Image Parsing

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What is Image Parsing

• simple and effective nonparametric approach to the problem of image parsing, namely labeling image regions

• Make use of global scene-level matching, superpixel-level matching and Markov random field (MRF) optimization.
Challenges

- the dataset is constantly expanding as people upload new photos
- Training can take days
- We want to work with large datasets
- Also, SIFT ow is fairly complex and expensive to solve.
Retrieval Set

• retrieval set of scenes whose content is used to interpret the test image
• retrieval set images are very similar to the test image in terms of spatial layout of the classes, so that we transfer labels at the level of superpixels
Relationship with Context

• simultaneously estimate a semantic label (e.g., building, car, person, etc.) and a geometric label (sky, ground, or vertical surface) while making sure the two types of labels assigned to the same region are consistent
Method Summary

1. Find a retrieval set of images similar to the query image
2. Segment the query image into superpixels and compute feature vectors for each superpixel
3. For each superpixel and each feature type, find the nearest-neighbor superpixels in the retrieval set according to that feature. Compute a likelihood score for each class based on the superpixel matches.
Method Summary

• 4. Use the computed likelihoods together with pairwise co-occurrence energies in an Markov Random Field (MRF) framework to compute a global labeling of the image. Alternatively, with modifications, the MRF framework can simultaneously solve for both semantic and geometric class labels
Global Features vs. Superpixel Features

- Global: Spatial pyramid, Gist, Color histogram
  (To decide the retrieval set)
- Superpixel:
  Shape, Location, Texture, Color, Appearance
  (To compute the closeness)
\[ L(s_i, c) = \log \frac{P(s_i | c)}{P(s_i | \bar{c})} = \log \prod_k \frac{P(f^k_i | c)}{P(f^k_i | \bar{c})} \]
\[ = \sum_k \log \frac{P(f^k_i | c)}{P(f^k_i | \bar{c})}, \quad (1) \]

\[ \frac{P(f^k_i | c)}{P(f^k_i | \bar{c})} = \frac{(n(c, N^k_i) + \epsilon) / n(c, D)}{(n(\bar{c}, N^k_i) + \epsilon) / n(\bar{c}, D)} \]
\[ = \frac{n(c, N^k_i) + \epsilon}{n(\bar{c}, N^k_i) + \epsilon} \times \frac{n(\bar{c}, D)}{n(c, D)}, \quad (2) \]
Interpretations

• Likelihood of superpixel $i$ to the class $c$ : independent multiplication in the neighbourhood of $f$. 
Math (cont.)

\[ J(c) = \sum_{s_i \in SP} E_{data}(s_i, c_i) + \lambda \sum_{(s_i, s_j) \in A} E_{smooth}(c_i, c_j), \]

\[ E_{data}(s_i, c_i) = -w_i \sigma(L(s_i, c_i)), \]

\[ E_{smooth}(c_i, c_j) = -\log\left[ (P(c_i|c_j) + P(c_j|c_i))/2 \right] \times \delta[c_i \neq c_j], \]

\[ H(c, g) = J(c) + J(g) + \mu \sum_{s_i \in SP} \varphi(c_i, g_i), \]
Interpretations

• Data and smoothness parameters to minimize,

• given a weight to superpixels

• Smoothness parameter is defined based on probabilities of label co-occurrence
Results

• boosted decision tree outputs a likelihood ratio score that is comparable to the one produced by nonparametric scheme but that gets about 2% higher accuracy for geometric classification

• MRF improves the results for both types of classes

• Stuff (people, car) results are better than Things (sky, road)
Results

Final system achieves a classification rate of 54.9% across all scene types.

As for joint semantic/geometric inference, it not only gives the highest overall accuracy in all cases, but is also much less prone to over-smoothing.