1. Deep learning (NN, RNN, LSTM, CNN etc…) with real time in python packages(numpy, tensorflow, keras, scikit learn, torch)
2. Machine learning algorithms
3. Statistics
4. Time series Forecasting
5. Time series Forecasting in Deep learning
6. Python API creation
7. NLP
8. Mongo DB
9. Timeseries DB
10. AWS
11. AZURE
12. GCP
13. Docker image creation
14. Kubernetes
15. GO

Machine Learning,

1. KNN-
   1. K nearest neighbour is the classification or regression supervised learning algorithm.
   2. When we split the data into train and test and fit to the KNeighborsClassifier, we need to give the number of neighbours.
   3. If any new datapoint is added into the dataset, based on the “Number of neighbours” it will get classified to the required class.
   4. For example, if neighbour = 1, then based on the nearest neighbour (using any distance formula) it will be classified.
   5. If we have neighbour =3, then based on the nearest for most of the data points, it will be classified for the respective class. Let’s consider I have green and red as two classifiers. If new datapoint comes, if the datapoint is close to two green points and one red point, then it will be classified as green point.
   6. We need to trade-off between choosing the neighbours, if we have less neighbours training accuracy will be good but not testing accuracy.
   7. KNN can be used for regression also. In regression, average of nearest points will be considered as final value. But for classification, mode of nearest points is considered.
2. Ridge regression
   1. Ridge regression is popular type of regularized linear regression that includes an L2 penalty. This has the effect of shrinking the coefficients for those input variables that do not contribute much to the prediction task.
   2. It penalizes the coefficients by α times. α is the hyperparameter, by default it is 1. Reducing the α and checking the which is the best fitted model.
   3. Ridge regression will not make the coefficients 0. It will reduce the least affected feature coefficient value to avoid overfitting.
3. Lasso regression
   1. Lasso regression is popular type of regularized linear regression that includes an L1 penalty. This has the effect of shrinking the coefficients for those input variables that do not contribute much to the prediction task. And makes the coefficients to 0. Sometimes this works as feature selection which will remove least affected features.
   2. It penalizes the coefficients by α times. α is the hyperparameter, by default it is 1. Reducing the α and checking the which is the best fitted model.
   3. Lasso regression will make the coefficients 0. It will reduce the least affected feature coefficient value to avoid overfitting.
4. Decision Tree
   1. Decision tree algorithm works for both classification and regression dataset.
   2. It works like, if else conditions to the data, like if size of the feature is less than some number then it is 0 else it is 1. Like this it creates multiple if else conditions for each feature. Since decision tree creates the tree structure for the individual feature, scalability/normalization of the feature is not required.
   3. It creates each data point into one leaf. If any datapoint is near to the leaf, then it is classified to the respective leaf type. But it will overfit.
   4. So, pre-pruning and post pruning techniques are used to avoid overfitting the model.
      1. Pre-pruning- Limiting the maximum depth of the tree, maximum number of leaves, minimum number of points in the node.
      2. Post-pruning- Building the tree and collapsing nodes which has little information.
   5. DecisionTreeClassifier from scikit learn library only does the pre-pruning.
   6. The main downside of decision trees is that even with the use of pre-pruning, they tend to overfit and provide poor generalization performance.
   7. In decision tree only single tree will be formed. However, in random forest, multiple trees will be formed which will increase the efficiency of model.
5. Random Forest
   1. The idea behind random forests is that each tree might do a relatively good job of predicting, but will likely be overfit on part of the data. If we build many trees, all of which work well and overfit in different ways, we can reduce the amount of overfitting by averaging their results.
   2. To build the random forest, we need to decide the number of trees to be created. It will be given as n\_estimators in RandomForestRegressor and RandomForestClassifier.
   3. It uses bootstrap splitting and create the trees on split data.
      1. bootstrap sample of the list ['a', 'b', 'c', 'd']. A possible bootstrap sample would be ['b', 'd', 'd', 'c']. Another possible sample would be ['d', 'a', 'd', 'a'].
   4. Instead of looking for the best test for each node, in each node the algorithm randomly selects a subset of the features, and it looks for the best possible test involving one of these features. The number of features that are selected is controlled by the max\_features parameter. This selection of a subset of features is repeated separately in each node, so that each node in a tree can make a decision using a different subset of the features.
   5. To make prediction using the random forest, the algorithm predicts from each tree. For the regression it takes the average of the values, for classification it does the soft voting, based on this it will classify the data point.
   6. Random forest is computationally expensive, but it can run in parallel by choosing the option of n\_jobs.
   7. Higher the number of trees the smoother the decision tree boundaries, but it is computationally expensive.
   8. It also gives importance to all the features unlike decision trees.
   9. Choosing the right hyperparameters like n\_estimators and max\_features is the challenging task.
6. Gradient boosted regression trees
   1. In contrast to the random forest approach, gradient boosting works by building trees in a serial manner, where each tree tries to correct the mistakes of the previous one.
   2. By default, there is no randomization in gradient boosted regression trees; instead, strong pre-pruning is used.
   3. Gradient boosted trees often creates shallow trees depth of one to five, which makes the model smaller and computes faster than random forest.
   4. Apart from the pre-pruning, learning rate also will be passed as hyperparameter. Using which it tries the learn from the previous trees.
   5. This algorithm also gives importance to features like random forest.
   6. The main parameters of gradient boosted tree models are the number of trees, n\_esti mators, and the learning\_rate, which controls the degree to which each tree is allowed to correct the mistakes of the previous trees.
7. SVM
8. Bayesian interface
9. Adboost
10. Xgboost
11. Markov chain
12. Monte Carlo simulations
13. ADDA
14. Ada Match
15. Self ensemble
16. Cross Validation

Statistics,

1. Pdf

Answer: probability for a continuous random variable is given by areas under pdf's

1. Cdf

Answer: Integration of pdf is cdf

1. Why p-value should be less than 5%?

Answer: If p-value is less than 5%, it means the data used for the model is greater than 95% of data. Let’s consider if we fit the features to the algorithm if we get one feature as p-value 0.38. This doesn’t contribute to model. Reason being, for that feature only 62% of the data getting used in model. Rest 38% of the data it doesn’t use. So, we remove that feature.

1. Contingency table

Answer: It is the tabular representation of the categorical data. Contingency table shows the frequency distribution of combinations of values of two discrete variable x and y.

Table

Description automatically generated

1. Degrees of freedom

Answer: In the most of formulae we are using n-1 in denominator. The reason for that could be if we use n then there will be slightly biased. But we do n-1 in denominator the bias will be reduced. However, it doesn’t matter much if the dataset is huge. And the n-1 is called as degrees of freedom.

1. Maximum likelihood estimation

Answer: If we have data with mean and standard deviation (sigma), the future data which is similar with current data will have same mean and standard deviation (sigma) of current data. So that it will increase the likelihood of estimation.

1. Central limit theorem

Answer: The central limit theorem (CLT) states that the distribution of sample means approximates a normal distribution as the sample size gets larger, regardless of the population's distribution.

1. Bootstrap

Answer: A sample taken with replacement from an observed dataset. The sample may not be in normal distribution.

1. Permutation test

Answer: The process of combining two groups of samples and randomly creating the sample from the combined group.

1. Resampling

Answer: Process of taking repeated samples from observed data. Repeated samples taking procedure can be bootstrap or permutation test.

1. Standardization or Normalization

Answer: Subtract each data point with its mean and divide it by standard deviation will make the data as Standardization or Normalization

1. Z distribution

Answer: It is nothing but the Standardization. Z distribution will have 0 mean and 1 SD.

1. T distribution

Answer: It is like Z test, but here it is sample standard distribution. However, Z test is population standard distribution. T test is very similar to Z test, but in T test it will have sd greater than 1. T test will have longer tails. Shape of the distribution looks like T shape. T distribution with high degrees of freedom will be exactly same as Z distribution.

1. One tail test

Answer: It will deal with situation where we are interested in testing hypothesis that the population mean is greater or less than the hypothesized value. So only one rejection region.

1. Two tail test

Answer: There will be 2 rejection regions one in each tail. If significance level is 5% then 2.5% in each tail is the rejection ratio.

1. Binomial distribution

Answer: If the outcome of the data is yes/no or True/False. Then it is in binomial distribution. Mean is np and variance are npq. Where q = 1-p

1. Poison distribution

Answer: If the data satisfies below 3 requirements, then it is Poison.

* The random events must take place in a unit of time or space.
* The number of events which might occur in any given unit of time or space must be theoretically unlimited.
* The probability of occurrence in any single unit of time or space is independent of occurrence in any other unit of time or space.

Mean and variance is µ

1. Exponential distribution
2. Chisquare test- It’s the procedure to test the observed count is as expected count which shows the independence. Like for example buy a particular item is independent of gender. In chisquare test, Expected(Ei) should be minimum of 5. If not adjust with adjacent cells and until all the Expected values are greater than 5. If degrees of freedom is 1 then subtracting 0.5 from the chi square formulae will give better results. For higher degrees of freedom we can use the existing formulae.
3. Fisher test- It is also same as Chisquare test to check independence. But it works only smaller dataset.
4. A/B testing – An A/B test is an experiment with two groups to establish which of two treatments, products, procedures, or the like is superior.
5. Stationary poison process
6. Stochastic proximity embedding (SPE)

**Key Points**

1. In the most of formulae we are using n-1 in denominator. The reason for that could be if we use n then there will be slightly biased. But we do n-1 in denominator the bias will be reduced. However, it doesn’t matter much if the dataset is huge. And the n-1 is called as degrees of freedom

Mathamatics,

1. Where does Fourier transform fit in ML models?
2. Wallet packet decomposition