

# Risk Measures

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## Functions to the Extended Real Line

Given  $f : \mathcal{M} \rightarrow \overline{\mathbb{R}}$ . The epigraph of  $f$  is:

$$\text{epf}(f) = \{(x, t) \in \mathcal{M} \times \mathbb{R} : f(x) \leq t\}$$

The effective domain is  $\text{dom}(f) = \{x \in \mathcal{M} : f(x) < +\infty\}$

Note that  $\text{dom}(f) = \text{proj}_{\mathcal{M}}(\text{epf}(f))$

Given a real number  $l$  we define the sub-level  $[f \leq l]$  by

$$[f \leq l] = \{x \in \mathcal{M} : f(x) \leq l\}$$

The function is called proper if  $f \not\equiv +\infty$  and  $f > -\infty$ .

# Functions to the Extended Real Line

## Examples

### Supremum Function

Given a family  $f_\lambda : \mathcal{M} \rightarrow \overline{\mathbb{R}}$ , for  $\lambda \in \Lambda$ . The supremum function  $f(x) = \sup_{\lambda \in \Lambda} f_\lambda(x) \in \overline{\mathbb{R}}$  is well defined. Also  $\text{epf}(f) = \cap_{\lambda \in \Lambda} \text{epf}(f_\lambda)$

### Sum of Functions

Given a sequence of functions  $f_i : \mathcal{M} \rightarrow \overline{\mathbb{R}}$ , for  $i = 1, 2, \dots, m$ .

Whenever

$(\cup_{i=1}^m \{x : f_i(x) = +\infty\}) \cap (\cup_{i=1}^m \{x : f_i(x) = -\infty\}) = \phi$ , the sum function  $f(x) = \sum_{i=1}^m f_i(x)$  is well defined. Also we have that  $\text{dom}(f) = \cap_{i=1}^m \text{dom}(f_i)$ .

### Indicator Function

Given any subset  $D \subset \mathcal{M}$ , the indicator function is defined by

$$\delta_D(x) = \begin{cases} 0 & \text{if } x \in D \\ +\infty & \text{otherwise} \end{cases}$$

## Lower Semicontinuous Functions

A function  $f : \mathcal{M} \rightarrow \overline{\mathbb{R}}$  is lower semicontinuous (l.s.c.) if its epigraph  $\text{epi}(f)$  is closed in  $\mathcal{M} \times \mathbb{R}$ .

1. A function  $f$  is l.s.c. if and only if the sub-level set  $[f \leq l]$  is closed for all  $l \in \mathbb{R}$ .
2. If  $\{f_\lambda\}_{\lambda \in \Lambda}$  is a family of l.s.c. functions, then  $\sup_{\lambda \in \Lambda} f_\lambda$  is also l.s.c.

## Convex Functions

“  $f$  IS CONVEX IF  $epf(f) \subset \mathcal{M} \times \mathbb{R}$  IS A CONVEX SET.”

Equivalently:  $f$  is convex if

$$f(tx + (1-t)y) \leq tf(x) + (1-t)f(y), \quad \forall x, y \in \text{dom}(f), \forall t \in [0, 1]$$

- ▶ If  $f$  is convex  $\Rightarrow \text{dom}(f)$  is convex.
- ▶ If  $f$  is convex  $\Rightarrow \{x : f(x) \leq M\}$  is convex, for all  $M \in \mathbb{R}$

# Fenchel Conjugate

For a normed space  $\mathcal{M}$ , there exists its dual space  $\mathcal{M}^*$  and a duality product  $\langle \cdot, \cdot \rangle : \mathcal{M} \times \mathcal{M}^* \rightarrow \mathbb{R}$ . Considering these elements, for a function  $f : \mathcal{M} \rightarrow \overline{\mathbb{R}}$ , we define its Fenchel conjugate  $f^* : \mathcal{M}^* \rightarrow \overline{\mathbb{R}}$  by

$$f^*(x^*) = \sup_{x \in \mathcal{M}} \langle x, x^* \rangle - f(x)$$

- ▶  $f^*$  is convex l.s.c.
- ▶ If  $g \leq f$ , then  $f^* \leq g^*$ .

# Fenchel Conjugate

## Proposition

Given a function  $f : \mathcal{M} \rightarrow \overline{\mathbb{R}}$ , we have

- ▶ If  $f$  is proper and there exist  $x^* \in \mathcal{M}^*$  and  $\alpha \in \mathbb{R}$  such that  $f(x) \geq \langle x, x^* \rangle - \alpha$  for all  $x$ , then  $f^*$  is proper.
- ▶ If  $f$  is convex proper l.s.c., then  $f^*$  is proper.

## Proposition

If  $f$  is convex, then  $x^* \in \partial f(x)$  if and only if  $f(x) + f^*(x^*) = \langle x, x^* \rangle$ .

# Fenchel Conjugate

## Lemma

For any function  $f$  we have that  $f \geq f^{**}$ .

## Lemma

If  $f$  is a proper convex l.s.c function then

$$f(x) = \sup_{L \leq f, L \text{ affine}} L(x)$$

## Theorem

If  $f$  is a proper convex l.s.c function then

$$f = f^{**}$$

**Remark.** For any function  $f$ , if  $g$  is proper convex l.s.c. and  $g \leq f$ , then  $g \leq f^{**} \leq f$ .



## Coherent Risk Measures

For a risk measure  $\rho : \mathcal{M} \rightarrow \overline{\mathbb{R}}$  with conjugate  $\rho^* : \mathcal{M}^* \rightarrow \overline{\mathbb{R}}$  we have that

- ▶ Translation invariance of  $\rho$  implies  $\mathbb{E}[Z^*] = 1$ , for all  $Z^* \in \text{dom}(\rho^*)$ .
- ▶ If  $\rho$  is monotone, then  $Z^* \geq 0$ , for all  $Z^* \in \text{dom}(\rho^*)$ .
- ▶ If  $\rho$  is positively homogeneous, then  $\rho^* = \delta_{\text{dom}(\rho^*)}$ .

# Coherent Risk Measures

## Proposition

A proper risk measure  $\rho$  is coherent l.s.c. if and only if there exists a convex closed  $\mathcal{U} \subset \{Z^* \geq 0 : \mathbb{E}[Z^*] = 1\}$  such that

$$\rho(Z) = \sup_{Z^* \in \mathcal{U}} \mathbb{E}[Z^* Z]$$

On these cases we have that

$$\partial\rho(Z) = \operatorname{argmax}_{Z^* \in \mathcal{U}} \mathbb{E}[Z^* Z] \subset \partial\rho(0) = \mathcal{U} = \operatorname{dom}(\rho^*)$$

**Example.**  $\mathcal{U} = \{\chi_\Omega\}$  and  $\mathcal{U} = \{Z^* \geq 0 : \mathbb{E}[Z^*] = 1\}$

# Coherent Risk Measures

## Proposition

For  $0 < \alpha < 1$  we have that

$$AVaR_\alpha(Z) = \max_{Z^* \in \mathcal{U}} \mathbb{E}[Z^* Z]$$

where  $\mathcal{U} = \{Z^* \geq 0 : Z^* \leq \frac{1}{\alpha}, \mathbb{E}[Z^*] = 1\}$ .

Moreover

$$\partial AVaR_\alpha(Z) = \left\{ Z^* : \begin{array}{ll} Z^* = \frac{1}{\alpha} & \text{if } Z > v \\ Z^* \in [0, \frac{1}{\alpha}] & \text{if } Z = v \\ Z^* = 0 & \text{if } Z < v \end{array}, \mathbb{E}[Z^*] = 1 \right\}$$

where  $v$  is a minimizer for the optimization problem that defines  $AVaR_\alpha(Z)$ .

**Proof.** We already know that  $\text{dom}(AVaR^*) = \mathcal{U} \subset \{Z^* \geq 0 : \mathbb{E}[Z^*] = 1\}$ . On the other hand, from the definition we have that

$$\begin{aligned}
AVaR^*(Z^*) &= \sup_Z \{\mathbb{E}[Z^* Z] - AVaR_\alpha(Z)\} \\
&= \sup_Z \{\mathbb{E}[Z^* Z] - \min_u \{u + \frac{1}{\alpha} \mathbb{E}[[Z - u]^+]\}\} \\
&= \sup_{Z, u} \{\mathbb{E}[Z^* Z] - u - \frac{1}{\alpha} \mathbb{E}[[Z - u]^+]\} \\
&= \sup_{Z, u} \{\mathbb{E}[Z^*(Z - u)] - \frac{1}{\alpha} \mathbb{E}[[Z - u]^+]\} \\
&= \sup_{Z, u} \{\mathbb{E}[(Z^* - \frac{1}{\alpha})(Z - u)^+] - \mathbb{E}[Z^*[Z - u]^+]\}
\end{aligned}$$

Now, we will prove that if  $Z^* \in \mathcal{U}$ , then  $Z^* \leq 1/\alpha$ . For that, assume that the set  $A := \{Z^* > 1/\alpha\}$  has positive probability. Then for each natural number  $n$  we can consider the random variable  $Z_n := n\chi_A$ . Then, plugging  $Z_n$  and  $u = 0$  in the last equality above, we have that

$$\begin{aligned}
AVaR^*(Z^*) &= \sup_{Z, u} \{\mathbb{E}[(Z^* - \frac{1}{\alpha})(Z - u)^+] - \mathbb{E}[Z^*[Z - u]^+]\} \\
&\geq \mathbb{E}[(Z^* - \frac{1}{\alpha})[Z_n]^+] = \mathbb{E}[(Z^* - \frac{1}{\alpha})n\chi_A] = n\mathbb{E}[(Z^* - \frac{1}{\alpha})\chi_A] > 0
\end{aligned}$$

then, as  $n \rightarrow +\infty$  we have that  $AVaR^*(Z^*) \rightarrow \infty$ , which contradicts the fact that  $Z^* \in \mathcal{U}$ . Thus  $Z^* \leq 1/\alpha$ . Also, taking  $Z^* \in \{Z^* \geq 0, \mathbb{E}[Z^*] = 1, Z^* \leq 1/\alpha\}$ , we have that  $Z^*(Z - u) \leq \frac{1}{\alpha}[Z - u]^+, \forall Z, u$ , and so

$AVaR^*(Z^*) = \sup_{Z, u} \{\mathbb{E}[Z^*(Z - u)] - \frac{1}{\alpha} \mathbb{E}[[Z - u]^+]\} \leq 0 < \infty$ , which implies that  $Z^* \in \mathcal{U}$ .

In this way, we have proven that  $\mathcal{U} = \{Z^* \geq 0, \mathbb{E}[Z^*] = 1, Z^* \leq 1/\alpha\}$ .

Now, we will characterize  $\partial AVaR_\alpha(Z)$ . For this, note that  $Z^* \in \partial AVaR_\alpha(Z)$  iff  $AVaR_\alpha(Z) = \mathbb{E}[Z^* Z]$  and  $Z^* \in \mathcal{U}$ . Let  $v$  a minimizer of

$AVaR_\alpha(Z) = \min_u u + (1/\alpha)\mathbb{E}[[Z - u]^+]$ . Then  $Z^* \in \partial AVaR_\alpha(Z)$  iff  $Z^* \in \mathcal{U}$  and  $\mathbb{E}[Z^* Z] = v + (1/\alpha)\mathbb{E}[[Z - v]^+]$ . This is equivalent to

$$\begin{aligned} 0 &= \mathbb{E}[Z^* Z] - v - (1/\alpha)\mathbb{E}[[Z - v]^+] \\ &= \mathbb{E}[Z^*(Z - v) - (1/\alpha)[Z - v]^+] \end{aligned}$$

Since  $Z^*(Z - v) - (1/\alpha)[Z - v]^+ \leq 0$ , we have that  $Z^*(Z - v) - (1/\alpha)[Z - v]^+ = 0$ . From this equality,

1. For  $\omega \in [Z > v]$ , we have  $(Z_\omega - v) = [Z_\omega - v]^+ > 0$ , so, since  $Z_\omega^*(Z_\omega - v) - (1/\alpha)[Z_\omega - v]^+ = 0$ , we have that  $Z_\omega^* = 1/\alpha$ .
2. For  $\omega \in [Z < v]$ , we have  $(Z_\omega - v) < 0$  and  $[Z_\omega - v]^+ = 0$ , so, we have that  $Z_\omega^*(Z_\omega - v) = 0$ , thus  $Z_\omega^* = 0$ .

This shows that

$$\partial AVaR_\alpha(Z) \subset \left\{ Z^* : \begin{array}{ll} Z^* = \frac{1}{\alpha} & \text{if } Z > v \\ Z^* \in \left[0, \frac{1}{\alpha}\right] & \text{if } Z = v \\ Z^* = 0 & \text{if } Z < v \end{array} , \mathbb{E}[Z^*] = 1 \right\}$$

Proving the other inclusion is straightforward.