A Discriminatively Trained, Multiscale, **Deformable Part Model**

by Pedro Felzenszwalb, David McAllester, and Deva Ramanan

CS381V Visual Recognition - Paper Presentation

Deformable objects

Images from D. Ramanan’s dataset

Slide credit:
Duan Tran

Deformable objects

Images from Caltech-256

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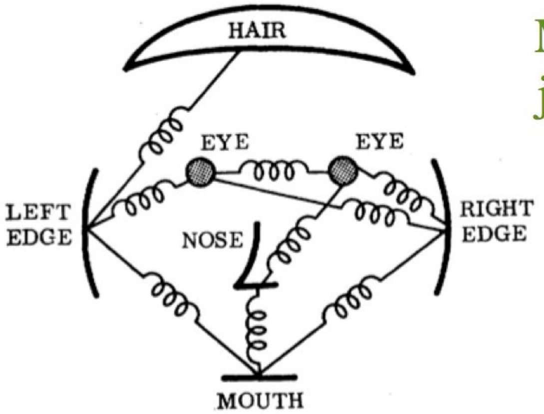
Deformable Part Model

- Introduced by Fischler and Elschlager in 1973
- Part-based models:
  - Each part represents local visual properties
  - “Springs” capture spatial relationships



Matching model to image involves joint optimization of part locations “stretch and fit”

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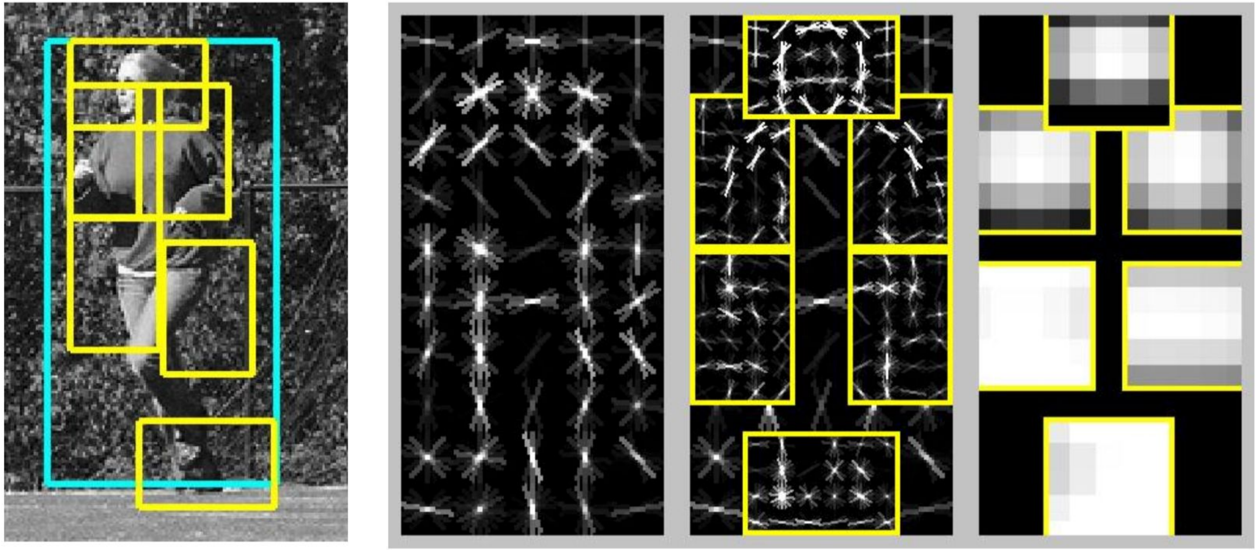
Deformable Part Model



Root Filter   Part Filters   Deformation Model

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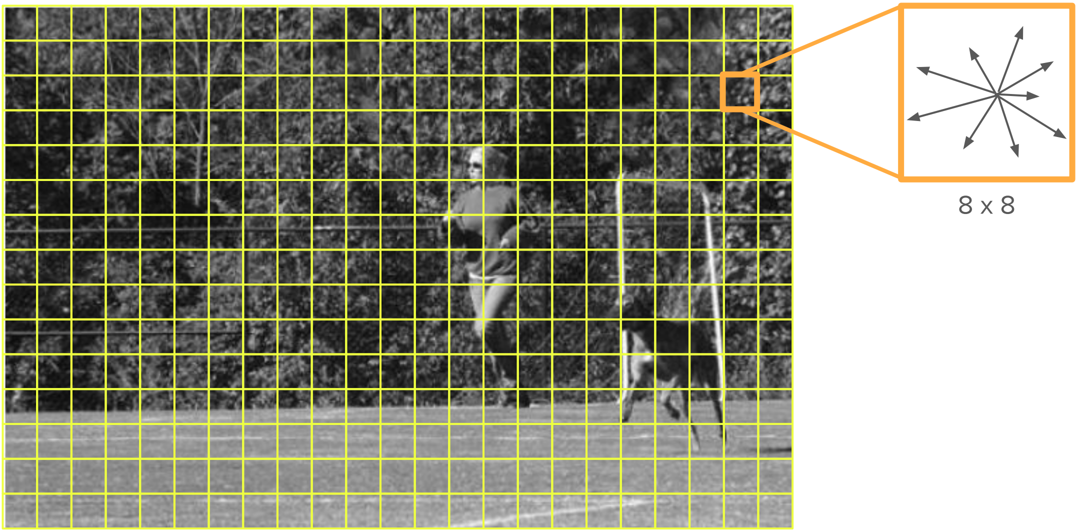
Step 1: HOG Pyramid



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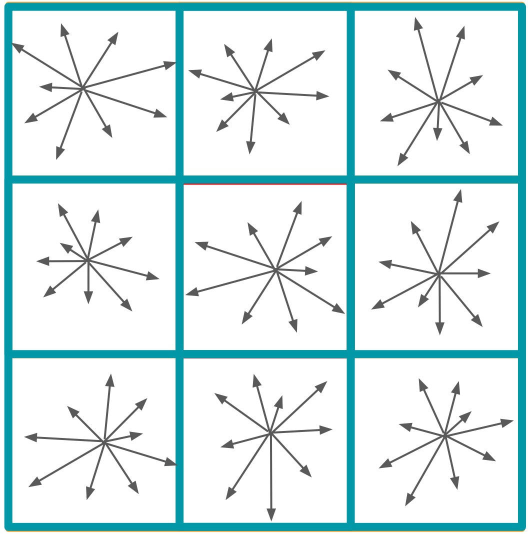
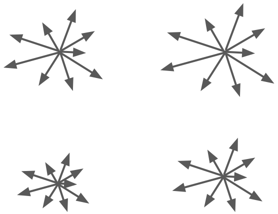
Step 1: HOG Pyramid

- Normalize w.r.t. the sum of histogram values in each 2 x 2 block containing the cell.



4 x 9 descriptor:



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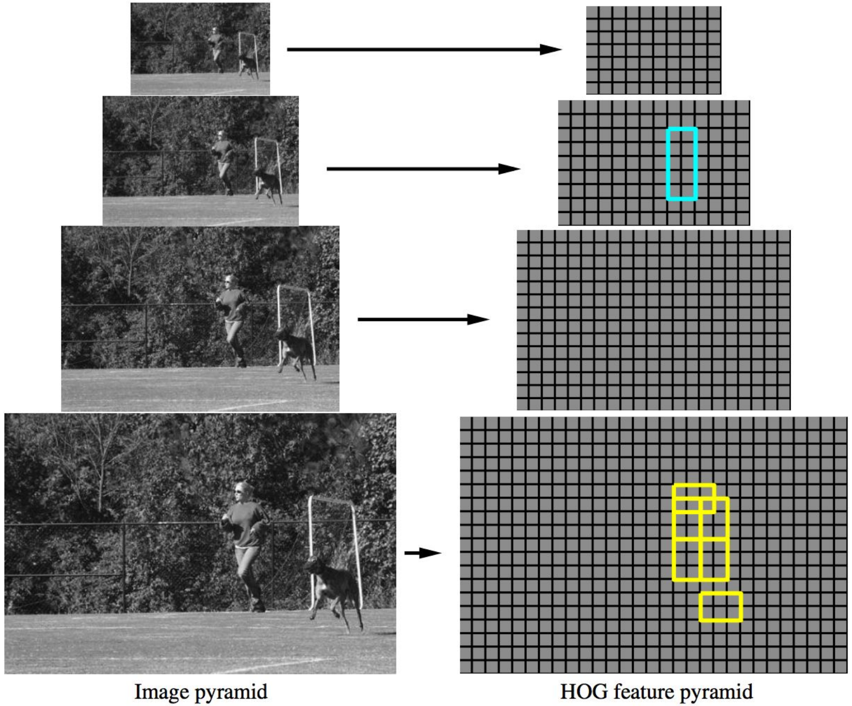
Step 1: HOG Pyramid



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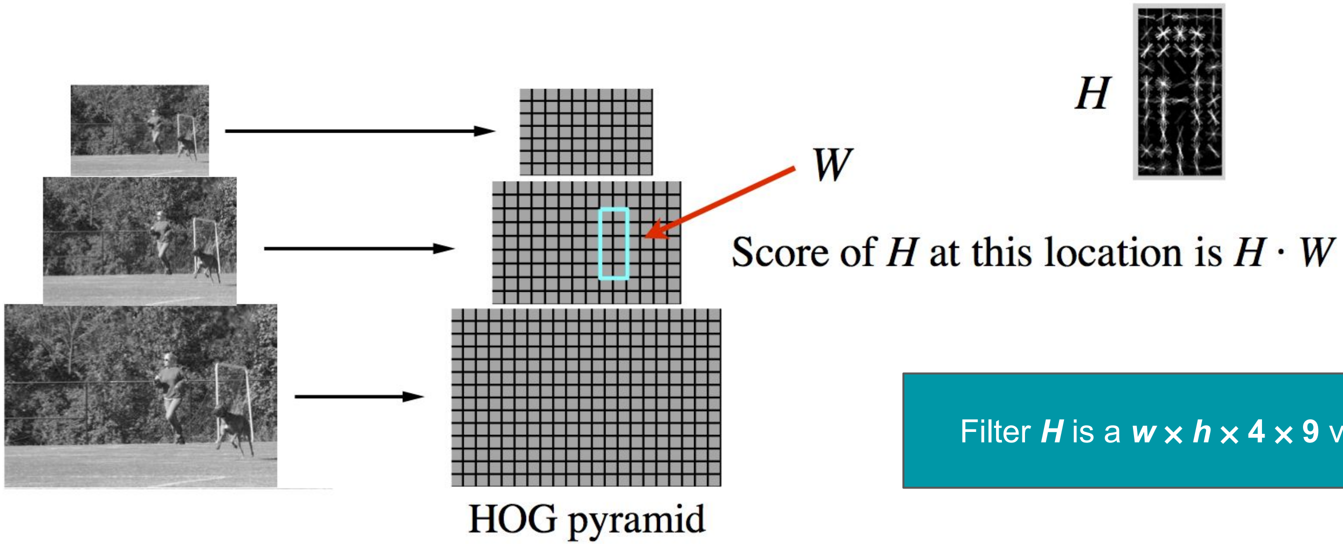
Filters

- Filters are rectangular templates defining weights for features
- Score is dot product of filter and subwindow of HOG pyramid



Filter ***H*** is a $\boldsymbol{w \times h \times 4 \times 9}$ vector.

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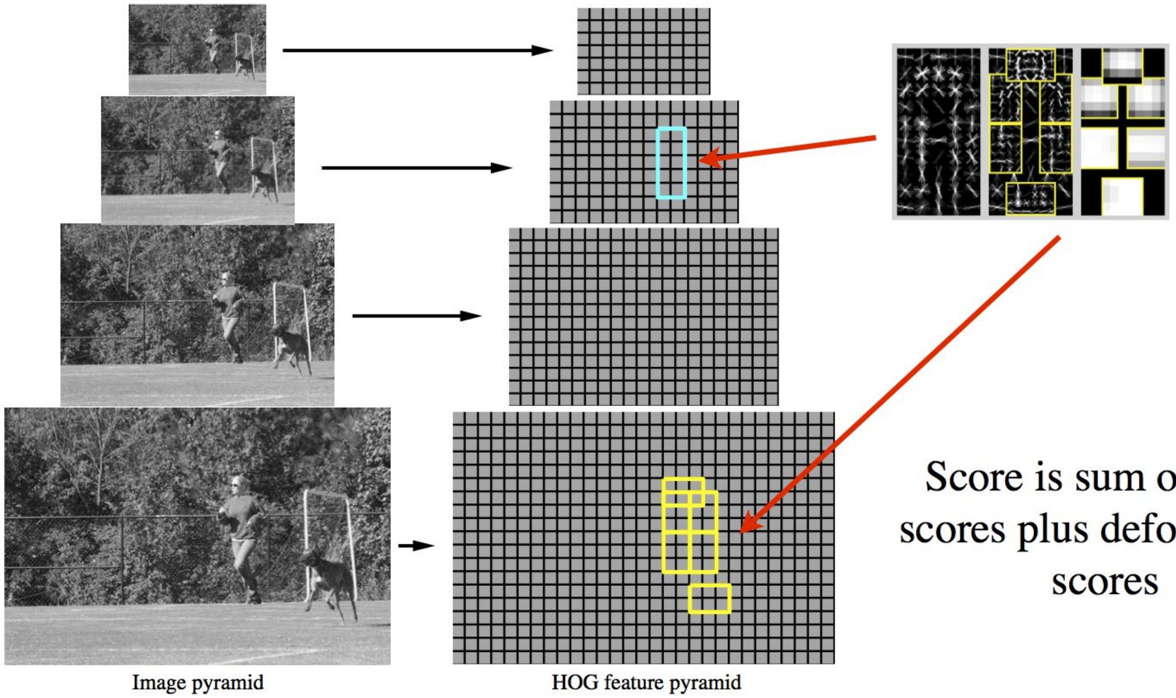
Object Hypothesis



Score is sum of filter scores plus deformation scores

Multiscale model captures features at two-resolutions

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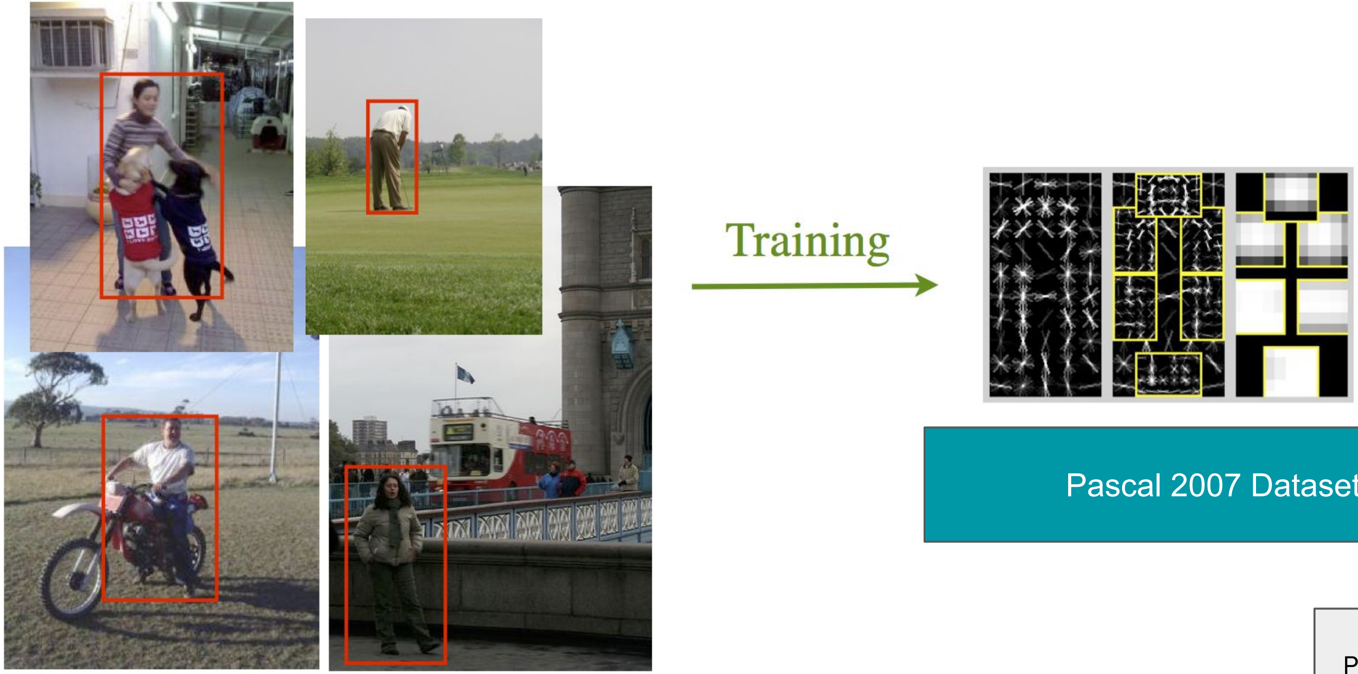
Training

- Training data consists of images with labeled bounding boxes
- Need to learn the model structure, filters and deformation costs



Pascal 2007 Dataset

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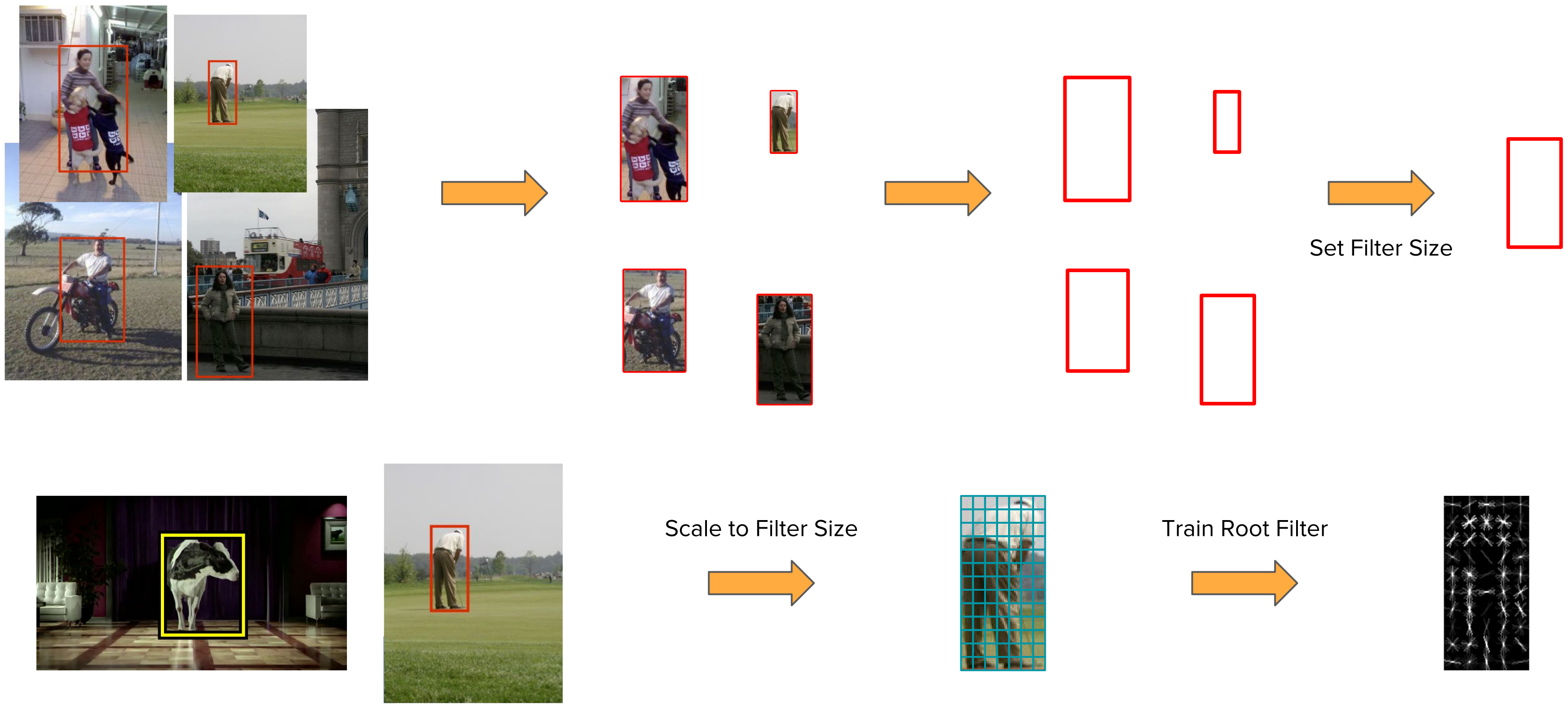
Step 2: Initialize Root Filter



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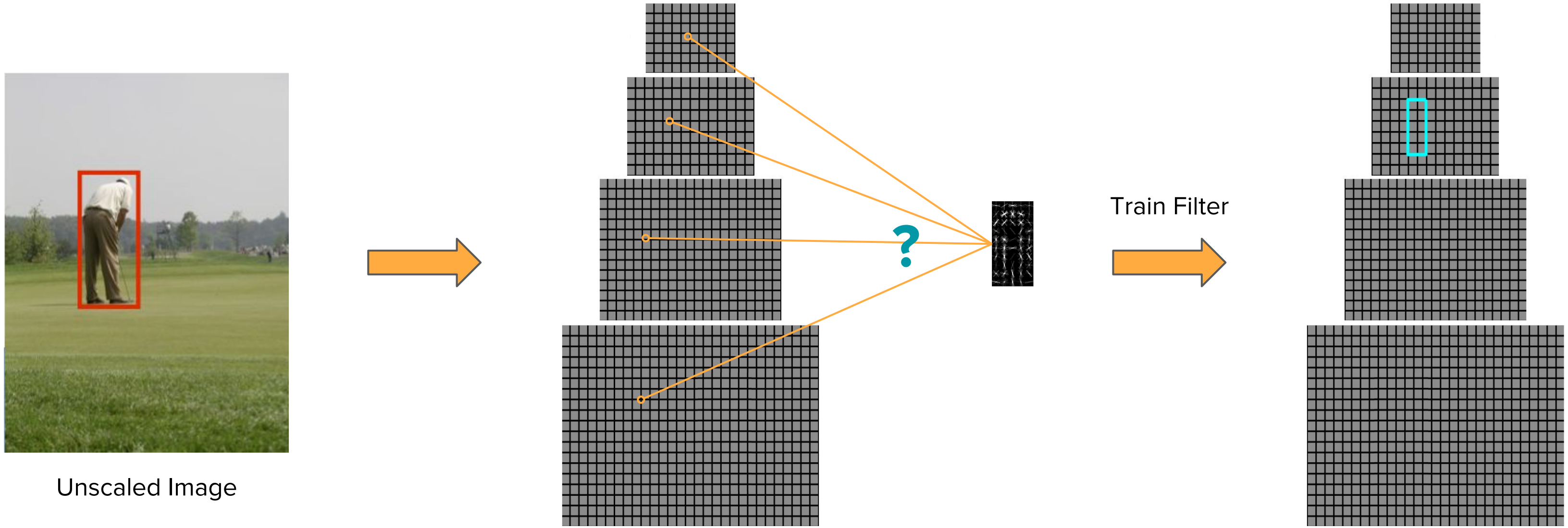
Step 2: Train Root Filter



Find best placement in HOG pyramid.

At least 50% overlap w/ ground truth.

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Step 2 Summary

1. Set filter size based on statistics in the data.
2. Train on unoccluded examples with SVM.
   - Scale each example to match the filter size.
   - Random subwindows of negative images give negative examples.
3. Find the best filter placement in the HOG pyramid for each training image.
   - Un-scaled training images.
   - At least 50% overlap.
4. Re-train using best placements.
   - Same negatives as before.
   - Iterate twice.

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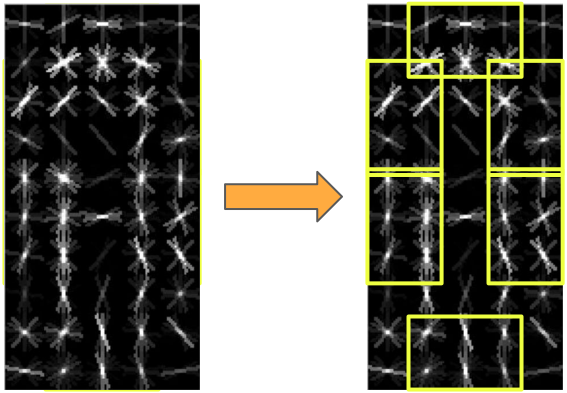
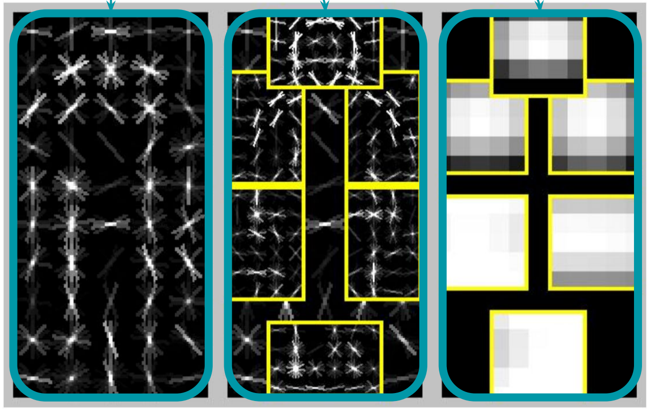
Step 3: Initialize Part Filters

- Train latent SVM on the full model:
  - $\beta = (F_0, F_1, \ldots, F_6, a_1, b_1, \ldots, a_6, b_6)$ are model parameters.



Trained Root Filter



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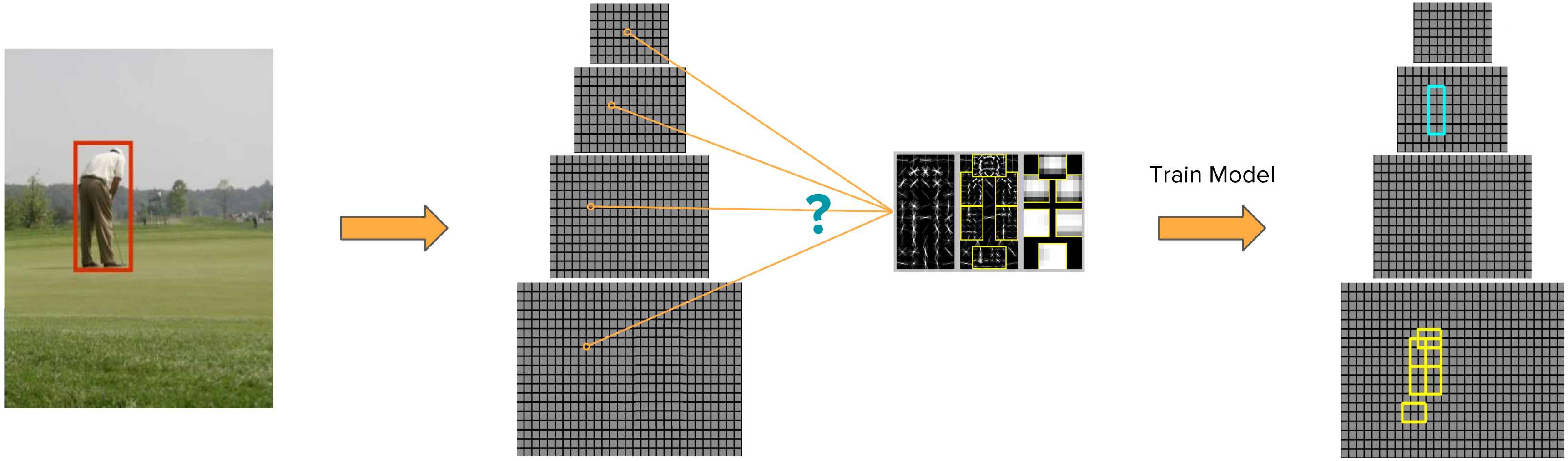
Step 3: Train Object Model



SVM Objective: $\beta^*(D) = \underset{\beta}{\operatorname{argmin}}\, \lambda||\beta||^2 + \sum_{i=1}^{n} \max(0, 1 - y_i \boxed{f_\beta(x_i)})$

Labeled training data (x_i, y_i).

$f_\beta(x) = \max_{z \in Z(x)} \boxed{\beta \cdot \Phi(x, z)}$

Score of placement ***z***.

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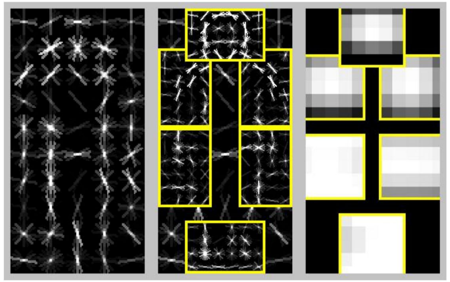
Step 3 Summary



1. Initialize 6 parts.
    - Position in areas of highest energy of root filter.
2. Train latent SVM on the full model:
    - $\beta = (F_0, F_1, \ldots, F_6, a_1, b_1, \ldots, a_6, b_6)$ are model parameters.
    - For each positive example, find best overall placement ***z***.
    - Use high-scoring regions in negative images as **hard negatives**.
    - Iterate 10 times. Each time cache as many hard negatives as can fit into memory.
        - Remove no-longer hard negatives.

SVM Objective: $$\beta^*(D) = \underset{\beta}{\operatorname{argmin}}\, \lambda||\beta||^2 + \sum_{i=1}^{n} \max(0, 1 - y_i \boxed{f_\beta(x_i)})$$

Labeled training data (x_i, y_i).

Score of placement ***z***.

$$f_\beta(x) = \max_{z \in Z(x)} \boxed{\beta \cdot \Phi(x, z)}$$

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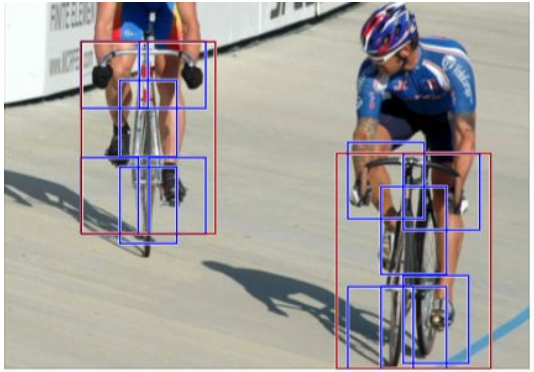
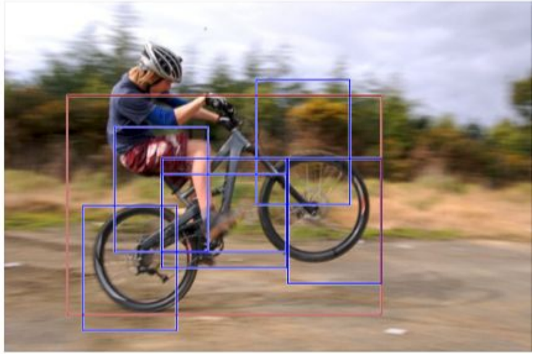
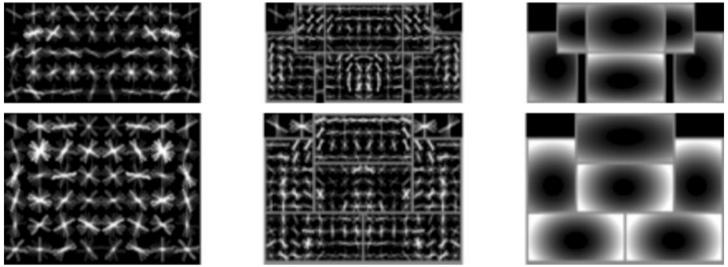
Results

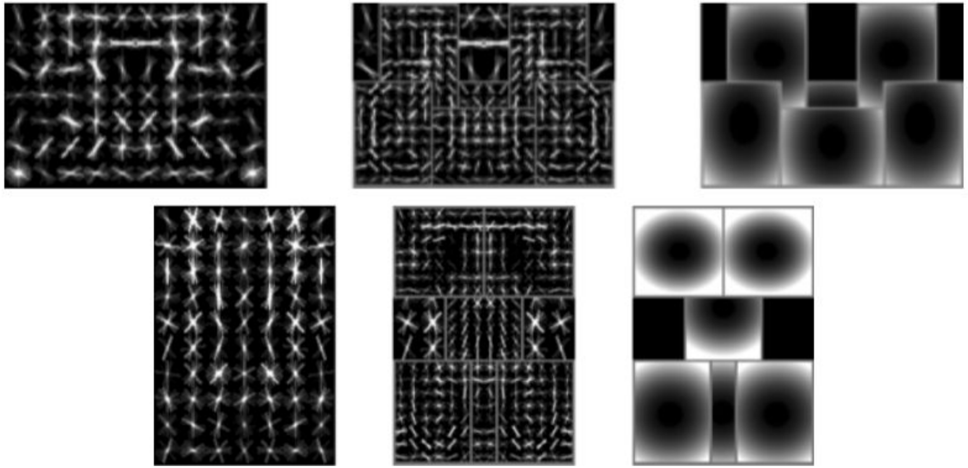
- Decent performance:
  - PASCAL 2007 challenge.
  - First place in 10/20 classes.
  - Second place in 6/20.
- Fast:
  - 3-4 hours training.
  - ~2s evaluation.







Car Model



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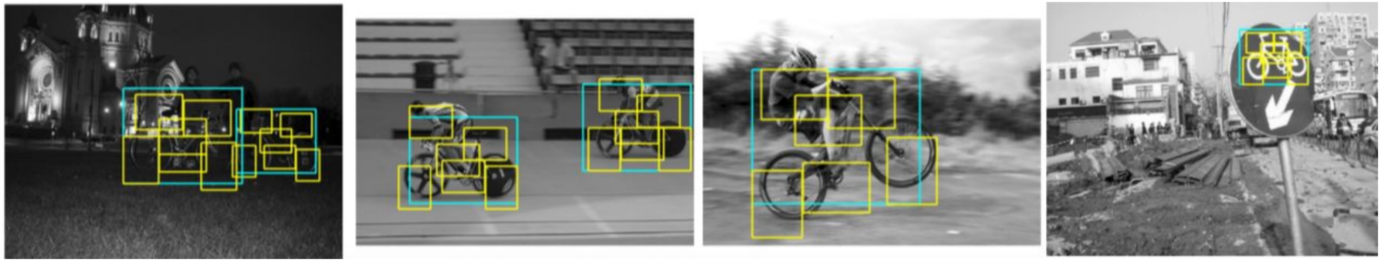
Person

Bottle

Bike



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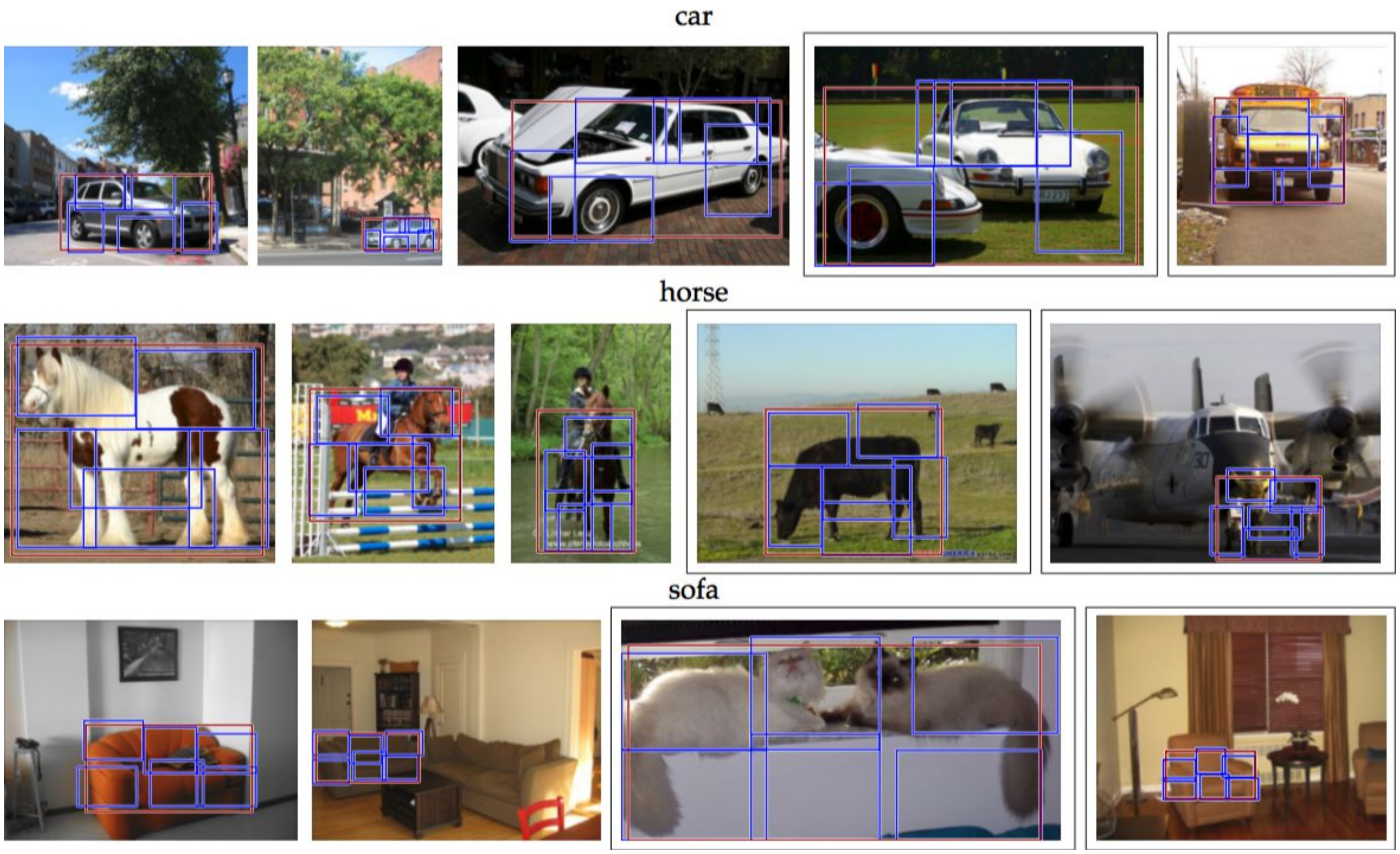

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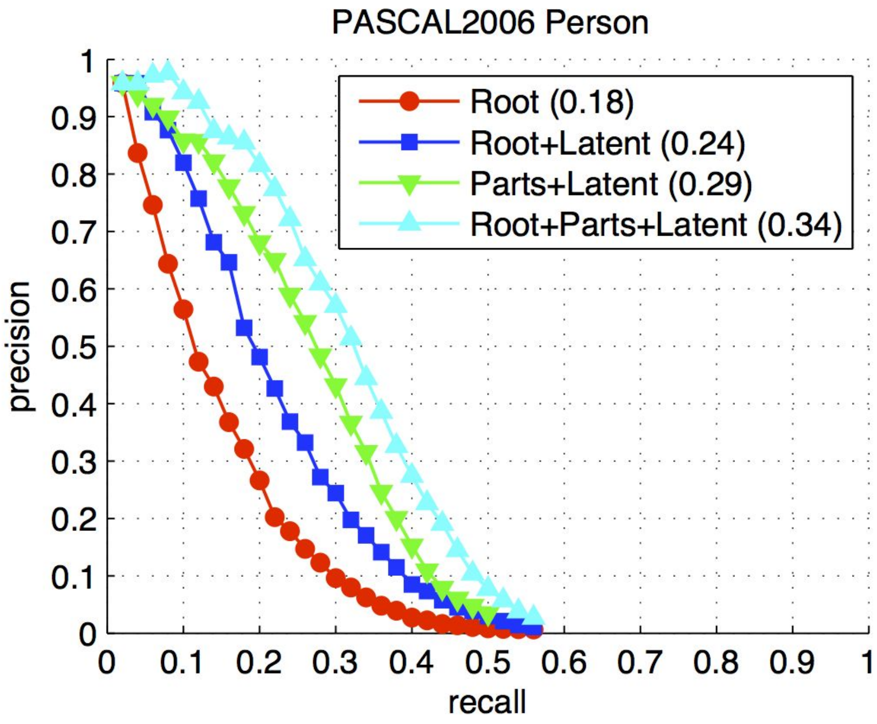
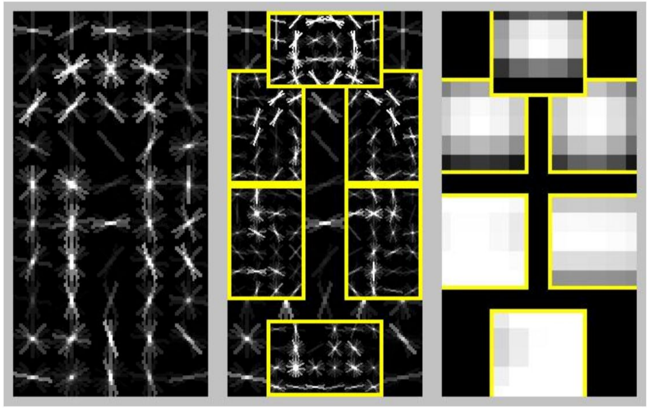
Component Analysis





Best overall results with all three components.

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Conclusion

- HOG pyramid representation.
- Root filter + part filters + latent placement variables.
    - Train with latent SVM.
- Hard negative mining.
- **Possible extensions?**
    - Deeper part hierarchies (parts of parts).
    - Multiple viewpoint models (front, side, back, etc.).
    - 3D pose estimation.
    - Visual words for parts: multi-class detection.

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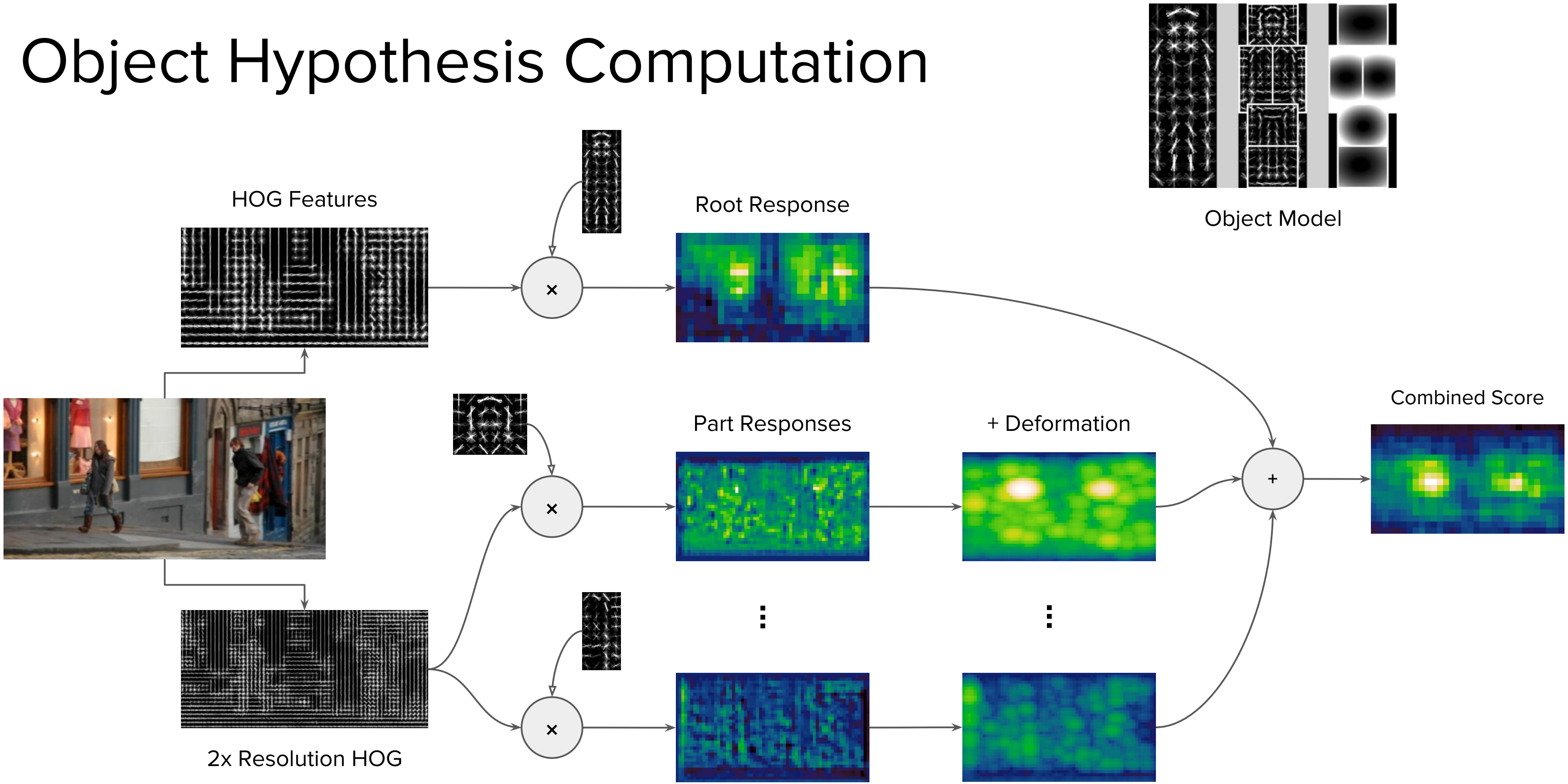
Object Hypothesis Computation



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