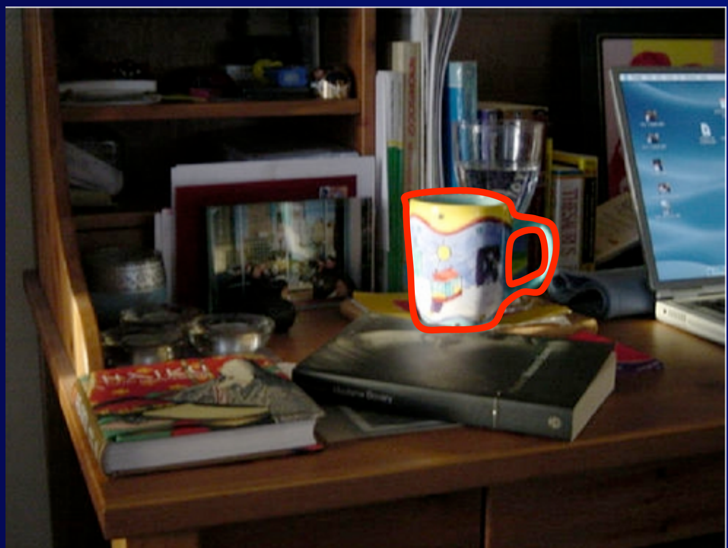
Learning deformable shape models from images

Goal: localize boundaries of new class instances

Training data




Test image



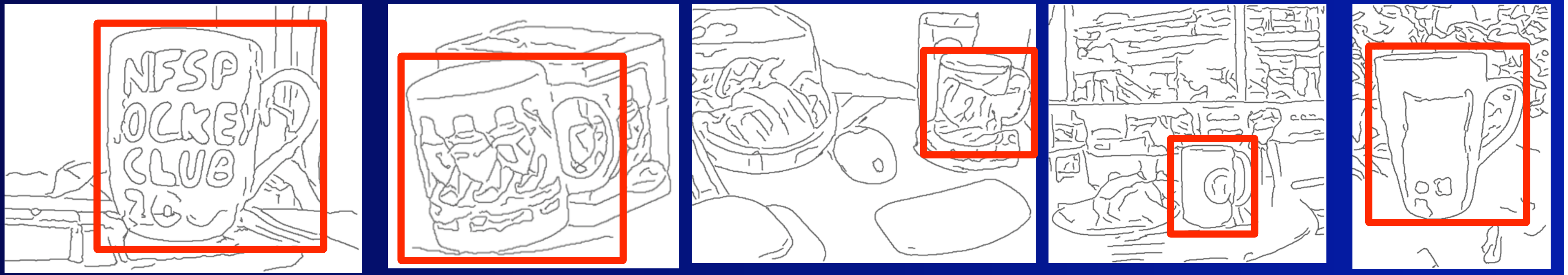
Training: *bounding-boxes*

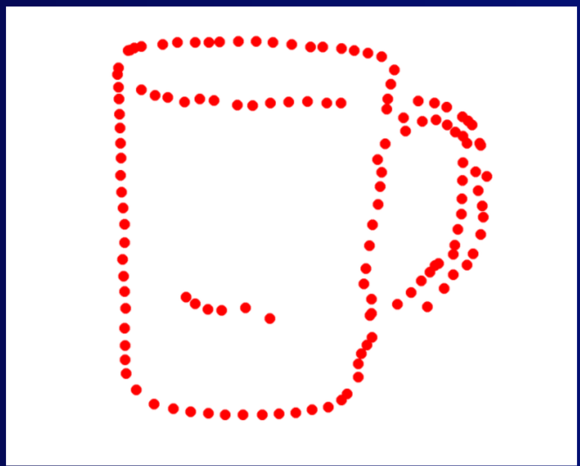
Testing: *object boundaries*

[Ferrari, Jurie, Schmid, IJCV09]

Learn a shape model from training images

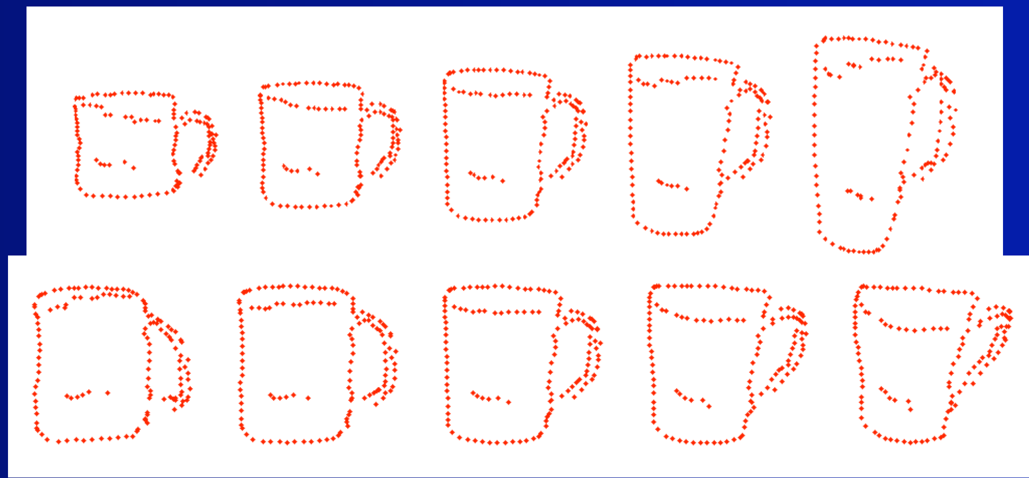
Training data





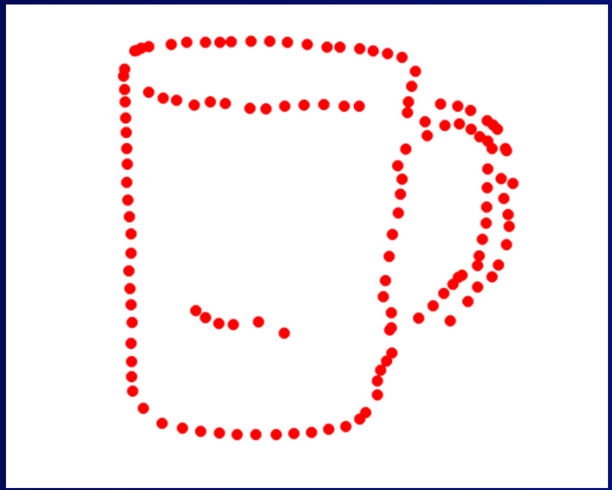
prototype shape

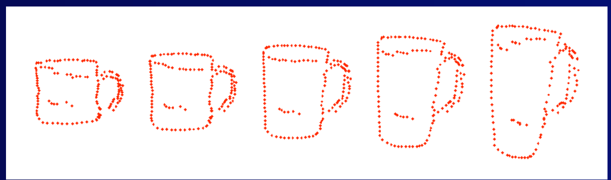
+

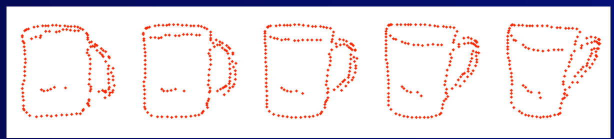


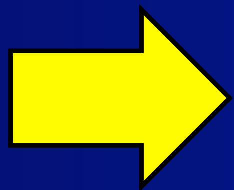
deformation model

Match it to the test image

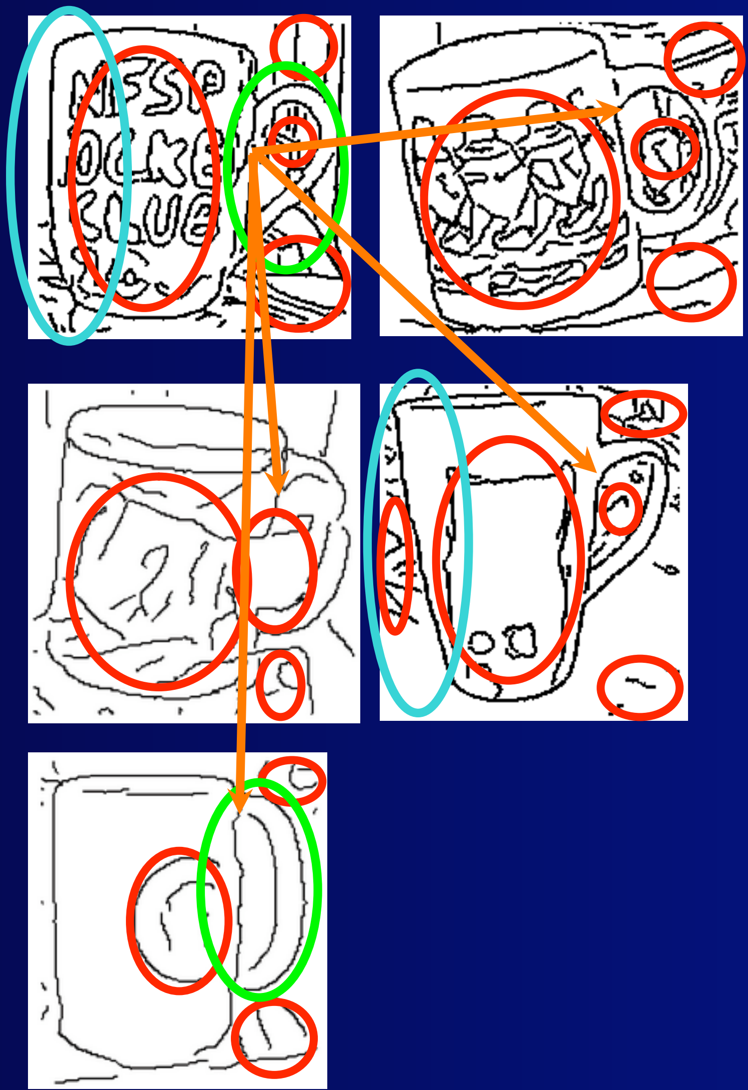








Challenges for learning



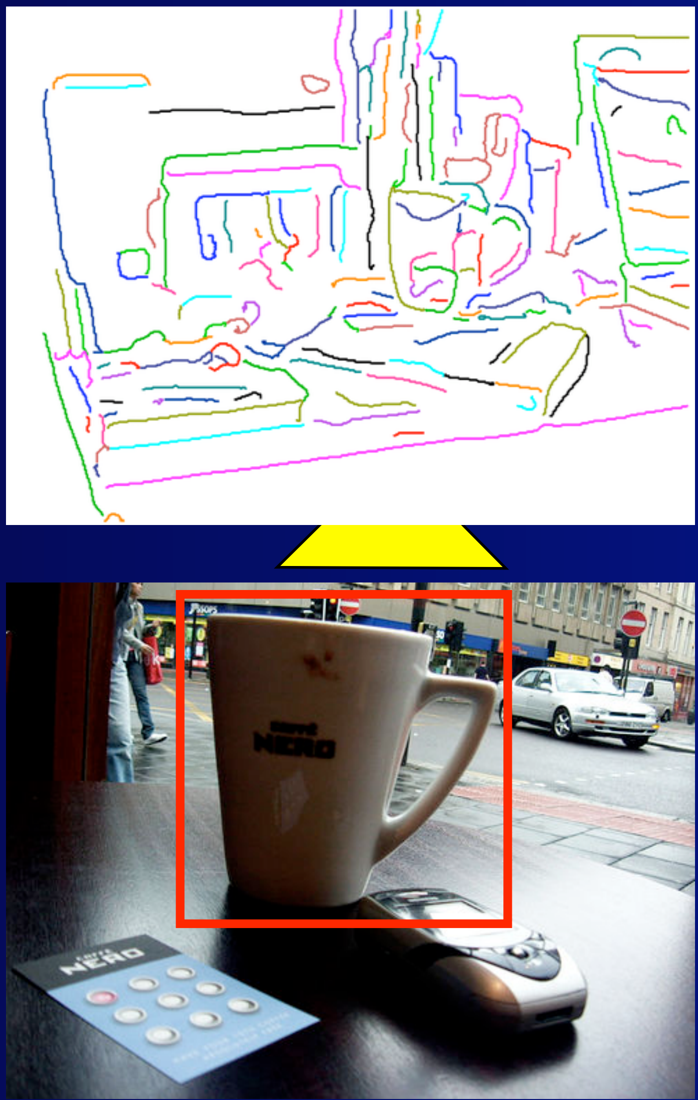
Main issue

which edgels belong
to the class boundaries ?

Complications

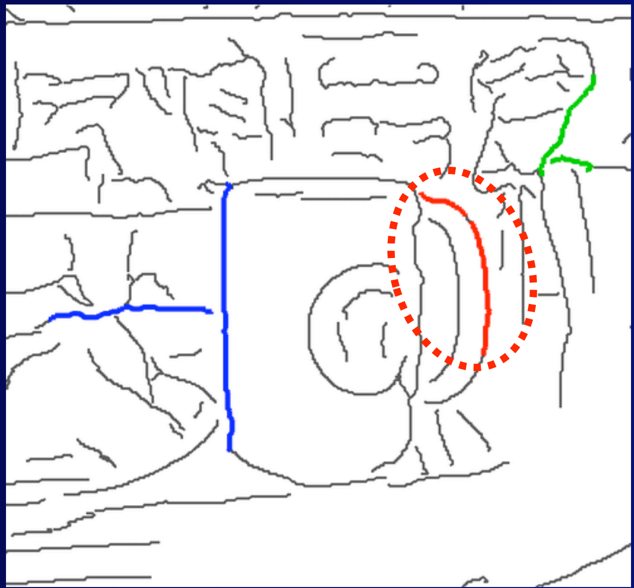
- intra-class variability
- missing edgels
- produce point correspondences
  (learn deformations)

Challenges for detection



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

Local contour features



PAS

Pair of Adjacent Segments

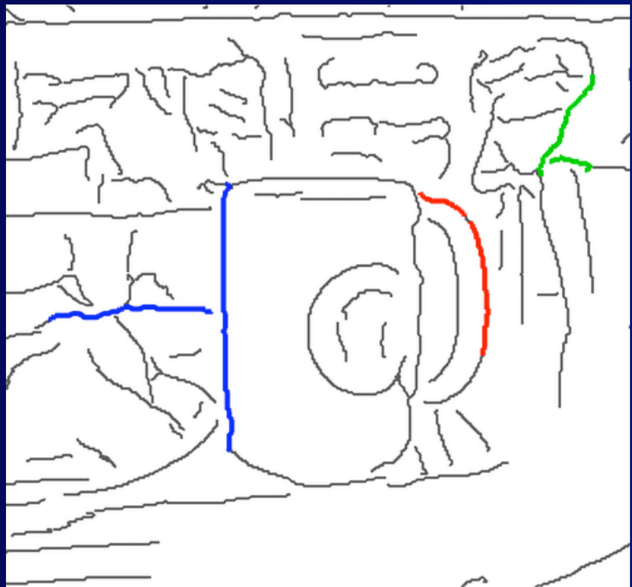
+ *robust*
  connect also across gaps

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

+ *invariant*
  to translation and scale

+ *intermediate complexity*
  good compromise between repeatability and informativity

Local contour features



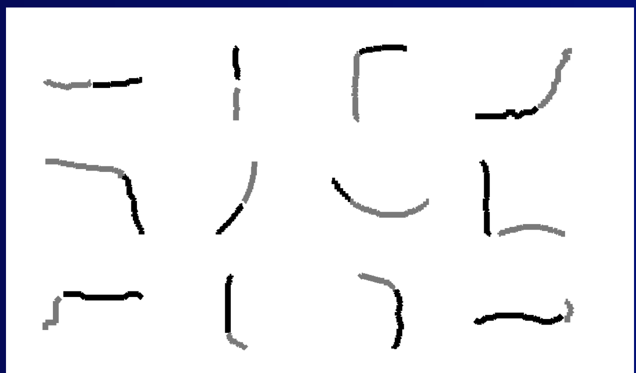
PAS

Pair of Adjacent Segments

two PAS in correspondence

⟶ translation+scale transform

⟶ use in Hough-like schemes

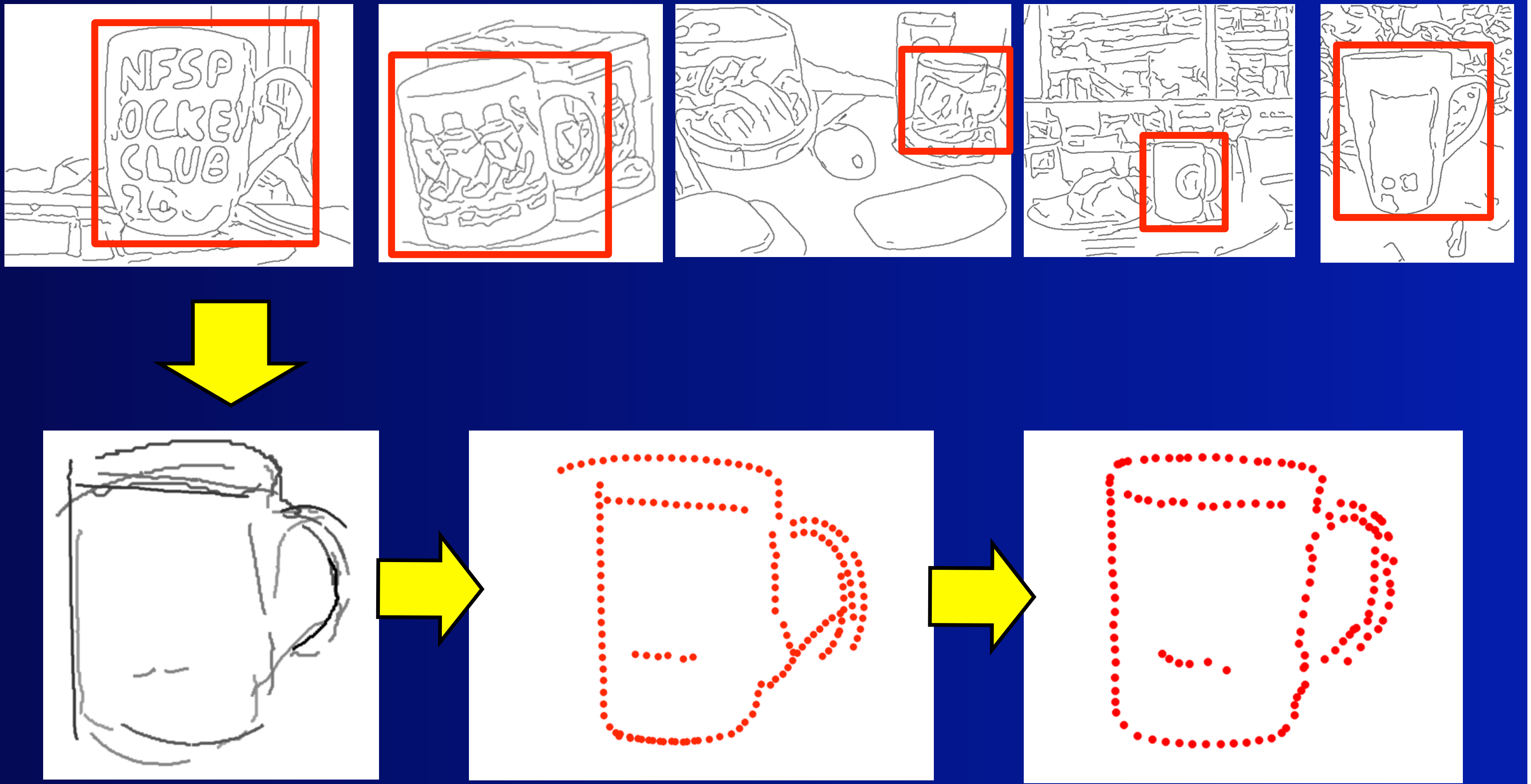


Clustering descriptors

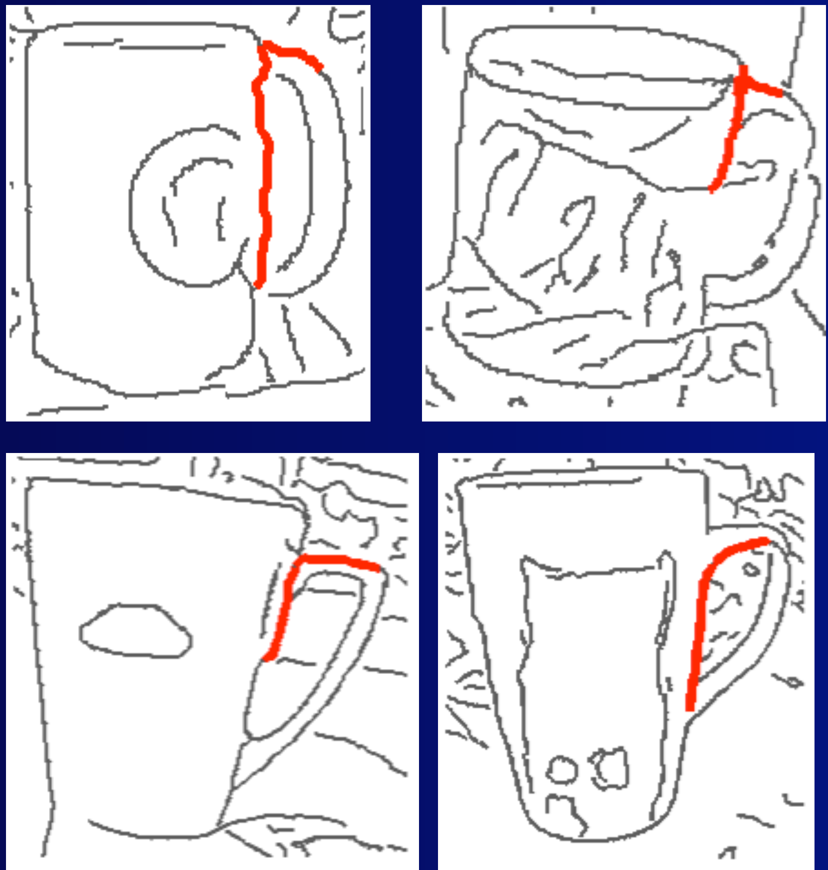
⟶ codebook of *PAS types*

(here from mug bounding boxes)

Learning: overview



Learning: finding model parts

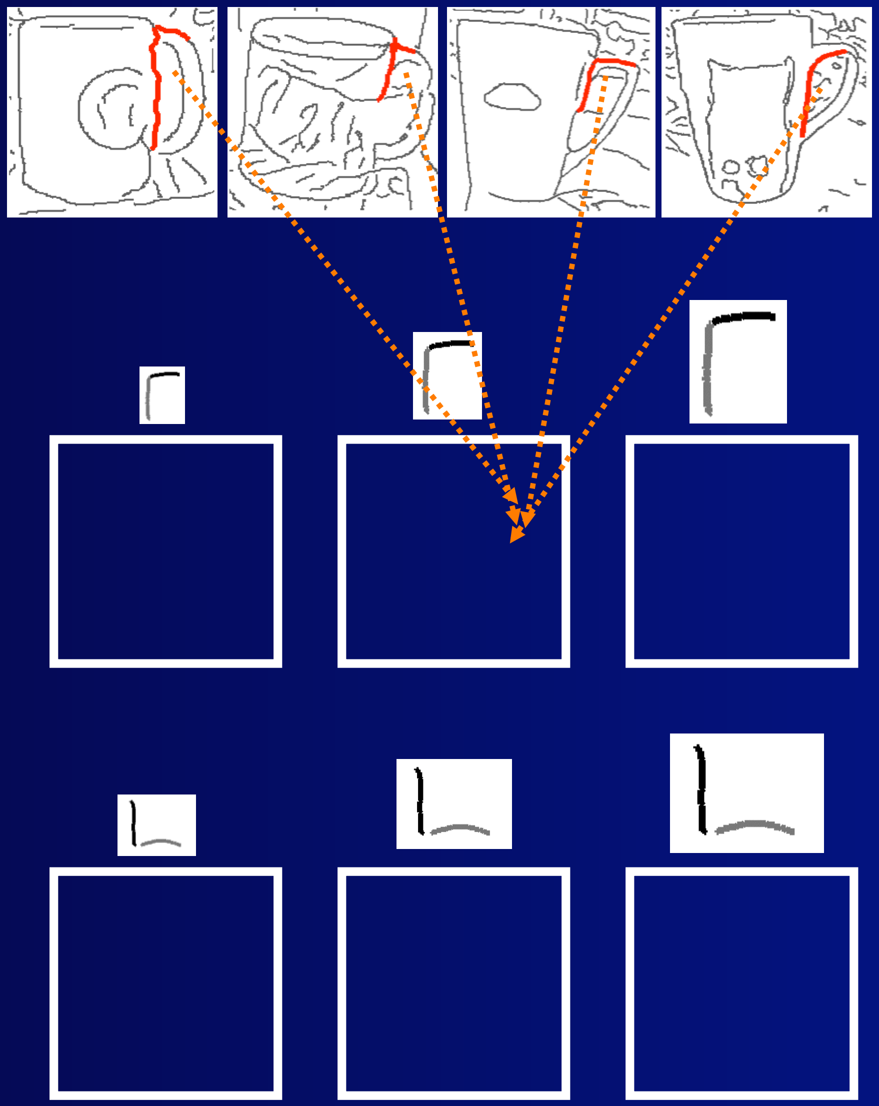


Intuition

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

Background and details specific to individual examples don't

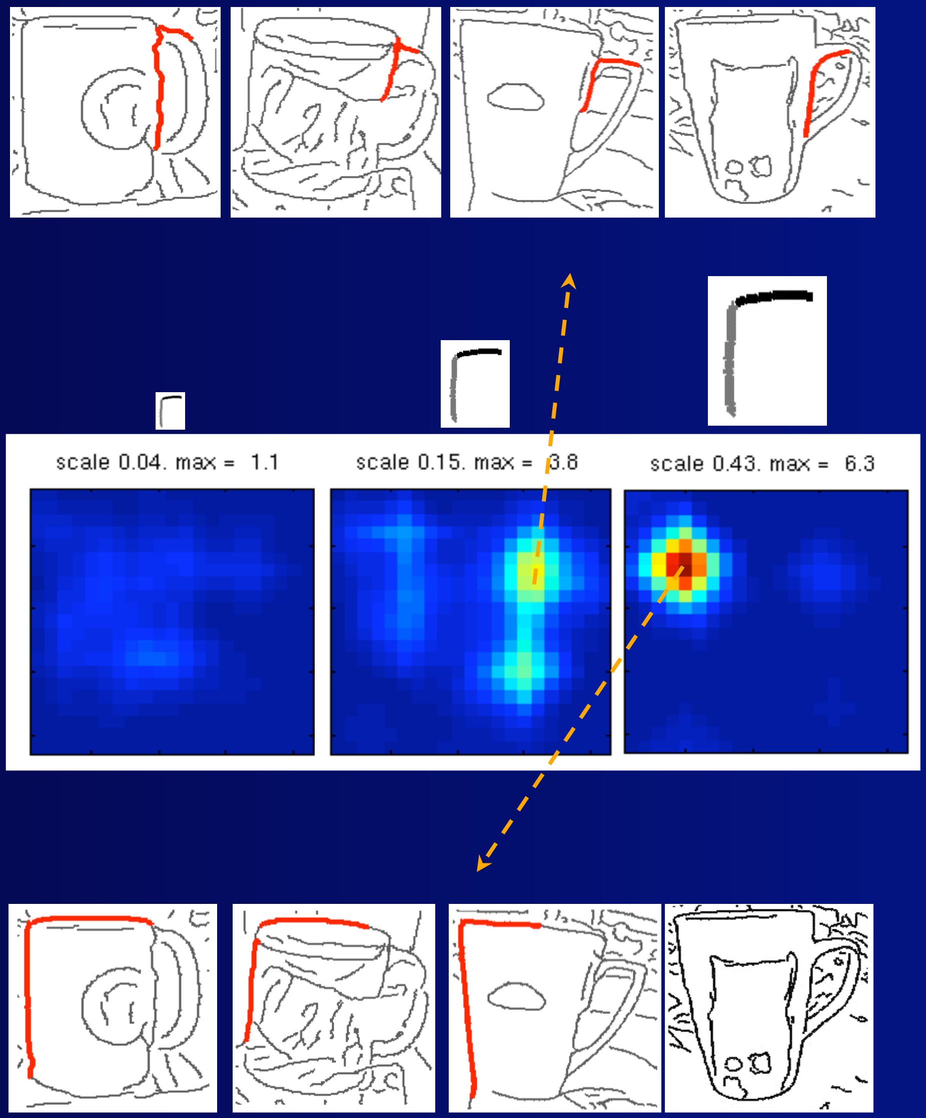
Learning: finding model parts



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

Cool, but not a shape yet

- multiple strokes
- adjacent parts don't fit together

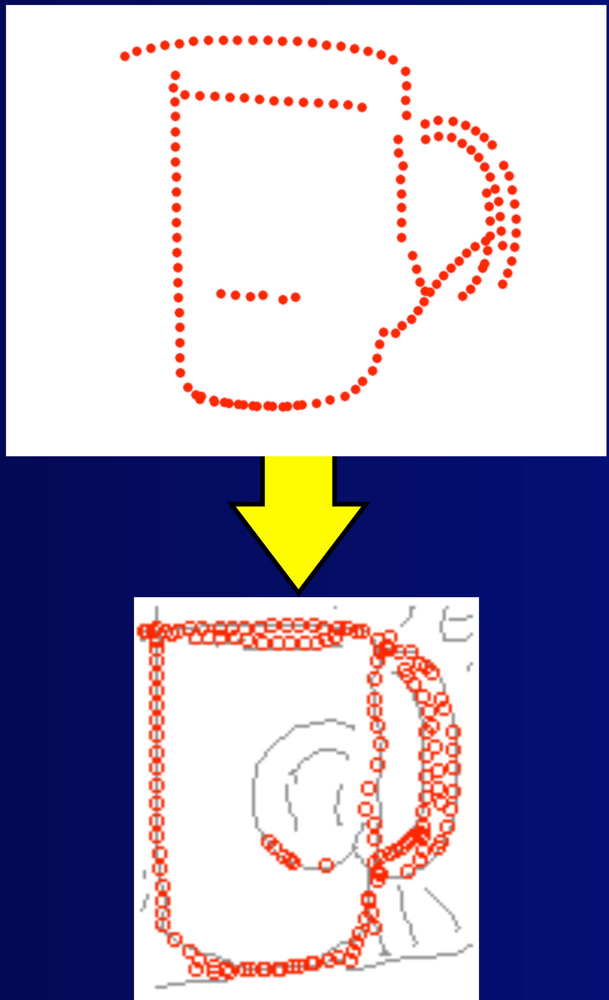
Why ?

- parts are learnt *independently*

Let's try to assemble parts into a proper whole

We want single-stroked, long continuous lines !

Learning: shape refinement



Idea

treat shape as deformable point set

and *match it back* onto training images

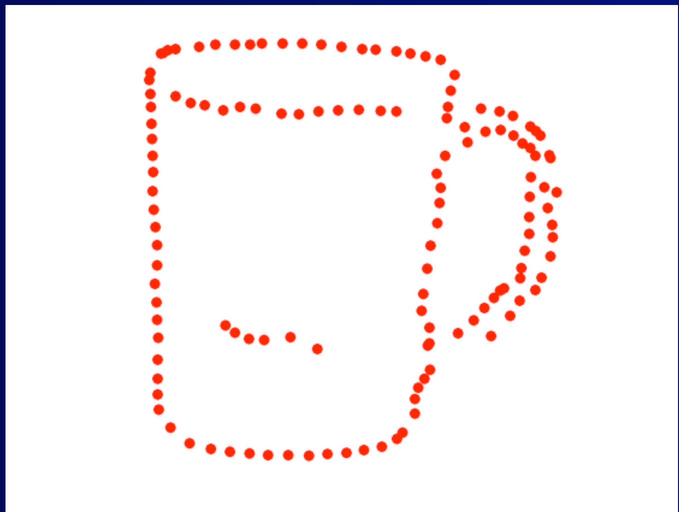
How ?

- 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

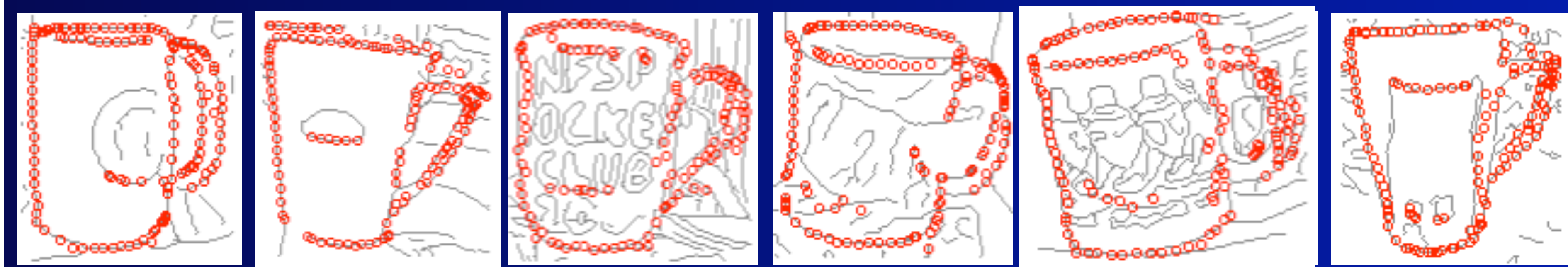
1. Match current model shape back to every training image

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

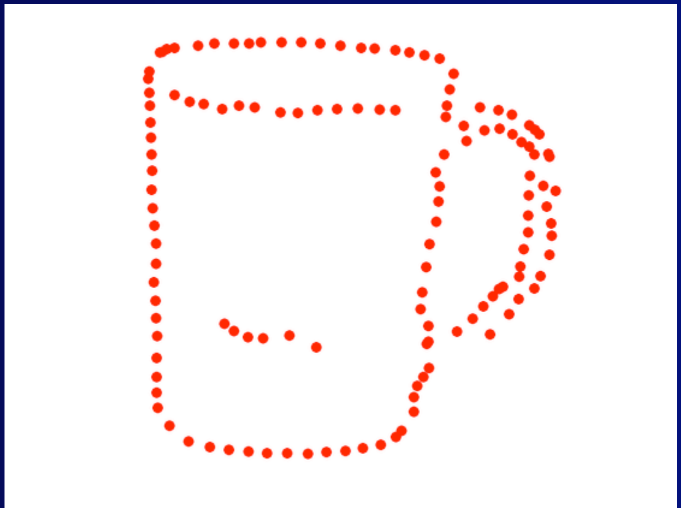
2. set model to mean shape

3. remove redundant points

4. if changed $\longrightarrow$ iterate to 1



Learning: shape refinement



Final model shape

+ clean (almost only class boundaries)

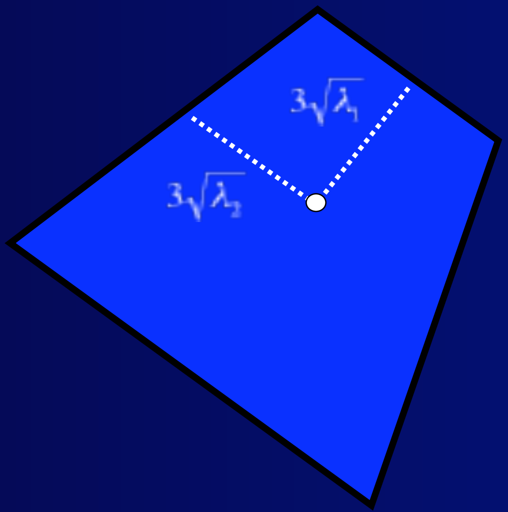
+ smooth, connected lines

+ 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

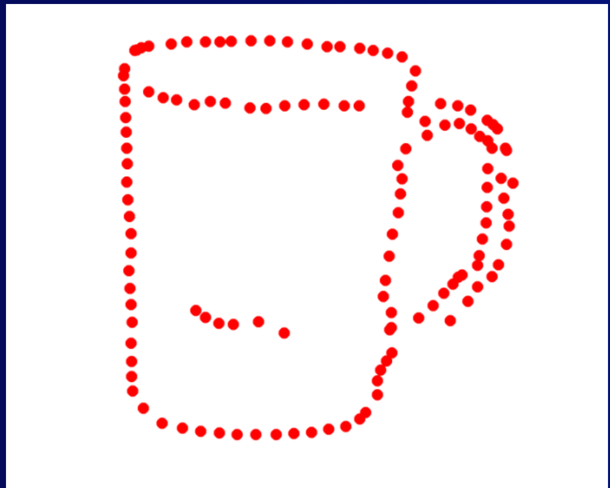
. top *n* eigenvectors covering 95% of variance

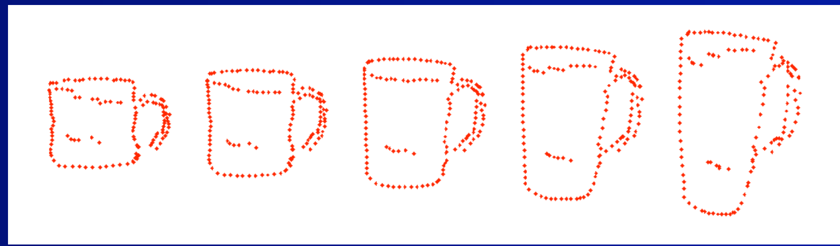
. associated eigenvalues λ_i (act as bounds)

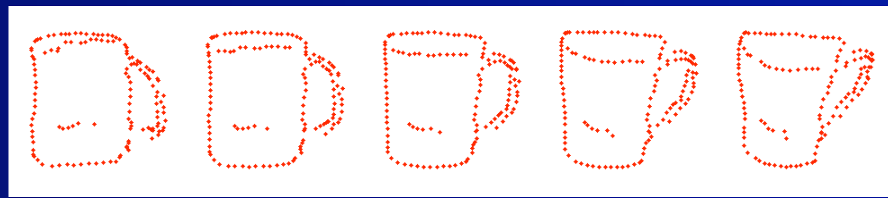
⟶ *valid region* of shape space

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

Learning completed !

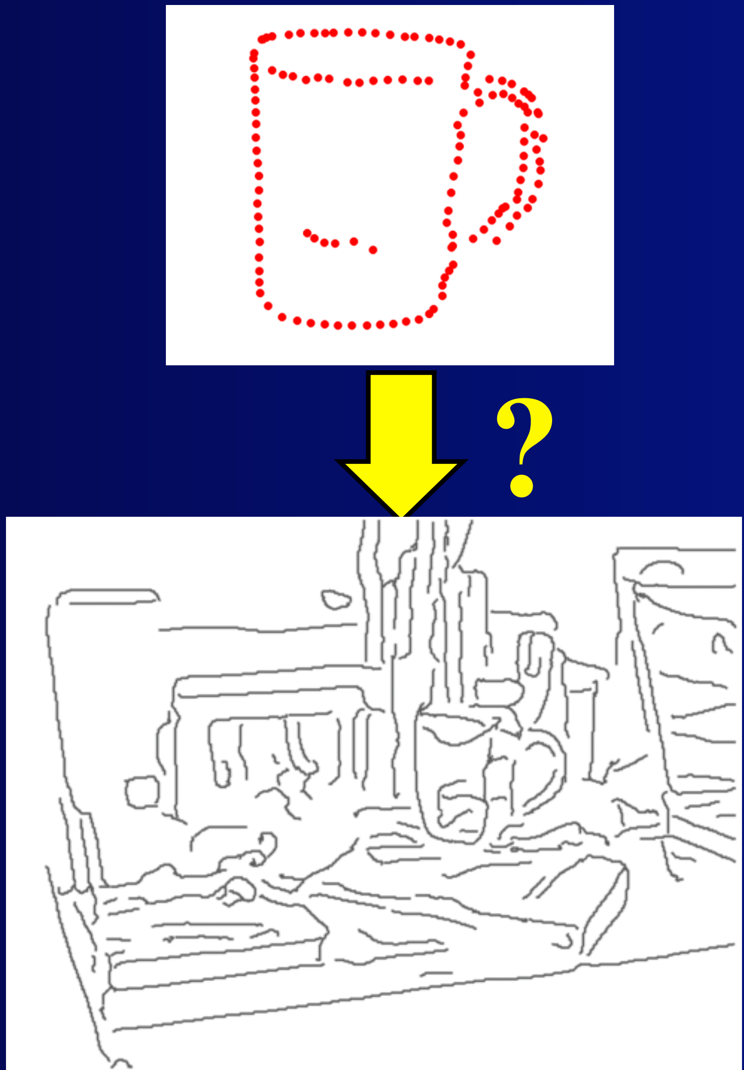






Automatic learning of
shapes, correspondences, and deformations
from unsegmented images

Object detection: overview



Goal

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

How ?

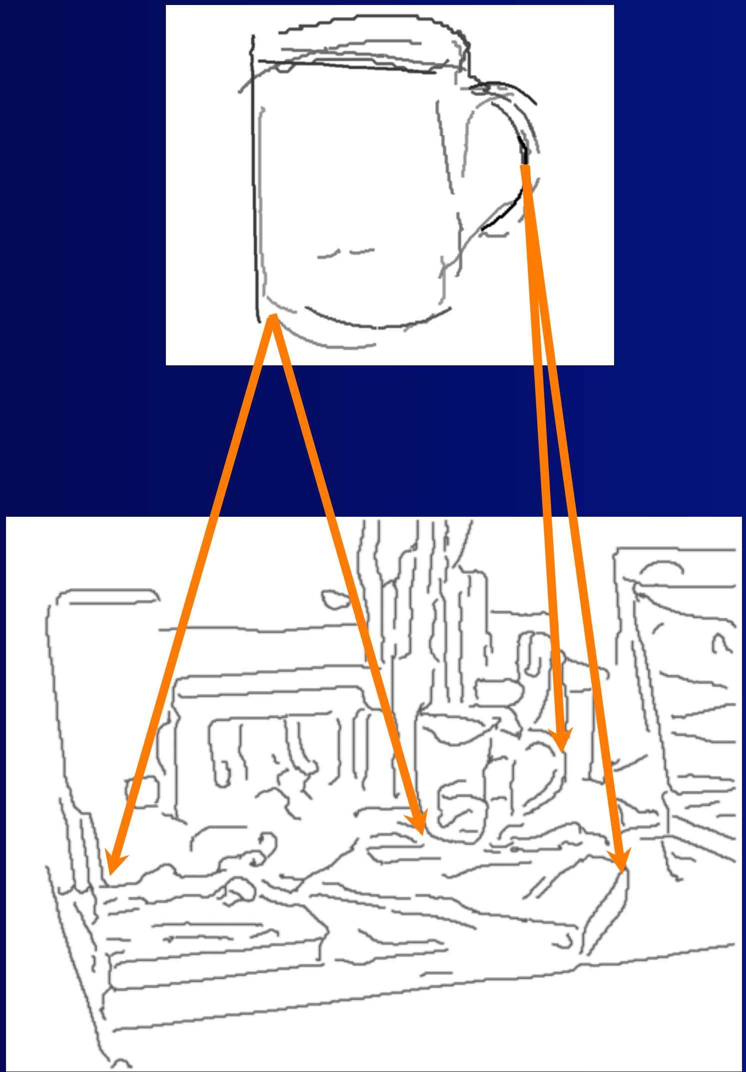
1. Hough voting over PAS matches
   ⟶ *rough* location+scale estimates

2. use to initialize TPS-RPM

   combination enables true pointwise shape matching to cluttered images

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

Object detection: Hough voting



Algorithm

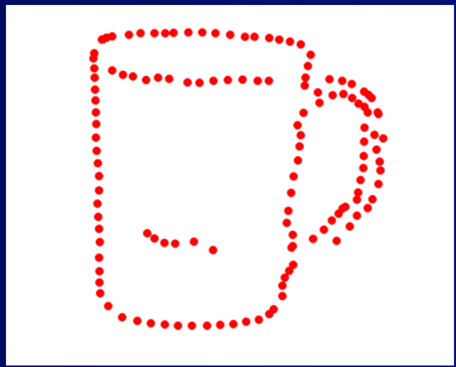
1. soft-match model parts to test PAS

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
   → vote in accumulator space

3. local maxima
   → 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: shape matching by TPS-RPM

Initialize

get point sets V and X

Goal

find correspondences M and 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

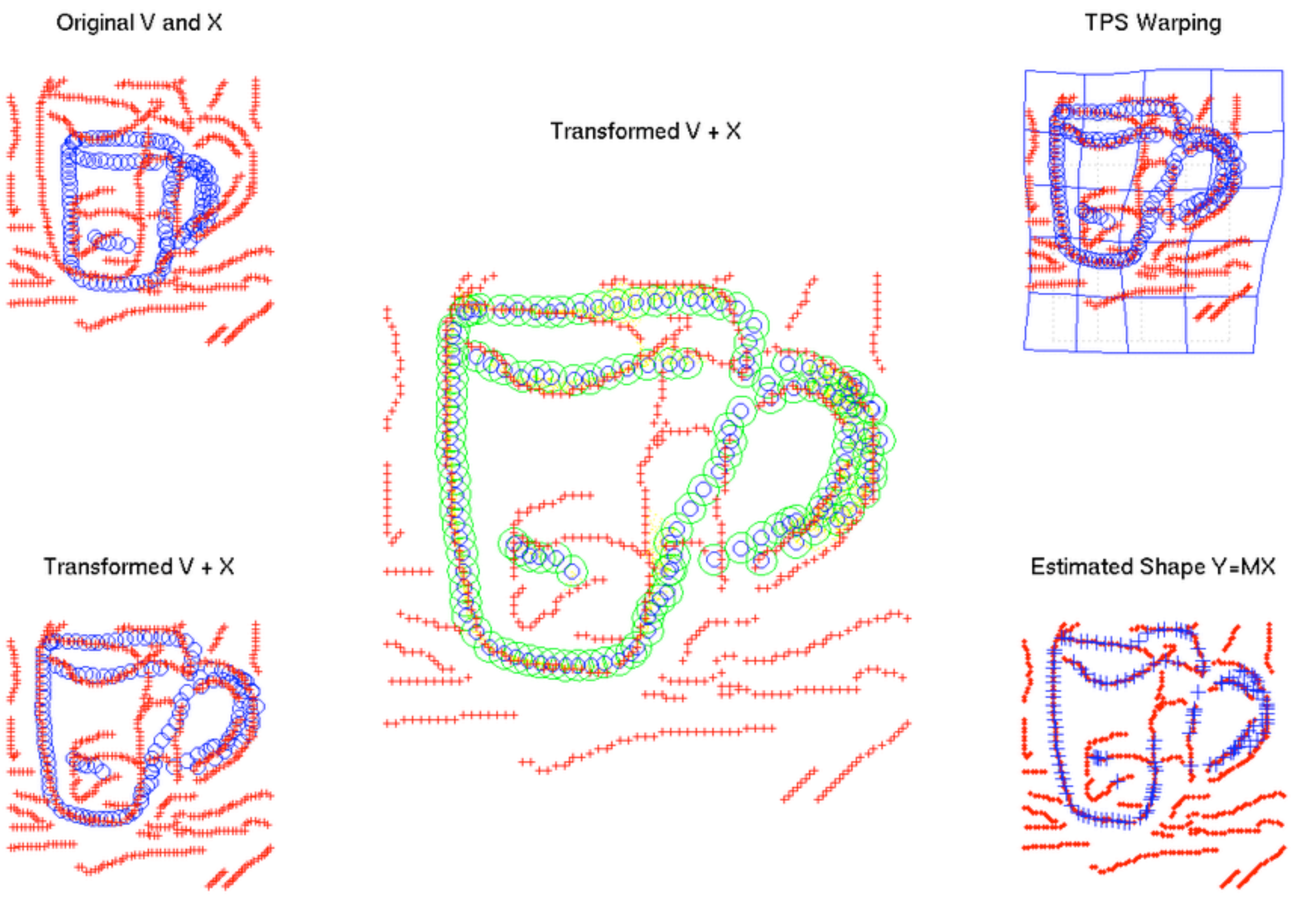
Deterministic annealing:
iterate with T decreasing

→ 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)

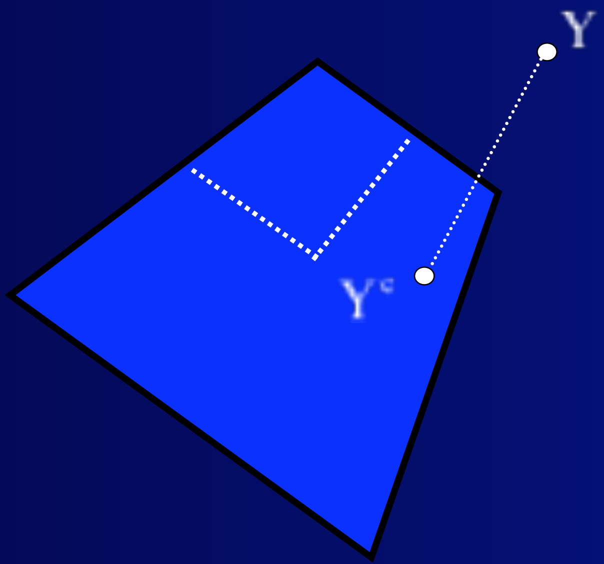
Constrained shape matching

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 ?

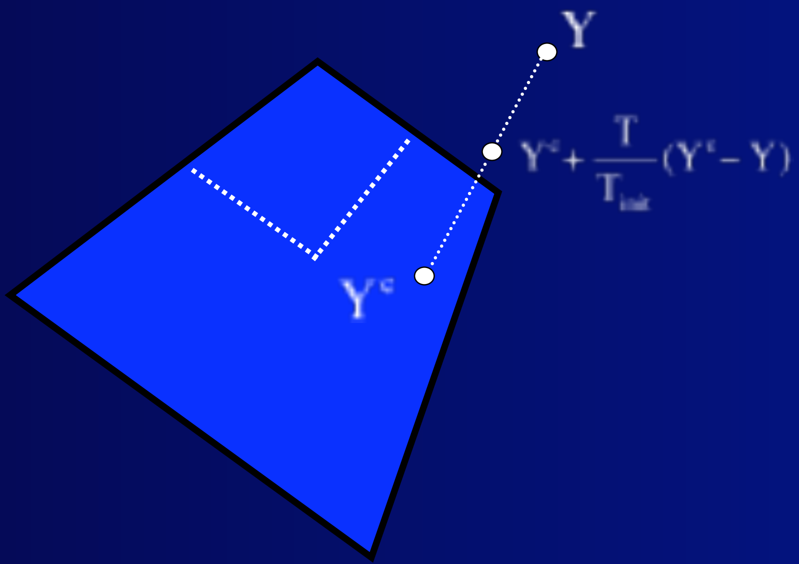
1. Update M

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

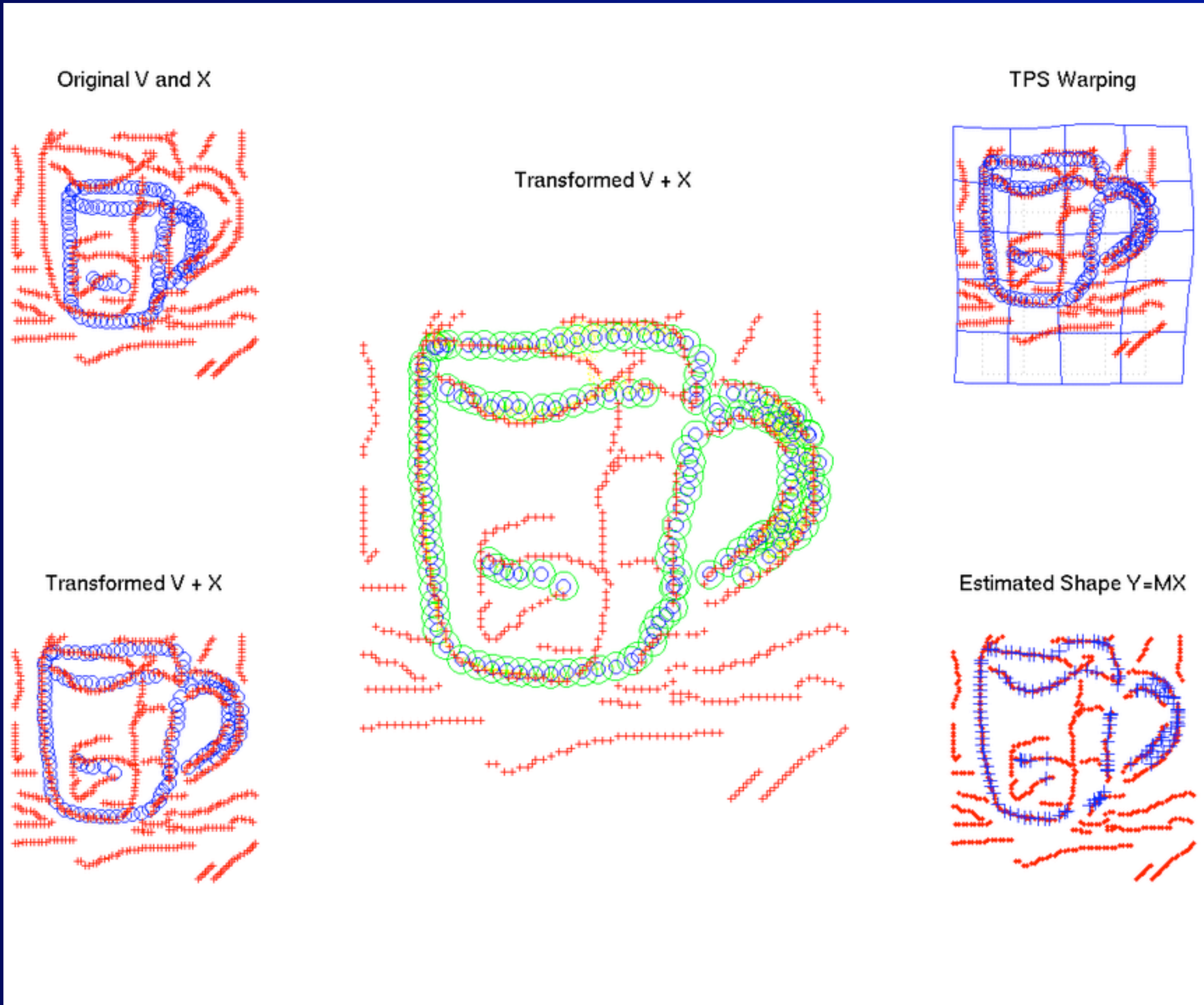
constrain optimization to explore only region of shape space spanned by training examples

Soft constraint variant

1. Update M
2. Update TPS:
   - Y = MX
   - $Y \leftarrow Y^c + \frac{T}{T_{init}}(Y^c - Y)$
   - fit regularized TPS to V⟷Y

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

Soft constrained TPS-RPM in action !



Object detection: constrained TPS-RPM

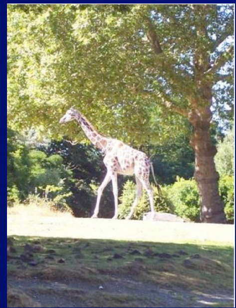
Soft constrained TPS-RPM

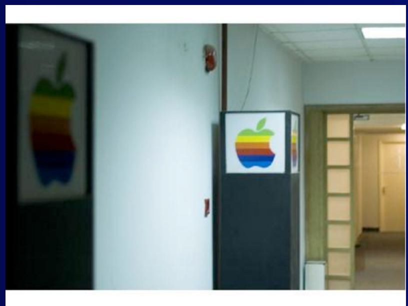
+ shapes fit data more accurately
+ shapes resemble class members
+ in spirit of deterministic annealing !
+ truly alters the search
  (not fix a posteriori)

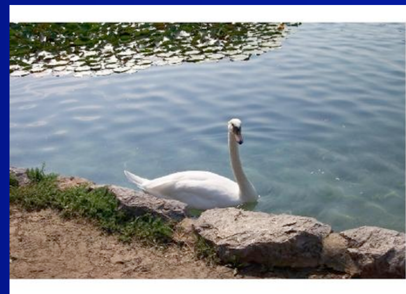
Does it really make a difference ?

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

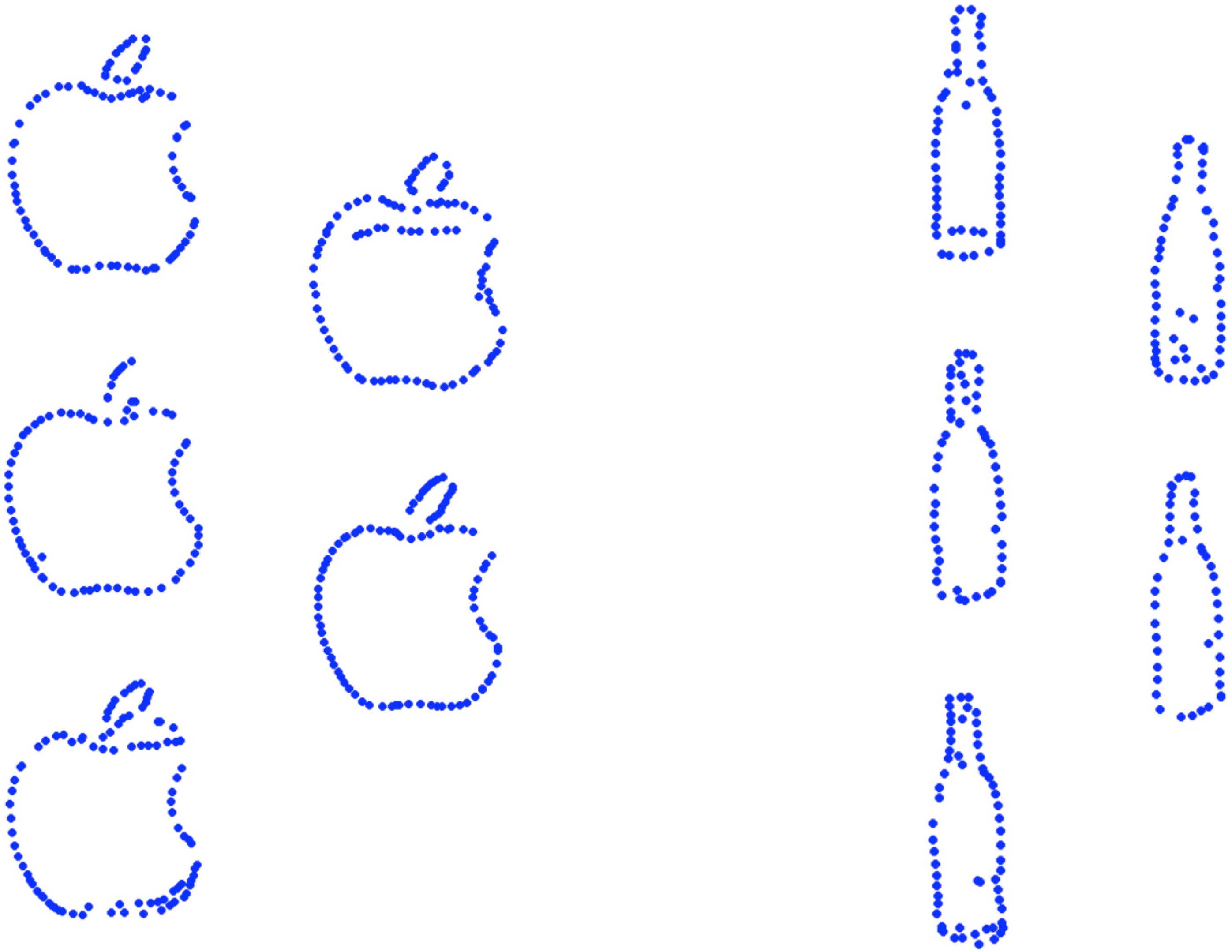
- training images: 5x random half of positive; test images: *all* non-train

Datasets: INRIA Horses

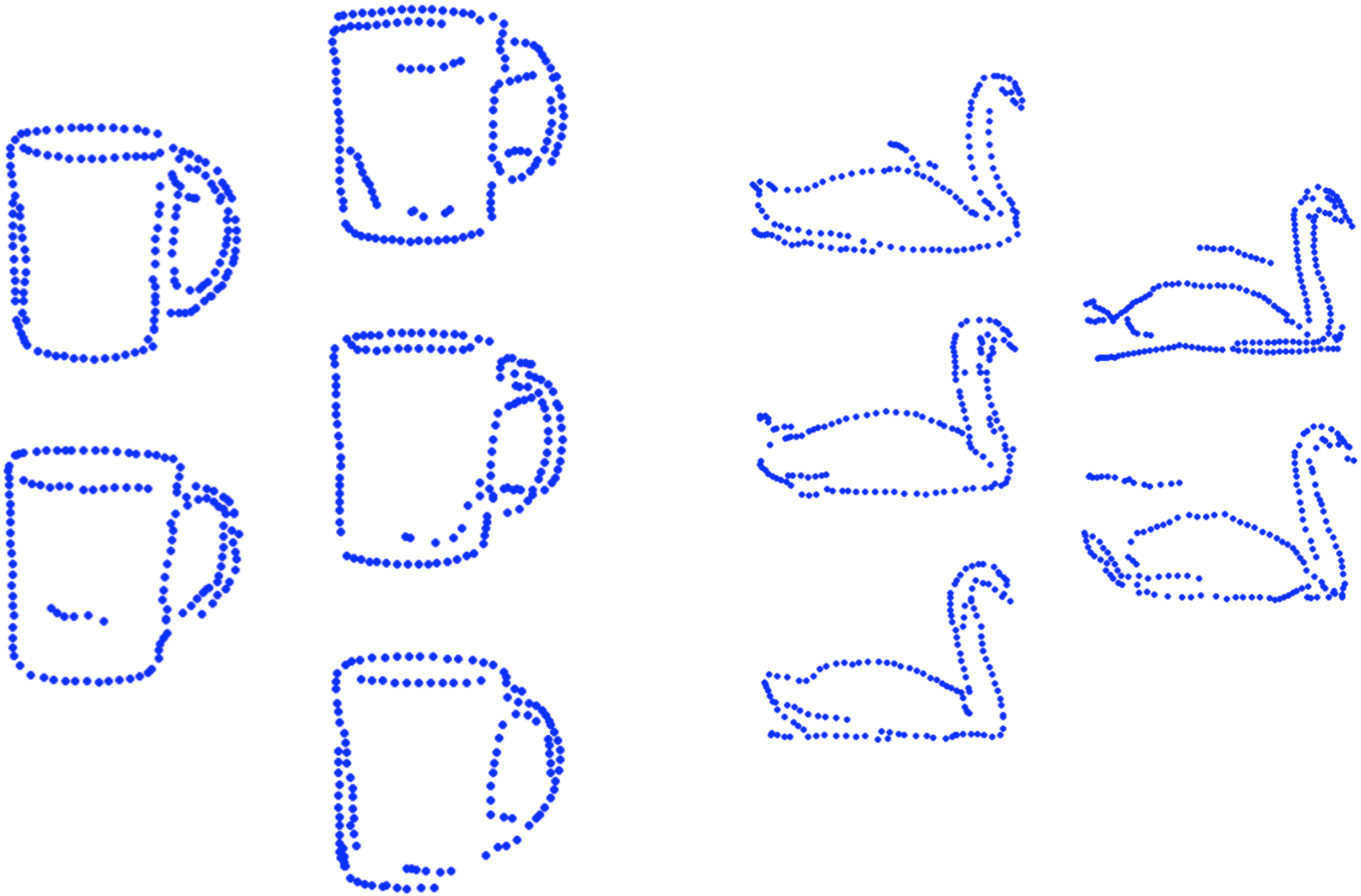



- 170 horse images + 170 non-horse ones
  - clutter, scale changes, various poses
- all parameters are kept fixed for all experiments
- training images: 5x random 50; test images: all non-train images

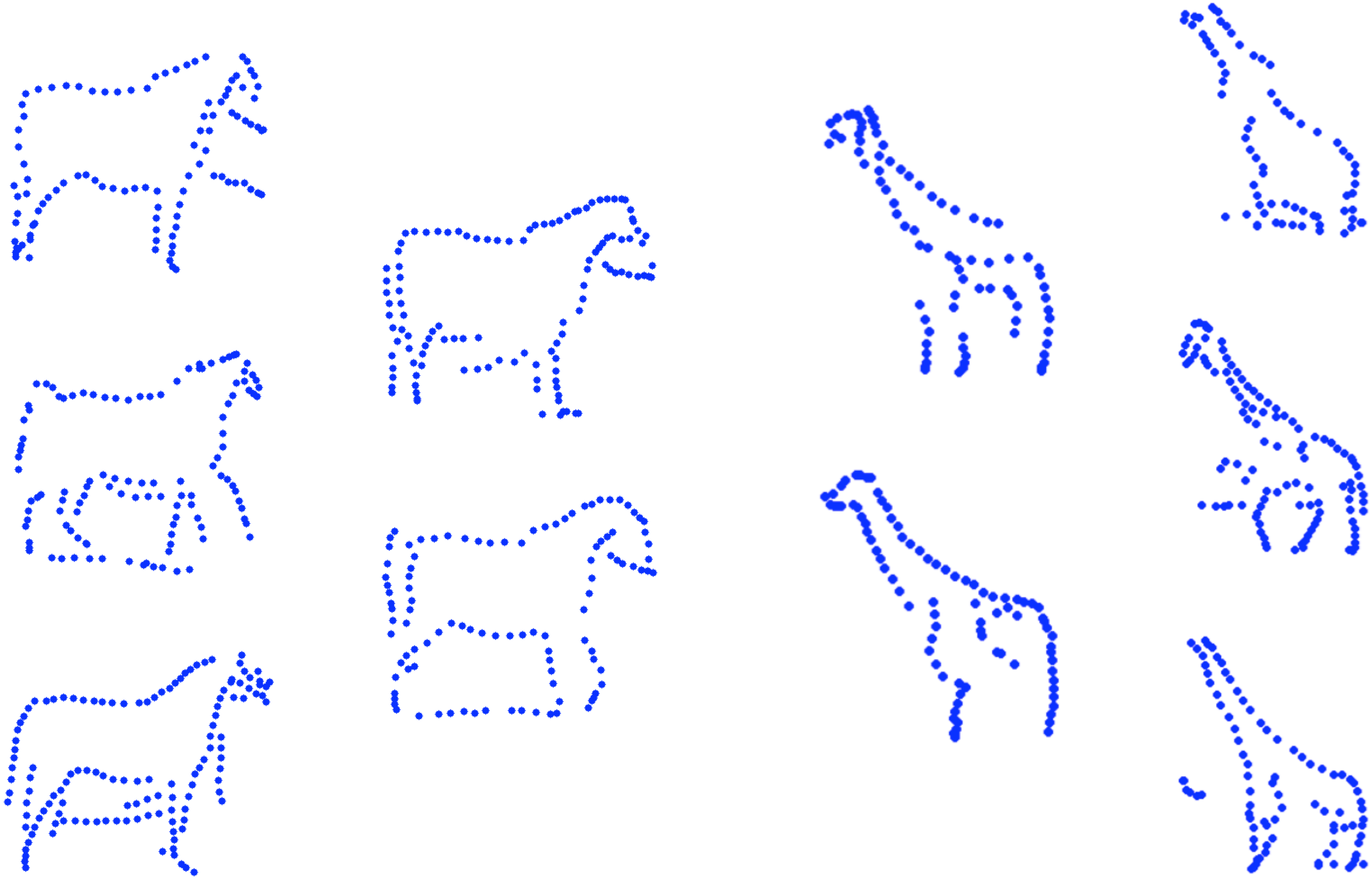
Results: all learned models



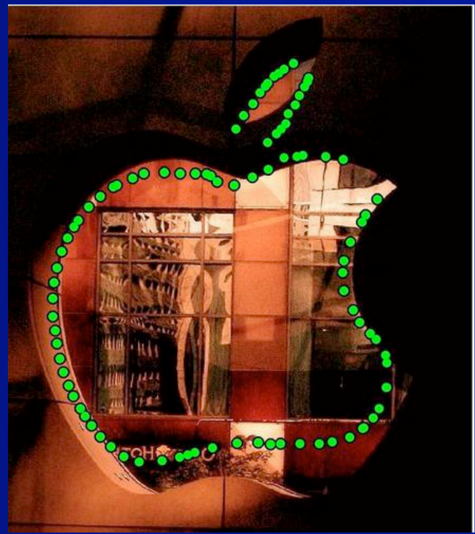
Results: all learned models

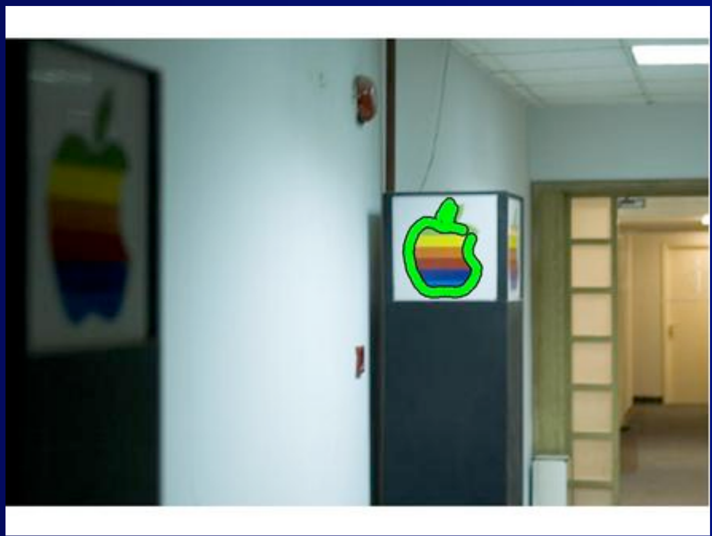


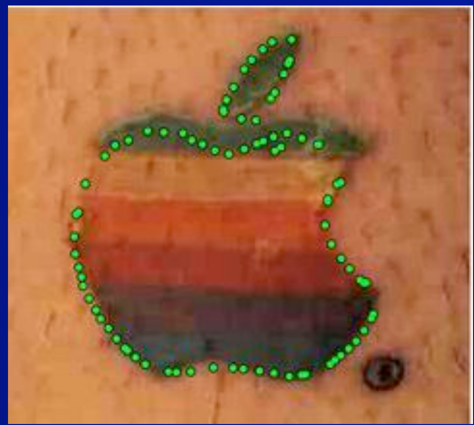
Results: all learned models



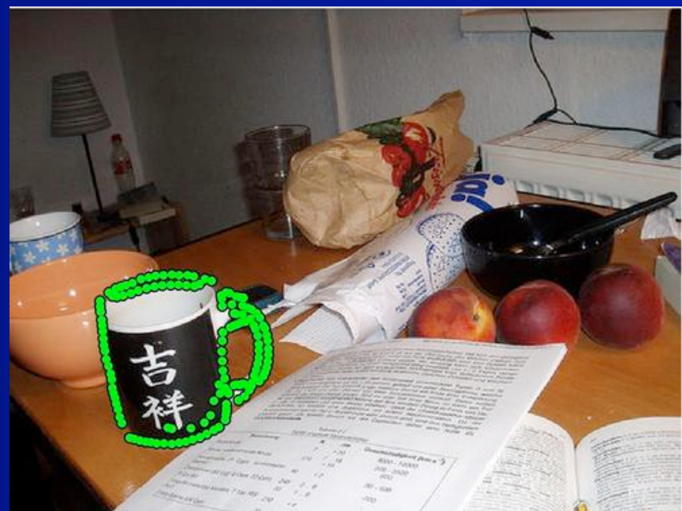
Results: apple logos



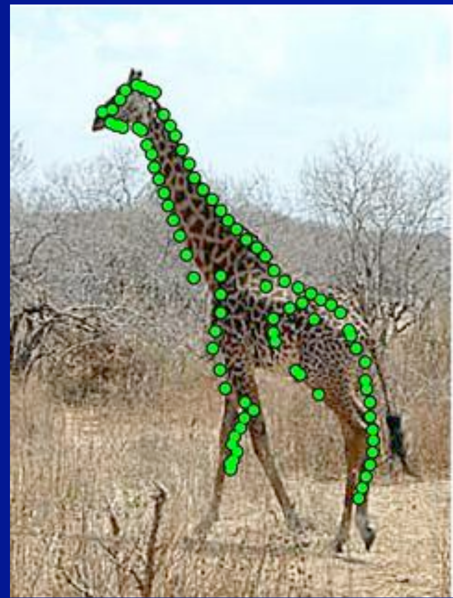




Results: mugs

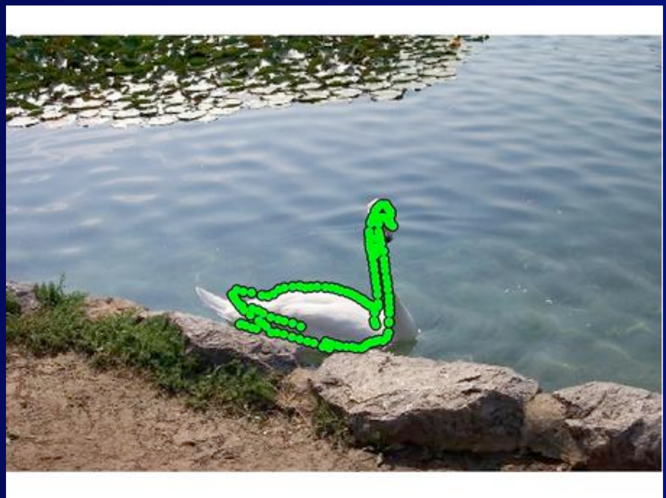


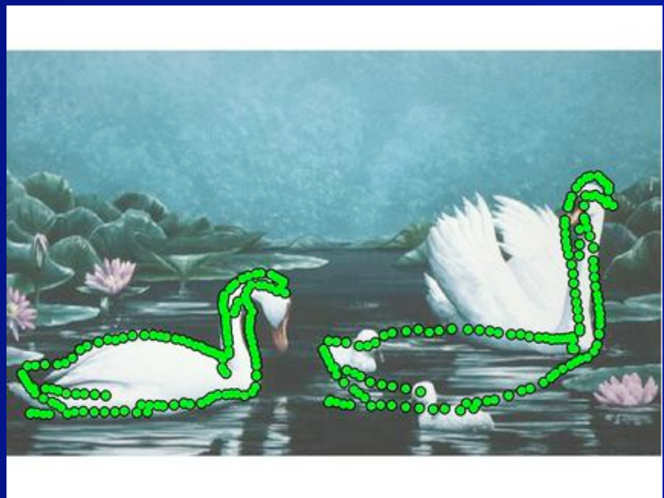
Results: giraffes



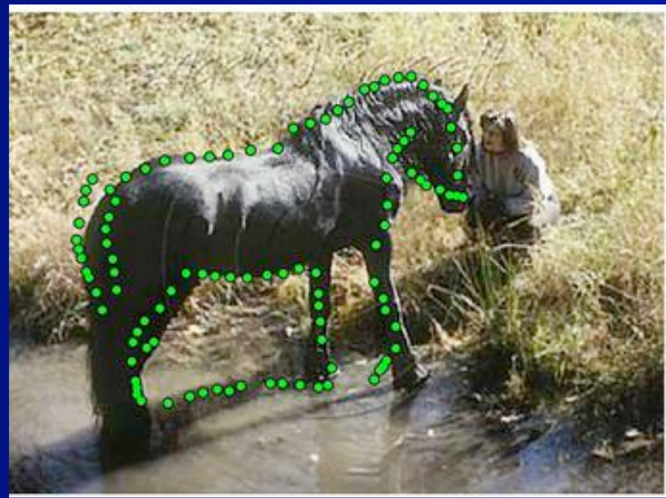
Results: bottles

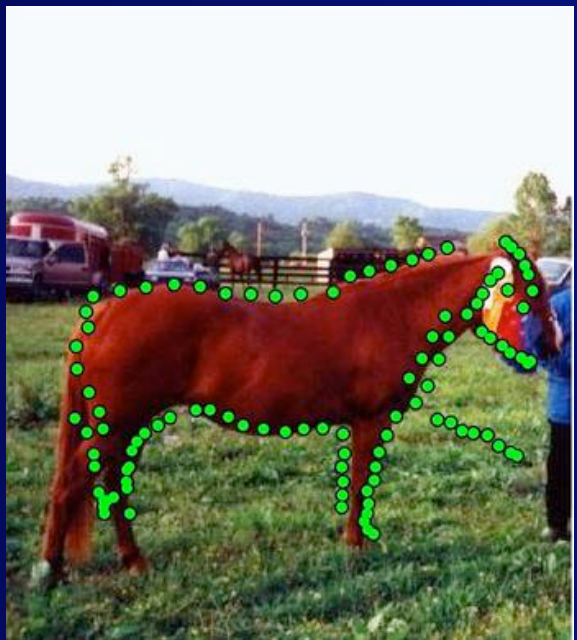
Results: swans





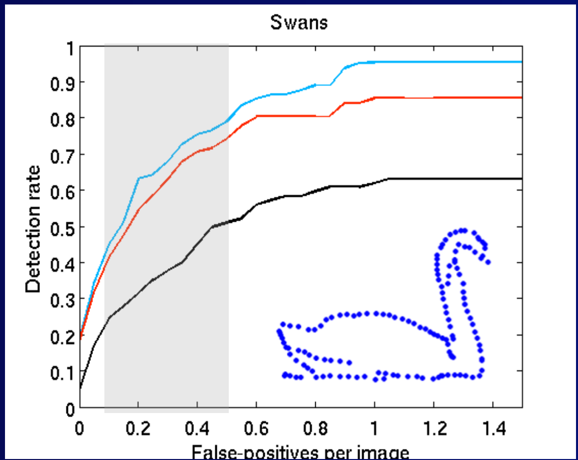
Results: horses



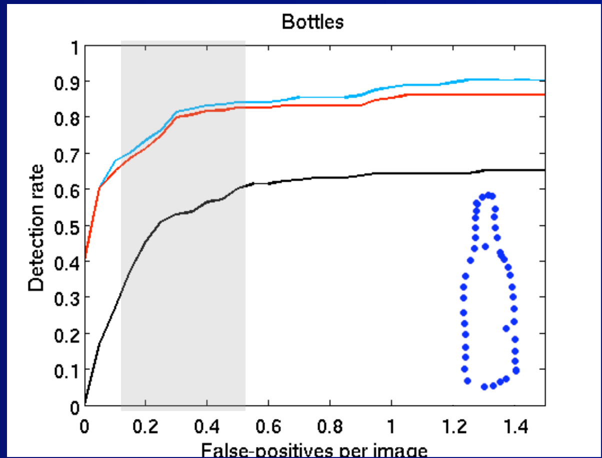


Results: detection-rate vs false-positives per image

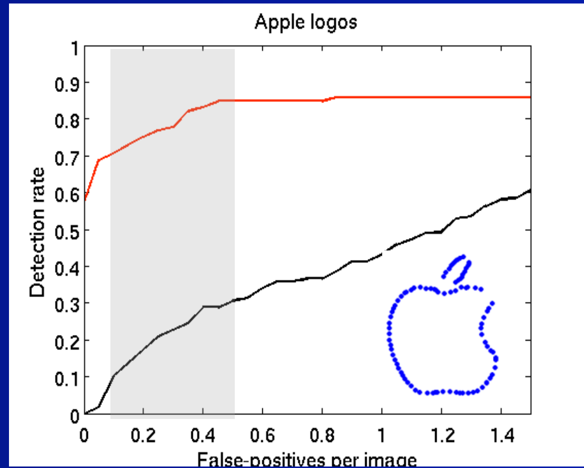
accuracy: 3.0



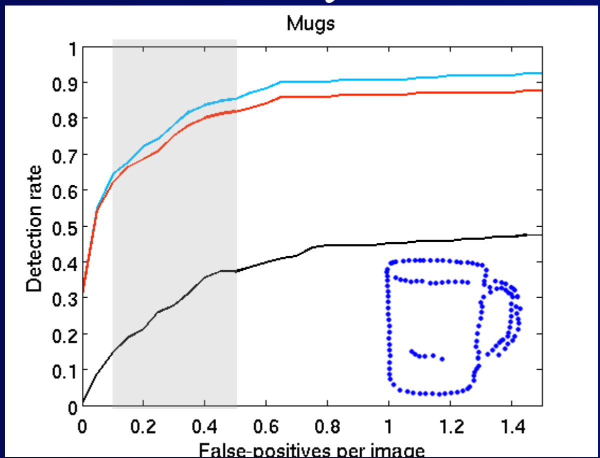
accuracy: 2.4



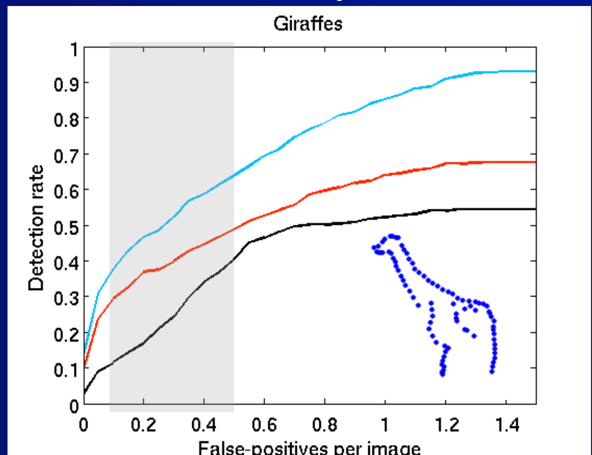
accuracy: 1.5



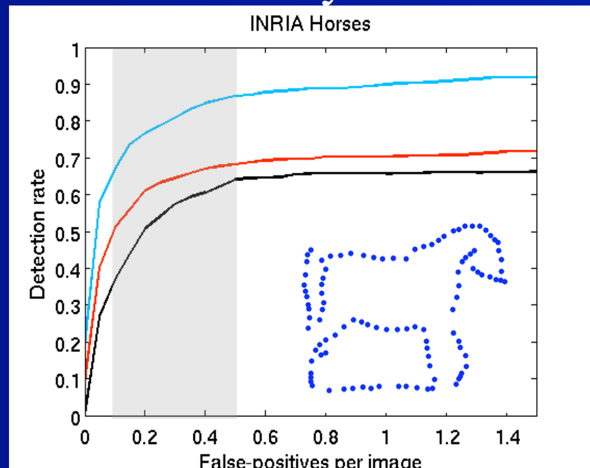
accuracy: 3.1



accuracy: 3.5



accuracy: 5.4

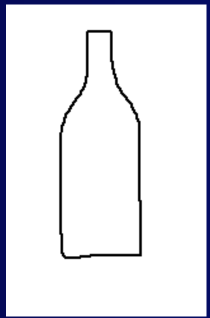


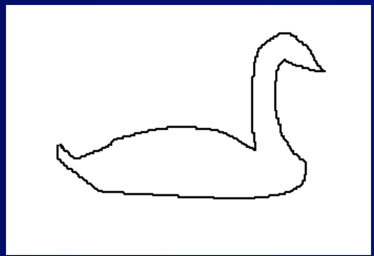
full system (>20% intersection)

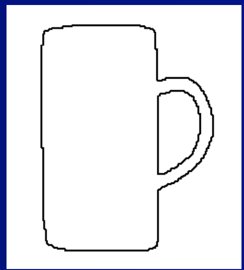
full system (PASCAL: $\cap / \cup$ >50%)

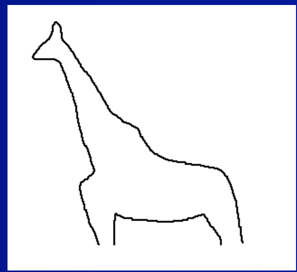
Hough alone (PASCAL)

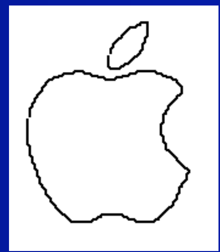
Results: Hand-drawings







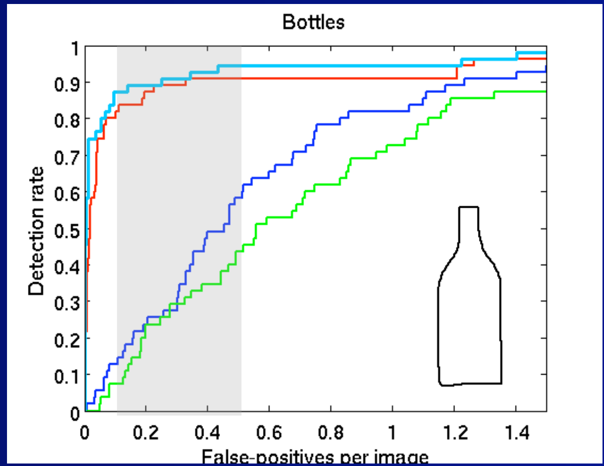


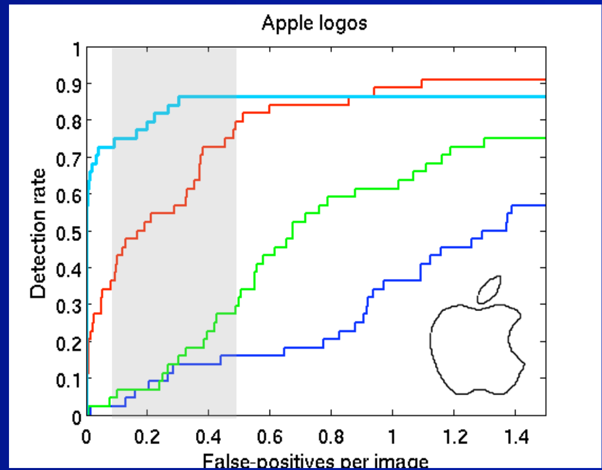


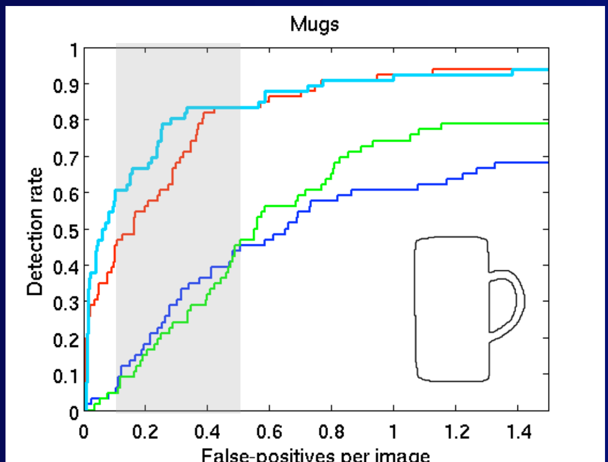
Same protocol as Ferrari et al, ECCV 2006:
match each hand-drawing to all 255 test images

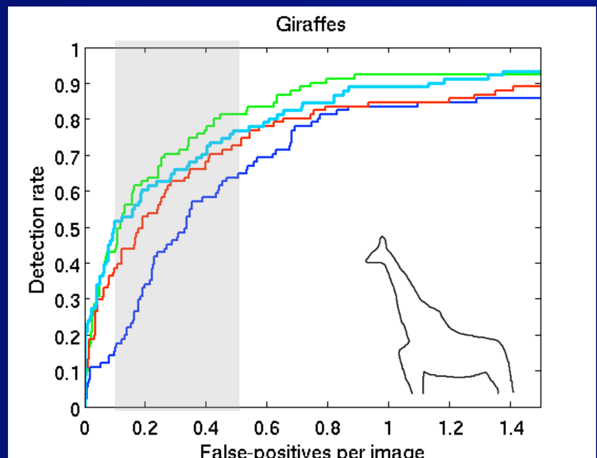
Results: detection-rate vs false-positives per image

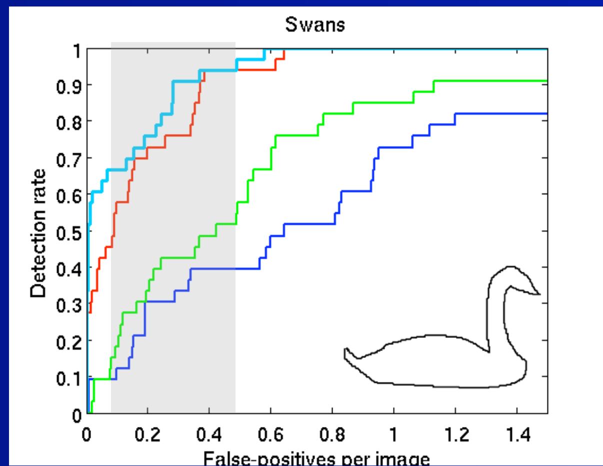
- our approach
- Ferrari, ECCV06
- chamfer
  (with orientation planes)
- chamfer
  (no orientation planes)











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)