ImageNet Classification

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April 23, 2013

Challenges

- Intraclass variation

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- Interclass similarity

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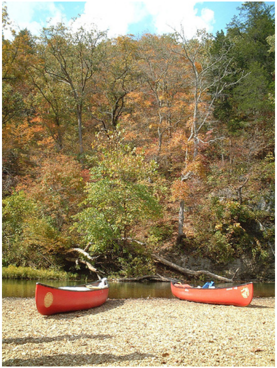
- Intraclass variation
- Interclass similarity
- Scale



Challenges

- Intraclass variation
- Interclass similarity
- Scale
- Pose

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- Intraclass variation
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- Pose
- Illumination

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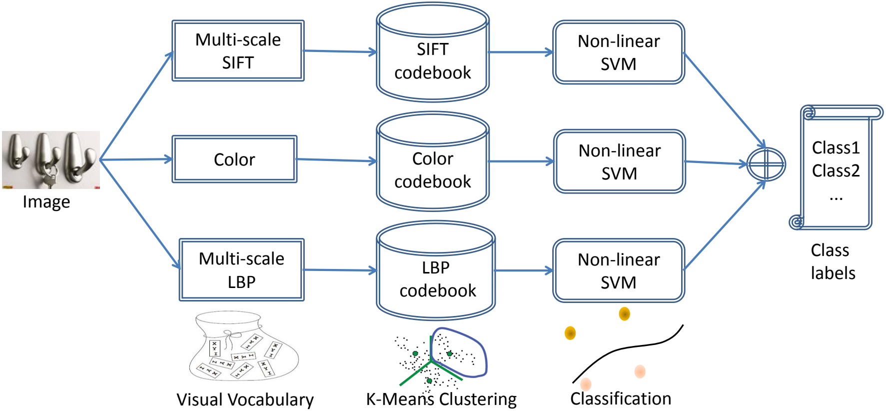
- Occlusion

Challenges

- Intraclass variation
- Interclass similarity
- Scale
- Pose
- Illumination
- Occlusion
- Clutter

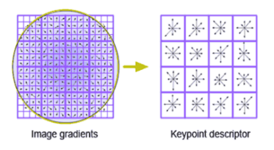
Methodology



Feature Descriptors

SIFT

128 dimensions



16 orientation histograms, 8 bins each.

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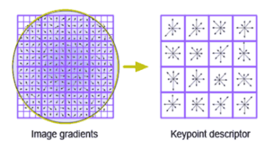

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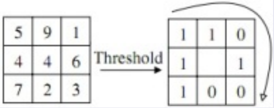
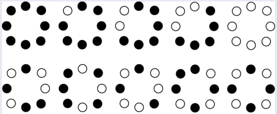
LBP

59 dimensions





Compute histogram of the 59 "U2" patterns.

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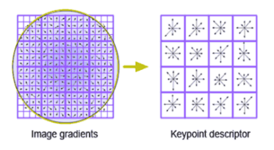

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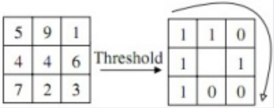

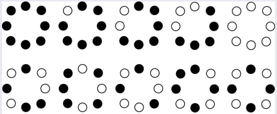

Compute histogram of the 59 “U2” patterns.

RG

64 dimensions

$$
\begin{aligned}
R &= \frac{r}{r+g+b} \\
G &= \frac{g}{r+g+b}
\end{aligned}
\qquad (1)
$$

R and G each quantized into 32-bin histogram.

Multi-Scale Dense Feature Extraction

Dense sampling at 3 scales

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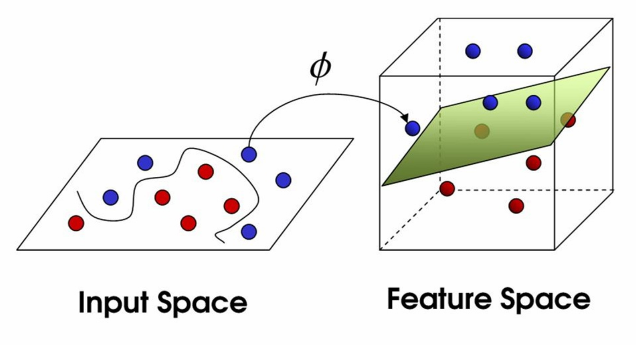
Bag of words

Classifiers

- Train three different SVM classifiers for each of the codebooks.



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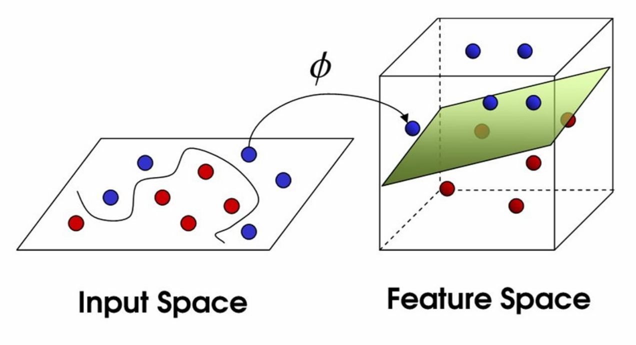
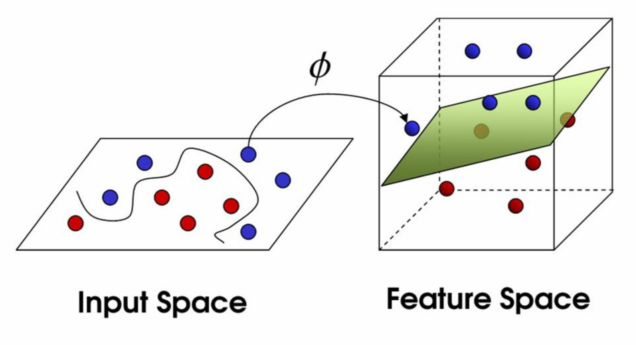
- Linear kernel does not work very well because the classes are not well separable in the feature space.



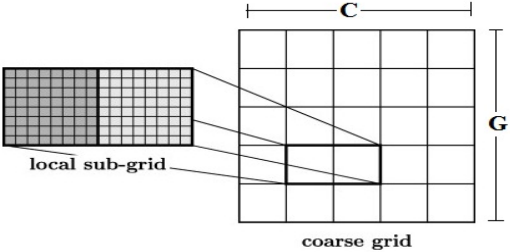
Classifiers

- Train three different SVM classifiers for each of the codebooks.
- Linear kernel does not work very well because the classes are not well separable in the feature space.
- Need to map the data to a higher dimensional space: **RBF kernel**.



Parameter Selection

- Effectiveness of SVM classifiers depends on the selection of the right set of parameters.



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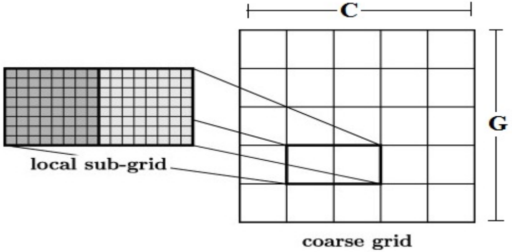
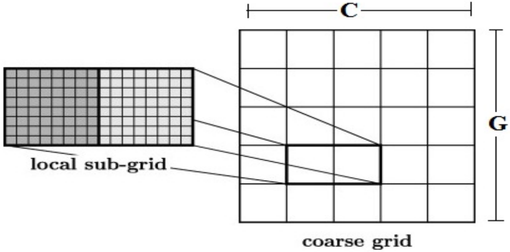
- Two different parameters for RBF-SVM: **soft margin parameter C** and **kernel width G**.

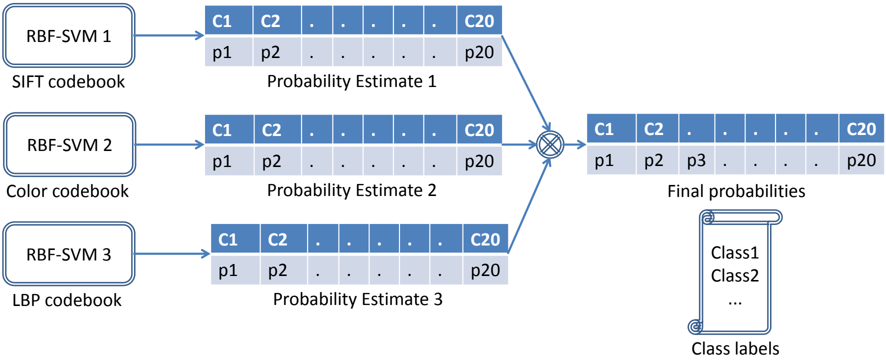


Parameter Selection

- Effectiveness of SVM classifiers depends on the selection of the right set of parameters.
- Two different parameters for RBF-SVM: **soft margin parameter C** and **kernel width G**.
- Coarse-to-fine grid search (with 5 fold cross validation) for selecting the optimum set of parameters.



Classifier Combination



Results

- Top-5 accuracy:
  - **Training Set**: 99.99%
  - **Validation Set**: 88.55%
  - **Test Set**: 88.94%

Validation Set Accuracy (%)	
SIFT	81.55
LBP	82.6
Color	77.58
All	**88.55**

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- Classes where the approach really works well: *odometer*, *rapeseed*, *website*.
- Classes where the approach does not work very well: *lopener*, *hatchet*, *cleaver*.

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Success

{'odometer','spatula','gondola','hook','elocomotive'}

Success

{'yflower','daisy','flamingo','ladle','plunger'}

Failure

{'plunger','ladle','spatula','hook','cleaver'}

Failure

{'odometer','daisy','flamingo','ladle','spatula'}

Questions?