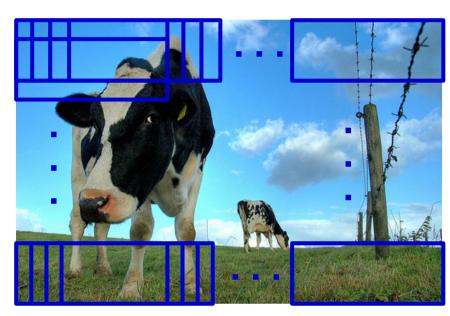
Segmentation as Selective Search for Object Recognition Koen E. A. van de Sande^{* 1}, Jasper R. R. Uijlings^{* 2}, Theo Gevers¹, Arnold W. M. Smeulders¹ *Both authors contributed equally, ¹University of Amsterdam (The Netherlands), ²University of Trento (Italy) UNIVERSITEIT VAN AMSTERDAM **Segmentation as Selective Search Object recognition Object Recognition Accuracy Object Recognition System: Training Pipeline** if overlap wit Selective search enables the use of more powerful features and classifiers: Selective search based on hierarchical grouping • Dense SIFT, OpponentSIFT and RGB-SIFT sampled at every pixel Initial segments from oversegmentation [Felzenszwalb2004] (using software from www.colordescriptors.com) Group adjacent regions on region-level similarity: Codebook size 4,096; spatial pyramid with depth 4 Texture (gradient orientations) **Exhaustive Search** Region size • SVM classifier with Histogram Intersection Kernel and Fast Approximation [Maji2009] Consider all scales of the hierarchy Initial negatives overlap 20-50% with positive examples Exhaustive search: • Retrain with false positives (found in the train set) as extra negatives Current state-of-the-art Search strategies using part-based models # windows to evaluate: Part-based [9] + Exhaustive search (baselin art-based [9] + Our selective search 100,000 - 1,000,000potted plan ➔ Simple-to-compute features ➔ Weak clasifiers aeroplane tv/monito **Multiple Complementary Color Spaces Selective Search** It is important to diversify the set of segmentations used: we combine multiple initial segmentations and different color spaces Color spaces with complementary invariance properties: 0.4 0.3 **Average Precision** some include shadow/shading pixels in a segment, others do not Constrain [Felzenszwalb2010] from exhaustive to selective search: **20x fewer boxes** -3% MAP **Benchmarks k=100,200** • **#1 localisation** in IMAGENET Large Scale Visual Recognition Challenge 2011 RGB+Opp+rgb RGB+Opp+rgb+H RGB+Opp Colour Spaces

Object recognition seeks to answer 2 questions:

- What is it?
- Where is it?





Adopt segmentation as selective search strategy



Different goal from segmentation:

prefer to generate many approximate locations over few and precise object delineations, because:

- objects whose locations are not generated can never be recognised
- 2. appearance and immediate nearby context are effective for object recognition.

Design considerations:

- High recall
 - ➔ Details on the right
- Coarse locations are sufficient → Use bounding boxes
- Fast to compute
- → Less than 10s/image

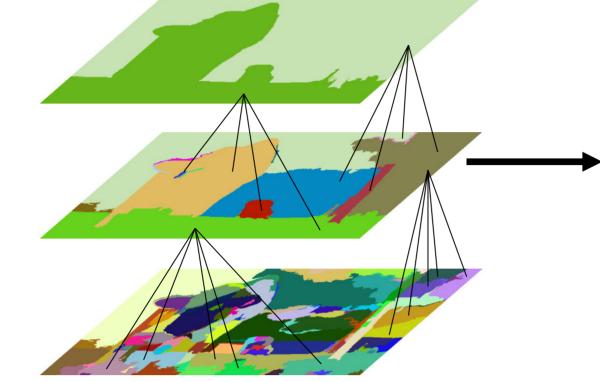
windows

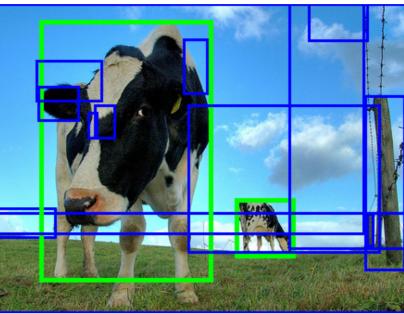
200 per class

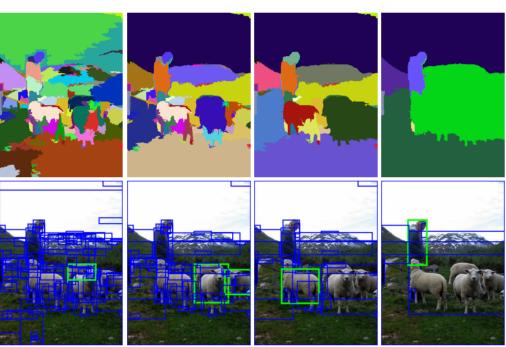
10,000

1,536

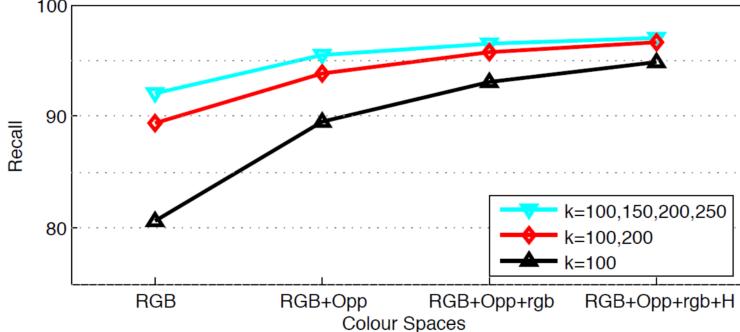
10,000 per class





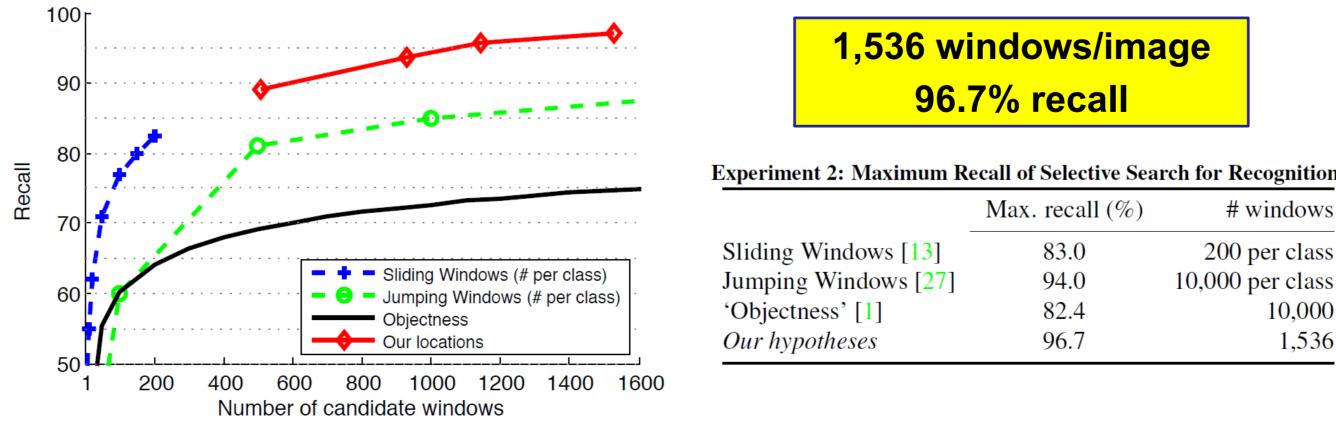






Recall of Selective Search

- Our object location windows are class-independent
- Achieves higher recall than Sliding Windows [Harzallah2009], Jumping Windows [Vedaldi2009] and 'Objectness' [Alexe2010]



• PASCAL VOC2010 test set (through independent evaluation server):

Improves the state-of-the-art by up to 8.5% AP (abso											
System	plane	bike	bird	boat	bottle	bus	car	cat	chair	cow	table
NLPR	.533	.553	.192	.210	.300	.544	.467	.412	.200	.315	.207
MIT UCLA [29]	.542	.485	.157	.192	.292	.555	.435	.417	.169	.285	.267
NUS	.491	.524	.178	.120	.306	.535	.328	.373	.177	.306	.277
UoCTTI [9]	.524	.543	.130	.156	.351	.542	.491	.318	.155	.262	.135
This paper	.582	.419	.192	.140	.143	.448	.367	.488	.129	.281	.287

Conclusion

- Adopted segmentation as selective search strategy: prefer to generate many approximate locations over few and precise object delineations, as (1) objects whose locations are not generated can never be recognised and (2) appearance and immediate nearby context are effective for object recognition.
- Highest recall to date for Pascal VOC 2007 test set: only 1,536 class-independent locations/image capture 96.7% of all objects.
- Highly effective for object recognition: improve the state-of-the-art for 8 out of 20 classes for up to 8.5% AP

