Arizona State University

RETRIEVING CLINICALLY RELEVANT DIABETIC RETINOPATHY IMAGES USING A MULTI-CLASS MULTIPLE-INSTANCE FRAMEWORK

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OUTLINE

- The DR Problem
- Literature
- Feature Space
- MIL to the Rescue
- *Rank-KNN*
- Experiments
- Results
- Conclusions

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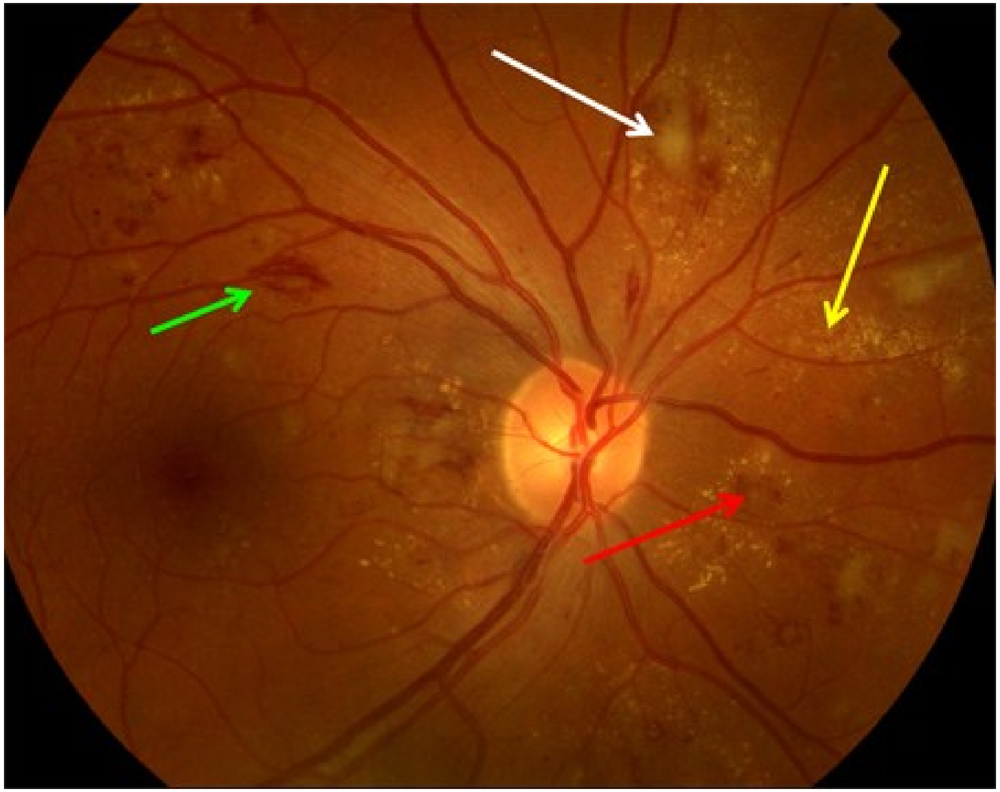
The DR Problem

- Diabetic retinopathy is a vision threatening social problem.
- WHO: 221 million people affected by 2010.

- Stages of DR:-
  - Non-Proliferative DR (includes MA, cotton wool spots etc..).
  - Proliferative DR (includes NV, mature NPDR symptoms, Hemorrhages).

- Early detection and treatment of DR is crucial.

The DR Problem



Yellow arrow: Exudates

Red arrow: Microaneurysms (MA)

White arrow: Cotton wool spot

Green arrow: Hemorrhage

Source: Moorfields Photographic Archive

The DR Problem

- To circumvent ophthalmological fatigue, computer-aided diagnosis plays a principal role.

- Idea:-
  - Retrieve *"clinically relevant"* images from previously diagnosed archives.
  - Clinically relevant = Similar lesions + similar severity levels (will be explained in detail later).
  - Helps in knowledge sharing and reutilization among experts.

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Literature

- CBIR systems for other medical applications:-
  - Neural image database [Chu94].
  - CT scan images [Kelly 95].
  - High-resolution computer tomography lung images [Shyu99].
- STARE project: The first attempt of performing CBIR on retinal images [Gupta96].
- Recent CBIR system for automated diagnosis of DR: [Chaum08].

Literature

- Recent work:
  - [Agurto12] Detection of Neovascularization in the Optic Disc.
  - [Quellec12] A MIL framework for diabetic retinopathy screening.
  - [Garg12] Telemedicine for Improving DR Evaluation.
- These groups have been working actively in DR related CAD research.
- Yet, there is *NO* solution available, which is unanimously accepted by the ophthalmological community.

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Feature Space

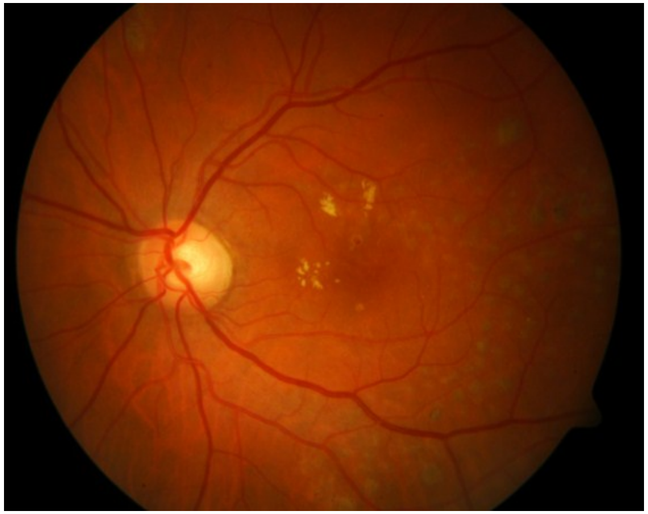
- Auto color correlogram (Auto CC) is the feature used [Venkatesan12].
- Tabular representation of indexed color pairs.
- Models the distribution of colors in an image.

- Feature dimensionality:- 256.

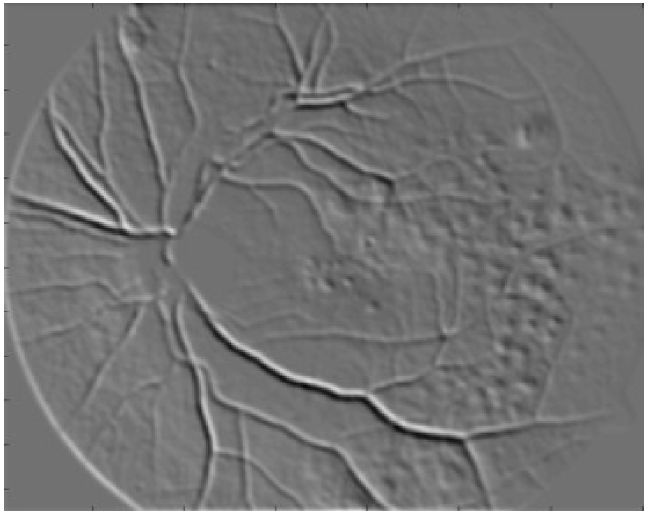
- Combined with statistics of steerable Gaussian filter response (SGF) and fast radial symmetric transform (FRST).

Feature Space

- SGF is widely used to detect presence of contours, lines and other geometrical structures [Freeman91].



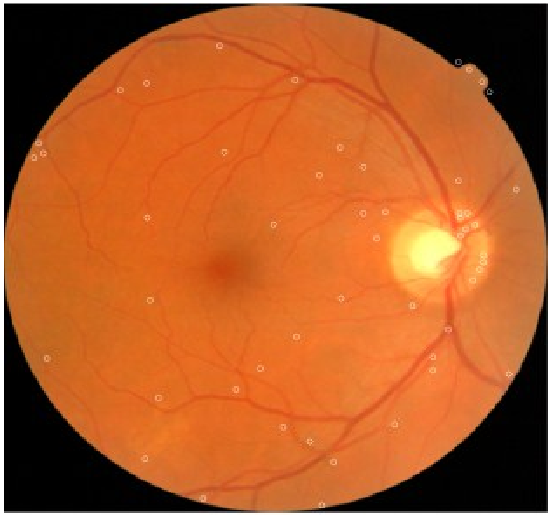
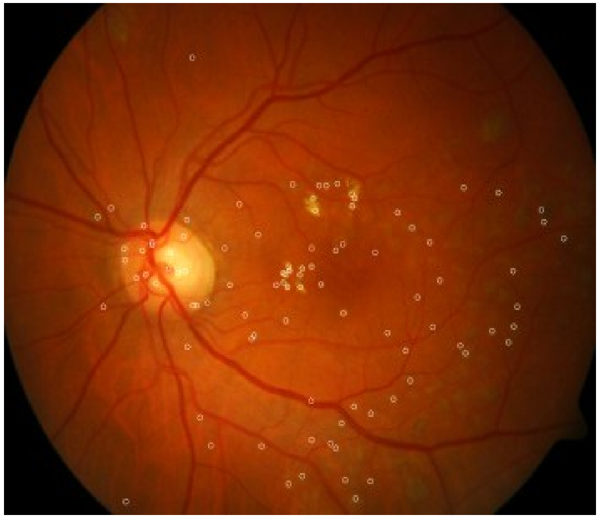
(a) Signal



(b) Filter response at 225°

Feature Space

- FRST – interest point detector [Loy03].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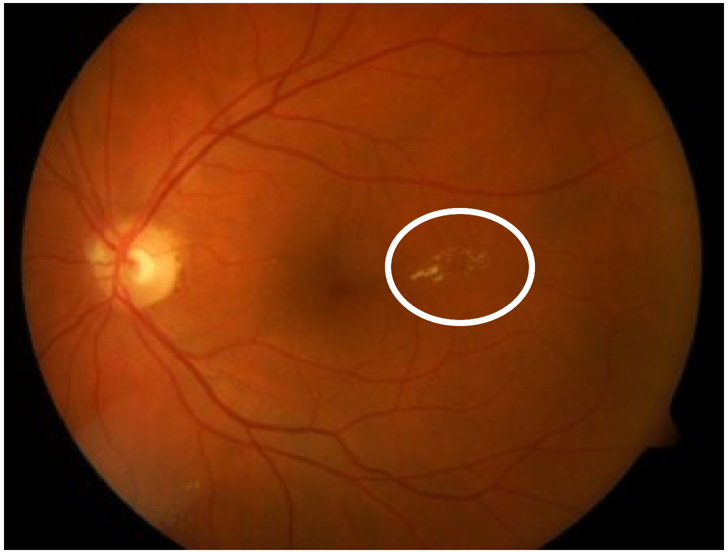
MIL to the Rescue

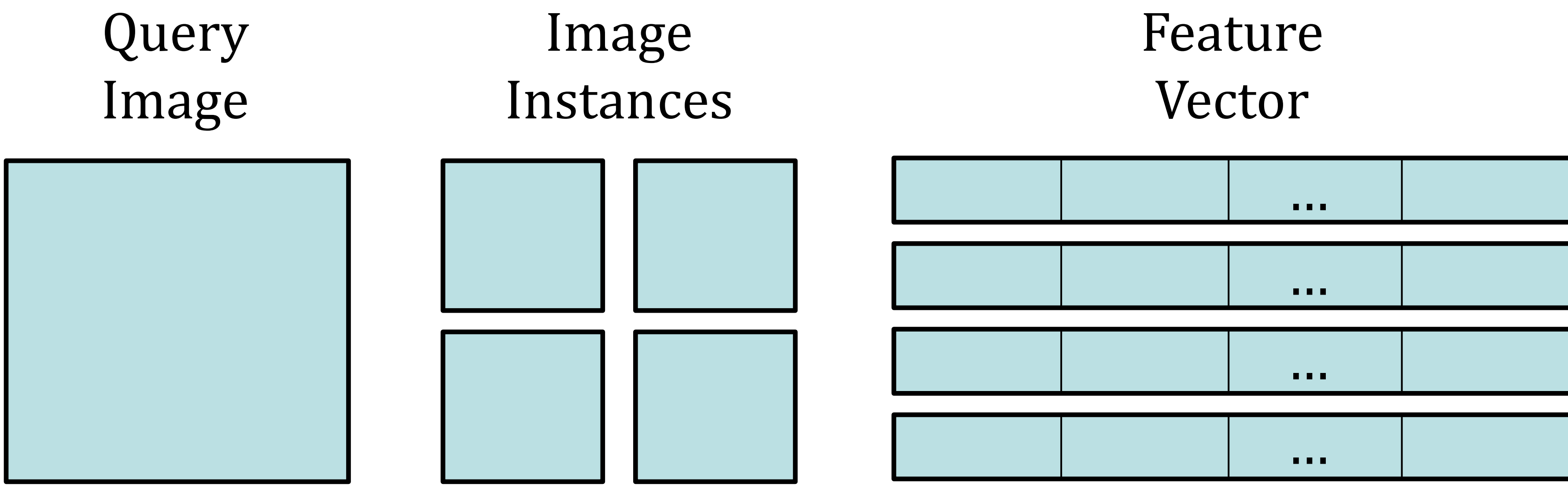
- AutoCC and other features are essentially global.
- Local descriptors do not work: too many landmarks.
- In a DR problem, global features will have low discriminative power because most of the image looks normal.
- Retrieval must be performed only based on the nature of lesions (minority).
- Possible option:
  - Multiple instance retrieval !



Localized lesion

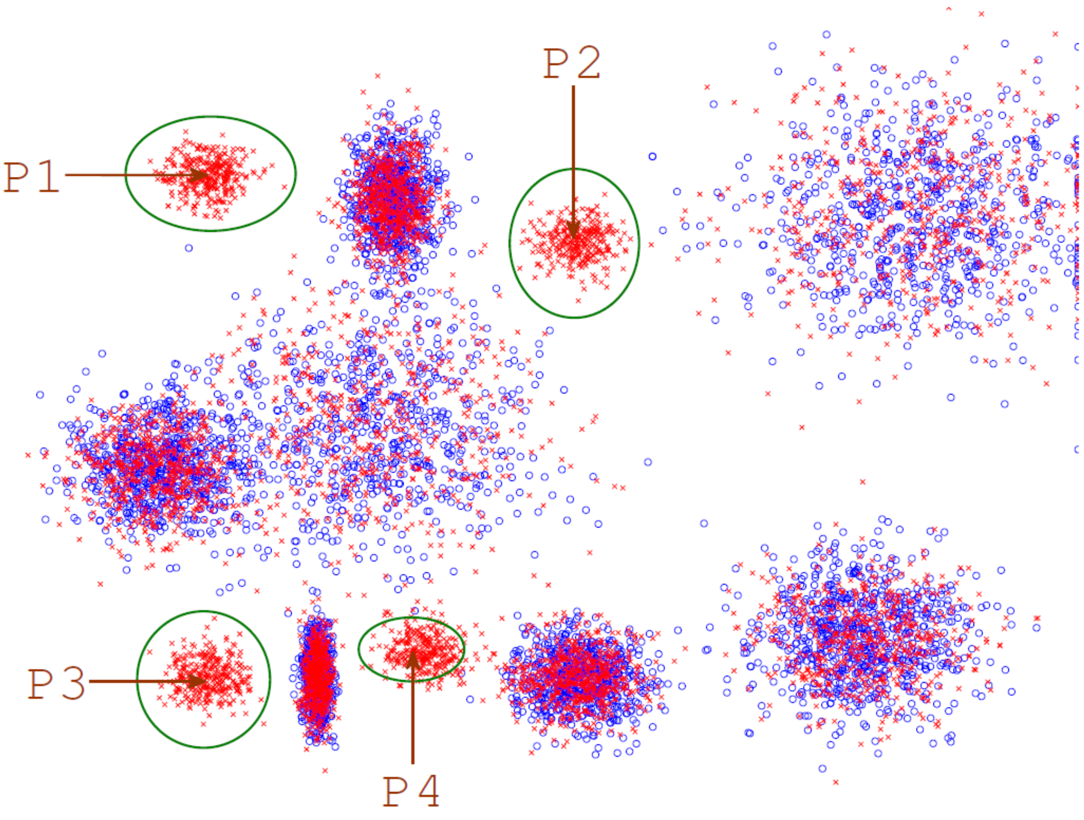
Let's see how

MIL to the Rescue



Multiple instance retrieval

MIL to the Rescue



MIL to the Rescue

- Multiple instance learning algorithms:
  - Learning axis parallel concepts [Dietterich97].
  - Diverse density [Maron98].
  - EMDD [Zhang01].
  - Citation-KNN [Wang02].
  - Multiple instance SVM [Andrews02].

The only retrieval algorithm

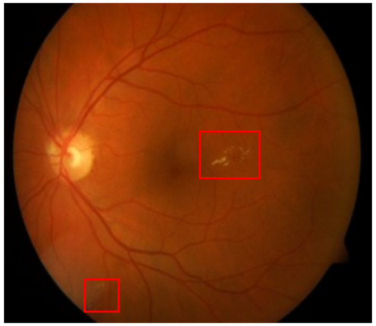
MIL to the Rescue

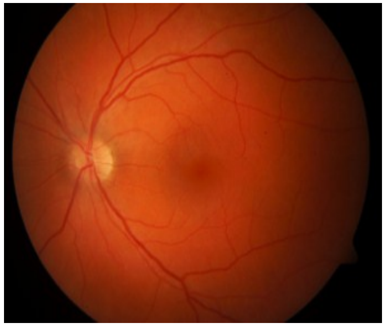
- Citation-*KNN*:
  - Similarity metric is the minimal Haussdorff distance between two bags.

$$d(A,B) = \min_{a \in A} \min_{b \in B} \| a - b \|$$

  - Minimal Haussdorff distance gives the minimum of minimum distances between all instances in two bags.

- Why not Citation-kNN?





- DR has an unique feature space
- Citation-kNN – designed for uniformly distributed negative samples
- DR has localized positive and negative samples

A special MIL retrieval algorithm!!!

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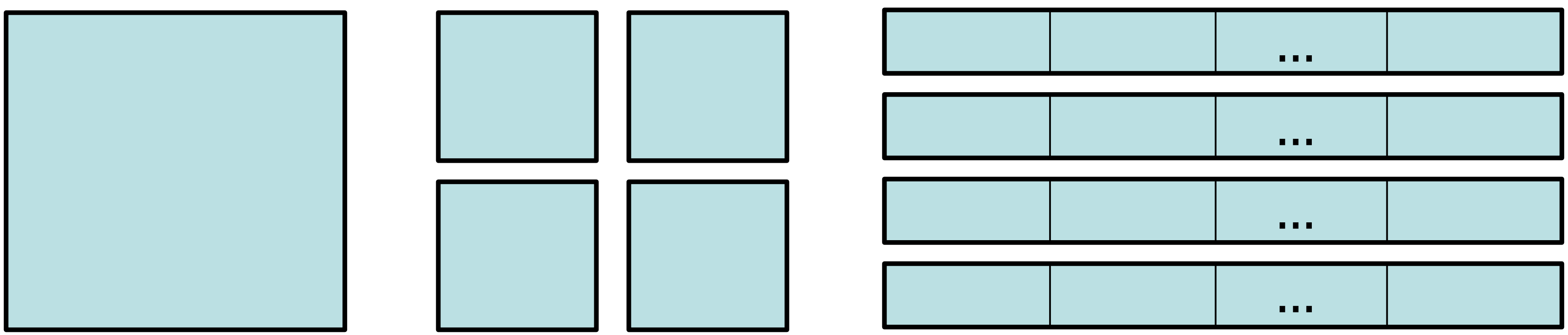
Rank-KNN

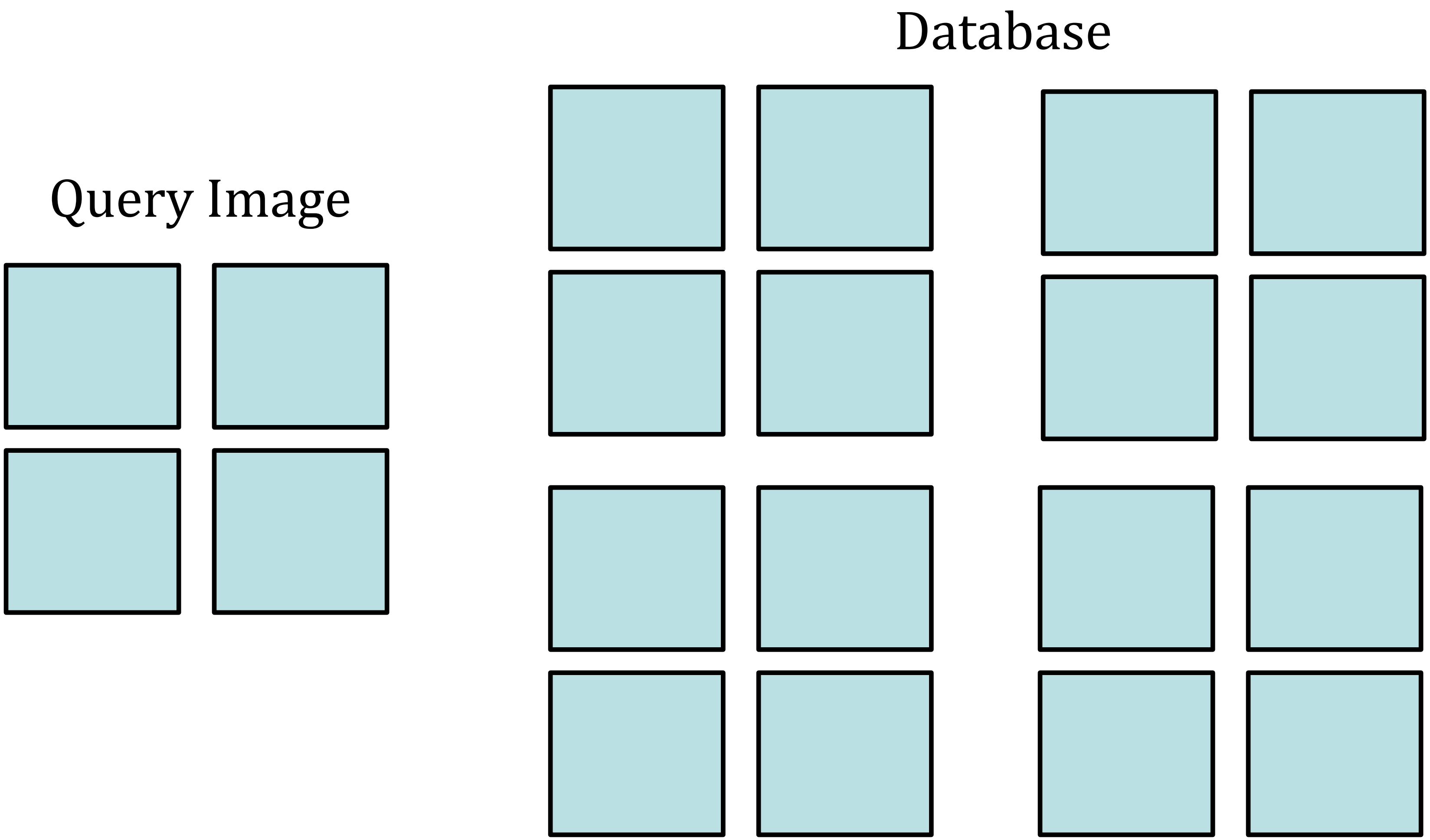
Query Image

Image Instances

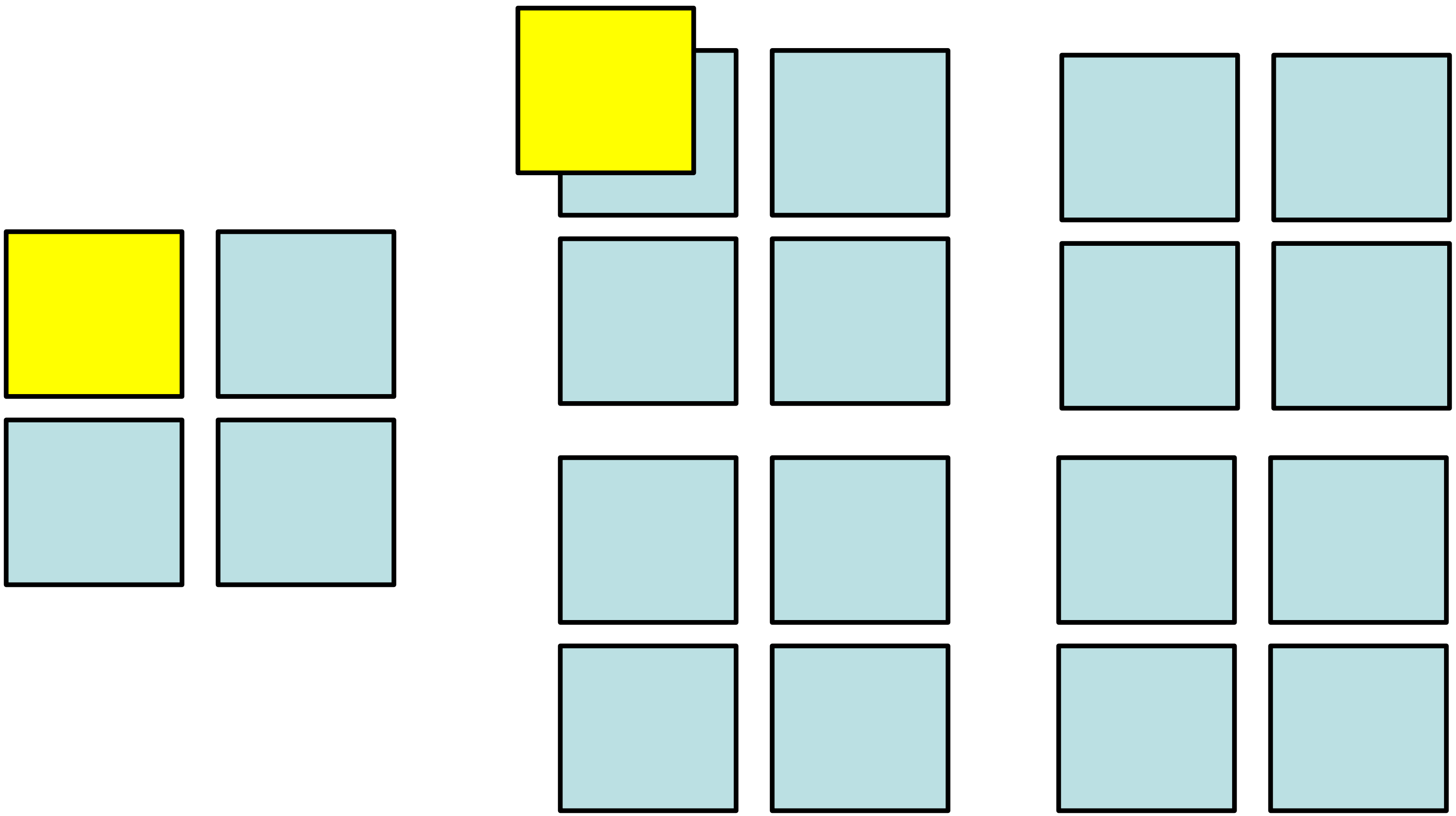
Feature Vector



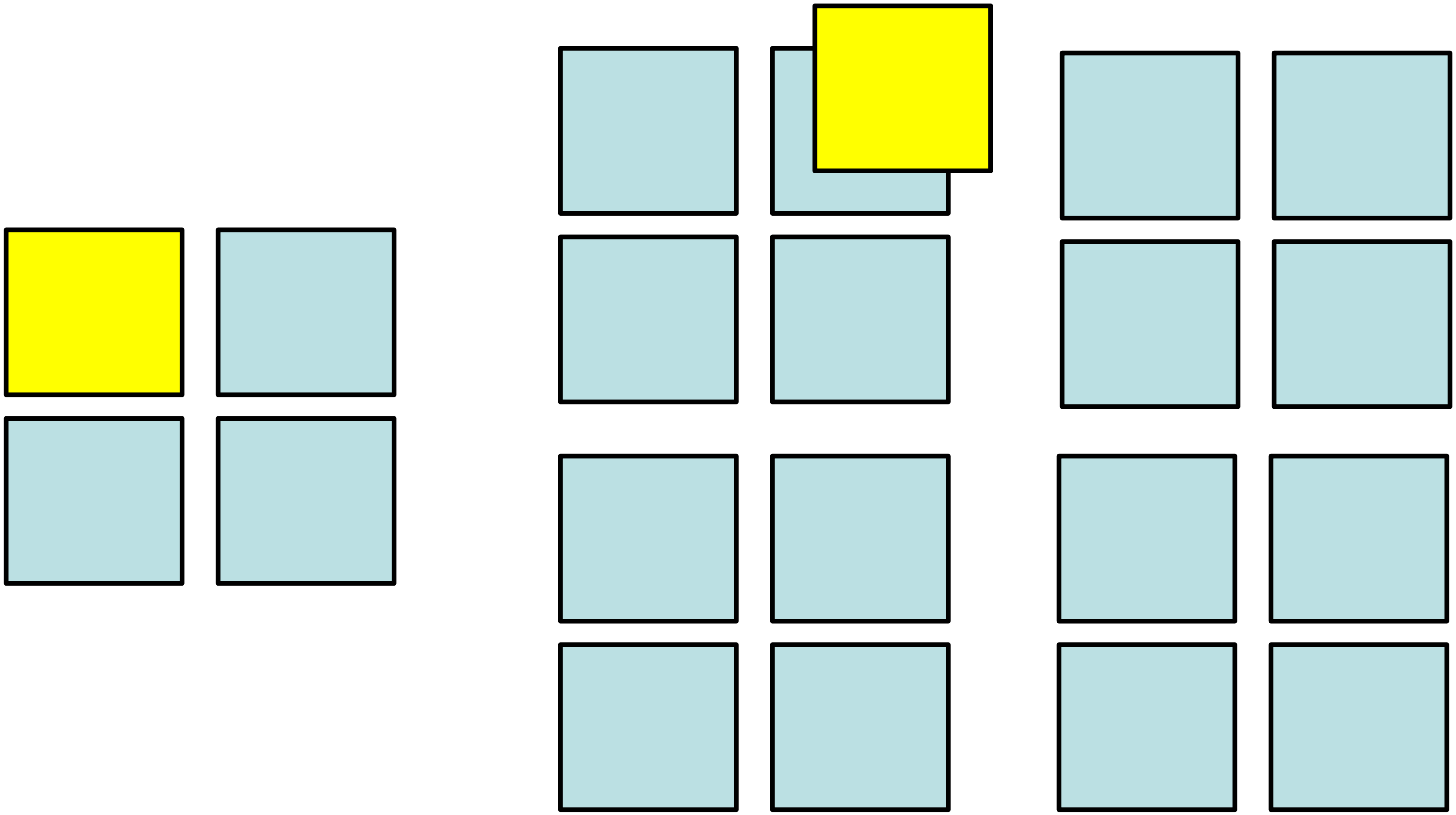
Rank-KNN



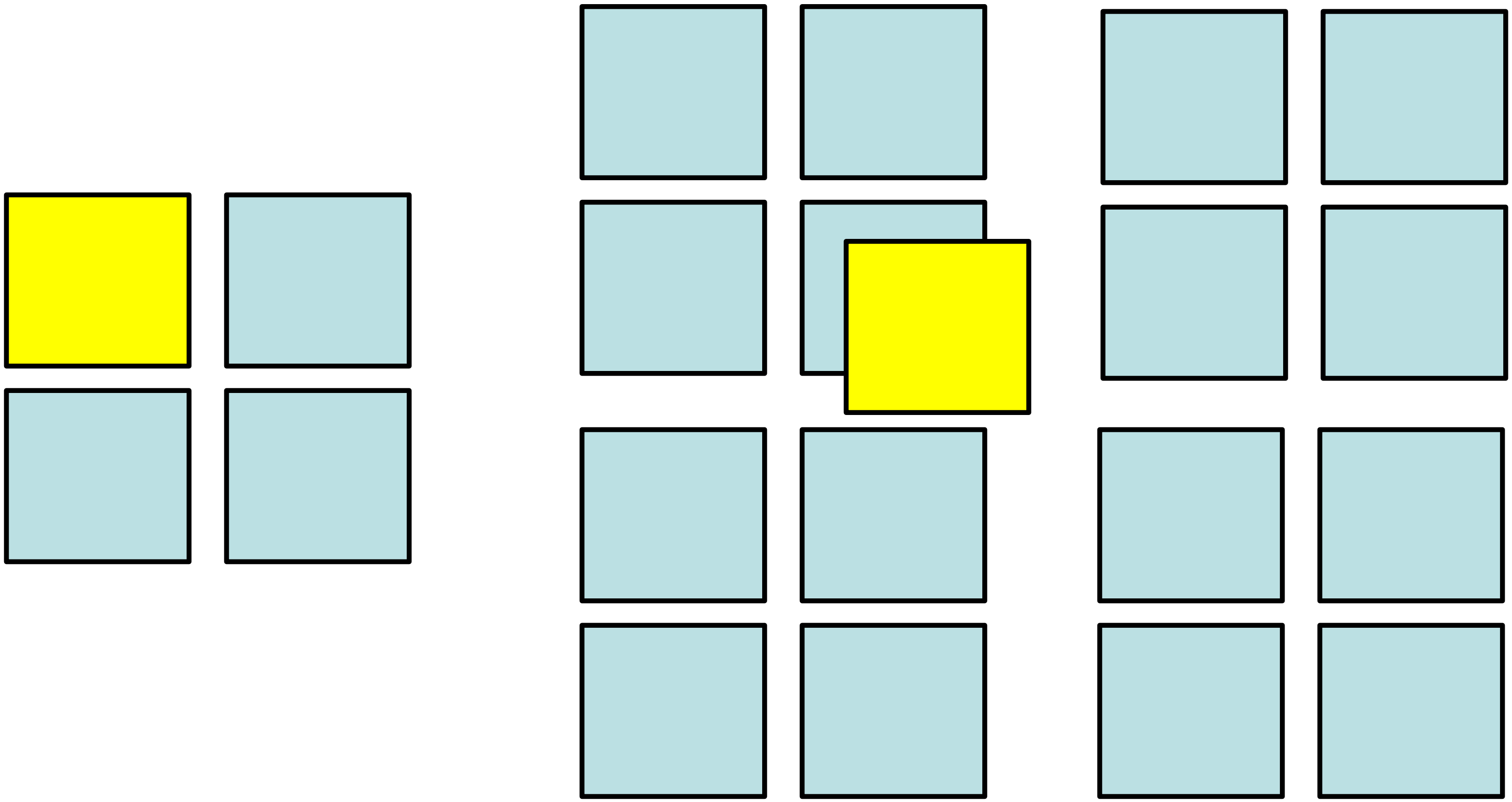
Rank-KNN



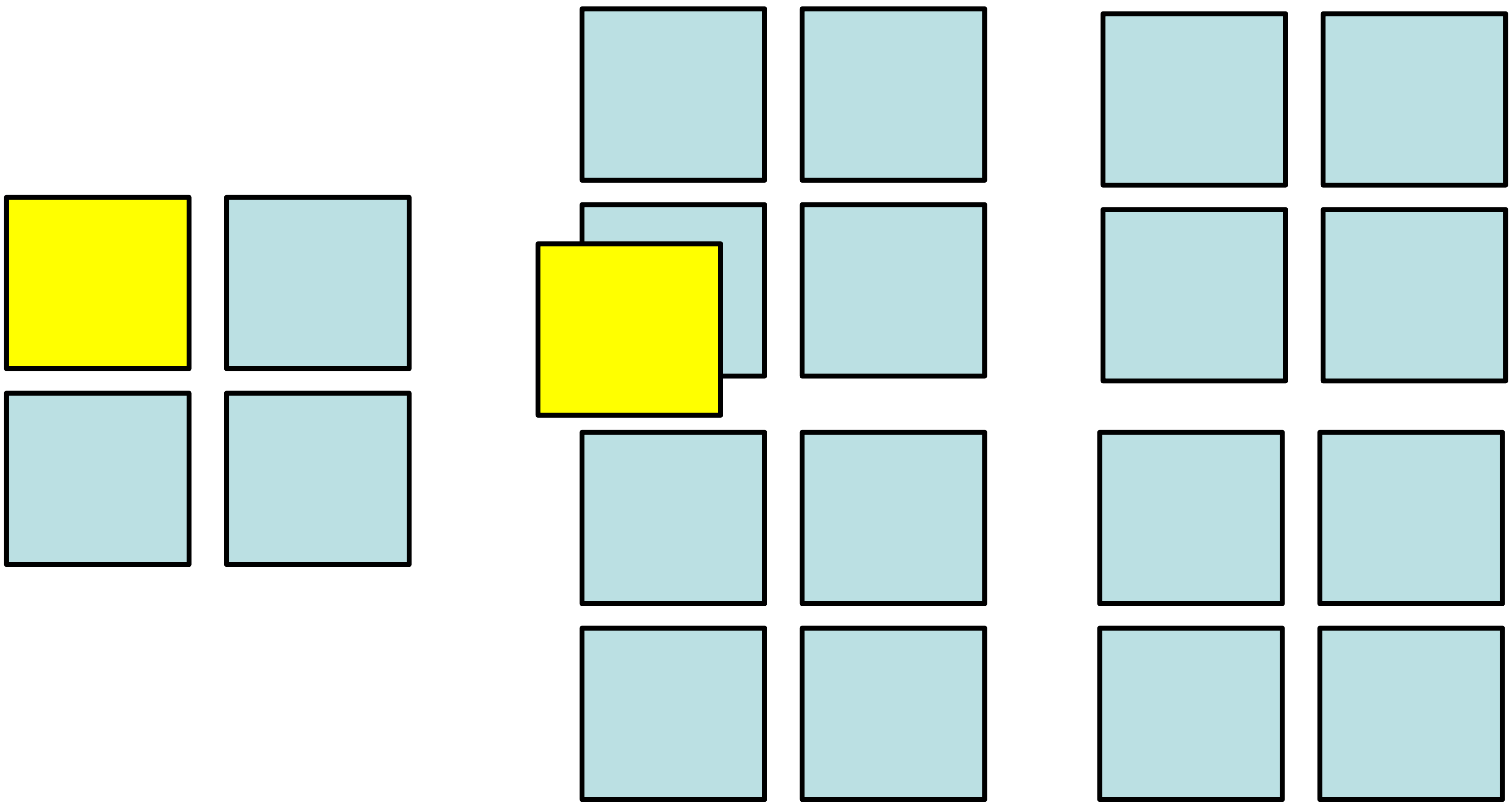
Rank-KNN



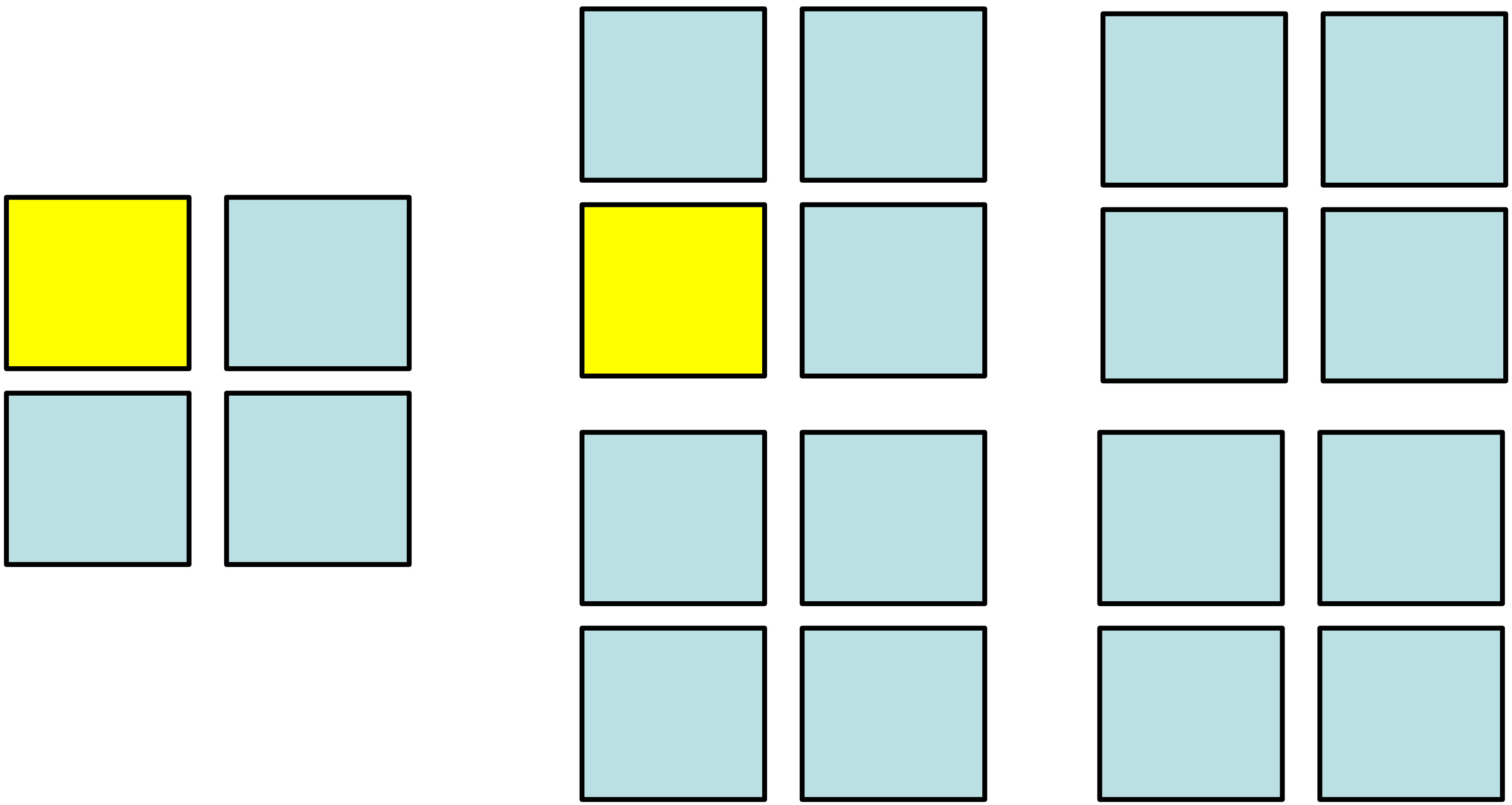
Rank-KNN



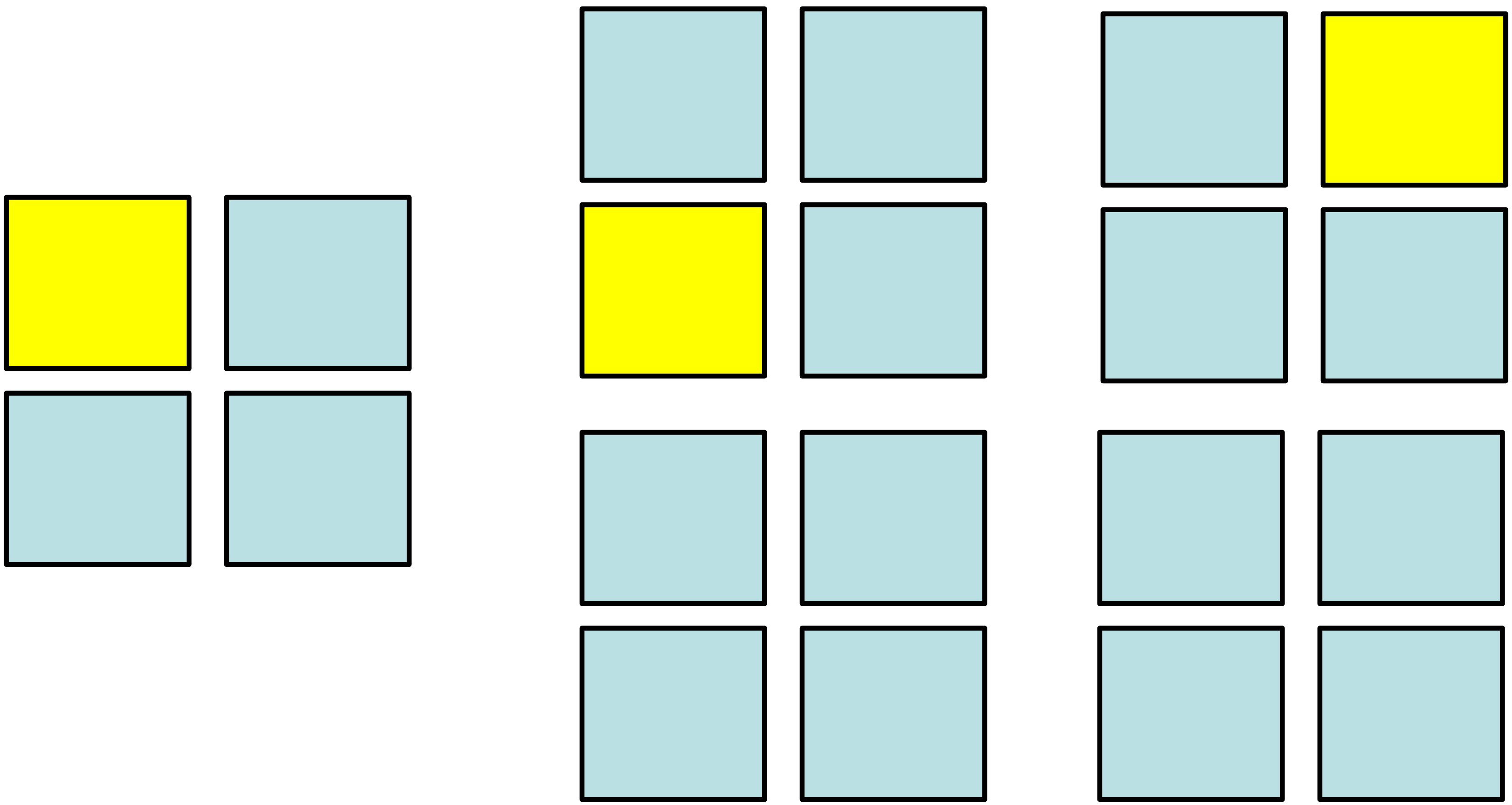
Rank-KNN



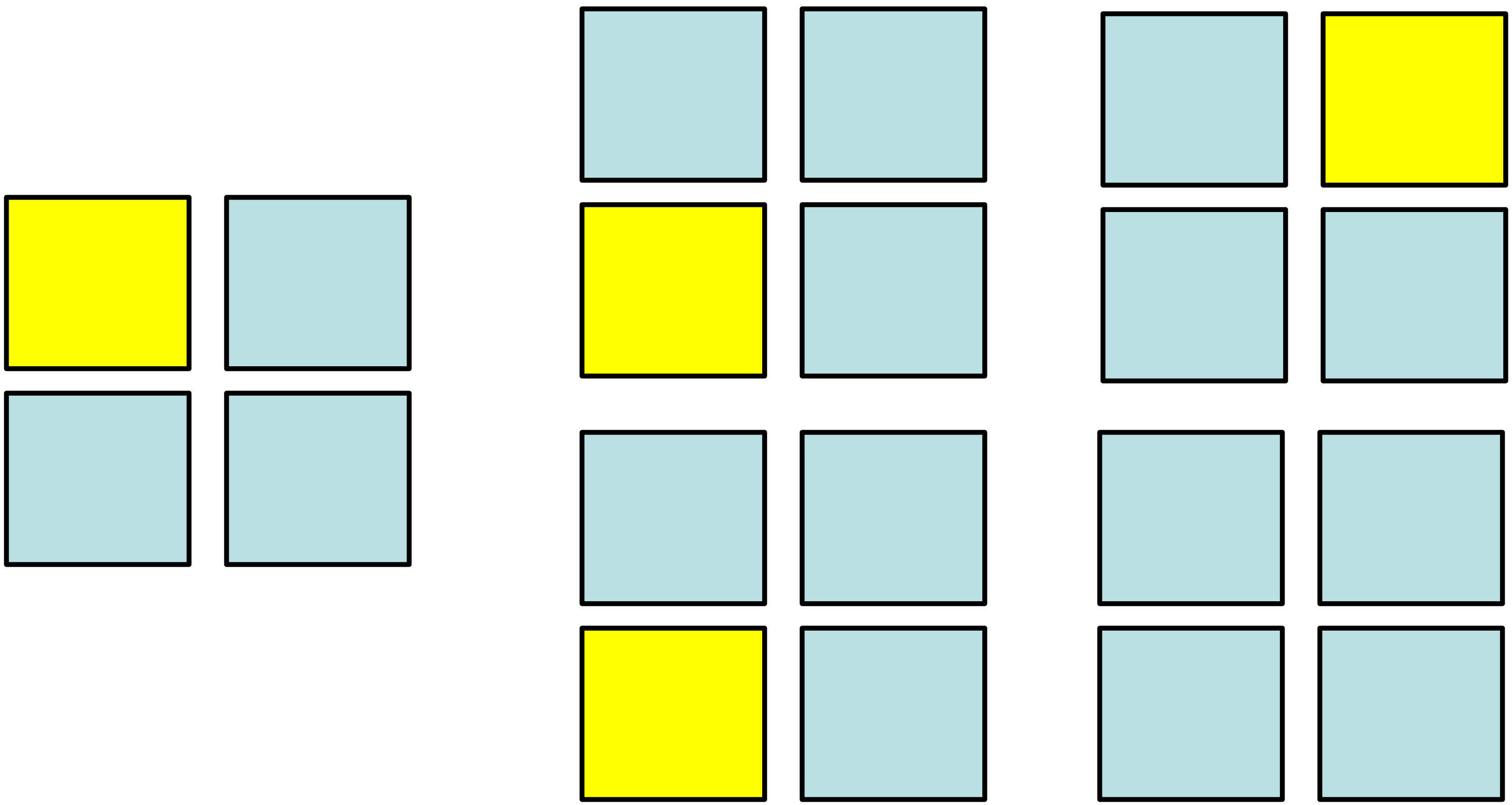
Rank-KNN



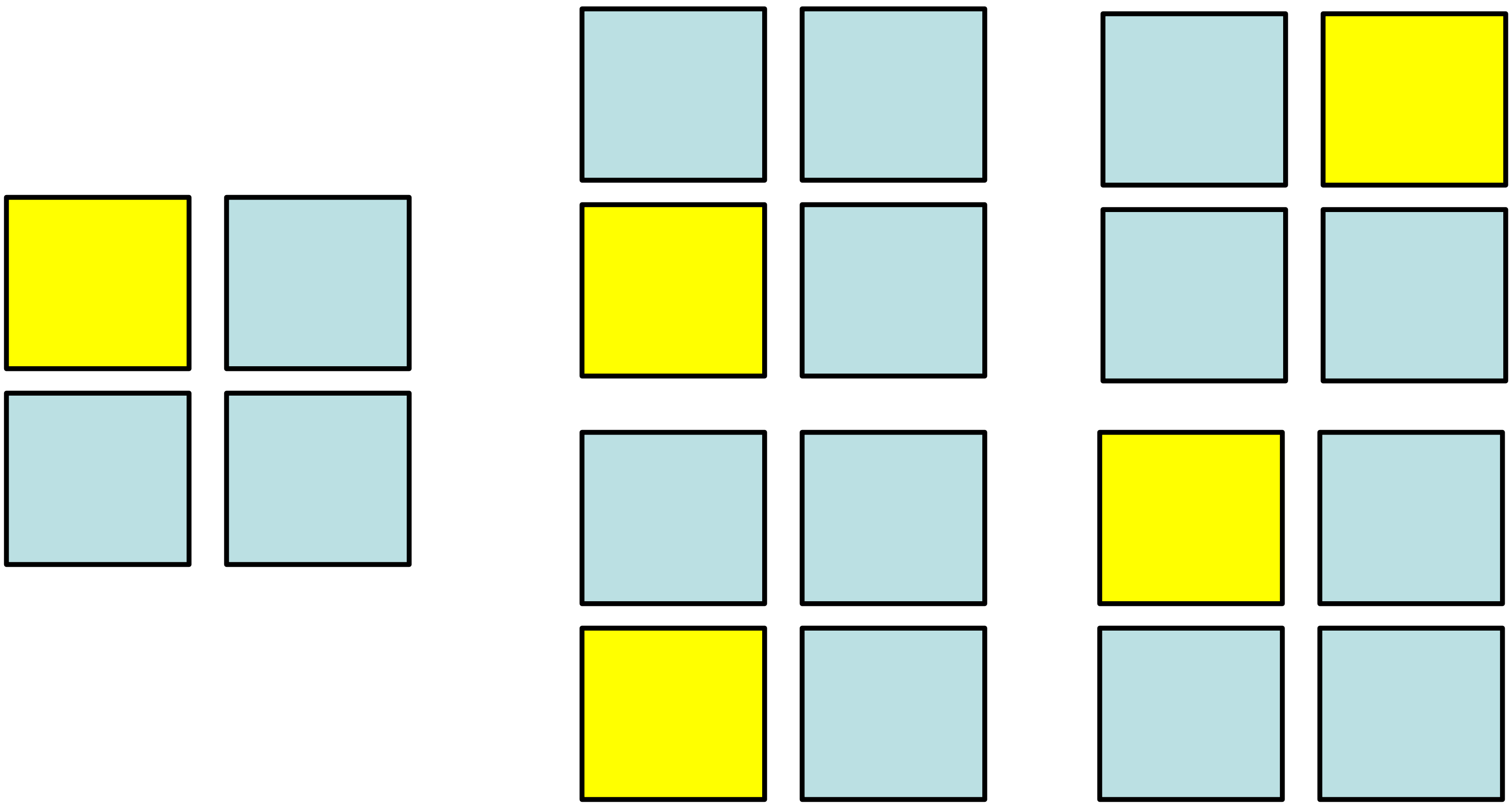
Rank-KNN



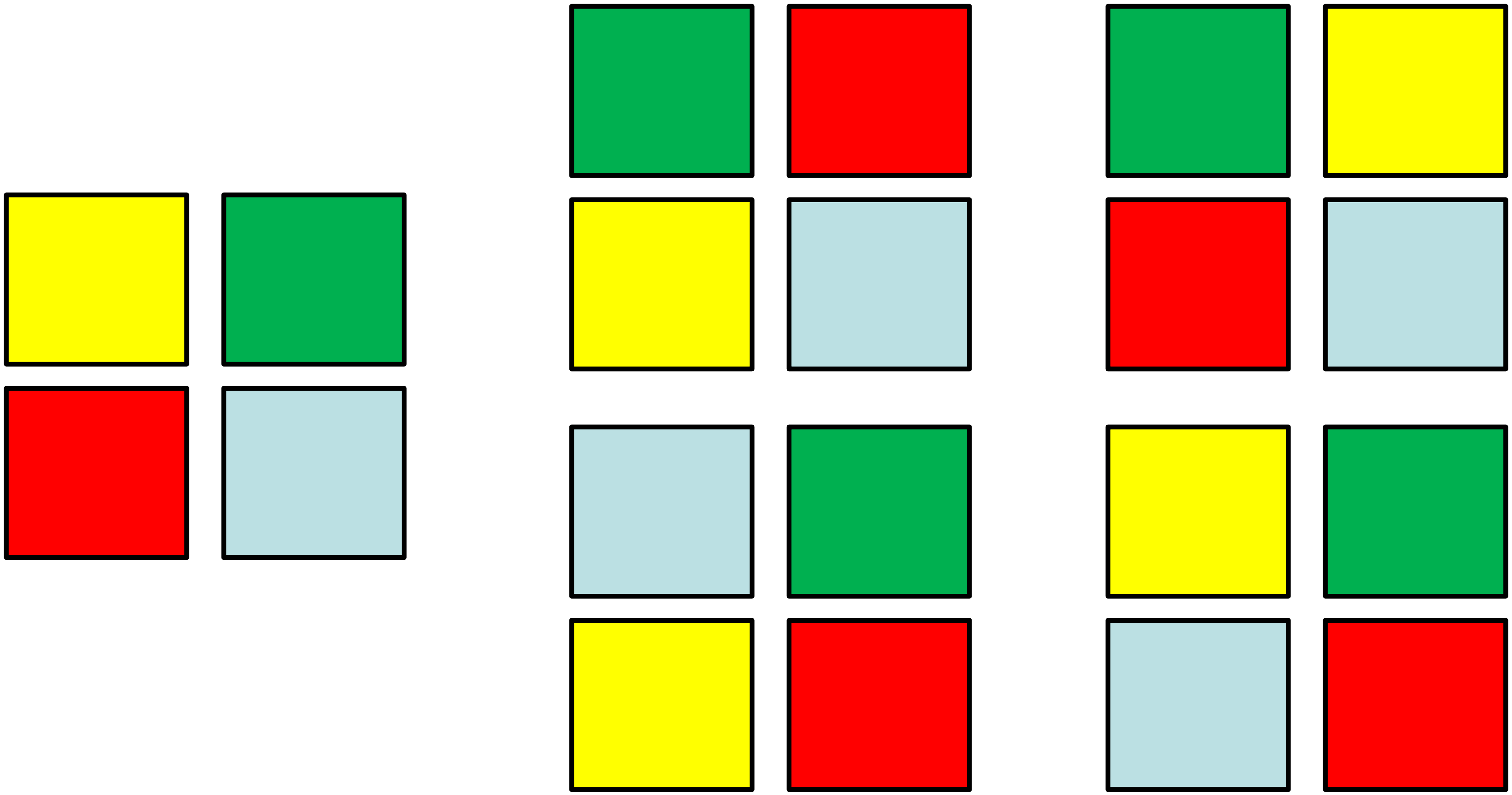
Rank-KNN



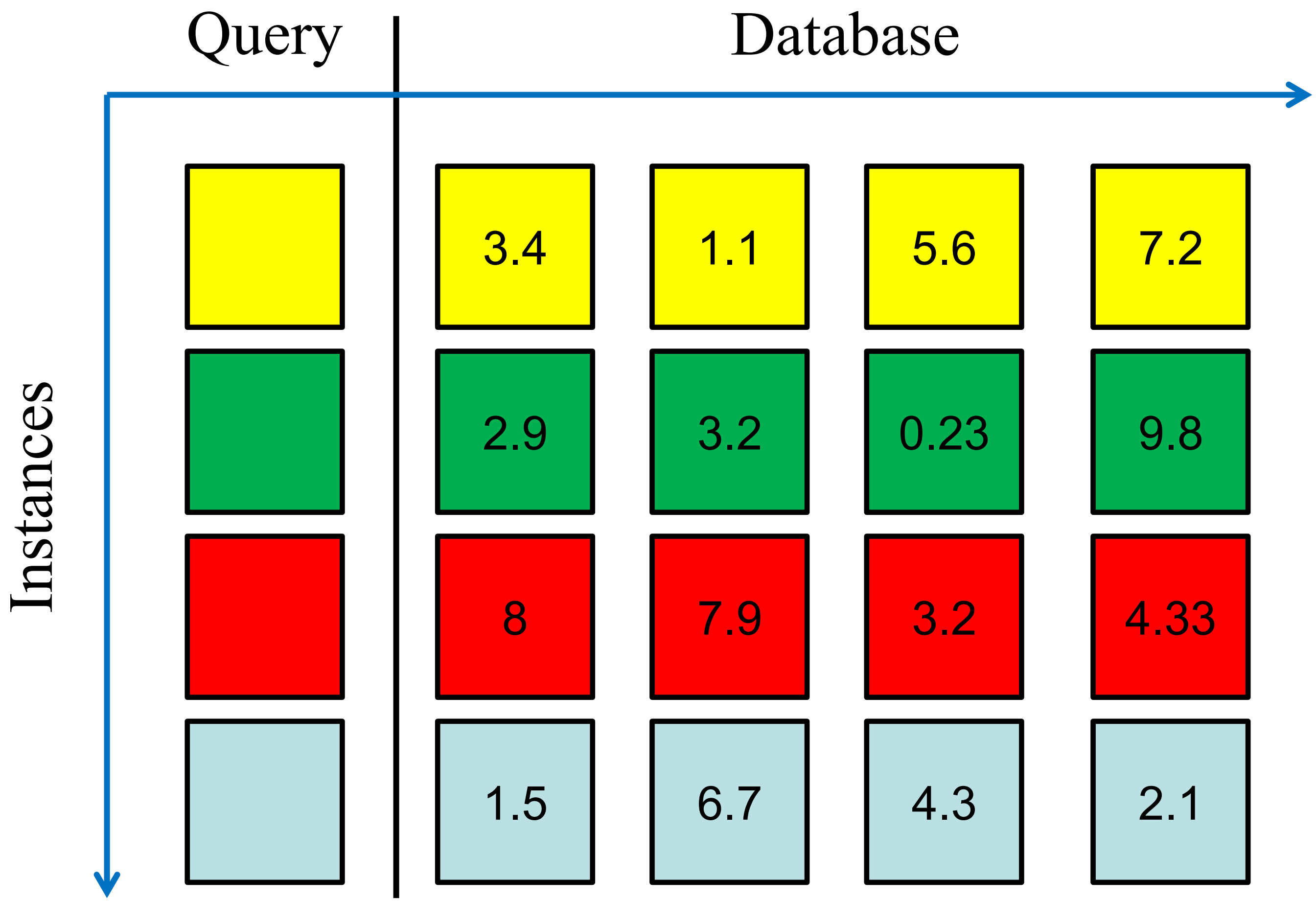
Rank-KNN



Rank-KNN



Rank-KNN

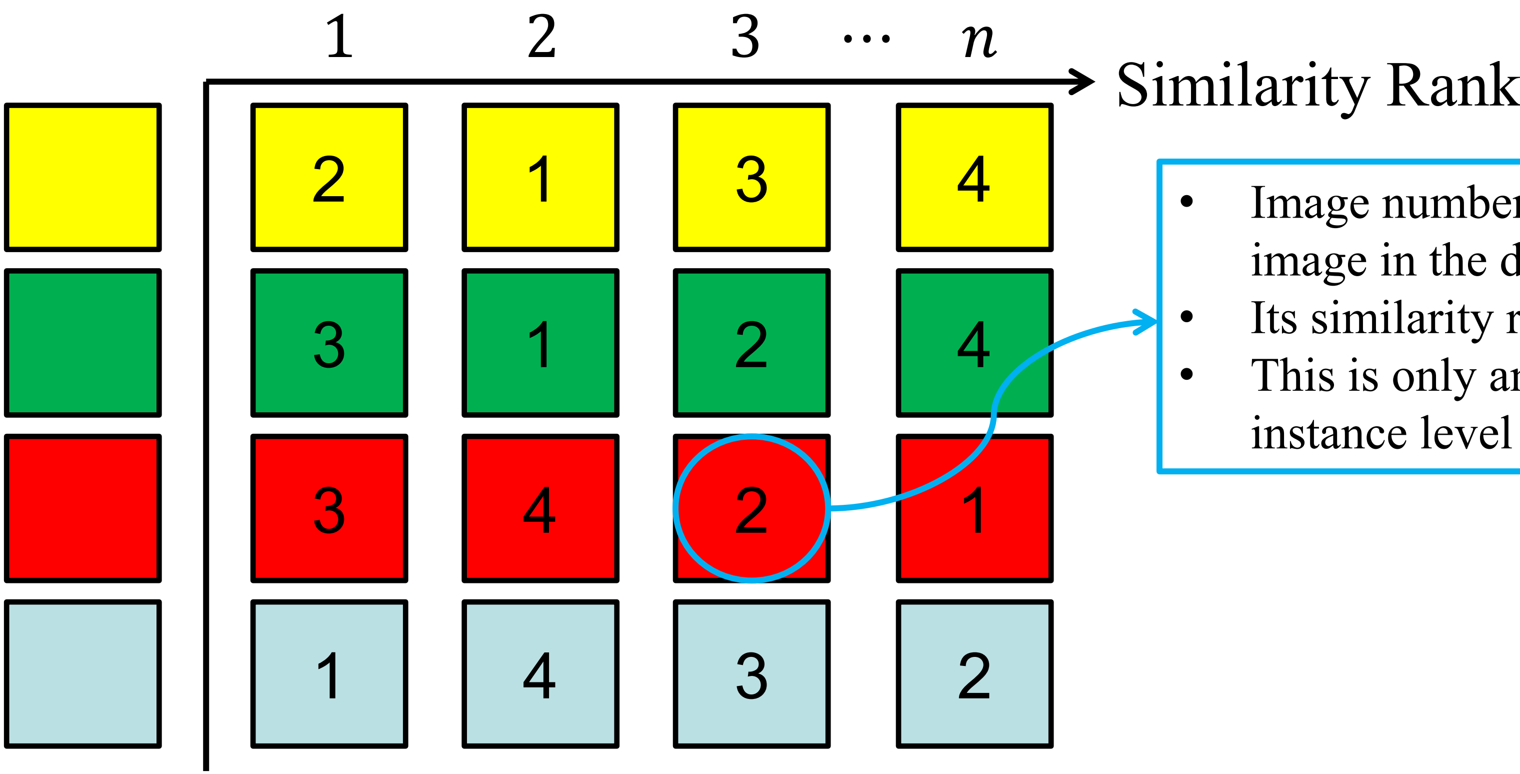

Query
Database
Instances
3.4
1.1
5.6
7.2
2.9
3.2
0.23
9.8
8
7.9
3.2
4.33
1.5
6.7
4.3
2.1

Rank-KNN

Similarity List

	1.1	3.4	5.6	7.2
	0.23	2.9	3.2	9.8
	3.2	4.33	7.9	8
	1.5	2.1	4.3	6.7

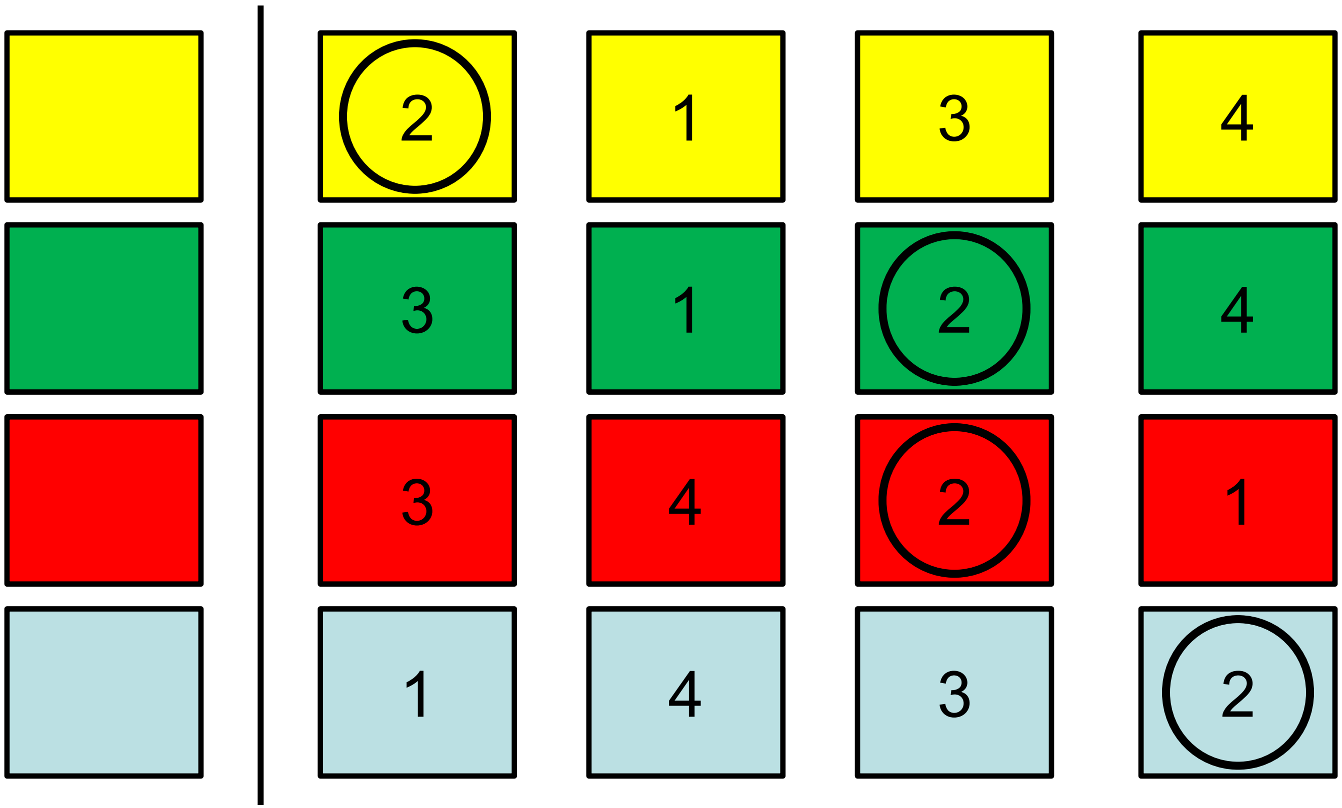
Rank-KNN



- Image number (second image in the database)
- Its similarity rank is 3.
- This is only an instance level rank!

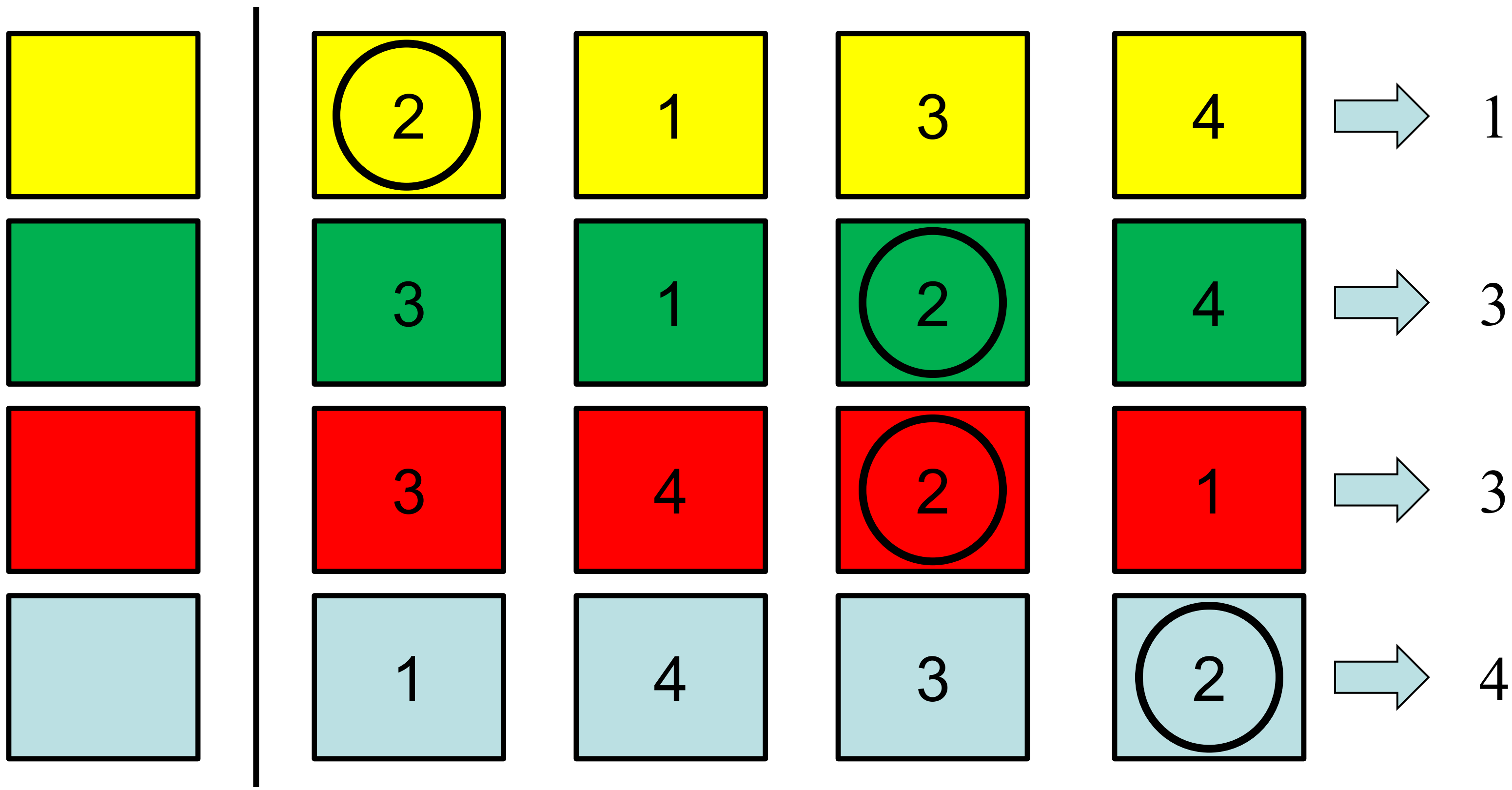
Rank-KNN

Creating Aggregated Similarity Rank (ASR)



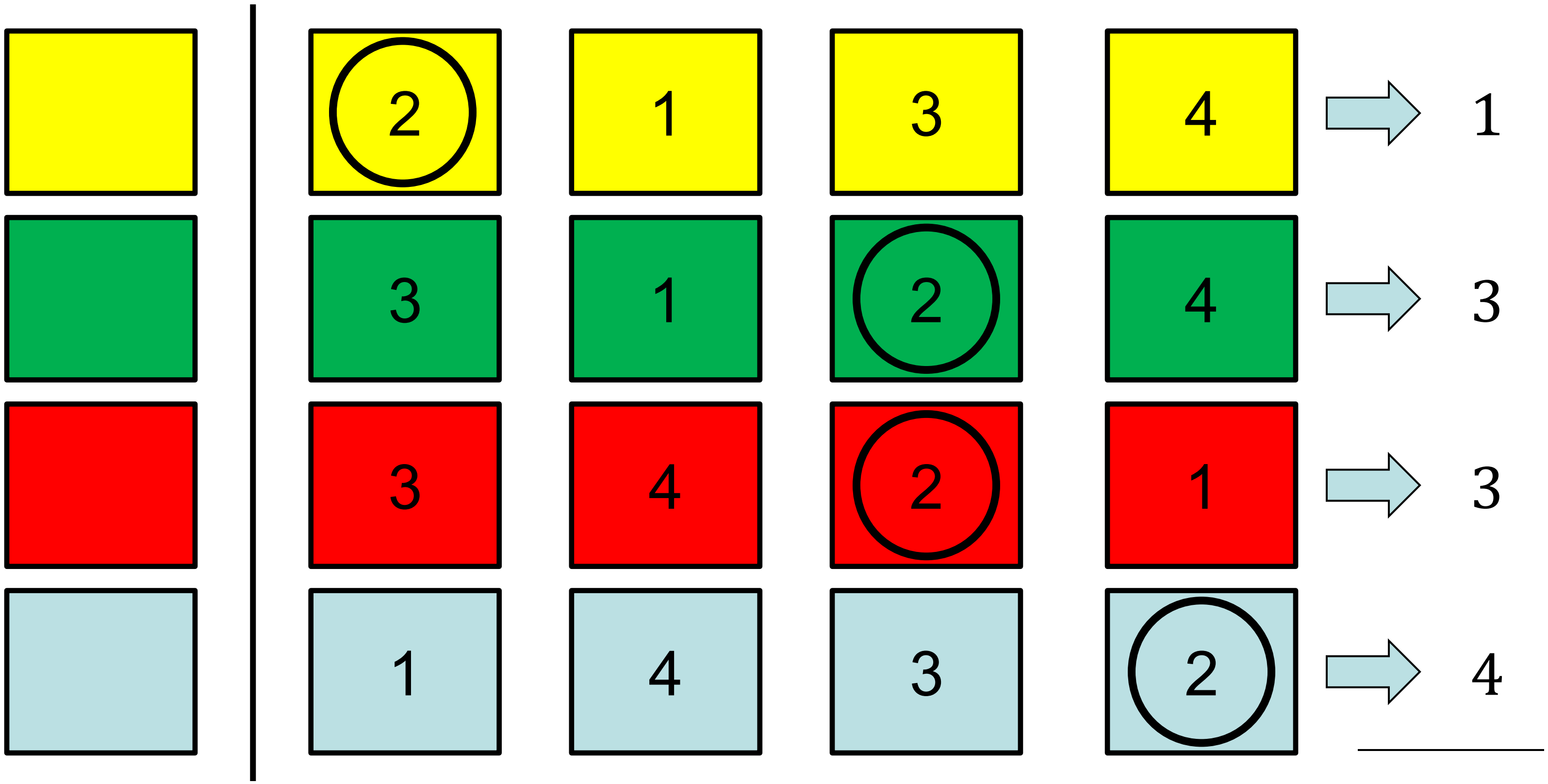
Rank-KNN

Creating Aggregated Similarity Rank (ASR)



Rank-KNN

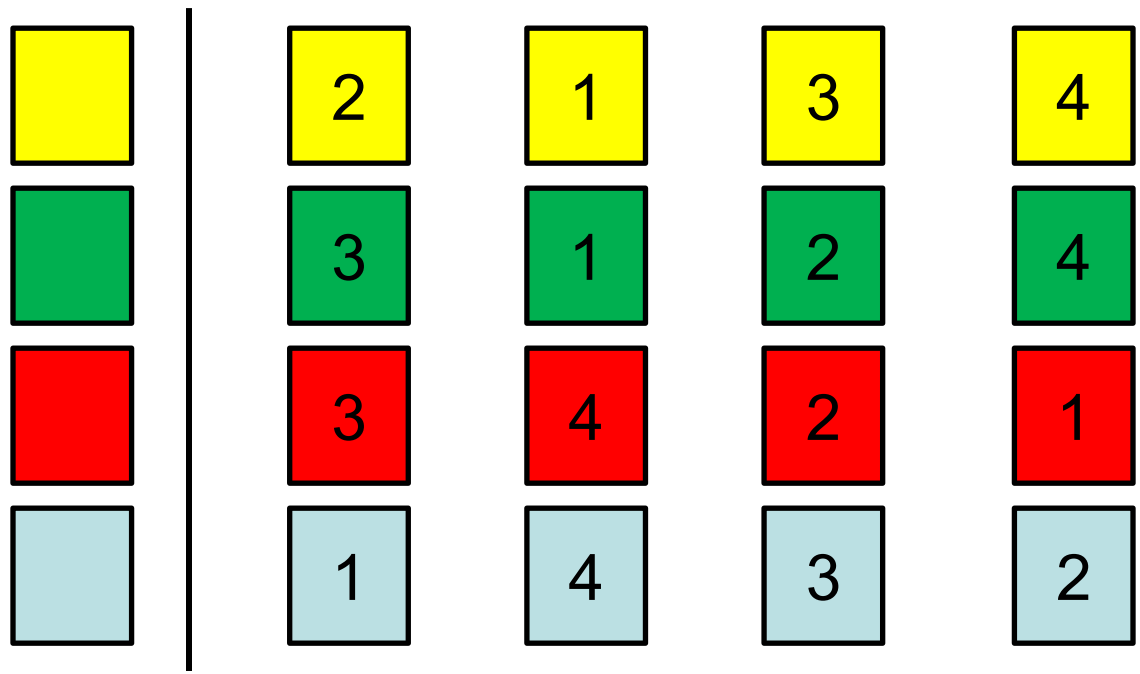
Creating Aggregated Similarity Rank (ASR)



$\text{ASR}(2) = 2.75$

Rank-KNN

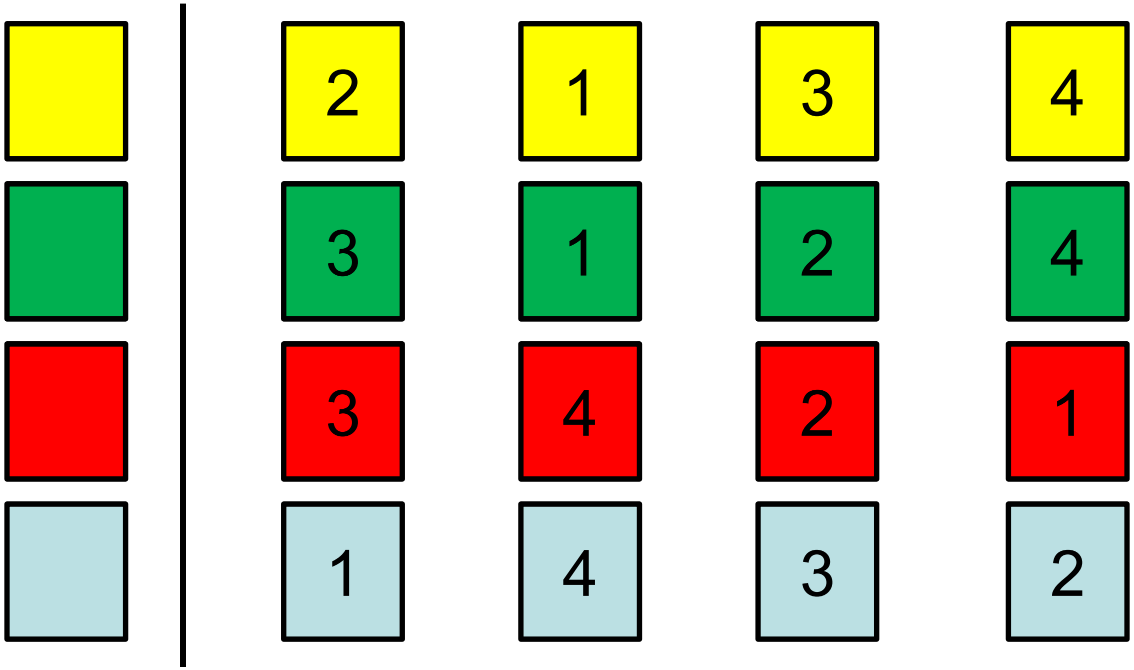
ASR (1) = 2.25
ASR (2) = 2.75
ASR (3) = 2
ASR (4) = 3



Rank-KNN

ASR (1) = 2.25
ASR (2) = 2.75
ASR (3) = 2
ASR (4) = 3

m-Rank (1) = 2
m-Rank (2) = 3
m-Rank (3) = 1
m-Rank (4) = 4



Sorting ASR:- Its indices gives *m*-Rank.

Rank-KNN

- Why Rank-*KNN* works?
  - Considers instance level similarity.
  - Transforms it to bag level rank.

  - Even if one instance is dissimilar, ASR will be high.
  - ASR will be low as long as images are clinically relevant.

Thus clinically relevant multiple instance retrieval can be performed without involving labels !

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Experiments

- The dataset consists of 425 images.
  - 160 normal images.
  - 181 PNDR images.
  - 84 PDR images.

- All 425 images in the database were individually queried and the top (k=) 5 images retrieved using the approach.

- The evaluation metrics used:-
  - $\geq k$-hit rate.
  - success at k^{th} rank.
  - mean accuracy at k^{th} rank.

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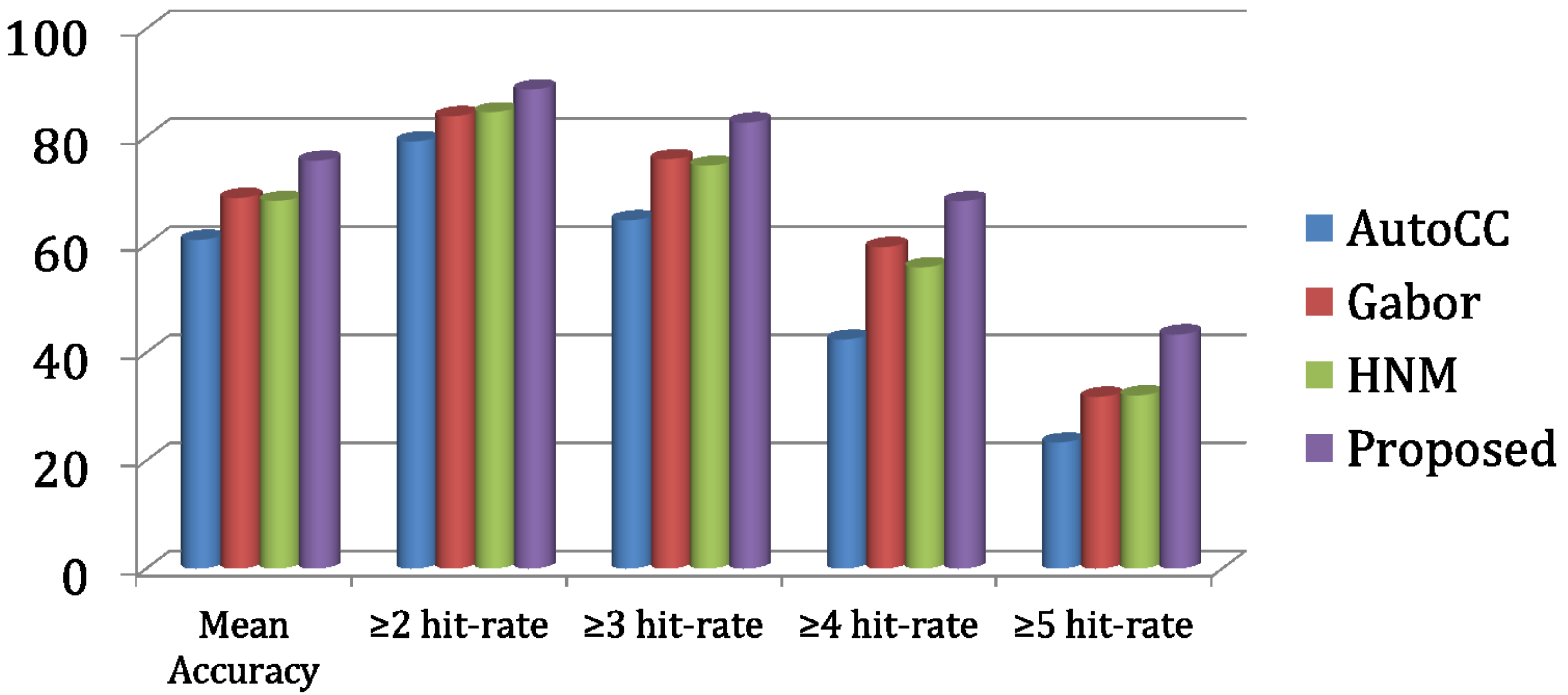
Results

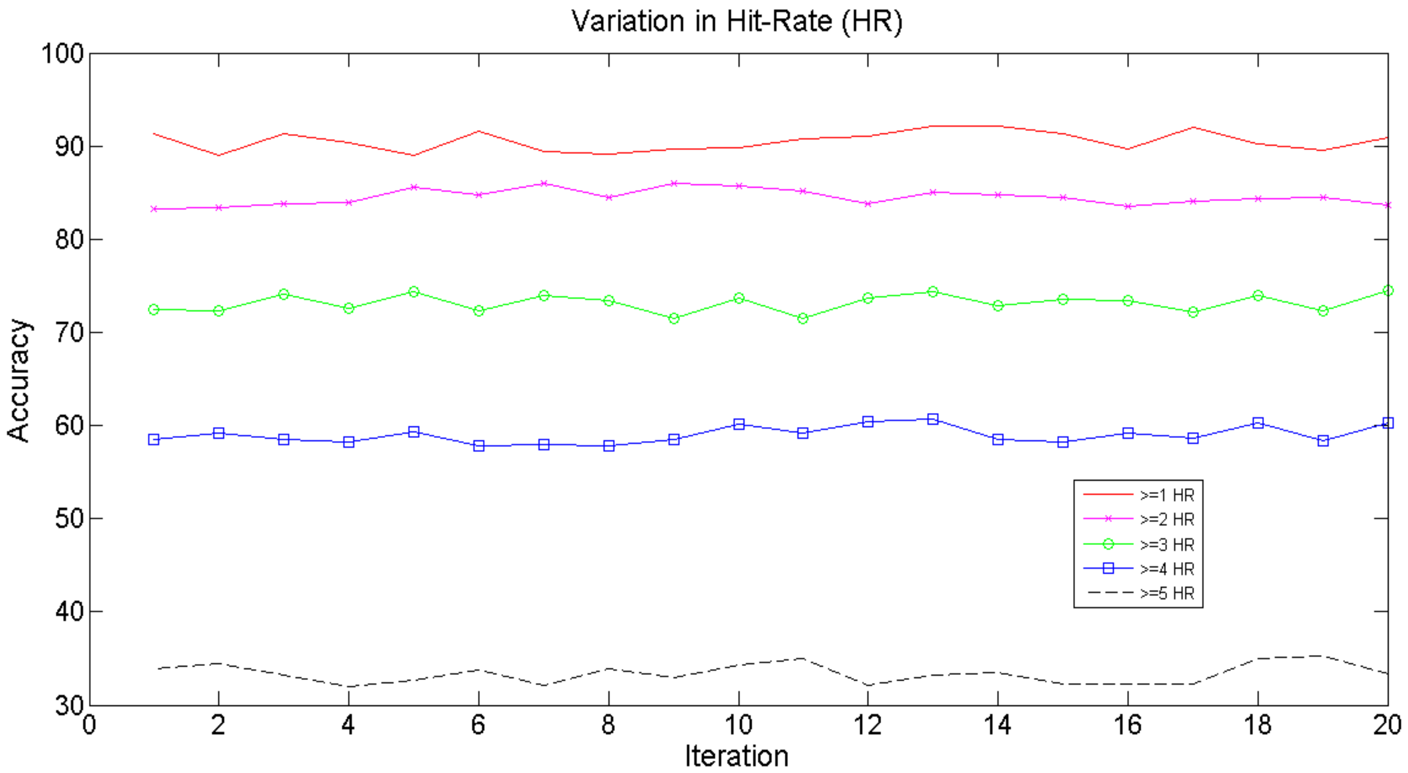

EvaluateDR
File Edit View Insert Tools Desktop Window Help
Load Image
Retrieve Images
More Images
Image ID Patient ID DR Severity Grade Type Visit
Clinical Comments:
Image ID Patient ID DR Severity Grade Type Visit
1 150 405 47A ST Baseline visit
2 100 297 60 ST Baseline visit
3 206 257 61B ST Baseline visit
4 67 408 47A ST Baseline visit
5 102 300 47C ST Baseline visit
Archive
Exit

Results

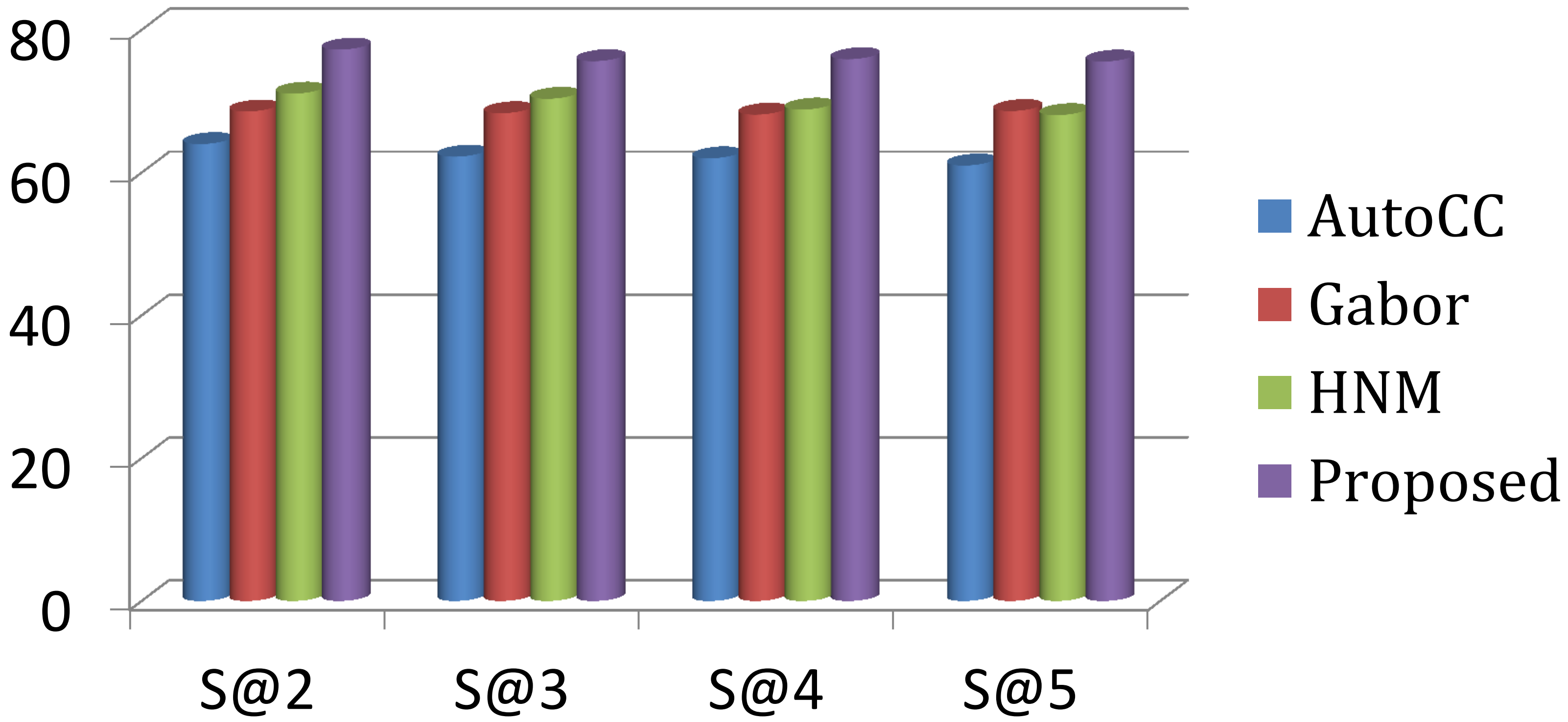

100
80
60
40
20
0
Mean Accuracy
≥2 hit-rate
≥3 hit-rate
≥4 hit-rate
≥5 hit-rate
AutoCC
Gabor
HNM
Proposed

Results

Reproducibility analysis



Results



Conclusions

- Presented a novel approach using MIL for retrieval of clinically-relevant DR images.
- Developed a set of features and a MIL retrieval algorithm customized for DR images.
- Results are consistent and better than prior-art CBIR methods.

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Thank You.