Different Ways to handle Multicollinearity

1. **Removing high correlated variables**
    a. This technique we can identify the correlation between the variables and identify the highly correlated variables and remove them
    b. The disadvantage is, we can loss the information as we removing the variables from the dataset

2. **Variance Inflation Factor(VIF):**
    a. VIF quantifies how much the variability of a regression coefficient is increased (inflated) due to multicollinearity among the independent variables.
    b. Calculate VIF value of each variable and then remove variable that has high VIF values

3. **Feature Selection**
    a. Selecting right features using methods like stepwise regression or recursive feature elimination can help automatically and select a subset of independent variables that are less correlated and more relevant to the dependent variable.
        i. **Forward Selection**: Start with an empty model and add variables one at a time, choosing the variable that improves the model's fit the most until no more significant variables can be added.
        ii. **Backward Elimination**: Start with a model that includes all predictors and iteratively remove the least significant variable (e.g., based on p-values) until no more variables can be removed without significantly reducing the model's fit.
        iii. **Stepwise**: A combination of forward selection and backward elimination, where variables are added or removed at each step based on their significance

4. **Dimensionality reduction techniques:**
    a. Principle Component Analysis
        i. PCA transforms the original variables into a new set of uncorrelated variables, called principal components. By selecting a subset of these components, you can reduce multicollinearity

    b. Partial Least Squares (PLS) Regression:

i. PLS is a dimensionality reduction technique that seeks to extract a set of orthogonal factors from the independent variables that are linear combinations of the original variables. PLS can help reduce multicollinearity by transforming the original variables into a smaller set of uncorrelated components

5. **Regularize Techniques:**
   a. Ridge Regression: Ridge regression adds a penalty to the size of regression coefficients, shrinking them towards zero. This penalty helps to reduce the impact of multicollinearity
   b. Lasso Regression: Similar to ridge regression, Lasso adds a penalty to the absolute size of the coefficients. Lasso tends to force some coefficients to exactly zero, effectively performing
6. **Collect More Data**: Sometimes multicollinearity arises due to insufficient data. Collecting more data can help spread out the variation and reduce correlations between predictors

Above are the ways to handle multicollinearity.