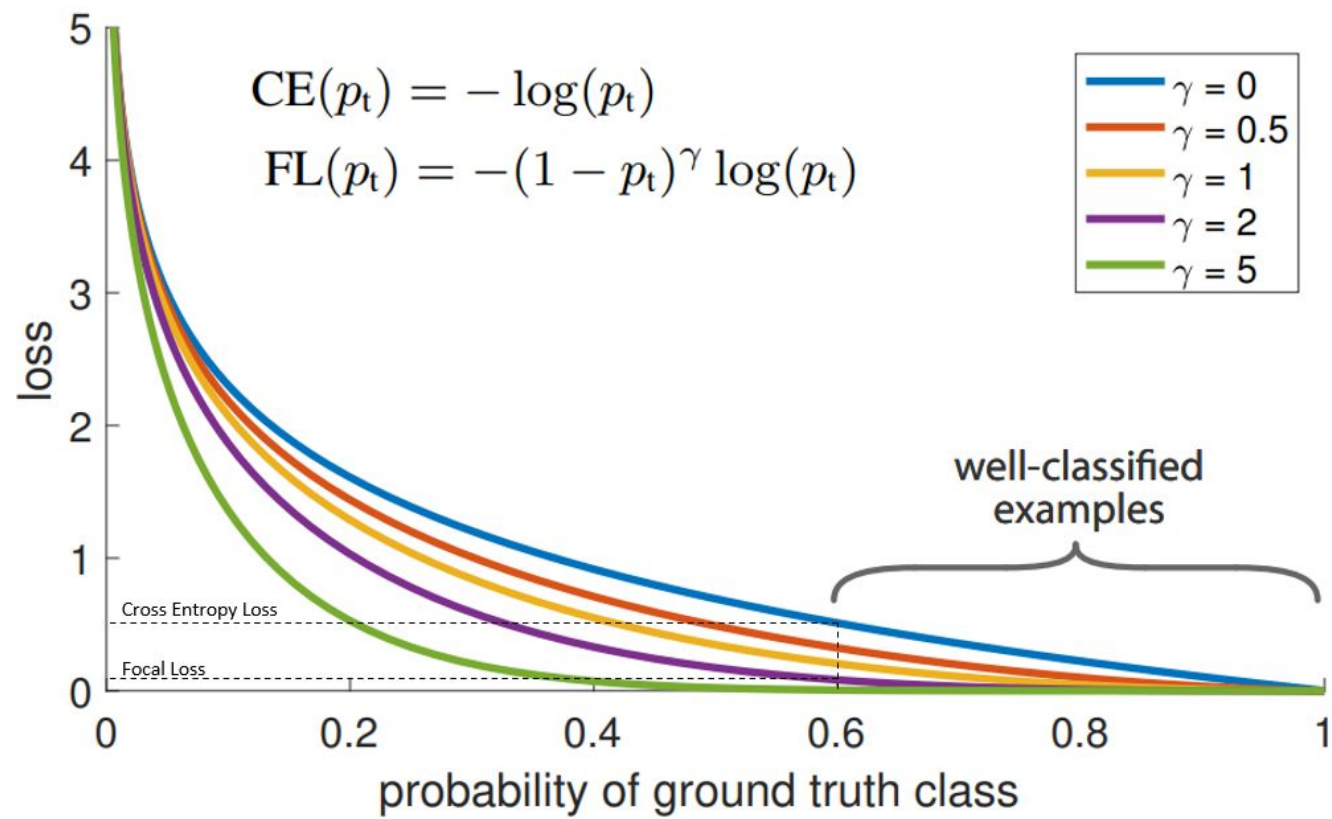
# FOCAL LOSS

**Focal loss** is used to address the issue of the class imbalance problem. A modulation term applied to the Cross-Entropy loss function, make it efficient and easy to learn for hard examples which were prevailing in One-Shot Object Detectors.

Formula for Focal Loss

$$\text{FL}(p_t) = -(1 - p_t)^\gamma \log(p_t)$$

# FOCAL LOSS



Source: <https://medium.com/swlh/focal-loss-what-why-and-how-df6735f26616>

# GET READY FOR CODE

Code: [https://drive.google.com/file/d/1uBlc4XxfUbx9ANUZV\\_9IFPLILedUaCH3/view?usp=sharing](https://drive.google.com/file/d/1uBlc4XxfUbx9ANUZV_9IFPLILedUaCH3/view?usp=sharing)

This Slide Link:

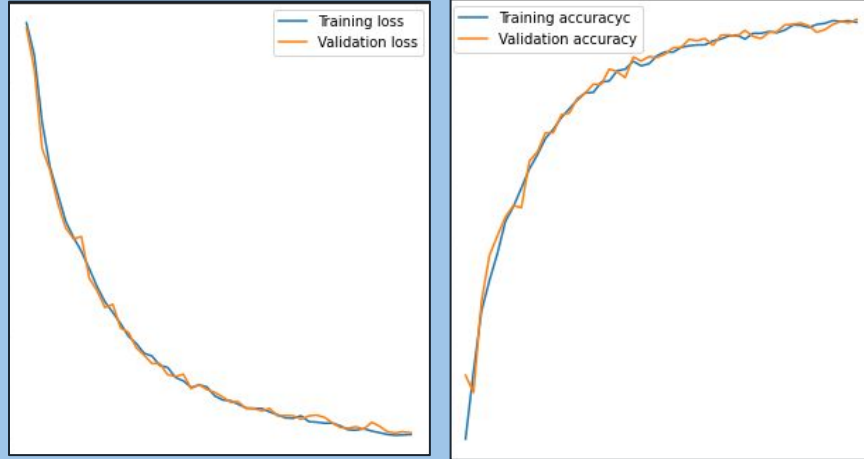
<https://docs.google.com/presentation/d/1vvGifORiDHUU3RgR4ELVNdy-cya0VNfU/edit?usp=sharing&ouid=114298130813356779276&rtpof=true&sd=true>

Visualizing 3D loss surface for cross-entropy loss: <https://losslandscape.com/explorer>

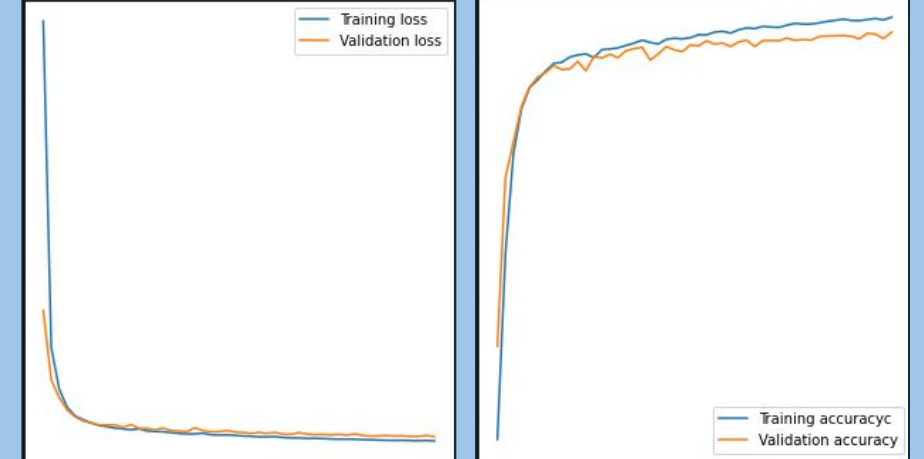
Other loss functions: <https://pytorch.org/docs/stable/nn.html#loss-functions>

Dataset: <https://drive.google.com/file/d/1CLqe8c3EWdlt2zBxRSuCdEXwVHqYjYuO/view?usp=drivesdk>

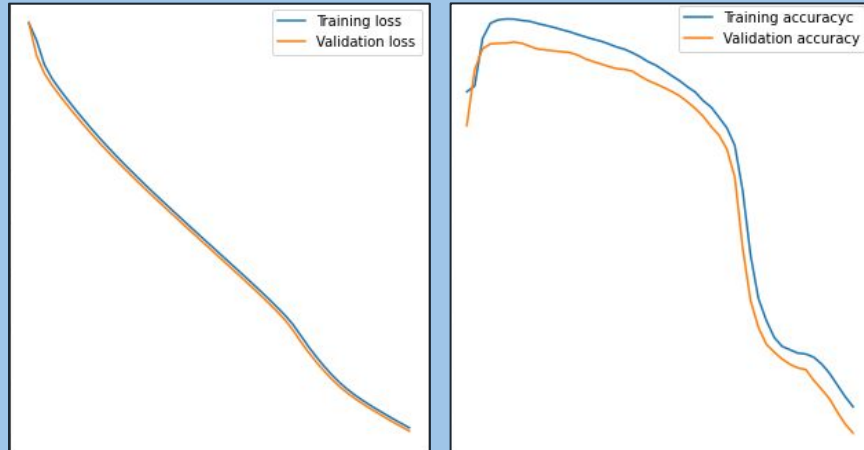
# Impact of Loss



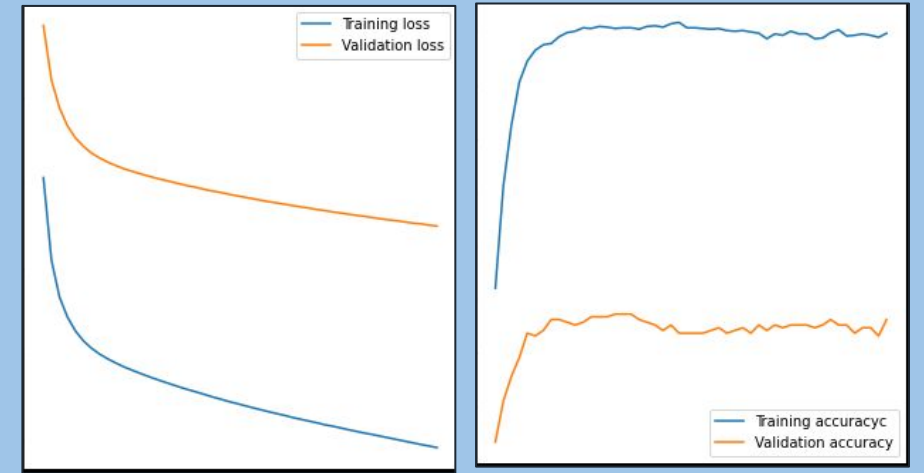
Cross Entropy Loss [Best val Acc: 91.70%]



Focal Loss [Best val Acc: 94.14%]



Hinge Loss [Best val Acc: 92.01%]



Negative Log Likelihood Loss [Best val Acc: 94.37%]

## Useful Links

- <https://wandb.ai/site/tutorial/multilayer-perceptrons>
- <https://lvmiranda921.github.io/notebook/2017/08/13/softmax-and-the-negative-log-likelihood/>
- <https://medium.com/analytics-vidhya/understanding-loss-functions-hinge-loss-a0ff112b40a1>
- <https://medium.com/swlh/focal-loss-what-why-and-how-df6735f26616>
- <https://amaarora.github.io/2020/06/29/FocalLoss.html>
- <https://pytorch.org/docs/stable/nn.html#loss-functions>
- [http://cs231n.stanford.edu/slides/2019/cs231n\\_2019\\_lecture03.pdf](http://cs231n.stanford.edu/slides/2019/cs231n_2019_lecture03.pdf)
- <https://www.youtube.com/watch?v=h7iBpEHGVNc>
- <https://www.youtube.com/watch?v=bjlfh3BvqSU>
- <https://www.youtube.com/watch?v=CkiT0Muz62g>

**THANK YOU**

