Large deviations for $L$-statistics
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Scheme

1. L-statistics : definition, expression, limit theorems.
2. Large deviations : some tools from the large deviations theory, a large deviations principle for some $L$-statistics.
3. Example : the uniform law.

## Definition of an L-statistics

$\left(X_{i}\right), i=1 \ldots n$ an i.i.d. sample with distribution function $F$, and $X_{(1)} \leq \cdots \leq X_{(n)}$ the associated order statistics.

Definition 1 An L-statistics is of the form :

$$
A_{n}=\frac{1}{n} \sum_{i=1}^{n} c_{n, i} b\left(X_{(i)}\right)
$$

where $c_{n, i}$ are some possibly $k$-dimensional coefficients and $b$ is some function from $\mathbb{R}$ to $\mathbb{R}$.

In many examples $b$ is the identity and $c_{n, i} \simeq a\left(\frac{i}{n}\right)$ for some bounded function $a$ on $[0,1]$.

## Examples of $L$-statistics

- $\alpha$-trimmed mean : $\frac{1}{n-2\lfloor\alpha n\rfloor} \sum_{i=\lfloor\alpha n\rfloor+1}^{n-\lfloor\alpha n\rfloor} X_{(i)}$. The corresponding function is $a(t)= \begin{cases}0 & \text { for } t<\alpha \text { or } t>1-\alpha \\ \frac{1}{1-2 \alpha} & \text { for } t \in[\alpha, 1-\alpha]\end{cases}$
- a part of D'Agostino's goodness-of-fit test statistics :

$$
D=\frac{\sum_{i=1}^{n}\left(i-(n+1) 2^{-1}\right) X_{(i)}}{n^{2} S_{n}}
$$

where $S_{n}^{2}$ is the sample variance.
The corresponding function is $a(t)=t-\frac{1}{2}$.

- Gini's difference mean : $\left(X_{i}\right), i=1 \ldots n$ an i.i.d. sample with distribution function $F$.
A dispersion parameter : $\theta=E\left(\left|X_{1}-X_{2}\right|\right)$ and its estimator

$$
T_{n}=\frac{1}{C_{n}^{2}} \sum_{i<j}\left|X_{i}-X_{j}\right|=\frac{1}{C_{n}^{2}} \sum_{i=1}^{n}(-n+2 i-1) X_{(i)}
$$

The corresponding function $a$ is

$$
a(t)=4\left(t-\frac{1}{2}\right)
$$

## Expression with the quantile function

For $G$ a distribution function, the associated quantile function is defined by its left continuous left inverse

$$
G^{-1}(t)=\inf \{x: G(x) \geq t\} \text { for } t \in[0,1]
$$

The empirical distribution function defined for $x \in \mathbb{R}$ by

$$
F_{n}(x)=\frac{1}{n} \sum_{i=1}^{n} 1_{\left\{X_{i} \leq x\right\}}
$$

admits as an inverse $F_{n}^{-1}: t \mapsto X_{(i)}$ for $\left.\left.t \in\right] \frac{i-1}{n}, \frac{i}{n}\right]$.

$$
A_{n} \simeq \frac{1}{n} \sum_{i=1}^{n} a\left(\frac{i}{n}\right) b\left(X_{(i)}\right)=\sum_{i=1}^{n} \int_{\frac{i-1}{n}}^{\frac{i}{n}} a\left(\frac{i}{n}\right) b\left(F_{n}^{-1}(t)\right) d t \simeq \int_{0}^{1} a(t) b\left(F_{n}^{-1}(t)\right) d t .
$$

## Limit properties for L-statistics

- Helmers (1978-1981), Vandemaele and Veraverbeke (1982) : approximation of $L$-statistics with $U$-statistics, and obtention of BerryEsseen bounds. Conditions on the coefficients $c_{n, i}, b$ the identity.
- Shorack and Wellner (1986) : treatment via empirical processes and obtention of weak and strong laws of large numbers, CLT and law of iterated logarithm. Conditions of boundedness of $a$ and $b$.
- More recently, for instance weaker sufficient conditions on $b$ (under rather strong conditions on $a$ ) obtained by Li, Rao and Tomkins (2001) for the obtention of the CLT and the LIL.


## Large deviations

$(X, \mathcal{B})$ is a topological space with its borelian sigma-algebra.
Definition 2 A sequence ( $P_{n}$ ) of probability measures on ( $X, \mathcal{B}$ ) satisfies a Large Deviations Principle (LDP) with speed $n$ if there exists a function $I: X \rightarrow[0,+\infty]$ lower-semicontinuous, called rate function, such that for all $A \in \mathcal{B}$

$$
-\inf _{x \in \tilde{A}} I(x) \leq \liminf _{n \rightarrow+\infty} \frac{1}{n} \log P_{n}(A) \leq \limsup _{n \rightarrow+\infty} \frac{1}{n} \log P_{n}(A) \leq-\inf _{x \in \bar{A}} I(x)
$$

The rate function $I$ is said to be good if its level sets are compact.
A sequence of random variables $\left(X_{n}\right)$ on a probability space $(\Omega, \mathcal{A}, P)$, is said to satisfy a LDP if the sequence of probability measures defined by $P_{n}=\mathcal{L}\left(X_{n}\right)$ satisfies a LDP.

## Tools from the theory of large deviations

Theorem 1 Contraction principle Let $\left(P_{n}\right)$ be a sequence of probability measures on $(X, \mathcal{B})$ which satisfies a LDP with good rate function $I, Y$ a metric space and $f: X \rightarrow Y$ a continuous function.

Then the sequence of probability measures on $Y P_{n} \circ f^{-1}$ satisfies a LDP with good rate function

$$
J(y)=\inf \{I(x): f(x)=y\} \text { for } y \in Y
$$

Definition 3 Exponential equivalence Let $\left(X_{n}\right)$ and $\left(Y_{n}\right)$ be random variables on a probability space $(\Omega, \mathcal{A}, P)$, with value in some metric space $(Y, d) .\left(X_{n}\right)$ and $\left(Y_{n}\right)$ are called exponentially equivalent if for every $\epsilon>0$,

$$
\limsup _{n \rightarrow \infty} \frac{1}{n} \log P\left(d\left(X_{n}, Y_{n}\right)>\epsilon\right)=-\infty
$$

Theorem 2 If a LDP with a good rate function holds for the random variables $\left(X_{n}\right)$ which are asymptotically equivalent to the r.v. $\left(Y_{n}\right)$, then the same holds for $\left(Y_{n}\right)$.

## Sanov's theorem

The space $\mathbb{P}(\mathbb{R})$ of all probability measures on $\mathbb{R}$ is equipped with the topology of weak convergence of probability measures.
Let $\left(X_{i}\right), i=1 \ldots n$ be an i.i.d. sample with law $P \in \mathbb{P}(\mathbb{R})$.
Definition 4 The empirical measure associated to this sample is

$$
\nu_{n}=\frac{1}{n} \sum_{i=1}^{n} \delta_{X_{i}}
$$

Theorem $3 \nu_{n}$ satisfies a LDP with good rate function

$$
I(Q)= \begin{cases}\int \log \left(\frac{d Q}{d P}\right) d Q & \text { for } Q \ll P \text { and } \log \left(\frac{d Q}{d P}\right) \in L_{1}(Q) \\ +\infty & \text { else. }\end{cases}
$$

## Exponentially equivalent statistics

Proposition 1 Let $T_{n, a}=\int_{0}^{1} a(t) F_{n}^{-1}(t) d t$ and $A_{n}=\frac{1}{n} \sum_{i=1}^{n} a\left(\frac{i}{n}\right) X_{(i)}$. Suppose the following hypotheses are satisfied:
(I) regularity of $a$ : for all $n$ there exists $b_{n}=o(1 / n)$ such that for all $i=1 \ldots n$

$$
\left\|\frac{1}{n} a\left(\frac{i}{n}\right)-\int_{\frac{i-1}{n}}^{\frac{i}{n}} a(t) d t\right\| \leq b_{n}
$$

(II) the domain of definition of the Laplace transform of $\left|X_{i}\right|$ is not reduced to $\{0\}$, then for every $\epsilon>0$,

$$
\lim _{n \rightarrow \infty} \frac{1}{n} \log P\left(\left\|A_{n}-T_{n, a}\right\|>\epsilon\right)=-\infty
$$

## LDP for $T_{n, a}$ obtained by contraction

Theorem 4 Suppose that
(III) $F$ has compact support included in $[-M, M]$ and that (IV) $a$ is bounded on $[0,1]$, then $T_{n, a}=\int_{0}^{1} a(t) F_{n}^{-1}(t) d t$ satisfies a LDP with good rate function

$$
J(C)=\inf \left\{I(G): G \text { is a d.f. on } \mathbb{R} \text { s.t. } \int_{0}^{1} a(t) G^{-1}(t) d t=C\right\} .
$$

## Statement of the LDP for $A_{n}$

Suppose that hypotheses
(I) regularity of $a$
(III) boudedness of the support of $F$
(IV) boundedness of $a$
are satisfied. Then $A_{n}$ satisfies a LDP with good rate function

$$
J(C)=\inf \left\{I(G): G \text { is a d.f.on } \mathbb{R} \text { s.t. } \int_{0}^{1} a(t) G^{-1}(t) d t=C\right\}
$$

## Example : the uniform law on $[0,1]$

We denote the uniform d.f. by $F: F(t)=t$ for $t \in[0,1]$. Let $\mathcal{X}$ be the set of all $x=G^{-1}$ for $G \ll F$. The elements of this set are derivable almost everywhere. For $x=G^{-1} \in \mathcal{X}$, let

$$
K(x):=I(G)=-\int_{0}^{1} \log x^{\prime}(t) d t
$$

Minimization problem ( $P$ ) : minimize

$$
K(x)= \begin{cases}-\int_{0}^{1} \log x^{\prime}(t) d t & \text { for } x \in \mathcal{X} \\ +\infty & \text { elsewhere }\end{cases}
$$

under the (possibly $k$-dimensional) constraint : $\int_{0}^{1} a(t) x(t) d t=C$. $J(C)$ is the value of the minimum.

## Result of the minimization

Suppose that $\int_{0}^{1} a(t) d t=0$, put $A(t)=\int_{t}^{1} a(s) d s$.

Proposition 2 The minimum value of the minimization problem ( $P$ ) is

$$
J(C)=1+\sup _{\lambda \in \mathbb{R}, \mu \in \mathbb{R}^{k}} \lambda+<\mu, C>+\int_{0}^{1} \log (-\lambda-<\mu, A(s)>) d s
$$

where $<,>$ denotes the usual scalar product in $\mathbb{R}^{k}$.

## Sketch of the proof

- formulation of $(P)$ in terms of $x^{\prime}=y$.
$(\tilde{P})$ Minimize $\tilde{K}(y)=-\int_{0}^{1} \log y(t) d t$ under the constraints

$$
\int_{0}^{1} A(s) y(s) d s=C, 0 \leq \int_{0}^{1} y(t) d t \leq 1
$$

- fix $\int_{0}^{1} y(t) d t=\alpha$, and obtain minimization problem $\left(P_{\alpha}\right)$, minimum found by a duality argument.
- minimax argument to find the minimum (over $\alpha$ ) of the minimum values for each ( $P_{\alpha}$ )
- final discussion.


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