



# Image Indexing

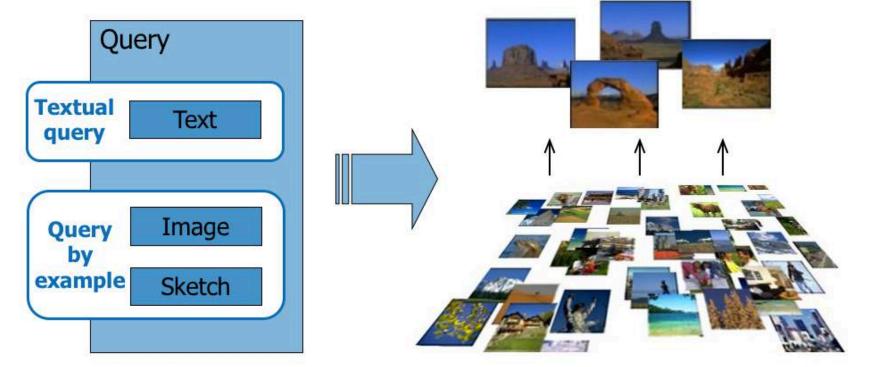
Eduardo Tavares



## Image Retrieval

✓ Description Based Image Retrieval (DBIR)

✓ Content Based Image Retrieval (CBIR)





## Levels of image retrieval

#### ✓ Level 1: Based on color, texture, shape features

Images are compared based on low-level features, no semantics involved

Level 2: Bring semantic meanings into the search

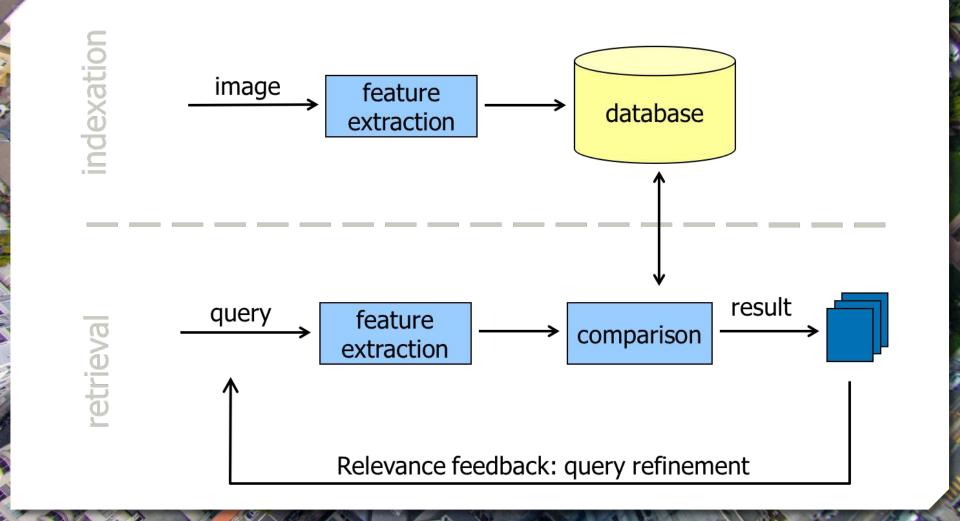
- E.g. identifying human beings, horses, trees, beaches
- Requires retrieval techniques of level 1

#### Level 3: Retrieval with abstract and subjective attributes

- Find pictures of a particular birthday celebration
- Find a picture of a happy beautiful woman
- Requires retrieval techniques of level 2 and very complex logic



## Common components of CBIR system





## **Problems and directions**

#### ✓ Low-level feature extraction

- How to represent an image in a compact and descriptive way?
- How to compare features, and, thus, images?
- High dimensional indexing
  - How to index huge amounts of high dimensional data?
- Visual interface for image browsing
  - How to visualize the results?



## Image features

Semantics

Shape

Levels of image content

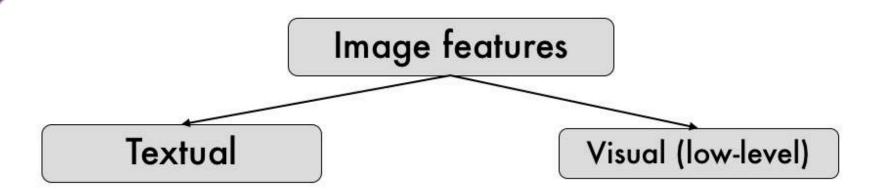
- Texture
- Color, lightness

Low-level features / visual features (signatures, descriptors)

Textual/metadata features



## Image features



#### Annotations and metadata:

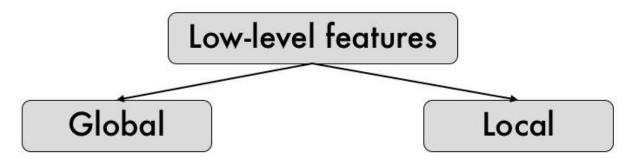
- tags/keywords;
- creation date;
- geo tags;
- name of the file;
- photography conditions (exposition, aperture, flash...).

Features extracted from pixel values:

- color descriptors;
- texture descriptors;
- shape descriptors;
- spatial layout descriptors.



## Image features



#### Describes the whole image:

- average intensity;
- average amount of red;

All pixels of the image are processed.

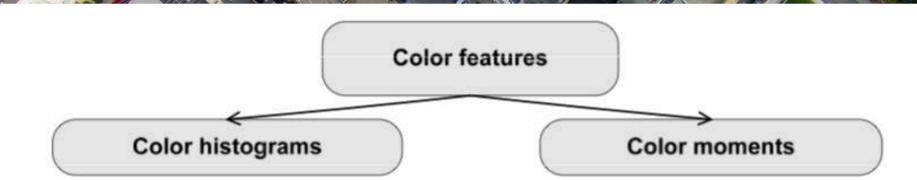
Describes one part of the image:

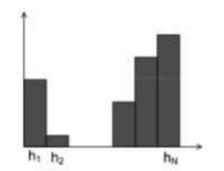
- average intensity for the left upper part;
- average amount of red in the center of the image;

Segmentation of the image is performed, pixels of a particular segment are processed to extract features.



## Color features





Statistical moments for every color channel

$$F(I) = (E_1^{I}, E_2^{I}, E_3^{I}, \sigma_1^{I}, \sigma_2^{I}, \sigma_3^{I}, \sigma_1^{I}, \sigma_2^{I}, \sigma_3^{I}, \sigma_1^{I}, \sigma_2^{I}, \sigma_3^{I}, \sigma_$$

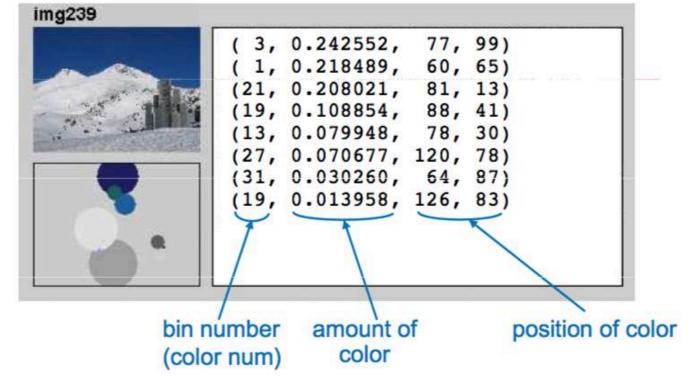
 $F(I) = (h_1^{I}, h_2^{I}, ..., h_N^{I})$ 

Metrics: L1, L2, L

Metrics: ~L<sub>1</sub>



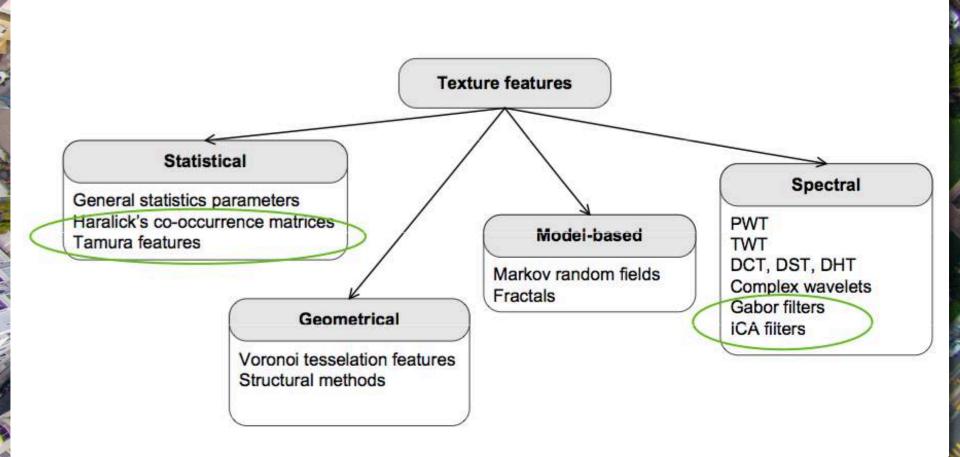
## Color features



- Disadvantage of histogram: spatial color layout is not considered.
- On heterogeneous collections moments are slightly better.
- Fusion of histograms and moments can lead to better results



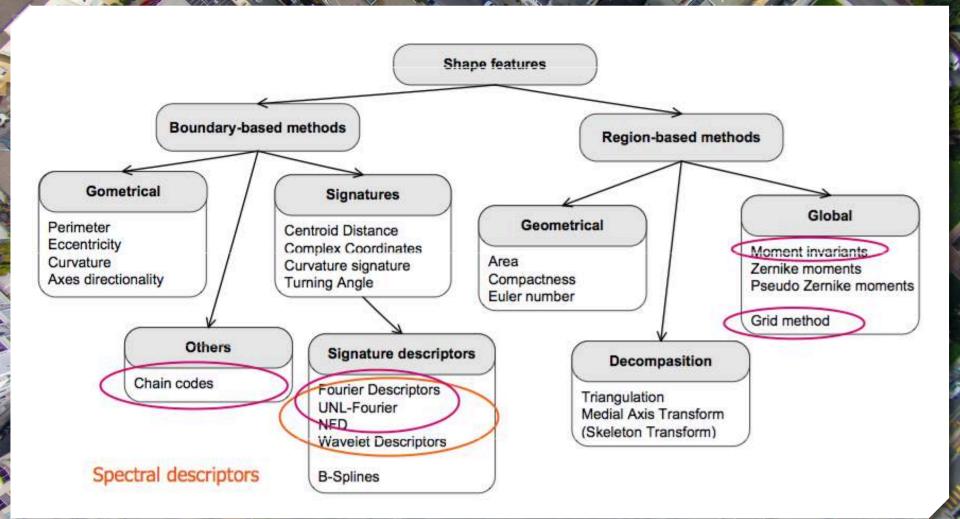
### Texture features





## Shape features

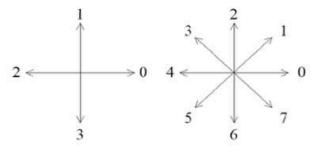
All a



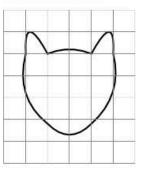


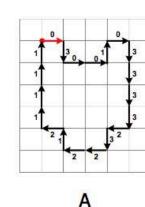
### Chain codes

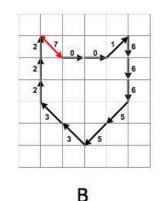
Directions for 4-connected and 8-connected chain codes:



#### Example:







A: 03001033332322121111 B: 70016665533222

Starting point invariance: minimal code

70016665533222 -> 00166655332227

Rotation invariance: codes subtraction

00166655332227 -> 01500706070051



### Local Descriptors

#### ✓ Features for local regions in the image

- Regions obtained by segmentation
- Regions of interest (Rol) around interest points (keypoints)
- ✓ Interest points: corners, edges and others

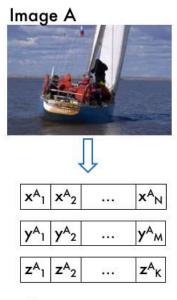
 Keypoints: points invariant to image translation, scale and rotation, and minimally affected by noise and small distortions

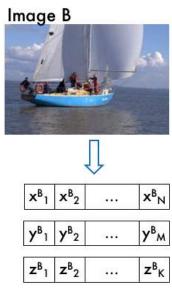


### Feature Spaces

 Feature vector – a vector of features, representing one image.

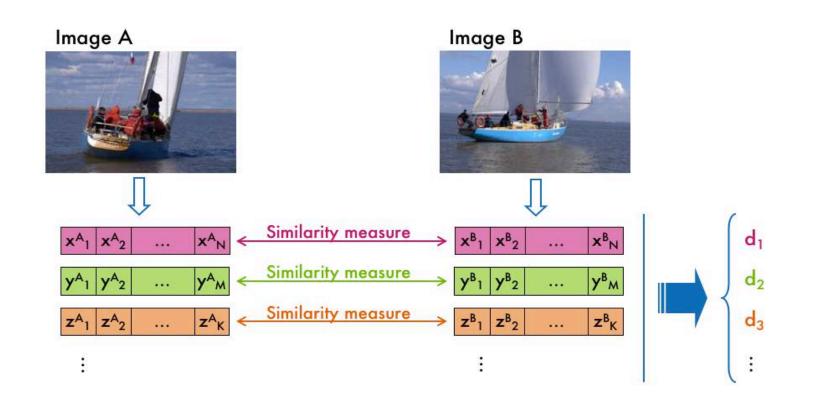
 Feature space – the set of all possible feature vectors with defined similarity measure.







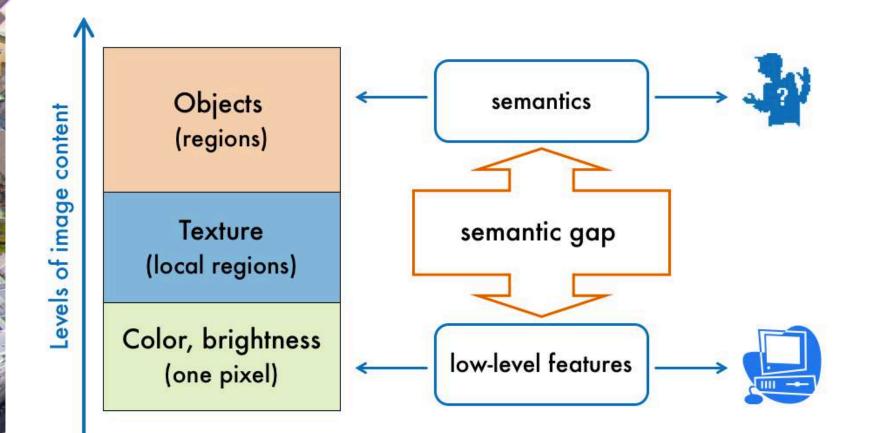
#### How to compare?



 $D = \sum c_i d_i$ 



## Problems: semantic gap



How to understand what is on the images?



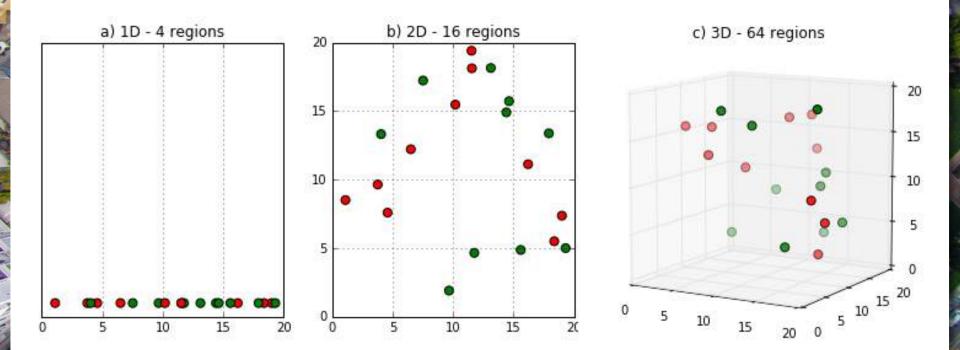
### Problems: semantic gap



How do we know that all these objects are lamps?

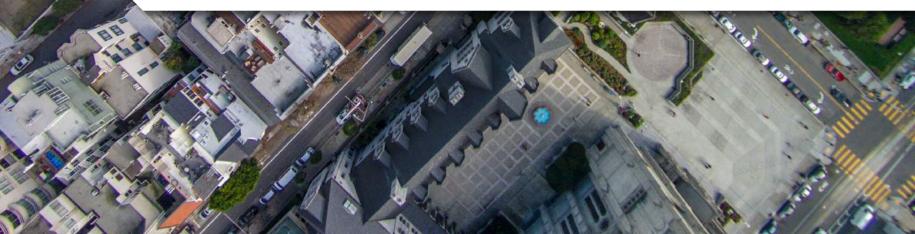


#### Problems: curse of dimensionality



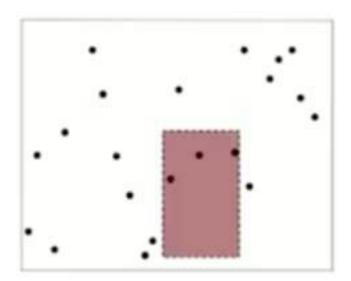


# Indexing techniques





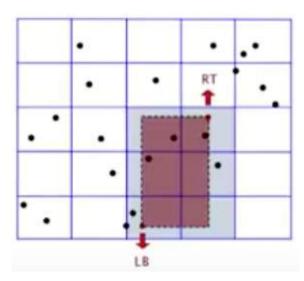
- ✓ Search for a 2D key.
- ✓ Range search: find all keys that lie in a 2D range.
- Range count: number of keys that lie in a 2D range.





Grid implementation:

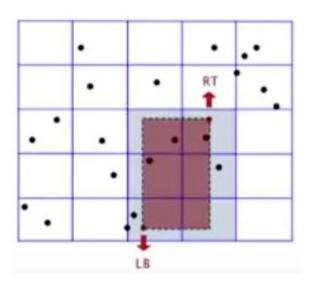
- ✓ Divide space into M-by-M grid of squares.
- Create list of points contained in each square.
- ✓ Range search: examine only squares that intersect 2D range query.





Choose grid square size to tune performance.

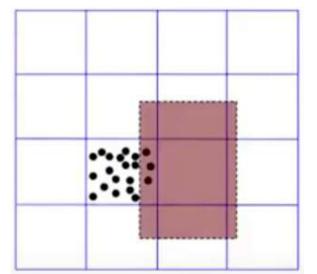
- ✓ Too small: wastes space
- ✓ Too large: too many points per square

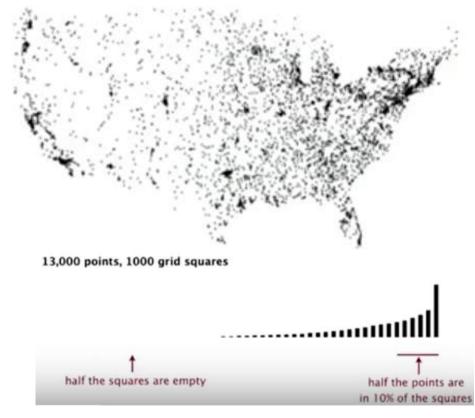




Problem: clustering, a well-known phenomenon in geometric data.

Need a method that adapts gracefully to data.







#### Space-partitioning trees

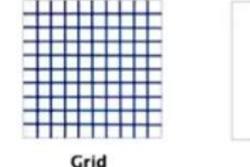
Use a tree to represent a recursive subdivision of 2D space.

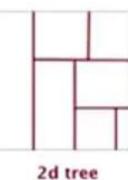
Grid. Divide space uniformly into squares.

**2D tree.** Recursively divide space into two halfplanes.

Quadtree. Recursively divide space into four quadrants.

**BSP tree.** Recursively divide space into two regions.

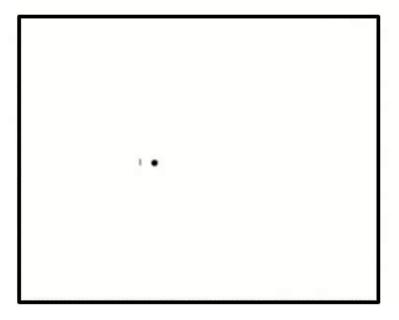




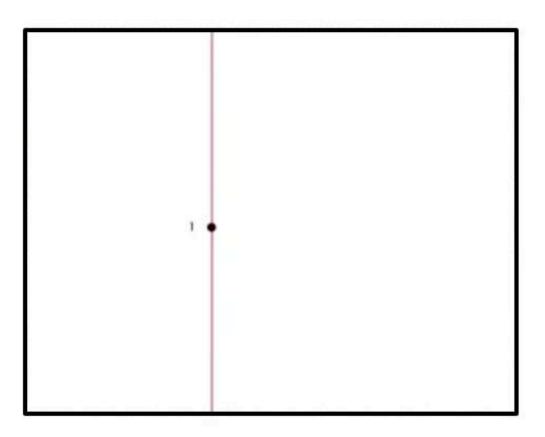


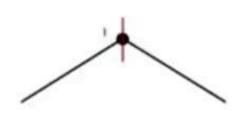




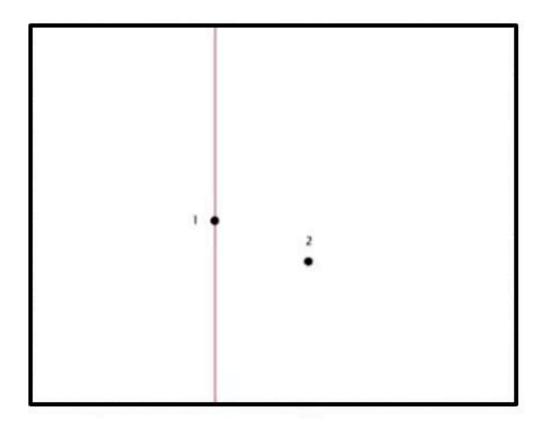




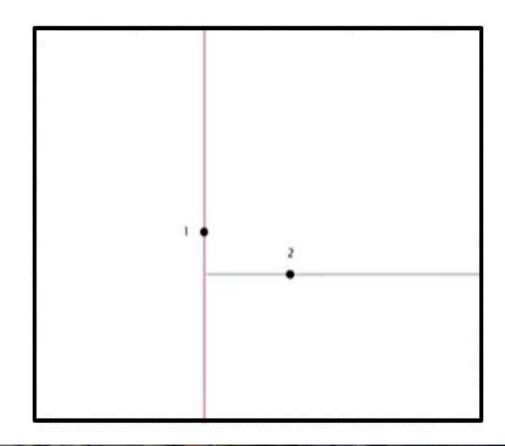


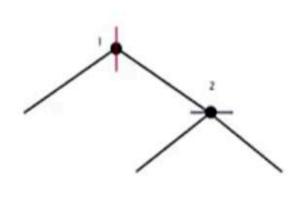




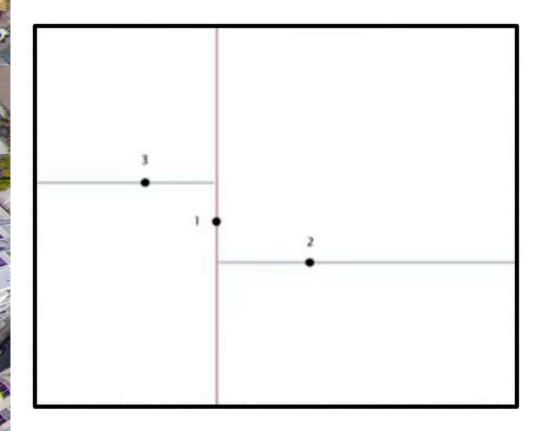


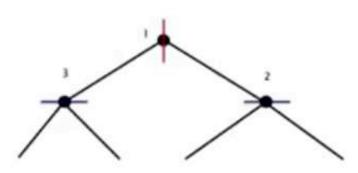




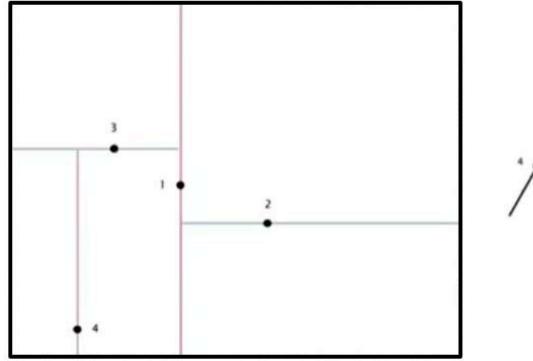


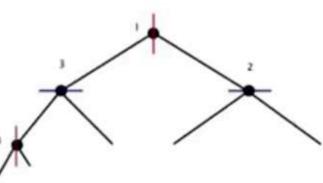




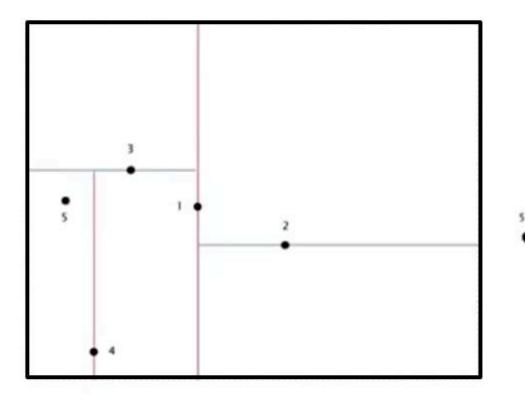


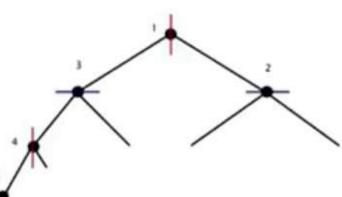




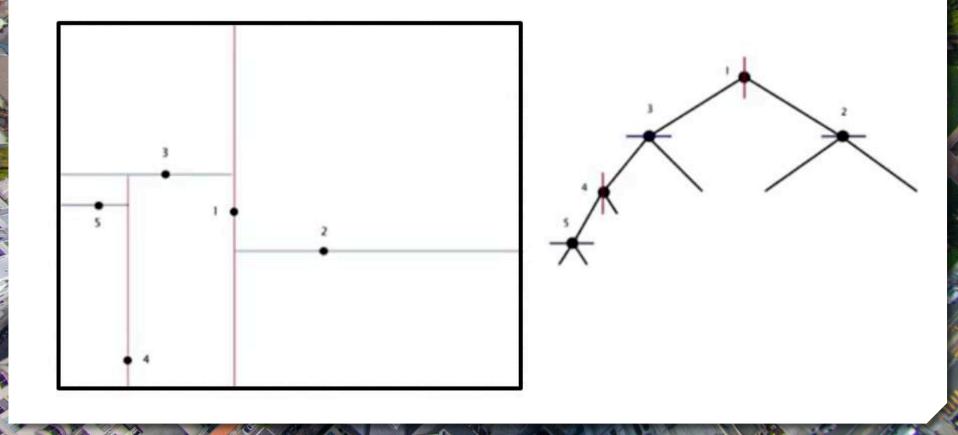




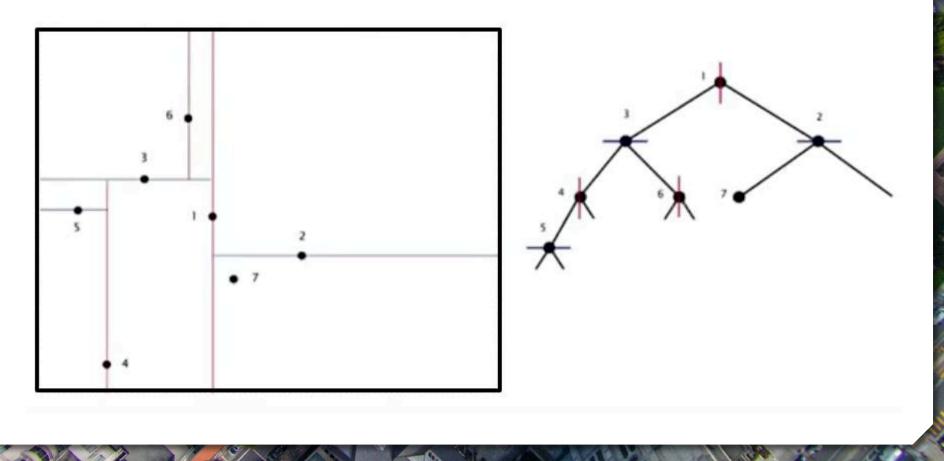




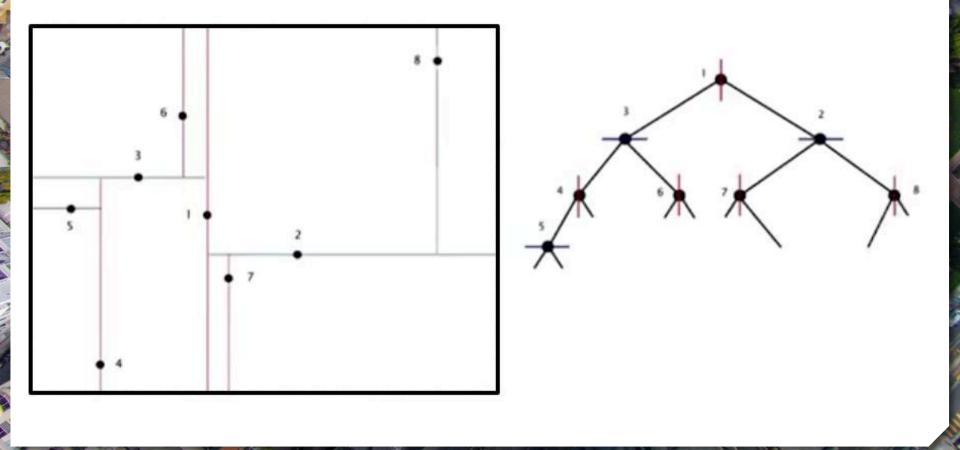




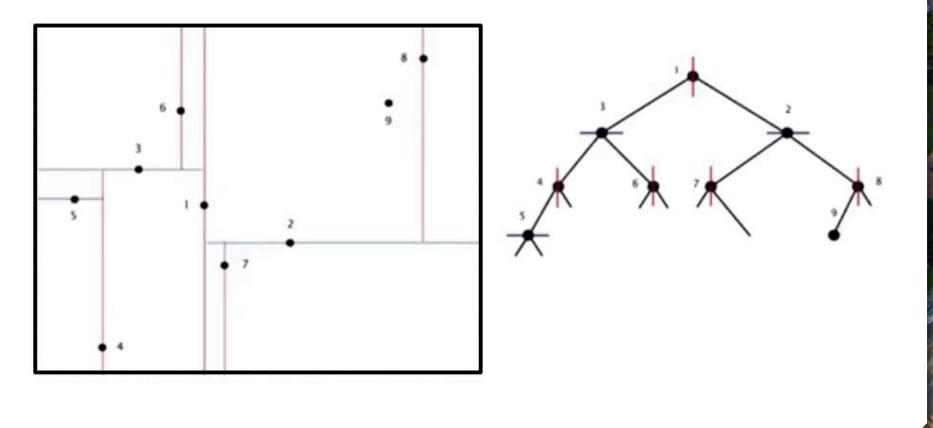








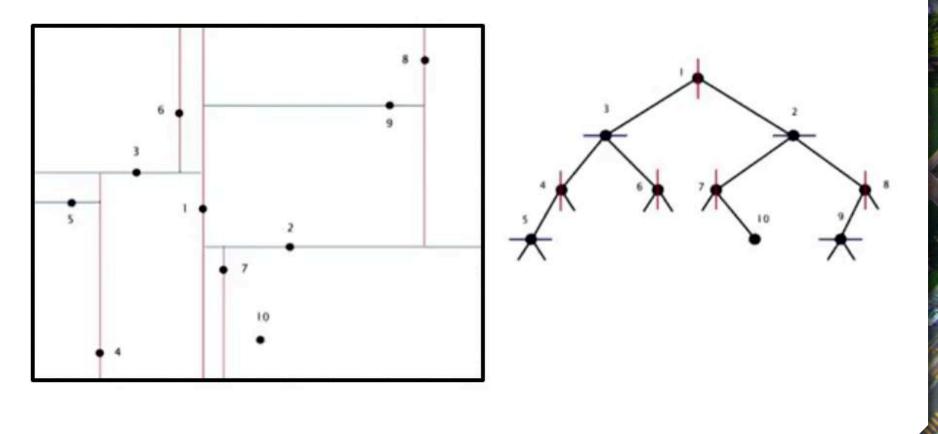






#### 2d-tree construction

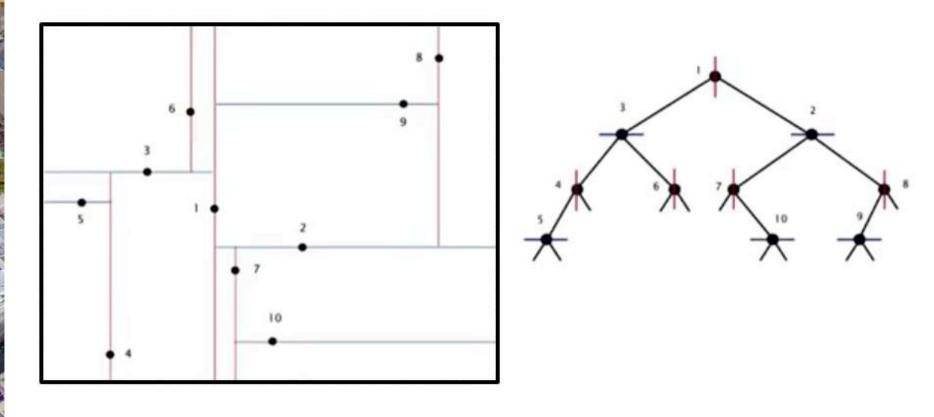
Recursively partition plane into two half-planes





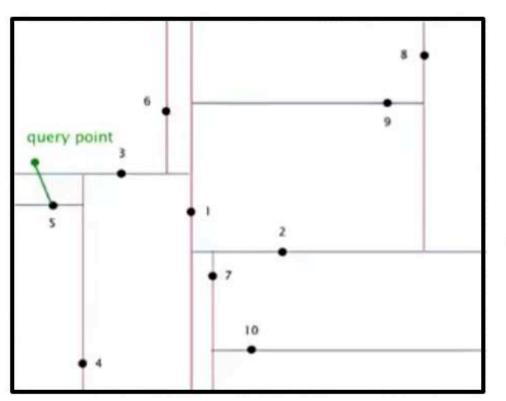
#### 2d-tree construction

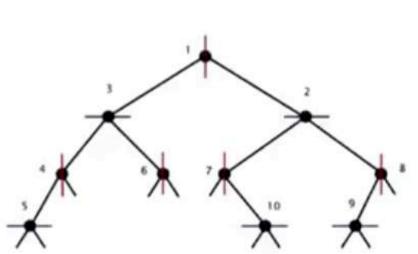
Recursively partition plane into two half-planes





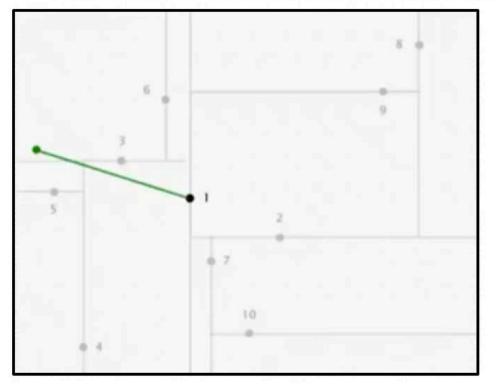
✓ Goal: find closest point to query point

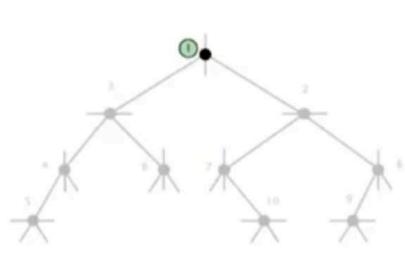






- Check distance from point in node to query point.
- Recursively search left/bottom (if it could contain a closer point).
- Recursively search right/top (if it could contain a closer point).

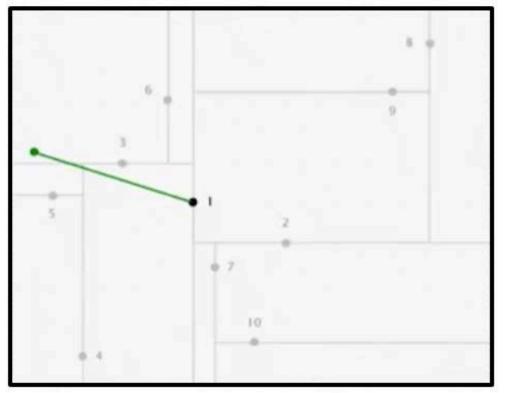


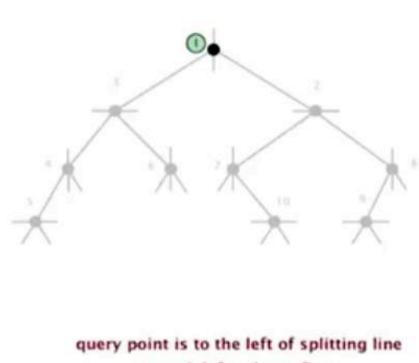


search root node compute distance from query point to 1 (update champion nearest neighbor)



- Check distance from point in node to query point.
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- Recursively search right/top (if it could contain a closer point).

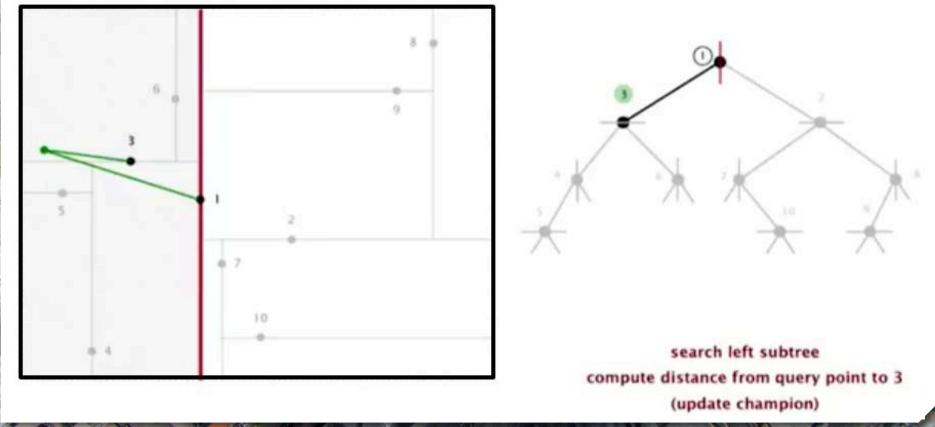




search left subtree first

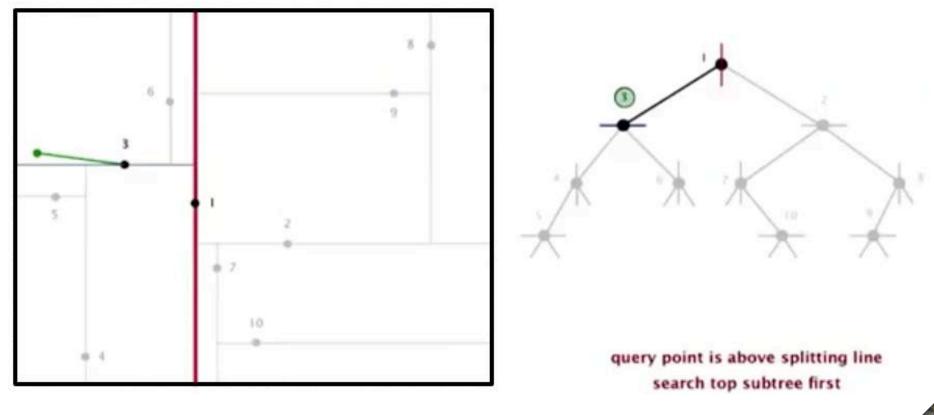


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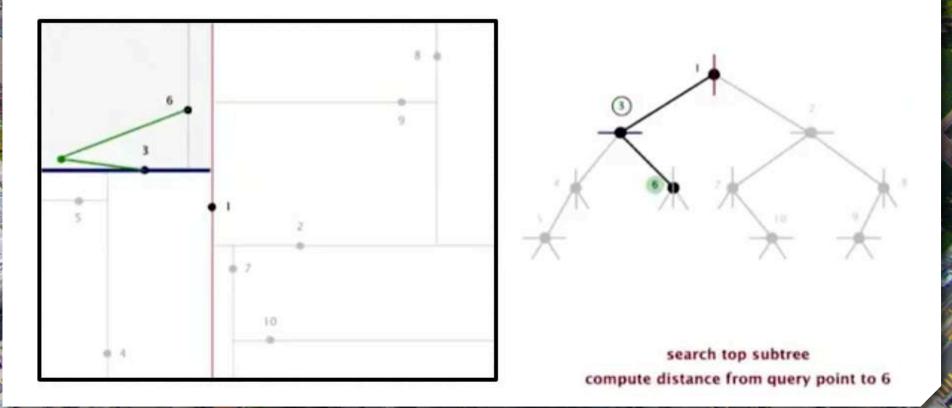


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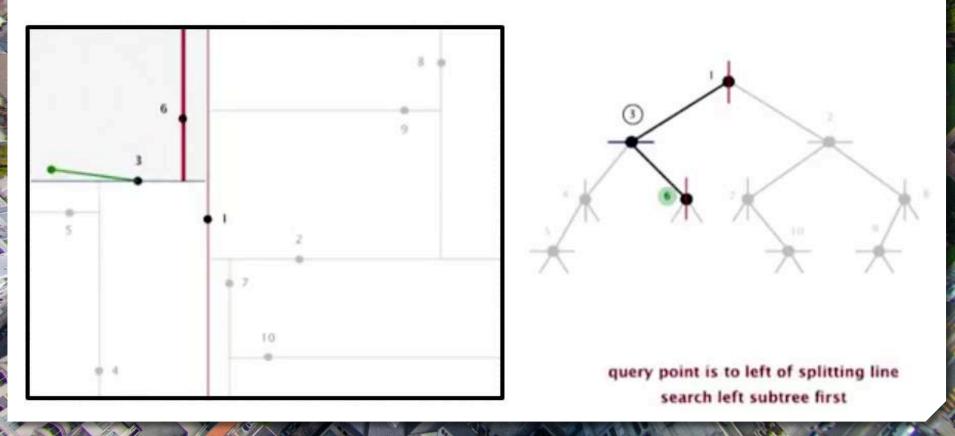


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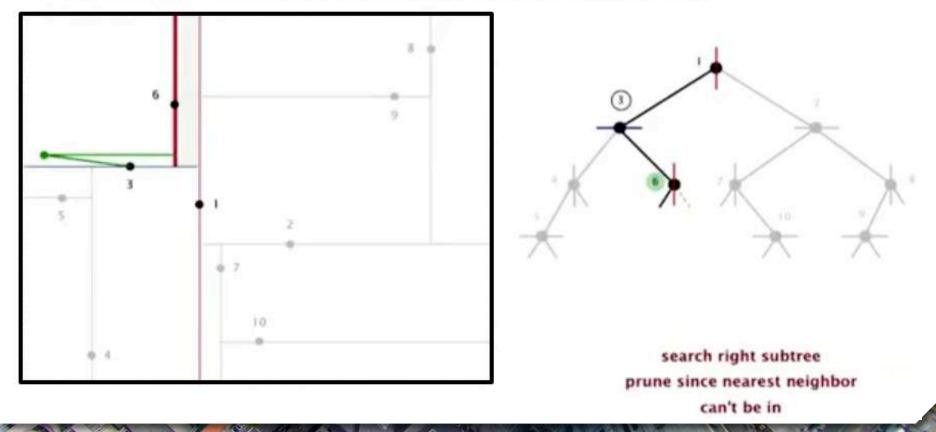


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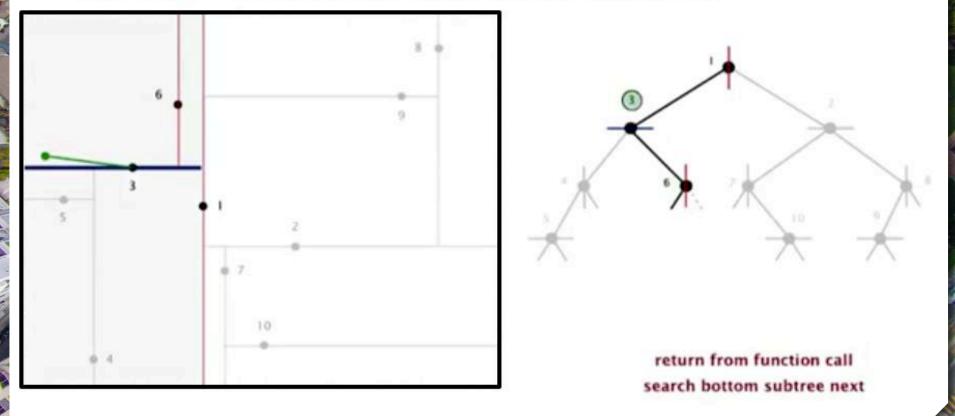


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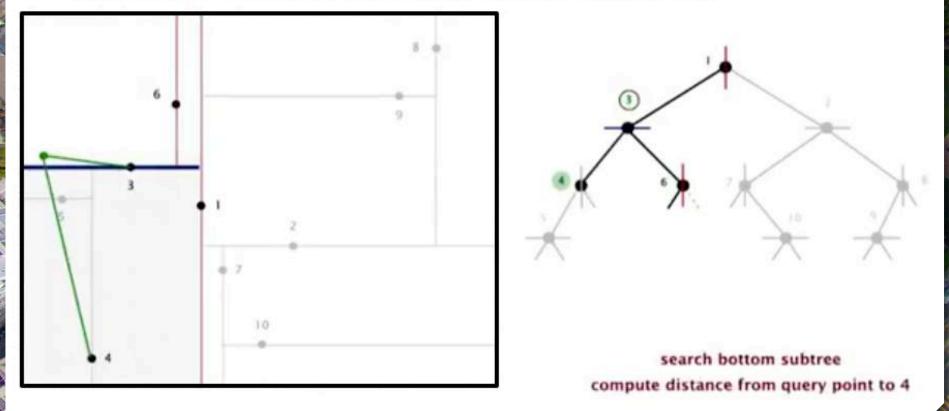


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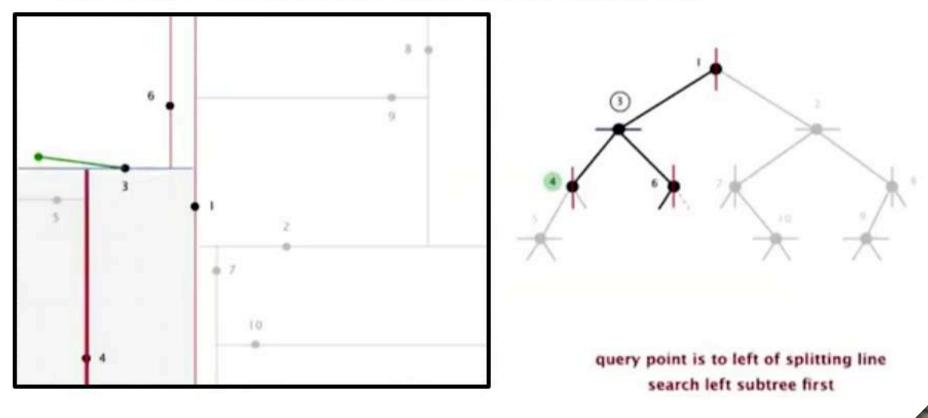


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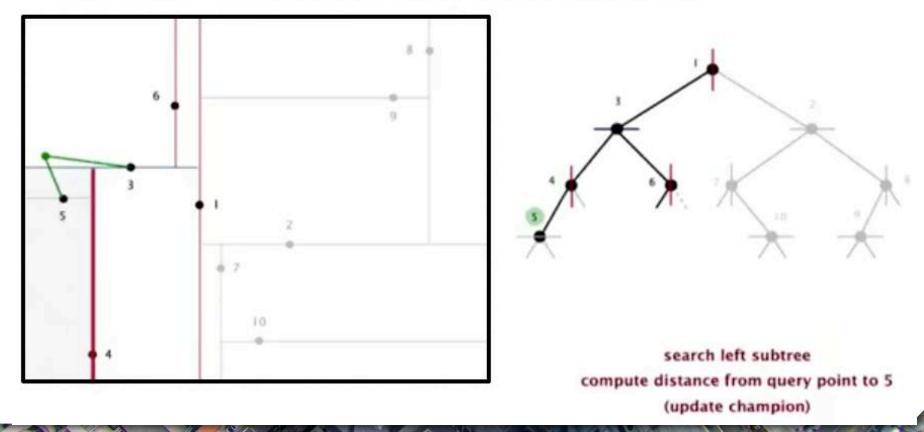


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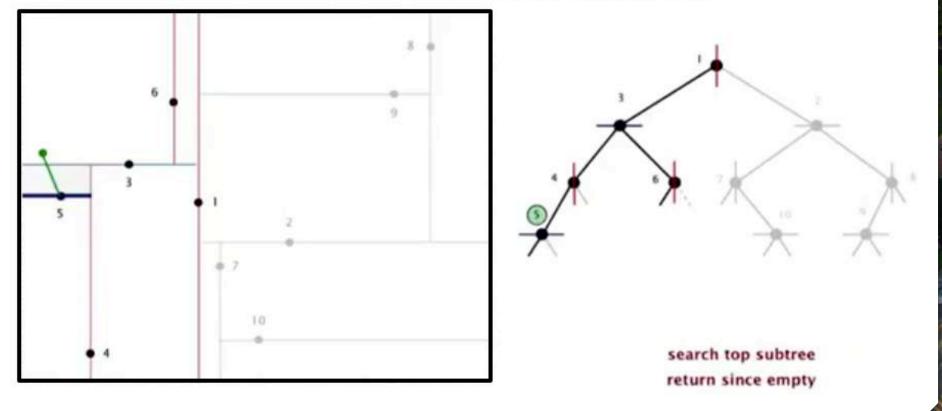


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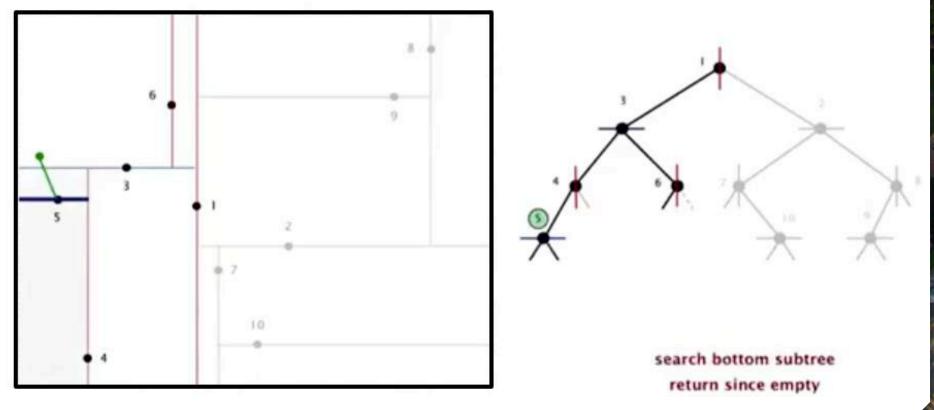


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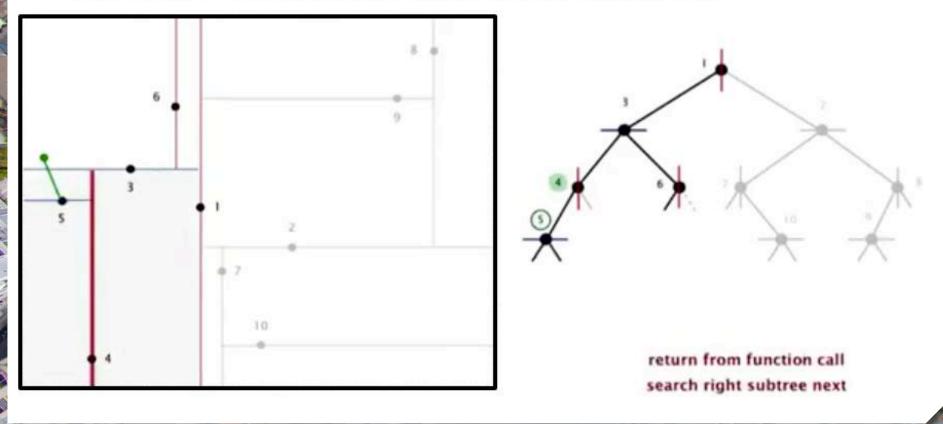


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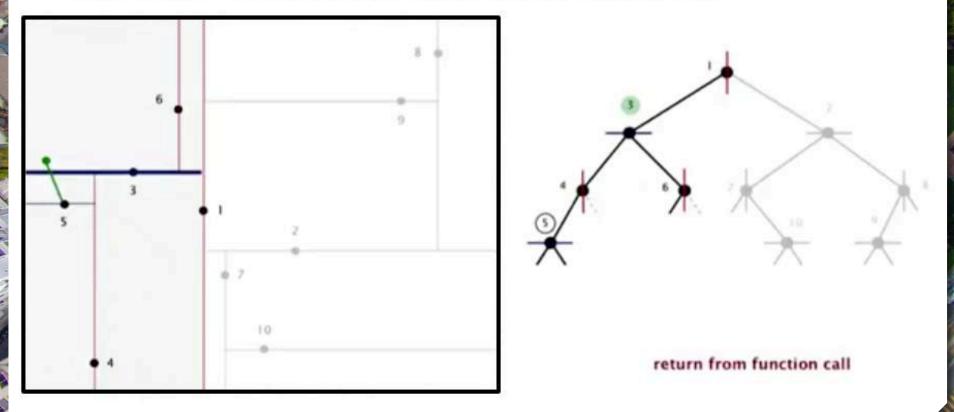


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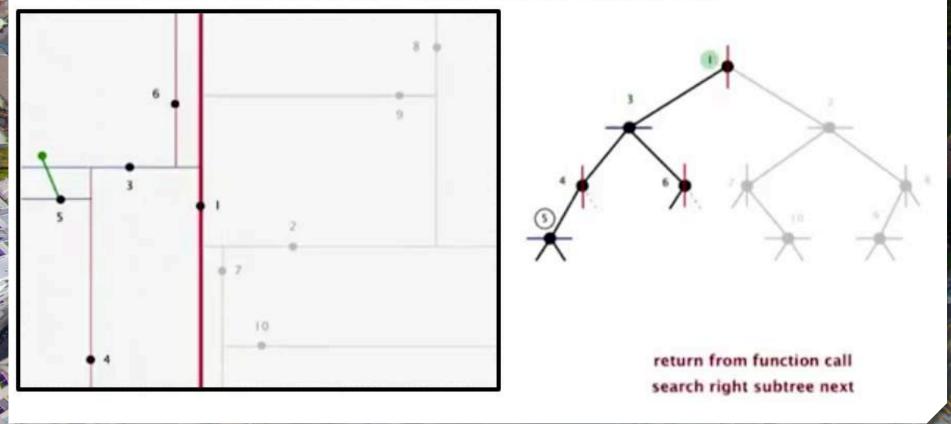


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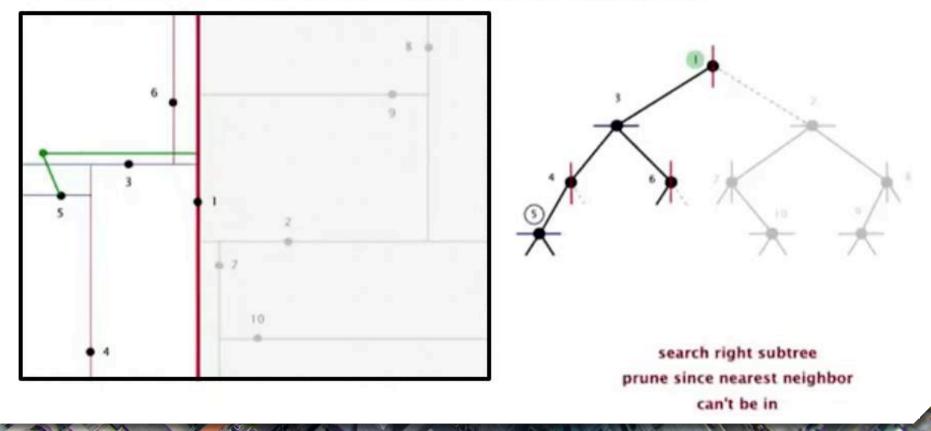


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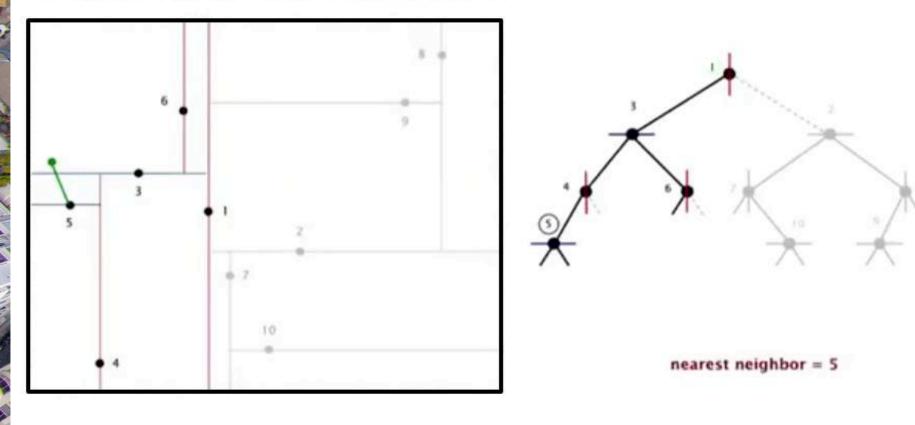
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Typical case. log N.

Worst case (even if tree is balanced). N.

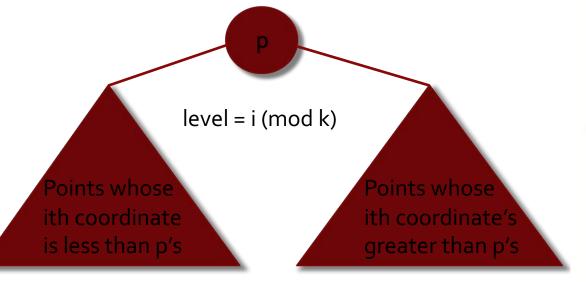


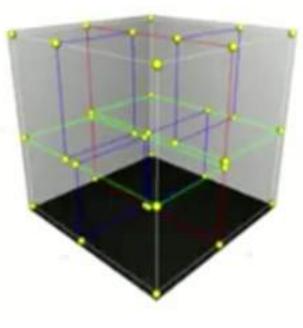


#### Kd-tree

Recursively partition k-dimensional space into 2 halfspaces.

Implementation: cycle trough dimensions à la 2d trees.





Adapts well to high-dimensional and clustered data Discovered by an undergrad in an algorithm class.



#### Detection of near-duplicates

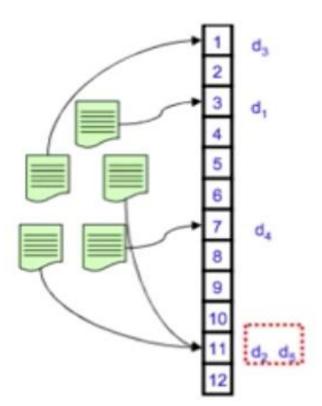
Similar files -> similar hash-code

For each file d:

- Generate K-bit hash-code
- Insert file into hash-table
- Collision -> possible duplicate
  Compare files in the same bucket

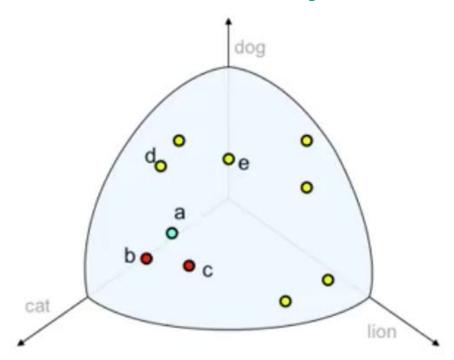
Can miss near-duplicates:

- ✓ Similar hash-codes ≠ same bucket
- Repeat L times with different hash-tables (randomized)



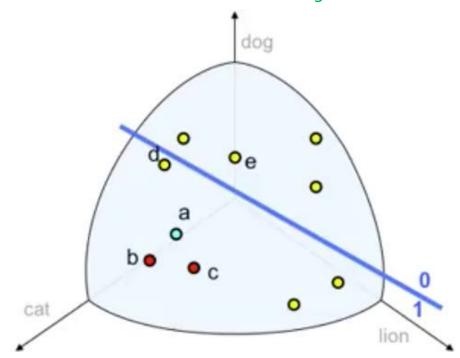


- **1**. Want: similar hash-codes for nearby points
- 2. Generate random hyperplanes:  $h_1 h_2 h_3$



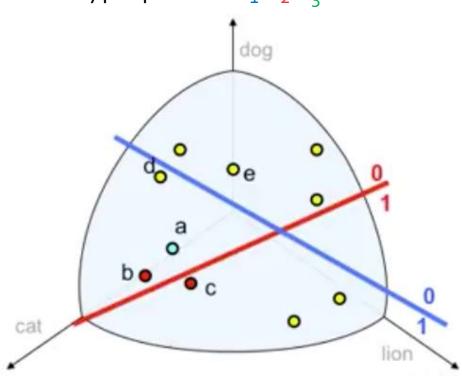


- **1**. Want: similar hash-codes for nearby points
- 2. Generate random hyperplanes:  $h_1 h_2 h_3$



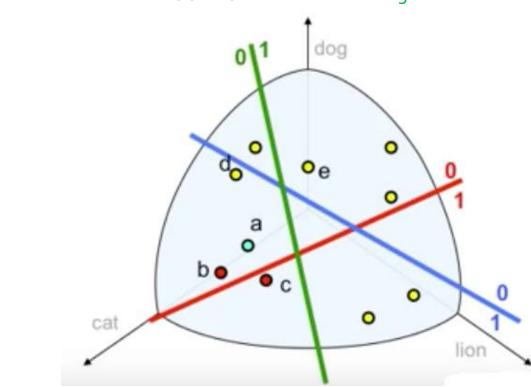


- **1**. Want: similar hash-codes for nearby points
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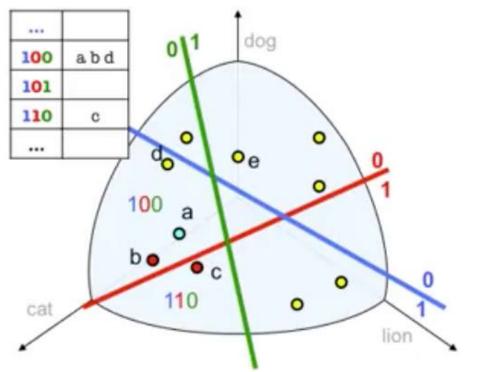


- 1. Want: similar hash-codes for nearby points
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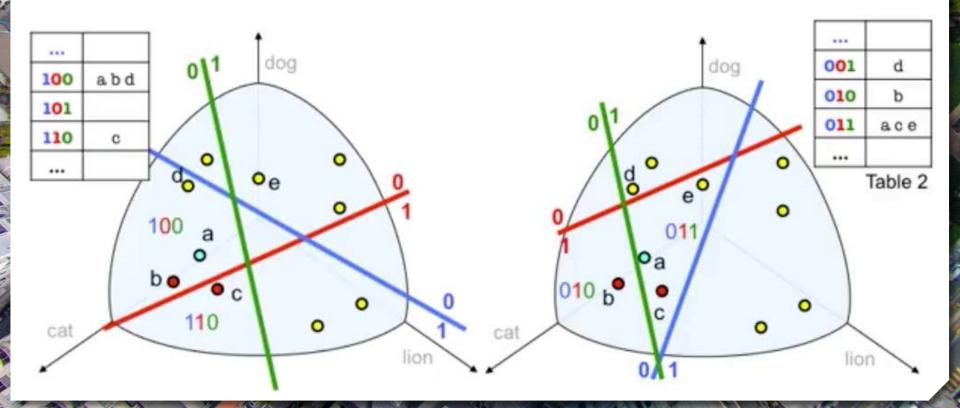


- 1. Want: similar hash-codes for nearby points
- 2. Generate random hyperplanes:  $h_1 h_2 h_3$
- 3. Compare **a** to points with same hash-code
  - **b** ... indeed similar to a
  - **d** ... false positive, will be eliminated
  - **c** ... different hash-code, will miss it





5. Repeat with different hyperplanes:  $h_4 h_5 h_6$ 





#### Acknowledgments





#### References

Jin, J. S. (2003). Indexing and Retrieving High Dimensional Visual Features, pages 178– 203. Springer Berlin Heidelberg, Berlin, Heidelberg.

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