

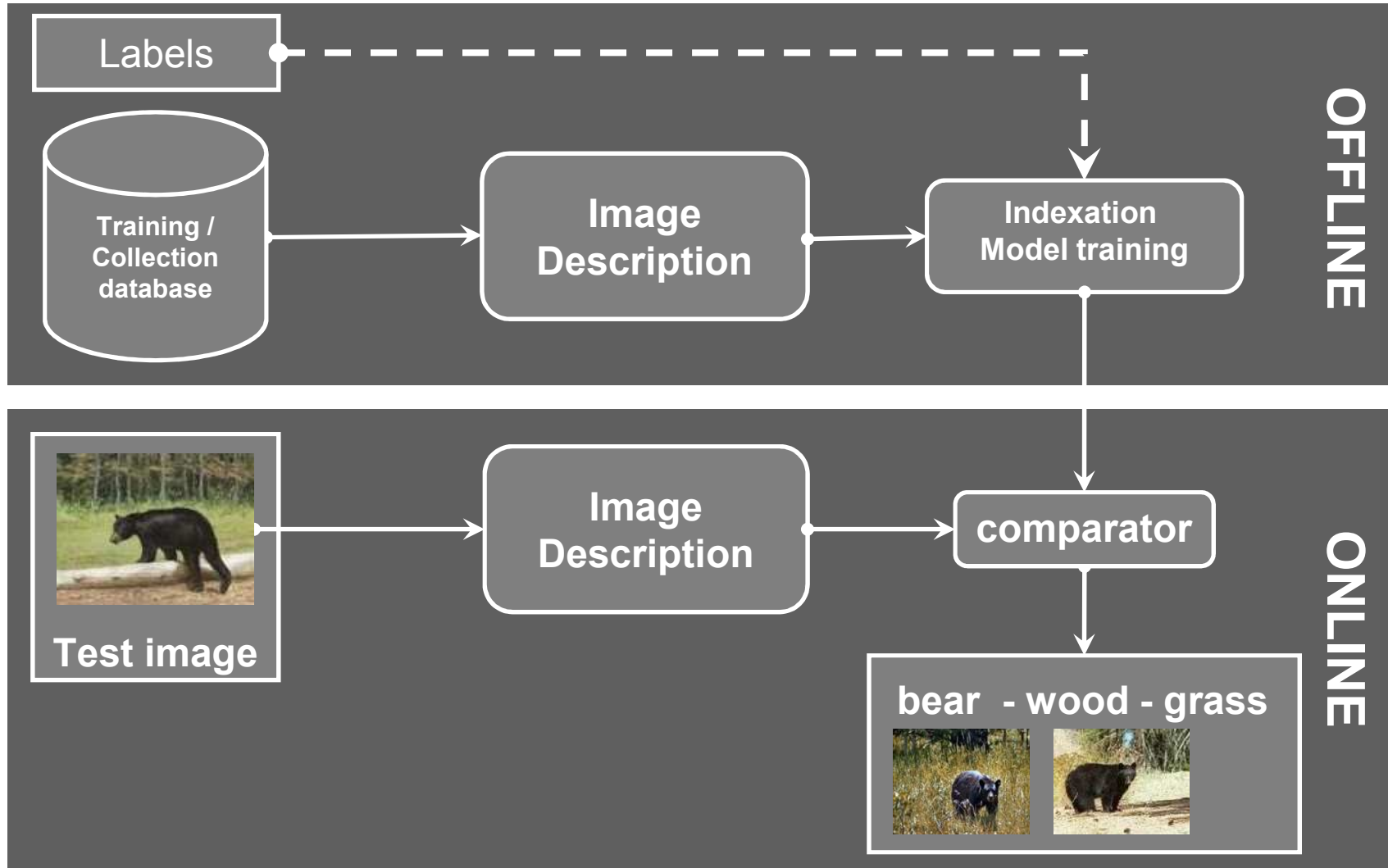


Constrained Local Enhancement of Semantic Features by Content-Based Sparsity

Youssef Tamaazousti, Hervé Le Borgne and Adrian Popescu

youssef.tamaazousti@cea.fr

Classification & Retrieval are linked



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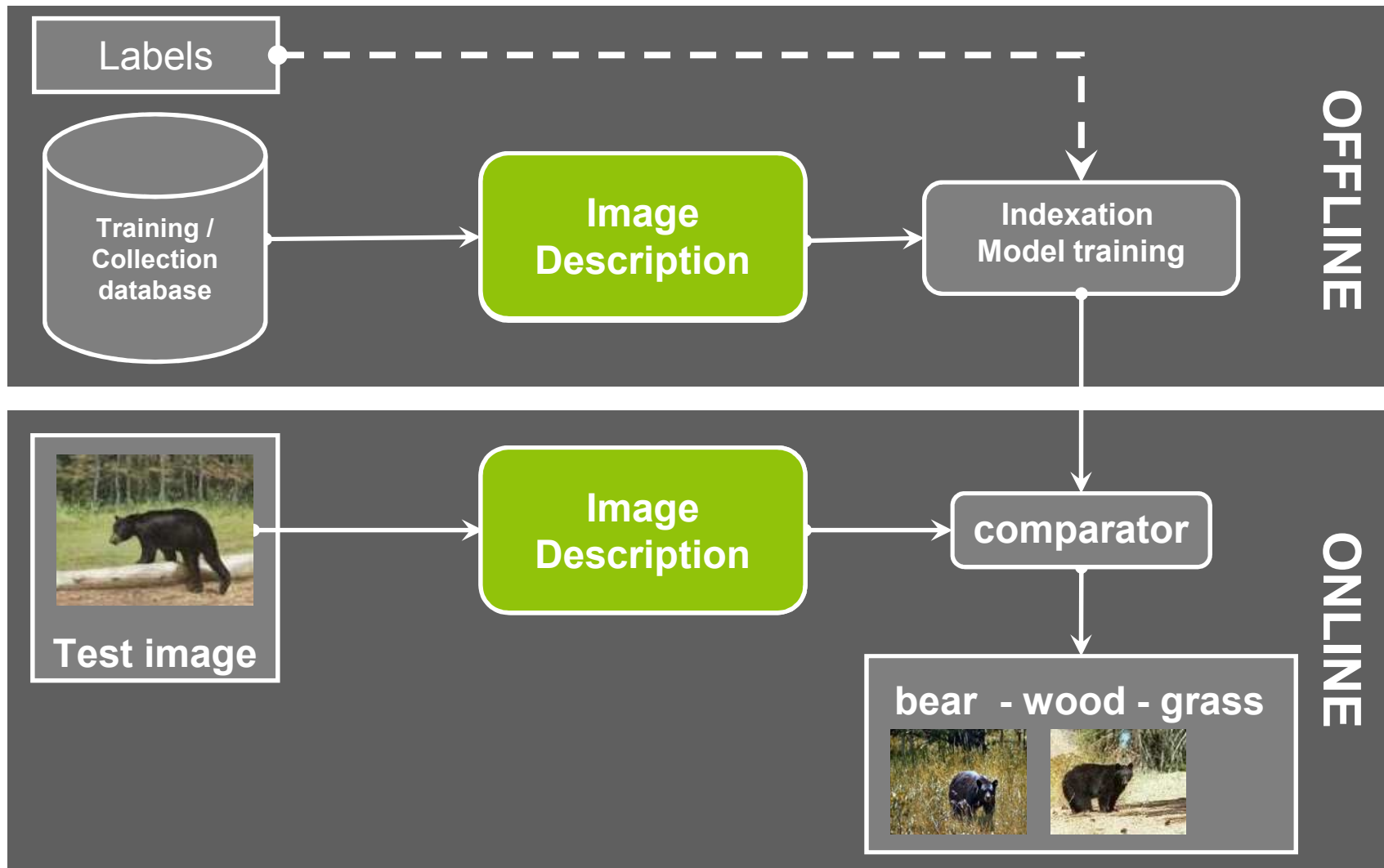
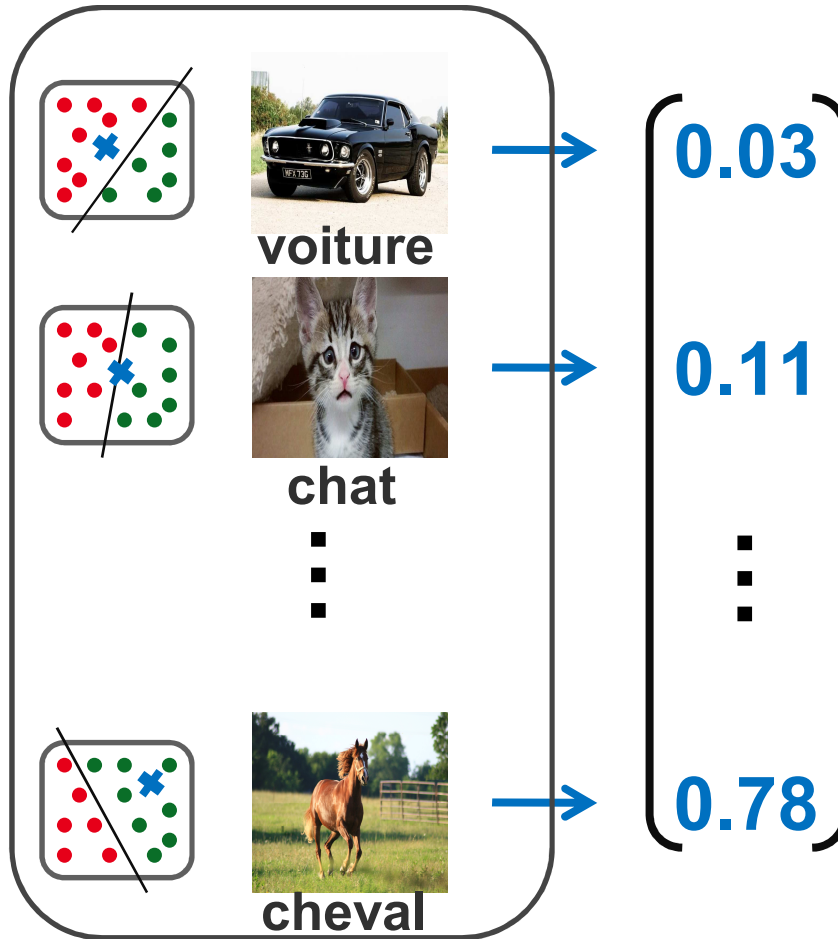


Image Description

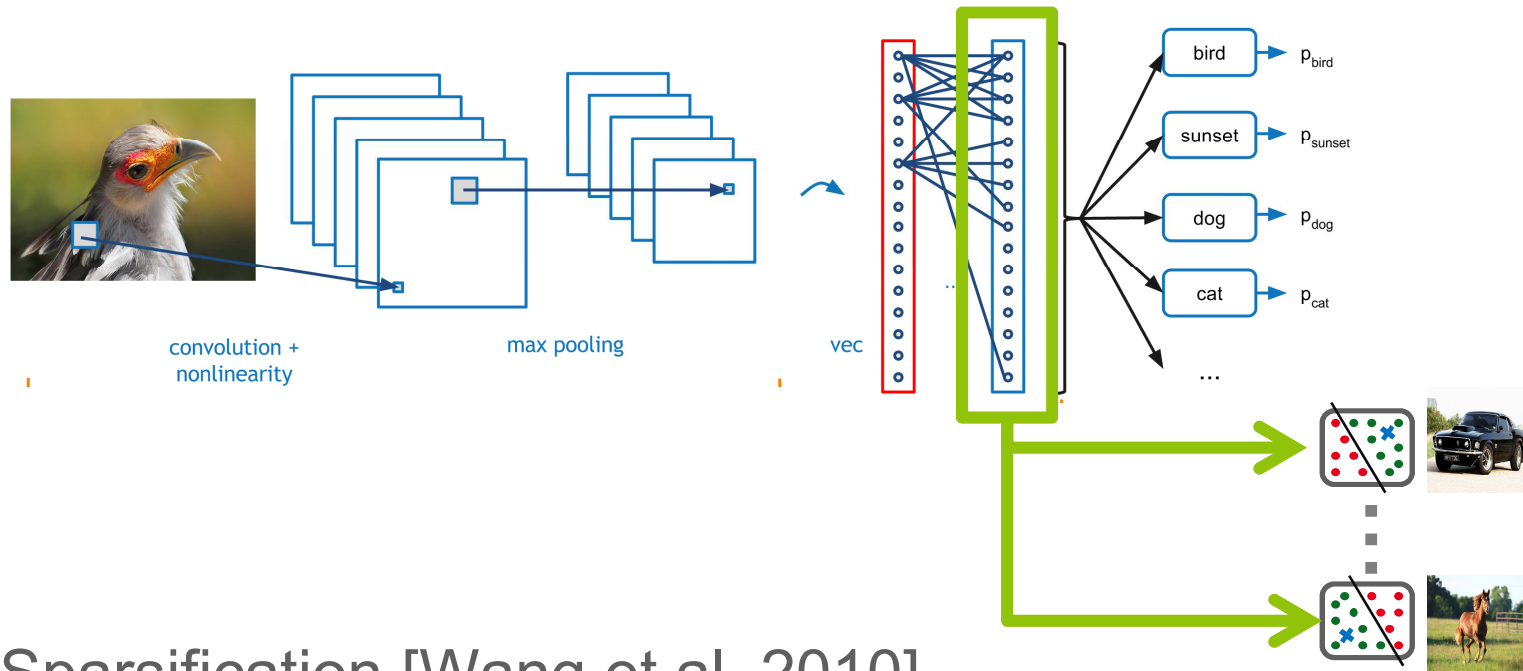
- **Low/Mid-Level Features**
 - Bag of Visual Words [Csurska *et al.* 2004]
 - Fischer Kernels [Perronnin & Dance 2007]
 - Fully-connected layers of a pre-trained CNN [Kriszhevshy *et al.* 2012]
- **Semantic Features**
 - Image described in terms of semantic concepts
 - [Torresani *et al.*, Li *et al.* 2010] (200 - 1500)
 - [Bergamo *et al.* 2012] (15000)

What is a Semantic Feature ?



Model

- **Ginsca et al. 2015**
 - First to use CNNs as mid-level features



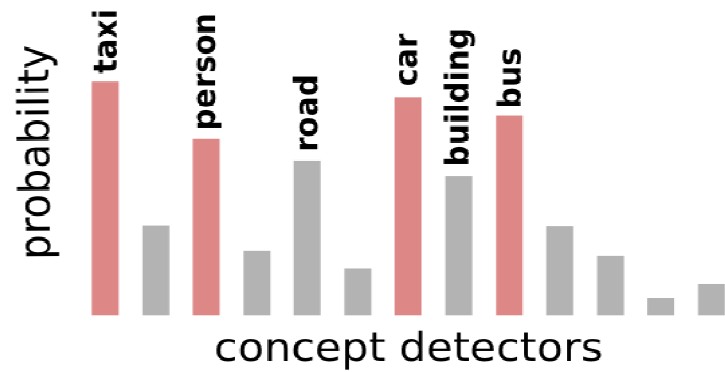
- Sparsification [Wang et al. 2010]
 - keep only the K largest concepts and set all others to 0
 - Inverse index scheme can be used



State-of-the-Art

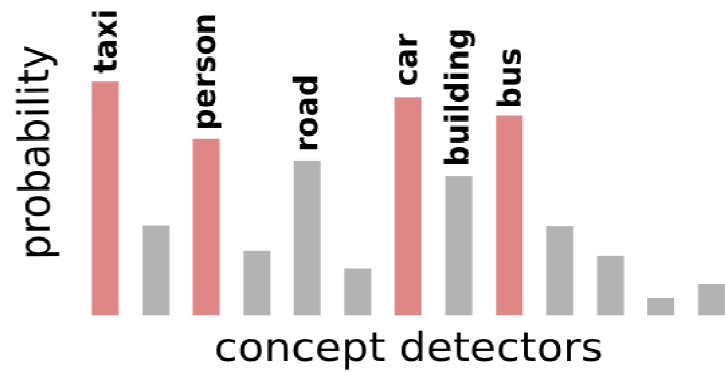


State-of-the-Art



State-of-the-Art

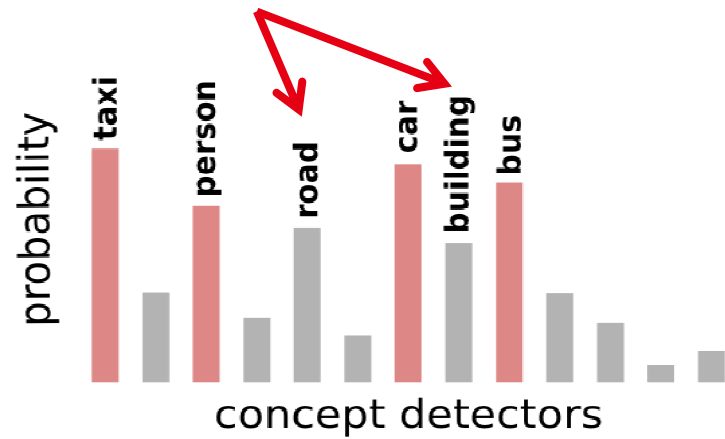
K = 4



State-of-the-Art

K = 4

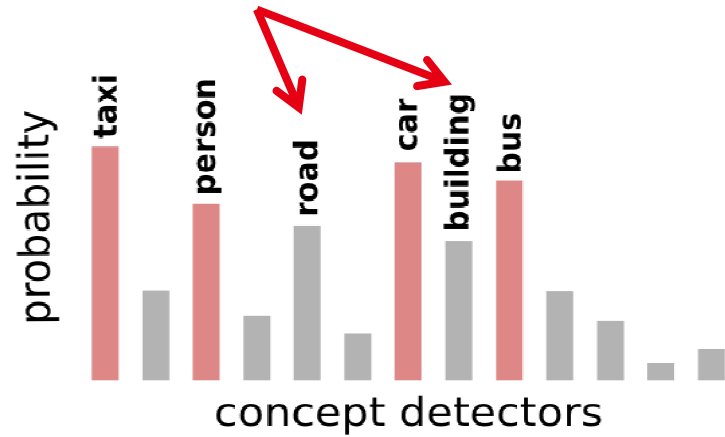
Missing relevant information



State-of-the-Art

K = 4

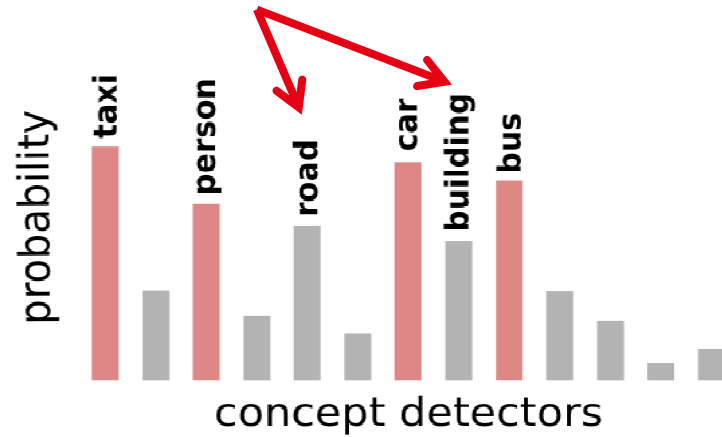
Missing relevant information



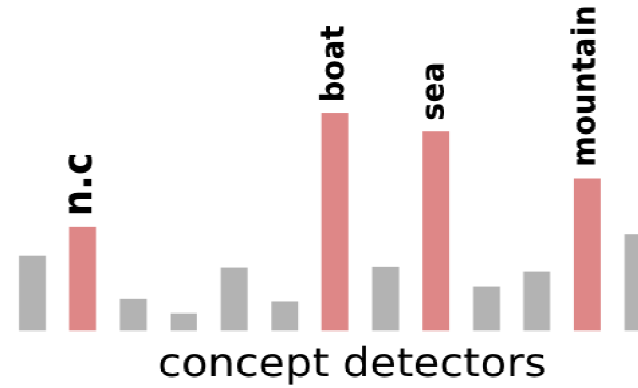
State-of-the-Art

K = 4

Missing relevant information



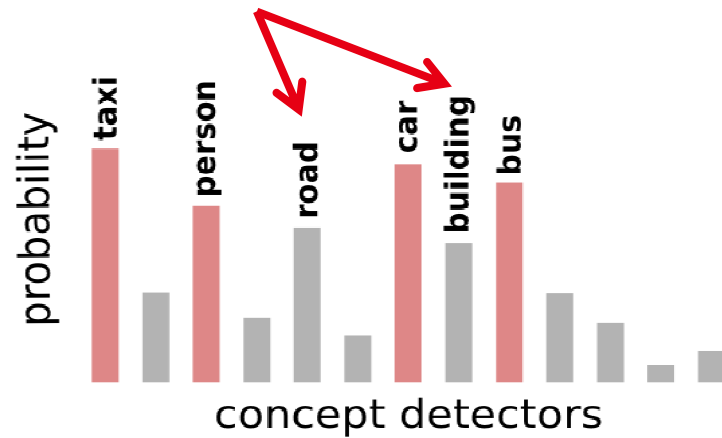
K = 4



State-of-the-Art

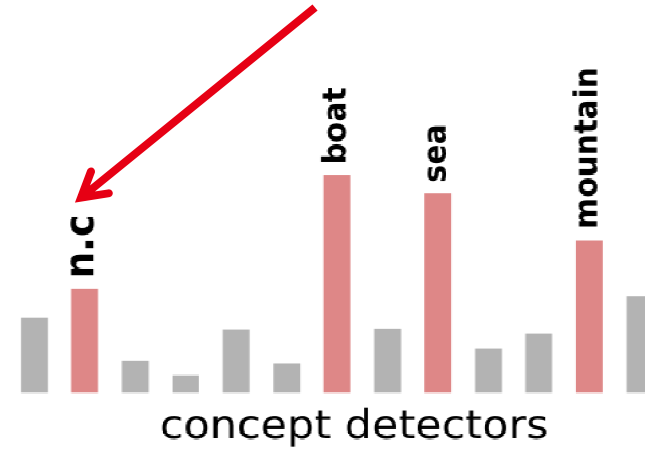
K = 4

Missing relevant information



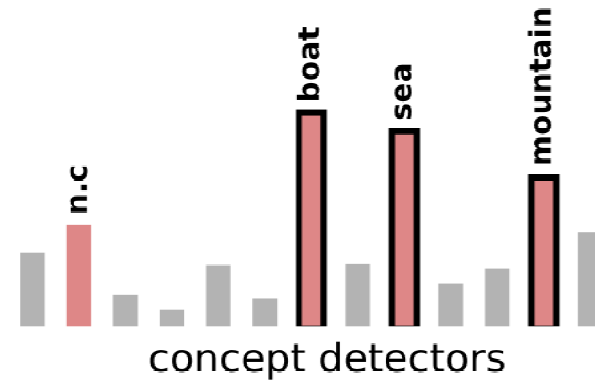
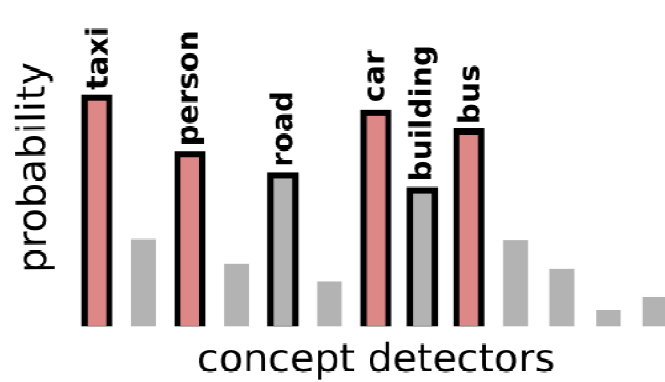
K = 4

Keep noisy information



n.c = noisy concept

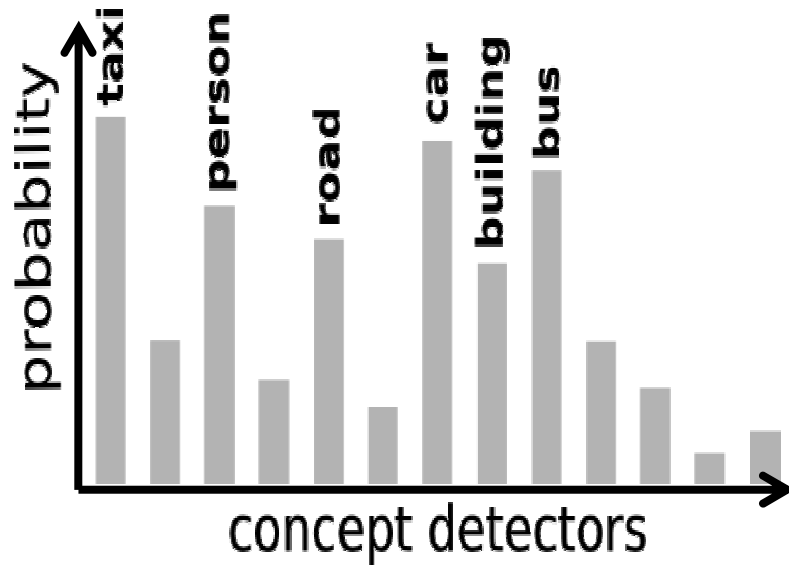
Proposed Approach: CBS



- How many concepts should we retain for each image?

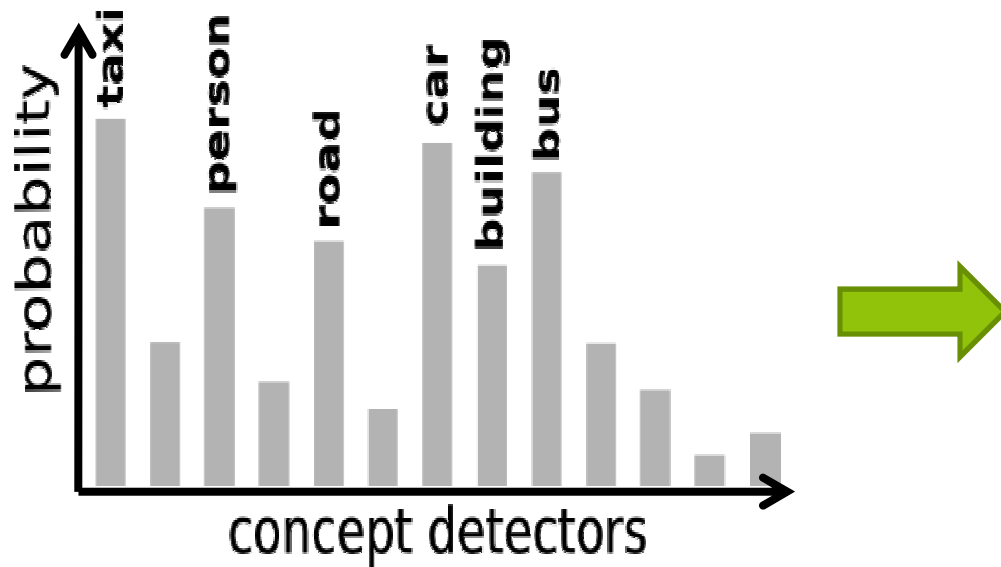
Proposed Approach: CBS

- Sparsification process



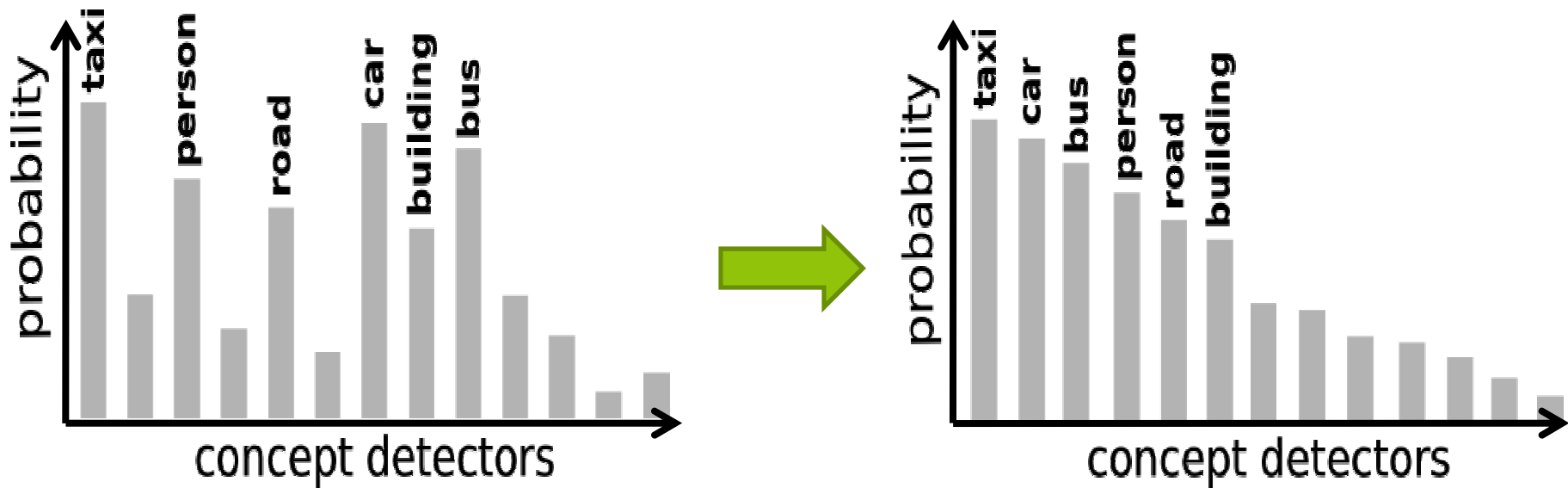
Proposed Approach: CBS

- Sparsification process



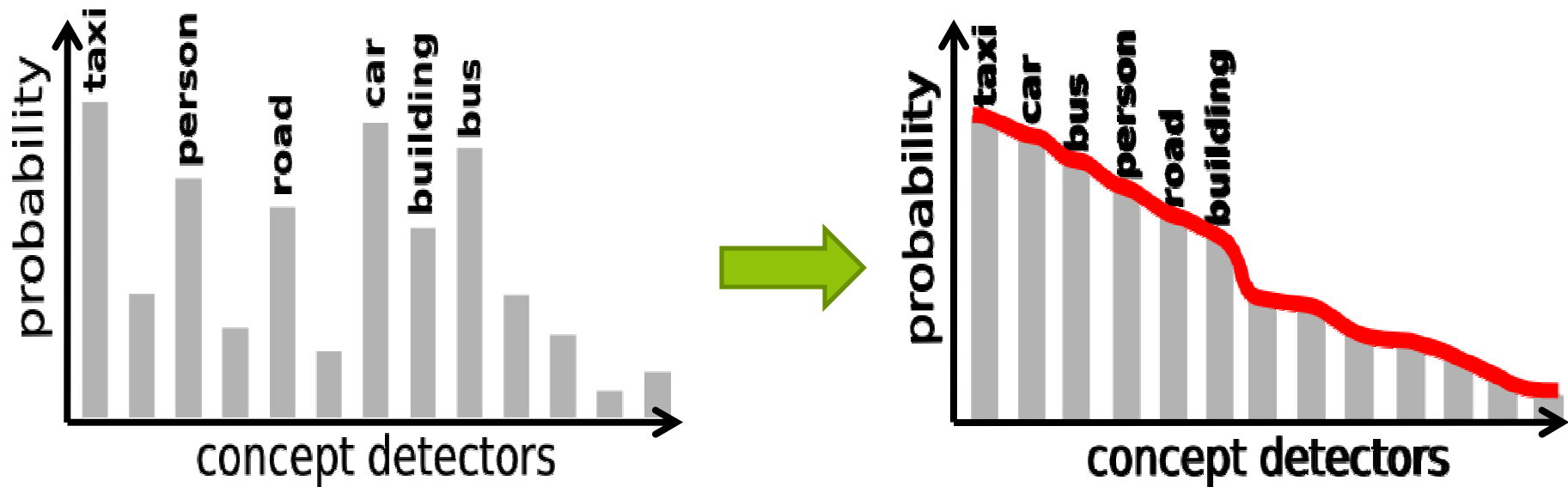
Proposed Approach: CBS

- Sparsification process



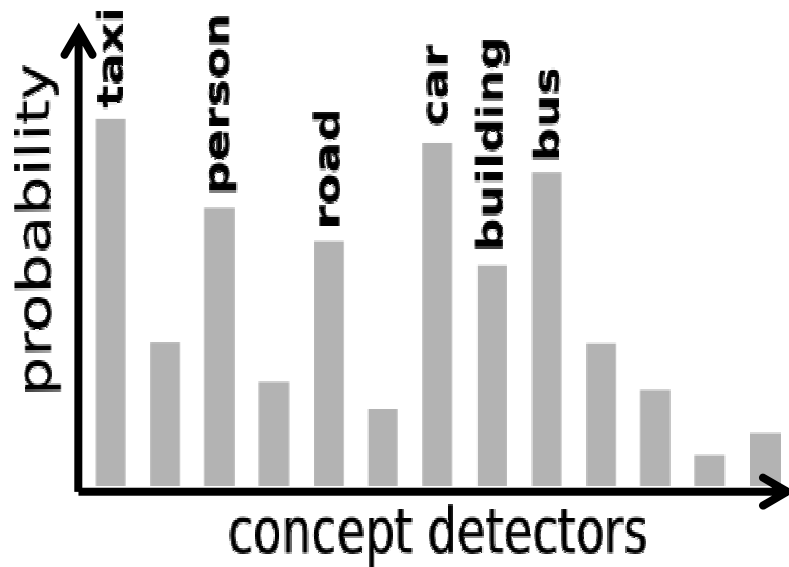
Proposed Approach: CBS

- Sparsification process



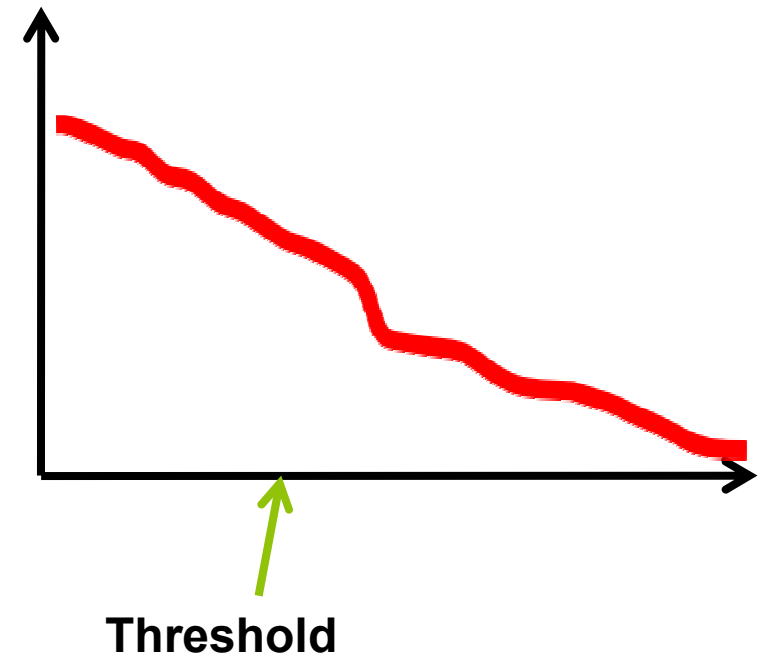
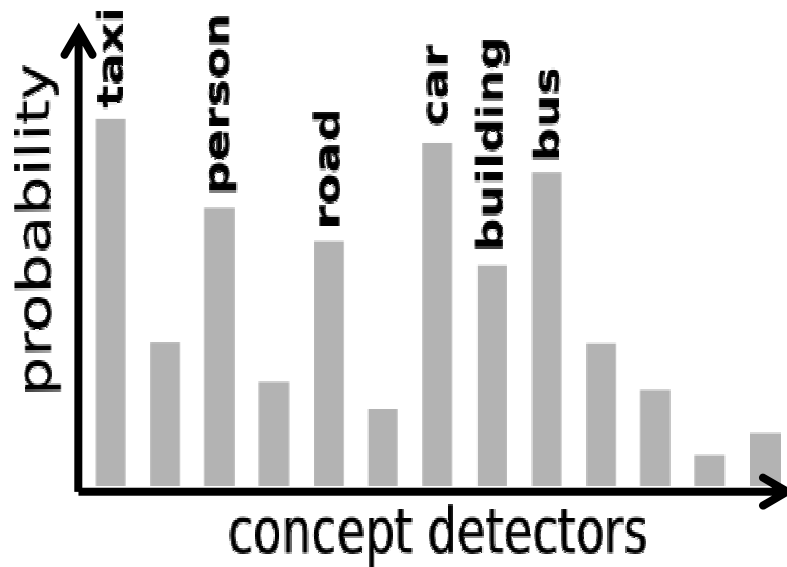
Proposed Approach: CBS

- Sparsification process



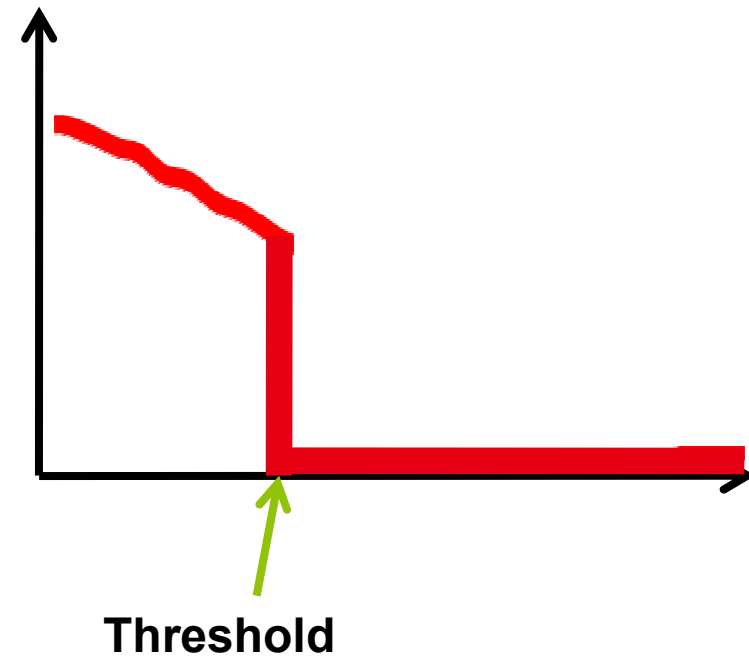
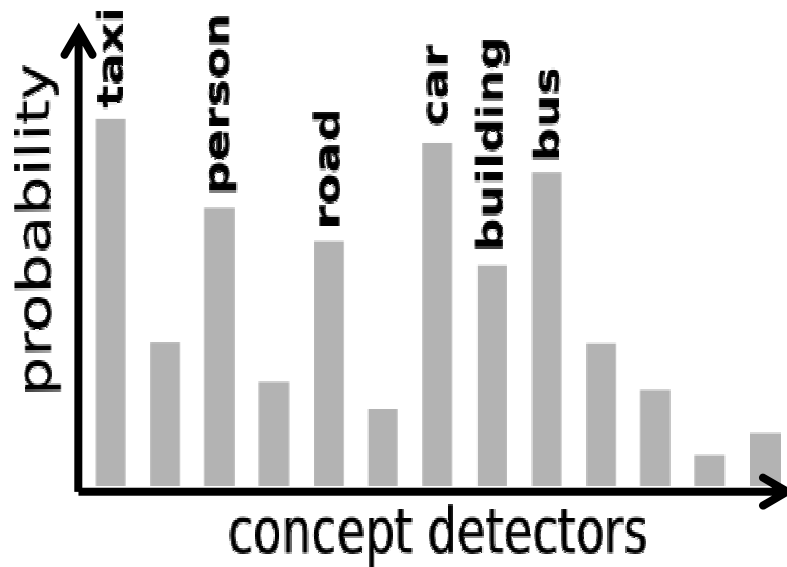
Proposed Approach: CBS

- Sparsification process



Proposed Approach: CBS

- Sparsification process



Proposed Approach: CBS

- Two things to consider:

NUMBER OF DOMINANT CONCEPTS



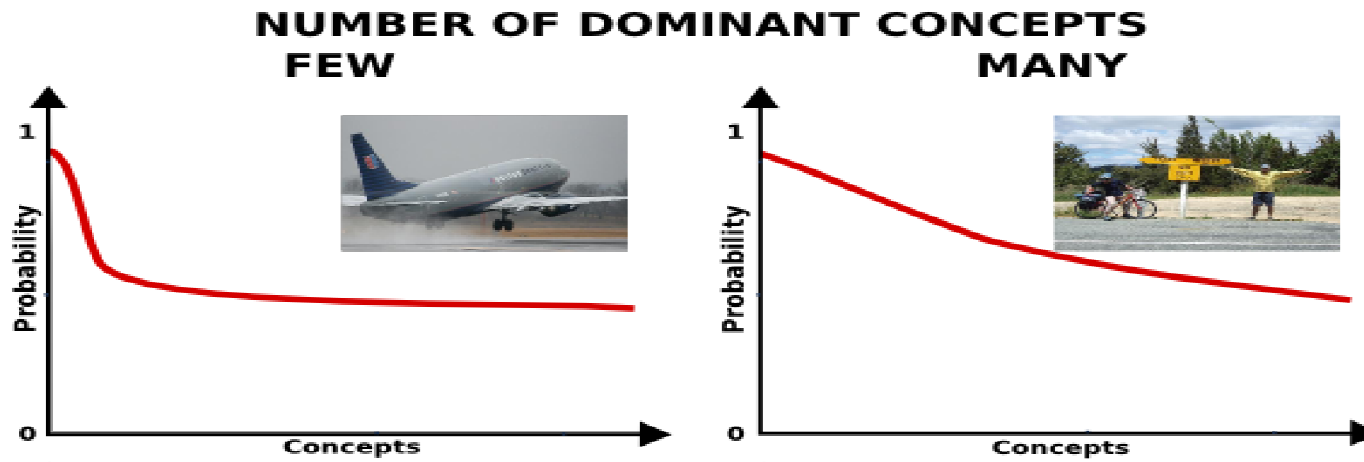
Proposed Approach: CBS

- Two things to consider:



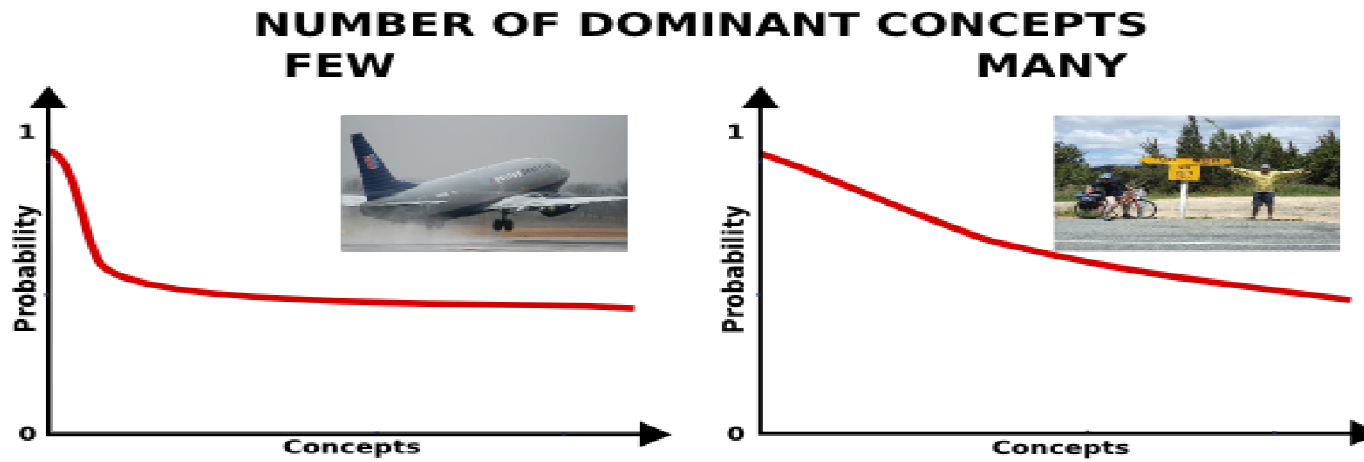
Proposed Approach: CBS

- Two things to consider:



Proposed Approach: CBS

- Two things to consider:



- **Modelisation**

Amount of concepts in the image

≈

Amount of information in the Semantic Feature

Proposed Approach: CBS

- Estimation : Shannon Entropy

Semantic Feature  Random Variable

Random Variable  Shannon Entropy

Proposed Approach: CBS

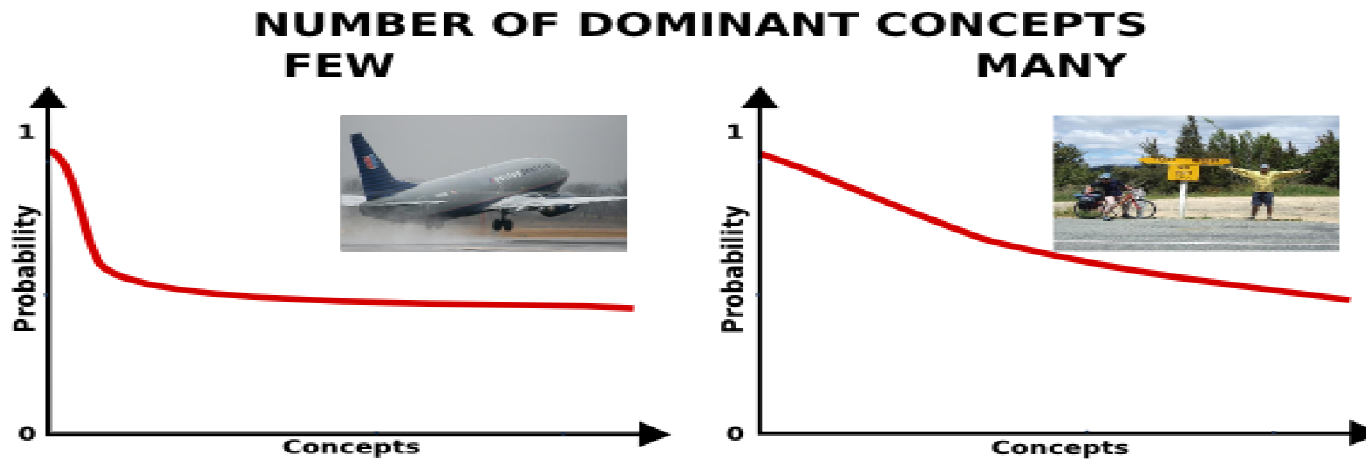
- Two things to consider:

NUMBER OF DOMINANT CONCEPTS



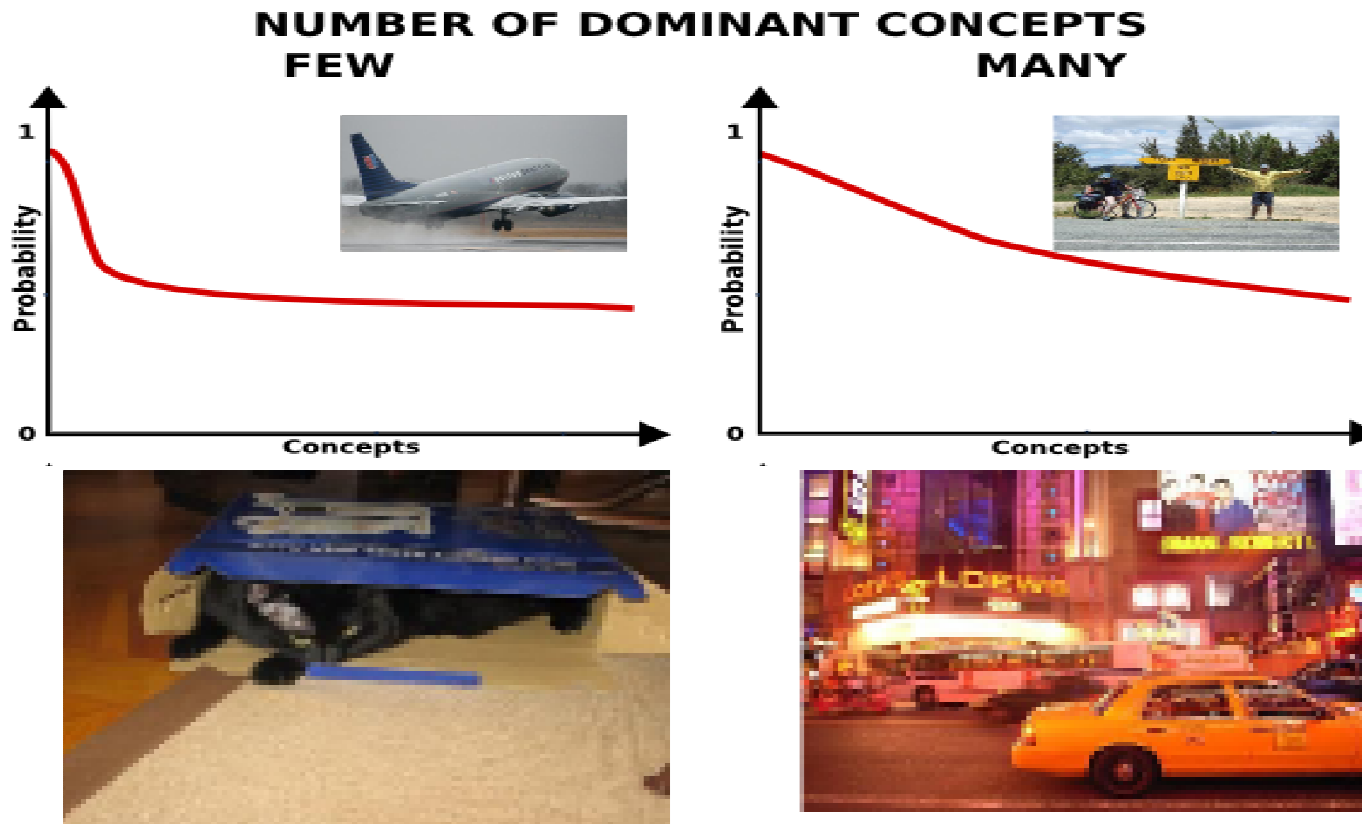
Proposed Approach: CBS

- Two things to consider:



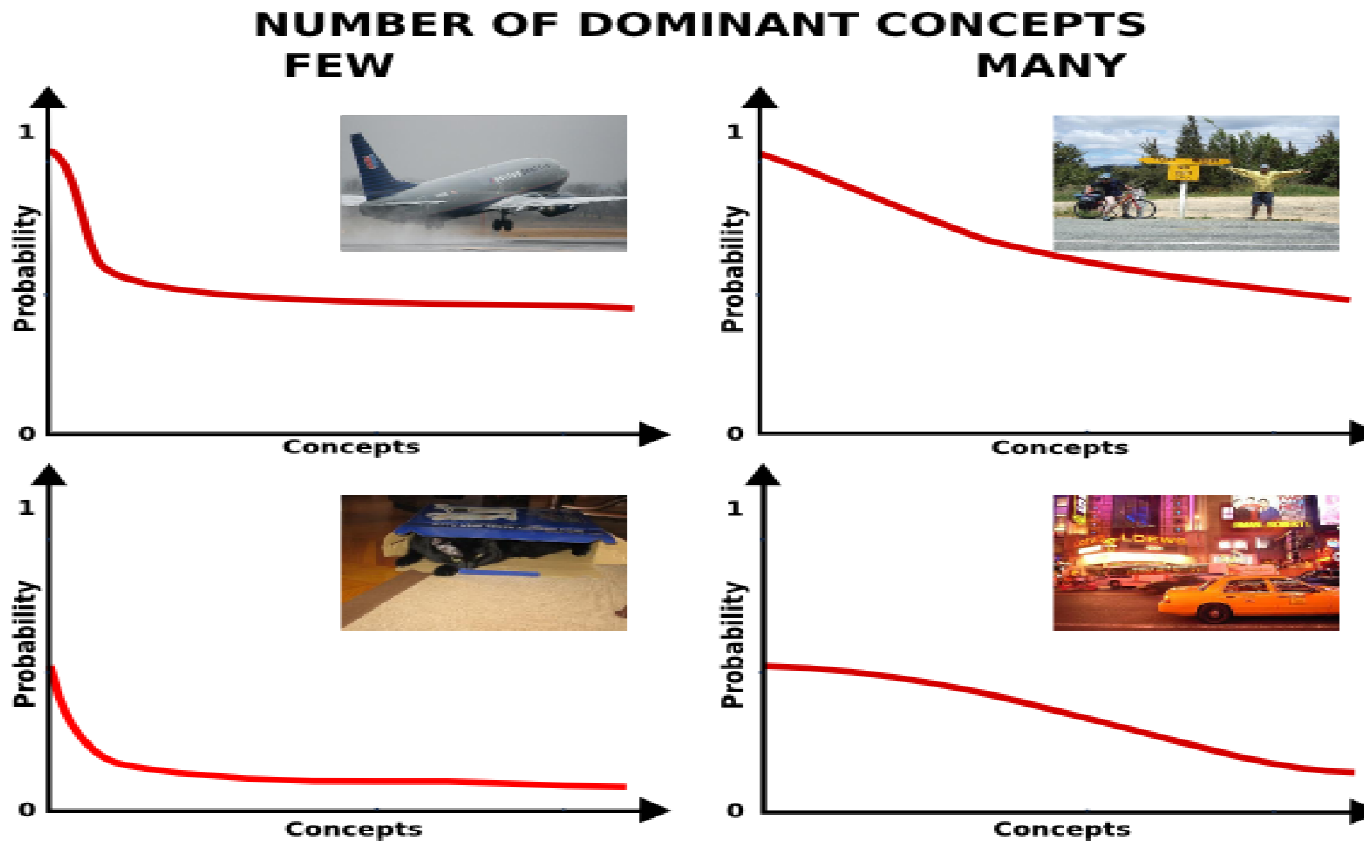
Proposed Approach: CBS

- Two things to consider:



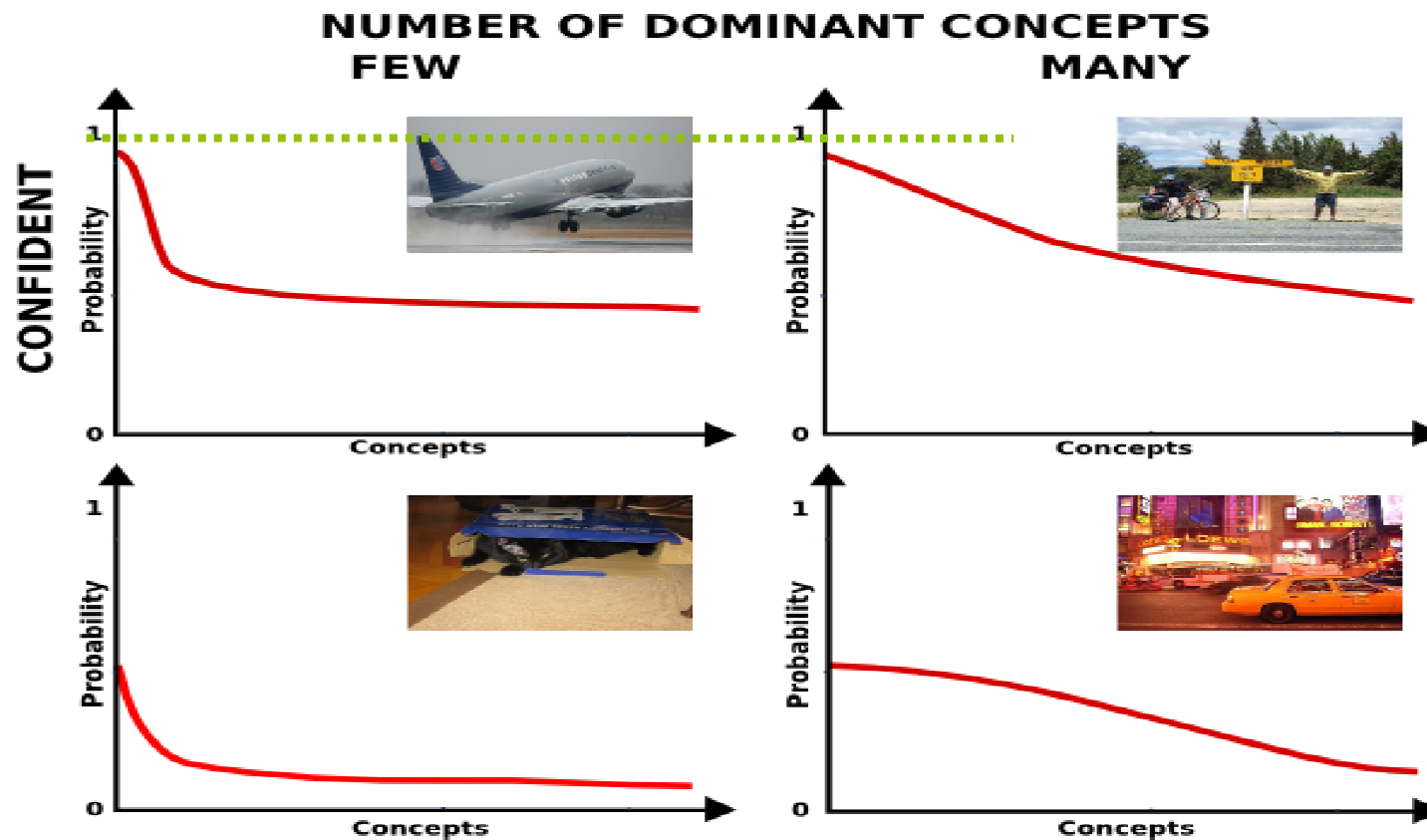
Proposed Approach: CBS

- Two things to consider:



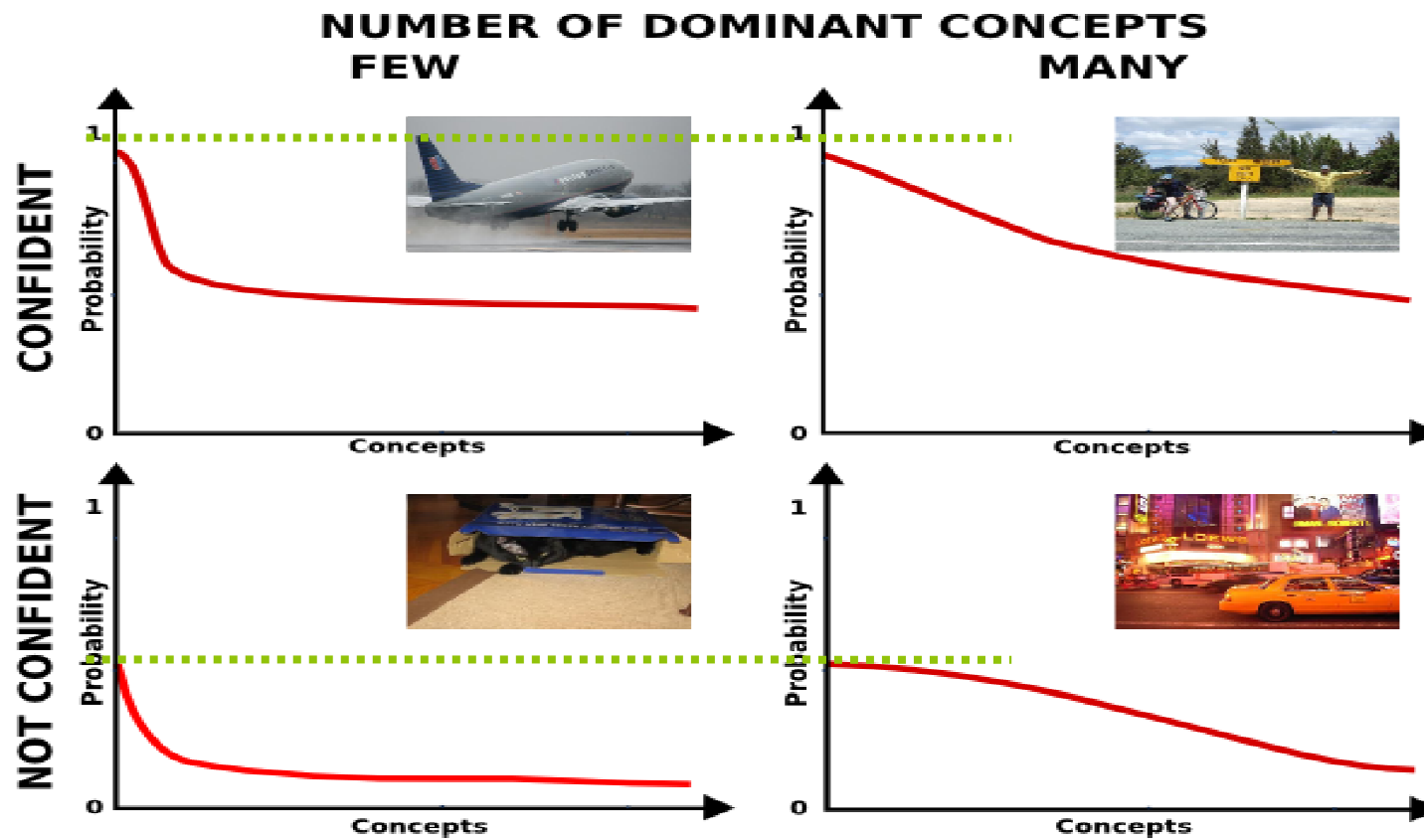
Proposed Approach: CBS

- Two things to consider:



Proposed Approach: CBS

- Two things to consider:



Proposed Approach: CBS

- **Modelisation**

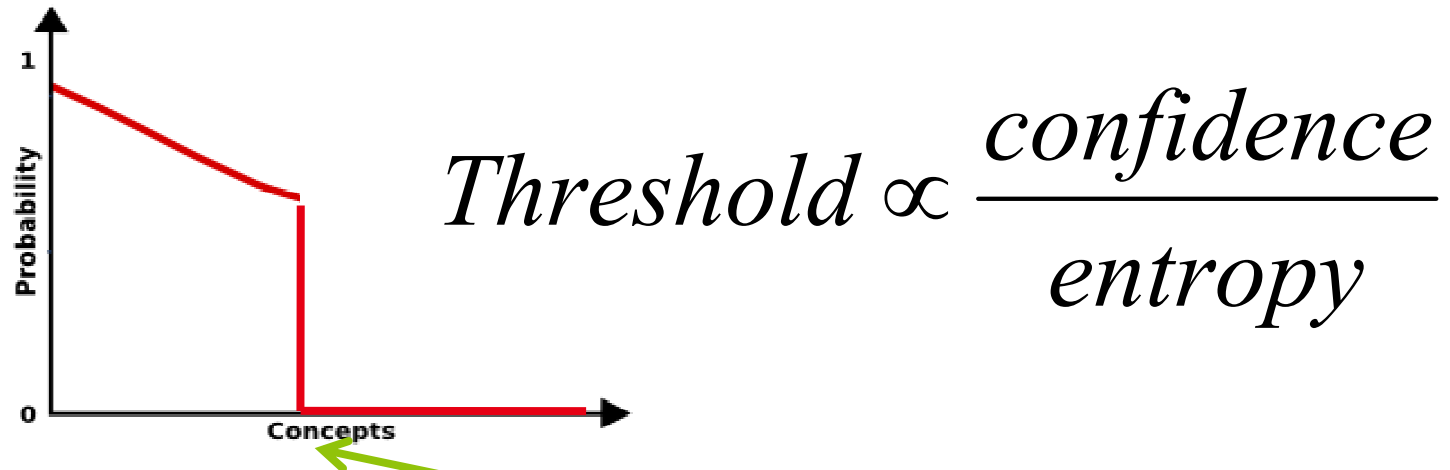
Confidence = value of the output detectors

- **Estimation**

- Maximum value of the feature

- **Final Estimation of the Threshold**

- Trade-off between entropy and confidence

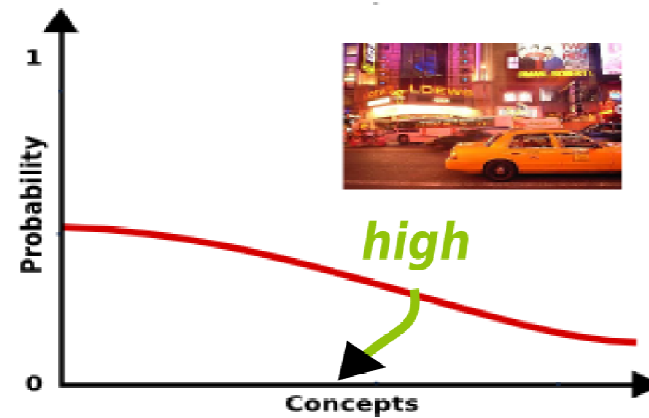
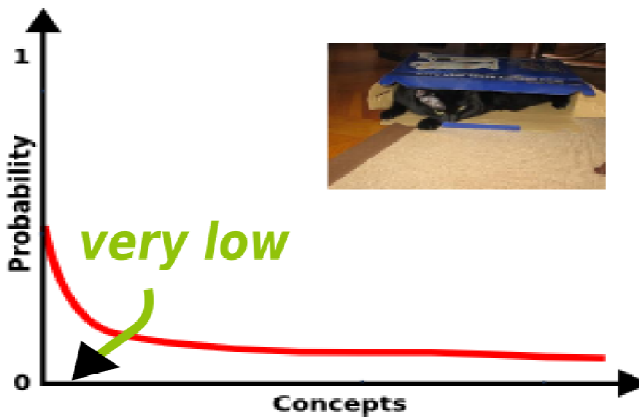
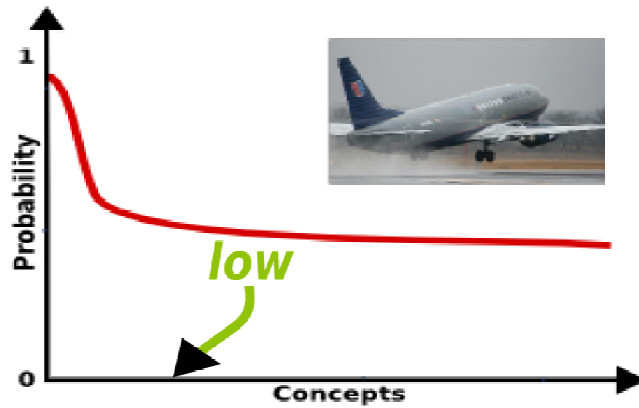


Threshold

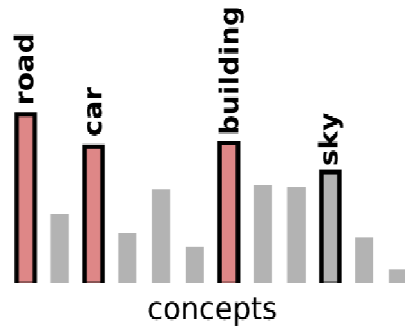
Proposed Approach: CBS

Output values (confidence)
high
low

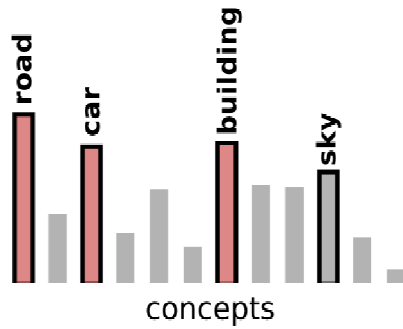
Entropy (# dominant concepts)
high
low



Proposed Approach: CLE

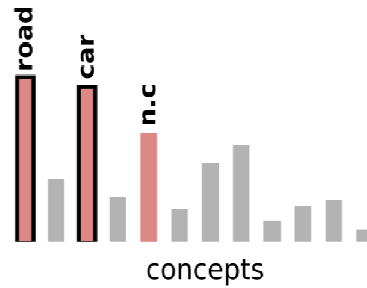
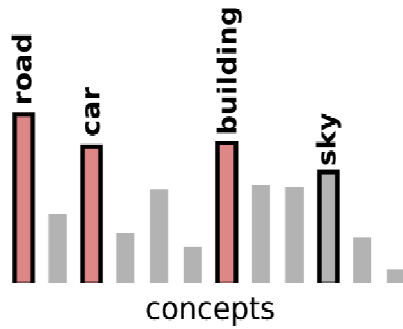


Proposed Approach: CLE



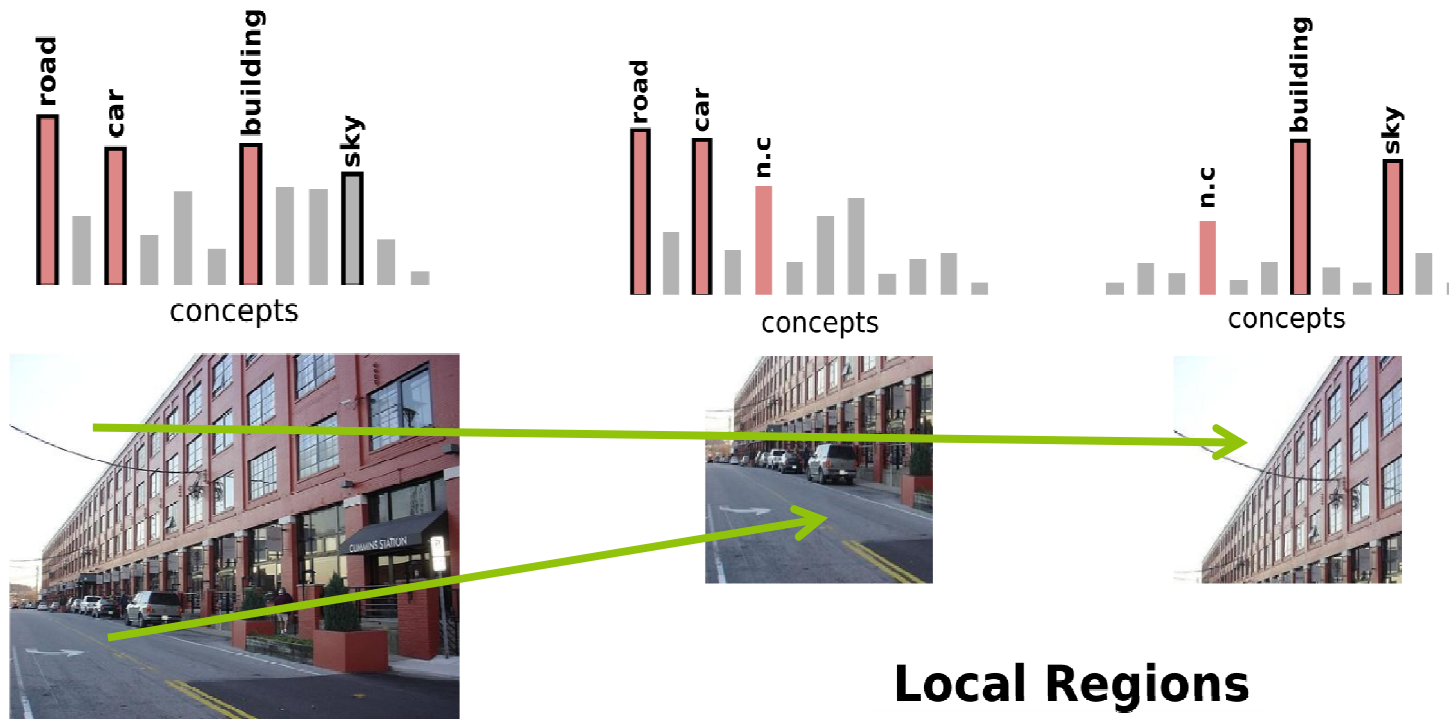
Local Regions

Proposed Approach: CLE



Local Regions

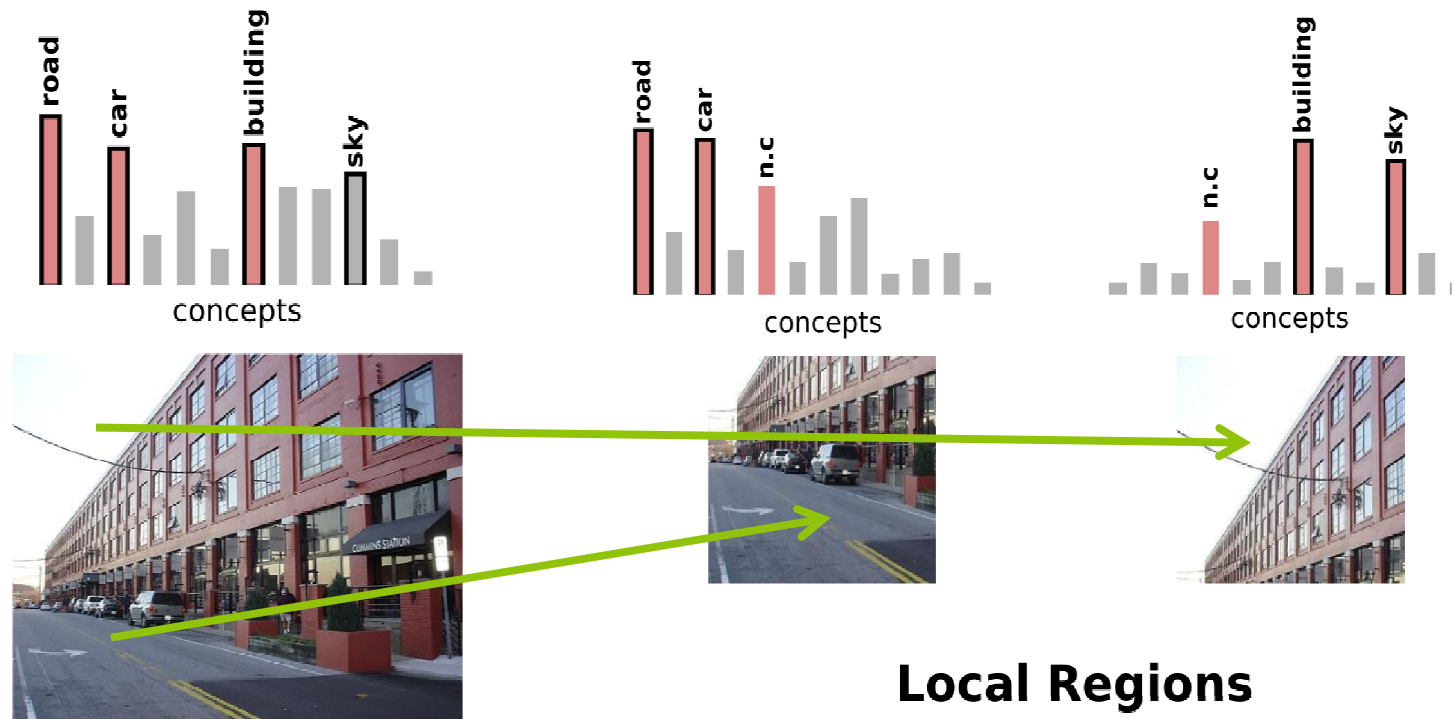
Proposed Approach: CLE



Local Regions

Proposed Approach: CLE

- Make more sense at local scale



- consider rich-information regions
- ignore low-information regions

Experimental Protocol

	Pascal VOC 07	Pascal VOC 12	MIT 67
Classification	✓ mAP	✓ mAP	✓ Accuracy
Retrieval	✓ mAP@K		✓ mAP@K

- **Pascal VOC 07**
 - Train/Collection: 5k – Test/Queries: 5k
- **Pascal VOC 12**
 - Train: 10k – Test: 10k
- **MIT Indoor 67**
 - Train/Collection: 5k – Test/Queries: 1k

Classification Results

Method		VOC 2007 mAP (in%)	VOC 2012 mAP (in%)
CNN	Oquab <i>et al.</i> , 2014	77.7	n.a.
	Chatfield <i>et al.</i> , 2014	82.42	83.2
	Wei <i>et al.</i> , 2014	81.5	81.7
	Simonyan <i>et al.</i> , 2015 (VGG fc7)	86.1	84.5
Semantic	Simonyan <i>et al.</i> , 2015 (VGG fc8)	77.4	77.2
	Bergamo <i>et al.</i> , 2012	53.2	49.3
	Torresani <i>et al.</i> (reimpl.)	82.4	81.7
	Ginsca <i>et al.</i> , 2015	82.8	81.7
	CLE (ours)	88.2	86.6

Fixed sparsification

Without sparsification



Classification Results

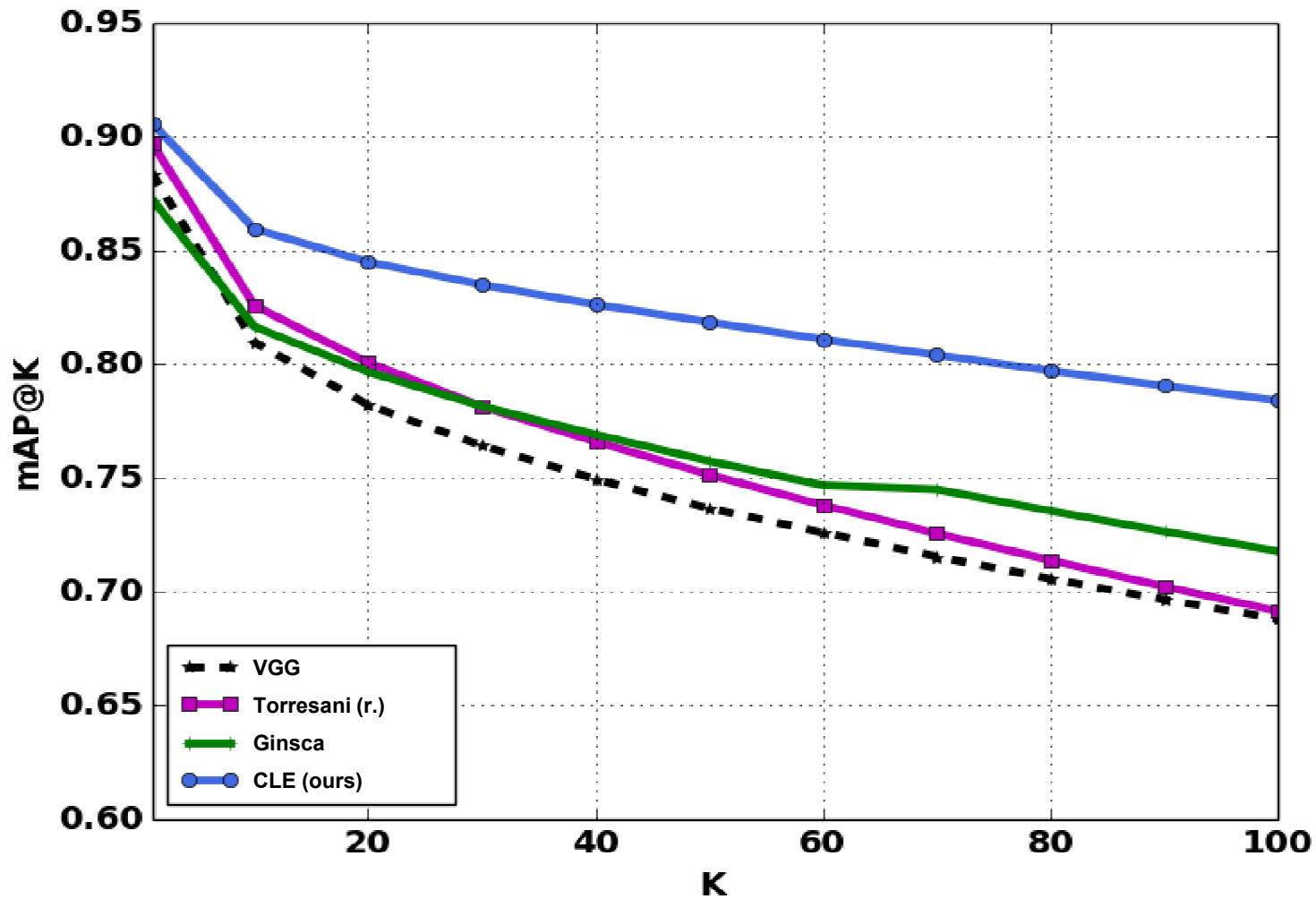
Scene classification

Method		MIT Indoor 67 Classification Accuracy (in%)
Doersch <i>et al.</i> , 2013		66.9
Oquab <i>et al.</i> , 2014		69.0
VGG (fc7)		65.8
Zhou <i>et al.</i> , 2014		68.2
Xie <i>et al.</i> , 2015 (Best paper)		70.1
Semantic	VGG (fc8)	48.7
	Bergamo <i>et al.</i> , 2012	44.6
	Torresani <i>et al.</i> , 2010 (r.)	58.9
	Ginsca <i>et al.</i> , 2015	61.5
	CLE (ours)	71.6

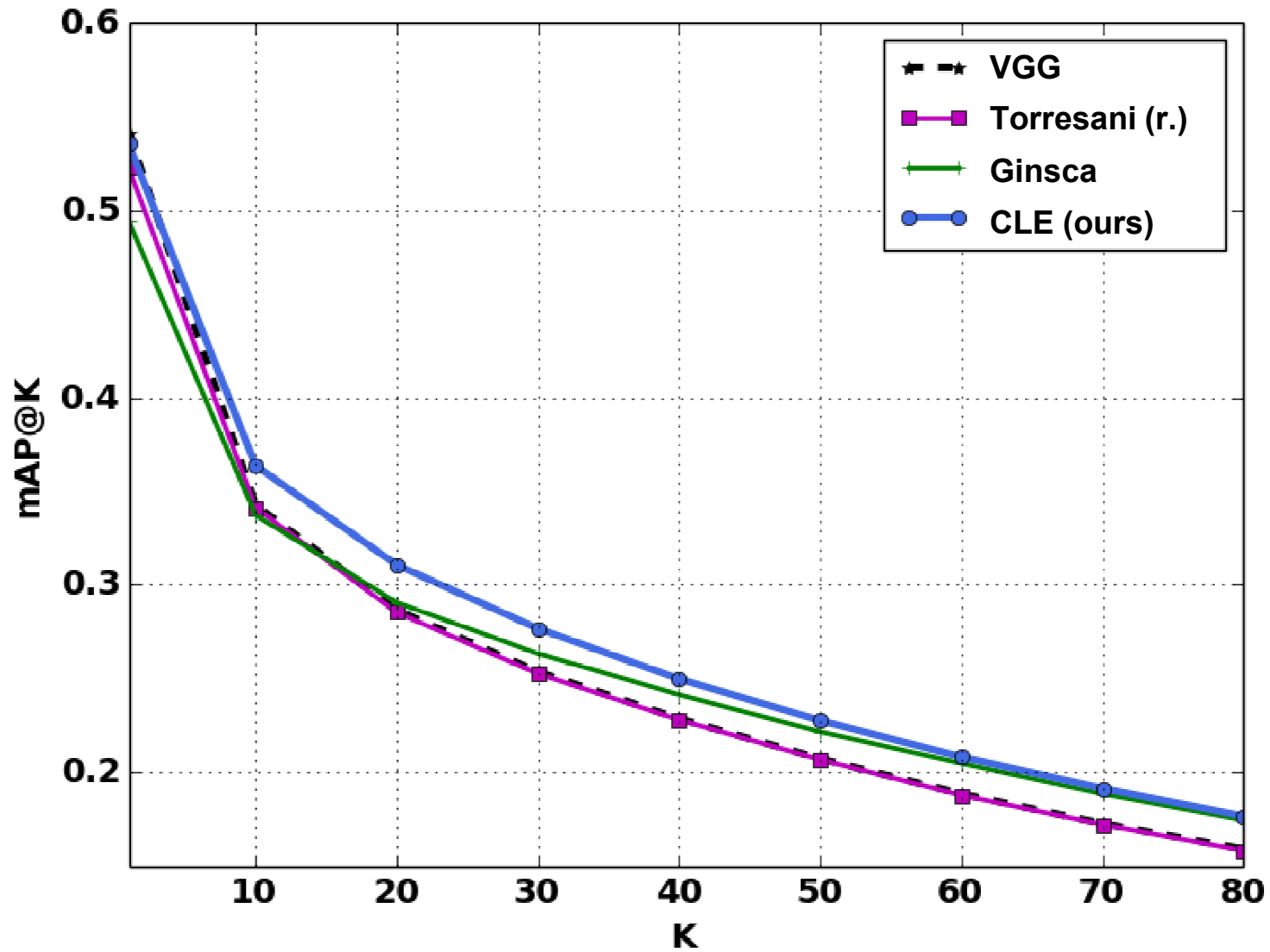
Naive sparsification

Without sparsification

Retrieval Results Objects (VOC07)



Retrieval Results Indoor scenes (MIT 67)



Conclusion

- **Novelty:**
 - New semantic image-representation
 - Level of sparsity adapted to the content of each image
 - Constrained local regions

- **Results:**
 - Image Classification
 - +2 points of mAP compared to the best CNN Feature
 - +5 points of mAP compared to the best Semantic Feature

 - Image Retrieval
 - +5 points of mAP compared to the best CNN Feature
 - +3 points of mAP compared to the best Semantic Feature

Thank you (questions ?)

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