Notes on hedging cryptos with spectral risk measures

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Abstract

We investigate different methods of hedging cryptocurrencies with Bitcoin futures. A useful generalisation of variance-based hedging uses spectral risk measures and copulas.

1. Optimal hedge ratio

Following (Barbi and Romagnoli, 2014), we consider the problem of the optimal hedge ratios by extending commmonly known minimum variance hedge ratio to more general risk measures and dependence structures.

Hedge portfolio: $R_t^h = R_t^S - hR_t^F$, involving returns of spot and future contract and where h is the hedge ratio
Optimal hedge ratio: $h^* = \text{argmin}_h \, \rho_\phi(s,h)$, for given confidence level $1-s$ (if applicable, e.g. in the case of VaR, ES), where ρ_ϕ is a spectral risk measure with weighting function ϕ (see below).
Corollary 2.1 of (Barbi and Romagnoli, 2014), corrected: Let R^S and R^F be two real-valued random variables on the same probability space $(\Omega, \mathcal{A}, \mathbf{P})$ with corresponding absolutely continuous copula $C^t_{R^S,R^F}(w,\lambda)$ and continuous

marginals F_{R^S} and F_{R^F}. Then, the s-quantile of R^h solves the following:

$$F_{R^h}(r^h) = 1 - \int_0^1 D_1 C_{R^S,R^F}\left\{w, F_{R^F}\left[\frac{F_{R^S}^{-1}(w) - r^h}{h}\right]\right\} dw.$$

[..]

Here $D_1 C(u,v) = \frac{\partial}{\partial u} C(u,v)$, which can be shown to fulfil (Cherubini *et al.*, 2011)

$$D_1 C_{X,Y}(F_X(x), F_Y(y)) = \mathbf{P}(Y \leq y | X = x).$$

2. Spectral risk measures

Spectral risk measure (Acerbi, 2002; Cotter and Dowd, 2006):

$$\rho_\phi = -\int_0^1 \phi(p)\, q_p \,\mathrm{d}p,$$

where q_p is the p-quantile of the return distribution and $\phi(s)$, $s \in [0,1]$, is the so-called *risk aversion function*, a weighting function such that[1]

(i) $\phi(p) \geq 0$,

(ii) $\int_0^1 \phi(p)\,\mathrm{d}p = 1$,

(iii) $\phi'(p) \leq 0$.

Examples: VaR, ES
Replacing the last property with $\phi'(p) > 0$ rules out risk-neutral behaviour.
Spectral risk measures are coherent (Acerbi, 2002).

[1]Note that the treatment in (Acerbi, 2002) is measure-based and therefore slightly different

2.1. Representation of spectral risk measures

To prevent numerical instabilities involving the quantile function, re-write spectral risk measures as follows:

- Integration by substitution: $\int_a^b g(\varphi(x))\,\varphi'(x)\,\mathrm{d}x = \int_{\varphi(a)}^{\varphi(b)} g(u)\,\mathrm{d}u.$
- Spectral risk measures: $-\int_0^1 \phi(p)\,F^{(-1)}(p)\,\mathrm{d}p$
- Set $\varphi(x) = F(x)$, $g(p) = \phi(p)\,F^{(-1)}(p)$.
- Then:
$$-\int_0^1 \phi(p)\,F^{(-1)}(p)\,\mathrm{d}p = -\int_{-\infty}^{\infty} \phi(F(x))\,x\,f(x)\,\mathrm{d}x.$$

2.2. Exponential spectral risk measures

- Choose exponential utiliy function: $U(x) = -\mathbf{e}^{-kx}$, where $k > 0$ is the Arrow-Pratt coefficient of absolute risk aversion (ARA).
- Coefficient of absolute risk aversion: $R_A(x) = -\dfrac{U''(x)}{U'(x)} = k$
- Coefficient of relative risk aversion: $R_R(x) = -\dfrac{xU''(x)}{U'(x)} = xk$
- Weighting function $\phi(p) = \lambda\mathbf{e}^{-k(1-p)}$, where λ is an unknown positive constant.
- Set $\lambda = \dfrac{k}{1-\mathbf{e}^{-k}}$ to satisfy normalisation.

- Exponential spectral risk measure:

$$\rho_\phi = \int_0^1 \phi(p)\, F^{(-1)}(p)\, \mathrm{d}p = \frac{k}{1-\mathbf{e}^{-k}} \int_0^1 \mathbf{e}^{-k(1-p)}\, F^{(-1)}(p)\, \mathrm{d}p.$$

  (If calculation of quantiles is a problem use change of variables above.)

- What exactly is the link between risk measure and utility? I think there is no direct link: the exponential risk measure is *inspired* by ARA utility.

3. D_1 Operator

The D_1 operator is given as

$$D_1 C_{X,Y}(F_X(x), F_Y(y)) = \mathbf{P}(Y \leq y | X = x).$$

In the context of the above notation, we obtain

$$\begin{aligned} D_1 C_{R^s,R^F}\{w, g(w)\} &= \mathbf{P}[R_F \leq F_F^{(-1)}\{g(w)\} | R_s = F_S^{(-1)}(w)] = \mathbf{P}\{V \leq g(w) | U = w\} \\ &= \frac{\mathbf{P}\{U \in \mathrm{d}w, V \leq g(w)\}}{\mathbf{P}(U \in \mathrm{d}w)} = \mathbf{P}\{U \in \mathrm{d}w | V \leq g(w)\} = \int_0^{g(w)} c(w,v)\, \mathrm{d}v. \end{aligned}$$

The last line can also be written as

$$\frac{\partial}{\partial w} C\{w, g(w')\}\big|_{w'=w}.$$

We give an explicit equation of the D_1 operator for Archimedean copulae.

The D_1 operator is defined as the partial derivatives of the first input to the copula function, so we fix the second argument while taking derivative with respect to the first, and then evaluate the function. we have

Function	Gumbel	Frank	Clayton	Independence
$\phi(t)$	$\{-\log(t)\}^\theta$	$-\ln\left\{\frac{\exp(-\theta t)-1}{\exp(-\theta)-1}\right\}$	$\frac{1}{\theta}(t^{-\theta}-1)$	Same to Gumbel where $\theta = 1$
$\phi^{-1}(t)$	$\exp(-t^{1/\theta})$	$\frac{-1}{\theta}\log[1+\exp(-t)\{\exp(-\theta)-1\}]$	$(1+\theta t)^{-\frac{1}{\theta}}$	
$\partial\phi(t)/\partial t$	$\theta\frac{\phi(t)}{t\log(t)}$	$\frac{\theta\exp(-\theta t)}{\exp(-\theta t)-1}$	$-t^{-(\theta+1)}$	
$\partial\phi^{-1}(t)/\partial t$	$\frac{-1}{\theta}t^{\frac{1}{\theta}-1}\phi^{-1}(t)$	$\frac{1}{\theta}\frac{\exp(-t)\{\exp(-\theta)-1\}}{1+\exp(-t)\{\exp(-\theta)-1\}}$	$\theta(1+\theta t)^{-\frac{1}{\theta}-1}$	

Table 1: Archemdean Copulae's Generator, Generator Inverse, and their derivative.

$$\left.\frac{\partial C\{v,g(w)\}}{\partial v}\right|_{v=w} = \left.\frac{\partial\phi^{-1}[\phi(v)+\phi\{g(w)\}]}{\partial[\phi(v)+\phi\{g(w)\}]}\frac{\partial[\phi(v)+\phi\{g(w)\}]}{\partial v}\right|_{v=w} \tag{1}$$

$$= \left.\frac{\partial\phi^{-1}[\phi(v)+\phi\{g(w)\}]}{\partial[\phi(v)+\phi\{g(w)\}]}\frac{\partial\phi(v)}{\partial v}\right|_{v=w} \tag{2}$$

$$= \frac{\partial\phi^{-1}[\phi(w)+\phi\{g(w)\}]}{\partial[\phi(w)+\phi\{g(w)\}]}\frac{\partial\phi(w)}{\partial w} \tag{3}$$

$$, \text{where } g(w) = F_{R^F}\left\{\frac{F_{R^S}^{-1}(w)-r^h}{h}\right\} \tag{4}$$

$$\tag{5}$$

4. Dependence

Dependence through copula (e.g. Student t, Clayton or Gumbel)

4.1. Archimedean copulas

- A well-studied one-parameter family of copulas are the **Archimedean copulas**.
- Let $\phi : [0,1] \to [0,\infty]$ be a continuous and strictly decreasing function with $\phi(1) = 0$ and $\phi(0) \leq \infty$.
- We define the **pseudo-inverse** of ϕ as

$$\phi^{(-1)}(t) = \begin{cases} \phi^{-1}(t), & 0 \leq t \leq \phi(0), \\ 0, & \phi(0) < t \leq \infty. \end{cases}$$

- If, in addition, ϕ is convex, then the following function is a copula:

$$C(u,v) = \phi^{(-1)}(\phi(u) + \phi(v)).$$

- Such copulas are called **Archimedean copulas**, and the function ϕ is called an **Archimedean copula generator**.
- Examples of Archimedean copulas are the **Gumbel** and the **Clayton** copulas:

$$\begin{aligned} C_{\theta,\mathrm{Gu}}(u,v) &= \exp\left\{-((-\ln u)^\theta + (-\ln v)^\theta)^{1/\theta}\right\}, && 1 \leq \theta < \infty, \\ C_{\theta,\mathrm{Cl}}(u,v) &= (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}, && 0 < \theta < \infty. \end{aligned}$$

- In the case of the Gumbel copula, the independence copula is attained when $\theta = 1$ and the comonotonicity copula is attained as $\theta \to \infty$.
- Thus, the Gumbel copula interpolates between independence and perfect dependence.
- In the case of the Clayton copula, the independence copula is attained as $\theta \to 0$, whereas the comonotonicity copula is attained as $\theta \to \infty$.

4.2. Elliptical Copulae

under construction

Definition 1. Elliptical Distribution. The d-dimensional random vector $\boldsymbol{y}$ has an elliptical distribution if and only if the characteristic function $\boldsymbol{t} \mapsto \mathbb{E}\{\exp(i\boldsymbol{t}^\top \boldsymbol{y})\}$ with $\boldsymbol{t} \in \mathbb{R}^d$ has the representation

$$\phi_g(\boldsymbol{t}; \boldsymbol{\mu}, \boldsymbol{\Sigma}, \boldsymbol{\nu}) = \exp(i\boldsymbol{t}^\top \boldsymbol{\mu}) g(\boldsymbol{t}^\top \boldsymbol{\Sigma} \boldsymbol{t}; \boldsymbol{\nu}) \tag{6}$$

where $g(\cdot; \nu) : [0, \infty[\mapsto \mathbb{R}$, $\nu \in \mathbb{R}^d$, and Σ is a symmetric positive semidefinite $d \times d$-matrix.

If r has a density, then the density of $\boldsymbol{y}$ is of the form

$$|\Sigma|^{\frac{1}{2}} g\{(\boldsymbol{y} - \boldsymbol{\mu})^\top \Sigma^{-1} (\boldsymbol{y} - \boldsymbol{\mu})\}. \tag{7}$$

The function $g(\cdot; \nu)$ is known as characteristic generator, whereas $\boldsymbol{\nu}$ is parameter that determines the shape, in particular the tai index of the distribution.

Corollary 1. *(Fang, 2018, equation 2.12) If $\boldsymbol{y}$ follows an elliptical distribution, then $\boldsymbol{y}$ has a stochastic representation*

$$\boldsymbol{y} = \boldsymbol{\mu} + r\boldsymbol{A}^\top \boldsymbol{u}, \tag{8}$$

where $r \in \mathbb{R}_+$ is independent of $\boldsymbol{u}$, and $\boldsymbol{A}^\top \boldsymbol{A} = \boldsymbol{\Sigma}$.

Distribution	$r \sim$	$g(\boldsymbol{t})$
Gaussian	χ_n	

Table 2: Generators of Elliptical Distributions summarised from (Fang, 2018, Chapter 2)

4.3. Gaussian Copula

The Gaussian or Normal copula is

$$C_{\Sigma}^{Ga}(x) = \frac{1}{(2\pi)^{d/2}|\Sigma|^{1/2}} \int_{-\infty}^{\Phi^{-1}(x_1)} \cdots \int_{-\infty}^{\Phi^{-1}(x_d)} \exp\left\{-\frac{1}{2} y^{\top} \Sigma^{-1} y\right\} dy_1 \dots dy_d \tag{9}$$

The copula density is

$$c_{\Sigma}^{Ga}(x) = \frac{1}{(2\pi)^{d/2}|\Sigma|^{1/2}} \exp\left\{-\frac{1}{2}\begin{pmatrix}\Phi^{-1}(x_1)\\ \vdots \\ \Phi^{-1}(x_d)\end{pmatrix}^{\top} \Sigma^{-1} - I \begin{pmatrix}\Phi^{-1}(x_1)\\ \vdots \\ \Phi^{-1}(x_d)\end{pmatrix}\right\} \tag{10}$$

Simplified notation bivariate Gaussian copula

$$C_{\rho}^{Ga}\{w, g(w)\} = \Phi_{\rho}[\Phi^{-1}(w), \Phi^{-1}\{g(w)\}], \tag{11}$$

where $g(w) : [0,1] \mapsto \mathbb{R}$ is defined above, ρ is the dependency parameter of a bivariate Gaussian copula, Φ_{ρ} is bivariate normal distribution with mean 0 and covariance $\begin{bmatrix}1 & \rho\\ \rho & 1\end{bmatrix}$, $\Phi(\cdot)$ is CDF of standard normal, $\phi(\cdot)$ is PDF of standard normal, $\Phi^{-1}(\cdot)$ is quantile function of standard normal.

The bivariate $D_1 C^{Ga}\{w, g(w)\}$ is

$$D_1 C_{\rho}^{Ga}\{w, g(w)\} = \int_{-\infty}^{\Phi^{-1}\{g(w)\}} \phi_{\rho}\{\Phi^{-1}(w), u\} du \cdot \frac{1}{\phi\{\Phi^{-1}(w)\}} \tag{12}$$

Proof.

$$D_1 C_\rho\{w, g(w)\} = \left.\frac{\partial C_\rho\{w, g(w')\}}{\partial w}\right|_{w'=w} \tag{13}$$

$$= \left.\frac{\partial \Phi_\rho[\Phi^{-1}(w), \Phi^{-1}\{g(w)\}]}{\partial \Phi^{-1}(w)} \frac{\partial \Phi^{-1}(w)}{\partial w}\right|_{w'=w} \tag{14}$$

$$= \frac{1}{2\pi\rho} \int_{-\infty}^{\Phi^{-1}\{g(w)\}} \exp\left\{-\frac{1}{2(1-\rho^2)} \Phi^{-1}(w)^2 - 2\rho\Phi^{-1}(w)u + u^2\right\} du \cdot \frac{1}{\phi\{\Phi^{-1}(w)\}} \tag{15}$$

□

The bivariate Gaussian Copula density $c^{Ga}\{w, g(w)\}$ is

$$c_\rho^{Ga}\{w, g(w)\} = \frac{\partial D_1 C_\rho^{Ga}\{w, g(w)\}}{\partial g(w)} \tag{16}$$

$$= \frac{\phi_\rho[\Phi^{-1}(w), \Phi^{-1}\{g(w)\}]}{\phi\{\Phi^{-1}(w)\}\phi[\Phi^{-1}\{g(w)\}]} \tag{17}$$

4.4. t-copulae

The t copula is to represent the dependency structure by t distribution (Fang *et al.*, 2002; Embrechts *et al.*, 2002). Demarta and McNeil (2005) extend this idea to skewed t copula and grouped t copula to allow more flexibility in the modelling of dependency structure.

4.4.1. Vanilla t-copula

The t-copula is

$$C^t_{\nu,\Sigma}(x) = \int_{-\infty}^{t_\nu^{-1}(x_1)} \cdots \int_{-\infty}^{t_\nu^{-1}(x_n)} \frac{\Gamma\left\{\frac{\nu+i}{2}\right\}}{\Gamma\left\{\frac{\nu}{2}\right\}(\pi\nu)^{i/2}|\Sigma|^{1/2}} \left(1 + \frac{y^\top \Sigma^{-1} y}{\nu}\right)^{-\frac{\nu+i}{2}} dy_1 \dots dy_n, \tag{18}$$

where t_ν^{-1} is the quantile function of a univariate student-t distribution with degree of freedom ν.

4.4.2. Skewed t copula

Mean variance mixture

4.4.3. Double-t copula

Hull and White (2006) present an alternative way to the Gaussian copula for valuing CDO tranches. The double-t copula model is a weighted sum of a common (or market) variable M and a idiosyncratic variable Z_i. The double-t copula is

$$X_i = w_i M + \sqrt{1 - w_i^2} Z_i \tag{19}$$

where M and Z_i are independent random variables with zero mean and unit variance, and X_i is an indicator variable for i^{th} asset. The authors map the time to default of the i^{th} obligor, t_i, to X_i,

$$F_{X_i}(x) = F_{t_i}(t). \tag{20}$$

In our case, we map X_i to log-returns of portfolio constituents,

$$F_{X_1}(x) = F_{r^S}(s) \text{ and } F_{X_2}(x) = F_{r^F}(t). \tag{21}$$

This is also known as percentile-to-percentile mapping(Hull, 2006). The reason for this mapping is to turn incomprehensible dependency structures into known structure.

4.4.4. Normal Inverse Gaussian Copula

Normal Inverse Gaussian (NIG) distribution is a flexible 4-parameter distribution that can produce fat tails and skewness, unlike student-t distribution, NIG's convolution is stable under certain conditions and the CDF, PDF and quantile function can still be computed sufficiently fast (Schlösser, 2011, chapter 5). NIG distribution is a mixture of normal and inverse Gaussian distribution.

Definition 2. Inverse Gaussian Distribution. A non-negative random variable Y has an Inverse Gaussian (IG) distribution with parameters $\alpha > 0$ and $\beta > 0$ if its density funcion is of the form

$$f_{\mathrm{IG}}(y; \alpha, \beta) = \frac{\alpha}{\sqrt{2\pi\beta}} y^{-1.5} \exp\left\{-\frac{(\alpha - \beta z)^2}{2\beta z}\right\} \tag{22}$$

The corresponding distribution function is:

$$F_{\mathrm{IG}}(y; \alpha, \beta) = \frac{\alpha}{\sqrt{2\pi\beta}} \int_0^y z^{-1.5} \exp\left\{-\frac{(\alpha - \beta z)^2}{2\beta z}\right\} dz. \tag{23}$$

We write $Y \sim \mathrm{IG}(\alpha, \beta)$.

Definition 3. Normal Inverse Gaussian Distribution. A random variable X has an Normal Inverse Gaussian (NIG) distribution with parameters α, β, μ and δ if its density funcion is of the form

$$X|Y = y \sim \Phi(\mu + \beta y, y) \tag{24}$$

$$Y \sim \mathrm{IG}(\delta\gamma, \gamma^2) \text{ with } \gamma \stackrel{\text{def}}{=} \sqrt{\alpha^2 - \beta^2} \tag{25}$$

The corresponding distribution function is:

$$F_{\mathrm{NIG}}(y; \alpha, \beta) = \frac{\alpha}{\sqrt{2\pi\beta}} \int_0^y z^{-1.5} \exp\left\{-\frac{(\alpha - \beta z)^2}{2\beta z}\right\} dz. \tag{26}$$

5. Estimation

5.1. Two-Stage Estimation

Joe (2005) study the efficiency of a two-stage estimation procedure of copula estimation. The authors also call this method inference function for margins IFM.

Pros

1. Almost as efficient as MLE methods but easier to be implemented
2. Yields an asymptotically Gaussian, unbiased estimate

Cons

1. Subject to specification of marginals Kim *et al.* (2007)

Our data

$$\boldsymbol{y} = \begin{bmatrix} y_{11} & \cdots & y_{1i} \\ \vdots & \ddots & \vdots \\ y_{n1} & \cdots & y_{ni} \end{bmatrix} \tag{27}$$

Let F and f be the joint cdf and joint density of $\boldsymbol{y}$ with parameters $\boldsymbol{\delta}$, and let F_i and f_i be the marginal cdf and marginal density for the i^{th} random variable with parameters $\boldsymbol{\theta}_i$, we have

$$f(\boldsymbol{y};\boldsymbol{\theta}_1,\boldsymbol{\theta}_2,\ldots\boldsymbol{\theta}_i,\boldsymbol{\delta}) = c\{F_1(\boldsymbol{y}_1;\boldsymbol{\theta}_1),F_2(\boldsymbol{y}_2;\boldsymbol{\theta}_2),\ldots,F_i(\boldsymbol{y}_1;\boldsymbol{\theta}_i);\boldsymbol{\delta}\}\prod_{j=1}^{i} f_i(\boldsymbol{y}_j;\boldsymbol{\theta}_j) \tag{28}$$

For a sample of size n, the log-likelihood of functions of the i^{th} univariate margin is

$$L_i(\theta_i) = \sum_{m=1}^{n} \log f_i(y_{mi};\theta_i), \tag{29}$$

and the log-likelihood function for the joint distribution is

$$L(\delta, \theta_1, \theta_2, \dots, \theta_i) = \sum_{m=1}^{n} \sum_{j=1}^{i} \log f(y_{mj}; \delta, \theta_1, \theta_2, ..., \theta_i) \tag{30}$$

In most cases, one does not have closed form estimators and numerical techniques are needed. Numerical ML estimation difficulty increase when the total number of parameters increases. The two-stage estimation is designed to overcome this problem.

The two-stage procedure is

1. estimate the univariate parameters from separate univariate likelihoods to get $\tilde{\boldsymbol{\theta}}_1, ..., \tilde{\boldsymbol{\theta}}_i$
2. maximize $L(\boldsymbol{\delta}, \tilde{\boldsymbol{\theta}}_1, \dots, \tilde{\boldsymbol{\theta}}_i)$ over $\boldsymbol{\delta}$ to get $\tilde{\boldsymbol{\delta}}$

Under regularity conditions [2] , $(\tilde{\boldsymbol{\theta}}_1, \dots \tilde{\boldsymbol{\theta}}_i, \tilde{\boldsymbol{\delta}})$ is the solution of

$$(\partial L_1/\partial \boldsymbol{\theta}_1^\intercal, \dots, \partial L_i/\partial \boldsymbol{\theta}_i^\intercal, \partial L/\partial \boldsymbol{\delta}_1^\intercal) = \mathbf{0} \tag{31}$$

For comparison, if we optimize L directly without the two-stage procedure (i.e. MLE), we solve for

$$(\partial L/\partial \boldsymbol{\theta}_1^\intercal, \dots, \partial L/\partial \boldsymbol{\theta}_i^\intercal, \partial L/\partial \boldsymbol{\delta}_1^\intercal) = \mathbf{0} \tag{32}$$

We denote the two solutions as $\tilde{\boldsymbol{\eta}} = (\tilde{\boldsymbol{\theta}}_1, \dots \tilde{\boldsymbol{\theta}}_i, \tilde{\boldsymbol{\delta}})$ for two-stage procedure; $\hat{\boldsymbol{\eta}} = (\hat{\boldsymbol{\theta}}_1, \dots \hat{\boldsymbol{\theta}}_i, \hat{\boldsymbol{\delta}})$ for MLE procedure. and compare the asymptotic relative efficiency of $\tilde{\boldsymbol{\eta}}$ and $\hat{\boldsymbol{\eta}}$.

Asymptotics: yet to be done.

Kim *et al.* (2007) show the estimation of $\boldsymbol{\theta}$ may be seriously affected. They compare the two-stage approach and Canonical Maximum Likelihood Method by simulation and conclude that Canonical Maximum Likelihood is prefered from a computational statistics and data analysis point of view.

[2]Regularity conditions include 1. $\exists \frac{\partial \log f(x;\theta)}{\partial \theta}, \frac{\partial^2 \log f(x;\theta)}{\partial \theta^2}, \frac{\partial^3 \log f(x;\theta)}{\partial \theta^3}$ for all x; 2. $\exists g(x), h(x) and H(x)$ such that for θ in a neighborhood $N(\theta_0)$ the relations $\left|\frac{\partial f(x;\theta)}{\partial theta}\right| \leq g(x)$, $\left|\frac{\partial^2 f(x;\theta)}{\partial \theta^2}\right| \leq h(x)$, $\left|\frac{\partial^3 f(x;\theta)}{\partial \theta^3}\right| \leq H(x)$ hold for all x, and $\int g(x)dx < \infty$, $\int h(x)dx < \infty$, $\mathbb{E}_\theta\{H(X)\} < \infty$ for $\theta \in N(\theta_0)$; 3. For each $\theta \in \Theta$, $0 < \mathbb{E}_\theta \left\{ \left(\frac{\partial \log f(X;\theta)}{\partial \theta} \right)^2 \right\}$. For detail see section 4.2.2 of Serfling (2009)

5.2. Canonical Maximum Likelihood Method

This approach was studied by Genest *et al.* (1995) and Shih and Louis (1995). One estimates the margins using empirical CDF

$$F_X(x) = \frac{1}{n+1} \sum_{i=1}^{n} 1(X_i \leq x) \tag{33}$$

,

we maximize the log-likelihood

$$L(\delta) = \sum_{i=1}^{n} \log[c_\delta\{F_X(X_i), F_Y(Y_i)\}] \tag{34}$$

This procedure does not require specification of marginals.

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