But what are Copulas?

Simply put, Copulas (as in VineCopula) are functions which are used to **create flexible multivariate dependencies** from marginal distributions. **What does that mean?**
What we're more accustomed to as a dependency between variables is **linear correlation**. Commonly, *correlation*. For example, if we let `Sales` be your dollar sales of kombucha per month, and `Advert` be your advertising costs, then the linear correlation between `Sales` and `Advert` is (very) roughly, the frequency at which they both vary in the same direction, when put on the same scale.

When linear correlation is close to 1, `Sales` and `Advert` mostly vary in the same direction. Otherwise, when it's close to -1, `Sales` and `Advert` mostly vary in opposite directions. But **linear correlation is… linear**. The intuition behind this, is the proportionality of the correlation coefficient with the slope of a simple linear regression model. Linearity implies, it doesn't take into account more complex, nonlinear types of dependencies which can occur quite frequently though.

Examples

Not familiar with R? You can skip this introductory code and report to the next section.

Code

```
devtools::install_github("Techtonique/esgtoolkit")
library(ESGtoolkit)

## Simulation parameters

# Number of risk factors
d <- 2

# Number of possible combinations of the risk factors
dd <- d*(d-1)/2

# Copula family : Gaussian -----
fam1 <- rep(1,dd)
# Correlation coefficients between the risk factors (d*(d-1)/2)
par0_1 <- 0.9
par0_2 <- -0.9

# Copula family : Rotated Clayton (180 degrees) -----
fam2 <- 13
par0_3 <- 2

# Copula family : Rotated Clayton (90 degrees) -----
fam3 <- 23
par0_4 <- -2


## Simulation of the d risk factors
```

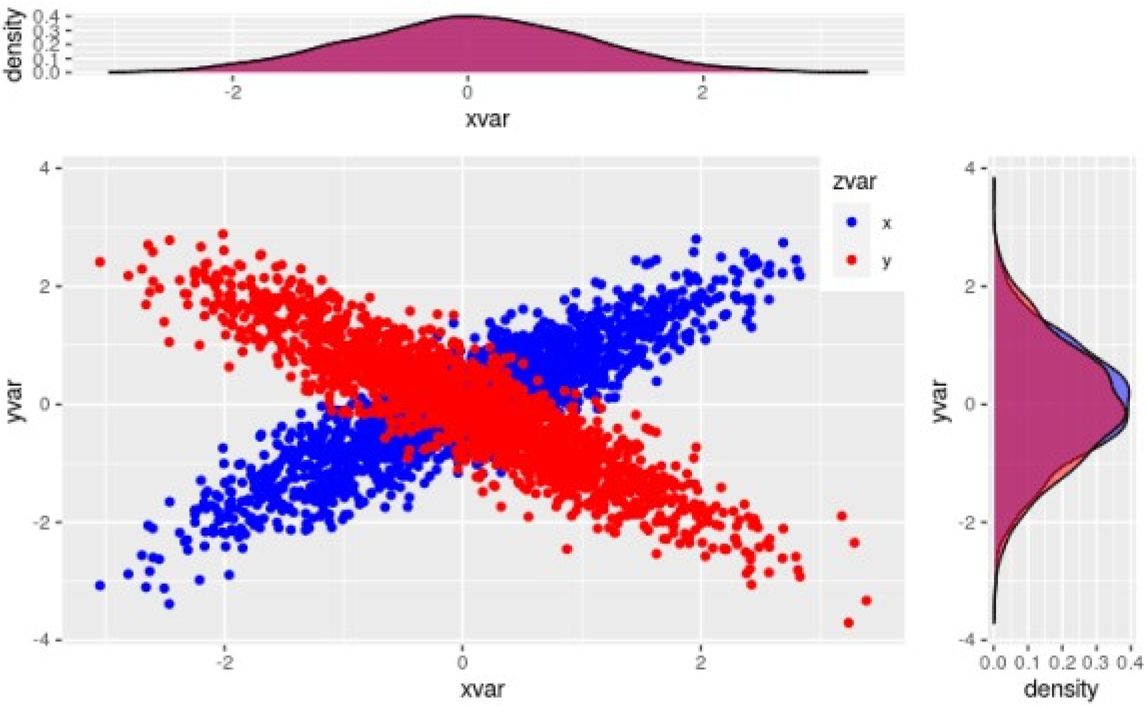
```
# number of simulations for each variable
nb <- 500

# Linear correlation = 1
s0_par1 <- simshocks(n = nb, horizon = 4,
family = fam1, par = par0_1)

# Linear correlation = -1
s0_par2 <- simshocks(n = nb, horizon = 4,
family = fam1, par = par0_2)

# Rotated Clayton Copula (180 degrees)
s0_par3 <- simshocks(n = nb, horizon = 4,
family = fam2, par = par0_3)

# Rotated Clayton Copula (90 degrees)
s0_par4 <- simshocks(n = nb, horizon = 4,
family = fam3, par = par0_4)
```

Linear correlation +1 and -1

Same distribution on the marginals (Normal), different type of dependency:

- blue: correlation = +1
- red: correlation = -1

```
ESGtoolkit::esgplotshocks(s0_par1, s0_par2)
```



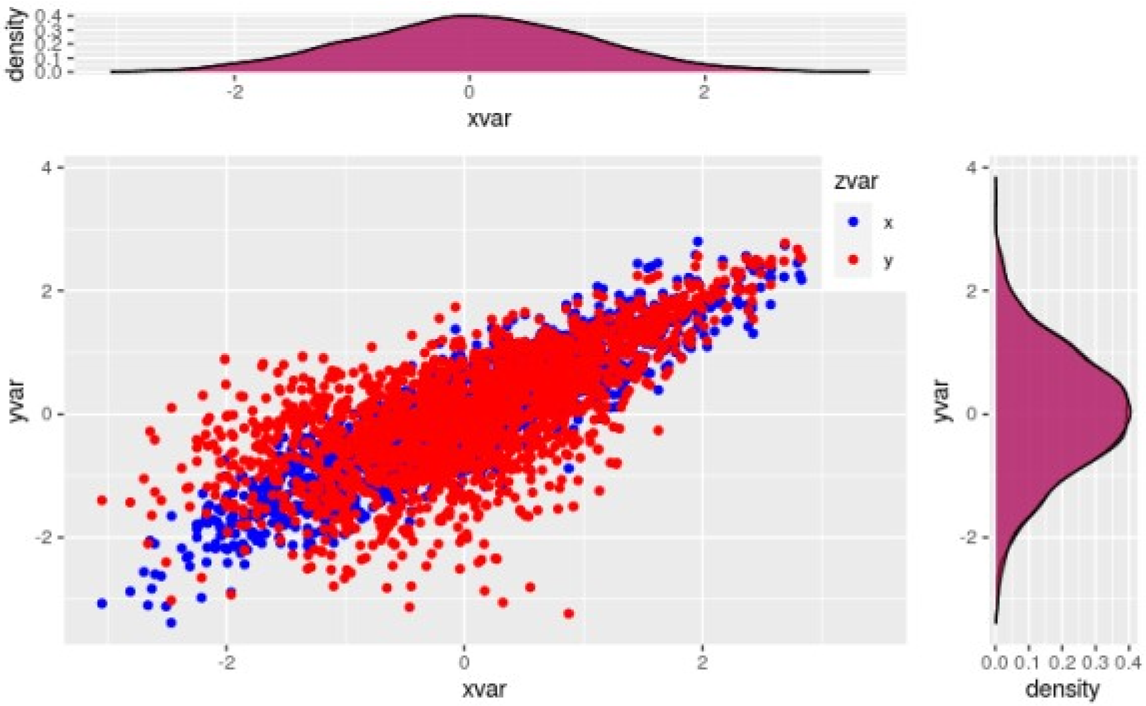
Correlation +1 and Rotated Clayton Copula (180 degrees)

Same distribution on the marginals (Normal), different type of dependency:

- blue: correlation = +1

- red: Rotated Clayton Copula (180 degrees)

```
ESGtoolkit::esgplotshocks(s0_par1, s0_par3)
```

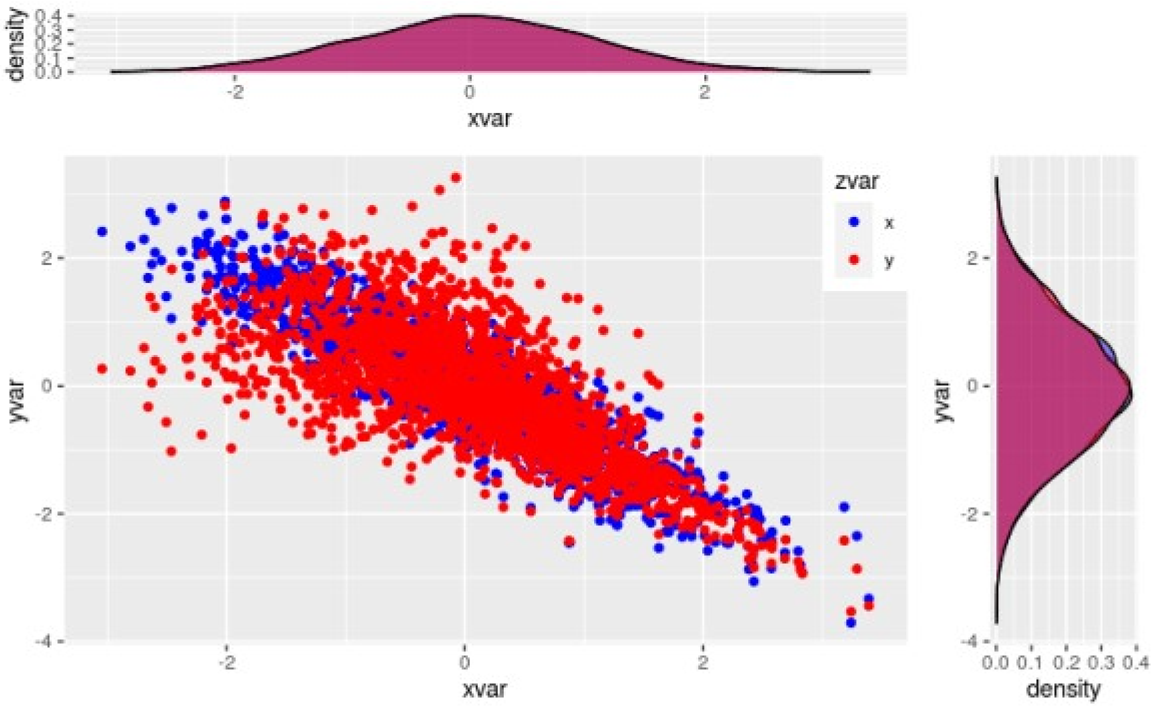


Correlation -1 and Rotated Clayton Copula (90 degrees)

Same distribution on the marginals (Normal), different type of dependency:

- blue: correlation = +1
- red: Rotated Clayton Copula (90 degrees)

```
ESGtoolkit::esgplotshocks(s0_par2, s0_par4)
```



When we observe rotated Clayton copula's simulated points in the second and third graphs, we see patterns which can't be reproduced when using linear correlation, with **actual danger**

zones: **wherever linear correlation *can't go* for certain**. For example, the **quadrant [-4, -2] x [-2, 0]** in the last graph.