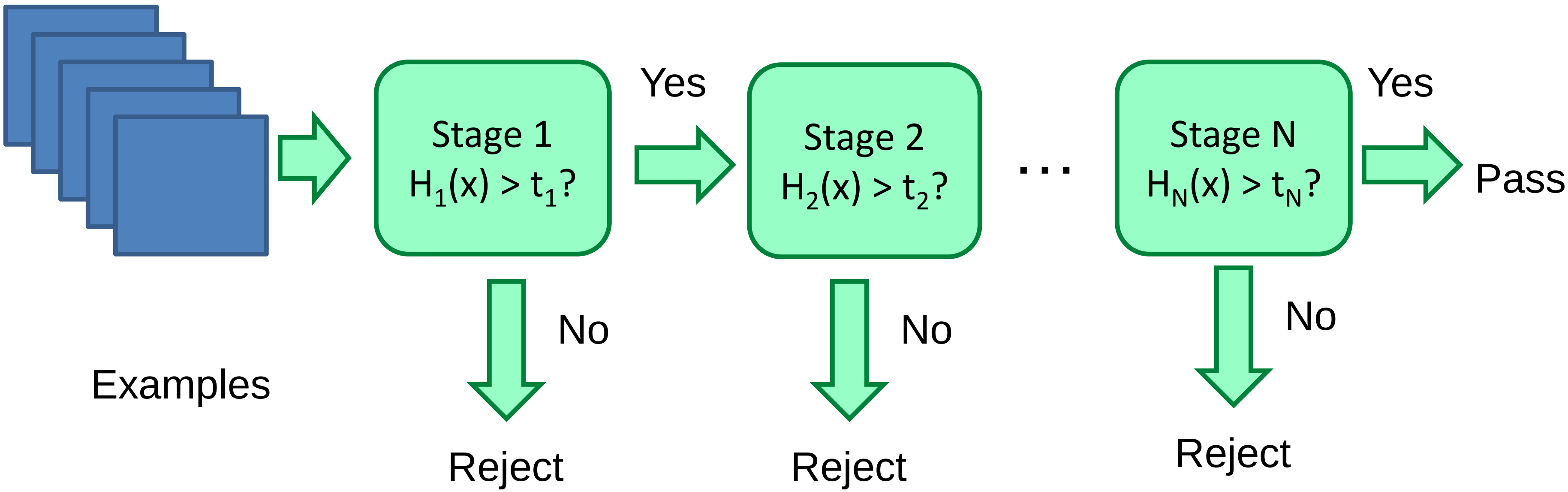
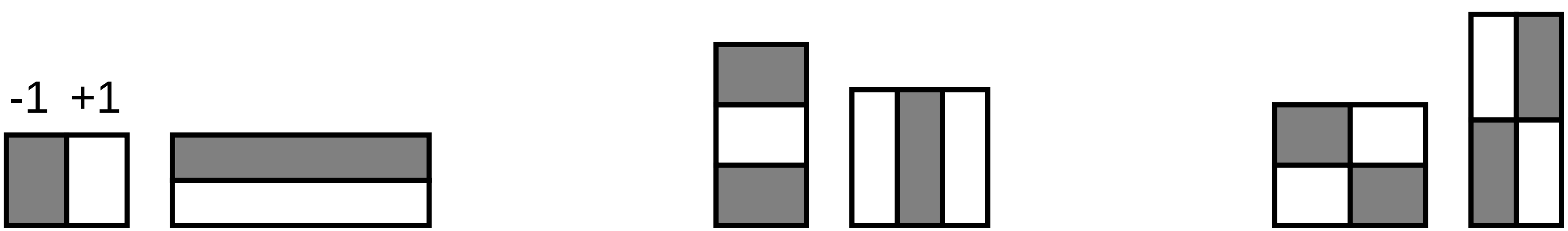
Cascade for Fast Detection



- 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



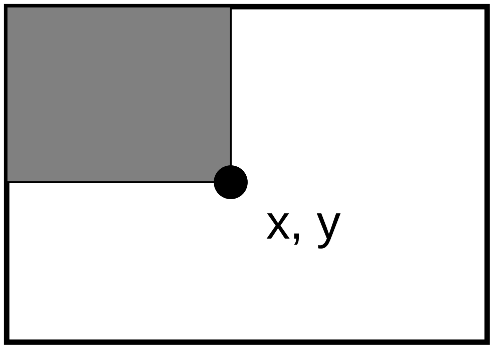
Two-rectangle features

Three-rectangle features

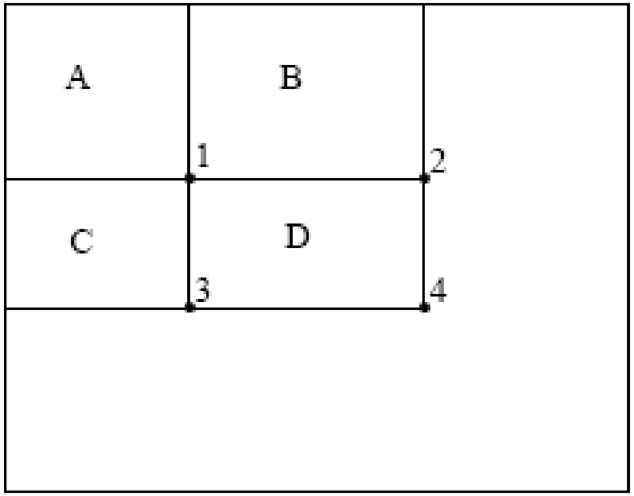
Etc.

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

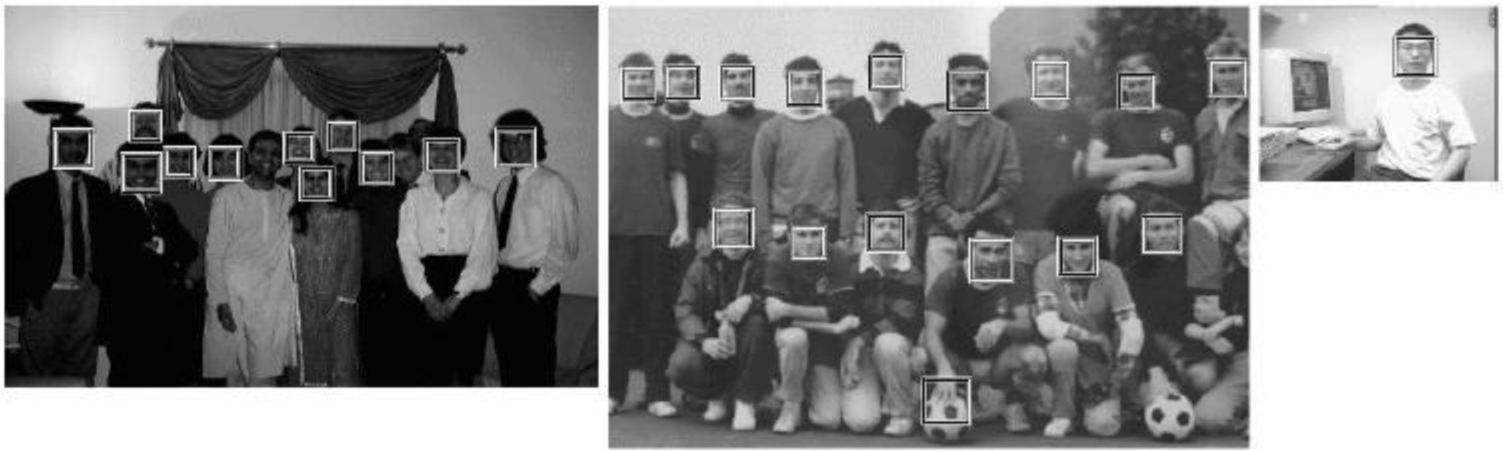
- Create a large pool of features (180K)
- Select features that are discriminative and work well together
  - “Weak learner” = feature + threshold + parity

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

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

Viola Jones Results

Speed = 15 FPS (in 2001)



Detector \ False detections	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

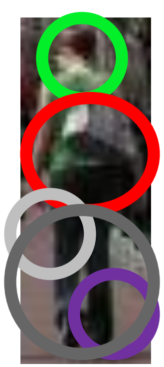
- Overview
- Viola-Jones
- Dalal-Triggs
- Deformable models
- Deep learning

Statistical Template

Object model = sum of scores of features at fixed positions

$$+3 + 2 - 2 - 1 - 2.5 = -0.5 \overset{?}{>} 7.5$$

Non-object



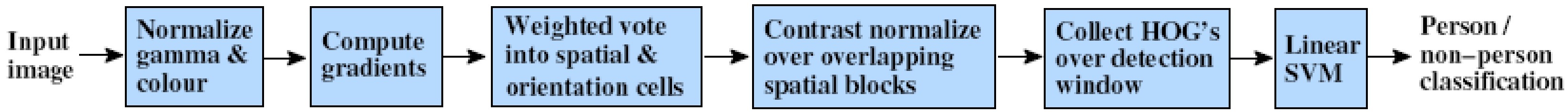
$$+4 + 1 + 0.5 + 3 + 0.5 = 10.5 \overset{?}{>} 7.5$$

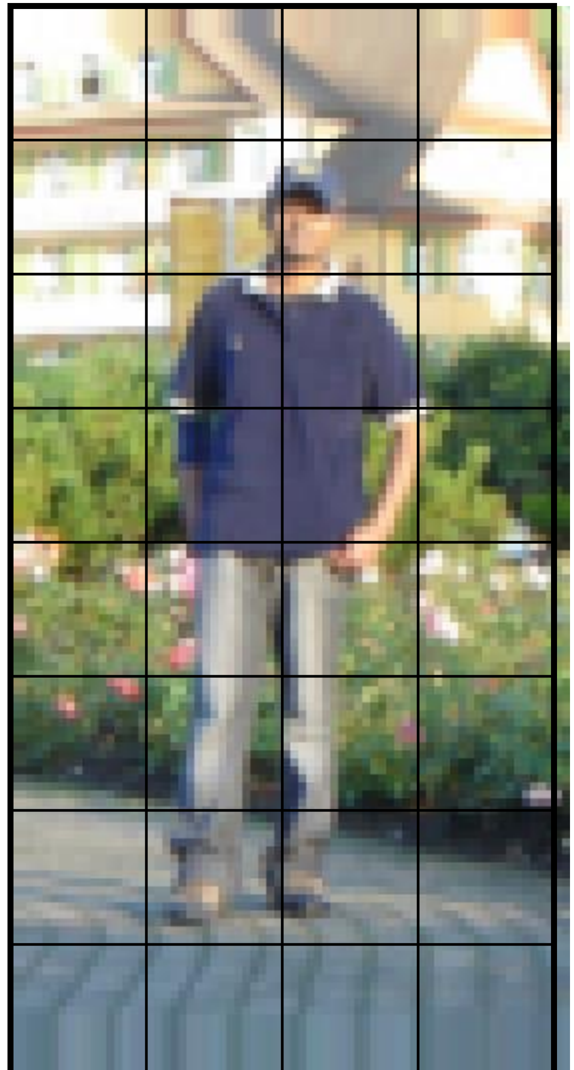
Object

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





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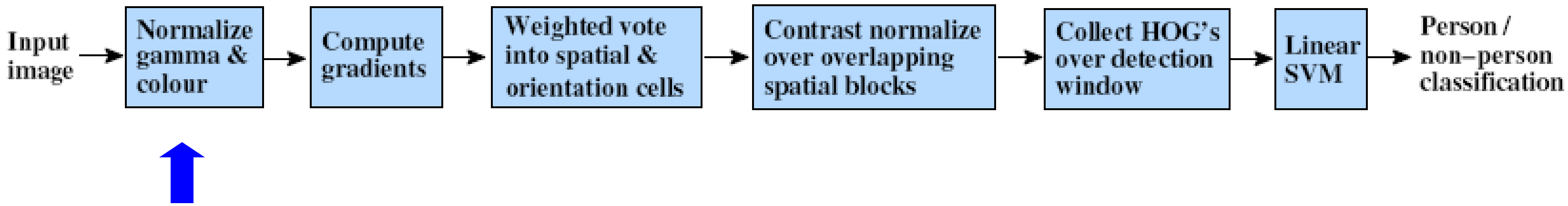
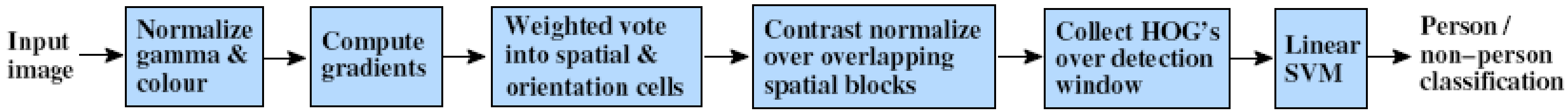


- Tested with
  - RGB
  - LAB
  - Grayscale

Slightly better performance vs. grayscale

- Gamma Normalization and Compression
  - Square root
  - Log

Very slightly better performance vs. no adjustment



Outperforms

-1	0	1

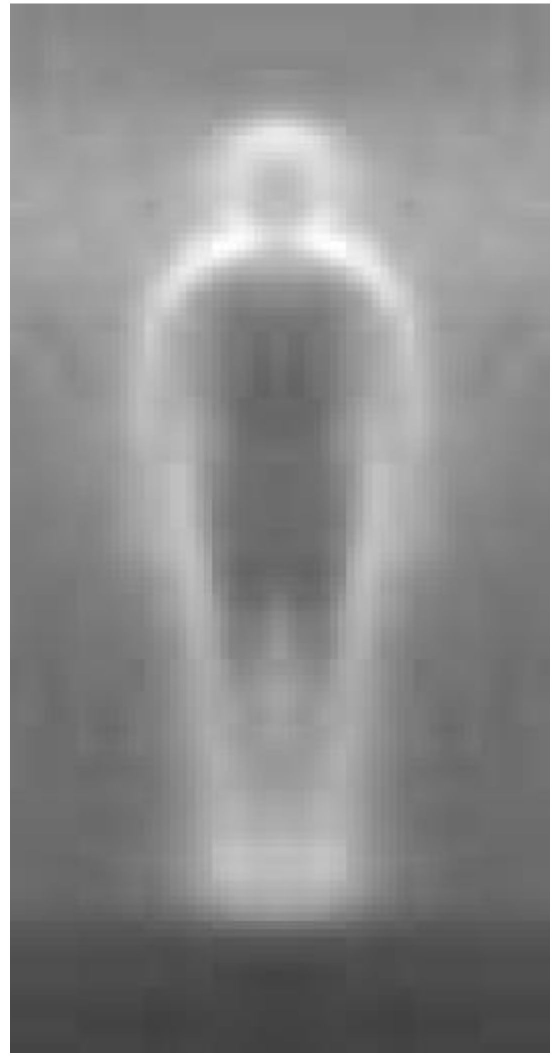
centered

-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

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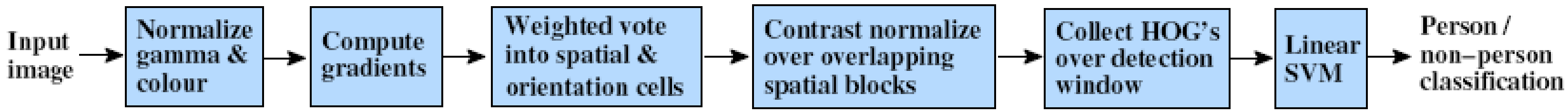
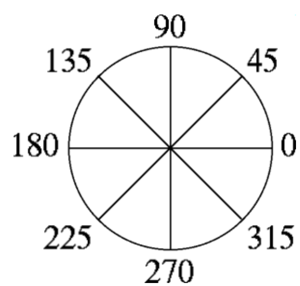
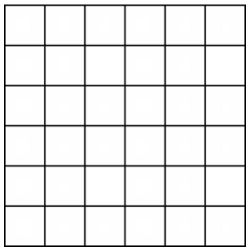


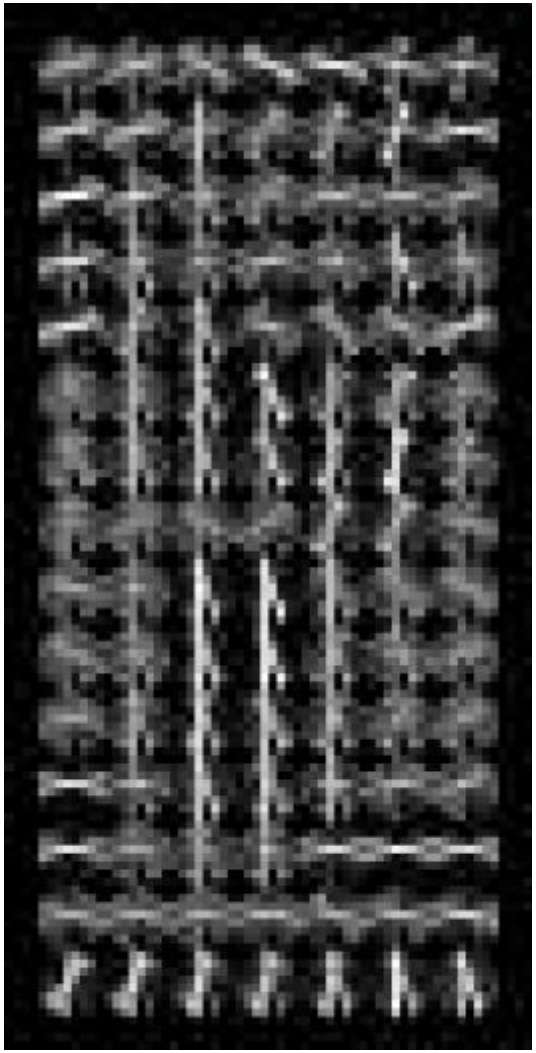
- Histogram of gradient orientations

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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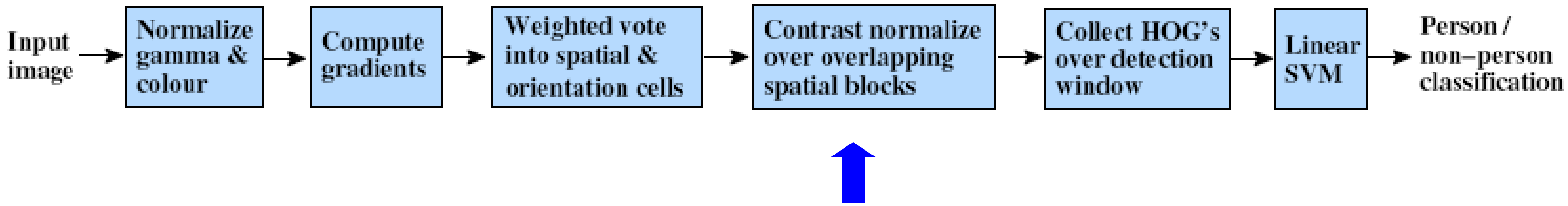
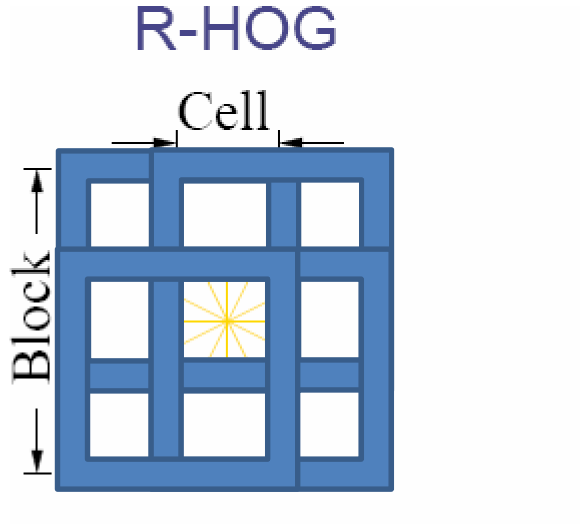


Normalize with respect to surrounding cells



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

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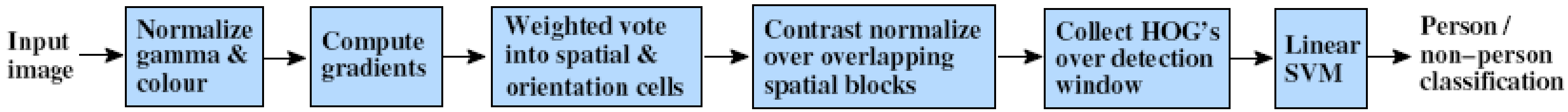
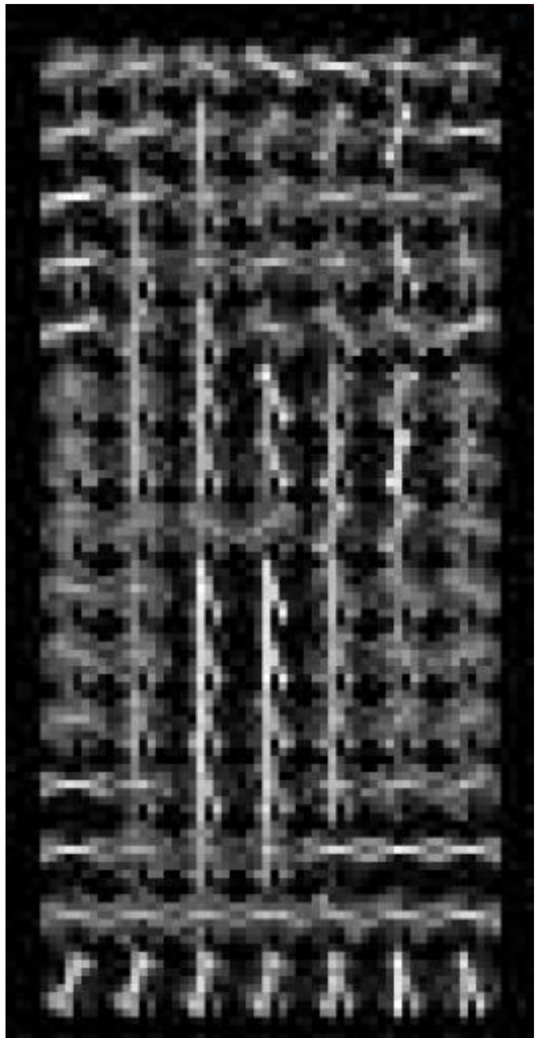


X=



Original Formulation

orientations

features = 15 x 7 x 9 x 4 = 3780

cells

normalizations by neighboring cells

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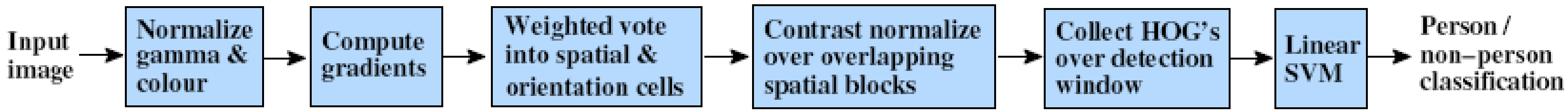
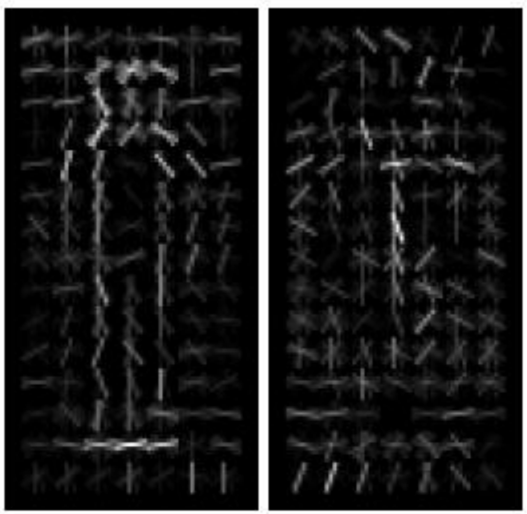
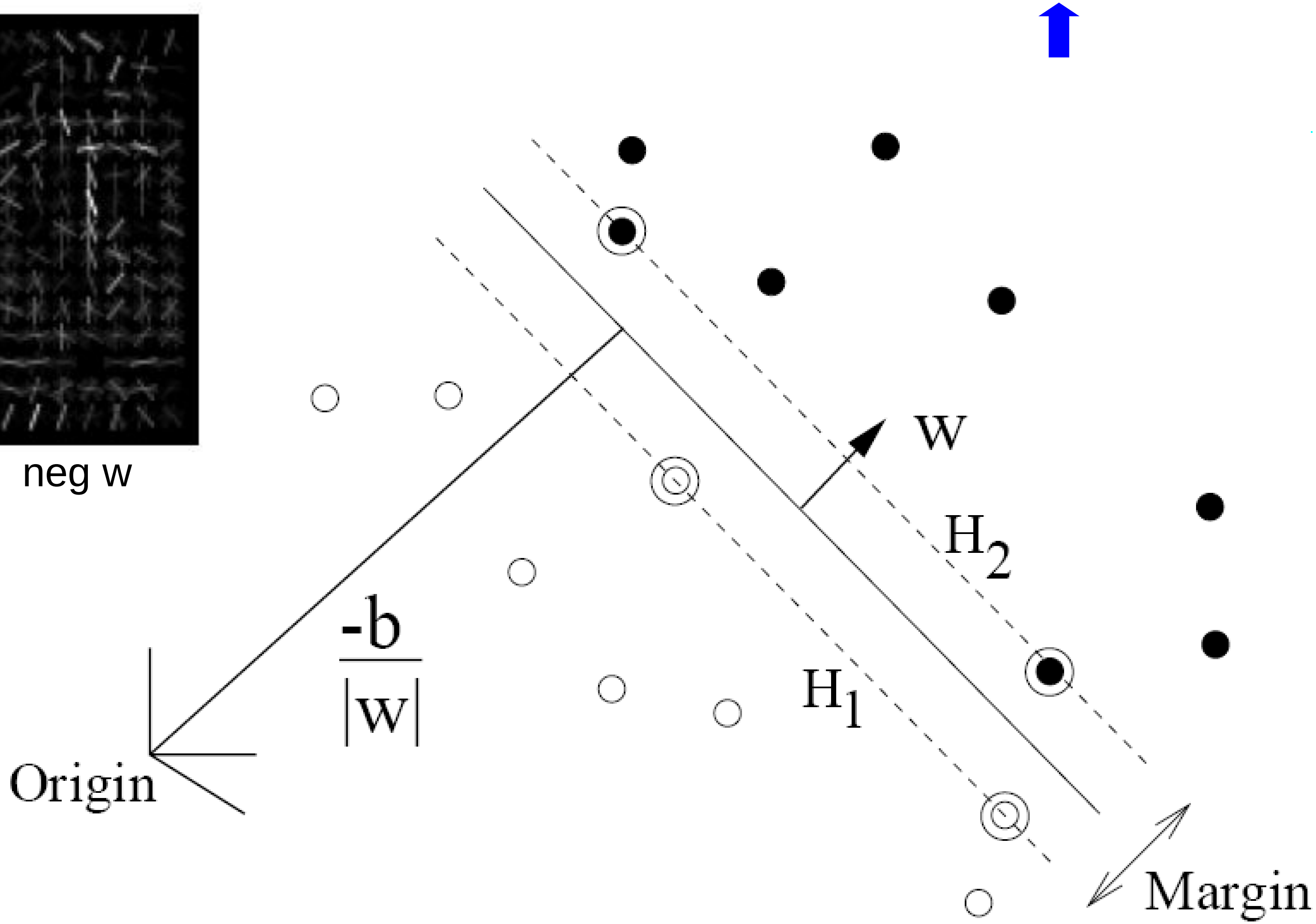




pos w neg w



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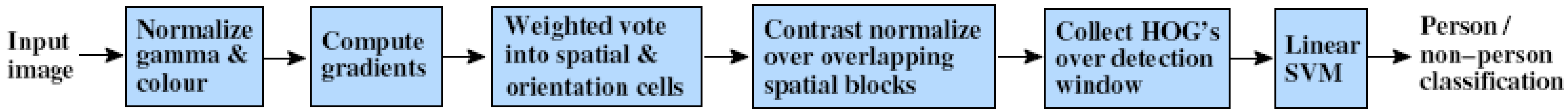

$$0.16 = w^T x - b$$

$$sign(0.16) = 1$$

$=>$ pedestrian

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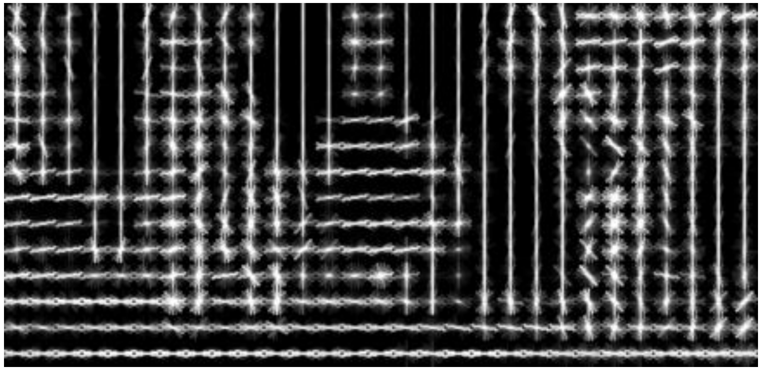
Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

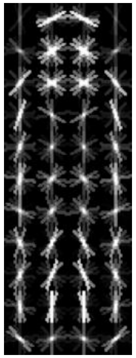
Pedestrian detection with HOG

- 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*

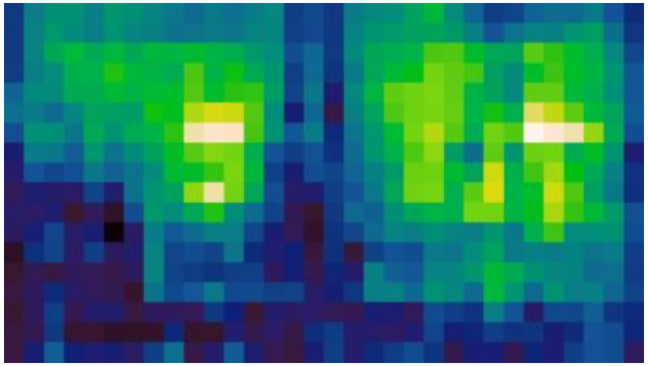
HOG feature map



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

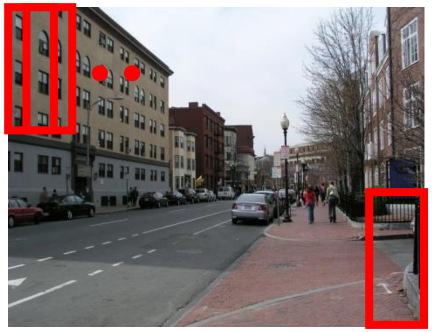
Weaknesses

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

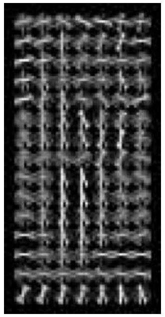
Tricks of the trade

- 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

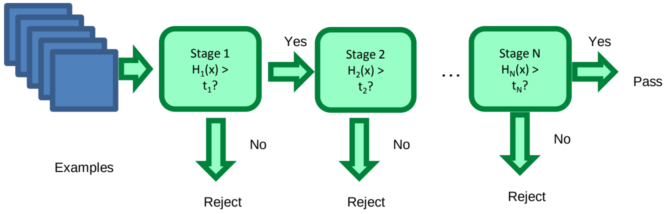
Things to remember



- 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