About Yor's problem.

## 4. Non-standard $\sigma$-fields: an equivalent measure <br> Boris Tsirelson (Tel Aviv University)

101. Theorem. There exists a probability measure on $[0,1]^{\mathbb{N}}$, that is equivalent to the Lebesgue measure, but the corresponding filtration is non-standard.
102. Theorem 101 is obtained from the following discrete case, similar to Corollary 19 that follows from Theorem 17.
103. Theorem. There exists a random sequence $\left\{X_{k}\right\}_{k \leq 0}$, taking values 0,1 only, having its joint distribution equivalent to the Bernoulli- $1 / 2$ measure, and such that its "markovization" satisfies

$$
\lim _{k \rightarrow-\infty} \iint \rho_{k}(x, y) \mu_{k}(d x) \mu_{k}(d y)>0
$$

for some metric $\rho_{0}$.
201. Any random sequence $\left\{X_{k}\right\}_{k}, X_{k} \in \mathcal{X}_{k}$, determines its "markovization"-the Markov process $\left\{X_{-\infty}^{k}\right\}_{k}, X_{-\infty}^{k}=\left(\ldots, X_{k-1}, X_{k}\right) \in \mathcal{X}_{-\infty}^{k}=\ldots \times \mathcal{X}_{k-1} \times \mathcal{X}_{k}$.
202. Applying the notion of parametrization to the "markovization" $\left\{X_{-\infty}^{k}\right\}_{k}$ of a random sequence $\left\{X_{k}\right\}_{k}$ with a distribution $P \in \mathcal{P}\left(\mathcal{X}_{-\infty}^{0}\right)$, we come to the following notion (in two equivalent forms).
(A) A parametrization of $P$ is a sequence of measurable maps

$$
\alpha_{k}:[0,1] \times \mathcal{X}_{-\infty}^{k-1} \rightarrow \mathcal{X}_{k}
$$

such that

$$
\begin{equation*}
\mathbb{E}\left(f\left(X_{k}\right) \mid X_{-\infty}^{k-1}\right)=\int_{0}^{1} f\left(\alpha_{k}\left(y, X_{-\infty}^{k-1}\right)\right) d y \tag{203}
\end{equation*}
$$

for any $k$ and any bounded measurable $f: \mathcal{X}_{k} \rightarrow \mathbb{R}$.
(B) A parametrization of $P$ is a two-component random sequence $\left\{\left(X_{k}, Y_{k}\right)\right\}_{k}$ (on a probability space) such that
the distribution of $\left\{X_{k}\right\}_{k}$ coincides with $P$,
$Y_{k}$ are independent and uniform on $[0,1]$,
$\forall k \quad \sigma\left(X_{k}\right) \subset \sigma\left(Y_{k}, X_{-\infty}^{k-1}\right)$,
$\forall n \quad \sigma\left\{Y_{k}: k>n\right\}$ is independent of $\sigma\left\{X_{k}, Y_{k}: k \leq n\right\}$.
The connection between (A) and (B) is given by

$$
\begin{equation*}
X_{k}=\alpha_{k}\left(Y_{k}, X_{-\infty}^{k-1}\right) \tag{204}
\end{equation*}
$$

It follows from (203) that

$$
\begin{equation*}
\mathbb{E}\left(f\left(X_{-\infty}^{k}\right) \mid X_{-\infty}^{k-1}\right)=\int_{0}^{1} f\left(X_{-\infty}^{k-1}, \alpha_{k}\left(y, X_{-\infty}^{k-1}\right)\right) d y \tag{205}
\end{equation*}
$$

for any $k$ and any bounded measurable $f: \mathcal{X}_{-\infty}^{k} \rightarrow \mathbb{R}$.
A parametrization is called generating, if

$$
\forall n \quad \sigma\left\{X_{k}: k \leq n\right\} \subset \sigma\left\{Y_{k}: k \leq n\right\} \vee \sigma_{-\infty}(X)
$$

206. Applying the above-described notions, connected with the KantorovichRubinstein metric, to the "markovization," we come to the following.

A measure $P \in \mathcal{P}\left(\mathcal{X}_{-\infty}^{0}\right)$ determines maps

$$
\begin{equation*}
\tilde{\nu}_{k}: \operatorname{SM}\left(\mathcal{X}_{-\infty}^{k}\right) \rightarrow \operatorname{SM}\left(\mathcal{X}_{-\infty}^{k-1}\right) \tag{207}
\end{equation*}
$$

and in addition

$$
\begin{equation*}
\tilde{\nu}_{k}: \operatorname{CM}\left(\mathcal{X}_{-\infty}^{k}\right) \rightarrow \operatorname{CM}\left(\mathcal{X}_{-\infty}^{k-1}\right) \tag{208}
\end{equation*}
$$

Define a chain of metrics as a sequence $\left\{\rho_{k}\right\}_{k}, \rho_{k} \in \operatorname{CM}\left(\mathcal{X}_{-\infty}^{k}\right)$, such that

$$
\begin{equation*}
\forall k \quad \rho_{k-1}=\tilde{\nu}_{k} \rho_{k} . \tag{209}
\end{equation*}
$$

(In fact, $\rho_{k}$ may be a pseudometric rather than a metric).
Any chain of metrics $\left\{\rho_{k}\right\}_{k}$ determines a sequence of numbers

$$
\begin{equation*}
\bar{\rho}_{k}=\iint \rho_{k}(x, y) \mu_{k}(d x) \mu_{k}(d y) \tag{210}
\end{equation*}
$$

where $\mu_{k}$ is the distribution of $X_{-\infty}^{k}$. The sequence is increasing (see Item 41) and hence it has a limit

$$
\bar{\rho}_{-\infty}=\lim _{k \rightarrow-\infty} \bar{\rho}_{k} .
$$

From Theorem 15 we obtain:
211. Theorem. If a measure $P$ admits a generating parametrization and is tail-trivial, then

$$
\bar{\rho}_{-\infty}=0
$$

for any chain of metrics.
212. The following particular case is of special interest for us. Let $\mathcal{X}_{0}=\mathcal{X}_{1}=\ldots$ $=\mathcal{X}_{n}=\{0,1\}$, and put

$$
\rho_{n}\left(\left(x_{0}^{\prime}, x_{1}^{\prime}, \ldots, x_{n}^{\prime}\right),\left(x_{0}^{\prime \prime}, x_{1}^{\prime \prime}, \ldots, x_{n}^{\prime \prime}\right)\right)=\max _{k=1, \ldots, n}\left|x_{k}^{\prime}-x_{k}^{\prime \prime}\right|
$$

for any $x^{\prime}=\left(x_{0}^{\prime}, x_{1}^{\prime}, \ldots, x_{n}^{\prime}\right), x^{\prime \prime}=\left(x_{0}^{\prime \prime}, x_{1}^{\prime \prime}, \ldots, x_{n}^{\prime \prime}\right)$ from $\mathcal{X}_{0}^{n}=\{0,1\}^{1+n}$. Note that the maximum is taken over $k=1, \ldots, n$ rather than $0,1, \ldots, n$; so, $\rho_{n}$ is a pseudometric rather than a metric.

A probability measure $P$ on $\mathcal{X}_{0}^{n}$ may be considered as a pair of probability measures $\mu, \nu$ on $\mathcal{X}_{1}^{n}=\{0,1\}^{n}$ :

$$
P\left(x_{0}, x_{1}, \ldots, x_{n} \mid x_{0}\right)= \begin{cases}\mu\left(x_{1}, \ldots, x_{n}\right), & \text { when } x_{0}=0 \\ \nu\left(x_{1}, \ldots, x_{n}\right), & \text { when } x_{0}=1\end{cases}
$$

together with a distribution of $X_{0}$. When such $P$ is given, we may construct a chain of metrics $\rho_{0}, \ldots, \rho_{n}$. We start from $\rho_{n}$ defined as above and finish at $\rho_{0}$, that is essentially one number $\rho_{0}(0,1)$. This number depends only on $\mu, \nu$ and may be considered a distance between them:

$$
\operatorname{KR}^{n}(\mu, \nu)=\rho_{0}(0,1) ;
$$

KR $^{n}$ means: $n$-step Kantorovich-Rubinstein distance. In order to prove the triangle inequality for $\mathrm{KR}^{n}$ it is enough to consider the case when $\mathcal{X}_{0}$ contains three points.
213. Consider the following condition on a random sequence $X_{1}, \ldots, X_{n}$ (each $X_{k}$ being $\pm 1$ ), or on its distribution $\mu \in \mathcal{P}\left(\{0,1\}^{n}\right)$ :

$$
\forall k \quad \forall x_{1}, \ldots, x_{k-1} \quad \frac{1-\varepsilon}{2} \leq \mathcal{P}\left(X_{k}=1 \mid X_{1}=x_{1}, \ldots, X_{k-1}=x_{k-1}\right) \leq \frac{1+\varepsilon}{2} .
$$

The set of measures $\mu$, satisfying this condition, will be denoted by $\mathcal{P}_{\varepsilon}^{n}$. The only measure belonging to $\mathcal{P}_{\varepsilon}^{n}$ for all $\varepsilon$ is the Bernoulli- $1 / 2$ measure $\mu_{0}$. The density $d \mu / d \mu_{0}$ of any $\mu \in \mathcal{P}_{\varepsilon}^{n}$ satisfies the following inequality:

$$
\begin{equation*}
\int\left(\frac{d \mu}{d \mu_{0}}\right)^{2} d \mu_{0} \leq\left(1+\varepsilon^{2}\right)^{n} \tag{214}
\end{equation*}
$$

It can be proved easily by induction in $n$.
The following lemma is the key to Theorem 103.
215. Lemma. For any $n$ and $\varepsilon$ there exist $N=2^{2 n}$ measures $\mu_{1}, \ldots, \mu_{N} \in \mathcal{P}_{\varepsilon}^{n}$ such that

$$
\begin{equation*}
\mathrm{KR}^{n}\left(\mu_{i}, \mu_{j}\right) \geq 1-\frac{C}{\varepsilon n} \tag{216}
\end{equation*}
$$

for any $i, j \in\{1, \ldots, N\}$; here $C$ is an absolute constant.
217. Remark. In fact, much more strong estimations are valid, than $2^{2 n}$ and $1-C /(\varepsilon n)$. But they are not needed for our purpose.
218. Remark. Note that $\varepsilon$ and $n$ appear in (216) in the combination $\varepsilon n$, while in (214) in another combination, essentially, $\varepsilon^{2} n$. Clearly, it is possible that $\varepsilon n \gg 1$ while $\varepsilon^{2} n \ll 1$. This is why the equivalence to the Bernoulli measure does not prevent the appearance of a non-standard filtration.

