Automatisches Bildverstehen

Visuelle Bildnavigation

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visual-computing.com



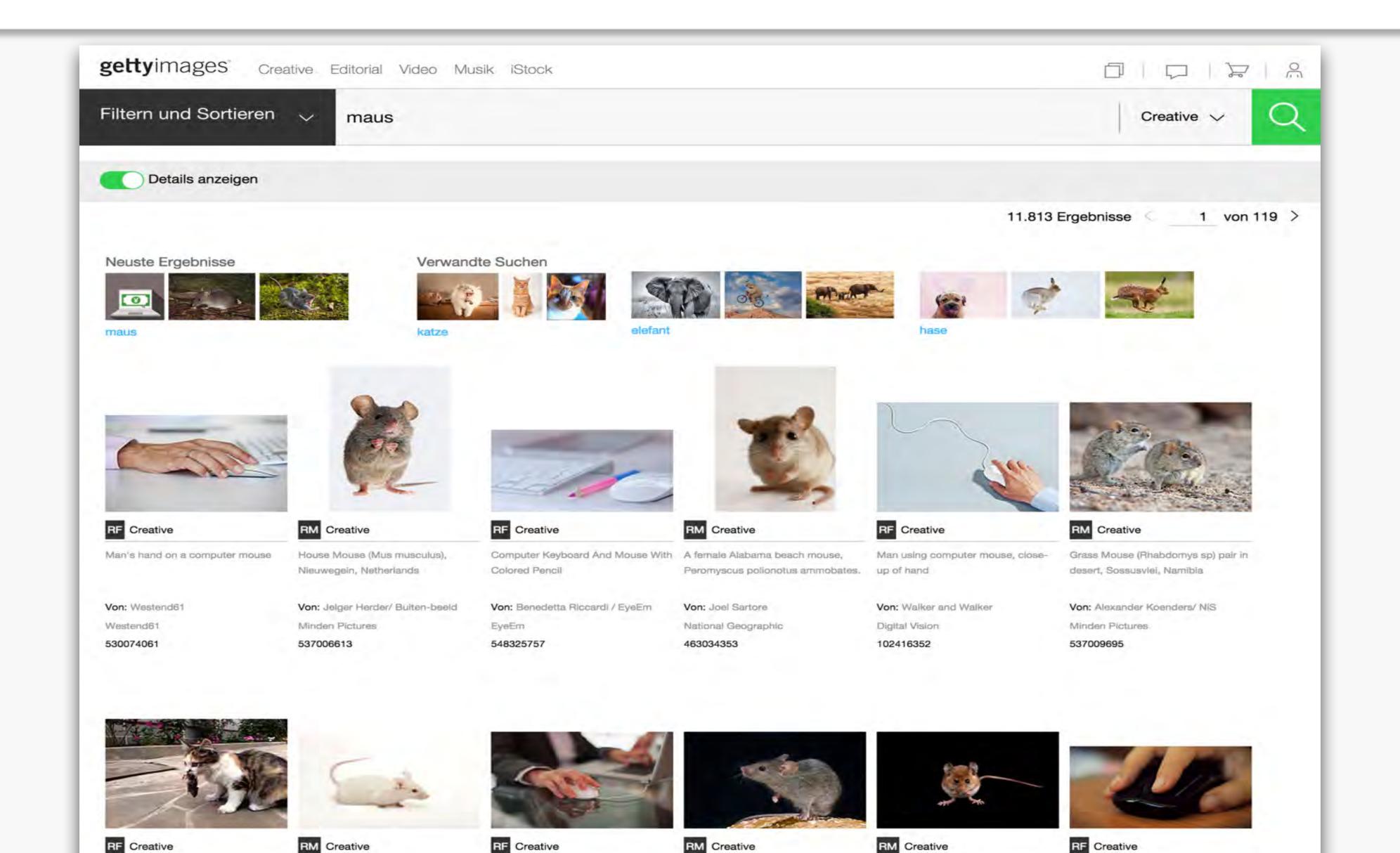


There are too many images

- Constantly growing number of images, thousands of results for a search
- Image search is very time consuming
- Only few images can be looked at simultaneously



Image search: The Actual Situation as you all know it ..



Keyword search

- Good keywording is expensive, keywords often are incomplete, overloaded or wrongly translated
- Exact keyword matching leads to finding everything or nothing

"meadow"

826,951 results:



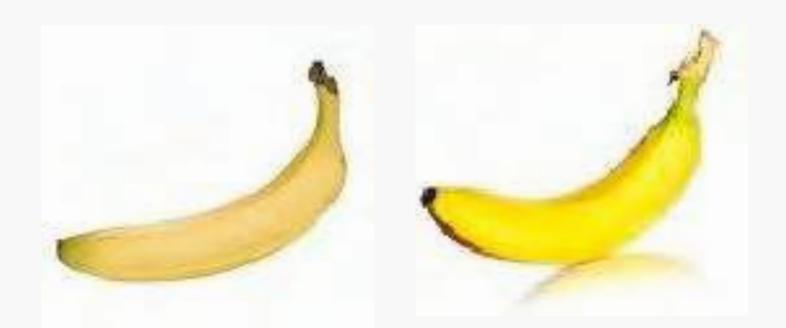
"meadow blue sky apple tree clouds flowers family"

3 results:



Low-Level Content based Image Search

 Low-level image search finds similar looking images.



 Does not understand the meaning of the images.





 Cannot find similar images that look different

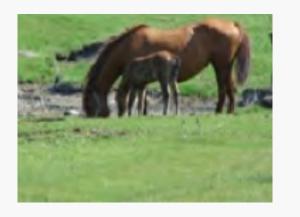




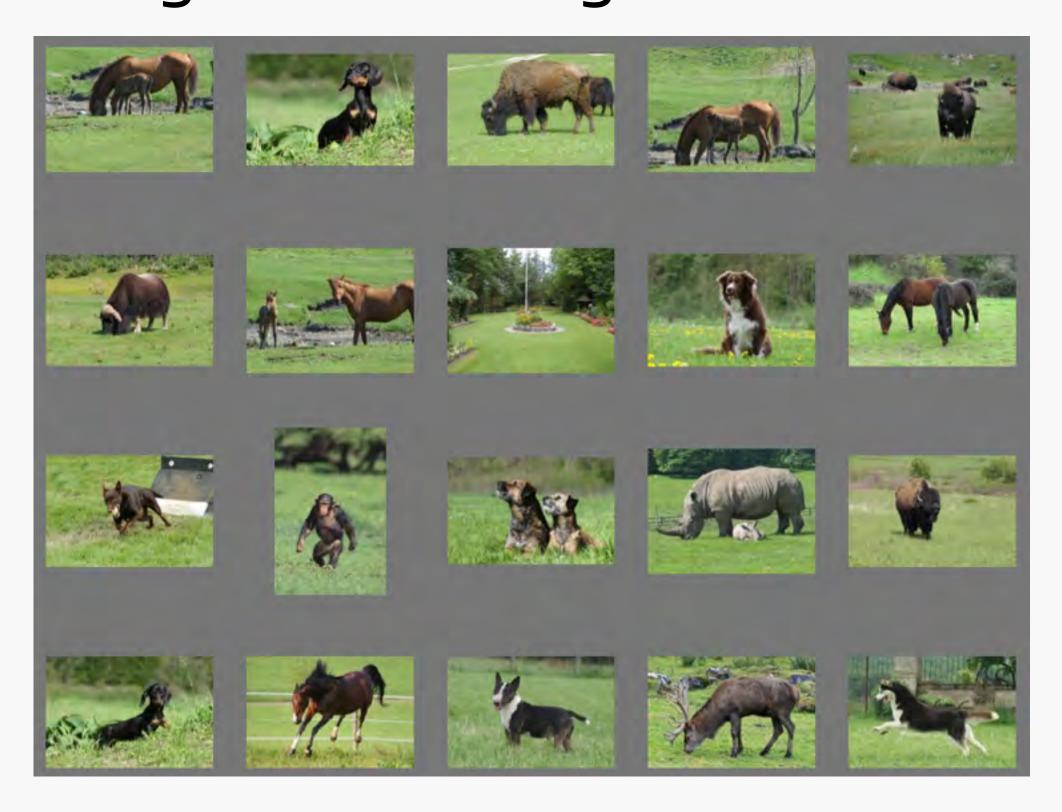
Problem of visual image search

Visual search finds similar looking images, but does not "understand" the meaning of the image.

Query:

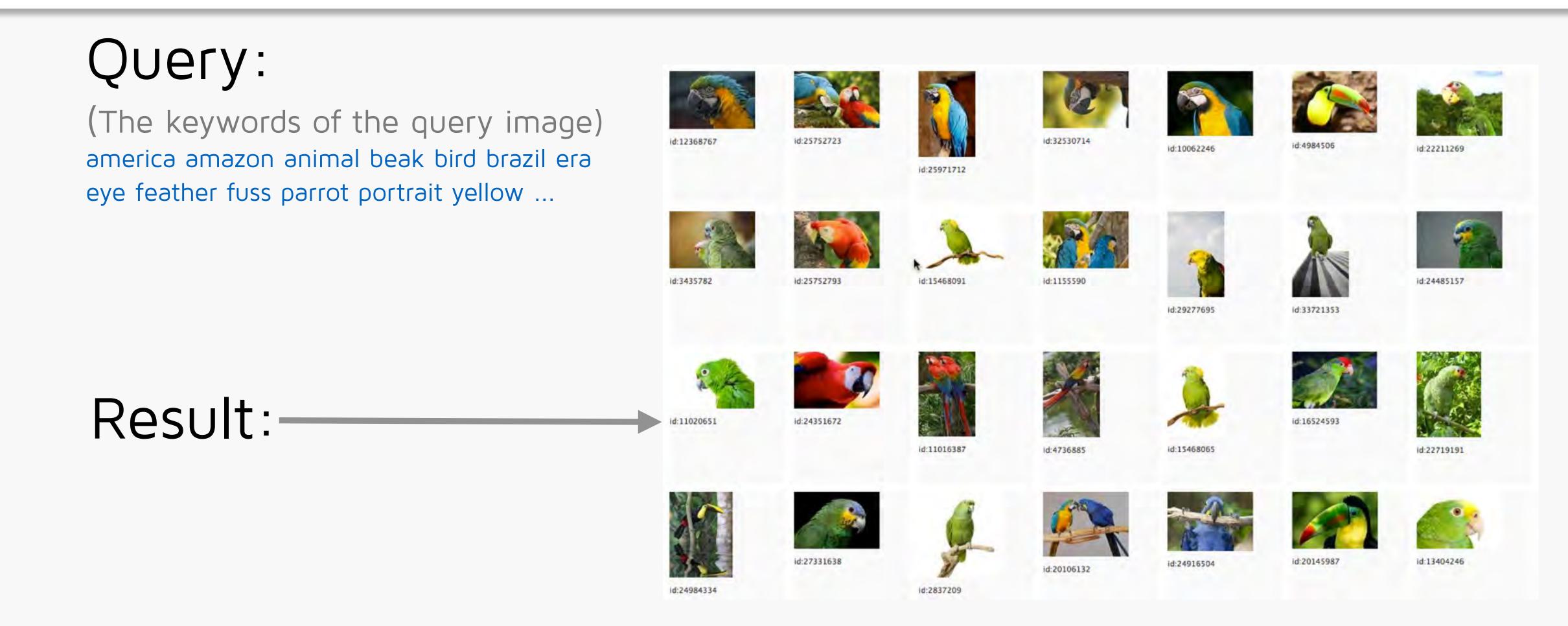


Result:



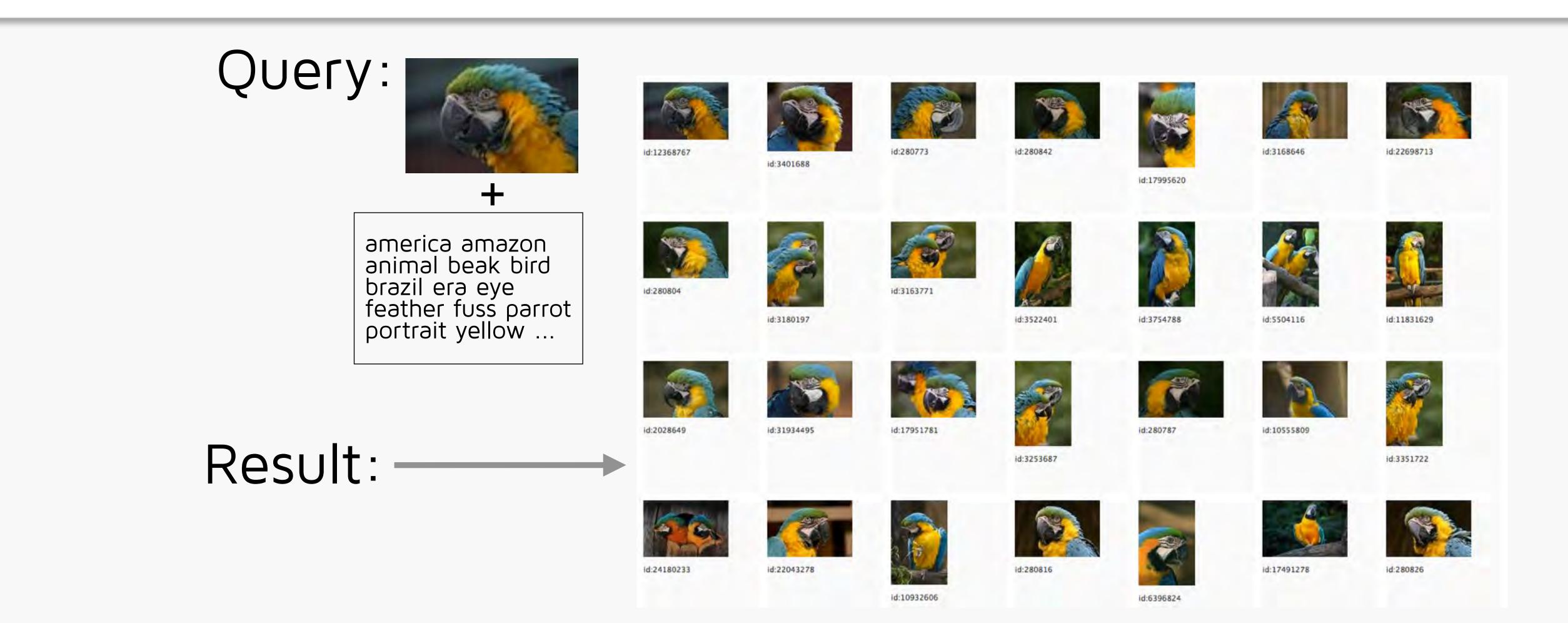
Visually similar images, context may be different

"More like this" search using image keywords



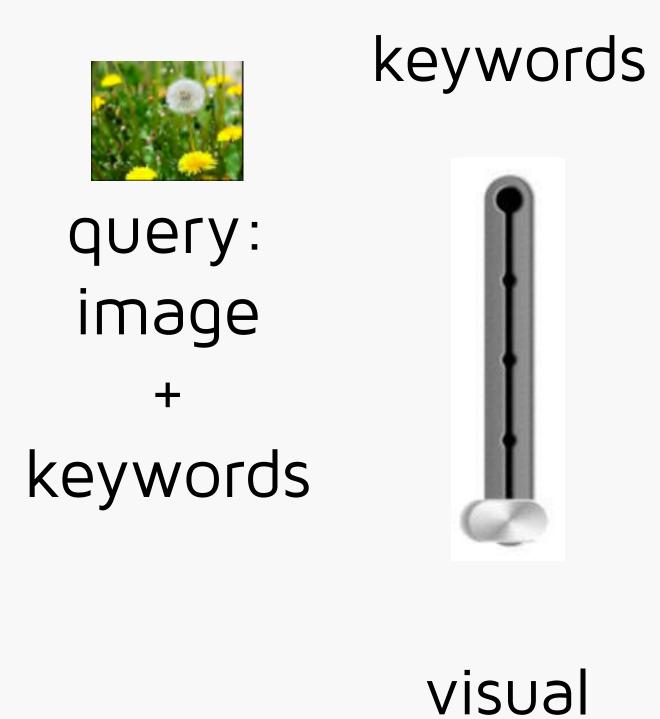
Similar image content, large appearance variations

Fusing visual and keyword search



+ Visually similar images and (!) + Similar content

Similarity Weighting





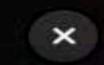
What can we do with this?

A fused search allows a unified similarity measure. This paves the way to:

- Improved image search results
- Automatic clustering of images

 But: No solution for untagged images (images without keywords)!

Enter keyword here



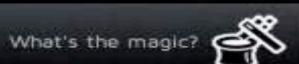


Images found

ms

by keywords

visually



fusing visual and keyword search Pixolution

Clustering Image Search Results



Clustering Image Search Results

palm

S

Q Search



What do we need to find image more easily?

Most images are untagged!

→ We need automatic image understanding

There are far too many images!

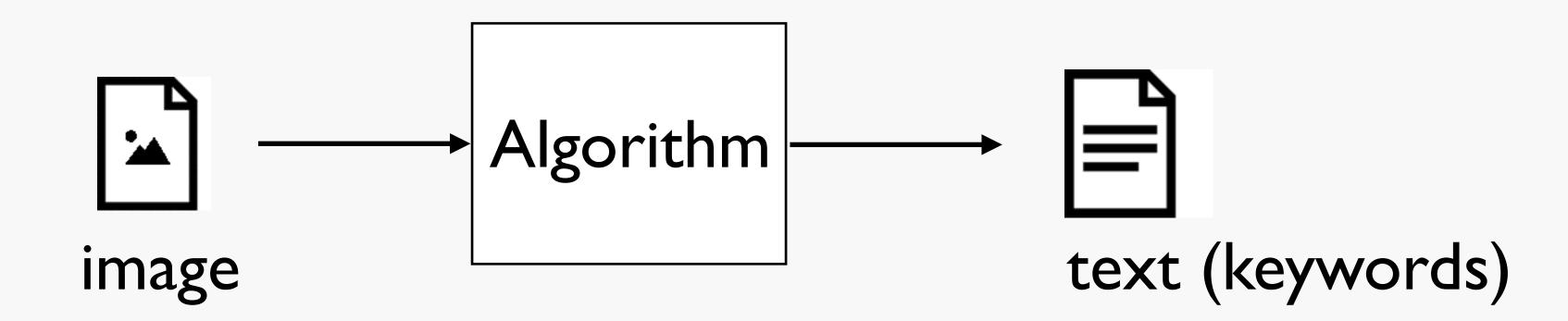
→ We need visual image browsing

Automatic Image Understanding

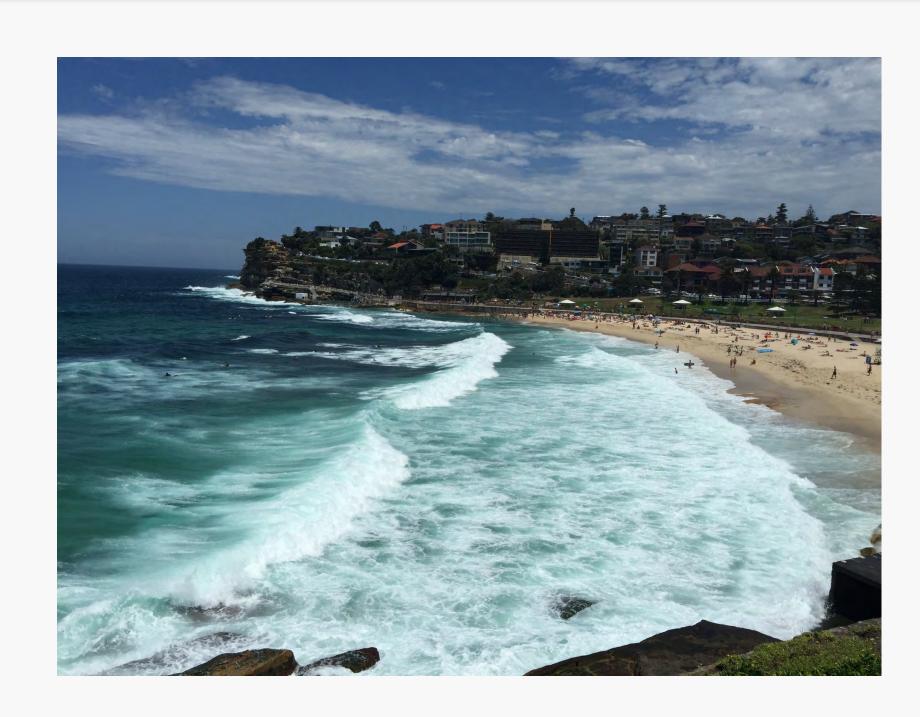


Image Understanding

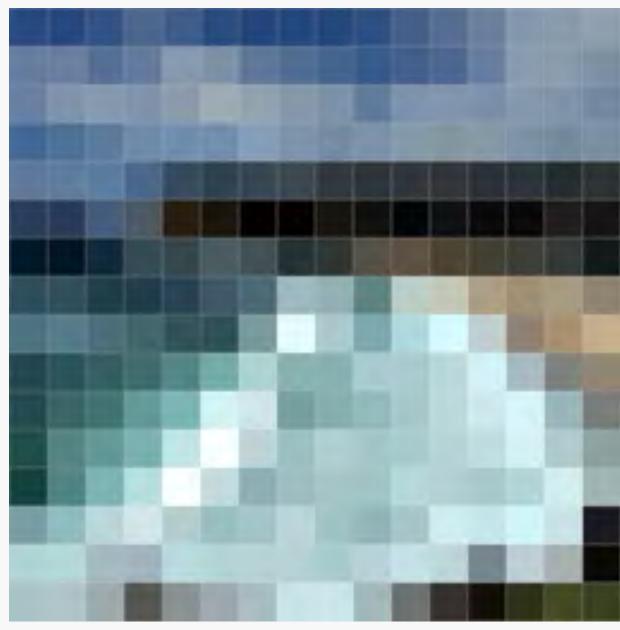
What is shown in this image?



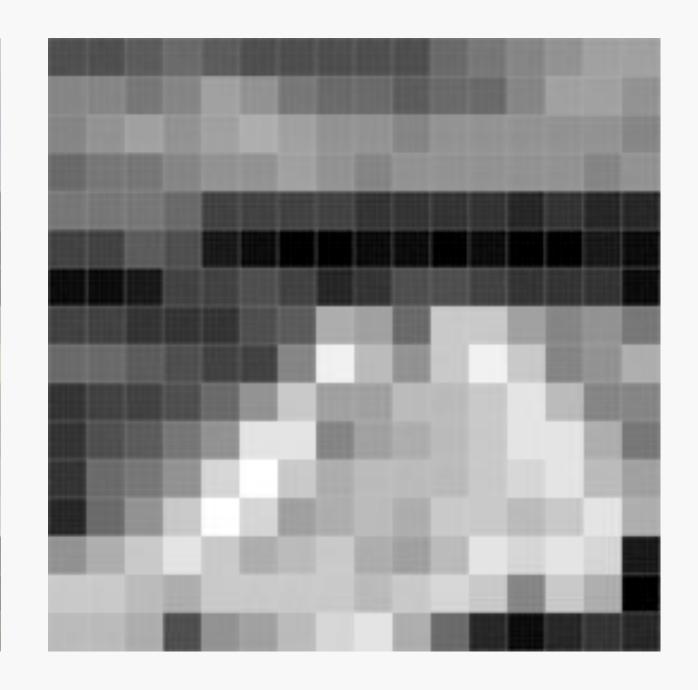
Automatic Image Understanding



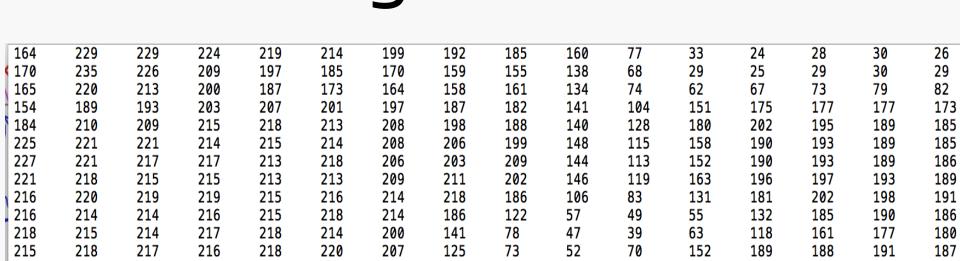
3264x2448 pixels 16.7 million colors



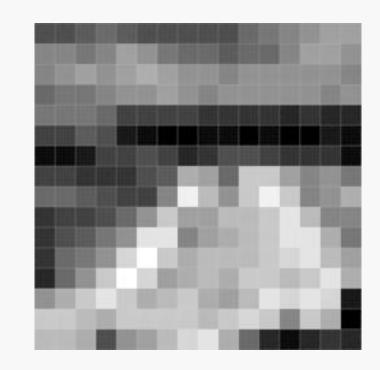
16x16 pixels



16x16 pixels
16 brightness levels



Automatic Image Understanding



16x16 pixels, 16 brightness levels

Number of possible images:

$$16^{16\times16} = 1.79 \cdot 10^{308} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519078902473361797697894230657273430\%} = 179^{769313486231590772930519079293051907929307929$$

540 827 237 163 350 510 684 586 298 239 947 245 938 479 716 304 835 356 329 624 %

224 137 216

More than the number of atoms in the universe: 10⁸⁰

Simple Case

Image with only 2 pixels



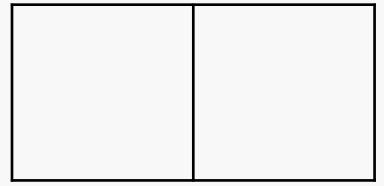
Only black or white colors

For possible images:







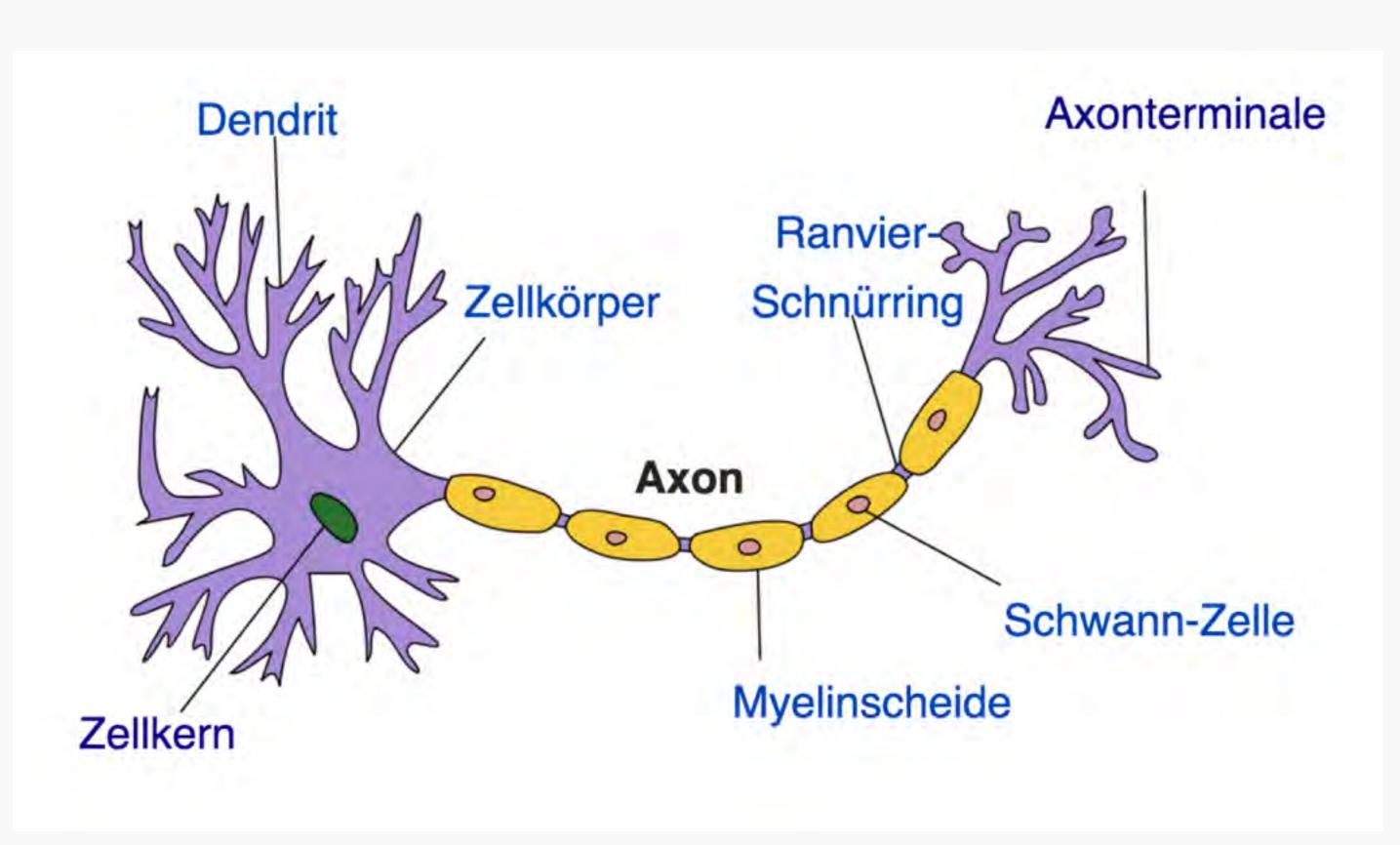


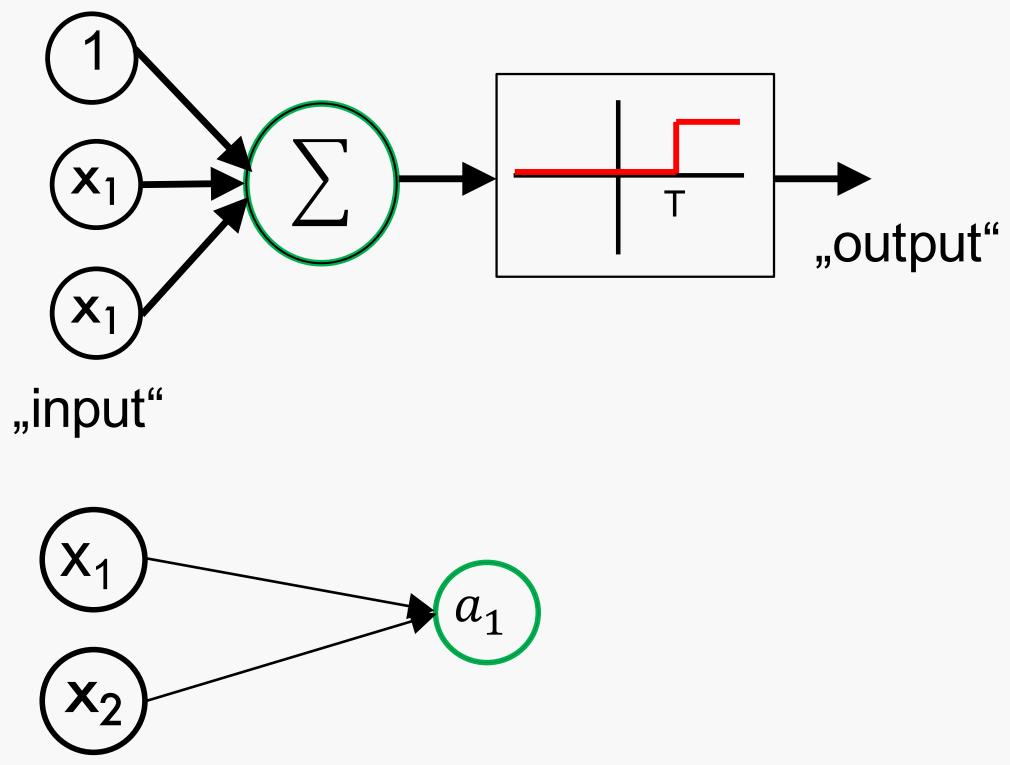
Simple Case

Possible questions: Are the pixels ...

both black?	both white?	both different?
yes	no	no
no	no	yes
no	no	yes
no	yes	no

(Artificial) Neural Network



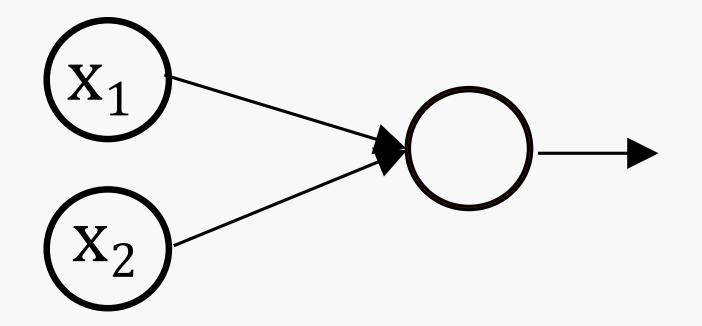


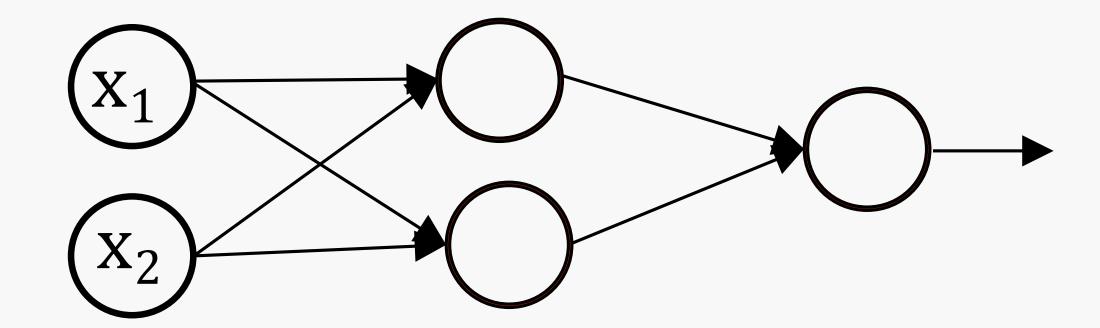
Neural Networks

... can be trained to answer these questions:

Are the pixels all white?

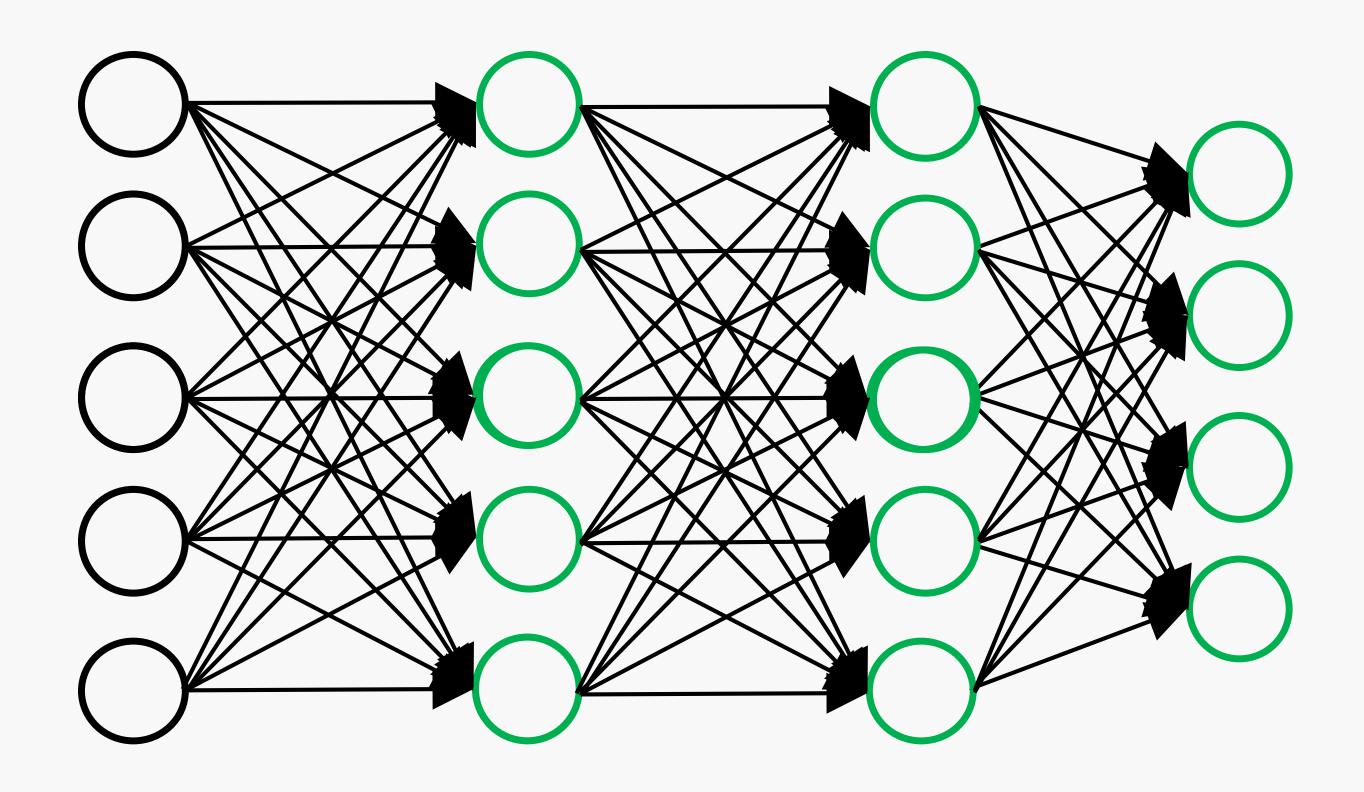
Are the pixels different?





Neural Networks

Extension to automatic image understanding



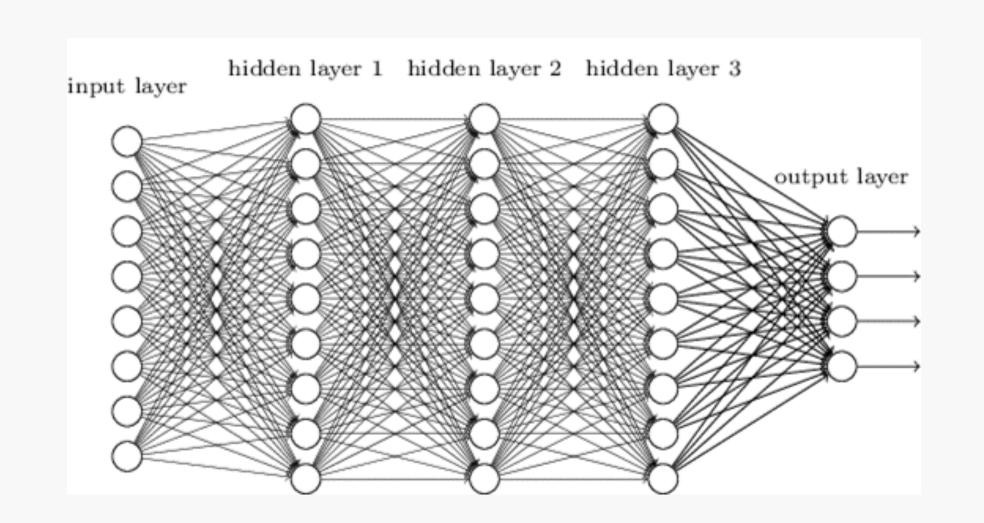
Neural Networks for Image Understanding

Problems:

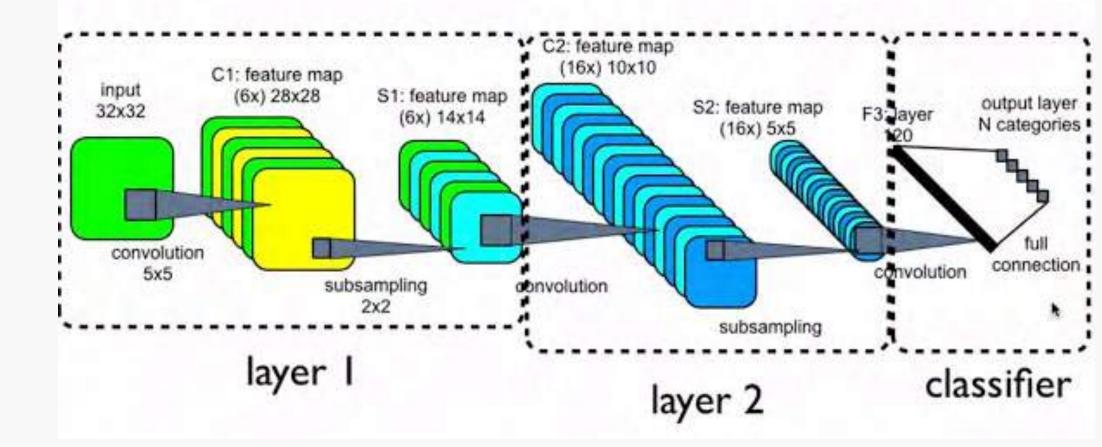
- Not enough example images
- Computers were too slow
- Too many parameters

All these problems were solved in the last years.

→ Deep Learning / Convolutional Neural Networks



Convolutional Neural Networks



Semi-automatic keywording

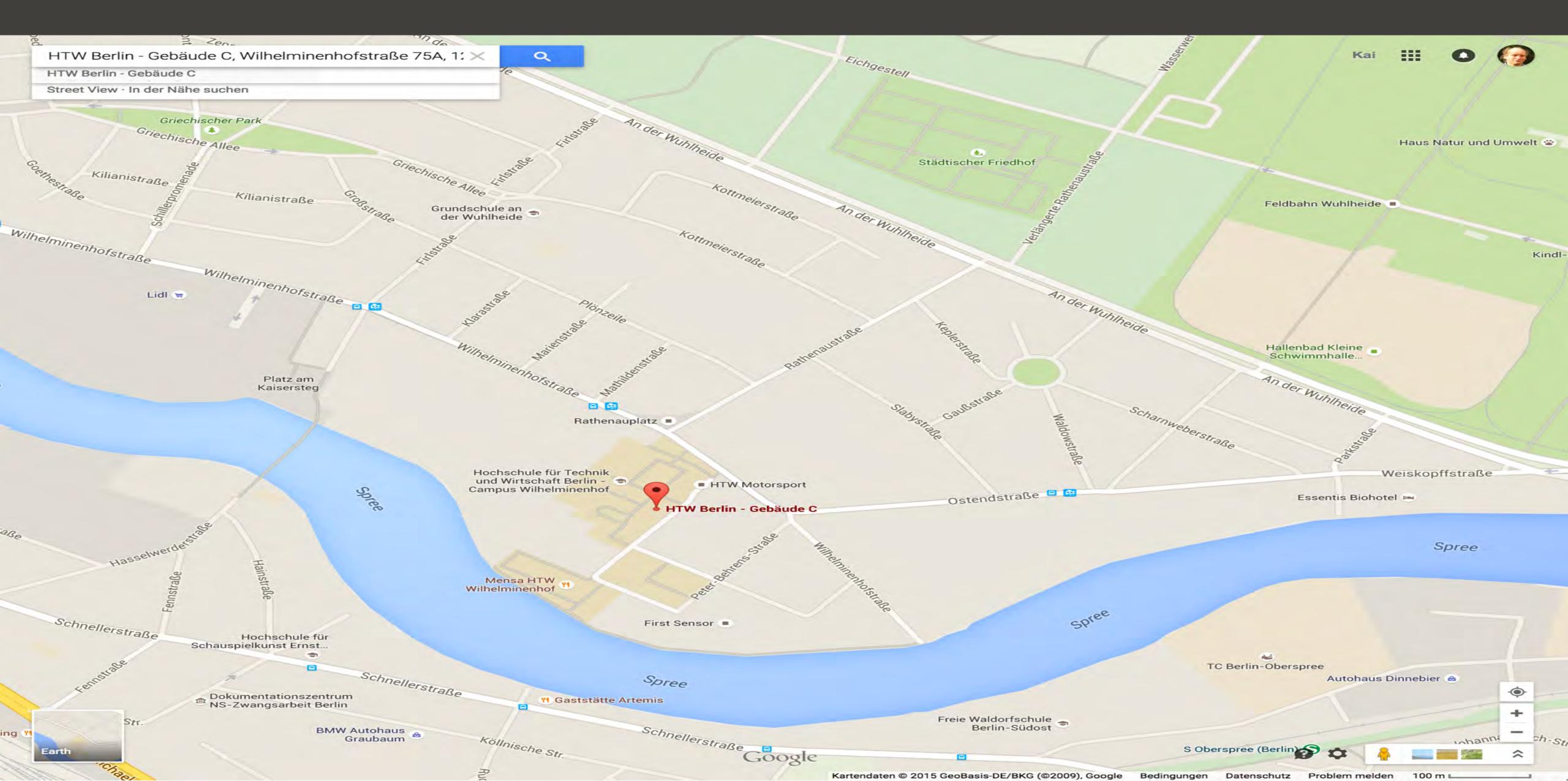


Image Browsing / Image Navigation

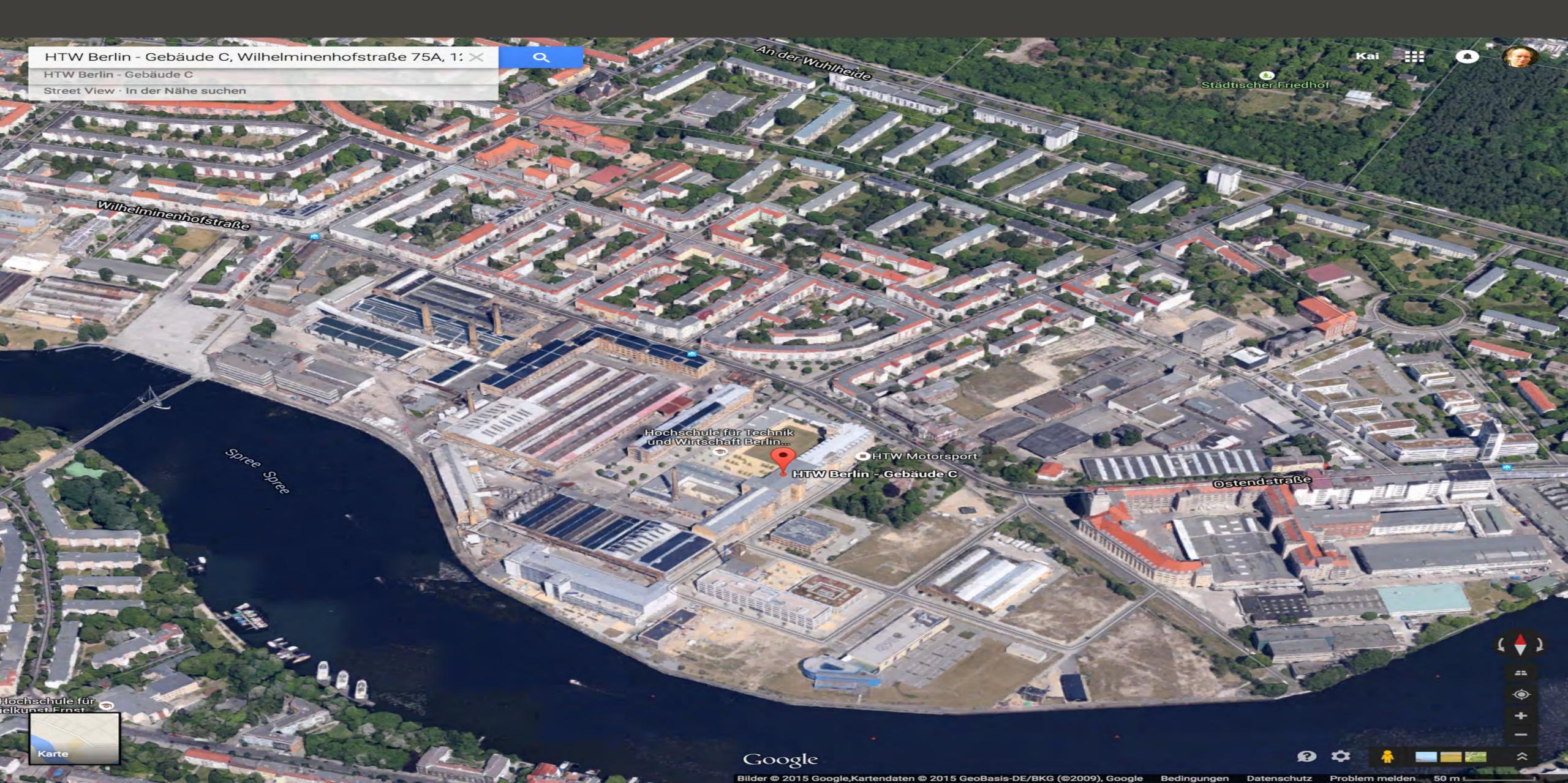
Instead of scrolling endless image lists:

Explore images!

Google Maps



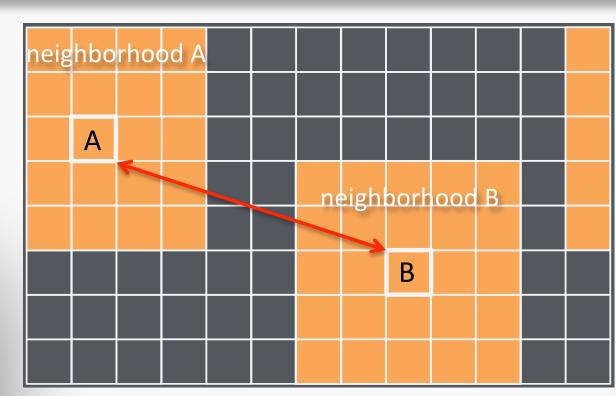
Google Earth



2D-Sorting by image swapping

unsorted



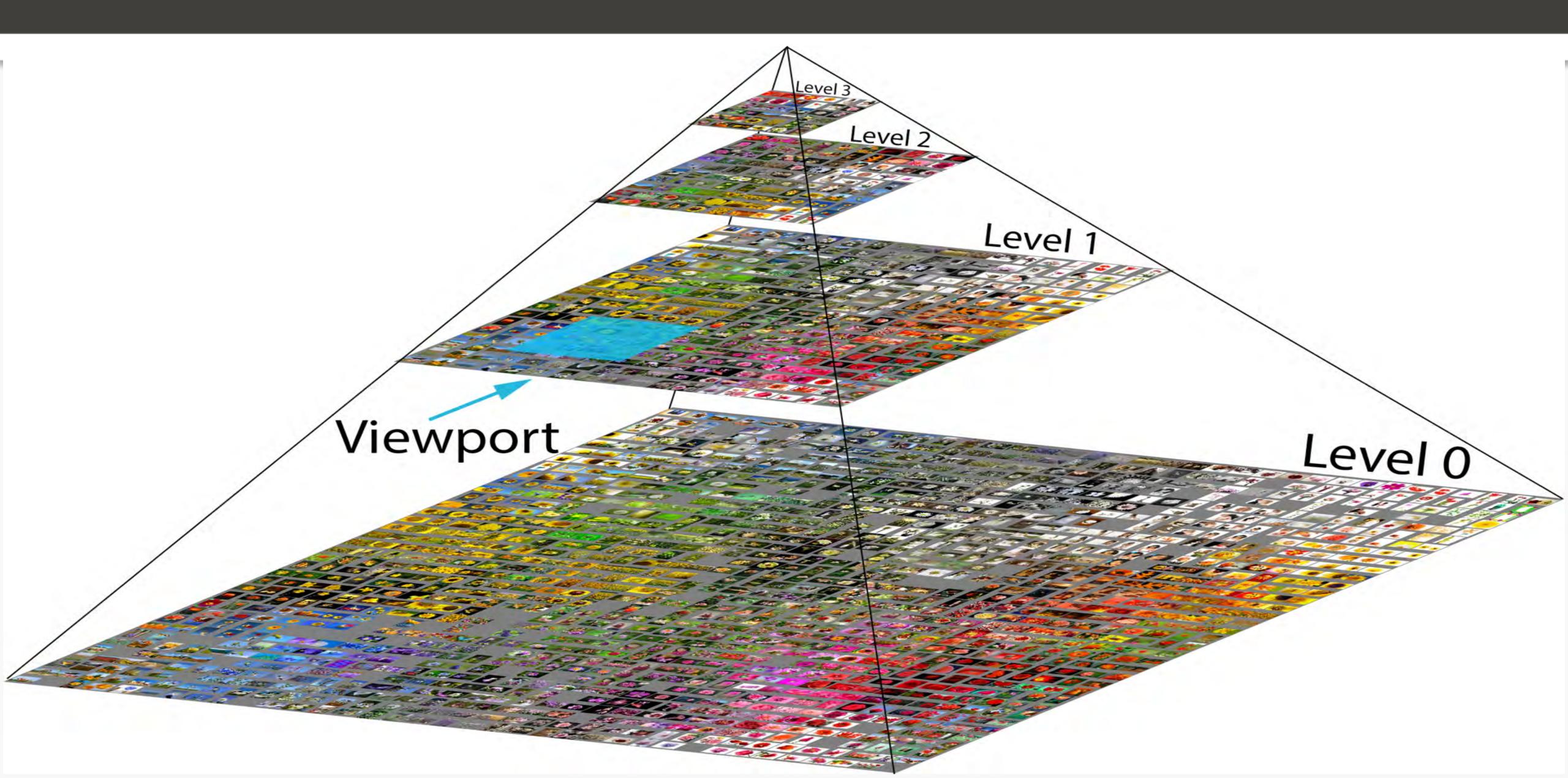




sorted

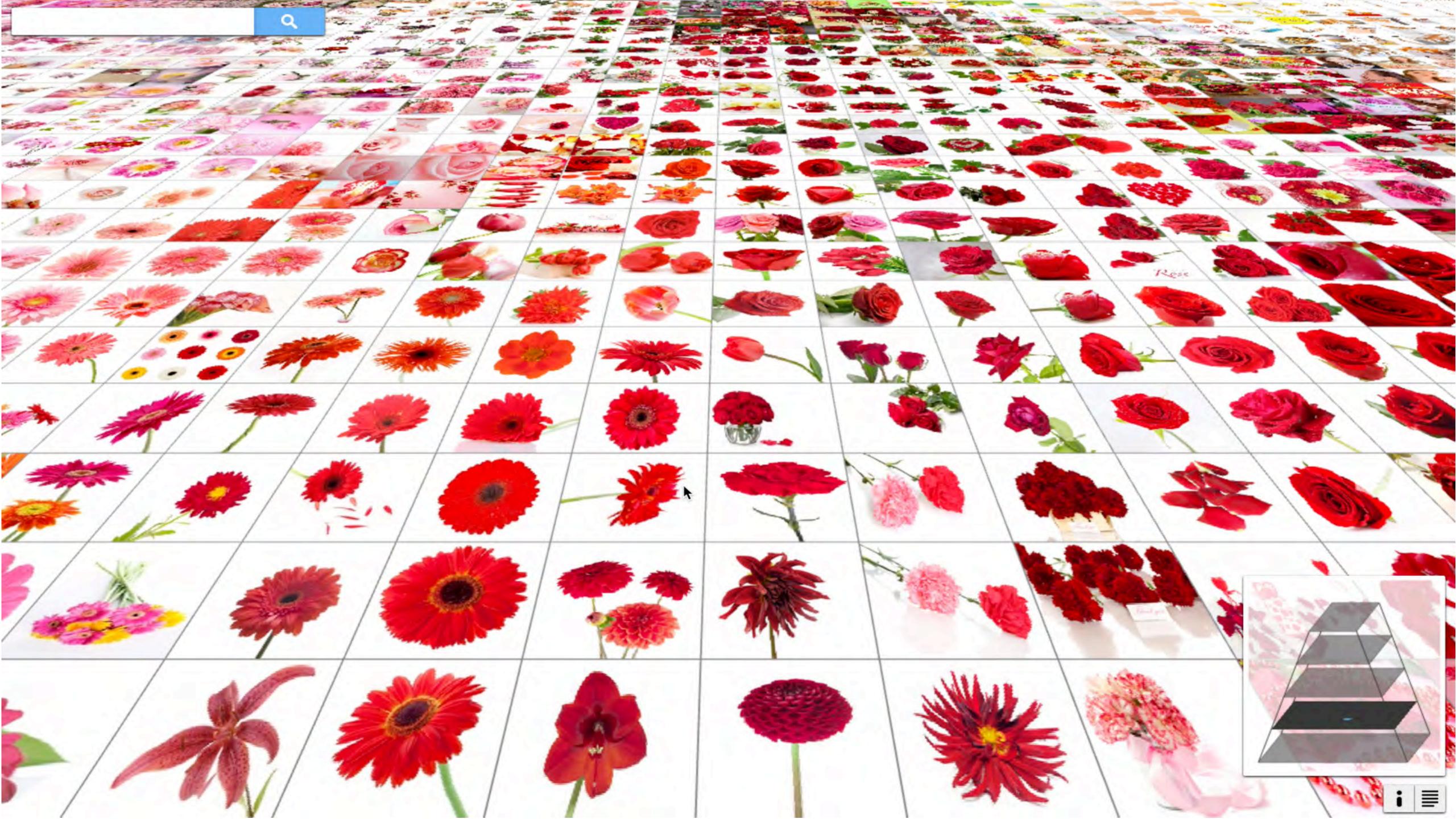


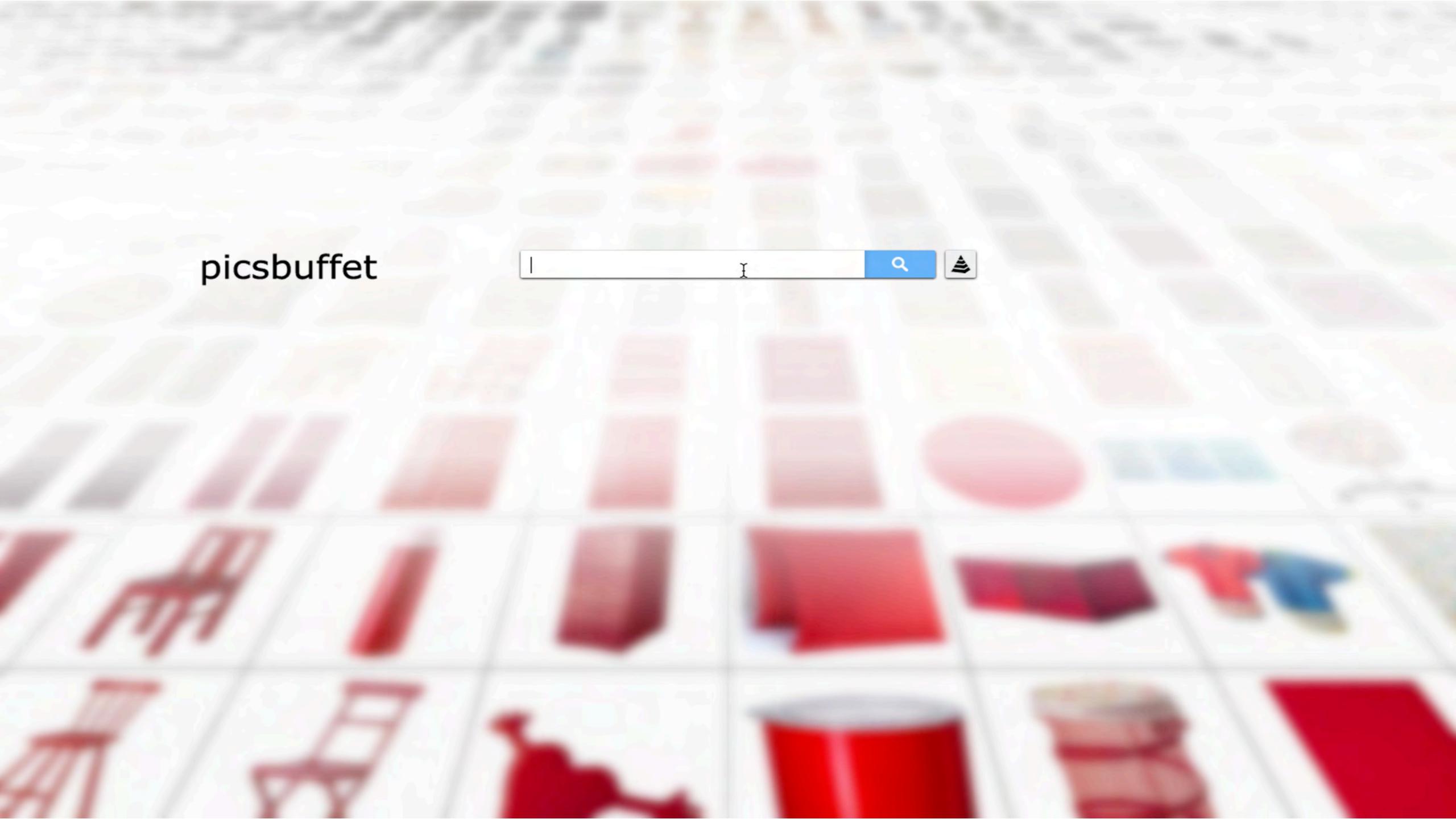
Visual image browsing



picsbuffet.com







Extension

- Image relationships are too complex to be perfectly mapped on a 2D map.
- Idea: Use a high dimensional graph instead of a 2D map.
- Problems:
 - 1. How to construct a useful graph with millions of images?

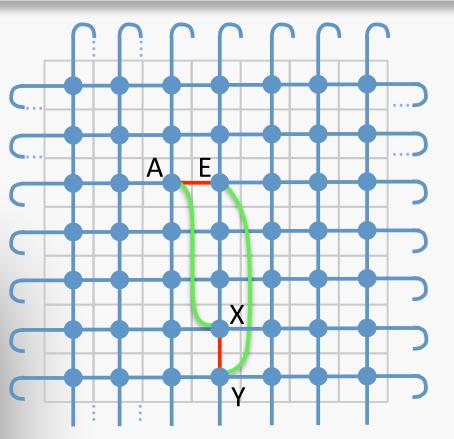
A distance map of 1 million images has 1 trillion entries (10¹²)

2. How to navigate the graph?

Graph-building by edge swapping

2D sorting



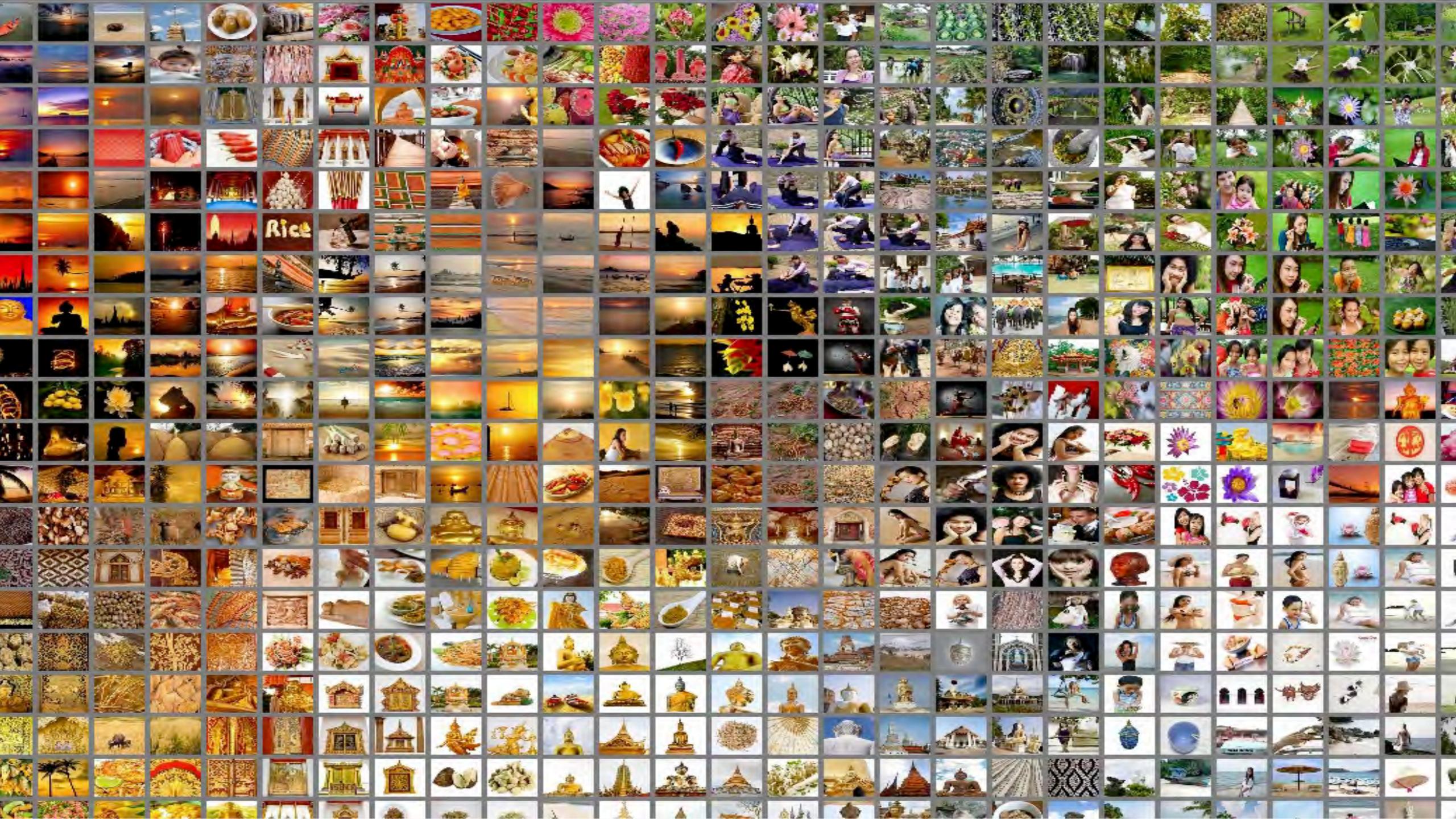






Graph Navigation

- Project fractions of the graph to a 2D map and perform instant 2D sorting
- Moving the map retrieves new images from the graph.



Thank you

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