1. What is Normalization & Standardization and how is it helpful?
   * **Normalization** is the process of scaling individual samples to have unit norm. In other words, it rescales the values of a feature to a fixed range, typically between 0 and 1. This is often done by subtracting the mean and dividing by the standard deviation of each feature.
   * **Standardization**, on the other hand, scales the features such that they have zero mean and unit variance. This is achieved by subtracting the mean and dividing by the standard deviation of each feature.

Both normalization and standardization are helpful in machine learning for several reasons:

* + **Improving convergence**: Algorithms like gradient descent often converge faster when features are scaled.
  + **Improving interpretability**: Scaling ensures that the features are on a similar scale, making it easier to interpret the importance of different features.
  + **Handling outliers**: Standardization can mitigate the impact of outliers on the model.
  + **Enhancing performance**: Some algorithms, particularly those based on distances or gradients, perform better with scaled features.

1. What techniques can be used to address multicollinearity in multiple linear regression?

Multicollinearity occurs when two or more predictor variables in a regression model are highly correlated. This can cause issues such as unstable coefficients estimates and reduced interpretability of the model. Here are some techniques to address multicollinearity:

* **Feature Selection**: Identify and remove redundant features. This can be done using techniques like backward elimination, forward selection, or stepwise regression.
* **Principal Component Analysis (PCA)**: Transform the original variables into a new set of uncorrelated variables (principal components) that capture most of the variance in the data. This can help mitigate multicollinearity.
* **Ridge Regression**: Introduce a penalty term to the regression model that penalizes large coefficients. This tends to shrink the coefficients towards zero and can reduce the impact of multicollinearity.
* **Variance Inflation Factor (VIF)**: Calculate the VIF for each predictor variable, which measures how much the variance of the estimated regression coefficients are inflated due to multicollinearity. Variables with high VIF values (typically above 5 or 10) may indicate multicollinearity issues.
* **Orthogonalization**: If possible, transform the predictor variables so that they are orthogonal (uncorrelated) with each other. This can be achieved through methods like Gram-Schmidt orthogonalization.

By applying these techniques, one can mitigate the negative effects of multicollinearity and build more stable and interpretable regression models.