Copula Fields and their Applications

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0. Introduction. The construction of stochastic processes from a family of consistent probability measures can be done by Kolmogorov's extention theorem (see [1]).

But the construction of stochastic processes from a family of nonconsistent probability measures can not always be done.

In this paper we propose the following problems and give the answers.

(P1). For any T > 0 and any family of Borel probability measures $\{\rho(t, dx)\}_{0 \le t \le T}$ on \mathbb{R}^d , construct a R^{d} -valued Markov process $\{X(t)\}_{0 \le t \le T}$ on a probability space (Ω, B, P) such that (0.1) $P(X(t) \in dx) = \rho(t, dx)$ for all $t \in [0, T]$. (P2). For any T > 0, any family of Borel probability measures $\{\rho(t, dx)\}_{0 \le t \le T}$ on R^d , and any Borel probability measure $\mu(dxdy)$ on R^{2d} for which $\int_{u=p^d} \mu(dxdy) = \rho(0, dx)$ and for which

 $\int_{d} \mu(dxdy) = \rho(T, dy), \text{ construct a } R^{d} \text{ -valued}$ reciprocal process (see [5]) $\{X(t)\}_{0 \le t \le T}$ on a

probability space (Ω, B, P) such that

(0.2) $P(X(t) \in dx) = \rho(t, dx)$ for all $t \in [0, T]$, (0.3) $P(X(0) \in dx, X(T) \in dy) = \mu(dxdy).$

Main idea is that of copula in the multivariate analysis (see [2,7,8]). We give the definition of a copula field, extending the idea, directly, to the path space.

We also give the applications to the stochastic control. (P1) is related to the stochastic quantizations (see [6] and references therein).

1. Copula fields and one dimensional case. In this section we show how to construct a real valued stochastic process from a family of Borel probability measures on R, extending directly the idea of copula, to the path space. We also give the definition of the copula field. In this section we denote by I the parameter space.

Let us give the definition of a copula for a real valued stochastic process which is well defined from [7], Theorems 6.2.4, 6.2.5.

Definition 1.1. For any real valued stochastic process $\{X(t)\}_{t \in I}$ on a probability space $(\Omega,$ **B**, **P**), the family $(C_A^X(u_1, \cdots, u_{*(A)}))_{A \subset I, *(A) < \infty}$ of copulas which satisfies the following is called a copula for $\{X(t)\}_{t \in I}$; for any $A = \{t_1^A, \cdots, t_n\}$ $\{t_{\#(A)}^A\} \subset I \text{ and any } x_1, \cdots, x_{\#(A)} \in R$ (1.1) $P(X(t_1^A) \le x_1, \cdots, X(t_{\#(A)}^A) \le x_{\#(A)}) =$ $C_A^X(F_{t_1^A}^X(x_1), \cdots, F_{t_{t_{t(A)}}}^X(x_{\#(A)})),$

where we put $F_t^X(x) = P(X(t) \le x)$.

Before we give the definition of a copulas field for a real valued stochastic process, let us give some notations. Denote by DF(R) the set of all continuous distribution functions on R. For $F \in DF(R)$, we can define the functions $F^*(u)$ $(0 \le u \le 1)$ by the following; put $F^*(0) \equiv$

$$\{\max\{x; F(x) = 0\} \text{ if } 0 \in Range(F), \\ -\infty \text{ if } 0 \notin Range(F), \}$$

(1.2) $F^*(u) \equiv \min\{x; F(x) = u\}$ for 0 < u < 1, $F^{*}(1) \equiv \begin{cases} \min\{x; F(x) = 1\} & \text{if } 1 \in Range(F), \\ \infty & \text{if } 1 \in F(x) \end{cases}$ if $1 \notin Range(F)$ (see [7], p. 49). Put $DF(R)^* \equiv \{F^*; F \in$ DF(R); $DF(R)_{I} \equiv \{\{F_{t}\}_{t \in I}; F_{t} \in DF(R) | t \in I\}$ $[I]; DF(R)_{I}^{*} \equiv \{\{F_{t}^{*}\}_{t \in I}; F_{t} \in DF(R) (t \in I)\}.$

Definition 1.2. For any real valued stochastic process $\{X(t; \omega)\}_{t \in I, \omega \in Q}$ on a probability space (Ω, B, P) , the copula field $\{C^{X}(F^{*};$ $\omega)(t)\}_{t\in I, \boldsymbol{F}^* \in DF(R)^*_{I}, \omega \in \mathcal{Q}} \text{ for } \{X(t; \omega)\}_{t\in I, \omega \in \mathcal{Q}} \text{ is defined as follows; for all } t \in I, \boldsymbol{F}^* = \{F_s^*\}_{s\in I} \in$ $DF(R)_{I}^{*}, \text{ and } P - a.a.\omega$ (1.3) $C^{X}(F^{*}; \omega)(t) = F_{t}^{*}(F_{t}^{X}(X(t; \omega))),$

When there is no confusion, we simply denote the

copula field by $C^{X}(F^{*})(t)$, omitting ω .

Remark 1.1. The copula for a real valued stochastic process $\{X(t)\}_{t \in I}$ is uniquely determined if and only if $F_t^x(x)$ is continuous in $x \in$ **R** for all $t \in I$. Copula field for a real valued stochastic process is unique. F^* is a quasi-inverse of F (see [7], p. 49), and our choice in (1.2) is convenient as we show in the next proposition whose proof is omitted.

Proposition 1.1. For any $F \in DF(R)$, F^* is strictly increasing, left continuous and has a right hand side limits, and the following holds; for any $u \in (0,1)$, and any $y \in R$,

(1.4) $F^*(u) \le y$ if and only if $u \le F(y)$.

The next theorem shows that a copula field for a real valued stochastic process is a path space version of the idea of copula.

Theorem 1.2. For any $\{F_t\}_{t \in I} \in DF(R)_I$, and any real valued stochastic process $\{X(t)\}_{t \in I}$ on a probability space (Ω, B, P) for which $\{F_t^X\}_{t \in I} \in DF(R)_I$, the stochastic process $\{Y(t) \equiv C^X(\{F_s^*\}_{s \in I})(t)\}_{t \in I}$ satisfies the following; for any $n \ge 1, t_1, \dots, t_n \in I(t_i \neq t_j \text{ if } i \neq j)$, and $y_1, \dots, y_n \in R$,

- (1.5)
 $$\begin{split} P(Y(t_1) \leq y_1, \cdots, Y(t_n) \leq y_n) &= \\ C^X_{(t_1, \cdots, t_n)}(F_{t_1}(y_1), \cdots, F_{t_n}(y_n)). \end{split}$$
 In particular, for any $y \in R$,
- (1.6) $P(Y(t) \le y) = F_t(y)$ for all $t \in I$.

Proof. Since (1.6) is a special case of (1.5) (see [7]), we only prove (1.5).

Since $P(0 < F_{t_1}^X(X(t_1)), \cdots, F_{t_n}^X(X(t_n)) < 1) = 1$, we have

$$(1.7) \quad P(Y(t_1) \le y_1, \cdots, Y(t_n) \le y_n) = P(F_{t_1}^*(F_{t_1}^X(X(t_1))) \le y_1, \cdots, F_{t_n}^*(F_{t_n}^X(X(t_n))) \le y_n) = P(F_{t_1}^X(Y(t_1)) \le F_{t_1}(y_1) \cdots$$

$$= F(F_{t_1}(X(t_1)) \leq F_{t_1}(y_1), \cdots, F_{t_n}(X(t_n)) \leq F_{t_n}(y_n)) \text{ (from Proposition 1.1)}$$

$$= C^X_{(t_1, \dots, t_n)}(F^X_{t_1}(z_1), \cdots, F^X_{t_n}(z_n))$$

$$= C^X_{(t_1, \dots, t_n)}(F_{t_1}(y_1), \cdots, F_{t_n}(y_n)).$$
Here we put $z_i = \sup\{x; F^X_{t_i}(x) \leq F_{t_i}(y_i)\}$ for 1
$$\leq i \leq n.$$

Q.E.D.

We get the following proposition easily.

Proposition 1.3. For any $F^* \in DF(R)_I^*$, and any real valued stochastic process $\{X(t)\}_{t \in I}$ on a probability space (Ω, B, P) for which $\{F_t^x\}_{t \in I} \in DF(R)_I$, the following holds.

(1). If $\{X(t)\}_{t \in I}$ is a Markov process, then so is $\{C^{X}(F^{*})(t)\}_{t \in I}$.

(2). If $\{X(t)\}_{t \in I}$ is a reciprocal process, then so is $\{C^{X}(F^{*})(t)\}_{t \in I}$.

As an application of Theorem 1.2, let us construct stochastic processes with special time dependence.

Theorem 1.4. For any T > 0, any family of distribution functions $\{F_t\}_{t \in [0,T]}$ on R for which $F_t \in DF(R)$ for 0 < t < T, and any Borel probability measure $\mu(dxdy)$ on R^2 for which $\mu((-$

 ∞ , x] × (- ∞ , ∞)) = $F_0(x)$ and for which $\mu((-\infty, \infty) \times (-\infty, y]) = F_T(y)$, there exists a real valued reciprocal process $\{Y(t)\}_{0 \le t \le T}$ on a probability space (Ω , **B**, **P**) such that for all $x, y \in R$

(1.8) $P(Y(t) \le x) = F_t(x)$ for all $0 \le t \le T$, (1.9) $P(Y(0) \le x, Y(T) \le y) = \mu((-\infty, x] \times (-\infty, y])$.

Proof. From Theorem 2.1 in [5], and the first part of section 3 in [5], there exists a real valued reciprocal process $\{X(t)\}_{0 \le t \le T}$ on a probability space (Ω, B, P) such that for $t \in (0, T)$

(1.10)
$$P(X(0) \in dx, X(t) \in dz, X(T) \in dy)$$

= $(T/(2\pi t(T-t)))^{1/2} \exp(|x-y|^2/(2T) - |x-z|^2/(2t) - |z-y|^2/(2(T-t)))$
 $dz\mu(dxdy).$

This is true from the following. Put for $0 \le s$ $< t < u \le T$, $x, y, z \in R$,

1.11)
$$q(s, x; t, y) = (2\pi(t-s))^{-1/2} \exp(-|y-x|^2/(2(t-s))),$$

$$(s, x; t, y; u, z) = q(s, x; t, y)q(t, y; u, z)/q(s, x; u, z).$$

Then p(s, x; t, y; u, z) is a reciprocal transition probability density function (see [5], section 3). For $\mu(dxdy)$ and p(s, x; t, y; u, z), there exists a reciprocal process $\{X(t)\}_{0 \le t \le T}$ on a probability space (Ω, B, P) such that (1.10) holds (see [5], Theorem 2.1).

Putting

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(1.

(1.12)
$$Y(t) \equiv \begin{cases} C^{X}(\{F_{s}^{*}\}_{s \in (0,T)})(t) & \text{if } 0 < t < T, \\ X(t) & \text{if } t = 0 \text{ or } T, \end{cases}$$

the proof is over from Theorem 1.2 and Proposition 1.3.

Q.E.D.

The following Theorem can be obtained in the same way as Theorem 1.4.

Theorem 1.5. For any T > 0, any family of distribution functions $\{F_t\}_{t \in [0,T]}$ on R for which $F_t \in DF(R)$ for 0 < t < T, there exists a real valued Markov process $\{Y(t)\}_{0 \le t \le T}$ on a probability space (Ω, B, P) such that $(1.13) \quad P(Y(t) \le x) = F.(x)$

$$F(I(t) \leq t) = F_t(t)$$

for all $x \in R$ and $0 \le t \le T$

Proof. From Theorem 3.2 in [5], there exists a real valued Markov process $\{X(t)\}_{0 \le t \le T}$ on a probability space (Ω, B, P) such that (1.10) holds and that

14)
$$P(X(0) \in dx) = dF_0(x),$$
$$P(X(T) \in dx) = dF_T(x).$$

Putting

(1.15) $Y(t) \equiv \begin{cases} C^X(\{F_s^*\}_{s \in (0,T)})(t) & \text{if } 0 < t < T, \\ X(t) & \text{if } t = 0 \text{ or } T, \end{cases}$ the proof is over from Theorem 1.2 and Proposition 1.3.

Q.E.D.

We close this section by giving the application to the stochastic control (see [3]).

Fix T > 0 and a probability space (Ω, B, P) . Let $h(t, x) : [0, T] \times R \mapsto R, G_1(x) : R \mapsto R$, and $G_2(x, y) : R^2 \mapsto R$ be bounded measurable, and put for a real valued stochastic process $\{X(t)\}_{0 \le t \le T}$,

(1.16)
$$J_1(X) = E\left[\int_0^T k(t, X(t)) dt + G_1(X(T))\right],$$
$$J_2(X) = E\left[\int_0^T k(t, X(t)) dt + G_2(X(0), X(T))\right].$$

The following theorem can be obtained from Theorems 1.4 and 1.5 and the proof is omitted.

Theorem 1.6. (O) For any $A \subseteq DF(R)_{(0,T)}$ and subset B_1 of the set of all distribution functions on R,

 $\begin{array}{ll} (1.17) & \inf\{J_1(X) \; ; \; \{F_t^X\}_{t \in (0,T)} \in A, \; F_T^X \in B_1\} \\ &= \inf\{J_1(X) \; ; \; \{F_t^X\}_{t \in (0,T)} \in A, \; F_T^X \in B_1, \\ \{X(t)\}_{0 \leq t \leq T} \; \text{is a Markov process}\}. \end{array}$

(I) For any $A \subset DF(R)_{(0,T)}$ and subset B_2 of the set of all Borel probability measures on R^2 ,

$$(1.18) \quad \inf\{J_{2}(X) ; \{F_{t}^{X}\}_{t \in (0,T)} \in A, P((X(0), X(T)) \in dxdy) \in B_{2}\} \\ = \inf\{J_{2}(X) ; \{F_{t}^{X}\}_{t \in (0,T)} \in A, P((X(0), X(T)) \in dxdy) \in B_{2}, \{Y(t)\} \quad \text{is a region cool process}\}$$

 $\{X(t)\}_{0 \le t \le T}$ is a reciprocal process $\{$.

2. Multidimensional case. In this section we consider (P1) when d > 1 and give the application to the stochastic control theory.

Theorem 2.1. Let $\{p(t, x)\}_{t\geq 0}$ be a family of probability density functions on \mathbb{R}^d . Then there exists a \mathbb{R}^d -valued Markov process $\{X(t)\}_{t\geq 0}$ on a probability space $(\Omega, \mathbf{B}, \mathbf{P})$ such that (2.1)

 $P(X(t) \in dx) = p(t, x) dx \text{ for all } t \in [0, \infty).$ Outline of Proof. Put for $t \ge 0$ and $x_1, \cdots, x_d \in R$,

$$(2.2) \quad F_{1}(t, x_{1}) = \int_{-\infty}^{x_{1}} dy_{1} \int_{R^{d-1}} p(t, (y_{1}, y)) dy_{1}$$

$$F_{k}(t, x_{k} \mid x_{1}, \cdots, x_{k-1})$$

$$= \int_{-\infty}^{x_{k}} dy_{k} \int_{R^{d-k}} p(t, (x_{1}, \cdots, x_{k-1}, y_{k}, z))$$

$$dz / \left(\int_{R^{d-k+1}} p(t, (x_{1}, \cdots, x_{k-1}, z)) dz \right)$$

if the denominator is positive,

0 otherwise,

for $k = 2, \dots d$. Then for $t \ge 0$, $k = 2, \dots d$, and $x_1, \dots, x_{k-1} \in R$, $F_1(t, x)$ and $F_k(t, x | x_1, \dots, x_{k-1})$ are continuous in x.

For the standard Wiener process $\{W(t)\}_{t \ge 0}$ (see [4]), put for $k = 2, \dots d$, (2.3) $X_1(t) = C^{W_1(1+\cdot)}(\{F_1(t, \cdot)^*\}_{t \in [0,\infty)})(t),$ $X_k(t) =$ $\int C^{W_k(1+\cdot)}(\{F_k(\{t, \cdot \mid X_1(t), \dots, X_{k-1}(t))^*\}_{t \in [0,\infty)})(t)$

$$if \int_{\mathbb{R}^{d-k+1}} p(t, (X_1(t), \cdots, X_{k-1}(t), z)) dz \neq 0, \\ W_k(1+t)$$
 otherwise

(see (1.3) for notation). Then it is easy to see that $\{(X_1(t), \cdots, X_d(t))\}_{t \ge 0}$ is a Markov process which satisfies (2.1), inductively in k, since W_i and W_j $(i \ne j)$ are independent of each other, and since $W(\cdot)$ is a Markov process (see [4]).

Q.E.D.

Next we give the application to the stochastic control (see [3]).

Fix T > 0 and a probability space (Ω, B, P) . Let $k(t, x) : [0, T] \times R^d \mapsto R$ and $G(x) : R^d \mapsto R$ be bounded measurable, and put for a R^d -valued stochastic process $\{X(t)\}_{0 \le t \le T}$ on (Ω, B, P) ,

(2.4)
$$J(X) \equiv E\left[\int_0^T k(t, X(t)) dt + G(X(T))\right].$$

The following theorem can be easily obtained from Theorem 2.1, and the proof is omitted.

Theorem 2.2. For any subset A of the set of all familes of $\{F_t\}_{t \in [0,T]}$ of continuous distribution functions on R^d ,

(2.5) $\inf\{J(X); \{F_t^X\}_{t \in [0,T]} \in A\}$ = $\inf\{J(X); \{F_t^X\}_{t \in [0,T]} \in A, \{X(t)\}_{0 \le t \le T}$ is a Markov process.

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