Risk Measures and Multistage Stochastic Programming



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Introduction

Definition

Let (Ω, \mathcal{F}) be a sample space on which uncertain losses $Z(\omega)$ are defined. For some space \mathcal{Z} of functions Z we understand risk measure as a function $\rho(Z)$ which maps \mathcal{Z} into extended real line $\overline{\mathbb{R}} = \mathbb{R} \cup \{\infty, -\infty\}$.

- We usually have $\mathcal{Z} = \mathcal{L}_p$ with $p \in [1, \infty)$.
- We assume that ρ is proper, i.e. $\rho(Z) \ge -\infty \ \forall Z \in \mathcal{Z}$ and the domain $\mathsf{dom}(\rho) = \{Z \in \mathcal{Z} : \rho(Z) < \infty\} \ne \emptyset$
- $Z, Z' \in \mathcal{Z}, Z \succeq Z'$ if $Z(\omega) \geq Z'(\omega)$ for a.e. $\omega \in \Omega$.
- The smaller *Z* is better, representing for instance costs.



Risk measures - examples

Let $H_Z(z) = P[Z < z]$ and denote the left side quantile $H_Z^{-1}(\alpha) = \inf\{t : H_Z(t) \ge \alpha\}.$

- variance $var(Z) = E[Z EZ]^2$
- semideviations $\sigma_p^+(Z) = \left(\mathbb{E} \left[Z \mathbb{E} Z \right]_+^p \right)^{1/p}$
- Value at Risk VaR $_{\alpha}(Z) = H_{Z}^{-1}(1 \alpha)$
- lacksquare Condition Value at Risk CVaR $_{lpha}(Z)=\inf_{t\in\mathbb{R}}\left\{t+lpha^{-1}\mathsf{E}\left[Z-t
 ight]_{+}
 ight\}$
- weighted mean deviation from a quantile $q_{\alpha}(Z) = \mathbb{E}\left[\max\left\{(1-\alpha)(H_Z^{-1}(\alpha)-Z),\alpha(Z-H_Z^{-1}(\alpha)\right\}\right]$
- etc.



Coherent Risk Measures

Definition

Risk measure ρ is said to be coherent if it satisfies:

1. Convexity: $\forall Z, Z' \in \mathcal{Z}$ and $\forall t \in [0, 1]$

$$\rho(tZ+(1-t)Z^{'})\leq t\rho(Z)+(1-t)\rho(Z^{'}).$$

- 2. Monotonicity: if $Z, Z' \in \mathcal{Z}$ and $Z \succeq Z'$ then $\rho(Z) \geq \rho(Z')$.
- 3. Translation equivariance: $\forall a \in \mathbb{R}, \ Z \in \mathcal{Z}: \rho(Z+a) = \rho(Z) + a$
- 4. Positive homogeneity: $\forall t > 0, \ Z \in \mathcal{Z}$: $\rho(tZ) = t\rho(Z)$
- CVaR is an example of coherent risk measure.



Conjugate duality

- With each space $\mathcal{Z} = \mathcal{L}_p(\Omega, \mathcal{F}, \mathsf{P})$ is associated its dual $\mathcal{Z}^* = \mathcal{L}_q(\Omega, \mathcal{F}, \mathsf{P})$ where $q \in [1, \infty)$ such that 1/p + 1/q = 1.
- Scalar product for $Z \in \mathcal{Z}$ and $\zeta \in \mathcal{Z}^*$ is given by

$$\langle \zeta, Z \rangle = \int_{\Omega} \zeta(\omega) Z(\omega) dP(\omega)$$

• Conjugate function $\rho^*(\zeta)$ is defined as:

$$\rho^*(\zeta) = \sup_{Z \in \mathcal{Z}} \left\{ \langle \zeta, Z \rangle - \rho(Z) \right\}$$

- □ always convex and lsc
- Biconjugate function $\rho^{**}(Z)$, which is conjugate of $\rho^*(Z)$:

$$\rho^{**}(Z) = \sup_{\zeta \in \mathcal{Z}^*} \left\{ \langle \zeta, Z \rangle - \rho^*(\zeta) \right\}$$



Conjugate duality

Theorem (Fenchel-Moreau)

Let \mathcal{Z} be a Banach space and $\rho: \mathcal{Z} \to \overline{\mathbb{R}}$ be a proper extended real valued convex function. Then

$$\rho^{**} = \operatorname{lsc} \rho.$$

- If ρ is convex, proper and lower semicontinuous then ρ^* is proper and $\rho^{**} = \rho$.
- We can use following equivalent form for convex risk measure:

$$\rho(Z) = \sup_{\zeta \in \mathcal{U}} \left\{ \langle \zeta, Z \rangle - \rho^*(\zeta) \right\}$$

where $\mathcal{U} = \mathsf{dom}(\rho^*)$.



Basic duality theorem

Theorem

Let $\rho: \mathcal{Z} \to \overline{\mathbb{R}}$ be convex, proper and lsc. Then for $\mathcal{U} = \mathsf{dom}(\rho^*)$ representation

$$\rho(Z) = \sup_{\zeta \in \mathcal{U}} \left\{ \langle \zeta, Z \rangle - \rho^*(\zeta) \right\}$$

holds. Moreover

- lacksquare ho is monotone iff $\forall \zeta \in \mathcal{U} : \zeta(\omega) \geq 0$ a.s.,
- ρ is translation equivariant iff $\forall \zeta \in \mathcal{U}: \int_{\Omega} \zeta \mathsf{dP} = 1$,
- ρ is positive homogeneous iff ρ is the support function of the set \mathcal{U} , i.e.

$$\rho(Z) = \sup_{\zeta \in \mathcal{U}} \langle \zeta, Z \rangle.$$



Basic duality theorem - proof

Representation

$$\rho(Z) = \sup_{\zeta \in \mathcal{U}} \{ \langle \zeta, Z \rangle - \rho^*(\zeta) \}$$

follows from Fenchel-Moreau theorem.

- Suppose ρ is monotone.
 - □ If $\zeta \in \mathcal{Z}^*$ is not nonnegative, then $\exists \Delta \in \mathcal{F} : P[\Delta] > 0, \zeta(\omega) < 0 \ \forall \omega \in \Delta.$
 - □ Define $\hat{Z} = I_{\Delta}$, then $\langle \zeta, \hat{Z} \rangle < 0$.
 - \Box For any $Z \in \text{dom}(\rho)$ define $Z_t = Z t\hat{Z}$.
 - □ Then $\rho^*(\zeta) \ge \sup_{t \in \mathbb{R}_+} \{\langle \zeta, Z_t \rangle \rho(Z_t)\} \ge \sup_{t \in \mathbb{R}_+} \{\langle \zeta, Z \rangle t \langle \zeta, \hat{Z} \rangle \rho(Z_t)\} = \infty$
- Suppose every $\zeta \in \mathcal{U}$ is nonnegative.
 - $\ \ \Box \ \ \forall \zeta \in \mathcal{U} \ \ \text{and} \ \ Z \succeq Z^{'} \ \ \text{we have} \ \ \langle \zeta, Z \rangle \geq \langle \zeta, Z^{'} \rangle$
 - □ That means if $Z \succeq Z'$ then $\rho(Z) \ge \rho(Z')$



Basic duality theorem - proof

- **Suppose** ρ is translation equivariant

 - \Box If $\int_{\Omega} \zeta \mathsf{dP}
 eq 1$ then $ho^*(\zeta) = \infty$
- Conversely $\int_{\Omega} \zeta dP = 1$
- Suppose ρ is positive homogeneous

 - $\rho^*(\zeta)$ is indicator function of some convex set
 - $\rho^*(\zeta)$ is indicator function of some convex set $\rho^*(\zeta) = 0$ for $\zeta \in \mathcal{U}$ (basic representation)
- Conversely

$$\Box \ \rho(tZ) = \sup_{\zeta \in \mathcal{U}} \langle \zeta, tZ \rangle = \sup_{\zeta \in \mathcal{U}} t \langle \zeta, Z \rangle = t \rho(Z)$$



Basic duality theorem - corollary

Let ρ be a coherent risk measure. Then

$$\rho(Z) = \sup_{\zeta \in \mathcal{U}} \langle \zeta, Z \rangle,$$

where \mathcal{U} is a set of probability density functions. Consequently we can write

$$\rho(Z) = \sup_{\zeta \in \mathcal{U}} \mathsf{E}_{\zeta} \left[Z \right].$$



Basic duality theorem - examples

lacksquare Conditional Value at Risk $(\mathcal{Z}=\mathcal{L}_1,\mathcal{Z}^*=\mathcal{L}_\infty)$

$$\mathsf{CVaR}_{lpha}(Z) = \sup_{\zeta \in \mathcal{U}} \langle \zeta, Z \rangle,$$

$$\mathcal{U} = \left\{ \zeta \in \mathcal{L}_{\infty}(\Omega, \mathcal{F}, \mathsf{P}) : \zeta(\omega) \in [0, \alpha^{-1}] \text{ a.s., } \mathsf{E}\left[\zeta\right] = 1 \right\}$$

■ Mean-Variance Risk Measure $(\mathcal{Z}^* = \mathcal{Z} = \mathcal{L}_2)$

$$\rho(Z) = \mathsf{E}[Z] + k\mathsf{var}[Z]$$

$$\rho(Z) = \sup \left\{ \langle \zeta, Z \rangle - \frac{1}{4k} \text{var} \left[\zeta \right] : \zeta \in \mathcal{Z}, \mathsf{E} \left[\zeta \right] = 1 \right\}$$



Extensions to multiperiod case

- Conditional risk mappings
 - □ details in Shapiro, A., Dentcheva, D., Ruszczynski A. (2009)
 - $\hfill\Box$ good interpretation on the scenario tree
- Multiperiod coherent risk measures
 - details in Shapiro, A., Dentcheva, D., Ruszczynski A. (2009)
 - □ general framework for multiperiod risk-averse optimization
- Multiperiod polyhedral risk measures
 - special class with nice properties and good tractability
 - details in Eichhorn, A. and Romisch W. (2005), Guigues, V. and Romisch W. (2010)



Conditional risk mappings

Definition

Let Ω be the sample space equipped with sigma algebras $\mathcal{F}_t, \mathcal{F}_{t+1}$ and a probability measure P on $(\Omega, \mathcal{F}_{t+1})$. Denote spaces $\mathcal{Z}_t = \mathcal{L}_p(\Omega, \mathcal{F}_t, \mathsf{P})$ and $\mathcal{Z}_{t+1} = \mathcal{L}_p(\Omega, \mathcal{F}_{t+1}, \mathsf{P})$. Mapping $\rho: \mathcal{Z}_{t+1} \to \mathcal{Z}_t$ is conditional risk mapping if it satisfies

1. Convexity: $\forall Z, Z' \in \mathcal{Z}_{t+1}$ and $\forall t \in [0, 1]$

$$\rho(tZ+(1-t)Z^{'}) \leq t\rho(Z)+(1-t)\rho(Z^{'}).$$

- 2. Monotonicity: if $Z, Z' \in \mathcal{Z}_{t+1}$ and $Z \succeq Z'$ then $\rho(Z) \succeq \rho(Z')$.
- 3. Translation equivariance: $\forall Y \in \mathcal{Z}_t, \ Z \in \mathcal{Z}_{t+1}$: $\rho(Z + Y) = \rho(Z) + Y$
- 4. Positive homogeneity: $\forall t > 0, \ Z \in \mathcal{Z}_{t+1}$: $\rho(tZ) = t\rho(Z)$



Conditional risk mappings - examples

- Conditional expectation $E[\cdot|\mathcal{F}_t]$
 - $\ \ \Box \ \ Z \in \mathcal{L}_p(\Omega, \mathcal{F}_{t+1}, \mathsf{P}), \ \mathcal{F}_t$ -measurability of $\mathsf{E}\left[Z|\mathcal{F}_t\right]$ is clear

$$\int_{\Omega} |\mathsf{E}\left[Z|\mathcal{F}_t\right]|^p \mathsf{dP} \leq \int_{\Omega} \mathsf{E}\left[|Z|^p|\mathcal{F}_t\right] \mathsf{dP} = \mathsf{E}\left[|Z|^p\right] < \infty$$

Conditional CVaR

$$\left[\mathsf{CVaR}_{\alpha}(Z|\mathcal{F}_t)\right](\omega) = \inf_{Y \in \mathcal{Z}_t} \left\{ Y(\omega) + \alpha^{-1} \mathsf{E}\left[(Z - Y)_+ | \mathcal{F}_t \right](\omega) \right\}$$

Conditional absolute semideviation:

$$\rho_{d|\mathcal{F}_t}(Z) = \mathsf{E}\left[Z|\mathcal{F}_t\right] + \mathsf{E}\left[\left(Z - \mathsf{E}\left[Z|\mathcal{F}_t\right]\right)_+|\mathcal{F}_t\right]$$



Conditional risk mappings - usage

- Let $(\Omega, \mathcal{F}, \mathsf{P})$ be a probability space and $\mathcal{F}_1 \subset \mathcal{F}_2 \subset \cdots \subset \mathcal{F}_T$ sequence of sigma algebras with $\mathcal{F}_1 = \{\emptyset, \Omega\}$, $\mathcal{F}_T = \mathcal{F}$. Let $\mathcal{Z}_t = \mathcal{L}_p(\Omega, \mathcal{F}_t, \mathsf{P})$ and $\rho_{t+1|\mathcal{F}_t} : \mathcal{Z}_{t+1} \to \mathcal{Z}_t$, t = 1, ..., T 1.
- Consider following multistage program

$$\min_{\mathbf{x}_{1} \in \mathcal{X}_{1}} f_{1}(\mathbf{x}_{1}) + \rho_{2|\mathcal{F}_{1}} \left(\inf_{\mathbf{x}_{2} \in \mathcal{X}_{2}(\mathbf{x}_{1}, \omega)} f_{2}(\mathbf{x}_{2}, \omega) + \cdots \right. \\
+ \rho_{T-1|\mathcal{F}_{T-2}} \left(\inf_{\mathbf{x}_{T-1} \in \mathcal{X}_{T-1}(\mathbf{x}_{T-2}, \omega)} f_{T-1}(\mathbf{x}_{T-1}, \omega) \right. \\
+ \rho_{T|\mathcal{F}_{T-1}} \left(\inf_{\mathbf{x}_{T} \in \mathcal{X}_{T}(\mathbf{x}_{T-1}, \omega)} f_{T}(\mathbf{x}_{T}, \omega) \right) \right) \right)$$



Conditional risk mappings - usage

- Denote $Z_t = \inf_{x_t \in \mathcal{X}_t(x_{t-1},\omega)} f_t(x_t,\omega)$
- By translation equivariance we have:

$$\rho_{T-1|\mathcal{F}_{T-2}}\left(Z_{T-1} + \rho_{T|\mathcal{F}_{T-1}}(Z_T)\right) = \rho_{T-1|\mathcal{F}_{T-2}} \circ \rho_{T|\mathcal{F}_{T-1}}(Z_{T-1} + Z_T)$$

Applying the same way we get coherent risk measure

$$\overline{\rho} = \rho_{2|\mathcal{F}_1} \circ \cdots \circ \rho_{T|\mathcal{F}_{T-1}}$$

Stochastic program using the composite measure

$$\min_{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T} \overline{\rho} \left(f_1(\mathbf{x}_1) + f_2(\mathbf{x}_2, \omega) + \dots + f_T(\mathbf{x}_T, \omega) \right)$$

s. t. $\mathbf{x}_1 \in \mathcal{X}_1, \ \mathbf{x}_t \in \mathcal{X}_t(\mathbf{x}_{t-1}, \omega), \ t = 2, \dots, T$



Multiperiod coherent risk measures

Denote $\mathcal{Z} = \mathcal{Z}_1 \times \cdots \times \mathcal{Z}_T$ and its dual $\mathcal{Z}^* = \mathcal{Z}_1^* \times \cdots \times \mathcal{Z}_T^*$.

Definition

We say that $\rho: \mathcal{Z} \to \mathbb{R}$ is a multiperiod coherent risk measure if it satisfies

- 1. Convexity: $\forall Z, Z' \in \mathcal{Z} \text{ and } \forall t \in [0, 1]$ $\rho(tZ + (1 t)Z') \leq t\rho(Z) + (1 t)\rho(Z')$.
- 2. Monotonicity: if $Z, Z' \in \mathcal{Z}$ and $Z \succeq Z'$ (componentwise) then $\rho(Z) \ge \rho(Z')$.
- 3. Translation equivariance:

$$\forall Z = (Z_1, ..., Z_T) \in \mathcal{Z}, \ Y_t \in \mathcal{Z}_t, \ a \in \mathbb{R}:$$

$$\rho(Z_1, ..., Z_t, Z_{t+1} + Y_t, ..., Z_T) = \rho(Z_1, ..., Z_t + Y_t, Z_{t+1}, ..., Z_T)$$

$$\rho(Z_1 + a, ..., Z_T) = \rho(Z_1, ..., Z_T) + a$$

4. Positive homogeneity: $\forall t > 0, \ Z \in \mathcal{Z}$: $\rho(tZ) = t\rho(Z)$

Multiperiod coherent risk measures

Theorem

Let $\rho: \mathcal{Z} \to \mathbb{R}$ be a multiperiod coherent risk measure. Then there exists a coherent risk measure $\overline{\rho}: \mathcal{Z}_T \to \mathbb{R}$ such that

$$\rho(Z_1,\ldots,Z_T)=\overline{\rho}(Z_1+\cdots+Z_T).$$

Moreover there exists nonempty, bounded set $\mathcal{U}_T \subset \mathcal{Z}_T^*$ of probability density functions such that dual representation

$$\rho(Z) = \sup_{\zeta \in \mathcal{U}} \langle \zeta, Z \rangle$$

holds with corresponding set $\mathcal U$ of the form

$$\mathcal{U} = \{ (\zeta_1, ..., \zeta_T) : \zeta_T \in \mathcal{U}_T, \ \zeta_t = \mathsf{E} \left[\zeta_T | \mathcal{F}_t \right] \}$$



Multiperiod coherent risk measures - examples

Linear combination of CVaR:

$$ho(Z_1,\ldots,Z_T) = \sum_{t=1}^T \lambda_t \mathsf{CVaR}_{lpha}(Z_t)$$

with weights $\sum_{t=1}^{T} \lambda_t = 1$

Maximal risk of all stages using CVaR:

$$\rho(Z_1,\ldots,Z_T) = \mathsf{CVaR}_{\alpha}\left(\min_{t=1,\ldots,T} Z_t\right)$$



Polyhedral risk measures

Definition

Risk measure $\rho: \mathcal{L}_p(\Omega, \mathcal{F}, \mathsf{P}) \to \overline{\mathbb{R}}$ is called polyhedral if there exist $k_1, k_2 \in \mathbb{N}, \ c_1, w_1 \in \mathbb{R}^{k_1} \ c_2, w_2 \in \mathbb{R}^{k_2}$, a nonempty polyhedral set $M_1 \subset \mathbb{R}^{k_1}$ and polyhedral cone $M_2 \subset \mathbb{R}^{k_2}$ such that:

$$ho(\mathcal{Z}) = \inf \left\{ \langle c_1, Y_1 \rangle + \mathsf{E} \left[\langle c_2, Y_2 \rangle \right] :
ight. \ Y_1 \in \mathcal{M}_1, \ Y_2 \in \mathcal{L}_p(\Omega, \mathcal{F}, \mathsf{P}), Y_2 \in \mathcal{M}_2 \ \textit{a.s.}, \ \langle w_1, Y_1 \rangle + \langle w_2, Y_2 \rangle = \mathcal{Z} \ \textit{a.s.} \right\}$$

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for every $Z \in \mathcal{L}_p(\Omega, \mathcal{F}, \mathsf{P})$.

Polyhedral risk measures - examples

Conditional Value at Risk

$$\begin{aligned} \mathsf{CVaR}_{\alpha}(Z) &= \mathsf{inf} \left\{ Y_1 + \frac{1}{\alpha} \mathsf{E} \left[Y_2^{(1)} \right] : \\ Y_1 &\in \mathbb{R}, Y_2 \in \mathcal{L}_1(\Omega, \mathcal{F}, \mathsf{P}) \\ Y_2 &\in \mathbb{R}_+ \times \mathbb{R}_+ \ \textit{a.s.}, \\ Y_2^{(1)} - Y_2^{(2)} &= Z - Y_1 \ \textit{a.s.} \right\} \end{aligned}$$

- Expected loss $E[Z \gamma]_+$ for some fixed γ .
- Dispersion measures

$$d_{\alpha}(Z) = \mathsf{E}\left[\alpha(Z - q_{\alpha})_{-} + (1 - \alpha)(Z - q_{\alpha})_{+}\right]$$



Multiperiod polyhedral risk measures

Definition

Multiperiod risk measure ρ on $\times_{t=1}^T \mathcal{L}_p(\Omega, \mathcal{F}, \mathsf{P})$ is called multiperiod polyhedral if there exist $k_t \in \mathbb{N}, \ c_t \in \mathbb{R}^{k_t}, t = 1, \ldots, T,$ $w_{t\tau} \in \mathbb{R}^{k_{t-\tau}}, t = 2, \ldots, T, \tau = 0, \ldots, t-1, \text{ a polyhedral set } M_1 \subset \mathbb{R}^{k_1} \text{ and polyhedral cones } M_t \subset \mathbb{R}^{k_t}, t = 2, \ldots, T \text{ such that:}$

$$\rho(Z) = \inf \left\{ E\left[\sum_{t=1}^{I} \langle c_t, Y_t \rangle\right] : \\ Y_t \in M_t \text{ a.s., } Y_t \in \mathcal{L}_p(\Omega, \mathcal{F}, \mathsf{P}), t = 1, \dots, T, \\ \sum_{\tau=0}^{t-1} \langle w_{t\tau}, Y_{t-\tau} \rangle = Z_t \text{ a.s., } t = 1, \dots, T \right\}$$



Multiperiod polyhedral risk measures - example

• Consider following risk averse problem:

$$\inf \rho \left(f_1(x_1, \xi_1), \sum_{\tau=1}^{2} f(x_{\tau}, \xi_{\tau}), \dots, \sum_{\tau=1}^{T} f(x_{\tau}, \xi_{\tau}) \right)$$

$$x_t \in \mathcal{X}_t \left(x_{t-1}, \xi_t \right), t = 1, \dots, T$$

• Let ρ be defined as:

$$ho(Z_1,\ldots,Z_T) = \lambda_1 \mathsf{E}\left[Z_T\right] + \sum_{t=2}^T \lambda_t \mathsf{CVaR}_{\alpha}(Z_t)$$

with
$$\sum_{t=1}^{T} \lambda_t = 1$$

Using the fact that CVaR is coherent we get:

$$ho(\cdot) = Z_1 + \lambda_1 \mathsf{E} \left[Z_T - Z_1 \right] + \sum_{t=2}^I \lambda_t \mathsf{CVaR}_{\alpha} (Z_t - Z_1)$$

Multiperiod polyhedral risk measures - example

And after some evaluation we get dynamic programming equations:

$$\inf_{x_1,w_2,\dots w_T} f(x_1,\xi_1) + \sum_{t=2}^T \lambda_t w_t + \mathcal{Q}_2(x_1,\xi_{[1]},\overline{Z}_1,w_2,\dots,w_T)$$

$$x_1 \in \mathcal{X}_1(x_0,\xi_1), w_t \in \mathbb{R}, t = 2,\dots, T$$
where $\overline{Z}_1 = 0$ and for $t = 2,\dots, T$:
$$\mathcal{Q}_t(x_{t-1},\xi_{[t-1]},\overline{Z}_{t-1},w_t,\dots,w_T) =$$

$$\mathsf{E}_{\xi_t|\xi_{[t-1]}} \left[\inf_{x_t,\overline{Z}_t} \delta_{tT} \lambda_1 \overline{Z}_t + \frac{\lambda_t}{\alpha} (w_t - \overline{Z}_t)_+ \right.$$

$$\left. + \mathcal{Q}_{t+1}(x_t,\xi_{[t]},\overline{Z}_t,w_{t+1},\dots,w_T) \right.$$

$$\overline{Z}_t = \overline{Z}_{t-1} + f_t(x_t,\xi_t), x_t \in \mathcal{X}_t(x_{t-1},\xi_t) \right]$$

References

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Conclusion

Thank you for your attention!

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