

50. On Characterizations of Projection Operators

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Let R be a lattice ordered linear space. A linear manifold M of R is said to be *normal*, if for any $a \in R$ we can find $x, y \in R$ such that

$$a = x + y \quad x \in M, \quad y \in M^\perp = \{y; x \perp y \text{ for } x \in M\}.$$

Such x depends only on a . So putting $Ta = x$ we can define an operator T from R to M . This operator is called a *projection operator* (cf. H. Nakano: *Modulated Semi-ordered Linear Space*, Tokyo (1950)).

Here, we will consider some characterizations of projection operators.

Theorem 1. *A linear operator T on R is a projection operator, if and only if it satisfies (1), (2).*

$$(1) \quad T(Tx) = Tx$$

$$(2) \quad 0 \leq Tx \leq x \quad \text{for all } x \geq 0.$$

Proof. Every projection operator is always linear and satisfies (1), (2) (cf. H. Nakano: *Modulated Semi-ordered Linear Space*, Tokyo (1950)).

Now, we suppose that a linear operator T satisfies conditions (1), (2). Putting $T^\perp = I - T$, T^\perp is obviously linear and satisfies conditions (1), (2) too. When we consider two subsets of R

$$A = \{x; Tx = 0\} \quad \text{and} \quad B = \{x; T^\perp x = 0\},$$

we have $A = T^\perp R$, $B = TR$, because

$$T(T^\perp a) = T(a - Ta) = Ta - T(Ta) = Ta - Ta = 0,$$

for any $a \in R$, and hence $T^\perp a \in A$. On the other hand, we see

$$a = a - Ta = T^\perp a,$$

for every $a \in A$, therefore $A = T^\perp R$. We obtain $B = TR$ likewise.

Every linear operator T , subject to the condition (2), satisfies

$$T(x \frown y) = Tx \frown Ty.$$

Because we see first obviously

$$Tx \frown Ty \geq T(x \frown y).$$

On the other hand, we have

$$\begin{aligned} x &= Tx + T^\perp x \geq Tx \frown Ty + T^\perp(x \frown y), \\ y &= Ty + T^\perp y \geq Tx \frown Ty + T^\perp(x \frown y) \end{aligned}$$

and hence

$$x \frown y \geq Tx \frown Ty + T^\perp(x \frown y),$$

that is,

$$T(x \frown y) \geq Tx \frown Ty.$$

Therefore

$$T(x \frown y) = Tx \frown Ty.$$

Then we find easily

$$T(x \smile y) = Tx \smile Ty,$$