


Generating Asset Return Scenarios using Copula Method



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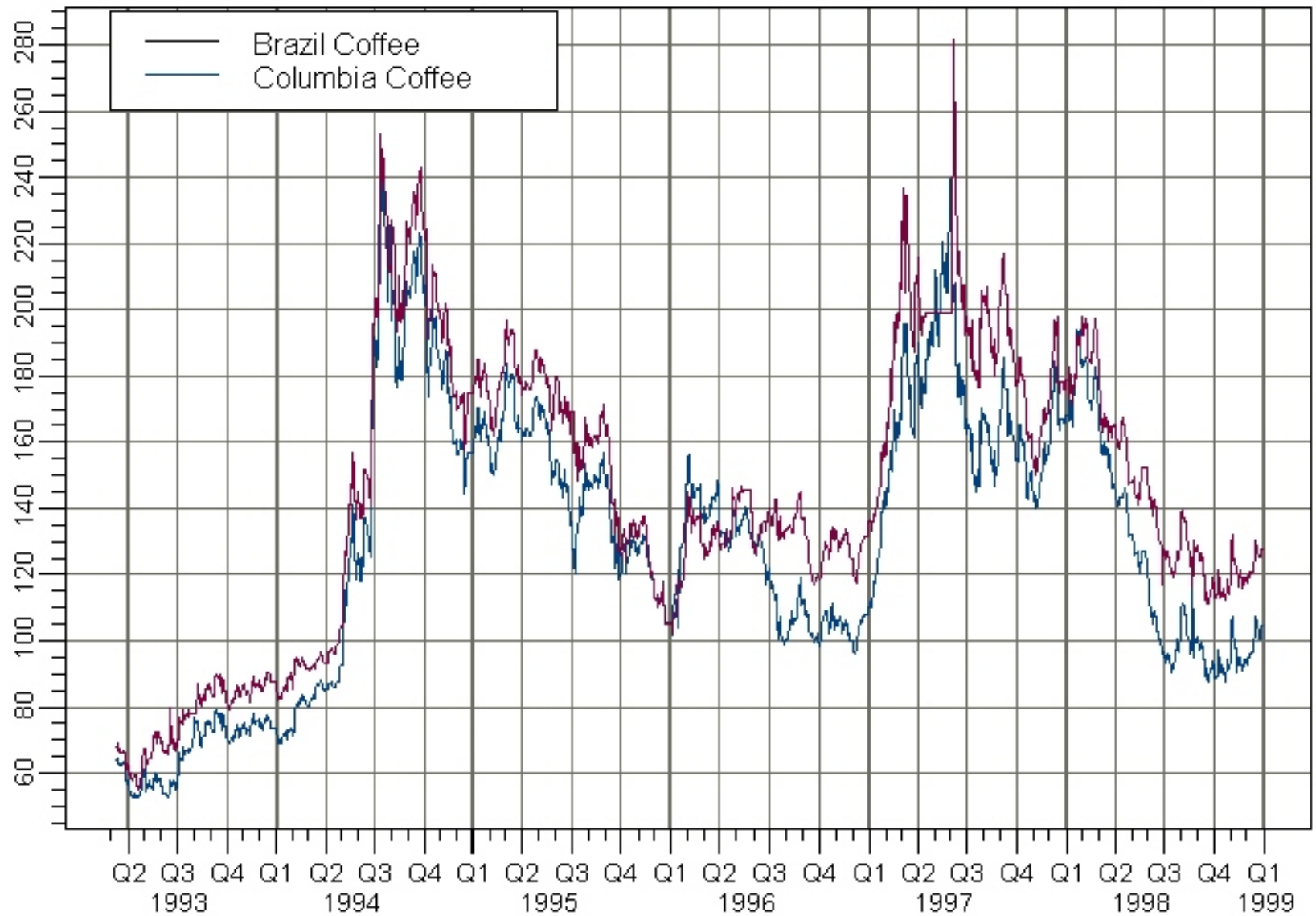
Motivation Example

Some coffee in the morning!

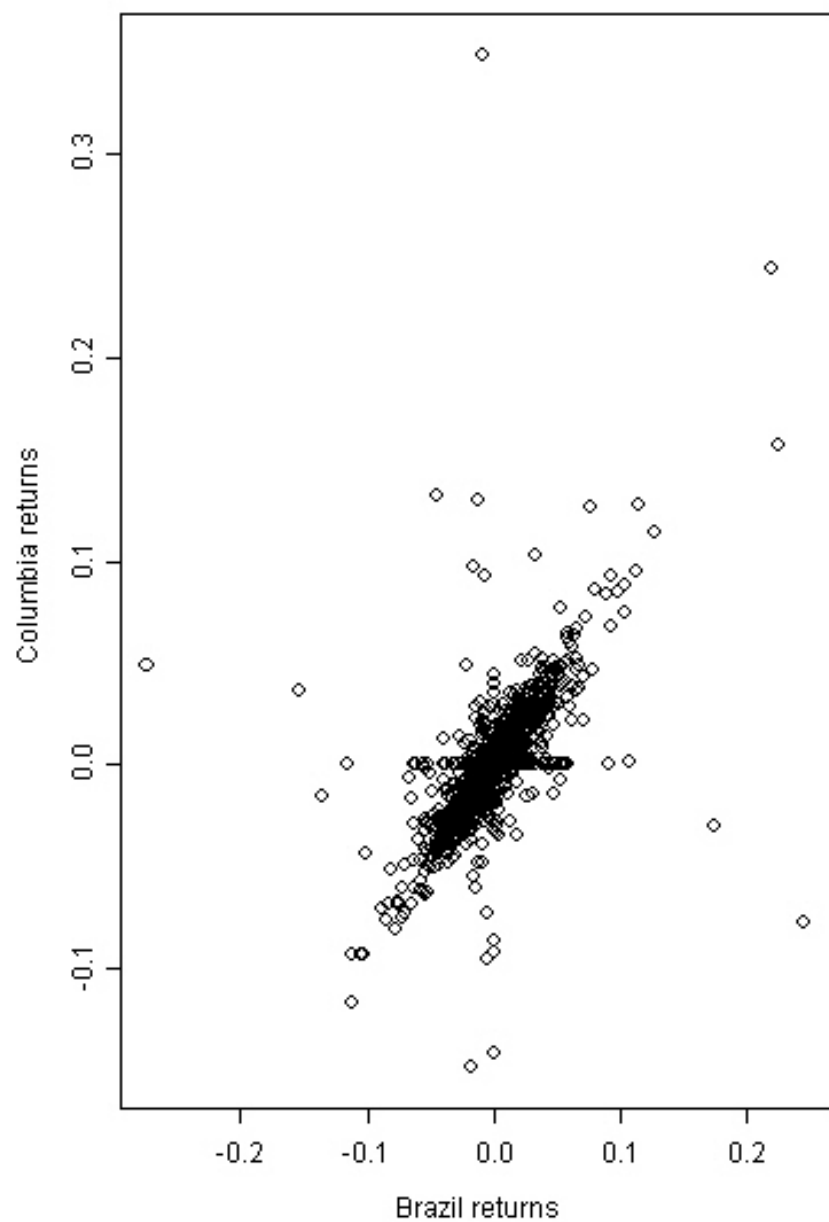
“Mathematician is a machine that turns
caffeine into theorems”

--Paul Erdos

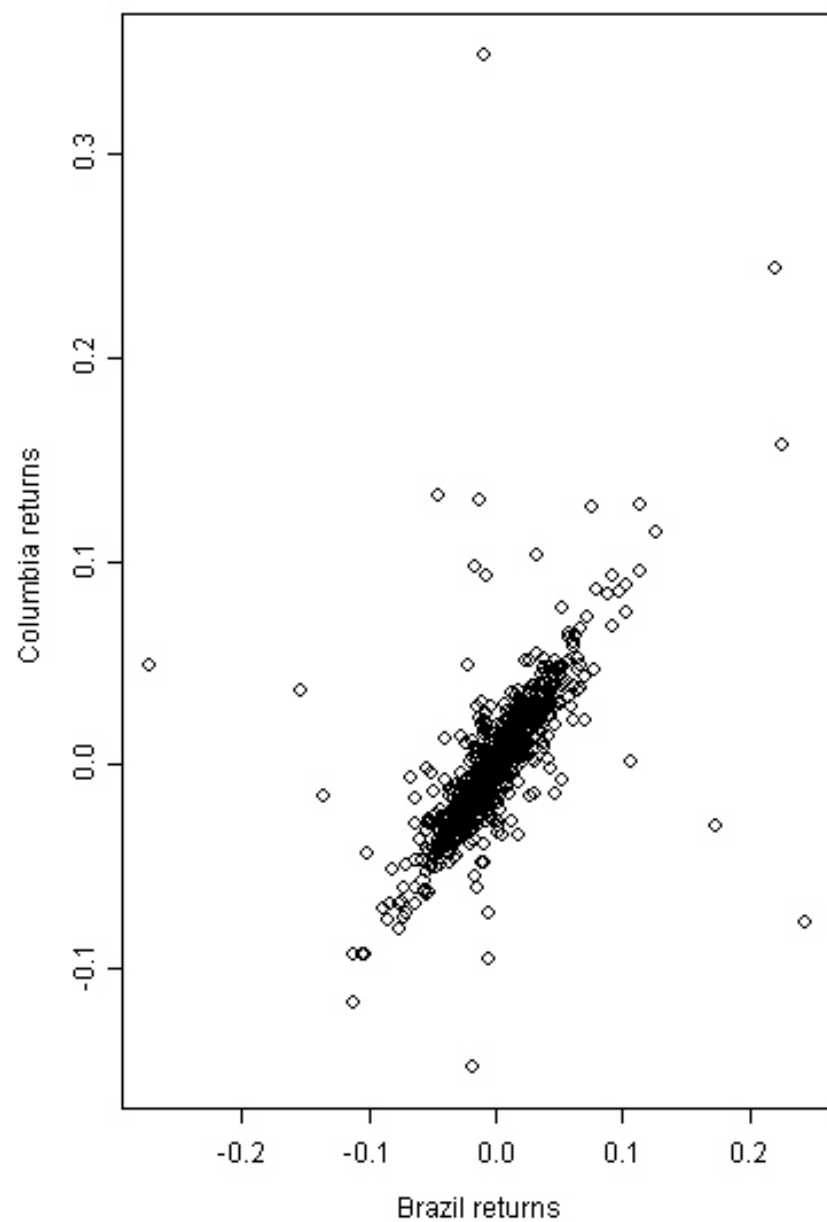
Daily Spot Price of Coffees



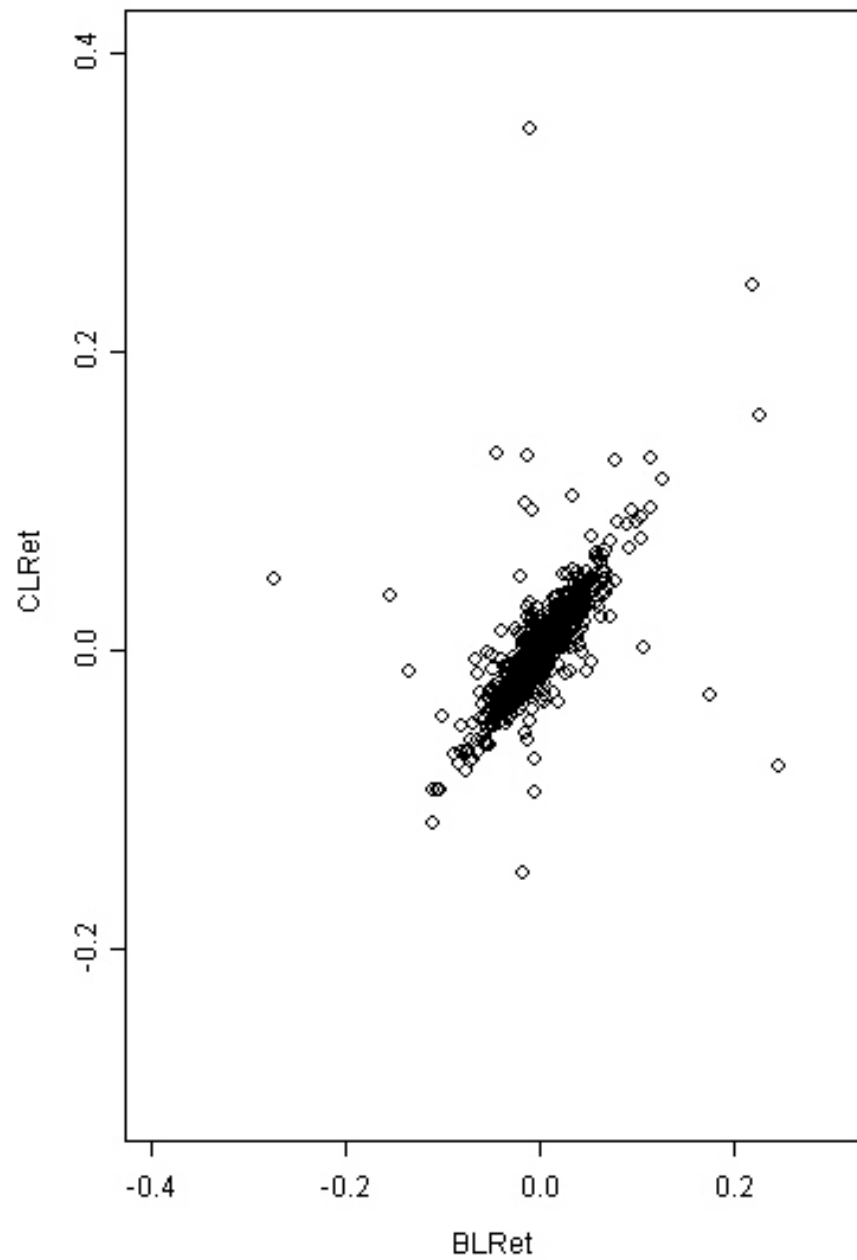
Zeros Retained



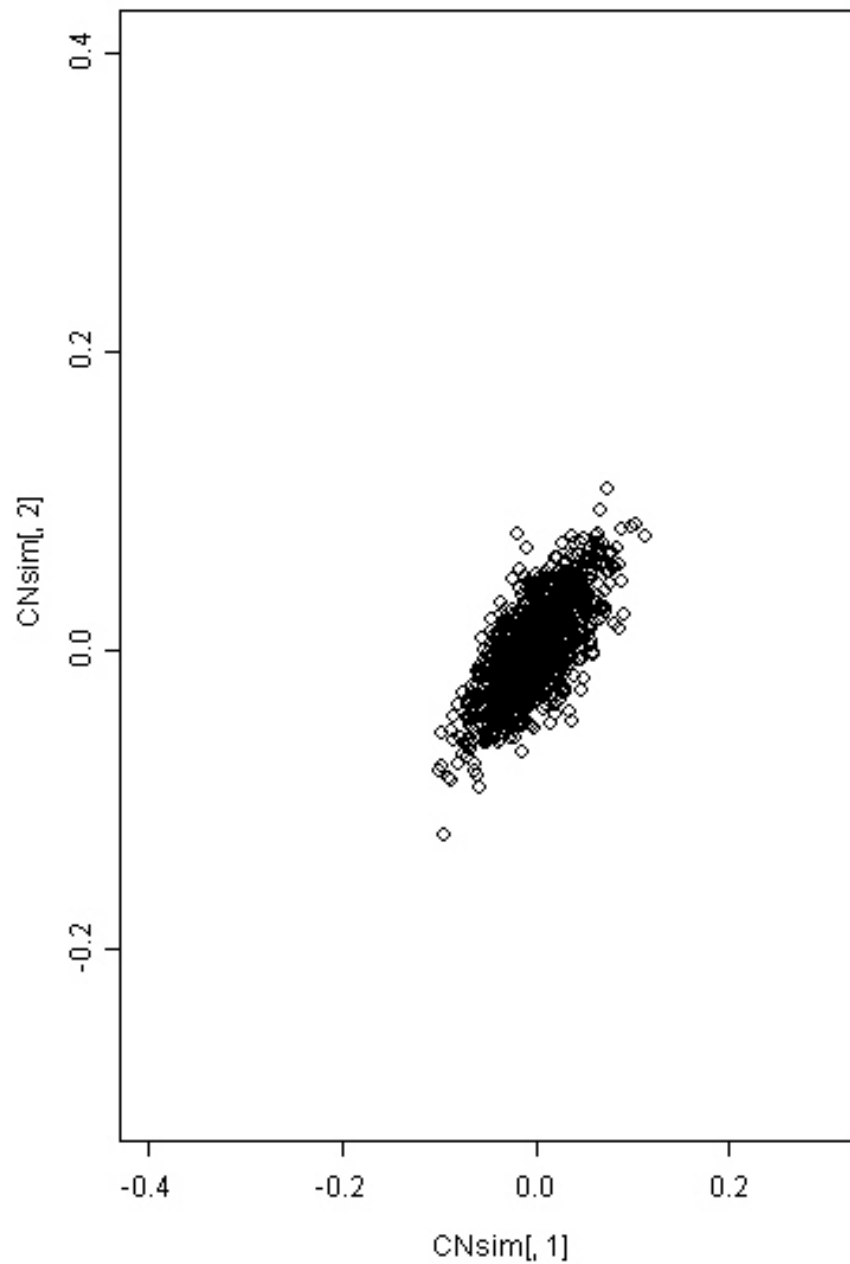
Zeros Removed



Actual Returns



Simulated Normal Returns



Motivations:

- We want to generate a set of returns for future scenarios.
Assuming we dismiss normality and generalise our simulation methodology in two main aspects:
 - We aim to allow marginal distributions that could take any arbitrary form.
 - We want to relax the modelling of dependence beyond the concept of correlation.

Problems

- How can we glue arbitrary return distributions together and still maintain their dependence structure?
- How can we model tail dependence and still keep the same marginal distributions?

Starter

□ Brief Historical Background

1940's: Hoeffding studied properties of multivariate distributions

1959: The word "Copula" appeared for the first time (Sklar 1959)

1998: Academic literature on how to use copulas in risk management (Embrechts et al. 1999)

2004: Some financial/insurance companies have started to use copulas as a risk management tool

X, Y r.v.;

$F(x), F(y)$

$F(x) = P[X \leq x], F(y) = P[Y \leq y]$

$H(x, y) = P[X \leq x, Y \leq y]$

	b1	b2	b3	...	b _k
a1	p _{1,1}	p _{1,2}	p _{1,3}	...	p _{1,k}
a2	p _{2,1}	p _{2,2}	p _{2,3}	...	p _{2,k}
...
...
a _m	p _{m,1}	p _{m,2}	p _{m,3}	...	p _{m,k}

$P(A=a_i \text{ and } B=a_j) := p_{i,j}$

Copula Function

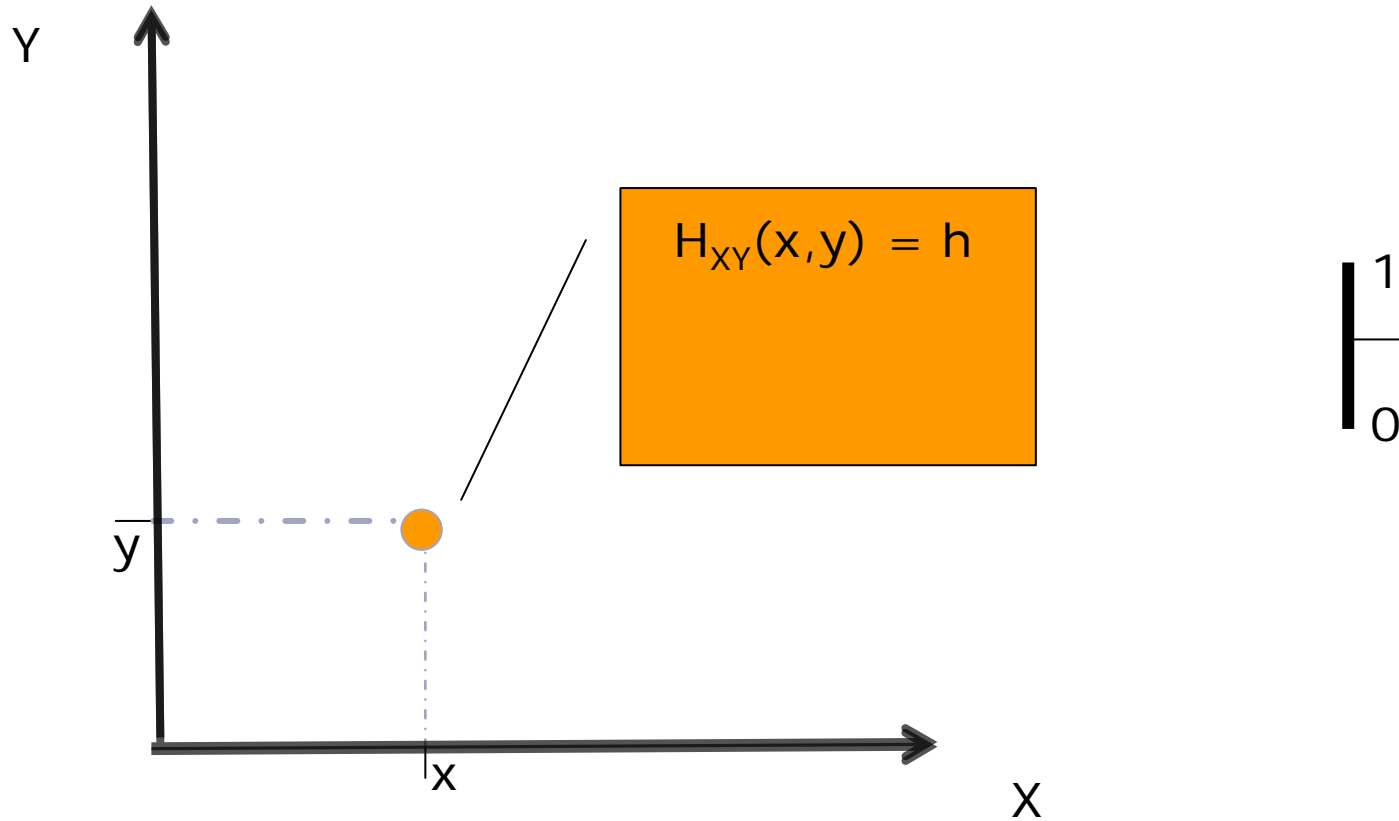
A copula is a multivariate distribution whose marginals are all uniform over $(0,1)$

$$C(u_1, \dots, u_d) = F(F_1^{-1}(u_1), F_2^{-1}(u_2), \dots, F_d^{-1}(u_d))$$

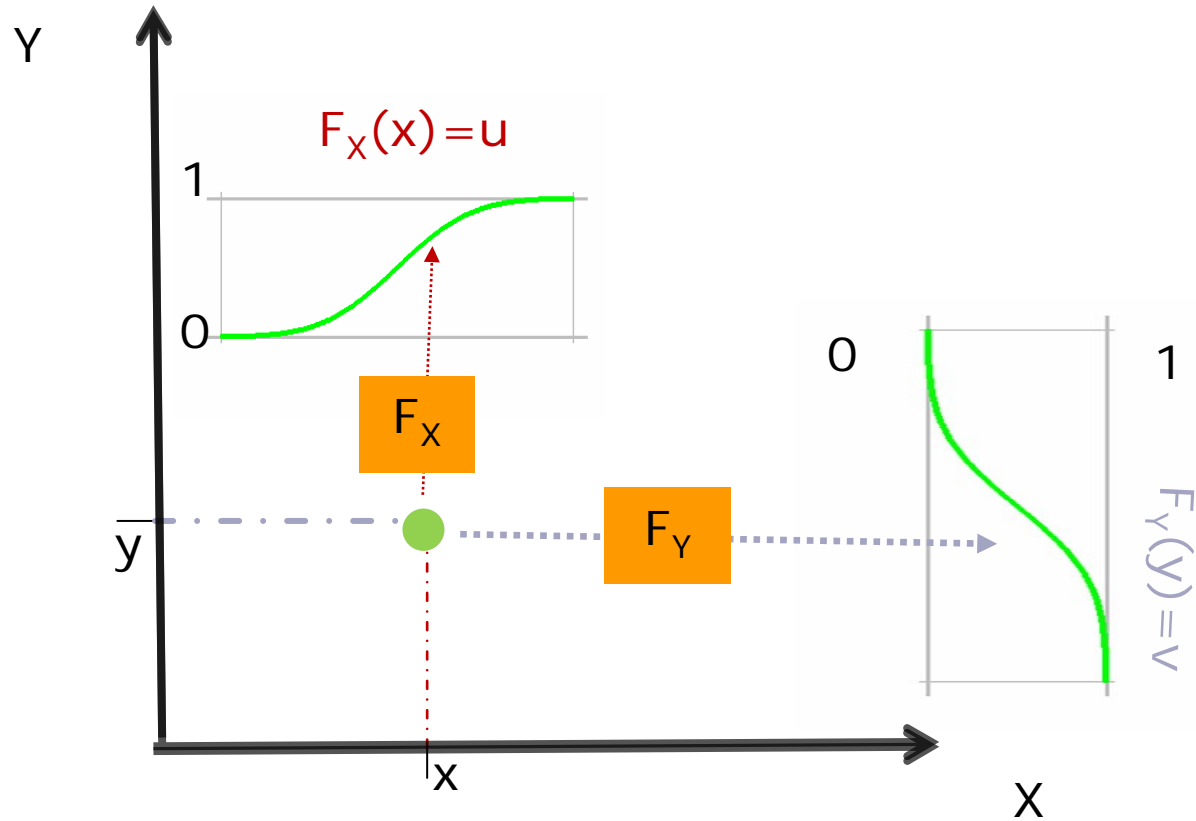
Sklar Theorem

$$H(x_1, \dots, x_d) = C(F_1(x_1), F_2(x_2), \dots, F_d(x_d))$$

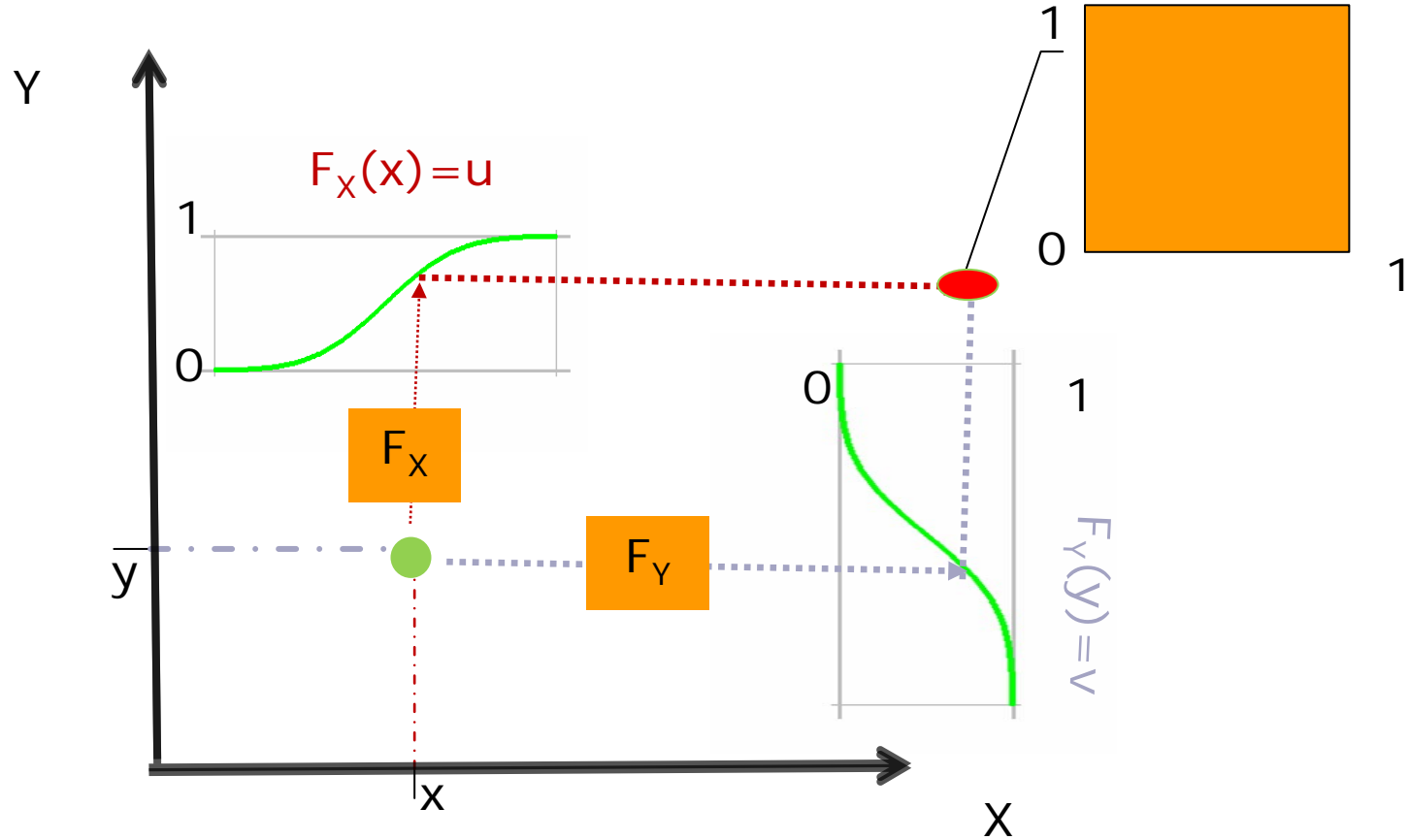
Copula Function



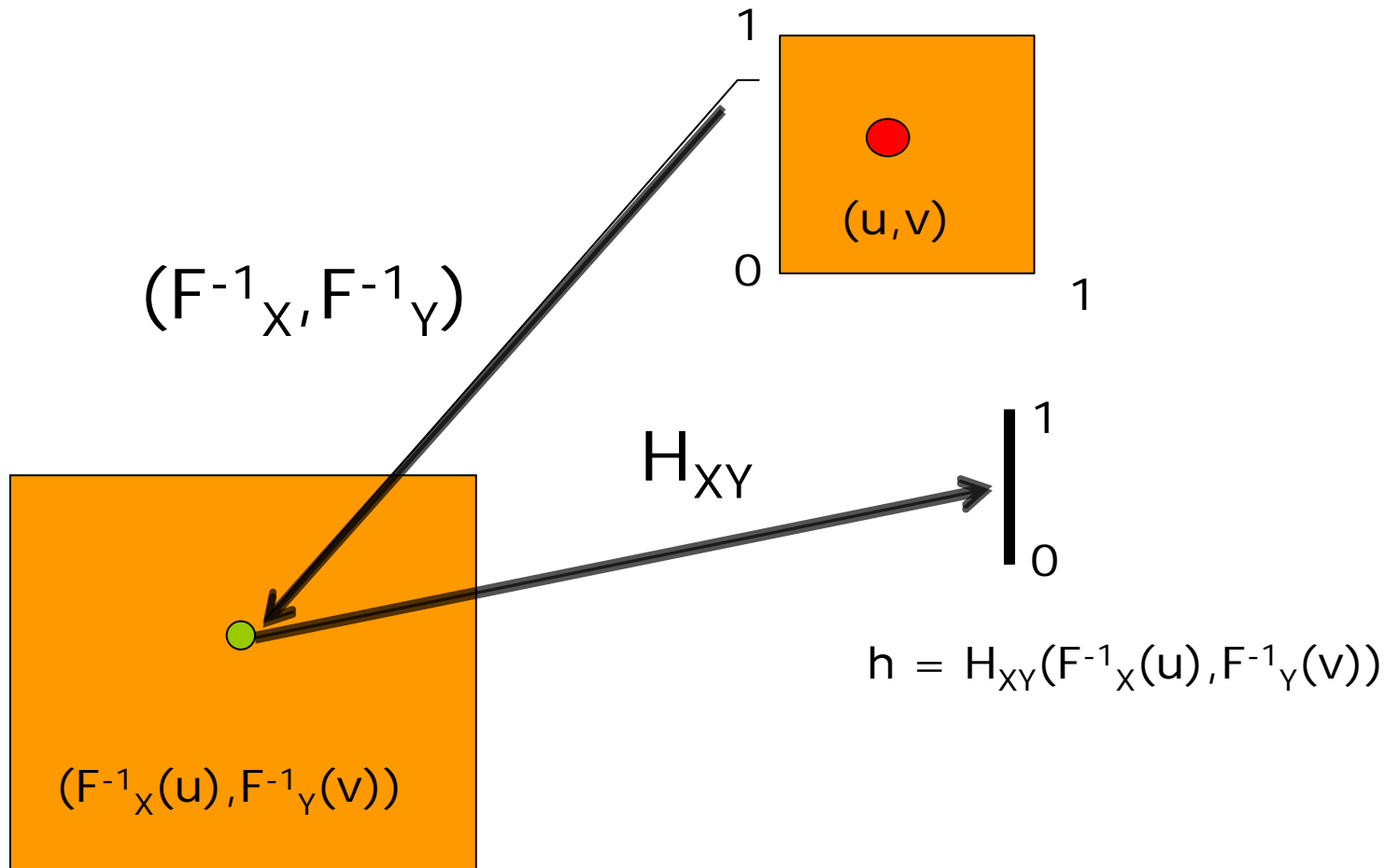
Copula Function



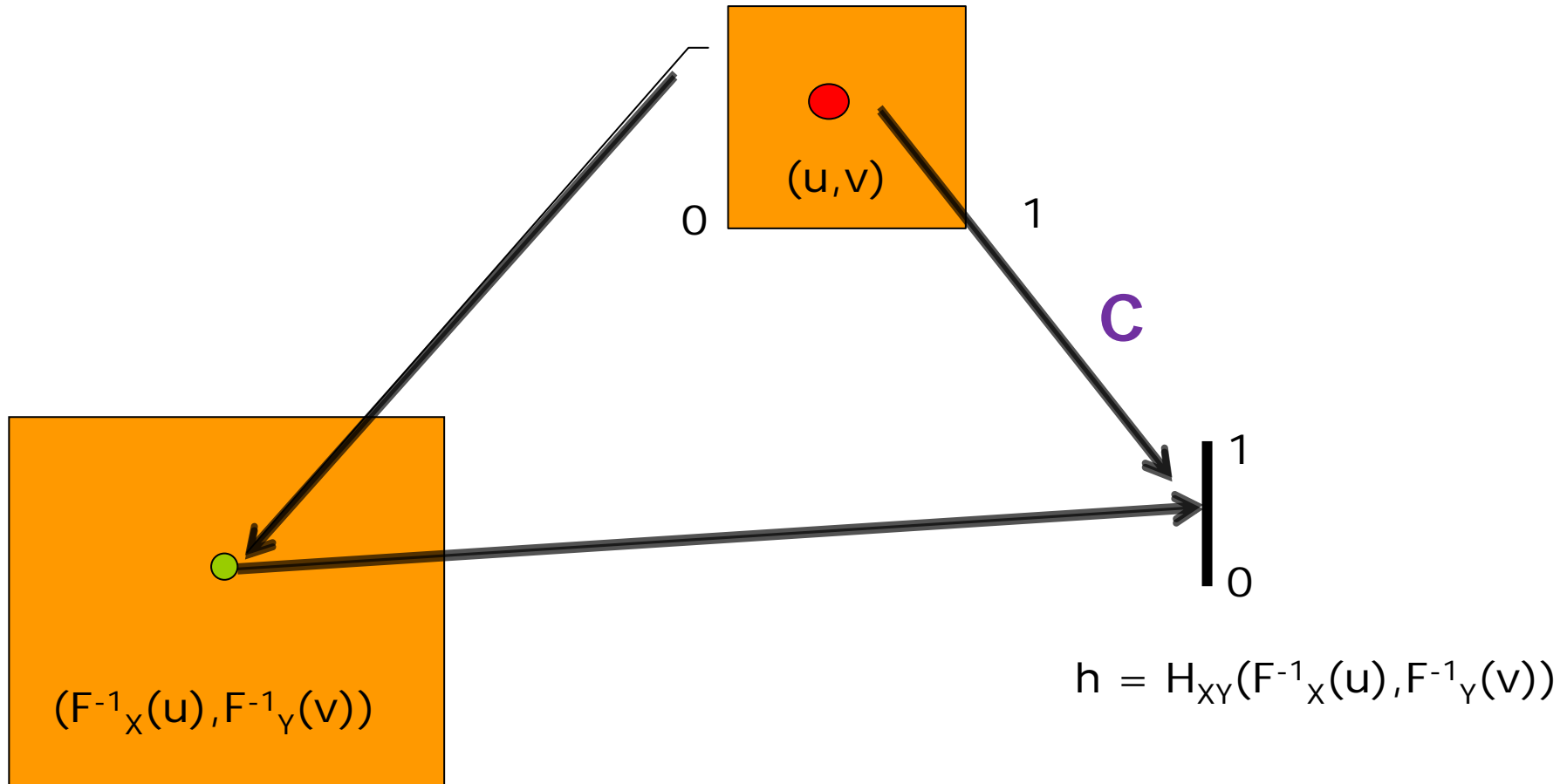
Copula Function



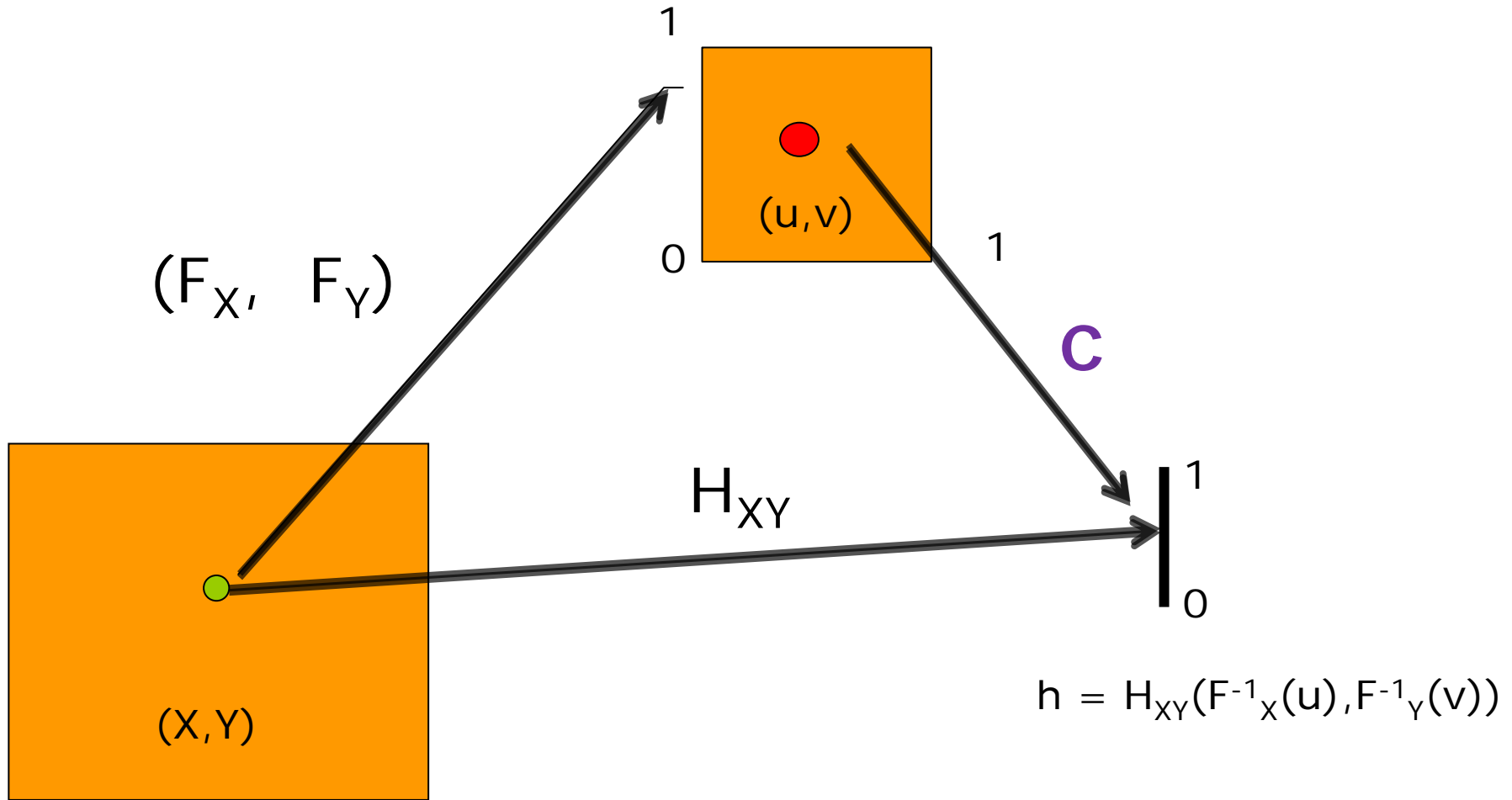
Copula Function



Copula Function



$$C(u, v) = F(F^{-1}(u), F^{-1}(v))$$



Example of Copulas

- Gaussian Copula
 with gaussian bivariate distribution

$$N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right]$$

$$C_\rho(u, v) = \Phi_\rho[\Phi^{-1}(u), \Phi^{-1}(v)]$$

where

Φ is the cdf of the univariate standard normal distribution

Φ_ρ is the cdf of the bivariate standard normal with correlation coefficient equal to ρ

$$C_\rho(u, v) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left\{\frac{-(s^2 - 2\rho st + t^2)}{2(1-\rho^2)}\right\} ds dt$$

T Copula

- Suppose that $X \sim t_d(v, 0, \rho)$ where v is the degree of freedom and ρ is a correlation matrix. The t copula is the unique copula of X

$$C_{v,\rho}^t(u) = \phi_\rho(t_v(X_1) \leq u_1, \dots, t_v(X_d) \leq u_d) = t_{v,\rho}(t_v^{-1}(u_1), \dots, t_v^{-1}(u_d))$$

- where t_v is the df of a standard univariate t distribution and $t_{v,\rho}$ is the joint distribution function of the vector $X \sim t_d(v, 0, \rho)$ and P is a correlation matrix; in two dimensions we use ρ to represent the correlation coefficient.

□ Monte Carlo Simulation

$$u_s \sim \text{uniform}(0,1)$$

$$r_{i,s} = F_{r_i}^{-1}(u_s)$$

- Uniform random numbers

$$(u_1, \dots, u_n)$$

- We can then calculate the marginals from

$$F_{r_1}^{-1}(u_1), \dots, F_{r_n}^{-1}(u_n)$$

$$F(r_1, \dots, r_n)$$

$$F(r_1, \dots, r_n) = C(F_{r_1}, \dots, F_{r_n})$$

-
- By using copula method we can separate the univariate margins and the multivariate dependence structure. This proves to be very convenient in scenario generation.
 - Estimate the copula function and the marginals...

Copula Estimation

- Nonparametric Copula Estimation
This means estimating both copula and marginals nonparametrically.
- Semi-parametric Copula Estimation
This means estimating copula parametrically and marginals nonparametrically.
- Parametric Copula Estimation
This means estimating copula and marginals with parametrical distribution families.



Exchange rates levels

□ > udeu

□		V1	V2	V3	V4
□	1	1/13/1993	Wed	0.82994	-0.0058507450
□	2	1/20/1993	Wed	0.81913	-0.0131106080
□	3	1/27/1993	Wed	0.81120	-0.0097281690
□	4	2/3/1993	Wed	0.84451	0.0402419450
□	5	2/10/1993	Wed	0.85034	0.0068796920
□	.				
□	.				
□	.				
□	670	11/16/2005	Wed	0.85486	0.0055954870
□	671	11/23/2005	Wed	0.85074	-0.0048311540
□	672	11/30/2005	Wed	0.85058	-0.0001880890
□	673	12/7/2005	Wed	0.84822	-0.0027784340
□	674	12/14/2005	Wed	0.83446	-0.0163552270
□	675	12/21/2005	Wed	0.84181	0.0087695270
□	676	12/28/2005	Wed	0.84359	0.0021122590

- The generalized extreme value distribution has cumulative distribution function

$$F(x; \mu, \sigma, \xi) = \exp \left\{ - \left[1 + \xi \left(\frac{x - \mu}{\sigma} \right) \right]^{-1/\xi} \right\}$$

```
> gev.fit(udeu[,4])
```

```
$conv
```

```
[1] 0
```

```
$nllh
```

```
[1] -2096.158
```

```
$mle
```

```
[1] -0.004137744  0.010695222 -  
0.219991515
```

-
- ❑ `> udata <- pgev(udeu[,4], -0.004137744, 0.010695222, -0.219991515)`
 - ❑ `> udata`
 - ❑ `[1] 0.310220171 0.115373162 0.193955938
0.999984767 0.732757263 0.142051992`
 - ❑ `[7] 0.578993885 0.762846581 0.806337804
0.386874173 0.120180369 0.107314578`
 - ❑ `[13] 0.380147579 0.170437690 0.510042400
0.100425218 0.496974735 0.950392736`
 - ❑ `[19] 0.703820563 0.449646472 0.315223805
0.859522662 0.878107694 0.992632619`
 - ❑ `[25] 0.500101462 0.741843191 0.840120239
0.314183211 0.938774817 0.542186545`
 - ❑ `[31] 0.606336751 0.073287592 0.352343272
0.214349782 0.004302800 0.220004760`
 - ❑ `.....`

Test

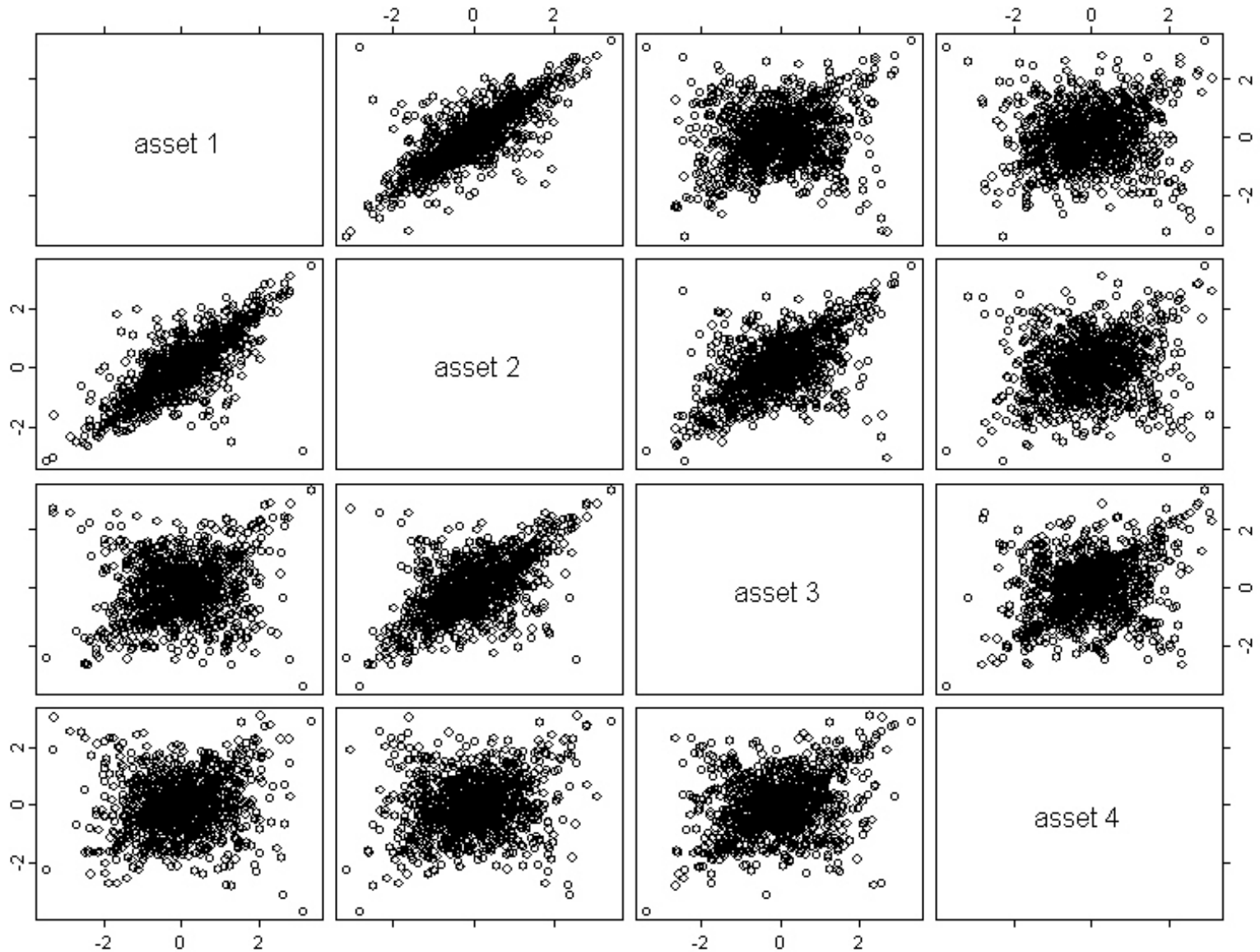
- We will use the copula approach to picture four mixtures of normals together, maintaining a specified correlation structure and modelling (symmetric) tail dependence according to a t-copula.
- To simulate a t-copula with ν degrees of freedom, we have to proceed the following steps:

Algorithms

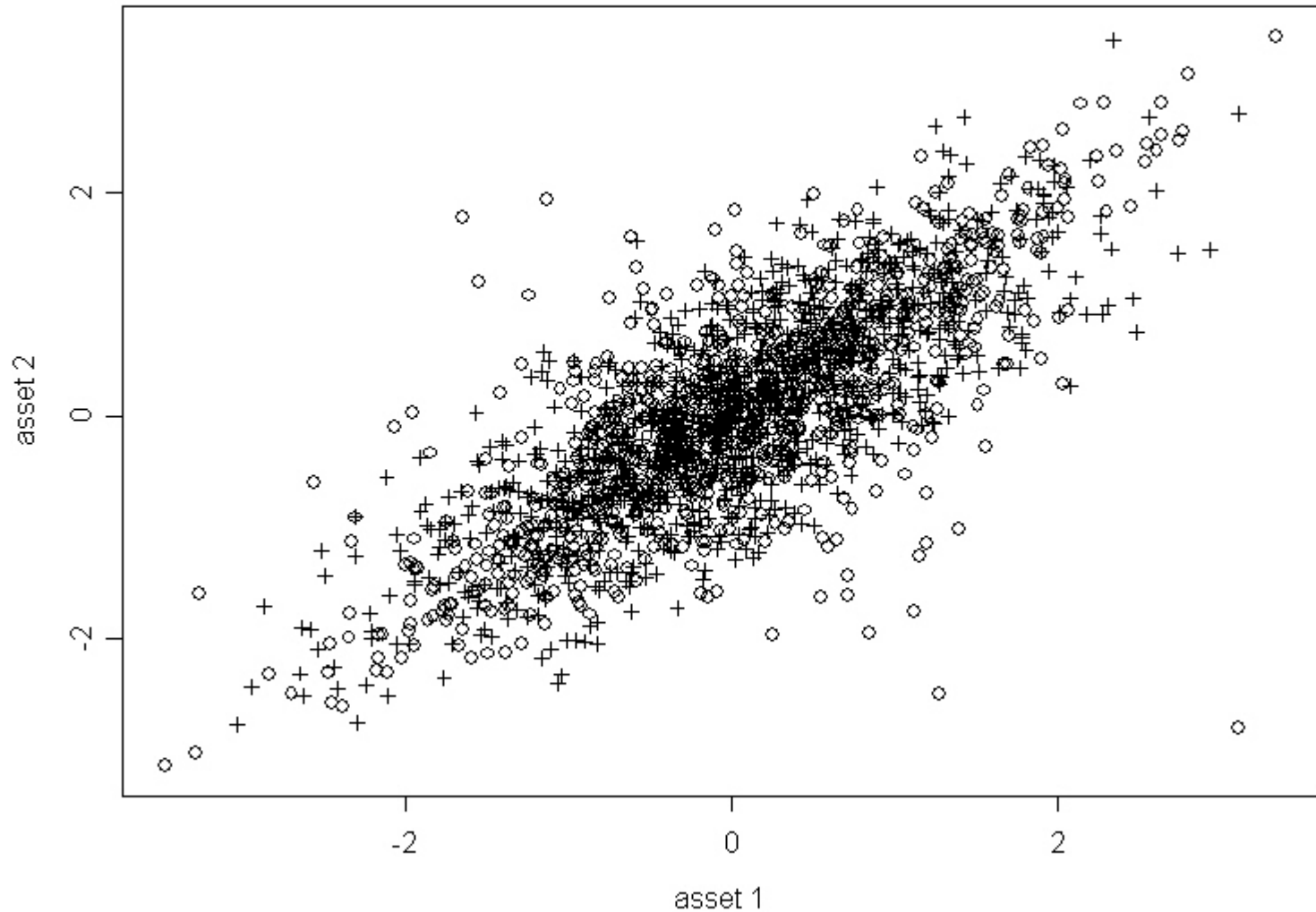
- Find the Cholesky decomposition $C_{cholesky}$ of the correlation matrix C (dimension $n \times n$)
- Draw a vector of n standard normals u and calculate $C_{cholesky} u$.
- Draw from $s \sim \chi_v^2$ and multiply the result of the second step by \sqrt{v} / \sqrt{s} i.e., calculate

$$x = C_{Cholesky} u \frac{\sqrt{v}}{\sqrt{s}}$$

- Each element of x (X_1, \dots, X_n) is inserted into the cumulative distribution function to arrive at uniformly distributed variables $u_i \sim t_v(x_i)$
- Repeat steps 2 – 4 (m) times.

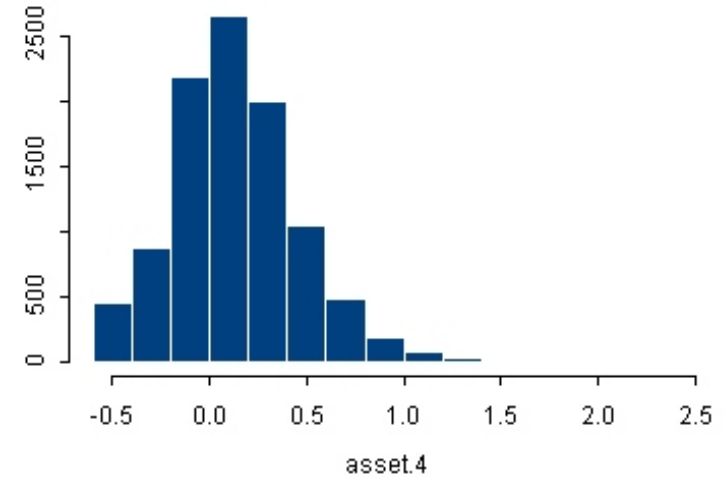
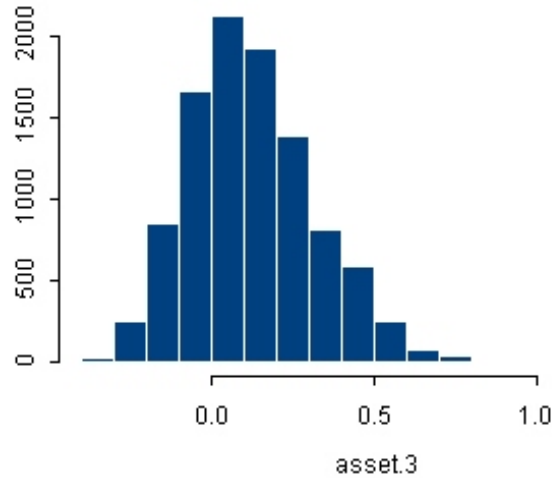
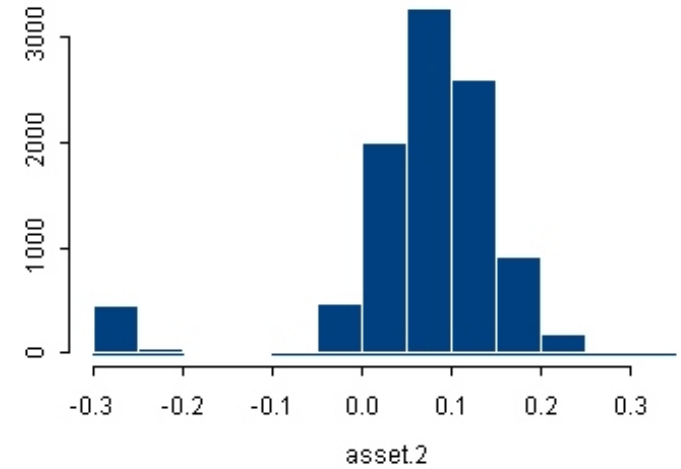
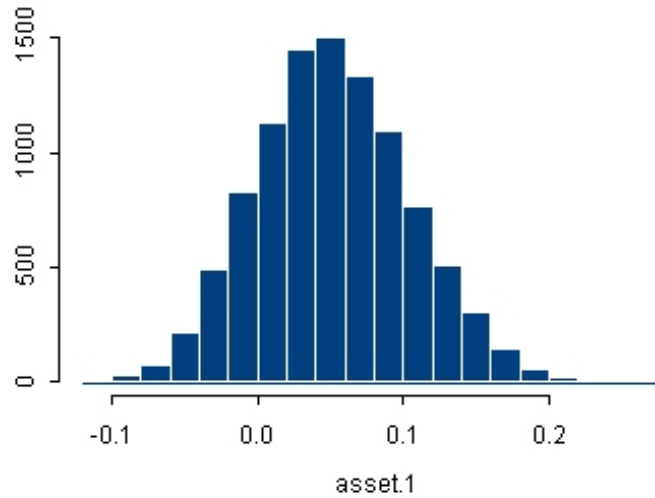


□ Graph 1: T Copula with 2 Degrees of Freedom and Standard Normal Margins



Graph 3

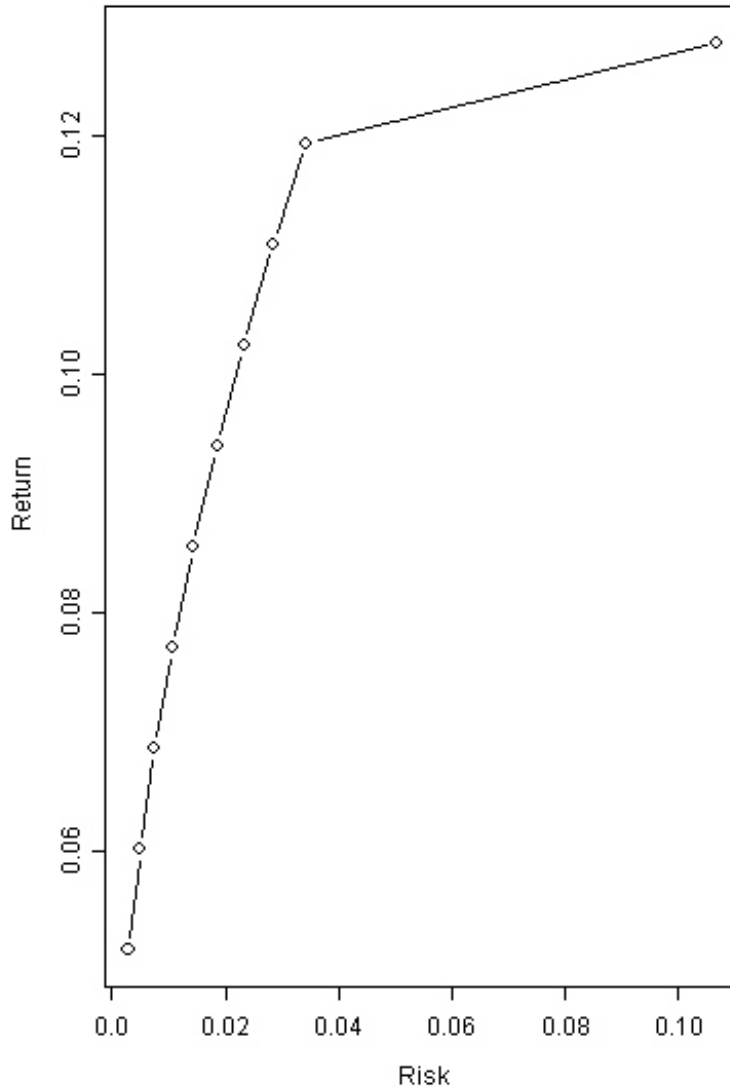
- Scatter plot for Normal Distribution versus t copula
- + t-copula; o standard normal



■ Graph 4: Marginal Distributions in Four-Asset Test Case.

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- Marginal distributions are glued together with the use of a t-copula and stored in the scenario matrix S .
 - Now we can code a scenario-based Markowitz optimisation, where portfolio variance is calculated using all scenarios for each weight allocation rather than by supplying a single covariance matrix.
 - We can then find the solutions for return points along the efficient frontier.

Mean - Variance Frontier



- It shows the solutions for ten return points along the efficient frontier. We can use these solutions as a reference point for the following scenario optimisation.

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- Next stage:
 - Implement CVaR model
 - Using ICA/CCA

Thank You !