

Statistical Extreme Value Theory (EVT) Part II

Eric Gilleland Research Applications Laboratory 21 July 2014, Trieste, Italy

National Center for Atmospheric Research



Poisson distribution applicable for modeling the *frequency* of exceeding a high threshold (i.e., low probability, rare, event).

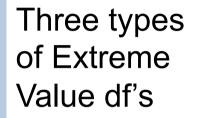
What about the intensity of values that exceed the threshold?

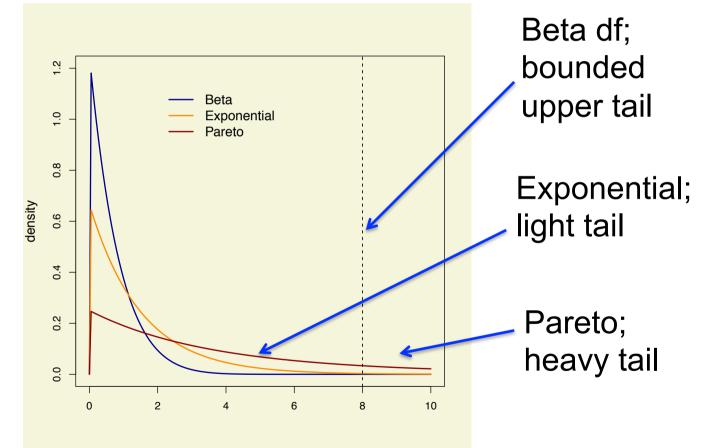


- X random variable
- Let Y = X u, conditional on X > u, where u is a high threshold.
- Model the "excesses" over the threshold.
- Y has an approximate generalized Pareto (GP) distribution for high u with cdf:

$$H(y;\sigma(u),\xi) = 1 - \left[1 + \xi \frac{y}{\sigma(u)}\right]^{-1/\xi}, y > 0, \ \xi \frac{y}{\sigma(u)} > 0$$
$$\sigma(u) > 0$$









- ξ < 0 yields the Beta cdf (bounded upper tail) upper bound at: u – σ(u) / ξ
- $\xi = 0$ yields the exponential cdf ("light" upper tail)
- $\xi > 0$ yields the Pareto cdf ("heavy" upper tail)

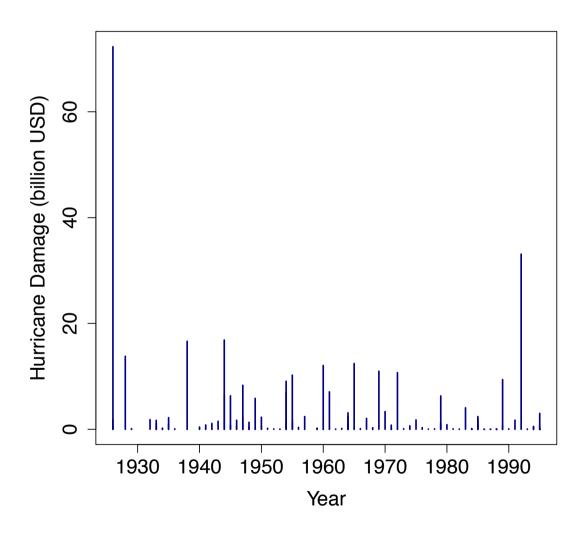


Connection between GEV and GP families

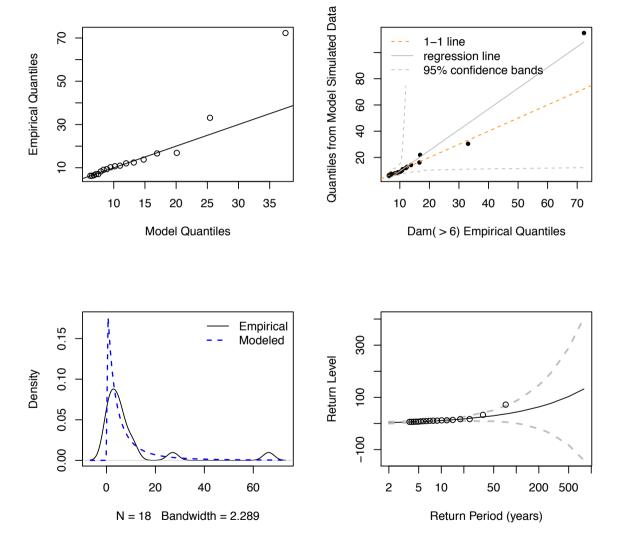
- Maximum $M_n \le u$ if no $X_i > u$, i = 1, 2, ..., n
- "Memoryless" property of exponential distribution Pr{ Y > y + y' | Y > y' } = Pr{ Y > y }
- Stability of GP distribution
 - Lose memoryless property (need to rescale)
 - If Y = X u (X > u) has exact GP distribution with parameters σ(u) > 0 and ξ, then excess over a higher threshold u' > u follows the GP distribution with parameters σ(u') > 0 and ξ, where

$$\sigma(u') = \sigma(u) + \xi(u' - u), u' > u$$











	95% lower Cl	Estimate	95% upper CI
$\sigma(u = 6 \text{ billion USD})$	1.03 billion USD	4.59 billion USD	8.15 billion USD
ξ	-0.15	0.51	1.18
100-year return level (billion USD)	0.65 billion USD	43.64 billion USD	86.64 billion USD

Peaks Over Threshold (POT): CAR GP return levels

- First need quantile of GP cdf
 - $x_p = H^{-1}(1 p; \sigma(u), \xi)$
 - = $(\sigma(u) / \xi) \times (p^{-\xi} 1), 0$
- Complication: must account for the rate, ζ, of exceeding the threshold for interpretability, as well as the number of events per year, n_v.
 - replace p^{-1} with m = return period of interest × $n_v \times \zeta$

Peaks Over Threshold (POT): CAR GP return levels

Hurricane example

Lack of structure in data: some years have no hurricanes, some one, some two, etc.

Reasonable to use an average number per year in place of n_v .

Peaks Over Threshold (POT): Threshold Selection



- The Bias-Variance Trade-Off
- Want a high threshold to obtain better GP approximation
- Want a lower threshold for more reliable estimation (more data!)
- Difficult to automate selection

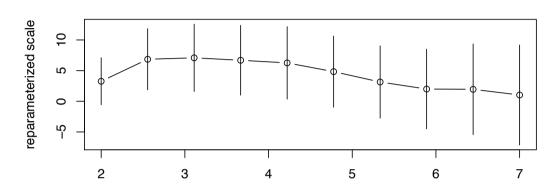
Peaks Over Threshold (POT): Threshold Selection

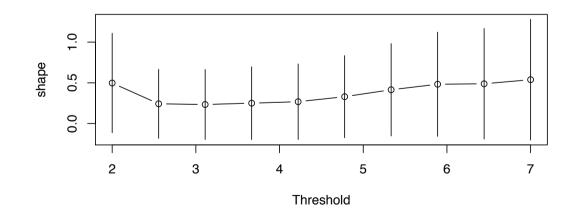
Invariance of GP above threshold

- ξ does not change
- $\sigma(u)$ is a function of the threshold
- The modification, $\sigma^* = \sigma(u) \xi u$, is no longer a function of the threshold, and does not change
- Check for stability in parameter estimates as the threshold varies.

Peaks Over Threshold (POT): Threshold Selection

NCAR





Peaks Over Threshold (POT): Dependence in Threshold Excess NCAR Data

- Remove dependence (e.g., decluster)
 - Runs declustering perhaps the simplest
- Model the dependence (e.g., through bivariate extreme value models)
- Concept of "extremal index"

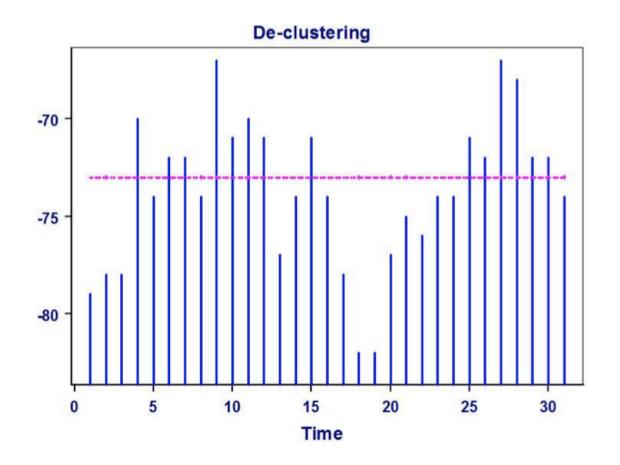
Peaks Over Threshold (POT): Dependence in Threshold Excess NCAR Data

Extremal Index, θ , $0 < \theta \le 1$

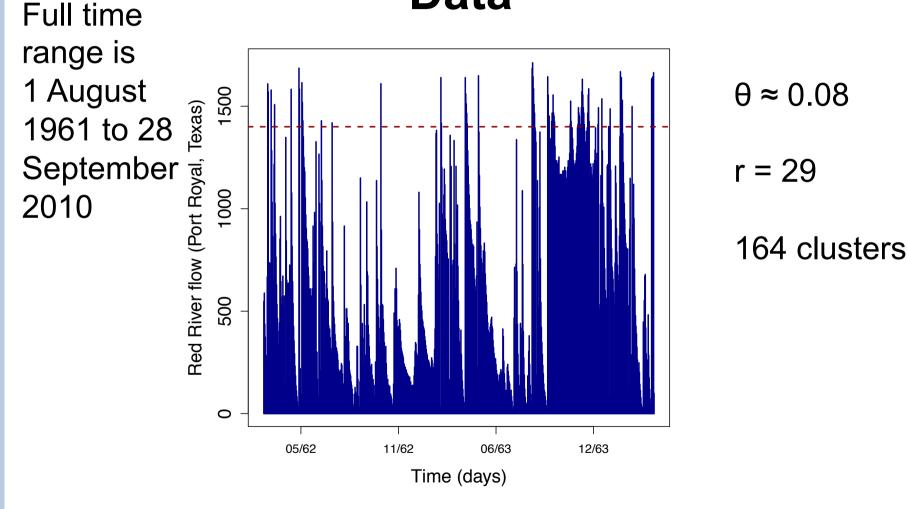
Mean cluster size $\approx 1 / \theta$

 θ = 1 implies a lack of clustering at high levels, and degree of clustering at high levels increases as θ decreases

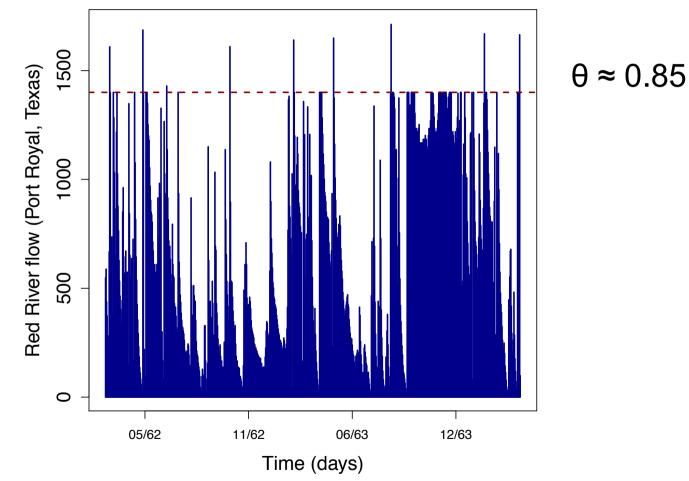
Peaks Over Threshold (POT): Dependence in Threshold Excess NCAR Data



Peaks Over Threshold (POT): Dependence in Threshold Excess NCAR Data



Peaks Over Threshold (POT): Dependence in Threshold Excess NCAR Data



Poisson-GP Model

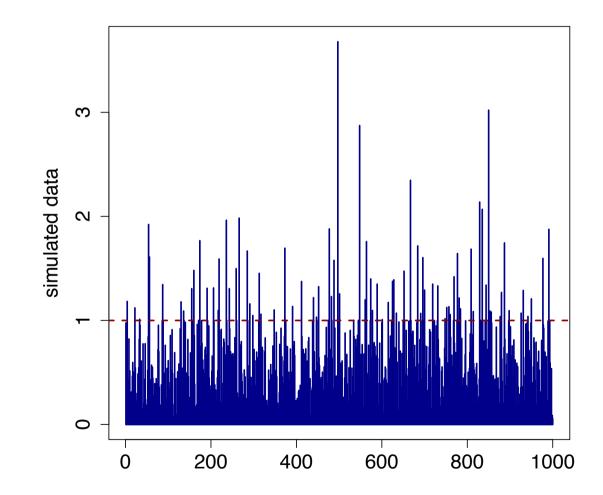
- Poisson process for exceeding a high threshold
 - Event: $X_t > u$
 - Rate parameter: λ
 - Number of events in [0, T] has Poisson distribution with parameter λT
- GP distribution for excess over threshold
 - Excess $Y_t = X_t u$ given $X_t > u$
 - Scale and Shape parameters

Point Process (PP) representation

- Subsumes Poisson-GP model
- GEV parameterization (connection to GEV)
- Can relate parameters of GEV(μ, σ, ξ) to those of the PP(λ, σ(u), ξ)
 - Shape parameter, ξ, is identical
 - $\ln \lambda = -(1/\xi) \ln(1 + \xi(u \mu) / \sigma)$
 - $\sigma(u) = \sigma + \xi(u \mu)$
- Need time scale, h, to take account of the block size for GEV (e.g., h ≈ 1/365.25 for daily data and annual blocks)

Point Process (PP) vs Poisson-GP

- Approaches are equivalent
- Poisson-GP model
 - Can obtain the same parameter estimates indirectly through the relationships between the two parameterizations
- Point Process
 - More convenient to quantify total uncertainty
 - Easier to interpret (eliminates dependence of parameters on the threshold)



ß 0 1-1 line 0 ė regression line 3.5 95% confidence bands 0 ω. 3.0 0 0 0 2.5 0 0 Observed Z_k Values Empirical Quantiles 0 0 0 2.5 0 N. 000 /000 1.5 0 0000 ഹ് 2.0 ത്ത് ത്ത് അ õ 1.0 1.5 an 0.5 <u>1</u>.0 1.0 1.5 2.0 2.5 3.0 0 5 1 2 3 4 Expected Values Model Quantiles Under exponential(1) Intensity Frequency

fevd(x = y, threshold = 1, type = "PP")

Poisson-GP estimation method

	95% lower Cl	Estimate	95% upper Cl
λ	0.07	0.08	0.10
σ(u)	0.28	0.40	0.53
ξ	-0.16	0.07	0.29

PP estimation method

	95% lower Cl	Estimate	95% upper Cl
μ	2.06	2.53	3.01
σ	0.20	0.51	0.82
ξ	-0.16	0.07	0.30

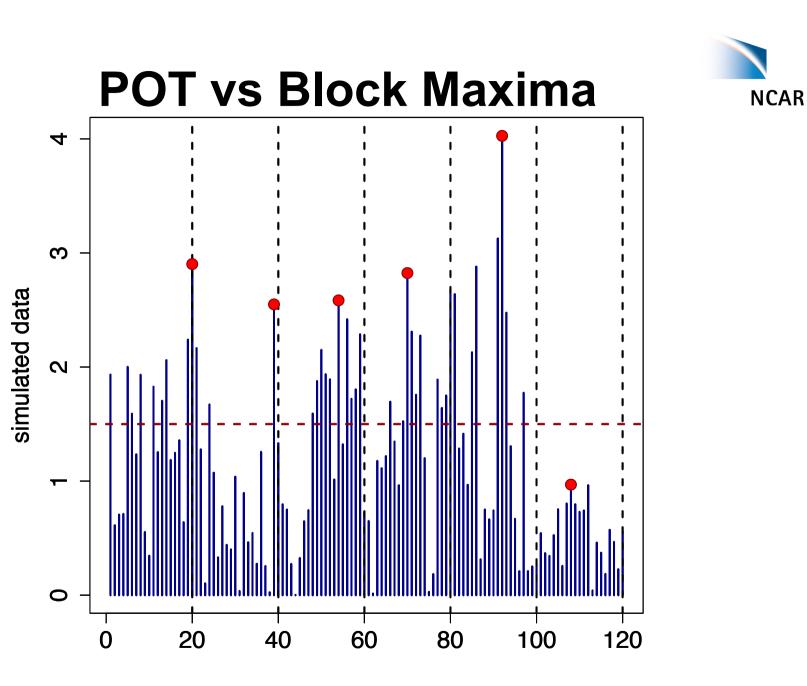
Verify that the two sets of parameter estimates are consistent

In
$$\lambda$$
 = -(1 / ξ) In(1 + ξ(u – μ) / σ ≈ 0.009

 $\lambda \approx 29.93$ (estimated on an annual maximum scale)

0.08 * 365.25 ≈ 29.22

 $\sigma(u) = \sigma + \xi(u - \mu) \approx 0.4$





Conclusion of Part II: Questions?