OpenTURNS Users Day #17

Focus on

« The extreme values modelling capacities

of OpenTURNS v1.23 »



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Both approaches are developped in the library:

- *Bloc maxima approach: based on the Generalized Extreme Value distribution (GEV)
- *Peak Over Threshold approach: based on the Generalized Pareto Distribution (GPD)

References:

- *Coles: « An introduction to statistical modelling of extreme values », Springer 2001
- *Beirlant: « Statistics of extremes: theory and application », Wiley, 2004.

Examples: all the examples developped by Coles are reproduced in the example documentation of the library.

Estimate tail

dependence coefficients on the wind

OpenTURNS An Open Source initiative for the Treatment of Uncertainties, Risks'N Statistics OpenTURNS 1.22 documentation .« Contents .» Common use cases .» Coles datasets

Coles datasets

- The portpirie sample gives the annual maximum sea levels recorded at Port Pirie, South Australia, from 1923 to 1987.
- The fremantle sample lists the annual maximum sea levels at Fremantle, Western Australia, versus mean annual value of Southern Oscillation Index, from 1897 to 1989.
- The racetime sample gives the fastest annual race time for the women 1500m over the period 1972-1992.
 The rain sample consists in a time series of daily rainfall accumulations in south-west England, recorded
- from 1914 to 1962.

 The wooster sample is a series of daily minimum temperatures recorded in Wooster (Ohio).
- The wind sample records the annual maximum wind speeds at two location in the US: Albany (New York) and Hartford (Connecticut), from 1944 to 1983.
- The wavesurge sample consist in measurements of wave and surge heights in south-west England.
- The **venice** sample gives the ten largest sea levels from 1931 to 1981, excluding 1935 in which only six values are available.

References

• [coles2001]

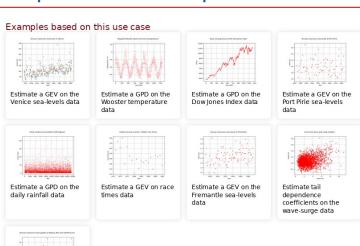
API documentation

class Coles

Data sets for the examples from [coles 2001].

Examples

>>> from openturns.usecases import coles
>>> data = coles.Coles().portpirie
>>> print(data[:3])





Block Maxima approach: based on the Generalized Extreme Value Distribution

GeneralizedExtremeValueFactory

	build(*args)	Estimate the distribution via maximum likelihood.	
	buildAsGeneralizedExtremeValue(*args)	Estimate the distribution as native distribution	
•	buildCovariates(*args)	Estimate a GEV from covariates.	
	buildEstimator(*args)	Build the distribution and the parameter distribution.	
•	buildMethodOfLikelihoodMaximization(sample)	Estimate the distribution from the $\it r$ largest order statistics.	
	$build {\tt MethodOfLikelihoodMaximizationEstimator} (sample)$	Estimate the distribution and the parameter distribution with the R-maxima method.	
•	buildMethodOfXiProfileLikelihood(sample[,r])	Estimate the distribution with the profile likelihood.	
	buildMethodOfXiProfileLikelihoodEstimator(sample)	Estimate the distribution and the parameter distribution with the profile likelihood.	
	buildReturnLevelEstimator(result m)	Estimate a return level and its distribution from the GEV parameters.	
	buildReturnLevelProfileLikelihood(sample, m)	Estimate a return level and its distribution wit the profile likelihood.	
	buildReturnLevelProfileLikelihoodEstimator()	Estimate (z_m, σ, ξ) and its distribution with the profile likelihood.	
	buildTimeVarying(*args)	Estimate a non stationary GEV from a time- dependent parametric model.	
	getBootstrapSize()	Accessor to the bootstrap size.	
	getClassName()	Accessor to the object's name.	
	getName()	Accessor to the object's name.	
	getOptimizationAlgorithm()	Accessor to the solver.	
	hasName()	Test if the object is named.	
	setBootstrapSize(bootstrapSize)	Accessor to the bootstrap size.	
	setName(name)	Accessor to the object's name.	
	setOptimizationAlgorithm(solver)	Accessor to the solver.	

Stationary GEV

- GEV estimate:
 - Max log-likelihood based on the maxima or the r highest maxima
 - Profile likelihood wrt ξ
- Model validation: QQ-plot, PP-Plot, Return level graph, model and Empirical pdf
- Return level estimate:
 - · Max log-likelihood
 - Profile likelihood wrt the return level



Block Maxima approach: based on the Generalized Extreme Value Distribution (GEV)

* Non stationary GEV: dependence to covariates

$$Z_t \sim \text{GEV}(\mu(t), \sigma(t), \xi(t))$$
 $Z_y \sim \text{GEV}(\mu(y), \sigma(y), \xi(y))$
 $Z_t \sim \text{GPD}(\sigma(t), \xi(t), u)$ $Z_y \sim \text{GPD}(\sigma(y), \xi(y), u)$

$$\theta_q(t) = h_q \left(\sum_{i=1}^{d_{\theta_q}} \beta_i^{\theta_q} \varphi_i^{\theta_q}(\tau(t)) \right) \qquad \theta_q(y_1^q, \dots, y_{d_q}^q) = h_q \left(\sum_{i=1}^{d_q} \beta_i^q y_i^q + \beta_{d_q+1}^q \right)$$

GeneralizedExtremeValueFactory

	build(*args)	Estimate the distribution via maximum likeli- hood.		
4	buildAsGeneralizedExtremeValue(*args)	Estimate the distribution as native distribution.		
$\overline{}$	buildCovariates(*args)	Estimate a GEV from covariates.		
*	buildTimeVarying(*args)	Estimate a non stationary GEV from a time- dependent parametric model.		

TimeVaryingResult

drawDiagnosticPlot()

	di awbiagnosticreot()	braw tre 4 asaar alagriostic plots.
	drawParameterFunction([parameterIndex])	Draw the parameter function.
Graphs $t \rightarrow \theta(t)$ or $y \rightarrow \theta(y)$	drawQuantileFunction(p)	Draw the quantile function.
	getClassName()	Accessor to the object's name.
	getDistribution(t)	Accessor to the Parent distribution at a given tim
Cropbet $\rightarrow \alpha (7(t)) \text{ or } t \rightarrow \alpha (7(t))$	getLogLikelihood()	Optimal log-likelihood value accessor.
Graphs $t \rightarrow q_p(Z(t))$ or $y \rightarrow q_p(Z(y))$	getName()	Accessor to the object's name.
	getNormalizationFunction()	Normalizing function accessor.
	getOptimalParameter()	Optimal parameter accessor.
Model validation (standardized distribution):	getParameterDistribution()	Accessor to the distribution of β .
model validation (standardized distribution).	getParameterFunction()	Parameter function accessor.
	getTimeGrid()	Accessor to the time grid.
OO plot DD Dlot Datum lavel group model and	hasName()	Test if the object is named.
QQ-plot, PP-Plot, Return level graph, model and	setLogLikelihood(logLikelihood)	Optimal log-likelihood value accessor.
	setName(name)	Accessor to the object's name.
	setParameterDistribution(parameterDistribution)	Accessor to the distribution of of β .
English and the old		

CovariatesResult

drawParameterFunction1D(*args)	Draw the parameter function.
drawParameterFunction2D(*args)	Draw the parameter function.
drawQuantileFunction1D(*args)	Draw the quantile function.
drawQuantileFunction2D(*args)	Draw the quantile function.
getClassName()	Accessor to the object's name.
getCovariates()	Covariates accessor.
getDistribution(covarlates)	Accessor to the Parent distribution at a given covariate vector.
getLogLikelihood()	Optimal likelihood value accessor.
getName()	Accessor to the object's name.
getNormalizationFunction()	Normalizing function accessor.
getOptimalParameter()	Optimal parameter accessor.
getParameterDistribution()	Accessor to the distribution of β .
getParameterFunction()	Parameter function accessor.
hasName()	Test if the object is named.
setLogLikelihood(logLikelihood)	Optimal likelihood value accessor.
setName(name)	Accessor to the object's name.
setParameterDistribution(parameterDistribution)	Accessor to the distribution of of eta .

* Model selection based on the Likelihood Ratio test

Hypothesis tests

Empirical pdf

• Graphs $t \rightarrow \theta(t)$ or $y \rightarrow \theta(y)$

HypothesisTest.ChiSquared(firstSample,)	Test whether two discrete samples are independent.	
HypothesisTest.LikelihoodRatioTest([, level])	Nested likelihood model selection.	



Block Maxima approach: based on the Generalized Extreme Value Distribution (GEV)

Model validation

• Four usual graphs: :

- QQ-plot,
- PP-Plot.
- Return level graph,
- •model and Empirical pdf

GeneralizedExtremeValueValidation

*	drawDiagnosticPlot()	Draw the 4 usual diagnostic plots.
	drawPDF()	Draw the estimated density and the data histogram.
*	drawReturnLevel()	Draw the return level with confidence interval.
	<pre>getClassName()</pre>	Accessor to the object's name.
	getConfidenceLevel()	Confidence level accessor.
	getName()	Accessor to the object's name.
	hasName()	Test if the object is named.
	setConfidenceLevel(confidenceLevel)	Confidence level accessor.
	setName(name)	Accessor to the object's name.

Performed on standardized distributions in case of time or covariates depdence

$$\hat{Z}_{t} \sim \text{GEV}(\mu(t), \sigma(t), \xi(t))
Z_{t} \sim \text{GPD}(\sigma(t), \xi(t), u)$$

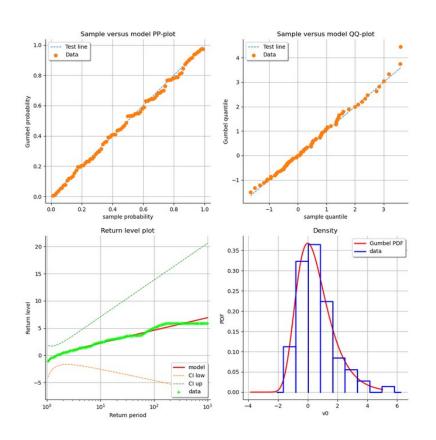
$$\hat{Z}_{t} = \frac{1}{\xi(t)} \log \left[1 + \xi(t) \left(\frac{Z_{t} - \mu(t)}{\sigma(t)} \right) \right]
\hat{Z}_{t} = \frac{1}{\xi(t)} \log \left[1 + \xi(t) \left(\frac{Z_{t} - \mu(t)}{\sigma(t)} \right) \right]$$



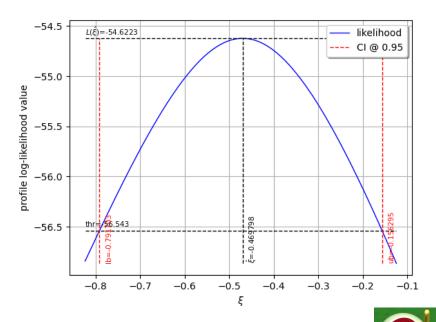
Block Maxima approach: based on the Generalized Extreme Value Distribution

(GEV)

Validation graphs



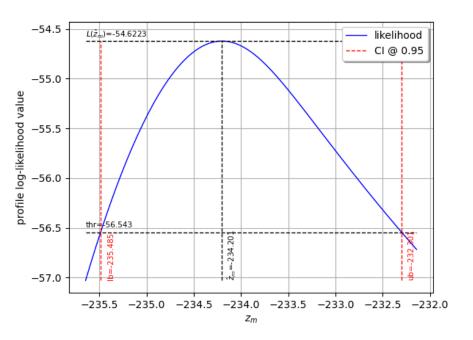
• ξ estimation from the profile likelihood profile likelihood



Block Maxima approach: based on the Generalized Extreme Value Distribution (GEV)

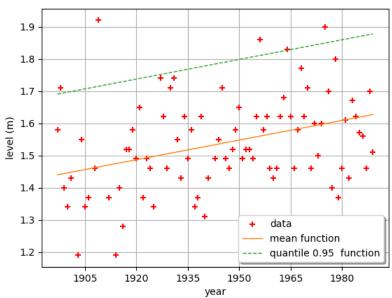
Return level estimation from the profile likelihood

profile likelihood



• $t \rightarrow \mu(t)$ of Z(t)

Annual maximum sea-levels at Fremantle - Linear $\mu(t)$





Peak Over Threshold approach: based on the Generalized Pareto Distribution (GPD)

GeneralizedParetoFactory

b	:1 d(*aras)	Build the distribution.
	ild(*args) ildAsGeneralizedPareto(*args)	Build the distribution. Build the distribution as a GeneralizedPareto type.
buildCovariates(*args)		Estimate a GPD from covariates.
bu:	ildEstimator(*args)	Build the distribution and the parameter distribution.
bu:	ildMethodOfExponentialRegression(sample)	Build the distribution based on the exponential regression estimator.
bu:	ildMethodOfLikelihoodMaximization(sample,u)	Estimate the distribution with the maximum likelihood method.
bu:	ildMethodOfLikelihoodMaximizationEstimator()	Estimate the distribution and the parameter distribution with the maximum likelihood method.
bu:	ildMethodOfMoments(sample)	Build the distribution based on the method of moments estimator.
bu:	ildMethodOfProbabilityWeightedMoments(sample)	Build the distribution based on the probability weighted moments estimator.
bu:	ildMethodOfXiProfileLikelihood(sample, u)	Estimate the distribution with the profile likelihood.
bu:	ildMethodOfXiProfileLikelihoodEstimator()	Estimate the distribution and the parameter distribution with the profile likelihood.
bu:	ildReturnLevelEstimator(result, sample, m)	Estimate a return level and its distribution from the GPD parameters.
bu:	ildReturnLevelProfileLikelihood(sample, u, m)	Estimate a return level and its distribution with the profile likelihood.
bu:	ildReturnLevelProfileLikelihoodEstimator()	Estimate $\left(z_{m},\xi\right)$ and its distribution with the profile likelihood.
bu:	ildTimeVarying(*args)	Estimate a non stationary GPD from a time- dependent parametric model.
dra	awMeanResidualLife(sample)	Draw the mean residual life plot.
dra	awParameterThresholdStability(sample,)	Draw the parameter threshold stability plot.
ge	tBootstrapSize()	Accessor to the bootstrap size.
	tClassName()	Accessor to the object's name.
ge	tName()	Accessor to the object's name.
ge	tOptimizationAlgorithm()	Accessor to the solver.
has	sName()	Test if the object is named.
se	tBootstrapSize(bootstrapSize)	Accessor to the bootstrap size.
se	tName(name)	Accessor to the object's name.
601	tOptimizationAlgorithm(solver)	Accessor to the solver.

Stationary GPD

- Threshold selection: Mean Residual Life
 Plot, Parameter Threshold Stability
- GPD estimate:
 - Max log-likelihood
 - Profile likelihood wrt ξ
- Model validation: QQ-plot, PP-Plot, Return level graph, model and Empirical pdf
- Return level estimate:
 - Max log-likelihood
 - Profile likelihood wrt the return level



Peak Over Threshold approach: based on the Generalized Pareto Distribution (GPD)

SamplePartition

ExtractFromDataFrame(partial)	Extract a partition from a pandas dataframe as a SamplePartition.
draw(threshold)	Draw clusters and peaks.
getClassName()	Accessor to the object's name.
getIndicesCollection()	Partition indices accessor.
getName()	Accessor to the object's name.
getPeakOverThreshold(threshold,r)	Compute extreme values using Peaks Over Threshold (POT) method.
getSample()	Sample accessor.
hasName()	Test if the object is named.
setName(name)	Accessor to the object's name.

- Non stationary GPD: select stationary periods and independent data
- Stationary period selection: use of pandas
- · Clusters and peak selection

Non stationary GPD: dependence to covariates

$$Z_t \sim \text{GEV}(\mu(t), \sigma(t), \xi(t)) \qquad Z_{\boldsymbol{y}} \sim \text{GEV}(\mu(\boldsymbol{y}), \sigma(\boldsymbol{y}), \xi(\boldsymbol{y}))$$

$$Z_t \sim \text{GPD}(\sigma(t), \xi(t), u) \qquad Z_{\boldsymbol{y}} \sim \text{GPD}(\sigma(\boldsymbol{y}), \xi(\boldsymbol{y}), u)$$

$$\theta_q(t) = h_q \left(\sum_{i=1}^{d_{\theta_q}} \beta_i^{\theta_q} \varphi_i^{\theta_q}(\tau(t)) \right) \qquad \theta_q(y_1^q, \dots, y_{d_q}^q) = h_q \left(\sum_{i=1}^{d_q} \beta_i^q y_i^q + \beta_{d_q+1}^q \right)$$

GeneralizedParetoFactory

*	buildTimeVaryin	g(*args)			Estimate a non stationary dependent parametric m	
\bigstar	buildCovariates(*args)	:0	(4)	Estimate a GPD from covariates.	9
	buildAsGeneraliz	edPareto(*	args)	- 1	Build the distribution as a General	lizedPareto type.
	build(*args)				Build the distribution.	· ·

- Graphs $t \to \theta(t)$ or $y \to \theta(y)$
- Graphs $t \rightarrow q_p(Z(t))$ or $y \rightarrow q_p(Z(y))$



Peak Over Threshold approach: based on the Generalized Pareto Distribution (GPD)

Model validation

• Four usual graphs: :

- QQ-plot,
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$$\hat{Z}_{t} = \frac{1}{\xi(t)} \log \left[1 + \xi(t) \left(\frac{Z_{t} - \mu(t)}{\sigma(t)} \right) \right]
\hat{Z}_{t} = \frac{1}{\xi(t)} \log \left[1 + \xi(t) \left(\frac{Z_{t} - \mu(t)}{\sigma(t)} \right) \right]$$



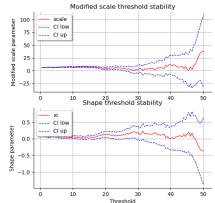
Peak Over Threshold approach: based on the Generalized Pareto Distribution (GPD)

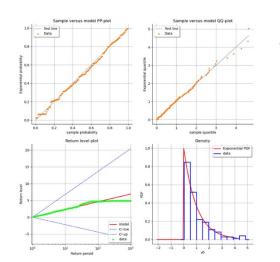
• Threshold selection: mean residual life plot and modified parameters graph



Threshold

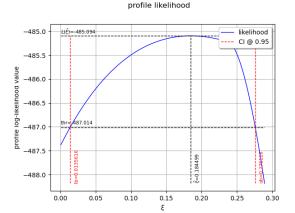
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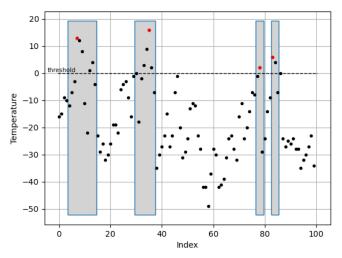


- Validation graphs
 - Clusters, Peaks over threshold

• ξ estimation from the profile likelihood



Temperature clusters

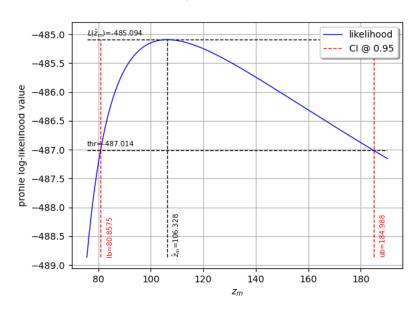




Peak Over Threshold approach: based on the Generalized Pareto Distribution (GPD)

Return level estimation from the profile likelihood





• $t \rightarrow \sigma(t)$ of Z(t)

Maximum rain - Linear $\sigma(t)$

