Common methods to manage multicollinearity:

**1. Remove Highly Correlated Predictors**

* **Identify Correlation:** Use correlation matrices or variance inflation factor (VIF) to identify highly correlated variables.
* **Drop Variables:** Remove one of the highly correlated variables from the model.

**NOTE:** high VIF indicates a high level of multicollinearity.

**2. Principal Component Analysis (PCA)**

* **Dimensionality Reduction:** PCA transforms the original features into a set of linearly uncorrelated components.
* **Use Components:** Replace the original predictors with the principal components in your model.

**3. Regularization Techniques**

* **Ridge Regression:** Adds a penalty equal to the square of the magnitude of coefficients (L2 regularization). It helps to mitigate multicollinearity by shrinking the coefficients.
* **Lasso Regression:** Adds a penalty equal to the absolute value of coefficients (L1 regularization). It can also help with feature selection by shrinking some coefficients to zero.

**4. Combine Variables**

* **Feature Engineering:** Combine correlated variables into a single feature using techniques like averaging, summing, or creating interaction terms.

**5. Use Domain Knowledge**

* **Expert Insights:** Incorporate domain knowledge to select the most important predictors and remove or combine less important ones.

**6. Data Collection**

* **Additional Data:** Collect more data to help distinguish between correlated predictors, although this may not always be feasible.

**7. Standardization of Predictors**

* **Normalize Data:** Standardize the predictor variables to have a mean of zero and a standard deviation of one. This doesn’t eliminate multicollinearity but can help in some cases by improving numerical stability.