Q1 Under-observing the features leads to a higher error in the training and unseen data samples. It is different from overfitting, where the model performs well in the training set but fails to generalize the learning to the testing set.

Underfitting occurs when our machine learning model is not able to capture the underlying trend of the data. To avoid the overfitting in the model, the fed of training data can be stopped at an early stage, due to which the model may not learn enough from the training data

Q2 1.Hold-out(data):-Rather than using all of our data for training, we can simply split our dataset into two sets: training and testing. A common split ratio is 80% for training and 20% for testing. 2.Cross-validation (data):-We can split our dataset into k groups (k-fold cross-validation). We let one of the groups to be the testing set (please see hold-out explanation) and the others as the training set, and repeat this process until each individual group has been used as the testing set (e.g., k repeats). 3.Data augmentation (data):-A larger dataset would reduce overfitting. If we cannot gather more data and are constrained to the data we have in our current dataset, we can apply data augmentation to artificially increase the size of our dataset. 4.Feature Selection:-If we have only a limited amount of training samples, each with a large number of features, we should only select the most important features for training so that our model doesn't need to learn for so many features and eventually overfit 5.L1 / L2 regularization (learning algorithm):-Regularization is a technique to constrain our network from learning a model that is too complex, which may therefore overfit. In L1 or L2 regularization, we can add a penalty term on the cost function to push the estimated coefficients towards zero (and not take more extreme values). 6.Remove layers / number of units per layer (model):-As mentioned in L1 or L2 regularization, an over-complex model may more likely overfit. Therefore, we can directly reduce the model's complexity by removing layers and reduce the size of our model. We may further reduce complexity by decreasing the number of neurons in the fully-connected layers 7.

Q3 Underfitting is a scenario in data science where a data model is unable to capture the relationship between the input and output variables accurately, generating a high error rate on both the training set and unseen data. list:-The model is too simple, So it may be not capable to represent the complexities in the data. 1.The input features which is used to train the model is not the adequate representations of underlying factors influencing the target variable. 2.The size of the training dataset used is not enough. 3.Excessive regularization are used to prevent the overfitting, which constraint the model to capture the data well. 4.Features are not scaled

Q4 If the algorithm is too simple (hypothesis with linear equation) then it may be on high bias and low variance condition and thus is error-prone. If algorithms fit too complex (hypothesis with high degree equation) then it may be on high variance and low bias. In the latter condition, the new entries will not perform well. Well, there is something between both of these conditions, known as a Trade-off or Bias Variance Trade-off. This tradeoff in complexity is why there is a tradeoff between bias and variance. An algorithm can't be more complex and less complex at the same time. For the graph, the perfect tradeoff will be like this.

Q5 We can determine whether a predictive model is underfitting or overfitting the training data by looking at the prediction error on the training data and the evaluation data. Your model is underfitting the training data when the model performs poorly on the training data. One way is to look at how well it performs on new data. If your model is overfitting, it will perform well on the training data but not so well on the test set with new data. If your model is underfitting, it will perform poorly on both the training dataset and the test set.

Q6 Bias represents the error due to overly simplistic assumptions in the learning algorithm. High bias can cause the model to underfit the data, leading to poor performance on both training and unseen data. Variance, on the other hand, reflects the model's sensitivity to small fluctuations in the training data For example, a linear regression model may have a high bias if the data has a non-linear relationship. 1.Use a more complex model: One of the main reasons for high bias is the very simplified model. it will not be able to capture the complexity of the data. In such cases, we can make our mode more complex by increasing the number of hidden layers in the case of a deep neural network. Or we can use a more complex model like Polynomial regression for non-linear datasets, CNN for image processing, and RNN for sequence learning. 2.Increase the number of features: By adding more features to train the dataset will increase the complexity of the model. And improve its ability to capture the underlying patterns in the data. 3.Reduce Regularization of the model: Regularization techniques such as L1 or L2 regularization can help to prevent overfitting and improve the generalization ability of the model. if the model has a high bias, reducing the strength of regularization or removing it altogether can help to improve its performance. 4.Increase the size of the training data: Increasing the size of the training data can help to reduce bias by providing the model with more examples to learn from the dataset.

Q7

Regularization refers to techniques that are used to calibrate machine learning models in order to minimize the adjusted loss function and prevent overfitting or underfitting. Figure 5: Regularization on an over-fitted model. Overfitting is a phenomenon that occurs when a Machine Learning model is constrained to the training set and not able to perform well on unseen data. That is when our model learns the noise in the training data as well. This is the case when our model memorizes the training data instead of learning the patterns in it. The commonly used regularization techniques are :

Lasso Regularization – L1 Regularization Ridge Regularization – L2 Regularization Elastic Net Regularization – L1 and L2 Regularization

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