Beyond Sliding Windows: Object Localization by *Efficient Subwindow Search*

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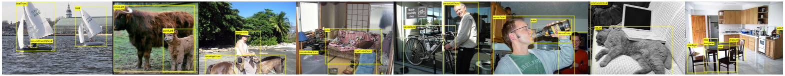
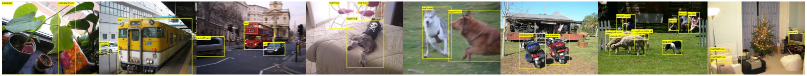
Identify all Objects in an Image





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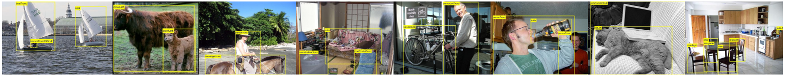

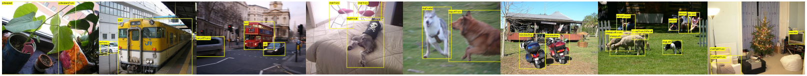

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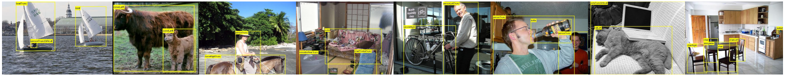

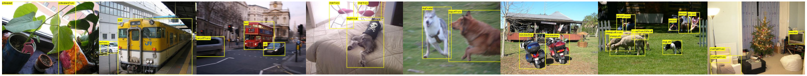

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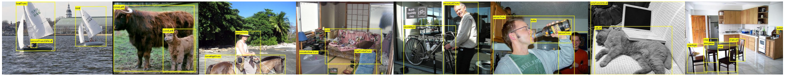

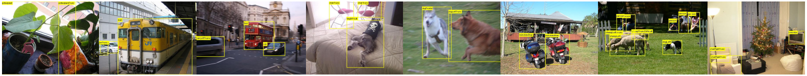

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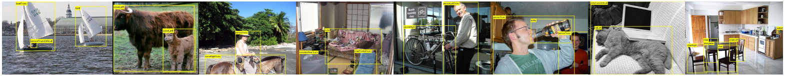

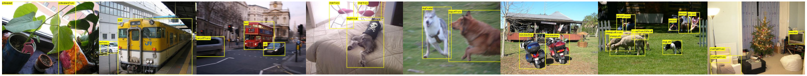

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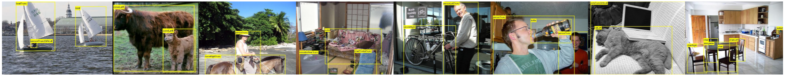

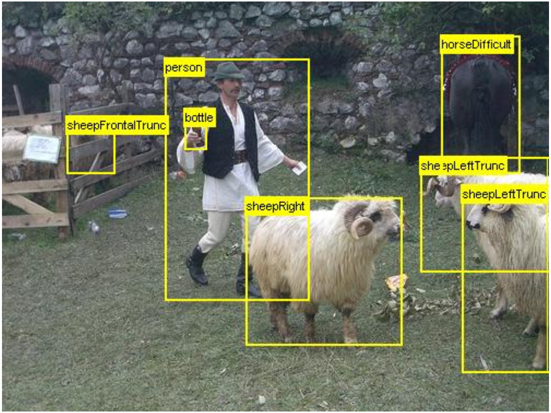

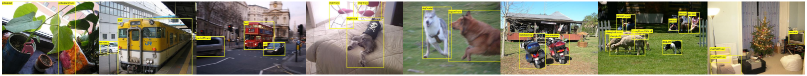

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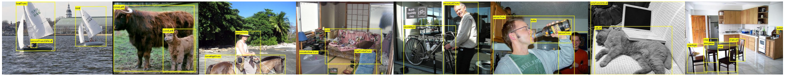

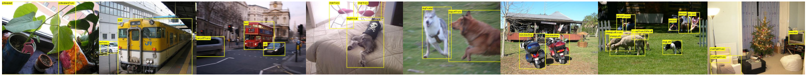

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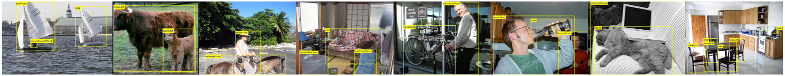
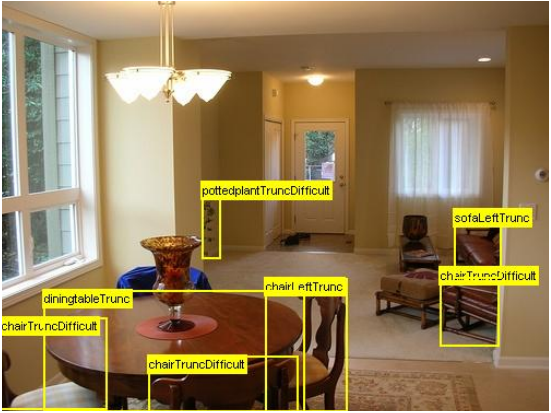
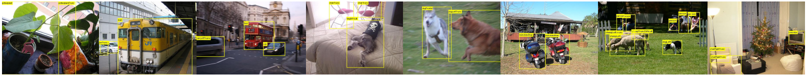






Overview...

- Object Localization
- **Sliding Window Classifiers**
- Efficient Subwindow Search
- Results

Sliding Window: Example

0.1

Sliding Window: Example

-0.2

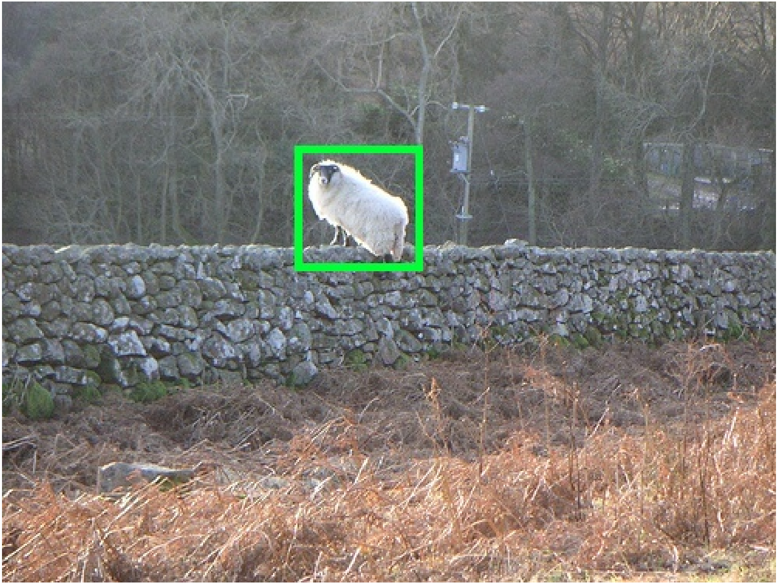
Sliding Window: Example

-0.1

Sliding Window: Example

0.1

Sliding Window: Example



...
1.5
...

Sliding Window: Example

0.5

Sliding Window: Example

0.4

Sliding Window: Example

0.3

Sliding Window: Example

0.1
-0.2
-0.1
0.1
...
1.5
...
0.5
0.4
0.3

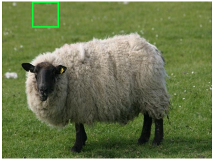
Sliding Window Classifier

approach: sliding window classifier

- evaluate classifier at candidate regions in an image - $\mathrm{argmax}_{B \in \mathcal{B}} f_I(B)$
- for a 640×480 pixel image, there are over *10 billion* possible regions to evaluate

sample a subset of regions to evaluate

- scale
- aspect ratio
- grid size



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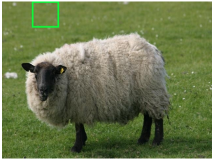


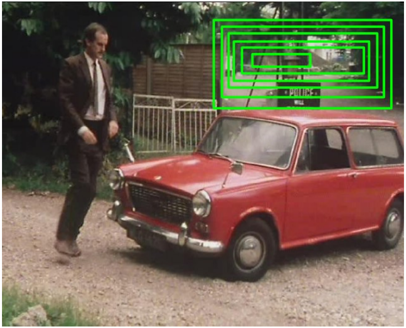
We need a better way to search the space of possible windows

Overview...

- Object Localization
- Sliding Window Classifiers
- **Efficient Subwindow Search**
- Results

Efficient Object Localization

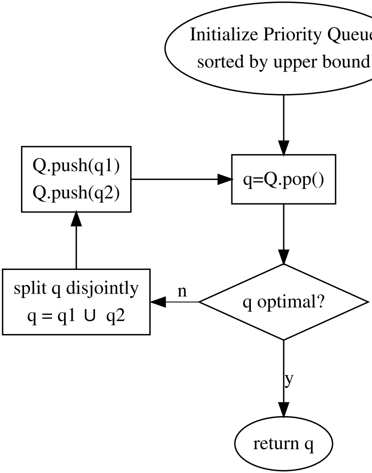
Problem: Exhaustive evaluation of $\text{argmax}_{B \in \mathcal{B}} f_I(B)$ is too slow.
Solution: Use the problem's *geometric structure*.



- Similar boxes have similar scores.
- Calculate scores for *sets of boxes* jointly (upper bound).
- If no element can contain the object, discard the set.
- Else, split the set into smaller parts and re-check, etc.

$\Rightarrow$ efficient branch & bound algorithm

Branch & Bound Search



Form a priority queue that stores *sets of boxes*.

- Optimality check is $O(1)$.
- Split is $O(1)$.
- Bound calculation depends on quality function. For us: $O(1)$
- No pruning step necessary

- $n \times m$ images: empirical performance $O(nm)$ instead of $O(n^2 m^2)$.
- no approximations, solution is globally optimal

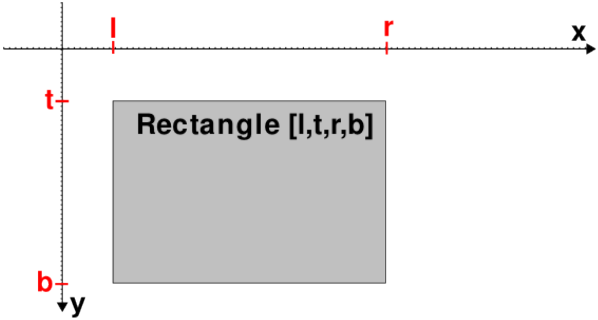
Branch & Bound

Branch & bound algorithms have three main design choices

- Parametrization of the search space
- Technique for splitting regions of the search space
- Bound used to select the most promising regions

Sliding Window Parametrization

- low dimensional parametrization of bounding box (left, top, right, bottom)

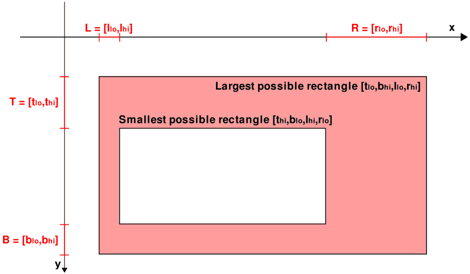


Sets of Rectangles

Branch-and-Bound works with subsets of the search space.

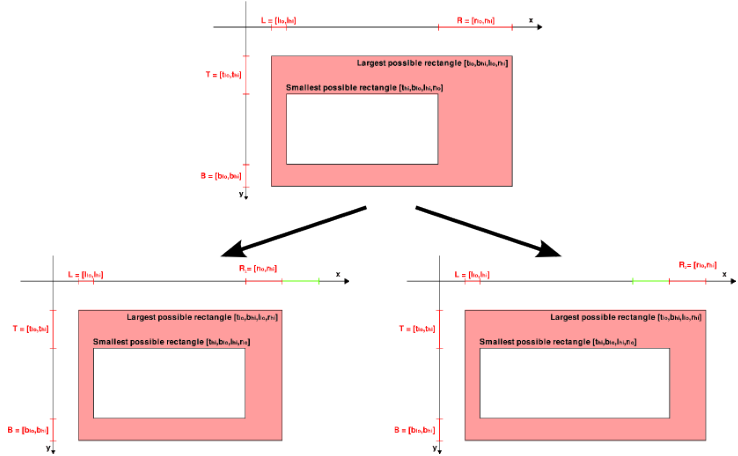
- Instead of four numbers $[l, t, r, b]$, store four intervals $[L, T, R, B]$:

$$
\begin{aligned}
L &= [l_{lo}, l_{hi}] \\
T &= [t_{lo}, t_{hi}] \\
R &= [r_{lo}, r_{hi}] \\
B &= [b_{lo}, b_{hi}]
\end{aligned}
$$



Branch-Step: Splitting Sets of Boxes

rectangle set $[L, R, T, B]$



$[L, R_1, T, B]$ with $R_1 := [r_{lo}, \lfloor \frac{r_{lo}+r_{hi}}{2} \rfloor]$

$[L, R_2, T, B]$ with $R_2 := [\lfloor \frac{r_{lo}+r_{hi}}{2} \rfloor + 1, r_{hi}]$

Bound-Step: Constructing a Quality Bound

We have to construct f^{upper} : { set of boxes } $\rightarrow \mathbb{R}$ such that

i) $f^{upper}(\mathcal{B}) \geq \max_{B \in \mathcal{B}} f(B)$,

ii) $f^{upper}(\mathcal{B}) = f(B), \quad$ if $\mathcal{B} = \{B\}$.

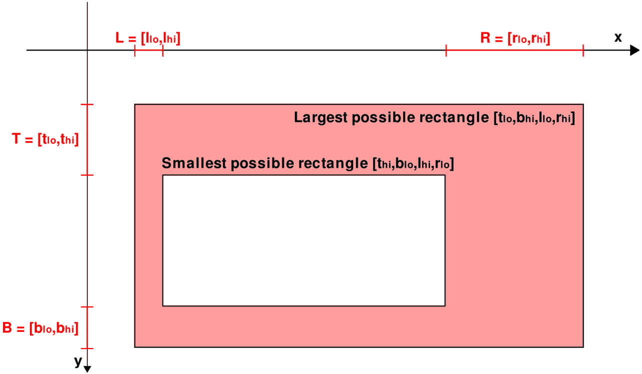
Example: SVM with Linear Bag-of-Features Kernel

- $f(B) = \sum_j \alpha_j \langle h^B, h^j \rangle \qquad h^B$ the histogram of the box B.
- $\qquad = \sum_j \alpha_j \sum_k h^B_k h^j_k = \sum_k h^B_k w_k, \quad$ for $w_k = \sum_j \alpha_j h^j_k$
- $\qquad = \sum_{x_i \in B} w_{c_i}, \qquad c_i$ the cluster ID of the feature x_i

Example: Upper Bound

- Set $f^+(B) = \sum_{x_i \in B} [w_i]_+, \quad f^-(B) = \sum_{x_i \in B} [w_i]_-$.
- Set B^{max} := *largest box in* $\mathcal{B}$, $\qquad B^{min}$:= *smallest box in* $\mathcal{B}$.
- $f^{upper}(\mathcal{B}) := f^+(B^{max}) + f^-(B^{min}) \qquad$ fulfills *i*) and *ii*).

Evaluating the Quality Bound for Linear SVMs



$$f(B) = \sum_{x_i \in B} w_i. \qquad f^{upper}(\mathcal{B}) = \sum_{x_i \in B^{max}} [w_i]_+ + \sum_{x_i \in B^{min}} [w_i]_-.$$

- Evaluating $f^{upper}(\mathcal{B})$ has same complexity as $f(B)$!
- Using integral images, this is $\mathcal{O}(1)$.

Bound-Step: Constructing a Quality Bound

It is easy to construct bounds for

- Boosted classifiers
- SVM
- Logistic regression
- Nearest neighbor
- Unsupervised methods ...

provided we have an appropriate image representation

- Bag of words
- Spatial pyramid
- χ^2
- Itemsets ...

The following require assumptions about the image statistics to implement

- Template based classifiers
- Pixel based classifiers

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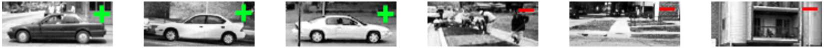
Results: UIUC Cars Dataset

- 1050 training images: 550 cars, 500 non-cars

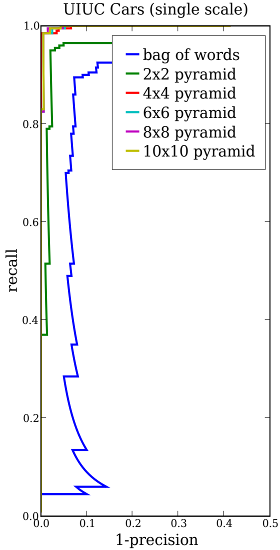


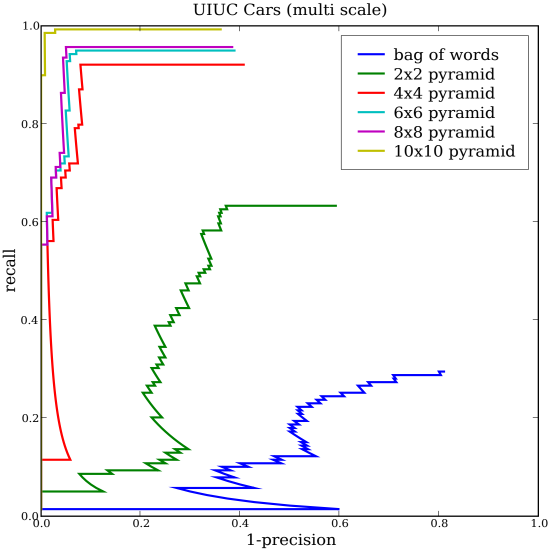
- 170 test images single scale

- 139 test images multi scale

Results: UIUC Cars Dataset

- Evaluation: *Precision-Recall curves with different pyramid kernels*





Results: UIUC Cars Dataset

- Evaluation: *Error Rate* where precision equals recall

method \data set	single scale	multi scale
10×10 spatial pyramid kernel	**1.5 %**	**1.4 %**
4×4 spatial pyramid kernel	1.5 %	7.9 %
bag-of-visual-words kernel	10.0 %	71.2 %
Agarwal et al. [2002,2004]	23.5 %	60.4 %
Fergus et al. [2003]	11.5 %	—
Leibe et al. [2007]	2.5 %	5.0%
Fritz et al. [2005]	11.4 %	12.2%
Mutch/Lowe [2006]	0.04 %	9.4%

UIUC Car Localization, previous best vs. our results

Results: PASCAL VOC 2007 challenge

We participated in the
PASCAL Challenge on Visual Object Categorization (VOC) 2007:

- most challenging and competitive evaluation to date
- training: ≈5,000 labeled images
- task: ≈5,000 new images, predict locations for 20 object classes

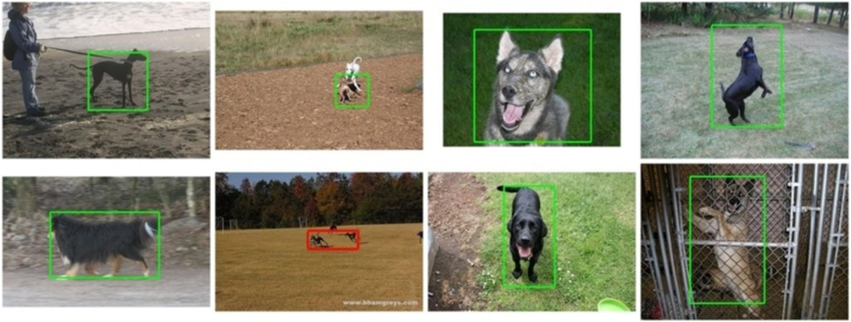
  `aeroplane, bird, bicycle, boat, bottle, bus, car, cat, chair, cow, diningtable, dog, horse, motorbike, person, pottedplant, sheep, sofa, train, tv/monitor`

  - natural images, downloaded from Flickr, realistic scenes
  - high intra-class variance

Results: PASCAL VOC 2007 challenge

Results:

- High localization quality: first place in 5 of 20 categories.
- High speed: $\approx 40ms$ per image (excl. feature extraction)



Example detections on VOC 2007 `dog`.

Results: PASCAL VOC 2007 challenge

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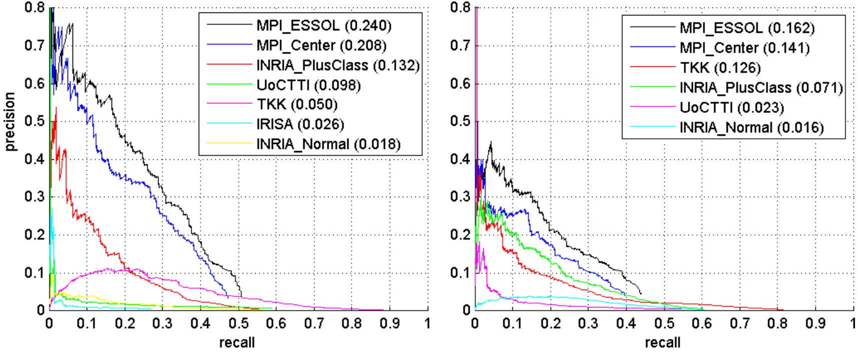
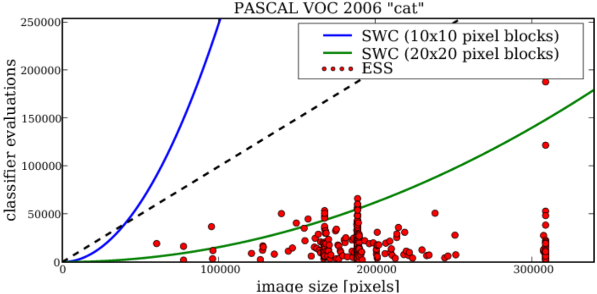
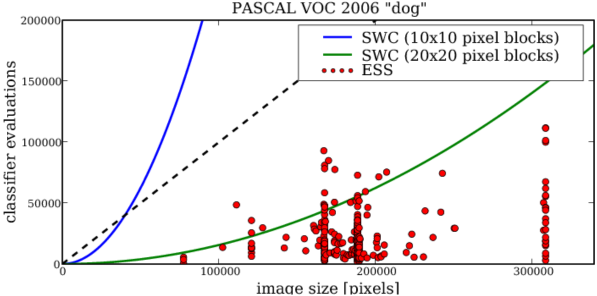


Precision–Recall curves on VOC 2007 `cat` (left) and `dog` (right).

Results: Prediction Speed on VOC2006





Extensions

Branch-and-bound localization allows efficient extensions:

- Multi-Class Object Localization:

$$(B, C)^{\text{opt}} = \underset{B \in \mathcal{B},\, C \in \mathcal{C}}{\operatorname{argmax}} \; f_I^C(B)$$

finds best object class $C \in \mathcal{C}$.

- Localized retrieval from image databases or videos

$$(I, B)^{\text{opt}} = \underset{B \in \mathcal{B},\, I \in \mathcal{D}}{\operatorname{argmax}} \; f_I(B)$$

find best image I in database $\mathcal{D}$.

Runtime is *sublinear* in $|\mathcal{C}|$ and $|\mathcal{D}|$.

Nearest Neighbor query for *Red Wings* Logo in 10,000 video keyframes in "Ferris Buellers Day Off"

Summary

- For a 640×480 pixel image, there are over *10 billion* possible regions to evaluate
- Sliding window approaches trade off runtime vs. accuracy
  - scale
  - aspect ratio
  - grid size
- *Efficient subwindow search* finds the maximum that would be found by an exhaustive search
  - efficiency
  - accuracy
  - flexibile
    - just need to come up with a bound

Source code is available online

Outlook: Learning to Localize Objects

Sucessful Sliding Window Localization has *two* key components:

- Efficiency of classifier evaluation $\longrightarrow$ this talk
- Training a discriminant suited to localization $\longrightarrow$ talk at ECCV 2008
  "Learning to Localize Objects with Structured Output Regression"