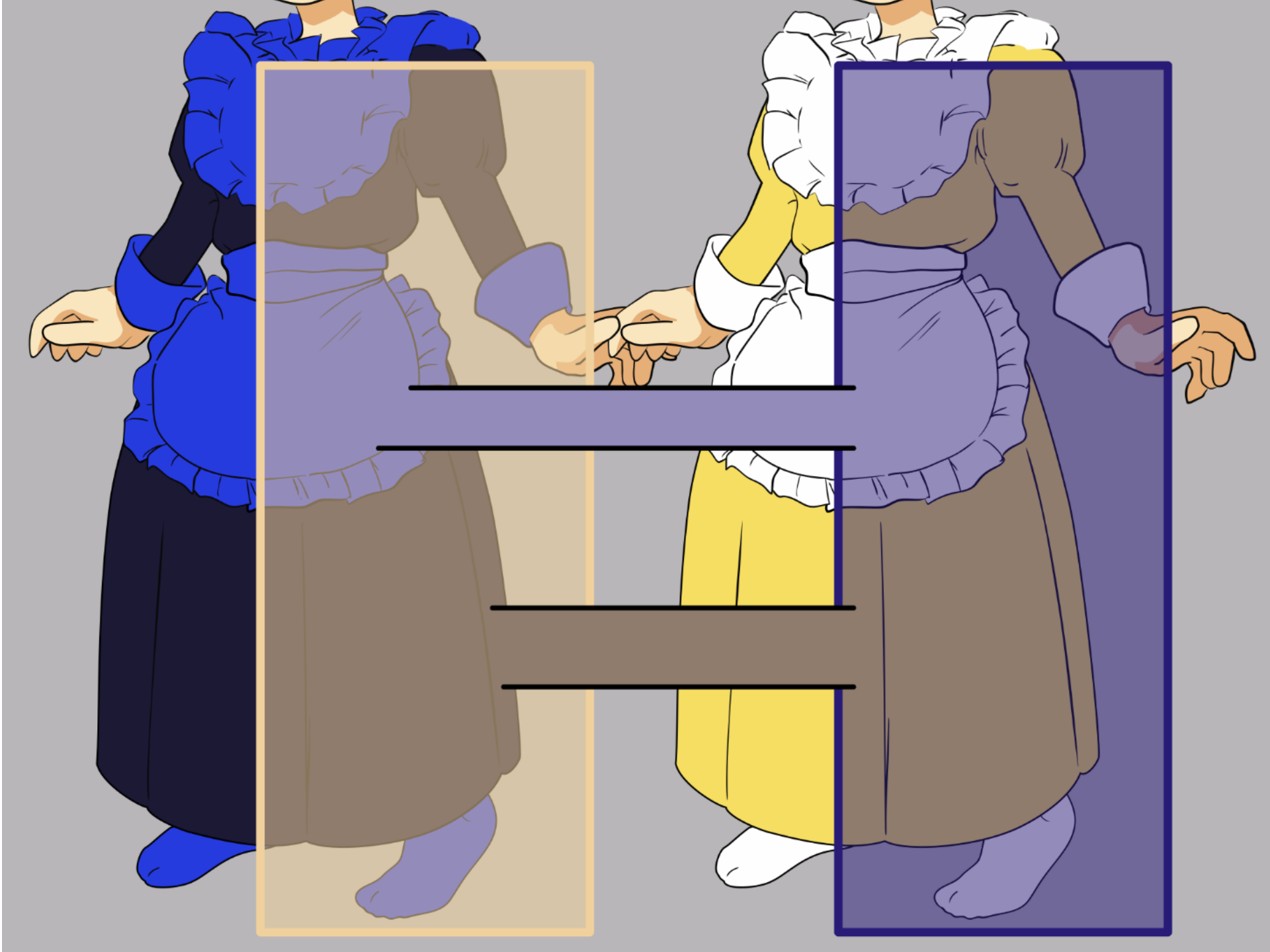
https://en.wikipedia.org/wiki/The_dress



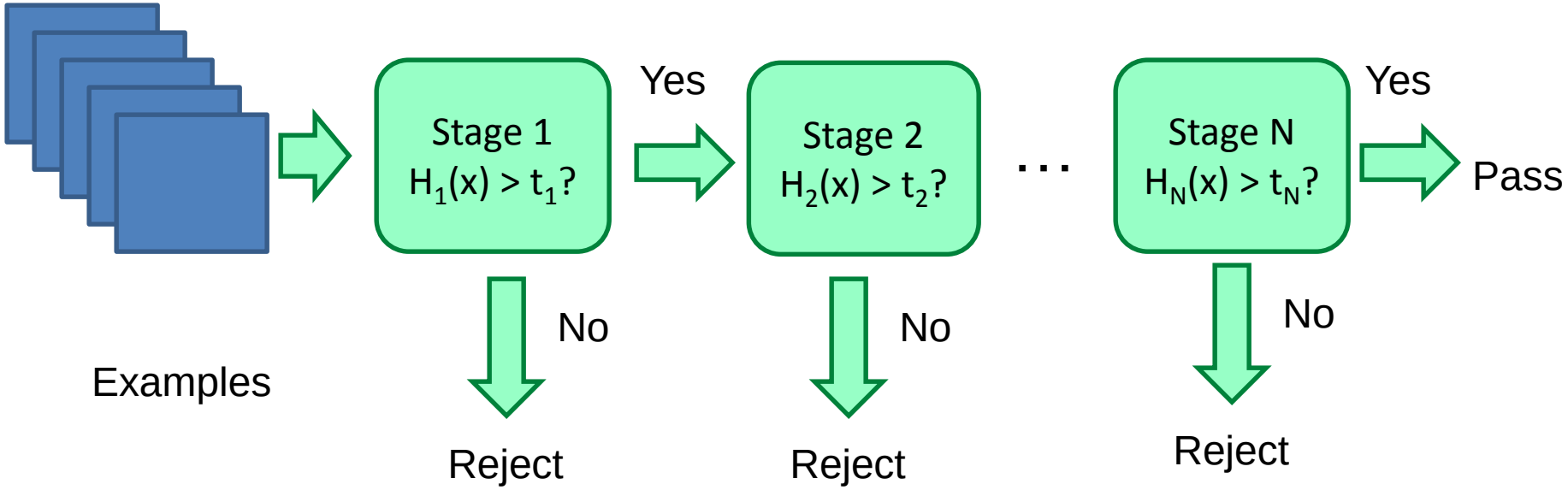
Recap: Viola-Jones sliding window detector

Fast detection through two mechanisms

- Quickly eliminate unlikely windows
- Use features that are fast to compute

Viola and Jones. Rapid Object Detection using a Boosted Cascade of Simple Features (2001).

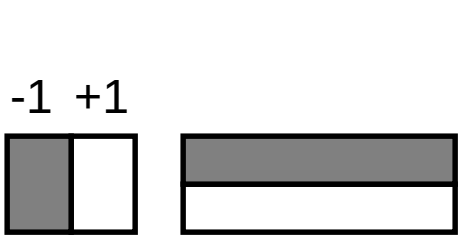
Cascade for Fast Detection



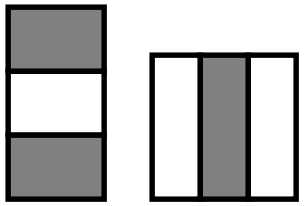
- Choose threshold for low false negative rate
- Fast classifiers early in cascade
- Slow classifiers later, but most examples don't get there

Features that are fast to compute

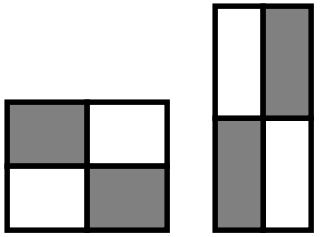
- "Haar-like features"
  - Differences of sums of intensity
  - Thousands, computed at various positions and scales within detection window



Two-rectangle features



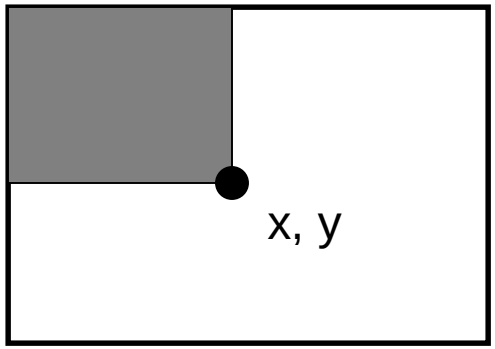
Three-rectangle features



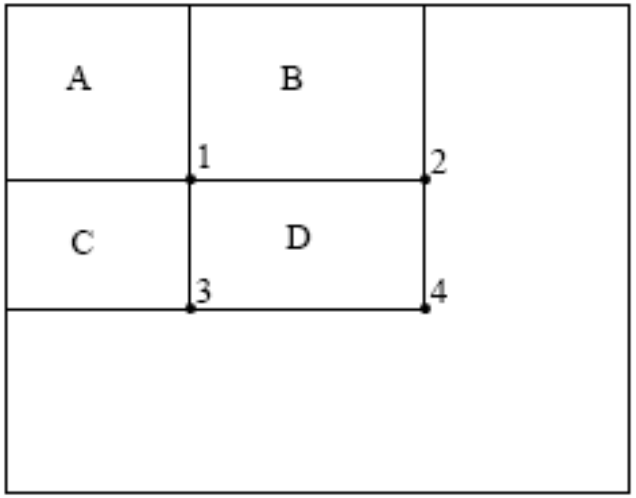
Etc.

Integral Images

- `ii = cumsum(cumsum(im, 1), 2)`



ii(x,y) = Sum of the values in the grey region



SUM within Rectangle D is
ii(4) - ii(2) - ii(3) + ii(1)

Feature selection with Adaboost

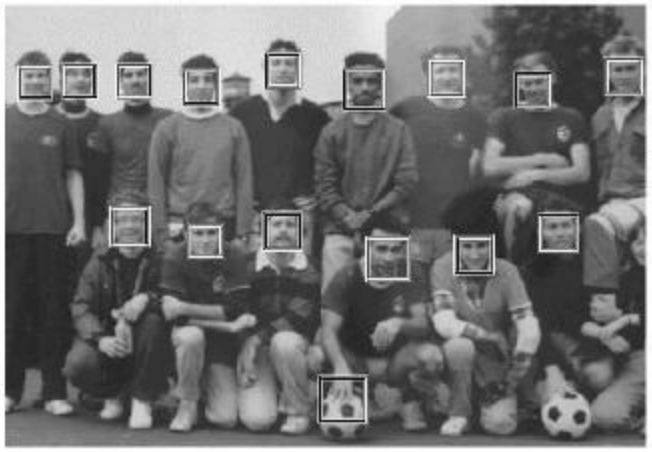
- Create a large pool of features (180K)
- Select features that are discriminative and work well together
  - "Weak learner" = feature + threshold + parity

$$h_j(x) = \begin{cases} 1 & \text{if } p_j f_j(x) < p_j \theta_j \\ 0 & \text{otherwise} \end{cases}$$

  - Choose weak learner that minimizes error on the weighted training set
  - Reweight

Viola Jones Results

Speed = 15 FPS (in 2001)



False detections / Detector	10	31	50	65	78	95	167
Viola-Jones	76.1%	88.4%	91.4%	92.0%	92.1%	92.9%	93.9%
Viola-Jones (voting)	81.1%	89.7%	92.1%	93.1%	93.1%	93.2 %	93.7%
Rowley-Baluja-Kanade	83.2%	86.0%	-	-	-	89.2%	90.1%
Schneiderman-Kanade	-	-	-	94.4%	-	-	-
Roth-Yang-Ahuja	-	-	-	-	(94.8%)	-	-

MIT + CMU face dataset

Object Detection

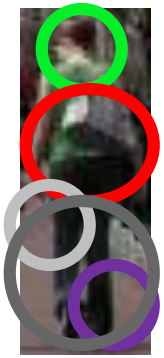
- Overview
- Viola-Jones
- Dalal-Triggs
- Deformable models
- Deep learning

Statistical Template

Object model = sum of scores of features at fixed positions

+3 +2 -2 -1 -2.5 = -0.5 ? > 7.5

Non-object



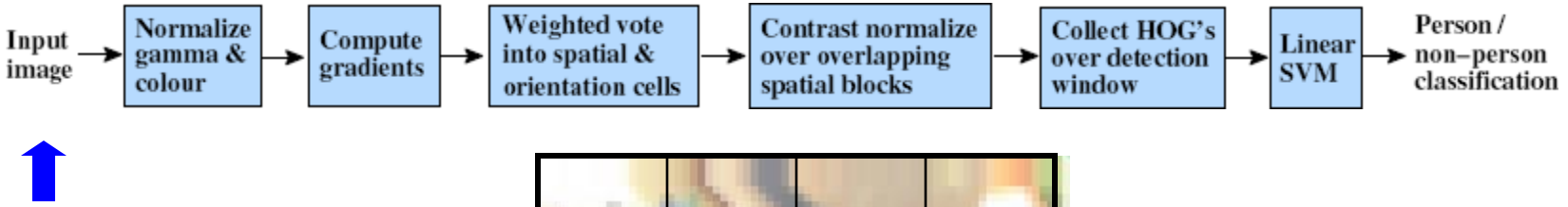
+4 +1 +0.5 +3 +0.5 = 10.5 ? > 7.5

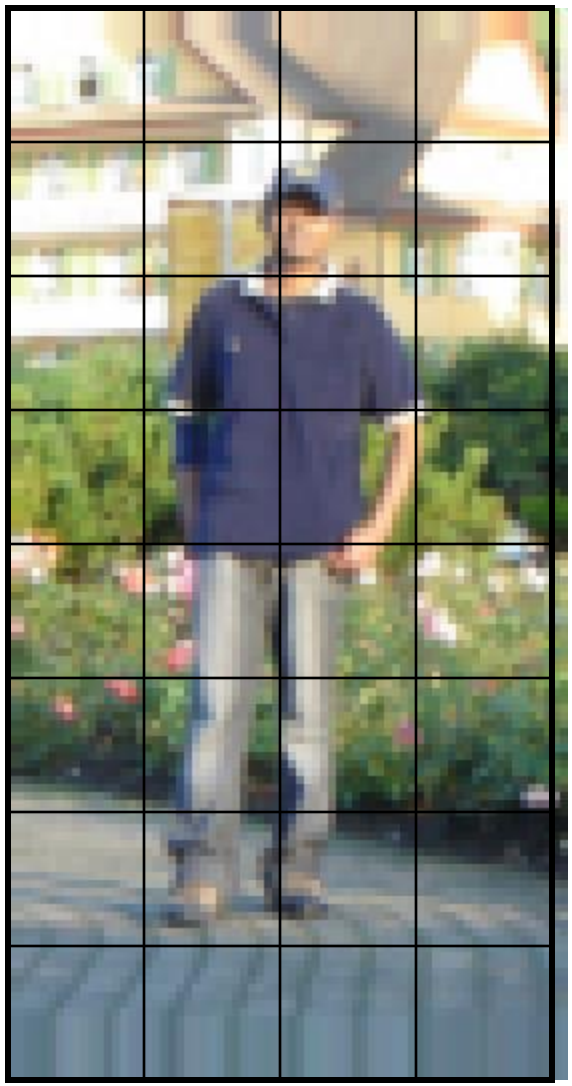
Object

Example: Dalal-Triggs pedestrian detector

1. Extract fixed-sized (64x128 pixel) window at each position and scale
2. Compute HOG (histogram of gradient) features within each window
3. Score the window with a linear SVM classifier
4. Perform non-maxima suppression to remove overlapping detections with lower scores

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05





Slides by Pete Barnum

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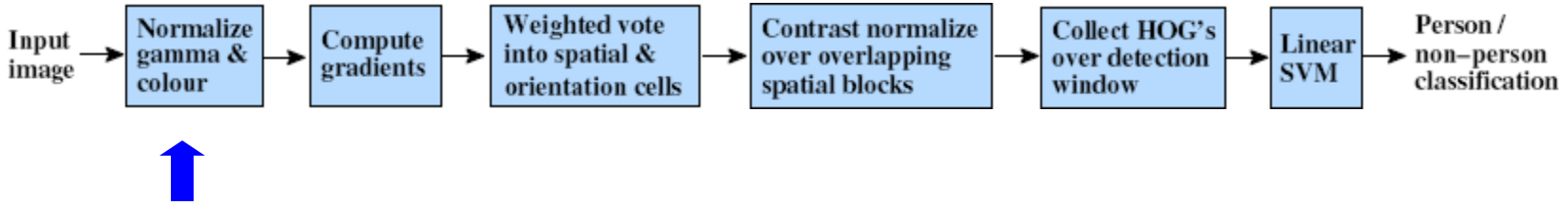
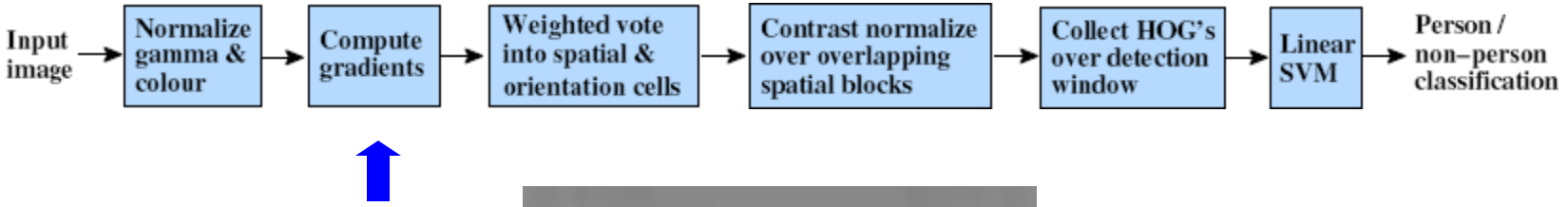


- Tested with
  - RGB
  - LAB
  - Grayscale

  } Slightly better performance vs. grayscale
- Gamma Normalization and Compression
  - Square root
  - Log

  } Very slightly better performance vs. no adjustment



Outperforms

-1	0	1

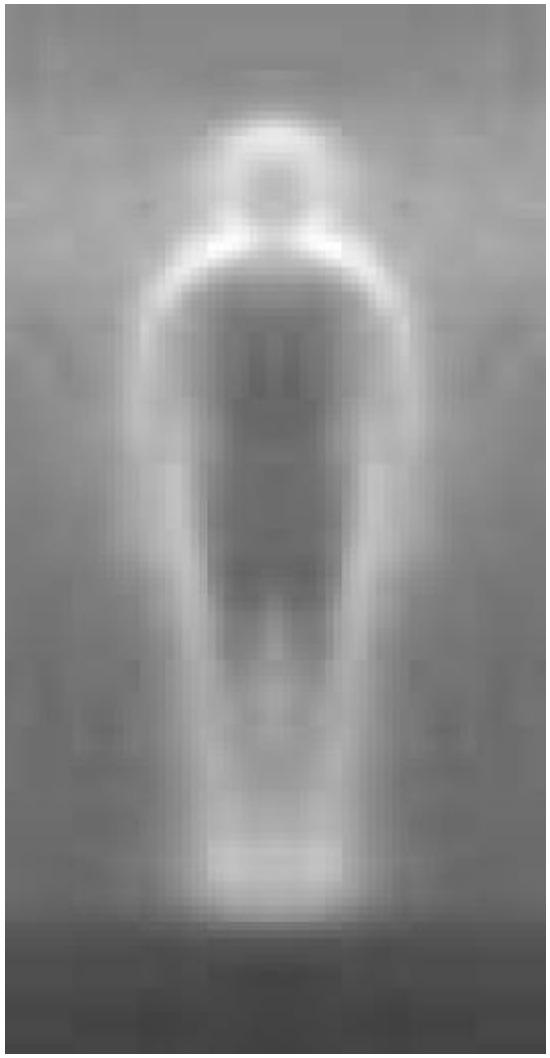
centered

-1	1

uncentered

1	-8	0	8	-1

cubic-corrected



0	1
-1	0

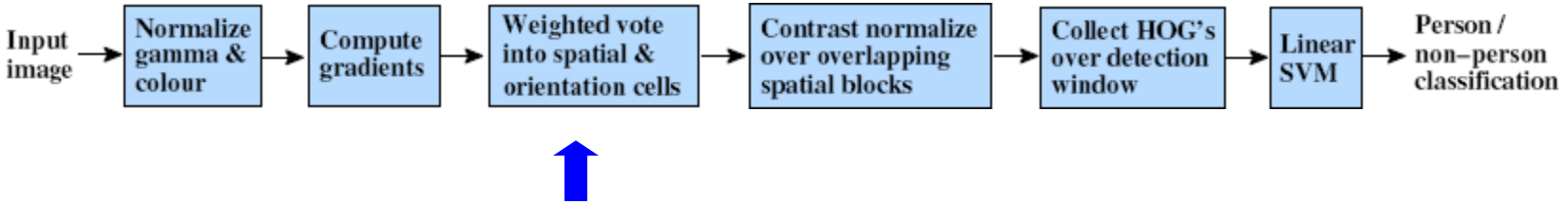
diagonal

-1	0	1
-2	0	2
-1	0	1

Sobel

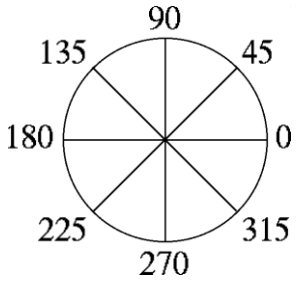
Slides by Pete Barnum

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

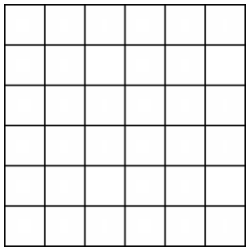


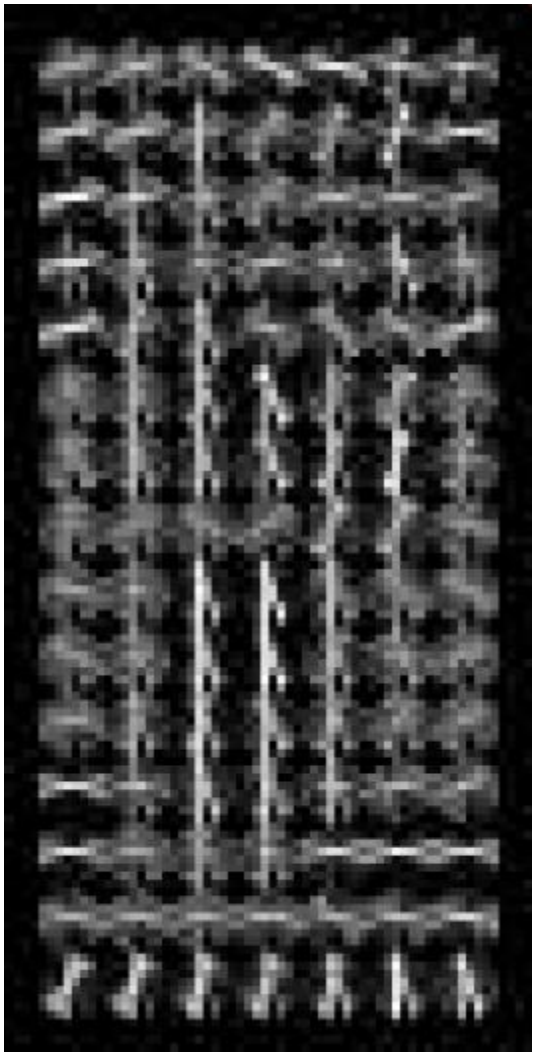
- Histogram of gradient orientations

Orientation: 9 bins
(for unsigned angles
0 -180)



Histograms in
k x k pixel cells





  - Votes weighted by magnitude
  - Bilinear interpolation between cells

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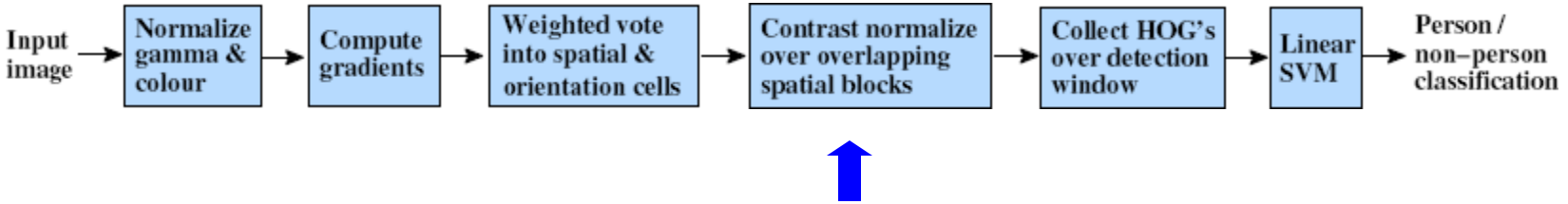
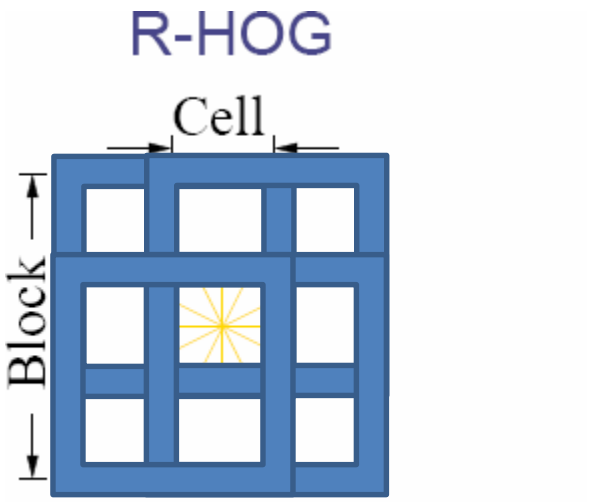
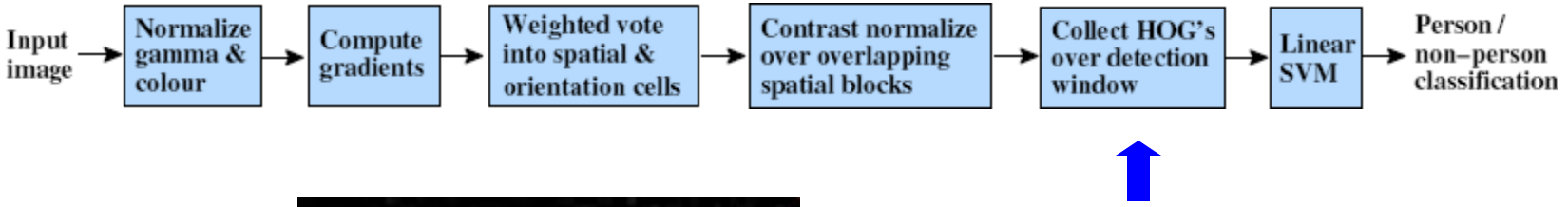


Normalize with respect to surrounding cells

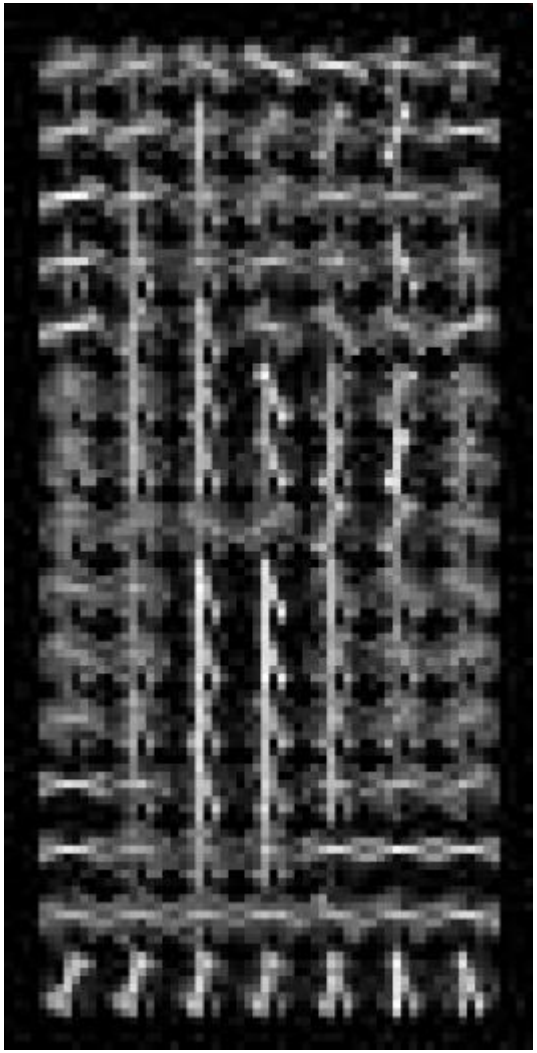


$$L2-norm: v \longrightarrow v/\sqrt{||v||_2^2+\epsilon^2}$$

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05



X=



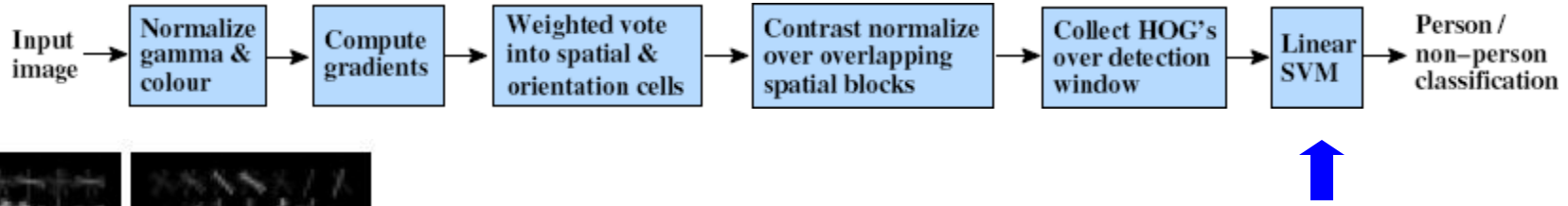
Original Formulation

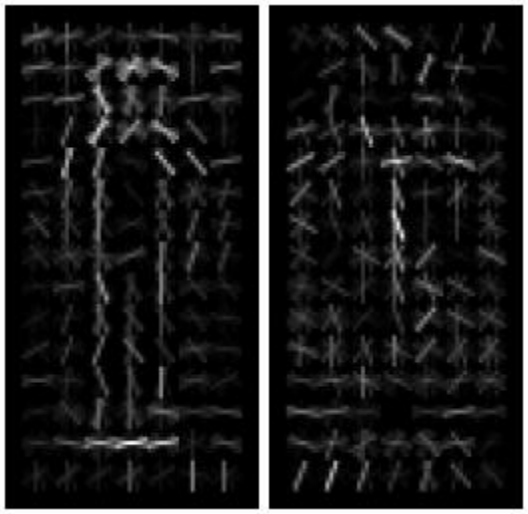
orientations

features = 15 x 7 x 9 x 4 = 3780

cells

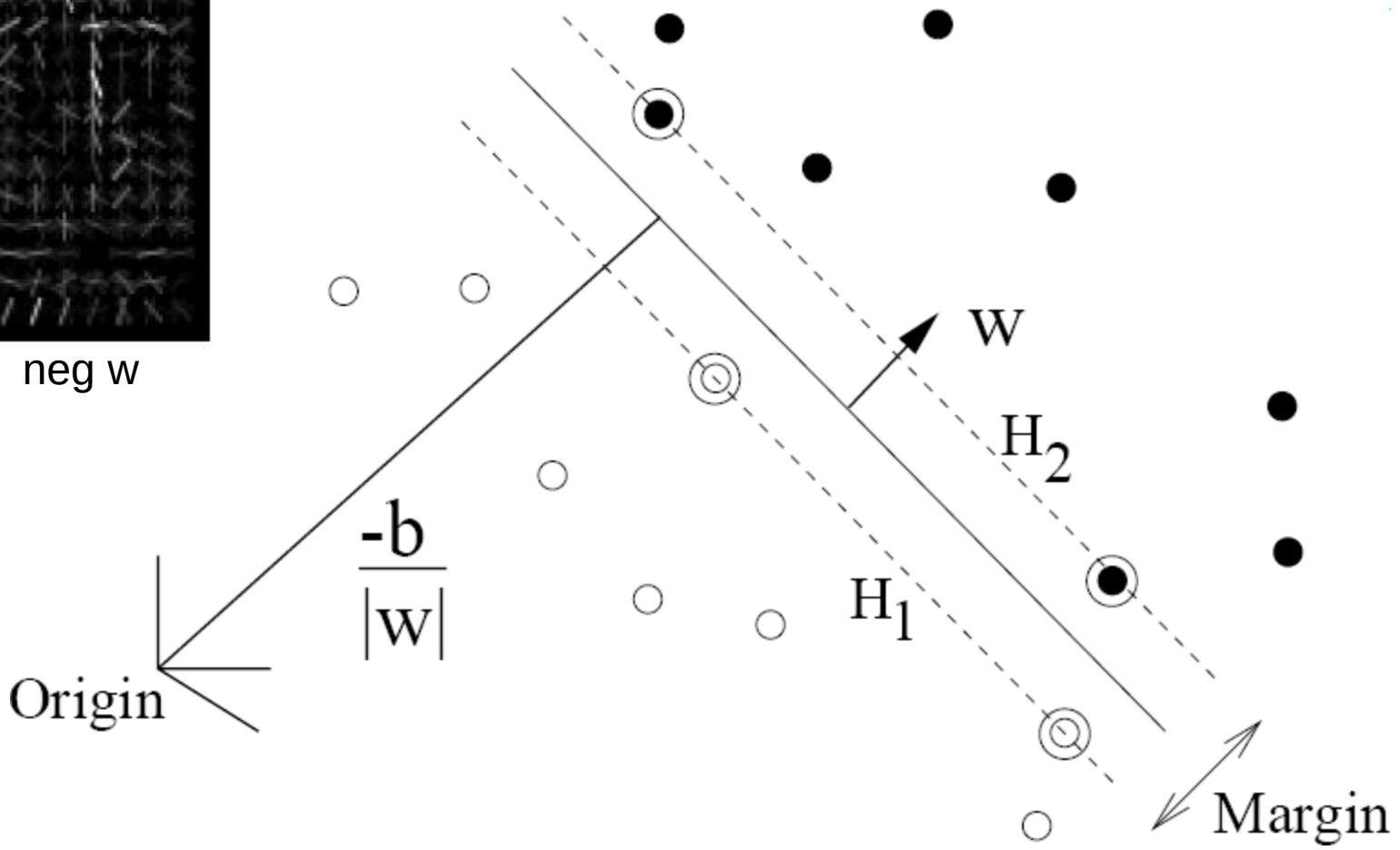
normalizations by neighboring cells





pos w

neg w



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Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

$$0.16 = w^T x - b$$

$$sign(0.16) = 1$$

$$=>$$ pedestrian

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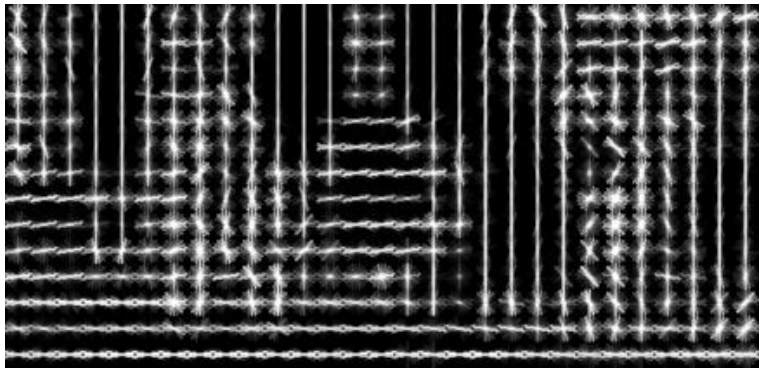
Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

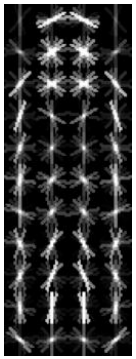
Pedestrian detection with HOG

- Train a pedestrian template using a linear support vector machine
- At test time, convolve feature map with template
- Find local maxima of response
- For multi-scale detection, repeat over multiple levels of a HOG *pyramid*

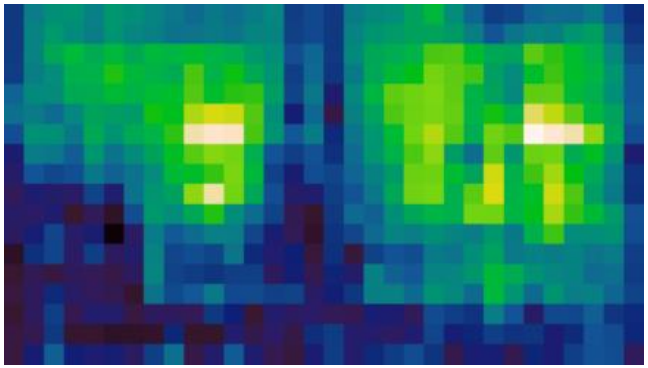
HOG feature map



Template



Detector response map



N. Dalal and B. Triggs, Histograms of Oriented Gradients for Human Detection, CVPR 2005

Something to think about…

- Sliding window detectors work
  - *very well* for faces
  - *fairly well* for cars and pedestrians
  - *badly* for cats and dogs
- Why are some classes easier than others?

Strengths and Weaknesses of Statistical Template Approach

Strengths

- Works very well for non-deformable objects with canonical orientations: faces, cars, pedestrians
- Fast detection

Weaknesses

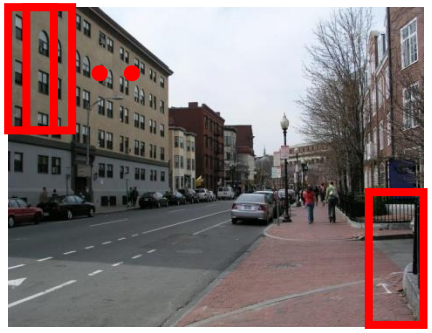
- Not so well for highly deformable objects or “stuff”
- Not robust to occlusion
- Requires lots of training data

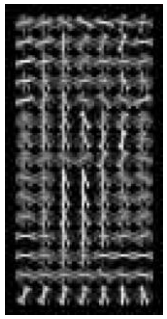
Tricks of the trade

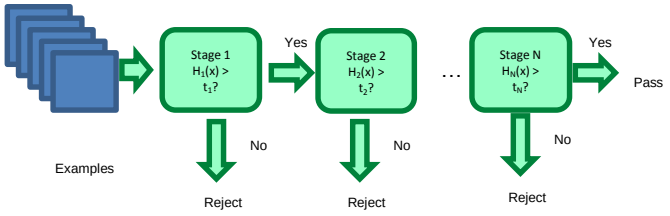
- Details in feature computation really matter
  - E.g., normalization in Dalal-Triggs improves detection rate by 27% at fixed false positive rate
- Template size
  - Typical choice is size of smallest detectable object
- “Jittering” to create synthetic positive examples
  - Create slightly rotated, translated, scaled, mirrored versions as extra positive examples
- Bootstrapping to get hard negative examples
  1. Randomly sample negative examples
  2. Train detector
  3. Sample negative examples that score > -1
  4. Repeat until all high-scoring negative examples fit in memory

Things to remember

- Sliding window for search
- Features based on differences of intensity (gradient, wavelet, etc.)
  - Excellent results require careful feature design
- Boosting for feature selection
- Integral images, cascade for speed
- Bootstrapping to deal with many, many negative examples





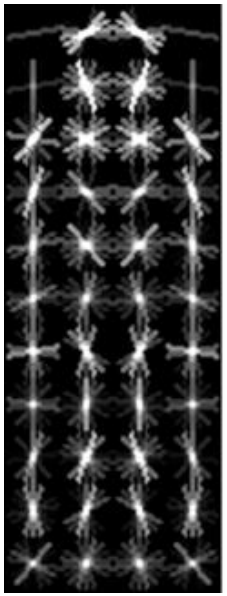


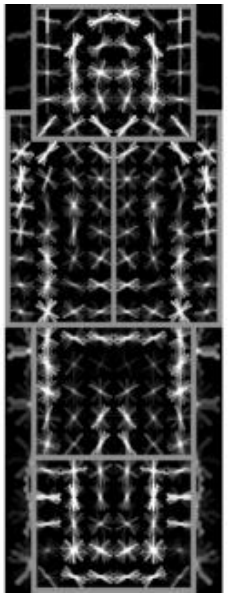
Discriminative part-based models

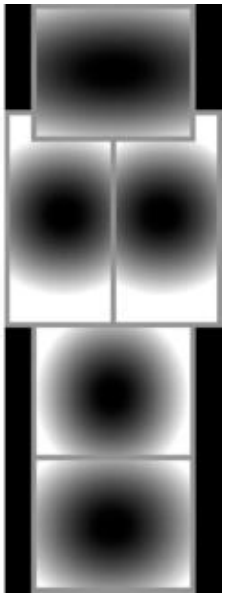
Root filter

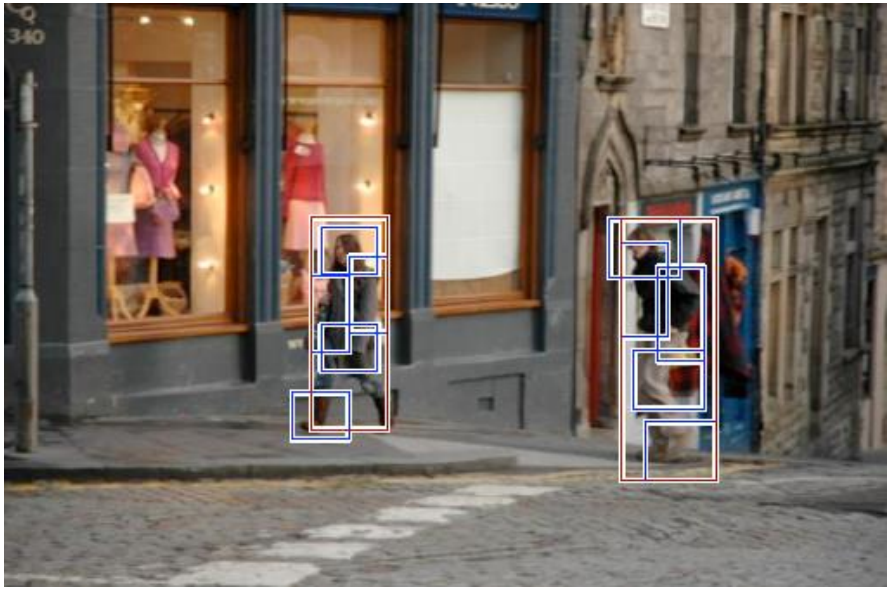
Part filters

Deformation weights





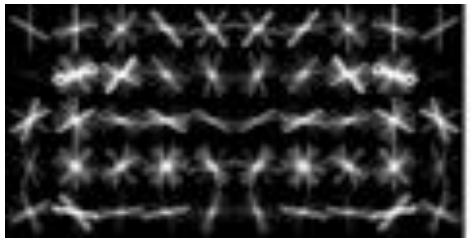
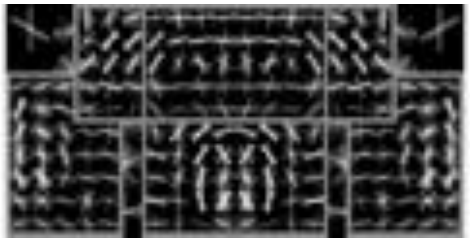
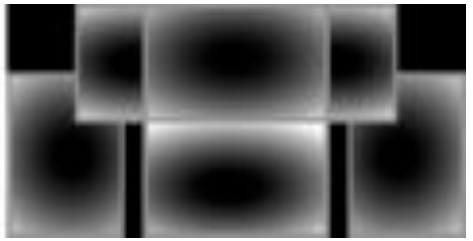




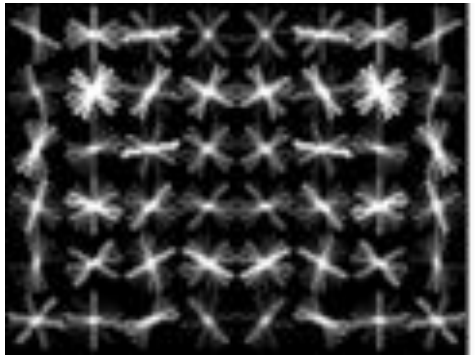
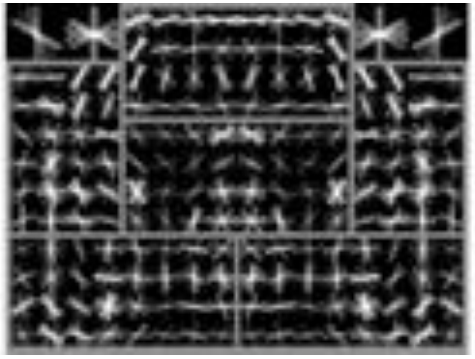
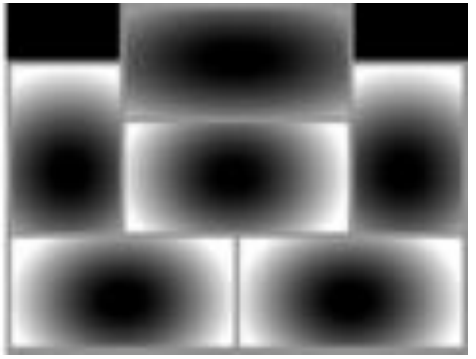
P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, Object Detection with Discriminatively Trained Part Based Models, PAMI 32(9), 2010

Car model

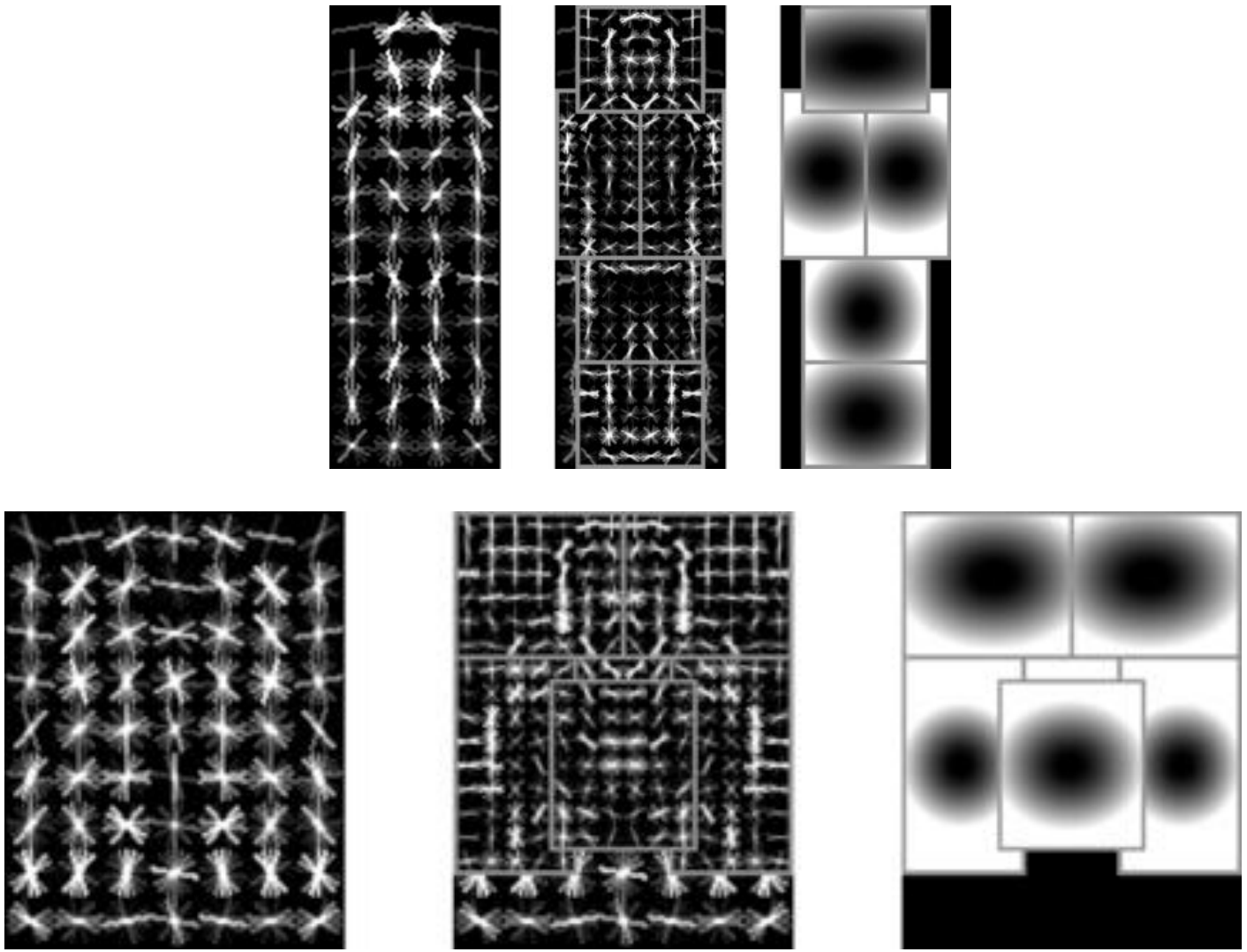
Component 1

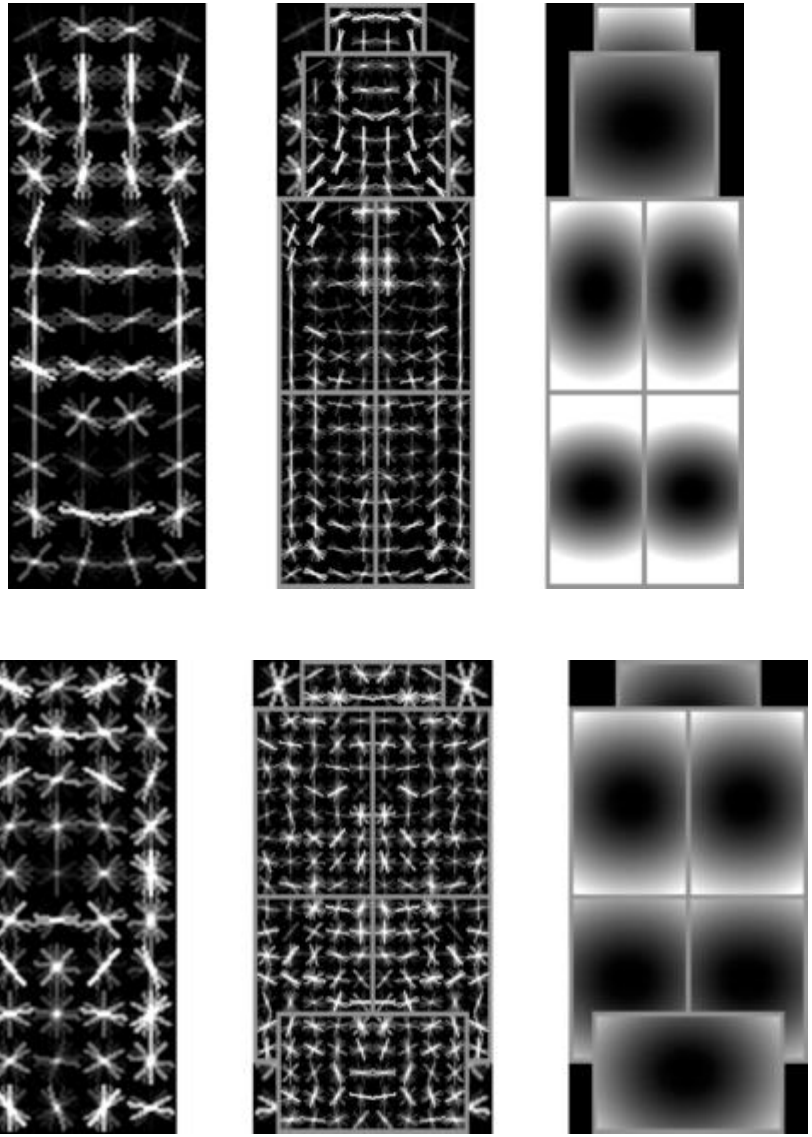
Component 2

Person model

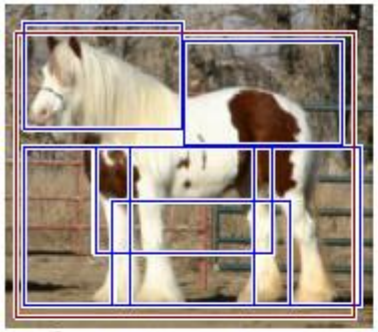
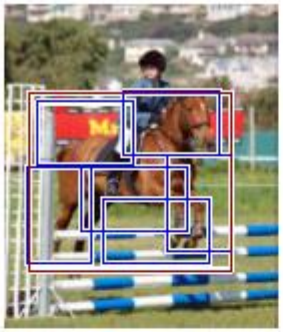
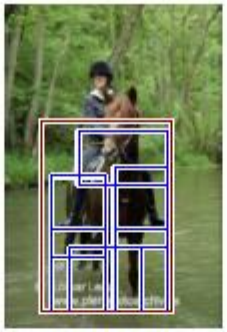
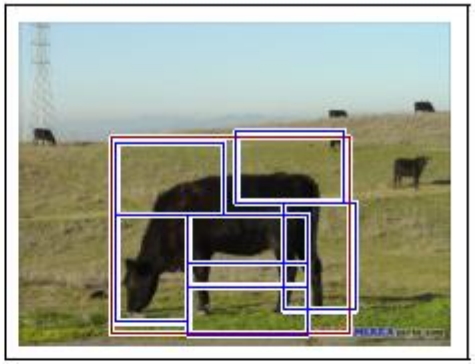
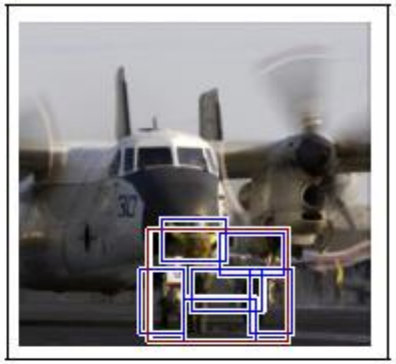


Bottle model

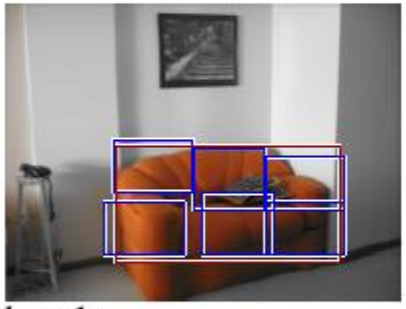


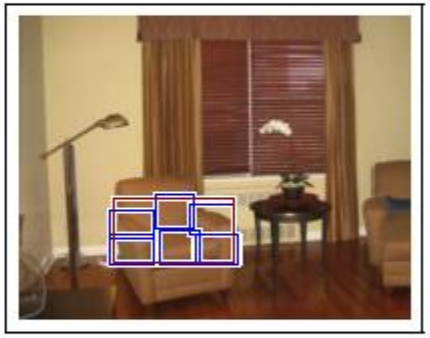
More detections

horse

sofa



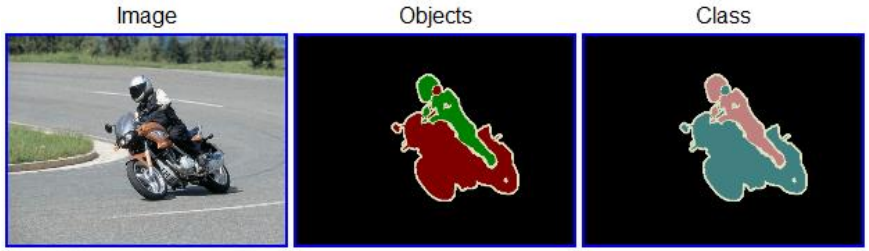



bottle




The PASCAL Visual Object Classes Challenge 2009 (VOC2009)

- Twenty object categories (aeroplane to TV/monitor)
- Three challenges:
  - Classification challenge (is there an X in this image?)
  - Detection challenge (draw a box around every X)
  - Segmentation challenge



Slides from Noah Snavely

Dataset: Collection

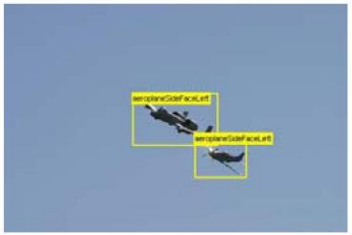
- Images downloaded from **flickr**
  - 500,000 images downloaded and random subset selected for annotation

Dataset: Annotation

- Complete annotation of all objects
- Annotated over web with written guidelines
  - High quality (?)

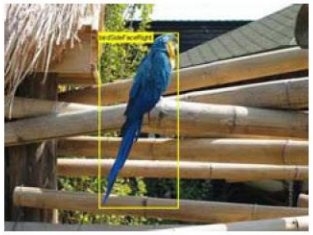
Examples

Aeroplane

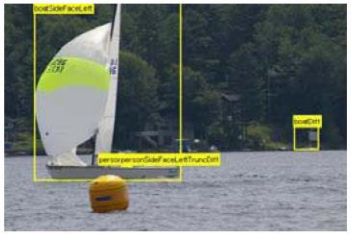


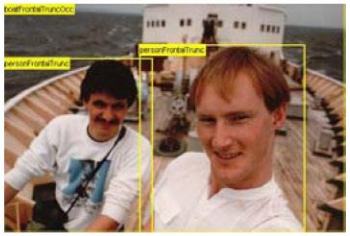
Bicycle

Bird



Boat





Bottle

Bus

Car

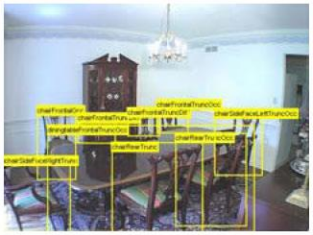
Cat

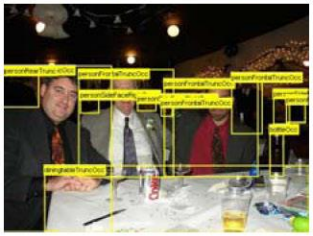
Chair

Cow

Examples

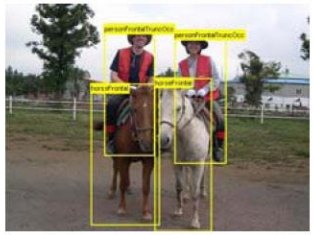
Dining Table



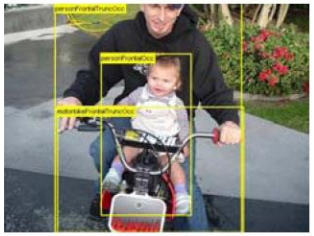


Dog

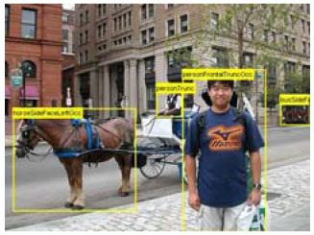
Horse

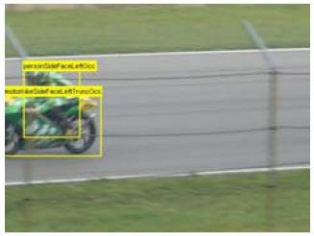


Motorbike

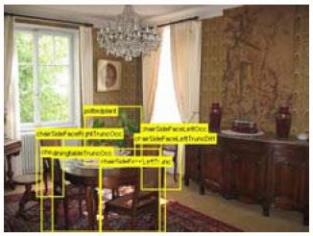


Person

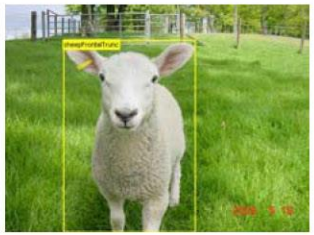




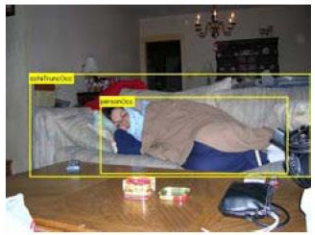
Potted Plant



Sheep

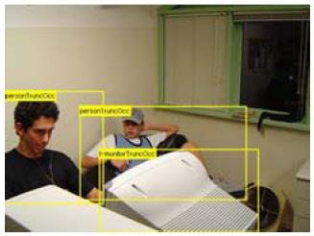


Sofa



Train

TV/Monitor



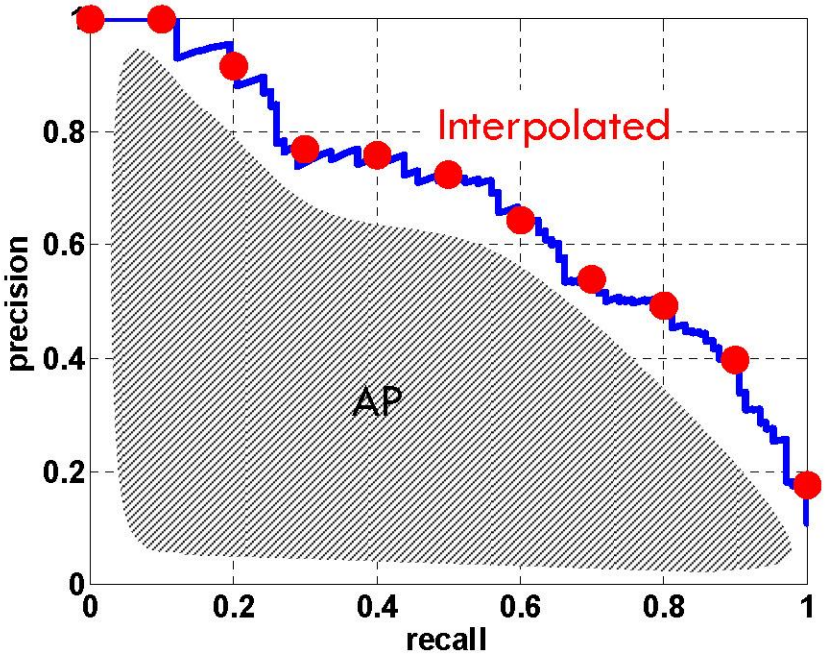
Classification Challenge

- Predict whether at least one object of a given class is present in an image

is there a cat?

Evaluation

- Average Precision [TREC] averages precision over the entire range of recall
  - Curve interpolated to reduce influence of "outliers"



- A good score requires both high recall and high precision
- Application-independent
- Penalizes methods giving high precision but low recall

Participation

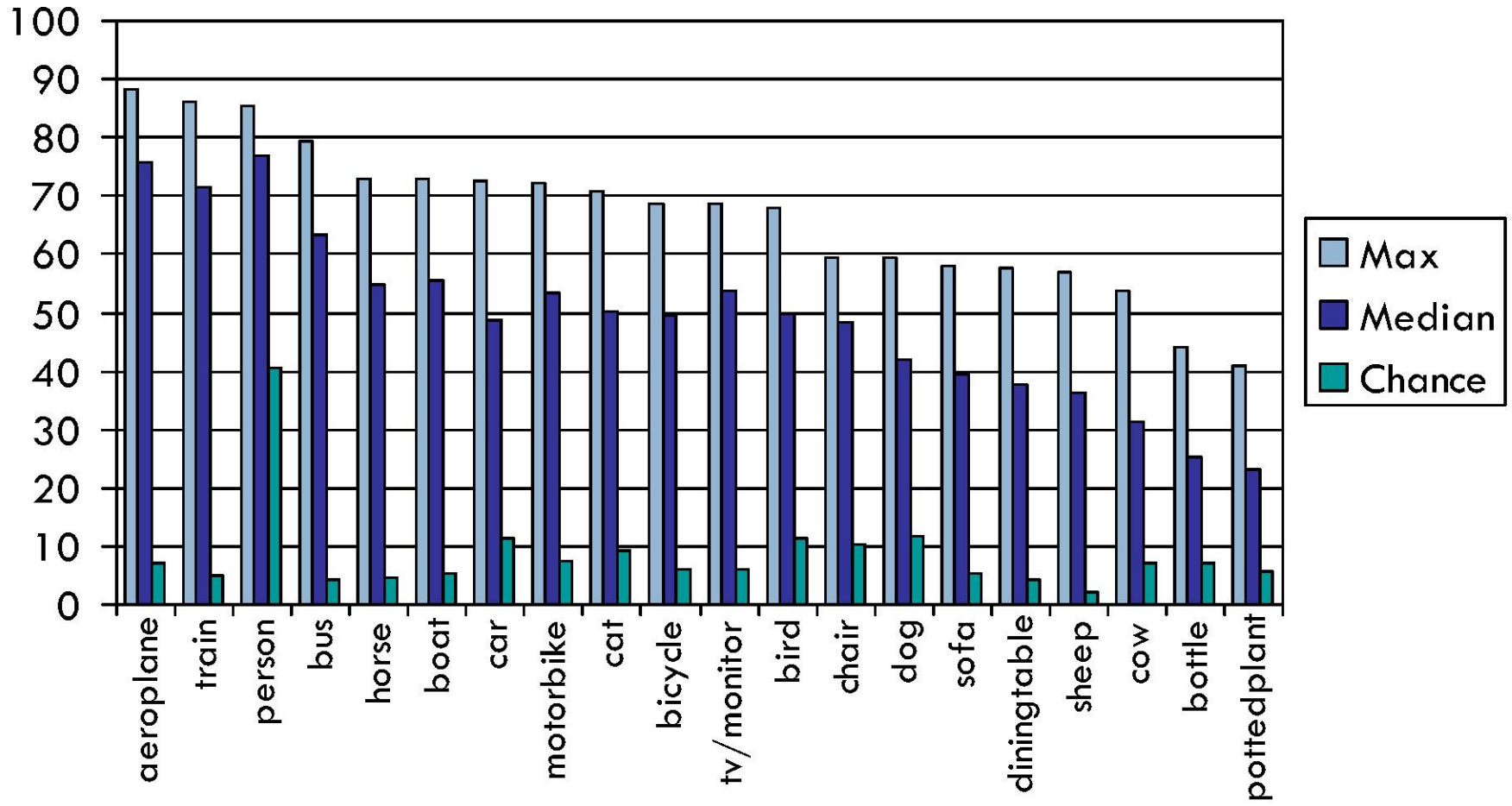
- 48 Methods, 20 Groups

Results: AP by Method and Class

	aero plane	bicycle	bird	boat	bottle	bus	car	cat	chair	cow	dining table	dog	horse	motor bike	person	potted plant	sheep	sofa	train	tv/ monitor
CVC_FLAT	85.3	57.8	66.0	66.1	36.2	70.6	60.6	63.5	55.1	44.6	53.4	49.1	64.4	66.8	84.8	37.4	44.1	47.9	81.9	67.5
CVC_FLAT-HOG-ESS	86.3	60.7	66.4	65.3	41.0	71.7	64.7	63.9	55.5	40.1	51.3	45.9	65.2	68.9	85.0	40.8	49.0	49.1	81.8	68.6
CVC_PLUS	86.6	58.4	66.7	67.3	34.8	70.4	60.0	64.2	52.5	43.0	50.8	46.5	64.1	66.8	84.4	37.5	45.1	45.4	82.1	67.0
FIRSTNIKON_AVGSRKDA	83.3	59.3	62.7	65.3	30.2	71.6	58.2	62.2	54.3	40.7	49.2	50.0	66.6	62.9	83.3	34.2	48.2	46.1	83.4	65.5
FIRSTNIKON_AVGSVM	83.8	58.2	62.6	65.2	32.0	69.8	57.7	61.1	54.5	44.0	50.3	49.6	64.6	61.7	83.2	33.4	46.5	48.0	81.6	65.3
FIRSTNIKON_BOOSTSRKDA	83.0	59.2	61.4	64.6	33.2	71.1	57.5	61.0	54.8	40.7	48.3	50.0	65.5	63.4	82.8	32.8	47.0	47.1	83.3	64.6
FIRSTNIKON_BOOSTSVMS	83.5	56.8	61.8	65.5	33.2	69.7	57.3	60.5	54.6	43.1	48.3	50.3	64.3	62.4	82.3	32.9	46.9	48.4	82.0	64.2
LEAR_CHI-SVM-MULT-LOC	79.5	55.5	54.5	63.9	43.7	70.3	66.4	56.5	54.4	38.8	44.1	46.2	58.5	64.2	82.2	39.1	41.3	39.8	73.6	66.2
NECUIUC_CDCV	88.1	68.0	68.0	72.5	41.0	78.9	70.4	70.4	58.1	53.4	55.7	59.3	73.1	71.3	84.5	32.3	53.3	56.7	86.0	66.8
NECUIUC_CLS-DTCT	88.0	68.6	67.9	72.9	44.2	79.5	72.5	70.8	59.5	53.6	57.5	59.0	72.6	72.3	85.3	36.6	56.9	57.9	85.9	68.0
NECUIUC_LL-CDCV	87.1	67.4	65.8	72.3	40.9	78.3	69.7	69.7	58.5	50.1	55.1	56.3	71.8	70.8	84.1	31.4	51.5	55.1	84.7	65.2
NECUIUC_LN-CDCV	87.7	67.8	68.1	71.1	39.1	78.5	70.6	70.7	57.4	51.7	53.3	59.2	71.6	70.6	84.0	30.9	51.7	55.9	85.9	66.7
UVASURREY_BASELINE	84.1	59.2	62.7	65.4	35.7	70.6	59.8	61.3	56.7	45.3	52.4	50.6	66.1	66.6	83.7	34.8	47.2	47.7	80.8	65.9
UVASURREY_MKFDA+BOW	84.7	63.9	66.1	67.3	37.9	74.1	63.2	64.0	57.1	46.2	54.7	53.5	68.1	70.6	85.2	38.5	47.2	49.3	83.2	68.1
UVASURREY_TUNECOLORKERNELSEL	85.0	62.8	65.1	66.5	37.6	73.5	62.1	62.0	57.4	45.1	54.5	52.5	67.7	69.8	84.8	39.1	46.8	49.9	82.9	68.1
UVASURREY_TUNECOLORSPECKDA	84.6	62.4	65.6	67.2	39.4	74.0	63.4	62.8	56.7	43.8	54.7	52.7	67.3	70.6	85.0	38.8	46.9	50.0	82.2	66.2

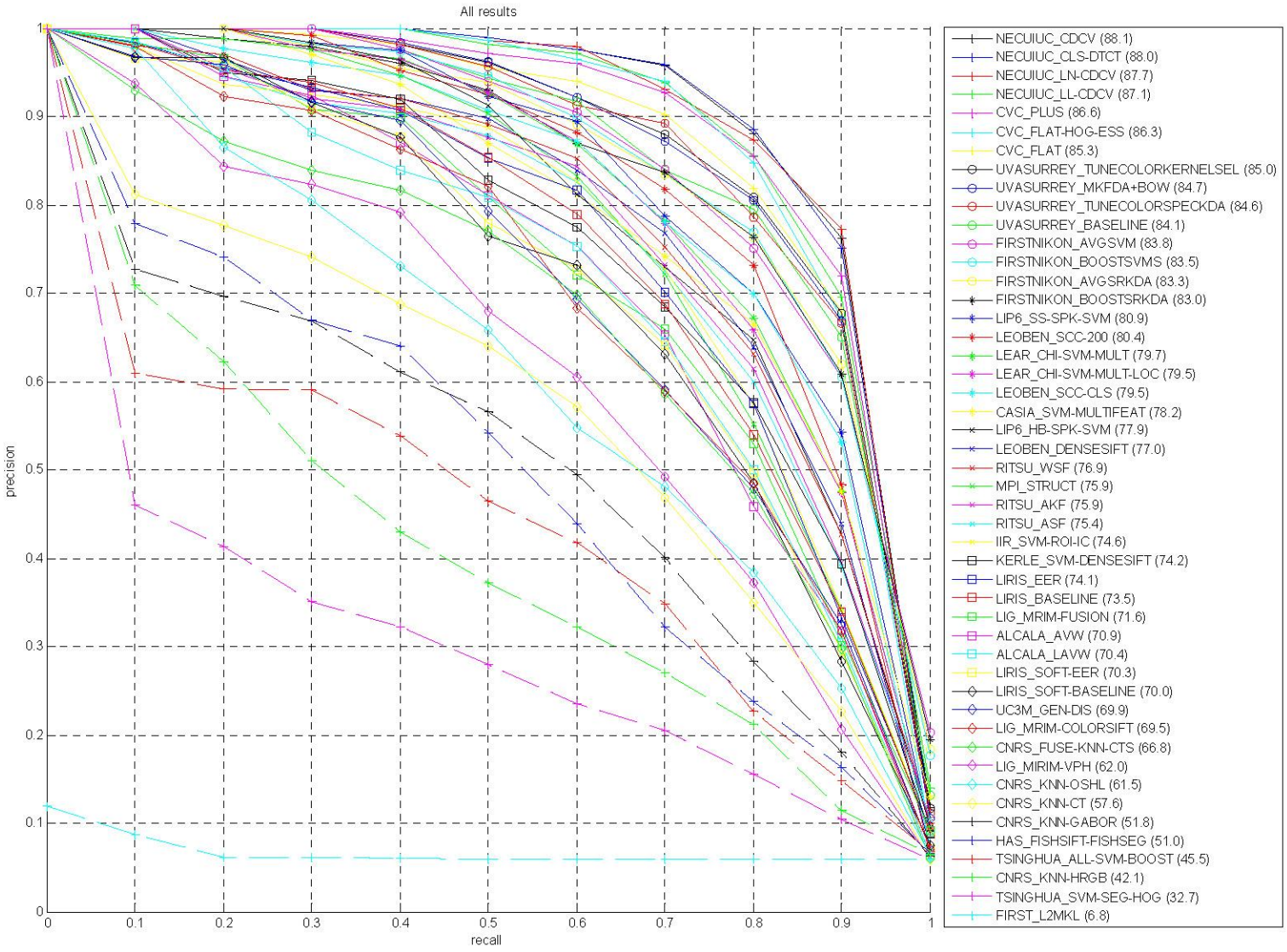
- Only methods in 1st, 2nd or 3rd place by group shown
- Groups: CVC, FIRST/Nikon, NEC/UIUC, UVA/Surrey

AP by Class

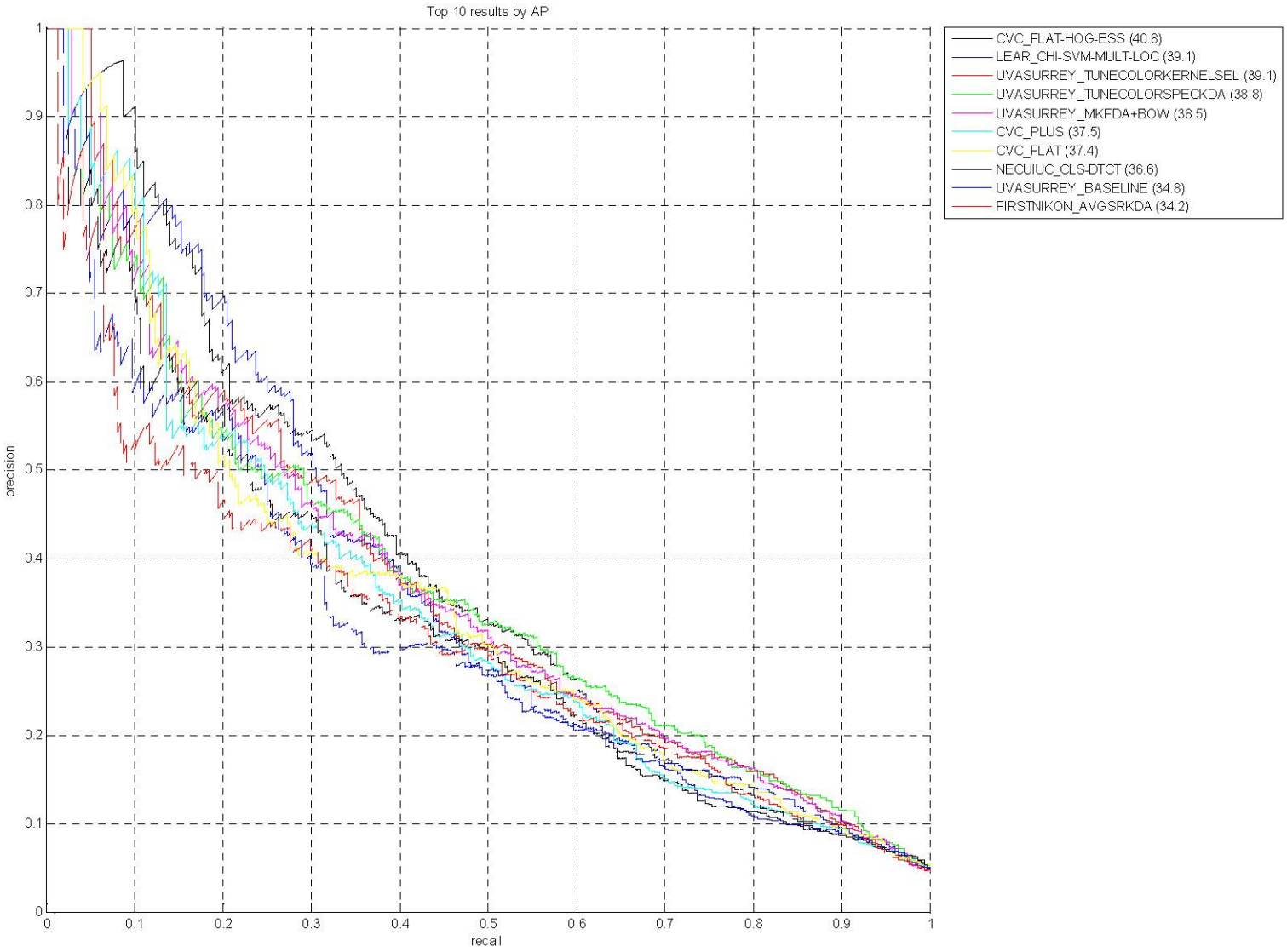


- Max AP: 88.1% (aeroplane) ... 40.8% (potted plant)

Precision/Recall: Aeroplane (All)



Precision/Recall: Potted plant (Top 10 by AP)

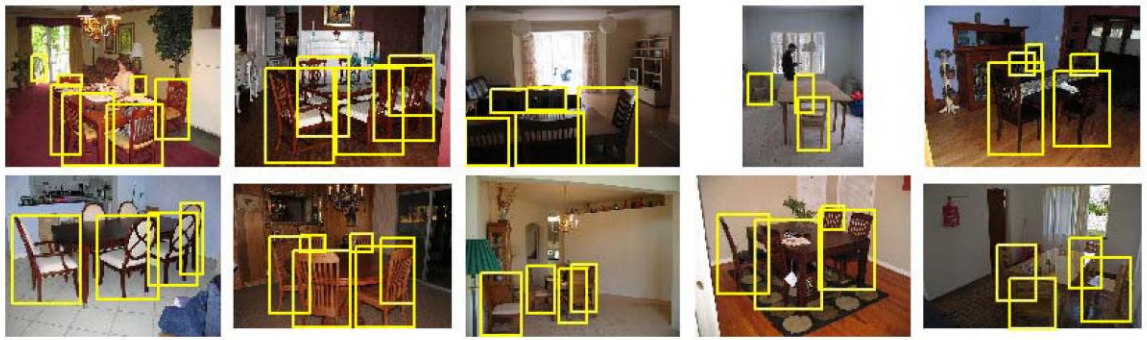


Ranked Images: Aeroplane

- Class images:
  Highest ranked

Ranked Images: Chair

- Class images:
  Highest ranked

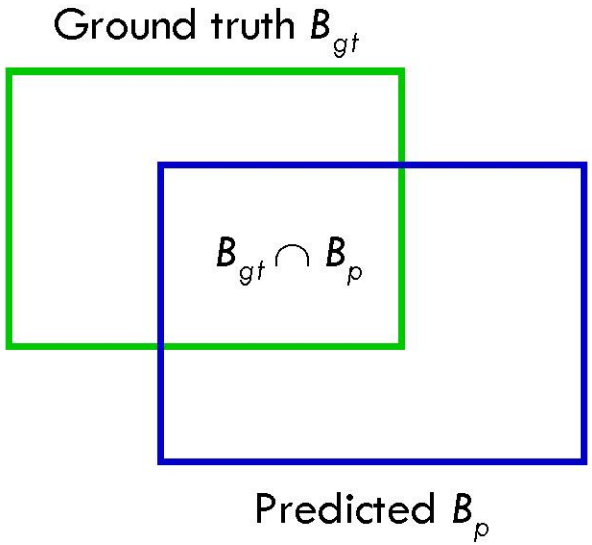


Detection Challenge

- Predict the bounding boxes of all objects of a given class in an image (if any)

Evaluating Bounding Boxes

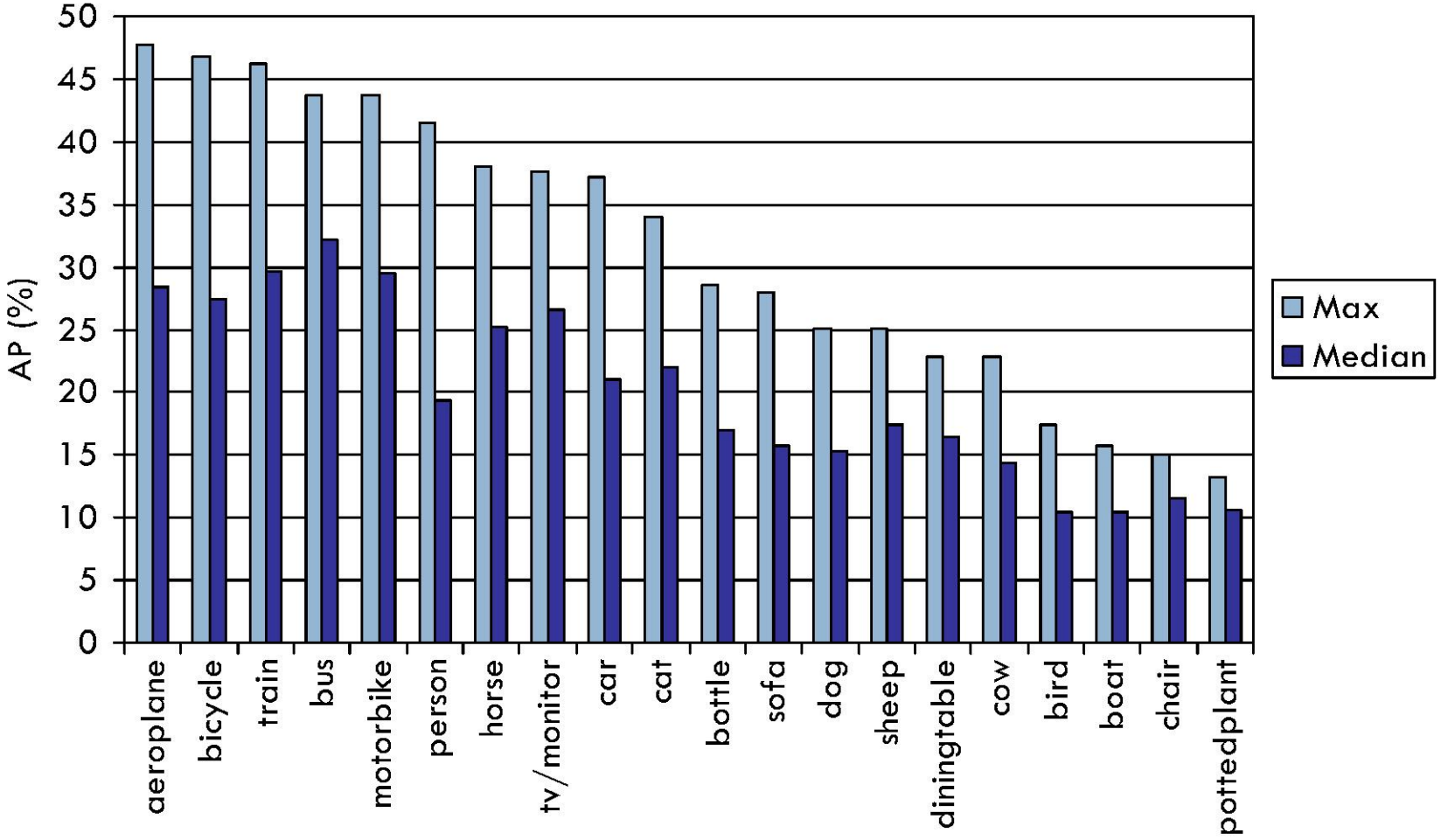
- Area of Overlap (AO) Measure



$$AO(B_{gt}, B_p) = \frac{|B_{gt} \bigcap B_p|}{|B_{gt} \bigcup B_p|}$$

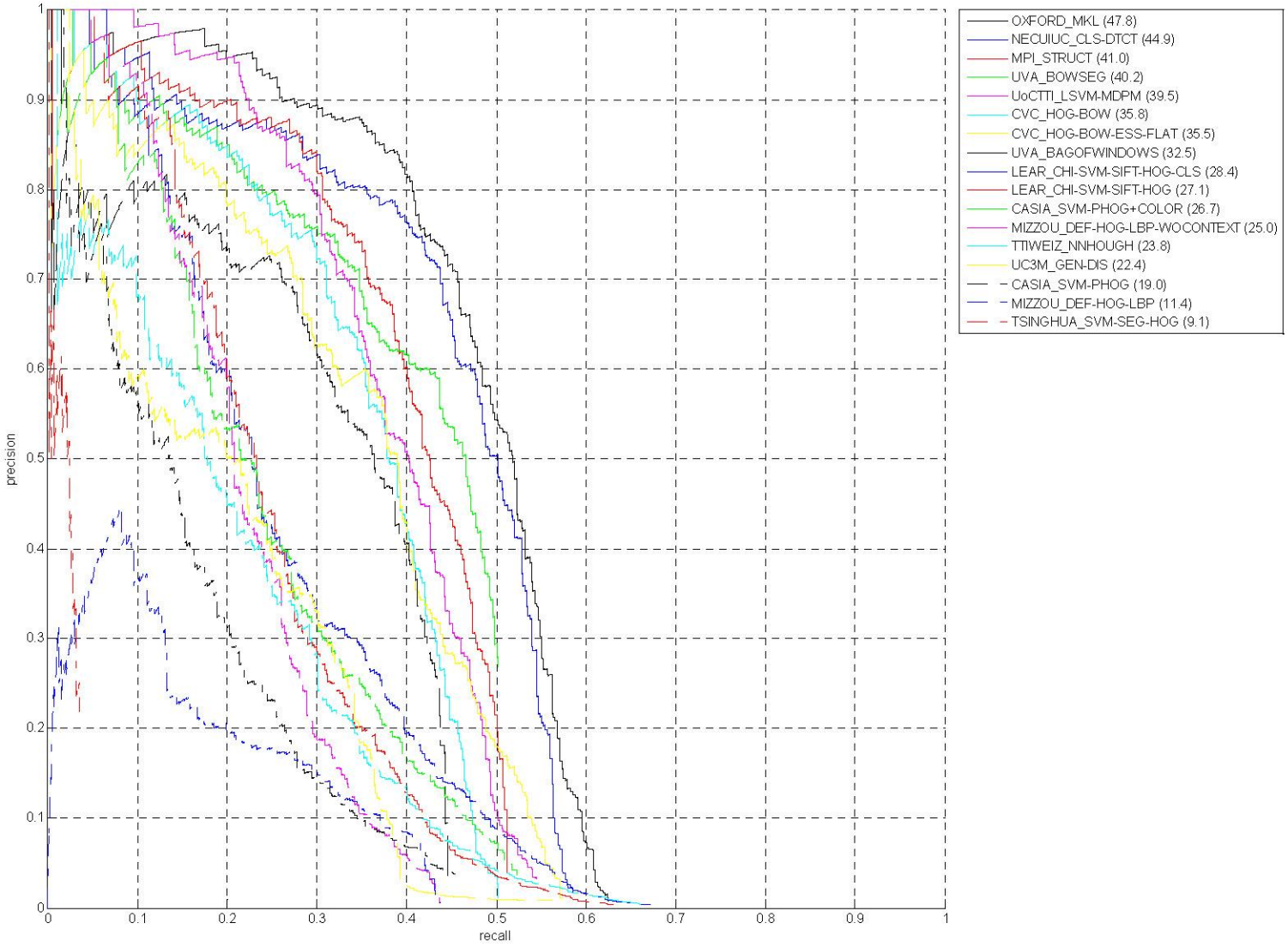
- Need to define a threshold *t* such that $AO(B_{gt},B_p)$ implies a correct detection: 50%

AP by Class

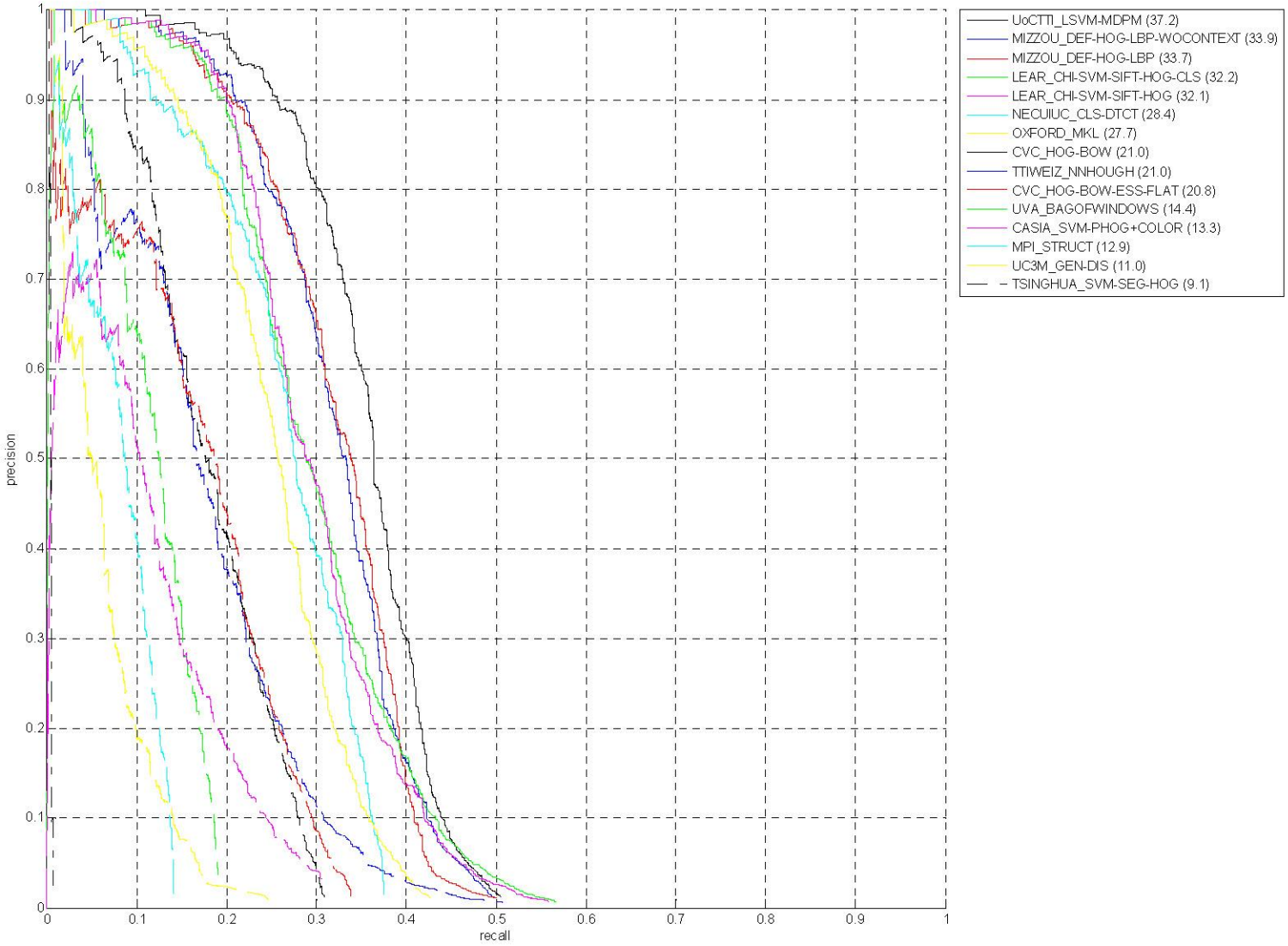


Chance essentially 0

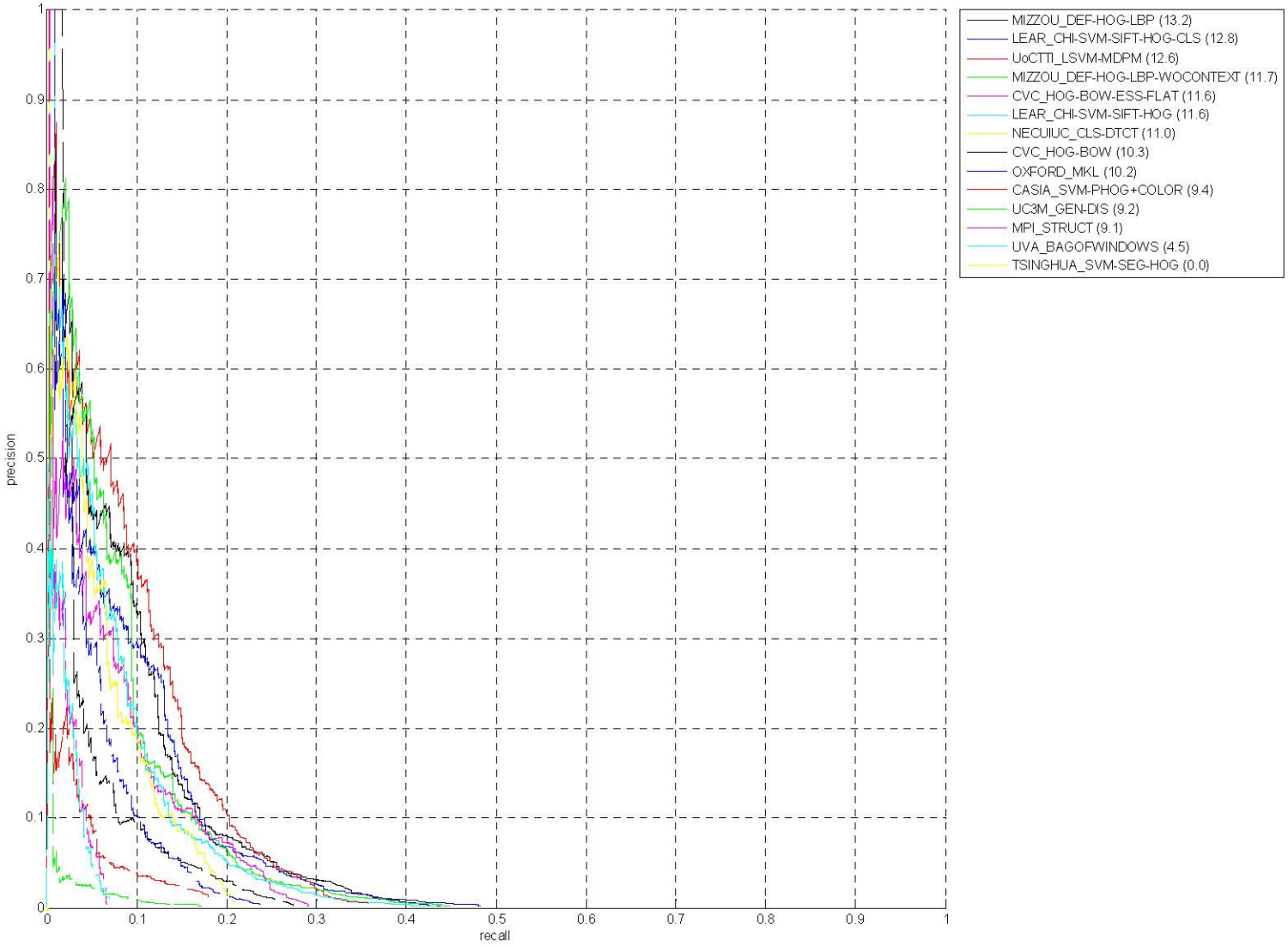
Precision/Recall - Aeroplane



Precision/Recall - Car



Precision/Recall – Potted plant



True Positives - Person

UoCTTI_LSVM-MDPM

MIZZOU_DEF-HOG-LBP

NECUIUC_CLS-DTCT

False Positives - Person

UoCTTI_LSVM-MDPM



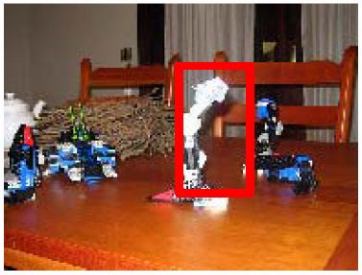


MIZZOU_DEF-HOG-LBP





NECUIUC_CLS-DTCT


“Near Misses” - Person

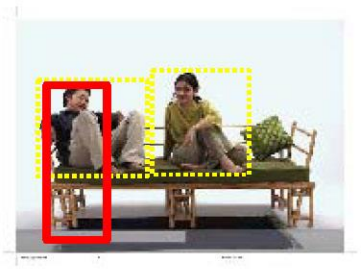
UoCTTI_LSVM-MDPM





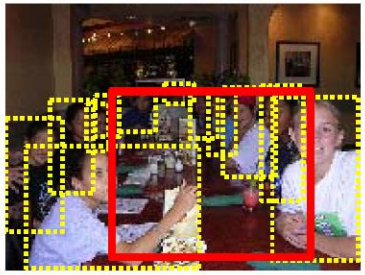
MIZZOU_DEF-HOG-LBP




NECUIUC_CLS-DTCT





True Positives - Bicycle

UoCTTI_LSVM-MDPM





OXFORD_MKL





NECUIUC_CLS-DTCT





False Positives - Bicycle

UoCTTI_LSVM-MDPM





OXFORD_MKL





NECUIUC_CLS-DTCT