A Machine Learning Guide

Institutionalized

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Machine Learning

Machine learning is a branch of artificial intelligence (AI) that involves teaching computers to learn from data, identify patterns, and make decisions without being explicitly programmed to do so. In simple terms, it's like teaching a computer to learn from examples.

Arthur Samuel's Definition (1959)

"Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed."

Tom Mitchell's Definition (1997)

"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."

Classical Programming vs Machine Learning

In classical programming, we provide logic and inputs to the machine which gives the outputs according to that logic.
In machine learning, we give only the input and output and the machine develops the logic based on the data.

Overfitting, Underfitting and Best Fit

Overfitting

Overfitting occurs when a machine learning model learns the training data too well, capturing noise or random fluctuations in the data rather than the underlying patterns.
This results in a model that performs well on the training data but poorly on unseen or new data.

Example:

Imagine you're trying to fit a curve to a set of data points. If you use a very high-degree polynomial function to fit the data, the curve might bend and twist to pass through every data point exactly, including outliers and noise. This curve might look great on the training data, but

when you try to predict new data points, it might behave erratically and produce inaccurate results because it's overly sensitive to small variations in the training data.

Underfitting
Underfitting occurs when a machine learning model is too simple to capture the underlying structure of the data. This results in a model that performs poorly both on the training data and on new data. Underfitting often happens when the model is too simplistic relative to the complexity of the underlying data.

Example:
Continuing with the curve fitting analogy, if you use a linear function (a straight line) to fit data that actually follows a nonlinear pattern, the resulting line might not capture the true relationship between the variables. It might have a high error rate both on the training data and on new data because it's not flexible enough to represent the underlying data structure.

Best Fit
Best fit, also known as a good fit or optimal fit, occurs when a machine learning model generalizes well to new, unseen data. This means the model accurately captures the underlying patterns in the data without being overly complex or too simplistic. Achieving the best fit involves finding a balance between capturing enough complexity to represent the data accurately and avoiding overfitting.

Example:
Going back to the curve fitting example, if you use a polynomial function of moderate degree to fit the data, the resulting curve might not pass through every data point exactly, but it captures the overall trend of the data without being overly sensitive to noise or outliers. This curve would likely perform well not only on the training data but also on new data, making it a good fit for the dataset.

Concept of Epochs?

One Epoch is one complete pass through entire training dataset. An epoch might consist of multiple iterations.

An iteration is one complete pass through “batch” of training dataset.

Eg, say my dataset has 1000 datapoints and I chose a batch size of 50.

i.e., number of iterations = 1000/ 50 = 20.

Now in each epoch model will go through 20 iterations, each iteration consisting of 50 datapoints.

The number of epochs required for convergence depends on factors such as the complexity of the model, the size of the dataset, and the learning rate.
Increasing the number of epochs beyond a certain point may lead to overfitting, where the model performs well on the training data but poorly on new, unseen data.

Here's a simplified process for deciding these parameters

1. Start with a small number of epochs and gradually increase it until you observe diminishing returns in performance improvement or signs of overfitting.
2. Choose a batch size that balances computational efficiency and model convergence. Experiment with different batch sizes to find the optimal one for your model and hardware setup.
3. Monitor the model's performance on a validation set during training to determine the appropriate number of epochs and batch size.

Gradient Descent Algorithm

Initialization: Start with initial values for the model parameters (weights and biases).
Compute Gradient: Calculate the gradient of the loss function with respect to each parameter. The gradient indicates the direction of the steepest increase in the loss function.
Update Parameters: Adjust the parameters in the direction opposite to the gradient to minimize the loss function. This is done by subtracting a fraction of the gradient (learning rate times gradient) from the current parameter values.
Repeat: Repeat the process iteratively until convergence or until a stopping criterion is met (e.g., maximum number of iterations).
Convergence: The algorithm converges when the change in the loss function becomes small or negligible, indicating that further iterations are unlikely to significantly improve the model.

Types of Gradient Descent

Convergent Gradient Descent: In convergent gradient descent, the algorithm successfully reaches the optimal solution, where the loss function is minimized. This occurs when the learning rate is chosen appropriately, and the optimization process progresses smoothly towards convergence.

Oscillating Gradient Descent: Oscillating gradient descent occurs when the learning rate is too high, causing the optimization process to oscillate around the optimal solution without converging. This can lead to slow convergence or instability in the optimization process.

Divergent Gradient Descent: Divergent gradient descent occurs when the learning rate is too high or the optimization process is unstable, causing the loss function to increase indefinitely. In this case, the algorithm fails to converge and may even diverge away from the optimal solution.

Factors Affecting Gradient Descent

Learning Rate: The choice of learning rate plays a crucial role in determining the convergence behavior of gradient descent. A too high learning rate can cause oscillations or divergence, while a too low learning rate can result in slow convergence.

Initialization: The initial values of the model parameters can affect the convergence behavior of gradient descent. Random initialization or initialization close to the optimal solution may lead to faster convergence.

Batch Size: Gradient descent can be applied with different batch sizes, such as batch gradient descent (using the entire dataset), mini-batch gradient descent (using subsets of the dataset), or stochastic gradient descent (using individual examples). The choice of batch size can affect convergence speed and optimization stability.

Cases in Gradient Descent
Moderate, slow convergence, oscillating, diverging. All based on value of learning rate.

Supervised Learning Types

Regression

1. Simple Linear
2. Multiple Linear
3. Polynimial
4. Lasso
5. Ridge
6. Decision Tree Regressor
7. Support Vector Machine Regression

Classification

1. Logistic Regression
2. Decision Tree Classifier
3. Support Vector Machine Classifier
4. Naive Bayes Classifier
5. K-nearest neighbour

Unsupervised Learning Types

Clustering

1. K means
2. DBSCAN
3. Hierarchical

Associate Rule Mining

Dimensionality Reduction

Anomaly Detection

Bias-Variance tradeoff

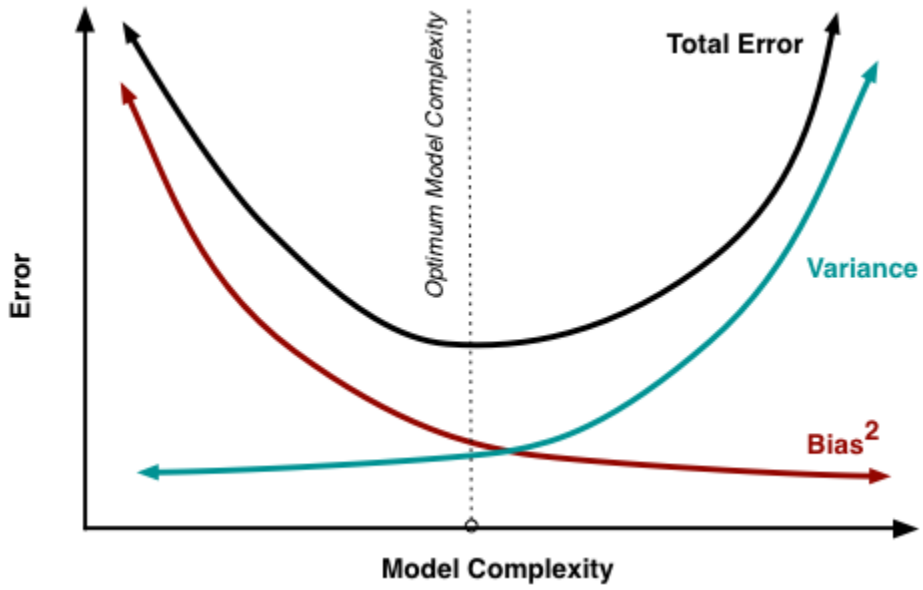
Bias: difference between the predicted and actual values of data is bias. High bias means there is large difference between predicted and actual values. High bias = high error on predicted values.

Variance: how much scattered the datapoints are with relation to each other. High variance means the datapoints are scattered.

Overfitting is low bias and high variance, means the predicted values are close to actual but those datapoints are spread from each other.

Underfitting is high bias and low variance, meant the predicted values are not correct, they differ largely from actual values but since the model is simpler thus the datapoints are close to each other.

What's desired is low bias and low variance of a model, which is called Best Fit Model.



Lasso & Ridge Regression

Also known as L1 & L2 regularizations. Lasso and Ridge are used to add penalty term to cost function so that the dependency on some features can be reduced. In Lasso and Ridge Regression our purpose is to reduce parameters (weights) as low as possible. This is done to resolve overfitting problem.

Lasso Regression equation,

$$Cost\ Function\ = \frac{1}{n}\sum_{i=1}^{n}\left(h_\theta(x)^i - y^i\right)^2 + \lambda \sum_{i=1}^{n} |slope|$$

$$\lambda = Hyperparameter$$

Ridge Regression equation,

$$SSE_{L_2} = \sum_{i=1}^{n}(y_i - \widehat{y_i})^2 + \lambda \sum_{j=1}^{P} {\beta_j}^2$$

The difference between **Lasso** and Ridge is that Lasso regression also helps in **Feature Selection** be eliminating some or few parameters with low significance.

Cost Function

Hypothesis:	$h_\theta(x) = \theta_0 + \theta_1 x$
Parameters:	θ_0, θ_1
Cost Function:	$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$
Goal:	$\underset{\theta_0, \theta_1}{\text{minimize}}\ J(\theta_0, \theta_1)$

Parameters vs Hyperparameters

Parameters	Hyperparameters
Variables learned by model during training	Settings or configurations set before training
Directly affects the predictions made by model	Indirectly affects the learning process of model
These can be adjusted automatically during training	These can't be adjusted during training, they are set before training
Eg, weights and biases	Eg, learning rate α, number of neurons, number of hidden layers, regularization strength λ of Lasso & Ridge regression, branches in decision tree
These are optimized using Gradient Descent optimization	These are optimized using, grid search, random search, bayesian optimization and hand tuning
These are crucial for the model to predict correct values	These are also crucial to prepare best learning settings for the model

Grid Search Optimization

In Grid search the best setting is found from predefined lists of settings.
This is a brute force optimization technique, it checks for each pairs of hyperparameters.
Eg, we have a = [10, 20, 30, 40] and b = [1, 2, 3, 4] as 2 hyperparameters.
Then, it will consider a grid of a and b and checks for each value of 'a' with 'b' and selects the most optimum setting.

Advantage:
Grid search finds the most optimal setting.
It is straight forward and easy to implement.

Disadvantage:
Grid search is computationally very expensive.
For large dimensional datasets, it might take very very large time.

Random Search Optimization

In random search, a grid is selected as well like grid search. But instead of searching each cell, it randomly picks cells and calculate accuracy for those settings. And finally gives the setting it found optimal.

Advantage:
Computationally very less expensive than grid search.
It can be used for datasets with higher dimensions.

Disadvantages:
It might not explore the most optimal setting, and can give less optimal setting as answer as well.
It doesn't learn from priorly checked experiments.
And it becomes difficult to predict next set of experiment

Bayesian Optimization

Bayesian optimization is a sequential model-based optimization technique used to find the optimal set of hyperparameters for a machine learning model. It leverages probabilistic models to approximate the objective function and intelligently select the next set of hyperparameters to evaluate based on past observations.

Advantages:
Efficiently explores the hyperparameter space and converges to the optimal solution with fewer evaluations compared to grid search or random search.
Automatically adapts to the structure of the objective function and identifies promising regions of the search space, making it suitable for complex and high-dimensional optimization problems.

Disadvantages:
Requires careful tuning of its own hyperparameters, such as the choice of surrogate model and acquisition function.
Can be computationally expensive and time-consuming for large-scale optimization problems or when evaluating complex objective functions.

Hand Tuning Optimization

Hand tuning, also known as manual tuning or trial and error, involves manually selecting hyperparameter values based on the practitioner's intuition, domain knowledge, and experimentation. It relies on human judgment and expertise to iteratively adjust hyperparameters until satisfactory performance is achieved.

Advantages:
Allows for fine-grained control and customization of hyperparameter values based on domain-specific knowledge and insights.
Can be straightforward to implement and interpret, especially for practitioners with expertise in the domain or familiarity with the model architecture.

Disadvantages:
Relies heavily on the practitioner's intuition and may lead to suboptimal or biased hyperparameter choices.
Can be time-consuming and resource-intensive, as it often involves manual experimentation and evaluation of multiple hyperparameter configurations.

Capacity of ML model

Capacity refers to the ability of a machine learning model to capture a wide range of patterns and relationships present in the data. Models with higher capacity have more flexibility and expressiveness, allowing them to learn complex mappings between input and output variables.

Characteristics:
High-capacity models have a greater number of parameters and are capable of fitting more intricate and detailed patterns in the data.
Low-capacity models have fewer parameters and are limited in their ability to capture complex relationships, often resulting in simpler, more generalized models.

Examples:
Neural networks with many layers and neurons **have high capacity** and can learn intricate features in images or text data.
Linear models like linear regression or logistic regression **have lower capacity** and can only capture linear relationships between variables.

Capacity can also be considered as a measure if the model might overfit or underfit.

Ways to reduce High Variance?

1. Using a more simpler model.
2. Using regularization techniques: Lasso and Ridge
3. Cross-Validation techniques: k-fold method
4. Feature Selection methods and filtering out non relevant features
5. Early Stopping when the performance of model starts to degrade
6. Ensemble methods

Coefficient of Determination/ R^2

The coefficient of determination, often denoted as R^2, is a statistical measure that indicates the proportion of the variance in the dependent variable that is predictable from the independent variables in a regression model. In simple terms, R^2 tells us how well the independent variables explain the variability of the dependent variable.

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \overline{y})^2}$$

SSR: sum squared regression
SST: sum squared total

Classification

Classification is another supervised learning technique used to separate datapoints into separate classes. Eg, classifying flowers from IRIS dataset into 3 categories.

Classification is done using Logistic Regression and is further divided into 3 categories:

1. Binary LR
(classifying in 2 classes)
Eg, spam/ non spam,
Rumour classification,
Comment analysis,
churn/ no churn,
Student pass/ fail

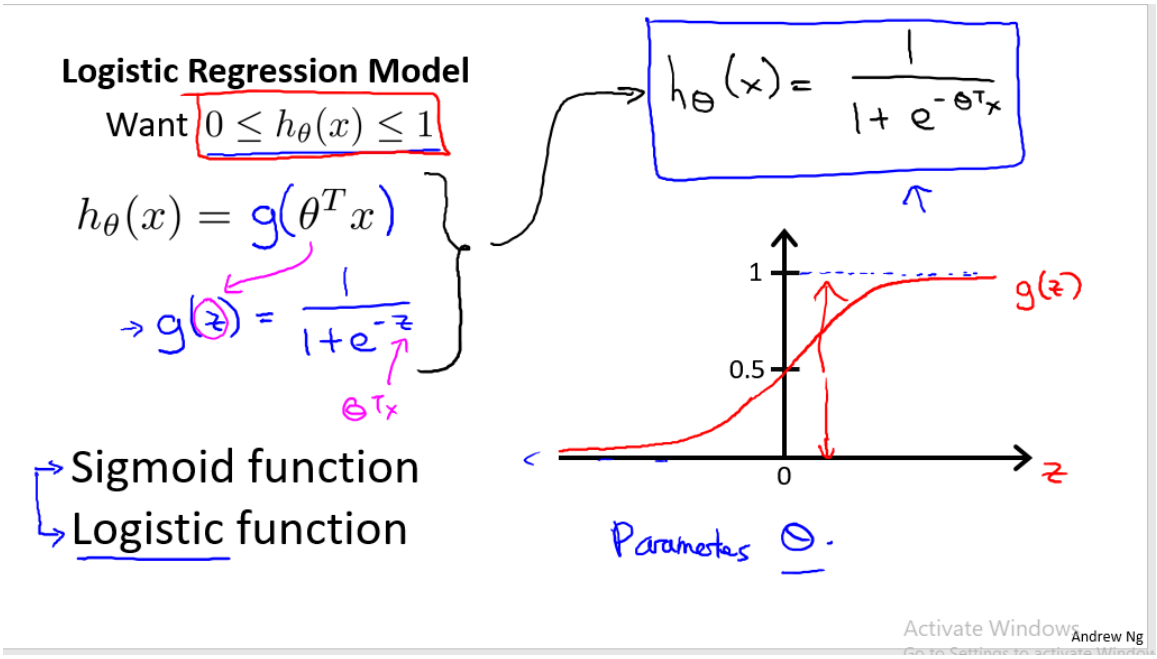
2. Multinomial LR
(classifying in more than 2 classes)
Eg, IRIS classification,
Sentiment analysis,

3. Ordinal LR
(classifying ordinal datapoints)
Eg, movie rating,
Grades classification

Why can't use Linear Regression instead of Logistic?

Linear regression predicts values in numerical-continuous range whereas we want classes in classification problems. Even if we used Linear regression, then also in case of outliers it might fail. Linear regression gives values which could be < 0 or > 1. Linear regression cost functions (MSE, MAE) may give **J** value negative, and for mis-classification they can't assign higher values to **J** as well.

For Binary Classification we use Sigmoid function to squash data in range from 0 to 1.



Cost Functions Used in Logistic Regression

Binary Cross-Entropy Loss (Log Loss): Used in binary logistic regression.
Categorical Cross-Entropy Loss: Used in multinomial logistic regression.

Desired qualities of cost function in Classification?

1. $J_W = 0$ if $\hat{y} = y$
2. Value of J should be very high in case of mis-classification
3. For consistency, J should always be >= 0, never yield negative values

Softmax Function

$$s\left(x_i\right) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}$$

The softmax function is commonly used in the output layer of neural networks for multiclass classification tasks. It converts the raw output scores of the network into probabilities, allowing for intuitive interpretation and comparison of class likelihoods. The predicted class is usually the one with the highest probability after applying the softmax function.

As the scores, zi's increases, the corresponding probabilities ŷi's also increase. However, the softmax function emphasizes the differences between the scores, leading to a more pronounced probability distribution.

Performance Metrics: Regression

1. Mean Squared Error (MSE)

Mean squared error is perhaps the most popular metric used for regression problems. It essentially finds the average of the squared difference between the target value and the value predicted by the regression model.

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(y_j - \check{y}_j)^2$$

Where:

y_j: ground-truth value

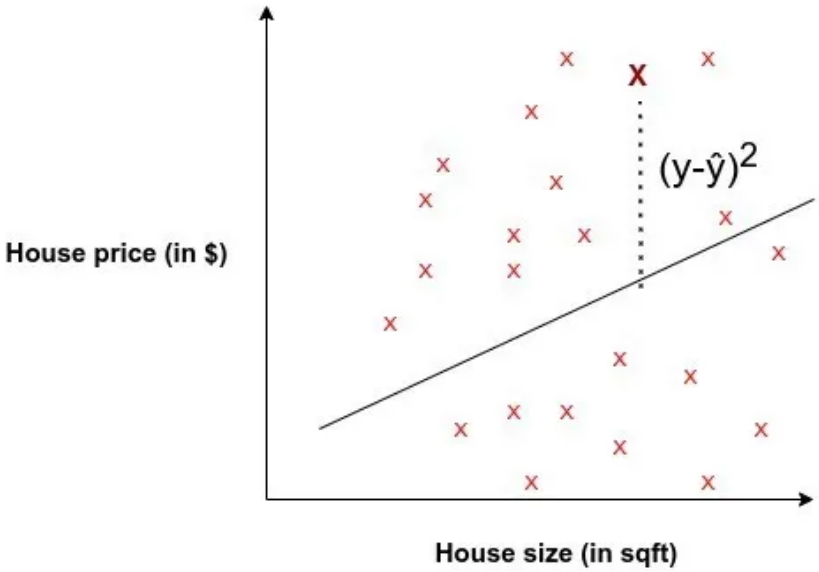
y_hat: predicted value from the regression model

N: number of datums

Performance metrics - MSE

Few key points related to MSE:

1. It's differentiable, so it can be optimized better.
2. It penalizes even small errors by squaring them, which essentially leads to an overestimation of how bad the model is.
3. Error interpretation has to be done with squaring factor(scale) in mind. For example in our Boston Housing regression problem, we got MSE=21.89 which primarily corresponds to (Prices)^2.
4. Due to the squaring factor, it's fundamentally more prone to outliers than other metrics.



2. Mean Absolute Error (MAE)

Mean Absolute Error is the average of the difference between the ground truth and the predicted values. Mathematically, its represented as :

$$MAE = \frac{1}{N}\sum_{j=1}^{N}|y_j - \check{y}_j|$$

Where:

y_j: ground-truth value

y_hat: predicted value from the regression model

N: number of datums

Few key points for MAE:

1. It's more robust towards outliers than MAE, since it doesn't exaggerate errors.
2. It gives us a measure of how far the predictions were from the actual output. However, since MAE uses absolute value of the residual, it doesn't give us an idea of the direction of the error, i.e. whether we're under-predicting or over-predicting the data.
3. Error interpretation needs no second thoughts, as it perfectly aligns with the original degree of the variable.
4. MAE is non-differentiable as opposed to MSE, which is differentiable.

3. Root Mean Squared Error (RMSE)

Root Mean Squared Error corresponds to the square root of the average of the squared difference between the target value and the value predicted by the regression model. Basically, sqrt(MSE). Mathematically it can be represented as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(y_j - \check{y}_j)^2}$$

It addresses a few downsides in MSE.

Few key points related to RMSE:

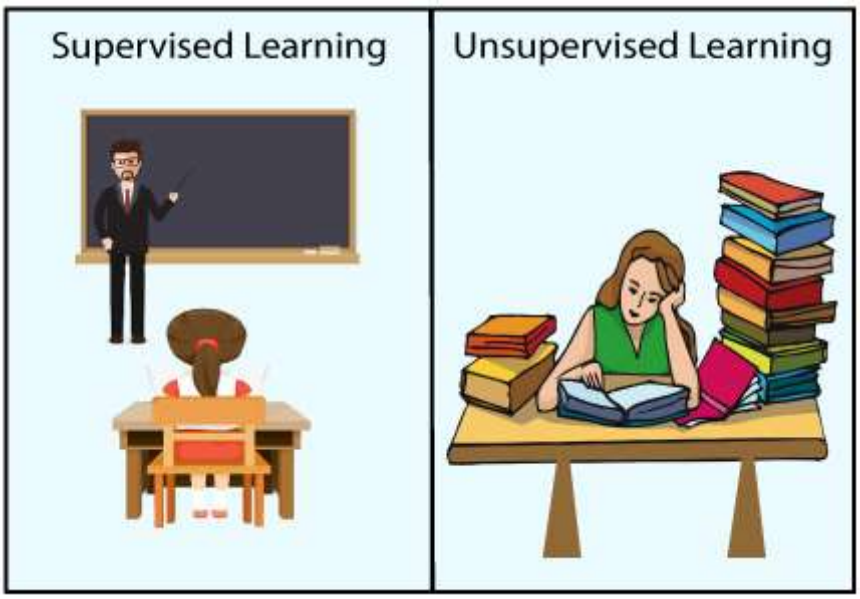
1. It retains the differentiable property of MSE.
2. It handles the penalization of smaller errors done by MSE by square rooting it.

3. Error interpretation can be done smoothly, since the scale is now the same as the random variable.
4. Since scale factors are essentially normalized, it's less prone to struggle in the case of outliers.

4. Coefficient of Determination: discussed above.

Difference between Supervised and Unsupervised Learning

Supervised and Unsupervised learning are the two techniques of machine learning. But both the techniques are used in different scenarios and with different datasets. Below the explanation of both learning methods along with their difference table is given.



Supervised Machine Learning:

Supervised learning is a machine learning method in which models are trained using labeled data. In supervised learning, models need to find the mapping function to map the input variable (X) with the output variable (Y).

$$Y = f(X)$$

Supervised learning needs supervision to train the model, which is similar to as a student learns things in the presence of a teacher. Supervised learning can be used for two types of problems: **Classification** and **Regression**.

Learn more Supervised Machine Learning

Example: Suppose we have an image of different types of fruits. The task of our supervised learning model is to identify the fruits and classify them accordingly. So to identify the image in supervised learning, we will give the input data as well as output for that, which means we will

train the model by the shape, size, color, and taste of each fruit. Once the training is completed, we will test the model by giving the new set of fruit. The model will identify the fruit and predict the output using a suitable algorithm.

Unsupervised Machine Learning:

Unsupervised learning is another machine learning method in which patterns inferred from the unlabeled input data. The goal of unsupervised learning is to find the structure and patterns from the input data. Unsupervised learning does not need any supervision. Instead, it finds patterns from the data by its own.

Learn more Unsupervised Machine Learning

Unsupervised learning can be used for two types of problems: **Clustering** and **Association**.

Example: To understand the unsupervised learning, we will use the example given above. So unlike supervised learning, here we will not provide any supervision to the model. We will just provide the input dataset to the model and allow the model to find the patterns from the data. With the help of a suitable algorithm, the model will train itself and divide the fruits into different groups according to the most similar features between them.

The main differences between Supervised and Unsupervised learning are given below:

Supervised Learning	Unsupervised Learning
Supervised learning algorithms are trained using labeled data.	Unsupervised learning algorithms are trained using unlabeled data.
Supervised learning model takes direct feedback to check if it is predicting correct output or not.	Unsupervised learning model does not take any feedback.
Supervised learning model predicts the output.	Unsupervised learning model finds the hidden patterns in data.
In supervised learning, input data is provided to the model along with the output.	In unsupervised learning, only input data is provided to the model.

The goal of supervised learning is to train the model so that it can predict the output when it is given new data.	The goal of unsupervised learning is to find the hidden patterns and useful insights from the unknown dataset.
Supervised learning needs supervision to train the model.	Unsupervised learning does not need any supervision to train the model.
Supervised learning can be categorized in **Classification** and **Regression** problems.	Unsupervised Learning can be classified in **Clustering** and **Associations** problems.
Supervised learning can be used for those cases where we know the input as well as corresponding outputs.	Unsupervised learning can be used for those cases where we have only input data and no corresponding output data.
Supervised learning model produces an accurate result.	Unsupervised learning model may give less accurate result as compared to supervised learning.
Supervised learning is not close to true Artificial intelligence as in this, we first train the model for each data, and then only it can predict the correct output.	Unsupervised learning is more close to the true Artificial Intelligence as it learns similarly as a child learns daily routine things by his experiences.
It includes various algorithms such as Linear Regression, Logistic Regression, Support Vector Machine, Multi-class Classification, Decision tree, Bayesian Logic, etc.	It includes various algorithms such as Clustering, KNN, and Apriori algorithm.

Note: The supervised and unsupervised learning both are the machine learning methods, and selection of any of these learning depends on the factors related to the structure and volume of your dataset and the use cases of the problem.

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Cross Validation in Machine Learning

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In **machine learning**, we couldn't fit the model on the training data and can't say that the model will work accurately for the real data. For this, we must assure that our model got the correct patterns from the data, and it is not getting up too much noise. For this purpose, we use the **cross-validation technique**. In this article, we'll delve into the process of cross-validation in machine learning.

What is Cross-Validation?

Cross validation is a technique used in machine learning to evaluate the performance of a model on unseen data. It involves dividing the available data into multiple folds or subsets, using one of these folds as a validation set, and training the model on the remaining folds. This process is repeated multiple times, each time using a different fold as the validation set. Finally, the results from each validation step are averaged to produce a more robust estimate of the model's performance. Cross validation is an important step in the machine learning process and helps to ensure that the model selected for deployment is robust and generalizes well to new data.

What is cross-validation used for?

The main purpose of cross validation is to prevent overfitting, which occurs when a model is trained too well on the training data and performs poorly on new, unseen data. By evaluating the model on multiple validation sets, cross validation provides a more realistic estimate of the model's generalization performance, i.e., its ability to perform well on new, unseen data.

Types of Cross-Validation

There are several types of cross validation techniques, including **k-fold cross validation, leave-one-out cross validation, and Holdout validation, Stratified**

Cross-Validation. The choice of technique depends on the size and nature of the data, as well as the specific requirements of the modeling problem.

1. Holdout Validation

In Holdout Validation, we perform training on the 50% of the given dataset and rest 50% is used for the testing purpose. It's a simple and quick way to evaluate a model. The major drawback of this method is that we perform training on the 50% of the dataset, it may possible that the remaining 50% of the data contains some important information which we are leaving while training our model i.e. higher bias.

2. LOOCV (Leave One Out Cross Validation)

In this method, we perform training on the whole dataset but leaves only one data-point of the available dataset and then iterates for each data-point. In LOOCV, the model is trained on $n-1$ samples and tested on the one omitted sample, repeating this process for each data point in the dataset. It has some advantages as well as disadvantages also.

An advantage of using this method is that we make use of all data points and hence it is low bias.

The major **drawback** of this method is that it leads to **higher variation** in the testing model as we are testing against one data point. If the data point is an outlier it can lead to higher variation. Another drawback is it **takes a lot of execution time** as it iterates over 'the number of data points' times.

3. Stratified Cross-Validation

It is a technique used in machine learning to ensure that each fold of the cross-validation process maintains the same class distribution as the entire dataset. This is particularly important when dealing with imbalanced datasets, where certain classes may be underrepresented. In this method,

1. The dataset is divided into k folds while maintaining the proportion of classes in each fold.

2. During each iteration, one-fold is used for testing, and the remaining folds are used for training.
3. The process is repeated k times, with each fold serving as the test set exactly once.

Stratified Cross-Validation is essential when dealing with classification problems where maintaining the balance of class distribution is crucial for the model to generalize well to unseen data.

4. K-Fold Cross Validation

In K-Fold Cross Validation, we split the dataset into k number of subsets (known as folds) then we perform training on the all the subsets but leave one(k-1) subset for the evaluation of the trained model. In this method, we iterate k times with a different subset reserved for testing purpose each time.

> ***Note:*** *It is always suggested that the value of k should be 10 as the lower value of k is takes towards validation and higher value of k leads to LOOCV method.*

Example of K Fold Cross Validation

The diagram below shows an example of the training subsets and evaluation subsets generated in k-fold cross-validation. Here, we have total 25 instances. In first iteration we use the first 20 percent of data for evaluation, and the remaining 80 percent for training ([1-5] testing and [5-25] training) while in the second iteration we use the second subset of 20 percent for evaluation, and the remaining three subsets of the data for training ([5-10] testing and [1-5 and 10-25] training), and so on.


```
Total instances: 25
Value of k     : 5
No. Iteration                 Training set observations
Testing set observations
 1      [ 5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24]
[0 1 2 3 4]
 2      [ 0  1  2  3  4 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24]
[5 6 7 8 9]
 3      [ 0  1  2  3  4  5  6  7  8  9 15 16 17 18 19 20 21 22 23 24]
[10 11 12 13 14]
 4      [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 20 21 22 23 24]
[15 16 17 18 19]
 5      [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19]
[20 21 22 23 24]
```

Comparison between cross-validation and hold out method

Advantages of train/test split:

1. This runs K times faster than Leave One Out cross-validation because K-fold cross-validation repeats the train/test split K-times.
2. Simpler to examine the detailed results of the testing process.

Advantages of cross-validation:

1. More accurate estimate of out-of-sample accuracy.

2. More “efficient” use of data as every observation is used for both training and testing.

Advantages and Disadvantages of Cross Validation

Advantages:

1. Overcoming Overfitting: Cross validation helps to prevent overfitting by providing a more robust estimate of the model’s performance on unseen data.
2. Model Selection: Cross validation can be used to compare different models and select the one that performs the best on average.
3. Hyperparameter tuning: Cross validation can be used to optimize the hyperparameters of a model, such as the regularization parameter, by selecting the values that result in the best performance on the validation set.
4. Data Efficient: Cross validation allows the use of all the available data for both training and validation, making it a more data-efficient method compared to traditional validation techniques.

Disadvantages:

1. Computationally Expensive: Cross validation can be computationally expensive, especially when the number of folds is large or when the model is complex and requires a long time to train.
2. Time-Consuming: Cross validation can be time-consuming, especially when there are many hyperparameters to tune or when multiple models need to be compared.
3. Bias-Variance Tradeoff: The choice of the number of folds in cross validation can impact the bias-variance tradeoff, i.e., too few folds may result in high variance, while too many folds may result in high bias.

Python implementation for k fold cross-validation

Step 1: Import necessary libraries.

Python3

```
from sklearn.model_selection import cross_val_score, KFold
from sklearn.svm import SVC
from sklearn.datasets import load_iris
```

Step 2: Load the dataset

let's use the iris dataset, a multi-class classification in-built dataset.

Python3

```
iris = load_iris()
X, y = iris.data, iris.target
```

Step 3: Create SVM classifier

svc is a Support Vector Classification model from scikit-learn.

Python3

```
svm_classifier = SVC(kernel='linear')
```

Step 4:Define the number of folds for cross-validation

Python3

```
num_folds = 5
kf = KFold(n_splits=num_folds, shuffle=True, random_state=42)
```

Step 5: Perform k-fold cross-validation

Python3

```
cross_val_results = cross_val_score(svm_classifier, X, y, cv=kf)
```

Step 6: Evaluation metrics

Python3

```
print(f'Cross-Validation Results (Accuracy): {cross_val_results}')
print(f'Mean Accuracy: {cross_val_results.mean()}')
```

Output:

```
Cross-Validation Results (Accuracy): [1.         1.         0.96666667
0.93333333 0.96666667]
Mean Accuracy: 0.9733333333333334
```

Frequently Asked Questions(FAQs)

1.What is K in K fold cross validation?

It represents the number of folds or subsets into which the dataset is divided for cross-validation. Common values are 5 or 10.

2.How many folds for cross-validation?

The number of folds is a parameter in K-fold cross-validation, typically set to 5 or 10. It determines how many subsets the dataset is divided into.

3.What is cross-validation example?

Split the dataset into five folds. For each fold, train the model on four folds and evaluate it on the remaining fold. The average performance across all five folds is the estimated out-of-sample accuracy.

4.What is the purpose of validation?

Validation assesses a model's performance on unseen data, helping detect overfitting. It ensures the model generalizes well and is not just memorizing the training data.

5. Why use 10-fold cross-validation?

10-fold cross-validation provides a balance between robust evaluation and computational efficiency. It offers a good trade-off by dividing the data into 10 subsets for comprehensive assessment.

G Gianluca Turcatel Dec 23, 2021 1 min read

Derivation of the Binary Cross Entropy Loss Gradient

The binary cross entropy loss function is the preferred loss function in binary classification tasks, and is utilized to estimate the value of the model's parameters through gradient descent. In order to apply gradient descent we must calculate the derivative (gradient) of the loss function w.r.t. the model's parameters. Deriving the gradient is usually the most tedious part of training a machine learning model.
In this article we will derive the derivative of the binary cross entropy loss function w.r.t. W, step by step.

The binary cross entropy loss is given by

$$L(\boldsymbol{W}) = -[\boldsymbol{y} * \log(\hat{\boldsymbol{y}}) + (1 - \mathbf{y}) * \log(1 - \hat{\boldsymbol{y}})] \quad (1)$$

y is the observed class, y_hat the prediction, W the model's parameters. Predictions are given by:

$$\hat{\boldsymbol{y}} = \sigma(z) = \frac{1}{1 + e^{-\boldsymbol{z}}} \quad (2)$$

z is equal to:

$$z = w_0 + x_1 * w_1 + x_2 * w_2 + \cdots + x_k * w_k = W^T X \quad (3)$$

To calculate the gradient of L(W) w.r.t. W we will use the chain rule:

$$\frac{\partial L(W)}{\partial W} = \frac{\partial L(W)}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial z} \frac{\partial z}{\partial W} \quad (4)$$

Let's derive the first term:

$$\frac{\partial L(W)}{\partial \hat{y}} = -\left(\frac{y}{\hat{y}} - \frac{1-y}{1-\hat{y}}\right) = \frac{\hat{y}-y}{\hat{y}(1-\hat{y})} \quad (5)$$

The second term is a little more complicated:

$$\frac{\partial \hat{y}}{\partial z} = \frac{\partial}{\partial z}\left[\frac{1}{1+e^{-z}}\right] = \frac{\partial}{\partial z}(1+e^{-z})^{-1} = \quad (6)$$

$$= -(1+e^{-z})^{-2}(-e^{-z}) = \frac{e^{-z}}{(1+e^{-z})^2} = \quad (7)$$

$$= \frac{1}{(1+e^{-z})} \frac{e^{-z}}{(1+e^{-z})} = \frac{1}{1+e^{-z}} \frac{(1+e^{-z})-1}{(1+e^{-z})} = \quad (8)$$

$$= \frac{1}{1+e^{-z}} \left(\frac{1+e^{-z}}{1+e^{-z}} - \frac{1}{1+e^{-z}}\right) = \quad (9)$$

$$= \frac{1}{1+e^{-z}}\left(1-\frac{1}{1+e^{-z}}\right) = \hat{y}(1-\hat{y}) \tag{10}$$

Done with the second term. The derivative of the third term is straight forward:

$$\frac{\partial z}{\partial W} = X \tag{11}$$

Now let's put everything together:

$$\frac{\partial L(W)}{\partial W} = \frac{\hat{y}-y}{\hat{y}(1-\hat{y})}\hat{y}(1-\hat{y})X = (\hat{y}-y)X \tag{12}$$

And there you have it: the derivative of the binary cross entropy loss function w.r.t. the model's parameters.

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#Python #MachineLearning #CrossEntropy #BinaryClassification

Performance Metrics: Classification Problems

Confusion Matrix

Confusion matrix is a tabular structure which denote the performance measure of a classification algorithm. It provides the comparision of model's predicted values and actual values based on test data.

The matrix displays four instances of possible conditions:

1. **True positives (TP):** occur when the model accurately predicts a positive data point.
2. **True negatives (TN):** occur when the model accurately predicts a negative data point.
3. **False positives (FP):** occur when the model predicts a positive data point incorrectly.
4. **False negatives (FN):** occur when the model mispredicts a negative data point.

		Actual	
		Dog	Not Dog
Predicted	Dog	**TP**	**FP**
	Not Dog	**FN**	**TN**

Precision

Precision measures the proportion of correctly predicted positive instances (true positives) out of all instances predicted as positive (true positives and false positives). It indicates the accuracy of positive predictions.

$$Precision = \frac{TP}{TP + FP}$$

Recall

Recall measures the proportion of correctly predicted positive instances (true positives) out of all actual positive instances (true positives and false negatives). It indicates the ability of the classifier to find all positive instances.

$$Recall = \frac{TP}{TP + FN}$$

Specificity

Specificity measures the proportion of correctly predicted negative instances (true negatives) out of all actual negative instances (true negatives and false positives). It indicates the ability of the classifier to correctly identify negative instances.

Sensitivity

Sensitivity measures the proportion of correctly predicted positive instances (true positives) out of all actual positive instances (true positives and false negatives). It indicates the ability of the classifier to find all positive instances.

$$\textbf{Sensitivity} = \frac{\textbf{True Positives}}{\textbf{True Positives} + \textbf{False Negatives}}$$

$$\textbf{Specificity} = \frac{\textbf{True Negatives}}{\textbf{True Negatives} + \textbf{False Positives}}$$

Accuracy

Accuracy measures the proportion of correctly classified instances (true positives and true negatives) out of the total number of instances. It indicates the overall correctness of the classifier's predictions.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

F1 Score

The F1 score is calculated as the harmonic mean of precision and recall. It combines both precision and recall into a single metric, providing a balance between the two measures.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

F1 Beta score

The F1 Beta score is a variant of the F1 score that allows for adjusting the relative importance of precision and recall using a parameter beta. It provides a way to emphasize either precision or recall based on the specific requirements of the classification task.

$$F\beta = \frac{(1 + \beta^2) \times Precision \times Recall}{\beta^2 \times Precision + Recall}$$

Where:

1. If β = 1, it is equivalent to the regular F1 score.
2. If β < 1, it emphasizes precision over recall.
3. If β >1, it emphasizes recall over precision.

Mis classification rate

Misclassification rate measures the proportion of incorrectly classified instances (false positives and false negatives) out of the total number of instances. It indicates the overall accuracy of the classifier.

MCR = 1 - Accuracy

Encoding Techniques for Classification Problems

Encoding techniques are used to convert categorical data to numeric, so that it becomes easier to deal with and make proper model.

One Hot Encoding

In this encoding type additional columns are added into the dataset, each column for a class type. Then, if the object belonged to a class it's class is set as 1 or hot and other set to 0 or cold.
Eg, there are three color categories R, G and B.

Object	Red	Green	Blue
Apples	1	0	0
Grapes	0	1	0
Blueberries	0	0	1

Advantages

1. It allows the use of categorical variables in models that require numerical input.
2. It can improve model performance by providing more information to the model about the categorical variable.
3. It can help to avoid the problem of ordinality, which can occur when a categorical variable has a natural ordering (e.g. "small", "medium", "large").

Disadvantages

1. It can lead to increased dimensionality, as a separate column is created for each category in the variable. This can make the model more complex and slow to train.
2. It can lead to sparse data, as most observations will have a value of 0 in most of the one-hot encoded columns.
3. It can lead to overfitting, especially if there are many categories in the variable and the sample size is relatively small.
4. One-hot-encoding is a powerful technique to treat categorical data, but it can lead to increased dimensionality, sparsity, and overfitting. It is important to use it cautiously and consider other methods such as ordinal encoding or binary encoding.

Label Encoding

In label encoding each class is assigned a label of unique integer value and no extra columns are created.

Object	Color	Label
Apples	Red	0
Grapes	Green	1
Blueberries	Blue	2

Advantages

1. **Simplicity:** It is straightforward to implement and understand. It involves converting categories into numerical labels, making it easy to work with for beginners.
2. **Compatibility with Algorithms:** Many machine learning algorithms, especially traditional ones like linear regression, decision trees, and support vector machines, require numerical input features. Label encoding provides a way to represent categorical data in a format compatible with these algorithms.
3. **Efficient Memory Usage:** It typically uses less memory than other encoding methods like one-hot encoding. This can be important when working with large datasets.

Disadvantages

1. **Ordinal Misinterpretation:** It assumes an ordinal relationship between the categories, which may not always be true. For nominal categorical data (where there's no inherent order among categories), label encoding can mislead the algorithm into treating the encoded values as ordinal, potentially leading to incorrect model results.
2. **Arbitrary Numerical Values:** The integers assigned during label encoding are random and do not convey meaningful category information. Machine learning algorithms might misinterpret these values as having numerical significance or relationships when there aren't any.
3. **Impact on Model Performance:** It can introduce unintended relationships between categories, especially in algorithms that rely on distance metrics (e.g., k-means clustering). The algorithm may interpret smaller numerical differences as more significant than they should be.
4. **Not Suitable for High Cardinality:** When dealing with categorical features with a high number of unique categories, label encoding can lead to a significant increase in dimensionality. This can negatively impact model performance and increase the risk of overfitting.

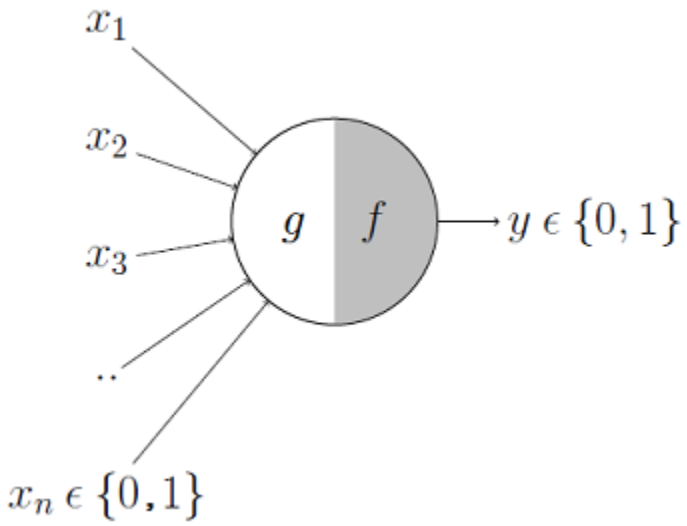
5. **Loss of Information:** It can result in a loss of information about the original categorical data, especially if the encoded values do not represent the true nature of the categories.

Ordinal Encoding

In this encoding type, integer values are assigned maintaining the ordinal structure of data. It is very similar to label encoding. Eg, I have {low, medium, high} then these can be represented as {0, 1, 2}.

McCulloch and Pitts Neuron Model

Proposed by Warren McCulloch and Walter Pitts in 1943 based on real world neuron structure.
It consisted of binary inputs {x1, x2, … , xn} values in {0, 1} with binary output {y} values in {0, 1}.



Inputs can be excitatory or inhibitory, means if the input is excitatory means they have more likelihood of firing an action and inhibitory inputs don't.
Output 'y' is 0 if any input Xi is 0, i.e., inhibitory.

$$g(x_1, x_2, x_3, ..., x_n) = g(\mathbf{x}) = \sum_{i=1}^{n} x_i$$

$$\begin{aligned} y = f(g(\mathbf{x})) &= 1 \quad if \quad g(\mathbf{x}) \geq \theta \\ &= 0 \quad if \quad g(\mathbf{x}) < \theta \end{aligned}$$

To implement AND using mc pitts neuron, the threshold value would be 3 considering two variable input size.
Similarly to implement OR using mc pitts, the threshold value would be 1 for two variable system.

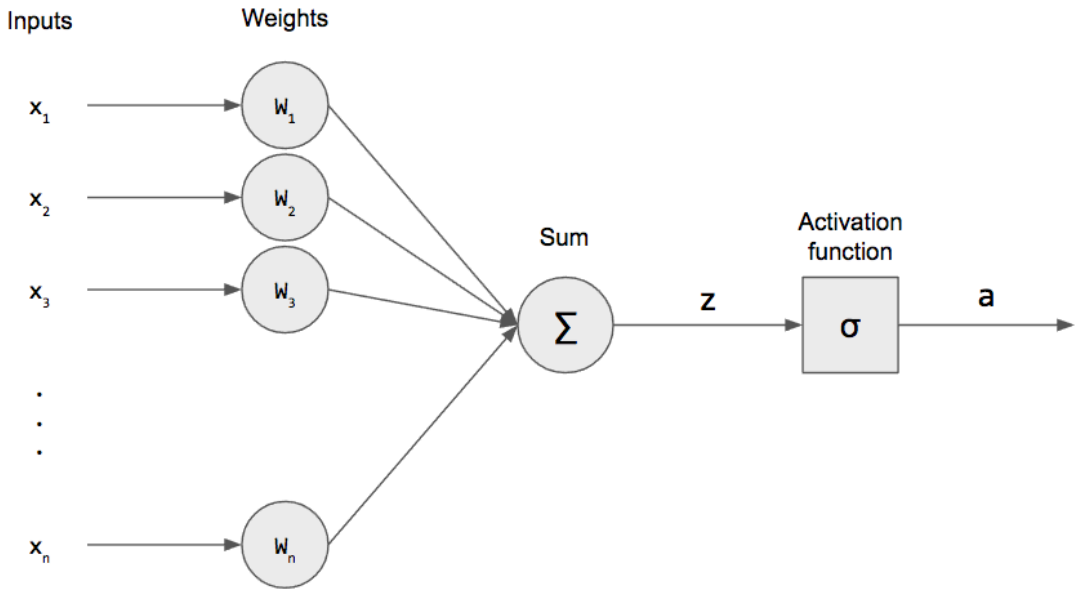
Implement OR, AND, NOR, NAND, XOR, XNOR using mc pitts here:

Linearly Separable
This means that the two classes can be separated linearly using a line or some hyperplane in higher dimension. Eg, during implementing AND using mc pitts, the inputs that produced output 1 and 0 are linearly separable as (1, 1) produced y = 1 and (0, 0), (0, 1), (1, 0) produced y = 0.

Non Linearly Separable
This means opposite of linearly separable. Eg, implementing XOR using mc pitts neuron, the input classes that produce outputs 0 and 1 can't be separated linearly.
(0, 0) and (1, 1) produced output 0 and others 1.

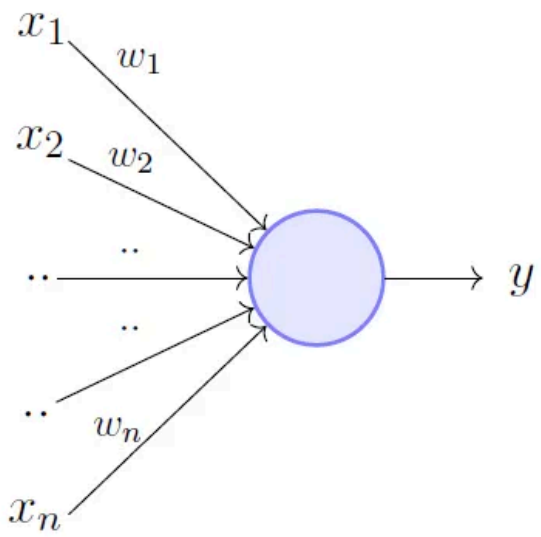
Perceptron Neuron Model

Frank Rosenblatt proposed the first perceptron neuron model in 1958, which was more complex that simple mc pitts neuron model. Later refined by Minsky and Papert in 1969.



Main difference than mc pitts
Introduction of weights, considering importance of some or more inputs.
Inputs not limited to boolean values.

Types of Perceptron Neurons
Single layer: Single layer perceptron can learn only linearly separable patterns.
Multilayer: Multilayer perceptrons can learn about two or more layers having a greater processing power.



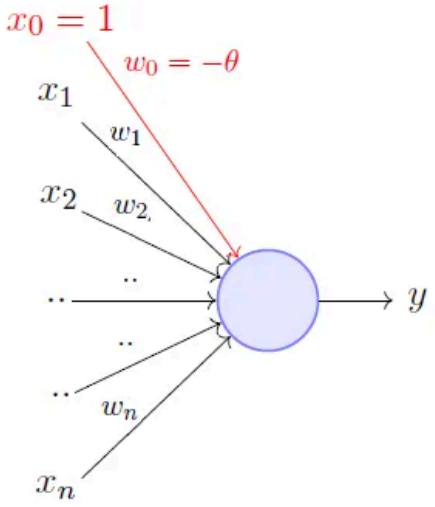
$$y = 1 \quad if \sum_{i=1}^{n} w_i * x_i \geq \theta$$

$$= 0 \quad if \sum_{i=1}^{n} w_i * x_i < \theta$$

Rewriting the above,

$$y = 1 \quad if \sum_{i=1}^{n} w_i * x_i - \theta \geq 0$$

$$= 0 \quad if \sum_{i=1}^{n} w_i * x_i - \theta < 0$$



A more accepted convention,

$$y = 1 \quad if \sum_{i=0}^{n} w_i * x_i \geq 0$$

$$= 0 \quad if \sum_{i=0}^{n} w_i * x_i < 0$$

$$where, \quad x_0 = 1 \quad and \quad w_0 = -\theta$$

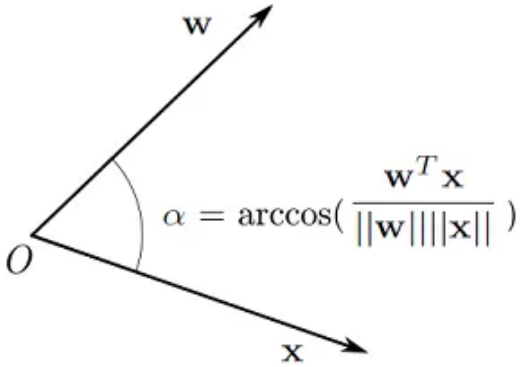
Algorithm: Perceptron Learning Algorithm

$P \leftarrow inputs \quad with \quad label \quad 1;$
$N \leftarrow inputs \quad with \quad label \quad 0;$
Initialize $\mathbf{w}$ randomly;
while !*convergence* **do**
  Pick random $\mathbf{x} \in P \cup N$;
  if $\mathbf{x} \in P \quad and \quad \mathbf{w}.\mathbf{x} < 0$ **then**
    $\mathbf{w} = \mathbf{w} + \mathbf{x}$;
  end
  if $\mathbf{x} \in N \quad and \quad \mathbf{w}.\mathbf{x} \geq 0$ **then**
    $\mathbf{w} = \mathbf{w} - \mathbf{x}$;
  end
end
//the algorithm converges when all the inputs are classified correctly

$$\mathbf{w} = [w_0, w_1, w_2, ..., w_n]$$
$$\mathbf{x} = [1, x_1, x_2, ..., x_n]$$
$$\mathbf{w} \cdot \mathbf{x} = \mathbf{w^T x} = \sum_{i=0}^{n} w_i * x_i$$

$$\mathbf{w}^T\mathbf{x} = \|\mathbf{w}\|\|\mathbf{x}\| cos\alpha$$

$$cos\alpha = \frac{\mathbf{w}^T\mathbf{x}}{||\mathbf{w}||||\mathbf{x}||}$$



Implementing OR, AND, XOR using perceptron here:

A network of $2^n + 1$ perceptron is not necessary but sufficient?

Any boolean function with 'n' inputs can be represented using 2^n neurons in single hidden layer and 1 extra neuron for output layer, thus completing $2^n + 1$ neurons.

However, this also means that there exists some another method which uses less than $2^n + 1$ neurons for a boolean function with 'n' inputs.

Thus, a network of $2^n + 1$ perceptron neurons is not necessary but sufficient.

Activation Functions

An activation function in a neural network is a mathematical function that determines the output of a neuron or a layer of neurons based on the weighted sum of inputs. The activation function introduces non-linearity to the network, allowing it to learn complex patterns and relationships in the data.

Purpose of Activation Functions

Introduce Non-linearity: Activation functions introduce non-linearity to the network, enabling it to approximate complex functions and learn non-linear patterns in the data.

Without activation functions, the network would be limited to representing linear transformations of the input data, making it unable to capture complex relationships.

Enable Learning Hierarchical Representations: Activation functions enable neural networks to learn hierarchical representations of data by transforming the input data into higher-dimensional feature spaces.

Each layer of the network applies a series of non-linear transformations to the input data, allowing the network to learn increasingly abstract and complex features.

Ensure Network Expressiveness: Activation functions play a crucial role in determining the expressiveness and representational power of the neural network.

By introducing non-linearity, activation functions enable neural networks to approximate arbitrary functions, making them powerful universal function approximators.

Stabilize Gradient Descent: Activation functions help stabilize the training process by controlling the flow of gradients during backpropagation.

Well-designed activation functions prevent issues such as vanishing or exploding gradients, which can hinder the convergence of the training algorithm.

Common Uses of Activation Functions

Classification: In classification tasks, activation functions such as softmax are used in the output layer to convert the raw output of the network into probabilities representing the likelihood of each class.

Non-linear Regression: Activation functions such as ReLU (Rectified Linear Unit) are commonly used in regression tasks to introduce non-linearity and capture complex relationships between input and output variables.

Feature Extraction: Activation functions in hidden layers help extract meaningful features from the input data by transforming it into higher-dimensional representations.

Regularization: Activation functions such as dropout or sigmoid help regularize the network by preventing overfitting and improving its generalization ability.

In summary, activation functions play a crucial role in neural network architectures by introducing non-linearity, enabling learning of complex patterns, and ensuring the network's expressiveness and stability during training. They are essential components of neural networks and are used in various tasks such as classification, regression, and feature extraction.

How a neural network of non - linear activation function behaves?
A neural network with a non-linear activation function exhibits behavior characterized by the ability to learn and represent complex patterns, extract hierarchical features from the input data, and solve a wide range of tasks that require non-linear mappings between input and output variables.

Linear Activation Function

A linear activation function computes a simple linear transformation of the input data and is suitable for regression tasks and specific architectures where linearity is desired. However, its lack of non-linearity limits its applicability to more complex tasks that require learning non-linear relationships in the data.

Advantages

1. **Simple:** Linear activation functions are straightforward and easy to understand, making them suitable for simple regression tasks.

2. **Stability:** The linear activation function provides stable gradients during training, making it less prone to issues such as vanishing or exploding gradients.

Disadvantages

1. **Limited Expressiveness:** Linear activation functions are not capable of learning complex patterns or non-linear relationships in the data, limiting the types of tasks they can be applied to.
2. **Unsuitable for Classification:** Linear activation functions are not suitable for classification tasks where non-linear decision boundaries are required, as they cannot capture non-linear relationships between input and output variables.
3. It is not possible to back propagate as the derivative of this function is constant.
4. All layers of neural network will collapse into 1.

1.

$$\textit{Binary step}$$

$$f(x) = \begin{cases} 0 & for\ x < 0 \\ 1 & for\ x \geqslant 0 \end{cases}$$

Range (f(x)) = {0,1}

2.

$$\textit{Linear}$$

$$f(x) = x$$

Range (f(x)) = (−∞,+∞)

Non Linear Activation Functions

Non-linear activation functions are mathematical functions used in neural networks to introduce non-linearity into the network's output. These functions are applied to the weighted sum of inputs and biases of neurons in the network, allowing the network to approximate complex non-linear relationships between input and output data. Non-linear activation functions are crucial for enabling neural networks to learn and represent intricate patterns and relationships in the data.

1. Sigmoid

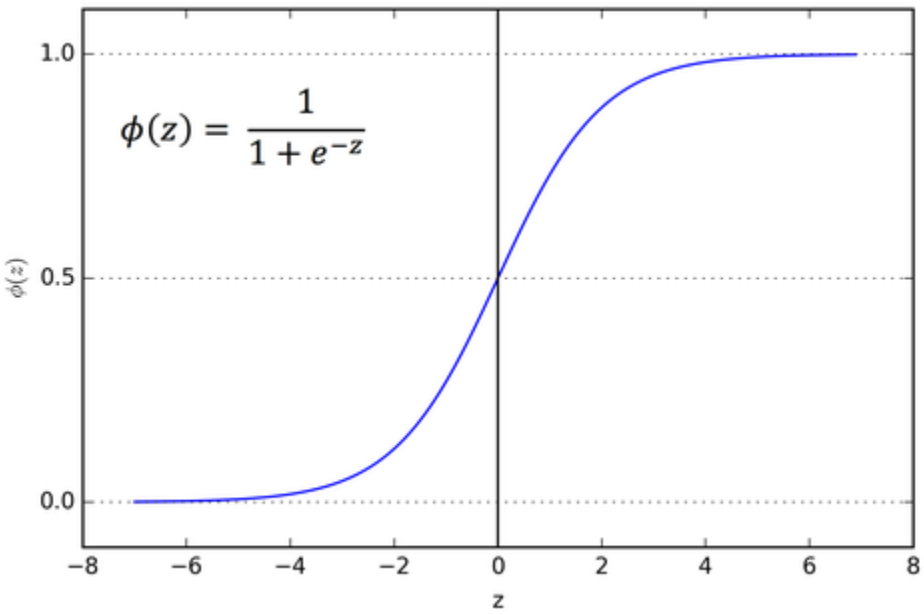
Normally used as the output of a binary probabilistic function.

Advantages

-> Gives you a smooth gradient while converging.
-> One of the best Normalised functions.
-> Gives a clear prediction(classification) with 1 & 0.

Disadvantages

-> Prone to Vanishing Gradient problem.
-> Not a zero-centric function(Always gives a positive values).
-> Computationally expensive function(exponential in nature).



2. Tanh

Normally used as the input of a binary probabilistic function.

Advantages

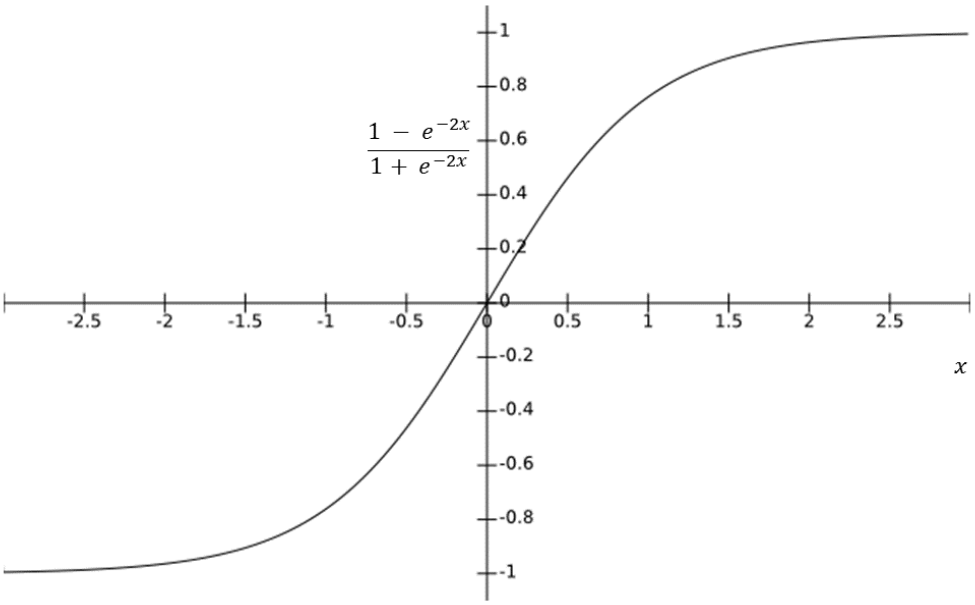
-> Zero-centric function unlike Sigmoid.

-> It is a smooth gradient converging function.

Disadvantages

-> Prone to Vanishing Gradient function.

-> Computationally expensive function(exponential in nature).



3. RELU (Rectified Linear Unit)

Advantages

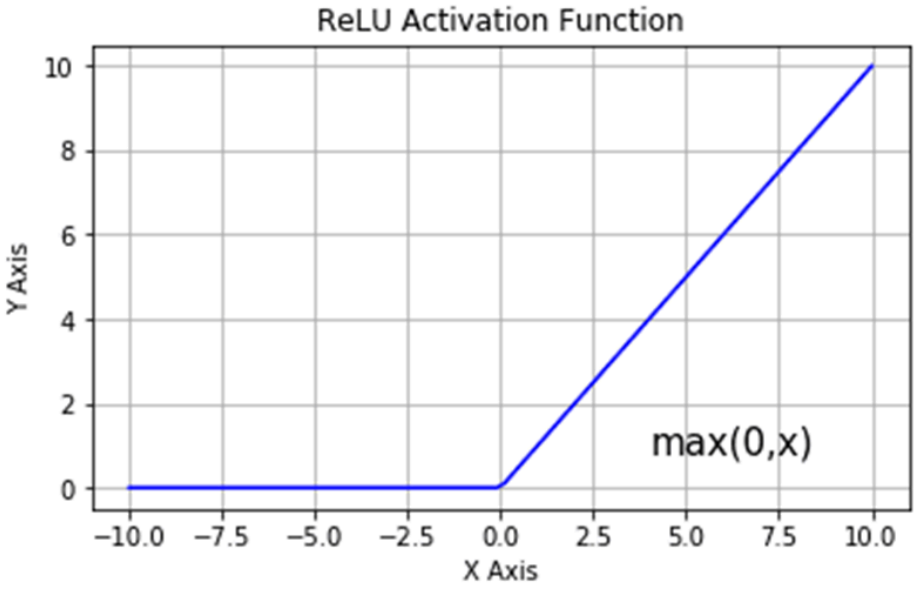
-> Can deal with Vanishing Gradient problem.

-> Computationally inexpensive function(linear in nature).

Disadvantages

-> Not a zero-centric function.

-> Gives zero value as inactive in the negative axis.



4. Leaky RELU

It is the same as of RELU function except it gives some partial value(0.01 instead zero as of RELU) in the negative axis.

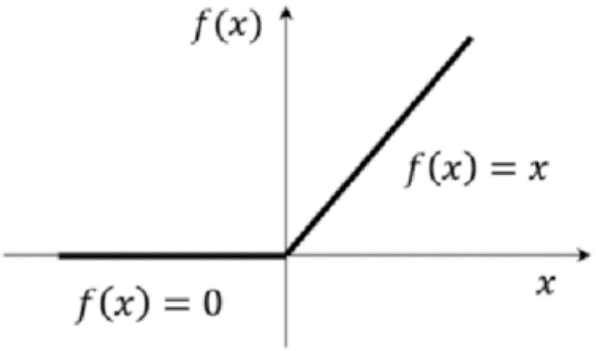
Advantages

-> Addresses the dying ReLU problem by allowing a small, non-zero gradient for negative inputs, preventing neurons from becoming inactive.

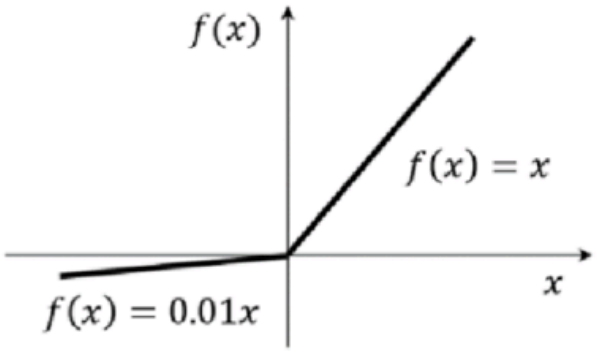
-> Provides better performance than ReLU in scenarios where dead neurons are prevalent.

Limitations

-> Introduces an additional hyperparameter (α) that needs to be tuned, which may require additional computational resources during hyperparameter optimization.



ReLU activation function



LeakyReLU activation function

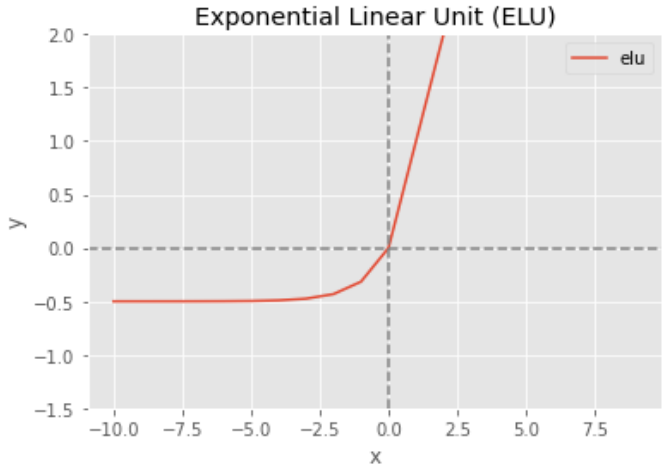
5. ELU (Exponential Linear Unit)

Advantages

-> Gives smoother convergence for any negative axis value.

-> For any positive output, it behaves like a step function and gives a constant output.

$$ELU(\alpha, x) = \begin{cases} x, & \text{if } x \geq 0 \\ \alpha(e^x - 1), & \text{otherwise} \end{cases}$$



6. SoftMax

Normally used as the output in multi-class classification problems to find out different probabilities for different classes(Unlike Sigmoid which is prefered for a binary-class classification).

Advantages

-> Suitable for multi-class classification tasks as it converts raw scores into probabilities, making it easy to interpret the output as class probabilities.

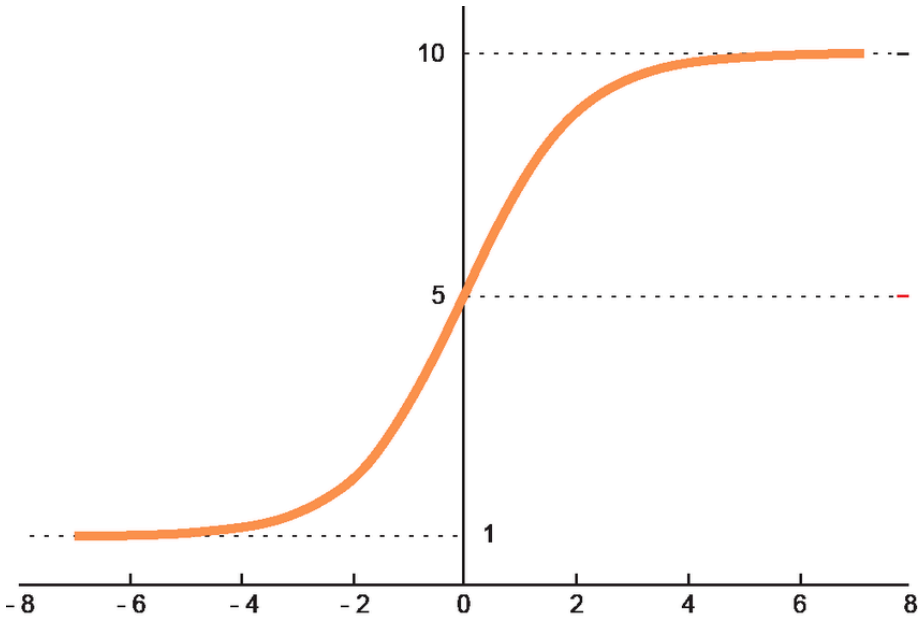
-> Encourages competition between classes, making it beneficial for tasks where only one class should be activated.

Limitations

-> Sensitive to outliers and large input values, which can result in numerical instability during training.

-> Not suitable for regression or binary classification tasks where a single output is desired.

$$f(x_i) = \frac{e^{x_i}}{\sum_i e^{x_i}}$$



7. PRELU (Parametric RELU)

The advantage of PRELU is it has the learning parameter function which fine-tunes the activation function based on its learning rate(unlike zero in the case of RELU and 0.01 in the case of Leaky RELU).

Advantages

-> Similar to Leaky ReLU, Parametric ReLU introduces a learnable parameter (α) that allows the network to adaptively adjust the slope of the negative part of the activation function.

-> Offers more flexibility compared to Leaky ReLU, as the slope can be learned from data.

Limitations

-> Requires additional parameters to be learned, increasing the model's complexity and the risk of overfitting.

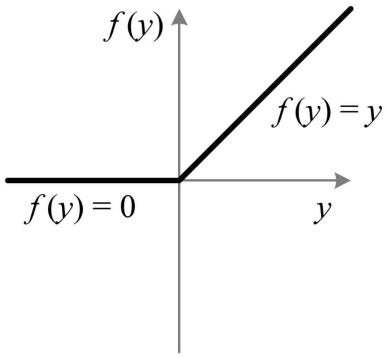
Leaky ReLUs [edit]

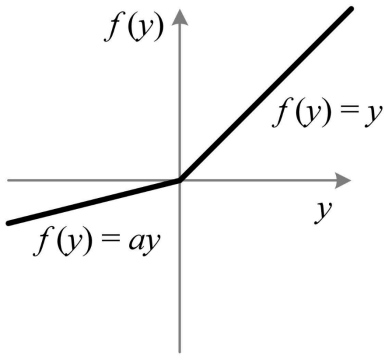
Leaky ReLUs allow a small, non-zero

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ 0.01x & \text{otherwise} \end{cases}$$

Parametric ReLUs take this idea furth

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ ax & \text{otherwise} \end{cases}$$





8. SWISH

Also known as self gated function. This activation function is one of the kinds that is being inspired by the use of the Sigmoid function inside an LSTM(Long Short Term Memory) based network.

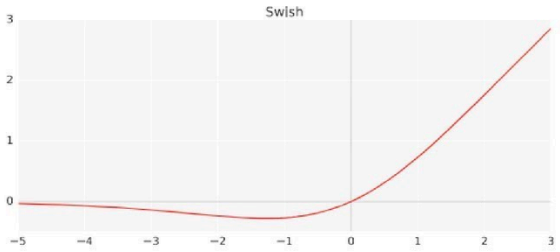
Advantages

-> Can deal with Vanishing Gradient problem.

-> The output is a workaround between RELU and Sigmoid function which helps in normalising the output.

Disadvantage

-> Computationally expensive function (as of Sigmoid).



Swish Activation Function

$f(x) = x * \text{sigmoid}(x)$

Self Gated Activation Function

New Activation By Google Mind

9. MaxOut

Also known as the Learnable Activation Function.

It has all the advantages of a RELU function but at the same time do not have its disadvantages.

$$h(x) = \max\left(Z_1, Z_2, \ldots, Zn\right)$$

$$h(x) = \max\left(W_1 \cdot x + b_1, W_2 \cdot x + b_2, \ldots, Wn \cdot x + bn\right)$$

10. SoftPlus

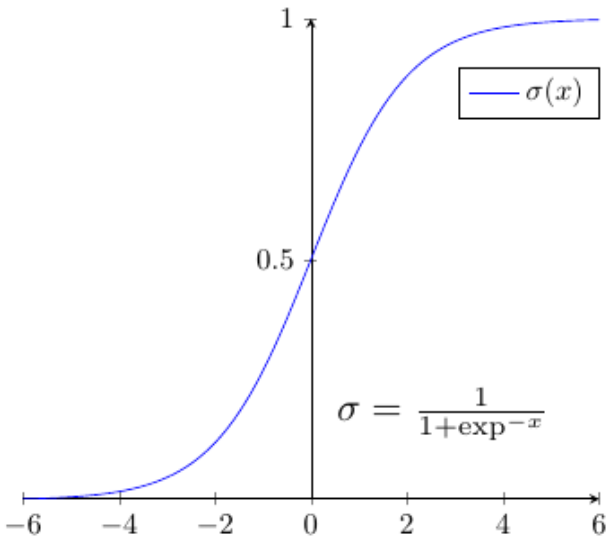
Advantages

-> Convergence of gradient is smoother than RELU function.

-> It can handle the Vanishing Gradient problem.

Disadvantage

-> Computationally expensive than RELU(as of exponential in nature).



11. Elish

Advantages

-> The Elish activation function introduces a learnable parameter (β) that controls the shape of the activation function, allowing the network to adaptively adjust the slope and curvature.

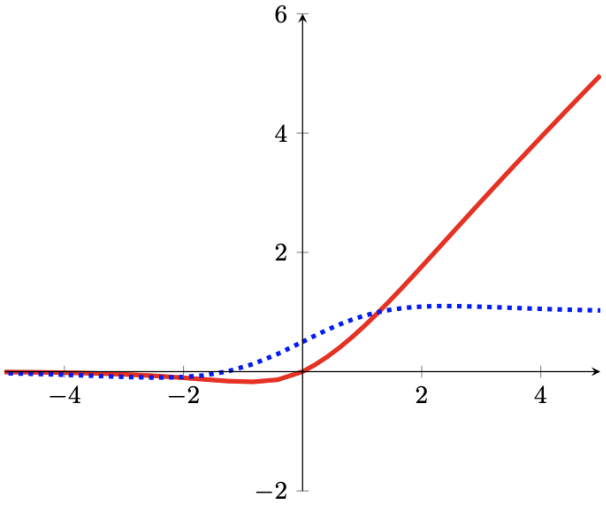
-> Offers flexibility in modeling complex relationships between input and output.

Limitations

-> Requires careful initialization and tuning of the β parameter, which may increase the complexity of model training and hyperparameter optimization.

$$f(x) = \frac{x}{1+e^{-x}} \text{ if } x \geq 0$$

$$f(x) = \frac{e^{x}-1}{1+e^{-x}} \text{ if } x < 0$$



$y(x) = \texttt{ELiSH}$

COST FUNCTIONS

The key difference between loss and cost functions lies in their scope: the loss function measures the performance of the model on individual data points, while the cost function measures the overall performance of the model across the entire dataset.

Cost Functions for Regression Models

1. **Mean Squared Error (MSE)**

   Advantages

   -> **Sensitive to large errors:** It penalizes larger errors more heavily than smaller errors.

   -> **Differentiable:** The MSE loss function is smooth and differentiable, making it suitable for gradient-based optimization algorithms.

   Disadvantages

   -> **Sensitive to outliers:** Outliers in the data can significantly impact the MSE, leading to suboptimal model performance.

   -> **Bias towards large errors:** Due to squaring the errors, MSE may overweight large errors compared to smaller errors, which may not be desired in some scenarios.

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

2. **Mean Absolute Error (MAE)**

   Advantages

   -> **Robust to outliers:** MAE is less sensitive to outliers compared to MSE, making it suitable for datasets with noisy or skewed distributions.

   -> **Intuitive interpretation:** MAE directly measures the average magnitude of errors, providing an intuitive understanding of model performance.

   Disadvantages

   -> **Less sensitive to small errors:** MAE treats all errors equally regardless of their magnitude, which may not be desirable in scenarios where small errors are more critical.

   -> **Not differentiable at zero:** MAE is not differentiable at zero, which can pose challenges for gradient-based optimization algorithms.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

3. **Huber Loss**

   A combination of MSE and MAE, which is less sensitive to outliers.

$$Huber = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{2}(y_i - \hat{y}_i)^2 \qquad |y_i - \hat{y}_i| \le \delta$$

$$Huber = \frac{1}{n}\sum_{i=1}^{n} \delta\left(|y_i - \hat{y}_i| - \frac{1}{2}\delta\right) \qquad |y_i - \hat{y}_i| > \delta$$

   Advantages

   -> **Robust to outliers:** Huber loss combines the best of MSE and MAE by providing a compromise between sensitivity to outliers and robustness.

   -> **Differentiable:** Huber loss is differentiable everywhere, making it suitable for gradient-based optimization.

Disadvantages

-> **Requires tuning of hyperparameter:** Huber loss introduces a hyperparameter (delta) that controls the threshold for switching between MSE and MAE, which may require tuning.

4. **Quantile Loss**
   Used for quantile regression, where different quantiles of the conditional distribution of the target variable are estimated.

Loss Functions for Classification Models

1. **Binary Cross Entropy Loss**
   Advantages
   -> **Suitable for binary classification:** Binary cross entropy is specifically designed for binary classification tasks and measures the difference between predicted probabilities and actual binary labels.
   -> **Encourages well-calibrated probabilities:** It encourages the model to output well-calibrated probabilities for binary classification.

   Disadvantages
   -> **Not suitable for multi-class problems:** Binary cross entropy is designed for binary classification tasks and cannot be directly applied to multi-class classification problems without modification.
   -> **Sensitive to class imbalance:** Binary cross entropy may produce biased predictions in scenarios with severe class imbalance.

$$L_{BCE} = -\frac{1}{n}\sum_{i=1}^{n}(Y_i \cdot \log \hat{Y}_i + (1 - Y_i) \cdot \log (1 - \hat{Y}_i))$$

2. **Categorical Cross Entropy Loss**
   Advantages
   -> **Suitable for multi-class classification:** Categorical cross entropy extends binary cross entropy to multi-class classification tasks and measures the difference between predicted probabilities and actual categorical labels.
   -> **Encourages well-calibrated probabilities:** Similar to binary cross entropy, it encourages the model to output well-calibrated probabilities for multi-class classification.

Disadvantages

-> **Sensitive to class imbalance:** Categorical cross entropy may produce biased predictions in scenarios with severe class imbalance, similar to binary cross entropy.

-> **Computationally expensive:** Computing categorical cross entropy involves calculating the logarithm of predicted probabilities, which can be computationally expensive for large datasets or high-dimensional output spaces.

$$H\left(y,\hat{y}\right) = -\sum_{i}^{n} y_i log\left(\hat{y}_i\right)$$

3. **Hinge Loss Function**

The hinge loss function is commonly used in binary classification tasks, particularly in support vector machines (SVMs). It measures the loss incurred by a model for misclassifying examples and encourages maximizing the margin between classes.

Advantages

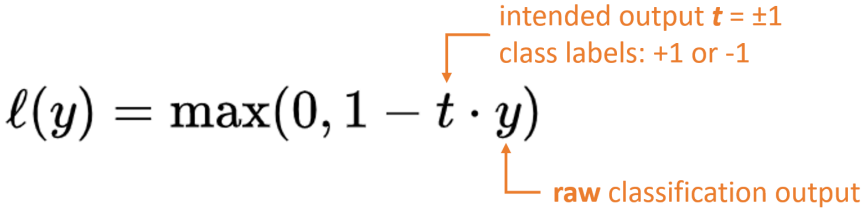
-> **Encourages large margin classification:** The hinge loss penalizes misclassifications more heavily as they move further away from the decision boundary, encouraging the model to maximize the margin between classes.

-> **Robust to outliers:** Hinge loss is less sensitive to outliers compared to other loss functions like squared error loss, making it suitable for datasets with noisy or skewed distributions.

Disadvantages

-> **Not differentiable at zero:** The hinge loss function is not differentiable at zero, which can pose challenges for gradient-based optimization algorithms. However, subgradient methods can be used to address this issue.

-> **Lack of probabilistic interpretation:** Unlike probabilistic loss functions such as binary cross-entropy, the hinge loss does not provide a probabilistic interpretation of model predictions. It focuses solely on margin maximization and does not directly encourage well-calibrated probabilities.



Back Propagation Algorithm

Backpropagation is an algorithm used to train neural networks by adjusting the weights and biases of the neurons to minimize the error between the predicted output and the actual output of the network.

Forward Pass

Input data is passed forward through the network, and calculations are performed at each layer to generate predictions.
The input data is multiplied by weights, and biases are added to produce an output at each neuron. Activation functions are applied to these outputs to introduce non-linearity.

Calculate Error

The error between the predicted output and the actual output (target) is calculated using a chosen loss function.

Backward Pass

Starting from the output layer, the algorithm works backward through the network to compute the gradient of the loss function with respect to each parameter (weight and bias).
This is done using the chain rule of calculus, which allows the algorithm to propagate the error backward layer by layer.

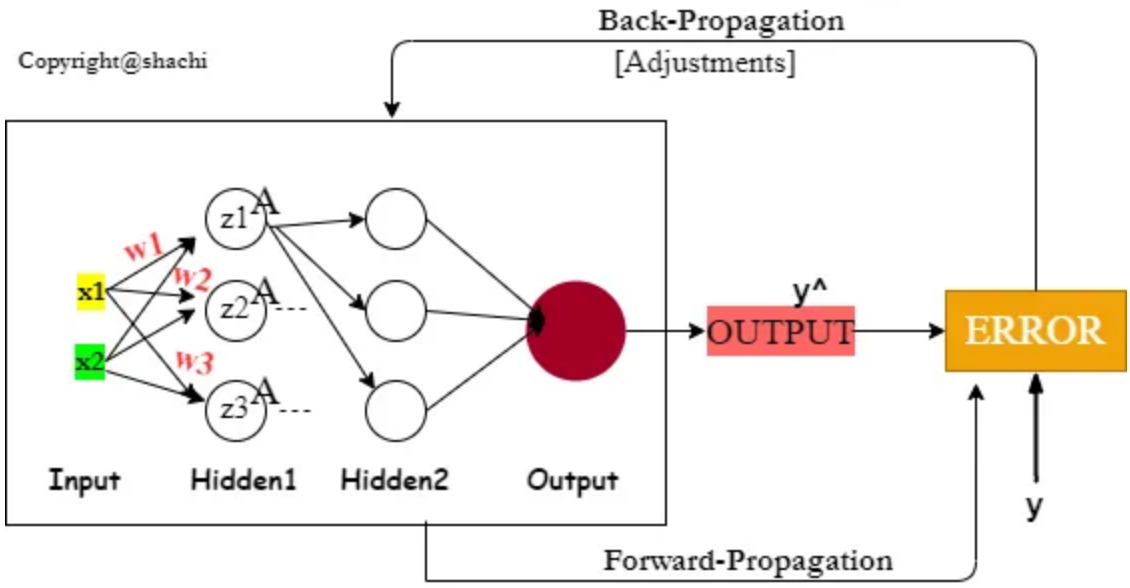
Update Weights and Biases

Using the gradients computed during the backward pass, the algorithm updates the weights and biases of the neurons to minimize the error.
This update is performed using an optimization algorithm such as gradient descent, which adjusts the parameters in the direction that reduces the error.

Repeat

Steps 1 to 4 are repeated iteratively for multiple epochs (passes through the entire dataset) until the error converges to a minimum or until a stopping criterion is met.

In summary, backpropagation is a key algorithm for training neural networks. It involves propagating the error backward through the network, calculating gradients, and updating parameters to minimize the error. This process is repeated iteratively until the network learns to make accurate predictions.



Why can't use Gradient Descent in neural networks?

Since, the total number of trainable parameters with or without bias can be very large in case of neural networks. So, the cost or computation cost becomes very expensive in case of using Gradient Descent.

This was one thing, other is that we can't tell the amount of error or proportion of error due to one parameter in case of Gradient Descent.

This is why we use Back Propogation Algorithm.

Advantages of Backpropagation

-> Efficient parameter updates for neural networks.

-> Handles complex architectures effectively.

-> Flexible with various activation functions and network structures.

-> Scales well to large datasets and high-dimensional inputs.

Disadvantages of Backpropagation

-> Requires differentiability of activation functions and loss functions.

-> Prone to getting stuck in local minima during optimization.

-> Sensitivity to initialization of model parameters.

-> Vulnerable to issues like vanishing or exploding gradients in deep networks.

Unsupervised Learning

Clustering is the task of partitioning a dataset into groups or clusters such that data points within the same cluster are more similar to each other than to those in other clusters, with the goal of discovering inherent structures or patterns in the data.

Distance Measures

Some properties:

1. $d(a, b) \geq 0$, (non-negativity)
2. $d(a, b) = 0 \Leftrightarrow a = b$ (definiteness)
3. $d(a, b) = d(b, a)$ (symmetry)
4. $d(a, c) \leq d(a, b) + d(b, c)$, for any $b \in X$ (triangle inequality)

Centroid/ Partitioning Based Clustering

Divides the dataset into k clusters where each data point belongs to the cluster with the nearest mean.

Eg, K-means

Connectivity Based Clustering

Builds a hierarchy of clusters by iteratively merging or splitting clusters based on their proximity to each other.

Eg, Hierarchical Clustering

Density-Based Clustering

Identifies clusters as dense regions of data points separated by low-density regions.

Eg, DBSCAN (Density-Based Spatial Clustering of Applications with Noise)

Graph-Based Clustering

Utilizes the graph representation of data, where data points are nodes and edges represent relationships or similarities between them, to partition the dataset into clusters.

Eg, Affinity Propagation

Compression-Based Clustering

Constructs a compact summary of the data using lossless compression techniques, where clusters are formed based on the similarity of the compressed representations of data points.

Eg, Spectral Clustering, BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies)

Distance Measures

1. Manhattan/ Cityblock/ L1 distance

$$d(x, y) = \sum_{i=1}^{n} |x_i - y_i|$$

2. Euclidean/ L2 distance

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

3. Cosine distance

Cosine similarity = $$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

Cosine distance = 1 - CS

4. Jaccard distance

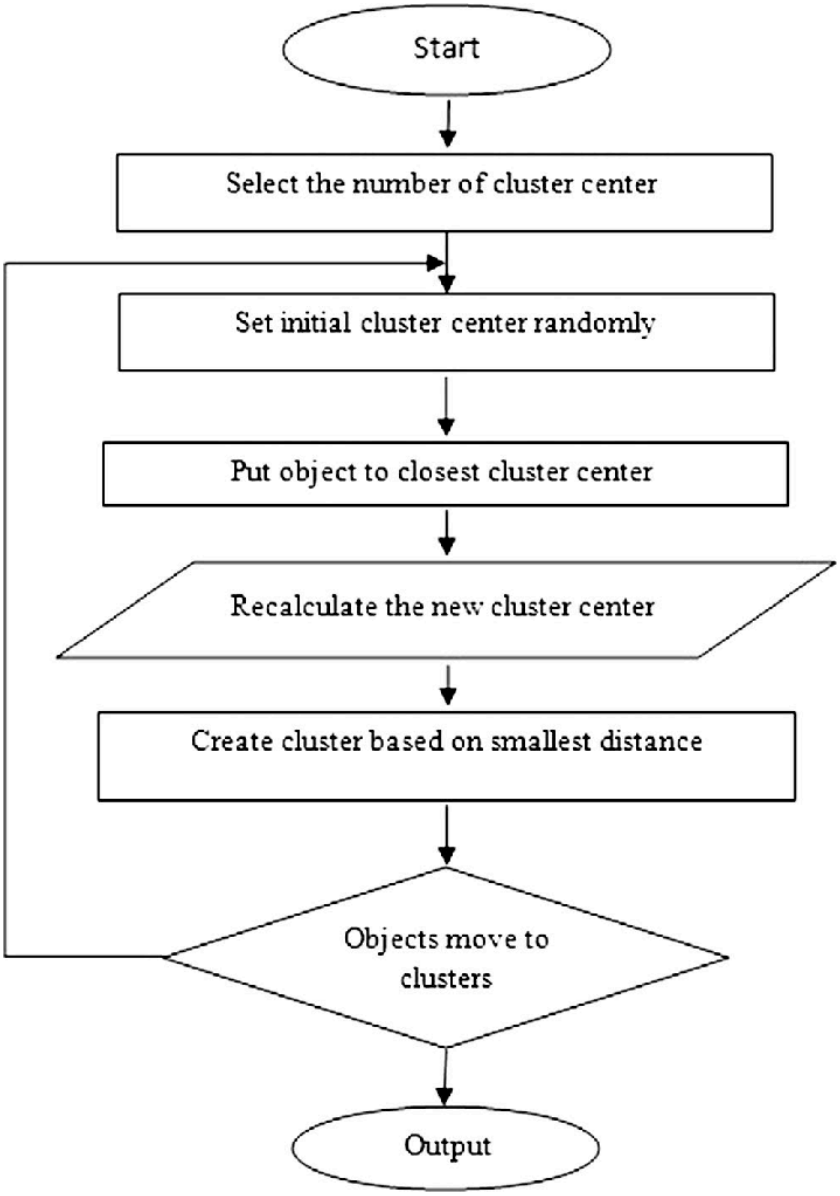
$$\begin{aligned} \text{Jaccard Distance} J_D(A, B) &= 1 - \text{Jaccard Similarity} J(A, B) \\ &= 1 - \frac{|A \cap B|}{|A \cup B|} \\ &= \frac{|A \cup B| - |A \cap B|}{|A \cup B|} \\ &= \frac{|A \triangle B|}{|A \cup B|} \end{aligned}$$

Clustering Algorithm

1. K-means Clustering

K-means clustering is an unsupervised learning algorithm that groups an unlabeled dataset into a predefined number of clusters, where each observation belongs to the cluster with the nearest mean. It works by minimizing the sum of distances between the data points and their corresponding cluster centroids.

Algorithm



Advantages

-> K-means is simple and easy to implement.
-> It is scalable for large datasets.
-> The algorithm guarantees convergence.

Disadvantages

-> The number of clusters needs to be pre-determined.
-> It is sensitive to outliers.
-> There's a risk of getting stuck in local minima.

Effect of K-means of crescent shaped dataset?

K-means clustering, which is a distance-based method, may not perform well on datasets with complex geometric shapes like crescent shapes. This is because K-means tends to create clusters based on the mean distance of points, leading to spherical clusters. Therefore, it might not correctly identify the separate crescent-shaped clusters, and instead, it might group them as a single cluster or divide them inappropriately. For complex shapes, density-based clustering methods might be more effective

2. Heirarchial Clustering

Hierarchical clustering is an unsupervised machine learning method that groups data into a tree-like cluster hierarchy based on similarity or distance. It doesn't require pre-determination of the number of clusters, unlike K-means.

There are two main types of hierarchical clustering:

1. **Agglomerative Clustering**: Also known as the bottom-up approach, it starts by considering each data point as a single cluster and then merges the closest pair of clusters iteratively until only one cluster is left.
2. **Divisive Clustering**: This is the reverse of agglomerative clustering, also known as the top-down approach. It starts with all data points in one cluster and splits the most heterogeneous cluster at each step until only singleton clusters of individual data points remain.

Dendrogram

A dendrogram is a tree-like diagram that shows the hierarchical relationship between objects. It is most commonly created as an output from hierarchical clustering.

Linkage Criteria in hierarchical clustering

- Single Linkage: The distance between two clusters is defined as the minimum distance between any single data point in the first cluster and any single data point in the second cluster.
- Complete (Maximum) Linkage: The distance between two clusters is defined as the maximum distance between any single data point in the first cluster and any single data point in the second cluster.
- Average Linkage: The distance between two clusters is defined as the average distance between all pairs of data points in the first and second clusters.
- Ward's Method: This method merges the two clusters that provide the smallest increase in the combined error sum of squares. It's an ANOVA-based approach.

solve numerical

Variants of Gradient Descent

1. Vanilla Gradient Descent:

- Vanilla Gradient Descent is the simplest form of gradient descent optimization.
- In this method, we update the parameters of the model (such as weights and biases in a neural network) by subtracting the gradient of the loss function with respect to the parameters multiplied by a learning rate from the current parameter values.
- Mathematically, the update rule for parameter (θ) at iteration (t) is:

$$[\theta_{t+1} = \theta_t - \eta \cdot \nabla J(\theta_t)]$$

Where (η) is the learning rate, $(J(\theta))$ is the loss function, and $(\nabla J(\theta))$ is the gradient of the loss function with respect to the parameters.

- Vanilla Gradient Descent can be slow to converge, especially in high-dimensional or non-convex optimization problems.

2. Momentum-based Gradient Descent:

- Momentum-based Gradient Descent improves upon Vanilla Gradient Descent by introducing a momentum term that helps accelerate the convergence process.
- The momentum term represents the accumulated gradient of previous iterations and helps the optimization algorithm to continue moving in the same direction, even if the current gradient is small.
- This helps to overcome oscillations and plateaus in the optimization landscape, leading to faster convergence.
- Mathematically, the update rule with momentum at iteration (t) is:

$$[v_{t+1} = \gamma \cdot v_t + \eta \cdot \nabla J(\theta_t)]$$

$$[\theta_{t+1} = \theta_t - v_{t+1}]$$

Where (v_t) is the momentum term, and (γ) is the momentum coefficient.

3. Stochastic Gradient Descent (SGD):

- Stochastic Gradient Descent is an optimization algorithm that updates the parameters using a single randomly selected data point (or a small batch of data points) at each iteration.
- Unlike Vanilla Gradient Descent, which computes the gradient using the entire dataset, SGD approximates the gradient using a subset of the data, which makes it faster and more scalable for large datasets.
- However, the stochastic nature of SGD introduces noise into the optimization process, which can lead to more erratic convergence behavior.
- SGD is commonly used in training neural networks and other machine learning models.
- Mathematically, the update rule for parameter (θ) using SGD at iteration (t) is:

$$[\theta_{t+1} = \theta_t - \eta \cdot \nabla J(\theta_t; x^{(i)}, y^{(i)})]$$

Where $((x^{(i)}, y^{(i)}))$ is a randomly selected data point, and $(\nabla J(\theta_t; x^{(i)}, y^{(i)}))$ is the gradient of the loss function with respect to the parameters computed using the selected data point.

4. Nesterov Accelerated Gradient Descent:

- Nesterov Accelerated Gradient Descent (NAG) is a variant of momentum-based gradient descent that reduces the oscillations typically seen in Momentum-based GD.
- It achieves this by calculating the gradient not at the current parameter values but at a point further ahead in the direction of momentum.
- This "lookahead" helps to correct the momentum direction more accurately, leading to faster convergence and improved stability.
- Mathematically, the update rule for parameter (θ) using NAG at iteration (t) is:

$$[v_{t+1} = \gamma \cdot v_t + \eta \cdot \nabla J(\theta_t - \gamma \cdot v_t)]$$

$$[\theta_{t+1} = \theta_t - v_{t+1}]$$

5. Minibatch Gradient Descent:

- Minibatch Gradient Descent is a compromise between Vanilla Gradient Descent and Stochastic Gradient Descent.
- In this method, instead of using the entire dataset or a single data point, a small random subset of the data (a minibatch) is used to compute the gradient at each iteration.
- This approach combines the advantages of SGD (faster convergence) with the stability of using more data points per iteration, making it a popular choice for training deep neural networks.
- Mathematically, the update rule for parameter (θ) using minibatch GD at iteration (t) is similar to SGD but with a minibatch of data:

$$[\theta_{t+1} = \theta_t - \eta \cdot \nabla J(\theta_t; \text{minibatch})]$$

In summary, each of these gradient descent optimization algorithms has its advantages and disadvantages, and the choice of algorithm depends on factors such as the problem's characteristics, the dataset size, and the computational resources available.

Support Vector Machines

Support Vector Machines (SVM) is a powerful supervised learning algorithm used for classification tasks. Let's break down SVM and its concepts:

1. Support Vector Machines (SVM):

- SVM is a machine learning algorithm used for regression and classification (mostly) tasks, where it tries to find a hyperplane in a high-dimensional space that best separates the data points into different classes.
- The goal of SVM is to find the optimal hyperplane that maximizes the margin between the classes, making it robust to new data points.

2. Margin in SVM:

- The margin in SVM refers to the distance between the support vectors (extreme points) of each class.
- The optimal hyperplane is the one that maximizes this margin, as it provides the largest separation between the classes and helps generalize well to unseen data.
- Larger margins indicate better generalization performance, while smaller margins may lead to overfitting.

3. Deciding the Best Hyperplane in SVM:

- The best hyperplane in SVM is determined by finding the one that maximizes the margin between the classes.
- This optimization problem involves finding the weights and bias terms of the hyperplane that minimize the classification error while maximizing the margin.
- SVM uses optimization techniques such as quadratic programming or gradient descent to solve this problem efficiently.

4. Types of SVM:

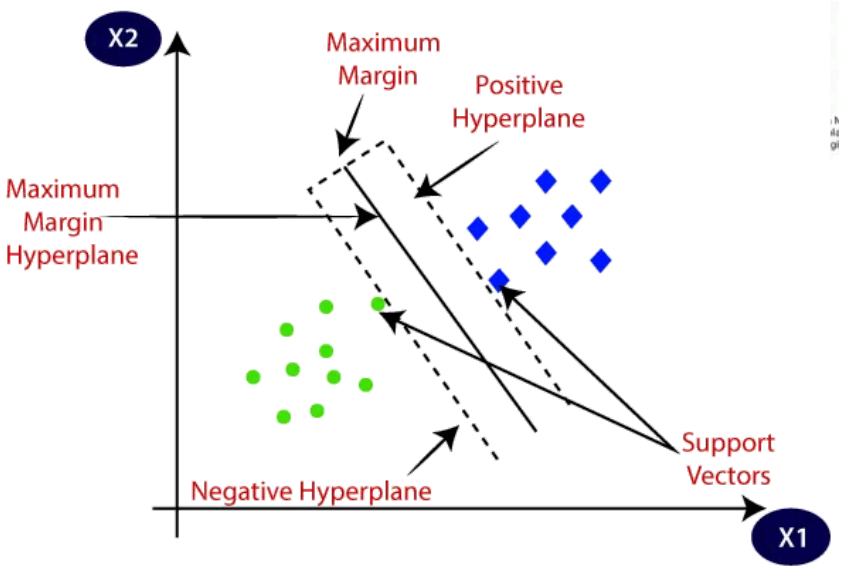
- SVM can be categorized into two main types based on the margin:
  - **Hard Margin SVM**: Assumes that the data is linearly separable and aims to find a hyperplane that perfectly separates the classes without any misclassifications.
  - **Soft Margin SVM:** Allows for misclassifications (errors) by introducing a slack variable that penalizes data points that fall on the wrong side of the margin. This makes the algorithm more robust to noisy or overlapping data.

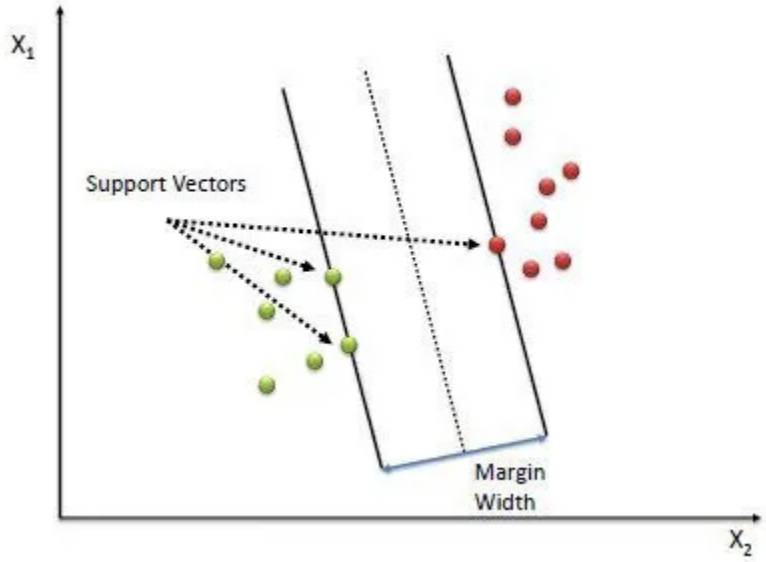
5. Hard Margin SVM vs. Soft Margin SVM:

- Hard Margin SVM: Works well when the data is linearly separable and there is no noise in the dataset. However, it may perform poorly or fail to converge if the data is not perfectly separable.

- Soft Margin SVM: Handles noisy or overlapping data by allowing for a certain amount of misclassification. It is more robust and flexible but may be sensitive to the choice of the regularization parameter (C), which controls the trade-off between margin maximization and classification error.

The goal of SVM is to find the optimal hyperplane (line in 2D) that separates the red points from the blue points with the maximum margin. This hyperplane is determined by the support vectors, which are the points closest to the hyperplane from each class. The margin is the distance between the hyperplane and the support vectors. In Soft Margin SVM, some points may fall within the margin or on the wrong side of the hyperplane, but the algorithm tries to minimize these errors while maximizing the margin.





Regularization Parameter (C) in SVM?

In Support Vector Machines (SVM), the regularization parameter, often denoted as (C), is a hyperparameter that controls the trade-off between maximizing the margin and minimizing the classification error on the training data.

Here's a simple explanation of the regularization parameter in SVM:

- Large (C):
- A large value of (C) indicates a high penalty for misclassifications.
- In this case, the SVM model will prioritize correctly classifying all training data points, even if it means reducing the margin between the classes.
- This leads to a Hard Margin SVM approach, where the model is less tolerant of misclassifications and tries to find the best possible decision boundary, even if it results in a narrower margin.

- Small (C):
- A small value of (C) indicates a lower penalty for misclassifications.
- In this case, the SVM model will prioritize maximizing the margin between the classes, even if it means allowing for more misclassifications on the training data.
- This leads to a Soft Margin SVM approach, where the model is more tolerant of misclassifications and focuses on finding a decision boundary with a wider margin, which may result in some misclassifications.

The choice of the regularization parameter (C) depends on the characteristics of the dataset and the desired balance between margin maximization and classification accuracy. A higher value of (C) tends to result in a more complex model with better training accuracy but may lead to overfitting, while a lower value of (C) tends to produce a simpler model with better generalization to unseen data but may sacrifice some training accuracy.

Linear SVM
A Linear SVM is used for linearly separable data, which means it can be separated into classes using a single straight line (in two dimensions) or a hyperplane (in higher dimensions).

For example, consider a set of points in a 2D space belonging to two different classes. If you can draw a straight line such that all points of one class are on one side of the line and points of the other class are on the other side, then the data is linearly separable. The goal of the Linear SVM is to find the “best” line or hyperplane that separates the classes.

The “best” hyperplane is the one that maximizes the margin between the classes. The margin is defined as the distance between the separating hyperplane (decision boundary) and the nearest data point from either class. The data points that touch the margin are called support vectors.

Non-linear SVM
A Non-linear SVM is used when the data is not linearly separable. In other words, you can’t draw a straight line (or hyperplane) to separate the classes.

In such cases, the data is transformed from the original feature space to a higher dimensional space where it becomes linearly separable. This transformation is done using a method called the kernel trick. The kernel function can map the input space into a higher-dimensional space, making it possible to perform linear separation in that space.

For example, consider a set of points in a 2D space belonging to two different classes, where points of one class are surrounded by points of the other class. In this case, you can’t draw a straight line to separate the classes. But if you transform the data into a 3D space, you might be able to separate the classes using a plane.

Primal Problem

The primal problem in SVM is about finding the best hyperplane that separates the data into two classes. The “best” hyperplane is the one that maximizes the margin between the two classes. The margin is defined as the distance between the hyperplane (decision boundary) and the nearest data point from either class.

However, in real-world scenarios, the data is often not perfectly separable. So, to handle this, SVM introduces something called “slack variables”. These slack variables allow some data points to be on the wrong side of the margin, or even the wrong side of the hyperplane. The goal then becomes to find the hyperplane that maximizes the margin while minimizing the sum of these slack variables.

Dual Problem

The dual problem of SVM comes into play when the data is not linearly separable. In such cases, SVM uses a technique called the “**kernel trick**” to transform the data into a higher-dimensional space where it becomes linearly separable.

The dual problem is a reformulation of the primal problem in this transformed space. It’s an optimization problem that aims to maximize the margin in the transformed space, subject to certain constraints. The solution to the dual problem provides a lower bound to the solution of the primal problem.

The advantage of the dual problem is that it only involves the data points that are support vectors (those that lie on or violate the margin), which makes the computation more efficient. Also, the dual problem allows for the use of the kernel trick, which enables SVM to solve non-linear classification problems.

Primal Problem of SVM:

Given a dataset $((\mathbf{x}_i, y_i))$ where $(i = 1, 2, ..., n)$, with $(\mathbf{x}_i)$ being the feature vector and (y_i) being the class label (+1 or -1), the primal problem of SVM aims to find the optimal parameters (w) and (b) of the hyperplane maximally separates the classes while minimizing the classification error.

We want to maximize the margin (M), which is defined as the distance between the hyperplane and the closest data point from either class. The equation for the margin can be expressed as:

$$[M = \frac{2}{\|w\|}]$$

To maximize the margin, we need to minimize $(\|w\|)$. Hence, the objective function of the primal problem is:

$$[\text{Minimize:} \quad \frac{1}{2}\|w\|^2]$$

Subject to the constraint that each data point is correctly classified with a margin of at least 1:

$$[y_i(w \cdot \mathbf{x}_i + b) \geq 1]$$

Where:
- (w) is the weight vector perpendicular to the hyperplane,
- (b) is the bias term,
- $(\|w\|^2)$ represents the squared Euclidean norm of the weight vector,
- The objective function $(\frac{1}{2}\|w\|^2)$ aims to minimize the L2-norm of the weight vector,
- The constraint $(y_i(w \cdot \mathbf{x}_i + b) \geq 1)$ ensures that each data point is correctly classified with a margin of at least 1.

To solve this optimization problem, we can use techniques such as gradient descent or quadratic programming to find the optimal values of $(w) and (b)$ that minimize the objective function while satisfying the constraints.

Dual Problem of SVM:
Given the primal problem of SVM:

$$[\text{Minimize:} \quad \frac{1}{2}\|w\|^2]$$
$$[\text{Subject to:} \quad y_i(w \cdot \mathbf{x}_i + b) \geq 1]$$

To derive the dual problem, we introduce Lagrange multipliers (α_i) for each inequality constraint:

$$[L(w, b, \alpha) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{n} \alpha_i (y_i(w \cdot \mathbf{x}_i + b) - 1)]$$

Where $(\alpha_i \geq 0)$ are the Lagrange multipliers.

To find the dual problem, we need to minimize the Lagrangian with respect to (w) and (b), and then maximize it with respect to (α).

1. Minimization with respect to (w) and (b):

Taking the derivatives of $(L(w, b, \alpha))$ with respect to (w) and (b) and setting them to zero, we get:

$$[\frac{\partial L}{\partial w} = w - \sum_{i=1}^{n} \alpha_i y_i \mathbf{x}_i = 0 \implies w = \sum_{i=1}^{n} \alpha_i y_i \mathbf{x}_i]$$

$$[\frac{\partial L}{\partial b} = -\sum_{i=1}^{n} \alpha_i y_i = 0 \implies \sum_{i=1}^{n} \alpha_i y_i = 0]$$

Substituting (w) back into the Lagrangian, we get:

$$[L(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j \mathbf{x}_i \cdot \mathbf{x}_j]$$

2. Maximization with respect to (α):

The dual problem is obtained by maximizing $(L(\alpha))$ with respect to (α) subject to the constraint $(\sum_{i=1}^{n} \alpha_i y_i = 0)$ and $(\alpha_i \geq 0)$

$$[\text{Maximize:} \quad W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j \mathbf{x}_i \cdot \mathbf{x}_j]$$

$$[\text{Subject to:} \quad \sum_{i=1}^{n} \alpha_i y_i = 0]$$

$$[\quad \alpha_i \geq 0, \quad \text{for } i = 1, 2, ..., n]$$

Where $(W(\alpha))$ is the objective function of the dual problem, and (α_i) are the Lagrange multipliers.

The dual problem of SVM is a quadratic optimization problem, which can be solved using methods such as quadratic programming to find the optimal values of (α_i). Once the optimal (α_i) are obtained, the weight vector (w) can be calculated using the formula $(w = \sum_{i=1}^{n} \alpha_i y_i \mathbf{x}_i)$, and the bias term (b) can be computed using the support vectors.

CNN, RNN and ANN:

1. Convolutional Neural Networks (CNNs):

- Purpose: Primarily used for image recognition and computer vision tasks.
- Structure: CNNs consist of convolutional layers, pooling layers, and fully connected layers.
- Convolutional Layers: Apply filters (kernels) to input images to detect features such as edges and textures.
- Pooling Layers: Reduce the spatial dimensions of the feature maps while retaining important information.
- Fully Connected Layers: Neurons in these layers are connected to all neurons in the previous layer, typically used for classification.
- Example: Recognizing objects in images, facial recognition, image classification.

2. Recurrent Neural Networks (RNNs):

- Purpose: Primarily used for sequential data processing, such as natural language processing (NLP) and time series prediction.
- Structure: RNNs have recurrent connections that allow information to persist over time steps.
- Memory Cells: RNNs use memory cells to store information about past inputs, which can influence the current output.
- Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU): Variants of RNNs that address the vanishing gradient problem and improve the ability to learn long-term dependencies.
- Example: Sentiment analysis, language translation, speech recognition.

3. Artificial Neural Networks (ANNs):

- Purpose: General-purpose neural networks used for various machine learning tasks, including classification, regression, and clustering.
- Structure: ANNs consist of input, hidden, and output layers of neurons.
- Feedforward Propagation: Information flows from the input layer through the hidden layers to the output layer without loops or cycles.
- Backpropagation: ANNs use backpropagation to adjust the weights of connections between neurons during training, minimizing the error between predicted and actual outputs.
- Example: Handwriting recognition, predicting house prices, fraud detection.

In summary, CNNs are specialized for image processing tasks, RNNs are suitable for sequential data analysis, and ANNs serve as a general framework for various machine learning applications. Each type of neural network has its strengths and weaknesses, and the choice depends on the nature of the data and the specific task at hand.

Ensemble Methods in Machine Learning

Ensemble methods in machine learning are techniques that combine multiple models to improve the overall performance and generalization of a predictive model. The basic idea is to leverage the collective wisdom of multiple models rather than relying on a single model. There are several types of ensemble methods, but two of the most popular ones are:

Bagging (Bootstrap Aggregating):
In bagging, multiple base models (often of the same type) are trained independently on different subsets of the training data, which are sampled with replacement (bootstrap samples).
Each base model is trained on a different subset of the data, and predictions are typically made by averaging the predictions of all base models (for regression) or using a voting mechanism (for classification).
Popular algorithms using bagging include Random Forests, which are an ensemble of decision trees, and Bagged Decision Trees.

Boosting:
Boosting works by sequentially training a series of weak learners (models that are slightly better than random guessing) and combining them into a strong learner.
Each weak learner is trained on a modified version of the dataset, where the weights of misclassified instances are increased in subsequent iterations.
Popular boosting algorithms include AdaBoost (Adaptive Boosting), Gradient Boosting Machines (GBM), XGBoost, and LightGBM.
Ensemble methods offer several advantages:

They often provide higher predictive accuracy compared to individual models, especially when the base models are diverse and complementary.
They are more robust to overfitting, as errors made by one model may be compensated by others in the ensemble.
They can handle a wide range of data types and modeling tasks.
However, ensemble methods also come with some drawbacks:

They are more computationally expensive and may require more resources compared to training a single model.
They can be more difficult to interpret and analyze compared to individual models.
Constructing an effective ensemble requires careful tuning of hyperparameters and selection of diverse base models.

Voting Classifier:
A voting classifier is a type of ensemble method in machine learning where multiple base models (classifiers) are used to make predictions on a given dataset, and the final prediction is determined by a majority vote (for classification tasks) or averaging (for regression tasks) among the predictions of the individual classifiers.

There are two main types of voting strategies in a voting classifier:

Hard Voting:
In hard voting, each base model predicts the class label for a given instance, and the final prediction is based on the majority class predicted by the base models.
For classification tasks, the class label that receives the most votes among the base models is chosen as the final prediction.
Hard voting is straightforward and typically used when the base models produce discrete predictions (e.g., class labels).

Soft Voting:
In soft voting, each base model provides a probability distribution over the possible classes for a given instance.
The final prediction is determined by averaging the predicted probabilities from all base models and selecting the class with the highest average probability.
Soft voting takes into account the confidence of each base model in its predictions and can provide more nuanced results compared to hard voting.
Soft voting is particularly useful when the base models can provide probability estimates, such as in logistic regression or models with probabilistic outputs like decision trees with probability estimates.

In summary, while both hard and soft voting classifiers aggregate predictions from multiple base models, they differ in how they combine these predictions. Hard voting relies on a majority vote of class labels, while soft voting considers the probability estimates from each base model to make a more informed decision. Choosing between hard and soft voting depends on the nature of the problem and the characteristics of the base models being used.

Decision Trees and Random Forests from “Gate Smashers”, explained nicely.

Learning Theory

Learning theory of machine learning is not about how to implement task but it is the study to understand feasibility in preparation of a model.
We try to understand,

1. Under what conditions learning process is possible or not?
2. If learning is possible then under what conditions learning is successful or not, i.e., our model predicts close to our hypothesis?

Our goal is to answer following questions:

1. Number of training examples required to learn successfully (Sample Complexity)?
2. Computational efforts required to converge to correct hypothesis (Computational Complexity)?
3. Number of mistakes the model makes before converging to correct hypothesis (Mistake Bound)?

PAC: https://www.baeldung.com/cs/probably-aproximately-correct
Just solve numericals and PYQs, you'll get idea.

Some more Questions

1. Hard Margin SVM vs Soft Margin SVM

	Hard Margin SVM	Soft Margin SVM
Linear Separability	Assumes data is perfectly separable	Allows for some misclassifications
Handling Noise	Sensitive to noisy or overlapping data	More robust to noisy data
Objective	Maximizes margin, no misclassifications allowed	Balances margin maximization and misclassifications
Regularization	No regularization (C = ∞)	Introduces regularization parameter (C)
Slack Variables	Does not use slack variables	Uses slack variables to penalize misclassifications
Flexibility	Less flexible, may fail if data is not separable	More flexible, can handle non-linearly separable data

2. One vs All and One vs One

The "one-vs-all" (OvA) and "one-vs-one" (OvO) are two common strategies used in multiclass classification tasks, especially when binary classification algorithms are employed. Here's how they differ:

1. One-vs-All (OvA):

- Approach: In the one-vs-all strategy, we train a single classifier per class, where each classifier is trained to distinguish between one class and the rest of the classes combined.

- Number of Classifiers: The number of classifiers is equal to the number of classes in the dataset.

- Training: During training, the data for each class are labeled as positive, while the data for all other classes are labeled as negative.

- Prediction: To classify a new sample, we run it through all classifiers and choose the class with the highest score or probability.

- Advantages:

- Simplicity: Only one classifier needs to be trained per class.
- Computational Efficiency: Suitable for large datasets with many classes.

- Disadvantages:

- Imbalanced Data: Imbalanced class distributions may affect classifier performance.
- Decision Boundaries: Decision boundaries can be complex, especially if classes are overlapping.

2. One-vs-One (OvO):

- Approach: In the one-vs-one strategy, we train $(C(C-1)/2)$ classifiers, where (C) is the number of classes. Each classifier is trained to distinguish between pairs of classes.

- Number of Classifiers: $(C(C-1)/2)$ classifiers are trained.

- Training: During training, each classifier is trained on a subset of the data containing samples from only two classes.

- **Prediction:** To classify a new sample, we run it through all pairwise classifiers, and the class that receives the most "votes" is chosen as the final prediction.

- Advantages:

- Binary Classification: Simplifies the classification task into multiple binary decisions.
- Robustness: More resilient to imbalanced class distributions and overlapping decision boundaries.

- Disadvantages:

- Increased Computational Complexity: Requires training multiple classifiers, which can be computationally expensive for large datasets or many classes.
- Dataset Size: The number of classifiers grows quadratically with the number of classes, which can become impractical for a large number of classes.

In summary, the choice between one-vs-all and one-vs-one strategies depends on factors such as the dataset size, class distribution, computational resources, and the desired trade-off between simplicity and performance.

3. Calculate number of times weights will be updated if optimization algorithm used is:
1. Vanilla Gradient Descent
2. Stochastic Gradient descent
3. Mini batch Gradient descent
4. Momentum based gradient descent

Given number of epochs as 'e', batch size as 'b' and iterations as 'i' and total datapoints ‘n’.

Vanilla Gradient Descent: In Vanilla Gradient Descent, the weights are updated once for each epoch. So, if ‘e’ is the number of epochs, the weights will be updated **e times**.

In **Stochastic Gradient Descent (SGD),** the weights are updated for each training example. So, if ‘n’ is the number of data points and ‘e’ is the number of epochs, the weights will be updated **e*n times**. This is because SGD updates the weights after each training example during each epoch. Please note that this assumes that all data points are used in each epoch.

Mini-Batch Gradient Descent: In Mini-Batch Gradient Descent, the weights are updated for each batch of training examples. So, if ‘i’ is the number of iterations (which is typically equal to the total number of training examples divided by the batch size), and ‘e’ is the number of epochs, the weights will be updated **e*i times**.

Momentum-Based Gradient Descent: The number of weight updates in Momentum-Based Gradient Descent is the same as in Vanilla Gradient Descent, SGD, or Mini-Batch Gradient Descent, depending on whether it’s applied to the whole dataset, individual training examples, or mini-batches. The difference is that Momentum-Based Gradient Descent incorporates a fraction of the previous weight update in the current update. But the frequency of updates remains the same.

4. Examples of each Learning type?

Supervised Learning:

- Email Filtering
- Handwritten Digit Recognition

Unsupervised Learning:

- Market Basket Analysis
- Clustering News Articles

Reinforcement Learning:

- Autonomous Driving
- Video Game AI

Semi-Supervised Learning:

- Text Classification
- Medical Image Analysis

Generative Adversarial Networks:

- Face Generation
- Artwork Generation

5. Linear, Polynomial and RBF kernels in SVM?

Linear SVM:
Linear SVM is the simplest form of SVM where the decision boundary is a linear hyperplane.
The linear kernel computes the dot product between the feature vectors in the original feature space.
Linear SVM works well when the classes are linearly separable, meaning they can be separated by a straight line or plane.
Example: Suppose we have a dataset with two classes (red and blue points) that are linearly separable. A linear SVM would find the optimal hyperplane (line in 2D, plane in 3D) that separates the two classes with the maximum margin.

Polynomial SVM:
Polynomial SVM uses polynomial kernel functions to map the original feature space into a higher-dimensional space.
The polynomial kernel computes the dot product raised to a power, allowing it to capture non-linear decision boundaries.
Polynomial SVM can handle data that is not linearly separable in the original feature space.
Example: Consider a dataset with two classes (red and blue points) that are not linearly separable in 2D. By using a polynomial kernel, SVM can project the data into a higher-dimensional space (e.g., 3D or higher) where it becomes linearly separable. In the higher-dimensional space, a hyperplane (plane or hyperplane) can separate the classes.

RBF (Radial Basis Function) SVM:
RBF SVM uses the Radial Basis Function kernel, also known as the Gaussian kernel, to map the data into a higher-dimensional space.
The RBF kernel measures the similarity between data points based on their Euclidean distance.
RBF SVM is capable of capturing complex, non-linear decision boundaries and is highly flexible.
Example: Suppose we have a dataset with two classes arranged in concentric circles. A linear SVM or polynomial SVM would struggle to separate the classes. However, an RBF SVM can map the data into a higher-dimensional space where it becomes linearly separable. By finding the optimal hyperplane in this higher-dimensional space, the RBF SVM can effectively classify the data.

In summary, linear SVM is suitable for linearly separable data, polynomial SVM is useful for capturing moderate non-linearities, and RBF SVM is powerful for handling highly non-linear data distributions. The choice of kernel depends on the complexity of the data and the desired performance of the SVM model.

6. Why do we need Momentum based Gradient Descent?

1. Acceleration of Convergence.
2. Robustness to noisy gradients.
3. Escape from local minima.
4. One can use large learning rates without fearing for divergence.
5. Uses last computed gradient to allow smooth convergence.
6. Reduced oscillations due to fewer fluctuations.

7. Analyze the demeanor of momentum based gradient descent in gentle slopes?

In gentle slopes, momentum-based gradient descent exhibits a behavior that enhances its convergence efficiency while minimizing oscillations around the optimal solution.

1. Gradual Descent: On gentle slopes, gradient descent makes small adjustments to parameters since the gradient is small.
2. Slow Convergence: Gradient descent progresses slowly toward the minimum on gentle slopes, requiring more iterations.
3. Reduced Oscillations: Gentle slopes experience fewer fluctuations in the loss function, leading to smoother convergence.
4. Efficient Optimization: Despite slow convergence, gradient descent efficiently optimizes parameters by continuously adjusting them towards the minimum.
5. Stable Updates: Updates made by gradient descent on gentle slopes are stable and not erratic, ensuring steady progress toward the minimum.

8. Define hyperplane, support vectors, margin

In SVM, a hyperplane is a decision boundary that separates classes in the feature space.

Support vectors are data points that lie closest to the hyperplane and are crucial for defining its position.

The margin is the distance between the hyperplane and the closest support vectors, and SVM aims to maximize this margin to improve generalization performance.

9. Optimization and Loss function for Logistic Regression and SVM?

Logistic:

- Optimization Function: ADAM
- Loss Function: Log loss

SVM:

- Optimization function: Quadratic optimizer
- Loss Function: Hinge loss

10. Why gradient descent can't be used in SVM for optimization purpose?

- May stuck in local minima
- Loss function of SVM is hinge loss, which is not differentiable at 0
- It may suffer from convex loss.
- For larger datasets with higher dimensions, gradient descent can be computationally expensive

11. A labeled image dataset consisting of 70, 000 training images and 11, 000 test images of 30x30 pixels of cats and dogs is given.

1. Construct a neural network architecture using a sequential model from Keras

2. Compile the model above

3. Fit and evaluate the model with training dataset.

```
from keras.models import Sequential
from keras.layers import Dense, Flatten
from keras.layers.convolutional import Conv2D
from keras.optimizers import Adam

# Assuming each image is 30x30x3 (last dimension for color channels)
input_shape = (30, 30, 3)

# Construct the neural network architecture
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=input_shape))
model.add(Flatten())  # Flattening the 2D arrays for fully connected layers
model.add(Dense(64, activation='relu'))
model.add(Dense(1, activation='sigmoid'))  # Binary classification

# Compile the model
model.compile(optimizer=Adam(), loss='binary_crossentropy', metrics=['accuracy'])

# Assuming train_images, train_labels are your training data and labels
model.fit(train_images, train_labels, epochs=10, batch_size=64)

# To evaluate the model on test data
# Assuming test_images, test_labels are your test data and labels
model.evaluate(test_images, test_labels)
```

12. Why we initialize the weight vector randomly in the neural network?

- To break symmetry
- Avoid exploding gradient descent
- Avoid vanishing gradient descent
- Promoting gradients exploration

13. Why max-pooling is not counted as a layer in convolutional neural network?

Since max-pooling does not introduce any new learnable parameters or perform complex operations like convolution, it is not considered a separate layer in the architecture of a CNN. Instead, it is typically treated as a component within the convolutional layers that helps in reducing the spatial dimensions of the feature maps while retaining important features.

14. Why Support Vector Machines are insensitive towards outliers? Justify.

- Introduction of regularization parameter, that is robust towards handling outliers.
- Insensitive loss function
- Generally maximal margin, this means outliers can't interfere in decision making boundary.

15. Derive primal problem for Soft margin SVM. Then convert it to Dual problem.

1. The primal problem for soft-margin SVM can be derived as follows:

Given:

- Training data: $((x_i, y_i))$, $(i = 1, 2, ..., N)$
- Feature vector $(x_i \in \mathbb{R}^d)$
- Class labels $(y_i \in \{-1, 1\})$
- Slack variables $(\xi_i \geq 0)$

Objective:

Minimize the following objective function:

$$[\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} \xi_i]$$

Subject to:

$[y_i(w \cdot x_i + b) \geq 1 - \xi_i]$

$[\xi_i \geq 0, \quad i = 1, 2, ..., N]$

This objective function represents a trade-off between maximizing the margin and minimizing the classification error, where (C) is the regularization parameter controlling the trade-off. The first term $(\frac{1}{2}\|w\|^2)$ represents the margin maximization, and the second term $(C\sum_{i=1}^{N}\xi_i)$ represents the penalty for misclassifications, weighted by the slack variables (ξ_i).

The constraints ensure that each data point lies on the correct side of the decision boundary with a margin of at least 1, and the slack variables (ξ_i) allow for some misclassifications (soft margin) while penalizing them based on their magnitude.

2. To convert the primal problem of soft-margin SVM to its dual problem, we first introduce Lagrange multipliers (α_i) for each inequality constraint. Then, we form the Lagrangian $(L(w,b,\xi,\alpha))$ as follows:

$$[L(w,b,\xi,\alpha)=\frac{1}{2}\|w\|^2+C\sum_{i=1}^{N}\xi_i-\sum_{i=1}^{N}\alpha_i[y_i(w\cdot x_i+b)-1+\xi_i]-\sum_{i=1}^{N}\mu_i\xi_i]$$

where $(\alpha_i\geq 0)and(\mu_i\geq 0)$ are the Lagrange multipliers.

Now, we need to find the saddle point of the Lagrangian, which involves minimizing with respect to (w), (b), and (ξ_i), and maximizing with respect to (α_i) and (μ_i).

Taking derivatives with respect to (w), (b), and (ξ_i) and setting them to zero, we get:

1. $$[\frac{\partial L}{\partial w}=w-\sum_{i=1}^{N}\alpha_i y_i x_i=0\Rightarrow w=\sum_{i=1}^{N}\alpha_i y_i x_i]$$
2. $$[\frac{\partial L}{\partial b}=-\sum_{i=1}^{N}\alpha_i y_i=0\Rightarrow\sum_{i=1}^{N}\alpha_i y_i=0]$$
3. $$[\frac{\partial L}{\partial \xi_i}=C-\alpha_i-\mu_i=0\Rightarrow C=\alpha_i+\mu_i]$$

Substituting these into the Lagrangian, we obtain the dual problem:

$$[\max_{\alpha} \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)]$$

Subject to:
$[0 \leq \alpha_i \leq C]$
$[\sum_{i=1}^{N} \alpha_i y_i = 0]$

This dual problem can be solved using optimization techniques such as the Sequential Minimal Optimization (SMO) algorithm to find the optimal values of (α_i), from which we can compute the optimal weights (w) and bias (b) of the SVM.

16. Explain shattering using one example?

If a classifier can accurately divide the points into positive and negative groups regardless of how we choose to label them, then this set of points is said to be shattered.

Consider a collection of points in a two-dimensional space as an actual example. Either red or blue labels can be placed next to each point. A classifier can spline a collection of points if it can draw a line in the plane with all the red points on one side and all the blue points on the other. This indicates that every point labeled as red or blue will result in the classifier properly classifying it.

17. Define VC Dimensions?

The VC dimension is a key notion in machine learning that quantifies a classifier's ability to understand complicated patterns in data. The greatest group of points that a classifier can split into two or more different regions is what is referred to as the size of the largest set. The VC dimension of a classifier and its capacity to shatter sets of points are closely correlated, with larger VC dimensions implying more capacity to shatter complicated sets of points. Contrarily, a classifier with a low VC dimension struggles to understand complicated patterns and is more likely to overfit or underfit the data.

Samples can be used to show how fracturing a group of points and the VC dimension are related. A linear classifier, for example, in a two-dimensional space, has a VC dimension of two, which indicates that it can break every set of two points but not all sets of three points. As opposed to this, a polynomial classifier in a two-dimensional space has a VC dimension that rises with the polynomial's degree, enabling it to break increasingly intricate collections of points.

18. Why Mean Squared Error is not used as a loss function in Binomial Logistic Regression?

- MSE gives output in positive real numbers, more than 1
- It can’t generate high value for misclassification, as in log loss misclassification penalty gives infinite value
- During optimization it can get stuck in local minimas as it is non convex

19. State two scenarios where support vector machines (SVM) algorithm performs better than other supervised machine learning algorithms.

- High dimensional spaces
- Non linear data

20. Primal vs Dual problem of svm

Primal Problem	Dual Problem
Optimization problem in the original feature space.	Optimization problem in the feature space defined by the kernel function.
Involves optimizing the weights and bias directly.	Involves optimizing the Lagrange multipliers.
Minimizes a convex quadratic function subject to linear constraints.	Maximizes a concave quadratic function subject to linear constraints.
More computationally expensive, especially for high-dimensional data.	Generally computationally more efficient, especially when the number of features is larger than the number of samples.
Suitable for solving problems with a large number of features but a small number of samples.	Suitable for solving problems with a large number of samples but a small number of features.
Directly provides the weights and bias for the linear decision boundary.	The decision boundary is implicitly defined by the support vectors.
Can handle nonlinear problems using kernel functions, but the computation can be costly.	Efficiently handles nonlinear problems using kernel functions, which implicitly map the data into a higher-dimensional space.
Prone to overfitting when the number of features is much larger than the number of samples.	Less prone to overfitting, especially when the number of samples is larger than the number of features.

21. Write two characteristics of SVM

Two characteristics of Support Vector Machines (SVMs) are:

Maximizing Margin: SVMs aim to find the hyperplane that maximizes the margin, which is the distance between the hyperplane and the closest data points (support vectors) from each class. By maximizing the margin, SVMs strive to achieve better generalization performance and robustness to noise in the data.

Kernel Trick: SVMs can efficiently handle nonlinear decision boundaries using the kernel trick. By implicitly mapping the input data into a higher-dimensional feature space, SVMs can find linear decision boundaries in the transformed space, effectively capturing complex relationships between features. This allows SVMs to handle nonlinear classification tasks without explicitly computing the transformation, making them versatile and powerful classifiers.

22. What is a kernel trick?

- Implicit mapping of input data into higher dimension space using kernel functions to computer inner product with feature vectors in original feature space
- Simply said, it transform non linearly separable datapoints to higher dimensions so that it becomes easy for a hyperplane to separate them
- Linear, polynomial and radial basis function

23. LInear svm vs Twin svm

Feature	Linear SVM	Twin SVM
Decision Boundary	Linear decision boundary.	Nonlinear decision boundary.
Kernel Trick	Does not use kernel trick.	Utilizes kernel trick for nonlinear classification tasks.
Complexity	Generally less complex and computationally efficient.	Can be more complex and computationally intensive, especially with kernel methods.
Margin Maximization	Focuses on maximizing the margin between classes.	Also focuses on maximizing the margin, but with additional constraints for twin vectors.
Support Vectors	Determines the decision boundary based on support vectors.	Introduces twin vectors in addition to support vectors for margin optimization.
Margin Width	Margin width may vary depending on data distribution and separation.	Twin SVM aims to achieve a wider margin by introducing twin vectors.
Application	Well-suited for linearly separable or nearly separable data.	Particularly useful for nonlinear classification tasks where a wider margin is desired.
Regularization	Can incorporate regularization to handle overfitting.	May require additional regularization techniques to prevent overfitting, especially with complex kernels.
Computational Efficiency	Generally more computationally efficient compared to Twin SVM.	Can be less computationally efficient, especially with complex kernels and large datasets.
Noise Sensitivity	More sensitive to noise in the data, especially in high-dimensional spaces.	May be less sensitive to noise due to the emphasis on maximizing the margin.
Training Speed	Faster training speed, especially with large, sparse datasets.	Training speed may be slower, especially with complex kernels and large datasets.

24. Define following terms- PAC Learning, Consistent Hypothesis, VC Dimension and shattering. Demonstrate in how many ways two data points with labels as 0 and 1, can be shattered by a straight line.

PAC Learning (Probably Approximately Correct Learning):
PAC Learning is a framework in computational learning theory that provides a mathematical framework for analyzing the efficiency and effectiveness of machine learning algorithms. In PAC learning, a learning algorithm is considered successful if it can produce a hypothesis that is "probably approximately correct" with high probability, given a certain amount of training data.

Consistent Hypothesis:
A hypothesis is said to be consistent with a dataset if it perfectly classifies all the examples in the dataset without any errors. In other words, a consistent hypothesis correctly predicts the labels of all the training examples.

VC Dimension (Vapnik-Chervonenkis Dimension):
VC Dimension is a measure of the capacity of a hypothesis space, which represents the set of all possible hypotheses that a learning algorithm can express. Informally, the VC dimension of a hypothesis space is the maximum number of points that can be shattered (perfectly classified) by any arrangement of points in the input space.

Shattering:
Shattering refers to the ability of a hypothesis space to perfectly classify all possible dichotomies (ways of dividing the data into two classes) of a given set of data points. A hypothesis space that can shatter a set of data points is said to have the maximum capacity to represent any dichotomy of the data.

Now, let's demonstrate in how many ways two data points with labels as 0 and 1 can be shattered by a straight line:

For two data points with labels 0 and 1, there are four possible dichotomies:

Both points labeled as 0.
Both points labeled as 1.
One point labeled as 0 and the other as 1.
One point labeled as 1 and the other as 0.

25. Consider a target function C= "Conjunction of n Boolean literals."
and Hypothesis function H trying to map input to target function. Find the minimum number of samples needed to make C PAC
Learnable with given values of ϵ, δ and n. δ = ϵ =0.05, n=10
δ = 0.01 ϵ =0.05, n=20
δ = ϵ =0.01, n= 40

Formula used:

$$[m \geq \frac{1}{\epsilon}\left(\ln(|H|) + \ln\left(\frac{1}{\delta}\right)\right)]$$

m is the number of samples.
H = 2^n

26. What is Naive Bayes Classifier?
Naive Bayes classifiers are a collection of classification algorithms based on Bayes' Theorem. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other.

Assumptions:

- Feature independence
- Features are equally important
- Continuous features are normally distributed
- No missing data

Bayes' Theorem finds the probability of an event occurring given the probability of another event that has already occurred. Bayes' theorem is stated mathematically as the following equation:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$
where A and B are events and P(B) ≠ 0

Basically, we are trying to find probability of event A, given the event B is true. Event B is also termed as evidence.

- P(A) is the priori of A (the prior probability, i.e. Probability of event before evidence is seen). The evidence is an attribute value of an unknown instance(here, it is event B).
- P(B) is Marginal Probability: Probability of Evidence.
- P(A|B) is a posteriori probability of B, i.e. probability of event after evidence is seen.

- P(B|A) is Likelihood probability i.e the likelihood that a hypothesis will come true based on the evidence.

Now, with regards to our dataset, we can apply Bayes' theorem in following way:

$P(y|X) = \frac{P(X|y)P(y)}{P(X)}$

where, y is class variable and X is a dependent feature vector (of size *n*) where:

$X = (x_1, x_2, x_3, ..., x_n)$

Just to clear, an example of a feature vector and corresponding class variable can be: (refer 1st row of dataset)