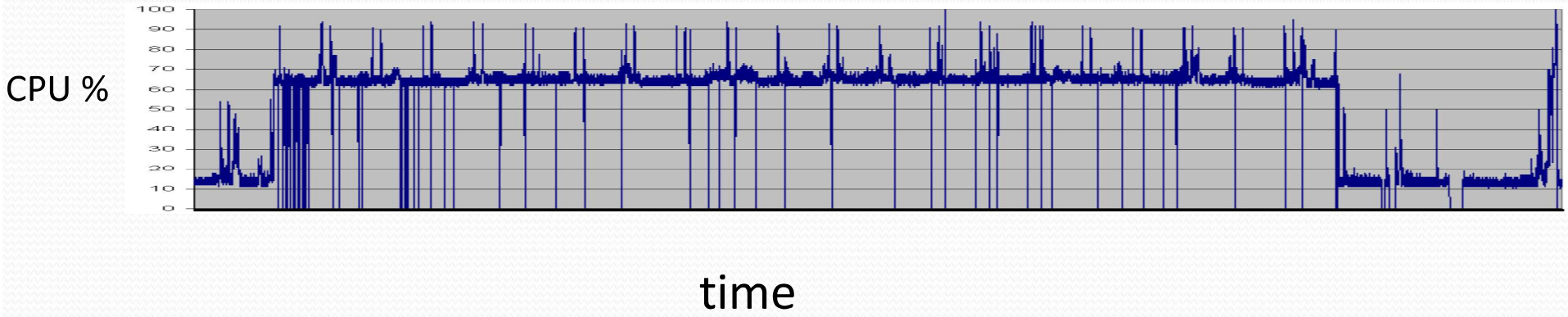
Some examples of complex representations

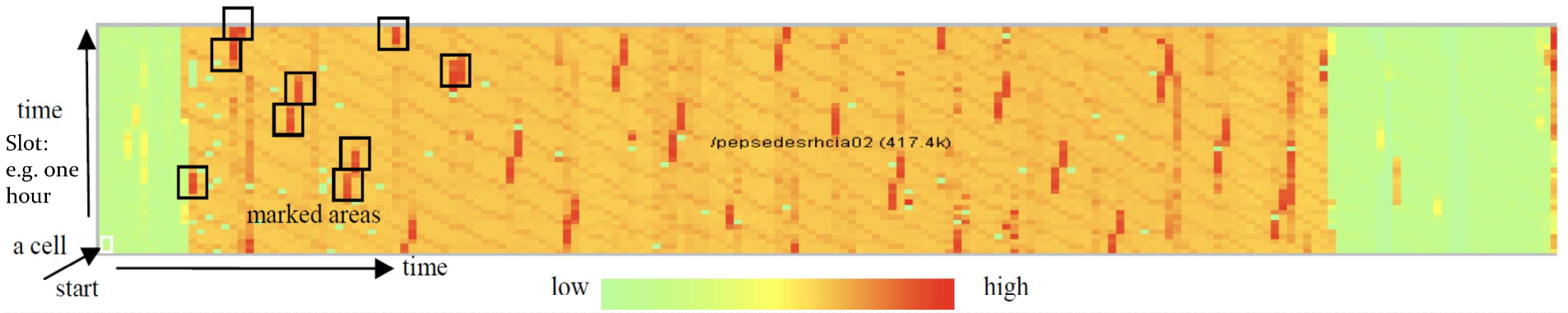
Example 1
Pixel oriented visualizations

Visual Analytics of Anomaly Detection in Large Data Streams
(paper from Daniel Keim group)

- You have to monitor a network composed of 8 systems with 16 servers each
- Each server provides basic information
  - CPU % occupation
  - DISK % occupation
  - MEM % occupation
  - …
  - That corresponds to 128 temporal data streams (overplotting !!)



Pixel oriented visualization overview



28 days (5 min windows), about 8k observations

Each observation takes a pixel

8 pixels (8 systems) per cell

The color codes the CPU %

Monitoring at server level

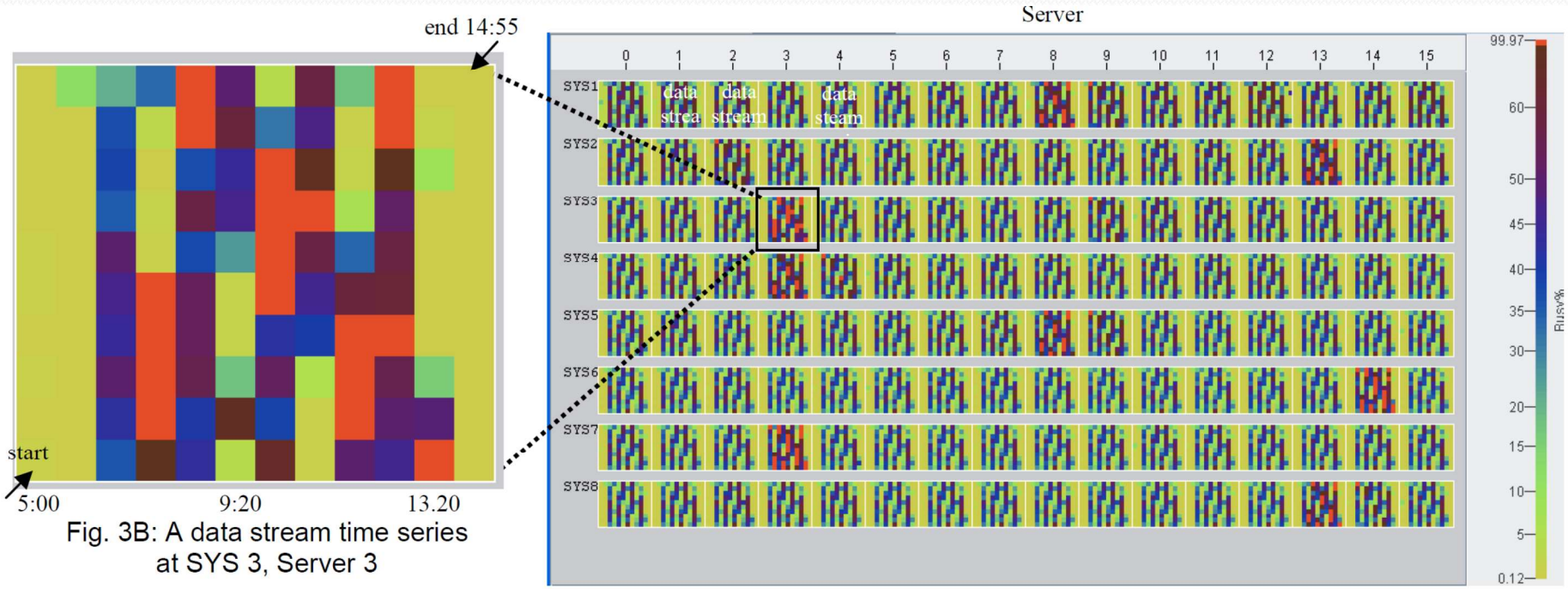


Fig. 3B: A data stream time series at SYS 3, Server 3

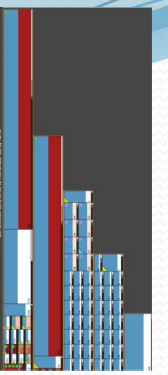
Color is preattentive!

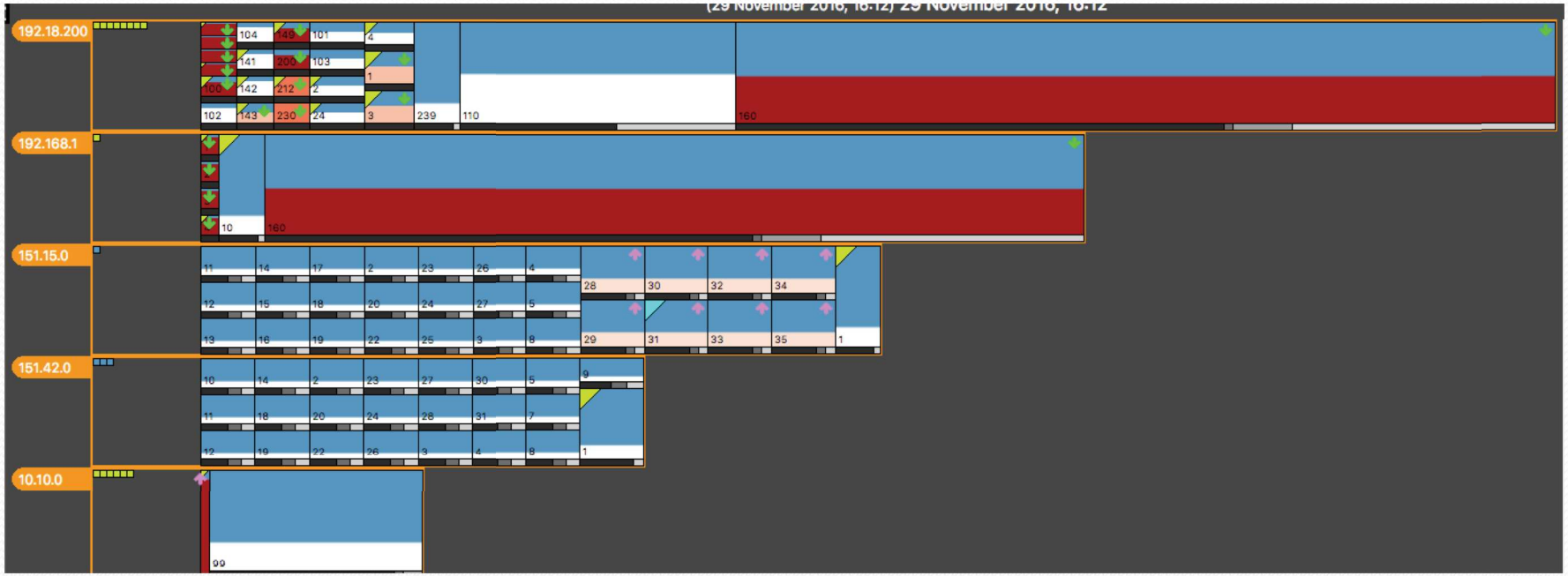
458757626808609928083982698028
747976296262867897187743671947
746588786758967329667287682085

Example 2
Security Domine

Combining/modifying existing representation

Histogram + 1 level treemap



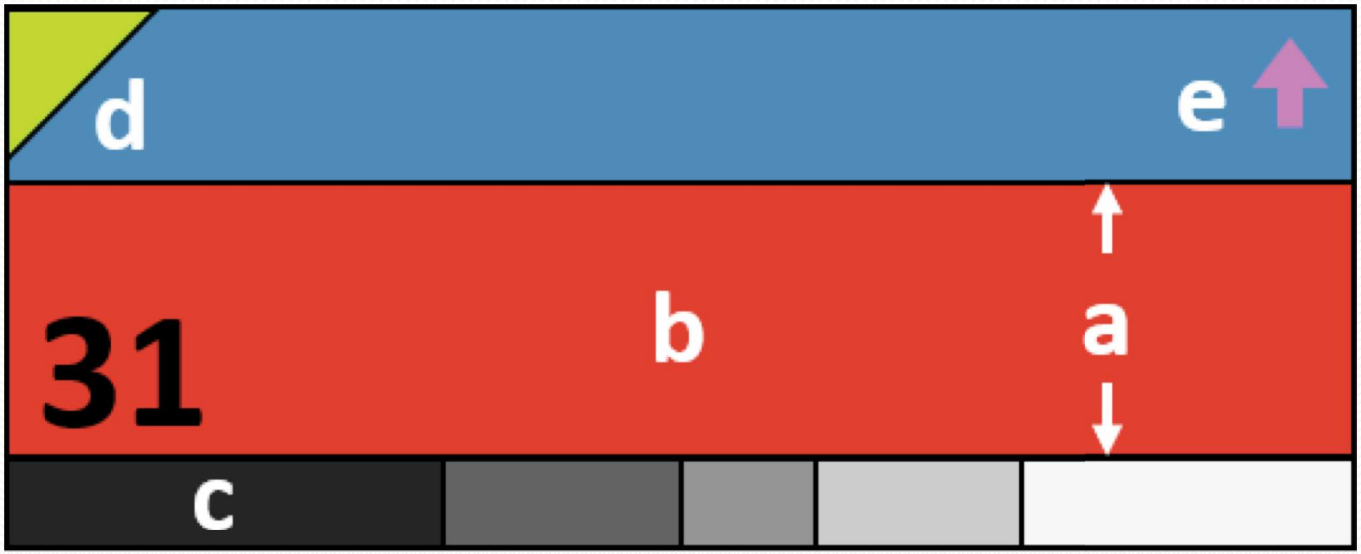


Length = number of vulnerabilities in a sub-network

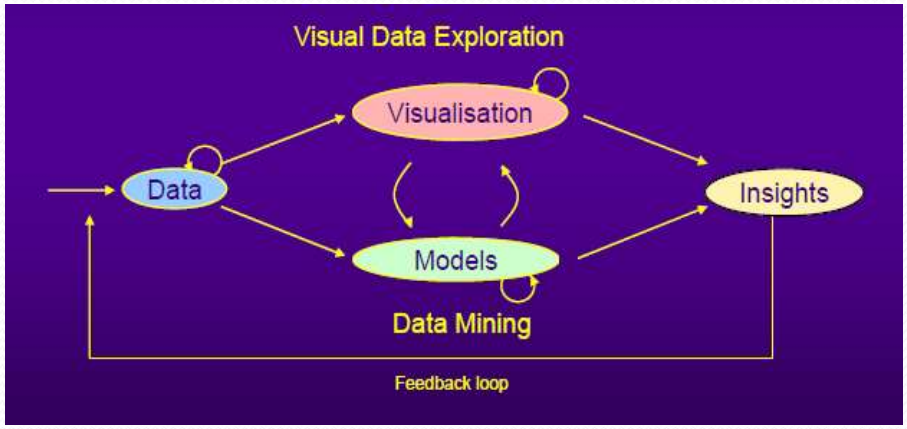
Size = number of vulnerabilities in a node

Special representation for nodes with 0 vulnerabilities

Node encoding



Role of analytics within representation phase



We can classify automatic activities in three main groups

1. Deriving new values from the dataset for ad-hoc visualization
   - This is the less standard and the more creative part of the process
2. Data reduction / data mining
   - Clustering /classification /…
   - Sampling
   - Dimensionality reduction (coming soon…)
3. Visualization improvement
   - Data distribution
   - Perceptual issues
   - Cognitive issues

Example 3
Information Retrieval Domine

Deriving new values from the dataset for ad-hoc visualization (you visualize DERIVED data)

The Context

- Information retrieval (IR) evaluation is not a theoretical issue
- In the last 20 years, large-scale evaluation campaigns have the goal of assessing performance of IR engines
  - TREC [Text REtrieval Conference] (USA) and CLEF [Cross-Language Evaluation Forum](Europe)
  - Hundreds of research groups
  - Producing a huge amount of valuable data to be analyzed, mined, and understood

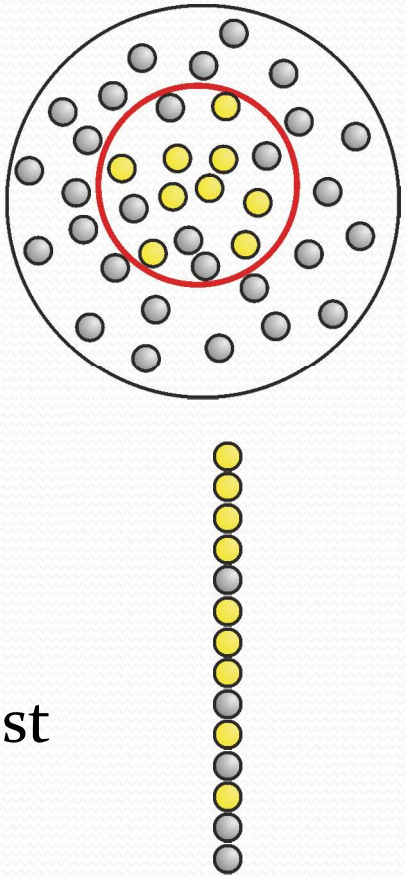
The Cranfield methodology

- Shared experimental collections :
  - To create comparable experiments
  - To evaluate their performance

- An experimental collection is a triple:
  - D is a set of documents
  - Q is a set of topics simulating actual user information needs (i.e., queries)
  - J is a (hand made!) set of relevance judgments, assigning a value to each document

Different experiment goals

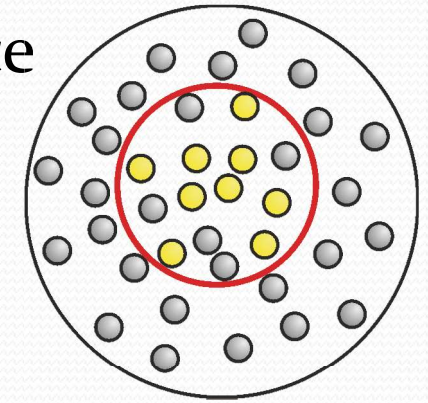
Given a topic q_i and a set of relevant and not relevant documents.



- Catch 'em all ! (the relevant ones)
  - Precision (only relevant ones) P=9/14≈64%
  - Recall (as many as possible) R=9/9 =100%
- Sort 'em all!
  - Rank the result to present to the user the most relevant documents in top position

Ranking!

- We focus on assessing the ranking quality in the challenging situation in which the relevance judgment is not binary
  - RANK: = 3 = 2 = 1 = 0



- Our goal is to provide precise indications on:
  - Misplaced documents (in the ranked list)
  - Quantitative problems rising from such misplacements

Modeling the problem

- We use a judgment function that assigns a value [0..k] to each document (0 non relevant, k highly relevant)
- We model the retrieved result with a ranked vector V of n elements
- Typical values: k=3, n=200
- The ground truth GT(V) function returns the relevance values

V	GT(V)
id1	3
id2	1
id3	2
id4	3
id5	2
id6	2
id7	3
…	…

Modeling the problem(cont.)

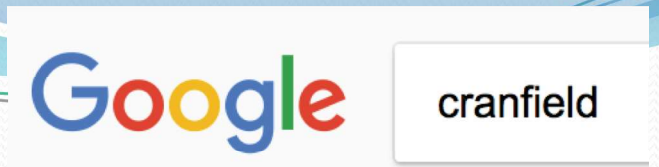
- For the end user, the value of a retrieved document is associated with its position in the vector (the lower the position the less likely the user will read it)
- We model it with a discounting function DF that progressively reduces the relevance of a document GT(V[i]) as i increases

$$DF(V[i]) = \begin{cases} GT(V[i]), & if\ i \leq x \\ GT(V[i])/\log_x(i), & if\ i > x \end{cases}$$

x=2 impatient users … x=10 patient users

GT(V)
3
1
2
3
2
2
3
…

You know this stuff…



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Cranfield is a village and civil parish in north west Bedfordshire, England, between Bedford and Milton Keynes. It has a population of 4,909, increasing to 5,369 ...

Modeling the problem(cont.)

- The overall quality of a result is evaluated using a discount cumulative gain function:

$$DCG(V,i) = \sum_{j=1}^{i} DF(V[j])$$

  - That estimates the information gained by a user that examines the first **i** documents of V

  - It is a summary measure and hides details

Modeling the problem(cont.)

- We consider the vector O, the optimal permutation of V that produces the highest DCG for each i

- We compute:
  - R_Pos, the relative position of documents in V with respect to their optimal position in O
  - Delta_gain(i), the difference of information gain DCG between V[i] and O[i]

Visualizing misplaced elements

The actual result

GT(V)	DF	DCG
3	3,00	3,00
1	1,00	4,00
2	1,26	5,26
3	1,50	6,76
2	0,86	7,62
2	0,77	8,40
3	1,07	9,47
2	0,67	10,13
0	0,00	10,13
1	0,30	10,43
0	0,00	10,43
3	0,84	11,27

OK

ABOVE

BELOW

The optimal result

GT(O)	DF	DCG
3	3,00	3,00
3	3,00	6,00
3	1,89	7,89
3	1,50	9,39
2	0,86	10,25
2	0,77	11,03
2	0,71	11,74
2	0,67	12,41
1	0,32	12,72
1	0,30	13,02
0	0,00	13,02
0	0,00	13,02

Misplaced elements and their numerical influence on DCG

The actual result

GT(V)	DF	DCG	DELTA GAIN
3	3,00	3,00	0,00
1	1,00	4,00	-2,00
2	1,26	5,26	-0,63
3	1,50	6,76	0,00
2	0,86	7,62	0,00
2	0,77	8,40	0,00
3	1,07	9,47	0,36
2	0,67	10,13	0,00
0	0,00	10,13	-0,32
1	0,30	10,43	0,00
0	0,00	10,43	0,00
3	0,84	11,27	0,84

OK

LOSS

GAIN

The optimal result

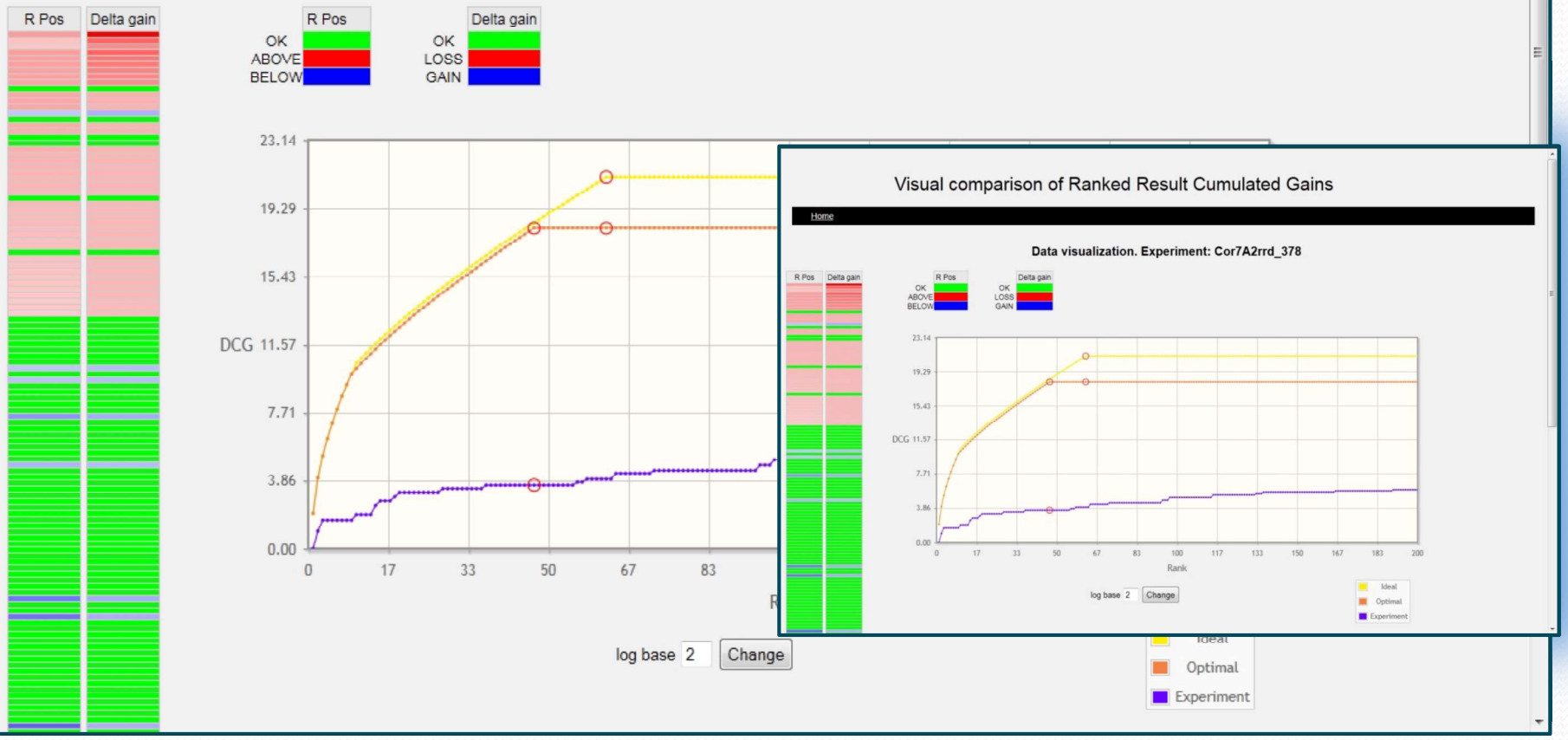
GT(O)	DF	DCG
3	3,00	3,00
3	3,00	6,00
3	1,89	7,89
3	1,50	9,39
2	0,86	10,25
2	0,77	11,03
2	0,71	11,74
2	0,67	12,41
1	0,32	12,72
1	0,30	13,02
0	0,00	13,02
0	0,00	13,02

promise

Visual comparison of Ranked Result Cumulated Gains

Home

Data visualization. Experiment: Cor7A2rrd_378



Visual comparison of Ranked Result Cumulated Gains
Home
Data visualization. Experiment: Cor7A2rrd_378

Representation=

Data (Data position and rank) + Derived data:

V	GT(V)
id1	3
id2	1
id3	2
id4	3
id5	2
id6	2
id7	3
...	...

Misplacement (color)
Delta Gain (color)
Computed using
DCG and R_Pos

GT(V)	DF	DCG	DELTA GAIN
3	3,00	3,00	0,00
1	1,00	4,00	-2,00
2	1,26	5,26	-0,63
3	1,50	6,76	0,00
2	0,86	7,62	0,00
2	0,77	8,40	0,00
3	1,07	9,47	0,36
2	0,67	10,13	0,00
0	0,00	10,13	-0,32
1	0,30	10,43	0,00
0	0,00	10,43	0,00
3	0,84	11,27	0,84

Example 4
Text analysis

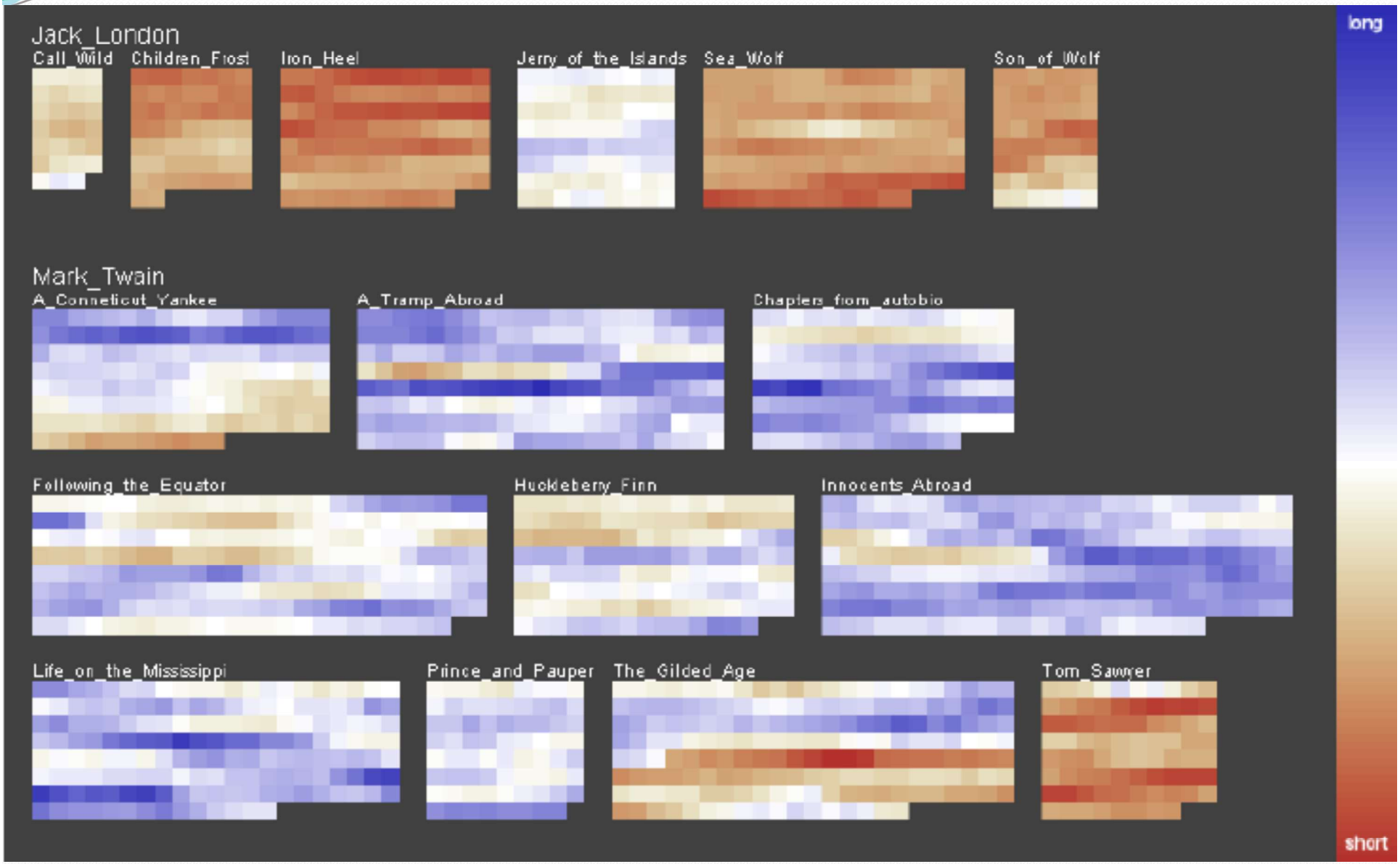
Deriving new values from the dataset for ad-hoc visualization (you visualize DERIVED data)

Deriving new values from the dataset for ad-hoc visualization

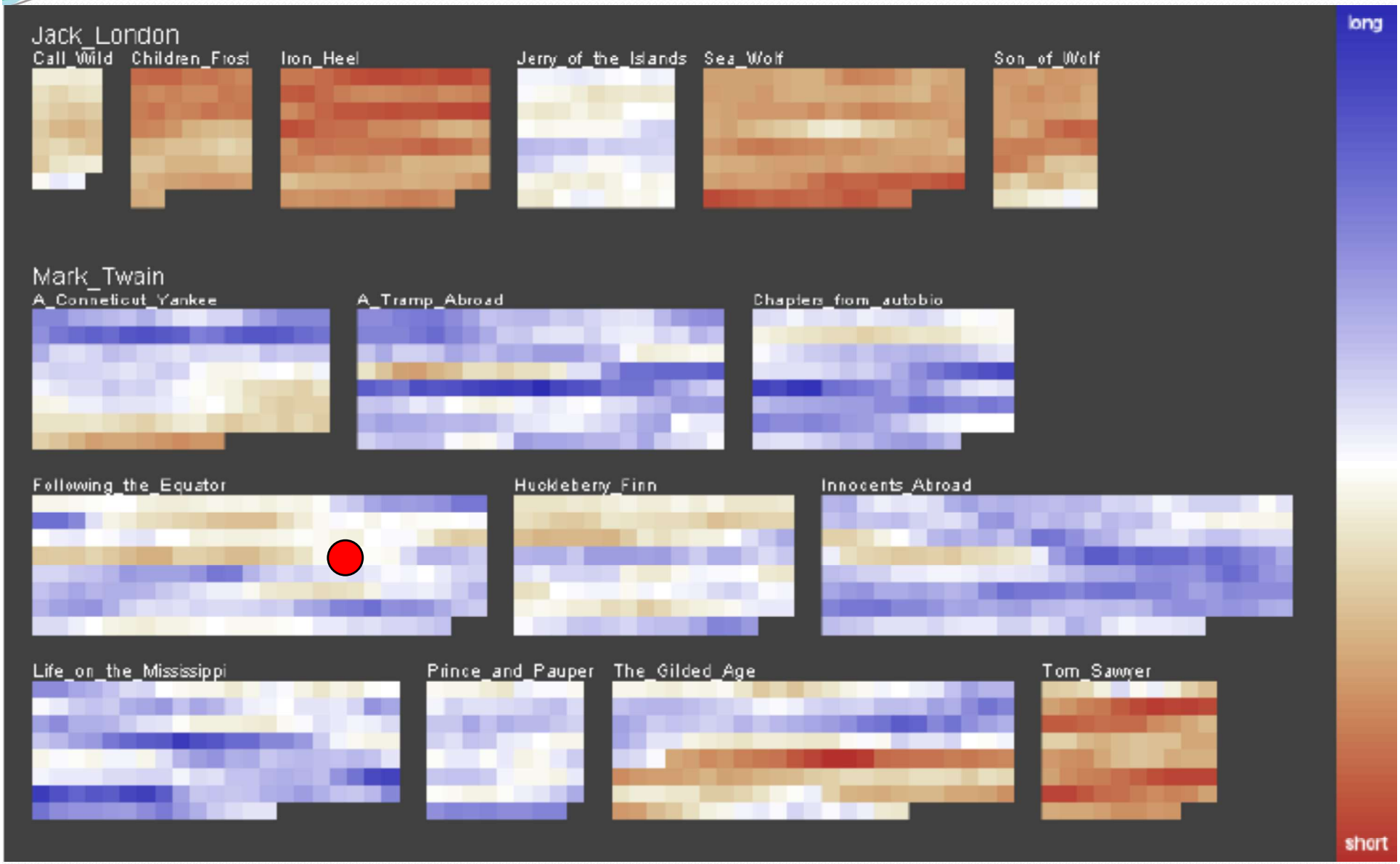
- How to visually compare J. London and M. Twain books ?
- [D. A. Keim and D. Oelke. Literature Fingerprinting: A New Method for Visual Literary Analysis. 2007 IEEE Symp. on Visual Analytics Science and Technology (VAST '07)]

1. Split the book in several text blocks (e.g., pages, paragraph, sentences)
2. Measure, for each text block, a relevant feature (e.g., average sentence length, word usage, etc.)
3. Associate the relevant feature to a visual attribute (e.g., color)
4. Visualize it

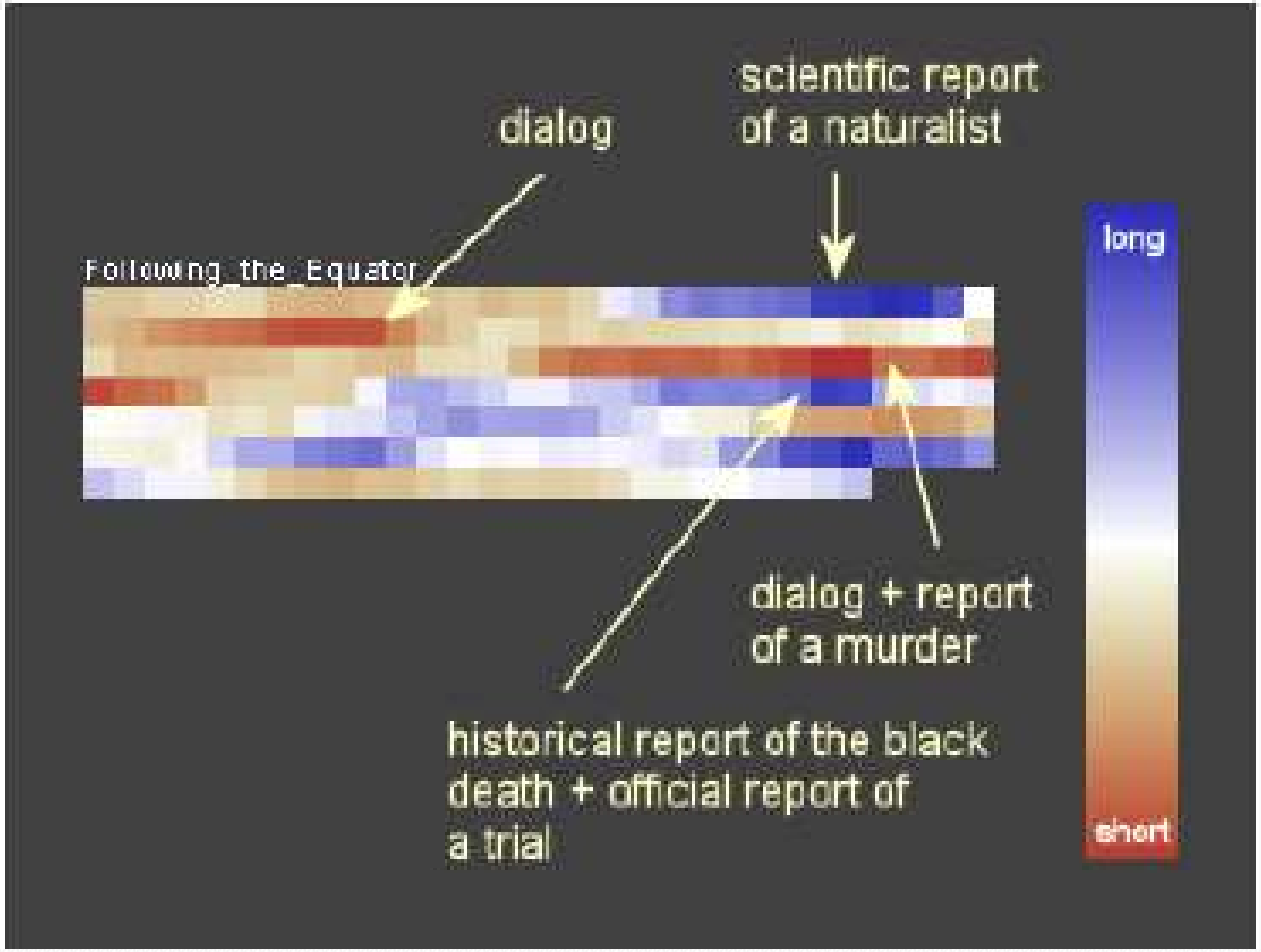
J.London vs M.Twain average sentence lengths



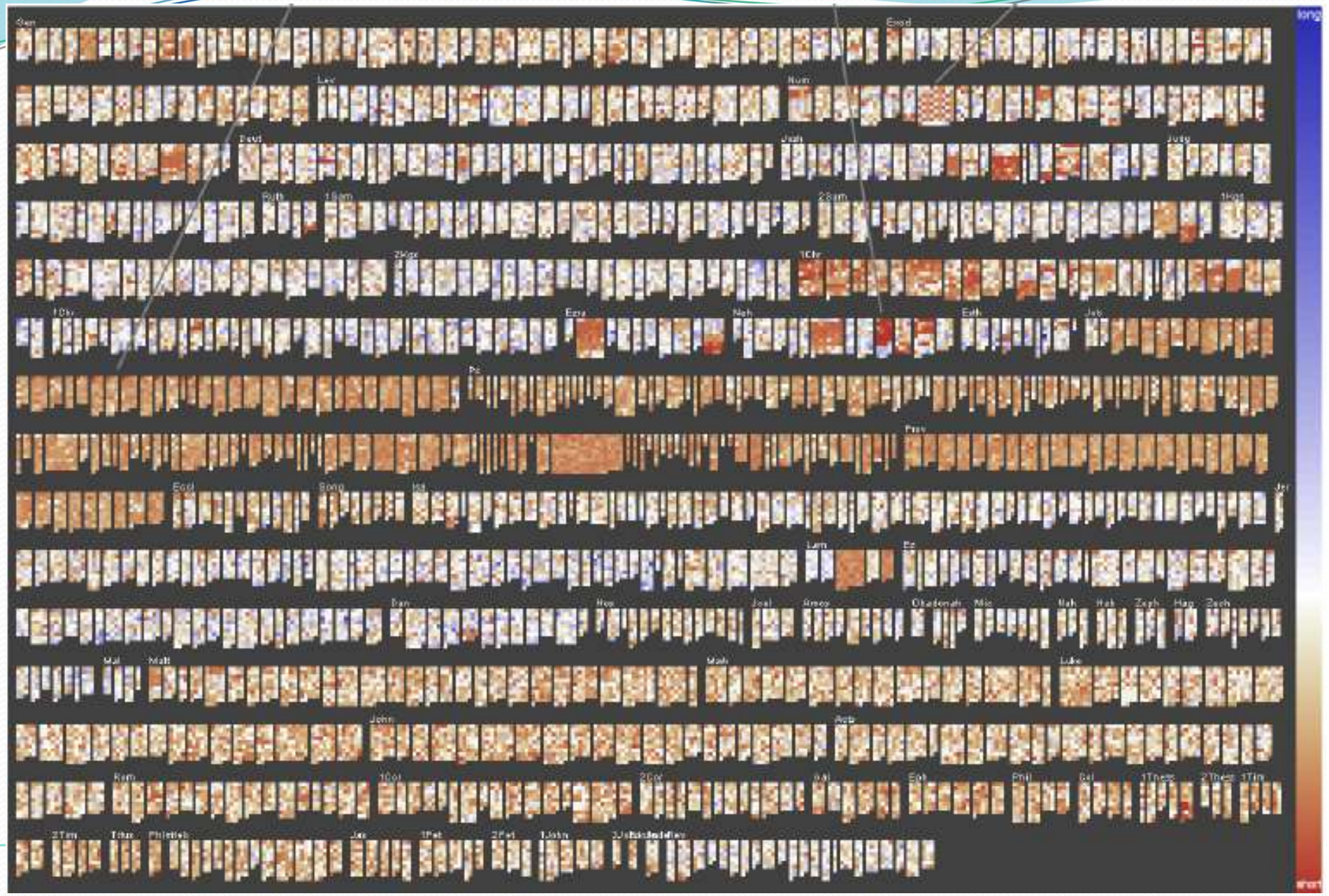
User interaction (a non uniform book?)



Details of a book



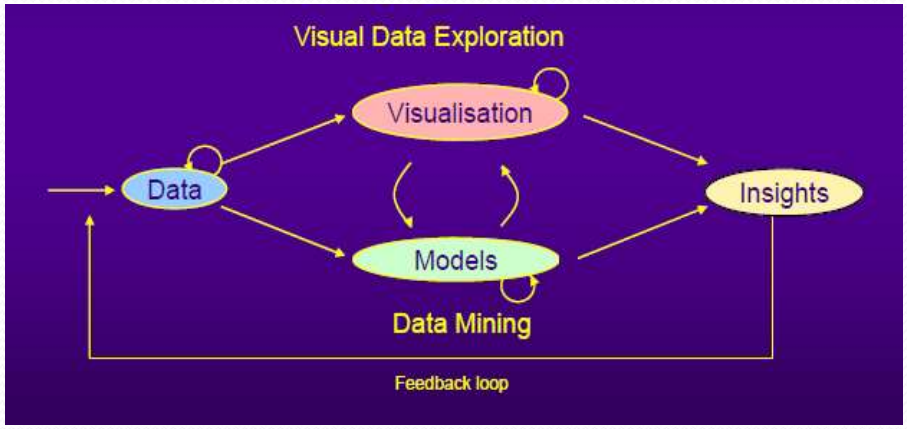
What about the Bible?



Example 5
Density maps

Improving the visualization using data distribution

Role of analytics within representation phase



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1. Deriving new values from the dataset for ad-hoc visualization
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   - Dimensionality reduction
3. Visualization improvement
   - Data distribution
   - Perceptual issues
   - Cognitive issues

Problem

- A very basic Infovis activity:

  mapping data values to a visual attribute (e.g., color, size, thickness, etc.)

$$D = \{ d_1, \ldots, d_{N_{Dv}} \}$$

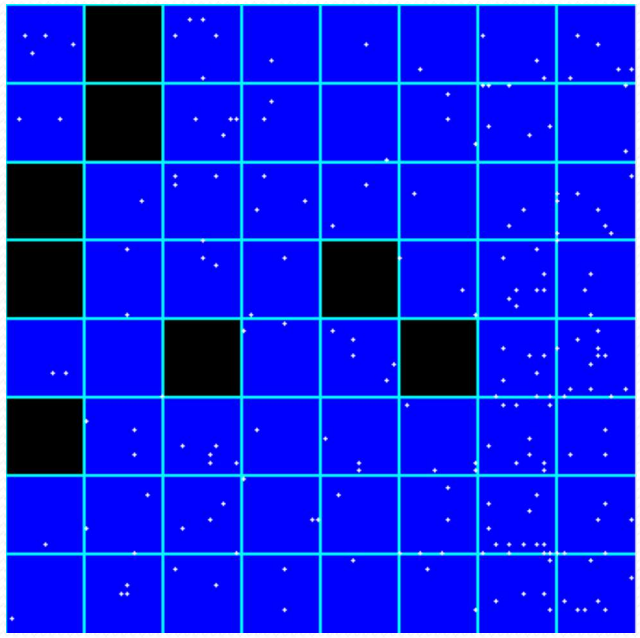
$$VisualAttribute = \{ C_1, \ldots, C_{N_L} \}$$

We discuss the matter in the context of
2D scatter plot density maps

Density maps

4 data items are plotted on the same pixel:**d=4**

empty pixel



8x8 pixels

we can **map** the density values to a 256 levels gray or color scale

In the example we borrow the Keim&Kriegel [KK95] color scale, presenting a monotonically increasing brightness

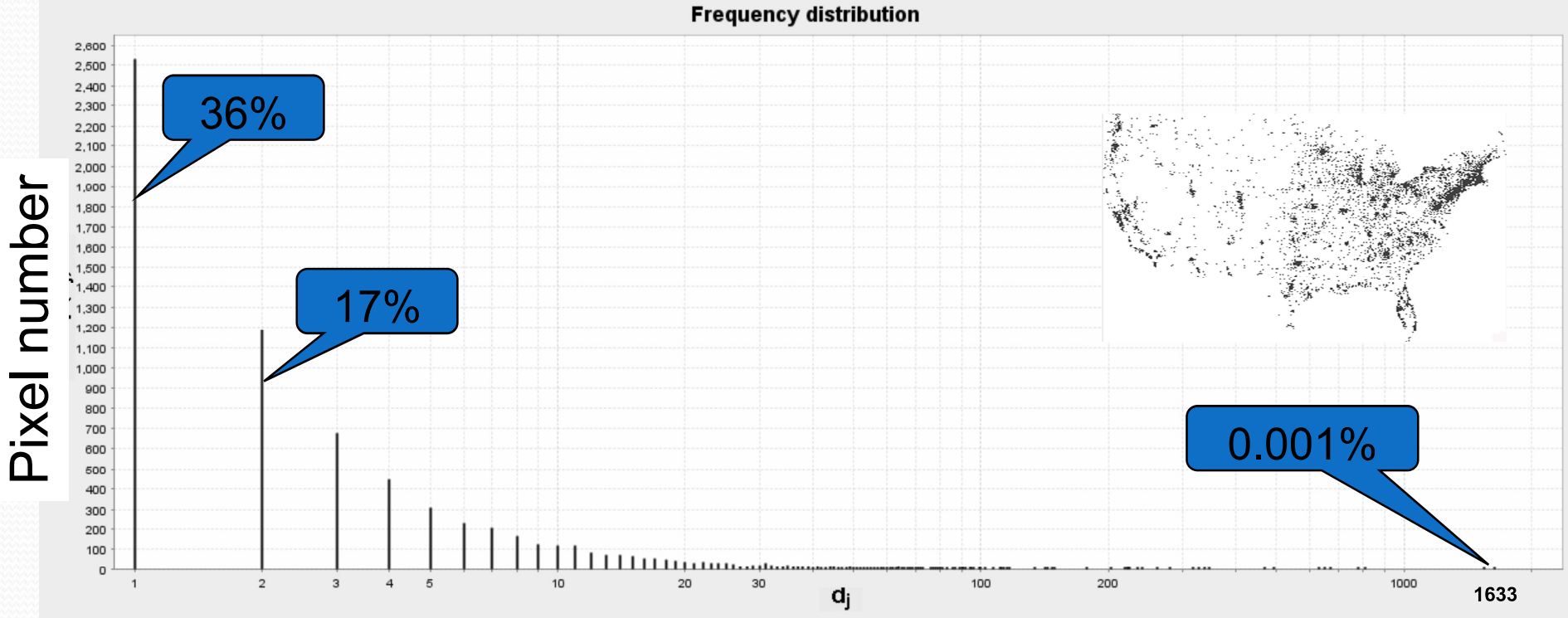
The case study (Infovis contest 2005)

The case study (Infovis contest 2005)

- About 60,000 USA companies plotted on a 800x450 (360,000 pixels) scatter plot
- N_{DV}=126 distinct density values (collisions on the same pixel) ranging on [1..1,633]
- N_{AP}=7,042 active pixels (i.e., hosting at least one company):
  - 2526 pixels (36%) host exactly one company (d=1)
  - 1182 pixels (17%) host two companies (d=2)
  - …
  - 1 pixel (0.0001 %) hosts 1633 companies (d=1633)

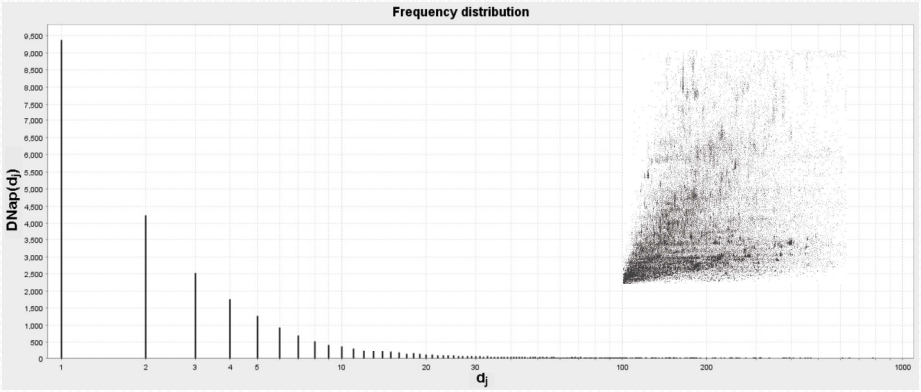
What is the source of the problem?

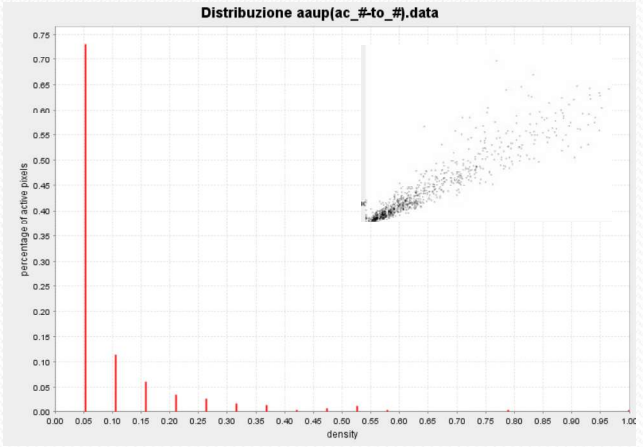
- The choice of the right **mapping** is crucial, because of density frequency distribution presents very skewed behaviour

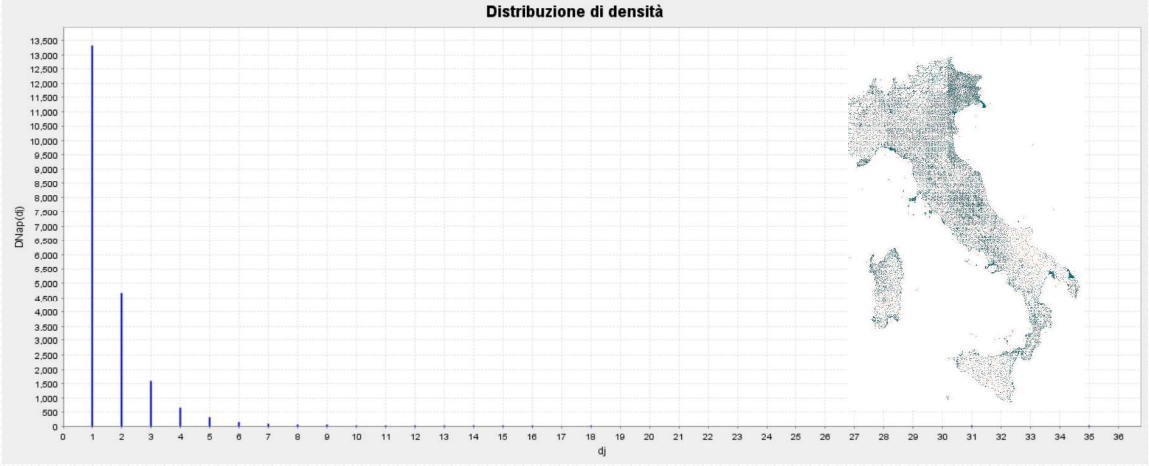


A (quick) parenthesis

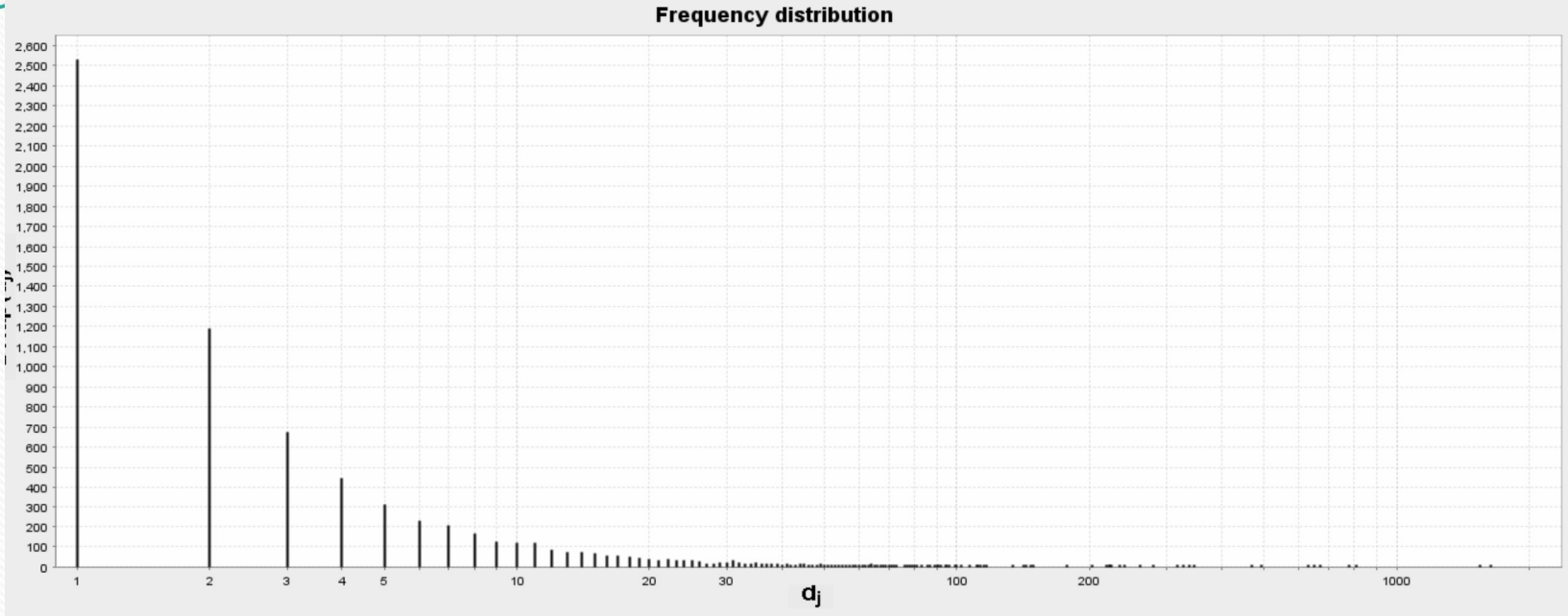
- This is not by chance: very often 2D scatter plots exhibit this density frequency distribution







The mapping



N_{DV}=126 different data densities = { 1, 2, … , 1,633 }

?

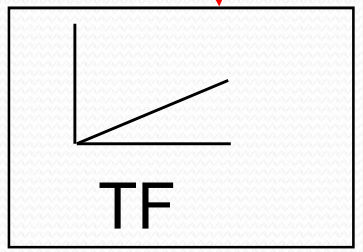
256 Color Codes = { 0,1, 2, … , 255}

Outline

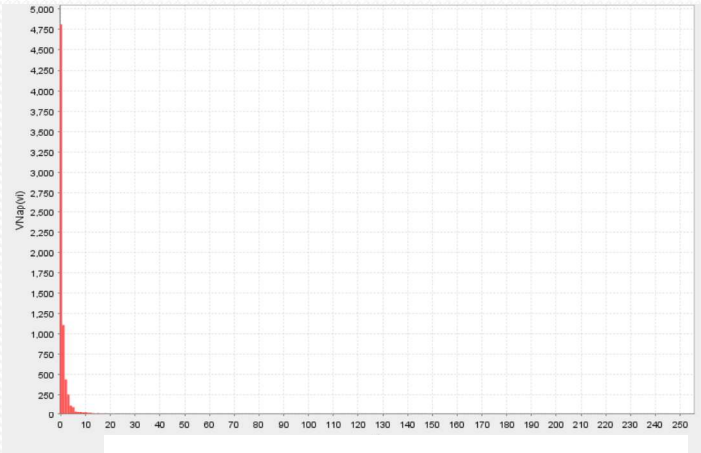
- The problem
- Available solutions
  - Linear mapping
  - Non linear mappings
- Our proposal
- Metrics and discussion
- Conclusions and future work

Linear mapping

$$ColorCode(d) = Round\left[255\,\frac{d - d_{min}}{d_{max} - d_{min}}\right]$$



- Straightforward solution
- Useless in this situation

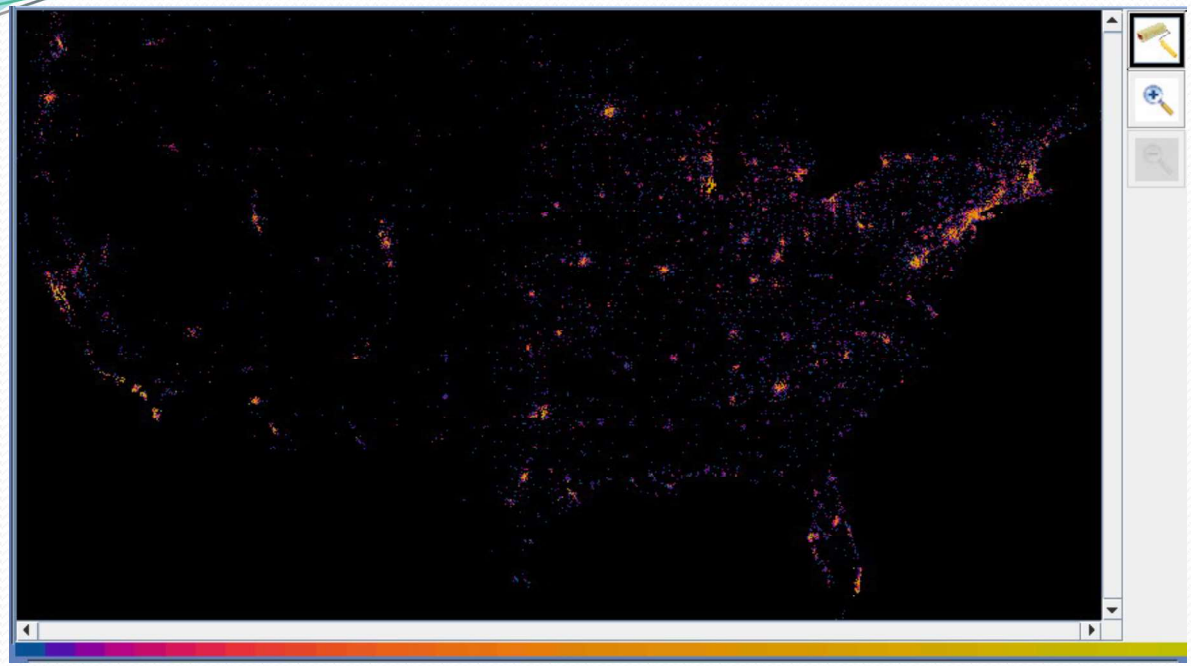


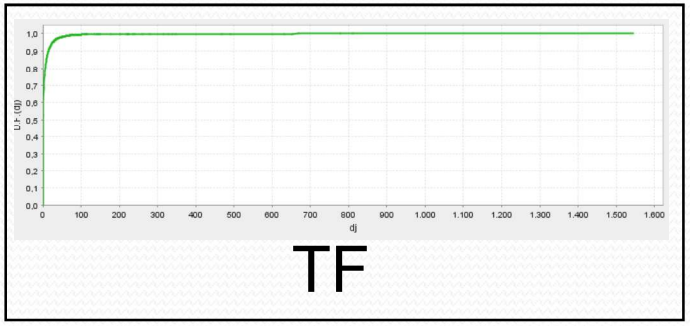
Color code frequency distribution

- Most pixels share very low color codes
- Few color codes are used (46 out of 256)
- **Different** low density values are represented by the **same** color code:
  densities in [1..10] are mapped on codes {1,2}

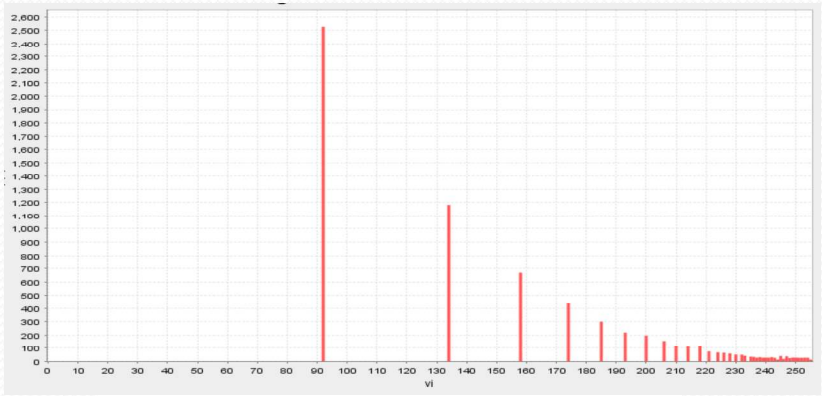
Density function mapping

$$ColorCode(d_j) = Round\left[255 \sum_{i=1}^{j} \frac{DN_{AP}(d_i)}{N_{AP}}\right]$$





- Hermann et al. [HMM00]
- Quite similar to histogram equalization
- Better than linear mapping



Color code frequency distribution

- Few color codes are used (39 out of 256)
- Lowest color code unnecessarily high
- Codes ranging only on [91..255]
- **Different** high density values are represented by the **same** color code: densities in [48..1,633] -> [250,255]

- The problem
- Available solutions
- Our proposal
  - Rationale
  - We have explored two different cases
    - One to one mapping
    - Uniform scale mapping
  - Visual comparison

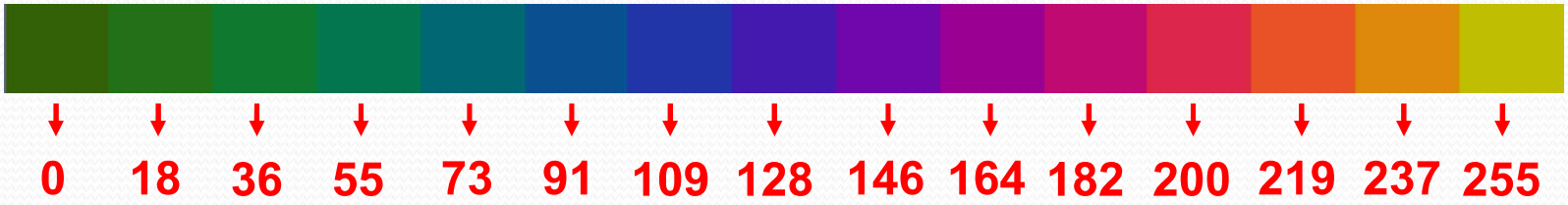
Rationale

We take into account that:

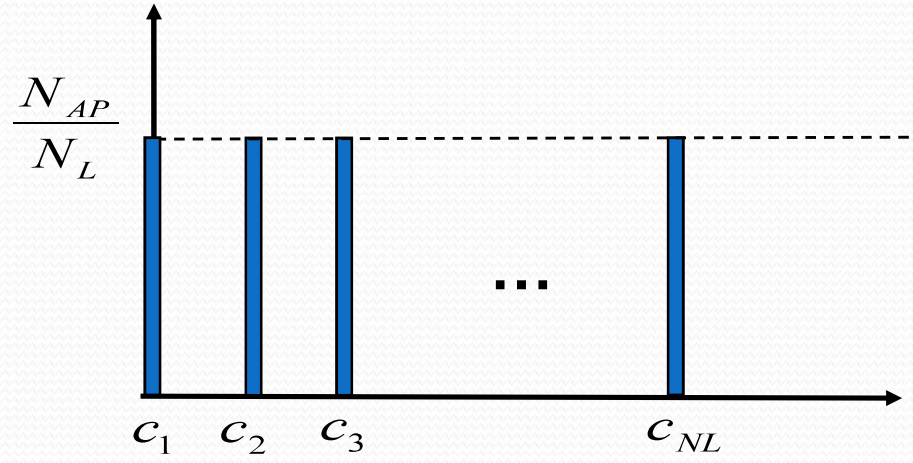
1. densities and color codes are discrete and finite
2. too close color codes are hardly distinguishable!
3. we need some objective quality metrics to validate/drive the mapping are needed

Uniform scale mapping

We use a reduced color scale, e.g. with 15 codes (N_L=15)JND!!



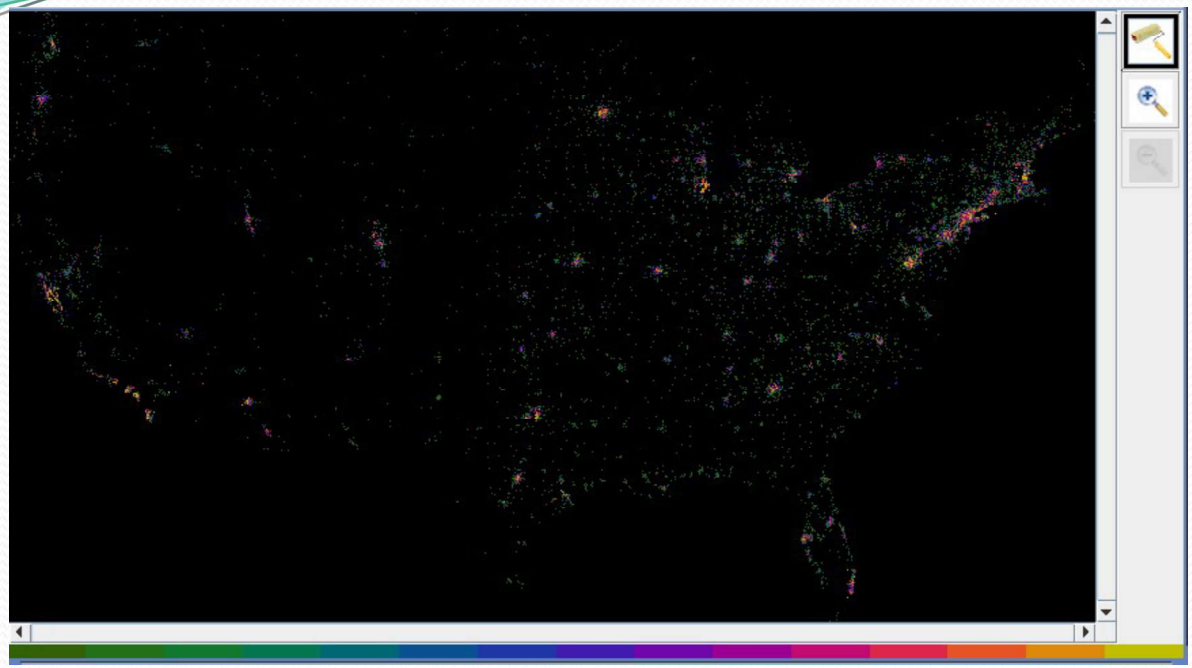
This implies that **different** density values will be **necessarily** represented by the **same** color code: to reduce the degradation the mapping is performed through an algorithm that tries to assign to each code the same number of pixels



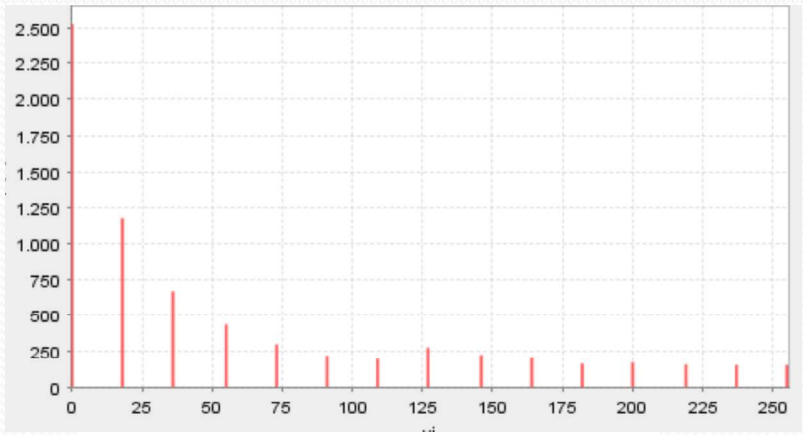
Target color code frequency distribution

uniform scale mapping

$$ColorCode(d_j) = DistributePixels$$



Because of densities are discrete the algorithm cannot ensure the N_{AP}/N_L value and through a peak analysis it minimizes the variance



Color code frequency distribution

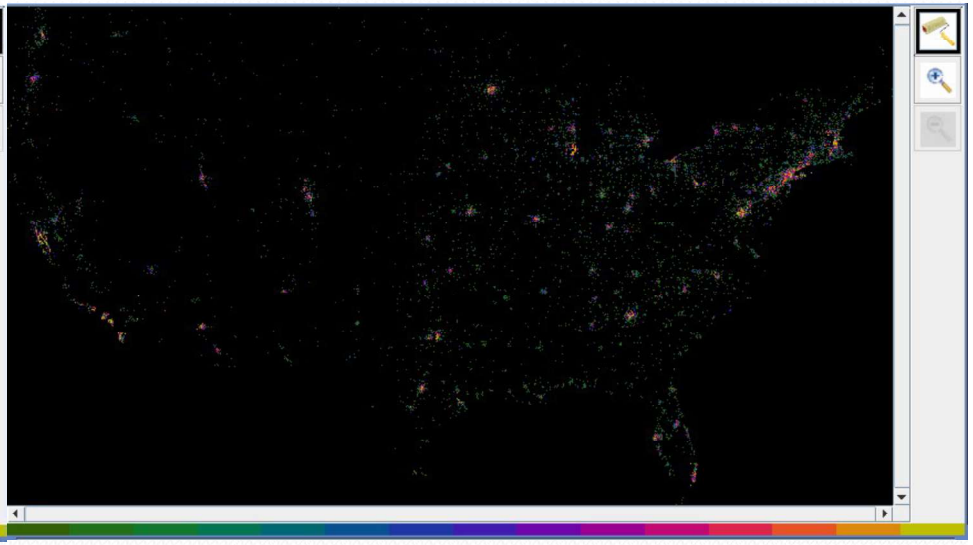
- Full color scale usage [0..255]
- All the color codes are used
- Maximum color code separation

Visual comparison

Linear mapping

Density function mapping

One to one mapping



Uniform scale mapping

Metrics

1. **C**olo**S**cale**U**sage: How many color codes is the mapping using?
2. **C**olor**S**cale**A**ctive**R**ange: What part of the color scale range is the mapping using?
3. **C**olor**S**eparation: How distinguishable are the used color codes?

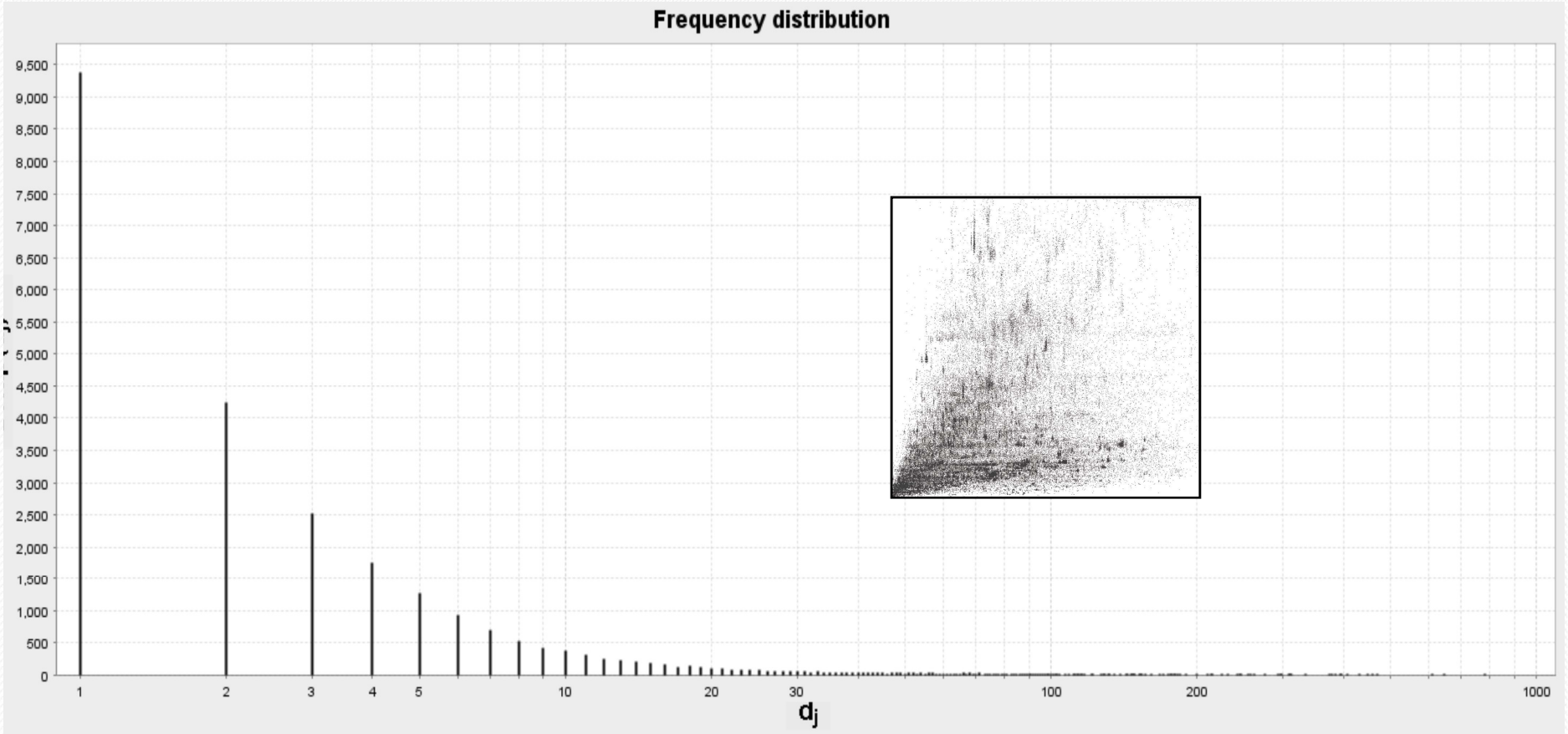
$$CSU = \frac{N_{UL}}{\min(N_{DV}, N_L)}$$

$$CsAR = \frac{C_{N_{UL}} - C_1}{C_{\max} - C_{\min}}$$

$$CS = \frac{\sum_{i=2}^{N_{UL}} (c_i - c_{i-1})}{N_{UL} - 1}$$

Postal parcels plotted by weight (x) and volume (y)

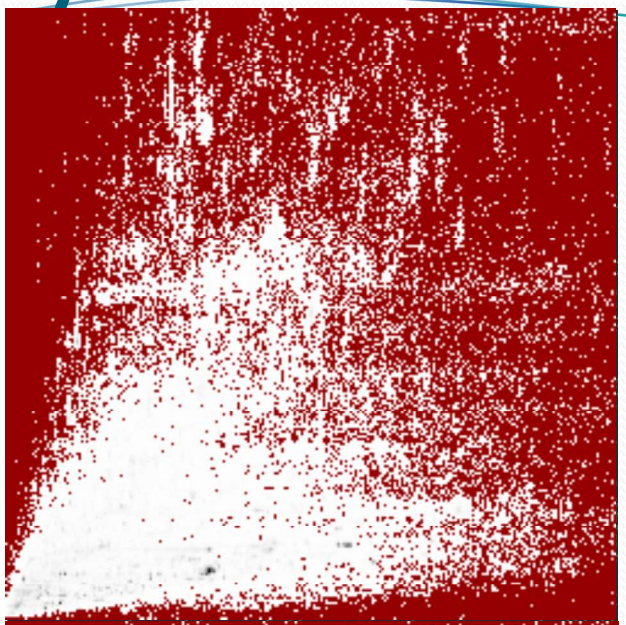
A new dataset



Grey scale

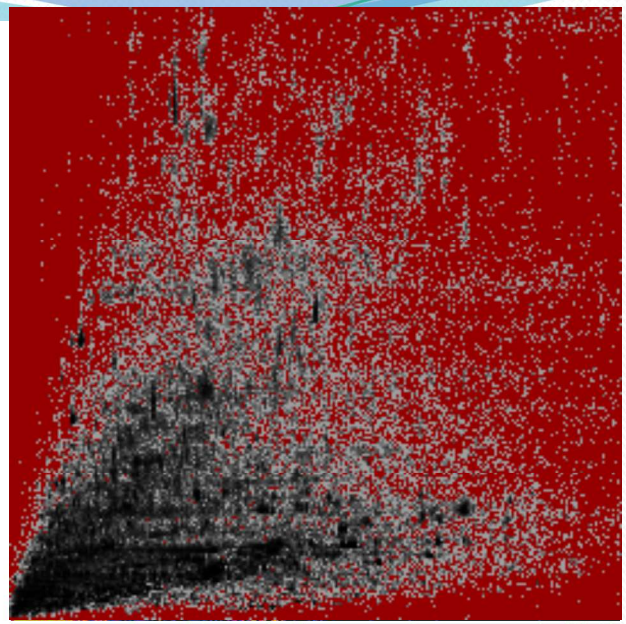
Linear

CSU=0.53
CsAR=1
CS=2.83



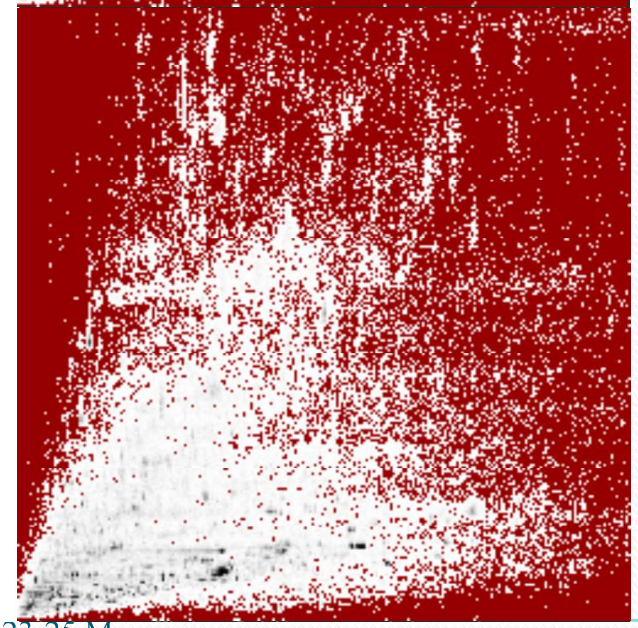
Density Function

CSU=0.18
CsAR=0.62
CS=5.23



One 2 One

CSU=1
CsAR=1
CS=1.47



Uniform color sc.

CSU=1
CsAR=1
CS=8.79