

Revealing Multimodality in Ensemble Weather Prediction

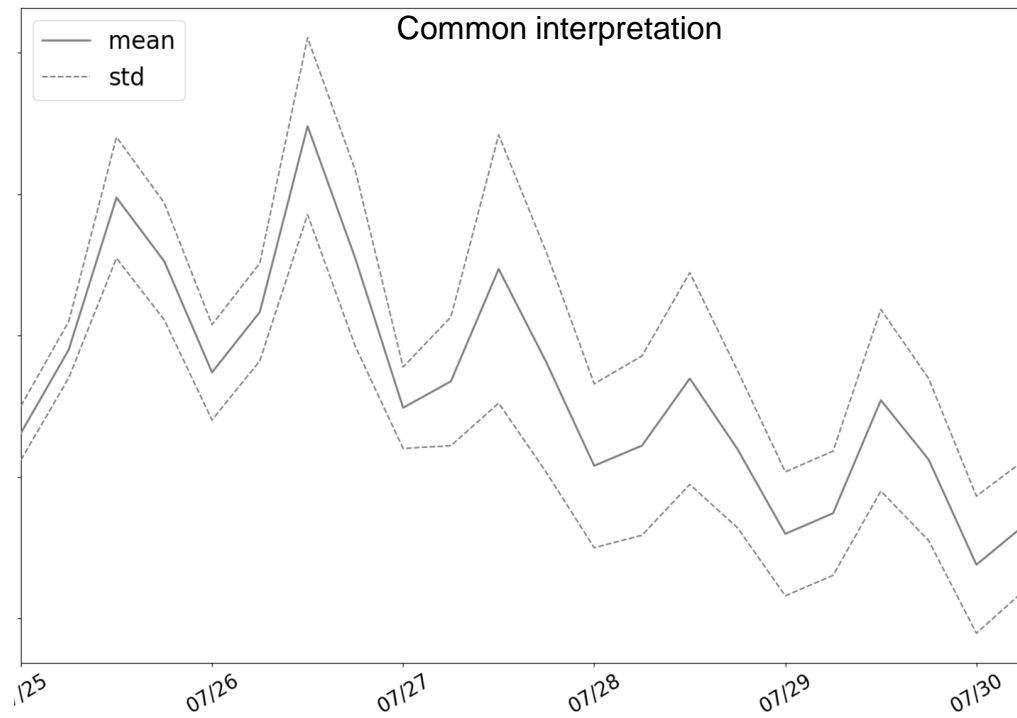
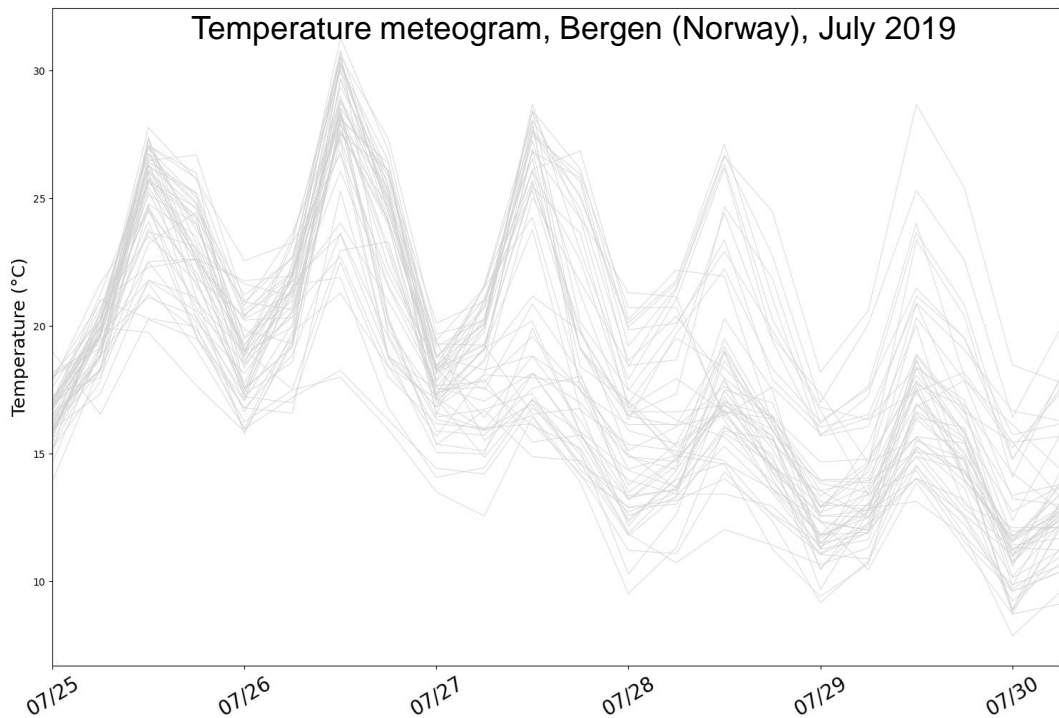
Thomas Spengler

Presentation prepared by Natacha Galmiche

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I. Context & motivation: Interpreting ensemble datasets



Ensemble data:

$N (= 50)$ univariate time series (each called *member*) evolved out of:

- Perturbed initial condition
- Different models

Common interpretation method:

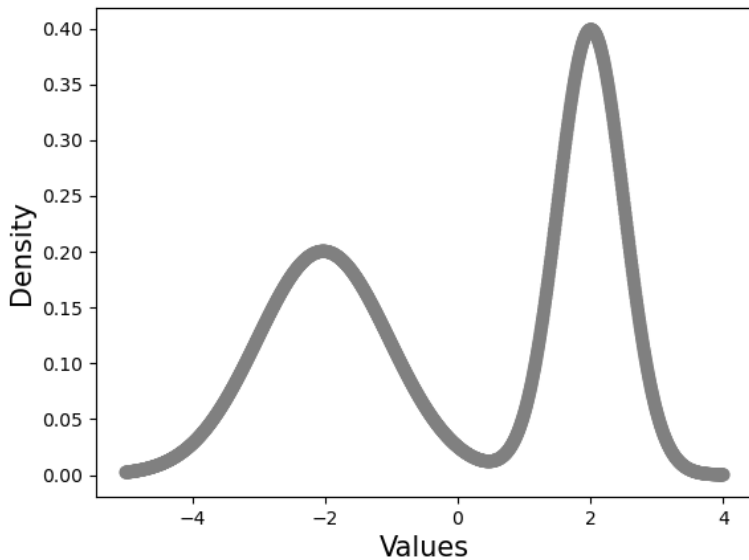
- **Mean** as expected value
- **Standard deviation** as uncertainty

What is a multimodal distribution?

Multimodality:

Number of modes (i.e likely outcomes) $k > 1$

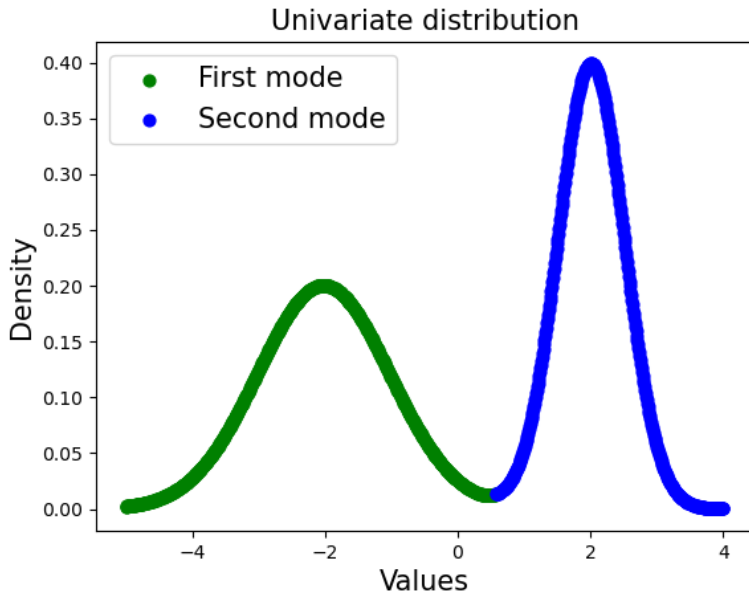
Univariate distribution



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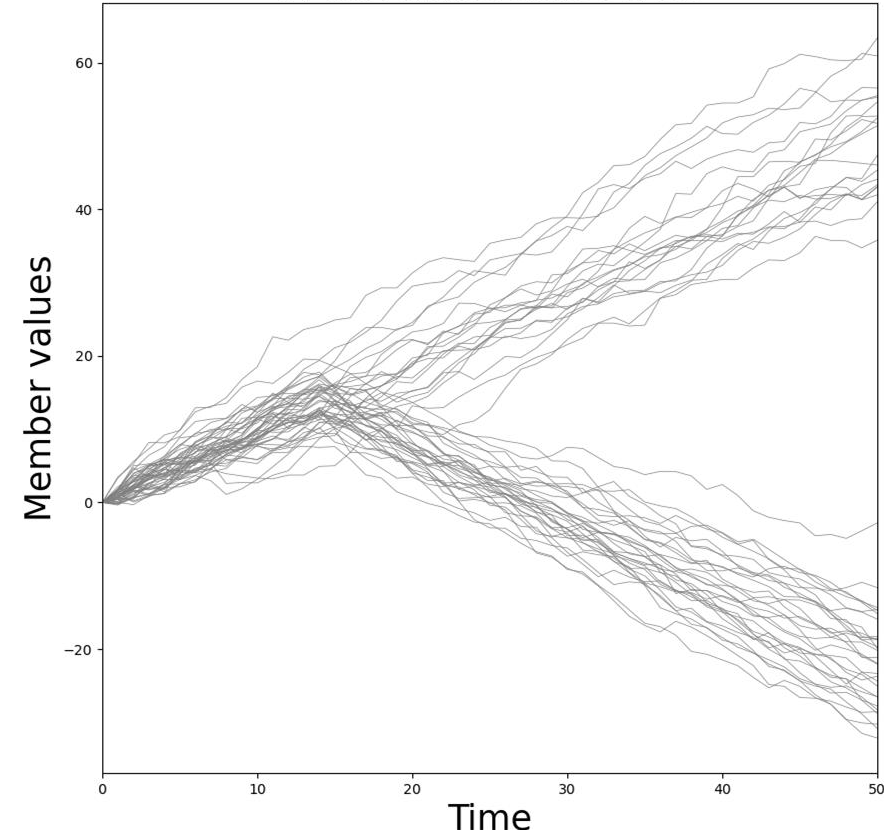
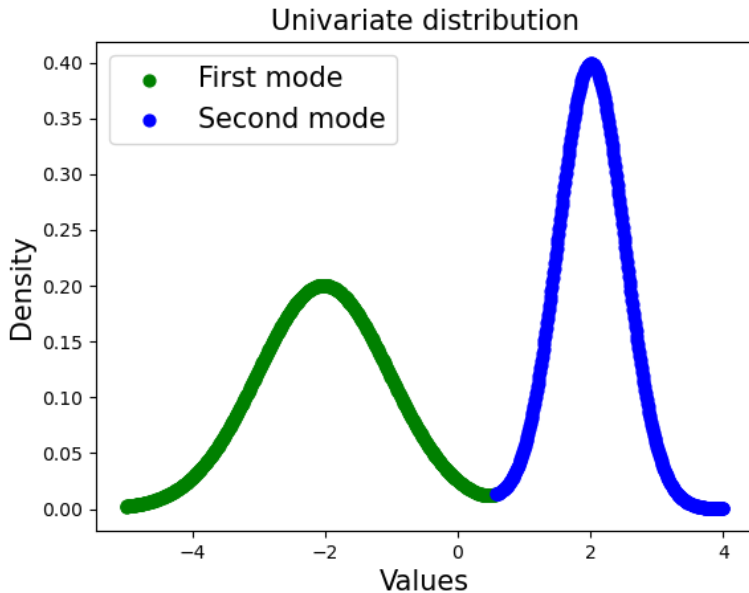


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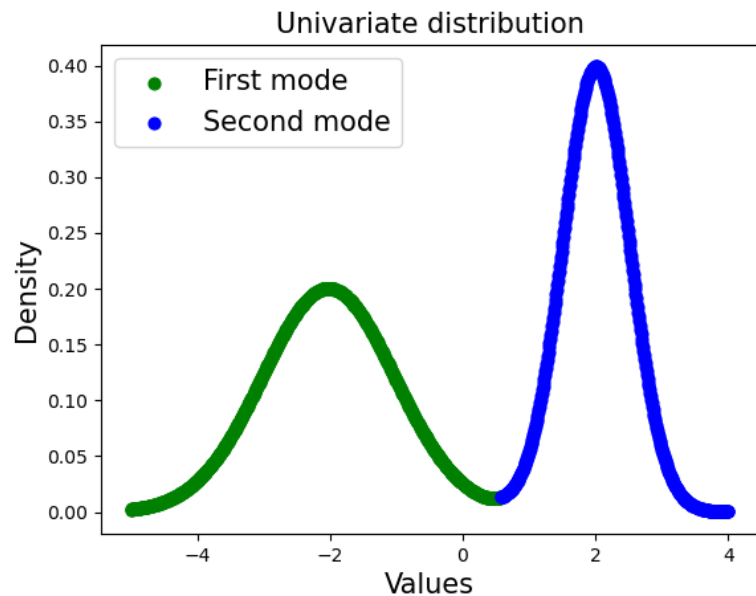
Random samples from a distribution
of univariate time series



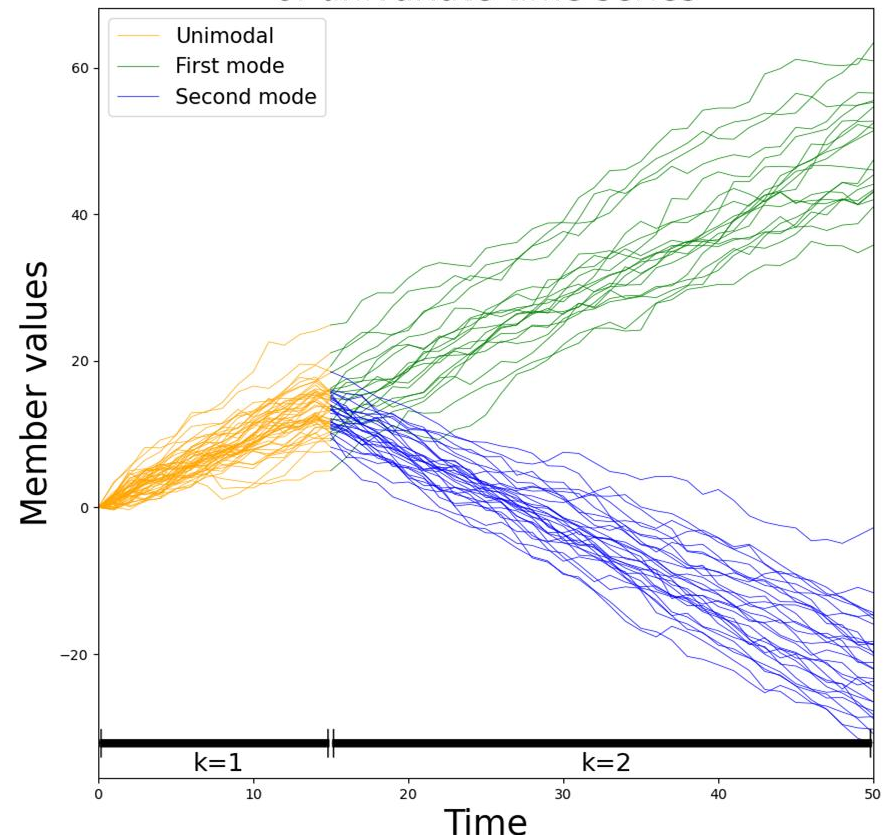
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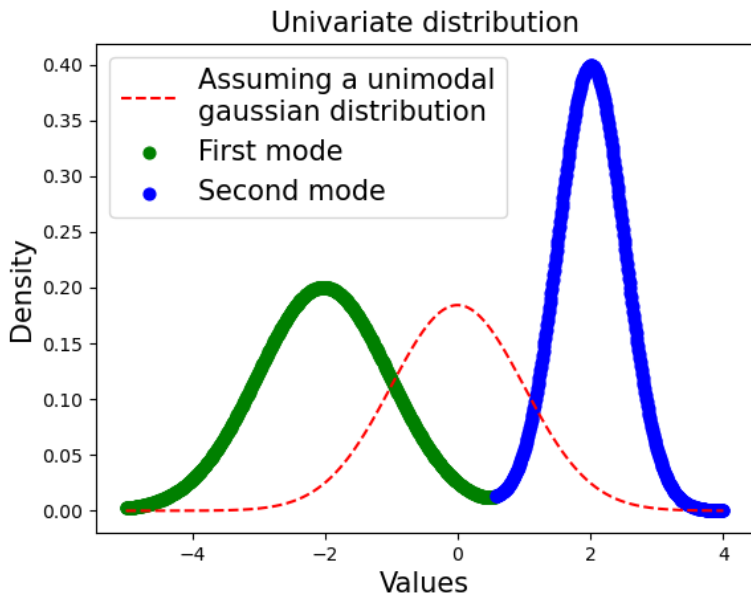
Multimodality:

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Problem?

“mean + std” method:

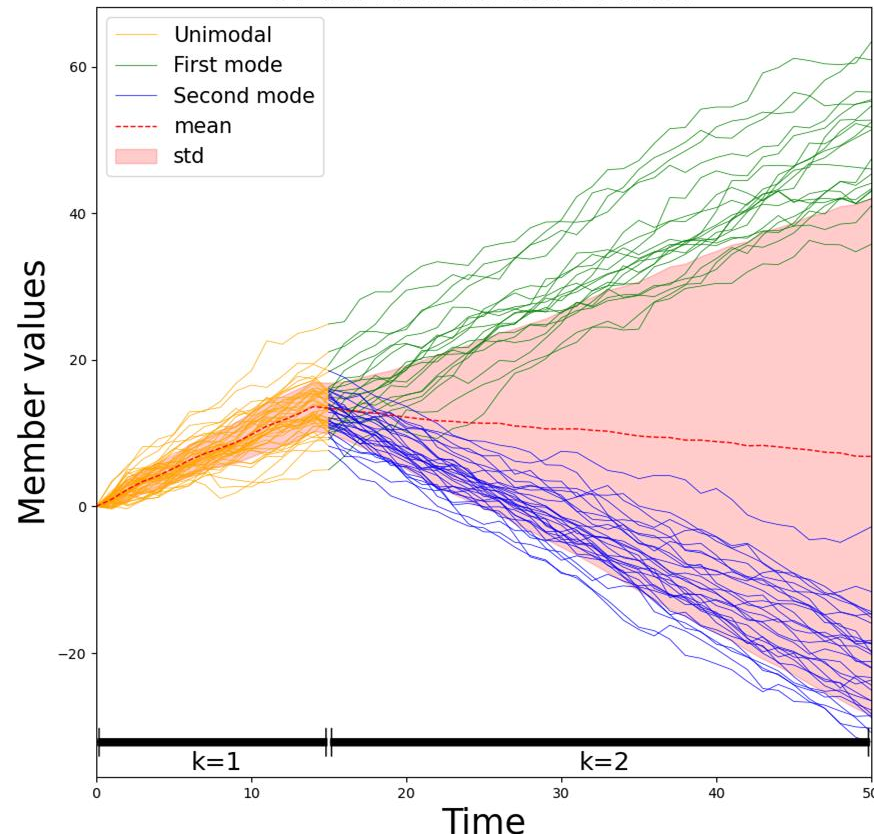
Assumes a unimodal Gaussian distribution



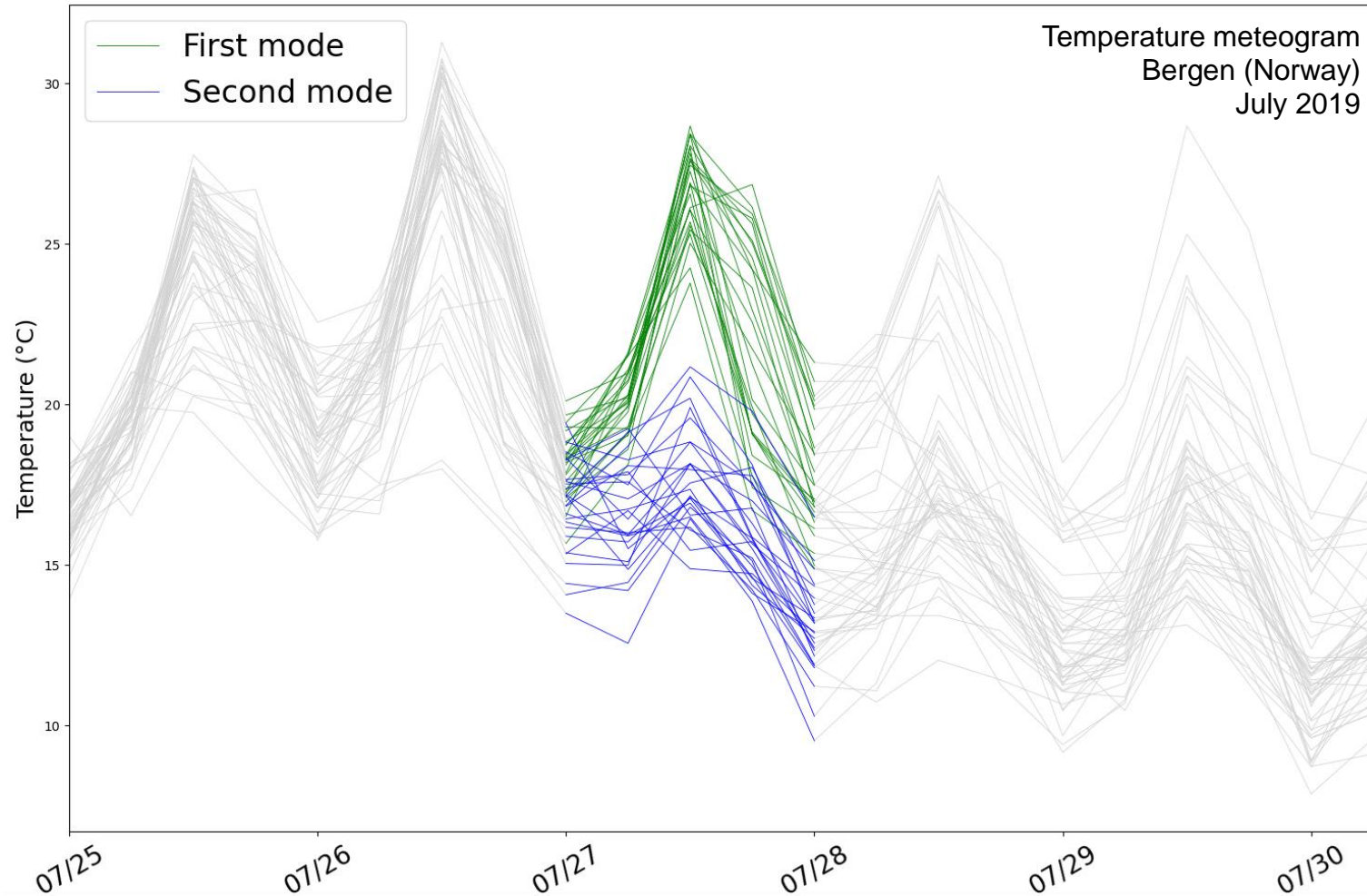
Result:

- Likely values are ignored
- Unlikely values are emphasized

Random samples from a distribution of univariate time series



Temperature meteogram
Bergen (Norway)
July 2019



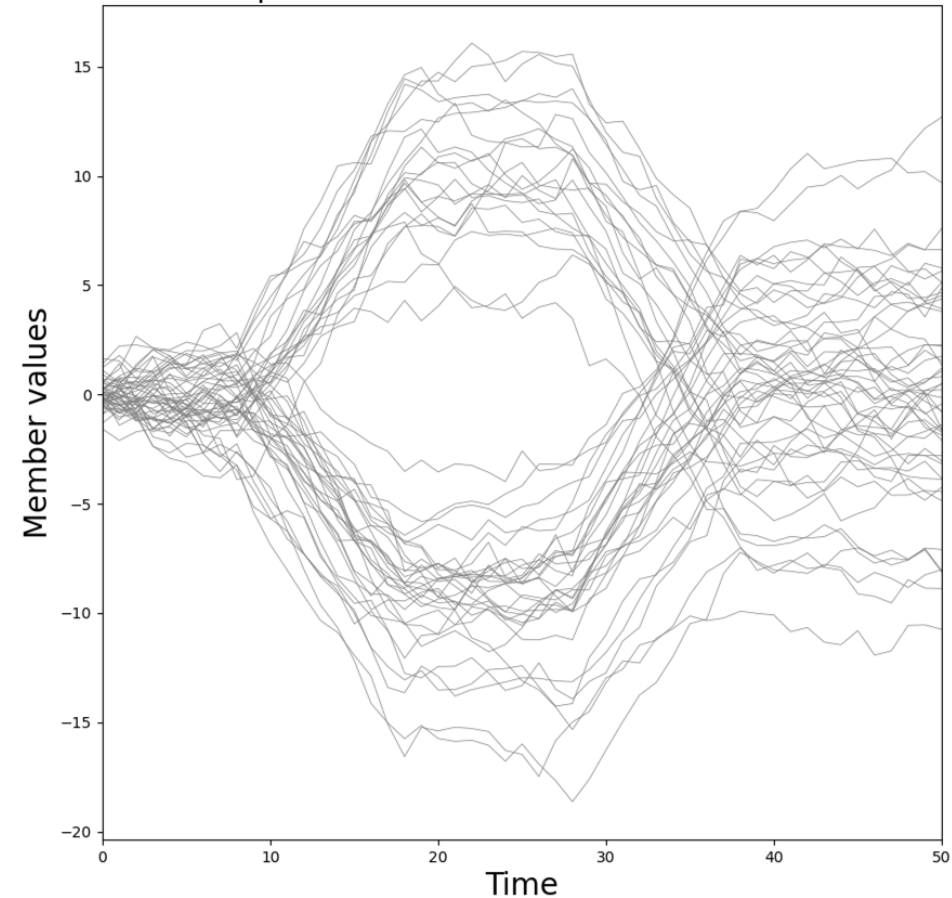
Atmospheric system:

Chaos + Stability
=> prone to multimodality

Tasks:

- T1. Estimate the number of modes k at each time step t
- T2. Summarize each mode at each t
- T3. Determine when modes appear and/or disappear
- T4. Determine all possible connections between modes

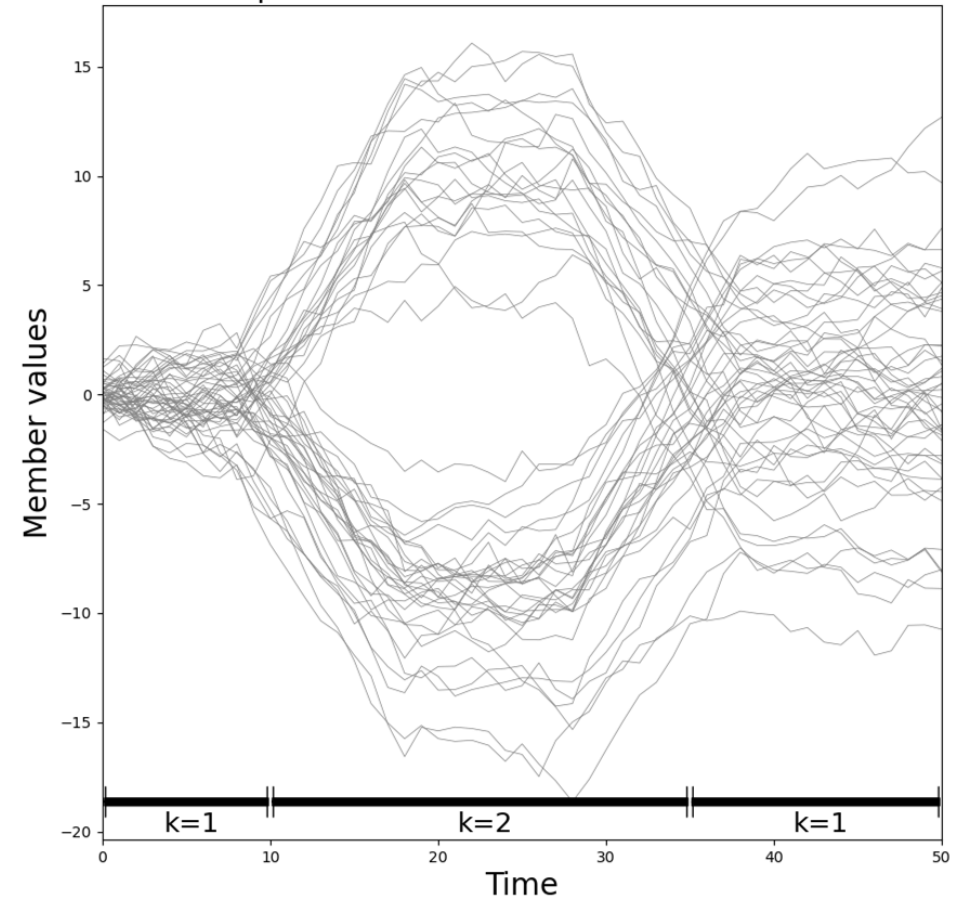
Random samples from a distribution of univariate time series



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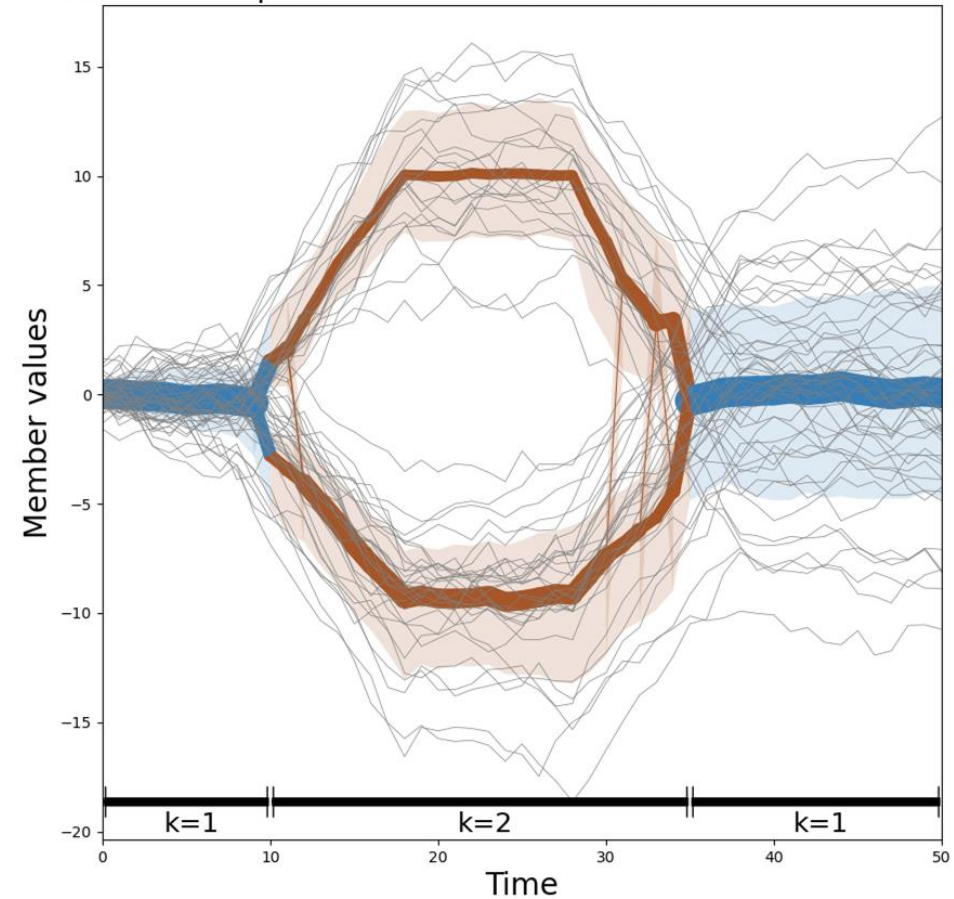
Random samples from a distribution of univariate time series



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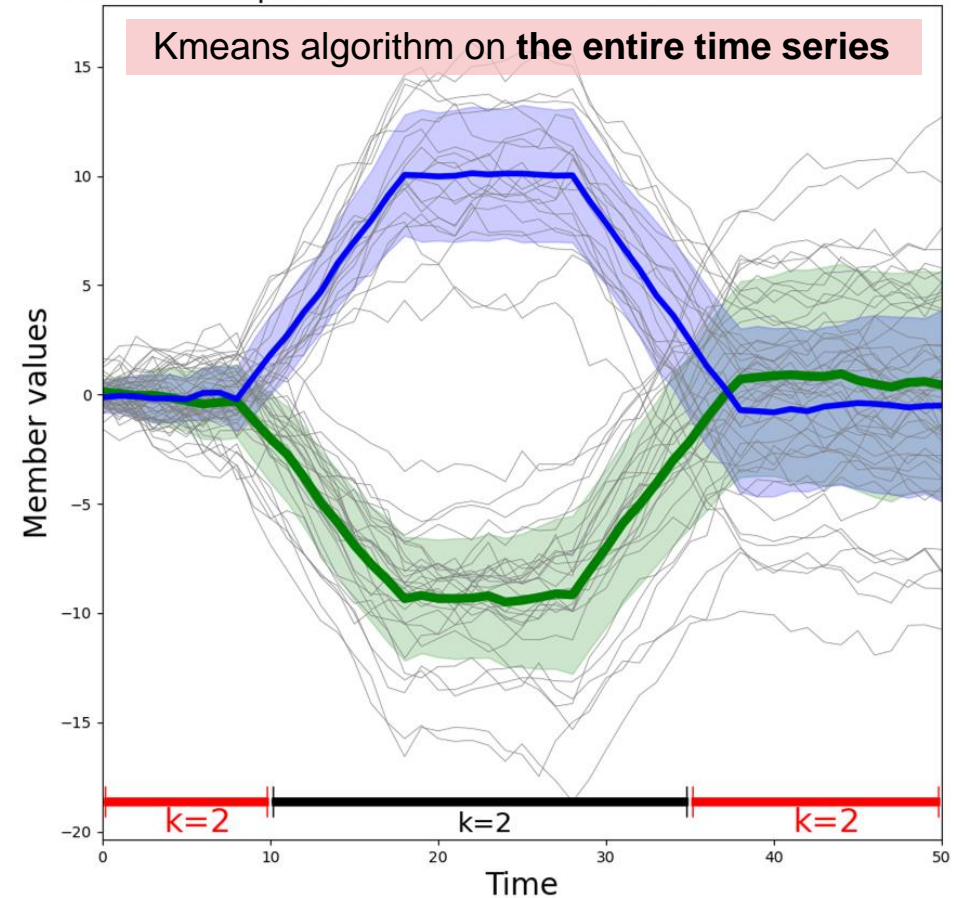
Random samples from a distribution of univariate time series



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II. Problem

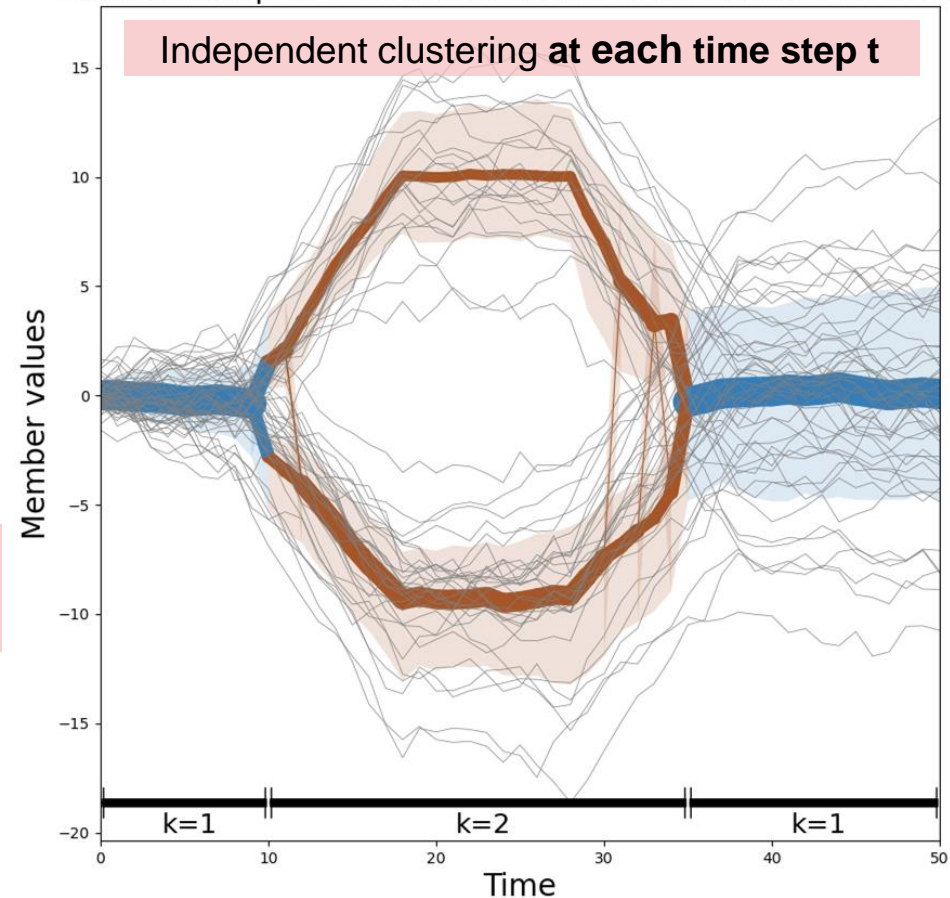
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Consequence:

We independently cluster the members at each time step

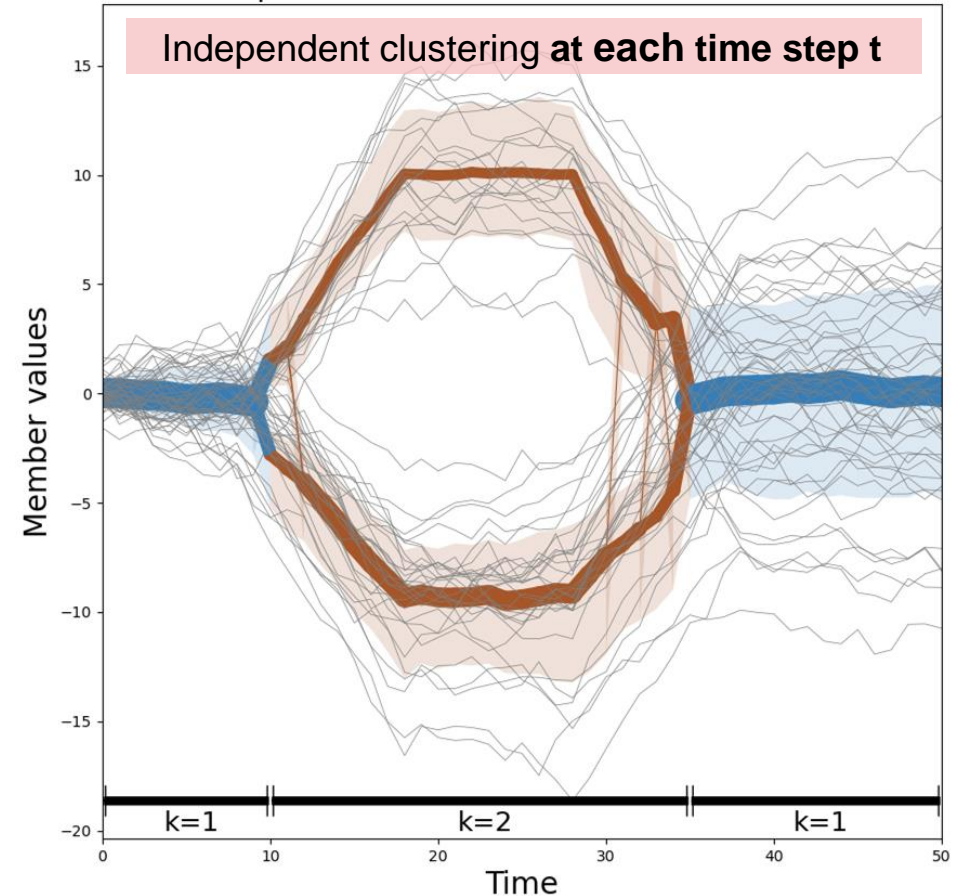
Random samples from a distribution of univariate time series



Design rationales:

1. The distribution can have any shape
 - Number of modes **k** and type of distribution unknown
2. All ensemble members matter
 - Outliers should not be ignored
3. All scales matter
 - Avoid thresholds
4. Not a black box
 - The process of **determining k**,
 - its uncertainty
 - and the consequences of choosing a particular **k** should remain transparent

Random samples from a distribution of univariate time series



Graph construction


For each time step t :

- 1) Cluster the data **assuming successively**
- 2) $k=1, 2, 3, \dots, N$
- 3) Associate **each assumption k** with a **score**
- 4) Define a **life span** for **each assumption k**
- 5) For each cluster, create a vertex
- 6) Create edges between vertices

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**A proxy for their
relevance**

III. Revealing multimodality

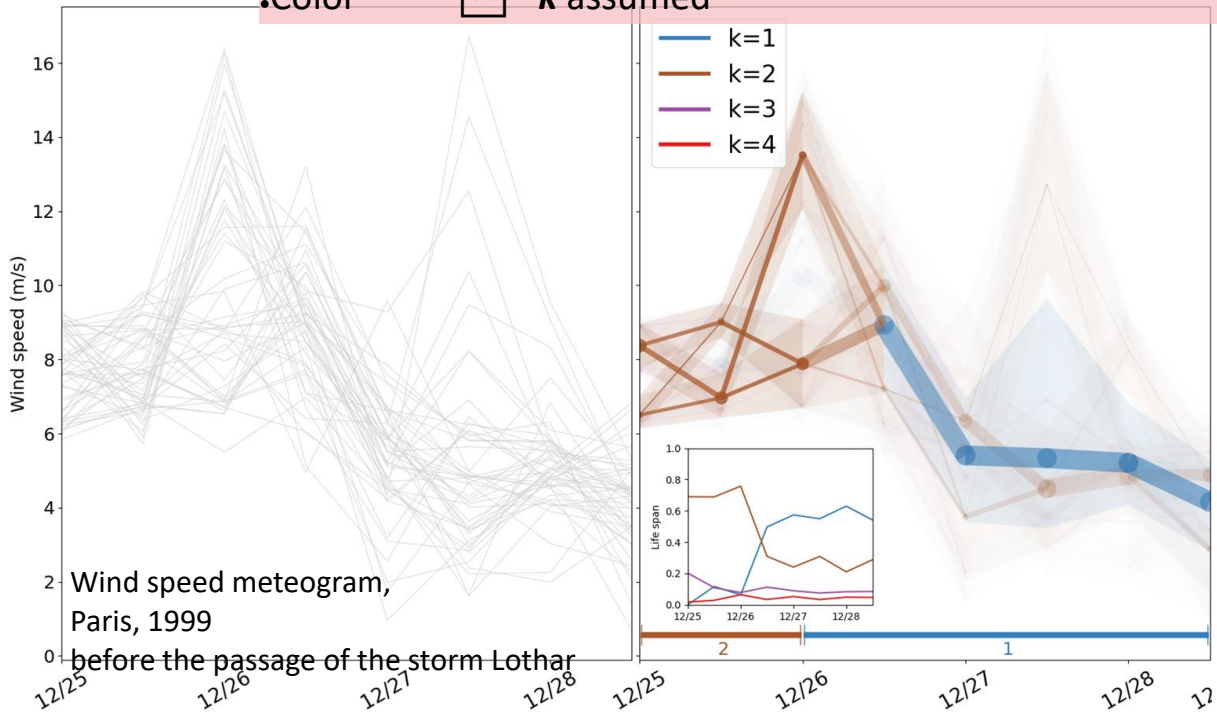
Visualization tools

Entire graph view:

Concurrently displays the clustering outcome for all k

• Opacity Life span

• Color k assumed



Effortless exploration & exposition of a threatening scenario

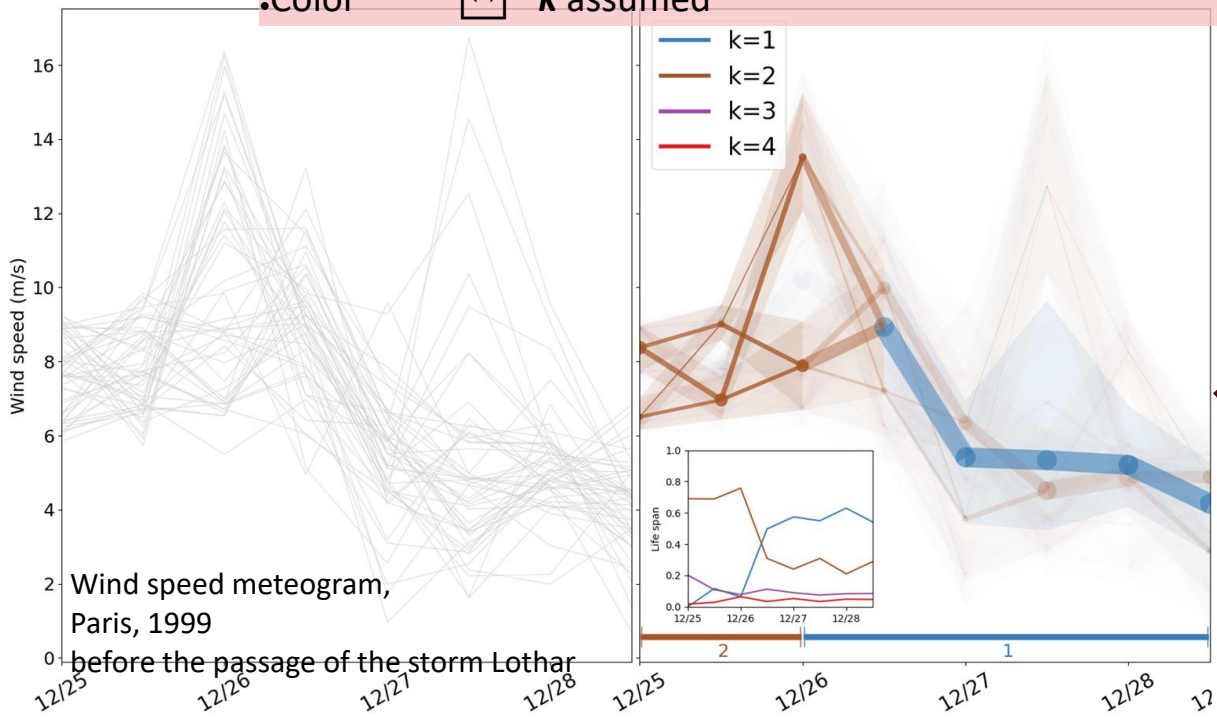
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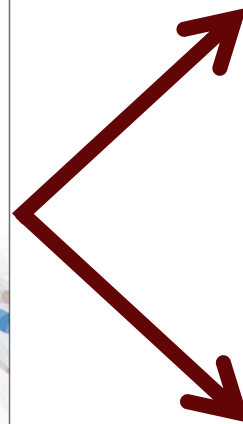
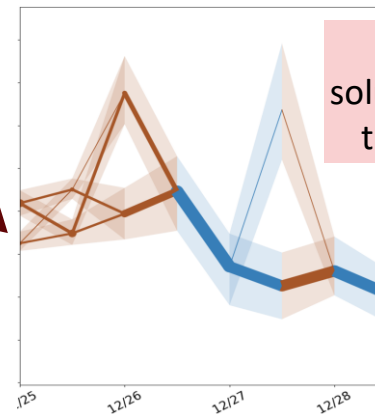
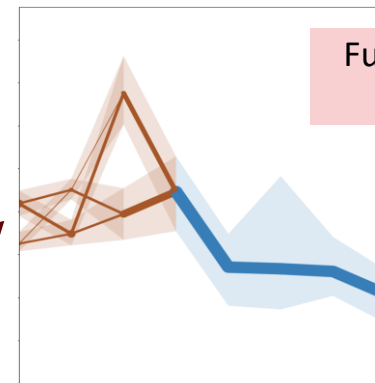
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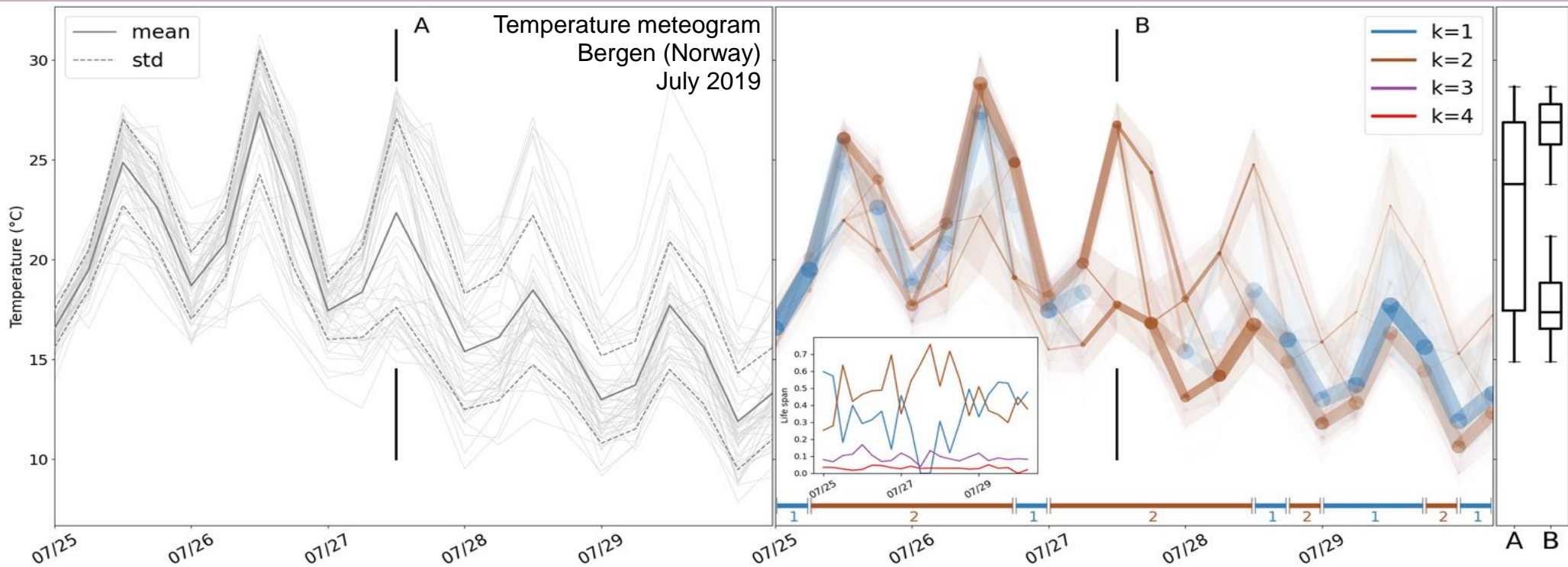
Most relevant components view

Most relevant interpretation
(automatic or user-defined)



III. Revealing multimodality

Application



On July 27 at noon

Mean and standard deviation:

“ $22.3 \pm 4.7^\circ\text{C}$ ”

Our method:

“51% probability of $18.0 \pm 1.6^\circ\text{C}$ and 49% prob of $26.2 \pm 1.0^\circ\text{C}$ ”

On July 28 at noon

Mean and standard deviation:

Upper bound = 22.8°C ... but 20% of the members are > 22.8 !

Ensemble weather prediction:

- Complex and chaotic system
- Prone to multimodality
- Large and small scales co-exist
- Of great socio-economic importance

Our method:

- Reveals multimodality & its uncertainty
- Aids the understanding of ensemble weather prediction
- Provide fully automated solutions
- Provide quantitative and qualitative information