LSTMs are commonly used for time series forecasting, especially for datasets with long-term dependencies. However, there are other machine learning models that may perform better for a given problem, such as ARIMA, SARIMA, Prophet, and Random Forest. The choice of the model depends on the nature of the data and the problem being solved. It is important to try multiple models, tune their hyperparameters, and compare their performance to find the best model for a given problem.

ARIMA (AutoRegressive Integrated Moving Average) is a popular time series forecasting model used for univariate time series data, i.e., where the data has only one variable. ARIMA models the relationship between the current observation and a linear combination of previous observations and residual errors, and it models the relationships between observations and their differences (integrated) over time.

SARIMA (Seasonal AutoRegressive Integrated Moving Average) is an extension of ARIMA that considers seasonality in time series data. It takes into account the repeating patterns in the data, such as daily, weekly, or yearly patterns. The seasonal component of the model is defined by the seasonal order, which consists of the seasonal autoregression (SAR), seasonal differences (I), and seasonal moving average (SMA) parameters.

In terms of comparison, ARIMA and SARIMA are classical time series models that are good for modeling univariate time series data. They are appropriate for data with linear or non-linear trends and with or without seasonality. Prophet is a newer model that is specifically designed to be flexible and easy to use, and it is suitable for time series with multiple seasonality. The choice of the best model depends on the nature of the time series data and the problem requirements. It's recommended to experiment with different models and select the one that provides the best performance for your particular time series data.

Prophet is a time series forecasting model developed by Facebook. It is designed to be flexible and easy to use, and it is suitable for time series with linear or non-linear growth patterns, as well as for time series with multiple seasonality. Prophet is a decomposable time series model, which means that it separates the time series into its trend, seasonality, and holiday components. The model can also incorporate additional information such as holidays and events, which can be used to improve the forecast accuracy.

SVMs (Support Vector Machines) are a powerful machine learning method that can be used for classification or regression tasks. SVMs can handle high-dimensional data well and are effective in cases where there is a clear separation between the different classes or where the decision boundary is nonlinear.

In the context of predicting COVID cases, SVMs can be used to analyze historical data to identify patterns and make predictions based on those patterns. In this specific case, the SVM model was trained on historical data of COVID cases and used to predict future cases based on trends identified in the historical data.

Polynomial regression fits a nonlinear relationship between the dependent variable and one or more independent variables by using polynomial functions. It can capture complex relationships between variables and can be useful when there are nonlinearities in the data.

Bayesian ridge regression is a probabilistic model that can be used for both linear and nonlinear regression tasks. It can be particularly useful when the number of independent variables is large and when there is collinearity among the independent variables.

In general, nonlinearities in the data refer to situations where the relationship between variables cannot be accurately modeled by a linear function. This means that as the values of the independent variables change, the corresponding changes in the dependent variable are not proportional or constant. In other words, the relationship between the variables is not a straight line.

Nonlinearities can arise for a variety of reasons, such as interactions between variables, threshold effects, or curvilinear relationships. When dealing with nonlinear data, linear models such as linear regression may not be appropriate, and nonlinear models such as polynomial regression, decision trees, or neural networks may be more effective. Nonlinear models have more flexibility in capturing the complexity of the relationships between variables, but they may also be more prone to overfitting or requiring more data to train effectively.