# ON DISTRIBUTIONS OF CONDITIONAL EXPECTATIONS 

## BY

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Abstract. Let $F$ and $G$ be distribution functions on $\boldsymbol{R}$. Then there exist a random variable $X$ and a $\sigma$-field $\mathfrak{A}$ satisfying $P(X<a)=F(a)$, $P(E(X \mid \mathfrak{H})<a)=G(a)$ iff $\int_{(a, \infty)}(F(t)-G(t)) d t \leqslant 0 \leqslant \int_{(-\infty, a)}(F(t)-G(t)) d t$ for any $a \in \boldsymbol{R}$. The consideration is kept on a rather elementary level.

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All distributions on $\boldsymbol{R}$ used in the paper have finite first moments. We shall give an elementary proof of the following

Theorem 1. For any distribution functions $F$ and $G$ on $\boldsymbol{R}$ the following conditions are equivalent:
(i) there exist a random variable $X$ and a $\sigma$-field of events $\mathfrak{H}$ satisfying

$$
P(X<a)=F(a), \quad P(E(X \mid \mathfrak{A})<a)=G(a) \quad \text { for } a \in \boldsymbol{R}
$$

(ii)

$$
\int_{(a, \infty)}(F(x)-G(x)) d x \leqslant 0 \leqslant \int_{(-\infty, a)}(F(x)-G(x)) d x \quad \text { for all } a \in \boldsymbol{R} .
$$

We start with some comments. Let distribution fünctions $F$ and $G$ correspond to random variables $Y$ and $Z$ defined on a classical probability space $\Omega=\left\{\omega_{1}, \ldots, \omega_{N}\right\}, P\left(\omega_{i}\right)=1 / N$. Then condition (ii) is equivalent to the classical majorization condition for sequences $\left(Y\left(\omega_{i}\right)\right)<\left(Z\left(\omega_{i}\right)\right)$. In this case Theorem 1 can be obtained by a classical and old construction of a suitable bistochastic matrix. In [3], a number of other relations between majorization and matrix theory are described. Some non-expected applications are also given.

[^0]On the other hand, condition (ii) is equivalent to the famous Karamata condition:

$$
\int \phi(x) d F(x) \leqslant \int \phi(x) d G(x) \quad \text { for any convex positive function } \phi
$$

given at first at [2]. Thus, for distributions concentrated on a bounded intervals, Theorem 1 is a very special case of (for example) Theorem T2 in [4]. But the general theory is abstract and based on the Choquet theorem. So, we show perhaps as much as possible on a completely elementary level. Distributions of some systems of random variables are specially interesting. Thus the Karamata condition is still attractive for probabilists and new methods appear; see [1] and [5]:

Now we establish some notation.
For convenience, random variables appearing in different formulas in the paper can be defined on different probability spaces. We use the standard notation: $p_{X}(A)=P(X \in A), F_{X}(a)=P(X \leqslant a), F_{p}(a)=p(-\infty, a), A \in$ Borel $R$, $a \in \boldsymbol{R}$, for a random variable $X$ and a probability distribution $p$ on $\boldsymbol{R}$.

We denote by $X^{1}\left(x^{1}, x^{2}\right)=x^{1}$ and $X^{2}\left(x^{1}, x^{2}\right)=x^{2}$ the coordinate functions on $\boldsymbol{R}^{2}$ and, for a distribution $d$ on $\boldsymbol{R}^{2}$, by $d_{X^{1}}$ and $d_{X^{2}}$ the margin distributions, by $d\left(X^{2} \mid X^{1}\right)$ and $d\left(X^{2} \mid X^{1}=t\right)$ the conditional distributions, and by $E_{d}\left(X^{2} \mid X^{1}\right)$ and $E_{d}\left(X^{2} \mid X^{1}=t\right)$ the conditional expectations. A special role will be played by the class

$$
\begin{equation*}
\mathscr{S}=\{F ; F \text { is a simple distribution function on } R\} \tag{1}
\end{equation*}
$$

thus $F \in \mathscr{S}$ if it describes probability concentrated on a finite set.
Lemma 2. If conditions (i) and (ii) are equivalent for any $F, G \in \mathscr{S}$, then (i) and (ii) are equivalent for any distribution functions $F$ and $G$ on $\boldsymbol{R}$.

Proof. Let $F$ and $G$ be any distribution functions satisfying (i). Denote by $d$ the joint distribution of the random variables $E(X \mid \mathfrak{M}), X$ on $R^{2}$. Let $\left(d_{n}\right)$ be a sequence of distributions on $\boldsymbol{R}^{2}$ concentrated on finite sets such that $d_{n} \rightarrow d$ weakly as $n \rightarrow \infty$, and

$$
E_{d_{n}}\left(X^{2} \mid X^{1}=t\right)=t \quad \text { if only } \quad d_{n, X^{1}}\{t\}>0
$$

Then, for random variables $X^{1}$ and $X^{2}$ on the probability space ( $R^{2}$, Borel $R^{2}, d_{n}$ ), the distribution functions $F^{n}=F_{X^{2}}$ and $G^{n}=F_{X^{1}}=F_{E\left(X^{2} \mid X^{1}\right)}$ satisfy (i), and thus (ii). Moreover, $F^{n} \rightarrow F$ and $G^{n} \rightarrow G$ weakly, and condition (ii) is satisfied for the original distribution functions $F$ and $G$.

Now, let the condition (ii) be satisfied. Then $\int t d F(t)=\int t d G(t)$ and we denote this value by $m$. For any sequences $\left(F^{n}\right)$ and $\left(G^{n}\right)$ in $\mathscr{S}$, satisfying
$F^{n} 1_{(-\infty, m)}$ decrease to $F 1_{(-\infty, m)}$,
$F^{n} 1_{(m, \infty)}$ increase to $F 1_{(m, \infty)}$,
$G^{n} 1_{(-\infty, m)}$ increase to $G 1_{(-\infty, m)}$,
$G^{n} 1_{(m, \infty)}$ decrease to $G 1_{(m,-\infty)}$,
we have (ii) for $F^{n}$ and $G^{n}$ instead of $F$ and $G$, respectively. Thus there exist some distributions $d_{n}$ on $\boldsymbol{R}^{2}$, appearing as the joint distributions of pairs $\boldsymbol{E}\left(\left(X_{n} \mid \mathfrak{U}_{n}\right), X_{n}\right)$, satisfying

$$
d_{n, X^{2}}=F^{n}, \quad d_{n, X^{1}}=G^{n}, \quad E_{d_{n}}\left(X^{2} \mid X^{1}\right)=X^{1} .
$$

Obviously, the sequence $\left(d_{n}\right)$ is a tide one and there exists a weak concentration point $d$. For the probability space ( $\boldsymbol{R}^{2}$, Borel $\boldsymbol{R}^{2}, d$ ), the coordinates $X^{1}$ and $X^{2}$ satisfy

$$
F_{X^{2}}=F, \quad F_{E_{d}\left(X^{2} \mid \mathfrak{Q}\right)}=G \quad \text { for } \mathfrak{A}=\sigma\left(X^{1}\right) .
$$

To prove" Theorem 1, it is enough to show some properties of the class $\mathscr{S}$, often elementary, concerned with conditions (i) and (ii). For $F \in \mathscr{S}$, let us put (2) $\mathscr{C}(F)=\{G \in \mathscr{P}$; (i) is satisfied $\}, \mathscr{S}(F)=\{G \in \mathscr{S}$; (ii) is satisfied $\}$.

Remark 3. If $G \in \mathscr{S}(F)$ and $H \in \mathscr{S}(G)$, then $H \in \mathscr{S}(F)$.
Lemma 4. For a random variable $X=\sum_{1 \leqslant i \leqslant n} \lambda_{i} 1_{A_{i}}$ with $\left(A_{1}, \ldots, A_{n}\right)$ being a partition of $\Omega$ on disjoint events, and for $\mathfrak{A}=\sigma\left(A_{1} \cup A_{2}, A_{3}, \ldots, A_{n}\right)$ we have

$$
F_{E(X \mid \mathfrak{2})} \in \mathscr{S}\left(F_{X}\right)
$$

Proof. An elementary calculation is sufficient. One can assume that $\lambda_{1}<\lambda_{2}$, and check that

$$
F_{X}-F_{E(X \mid \mathfrak{e g})}(x)= \begin{cases}0 & \text { for } x<\lambda_{1} \\ P\left(A_{1}\right) & \text { for } \lambda_{1} \leqslant x<\lambda \\ -P\left(A_{2}\right) & \text { for } \lambda \leqslant x<\lambda_{2} \\ 0 & \text { for } x \geqslant \lambda_{2}\end{cases}
$$

for $\lambda=\left(\lambda_{1} P\left(A_{1}\right)+\lambda_{2} P\left(A_{2}\right)\right)\left(P\left(A_{1}\right)+P\left(A_{2}\right)\right)^{-1}$.
Lemma 5. According to (1) and (2), $\mathscr{C}(F)$ is contained in $\mathscr{S}(F)$ for $F \in \mathscr{S}$.
Proof. Let $F_{X}, F_{E(X \mid \mathfrak{r})} \in \mathscr{S}$ and, for simplicity, $\mathfrak{A}=\sigma(E(X \mid \mathfrak{Y}))$. Let us put $\mathscr{B}=\sigma(\sigma(X) \cup \mathfrak{A})$. To use Lemma 4, we take (finite) $\sigma$-fields $\mathfrak{A}=\mathfrak{A}_{0} \subset \ldots \subset \mathfrak{A}_{n}=\mathscr{B}$ in such a way that for fixed $i, 1 \leqslant i \leqslant n$, there exists a partition $A_{1}, \ldots, A_{m}$ of $\Omega$ satisfying

$$
\mathfrak{A}_{i}=\sigma\left(A_{1}, \ldots, A_{m}\right), \quad \mathfrak{\Re}_{i-1}=\sigma\left(A_{1} \cup A_{2}, A_{3}, \ldots, A_{m}\right) .
$$

Then $F_{E\left(X \mid \mathfrak{A}_{i-1}\right)} \in \mathscr{S}\left(F_{\mathbf{E}\left(X \mid \mathfrak{A}_{i}\right)}\right)$ by Lemma 4. Thus, $F_{E(X \mid \mathfrak{2})}$ belongs to $\mathscr{S}\left(F_{X}\right)$ by Remark 3.

Lemma 6. According to (1) and (2), the relations $G \in \mathscr{C}(F)$ and $H \in \mathscr{C}(G)$ imply $H \in \mathscr{C}(F)$.

Proof. By assumption, $F=F_{X}, G=F_{E(X \mid Y)}, G=F_{\tilde{X}}, H=F_{E(\tilde{X} \mid \tilde{Y})}$, and one can assume that random variables $X, Y, \tilde{X}, \tilde{Y}$ are defined on the same probability space and that $E(X \mid Y)=Y$ and $E(\tilde{X} \mid \tilde{Y})=\tilde{Y}$. On $R^{3}$, there exists
a distribution $d^{(3)}$ satisfying

$$
\begin{gathered}
d_{X}^{(3)}=p_{\tilde{X}}, \quad d^{(3)}\left(X^{2} \mid X^{1}=x^{1}\right)=P\left(\tilde{X} \mid \tilde{Y}=x^{1}\right) \\
d^{(3)}\left(X^{3} \mid X^{1}=x^{1}, X^{2}=x^{2}\right)=P\left(X \mid Z=x^{2}\right)
\end{gathered}
$$

Then $d_{X^{3}}^{(3)}=X, E_{d^{(3)}}\left(X^{3} \mid X^{1}\right)=X^{1}, d_{X^{1}}^{(3)}=p_{\tilde{Y}}$ and the proof is complete.
Lemma 7. Assume that a random variable $X$ is defined on a probability space without atoms and that $X=a$ on $A$ and $X=d$ on $D$ for some numbers $a<b \leq c<d$ and events $A$ and $D$. Then, for some partition $B, C$ of the event $A \cup D$ with $P(C)=P(A)$ and $P(B)=P(D)$, we have $E(X \mid B)=b$ or $E(X \mid C)=c$.

The proof goes by an elementary calculation.
Lemma 8. According to notation (1) and (2), $\mathscr{S}(F)$ is contained in $\mathscr{C}(F)$ for $F \in \mathscr{S}$.

Proof. Let $G \in \mathscr{S}(F)$ for some distribution functions $F, G \in \mathscr{S}$. Let us put

$$
\begin{aligned}
a=\sup \{x ; F(t) & =G(t) \text { for } t<x\}, \quad d=\inf \{x ; F(t)=G(t) \text { for } t>x\}, \\
b & =\sup \{x ; F, G \text { are constant on }(a, b)\}, \\
c & =\inf \{x ; F, G \text { are constant on }(c, d)\} .
\end{aligned}
$$

Let $X$ be a random variable defined on a probability space without atoms, satisfying $F_{X}=F$. Obviously, there exist events $A \subset(X=a)$ and $D \subset(X=d)$ satisfying

$$
\begin{array}{ll}
P(A)=F(t)-G(t) & \text { for } t \in(a, b), \\
P(D)=G(t)-F(t) & \text { for } t \in(c, d) .
\end{array}
$$

Let a $\sigma$-field $\mathfrak{A}$ be generated by events $(X=x) \cap(A \cup D)^{c}$ for $x \in R$, and events $B$ and $C$ be defined as in Lemma 7. Then the distribution function $F_{1}=F_{E\left(X \mid{ }_{2}\right)}$ satisfies

$$
\begin{gathered}
F_{1} \in \mathscr{C}(F), \quad G \in \mathscr{S}\left(F_{1}\right), \\
G(t)=F_{1}(t) \quad \text { for } t \in\left(-\infty, a_{1}\right) \cup\left(d_{1}, \infty\right), \\
F(t)=F_{1}(t) \quad \text { for } t \in\left(a_{1}, d_{1}\right), a_{1} \geqslant a, d_{1} \leqslant d,
\end{gathered}
$$

and $a_{1}=b$ or $d_{1}=c$.
In consequence, one can obtain a sequence of distribution functions $F_{0}, \ldots, F_{n}$ satisfying $F_{0}=F, F_{n}=F, F_{i} \in \mathscr{C} F_{i-1}, i=1, \ldots, n$. By Lemma 6, the proof is completed.

Our Theorem 1 is a consequence of Theorem 1 and Lemmas 5 and 8.

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