



INTRODUCTION TO GENERALIZED UNIVARIATE MODELS: MODELS FOR BINARY OUTCOMES

EDF 9780: Multivariate Modeling

Expanding your linear models knowledge to models for outcomes that are **not** conditionally normally distributed

- A class of models called Generalized Linear Models

A furthering of our Maximum Likelihood discussion: how knowledge of distributions and likelihood functions makes virtually any type of model possible (in theory)

An example of generalized models for binary data using logistic regression

AN INTRODUCTION TO GENERALIZED MODELS

Statistical models can be broadly organized as:

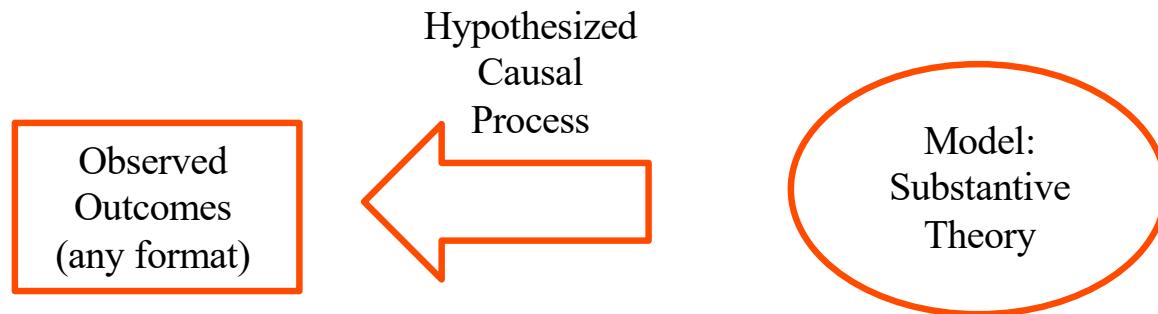
- General (normal outcome) vs. Generalized (not normal outcome)
- One dimension of sampling (one variance term per outcome) vs. multiple dimensions of sampling (multiple variance terms)
 - Fixed effects only vs. mixed (fixed and random effects = multilevel)

All models have **fixed effects**, and then:

- General Linear Models: conditionally normal distribution for data, fixed effects, no random effects
- General Linear **Mixed** Models: conditionally normal distribution for data, fixed **and random effects**
- Generalized Linear Models: **any conditional distribution for data**, fixed effects through **link functions**, no random effects
- Generalized Linear **Mixed** Models: **any conditional distribution for data**, fixed **and random effects** through **link functions**

“**Linear**” means the fixed effects predict the *link-transformed DV* in a linear combination of (effect*predictor) + (effect*predictor)...

Unpacking the Big Picture



Substantive theory: what guides your study

Hypothetical causal process: what the statistical model is testing when estimated

Observed outcomes: what you collect and evaluate based on your theory

- Outcomes can take many forms:
 - Continuous variables (e.g., time, blood pressure, height)
 - Categorical variables (e.g., likert-type responses, ordered categories, nominal categories)
 - Combinations of continuous and categorical (e.g., either 0 or some other continuous number)

The Goal of Generalized Models



Generalized models map the substantive theory onto the **sample space** of the observed outcomes

- **Sample space** = type/range/outcomes that are possible

The general idea is that the statistical model will not approximate the outcome well if the assumed distribution is not a good fit to the sample space of the outcome

- If model does not fit the outcome, the findings cannot be believed

The key to making everything work is the use of differing statistical distributions for the outcome

Generalized models allow for different distributions for outcomes

- The mean of the distribution is still modeled by the model for the means (the fixed effects)
- The variance of the distribution may or may not be modeled (some distributions don't have variance terms)

Generalized Linear Models → General Linear Models whose residuals follow some not-normal distribution and in which a link-transformed Y is predicted instead of Y

Many kinds of non-normally distributed outcomes have some kind of generalized linear model to go with them:

- Binary (dichotomous)
 - Unordered categorical (nominal)
 - Ordered categorical (ordinal)
 - Counts (discrete, positive values)
 - Censored (piled up and cut off at one end – left or right)
 - Zero-inflated (pile of 0's, then some distribution after)
 - Continuous but skewed data (pile on one end, long tail)
- These two are often called
“multinomial” inconsistently

Some Links/Distributions (from Wikipedia)



Common distributions with typical uses and canonical link functions

Distribution	Support of distribution	Typical uses	Link name	Link function	Mean function
Normal	real: $(-\infty, +\infty)$	Linear-response data	Identity	$\mathbf{X}\beta = \mu$	$\mu = \mathbf{X}\beta$
Exponential	real: $(0, +\infty)$	Exponential-response data, scale parameters	Inverse	$\mathbf{X}\beta = \mu^{-1}$	$\mu = (\mathbf{X}\beta)^{-1}$
Gamma			Inverse squared	$\mathbf{X}\beta = \mu^{-2}$	$\mu = (\mathbf{X}\beta)^{-1/2}$
Inverse Gaussian					
Poisson	integer: $[0, +\infty)$	count of occurrences in fixed amount of time/space	Log	$\mathbf{X}\beta = \ln(\mu)$	$\mu = \exp(\mathbf{X}\beta)$
Bernoulli	integer: $[0, 1]$	outcome of single yes/no occurrence			
Binomial	integer: $[0, N]$	count of # of "yes" occurrences out of N yes/no occurrences			
Categorical	integer: $[0, K]$ K-vector of integer: $[0, 1]$, where exactly one element in the vector has the value 1	outcome of single K-way occurrence	Logit	$\mathbf{X}\beta = \ln\left(\frac{\mu}{1-\mu}\right)$	$\mu = \frac{\exp(\mathbf{X}\beta)}{1 + \exp(\mathbf{X}\beta)} = \frac{1}{1 + \exp(-\mathbf{X}\beta)}$
Multinomial	K-vector of integer: $[0, N]$	count of occurrences of different types (1 .. K) out of N total K-way occurrences			

3 Parts of a Generalized Linear Model



Link Function (main difference from GLM):

How a non-normal **outcome gets transformed** into something we can predict that is more continuous (unbounded)

For outcomes that are already normal, general linear models are just a special case with an “identity” link function ($Y * 1$)

Model for the Means (“Structural Model”):

How predictors **linearly** relate to the link-transformed outcome

$$\text{New link-transformed } Y_p = \beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p$$

Model for the Variance (“Sampling/Stochastic Model”):

If the errors aren’t normally distributed, then what are they?

Family of alternative distributions at our disposal that map onto what the distribution of errors could possibly look like

Generalized models work by providing a mapping of the theoretical portion of the model (the right hand side of the equation) to the sample space of the outcome (the left hand side of the equation)

The mapping is done by a feature called a link function

The link function is a non-linear function that takes the linear model predictors, random/latent terms, and constants and puts them onto the space of the outcome observed variables

Link functions are typically expressed for the mean of the outcome variable (we will only focus on that)

In generalized models, the variance is often a function of the mean

The link function expresses the conditional value of the mean of the outcome $E(Y_p) = \hat{Y}_p = \mu_y$ (E stands for expectation)...

...through a (typically) non-linear **link function** $g(\cdot)$ (when used on conditional mean); or its inverse $g^{-1}(\cdot)$ when used on predictors...

...of the observed predictors (and their regression weights):

$$\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p$$

Meaning:

$$E(Y_p) = \hat{Y}_p = \mu_y = g^{-1}(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p)$$

The term $\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p$ is called the **linear predictor**

- Within the function, the values are linear combinations
- Model for the means (fixed effects)

Our familiar general linear model is a member of the generalized model family (it is **subsumed**)

- The link function is called the identity, the linear predictor is unchanged

The normal distribution has two parameters, a mean μ and a variance σ^2

- Unlike most distributions, the normal distribution parameters are directly modeled by the GLM using the “identity link function”

The expected value of an outcome from the GLM was

$$E(Y_p) = \hat{Y}_p = \mu_y = g^{-1}(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p) = \beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p$$

In conditionally normal GLMs, the inverse link function is called the identity:

$$g^{-1}(\cdot) = 1 * (\text{linear predictor})$$

- The identity does not alter the predicted values – they can be any real number
- This matches the sample space of the normal distribution – the mean can be any real number

And...About the Variance



The other parameter of the normal distribution described the variance of an outcome – called the error variance

We found that the model for the variance for the GLM was:

$$V(Y_p) = V(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p + e_p) = V(e_p) = \sigma_e^2$$

This term directly relates to the variance of the outcome in the normal distribution

- We will quickly see distributions where this doesn't happen

GENERALIZED LINEAR MODELS FOR BINARY DATA

Today's Data Example



To help demonstrate generalized models for binary data, we borrow from an example listed on the UCLA ATS website:

<https://stats.idre.ucla.edu/stata/dae/ordered-logistic-regression/>

Data come from a survey of 400 college juniors looking at factors that influence the decision to apply to graduate school:

- Y (outcome): student rating of likelihood he/she will apply to grad school – (0 = unlikely; 1 = somewhat likely; 2 = very likely)
 - We will first look at Y for two categories (0 = unlikely; 1 = somewhat or very likely) - this is to introduce the topic for you **Y is a binary outcome**
 - You wouldn't do this in practice (use a different distribution for 3 categories)
- ParentEd: indicator (0/1) if one or more parent has graduate degree
- Public: indicator (0/1) if student attends a public university
- GPA: grade point average on 4 point scale (4.0 = perfect)

Descriptive Statistics for Data



Analysis Variable : GPA				
N	Mean	Std Dev	Minimum	Maximum
400	2.998925	0.3979409	1.9	4

Likelihood of Applying (1 = likely)				
Lapply	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	220	55	220	55
1	180	45	400	100

APPLY	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	220	55	220	55
1	140	35	360	90
2	40	10	400	100

Parent Has Graduate Degree				
parentGD	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	337	84.25	337	84.25
1	63	15.75	400	100

Student Attends Public University				
PUBLIC	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	343	85.75	343	85.75
1	57	14.25	400	100

If Y_p is a binary (0 or 1) outcome...

- Expected mean is proportion of people who have a 1 (or “p”, the probability of $Y_p = 1$ in the sample)
- The **probability of having a 1** is what we’re trying to predict for each person, given the values of his/her predictors
- General linear model: $\mathbf{Y}_p = \beta_0 + \beta_1 \mathbf{x}_p + \beta_2 \mathbf{z}_p + e_p$
 - β_0 = expected probability when all predictors are 0
 - β s = expected change in probability for a one-unit change in the predictor
 - e_p = difference between observed and predicted values
- Model becomes $Y_p = (\text{predicted probability of 1}) + e_p$

But if Y_p is binary, then e_p can only be 2 things:

$$e_p = Y_p - \hat{Y}_p$$

If $Y_p = 0$ then $e_p = (0 - \text{predicted probability})$

If $Y_p = 1$ then $e_p = (1 - \text{predicted probability})$

The mean of errors would still be 0...by definition

But variance of errors can't possibly be constant over levels of X like we assume in general linear models

- The mean and variance of a binary outcome are **dependent!**
- As shown shortly, mean = p and variance = $p*(1-p)$, so they are tied together
- This means that because the conditional mean of Y (p, the predicted probability) $= 1$) is dependent on X, *then so is the error variance*

A General Linear Model With Binary Outcomes?

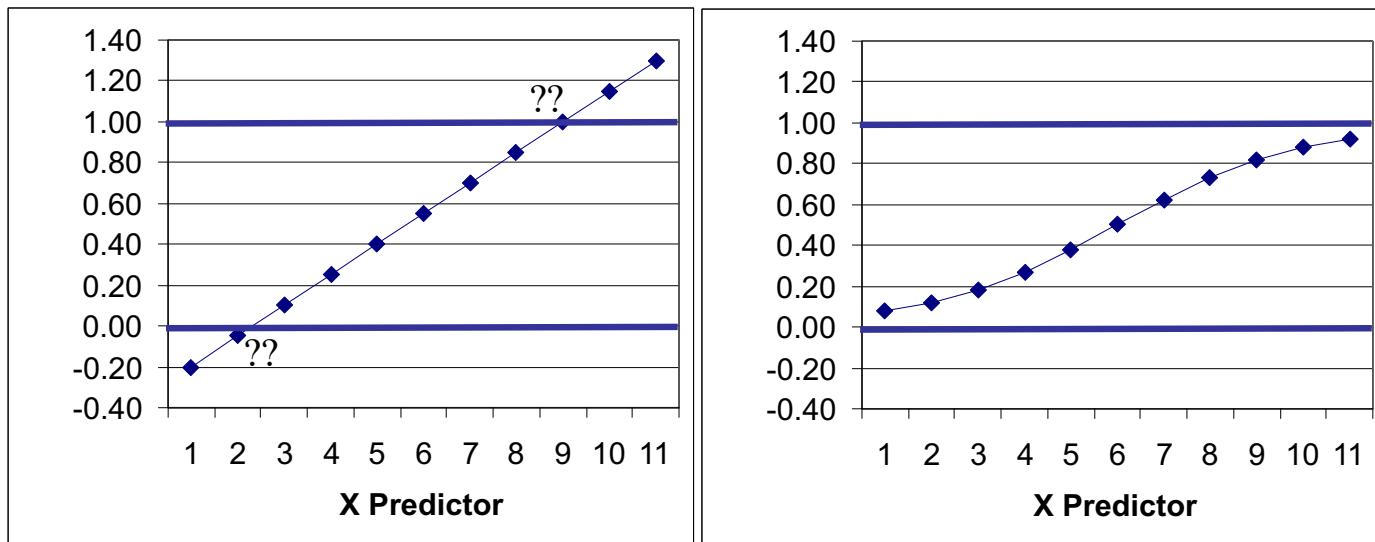


How can we have a linear relationship between X & Y?

Probability of a 1 is bounded between 0 and 1, but predicted probabilities from a linear model aren't bounded

- Impossible values

Linear relationship needs to 'shut off' somehow → made nonlinear



*General = model for continuous, conditionally normal outcome

Restricted range (e.g., 0 to 1 for binary item)

- Predictors should not be linearly related to observed outcome
→ Effects of predictors need to be 'shut off' at some point to keep predicted values of binary outcome within range

Variance is dependent on the mean, and not estimated

- Fixed (→predicted value) and random (error) parts are related
→ So residuals can't have constant variance

Further, residuals have a limited number of possible values

- Predicted values can each only be off in two ways
→ So residuals can't be normally distributed

The Binary Case: Bernoulli Distribution



For items that are binary (dichotomous/two options), a frequent distribution chosen is the Bernoulli distribution (the Bernoulli distribution is also called a one-trial binomial distribution):

Notation: $Y_p \sim B(p_p)$ (where p is the conditional probability of a 1 for person p)

Sample Space: $Y_p \in \{0,1\}$ (Y_p can either be a 0 or a 1)

Probability Density Function (PDF):

$$f(Y_p) = (p_p)^{Y_p} (1 - p_p)^{1 - Y_p}$$

Expected value (mean) of Y: $E(Y_p) = \mu_{Y_p} = p_p$

Variance of Y: $V(Y_p) = \sigma_{Y_p}^2 = p_p(1 - p_p)$

Note: p_p is the only parameter – so we only need to provide a link function for it...

Rather than modeling the probability of a 1 directly, we need to transform it into a more continuous variable with a **link function**, for example:

We could transform **probability** into an **odds ratio**:

- Odds ratio: $(p / 1-p) \rightarrow \text{prob}(1) / \text{prob}(0)$
- If $p = .7$, then $\text{Odds}(1) = 2.33$; $\text{Odds}(0) = .429$
- Odds scale is way skewed, asymmetric, and ranges from 0 to $+\infty$
 - Nope, that's not helpful

Take natural log of odds ratio → called “logit” link

- $\ln(p / 1-p) \rightarrow \text{Natural log of } (\text{prob}(1) / \text{prob}(0))$
- If $p = .7$, then $\ln(\text{Odds}(1)) = .846$; $\ln(\text{Odds}(0)) = -.846$
- Logit scale is now symmetric about 0 → DING

The logit link is one of many used for the Bernoulli distribution

- Names of others: Probit, Log-Log, Complementary Log-Log

Turning Probability into Logits



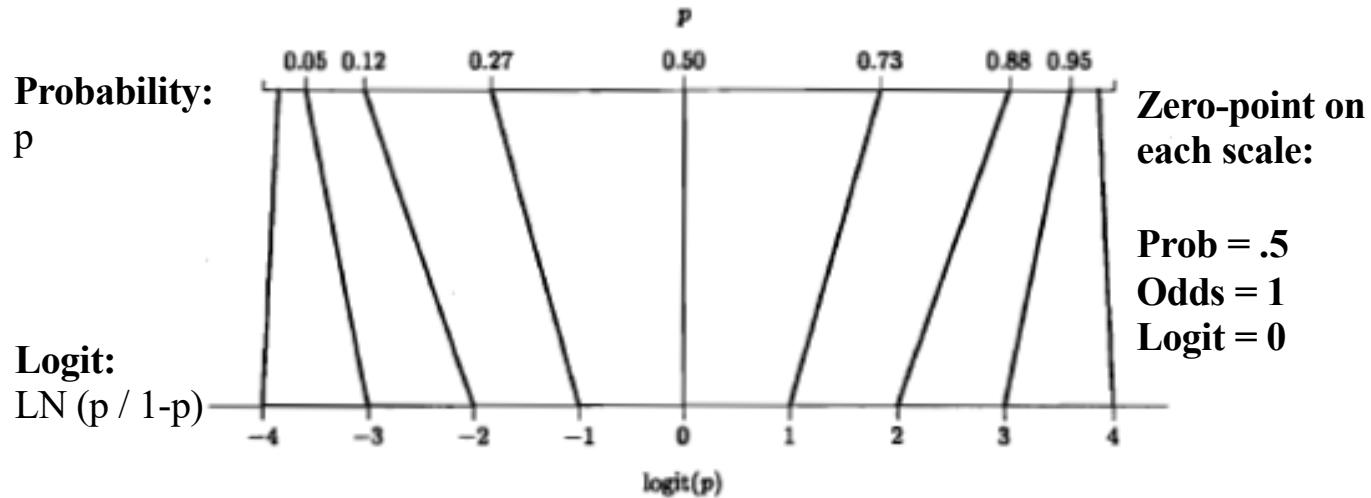
Logit is a nonlinear transformation of probability:

Equal intervals in logits are NOT equal in probability

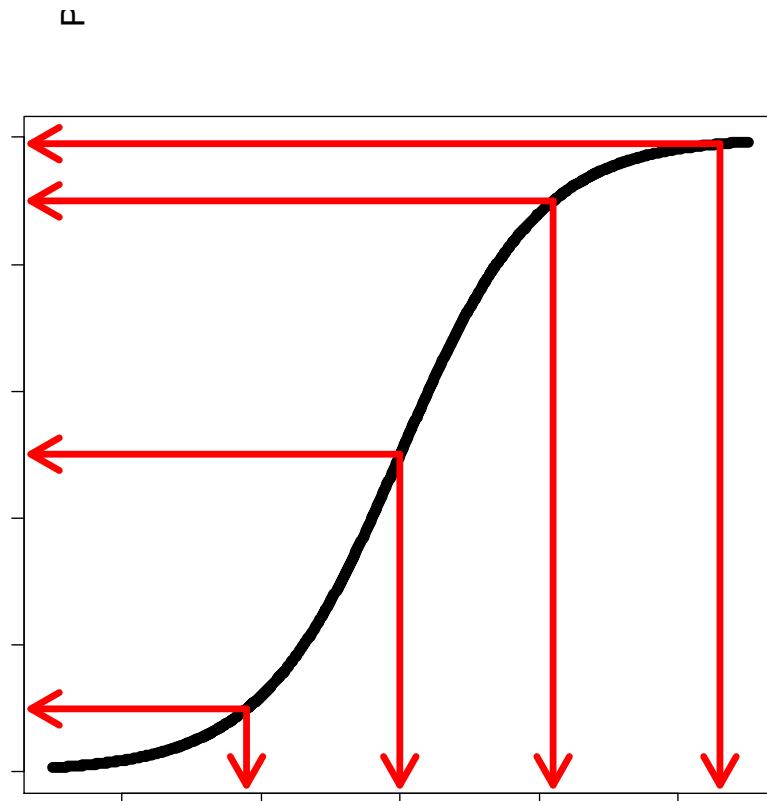
The logit goes from $\pm\infty$ and is symmetric about prob = .5 (logit = 0)

This solves the problem of using a linear model

The model will be **linear with respect to the logit**, which translates into nonlinear with respect to probability (i.e., it **shuts off as needed**)



Transforming Probabilities to Logits



Probability	Logit
0.99	4.6
0.90	2.2
0.50	0.0
0.10	-2.2

Can you guess what a probability of .01 would be on the logit scale?

In the terminology of generalized models, the link function for a logit is defined by
(log = natural logarithm):

$$g(E(Y_p)) = \log\left(\frac{P(Y_p = 1)}{(1 - P(Y_p = 1))}\right) = \underbrace{\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p}_{\text{Linear Predictor}}$$

A logit can be translated to a probability with some algebra:

$$\begin{aligned} \exp\left[\log\left(\frac{P(Y_p = 1)}{(1 - P(Y_p = 1))}\right)\right] &= \exp[\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p] \\ \Leftrightarrow (1 - P(Y_p = 1)) \left[\frac{P(Y_p = 1)}{(1 - P(Y_p = 1))} \right] &= (\exp[\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p]) (1 - P(Y_p = 1)) \end{aligned}$$

Continuing:

$$\begin{aligned} P(Y_p = 1) &= (\exp[\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p]) - ((\exp[\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p])P(Y_p = 1)) \\ P(Y_p = 1)(1 - \exp[\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p]) &= \exp[\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p] \end{aligned}$$

Which finally gives us:

$$P(Y_p = 1) = \frac{\exp(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p)}{1 + \exp(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p)}$$

Linear Predictor

Therefore, the inverse logit (un-logit...or $g^{-1}(\cdot)$) is:

$$E(Y_p) = g^{-1}(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p) = \frac{\exp(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p)}{1 + \exp(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p)}$$

Written Another Way...



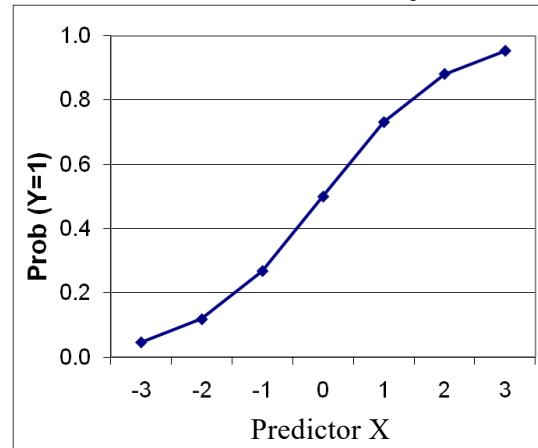
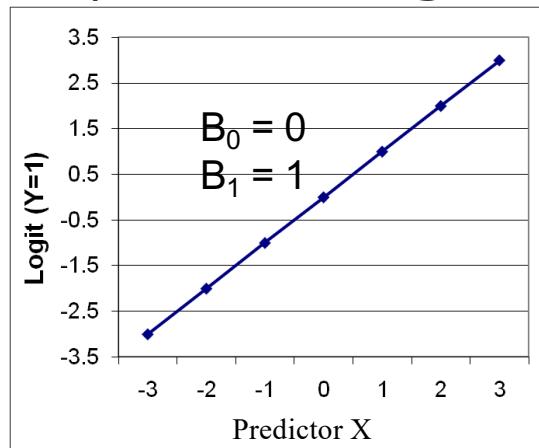
The inverse logit $g^{-1}(\cdot)$ has another form that is sometimes used:

$$\begin{aligned} E(Y_p) &= g^{-1}(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p) \\ &= \frac{\exp(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p)}{1 + \exp(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p)} \\ &= \frac{1}{1 + \exp(-(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p))} \\ &= \left(1 + \exp(-(\beta_0 + \beta_1 X_p + \beta_2 Z_p + \beta_3 X_p Z_p))\right)^{-1} \end{aligned}$$

Nonlinearity in Prediction

The relationship between X and the probability of response=1 is “**nonlinear**” → **an s-shaped logistic curve** whose shape and location are dictated by the estimated fixed effects

Linear with respect to the **logit**, **nonlinear** with respect to **probability**



The logit version of the model will be easier to explain; the probability version of the prediction will be easier to show

Putting it Together with Data: The Empty Model



The empty model (under GLM):

$$Y_p = \beta_0 + e_p$$

where $e_p \sim N(0, \sigma_e^2)$ $E(Y_p) = \beta_0$ and $V(Y_p) = \sigma_e^2$

Linear Predictor

The empty model for a Bernoulli distribution with a logit link:

$$g(E(Y_p)) = \text{logit}(P(Y_p = 1)) = \text{logit}(p_p) = \beta_0$$

$$p_p = P(Y_p = 1) = E(Y_p) = g^{-1}(\beta_0) = \frac{\exp(\beta_0)}{1 + \exp(\beta_0)}$$

$$V(Y_p) = p_p(1 - p_p)$$

Note: many generalized LMs don't list an error term in the linear predictor – is for the expected value and error usually has a 0 mean so it disappears

We could have listed e_p for the logit function

- e_p would have a logistic distribution with a zero mean and variance $\frac{\pi^2}{3} = 3.29$
- Variance is fixed – cannot modify variance of Bernoulli distribution after modeling the mean

LOGISTIC REGRESSION IN R

The ordinal package is useful for modeling categorical dependent variables

We will use the `clm()` function

- `clm` stands for cumulative linear models

Unpacking clm() Function Syntax



Example syntax below for empty model differs only slightly from lm() syntax we have already seen

```
# response variable must be a factor:  
data01$Lapply = factor(data01$Lapply)  
  
# EMPTY MODEL PREDICTING DICHOTOMOUS (0/1): Likely To Apply; Modeling Prob of 1  
model01 = clm(formula = Lapply ~ 1, data = data01, control = clm.control(trace = 1))  
summary(model01)
```

The dependent variable must be stored as a factor

The formula and data arguments are identical to lm()

The control argument is only used here to show iteration history of the ML algorithm

Empty Model Output



The empty model is estimating one parameter: β_0

However, for this package, the logistic regression is formed using a threshold (τ_0) rather than intercept rather

Here $\beta_0 = -\tau_0$

```
> summary(model01)
formula: Lapply ~ 1
data:   data01

link threshold nobs logLik  AIC    niter max.grad cond.H
logit flexible  400  -275.26 552.51 3(0)  3.31e-14 1.0e+00

Threshold coefficients:
            Estimate Std. Error z value
0|1     0.2007    0.1005  1.997
|
```

$\tau_0 = 0.2007$, so...

$\beta_0 = -0.2007$ (0.1005): interpreted as the predicted logit of $y_p = 1$ for an individual when all predictors are zero

- Because of the empty model, this becomes average logit for sample
- Note: $\exp(-.2007)/(1+\exp(-.2007)) = .55$ – the sample mean proportion

The log-likelihood is -256.26

- Used for nested model comparisons

The AIC is 552.51

- Used for non-nested model comparisons

Predicting Logits, Odds, & Probabilities:

Coefficients for each form of the model:

Logit: $\text{Log}(p_p/1-p_p) = \beta_0$

- Predictor effects are **linear and additive** like in regression, but what does a 'change in the logit' mean anyway?
- Here, we are saying the average logit is -.2007

Odds: $(p_p/1-p_p) = \exp(\beta_0)$

- A compromise: effects of predictors are **multiplicative**
- Here, we are saying the average odds of applying to grad school is $\exp(-.2007) = .819$

Prob: $P(y_p=1) = \exp(\beta_0)/(1 + \exp(\beta_0))$

- Effects of predictors on probability are **nonlinear and non-additive** (no "one-unit change" language allowed)
- Here, we are saying the average probability of applying to grad school is .550

MAXIMUM LIKELIHOOD ESTIMATION OF GENERALIZED MODELS

The process of ML estimation in Generalized Models is similar to that from the GLM, with two exceptions:

- The error variance is not estimated
- The fixed effects do not have closed form equations (so are now part of the log likelihood function search)

We will describe this process for the previous analysis, using our grid search

Here, each observation has a Bernoulli distribution where the “height” of the curve is given by the PDF:

$$f(Y_p) = (p_p)^{Y_p} (1 - p_p)^{1-Y_p}$$

The generalized linear model then models

$$E(Y_p) = p_p = \frac{\exp(\beta_0)}{1 + \exp(\beta_0)}$$

The likelihood function shown previously was for one observation, but we will be working with a sample

Assuming the sample observations are independent and identically distributed, we can form the joint distribution of the sample

Multiplication comes from independence assumption:
Here, $L(\beta_0|Y_p)$ is the Bernoulli PDF for Y_p using a logit link for β_0

$$\begin{aligned}
 L(\beta_0|Y_1, \dots, Y_N) &= L(\beta_0|Y_1) \times L(\beta_0|Y_2) \times \cdots \times L(\beta_0|Y_N) \\
 &= \prod_{p=1}^N f(Y_p) = \prod_{p=1}^N p_p^{Y_p} (1 - p_p)^{1-Y_p} \\
 &= \prod_{p=1}^N \left(\frac{\exp(\beta_0)}{1 + \exp(\beta_0)} \right)^{Y_p} \left(1 - \left(\frac{\exp(\beta_0)}{1 + \exp(\beta_0)} \right) \right)^{1-Y_p}
 \end{aligned}$$

The Log Likelihood Function



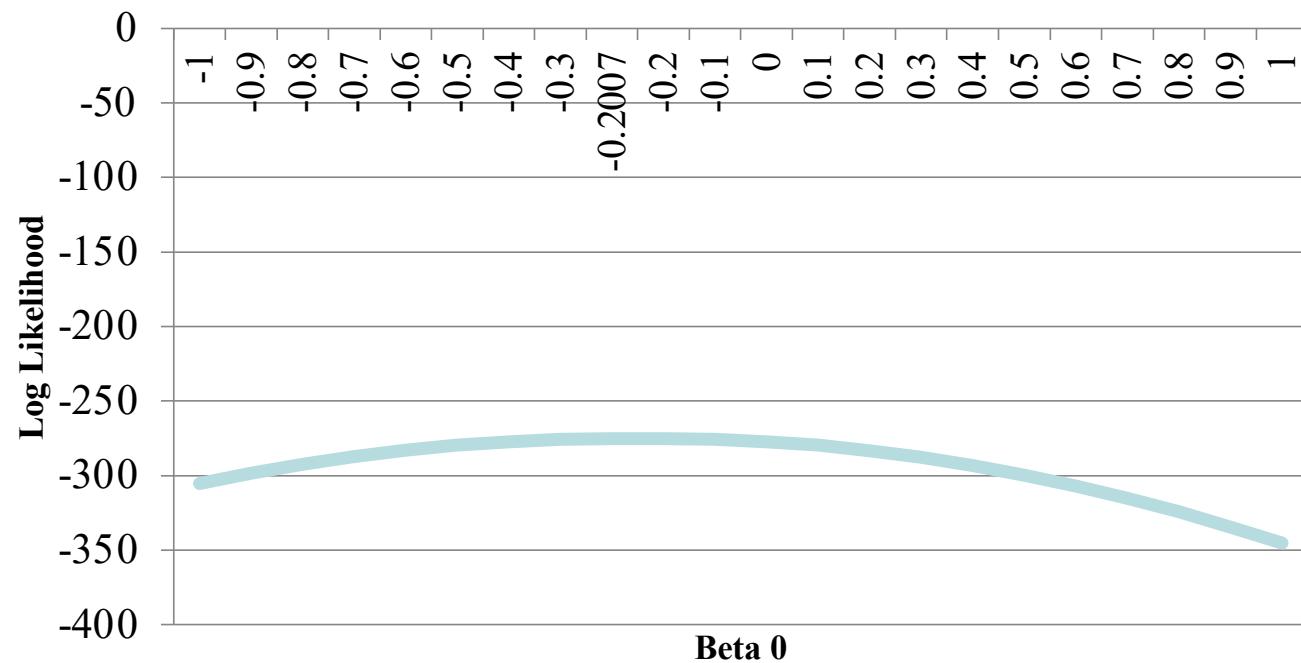
The log likelihood function is found by taking the natural log of the likelihood function:

$$\begin{aligned}\log L(\beta_0 | Y_1, \dots, Y_N) &= \log(L(\beta_0 | Y_1) \times L(\beta_0 | Y_2) \times \dots \times L(\beta_0 | Y_N)) \\&= \sum_{p=1}^N \log(L(\beta_0 | Y_p)) = \sum_{p=1}^N \log[p_p^{Y_p} (1 - p_p)^{1 - Y_p}] \\&= \sum_{p=1}^N Y_p \log(p_p) + (1 - Y_p) \log(1 - p_p) \\&= \sum_{p=1}^N Y_p \log\left(\frac{\exp(\beta_0)}{1 + \exp(\beta_0)}\right) + (1 - Y_p) \log\left(1 - \frac{\exp(\beta_0)}{1 + \exp(\beta_0)}\right)\end{aligned}$$

Grid Search of the Log Likelihood Function



Just like we did for the normal distribution, we can plot the log likelihood function for all possible values of β_0



Iteration History from clm()



We can show the history of iterations, where the “value” column is -1 times the log-likelihood

```
> model01 = clm(formula = Lapply ~ 1, data = data01, control = clm.control(trace = 1))
iter: step factor:    Value:    maxlgradl:    Parameters:
  0: 1.000000e+00: 277.259: 2.000e+01:  0
nll reduction: 2.00332e+00
  1: 1.000000e+00: 275.256: 6.640e-02:  0.2
nll reduction: 2.22672e-05
  2: 1.000000e+00: 275.256: 2.222e-06: 0.2007
nll reduction: -5.68434e-14
  3: 1.000000e+00: 275.256: 3.308e-14: 0.2007
```

At the maximum ($\beta_0 = -0.2007$) we now assume that the parameter β_0 has a normal distribution

- Only the **data** Y have a Bernoulli distribution

Putting this into statistical context:

$$\beta_0 \sim N\left(\hat{\beta}_0, se(\hat{\beta}_0)^2\right)$$

This says that the true parameter β_0 has a mean at our estimate and has a variance equal to the square of the standard error of our estimate

ADDING PREDICTORS TO THE EMPTY MODEL

Adding Predictors to the Empty Model



Having examined how the logistic link function works and how estimation works, we can now add predictor variables to our model:

$$\begin{aligned} g(E(Y_p)) &= \text{logit}(P(Y_p = 0)) = \text{logit}(p_p) \\ &= \beta_0 + \beta_1 \text{PARED}_p + \beta_2(\text{GPA}_p - 3) + \beta_3 \text{PUBLIC}_p \end{aligned}$$

$$\begin{aligned} p_p &= E(Y_p) = g^{-1}(\beta_0 + \beta_1 \text{PARED}_p + \beta_2(\text{GPA}_p - 3) + \beta_3 \text{PUBLIC}_p) \\ &= \frac{\exp(\beta_0 + \beta_1 \text{PARED}_p + \beta_2(\text{GPA}_p - 3) + \beta_3 \text{PUBLIC}_p)}{1 + \exp(\beta_0 + \beta_1 \text{PARED}_p + \beta_2(\text{GPA}_p - 3) + \beta_3 \text{PUBLIC}_p)} \end{aligned}$$

$$V(Y_p) = p_p(1 - p_p)$$

- Here PARED is Parent Education, PUBLIC is Public University, and GPA is Grade Point Average (centered at a value of 3)
- For now, we will omit any interactions (to simplify interpretation)
- We will also use the default parameterization (modeling Y = 0)

First...the syntax

```
# MODEL 02: ADDING PREDICTORS TO THE EMPTY MODEL
model02 = clm(formula = Lapply ~ 1 + PARED + PUBLIC + GPA3,
               data = data01, control = clm.control(trace = 1))
```

The algorithm iteration history:

```
> # MODEL 02: ADDING PREDICTORS TO THE EMPTY MODEL
> model02 = clm(formula = Lapply ~ 1 + PARED + PUBLIC + GPA3,
+                 data = data01, control = clm.control(trace = 1))
iter: step factor:    Value:    max|grad|:    Parameters:
  0: 1.000000e+00: 277.259: 2.000e+01:  0 0 0 0
nll reduction: 1.22751e+01
  1: 1.000000e+00: 264.984: 5.723e-01:  0.3322 1.014 -0.1885 0.5169
nll reduction: 2.13685e-02
  2: 1.000000e+00: 264.962: 4.991e-03:  0.3382 1.059 -0.2005 0.5481
nll reduction: 1.17396e-06
  3: 1.000000e+00: 264.962: 3.705e-07:  0.3382 1.06 -0.2006 0.5482
```

Question #1: does this model fit better than the empty model?

$$H_0: \beta_1 = \beta_2 = \beta_3 = 0$$

H_1 : At least one not equal to zero

```
anova(model01, model02)
```

Likelihood Ratio Test Statistic = Deviance =
 $-2*(-275.26 - -264.96) = 20.586$

- -275.26 is log likelihood from empty model
- -264.96 is log likelihood from conditional model

DF = 4 – 1 = 3

Parameters from empty model = 1

Parameters from this model = 4

P-value: $p = .0001283$

- Conclusion: reject H_0 ; this model is preferred to empty model

```
> anova(model01, model02)
Likelihood ratio tests of cumulative link models:

formula:                                link: threshold:
model01 Lapply ~ 1                      logit flexible
model02 Lapply ~ 1 + PARED + PUBLIC + GPA3 logit flexible

no.par   AIC  logLik LR.stat df Pr(>Chisq)
model01     1 552.51 -275.26
model02     4 537.92 -264.96 20.586  3  0.0001283 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Parameter Estimates:

```
> summary(model02)
formula: Lapply ~ 1 + PARED + PUBLIC + GPA3
data:    data01

link threshold nobs logLik AIC   niter max.grad cond.H
logit flexible  400 -264.96 537.92 3(0) 3.71e-07 1.0e+01

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
PARED      1.0596    0.2974  3.563 0.000367 ***
PUBLIC     -0.2006    0.3053 -0.657 0.511283  
GPA3       0.5482    0.2724  2.012 0.044178 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Threshold coefficients:
            Estimate Std. Error z value
0|1      0.3382    0.1187  2.849
```

Intercept $\beta_0 = -0.3382$ (0.1187): this is the predicted value for the **logit of $y_p = 1$** for a person with: 3.0 GPA, parents without a graduate degree, and at a private university

- Converted to a probability: .417 – probability a student with 3.0 GPA, parents without a graduate degree, and at a private university is likely to apply to grad school ($y_p = 1$)

parentGD: $\beta_1 = 1.0596$ (0.2974); $p = .0004$

The change in the **logit of $y_p = 1$** for every one-unit change in parentGD...or, the difference in the **logit of $y_p = 1$** for students who have parents with a graduate degree

Because logit of $y_p = 1$ means a rating of “likely to apply” this means that students who have a parent with a graduate degree are more likely to rate the item with a “likely to apply”

The quantification of **how much** less likely a student is to respond with “unlikely to apply” can be done using odds ratios or probabilities:

Odds Ratios:

- Odds of “likely to apply” ($Y=1$) for student **with** parental graduate degree:
 $\exp(\beta_0 + \beta_1) = 2.05$
- Odds of “likely to apply” ($Y=1$) for student **without** parental graduate degree:
 $\exp(\beta_0) = .713$
- Ratio of odds = $2.88525 = \exp(\beta_1)$ - meaning, a student **with** parental graduate degree has almost 3x the odds of rating “likely to apply”

Probabilities:

- Probability of “likely to apply” for student **with** parental graduate degree:
$$\frac{\exp(\beta_0 + \beta_1)}{1+\exp(\beta_0 + \beta_1)} = .673$$
- Probability of “likely to apply” for student **without** parental graduate degree:
$$\frac{\exp(\beta_0)}{1+\exp(\beta_0)} = .416$$

PUBLIC: $\beta_2 = -0.2006$ (0.3053); $p = .5113$:

The change in the **logit of $y_p = 1$** for every one-unit change in GPA...

But, PUBLIC is a coded variable where 0 represents a student in a private university, so this is the difference in logits of the **logit of $y_p = 1$** for students in public vs private universities

Because logit of 1 means a rating of “likely to apply” this means that students who are at a public university are more unlikely to rate “likely to apply”

The quantification of **how much** more likely a student is to respond with “likely to apply” can be done using odds ratios or probabilities:

Public	Logit	Odds of 1	Prob = 1
1	-0.539	0.583	0.368
0	-0.338	0.713	0.416

The odds are found by: $\exp(\beta_0 + \beta_3 PUB_p)$

The probability is found by: $\frac{\exp(\beta_0 + \beta_3 PUB_p)}{1 + \exp(\beta_0 + \beta_3 PUB_p)}$

GPA3: $\beta_2 = 0.5482$ (0.2724); $p = .0442$:

The change in the **logit of $y_p = 1$** for one-unit change in GPA

Because logit of $y_p = 1$ means a rating of “likely to apply” this means that students who have a higher GPA are more likely to rate “likely to apply”

The quantification of **how much** more likely a student is to respond with “likely to apply” can be done using odds ratios or probabilities:

GPA3	Logit	Odds of 1	Prob = 1
1	0.210	1.234	0.552
0	-0.338	0.713	0.416
-1	-0.886	0.412	0.292
-2	-1.435	0.238	0.192

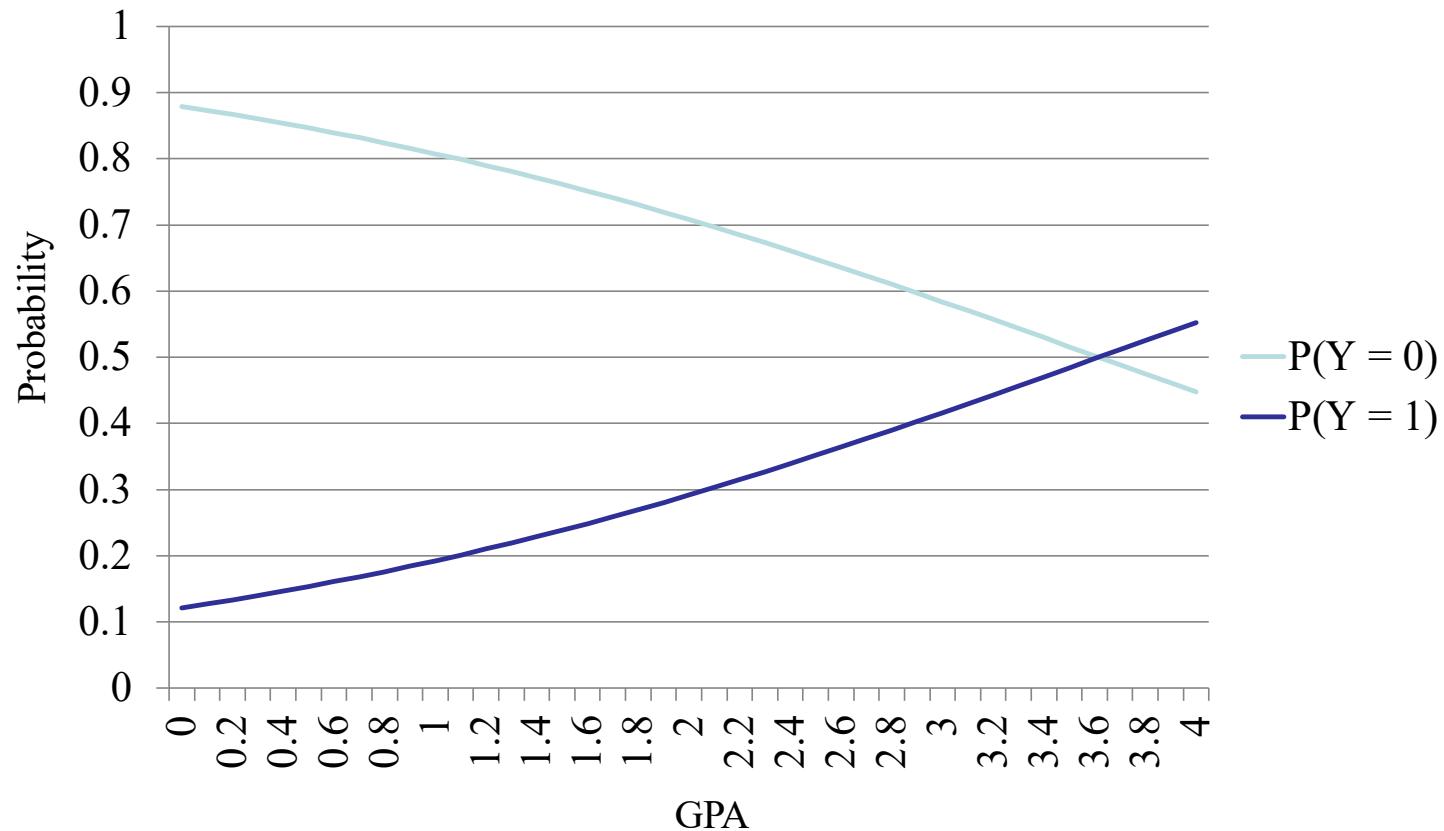
The odds are found by: $\exp(\beta_0 + \beta_2(GPA_p - 3))$

The probability is found by: $\frac{\exp(\beta_0 + \beta_2(GPA_p - 3))}{1 + \exp(\beta_0 + \beta_2(GPA_p - 3))}$

Plotting GPA



Because GPA is an **unconditional** main effect, we can plot values of it versus probabilities of rating “likely to apply”



In general, the linear model interpretation that you have worked on to this point still applies for generalized models, with some nuances

For logistic models with two responses:

- Regression weights are now for LOGITS
- The direction of what is being modeled has to be understood ($Y = 0$ or $= 1$)
- The change in odds and probability is not linear per unit change in the IV, but instead is linear with respect to the logit
 - Hence the term “linear predictor”
- Interactions will still:
 - Modify the conditional main effects
 - Simple main effects are effects when interacting variables = 0

WRAPPING UP

Generalized linear models are models for outcomes with distributions that are not necessarily normal

The estimation process is largely the same: maximum likelihood (or methodsis still the gold standard as it provides estimates with understandable properties

Learning about each type of distribution and link takes time:

- They all are unique and all have slightly different ways of mapping outcome data onto your model

Logistic regression is one of the more frequently used generalized models – binary outcomes are common