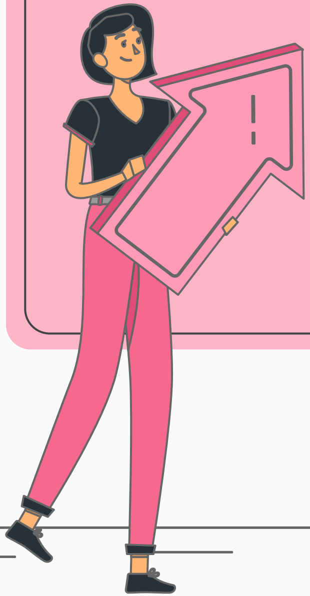
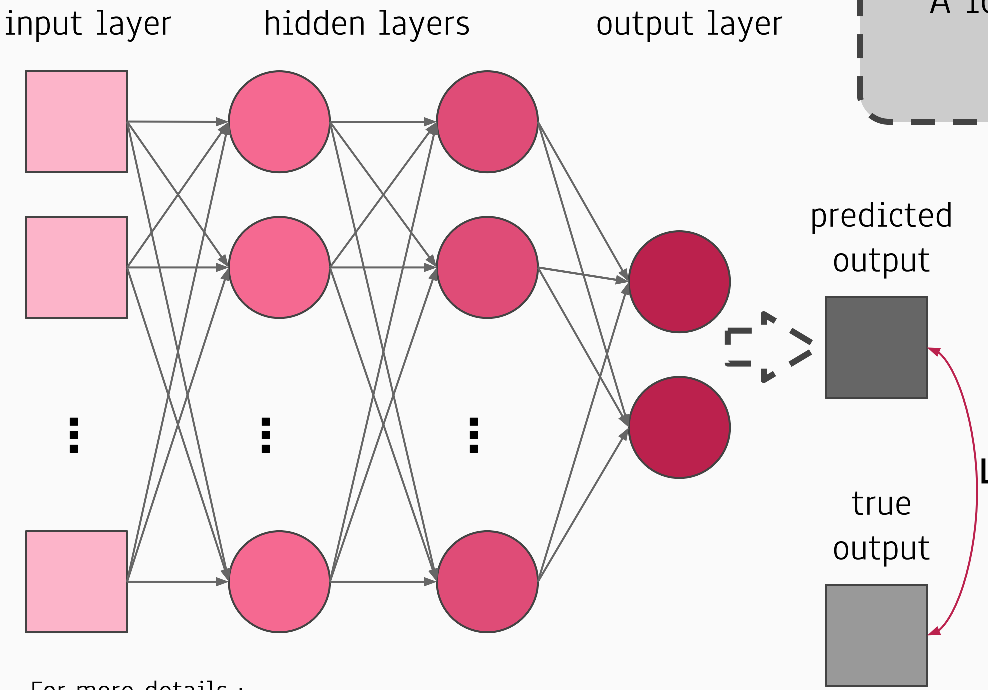
REGRESSION LOSS FUNCTIONS



SureStart

LOSS FUNCTION



A loss function is a measure of **error** between the model's predicted value and the actual value.

In the context of Machine Learning:

Loss function is a method of evaluating "how well your algorithm models your dataset".

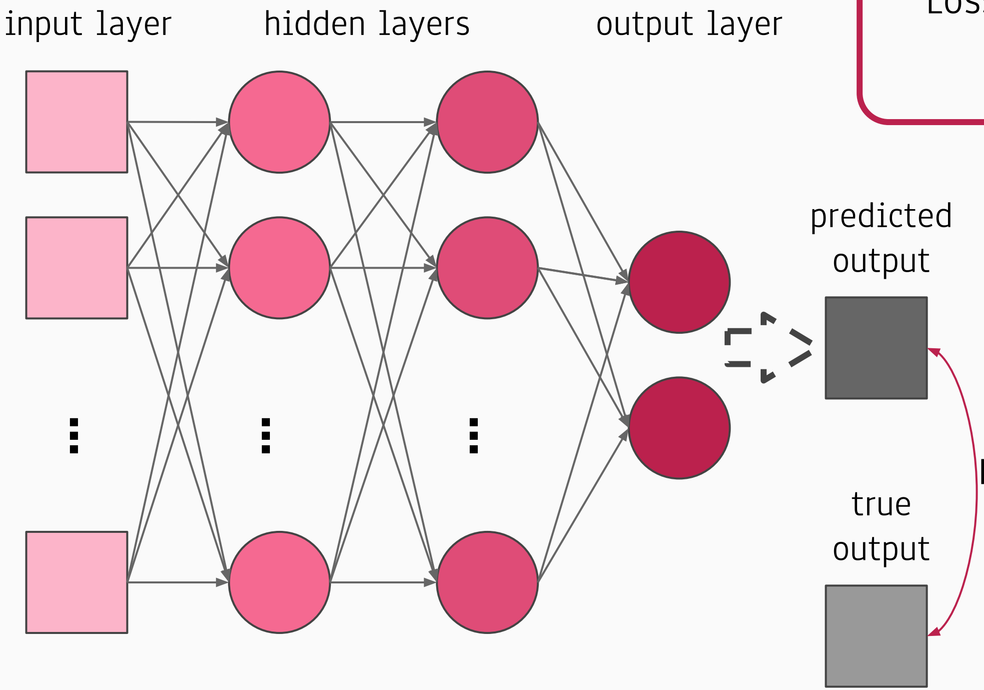
Loss = J (pred, true)

It also indicates if the algorithm is **improving** the model's performance *after tuning any parameter*.

For more details : https://medium.com/@zeeshanmulla/cost-activation-loss-function-neural-network-deep-learning-what-are-these-91167825a4de

SYNONYMS OF LOSS FUNCTION

Loss function, cost function, objective function or error function are synonyms and can be used interchangeably .



Loss is nothing but a prediction error of an ML model. Sometimes a loss function or cost function is computed for a single training sample; at other times it is computed for a mini-batch of the training set.

Loss = J (pred, true)

If pred is very far off from true, the loss value will be *very high*.

If both values are almost similar, the loss value will be *very low*.

TYPES OF LOSS FUNCTION

REGRESSION

Predict continuous and numerical value.

E.g., predicting the appropriate price of a product, predicting the number of sales each day, height of a person

CLASSIFICATION

Predict a categorical outcome (number of classes)

E.g., objects in an image, topics in emails, suitable products to advertise

Mean Squared Error Loss
Mean Squared Logarithmic Error Loss
Mean Absolute Error Loss

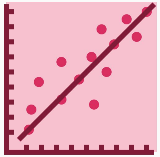
BINARY CLASSIFICATION

Binary Cross-Entropy
Hinge Loss
Squared Hinge Loss

MULTI-CLASS CLASSIFICATION

Multi-Class Cross-Entropy
Sparse Multiclass Cross-Entropy
Kullback Leibler Divergence

COMMON LOSS FUNCTIONS FOR REGRESSION



Mean Squared Error Loss (MSE)

MSE is calculated as the average of the squared differences between the predicted and actual values.

- *Mathematically, MSE is the preferred loss function if the distribution of the target variable is Gaussian, and the target value doesn't have any outliers.*
- *The squaring of errors means that larger mistakes result in higher error than smaller mistakes.*

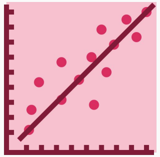
Mean Absolute Error Loss (MAE)

MAE is calculated as the average of the absolute difference between the actual and predicted values.

- *MAE is appropriate if the data samples have properties of Gaussian distribution and have a tendency towards outliers.*

Outliers are the large or small values far from the mean value of all the observation. Simply, an outlier is an extremely high or extremely low value in a dataset.

COMMON LOSS FUNCTIONS FOR REGRESSION



Mean Squared Error Loss (MSE)

MSE is calculated as the average of the squared differences between the predicted and actual values.

Mean Absolute Error Loss (MAE)

MAE is calculated as the average of the absolute difference between the actual and predicted values.

Steps for computing MSE:

1. Take the difference between your model's predictions and the actual value
2. Square the difference
3. Compute the average of the squared differences.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Legend:

- i - index of sample
- $\hat{y}$ - predicted value
- y - expected value
- n - number of samples in dataset

ANOTHER LOSS FUNCTION FOR REGRESSION

Mean Squared Logarithmic Error Loss (MSLE)

MSLE calculates the natural logarithm of each of the predicted values, then calculate the mean squared error.

- *The MSLE is smoother than MSE and will not be so strongly affected by the occasional wildly incorrect prediction.*

- *As a loss measure, it may be more appropriate when the model is predicting unscaled quantities; (unscaled input variables of data may have different units e.g. feet, kilometers, and hours).*

$$MSLE = \frac{1}{n}\sum_{i=1}^{n}(log(y_i + 1) - log(\hat{y}_i + 1))^2$$