

# From Estimating Linear Forms to Conic Representations of Convex-Concave Functions and Monotone Vector Fields

**Arkadi Nemirovski**

Georgia Institute of Technology

*joint research with*

**Anatoli Juditsky**

Université Grenoble Alpes

**Optimization Without Borders**

a.k.a.

**Nesterov 65 & Protasov 50**

Sochi Sirius July 14 2021

# Dear Yura & Volodya, Happy Birthdays! Till 120!

**Disclaimer:** *This talk is **not** about new algorithms of Convex Optimization. It is about **extending the scope** of existing algorithms.*

**Full version:** A. Juditsky, A. Nemirovski, *On well-structured convex-concave saddle point problems and variational inequalities with monotone operators.*

<https://arxiv.org/pdf/2102.01002.pdf>, to appear in *Optimization Methods and Software*

## Advertising Example

**Statistical problem:** Given a polyhedral subset  $\mathcal{X} = \{x : Rx \leq r\}$  of  $n$ -dimensional probabilistic simplex,  $m \times n$  column-stochastic matrix  $\mathcal{A}$ , linear form  $g(z) = g^T z$  on  $\mathbb{R}^n$ , and  $K$  i.i.d. observations  $\omega_k \sim \mathcal{A}x_*$  stemming from unknown signal  $x_* \in \mathcal{X}$ , we want to recover  $g^T x_*$

**Fact [Statistics]:** Near-optimal in the minimax sense recovery of  $g^T x_*$  reduces to solving the convex (and thus efficiently solvable) problem

$$\min_{\alpha > 0, \phi} \left\{ \max_{x: Rx \leq r, y: Ry \leq r} \frac{1}{2} \left[ \alpha \ln \left( \sum_i e^{\phi_i/\alpha} [\mathcal{A}x]_i \right) + \alpha \ln \left( \sum_i e^{-\phi_i/\alpha} [\mathcal{A}y]_i \right) + g^T [y - x] \right] + C\alpha \right\}$$

**But:** implicit nature of the objective—presence of  $\max_{x: Rx \leq r, y: Ry \leq r}$ —prevents utilizing highly efficient and reliable “off the shelf” convex programming solvers.

• Applying techniques to be outlined in the talk, the problem can be rewritten equivalently, *in a systematic fashion*, as

$$\min_{\alpha > 0, \phi, \lambda^\pm, u_\pm, \mu_\pm, \xi^\pm, \eta^\pm} \left\{ \frac{1}{2} [u_+ + u_-] + C\alpha : \left\{ \begin{array}{l} \xi^+ \geq \lambda^+, \eta^+ \geq 0, \xi^- \geq \lambda^-, \eta^- \geq 0; \\ R^T \eta^+ - \mathcal{A}^T \xi^+ = -g, r^T \eta^+ \leq \alpha - \mu_+ + u_+, \\ R^T \eta^- - \mathcal{A}^T \xi^- = g, r^T \eta^- \leq \alpha - \mu_- + u_-; \\ \phi_i - \mu_+ + \alpha \ln(\alpha/\lambda_i^+) \leq 0, -\phi_i - \mu_- + \alpha \ln(\alpha/\lambda_i^-) \leq 0, \forall i \end{array} \right. \right\}.$$

The reformulated problem possesses explicitly given objective and constraints and can be fed “as is” to “off the shelf” software like CVX.

## Well-Structured Convex Problems

- ♣ A convex program  $\min_{x \in X} f(x)$  always has a lot of a priori known structure – otherwise, how could you know that the problem is convex?
- ♥ A good algorithm, in contrast to black-box-oriented “universal” algorithms like the Ellipsoid Method, should utilize a priori knowledge of the structure (think about Simplex Method fully adjusted to LP!)
- ♠ **However:** “structure” has no formal definition: we recognize it (say, in LP) only *after* we see it...

♣ One of the outcomes of Interior Point Revolution was discovering a specific “structure-revealing” reformulation of a convex problem – *conic formulation*

$$\min_x \{c^T x : Ax - b \in \mathbf{K}\}$$

where  $\mathbf{K}$  is

—in theory, a regular (closed convex pointed with nonempty interior) cone (no more “structure-revealing” than in the standard Mathematical Programming formulation)

—in optimization practice, a cone from Magic Family comprised of direct products of

(a) nonnegative rays  $\mathbb{R}_+$ , (b) Lorentz cones  $\mathbf{L}^n = \{x \in \mathbb{R}^n : x_n \geq \sqrt{\sum_{i=1}^{n-1} x_i^2}\}$ , and (c) semidefinite cones  $\mathbf{S}_+^n = \{X = X^T \in \mathbb{R}^{n \times n} : u^T X u \geq 0 \forall u\}$ .

• Conic problems from Magic family can be solved to high accuracy in few iterations by “unified” interior point polynomial time algorithms with steadily improving “off the shelf” implementations.

♠ *For all practical purposes, Convex Optimization is within the grasp of Magic Conic Programming. Reducing problem of interest to a magic one requires utilizing, on a case-by-case basis, a priori knowledge of problem’s structure, whatever it means.*

♣ **Reduction** of problem of interest, given in the Mathematical Programming “maiden form” as

$$\min_x \{f_0(x) : f_i(x) \leq 0, i \leq m, x \in X\} \quad (MP)$$

to a Magic problem is immediate when we have at our disposal *semidefinite representations* of objective, constraints, and the domain of (MP).

♠ Given family of regular cones  $\mathcal{C}$  containing nonnegative rays and closed w.r.t. taking finite direct products and passing from a cone to its dual,

—  $\mathcal{C}$ -representation of a set  $X \subset \mathbb{R}^n$  is

$$X = \{x : \exists u : Ax + Bu - c \in \mathbf{K}\} \text{ with } \mathbf{K} \in \mathcal{C}$$

— as affine image of inverse affine image of a cone from  $\mathcal{C}$ .

—  $\mathcal{C}$ -representation of a function  $f : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$  is  $\mathcal{C}$ -representation

$$t \geq f(x) \Leftrightarrow \exists u : A[x; t] + Bu - c \in \mathbf{K} \text{ with } \mathbf{K} \in \mathcal{C}$$

of the epigraph  $\text{Epi}\{f\} = \{[x; t] : t \geq f(x)\}$  of  $f$ .

♠ **Observation:** Given  $\mathcal{C}$ -representations of components of (MP):

$$\{t \geq f_i(x) \Leftrightarrow \exists u_i : A_i[x; t] + B_i u_i - c_i \in \mathbf{K}_i\}, 0 \leq i \leq m \ \& \ X = \{x : \exists u : Ax + Bu - c \in \mathbf{K}\}$$

(MP) can be immediately reformulated as the conic problem

$$\min_{t, u, \{u_i\}} \left\{ t : \begin{bmatrix} A_0[x; t] + B_0 u_0 - c_0 \\ \vdots \\ A_m[x; 0] + B_m u_m - c_m \\ Ax + Bu - c \end{bmatrix} \in \underbrace{\mathbf{K}_0 \times \mathbf{K}_1 \times \dots \times \mathbf{K}_m \times \mathbf{K}}_{\in \mathcal{C}} \right\}$$

on a cone from  $\mathcal{C}$ .

♠ **Reduction** of convex problem of interest to  $\mathcal{C}$ -conic problem heavily utilizes *calculus of  $\mathcal{C}$ -Representations (CR's) of functions and sets*.

♡ **Raw Materials of Calculus** do depend on  $\mathcal{C}$  and are comprised by “elementary” functions/sets with  $\mathcal{C}$ -representations obtained on case-by-case basis by bare hands, e.g.

- halfspace:

$$\{[x; t] : t \geq a^T x\} = \{[x; t] : t - a^T x \in \mathbb{R}_+\}$$

- hypograph of geometric mean, assuming  $\mathcal{C}$  contains Lorentz cones:

$$\begin{aligned} & \{x \geq 0, y \geq 0, t \leq \sqrt{xy}\} \\ & \quad \updownarrow \\ & \left\{ [x; y; t] : \exists \tau : \underbrace{x \geq 0, y \geq 0, \tau \geq t, \sqrt{4\tau^2 + (x - y)^2} \leq x + y}_{\Leftrightarrow [[x; y; \tau - t]; [2\tau; x - y; x + y]] \in \mathbb{R}_+^3 \times \mathbf{L}^3} \right\} \end{aligned}$$

- sum of  $k$  leading eigenvalues of symmetric matrix, assuming  $\mathcal{C}$  contains semidefinite cones:

$$\{t \geq \sum_{i=1}^k \lambda_i(X)\} \Leftrightarrow \{\exists Z, s : X \preceq Z + sI_n, Z \succeq 0, \text{Tr}(Z) + ks \leq t\}$$

[ $\lambda_1(X) \geq \lambda_2(X) \geq \dots \geq \lambda_n(X)$  are eigenvalues of  $X \in \mathbf{S}^n$ ]

♥ **Calculus rules** are simple, fully algorithmic and *completely independent of what  $\mathcal{C}$  is*. These rules say that *all basic convexity-preserving operations with functions and sets, as applied to  $\mathcal{C}$ -representable operands, produce  $\mathcal{C}$ -representable results with  $\mathcal{C}$ -representations readily given by those of the operands*. This includes

♠ For sets:

- taking finite intersections, direct products, arithmetic sums, affine and inverse affine images
- taking convex hulls of finite unions<sup>†</sup>, conic hulls<sup>†</sup>, polars<sup>†</sup>
- passing from a set to its recessive cone<sup>†</sup> and to its support function<sup>†</sup>

♠ For functions:

- taking linear combinations with nonnegative coefficients, affine substitution of variables, projective transformation
- direct summation  $f_i(x_i), i = 1, \dots, m \mapsto f(x_1, \dots, x_m) = \sum_i f_i(x_i)$
- passing from functions  $f_1, \dots, f_m, F$  to their composition  $F(f_1(\cdot), \dots, f_m(\cdot))$ , under standard monotonicity assumptions ensuring convexity of the composition
- partial minimization<sup>†</sup>, passing from function to its Fenchel conjugate<sup>†</sup>

♥ *Operations marked <sup>†</sup> require mild regularity assumptions like closedness/compactness of some operands and/or essentially strict feasibility of their  $\mathcal{C}$ -representations*



♠ **Note:** Fully algorithmic calculus of  $\mathcal{C}$ -representations can be built into a compiler. For the family of Magic cones, this is what is done by CVX

*Michael Grant and Stephen Boyd. CVX: Matlab software for disciplined convex programming*

<http://cvxr.com/cvx>

- CVX is second-to-none in terms of its scope and user-friendliness “go-between” for processing well-structured convex problems reduced to (or well approximated by) Linear/Second Order Conic/Semidefinite Programming.
- CVX gets on input high level description of objective and constraints and uses calculus of Magic conic representations (a.k.a. **SDR**'s - *SemiDefinite Representations*) to recognize that subsequent steps in this description are covered by calculus (this is where *disciplined* comes from). If it is the case, CVX automatically applies calculus rules to end up with semidefinite reformulation of the problem and sends the resulting “standard form” SDP to SDP solver.
- The solution found by the solver is then “transformed back” to the original “problem language” and returned to the user.

♠ CVX is extremely user-friendly.

**Example:** Inscribing largest volume ellipsoid into polytope  $\{x : Ax \leq b\}$ .

• **Human formulation:** Given  $m \times n$  matrix  $A$  with rows  $a_i^T$  and  $b \in \mathbb{R}^m$ , maximize  $\text{Det}(X)$  over  $X \in \mathbb{S}_+^n$  and  $c \in \mathbb{R}^n$  such that  $\|Xa_i\|_2 + a_i^T c \leq b_i, i \leq i \leq m$ .

**Explanation:** We represent a candidate ellipsoid as  $E = \{c + Xu : \|u\|_2 \leq 1\}$  with  $X \succeq 0$ . The constraints on  $X$  and  $c$  state that  $E \subset \{x : Ax \leq b\}$ , and  $\text{Det}(X)$  is proportional to the volume of  $E$ .

• **CVX formulation:**

```
[m,n]=size(A)
cvx_begin
variable c(n,1)
variable X(n,n) symmetric
X == semidefinite(n)
for i=1:n
    norm(A(i,:)*X)+A(i,:)*c <= b(i)
end
maximize det_rootn(X)
cvx_end
```

**Note:** CVX is enough intelligent to know SDR of  $-\text{Det}^{1/n}(X), X \in \mathbb{S}_+^n$  (`-det_rootn(X)` in CVX), same as SDR's of tens of other useful functions.

♣ **Our goal:** *To define conic representations of “well-structured” convex-concave functions and monotone vector fields and to develop calculus of these representations, with the ultimate goal to reduce the associated Saddle Point problems and Variational Inequalities to conic programs.*

♠ **Convention:** *From now on we fix a family  $\mathcal{C}$  of regular cones in Euclidean spaces which contains nonnegative rays,  $\mathbb{L}^3$ , and is closed w.r.t. taking finite direct products and passing from a cone  $\mathbb{K}$  to its dual  $\mathbb{K}^*$ .*

(!) Unless otherwise is explicitly stated, all cones below belong to  $\mathcal{C}$ .

**Terminology:** A conic constraint  $Ax - b \in \mathbf{K}$  is called *essentially strictly feasible (e.s.f.)*, if the cone  $\mathbf{K}$  can be represented as  $\mathbf{K} = \mathbf{M} \times \mathbf{P}$  with regular  $\mathbf{M}$  and polyhedral  $\mathbf{P}$  in such a way that

$$\exists \bar{x} : A\bar{x} - b \in [\text{int } \mathbf{M}] \times \mathbf{P}.$$

# Conic Representations of Convex-Concave Functions [Jud&N.'21]

**Definition.** Let  $\mathcal{X}, \mathcal{Y}$  be nonempty convex sets given by  $\mathcal{C}$ -representations:

$$\mathcal{X} = \{x : \exists \xi : Ax + B\xi - c \in \mathbf{K}_{\mathcal{X}}\}, \quad \mathcal{Y} = \{y : \exists \eta : Cy + D\eta - e \in \mathbf{K}_{\mathcal{Y}}\}$$

and let  $\psi(x; y) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$  be a continuous convex-concave function.  $\psi$  is called  $\mathcal{C}$ -representable ( $\mathcal{C}r$ ) on  $\mathcal{X} \times \mathcal{Y}$ , if it admits a  $\mathcal{C}$ -representation ( $\mathcal{C}R$ ):

$$\forall (x \in \mathcal{X}, y \in \mathcal{Y}) : \psi(x; y) = \inf_{f, t, u} \left\{ f^T y + t : Pf + tp + Qu + Rx - s \in \mathbf{K} \right\}$$

We call the above  $\mathcal{C}R$  essentially strictly feasible (e.s.f.), if the conic constraint

$$Pf + tp + Qu + [Rx - s] \in \mathbf{K}$$

in variables  $f, t, u$  is e.s.f. for every  $x \in \mathcal{X}$ .

**Motivation:** In the situation of Definition, the set

$$\Psi = \{[x; f; t] : x \in \mathcal{X}, f^T y + t \geq \psi(x; y) \forall y \in \mathcal{Y}\} \quad (!)$$

is convex, and by usual Fenchel duality in  $y$ -variable, one has

$$\psi(x; y) = \inf_{f, t} \{f^T y + t : (x, f, t) \in \Psi\} \quad \forall (x, y) \in \mathcal{X} \times \mathcal{Y} \quad (!!)$$

$\mathcal{C}R$  is obtained from (!! ) by replacing  $\Psi$  (which by itself can be too complicated to be  $\mathcal{C}r$ ) with a (perhaps, smaller)  $\mathcal{C}r$  set which still ensures (!!).

**Note:** The convex set  $\Psi$  is a natural candidate to the role of the *epigraph* of convex-concave function  $\psi$  on  $\mathcal{X} \times \mathcal{Y}$  – look what happens when  $\mathcal{Y} = \{0\}$ .

$\mathcal{X} = \{x : \exists \xi : Ax + B\xi - c \in \mathbf{K}_x\}, \mathcal{Y} = \{y : \exists \eta : Cy + D\eta - e \in \mathbf{K}_y\}$
$\forall (x \in \mathcal{X}, y \in \mathcal{Y}) : \psi(x; y) = \inf_{f, t, u} \{f^T y + t : Pf + tp + Qu + Rx - s \in \mathbf{K}\}$

♠ **Main Observation:** Assume  $\mathcal{Y}$  is compact with e.s.f.  $\mathcal{C}\mathcal{R}$ . Then the problem

$$\min_{x \in \mathcal{X}} \left\{ \bar{\psi}(x) = \max_{y \in \mathcal{Y}} \psi(x; y) \right\} \quad (P)$$

reduces to the explicit  $\mathcal{C}$ -conic problem

$$\min_{x, \xi, f, t, u, \lambda} \left\{ \begin{array}{l} Pf + tp + Qu + Rx - s \in \mathbf{K} \\ t - e^T \lambda : C^T \lambda + f = 0, D^T \lambda = 0, \lambda \in \mathbf{K}_y^* \\ Ax + B\xi - c \in \mathbf{K}_x \end{array} \right\} \quad (Q)$$

“reduces” meaning that the  $x$ -component of a feasible solution  $\zeta = (x, \xi, f, t, u, \lambda)$  to (Q) is a feasible solution to (P) with the value of the objective of (P) at  $x$  being  $\leq$  the value of the objective of (Q) at  $\zeta$ , and the optimal values in (P) and (Q) are the same.

$\Rightarrow$  For every  $\epsilon > 0$ , every feasible  $\epsilon$ -optimal approximate solution to (Q) induces feasible  $\epsilon$ -optimal approximate solution to (P).

$\mathcal{X} = \{x : \exists \xi : Ax + B\xi - c \in \mathbf{K}_x\}, \mathcal{Y} = \{y : \exists \eta : Cy + D\eta - e \in \mathbf{K}_y\}$
$\forall (x \in \mathcal{X}, y \in \mathcal{Y}) : \psi(x; y) = \inf_{f,t,u} \{f^T y + t : Pf + tp + Qu + Rx - s \in \mathbf{K}\}$

## Reason for Main Observation:

$$\begin{aligned}
\min_{x \in \mathcal{X}} \max_{y \in \mathcal{Y}} \psi(x; y) &= \min_{x \in \mathcal{X}} \max_{y \in \mathcal{Y}} \inf_{f,t,u} \{f^T y + t : Pf + tp + Qu + Rx - s \in \mathbf{K}\} \\
&= \min_{x \in \mathcal{X}} \inf_{f,t,u} \left\{ \left[ \max_{y \in \mathcal{Y}} f^T y \right] + t : Pf + tp + Qu + Rx - s \in \mathbf{K} \right\} \\
&= \inf_{x \in \mathcal{X}, f, t, u} \left\{ \left[ \max_{y, \eta} \{f^T y : Cy + D\eta - e \in \mathbf{K}_y\} \right] + t : Pf + tp + Qu + Rx - s \in \mathbf{K} \right\} \\
&= \inf_{x \in \mathcal{X}, f, t, u} \left\{ \left[ \min_{\lambda \in \mathbf{K}_y^*} \{-e^T \lambda : C^T \lambda + f = 0, D^T \lambda = 0\} \right] + t : Pf + tp + Qu + Rx - s \in \mathbf{K} \right\} \\
&\quad \text{[by Conic Duality]} \\
&= \inf_{x \in \mathcal{X}, \lambda \in \mathbf{K}_y^*, f, t, u} \left\{ t - e^T \lambda : \begin{array}{l} Pf + tp + Qu + Rx - s \in \mathbf{K} \\ C^T \lambda + f = 0, D^T \lambda = 0 \end{array} \right\}
\end{aligned}$$

♠ **Fact** [“Symmetry”]: *Essentially strictly feasible CR*

$$\forall (x \in \mathcal{X}, y \in \mathcal{Y}) : \psi(x; y) = \inf_{f, t, u} \left\{ f^T y + t : Pf + tp + Qu + Rx - s \in \mathbf{K} \right\}$$

*of continuous convex-concave function  $\psi(x; y) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$  induces explicit CR*

$$\forall (\tilde{x} \in \tilde{\mathcal{X}}) : \tilde{\psi}(\tilde{x}, \tilde{y}) = \inf_{\tilde{f}, \tilde{t}, \tilde{u}} \left\{ \tilde{f}^T \tilde{y} + \tilde{t} : \begin{array}{l} \tilde{f} = R^T \tilde{u}, \tilde{t} + s^T \tilde{u} = 0, Q^T \tilde{u} = 0, \\ p^T \tilde{u} = 1, P^T \tilde{u} = \tilde{x}, \tilde{u} \in \mathbf{K}^* \end{array} \right\}$$

*of the “symmetric entity” – convex-concave function*

$$\tilde{\psi}(\tilde{x}, \tilde{y}) := -\psi(\tilde{y}; \tilde{x}) : \tilde{\mathcal{X}} \times \tilde{\mathcal{Y}} := \mathcal{Y} \times \mathcal{X} \rightarrow \mathbb{R}.$$

*implying, in the case of compact  $\mathcal{X}$  with e.s.f. CR, explicit C-conic reformulation of the problem*

$$\max_{y \in \mathcal{Y}} \left[ \underline{\psi}(y) := \min_{x \in \mathcal{X}} \psi(x; y) \right]$$



## Calculus of $C_r$ Functions: “Generic” Raw materials

♣ The following continuous convex-concave functions  $\psi(\cdot; \cdot) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$  are  $C_r$  with explicit  $CR$ 's:

- $\psi(x; y) = a(x)$  where  $a(x)$ ,  $\text{Dom } a \supset \mathcal{X}$ , is given by explicit  $CR$
- $\psi(x; y) = -b(y)$  where  $b(y)$ ,  $\text{Dom } b \supset \mathcal{Y}$ , is given by explicit e.s.f.  $CR$
- Bilinear functions  $\psi(x; y) \equiv a^T x + b^T y + x^T A y + c$
- **Generalized bilinear functions.** Let  $\mathbf{U} \in \mathcal{C}$ , and  $E$  be embedding Euclidean space of the cone  $\mathbf{U}$ . Then the following functions are  $C_r$  with explicit  $CR$ 's:

**a)** functions of the form  $\psi(x; y) = \langle F(x), y \rangle : \mathcal{X} \times \mathbf{U}^* \rightarrow \mathbb{R}$ , where

- $\mathcal{X}$  is given by explicit  $CR$
- $F(x) : \mathcal{X} \rightarrow E$  is continuous with  $\mathbf{U}$ -epigraph  $\{(x, U) : U - F(x) \in \mathbf{U}\}$  given by explicit  $CR$ .

**b)** functions of the form  $\psi(x; u) = \langle x, G(y) \rangle : \mathbf{U} \times \mathcal{Y} \rightarrow \mathbb{R}$ , where

- $\mathcal{Y}$  is given by explicit  $CR$
- $G(y) : \mathcal{Y} \rightarrow E$  is continuous with  $\mathbf{U}^*$ -hypograph  $\{(y, U) : G(y) - U \in \mathbf{U}^*\}$  given by explicit e.s.f.  $CR$

**c)** functions of the form  $\psi(x; y) = \langle F(x), G(y) \rangle : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$ , where

- $\mathcal{X}$  and  $\mathcal{Y}$  are given by explicit  $CR$ 's
- $F(x) : \mathcal{X} \rightarrow \mathbf{U}$  is continuous with  $\mathbf{U}$ -epigraph given by explicit  $CR$
- $G(y) : \mathcal{Y} \rightarrow \mathbf{U}^*$  is continuous with  $\mathbf{U}^*$ -hypograph given by explicit e.s.f.  $CR$

**Illustration:** Let  $\mathcal{C}$  contain semidefinite cones,  $\mathcal{X} = \mathbb{R}^{m \times n}$ ,  $\mathcal{Y} = \mathbf{S}_+^n$ . The function

$$\psi(x; y) = \text{Tr}(x^T x y^{1/2}) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$$

is a Generalized Bilinear function of type c) given by the data

$$\mathbf{U} = \mathbf{S}_+^n, F(x) = x^T x, G(y) = y^{1/2}.$$

The corresponding Calculus rule results in

$$\forall (x \in \mathbb{R}^{m \times n}, y \in \mathbf{S}_+^n) :$$

$$\psi(x; y) = \inf_{f, t, u=(z, \beta, \gamma)} \left\{ \text{Tr}(fy) + t : \left\{ \begin{array}{l} f \in \mathbf{S}^n, \beta \in \mathbb{R}^{n \times n}, \gamma \in \mathbf{S}^n, z \in \mathbf{S}^n \\ t = \text{Tr}(\gamma), z \preceq \beta + \beta^T \\ \left[ \begin{array}{c|c} f & \beta \\ \beta^T & \gamma \end{array} \right] \succeq 0, \left[ \begin{array}{c|c} z & x^T \\ x & I_m \end{array} \right] \succeq 0 \end{array} \right\} \right\}.$$

## Calculus of $CR$ Functions: “Ad Hoc” Raw materials

### A. The function

$$\psi(x; y) = -\frac{x}{x + y + 1} : \underbrace{\mathbb{R}_+}_x \times \underbrace{\mathbb{R}_+}_y \rightarrow \mathbb{R}$$

admits  $CR$

$$\psi(x; y) = \min_{f, t, u} \left\{ fy + t : u \geq 0, \left[ \begin{array}{c|c} x & s \\ \hline s & f \end{array} \right] \succeq 0, \left[ \begin{array}{c|c} t - f + 1 & 1 - s \\ \hline 1 - s & 1 \end{array} \right] \succeq 0 \right\}.$$

**B.** Let  $\mathcal{X} \subset \mathbb{R}^m$ ,  $\mathcal{Y} \subset \mathbb{R}_+^m \setminus \{0\}$  are  $CR$ , and  $\mathcal{Y}$  be compact. The function

$$\psi(x; y) = \ln \left( \sum_{i=1}^m e^{x_i y_i} \right) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$$

admits representation

$$\psi(x; y) = \inf_{f, t, u} \{ f^T y + t : f_i \geq e^{x_i + u} \forall i \ \& \ t \geq -u - 1 \}$$

This is  $CR$ , provided that  $\mathcal{C}$  contains the exponential cone

$$\mathbf{E} = \text{cl}\{[t; s; r] : t \geq s e^{r/s} \ \& \ s > 0\}.$$

**Note:** “For all practical purposes,”  $\mathbf{E}$  is SDr. Formally: *conic constraints involving  $\mathbf{E}$  are polynomially reducible to semidefinite (in fact, even linear) constraints.*

♠ Here is the  $CR$  of a function  $E(x)$  approximating  $\exp\{x\}$  in the range  $-700 \leq x \leq 700$  (the range of exponent which “lives in computer”) within relative error  $\leq 3.e-11$ :

$$t \geq E(x) := \left[ \sum_{\ell=0}^6 \frac{(x/2^{15})^\ell}{\ell!} \right]^{[2^{15}]}$$

⇕

$\exists u_0, u_1, u_2, u_3, v, \tau_1, \tau_2, \tau_3, s, w_1, \dots, w_{14} :$

$$-700 \leq x \leq 700$$

$$\frac{x}{32768} + 1 \leq u_0, \quad 0 \leq u_1 \leq \sqrt{\tau_1 u_0}, \quad 0 \leq u_2 \leq \sqrt{u_0}, \quad 0 \leq u_3 \leq \sqrt{u_1 u_2}, \quad u_0 \leq \sqrt{u_3}$$

$$\left( \frac{x}{32768} + \frac{5}{3} \right)^2 \leq v, \quad v^2 \leq \tau_2, \quad \left( \frac{x}{32768} + \frac{1963}{855} \right)^2 \leq \tau_3, \quad s \geq \frac{78871}{5540400} + \frac{19\tau_3}{144} + \frac{\tau_2}{48} + \frac{\tau_1}{720}$$

$$w_1 \geq s^2, \quad w_2 \geq w_1^2, \quad \dots, \quad w_{14} \geq w_{13}^2, \quad t \geq w_{14}^2$$

**C.** Let  $p > 1$ ,  $\mathcal{X} \subset \mathbb{R}^m$  and  $\mathcal{Y} \subset \mathbb{R}_+^m$  be  $\mathcal{CR}$ , and  $\theta_i(x) : \mathcal{X} \rightarrow \mathbb{R}_+$ ,  $1 \leq i \leq m$ , be  $\mathcal{CR}$ . Then the function

$$\psi(x; y) = \left( \sum_{i=1}^m \theta_i^p(x) y_i \right)^{1/p} : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$$

admits representation

$$\psi(x; y) = \inf_{[f; t]} \left\{ f^T y + t : t \geq 0, f \geq 0, t^{\frac{p-1}{p}} f_i^{\frac{1}{p}} \geq \kappa \theta_i(x), i \leq m \right\}$$

$$\left[ \kappa = p^{-1} (p-1)^{\frac{p-1}{p}} \right]$$

which is  $\mathcal{CR}$ , provided  $p$  is rational.

**D.** Let  $\mathcal{X} \subset \mathbb{R}^{m \times n}$  and  $\mathcal{Y} \subset \mathbf{S}_+^m$  be SDr. Then the function

$$\psi(x; y) = 2\sqrt{\text{Tr}(x^T y x)} : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$$

admits SDr

$$\forall (x \in \mathcal{X}, y \in \mathcal{Y}) : \psi(x; y) = \inf_{f, t} \left\{ \text{Tr}(y f) + t : \left[ \begin{array}{c|c} f & x \\ \hline x^T & t I_n \end{array} \right] \succeq 0 \right\}$$

This is how **D** works in Robust Markowitz Portfolio Selection

$$\min_{x \in \mathcal{X}} \max_{y \in \mathcal{Y}} \left[ -r^T x + 2\mu \sqrt{x^T y x} \right] \quad (M)$$

where  $x \in \mathbb{R}^n$  is composition of portfolio,  $r$  is the vector of expected returns,  $\mu > 0$  is “safety parameter,”  $y$  is the uncertain covariance matrix of the returns running through the set

$$\mathcal{Y} = \{y \in \mathbf{S}_+^n : \sum_{\tau} [a_{i\tau}^T y b_{i\tau} + b_{i\tau} y a_{i\tau}^T] \preceq p_i, i \leq I, y_- \leq y \leq y_+\} \quad [\leq \text{acts entrywise}]$$

(M) is equivalent to the explicit SDP

$$\min_{x, s, \{\alpha_i\}, M_{\pm}} \left\{ \begin{array}{l} -r^T x + \mu \left[ s + \sum_i \text{Tr}(\alpha_i p_i) + \text{Tr}(M_+ y_+ - M_- y_-) \right] : \\ \left[ \begin{array}{c|c} \sum_i \sum_{\tau} [a_{i\tau} \alpha_i b_{i\tau}^T + b_{i\tau} \alpha_i a_{i\tau}^T] + M_+ - M_- & x \\ \hline x^T & s \end{array} \right] \succeq 0 \\ \alpha_i \succeq 0, i \leq I, M_{\pm} \geq 0, x \in \mathcal{X} \end{array} \right\}$$

## Calculus of $\mathcal{C}r$ Functions: Calculus rules

♣ The following operations with  $\mathcal{C}r$  operands yield  $\mathcal{C}r$  convex-concave functions with  $\mathcal{C}R$ 's readily given by  $\mathcal{C}R$ 's of the operands:

- Direct summation:

$$\begin{aligned} & \{\psi_i(x_i; y_i) : \mathcal{X}_i \times \mathcal{Y}_i \rightarrow \mathbb{R}, \theta_i > 0\}_{i \leq K} \\ \Rightarrow \psi(x_1, \dots, x_K; y_1, \dots, y_K) &= \sum_i \theta_i \psi_i(x_i; y_i) : [\mathcal{X}_1 \times \dots \times \mathcal{X}_K] \times [\mathcal{Y}_1 \times \dots \times \mathcal{Y}_K] \rightarrow \mathbb{R} \end{aligned}$$

- Taking conic combinations:

$$\begin{aligned} & \{\psi_i(x; y) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}, \theta_i > 0\}_{i \leq K} \\ \Rightarrow \psi(x; y) &= \sum_i \theta_i \psi_i(x; y) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R} \end{aligned}$$

- Affine substitution of variables:

$$\begin{aligned} & \{A(x) = Ax + a : \mathcal{X} \rightarrow \mathcal{X}^+, B(y) = By + b : \mathcal{Y} \rightarrow \mathcal{Y}^+, \psi_+(\xi; \eta) : \mathcal{X}^+ \times \mathcal{Y}^+ \rightarrow \mathbb{R}\} \\ \Rightarrow \psi(x; y) &= \psi_+(A(x); B(y)) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R} \end{aligned}$$

- Projective transformation in  $x$ -variable:

$$\begin{aligned} & \{\psi(x; y) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}\} \\ \Rightarrow \mathcal{X}_+ := \{(x, \alpha) : \alpha > 0, \alpha^{-1}x \in \mathcal{X}\} & \& \psi_+((x, \alpha); y) := \alpha \psi(x/\alpha; y) : \mathcal{X}^+ \times \mathcal{Y} \rightarrow \mathbb{R} \end{aligned}$$

♣ The following operations with  $\mathcal{C}r$  operands yield  $\mathcal{C}r$  convex-concave functions with  $\mathcal{C}R$ 's readily given by  $\mathcal{C}R$ 's of the operands:

- Superposition in  $x$ -variable:

$$\mathcal{X}, \mathcal{Y}, \mathbb{R}^n \supset \mathcal{Z} : \mathcal{C}r, \mathbb{R}^n \supset \mathbf{U} \in \mathcal{C}$$

$$\psi_+(z; y) : \mathcal{Z} \times \mathcal{Y} : \mathcal{C}r \text{ and } \mathbf{U}\text{-monotone in } z: y \in \mathcal{Y}, z, z' \in \mathcal{Z}, z' - z \in \mathbf{U} \Rightarrow \psi_+(z; y) \leq \psi_+(z'; y)$$

$$X(x) : \mathcal{X} \rightarrow \mathcal{Z} : \text{with } \mathcal{C}r \text{ } \mathbf{U}\text{-epigraph } \{[x; z] \in \mathcal{X} \times \mathcal{Z} : z - X(x) \in \mathbf{U}\}$$

$$\Rightarrow \psi(x; y) = \psi_+(X(x); y) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$$

- Partial maximization in  $y$ -variable:

$$\mathcal{X}, \mathcal{Y}, \phi(x; y) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R} : \mathcal{C}r$$

$$\mathcal{Y} \in \mathbb{R}_w^p \times \mathbb{R}_z^q : \text{compact with } \mathcal{C}r \mathcal{Y} = \{[w; z] : \exists v : Aw + Bz + Cv - d \in \mathbf{K}\}$$

such that for all  $[w; h] \in \mathcal{Y}$  conic constraint  $Bz + Cv + [Aw - d] \in \mathbf{K}$  in variables  $z, v$  is e.s.f.

$$\max_{z: [w; z] \in \mathcal{Y}} \psi(x; [w; z]) \text{ is continuous on } \mathcal{X} \times \{\mathcal{W} := \{w : \exists z : [w; z] \in \mathcal{Y}\}\}$$

$$\Rightarrow \bar{\psi}(x; w) := \max_{z: [w; z] \in \mathcal{Y}} \psi(x; [w; z]) : \mathcal{X} \times \mathcal{W} \rightarrow \mathbb{R}$$

**Note:** By Symmetry, Calculus extends to projective transformation and superposition in  $y$ -variable and partial minimization in  $x$ -variable.



- ♣ The following operation with  $\mathcal{C}r$  operands yields  $\mathcal{C}r$  convex-concave function with  $\mathcal{C}R$  readily given by  $\mathcal{C}R$ 's of the operands:
- Taking Fenchel conjugate:

$\mathcal{X}, \mathcal{Y}, \phi(x; y) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R} : \mathcal{C}r$  given by e.s.f.  $\mathcal{C}R$ 's, with compact  $\mathcal{X}, \mathcal{Y}$  and with e.s.f. conic constraint  $D^T \lambda = 0$  &  $\lambda \geq_{\mathbb{K}_y^*} 0$  in variable  $\lambda$

$$\Rightarrow \phi_*(p, q) = \max_{x \in \mathcal{X}} \min_{y \in \mathcal{Y}} [p^T x + q^T y - \phi(x; y)] : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$$

**Illustration:** We have build  $CR$  for

$$\psi(x; y) : -\frac{x}{x + y + 1} : \mathbb{R}_+^2 \rightarrow \mathbb{R}.$$

By Calculus, this  $CR$  induces  $CR$ 's of functions of the form

$$-\frac{\alpha(x)}{\alpha(x) + \beta(y) + 1} : \text{Dom } \alpha \times \text{Dom } \beta \rightarrow \mathbb{R}$$

$[\alpha, \beta : \text{nonnegative concave with } CR \text{ hypographs}]$

## Conic Representations of Monotone Vector Fields

♠ **Preliminaries.** Let  $\mathcal{X} \subset E = \mathbb{R}^n$  be a nonempty convex set and  $F(x) : \mathcal{X} \rightarrow E$  be a vector field.  $F$  is called *monotone* on  $\mathcal{X}$ , if  $\langle F(x) - F(y), x - y \rangle \geq 0 \forall x, y \in \mathcal{X}$ .

Variational Inequality induced by  $F, \mathcal{X}$  reads

$$\text{Find } x_* \in \mathcal{X} \text{ such that } \langle F(x), x - x_* \rangle \geq 0 \forall x \in \mathcal{X} \quad \text{VI}(F, \mathcal{X})$$

**Convention:** From now on, if otherwise is not explicitly stated, vector fields  $F : \mathcal{X} \rightarrow E$  in question are assumed to be monotone and continuous on their convex domains  $\mathcal{X}$ . In this case,

*Solutions to  $\text{VI}(F, \mathcal{X})$  are exactly the points  $x_* \in \mathcal{X}$  such that  $\langle F(x_*), x - x_* \rangle \geq 0 \forall x \in \mathcal{X}$ .  
Solutions do exist when  $\mathcal{X}$  is compact*

♥ **Inaccuracy** of a candidate solution  $x \in \mathcal{X}$  to  $\text{VI}(F, \mathcal{X})$  is quantified by *dual gap*

$$\epsilon_{\text{VI}}[x|\mathcal{X}] = \max_{y \in \mathcal{X}} \langle F(y), x - y \rangle$$

**Basic examples** of monotone vector fields:

- Gradient field  $F(x) = \nabla f(x)$  of  $C^1$  convex function  $f : \mathcal{X} \rightarrow \mathbb{R}$
- Vector field  $F(u; v) = [\nabla_u \psi(u; v); -\nabla_v \psi(u; v)]$  stemming from  $C^1$  convex-concave function  $\psi(u; v) : \mathcal{X} := \mathcal{U} \times \mathcal{V} \rightarrow \mathbb{R}$ .

In the first case, solutions to  $\text{VI}(F, \mathcal{X})$  are the minimizers of  $f$  on  $\mathcal{X}$ , in the second – saddle point of  $\psi$  on  $\mathcal{U} \times \mathcal{V}$ .

**Observation** [Nesterov&N'94]: Given a continuous monotone vector field  $F : \mathcal{X} \rightarrow \mathcal{R}$ ,  $\mathcal{X} \subset E = \mathbb{R}^n$ , let

$$\mathfrak{T}[F, \mathcal{X}] = \{[t; g; x] \in \mathbb{R} \times E \times E : x \in \mathcal{X}, t - \langle g, y \rangle \geq \langle F(y), x - y \rangle \forall y \in \mathcal{X}\}.$$

Then

**A.**  $\mathfrak{T}[F, \mathcal{X}]$  is a convex set which contains all triples  $[\langle F(x), x \rangle; F(x); x]$ ,  $x \in \mathcal{X}$ ; this set is closed provided  $\mathcal{X}$  is so. Besides this,  $\mathfrak{T}[F, \mathcal{X}]$  is *t-monotone*:

$$[t; g; x] \in \mathfrak{T}[F, \mathcal{X}] \text{ and } t' \geq t \Rightarrow [t'; g; x] \in \mathfrak{T}[F, \mathcal{X}].$$

**B.** For  $\epsilon \geq 0$ , let

$$\mathcal{X}_*(\epsilon) = \{[g; t] \in E \times \mathbb{R} : \sup_{y \in \mathcal{X}} [t - \langle g, y \rangle] \leq \epsilon\},$$

so that  $\mathcal{X}_*(\epsilon)$  is a nonempty closed convex set. Then for every  $\epsilon \geq 0$ , feasible  $\epsilon$ -solutions to  $\text{VI}(F, \mathcal{X})$  – points  $x \in \mathcal{X}$  with  $\epsilon_{\text{VI}}[x|\mathcal{X}] \leq \epsilon$  – are exactly the points

$$x : \exists (t, g) : [t; g; x] \in \mathfrak{T}[F, \mathcal{X}] \ \& \ [t; g] \in \mathcal{X}_*(\epsilon). \quad (!)$$

**Note:** Were we given *CR*'s of  $\mathfrak{T}[F, \mathcal{X}]$  and of  $\mathcal{X}_*(\epsilon)$ , (!) would reduce finding  $\epsilon$ -solution to  $\text{VI}(F, \mathcal{X})$  to solving *C*-conic problem. *CR* of  $\mathcal{X}_*(\epsilon)$  “is cheap” – it is readily given by e.s.f. *CR* of  $\mathcal{X}$ . In contrast,  $\mathfrak{T}[F, \mathcal{X}]$  can be too complicated to admit explicit *CR*.

In the sequel, we intend to replace in (!) the set  $\mathfrak{T}[F, \mathcal{X}]$  with a smaller *Cr* set which still is “rich enough” for our ultimate goal.

$F : \mathcal{X} \rightarrow E = \mathbb{R}^n$ : continuous monotone vector field on convex domain

$$\begin{aligned} \mathfrak{T}[F, \mathcal{X}] &= \{[t; g; x] \in \mathbb{R} \times E \times E : x \in \mathcal{X}, t - \langle g, y \rangle \geq \langle F(y), x - y \rangle \forall y \in \mathcal{X}\} \\ \Rightarrow \mathcal{X}_*(\epsilon) &= \{[g; t] \in E \times \mathbb{R} : \sup_{y \in \mathcal{X}} [t - \langle g, y \rangle] \leq \epsilon\} \end{aligned}$$

**Definition.**  $\mathcal{C}$ -representation of  $(F, \mathcal{X})$  is a conic constraint

$$Xx + Gg + tT + Uu - a \in \mathbf{K}$$

in variables  $t \in \mathbb{R}, g, x \in E, u \in \mathbb{R}^k$  with  $t$ -monotone projection

$$\mathcal{T} := \{[t; g; x] : \exists u : Xx + Gg + tT + Uu - a \in \mathbf{K}\}$$

of the solution set on the space of  $t, g, x$  variables satisfying the inclusions

$$\{[t; F(x); x] : t > \langle F(x), x \rangle, x \in \mathcal{X}\} \subset \mathcal{T} \subset \mathfrak{T}[F, \mathcal{X}]$$

## Conic Form of Variational Inequality with $\mathcal{C}$ -Representable Monotone Vector Field

**Theorem** [Jud&N'21] Assume that  $\mathcal{X} \subset E = \mathbb{R}^n$  is nonempty convex compact set given by e.s.f.  $\mathcal{CR}$  :

$$\mathcal{X} = \{x : \exists v : Ax + Bv - b \in \mathbf{L}\}$$

and that continuous monotone vector field  $F : \mathcal{X} \rightarrow E$  admits  $\mathcal{CR}$  given by conic constraint

$$Xx + Gg + tT + Uu - a \in \mathbf{K}$$

in variables  $t, g, x, u$ .

Then for every  $\epsilon > 0$  finding  $\epsilon$ -solution to  $\text{VI}(F, \mathcal{X})$  reduces to finding feasible solution to an explicit feasible conic constraint

$$Xx + Gg + tT + Uu - a \in \mathbf{K}, A^T \lambda = g, B^T \lambda = 0, t - b^T \lambda \leq \epsilon, \lambda \in \mathbf{L}^* \quad (!)$$

in variables  $t, g, x, \lambda$ . Specifically,  $x$ -component of feasible solution to (!) is a feasible  $\epsilon$ -solution to  $\text{VI}(F, \mathcal{X})$ .

## Calculus of $CR$ 's of Monotone Vector Fields: Raw materials

♣ The following monotone vector fields  $F : \mathcal{X} \rightarrow E$  are  $CR$  with explicit  $CR$ 's:

- Affine monotone field  $F(x) = Ax + b : E \rightarrow E$  [ $A + A^T \succeq 0$ ]
- Gradient vector field  $F(x) = \nabla f(x)$  of  $C^1$  convex function  $f : \mathcal{X} \rightarrow \mathbb{R}$ , provided that  $\mathcal{X}$  is convex compact set and the epigraph  $\{(x, t) : x \in \mathcal{X}, t \geq f(x)\}$  of  $f$  on  $\mathcal{X}$  is given by e.s.f.  $CR$
- Monotone vector field  $F(u; v) = [\nabla_u \psi(u; v); -\nabla_v \psi(u; v)] : \mathcal{U} \times \mathcal{V} \rightarrow \mathbb{R}^{n_u + n_v}$  associated with  $C^1$  convex-concave function  $\psi$ , provided that  $\mathcal{U}, \mathcal{V}$  are convex compact, and  $\mathcal{U}, \mathcal{V}, \psi$  are given by e.s.f.  $CR$ 's
- Rational monotone *univariate* vector field  $F(x) = \frac{p(x)}{q(x)} : \mathcal{X} = [0, 1] \rightarrow \mathbb{R}$  ( $p, q$  are algebraic polynomials,  $q > 0$  on  $\mathcal{X}$ )

## Calculus of $CR$ 's of Monotone Vector Fields: Calculus Rules

♣ The results of the following monotonicity-preserving operations with  $Cr$  monotone vector fields are  $Cr$ , with  $CR$ 's readily given by  $CR$ 's of operands:

- Restriction on  $\mathcal{C}$ -representable set
- Direct summation
- Taking linear combinations with nonnegative coefficients
- Affine substitution of variables:  $CR$ 's of  $\mathcal{X}$  and of continuous monotone vector field  $F : \mathcal{X} \rightarrow \mathbb{R}^m$  explicitly induce a  $CR$  of the field

$$G(y) = A^T F(Ay + b) : \mathcal{Y} := \{y \in \mathbb{R}^n : Ay + b \in \mathcal{X}\} \rightarrow \mathbb{R}^n \quad [A : m \times n, \mathcal{Y} \neq \emptyset]$$



♠ **Illustration:** Consider *Convex Nash Equilibrium* problem, where  $n \geq 2$  players make selections  $x_i \in \mathcal{X}_i$ , with  $\mathcal{C}R$  convex compact sets  $\mathcal{X}_i$ . As a result of these selections, loss of  $i$ -th player is a known  $C^1$  function  $\psi_i(x_1, \dots, x_n)$ ,  $i \leq n$ .

• Nash Equilibrium  $x^* \in \mathcal{X} = \mathcal{X}_1 \times \dots \times \mathcal{X}_n$  is given by

$$x_i^* \in \underset{x_i \in \mathcal{X}_i}{\text{Argmin}} \psi_i(x_1^*, \dots, x_{i-1}^*, x_i, x_{i+1}^*, \dots, x_n^*), \quad 1 \leq i \leq n$$

— a selection where no player can reduce loss by unilateral action.

• Nash Equilibrium Problem is called convex, if

a)  $\psi_i$  is convex in  $x_i$  and jointly concave in all  $x_j$  with  $j \neq i$ ,  $1 \leq i \leq n$ , and

b)  $\phi(x) := \sum_i \psi_i(x)$  is convex.

In this case, the vector field

$$F(x_1, \dots, x_n) = [\nabla_{x_1} \psi_1(x); \dots; \nabla_{x_n} \psi_n(x)]$$

is monotone, and Nash Equilibria are exactly the solutions to  $\text{VI}(F, \mathcal{X})$ .

♥ **Fact** [Jud&N'21]  $\mathcal{C}R$  of  $F$  is readily given by  $\mathcal{C}R$ 's of the monotone vector fields associated with convex-concave functions  $\psi_i(\cdot)$  and with the convex function  $\phi$  and as such can be obtained by utilizing the related components of our Calculus.