Purpose of Homoscedasticity

❖ Homoscedasticity is one of the quiet assumptions behind regression models, and when it holds, your results are more dependable. Calculations like standard errors and p-values rely on the idea that variance stays consistent across the data. When that's true, the model's statistical output aligns more closely with the actual uncertainty in your predictions.

❖ But if the variance shifts, those numbers become less trustworthy. A model might flag a result as significant when it isn't, or miss meaningful patterns because the spread of errors throws off the estimates. That disconnect can lead teams to make decisions based on analysis that looks solid but quietly misleads. This matters even more at the edges of your data. Predictions for high-value customers, niche products, or low-volume segments carry more weight and risk. If your model handles those cases with the same accuracy as the middle of the range, you can act with more confidence.

Purpose of Heteroscedasticity

❖ Heteroskedasticity happens when your model's errors don't behave consistently across the data. Instead of an even spread of residuals, the variance increases or decreases depending on the value of your input. It's the opposite of homoscedasticity, and it can quietly distort everything from your confidence intervals to the weight you give to certain variables.

❖ Once you've identified heteroskedasticity in your model, the next step is figuring out how to manage it. While there's no single fix, there are proven techniques that help stabilize variance and improve the reliability of your results.

❖ One of the most common techniques is transforming variables that drive inconsistent variance. Log transformations are beneficial when residuals grow with the size of the input. Compressing larger values can reduce

error spread and bring predictions back in line. If a log doesn't quite fit, square root or Box-Cox transformations offer alternatives.

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