

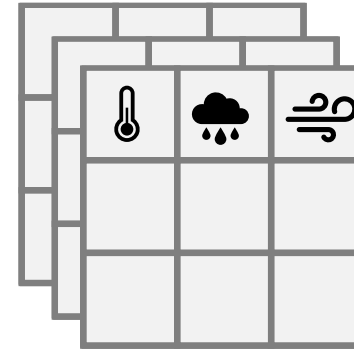
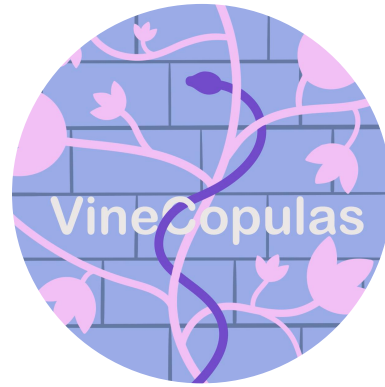
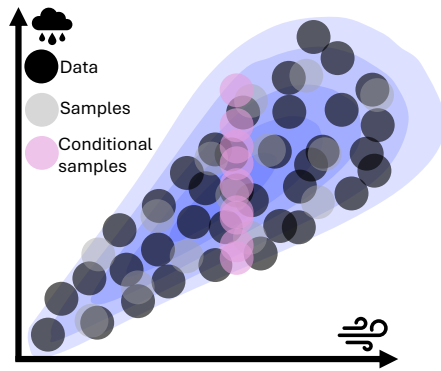
Introduction to Vine Copulas

Judith Claassen

The MYRIAD-EU project has received funding from the European Union's Horizon 2020 research and innovation programme call H2020-LC-CLA-2018-2019-2020 under grant agreement number 101003276



Contents



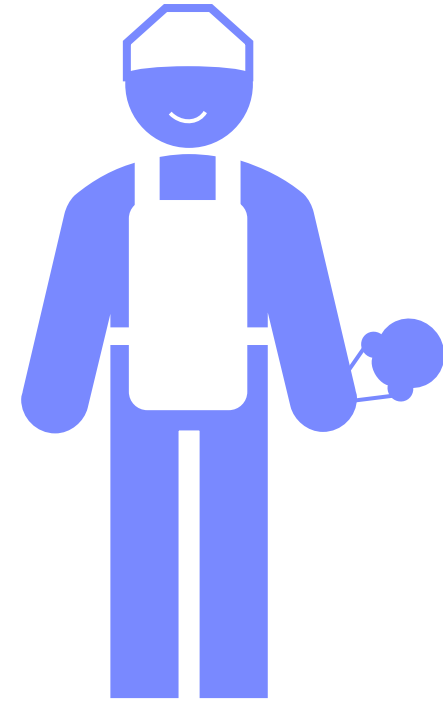
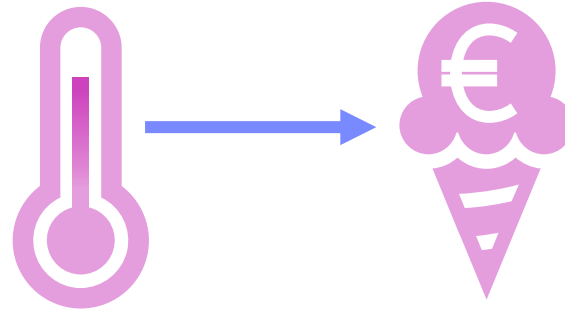
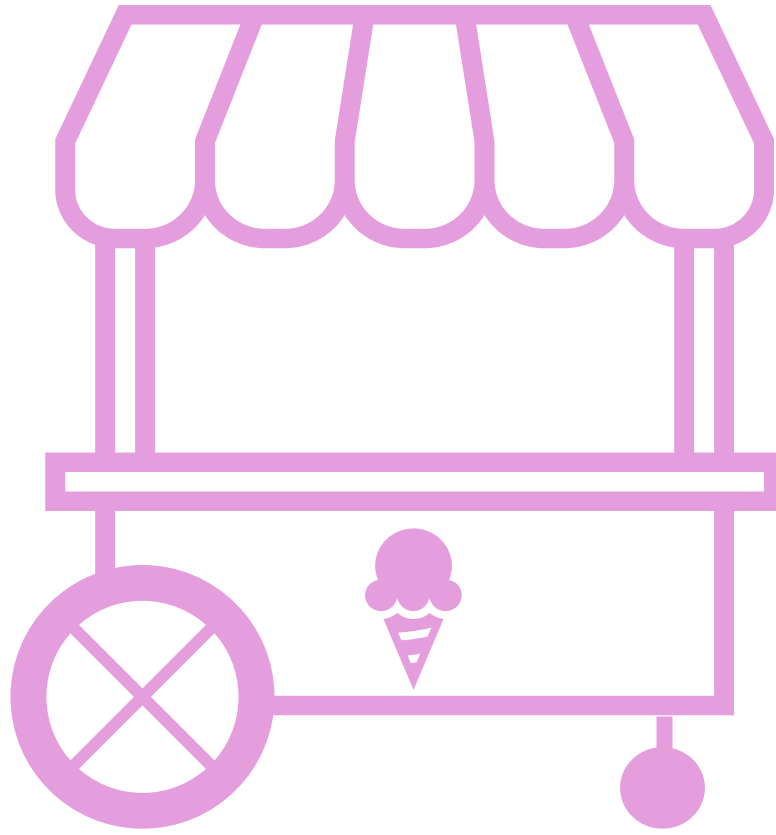
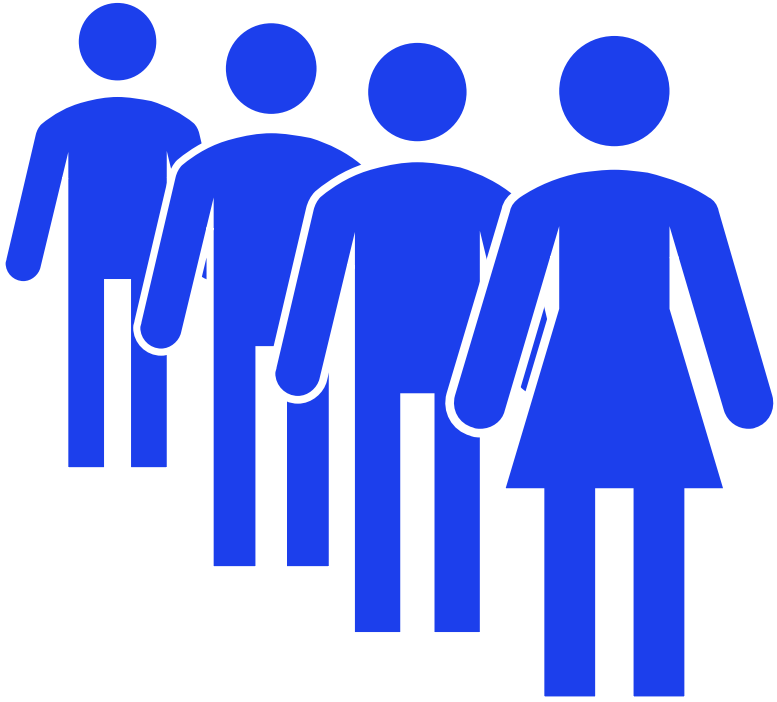
Introduction

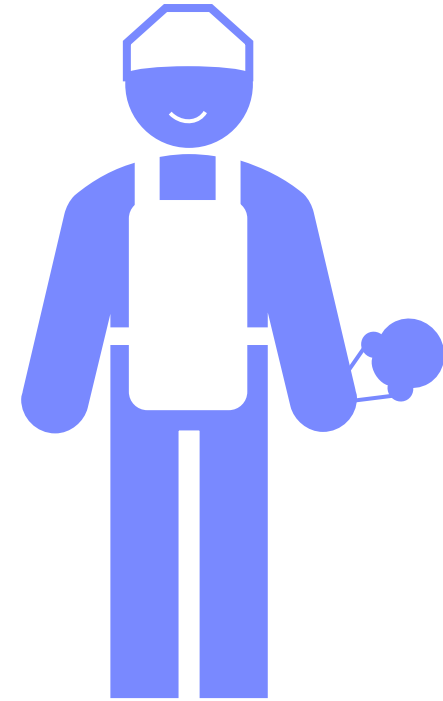
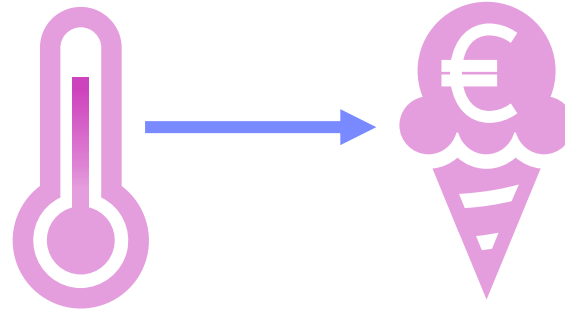
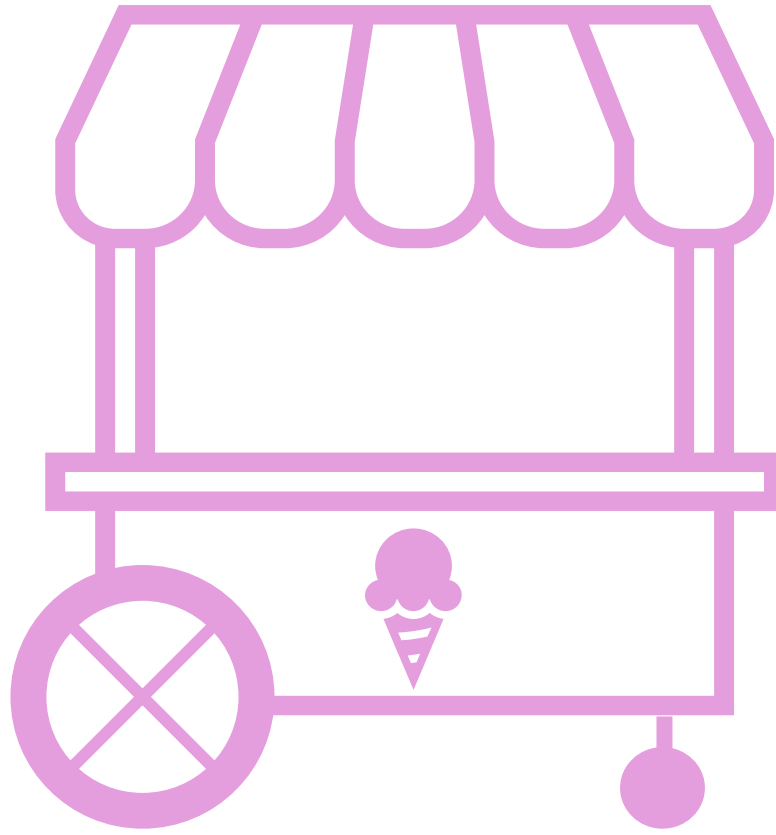
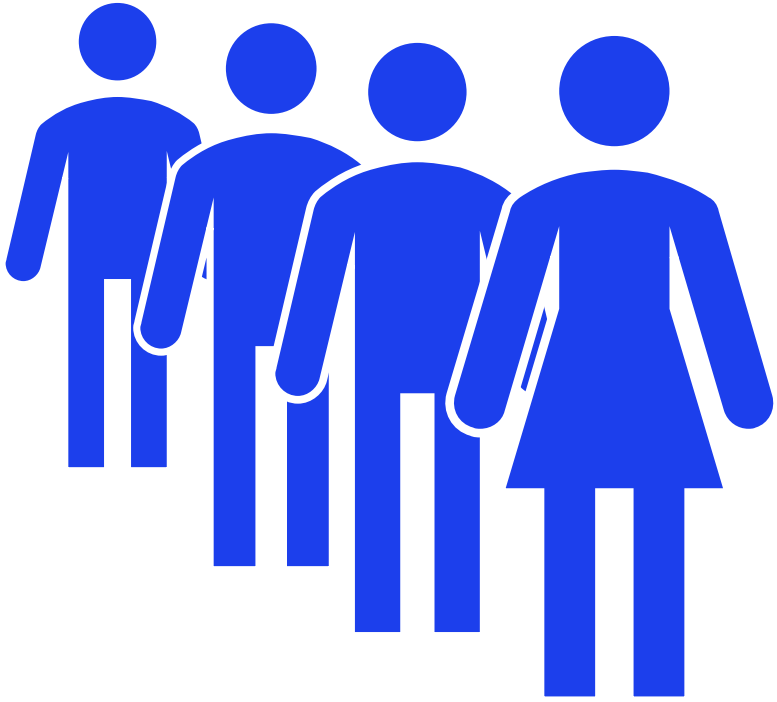
The
VineCopulas
Python
Package

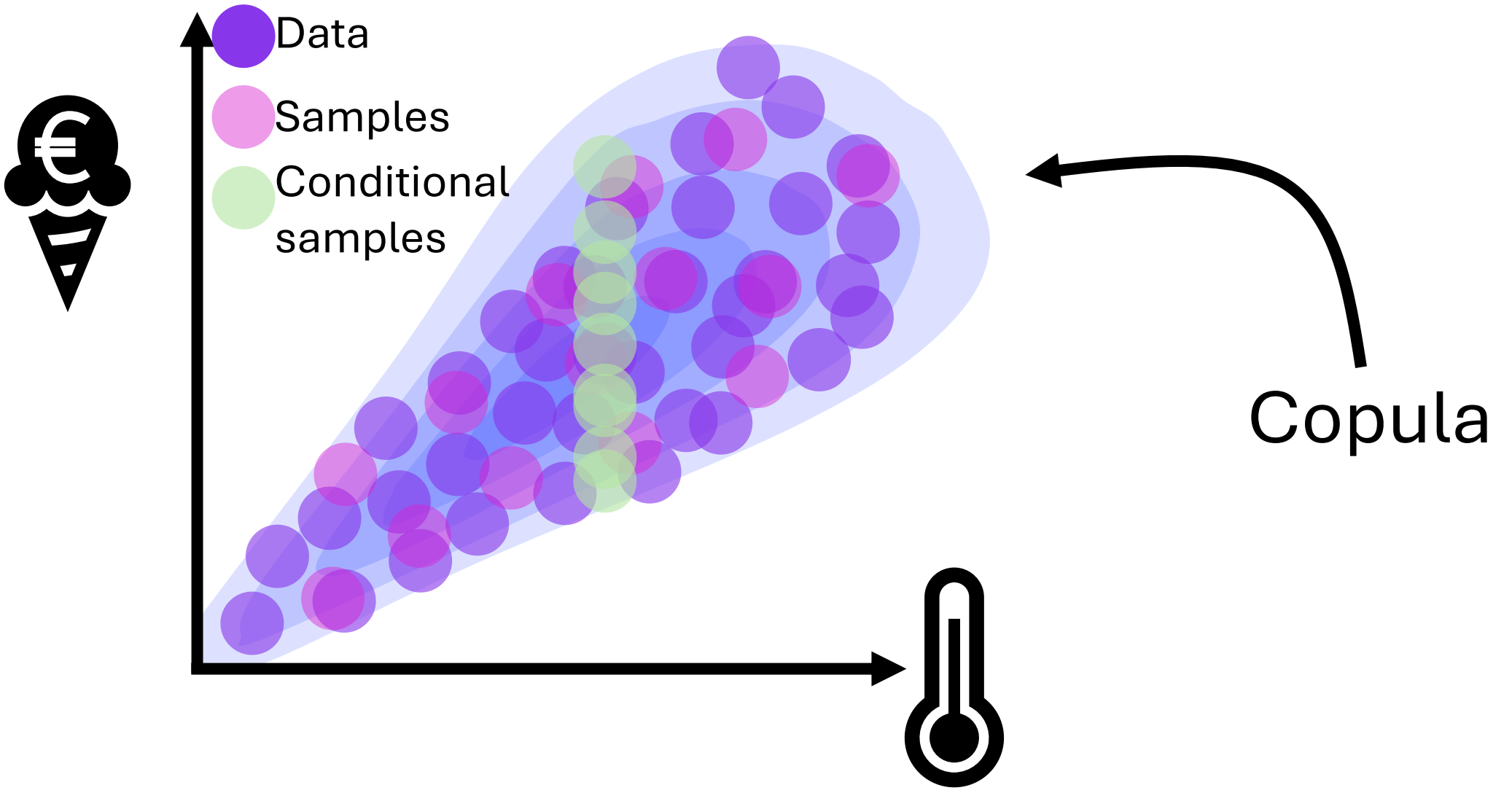
Example how
VineCopulas
can be used in
research

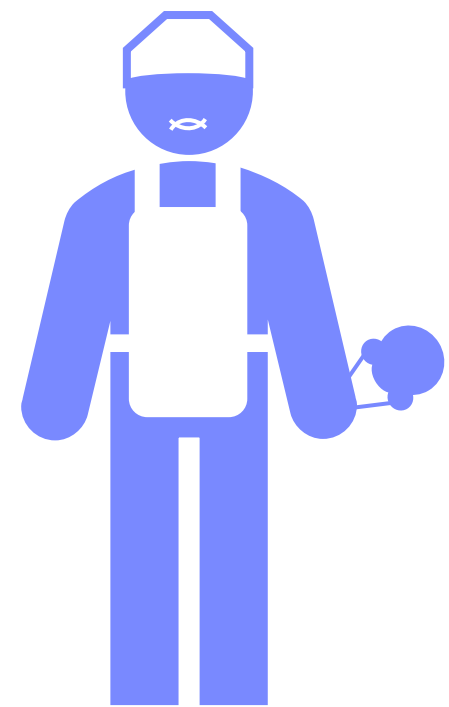
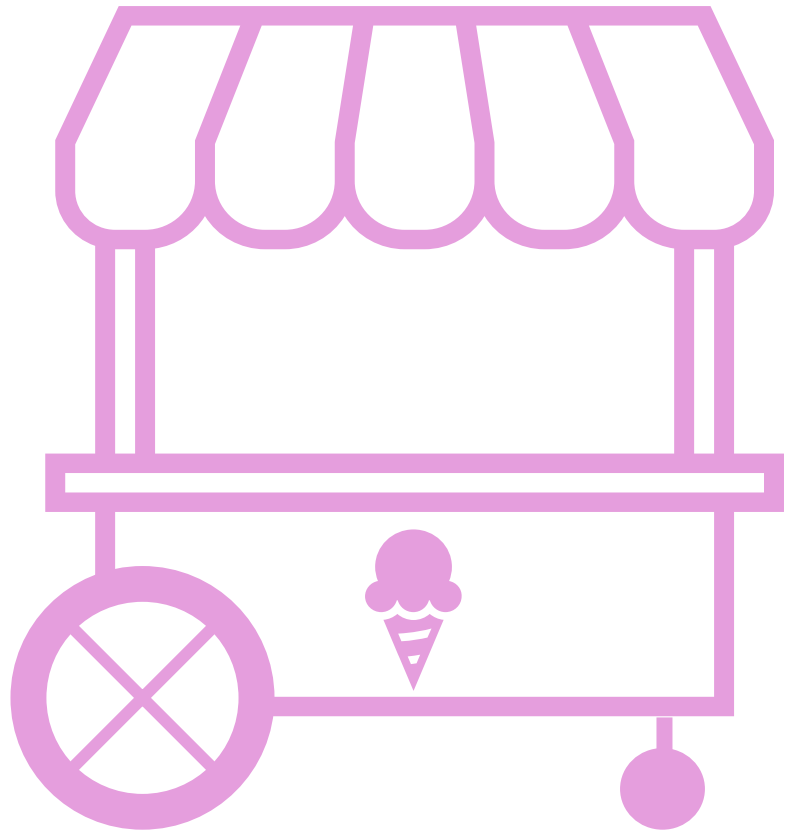
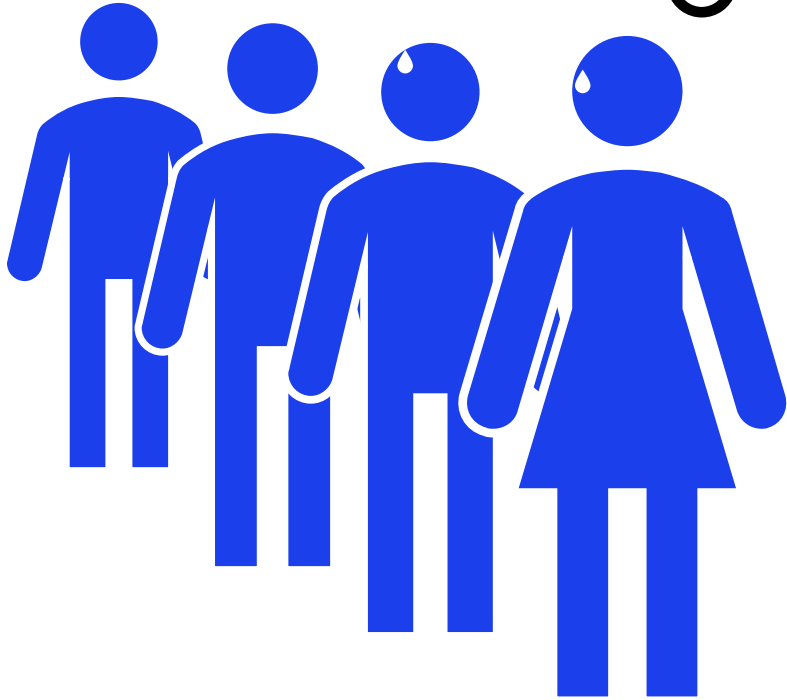
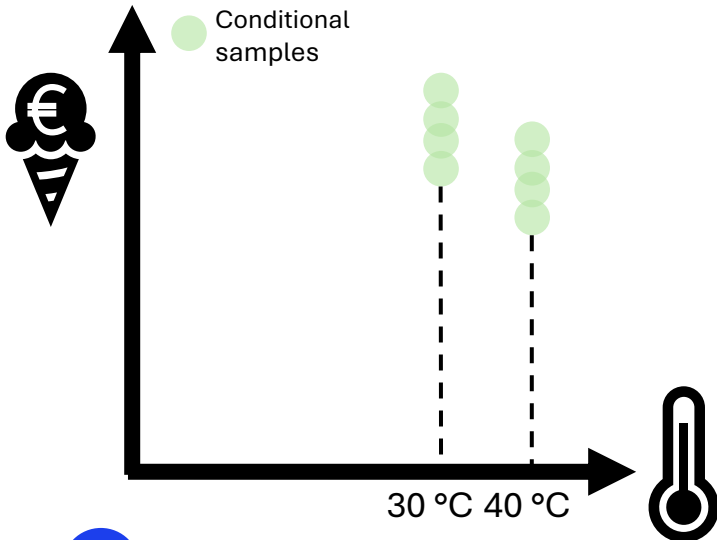


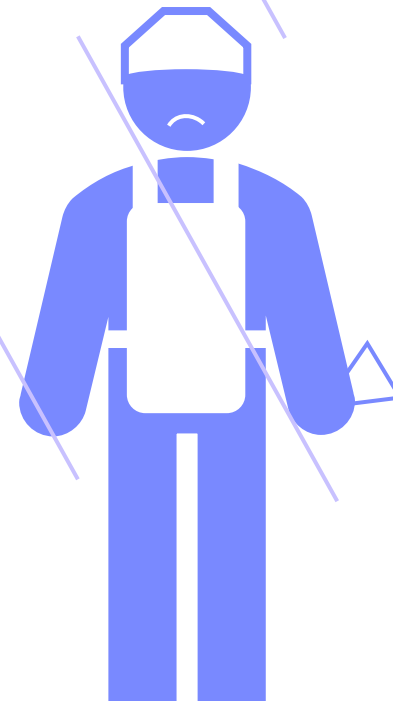
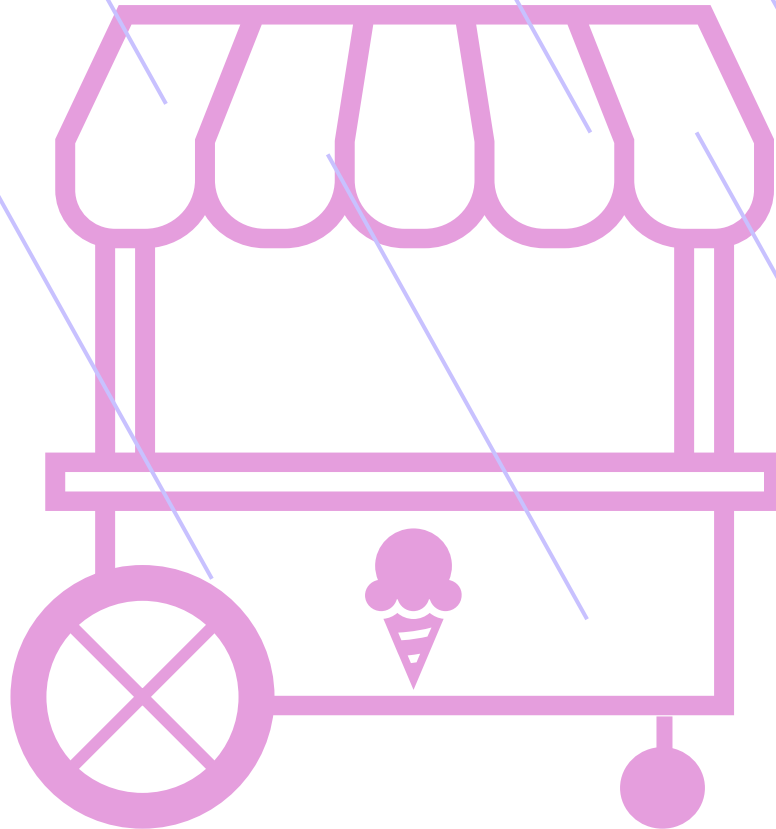
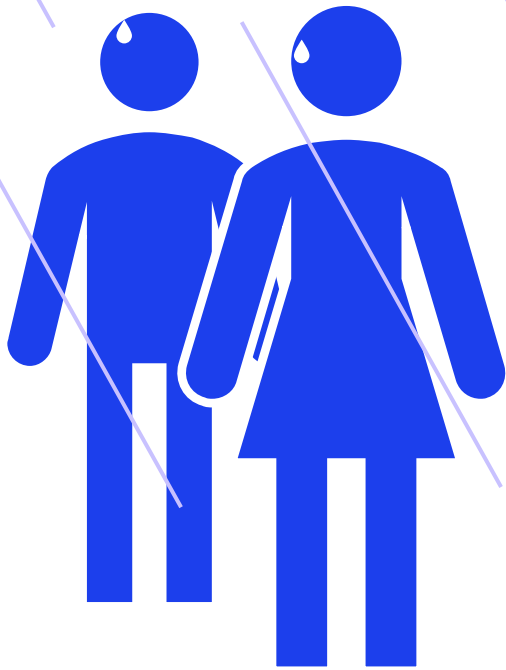
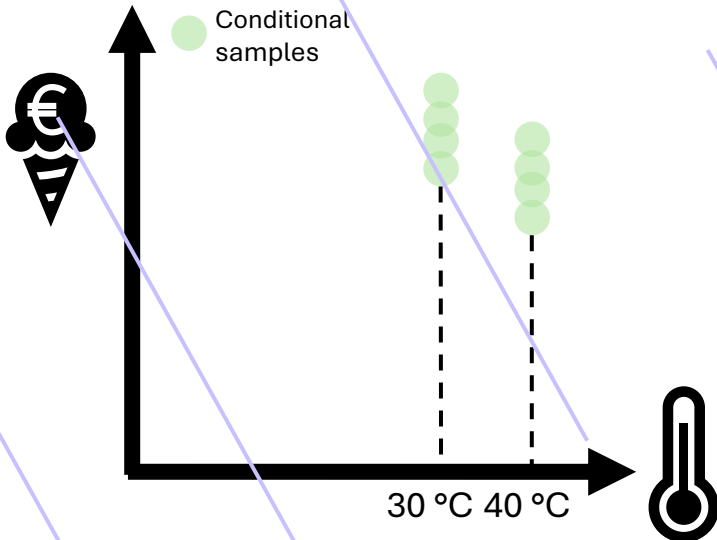




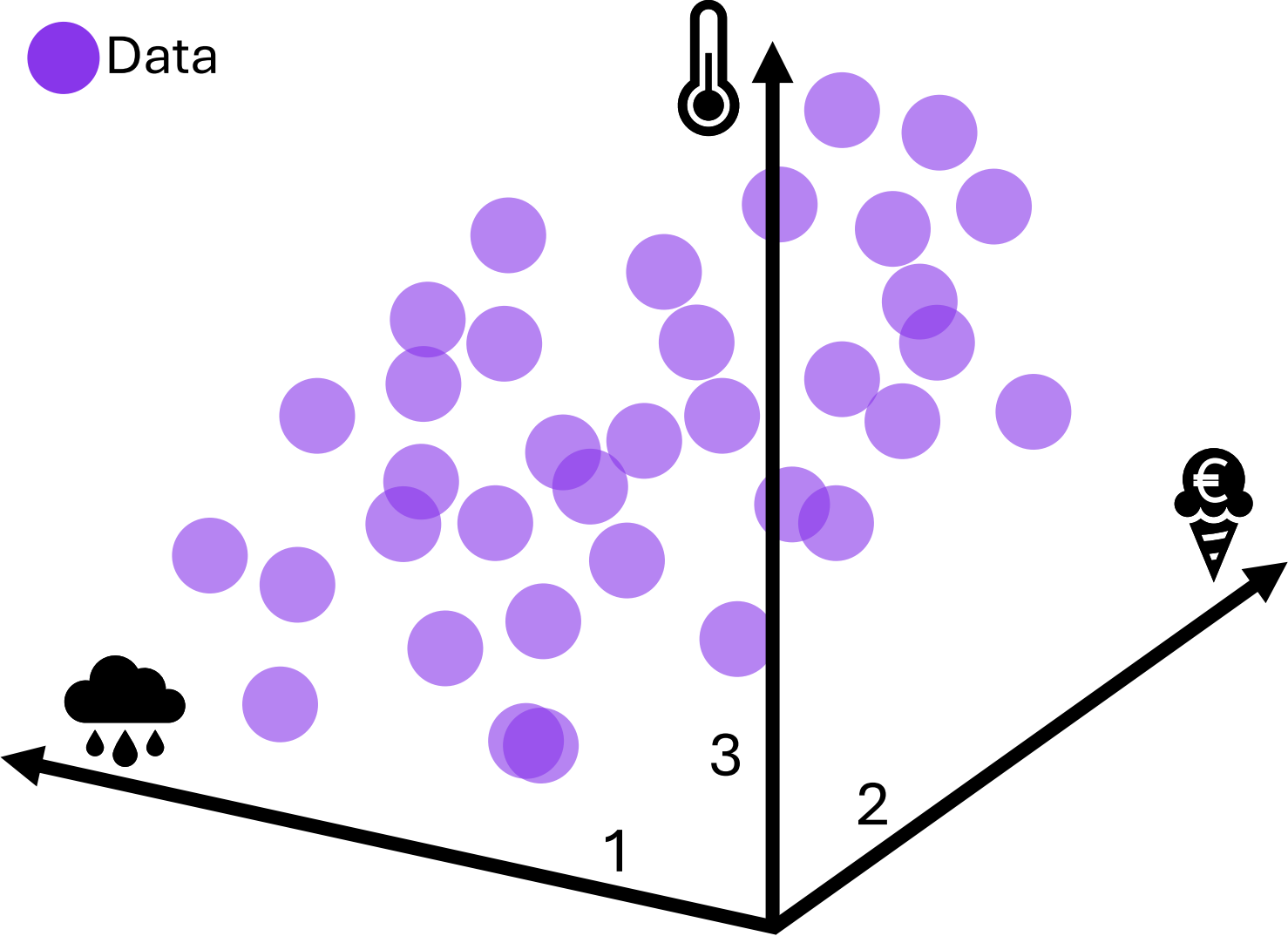




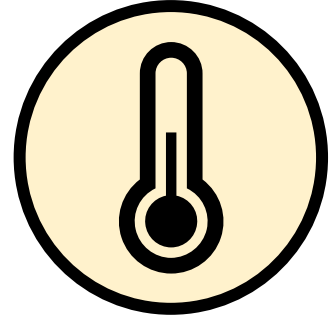
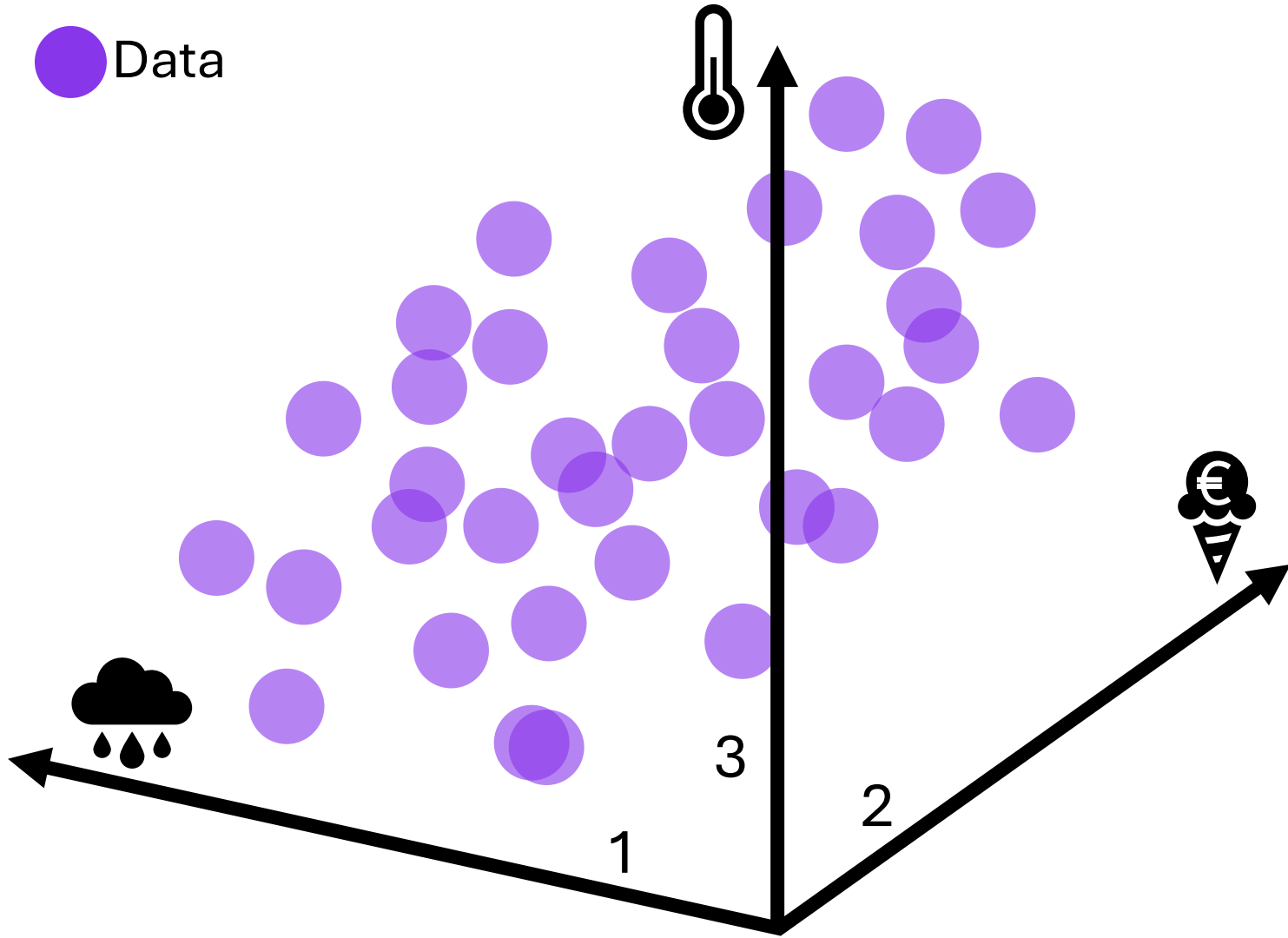




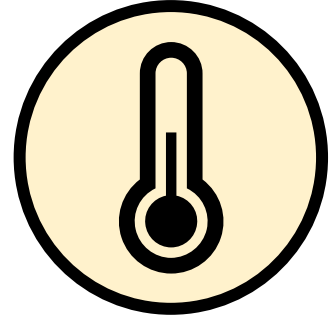
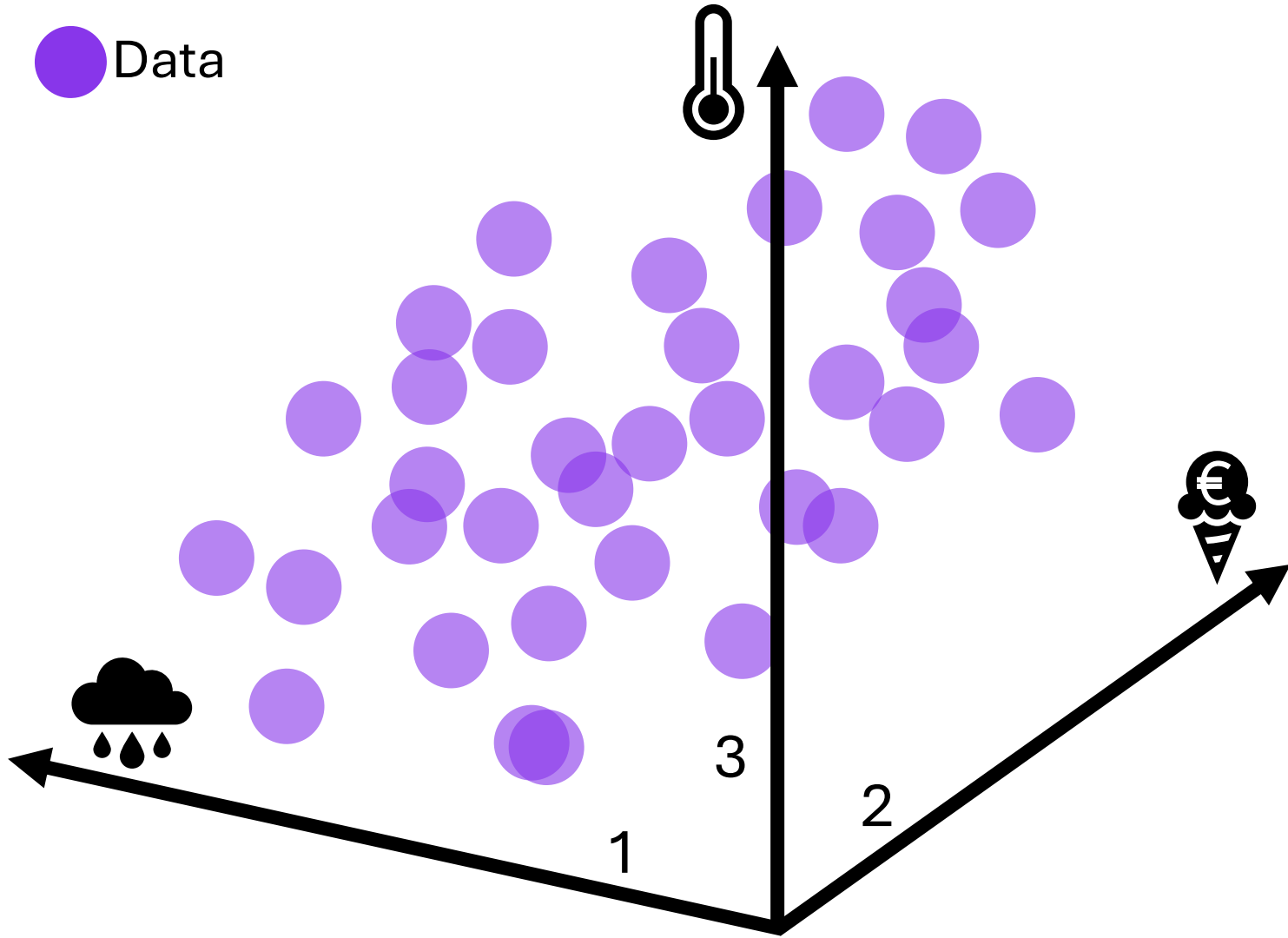
● Data



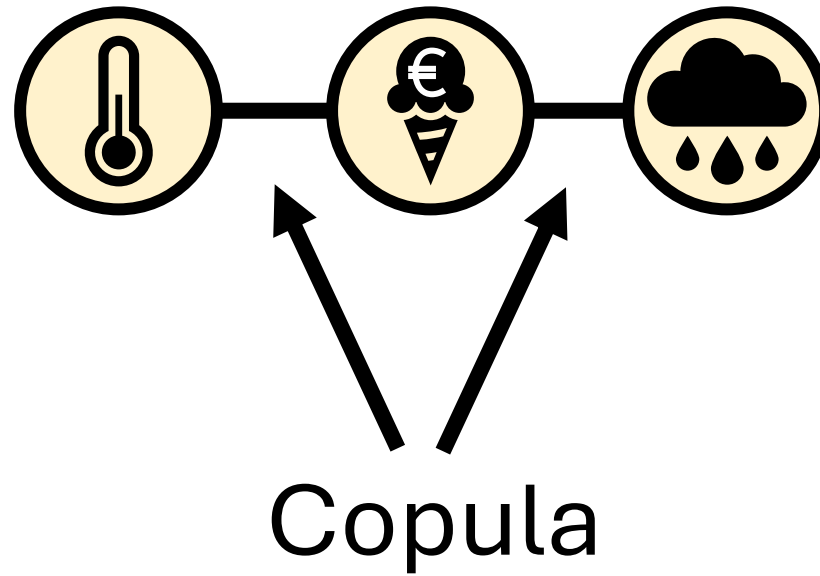
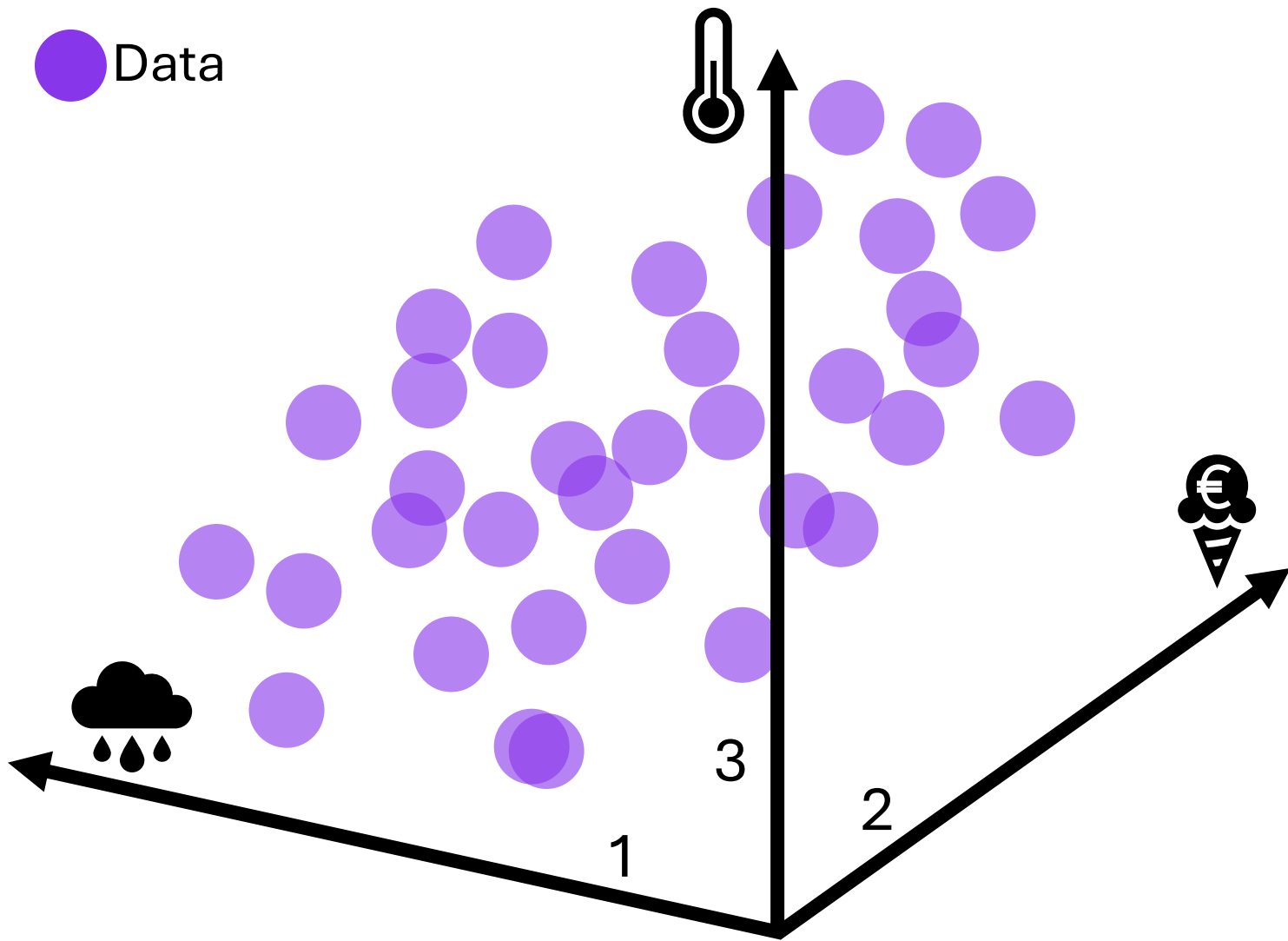
● Data



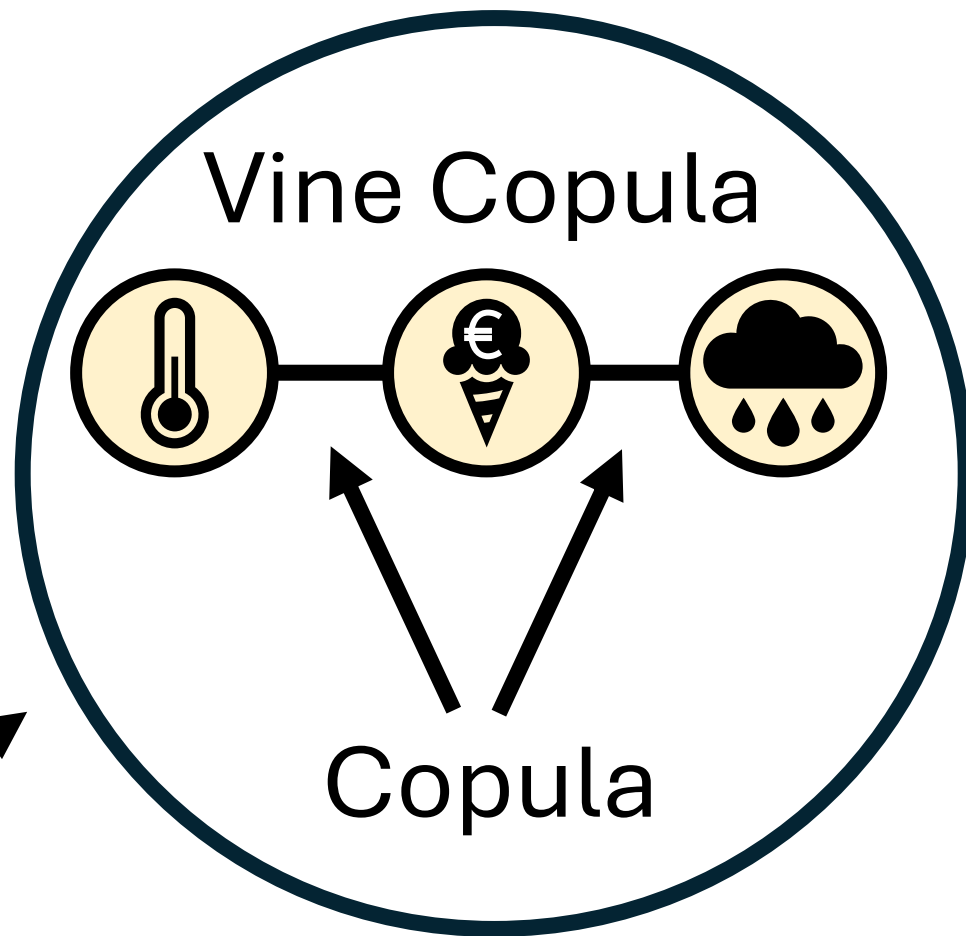
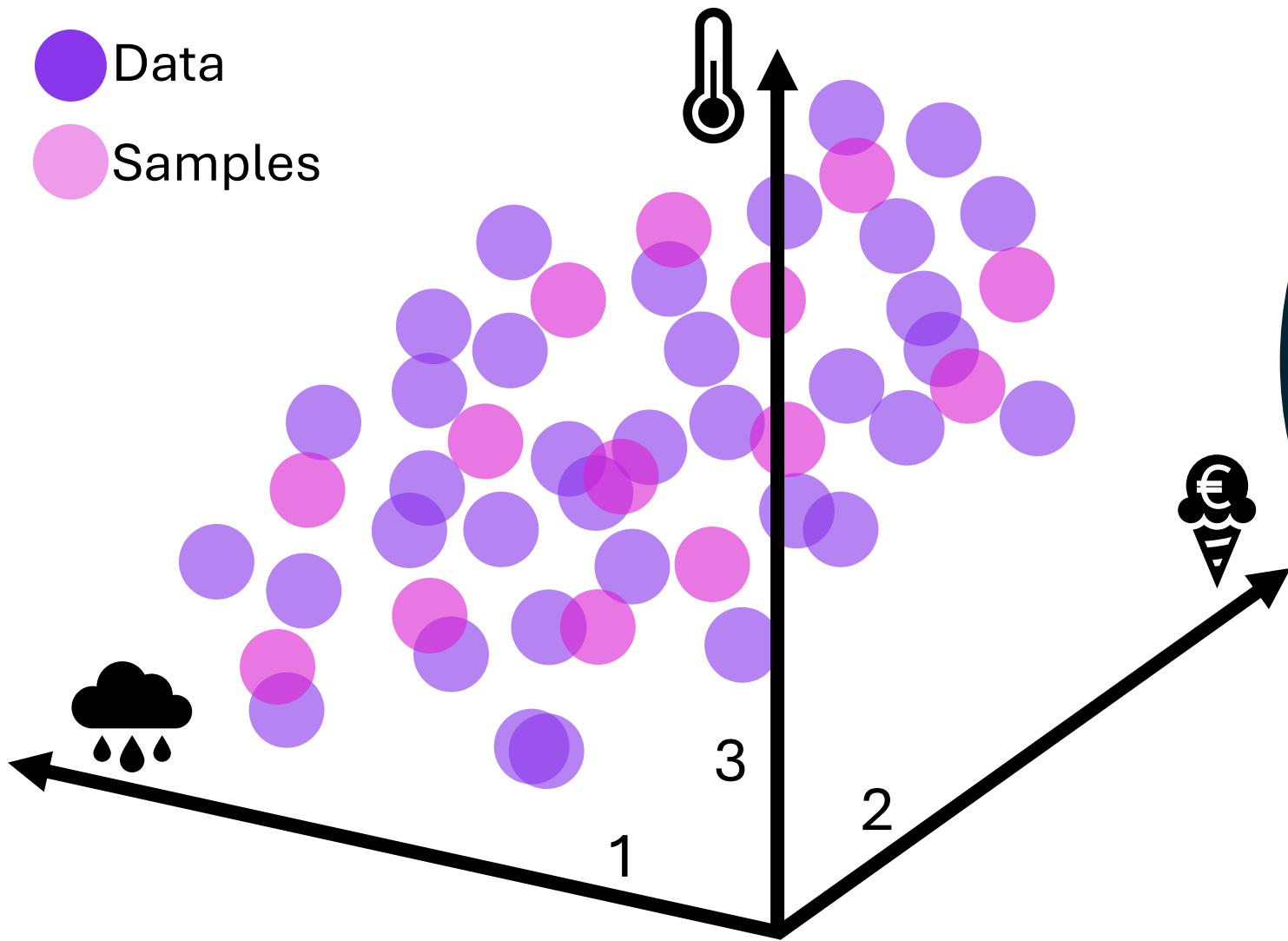
● Data



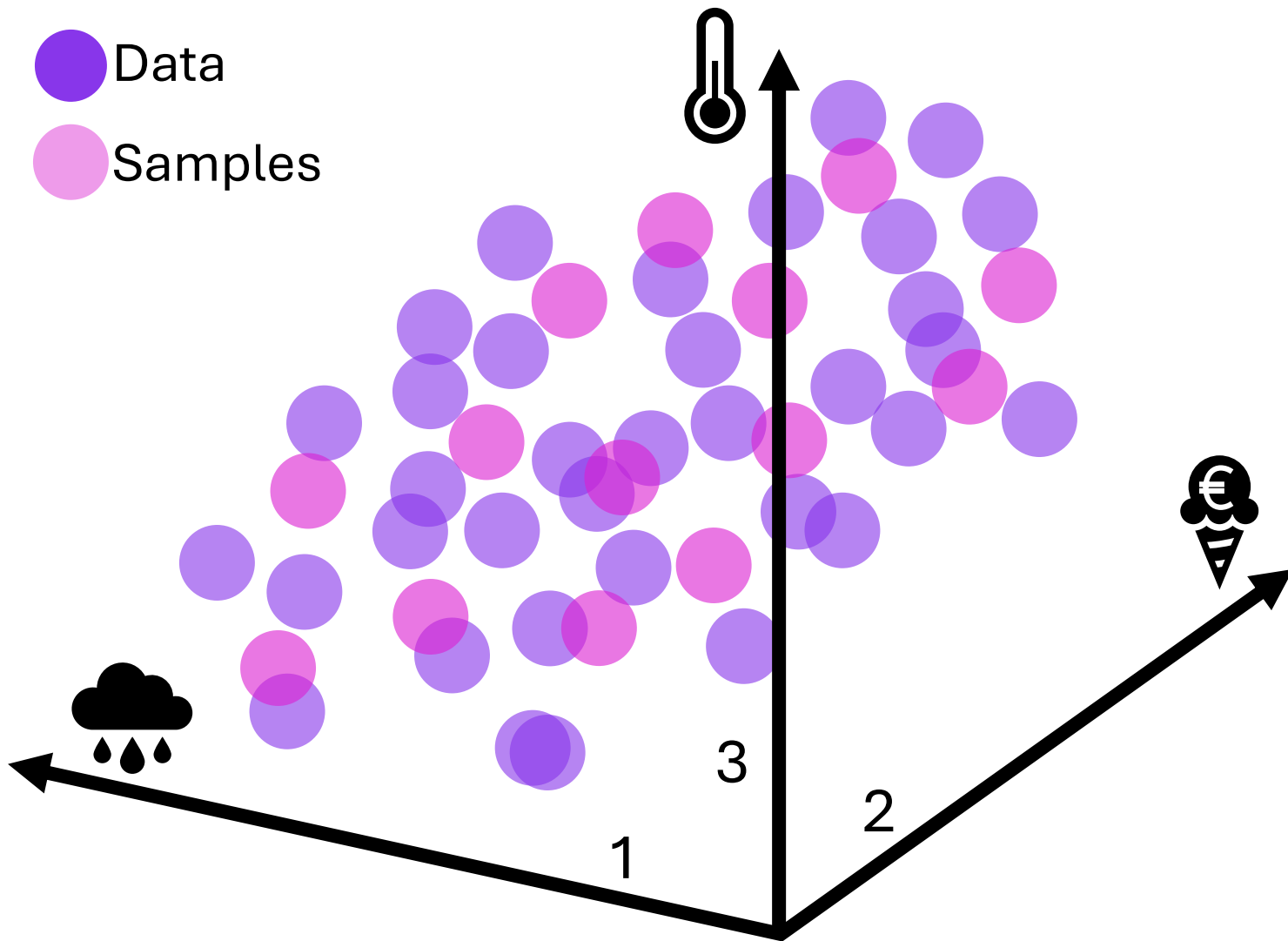
● Data



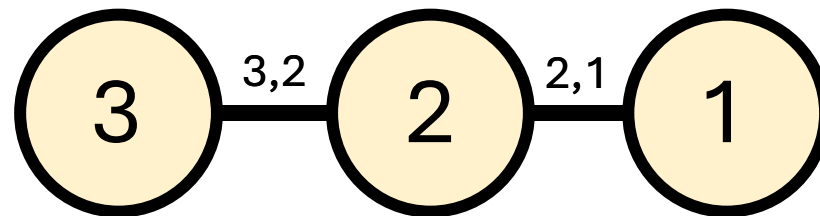
- Data
- Samples



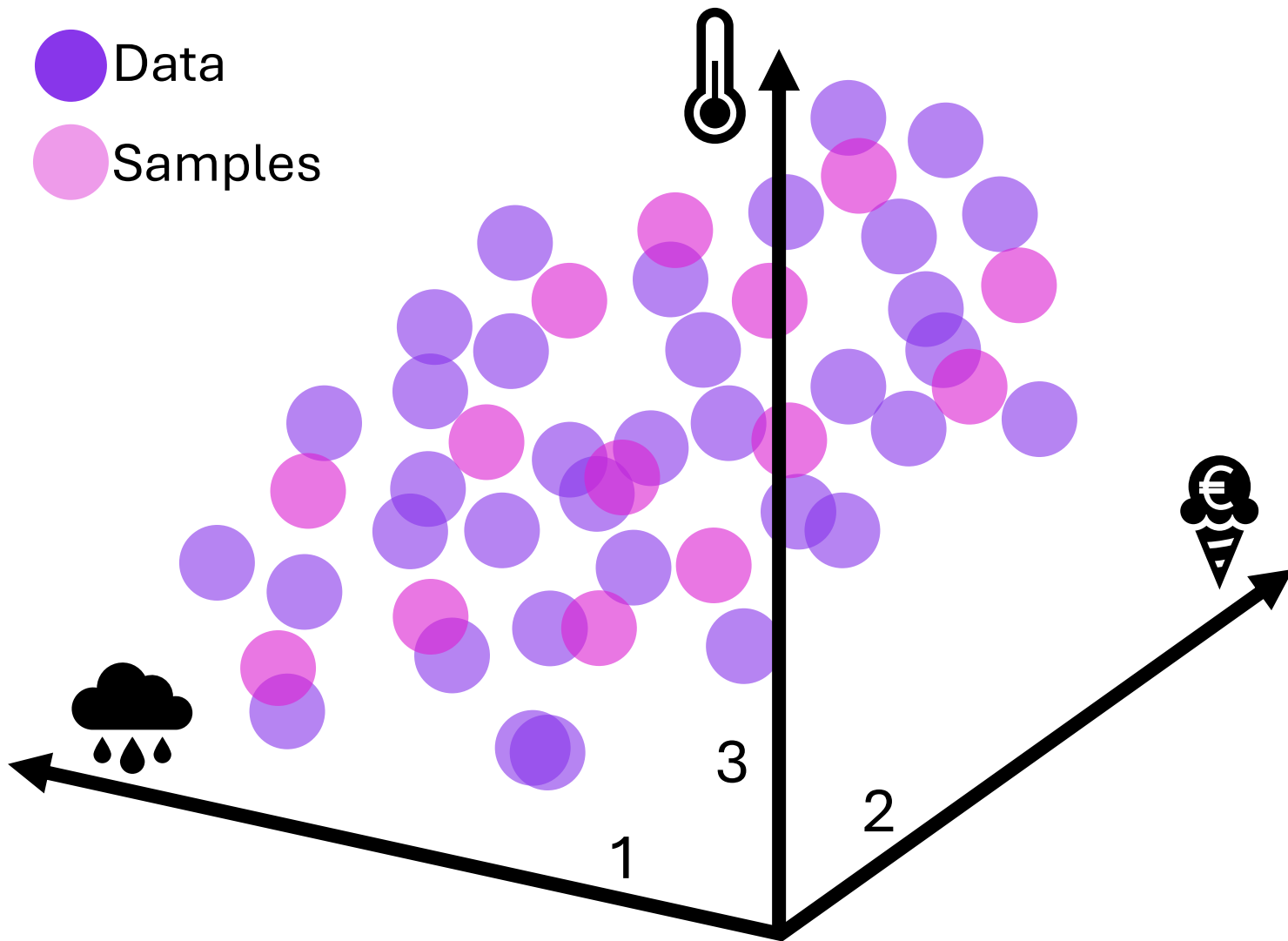
● Data
● Samples



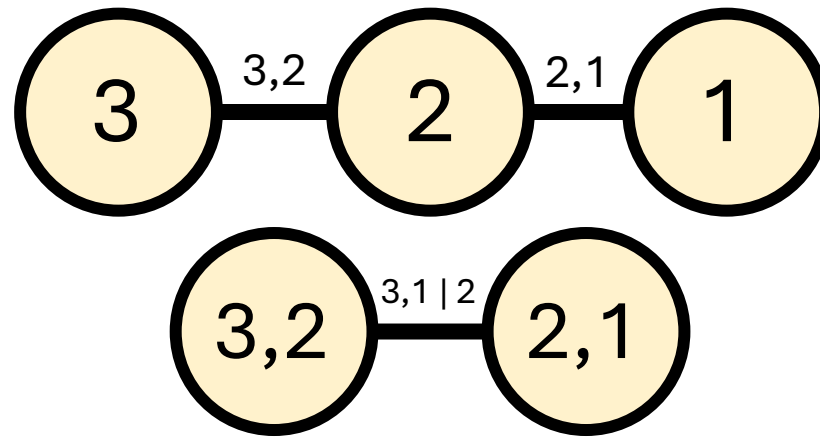
Vine Copula



● Data
● Samples

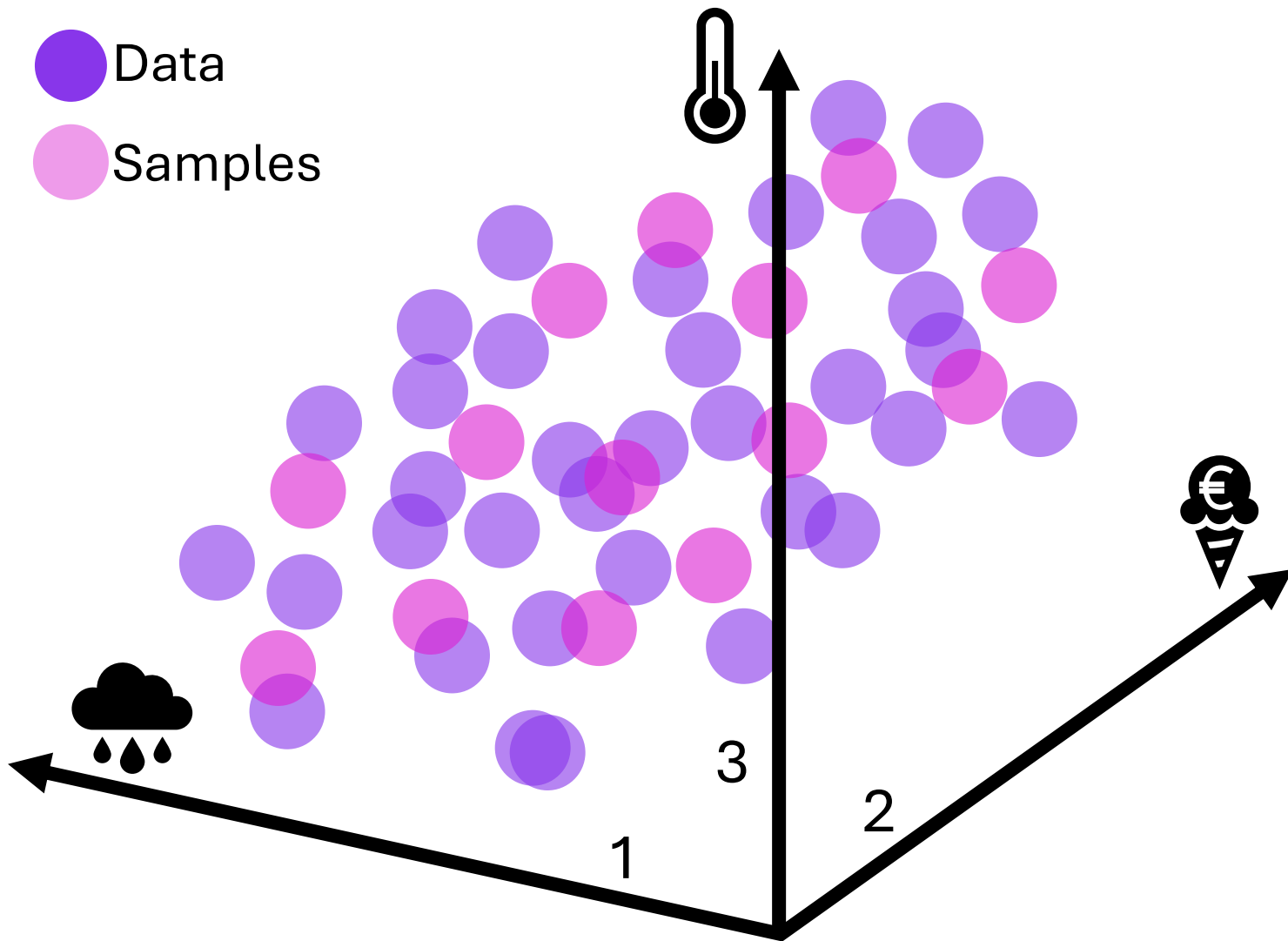


Vine Copula

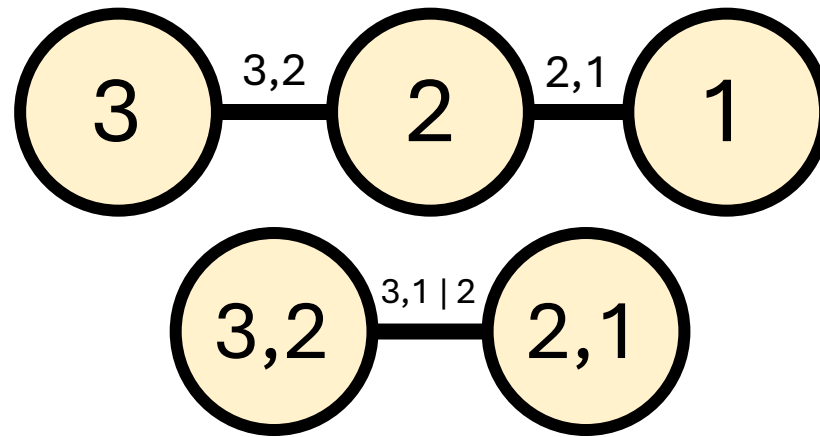


- For each vine copula with d variables, there are 2^{d-1} implied sampling orders (Cooke et al., 2015).
- Possible sampling orders: [1,2,3], [3,2,1], [2,1,3], [2,3,1]

● Data
● Samples

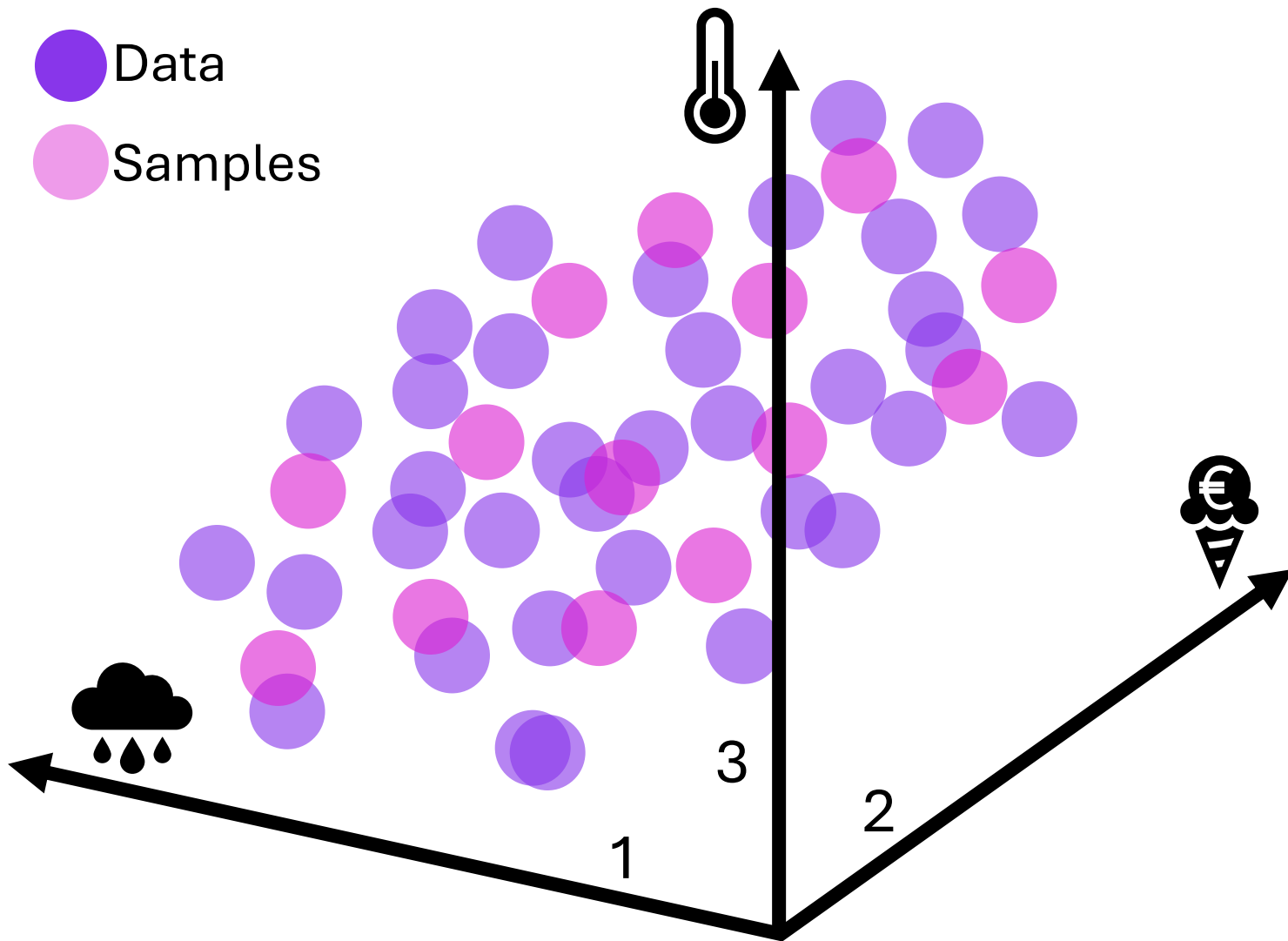


Vine Copula

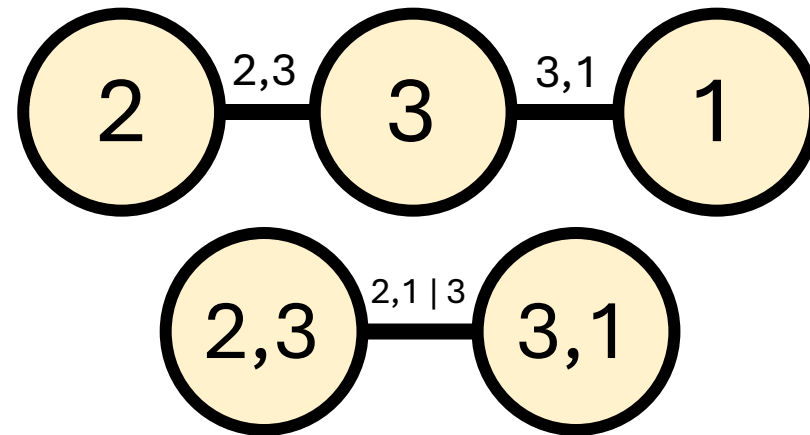


- For each vine copula with d variables, there are 2^{d-1} implied sampling orders (Cooke et al., 2015).
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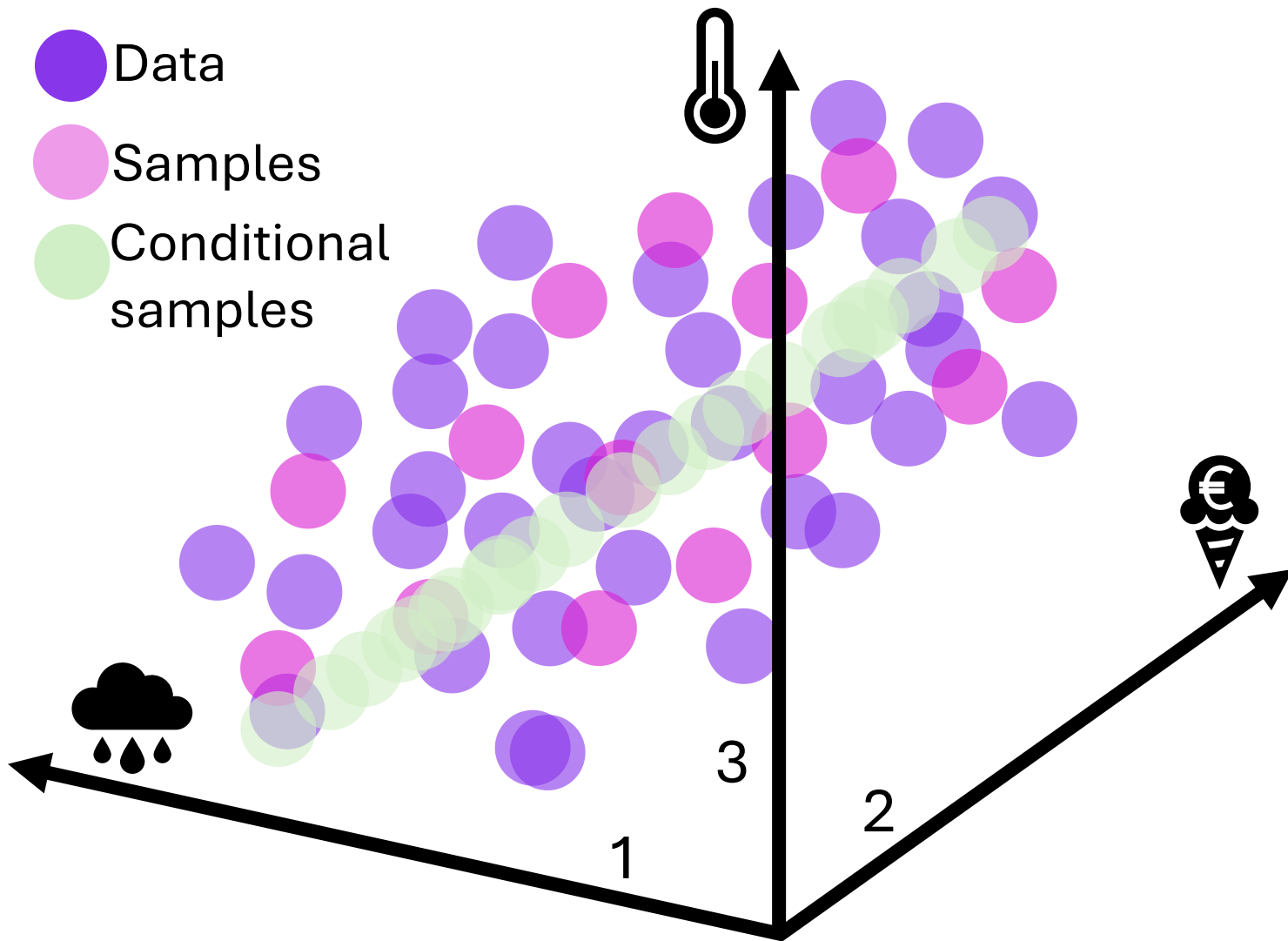
● Data
● Samples



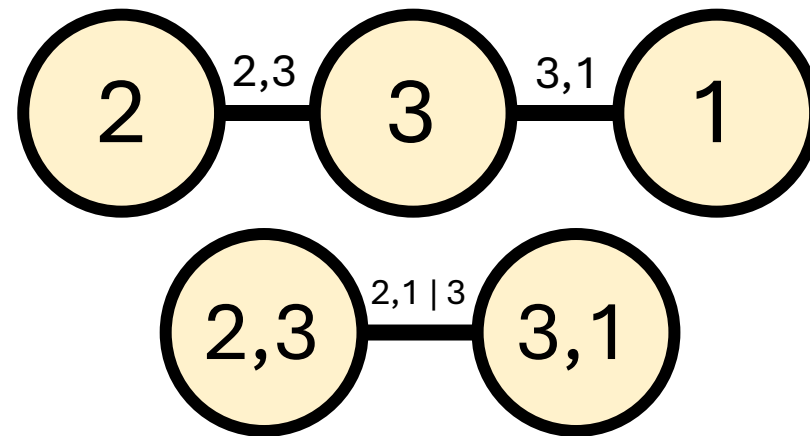
Vine Copula



- Possible sampling orders:
[2,3,1], [1,3,2], [3,1,2], [3,2,1]



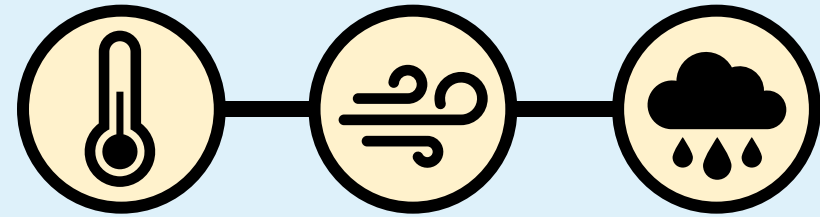
Vine Copula



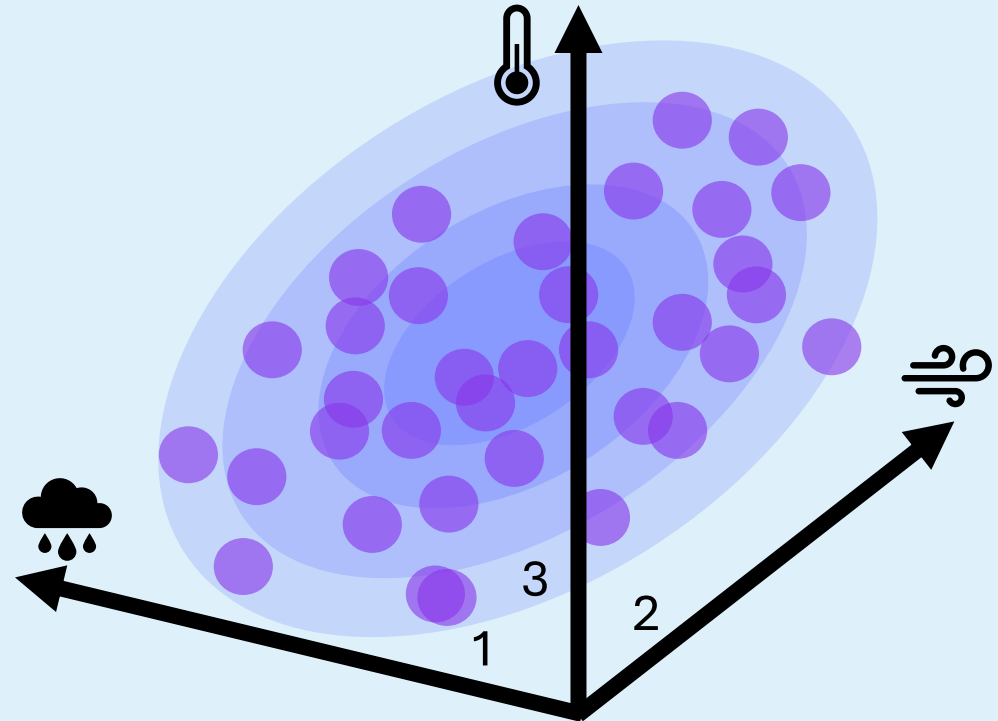
- Possible sampling orders:
 [2,3,1], [1,3,2], [3,1,2], [3,2,1]

Python Code

```
## VineCopulas
import(vinecopulas)
## load data
t2m = load(temperature)
pr = load(precipitation)
ws = load(windspeed)
## fit vine-copula
fit.vinecopula(t2m,pr,ws)
```

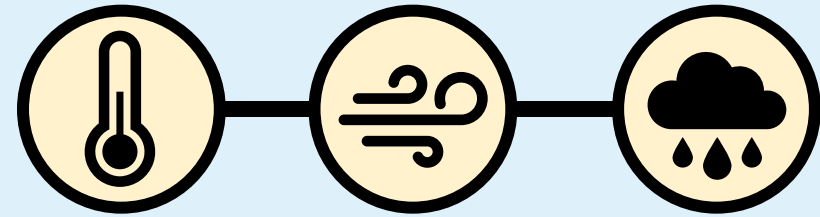


● Data

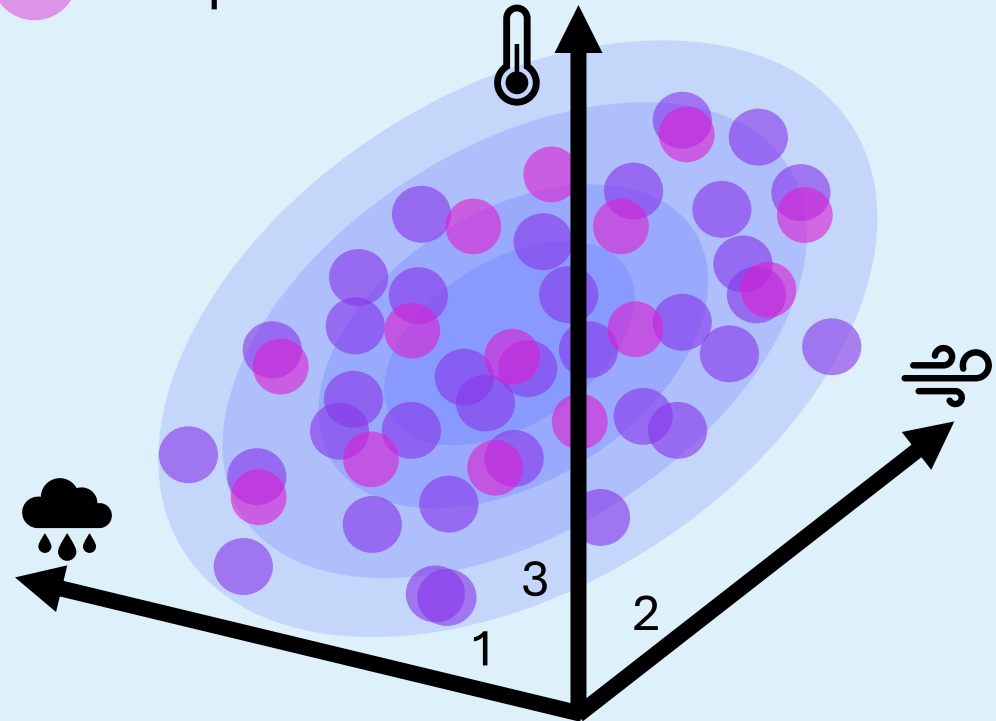


Python Code

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## VineCopulas
import(vinecopulas)
## load data
t2m = load(temperature)
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## fit vine-copula
fit.vinecopula(t2m,pr,ws)
## generate random samples
sample.vinecopula(t2m,pr,ws)
```

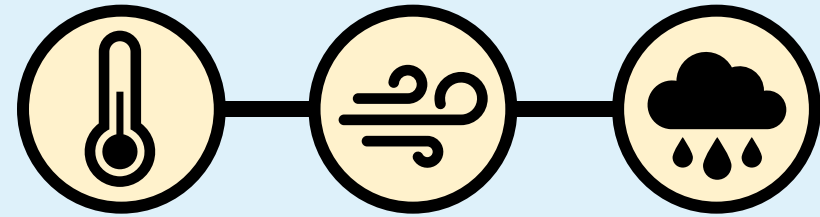


● Data
● Samples

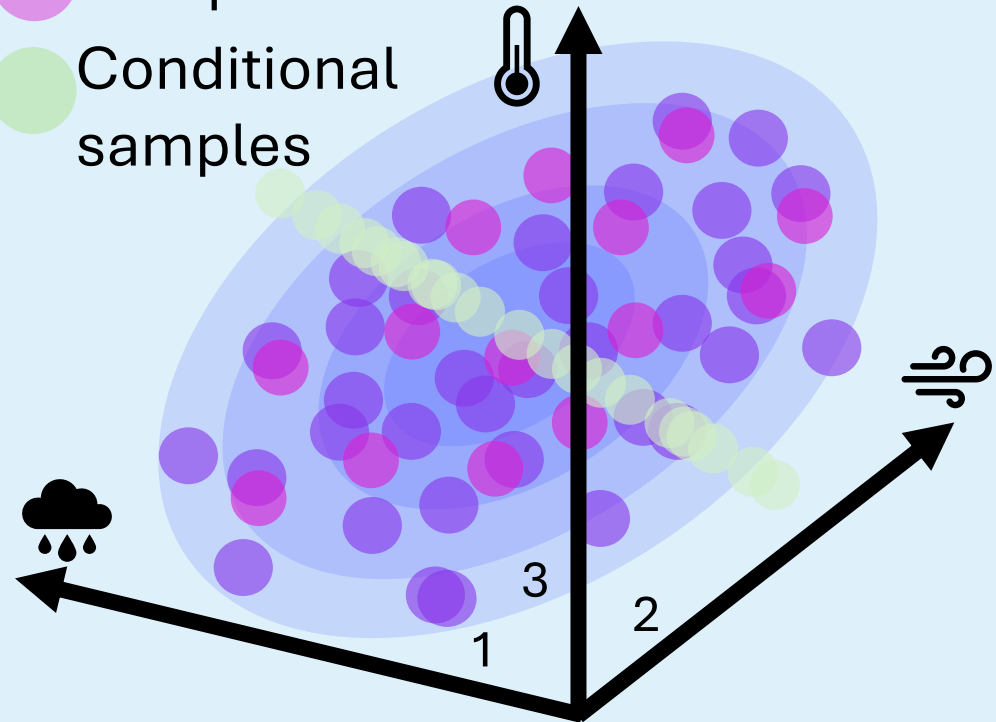


Python Code

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## VineCopulas
Import(vincecopulas)
## load data
t2m = load(temperature)
pr = load(precipitation)
ws = load(windspeed)
## fit vine-copula
fit.vinecopula(t2m,pr,ws)
## generate random samples
sample.vinecopula(t2m,pr,ws)
## generate conditional samples
sampleconditional.vinecopula(ws)
## fit conditional vine
fitconditional.vinecopula(ws)
```

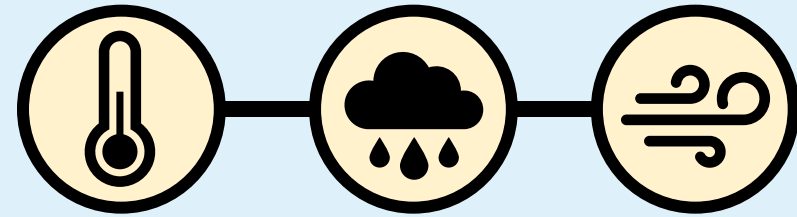





- Data
- Samples
- Conditional samples

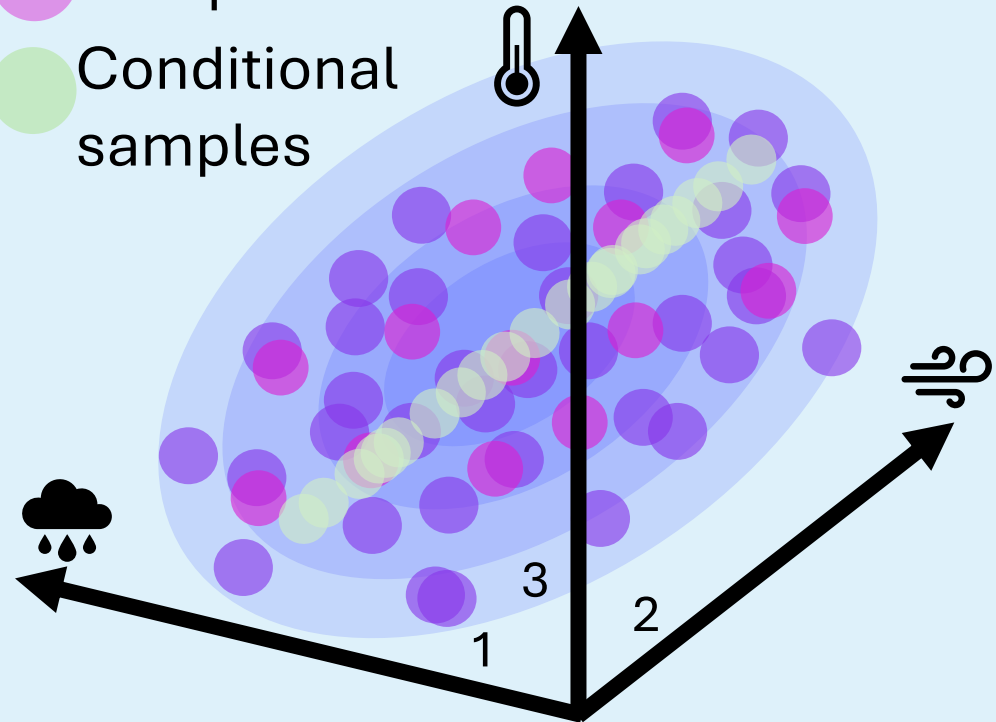


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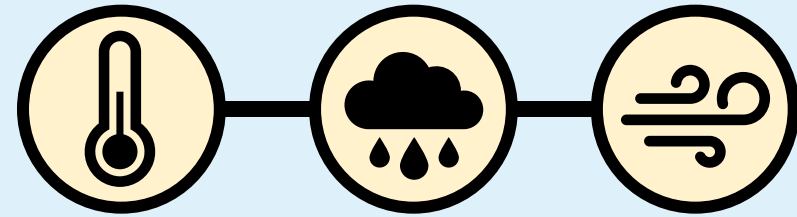





-  Data
-  Samples
-  Conditional samples

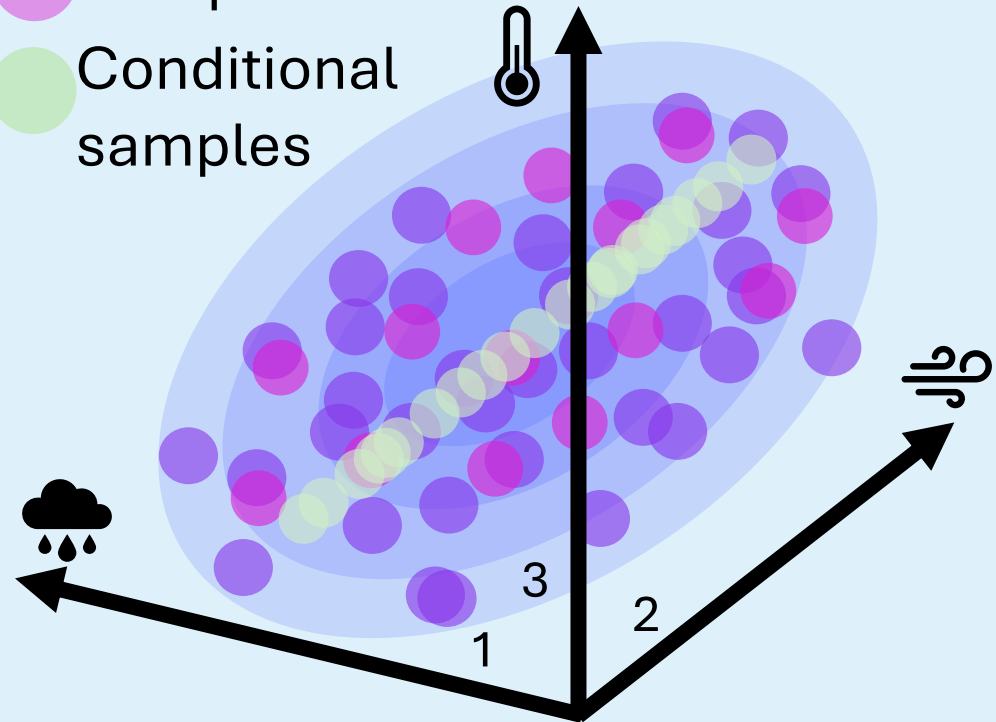


Python Code

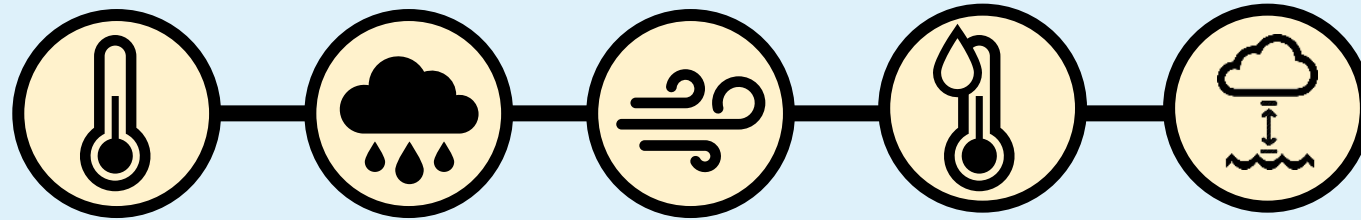
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-  Data
-  Samples
-  Conditional samples



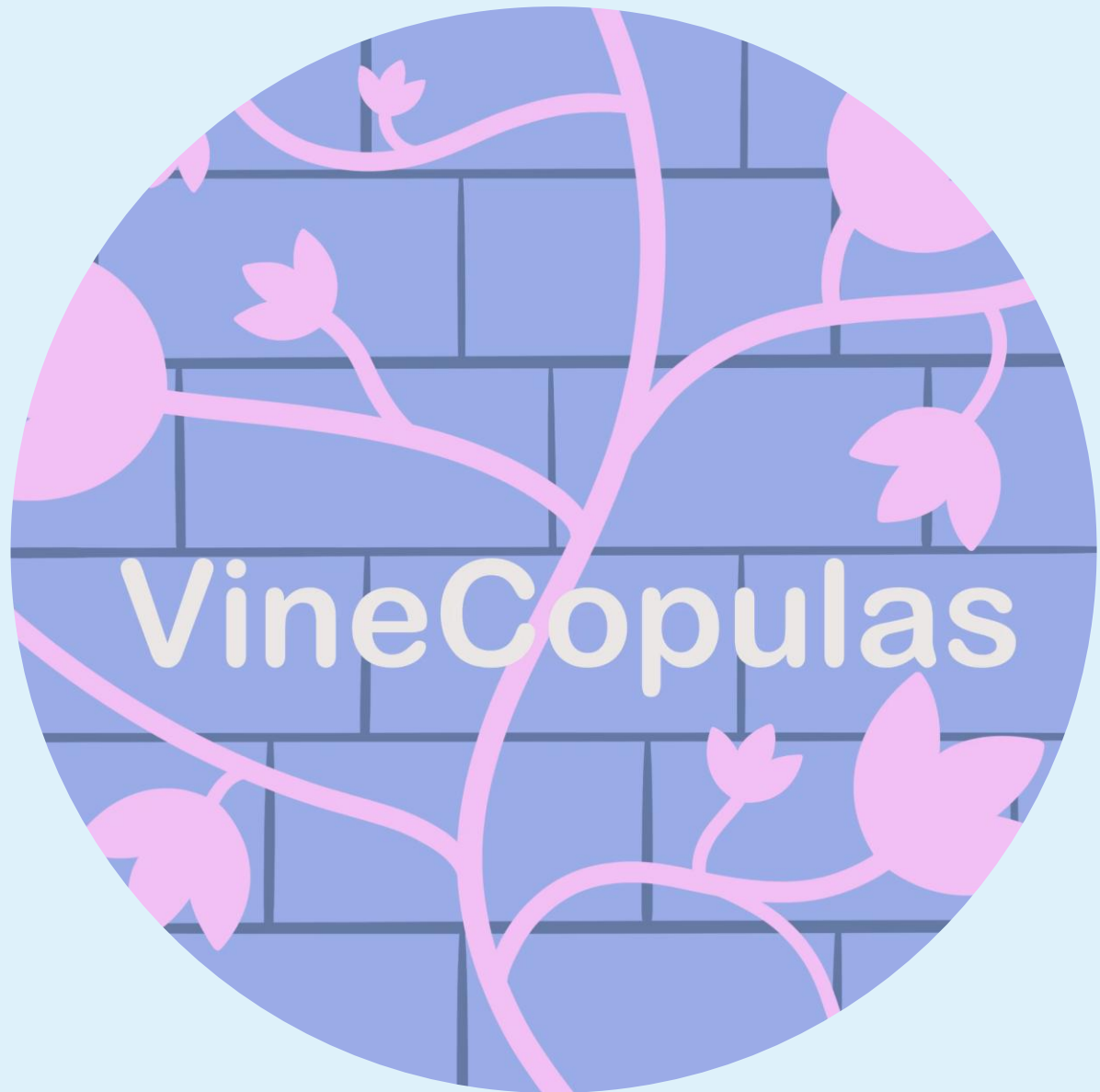
More Variables



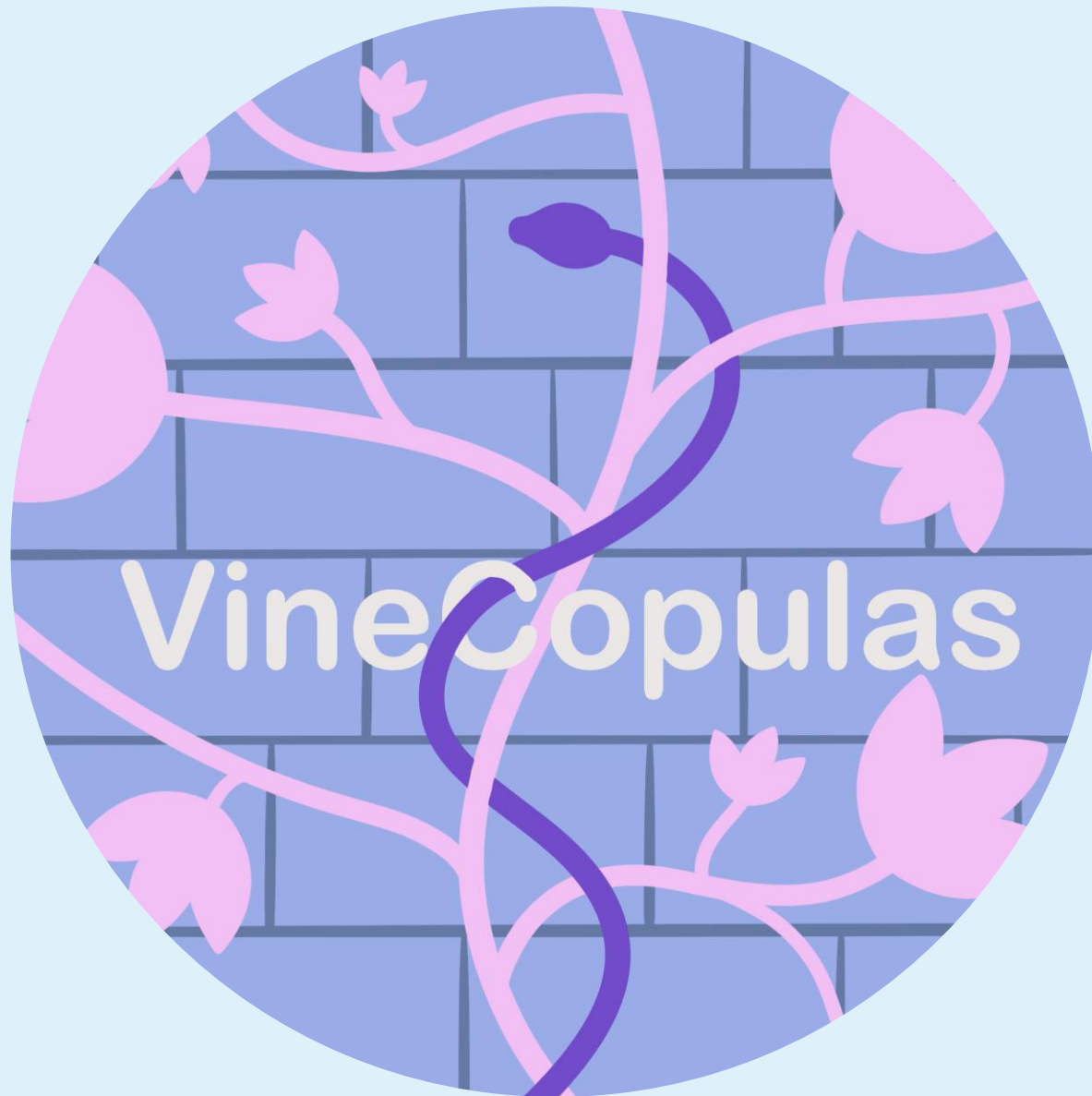
- While a vine copula with 3 variables only has 3 structures, the number of possible structures increases exponentially as

$$d! \times 2^{\frac{(d-2)(d-3)}{2}-1} \text{ (Morales Napoles, 2011)}$$

- Meaning 5 variables already has 480 possible structures, and with 6 values this already increases to 23000

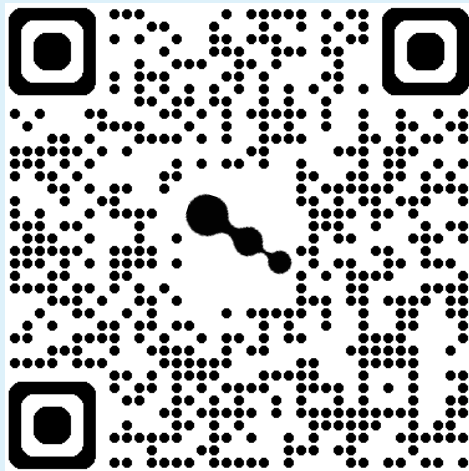
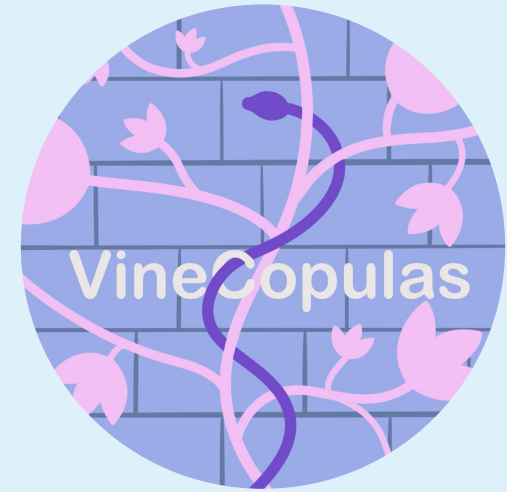


VineCopulas



Vine Copulas

Open-source Python Package



Paper

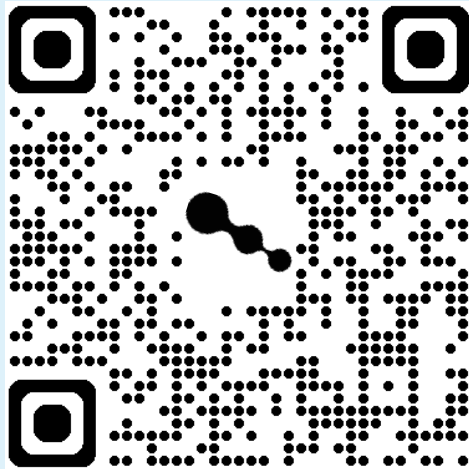
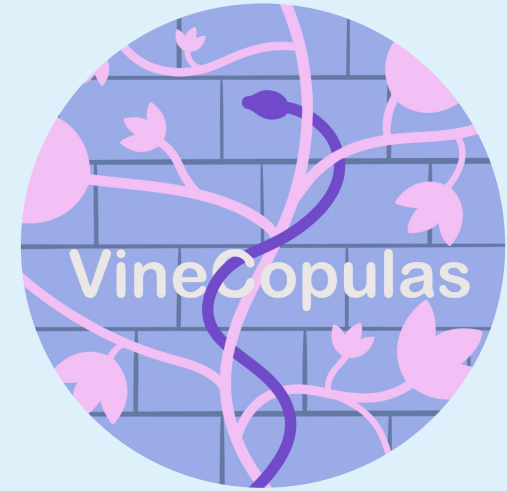


GitHub



Documentation

Open-source Python Package



Paper



GitHub



Documentation

🏠 vinecopulas



latest ▾

Home

Bivariate Copulas

Vine Copulas

API Reference

🏠 / Welcome to VineCopulas's documentation!

[View page source](#)

Welcome to VineCopulas's documentation!

VineCopulas is a Python package that is able to:

- Fit both [bivariate](#) and [vine copulas](#)
- Simulate from both [bivariate](#) and [vine copulas](#)
- Allow for both [discrete](#) as well as [continuous](#) input data
- Draw conditional samples for any variables of interest with the use of [bivariate copulas](#) and different [vine](#) structures

Installation

```
pip install vinecopulas
```

Documentation Contents

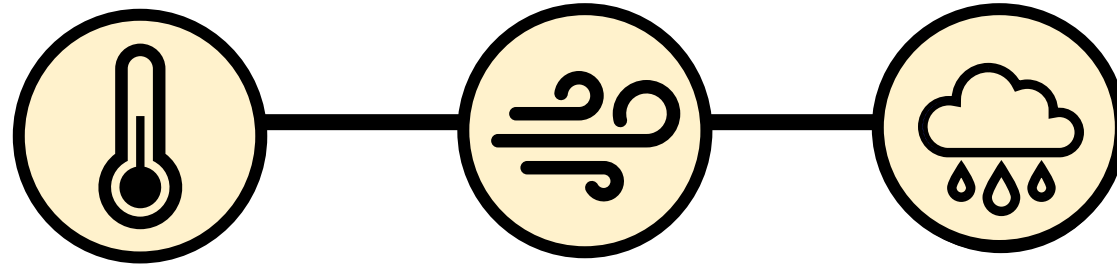
- [Home](#)
- [Bivariate Copulas](#)
- [Vine Copulas](#)
- [API Reference](#)

Getting Started

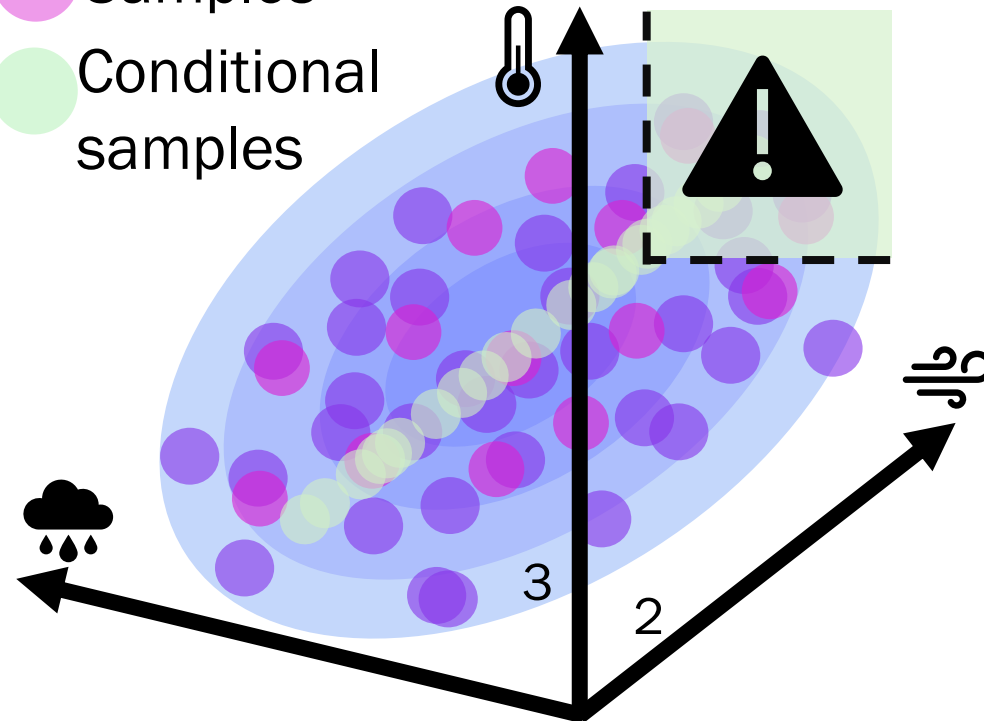
QR code to tutorial

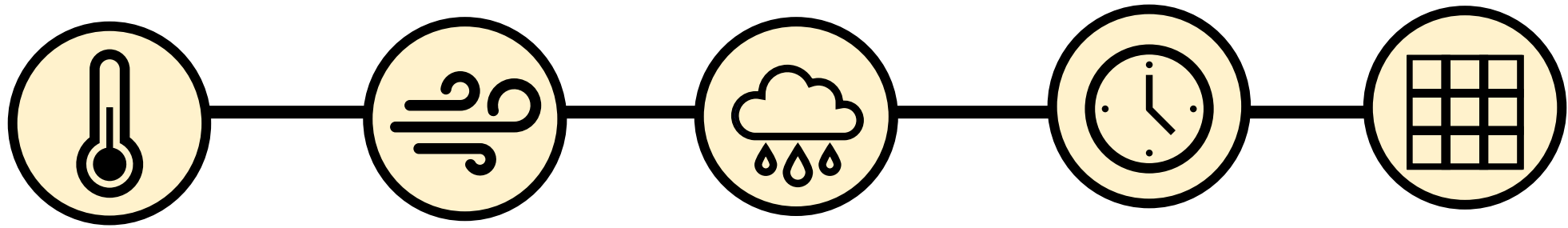


Using VineCopulas to generate stochastic weather data and understand co-occurring extremes

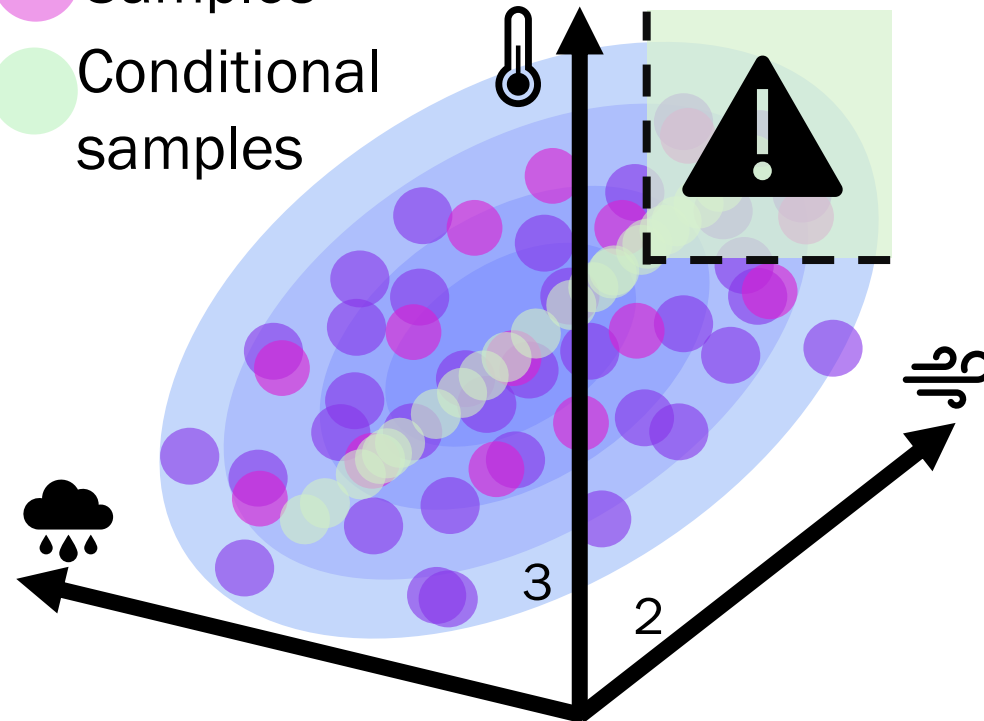


- Data
- Samples
- Conditional samples

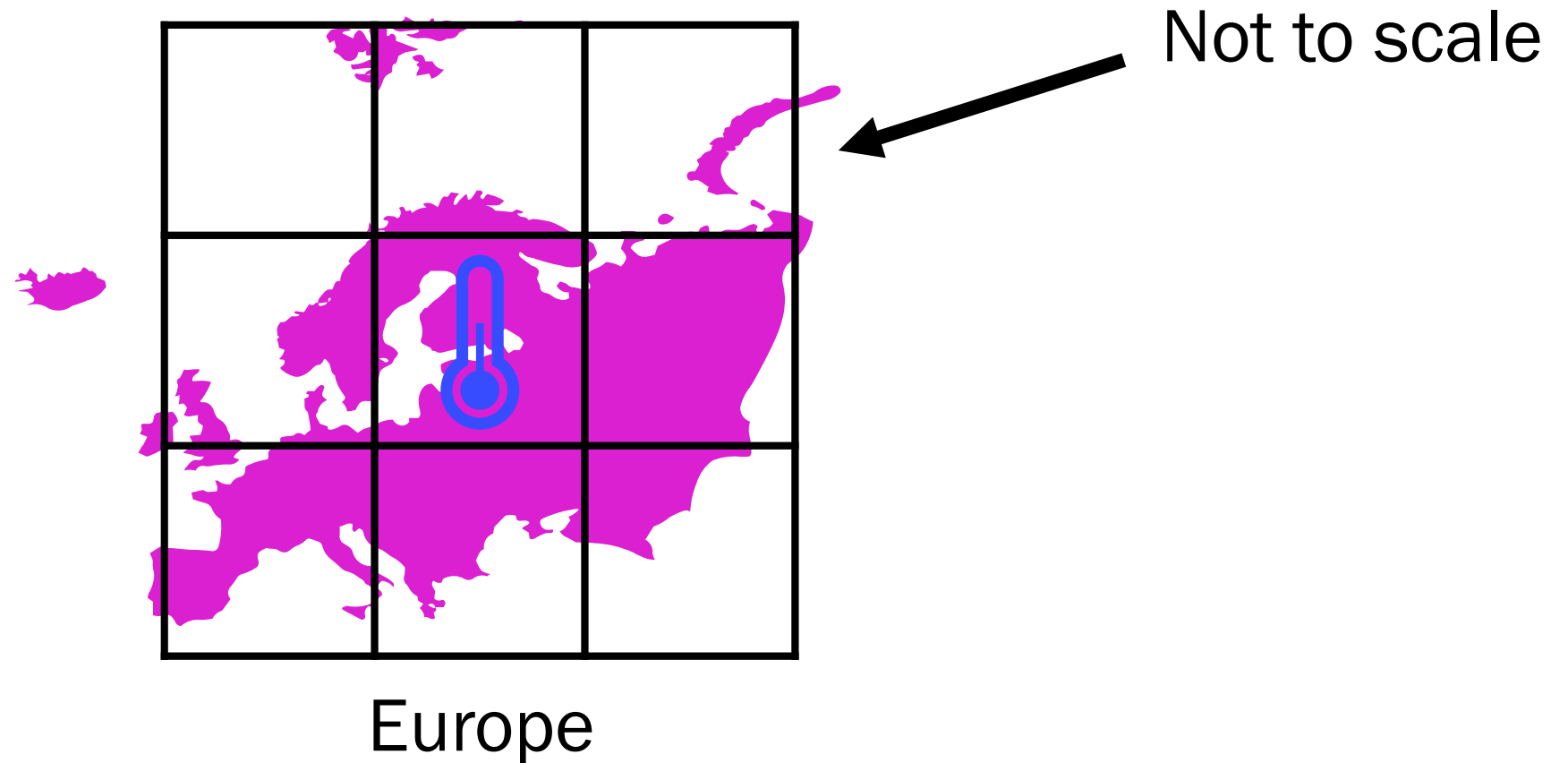




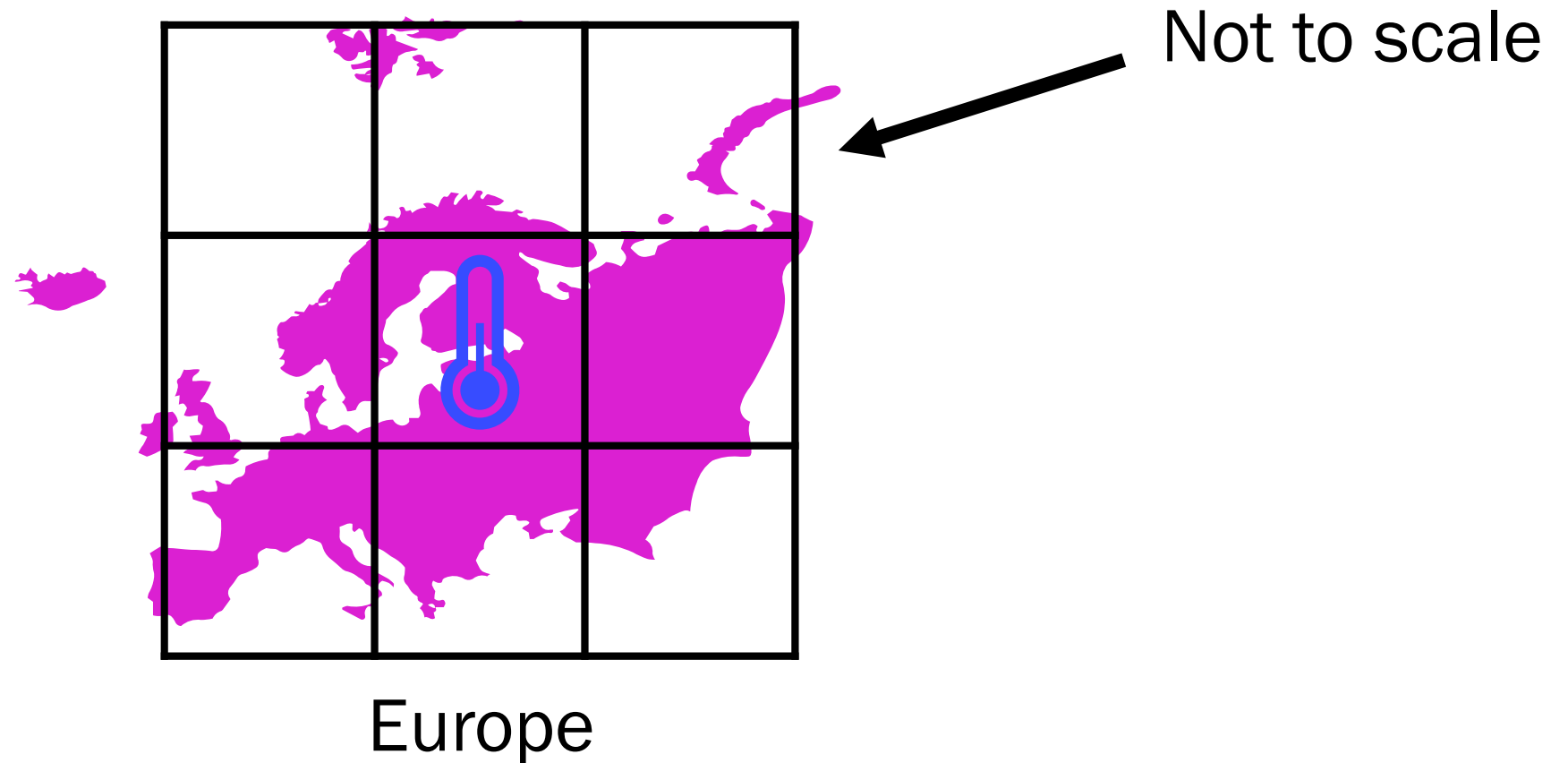
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- Samples
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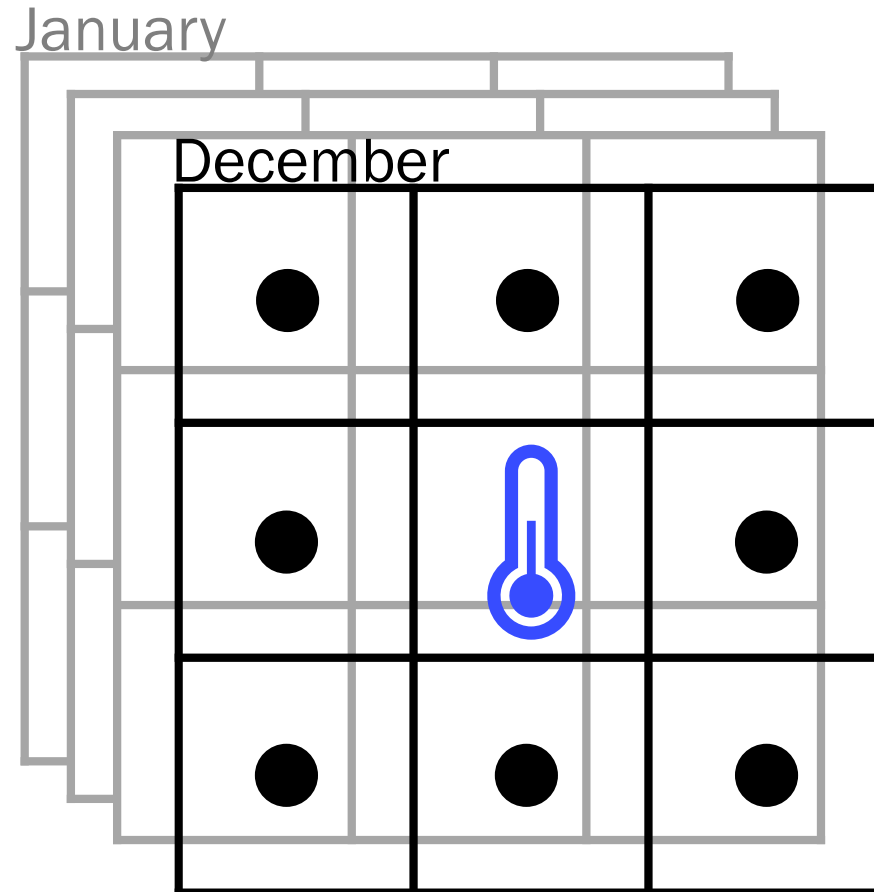
Model Setup: spatiotemporal dependencies



Model Setup: spatiotemporal dependencies



Model Setup: spatiotemporal dependencies



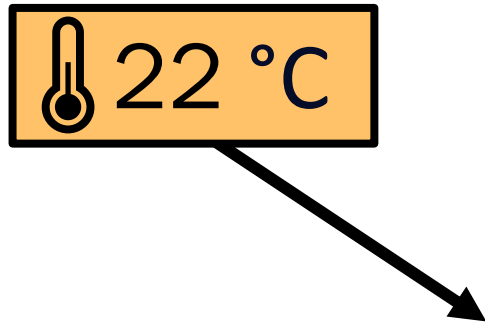
Marginal distribution per season per grid cell

Model Setup: spatiotemporal dependencies

7	2	6
4	1	3
8	5	9

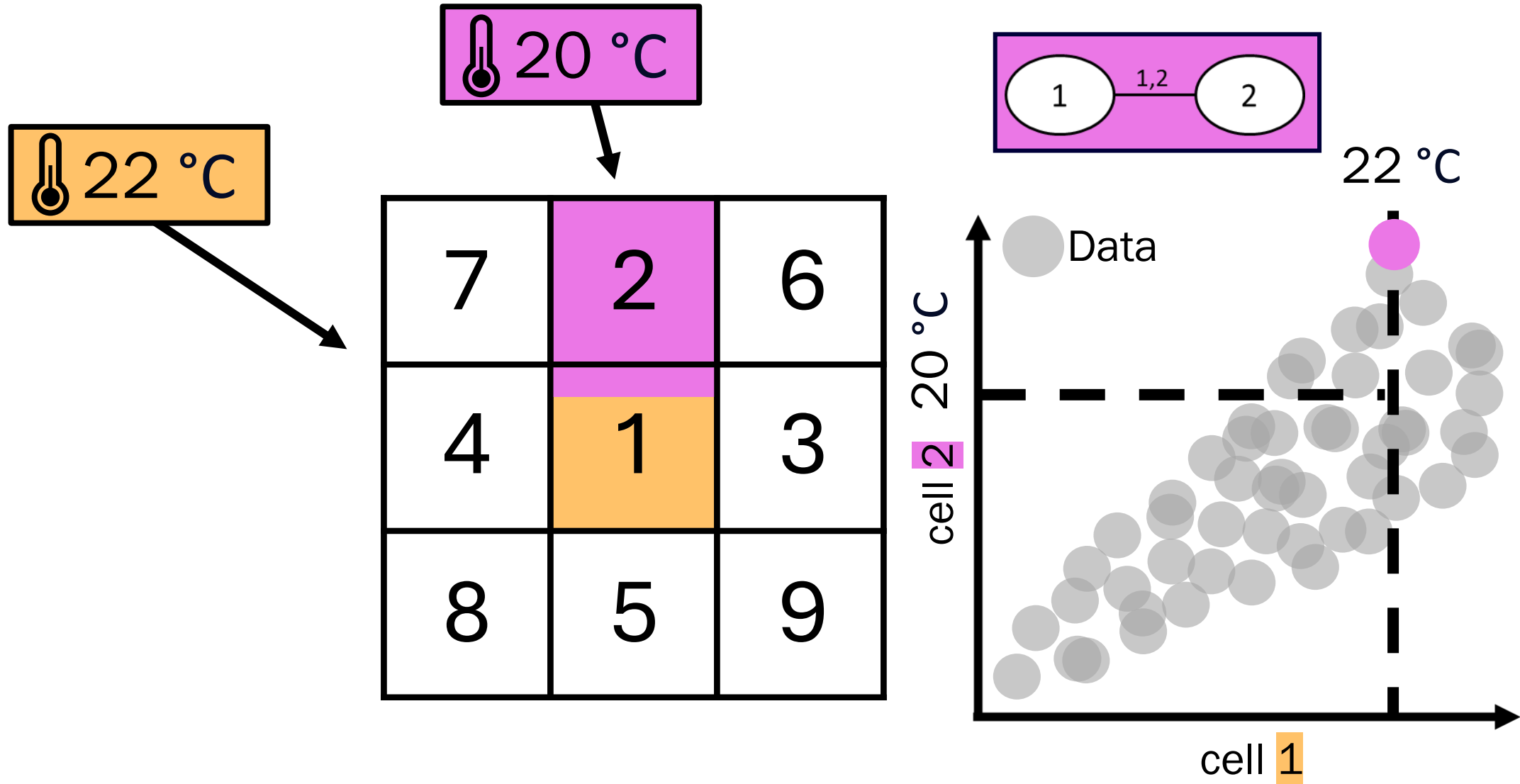
Number the grid cells for a sampling order

Model Setup: spatiotemporal dependencies

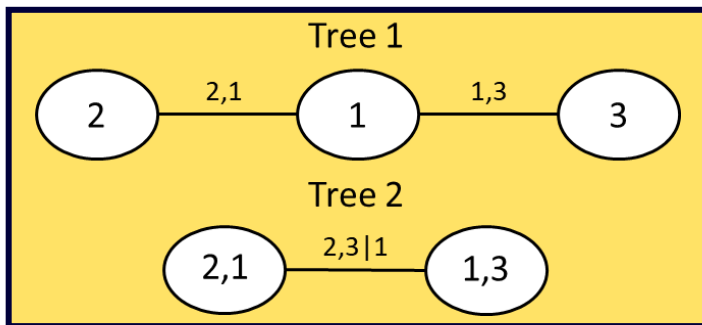
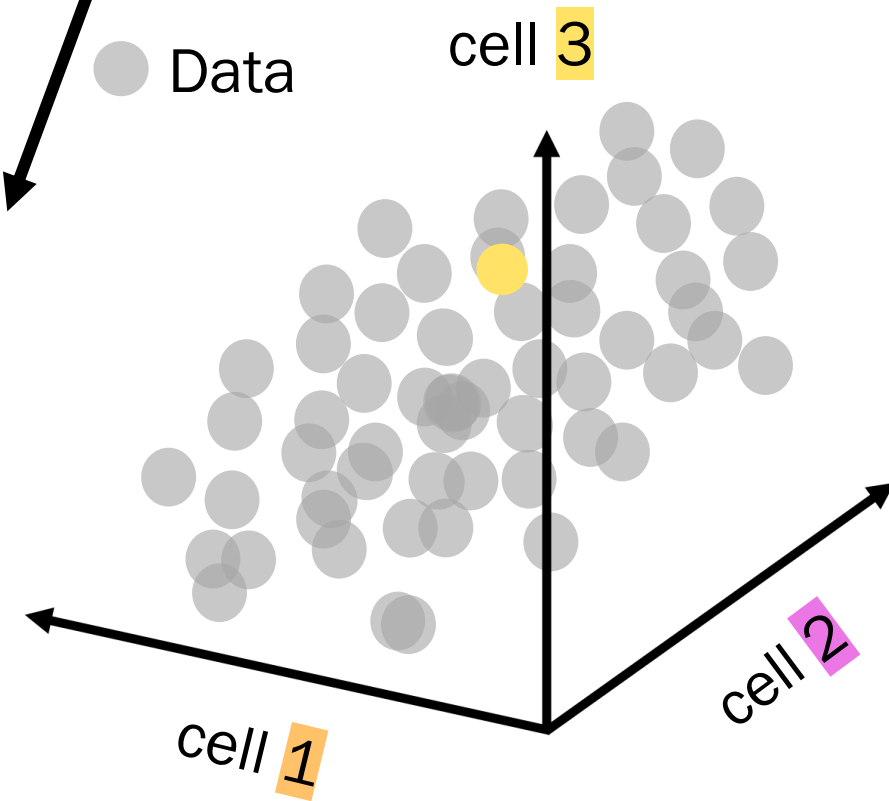
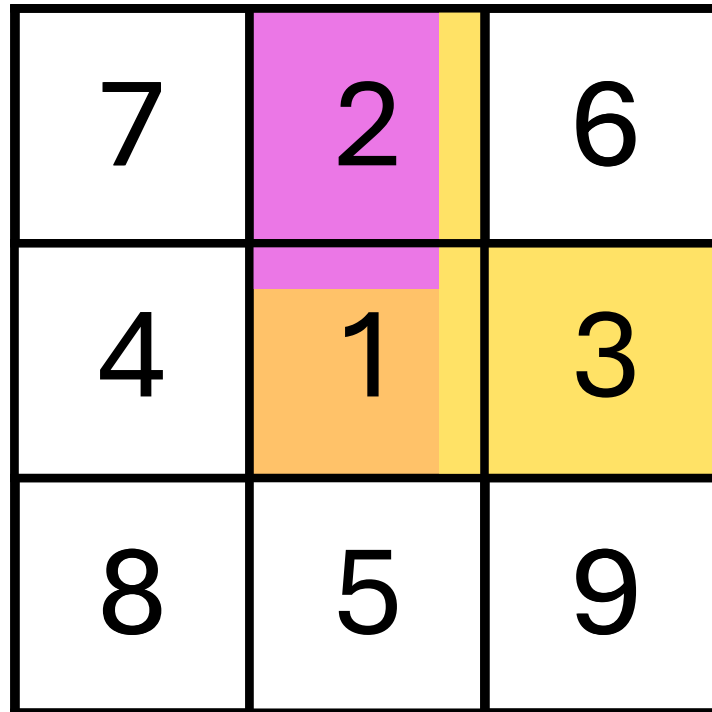
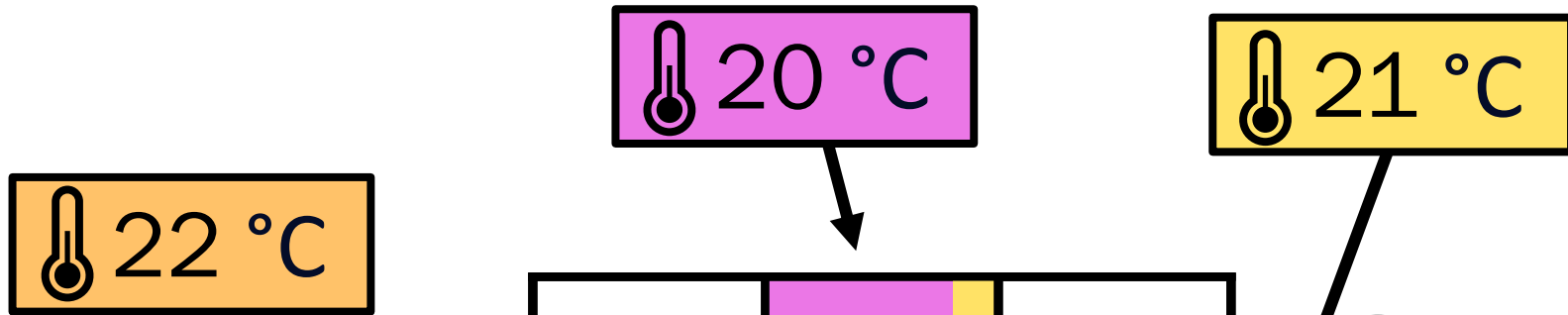


7	2	6
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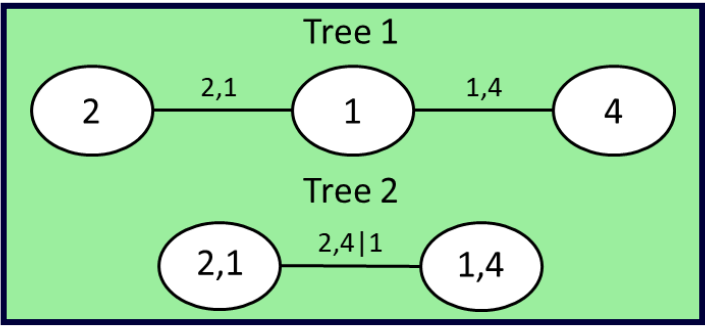
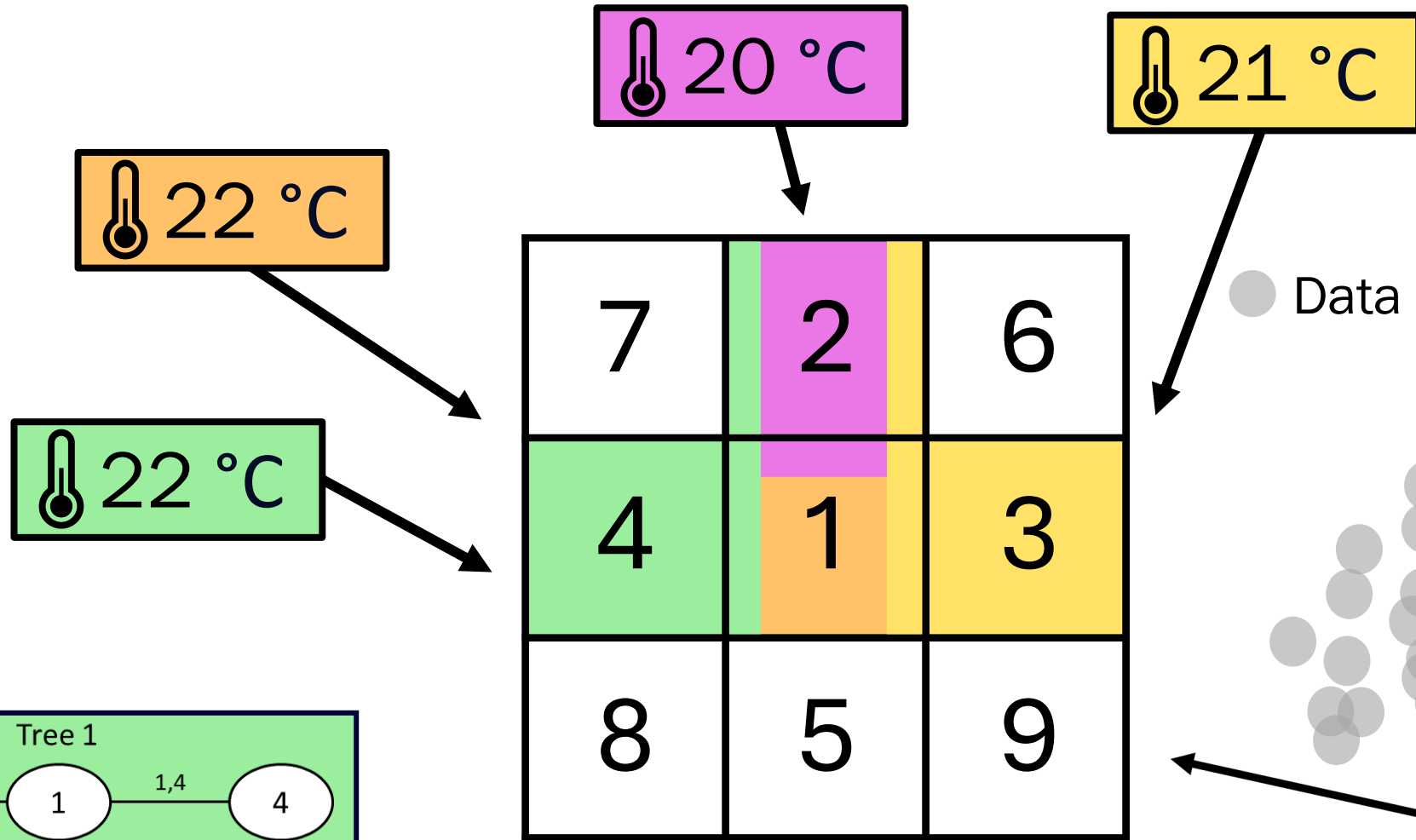
Model Setup: spatiotemporal dependencies



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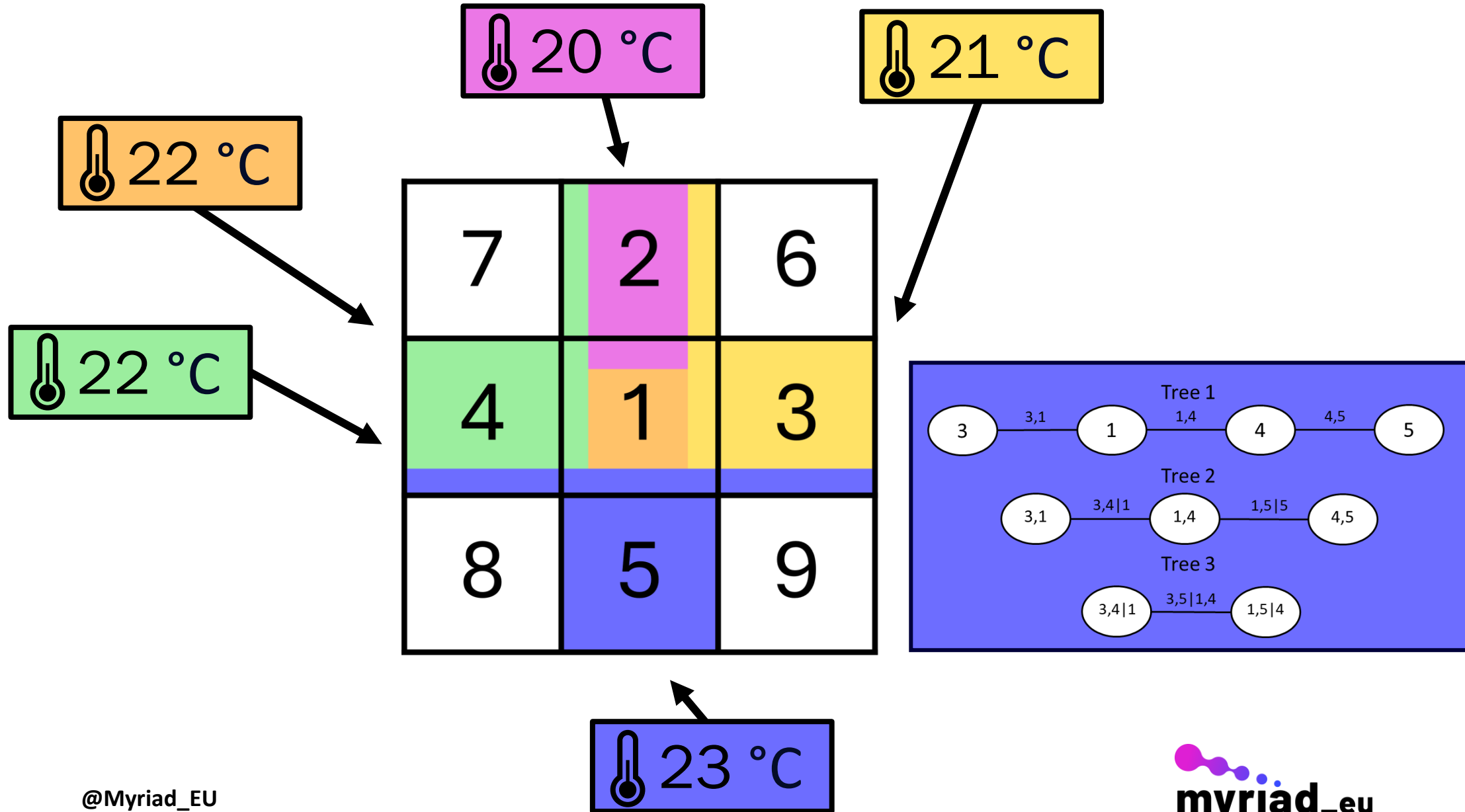


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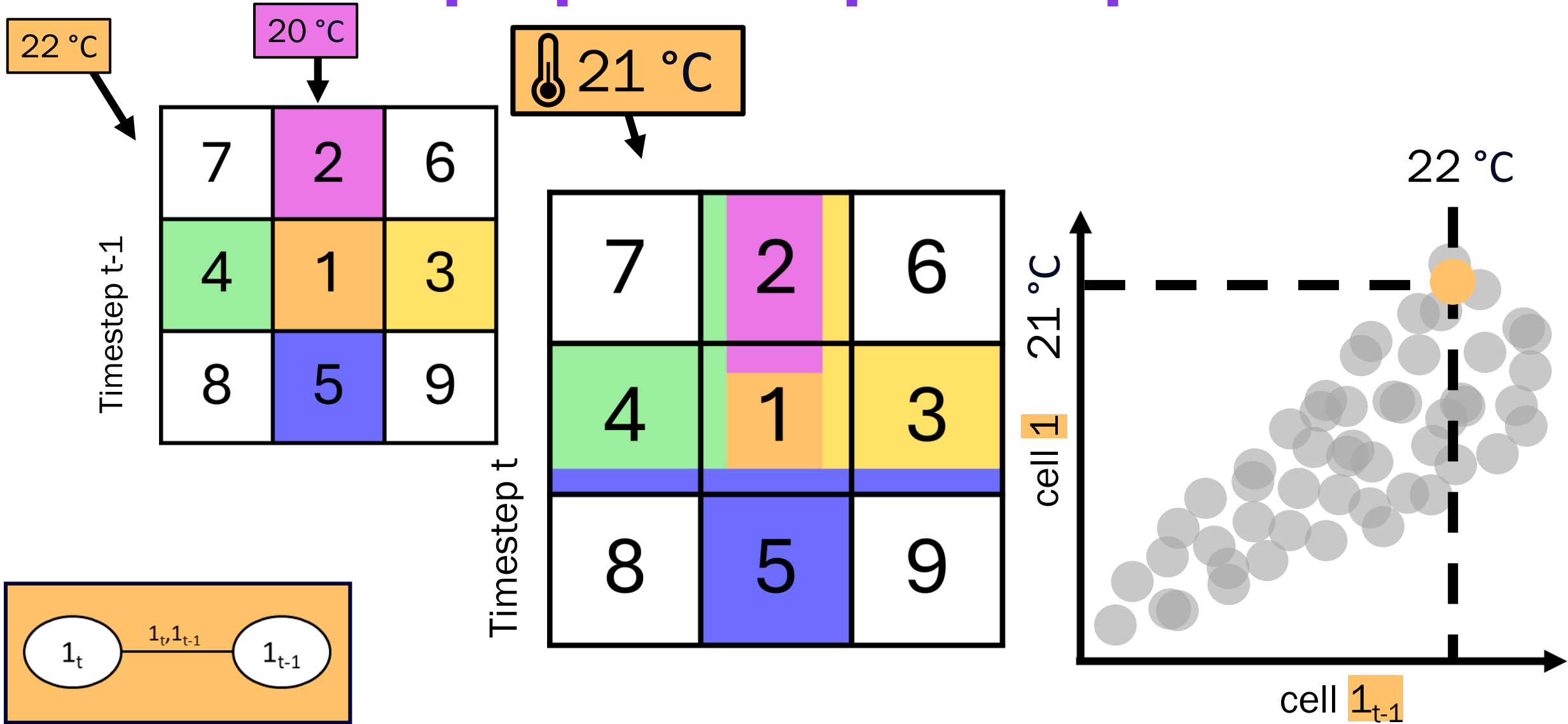


@Myriad_EU

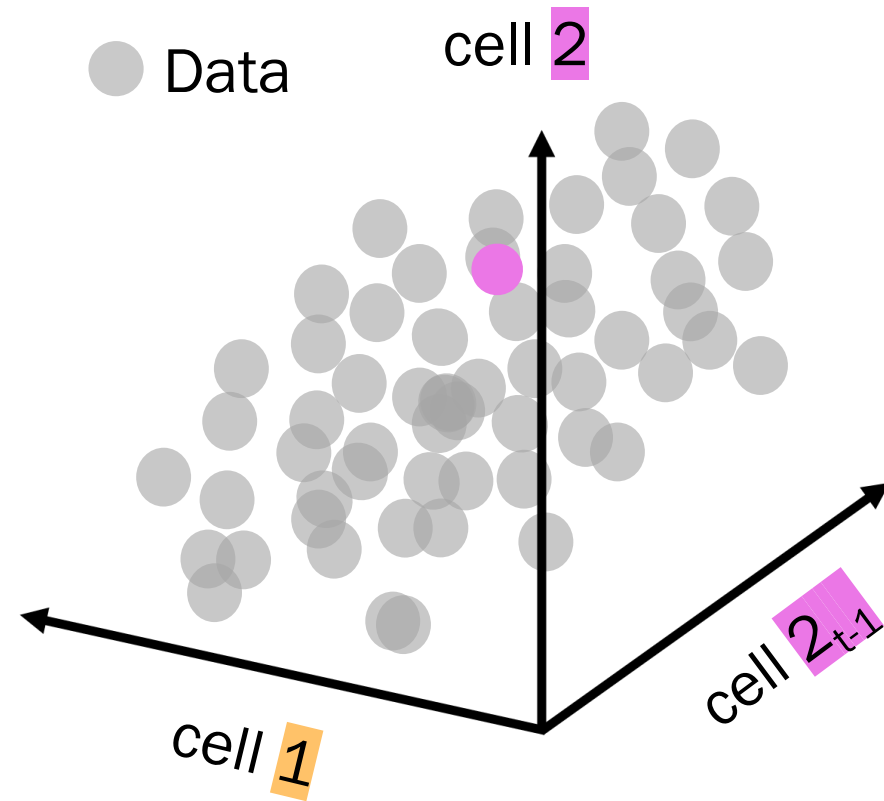
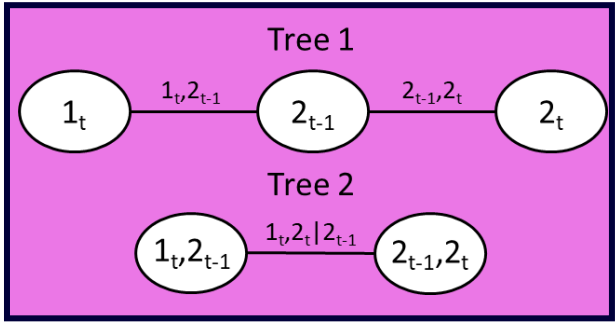
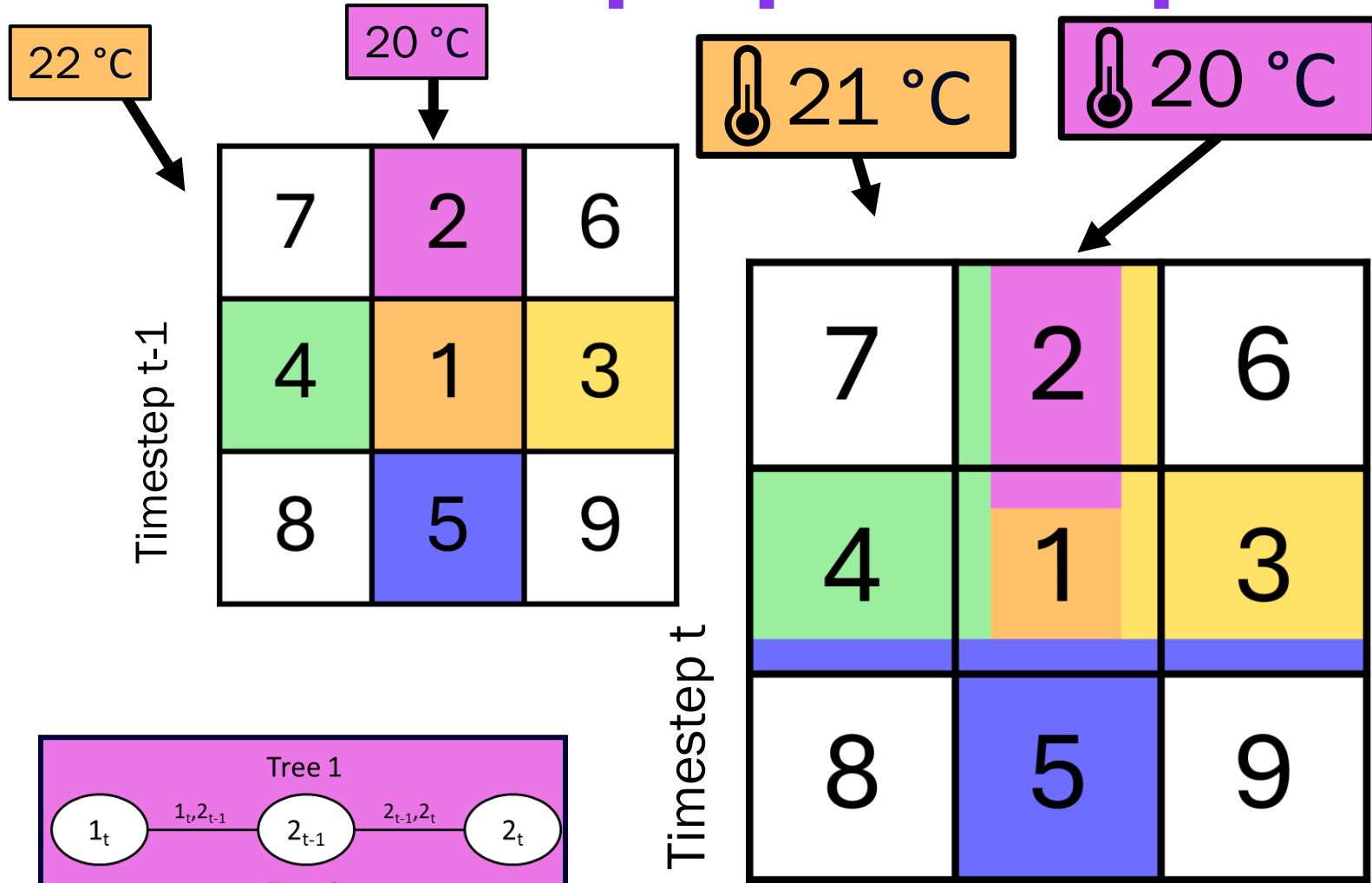
Model Setup: spatiotemporal dependencies



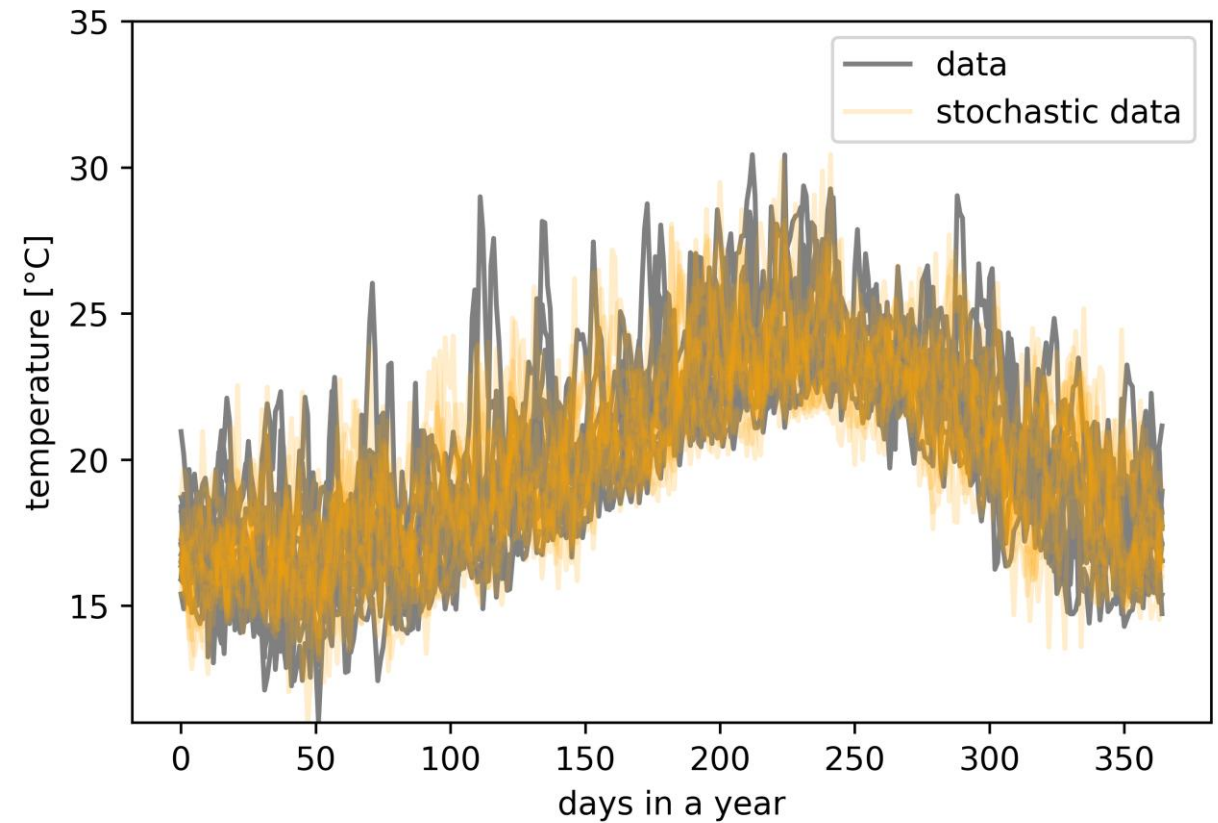
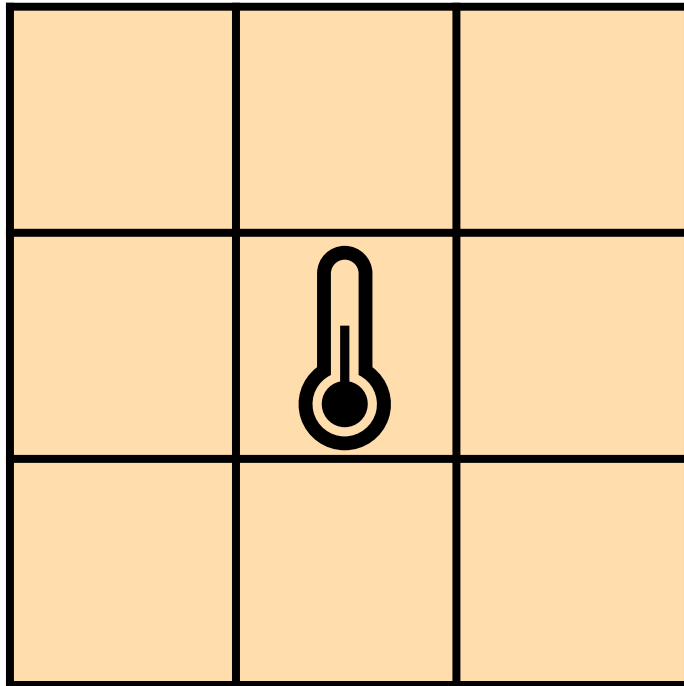
Model Setup: spatiotemporal dependencies



Model Setup: spatiotemporal dependencies

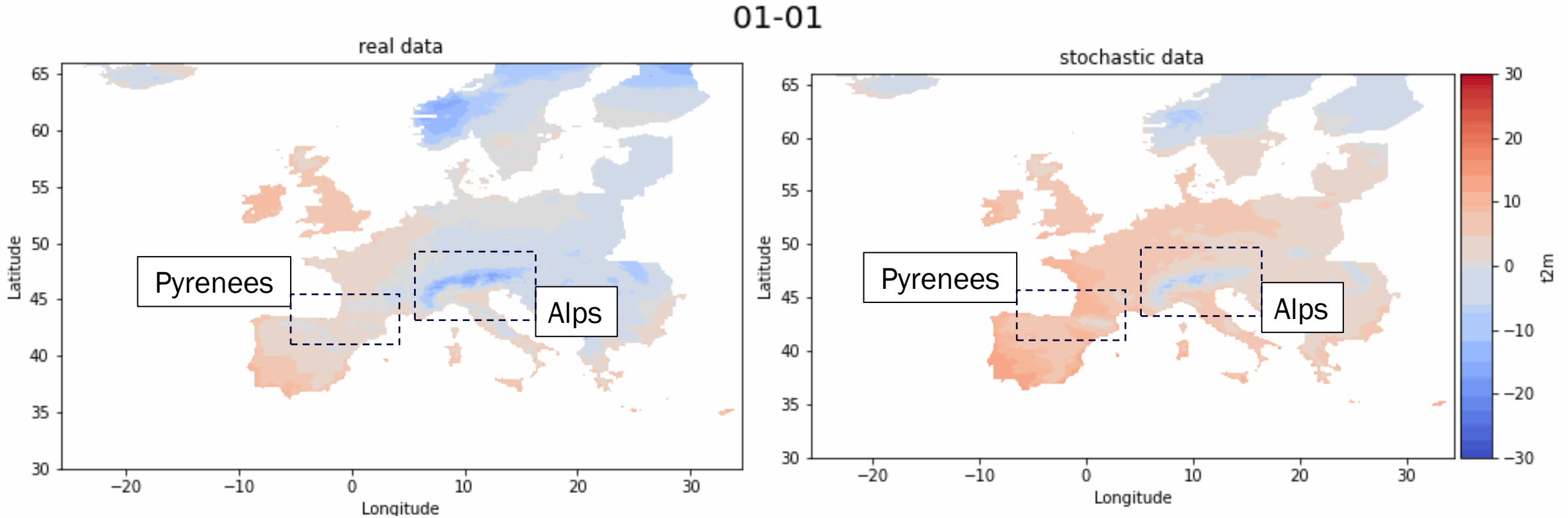


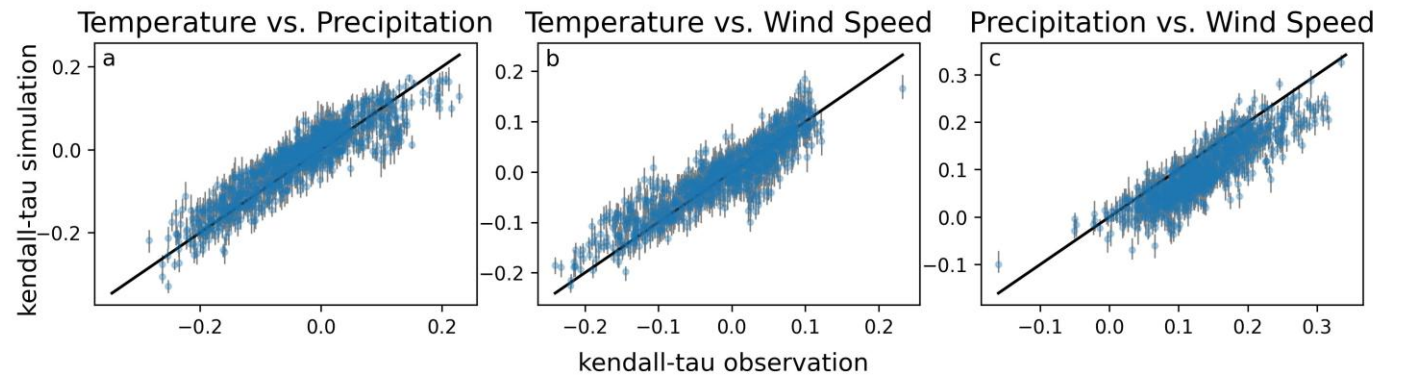
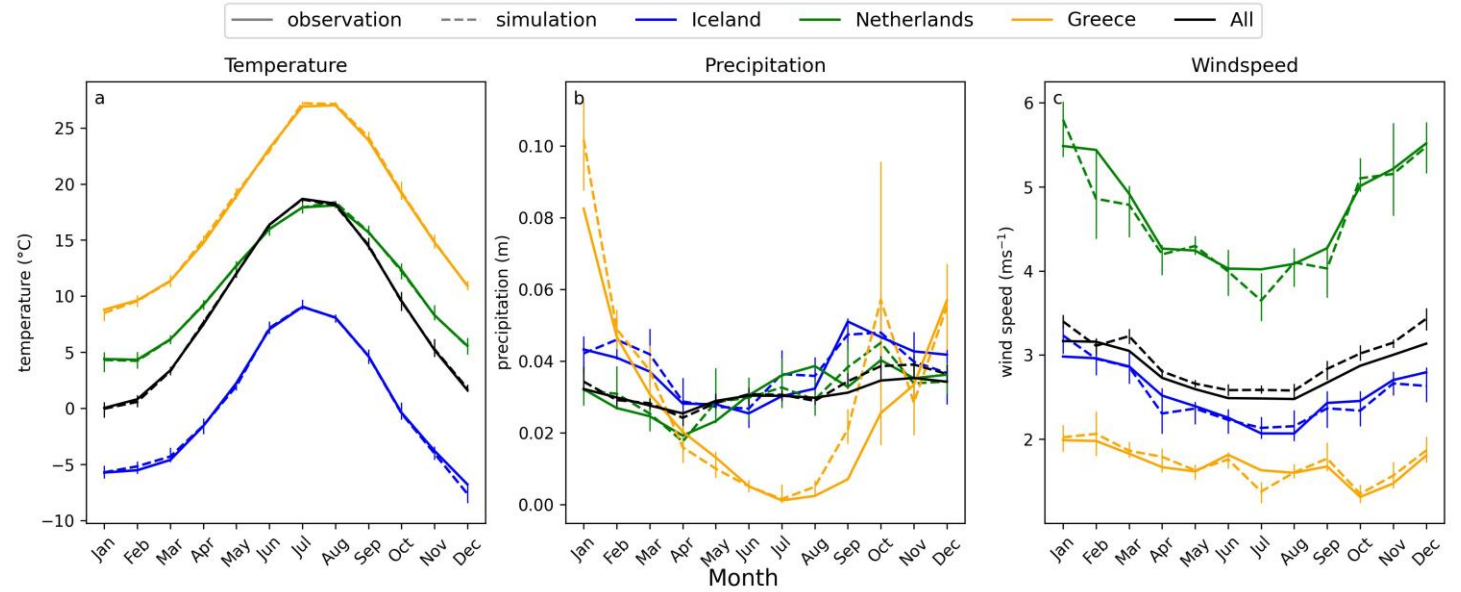
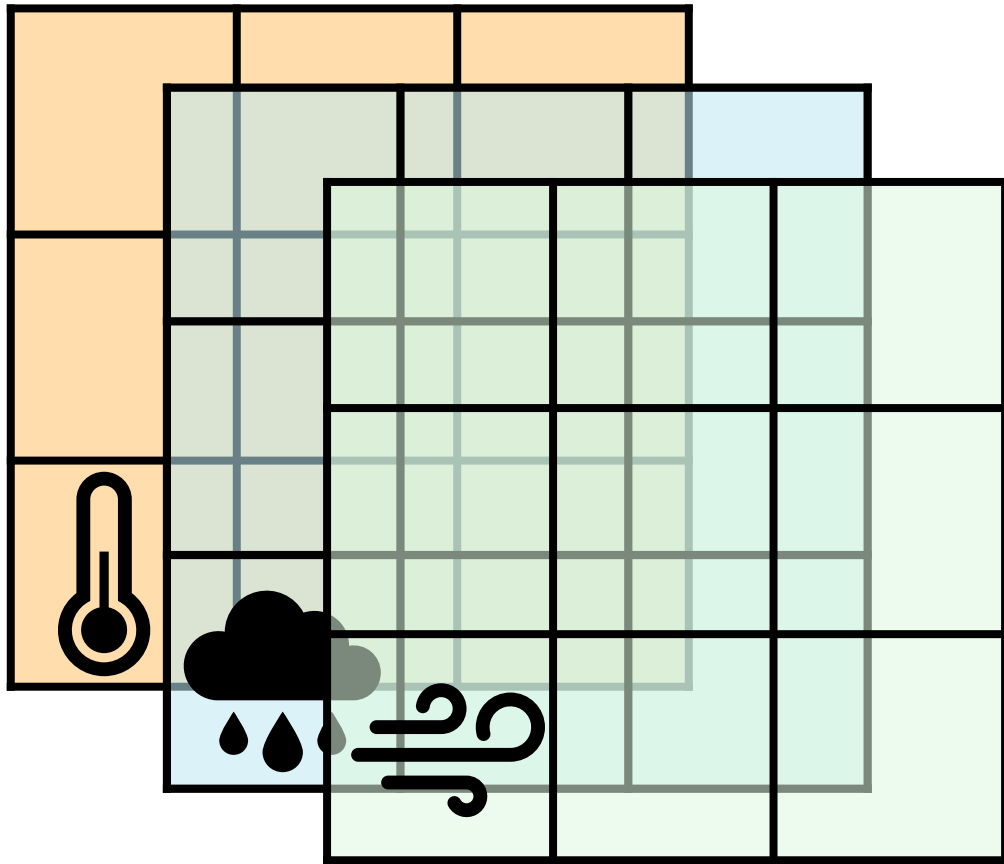
Model Setup: spatiotemporal dependencies



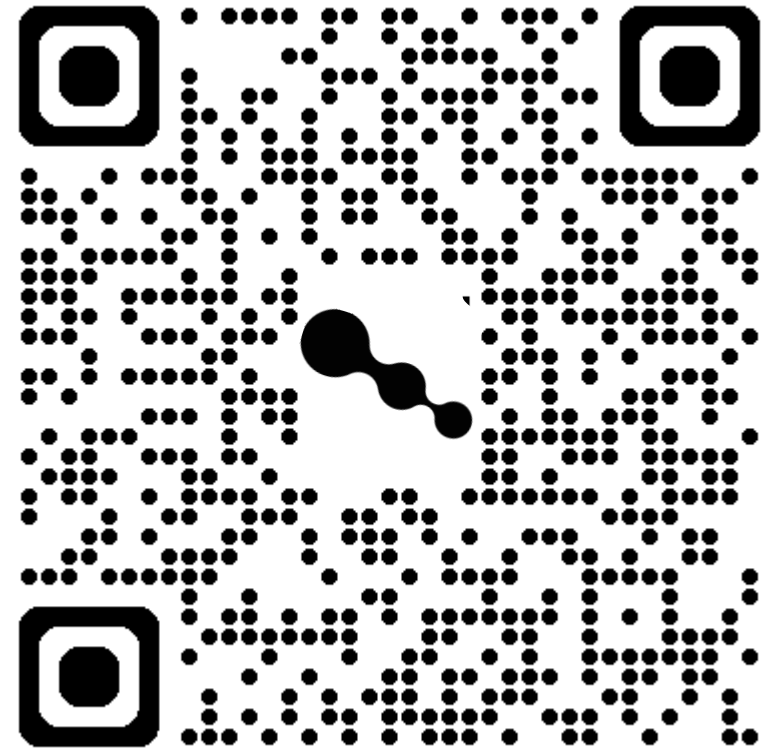
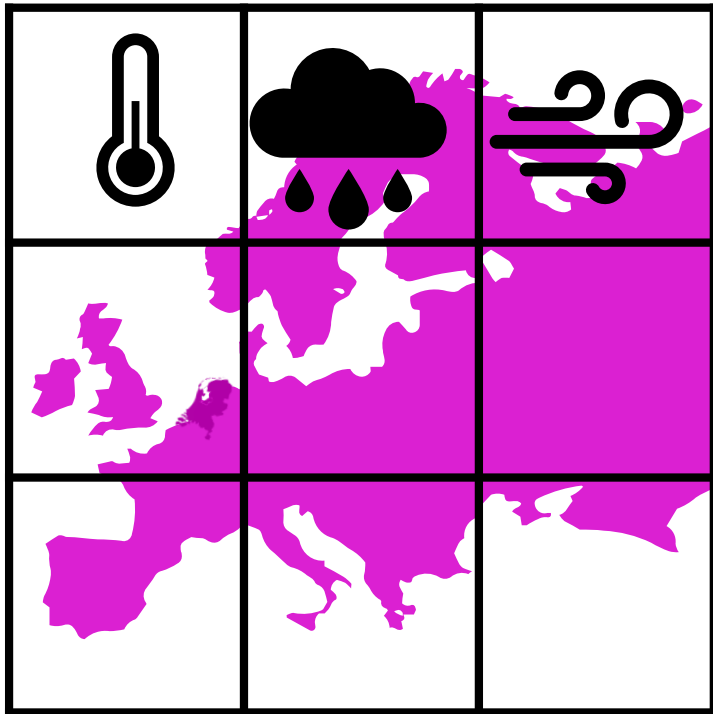
Model Setup: spatiotemporal dependencies

One year of daily mean temperature



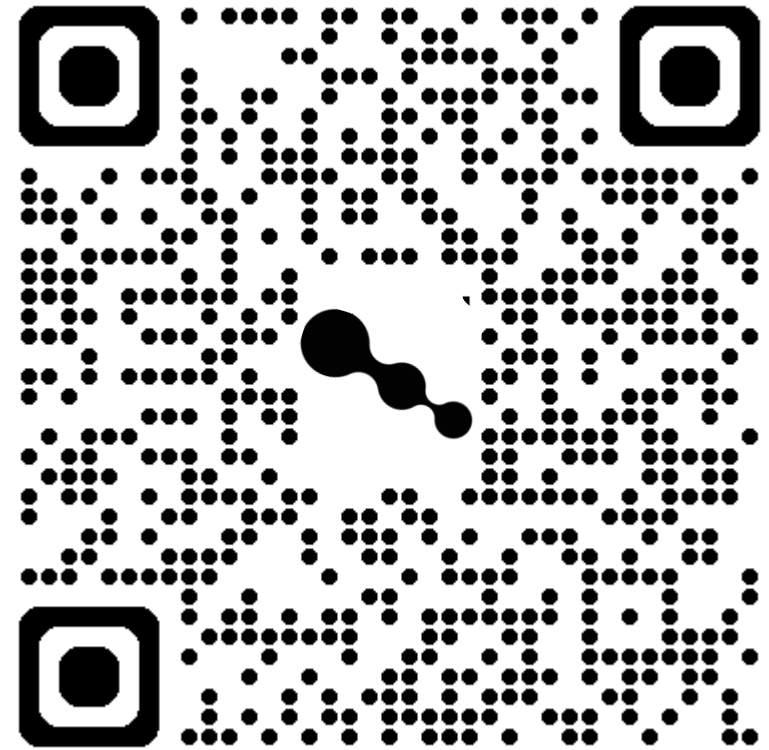
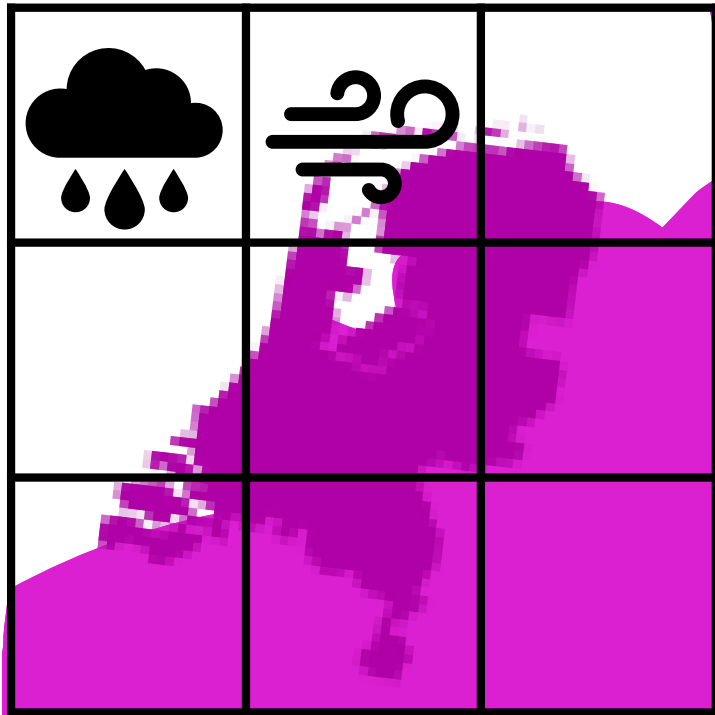


MYRIAD-Stochastic vine-copula Model (MYRIAD-SIM)



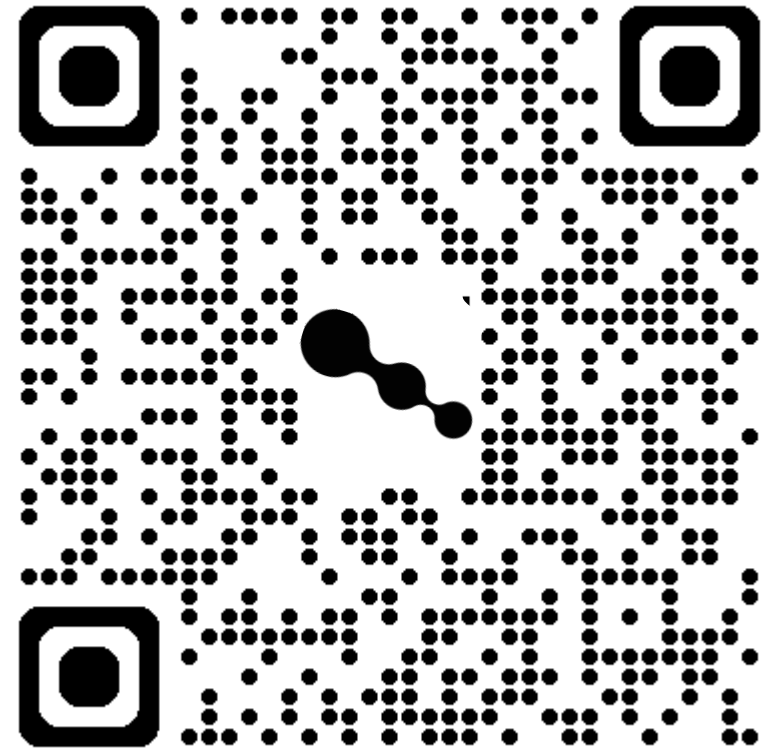
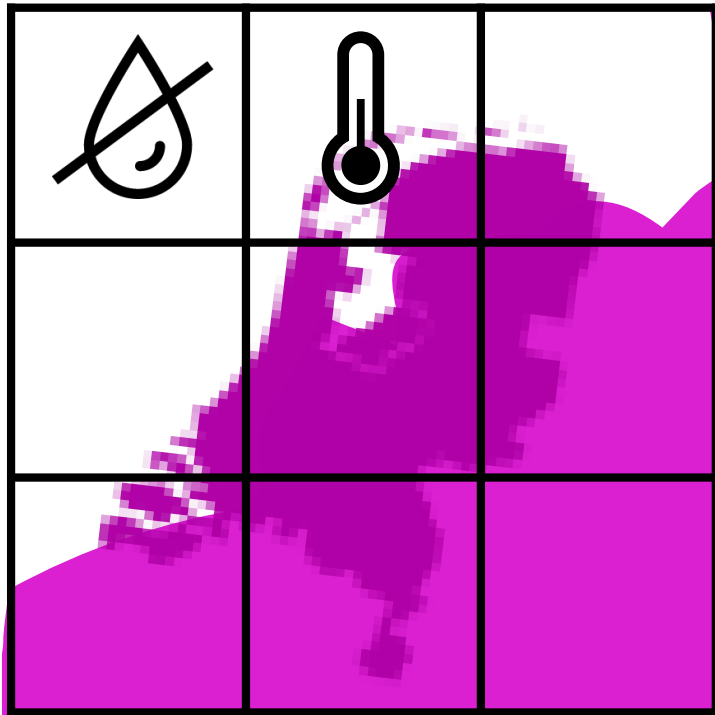
Paper in Nature: Scientific data

MYRIAD-Stochastic vine-copula Model (MYRIAD-SIM)



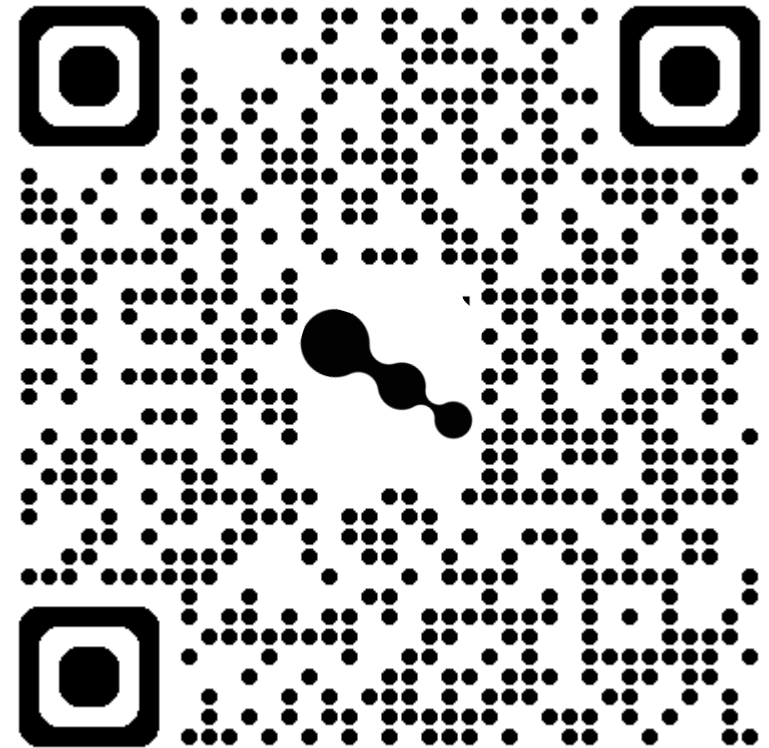
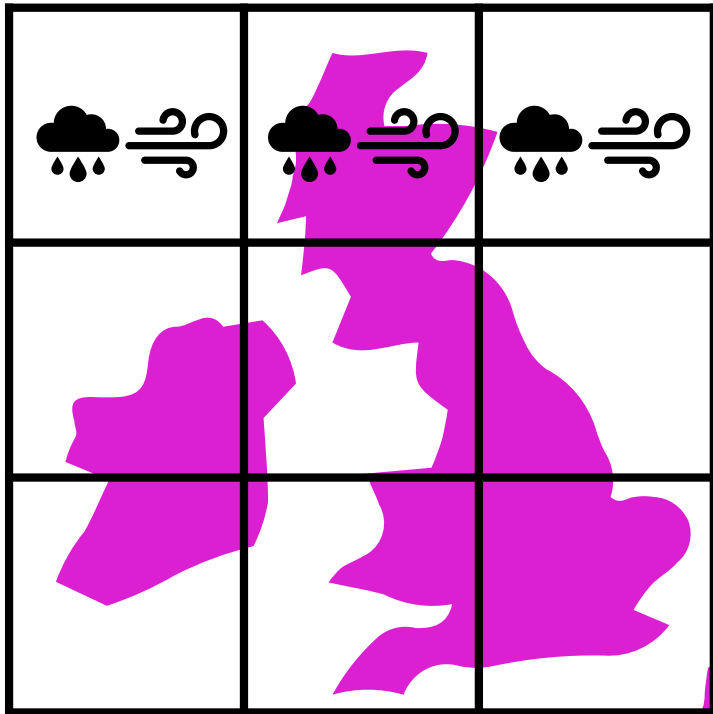
Paper in Nature: Scientific data

MYRIAD-Stochastic vine-copula Model (MYRIAD-SIM)



Paper in Nature: Scientific data

MYRIAD-Stochastic vine-copula Model (MYRIAD-SIM)



Paper in Nature: Scientific data

Using Stochastic Data to Simulate and Communicate Alternative Multi-Hazard Weather Extreme Events

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Stochastic weather generators (SWG) create realistic weather data beyond the historical record by capturing key statistical patterns. We present MYRIAD-SIM, a new spatiotemporal SWG that simulates temperature, wind speed, and precipitation while capturing relationships across variables, space, and time using conditional vine copulas. The model can generate plausible high-impact weather scenarios and compound events. For example, the 2022 storm sequence Dudley–Eunice–Franklin can be simulated as alternative triple-storm events with different wind speeds and rainfall. These stochastic counterfactuals help communicate multi-risk through concrete event-based narratives rather than abstract probabilities.



Sharing is encouraged



Conference Abstract



Outstanding Student & PhD candidate Presentation contest

This presentation participates in OSPP

The MYRIAD-Stochastic vine-copula Model (MYRIAD-SIM)¹

a) Best fit distribution for each grid cell for each month and each variable.

b) The grids on the area of interest are numbered. This numbering determines the sampling order.

c) In timestep 1 ($t=1$), the model sequentially samples each grid cell based on previously sampled neighboring cells using pre-fit vine copulas. E.g., the variables in cell 2 is sampled based on 1 using a specific vine copula.

d) In the subsequent timesteps, each grid cell is sampled using the same order as in $t=1$, and their value in the previous timestep. For example, cell 2 is sampled based on 1 and 2_{t-1} using a vine copula.

MYRIAD-Stochastic vine-copula Model (MYRIAD-SIM) is a stochastic weather generator that models spatiotemporal dependencies for a variety of variables using vine copulas in the VineCopulas Python package². Powered by Weatherspy.

Method to define stochastic events

Case selection

- Cases are selected based on high impact
- The case involves multiple hazard drivers
- The case unfolds through time

Proxy selection

For each case, the weather conditions that was driving the impact is identified as a proxy for similar (impactful) conditions.

Model run

The model is fit and run for:

- Area of interest
- Variables of interest
- Resolution of interest
- 1000 years

Identifying stochastic events

- Apply proxy conditions to the stochastic data
- Identify stochastic events like the multi-hazard case study

Case description

Triple Storm UK & Ireland

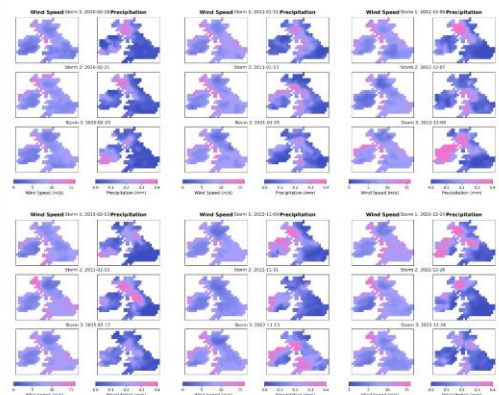
Wind Speed Dudley: 2022-02-16 **Precipitation** Eunice: 2022-02-18 **Franklin: 2022-02-20**

Case description Triple storm: Flooding, Wind damage, Fatalities, Power outage, Insurance claims.

Proxy condition 3 storms in 6 days. E.g., Wind and rainfall exceeding 10 m/s and 0.2 m, or the 99th and 99th percentiles, respectively.

Examples of alternative scenarios

Below are examples of stochastic triple storm events derived from the MYRIAD-SIM output. These examples illustrate how the stochastic events can differ from the original, providing us with counterfactuals.



Narrative and statistics to communicate risk

Statistics + narrative together are more effective for communication than either alone.

We use case descriptions and stochastic events to give context to their severity.

Get in touch

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1. Claassen, J. N., Koks, E. E., de Ruiter, M. C., Ward, P. J., & Jäger, W. S. (2025). A Synthetic European Weather Dataset Based on Spatiotemporal Vine Copulas. *Scientific Data*, 12(1), <https://doi.org/10.1038/s41597-025-06015-3>

2. Claassen, J. N., Koks, E. E., de Ruiter, M. C., Ward, P. J., & Jäger, W. S. (2024). VineCopulas: an open-source Python package for vine copula modelling. *Journal of Open Source Software*, 9(101), 6728. <https://doi.org/10.21105/joss.06728>

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Conference Abstract



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