Q. Why is data scaling important to machine learning regression models?

A. Data scaling is important in machine learning regression models for several reasons:

Faster convergence: When the input features have different scales, the cost function may have elongated bowl-shaped contours, which make it difficult for the optimization algorithm to converge quickly. By scaling the input features, we can make the cost function more symmetric and thus easier to optimize.

Improved accuracy: Scaling the input features can also improve the accuracy of the model by reducing the impact of features with larger magnitudes on the prediction. This is because features with larger magnitudes will dominate the cost function, making it difficult for the model to learn from other features with smaller magnitudes.

Regularization: Scaling can also help to prevent overfitting of the model. Regularization techniques like L1 and L2 regularization penalize the coefficients of the features in the model. When the input features have different scales, the regularization term may be dominated by the features with larger magnitudes, making it difficult for the model to learn from other features.

Overall, data scaling is an important preprocessing step in machine learning regression models to ensure that the model is able to learn from all the input features effectively and produce accurate predictions.

Q. Then, how can I interpret scaled regression coefficients?

A. Interpreting the coefficients of a regression model that uses scaled input features requires a slightly different approach than interpreting coefficients in a model without scaling. Here are some key points to consider when interpreting scaled regression coefficients:

Magnitude: The magnitude of the coefficients is no longer directly comparable because the scaling changes the units of the input features. Instead, you can compare the relative magnitudes of the coefficients to see which features have a larger or smaller impact on the output variable.

Direction: The sign of the coefficient still indicates the direction of the relationship between the input feature and the output variable. A positive coefficient indicates a positive relationship (i.e., as the input feature increases, the output variable increases), and a negative coefficient indicates a negative relationship (i.e., as the input feature increases, the output variable decreases).

Importance: The importance of the coefficients is still relevant, but it should be based on the magnitude of their impact on the output variable relative to the impact of other features in the model. You can use techniques like feature selection or regularization to identify the most important features in the model.

Interpretation: The interpretation of the coefficients is still related to the change in the output variable that is associated with a one-unit change in the input feature. However, the "one-unit" change is now scaled according to the scaling factor of the input feature. For example, if the input feature was scaled by a factor of 10, then a one-unit change in the scaled feature corresponds to a 10-unit change in the original feature.

In summary, interpreting scaled regression coefficients requires taking into account the scaling factor of the input features, and focusing on the relative magnitudes and directions of the coefficients to understand their impact on the output variable.

Q. There is no method to restore scaled regression coefficients?

A. It is generally not recommended to "restore" scaled regression coefficients to their original scale because the scaling transformation changes the units and magnitudes of the input features. However, there are some cases where you may need to report or interpret the coefficients in the original scale, such as when communicating results to non-technical stakeholders or comparing coefficients across different models.

To restore the scaled regression coefficients to their original scale, you can use the following formula:

Original Coefficient = Scaled Coefficient \* (Standard Deviation of the Input Feature / Standard Deviation of the Scaled Input Feature)

where the Standard Deviation of the Input Feature is the standard deviation of the original unscaled input feature, and the Standard Deviation of the Scaled Input Feature is the standard deviation of the input feature after scaling. This formula adjusts the scaled coefficient for the scaling factor of the input feature, so that the resulting coefficient is in the same units as the original unscaled coefficient.

However, it is important to note that restoring the scaled coefficients to the original scale can be misleading and should be done with caution. The original unscaled coefficients reflect the relationship between the input features and the output variable in the original units and magnitudes of the data, while the scaled coefficients reflect the relationship between the input features and the output variable after standardizing the data. Comparing or interpreting coefficients in different scales can be misleading and may not accurately reflect the true relationship between the input features and the output variable.