

# Strong Law of Large Numbers on the Kôpka D-posets

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## Definition

*The structure  $(D, \leq, \ominus, 0, 1)$  is called a  $D$ -poset if the relation  $\leq$  is a partial ordering on  $D$ ,  $0$  is the smallest and  $1$  is the largest element on  $D$  and*

- 1  $b \ominus a$  is defined iff  $a \leq b$ ,
- 2 if  $a \leq b$  then  $b \ominus a \leq b$  and  $b \ominus (b \ominus a) = a$ ,
- 3  $a \leq b \leq c \Rightarrow c \ominus b \leq c \ominus a$ ,  $(c \ominus a) \ominus (c \ominus b) = b \ominus a$ .

## Definition

Let  $(D, \leq, \ominus, 0, 1)$  be a  $D$ -poset. It is called the *Kôpka  $D$ -poset*, if there is a binary operation  $* : D \times D \rightarrow D$ , which is commutative, associative and has the following properties:

- 1  $a * 1 = a, \forall a \in D;$
- 2  $a \leq b \Rightarrow a * c \leq b * c, \forall a, b, c \in D;$
- 3  $a \ominus (a * b) \leq 1 \ominus b, \forall a, b \in D.$

## Definition

*D-poset is called  $\sigma$ -complete if every subset of countable elements has the supremum and the infimum.*

## Definition

*Kôpka D-poset  $(D, \ominus, *, 0, 1)$  is called continuous if the following holds:*

$$a_n \nearrow a \Rightarrow b * a_n \nearrow b * a, \forall a_n, a, b \in D.$$

## Definition

A state on a  $D$ -poset  $D$  is any mapping  $m : D \rightarrow [0, 1]$  satisfying the following properties:

- 1  $m(1) = 1, m(0) = 0;$
- 2  $a_n \nearrow a \Rightarrow m(a_n) \nearrow m(a), \forall a_n, a \in D;$
- 3  $a_n \searrow a \Rightarrow m(a_n) \searrow m(a), \forall a_n, a \in D.$

The state  $m$  is called additive, if

$$a, b \in D, a \leq b \Rightarrow m(b) = m(a) + m(b \ominus a).$$

## Remark

If  $D$  is a  $D$ -lattice, then the state  $m$  is additive if

$$m(a \vee b) = m(a) + m(b)$$

whenever  $a \wedge b = 0, a, b \in D.$

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If  $D$  is a  $\sigma$ -complete  $D$ -lattice, then  $m$  is called  $\sigma$ -additive, if

$$m \left( \bigvee_{i=1}^{\infty} a_i \right) = \sum_{i=1}^{\infty} m(a_i)$$

whenever  $a_i \wedge a_j = 0$  ( $i \neq j$ ),  $a_i \in D$  ( $i = 1, 2, \dots$ ).

## Proposition

Let  $D$  be a  $\sigma$ -complete  $D$ -lattice,  $m : D \rightarrow [0, 1]$  be a state. If the state  $m$  is additive, then it is  $\sigma$ -additive.

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## Definition

Let  $\mathcal{J} = \{(-\infty, t); t \in \mathbb{R}\}$ . An observable on  $D$  is any mapping  $x : \mathcal{J} \rightarrow D$  satisfying the following conditions:

- 1  $A_n \nearrow \mathbb{R} \Rightarrow x(A_n) \nearrow 1$ ,
- 2  $A_n \searrow \emptyset \Rightarrow x(A_n) \searrow 0$ ,
- 3  $A_n \nearrow A \Rightarrow x(A_n) \nearrow x(A)$ .

## Definition

Let  $x : \mathcal{J} \rightarrow D$  be an observable on a  $\sigma$ -complete  $D$ -poset  $D$  and  $a, b \in \mathbb{R}$ . Then

$$x([a, b]) = x((-\infty, b)) \ominus x((-\infty, a)).$$

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## Definition

Let  $x : \mathcal{J}^* \rightarrow D$  be an observable in a  $D$ -poset  $D$ ,  $\alpha, \beta, t$  be real numbers,  $\alpha > 0$ . Then

$$(\alpha x + \beta)((-\infty, t)) = x\left(\left(-\infty, \frac{t - \beta}{\alpha}\right)\right)$$

and

$$(\alpha x + \beta)([-t, t]) = x\left(\left[-\frac{t + \beta}{\alpha}, \frac{t - \beta}{\alpha}\right]\right).$$

# A Construction of the Distribution Function

## Theorem

Let  $x : \mathcal{J} \rightarrow D$  be an observable,  $m : D \rightarrow [0, 1]$  be a state. Define a mapping  $F : \mathbb{R} \rightarrow [0, 1]$  by the formula

$$F(t) = m(x((-\infty, t))).$$

Then  $F$  is a distribution function.

There exists exactly one probability measure  $\lambda_F : \mathcal{B}(\mathbb{R}) \rightarrow [0, 1]$  such that

$$\lambda_F([a, b)) = F(b) - F(a)$$

for any  $a, b \in \mathbb{R}, a < b$ .

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## Definition

*An observable  $x : \mathcal{J} \rightarrow D$  is integrable, if there exists*

$$E(x) = \int_{\mathbb{R}} t dF(t),$$

*where  $F$  is the distribution function of  $x$ . It is square integrable, if there exists the dispersion*

$$\sigma^2(x) = \int_{\mathbb{R}} t^2 dF(t) - E(x)^2.$$

## Independent random variables

$\xi, \eta : \Omega \rightarrow \mathbb{R}$ :

$$P(\xi^{-1}(A) \cap \eta^{-1}(B)) = P(\xi^{-1}(A)) \cdot P(\eta^{-1}(B))$$

$\forall A, B \in \mathcal{B}(\mathbb{R})$

## Product of measures

There exists exactly one probability measure

$$\lambda_{F_1} \times \lambda_{F_2} : \mathcal{B}(\mathbb{R}^2) \rightarrow [0, 1]$$

such that

$$\lambda_{F_1} \times \lambda_{F_2}(A \times B) = \lambda_{F_1}(A) \cdot \lambda_{F_2}(B)$$

for any  $A, B \in \mathcal{B}(\mathbb{R})$ .

## Probability distribution of the sum $\xi + \eta$

$$P(\{\omega; \xi(\omega) + \eta(\omega) < t\}), t \in \mathbb{R}.$$

$$T : \Omega \rightarrow \mathbb{R}^2, T(\omega) = (\xi(\omega), \eta(\omega)),$$

$$g : \mathbb{R}^2 \rightarrow \mathbb{R}, g(u, v) = u + v.$$

$$\xi(\omega) + \eta(\omega) < t,$$

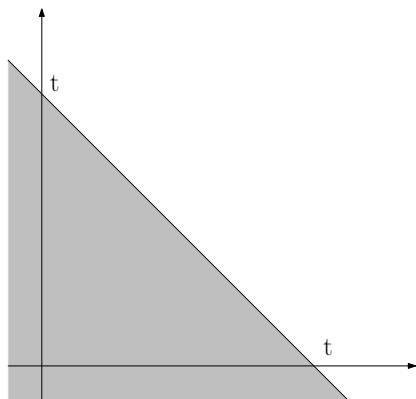
$$\Leftrightarrow$$

$$\omega \in T^{-1}(g^{-1}((-\infty, t))).$$

$$P(\{\omega, \xi(\omega) + \eta(\omega) < t\}) = P(T^{-1}(g^{-1}((-\infty, t)))).$$



# Independence in a classic probability space $(\Omega, \mathcal{S}, P)$



$$g^{-1}((-\infty, t)) = \Delta_t = \{(u, v) \in \mathbb{R}^2; u + v < t\}$$

## Theorem

Let  $\xi, \eta : \Omega \rightarrow \mathbb{R}$  be independent random variables,  
 $\Delta_t = \{(u, v) \in \mathbb{R}^2; u + v < t\}, t \in \mathbb{R}, T = (\xi, \eta) : \Omega \rightarrow \mathbb{R}^2$ . Then

$$P(T^{-1}(\Delta_t)) = \lambda_{F_1} \times \lambda_{F_2}(\Delta_t)$$

for any  $t \in \mathbb{R}$ .

## Definition

Let  $D$  be a D-poset,  $x_1, \dots, x_n : \mathcal{J}^* \rightarrow D$  be observables,  $\Delta_t^n = \{(u_1, \dots, u_n) \in \mathbb{R}^n; u_1 + \dots + u_n < t\}$ ,  $\mathcal{M}_n = \{\Delta_t^n; t \in \mathbb{R}\}$ . The observables are called to be independent, if there exists a mapping  $h_n : \mathcal{M}_n \rightarrow D$  with the following properties:

- 1  $t \nearrow t_0 \Rightarrow h_n(\Delta_t^n) \nearrow h_n(\Delta_{t_0}^n)$ ,
- 2  $t \nearrow \infty \Rightarrow h_n(\Delta_t^n) \nearrow 1$ ,
- 3  $t \searrow -\infty \Rightarrow h_n(\Delta_t^n) \searrow 0$ ,
- 4  $m(h_n(\Delta_t^n)) = \lambda_{F_1} \times \dots \times \lambda_{F_n}(\Delta_t^n), t \in \mathbb{R}$ .

## Theorem

*Let  $D$  be a  $\sigma$ -complete continuous Kôpka D-poset,  $m : D \rightarrow [0, 1]$  be an additive state,  $x, y : \mathcal{J}^* \rightarrow D$  be observables and let*

$$m(x(A) * y(B)) = m(x(A)) \cdot m(y(B))$$

*$\forall A, B \in \mathcal{J}^*$ . Then  $x, y$  are independent in the sense of the previous Definition.*

Riečan, Lašová, 2010

$$\alpha_{t,n}^2 = \{(i, j); \frac{1}{2^n}(i + j) < t\}$$

$$h_2(\Delta_t^2) = \bigvee_{n=1}^{\infty} \bigvee_{(i,j) \in \alpha_{t,n}^2} x\left(\left[\frac{i-1}{2^n}, \frac{i}{2^n}\right)\right) * y\left(\left[\frac{j-1}{2^n}, \frac{j}{2^n}\right)\right)$$

## Theorem

Define  $y_n : \mathcal{J}^* \rightarrow D$  by the equality  $y_n((-\infty, t)) = h_n(\Delta_t^n)$ .  
Then  $y_n$  is an observable.

## Definition

Let  $x_1, \dots, x_n : \mathcal{J}^* \rightarrow D$  be independent observables. Then the observable  $y_n : \mathcal{J}^* \rightarrow D$  defined in previous Theorem is called the sum of observables  $x_1, \dots, x_n$ ,  $y_n = \sum_{i=1}^n x_i$ , i.e.

$$\left(\sum_{i=1}^n x_i\right)((-\infty, t)) = h_n(\Delta_t^n), t \in \mathbb{R}.$$

## Definition

Let  $(x_n)_{n=1}^{\infty}$  be a sequence of observables on a  $\sigma$ -complete  $D$ -poset  $D$  with a state  $m$ . We say that this sequence converges in measure  $m$  to 0 if for each  $0 < \epsilon \in \mathbb{R}$

$$\lim_{n \rightarrow \infty} m(x_n((-\epsilon, \epsilon))) = 1$$

and that it converges to zero  $m$ -almost everywhere if

$$\lim_{l \rightarrow \infty} \lim_{k \rightarrow \infty} \lim_{i \rightarrow \infty} m \left( \bigwedge_{n=k}^{k+i} x_n \left( \left( -\frac{1}{l}, \frac{1}{l} \right) \right) \right) = 1.$$

Probability space  $(\mathbb{R}^{\mathbb{N}}, \sigma(\mathcal{C}), P)$

$$\mathcal{C} = \{A \subset \mathbb{R}^{\mathbb{N}}; A = \pi_n^{-1}(B), B \in \mathcal{B}(\mathbb{R}^n), n \in \mathbb{N}\}$$

$$P_n(A \times \mathbb{R}) = P_{n-1}(A), A \in \mathcal{B}(\mathbb{R}^{n-1}), n \in \mathbb{N}$$

$$\pi_n((u_i)_{i=1}^{\infty}) = (u_1, u_2, \dots, u_n).$$

By the Kolmogorov consistency theorem there exists a probability measure  $P : \sigma(\mathcal{C}) \rightarrow [0, 1]$  such that

$$P(\pi_n^{-1}(B)) = P_n(B) = \lambda_{F_1} \times \dots \times \lambda_{F_n}(B)$$

for any  $B \in \mathcal{B}(\mathbb{R}^n), n \in \mathbb{N}$ .



# "Translation formulas"

Random variable  $\xi_n : \mathbb{R}^{\mathbb{N}} \rightarrow \mathbb{R}$

$$\xi_n((u_i)_{i=1}^{\infty}) = u_n$$

$$P(\xi_1 + \dots + \xi_n < t) = m \left( \left( \sum_{i=1}^n x_i \right) ((-\infty, t)) \right)$$

$$P(a \leq \xi_1 + \dots + \xi_n < b) = m \left( \left( \sum_{i=1}^n x_i \right) ([a, b)) \right)$$

## Theorem (Central limit theorem)

Let  $D$  be a  $\sigma$ -complete  $D$ -poset,  $(x_n)_{n=1}^{\infty}$  be an independent sequence of equally distributed square integrable observables,  $E(x_n) = a$ ,  $\sigma^2(x_n) = \sigma^2$ ,  $(n = 1, 2, \dots)$ . Then for any  $t \in \mathbb{R}$

$$\lim_{n \rightarrow \infty} m \left( \frac{\frac{1}{n} \sum_{i=1}^n x_i - a}{\frac{\sigma}{\sqrt{n}}} ((-\infty, t)) \right) = \Phi(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^t e^{-\frac{x^2}{2}} dx.$$

## Theorem (Weak law of large numbers)

Let  $D$  be a  $D$ -poset with an additive state  $m : D \rightarrow [0, 1]$ , let  $(x_n)_{n=1}^{\infty}$  be an independent sequence of integrable observables having the same probability distribution,  $E(x_n) = a$ , ( $n = 1, 2, \dots$ ). Then the sequence

$$\frac{\sum_{i=1}^n x_i}{n} - a$$

converges in measure  $m$  to 0.

## Theorem (Strong law of large numbers)

Let  $D$  be a  $\sigma$ -complete  $D$ -poset,  $(x_n)_{n=1}^{\infty}$  be a sequence of independent, square integrable observables, such that

$\frac{\sum_{n=1}^{\infty} \sigma^2(x_n)}{n^2} < \infty$ . Then the sequence of observables

$$\frac{x_1 - E(x_1) + x_2 - E(x_2) + \dots + x_n - E(x_n)}{n} \quad (n = 1, 2, 3, \dots)$$

converges  $m$ -almost everywhere to 0.

$$\eta_n = \frac{\xi_1 - E(\xi_1) + \dots + \xi_n - E(\xi_n)}{n},$$

$$y_n = \frac{\sum_{i=1}^n x_i - (E(x_1) + \dots + E(x_n))}{n}$$

$$P\left(\bigcap_{n=k}^{k+i} \eta_n^{-1}\left(\left[-\frac{1}{l}, \frac{1}{l}\right]\right)\right) \leq m\left(\bigwedge_{n=k}^{k+i} y_n\left(\left[-\frac{1}{l}, \frac{1}{l}\right]\right)\right)$$

(Riečan – Neubrunn, 1997)