## Archimax Copulas

## Arthur Charpentier

charpentier.arthur@uqam.ca
http ://freakonometrics.hypotheses.org/
based on joint work with

A.-L. Fougères, C. Genest and J. Nešlehová

## UQĀM .ill Quantact <br> Université du Québec à Montréal

March 2014, CIMAT, Guanajuato, Mexico.


## Agenda

- Copulas
- Standard copula families
- Elliptical distributions (and copulas)
- Archimedean copulas
- Extreme value distributions (and copulas)
- Archimax copulas
- Archimax copulas in dimension 2
- Archimax copulas in dimension $d \geq 3$


## Copulas, in dimension $d=2$

## Definition 1

A copula in dimension 2 is a c.d.f on $[0,1]^{2}$, with margins $\mathcal{U}([0,1])$.

Thus, let $C(u, v)=\mathbb{P}(U \leq u, V \leq v)$, where $0 \leq u, v \leq 1$, then

- $C(0, x)=C(x, 0)=0 \quad \forall x \in[0,1]$,
- $C(1, x)=C(x, 1)=x \quad \forall x \in[0,1]$,
- and some increasingness property



## Copulas, in dimension $d=2$

## Definition 2

A copula in dimension 2 is a c.d.f on $[0,1]^{2}$, with margins $\mathcal{U}([0,1])$.

Thus, let $C(u, v)=\mathbb{P}(U \leq u, V \leq v)$,
where $0 \leq u, v \leq 1$, then

- $C(0, x)=C(x, 0)=0 \quad \forall x \in[0,1]$,
- $C(1, x)=C(x, 1)=x \quad \forall x \in[0,1]$,
- If $0 \leq u_{1} \leq u_{2} \leq 1,0 \leq v_{1} \leq v_{2} \leq 1$
$C\left(u_{2}, v_{2}\right)+C\left(u_{1}, v_{1}\right) \geq C\left(u_{1}, v_{2}\right)+C\left(u_{2}, v_{1}\right)$
(concept of 2-increasing function in $\mathbb{R}^{2}$ )
see $C(u, v)=\int_{0}^{v} \int_{0}^{u} \underbrace{c(x, y)}_{\geq 0} \mathrm{~d} x \mathrm{~d} y$ with the density notation.


## Copulas, in dimension $d \geq 2$

The concept of $d$-increasing function simply means that

$$
\mathbb{P}\left(a_{1} \leq U_{1} \leq b_{1}, \ldots, a_{d} \leq U_{d} \leq b_{d}\right)=\mathbb{P}(\boldsymbol{U} \in[\boldsymbol{a}, \boldsymbol{b}]) \geq 0
$$

where $\boldsymbol{U}=\left(U_{1}, \ldots, U_{d}\right) \sim C$ for all $\boldsymbol{a} \leq \boldsymbol{b}$ (where $a_{i} \leq b i$ ).
Definition 3
Function $h: \mathbb{R}^{d} \rightarrow \mathbb{R}$ is $d$-increasing if for all rectangle $[\boldsymbol{a}, \boldsymbol{b}] \subset \mathbb{R}^{d}, V_{h}([\boldsymbol{a}, \boldsymbol{b}]) \geq 0$, where

$$
\begin{equation*}
V_{h}([\boldsymbol{a}, \boldsymbol{b}])=\Delta_{\boldsymbol{a}}^{\boldsymbol{b}} h(\boldsymbol{t})=\Delta_{a_{d}}^{b_{d}} \Delta_{a_{d-1}}^{b_{d-1}} \ldots \Delta_{a_{2}}^{b_{2}} \Delta_{a_{1}}^{b_{1}} h(\boldsymbol{t}) \tag{1}
\end{equation*}
$$

and for all $t$, with

$$
\begin{equation*}
\Delta_{a_{i}}^{b_{i}} h(\boldsymbol{t})=h\left(t_{1}, \ldots, t_{i-1}, b_{i}, t_{i+1}, \ldots, t_{n}\right)-h\left(t_{1}, \ldots, t_{i-1}, a_{i}, t_{i+1}, \ldots, t_{n}\right) \tag{2}
\end{equation*}
$$

## Copulas, in dimension $d \geq 2$

## Definition 4

A copula in dimension $d$ is a c.d.f on $[0,1]^{d}$, with margins $\mathcal{U}([0,1])$.
Theorem 1 . If $C$ is a copula, and $F_{1}, \ldots, F_{d}$ are univariate c.d.f., then

$$
\begin{equation*}
F\left(x_{1}, \ldots, x_{n}\right)=C\left(F_{1}\left(x_{1}\right), \ldots, F_{d}\left(x_{d}\right)\right) \forall\left(x_{1}, \ldots, x_{d}\right) \in \mathbb{R}^{d} \tag{3}
\end{equation*}
$$

is a multivariate c.d.f. with $F \in \mathcal{F}\left(F_{1}, \ldots, F_{d}\right)$.
2. Conversely, if $F \in \mathcal{F}\left(F_{1}, \ldots, F_{d}\right)$, there exists a copula $C$ satisfying (3). This copula is usually not unique, but it is if $F_{1}, \ldots, F_{d}$ are absolutely continuous, and then,

$$
\begin{equation*}
C\left(u_{1}, \ldots, u_{d}\right)=F\left(F_{1}^{-1}\left(u_{1}\right), \ldots, F_{d}^{-1}\left(u_{d}\right)\right), \quad \forall\left(u_{1},, \ldots, u_{d}\right) \in[0,1]^{d} \tag{4}
\end{equation*}
$$

where quantile functions $F_{1}^{-1}, \ldots, F_{n}^{-1}$ are generalized inverse (left cont.) of $F_{i}$ 's.
If $\boldsymbol{X} \sim F$, then $\boldsymbol{U}=\left(F_{1}\left(X_{1}\right), \cdots, F_{d}\left(X_{d}\right)\right) \sim C$.

## Survival (or dual) copulas

Theorem 2 1. If $C^{\star}$ is a copula, and $\bar{F}_{1}, \ldots, \bar{F}_{d}$ are univariate s.d.f., then

$$
\begin{equation*}
\bar{F}\left(x_{1}, \ldots, x_{n}\right)=C^{\star}\left(\bar{F}_{1}\left(x_{1}\right), \ldots, \bar{F}_{d}\left(x_{d}\right)\right) \forall\left(x_{1}, \ldots, x_{d}\right) \in \mathbb{R}^{d} \tag{5}
\end{equation*}
$$

is a multivariate s.d.f. with $F \in \mathcal{F}\left(F_{1}, \ldots, F_{d}\right)$.
2. Conversely, if $F \in \mathcal{F}\left(F_{1}, \ldots, F_{d}\right)$, there exists a copula $C^{\star}$ satisfying (5). This copula is usually not unique, but it is if $F_{1}, \ldots, F_{d}$ are absolutely continuous, and then,

$$
\begin{equation*}
C^{\star}\left(u_{1}, \ldots, u_{d}\right)=\bar{F}\left(\bar{F}_{1}^{-1}\left(u_{1}\right), \ldots, \bar{F}_{d}^{-1}\left(u_{d}\right)\right), \quad \forall\left(u_{1},, \ldots, u_{d}\right) \in[0,1]^{d} \tag{6}
\end{equation*}
$$

where quantile functions $F_{1}^{-1}, \ldots, F_{n}^{-1}$ are generalized inverse (left cont.) of $F_{i}$ 's.
If $\boldsymbol{X} \sim F$, then $\boldsymbol{U}=\left(F_{1}\left(X_{1}\right), \cdots, F_{d}\left(X_{d}\right)\right) \sim C$ and $\mathbf{1}-\boldsymbol{U} \sim C^{\star}$.

## Benchmark copulas

## Definition 5

The independent copula $C^{\perp}$ is defined as

$$
C^{\perp}\left(u_{1}, \ldots, u_{n}\right)=u_{1} \times \cdots \times u_{d}=\prod_{i=1}^{d} u_{i}
$$

## Definition 6

The comonotonic copula $C^{+}$(the Fréchet-Hoeffding upper bound of the set of copulas) is the copula defined as $C^{+}\left(u_{1}, \ldots, u_{d}\right)=\min \left\{u_{1}, \ldots, u_{d}\right\}$.


## Spherical distributions

## Definition 7

Random vector $\boldsymbol{X}$ as a spherical distribution if

$$
\boldsymbol{X}=R \cdot \boldsymbol{U}
$$


where $R$ is a positive random variable and $\boldsymbol{U}$ is uniformly distributed on the unit sphere of $\mathbb{R}^{d}$, with $R \Perp \boldsymbol{U}$.
E.g. $\boldsymbol{X} \sim \mathcal{N}(\mathbf{0}, \mathbb{I})$.


Those distribution can be non-symmetric, see Hartman \& Wintner (AJM, 1940) or Cambanis, Huang \& Simons (JMVA, 1979))

## Elliptical distributions

## Definition 8

Random vector $\boldsymbol{X}$ as a elliptical distribution if

$$
\boldsymbol{X}=\boldsymbol{\mu}+R \cdot \boldsymbol{A} \cdot \boldsymbol{U}
$$

where $R$ is a positive random variable and $\boldsymbol{U}$ is uniformly distributed on the unit sphere of $\mathbb{R}^{d}$, with $R \Perp \boldsymbol{U}$, and where $A$ satisfies $\boldsymbol{A} \boldsymbol{A}^{\prime}=\boldsymbol{\Sigma}$.
E.g. $\boldsymbol{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.


Elliptical distribution are popular in finance, see e.g. Jondeau, Poon \& Rockinger (FMPM, 2008)

## Archimedean copula

## Definition 9

If $d \geq 2$, an Archimedean generator is a function $\phi:[0,1] \rightarrow[0, \infty)$ such that $\phi^{-1}$ is $d$-completely monotone (i.e. $\psi$ is $d$-completely monotone if $\psi$ is continuous and $\left.\forall k=0,1, \ldots, d,(-1)^{k} \mathrm{~d}^{k} \psi(t) / \mathrm{d} t^{k} \geq 0\right)$.
Definition 10
Copula $C$ is an Archimedean copula is, for some generator $\phi$,

$$
C\left(u_{1}, \ldots, u_{d}\right)=\phi^{-1}\left[\phi\left(u_{1}\right)+\ldots+\phi\left(u_{d}\right)\right], \forall u_{1}, \ldots, u_{d} \in[0,1] .
$$

## Exemple1

$\phi(t)=-\log (t)$ yields the independent copula $C^{\perp}$.
$\phi(t)=[-\log (t)]^{\theta}$ yields Gumbel copula $C_{\theta}$ (note that $\psi(t)=\phi^{-1}(t)=\exp \left[-t^{1 / \theta}\right]$ ).

## Archimedean copula, exchangeability and frailties

Consider residual life times $\boldsymbol{X}=\left(X_{1}, \cdots, X_{d}\right)$ conditionally independent given some latent factor $\Theta$, and such that $\mathbb{P}\left(X_{i}>x_{i} \mid \Theta=\theta\right)=\bar{B}_{i}\left(x_{i}\right)^{\theta}$. Then

$$
\bar{F}(\boldsymbol{x})=\mathbb{P}(\boldsymbol{X}>\boldsymbol{x})=\psi\left(-\sum_{i=1}^{n} \log \bar{F}_{i}\left(x_{i}\right)\right)
$$

where $\psi$ is the Laplace transform of $\Theta, \psi(t)=\mathbb{E}\left(e^{-t \Theta}\right)$. Thus, the survival copula of $\boldsymbol{X}$ is Archimedean, with generator $\phi=\psi^{-1}$.
See Oakes (JASA, 1989).

Conditional independence, continuous risk factor


Conditional independence, continuous risk factor


## Stochastic representation of Archimedean copulas

Consider some striclty positive random variable $R$ independent of $\boldsymbol{U}$, uniform on the simplex of $\mathbb{R}^{d}$. The survival copula of $\boldsymbol{X}=R \cdot \boldsymbol{U}$ is Archimedean, and its generator is the inverse of Williamson $d$ transform,


$$
\phi^{-1}(t)=\int_{x}^{\infty}\left(1-\frac{x}{t}\right)^{d-1} \mathrm{~d} F_{R}(t)
$$

Note that $R \stackrel{\mathcal{L}}{=} \phi\left(U_{1}\right)+\cdots+\phi\left(U_{d}\right)$.

See Nešlehová \& McNeil (AS, 2009).

## Archimedean copula and distortion

Definition 11
Function $h:[0,1] \rightarrow[0,1]$ defined as $h(t)=\exp [-\phi(t)]$ is called a distortion function.
Genest \& Rivest (SPL, 2001), Morillas (M, 2005) considered distorted copulas (also called multivariate probability integral transformation)
Definition 12
Let $h$ be some distortion function, and $C$ a copula, then

$$
C_{h}\left(u_{1}, \ldots, u_{d}\right)=h^{-1}\left(C\left(h\left(u_{1}\right), \cdots, h\left(u_{d}\right)\right)\right)
$$

is a copula.
Exemple2
If $C=C^{\perp}$, then $C_{h}^{\perp}$ is the Archimedean copula with generator $\phi(t)=-\log h(t)$.

## Nested Archimedean copula, and hierarchical structures

Consider $C\left(u_{1}, \cdots, u_{d}\right)$ defined as

$$
\phi_{1}^{-1}\left[\phi_{1}\left[\phi_{2}^{-1}\left(\phi_{2}\left[\cdots \phi_{d-1}^{-1}\left[\phi_{d-1}\left(u_{1}\right)+\phi_{d-1}\left(u_{2}\right)\right]+\cdots+\phi_{2}\left(u_{d-1}\right)\right)\right]+\phi_{1}\left(u_{d}\right)\right]\right.
$$

where $\phi_{i}$ 's are generators. Then $C$ is a copula if $\phi_{i} \circ \phi_{i-1}^{-1}$ is the inverse of a Laplace transform, and is called fully nested Archimedean copula. Note that partial nested copulas can also be considered,


## (Univariate) extreme value distributions

Central limit theorem, $X_{i} \sim F$ i.i.d. $\frac{\bar{X}_{n}-b_{n}}{a_{n}} \xrightarrow{\mathcal{L}} S$ as $n \rightarrow \infty$ where $S$ is a non-degenerate random variable.
Fisher-Tippett theorem, $X_{i} \sim F$ i.i.d., $\frac{X_{n: n}-b_{n}}{a_{n}} \xrightarrow{\mathcal{L}} M$ as $n \rightarrow \infty$ where $M$ is a non-degenerate random variable.

Then

$$
\mathbb{P}\left(\frac{X_{n: n}-b_{n}}{a_{n}} \leq x\right)=F^{n}\left(a_{n} x+b_{n}\right) \rightarrow G(x) \text { as } n \rightarrow \infty, \forall x \in \mathbb{R}
$$

i.e. $F$ belongs to the max domain of attraction of $G, G$ being an extreme value distribution : the limiting distribution of the normalized maxima.

$$
-\log G(x)=(1+\xi x)_{+}^{-1 / \xi}
$$

## (Multivariate) extreme value distributions

Assume that $\boldsymbol{X}_{i} \sim F$ i.i.d.,

$$
F^{n}\left(\boldsymbol{a}_{n} \boldsymbol{x}+\boldsymbol{b}_{n}\right) \rightarrow G(\boldsymbol{x}) \text { as } n \rightarrow \infty, \forall \boldsymbol{x} \in \mathbb{R}^{d}
$$

i.e. $F$ belongs to the max domain of attraction of $G, G$ being an (multivariate) extreme value distribution : the limiting distribution of the normalized componentwise maxima,

$$
\begin{gathered}
\boldsymbol{X}_{n: n}=\left(\max \left\{X_{1, i}\right\}, \cdots, \max \left\{X_{d, i}\right\}\right) \\
-\log G(\boldsymbol{x})=\mu([\mathbf{0}, \infty) \backslash[\mathbf{0}, \boldsymbol{x}]), \forall \boldsymbol{x} \in \mathbb{R}_{+}^{d}
\end{gathered}
$$

where $\mu$ is the exponent measure. It is more common to use the stable tail dependence function $\ell$ defined as

$$
\ell(\boldsymbol{x})=\mu\left([\mathbf{0}, \boldsymbol{\infty}) \backslash\left[\mathbf{0}, \boldsymbol{x}^{-1}\right]\right), \forall \boldsymbol{x} \in \mathbb{R}_{+}^{d}
$$

i.e.

$$
-\log G(\boldsymbol{x})=\ell\left(-\log G_{1}\left(x_{1}\right), \cdots, \log G_{d}\left(x_{d}\right)\right), \forall \boldsymbol{x} \in \mathbb{R}^{d}
$$

Note that there exists a finite measure $H$ on the simplex of $\mathbb{R}^{d}$ such that

$$
\ell\left(x_{1}, \cdots, x_{d}\right)=\int_{\mathcal{S}_{d}} \max \left\{\omega_{1} x_{1}, \cdots, \omega_{d} x_{d}\right\} d H\left(\omega_{1}, \cdots, \omega_{d}\right)
$$

for all $\left(x_{1}, \cdots, x_{d}\right) \in \mathbb{R}_{+}^{d}$, and $\int_{\mathcal{S}_{d}} \omega_{i} d H\left(\omega_{1}, \cdots, \omega_{d}\right)=1$ for all $i=1, \cdots, n$.
Definition 13
Copula $C:[0,1]^{d} \rightarrow[0,1]$ is an multivariate extreme value copula if and only if there exists a stable tail dependence function such that $\ell$

$$
C_{\ell}\left(u_{1}, \cdots, u_{d}\right)=\exp \left[-\ell\left(-\log u_{1}, \cdots,-\log u_{d}\right)\right]
$$

Assume that $\boldsymbol{U}_{i} \sim \Gamma$ i.i.d.,

$$
\Gamma^{n}\left(\boldsymbol{u}^{\frac{1}{n}}\right)=\Gamma^{n}\left(u_{1}^{\frac{1}{n}}, \cdots, u_{d}^{\frac{1}{n}}\right) \rightarrow C_{\ell}(\boldsymbol{u}) \text { as } n \rightarrow \infty, \forall \boldsymbol{x} \in \mathbb{R}^{d}
$$

i.e. $\Gamma$ belongs to the max domain of attraction of $C_{\ell}, C_{\ell}$ being an (multivariate) extreme value copula, $\Gamma \in \operatorname{MDA}\left(C_{\ell}\right)$.

## The stable tail dependence function $\ell(\cdot)$

Observe that
$n\left[1-C\left(1-\frac{x_{1}}{n}, \cdots, 1-\frac{x_{d}}{n}\right)\right] \rightarrow \underbrace{-\log \left[\Gamma\left(e^{-x_{1}}, \cdots, e^{-x_{1}}\right)\right]}_{=\ell(\boldsymbol{x})}$

## Exemple3

Gumbel copula, $\theta \in[1,+\infty]$,

$$
\ell_{\theta}\left(x_{1}, \cdots, x_{d}\right)=\left(x_{1}^{\theta}+\cdots+x_{d}^{\theta}\right)^{1 / \theta}=\|\boldsymbol{x}\|_{\theta} \quad \forall \boldsymbol{x} \in \mathbb{R}_{+}^{d}
$$



Function $\ell(\cdot)$ statisfies

$$
\underbrace{\max \left\{x_{1}, \cdots, x_{d}\right\}}_{\substack{\text { (asympt.) comonotonicity } \\ \ell_{\infty}(\boldsymbol{x})}} \leq \ell(\boldsymbol{x}) \leq \underbrace{x_{1}+\cdots+x_{d}}_{\substack{\text { (asympt.) independence } \\ \ell_{1}(\boldsymbol{x})}}
$$

## The stable tail dependence function $\ell(\cdot)$

Function $\ell(\cdot)$ is homogeneous, $\ell(t \cdot \boldsymbol{x})=t \cdot \ell(\boldsymbol{x}) \forall t \in \mathbb{R}_{+}$.
$\longrightarrow$ consider the restriction of $\ell(\cdot)$ on the unit simplex $\Delta_{d-1}$,

$$
\ell(\boldsymbol{x})=\|\boldsymbol{x}\|_{1} \cdot \underbrace{\ell\left(\frac{x_{1}}{\|\boldsymbol{x}\|}, \cdots, \frac{x_{d}}{\|\boldsymbol{x}\|}\right)}_{\ell(\boldsymbol{\omega})}=\|\boldsymbol{x}\|_{1} \cdot A\left(\omega_{1}, \cdots, \omega_{d-1}\right)
$$

where $A(\cdot)$ is Pickands dependence function. Observe that

$$
\max \left\{\omega_{1}, \cdots, \omega_{d-1}, \omega_{d}\right\} \leq A\left(\omega_{1}, \cdots, \omega_{d-1}\right) \leq 1, \quad \forall \boldsymbol{\omega} \in \Delta_{d-1}
$$

## What do we have in dimension 2 ?

$C$ is an Archimedean copula if $C=C_{\phi}$

$$
C_{\phi}(u, v)=\phi^{-1}[\phi(u)+\phi(v)]
$$

$C$ is an extreme value copula if $C=C_{A}=C_{\ell}$

$$
\left\{\begin{array}{l}
C_{A}(u, v)=\exp \left(\log [u v] A\left(\frac{\log [v]}{\log [u v]}\right)\right) \\
C_{\ell}(u, v)=\exp [-\ell(-\log u,-\log v)]
\end{array}\right.
$$

where $A:[0,1] \rightarrow[1 / 2,1]$ is Pickands dependence function, convex, with

$$
\max \{\omega, 1-\omega\} \leq A(\omega) \leq 1, \forall \omega \in[0,1]
$$

## Exemple4

$A(\omega)=1$ yields the independent copula, $C^{\perp}$.

## What do we have in dimension 2 ?

## Exemple5

$\phi(t)=[-\log (t)]^{\theta}$ yields Gumbel copula $C_{\theta}$.
$A(\omega)=\left[\omega^{\theta}+(1-\omega)^{\theta}\right]^{1 / \theta}$ yields Gumbel copula $C_{\theta}$.
Definition 14
$C$ is an Archimax copula (from Capéerà, Fougères \& Genest (JMVA, 2000)) if
$C=C_{\phi, A}$

$$
C_{\phi, A}(u, v)=\phi^{-1}\left[[\phi(u)+\phi(v)] A\left(\frac{\phi(u)}{\phi(u)+\phi(v)}\right)\right]
$$

Note that there is a frailty type construction, see C. (K, 2006) : given $\Theta, \boldsymbol{X}$ has (survival) copula $C_{A}, \Theta$ has Laplace transform $\phi^{-1}$.
Note that $C_{\phi, A}$ is the distorted version of copula $C_{A}$.

## What do we have in dimension $d \geq 3$ ?

Definition 15
$C$ is an Archimax copula (from C., Fougères, Genest \& Nešlehová (JMVA, 2014)) if $C=C_{\phi, \ell}$

$$
C_{\phi, \ell}\left(u_{1}, \cdots, u_{d}\right)=\phi^{-1}\left[\ell\left(\phi\left(u_{1}\right)+\cdots+\phi\left(u_{d}\right)\right)\right]
$$

This function is a copula function.

## Stochastic representation of Archimax copulas

Theorem 3
$C_{\phi, \ell}$ is the survival copula of $\boldsymbol{X}=\boldsymbol{T} / \Theta$ where $\Theta$ has Laplace transform $\phi^{-1}$, independent of random vector $\boldsymbol{T}$ satisfying

$$
\mathbb{P}(\boldsymbol{T}>\boldsymbol{t})=\exp [-\ell(\boldsymbol{t})]=C_{\ell}\left(e^{-\boldsymbol{t}}\right)
$$

(see also Li (JMVA, 2009) and Marshall \& Olkin (JASA, 1988)).

## Limiting behavior of Archimax copulas

One can wonder what would be the max-domain of attraction of that copula?

$$
C_{\phi, \ell} \in \operatorname{MDA}\left(C_{\ell^{\star}}\right)
$$

If $\psi=\phi^{-1}$ is such that $\psi(1-s)$ is regularly varying at 0 with index $\theta \in[1,+\infty]$, then $C_{\phi, \ell}$ belongs to the max domain of attraction of

$$
C_{\ell^{\star}}\left(u_{1}, \cdots, u_{d}\right)=\exp \left[-\ell^{\frac{1}{\theta}}\left(\left|\log \left(u_{1}\right)\right|^{\theta}, \cdots,\left|\log \left(u_{d}\right)\right|^{\theta}\right)\right]
$$

(see also C. \& Segers (JMVA, 2009) and Larsson \& Nešlehová (AAP, 2011) in the case of Archimedean copulas).
forthcoming book (April 2014),
Computational Actuarial Science with R
for additional information
http ://freakonometrics.hypotheses.org/

## The R Series <br> Computational Actuarial Science with R


ctatred by
Arthur Charpentior

