

1. The classical models are useful, if applicable, because they are very well developed and conventionally recognized through their broad range of use. However they may not be a perfect fit for your model and you may end up sacrificing some precision in the use of the equivalence. A model that you create under different parameters may not be as easy to work with as those that are the classical standard, but they have more leeway to be manipulated to most accurately represent your data without approximation.
2. The four key assumptions of the GLM approach are (1) Normality, (2) Constant variance, (3) Independence, and (4) Fixed X. Normality refers to the residuals of the model are normally distributed, it does not refer to the distribution of the data itself. Constant variance means the parameter for data spread is constant, and that variability does not depend on the value of the response variable. Independence states that the observations are all independent of each other, so the value of one data point does not tell us anything about the value of another. Fixed X means that there is, hypothetically, no measurement error in the values of the predictor variable, that the measurements were conducted with perfect accuracy.
3. The normality assumption deals with residuals from the data set, not the response variables themselves. The residuals are the differences between the predicted and observed values, representing the vertical distance between the two. If the data was repeatedly sampled, using the same values for predictor variables, then the residuals for each value of the response variables would themselves be normally distributed. The implication with repeated sampling is that the residuals would triangulate around the predicted value in a normal distribution.