# A NON-SYMMETRIC LOGIT MODEL AND GROUPED PREDICTAND CATEGORY DEVELOPMENT

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# LOGISTIC REGRESSION

Fits a binary predictand to one or more predictors



Produces a symmetric curve

# Questions

• Why should the curve be symmetric

A non-symmetric curve may fit the data better

# • What about multiple predictand categories?

- A quasi-continuous variable can be categorized into several binary variables
- Each binary can be fit with logistic regression
- However, the curves may overlap, and the estimates will be inconsistent, e.g.,

P (1 inch snow) > P (2 inches snow)



# **Example and Data**

Example

Relate probability of precip in categories to cube root of model qpf

Data used

GFS output, 24-h projection, 12-h accumulated qpf in mm

Observations of 12-h precip in inches 24 hours after model run time

24 Stations in Pacific Northwest

Two cool seasons, October-March

2011-12 (development); 2012-13 (independent)

Categories  $\geq$  .01,  $\geq$  0.1,  $\geq$  0.25,  $\geq$  0.5,  $\geq$  0.75,  $\geq$  1.0



## Non-Symmetric Logistic Regression

f(q) = a + bq

Include another predictor q'

$$q' = q - q^*$$
 when  $q > q^*$ 

q' = 0 otherwise

Parallels piecewise linear in linear regression (changes slope at q\*)

$$f(q) = a_{ns} + b_{ns}q + c_{ns}q'$$



#### Summary—Non symmetric Development

- Demonstrated <u>concept</u> but was of limited practical use on this data set.
- Total sample size is not the only consideration, but sample on both sides of q\*
- Potential for non-symmetric in situations where relationship is non-monotonic

Grouped Category Development—Method 1 Separation Constant Option

Independently-derived curves for different thresholds may give inconsistent results.

Possible Inconsistencies can be avoided by grouping the data for all categories and including a 2<sup>nd</sup> predictor which denotes group membership, as Wilks has suggested (*Meteorological Applications*, **16**, 2009).

$$f(q) = a_1 + b_1 q + c_1 g$$

g for each category can be given the value where the individual curves cross 50% in the units of the predictor, cube root mm

# Grouped Category Development—Method 2 Binary Predictor Option

Possible Inconsistencies can be avoided by grouping the data for all categories and including binary predictors which denote group membership

$$f(q) = a_2 + b_2 q + \sum c_i B_i$$



# Grouped Category Development—Method 1

 $f(q) = a_1 + b_1 q + c_1 g$ 

The choice of g is critical.

Suppose g was given the value of the individual category limits in inches of precipitation (e.g., 0.01, 0.25).

#### LOGIT FITS OF QPF CATEGORIES TO CUBE ROOT OF MODEL QPF 50% AND CATEGORICAL AMOUNTS IN INCHES SEPARATION VALUES



### Summary

## Grouped Category Development—Method 1

Probabilities are consistent (lines do not cross).

Defining a value for group membership is important when > 2 groups

When only 2 groups, values do not matter

- Definition of group membership requires knowledge of predictor predictand relationship. A good definition for one predictor may not be good for another predictor, either individually or in combination with the first.
- If a functional form for group membership is known, then the probability of <u>any</u> group definition can be calculated from the single equation.
- For a single predictor, only three constants are fit.

### Summary

## Grouped Category Development—Method 2

Probabilities are consistent (lines do not cross).

- Defining a value for group membership is by definition = 1
  - When only 2 groups, grouping not necessary—one equation is sufficient
- Definition of group membership does <u>not</u> require knowledge of predictor predictand relationship; extension to multiple predictors is not a problem
  - There is no functional form for group membership, and the probability of <u>any</u> group definition <u>cannot</u> be calculated.
- For a single predictor, the number of constants fit = the number of categories plus 1