

# Rare Binary Regression

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# Motivation

# Binary regression

# Generalized extreme value

- ▶ Link function is defined as

$$G(z_i) = 1 - \exp(-z_i)$$

where

$$z_i = \begin{cases} (1 - \xi \mathbf{X}_i \boldsymbol{\beta})^{1/\xi} & \xi \neq 0 \\ \exp(-\mathbf{X}_i \boldsymbol{\beta}) & \xi = 0 \end{cases}$$

is standardized to give unit Fréchet distribution.

- ▶ Note: The cloglog link is a special case when  $\xi = 0$

# Spatial setting: Logit and probit

# Spatial setting: GEV

# Max-stable processes

# Random effects representation

- ▶ Problem:  $n$  is very large, and computationally challenging to work with
- ▶ Consider a set of  $L \ll n$  knots  $\mathbf{v}_1, \dots, \mathbf{v}_L$
- ▶ At each knot, there is a random effect
  - ▶ Logit and probit methods use Gaussian random effects
  - ▶ GEV method uses Positive stable random effects



# Random effects representation

- ▶ Logit and probit use kriging

$$z_i = \mathbf{X}_i \boldsymbol{\beta} + \theta_i$$

- ▶ The random effect impacts the marginal distribution for the GEV

$$\theta_i = \left[ \sum_{l=1}^L A_l w_l (\mathbf{s}_i)^{1/\alpha} \right]^\alpha$$

# Method

- ▶ Two-main steps for model fitting
- ▶ First, fit a pairwise composite likelihood
  - ▶ Pairwise composite likelihood estimates used for initial values in MCMC
- ▶ Then, fit a hierarchical random effects model using MCMC

# Pairwise composite likelihood

- ▶ We use a censored pairwise composite likelihood
  - ▶ Marginalizes out random effects
- ▶ Common in extremes
  - ▶ Bivariate distributions are computationally tractable
  - ▶ Only latent values where  $Y = 1$  inform likelihood

- ▶  $Y | \dots \stackrel{ind}{\sim} \text{Bernoulli}(\pi_i)$
- ▶  $\pi_i = 1 - \exp \left\{ \sum_{l=1}^L A_l \left[ \frac{w_l(\mathbf{s}_i)}{z_i} \right] \right\}$
- ▶  $z_i = \begin{cases} (1 - \xi \mathbf{X}_i \boldsymbol{\beta})^{1/\xi} & \xi \neq 0 \\ \exp(-\mathbf{X}_i \boldsymbol{\beta}) & \xi = 0 \end{cases}$
- ▶  $A_l \stackrel{iid}{\sim} \text{PS}(\alpha)$
- ▶  $w_l(\mathbf{s}_i)$  is a scaled Gaussian kernel

# Questions

- ▶ Questions?
- ▶ Thank you for your attention.

# References