

Knowing a Good HOG Filter When You See It:
Efficient Selection of Filters for Detection



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Visual Category as Collection of filters

Poselets



Mid Level Discriminative Patches

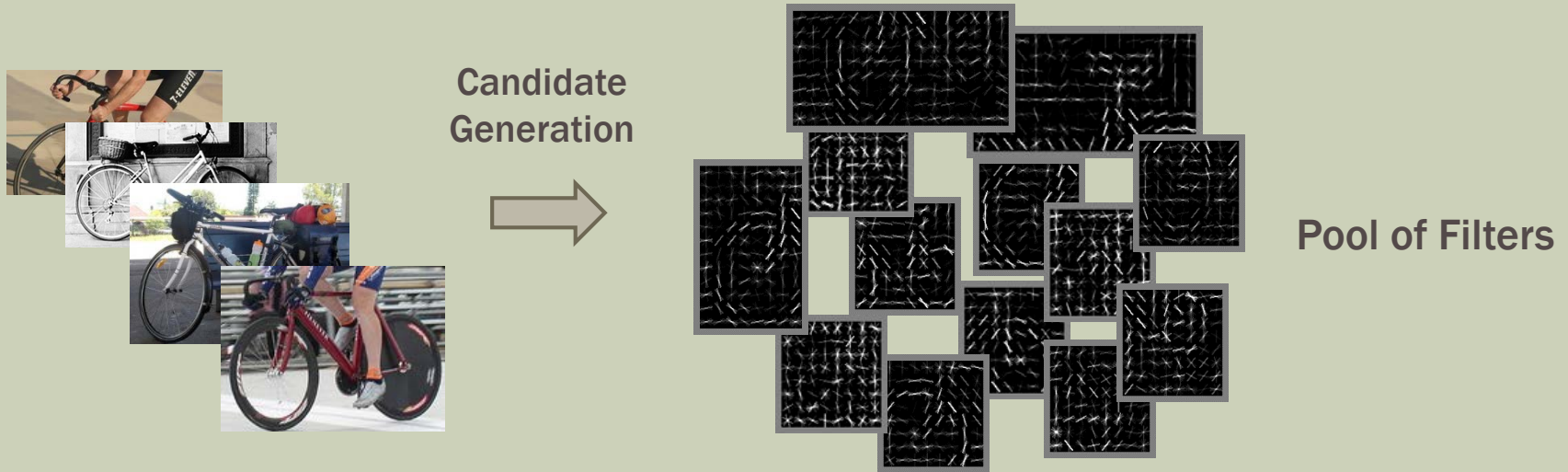


Exemplar SVMs

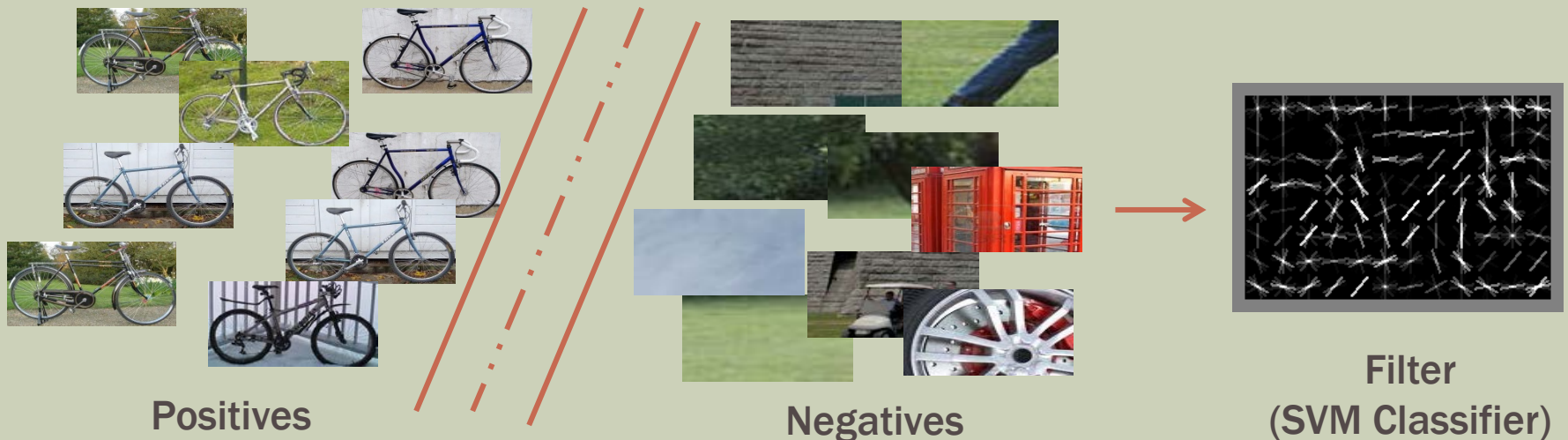


Candidate Generation

- Generation of a large pool of filters.

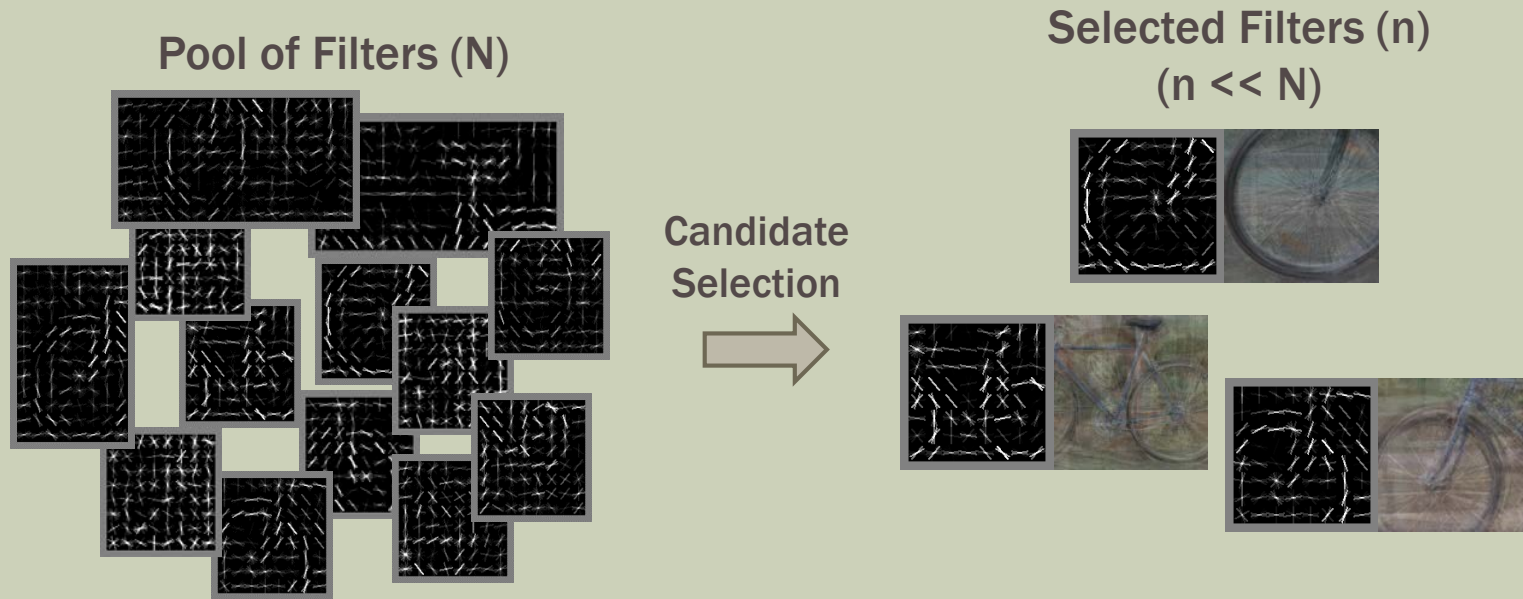


- Filters are generated using positives and negatives examples.

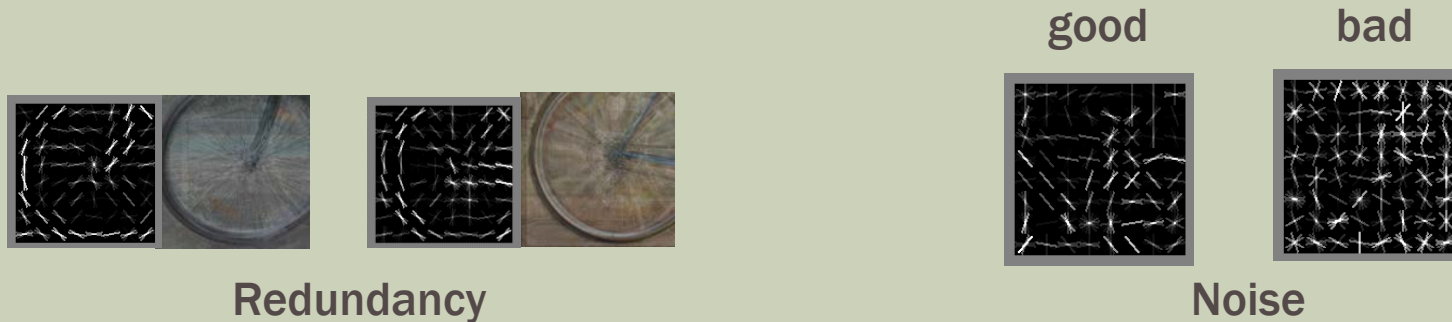


Candidate Selection

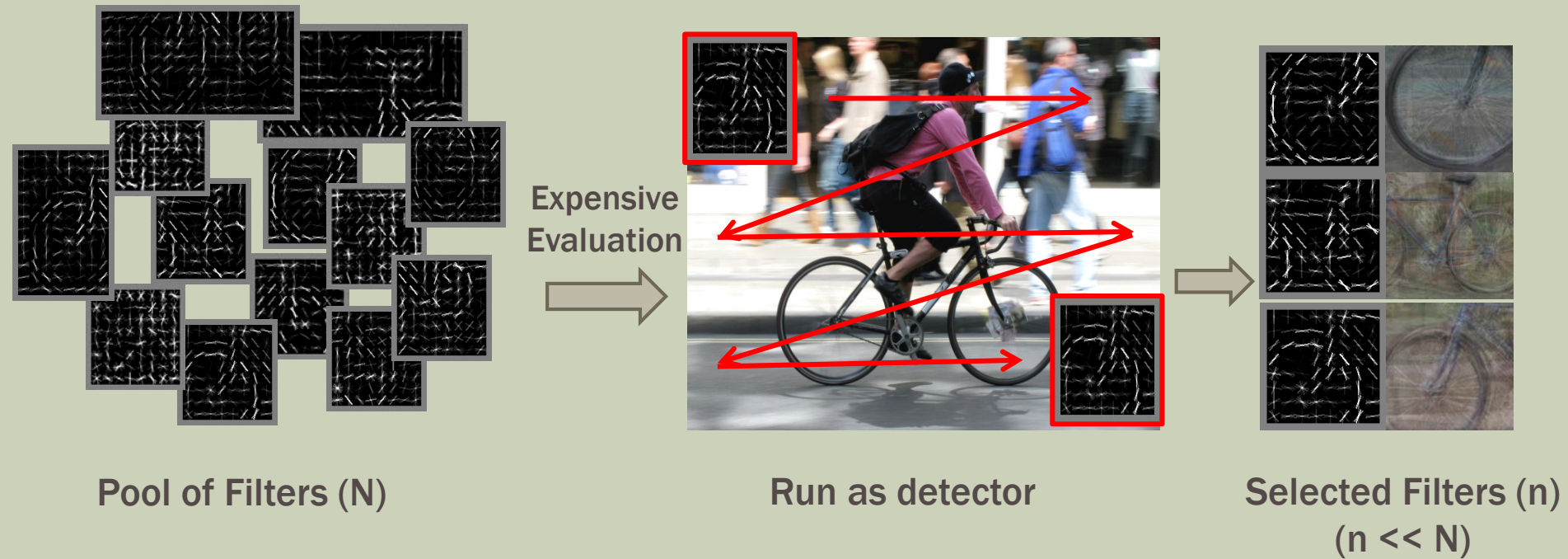
- Impractical to use all generated filters.



- Two sources of inefficiency

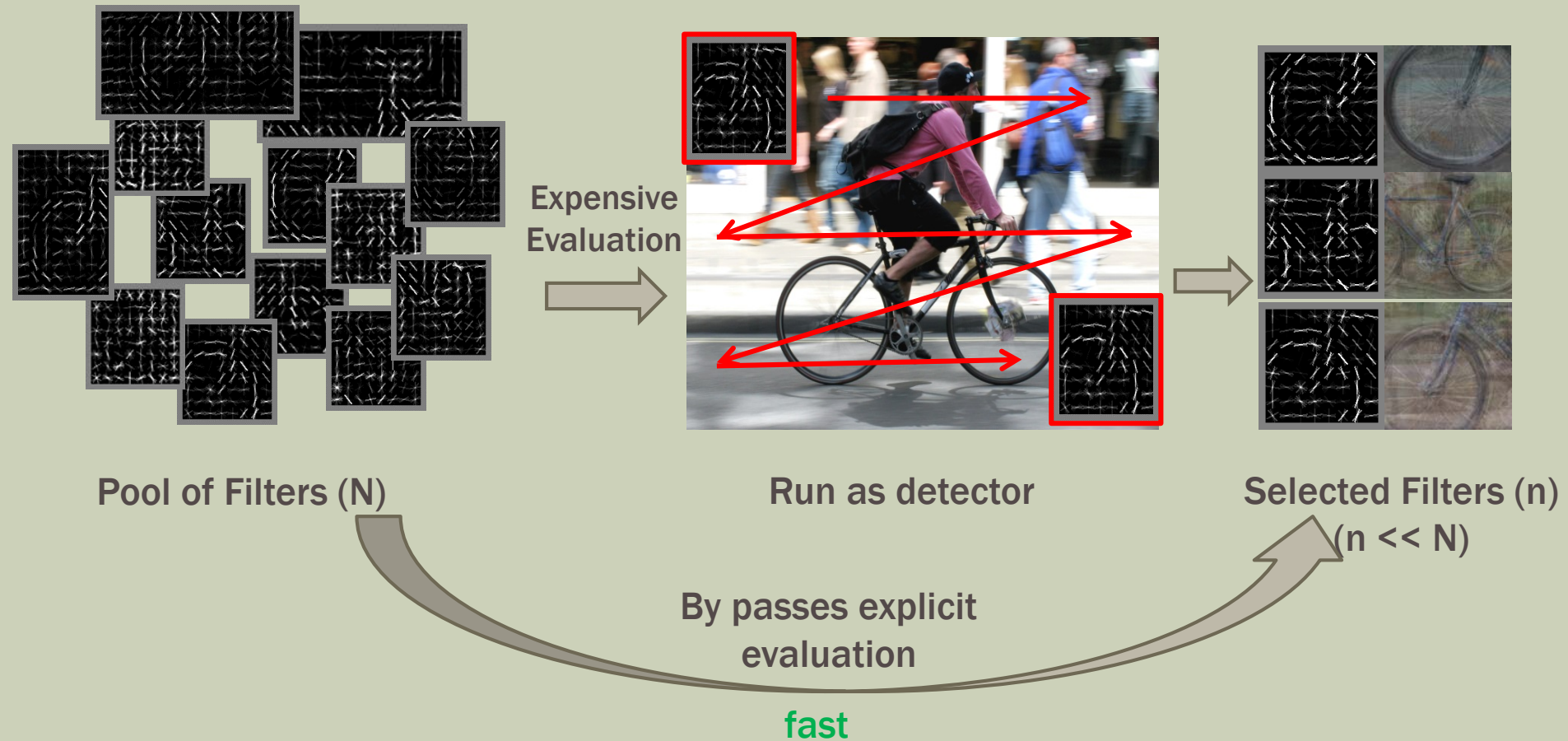


Candidate Selection Cont...



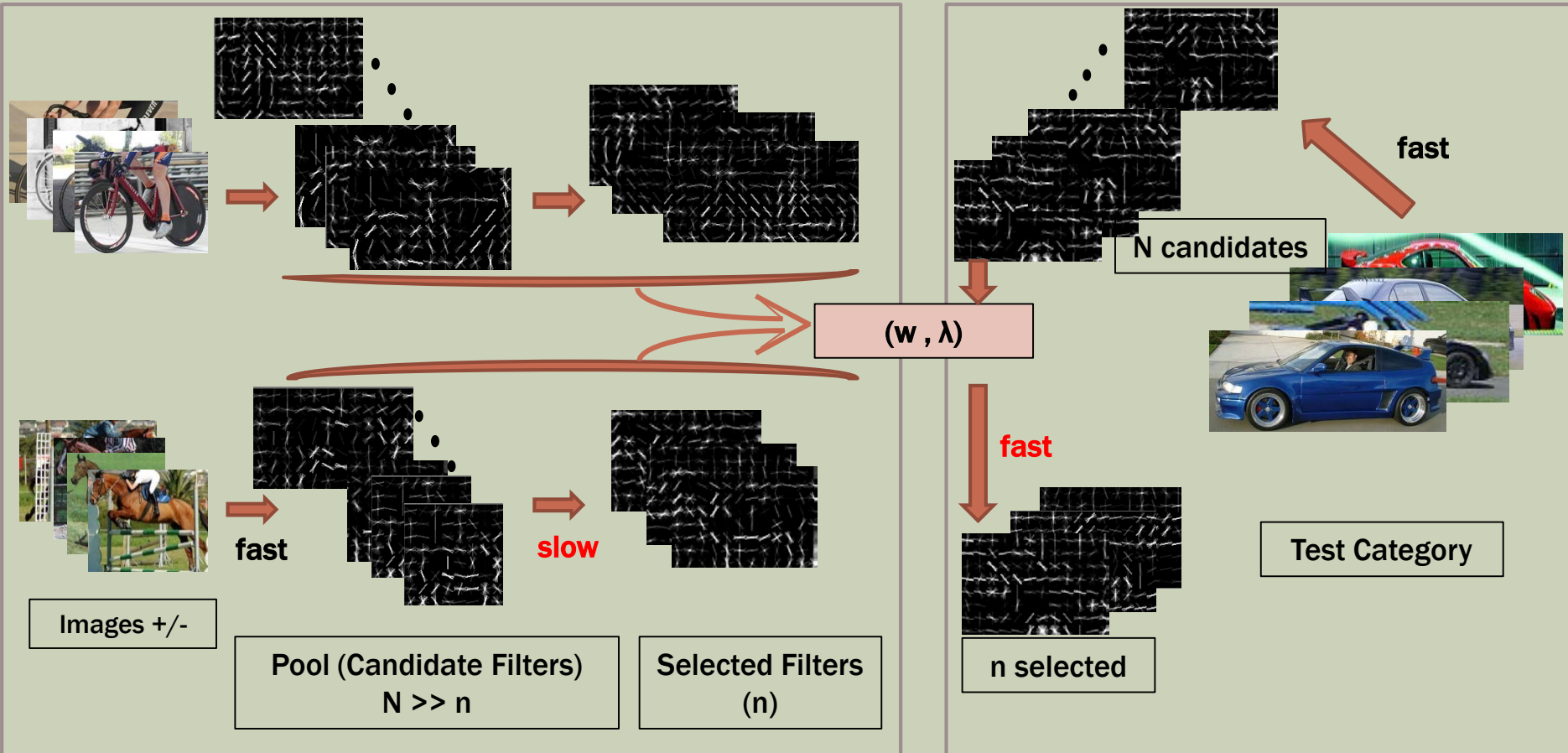
Bottleneck

What we Propose



Our Contribution : fast automatic selection of a subset of discriminative and non redundant filters given a collection of filters

Category Independent Model



- Can rank filters as accurately as a direct evaluation on thousands of examples.

Poselets

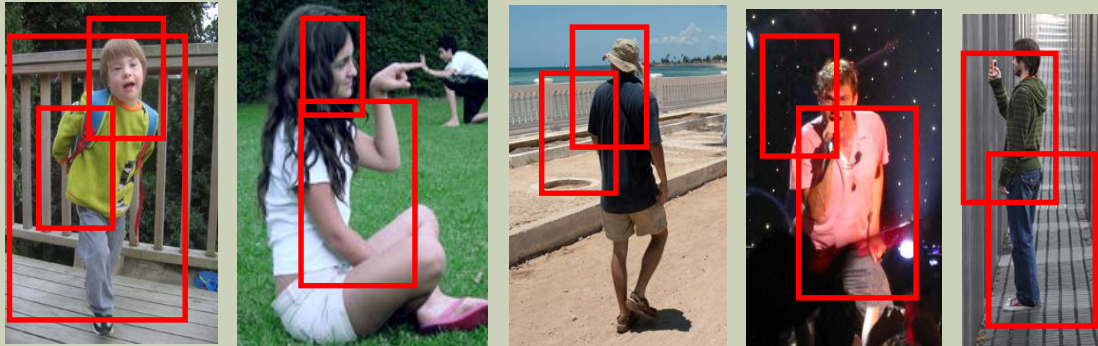
- Poselets are semantically aligned discriminative patterns that capture parts of object.



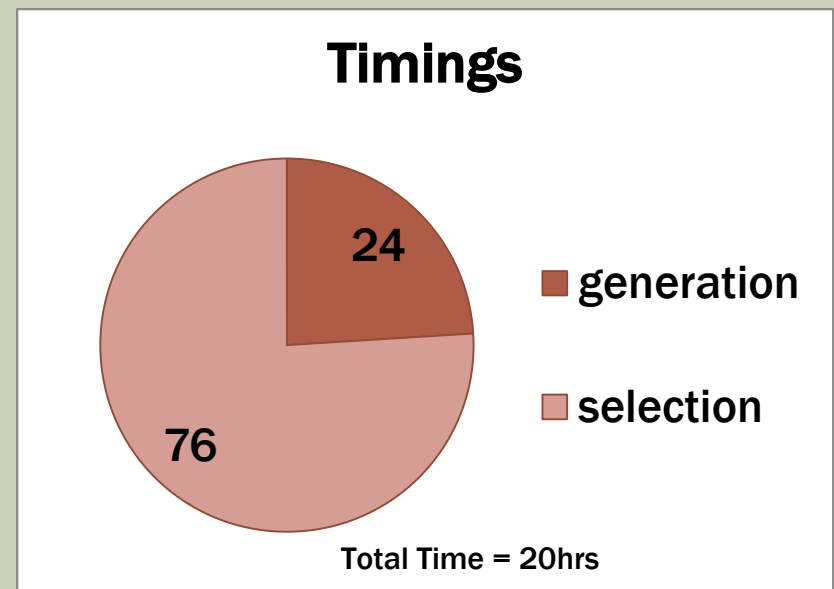
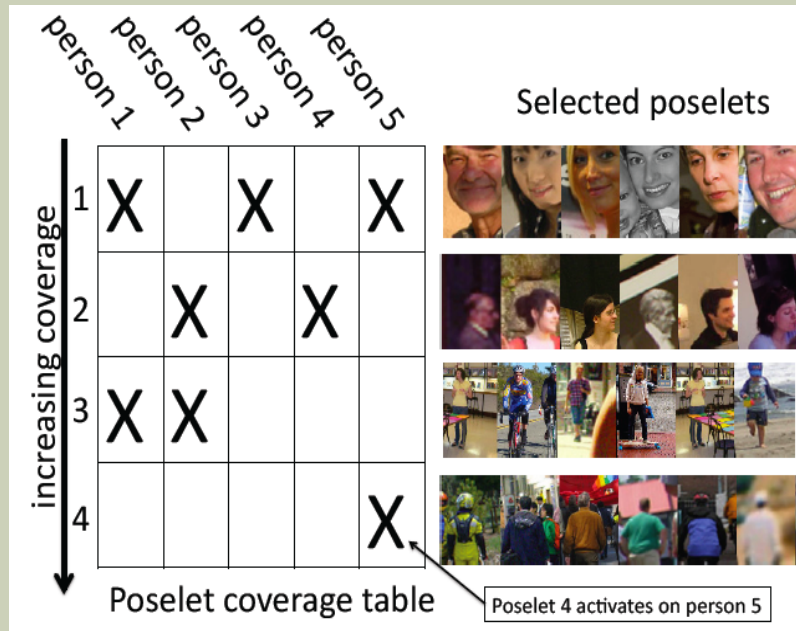
- Patches are often far visually, but they are close semantically

Poselet Architecture

■ Candidate Generation :

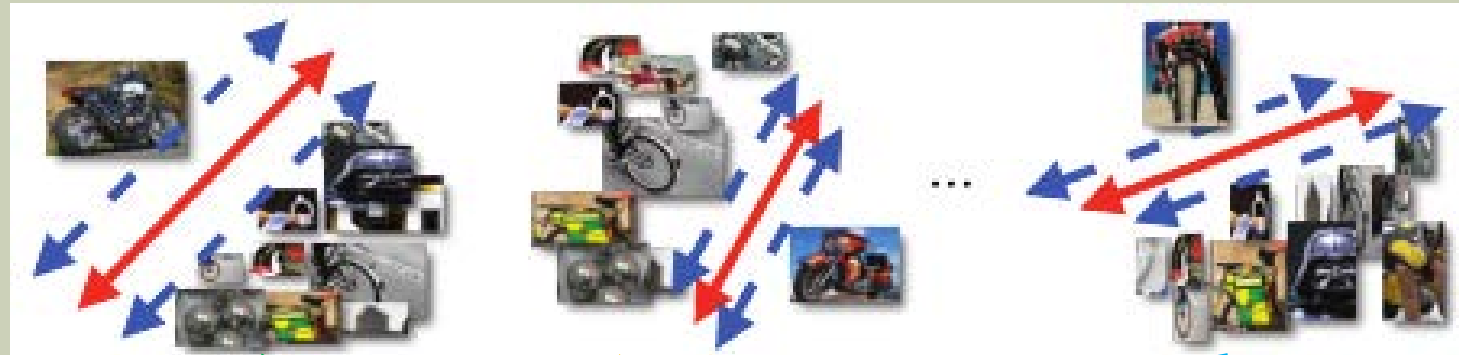


■ Candidate Selection :

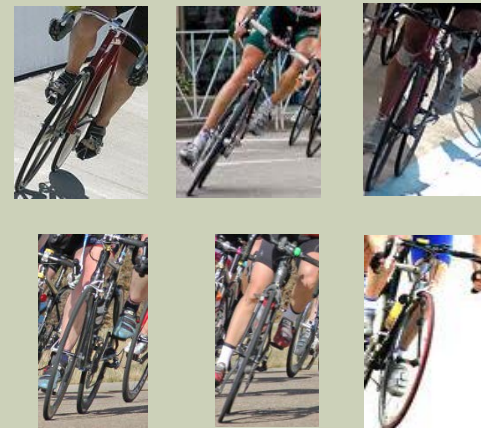
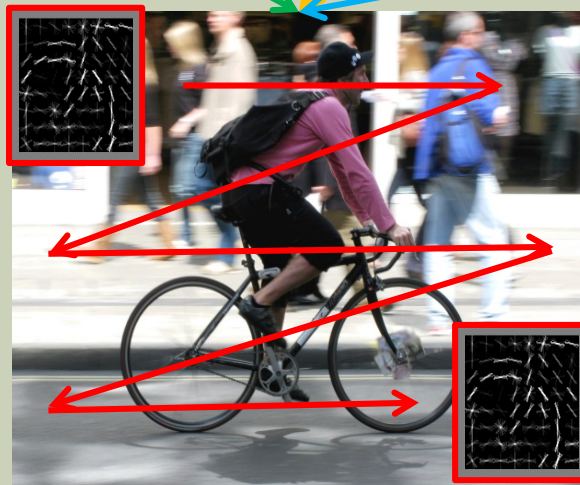


ESVM

SVM for each positive example



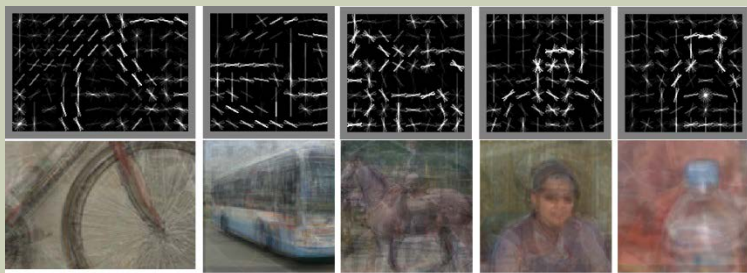
Test time



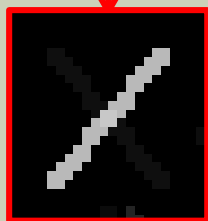
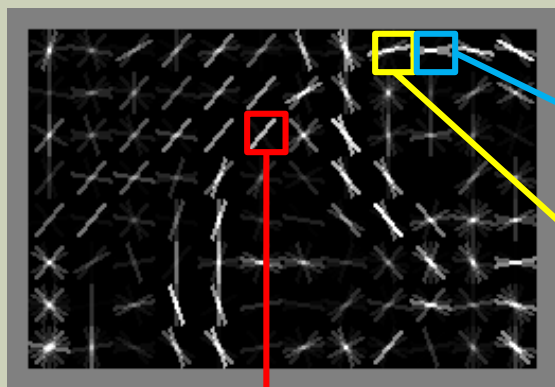
Redundant Exemplars

- Save significantly in training time if we can quickly select small set of relevant exemplars.

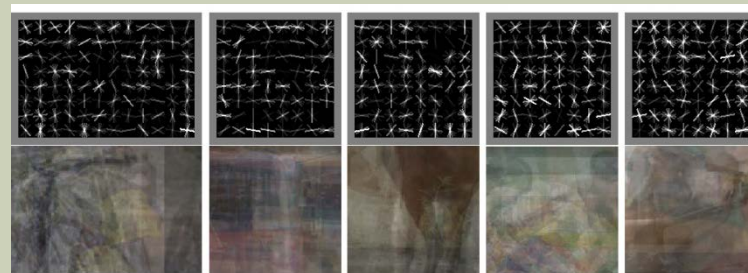
Good / Bad Filters



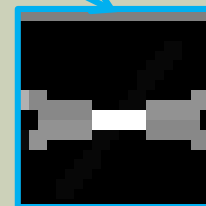
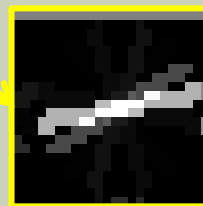
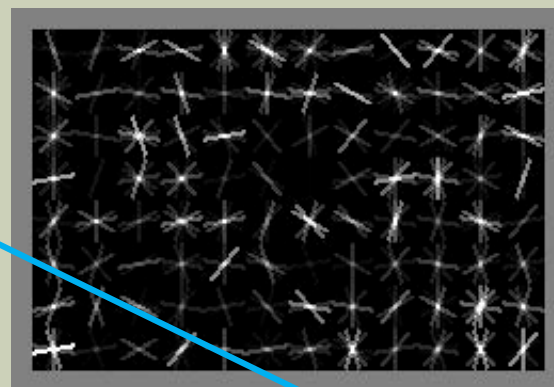
Good Filters



Gradient orientation within a cell
(active simultaneously)



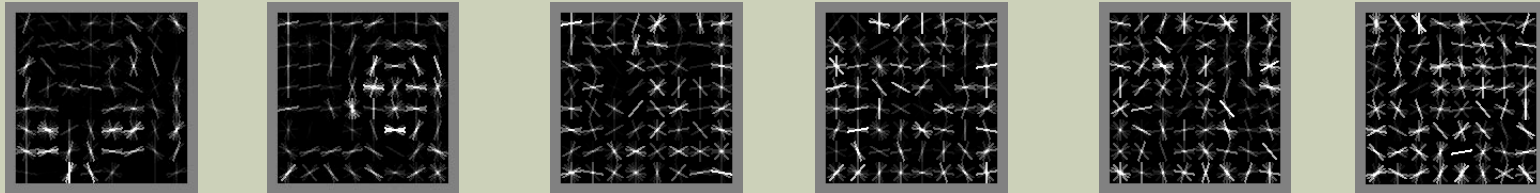
Bad Filters



Gradient orientation of neighboring cells
(lines, curves)

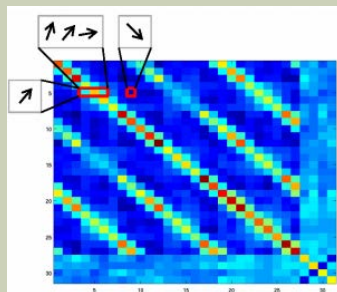
Features for filter Ranking

- **Norm:** consistent with high degree of alignment.
- **Normalized Norm:** Makes norm invariant to filter dimension.

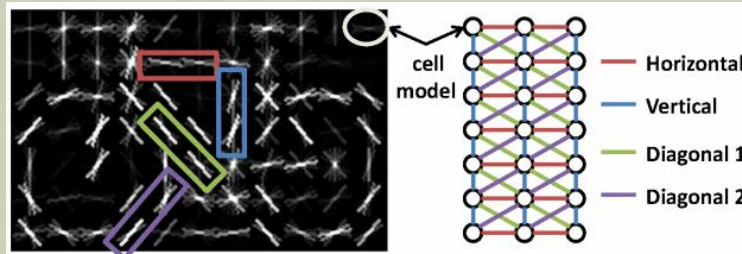


Decreasing Norm

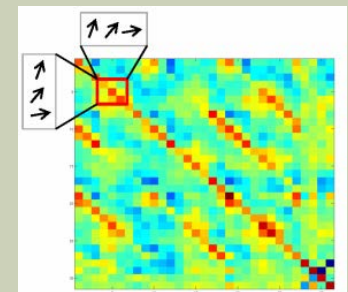
- **Cell Covariance:** Different orientation bins within a cell are highly structured. Gao et al. ECCV 2012
- **Cell Cross Covariance:** Strong correlation between filter weights in nearby spatial locations.



Cell Covariance



Cell Cross Covariance



Learning to Rank Filters

- $\Phi(f)$ – representation of filter f
- Goal : model ranking score of f by a linear function $\langle \mathbf{w}, \Phi(f) \rangle$
- Training data : $\{f_{g,i}\}, y_{g,i}$
 - $g = 1, \dots, G$ where G is number of training categories.
 - $i = 1, \dots, N$ where N is number of filters per category.
 - $y_{g,i}$ is estimated quality, obtained by expensive method.
- $f_{g,i}$ is ordered in descending value of $y_{g,i}$
- $\Delta_{g,i,j} = y_{g,i} - y_{g,j}$, for $i > j$ measures how much better $f_{g,i}$ is from $f_{g,j}$
- $\delta\Phi_{g,i,j} = \Phi(f_{g,i}) - \Phi(f_{g,j})$

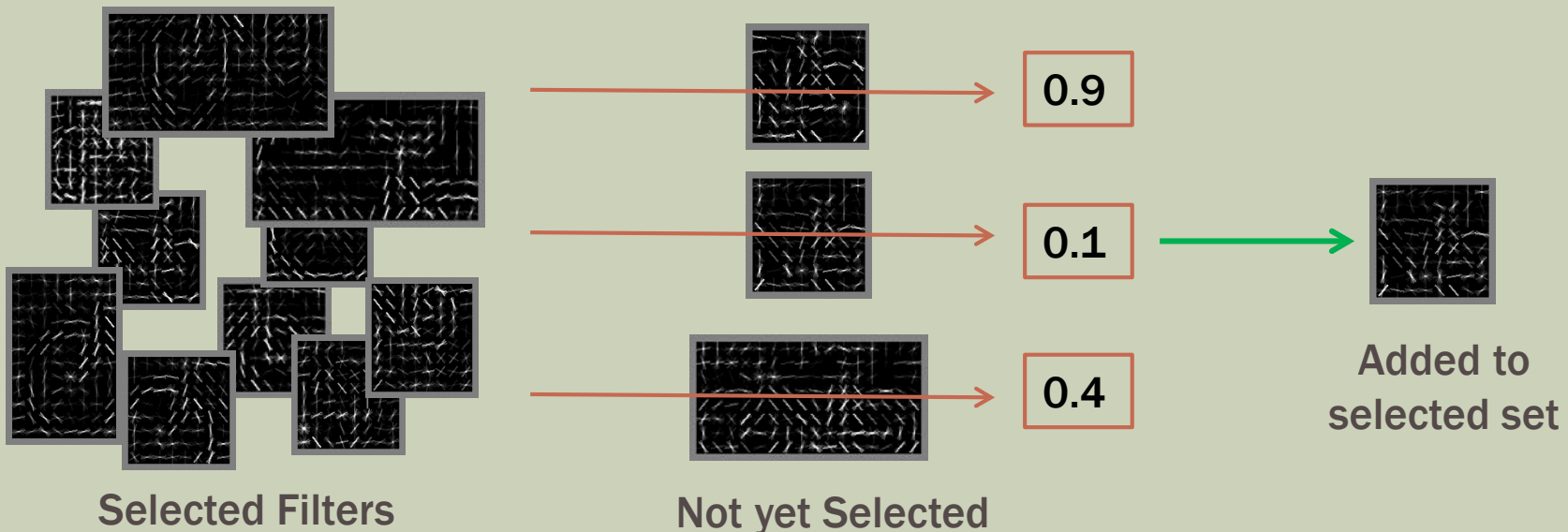
$$\min_{\mathbf{w}} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{g=1}^G \sum_{i=1}^{N-1} \sum_{j=i+1}^N [1 - \langle \mathbf{w}, \delta\phi_{g,i,j} \rangle]_+ \Delta_{g,i,j}$$

- Slack rescaled hinge loss

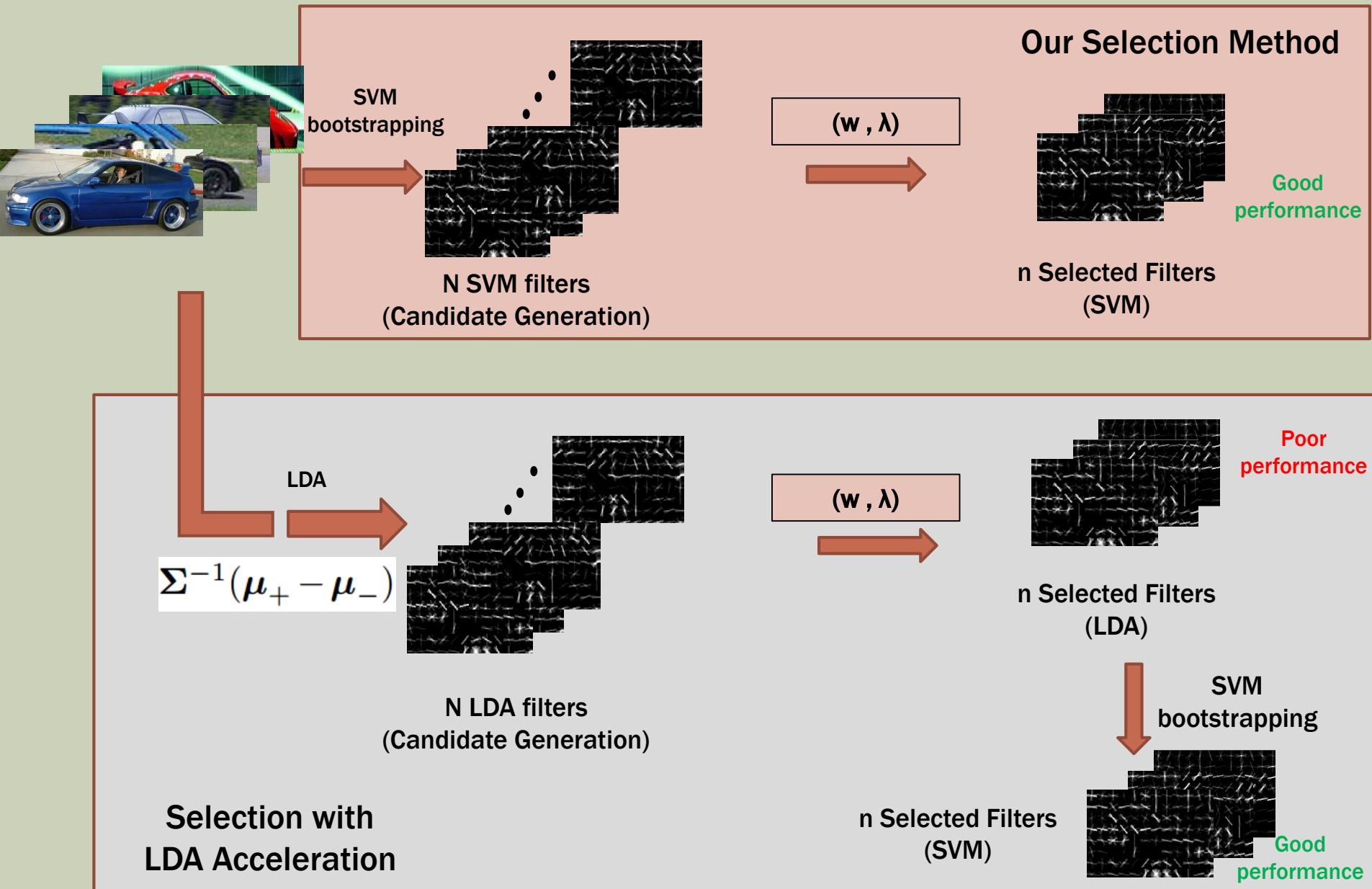
Greedy approximation for Diversity

- Selected parts should be individually good and complimentary.
- First filter - $\operatorname{argmax}_i \hat{y}_i$
- t filters selected so far
- Select next filter using following

$$\operatorname{argmax}_i \left\{ \hat{y}_i - \lambda \max_{j=1, \dots, t} A_{i,j} \right\}$$



LDA Acceleration



Experiments with Poselets



Test category



Filters used for training from remaining categories

- 800 poselet filters for each category
- Goal : given a category select 100 out of 800 filters
- Ranking task
- Detection task

Performance of Ranker

- Predicted ranking vs true ranking as per AP scores.

Norm < **Σ - Norm** < **Rank** < **Rank**
(svm) < **(svm)** < **(lda)** < **(svm)**

Gao et al. ECCV 2012

Detection Results

By constructing a poselet detector using selected filters

Speed up w.r.t. Oracle

8x

Rank (lda) + Div
2X Seeds

3x

Rank (svm) + Div

1x

Oracle (expensive evaluation)

3x

Σ - Norm (svm) + Div

3x

Norm (svm) + Div

8x

Rank (lda) + Div

Rank (svm) 3x

10% Val

2.4x

Order of magnitude
Speed up.

Σ - Norm (svm)

3x

Improved performance
than Oracle

Norm (svm)

3x

Random

8x

Increasing Performance

Experiments with exemplar SVMs

- Each category has 630 exemplars on average.
- Goal select 100 exemplars such that they reproduce result for optimal set of 100 exemplars.
- Optimal set – weights of each exemplar in the final scoring model. (Oracle)
- Frequency of exemplars



Frequent Exemplar



Rare Exemplar

- We have presented an automatic mechanism for selecting diverse set of discriminative filters.
- Order of magnitude improvement in training time.
- Our approach is applicable to any discriminative architecture that uses a collection of filters.
- Insight into what makes a good filter for object detection.
- Can be used as an attention mechanism during test time
 - Reduce number of convolutions / hashing lookups.

Bottom line: One can tell whether a filter is useful for a category without knowing what that category is, just by “looking” at the filter.