

VLFeat

An Open and Portable Library of Computer Vision Algorithms

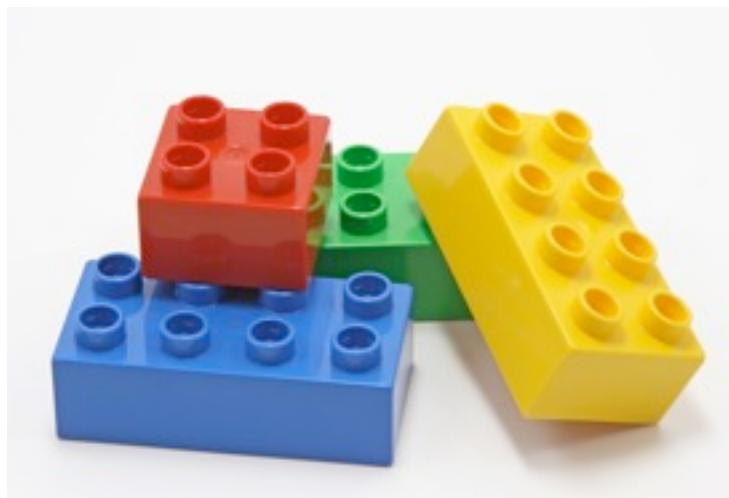
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UCLA



Plan

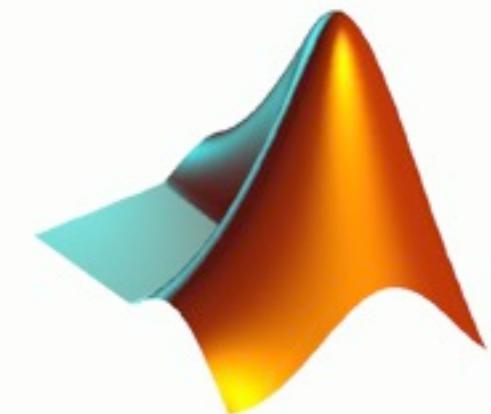
- The VLFeat library
 - SIFT example (`vl_sift`)
- Caltech-101 running example
- Visual descriptors
 - PHOW feature (fast dense SIFT, `vl_phow`)
 - Vector Quantization (Elkan, `vl_kmeans`, `vl_kdtreebuild`,
`vl_kdtreequery`)
 - Spatial histograms (`vl_binsum`, `vl_binsearch`)
- Learning and classification
 - Fast linear SVMs
 - PEGASOS (`vl_pegasos`)
 - Fast non-linear SVMs
 - Homogeneous kernel maps (`vl_homkermapper`)
- Other VLFeat features



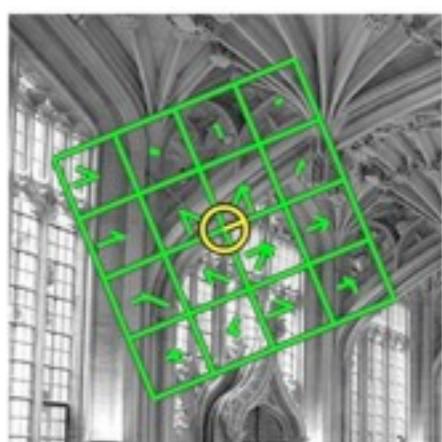
computer vision
building blocks



GPL



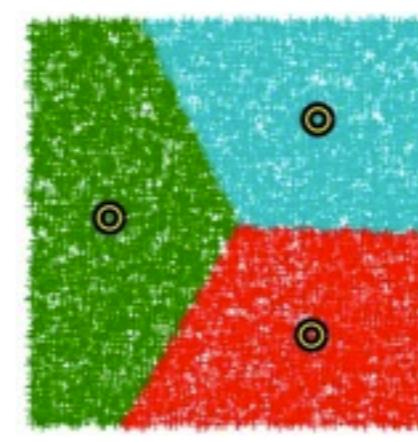
MATLAB



features

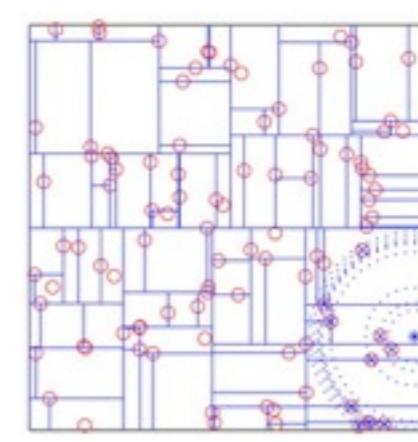


,



clustering

,



matching

...

Running VLFeat



Mac



Linux

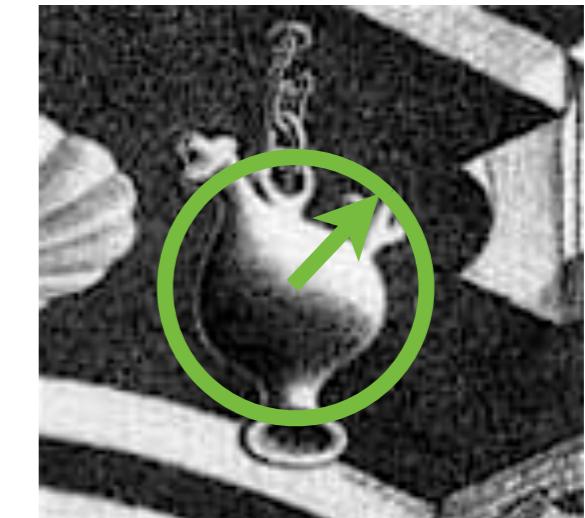


Windows

- **VLFeat.org**
- Quick start
 1. Get **binary package**
`wget http://www.vlfeat.org/download/vlfeat-0.9.9-bin.tar.gz`
 2. Unpack
`tar xzf vlfeat-0.9.9-bin.tar.gz`
 3. Setup MATLAB
`run('VLROOT/toolbox/vl_setup')`

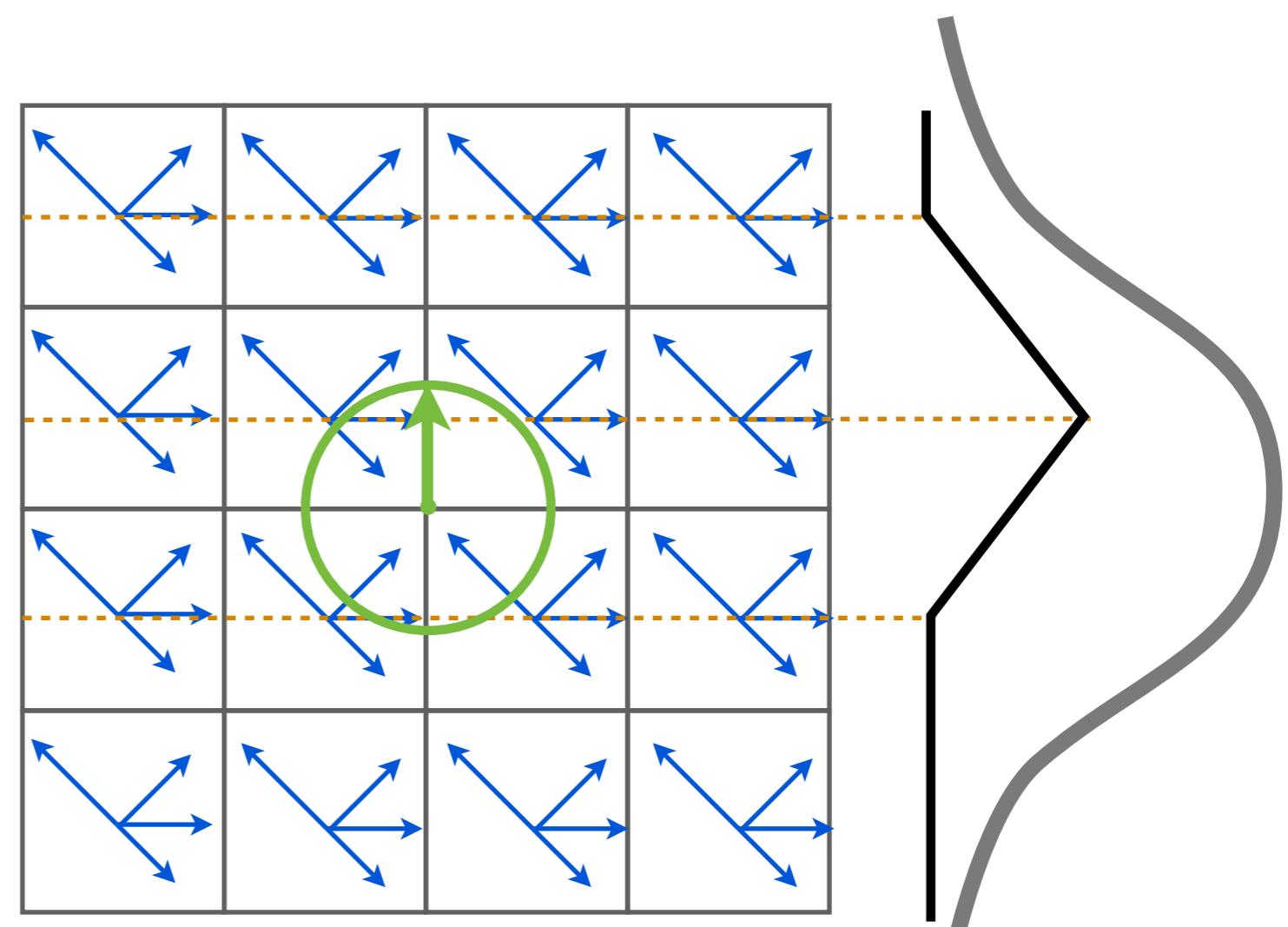
Demo: SIFT features

- **SIFT keypoint [Lowe 2004]**
 - extrema of the DoG scale space
 - blob-like image structure
 - oriented



- **SIFT descriptor**

- 4 x 4 spatial histogram of gradient orientations
- linear interpolation
- Gaussian weighting



Demo: Computing SIFT features

- Output-equivalent to D. Lowe's implementation
- Example

1. load an image

```
imPath = fullfile(vl_root, 'data', 'a.jpg') ;
im = imread(imPath) ;
```

2. convert into float array

```
im = im2single(rgb2gray(im)) ;
```

3. run SIFT

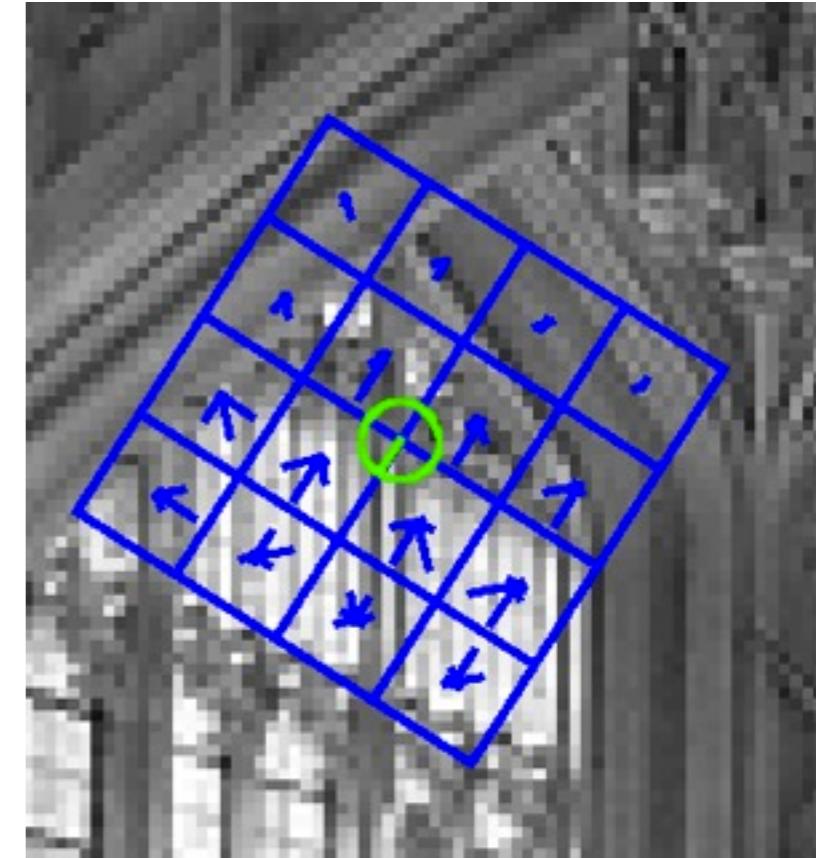
```
[frames, descrs] = vl_sift(im) ;
```

4. visualize keypoints

```
imagesc(im) ; colormap gray; hold on ;
vl_plotframe(frames) ;
```

5. visualize descriptors

```
vl_plotsiftdescriptor(...  
descrs(:,432), frames(:,432)) ;
```



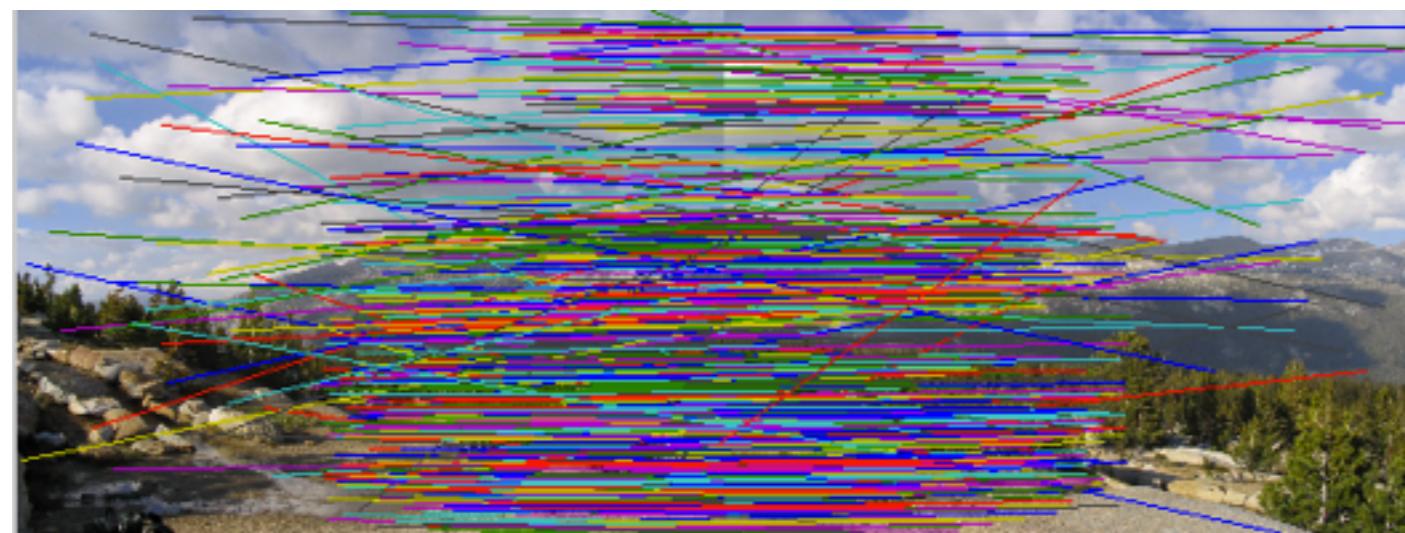
Demo: Matching & Stitching



- Matching code

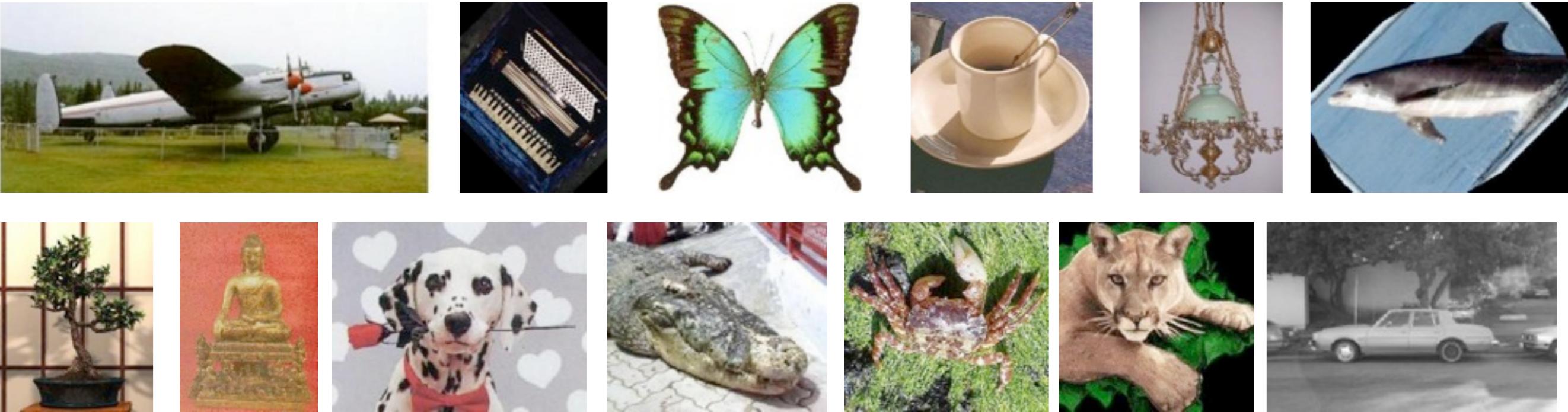
```
[f1,d1] = vl_sift(im2single(rgb2gray(im1))) ;  
[f2,d2] = vl_sift(im2single(rgb2gray(im2))) ;  
[matches, scores] = vl_ubcmatch(d1,d2) ;
```

684 tentative matches

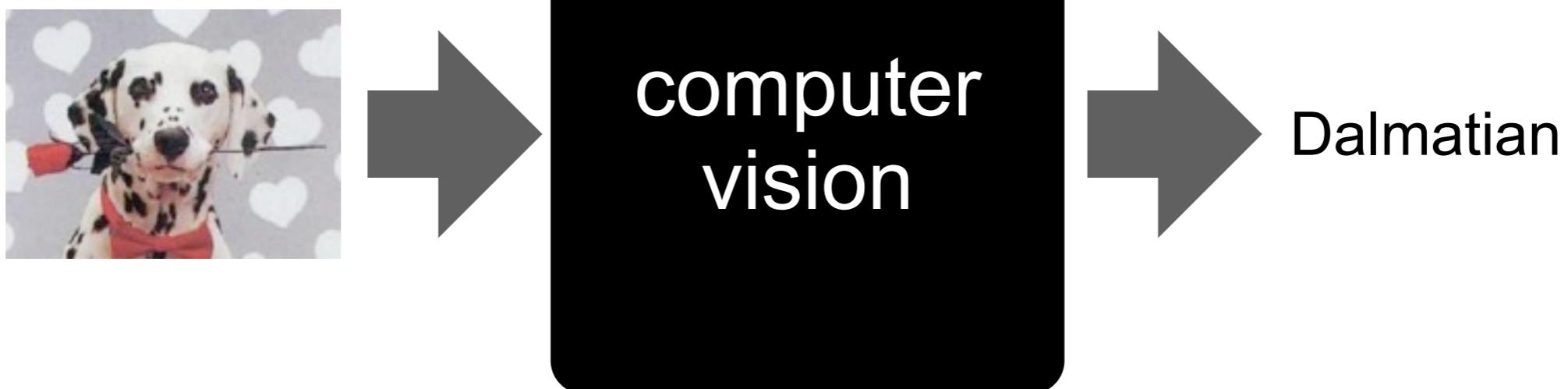


Running example: Caltech-101

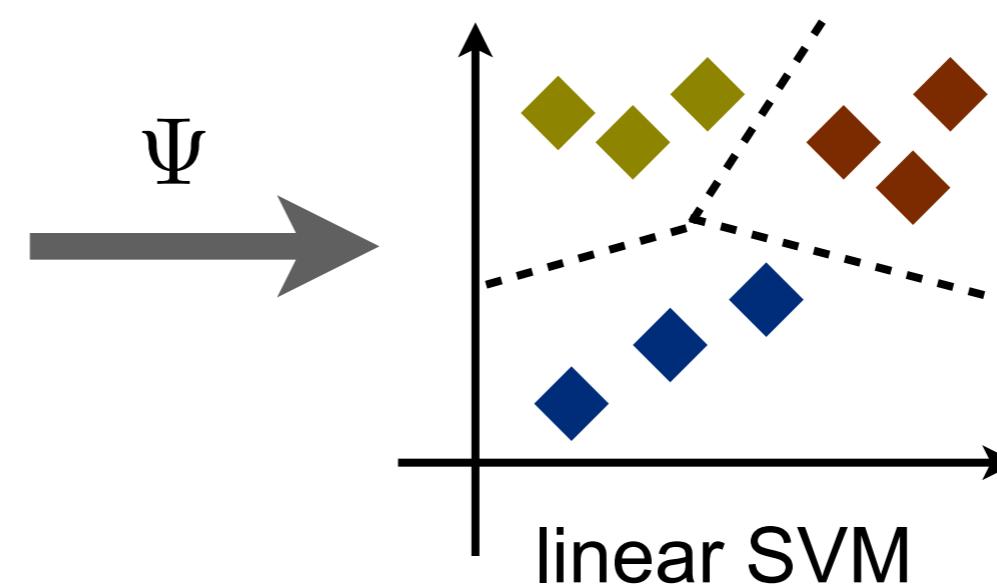
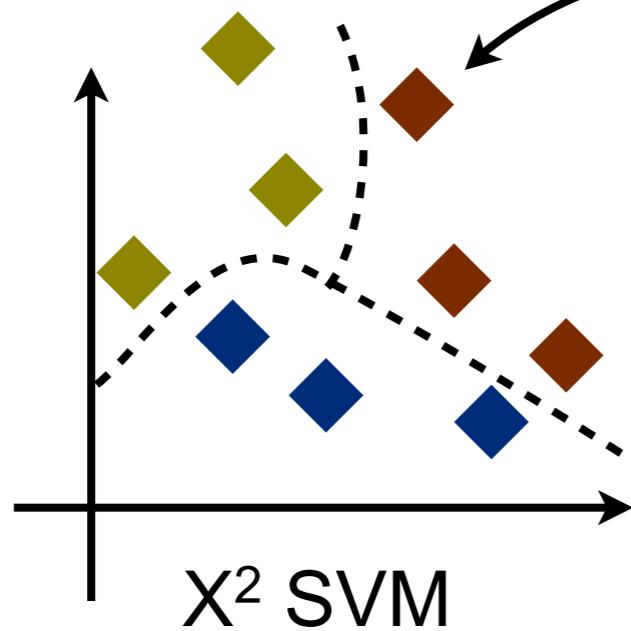
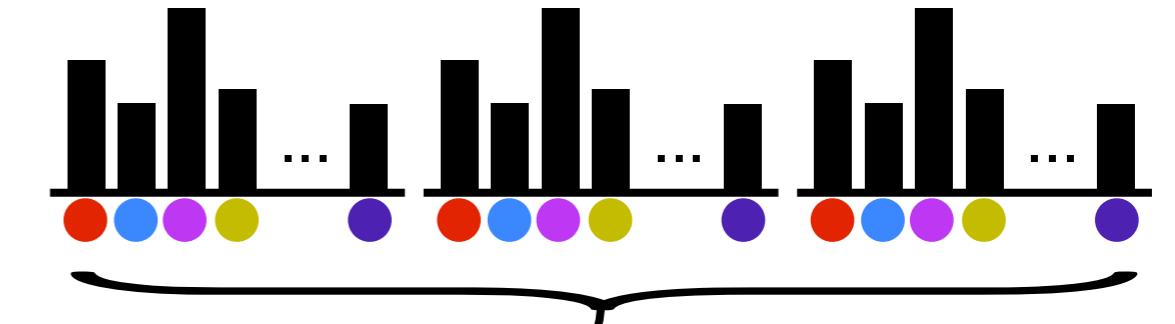
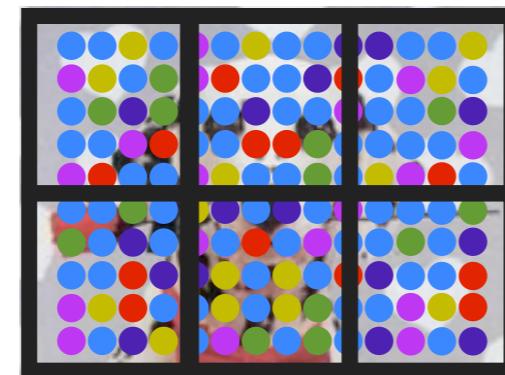
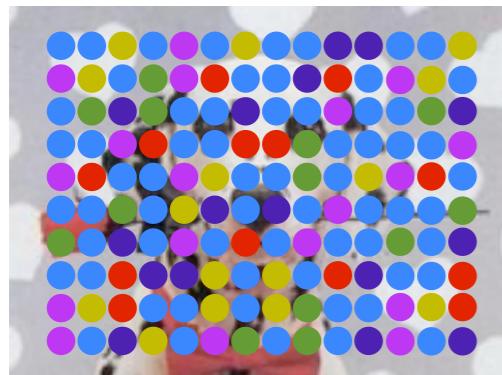
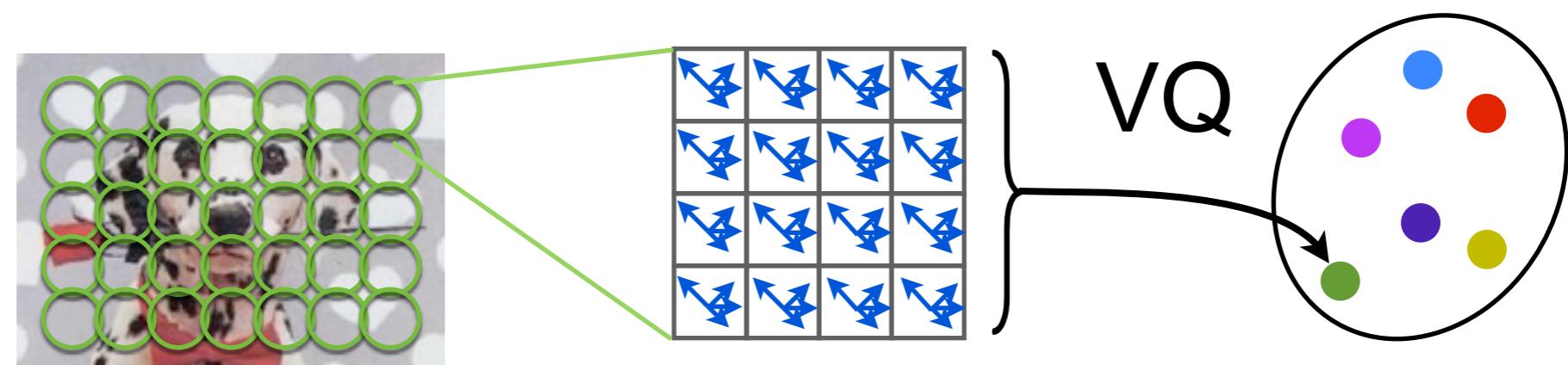
102 semantic labels



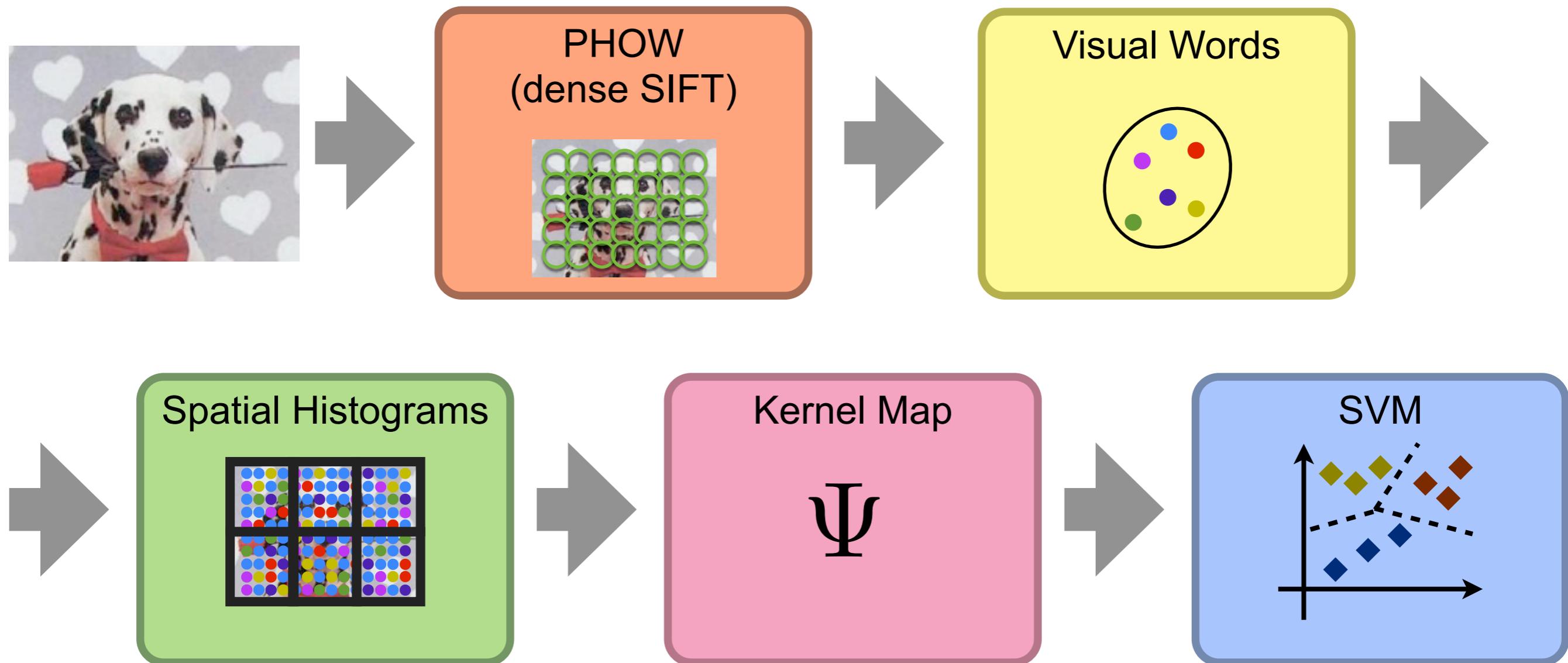
[Fei-Fei et al. 2003]



Running example: System



Running example: Components



- Complete source code available
 - `phow_caltech101.m`
 - <http://www.vlfeat.org/applications/apps.html#apps.caltech-101>

Running example: Complete code

```

function phow_caltech101
% PHOW_CALTECH101 Image classification in the Caltech-101 dataset
% A quick test should run out of the box by running PHOW_CALTECH101
% from MATLAB (provided that VLFeat is correctly installed).
%
% The program automatically downloads the Caltech-101 data from the
% internet and decompresses it in CONF.CALDIR, which defaults to
% 'data/caltech-101'. Change this path to the desired location, for
% instance to point to an existing copy of the data.
%
% Intermediate files are stored in the directory CONF.DATADIR.
%
% To run on the entire dataset, change CONF.TINYPROBLEM to
% FALSE.
%
% To run with a different number of training/testing images, change
% CONF.NUMTRAIN and CONF.NUMTEST. By default 15 training images are
% used, which should result in about 65% performance (this is quite
% remarkable for a single descriptor).

% AUTORIGHTS

conf.calDir = 'data/caltech-101' ;
conf.dataDir = 'data/' ;
conf.autoDownloadData = true ;
conf.numTrain = 15 ;
conf.numTest = 15 ;
conf.numClasses = 102 ;
conf.numWords = 800 ;
conf.numSpatialX = 4 ;
conf.numSpatialY = 4 ;
conf.svm.C = 10 ;
conf.svm.solver = 'pegasos' ;
conf.phowOpts = {} ;
conf.clobber = false ;
conf.tinyProblem = false ;
conf.prefix = 'baseline' ;
conf.randSeed = 1 ;

if conf.tinyProblem
    conf.prefix = 'tiny' ;
    conf.numClasses = 5 ;
    conf.numSpatialX = 2 ;
    conf.numSpatialY = 2 ;
    conf.numWords = 300 ;
    conf.phowOpts = {'Verbose', 2, 'Sizes', 7, 'Step', 3, 'Co
true} ;
end

conf.vocabPath = fullfile(conf.dataDir, [conf.prefix '-voca
conf.histPath = fullfile(conf.dataDir, [conf.prefix '-hists
conf.modelPath = fullfile(conf.dataDir, [conf.prefix '-m
conf.resultPath = fullfile(conf.dataDir, [conf.prefix '-
result.mat']) ;

randn('state',conf.randSeed) ;
rand('state',conf.randSeed) ;
vl_twister('state',conf.randSeed) ;

% -----
% Download Caltech-101 data
% -----

if ~exist(conf.calDir, 'dir') || ...
    (~exist(fullfile(conf.calDir, 'airplanes'), 'dir') && ...
    ~exist(fullfile(conf.calDir, '101_ObjectCategories'),
'airplanes')))
    if ~conf.autoDownloadData
        error...
            ['Caltech-101 data not found. ' ...
            'Set conf.autoDownloadData=true to download the required
data.'] ;
    end
    vl_xmkdir(conf.calDir) ;
    calUrl = ['http://www.vision.caltech.edu/Image_Datasets/' ...
        'Caltech101/101_ObjectCategories.tar.gz'] ;
    fprintf('Downloading Caltech-101 data to "%s''. This will take a
while.', conf.calDir) ;
    untar(calUrl, conf.calDir) ;
end

if ~exist(fullfile(conf.calDir, 'airplanes'), 'dir')
    conf.calDir = fullfile(conf.calDir, '101_ObjectCategories') ;
end
% -----
```

• single file

• ~ 240 lines

• all inclusive

```

%
% -----
% classes = dir(conf.calDir) ;
% classes = classes([classes.isdir]) ;
% classes = {classes(3:conf.numClasses+2-1).name} ;

images = {} ;
imageClass = {} ;
for ci = 1:length(classes)
    ims = dir(fullfile(conf.calDir, classes{ci}, '*.jpg'))' ;
    ims = vl_colsubset(ims, conf.numTrain + conf.numTest) ;
    ims = cellfun(@(x)fullfile(classes{ci},x),
{ims.name}, 'UniformOutput',false) ;
    images = {images{:}, ims{:}} ;
    imageClass{end+1} = ci * ones(1,length(ims)) ;
end
selTrain = find(mod(0:length(images)-1, conf.numTrain+conf.numTest) <
conf.numTrain) ;
selTest = setdiff(1:length(images), selTrain) ;
imageClass = cat(2, imageClass{:}) ;

%
% -----
% Train vocabulary
%
if ~exist(conf.vocabPath) || conf.clobber
    % Get some PHOW descriptors to train the dictionary
        % It's better to have more than less
    % -----
```

Setup data

```

    save(conf.histPath, 'hists') ;
else
    load(conf.histPath) ;
end
% -----
% -----
% Compute feature map
%
psix = vl_homkermap(hists, 1, .7, 'kchi2') ;
% -----
% -----
% Train SVM
%
biasMultiplier = 1 ;

if ~exist(conf.modelPath) || conf.clobber
    switch conf.svm.solver
        case 'pegasos'
            lambda = 1 / (conf.svm.C * length(selTrain)) ;
            models = [] ;
            for ci = 1:length(classes)
                perm = randperm(length(selTrain)) ;
                fprintf('Training model for class %s\n', classes{ci}) ;
                2 * (imageClass(selTrain) == ci) - 1 ;
                models(:,ci) = vl_pegasos(psix(:,selTrain(perm)), ...
                    int8(y(perm)), lambda, ...
                    'NumIterations', 20/lambda, ...
                    'BiasMultiplier', biasMultiplier) ;
            end
            ibilinear =
            = train(imageClass(selTrain)', ...
                sparse(double(psix(:,selTrain))), ...
                sprintf(' -s 3 -B 1 -c %f', conf.svm.C), ...
                'col') ;
            s = model.w' ;
        end
        .modelPath, 'models') ;
        .modelPath) ;
    end
% -----
% Test SVM and evaluate
%
the class of the test images
;
length(classes)
, :) = models(1:end-1,ci)' * psix + models(end,ci) * 
        % -----
        % -----
        % Compute the confusion matrix
        idx = sub2ind([length(classes), length(classes)], ...
            imageClass(selTest), imageEstClass(selTest)) ;
        confus = zeros(length(classes)) ;
        confus = vl_binsum(confus, ones(size(idx)), idx) ;
        % Plots
        figure(1) ; clf;
        subplot(1,2,1) ;
        imagesc(scores(:,[selTrain selTest])) ; title('Scores') ;
        set(gca, 'ytick', 1:length(classes), 'yticklabel', classes) ;
        subplot(1,2,2) ;
        imagesc(confus) ;
        title(sprintf('Confusion matrix (%.2f %% accuracy)', ...
            100 * mean(diag(confus)/conf.numTest) )) ;
        print('-depsc2', [conf.resultPath '.ps']) ;
        save([conf.resultPath '.mat'], 'confus', 'conf') ;
        % -----
        function im = imageStandarize(im)
        % -----
        im = im2single(im) ;
        if size(im,1) > 480, im = imresize(im, [480 NaN]) ; end
    end
% -----
```

Andrea Vedaldi and Brian Fulkerson

Running example: Complete code

```

function phow_caltech101
% PHOW_CALTECH101 Image
% A quick test should
% from MATLAB (provide
%
% The program automatically
% interred and decompres
% 'data/caltech-101'.
% instance to point to
%
% Intermediate files
%
% To run on the entire dataset, set CONF.TINYPROBLEM to
% FALSE.
%
% To run with a subset, set
% CONF.NUMTRAIN and
% CONF.NUMTEST to
% used, which should
% be quite
%
% AUTORIGHTS
%
conf.calDir = 'data';
conf.dataDir = 'data';
conf.autoDownloadData = true;
conf.numTrain = 15;
conf.numTest = 15;
conf.numClasses = 102;
conf.numWords = 800;
conf.numSpatialX = 5;
conf.numSpatialY = 5;
conf.svm.C = 10;
conf.svm.solver = 'liblinear';
conf.phowOpts = {};
conf.clobber = false;
conf.tinyProblem = false;
conf.prefix = 'base';
conf.randSeed = 1;

if conf.tinyProblem
    conf.prefix = 'tiny';
    conf.numClasses = 5;
    conf.numSpatialX = 3;
    conf.numSpatialY = 3;
    conf.numWords = 3;
    conf.phowOpts = {};
end

conf.vocabPath = fullfile(conf.calDir, 'vocab.mat');
conf.histPath = fullfile(conf.calDir, 'hists.mat');
conf.modelPath = fullfile(conf.calDir, 'model.mat');
conf.resultPath = fullfile(conf.calDir, 'result.mat');

randn('state',conf.randSeed);
rand('state',conf.randSeed);
vl_twister('state',conf.randSeed);

% -----
% ----- Caltech-101 data
% -----
%
% if ~exist(conf.calDir)
%     (~exist(fullfile(conf.dataDir, 'caltech-101')) || ~exist(fullfile(conf.dataDir, 'airplanes'))))
%     error('...');
%     ['Caltech-101', 'airplanes']);
%     'Set conf.autoDownloadData to true if you want to download the required
%     data.');
% end
%
% vl_xmkdir(conf.calDir);
% calUrl = ['http://www.vlfeat.org/edu/datasets/...'];
% printf('Download from %s...\n', calUrl);
% while(~urlread(calUrl));
%     untar(calUrl, conf.calDir);
% end

if ~exist(fullfile(conf.calDir, 'classes.mat'));
    conf.calDir = fullfile(conf.dataDir, 'caltech-101');
    classes = dir(conf.calDir);
    classes = classes([classes.isdir]);
end

% -----
% ----- Setup data
% -----
%
classes = {classes(3:conf.numClasses+2-1).name} ;
tech-101 dataset
using PHOW_CALTECH101
installed).

ch-101 data from the
which defaults to
resided location, for
data.

Intermediate files
y CONF.DATADIR.

To run on the entire dataset, set CONF.TINYPROBLEM to
FALSE.

To run with a subset, set
CONF.NUMTRAIN and
CONF.NUMTEST to
used, which should
be quite
remarkable for

% AUTORIGHTS

% ----- PHOW (dense SIFT) -----
%
% images, change
% training images are
% (this is quite
%
% ----- Visual Words -----
%
% Quantize the descriptors to get the visual words
words = vl_kmeans(descrs, conf.numWords, 'verbose', 'algorithm',
'elkan') ;
save(conf.vocabPath, 'words') ;
else
load(conf.vocabPath) ;
end

% ----- Spatial Histograms -----
%
% Compute spatial histograms
hists = {} ;
% par
for ii = 1:length(images)
    fprintf('Processing %s (%.2f %%)\n', images(ii), 100 * ii / length
(images));
    im = imread(fullfile(conf.calDir, images(ii))) ;
    im = imageStandarize(im) ;
    [frames, descrs] = vl_phow(im, conf.phowOpts{:}) ;

    % quantize appearance
[drop, binsa] = min(vl_alldist(words, single(descrs)), [], 1) ;

    % quantize location
width = size(im, 2) ;
height = size(im, 1) ;
binsx = vl_binsearch(linspace(1,width,conf.numSpatialX+1), frames
(1,:)) ;
binsy = vl_binsearch(linspace(1,height,conf.numSpatialY+1), frames
(2,:)) ;

    % combined quantization
bins = sub2ind([conf.numSpatialY, conf.numSpatialX,
conf.numWords], ... binsy,binsx,binsa) ;
hist = zeros(conf.numSpatialY * conf.numSpatialX * conf.numWords,
1) ;
hist = vl_binsum(hist, ones(size(bins)), bins) ;
hist = single(hist / sum(hist)) ;

    hists{ii} = hist ;
end

hists = cat(2, hists{:}) ;
save(conf.histPath, 'hists') ;
else
load(conf.histPath) ;
end

% ----- Kernel Map -----
%
% Compute feature map
psix = vl_homkermap(hists, 1, .7, 'kchi2') ;

% ----- Train SVM -----
%
biasMultiplier = 1 ;

if ~exist(conf.modelPath) || conf.clobber
switch conf.svm.solver
case 'pegasos'
lambda = 1 / (conf.svm.C * length(selTrain)) ;
models = [] ;
for ci = 1:length(classes)
perm = randperm(length(selTrain)) ;
fprintf('Training model for class %s\n', classes{ci}) ;
y = 2 * (imageClass(selTrain) == ci) - 1 ;
models(:,ci) = vl_pegasos(psix(:,selTrain(perm)), ...
int8(y(perm)), lambda, ...
'NumIterations', 20/lambda, ...
'BiasMultiplier', biasMultiplier) ;
end
case 'liblinear'
model = train(imageClass(selTrain)', ...
sparse(double(psix(:,selTrain))), ...
sprintf(' -s 3 -B 1 -c %f', conf.svm.C), ...
'col') ;
models = model.w' ;
end
save(conf.modelPath, 'models') ;
else
load(conf.modelPath) ;
end

% ----- Test SVM and evaluate -----
%
% Estimate the class of the test images
scores = [] ;
for ci = 1:length(classes)
scores(ci, :) = models(1:end-1,ci)' * psix + models(end,ci) *
biasMultiplier ;
end
[drop, imageEstClass] = max(scores, [], 1) ;

% Compute the confusion matrix
idx = sub2ind([length(classes), length(classes)], ...
imageClass(selTest), imageEstClass(selTest)) ;
confus = zeros(length(classes)) ;
confus = vl_binsum(confus, ones(size(idx)), idx) ;

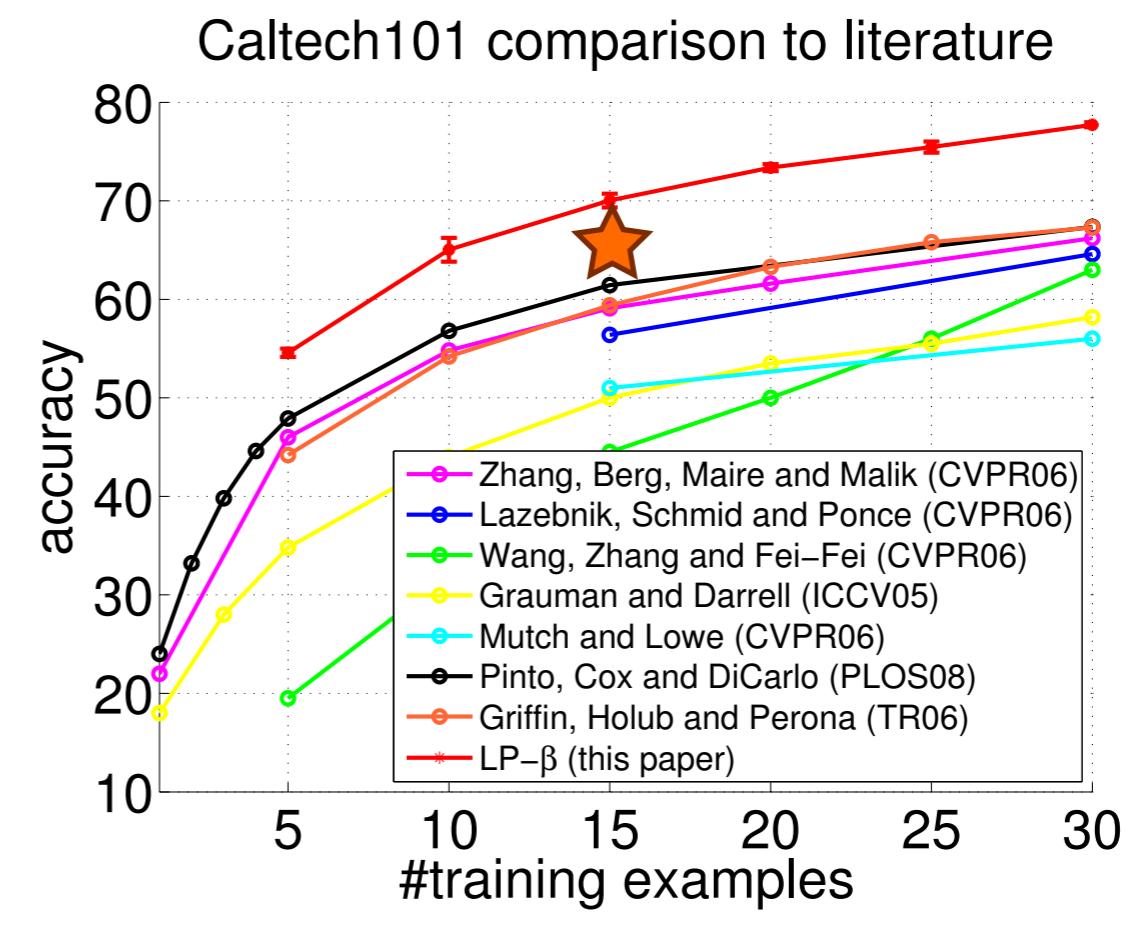
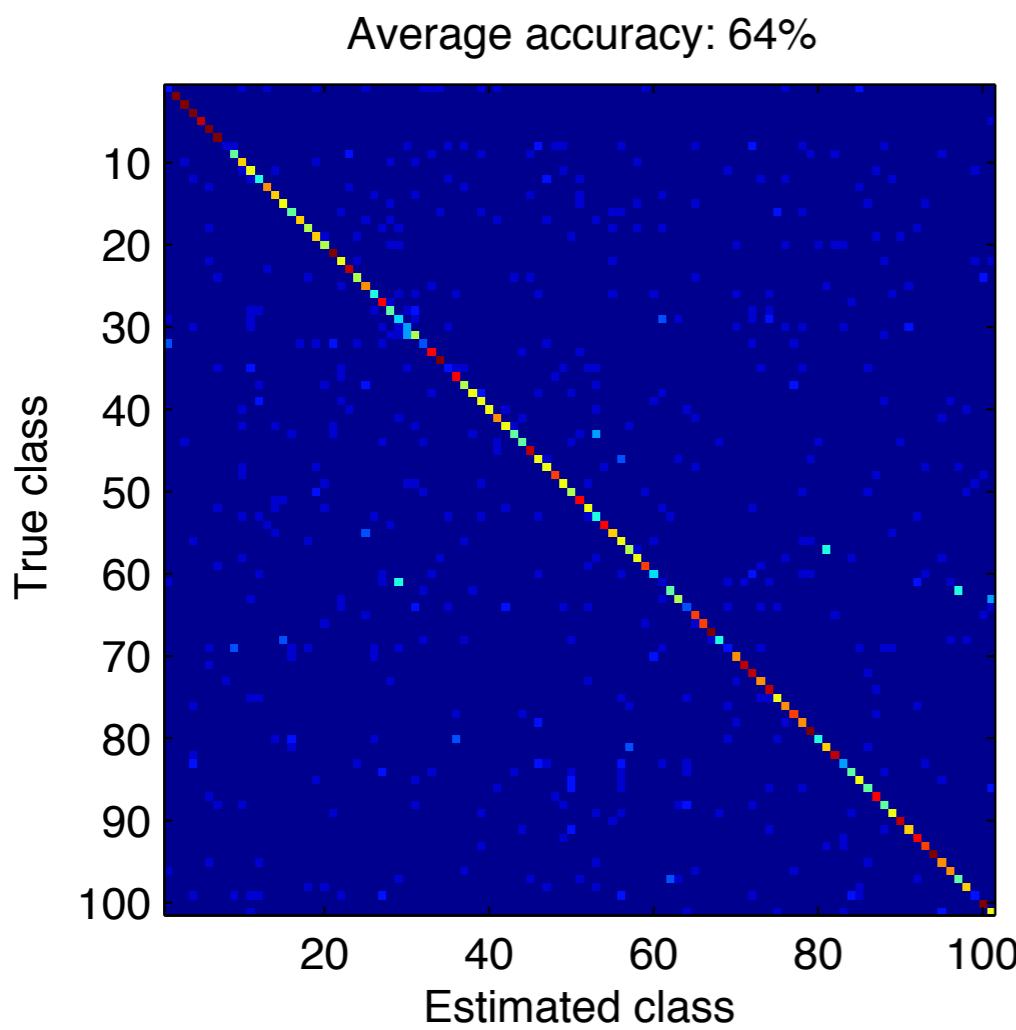
% Plots
figure(1) ; clf;
subplot(1,2,1) ;
imagesc(scores(:,[selTrain selTest])) ; title('Scores') ;
set(gca, 'ytick', 1:length(classes), 'yticklabel', classes) ;
subplot(1,2,2) ;
imagesc(confus) ;
title(sprintf('Confusion matrix (%.2f %% accuracy)', ...
100 * mean(diag(confus)/conf.numTest) )) ;
print('-depsc2', [conf.resultPath '.ps']) ;
save([conf.resultPath '.mat'], 'confus', 'conf') ;

% -----
% ----- function im = imageStandarize(im)
%
im = im2single(im) ;
if size(im,1) > 480, im = imresize(im, [480 NaN]) ; end

```

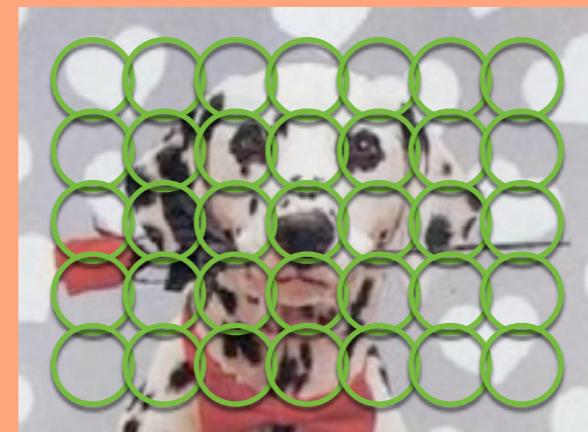
Running example: Results

- Among the best single-feature methods on Caltech-101
 - PHOW (dense SIFT)
 - 15 training - 15 testing images
 - 64-66% average accuracy
- Fast training and testing



Courtesy Peter Gehler

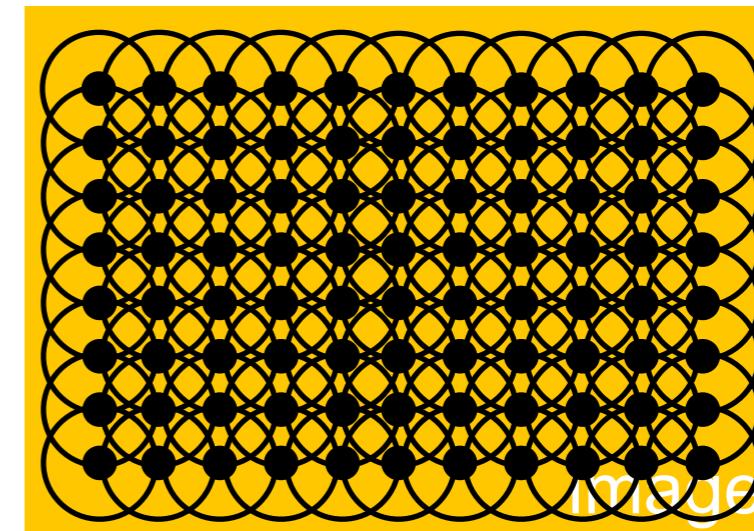
PHOW (dense SIFT)



Dense SIFT: PHOW features

- **PHOW features**

- [Bosch et al. 2006], [Bosch et al. 2007]
- dense multiscale SIFT
- uniform spacing (e.g. 5 pixels)
- four scales (e.g. 5, 7, 10, 12 pixels)



- **Direct implementation**

- for each scale
 - create a list of keypoints
 - call **vl_sift**



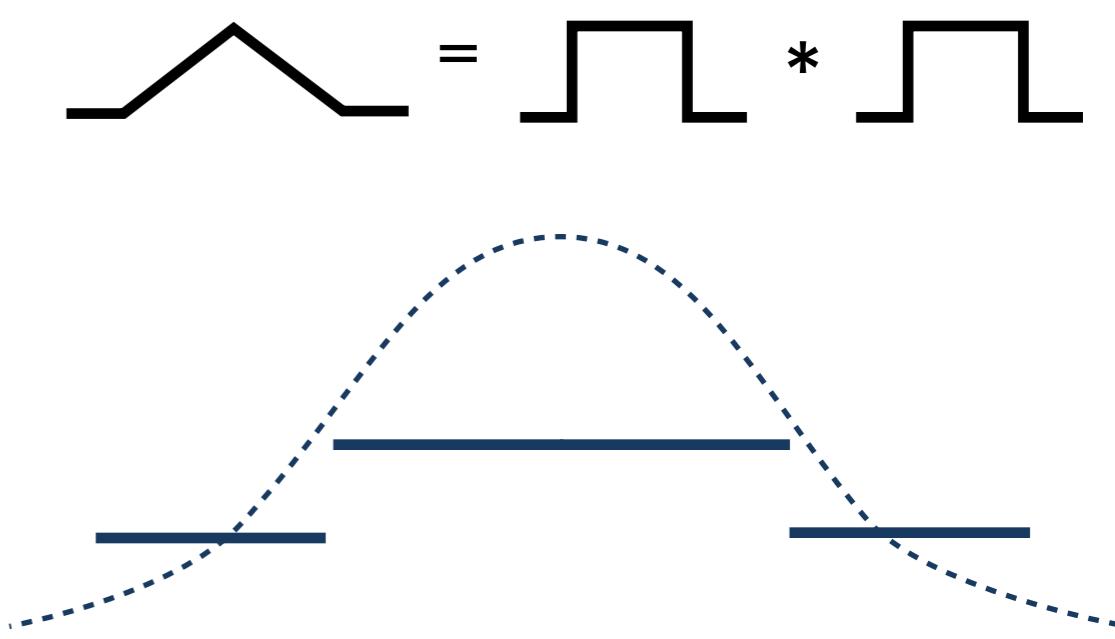
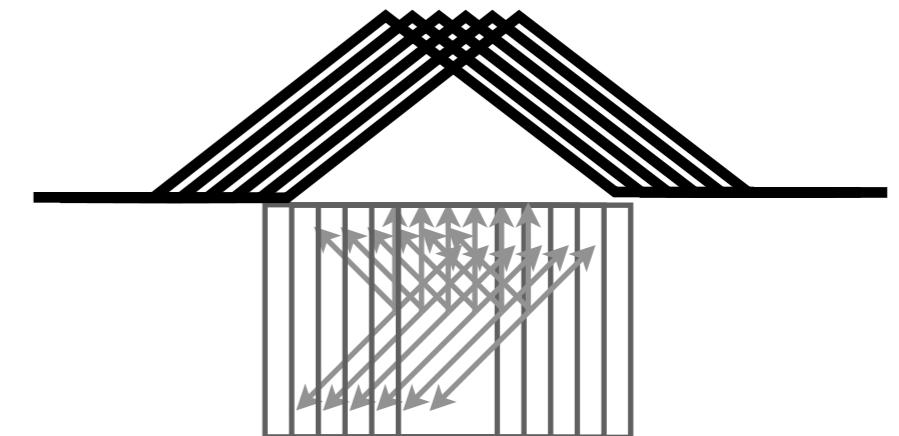
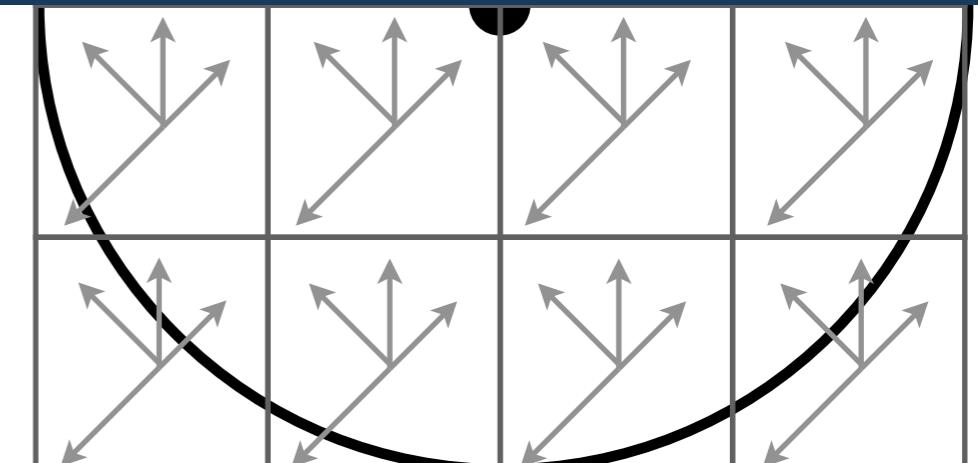
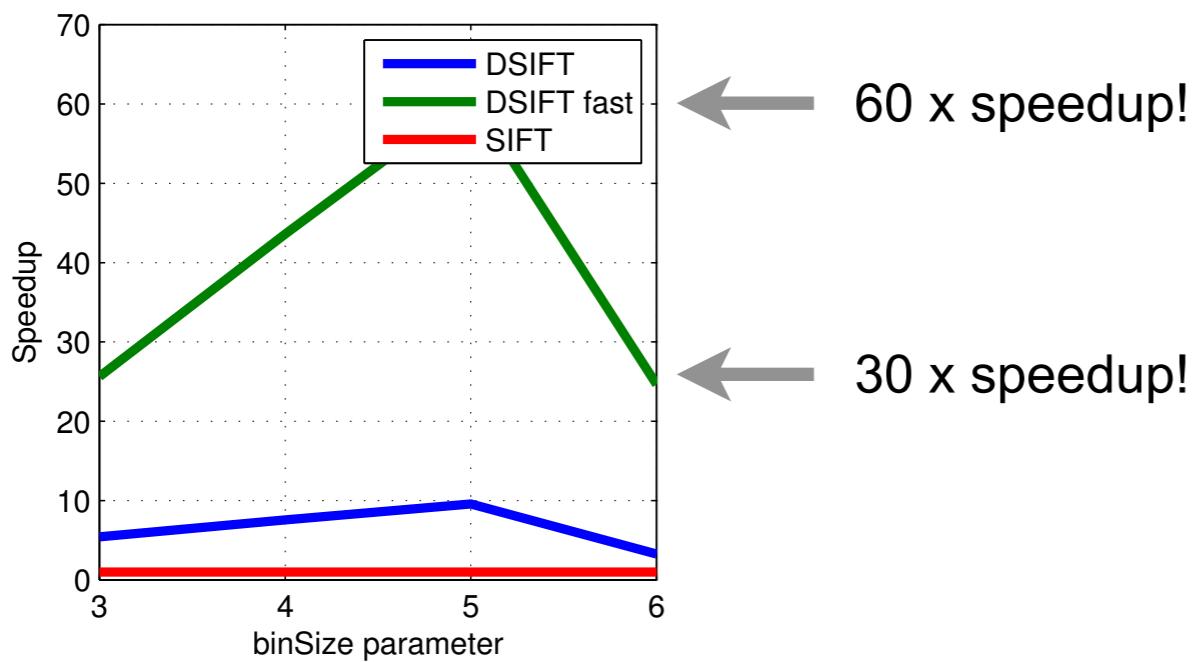
```

step = 5 ;
for s = [5, 7, 10, 12]
    [x, y] = meshgrid(1:step:width, 1:step:height) ;
    frames = [x(:)' ; y(:)'] ;
    frames(3,:) = s / 3 ;
    frames(4,:) = 0 ;
    [frames, descrs] = vl_sift(im, 'Frames', frames) ;
end

```

Accelerating dense SIFT

- Large **speedup** by exploiting
 - same scale and orientation
 - uniform sampling
- **Dense SIFT**
 - linear interpolation = convolution
 - convolution by integral images
 - piecewise approximation of Gaussian window
- Implemented by **`vl_dsift`**



Dense SIFT: The fast version

- PHOW = Fast dense SIFT at multiple scales

Use `vl_imsmooth` compute the scale space.

```
for i = 1:4
    ims = vl_imsmooth(im, scales(i) / 3) ;
    [frames{s}, descrs{s}] = ...
        vl_dsift(ims, 'Fast', ...
            'Step', step, 'Size', scales(i)) ;
end
```

- Remark

- for demonstration only!
- in practice use the provided wrapper

```
[frames, descrs] = vl_phow(im) ;
```

Accelerating dense SIFT: related methods

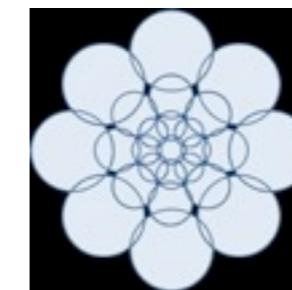
- **SURF**

- [Bay et al. 2008]
- Original closed source
<http://www.vision.ee.ethz.ch/~surf/index.html>
- OpenSURF
<http://www.chrisevansdev.com/computer-vision-opensurf.html>



- **Daisy**

- [Tola et al. 2010]
- <http://cvlab.epfl.ch/~tola/daisy.html>



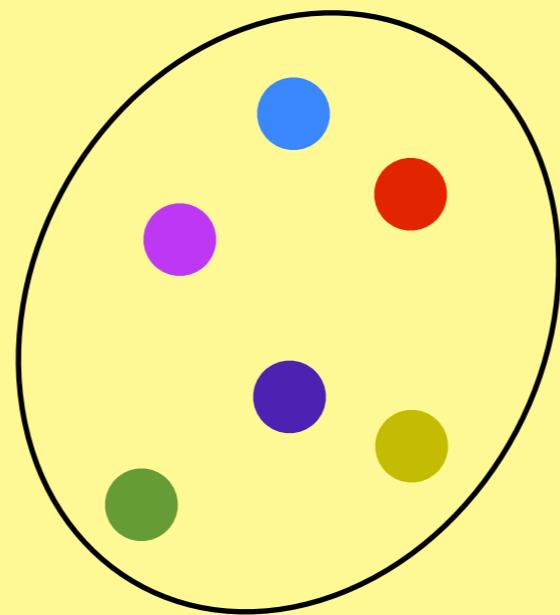
- **GPU-SIFT**

- [S. N. Sinha et al. 2010]
- http://cs.unc.edu/~ssinha/Research/GPU_KLT/

- **SiftGPU**

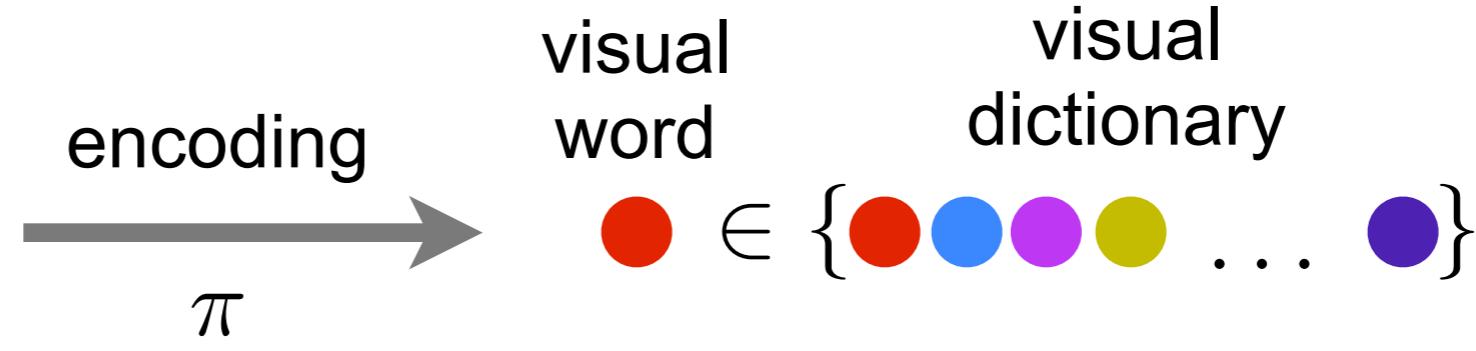
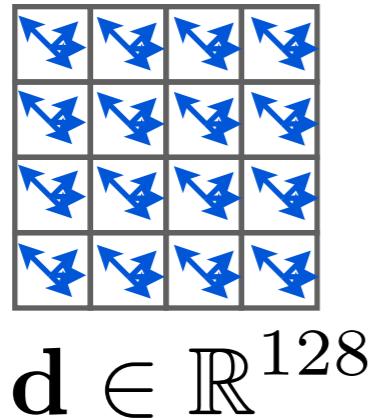
- [C. Wu 2010]
- <http://www.cs.unc.edu/~ccwu/siftgpu/>

Visual Words



Visual words

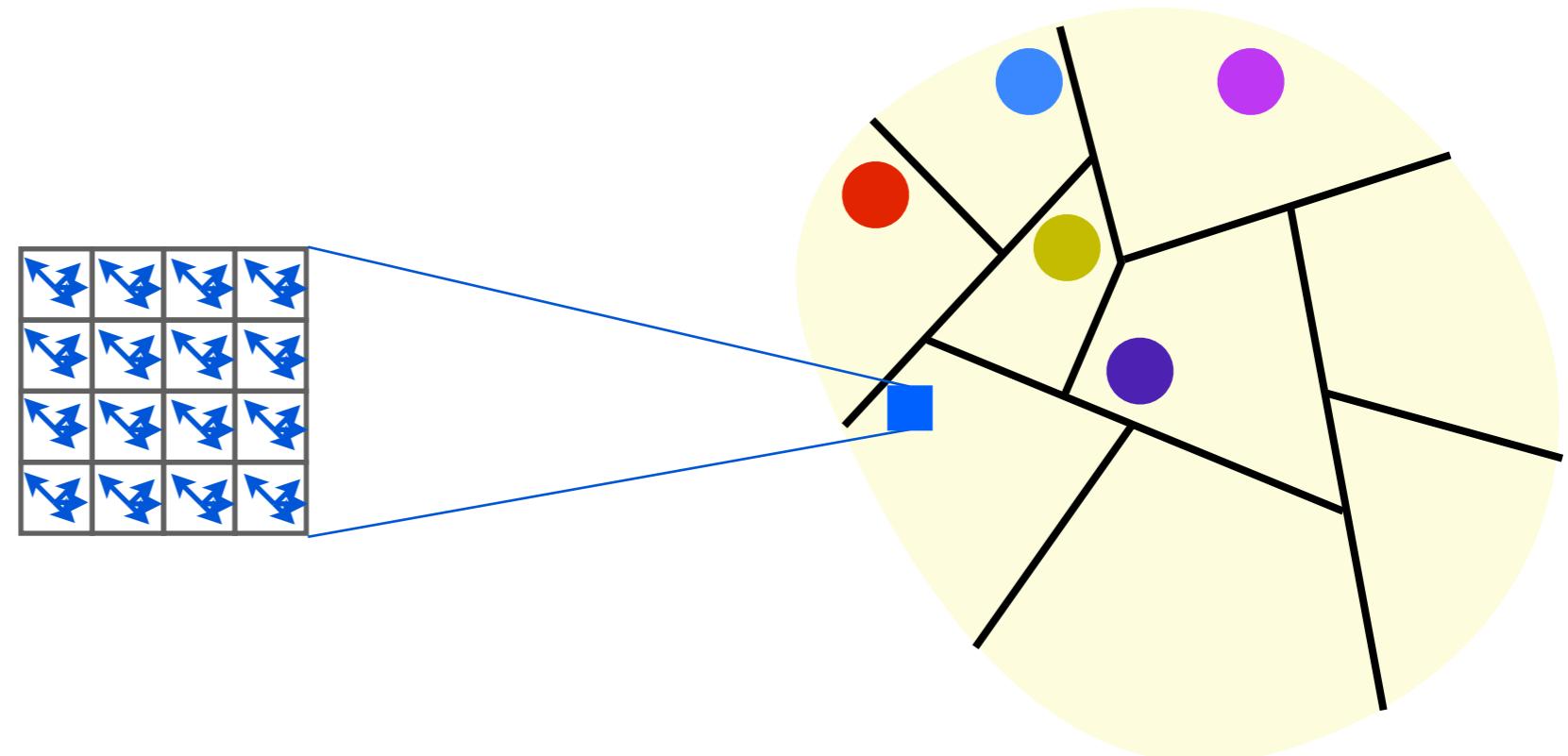
- Visual words



- Encoding = clustering

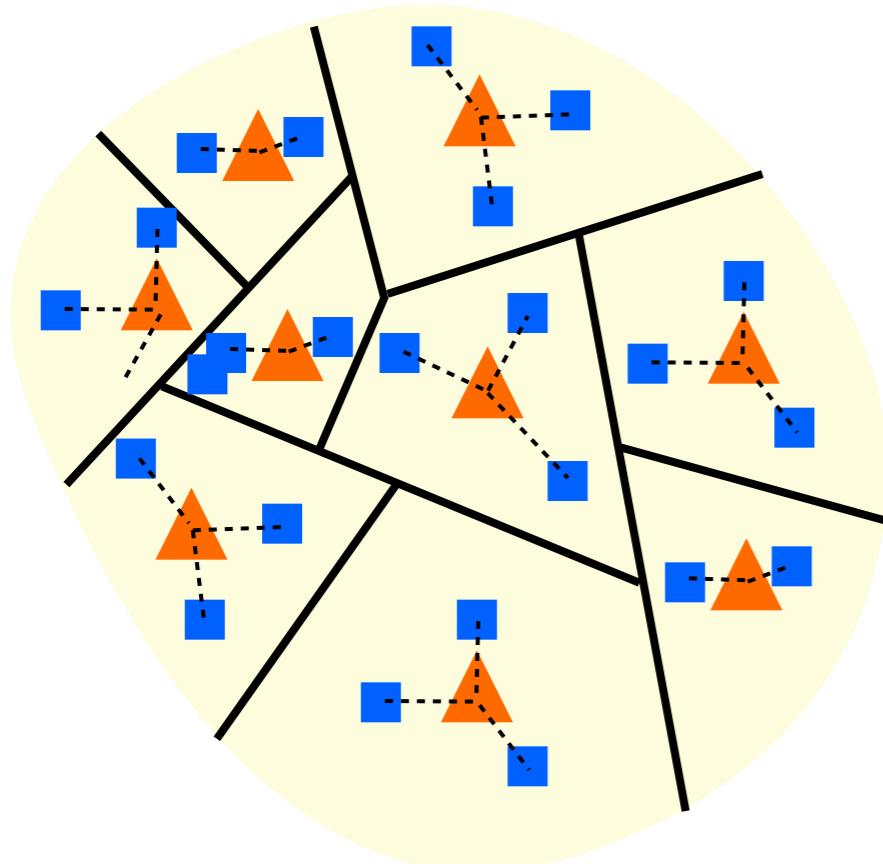
- vector quantization (k-means)
[Lloyd 1982]
- agglomerative clustering
[Leibe et al. 2006]
- affinity propagation
[Frey and Dueck 2007]
- ...

[Sivic and Zisserman 2003]



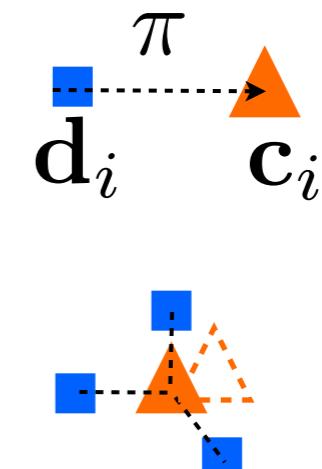
k-means

- Optimize reconstruction cost



$$E(\pi, \mathbf{c}_1, \dots, \mathbf{c}_K) = \sum_{i=1}^M \|\mathbf{d}_i - \mathbf{c}_{\pi(\mathbf{d}_i)}\|^2$$

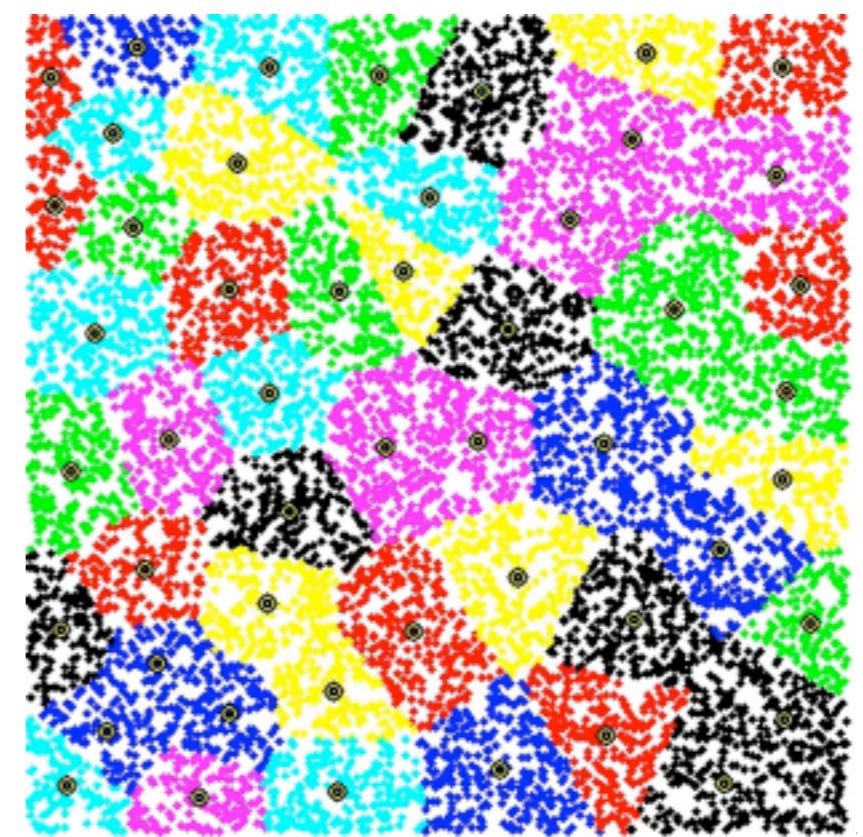
- ① reassign points to closest centers
- ② fit centers to assigned points



- As simple as you expect

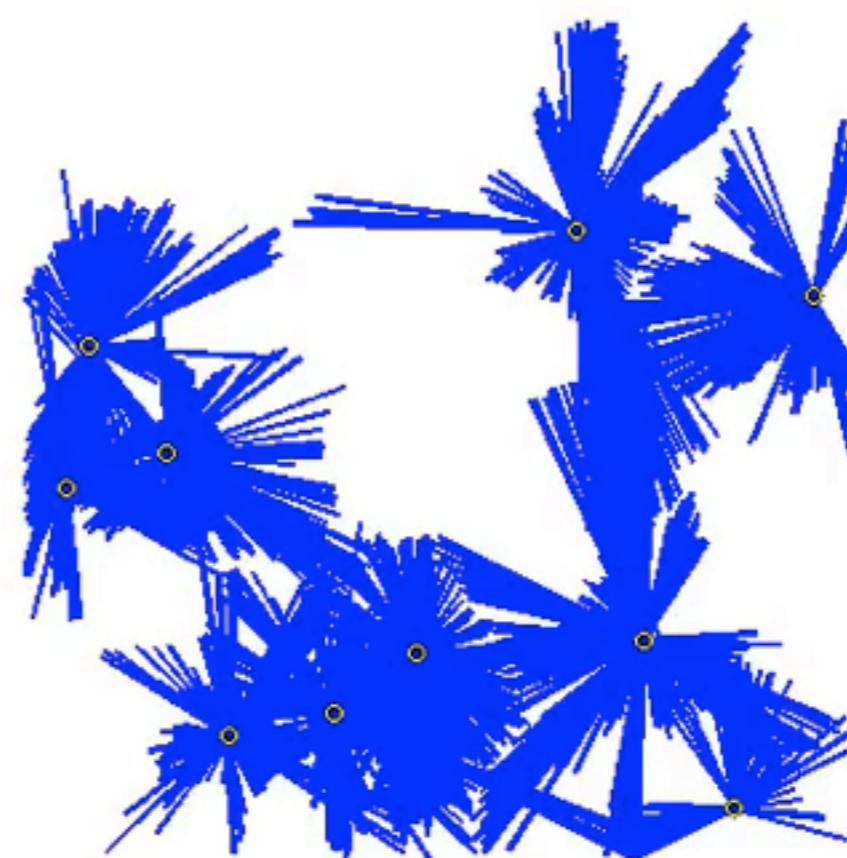
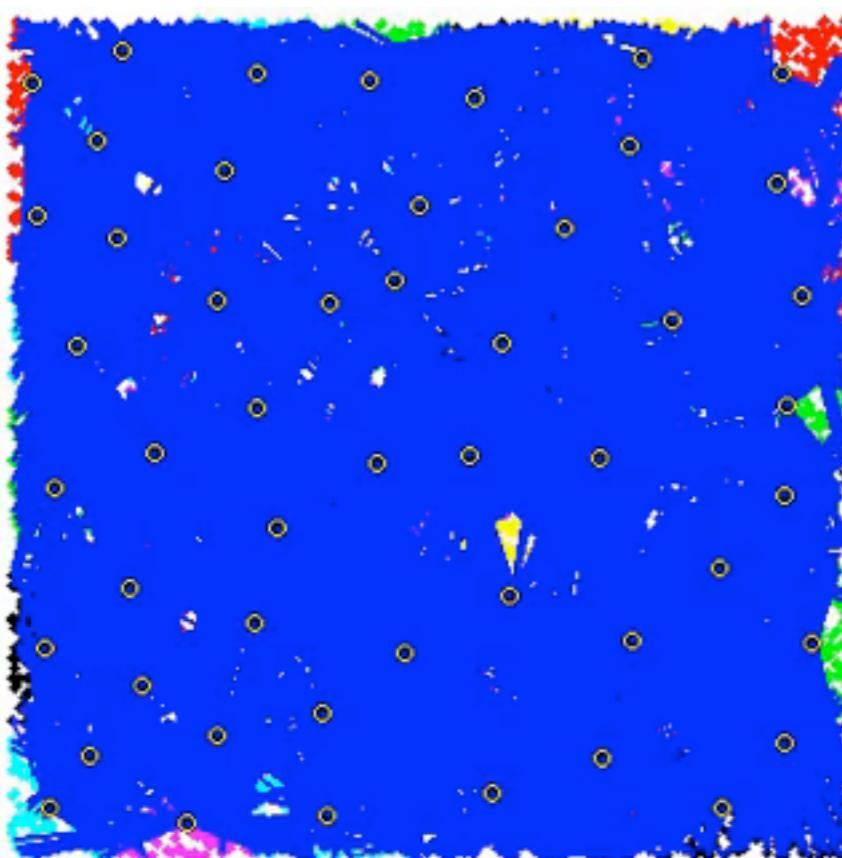
```
centers = vl_kmeans(descrs, K);
```

- Much faster than MATLAB builtin



Faster k-means

- **Bottleneck**
 - assign point to closest center
 - needs to compare each point to each center
- **Speedup**
 - if centers change little, then most assignment don't change
 - can keep track with triangle inequality
 - [Elkan 2003]
 - `centers = vl_kmeans(descrs, K, 'Algorithm', 'Elkan');`

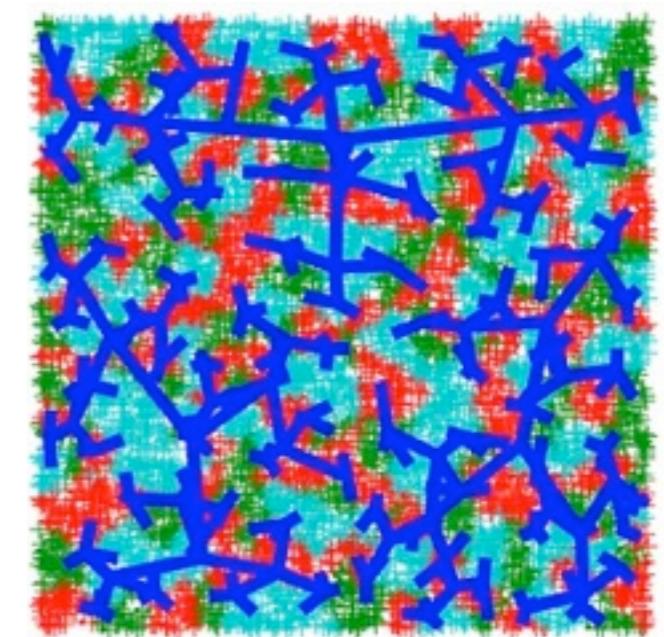
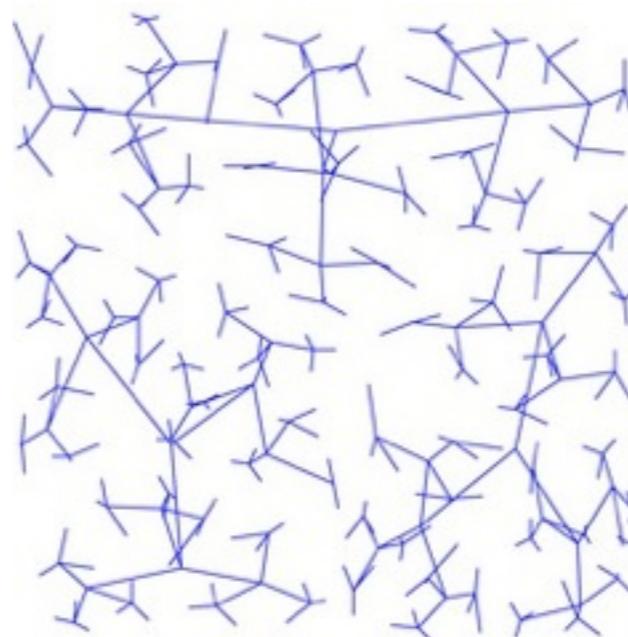


Vector-to-center
comparison

Speeding-up encoding

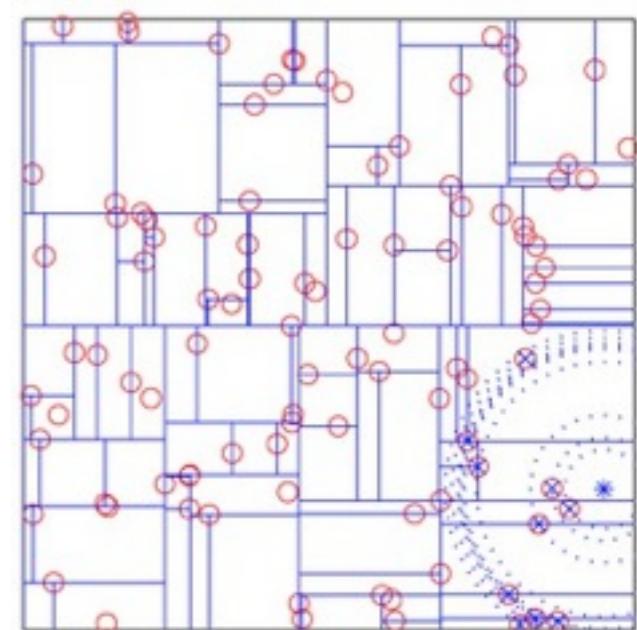
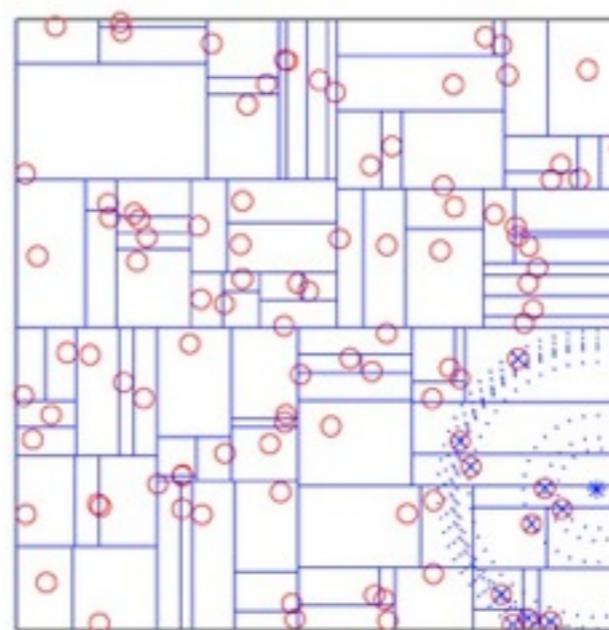
- **Hierarchical k-means clustering**

- [Nistér and Stewénius 2006]
[Hastie et al. 2001]
- apply k-means recursively
- logarithmic encoding
- **`vl_hikmeans`**



- **kd-trees**

- multi-dimensional logarithmic search
[Friedman et. al 1977]
- best-bin search and random forests
[Muja and Lowe 2009]



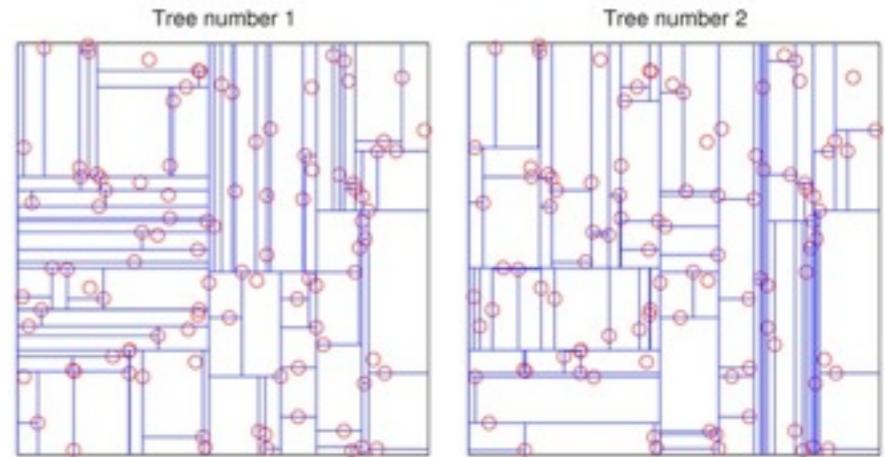
Randomized kd-tree forests

- **Build the tree**

```
kdtree = vl_kdtreebuild(X) ;
```

- random forests

```
kdtree = vl_kdtreebuild(X, 'NumTrees', 2) ;
```



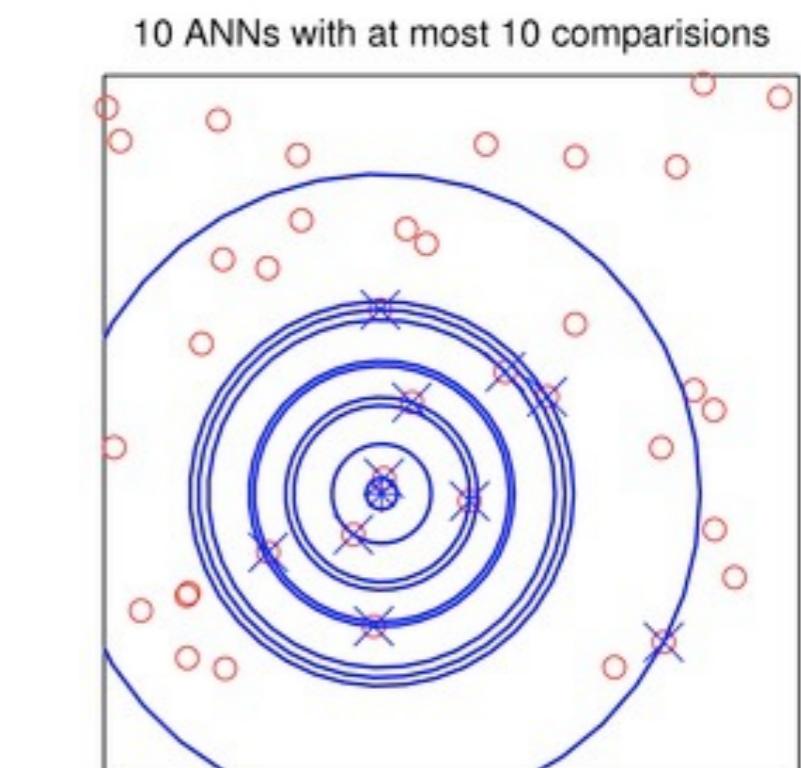
- **Query the tree**

- Exact nearest neighbors

```
[ind, dist] = vl_kdtreequery(kdtree, X, Q, ...
    'NumNeighbors' 10) ;
```

- Approximate nearest neighbors

```
[ind, dist] = vl_kdtreequery(kdtree, X, Q, ...
    'NumNeighbors' 10, ...
    'MaxComparisons', 10)
```



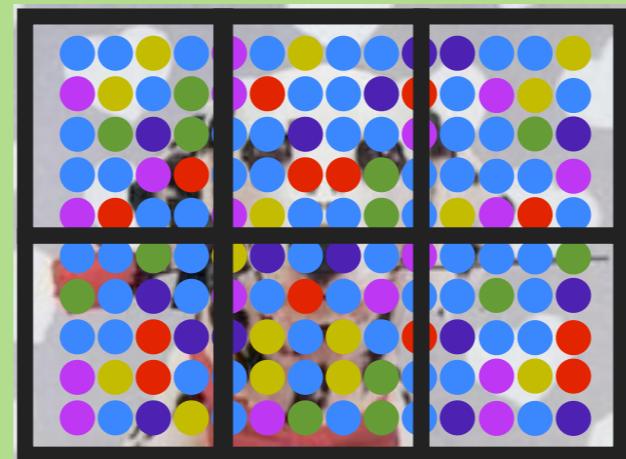
- Random kd-tree forest implementation

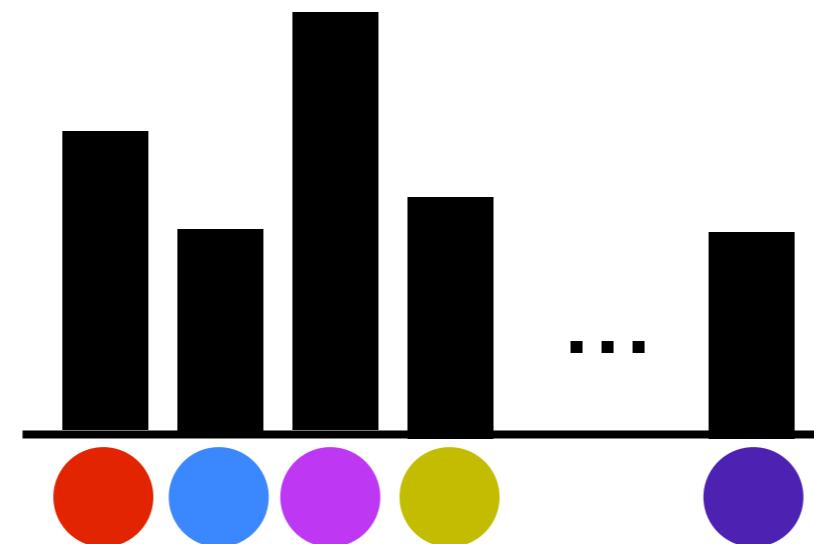
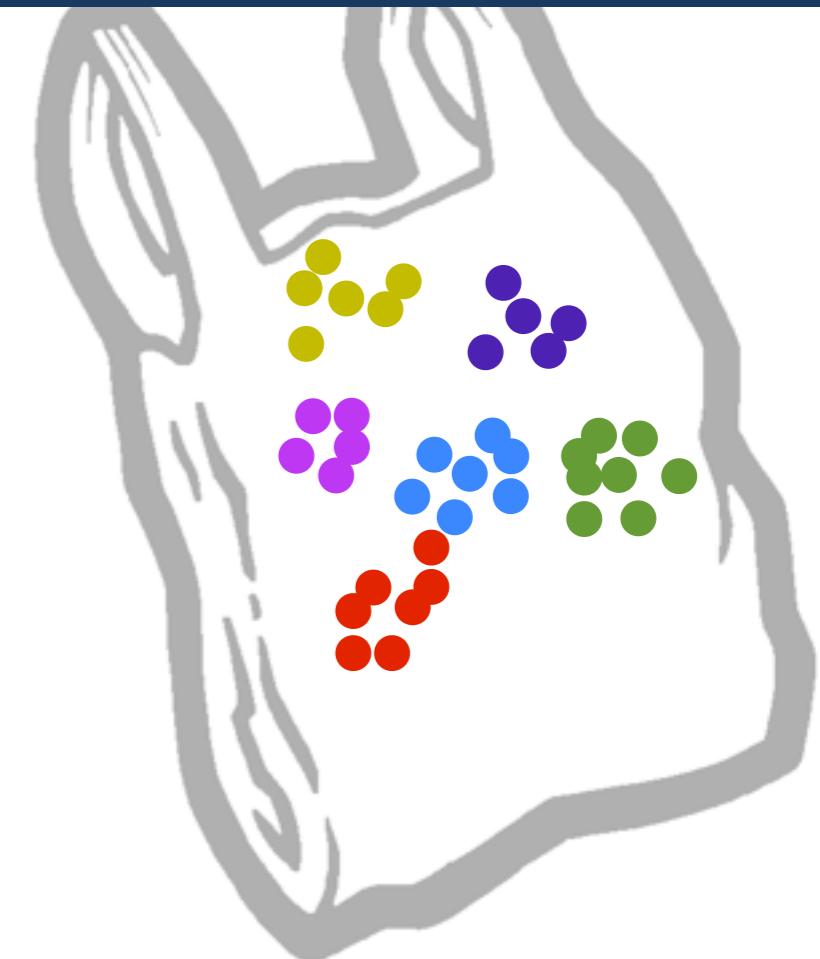
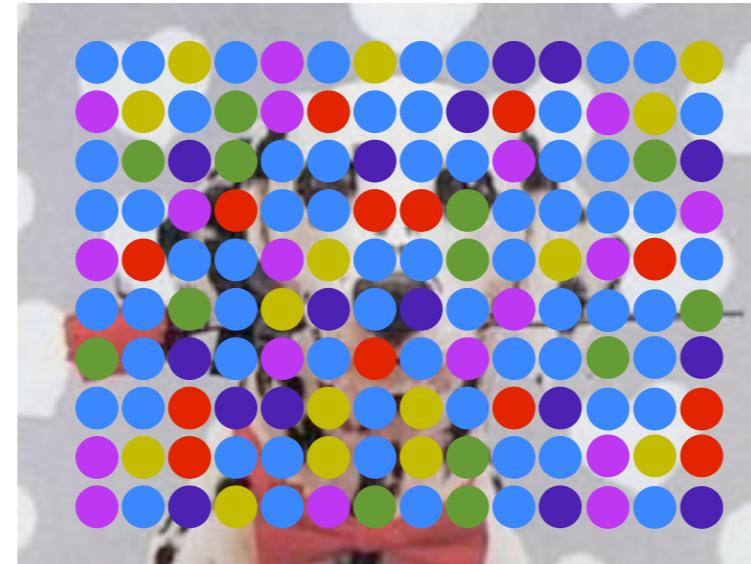
- Equivalent to FLANN

- [Muja and Lowe 2009]

- <http://www.cs.ubc.ca/~mariusm/index.php/FLANN/FLANN>

Spatial Histograms



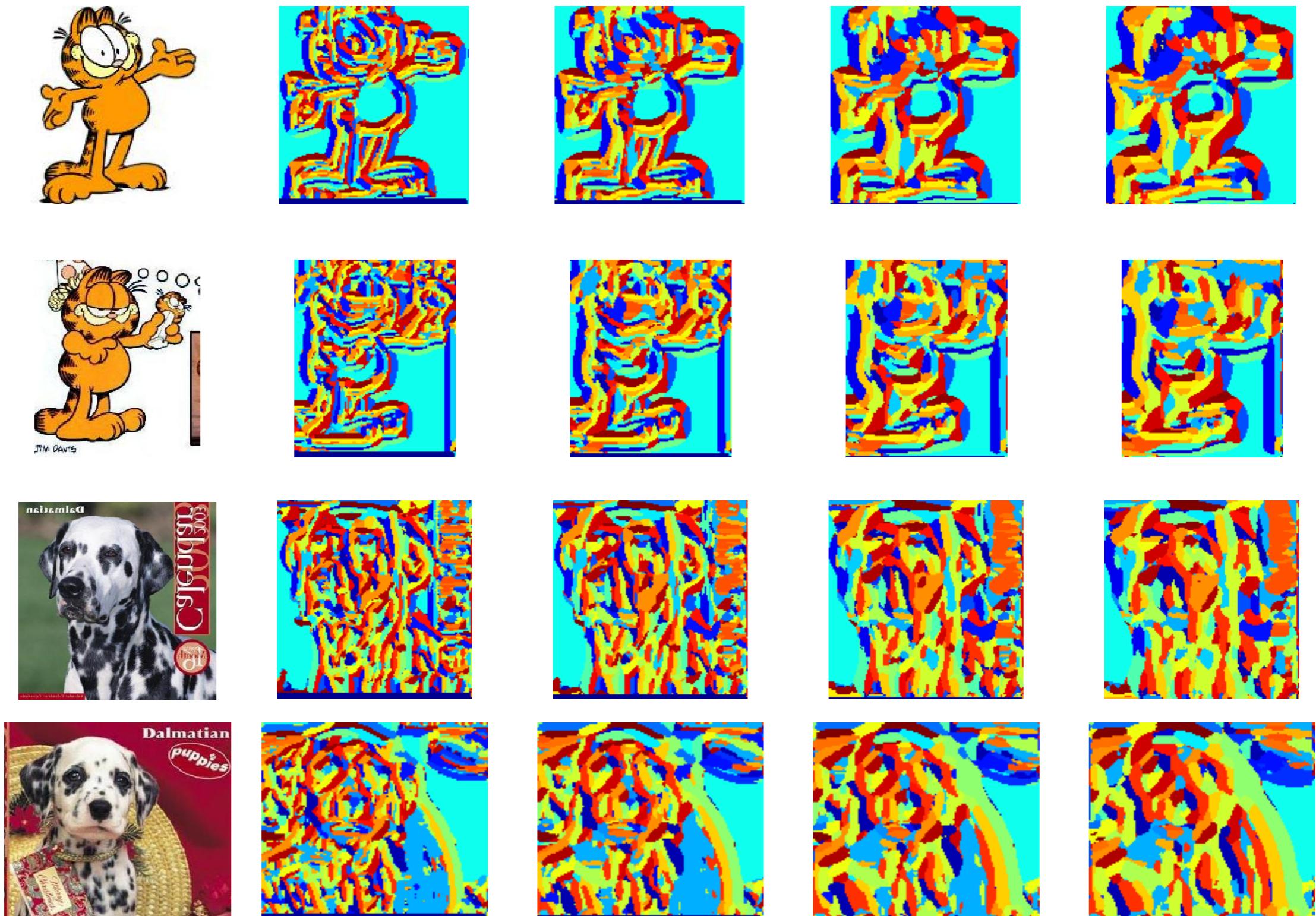


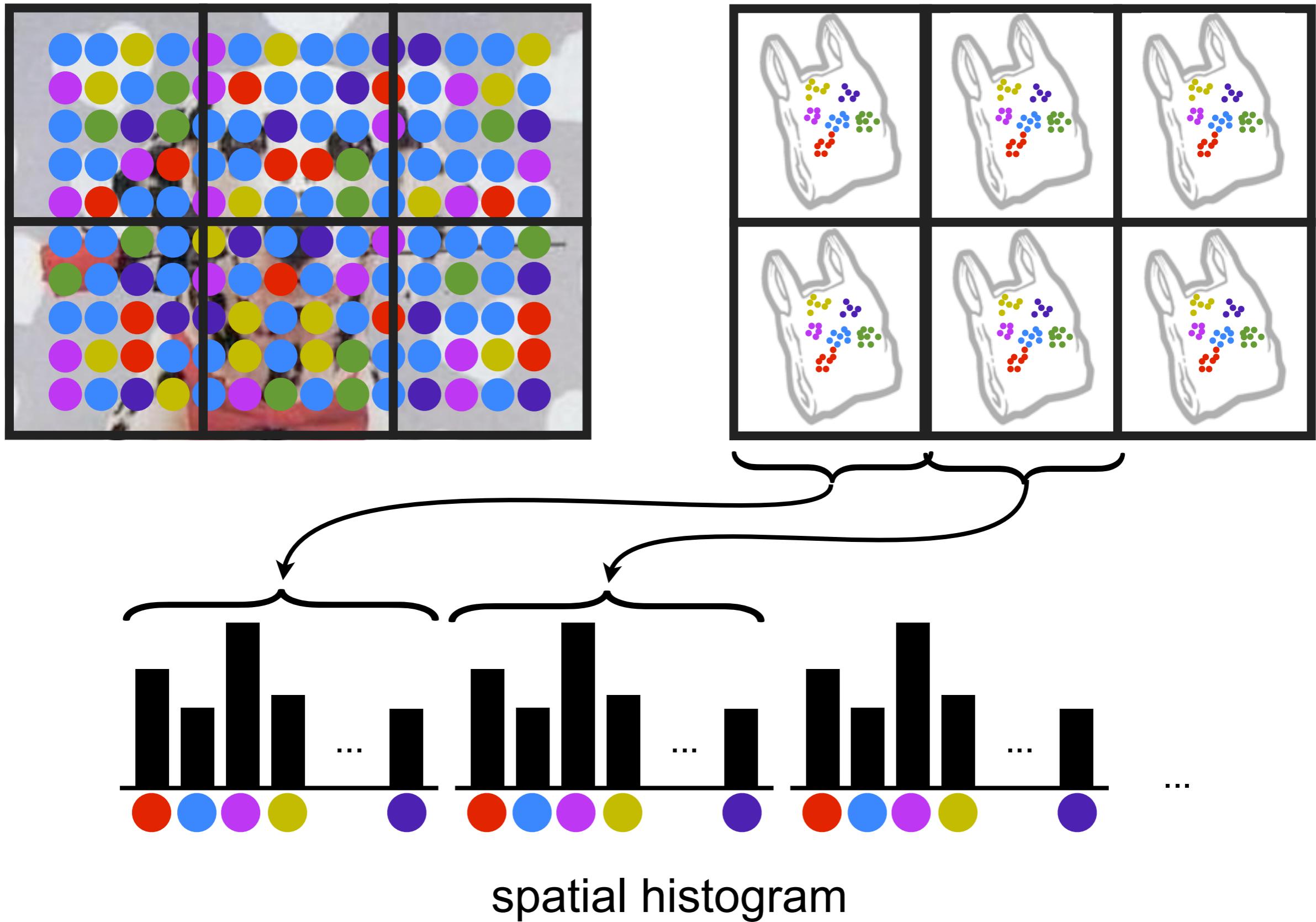
[Csurka et al. 2004]

histogram (bag) of visual words

Example encodings

SIFT descriptor scale





VLFeat utility functions

- MEX-accelerated primitives
- Speed-up MATLAB in key operations
- Examples:

- **Binning**

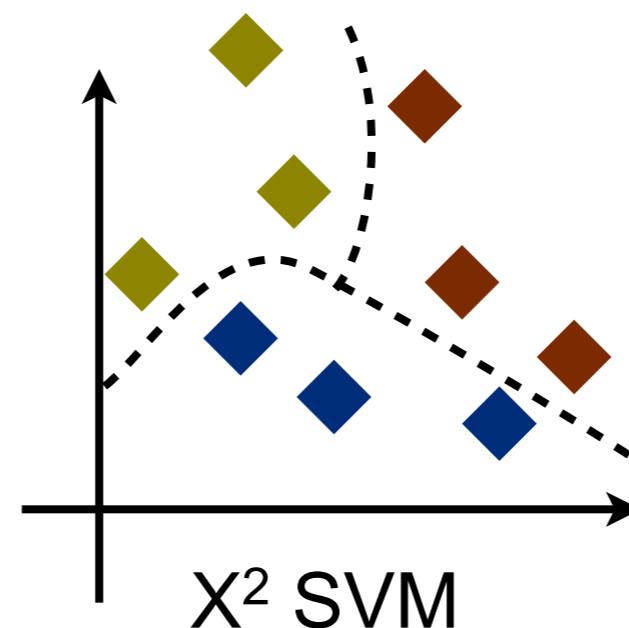
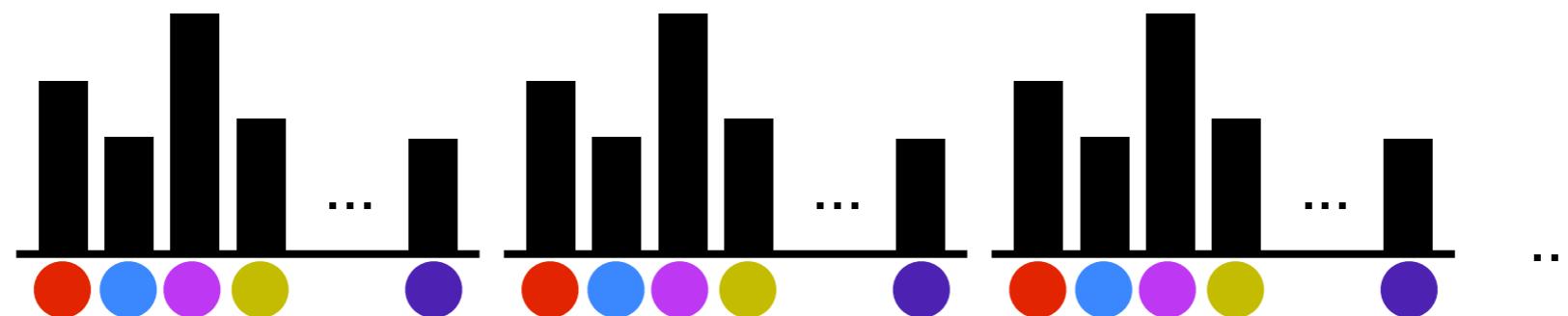
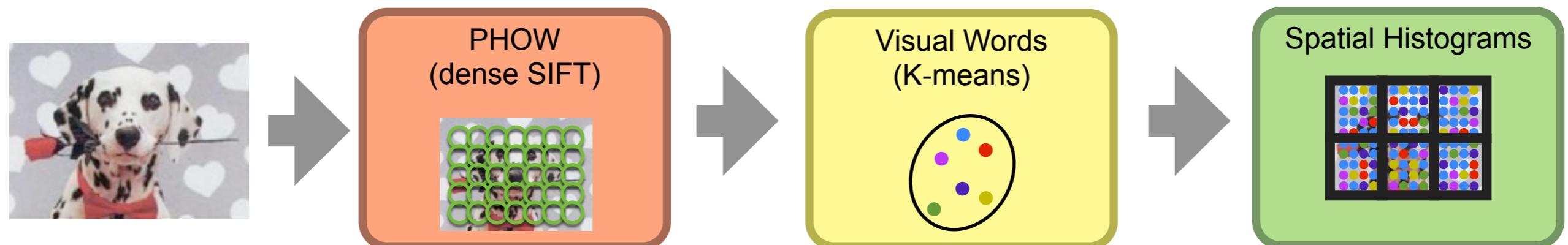
```
% quantize location
binsx = vl_binsearch(linspace(1,width,conf.numSpatialX+1), frames(1,:)) ;
binsy = vl_binsearch(linspace(1,height,conf.numSpatialY+1), frames(2,:)) ;
```

- **Binned summations**

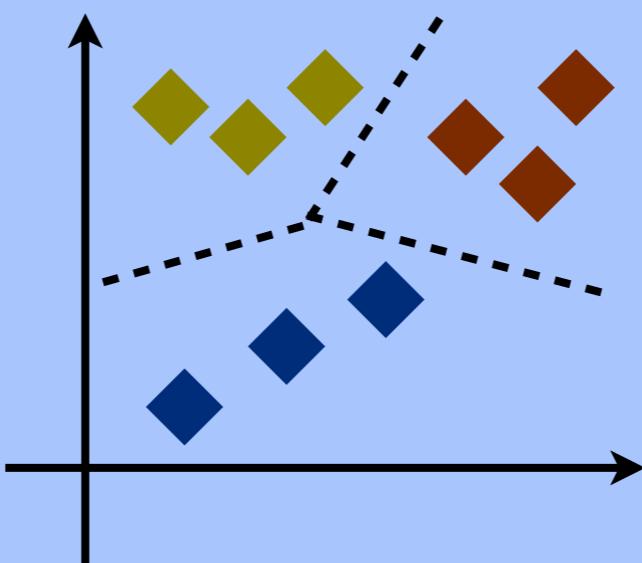
```
% histogram computation
bins = sub2ind([conf.numSpatialY, conf.numSpatialX, conf.numWords], ...
               binsy,binsx,binsa) ;
hist = zeros(conf.numSpatialY * conf.numSpatialX * conf.numWords, 1) ;
hist = vl_binsum(hist, ones(size(bins)), bins) ;
```

Summary: image descriptors

30



SVM



Fisher discriminant	LDA	Dirichelet processes
	kernel density estimation	separating hyperplane
kernel methods	logistic regression	
	nearest neighbors	topic models

AdaBoost



random forests

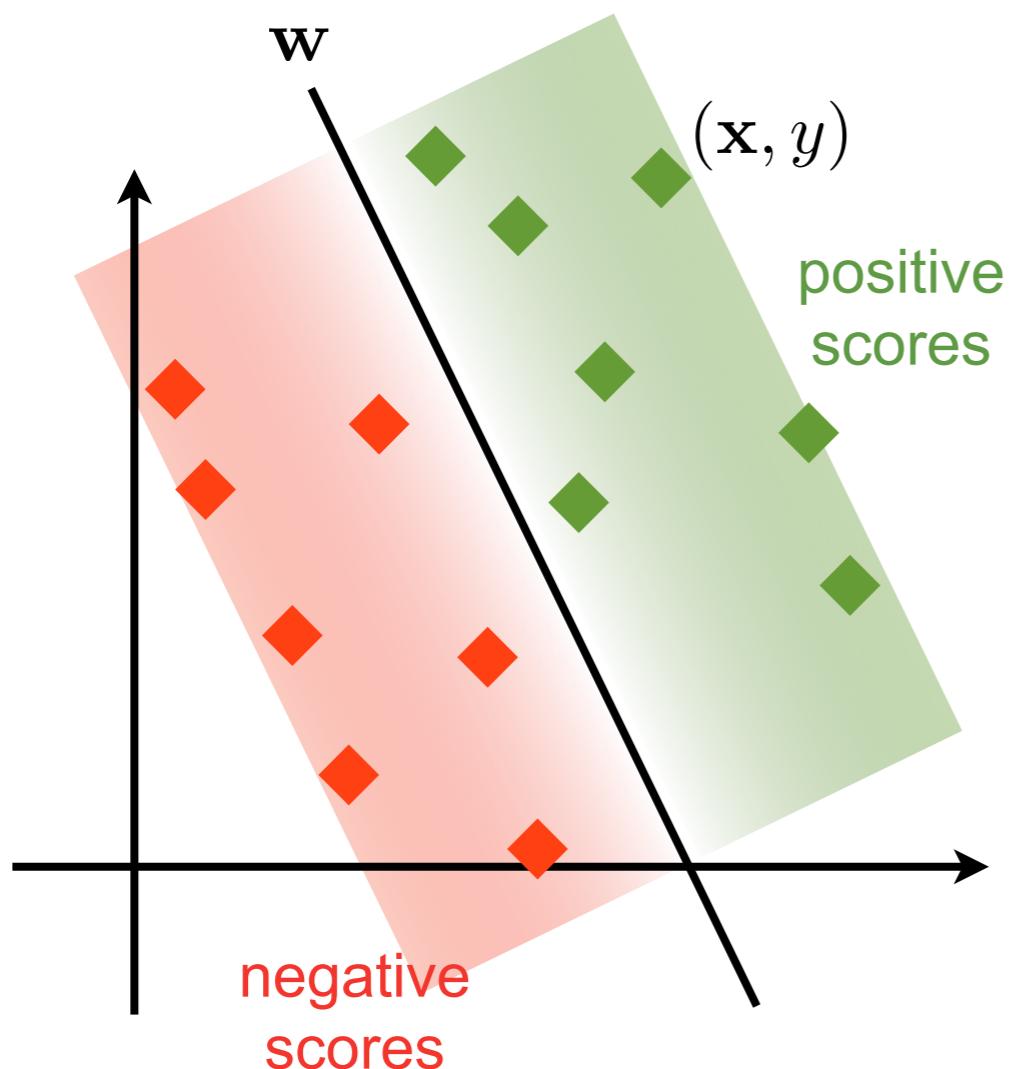
- **SVMs**

- often *state-of-the-art*
- *simple* to use and tune
- *efficient* with the latest improvements

[Shawe-Taylor and Cristianini 2000]

[Schölkopf and Smola 2002]

[Hastie et al. 2003]



Discriminant score

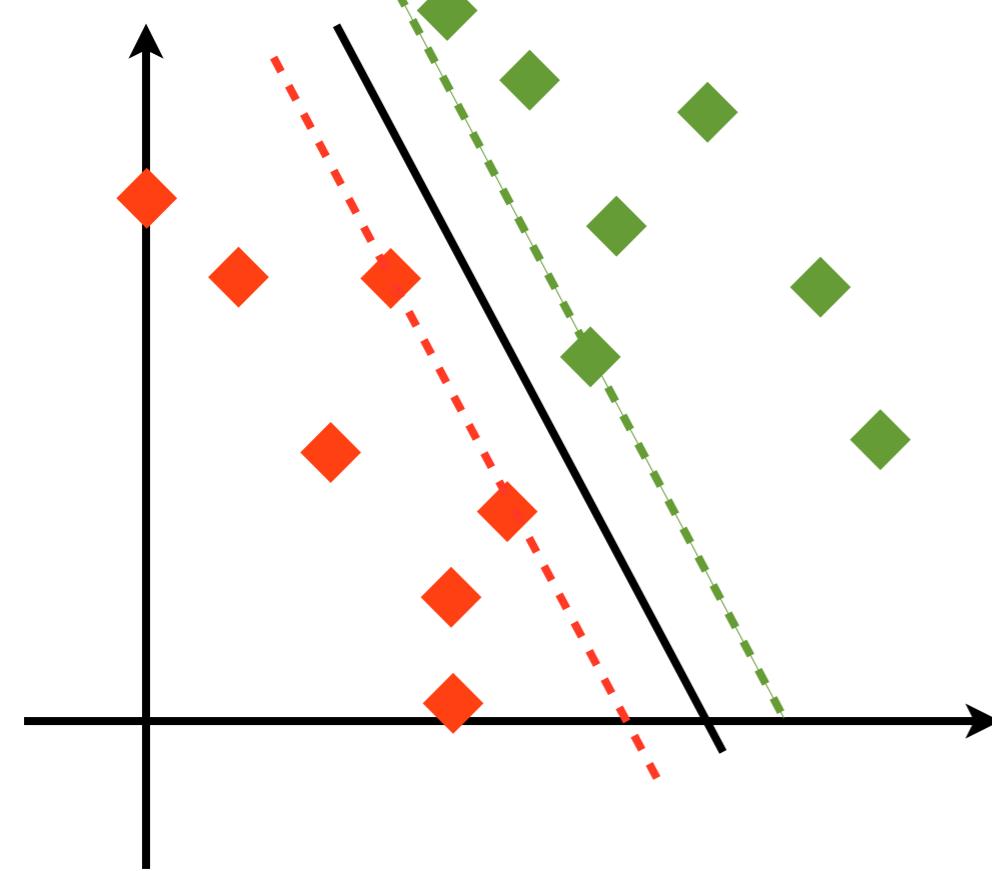
$$f(\mathbf{x}; \mathbf{w}) = \langle \mathbf{w}, \mathbf{x} \rangle$$

$$\min_{\mathbf{w}} \frac{\lambda}{2} \|\mathbf{w}\|^2 + \frac{1}{N} \sum_{i=1}^N \ell(\mathbf{w}; (\mathbf{x}_i, y_i))$$

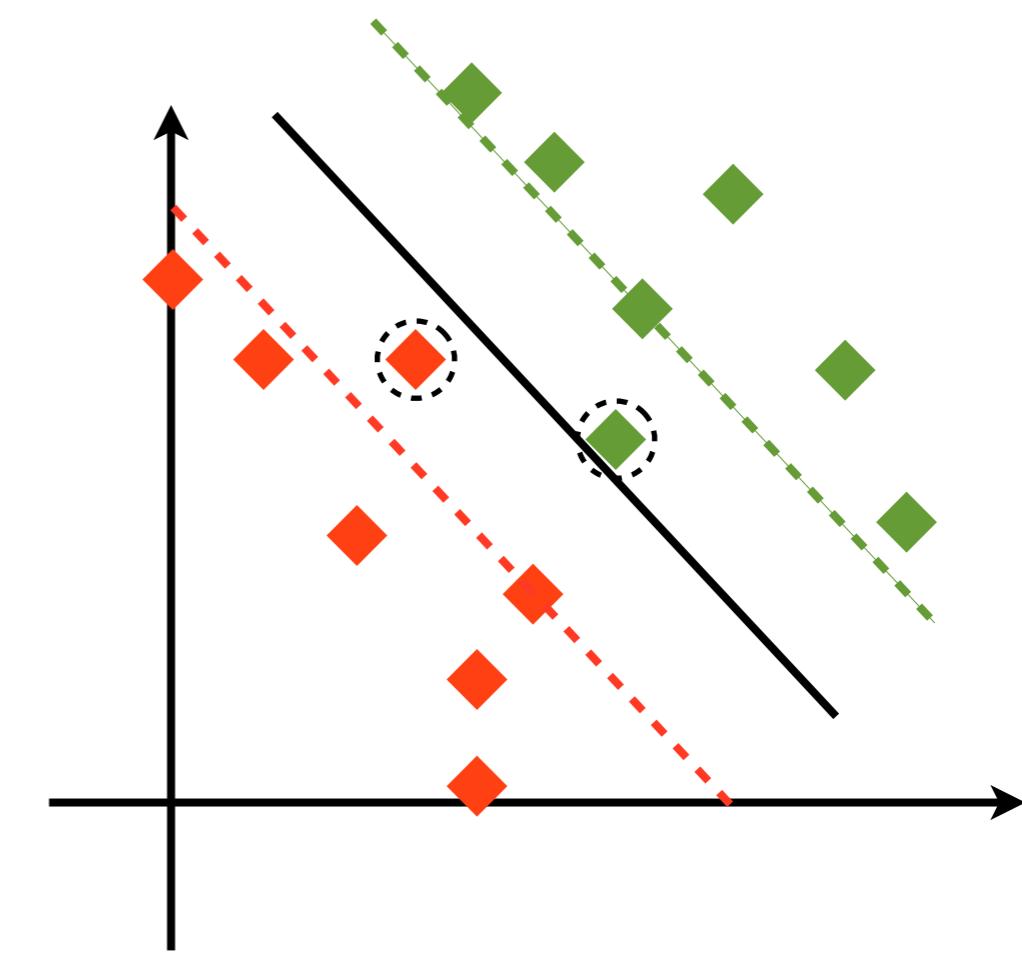
$$\min_{\mathbf{w}} \frac{\lambda}{2} \|\mathbf{w}\|^2 + \frac{1}{N} \sum_{i=1}^N \ell(\mathbf{w}; (\mathbf{x}_i, y_i))$$

hard loss

$$\ell(\mathbf{w}; (\mathbf{x}, y)) = \begin{cases} 0, & y\langle \mathbf{w}, \mathbf{x} \rangle > 1, \\ +\infty, & \text{otherwise.} \end{cases}$$

**hinge loss**

$$\ell(\mathbf{w}; (\mathbf{x}, y)) = \begin{cases} 0, & y\langle \mathbf{w}, \mathbf{x} \rangle > 1, \\ 1 - y\langle \mathbf{w}, \mathbf{x} \rangle, & \text{otherwise.} \end{cases}$$



Linear SVM: Fast algorithms

- **SVM^{perf}**

- [Joachims 2006]
- http://www.cs.cornell.edu/People/tj/svm_light/svm_perf.html
- cutting plane + one slack formulation
- **from superlinear to linear complexity**

- **LIBLINEAR**

- [R.-E. Fan et al. 2008]
- <http://www.csie.ntu.edu.tw/~cjlin/liblinear/>

L1 loss

$$\ell(\mathbf{w}; (\mathbf{x}, y)) = \max\{0, 1 - y\langle \mathbf{w}, \mathbf{x} \rangle\}$$

L2 loss

$$\ell(\mathbf{w}; (\mathbf{x}, y)) = (\max\{0, 1 - y\langle \mathbf{w}, \mathbf{x} \rangle\})^2$$

logistic loss

$$\ell(\mathbf{w}; (\mathbf{x}, y)) = \log(1 + \exp(-y\langle \mathbf{w}, \mathbf{x} \rangle))$$

L2 regularizer

$$\frac{\lambda}{2} \sum_{i=1}^D w_i^2$$

L1 regularizer

$$\frac{\lambda}{2} \sum_{i=1}^D |w_i|$$

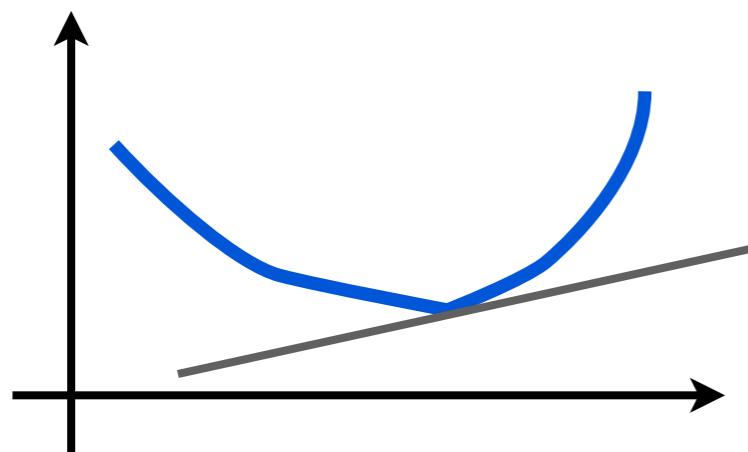
Linear SVM: PEGASOS

- [S. Shalev-Shwartz et al. 2010]
- <http://www.cs.huji.ac.il/~shais/code/index.html>

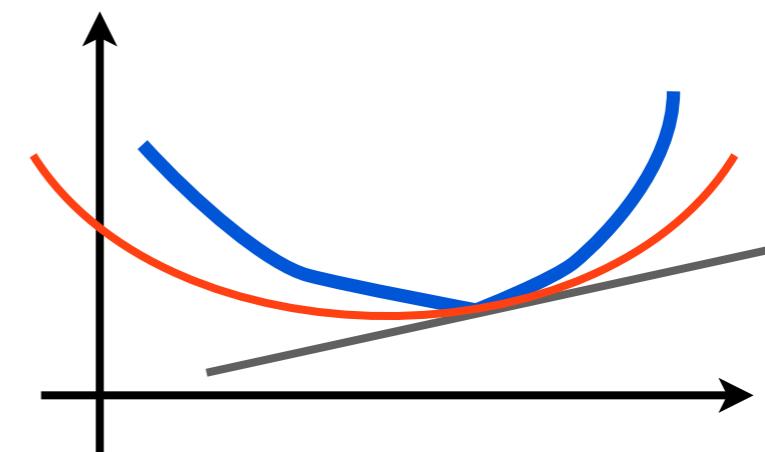
1 Pick a random data point (\mathbf{x}_i, y_i)

$$2 \quad \nabla E_t(\mathbf{w}) = \begin{cases} \lambda \mathbf{w}_t, & y_i \langle \mathbf{w}, \mathbf{x}_i \rangle > 1, \\ \lambda \mathbf{w}_t - y_i \mathbf{x}_i, & \text{otherwise.} \end{cases}$$

$$3 \quad \mathbf{w}_{t+1} = \mathbf{w}_t - \frac{1}{\lambda t} \nabla E_t(\mathbf{w})$$



non differentiable objective
⇒ **sub-gradient**



strongly-convex objective
⇒ **optimal schedule**

VLFeat PEGASOS

- **training**

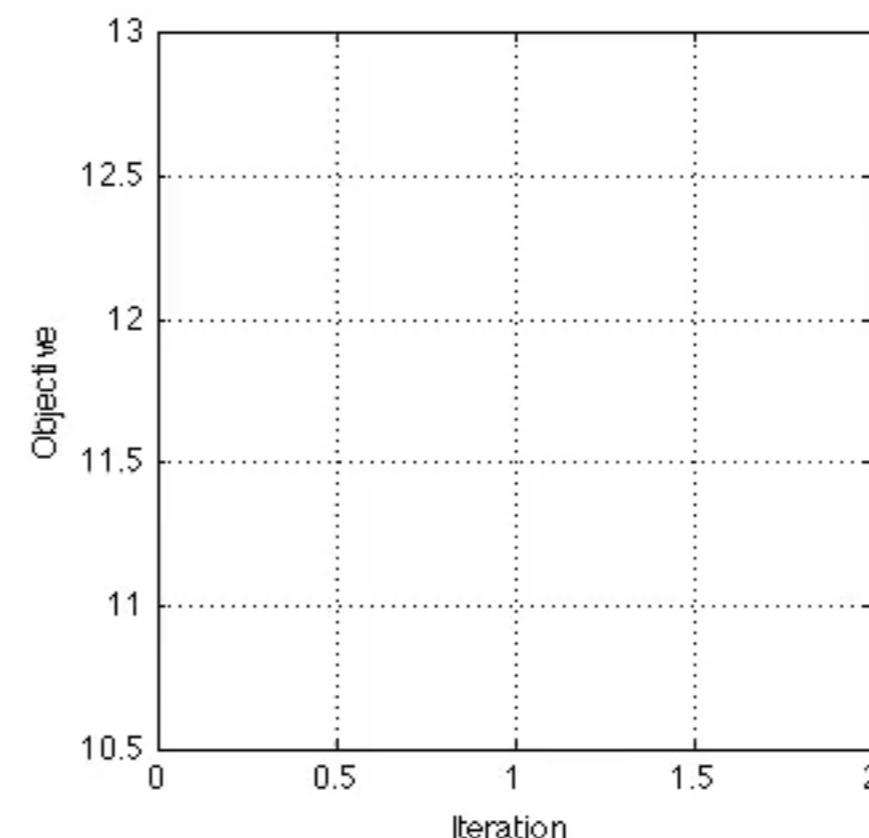
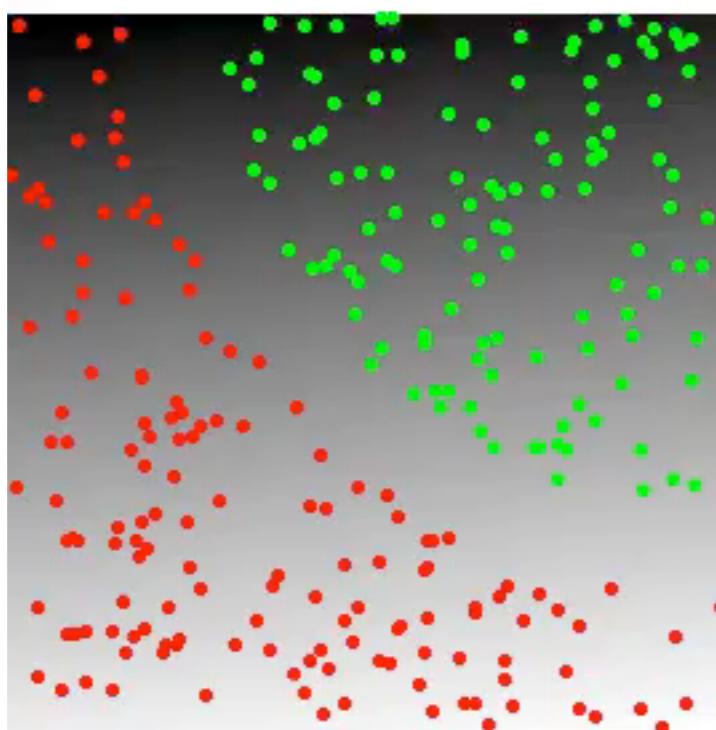
`w = vl_pegasos(x, y, lambda)`

- **testing**

`w' * x`

- Observations:

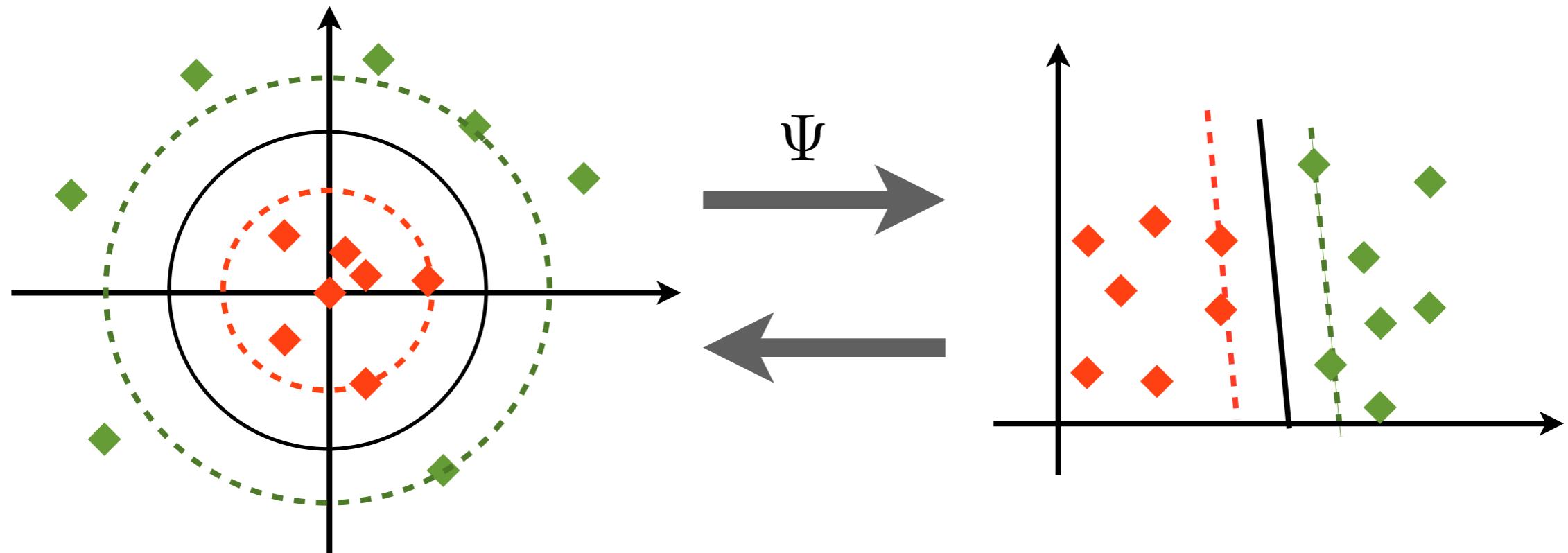
- gets a rough solution very quickly
- many solutions almost as good
- testing dominated by generalization error



Kernel Map

Ψ

- Generalize SVM through a *feature map*



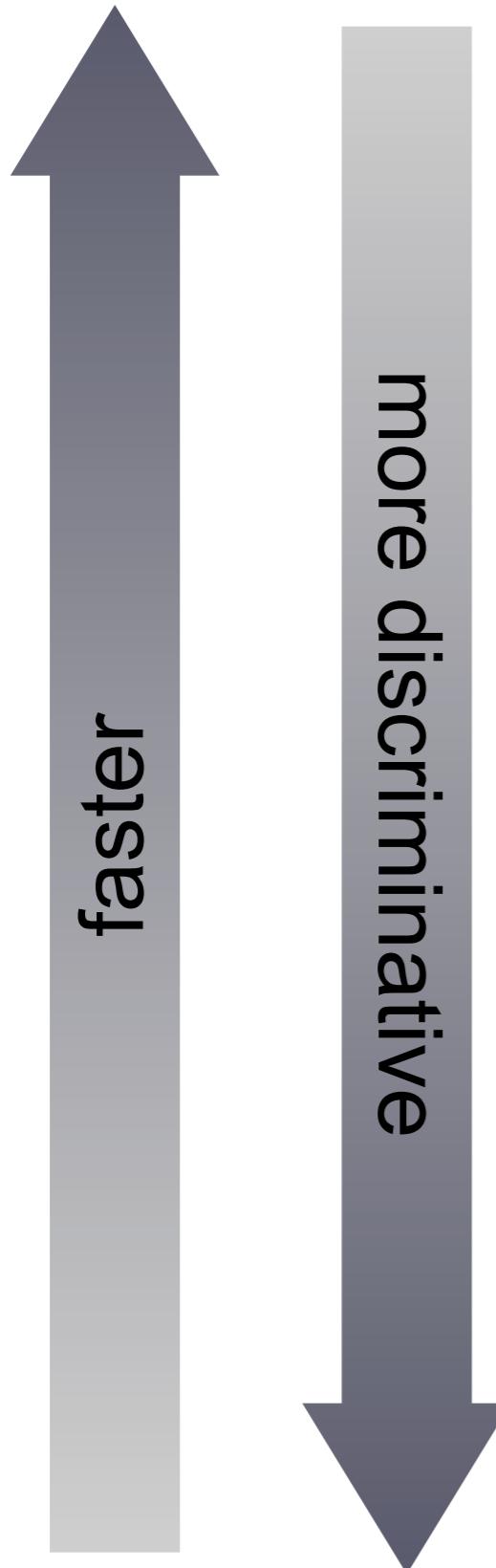
- The feature map may be defined implicitly by a **kernel function**

$$\mathbf{w} = \sum_{i=1}^N \beta_i \Psi(\mathbf{x}_i)$$

$$\langle \mathbf{w}, \Psi(\mathbf{x}) \rangle = \sum_{i=1}^N \beta_i \langle \Psi(\mathbf{x}_i), \Psi(\mathbf{x}) \rangle$$

$$K(\mathbf{x}_i, \mathbf{x}) = \langle \Psi(\mathbf{x}_i), \Psi(\mathbf{x}) \rangle$$

Common kernels



linear

$$K(\mathbf{x}, \mathbf{y}) = \sum_{l=1}^D \mathbf{x}_l \mathbf{y}_l$$

[Zhang et al. 2007]
[Vedaldi et. al 2010]

Fast kernel and
distance
matrices with
vl_alldist

additive

$$K(\mathbf{x}, \mathbf{y}) = \sum_{l=1}^D k(\mathbf{x}_l, \mathbf{y}_l)$$

additive RBF

$$K(\mathbf{x}, \mathbf{y}) = \exp\left(-\frac{1}{2\sigma^2} \sum_{l=1}^D d^2(\mathbf{x}_l, \mathbf{y}_l)\right)$$

Common kernels

faster

e discriminative

$l=1$

additive

$$K(\mathbf{x}, \mathbf{y}) = \sum_{l=1}^D k(\mathbf{x}_l, \mathbf{y}_l)$$

additive RBF

$$K(\mathbf{x}, \mathbf{y}) = \exp\left(-\frac{1}{2\sigma^2} \sum_{l=1}^D d^2(\mathbf{x}_l, \mathbf{y}_l)\right)$$

Hellinger's

$$k(x, y) = \sqrt{xy}$$

$$d^2(x, y) = (\sqrt{x} - \sqrt{y})^2$$

X²

$$k(x, y) = \frac{2xy}{x + y}$$

$$d^2(x, y) = \frac{(x - y)^2}{x + y}$$

intersection

$$k(x, y) = \min\{x, y\} \quad d^2(x, y) = |x - y|$$

Non-linear SVMs

- **LIBSVM**
 - [C.-C. Chang and C.-J. Lin 2001]
 - <http://www.csie.ntu.edu.tw/~cjlin/libsvm/>
- **SVM^{light}**
 - [T. Joachims 1999]
 - <http://svmlight.joachims.org>
- Many other open source implementations ...



bottleneck
support vector expansion

Speeding-up non-linear SVMs

- Avoid support vector expansion
- Actually compute the feature map $\Psi(\mathbf{x})$ $K(\mathbf{x}, \mathbf{y}) = \langle \Psi(\mathbf{x}), \Psi(\mathbf{y}) \rangle$
- Exact feature map is usually:

hard to compute

high dimensional

- Seek for approximations $\widehat{\Psi}(\mathbf{x})$ $K(\mathbf{x}, \mathbf{y}) \approx \langle \widehat{\Psi}(\mathbf{x}), \widehat{\Psi}(\mathbf{y}) \rangle$
 - low dimensional
 - efficient computation
 - good approximation quality

reduced expansions

[C. K. I. Williams and M. Seeger 2001]
[Bach and Jordan 2006]
[Bo and Sminchiescu 2009]

direct approximations

VLFeat homogeneous kernel map

- [Vedaldi and Zisserman 2010]
- Closed feature maps by Fourier transform in log domain

Hellinger's

$$k(x, y) = \sqrt{xy}$$

$$\Psi(x) = \sqrt{x}$$

Intersection

$$k(x, y) = \min\{x, y\}$$

$$\Psi(x) = \sqrt{\frac{2x}{\pi(1 + 4\omega^2)}} e^{i\omega \log x}$$

X²

$$k(x, y) = \frac{2xy}{x + y}$$

$$\Psi(x) = \sqrt{x \operatorname{sech}(\pi\omega)} e^{i\omega \log x}$$

- Approximate by uniform sampling and truncation

X² 3x approximation

$$\widehat{\Psi}(x) = \begin{bmatrix} 0.8 \sqrt{x} \\ 0.6 \sqrt{x} \cos(0.6 \log x) \\ 0.6 \sqrt{x} \sin(0.6 \log x) \end{bmatrix}$$

VLFeat homogeneous kernel map

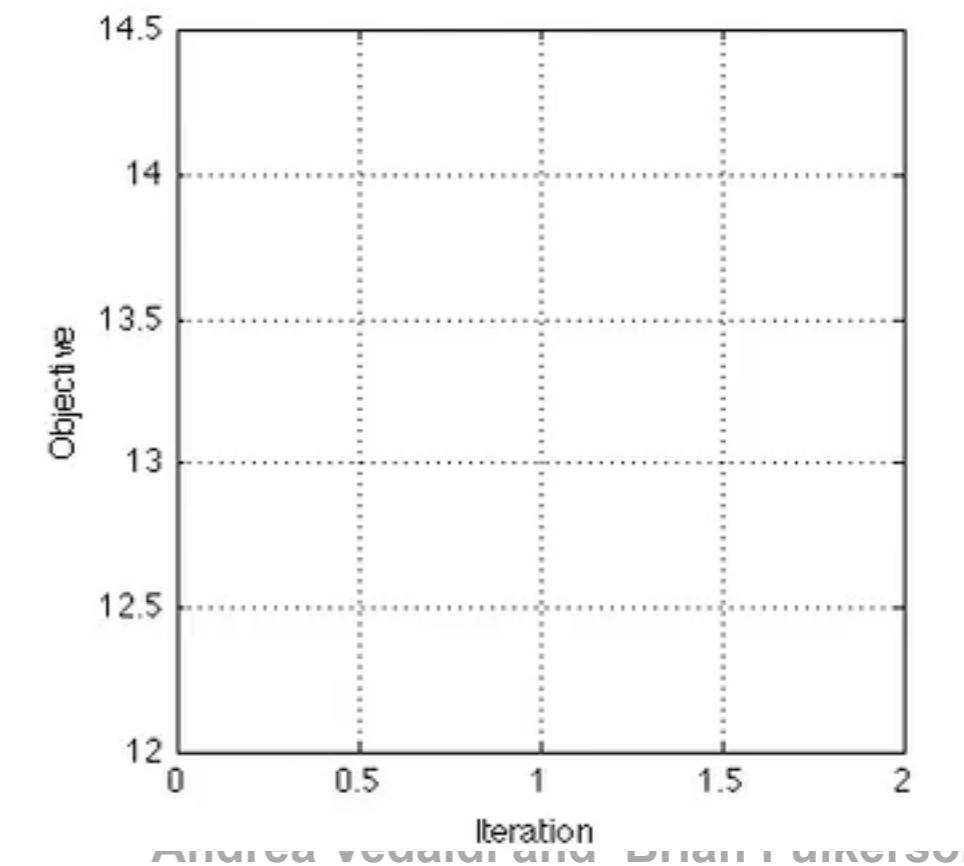
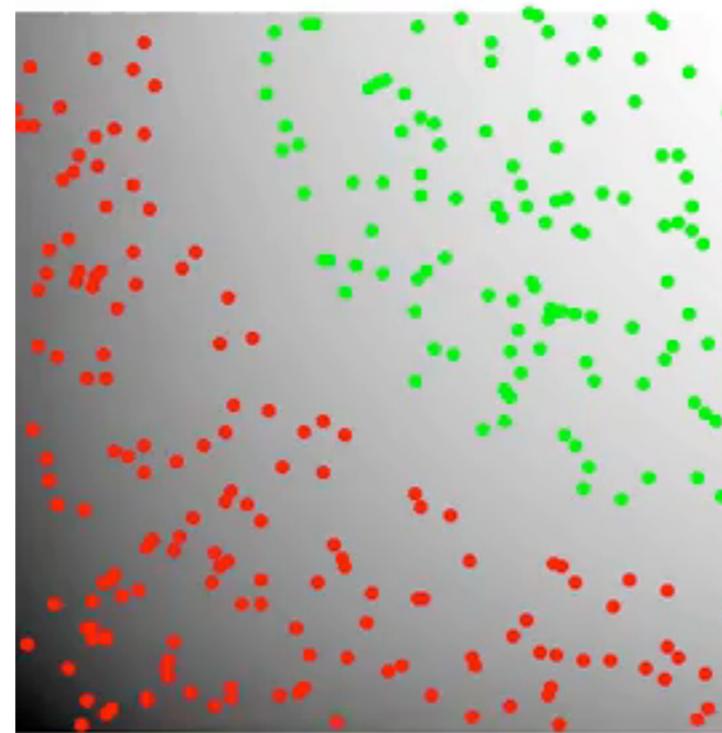
- **x** data (along columns)
- **Linear SVM**

```
w = vl_pegasos(x, y, lambda)
```

- **χ^2 SVM**

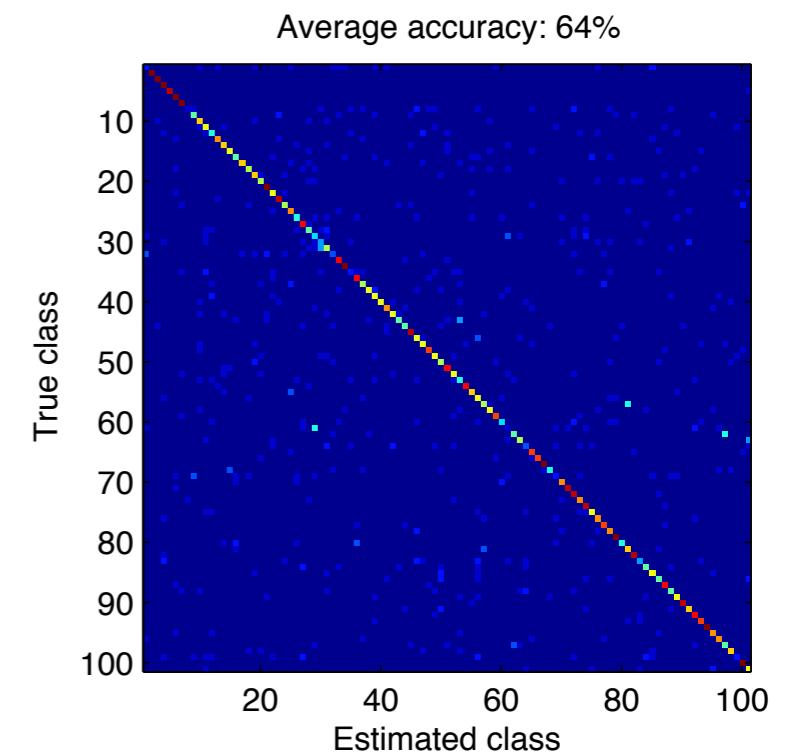
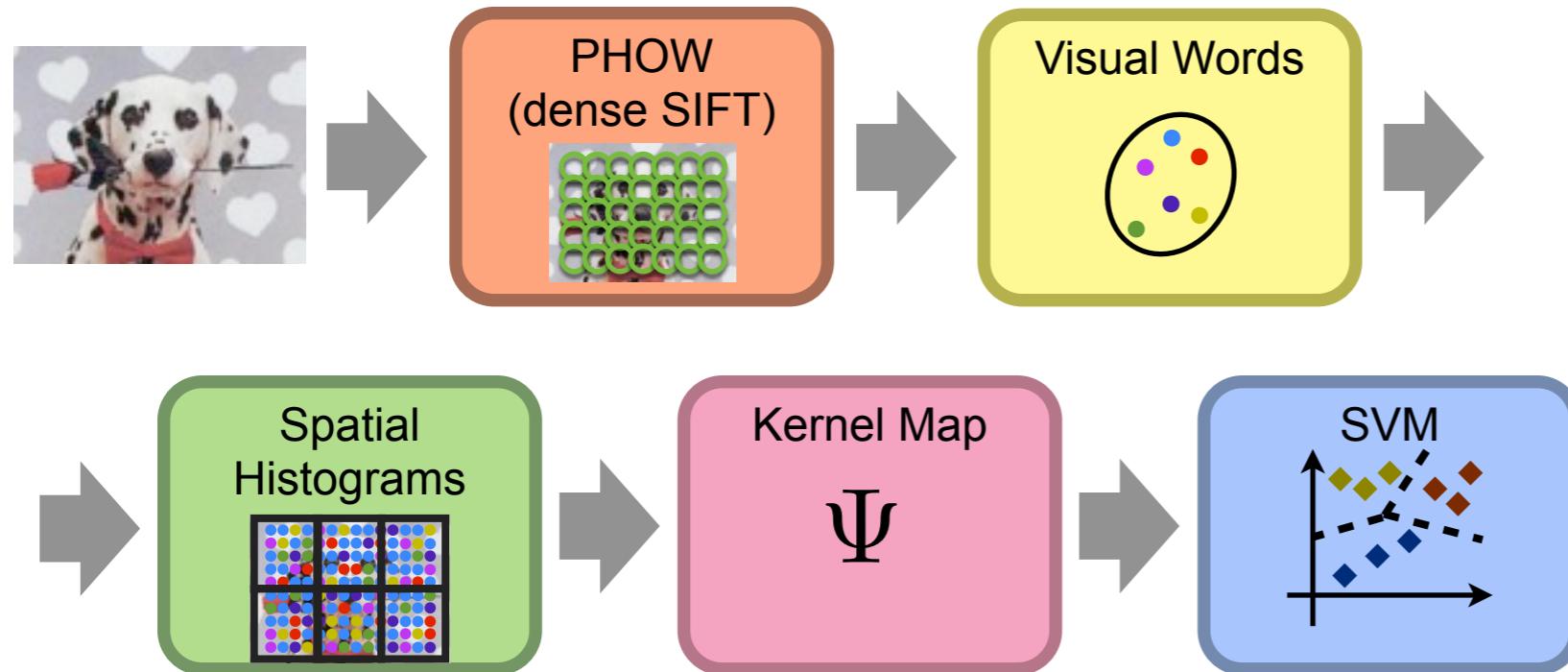
```
psix = vl_homkermap(x, 1, .6, 'kchi2') ;
w = vl_pegasos(psix, y, lambda) ;
```

- Advantages
 - universal (no training)
 - fast computation
 - high accuracy
 - on-line training and HOG like detectors



Other direct feature maps

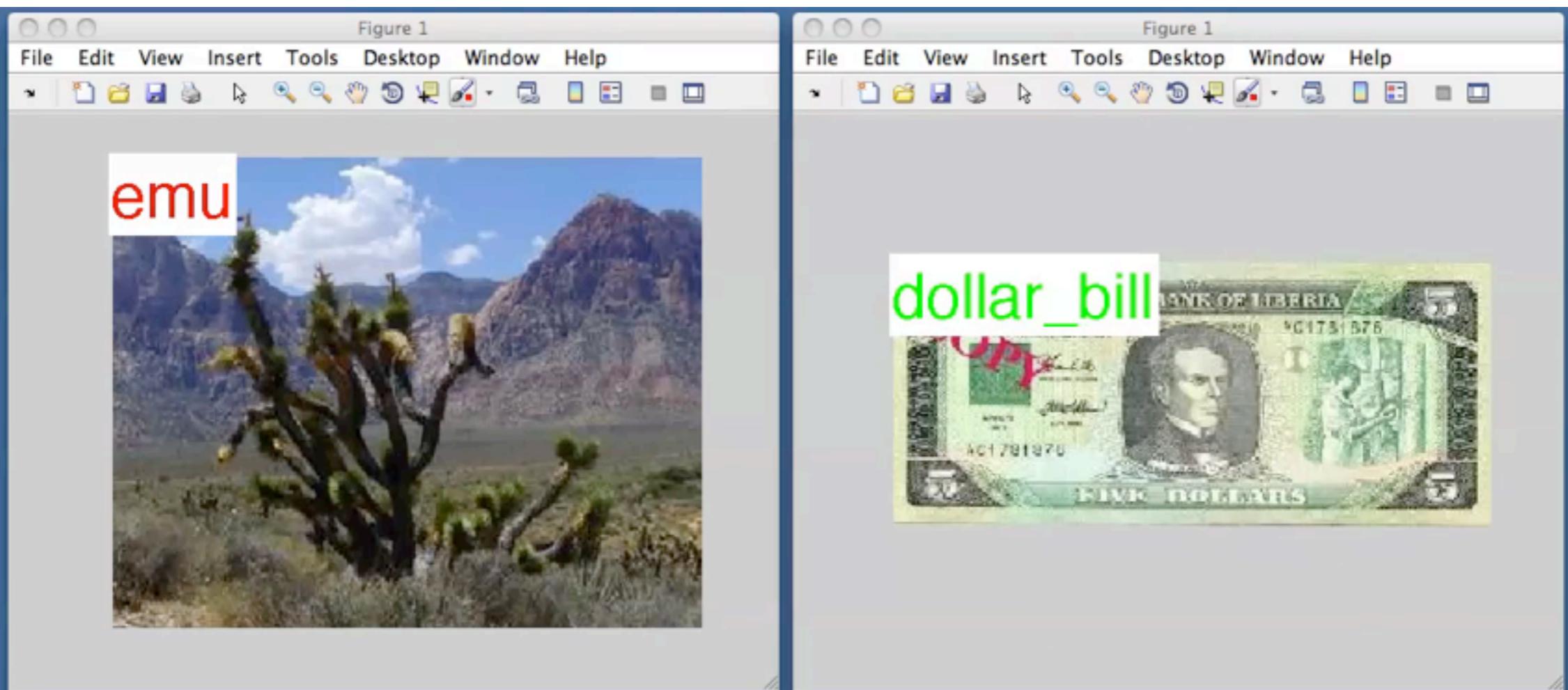
- **Explicit map for intersection kernel**
 - [Maji et al. 2008] and [Maji and Berg 2009]
 - <http://www.cs.berkeley.edu/~smaji/projects/ped-detector/>
 - <http://www.cs.berkeley.edu/~smaji/projects/add-models/>
- **Additive kernel-PCA** for additive kernels
 - [Perronnin et al. 2010]
- **Random Fourier features** for RBF kernels
 - [Rahimi and Recht 2007]
 - <http://people.csail.mit.edu/rahimi/random-features/>



- **PHOW features**
 - Fast dense SIFT ([vl_dsift](#))
- **Visual Words**
 - Elkan k-means ([vl_kmeans](#))
- **Spatial Histograms**
 - Convenience functions
([vl_binsum](#), [vl_binsearch](#))
- **Linear SVM**
 - PEGASOS ([vl_pegasos](#))
- **X² SVM**
 - Homogeneous kernel map
([vl_homkermap](#))

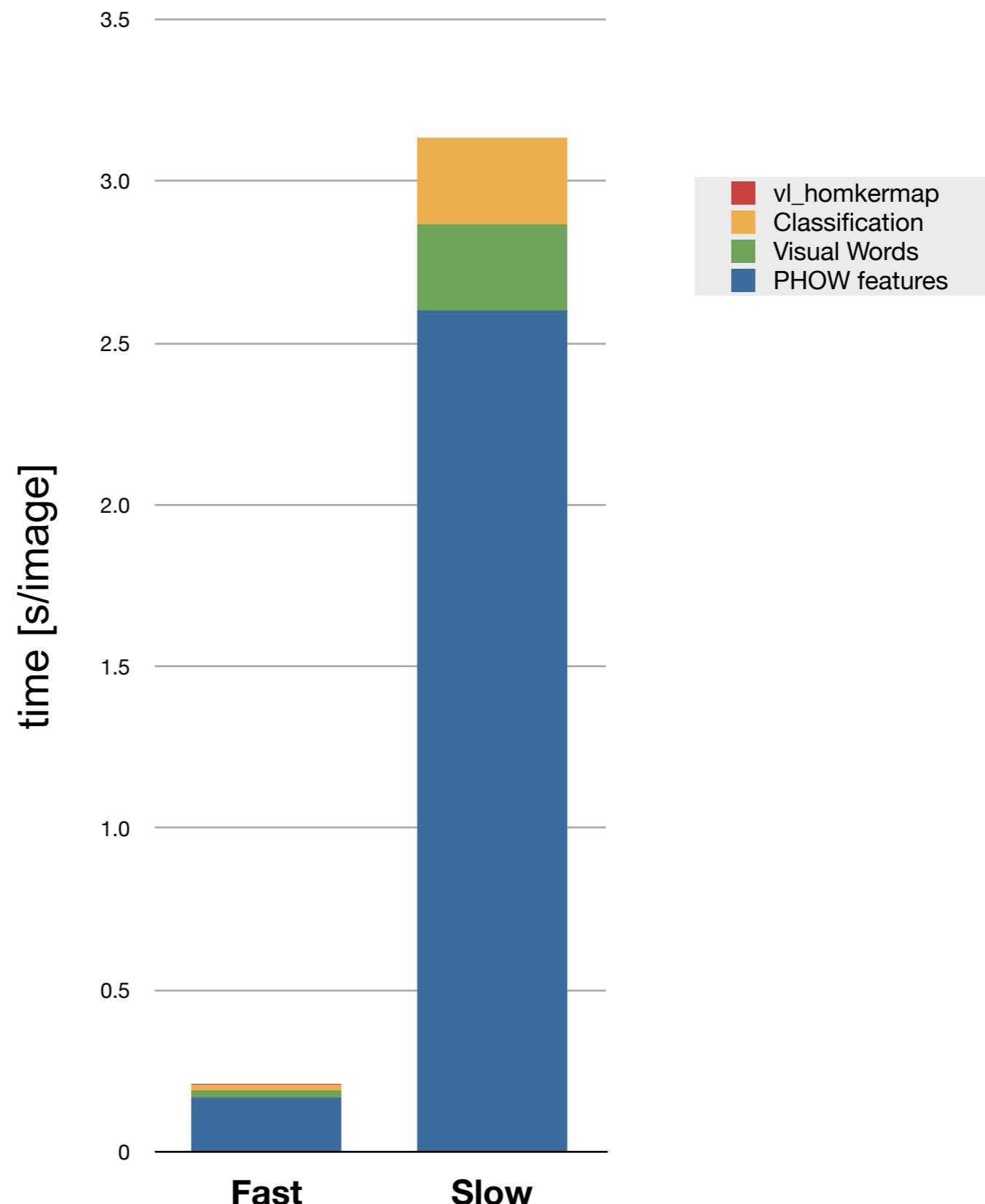
Demo

- Real time classification, 15 training images, 102 classes, 64% accuracy
- **Left**
standard dense SIFT, kernelized SVM
- **Right**
fast dense SIFT, kdtree, homogeneous kernel map SVM

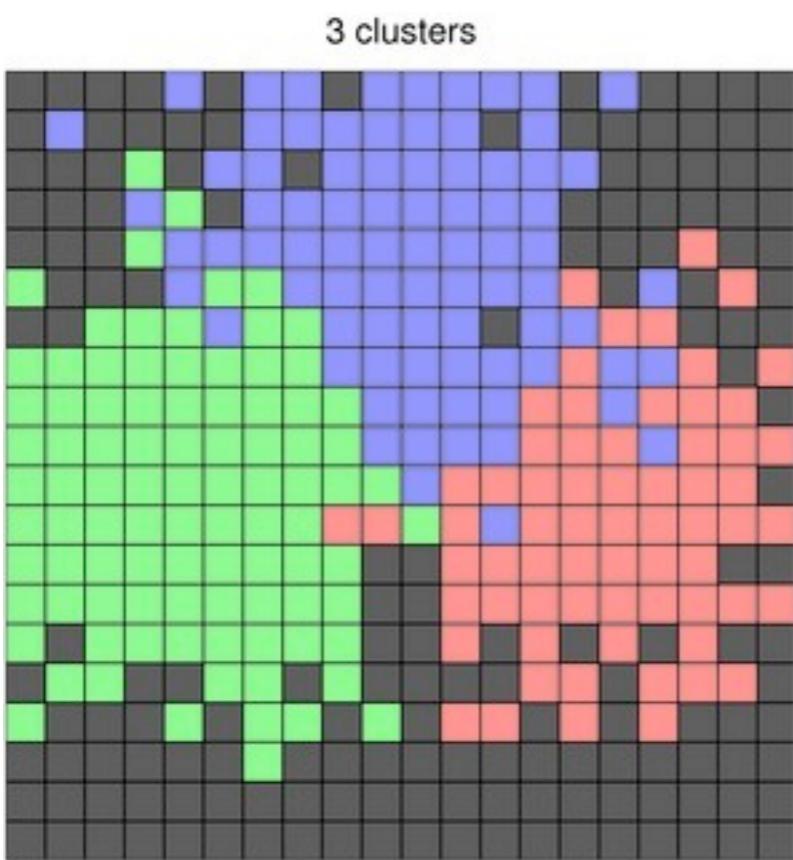
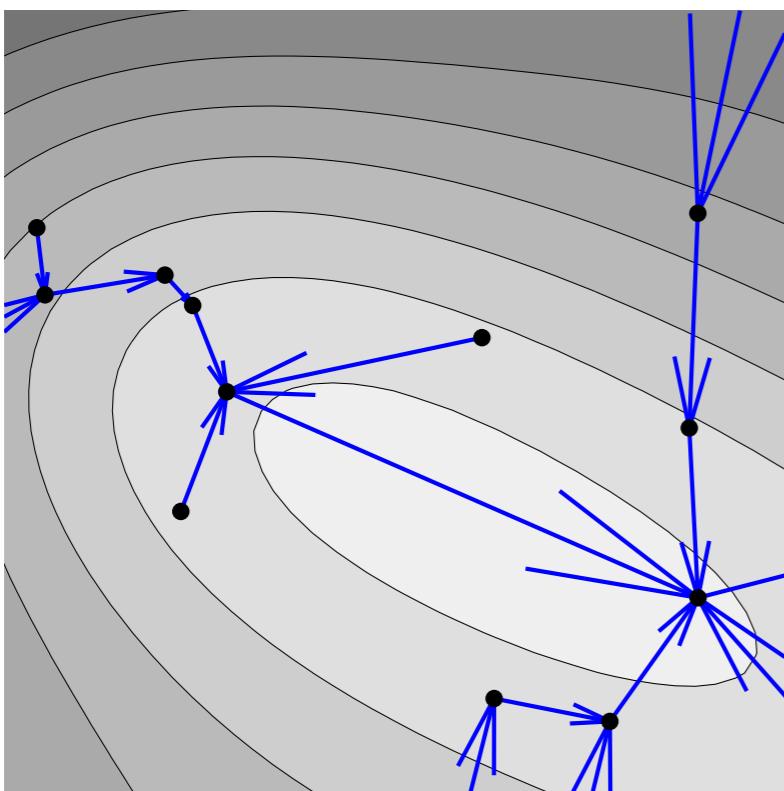


Demo: Speedups

- Feature extraction: 15x
- Feature quantization: 12x
- Classification: 13x
- Overall: 15x



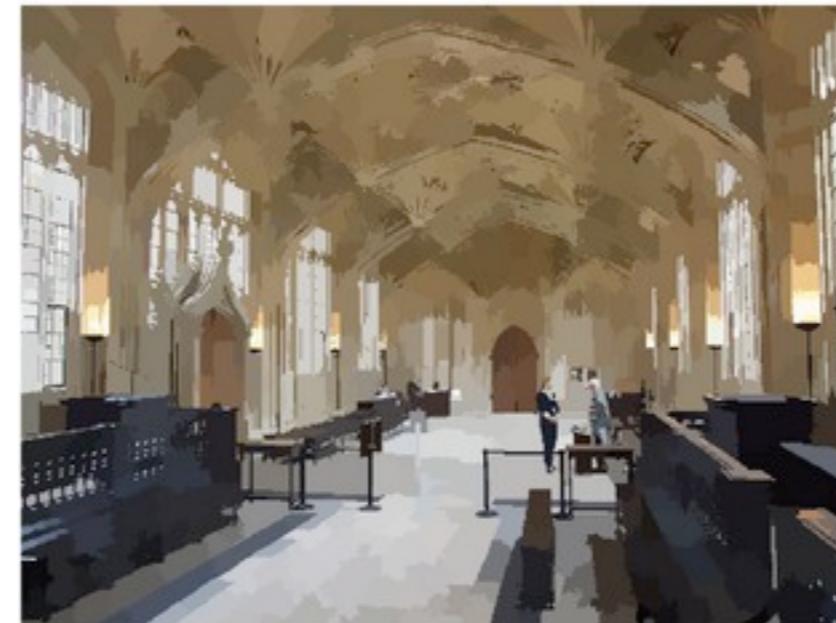
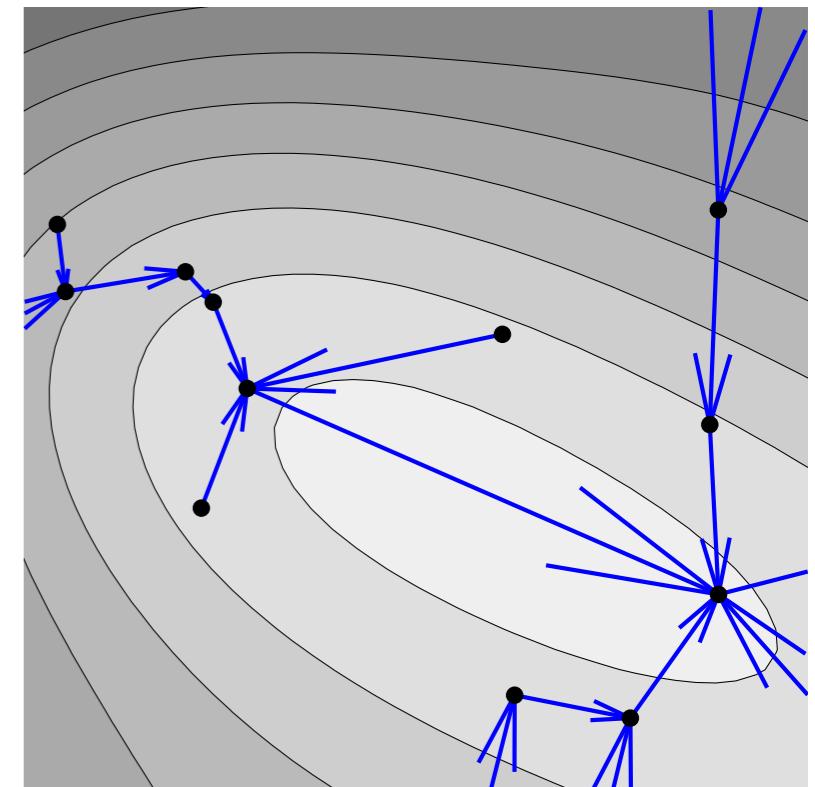
Other features



Quick shift

- Mode seeking algorithm (like mean shift)
 - [Comaniciu and Meer 2002]
[Vedaldi et. al 2008]
 - Connect to the nearest point with higher energy.
 - Break links > maxdist to form clusters.

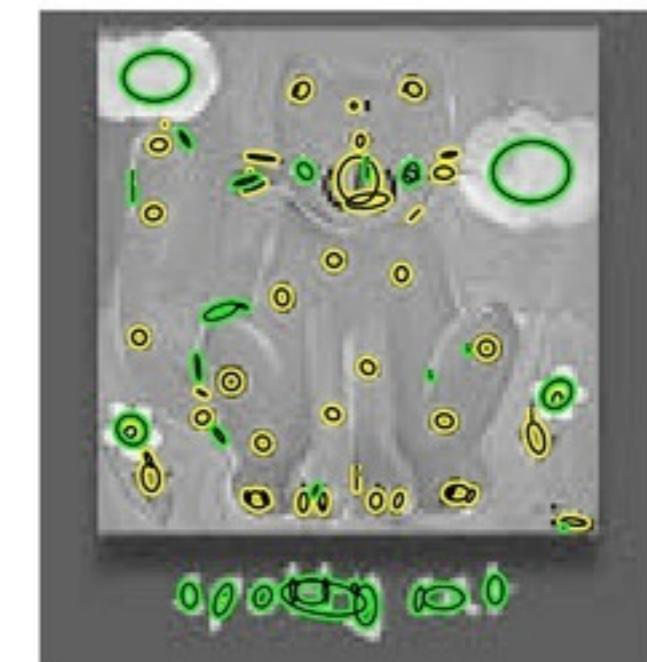
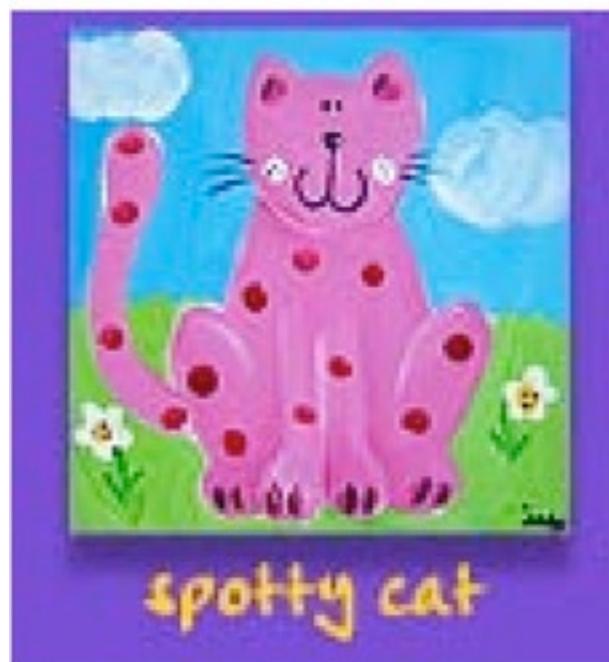
```
ratio = 0.5;
kernelsize = 2;
Iseg = vl_quickseg(I, ratio, kernelsize, maxdist) ;
```



maxdist = 10;



maxdist = 20;
Andrea Vedaldi and Brian Fulkerson



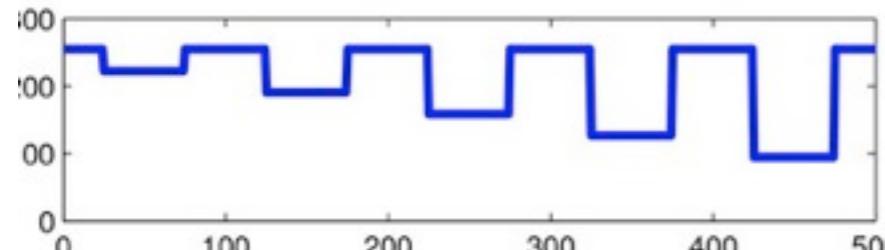
- Extracts MSER regions **regions** and fitted ellipses **frames**:

```
Ig = uint8(rgb2gray(I)) ;  
[regions, frames] = vl_mserv(Ig) ;
```

[Matas et al. 2002]

- Control region stability:

```
[regions, frames] = vl_mserv(Ig, ...  
    'MinDiversity', 0.7, ...  
    'MaxVariation', 0.2, ...  
    'Delta', 10) ;
```



delta = 1



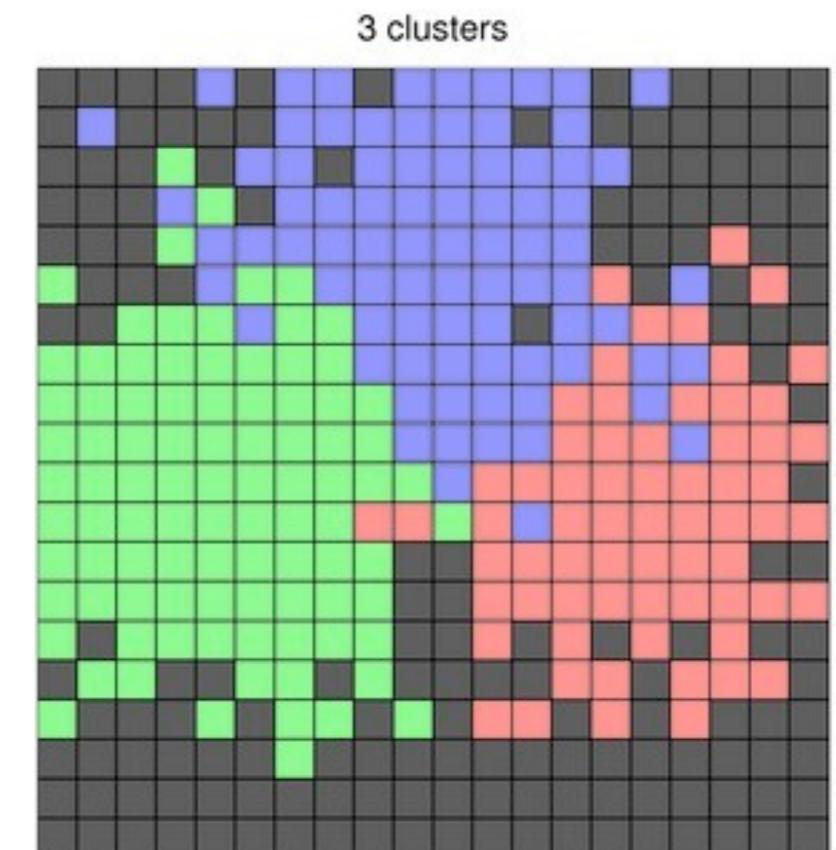
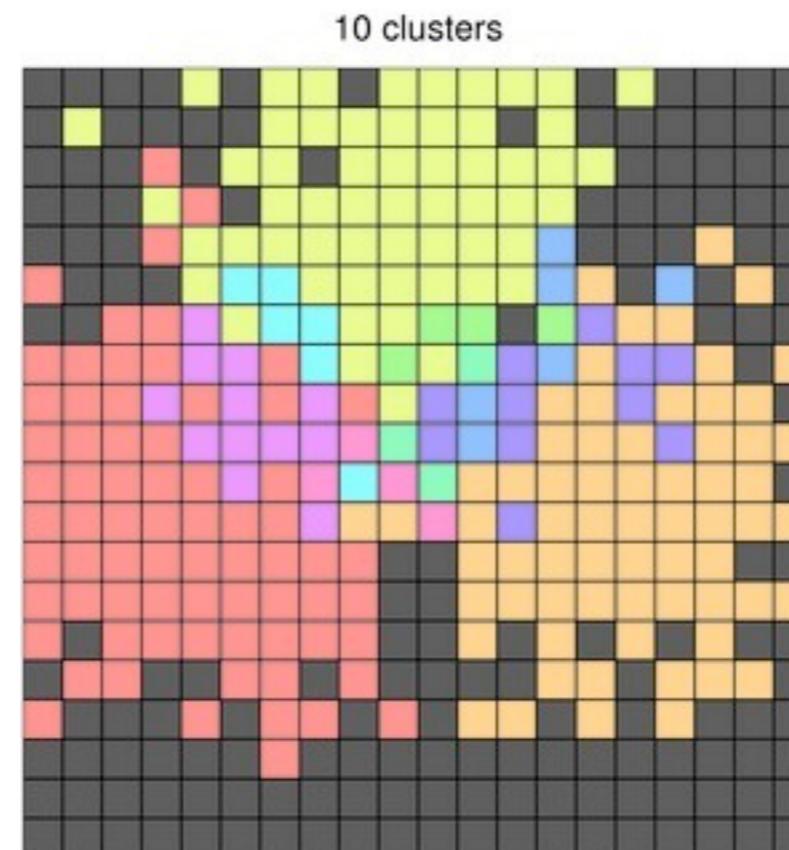
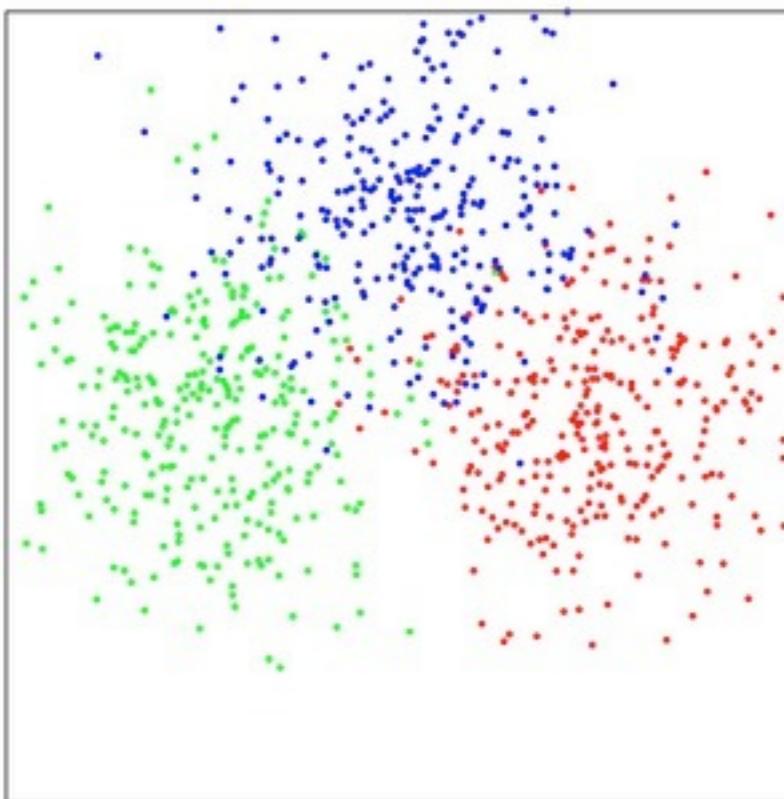
delta = 32



Agglomerative Information Bottleneck (AIB)

- Merge (visual) words while preserving information
 - given word-class co-occurrence matrix P_{cx}
 $[parents, cost] = \text{vl_aib}(P_{cx}) ;$
 - produces a tree of merged words
 - tree cut
 = partition of words
 = simplified dictionary

[Slonim and Tishby 1999]
 [Fulkerson et al. 2008]

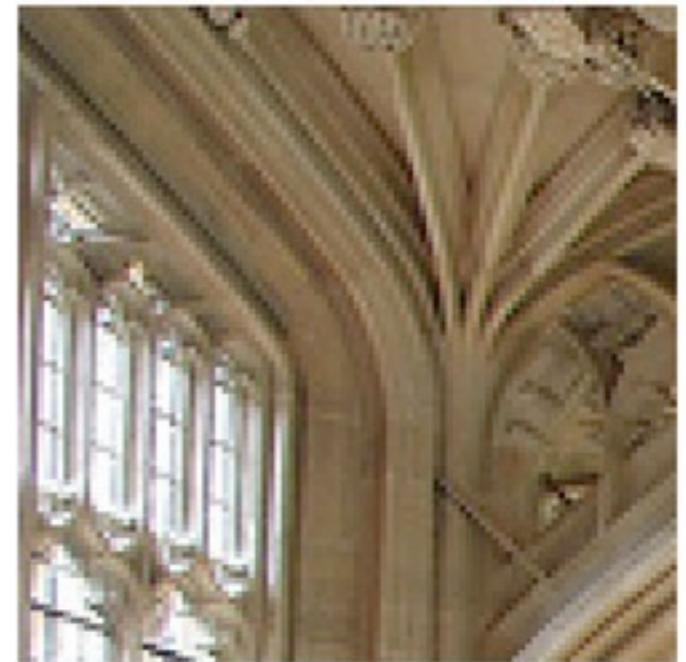


Fast image distance transform

- [Felzenszwalb and Huttenlocher 2004]
- Compute feature responses (e.g. edges):


```
edges = zeros(imsiz) + inf ;
edges(edge(rgb2gray(im), 'canny')) = 0 ;
```
- For each point, find `nearest` edge and its `distance`:


```
[distance, nearest] = vl_imdisttf(single(edges));
```



- Built-in MATLAB help

help `vl_sift`

VL_SIFT Scale-Invariant Feature Transform
 $F = VL_SIFT(I)$ computes the SIFT frames [1] (keypoints) F of the image I . I is a gray-scale image in single precision. Each column of F is a feature frame and has the format $[X;Y;S;TH]$, where X,Y is the (fractional) center of the frame, S is the scale and TH is the orientation (in radians).

$[F,D] = VL_SIFT(I)$ computes the SIFT descriptors [1] as well. Each column of D is the descriptor of the corresponding frame in F . A descriptor is a 128-dimensional vector of class `UINT8`.

`VL_SIFT()` accepts the following options:

Octaves:: [maximum possible]
Set the number of octave of the DoG scale space.

Levels:: [3]
Set the number of levels per octave of the DoG scale space.

FirstOctave:: [0]
Set the index of the first octave of the DoG scale space.

PeakThresh:: [0]
Set the peak selection threshold.

EdgeThresh:: [10]
Set the non-edge selection threshold.

NormThresh:: [-inf]
Set the minimum l2-norm of the descriptors before normalization. Descriptors below the threshold are set to zero.

Magnif:: [3]
Set the descriptor magnification factor. The scale of the keypoint is multiplied by this factor to obtain the width (in pixels) of the spatial bins. For instance, if there are 4 spatial bins along each spatial direction, the ``side'' of the descriptor is approximatively $4 * MAGNIF$.

WindowSize:: [2]
Set the variance of the Gaussian window that determines the descriptor support. It is expressend in units of spatial bins.

- Also available as HTML

http://www.vlfeat.org/doc/mdoc/VL_SIFT.html

[Index](#) [Prev](#) [Next](#)

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VL_SIFT() accepts the following options:

Octaves [maximum possible]

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Levels [3]

Set the number of levels per octave of the DoG scale space.

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Set the index of the first octave of the DoG scale space.

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Set the peak selection threshold.

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Set the descriptor magnification factor. The scale of the keypoint is multiplied by this factor to obtain the width (in pixels) of the spatial bins. For instance, if there are 4 spatial bins along each spatial direction, the ``side'' of the descriptor is approximatively $4 * MAGNIF$.

WindowSize [2]

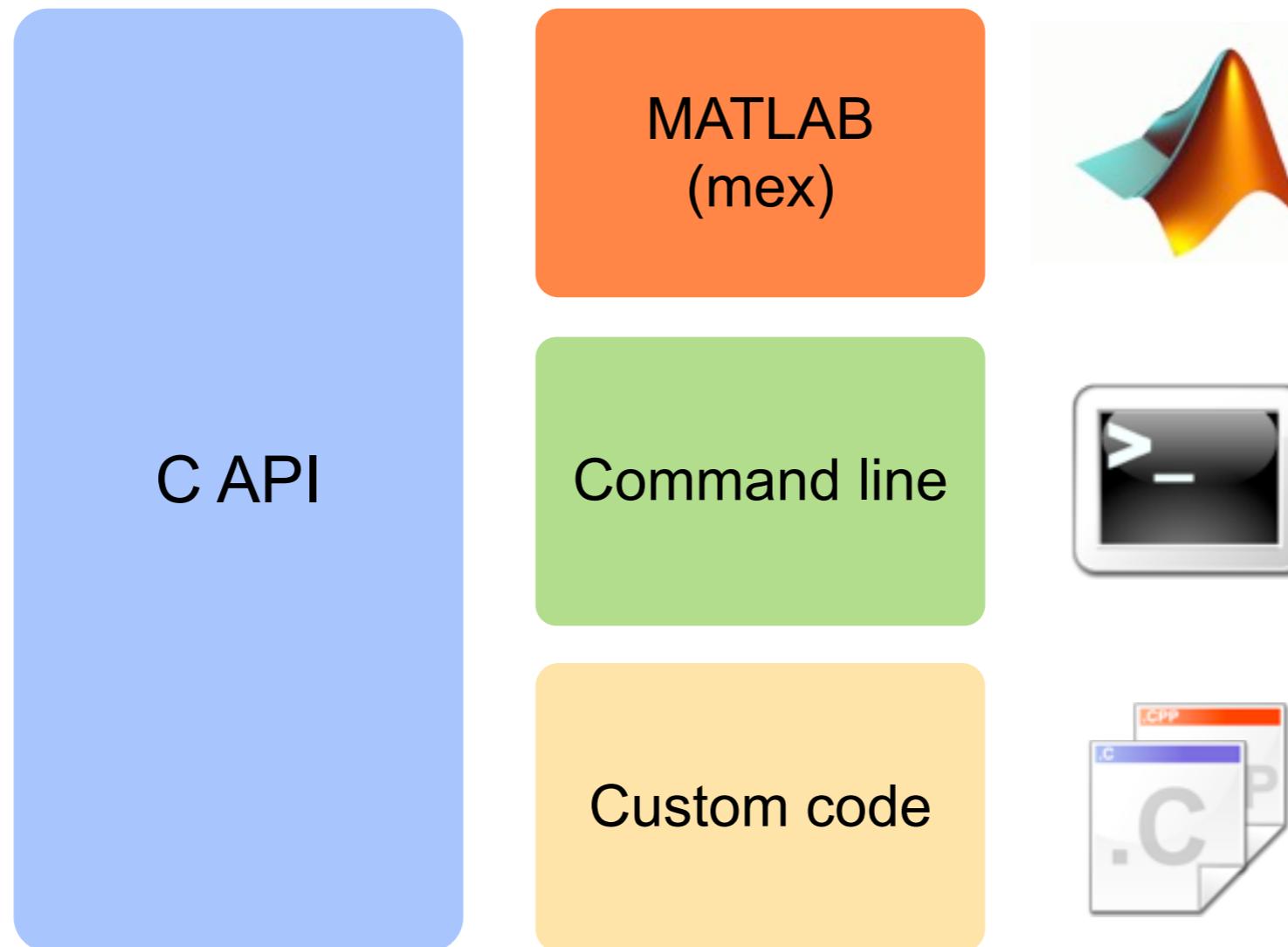
Set the variance of the Gaussian window that determines the descriptor support. It is expressend in units of spatial bins.

Frames [not specified]

If specified, set the frames to use (bypass the detector). If frames are not passed in order of increasing scale, they are re-ordered.

Orientations

- Components



- No dependencies
- C implementation

• Full algorithm details

- embedded in source code
- Doxygen format <http://www.doxygen.org>

number of scale levels per octave	detector	vl_sift_new	features
SIFT detector	vl_sift_new		can affect the number of extracted keypoints
edge threshold	SIFT detector	vl_sift_set_edge_thresh	decrease to eliminate more keypoints
peak threshold	SIFT detector	vl_sift_set_peak_thresh	increase to eliminate more keypoints

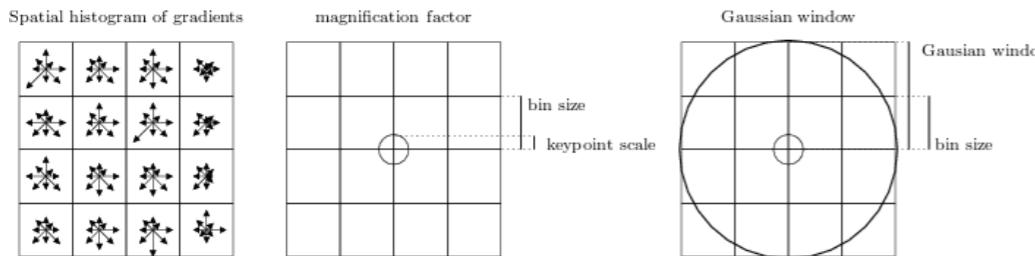
Summary of the parameters influencing the SIFT detector.

SIFT Descriptor

See also:

[Descriptor technical details](#)

A SIFT descriptor is a 3-D spatial histogram of the image gradients in characterizing the appearance of a keypoint. The gradient at each pixel is regarded as a sample of a three-dimensional elementary feature vector, formed by the pixel location and the gradient orientation. Samples are weighed by the gradient norm and accumulated in a 3-D histogram h , which (up to normalization and clamping) forms the SIFT descriptor of the region. An additional Gaussian weighting function is applied to give less importance to gradients farther away from the keypoint center. Orientations are quantized into eight bins and the spatial coordinates into four each, as follows:

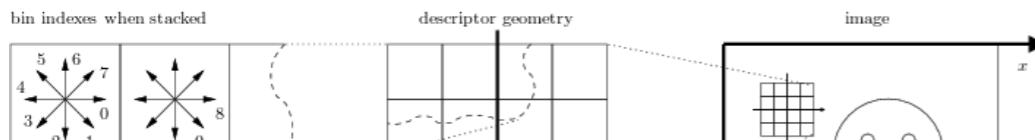


The SIFT descriptor is a spatial histogram of the image gradient.

SIFT descriptors are computed by either calling [vl_sift_calc_keypoint_descriptor](#) or [vl_sift_cal_keypoint_descriptor_raw](#). They accept as input a keypoint frame, which specifies the descriptor center, its size, and its orientation on the image plane. The following parameters influence the descriptor calculation:

- **magnification factor**. The descriptor size is determined by multiplying the keypoint scale by this factor. It is set by [vl_sift_set_magnif](#).
- **Gaussian window size**. The descriptor support is determined by a Gaussian window, which discounts gradient contributions farther away from the descriptor center. The standard deviation of this window is set by [vl_sift_set_window_size](#) and expressed in unit of bins.

VLFeat SIFT descriptor uses the following convention. The y axis points downwards and angles are measured clockwise (to be consistent with the standard image convention). The 3-D histogram (consisting of $8 \times 4 \times 4 = 128$ bins) is stacked as a single 128-dimensional vector, where the fastest varying dimension is the orientation and the slowest the y spatial coordinate. This is illustrated by the following figure.



[vl_kmeans_get_centers](#) to obtain the `numCluster` cluster centers. Use [vl_kmeans_push](#) to quantize new data points.

Initialization algorithms

[kmeans.h](#) supports the following cluster initialization algorithms:

- **Random data points** ([vl_kmeans_init_centers_with_rand_data](#)) initialize the centers from a random selection of the training data.
- **k-means++** ([vl_kmeans_init_centers_plus_plus](#)) initialize the centers from a random selection of the training data while attempting to obtain a good coverage of the dataset. This is the strategy from [1].

Optimization algorithms

[kmeans.h](#) supports the following optimization algorithms:

- **Lloyd** [2] ([VIKMeansLloyd](#)). This is the standard k-means algorithm, alternating the estimation of the point-to-cluster membership and of the cluster centers (means in the Euclidean case). Estimating membership requires computing the distance of each point to all cluster centers, which can be extremely slow.
- **Elkan** [3] ([VIKMeansElkan](#)). This is a variation of [2] that uses the triangular inequality to avoid many distance calculations when assigning points to clusters and is typically much faster than [2]. However, it uses storage proportional to the square of the number of clusters, which makes it unpractical for a very large number of clusters.

Technical details

Given data points $x_1, \dots, x_n \in R^d$, k-means searches for k vectors $c_1, \dots, c_n \in R^d$ (cluster centers) and a function $\pi : \{1, \dots, n\} \rightarrow \{1, \dots, k\}$ (cluster memberships) that minimize the objective:

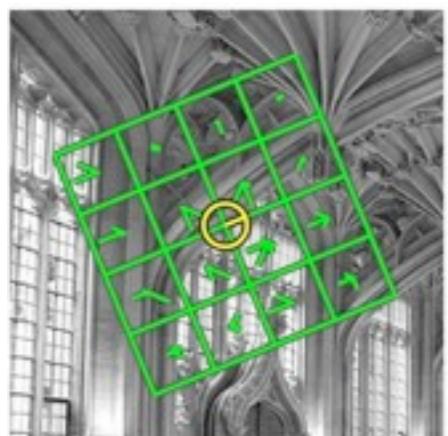
$$E(c_1, \dots, c_n, \pi) = \sum_{i=1}^n d^2(x_i, c_{\pi(i)})$$

A simple procedure due to Lloyd [2] to locally optimize this objective alternates estimating the cluster centers and the membership function. Specifically, given the membership function π , the objective can be minimized independently for each c_k by minimizing

$$\sum_{i:\pi(i)=k} d^2(x_i, c_k)$$

For the Euclidean distance, the minimizer is simply the mean of the points assigned to that cluster. For other distances, the minimizer is a generalized average. For instance, for the l^1 distance, this is the median. Assuming that computing the average is linear in the number of points and the data dimension, this step requires $O(nd)$ operations.

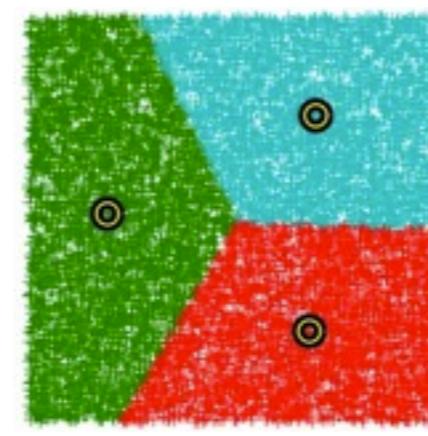
Summary



features

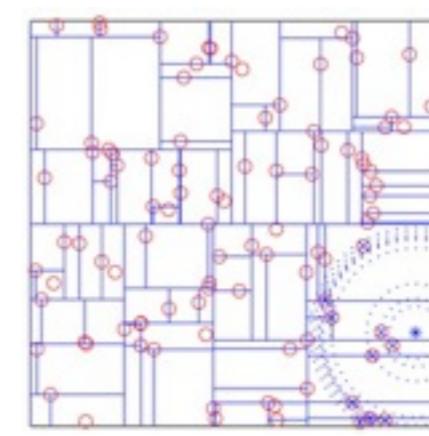


,



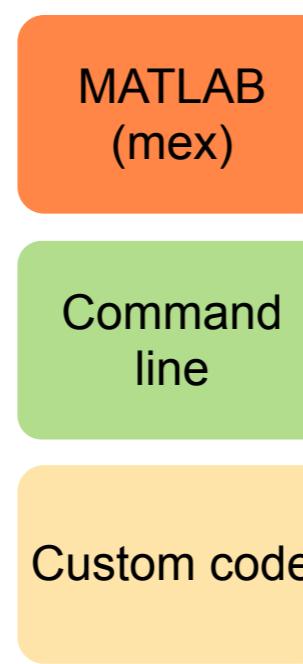
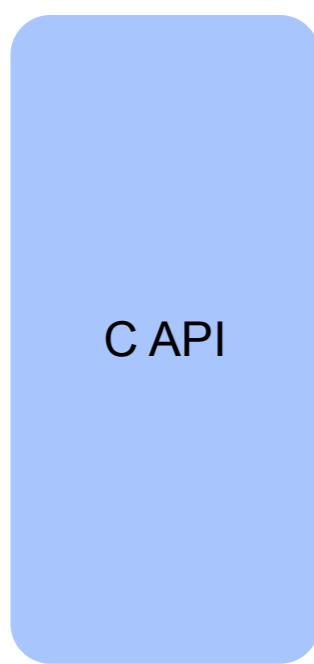
clustering

,

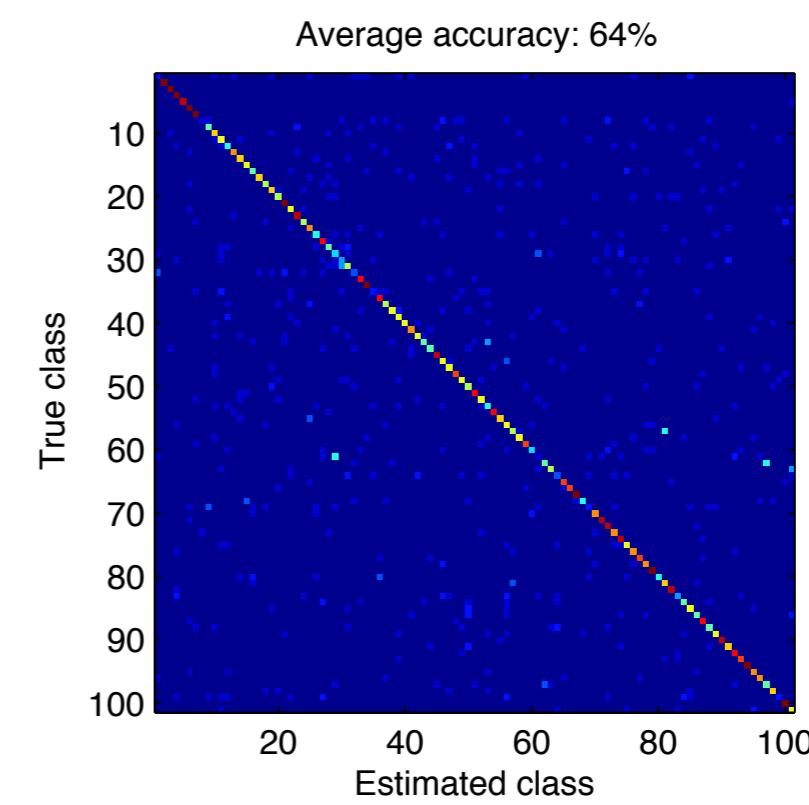
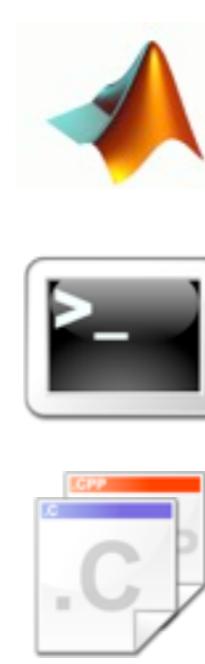


matching

• • •



Command
line



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