7.	It aim is to basically increase chances of success and not accuracy	Aim to increase in accuracy not about success ratio	Aims to achieve highest ranks of accuracy trained with large amount of data
8.	3 categories of AI are ANI, AGI, ASI ↓ Narrow General Super	3 categories are supervised, unsupervised Reinforcement	unsupervised pretrained Convolutional neural Recurrent Neural Recursive neural
9.	Ex) - Google's AI-powered prediction, Uber, Lyft, Autopilot etc	personal assistance Siri, Alexa Email spam	sentiment based news aggregation Caption generation
10.	Rule based, knowledge-based data driven systems	trail and error mechanism	heirarical manner Complex representation of data.

6. What is statistical learning? What is the objective of statistical learning?

Ans Statistical learning theory is a framework for machine learning drawing from the fields of statistics and functional analysis.

It deals with statistical inference problem of finding a predictive function based on data.

Statistical learning theory has lead to successful applications in fields such as Computer vision, speech recognition and bioinformatics.

From perspective of statistical learning, supervised learning is best understood (from training set of data) as we know supervised problems are either regression or Classification problem, regression produces continuous value and classification produces discrete value

Objectives of Statistical learning are:-

- → Minimizing the loss or Empherical risk
- → provide a framework for studying the problem of inference.
- → Gaining knowledge, making predictions, making decisions or constructing models from a set of data.
- → understanding relationships in data, provide insights into underlying pathers in complex datasets.

Example MSE → is standard loss function utilized in most regression tasks since it directs the model to optimize to minimise the squared difference between predicted and target value.

$$MSE = \frac{1}{n} \sum_{(x,y \in D)}^{n} (Y - \hat{Y}_i)^2$$

where $\hat{y}$ = predicted value of target value

n = number of training example in Data set D

Y = actual target attribute value.

7. How Regression and classification are different? Explain in detail with real time examples?

Ans

Classification and Regression are both supervised learning algorithms that can be used for forecasting in ML and operate with labelled datasets.

Classification :- Classification is the process of discovering or identifying a design or role which helps to separate them into several categorical classes. If - Then law is used.

Regression :- Regression is the method of discovering a function or a model for separating the real values data instead of using distinct values or group, it measures quantity of data.

The main distinction between these two is based on how they are used on particular ML problems

-> Regression algorithms are used to determine continuous values such as price, income age etc

-> whereas classification algorithms are used to determine or classify distinct values such as Real or fake, spam or not spam etc.

There are multiple types of classification algorithms like logistic regression, k-nearest neighbour, Decision tree, Naive Bayes etc.

Regression algorithms like - simple linear, multiple linear, polynomial regression, Random forest, Decision tree etc.

Real time examples :-

Classification - voice recognition, spam emails ; identification of cancer cells.

Let us consider suppose there is a match going on, we want to predict probability of winning team on basis of some parameters reported earlier. Then there will be two signs, Yes or NO. We logistic regression is classification to estimate probability of data points belonging either to team A or team B

Regression - House price prediction, weather prediction. Regression example where we are finding probability of rainfall in some specific regions with the aid of some parameters reported earlier. The chance correlated with rain.

8 How to estimate the loss function in statistical learning. Discuss how to assess model accuracy?

Ans Statististical learning theory is a framework for machine learning drawing from the field of statistics and functional analysis.

* we know that from perspective of statistical learning, is better understood from supervised learning.

Loss function - It's a method of evaluating how well your algorithm models your dataset. If your predictions are totally off, your loss function will output a higher number. If they're pretty good, it'll output a lower number

* loss functions are related to model accuracy a key component of AI/ML governance
* we can design our loss function, for each prediction that we make, our loss function will simply measure the absolute difference between our prediction and actual value. In mathematical notation, it will look like -

abs(Y- predicted - Y- actual)

There are many types of loss functions being used some of which are:-

(i) Mean Squared Error
(ii) Likelihood loss
(iii) log loss (cross entropy loss)

* In assessing the model's accuracy mean squared error method is helpful, it is the workhorse of basic loss function; its easy to understand and implement and generally works pretty well.
* To calculate MSE, you take the difference between your predictions and ground truth, square it and average it out across whole dataset.

MSE = mean squared error

$$= \frac{1}{n} \sum_{(x,y \in D)} (Y_i - \hat{Y}_i)^2$$

Y = actual target attribute

$\hat{Y}$ = predicted value of target value

n = no of training example in Data set D.

Accuracy is perhaps the best-known ml model validation method used in Evaluating classification problem. because of it's

Simplicity :- Accuracy is a good metric to assess.

* Accuracy is used in many problems to tell the percentage of correct prediction made by a model.
* Accuracy score in ml is an Evaluating metric that measures the number of correct predictions made by a model in relation to total number of predictions made.
* we calculate it by dividing the number of correct predictions by total number of predictions.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total Number of predictions}}$$

In this way we can Estimate loss function in statistical learning and assess accuracy.

9. Define the terms overfitting and underfitting? How can we resolve these issues.

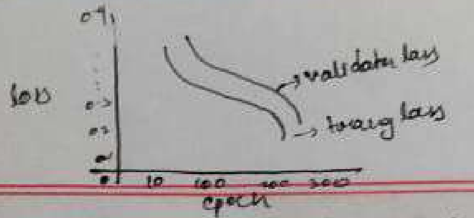
Ans:- we know that a there are multiple issues associated with machine learning. that may be caused due to two main reasons: Bad data and Bad algorithm

* In regard to Bad algorithm we have 2 different issues called :- underfitting and overfitting.

Overfitting of training data -

we know that humans make overgeneralization of thing which unfortunately can be the trap of machines too, that trap is particularly called as overfitting of data.

underfitting ←

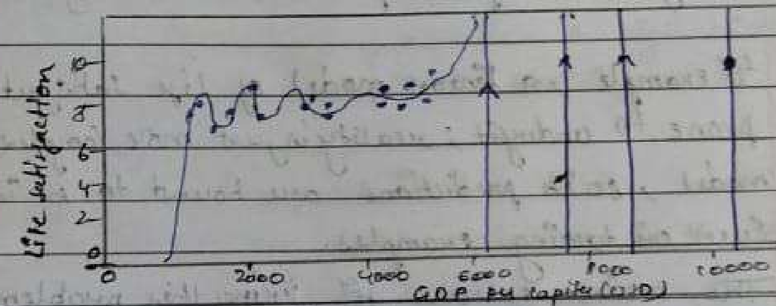


validation loss is greater than training loss

Overfitting means model performs well on training data but it does not generalize well.

→ Overfitting happens when the model is too complex relative to amount and noiseness of training data possible.

Consider following example of a high-degree polynomial life satisfaction model that strongly overfits training data



Complex models such as deep neural networks can detect subtle patterns in the data, but if the set is noisy, or if it is too small then the model is likely to detect patterns in the noise itself obviously these patterns will not generalize to new instances.

Here are some of the possible solutions for overfitting.

- Simplify the model by selecting one with fewer parameters like a linear model rather than a high-degree polynomial model by reducing the number of attributes in training data or by constraining the model
- Gather more training data
- Reduce the noise in the training data
- fix data errors and remove outliers

method of reduce the risk of overfitting is called regulari

Underfitting of training data :-

Underfitting of training data is opposite of overfitting.

* Underfitting of data occurs when your model is too simple to learn the underlying structure.
* It provides inaccurate results for both training data and test sets and has high bias
* It fails to capture patterns in training data.

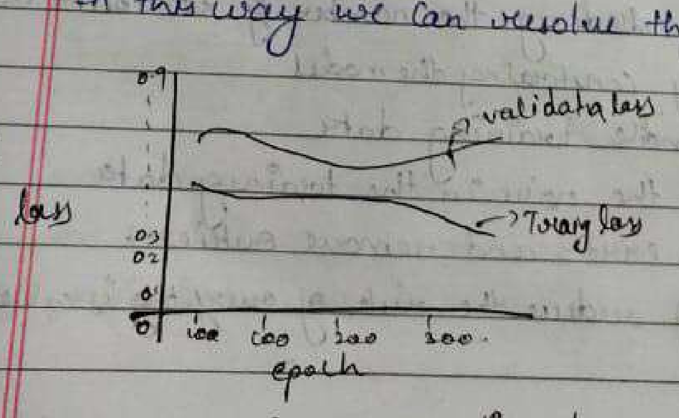
For example, a linear model of life satisfaction is prone to underfit ; reality is just more complex than the model, so its predictions are bound to be inaccurate Even on training examples.

The main options for fixing this problem:

1. Select a more powerful model, with more parameters
2. Feed better features to the learning algorithm (Feature Engineering)
3. Reduce the Constraints on model
   Reduce regularization hyperparameter.

In this way we can resolve these issues.

overfitting



validata loss increases continuously and Traing loss decrease.

10. Describe bias and variance? Explain Bias variance tradeoffs in statistical learning?

Ans An important theoretical result of statistics and Machine learning is the fact that a model's generalization error can be expressed as the sum of 3 very different errors :-

Bias :-

This part of generalization error is due to wrong assumptions, such as assuming that the data is linear when it is actually quadratic. A high-bias model is most likely to underfit the training data.

Variance :- This part is due to the model's excessive sensitivity to small variations in the training data. A model with many degree of freedom (such as a high-degree polynomial model) is likely to have high variance and thus overfit the training data.

Irreducible error :- This part is due to the noiseness of the data itself. The only way to reduce this part of the error is to clean up the data.

Increasing a model's complexity will typically increase it's variance and reduce it's bias.

Conversely, reducing a model's complexity increases it's bias and reduces it's variances.

This is why it is called as trade-off.

They are complement of each other and finding the results to balance of values is known as Bias-Variance Tradeoffs.

Gives good fit model.