

Generalized differentiation of probability functions

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- Motivating applications

2 Tools

- Generalized (sub-)differentiation
- Elliptically symmetric random vectors

3 Arbitrary index sets

- Representation of the probability function
- Subdifferential estimates for the resolvent map
- Subdifferential estimates for the probability function

4 Better formulæ

- through equicontinuous subdifferentiability
- through some degree of compactness

1 Introduction

■ Motivating applications

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Probability constraints

- A probabilistic constraint is a constraint of the type

$$\varphi(x) := \mathbb{P}[g(x, \xi) \leq 0] \geq p, \quad (1)$$

where $g : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^k$ is a map, $\xi \in \mathbb{R}^m$ a (multi-variate) random variable. They arise in many applications. For instance cascaded Reservoir management.

- We will however be interested in the situation:

$$\varphi(x) := \mathbb{P}[g_t(x, \xi) \leq 0, \forall t \in T] \geq p, \quad (2)$$

where $g_t : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$ is a map and T an “arbitrary index set”.

Unit commitment - probust

- In unit commitment problems under uncertainty, one may have to find appropriate generation levels while accounting for uncertainty on load and / or wind. This may lead to a classic probability constraint of the form

$$\varphi(x) := \mathbb{P}[Ax \geq \xi] \geq p. \quad (3)$$

- However defaults on generation may occur, leading to uncertainty on A . It may be so that such uncertainty is less well understood and it is more meaningful to consider “robust” ideas:
- we know of perturbations $A(u)$, for all $u \in \mathcal{U}$, with \mathcal{U} the uncertainty set.
- Then one faces the “probust” constraint:

$$\varphi(x) := \mathbb{P}[A(u)x \geq \xi, \forall u \in \mathcal{U}] \geq p. \quad (4)$$

- See, e.g., [van Ackooij et al.(2016)].

Unit commitment - robustly

- It is clear that any feasible point to:

$$\varphi(x) := \mathbb{P}[A(u)x \geq \xi, \forall u \in \mathcal{U}] \geq p. \quad (5)$$

- satisfies the “robility” constraint:

$$\varphi(x) := \mathbb{P}[A(u)x \geq \xi] \geq p, \forall u \in \mathcal{U} \quad (6)$$

- but the inverse need not hold. The latter may be seen to have a link with distributionally robust optimization.

Networks - Induced uncertainty

- In several management problems, an underlying network structure is present and ought to be accounted for.
- However the potentially arbitrary complex structure of the network “acts” on uncertainty (much like recourse).
- Uncertainty is actually a phenomenon occurring in nodes.
- Then uncertainty related to the network means, for instance, existence of a “feasible flow”.
- the probability constraint then reads: for sufficient random realizations, there exists a feasible flow.

Networks - Induced uncertainty II

- An interesting application is gas-networks, where under some structural properties on the network (tree structure or a few fundamental cycles): the implicit conditions can be recast as regular inequality systems (this is non-trivial, e.g., references in [González Gradón et al.(2017)]).
- The existence of uncertainty on friction coefficients leads again to robust constraints, since assuming knowledge of distributions of friction coefficients is not reasonable.

PDE constrained

- In certain optimization problems from engineering, e.g., optimal design of off-shore wind turbines, one deals with computing some optimal shape or structure while having to account for uncertainty.
- the given uncertainty could for instance represent stochastic loadings or environmental stress conditions
- by considering the Karhunen-Loève expansion of this uncertainty (e.g., stochastic field), one can argue that uncertainty is caused by a “finite dimensional random vector” (the uncertain coefficients in this expansion).
- However, the dynamics of the system are best described by a PDE.
- We refer to [Farshbaf-Shaker et al.(2017)] for details

PDE constrained II

- This gives for instance problems of the form :

$$\min_{x,u} \mathbb{E} (L(y(x, \omega), u(x)))$$

s.t. $y(x, \omega)$ is solution to:

$$-\nabla_x \cdot (\kappa(x) \nabla_x y(x, \omega)) = r(x, \omega), (x, \omega) \in D \times \Omega$$

$$n \cdot (\kappa(x) \nabla_x y(x, \omega)) + \alpha y(x, \omega) = u(x), (x, \omega) \in \partial D \times \Omega,$$

$$p \leq \mathbb{P}[\omega \in \Omega : y(x, \omega) \leq \bar{y}(x) \forall x \in C],$$

where $C \subseteq D \subseteq \mathbb{R}^3$,

- x, u belong to appropriate Sobolev spaces (u being some Boundary control)
- \bar{y} is some reference state behaviour.

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Generalized sub-differentials - Motivation

- Even with smooth data g and a finite index set T , φ need not be smooth.
- φ itself is never concave (on the whole space). However some transform of φ might be concave (e.g., taking the log), or φ might be concave on some portion of the space.
- That φ might fail to be smooth is not a problem. However it requires the use of “sub-differentials”.
- As a potentially non-smooth, non-convex object, the sub-differential needs to differ from the usual sub-differential of convex analysis.

Generalized sub-differentials - Definitions

- Let $f : X \rightarrow \mathbb{R} \cup \{\infty\}$ be a map and consider \bar{x} such that $f(\bar{x}) < \infty$, then

$$\partial^{\mathbb{F}} f(\bar{x}) = \left\{ x^* \in X^* : \liminf_{u \rightarrow \bar{x}} \frac{f(u) - f(\bar{x}) - \langle x^*, u - \bar{x} \rangle}{\|u - \bar{x}\|} \geq 0 \right\}. \quad (7)$$

is the Fréchet subdifferential of f at \bar{x} ,

- We also introduce

$$\partial^{\mathbb{M}} f(\bar{x}) := \{w^* - \lim x_n^* : x_n^* \in \partial^{\mathbb{F}} f(x_n), \text{ and } x_n \xrightarrow{f} \bar{x}\},$$

$$\partial^{\infty} f(\bar{x}) := \{w^* - \lim \lambda_n x_n^* : x_n^* \in \partial^{\mathbb{F}} f(x_n), x_n \xrightarrow{f} \bar{x} \text{ and } \lambda_n \rightarrow 0^+\},$$

are the Mordukhovich and singular Mordukhovich subdifferential respectively.

Elliptical distributions

Definition

We say that the random vector $\xi \in \mathbb{R}^m$ is elliptically symmetrically distributed with mean μ , covariance matrix Σ and generator $\theta : \mathbb{R}_+ \rightarrow \mathbb{R}_+$, notation $\xi \sim \mathcal{E}(\mu, \Sigma, \theta)$ if and only if its density $f : \mathbb{R}^n \rightarrow \mathbb{R}_+$ is given by:

$$f(x) = (\det \Sigma)^{-\frac{1}{2}} \theta((x - \mu)^T \Sigma^{-1} (x - \mu)). \quad (8)$$

Variance Reducing representation of φ

- When $\xi \sim \mathcal{E}(\mu, \Sigma, \theta)$ and $\Sigma = LL^T$ is the Cholesky decomposition of Σ , ξ admits a spherical radial decomposition
- $\xi = \mu + \mathcal{R}L\zeta$, where ζ is uniformly distributed on $\mathbb{S}^{m-1} = \{z \in \mathbb{R}^m : \|z\| = 1\}$, \mathcal{R} a radial distribution independent of ζ .
- \mathcal{R} possesses a density given by:

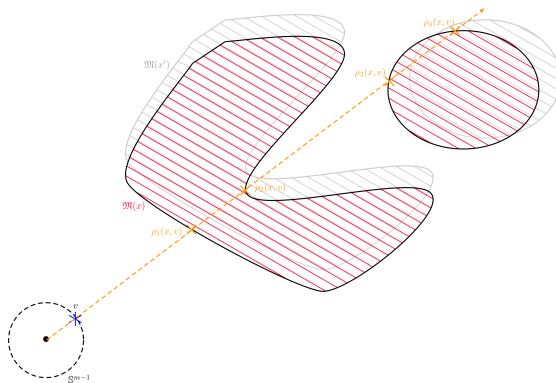
$$f_{\mathcal{R}}(r) = \frac{2\pi^{\frac{m}{2}}}{\Gamma(\frac{m}{2})} r^{m-1} \theta(r^2). \quad (9)$$

- For any Lebesgue measurable set $M \subseteq \mathbb{R}^m$ its probability may be represented as

$$\mathbb{P}(\xi \in M) = \int_{v \in \mathbb{S}^{m-1}} \mu_{\mathcal{R}}(\{r \geq 0 : \mu + rLv \cap M \neq \emptyset\}) d\mu_{\zeta}(v), \quad (10)$$

where $\mu_{\mathcal{R}}$ and μ_{ζ} are the laws of \mathcal{R} and ζ , respectively.

Illustration of the decomposition



Hypothesis in this work

- We assume that $z \mapsto g_t(x, z)$ is convex for each t ,
- We also assume that each g_t is continuously differentiable in both arguments.

Hypothesis: Consequences

- Let $D_t := \{x \in X : g_t(x, 0) < 0\}$
- We can entail from $g_t(x, 0) < 0$ the existence of a map $\rho_t : D_t \times \mathbb{R}^m \rightarrow \mathbb{R}_+ \cup \{\infty\}$, continuously differentiable on its domain such that

$$g_t(x, rLv) = 0 \text{ if and only if } r = \rho_t(x, v) \quad (11)$$

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Variance Reducing representation of φ

Proposition (vA, Perez-Aros (2018))

Let D be defined as $D := \bigcap_{t \in T} D_t$. Then we define the map $\rho : D \times \mathbb{S}^{m-1} \rightarrow \mathbb{R}_+$ as

$$\rho(x, v) := \inf_{t \in T} \rho_t(x, v), \quad (12)$$

where $\rho_t : D_t \times \mathbb{S}^{m-1} \rightarrow \mathbb{R}_+$ and D_t is as before. Then for any $x \in D$, $v \in \mathbb{S}^{m-1}$, it holds that

$$\{r \geq 0 : g(x, rLv) \leq 0\} = [0, \rho(x, v)], \quad (13)$$

where $[0, \infty] = [0, \infty)$ is intended. Hence, for $x \in D$,

$$\varphi(x) = \int_{v \in \mathbb{S}^{m-1}} F_{\mathcal{R}}(\rho(x, v)) d\mu_{\zeta}(v) \quad (14)$$

Some difficulties

- The map ρ need not be solution to $g(x, rLv) = 0$ with g the supremum function!

Example

Consider the functions $g_n : \mathbb{R} \times \mathbb{R}^2 \rightarrow \mathbb{R}$ given by

$$g_n(x, z) = \begin{cases} x^2 - 1 & \text{if } z_1^2 + z_2^2 \leq 1 \\ x^2 + n(z_1^2 + z_2^2 - 1)^2 - 1 & \text{if } z_1^2 + z_2^2 > 1, \end{cases}$$

the supremum of this family is

$$g(x, z) = \begin{cases} x^2 - 1 & \text{if } z_1^2 + z_2^2 \leq 1, \\ +\infty & \text{if } z_1^2 + z_2^2 > 1. \end{cases}$$

Consequently, for any $v \in \mathbb{S}^{m-1}$, $\{r : g(0, rv) \leq 0\} = [0, 1]$ and there is no $r > 0$ such that $g(0, rv) = 0$. Moreover for any $x \in [0, 1]$ and $v \in \mathbb{S}^{m-1}$, we

can compute $\rho_n(x, v) = \sqrt{1 + \sqrt{\frac{1-x^2}{n}}}$ and establish $\rho(x, v) = 1$.

Some difficulties II

- Although ρ is automatically u.s.c. (as the inf over a family of C1 maps), it may fail to be l.s.c. - additional assumptions will be needed.

Corollary

Moreover, for $x \in D^\circ := \{x \in X : g(x, 0) < 0\}$, one has that, if there exists $r > 0$ such that $g(x, rLv) = 0$, then $r = \rho(x, v)$. In particular, if $g|_{D^\circ \times \mathbb{R}^m}$ is finite valued the function ρ has the following alternative representation

$$\rho(x, v) = \begin{cases} r & \text{such that } g(x, rLv) = 0 \\ +\infty & \text{otherwise} \end{cases} \quad (15)$$

Continuity of the resolvent map

Proposition

Let x_0 be a point in X such that there exists a neighbourhood U of x_0 such that:

- The function ρ is solution to $g(\cdot, rL) = 0$.
- $g(x, 0) < 0$ for all $x \in U$.
- The set $\mathfrak{K} := \{(x, z) \in U \times \mathbb{R}^m : g(x, z) = 0\}$ is closed.

Then $\rho(x_n, v_n) \rightarrow \rho(x, v)$ for every sequence $U \times \mathbb{S}^{m-1} \ni (x_n, v_n) \rightarrow (x, v) \in U \times \mathbb{S}^{m-1}$.

Subdifferential estimates

Proposition (vA, Perez-Aros (2018))

Under the previous assumptions for every $x \in U$ the (regular) partial Mordukhovich sub-differential of ρ satisfies:

$$\partial_x^M \rho(\bar{x}, v) \subseteq \left\{ x^* \in X^* : \begin{array}{l} \exists \varepsilon_n \rightarrow 0^+, x_n \rightarrow \bar{x}, \exists t_n \in T_{\varepsilon_n}(x_n, v), \\ \text{s.t. } \rho_{t_n}(x_n, v) \rightarrow \rho(\bar{x}, v), \\ x^* = w^* - \lim_{n \rightarrow \infty} - \frac{\nabla_x g_{t_n}(x_n, \rho_{t_n}(x_n, v)Lv)}{\langle \nabla_x g_{t_n}(x_n, \rho_{t_n}(x_n, v)Lv), Lv \rangle} \end{array} \right\} \quad (16a)$$

and the (singular) (partial) Mordukhovich sub-differential satisfies:

$$\partial_x^\infty \rho(\bar{x}, v) \subseteq \left\{ x^* \in X^* : \begin{array}{l} \exists \varepsilon_n, \lambda_n \rightarrow 0^+, x_n \rightarrow \bar{x}, \exists t_n \in T_{\varepsilon_n}(x_n, v), \\ \text{s.t. } \rho_{t_n}(x_n, v) \rightarrow \rho(\bar{x}, v), \\ x^* = w^* - \lim_{n \rightarrow \infty} - \lambda_n \frac{\nabla_x g_{t_n}(x_n, \rho_{t_n}(x_n, v)Lv)}{\langle \nabla_x g_{t_n}(x_n, \rho_{t_n}(x_n, v)Lv), Lv \rangle} \end{array} \right\} \quad (16b)$$

An example

- Already when $T = \{\bar{t}\}$ is a singleton, g can not be entirely arbitrary.

Example

Consider $g(x, z_1, z_2) = \alpha(x)e^{h(z_1)} + z_2 - 1$ as a map $g : \mathbb{R} \times \mathbb{R}^2 \rightarrow \mathbb{R}$. with $\alpha(x) = x^2, x \geq 0$ and 0 otherwise. Moreover $h(t) = -1 - 4 \log(1 - \Phi(t))$, with Φ the c.d.f of a standard Gaussian r.v. Now with $\xi \sim \mathcal{N}(0, I)$, it follows that

- g is continuously differentiable, convex in (z_1, z_2)
- $g(0, 0, 0) < 0$
- $\varphi(x) := \mathbb{P}[g(x, \xi_1, \xi_2) \leq 0]$ is not locally Lipschitzian at $x = 0$.

Restricted growth

- This example makes it clear that some care should be taken with “unbounded directions”. Hence we introduce:

Definition

For any $x \in X$ and $l > 0$, we define

$$C_l(x) := \left\{ h \in X : \langle \nabla_x g_t(x', z), h \rangle \leq l \|L^{-1}z\|^{-m} \theta^{-1}(\|L^{-1}z\|^2) \|h\| \quad \forall x' \in \mathbb{B}_{1/l}(x), \quad \|L^{-1}z\| \geq l, \quad \forall t \in T \right\} \quad (17)$$

as the uniform l -cone of nice directions at x . Here θ^{-1} is defined as

$$\theta^{-1}(t) = \begin{cases} \frac{1}{\theta(t)} & \text{if } \theta(t) \neq 0, \\ +\infty & \text{if } \theta(t) = 0. \end{cases} \quad (18)$$

Moreover, we recall that its polar cone is denoted as $C_l^*(x)$.

Main result - I

Theorem (vA, Perez-Aros (2018))

Let $\xi \in \mathbb{R}^m$ be an elliptically symmetrically distributed random vector with mean 0, correlation matrix $R = LL^T$ and continuous generator. Consider the probability function $\varphi : X \rightarrow [0, 1]$, where X is a (separable) reflexive Banach space defined as

$$\varphi(x) = \mathbb{P}[g_t(x, \xi) \leq 0, \forall t \in T], \quad (19)$$

where $g_t : X \times \mathbb{R}^m \rightarrow \mathbb{R}$ are continuously differentiable maps convex in the second argument and T is an arbitrary index set.

Let $\bar{x} \in X$ be such that ...

Then the following formulæ hold true: ...

Main result - I

Theorem (vA, Perez-Aros (2018))

Let $\xi \in \mathbb{R}^m$ be an elliptically ... Let $\bar{x} \in X$ be such that

- 1** *a neighbourhood U of \bar{x} can be found such that $g|_{U \times \mathbb{R}^m}$ is finite valued and $\sup_{t \in T} g_t(x', 0) < 0$ for all $x' \in U$.*
- 2** *the set $\{(x, z) : g(x, z) = 0\}$ is closed in $U \times \mathbb{R}^m$*
- 3** *the outer-estimate S of $\partial_x^M \rho(x, v)$ is locally bounded at \bar{x} , $v \in \mathbb{S}^{m-1}$ such that $\rho(\bar{x}, v) < \infty$.*
- 4** *Either there exists $l > 0$ such that $C_l(\bar{x})$ has non-empty interior, or $M(\bar{x}) := \{z \in \mathbb{R}^m : g(\bar{x}, z) \leq 0\}$ is bounded.*

Then the following formulæ hold true: ...

Main result - I

Theorem (vA, Perez-Aros (2018))

Let $\xi \in \mathbb{R}^m$ be an elliptically ...

Let $\bar{x} \in X$ be such that ...

Then the following formulæ hold true:

- [(i)] $\partial^M \varphi(\bar{x}) \subseteq \text{cl}^* \left\{ \int_{v \in \mathbb{S}^{m-1}} \partial_x^M e(\bar{x}, v) d\mu_\zeta(v) - C_I^*(\bar{x}) \right\}$

- [(ii)] Provided that X is finite-dimensional,

$$\partial^M \varphi(\bar{x}) \subseteq \int_{v \in \mathbb{S}^{m-1}} \partial_x^M e(\bar{x}, v) d\mu_\zeta(v) - C_I^*(\bar{x}).$$

- [(iii)] $\partial^\infty \varphi(\bar{x}) \subseteq -C_I^*(\bar{x}).$

- [(vi)] $\partial^C \varphi(\bar{x}) \subseteq \overline{\text{co}} \left\{ \int_{v \in \mathbb{S}^{m-1}} \partial_x^M e(\bar{x}, v) d\mu_\zeta(v) - C_I^*(\bar{x}) \right\},$

where ∂^M , ∂^C and ∂^∞ refer respectively to the limiting (or Mordukhovich), the Clarke and (limiting) singular sub-differential sets of a map.

Moreover, the set $C_I^*(\bar{x})$ can be replaced by $\{0\}$ if $M(\bar{x})$ is bounded.

Main result - I

Theorem (vA, Perez-Aros (2018))

Finally, for every $v \in F(\bar{x}) = \text{Dom}(\rho(x, \cdot))$

$$\partial_x^M e(\bar{x}, v) \subseteq f_{\mathcal{R}}(\rho(\bar{x}, v)) S^M(\bar{x}, v)$$

with

$$S^M(\bar{x}, v) \subseteq \left\{ x^* \in X^* : \begin{array}{l} \exists \varepsilon_n \rightarrow 0^+, x_n \rightarrow \bar{x}, \exists t_n \in T_{\varepsilon_n}(x_n, v), \\ \text{s.t. } \rho_{t_n}(x_n, v) \rightarrow \rho(\bar{x}, v), \\ x^* = w^* - \lim_{n \rightarrow \infty} - \frac{\nabla_x g_{t_n}(x_n, \rho_{t_n}(x_n, v)Lv)}{\langle \nabla_z g_{t_n}(x_n, \rho_{t_n}(x_n, v)Lv), Lv \rangle} \end{array} \right\} \quad (19)$$

Discussion of the assumptions

When the family $\{g_t\}_{t \in T}$ is uniformly locally Lipschitzian at \bar{x} , i.e., iff at every $\bar{z} \in \mathbb{R}^m$:

$$\limsup_{z \rightarrow \bar{z}} \sup \{ \|\nabla g_t(x, z)\| \mid x \in U, t \in T \} < \infty. \quad (20)$$

Then

- if $g(\bar{x}, 0)$ is finite, then on some neighbourhood $U : g_{U \times \mathbb{R}^m}$ is finite valued
- if $g(\bar{x}, 0) < 0$ then this holds on a neighbourhood
- the set \mathcal{S} is locally bounded

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through equicontinuous subdifferentiability

Motivation

- The previous Theorem has given us already a first formula: an outer-estimate of the various subdifferentials.
- The outer estimate involves \mathcal{S} , related to special limits
- If \mathcal{S} , can be replaced by a smaller set, better formulæ may result.
- This will require some additional assumptions

Equicontinuous subdifferentiability

Definition

Let $f_t : X \rightarrow \mathbb{R} \cup \{\infty\}$ be a family of l.s.c. functions indexed by $t \in T$. The family is called strongly equicontinuously subdifferentiable at $\bar{x} \in X$ if for any weak-* neighbourhood V^* of the origin in X^* there is some $\varepsilon > 0$ such that

$$\partial^M f_t(x) \subseteq \partial^M f_t(\bar{x}) + V^*, \quad (21)$$

for all $t \in T_\varepsilon(x)$ $x \in \mathbb{B}_\varepsilon(\bar{x})$, with $|f_t(x) - f(\bar{x})| \leq \varepsilon$ where $T_\varepsilon(x)$ refers to the ε -active index set related to the supremum function of the family f_t .

Main Result - II

Theorem (vA, Perez-Aros (2018))

Let $\xi \in \mathbb{R}^m$ be an elliptically symmetrically distributed random vector with mean 0, correlation matrix $R = LL^T$ and continuous generator. Consider the probability function $\varphi : X \rightarrow [0, 1]$, where X is a reflexive Banach space defined as

$$\varphi(x) = \mathbb{P}[g_t(x, \xi) \leq 0, \forall t \in T], \quad (22)$$

where $g_t : X \times \mathbb{R}^m \rightarrow \mathbb{R}$ are continuously differentiable maps convex in the second argument and T is an arbitrary index set. Then let $\bar{x} \in X$ be such that the assumptions 1-4 **as before** hold and in addition:

- 1** that at any $v \in \mathbb{S}^{m-1}$, the family of resolvent mappings $\{\rho_t(\cdot, v)\}_{t \in T}$ is strongly equicontinuously subdifferentiable at \bar{x} .

Then in the previous formulæ we may consider

$$\partial_x^M e(\bar{x}, v) \subseteq f_{\mathcal{R}}(\rho(\bar{x}, v)) \bigcap_{\varepsilon > 0} \text{cl}^{w*} \left\{ -\frac{\nabla_x g_t(\bar{x}, \rho_t(\bar{x}, v)Lv)}{\langle \nabla_x g_t(\bar{x}, \rho_t(\bar{x}, v)Lv), Lv \rangle} : \begin{array}{l} x \in \mathbb{B}(\bar{x}, v), \ t \in T_{\varepsilon}^P(x, v) \\ \text{with } |\rho_t(x, v) - \rho(\bar{x}, v)| \leq \varepsilon \end{array} \right\}.$$

at $v \in F(\bar{x}) = \mathcal{D}\text{om}(\rho(\bar{x}, v))$.

through some degree of compactness

Some compactness assumptions

Assumption

Let T be a metric space and there exists a neighbourhood U of \bar{x} such that:

- 1 $g|_{U \times \mathbb{R}^m}$ is finite valued.
- 2 $g(x, 0) < 0$ for all $x \in U$.
- 3 The function $G : T \times U \times \mathbb{R}^m \rightarrow X \times X^* \times \mathbb{R}^m$ given by $G(t, x, z) = (g_t(x, v), \nabla_x g_t(x, z), \nabla_z g_t(x, z))$ is continuous.
- 4 The active index set $T^g(x, z)$ is non-empty for every $(x, z) \in \mathcal{K} = \{(x, z) \in U \times \mathbb{R}^m : g(x, z) = 0\}$.
- 5 The set $\bigcup_{(x, z) \in \mathcal{K}} T^g(x, z)$ is relatively compact.

through some degree of compactness

Implications of these assumptions

Lemma

Under the *compactness Assumptions* one has that:

- 1 the set \mathcal{R} is closed.
- 2 for every $T \times U \times \mathbb{S}^{m-1} \ni (t_n, x_n, v_n) \rightarrow (t, x, v) \in T \times U \times \mathbb{S}^{m-1}$,
 $\rho_{t_n}(x_n, v_n) \rightarrow \rho_t(x, v)$.
- 3 the set $T_\varepsilon^\rho(x, v)$ is closed for every $(x, v) \in U \times \mathbb{S}^{m-1}$.

through some degree of compactness

Explicit growth condition

Definition

Let $\theta_{\mathcal{R}} : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ be an increasing mapping such

$$\lim_{r \rightarrow +\infty} r f_{\mathcal{R}}(r) \theta_{\mathcal{R}}(r) = 0. \quad (23)$$

We say that $\{g_t : t \in T\}$ satisfies the $\theta_{\mathcal{R}}$ -growth condition uniformly on T at \bar{x} if for some $l > 0$

$$\|\nabla_x g_t(x, z)\| \leq l \theta_{\mathcal{R}}\left(\frac{\|z\|}{\|L\|}\right) \text{ for all } x \in \mathbb{B}_{1/l}(\bar{x}) \quad \forall z : \|z\| \geq l; \quad \forall t \in T. \quad (24)$$

through some degree of compactness

Main Result - III

Theorem (vA, Perez-Aros (2018))

Let $\xi \in \mathbb{R}^m$ be an elliptically symmetrically distributed random vector with mean 0, correlation matrix $R = LL^T$ and continuous generator. Consider the probability function $\varphi : X \rightarrow [0, 1]$, where X is a reflexive Banach space defined as

$$\varphi(x) = \mathbb{P}[g_t(x, \xi) \leq 0, \forall t \in T], \quad (25)$$

where $g_t : X \times \mathbb{R}^m \rightarrow \mathbb{R}$ are continuously differentiable maps convex in the second argument and T is a metric space. Then let $\bar{x} \in X$ be such that

1 the compactness assumptions hold

2 Either $\{g_t : t \in T\}$ satisfies the $\theta_{\mathcal{R}}$ -growth condition uniformly on T at \bar{x} , or $M(\bar{x}) := \{z \in \mathbb{R}^m : g(\bar{x}, z) \leq 0\}$ is bounded.

Then φ is locally Lipschitz at \bar{x} and the following formulæ hold true:

$$\partial^M \varphi(\bar{x}) \subseteq \text{cl}^{w*} \int_{v \in F(\bar{x})} \left\{ -f_{\mathcal{R}}(\rho(x, v)) \frac{\nabla_x g_t(x, \rho(x, v)Lv)}{\langle \nabla_z g_t(x, \rho(x, v)Lv), Lv \rangle} : t \in T^P(x, v) \right\} d\mu_{\zeta}(v) \quad (26a)$$

$$\partial^C \varphi(\bar{x}) \subseteq \int_{v \in F(\bar{x})} \text{Co} \left\{ -f_{\mathcal{R}}(\rho(x, v)) \frac{\nabla_x g_t(x, \rho(x, v)Lv)}{\langle \nabla_z g_t(x, \rho(x, v)Lv), Lv \rangle} : t \in T^P(x, v) \right\} d\mu_{\zeta}(v), \quad (26b)$$

where ∂^M refers to the limiting (or Mordukhovich) sub-differential and ∂^C to the Clarke-subdifferential.

Summary

In this talk we have discussed recent results on differentiation for probability functions acting on infinite systems. The results have been taken from:

- W. van Ackooij and P. Pérez-Aros. [Generalized differentiation of probability functions acting on an infinite system of constraints](#).
Submitted draft - available soon on arxiv, pages 1–24, 2018

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