Category-level localization

Cordelia Schmid

Category-level localization

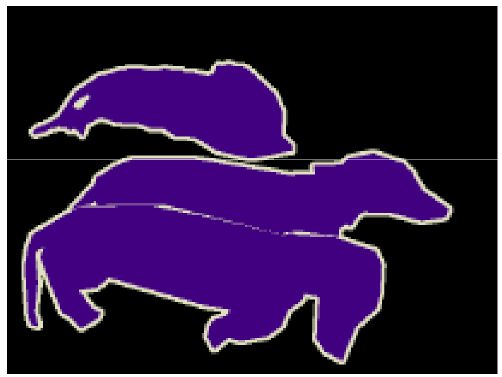
- Localization of object outlines

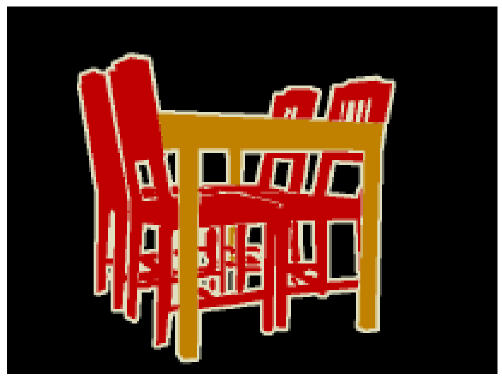
Learning shape-based models

Localizing the objects with the learnt models

Category-level localization

- Localization of object pixels
  - Pixel-level classification, segmentation



Overview

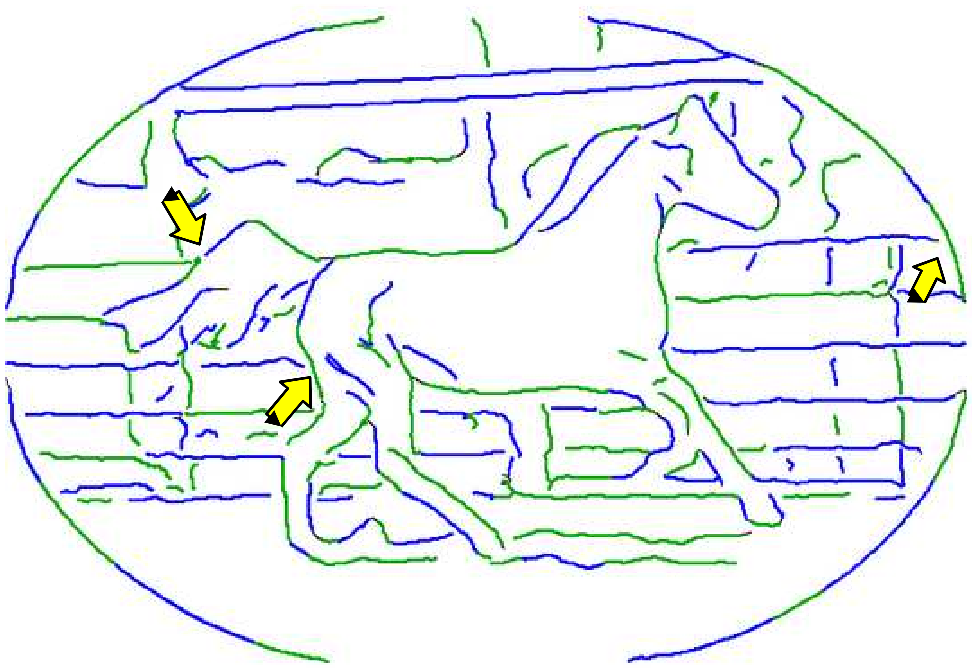
- *Shape-based descriptors*
- Learning deformable shape models

Shape-based features for localization

- Classes with characteristic shape
  - appearance, local patches are not adapted
  - shape-based descriptors are necessary

[Ferrari, Fevrier, Jurie & Schmid, PAMI’08]

Pairs of adjacent segments (PAS)

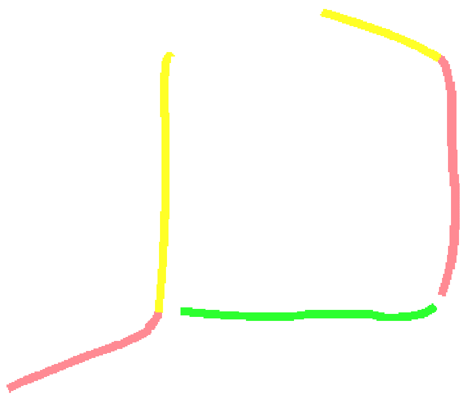


Contour segment network

[Ferrari et al. ECCV'06]

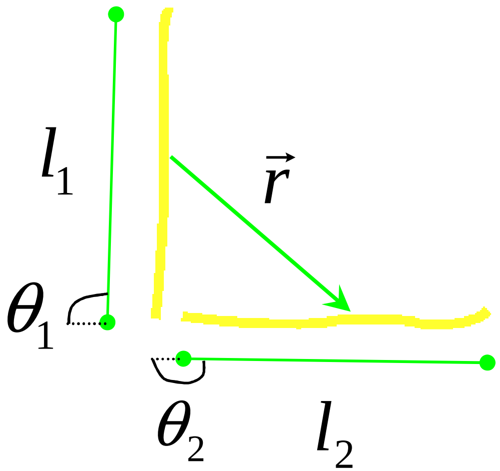
1. Edgels extracted with Berkeley boundary detector
2. Edgel-chains partitioned into straight contour segments
3. Segments connected at edgel-chains' endpoints and junctions

Pairs of adjacent segments (PAS)



Contour segment network

PAS = groups of two connected segments



PAS descriptor:

$$\left(\frac{r_x}{\|\vec{r}\|}, \frac{r_y}{\|\vec{r}\|}, \theta_1, \theta_2, \frac{l_1}{\|\vec{r}\|}, \frac{l_2}{\|\vec{r}\|} \right)$$

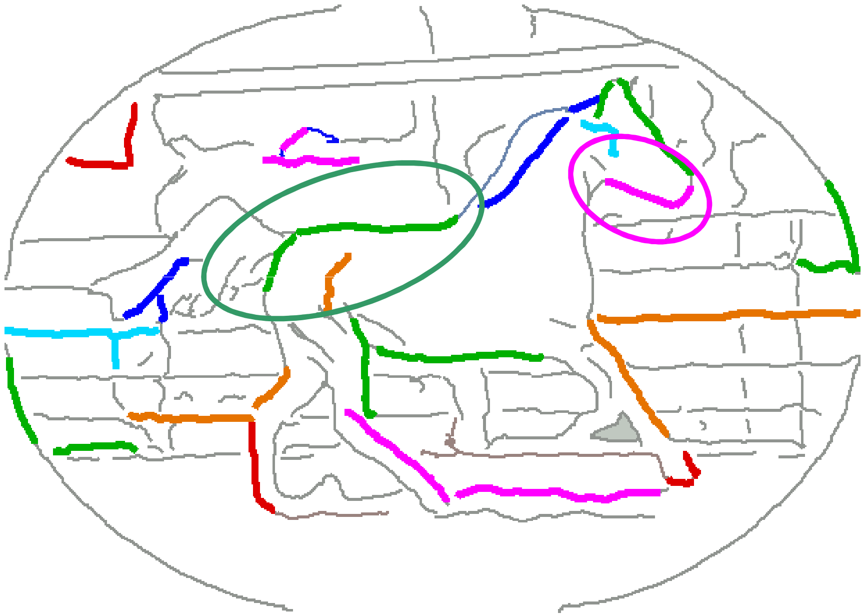
encodes *geometric* properties of the PAS

scale and translation invariant

compact, 5D

Features: pairs of adjacent segments (PAS)

Example PAS



Why PAS ?

+ can cover pure portions of the object boundary

+ intermediate complexity: good repeatability-informativeness trade-off

+ scale-translation invariant

+ connected: natural grouping criterion (need not choose a grouping neighborhood or scale)

PAS codebook

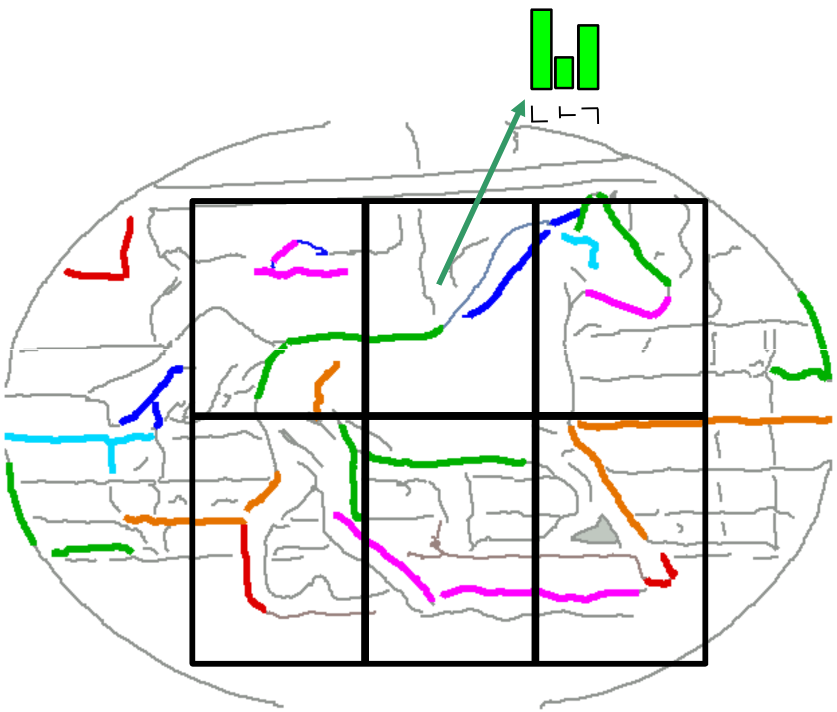
PAS descriptors are clustered into a vocabulary

a few types from 15 indoor images

- Frequently occurring PAS have intuitive, natural shapes
- As we add images, number of PAS types converges to just ~100
- Very similar codebooks come out, regardless of source images

→ general, simple features

Window descriptor



1. Subdivide window into tiles

2. Compute a separate bag of PAS per tile

3. Concatenate these semi-local bags

\+ distinctive:

records *which* PAS appear *where*

weight PAS by average edge strength

\+ flexible*:*

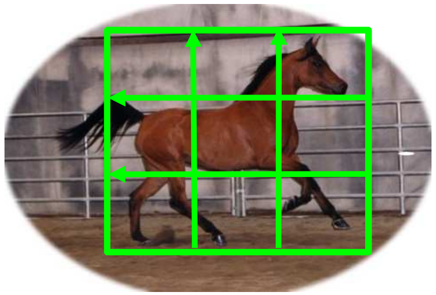
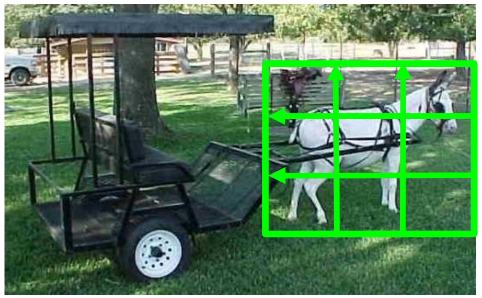
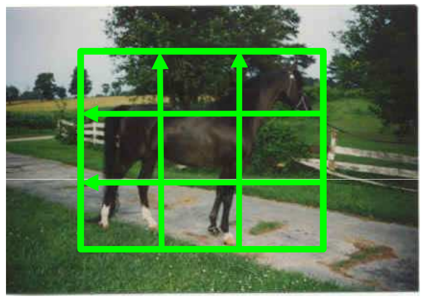
soft-assign PAS to types, coarse tiling

\+ fast:

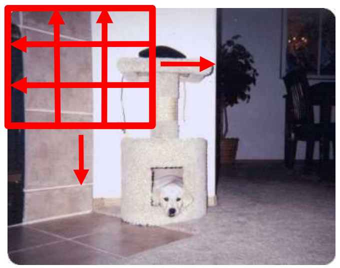
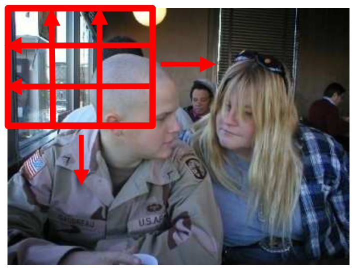
computation with Integral Histograms

Training

1. Learn mean positive window dimensions $M_w \times M_h$
2. Determine number of tiles T
3. Collect positive example descriptors

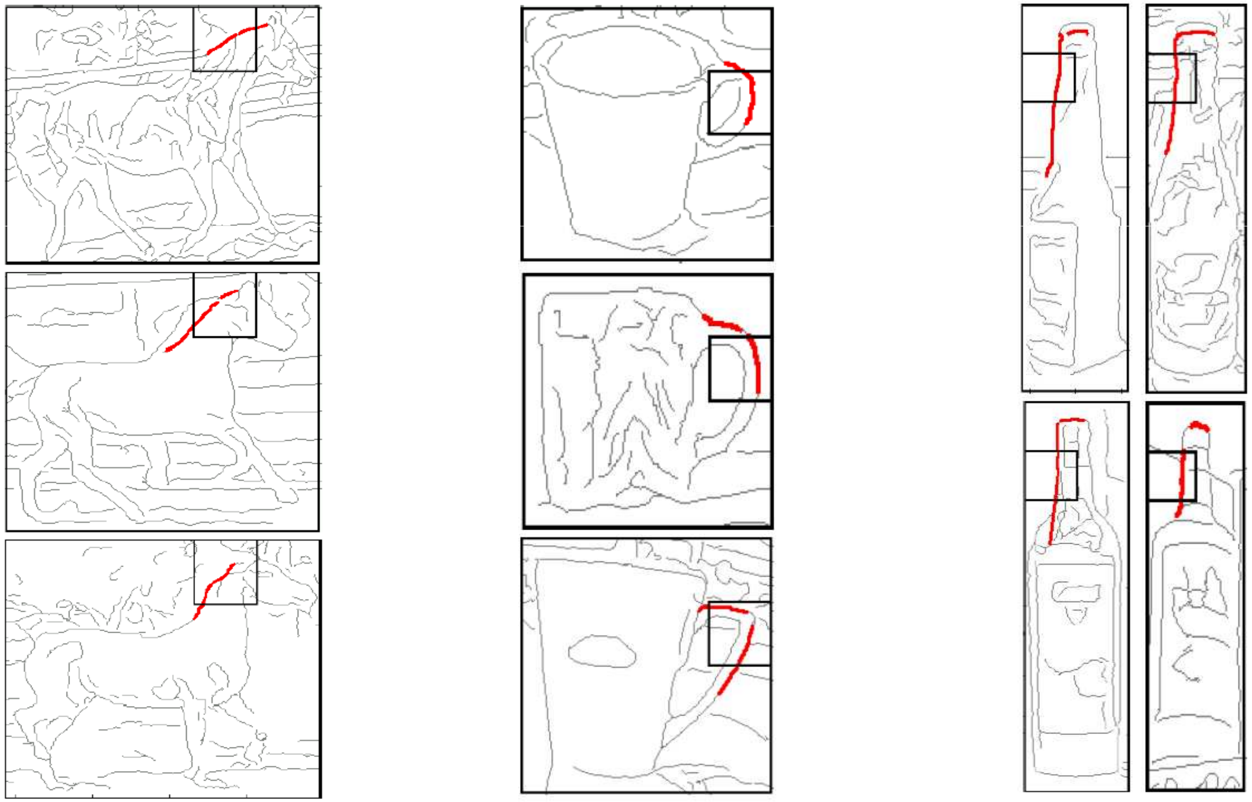
4. Collect negative example descriptors:
   slide $M_w \times M_h$ window over negative training images


Training

5. Train a linear SVM from positive and negative window descriptors

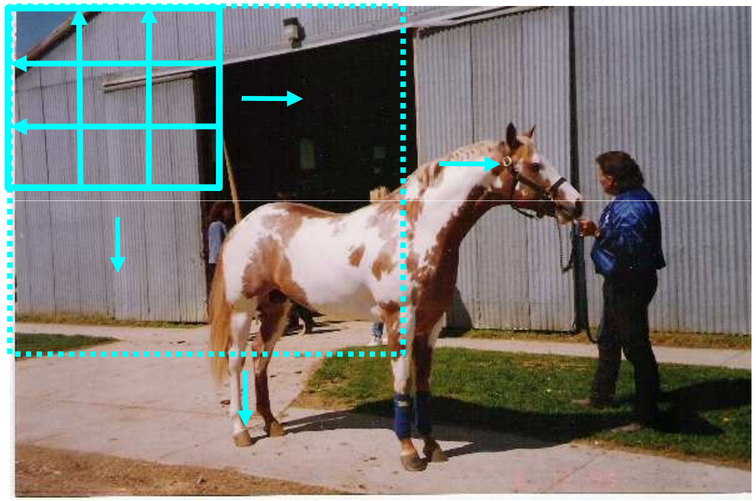
A few of the highest weighed descriptor vector dimensions (= 'PAS + tile')



+ lie on object boundary (= local shape structures common to many training exemplars)

Testing

1. Slide window of aspect ratio M_w / M_h at multiple scales

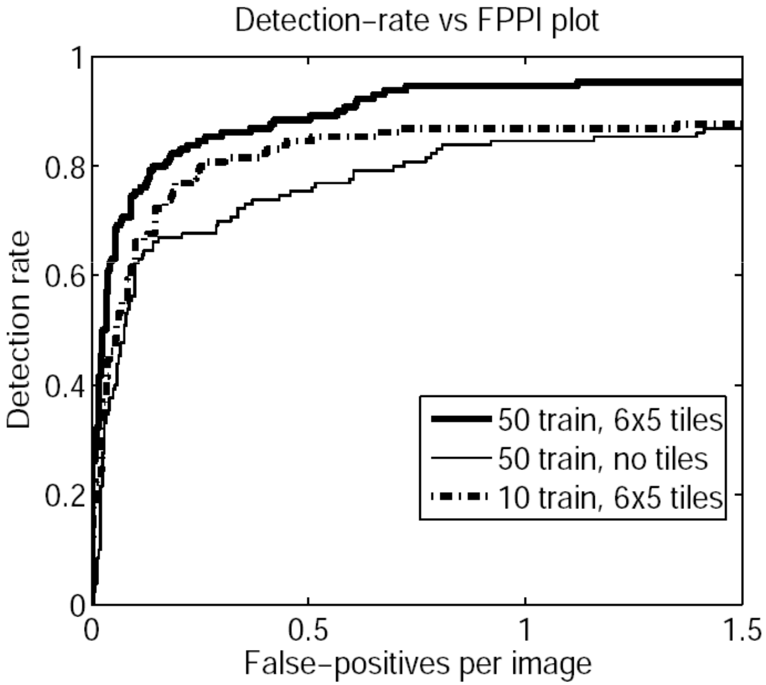


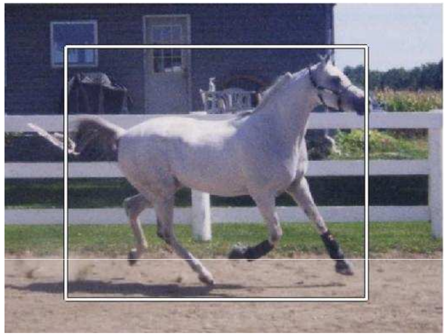
2. SVM classify each window + non-maxima suppression

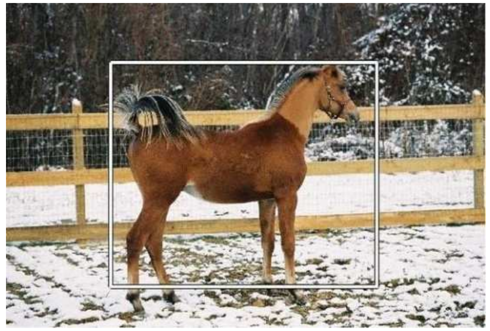
$\longrightarrow$ detections

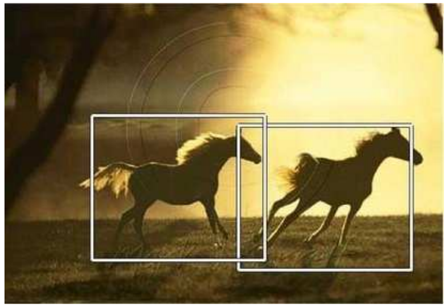
Experimental results – INRIA horses

Dataset: 170 positive + 170 negative images (training = 50 pos + 50 neg)
wide range of scales; clutter









(missed and FP)

+ tiling brings a substantial improvement
optimum at T=30 → used for all other experiments

+ works well: 86% det-rate at 0.3 FPPI (50 pos + 50 neg training images)

Experimental results – INRIA horses

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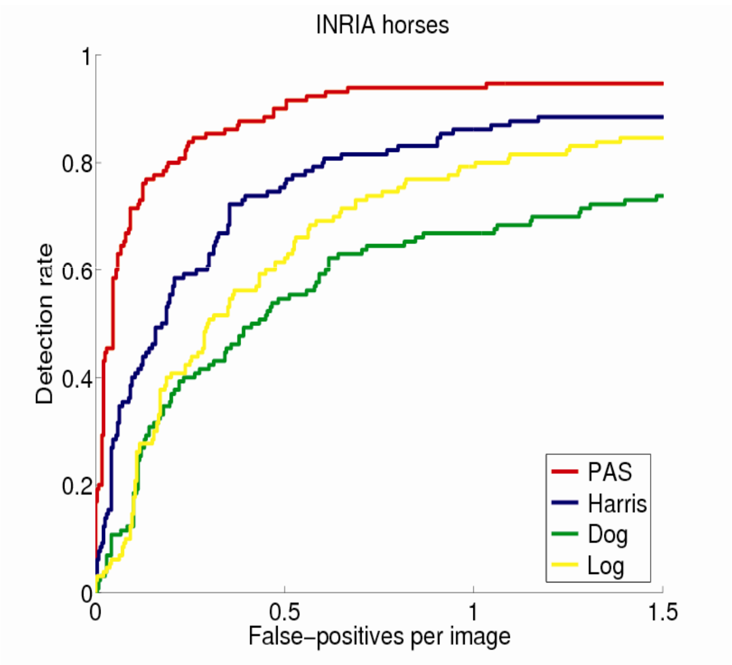
wide range of scales; clutter



+ PAS better than any interest point detector

- all interest point (IP) comparisons with T=10, and 120 feature types (= optimum over INRIA horses, and ETHZ Shape Classes)
- IP codebooks are class-specific

Results – ETH shape classes

Dataset: 255 images, 5 classes; large scale changes, clutter

training = half of positive images for a class

+ same number from the other classes (1/4 from each)

testing = all other images

Results – ETH shape classes

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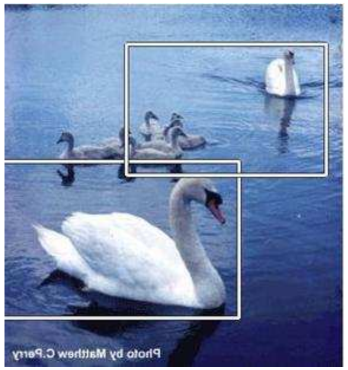
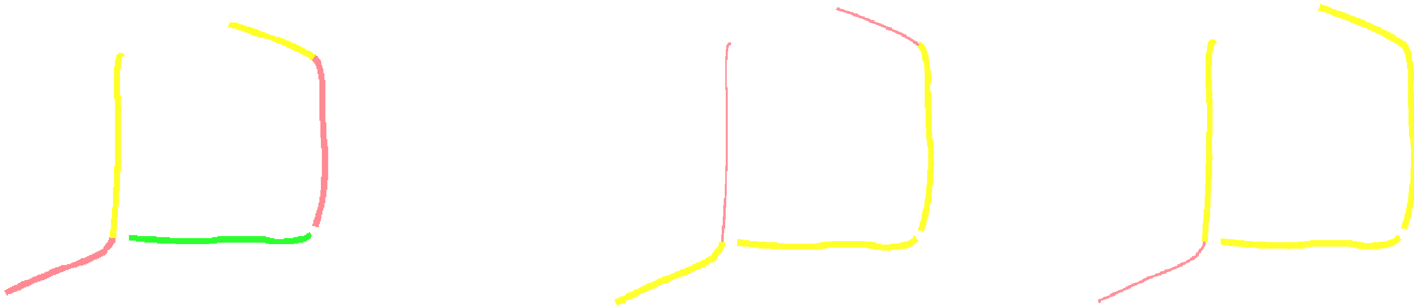


Missed

Generalizing PAS to *k*AS

*k*AS: any path of length *k* through the contour segment network



segment network   3AS   4AS

scale+translation invariant descriptor with dimensionality 4*k*-2

k = feature complexity; higher *k* more informative, but less repeatable

overall mean det-rates (%)

	1AS	PAS	3AS	4AS
0.3 FPPI	69	77	64	57
0.4 FPPI	76	82	70	64

PAS do best !

Overview

- Localization with shape-based descriptors
- *Learning deformable shape models*

Learning deformable shape models from images

Training data

Goal: localize boundaries of class instances

Test image

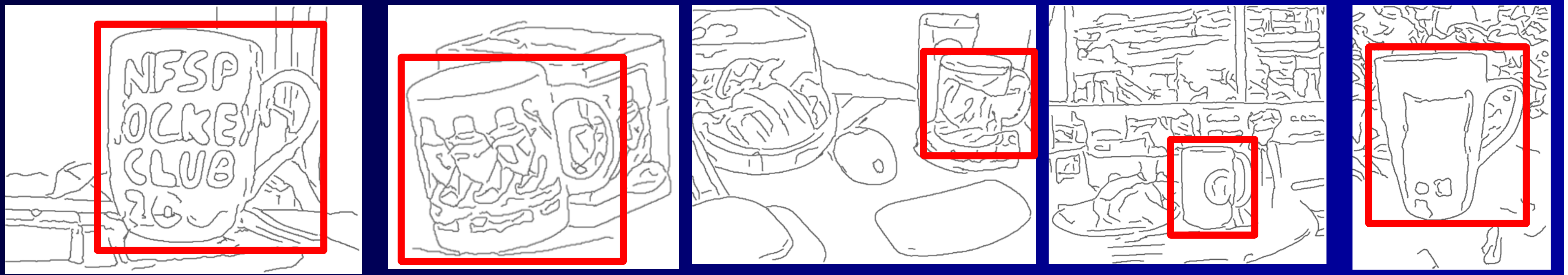
Training: *bounding-boxes*

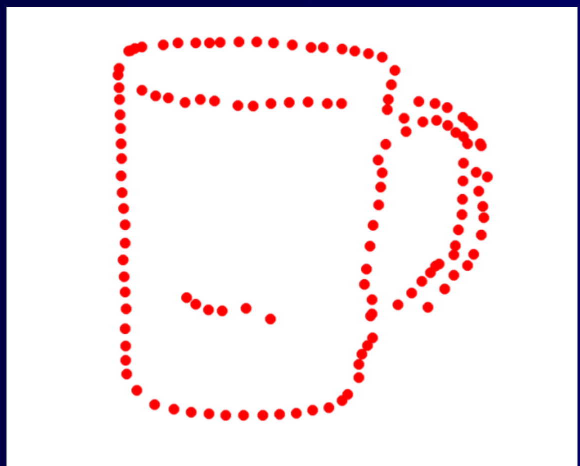
Testing: *object boundaries*

[Ferrari, Jurie, Schmid, IJCV10]

Learn a shape model from training images

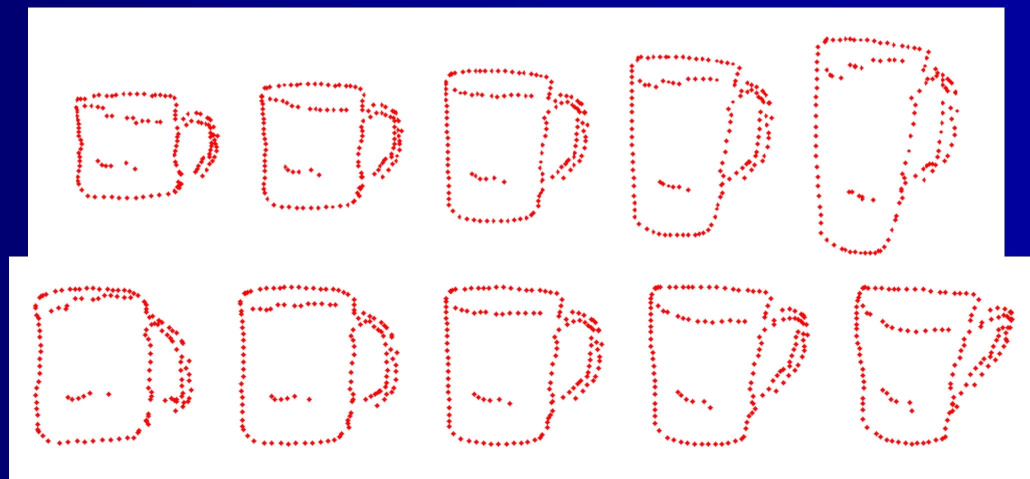
Training data





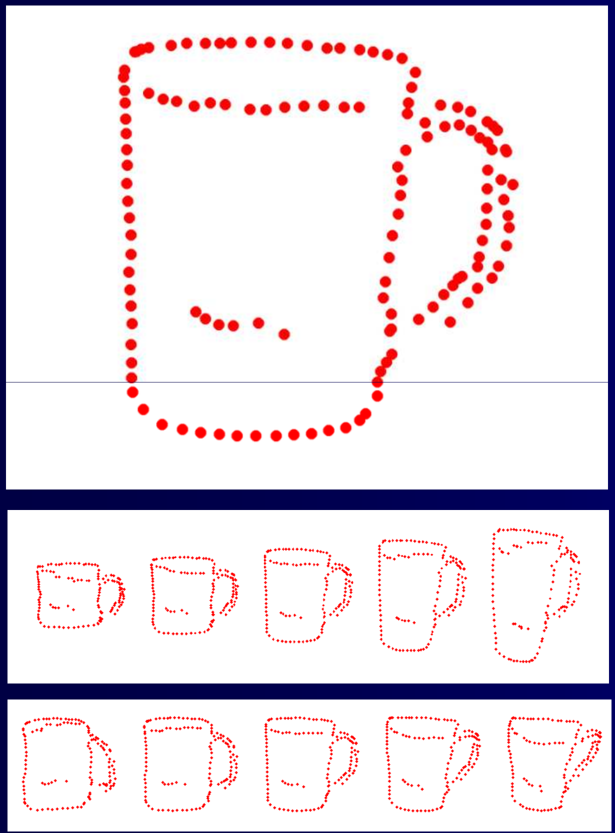
prototype shape

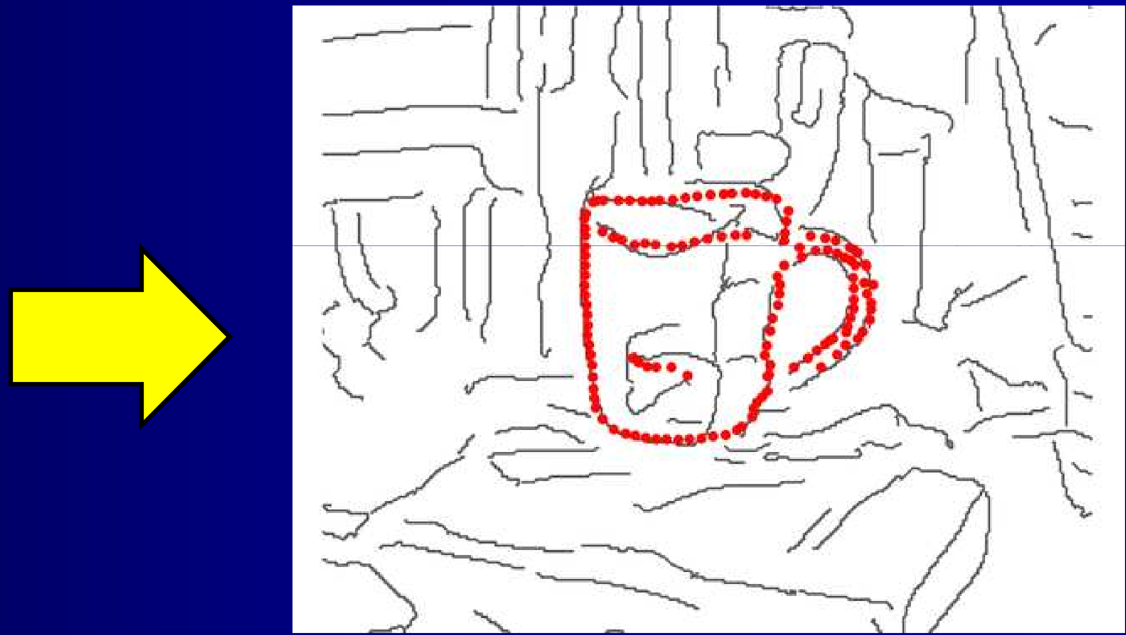
+



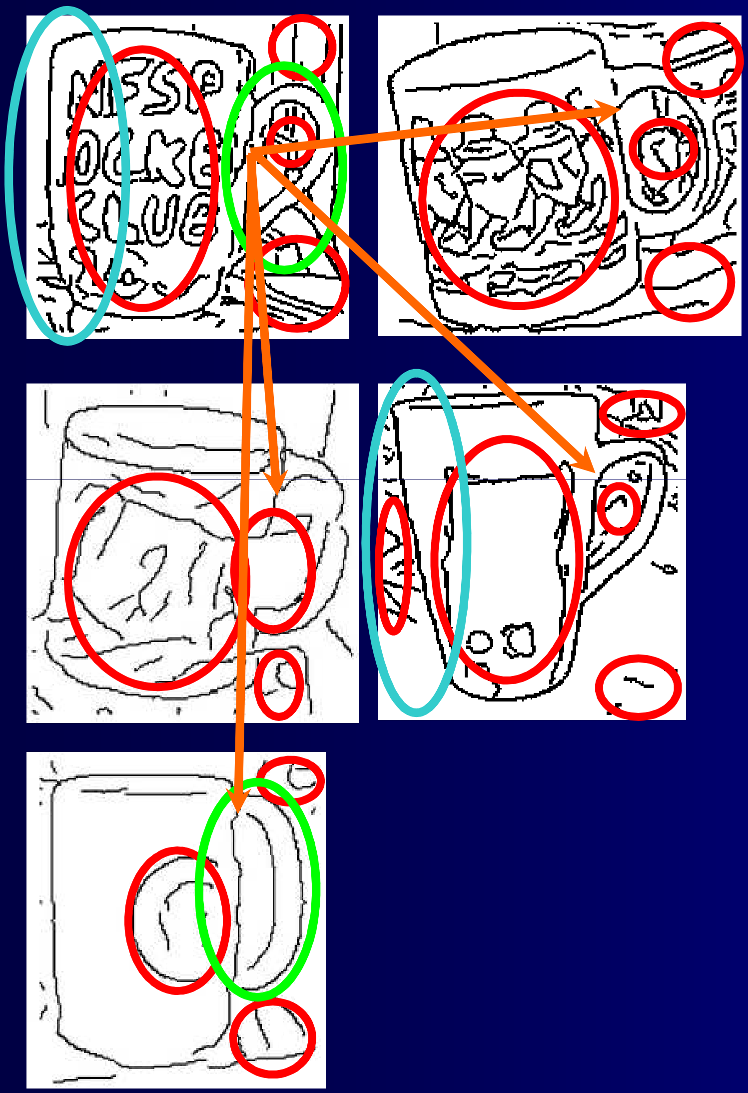
deformation model

Match it to the test image





Challenges for learning



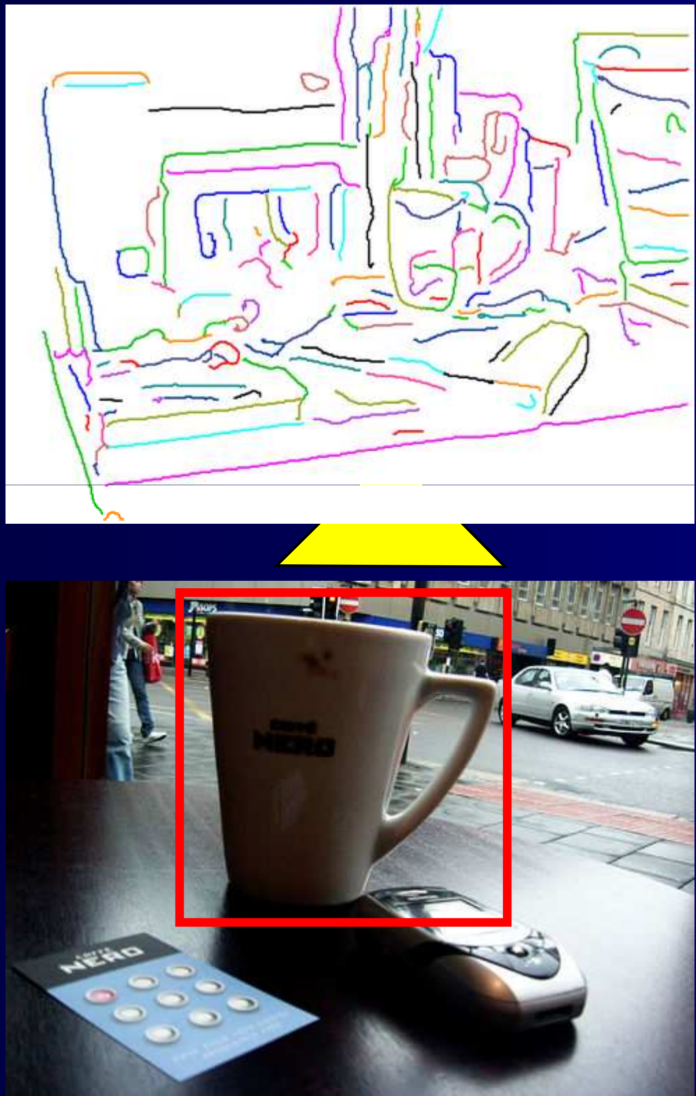
Main issue

which edgels belong
to the class boundaries ?

Complications

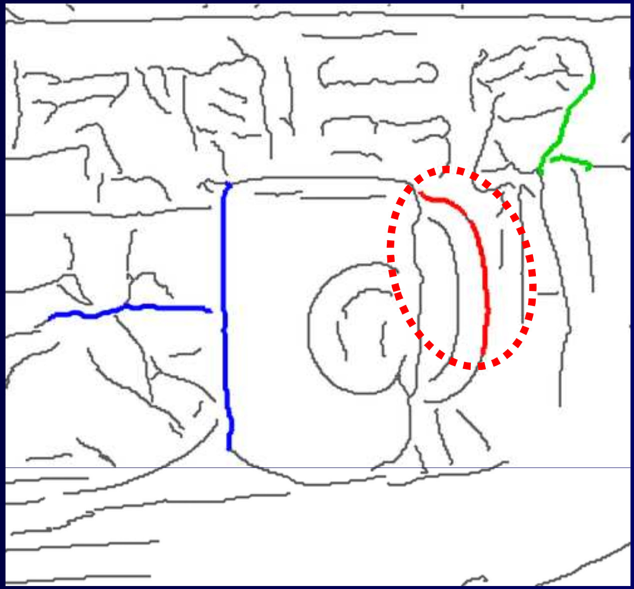
- intra-class variability
- missing edgels
- produce point correspondences
  (learn deformations)

Challenges for detection



- scale changes
- intra-class variability
- clutter
- fragmented and incomplete contours

Local contour features



PAS

Pair of Adjacent Segments

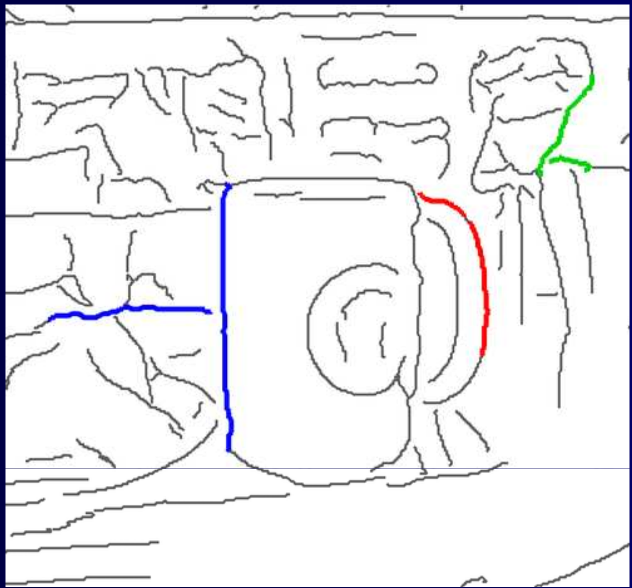
+ *robust*
  connect also across gaps

+ *clean*
  descriptor encodes the
  two segments *only*

+ *invariant*
  to translation and scale

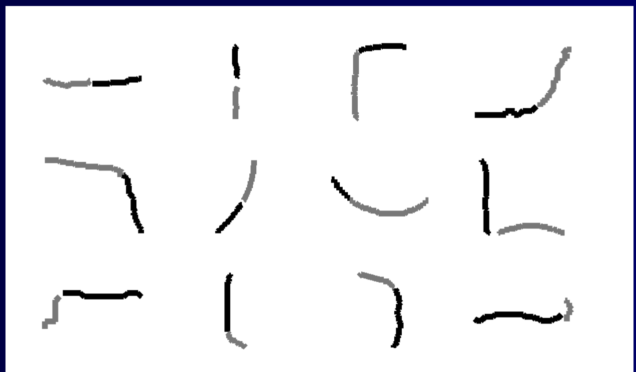
+ *intermediate complexity*
  good compromise between
  repeatability and informativity

Local contour features



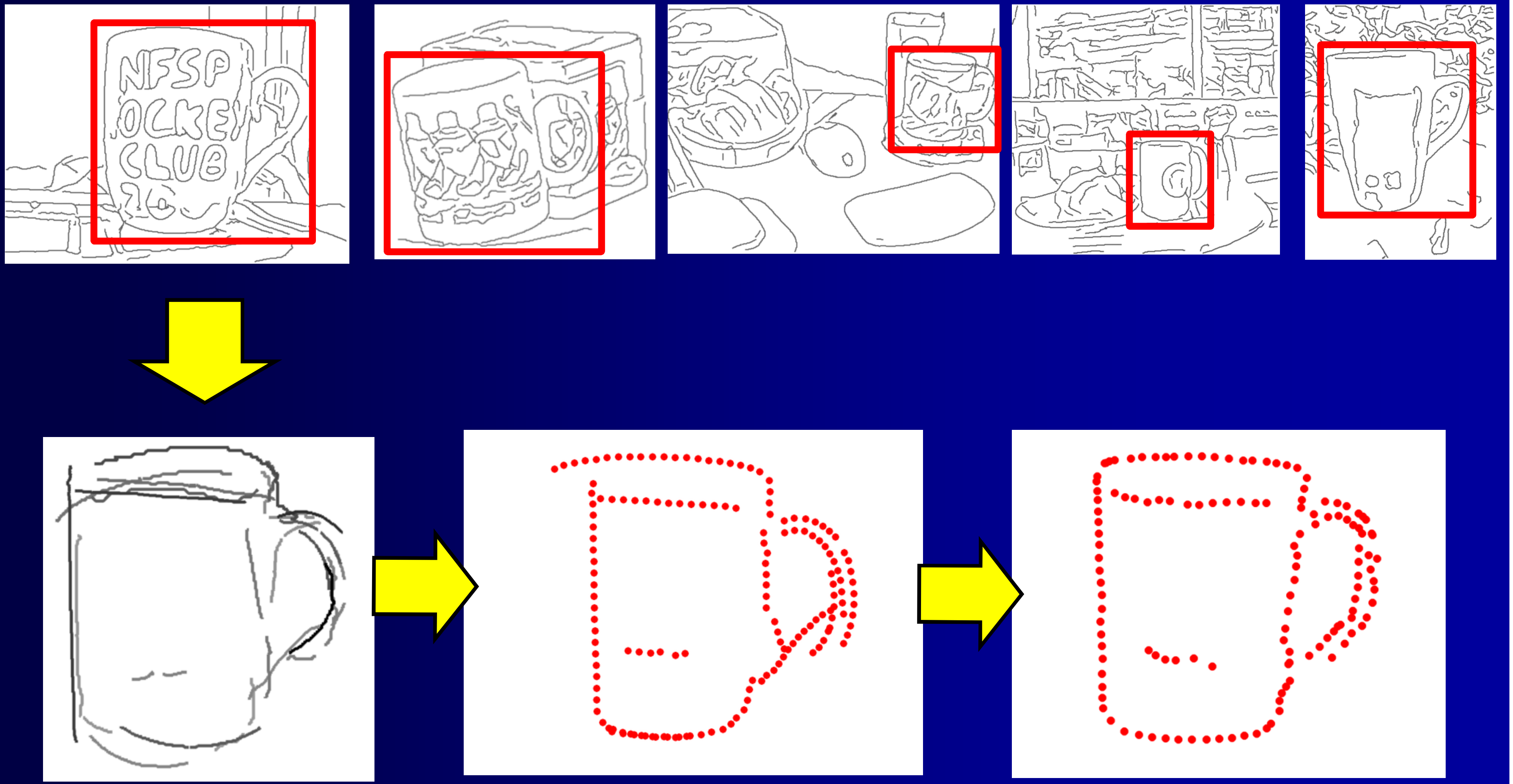
PAS
Pair of Adjacent Segments

two PAS in correspondence
⟶ translation+scale transform
⟶ use in Hough-like schemes



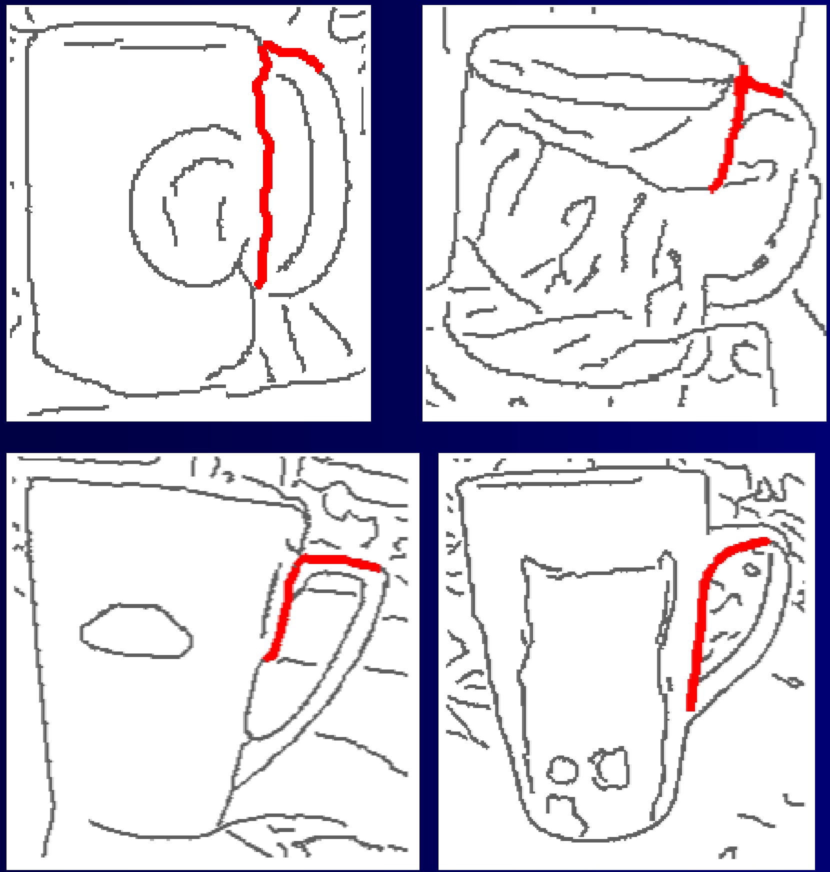
Clustering descriptors
⟶ codebook of *PAS types*
(here from mug bounding boxes)

Learning: overview



find models parts   assemble an initial shape   refine the shape

Learning: finding model parts

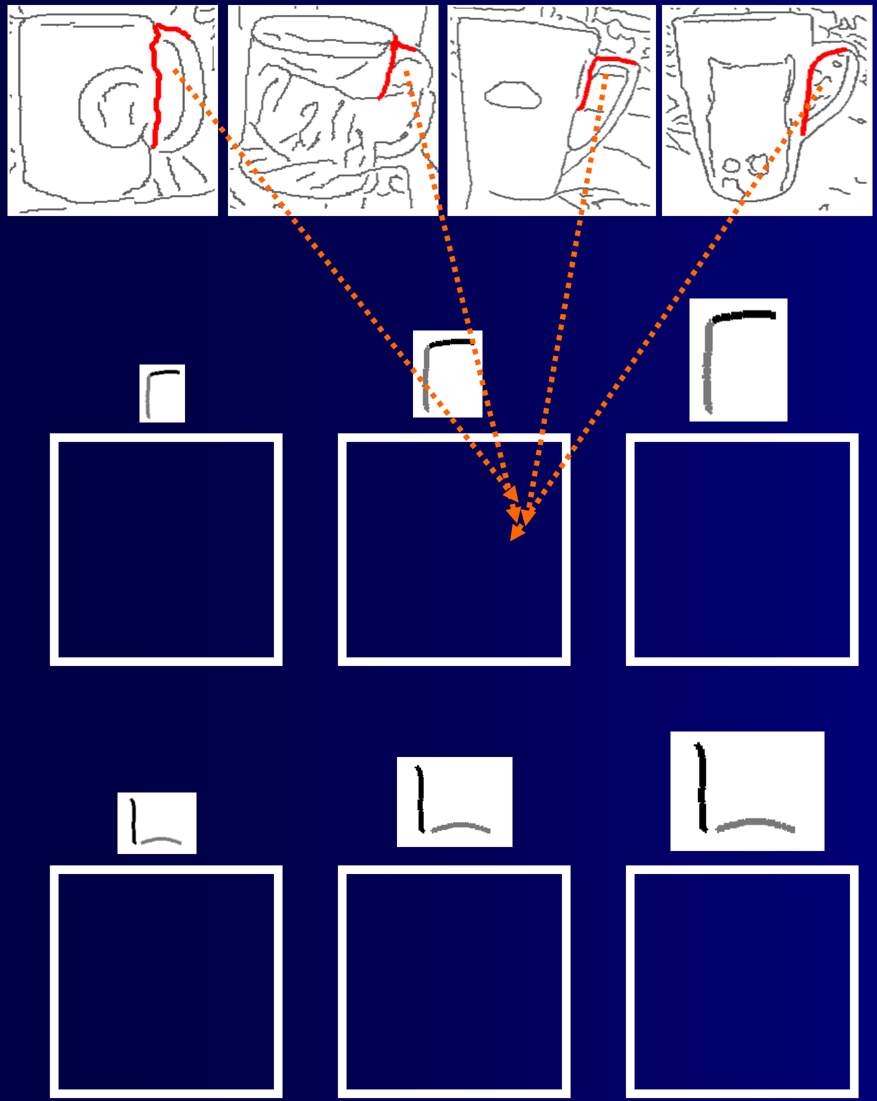


Intuition

PAS on class boundaries reoccur at similar locations/scales/shapes

Background and details specific to individual examples don't

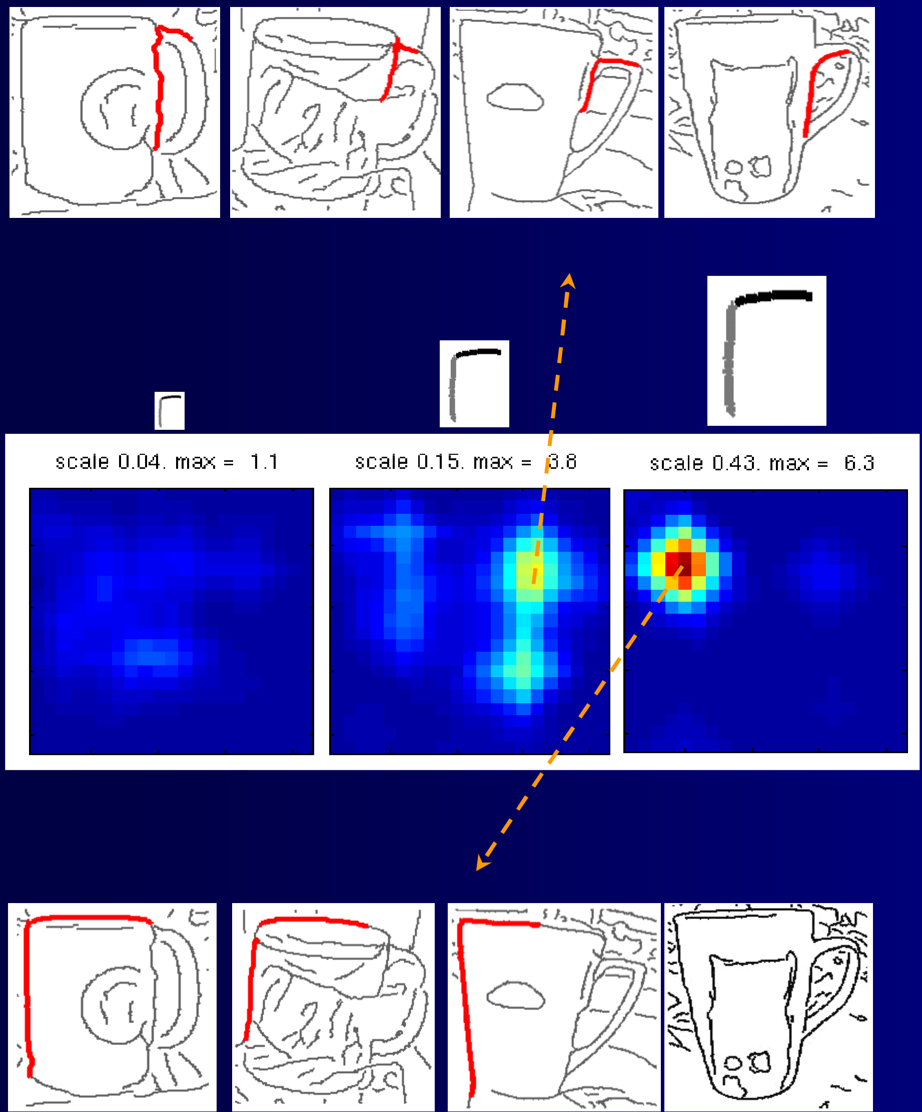
Learning: finding model parts



Algorithm

1. align bounding-boxes up to translation/scale/aspect-ratio
2. create a separate voting space per PAS type
3. soft-assign PAS to types
4. PAS cast 'existence' votes in corresponding spaces

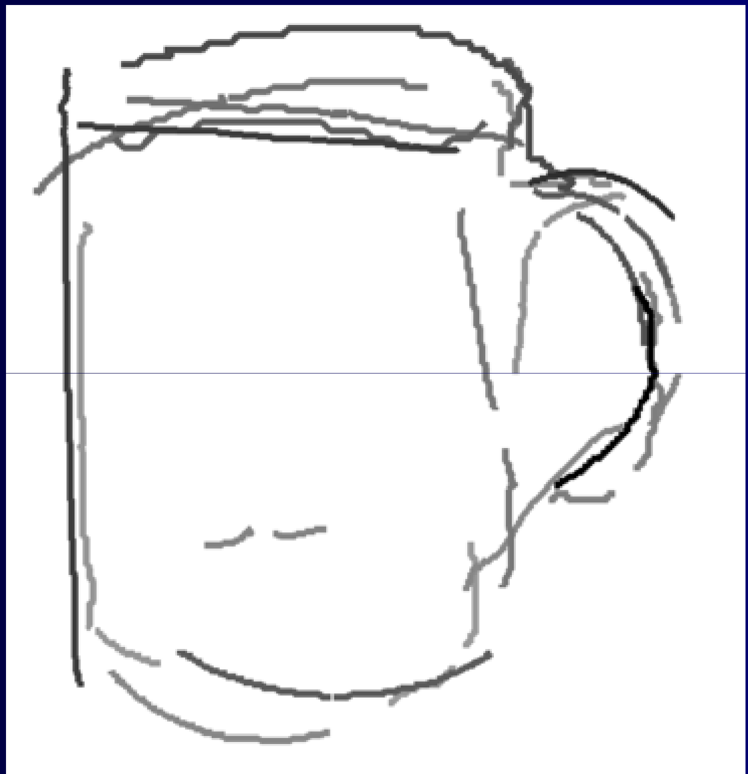
Learning: finding model parts



Algorithm

1. align bounding-boxes up to translation/scale/aspect-ratio
2. create a separate voting space per PAS type
3. soft-assign PAS to types
4. PAS cast ‘existence’ votes in corresponding spaces
5. local maxima ⟶ model parts

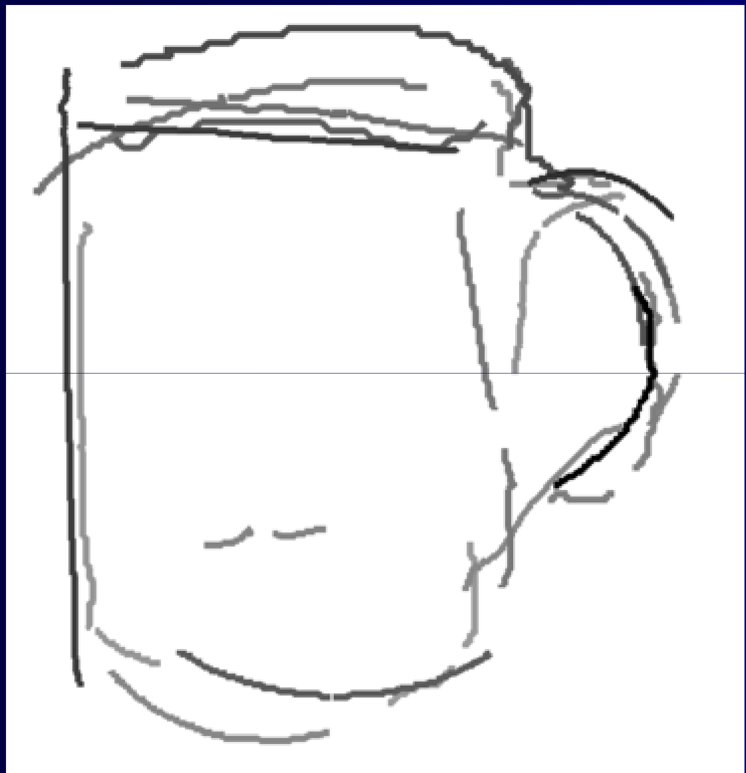
Learning: finding model parts



Model parts

- location + size (wrt canonical BB)
- shape (PAS type)
- strength (value of local maximum)

Learning: finding model parts



Why does it work ?

Unlikely unrelated PAS have similar location *and* size *and* shape

⟶ form no peaks !

Important properties

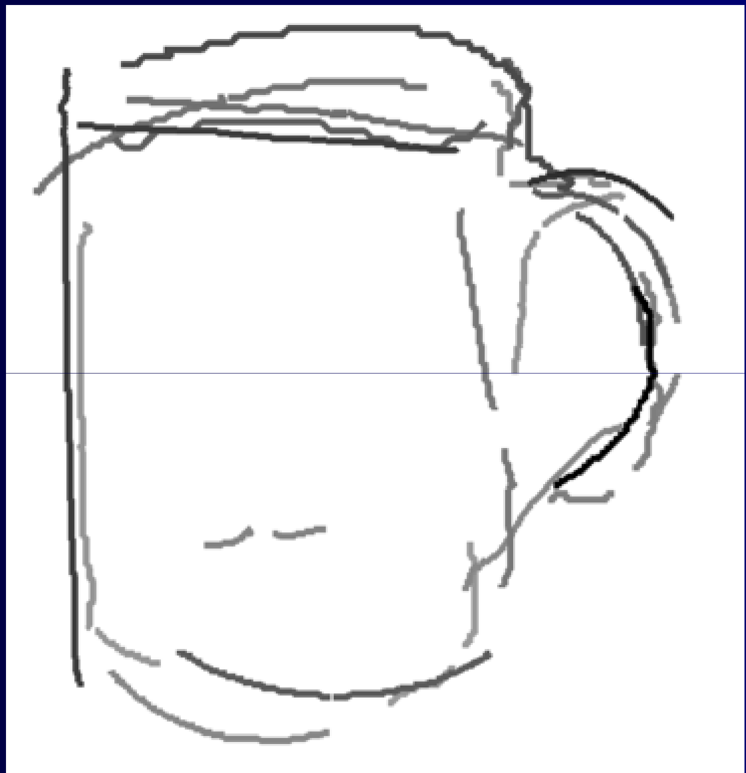
+ see all training data at *once*

⟶ robust

+ linear complexity

⟶ efficient large-scale learning

Learning: assembling an initial shape



best occurrence for each part

Not a shape yet

- multiple strokes
- adjacent parts don't fit together

Why ?

- parts are learnt *independently*

Let's try to assemble parts into a proper whole

We want single-stroked, long continuous lines !

Learning: assembling an initial shape

all occurrences in a few training images

Observation

each part has several occurrences

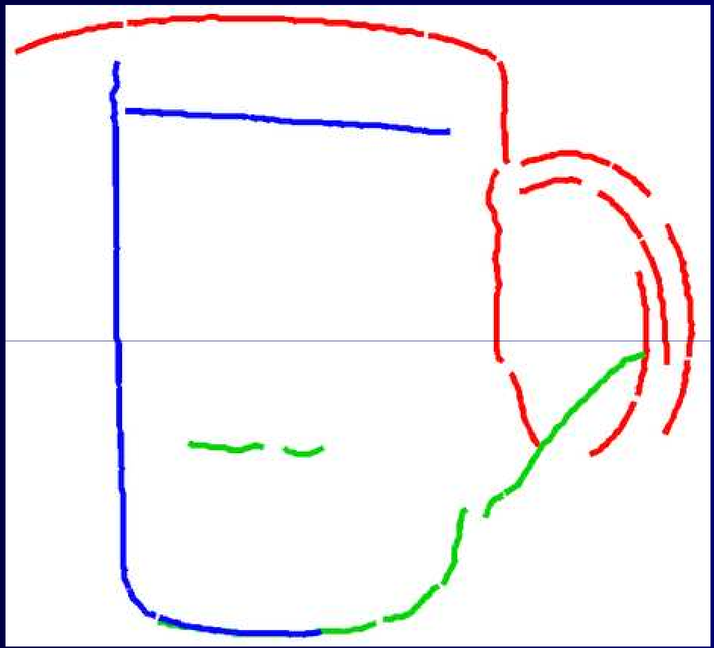
$\downarrow$

can assemble shape variations by selecting different occurrences

Idea

select occurrences so as to form larger connected aggregates

Learning: assembling an initial shape



Hey, this starts to look like a mug !

+ segments fit well within a block

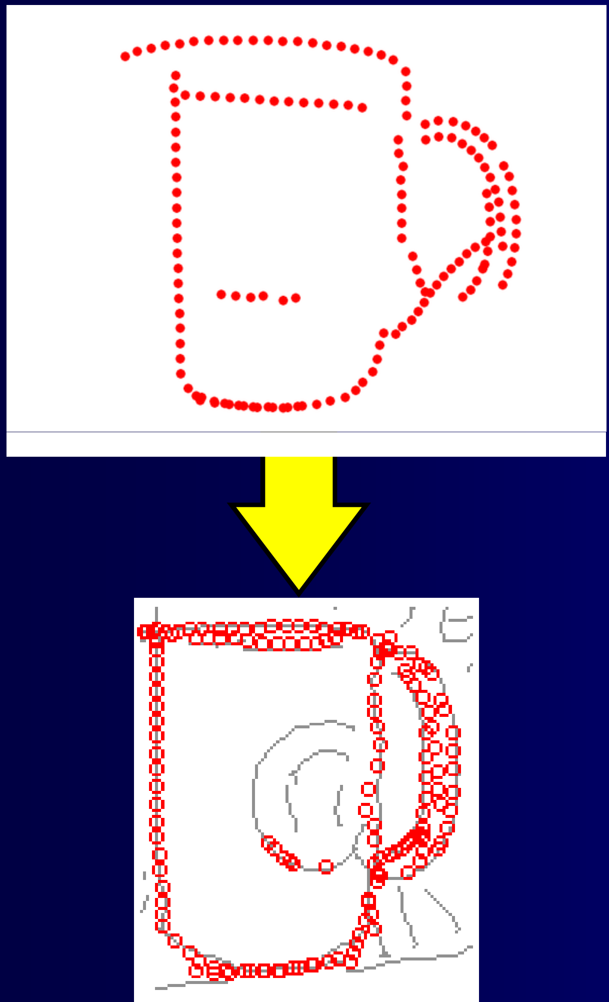
+ most redundant strokes are gone

Can we do better ?

- discontinuities between blocks ?

- generic-looking ?

Learning: shape refinement



Idea

treat shape as deformable point set

and *match it back* onto training images

How ?

- robust non-rigid point matcher: TPS-RPM
  (thin plat spline – robust point matching)
- strong initialization:
  align model shape BB over training BB

  ⟶ likely to succeed

Chui and Rangarajan, *A new point matching algorithm for non-rigid registration*, CVIU 2003

Learning: shape refinement

Shape refinement algorithm

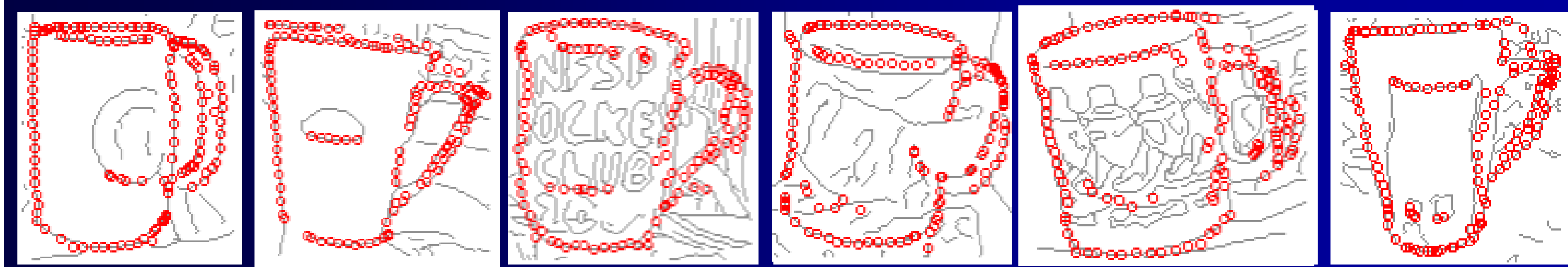
1. Match current model shape back to every training image

   backmatched shapes are in full point-to-point correspondence !

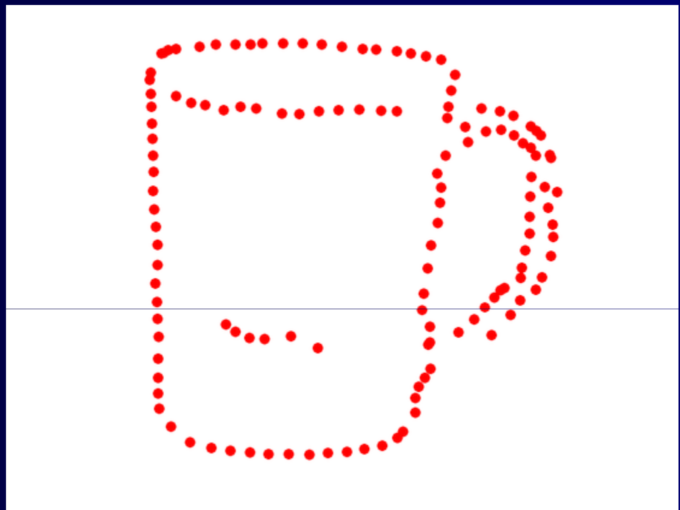
2. set model to mean shape

3. remove redundant points

4. if changed $\longrightarrow$ iterate to 1



Learning: shape refinement



Final model shape

+ clean (almost only class boundaries)

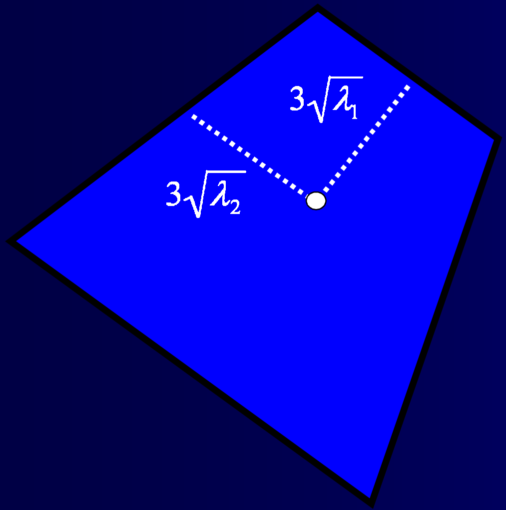
+ smooth, connected lines

+ generic-looking

+ fine-scale structures recovered (handle arcs)

+ accurate point correspondences spanning training images

Learning: shape deformations



• = mean shape

From backmatching

intra-class variation examples,
in complete correspondence

↓

Apply Cootes' technique

1. shapes = vectors in 2p-D space
2. apply PCA

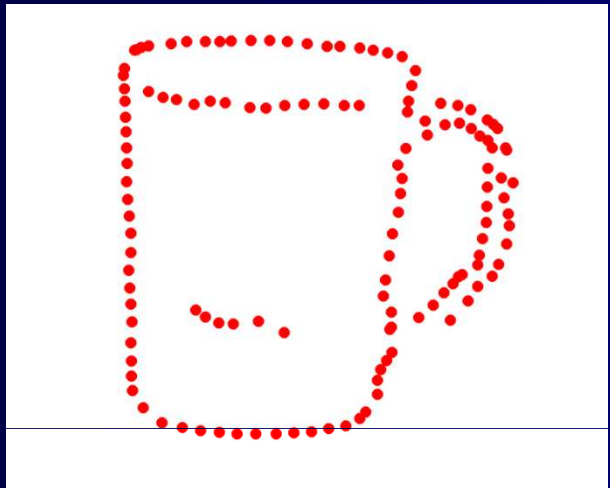
Deformation model

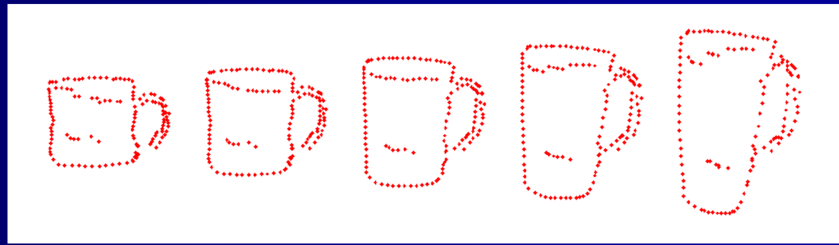
. top *n* eigenvectors covering 95% of variance
. associated eigenvalues λ_i (act as bounds)

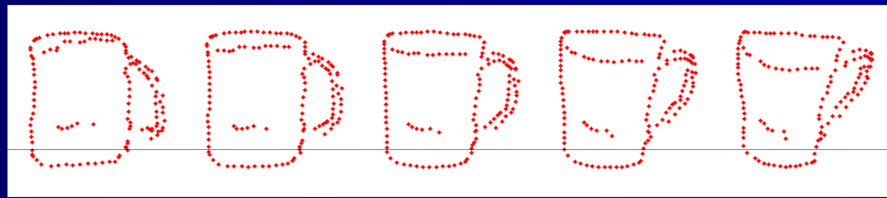
⟶ *valid region* of shape space

Tim Cootes, *An introduction to Active Shape Models, 2000*

Learning completed !

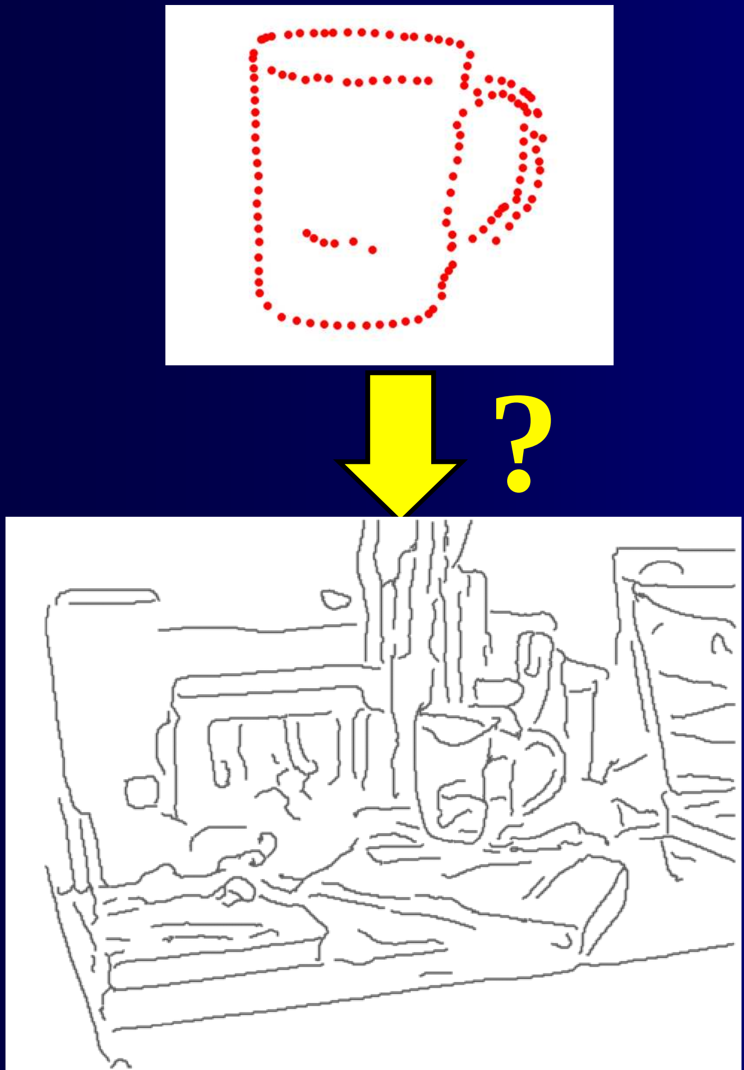






***Automatic learning of
shapes, correspondences, and deformations
from unsegmented images***

Object detection: overview



Goal

given a test image, localize class instances up to their boundaries

How ?

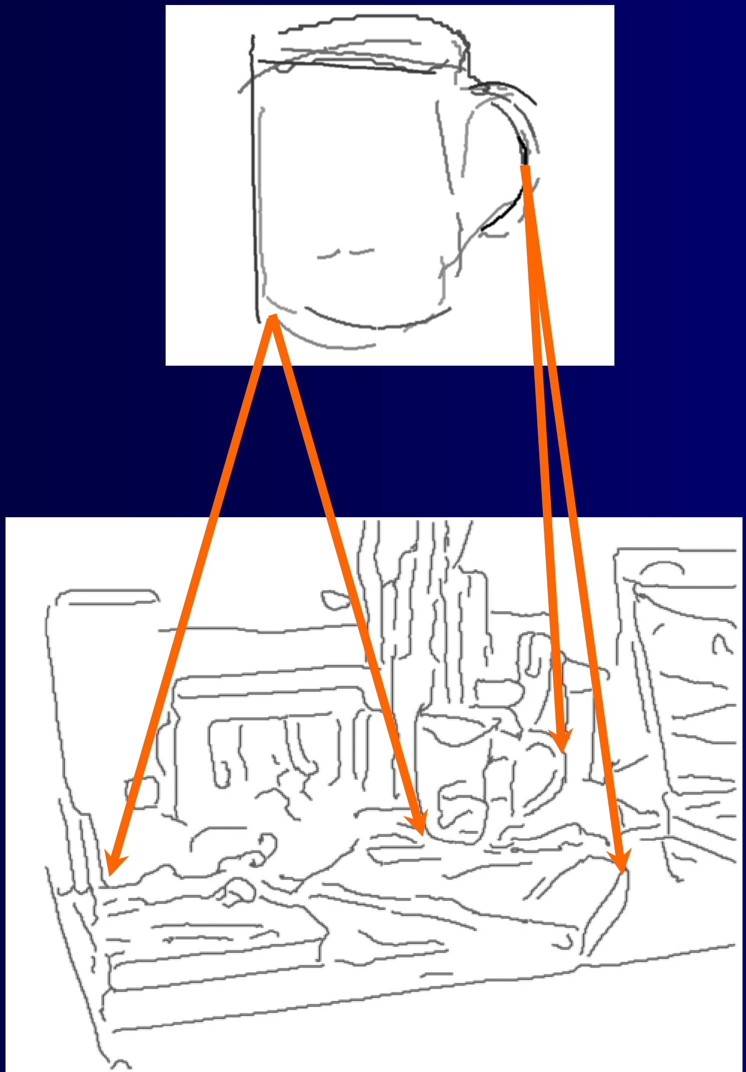
1. Hough voting over PAS matches
   ⟶ *rough* location+scale estimates

2. use to initialize TPS-RPM

   combination enables true pointwise shape matching to cluttered images

3. constrain TPS-RPM with learnt deformation model
   ⟶ better accuracy

Object detection: Hough voting



Algorithm

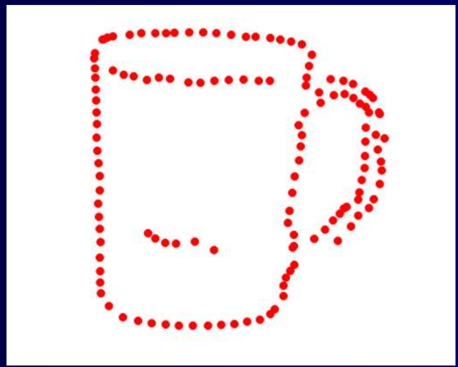
1. soft-match model parts to test PAS

2. each match
   → translation + scale change
   → vote in accumulator space

3. local maxima
   → rough estimates of object candidates

Leibe and Schiele, DAGM 2004; Shotton et al, ICCV 2005; Opelt et al. ECCV 2006

Object detection: Hough voting



Algorithm

1. soft-match model parts to test PAS

2. each match
   → translation + scale change
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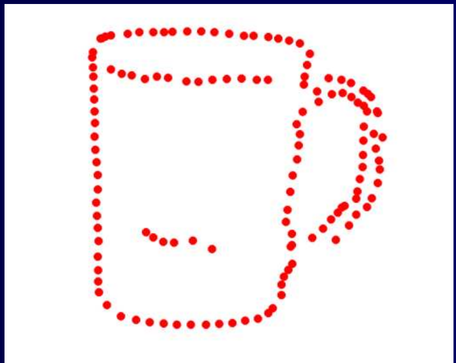
   → rough estimates of object candidates

initializations for shape matching !

Leibe and Schiele, DAGM 2004; Shotton et al, ICCV 2005; Opelt et al. ECCV 2006

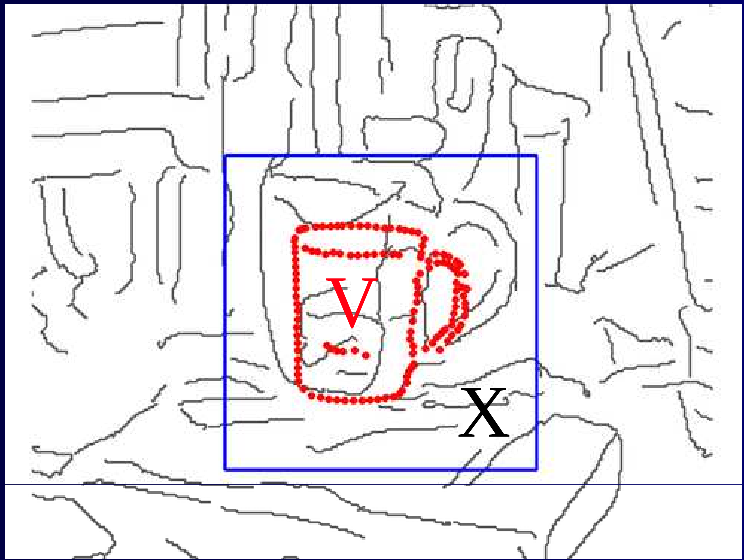
Object detection: Hough voting



Remember … soft !

- vote $\propto$ shape similarity
- vote $\propto$ edge strength of test PAS
- vote $\propto$ strength of model part
- spread vote to neighboring location and scale bins

Object detection: shape matching by TPS-RPM



Initialize
get point sets V (model) and X (edge points)

Goal
find correspondences M &
non-rigid TPS mapping

M = (|X|+1)x(|V|+1) soft-assign matrix

Algorithm

1. Update M based on
   dist(TPS,X) + orient(TPS,X) + strength(X)

2. Update TPS:
   - Y = MX
   - fit regularized TPS to V⟷Y

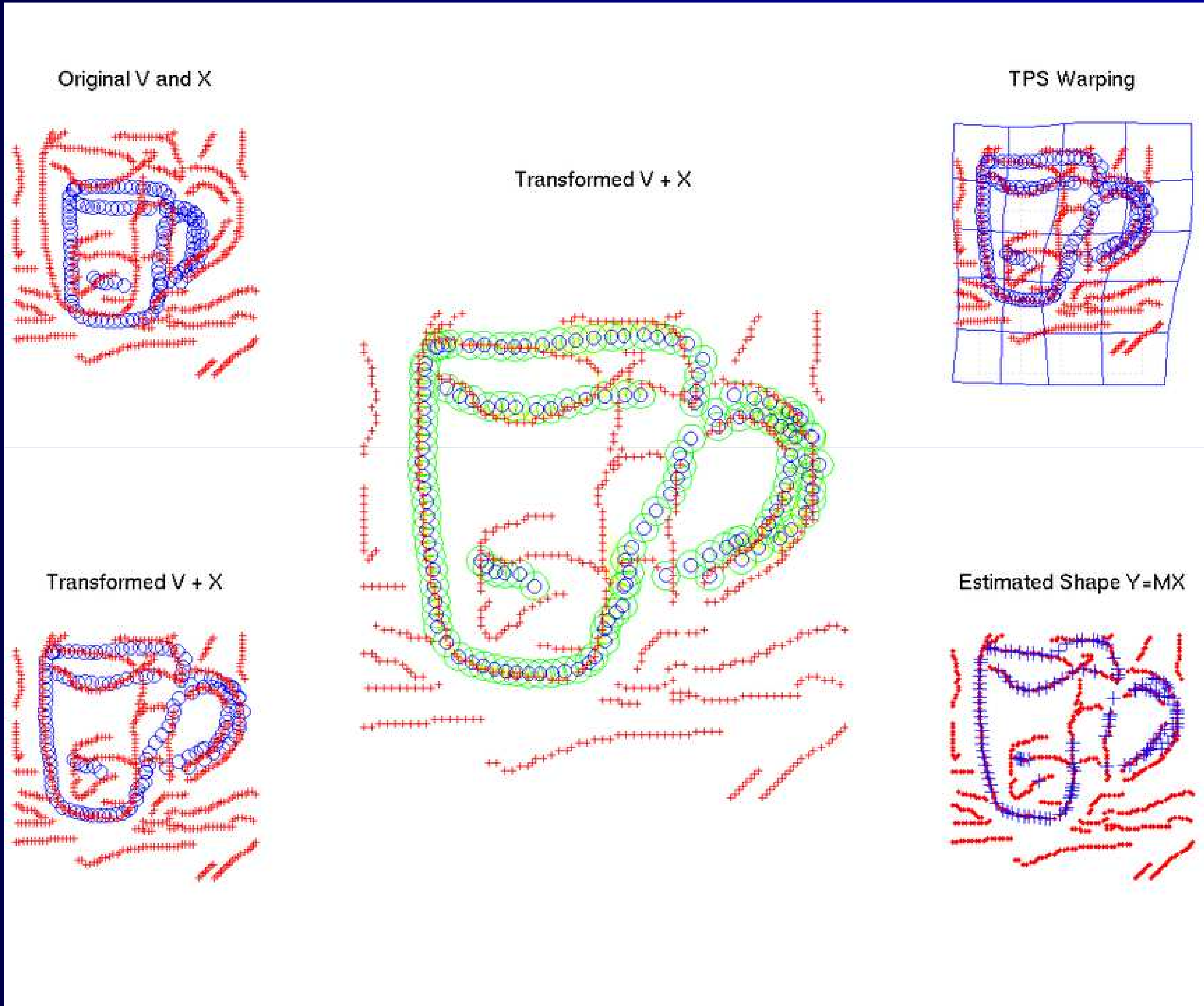
Deterministic annealing:
iterate with T decreasing

→ M less fuzzy (looks closer)

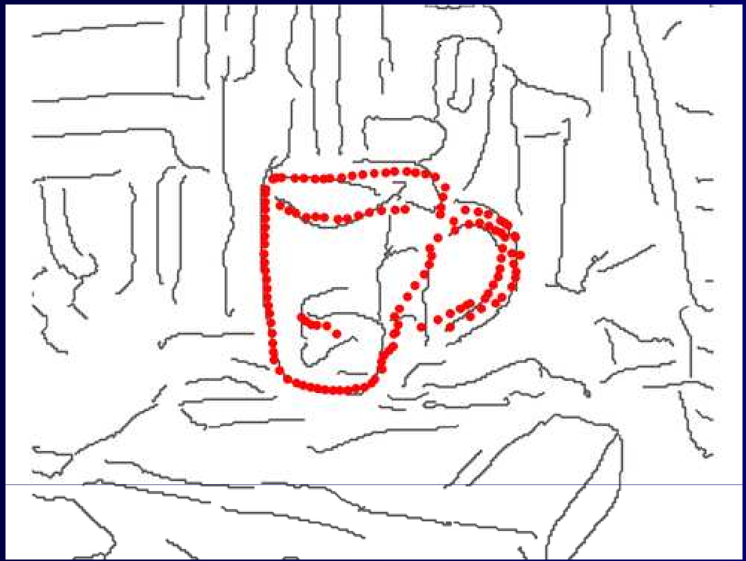
→ TPS more deformable

Chui and Rangarajan, *A new point matching algorithm for non-rigid registration*, CVIU 2003

TPS-RPM in action !



Object detection: constrained TPS-RPM



Output of TPS-RPM

nice, but sometimes inaccurate
or even not mug-like

Why ?
generic TPS deformation model
(prefers smoother transforms)

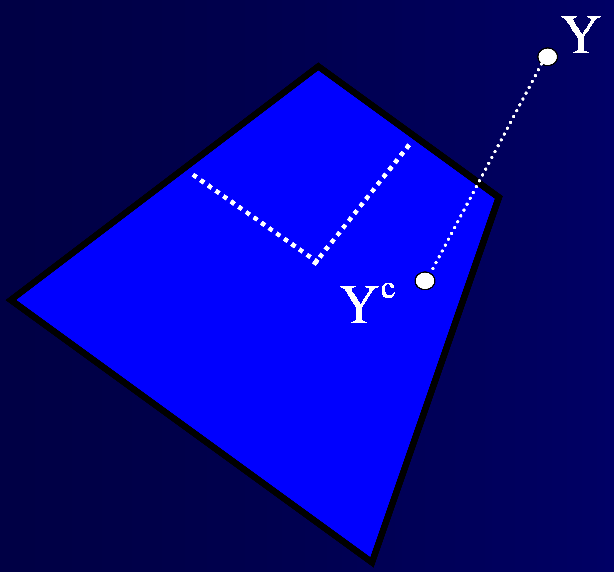
Constrained shape matching

constrain TPS-RPM by learnt
class-specific deformation model

+ only shapes similar to class members

+ improve detection accuracy

Object detection: constrained TPS-RPM



General idea

constrain optimization to explore only region of shape space spanned by training examples

How to modify TPS-RPM ?

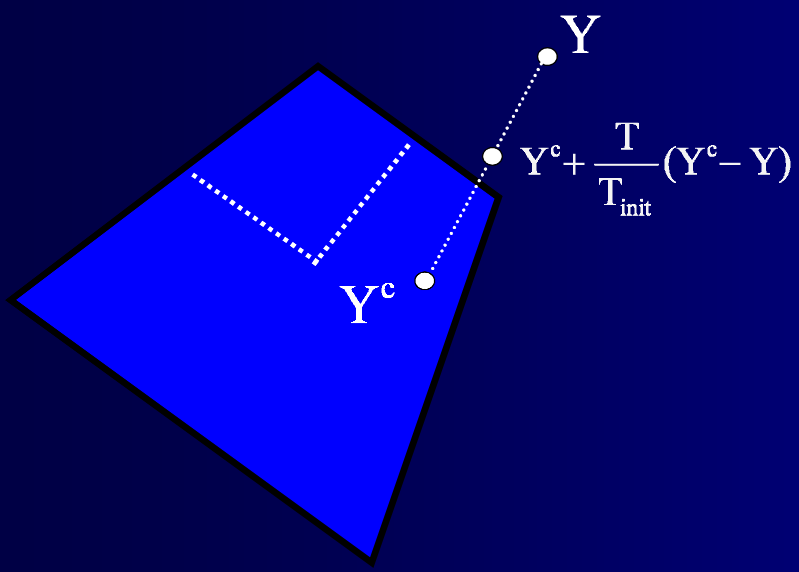
1. Update M

2. Update TPS:

   - $Y = MX$
   - $Y \leftarrow Y^c$
   - fit regularized TPS to $V \longleftrightarrow Y$

hard constraint,
sometimes too restrictive

Object detection: constrained TPS-RPM



General idea

constrain optimization to explore only region of shape space spanned by training examples

Soft constraint variant

1. Update M

2. Update TPS:

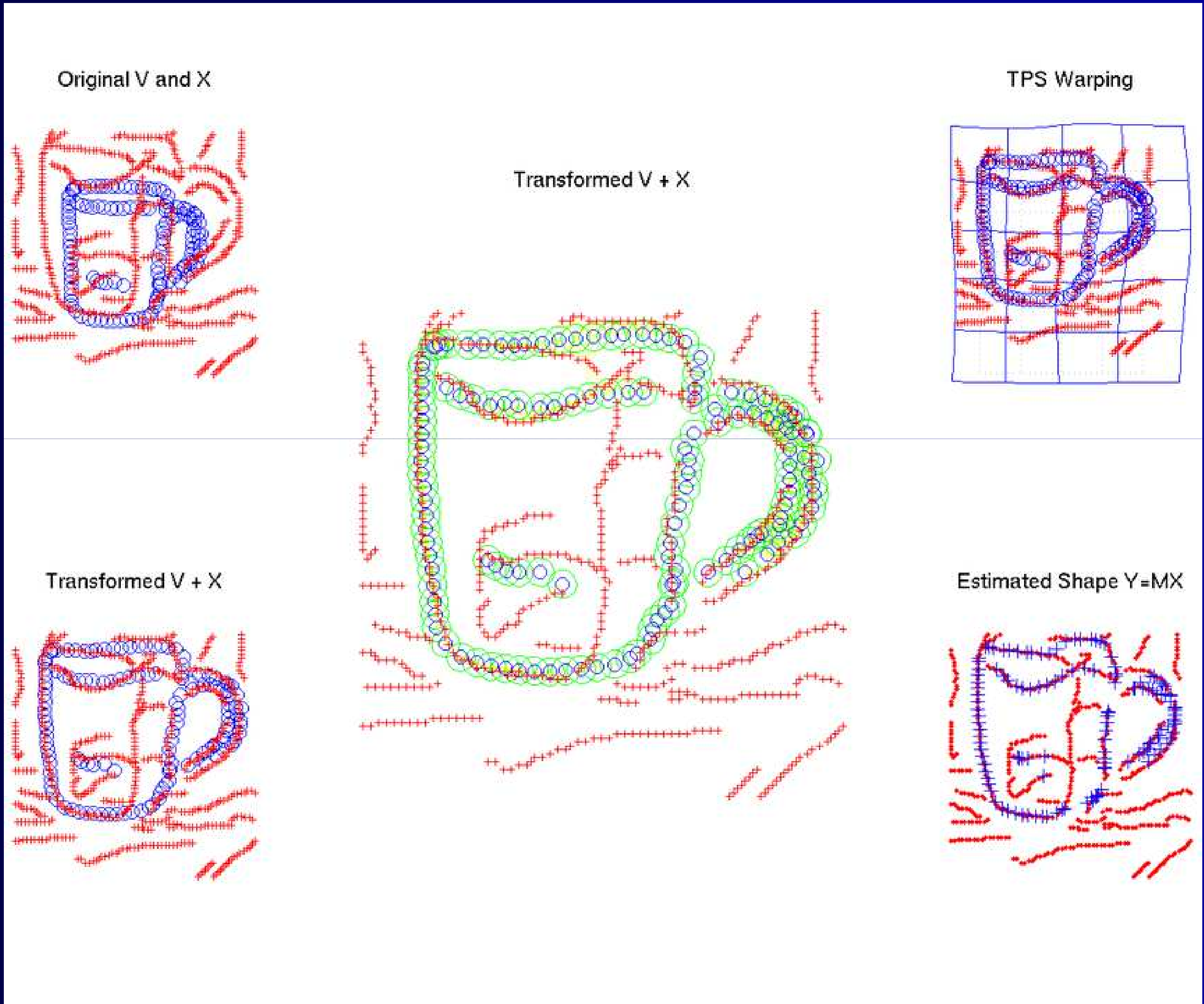
   - Y = MX

   - $Y \leftarrow Y^c + \dfrac{T}{T_{init}}(Y^c - Y)$

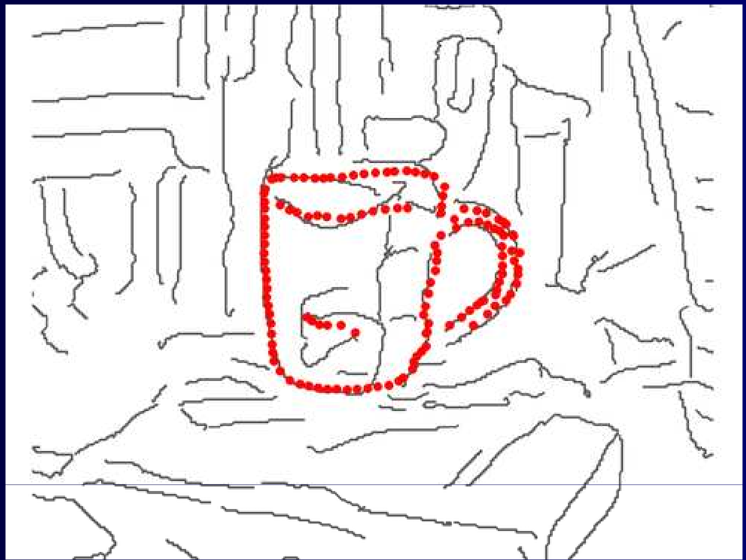
   - fit regularized TPS to $V \longleftrightarrow Y$

soft constraint,
Y is *attracted* by the valid region

Soft constrained TPS-RPM in action !



Object detection: constrained TPS-RPM



Soft constrained TPS-RPM

+ shapes fit data more accurately
+ shapes resemble class members
+ in spirit of deterministic annealing !
+ truly alters the search
  (not fix a posteriori)

Does it really make a difference ?

when it does, it’s really noticeable
(about 1 in 4 cases)

Datasets: ETHZ Shape Classes

- 255 images from *Google-images*, and *Flickr*
    - uncontrolled conditions
    - variety: indoor, outdoor, natural, man-made, …
    - wide range of scales (factor 4 for swans, factor 6 for apple-logos)
- all parameters are kept fixed for all experiments
- training images: 5x random half of positive; test images: *all* non-train

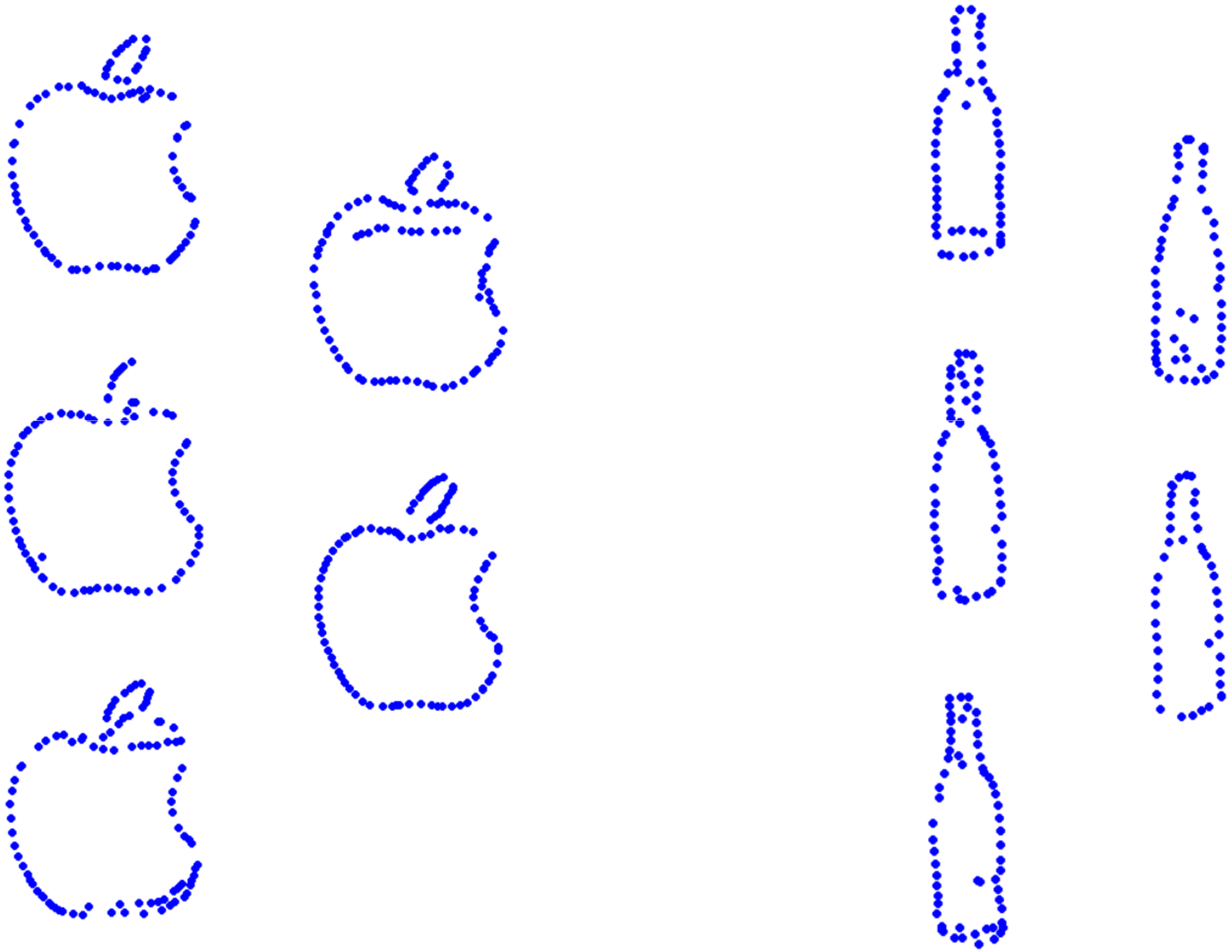
Datasets: INRIA Horses



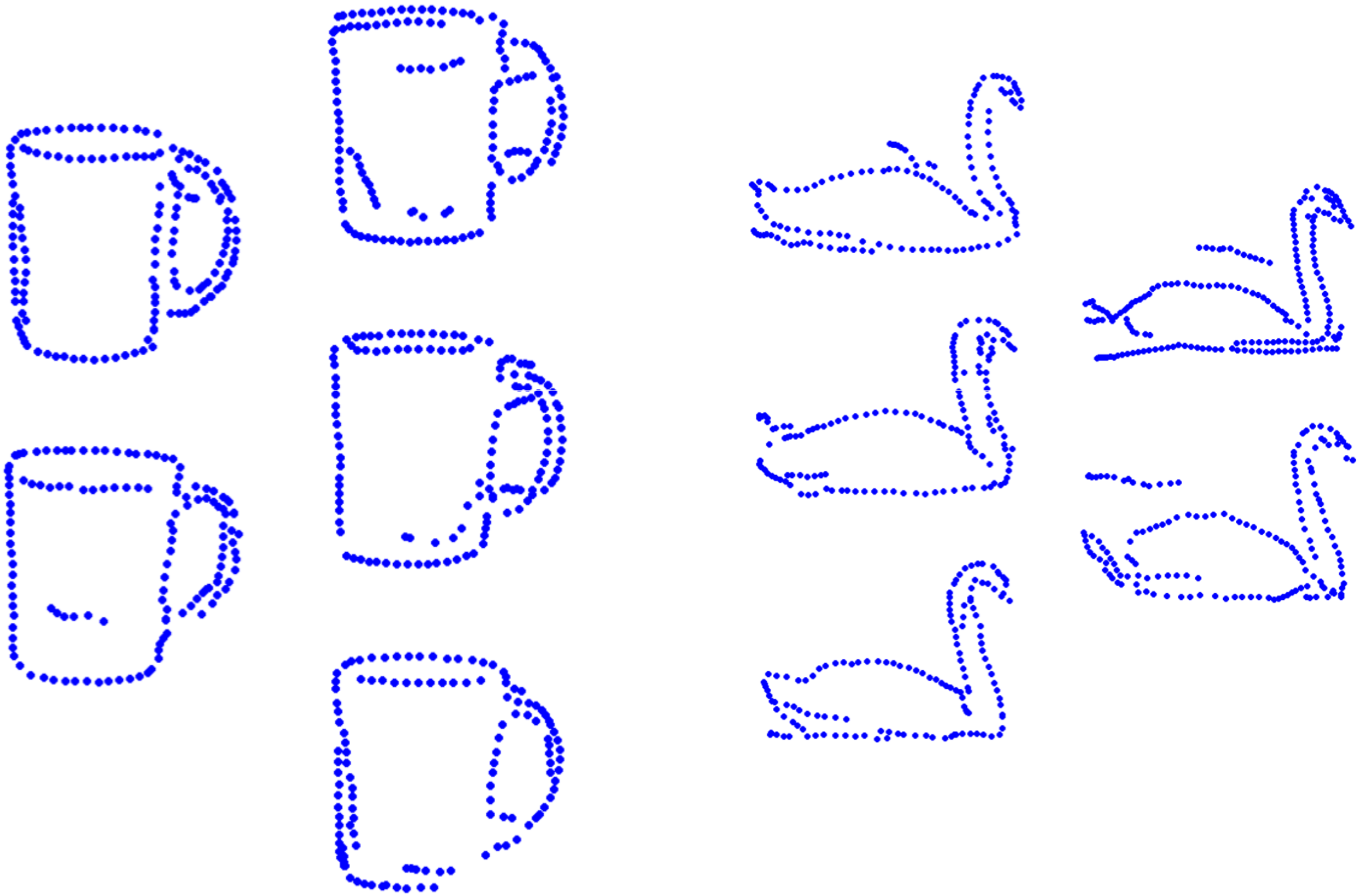

- 170 horse images + 170 non-horse ones
  - clutter, scale changes, various poses

- all parameters are kept fixed for all experiments
- training images: 5x random 50; test images: all non-train images

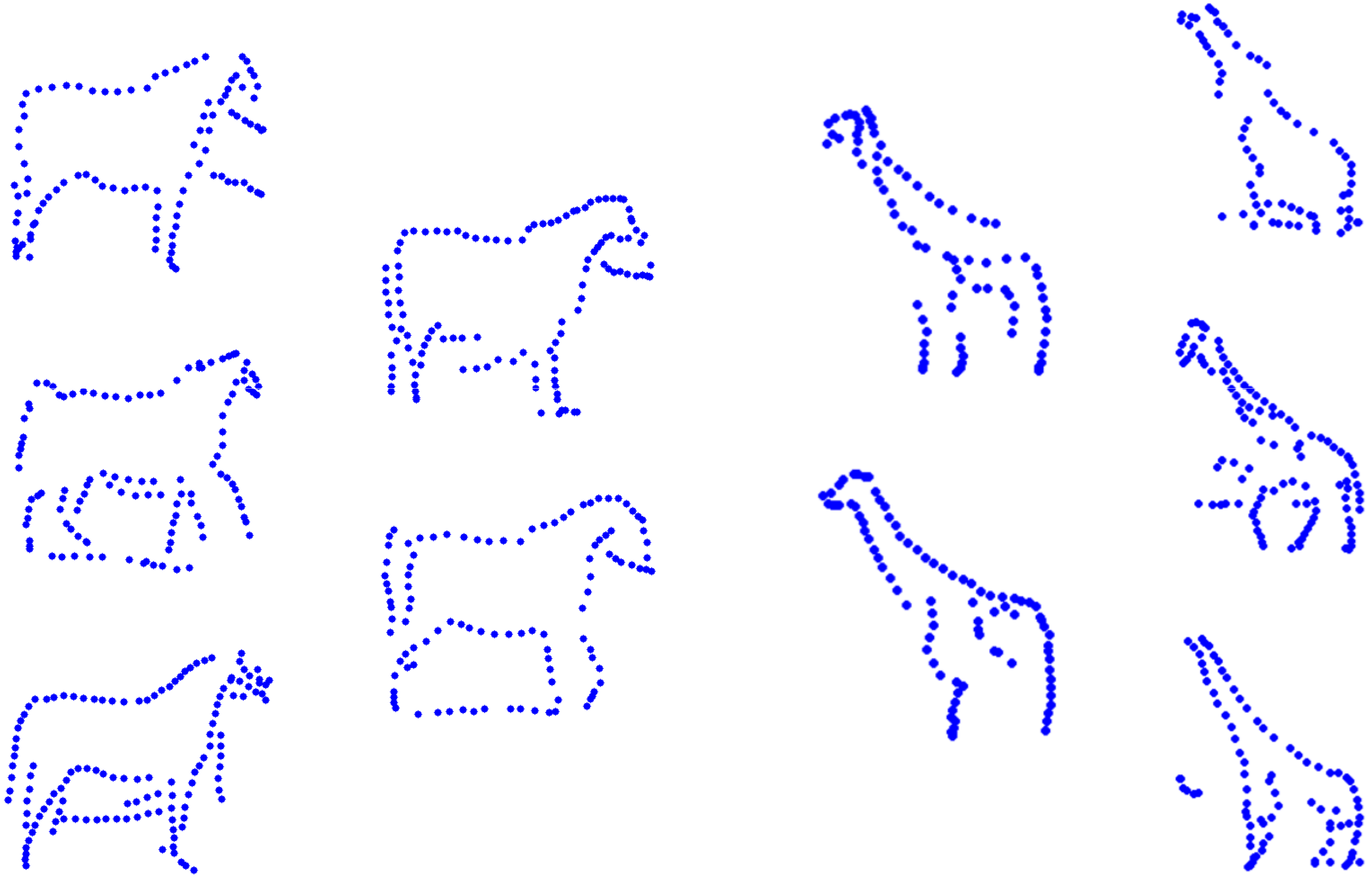
Results: all learned models



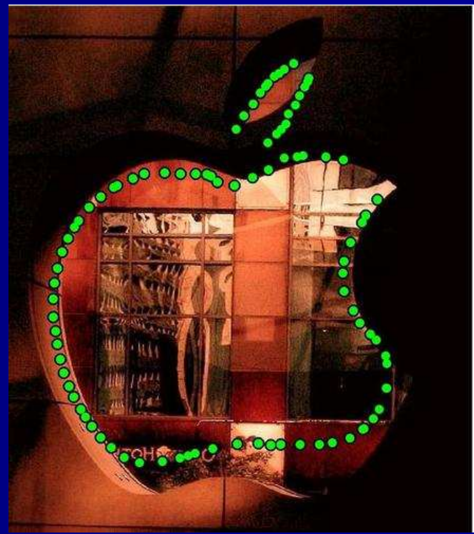
Results: all learned models

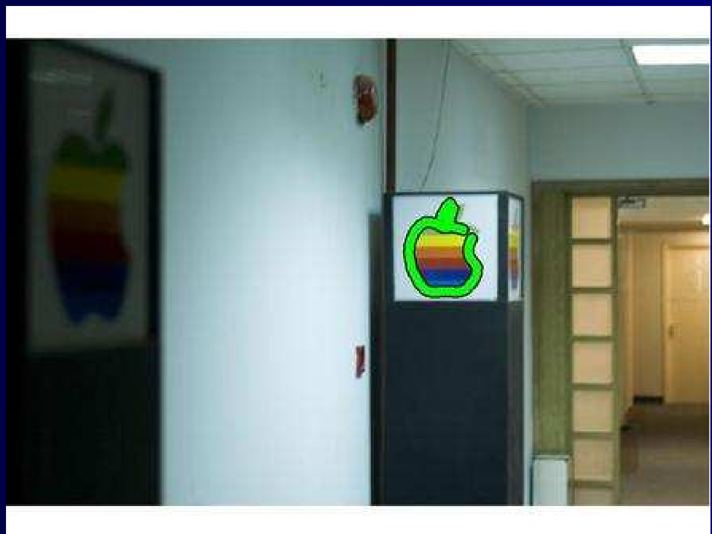


Results: all learned models



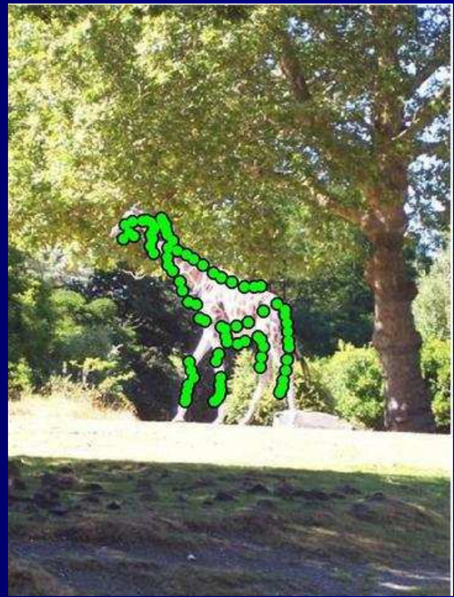
Results: apple logos

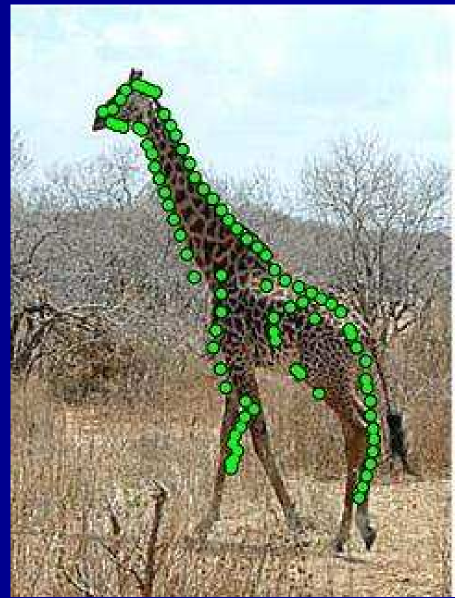




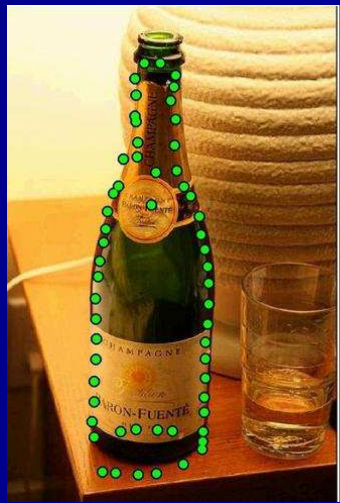
Results: mugs

Results: giraffes

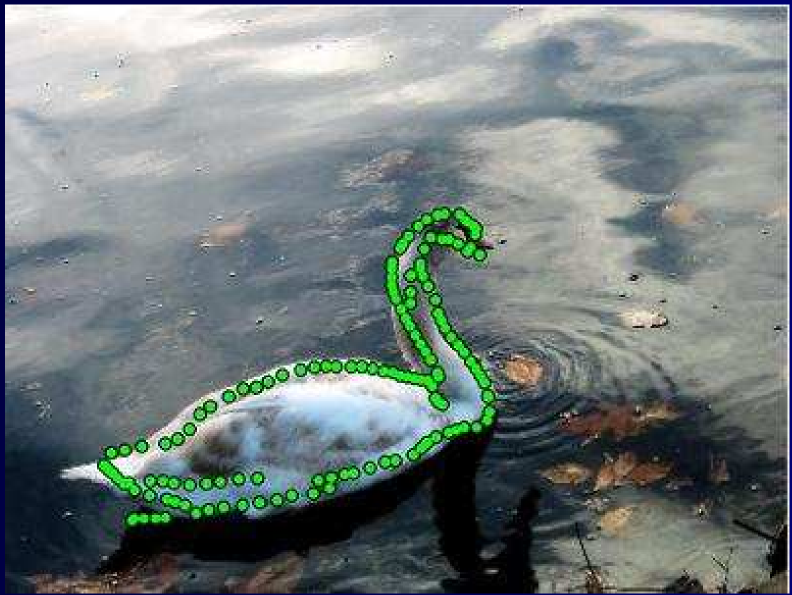


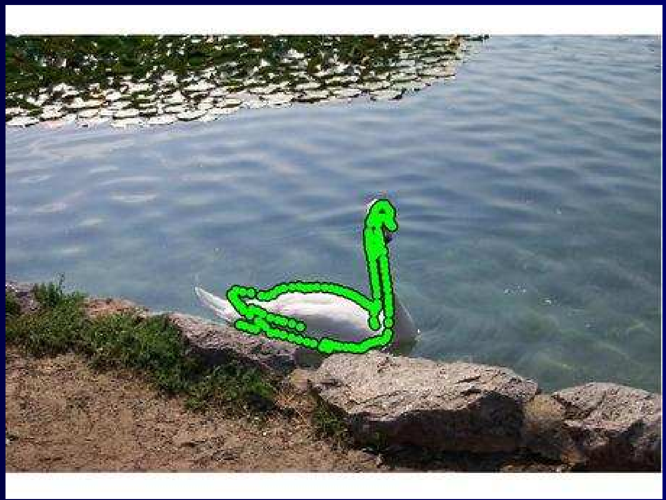


Results: bottles

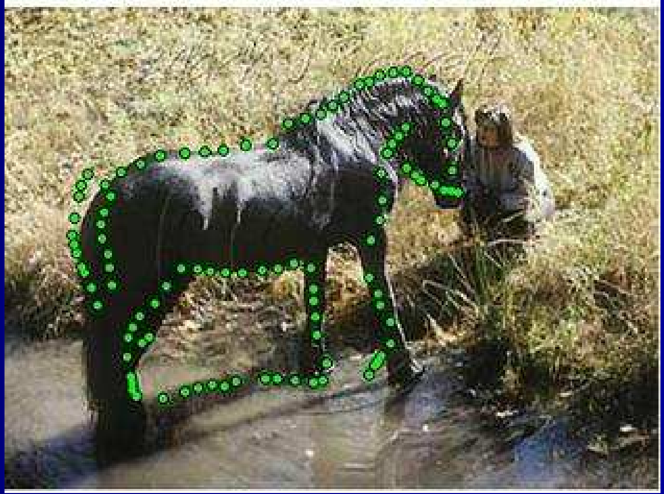


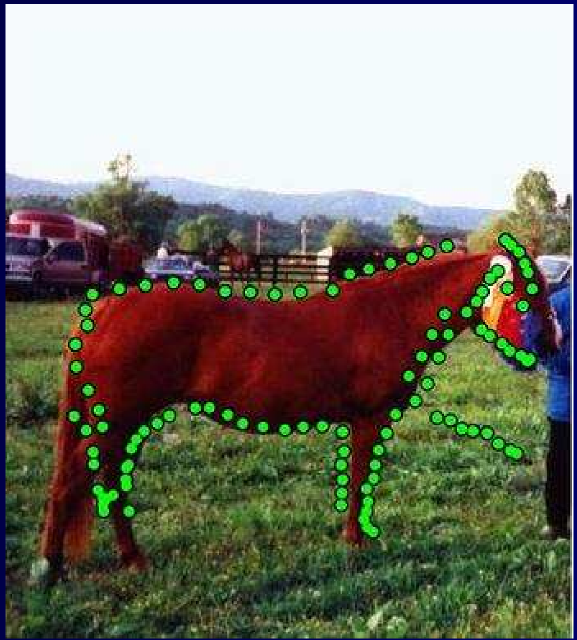
Results: swans

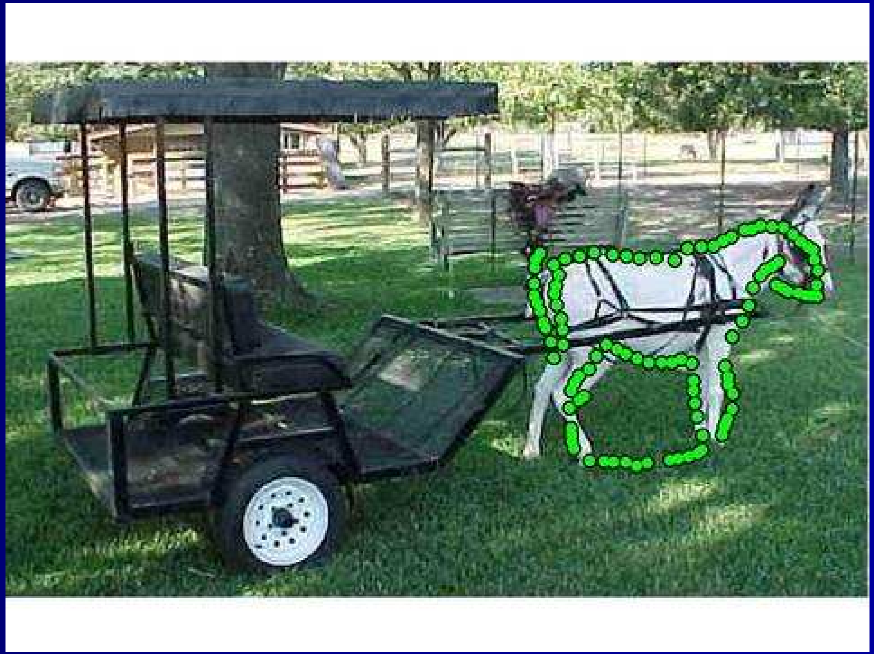




Results: horses

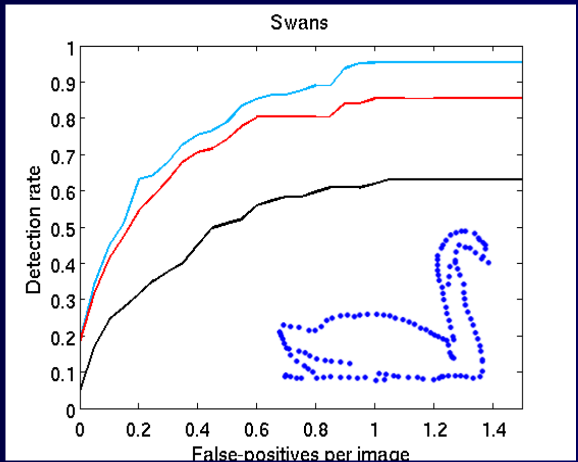




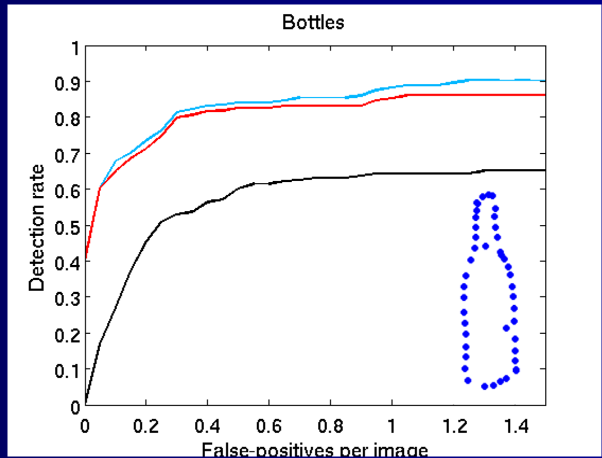


Results: detection-rate vs false-positives per image

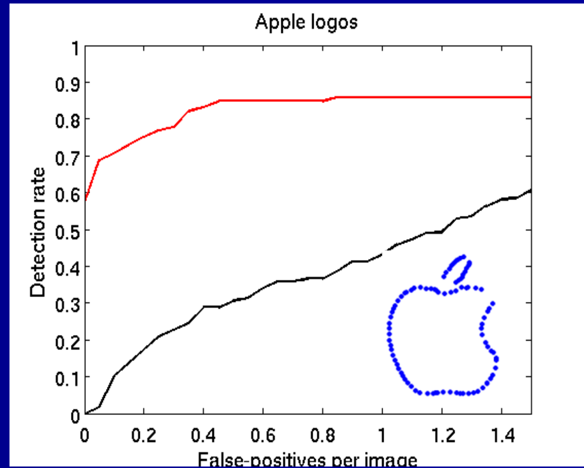
accuracy: 3.0



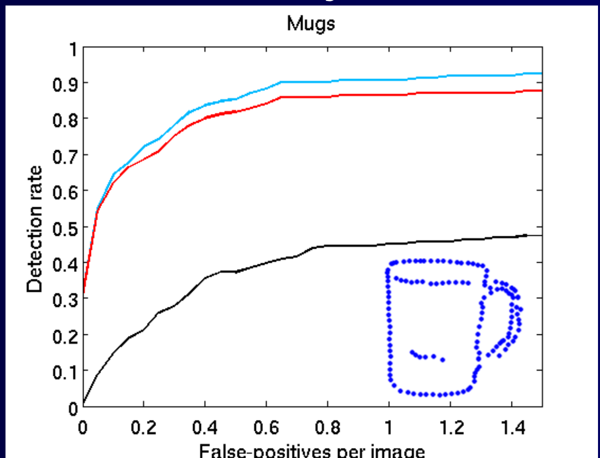
accuracy: 2.4



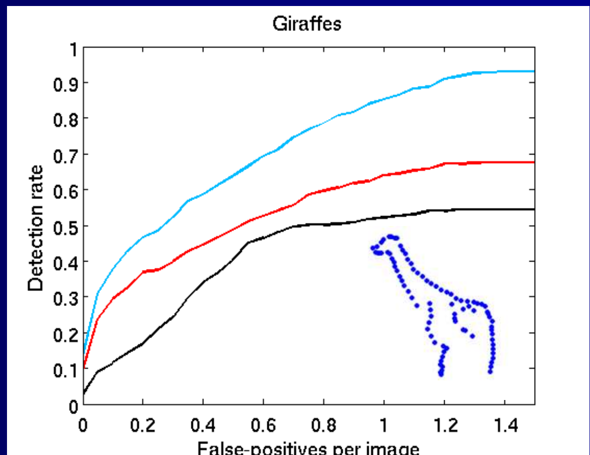
accuracy: 1.5



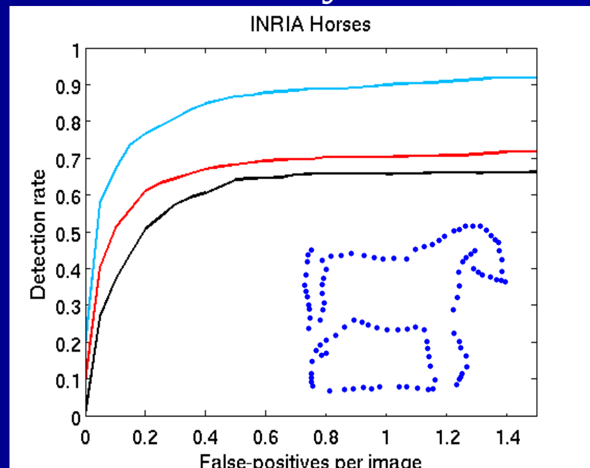
accuracy: 3.1



accuracy: 3.5



accuracy: 5.4

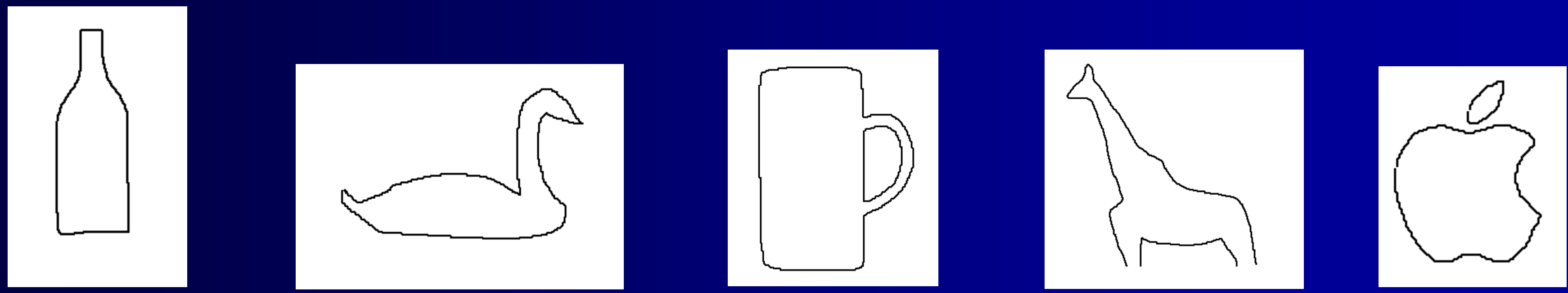


full system (>20% intersection)

full system (PASCAL: $\cap / \cup$ >50%)

Hough alone (PASCAL)

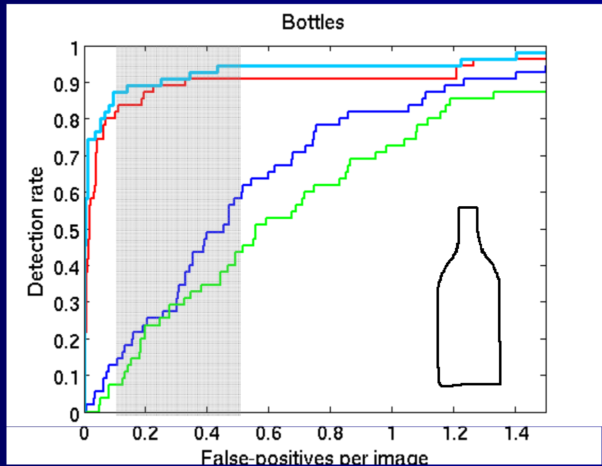
Results: Hand-drawings

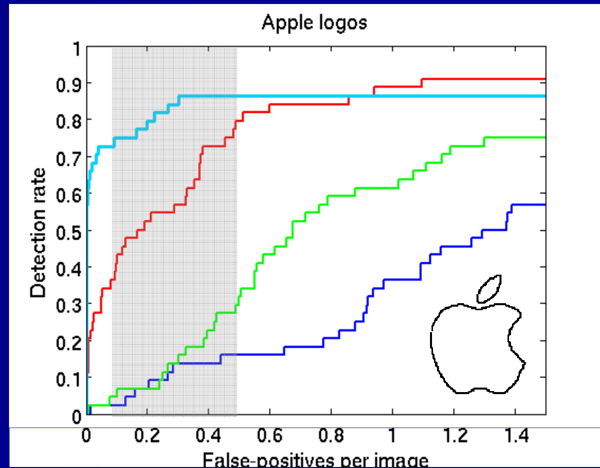


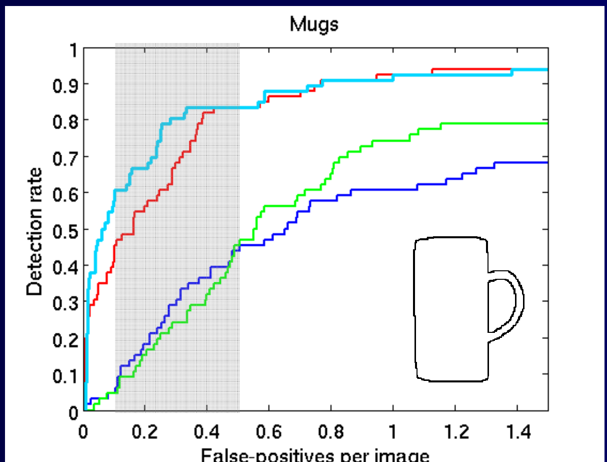
Same protocol as Ferrari et al, ECCV 2006:
match each hand-drawing to all 255 test images

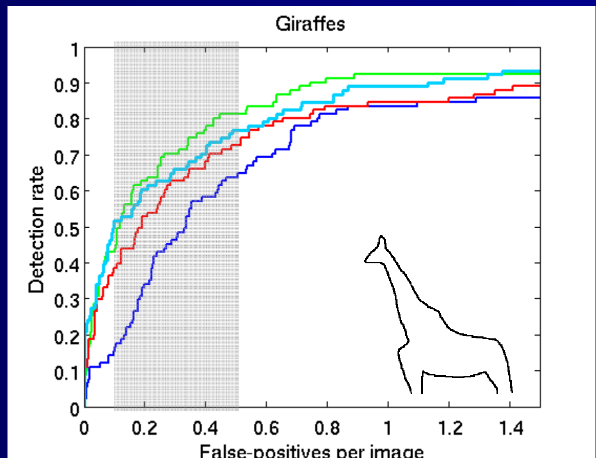
Results: detection-rate vs false-positives per image

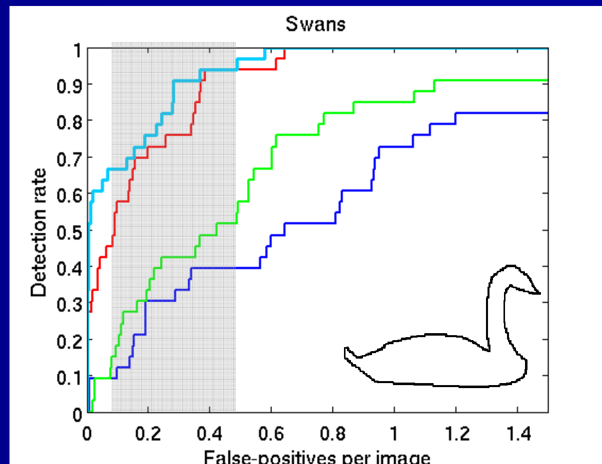
- our approach
- Ferrari, ECCV06
- chamfer
  (with orientation planes)
- chamfer
  (no orientation planes)











Conclusions

1. learning shape models from images

2. matching them to new cluttered images

+ detect object boundaries while needing only BBs for training

+ effective also with hand-drawings as models

+ deals with extensive clutter, shape variability, and large scale changes

- can’t learn highly deformable classes (e.g. jellyfish)

- model quality drops with very high training clutter/fragmentation (giraffes)