

VARIATIONAL ANALYSIS: APPROXIMATION METHODOLOGY

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A STOCHASTIC LINEAR PROGRAM?

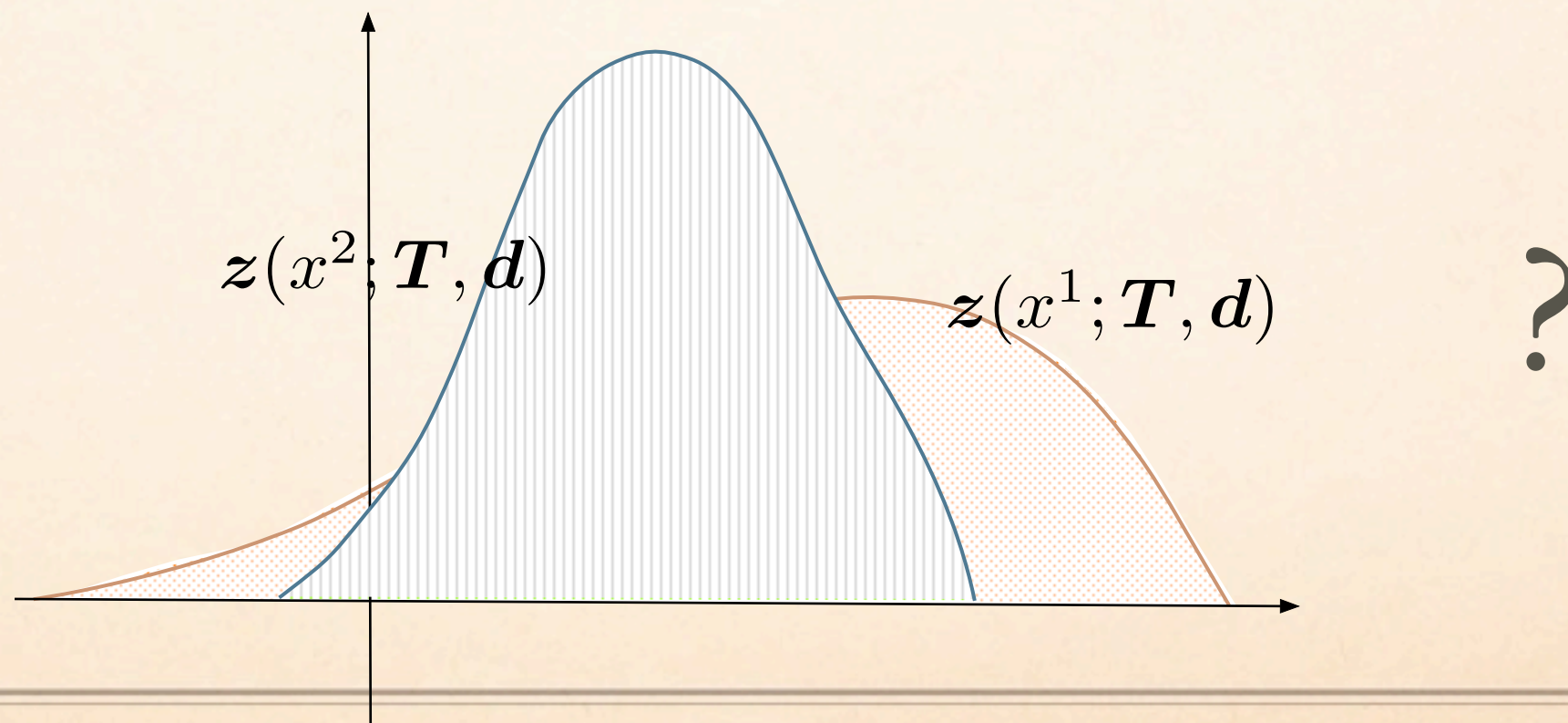
$\min z = \langle c, x \rangle$ such that $Tx \leq d$, $x \in \mathbb{R}_+^n$, say 4 variables, 2 constraints

c_j = unit cost of activity j , nonegative activities $x_j \geq 0$

t_{ij} = # units of i -resource consumed by activity j , random

d_i = i -resource units available, random

Decision problem: choose best x ! best returns distribution $z(x; T, d)$



A PRODUCT MIX PROBLEM

$\min \langle c, x \rangle$ such that $Tx \leq d$, $x \in \mathbb{R}_+^n$, say 4 variables, 2 constraints

$c_j = -$ profit of activity x_j

per dresser production profit (manufacturer)

$t_{ij} =$ per unit i -resource consumed by activity j

time consumed for carpentry and finishing

$d_i =$ i -resource units available

of hours available for carpentry and finishing

but actually t_{ij} and d_i are random variables \Rightarrow additional 'overtime'

$\min \langle c, x \rangle + \mathbb{E} \{ \langle q, y \rangle \}$ such that $y \geq Tx - d$, $x \in \mathbb{R}_+^n$, $y \geq 0$.

(T, d) uniformly distributed components \Rightarrow infinite # of variables, constraints

discretized, say each 4-values, \Rightarrow l.p. with $\approx 2 \cdot 10^6$ variables, constraints

1. consistent approximation? 2. design of solution procedures

VALUATION

environment process: $\{\xi^t \in \mathbb{R}^d\}_{t=0}^T$ history: $\vec{\xi}^t$, $\xi = \xi^T$

price process: $S^t(\vec{\xi}) \in \mathbb{R}^n$; numéraire (risk-free): $S_1^t \equiv 1$

contingent claims: $\left\{G^t(\vec{\xi})\right\}_{t=1}^T$; investment strategy: $\left\{X^t(\vec{\xi})\right\}_{t=0}^T$

portfolio value at t : $\langle S^t(\vec{\xi}), X^t(\vec{\xi}) \rangle$

PRICING: T-bonds, options, swaps, insurance contracts, mortgages, ...

$\max \mathbb{E} \left\{ \langle S^T, X^T \rangle \right\}$ such that $\langle S^t, X^t \rangle \leq G^t + \langle S^t, X^{t-1} \rangle$, $t = 1 \rightarrow T$

$\langle S^0, X^0 \rangle \leq G^0$, $\langle S^T, X^T \rangle \leq G^T$ a.s.

What if the random vectors are not discrete? What if $t \in [0, T]$?

Associated Risk-Neutral Probabilities: exists?, can be approximated?

HOMOGENIZATION

conductor: $\Omega \subset \mathbb{R}^3$, composite ≥ 2 materials,
 $0 \leq a(\xi, x) \leq \kappa_{\text{bdd}}$, stationary process w.r.t. location
 heat u : with rapidly varying stochastic coefficients
 $\nabla \cdot (a(\xi, x) \nabla u(\xi, x)) = h(x)$, $x \in \Omega$ & bdry conditions
 homogenized equation with effective coefficient a

$$\nabla \cdot (a(x) \nabla u(x)) = h(x), \quad x \in \Omega \quad \& \quad \text{bdry cond.}$$

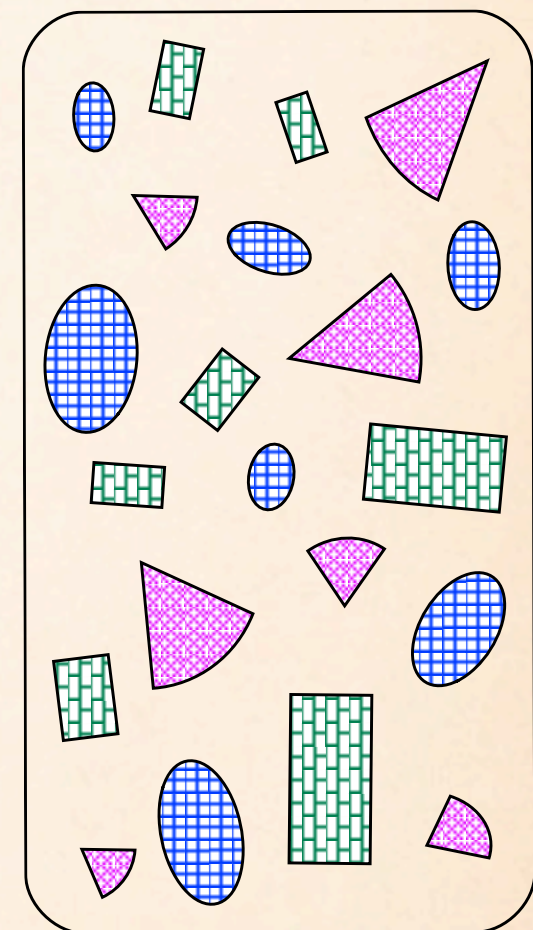
such that $u(x) = \mathbb{E} \{ u(\xi, x) \}$. $a(x) \neq \mathbb{E} \{ a(\xi, x) \}$

$$\min_{u \in H_0^1(\Omega)} g(\xi, u) = \frac{1}{2} \int_{\Omega} a(\xi, x) |\nabla u|^2 dx - \langle h, u \rangle$$

$g : L^2 \rightarrow (-\infty]$, to be minimized for all ξ

homogenization: find g^{hom} such that

$$\mathbb{E} \{ u(\xi, \cdot) \} = \bar{u}(\cdot) \in \arg \min \left[g^{\text{hom}}(u) \mid u \in H_0^1(\Omega) \right]$$



OPTIMALITY CONDITIONS

$$\min \mathbb{E}\{f_0(\xi, x)\} \text{ such that } \text{prob}\{f_i(\xi, x) \leq 0, i = 1, \dots, m\} \leq \alpha$$

simplifying: $\alpha = 1$, $f_i(\xi, x) = f_i(x)$, constraint qualification satisfied,

Optimality conditions (KKT) or stationary point

\bar{x} optimal if $\exists \bar{y} = (\bar{y}_1, \dots, \bar{y}_m)$ such that

a) $f_i(\bar{x}) \leq 0, i = 1, \dots, m$

b) $\bar{y}_i \geq 0$ and $\bar{y}_i \perp f_i(\bar{x}), i = 1, \dots, m$

c) $0 \in \nabla \left(Ef_0(x) + \sum_{i=1}^m \bar{y}_i f_i(x) \right) = \mathbb{E}\{\nabla f_0(\xi, x)\} + \sum_{i=1}^m \bar{y}_i \nabla f_i(x)$

OPTIMALITY CONDITIONS

Solving the "generalized equation":

$$C(\xi) = \left\{ (x, y) \left| \begin{array}{l} f_i(x) \leq 0, y_i \geq 0, y_i \perp f_i(x), \quad i = 1 \rightarrow m \\ 0 \in \left[\nabla f_0(\xi, x) + \sum_{i=1}^m y_i \nabla f_i(x) \right] \end{array} \right. \right\}$$

$$C : \Xi \rightrightarrows (\mathbb{R}^n \times \mathbb{R}^m), \quad (\bar{x}, \bar{y}) \in \mathbb{E}\{C(\xi)\}$$

$$\text{sample } \xi^k, (x^k, y^k) \in C(\xi^k), \quad ? \frac{1}{v} \sum_{k=1}^v (x^k, y^k) \rightarrow_{?} (\bar{x}, \bar{y}).$$

WHAT TO REMEMBER?

- ❖ Stochastic problems get quickly unmanageably large
- ❖ Approximation (discretization, sampling, ...) is a must
- ❖ Approximation “of the classical type” might or might not work, including the standard approx. of stochastic processes
- ❖ The presence of constraints, in particular inequality constraints, radically changes the paradigm.
- ❖ The search for “averaged solution” doesn’t result from straightforward averaging.

VARIATIONAL PROBLEMS

Optimization: $\min f(x)$ sucht that $x \in X \subset \mathcal{X}$

Variational Inequality: $x \in C$ such that $-G(x) \in N_C(x)$

Complementarity Problems: $0 \leq x \perp H(x) \geq 0$

Generalized Equations: $S(x) \ni 0, S : X \rightrightarrows U$ (set-valued)

Economic Equilibrium: $\forall a \in \mathcal{A}, x \in \operatorname{argmax}_{C_a} u_a(p, x)$

market equilibrium: $0 \leq p$ such that $D(p, x_A) \in N_C(p)$

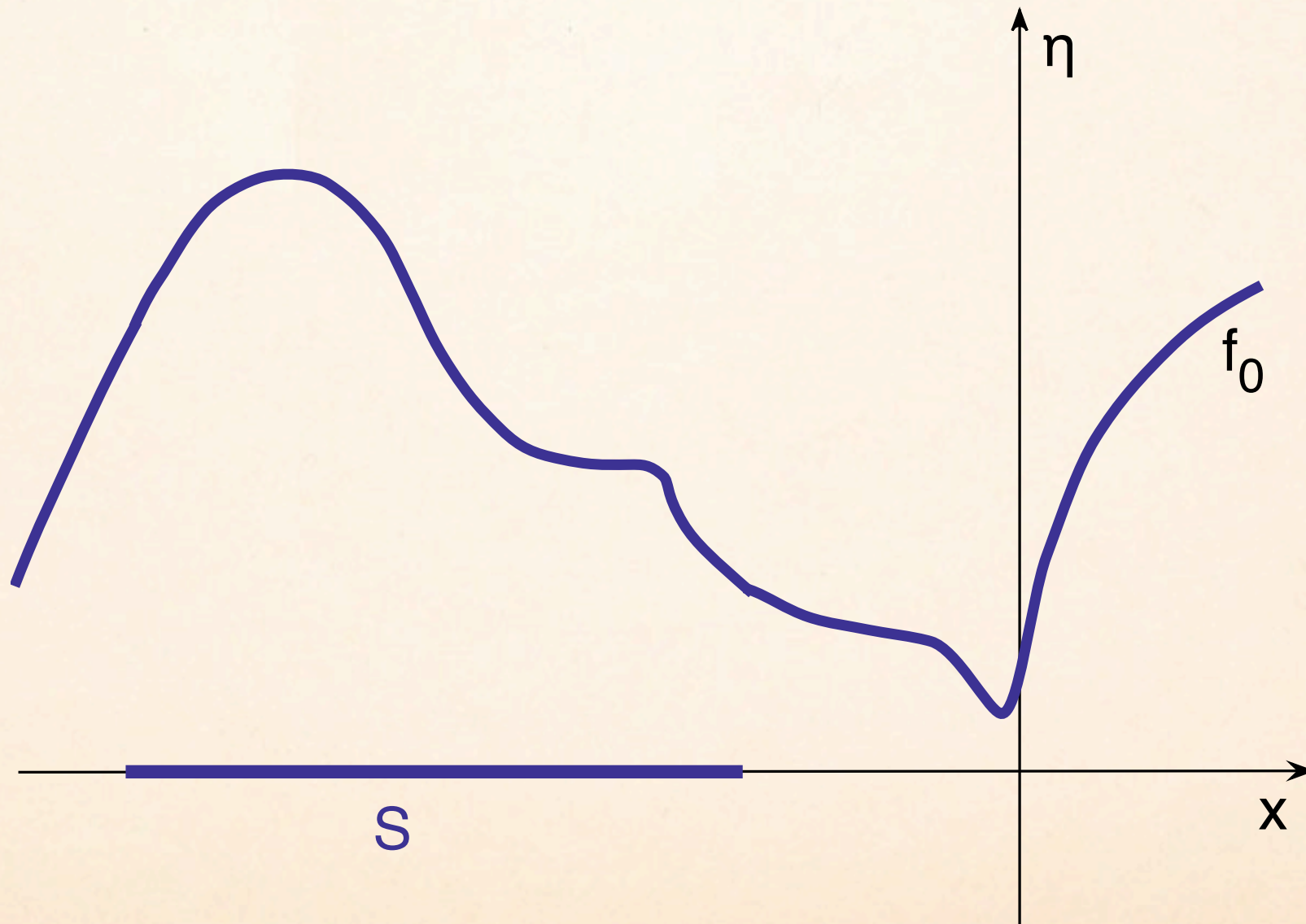
Nash Games: $\bar{x}_a \in \operatorname{argmax} r_a(x_a, \bar{x}_{-a}), \quad \forall a \in \mathcal{A}$

Each one comes with applications in a stochastic environment

OPTIMIZATION PROBLEM

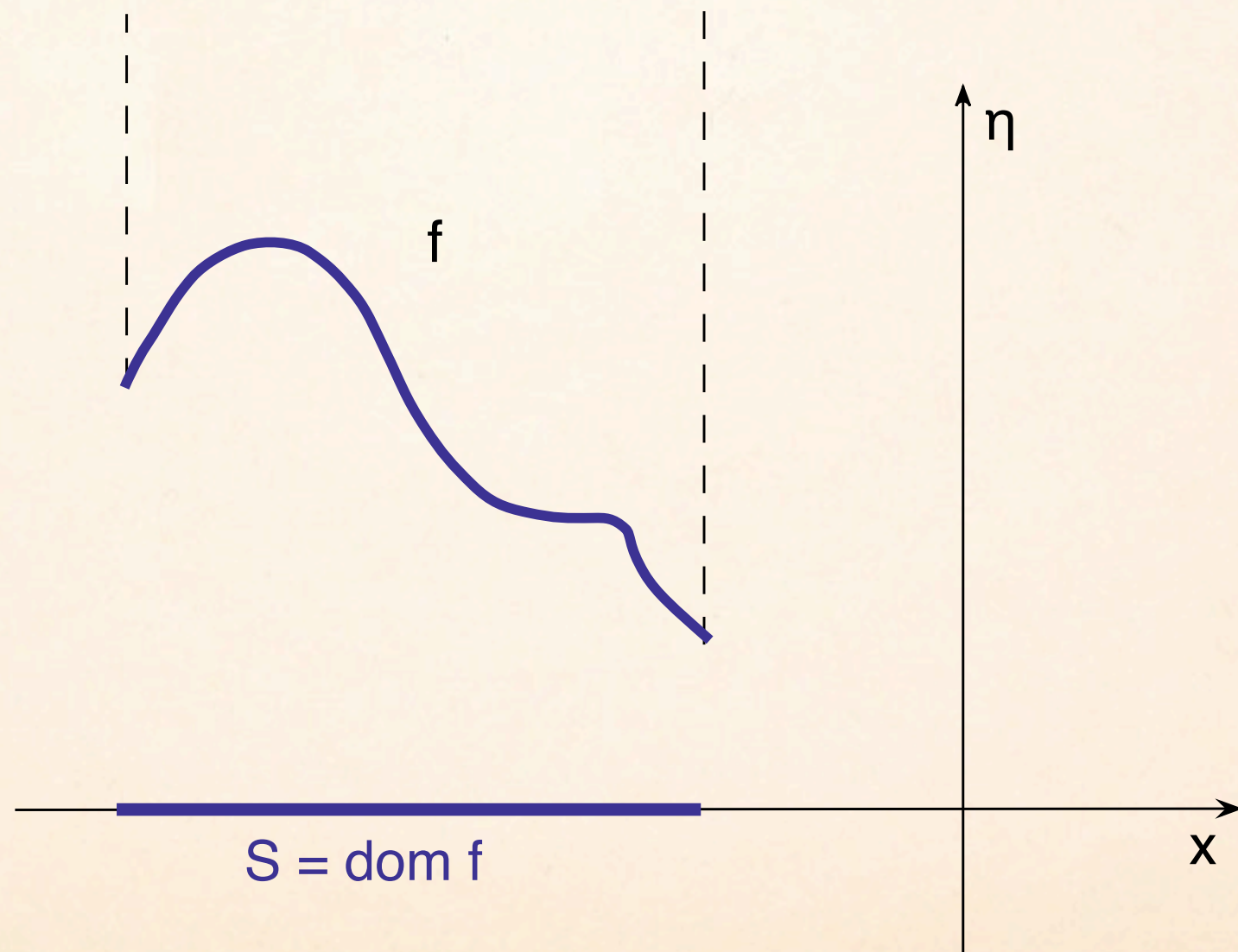
$$\min f(x), x \in S,$$

$$S = \{x \in \mathbb{R}^n \mid f_i(x) \leq 0, i = 1 \rightarrow s, f_i(x) = 0, i = s + 1 \rightarrow m\}$$



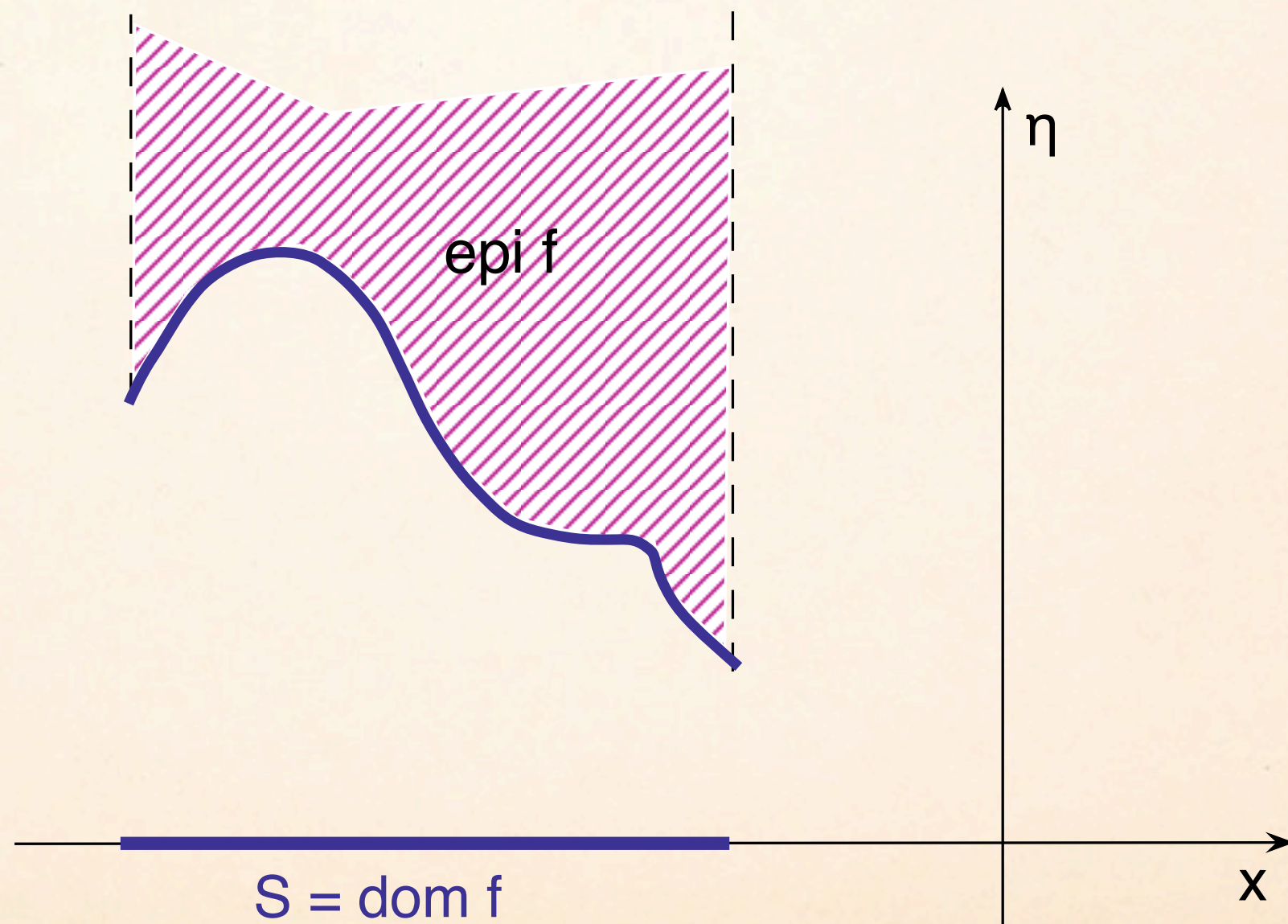
EXTENDED-REAL VALUED FCN

$\min f$ on \mathbb{R}^n , $f = f_0 + \iota_S(x)$, ι_S indicator function of S



FUNCTIONS & EPIGRAPHS

$$\text{epi } f = \{(x, \alpha) \mid f(x) \leq \alpha\}$$



FUNCTIONS & EPIGRAPHS

$$\text{epi } f = \{(x, \alpha) \mid f(x) \leq \alpha\}$$

$$f \text{ lsc at } x : \liminf_{x' \rightarrow x} f(x') \geq f(x), \quad f \text{ usc at } x : \limsup_{x' \rightarrow x} f(x') \leq f(x)$$

$$f \text{ lsc} \Leftrightarrow \text{epi } f \text{ closed}$$

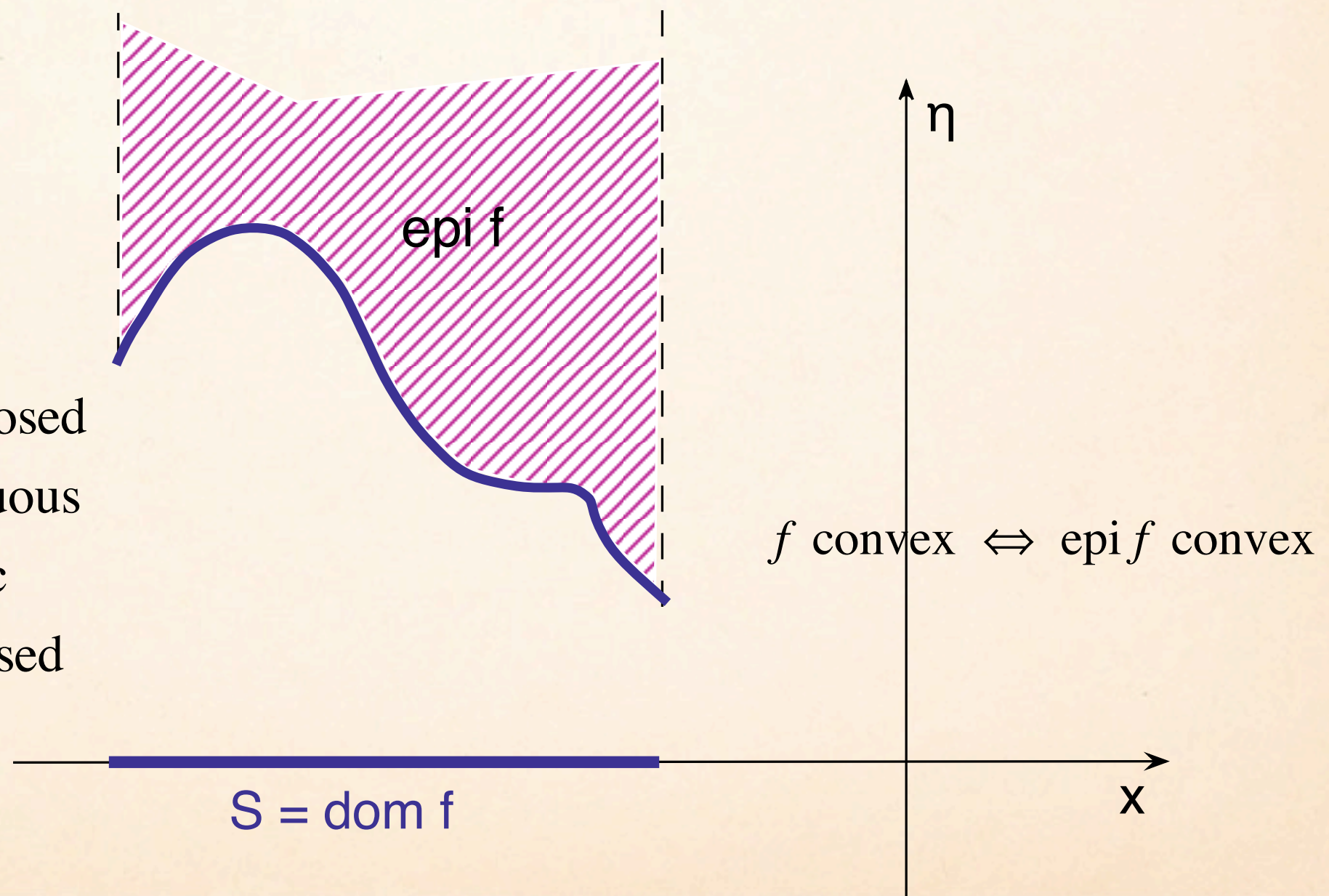
$$f \text{ usc} \Leftrightarrow \text{hypo } f \text{ closed}$$

$$f \text{ lsc} \Leftrightarrow \text{epi } f \text{ closed}$$

lower semicontinuous

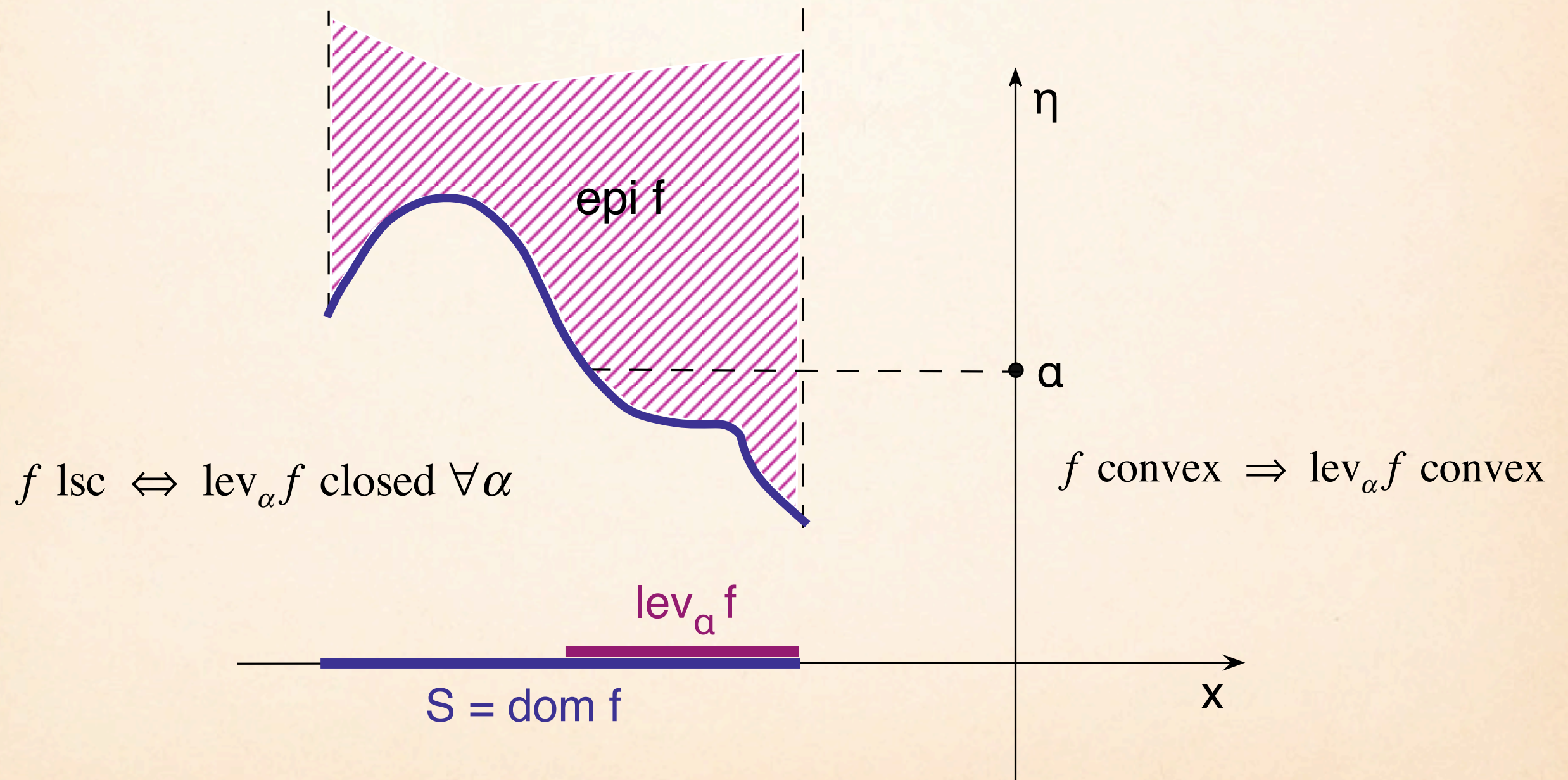
$$f \text{ usc} \Leftrightarrow -f \text{ lsc}$$

$$\Leftrightarrow \text{hypo } f \text{ closed}$$



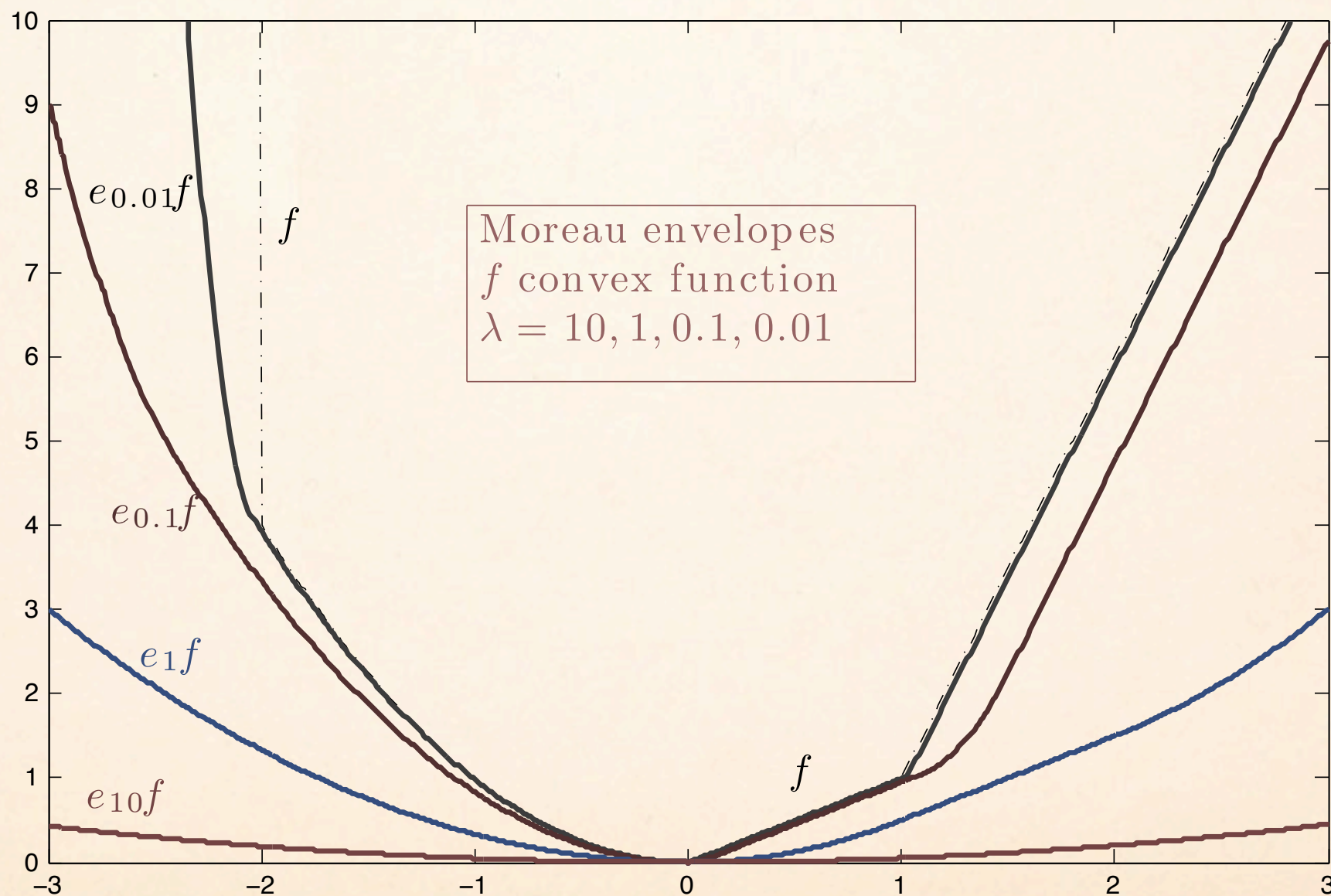
LEVEL SETS & CONSTRAINTS

$$\text{lev}_\alpha = \{x \in \mathbb{R}^n \mid f(x) \leq \alpha\}$$



EPI-SUMS (INF-CONVOLUTION)

$$\text{epi } f \# \text{ epi } g = \inf_w \{f(w) + g(w - x)\} \quad e_\lambda f(x) \text{ with } g = \frac{1}{2\lambda} |\cdot|$$



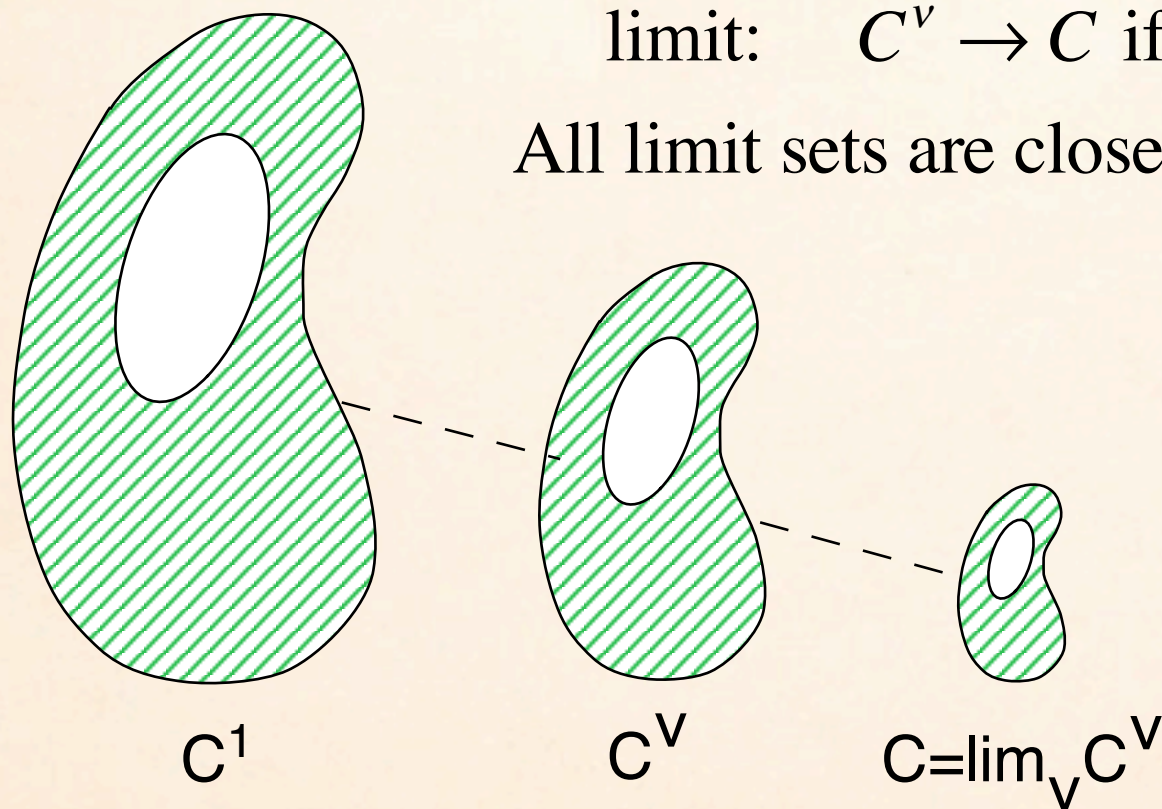
APPROXIMATION: CONVERGENCE

outer limit: $Ls_v C^v = \{x \in \text{cluster-points}\{x^v\}, x^v \in C^v\}$

inner limit: $Li_v C^v = \{x = \lim_v x^v, x^v \in C^v \subset \mathbb{R}^n\} \subset Ls_v C^v$

limit: $C^v \rightarrow C$ if $C = Li_v C^v = Ls_v C^v$ (Painlevé)

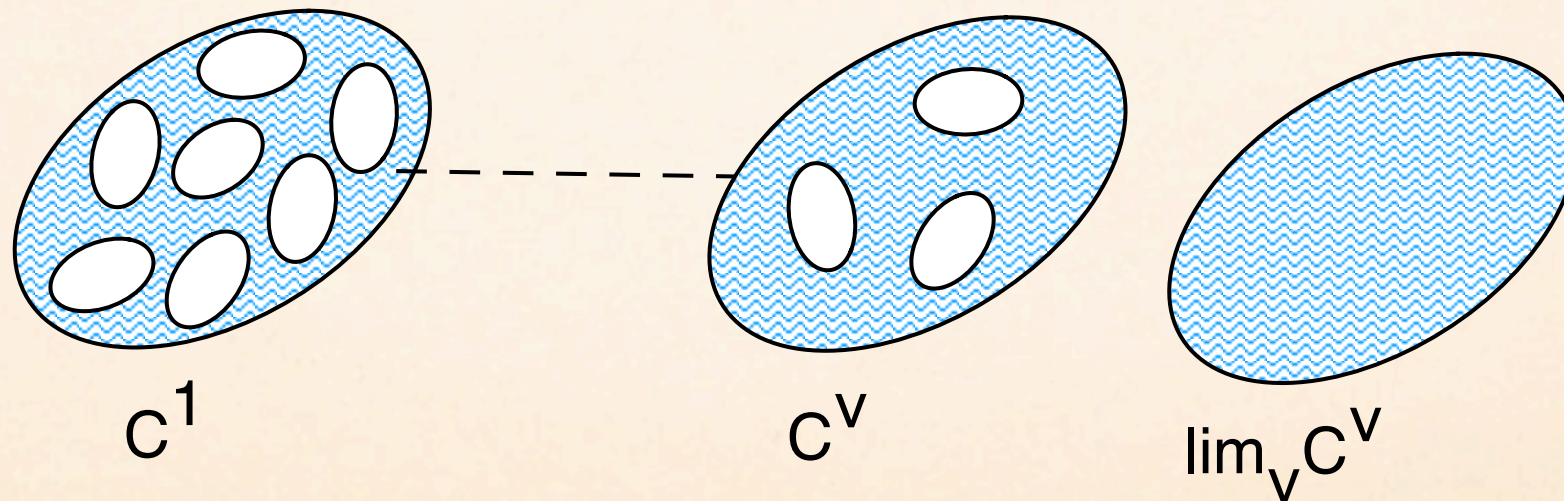
All limit sets are closed



CONVEX LIMIT SETS

$$C^v \text{ convex} \Rightarrow \text{Li}_v C^v \text{ convex} \Rightarrow \text{Lm}_v C^v \text{ convex (if it exists)} \\ \not\Rightarrow \text{Ls}_v C^v \text{ convex}$$

but convexity can result from taking limits



EPI-LIMITS

$$\{f^v : \mathbb{R}^n \rightarrow \bar{\mathbb{R}}, v \in \mathbb{N}\}$$

lower epi-limit: $e\text{-li}_v f^v$ such that $\text{epi}(e\text{-li}_v f^v) = \text{Ls}_v \text{epi } f^v$

upper epi-limit: $e\text{-ls}_v f^v$ such that $\text{epi}(e\text{-ls}_v f^v) = \text{Li}_v \text{epi } f^v$

epi-limit: $f^v \xrightarrow[e]{} f$ when $f = e\text{-li}_v f^v = e\text{-ls}_v f^v$, $f = e\text{-lm}_v f^v$

all epi-limits are lsc (closed epigraphs), $e\text{-li}_v f^v \leq e\text{-ls}_v f^v$

f^v convex $\Rightarrow e\text{-ls}_v f^v$ is convex and so is $e\text{-lm}_v f^v$ (if it exists)

Convergence of level sets / constraint sets:

$$f \leq e\text{-li}_v f^v \Leftrightarrow \text{Ls}_v(\text{lev}_{\alpha_v} f^v) \subset \text{lev}_{\alpha} f \quad \forall \alpha_v \rightarrow \alpha$$

$$f \geq e\text{-ls}_v f^v \Leftrightarrow \text{Ls}_v(\text{lev}_{\alpha_v} f^v) \subset \text{lev}_{\alpha} f \quad \text{for some } \alpha_v \rightarrow \alpha$$

Operations: sums, scalar multiplication, epi-sums

SV-CONVERGENCE SOLUTIONS, MINIMIZERS, ...

A^ν solutions of (generalized) equations
minimizers of a sequence of functions
saddle points or min-sup points of bifunctions
 ε - A^ν : $\varepsilon > 0$ approximate solutions, minimizers,
 A solution set, minimizers, ... of corresponding limit

Definition: A^ν **sv-converge** to A , written $A^\nu \Rightarrow_{sv} A$, if

a) $\bar{x} \in \text{cluster-points} \{x^\nu \in A^\nu\} \Rightarrow \bar{x} \in A$

b) $\bar{x} \in A \Rightarrow \exists \varepsilon_\nu \searrow 0, x^\nu \in \varepsilon_\nu\text{-}A^\nu \rightarrow \bar{x}$

CONVERGENCE OF MINIMIZERS

SV-CONVERGENCE OF MINIMIZERS

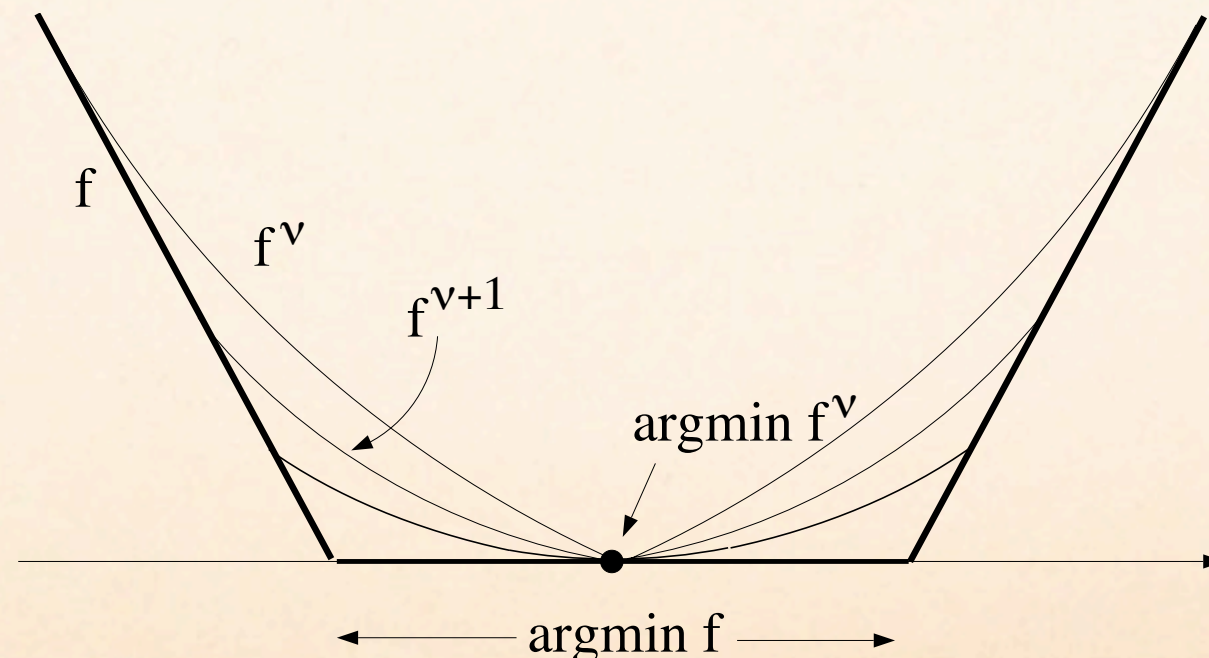
$$f^v \xrightarrow{e} f, x \in \text{cluster} \{x^v \in \arg \min f^v\} \Rightarrow x \in \arg \min f$$

$$f^v \xrightarrow{e} f, \inf f \in \mathbb{R}, x \in \arg \min f \Rightarrow \exists \varepsilon_v \searrow 0, x^v \in \varepsilon_v\text{-arg min } f^v \rightarrow x$$

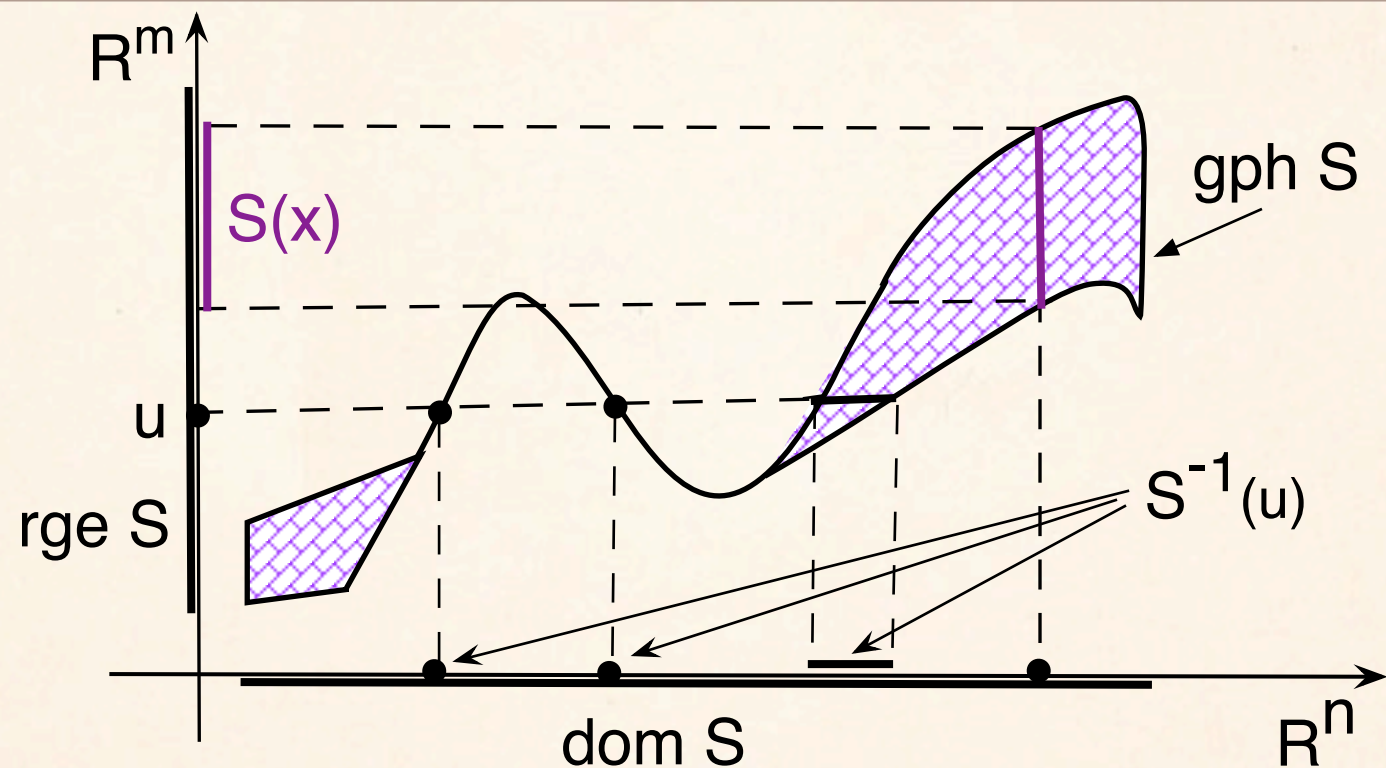
$$f^v \xrightarrow{e} f \not\Rightarrow \arg \min f^v \rightarrow \arg \min f$$

$$f^v \xrightarrow{e} f, \inf f^v \rightarrow \inf f \in \mathbb{R} \Leftrightarrow \{f^v\}_{v \in \mathbb{N}} \text{ epi-tight, i.e.}$$

$$\forall \varepsilon > 0, \exists B \text{ compact s.t. } \inf_B f^v \leq \inf f^v + \varepsilon, \forall v \geq v_\varepsilon$$



SET-VALUED MAPPINGS



S osc (outer semicontinuous) at \bar{x} if $\text{Ls}_{x \rightarrow \bar{x}} S(x) \subset S(\bar{x})$

S osc \Leftrightarrow gph S closed

S isc (inner semicontinuous) at \bar{x} if $\text{Li}_{x \rightarrow \bar{x}} S(x) \supset S(\bar{x})$

S continuous if it's isc and osc

GRAPHICAL CONVERGENCE SV-CONVERGENCE OF SOLUTIONS

$S^v \rightarrow_g S$ when $\text{gph } S^v \rightarrow \text{gph } S$ (as subsets of $\mathbb{R}^n \times \mathbb{R}^m$)

Generalized Equations \sim Inclusions

$S^v, S : \mathbb{R}^n \rightrightarrows \mathbb{R}^m$, $S^v(x) \ni u^v$, $S(x) \ni \bar{u}$ and $S^v \rightarrow_g S, u^v \rightarrow \bar{u}$. Then

$$\bar{x} \in \text{cluster-pts} \left\{ x^v \mid S^v(x^v) \ni u^v \right\} \Rightarrow S(\bar{x}) \ni \bar{u}$$

$$S(\bar{x}) \ni \bar{u} \Rightarrow \exists \hat{u}^v \rightarrow \bar{u} \text{ with } S^v(\hat{x}^v) \ni \hat{u}^v \text{ and } \hat{x}^v \rightarrow \bar{x}$$

$S^v \rightarrow_p S$ pointwise doesn't yield convergence of sol'ns

Applications: $F(x) = b$, $-G(x) \in N_C(x), \dots$ variational problems

RATES OF CONVERGENCE

Excess distance function:

$$e_\rho(A, B) = \inf \{ \eta \geq 0 \mid A \cap \rho\mathbb{B} \subset B + \eta\mathbb{B} \}, \quad \rho > 0$$

Estimate of set distance:

$$\hat{dl}_\rho(A, B) = \max[e_\rho(A, B), e_\rho(B, A)]$$

Set-distance:

$$dl_\rho(A, B) = \max_{x \in \rho\mathbb{B}} |d(x, A) - d(x, B)|,$$

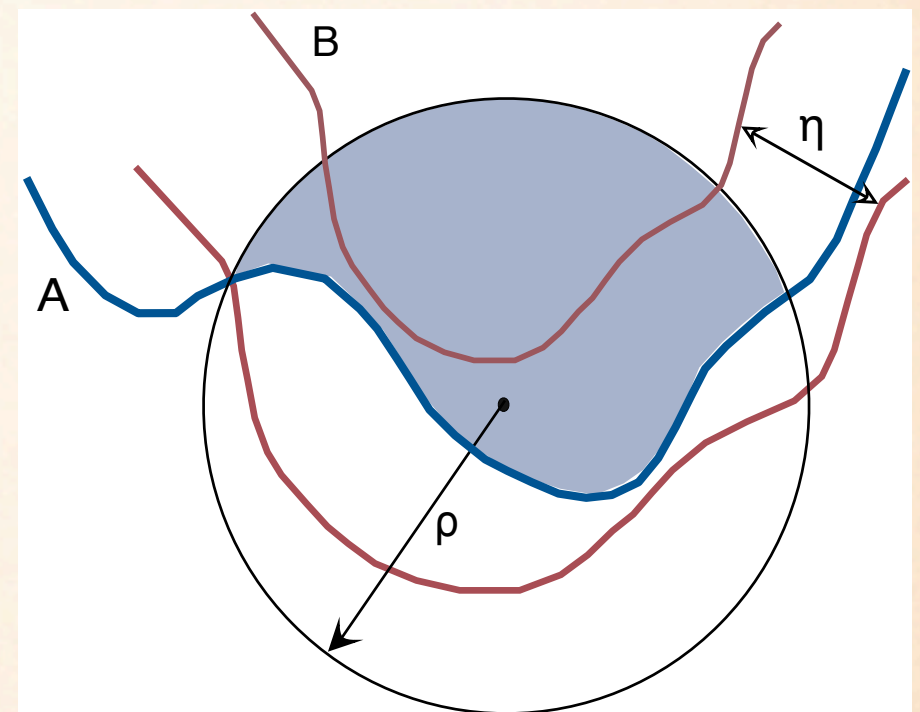
$$d(x, C) = \inf_{y \in C} |y - x|$$

Pompeiu-Hausdroff distance: $\rho = \infty$

$$\hat{dl}_\rho(A, B) \leq dl_\rho(A, B) \leq \hat{dl}_{\rho'}(A, B),$$

$$\rho' \geq 2\rho + \max[d(0, A), d(0, B)]$$

$$C^\nu \rightarrow C \Leftrightarrow dl_\rho(C^\nu, C) \rightarrow 0 \Leftrightarrow \hat{dl}_\rho(C^\nu, C) \rightarrow 0 \quad \forall \rho \geq 0$$



EPI-DISTANCE

$\text{lsc-fcns}(\mathbb{R}^n) =$ space of all lsc functions from $\mathbb{R}^n \rightarrow \bar{\mathbb{R}} = [-\infty, \infty]$

$$\hat{dl}_\rho(f, g) = \hat{dl}_\rho(\text{epi } f, \text{epi } g), \quad dl_\rho(f, g) = dl_\rho(\text{epi } f, \text{epi } g), \quad \rho \geq 0$$

$$\mathbb{B}^{n+1} = \mathbb{B}^n \times [-1, 1]$$

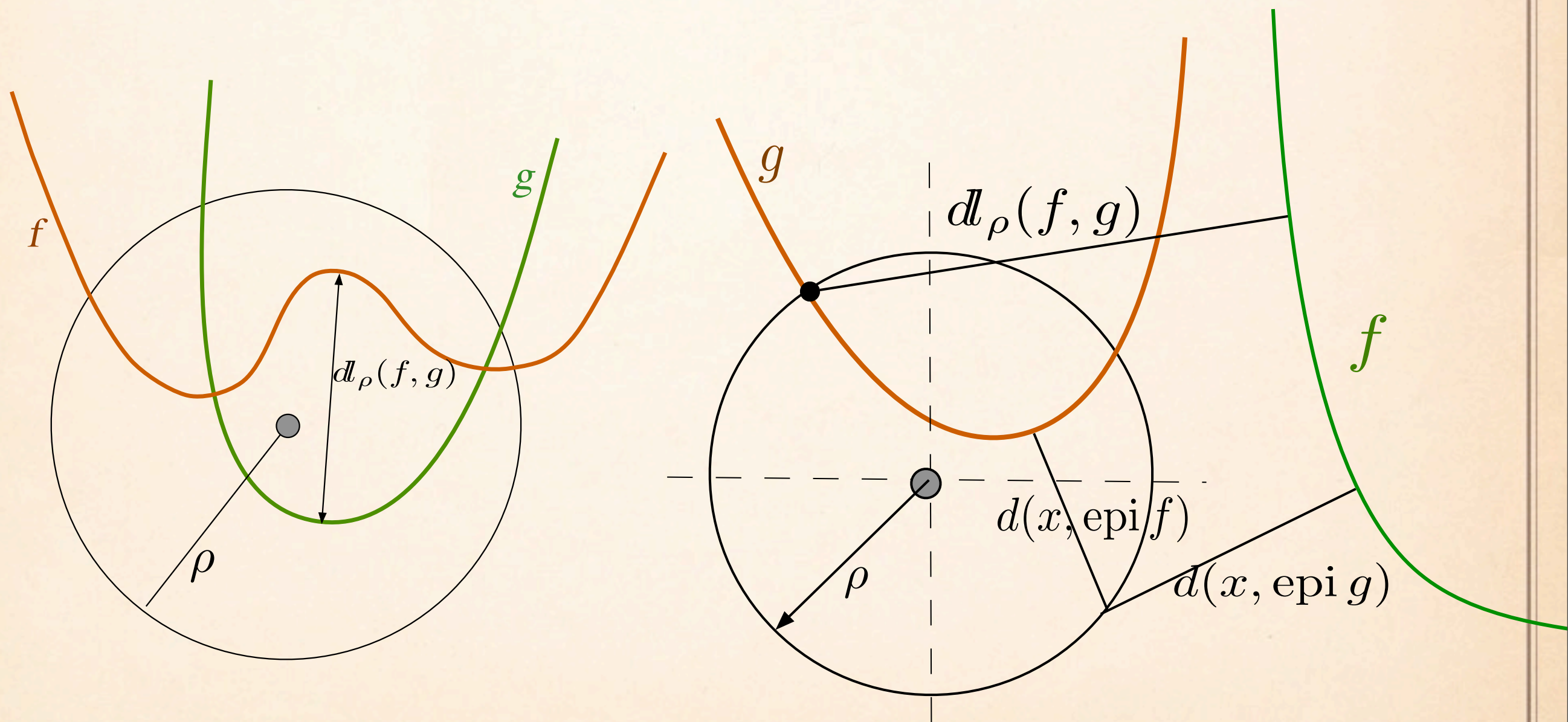
$$dl(f, g) = \int_{\rho \geq 0} e^{-\rho} dl_\rho(f, g) d\rho, \quad \text{epi-distance}$$

$$f^\nu, f \in \text{lsc-fcns}(\mathbb{R}^n), f^\nu \rightarrow_e f \Leftrightarrow dl(f^\nu, f) \rightarrow 0$$

$$\text{also } dl_\rho(f^\nu, f) \rightarrow 0, \forall \rho \geq \bar{\rho} > 0, \dots$$

$(\text{lsc-fcns}(\mathbb{R}^n) \setminus \{f \equiv \infty\}, dl)$ complete metric space

EPI-DISTANCE

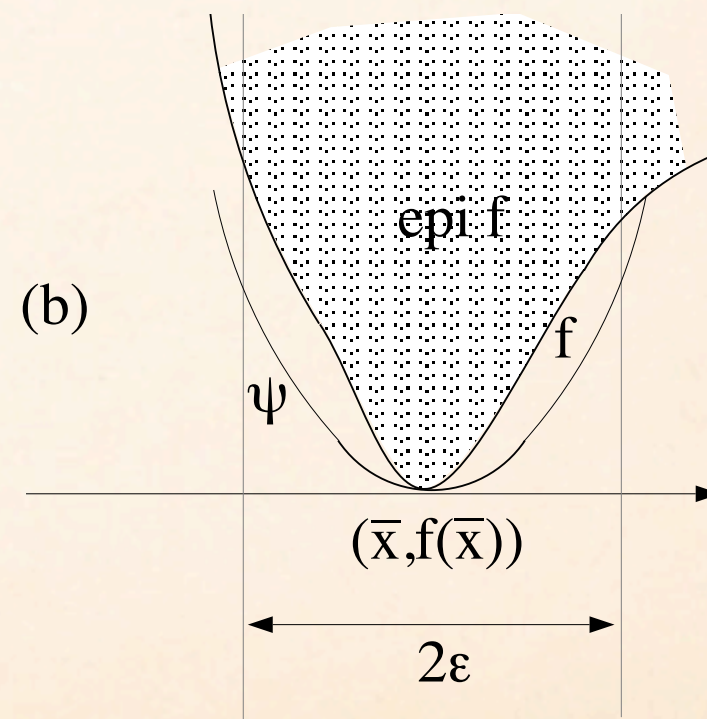
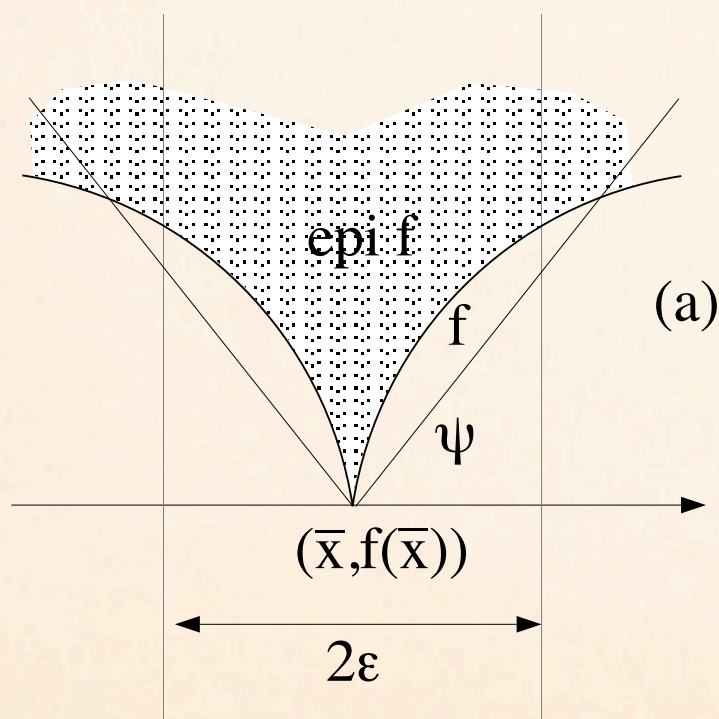


QUANTITATIVE ESTIMATE

under ψ -conditioning for $f, g \in \text{lsc-fcns}(\mathbb{R}^n)$, $\inf f, \inf g \in \mathbb{R}$

$$|\min_{\rho\mathbb{B}} g - \min f| \leq dl_{\rho}(f, g)$$

$$\arg \min_{\rho\mathbb{B}} g \subset \arg \min f + \psi(dl_{\rho}(f, g))\mathbb{B}$$



APPROXIMATE SOLUTIONS: QUANTITATIVE ESTIMATE

$f, g : \mathbb{R}^n \rightarrow \bar{\mathbb{R}}$, proper, lsc, convex functions

$\arg \min f, \arg \min g \neq \emptyset$

ρ_0 large enough so that $\rho_0 \mathbb{B}$ meets $\arg \min f$ & $\arg \min g$

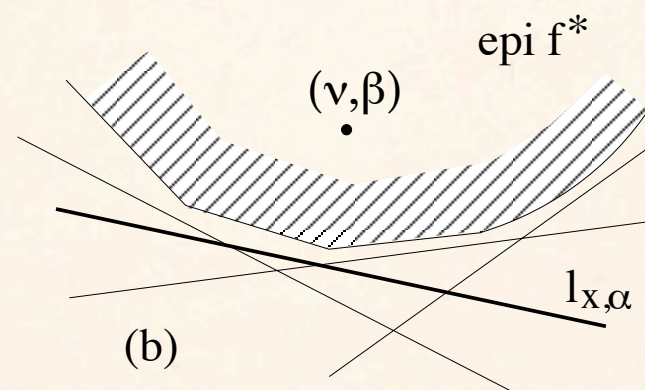
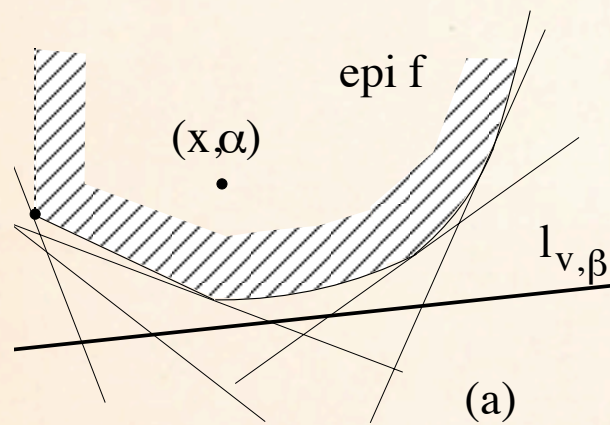
$\min f \geq -\rho_0, \min g \geq -\rho_0$

Then, with $\rho > \rho_0, \epsilon > 0, \bar{\eta} = dl_\rho(f, g)$

$$\begin{aligned} d\hat{l}_\rho(\epsilon\text{-arg min } f, \epsilon\text{-arg min } g) &\leq \bar{\eta} \left(1 + \frac{2\rho}{\bar{\eta} + \epsilon/2} \right) \\ &\leq (1 + 4\rho / \epsilon) d\hat{l}_\rho(f, g) \end{aligned}$$

CONVEX FUNCTIONS

(Wijsman) $f^v \xrightarrow{e} f \Leftrightarrow (f^v)^* \xrightarrow{e} f^* = \sup_x (\langle v, x \rangle - f(x)), \quad f^v \text{ lsc, convex}$



conjugate
functions

$$f^v \xrightarrow{e} f \not\Leftrightarrow f^v \xrightarrow{p} f \text{ (pointwise)} \quad \& \quad f^v \xrightarrow{p} f \not\Leftrightarrow f^v \xrightarrow{e} f$$

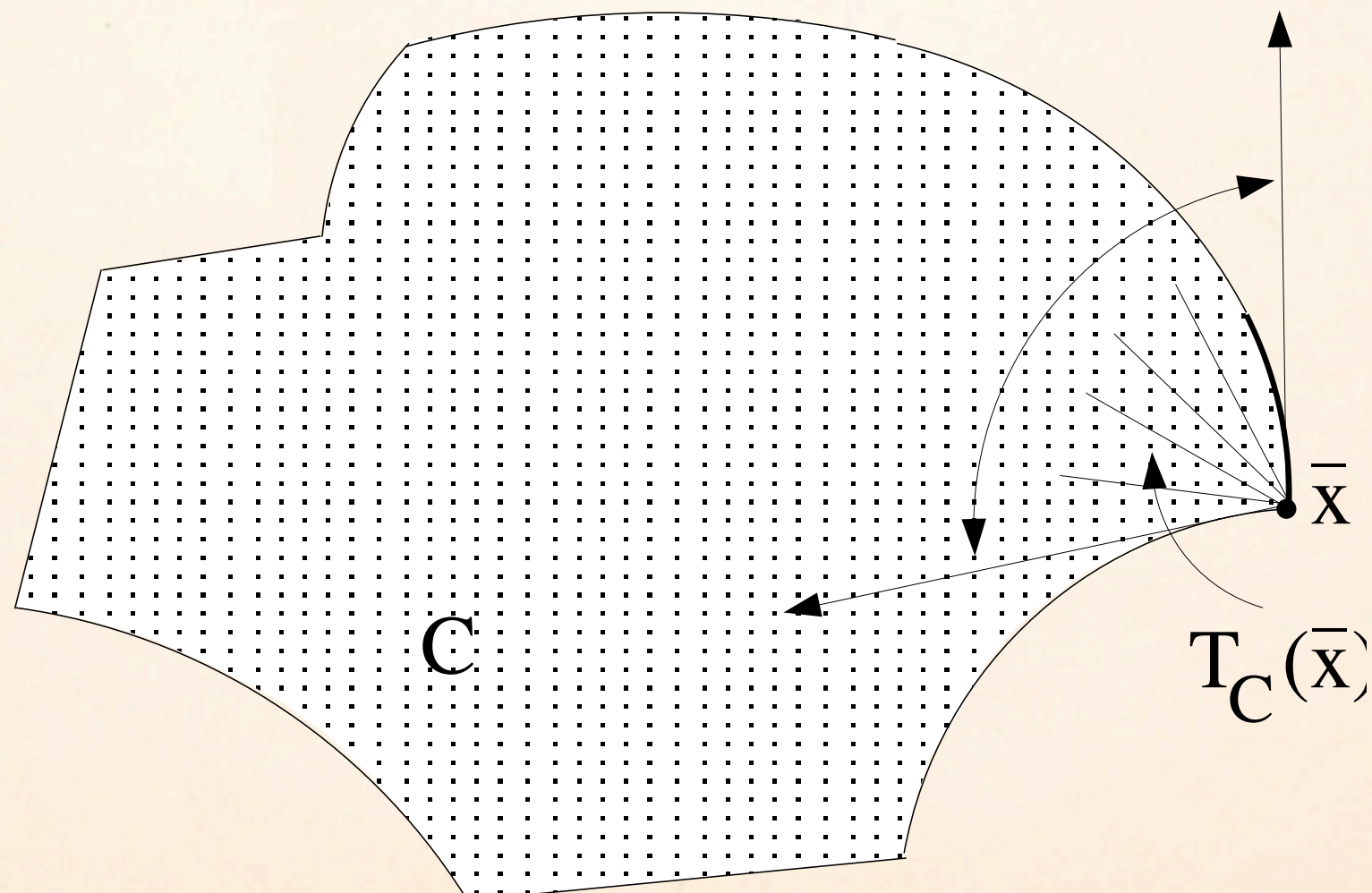
$$f^v \xrightarrow{e} f \equiv f^v \xrightarrow{p} f \Leftrightarrow \{f^v\}_{v \in \mathbb{N}} \text{ is equi-lsc}$$

$$\text{(Walkup-Wets)} \quad dl_{csm}(f, g) = dl_{csm}(f^*, g^*) \quad [\approx dl(f, g) = dl(f^*, g^*)]$$

VARIATIONAL GEOMETRY

TANGENT CONE

$w \in T_C(x)$, tangent to C at $x \in C$, if $|x^\nu - x| / \tau_\nu \rightarrow w$ for $x^\nu \xrightarrow{C} x, \tau_\nu \searrow 0$



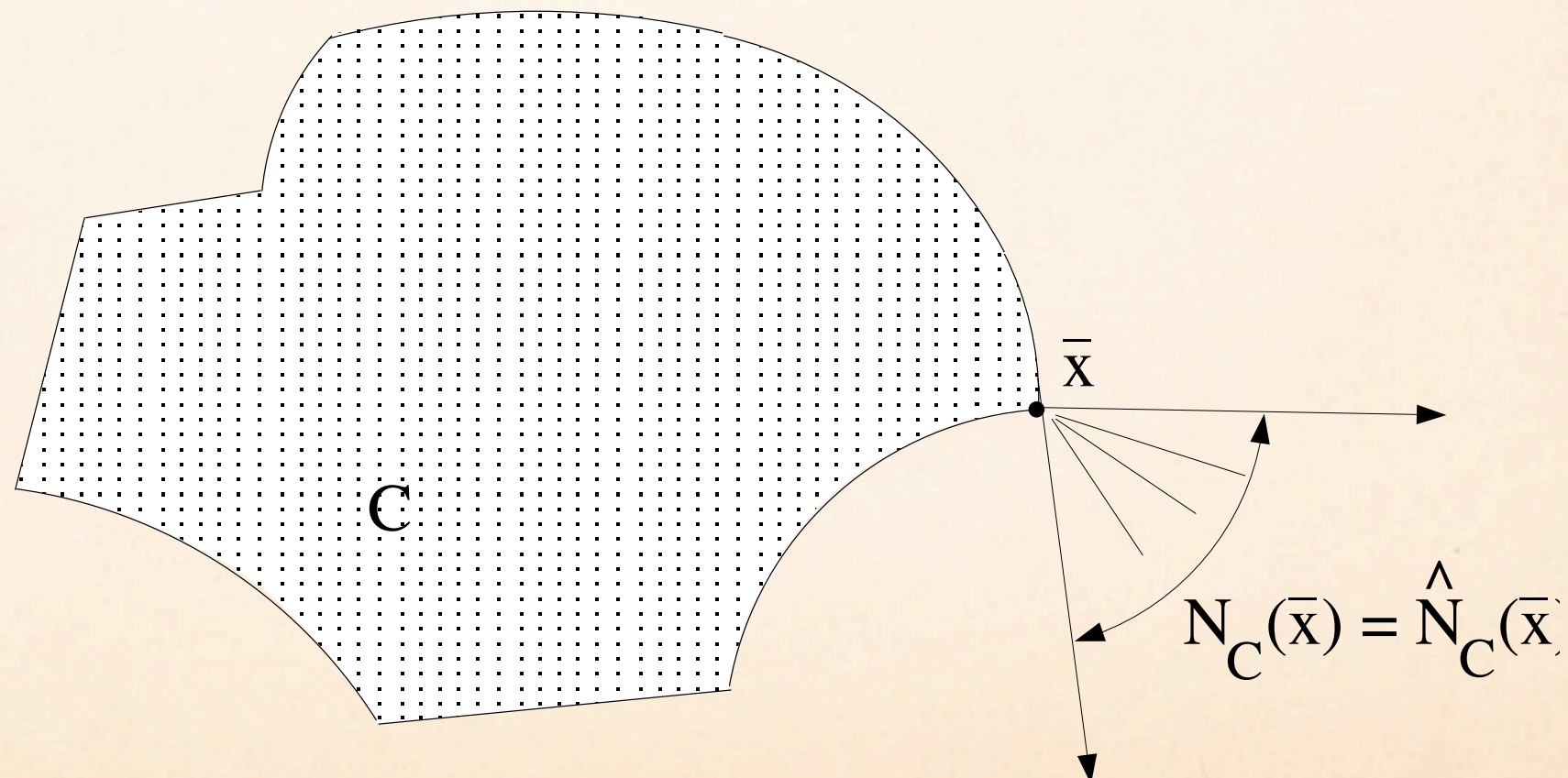
VARIATIONAL GEOMETRY

NORMAL CONE

$v \in \hat{N}_C(\bar{x})$, regular normal at $\bar{x} \in C$, if $\langle v, x - \bar{x} \rangle \leq o(\|x - \bar{x}\|)$, $\forall x \in C$

$v \in N_C(\bar{x})$, normal at $\bar{x} \in C$, if $\exists x^v \xrightarrow{C} \bar{x}$ and $v^v \rightarrow v$ with $v^v \in \hat{N}_C(x^v)$

normal cones: closed cones, $\hat{N}_C(\bar{x})$ convex



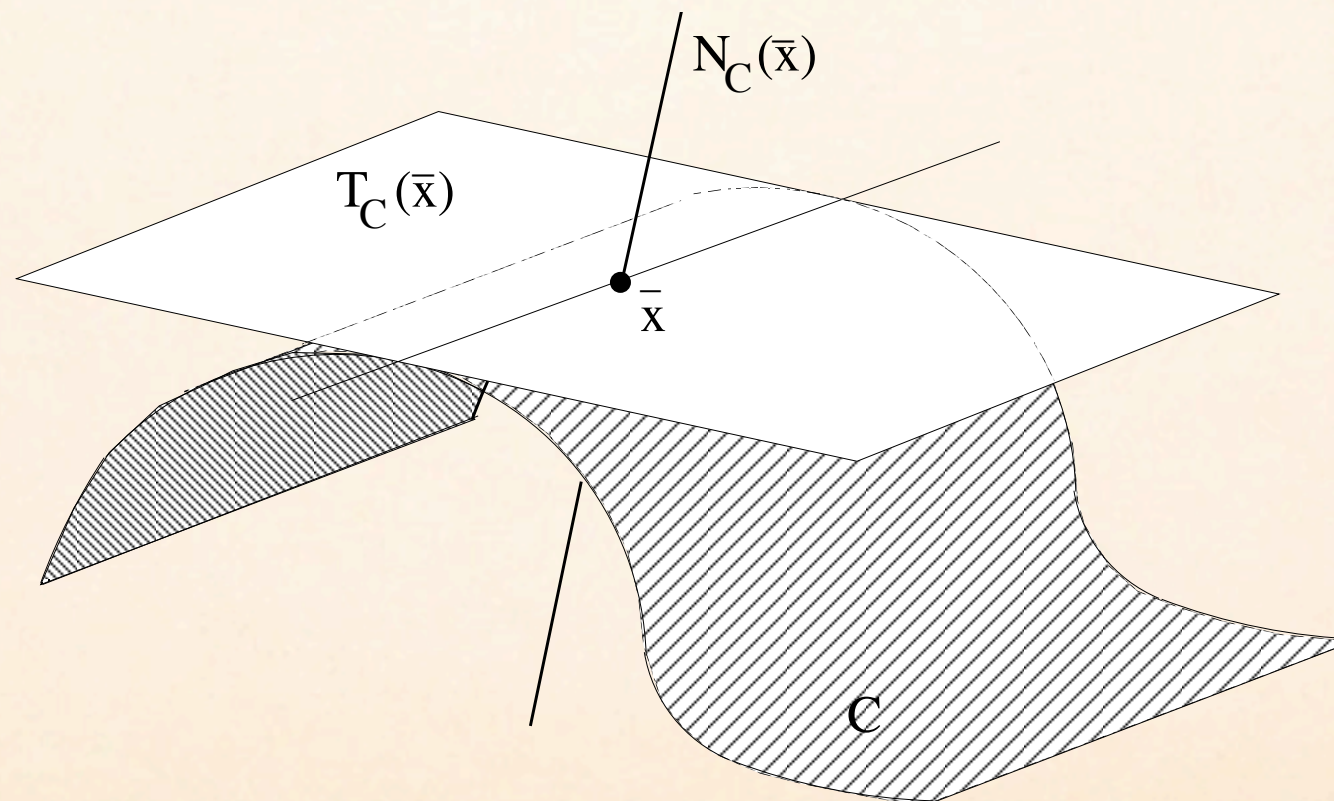
CLARKE REGULARITY

C **Clarke regular** at \bar{x} if C locally closed & $N_C(x) = \hat{N}_C(\bar{x})$

which implies $N_C(\bar{x})$ is convex if C regular at \bar{x}

In general, $N_C(\bar{x}) = \text{Ls}_{x \rightarrow_C \bar{x}} N_C(x) \supset \hat{N}_C(\bar{x})$

Smooth manifolds and closed convex set are regular (also locally)



SUBGRADIENTS

$v \in \hat{\partial}f(\bar{x})$ regular subgradient if $f(x) \geq f(\bar{x}) + \langle v, x - \bar{x} \rangle + o(\|x - \bar{x}\|)$

$$\hat{\partial}f(\bar{x}) = \left\{ v \mid (v, -1) \in \hat{N}_{\text{epi } f}(\bar{x}, f(\bar{x})) \right\}, \text{ closed and convex}$$

$v \in \partial f(\bar{x})$ subgradient if $\exists x^v \rightarrow_f \bar{x}, v^v \in \hat{\partial}f(x^v)$ with $v^v \rightarrow v$

$$\partial f(\bar{x}) = \left\{ v \mid (v, -1) \in N_{\text{epi } f}(\bar{x}, f(\bar{x})) \right\}, \text{ closed}$$

$x \mapsto \partial f(x)$ osc f -attentive convergence: $\Rightarrow \text{Ls}_{x \rightarrow_f \bar{x}} \partial f(x) \subset \partial f(\bar{x})$

f differentiable at $\bar{x} : \hat{\partial}f(\bar{x}) = \nabla f(\bar{x}) = \partial f(\bar{x})$

f regular at $\bar{x} : f$ locally lsc with $\partial f(\bar{x}) = \hat{\partial}f(\bar{x})$ (f locally convex, e.g)

$$\partial \iota_C(x) = N_C(x) \text{ when } C \text{ is convex}$$

OPTIMALITY

$\min f = f_0 + \iota_C$, optimality: " $0 \in \partial f(\bar{x})$ "

generally, $\partial(f + g) \neq \partial f + \partial g$

$\mathbb{C}.\mathbb{Q}.$ (Constraint Qualification): $-N_C(\bar{x}) \cap \partial^\infty f_0(\bar{x}) = \{0\}$

$v \in \partial^\infty f_0(\bar{x}) =$ horizon subgradient if

$$\exists x^v \rightarrow_f \bar{x}, v^v \in \hat{\partial} f(x^v), \lambda_v \searrow 0 \text{ \& } \lambda_v v^v \rightarrow v$$

with $\mathbb{C}.\mathbb{Q}.$ \bar{x} locally optimal $\Rightarrow \partial f_0(\bar{x}) + N_C(\bar{x}) \ni 0$

f convex (\Rightarrow regular), $\partial f_0(\bar{x}) + N_C(\bar{x}) \ni 0 \Rightarrow$

globally optimal (without $\mathbb{C}.\mathbb{Q}.$)

ATTOUCH'S THEOREM

(initial proof: via Moreau envelopes)

$f^v, f : \mathbb{R}^n \rightarrow \bar{\mathbb{R}}$, proper, convex, lsc and $\lambda > 0$

The following are equivalent:

a) $f^v \rightarrow_e f$

b) the mappings $\partial f^v \rightarrow_g \partial f$ and

$$\exists v^v \in \partial f^v(x^v), \bar{v} \in \partial f(\bar{x}), (x^v, v^v) \rightarrow (\bar{x}, \bar{v}), f^v(x^v) \rightarrow f(\bar{x})$$

(convergence of an integration constant)

c) $P_\lambda f^v \rightarrow_p P_\lambda f = \arg \min_w \left\{ f(w) + \frac{1}{2\lambda} |w - \bullet|^2 \right\}$ and

$$\exists \bar{x}, x^v \rightarrow \bar{x} \text{ such that } e_\lambda f^v(x^v) \rightarrow e_\lambda f(\bar{x})$$

in situation b): also $f^{v*}(v^v) \rightarrow f^*(\bar{v})$

II. MOPEC

*“Multi-Optimization Problems
with Equilibrium Constraints”*

THE MOPEC “FAMILY” ...

- ❖ saddle-point problems: Lagrangians, zero-sum games, Hamiltonians
- ❖ equilibrium: classical mechanics, Wardrop, economic (Walras, etc.)
- ❖ variational inequalities: finance, ecological models, complementarity, PDE
- ❖ non-cooperative games: pricing, generalized Nash equilibrium
- ❖ finding fixed points: Brouwer-type, Kakutani-type (set-valued), MPEC
- ❖ minimal surface problems, ... , mountain pass solutions,
- ❖ ... and the dynamic versions, and the **stochastic (dynamic)** versions.
- ❖ solving inclusions (equivalently, generalized equations): $S(x) \ni 0$

PRIMARY OBJECTIVE: CONSTRUCTIVE THEORY

- ❖ Exhibits and exploits the interrelation between these problems
- ❖ Existence theory: (mostly, not exclusively)
 - ❖ Aubin & Ekeland, “Applied Nonlinear Analysis” (Chap. 6), 1984
 - ❖ Facchinei & Pang, “Finite Dimensional Variational Inequalities and Complementarity problems” (2003)
 - ❖ Iusem & Sosa (+ Kasay), “Existence of solutions to equilibrium problems” (2005-....)
- ❖ Approximation theory \Rightarrow algorithmic strategies + existence

SADDLE FUNCTIONS EPI/HYPO CONVERGENCE

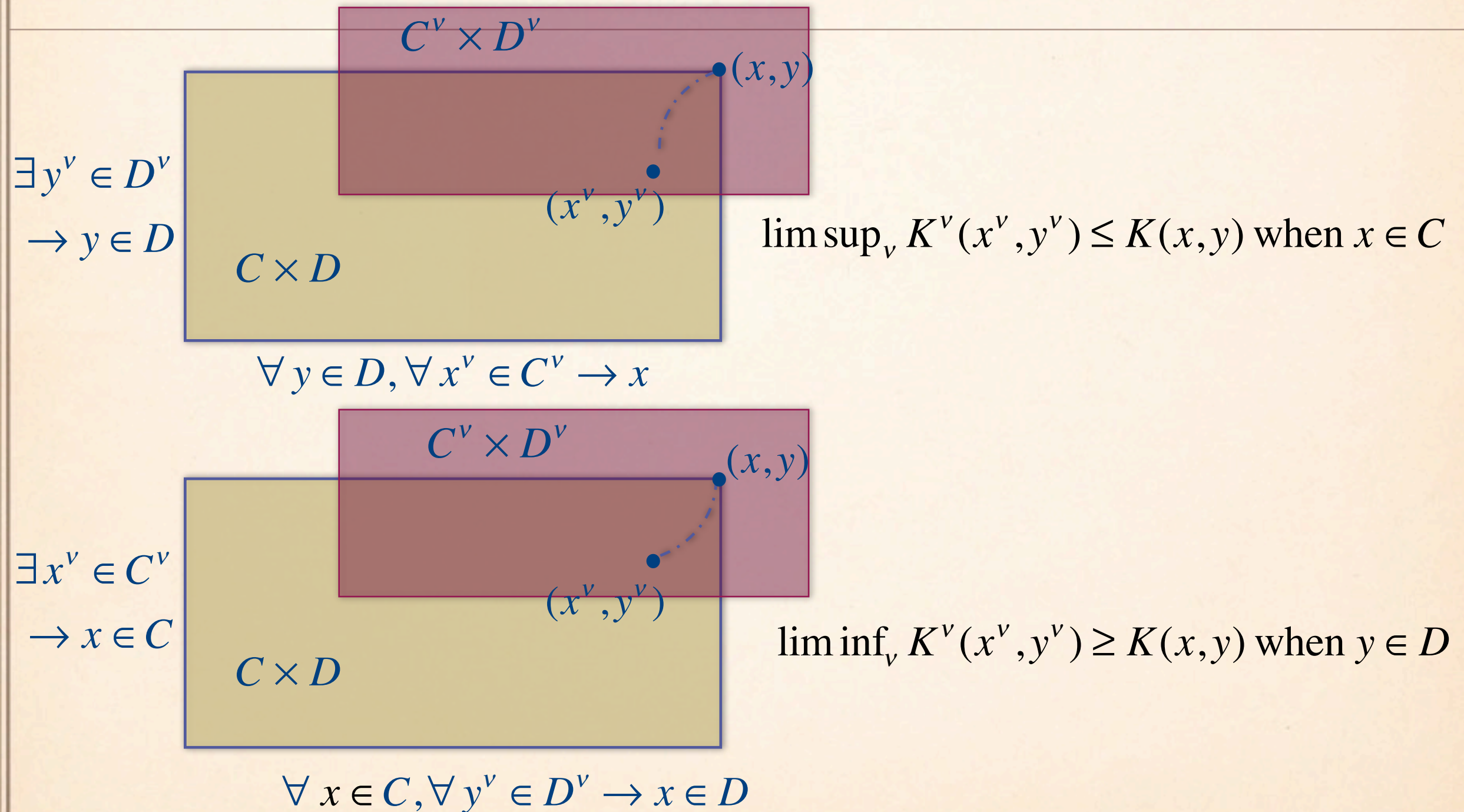
- *Lagrangians (concave/convex)*

- *zero-sum games*

- *Hamiltonians*

EPI/HYPO-CONVERGENCE

finite-valued bifunctions



CONVERGENCE: SADDLE POINTS

$$K^v \xrightarrow{e/h} K : C \times D \rightarrow \mathbb{R}, \varepsilon_v \searrow 0, (x^v, y^v) \in \varepsilon_v\text{-sdl}(K^v)$$

$$(\bar{x}, \bar{y}) = \lim_{v \in N \subset \mathbb{N}} (x^v, y^v), \quad N \sim \text{subsequence}$$

$$\Rightarrow (\bar{x}, \bar{y}) \in \text{sdl}(K) \quad \& \quad K(\bar{x}, \bar{y}) = \lim_{v \in N \subset \mathbb{N}} K^v(x^v, y^v)$$

in the convex/concave case \Rightarrow convergence primal/dual solutions

ancillary tight (\sim y -compact): $\forall \varepsilon > 0, \exists B_\varepsilon$ compact, v_ε

$$\forall v \geq v_\varepsilon, \sup_{B_\varepsilon \cap D^v} K^v(x^v, \bullet) \geq \sup_{D^v} K^v(x^v, \bullet) - \varepsilon$$

e/h-convergence + ancillary tight \Rightarrow sv-convergence saddle points

ZERO-SUM GAMES

$$x^* \in \arg \max_{x \in X} u(x, y^*), \quad y^* \in \arg \min_{y \in Y} u(x^*, y)$$

$$(x^*, y^*) \in \text{sdl}(u)$$

if X, Y convex, compact (\Rightarrow tight)

$\forall y, x \mapsto u(x, y)$ concave, usc, $\forall x, y \mapsto u(x, y)$ convex, lsc

\Rightarrow the zero-sum game $G = \{(X, u), (Y, -u)\}$ has a solution

moreover, $X^\nu \rightarrow X, Y^\nu \rightarrow Y, u^\nu \xrightarrow{e/h} u$ (with same properties)

\Rightarrow their solutions (x^ν, y^ν) cluster to solution of G

also the case for approximate solutions

VARIATIONAL INEQUALITIES

- ❖ $G : C \rightarrow \mathbb{R}^n$, $C \subset \mathbb{R}^n$ non-empty, convex set
- ❖ find $\bar{u} \in C$ such that $-G(\bar{u}) \in N_C(\bar{u})$
$$v \in N_C(\bar{u}) \Leftrightarrow \langle v, u - \bar{u} \rangle \leq 0, \forall u \in C$$
- ❖ let $C^\nu \rightarrow C$, $G^\nu : C^\nu \rightarrow \mathbb{R}^n$ continuous
- ❖ S^ν solution set of approximating problems
 S solution of the limit problem. Does $S^\nu \rightarrow S$?

V.I.: THE GAP FUNCTION

- ◆ Let $K(u, v) = \langle G(u), v - u \rangle$ on $\text{dom } K = C \times C$
- ◆ then $-G(\bar{u}) \in N_C(\bar{u})$ if and only if
- ◆ $\bar{u} \in \text{maxinf point}$ of K with $K(\bar{u}, \bullet) \geq 0$
- ◆ $K^\nu(u, v) := \langle G^\nu(u), v - u \rangle$, $\text{dom } K^\nu = C^\nu \times C^\nu$
- ◆ $u^\nu \in \arg \max\text{-inf } K^\nu$ with $K^\nu(u^\nu, \bullet) \geq 0$
- ◆ $K^\nu \xrightarrow{?} K$ and ...
- ◆ $\bar{u} \in \text{cluster points } \{u^\nu\} \Rightarrow ? \bar{u} \in \arg \min\text{-sup } K$

NON-COOPERATIVE GAMES

❖ $a \in \mathcal{A}$, payoff: $u_a(x_a, x_{-a}) : \mathbb{R}^N \rightarrow \bar{\mathbb{R}}$, \therefore includes $x_a \in C(x_{-a})$

❖ Generalized Nash equilibrium: $(\bar{x}_a, a \in \mathcal{A})$ such that

$$\forall a \in \mathcal{A}, \bar{x}_a \in \arg \max u_a(x_a, \bar{x}_{-a})$$

❖ Nikaido-Isoda function:

$$N(x, y) = \sum_{a \in \mathcal{A}} u_a(x_a, x_{-a}) - \sum_{a \in \mathcal{A}} u_a(y_a, x_{-a})$$

❖ $\bar{x} = (\bar{x}_a, a \in \mathcal{A})$ is a Nash equilibrium

$$\Leftrightarrow \bar{x} \in \arg \max \inf N, \quad N(\bar{x}, \bullet) \geq 0$$

APPROXIMATING GAMES

- ◆ Nikaido-Isoda functions of approximating games

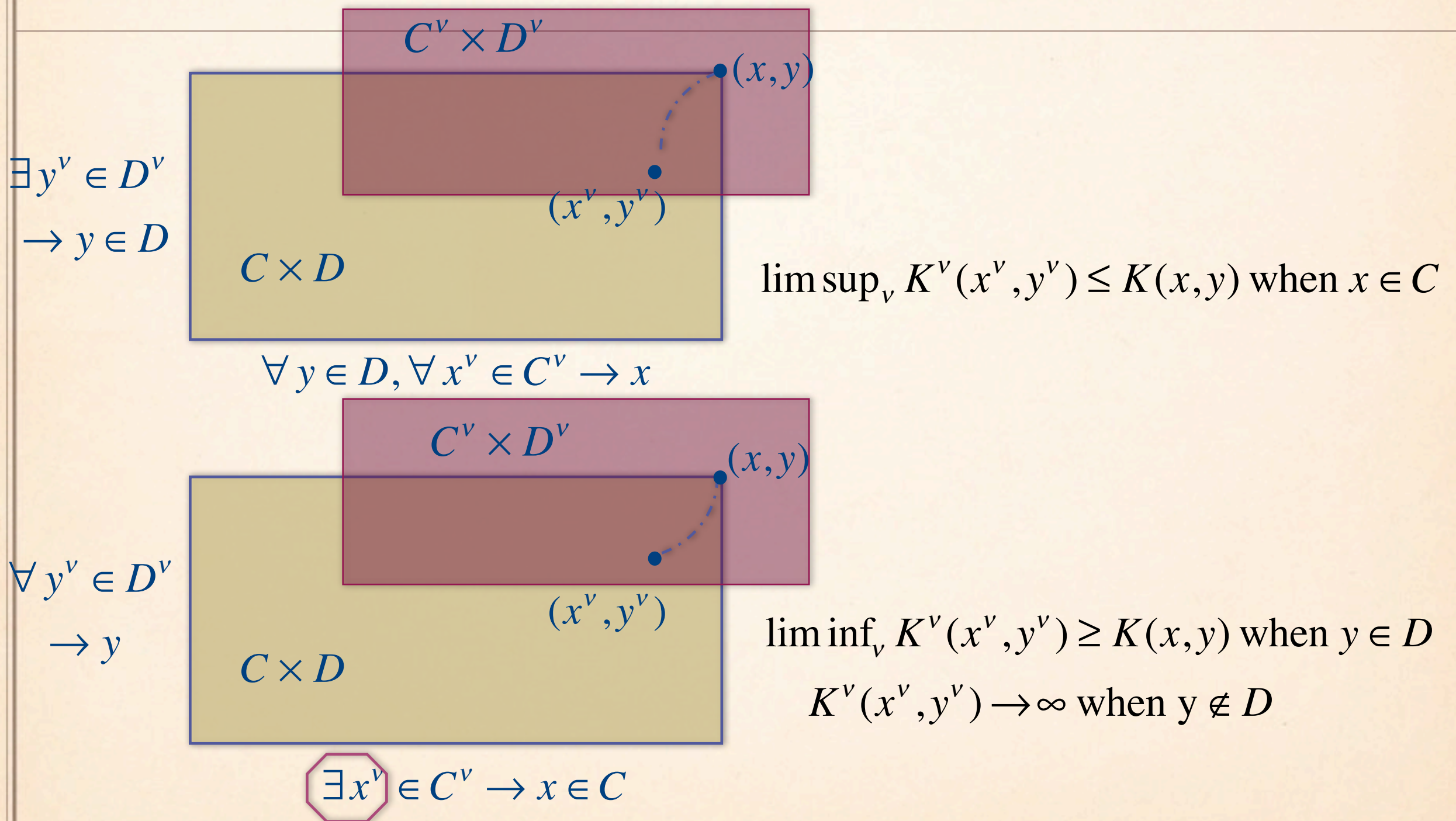
$$N^v(x, y) = \sum_{a \in A} u_a^v(x_a, x_{-a}) - \sum_{a \in A} u_a^v(y_a, x_{-a})$$

- ◆ $x^v \in \arg \max\text{--}\inf N^v$, $\bar{x} \in$ cluster points $\{x^v\}$

$$N^v \xrightarrow{?} N \text{ and } \dots$$

- ◆ $\Rightarrow ? \bar{x} \in \arg \max\text{--}\inf N \sim$ equilibrium point

LOPSIDED CONVERGENCE



ANCILLARY-TIGHTLY ~ 'COMPACT IN Y'

THM. $K_{C^v \times D^v}^v \xrightarrow{lop.} K_{C \times D}$ & ancillary-tightly,

$\bar{x} \in \text{cluster points of } \{x^v \in \text{maxinf } K_{C^v \times D^v}^v\}_{v \in \mathbb{N}} \Rightarrow \bar{x} \in \text{maxinf } K_{C \times D}$

$K_{C^v \times D^v}^v \xrightarrow{lop \text{ ancillary-tight}} K_{C \times D}$ if $K_{C^v \times D^v}^v \xrightarrow{lop} K_{C \times D}$ and

(b) $\forall x \in C, \exists x^v \rightarrow x, \forall y^v \in D^v$ and $y^v \rightarrow y$:

$\liminf K^v(x^v, y^v) \geq K(x, y)$ if $y \in D$

$K^v(x^v, y^v) \rightarrow \infty$ if $y \notin D$

but also $\forall \varepsilon > 0, \exists B_\varepsilon$ compact (depends on $x^v \rightarrow x$):

$$\inf_{B_\varepsilon \cap D^v} K^v(x^v, \cdot) \leq \inf_{D^v} K^v(x^v, \cdot) + \varepsilon, \quad \forall v \geq v_\varepsilon$$

... EVEN BETTER : CONVERGENCE

$K_{C^v \times D^v}^v \rightarrow K_{C \times D}$ lop. ancillary-tightly,

(i) $x^v \in \varepsilon$ -maxinf $K_{C^v \times D^v}^v$, \bar{x} cluster point of $\{x^v\}_{v \in \mathbb{N}}$

$\Rightarrow \bar{x} \in \varepsilon$ -maxinf $K_{C \times D}$

(ii) $x^v \in \varepsilon_v$ -maxinf $K_{C^v \times D^v}^v$, \bar{x} cluster point of $\{x^v\}_{v \in \mathbb{N}}$

& $\varepsilon_v \searrow 0 \Rightarrow \bar{x} \in \text{maxinf } K_{C \times D}$ (special: unique)

(iii) $\bar{x} \in \text{maxinf } K_{C \times D} \Rightarrow \exists \varepsilon_v \searrow 0$ & $x^v \in \varepsilon_v$ -maxinf $K_{C^v \times D^v}^v$

such that $x^v \rightarrow \bar{x}$,

Under **tight-lop**: convergence of the full ε_v -maxinf sets
and convergence of values

KY FAN FCNS & INEQUALITY

$K : C \times C \rightarrow \mathbb{R}$ Ky Fan function if

(a) $\forall y \in C: x \mapsto K(x, y)$ usc on C

(b) $\forall x \in C: y \mapsto K(x, y)$ convex on C

K Ky Fan fcn, $\text{dom } K = C \times C + C$ compact

$$\Rightarrow \arg \max\text{--}\inf K \neq \emptyset$$

if $K(x, x) \geq 0$ on $\text{dom } K$, $\bar{x} \in \arg \max\text{--}\inf K$

$$\Rightarrow \inf_y K(\bar{x}, y) \geq 0.$$

Improvements: Iusem, Kasay, Sosa (locals)

Lignola, Nessah, Tian, X. Yu, ...

KY FAN'S INEQUALITY: AN EXTENSION

$K^v \rightarrow K$ lopsided tightly with $C^v \rightarrow C$,

K^v Ky Fan $\Rightarrow K$ Ky Fan fcn

& if $\forall v : \arg \max\text{--}\inf K^v \neq \emptyset$

$\bar{x} \in \text{cluster-pts } \{\arg \max\text{--}\inf K^v\}$

$\Rightarrow \bar{x} \in \arg \max\text{--}\inf K \text{ \& } K(\bar{x}, \bullet) \geq 0$

Application: guideline for approximation schemes
truncations, coercivity, ...

LINEAR COMPLEMENTARITY PROBLEMS

LCP: find $z \geq 0$, $Mz + q \geq 0$ and $(Mz + q) \perp z$

$K(z, v) = \langle Mz + q, v - z \rangle$ on $\mathbb{R}_+^n \times \mathbb{R}_+^n$, Ky Fan fcn

approx. $z \in [0, r^v]$, $M^v z + q^v \geq 0$ and $(M^v z + q^v) \perp z$

$K^v(z, v) = \langle M^v z + q^v, v - z \rangle$ on $[0, r^v] \times \mathbb{R}_+^n$

$\triangle K^v \rightarrow_{lop} K$ when $M^v \rightarrow M, q^v \rightarrow q, r^v \nearrow \infty$

$\triangle K^v \rightarrow_{lop} K$ ancillary tightly when also

$$P^v = \{z \in [0, r^v] \mid M^v z + q^v \geq 0\} \rightarrow P = \{z \geq 0 \mid Mz + q \geq 0\}$$

\Rightarrow cluster points of sol'ns of approx. solve **LCP**

$\left(\text{note : int } P \neq \emptyset, \text{ no row of } [M, q] = 0 \Rightarrow P^v \rightarrow P \right)$
 $\triangle K^v \rightarrow_{lop} K$ tightly (study of quadratic forms)

VARIATIONAL INEQUALITIES

- ❖ $-G(u) \in N_C(u)$, G continuous, C convex, compact
- ❖ bifunction: $K(u, v) = \langle G(u), v - u \rangle$ on $C \times C$, Ky Fan fcn & $K(u, u) \geq 0$
- ❖ **THM**: $C^\nu \rightarrow C \Rightarrow C^\nu$ compact $\nu \geq \bar{\nu}$, G^ν continuous
 $G^\nu \xrightarrow{\text{cont}} G : G^\nu(x^\nu) \rightarrow G(x), \quad \forall x^\nu \in C^\nu \rightarrow x$
 $K^\nu(u, v) = \langle G^\nu(u), v - u \rangle$ on $\text{dom } K^\nu = C^\nu \times C^\nu$

lop-converge ancillary tightly to $K \Rightarrow$ sol'ns converge

Continuous convergence (?):

$$\text{sol'ns } S^\nu = G^\nu + N_{C^\nu} \ni 0 \rightarrow \text{sol'ns } S = G + N_C \ni 0$$

FIXED POINTS (SET-VALUED)

find $x \in C$ (convex) : $x \in S(x)$, $S : C \Rightarrow C \subset \mathbb{R}^n$, osc (gph S closed)

$$K(x, v) = \sup \{ \langle x - v, z - x \rangle \mid z \in S(x) \subset C \}$$

K a Ky Fan fcn, convex in v , usc in x (sup-projection) + $K(x, x) \geq 0$

Approx. bifunctions: $K^v(x, v) = \sup \{ \langle x - v, z - x \rangle \mid z \in S^v(x) \subset C^v \}$

THM. $C^v \rightarrow C$, gph $S^v \rightarrow$ gph S (as sets), C compact. Then,

$\forall \varepsilon_v \searrow 0$, $\bar{x} \in$ cluster points $\{x^v \in \varepsilon_v\text{-maxinf } K^v\}$ is a maxinf point of K ,
i.e., a fixed point of S . (lop-convergence is tight)

an Application (J.S. Pang) - Cognitive radio multi-user game

$f : C \rightarrow C \subset \mathbb{R}^n$ continuous, C compact, convex, \bar{x} fixed point

Perturbation (ε -enlargement): $S(\cdot; \varepsilon) : C \Rightarrow C$, osc, $S(\cdot; 0) = f$

For ε near 0: existence? $\exists x^\varepsilon \in S(x^\varepsilon, \varepsilon) = S^\varepsilon(x)$, $x^\varepsilon \rightarrow \bar{x}$?

LOP- & EPI/HYPO-CONVERGENCE

1. $L^v \xrightarrow[\text{lop}]{} L \not\Rightarrow L^v \xrightarrow[\text{e/h}]{} L$

2. $L^v \xrightarrow[\text{e/h}]{} L$ & convex-concave $\Rightarrow L^v \xrightarrow[\text{lop}]{} L$

3. epi/hypo- = hypo/epi-convergence

4. $L^v \xrightarrow[\text{e/h}]{} L \Rightarrow$ convergence of saddle points

\Rightarrow convergence of approximate saddle points
(without ancillary tightness)

5. Existence requires tightness-conditions (~coercivity, e.g.)

UNIQUENESS OF LOP- & EPI/HYPO LIMITS

CONVINCING EXAMPLES (?)

- ❖ Lagrangians: $L^v(x, y) = f_0^v(x) + \sum_{i=1}^m y_i f_i^v(x)$ on $X^v \times (\mathbb{R}^s \times \mathbb{R}^{m-s})$
- ❖ Lopsided convergence (maxmin-framework) - sufficient conditions $f_0^v, f_1^v, \dots, f_m^v$ hypo-converge to f_0, f_1, \dots, f_m on $X^v \rightarrow X$
 - ❖ $\{f_i^v, v \in \mathbb{N}\}$ is equi-usc, $i = 0, \dots, m$
 - ❖ Constraint Qualification: $S^v = \{x \mid f_i^v \geq 0, i = 1, \dots, m\} \rightarrow S$
 - ❖ concave-convex case (epi/hypo): $\text{int } S \neq \emptyset$
- ❖ lop-limit L is unique

VARIATIONAL INEQUALITIES

$C^v \rightarrow C, \quad G^v: C^v \rightarrow \mathbb{R}^n$ continuous, C^v convex
 $-G^v(x) \in N_{C^v}, \quad v \in \mathbb{N}$

THM: $C^v \rightarrow C \Rightarrow C$ compact $v \geq \bar{v}, G^v$ continuous

$G^v \xrightarrow{cont} G: G^v(x^v) \rightarrow G(x), \quad \forall x^v \in C^v \rightarrow x$

$K^v(u, v) = \langle G^v(u), v - u \rangle$ on $\text{dom } K^v = C^v \times C^v$

lop-converge ancillary tightly to $K \Rightarrow$ sol'ns converge

lop-limit: $-G(x) \in N_C(x)$ uniquely determined

MPEC (GENERALIZED?)

max $g(x)$ such that $x \in S(x)$, g continuous, $S : C \Rightarrow C$ convex

bifunction: $K(x, v) = g(x) + \sup_z \{ \langle x - v, z - x \rangle \mid z \in S(x) \}$

V.I.-constraint: $S(x) = N_C(x) + G(x) + Ix$ on C

LCP: $S(x) = \langle Mx + q, v - x \rangle + Ix$ on \mathbb{R}_+^n

$\bar{x} \in \arg \max - \inf K \Rightarrow \bar{x}$ solves MPEC.

approximating bifunctions: $S^v : C^v \Rightarrow C$

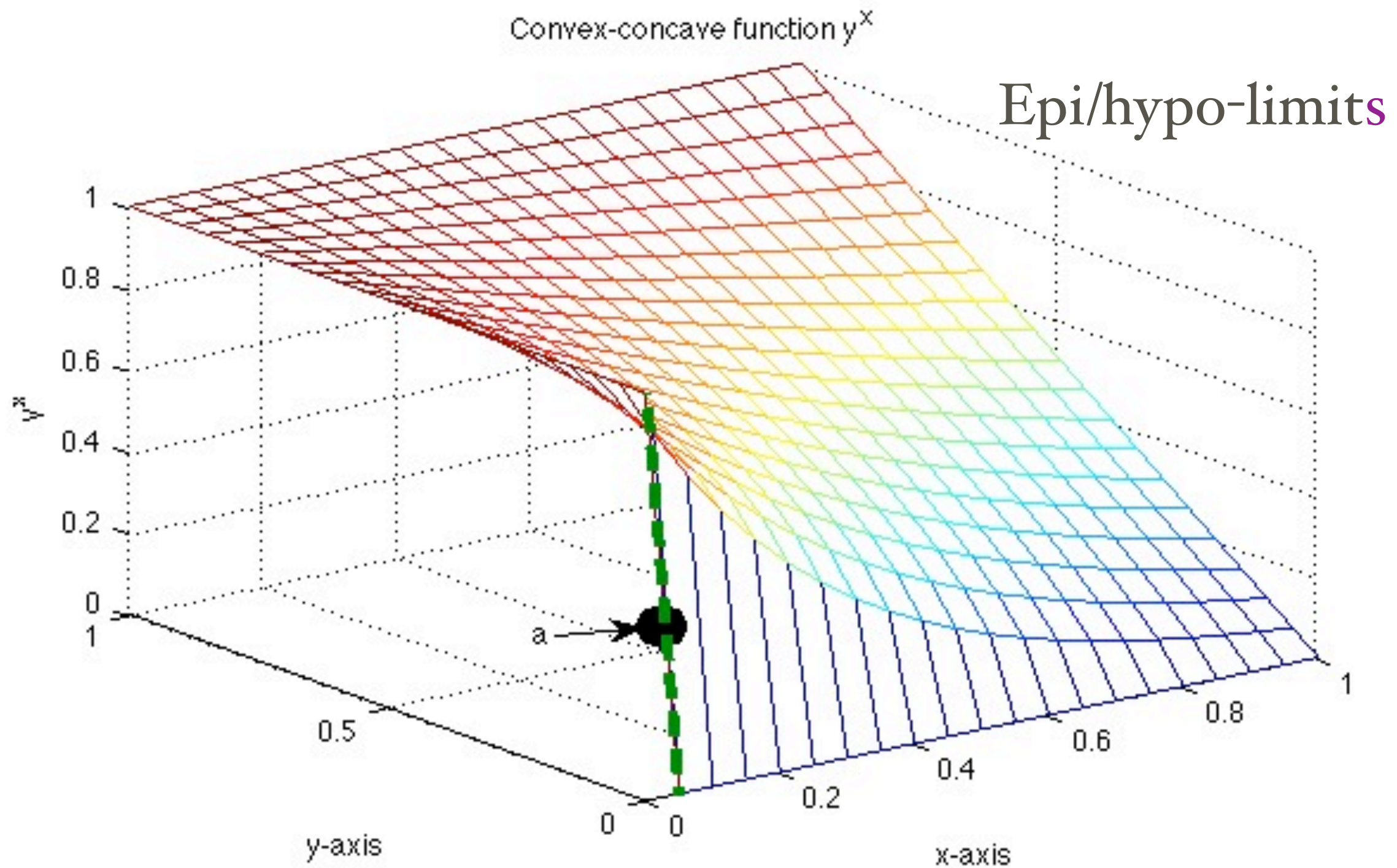
$K^v(x, v) = g^v(x) + \sup_z \{ \langle x - v, z - x \rangle \mid z \in S^v(x) \}$

$C^v \rightarrow C$, $\text{gph } S^v \rightarrow \text{gph } S$, g^v hypo-converges to g

then $K^v \xrightarrow{lop} K$ & K unique

$$K^v(x, y) \equiv y^x$$

Uniqueness fails!



WALRAS EQUILIBRIUM

- ❖ $\forall a \in A: d_a(p) \in \arg \max \left\{ u_a(x_a) \mid \langle p, x_a \rangle \leq \langle p, e_a \rangle \right\}$
 $s(p) = \sum_a (e_a - d_a(p))$ excess supply
- ❖ find $\bar{p} \in \Delta$ (unit simplex) so that $s(\bar{p}) \geq 0$
- ❖ **Walrasian:** $W(p, q) = \langle q, s(p) \rangle$ Ky Fan fcn
- ❖ $\bar{p} \in \max \inf W, W(\bar{p}, \bullet) \geq 0 \iff s(\bar{p}) \geq 0$
- ❖ conditions: $u_a^v \rightarrow_{hypo} u_a, e_a^v \rightarrow e_a \in \text{int dom } u_a \implies$
- ❖ **Convergence:** W^v lop-converges ancillary-tight to W

AUGMENTED WALRASIAN

$$W(p, q) = \langle q, s(p) \rangle \text{ on } \Delta \times \Delta$$

$$\tilde{W}_r(p, q) = \sup_z \left\{ W(p, z) \mid \|z - q\|^o \leq r \right\} \text{ **lop-converges}$$

$$q^{k+1} = \arg \max_{q \in \Delta} \left[\max_z \langle z, s(p^k) \rangle \mid \|z - q\|^o \leq r_k \right]$$

minimizing a linear form on a ball

reduces to finding the largest element of $s(p^k)$

$$p^{k+1} = \arg \min_{p \in \Delta} \left[\max_z \langle z, s(p) \rangle \mid \|z - q^{k+1}\|^o \leq r_{k+1} \right]$$

as $r_k \nearrow \infty, p^k \rightarrow \bar{p}$ (local quad. approx. Nocedal, Powell)

experiments: 10 agents, 150 goods (easy!)

III. RANDOM SETS AND MAPPINGS

RANDOM CLOSED SETS

$(\Xi, \mathcal{A}, \mu), \Xi \subset \mathbb{R}^N \quad \Rightarrow :$ set-valued mapping,

$C : \Xi \Rightarrow \mathbb{R}^d, C(\xi) \subset \mathbb{R}^d$ closed set for all $\xi \in \Xi$

& $C^{-1}(O) = \{\xi \mid C(\xi) \cap O \neq \emptyset\} \in \mathcal{A}, \forall O \subset \mathbb{R}^n, \text{open (measurability)}$

$\Rightarrow \text{dom } C = C^{-1}(\mathbb{R}^d) \in \mathcal{A}$

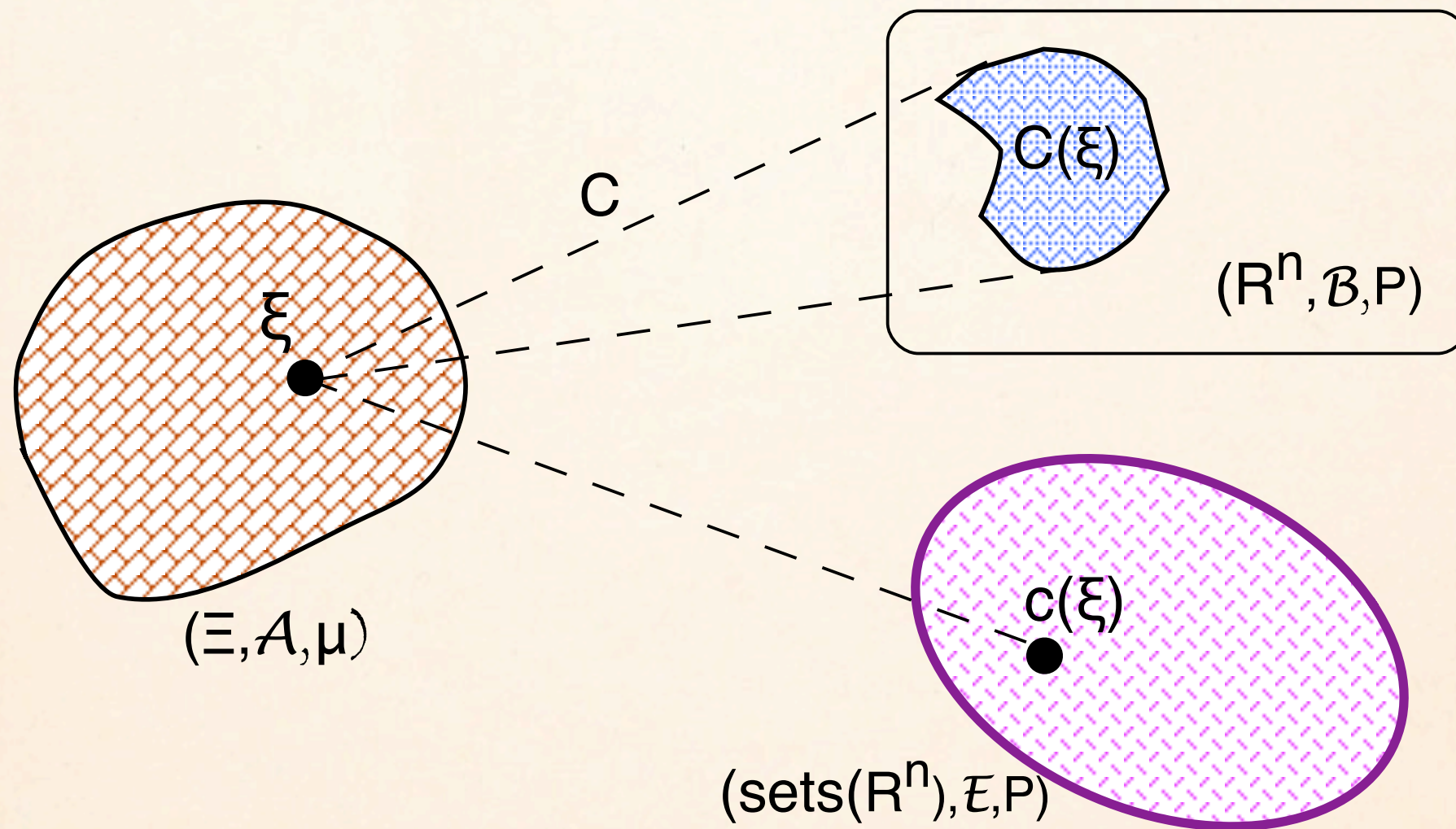
$c : \Xi \rightarrow \text{sets}(\mathbb{R}^d), c(\xi) \sim C(\xi), \mathcal{F}_O = \{F \subset \mathbb{R}^d \text{ closed} \mid F \cap O \neq \emptyset\}$

$(\text{sets}(\mathbb{R}^n), \mathcal{E}), \mathcal{E} \text{ Effros field} = \sigma - \{\mathcal{F}_O \in \text{sets}(\mathbb{R}^n), O \text{ open}\},$

$C \text{ measurable} \Leftrightarrow c \text{ measurable } [c^{-1}(\mathcal{F}_O) \in \mathcal{A}]$

$\mathcal{E} = \mathcal{B}$ Borel field (\mathbb{R}^d separable metric space)

SET- & SINGLE-VALUED



CASTAING REPRESENTATION & GRAPH-MEASURABILITY

❖ a random closed set C always admits a measurable selection!

❖ (with $\text{dom } C$ measurable) C is a random closed set \Leftrightarrow
it admits a Castaing representation: \exists a countable family

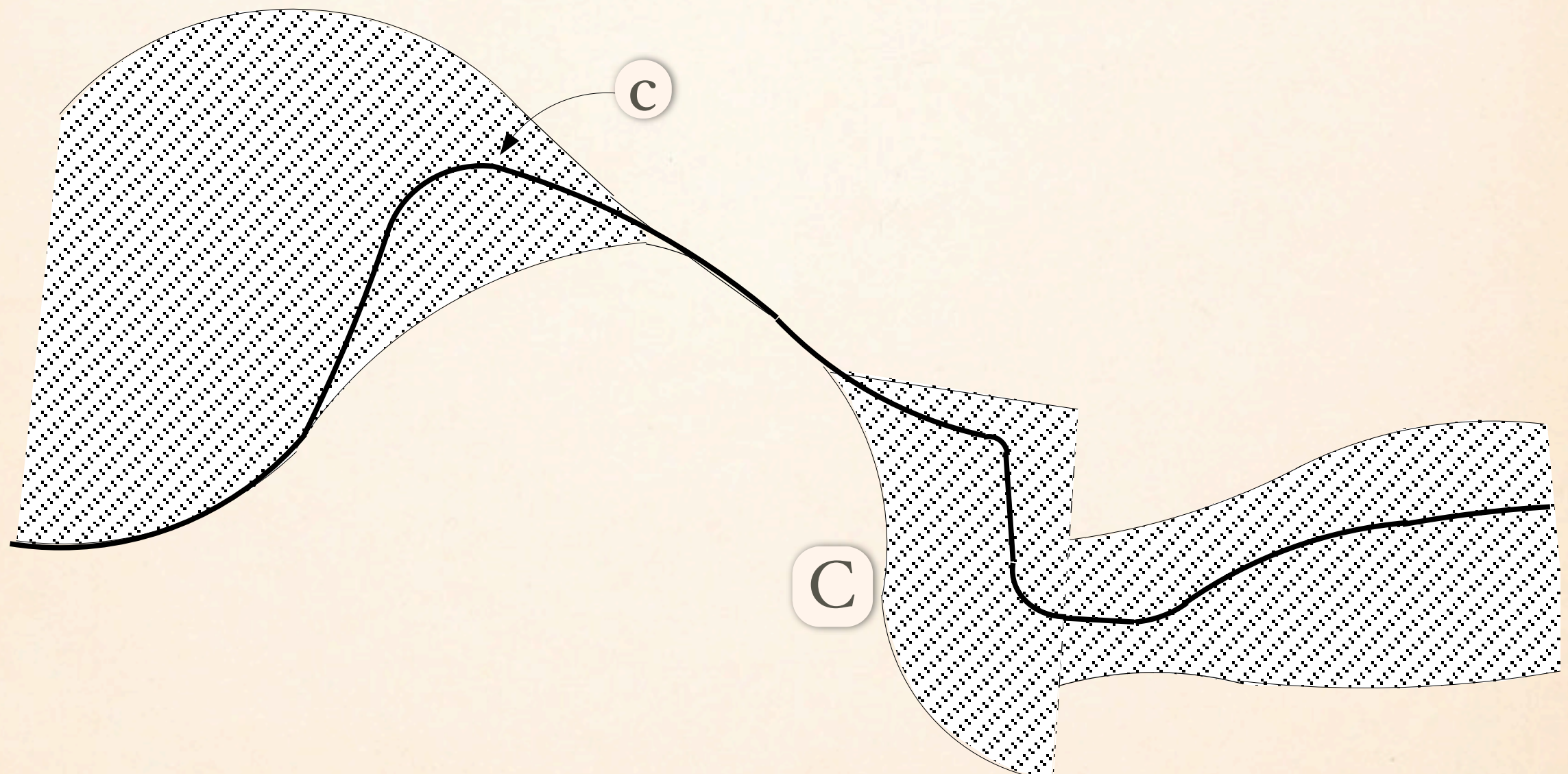
$$\{x^v : \text{dom } C \rightarrow \mathbb{R}^m, \text{ meas.-selections} \}$$

$$\text{cl} \bigcup_{v \in \mathbb{N}} x^v = C(\xi), \forall \xi \in \text{dom } C \subset \Xi$$

❖ (Ξ, \mathcal{A}) μ -complete for some μ ,

C random set $\Leftrightarrow \text{gph } C \mathcal{A} \otimes \mathcal{B}^n$ -measurable

MEASURABLE SELECTION



SET-CONVERGENCE TOPOLOGY

$\mathcal{F} = \text{cl-sets}(\mathbb{R}^d)$, all closed subsets of \mathbb{R}^d

$\mathcal{F}^D = \text{subsets } \mathbb{R}^d \text{ that miss } D = \{F \cap D = \emptyset\}$

$\mathcal{F}_D = \text{subsets } \mathbb{R}^d \text{ that hit } D = \{F \cap D \neq \emptyset\}$

Hit-and-miss topology ($= \tau_f$ Fell topology)

subbase: $\{\mathcal{F}^K \mid K \text{ compact}\} \ \& \ \{\mathcal{F}_O \mid O \text{ open}\}$

$\mathbb{B}(x, \rho)$ closed ball, center x radius ρ , $\mathbb{B}^o(x, \rho)$ open

\sim subbase $\left\{ \mathcal{F}^{\mathbb{B}(x, \rho)}, \mathcal{F}_{\mathbb{B}^o(x, \rho)} \mid x \in \mathbb{Q}^d, \rho \in \mathbb{Q}_{++} \right\}$

countable base: $\left\{ \mathcal{F}^{\mathbb{B}(x^1, \rho_1) \cup \dots \cup \mathbb{B}(x^r, \rho_r)} \cap \mathcal{F}_{\mathbb{B}^o(x^1, \rho_1) \cup \dots \cup \mathbb{B}^o(x^s, \rho_s)} \right\}$

$(\mathcal{F} = \text{cl-sets}(\mathbb{R}^d), \tau_f)$ compact, metrizable space

A.S.-CONVERGENCE

- * $\{C^v : \Xi \rightrightarrows \mathbb{R}^d, v \in \mathbb{N}\}$ random closed sets
- * a.s. convergence: $\text{Li}_v(C^v)$ & $\text{Ls}_v(C^v)$ random closed sets
 $C^v \rightarrow C$ a.s. $\Rightarrow C$ random closed set on $\Xi_0, \mu(\Xi_0) = 1$
- * $C^v \rightarrow C$ μ -a.s. and $\text{dom } C^v = \text{dom } C$. Then,
 \exists Castaing representations of $C^v \rightarrow$ a Castaing representation of C
If $x : \Xi \rightarrow \mathbb{R}^d$ is a measurable selection of C , then
 $\exists x^v : \Xi \rightarrow \mathbb{R}^d$ selections of C^v converging μ -a.s. to x
- * 'Egorov's Theorem': $C^v \rightarrow C$ μ -a.s. $\Leftrightarrow C^v \rightarrow C$ almost uniformly

CONVERGENCE IN PROBABILITY

Let $\varepsilon^o C = \{x \in \mathbb{R}^m \mid d(x, C) < \varepsilon\}$, C^v, C random sets

$$\Delta_{\varepsilon, v} = (C^v \setminus \varepsilon^o C) \cup (C \setminus \varepsilon^o C^v)$$

μ -a.s. convergence: $\mu\{\xi \mid C^v(\xi) \rightarrow C(\xi)\} = 1$

in probability: $\mu[\Delta_{\varepsilon, v}^{-1}(K)] \rightarrow 0, \forall \varepsilon > 0, K \in \mathcal{K}$

C^v converges to C in probability

$\Leftrightarrow dl(C^v, C) \rightarrow 0$ in probability

\Leftrightarrow every subsequence of $\{C^v\}_{v \in \mathbb{N}}$

contains a sub-subsequence converging μ -a.s to C

i.e., in probability \Rightarrow in distribution $\left[\int h(\xi) dl(C^v(\xi), C(\xi)) \mu(d\xi) \rightarrow 0 \right]$

DISTRIBUTION OF A RANDOM SET

Borel σ -field: $\mathcal{B} = \sigma\{-\mathcal{F}^K | K \text{ compact}\}$ or $\sigma\{-\mathcal{F}_O | O \text{ open}\} \dots$

Distribution (P, \mathcal{B}) regular, \mathcal{K} compact subsets \mathbb{R}^d

determined by values on $\{\mathcal{F}^K | K \in \mathcal{K}\}$ or $\{\mathcal{F}_K | K \in \mathcal{K}\}$

Distribution function (Choquet capacity):

$T : \mathcal{K} \rightarrow [0,1], T(\emptyset) = 0$ and $\forall \{K^\nu, \nu \in \{0\} \cup \mathbb{N}\} \subset \mathcal{K} :$

a) $T(K^\nu) \searrow T(K)$ when $K^\nu \searrow K$ (\sim usc on \mathbb{R})

b) $\{D_\nu : \mathcal{K} \rightarrow [0,1]\}_{\nu \in \mathbb{N}}$ where $D_0(K^0) = 1 - T(K^0)$

$D_1(K^0; K^1) = D_0(K^0) - D_0(K^0 \cup K^1)$ and for $\nu = 2, \dots$

$D_\nu(K^0; K^1, \dots, K^\nu) = D_{\nu-1}(K^0; K^1, \dots, K^{\nu-1}) - D_{\nu-1}(K^0 \cup K^\nu; K^1, \dots, K^{\nu-1})$

(\sim monotonicity on \mathbb{R})

EXISTENCE-UNIQUENESS T

P on \mathcal{B} determines a unique **distribution function** T on \mathcal{K}

$$T(K) = P(\mathcal{F}_K)$$

$$D_v(K^0; K^1, \dots, K^v) = P(\mathcal{F}^{K^0} \cap \mathcal{F}_{K^1} \cap \dots \cap \mathcal{F}_{K^v})$$

T on \mathcal{K} determines a unique probability measure P .

Proof. via Choquet Capacity Theorem (Matheron)
probabilistic arguments (Salinetti-Wets)

$C : \Xi \Rightarrow \mathbb{R}^d$ a random closed set

(P, \mathcal{B}) induced probability measure:

$$P(\mathcal{F}_G) = \mu[C^{-1}(G)] \quad \forall G \in \mathcal{B}, \quad T(K) = \mu[C^{-1}(K)] \quad \forall K \in \mathcal{K}$$

CONVERGENCE IN DISTRIBUTION

random sets C^ν converge in distribution to C when

induced P^ν narrow-converge to $P : P^\nu \rightarrow_n P$

$\Leftrightarrow T^\nu \rightarrow_p T$ on $\mathcal{K}_{T\text{-cont}}$ (convergence of distribution functions)

what is $\mathcal{K}_{T\text{-cont}}$?

a) $\forall C^\nu, \nu \in N, \exists$ converging subsequence (pre-compact)

b) $K^\nu \nearrow K = \text{cl} \bigcup_\nu K^\nu$ regularly if $\text{int } K \subset \bigcup_\nu K^\nu$

c) distribution (fcn) continuity: $\lim_\nu T(K^\nu) = T(\text{cl} \bigcup_\nu K^\nu)$

d) convergence $T^\nu \rightarrow_p T$ on \mathcal{C}_T continuity set $\Rightarrow P^\nu \rightarrow_n P$

e) $P^\nu \rightarrow_n P \Leftrightarrow T^\nu \rightarrow_p T$ on $\mathcal{C}_T^{ub} = \mathcal{C}_T \cap \mathcal{K}^{ub}$

$\mathcal{K}^{ub} =$ finite union of rational ball, positive radius

f) $\varepsilon \mapsto T(K + \varepsilon \mathbb{B})$: countable number of distontinuites

A DETOUR ABOUT RATES

$T^\nu \rightarrow_p T$ on $C_T \Leftrightarrow P^\nu \rightarrow_n P$ (Polish space (E, d))

P^ν, P defined on \mathcal{B}

probability sc-measures on cl-sets(E): λ

(i) $\lambda \geq 0$, (ii) $\lambda \nearrow \lambda(C^1) \leq \lambda(C^2)$ if $C^1 \subset C^2$

(iii) λ is τ_f -usc on cl-sets(E), (iv) $\lambda(\emptyset) = 0, \lambda(E) = 1$

(iv) λ modular: $\lambda(C^1) + \lambda(C^2) = \lambda(C^1 \cup C^2) + \lambda(C^1 \cap C^2)$

P and $\lambda = P_{\text{cl-sets}}$ define each other uniquely (E complete \Rightarrow tight)

$\{P^\nu, \nu \in \mathbb{N}\}$ tight: $P^\nu \rightarrow_n P \Leftrightarrow \lambda^\nu \rightarrow_h \lambda$ ($\sim - \lambda^\nu \rightarrow_e -\lambda$) on cl-sets(E)

tightness \sim equi-usc of $\{\lambda^\nu\}_{\nu \in \mathbb{N}}$ at \emptyset

rates: $dl(\lambda^\nu, \lambda) \rightarrow 0$ (for \mathbb{R} -valued r.v., related to Skorohod distance)

RANDOM SET: EXPECTATION

$$EC = \mathbb{E}\{C(\xi)\} = \left\{ \int_{\Xi} x(\xi) \mu(d\xi) \mid x(\cdot) \text{ } \mu\text{-summable selection} \right\}$$

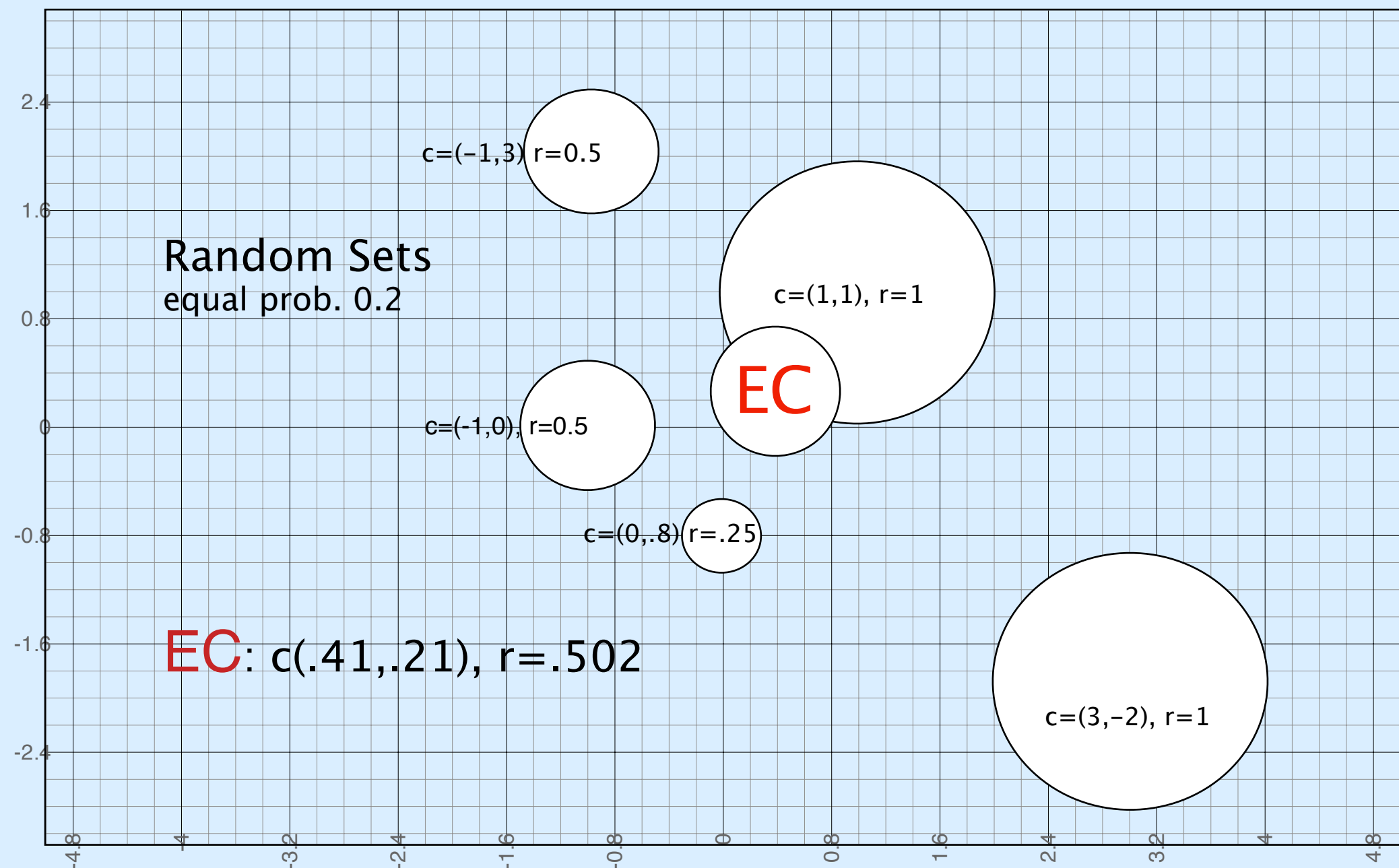
..not necessarily closed even when C is closed-valued

Convexity.

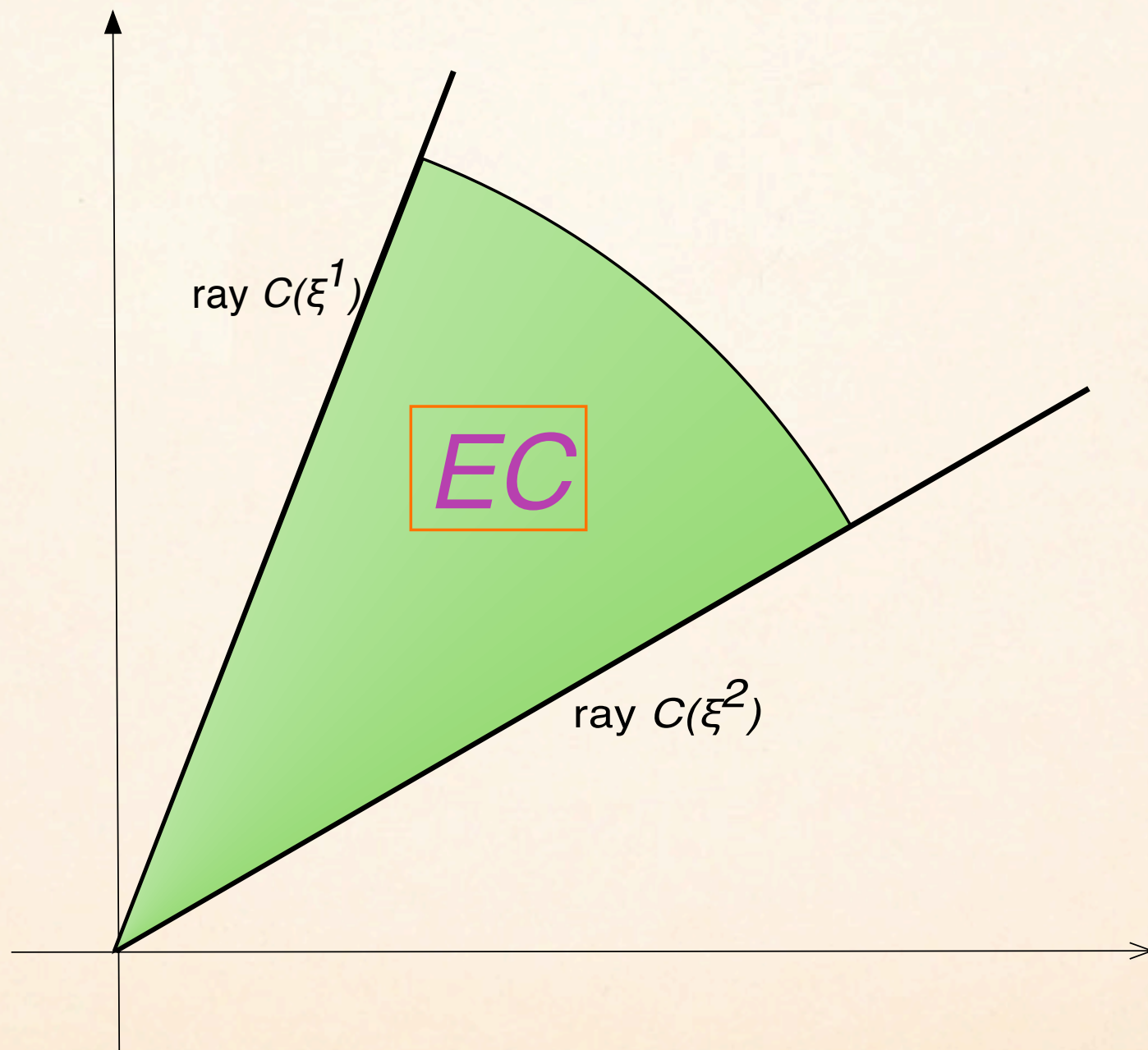
C μ -atom convex $\Rightarrow EC$ is convex

(certainly when P is atomless).

EXPECTATION: BOUNDED RANDOM SETS



EXPECTATION: UNBOUNDED RANDOM SETS



STRONG LAW OF LARGE NUMBERS

ARTSTEIN & HART

$C : \Xi \rightrightarrows \mathbb{R}^m$ measurable, $\{\xi^v, v \in \mathbb{N}\}$ iid Ξ -valued random variables

$C(\xi^v)$ iid random sets (i.e. induced P^v independent and identical)

$EC = \mathbb{E}\{C(\cdot)\} = \left\{ \int_{\Xi} x(\xi) \mu(d\xi) \mid x \mu\text{-summable } C(\xi)\text{-selection} \right\}$

independence \Rightarrow all (measurable) selections are independent

$\{C(\xi^v) : \Xi \rightrightarrows \mathbb{R}^m \ v \in \mathbb{N}\}$ iid with $EC \neq \emptyset$. Then, with

$$C^v(\xi^\infty) = v^{-1} \left(\sum_{k=1}^v C(\xi^k) \right) \rightarrow \bar{C} = \text{cl con } EC \ \mu^\infty\text{-a.s.}$$

$\text{Ls}_v C^v(\xi^\infty) \subset \bar{C} \Leftrightarrow \limsup_v \sigma_{C^v} \leq \sigma_{\bar{C}}$ support functions

$\text{Li}_v C^v(\xi^\infty) \supset \bar{C}$ relies on LLN for (vector-valued) selections

RESOURCES ALLOCATIONS AVERAGE OF EPI-SUMS

$q \in \mathbb{R}_{++}^n$, q central resources allocated to v firms

Optimal allocation: p_i production functions

suppose k large, $p_i = p_i(\xi, x)$ with $\xi \in \Xi$,

$$\forall \xi: \quad z_v(\xi, q) = \max \quad v^{-1} \sum_{i=1}^v p_i(\xi, x^i) \quad \text{s.t.} \quad v^{-1} \sum_{i=1}^k x^i \leq q$$

(Ξ, \mathcal{A}, μ) , p_i : usc in x , jointly measurable $\mathcal{A} \otimes \mathcal{B}$

"Limit" Problem:

$$z(q) = \max \int p(\xi, x(\xi)) d\mu \quad \text{s.t.} \quad \int x(\xi) d\mu \leq q$$

Suppose $\{p_i(\xi, \cdot) \in \text{lsc-fcns}(\mathbb{R}^n)\}$ are iid \Leftrightarrow epi p_i iid

Then, $z_v(\xi, q) \rightarrow z(q)$ μ -a.s. where $p = p_1$ if μ nonatomic
or $-p = \text{con } -p_1$ (must not depend on ξ)

Argument: set-LLN on hypographs (\sim epi $-p_i$)

SAMPLE AVERAGE APPROXIMATION

stochastic variational problem: $\bar{S}(x) = \mathbb{E}\{S(\xi, x)\} \ni 0$

$S : \Xi \times \mathbb{R}^n \rightrightarrows \mathbb{R}^m$ random set-valued mapping

ξ random vector with values $\xi \in \Xi \subset \mathbb{R}^N$

solution (a 'stationary point') $\bar{x} \in \bar{S}^{-1}(0)$

—○ —○ —○ —○ —○ —○ —○ —○ —○ —○ —○ —○ —○ —○ —○ —○ —○ —○ —○

sample $\vec{\xi}^v = (\xi^1, \dots, \xi^v)$ of ξ

$\frac{1}{v} \left(\sum_{k=1}^v S(\xi^k, x) \right) = S^v(\vec{\xi}^v, x) \ni 0$, approximating system?

i.e., $(S^v)^{-1}(0) \xrightarrow{?} \bar{S}^{-1}(0)$ a.s.

STOCHASTIC OPTIMIZATION

$\min Ef(x) = \mathbb{E}\{f(\xi, x)\}$ --stationary point-- $\partial Ef(x) \ni 0$

assuming $\mathbb{E}\{\partial f(\xi, x)\} = \partial Ef(x)$ (not generally correct)

could $\partial Ef(x) \ni 0$ get replaced (?) by

$$v^{-1} \left(\sum_{k=1}^v \partial f(\xi^k, x) \right) \ni 0 \text{ from sample } \vec{\xi}^v$$

$\text{dom } Ef \approx \bigcap_{\xi \in \Xi} \text{dom } f(\xi, \cdot),$

unless $\xi \mapsto \text{dom } f(\xi, \cdot)$ constant,

interchanging \mathbb{E} & ∂ is only exceptionally valid

STOCHASTIC V.I. (VARIATIONAL INEQUALITY)

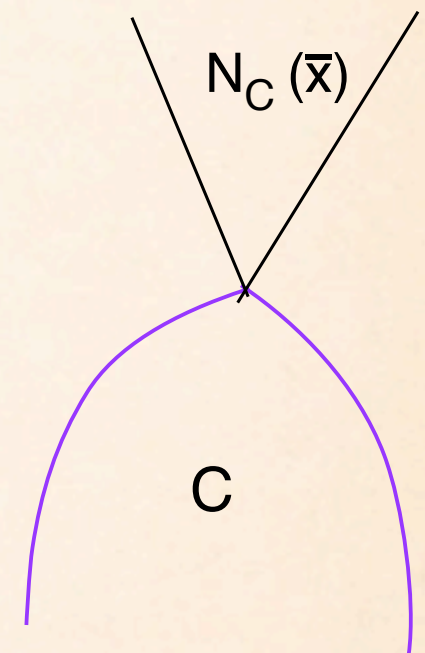
$\xi = (\xi^1, \xi^2, \dots)$, $G^v(\cdot, x)$ σ -(ξ^1, \dots, ξ^v) measurable

$-G^v(\xi, x) \in N_C(x)$, C compact, convex

$G^v(\xi, \cdot) \rightarrow^? G(\xi, \cdot)$

$x^v(\xi)$ solution of $-G^v(\xi, x) \in N_C(x)$ for sample $\xi \approx \vec{\xi}^v$
does $x^v(\xi) \rightarrow$ a solution of $-G(\xi, x) \in N_C(x)$? a.s.

what if C depends on v, ξ : sequence of random sets $C^v(\xi)$



RANDOM MAPPINGS

$$S : \Xi \times E \rightrightarrows \mathbb{R}^m, \quad E \subset \mathbb{R}^n$$

$\mathcal{A} \otimes \mathcal{B}^n$ -jointly measurable: $S^{-1}(O) \in \mathcal{A} \otimes \mathcal{B}^n$, O open

$\Rightarrow \forall x : \xi \mapsto S(\xi, x)$ a random set

random closed set when S is closed-valued

$ES : E \rightrightarrows \mathbb{R}^m$ with $ES(x) = \mathbb{E}\{S(\xi, x)\}$ **expected mapping**

ES convex-valued when $\xi \mapsto S(\xi, \cdot)$ μ -atom convex

Law of Large Numbers for random sets applies

SAMPLE AVERAGE APPROXIMATIONS

$\xi = (\xi^1, \xi^2, \dots)$ iid, sample $\vec{\xi}^v = (\xi^1, \dots, \xi^v)$

SAA-mapping: given $S : \Xi \times E \rightrightarrows \mathbb{R}^m$ random mapping

$S^v : \Xi^\infty \times E \rightrightarrows \mathbb{R}^m$ with

$$\forall \xi \in \Xi^\infty, x \in E : S^v(\xi, x) = \frac{1}{v} \sum_{k=1}^v S(\xi^k, x) = S^v(\vec{\xi}^v, x)$$

S^v depends only on $\vec{\xi}^v$

SAA-mappings S^v are random mappings

not necessarily closed-valued

(the sum of closed sets is not necessarily closed)

POINTWISE LIMITS: SAA-MAPPINGS

$ES(x) = \mathbb{E}\{S(\xi, x)\} \neq \emptyset$, then

$$\forall x \in X : S^\nu(\xi, x) \rightarrow \text{cl con } ES(x) =: \bar{S}(x) \quad \mu^\infty\text{-a.s.}$$

If $S(\cdot, x)$ is P -atom convex, $S^\nu(\xi, \cdot) \rightarrow \text{cl } ES(x) =: \bar{S}(x) \quad \mu^\infty\text{-a.s.}$

Proof: LLN for random sets. \square

CONSISTENT APPROXIMATIONS?

$$S^\nu(\xi, \cdot) \xrightarrow[\text{point}]{} \bar{S} \quad \mu^\infty\text{-a.s.} \Rightarrow ? \quad S^\nu(\xi, \cdot)^{-1}(0) \Rightarrow_a \bar{S}^{-1}(0)$$

sometimes!

graphical rather than pointwise convergence is required

$$S^\nu(\xi, \cdot) \xrightarrow[\text{gph}]{} \bar{S} \quad \mu^\infty\text{-a.s. is needed}$$

relationship between graphical and pointwise convergence?

GRAPHICAL & POINTWISE

$D, D^\nu : X \rightrightarrows \mathbb{R}^m$. Then, $D^\nu \xrightarrow[\text{point}]{} D$ and $D^\nu \xrightarrow[\text{gph}]{} D$ (at x)

$\Leftrightarrow \{D^\nu, \nu \in \mathbb{N}\}$ are equi-osc (asymptotically) (at x)

\sim Arzela-Ascoli Theorem for set-valued mappings

S random mapping, μ^∞ -a.s., $S^\nu(\xi, \cdot) \xrightarrow[\text{point}]{} \text{cl con } ES = \bar{S}$

then $S^\nu \xrightarrow[\text{gph}]{} \bar{S} \Leftrightarrow \{S^\nu, \nu \in \mathbb{N}\}$ are equi-osc (asymptotically)

EQUI-OSC MAPPINGS

$D : X \rightrightarrows \mathbb{R}^m, X \subset \mathbb{R}^n$ is osc if gph S is closed

osc at \bar{x} if $D(\bar{x}) \supset \text{Ls}_{x^v \rightarrow \bar{x}} D(x^v)$

\sim given any $\rho > 0, \varepsilon > 0$

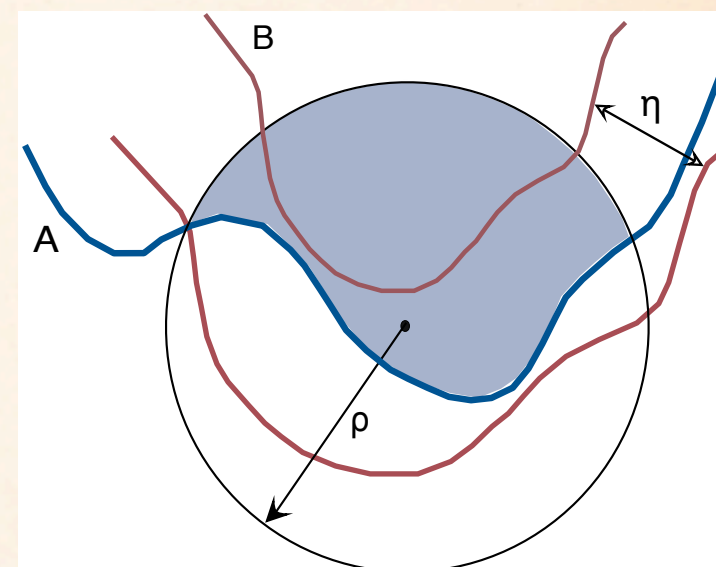
$\exists V \in N(\bar{x}) : e_\rho(D(x), D(\bar{x})) < \varepsilon, \forall x \in V$

$\{D^v : X \rightrightarrows \mathbb{R}^m\}$ are equi-osc at \bar{x}

\sim given any $\rho > 0, \varepsilon > 0$

$\exists V \in N(\bar{x}) : e_\rho(D^v(x), D^v(\bar{x})) < \varepsilon, \forall x \in V$

$V = V(\rho, \varepsilon)$ doesn't depend on v .



GRAPHICAL CONVERGENCE OF SAA-MAPPINGS

$S: \Xi \times X \rightrightarrows \mathbb{R}^m$ random mapping, (Ξ, \mathcal{A}, μ)

μ^∞ -a.s.: $S^v(\xi, \cdot) \xrightarrow{\text{gph}} \bar{S}$ at $\bar{x} \Leftrightarrow$ SAA-mappings $\{S^v(\xi, \cdot)\}$ equi-osc at \bar{x}

\Rightarrow sol'ns of $S^v(\xi, \cdot) \ni 0 \xrightarrow{v} \text{sol'ns of } \bar{S}(\cdot) \ni 0$

Sufficient conditions: μ^∞ -a.s.

$S(\xi, \cdot)$ stably osc & steady under averaging $\Rightarrow \{S^v(\xi, \cdot)\}$ equi-osc

Law of large Numbers for Random Mappings

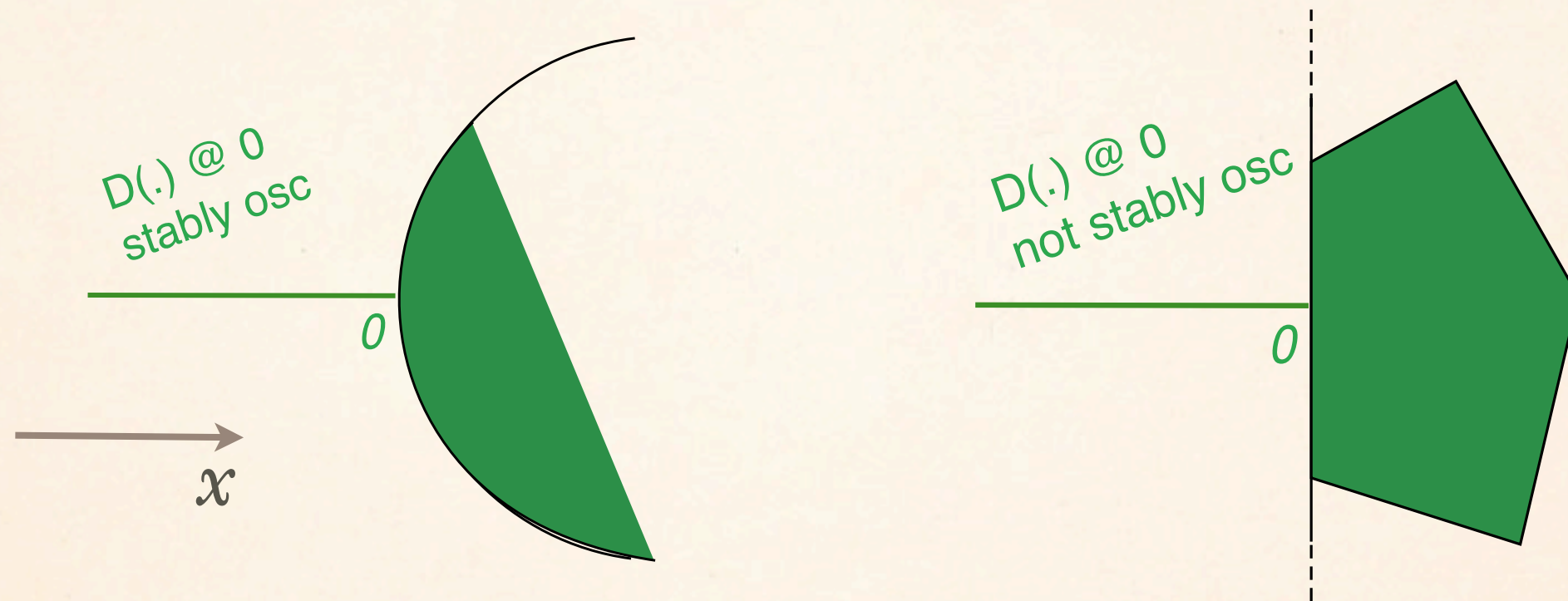
S random osc mapping: $\Xi \times \mathbb{R}^n \rightrightarrows \mathbb{R}^m$

stably osc & steady under averaging

ξ^1, ξ^2, \dots , iid random variables (values in Ξ), distribution μ

Then, $v^{-1} \sum_{k=1}^v S(\xi^k, \cdot) \xrightarrow{\text{gph}} \bar{S} = \text{cl con } E\{S(\xi^0, \cdot)\} \quad \mu^\infty\text{-a.s.}$

STABLY OSC

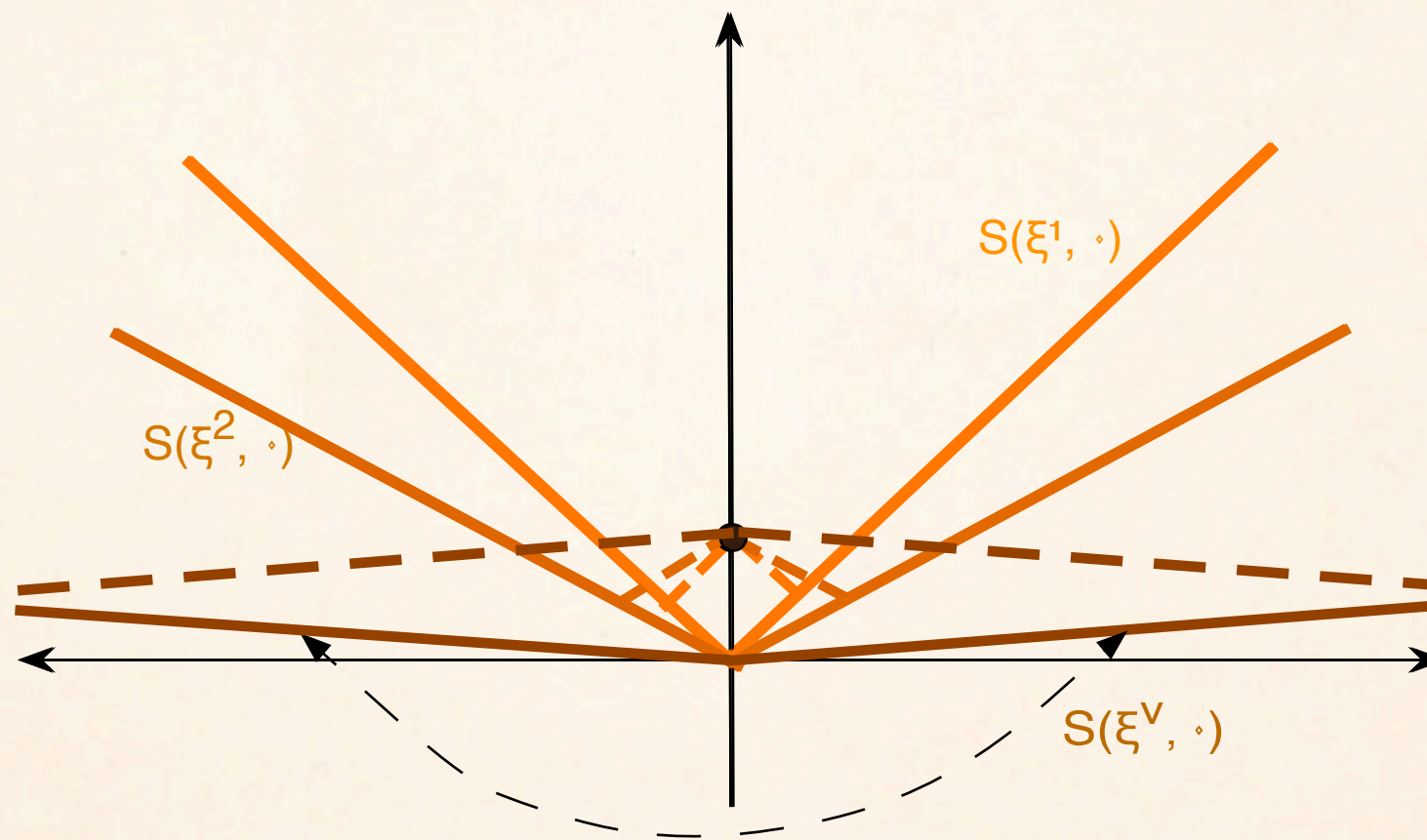


S stably osc near \bar{x} if μ -a.s.,

$\forall \rho > 0, \varepsilon > 0, \exists W \in \mathcal{N}(\bar{x}) \text{ \& } \eta \mathbb{B} \text{ } (\eta > 0) :$

$$e_\rho(S(\xi, x'), S(\xi, x)) < \varepsilon, \forall x' \in x + \eta \mathbb{B}, x \in W$$

STEADY UNDER AVERAGING



$u \in S^v(\vec{\xi}^v, x) \cap \rho\mathbb{B} \Rightarrow \exists \hat{\rho} \geq \rho, u^k \in S(\xi^k, x) \cap \hat{\rho}\mathbb{B}$ such that

$$u = v^{-1}(u^1 + \cdots + u^v); \quad S^v(\vec{\xi}^v, x) \cap \rho\mathbb{B} \subset \frac{1}{v} \left[\sum_{k=1}^v S(\xi^k, x) \cap \hat{\rho}\mathbb{B} \right]$$

STEADY UNDER AVERAGING & STABLY OSC

$\text{rge } S \subset B$ bounded \Rightarrow steady under averaging

S cone-valued and $\text{rge } S \subset$ pointed cone K . Then,

$\bar{S} = ES$ and \Rightarrow steady under averaging.

S, R steady under averaging \Rightarrow so is $S + R$

$R(\xi, x) = R(x) \Rightarrow R$ steady under averaging

$\text{rge } S$ bounded + R constant \Rightarrow steady under averaging

$G(\xi, x) + N_C(x) \Rightarrow$ steady under averaging (V.I.)

$G : \Xi \times X \rightarrow \mathbb{R}^n$ is bounded

S, R stably osc $\Rightarrow S + R$ stably osc

although D^1, D^2 osc $\nRightarrow D^1 + D^2$ osc

\mathbb{B} closed, convex $x \mapsto N_{\mathbb{B}}(x)$ osc

but not stably osc ($x^\vee \in \text{int } \mathbb{B} \rightarrow \bar{x} \in \text{bdry } \mathbb{B}$)

IMPLEMENTING SAA ** LOCALLY

$$EG(x) = \mathbb{E}\{G(\xi, x)\} \in S(x)$$

(V.I.: $S = N_C$, applied to option pricing, ...)

$$G^v(\vec{\xi}^v, \cdot) = v^{-1} \sum_{k=1}^v G(\xi^k, x). \quad \text{Assume } G^v(\vec{\xi}^v, \cdot), EG \in C^1(\mathbb{R}^n; \mathbb{R}^n),$$

\bar{x} strongly regular solution [Robinson] of $EG(x) \in S(x)$,

$\exists V \in N(\bar{x}), \rho > 0$ such that $\forall z \in \rho\mathbb{B}$:

$$z + EG(\bar{x}) + \nabla EG(\bar{x})(x - \bar{x}) \in S(x)$$

has a unique solution $\bar{x}(z) \in V$, Lipschitz continuous on $\rho\mathbb{B}$, and

$$\left\| G^v(\vec{\xi}^v, \cdot) - EG \right\| \rightarrow 0 \text{ } \mu\text{-a.s.} \quad \text{Then, for } v \text{ sufficiently large}$$

on a neighborhood of \bar{x} , $G^v(\vec{\xi}^v, \cdot) \in S(x)$ has a unique solution

$$\bar{x}(\vec{\xi}^v) \rightarrow \bar{x} \quad \mu\text{-a.s.}$$

IMPLEMENTING SAA ** EXAMPLE

stochastic program with recourse (simple): ξ uniform on $[1,2]$

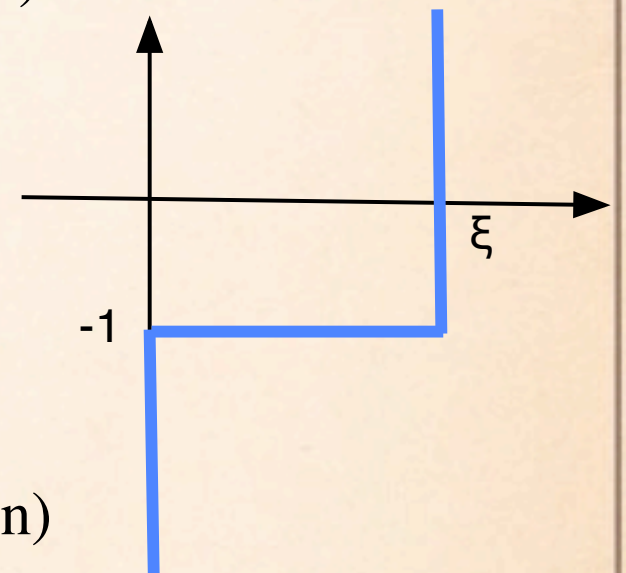
$$\min_{x, y_\xi} \mathbb{E} \left\{ -x \mid x + y_\xi \leq \xi, x \in [0, 2], y_\xi \geq 0 \right\} = \min (Ef(x) = \mathbb{E} \{ f(\xi, x) \})$$

$$f(\xi, x) = -x + l_{[0, 2]} + l_{(-\infty, \xi]} = -x + l_{[0, \xi]}$$

to solve $0 \in \partial Ef(x)$ gets replaced by $0 \in v^{-1} \sum_{k=1}^v S(\xi^k, x) = S^v(\vec{\xi}^v, x)$

$$S(\xi, x) = \partial f(\xi, x) = -1 + N_{[0, \xi]}(x), \quad \text{dom } S(\xi, \cdot) = [0, \xi]$$

$$= \begin{cases} (-\infty, -1] & \text{when } x = 0, \\ -1 & \text{for } x \in (0, \xi), \\ [1, \infty) & \text{when } x = \xi \end{cases}$$



Solution of $0 \in S^v(\vec{\xi}^v, x) : x^v = \min \{ \xi^1, \dots, \xi^v \} \rightarrow_{\text{a.s.}} \bar{x} = 1$ (opt. sol'n)

but x^v is never a feasible solution,

$\nexists y_\xi \geq 0$ such that $x^v + y_\xi \leq \xi$ when $\xi \in [1, x^v)$

Problem: $\partial Ef(x) \neq \mathbb{E} \{ \partial f(\xi, x) \}$ *** interchange is not valid.

IV. RANDOM LSC FUNCTIONS

STOCHASTIC PROGRAM WITH RECOURSE

$$f(\xi, x) = f_{10}(x) + \inf_{y \in Y} \left\{ f_{20}(\xi; x, y) \mid f_{2i}(\xi; x, y) \leq 0, i = 1, \dots, m_2 \right\}$$

when $f_{1i}(x) \leq 0, i = 1, \dots, m_1,$

$= \infty$ otherwise

2-stage **stochastic program with recourse**: $\min_{x \in \mathbb{R}^n} E \{ f(\xi, x) \}$

$$f(\xi, x(\cdot)) = \begin{cases} f_0(\xi, x(\cdot)) & \text{if } x(\xi) \in C(\xi, x(\xi)) \text{ a.s.} \\ \infty & \text{otherwise} \end{cases}.$$

with $\xi \mapsto x(\xi)$ & $\xi \mapsto C(\xi, x(\xi)) \in \mathcal{N}_\infty$ (non-anticipative)

(dynamic) stochastic programs with recourse

$$\min_{x \in \mathcal{N}^a} E \{ f(\xi, x(\xi)) \}$$

SOLVING VIA APPROXIMATION

$P^\nu \rightarrow_n P$ usually a discretization (P^ν)

say, generated via taking conditional expectation, ...

$$\min_{x \in \mathbb{R}^n} E^\nu f = \mathbb{E}^\nu \{f(\xi, x)\} = \int_{\Xi} f(\xi, x) P^\nu(d\xi)$$

$$\text{approximates } \min_{x \in \mathbb{R}^n} E f = \int_{\Xi} f(\xi, x) P(d\xi) ?$$

If $E f^\nu \rightarrow_e E f$ then " $\arg \min E f^\nu \rightarrow \arg \min E f$ "

& " ε -arg min $E f^\nu \rightarrow \varepsilon$ -arg min $E f$ " (confidence intervals)

holds if $\{P^\nu, \nu \in \mathbb{N}\}$ is f -tight: for all $x \in \text{dom } E f$,

$$\forall \varepsilon > 0, \exists \text{ compact } K_\varepsilon \text{ such that } \int_{\Xi \setminus K_\varepsilon} |f(\xi, x)| P^\nu(d\xi) < \varepsilon$$

certainly the case when $\text{supp } P^\nu$ is bounded

SOLVING VIA SAMPLING

ξ^1, ξ^2, \dots iid samples of ξ (or p.iid)

$$\arg \min_{x \in X} \frac{1}{v} \sum_{k=1}^v f(\xi^k, x) \xrightarrow{?} \arg \min_{x \in X} E \{ f(\xi, x) \}$$

$$\text{Set: } Ef(x) = E \{ f(\xi, x) \} = \int_{\Xi} f(\xi, x) P(d\xi),$$

(random) empirical measure P^v , $\text{prob}[\xi = \xi^k] = v^{-1}$

$$\xi^\infty = (\xi^1, \xi^2, \dots), "E^v f(\xi^\infty, x)" = E^v f(x) = \int f(\xi, x) P^v(d\xi)$$

$$E^v f \xrightarrow{?} Ef \quad \mu^\infty\text{-a.s.} \quad (\arg \min^v \Rightarrow_a \arg \min)$$

STATISTICAL ESTIMATION

FUSION OF HARD & SOFT INFORMATION

Observation (hard data): $\xi^1, \xi^2, \dots, \xi^v$

Soft data (non-data knowledge):

- Support: (un)bounded

- density or discrete distribution,

- bounds on expectation, moments,

- heavy tails

- shape: unimodal, decreasing, parametric class

Softer data (modeling assumptions):

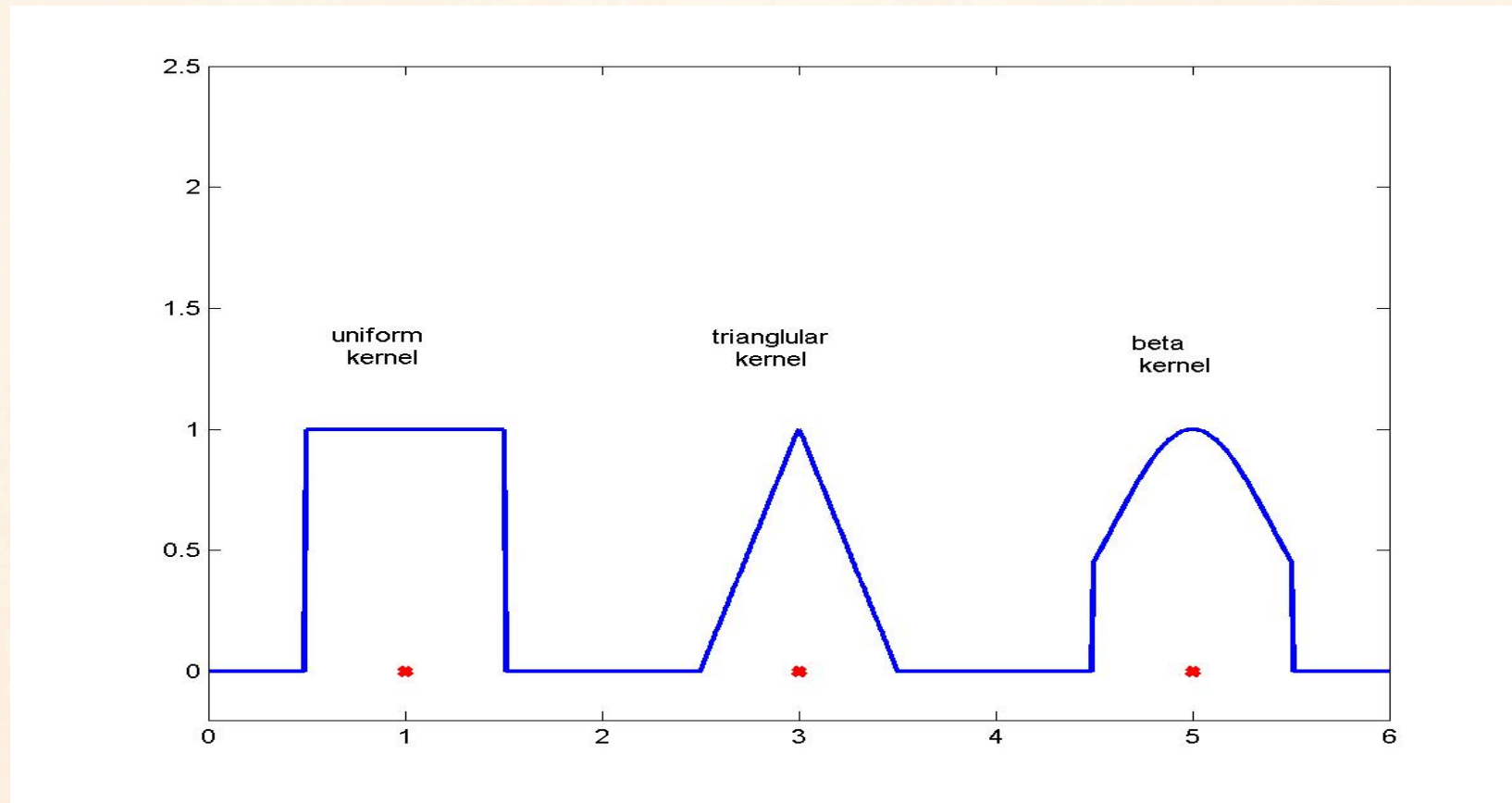
- see above + ...

- level of smoothness, 'Bayesian' neighborhood, ..

POTENTIAL APPLICATIONS

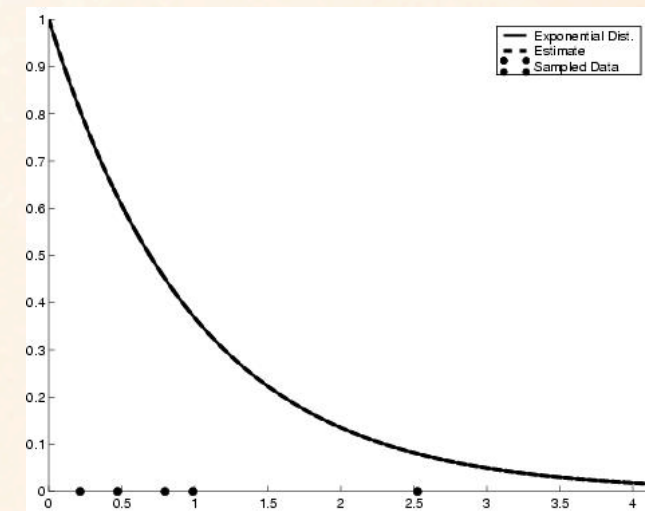
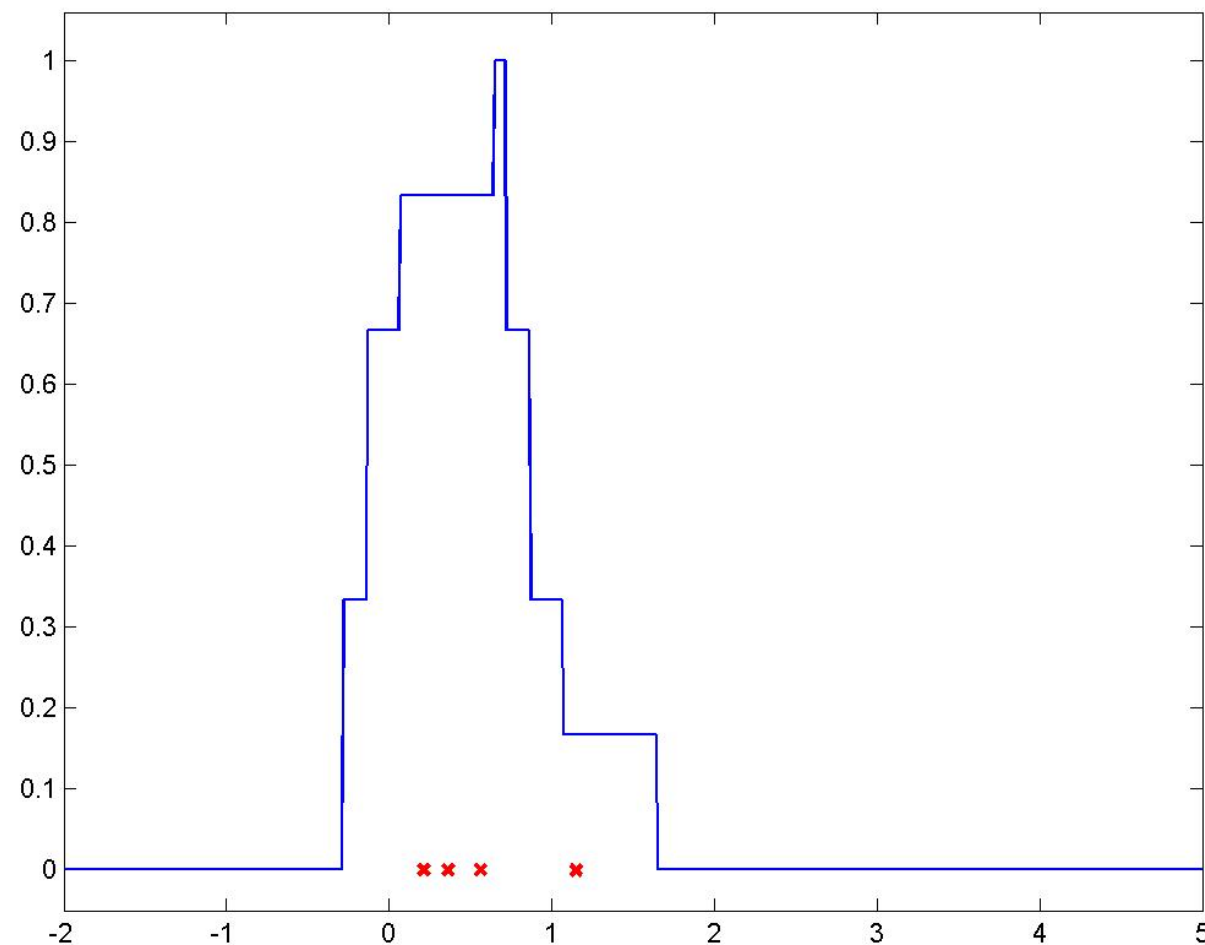
- Estimating (cum.) distribution functions
- Estimating coefficient of time series
- Estimating coefficients of stochastic differential equation (SDE)
- Estimating financial curves (zero-curves)
- Kalman filtering
- Dealing with lack of data: *few observations*
- Estimating density functions h^{est} (non-parametric)

KERNEL ESTIMATES



“frequentist” viewpoint: observations
optimal bandwidth: kernel support

KERNEL ESTIMATES: LOW DATA



$\nu=5$ samples
exponential distribution

... AS STOCHASTIC OPTIMIZATION

$$\max E^v \{ \ln h(x) \} = \frac{1}{v} \sum_{l=1}^v \ln h(x_l)$$

such that $\int h(x) dx = 1$,

$$h(x) \geq 0, \quad \forall x \in \mathbb{R}^n$$

$$h \in A^v \subset H$$

$E^v \{ \ln h(x) \} \sim \max \prod_{l=1}^v h(x_l)$ maximum likelihood

A^v soft information (constraint set)

H : density functions space, $C^2(\mathbb{R}^n)$, $HRKS(\text{supp } h)$, $H^1(\text{supp } h)$

NUMERICAL PROCEDURES

1. $h \simeq \sum_{k=1}^q u_k \varphi_k(\cdot)$ φ_k basis-functions

Fourier coefficients, wavelets, kernel-like functions

2. $h(x) = e^{-s(x)}$, s epi-spline of order n (cubic, quadratic, ...)

$$s(x) = s_0 + v_0 x + \int_0^x dr \int_0^r dt z(t), \quad z(t) \equiv z_k \text{ on } (x_k, x_{k+1}]$$

$$= s_0 + v_0 x + \sum_{j=1}^k a_{kj} z_k \text{ when } x \in (x_k, x_{k+1}]$$

ESTIMATION PROBLEM $X = \mathbb{R}$

$$\max E^v \{ \ln h(x) \} \sim \min \frac{1}{v} \sum_{l=1}^v s(x_l)$$

$$\text{such that } \int_{\text{"supp" } h} e^{-s(x)} dx \leq 1, \quad (h \geq 0)$$

$$z_k \in [-\kappa_l, \kappa_u] \text{ 'constrained'-spline}$$

$$\text{unimodal: } \kappa_l = 0$$

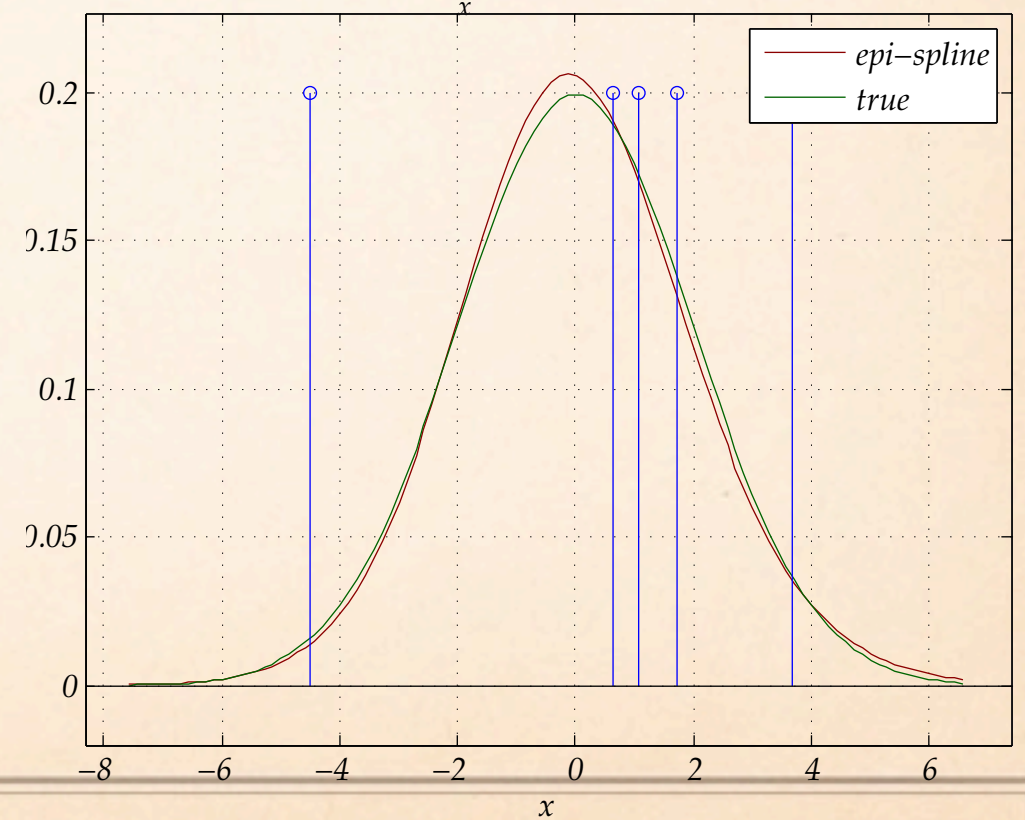
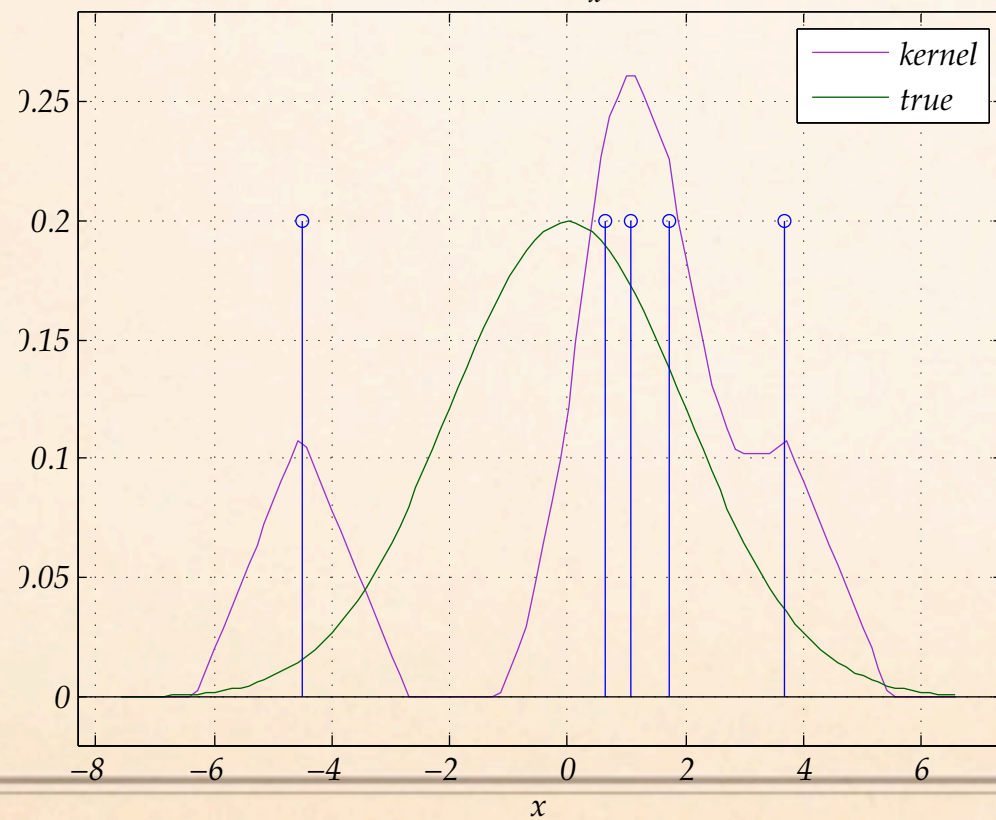
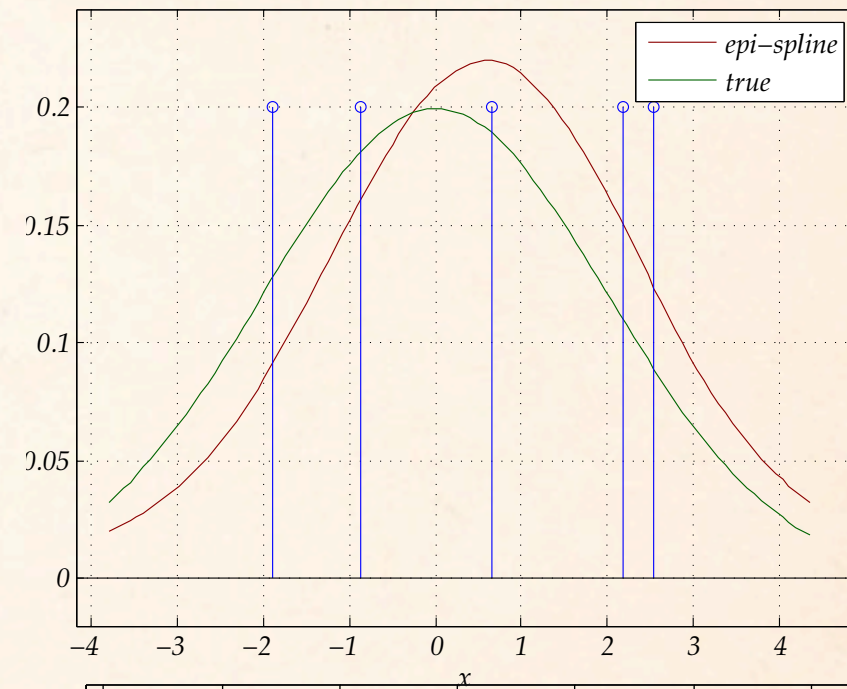
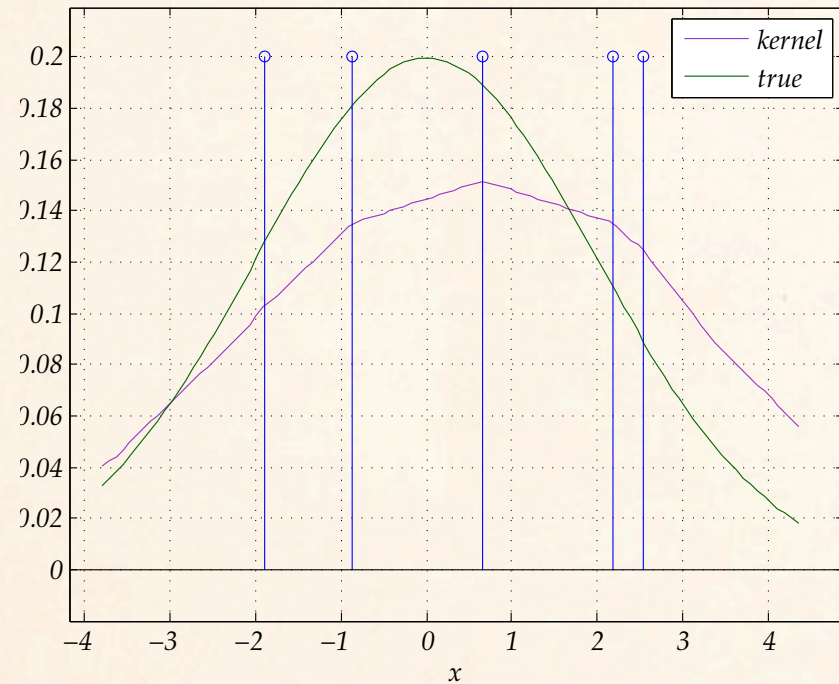
$$s(x) = s_0 + v_0 x + \sum_{j=1}^k a_{kj} z_k \text{ when } x \in (x_k, x_{k+1}]$$

constraints on z_k : on curvature of s

on "supp h ": bounds on support of h

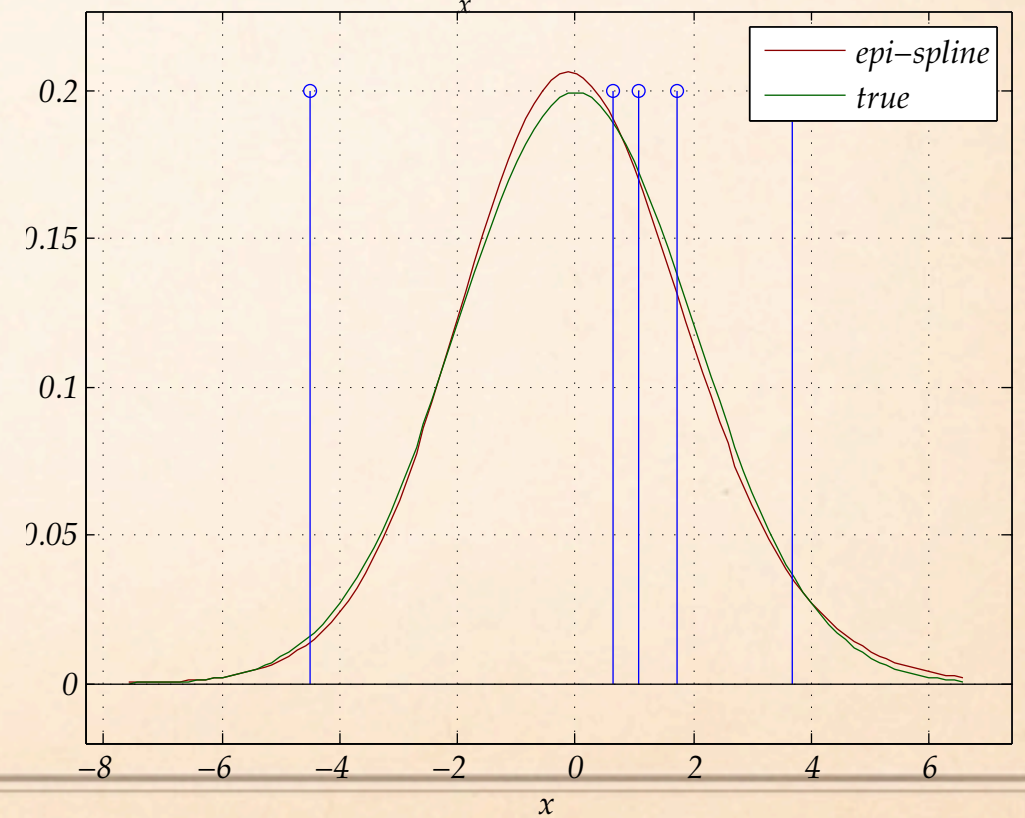
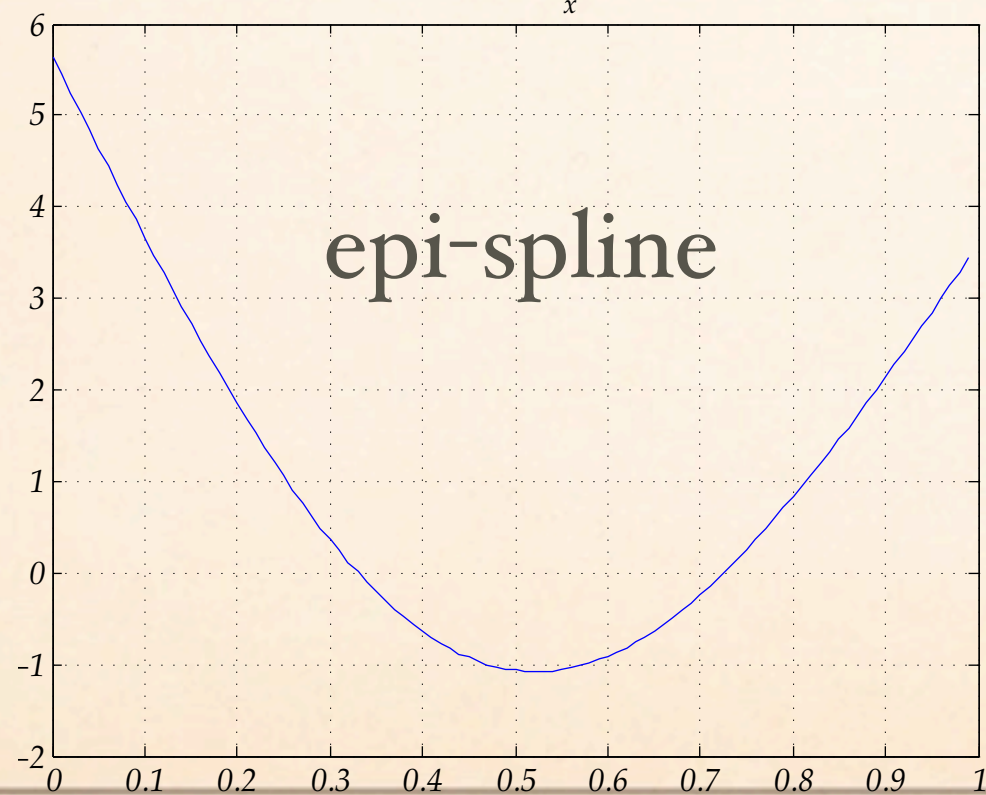
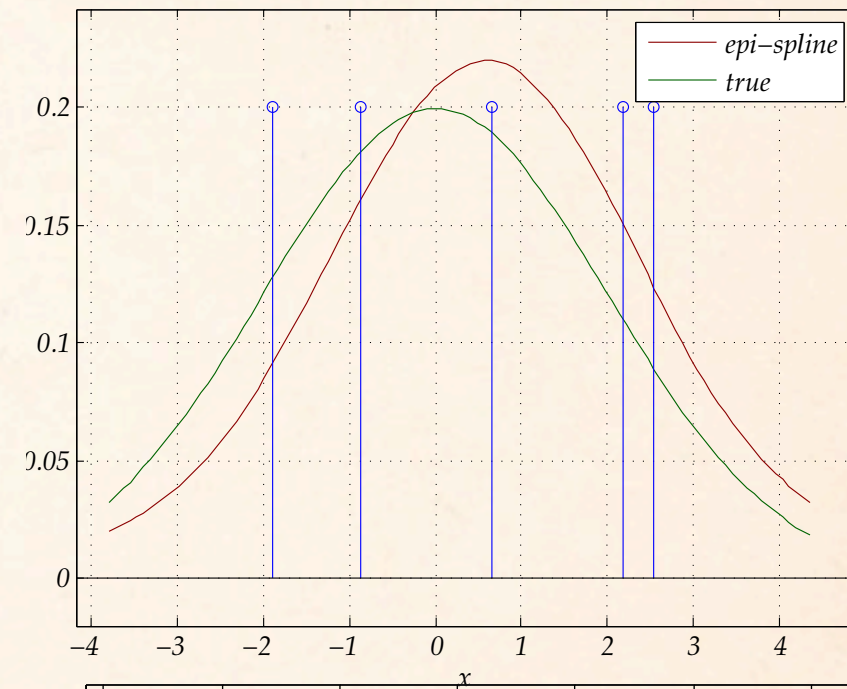
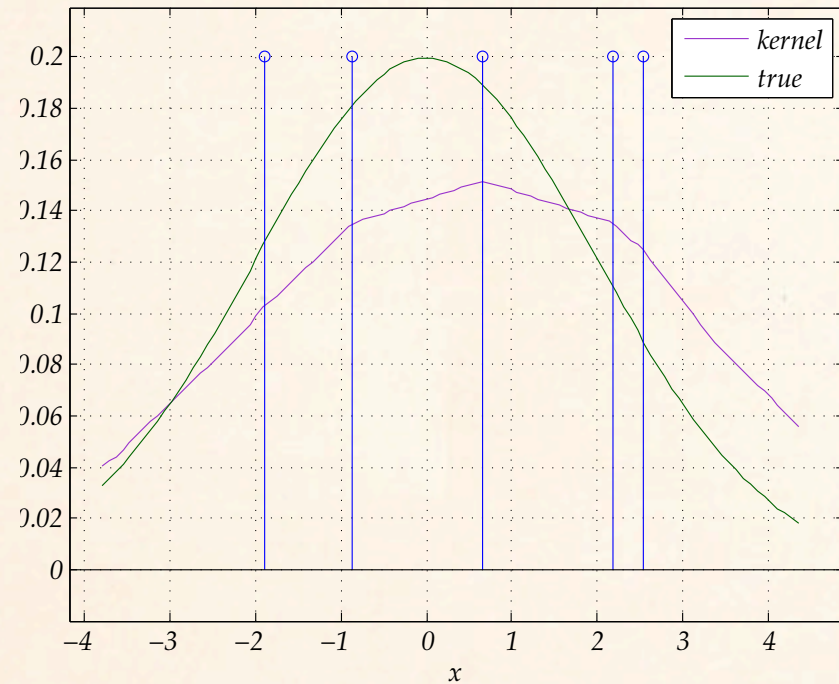
NORMAL DISTRIBUTION

KERNEL & EPI-SPLINE ESTIMATES

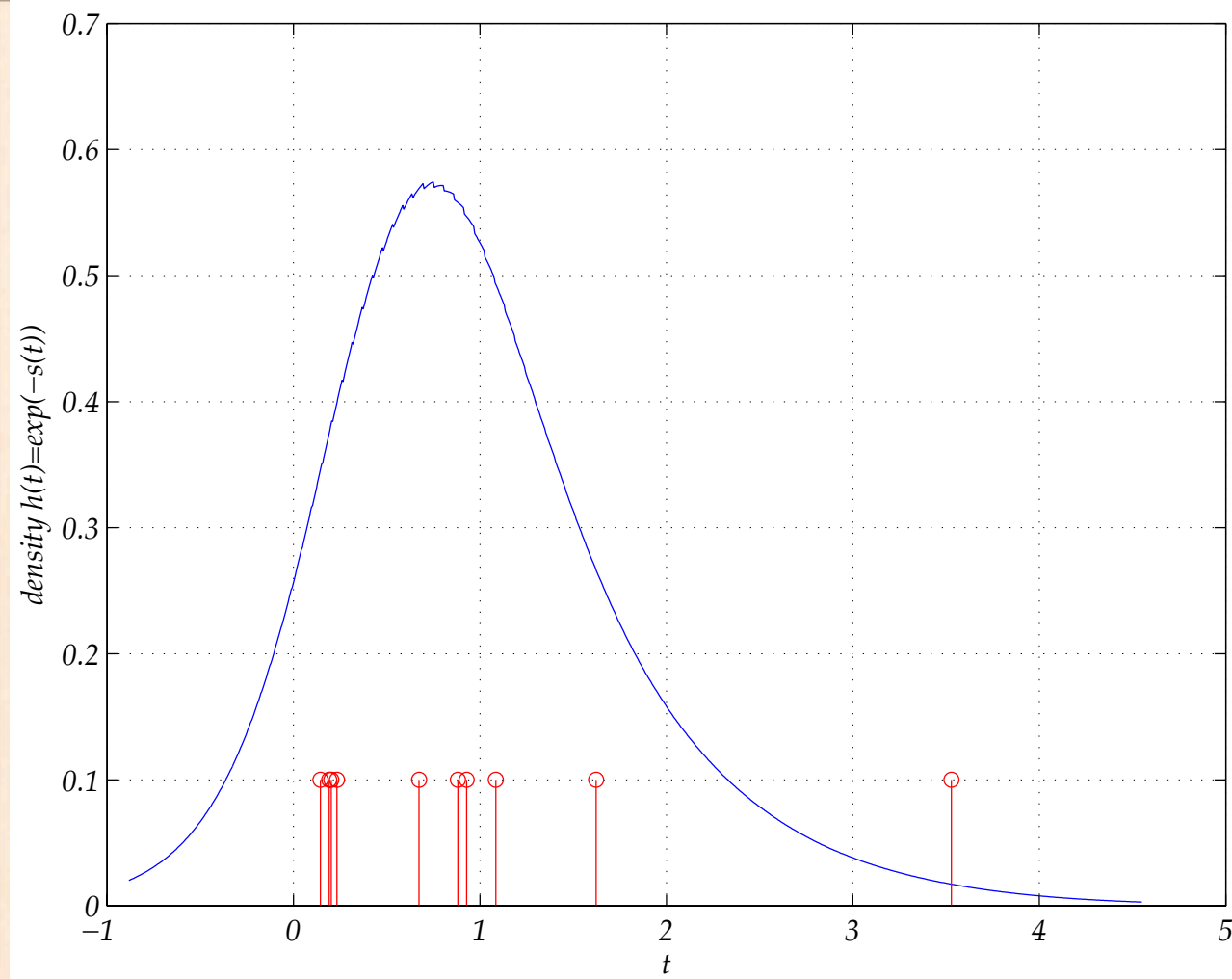


NORMAL DISTRIBUTION

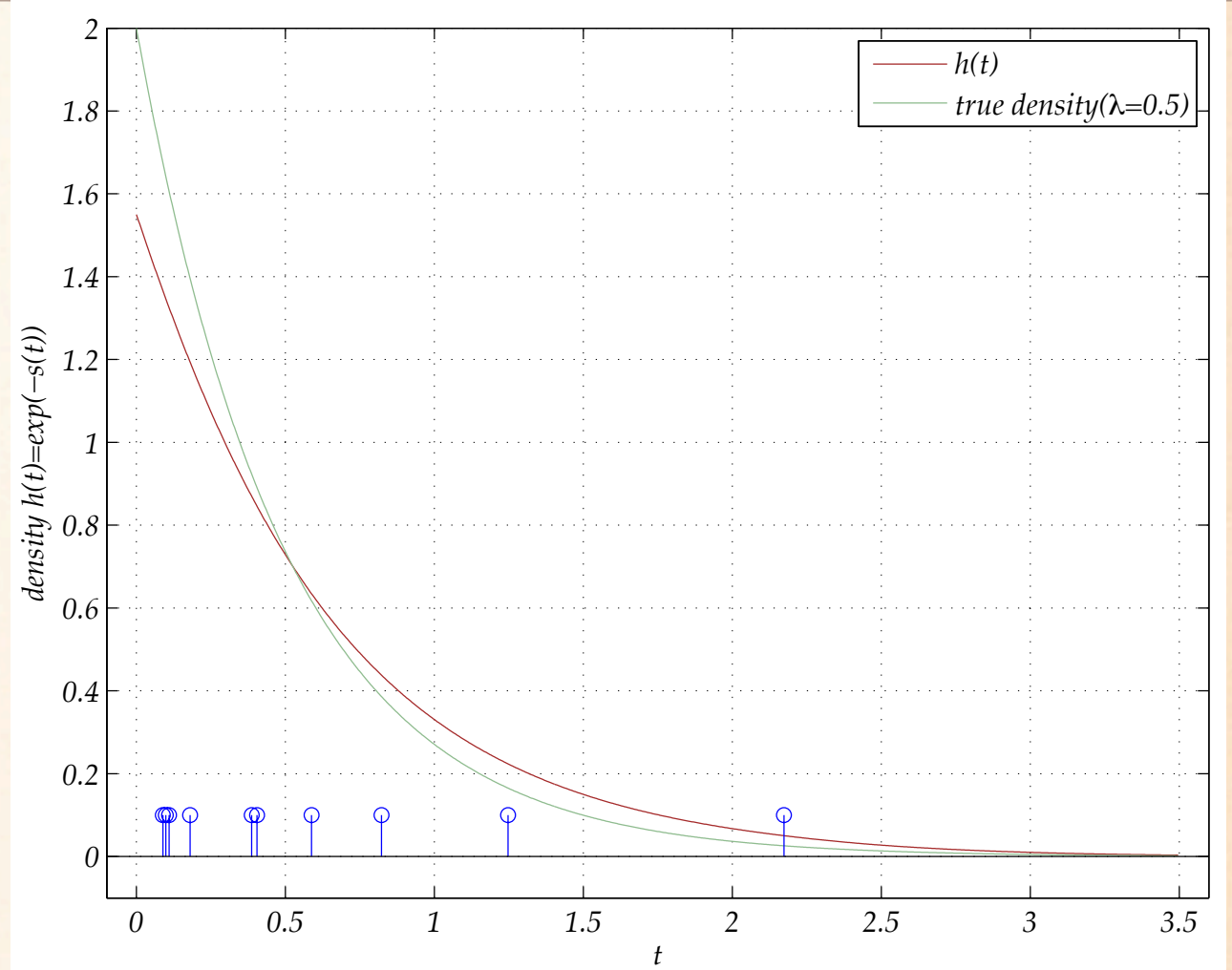
KERNEL & EPI-SPLINE ESTIMATES



KERNEL & EPI-SPLINE ESTIMATED SAMPLES FROM EXPONENTIAL DISTRIBUTION



kernel-based estimate
 R -stat



epi-spline based estimate
soft info: support \mathbb{R}_+
 b decreasing

FUNCTIONAL LLN

[Kolmogorov, Mourier ('53)] X separable Banach space
 $\{f^v : \Xi \times X \rightarrow \mathbb{R}, v \in \mathbb{N}\}$, iid and $\mathbb{E}\{|f(\xi, \cdot)|\} < \infty$. Then,
 $\forall x \in X, \frac{1}{v} \sum_{k=1}^v f^k(\xi, x) \rightarrow Ef^k(x) = \mathbb{E}\{f^k(\xi, x)\} \mu\text{-a.s.}$

For our purposes:

- a) $\mathbb{E}\{|f(\xi, \cdot)|\} < \infty$ but f is $\bar{\mathbb{R}}$ -valued!
- b) convergence is pointwise \nRightarrow arg min convergence

LLN FOR RANDOM LSC FUNCTIONS

ξ^1, ξ^2, \dots iid samples of ξ (or p.iid)

(random) empirical measure P^ν , $\text{prob}[\xi = \xi^k] = \nu^{-1}$

$\xi^\infty = (\xi^1, \xi^2, \dots)$, " $\mathbb{E}^\nu \{f(\xi^\infty, x)\}$ " = $E^\nu f(x)$

$$= \int f(\xi, x) P^\nu(d\xi) = \frac{1}{\nu} \sum_{k=1}^{\nu} f(\xi^k, x)$$

LLN (# 1): $E^\nu f \xrightarrow[\text{epi}]{} Ef \quad \mu^\infty\text{-a.s.}$ $\xi \mapsto \inf_{x \in X} f(\xi, x)$ summable

" $\arg \min_{x \in X} E^\nu f \rightarrow \arg \min_{x \in X} Ef$ " $\mu^\infty\text{-a.s.}$

f random lsc *convex* function, $f(\xi, \cdot)$ convex

$\Rightarrow \partial E^\nu f \xrightarrow[\text{gph}]{} \partial Ef \quad \mu^\infty\text{-a.s.}$ (Attouch's Theorem)

solutions of $\partial E^\nu f \ni 0 \xrightarrow{a} \text{solutions of } \partial Ef \ni 0 \quad \mu^\infty\text{-a.s.}$

$\partial E^\nu f = E^\nu \partial f$? sometimes but not always

LLN (#2) RANDOM LSC FUNCTIONS

(X, d) Polish (also, a linear space, for convenience)

$\forall \lambda > 0, \rho \geq 0 : d_{\lambda, \rho}(f, g) = \sup_{x \in \rho \mathbb{B}} |e_\lambda f(x) - e_\lambda g(x)|$, f, g proper lsc-fcns(X)

metric: $m_\lambda(f, g) = \int_0^\infty e^{-\rho} d_{\lambda, \rho}(f, g) d\rho$, topologically $\equiv dl$, τ_{aw} topology

$\lambda > 0$ sufficiently small, $m_\lambda d(f^\nu, f) \rightarrow 0 \Leftrightarrow f^\nu \xrightarrow[\text{epi}]{} f$

(ξ^0, ξ^1, \dots) iid values in $\Xi \subset \mathbb{R}^N$, support of μ

$f : \Xi \times X \rightarrow \bar{\mathbb{R}}$ random lsc function such that

$S = \{f(\xi, \cdot) \mid \xi \in \Xi\}$ separable subspace of $(\text{proper lsc-fcns}(X), \tau_{aw})$

$d_{\lambda, \rho}(E^\nu f, e_\eta E^\nu f) \searrow 0$ μ^∞ -a.s. as $\eta \searrow 0$, \forall samples $\vec{\xi}^\nu$

$d_{\lambda, \rho}(E f, e_\eta E f) \searrow 0$ μ^∞ -a.s. as $\eta \searrow 0$.

f random lsc convex function

Then, $E^\nu f \xrightarrow[\text{aw-epi}]{} E f$ μ^∞ -a.s

AUTO-REGRESSIVE TIME SERIES

$$Y_t = a_0 + a_1 Y_{t-1} + \cdots + a_p Y_{t-p} + \zeta_t, \quad t = \dots, 0, 1, \dots$$

data: $\eta_{1-p}, \dots, \eta_v$, non-data info: $a_1 \geq a_2 \geq \cdots \geq a_p$,

$$f(\xi^t, a) = \begin{cases} \left| \eta_t - a_0 - \eta_{t-1} a_1 - \cdots - \eta_{t-p} a_p \right|^2 & \text{if } a_1 \geq \cdots \geq a_p, \\ \infty & \text{otherwise} \end{cases}$$

$$f : \Xi \times \mathbb{R}^{p+1} \rightarrow \mathbb{R}, \quad \{\xi^t\} \text{ stationary}$$

$$(\bar{a}_0^v, \bar{a}_1^v, \dots, \bar{a}_p^v) \in \arg \min \frac{1}{v} \sum_{t=1}^p f(\xi^t, a)$$

$$\stackrel{?}{\rightarrow} (\bar{a}_0, \bar{a}_1, \dots, \bar{a}_p) \in \arg \min \mathbb{E} \{ f(\xi, a) \mid \mathcal{I} \} \text{ (invariant field)}$$

Ergodic Theorem: $f : \Xi \times X \rightarrow \bar{\mathbb{R}}$ random lsc fcn,

$\vartheta : \Xi \rightarrow \Xi$ ergodic measure preserving transformation

$$\frac{1}{v} \sum_{k=1}^v f(\vartheta^k(\xi), \bullet) \xrightarrow{epi} Ef \text{ a.s.}, \quad \inf_x f(\bullet, x) \text{ summable}$$

HOMOGENIZATION

conductor: $\Omega \subset \mathbb{R}^3$, composite ≥ 2 materials,
 \neq conductivity spatial location: $a(\xi, x)$ dependend
 $0 \leq a(\xi, x) \leq \kappa_{\text{bdd}}$, stationary process w.r.t. location
heat u : with rapidly varying stochastic coefficients

$$\nabla \cdot (a(\xi, x) \nabla u(\xi, x)) = h(x), \quad x \in \Omega$$

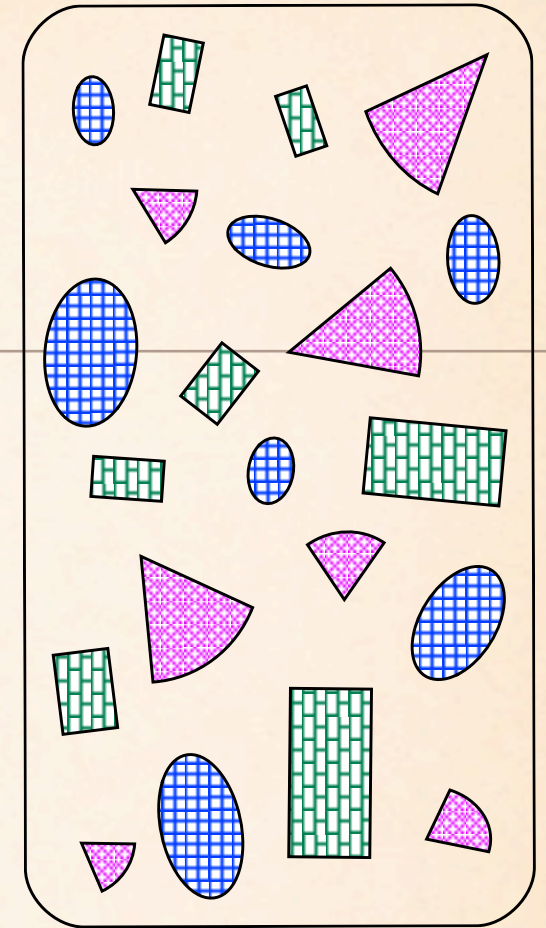
$$u(\xi, x) = 0, \quad x \in \text{bdry } \Omega$$

homogenized equation with effective coefficient a

$$\nabla \cdot (a(x) \nabla u(x)) = h(x), \quad x \in \Omega$$

$$u(\xi) = 0, \quad x \in \text{bdry } \Omega$$

such that $u(x) = \mathbb{E} \{u(\xi, x)\}$. $a(x) \neq \mathbb{E} \{a(\xi, x)\}$



HOMOGENIZATION

A “NUMERICAL” METHODOLOGY

$$\min_{u \in H_0^1(\Omega)} g(\xi, u) = \frac{1}{2} \int_{\Omega} a(\xi, x) |\nabla u|^2 dx - \langle h, u \rangle$$

$g : L^2 \rightarrow (-\infty]$, to be minimized for all ξ

homogenization: find g^{hom} such that

$$\mathbb{E} \{ u(\xi, \cdot) \} = \bar{u}(\cdot) \in \arg \min \left[g^{\text{hom}}(u) \mid u \in H_0^1(\Omega) \right]$$

—○—○—○—○ conjugate duality —○—○—○—○

$$g^{\text{hom}}(u) = \left(\text{epi-} \int_{\Xi} g(\xi, \cdot) \star P(d\xi) \right)(u) \text{ on } H_0^1(\Omega)$$

$$\left(\text{epi-} \int_{\Xi} g(\xi, \cdot) \star P(d\xi) \right)(x) = \text{epi-integral}$$

$$\inf_{z(\cdot)} \left\{ \int_{\Xi} g(\xi, z(\xi)) P(d\xi) \mid \int_{\Xi} z(\xi) P(d\xi) = x \right\}$$

approximation: $\theta \star f(\cdot) = \theta f(\theta^{-1} \cdot)$

$$\bar{u}^v \in \arg \min \left\{ v^{-1} \star \left(g(\xi^1, \cdot) \# \cdots \# g(\xi^v, \cdot) \right) \mid u \in H_0^1(\Omega) \right\}$$

Ergodic
Theorem

RANDOM LSC FUNCTIONS

[ROCKAFELLAR: NORMAL INTEGRANDS]

$f : \Xi \times X \rightarrow \bar{\mathbb{R}}$ a **random lsc function**

(X, d) Polish space, Borel field \mathcal{B}

$(\Xi, \mathcal{A}, \mathcal{P})$ probability space

(a) $f(\xi, \cdot)$ lsc $\forall \xi \in \Xi$

(b) $(\xi, x) \mapsto f(\xi, x)$ $\mathcal{A} \times \mathcal{B}^n$ -measurable (jointly)

(a & b) imply $\xi \mapsto \text{epi } f(\xi, \cdot) = \text{epi } f(\xi)$ is a **closed random set**

$\text{epi } f : \Xi \rightrightarrows X \times \mathbb{R}$ (\Rightarrow all properties can be transferred)

$\text{epi } f(\xi) \subset X \times \mathbb{R}$ closed epigraph for all $\xi \in \Xi$

& $(\text{epi } f)^{-1}(O) = \{\xi \mid \text{epi } f(\xi) \in O\} \in \mathcal{A}, \forall O \subset X \times \mathbb{R}, \text{ open}$

$\Rightarrow \text{dom epi } f = (\text{epi } f)^{-1}(X \times \mathbb{R}) \in \mathcal{A}$ (measurable set)

EXAMPLES: RANDOM LSC FCNS

$f : \Xi \times X \rightarrow \mathbb{R}$, \mathcal{A} -measurable in ξ , continuous in x

f and $-f$ are random lsc functions

f is a *Carathéodory random lsc function*

$f(\xi, x) \equiv g(x)$, g lsc

Ξ Borel subset of \mathbb{R}^d , f lsc \Rightarrow random lsc function

$f(\xi, x) = \iota_{C(\xi)}(x)$ with C random closed set

$f(\xi, x) = f_0(\xi, x) + \iota_{C(\xi)}(x)$ is a random lsc function

when f_0 random lsc function, C random closed set

Proof. $\text{epi } f(\xi) = \text{epi } f_0(\xi) \cup [C(\xi) \times \mathbb{R}]$

RANDOM LSC FCNS: PROPERTIES

f random lsc function

$\Rightarrow \text{lev}_\alpha f(\xi, \cdot)$ random closet set

$\Rightarrow \xi \mapsto p(\xi) = \inf_x f(\xi, \cdot)$ is \mathcal{A} -measurable

$p(\xi) = \inf_v \alpha_v(\xi)$ with

$\{(x^v, \alpha_v)\}_{v \in \mathbb{N}}$ Castaing representation of $\text{epi } f$

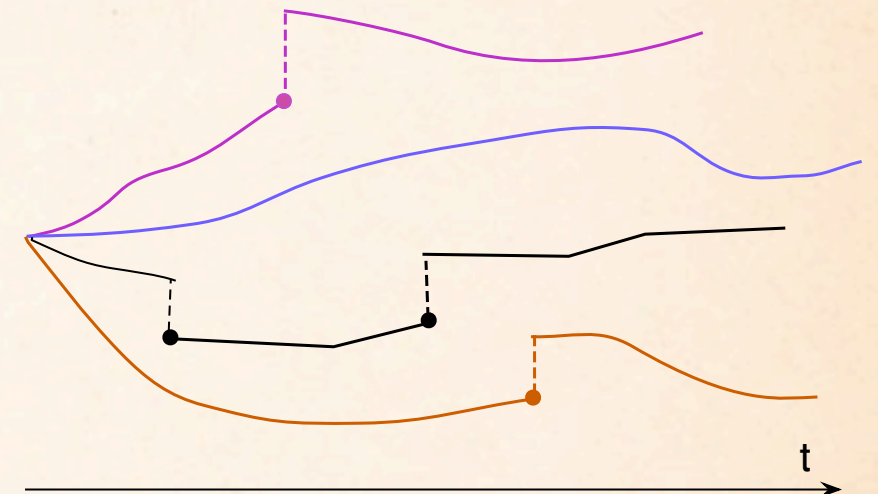
$\Rightarrow \xi \mapsto \arg \min f(\xi, \cdot) = \{x \mid f(\xi, x) \leq p(\xi)\}$ is \mathcal{A} -measurable

$\Rightarrow \exists \mathcal{A}$ -measurable selections: $f(\xi, \bar{x}(\xi)) = \min_x f(\xi, \cdot)$

Moreau envelopes: $e_{\lambda(\xi)} f(\xi, \cdot)$ are random lsc functions

$\lambda(\xi) > 0$ sufficiently small

$e_{\lambda(\xi)} f$ Carathéodory random lsc function



RANDOM CONSTRAINT SYSTEMS

$C : \Xi \rightrightarrows \mathbb{R}^n$ random closed set

$f_i : \Xi \times \mathbb{R}^n \rightarrow \bar{\mathbb{R}}$ random lsc function, $i \in I_1$

$f_i : \Xi \times \mathbb{R}^n \rightarrow \mathbb{R}$ Carathéodory random lsc fcn, $i \in I_2$

$\alpha_i : \Xi \rightarrow \mathbb{R}$ random variable $i \in I_1 \cup I_2$ (countable index)

Then, $S : \Xi \rightrightarrows \mathbb{R}^n$ is a random closed set where

$$S(\xi) = \left\{ x \in C(\xi) \left| \begin{array}{l} f_i(\xi, x) \leq \alpha_i(\xi), \ i \in I_1 \\ f_i(\xi, x) = \alpha_i(\xi), \ i \in I_2 \end{array} \right. \right\}$$

EPI-TOPOLOGY: REVIEW

$$\{f^v : \mathbb{R}^n \rightarrow \bar{\mathbb{R}}, v \in \mathbb{N}\}$$

$$\text{epi}(\text{e-li}_v f^v) = \text{Ls}_v \text{epi } f^v, \quad \text{epi}(\text{e-ls}_v f^v) = \text{Li}_v \text{epi } f^v$$

$$\text{epi-limit: } f^v \xrightarrow[e]{} f \text{ when } f = \text{e-li}_v f^v = \text{e-ls}_v f^v, \quad f = \text{e-lm}_v f^v$$

Hit-and-Miss topology translated to $\text{lsc-fcns}(\mathbb{R}^n) : \tau_{\text{epi}}$

subbase: hit open sets, miss compact sets

$$\{g \in \text{lsc-fcns}(\mathbb{R}^n) \mid \inf_O g < \alpha\} \quad \{g \in \text{lsc-fcns}(\mathbb{R}^n) \mid \inf_K g > \alpha\}$$

$(\text{lsc-fcns}(\mathbb{R}^n), \tau_{\text{epi}})$ compact, metrizable space -- dl a metric

$$f \geq \text{e-ls}_v f^v \Leftrightarrow \limsup_v (\inf_O f^v) \geq \inf_O f, \quad \forall O \text{ open } (\inf_O \text{usc})$$

$$f \leq \text{e-li}_v f^v \Leftrightarrow \liminf_v (\inf_K f^v) \leq \inf_K f, \quad \forall K \text{ compact } (\inf_K \text{lsc})$$

SCALARIZATION

Effrös field for lsc-fcns(\mathbb{R}^n): \mathcal{E} ($= \mathcal{B}_X, X$ Polish)

generated by $\mathcal{A}_{D,\alpha} = \{f \in \text{lsc-fcns}(X) \mid \inf_D f \leq \alpha\}$, D closed or open

distribution of a random lsc function $f : \Xi \times \mathbb{R}^n \rightarrow \bar{\mathbb{R}}$

$$P_f(\mathcal{A}) = \mu\{\xi \in \Xi \mid f(\xi, \cdot) \in \mathcal{A}\}, \mathcal{A} \in \mathcal{E}$$

$\pi_D(\xi) = \inf_{x \in D} f(\xi, x)$ with $f : \Xi \rightarrow \text{lsc-fcns}(X)$, X Polish

then f random lsc fcn $\Leftrightarrow \xi \mapsto \pi_D(\xi)$ measurable for all $D \in \mathcal{D}$

where \mathcal{D} is anyone of the following:

a) all closed (or open) sets

b) all open rational balls, centers at R dense subset of X

c) if X is σ -compact, all closed rational balls, ...

$\{\pi_{x,\rho}, x \in R, \rho \in \mathbb{Q}_+\}$ countable collection $\bar{\mathbb{R}}$ -valued r.v.

inherit independence, identically distributed

ERGODICITY

$\{f^v : \Xi \times X \rightarrow \bar{\mathbb{R}}, v \in \mathbb{N}\}$ random lsc functions

$\{\pi_{x,\rho}^v = \inf_{\mathbb{B}(x,\rho)}, x \in R, \rho \in \mathbb{Q}_+\}$ countable collection $\bar{\mathbb{R}}$ -valued r.v.

f^v independent: $\{v_1, v_2, \dots, v_k\} \subset \mathbb{N}, \alpha_1, \alpha_2, \dots, \alpha_k \in \mathbb{R} \cup \{\infty\}$

$x^1, x^2, \dots, x^k \in R, \rho_1, \rho_2, \dots, \rho_k \in \mathbb{Q}_{++}$

$$P\left\{\xi \in \Xi \mid \pi_{\mathbb{B}(x^i, \rho_i)}^{v_i}(\xi) < \alpha_i, i = 1 \rightarrow k\right\} = \prod_{i=1}^k P\left\{\xi \in \Xi \mid \pi_{\mathbb{B}(x^i, \rho_i)}^{v_i}(\xi) < \alpha_i\right\}$$

stationarity: joint distributions of f^{v_1}, \dots, f^{v_k} invariant under shift

$\varphi : \Xi \rightarrow \Xi$ meas. preserving transformation: $P(\varphi^{-1}(A)) = P(A), \forall A \in \mathcal{A}$

\mathcal{I} invarian σ -field: $P(\varphi^{-1}(A) \Delta A) = 0$

φ ergodic if \mathcal{I} is trivial $P(A) \in \{0, 1\} \forall A \in \mathcal{I}$

$\{f^v, v \in \mathbb{N}\}$ ergodic $\Leftrightarrow \{f \circ \varphi^v, v \in \mathbb{N}\}$ for φ associated meas. p. transform.

$\Rightarrow \forall O$ open $\{\pi_O \circ \varphi^v, v \in \mathbb{N}\}$ ergodic sequence of $\bar{\mathbb{R}}$ -valued r.v.

ERGODIC THEOREM

(X, d) Polish, (Ξ, \mathcal{A}, μ) probability space

$\varphi: \Xi \rightarrow \Xi$ a measure preserving transformation

\mathcal{I} its invariant σ -field

$f: \Xi \times X \rightarrow \bar{\mathbb{R}}$ random lsc function, inf-locally summable:

$$\forall x \in X, \exists V \in \mathcal{N}_{\text{closed}}(x): \mathbb{E} \left\{ \pi_X(\xi) = \inf_V f(\xi, x) \right\} > -\infty$$

$$\Rightarrow \mathcal{R} \subset \mathcal{A}, \exists E^{\mathcal{R}} f(\xi, \cdot) \text{ random lsc fcn}$$

\exists countable dense subset of $\text{epi } E^{\mathcal{I}} f(\xi, \cdot)$ μ -a.s.

$\text{epi } f(\xi, \cdot)$ solid set, $\text{cl}(\text{int}(\text{epi } g)) = \text{epi } g$ (cont. on $\text{dom } g$)

Then,

$$\frac{1}{v} \sum_{k=1}^v f(\varphi^k(\xi), \cdot) \xrightarrow[\text{epi}]{} E^{\mathcal{I}} f(\xi, \cdot) \quad \mu\text{-a.s.}$$

$$\xrightarrow[\text{epi}]{} Ef \quad \mu\text{-a.s. when } \varphi \text{ is ergodic}$$

LSC STOCHASTIC PROCESSES

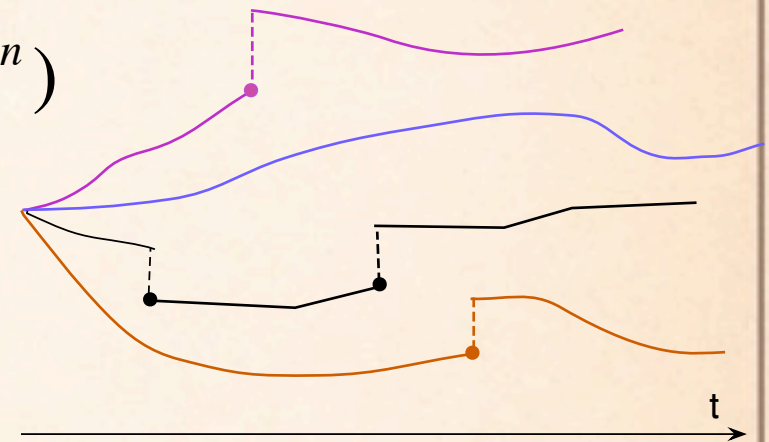
$\{f^v : \mathbb{R}^n \rightarrow \bar{\mathbb{R}}, v \in \mathbb{N}\}$ stochastic process with lsc-paths (\mathbb{R}^n)

$(\text{lsc-fcns}(\mathbb{R}^n), \tau_{\text{epi}})$ compact metrizable space -- dl a metric

τ_{epi} can be generated by $x \in \mathbb{Q}^n, \rho \in \mathbb{Q}_{++}, \alpha \in \mathbb{Q}$

$$\left\{ g \in \text{lsc-fcns}(\mathbb{R}^n) \mid \inf_{\mathbb{B}^o(x, \rho)} g < \alpha \right\} \quad \left\{ g \in \text{lsc-fcns}(\mathbb{R}^n) \mid \inf_{\mathbb{B}(x, \rho)} g > \alpha \right\}$$

a.s.-, in probability, in distribution convergence \sim as for their epigraphs



process $\{f^v : \mathbb{R}^n \rightarrow \bar{\mathbb{R}}, v \in \mathbb{N}\}$ converges in distribution in

'classical' sense (i.e., pointwise) \Rightarrow epi-converge in distribution

if the paths $x \mapsto f^v(\xi, x)$ are equi-lsc μ -a.s.:

$$\forall x, \varepsilon > 0, \exists V \in \mathcal{N}(x) : \inf \{ f^v(\xi, x) \mid x \in V \} > \min[\varepsilon^{-1}, \inf f^v(\xi, \cdot) - \varepsilon]$$

DISTANCE & INDICATOR FUNCTIONS

$\{C^v : \Xi \Rightarrow \mathbb{R}^m, v \in \mathbb{N}\}$ random closed sets

(set-)converge in distribution to $C \Leftrightarrow$

processes $\{d(C^v(x, \cdot), v \in \mathbb{N})\}$ converge

in distribution to $d(C(x, \cdot))$ for all $x \in \mathbb{R}^m$

$C^v(\xi) = \text{ray through } (1, v^{-1})$

$C(\xi) = \{(0,0)\}$, $\tilde{C}(\xi) = \text{ray through } (1,0)$

C^v converges in distribution to \tilde{C} (clearly)

but ι_{C^v} converges in distribution to ι_C (exercise)

... IN DISTRIBUTION OF SELECTIONS

$\{C^v : \Xi \Rightarrow \mathbb{R}^m, v \in \mathbb{N}\}$ random closed sets

converge in distribution to C . Then,

\exists measurable selections x^v of C^v

converging in distribution to a selection of C .

(also holds for Castaing representations)

$\{f^v : \Xi \times X \rightarrow \bar{\mathbb{R}}, v \in \mathbb{N}\}$ random lsc functions

epi-converge in distribution to f

$\xi \mapsto \arg \min f^v(\xi, \cdot)$ are random sets \Rightarrow

selections (minimizers) converge in distribution if

$(\arg \min f^v)$ converge in distribution

1. $f^v \rightarrow f$ + epi-tightness $\Rightarrow \inf f^v \rightarrow \inf f$ in distribution

2. + under μ -a.s. convergence, $\arg \min f^v(\xi, \cdot) \xrightarrow{p} \arg \min f(\xi, \cdot)$

V. EXPECTATION FUNCTIONALS □□ CALCULUS

EXPECTATION FUNCTIONALS

$f : \Xi \times \mathcal{X} \rightarrow \bar{\mathbb{R}}$, random lsc function,

$\mathcal{X} \subset \mathcal{M}(\Xi, \mathcal{A}; \mathbb{R}^n) : \mathcal{L}^p(\Xi, \mathcal{A}, \mu; \mathbb{R}^n), \dots$

others: $C((\Xi, \tau); \mathbb{R}^n)$, Orlicz, Sobolev, lsc-fcns(\mathbb{R}^n)

$$Ef(x) = \int_{\Xi} f(\xi, x(\xi)) \mu(d\xi) = \mathbb{E}\{f(\xi, x(\xi))\}$$
$$= \infty \text{ whenever } \int_{\Xi} f_+(\xi, x(\xi)) \mu(d\xi) = \infty$$

$Ef : \mathcal{X} \rightarrow \bar{\mathbb{R}}$ always defined

Regression: (\mathcal{X} is not a linear space)

$$\min \left\{ \int_{y \in \mathbb{R}} \int_{x \in [0,1]^n} \phi(y - h(x)) P(dx, dy) \mid h \in \text{lsc-fcns}(\mathbb{R}) \cap \mathcal{H} \right\}$$

\mathcal{H} shape restrictions (convex, unimodal, ...)

DECOMPOSABILITY

$\mathcal{X} \subset \mathcal{M}$ decomposable (w.r.t. μ) when

$\forall x^0 \in \mathcal{X}, A \in \mathcal{A}$ and $x^1 : A \rightarrow \mathbb{R}^n \in \mathcal{M}$, bounded

$$x(\xi) = \begin{cases} x^0(\xi) & \text{for } \xi \in \Xi \setminus A \\ x^1(\xi) & \text{for } \xi \in A \end{cases}$$

$\Rightarrow \mathcal{X}$ is a linear space ($0 \in \mathcal{X}$)

$\mathcal{L}^p(\Xi, \mathcal{A}, \mu; \mathbb{R}^n)$, \mathcal{M} are decomposable

$C(\Xi, \mathcal{A}; \mathbb{R}^n)$, constant-fcns(Ξ) not decomposable

f random lsc function, $Ef \not\equiv \infty$ on \mathcal{X} . Then,

$$\inf_{x \in \mathcal{X}} \int_{\Xi} f(\xi, x(\xi)) \mu(d\xi) = \int_{\Xi} \left[\inf_{x \in \mathbb{R}^n} f(\xi, x) \right] \mu(d\xi)$$

$$\bar{x} \in \arg \min_{x \in \mathcal{X}} Ef(x) \Leftrightarrow \bar{x}(\xi) \in \arg \min_{x \in \mathbb{R}^n} f(\xi, x) \mu\text{-a.s.} \text{ (inf } ES > -\infty)$$

INTERCHANGE OF SUBDIFFERENTIATION AND INTEGRATION

$f : \Xi \times \mathbb{R}^n \rightarrow \mathbb{R} \cup \{\infty\}$, random convex lsc function,

$Ef : \mathcal{X} \rightarrow \bar{\mathbb{R}}$, here $\mathcal{X} = \mathcal{L}^\infty(\Xi, \mathcal{A}, \mu; \mathbb{R}^n)$

\mathcal{G} subfield of \mathcal{A} (possibly the trivial field $= \{\emptyset, \Xi\}$)

$f^{\mathcal{G}} : \Xi \times \mathbb{R}^n \rightarrow \bar{\mathbb{R}}$ with $f^{\mathcal{G}}(\xi, x) = \int_{\Xi} f(\zeta, x) P^{\mathcal{G}}(d\zeta | \xi)$

$Ef^{\mathcal{G}} : \tilde{\mathcal{X}} \rightarrow \bar{\mathbb{R}}$, here $\tilde{\mathcal{X}} = \mathcal{L}^\infty(\Xi, \mathcal{G}, \mu; \mathbb{R}^n)$

assume Ef & Ef^* finite for some \mathcal{G} -measurable functions $x(\bullet)$

$\partial^* Ef \subset (\mathcal{L}_n^\infty)^* = \mathcal{L}^1(\Xi, \mathcal{A}, \mu; \mathbb{R}^n) \oplus S(\Xi, \mathcal{A}, \mu; \mathbb{R}^n)$

$\partial^* Ef(x) = \partial Ef(x) + N_{\text{dom } Ef}^S(x)$, $\partial Ef(x) = \{v \in \mathcal{L}^1 | v(\xi) \in \partial f(\xi, x(\xi)) \text{ } \mu\text{-a.s.}\}$

$\partial^* Ef^{\mathcal{G}}(x) = \partial Ef^{\mathcal{G}}(x) + N_{\text{dom } Ef^{\mathcal{G}}}^S(x)$, $\partial Ef^{\mathcal{G}}(x) = \dots$ in $\mathcal{L}_n^1(\mathcal{G})$

$$x \in \mathcal{L}_n^\infty, \quad \partial Ef^{\mathcal{G}}(x) = \mathbb{E}^{\mathcal{G}} \{ \partial f(\xi, x(\xi)) \} \text{ } \mu\text{-a.s. ?}$$

VALIDATING THE INTERCHANGE

$f : \Xi \times \mathbb{R}^n \rightarrow \mathbb{R} \cup \{\infty\}$, random convex lsc fcn, $Ef : \mathcal{L}_n^\infty \rightarrow \bar{\mathbb{R}}$, $\mathcal{G} \subset \mathcal{A}$,

suppose $\xi \mapsto D(\xi) = \text{cl dom } f(\xi, \cdot)$ \mathcal{G} -measurable

$Ef(x) < \infty : \forall \mathcal{G}$ -measurable selection of D (+ summ. condition)

Then, $\forall x \in \mathcal{L}_n^\infty(\mathcal{G}) : \partial Ef^{\mathcal{G}}(\xi, x(\xi)) = \mathbb{E}^{\mathcal{G}} \{ \partial f(\xi, x(\xi)) \}$ μ -a.s.

i.e., the closed-valued \mathcal{G} -measurable mappings $\partial Ef^{\mathcal{G}} = \mathbb{E}^{\mathcal{G}} \partial f$ μ -a.s.

$\inf \mathbb{E} \{ f(\xi, x^1(\xi), x^2(\xi)) \}$, $x^1 \in \mathcal{L}_n^\infty(\mathcal{G})$, $x^2 \in \mathcal{L}_n^\infty(\mathcal{A})$

$\exists h \in \mathcal{L}^1(\mathcal{A})$ such that $(x^1, x^2) \in \text{dom } f(\xi, \cdot, \cdot) \Rightarrow |f(\xi, x^1, x^2)| < \infty$

$\xi \mapsto D_1(\xi) = \text{cl} \{ x^1 \in \mathbb{R}^n \mid \exists x^2 : f(\xi, x^1, x^2) < \infty \}$ \mathcal{G} -measurable

$\inf Eg(x^1)$ on $x^1 \in \mathcal{L}_n^\infty(\mathcal{G})$ with $g(\xi, x^1) = \mathbb{E}^{\mathcal{G}} \left[\inf_{x^2 \in \mathbb{R}^n} f(\cdot, x^1, x^2) \right](\xi)$

is "equivalent" to given problem. [Consider $\mathcal{G} = \{ \emptyset, \mathbb{R}^n \}$]

$\min_{x, y_\xi} \{ -x^1 \mid x^1 + x_\xi^2 \leq \xi, x^1 \in [0, 2], x_\xi^2 \geq 0 \} = \min (Ef(x) = \mathbb{E} \{ f(\xi, x) \})$

$f(\xi, x) = -x^1 + \iota_{[0, 2]} + \iota_{(-\infty, \xi]} = -x^1 + \iota_{[0, \xi]}$

$\mathcal{G} = \{ \emptyset, [1, 2] \}$, $D(\xi) = [0, \xi]$ is not \mathcal{G} -measurable!

PRICING A CONTINGENT CLAIM

environment process: $\{\xi^t \in \mathbb{R}^d\}_{t=0}^T$ history: $\vec{\xi}^t$, $\xi = \xi^T$

price process: $S^t(\vec{\xi}) \in \mathbb{R}^n$; numéraire (risk-free): $S_1^t \equiv 1$

contingent claims: $\left\{G^t(\vec{\xi})\right\}_{t=1}^T$; investment strategy: $\left\{X^t(\vec{\xi})\right\}_{t=0}^T$

portfolio value at t : $\langle S^t(\vec{\xi}), X^t(\vec{\xi}) \rangle$

PRICING: T-bonds, options, swaps, insurance contracts, mortgages, ...

$\max \mathbb{E}\{\langle S^T, X^T \rangle\}$ such that $\langle S^t, X^t \rangle \leq G^t + \langle S^t, X^{t-1} \rangle$, $t = 1 \rightarrow T$

(T+1)-stage linear stoch. opt. $\langle S^0, X^0 \rangle \leq G^0$, $\langle S^T, X^T \rangle \leq G^T$ a.s.

feasible if $G^0 + \dots + G^T \geq 0 \quad \forall \xi$, with arbitrage when unbounded

prob[$\xi = \xi$] = p_ξ & finite support: $\max \sum_{\xi \in \Xi} p_\xi \langle S^T(\xi), X^T(\xi) \rangle \dots$

RISK NEUTRAL PROBABILITIES: DUALITY

pricing via risk-neutral probabilities (obtained from dual variables)

$$f(\xi, x(\xi)) = \begin{cases} -\langle S^T(\xi), X^T(\xi) \rangle & \text{when } x(\xi) \in C(\xi) \\ \infty & \text{otherwise} \end{cases}$$

$$x(\xi) = \left(X^0(\xi^0), \dots, X^T(\vec{\xi}^T) \right), \quad C(\xi) = \{x(\xi) \mid \text{satisfies the constraints a.s.}\}$$

$$\min_{x \in \mathcal{N} \subset \mathcal{M}} \mathbb{E} \{ f(\xi, x(\xi)) \}, \quad f \text{ random convex lsc function}$$

\mathcal{L}^1 - "Perfect" duality: (1) $\mathbb{C}.\mathbb{Q}.$ ($\mathcal{M} = \mathcal{L}_n^\infty$), (2) $\xi \mapsto C(\xi)$ nonanticipative

$$\forall t : \mathbb{E} \left\{ C(\xi) \middle| \vec{\xi}^{\rightarrow t} \right\} \vec{\xi}^{\rightarrow t} \text{-measurable (depend only on past history)}$$

Pricing a contingent claim doesn't satisfy (2) \Rightarrow no "perfect" duality

Full duality requires: dual variables $\in \mathcal{L}_n^1 \oplus S_n$, but ...

i.e., the risk-neutral probabilities are in $\mathcal{L}_n^1 \oplus S_n$!

SOLUTION PROCEDURES FOR STOCHASTIC VARIATIONAL PROBLEMS

INFORMATION-DECISION PROCESS

$$\xi^0 \rightarrow x^1(\xi^0) = x^1 \rightarrow \xi^1 \rightarrow x^2(\xi^0, \xi^1) \rightarrow \xi^2$$

More specifically,

(dynamic) Stochastic Programs with Recourse:

$$\min_{x \in \mathcal{N}^a} \mathbb{E} \{ f(\xi, x(\xi)) \}$$

time scale: $t = 0, 1, 2, \dots, T$, $x(\xi) = (x^1(\xi), \dots, x^T(\xi))$

$$\xi = (\xi^0, \xi^1, \dots, \xi^T)$$

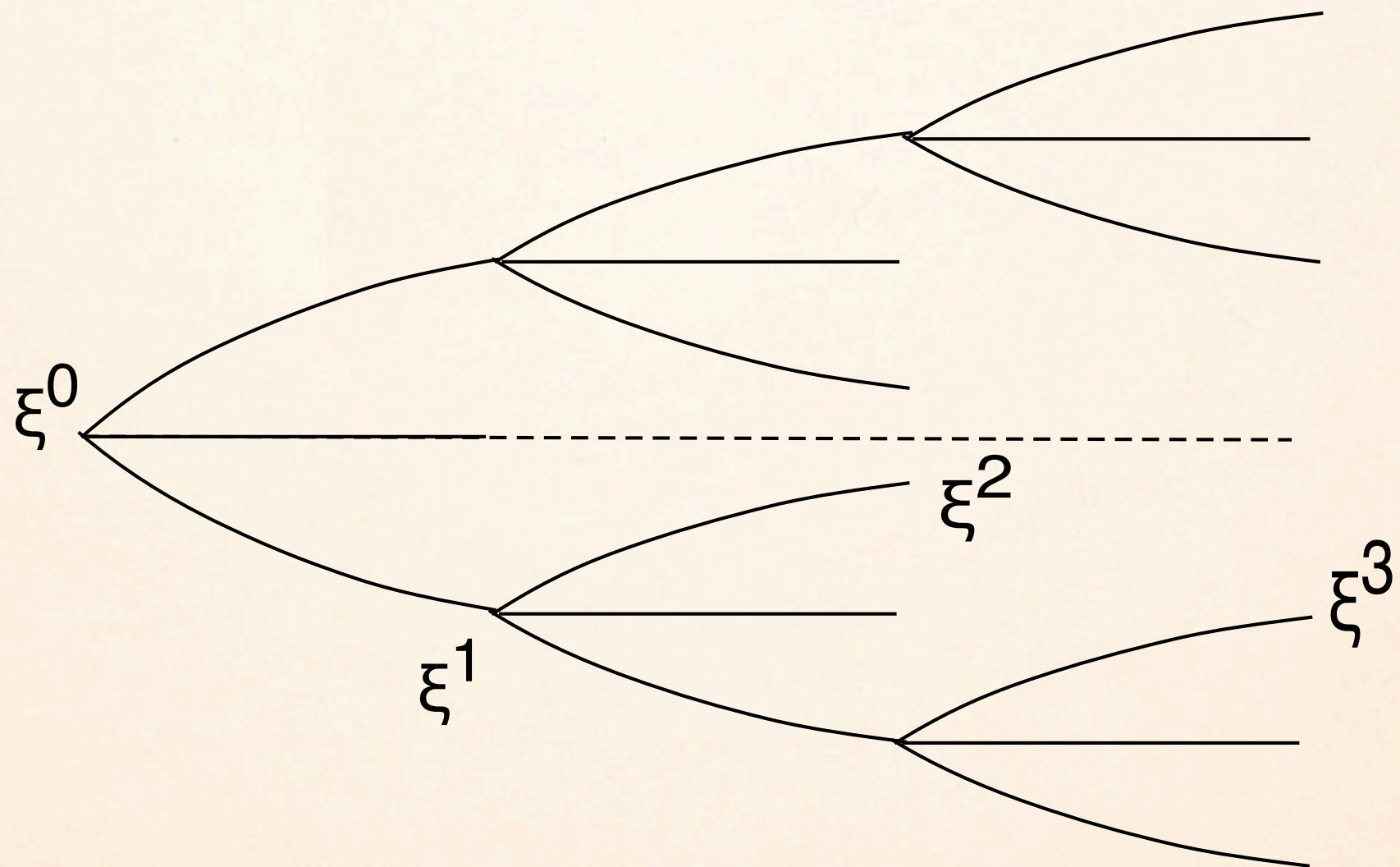
information (observation) available at time t : \mathcal{A}_{t-1}

filtration: $\mathcal{A}_0 \subset \mathcal{A}_1 \subset \dots \subset \mathcal{A}_T = \mathcal{A}$, \mathcal{A}_0 trivial

$x \in \mathcal{N}^a$ if x^t \mathcal{A}_{t-1} -measurable $\approx \sigma$ -field($\overset{\rightarrow v-1}{\xi}$)

here ξ^0 deterministic, $x^1(\xi) \equiv x^1$

DISCRETE SCENARIO TREE



DETERMINISTIC EQUIVALENT

$$\min_{x \in \mathcal{N}^a} \mathbb{E} \{ f(\xi, x(\xi)) \} = \mathbb{E} \left\{ \mathbb{E} \left\{ \mathbb{E} \left\{ f(\xi, x(\xi)) \middle| \mathcal{A}_T \middle| \cdots \middle| \mathcal{A}_1 \middle| \mathcal{A}_0 \right\} \right\} \right\}$$

"time-staged objective":

$$= f_1(x^1) + \mathbb{E} \left\{ f_2(\xi; x^1, x^2(\xi)) + \mathbb{E} \left\{ f_3(\xi; x^1, x^2(\xi), x^3(\xi)) \middle| \mathcal{A}_2 \right\} \middle| \mathcal{A}_1 \right\} \quad \dots$$

$$= f_1(x^1) + \mathbb{E} \left\{ f_2(\xi; x^1, x^2(\xi)) + EQ_2(\xi; x^1, x^2(\xi)) \middle| \mathcal{A}_1 \right\}$$

$$EQ_2(\xi; x^1, x^2(\xi)) = \mathbb{E} \left\{ \inf_{x^3 \in \mathbb{R}^{n_3}} f_3(\xi; x^1, x^2(\xi), x^3) \middle| \mathcal{A}_2 \right\}$$

$$= f_1(x^1) + \mathbb{E} \left\{ EQ_1(\xi; x^1, x) \middle| \mathcal{A}_1 \right\}$$

$$EQ_1(\xi; x^1) = \mathbb{E} \left\{ \inf_{x^2 \in \mathbb{R}^{n_2}} f_2(\xi; x^1, x^2) + EQ_2(\xi; x^1, x^2) \middle| \mathcal{A}_1 \right\}$$

$$= f_1(x^1) + EQ_1(x^1)$$

SOLUTION PROCEDURES

$$\min_{x \in \mathcal{N}^a} \mathbb{E} \{ f(\xi, x(\xi)) \} = \min_{x^1 \in \mathbb{R}^{n_1}} f_1(x^1) + EQ_1(x^1)$$

$$EQ_1(\xi; x^1) = \mathbb{E} \left\{ \inf_{x^2 \in \mathbb{R}^{n_2}} f_2(\xi; x^1, x^2) + EQ_2(\xi; x^1, x^2) \middle| \mathcal{A}_1 \right\}$$

$$EQ_2(\xi; x^1, x^2(\xi)) = \mathbb{E} \left\{ \inf_{x^3 \in \mathbb{R}^{n_3}} f_3(\xi; x^1, x^2(\xi), x^3) \middle| \mathcal{A}_2 \right\}$$

deterministic optimization! convex when f random lsc convex function

in theory: any algorithmic procedure!

hurdles: values, (sub)gradients, "Hessians" of $f_1(x^1) + EQ_1(x^1)$

are either not accessible or at best, computationally EXPENSIVE

Approaches: $\mu^v \sim \mu \Rightarrow$ approximating stochastic process $\{\xi_t, t \leq T\}$

sampling: a) same as approximation except μ^s random measure

b) SAA-strategy for $\partial \left(\mathbb{E} \{ f(\xi, x(\xi)) \} + N_{\mathcal{N}^a}(x(\xi)) \right)$

SEQUENTIAL L.P. STRATEGY

$\min f_0(x), \quad x \in X \in \mathbb{R}^n, \quad f_0$ linear (not essential)

$f_i(x) \leq 0, \quad i = 1, \dots, s, \quad f_i(s) = 0, i = s + 1, \dots, m$ (affine)

in the $s + 1$ first constraints: $f_i(x) = \sup_{t \in T} f_{i,t}(x), \quad f_i \geq f_{i,t}$ affine

0. $v = 0$, pick polytope (box) $K^0 \ni x^{opt}$

1. $x^v \in \arg \min f_0$ on K^v , set $i_v : f_{i_v}(x^v) = \max_{1 \leq i \leq s} f_i(x^v)$

if $f_{i_v}(x^v) \leq 0, x^v$ optimal, otherwise go to 2.

2. return to 1. with $K^{v+1} = K^v \cap \left\{ \left\langle \nabla f_{i_v}(x^v), x - x^v \right\rangle + f_{i_v}(x^v) \leq 0 \right\}$

when f_0 is not linear (but convex): $\min \theta$ such that $f_0(x) - \theta \leq 0$

convergence: finite # of steps or iterates cluster to optimal sol'n

SLP FOR STOCHASTIC PROGRAMS

$$\min f_1(x) + EQ_1(x) \text{ s.t. } Ax = b, x \geq 0 \quad (x = x^1)$$

$$EQ_1(x) = \sum_{l=1}^L p_l Q_1(\xi^l, x) \quad L \text{ large}$$

$$Q_1(\xi^l, x) = \inf_{x^2 \in X_2} \{f_2(\xi^l; x, x^2) + (EQ_2(\cdots))\}$$

$$\text{dom } EQ_1 = \bigcap_{l=1}^L \text{dom } Q_1(\xi^l, \cdot) = \bigcap_{l=1}^L \{x \mid \exists x^2 \in X_2, f_2(\xi^l; x, x^2) < \infty\}$$

$$0. v = r = s = 0$$

1. $v = v + 1$, solve: $\min f_1(x) + \theta$, $Ax = b$, $x \geq 0$ such that

$$\text{(feasibility cuts)} \quad \langle E_k, x \rangle \geq e_k, \quad k = 1 \rightarrow r$$

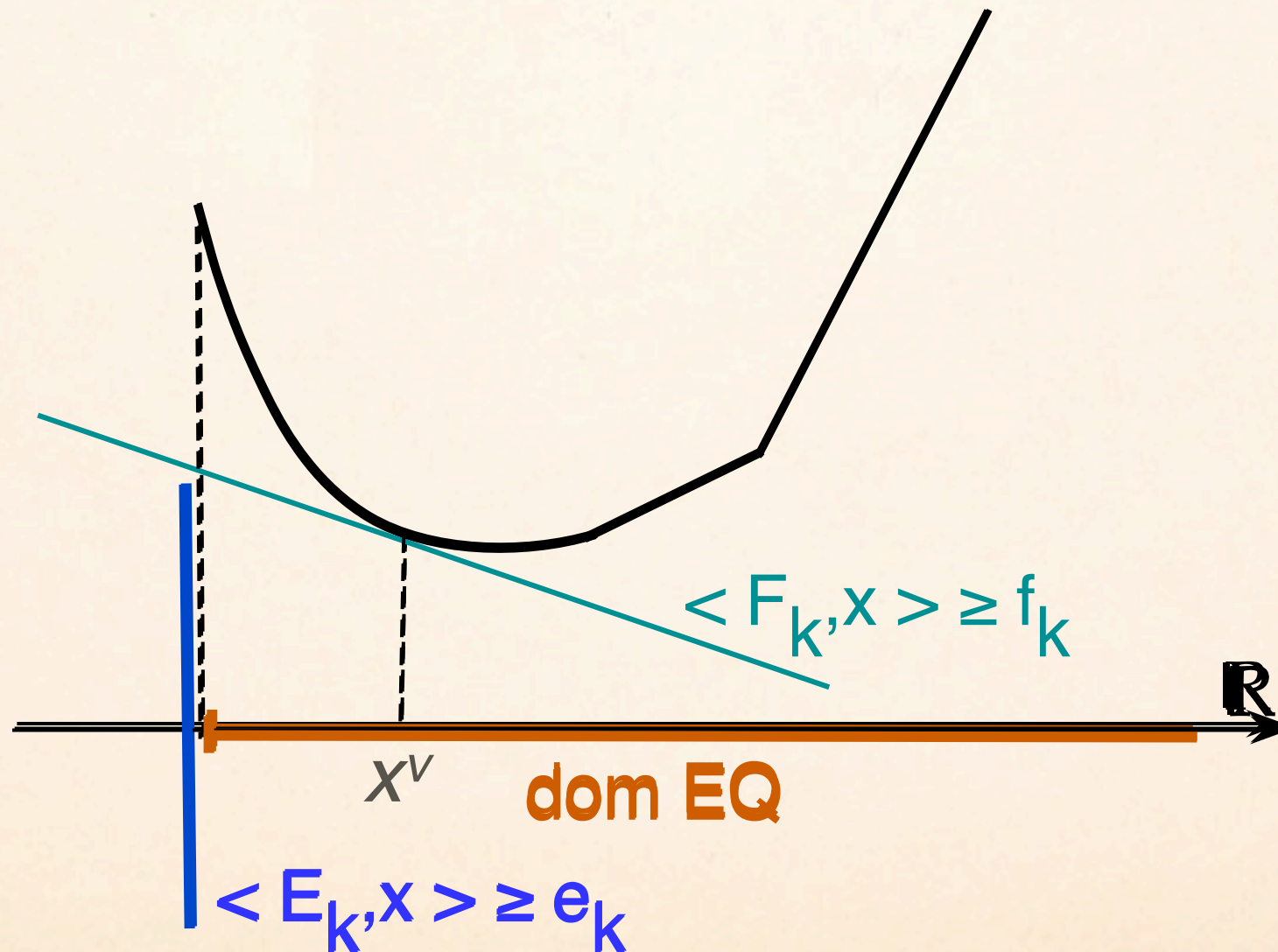
$$\text{(optimality cuts)} \quad \langle F_k, x \rangle + \theta \geq f_k, \quad k = 1 \rightarrow s$$

2. generate feasibility cuts: check if $x \in \text{dom } EQ_1$.

No: E_k separates x from $\text{dom } EQ_1$, go to 1. Yes, go to 3.

3. generate optimality cuts: $F_k \in \partial EQ_1(x^k)$, go to 1.

GENERATING CUTTING HYPERPLANES



STOCHASTIC QUASI-GRADIENTS (~ SAA-APPROACH)

$$\min Ef(x) = \mathbb{E}\{f(\xi, x)\} \text{ on } X \subset \mathbb{R}^n,$$

$$X \text{ convex (compact), } f : \Xi \times \mathbb{R}^n \rightarrow \mathbb{R}$$

$$f(\xi, \cdot) \text{ convex (gen. semi-smooth)}$$

$$x^{v+1} = \text{prj}_X(x^v - \lambda_v d^v), \text{ descent direction, step size}$$

$$d^v : \text{stochastic quasi-gradient}$$

$$\mathbb{E}\{d^v \mid x^0, \dots, x^v\} \in \partial Ef(x^v) + \eta_v$$

$$\text{for example: } d^v \in \partial f(\xi^v, x^v) \text{ sample } \xi^v$$

$$\text{or } d^v \in \partial \left(\sum_{l=1}^L f(\xi^l, x^v) \right) \text{ sample } \xi^1, \dots, \xi^L$$

$$\text{convergence: } \rho_v \geq 0, \sum_{v=0}^{\infty} \rho_v = \infty, \sum_{v=0}^{\infty} \rho_v^2 < \infty$$

HERE-&-NOW VS. WAIT-&-SEE

◆ Basic Process: decision --> observation --> decision
$$x^1 \rightarrow \xi \rightarrow x_\xi^2$$

◆ Here-&-now problem!
not all contingencies available at time 0
 x^1 can't depend on ξ !

◆ Wait-&-see problem
implicitly all contingencies available at time 0
choose (x_ξ^1, x_ξ^2) after observing ξ

◆ incomplete information to anticipative information ?

Fundamental Theorem of Stochastic Optimization

A here-and-now problem can be “reduced” to a
wait-and-see problem by introducing the


appropriate ‘information’ costs
(price of non-anticipativity)

PRICE OF NON-ANTICIPATIVITY

Here-&-now

$$\begin{aligned} \min \mathbb{E} \{ f(\xi, x^1, x_\xi^2) \} \\ x^1 \in C^1 \subset \mathbb{R}^n, \\ x_\xi^2 \in C^2(\xi, x^1), \forall \xi. \end{aligned}$$

Explicit non-anticipativity

$$\begin{aligned} \min \mathbb{E} \{ f(\xi, x_\xi^1, x_\xi^2) \} \\ x_\xi^1 \in C^1 \subset \mathbb{R}^n, \\ x_\xi^2 \in C^2(\xi, x_\xi^1), \forall \xi. \\ x_\xi^1 = \mathbb{E} \{ x_\xi^1 \} \quad \forall \xi \\ w_\xi \perp c^{\text{ste}} \text{ functions} \\ \Rightarrow \mathbb{E} \{ w_\xi \} = 0 \end{aligned}$$


ADJUSTED HERE-&-NOW

$$\min \mathbb{E} \left\{ f(\xi, x^1, x_\xi^2) \right\} \text{ such that } x^1 \in C^1 \subset \mathbb{R}^n, \quad x_\xi^2 \in C^2(\xi, x^1), \quad \forall \xi$$

x^1 must be \mathcal{G} -measurable, $\mathcal{G} = \sigma\{-\emptyset, \Xi\}$

x^2 is \mathcal{A} -measurable, $\mathcal{A} \supset \mathcal{G}$,

in general, interchange \mathbb{E} & ∂ is not valid

required: $\forall \xi, x^1 \in C^1, C^2(\xi, x^1) \neq \emptyset$ \mathcal{G} -measurability of constraints

Now, suppose w_ξ are the (optimal) non-anticipativity multipliers (prices)

$$\min \mathbb{E} \left\{ f(\xi, x_\xi^1, x_\xi^2) - \langle w_\xi, x_\xi^1 \rangle + \langle w_\xi, \mathbb{E}\{x_\xi^1\} \rangle \right\}$$

$$\text{such that } x_\xi^1 \in C^1 \subset \mathbb{R}^n, \quad x_\xi^2 \in C^2(\xi, x_\xi^1), \quad \forall \xi$$

Interchange is now O.K. , $\mathbb{E} \left\{ \langle w_\xi, \mathbb{E}\{x_\xi^1\} \rangle \right\} = \langle \mathbb{E}\{w_\xi\}, \mathbb{E}\{x_\xi^1\} \rangle = 0$, yields

$$\forall \xi, \text{ solve: } \min f(\xi, x^1, x^2) - \langle w_\xi, x^1 \rangle \text{ s.t. } x^1 \in C^1, \quad x^2 \in C^2(\xi, x^1)$$

a collection of deterministic optimization problems in $\mathbb{R}^{n_1+n_2}$

FINDING w_ξ

Progressive Hedging Algorithm

0. $w^0(\cdot)$ such that $\mathbb{E}\{w^0(\xi)\} = 0$, $v = 0$. Pick $\rho > 0$

1. for all ξ :

$$(x_\xi^{1,v}, x_\xi^{2,v}) \in \arg \min f(\xi; x^1, x^2) - \langle w_\xi^v, x^1 \rangle$$

$$x^1 \in C^1 \subset \mathbb{R}^{n_1}, x^2 \in C^2(\xi, x^1) \subset \mathbb{R}^{n_2}$$

2. $\bar{x}^{1,v} = \mathbb{E}\{x_\xi^{1,v}\}$. Stop if $|x_\xi^{1,v} - \bar{x}^{1,v}| = 0$ (approx.)

otherwise $w_\xi^{v+1} = w_\xi^v + \rho[x_\xi^{1,v} - \bar{x}^{1,v}]$, return to 1. with $v = v + 1$

Convergence: add a proximal term

$$f(\xi; x^1, x^2) - \langle w_\xi^v, x^1 \rangle - \frac{\rho}{2} |x^1 - \bar{x}^{1,v}|^2$$

linear rate in $(x^{1,v}, w^v)$... eminently parallelizable

PH: IMPLEMENTATION

implementation: choice of ρ ... scenario (\times), decision (+) dependent

(heuristic) extension to problems with integer variables

non-convexities: e.g. ground-water remediation with non-linear PDE recourse

asynchronous

partitioning (= different information feeds)

$$\min \mathbb{E} \{ f(\xi, x) \} \quad \text{such that } x \in C = \bigcap_{\xi \in \Xi} C_{\xi}$$

$S = \{ \Xi_1, \Xi_2, \dots, \Xi_N \}$ a partitioning of Ξ , $p_n = \mu(\Xi_n)$

$$\mathbb{E} \{ f(\xi, x) \} = \sum_n p_n \mathbb{E} \{ f(\xi, x) \mid \Xi_n \} \quad (\text{Bayes})$$

defining $g(n, x) = \mathbb{E} \{ f(\xi, x) \mid \Xi_n \}$ if $x \in C_n = \bigcap_{\xi \in \Xi_n} C_{\xi}$

solve the problem as: $\min \sum_{n=1}^N p_n g(n, x)$

MULTISTAGE STOCHASTIC PROGRAMS

$$\min_{x \in \mathcal{N}^a} \mathbb{E} \{ f(\xi, x(\xi)) \}, \quad x(\xi) = (x^1(\xi), \dots, x^T(\xi))$$

filtration : $\mathcal{A}_0 \subset \mathcal{A}_1 \subset \dots \subset \mathcal{A}_T = \mathcal{A}$, \mathcal{A}_0 trivial

$x \in \mathcal{N}^a$ if x^t \mathcal{A}_{t-1} -measurable $\approx \sigma$ -field($\overset{\rightarrow v-1}{\xi}$)

(here ξ^0 deterministic, $x^1(\xi) \equiv x^1$)

under usual $\mathbb{C}.\mathbb{Q}$. (convex case): $\bar{x} \in \mathcal{X}$ optimal if

$$\exists \bar{w} \perp \mathcal{N}^a, \bar{w} \in \mathcal{X}^* \text{ such that } \bar{x} \in \arg \min_{x \in \mathcal{X}} E f(x) - \mathbb{E} \{ \langle \bar{w}, x \rangle \}$$

$$\bar{w} \perp \mathcal{N}^a \Leftrightarrow \mathbb{E} \{ \bar{w}(\xi) | \mathcal{A}_{t-1} \} = 0, \forall t = 1, \dots, T$$

\bar{w} non-anticipativity prices

at which to buy the right to adjust decision (after observation)

can be viewed as insurance premiums,

PROGRESSIVE HEDGING ALGO.

0. initialize: pick $w^0(\xi) \in (\mathcal{N}^a)^\perp$, $\hat{x}_0, \rho > 0, v = 1$

1. $\forall \xi \in \Xi$, solve (approximately): $\min f^v(\xi, x), x \in \text{dom } f(\xi, \cdot)$

$$f^v(x, \xi) = f(x, \xi) + \sum_{t=1}^T \left[\langle w_{v-1}^t(\xi), x^t \rangle + \frac{\rho}{2} |x^t - \hat{x}^{t,v-1}|^2 \right]$$

minimizer: $x_v(\xi) = (x_v^1(\xi), \dots, x_v^T(\xi))$, $\xi \in \Xi$

2. $w_v^t(\xi) = w_{v-1}^t(\xi) + \rho(x_v^t(\xi) - \hat{x}_v^t(\xi))$ where $\hat{x}_v^t(\xi)$ = "averaged" solution

$$\hat{x}_v^t(\xi) = \mathbb{E}\{\mathbf{x}_v^t(\cdot) \mid A\}(\xi) \text{ for each } A \in \mathcal{A}_t$$

go to 1. with $v = v + 1$

convergence: linear in (x, w)

WALRAS EQUILIBRIUM

agent's problem: Agents: $a \in \mathcal{A}$, $|\mathcal{A}|$ finite, possibly "large"

$\bar{x}_a \in \arg \max u_a(x_a)$ so that $\langle p, x_a \rangle \leq \langle p, e_a \rangle$, $x_a \in X_a$

e_a : endowment of agent a , $e_a \in \text{int } X_a$

u_a : utility of agent a , concave, usc

$u_a : X_a \rightarrow \mathbb{R}$, $X_a \subset \mathbb{R}^n$ (survival set) convex

market clearing: $s(p) = \sum_{a \in \mathcal{A}} (e_a - \bar{x}_a)$ excess supply

equilibrium price: $\bar{p} \in \Delta$ such that $s(\bar{p}) \geq 0$, Δ unit simplex

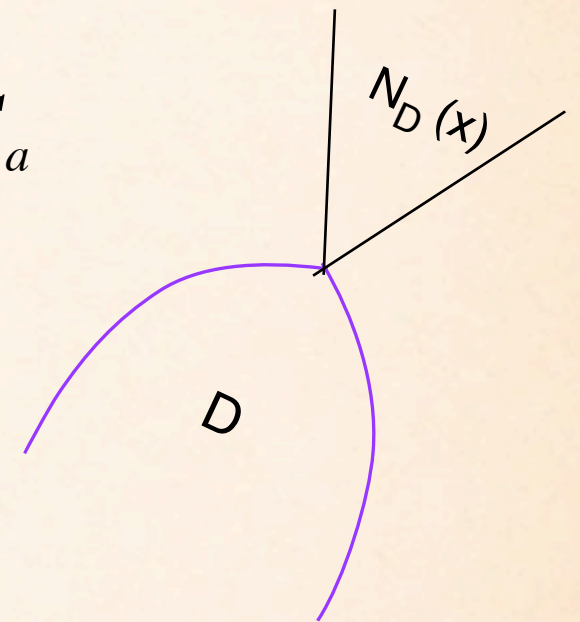
VARIATIONAL INEQUALITY

$c_a = \arg \max_x u_a(x)$ so that $\langle p, x \rangle \leq \langle p, e \rangle, x \in C_a$

$$\sum_a (e_a - c_a) = s(p) \geq 0.$$



$$N_D(\bar{z}) = \{v | \langle v, z - \bar{z} \rangle \leq 0, \forall z \in D\}$$



$$G(p, (x_a), (\lambda_a)) = \left[\sum_a (e_a - x_a); (\lambda_a p - \nabla u_a(x_a)); \langle p, e_a - x_a \rangle \right]$$

$$D = \Delta \times \left(\prod_a C_a \right) \times \left(\prod_a \mathbb{R}_+ \right)$$

$$-G(\bar{p}, (\bar{x}_a), (\bar{\lambda}_a)) \in N_D(\bar{p}, (\bar{x}_a), (\bar{\lambda}_a))$$

$$D \text{ unbounded} \rightarrow \hat{D} \text{ bounded}$$

EQUILIBRIUM: STOCHASTIC ENVIRONMENT

$$(c_a^1, y_a, c_{a,\xi}^2) = \arg \max_{x^1, y \in \mathbb{R}^L, x_{\cdot}^2 \in \mathcal{M}} u_a^1(x^1) + \mathbb{E}^a \{u_a^2(\xi, x^2(\xi))\}$$

$$\text{such that } \langle p^1, x_a^1 + T_a^1 y \rangle \leq \langle p^1, e_a^1 \rangle$$

$$\langle p_{\xi}^2, x_{a,\xi}^2 \rangle \leq \langle p_{\xi}^2, e_{a,\xi}^2 + T_{a,\xi}^2 y \rangle, \quad \forall \xi \in \Xi$$

$$x_a^1 \in X_a^1, \quad x_{a,\xi}^2 \in X_{a,\xi}^2, \quad \forall \xi \in \Xi$$

$\mathbb{E}^a \{\bullet\}$ rational expectation with respect to a -beliefs, Ξ finite support

2-stage stochastic programs with recourse

solution procedures & approximation theory "well-established"

$T_a^1, T_{a,\xi}^2$: input-output matrices (production, investments)

$$e_a^1 \in \text{int } X_a^1, \quad e_{a,\xi}^2 \in \text{int } X_{a,\xi}^2 \quad \text{for all } \xi$$

MARKET CLEARING

excess supply:

$$\text{agent-}a: \left(c_a^1, y_a^1, \{c_{a,\xi}^2\}_{\xi \in \Xi} \right)$$

$$\sum_{a \in \mathcal{A}} \left(e_a^1 - (c_a^1 + T_a^1 y_a) \right) = s^1 \left(p^1, \{p_\xi^2\}_{\xi \in \Xi} \right) \geq 0$$

and for all $\xi \in \Xi$:

$$\sum_{a \in \mathcal{A}} \left((e_{a,\xi}^2 + T_{a,\xi}^2) - c_{a,\xi}^2 \right) = s_\xi^2 \left(p^1, \{p_\xi^2\}_{\xi \in \Xi} \right) \geq 0$$

Walras' auctioneer:

$$\max_{p=(p^1, \{p_\xi^2\}_{\xi \in \Xi})} \inf_{q=(q^1, \{q_\xi^2\}_{\xi \in \Xi})} \mathbb{E} \{ \langle q, s \rangle \}, \quad s = \left(s^1, \{s_\xi^2\}_{\xi \in \Xi} \right)$$

AGENT'S PROBLEM: DISAGGREGATION

with $p_{\diamond} = \left(p^0, \{p_{\xi}^1\}_{\xi \in \Xi} \right)$

$(c_{a,\xi}^1, y_a, c_{a,\xi}^2) \in$

$$\arg \max_{x^1 \in \mathbb{R}^I, y \in \mathbb{R}^L, x^2 \in \mathbb{R}^L} \left\{ u_a^1(x^1) - \langle \bar{w}_{a,\xi}, (x^1, y) \rangle + u_a^2(\xi, x^2) \right\}$$

$$\langle p^1, x^1 \rangle \leq \langle p^1, e_a^1 - T_a^1 y \rangle$$

$$\langle p_{\xi}^2, x^2 \rangle \leq \langle p_{\xi}^2, e_{a,\xi}^2 + T_{a,\xi}^2 y \rangle,$$

$$x^1 \in X_a^1, \quad x^2 \in X_{a,\xi}^2.$$

solved for each ξ separately

INDIVIDUALLY COMPLETED MARKET

$\forall \xi \in \Xi$ (separately),

agent's problem (individually completed market):

$$(c_a^1, y_a, c_{a,\xi}^2) \in \arg \max \left\{ u_a^{w_{a,\xi}}(x^1, y, x^2) \text{ on } \hat{X}_{a,\xi}(p^1, p_\xi^2) \right\}$$

for $\{w_{a,\xi}\}_{\xi \in \Xi}$ associated with (p^0, p_ξ^1)

clear market:

$$s^1(p^1, p_\xi^2) \geq 0, \quad s_\xi^2(p^1, p_\xi^2) \geq 0$$

★ Arrow-Debreu ‘un-stochastic’ equilibrium problem

EXAMPLE USING PATH-SOLVER

- ◆ Economy: (5 goods)
 - Skilled & unskilled workers
 - Businesses: Basic goods & leisure
 - Banker: bonds (riskless), 2 stocks
- ◆ 2-stages, 280 scenarios, 2776 scenarios
- ◆ utilities: CES-functions (gen. Cobb-Douglas)
 - Utility in stage 2 assigned to financial instruments
 - only used for transfer in stage 1
- ◆ on laptop: ~4 min, ~14 min, but
extremely parallelizable algorithm

PATH-SOLVER: CONVERGENCE

objective: $u_a^1(x^1) + u_a^2(x^2) \Rightarrow$

$$u_a^1(x^1) - \langle w_{a,\xi}^v, (x^1, y) \rangle - \frac{\rho}{2} |(x^1, y) - (\hat{x}_a^{1,v}, \hat{y}_a^v)|^2 + u_a^2(x^2)$$

updating:

$(\hat{x}_a^{1,v}, \hat{y}_a^v) = \mathbb{E}^a \left\{ (c_{a,\xi}^{0,v}, y_{a,\xi}^v) \right\}$ projection on non-anticipative subspace

$$w_{a,\xi}^{v+1} = w_{a,\xi}^v + \rho_a \left((c_{a,\xi}^{0,v}, y_{a,\xi}^v) - (\hat{x}_a^{1,v}, \hat{y}_a^v) \right)$$

convergence: $\rho_a > 0$

also requires a proximal term to support

the convergence of the equilibrium prices $p_\diamond = \left(p^0, \{ p_\xi^1 \}_{\xi \in \Xi} \right)$