Image representations using local image descriptors

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Image classification

- Food & Restaurant domain
- Unconstrained images
- Manual tags
- Food / Non-food

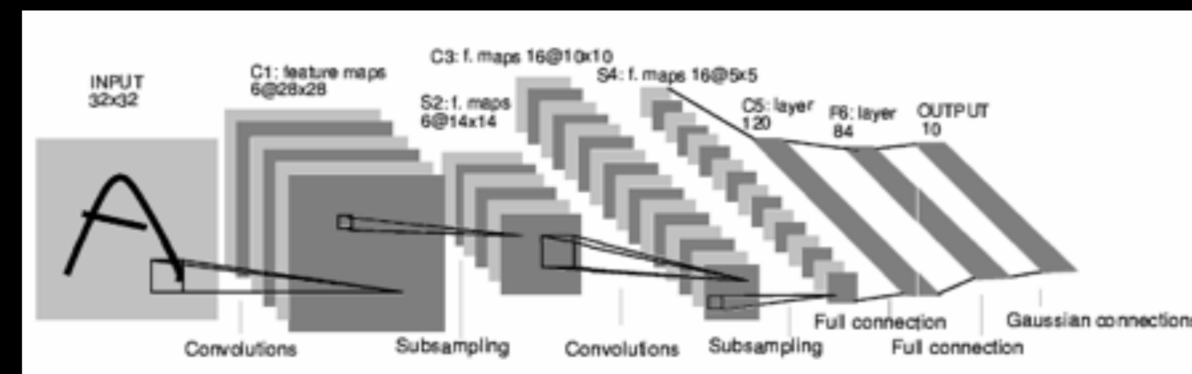






Current trend

- Deep Learning: CNN
  - As Feature Extractor & Classifier
  - As Feature Extractor



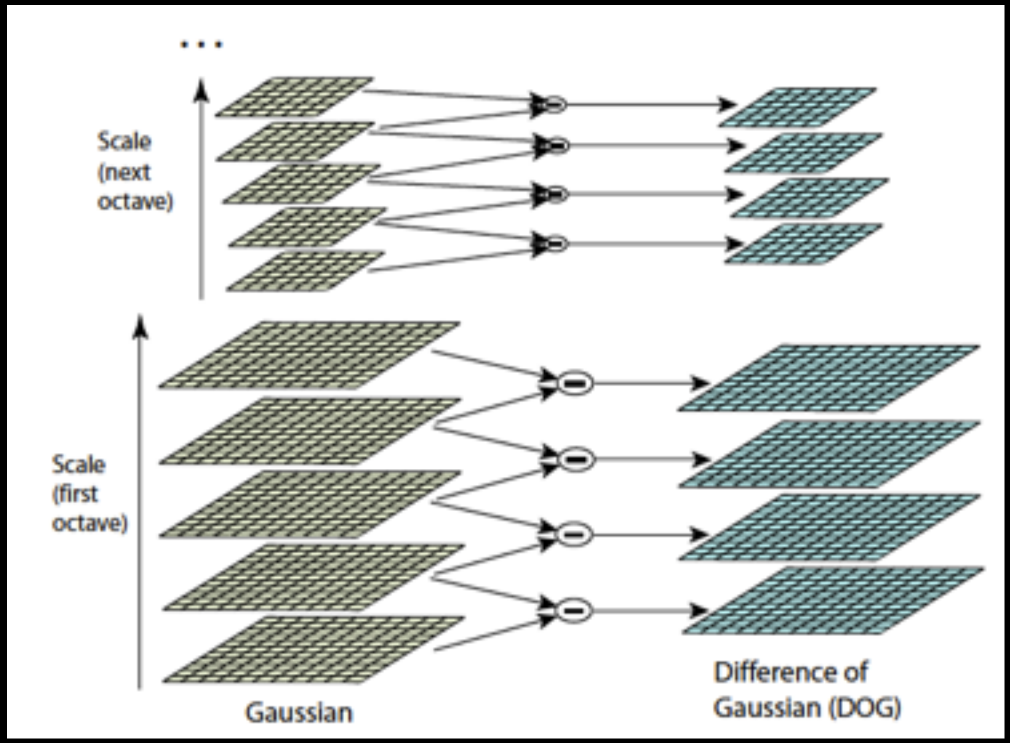
- Pro: problem-dependent Feature Extractor
- Cons
  - Neural Networks training
  - Requires special hardware
- Another solution: traditional image descriptors + classifier

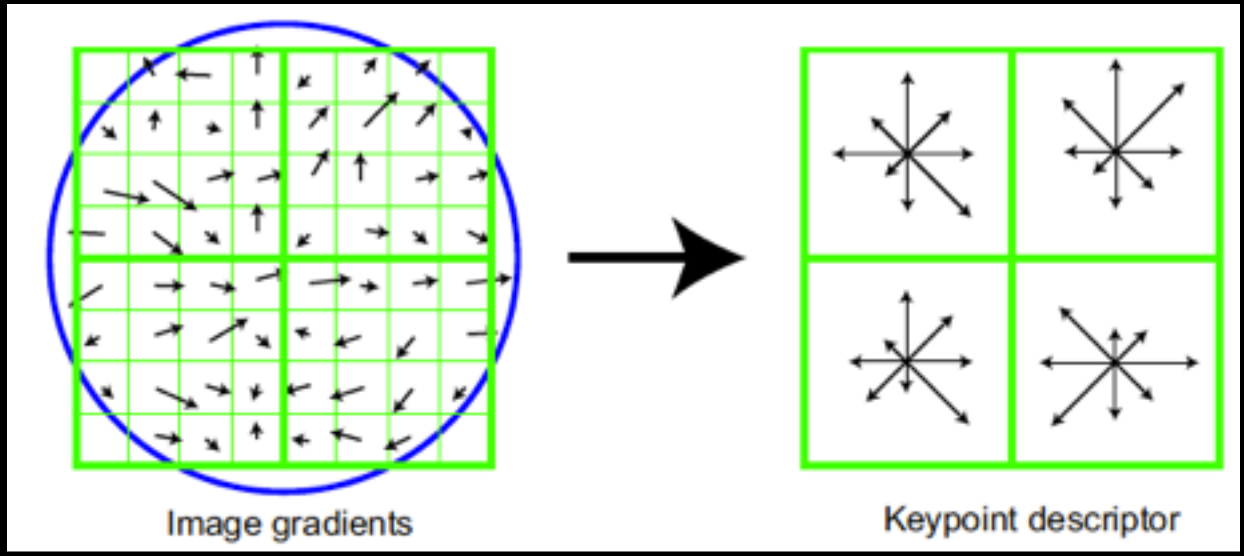
Image descriptors

- Global descriptors
  - Histogram of colors, Histogram of Local Binary Patterns (LBPs)
  - Gabor filters, GIST
- Local descriptors
  - SIFT, SURF
  - MSER
- Global descriptor using local descriptors
  - Bag of Features (BoF)
  - Spatial Pyramid Matching (SPM)
  - Locality-constrained Linear Coding (LLC)

SIFT & BoF

- Extract SIFT vectors from all images
- 128 dimensions
- Clustering SIFT vectors (k-means)
- 1 cluster = 1 visual word
- Input image
  - Extract SIFT vectors (Dense SIFT)
  - Put each SIFT vector into the closest cluster
  - Histogram of visual words





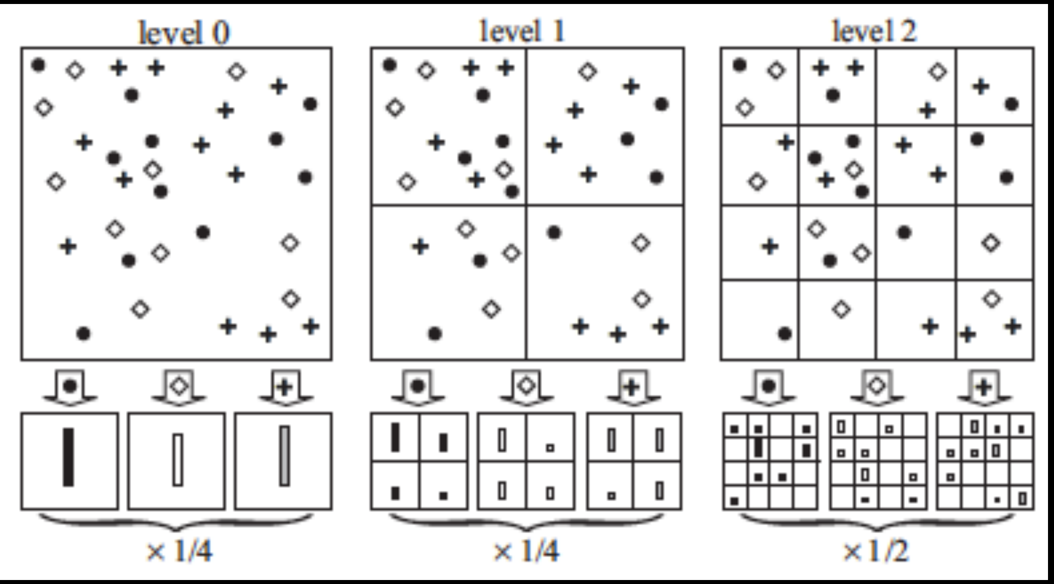
Some results

- 5-fold cross validation
- GIST + SVM with RBF kernel: 85.57%
- SIFT-BoF (2000)+ SVM with kernels

1. Histogram Intersection kernel: $k(x,y) = \sum_i \min\{x_i, y_i\}$	89.69
2. Chi-square kernel: $k(x,y) = \sum_i \frac{x_i y_i}{(x_i+y_i)}$	89.68
3. Hellinger kernel: $k(x,y) = \sqrt{\sum_i x_i y_i}$	84.27
4. Jensen-Shannon kernel: $k(x,y) = \frac{1}{2}\sum_i \left(x_i \log_2 \frac{(x_i+y_i)}{x_i} + y_i \log_2 \frac{(x_i+y_i)}{y_i}\right)$	89.03

SPM

- Multi-scale analysis
  - Compute descriptors at different resolutions
  - Compute descriptors at basic resolution but summing at different resolutions



- SPM
  - Dense SIFT
  - Level l splits image into $2^l x 2^l = 4^l$ areas
  - In each area, compute histogram of M visual words
  - Concatenate into a big histogram with weighting

Sparse SPM

- SPM are often used with SVM using RBF kernel
- SPM: M=2000, L=3 → 42,000 bins but most are 0
- Sparse SPM
  - **Sparse coding** instead of **basic cluster assignment**

$$\min_{u_1,\dots,u_m} \sum_{i=1}^{M} \|x_i - V u_i\|^2 + \lambda |u_i|$$

subject to $\|v_k\| \leq 1.$

$$\min_{u_1,\dots,u_m} \sum_{i=1}^{M} \|x_i - V u_i\|^2$$

subject to $Card(u_i) = 1, |u_i| = 1, u_i \geq 0, \forall i$

  - **Max-pooling** instead of sum
- Not histogram, **used with linear SVM**

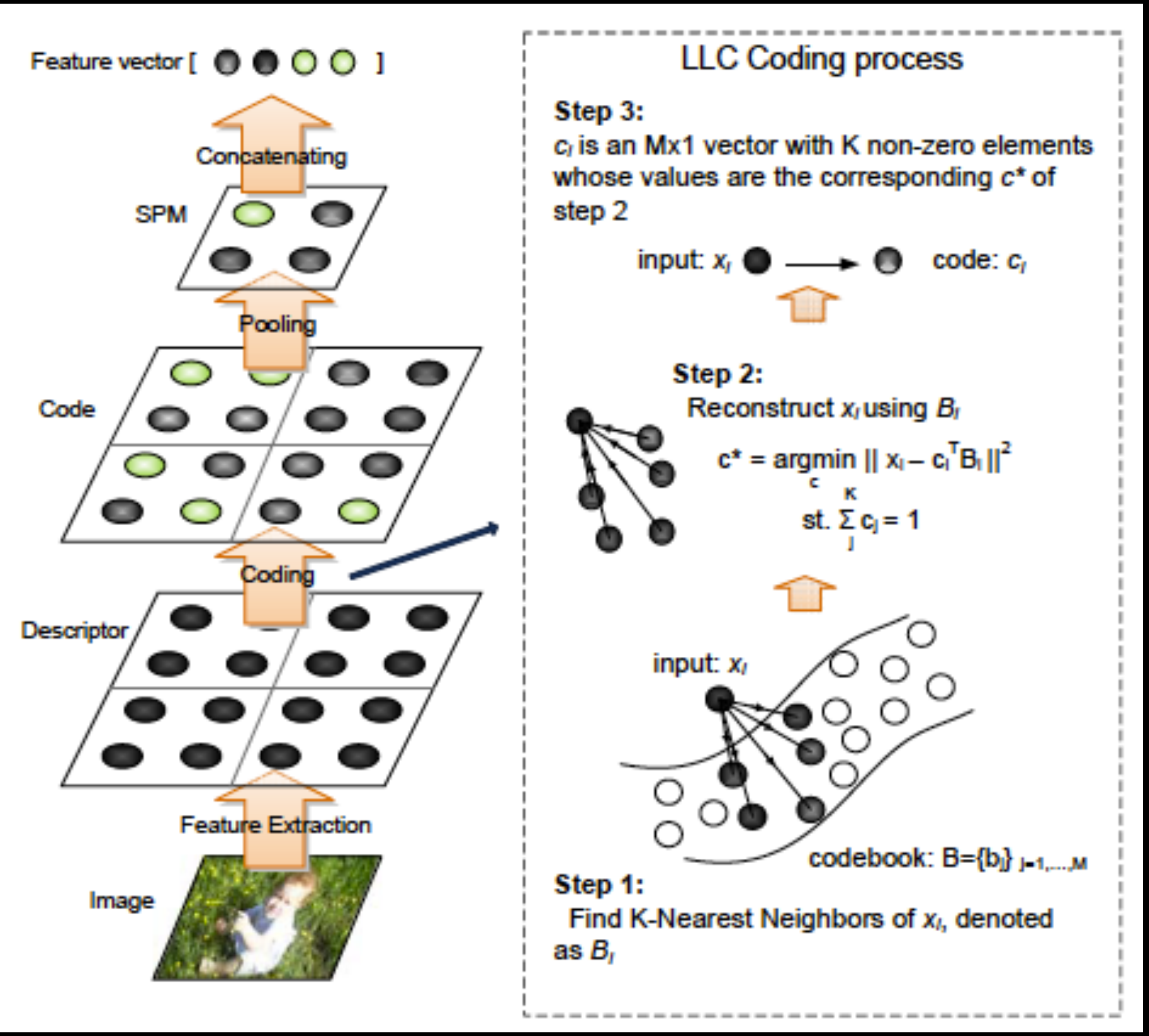
LLC

- Locality is more important than sparsity
- Locality = neighbors in the codebook
- **LLC problem**

$$\min_{C} \sum_{i=1}^{M} \|x_i - Bc_i\|^2 + \lambda \|d_i \odot c_i\|^2$$

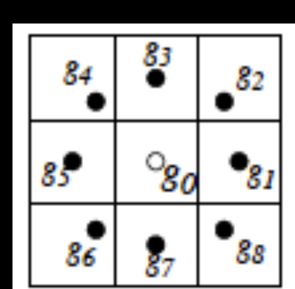
subject to $1^T c_i = 1$

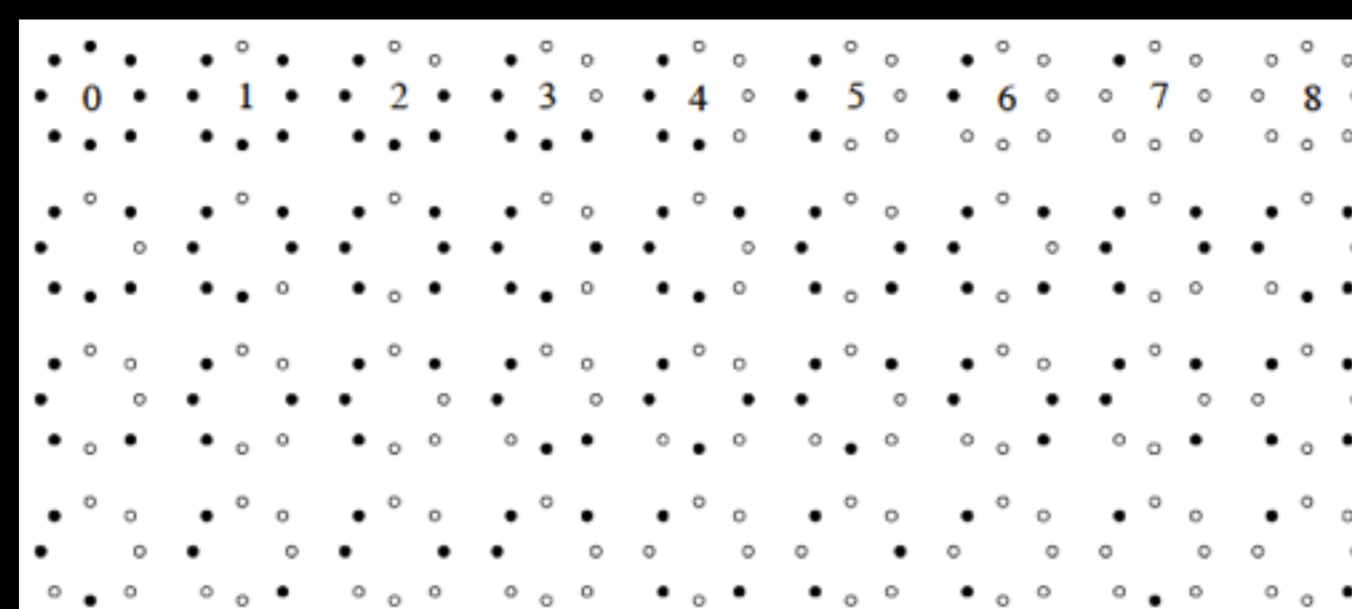
$$d_{im} = \exp\left(\frac{1}{Z\sigma}\|x_i - b_m\|^2\right)$$
$$Z = \max_k \|x_i - b_k\|^2,$$



Results

- M=2000, L=3, K=5 : 42,000 dimensions
- Non-zero ~2,900 dimensions
- 0.39 sec/image
- Linear SVM
  - LLC with SIFT: 91.48%
  - LLC with **U-RI-LBP**: 90.20%





Thank you

Q & A

References

- **SPM:** Beyond Bag of Features: Spatial Pyramid Matching for Natural Scene Categories, CVPR 2006
- **ScSPM:** Linear Spatial Pyramid Matching Using Sparse Coding for Image Classification, CVPR 2009
- **LLC:** Locality-constrained Linear Coding for Image Classification, CVPR 2010