

# Prediction and verification of extremes

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Outline

### What are Extremes?

#### • Weather and Climate:

Rare, exceptional, "big" and potential of **high impact** complex and multivariate phenomena

#### Mathematically:

Block maxima or exceedances over high threshold Events in tail of distribution



Snow storm Münsterland November 2005 Harald Schmidt Show

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## The verification problem

- Small number of observed events
- Weak representation of extremes in models – calibration
- Standard verification measures degenerate as event rarity increases
- Large uncertainties in predictions and verification measures

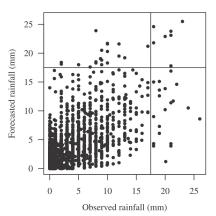


FIG. 1. Forecasted 6-h rainfall accumulations against observations at Eskdalemuir.

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From Ferro and Stephenson (2011)

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### Outline

- 1. Extreme value theory
  - a Univariate extreme value theory
  - b Bivariate extremes
- 2. Deterministic prediction/verification
  - a Contingency table
  - b Extreme value model
  - c Extremal dependence indices
- 3. Probabilistic prediction/verification
  - a Proper scoring rules
  - b Proper scoring rules for extremes
  - c Downscaling of precipitation extremes

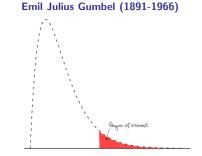






# "Il est impossible que l'improbable n'arrive jamais"

- Extremal indices
   95% quantile of daily precipitation:
   9mm im winter, 15mm summer
- Not really extreme!
- Extreme: Q100



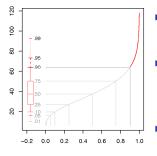
# "Going beyond the range of the data" (Philippe Naveau) Probabilistic concept on asymptotic behaviour of extremes





Extreme value theory – univariate Extreme value theory – bivariate

Extreme value theory "Going beyond the range of the data"



- Limit theorem for sample maxima

   -> asymptotic distribution of extremes
- ▶ Condition of max-stability (de Haan, 1984)
   → Maxima follow a generalized extreme value distribution (GEV)
  - universal behaviour of extremes  $\rightarrow$  allows for extrapolation!

In praxis not enough - not in asymptotitic limit - bad convergence

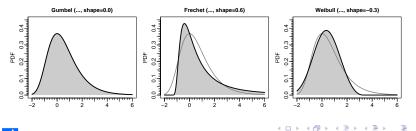


#### Generalised extreme value distribution (GEV)

Maxima of large samples  $X_N = \max\{z^{(1)}, \ldots, z^{(N)}\}$  asymptotically follow  $N \to \infty$  a GEV

$$\mathcal{G}_X(x) = \left\{egin{array}{c} \exp(-(1+\xirac{x-\mu}{\sigma})^{-1/\xi})_+, & \xi
eq 0 \ \exp(-\exp(-rac{xfor-\mu}{\sigma})), & \xi=0 \end{array}
ight.,$$



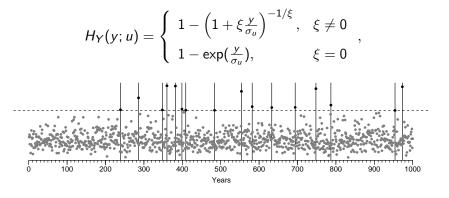


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## Generalised Pareto distribution (GPD)

Analogue to GEV, but for peaks-over-threshold (POT) Y = X - uasymptotically for  $u \to \infty$  follow a GPD





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GPD class:

Extreme value theory Deterministic prediction/verification Probabilistic prediction/verification

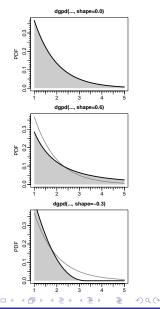
Generalised Pareto distribiton (GPD)

 $\xi = 0$  Exponential distribution (Gumbel type)

 $\xi > 0$  Pareto tail (Fréchet type)

 $\xi < 0$  Beta (Weibull type)

Extreme value theory – univariate Extreme value theory – bivariate



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#### Petra Friederichs Prediction and verification of extremes

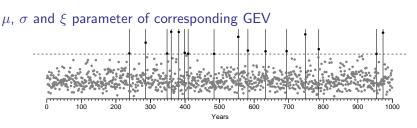


#### **Poisson point process**

For high theshold u,  $X_i > u$  is asymptotically a Poisson point process on  $[0, 1] \times (u, \infty)$  with intensity

$$\Lambda(A) = (t_2 - t_1) \left( 1 + \xi \left( \frac{y - \mu}{\sigma} \right) \right)^{-1/\xi}$$

for 
$$A = [t_1, t_2] \times (u, z)$$





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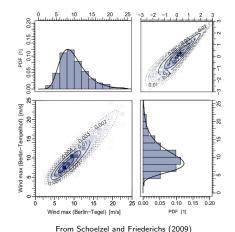
#### Multivariate extreme value statistics

### Marginal distribution:

Standard Fréchet or Gumbel

#### **Dependence structure:**

- Limit theorem for multivariate sample maxima
- Max-stability for marginals and dependence structure



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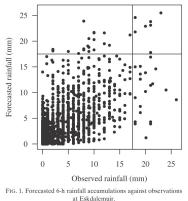
Extreme value theory – univariate Extreme value theory – bivariate

#### Bivariate EVD – dependence structure

$$Pr(X \le x, Y \le y) = \exp\{-V(x, y)\}$$

$$\chi = \lim_{z \to \infty} \Pr(X > z | Y > z)$$

- $\chi \neq 0$  asymptotic dependence
- χ = 0 asymptotic
   independence



From Ferro and Stephenson (2011)

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# 1. Conclusions

- Extreme value theory universal law for extreme values
  - Univariate GEV or GPD; Poisson point process
  - Multivariate Marginals and dependence structure
- Max-stability characteristics of extremes unchanged
  - Tail behaviour shape parameter  $\xi$
  - Dependence structure asymptotic dependence or independence

#### Extrapolation to really extreme values



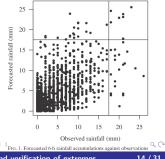
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**Contingency table** 

#### **Contingency table for infinite sample**

	event observed	non-event observed	
event	Pr(X > x, Y > y)	$Pr(X \leq x, Y > y)$	Pr(Y > y)
forecasted	= Hp	=F(1-p)	
non-event	$Pr(X > x, Y \leq y)$	$Pr(X \leq x, Y \leq y)$	$Pr(Y \leq y)$
forecasted	= (1 - H)p	= (1-F)(1-p)	
	Pr(X > x) = p (baserate)	$Pr(X \leq x) = 1 - p$	







#### Extreme value model

Transform bivariate random variable

$$ilde{X} = -\log(1-F_X(X)) \qquad ilde{Y} = -\log(1-F_Y(Y)),$$

u and v are (1-p)-quantiles –  $F_X(u) = 1-p$  and  $F_Y(v) = 1-p$ 

Let  $Z = \min{\{\tilde{X}, \tilde{Y}\}}$ 

$$Pr(X > u, Y > v) = Pr(Z > -\log p)$$

Extreme value theory (Ledford, Tawn, 1996; Ferro, 2007)

$$Pr(Z > -\log p) = \kappa p^{1/\eta}.$$
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Contingency table Extreme value model Extremal dependence indices

### Contingency table for extreme value model

Ferro (2007)

	event observed	non-event observed	
event	Pr(X > u, Y > v)	$Pr(X \leq u, Y > v)$	р
forecasted	$=\kappa p^{1/\eta}$	$= p - \kappa p^{1/\eta}$	
non-event	$Pr(X > u, Y \leq v)$	$Pr(X \leq u, Y \leq v)$	1-p
forecasted	$= p - \kappa p^{1/\eta}$	$= 1 - 2p + \kappa p^{1/\eta}$	
	р	1-p	



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Contingency table Extreme value model Extremal dependence indices

#### Contingency table for extreme value model

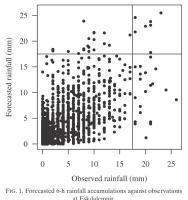
Maximum likelihood estimators

$$\hat{\eta} = \min\{1, \frac{1}{m} \sum_{t: z_t > w_0} (z_t - w_0)\},$$

*m* is number of  $z_t > w_0$ 

$$\hat{\kappa} = \frac{m}{n} \exp\left(\frac{w_0}{\hat{\eta}}\right).$$

 $w_0 < p$ , but large enough for extreme value model to be valid





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### **Extremal dependence indices**

Ferro and Stephenson (2011) propose EDI and SEDI

$$EDI = \frac{\log F - \log H}{\log F + \log H}$$

$$SEDI = \frac{\log F - \log(1 - F) - \log H + \log(1 - H)}{\log F + \log H + \log(1 - F) + \log(1 - H)}$$

both of which are equitable, independent of baseline p, do have non-degenerate limits



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Contingency table Extreme value model Extremal dependence indices

# 2. Conclusions

- Contingency table for extreme value model
- EDI and SEDI scores for extreme events



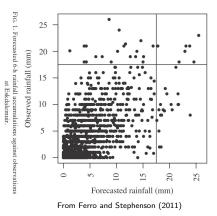
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Proper scoring rules Proper scoring rules for extremes Downscaling of Precipitation – Dresden

# **Probabilistic prediction**

- Rarity of events probabilistic prediction
- Provides more information for decision makers
- Predictive distribution
   *F* ∈ *F*
- Observation  $Y \in \Omega_Y$



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### Proper scoring rules

According to Gneiting and Raftery (2007): A Score function is **proper** if

$$E_F[S(F,Y)] = \int_{\Omega_Y} S(F,y) dF(y) \le E_F[S(G,Y)], \quad F,G \in \mathcal{F}$$

and strictly proper  $E_F[S(F, Y)] = E_F[S(G, Y)]$  only if F = G



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### Continuous ranked probability score

$$CRPS(F, y) = \int_{-\infty}^{\infty} (F(t) - I_{y \le y})^2 dt$$
  
=  $\int S_{BS}(y, F_Y, u) du$  Brier score  
=  $2 \int_0^1 (I_{y \le F^{-1}(\tau)} - \tau) (F^{-1}(\tau) - y) d\tau$   
=  $2 \int_0^1 S_{QS}(y, F_Y, \tau) d\tau$  Quantile score

Logarithmic score

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$$LogS(F, y) = -\log f(y), \quad f(y) = F'(y),$$



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Proper scoring rules Proper scoring rules for extremes Downscaling of Precipitation – Dresden

### **Proper scoring rules – focus on extremes**

WRONG!: Conditioning verification on a subset of observations Lerch et al. (2015)

**CORRECT**!: Stratify with respect to forecasts Gneiting and Ranjan (2011); Diks et al. (2011)



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Weighted CRPS

Gneiting, Ranjan (2011)

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**Threshold-weighted CRPS** 

$$\operatorname{CRPS}^{u}(F, y) = \int_{-\infty}^{\infty} \left(F(t) - I_{y \leq y}\right)^{2} u(t) dt$$

#### **Quantile-weighted CRPS**

$$CRPS^{q}(F, y) = 2 \int_{0}^{1} (I_{y \le F^{-1}(\tau)} - \tau) (F^{-1}(\tau) - y) q(\tau) d\tau$$





### Conditional and censored likelihood score

Diks et al. (2011)

**Conditional likelihood score** 

$$\operatorname{CL}(F, y) = -I_{y \in A} \log \left( \frac{f(y)}{\int_{A} f(s) ds} \right)$$

#### Censored likelihood score

$$\operatorname{CSL}(F, y) = -\left(I_{y \in A} \log f(y) + I_{y \in A^{C}} \log \left(\int_{A^{C}} f(s) ds\right)\right)$$



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### Non-stationary Poisson point process

Friederichs (2010)

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Intensity

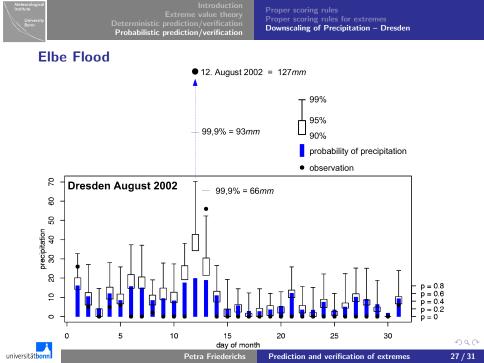
$$\Lambda(A) = (t_2 - t_1) \left( 1 + \xi \left( \frac{y - \mu}{\sigma} \right) \right)^{-1/\xi}$$

Parameters (linearly) depend on covariate **X X** information from (large-scale) model

$$\mu \rightarrow \boldsymbol{\mu}^T \mathbf{X} \qquad \sigma \rightarrow \exp(\boldsymbol{\varsigma}^T \mathbf{X}) \qquad (\boldsymbol{\xi} \rightarrow \boldsymbol{\xi}^T \mathbf{X})$$

Similar to ensemble model output statistics (EMOS)

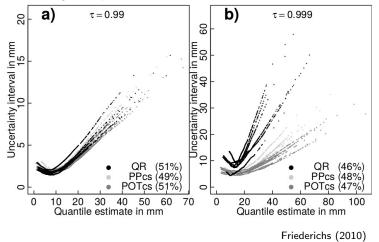






Proper scoring rules Proper scoring rules for extremes Downscaling of Precipitation – Dresden

#### **Uncertainty of quantile estimates**





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# 3. Conclusions

- Proper scoring rules remain proper
  - when weighting with respect to predictive distribution as proposed in Gneiting and Ranjan (2011)
  - ▶ for conditional or censored predictive densities as proposed in Diks et al (2011)
- Postprocessing using EVT provides skilful and reliable predictive distributions for extremes
  - Reduces uncertainty in predictive distribution



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