Image Search with Deep Learning

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Class Objectives are:

- **CNN based approaches**
  - **Consider different regions, attention, and local features**
  - **Discuss applications**

- **At the prior class:**
  - **Discussed unsupervised hashing techniques based on hyperplanes and hyperspheres**
  - **Talked about supervised approach using deep learning**

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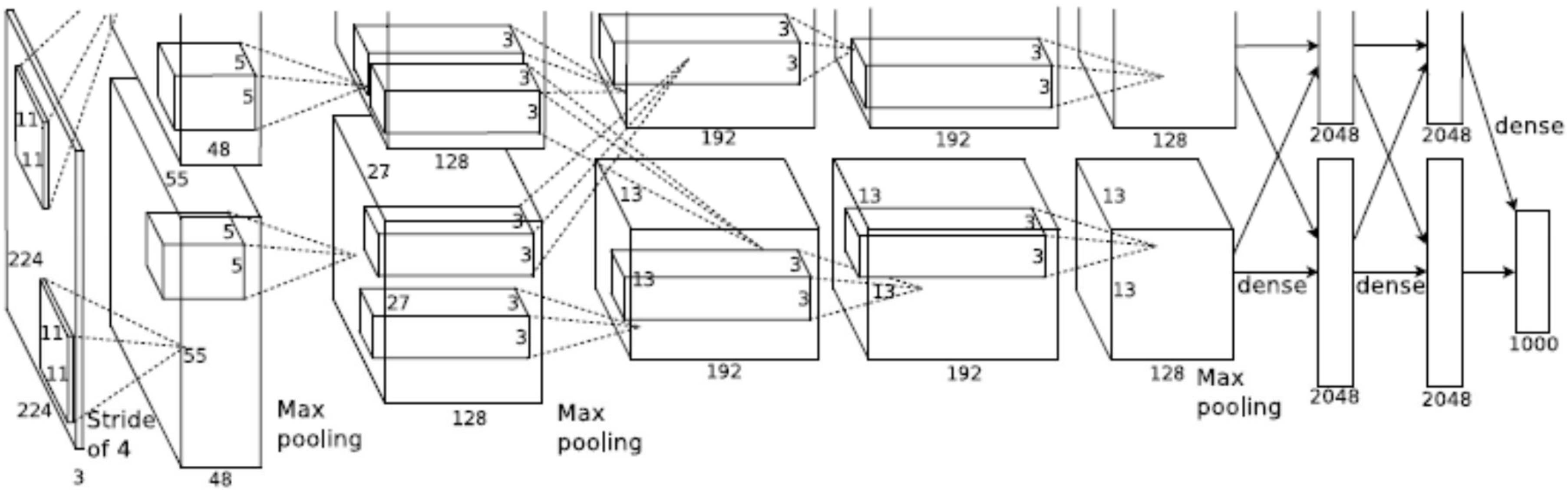
PA2

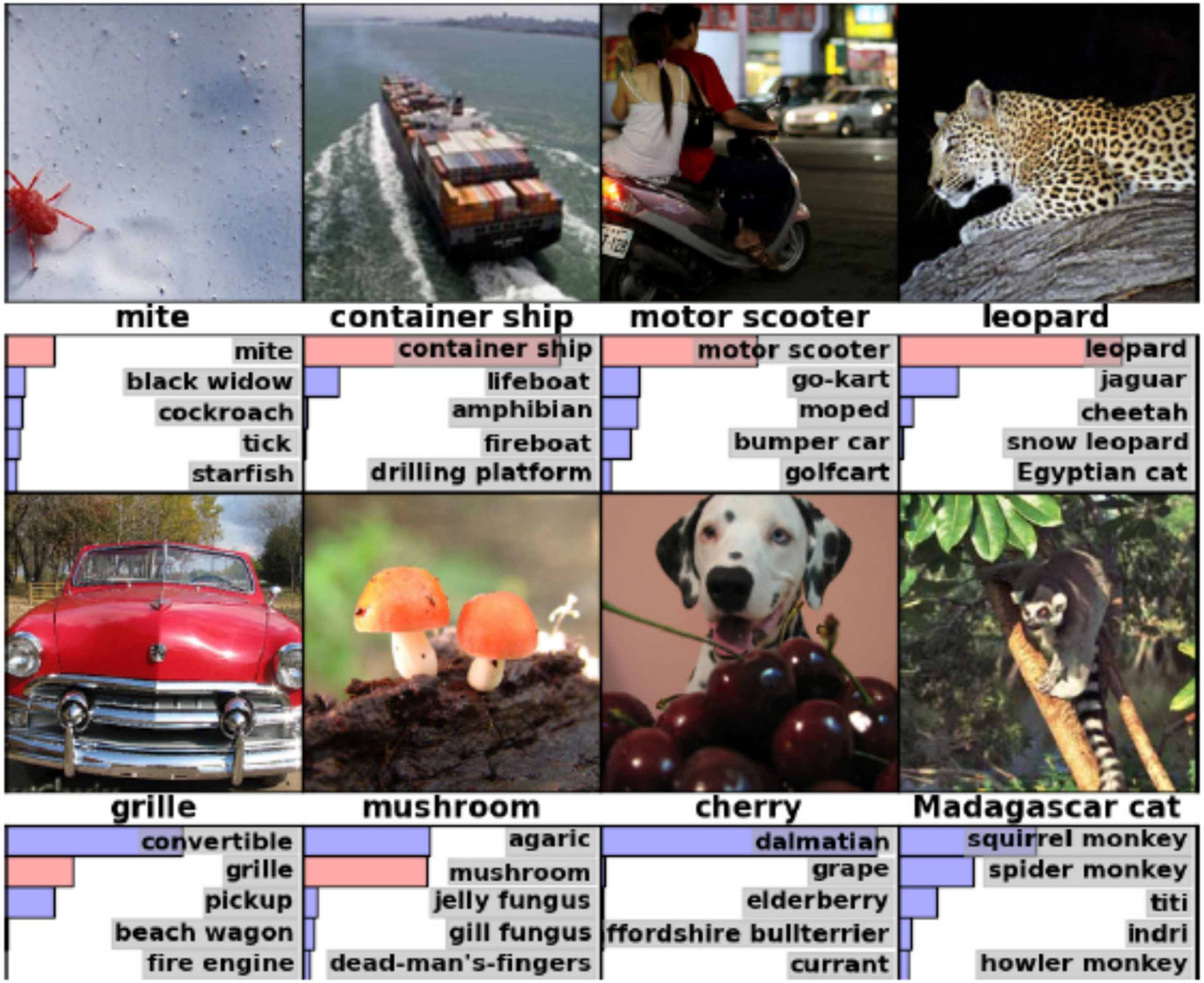
- **Apply binary code embedding and inverted index to PA1**
  - **k-means or product quantization (PQ) for inverted index**
  - **Spherical hashing or PQ for binary code embedding**

ImageNet Classification with Deep Convolutional Neural Networks [NIPS 12]

- Rekindled interest on CNNs
  - Use a large training images, ImageNet, of 1.2 M labelled images
  - Use GPU w/ rectifying non-linearities

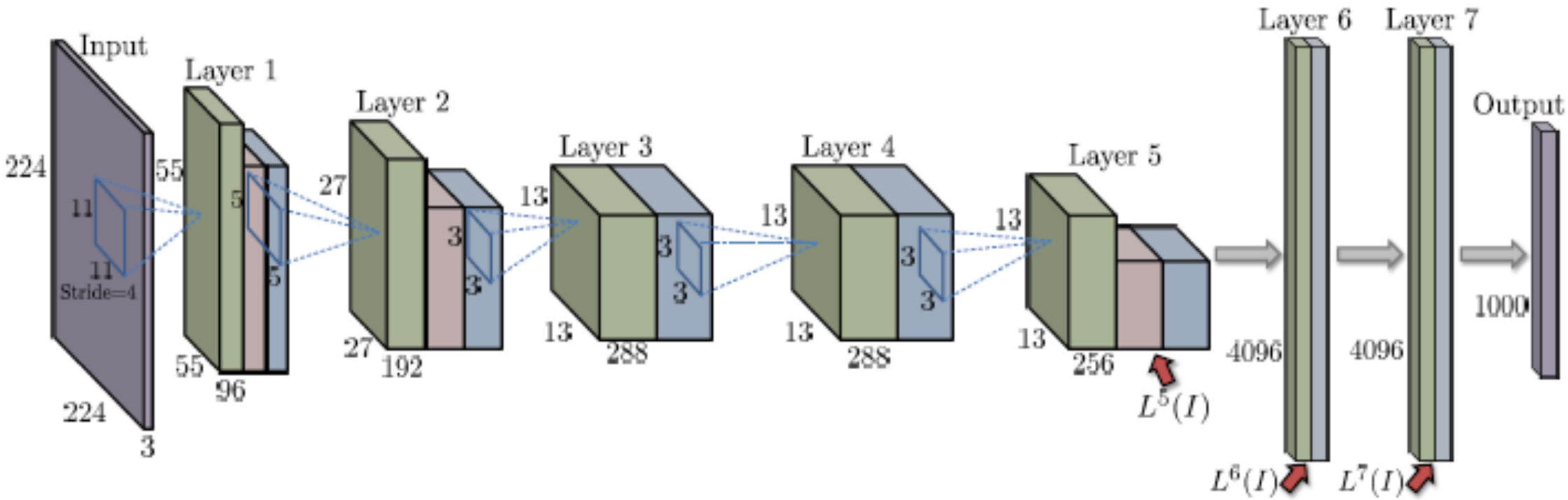


Tested on ILSVRC-2010



Neural Codes for Image Retrieval [ECCV 14]

- **Uses top layers of CNNs as high-level global descriptors (Neural Codes) for image search**



Sum Pooling and Centering Priors

- **Inspired by many prior aggregated features (e.g., BoW)**
  - **Use convolution layers as local features**

- **Aggregation**
  - **Simply sums those local features or**
  - **Considers centering priors w/ varying weights**

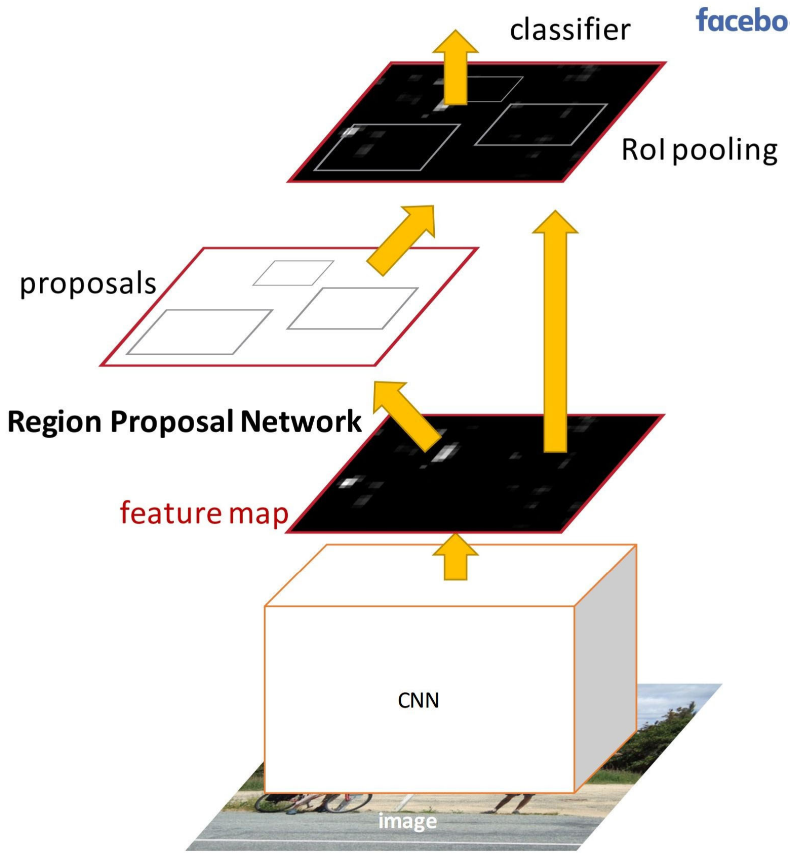
$$\psi_1(I) = \sum_{y=1}^{H} \sum_{x=1}^{W} f_{(x,y)}$$

Method	Holidays	Oxford5K (full)	Oxford105K (full)	UKB
Fisher vector, k=16	0.704	0.490	—	—
Fisher vector, k=256	0.672	0.466	—	—
Triangulation embedding, k=1	0.775	0.539	—	—
Triangulation embedding, k=16	0.732	0.486	—	—
Max pooling	0.711	0.524	0.522	3.57
Sum pooling (SPoC w/o center prior)	0.802	0.589	0.578	3.65
SPoC (with center prior)	0.784	0.657	0.642	3.66

Ack.: Aggregating Deep Convolutional Features for Image Retrieval

Localization: Faster R-CNN

- **Insert a Region Proposal Network (RPN) after the last convolutional layer**
- **RPN trained to produce region proposals directly**
  - **No need for external region proposals!**
- **Use RoI pooling and an upstream classifier and bbox regressor just like Fast R-CNN**

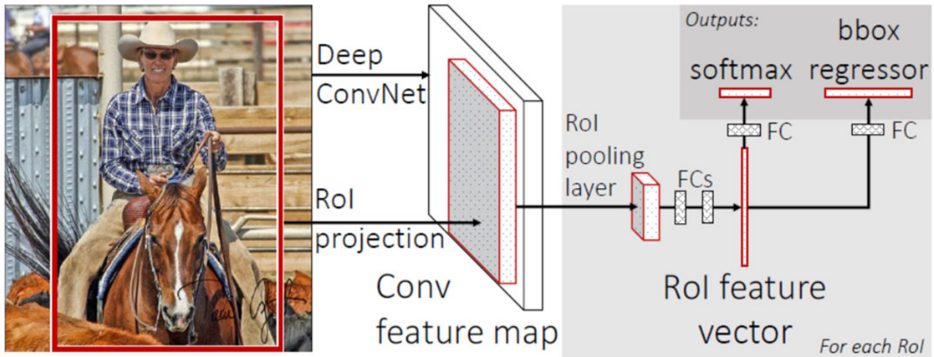


Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Slide credit: Ross Girschick

Faster R-CNN: Results

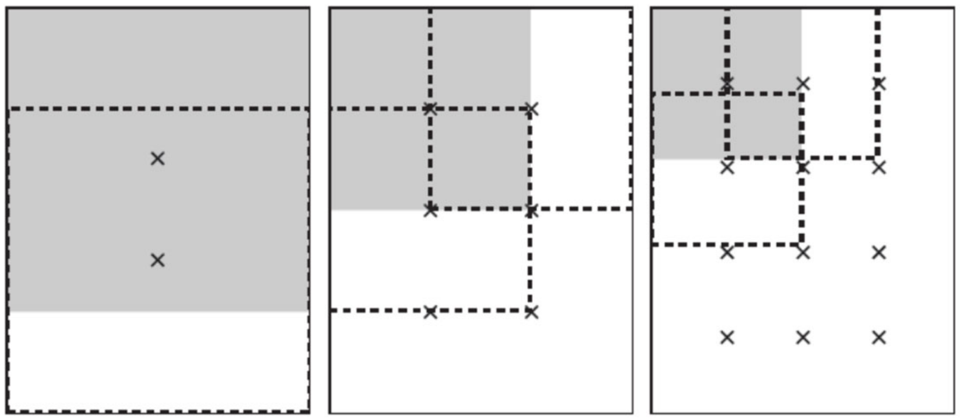
	R-CNN	Fast R-CNN	Faster R-CNN
Test time per image (with proposals)	50 seconds	2 seconds	**0.2 seconds**
(Speedup)	1x	25x	**250x**
mAP (VOC 2007)	66.0	**66.9**	**66.9**



Fast R-CNN: rely upon external region proposal

R-MAC: Regional Maximum Activation of Convolutions

- **Use maximum activation of convolutions for translation invariance**
- **Consider uniformly generated regions with different scales, and sum their features**



Ack.: PARTICULAR OBJECT RETRIEVAL WITH INTEGRAL MAX-POOLING

Fine-Tuning for Search

- **Use CNN features that were trained with ImageNet**
- **Retraining with a task-specific dataset achieve higher accuracy**
  - **Can lower accuracy when using dissimilar datasets**

Fine-Tuning for Search

Results before & after retraining

Neural codes trained on ILSVRC					
Layer 5	9216	0.389	—	0.690*	3.09
Layer 6	4096	0.435	0.392	0.749*	3.43
Layer 7	4096	0.430	—	0.736*	3.39
After retraining on the Landmarks dataset					
Layer 5	9216	0.387	—	0.674*	2.99
Layer 6	4096	0.545	0.512	**0.793***	3.29
Layer 7	4096	0.538	—	0.764*	3.19
After retraining on turntable views (Multi-view RGB-D)					
Layer 5	9216	0.348	—	0.682*	3.13
Layer 6	4096	0.393	0.351	0.754*	3.56
Layer 7	4096	0.362	—	0.730*	3.53

Landmark dataset has similar images to Oxford

Ack.: Neural Codes for Image Retrieval

Dimension Reduction

- **CNN features (4096D) are robust to PCA compression**
  - **Maintain accuracy by 256 D**

Dimensions	16	32	64	128	256	512
Oxford						
Layer 6	0.328	0.390	0.421	0.433	0.435	0.435
Layer 6 + landmark retraining	0.418	0.515	0.548	0.557	0.557	0.557
Layer 6 + turntable retraining	0.289	0.349	0.377	0.391	0.392	0.393

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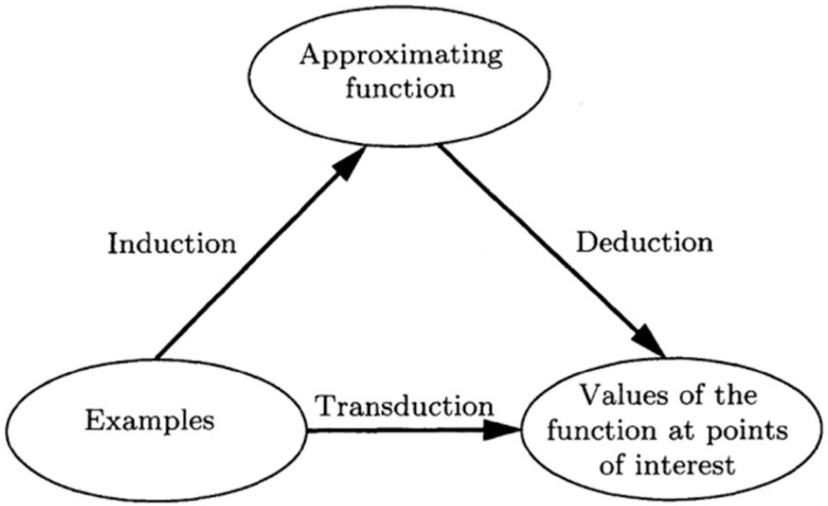
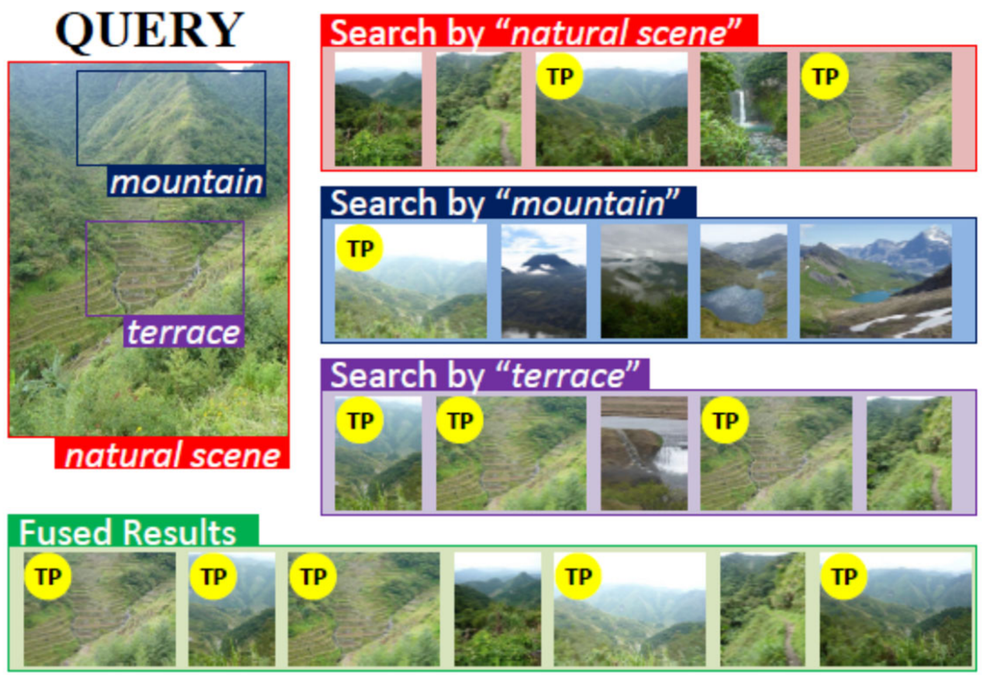
Image Classification and Retrieval are ONE [ICMR 15]

- **Handle the classification and search in a unified framework**
  - **Uses region proposals, and nearest neighbor search for both problems**
- **Image search (kNN) is transductive learning**



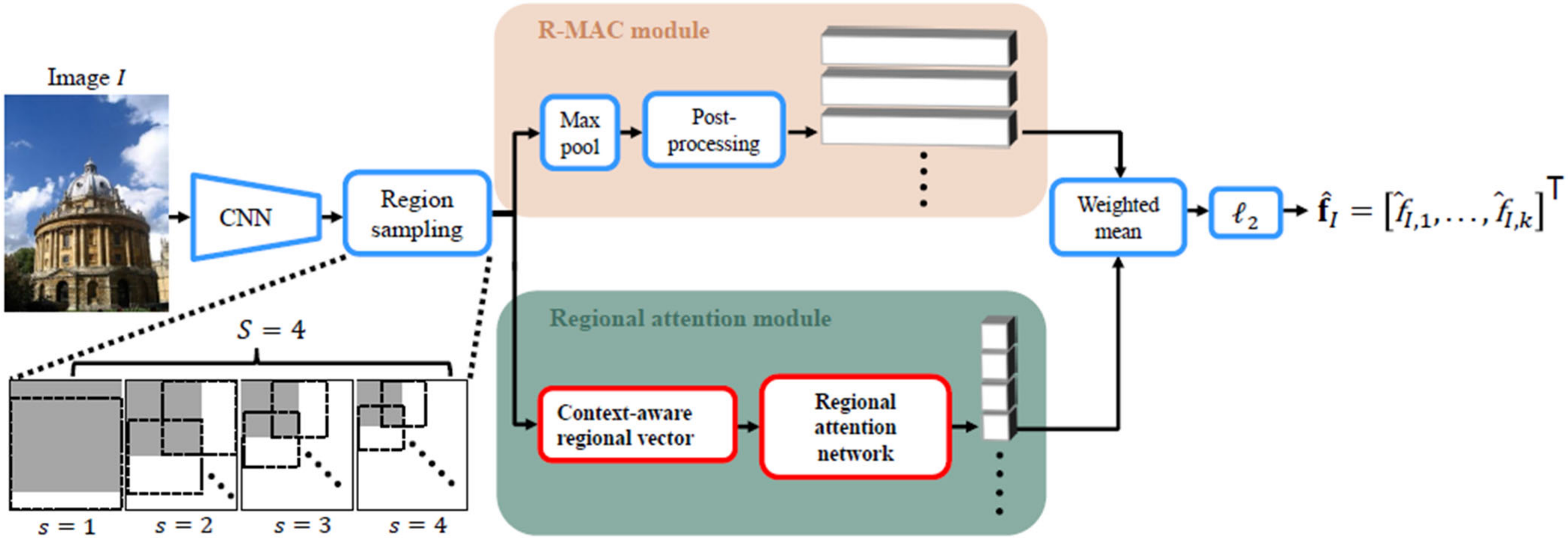


Regional Attention Based Deep Feature for Image Retrieval

- **Apply the attention (or saliency) to regional features for image retrieval**
  - **Train attention weights based on classification**

(a) Sheep - 26%, Cow - 17% (b) Importance map of '*sheep*'

Ack. Tech talk



HardNet: Deep Learning based Local Features

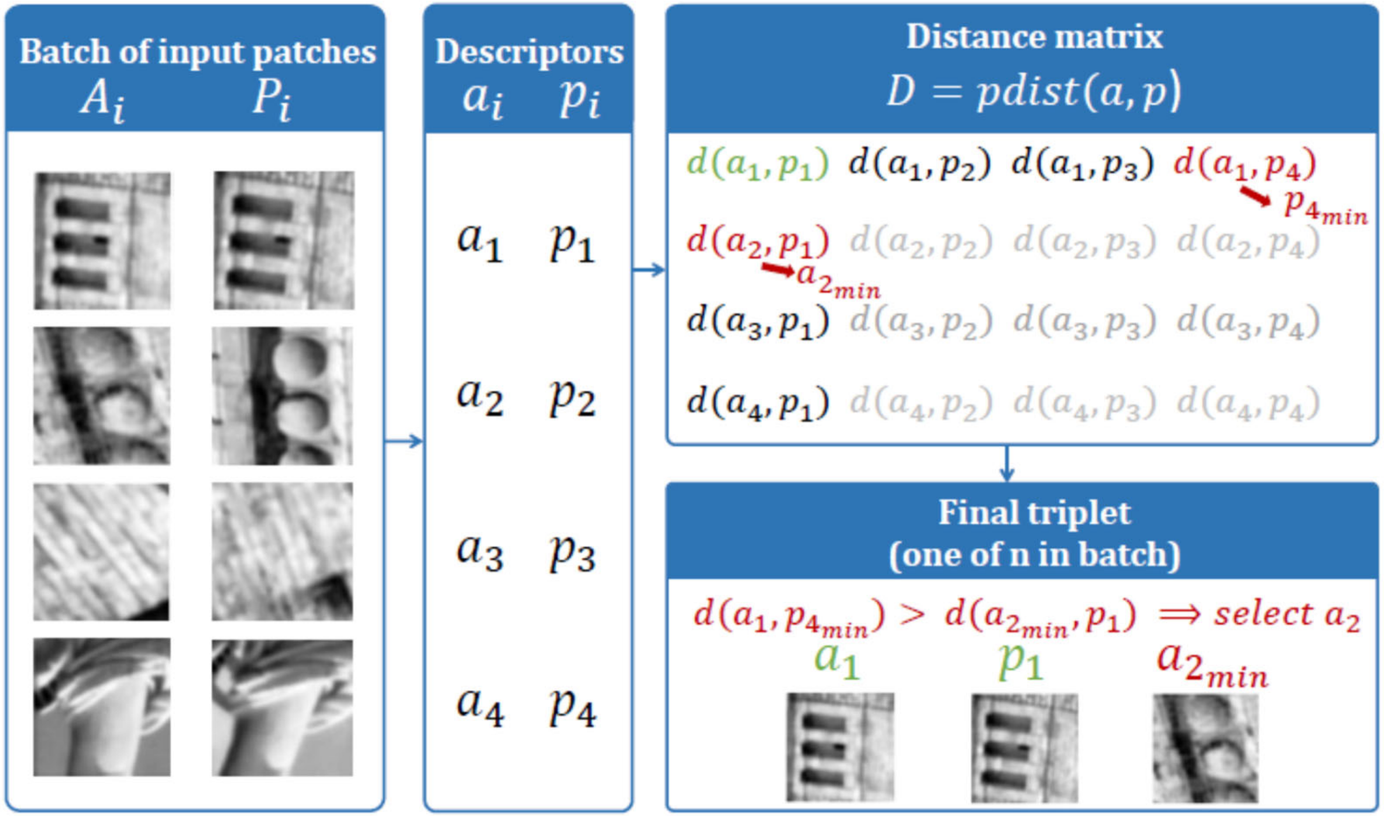
- **Propose a local descriptor learning loss**
  - **Similar to a triplet loss**
  - **Get a higher matching accuracy than SIFT**

- **Triplet loss w/ anchor, its positive, and its negative**
  - **Compute feature in a way:** $D(a,p) < D(a,n)$

Working hard to know your neighbor's margins: Local descriptor learning loss, NIPS

Sampling Procedure

- **Given an anchor patch a_1, we extract its positive patch p_1**
  - **Use traditional matching techniques (e.g., DoG)**
- **Find its hard negative**



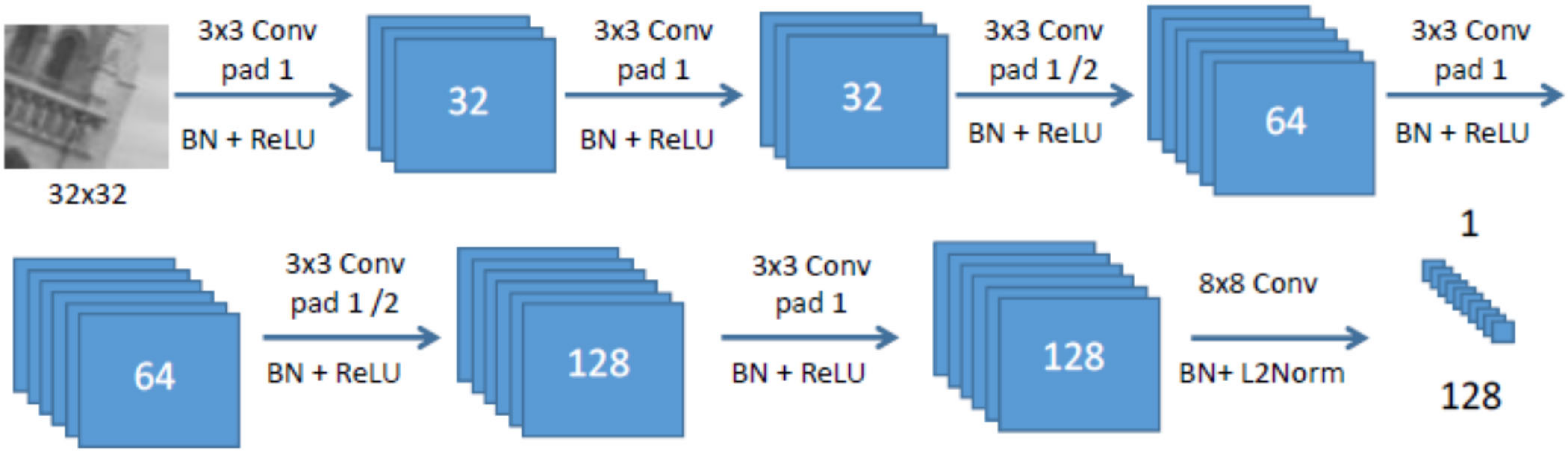
Find a patch that is incorrectly close to a_1

Find a patch that is incorrectly close to p_1

Between two patches, pick the worst

Model Architecture

- **Input: 32x32 grayscale input patches**
- **Output: 128D descriptor**

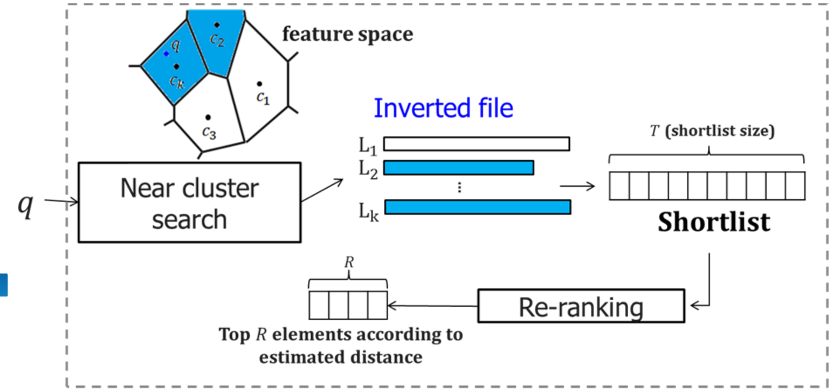


Performance Comparisons over Prior Features

- **Overall, it shows better accuracy, as it is trained with additional datasets**
  - **BoW: Bag-of-Words, QE: Query Expansion, SV: Spatial Verification**

	Oxford5k			Paris6k		
Descriptor	BoW	BoW+SV	BoW+QE	BoW	BoW+SV	BoW+QE
TFeat-M* [23]	46.7	55.6	72.2	43.8	51.8	65.3
RootSIFT [10]	55.1	63.0	78.4	59.3	63.7	76.4
L2Net+ [24]	**59.8**	67.7	80.4	**63.0**	66.6	77.2
HardNet	59.0	67.6	**83.2**	61.4	**67.4**	**77.5**
HardNet+	**59.8**	**68.8**	83.0	61.0	67.0	**77.5**
HardNet++	**60.8**	**69.6**	**84.5**	**65.0**	**70.3**	**79.1**

Summary


feature space
Inverted file
q
Near cluster search
L_1
L_2
L_k
T (shortlist size)
Shortlist
R
Re-ranking
Top R elements according to estimated distance

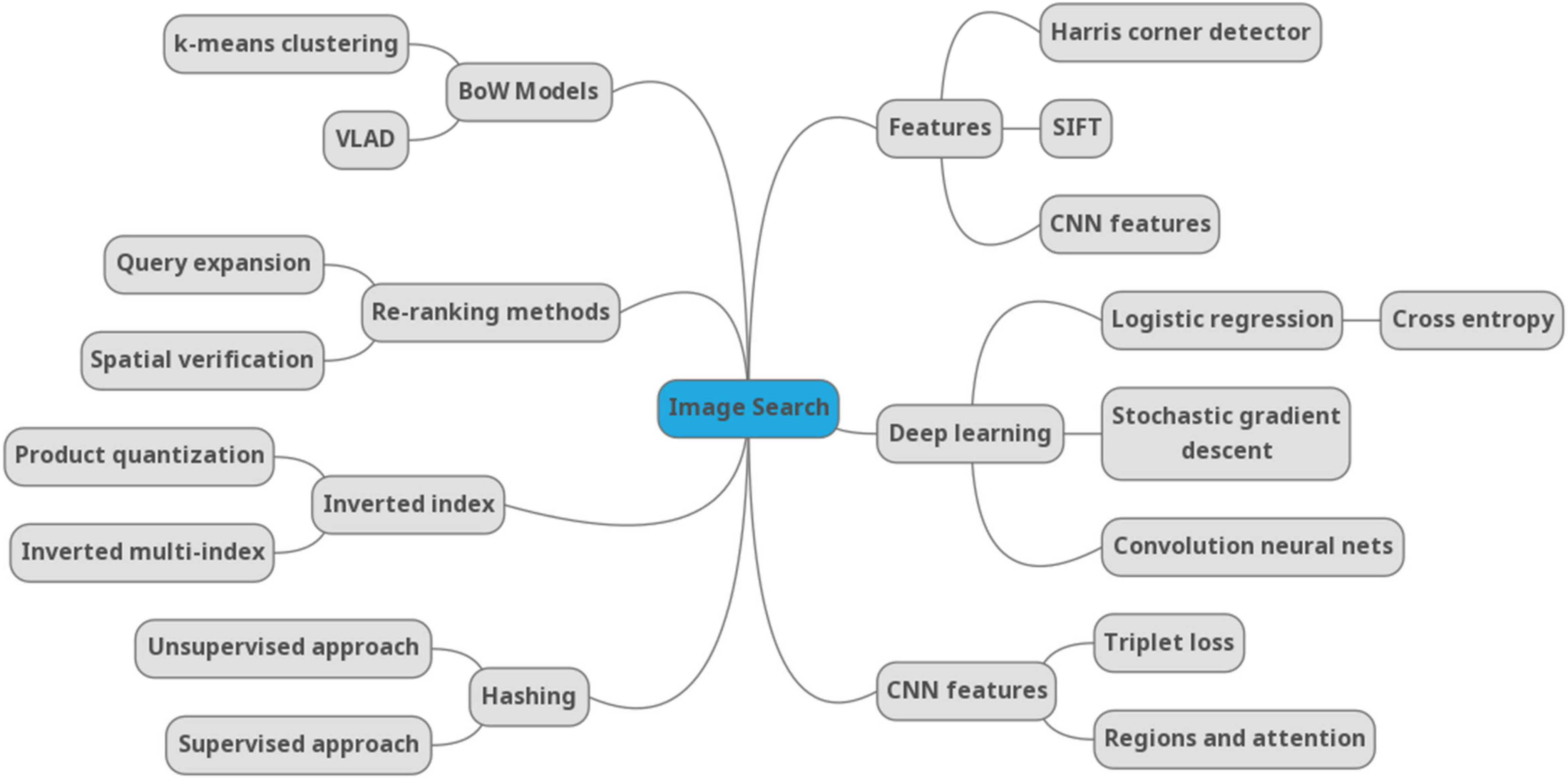
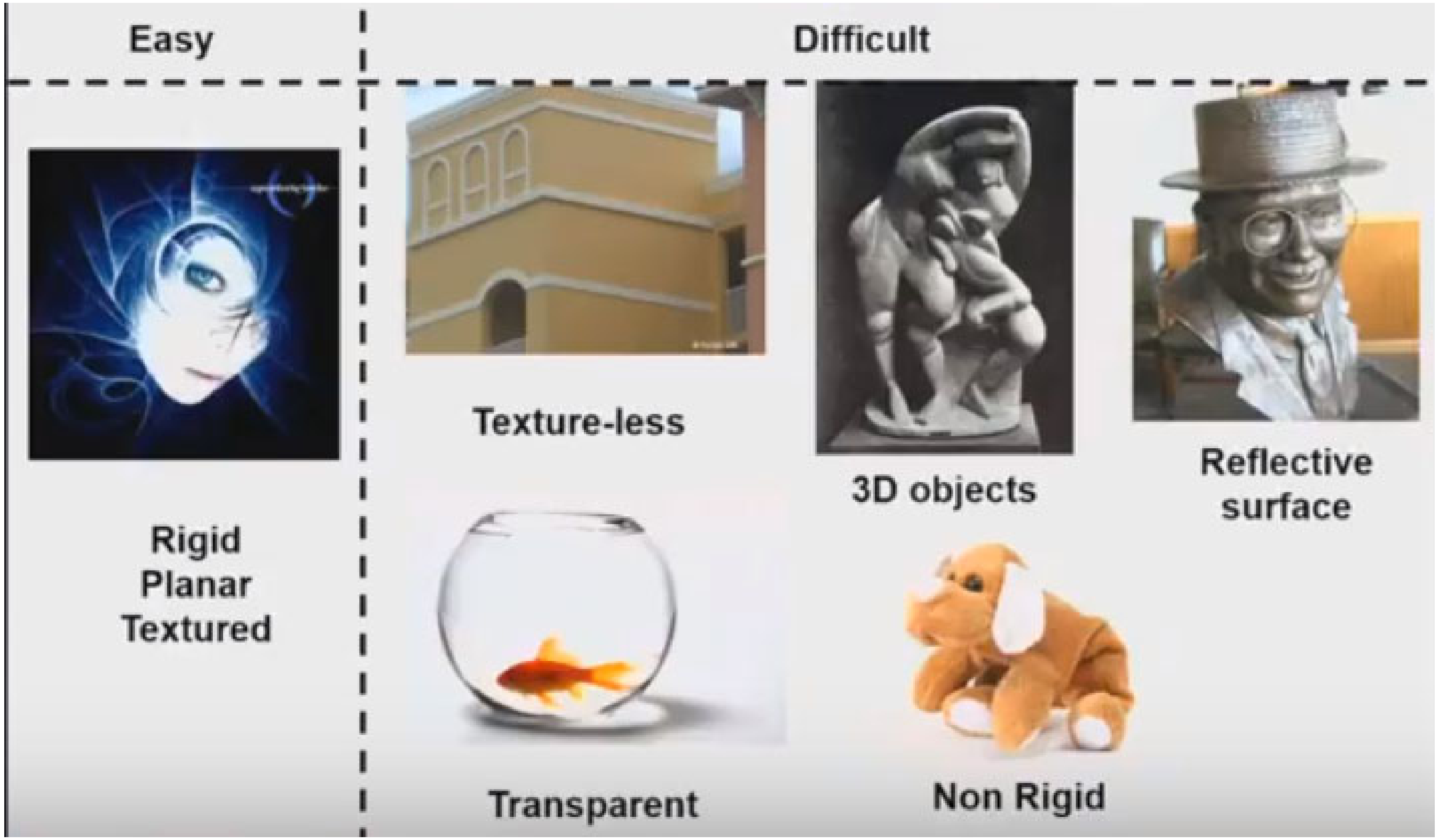


Image Search
BoW Models
k-means clustering
VLAD
Re-ranking methods
Query expansion
Spatial verification
Inverted index
Product quantization
Inverted multi-index
Hashing
Unsupervised approach
Supervised approach
Features
Harris corner detector
SIFT
CNN features
Deep learning
Logistic regression
Cross entropy
Stochastic gradient descent
Convolution neural nets
CNN features
Triplet loss
Regions and attention

Limitations of Image Search



Ack: Vijay Chandrasekhar

- **Large-scale video retrieval**
  - **30 frames per sec., 5 billion shared video at youtube**

Applications and Extension of Image Search

- Content and context based hashing, indexing, search and retrieval of multimedia data
- Multimodal or cross-modal content analysis and retrieval
- Advanced descriptors and similarity metrics for multimedia data
- Complex multimedia event detection and recounting

Ack: Call for papers of ACM ICMR

Applications and Extension of Image Search

- Learning and relevance feedback and HCI issues in multimedia retrieval
- Query models and languages for multimedia retrieval
- Fine-grained visual search
- Image/video summarization and visualization
- Mobile visual search

Class Objectives were:

- CNN based approaches
  - Consider different regions within or outside the end-to-end training
  - Utilize attention and local features
  - Discuss applications
- Discussed limitations of current techniques and future research directions

Homework for Every Class

- **Come up with one question on what we have discussed today**
  - **Write questions three times**
- **Go over recent papers on image search, and submit their summary before Tue. class**