5.1: Logistic Regression

Dr. Bean - Stat 5100

1 Why Logistic Regression?

Recall the linear regression model

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_{p-1} X_{p-1} + \epsilon \qquad (\epsilon \sim N(0, \sigma^2)).$$

What are some properties of the variable Y that are required for $\epsilon \sim N(0, \sigma^2)$.

- Y must be linearly related to $X_1, \ldots X_{p-1}$.
- Y must be a **continuous, quantitative** variable

1.1 Why not regression on categorical data?

Consider fitting a regression model where we use age to try and predict whether or not a person has a disease (a 0-1 variable).

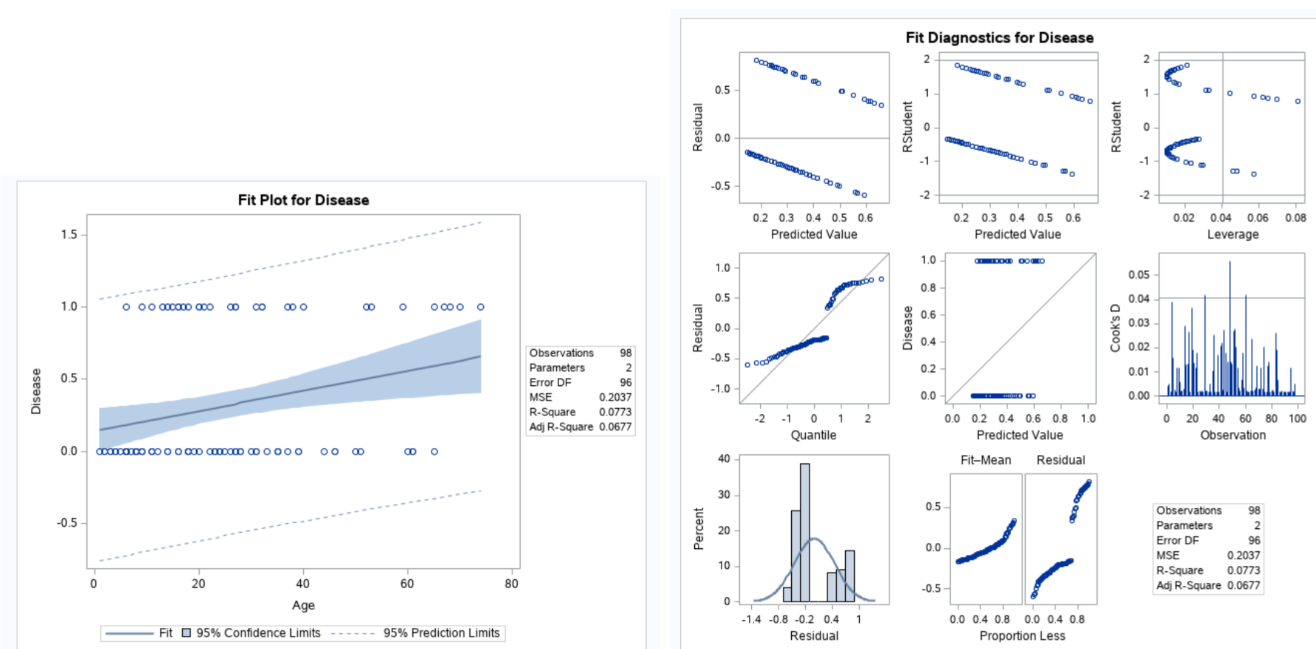

Figure 1: Fit plot and residual diagnostics for regression model that uses age to predict the presence/absence of a disease.

It is for this reason that instead of trying to predict the **value** of a categorical predictor, we should rather try to predict the **probability** of occurrence π_i,

$$\pi_i = \beta_0 + \beta_1 X_{i,1} + \cdots + \beta_{p-1} X_{i,p-1} + \epsilon_i \qquad (\epsilon \sim N(0, \sigma^2)). \tag{1}$$

However, based on the previous example, what are some of the issues with trying to predict the probability using (1)?

- We don't actually know π_i.
- Model can predict negative probabilities or probabilities above 1.
- Residual assumptions never satisfied (impossible for residuals to be normally distributed).

2 Transforming Probabilities

Because regression works best with **unconstrained** variables (i.e. variables that can theoretically take on any value). We need to find a transformation that maps $\pi \in [0,1]$ to $f(\pi) \in (-\infty, \infty)$.

Solution: log-odds ratio.

- $\pi \to [0,1]$
- $\frac{\pi}{1-\pi} \to [0,\infty)$
- $L = \log\left(\frac{\pi}{1-\pi}\right) \to (-\infty,\infty)$

The **probit** function is another common transformation that achieves similar results.

- Probit: $Q_i = Z_{\pi_i} \to$ Z score (of a standard normal distribution) associated with the percentile π_i.

Other "S" shape curves exist, which tend to reach similar conclusions.

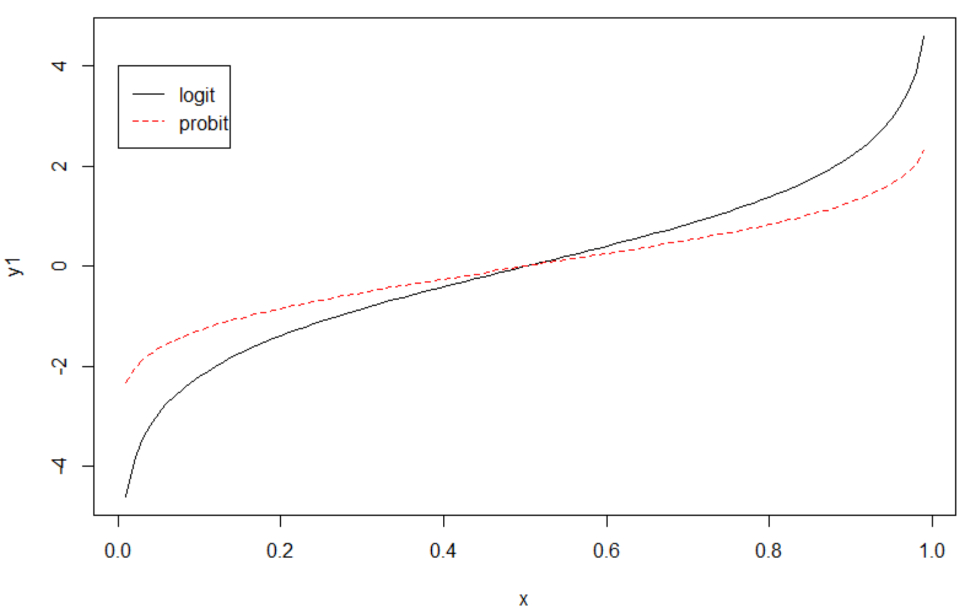

Figure 2: Visualization of logit and probit function for various probabilities.

3 Logistic Regression

$$L_i = \beta_0 + \beta_1 X_{i,1} + \cdots + \beta_{p-1} X_{i,p-1} + \epsilon_i$$

- b_k estimates obtained from MLE-based iterative procedure (Newton-Raphson, Fisher)
- Transform estimates $\hat{L}_i = b_0 + b_1 X_{i,1} + \cdots + b_{p-1} X_{i,p-1}$ back to probability scale.

$$\hat{\pi}_i = \frac{1}{1 + e^{-\hat{L}_i}} \qquad\qquad O\hat{dd}s_i = e^{\hat{L}_i}$$

3.1 Interpretation of Estimates

- $X_{i,1} = \cdots = X_{i,p-1} = 0 \implies \hat{L}_i = b_0 \implies O\hat{dd}s_i = e^{b_0}$
- Hold $X_{i,2} = \cdots = X_{i,p-1} = 0$, increase $X_{i,1}$ from 0 to 1

$$\implies \hat{L}_i = b_0 + b_1 \implies O\hat{dd}s_i = e^{b_0 + b_1} = e^{b_0} e^{b_1}$$

- Thus, an increase in one unit in X_j *multiplies the odds* (in favor of $Y = 1$) by a factor of e^{b_j}.
  - Note that it is the *odds* that are multiplied, **not** the probability.
- Alternative Interpretation: the odds of $Y = 1$ change by $100(e^{b_j} - 1)\%$ per unit increase in X_j while holding other predictors constant.
  - Example (Handout 5.1.1): b_j for sector is 1.57 $\implies e^{1.57} = 4.83$.
  - "Holding all other predictors constant, the odds of having disease are $100(4.83 - 1) = 383\%$ greater in Sector 2 than in Sector 1.
- The "Odds Ratio" for X_j (odds of $Y = 1$ when $X_j + 1$ vs odds of $Y = 1$ when X_j)

$$\frac{e^{b_0 + b_1 X_1 + \cdots + \mathbf{b_j(X_j+1)} + \cdots + b_{p-1} X_{p-1}}}{e^{b_0 + b_1 X_1 + \cdots + \mathbf{b_j(X_j)} + \cdots + b_{p-1} X_{p-1}}} = e^{b_j}$$

3.2 Inference with Estimates

- Single Variable Test:
  - $H_0 : \beta_j = 0$ (X_j has no effect on $P(Y = 1)$).
  - Test statistic: $t = \frac{b_j}{SE\{b_j\}}$ (standard normal for "large" N).
  - $\implies t^2 \sim \chi^2_1$ (obtain confidence intervals from here)
    - * This approach is called the "Wald Test"
- Subset variables test:
  - $H_0 : \beta_{p-H} = \cdots = \beta_{p-1} = 0$
    - * reorder the X variables so that the subset we are checking for comes last
  - Let L_{full} be the likelihood associated with the full model
  - Test statistics: $\chi^2 = -2 \log \frac{L_{red}}{L_{full}}$
  - Under $H_0 : \chi^2 \sim \chi^2_H$

- Overall model test:

$$\text{Model}\chi^2 = -2\log L_{intercept} + 2\log L_{int\&covariates}$$

  - Often called the **deviance**, DEV or $DEV(X_0, X_1, X_{p-1})$

- Conditional Effect plot: predicted $\hat{\pi}$ vs one predictor X_j

  - While holding all other predictors at some constant level. The default level in SAS is the mean (average) of each variable.

4 Goodness of Fit Measures:

- Pseudo R-square: $\frac{\chi^2}{\chi^2+n}$ (χ^2 from model test)
- Hosmer-Lemeshow Goodness of Fit Test
  - H_0 : logistic regression response function is appropriate
  - Based on sorted $\hat{\pi}$ values, group observations into 5-10 roughly equal sized groups.
  - Within each group, look at the total observed numbers of $Y = 1$ and $Y = 0$
  - Based on the model fit, calculate the total *expected* numbers of $Y = 1$ and $Y = 0$.
  - Test statistic χ^2 is sum (across groups) of $\frac{(observed-expected)^2}{expected}$
- "Concordance" - look at all pairs of observations with different Y
  - Let n_c be the # of "concordant" pairs (observed $Y = 1$ has larger $\hat{\pi}$)
  - Let n_d be the # of "discordant" pairs (observed $Y = 1$ has smaller $\hat{\pi}$)
  - Let n_t be the # of "tied" paired (observed $Y = 1$ and $Y = 0$ have same $\hat{\pi}$ (likely due to identical X-profiles)
  - Define rank correlation indices (larger is better):

$$\text{Somers' } D = \frac{n_c - n_d}{n_c + n_d + n_t}$$

$$\gamma = \frac{n_c - n_d}{n_c + n_d}$$

$$\text{Tau-a} = \frac{n_c - n_d}{0.5(n-1)n}$$

$$\text{AUC} = \frac{n_c + 0.5n_t}{n_c + n_d + n_t}$$

- ROC (Receiver Operating Characteristic) Curve
  - Sort all observations from the smallest to biggest $\hat{\pi}$.
  - At each position in the list:
    - Use $\hat{\pi}$ as threshold for $\hat{Y} = 1$, moving cutoff from the standard 0.5 threshold.

* Calculate sensitivity: (proportion $Y_i = 1$ values with $\hat{Y}_i = 1$).
* Calculate specificity: (proportion $Y = 0$ values with $\hat{Y} = 0$).
  - Sensitivity and Specificity - think smoke alarms.
* False positive rate (prop $Y = 0$ values with $\hat{Y} = 1$) = 1 - specificity
* Plot false positives against true positive rates (sensitivity)
* Calculate the area under the curve.

Given the three ROC curves in Figure 3, which model has the best predictive power and why?

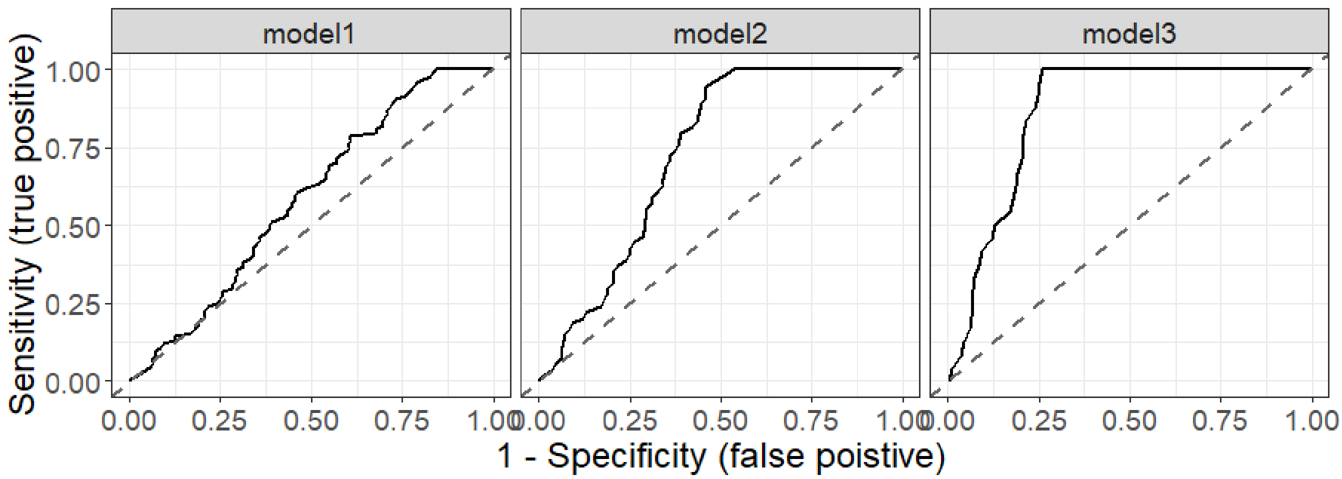

Figure 3: Comparison of three ROC curves.

Model 3 is the most accurate. The model sensitivity increases much faster than the false positive rate.

5 Multicollinearity

Recall that multicollinearity occurs when X variables are highly correlated with each other. It has **nothing** to do with the response variable Y.

As in OLS, multicollinearity inflates the variance of the b_k estimates, making them hard to interpret/test for significance.

As in OLS, stepwise selection and all possible regression methods exist to "score" each combination of explanatory variables and select a best model.

6 Outliers in Logistic Regression

If Y can only take on two values (0 or 1), how are outlier values possible?

An outlier is a point for which the observation strongly disagrees with the predicted probability.

- Define "deviance residual" as

$$dev_i = \text{sign}(Y_i - \hat{\pi}_i)\sqrt{-2\left(Y_i \log \hat{\pi}_i + (1 - Y_i)\log(1 - \hat{\pi}_i)\right)}$$

  - The more certain we are (probability near 0 or 1), the more potential we have to be very wrong.

- $DEV(X_0, \cdots X_{p-1}) = \sum_i dev_i^2$

- "Outliers" are values not well represented by the model

- "Half-normal probability plot - observed $|dev_i|$ vs expected value under normality

  - **However,** since the residuals are not normally distributed, we asses differences from our expectation using simulations based on $\hat{\pi}_i$.
    - * Create 19 simulations by generating a "new" response variable where the values of $Y_{new,i} \sim Bernoulli(\hat{\pi}_i)$
  - Simulated envelop (SEE 5.1.1 MACRO ON CANVAS) plots the minimum, maximum, and mean of the 19 simulations
    - * Why 19 simulations? - Since our observed deviances represent the 20th observation, the probability that our deviances will fall outside the envelope is less than 5% IF the fitted model is appropriate.
    - * Points falling outside in the envelop in the upper right corner of the plot are evidence of outliers/bad fits.

7 Influential Observations

Influential observations have the same effect on model coefficients as they did in OLS.

Diagnostics (similar to Leverage and DFBETAS):

- $\Delta D_i : DEV - DEV_{(i)}$

  - Measures decrease in "misfit" when obs. i is ignored. (essentially measures the "poorness of fit for observation i).
  - "large" $\Delta D_i \implies$ obs. i overly influences model fit
  - SAS: DIFDEV - one step difference in deviance

- ΔB_i

  - Similar to Cook's distance, measures influence of obs. i on the estimates b_j
  - SAS: C - confidence interval displacement C

- $\Delta \chi_i^2$

  - Similar to ΔD_i: "poorness of fit" for obs i
  - SAS: DIFCHISQ - one step difference in Pearson χ^2

Unlike in OLS, there is no consistent numerical rule of thumbs to determine thresholds for the Δ measures.

Instead, we will simply rely on graphical diagnostics.

- $\Delta D_i, \Delta B_i, \Delta X_i^2$ vs Observation Number - look for extreme values
- ΔD_i vs $\hat{\pi}_i$ (or ΔX_i^2 vs $\hat{\pi}_i$)
  - Look for points with low $\hat{\pi}$ but $Y_i = 1$ (upper left corner) OR high $\hat{\pi}$ but $Y = 0$ (upper right corner) which are much different than the overall pattern
  - (Optional) plot different size points where point size is determined by ΔB_i

8 Remedial Measures

Similar to OLS:

- Look for typos in the data
- Consider transformations of the X variables
- Consider dropping problematic points (only if you have a good argument for removing them).

9 Final Thought

If you have a lot of explanatory variables, you should strongly consider classification trees and random forest for classification.