UNIVERSITÀ
DEGLI STUDI
DI PADOVA

DETECTION OF EVENTS IN RINGEBU AND HEDDAL STAVE CHURCHES

USING CLUSTERING AND OTHER METHODS

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Case Study: Ringebu and Heddal stave churches

Ringebu Stave church

Heddal Stave church

Summary

- Dataset presentation
  - Temperature and Relative Humidity time series
  - Mixing Ratio
  - Metadata and Event features

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- Unsupervised Learning
  - Density Peaks Clustering Algorithm
  - Dataset Analysis with DPC

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  - Temperature and Relative Humidity time series
  - Mixing Ratio
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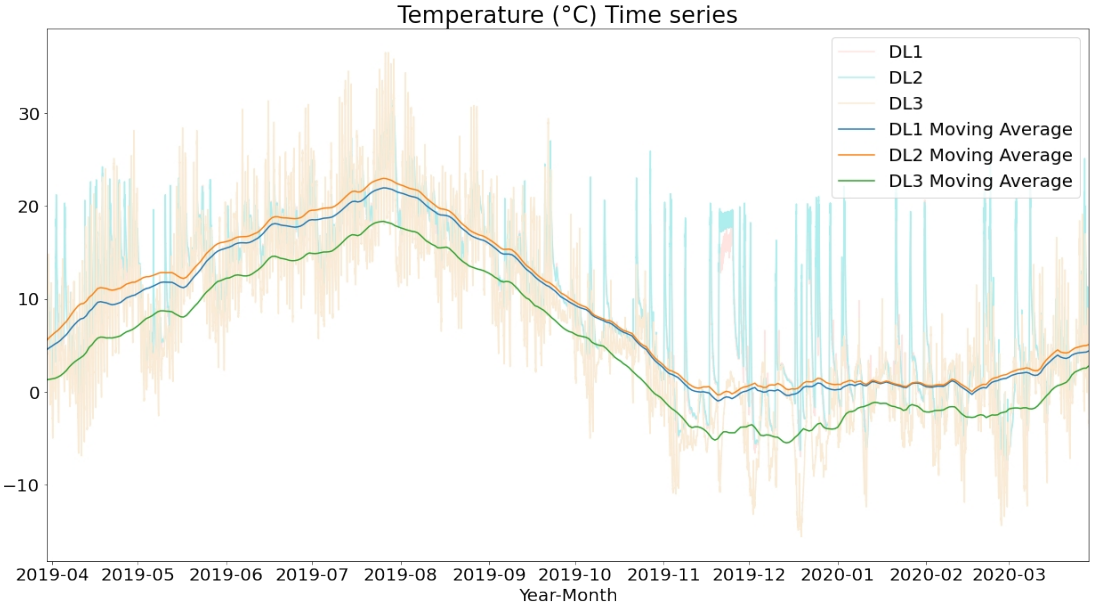
- Unsupervised Learning
  - Density Peaks Clustering Algorithm
  - Dataset Analysis with DPC
- Supervised Learning:
  - CNN for Time series analysis
  - Unexpected Mixing Ratio Peaks method

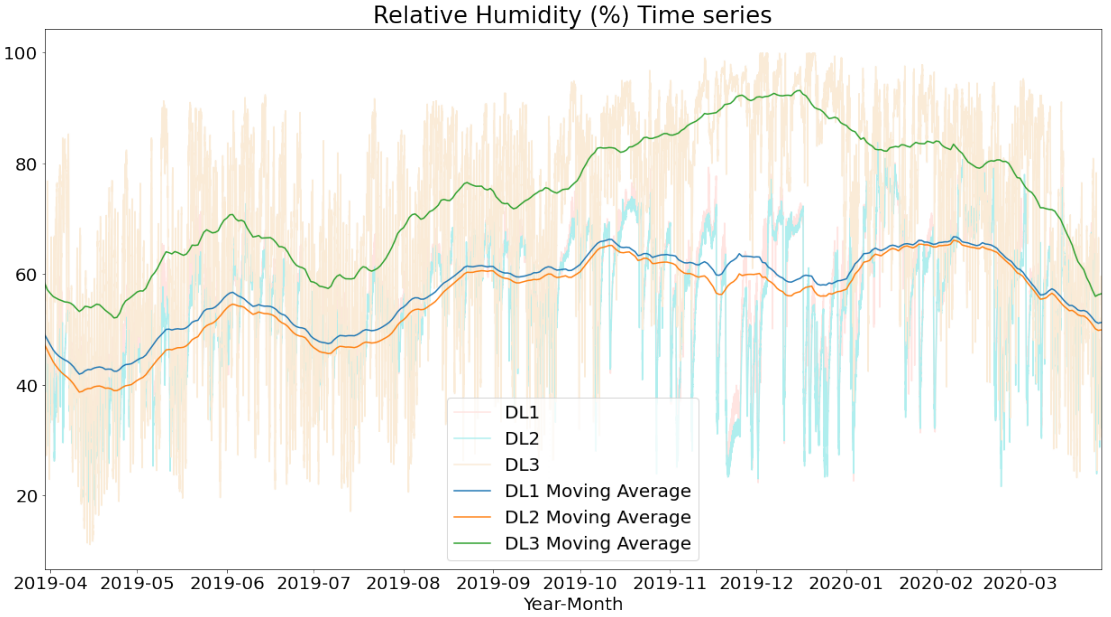
DATASET PRESENTATION

Dataset Presentation: T and RH time series

- Temperature (°C)
- Relative Humidity (%)

Sensor	Quantity	Position	Frequency
DL1	RH, T	INDOOR	5 min
DL2	RH, T	INDOOR	5 min
DL3	RH, T	OUTDOOR	15 min



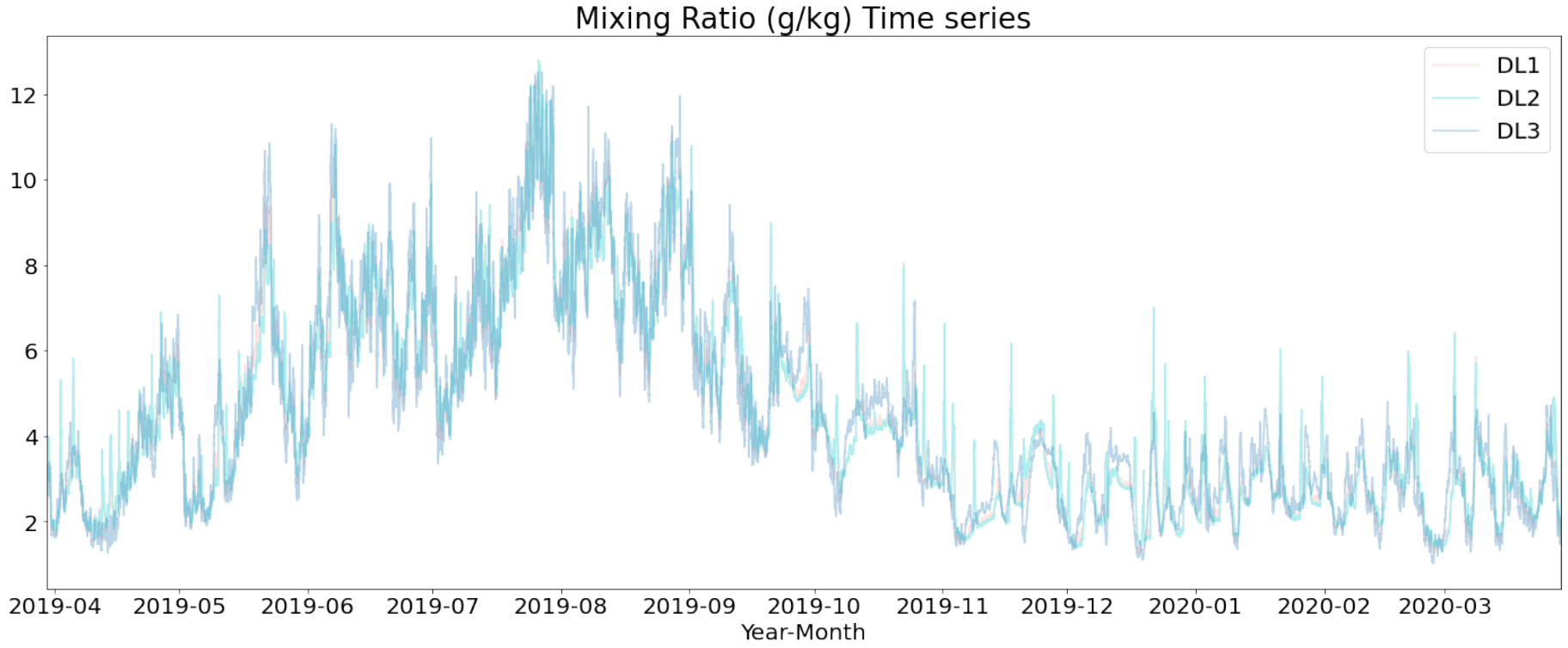


Dataset Presentation: Mixing Ratio

MR combines information from temperature (T) and relative humidity (RH)

$$\mathrm{MR} = A \times \frac{10^{B(T)} \times RH}{p_{atm} - (C \times 10^{B(T)} \times RH)}$$

- $A = 38.015 \frac{g \cdot hPa}{kg}$
- $B(T) = \frac{7.65 \cdot T}{243.12 + T}$
- $C = 0.06112\ hPa$



Dataset Presentation: Metadata and Events features

Start	Duration (h)	End	Event	People	Start Heating
4/12/2019 11:00	1	4/12/2019 12:00	Funeral	75	4/12/2019 6:00
4/14/2019 11:00	1	4/14/2019 12:00	Service	72	4/14/2019 4:40
4/16/2019 11:00	1	4/16/2019 12:00	Easter	150	/
4/18/2019 19:00	1	4/18/2019 20:00	Easter	24	/

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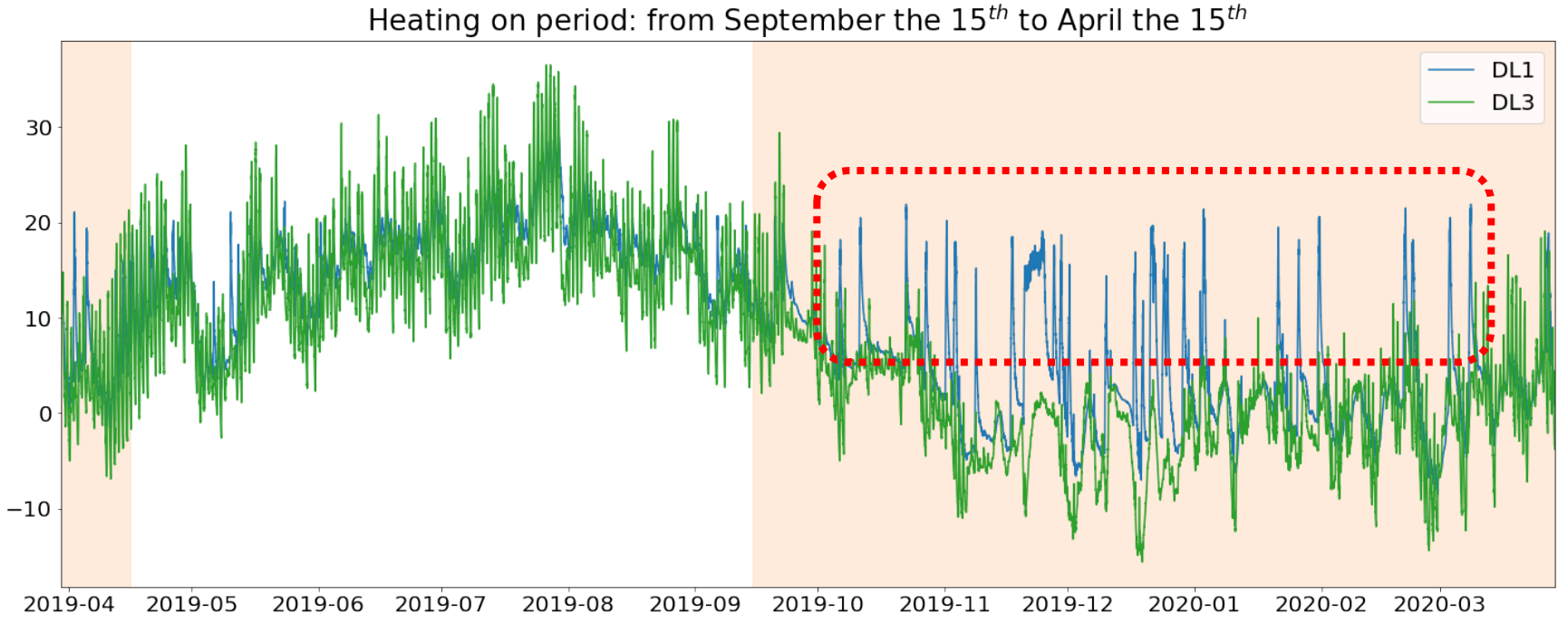
4/18/2019 19:00	1	4/18/2019 20:00	Easter	24	/

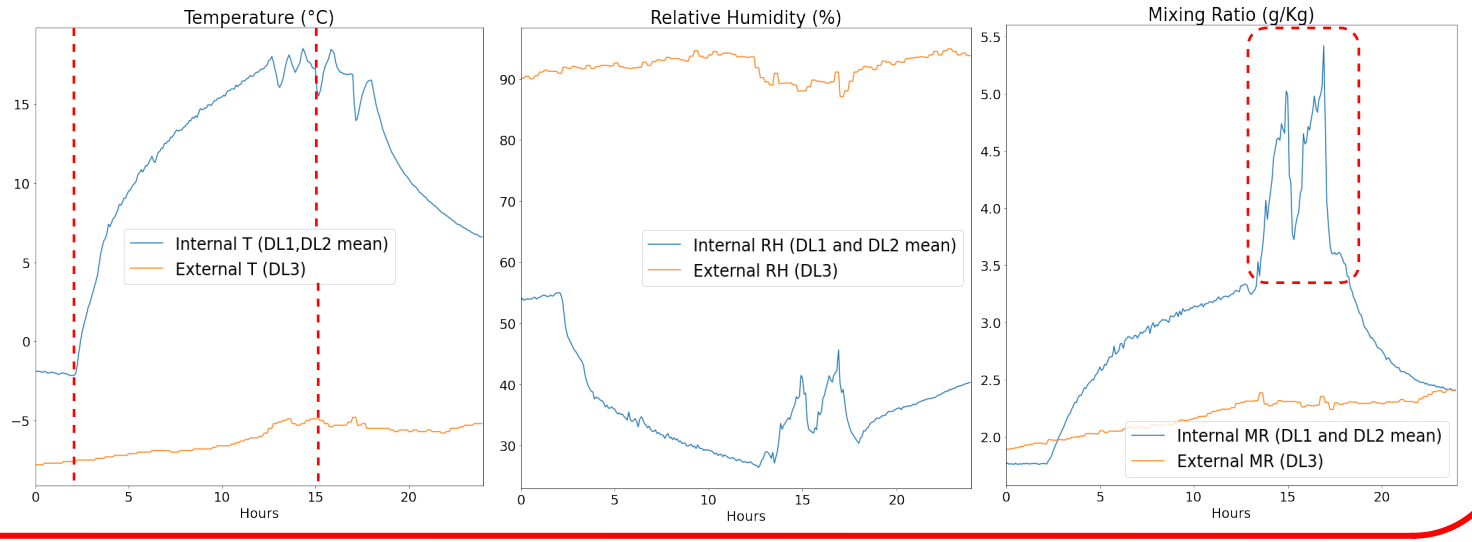


Dataset Presentation: Metadata and Events features

Christmas eve, 2019/12/24:

- Event 1: 14:00, 240 people
- Event 2: 16:00, 240 people

➢ Start heating: 2.50



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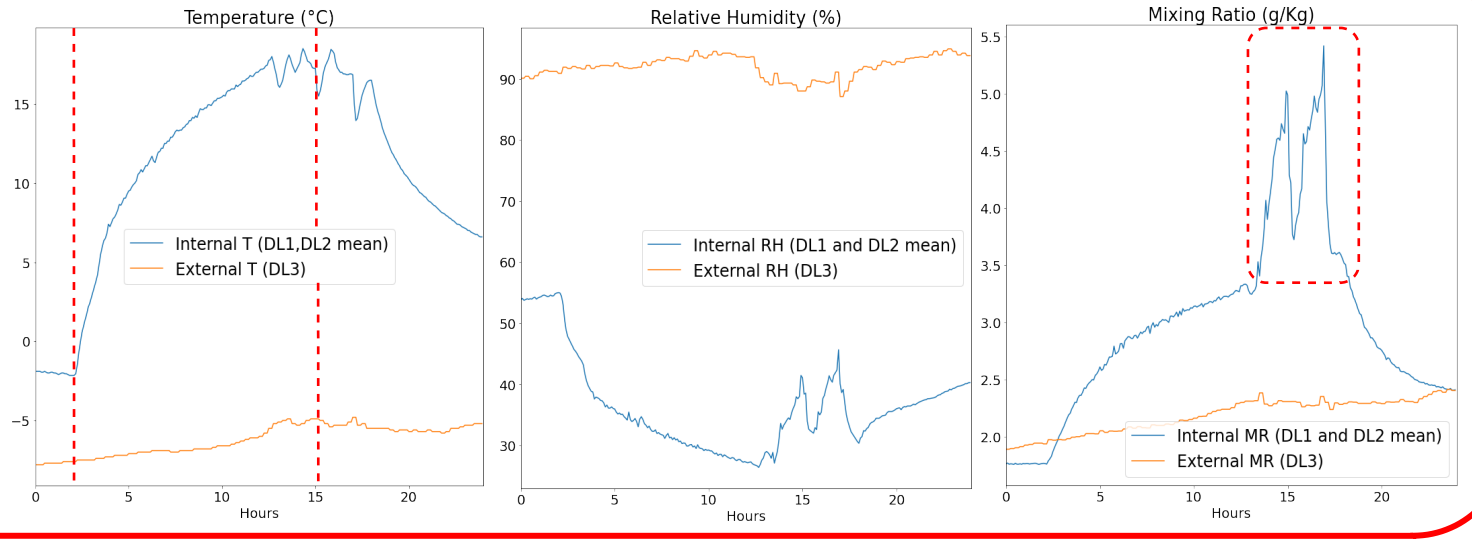
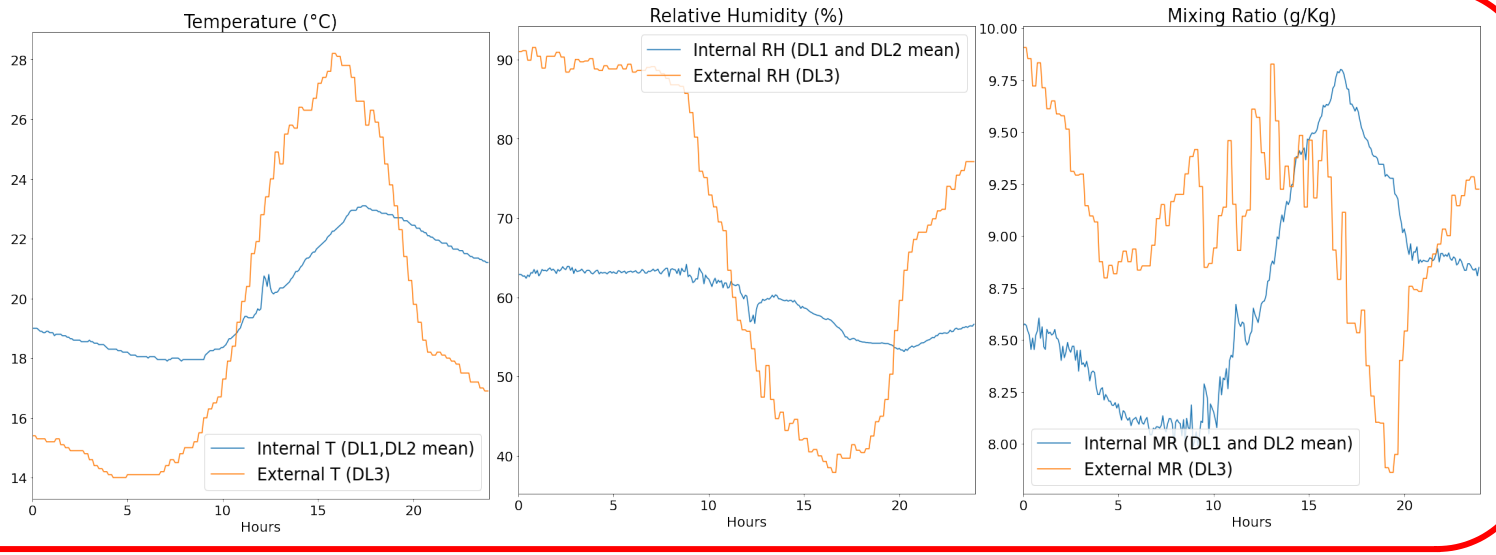


Visitors 2019/07/22:

- Event: 17:20, 243 people

➢ No heating



UNSUPERVISED LEARNING:
Density Peak Clustering

Unsupervised Learning: DPC

The DPC can be divided in 3 steps:

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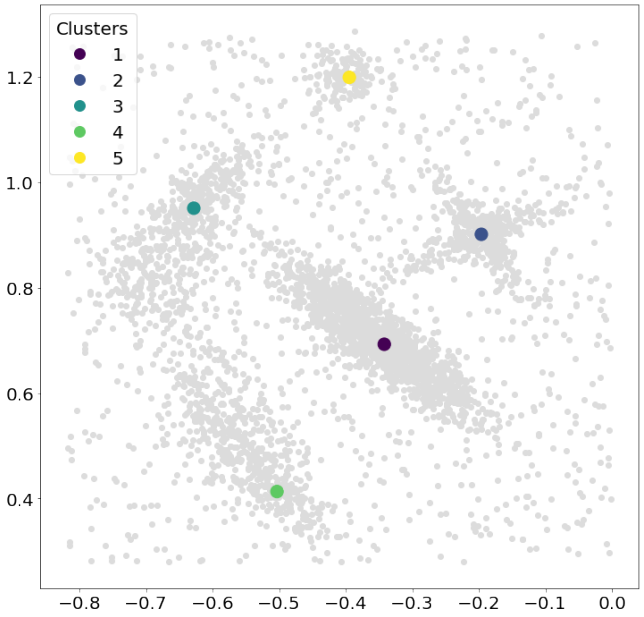
1)FINDING CLUSTERS CENTERS



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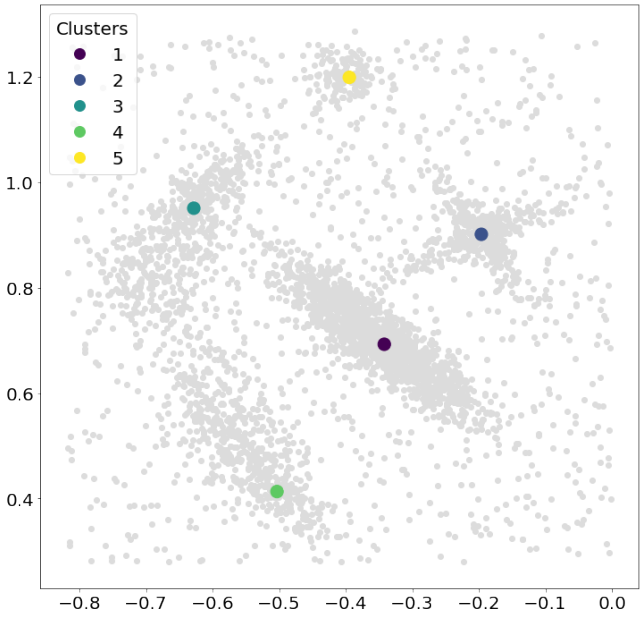
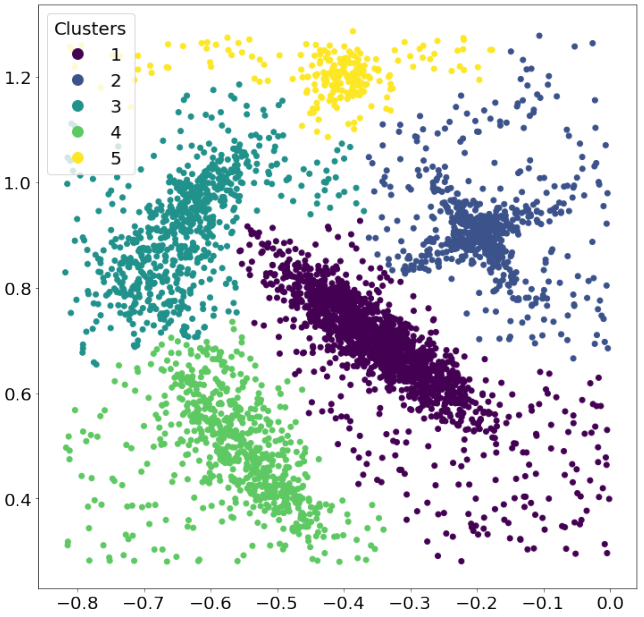


2)ASSIGNING EACH POINT TO A CLUSTER



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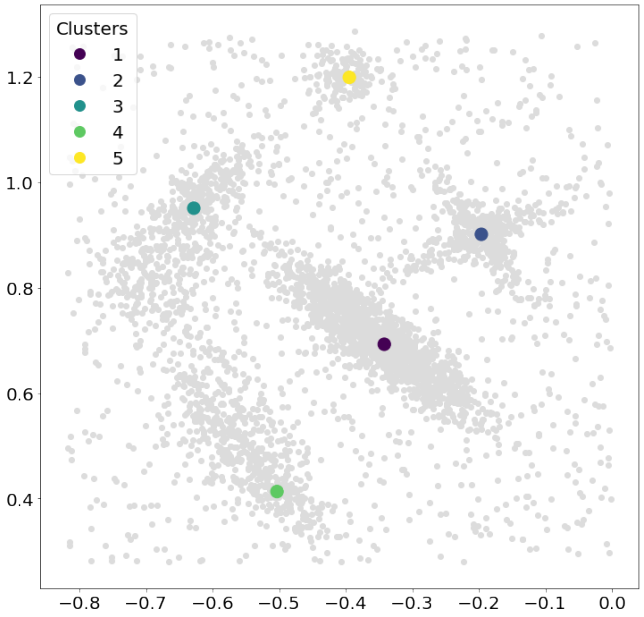

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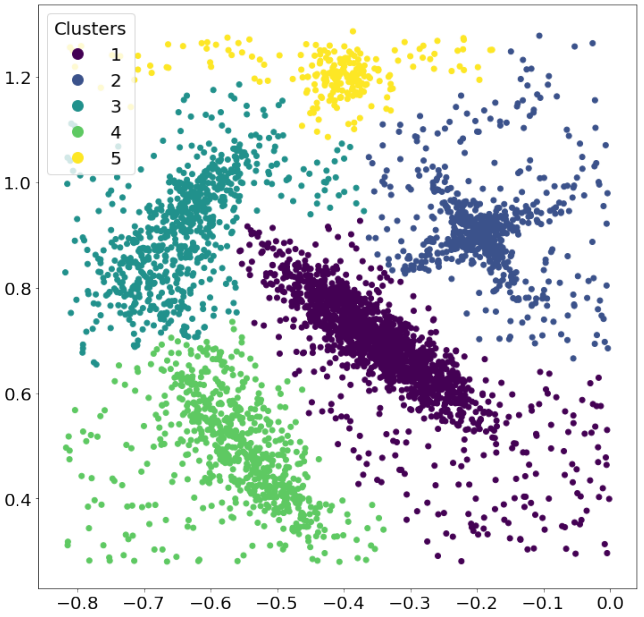
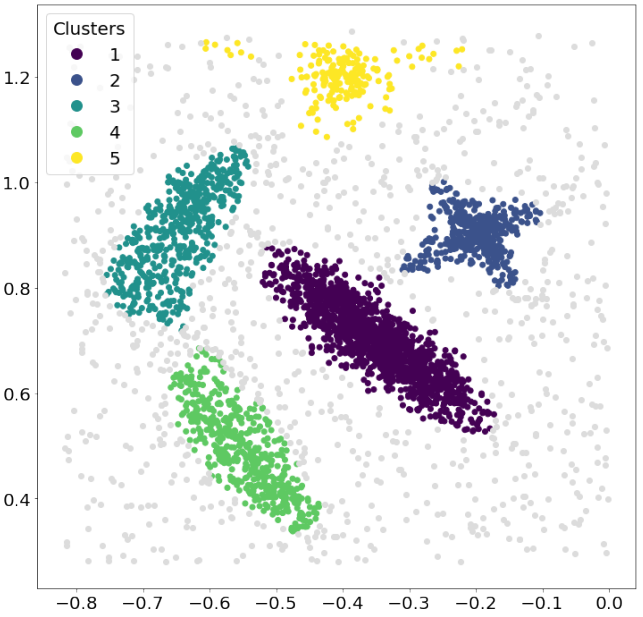


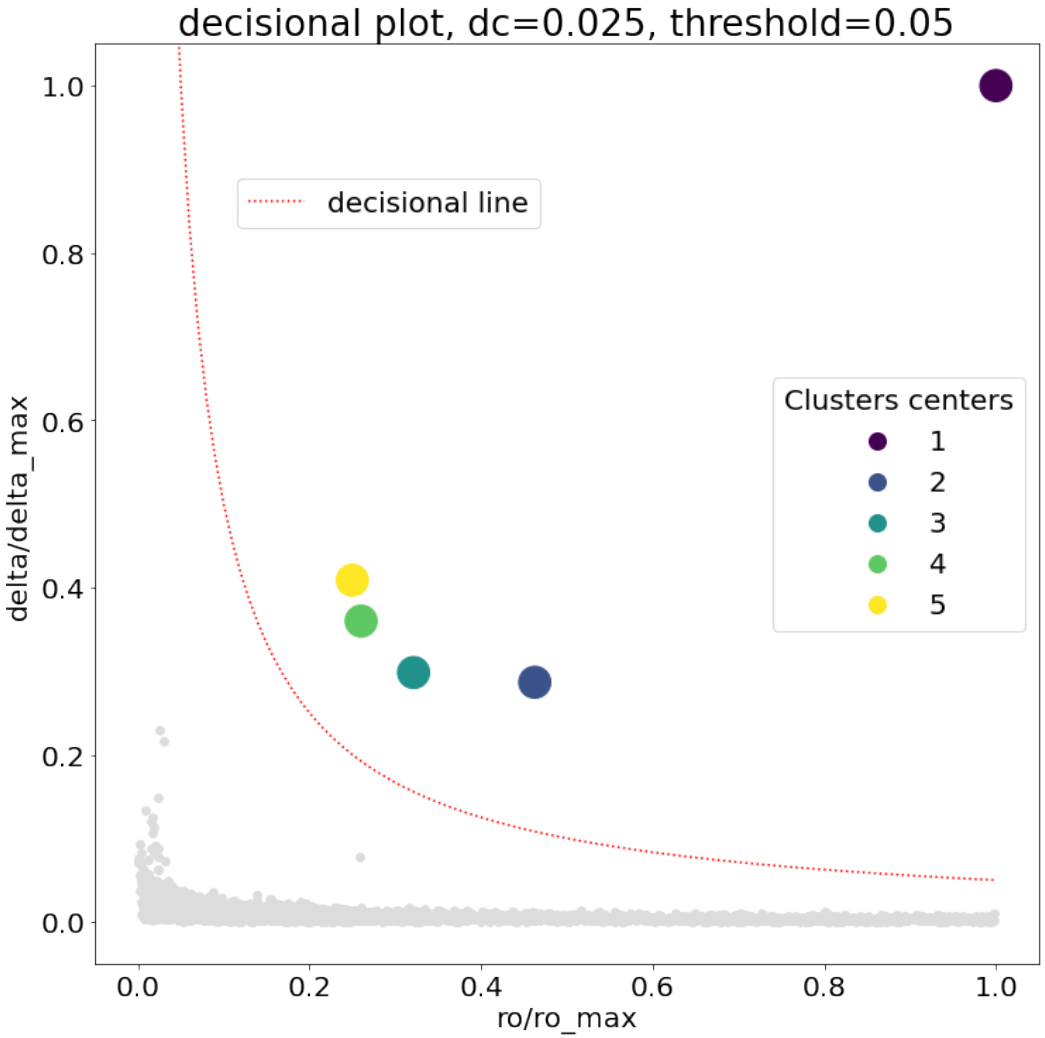
3)FINDING NOISE



Unsupervised Learning: DPC – Finding clusters centers

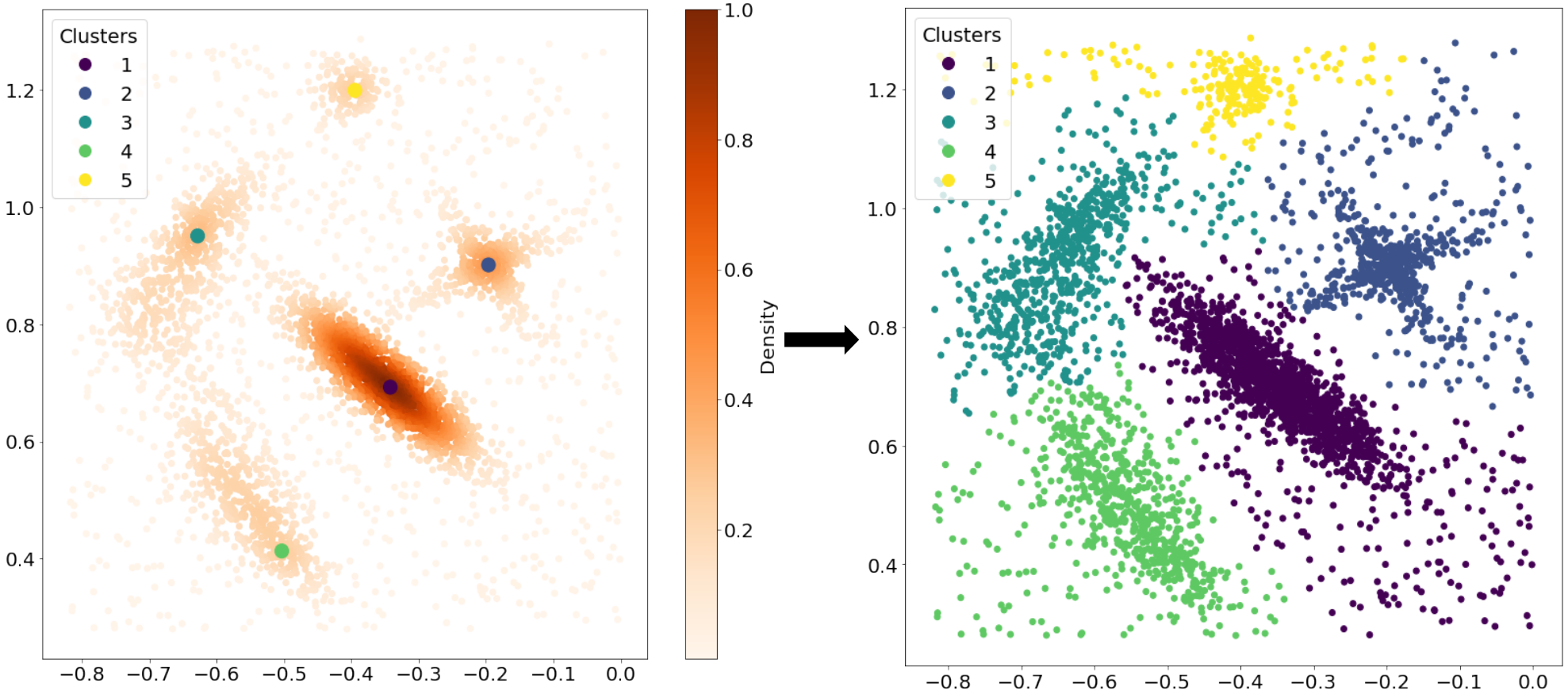
- $\rho_i = \sum_j \mathcal{N}(d_{ij}, d_c)$ where:
  - $d_{ij} =$ *distance between the* i^{th} *and* j^{th} *points*
  - $\mathcal{N}(x, d_c) = e^{-\frac{1}{2}\cdot\left(\frac{x}{d_c}\right)^2}$
- $\delta_i = \min_{j:\rho_j>\rho_i} d_{ij}$
- Decisional line:

$$\rho \cdot \delta = threshold$$



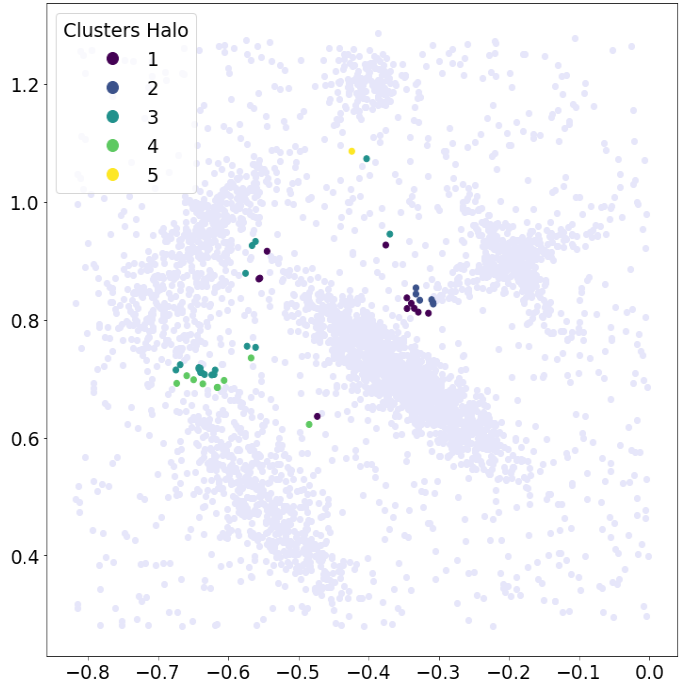
Unsupervised Learning: DPC – Assigning data to clusters centers

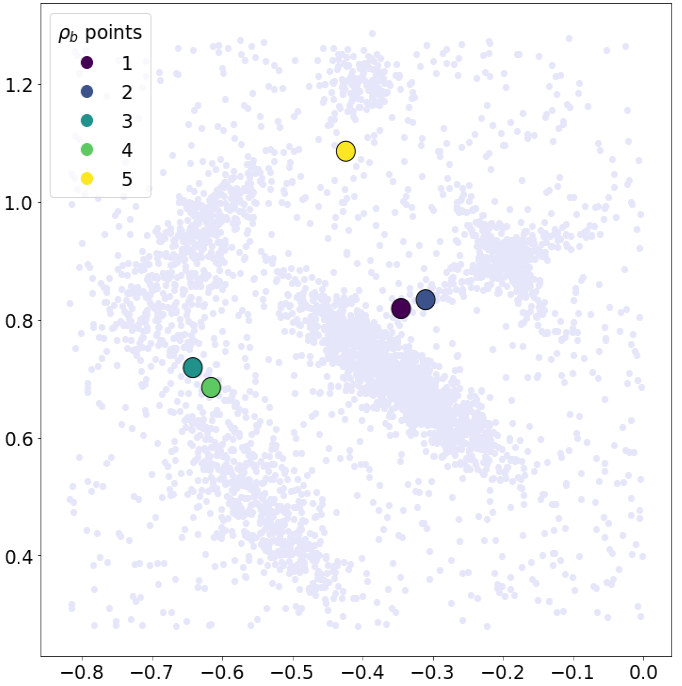
Each point is assigned to the same cluster as its nearest neighbor of highest density:

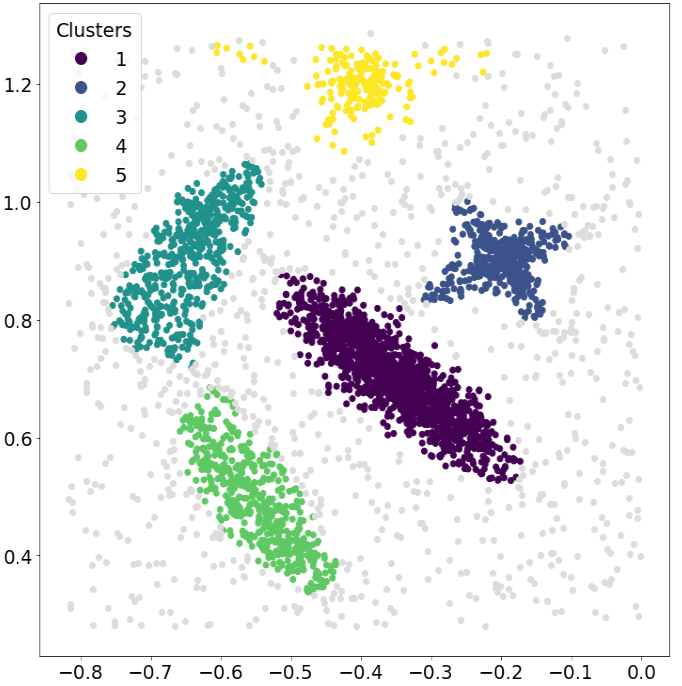


Unsupervised Learning: DPC – Finding noise

- ***CLUSTER BORDER REGION:*** set of points assigned to the cluster but within a distance d_c from points belonging to other clusters.
- ***CLUSTER NOISE:*** cluster points whose density is less than ρ_b which is the highest density in the cluster's border region



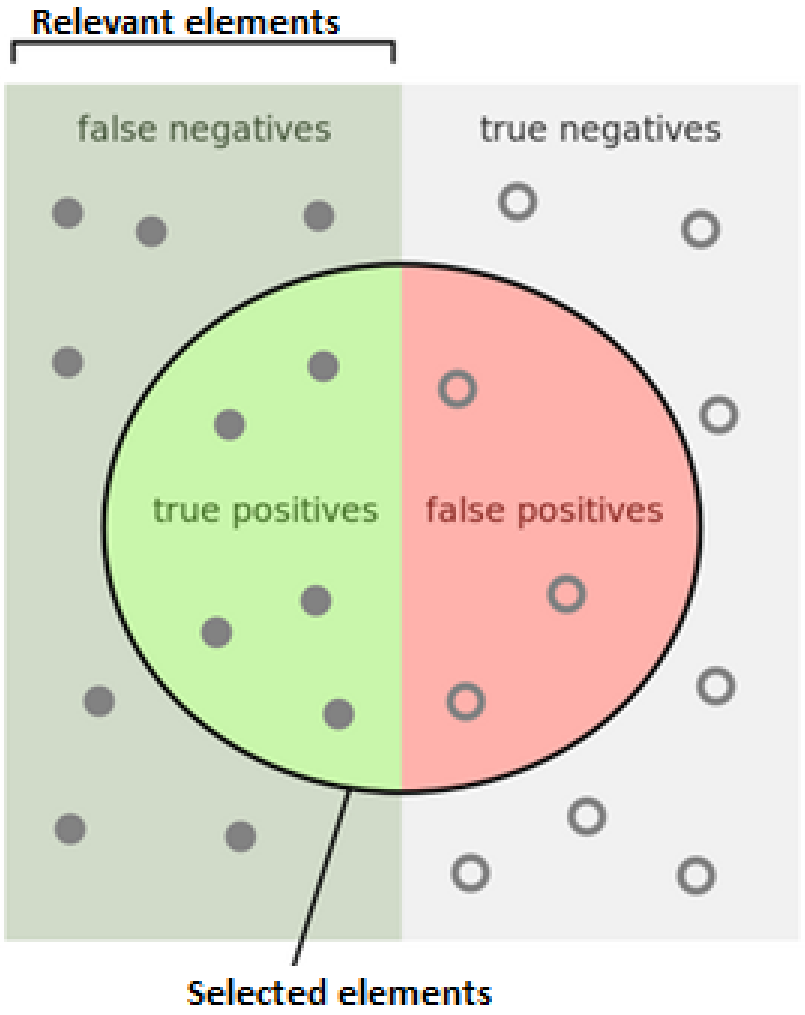




CHURCHES DATA ANALYSIS WITH DENSITY PEAK CLUSTERING

How do we check the performances?

Recall and Precision



How many selected items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{selected elements}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{relevant elements}}$$

Normalized Mutual Information

$$NMI(Y, C) = \frac{2 \times I(Y; C)}{[H(Y) + H(C)]}$$

where,

1) Y = class labels
2) C = cluster labels
3) H(.) = Entropy
4) I(Y;C) = Mutual Information b/w Y and C

RINGEBU

Variables – RINGEBU

NOTE: all the variables have been divided by their mean

Variables – RINGEBU

WITHOUT TEMPERATURE

- Standard Deviation of the difference of the internal and external Mixing Ratios (std_Diff_MR)

- Standard Deviation of the internal Relative Humidity (std_RHin)

- Standard Deviation of the internal Mixing Ratio (std_Der_MRin)

NOTE: all the variables have been divided by their mean

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WITH TEMPERATURE

- Standard Deviation of the first derivative of the internal Temperature (std_Der_Tin)

- Standard Deviation of the first derivative of the internal Relative Humidity (std_Der_RHin)

- Standard Deviation of the first derivative of the internal Mixing Ratio (std_der_MRin)

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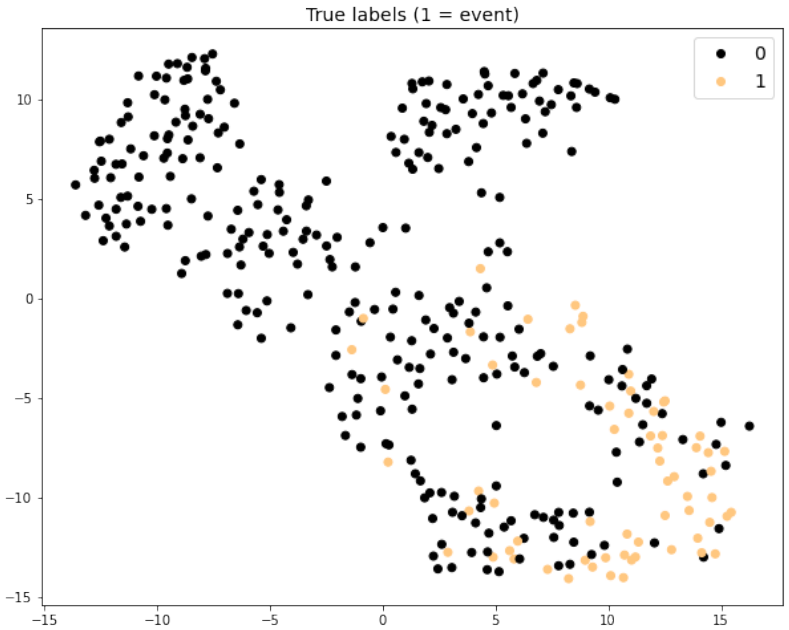
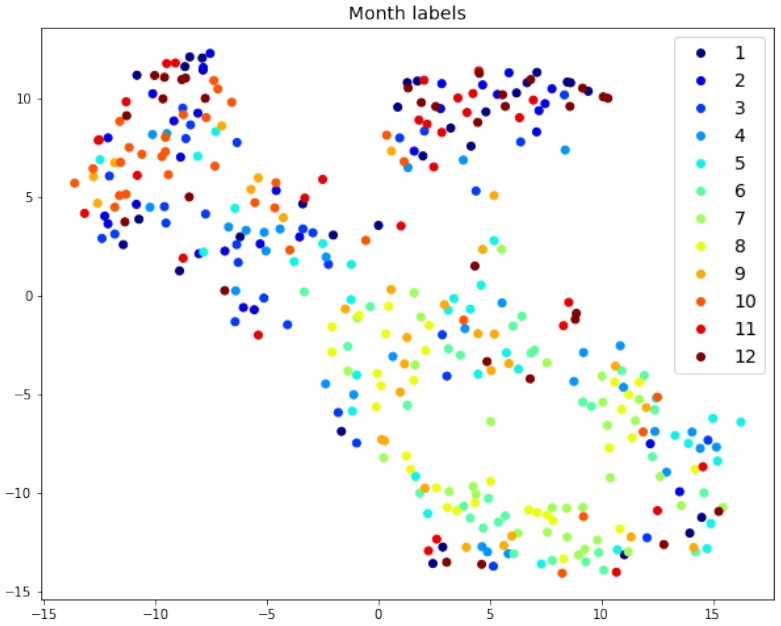
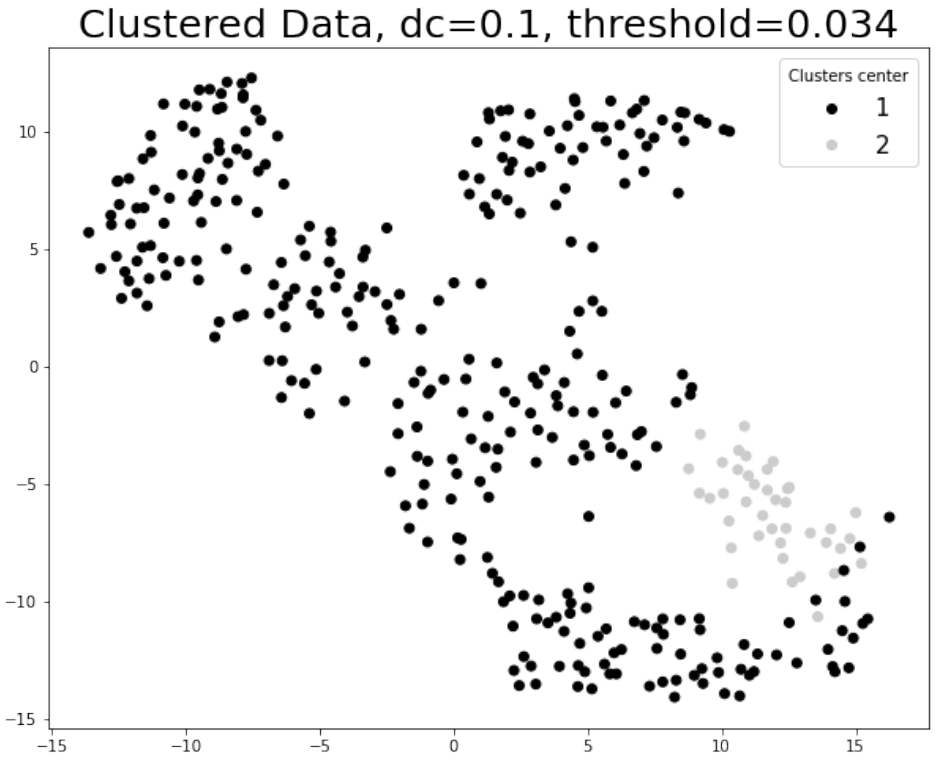
WITHOUT TEMPERATURE

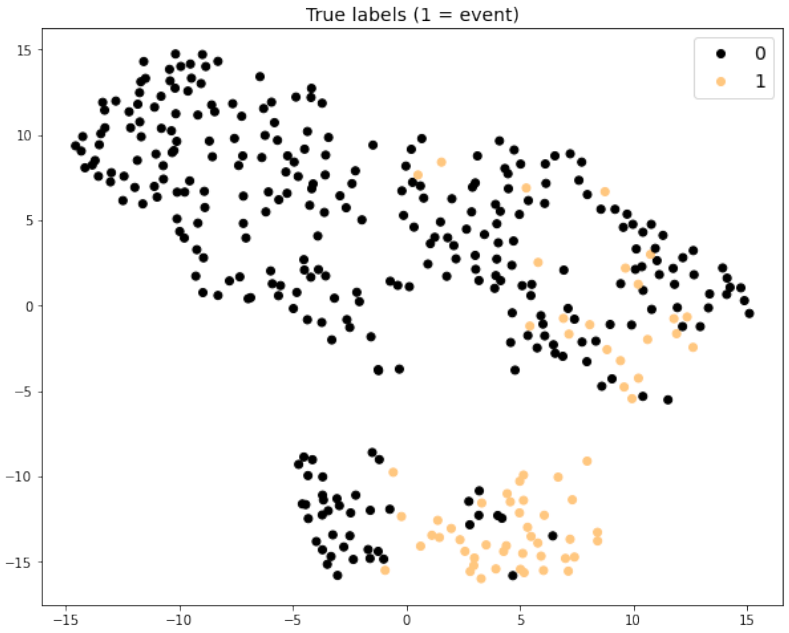


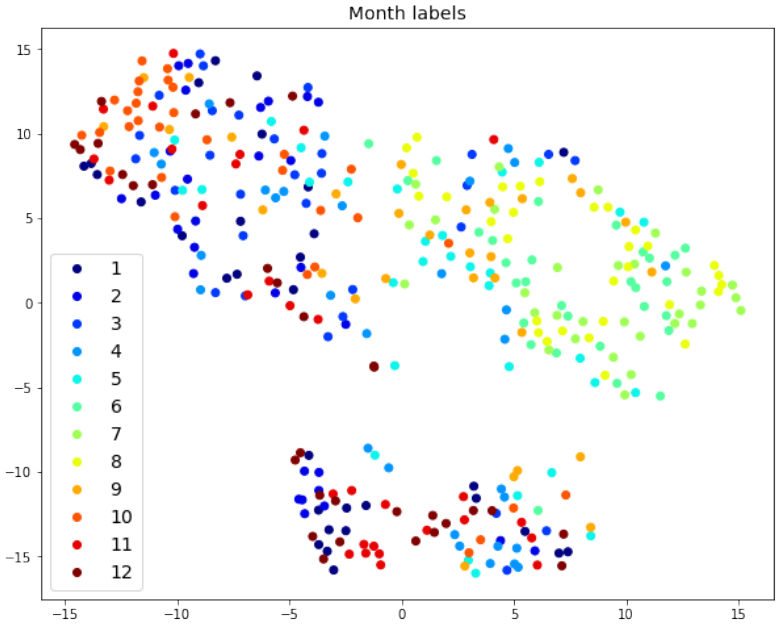


NMI: 0.072
Precision: 0.475
Recall: 0.292

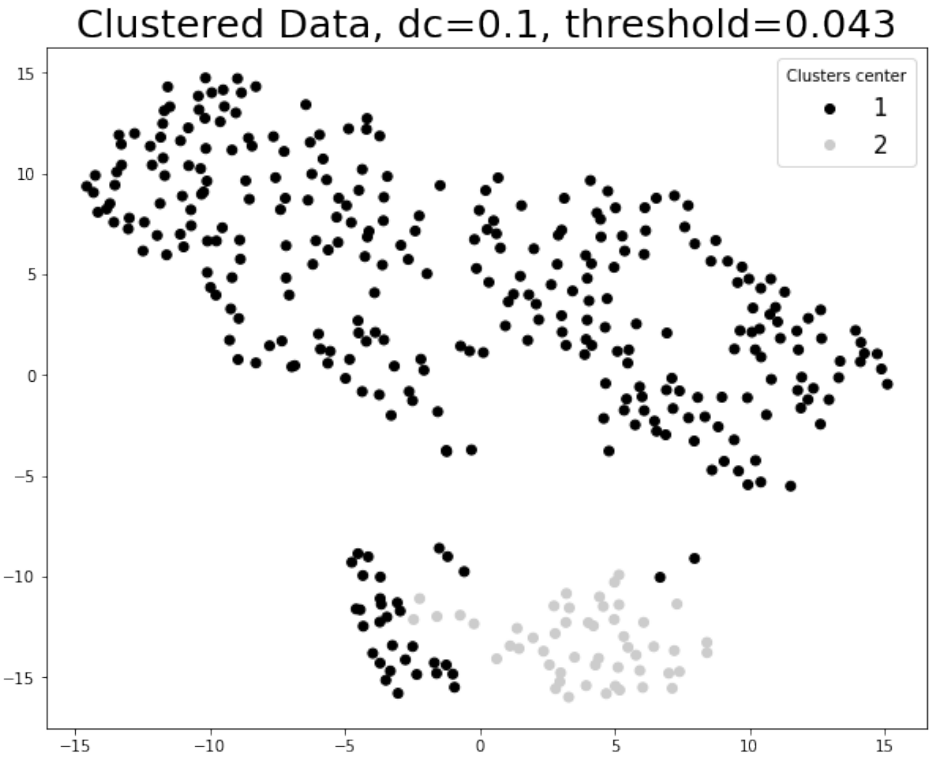


WITH TEMPERATURE



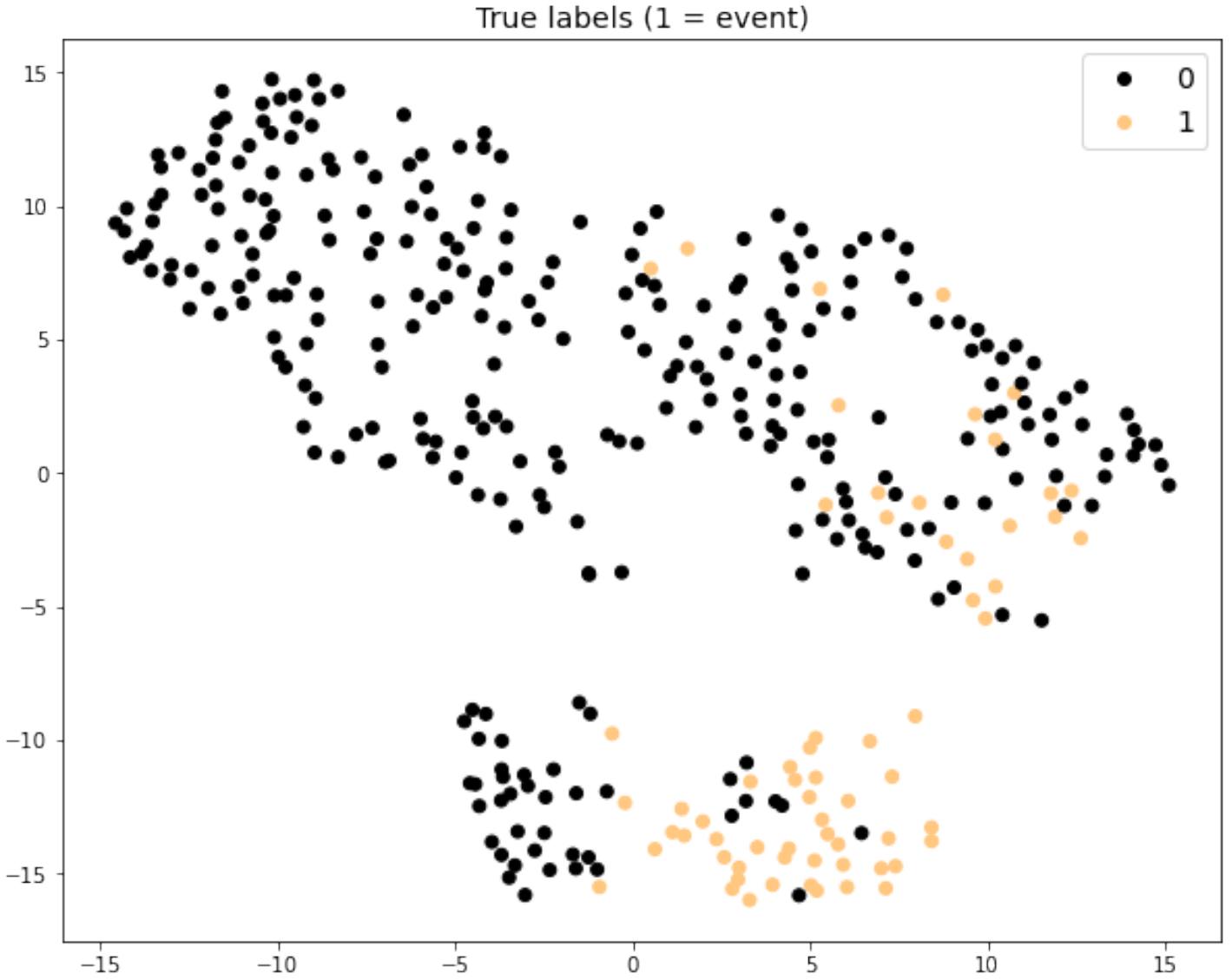


NMI: 0.336
Precision: 0.765
Recall: 0.6



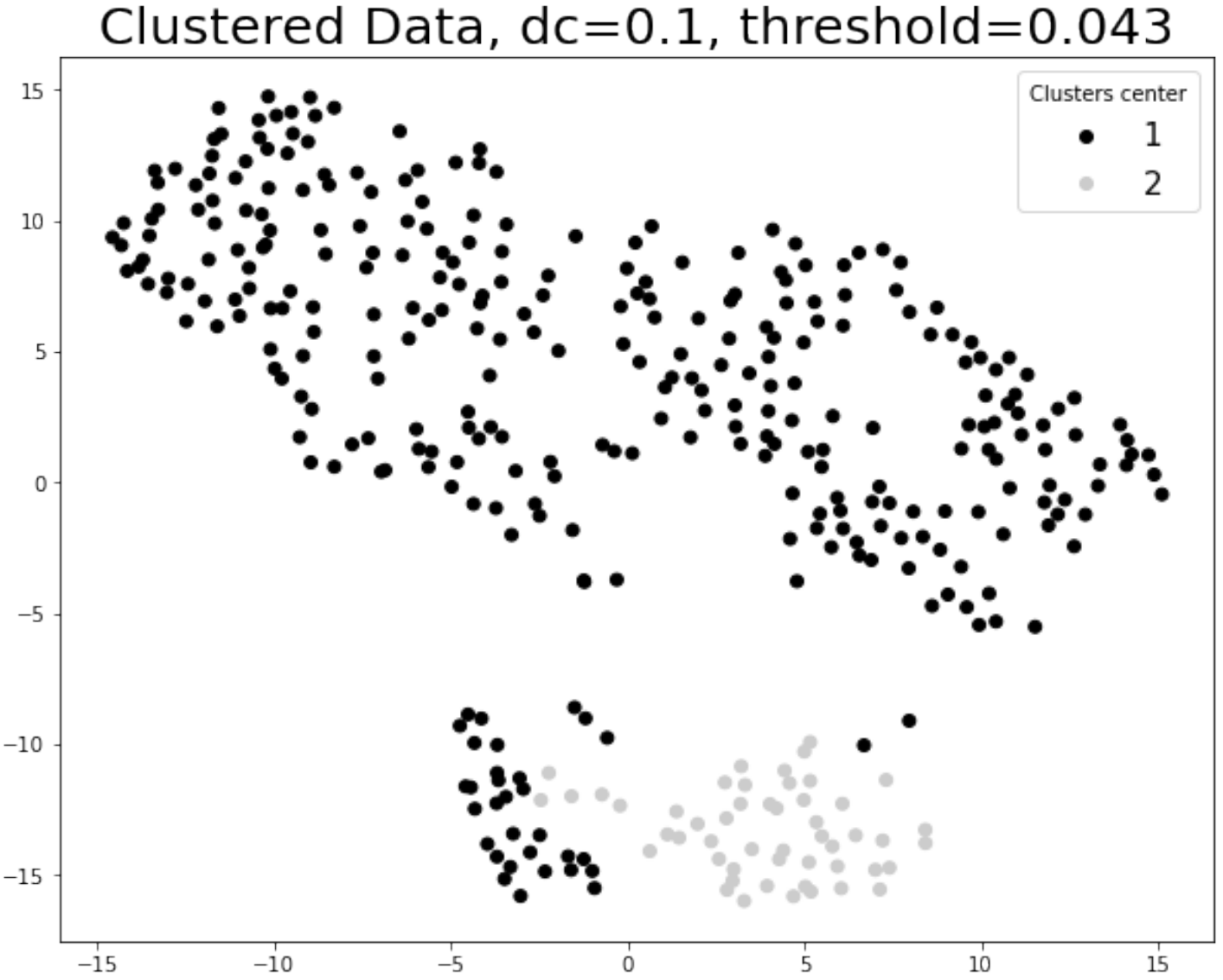
WITH TEMPERATURE

- There are two areas with events

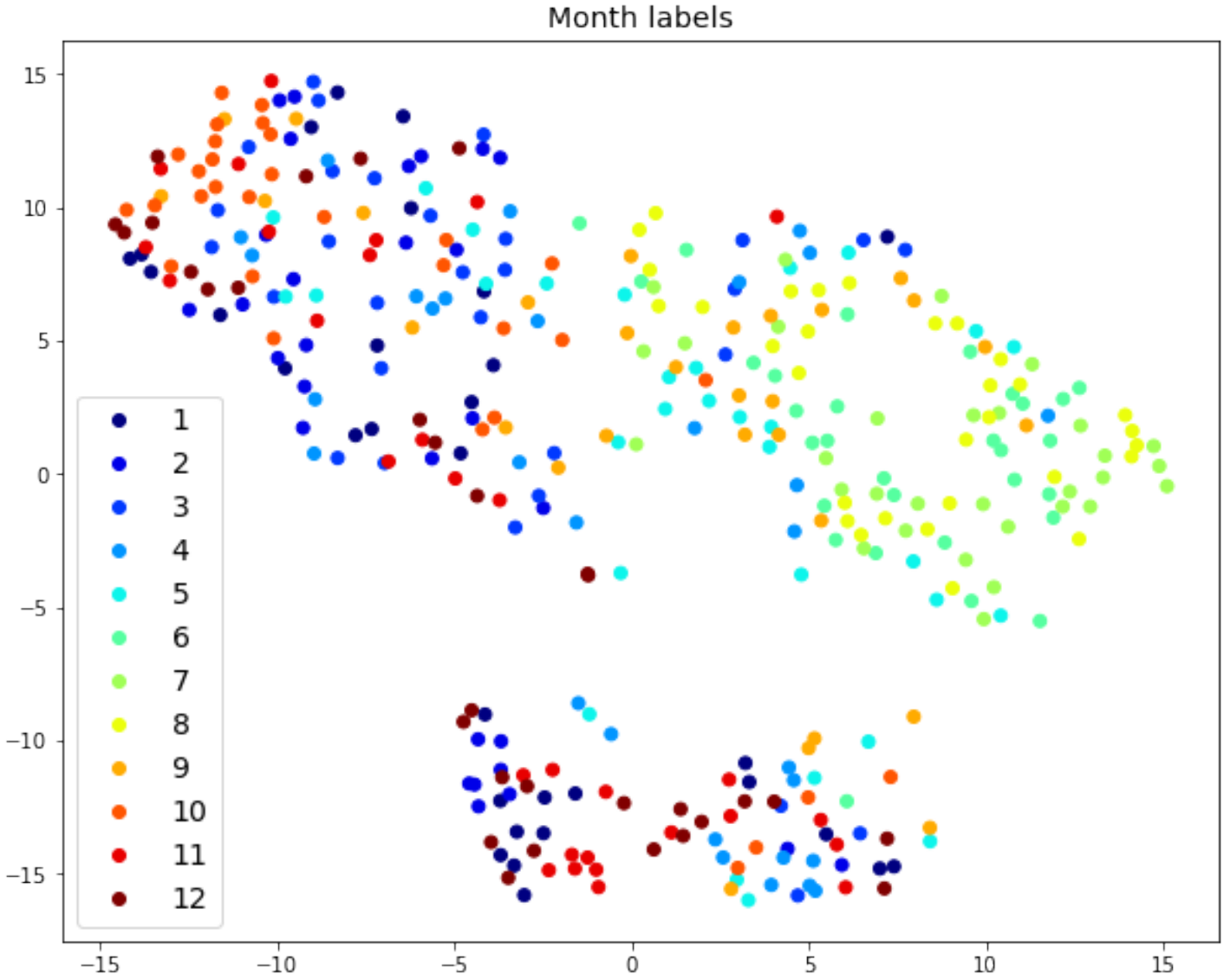


WITH TEMPERATURE

- The clustering algorithm separates just one of the two areas with events

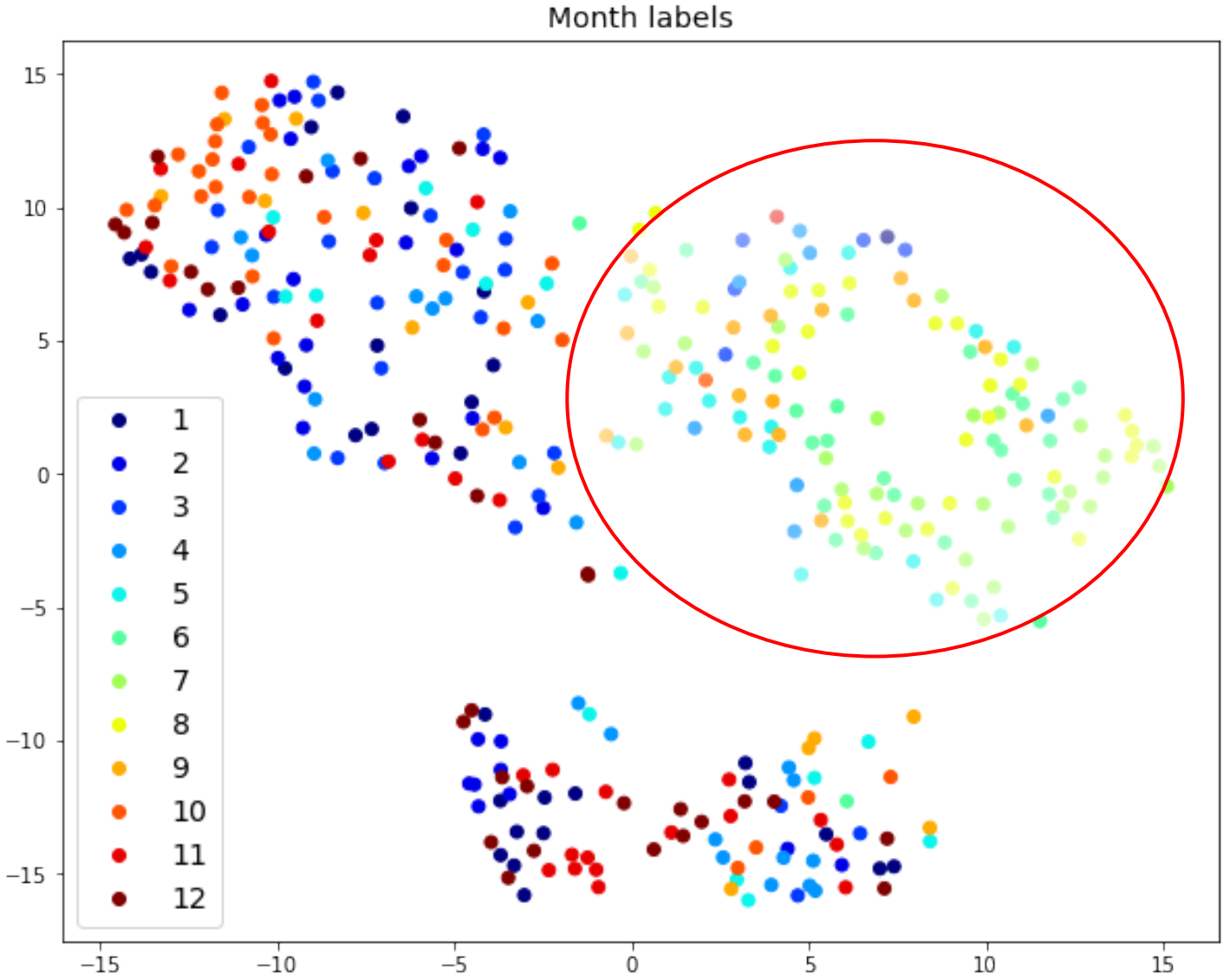


WITH TEMPERATURE

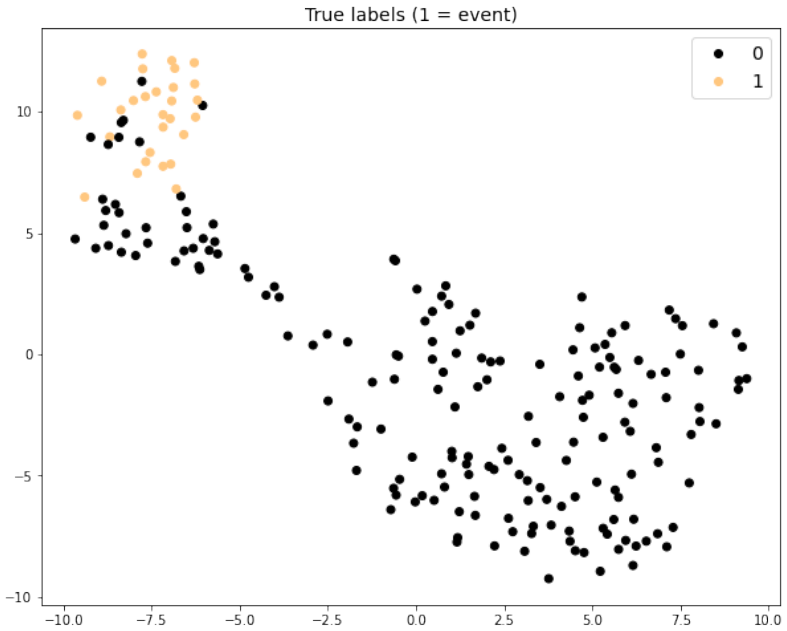


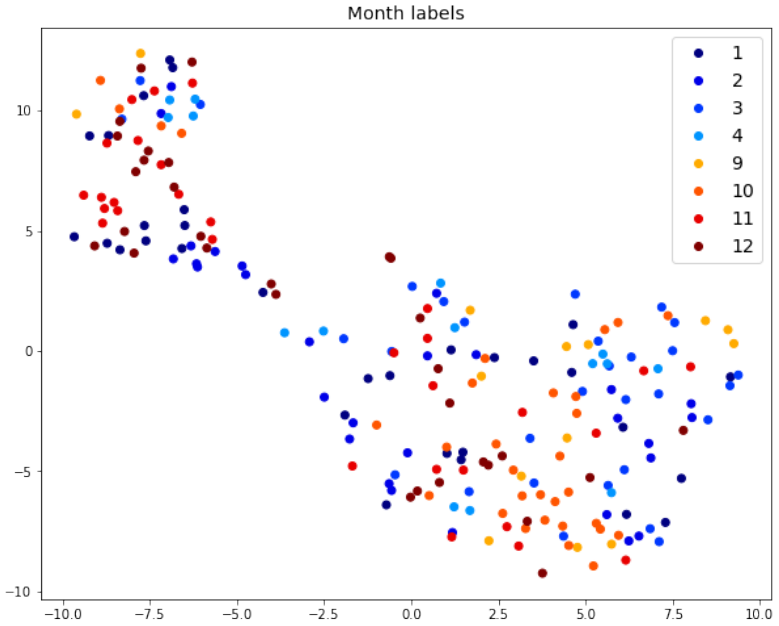
WITH TEMPERATURE

- There is a problem with spring and summer

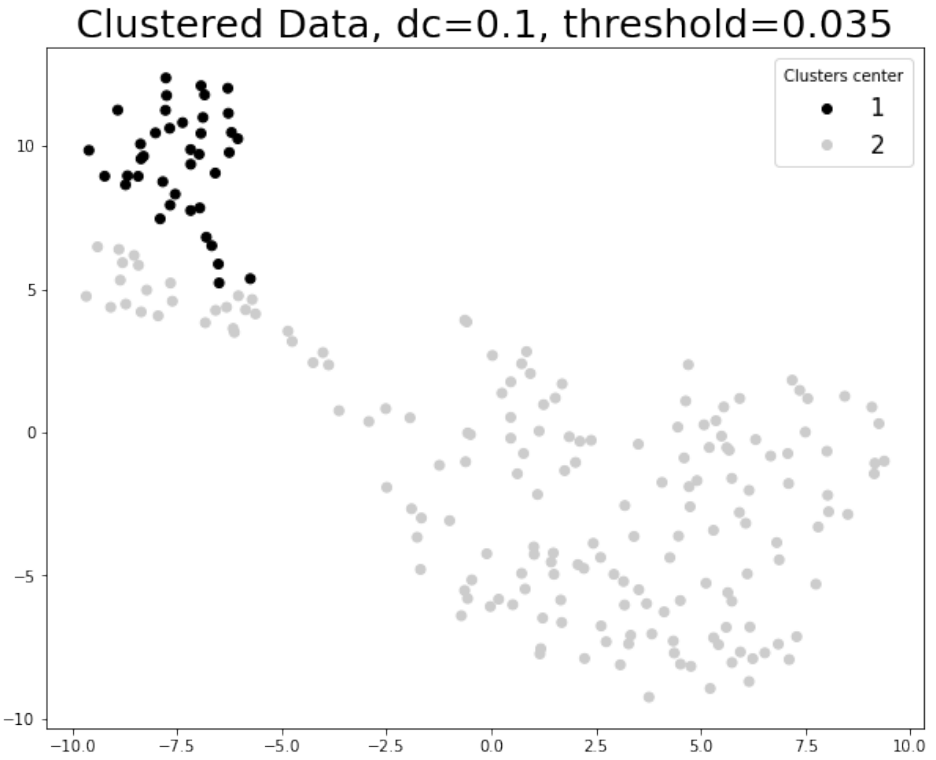


ONLY WINTER/AUTUMN DATA





NMI: 0.571
Precision: 0.692
Recall: 0.964



Method repeatability: HEDDAL

Variables - HEDDAL

NOTE: all the variables have been divided by their mean

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- Standard Deviation of the internal Mixing Ratio (std_MRin)

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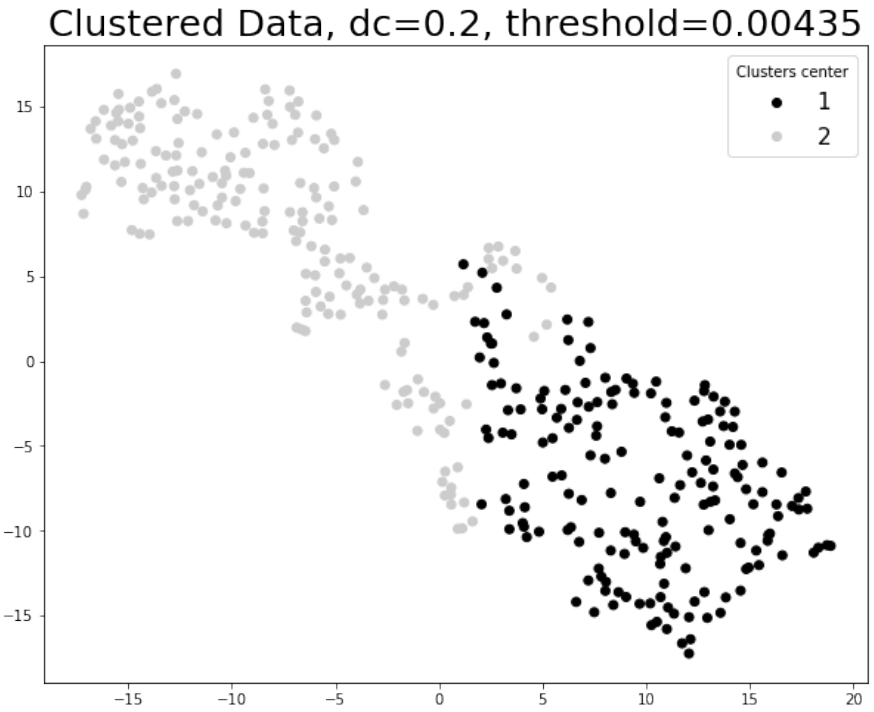
Data repeatability: HEDDAL

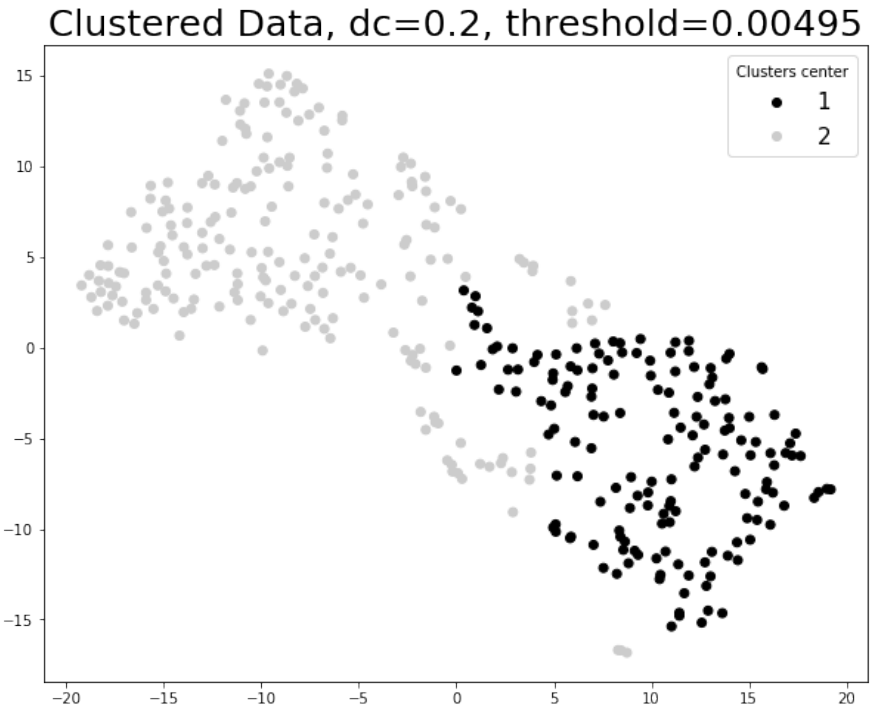
- The two clusters have similar form, with and without temperature information

- No temperature



NMI: 0.119
Precision: 0.153
Recall: 1

- Temperature

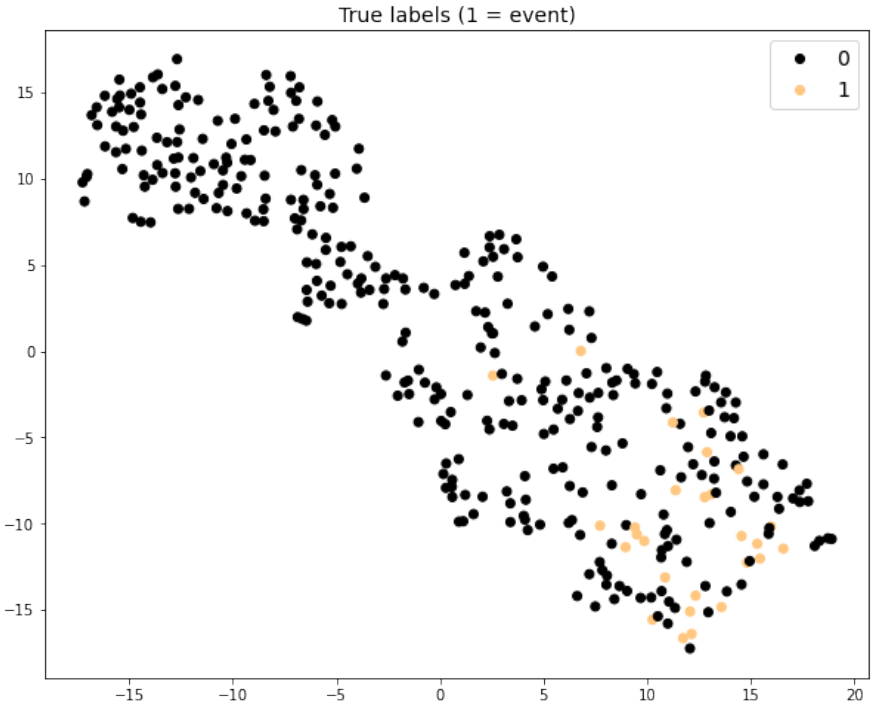


NMI: 0.111
Precision: 0.164
Recall: 0.962

Data repeatability: HEDDAL

- Also the events are in the same areas

- No temperature



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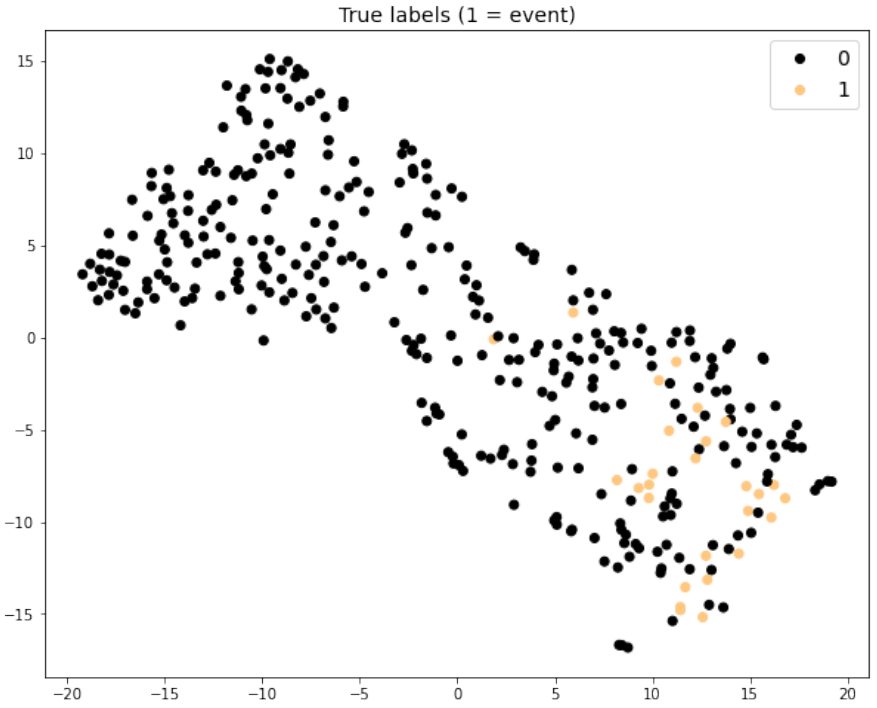
- Temperature

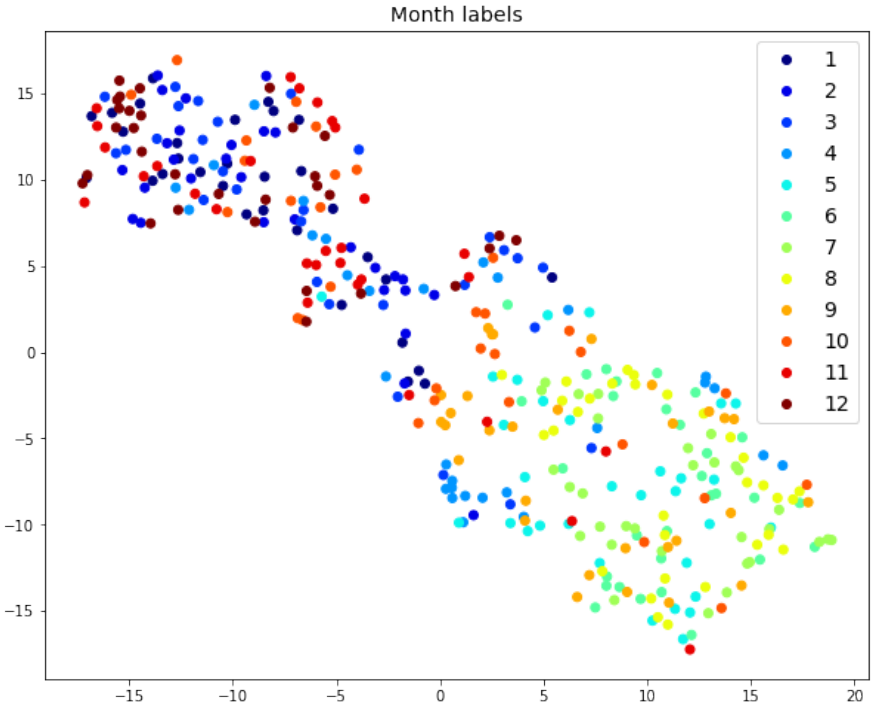


NMI: 0.111
Precision: 0.164
Recall: 0.962

Data repeatability: HEDDAL

- In the Heddal case the clustering has the effect of splitting summer/spring and autumn/winter

- No temperature



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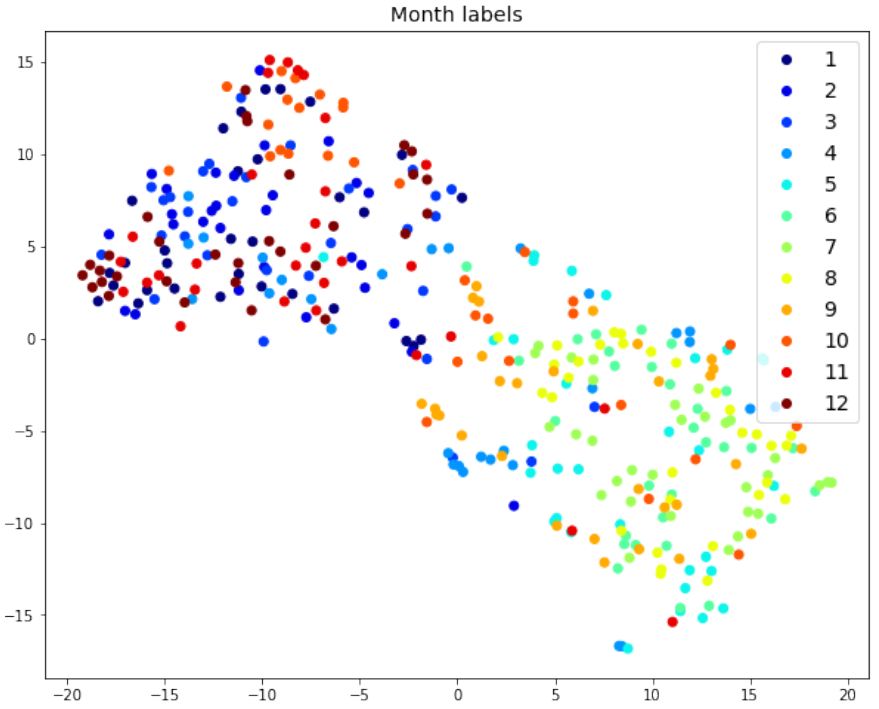

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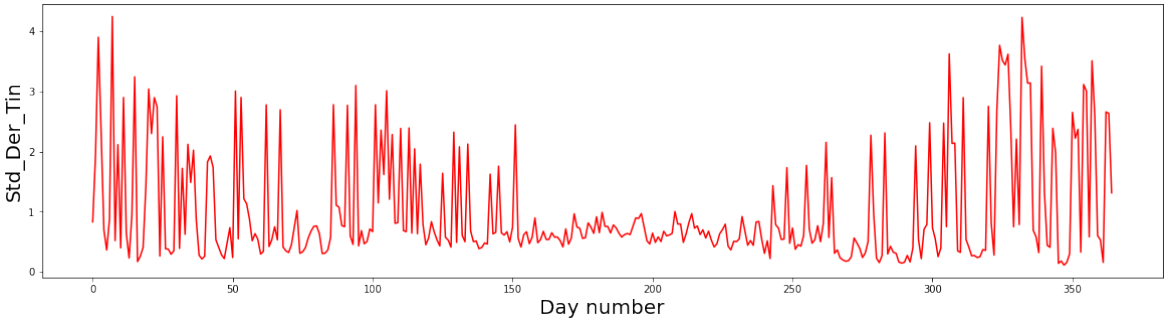
Best cluster performances

Best variables

- Standard Deviation of the first derivative of the internal Temperature (**std_Der_Tin**)



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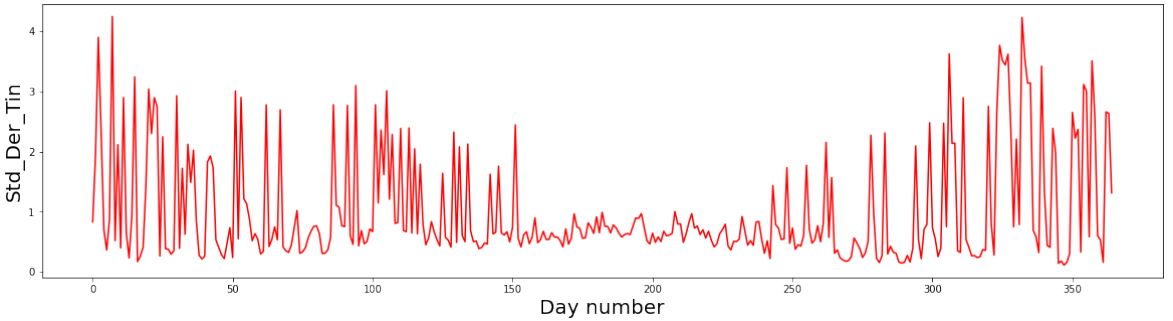
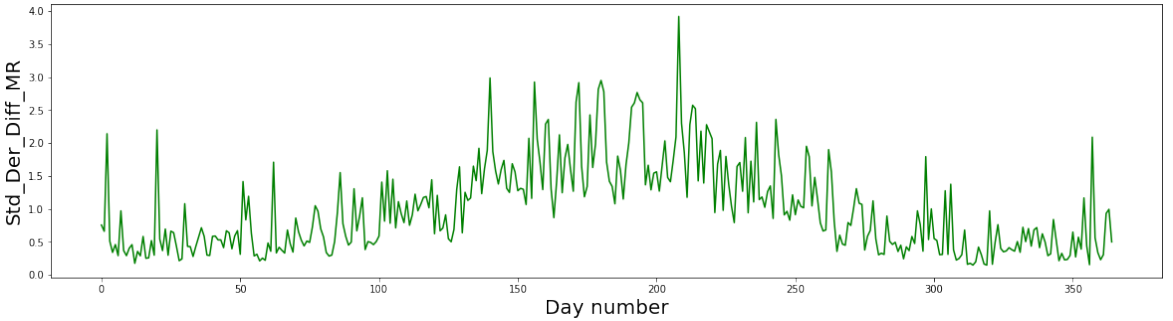


- Standard Deviation of the first derivative of difference of the internal and external Mixing Ratios (**std_Der_Diff_MR**)



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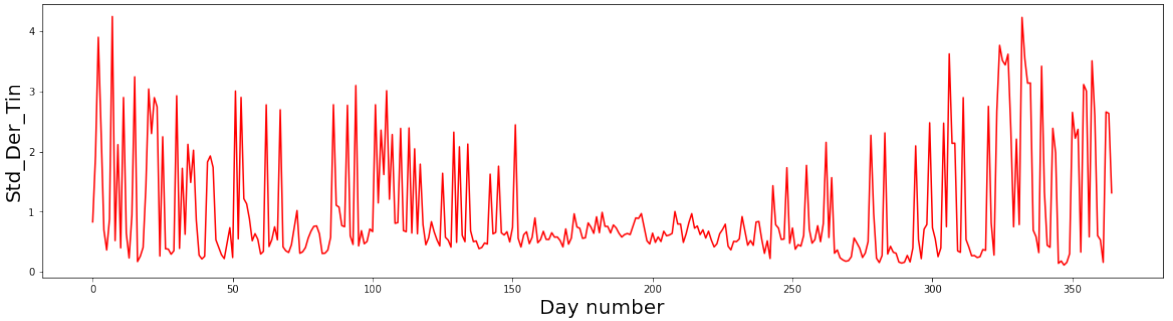
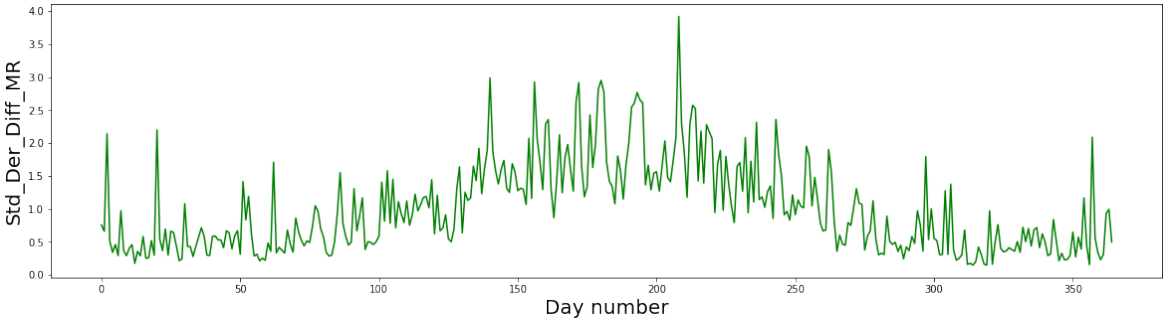
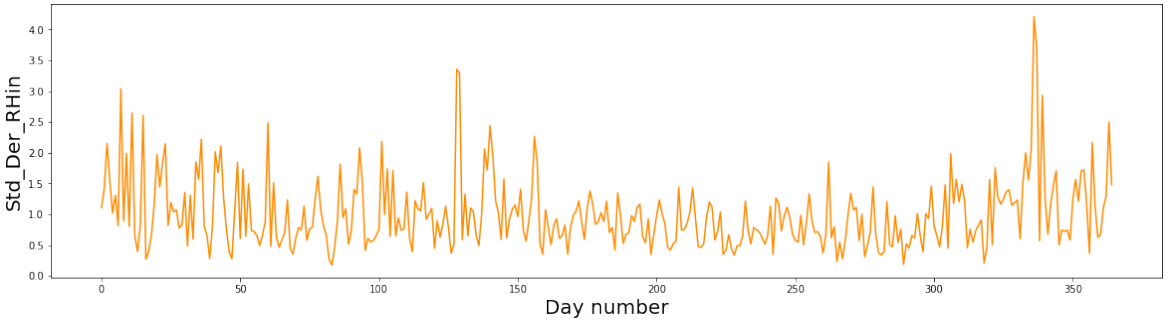
- Standard Deviation of the first derivative of the internal Temperature (**std_Der_Tin**)



- Standard Deviation of the first derivative of difference of the internal and external Mixing Ratios (**std_Der_Diff_MR**)



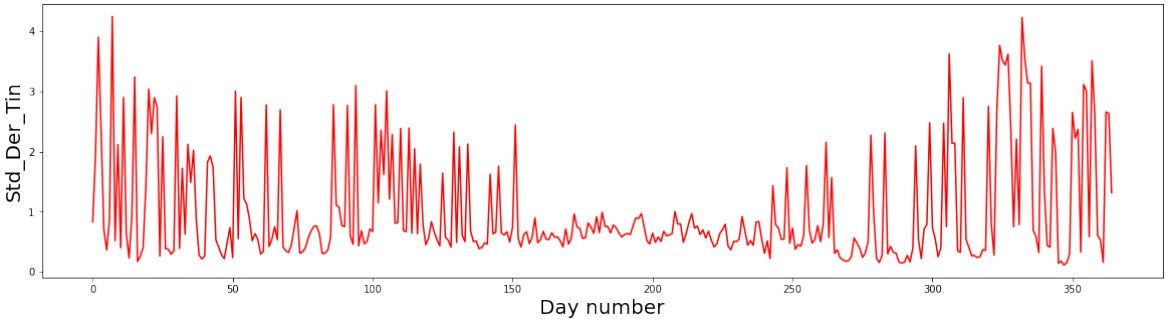
- Standard Deviation of the first derivative of the internal Relative Humidity (**std_Der_RHin**)



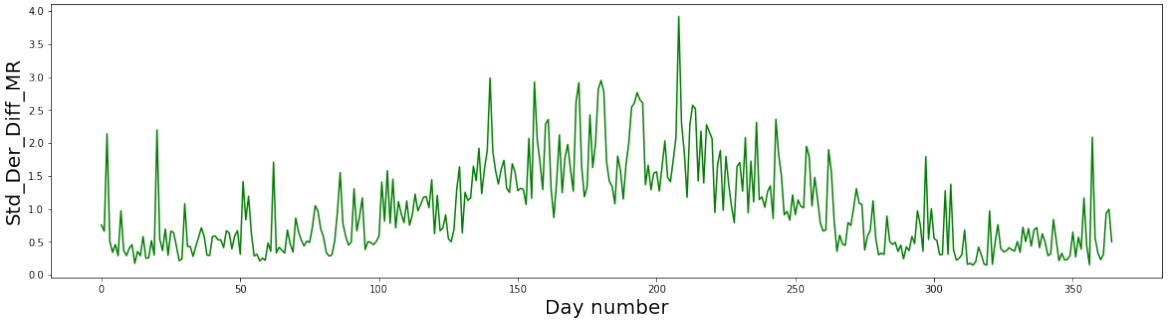
NOTE: all the variables have been divided by their mean

Best variables

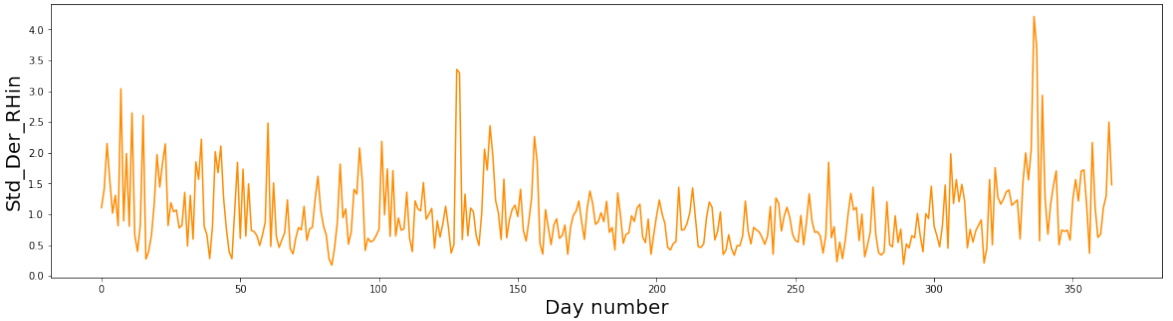
- Standard Deviation of the first derivative of the internal Temperature (**std_Der_Tin**)



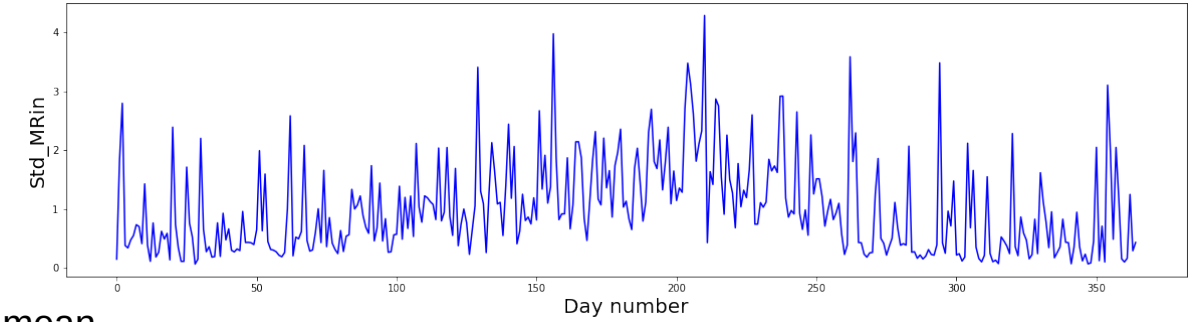
- Standard Deviation of the first derivative of difference of the internal and external Mixing Ratios (**std_Der_Diff_MR**)



- Standard Deviation of the first derivative of the internal Relative Humidity (**std_Der_RHin**)

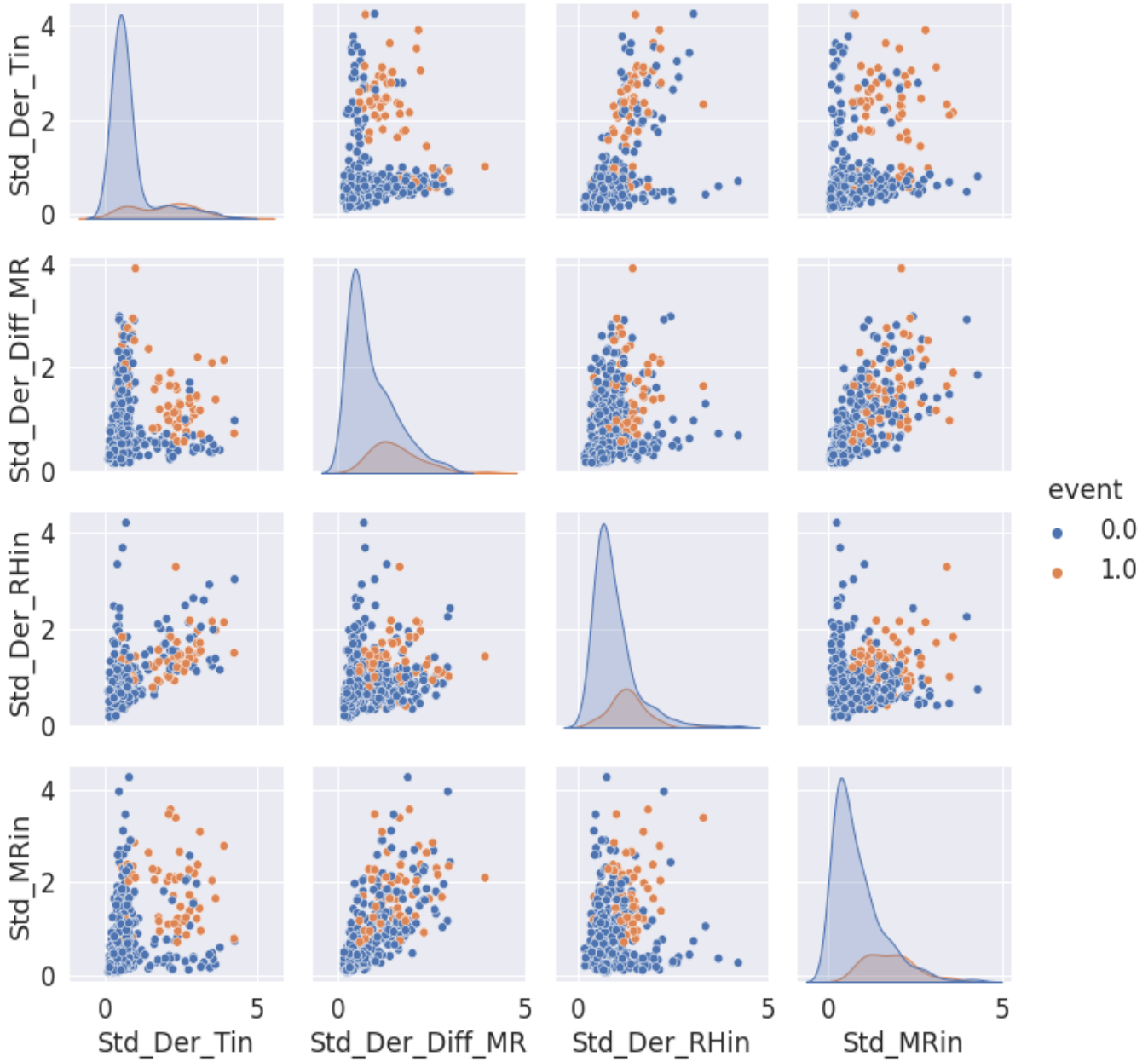


- Standard Deviation of the internal Mixing Ratio (**std_MRin**)



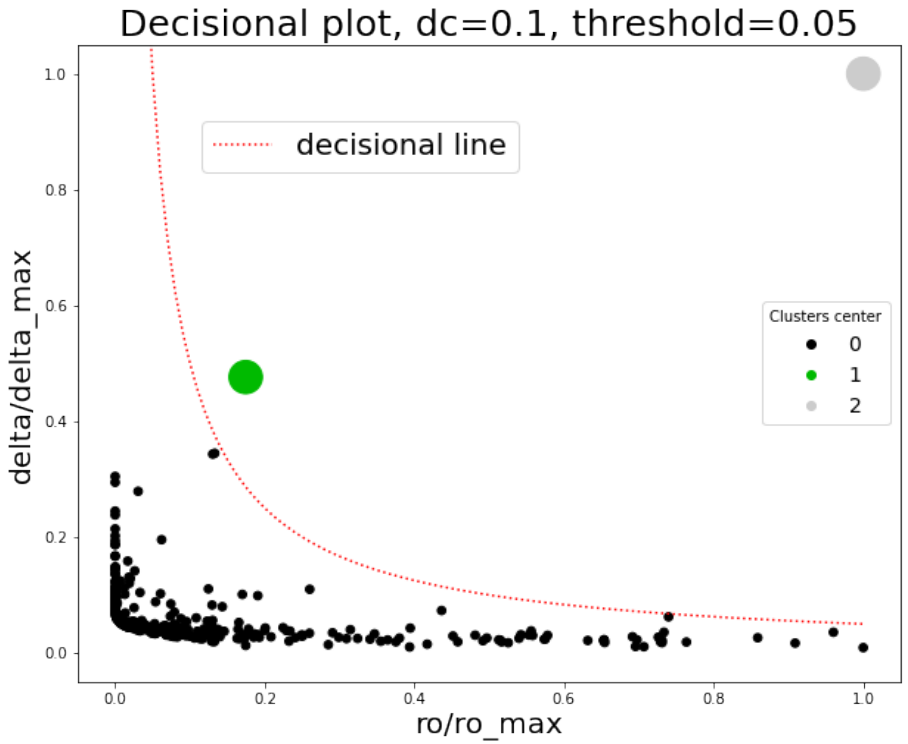
NOTE: all the variables have been divided by their mean

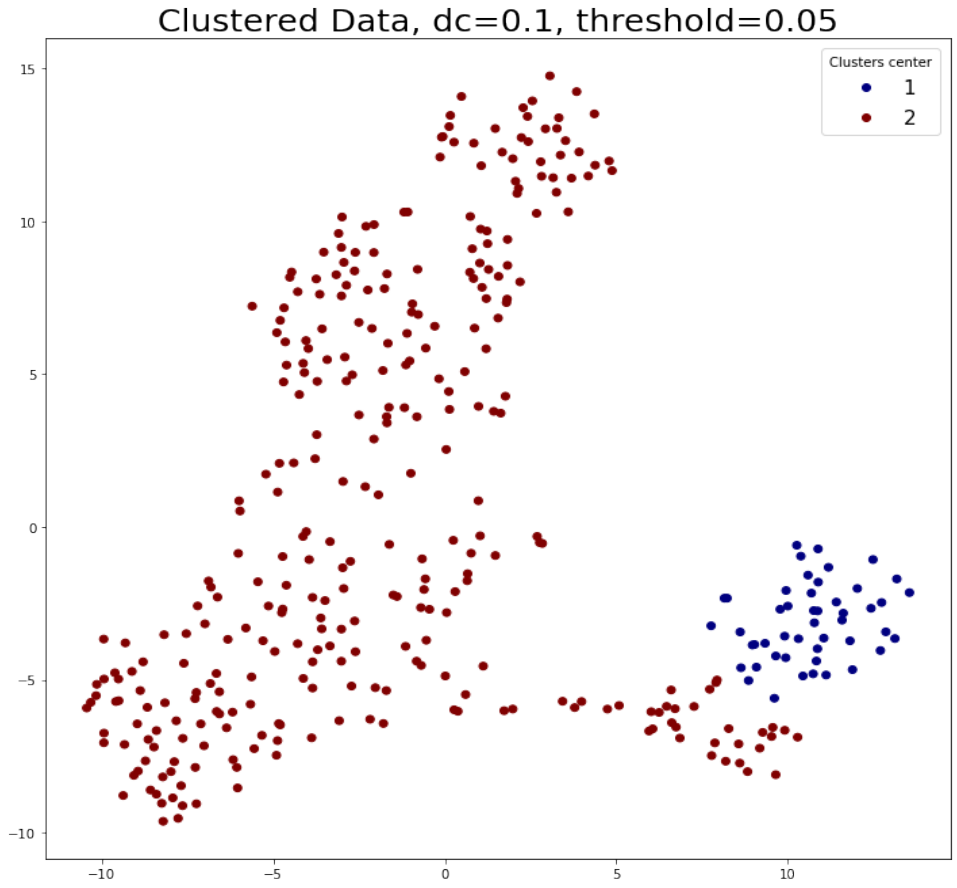
2D graphical visualization



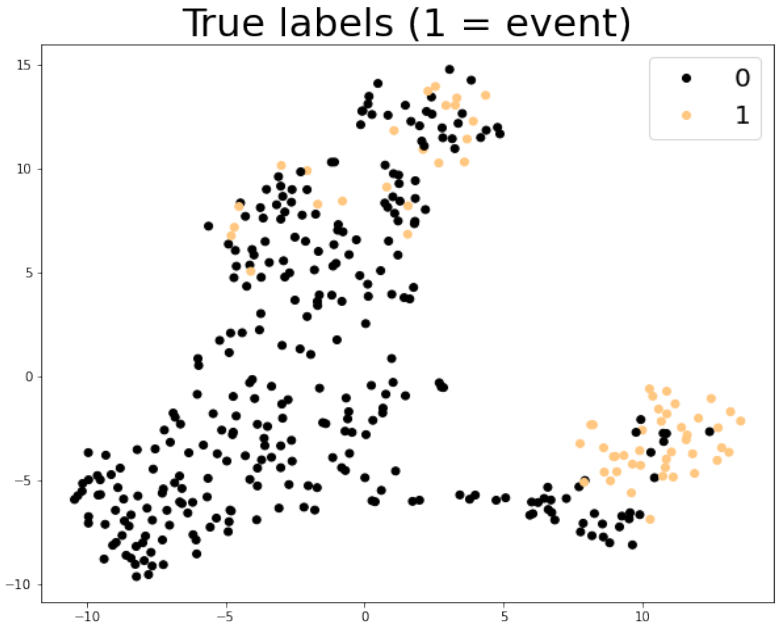
RINGEBU – Cluster results

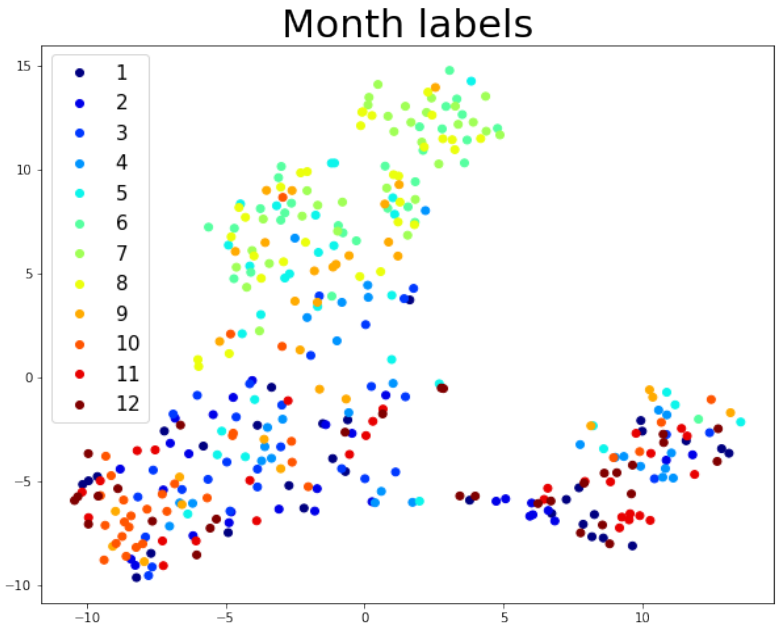
NMI: 0.395
Precision: 0.833
Recall: 0.615

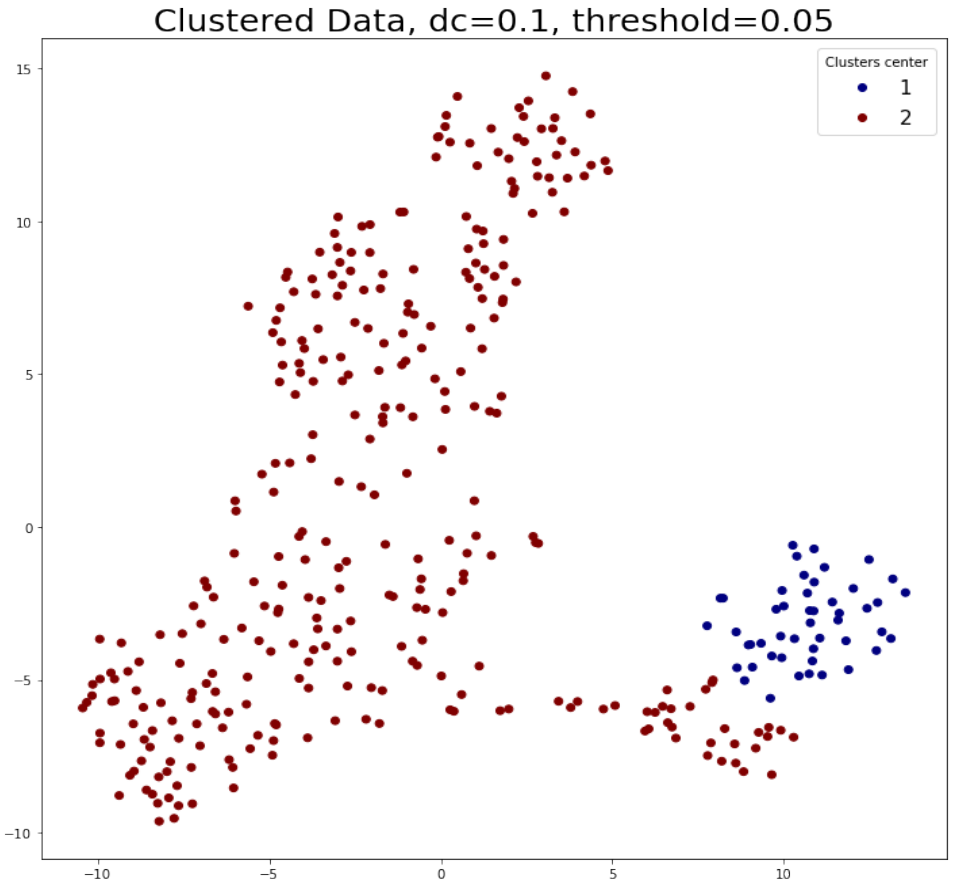




TRUE LABELS


True labels (1 = event)
0
1


Month labels
1
2
3
4
5
6
7
8
9
10
11
12


Clustered Data, dc=0.1, threshold=0.05
Clusters center
1
2

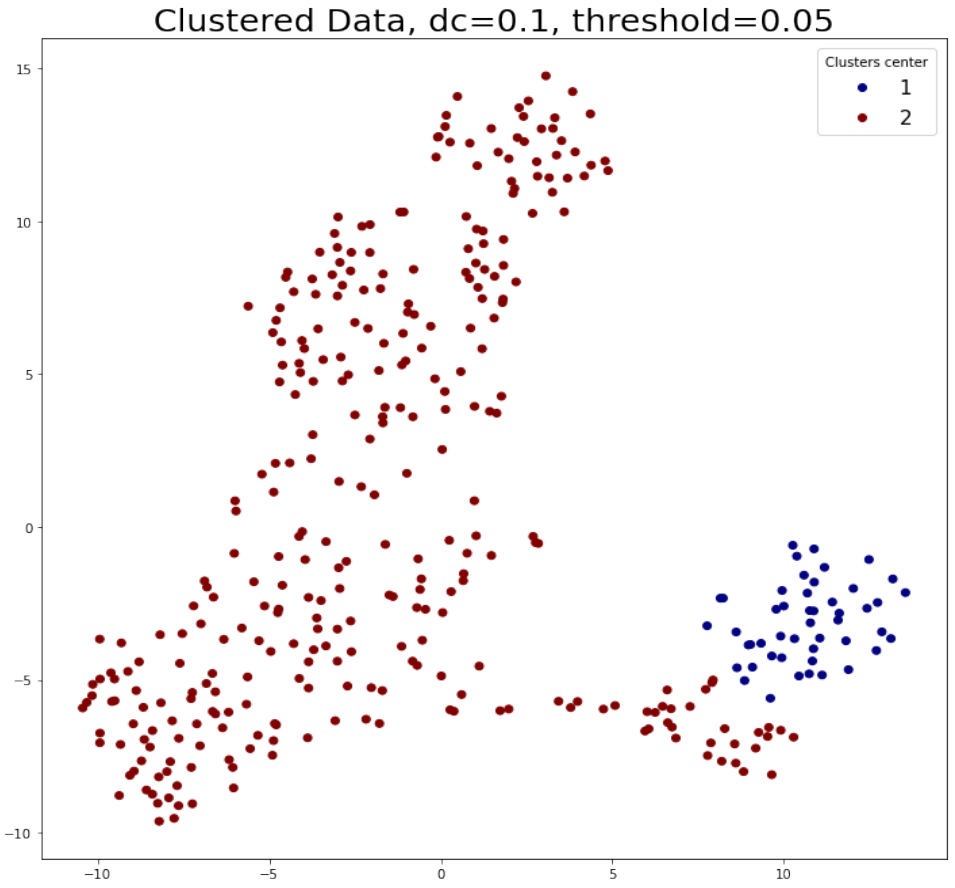
Some problems...

Labels: Event days

NMI: 0.395
Precision: 0.833
Recall: 0.615

Labels: Heating days

NMI: 0.781
Precision: 1.0
Recall: 0.842



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Labels: Event days

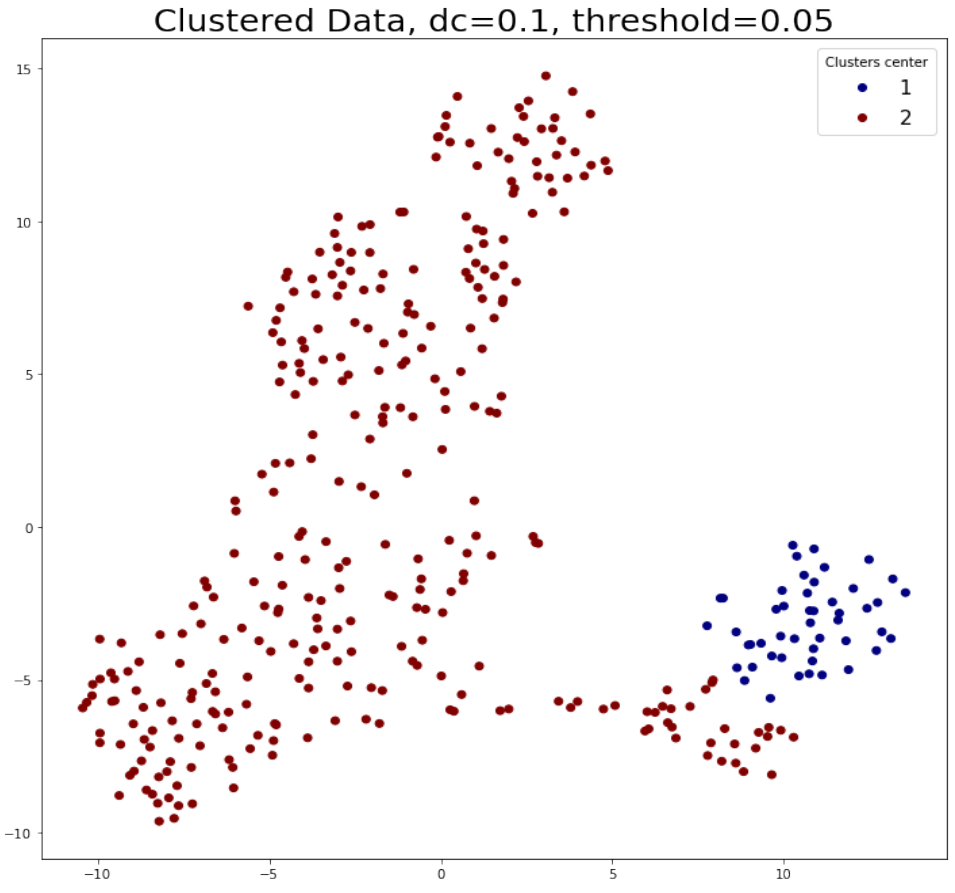
NMI: 0.395
Precision: 0.833
Recall: 0.615

Labels: Heating days

NMI: 0.781
Precision: 1.0
Recall: 0.842

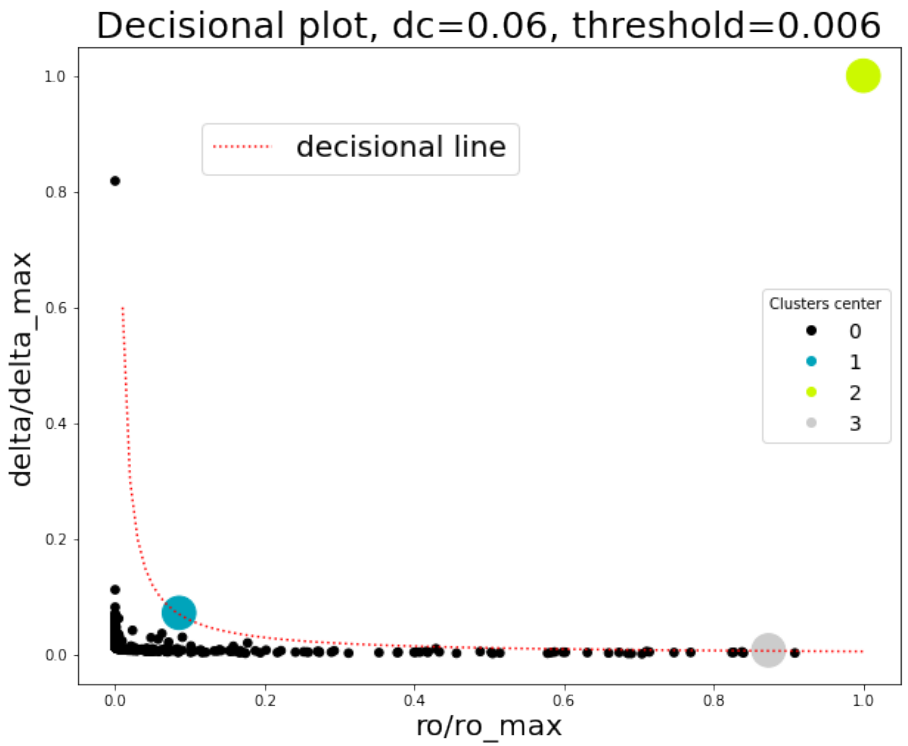
Labels: Winter event days

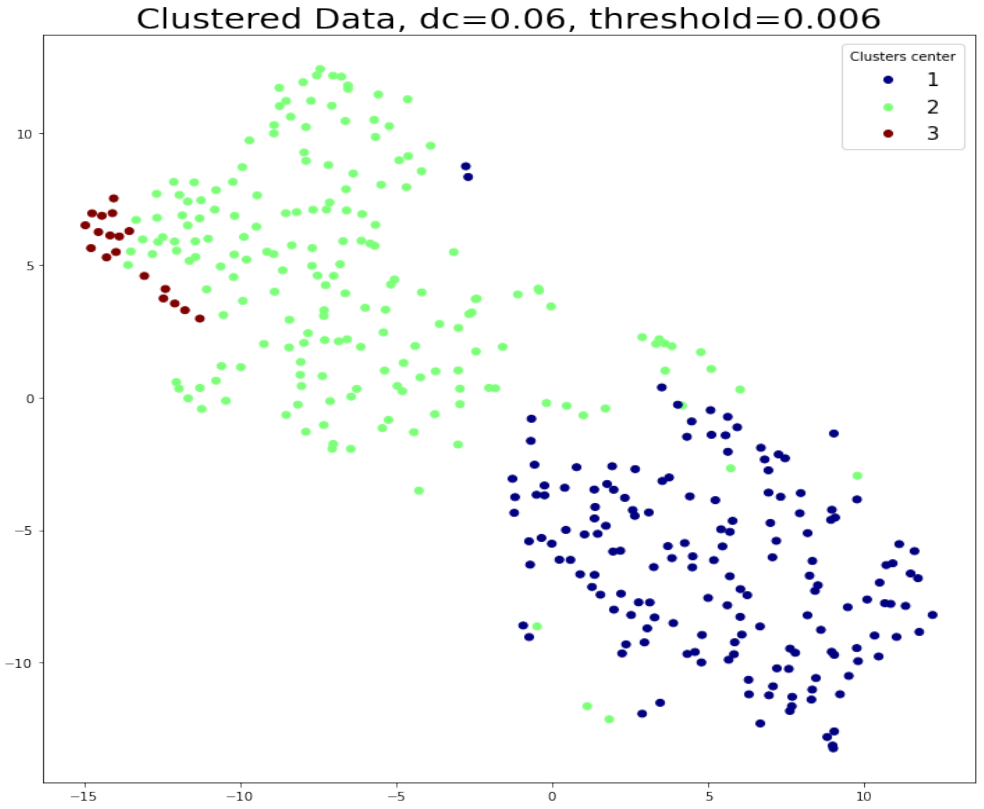
NMI: 0.445
Precision: 0.542
Recall: 0.929



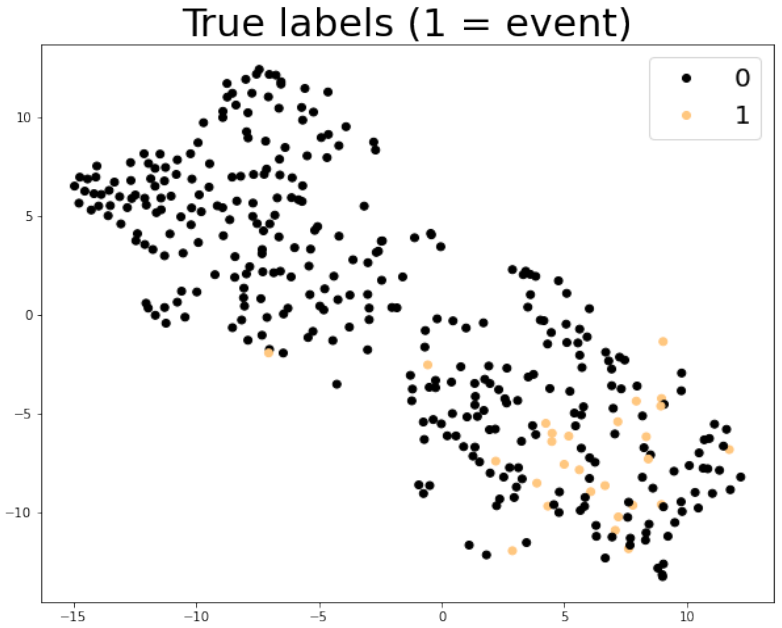
HEDDAL – Cluster results

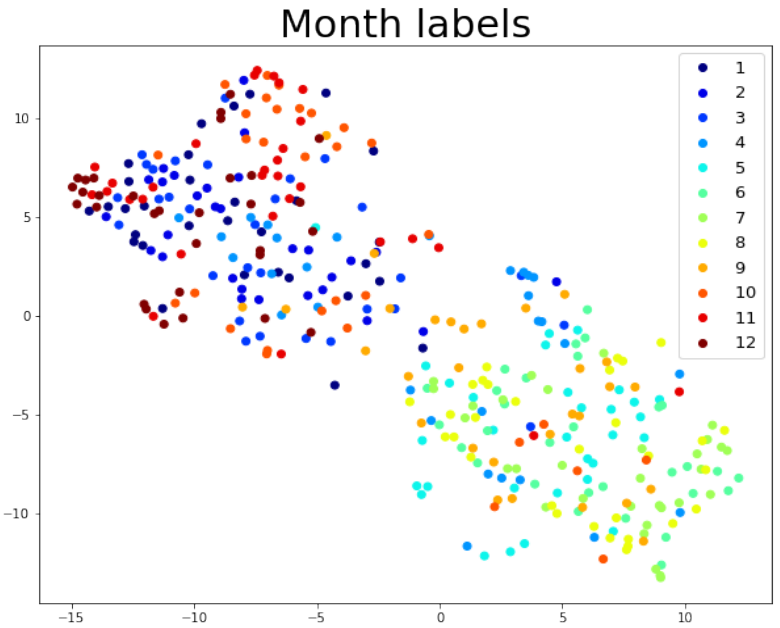
NMI: 0.093
Precision: 0.161
Recall: 0.963





TRUE LABELS


True labels (1 = event)
0
1


Month labels
1
2
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6
7
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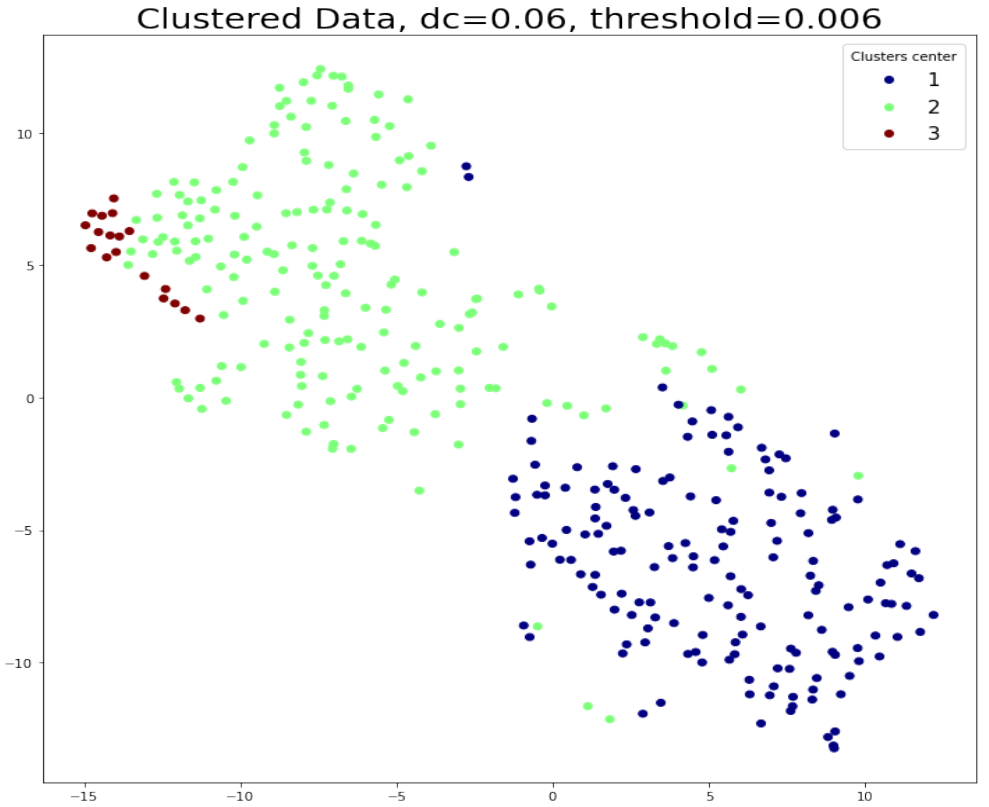
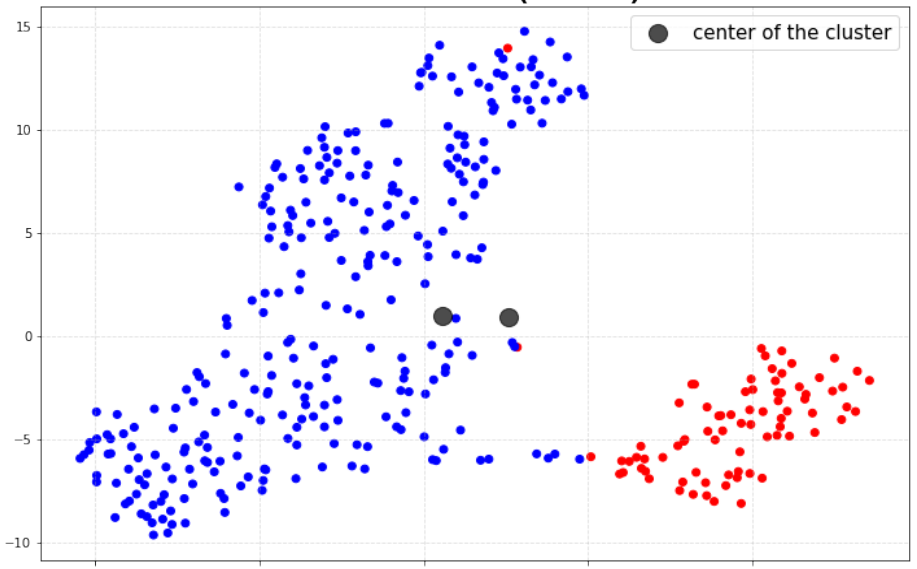
9
10
11
12


Clustered Data, dc=0.06, threshold=0.006
Clusters center
1
2
3

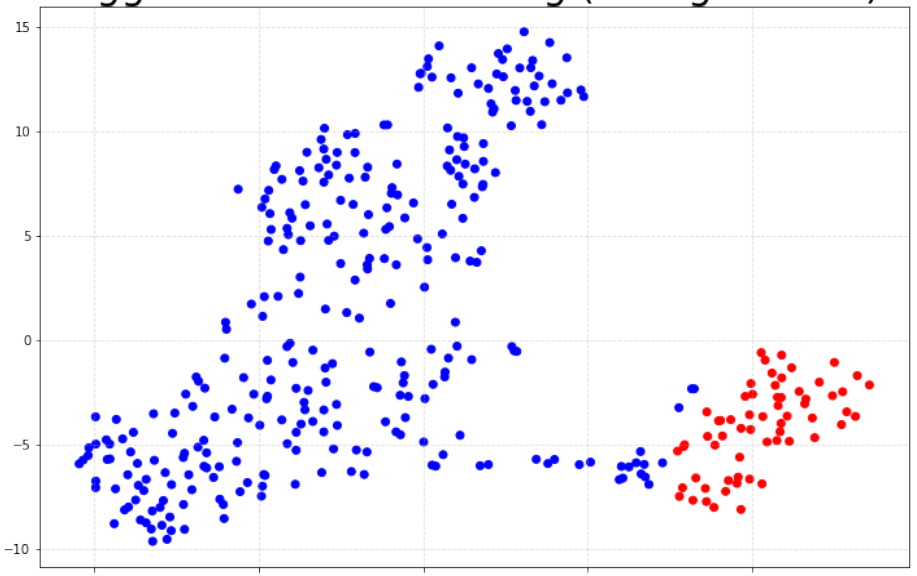
And what about other cluster algorithms?

Results

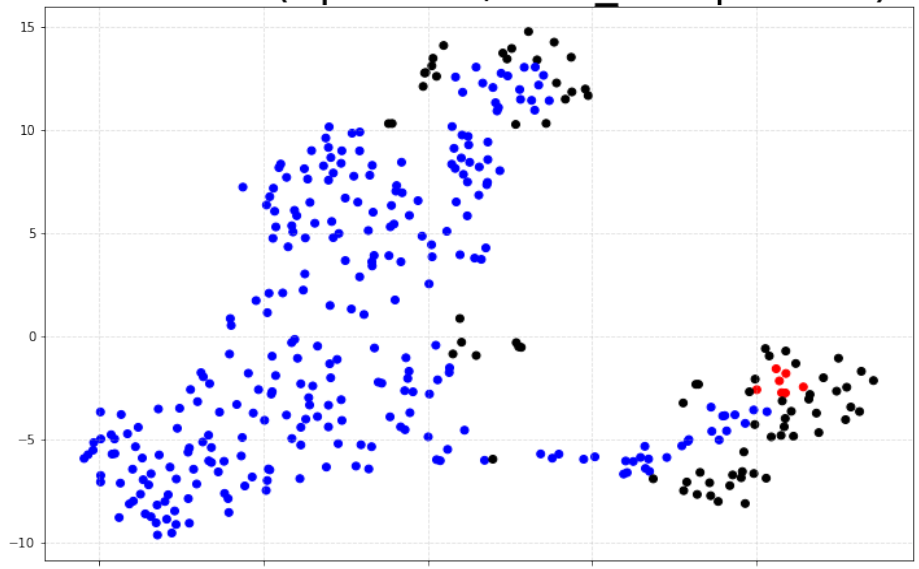
K-means (K=2)



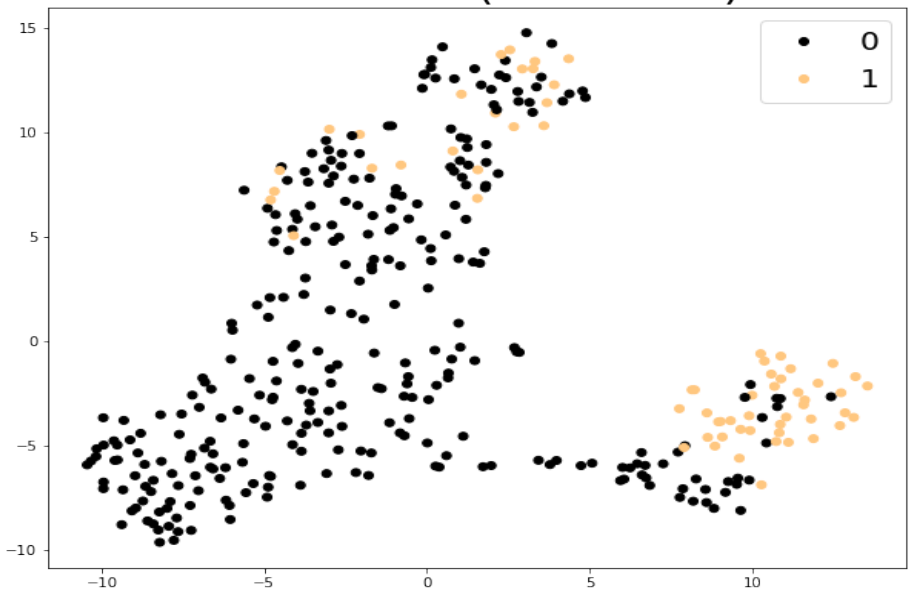
Agglomerative Clustering (linkage=ward)



DBSCAN (eps=0.5, min_samples=7)



True labels (1 = event)



Cluster Recap

	KMEAN	AGGLOMERATIVE	DBSCAN	DENSITY PEAK
PRECISION	0.544	0.629	0.714	0.833
RECALL	0.662	0.600	0.077	0.615
NMI	0.216	0.246	0.139	0.395

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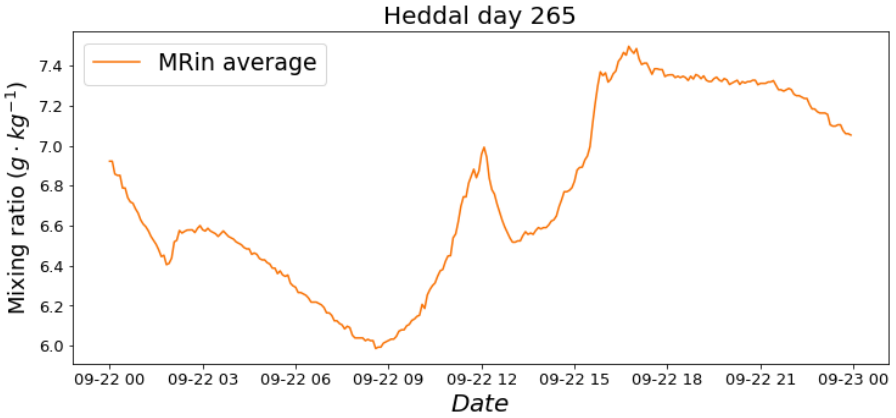
- The density peak method is the ***best cluster*** method...
- ...but its ***performances*** are not very high
- It is strongly ***dependent on the heating*** and it does not work well in the hottest months
- In the ***Heddal church*** is more difficult to identify the events (the heating is no longer a discriminant)

SUPERVISED LEARNING

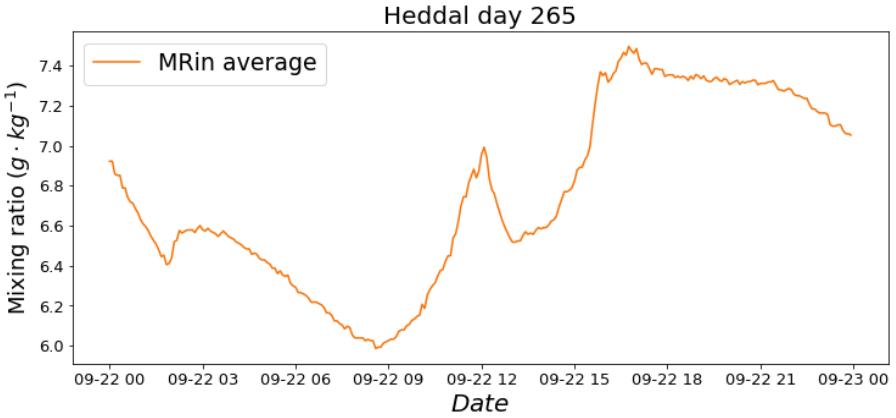
Convolutional Neural Network

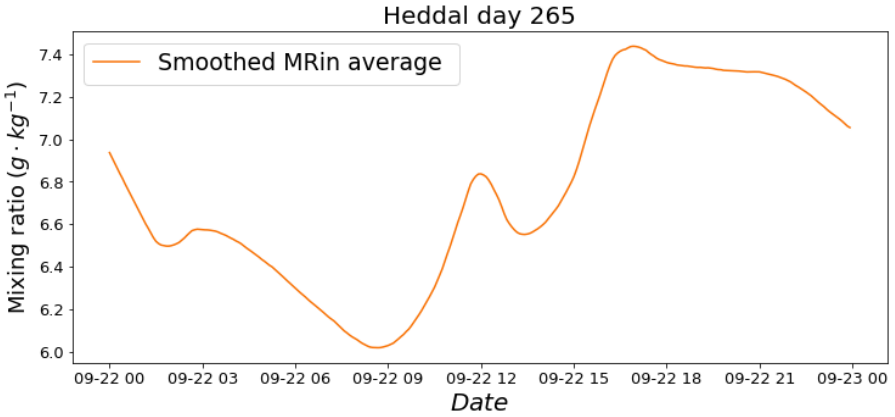
Data Manipulation



1) **Average** between the value of the MRin of the two sensors

Data Manipulation

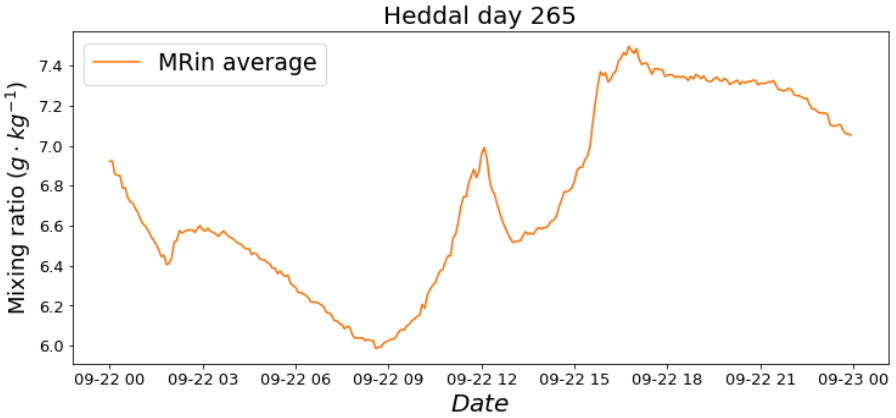




1) **Average** between the value of the MRin of the two sensors

2) **Smooth** of the series to delete the random fluctuations

Data Manipulation



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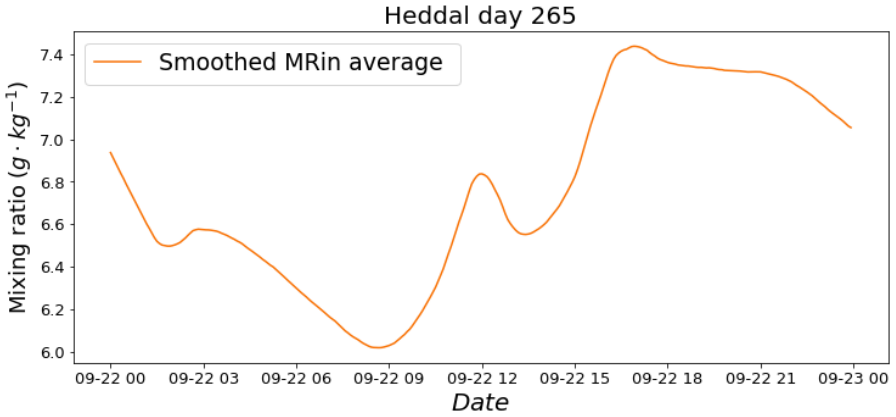

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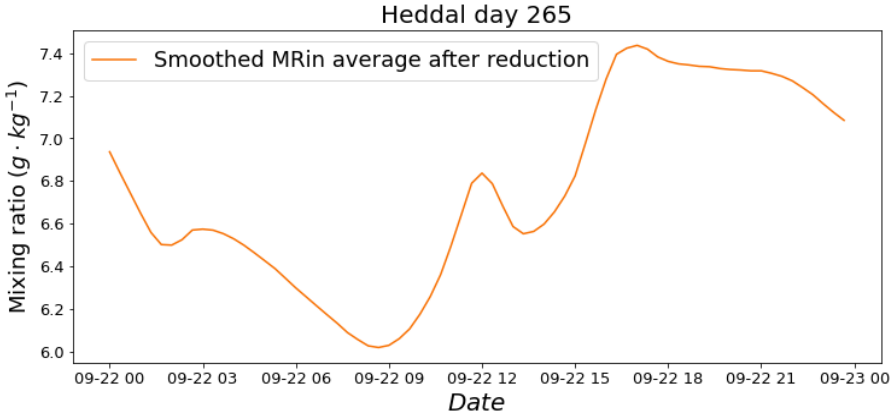
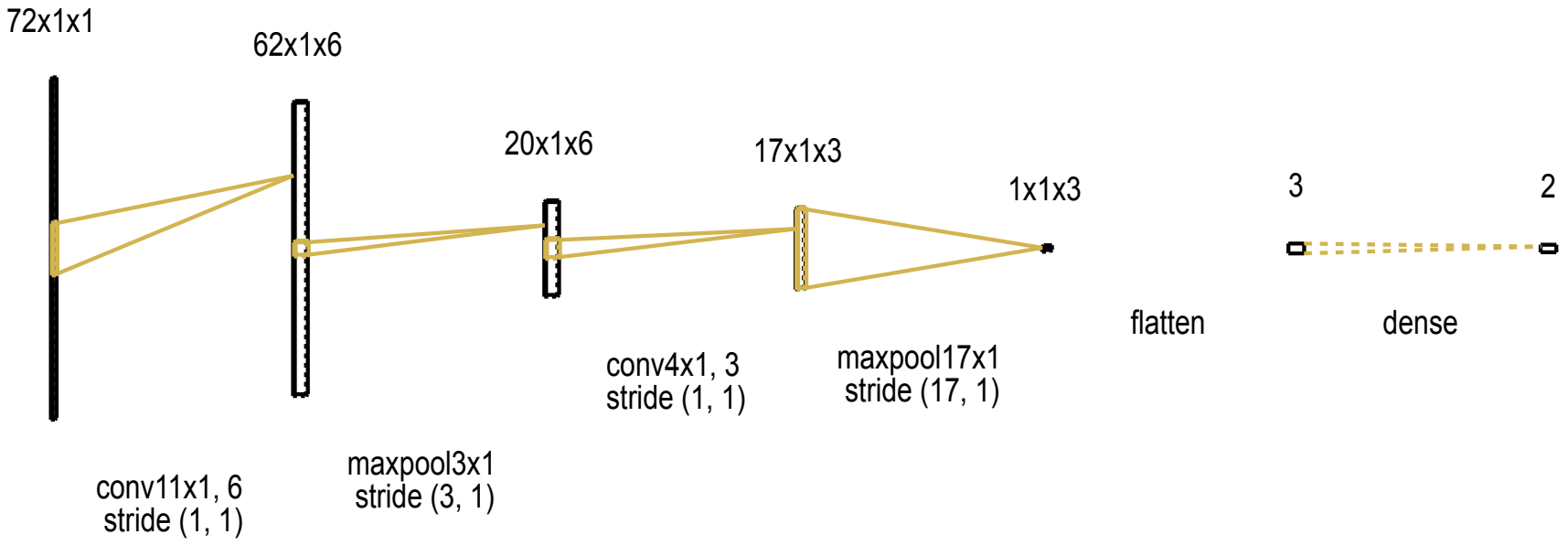


3) **Reduction** of the series taking a sample every four

Architecture

Mirror augmentation: all the series are mirrored reversing the order of its values and keeping the same label of the original one.

Note: we have made the augmentation only on the day with events



Total trainable parameters: 155

Architecture

Max epochs	Batch size	Activ. Fun.	Activ. Fun. out	Loss	Gradient	Patience
400	32	Relu	Softmax	Categorical cross-entropy	Adam	20

The number of sample is: 730 (N = Ringebu + Heddal)
The size of the training set is: 438 (0.6*N)
The size of the validation set is: 183 (0.25*N)
The size of the test set is: 109 (0.15*N)

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UNSTABLE RESULTS

0.200 < NMI < 0.600

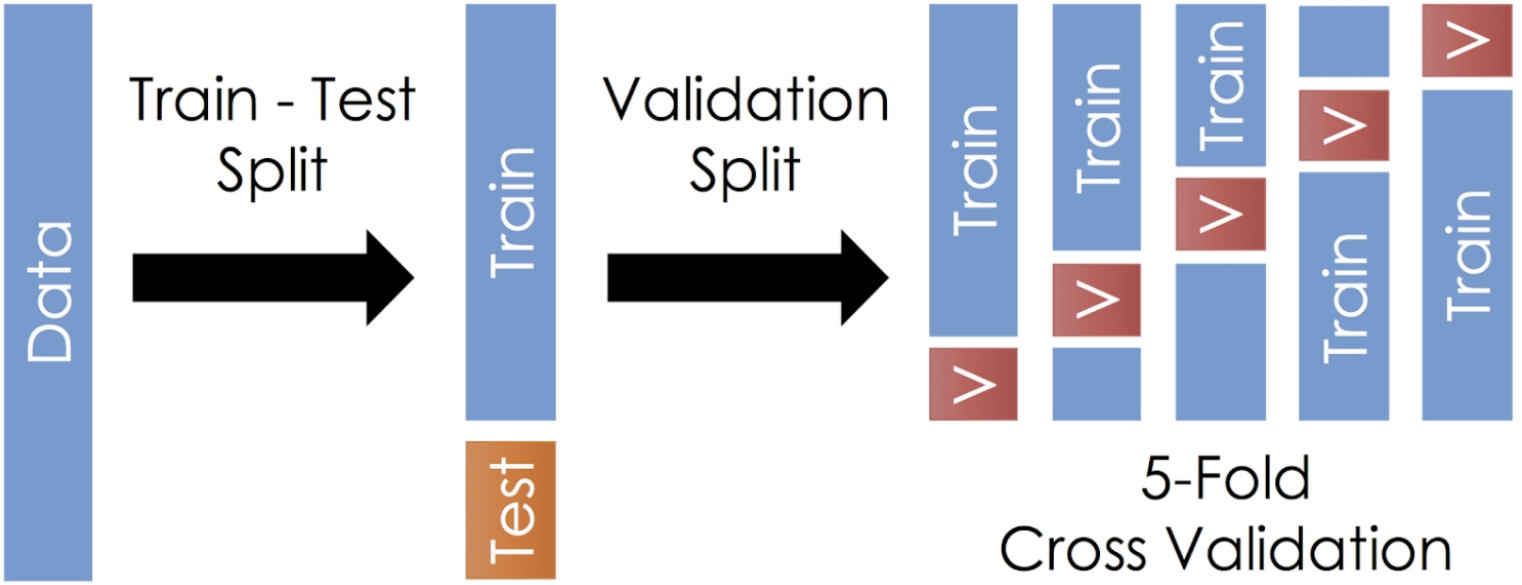
K-fold cross validation (K=5)

1) **Partition** (training) set of m samples into k folds of size m/k

2) For each fold:

   - **train** on the union of the other folds
   - **estimate loss** (for learned hypothesis) on the selected fold

3) Estimate of the true loss as the **average** of the estimated errors



Results

Score per fold

> **Fold 1** - Loss: 0.183 - Accuracy: 0.942 - NMI: 0.473

> **Fold 2** - Loss: 0.259 - Accuracy: 0.892 - NMI: 0.390

> **Fold 3** - Loss: 0.428 - Accuracy: 0.758 - NMI: 0.080

> **Fold 4** - Loss: 0.211 - Accuracy: 0.925 - NMI: 0.567

> **Fold 5** - Loss: 0.407 - Accuracy: 0.867 - NMI: 0.320

Average scores for all folds:

> **Accuracy:** 0.877

> **Loss:** 0.298

> **NMI:** 0.366

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Average scores for all folds:

> **Accuracy:** 0.877

> **Loss:** 0.298

> **NMI:** 0.366

MORE STABLE RESULTS

0.300 < NMI < 0.450

UMR Peak Method

UMR Peak: A new approach

- "**UMR Peak**" stands for: *Unexpected Mixing Ratio Peak*

This method consists in two steps:

1) *Data manipulation* : extracting *one feature* per day starting from **MR** measurements.

2) Binary classification : supervised learning with *one parameter* .

UMR Peak: Data manipulation

- This data manipulation is based on a heuristic assumption:

  “ Days with events are characterized by at least one **MRin** peak not explained by **MRout** ”

UMR Peak: Data manipulation

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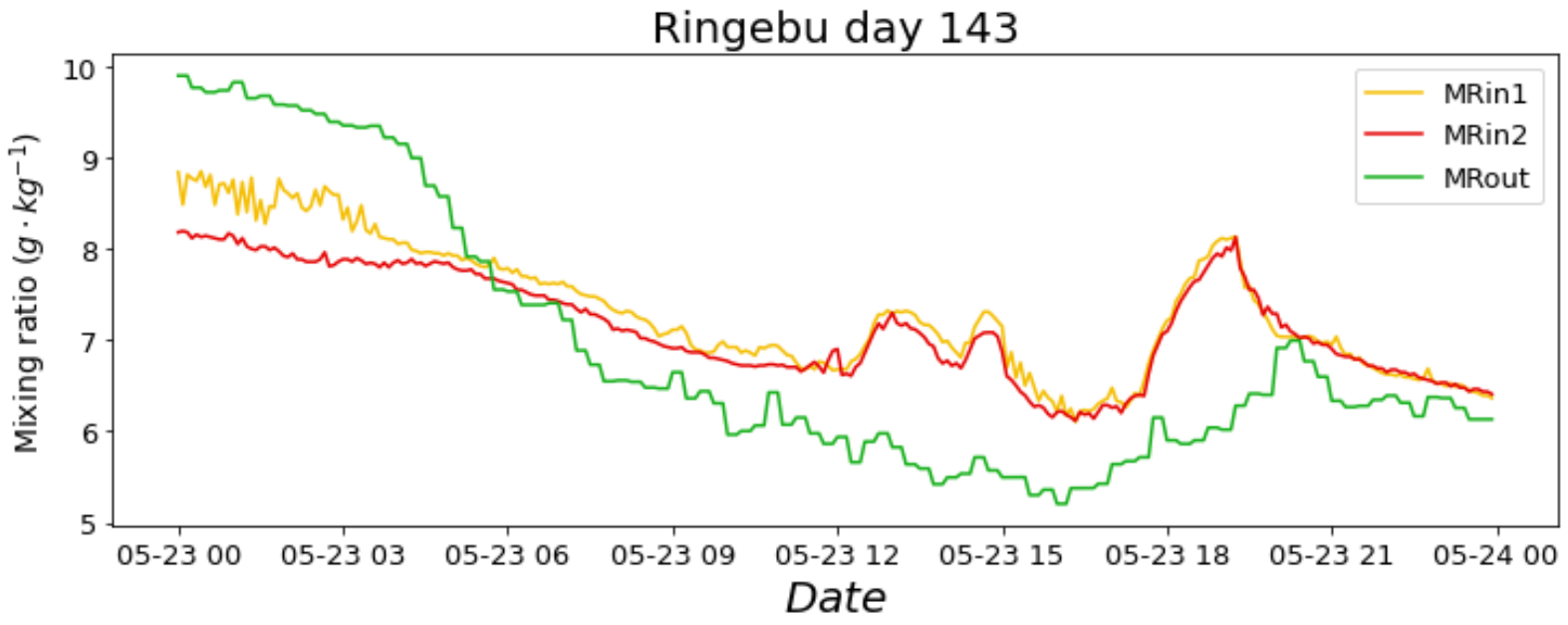
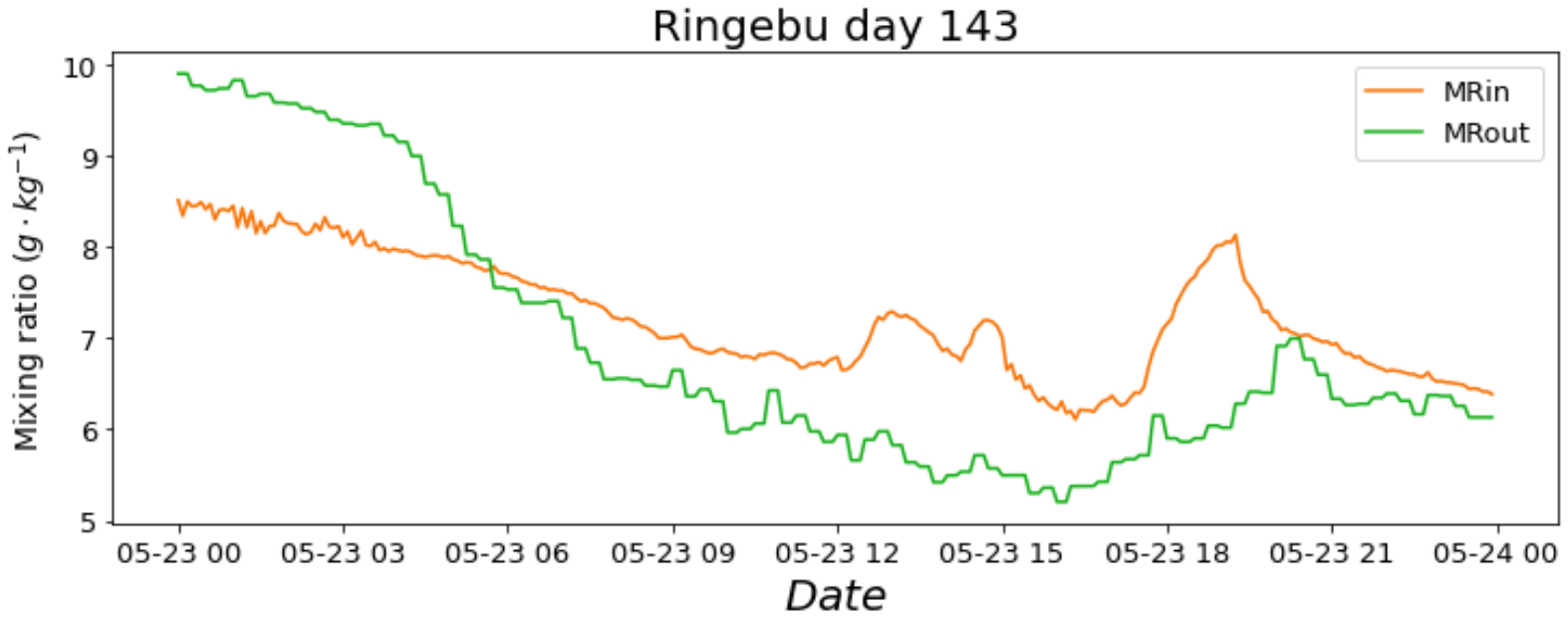
  “ Days with events are characterized by at least one **MRin** peak not explained by **MRout** ”

- The starting point is **MR** measured by the three sensors:



UMR Peak: Data manipulation

- First of all we compute **MRin** as average of the **MR** measured by the two internal sensors.

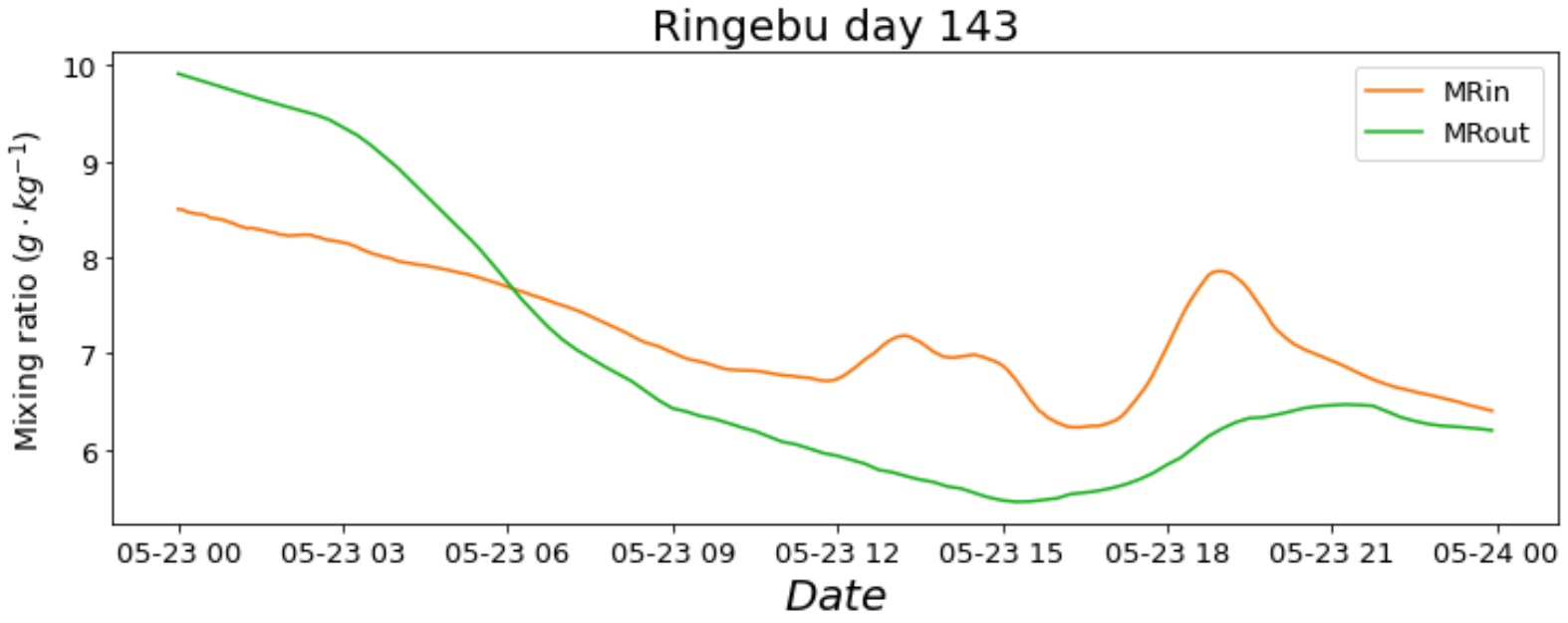


UMR Peak: Data manipulation

- First of all we compute **MRin** as average of the **MR** measured by the two internal sensors.

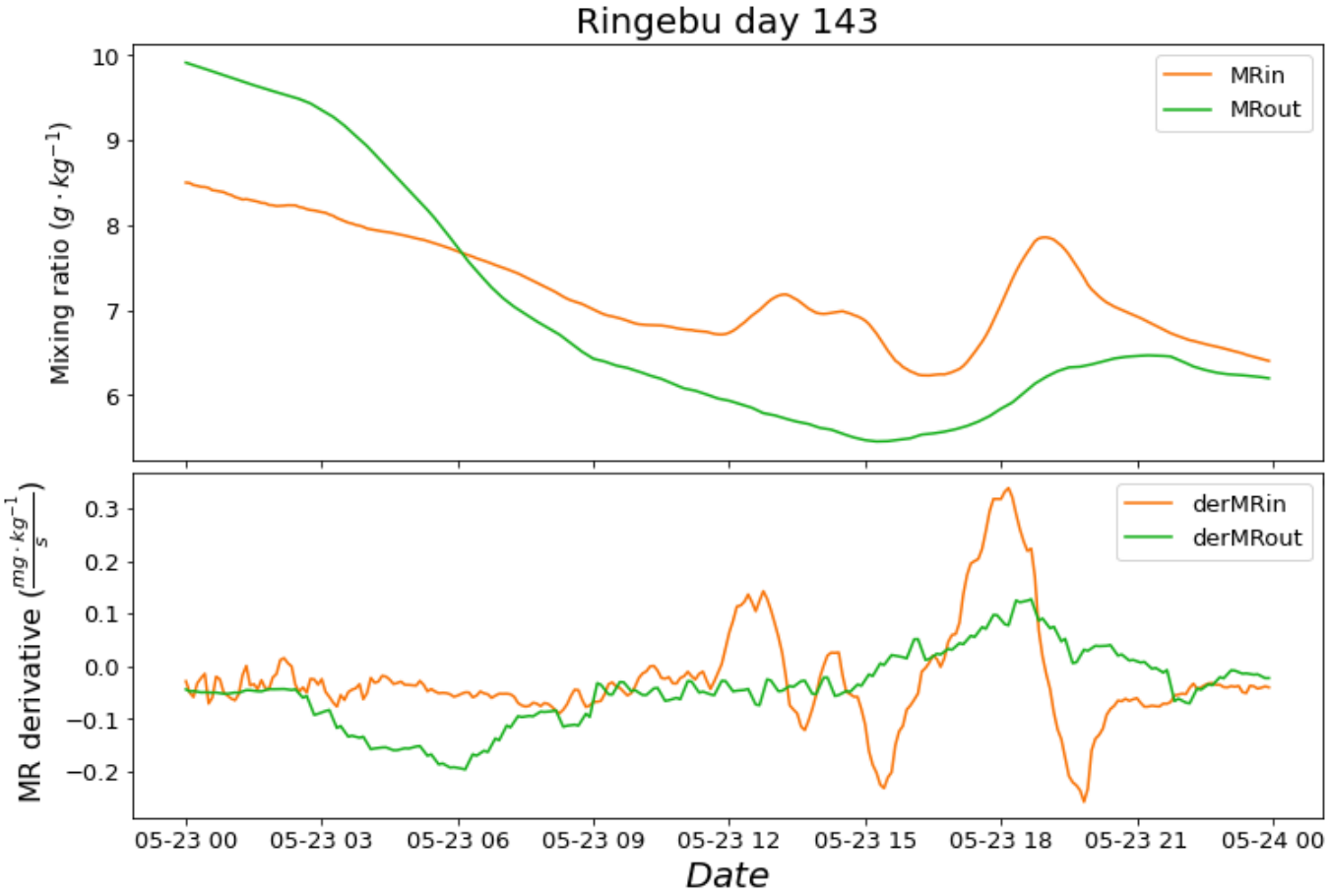
- Then we smooth both **MRin** and **MRout** (the whole dataset).
  This procedure is arbitrary and it depends on how data are measured. Our choice is:

  - **MRin** average window: *7 measurements* before and after the one considered;
  - **MRout** average window: *21 measurements* before and after the one considered.



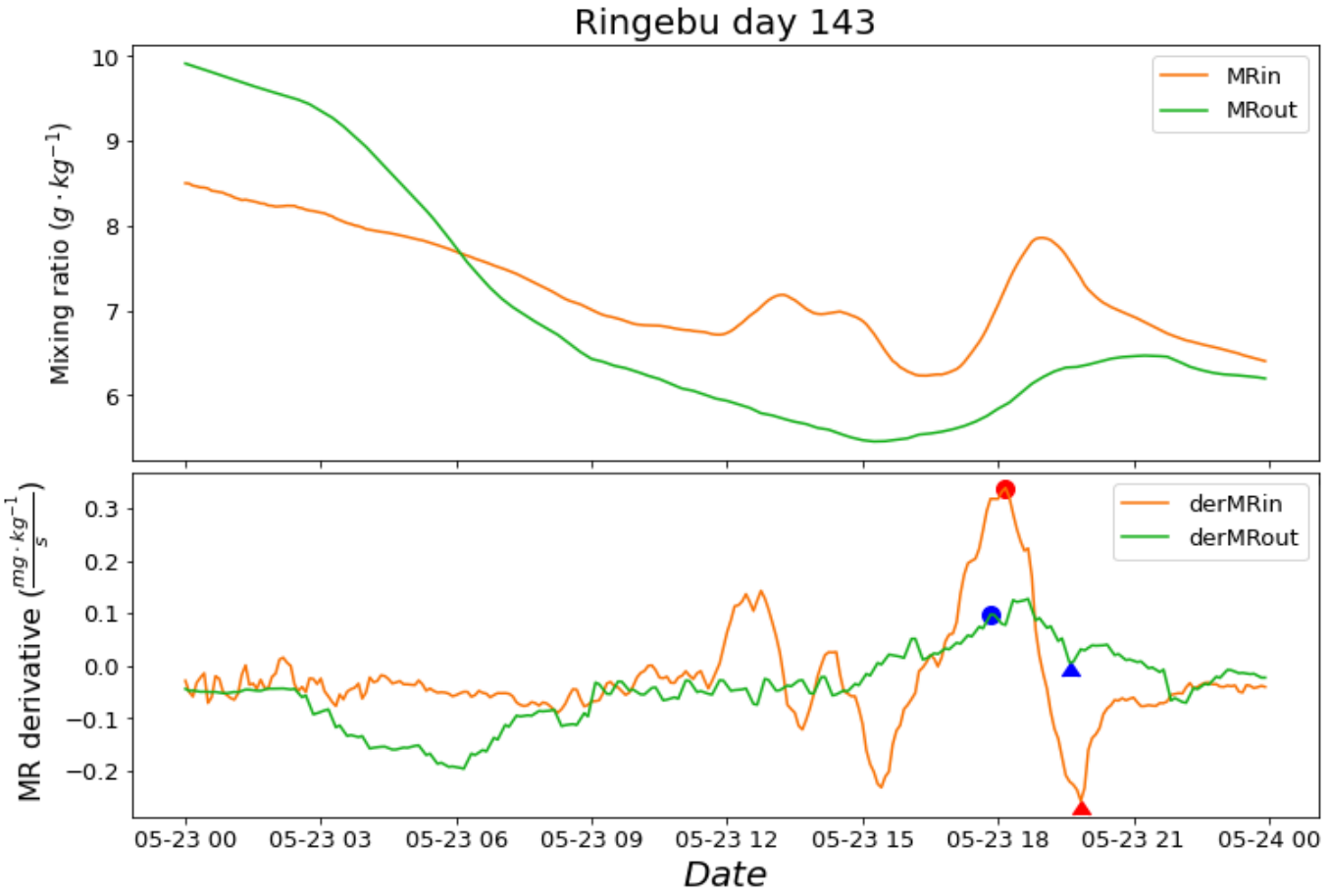
UMR Peak: Data manipulation

- At this point we compute the first discrete derivative of **MRin** and **MRout**.
  The discretization step is 5 minutes = 300 s .



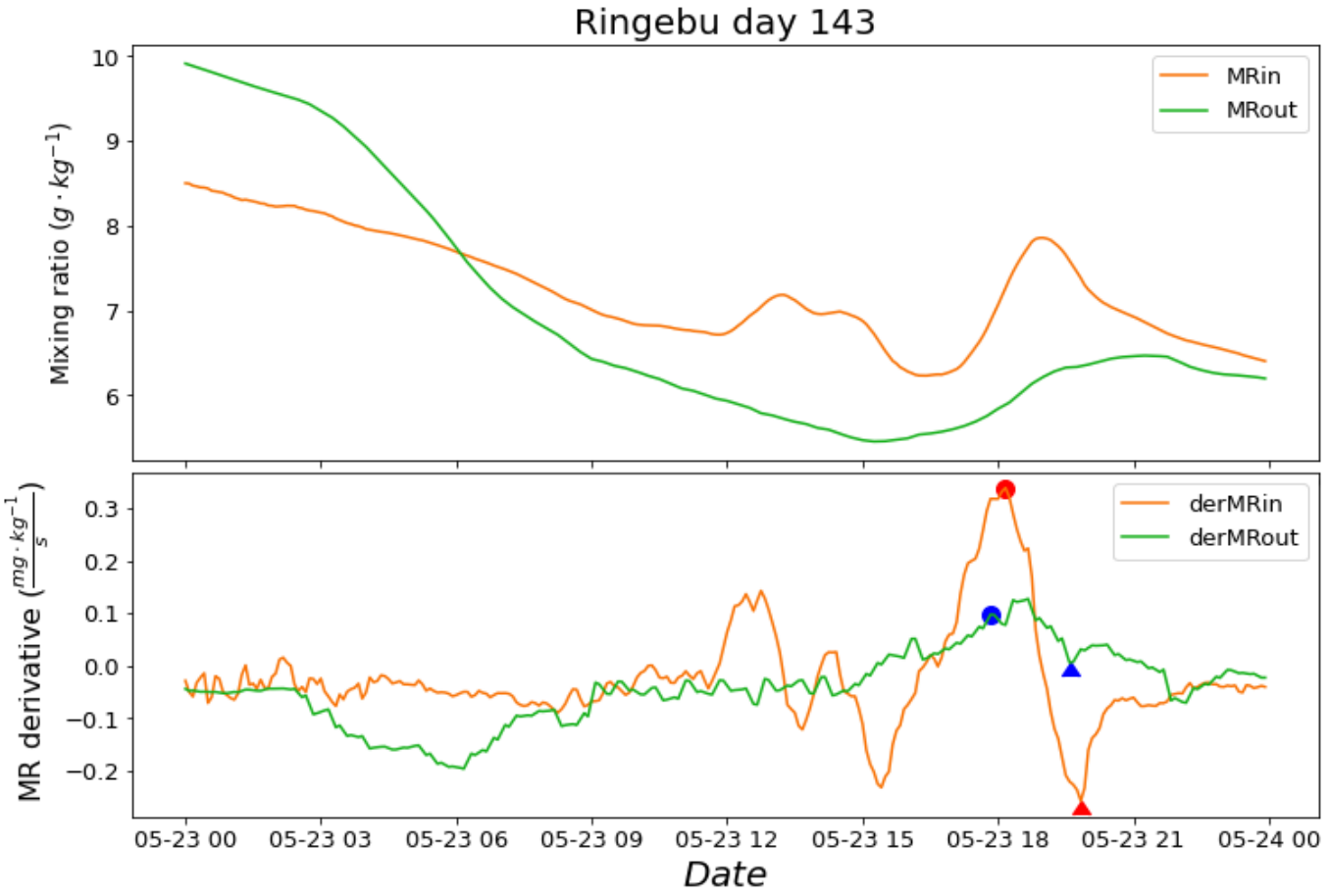
UMR Peak: Data manipulation

- And we find 4 *derivatives values* : ● = max(**derMRin**)



UMR Peak: Data manipulation

- And we find 4 *derivatives values* : ● = max(**derMRin**)
  ▲ = min(**derMRin**) happened after ●



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- And we find 4 *derivatives values* :
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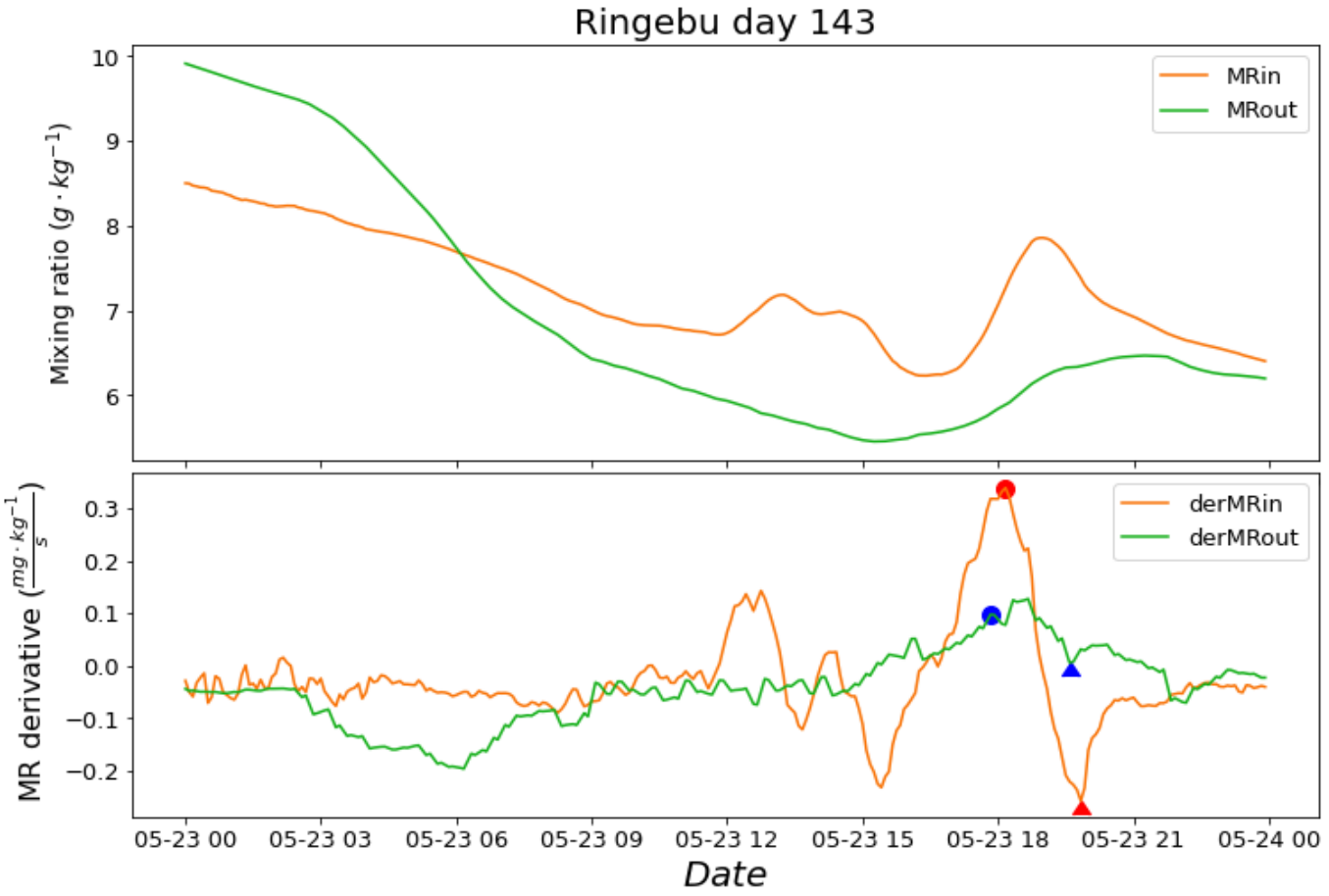
  - ● = max(**derMRout**) happened before ●



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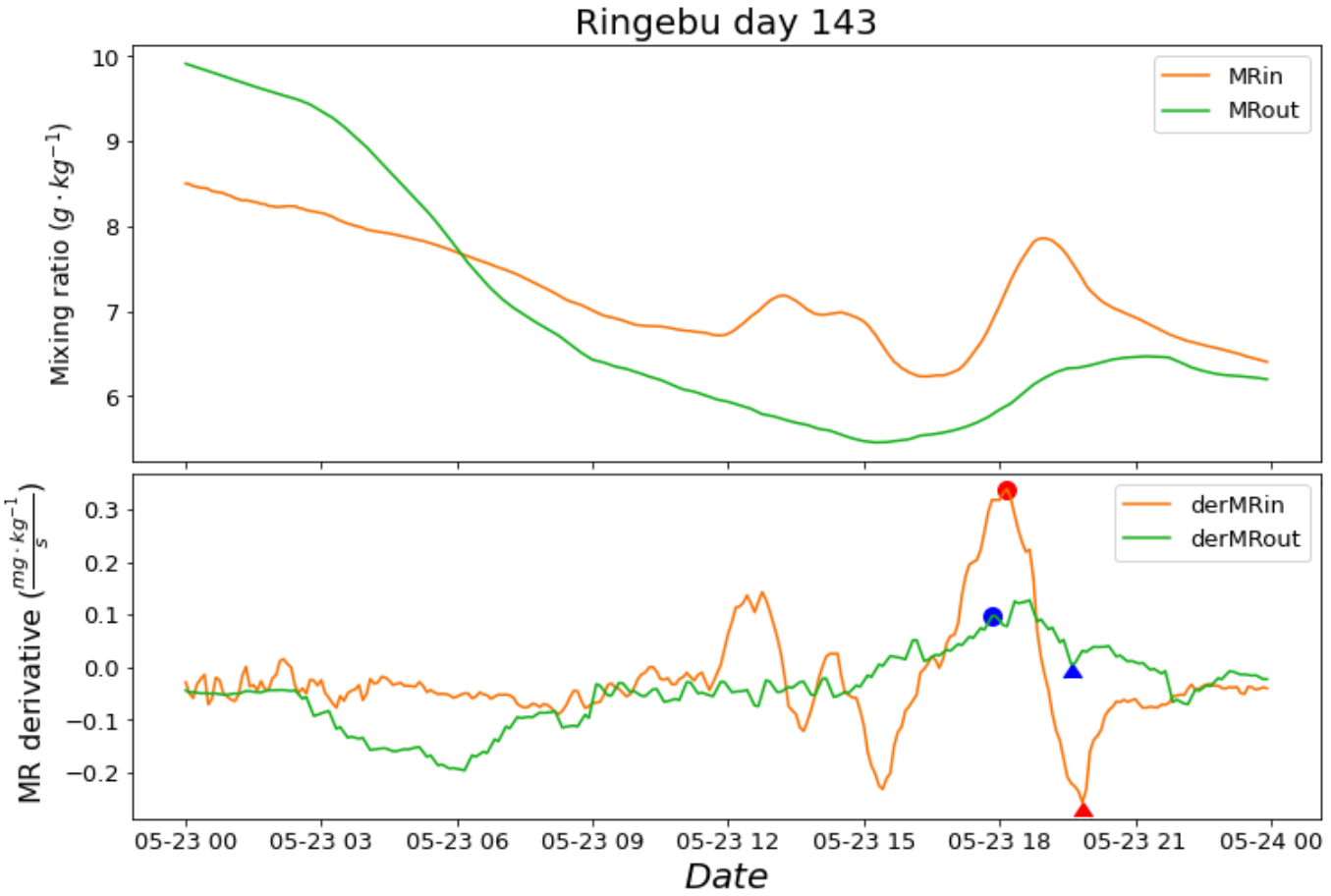
- And we find 4 *derivatives values* :

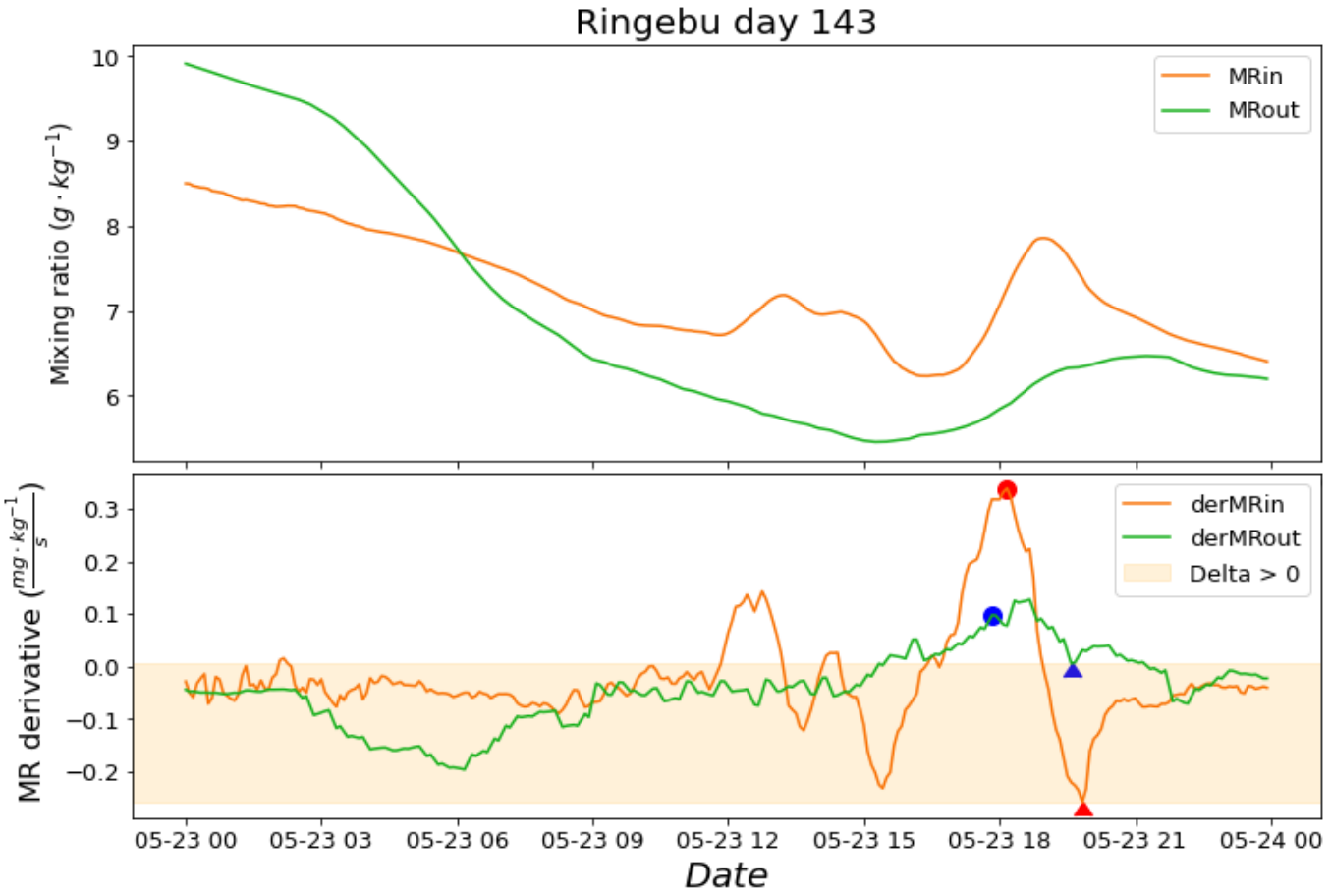
● = max(**derMRin**)
▲ = min(**derMRin**) happened after ●
● = max(**derMRout**) happened before ●
▲ = min(**derMRout**) happened before ▲ and after ●



UMR Peak: Data manipulation

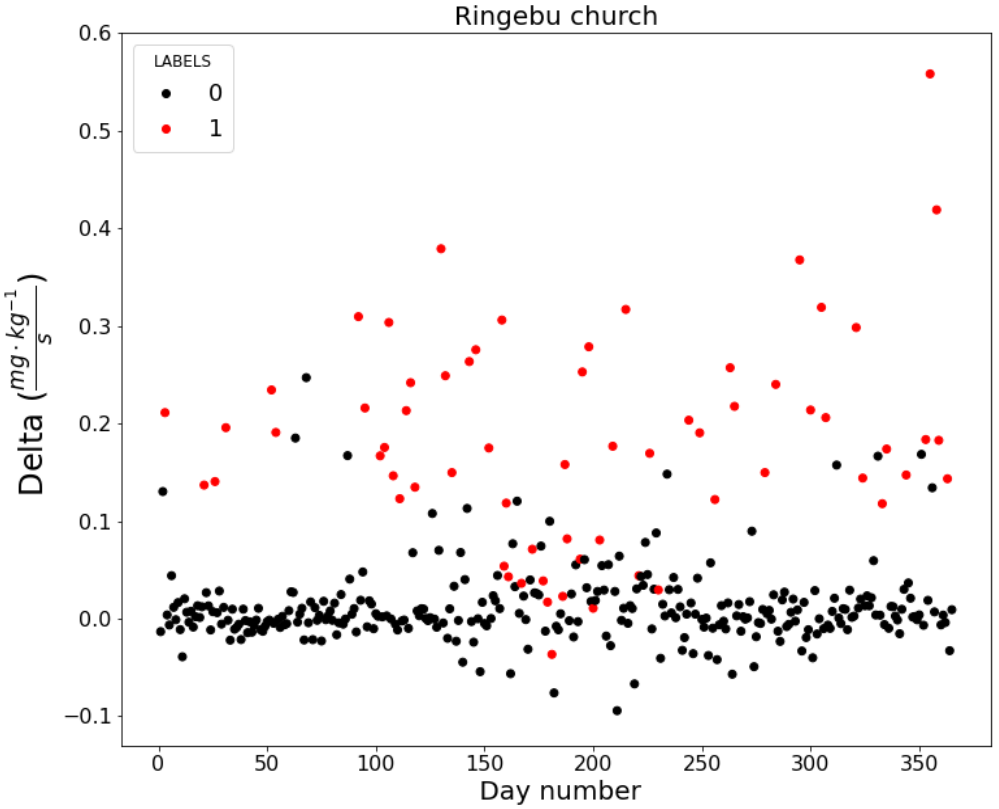
- From these values we can valuate our feature:

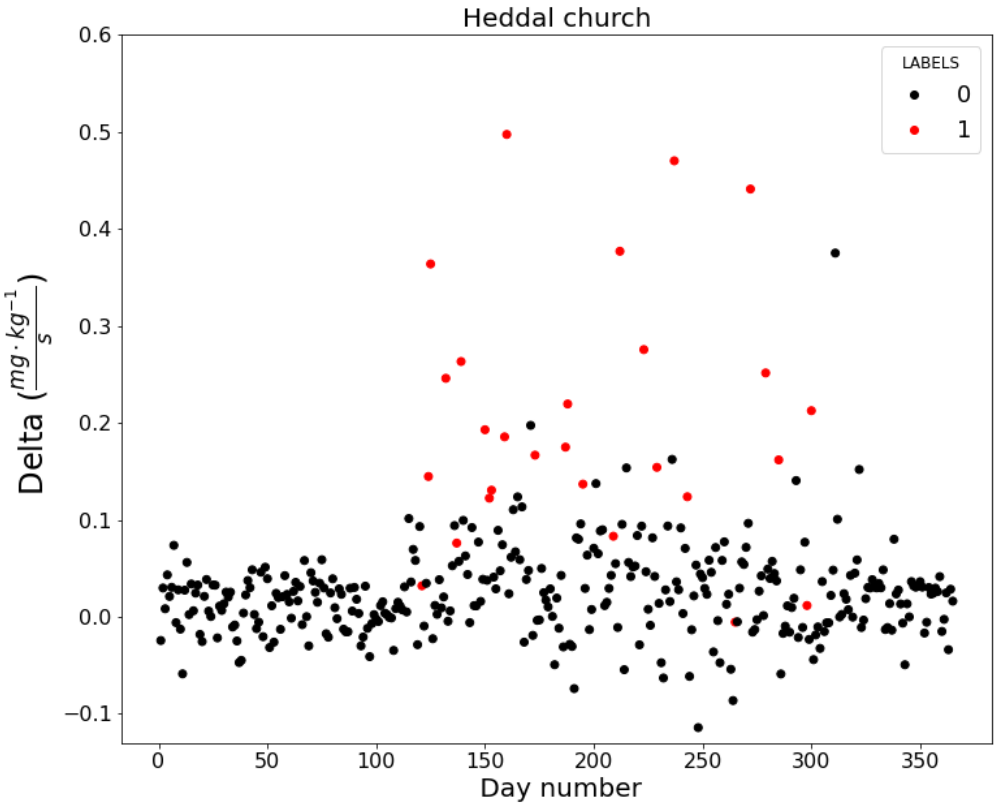
Delta := max(● - ● , ▲ - ▲)



UMR Peak: Delta space

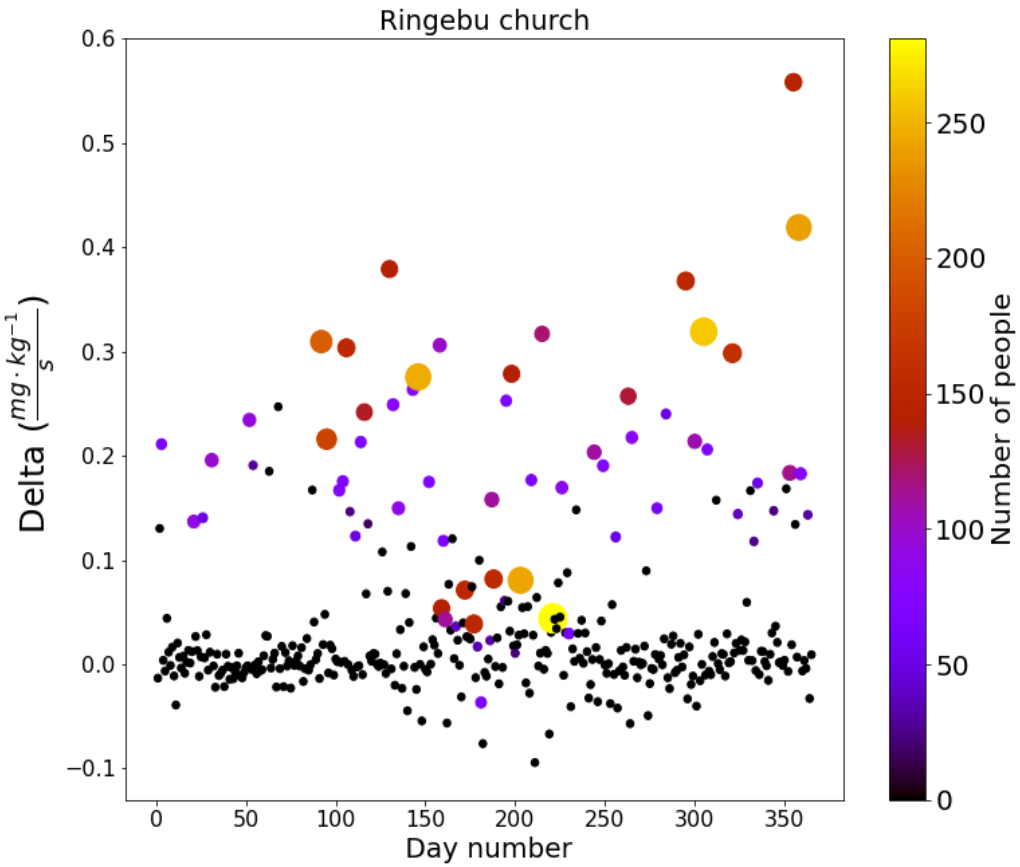
Label 1 = event

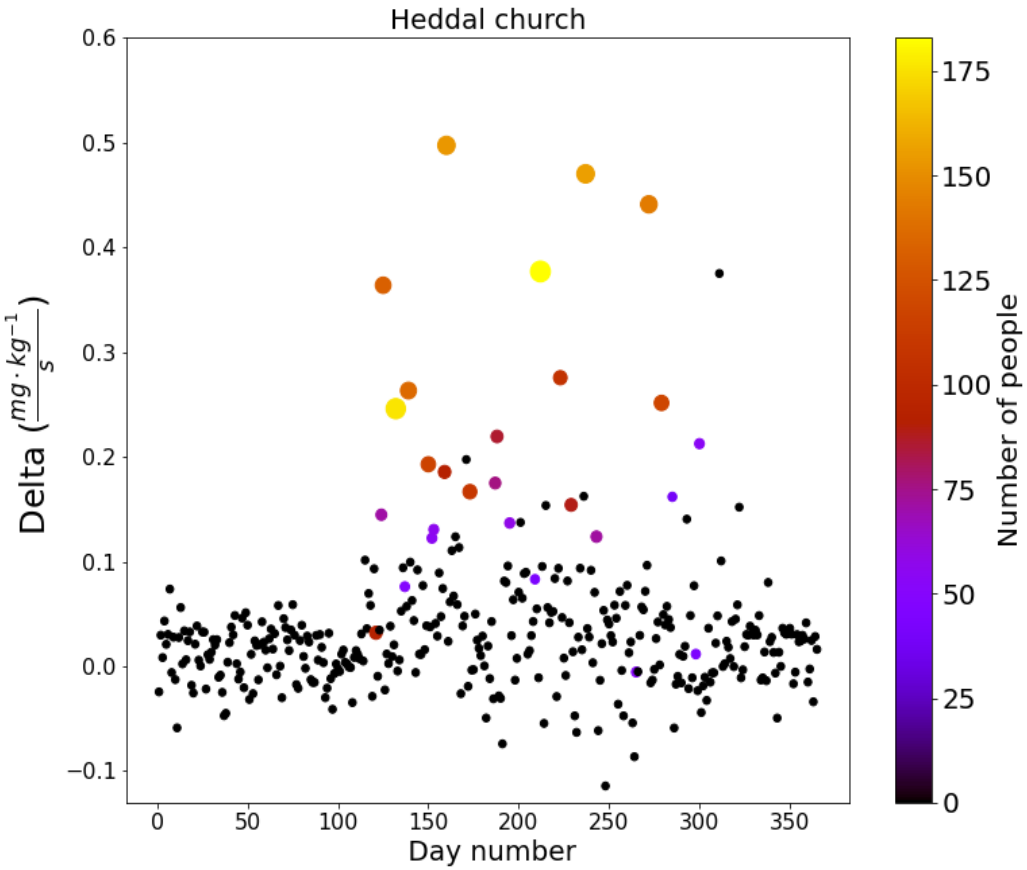




UMR Peak: Delta space

- Colors represent the **number of people** that partecipated to an event:

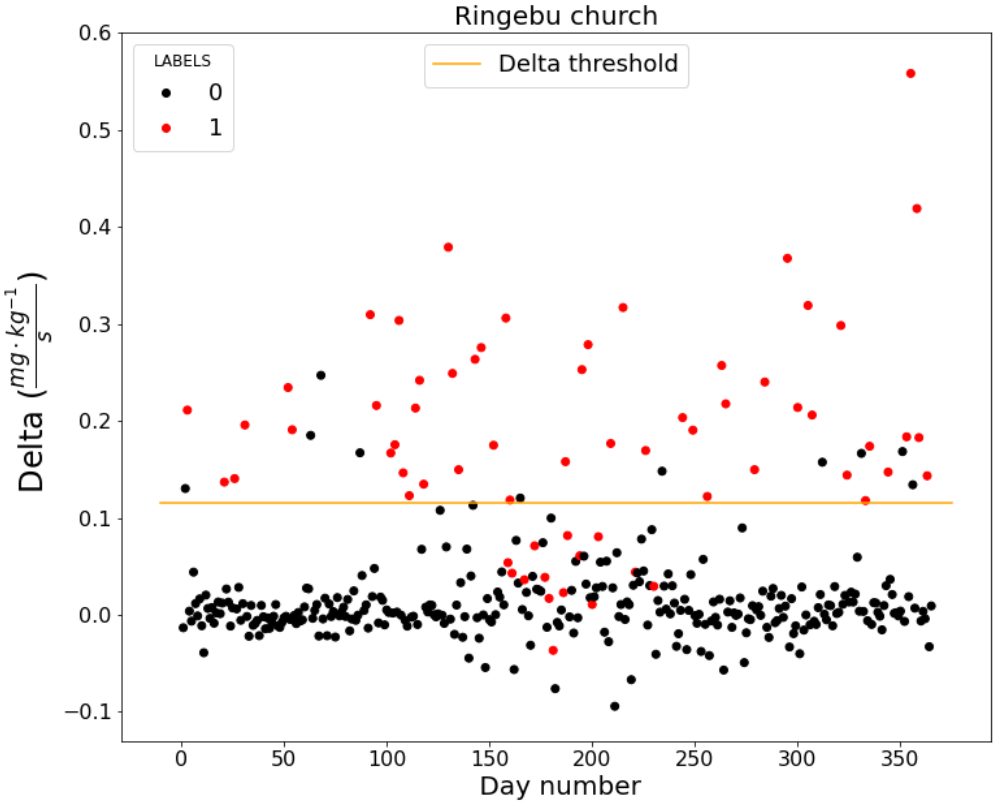


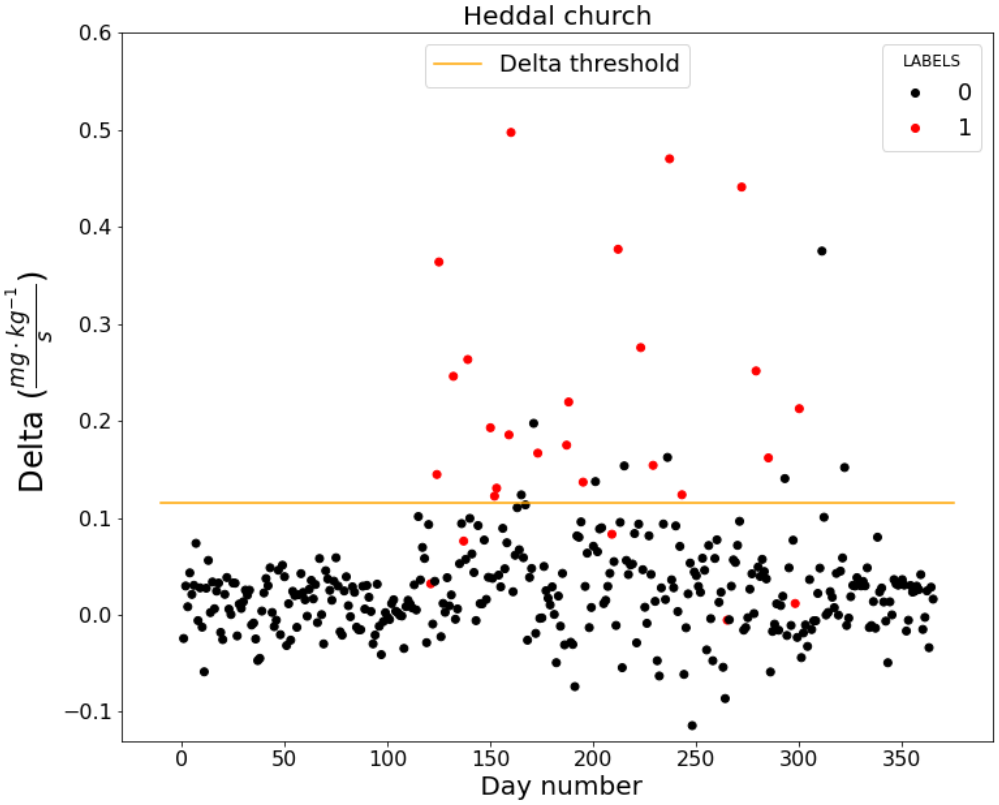


UMR Peak: Binary classification

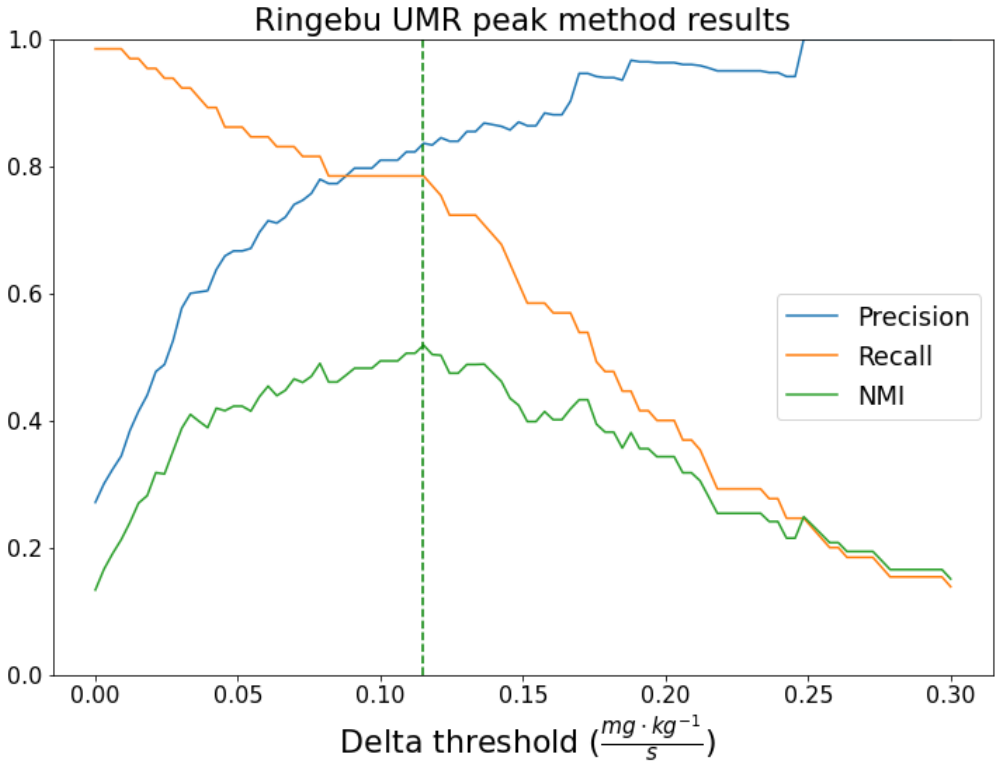
- A day is predicted with label 1 if: **Delta** > **Delta threshold**
- **Delta threshold** value is found maximizing **NMI** (supervised learning).

Label 1 = event

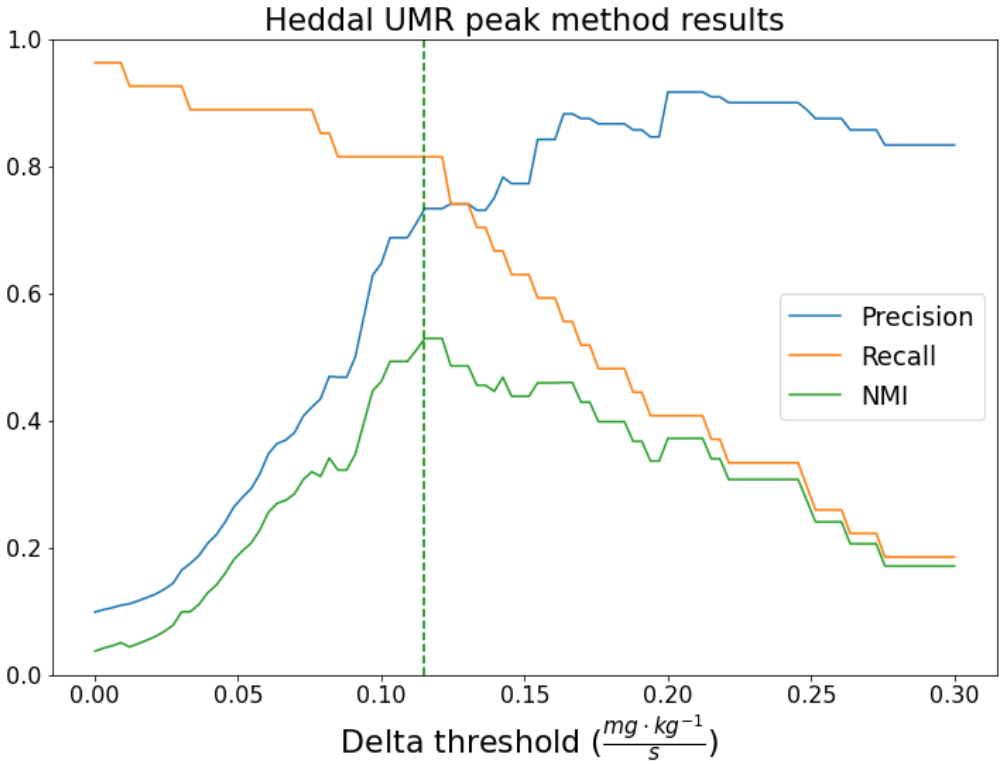




UMR Peak: Results



Delta Threshold = 0.115 mg/(kg*s)
Precision = 0.84
Recall = 0.78
NMI = 0.52

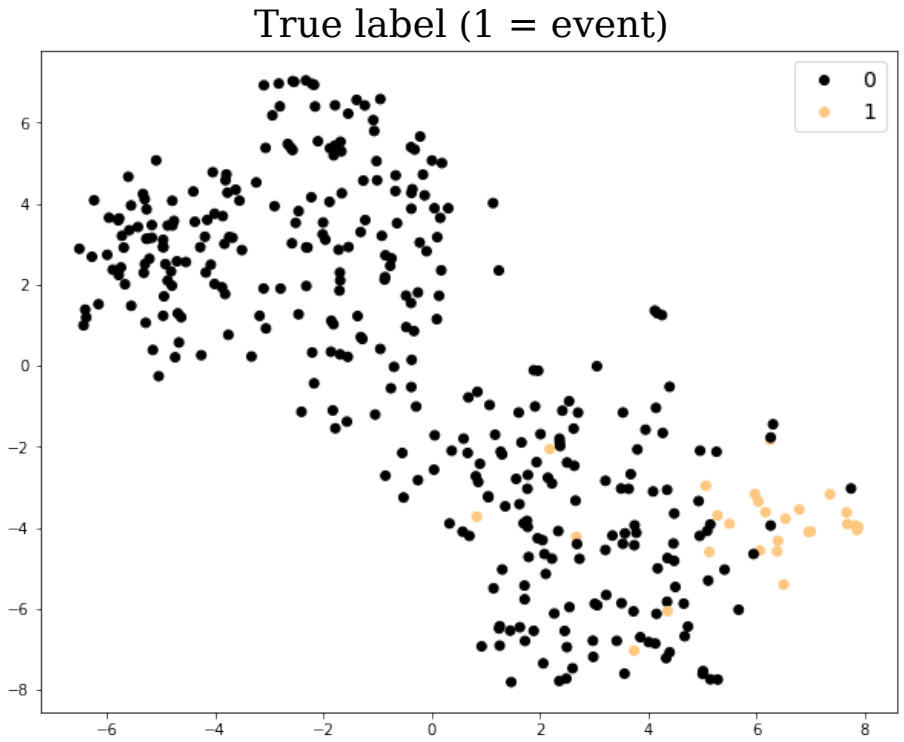


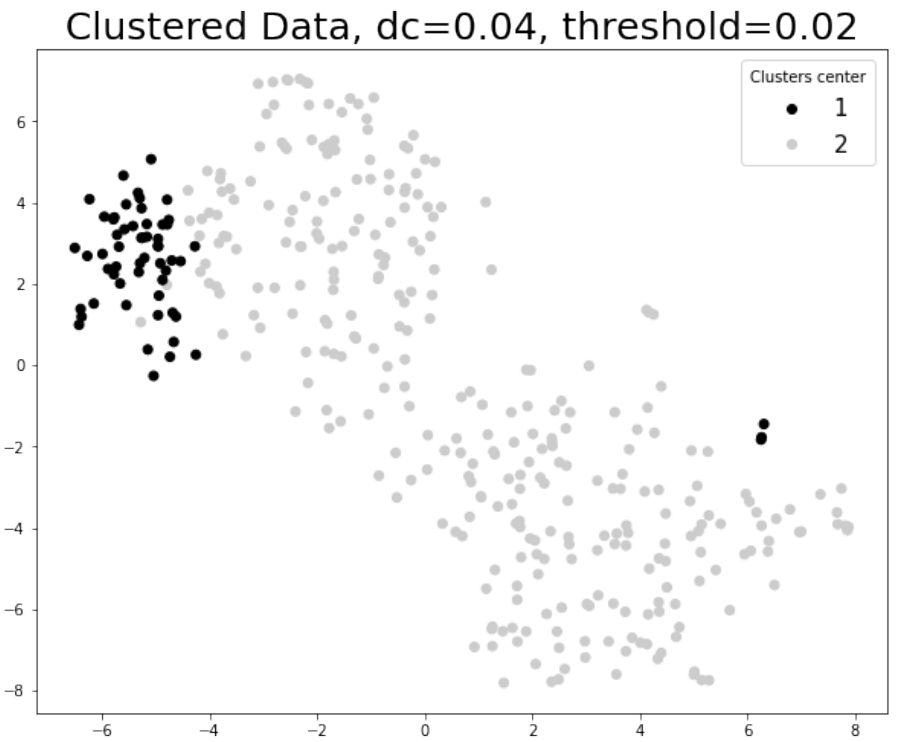
Delta Threshold = 0.115 mg/(kg*s)
Precision = 0.73
Recall = 0.82
NMI = 0.53

- Precision and recall are computed w.r.t. label 1

UMR Peak: Clustering?

- What if we use **Delta** as additional variable to the clustering?
  Unfortunately It does not help in creating clusters:

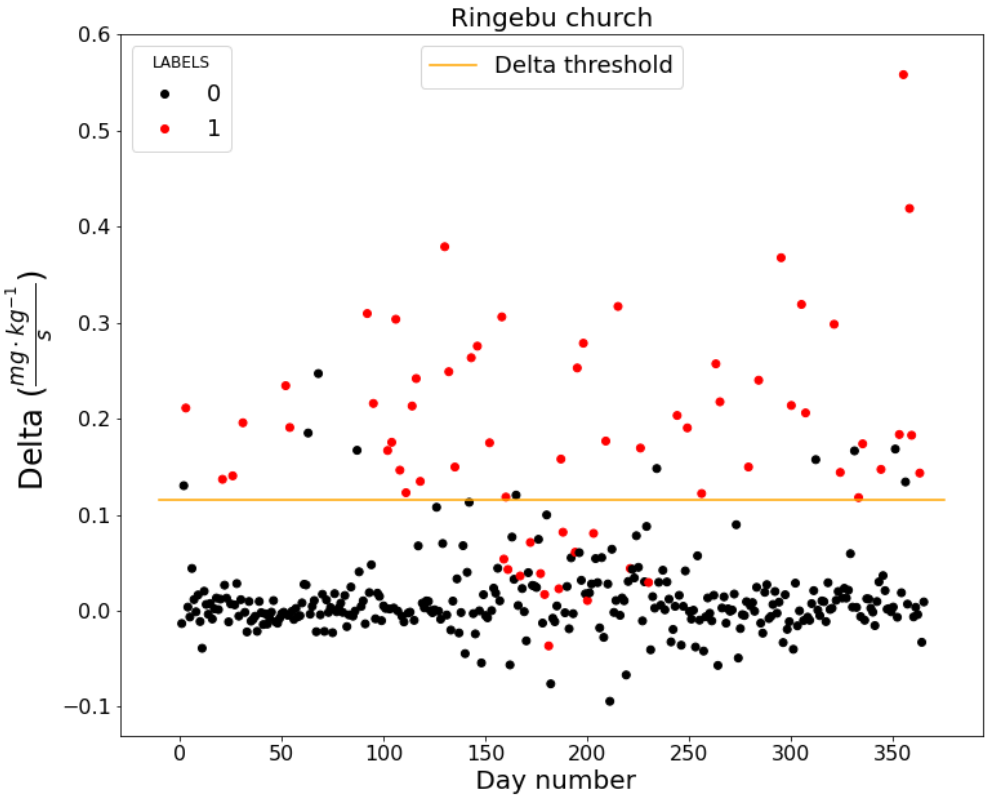


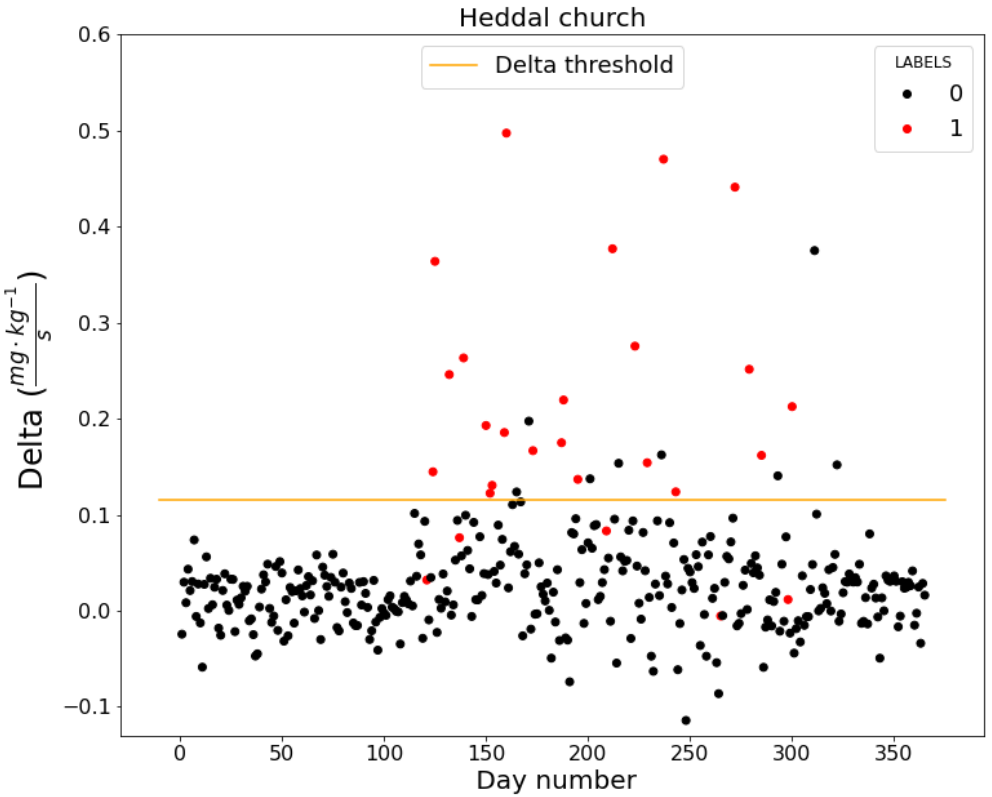


- Performance over Heddal: **precision : 0.08**
  recall : 1
  NMI : 0.01

Comment on results

- There are days with high value of **Delta**, but with label 0 (no event). Why?





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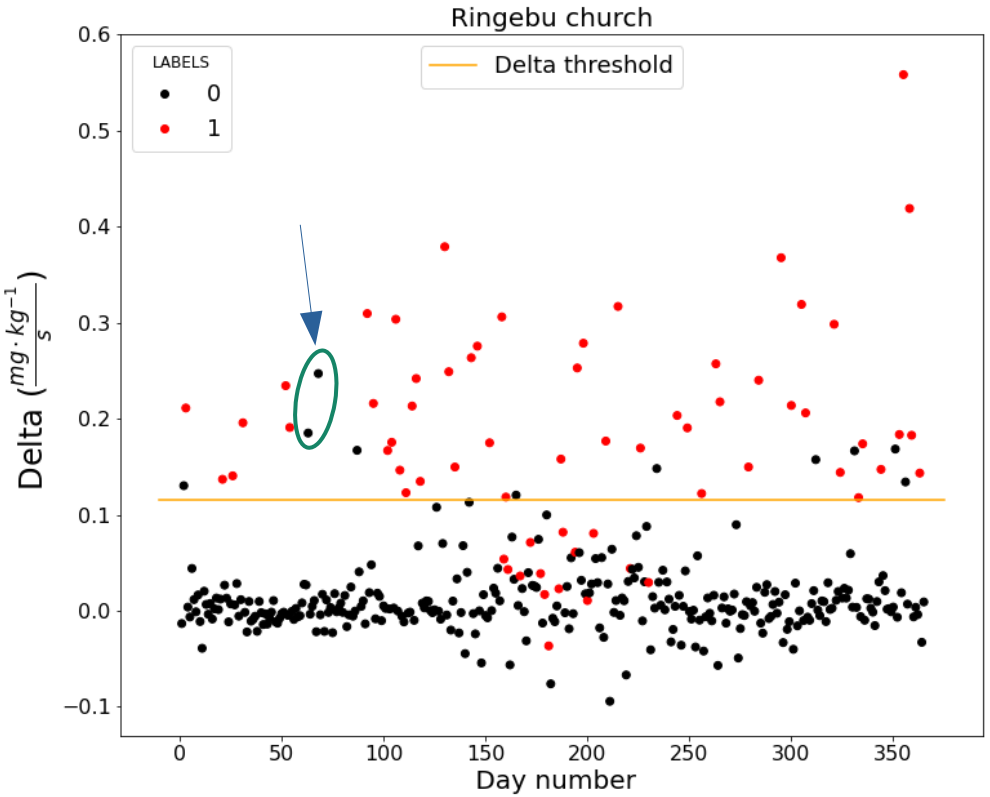

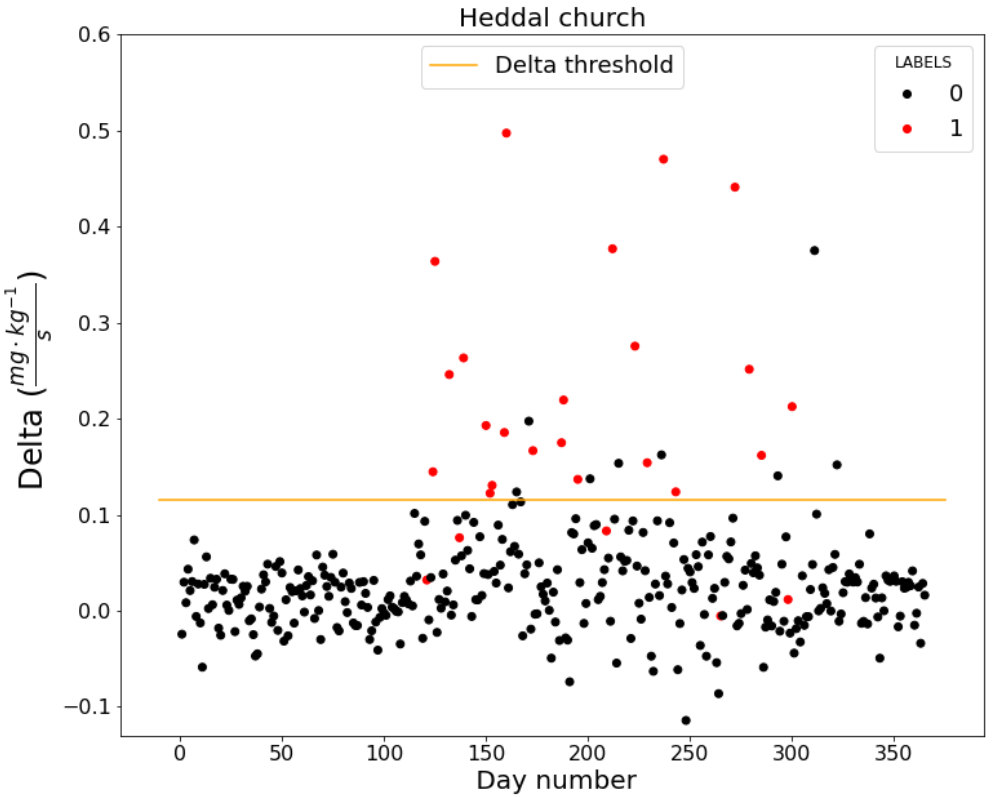

Comment on results

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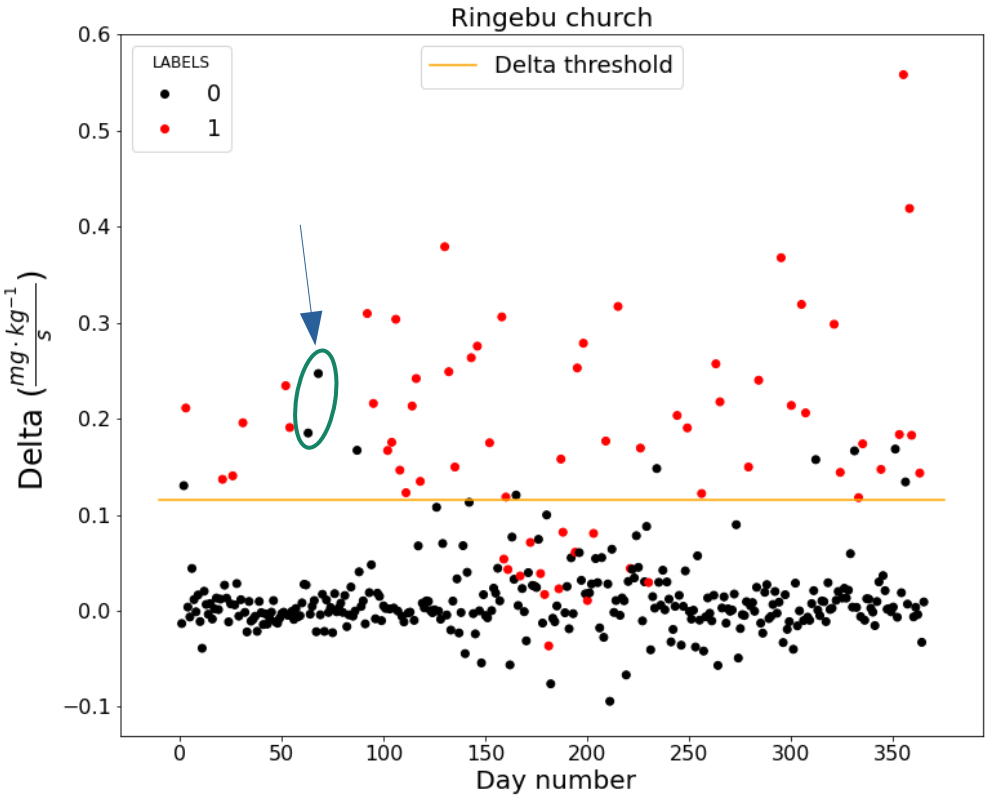

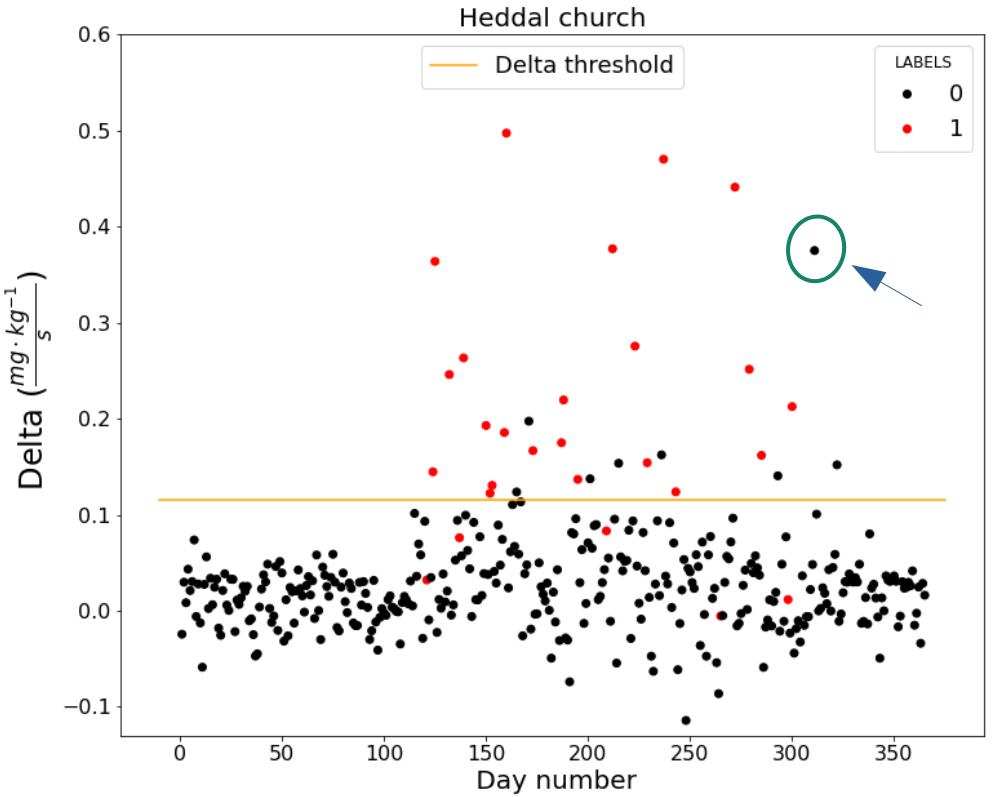

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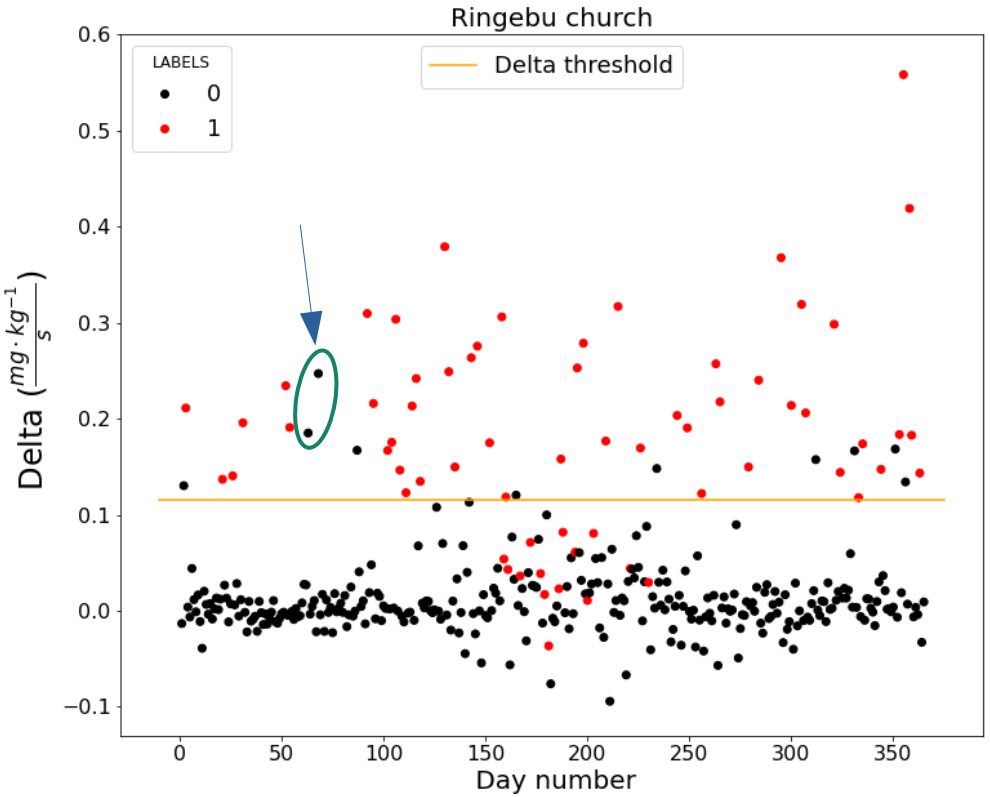
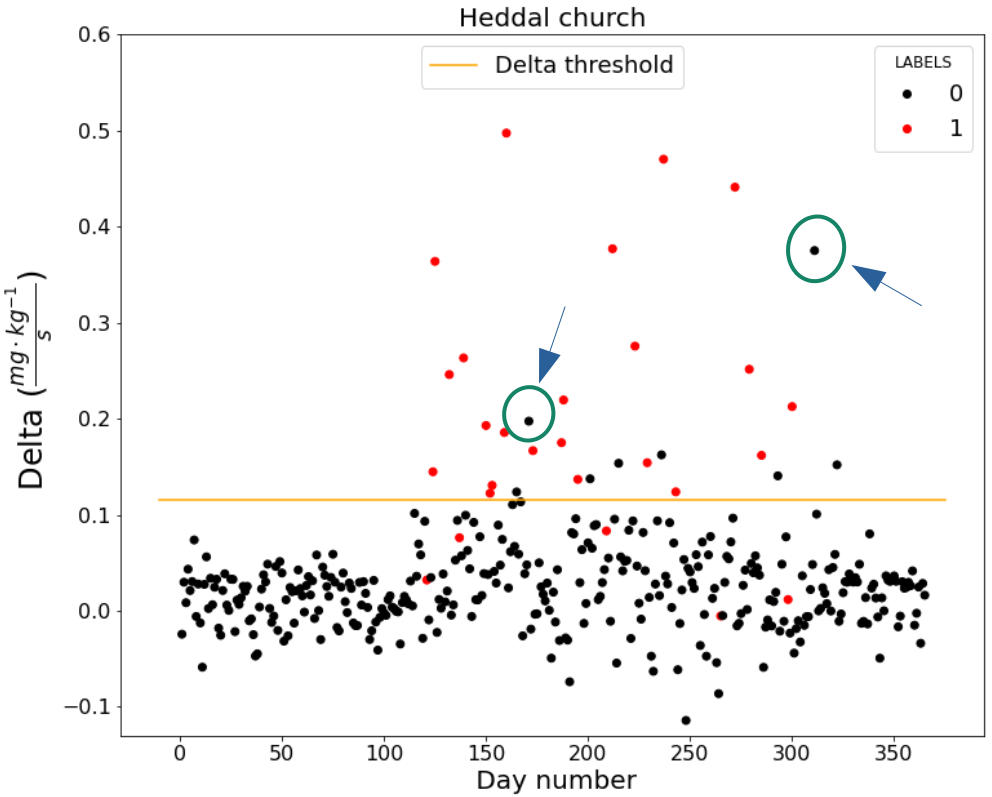
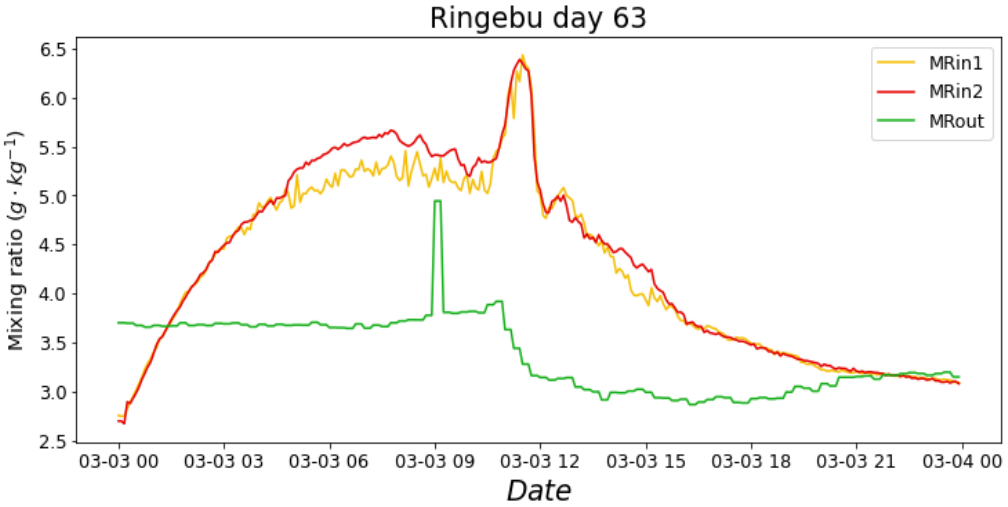
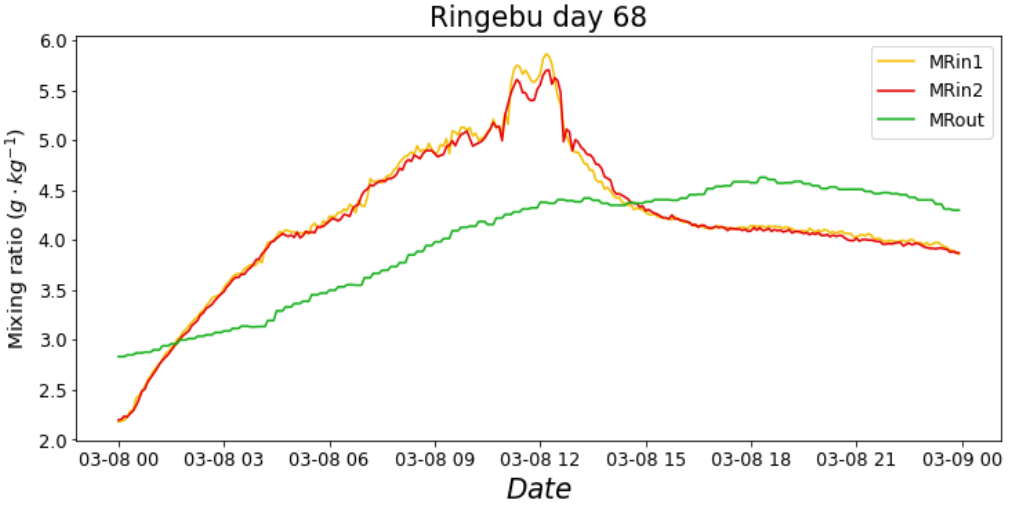




Comment on results

- Having a closer look to them:





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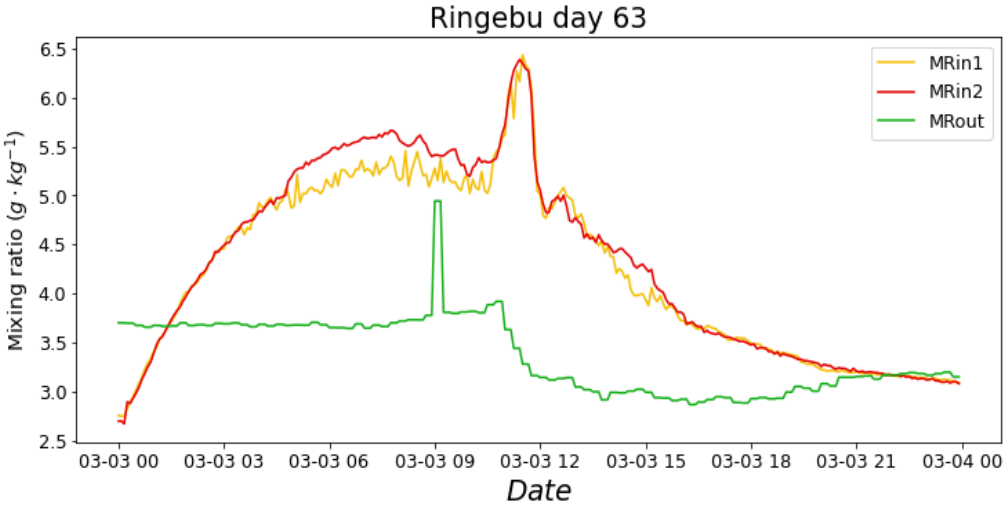

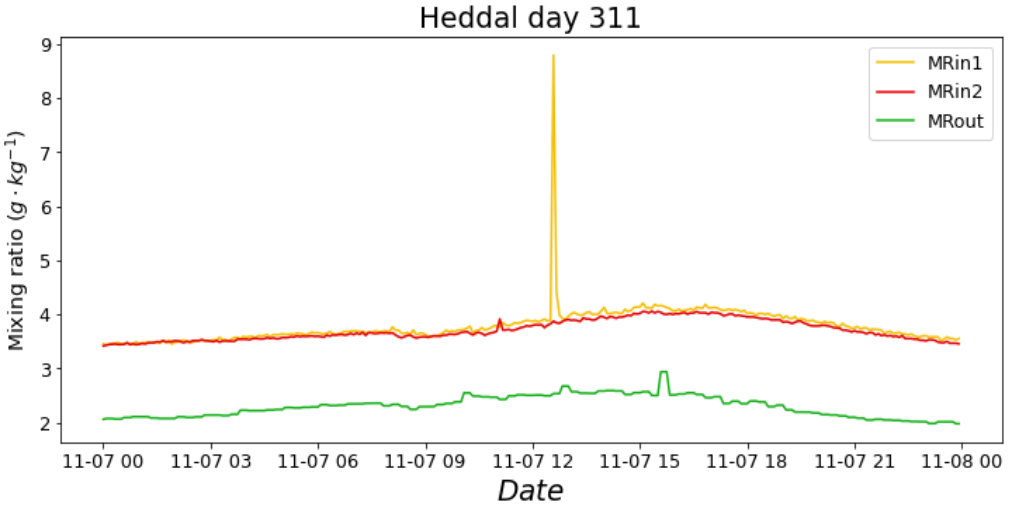

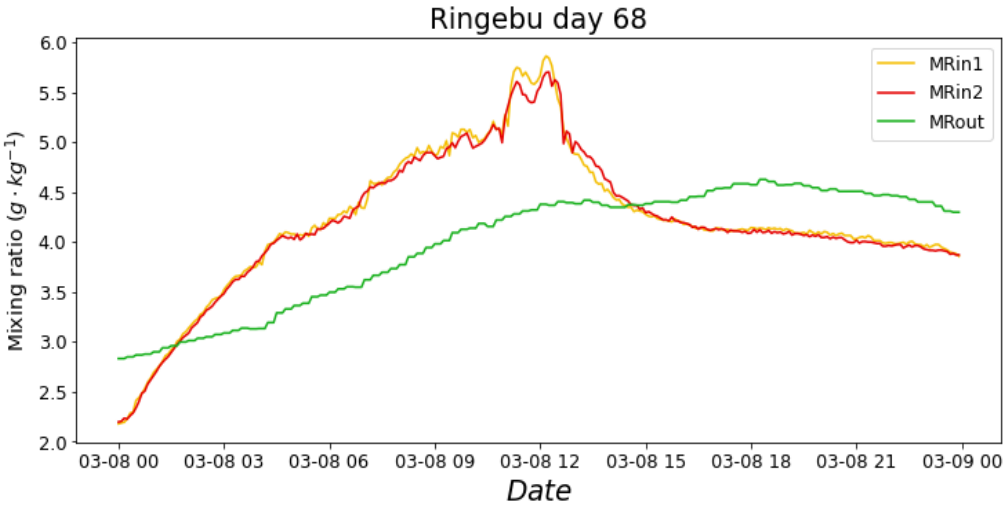

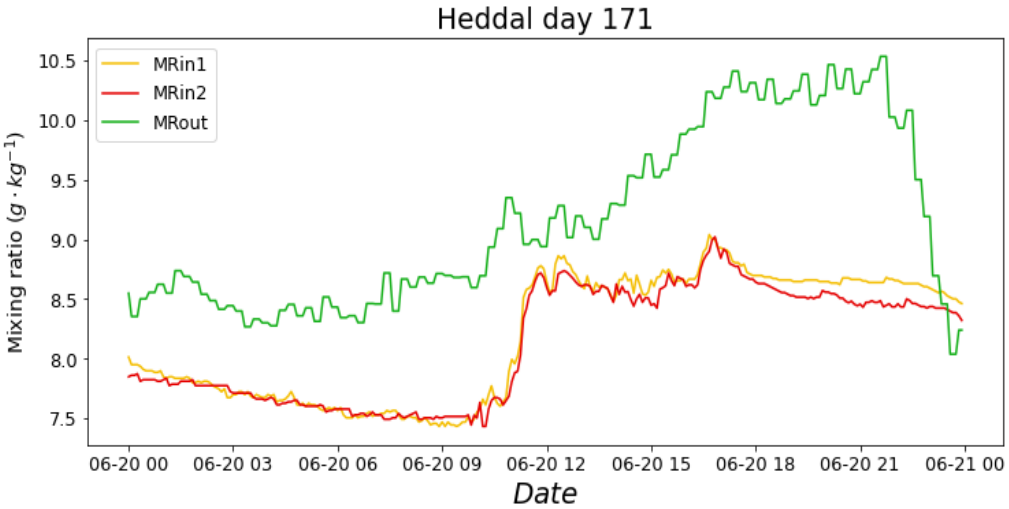

Conclusions

Results recap :

Method	***Church***	***Precision***	***Recall***	***NMI***
Clustering	Ringebu	0.83	0.62	**0.40**
	Heddal	0.16	0.96	**0.09**
Convolutional NN	Both	unstable	unstable	**0.2 - 0.5**
UMR peak	Ringebu	0.84	0.78	**0.52**
	Heddal	0.73	0.82	**0.53**

Conclusions

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	Heddal	0.73	0.82	**0.53**

Methods limitations :

- *Clustering* recognizes heating and not event with people;
- *CNN* results are unstable due to the small number of data;
- *UMR peak* uses an arbitrary smoothing procedure.

Conclusions

Results recap :

Method	*Church*	*Precision*	*Recall*	*NMI*
Clustering	Ringebu	0.83	0.62	**0.40**
	Heddal	0.16	0.96	**0.09**
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UMR peak	Ringebu	0.84	0.78	**0.52**
	Heddal	0.73	0.82	**0.53**

Final considerations :

- There are days that probably have wrong label, all results are affected by it;
- Best results are obtained with data manipulation strictly based on the problem to solve. “Data work” is not less important than “model work” .

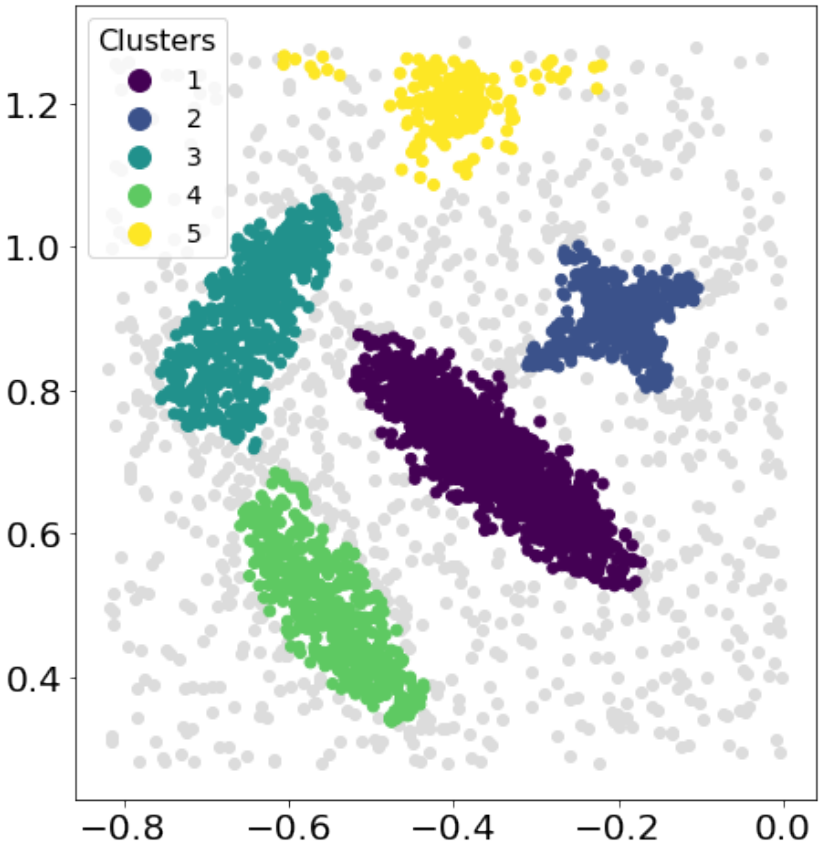
THANK YOU
FOR YOUR ATTENTION

Appendix: Noise estimation - Strictness

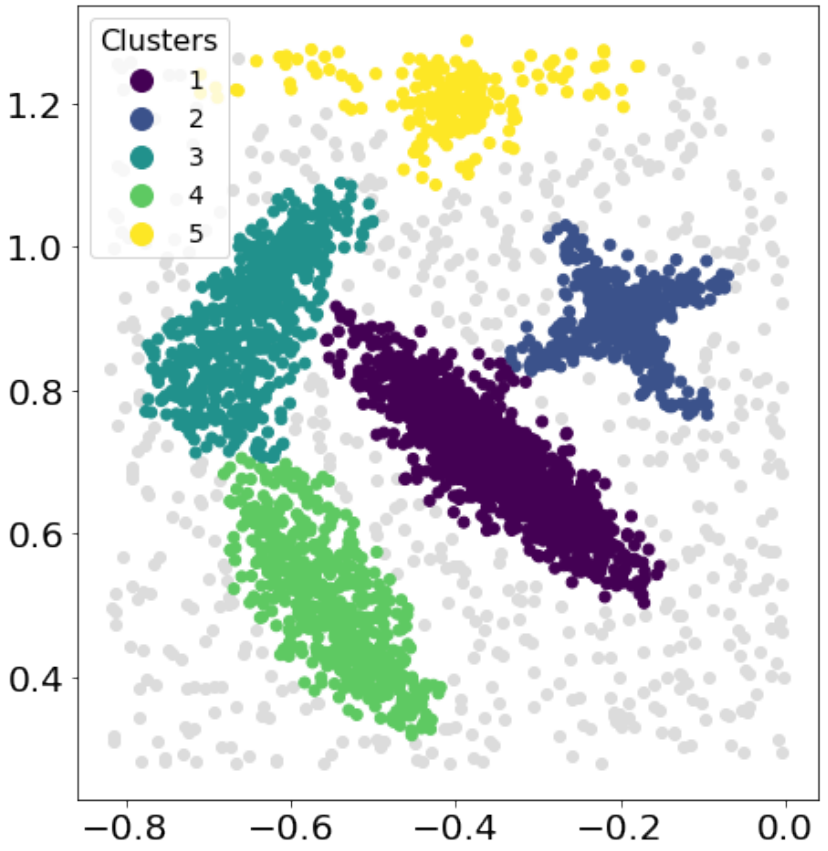
$$stricteness \in [0,1]$$

$$\rho_b^{strict} = \text{strictness} \cdot \max_{j \in border} \rho_j$$

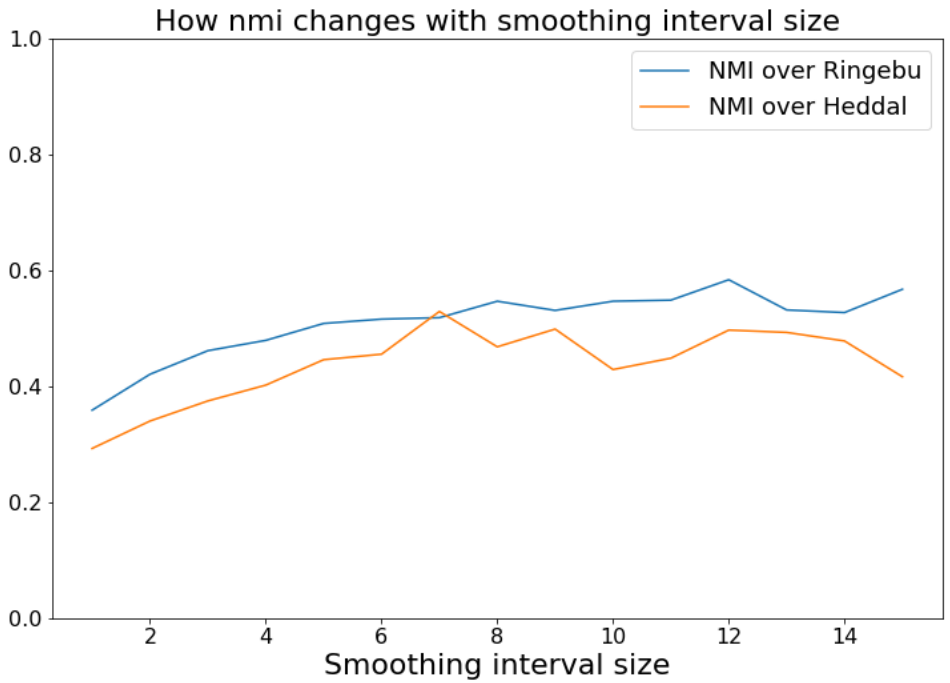
Strictness=1

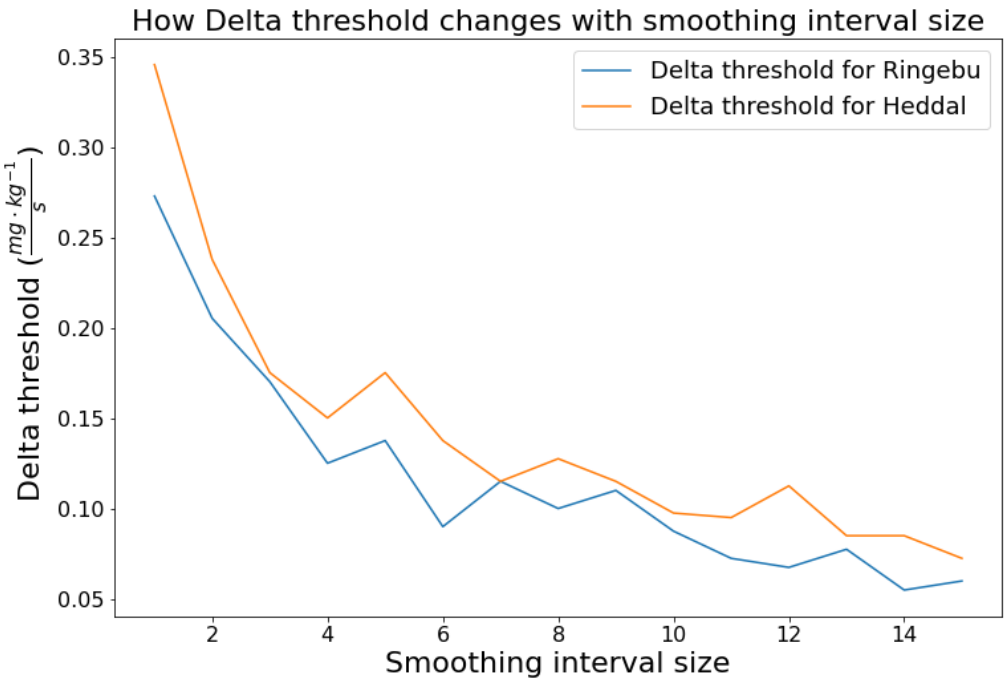


Strictness=0.5



Appendix: How does smooth affect UMR Peak?





- *Smoothing interval size* := number of considered measurements before and after every point in performing **MRin** moving average.
  For **MRout** this number is 3 * *Smoothing interval size* .
- Good *Smoothing interval sizes* seem to be from 7 to 12 measurements.
  (The one used in our analysis is 7)

Appendix: Ringebu summer days

- Here we can see the raw MR measurements of four Ringebu summers day with events. It is easy to understand why their predicted label is 0: **MRin** follows **MRout**.