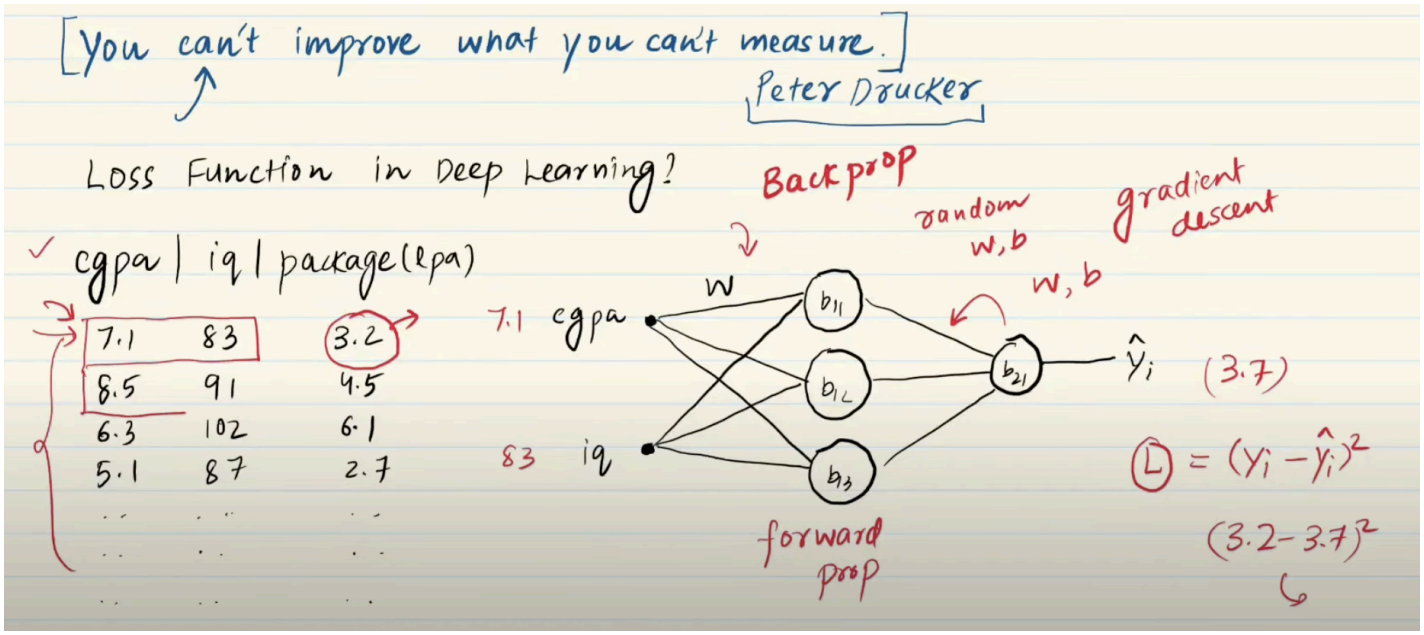
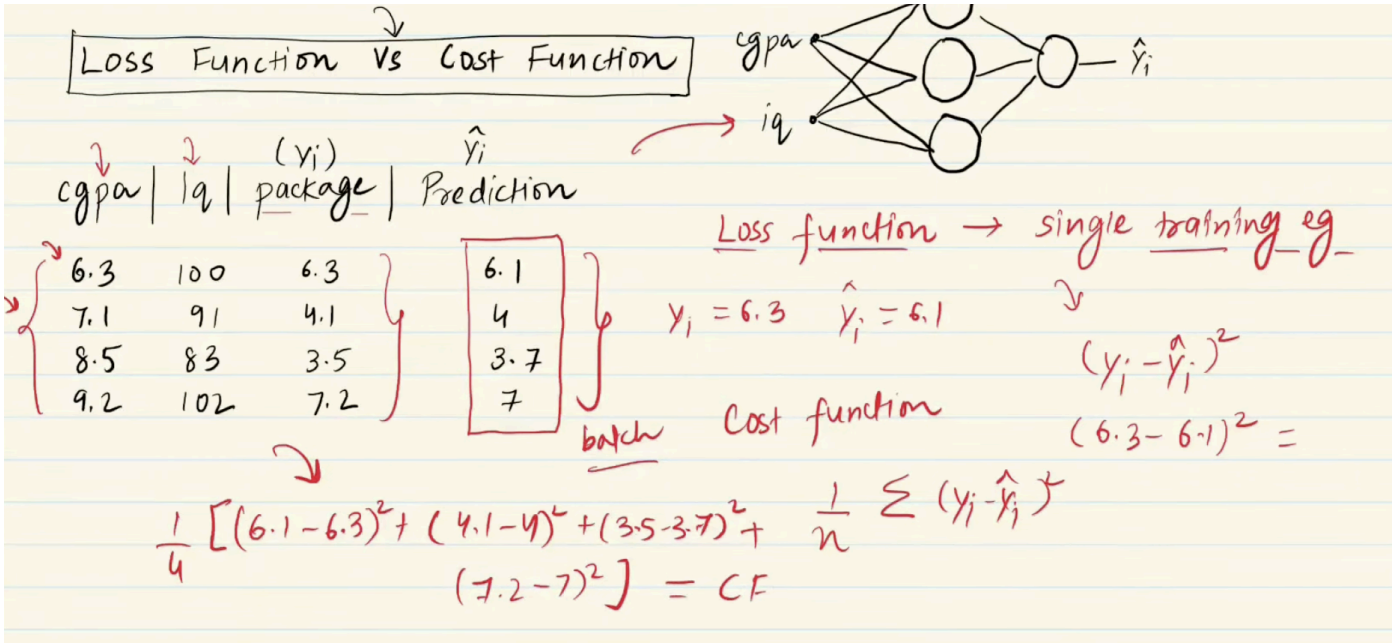
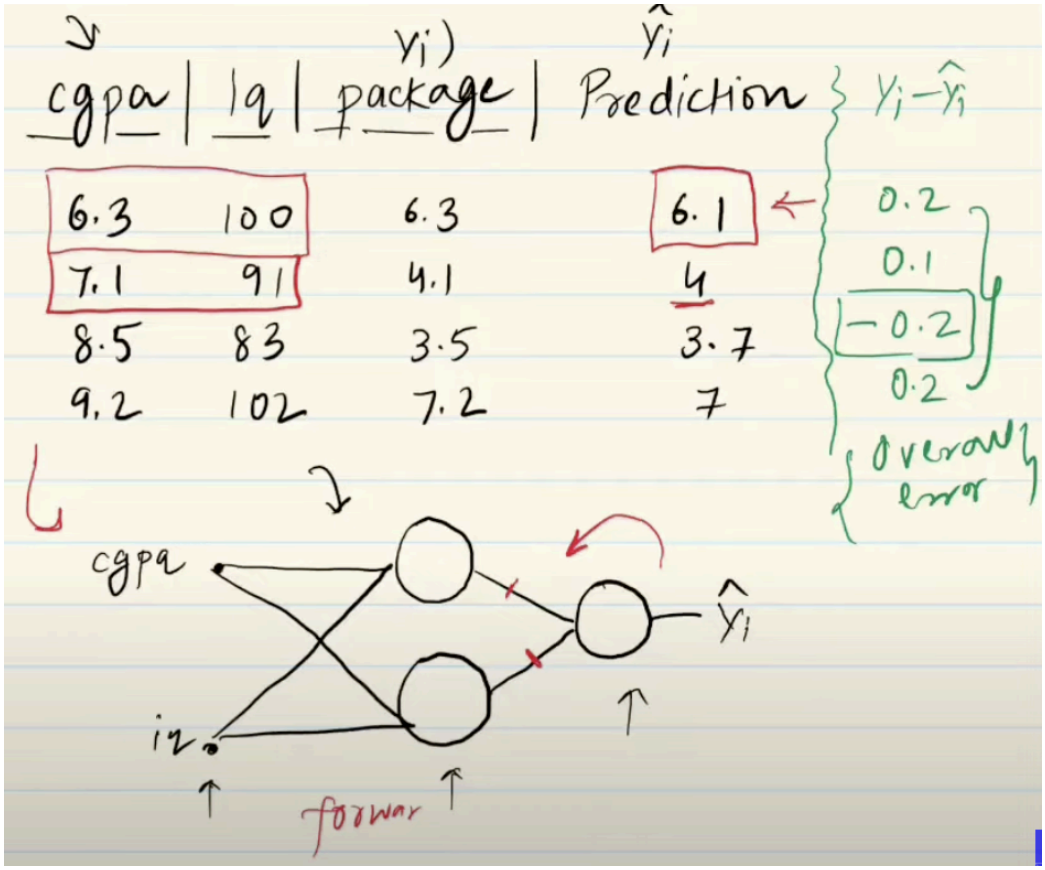
Lecture 4
Loss functions

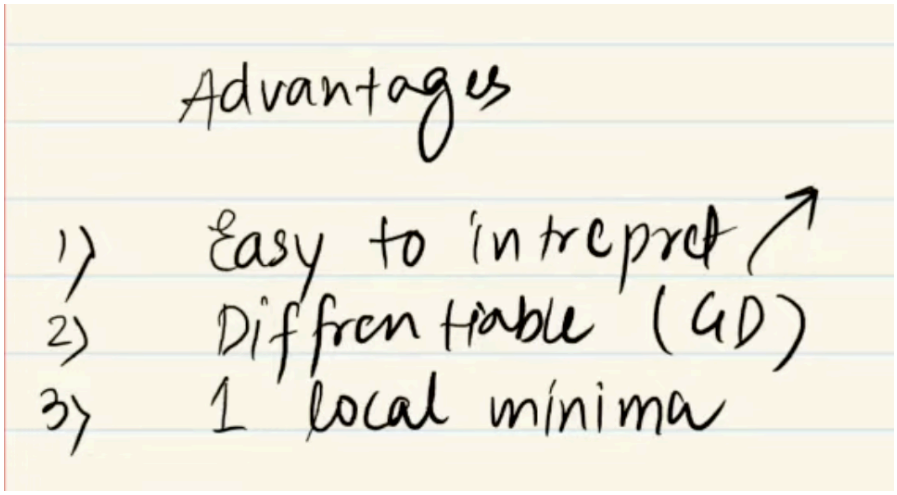
Read from: https://medium.com/@ibtedaazeem/loss-functions-in-deep-learning-e4bd353ea08a



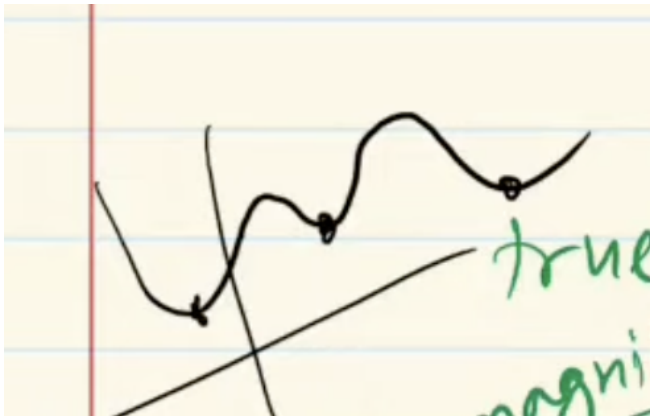


Mean squared error (L2 loss)
Why squared?

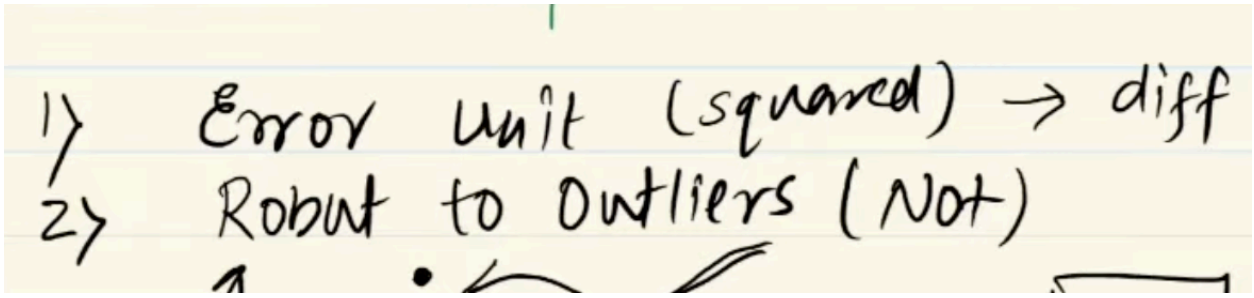




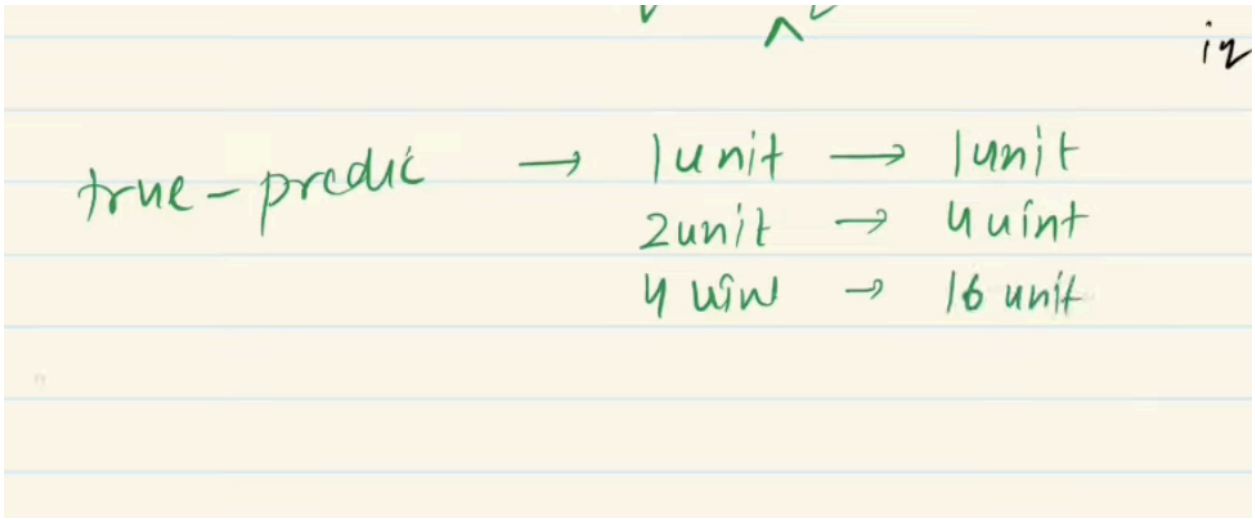
1 local minima means: there exists one value of weight and bias for which loss is minimum
Unlike this, where multiple solutions exist.



Drawback



Error unit is squared:



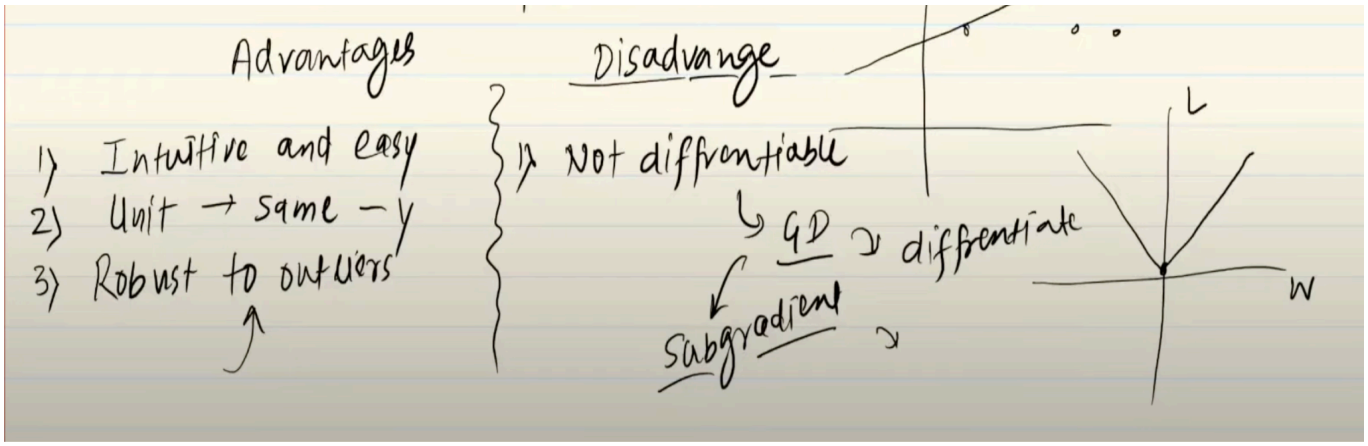
Error gets magnified due to the squared unit , weight updates will be drastic for points away (these points will be punished more) from the line, and causing the line to move further away.

Not robust to outliers:

A student has a Package high, error becomes too high due to squared difference. The line deviated from the true nature of the data.

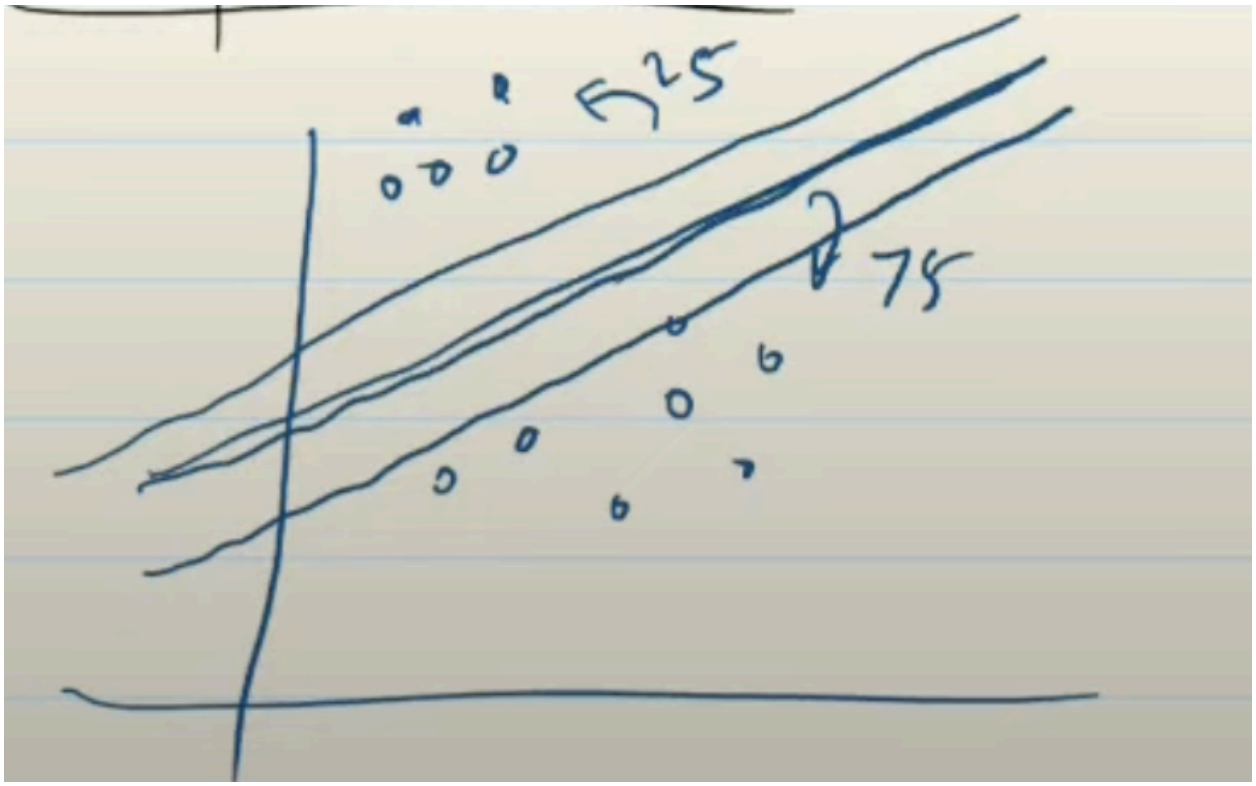
Note: the last layer neuron must use a linear activation function for regression problems.

Mean absolute error (L1 loss)



Huber loss

Assume out data has 25% outliers the above methods wont behave well



3. Huber Loss ✓

$$L = \begin{cases} \frac{1}{2}(y-\hat{y})^2 & \text{for } |y-\hat{y}| \le \delta \\ \delta|y-\hat{y}| - \frac{1}{2}\delta^2 & \text{otherwise} \end{cases}$$

mse

mae

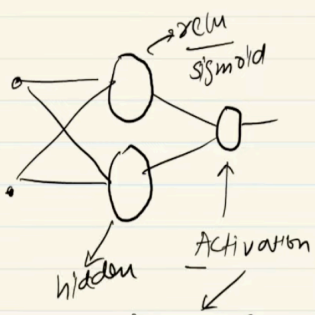
4. Classification loss function

4. Binary Cross Entropy

→ classification

→ Two classes

cgpa	iq	placement (1 / 0)
8	80	1
7	70	0
6	60	0

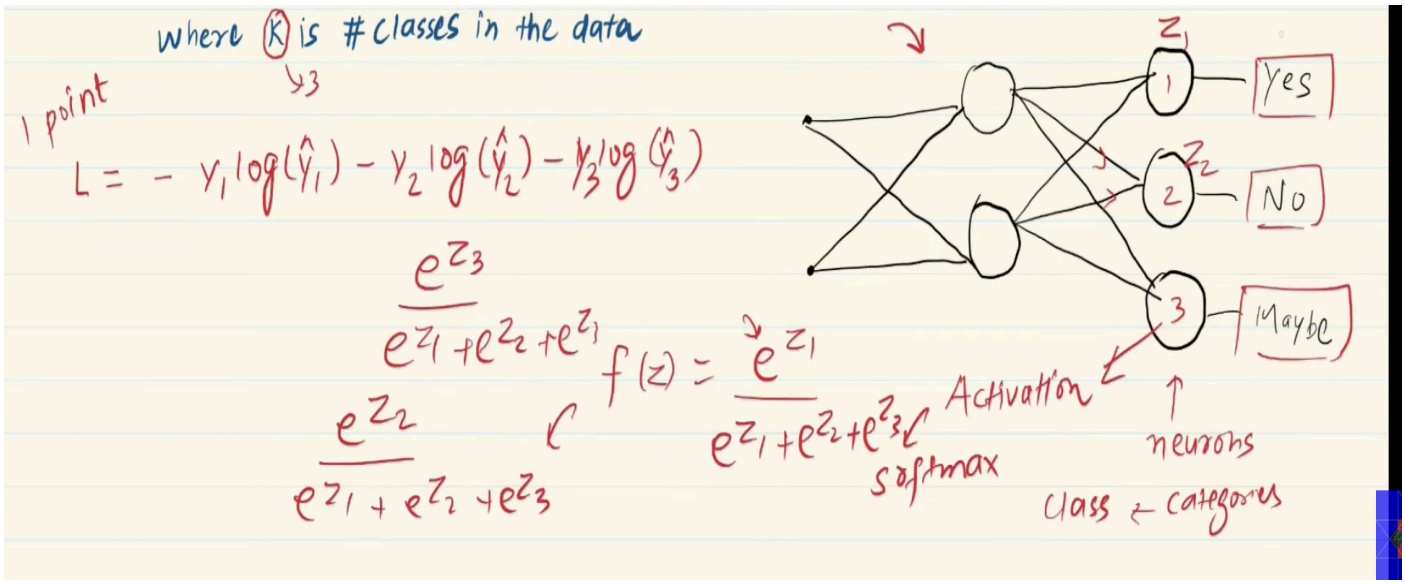


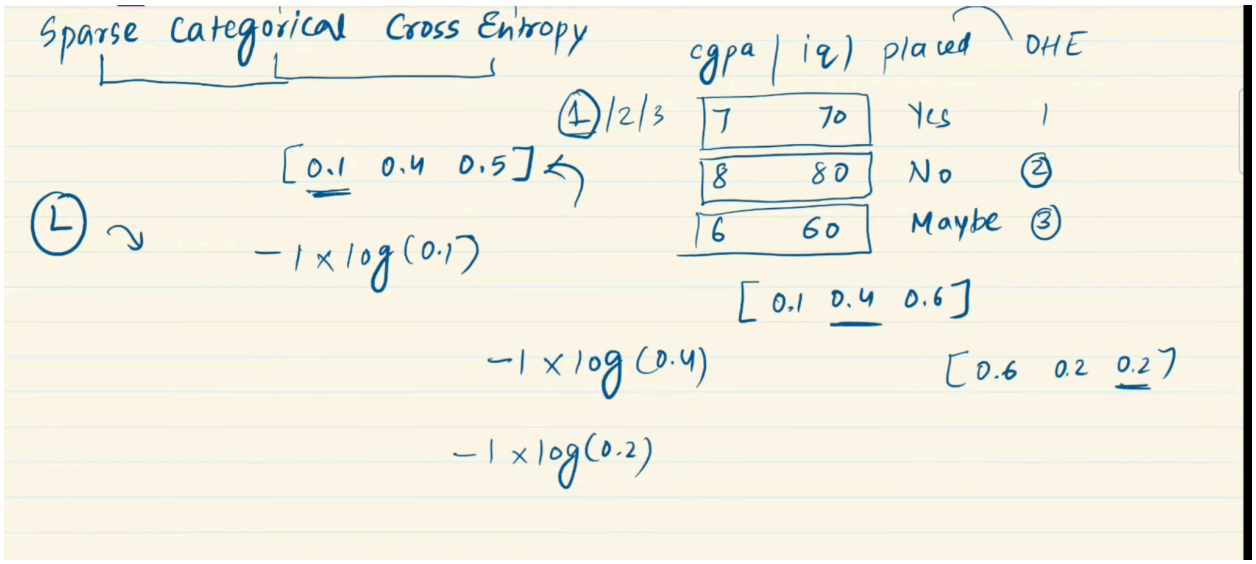
$$\text{Loss function} = -y \log(\hat{y}) - (1-y)\log(1-\hat{y})$$

y → actual value / target

$\hat{y}$ → NN prediction

$$\text{cost function} = -\frac{1}{n}\left[\sum_{i=1}^{n} y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)\right]$$





Why integers (1, 2, 3…) don't add extra weight

The integers here are not treated as numeric values like regression targets.
Instead, they are indices that point to a class.

Example:
Suppose model output (softmax) for 3 classes is `[0.1, 0.7, 0.2]`.

- **If the true label is `1` (class index), the loss only looks at the probability of index `1` (here `0.7`).**
- **Loss = `-log(0.7)`.**

It doesn't matter that the label is `2` or `3` numerically larger. The loss function does not treat "3" as three times "1" — it just uses it as a lookup index.

So why use Sparse Categorical Crossentropy?

- **Saves memory and computation (no need for one-hot vectors).**
- **Convenient when you have many classes.**
- **Both methods give the same result.**