Classification-Based Browsing for Image Databases

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Image Search

The number of digital images is quickly increasing:

- World Wide Web
- Digital camera
- Mobile phones

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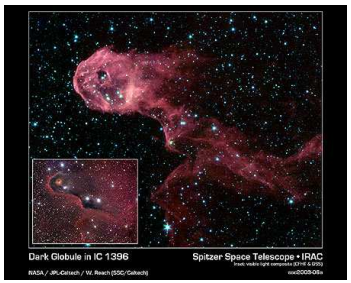
Such image collections need to be **organised** *in order to be* **retrieved** *efficiently*

Applications

- Private photograph collections (on a regular computer or a mobile device)
- Image providers catalogues
- Specialised image banks (astronomy. . .)

PHOTOGRAPH

ECOGRAPHY (MEDICAL IMAGE)



SPACE PHOTOGRAPH

SATELLITE IMAGE

Image Specificities

- *Multimedia* suggests the use of different kinds of data together...
- ...However we use it for *non-classical* data

Image Specificities

- *Multimedia* suggests the use of different kinds of data together...
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Multimedia Data

- Can not be normalised
- Variable information density
- Information depends on the observer

Problem & Goal

Problem:

- Images are difficult to describe.
- Most people do not want to take the time to annotate their images.
- Proposals based on retrieval are difficult for users.

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Goal

Build a proposal of **image search by navigation** to complement image retrieval. It should be:

- **Easy to use:** the user interaction should be mainly mouse clicks.
- **Fast and responsive:** the user should not have to wait for the results.
- **Scalable:** it should be applicable to large collections.

Part I

State of The Art

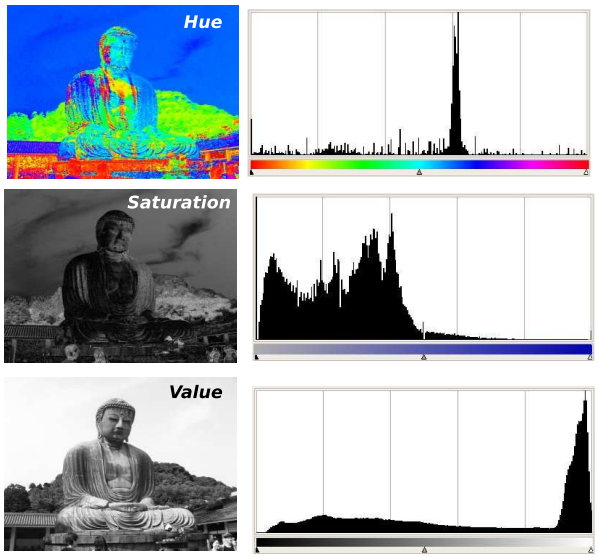
Outline

Outline

Content Information vs. Annotations

Content Information vs. Annotations

Content Information



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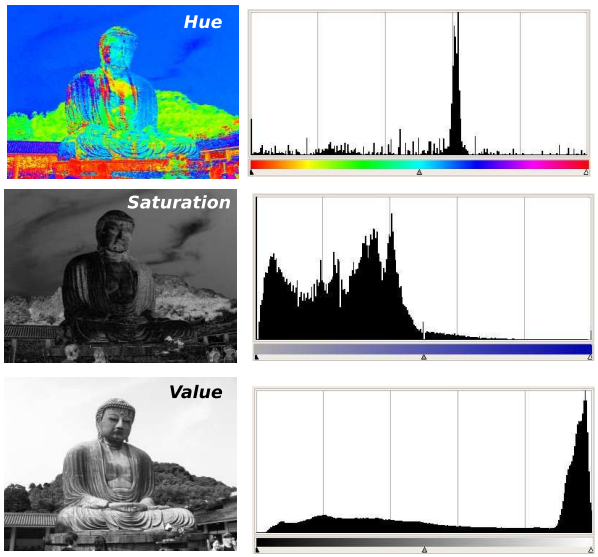

Annotations

- Buddha
- Kamakura
- Japan
- Monument

Content Information vs. Annotations

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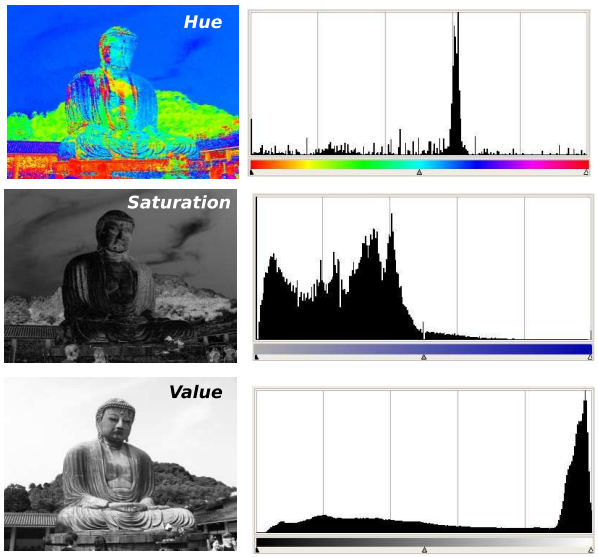

◯ Objective, automatic
× Semantic gap

Annotations

- Buddha
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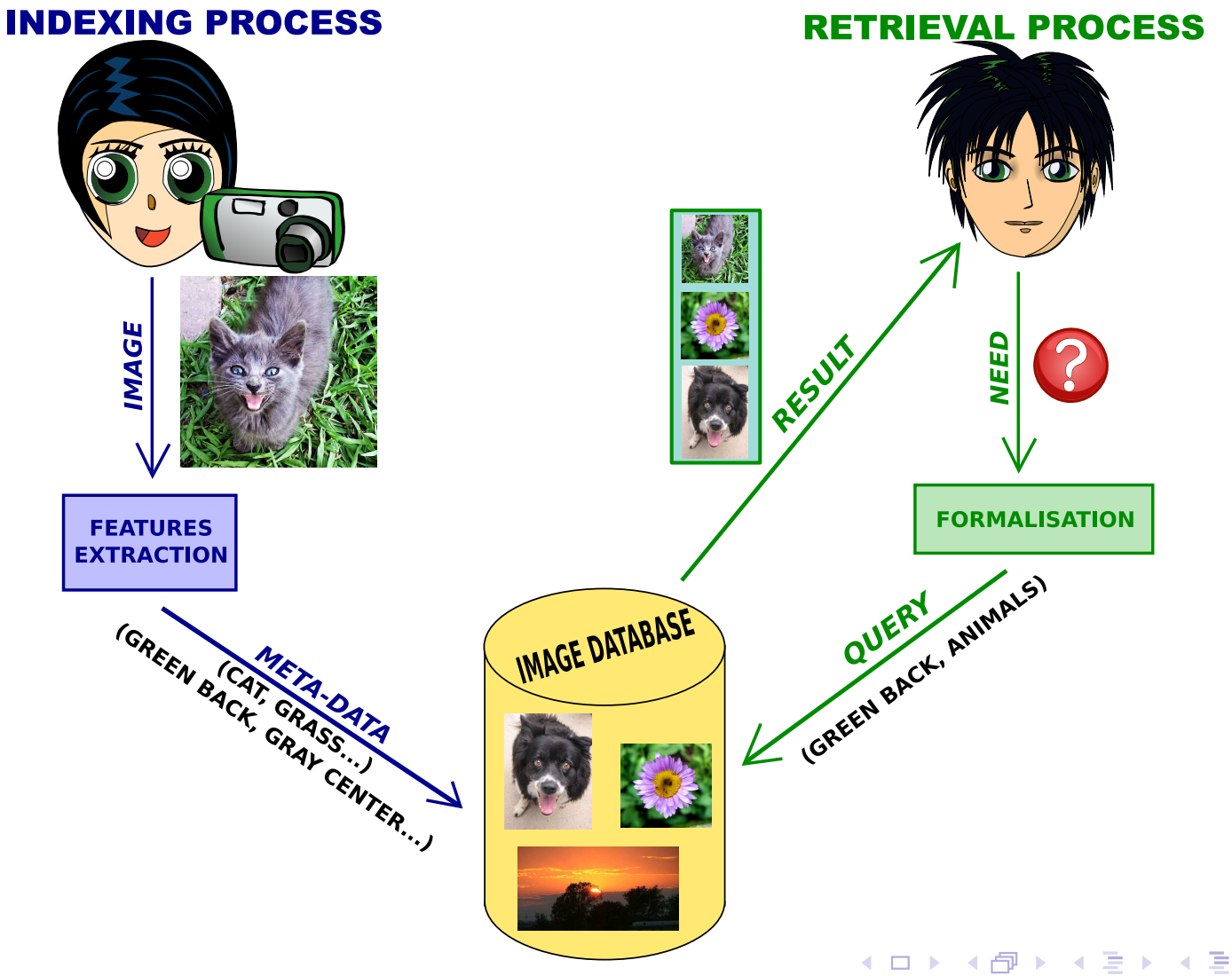
◯ Good semantics
× Subjective, manual
(→ cost)

Outline

Image Retrieval in a Nutshell



Defining the Search

Different kinds of search methods (not an exhaustive list):

- Retrieval
  - Formal queries
  - Similarity search
  - Queries with relevance feedback
- Navigation

Formal Queries (Chabot, by Ögle & Stonebraker)

```
RETRIEVE (q.all) FROM q IN photocd_bib WHERE
    q.shoot_date$>$"Jan 1 2000" and
    MeetsCriteria("MostlyBlue",q.histogram) and
    MeetsCriteria("SomeWhite",q.histogram)
```

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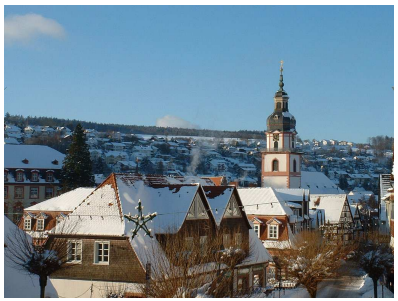

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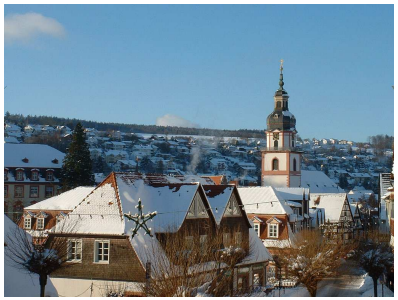
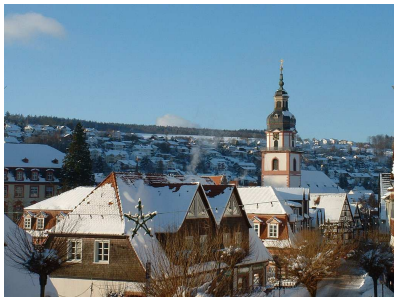


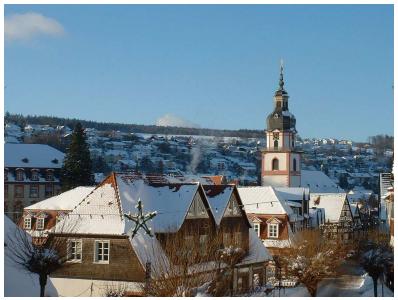
Problem: who is able to write this kind of query?

Similarity Search - Sample Image

Similarity Search - Sample Image



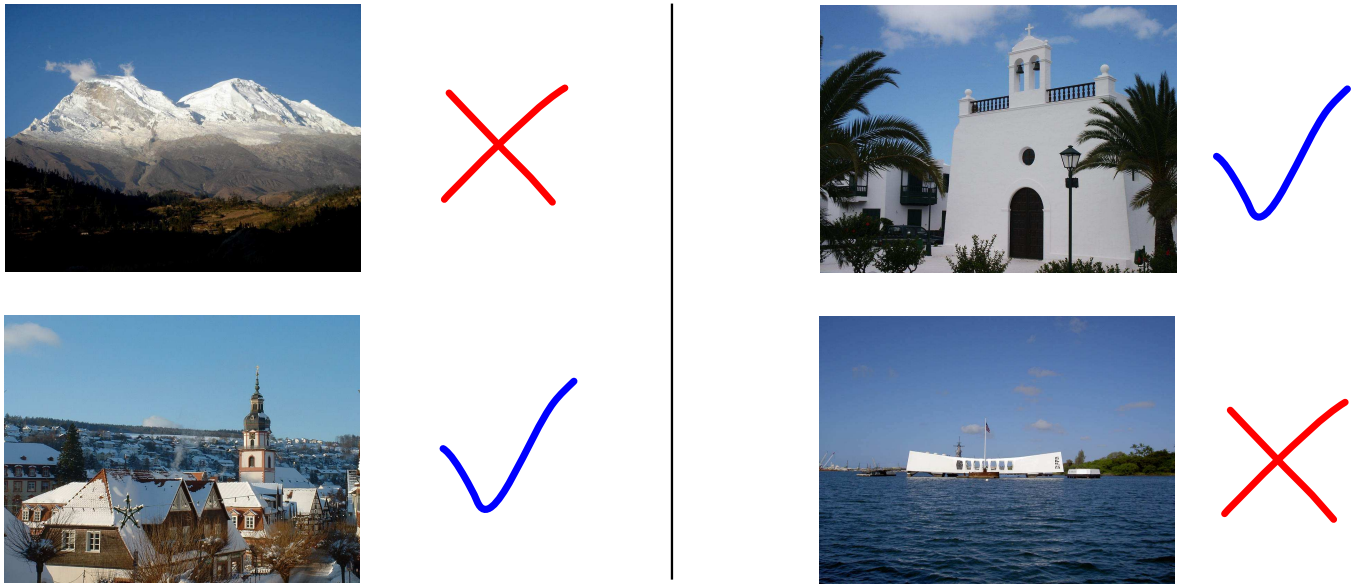
Similarity Search - Sample Image



Problem: usually, the user has no sample image.

Relevance Feedback

The user marks "good" images and "bad" images.



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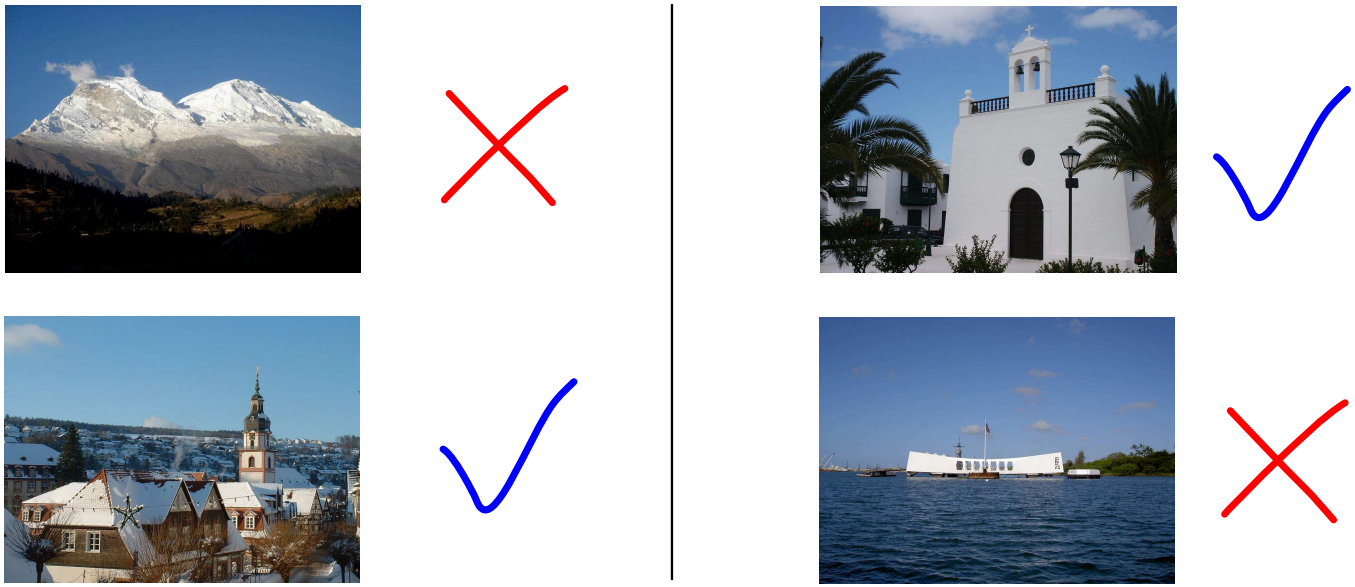
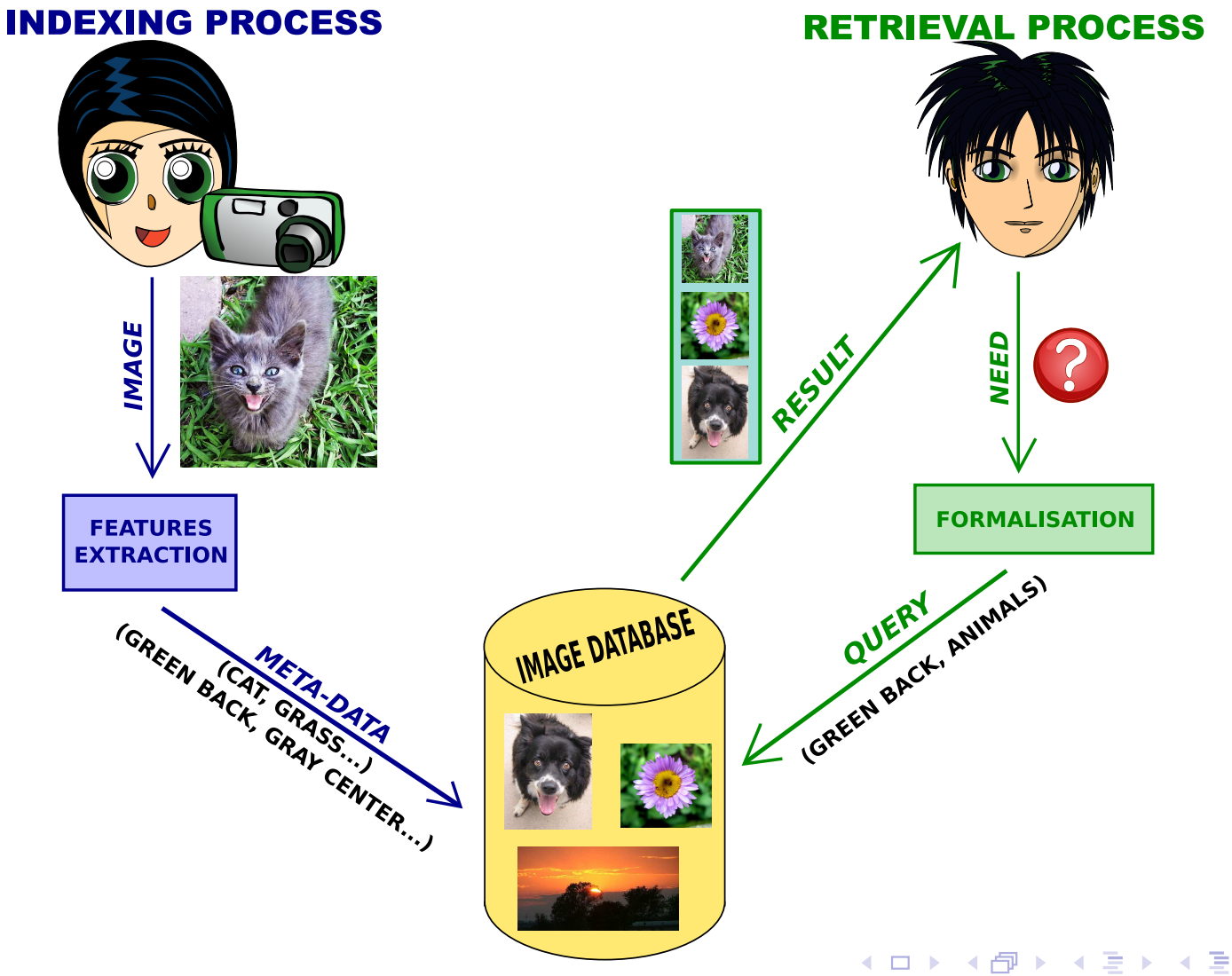


Problem: write a query that accepts all examples and reject all counter-example is known to be **NP-complete** .

Image Retrieval (Reminder)



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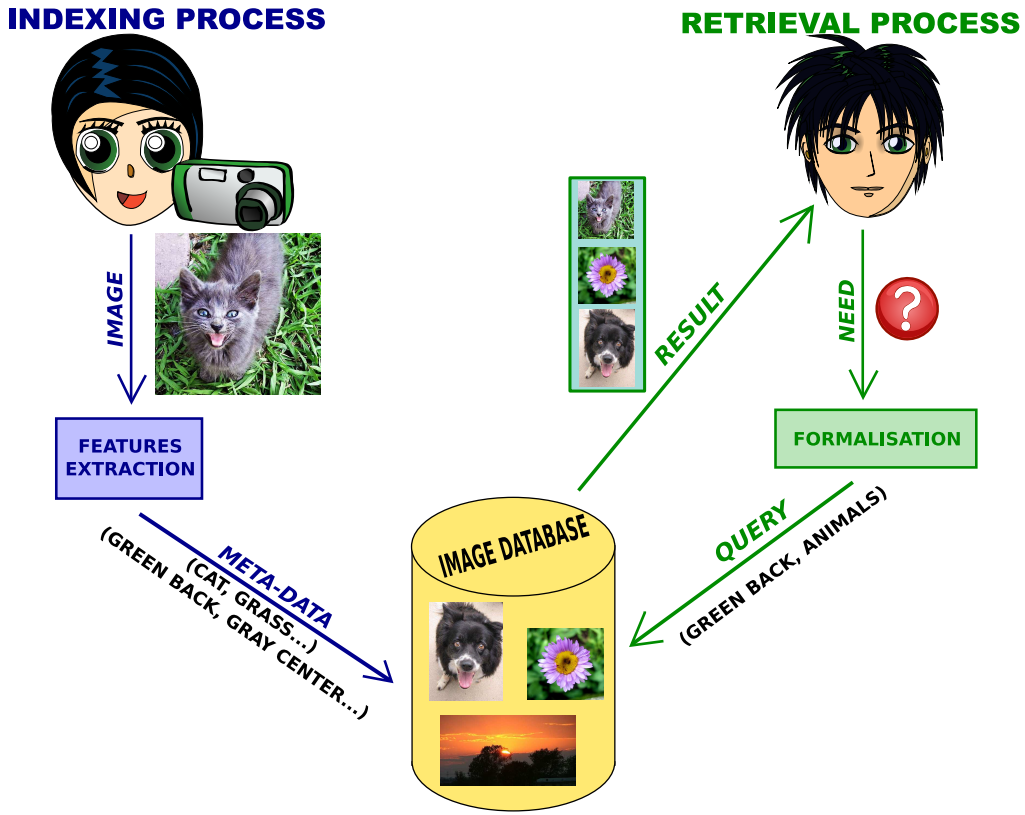
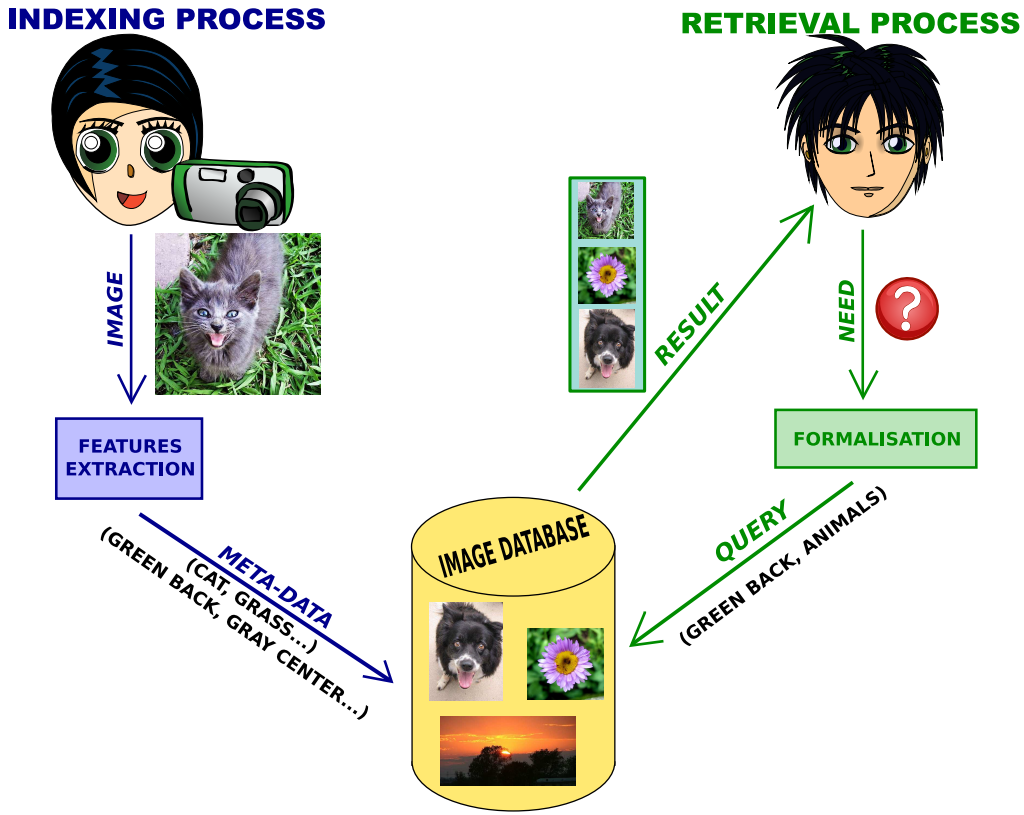


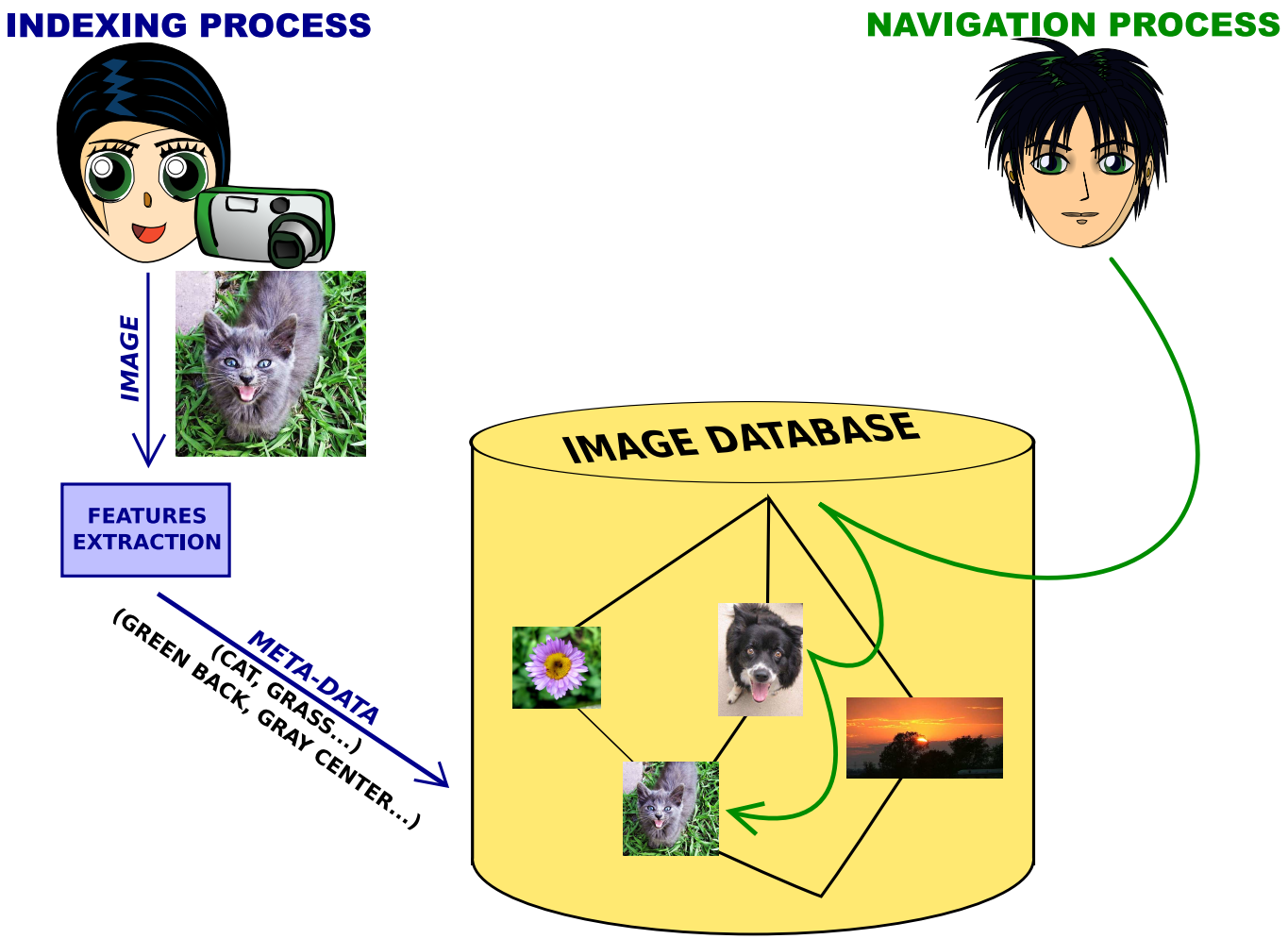
- *PROBLEM 1*: Formalisation is not trivial.
- *PROBLEM 2*: Query processing can be costly.

Image Retrieval (Reminder)



- *Assumption*: There are **few insertions**.
- *Assumption*: There are **a lot of searches** (at best $O(log(n))$).

Why Navigation?



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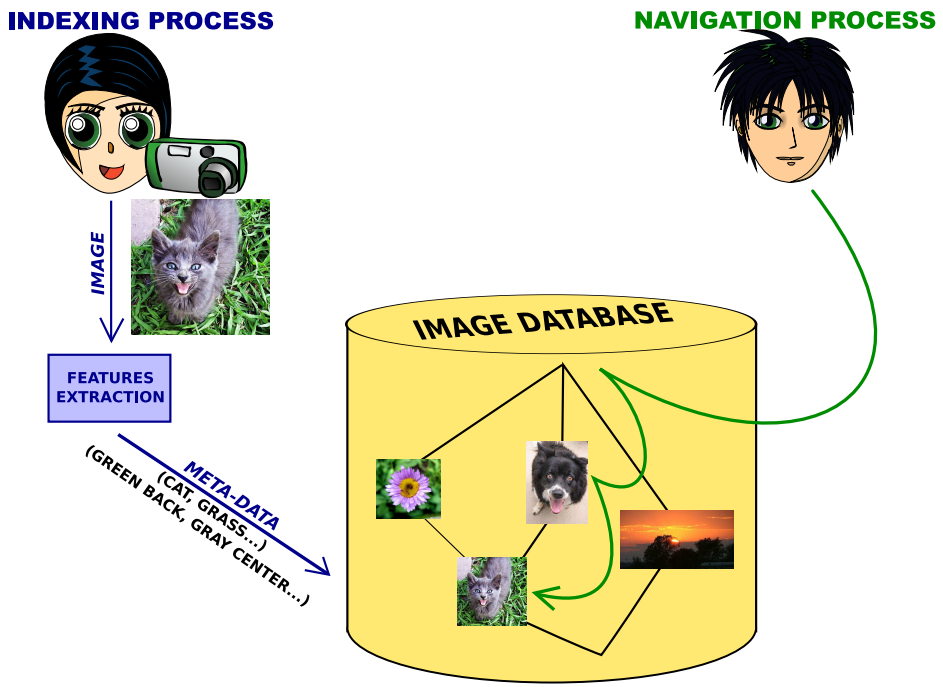


The cost of insertion is higher, but:

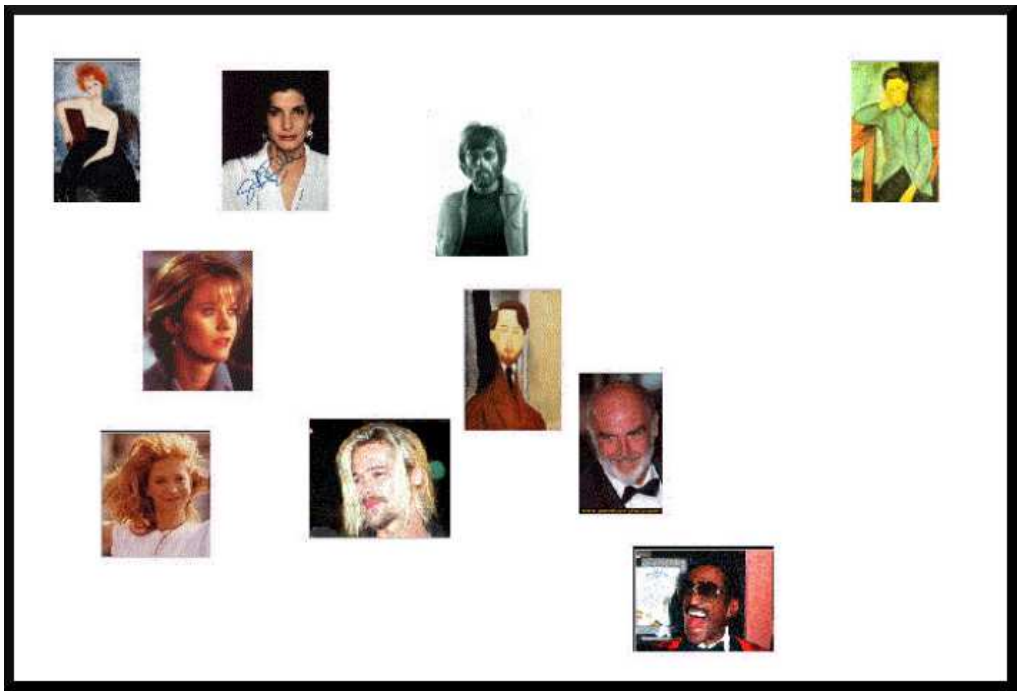
- *NO FORMALISATION PHASE*: Easy for the user.
- *NO QUERY PROCESS PHASE*: Quick and responsive.

Previous Work linked to Navigation

There are few proposals on navigation. It can still be compared to:

- Show the images on a map, according to location only (Geobloggers. . .): *Limited to place.*
- Combine the place and the time space into *events*: *Use only two dimensions is limited.*
- Organise the images on a virtual space according to content similarity (Santini's El Niño. . .): *Based on retrieval → long processing time.*

A Modigliani's Painting with Similar Images (Santini)



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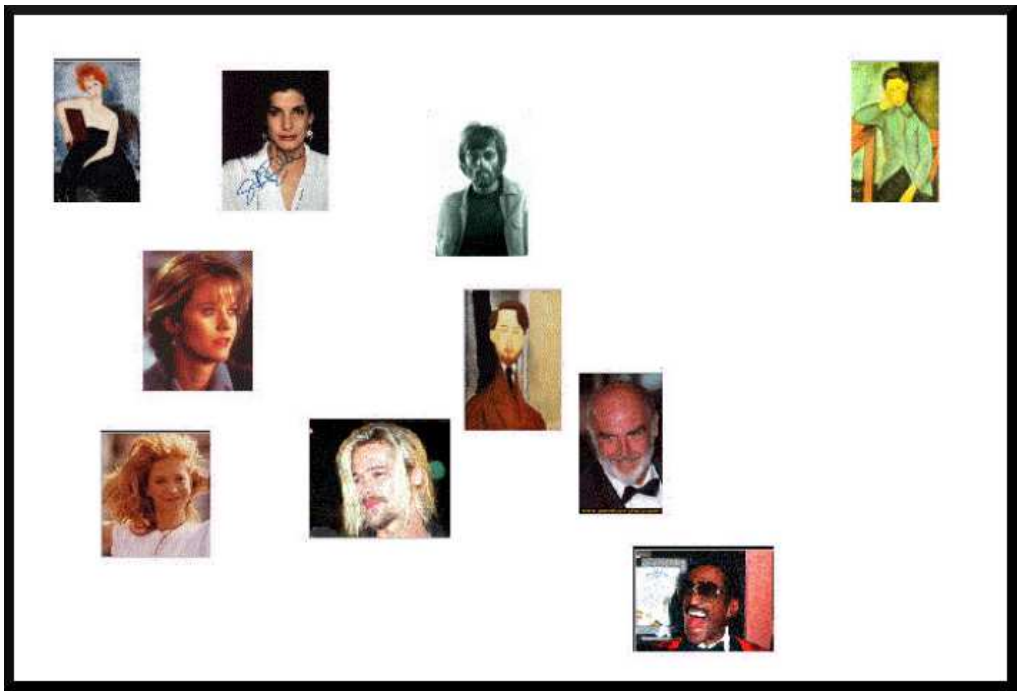

PROBLEM: Based on retrieval, with a costly query process.

Part II

Efficient Structures for Navigating an Image Collecti

Outline

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Goal

Provide a system for navigation-based image search.

- Define a metamodel to describe images.
- Define a navigation structure for the user.

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- Define a metamodel to describe images.
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Objectives

- Metamodel:
  - **Low cost:** the metrics should be fast to process.
  - **Match human perception:** the metrics should have a meaning for a human observer.
- Navigation:
  - **Easy to use:** the user interaction should be mainly mouse clicks.
  - **Fast and responsive:** the user should not have to wait for the results.

Work Domain

We restrict our study to "classical" photographs:

- Rectangular, with no transparency channel
- Colour images
- Excluding specific images, such as:
  - Medical images
  - Satellite images
  - Photographs of the space

Meta-Model Overview

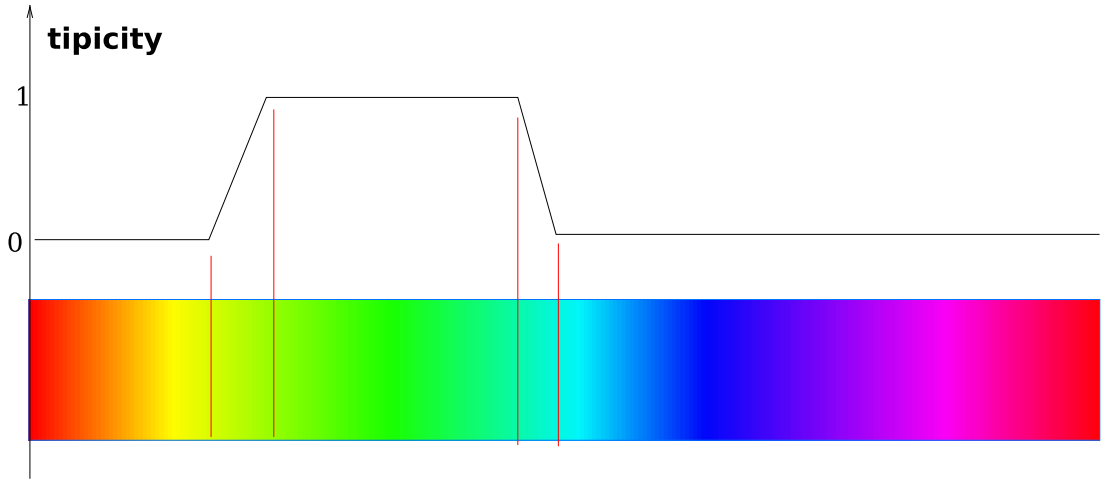
Our model is based on content information:

- Dominant colours for each part of a syntactical division (similar to the use of histograms, a fast to calculate metric)
- General geometrical measures (orientation, elongation and size)

Merits

- **Fuzzy logic** $\longrightarrow$ good representation of the human perception.
- **Syntactical division** $\longrightarrow$ more efficient than segmentation but still offers a good semantic separation.

Fuzzy Logic (the green label)



A fuzzy subset is defined by a *trapeze*. A fuzzy label is a description associated to a tipicity.

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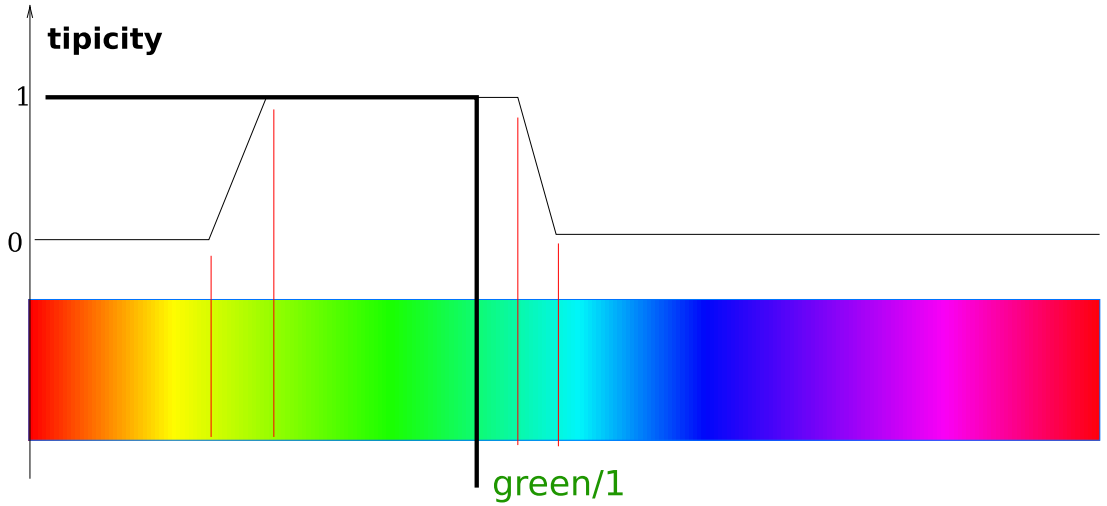

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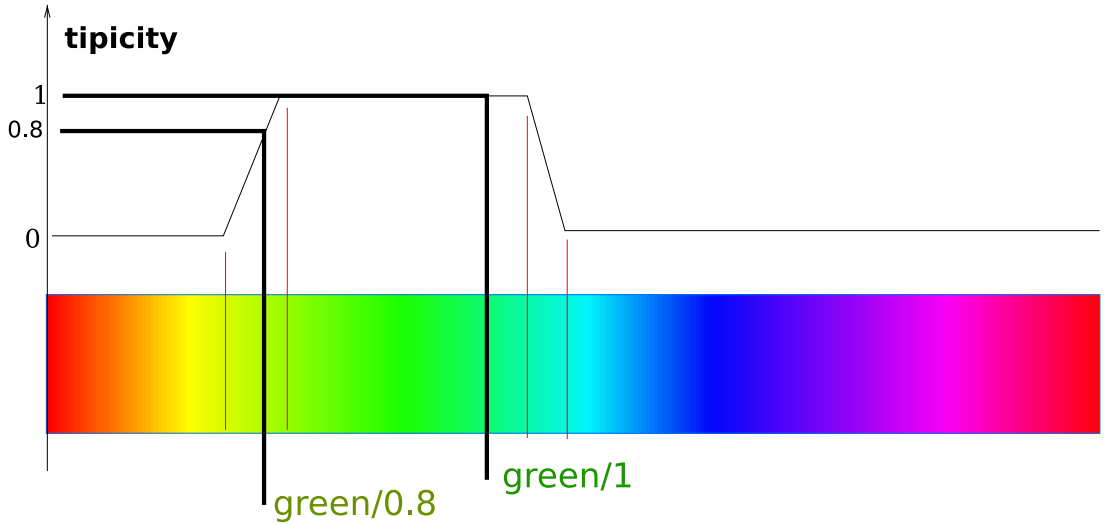

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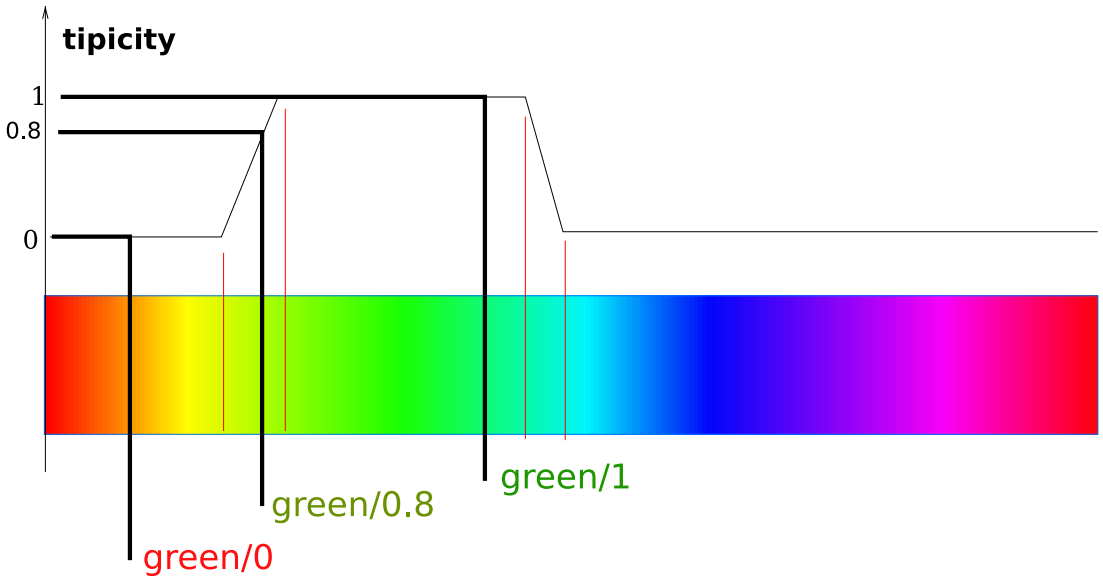

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- $green/1 \longrightarrow$ a green pixel.
- $green/0.8 \longrightarrow$ an *almost* green pixel.
- $green/0 \longrightarrow$ a *not* green pixel.

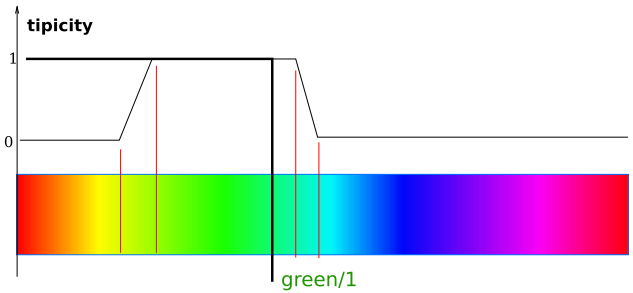
Segmentation of the Colour Space

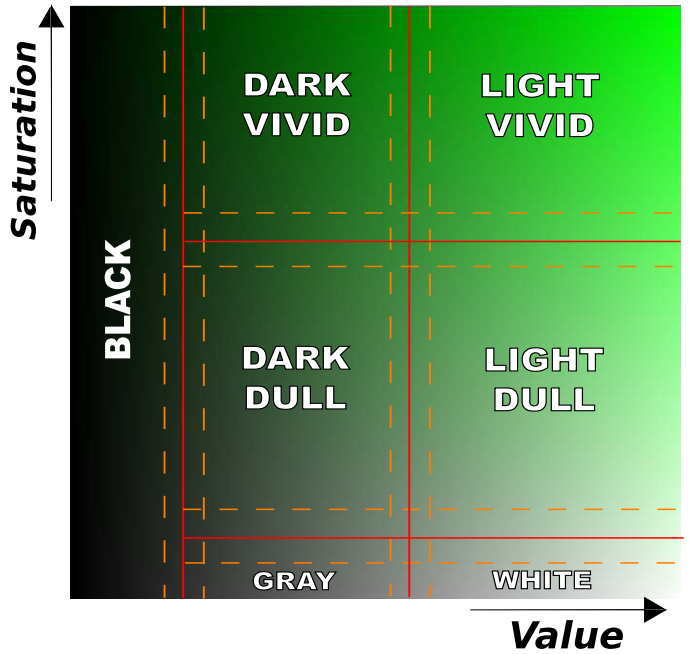
- We chose the HSV (Hue, Saturation, Value) model, each property makes sense for human observers
- 7 fuzzy subsets are defined on hue
- For a given hue, the saturation/value plan is divided into black, white, grey and 4 coloured parts

Examples of labels

- Black
- Light Desaturated Red *(i.e. "pink")*
- Dark Saturated Blue

Saturation and Value





Heuristic Segmentation

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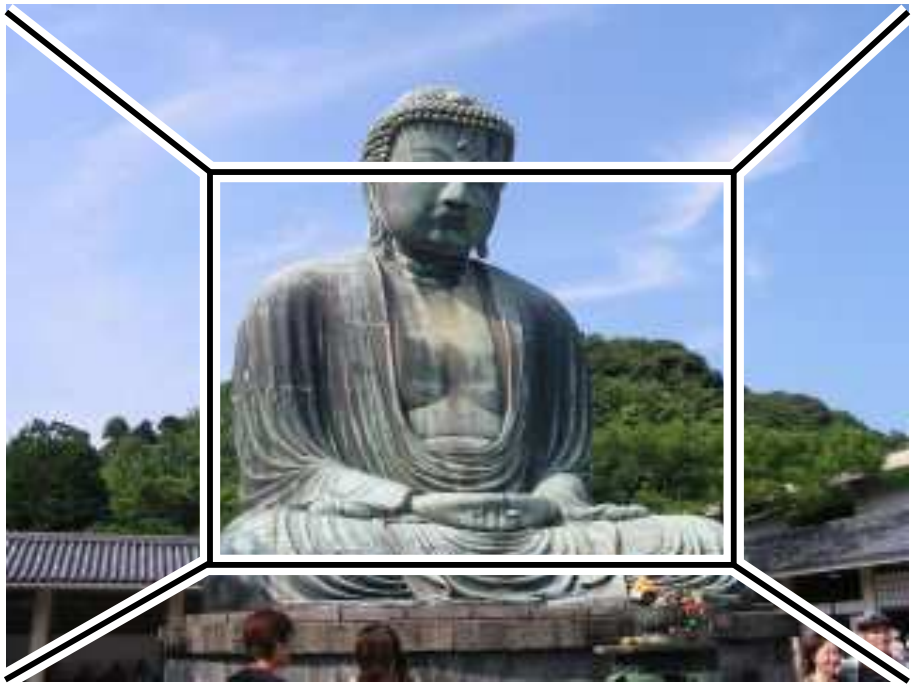
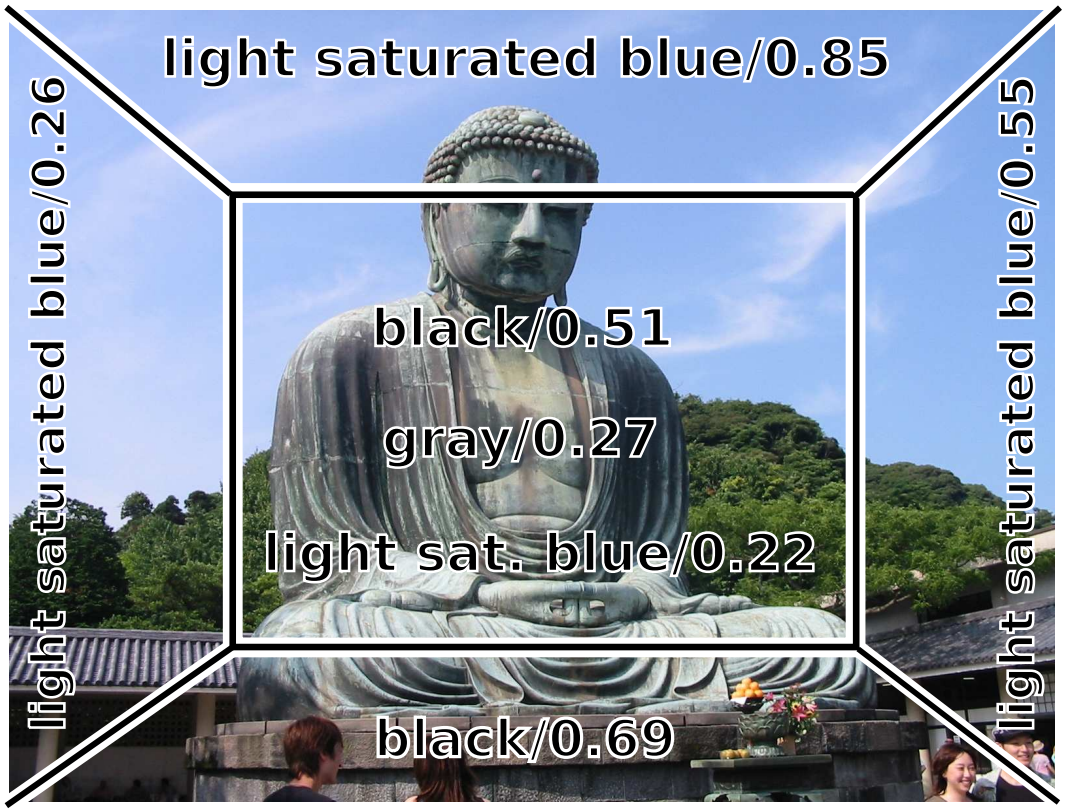


Used Properties

- $\mathcal{D}_{area} = \{tiny, small, medium, large, huge\}$
- $\mathcal{D}_{orientation} = \{portrait, square, landscape\}$
- $\mathcal{D}_{elongation} = \{none, standard, panoramic, elongated\}$
- $\mathcal{D}_{colour} = \mathcal{C} \times \{top, bottom, left, right, centre\}$

$\mathcal{C}$ being the set of colours defined as:
$\mathcal{C} = \{white, gray, black\}$
$\bigcup(\{red, orange, \ldots, cyan, magenta\} \times \{vivid, light\} \times \{dark, light\})$

Properties of the Big Buddha Photograph



+ landscape/1, standard/1, large/0.70, medium/0.30

Conclusions on the Metamodel

The metamodel we defined:

- **Has a low cost:** histograms are fast to calculate.
- **Match human perception:** the fuzzy division of the colour space and the syntactical division of the images gives good semantic measures.

Galois' Lattice

A *lattice* is a graph structure:

- Directed
- With no cycle
- Featuring a unique minimal node (no parents) and a unique maximal node (no child)

Galois' Lattice

A Galois' lattice is a special kind of lattice built from a binary relationship.

- Each node is a couple (images, properties) (I, P)
- If (I_2, P_2) is a child node of (I_1, P_1), then $I_2 \subset I_1$ and $P_1 \subset P_2$

Why choose Galois' Lattices?

Benefits for the user:

- The links between the nodes are semantic
  $\longrightarrow$ **understandable for the user**.
- the browsing is optimal (no calculation)
  $\longrightarrow$ **fast and responsive**.
- The user can go back very easily
  $\longrightarrow$ **helps to correct the users' mistakes.**

Benefits for the system:

- Can be used both as index and retrieval.
- Intrinsically a multi-dimensional classification technique.
- Insensitive to correlations.

Note: the high complexity of the construction algorithm limits us in the collection size (not adaptated to the world wide web).

Example (1/2)

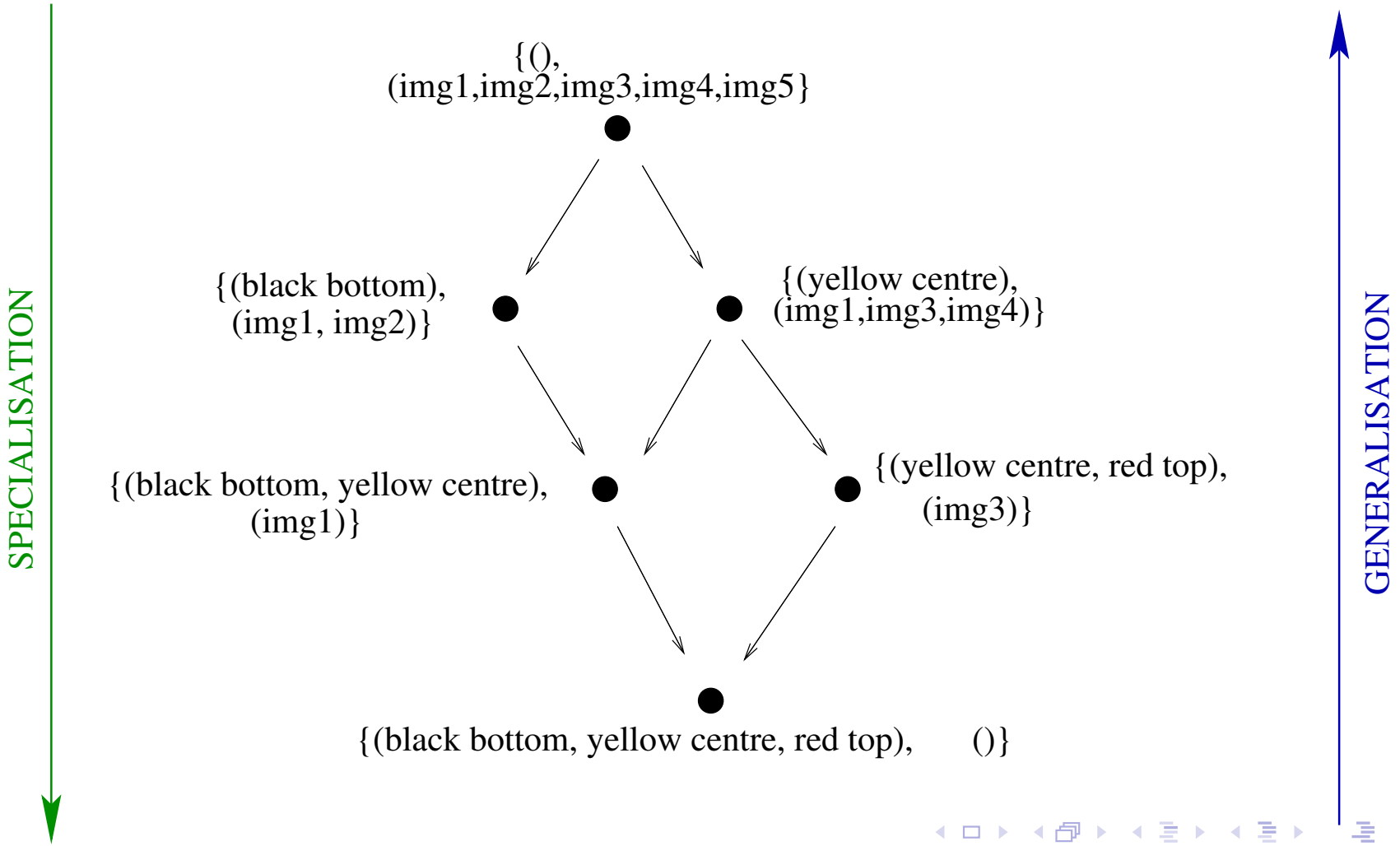
Consider the following images/properties relationship:

$$\begin{aligned} R = \{ \quad & (img_1, blackbottom), (img_1, yellowcentre), \\ & (img_2, blackbottom), \\ & (img_3, yellowcentre), (img3, redtop), \\ & (img4, yellowcentre) \qquad \} \end{aligned}$$

	*img*1	*img*2	*img*3	*img*4
blackbottom	1	1	0	0
yellowcentre	1	0	1	1
redtop	0	0	1	0

Example (2/2)

The associated Galois' lattice is:



A Bigger Lattice

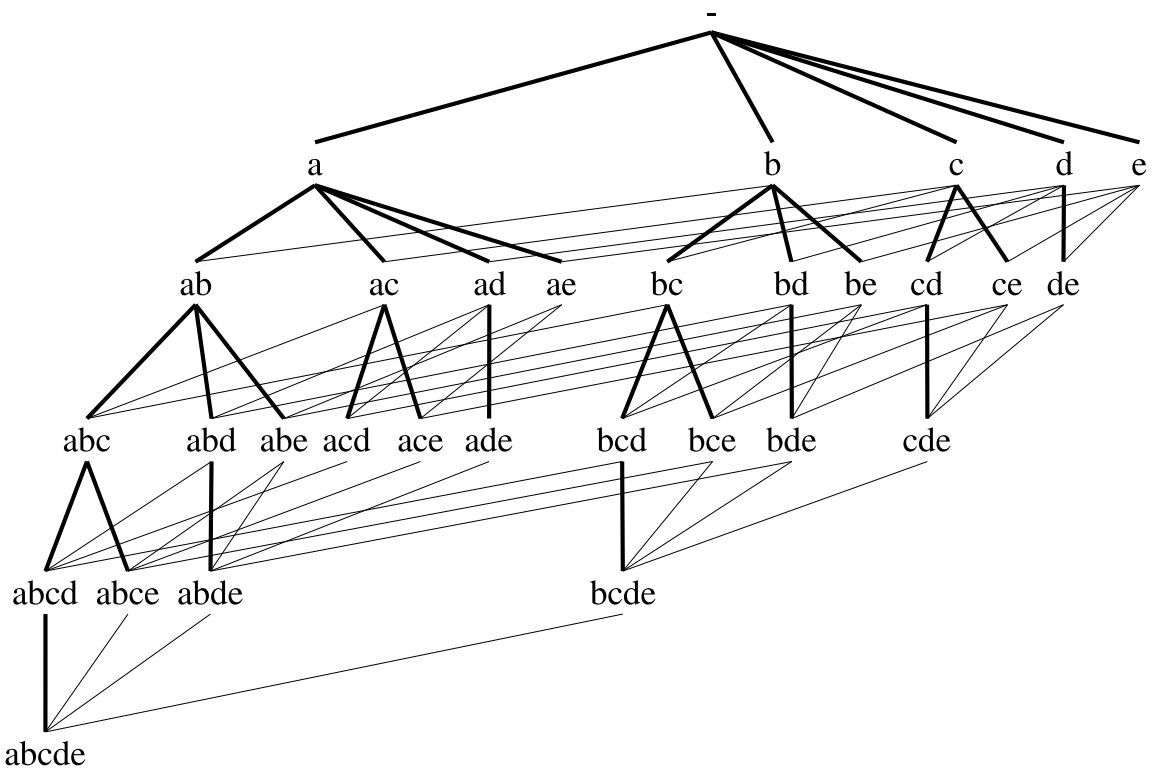


Figure: A bigger Galois' lattice

Constructing a Galois' Lattice

- We need an incremental algorithm
  - Godin et. al published such an algorithm in 1995

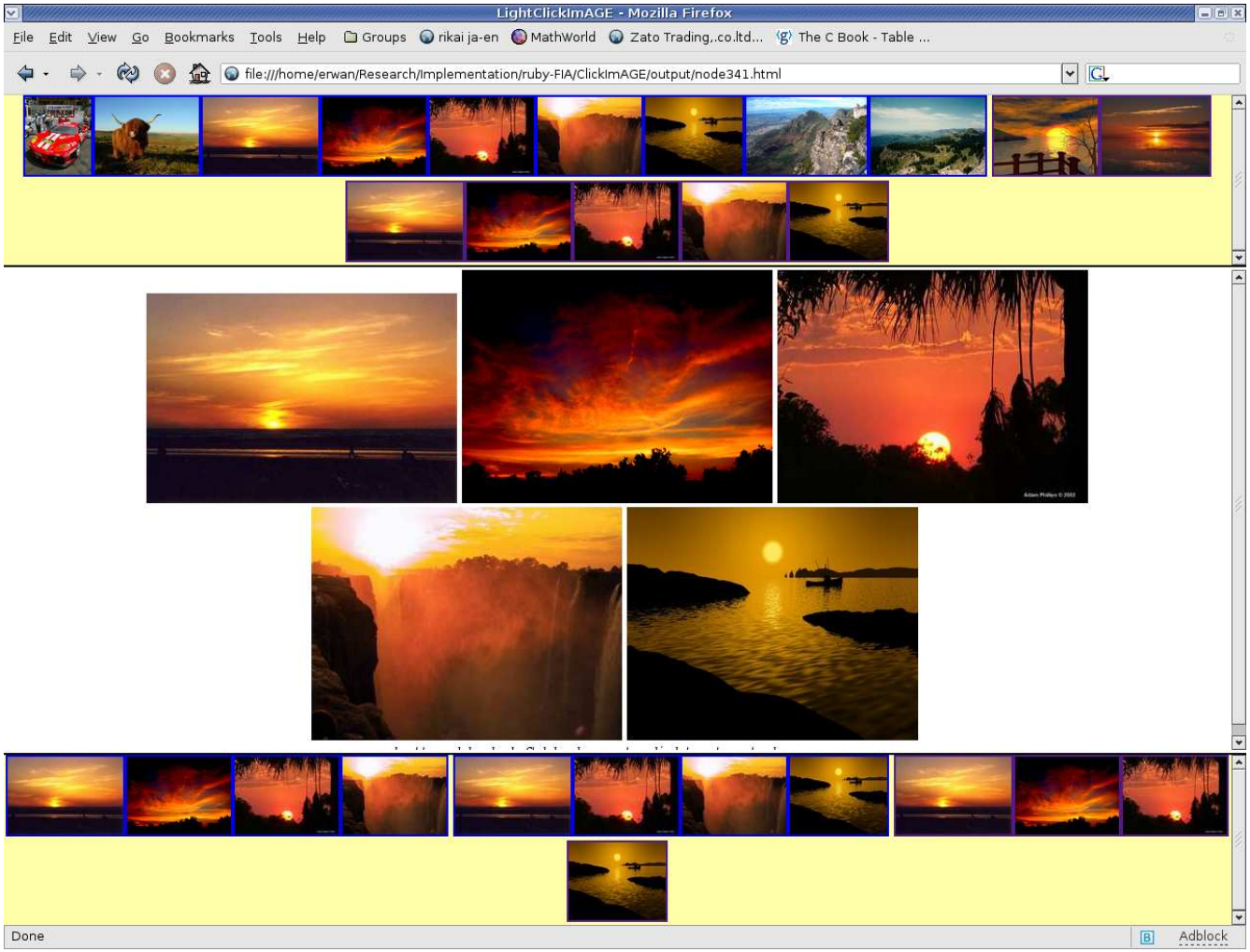
Complexity:

- Time complexity *in the worst case*: exponential (e^n) with respect to the total number of images
- Empirical average time complexity:
  - Add an element: $o(n)$ with respect to the initial number of images
  - From scratch: $o(n^2)$ with respect to the total number of images
  - For large dataset: the limit is known to be $n.log(n)$.

Hypermedia Representation (User-Interface)

- The lattice is built on an images-descriptions binary relationship;
- For each node, a detailed representation and a quick representation is defined;
- Each node is represented as an hypermedia page (XHTML)
- The user can browse the resulting set of web pages to find the image he/she is looking for

User Interface



Data Set

About 5,000 images, extracted from Flickr (http://flickr.com) using some of the most popular tags: *art*, *city*, *flower*, *party*, *sunsets*, *travel*, *birthday*, *dog*, *snow*, and *nature*.

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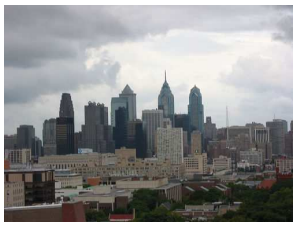


CITY

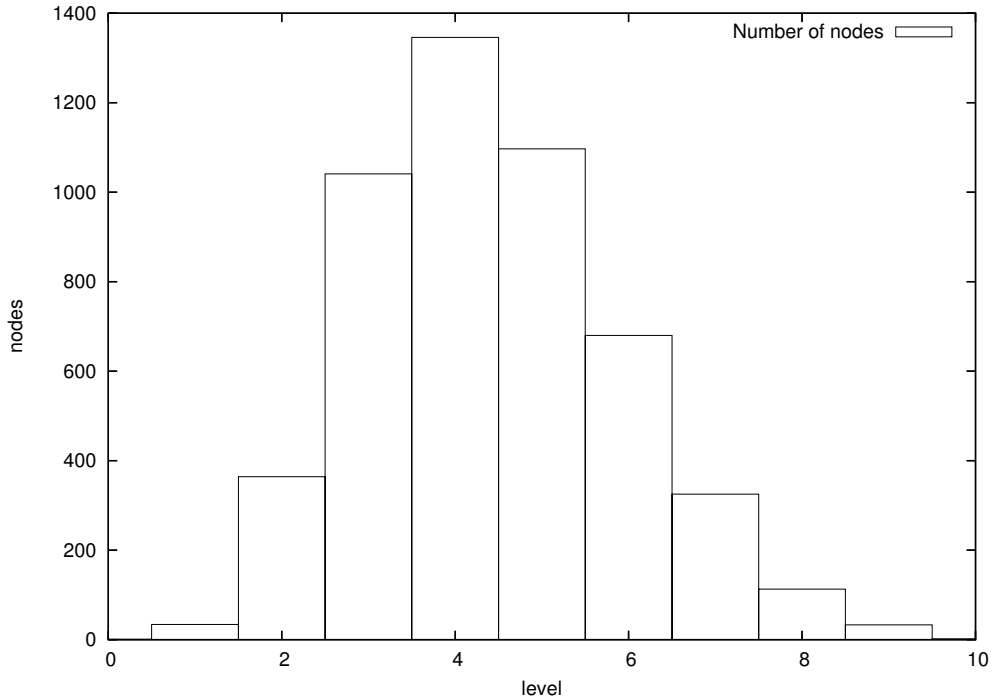
SNOW

FLOWER

DOG

SUNSET

Statistics on the Resulting Lattice



Number of nodes by level (level n = n properties).

Conclusion

Several advantages:

- **Easy to use**, since there is no query formalisation phase.
- **Very fast to navigate** through a graph structure that has been computed off-line (no calculation, optimal).
- It is insensitive to correlations.
- It helps to correct the users' mistakes very easily.

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But drawbacks:

- The time complexity of the construction algorithm is $O(n^2)$ $\longrightarrow$ scalability problem.
- A local explosion of the number of nodes may appear.

Outline

Problem Definition

- Regarding the complexity ($O(n^2)$) of the construction algorithm, to build a lattice with more than about 10,000 images would be very long.
- Additionnally, such a lattice would be too big to be browsed comfortably by the user.
- However, there are databases much bigger than this (several millions for Corbis)

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Problem

Considering the scalability limits of Galois' lattices, can these graphs be useful for such large collections?

A Galois' Lattice of Clusters

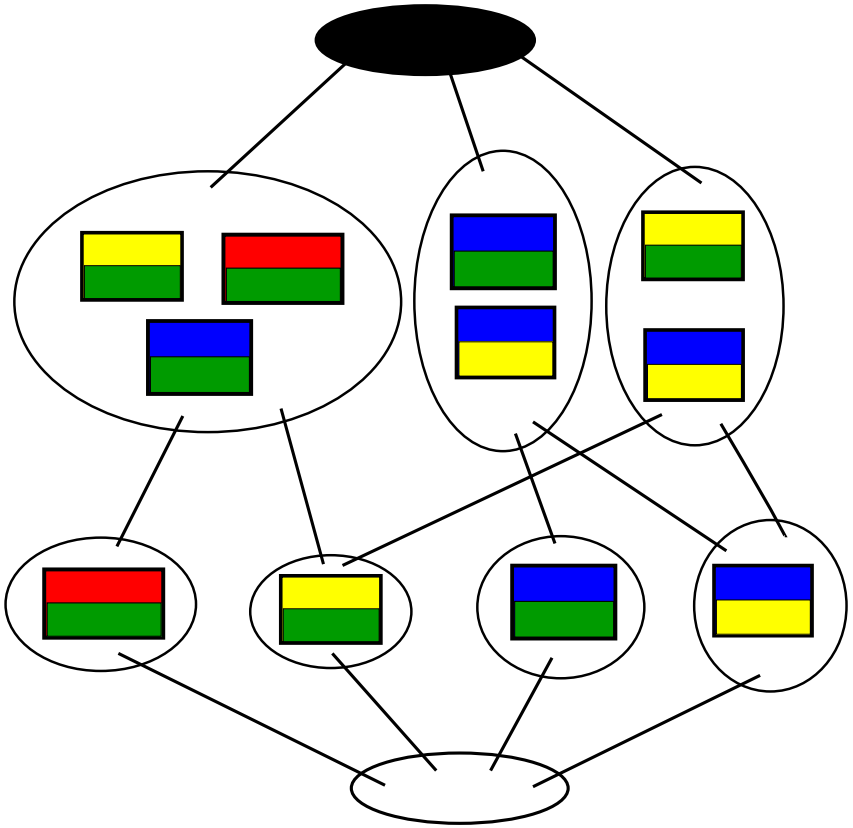
Associate a clustering technique to our Galois' lattice proposal.

1. The meta-data of images are calculated.
2. Images are organised into clusters of similar images (using a linear time complexity algorithm)
3. A Galois' lattice is built on the clusters
4. Navigation becomes on *two-levels*
   - inter-cluster navigation
   - intra-cluster navigation

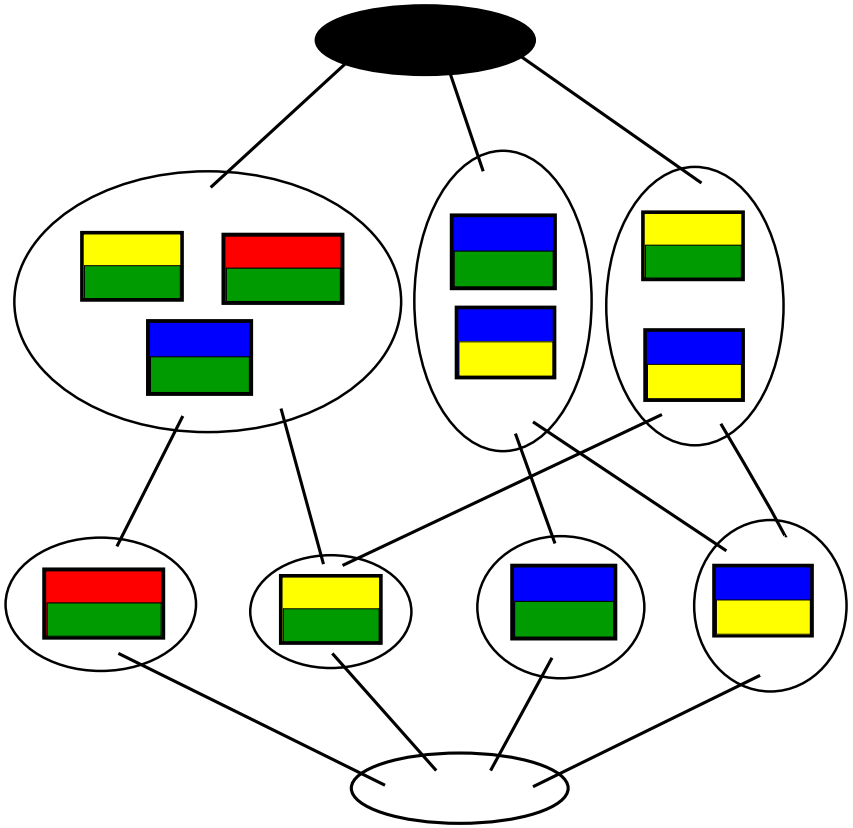
Benefits

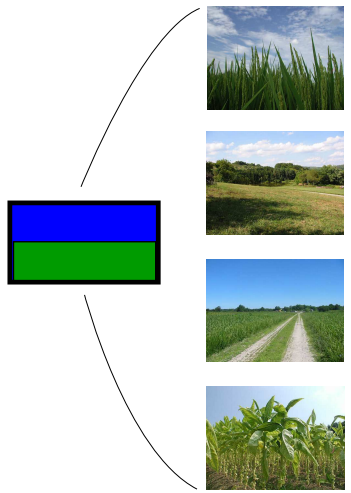
- Time complexity: square $O(n^2)$ $\rightarrow$ **linear** $O(n + \left(\frac{n}{C}\right)^2)$ (n for the clustering and $\left(\frac{n}{C}\right)^2$) for the lattice construction - with C number of clusters, $\left(\frac{n}{C}\right)^2 \ll n$.
- Images grouped by clusters $\rightarrow$ easier for the user to browse the collection.

A Navigation on Two Levels



A Navigation on Two Levels





The Clustering Technique

1. Based on the techniques of SaintEtiQ
2. Using the fuzzy descriptions detailed in previous part
   - *e.g.* $1.0/$*vivid dark green* $+ 0.8/$*vivid light blue*
3. A cluster hierarchy is built incrementally
   - from the most general (the *root*)
   - to the more specific (the *leaves*)
4. Each cluster is labelled using a notation similar to images
5. Linear time complexity ($O(n)$, results from SaintEtiQ)

The SaintEtiQ projet

- SEQ is a clustering project from Nantes University (France)
- It uses fuzzy logic to generate summaries of data (in the general case)
- Main authors:
  - Noureddine Mouaddib
  - Guillaume Raschia
  - Régis Saint-Paul
- G. Raschia, N. Mouaddib, A fuzzy set-based approach to database summarization, *Int. Journal of Fuzzy Sets and Systems*, 129(2):137-162, July 2002
- http://www.simulation.fr/seq/ *(English)*

What is a Clustering?

Given a sequential presentation of tuples (images) and their associated descriptions, the main goals of concept formation are:

1. identifying clusters that group the tuples into categories;
2. defining an intentional description (i.e., a summary) that corresponds to each category;
3. organising these summaries into a hierarchy.

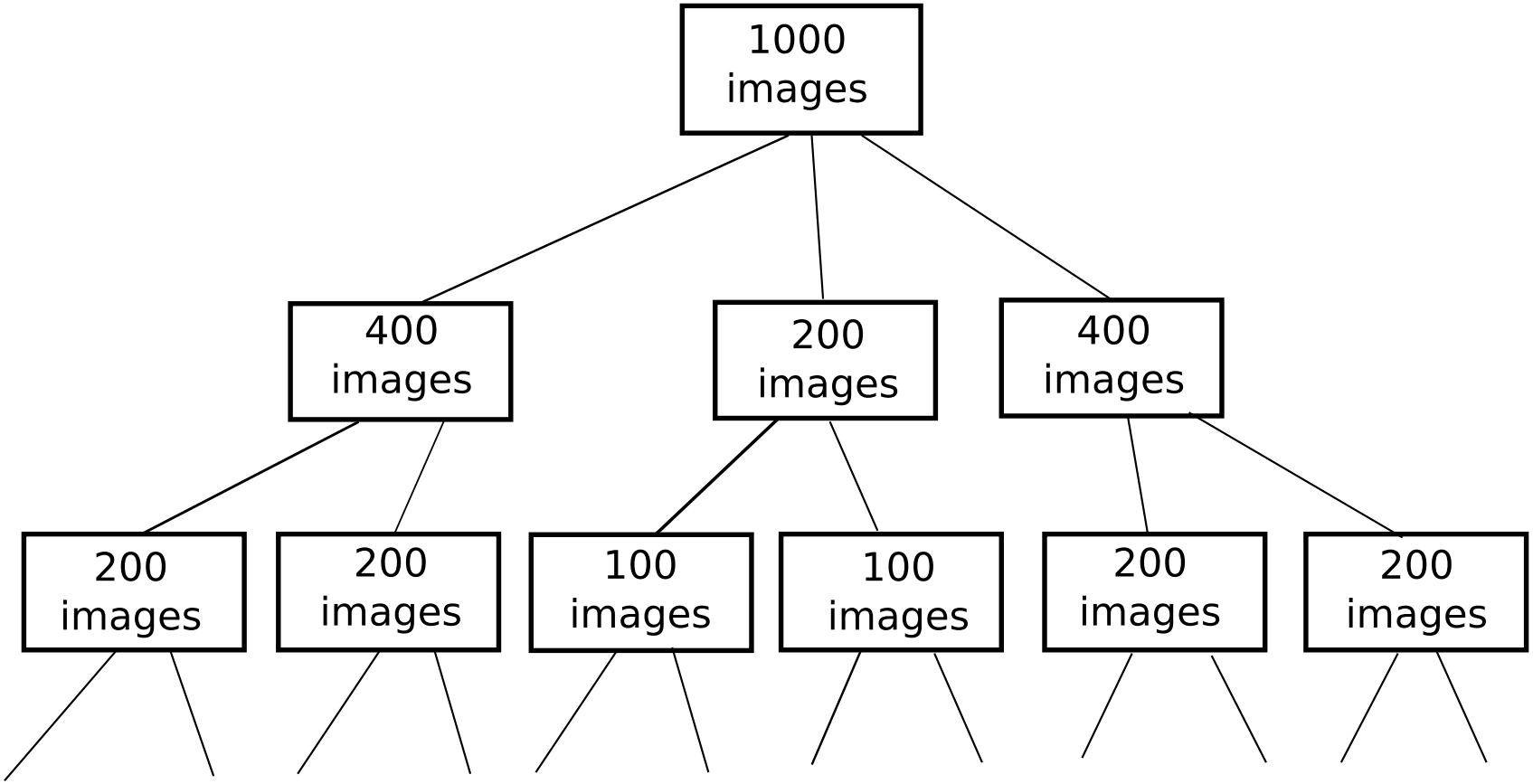
Additionally, in our case the learning is incremental.

Incremental Algorithm

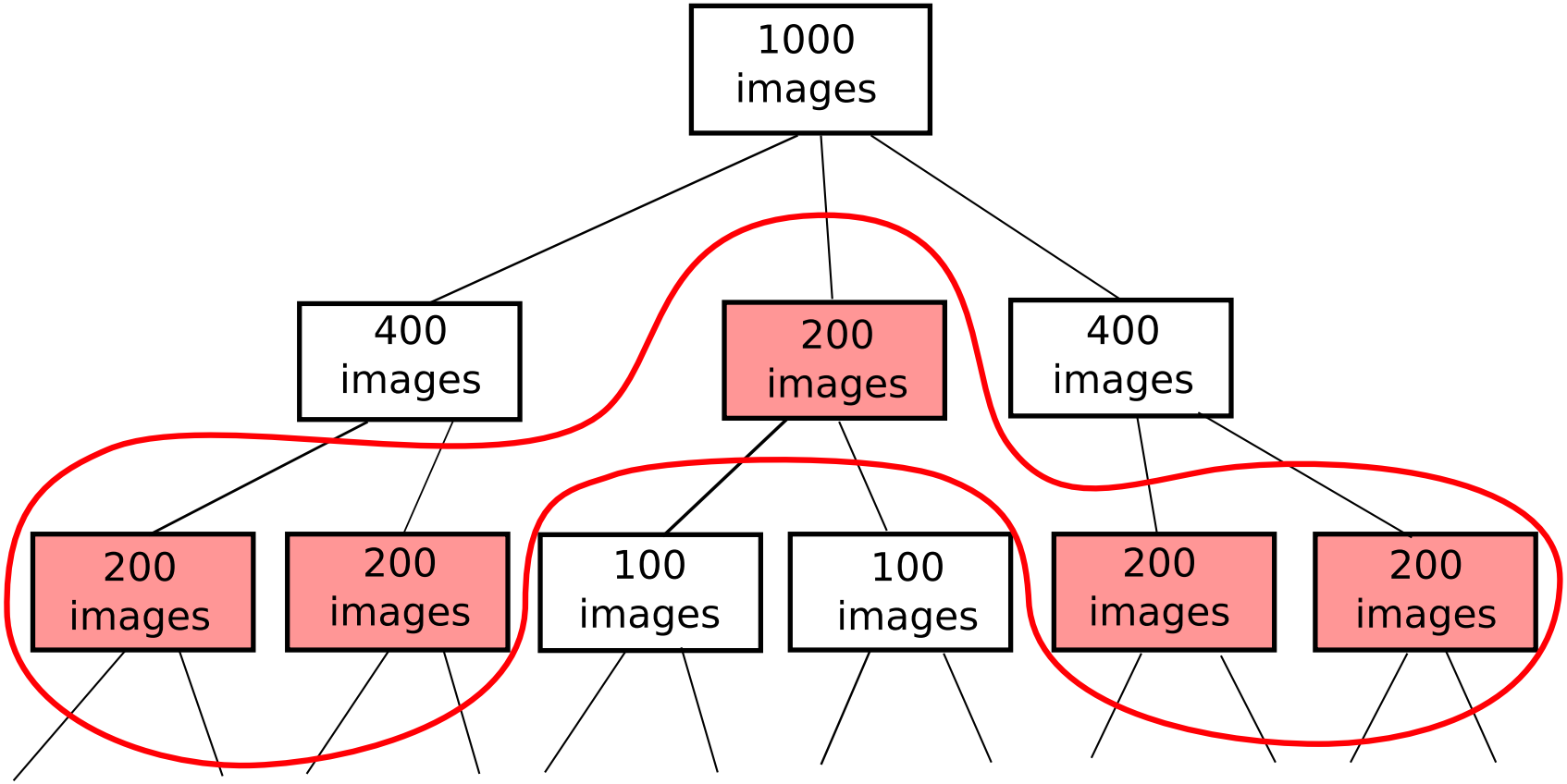
Inserting a New Tuple in the Cluster Hierarchy:

```
Insert(Node n, Image i)
  if n.children == [] // Leaf node
    add(n, i);
    return;
  else
    result = Match(n.children); // Ordered list
    if StrongMatch(i, result[0]);
      Insert(result[0], i)
    else
      CreateNewNode(n, i);
    EvaluateSplitting(result[0]);
    EvaluateMerging(result[0], result[1]);
end of Insert;
```

Selecting Clusters for the Lattice Generation



Selecting Clusters for the Lattice Generation



Hypermedia Representation

From the user point of view, the navigation becomes *two-levels*.

- *Inter-clusters* navigation: similar to navigating a lattice of images.
- *Intra-clusters* navigation
  - The average cluster size is about 200 elements

We assume that a user can view about **50 thumbnails** on the same screen. Thus, for about **200 images** a navigation structure is not required.

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Problem

How to select the first 50 elements to present?

Algorithm

Selecting the best n representatives of the cluster z (recursive algorithm) for intra-cluster search:

```
Choose(n integer, z cluster) returns a set of images
  if (z content <= n) then
     return all z content
  else if (z is a leaf) then
     return n random samples
  else return for (each z_child) do
     Choose((n / number_of_children(z)), z_child )
end of Choose;
```

Conclusion

We associate a scalable clustering technique to our Galois' lattice approach.

- Time complexity for construction:
  square $O(n^2) \rightarrow$ **linear** $O(n + \left(\frac{n}{C}\right)^2)$ (n number of images).
- The two-levels approach makes navigation easier for the user.

We can provide a navigation structure for very large databases

Example

5,000 clusters of 200 images $\rightarrow$ 1,000,000 images

Outline

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- A Galois lattice being a multidimensional structure, naive approaches to modify it may be exponential.

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Goal

Provide the user an efficient way to personalise the structure to his needs.

(Feedback querying provides an answer, but the problem of query generation is NP-complete.)

Masking Lattices

We propose to provide **user-personalisation** by applying user-defined *masks*. The resulting lattice is called a **sub-lattice** of the Galois' lattice.

- During the retrieval process, the user selects either *elements* to mask or *properties* to mask.
- At any time, the user can ask for calculation of a *lattice mask*.

Benefits

- *Efficient way to provide user-personalisation.*

Processing is done before-hand, on a sub-lattice each step's time complexity is $O(1)$. $\neq$ Feedback querying: NP-complete problem.

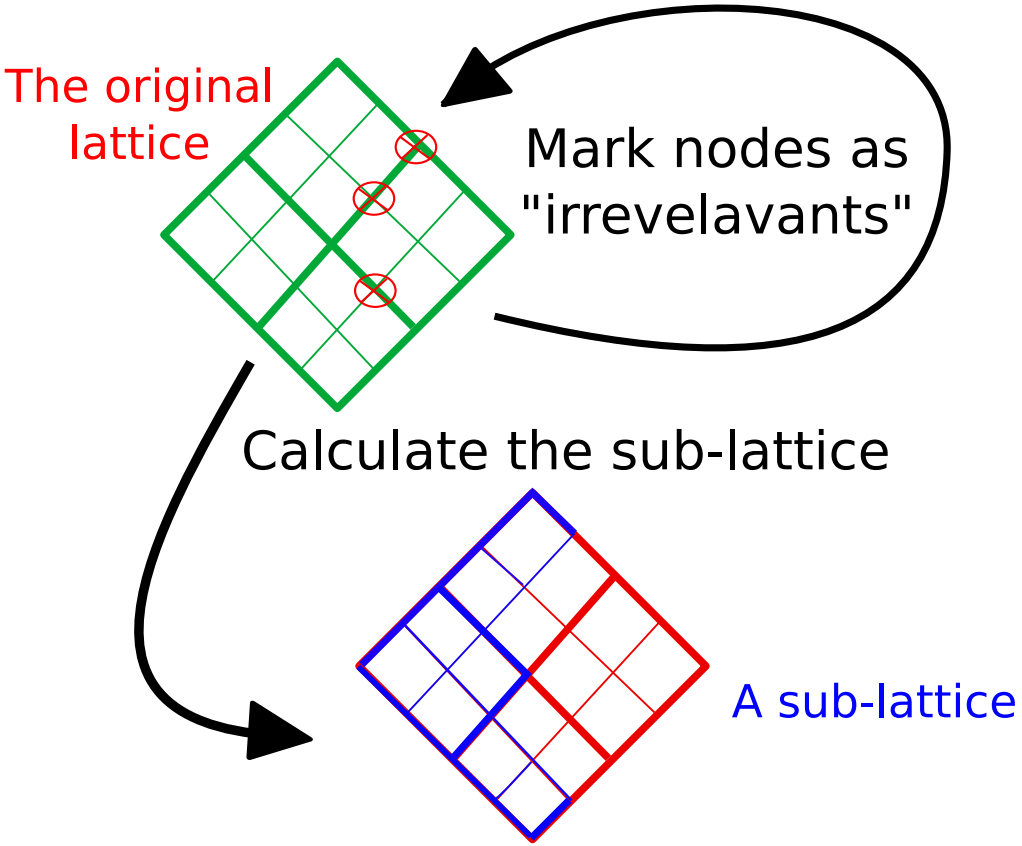
Algorithm

The user can mark nodes as *irrelevant* for his search. To determine the nodes and edges to mask:

- Minimum and maximum nodes cannot be masked,
- Any edge connecting a masked node will be masked,
- Edges are added to ensure unicity of the *min* and the *max*
- Nodes are merged to avoid nodes with a single child or single parent

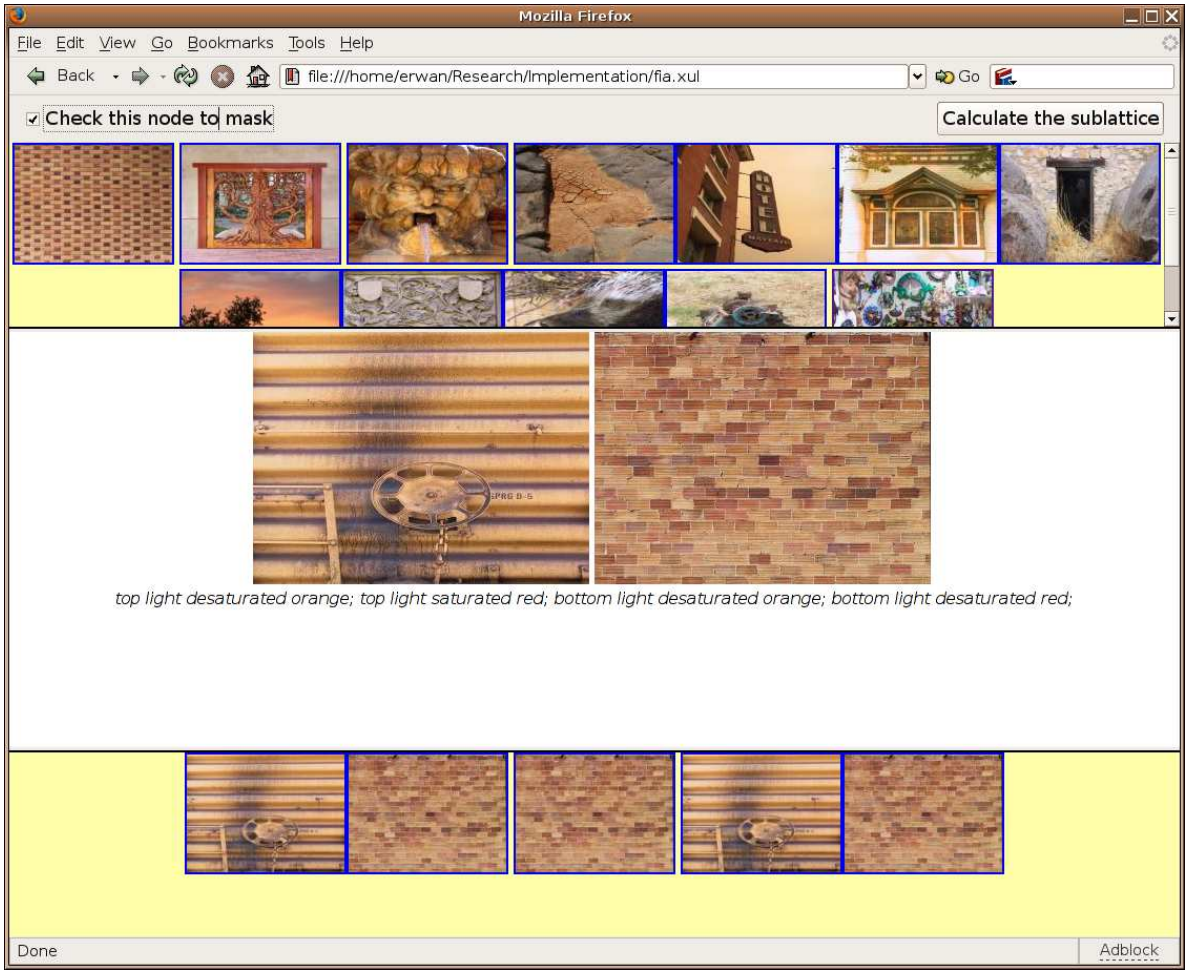
Algorithmic complexity: $O(n)$ (n being the number of nodes to mask).

Process



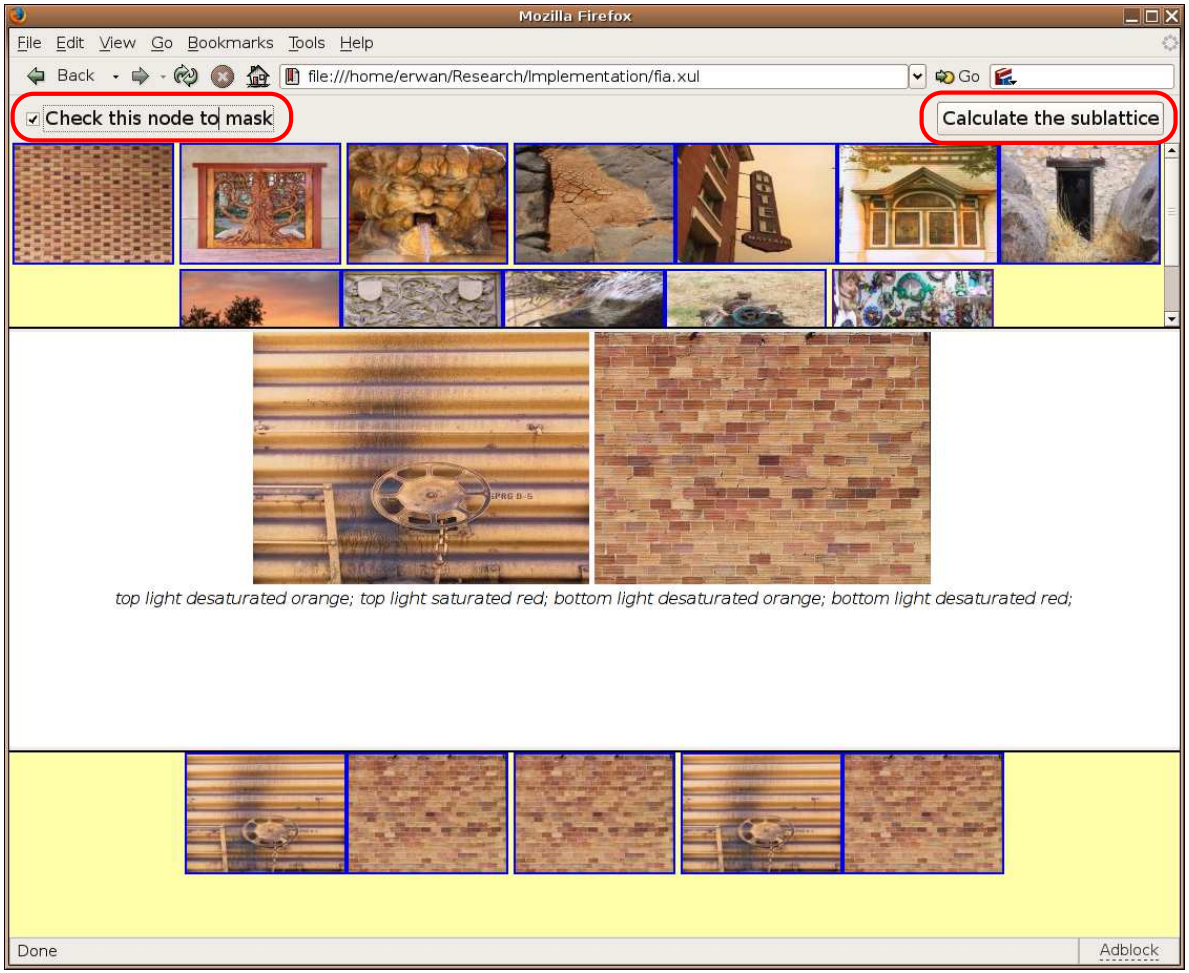
Masking a Lattice (From the User Point of View)

Example



An irrelevant node

Example



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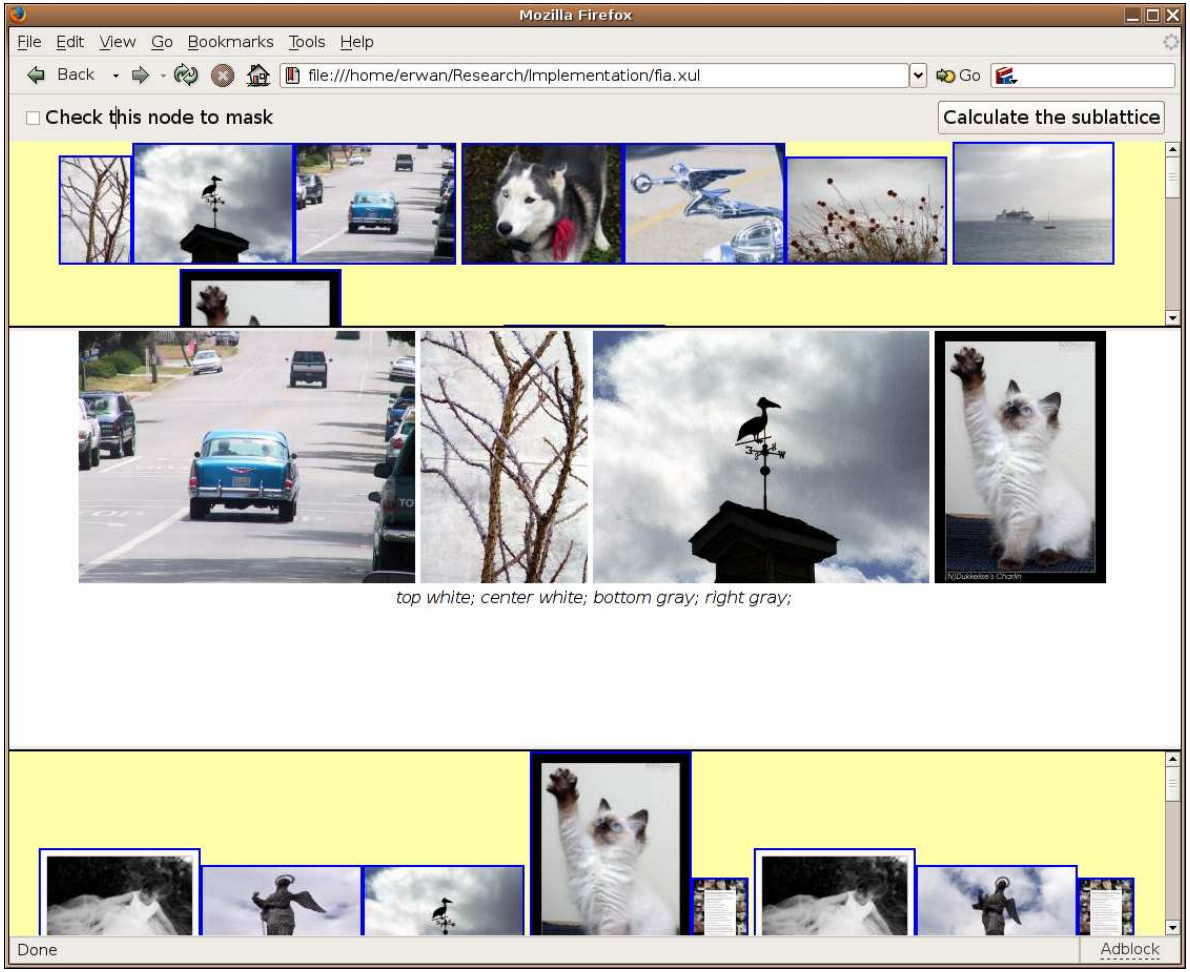

A more relevant structure

Conclusions

Our proposal:

- Provides user-personalisation, allowing users to define sub-lattices.
- Does not deny the performances advantages.

Compared to other systems, it is:

- More relevant than a system based solely on a pre-calculated structure.
- More efficient than a system based on feed-back querying ($O(n)$ for the sub-lattice calculation, $O(1)$ for navigation).

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Virtual Node: a node with no image matching its exact set of properties. Virtual nodes are required for the navigation, but too many virtual nodes make the navigation more difficult.

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Virtual Node: a node with no image matching its exact set of properties. Virtual nodes are required for the navigation, but too many virtual nodes make the navigation more difficult.
Example: Using a threshold of 0.3:

- $\{blue/0.5, red/0.31\}$, $\{blue/0.5, yellow/0.31\}$ and $\{blue/0.5, green/0.31\}$ will lead to the creation of **3 nodes**
- $\{blue/0.5, red/0.29\}$, $\{blue/0.5, yellow/0.29\}$ and $\{blue/0.5, green/0.29\}$ will be integrated into the **same node**.

Our Approach: Insertion by Node Matching

Idea

When inserting a new image (with fuzzy value associated), try to match an existing node for the binarisation process.

- The building process remains incremental;
- New images are inserted into existing nodes rather than in a new node.

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When inserting a new image (with fuzzy value associated), try to match an existing node for the binarisation process.

- The building process remains incremental;
- New images are inserted into existing nodes rather than in a new node.

Benefits

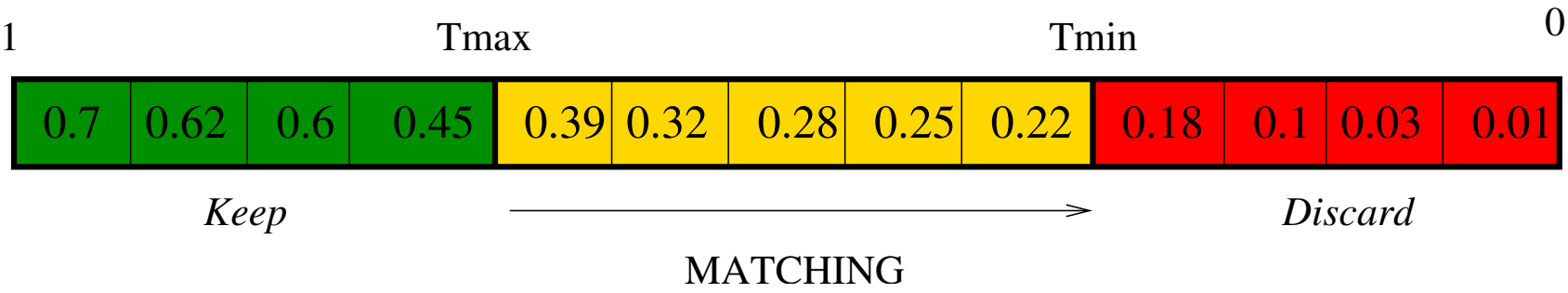
- The number of nodes is reduced without information loss.
- Thus, the average path to a given image is shortened.
- The number of element in each node is increased.

To search images in such a structure is easier.

Algorithm

For a given image:

- Descriptions are ordered by tipicity
- Descriptions under a T_{min} threshold are discarded, descriptions over a T_{max} threshold are kept;
- Starting from the set of descriptions under T_{min}, we remove descriptions successively and try to match the resulting key with existing keys in the lattice;
- If no match can be found, an average threshold is used.



Experiments

Done on the collection of Flickr.com images described previously (5,000 images);

- Navigation structures built for:
  - The naive solution (constant threshold);
  - Our proposal (node matching).
- Metrics: the structure quality:
  - Cardinal;
  - Average node size;
  - Ratio of *real* nodes (opposed to *virtual* nodes).
- The resulting structures have been tested on a few users.

Results: Real nodes

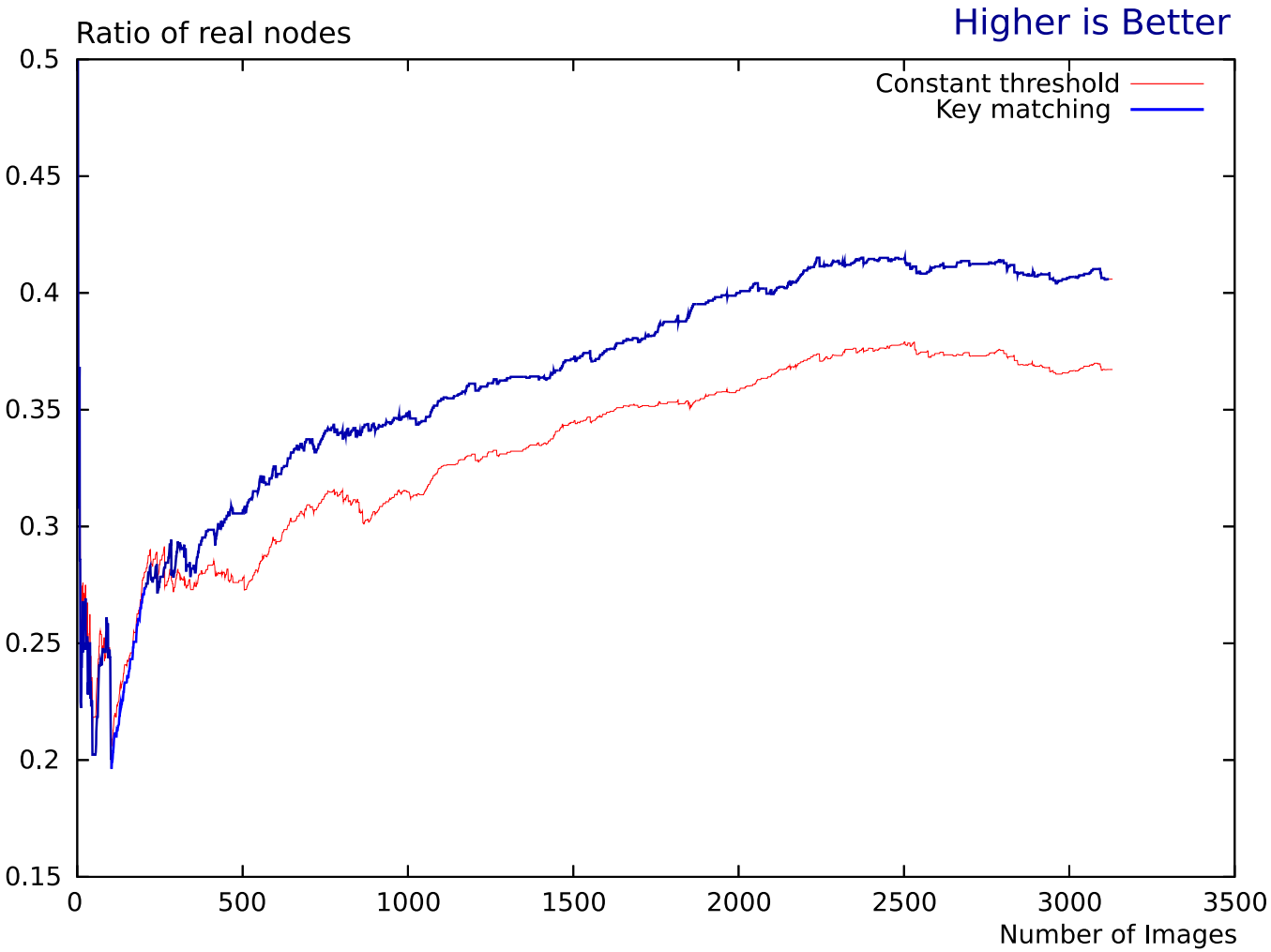


Figure: Ratio of Real Nodes in the Lattice

Results: Total Number of Nodes

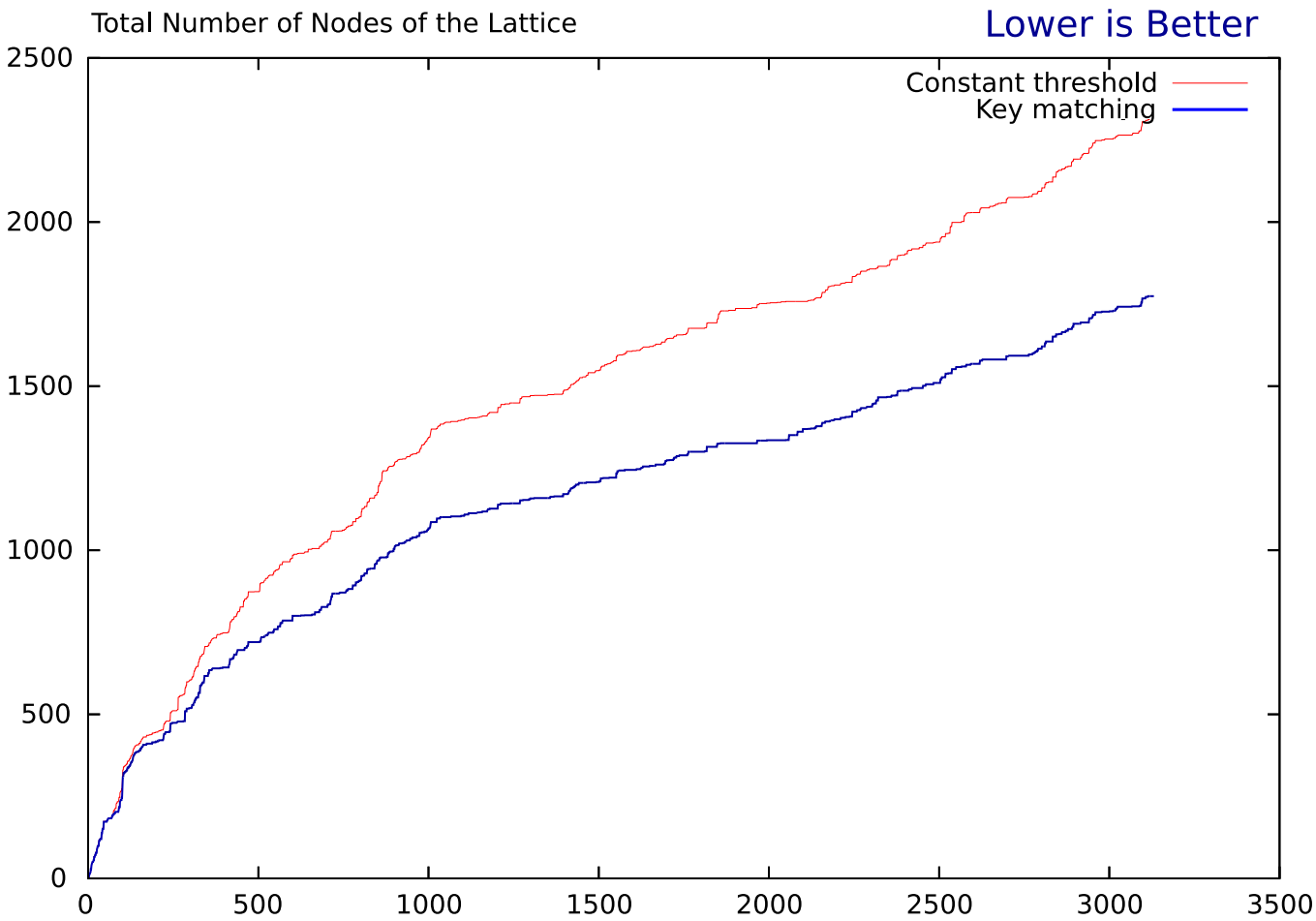


Figure: Total Number of Nodes

Results: Average Size of a Node

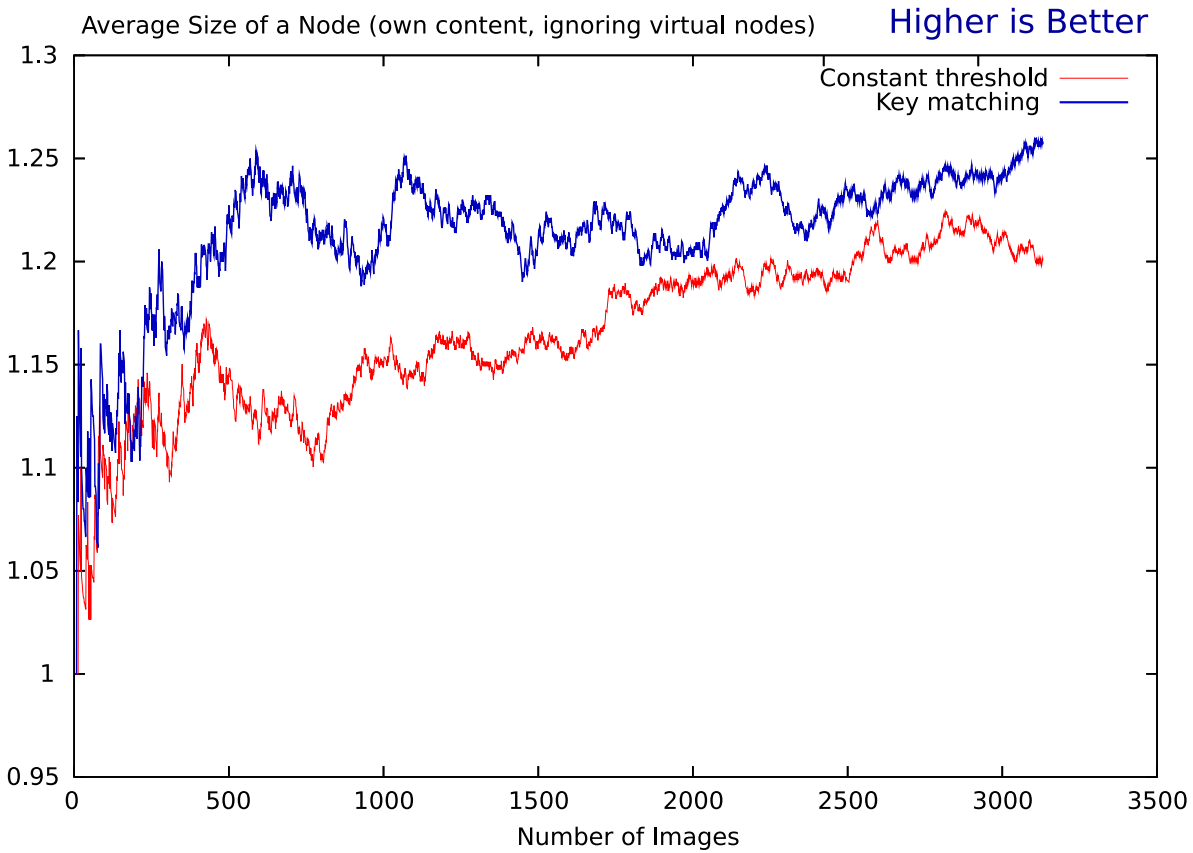


Figure: Average Size of a Node (excluding virtual nodes)

Results: Average Size of a Node

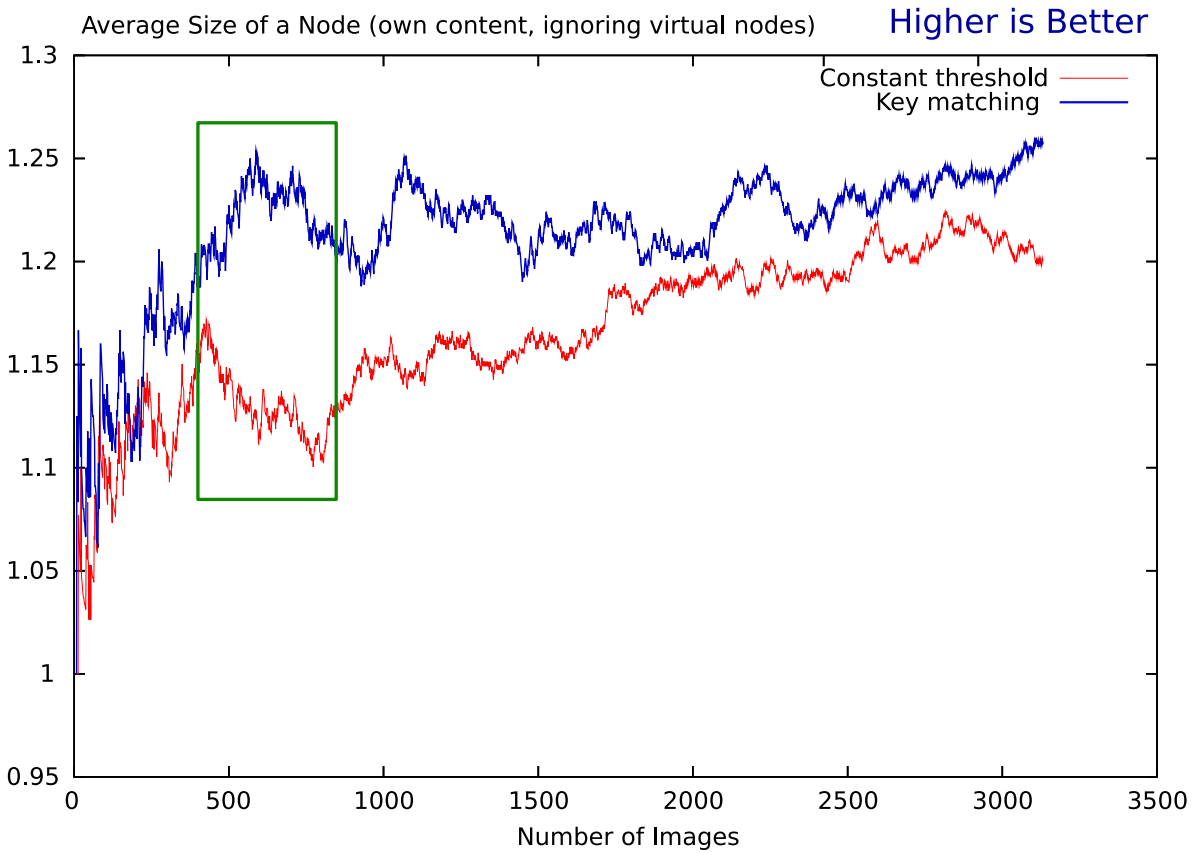


Figure: Average Size of a Node (excluding virtual nodes)

Conclusions

Node matching insertion produced a structure of better quality than other approaches:

- The number of nodes is reduced without information loss.
- Thus, the average path to a given image is shortened.
- The number of element in each node is increased.

Consequently, the user experience is better due to a more compact structure.

Part III

Conclusion

Outline

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Achievements

In this study, we looked for a way to replace query by navigation in image databases.

- We presented a technique to search for images by browsing an hypermedia representation of a Galois lattice
- We presented several extensions to:
  - Address the scalability problem by using a clustering technique
  - Allow the user to customise the structure for his needs
  - Make a better use of the fuzzy description of the images to build a better structure

Benefits and Limits

Benefits:

- **Easy to use:** the user does not have to describe formally his needs, he just selects the images he "likes". He can still give feedback to personalise the search.
- **Fast and responsive:** browsing is optimal since it is done on a static structure.
- **Scalable:** Associated with a clustering technique, it can reach very large collections.

Limits:

- Not applicable for open collections such as the World Wide Web.

Outline

Further Work

- Application to other media types, such as video. Requires:
  - A suitable metamodel
  - A compact way to represent the medium
- Mobile computing
  - Insertion requires no interaction
  - A mobile phone can provide additional metadata
  - The user interaction is very simple