

# Visual Category Recognition using Information-Theoretic Co-clustering

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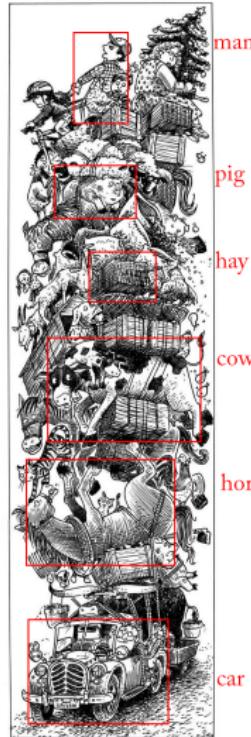
Feb.25,2012



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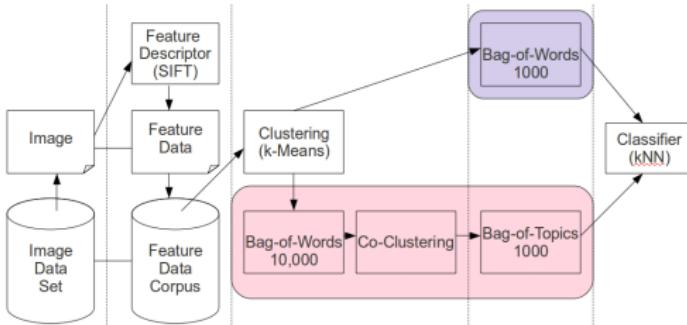
- Introduction: Visual Categorization
- Current practice: Bag-of-Features Model
- Problem: Semantic scatter
- Idea: Visual Topic  $\leftarrow \sum$  Visual Words
- Approach: Information-Theoretic Co-Clustering
- Solution: Bag-of-Topics Model
- Experiments: multiple Datasets and Dictionary sizes
- Summary

# Visual Category Recognition



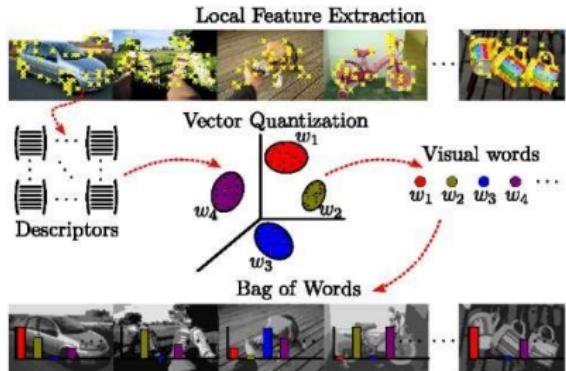
## Definition

Detect presence of an instance of a visual category in an image.



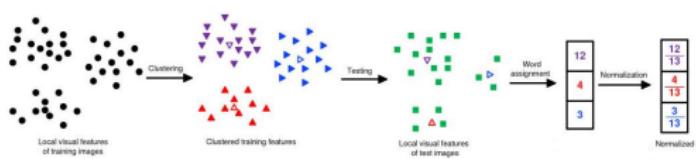
## Visual Categorization Pipeline

# Bag-of-Features



## Visual Word

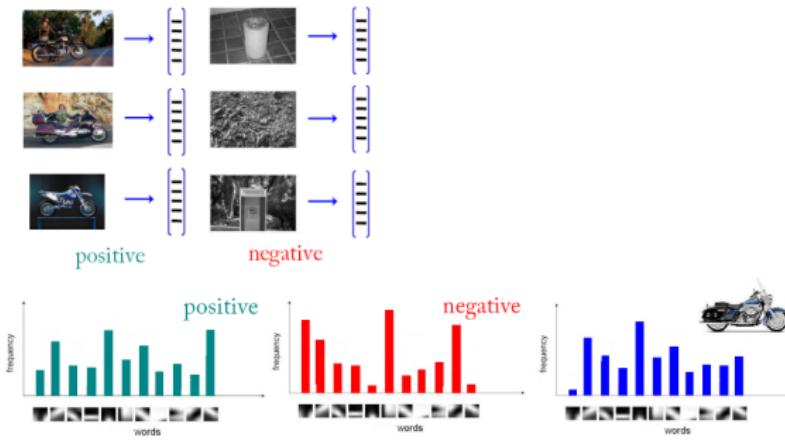
Representative feature vector (generally centroid) of each cluster.



## Image Histogram

Histogram of assignments of image feature vectors to visual words.

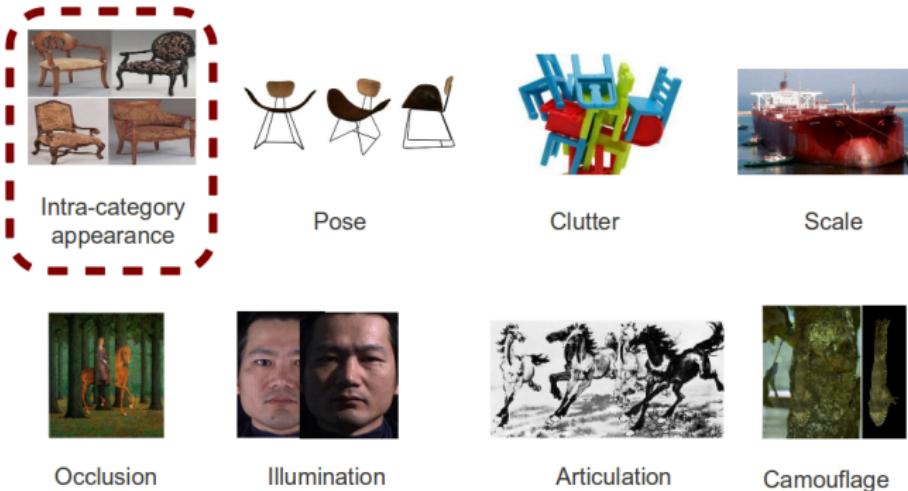
# Discriminative Dictionary



## Basic Intuition

If normalized image histogram of **test sample** is closer to trained **positive histogram** then image is classified as positive (motorcycle).

# Challenges



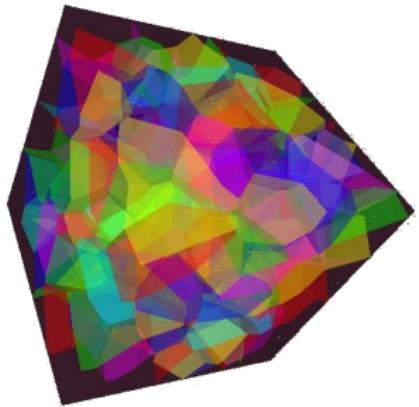
Several variations in visual category appearance render category recognition very difficult.

# Intra-category appearance variation



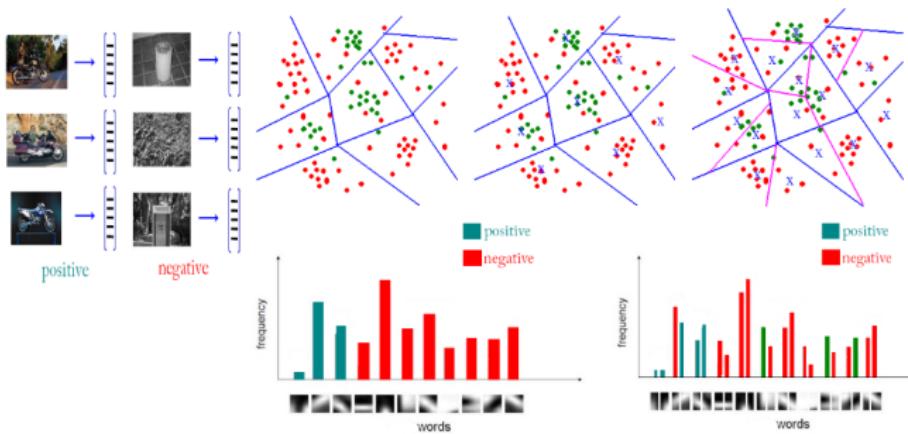
- Small variations in instances of object part causes associated descriptors to get scattered in feature space.

# Semantic Scatter



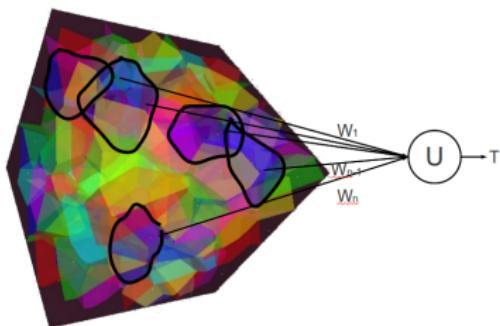
- Small variations in instances of object part causes associated descriptors to get scattered in feature space.
- Descriptors of different categories are inter-leaved in feature space (local patch descriptors have low specificity).

# Towards Discriminative Dictionary



- Increase dictionary size to split up interleaved feature vectors.
- Dictionary learning is unsupervised  $\Rightarrow$  discriminative dictionary not assured.

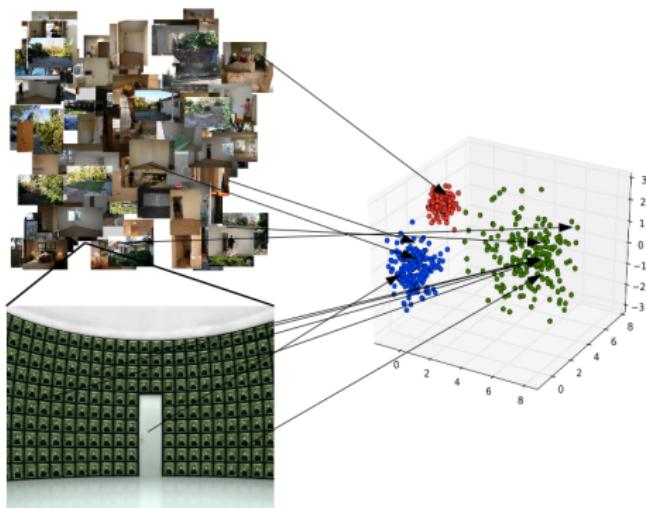
$$\text{Visual Topic} \leftarrow \sum \text{Visual Words}$$



### Idea

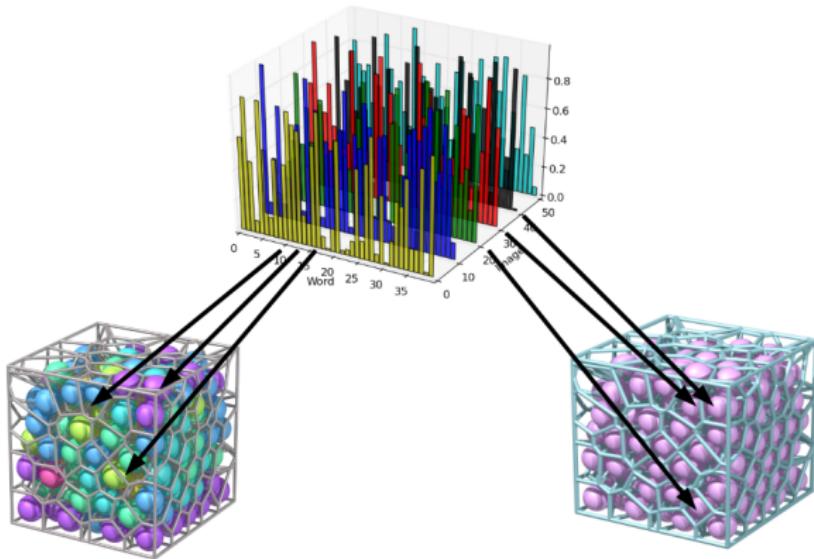
- Combine visual words which are semantically related and create a visual topic.
- Dictionary of visual topics should be more robust to intra-category variation.

# Visual Word Distribution



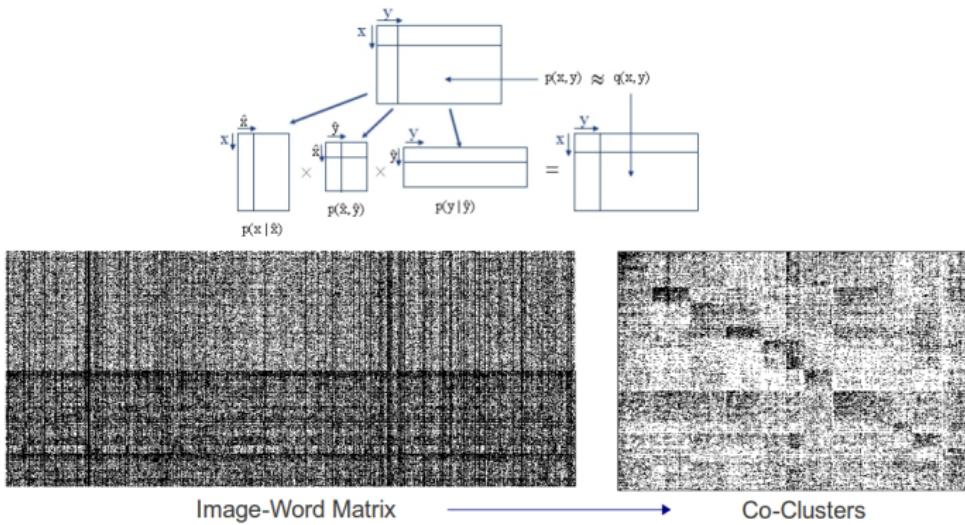
- Visual word selection is based entirely on distribution density of feature vectors independent of image source.
- Distribution across images important for selection of visual word.

# Image-Word Distribution



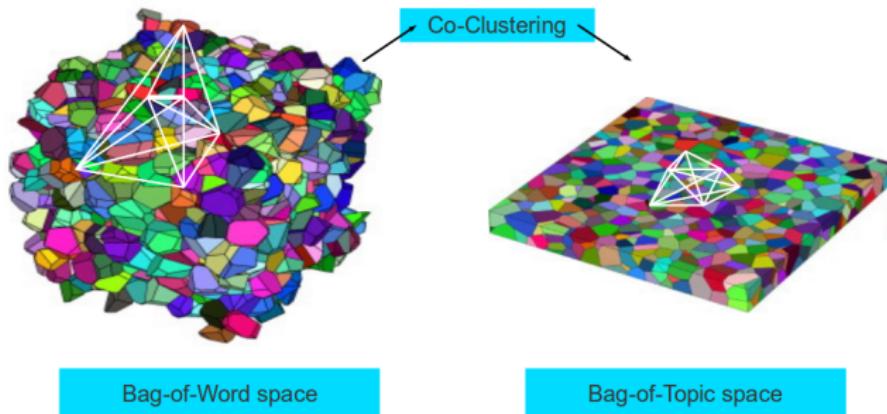
- Word distribution across images  $\propto$  semantic equivalence.
- Histogram distribution across words  $\propto$  image similarity.

# Co-Clustering



- Formulate the image-word matrix as a joint probability distribution.
- Optimal co-clustering maximizes mutual information between clustered random variables.

# Bag-of-Topics $\leftarrow$ Bag-of-Words

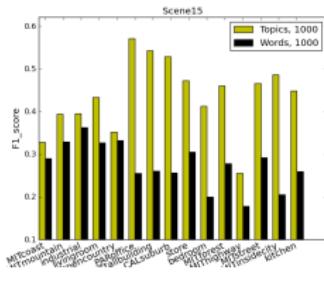
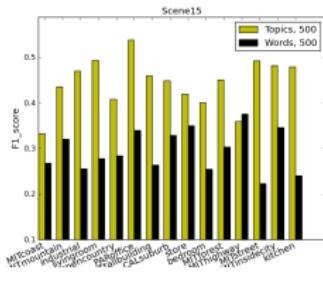
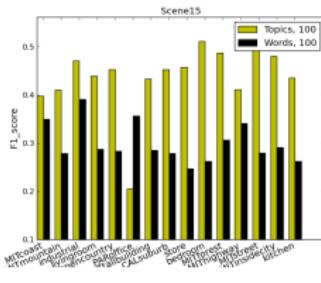


- Image histogram feature vectors in high-dimensional visual words space are projected to lower dimensional visual topic space.
- The distance between feature vectors from the same category is reduced.

# Experiment

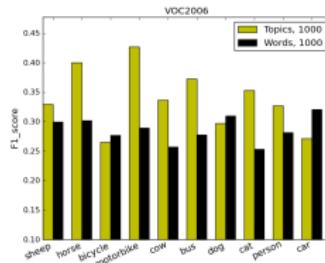
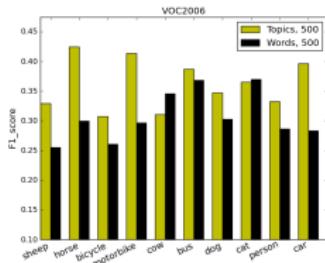
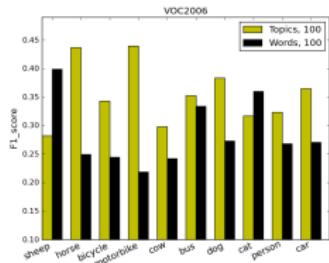
- Feature Descriptor : SIFT : Affine invariant local image patch descriptor
- Data set:
  - Scene 15 : 15 visual categories of natural indoor and outdoor scenes. Each category has about 200 to 400 images and the entire dataset has 4485 images.
  - Pascal VOC2006 : It has 10 visual categories with about 175 to 650 images per category. There are a total of 5304 images.
  - Pascal VOC2007 : It has 20 visual categories. Each category contains images ranging from 100 to 2000, with 9963 images in all.
  - Pascal VOC2010 : It has 20 visual categories with 300 to 3500 images per category. There are a total of 21738 images.
- Classifier : k-NN

# Scene-15 Dataset



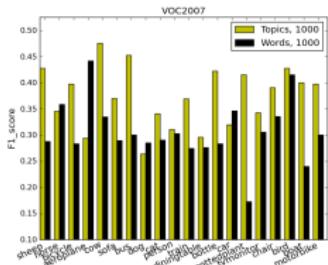
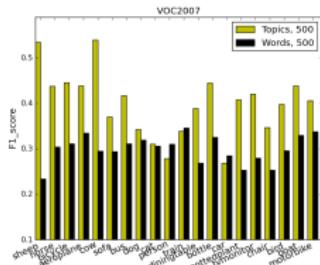
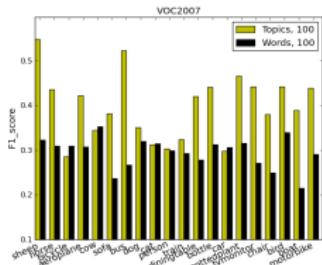
F1-score across categories for 100, 500, and 1000 visual Topics.

# PASCAL VOC2006 Dataset



F1-score across categories for 100, 500, and 1000 visual Topics.

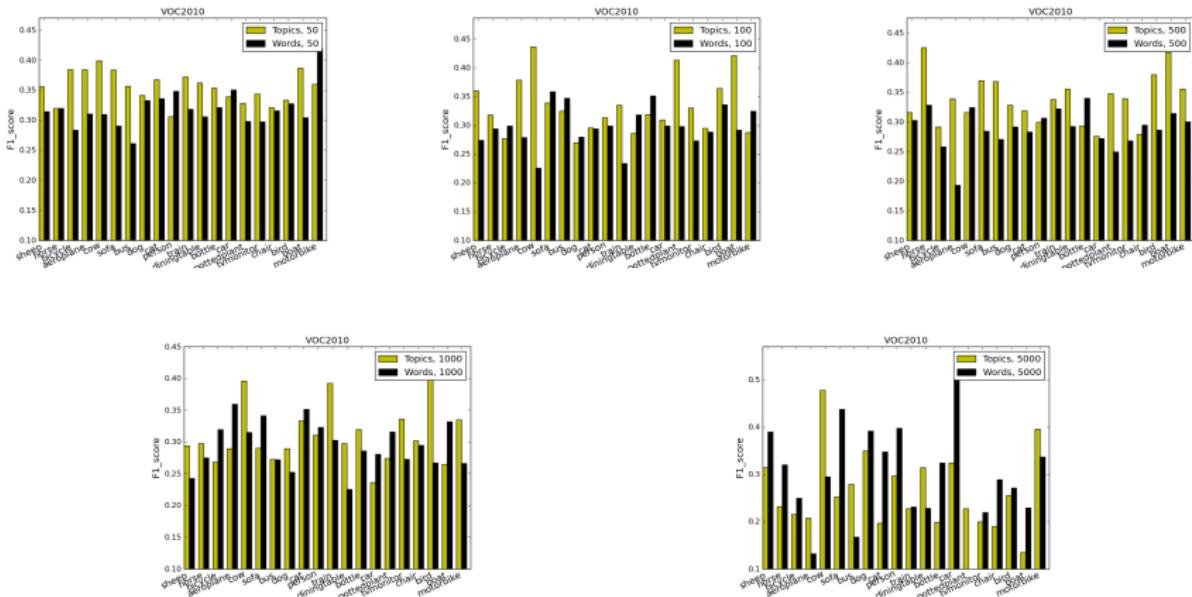
# PASCAL VOC2007 Dataset



F1-score across categories for 100, 500, and 1000 visual Topics.

# Dictionary Size

10,000 words → n Topics. Appropriate number of Topics?



Large dictionary becomes category dependent.

# Summary

Bag-of-Features is limited: unsupervised clustering.

Significant intra-category appearance variation: semantic scatter.

Visual Topic  $\leftarrow \sum$  Visual Word.

Co-clustering Image-Word distribution.

Semantic dimensionality reduction.

END

