

### 3 The main theorems of decision theory

#### 3.1 Admissibility and completeness

**Definition 18.** A decision rule  $\delta_1$ , is said to be as good as a rule  $\delta_2$ , if  $R(\theta, \delta_1) \leq R(\theta, \delta_2)$  for all  $\theta \in \Theta$ . A rule  $\delta_1$ , is said to be better than a rule  $\delta_2$ , if  $R(\theta, \delta_1) \leq R(\theta, \delta_2)$  for all  $\theta \in \Theta$  and a strict inequality holds for at least one  $\theta$ . Two rules are said to be equivalent if  $R(\theta, \delta_1) = R(\theta, \delta_2)$  for all  $\theta \in \Theta$ .

The Bayes and the minimax ordering are consistent with this natural definition of order.

**Definition 19.** A rule  $\delta$  is said to be admissible if there exists no rule better than  $\delta$ .

**Definition 20.** A class  $\mathcal{C} \subset \mathcal{D}^*$ , is said to be complete, if, given any rule  $\delta \in \mathcal{D}^*$  not in  $\mathcal{C}$ , there exists a rule  $\delta_0 \in \mathcal{C}$  that is better than  $\delta$ . A class  $\mathcal{C}$  is said to be essentially complete if, given any rule  $\delta \in \mathcal{D}^*$  not in  $\mathcal{C}$ , there exists a rule  $\delta_0 \in \mathcal{C}$  that is as good as  $\delta$ .

**Lemma 1.** The class of all admissible rules is a subset of any complete class.

**Lemma 2.** If  $\mathcal{C}$  is essentially complete and there exists an admissible  $\delta \notin \mathcal{C}$ , then there exists a  $\delta' \in \mathcal{C}$  which is equivalent to  $\delta$ .

**Definition 21.** A class  $\mathcal{C}$  of decision rules is said to be minimal complete if  $\mathcal{C}$  is complete and if no proper subset of  $\mathcal{C}$  is complete. A class  $\mathcal{C}$  of decision rules is said to be minimal essentially complete if  $\mathcal{C}$  is essentially complete and if no proper subset of  $\mathcal{C}$  is essentially complete.

**Theorem 2.** If a minimal complete class exists, it consists of exactly the admissible rules.

#### 3.2 Admissibility of Bayes rules

**Theorem 3.** If, for a given distribution  $\tau$ , a Bayes rule with respect to  $\tau$  is unique up to equivalence then this Bayes rule is admissible.

**Theorem 4.** Assume that the support of  $\tau$  is  $\Theta$ , and that  $\Theta$  is finite. If a Bayes rule against  $\tau$  exists then it is admissible.

**Example 7.** Let  $\Theta = \{\theta_1, \theta_2\}$  and take  $S = [1, 2] \times [0, 1]$ . The Bayes rules against  $\tau = (1, 0)$  are not admissible.

**Theorem 5.** Assume that the support of  $\tau$  is  $\Theta$ , and that  $\Theta = \mathbb{R}$ . Let  $R(\theta, \delta)$  be a continuous function of  $\theta$  for all  $\delta \in \mathcal{D}^*$ . If a Bayes rule against  $\tau$  exists and has a finite risk then it is admissible.

## 4 The Complete Class Theorem

**Definition 22.** A set  $S \in \mathbb{R}^k$  is said to be bounded from below if  $\min_{1 \leq i \leq k} y_i \geq -M$  for some  $M < \infty$  and for all  $y \in S$ .

**Definition 23.** The lower quantant of a point  $x \in \mathbb{R}^k$  is

$$Q_x = \{y : y_i \leq x_i, 1 \leq i \leq k\}.$$

**Definition 24.** A point  $x$  is said to be a lower boundary point of a convex  $S \subset \mathbb{R}^k$  if  $Q_x \cap \bar{S} = x$ . The set of lower boundary points of  $S$  is denoted by  $\lambda(S)$ .

**Definition 25.** A convex set  $S \subset \mathbb{R}^k$  is said to be closed from below if  $\lambda(S) \subset S$ .

**Lemma 3.** If a nonempty convex set is bounded from below, then  $\lambda(S)$  is not empty.

**Theorem 6.** Suppose  $\Theta$  is finite and that the risk set is bounded from below and closed from below. The class of decision rules

$$\mathcal{D}_0 = \{\delta \in \mathcal{D}^* : (R(\theta_1, \delta), \dots, R(\theta_k, \delta)) \in \lambda(S)\}$$

is then a minimal complete class.

**Corollary 1.** The class  $\mathcal{D}_0$  consists exactly of the admissible rules.

**Theorem 7 (The Separating Hyperplane Theorem).** Let  $S_1$  and  $S_2$  be two disjoint convex subsets of  $\mathbb{R}^k$ . Then there exists a vector  $p \neq 0$  such that  $p'x \leq p'y$  for all  $x \in S_1$  and  $y \in S_2$ .

**Theorem 8.** If  $\delta$  is admissible and  $\Theta$  is finite, then  $\delta$  is Bayes (with respect to some  $\tau$ ).

**Theorem 9 (The Complete Class Theorem).** If, for a given decision problem with finite  $\Theta$ , the risk set is bounded from below and closed from below, then the class of all Bayes rules is complete and the admissible Bayes rules form a minimal complete class.