**Q1. How do you assess the quality of Machine learning predictive models discuss one in detail?**

Ans)

Evaluating the performance of a Machine learning model is one of the important steps while building an effective ML model. To evaluate the performance or quality of the model, different metrics are used, and these metrics are known as performance metrics or evaluation metrics. These performance metrics help us understand how well our model has performed for the given data. In this way, we can improve the model's performance by tuning the hyper-parameters. Each ML model aims to generalize well on unseen/new data, and performance metrics help determine how well the model generalizes on the new dataset.

**1. Performance Metrics for Classification**

In a classification problem, the category or classes of data is identified based on training data. The model learns from the given dataset and then classifies the new data into classes or groups based on the training. It predicts class labels as the output, such as Yes or No, 0 or 1, Spam or Not Spam, etc. To evaluate the performance of a classification model, different metrics are used, and some of them are as follows:

Accuracy

Confusion Matrix

Precision

Recall

F-Score

AUC(Area Under the Curve)-ROC

**2. Performance Metrics for Regression**

Regression is a supervised learning technique that aims to find the relationships between the dependent and independent variables. A predictive regression model predicts a numeric or discrete value. The metrics used for regression are different from the classification metrics. It means we cannot use the Accuracy metric (explained above) to evaluate a regression model; instead, the performance of a Regression model is reported as errors in the prediction. Following are the popular metrics that are used to evaluate the performance of Regression models:

Mean Absolute Error

Mean Squared Error

R2 Score

Adjusted R2

**Predictive modelling**

In short, predictive modeling is a statistical technique using machine learning and data mining to predict and forecast likely future outcomes with the aid of historical and existing data. It works by analyzing current and historical data and projecting what it learns on a model generated to forecast likely outcomes. Predictive modeling can be used to predict just about anything, from TV ratings and a customer’s next purchase to credit risks and corporate earnings.

A predictive model is not fixed; it is validated or revised regularly to incorporate changes in the underlying data. In other words, it’s not a one-and-done prediction. Predictive models make assumptions based on what has happened in the past and what is happening now. If incoming, new data shows changes in what is happening now, the impact on the likely future outcome must be recalculated, too. For example, a software company could model historical sales data against marketing expenditures across multiple regions to create a model for future revenue based on the impact of the marketing spend.

Successful use of predictive analytics depends heavily on unfettered access to sufficient volumes of accurate, clean and relevant data. While predictive models can be extraordinarily complex, such as those using decision trees and k-means clustering, the most complex part is always the neural network; that is, the model by which computers are trained to predict outcomes. Machine learning uses a neural network to find correlations in exceptionally large data sets and “to learn” and identify patterns within the data.

In a nutshell, predictive analytics reduce time, effort and costs in forecasting business outcomes. Variables such as environmental factors, competitive intelligence, regulation changes and market conditions can be factored into the mathematical calculation to render more complete views at relatively low costs.

Examples of specific types of forecasting that can benefit businesses include demand forecasting, headcount planning, churn analysis, external factors, competitive analysis, fleet and IT hardware maintenance and financial risks.

**Q2. Interpretable machine learning is a useful umbrella term that captures the “extraction of relevant knowledge from a machine-learning model concerning relationships either contained in data or learned by the model”. Justify the need and limitation of, Interpretability of the ML model.**

**Ans)**

**Q3. Discuss the model-agnostic global interpretation techniques.**

**Q4. Differentiate global methods are local Agnostic methods.**

**Q5. Discuss the interpretation of weight in the linear regression model on the following type of features.**

* **Numerical feature**
* **Categorical**
* **Binary feature:**

**Q6. Using statistical model summary that gives direct access to the coefficients, the standard errors, the t-statistics, and the p-values for each feature, how one can interpret the ML model? Discuss using some examples.**