# CONSISTENCY IN THE RECONSTRUCTION OF PATTERNS FROM SAMPLE DATA 

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1. Introduction and summary. Let $A$ be a $k$-dimensional Euclidean region having unit volume. An $m$-colors pattern is a partition $P_{A}$ of $A$ into $m$ sets $A_{i}, i=1, \ldots, m$ with positive volume. $P_{A}$ is called a random pattern if in addition the partition of $A$ is a realization of a random process with the following stationarity and isotropy properties:
(i) for all points $s \in A, P\left(s \in A_{i}\right)=p_{i}, i=1, \ldots, m$
(ii) for all pair of points $s, s^{\prime} \in A$ with distance $\left|s-s^{\prime}\right|=d$ between them, $P\left(s^{\prime} \in A_{i} \mid s \in A_{j}\right)=P_{i j}(d), i, j=1, \ldots, m$.

In [1], Switzer defines a reconstruction rule which produces an estimated reconstruction of the pattern using information obtained from $n$ fixed sample-points $s_{1} \ldots s_{n}$ of $A$. To evaluate the accuracy of a reconstruction rule $\delta$, applied to $n$ sample-points, he proposes the loss function:

$$
L_{n}=1-\mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right]
$$

where ${ }_{n} P_{A}^{\delta}$ is the partition of $A$ obtained from the reconstruction rule $\delta$ applied to the $n$ sample-points; ${ }_{n} P_{A}^{\delta} \cap P_{A}$ is the set of points which have the same color in ${ }_{n} P_{A}^{\delta}$ and $P_{A} ; \mu$ is the Lebesgue measure.

In this note we define a notion of consistency for a reconstruction rule when the number of fixed sample-points increase and we give sufficient conditions under which the simple nearest-point rule [1] is consistent.

## 2. Consistency for a Reconstruction rule

Definition. A rule for the reconstruction of a random pattern is consistent if the corresponding sequence of random variables $\left\langle L_{n}\right\rangle$ converges in probability to zero.

Theorem. A reconstruction rule $\delta$ is consistent if and only if

$$
\lim _{n \rightarrow \infty} E \mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right]=1
$$

Proof. $\left\langle 1-\mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right]\right\rangle$ is a sequence of random variables taking all their values on $[0,1]$; if $\lim _{n \rightarrow \infty} E \mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right]=1$ then $\lim _{n \rightarrow \infty} E\left(1-\mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right]\right)^{2}=0$ and hence $\left\langle L_{n}\right\rangle$ converges in probability to zero.

Conversely suppose that for all positive $\epsilon$ and $\delta$ there is an $N_{\varepsilon, \delta}$ such that for all $n>N_{\delta, \delta}$ :

$$
P\left(\mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right]<1-\epsilon\right)<\delta
$$

Since

$$
E \mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right]=\int_{0}^{(1-\varepsilon)^{-}} x d Q_{n}(x)+\int_{(1-\varepsilon)^{+}}^{1} x d Q_{n}(x)
$$

where $Q_{n}$ is the distribution of $\mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right]$, then

$$
(1-\varepsilon)\left[1-P\left(\mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right]<1-\varepsilon\right)\right] \leq E \mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right] \leq 1
$$

Therefore for all $n>N_{\varepsilon, \delta}$

$$
(1-\varepsilon)(1-\delta)<E \mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right] \leq 1
$$

and

$$
\lim _{n \rightarrow \infty} E \mu\left[{ }_{n} P_{A}^{\delta} \cap P_{A}\right]=1
$$

Q.E.D.
3. Application to the simple nearest-point rules $\delta^{\prime}$. The color assigned to a point $s \in A$, by the simple nearest-point rule, is the color of the unique sample-point $N(s)$ nearest to $s$ (if $s \in A$ has not a unique nearest-sample point we assign to $s$ an arbitrary color). For that rule Switzer [1, p. 139, Theorem 1] has shown that

$$
E \mu\left[{ }_{n} P_{A}^{\delta \prime} \cap P_{A}\right]=\sum_{j=1}^{m} p_{j} \sum_{i=1}^{n} \int_{S_{i}} P_{j j}\left[\left|s-s_{i}\right|\right] d \mu(s)
$$

where $S_{i}=\left\{s \in A: N(s)=s_{i}\right\}$.
As a consequence of our theorem we obtain:
Corollary 1. $\delta^{\prime}$ is consistent if and only if for all $j$ such that $p_{j}>0$,

$$
\lim _{n \rightarrow \infty} \sum_{i=1}^{n} \int_{S_{i}} P_{j j}\left[\left|s-s_{i}\right|\right] d \mu(s)=1
$$

From Corollary 1, the following corollary can be easily proved.
Corollary 2. If for all $j$ such that $p_{j}>0, P_{j j}$ is a nonincreasing function, strictly decreasing in a neighbourhood of zero, and such that $P_{j j}(0)=1$ then $\delta^{\prime}$ is consistent if

$$
\begin{equation*}
\lim _{n \rightarrow \infty} \max _{1 \leq i \leq n} \sup _{S_{i}}\left|s-s_{i}\right|=0 . \tag{1}
\end{equation*}
$$

In the case where $k=2, m=2$ and

$$
\begin{align*}
& P_{11}(d)=p_{1}+\left(1-p_{1}\right) e^{-c d}  \tag{2}\\
& P_{22}(d)=\left(1-p_{1}\right)+p_{1} e^{-c d} c>0 .
\end{align*}
$$

Switzer [1, p. 142] considers certain types of arrangements for the sample-points. Because the functions given by (2) satisfy the conditions of Corollary 2 we can make the following observations about some arrangements suggested by Switzer:
(1) If the sample-points are placed at the vertices of a square grid then $\delta^{\prime}$ is
consistent ( $n \rightarrow \infty$ means here that the number of squares in the grid goes to infinity).
(2) If the sample-points are placed at the vertices of an equilateral triangular grid then $\delta^{\prime}$ is consistent ( $n \rightarrow \infty$ means here that the number of triangles in the grid goes to infinity).
(3) In the case called "line sampling with spacing $\sigma$ " the condition (1) of Corollary 2 is not satisfied. Moreover, we have

$$
\lim _{n \rightarrow \infty} 1-E \mu\left[{ }_{n} P_{A}^{\delta^{\prime}} \cap P_{A}\right]=2 p_{1}\left(1-p_{1}\right)\left[1-2\left(1-e^{-1 / 2 c \sigma}\right)(c \sigma)^{-1}\right]
$$

which is not zero for any $\sigma>0$, then in that case $\delta^{\prime}$ is not consistent.
Remark. We have supposed that the color observed at each sample-point is the color of that point (i.e. there is no "measurement error"). The following example shows that this assumption is important for the validity of Corollary 2. Denote by $Y_{s_{i}}$ the observation made at the point $s_{i}$; suppose that $Y_{s_{i}}$ is a random variable with values in $\{1, \ldots, m\}$ (the event $Y_{s_{i}}=j$ is interpreted as "the point $s_{i}$ is observed to be in $A_{j}{ }^{\prime \prime}$ ). In addition, suppose that for each $i=1, \ldots n$,

$$
P\left[Y_{s_{i}}=j \mid s_{i} \in A_{k}\right]=f_{j k}, \quad k, j=1, \ldots, m
$$

and that the distribution of $Y_{s_{i}}$ does not depend on the pattern in any other way. It is easy (cf. [2]) to prove that

$$
E \mu\left[{ }_{n} P_{A}^{\delta^{\prime}} \cap P_{A}\right]=\sum_{j=1}^{m} p_{j} \sum_{i=1}^{n} \int_{S_{i}} \sum_{k=1}^{m} f_{j k} P_{k j}\left(\left|s-s_{i}\right|\right) d \mu(s) .
$$

Then, under the conditions of Corollary 2, if there exists a $j$ such that $p_{j}>0$ and $f_{j j}<1, \delta^{\prime}$ is not consistent even if (1) is satisfied.

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## References

1. P. Switzer, Reconstructing patterns from sample data, Ann. Math. Statist. 38 (1967), 138-154.
2. -, Mapping a geographically correlated environment, Technical Report No. 145, Stanford University, 1969.

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