

# MULTIPLE INSTANCE CLASSIFICATION IN THE IMAGE DOMAIN

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## Two tigers on the grass

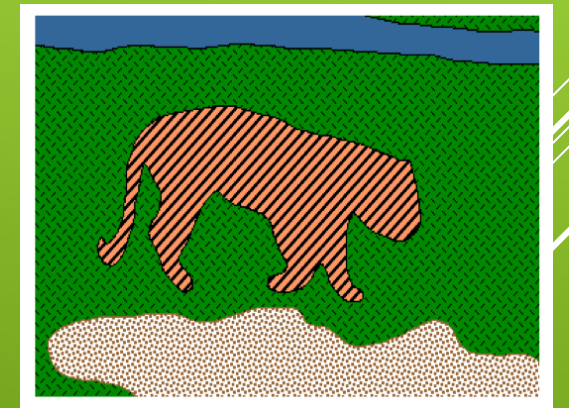
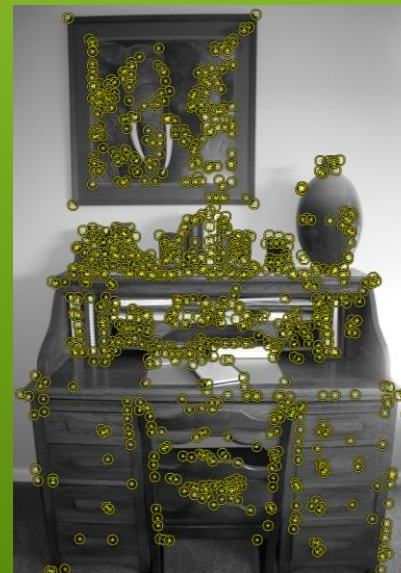
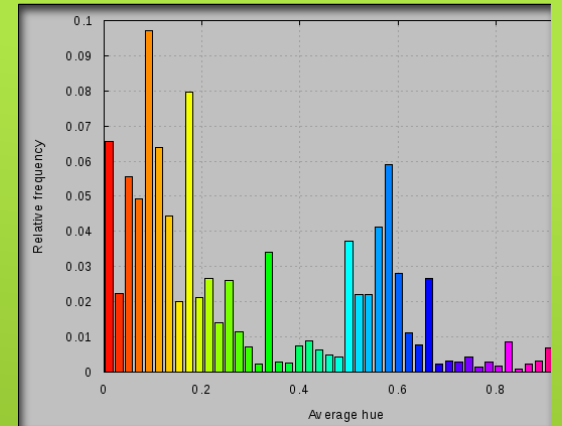
- ▶ Searching for images of interest based on their visual content
  - ▶ Retrieve the images most visually similar to a given query image
- ▶ Different wrt concept-based image retrieval
  - ▶ Uses text-based techniques

# CONTENT-BASED IMAGE RETRIEVAL

- ▶ Evaluating the similarity between two images entails:
  - ▶ Automatically extract *features/descriptors* from the images
  - ▶ Compare such features to assess a *similarity score*
  - ▶ The higher the score, the more similar the images' contents are

## SIMILARITY-BASED CBIR

- ▶ Global features describe the visual content of an image as a whole
  - ▶ Color histograms
- ▶ Local features describe the visual characteristics of a (small) set of image pixels
  - ▶ Region descriptors
  - ▶ Salient point descriptors
- ▶ Nowadays, the latter overshadow the former



# A BIT OF HISTORY

- ▶ Typically by classifying a set of query images (whose class is known) over a knowledge base of images

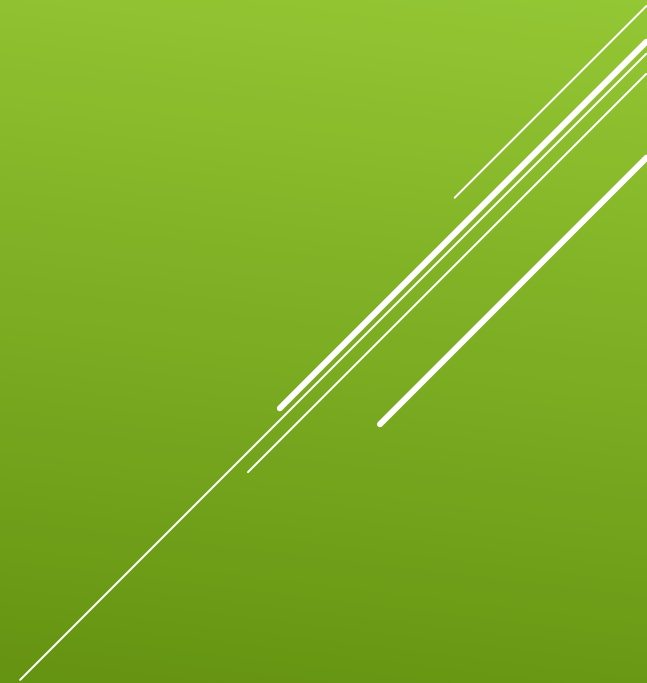
“A feature that performs well for the task of classification on a certain data set, it will most probably be a good choice for retrieval of images from that data set, too.”

*Desalaers, Keysers, Ney. Inf. Retr., 2008*

HOW DO YOU ASSESS EFFECTIVENESS  
OF A CBIR SYSTEM/TECHNIQUE?

- ▶ Most of the proposed techniques lack emphasis on classification techniques
- ▶ And what about efficiency?
  - ▶ Indexing, anyone?

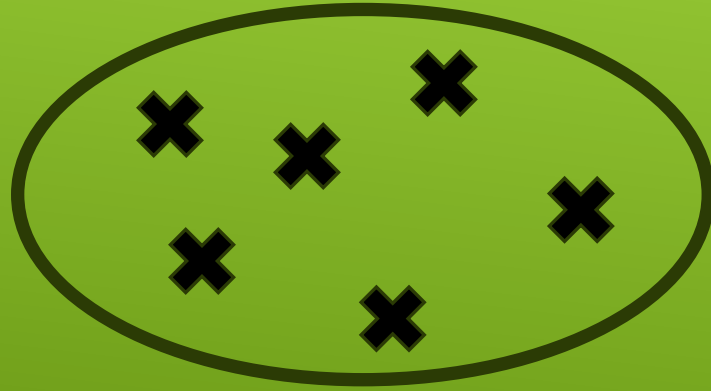
HOWEVER...



- ▶ A number of classification techniques drawn from the realm of Machine Learning
- ▶ Local features perfectly fit the scenario of applicability of MIC
- ▶ It could help researchers working in CBIR to evaluate their proposed features and/or indexing techniques in a more structured way
  - ▶ What are the alternatives at hand?
- ▶ Each technique also suggests a retrieval method

## INTRODUCING MULTIPLE INSTANCE CLASSIFICATION (MIC)

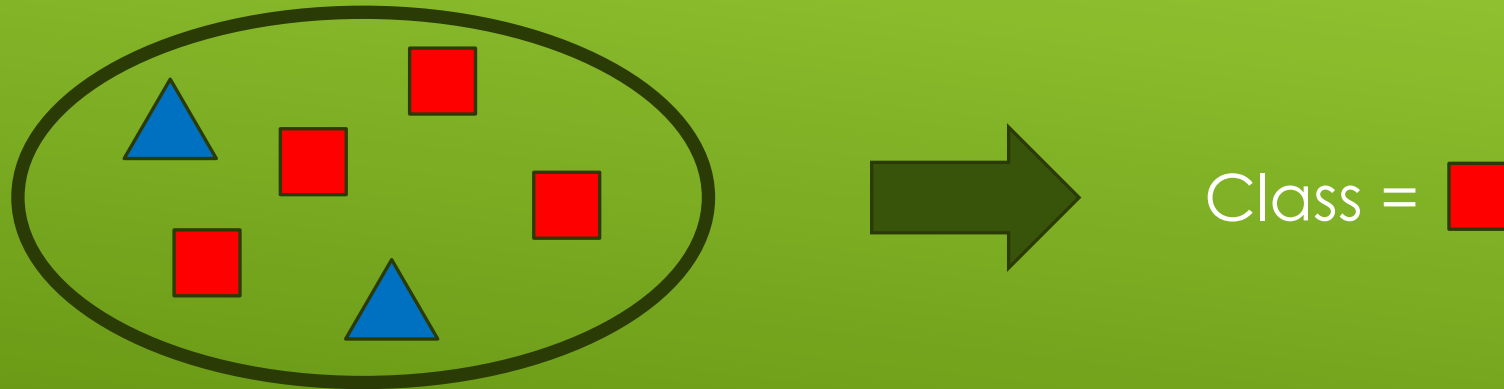
- ▶ Each object (*image*) is seen as a *bag* of individual *instances* (*features/descriptors*)
- ▶ The *class* of each bag can be transferred to all (or some) of its instances



THE MIC MODEL

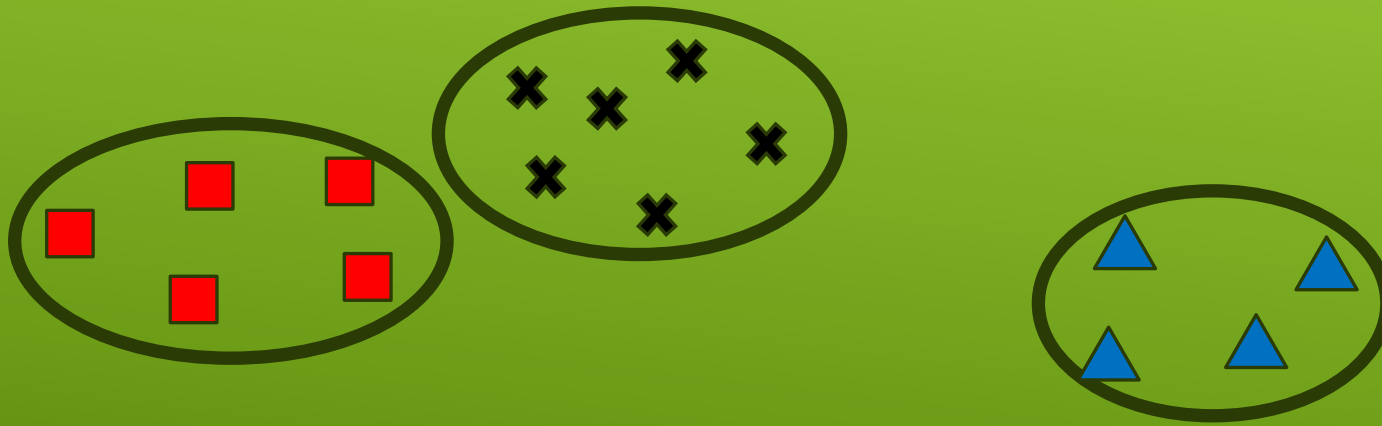


- ▶ The discriminative information lies at the instance level
  - ▶ Classification is performed on instances
    - ▶ For example, using a distance between descriptors
  - ▶ The overall classification is performed by *aggregating* classifications obtained at the instance level
- ▶ Retrieval (and indexing) is based on instances (local features)



# INSTANCE SPACE PARADIGM

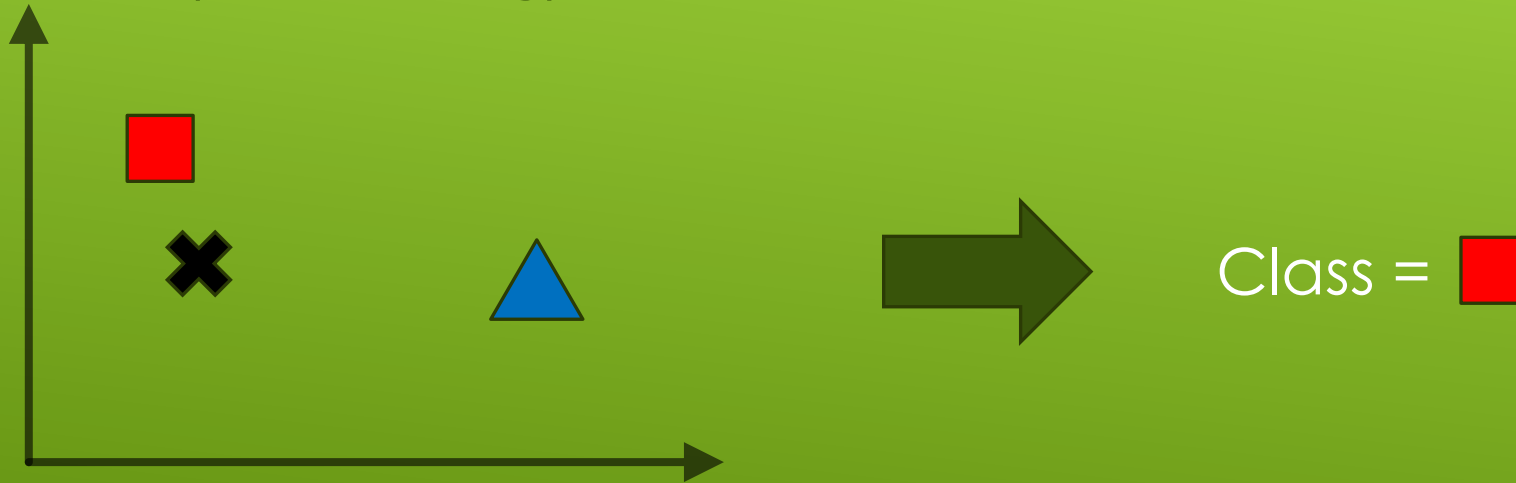
- ▶ The discriminative information lies at the bag level
  - ▶ This cannot be distributed to instances
  - ▶ The overall classification is performed by *aggregating* distances at the instance level
    - ▶ For example, using an overall *distance* function between images
    - ▶ Commonly used aggregators: EMD, Hausdorff, etc.
- ▶ Retrieval (and indexing) is based on images



BAG SPACE PARADIGM

Class = [red square]

- ▶ Each bag is mapped to a single feature vector
  - ▶ A vector-based classifier is exploited
  - ▶ Only makes sense when the number of instances in a bag is very high
    - ▶ Example: Bag-Of-Visual-Words
- ▶ Retrieval (and indexing) is based on vectors



EMBEDDED SPACE PARADIGM

- ▶ Comparing performance of two local features
  - ▶ WINDSURF region-based features
    - ▶ On average, 4-5 regions per image (ES not applicable)
  - ▶ SIFT salient point descriptors
    - ▶ On average, thousands of keypoints per image
- ▶ Alternatives implemented on top of the WINDSURF framework
  - ▶ Provides algorithms and indexing structures for efficient query processing based on local features
  - ▶ All three paradigms are implemented
  - ▶ M-tree indexing instances (descriptors), bags (images), and vectors

## EXAMPLE OF USE

features	WINDSURF	SIFT
Instance Space	Accuracy: <b>good</b> Efficiency: <b>very good</b>	Accuracy: <b>very good</b> Efficiency: <b>very bad</b>
Bag Space	Accuracy: <b>bad</b> Efficiency: <b>very good</b>	Accuracy: <b>bad</b> Efficiency: <b>bad</b>
Embedded Space	Not applicable	Accuracy: <b>good</b> Efficiency: <b>very good</b>

## COMPARISON OF ALTERNATIVES

- ▶ MIC can be a handy tool for researchers in CBIR
- ▶ When proposing features, always consider *all* available alternatives
- ▶ And never forget efficiency!

LESSONS LEARNED

