

# Computational aspects of robust optimized certainty equivalent

LUDOVIC TANGPI

Fakultät für Mathematik, Universität Wien

based on a joint work with DANIEL BARTL AND SAMUEL DRAPEAU

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# Motivation

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### OCE definition

Let  $X : \Omega \rightarrow \mathbb{R}$  be a future **uncertain** loss with distribution  $\mu_X$ ; and  $I : \mathbb{R} \rightarrow \mathbb{R}$  a loss function.

$$\text{OCE}(X) = \inf_{m \in \mathbb{R}} \left( \int I(x - m) d\mu_X + m \right) \equiv \text{OCE}(\mu_X)$$

Ben-Tal & Teboulle (1986, 2007);

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$$\text{OCE}(X) = \inf_{m \in \mathbb{R}} \left( \int l(x - m) d\mu_X + m \right) \equiv \text{OCE}(\mu_X)$$

Ben-Tal & Teboulle (1986, 2007); Cheridito & Li (2009); Cherny & Kupper (2007); Barrieu & El Karoui (2007); Drapeau et. al (2014); Backhoff & T. (2016)

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- **Minimize** the allocation cost:

$$OCE(\mu_X) := \inf_{m \in \mathbb{R}} \left( \int l(x - m) d\mu_X + m \right)$$

- $l(x) = e^x - 1 \rightsquigarrow$  Entropy:

$$\text{OCE}(\mu_X) = \text{Ent}(\mu_X) := \log \int e^x d\mu_X$$

- $l(x) = x^+/\alpha \rightsquigarrow$  Average value-at-risk:

$$\text{OCE}(\mu_X) = \text{AVaR}_\alpha(\mu_X) = \frac{1}{\alpha} \int_0^\alpha \text{VaR}_u(\mu_X) du$$



- In practice  $\mu_X$  is not precisely known
- If the distribution  $\mu_X \in \mathcal{D}$  for some  $\mathcal{D} \subseteq \mathcal{M}_1$ , then

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- $\leadsto$  infinite dimensional optimization problem!
- Monetary risk measure? robust representation? **computational issues?** deviation from non-robust counterpart?

# Optimal transport-type ambiguity sets

## OCE of a ball

### Notation

Let  $c : \mathbb{R} \times \mathbb{R} \rightarrow [0, \infty]$  be lsc. For  $\delta > 0$  and a baseline distribution  $\mu_0 \in \mathcal{M}_1$ , put

$$B_\delta(\mu_0) := \{\mu \in \mathcal{M}_1 : d_c(\mu_0, \mu) \leq \delta\}$$

with the "transport-like distance"

$$d_c(\mu, \nu) := \inf \left\{ \int c d\pi : \pi \in \mathcal{M}_1(\mathbb{R}^2) \text{ with } \pi(\cdot \times \mathbb{R}) = \mu, \pi(\mathbb{R} \times \cdot) = \nu \right\}.$$

Consider:

$$\text{OCE}(B_\delta(\mu_0)) = \inf_m \sup_{\mu \in B_\delta(\mu_0)} \left( \int l(x - m) d\mu + m \right)$$

- If  $c(x, y) = 1_{x \neq y}$ ,  $2d_c = TV$ , the total variation
- If  $c(x, y) = |x - y|^p$ ,  $d_c^{1/p} = W_p$ , the  $p$ -Wassestein distance.
- $d_c$  is a "better distance" than  $\phi$ -divergences as it does not require absolute continuity.

cf. e.g. Glasserman & Xu (2014); Hansen & Sargen (2001); Jian & Guan (2015).

## Theorem

If  $I : \mathbb{R} \rightarrow \mathbb{R} \cup \{\infty\}$  is **measurable and bounded from below**, assume  $c(x, y) = \tilde{c}(x - y)$  for some  $\tilde{c} : \mathbb{R} \rightarrow [0, \infty]$  s.t.

- $\inf_x \tilde{c}(x) = 0$
- $\liminf_{|x| \rightarrow +\infty} \tilde{c}(x) = +\infty$ .

Then,

$$OCE(B_\delta(\mu_0), I) = \inf_{\lambda \geq 0} (OCE(\mu_0, I^{\lambda c}) + \lambda \delta),$$

with  $I^c(x) := \sup_{y \in \mathbb{R}} (I(y) - c(x, y))$ , the  $c$ -transform of  $I$ .

## Example

- **Average value-at-risk** For  $\ell(x) = x^+/\alpha$  and  $c(x, y) = |y - x|$ ;  $d_c = 1$  – Wasserstein distance

$$\text{AVaR}_\alpha(\mathbf{B}_\delta(\mu_0)) = \text{AVaR}_\alpha(\mu_0) + \frac{\delta}{\alpha}$$

Thank You!