A Graphical Tool for the Detection of Modes in Continuous Data

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OUTLINES

1. Visual representations/mode estimation of small size continuous-valued datasets
2. Density estimation and time-frequency analysis
3. A graphical tool for continuous data representation
4. Conclusion

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MODE ESTIMATION

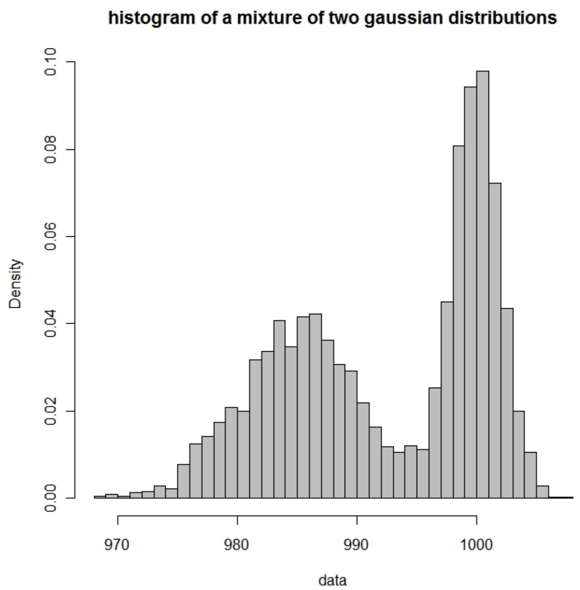
- The mode is one of the most explicit information about a dataset.
- In [Bi03], a method is proposed to find the mode of mono-modal continuous datasets.
- No extension to this work to our knowledge.
- How to determine the number of modes ?

Here, we propose a graphical tool that helps in the visualization of the distribution of a continuous dataset.

[Bi03] Bickel, D. (2003). Robust and efficient estimation of the mode of continuous data: The mode as a viable measure of central tendency, Journal of statistical computation and simulation, vol. 73, Issue 12, pp. 899-912.

VISUAL ANALYSIS OF CONTINUOUS DATASETS

Visualization provides a good mean to determine the number of modes. Morevoer, it helps in the crucial steps of understanding the dataset.



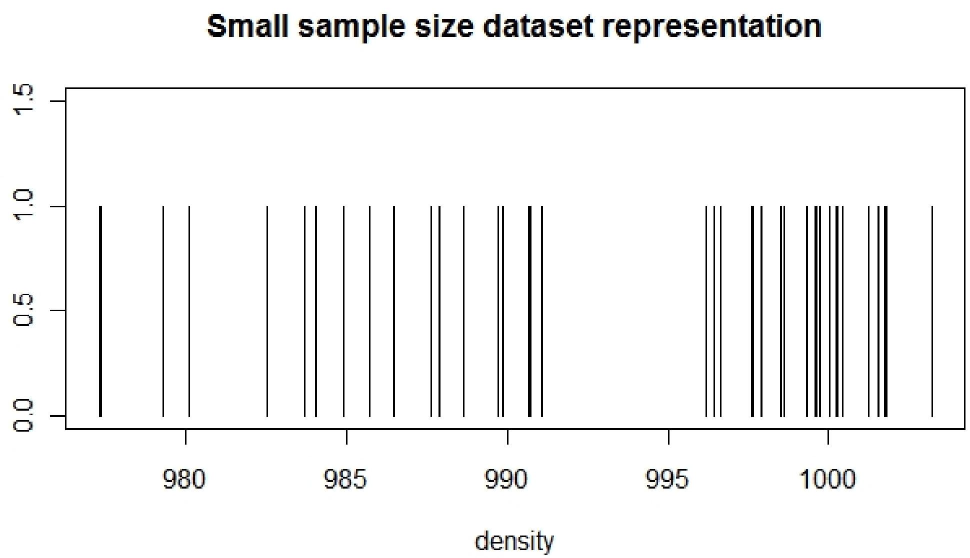


Figure 1: *There is no problem to visualize the distribution when the population is important enough (constant width/surface histograms, density estimation, etc.), but when the samples are not numerous enough, it is more complicated...*

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DENSITY ESTIMATION BY KERNEL METHOD

- Convolution of the dataset and a dedicated kernel
- Implemented in the **R** function `density()`
- Choice of the “shape” of the kernel? (gaussian, epanechnikov, triangular, cosine, etc.)
- Choice of the kernel size, depending on the density of the dataset (interval between items).

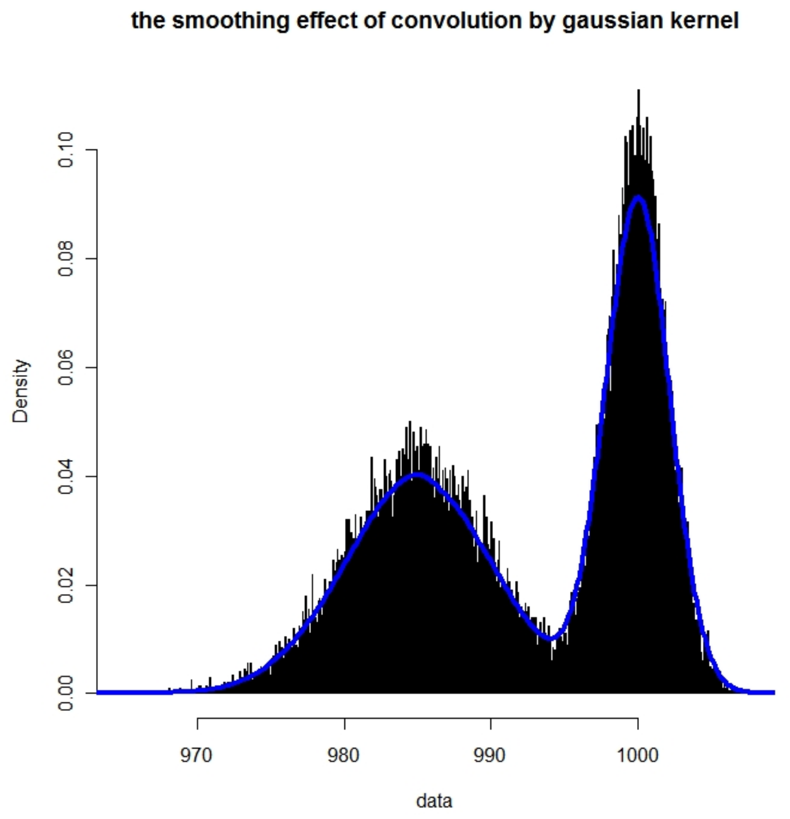

Figure 2: *The smoothing property of convolution is used to estimate the density.*

CONVOLUTION IN SIGNAL PROCESSING

Convolutions are widely used in signal processing :

- To identify a pattern (kernel = pattern to find)
- To smooth/filter a signal
- etc.

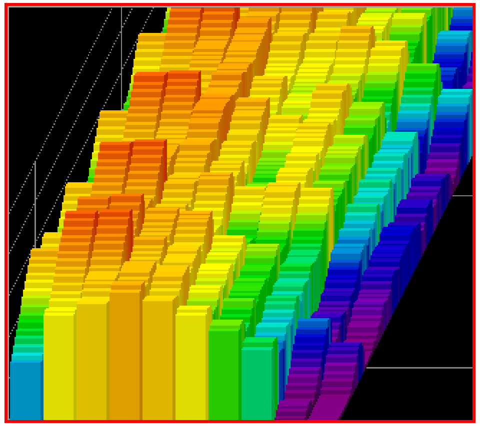

Figure 3: *Sliding window fourier representation.*

In general, it is the basis for time-frequency analysis:

- Convolution in the time domain corresponds to product in Fourier domain
- Fourier analysis applied to sliding windows leads to temporal analysis
- Wavelet theory is based on convolution (sliding windows) analysis at various scales (various kernel sizes)

PATTERN RECOGNITION AND SHAPE DESCRIPTION

- Similar problem in Computer Vision : time-frenquency analysis to decribe the parametric curve of shape.

- CSS (Curvature Scale Space) descriptors [Mok92] are amongst the most efficient shape descriptors (MPEG7).

- CSS descriptors are based on the multi-scale convolution of a parametric curve with a gaussian kernel.

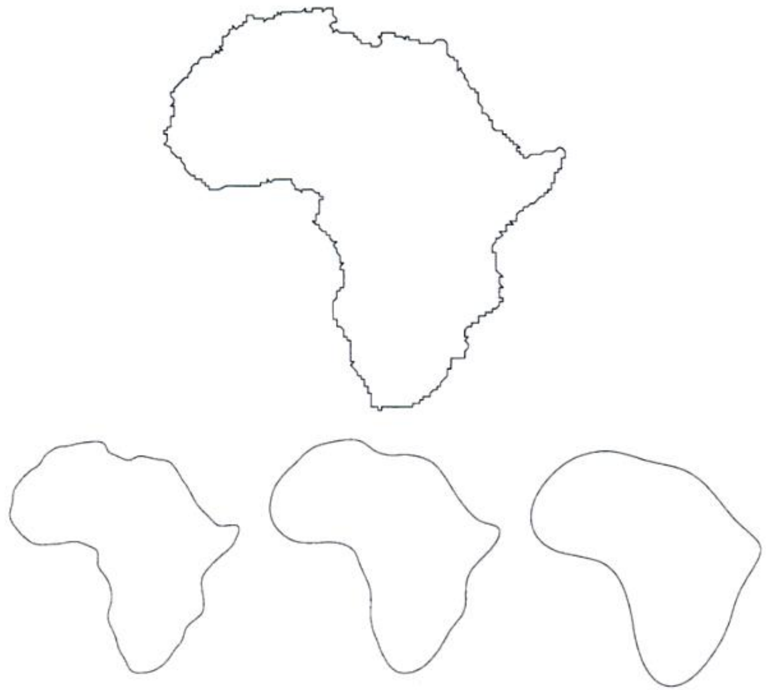

Figure 4: *[Mok92] The CSS captures the global distribution of a shape at various scales.*

[Mok92] Mokhtarian, F. and Mackworth, A. K.(1992). A Theory of Multiscale, Curvature-Based Shape Representation for Planar Curves, IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 14, Issue 8, pp. 789-805.

APPLICATION TO STATISTICS

- Performing a multi-scale description of the dataset.
- The dataset is considered as a shape to describe (i.e. as a histogram).
- Kernel : Gaussian (as with the CSS descriptors).
- This idea has already been presented [Gri**] in 2005 in PAMI (the same journal as for [Mok92]).
- The point was to apply the mean shift algorithm at various scales to find the mode of the distribution.
- Practically, it corresponds to traverse the plots of the multiscale representation to find a maximum value.
- It remains unpubished...

[Gri]** Griffin, L. D., Lilholm, M. (unpublished). A Multiscale Mean Shift Algorithm for Mode Estimation. Submitted in 2005 to IEEE Transaction on Pattern Analysis Machine Intelligence.

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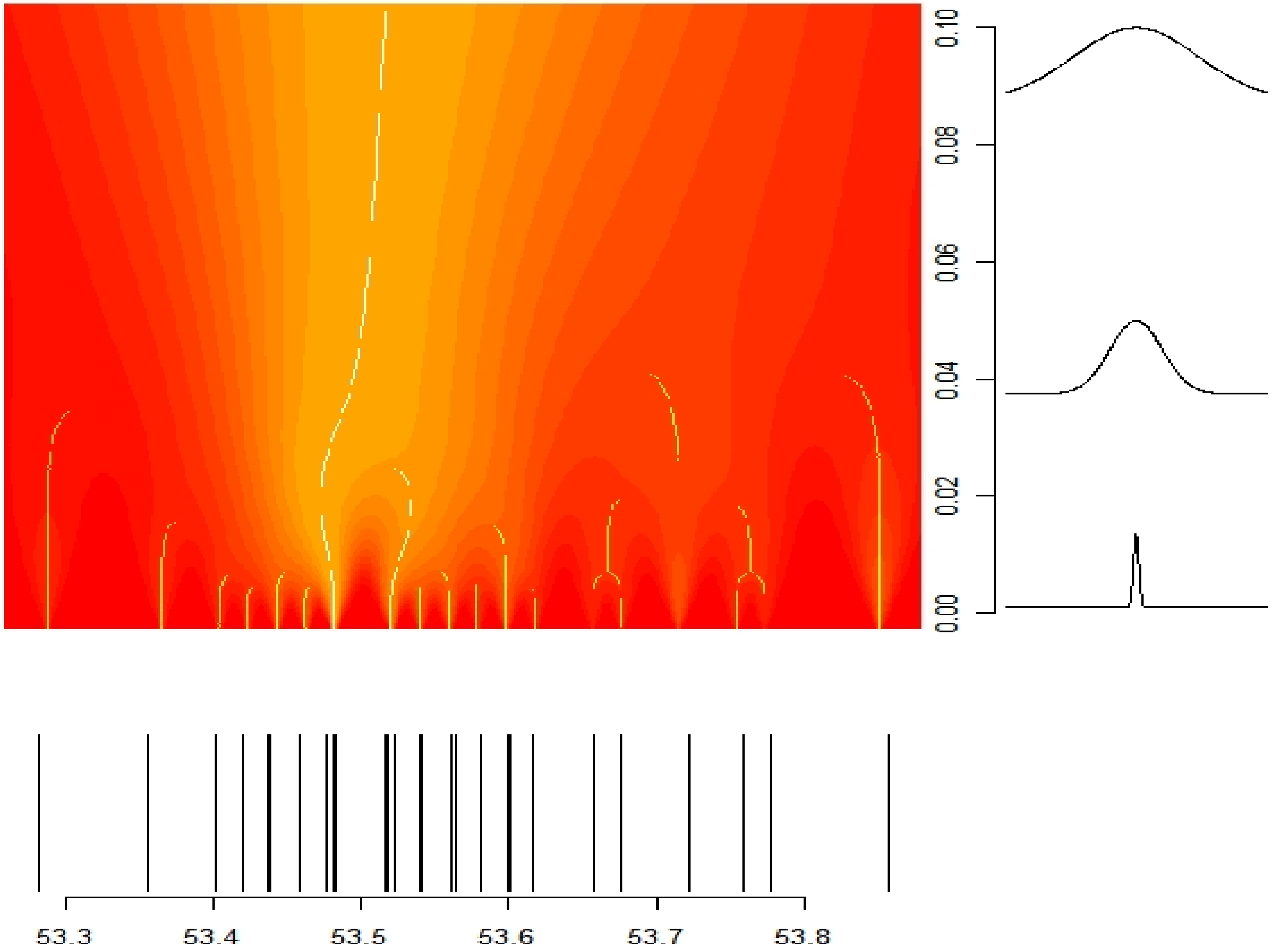
APPLICATION TO VISUALIZATION



DETAILS OF THE CODE

Basically, the algorithm loops on the `dentisty()` function with various sizes of kernel:

```
...
# MatConv = matrix of the graphical representation
# It is constructed line by line

    for (ibw in (1):(length(axeOrd))) {
         mode <- density(data , bw=axeOrd[ibw],
                         kernel = "gaussian",
                         n=length(axeAbs),
                         from=newMinData, to=newMaxData);
         valueLine <- mode$y/max(mode$y);         # the values are normalized
         maxLine <- localMode(valueLine );        # Local max
         MatConv[ibw,] <- valueLine + maxLine ;   # artifact for representation
    }

# display
...
```

PARAMETERS

data: Vector of the mono-valued dataset.

percentmargin: Size of the margin, so that the extremal value are not stuck to the border of the image.

sizeKerMin: Minimal value for the size of the kernel.

sizeKerMax: Maximal value for the size of the kernel.

bwLen: Number of convolutions with a different kernel. It corresponds to the number of lines in the display.

ImWidth: Width of the display.

jitterOrHist: Flag indicating the representation of the data in the lower part of the graphical representation. - 0 : automatic 1 : jittered density diagram 2 : histogram.

PERFORMANCE

- Execution time : between 5 and 10 seconds for a reasonnable number iterations of the `density()` function.
- The code is rather light.
- Most of the ressources are necessary for the display.
- It is possible to run it even on large datasets (several hundreds of items) and on which classical visualization tools are efficient.
- The limits come from the the size of the screen which limits the resolution of the display rather than the size of the dataset.

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IN A NUTSHELL...

Efficent visualization tool :

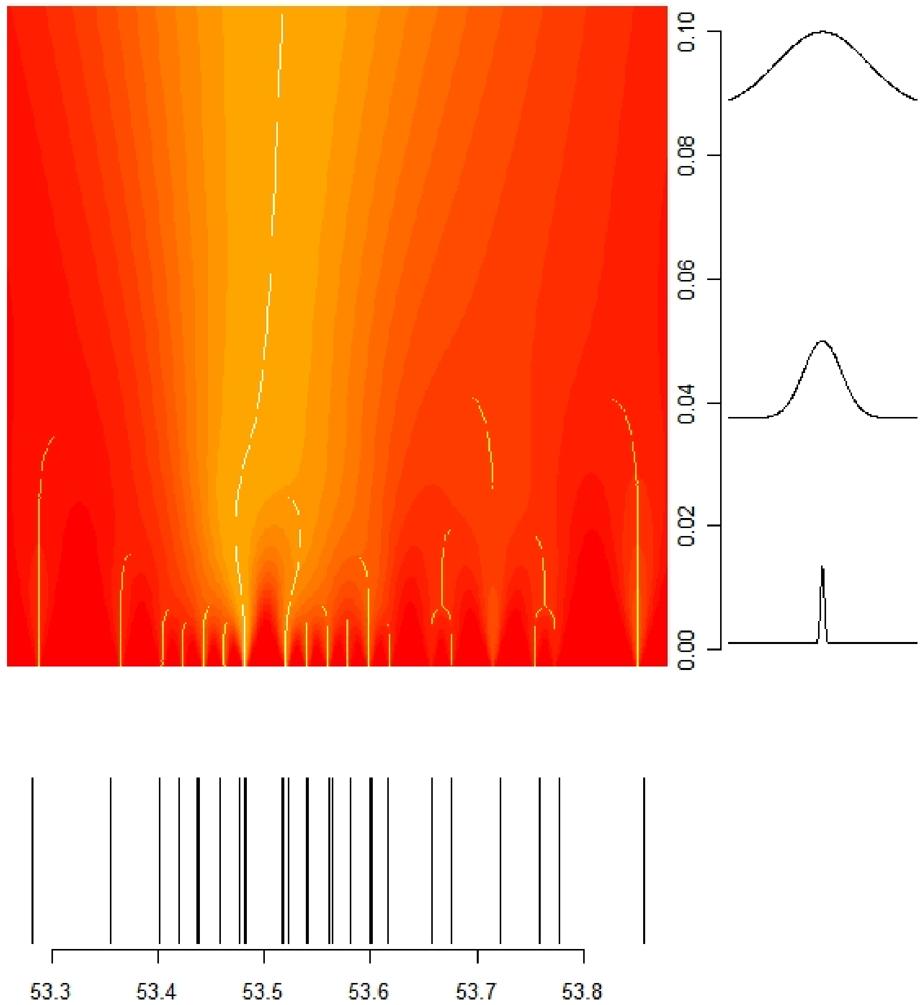
- for small sample continuous datasets
- adaptable thanks to several parameters
- computationaly acceptable

Based on :

- Multiscale gaussian convolutions
- Classical shape description methods
- Previous work has attempted to adapt this computer science background to statistics

OUTLOOK

- Dendrogram-like plot
- Interests for classification
- Future work will be focused on extracting knowledge from this “dendrogram”



QUESTION SESSION

- Thank you for your attention.

- Do you have any question ?