

Diagnosing Error in Object Detectors

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Object detection is a collection of problems

Intra-class Variation for “Airplane”

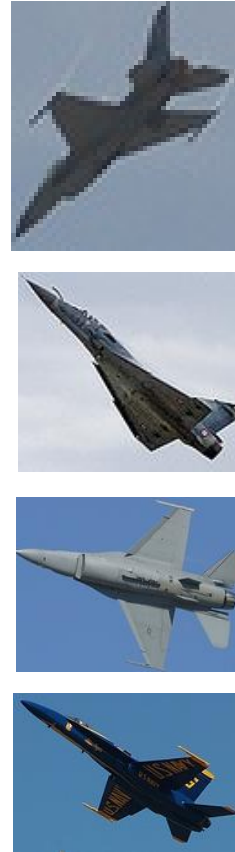
Occlusion



Shape



Viewpoint



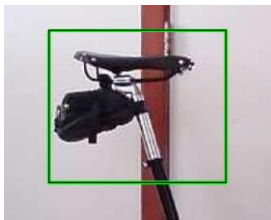
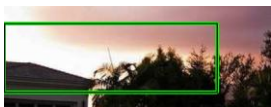
Distance



Object detection is a collection of problems

Confusing Distractors for “Airplane”

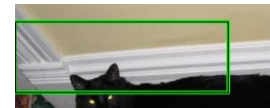
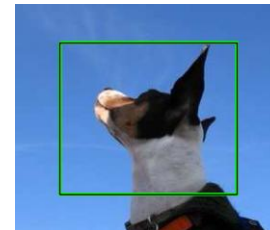
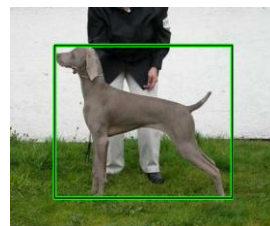
Background



Similar Categories



Dissimilar Categories



Localization Error

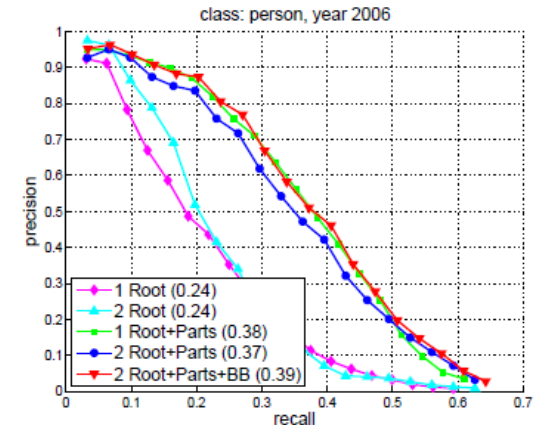


How to evaluate object detectors?

- Average Precision (AP)
 - Good summary statistic for quick comparison
 - Not a good driver of research

	aero	bike	bird	boat	bottle	bus
a) base	.290	.546	.006	.134	.262	.394
b) BB	.287	.551	.006	.145	.265	.397
c) context	.328	.568	.025	.168	.285	.397

Typical evaluation through comparison of AP numbers

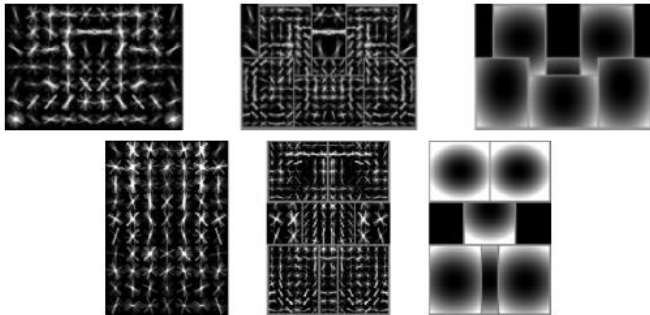
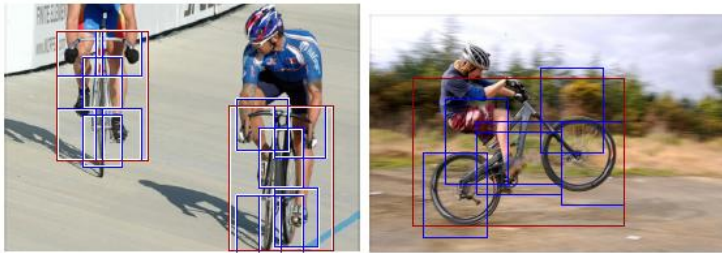


- We propose tools to evaluate
 - where detectors fail
 - potential impact of particular improvements

Detectors Analyzed as Examples on VOC 2007

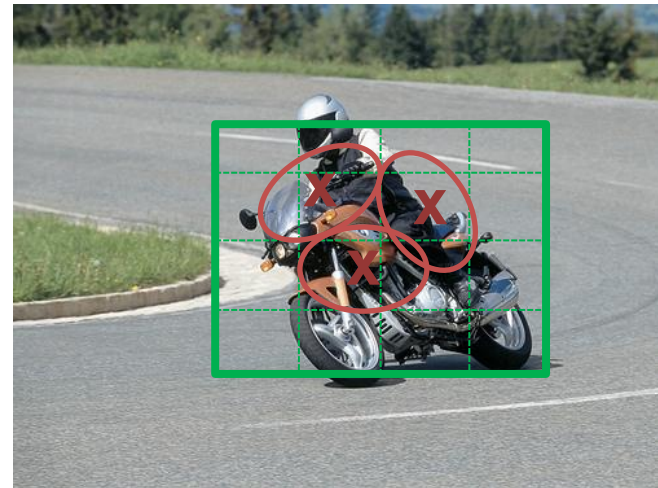
Deformable Parts Model (DPM)

- Sliding window
- Mixture of HOG templates with latent HOG parts



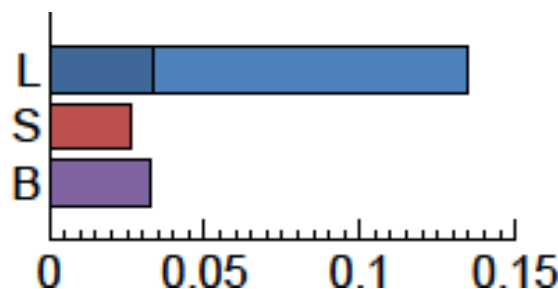
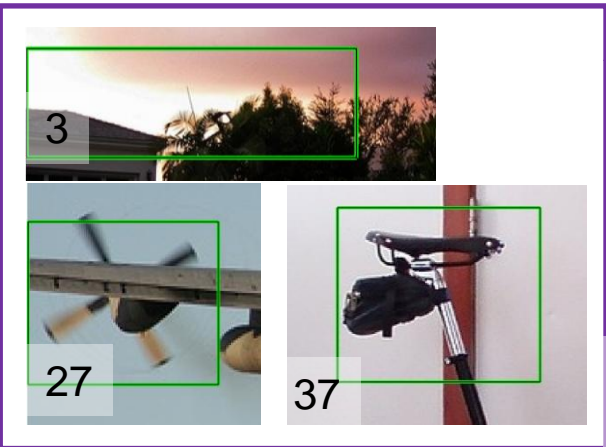
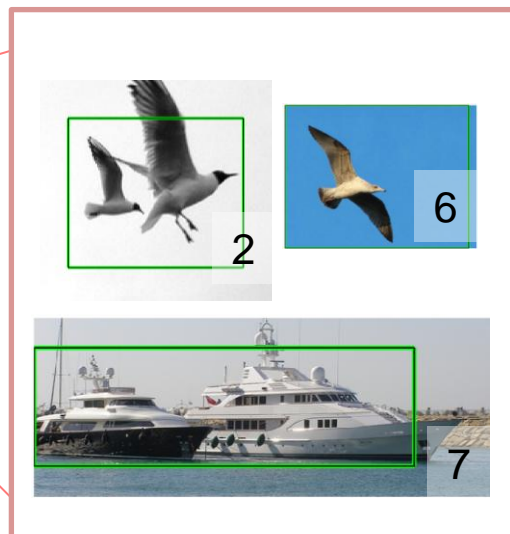
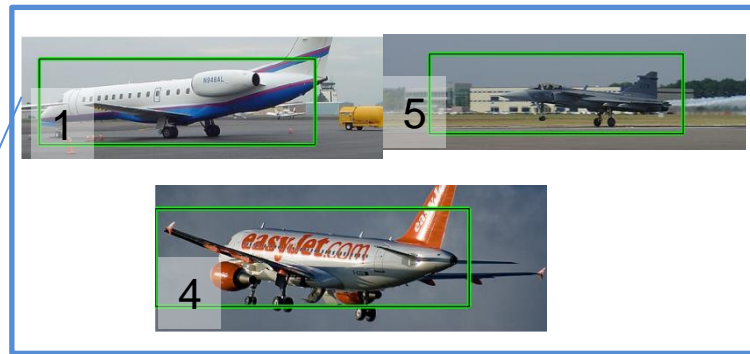
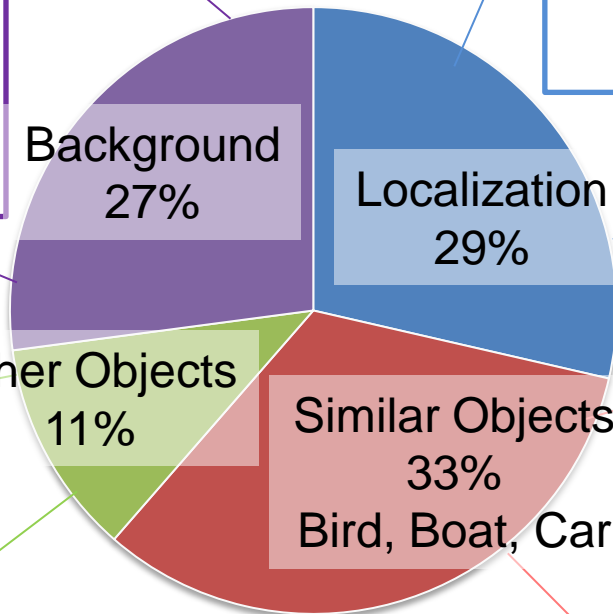
Multiple Kernel Learning (MKL)

- Jumping window
- Various spatial pyramid pool of words features combined with MKL



Top false positives: Airplane (DPM)

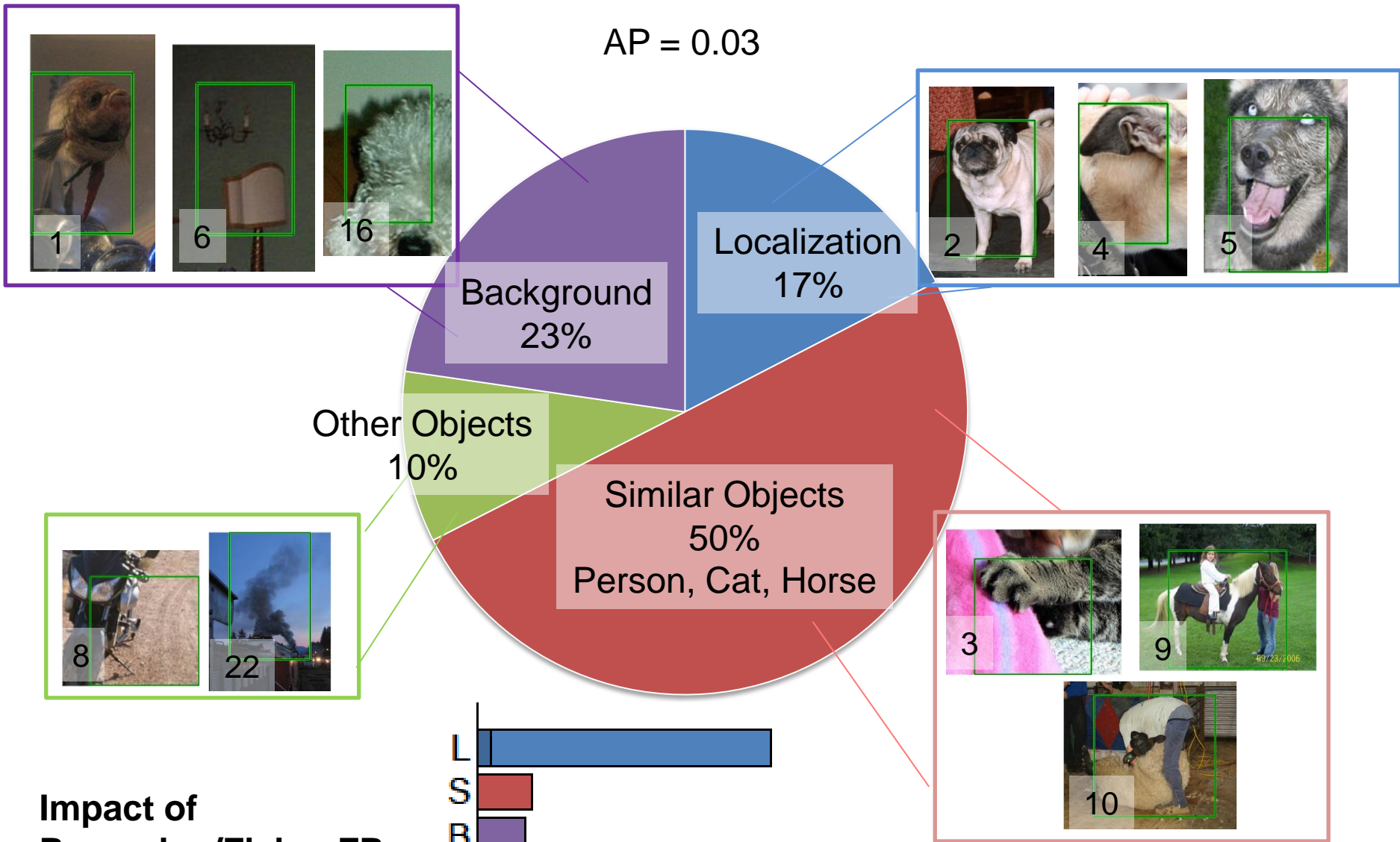
AP = 0.36



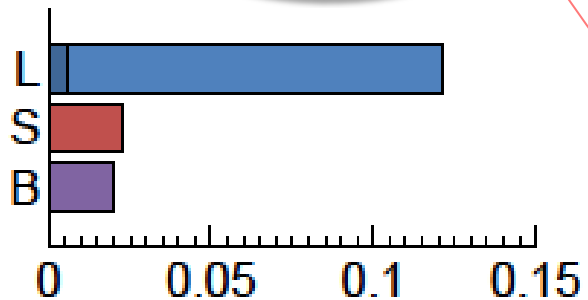
Impact of Removing/Fixing FPs

Top false positives: Dog (DPM)

AP = 0.03

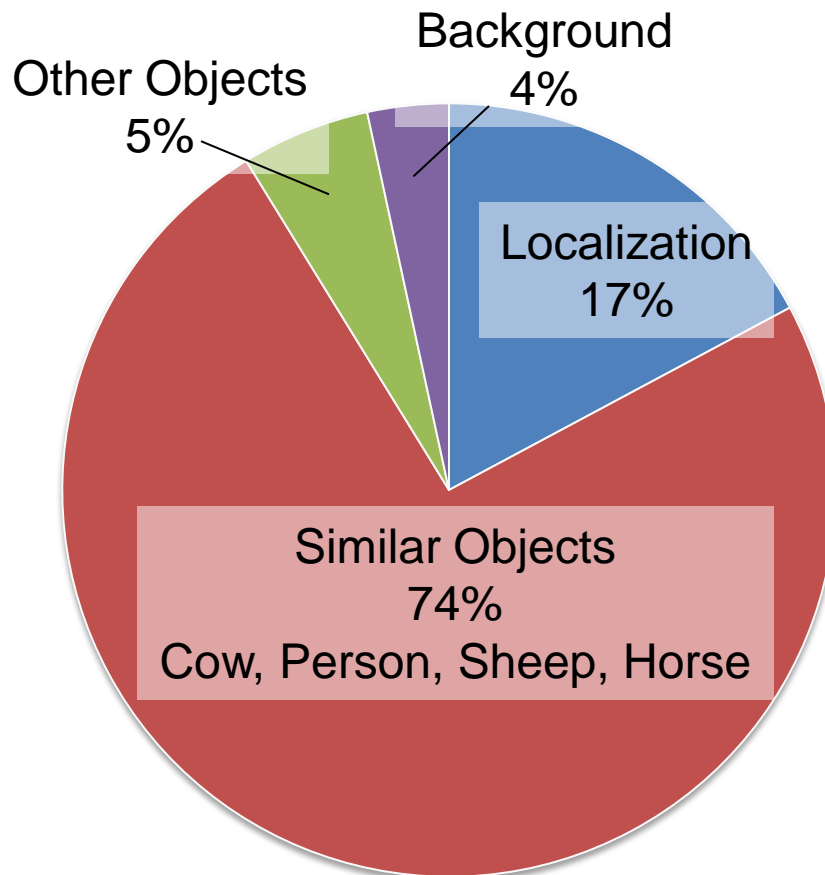


Impact of Removing/Fixing FPs

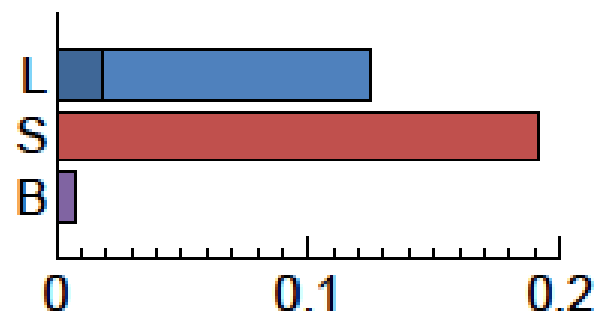


Top false positives: Dog (MKL)

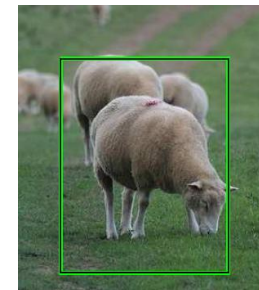
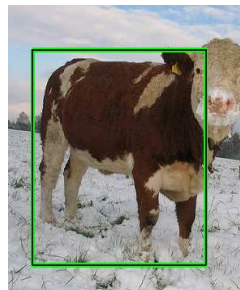
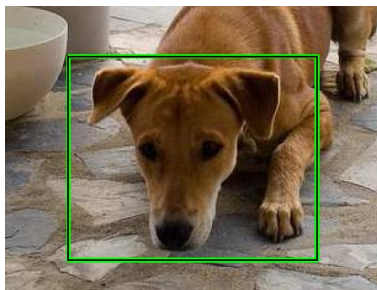
AP = 0.17



Impact of Removing/Fixing FPs

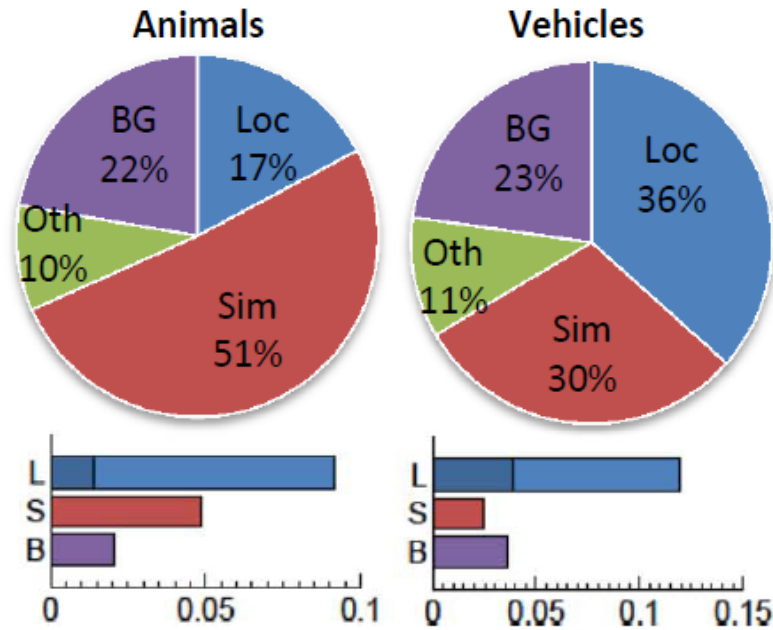


Top 5 FP

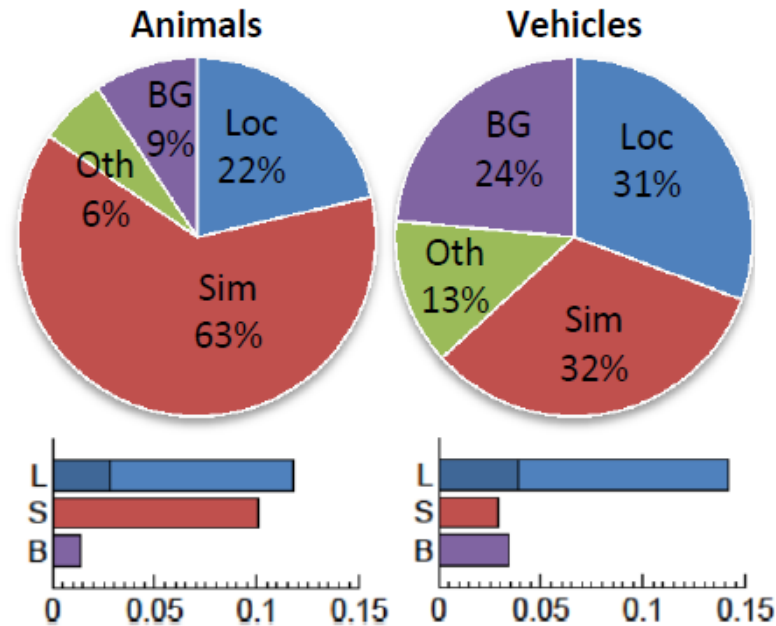


Summary of False Positive Analysis

DPM v4
(FGMR 2010)



MKL
(Vedaldi et al. 2009)

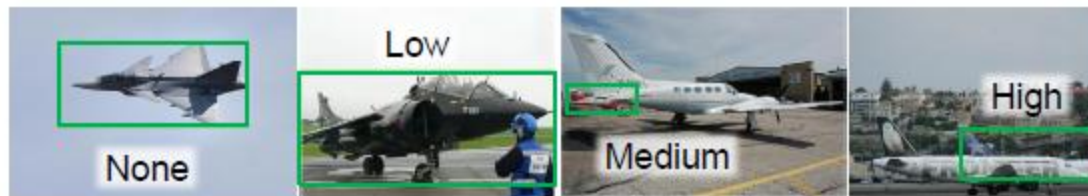


Analysis of object characteristics

Additional annotations for seven categories:
occlusion level, parts visible, sides visible



Level of occlusion: 2 (moderate)
Parts visible: bike body, handlebars, wheel
Parts not visible: seat
View: side visible (front, top, etc., not visible)
Area: 3233 pixels
Aspect Ratio (w/h): 1.24



Occlusion Level

Normalized Average Precision

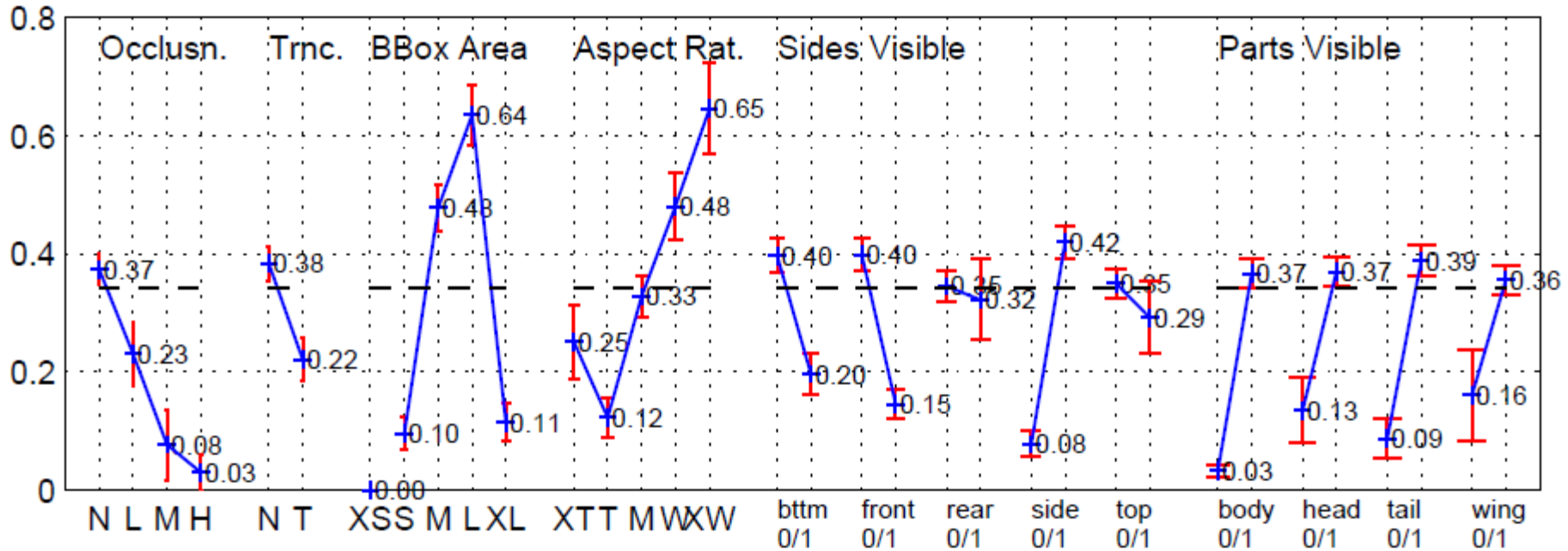
- Average precision is sensitive to number of positive examples

$$\text{Precision} = \frac{\text{TruePositives}}{\text{TruePositives} + \text{FalsePositives}}$$

$$\text{TruePositives} = \text{Recall} * N_j \leftarrow \begin{array}{l} \text{Number of object} \\ \text{examples in subset } j \end{array}$$

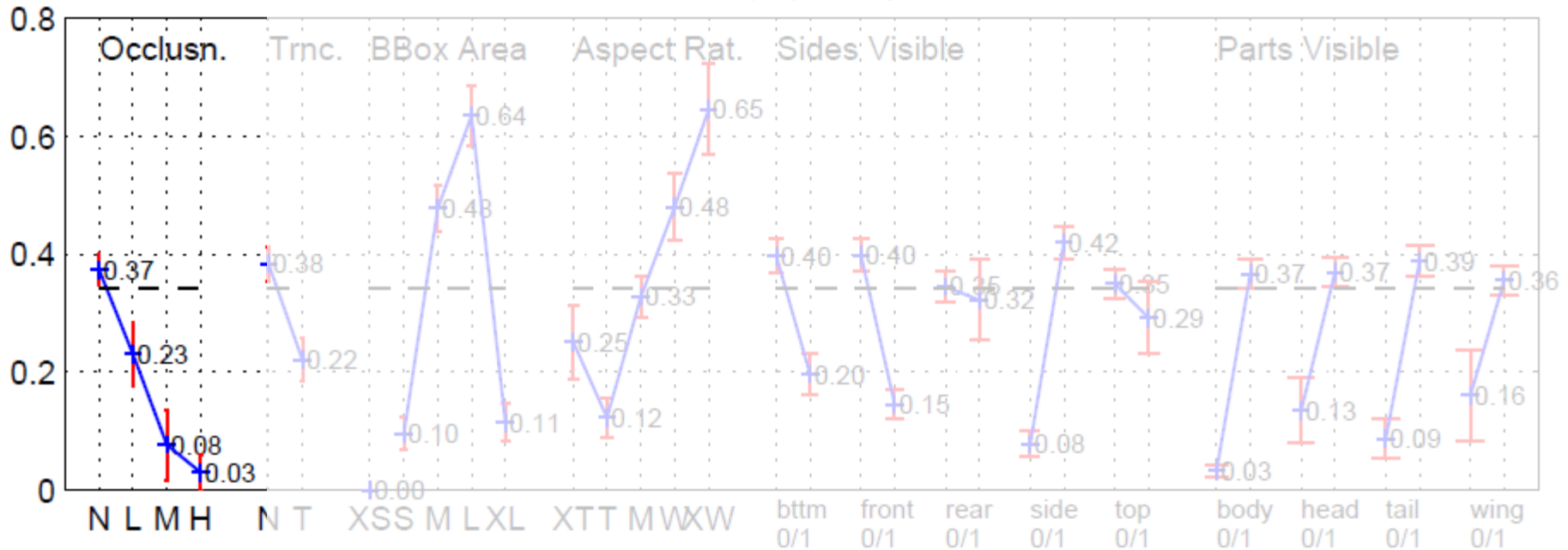
- Normalized average precision: replace variable N_j with fixed N

Object characteristics: Aeroplane



Object characteristics: Aeroplane

Occlusion: poor robustness to occlusion, but little impact on overall performance

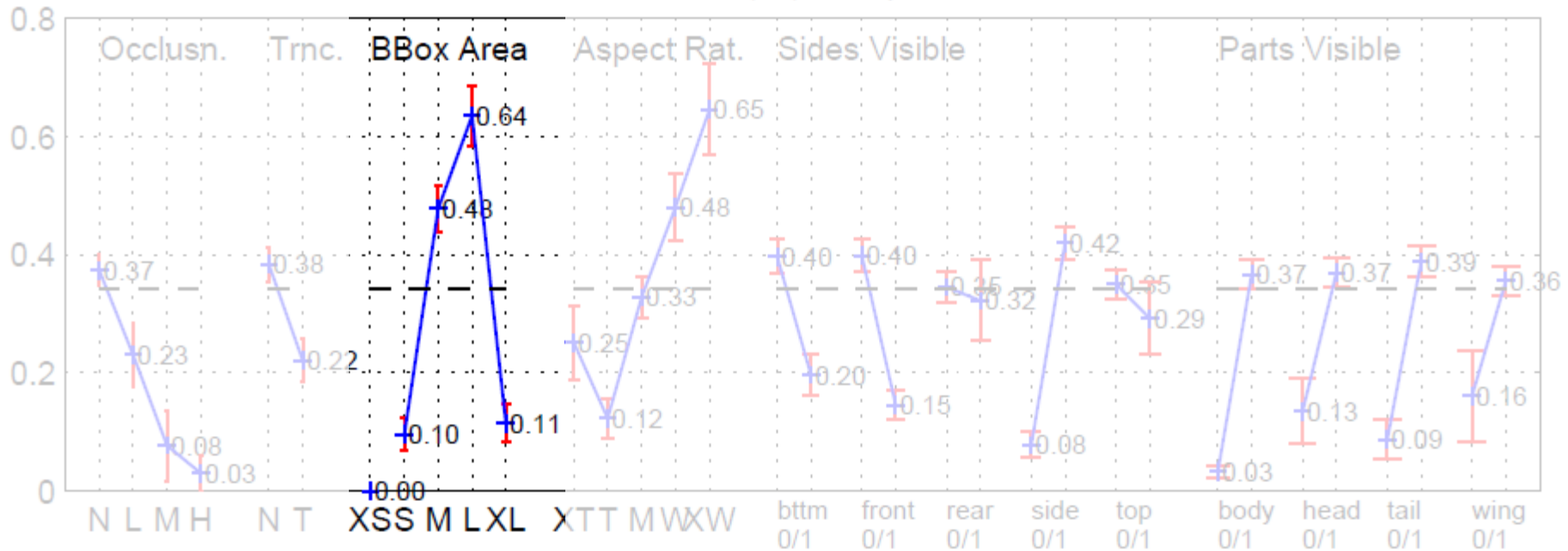


Easier (None)

Harder (Heavy)

Object characteristics: Aeroplane

Size: strong preference for average to above average sized airplanes



Large



Medium



X-Large



Small



X-Small

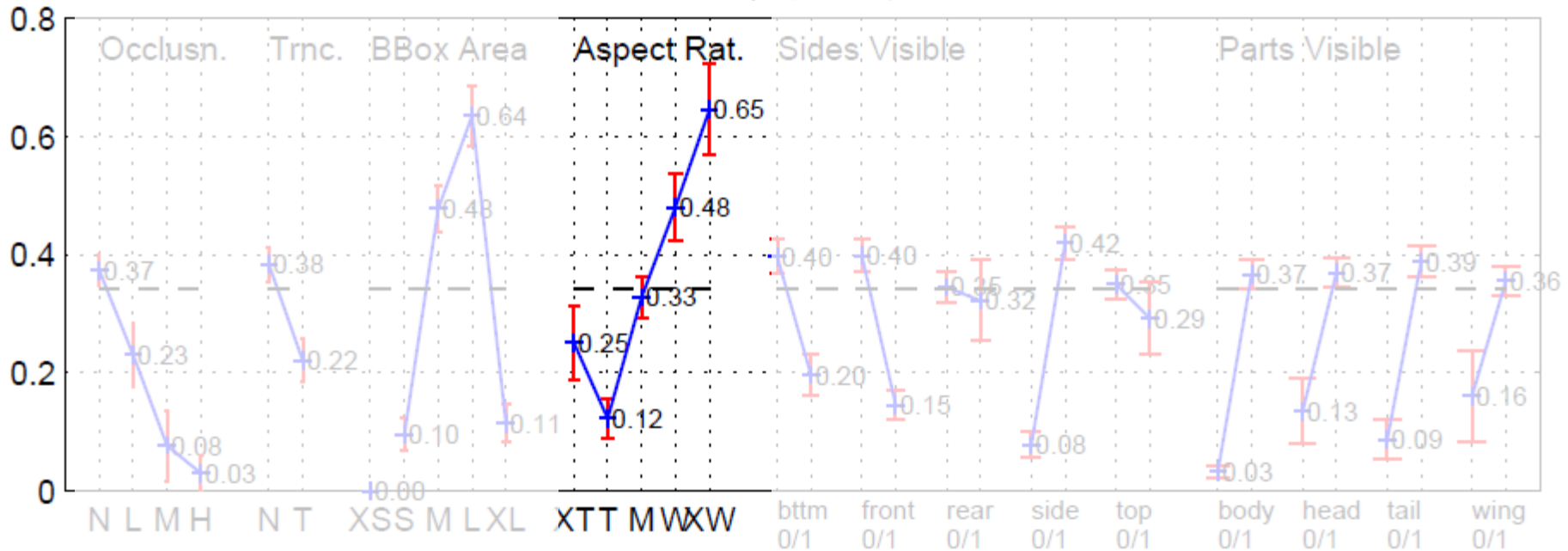


Easier

Harder

Object characteristics: Aeroplane

Aspect Ratio: 2-3x better at detecting wide (side) views than tall views



X-Wide



Wide



Medium



X-Tall



Tall

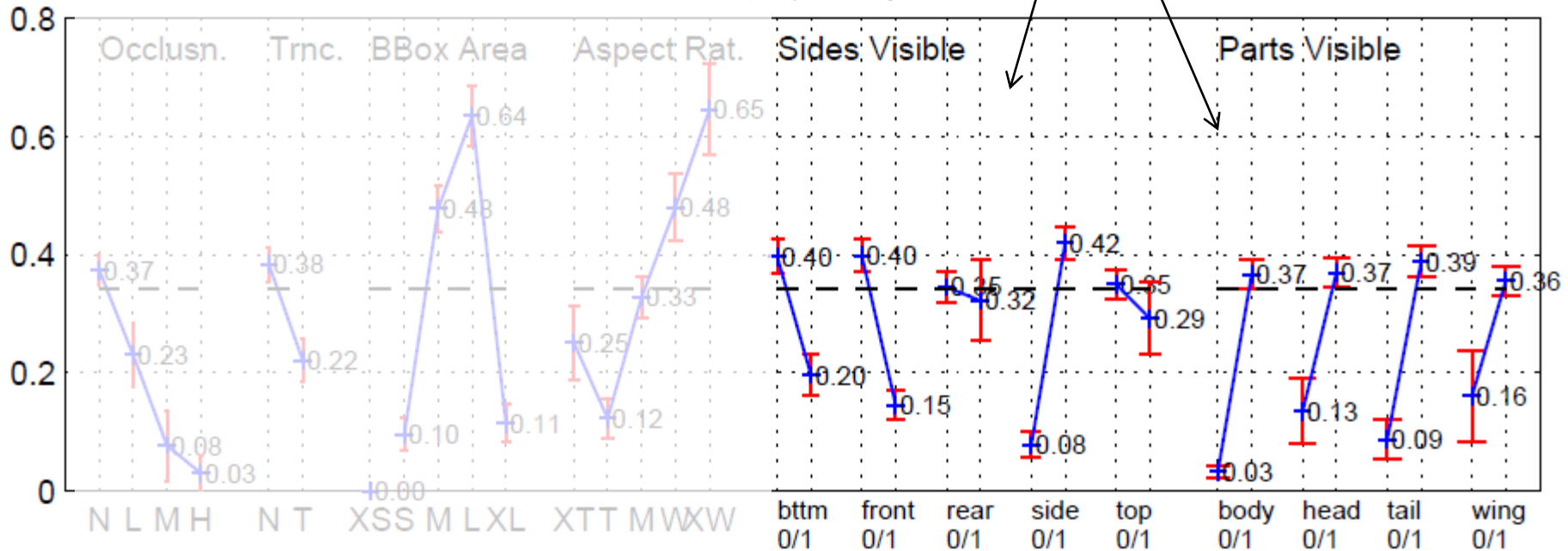


Easier (Wide)

Harder (Tall)

Object characteristics: Aeroplane

Sides/Parts: best performance = direct side view with all parts visible

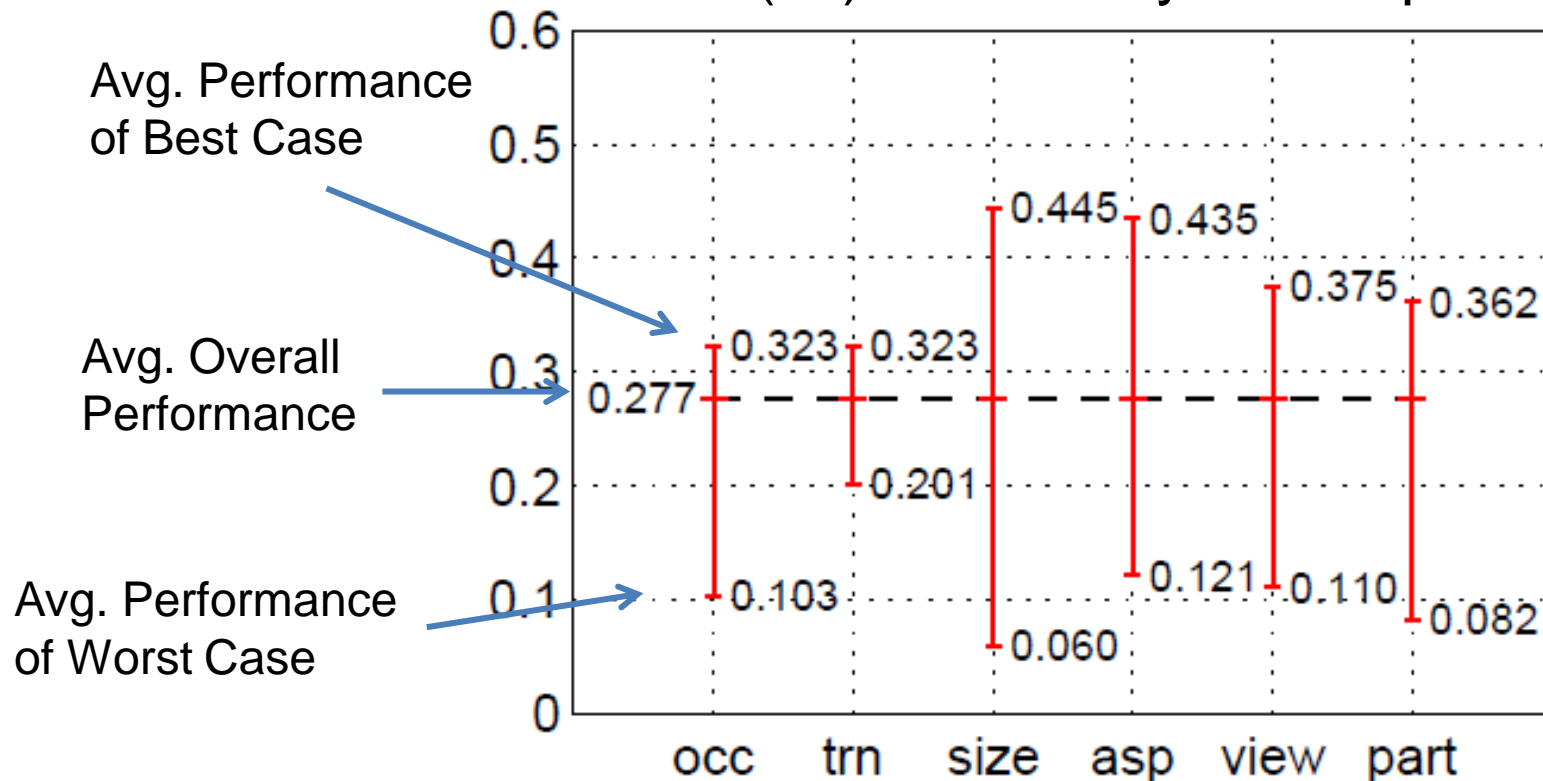


Easier (Side)

Harder (Non-Side)

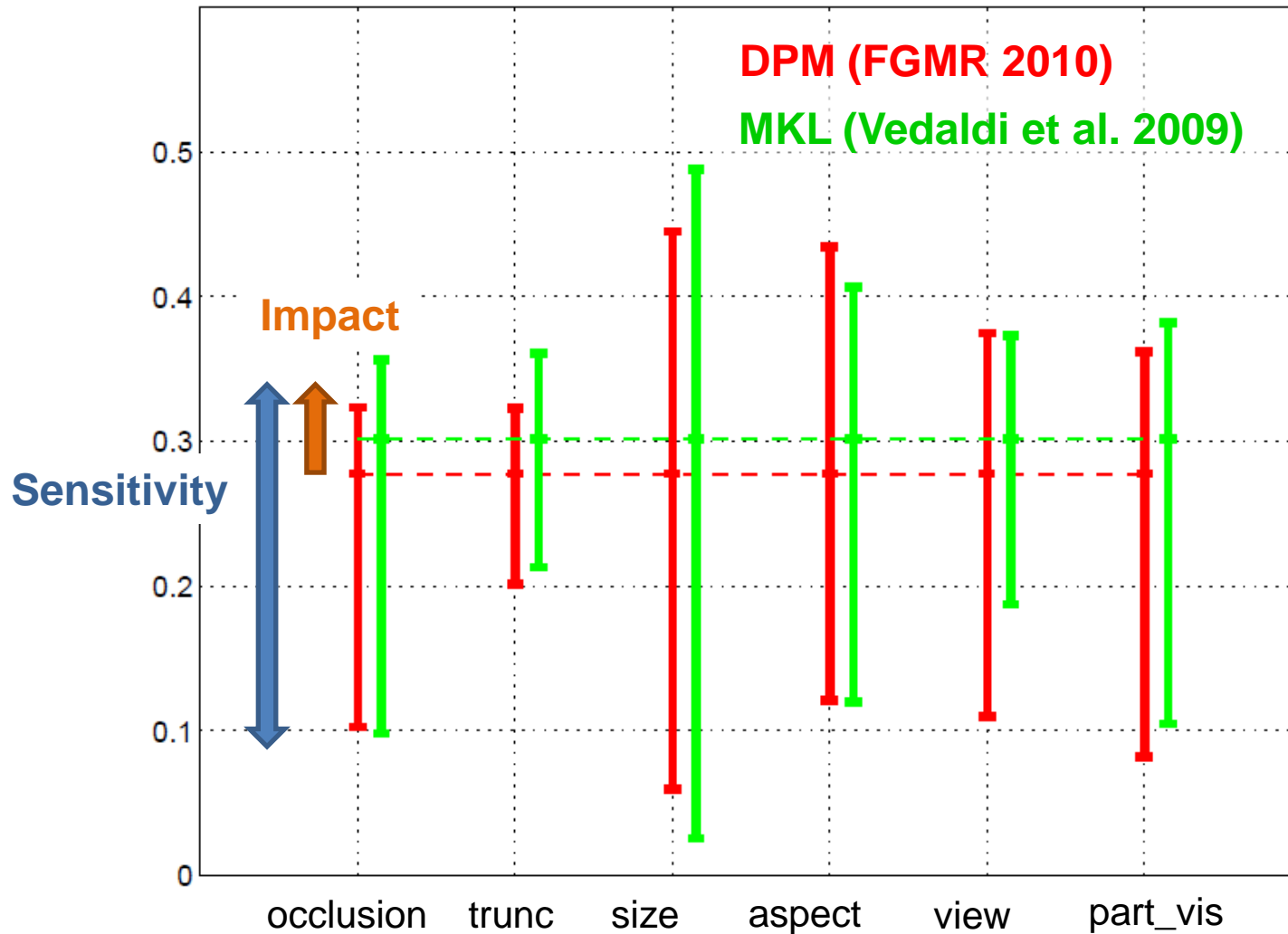
Summarizing Detector Performance

DPM (v4): Sensitivity and Impact



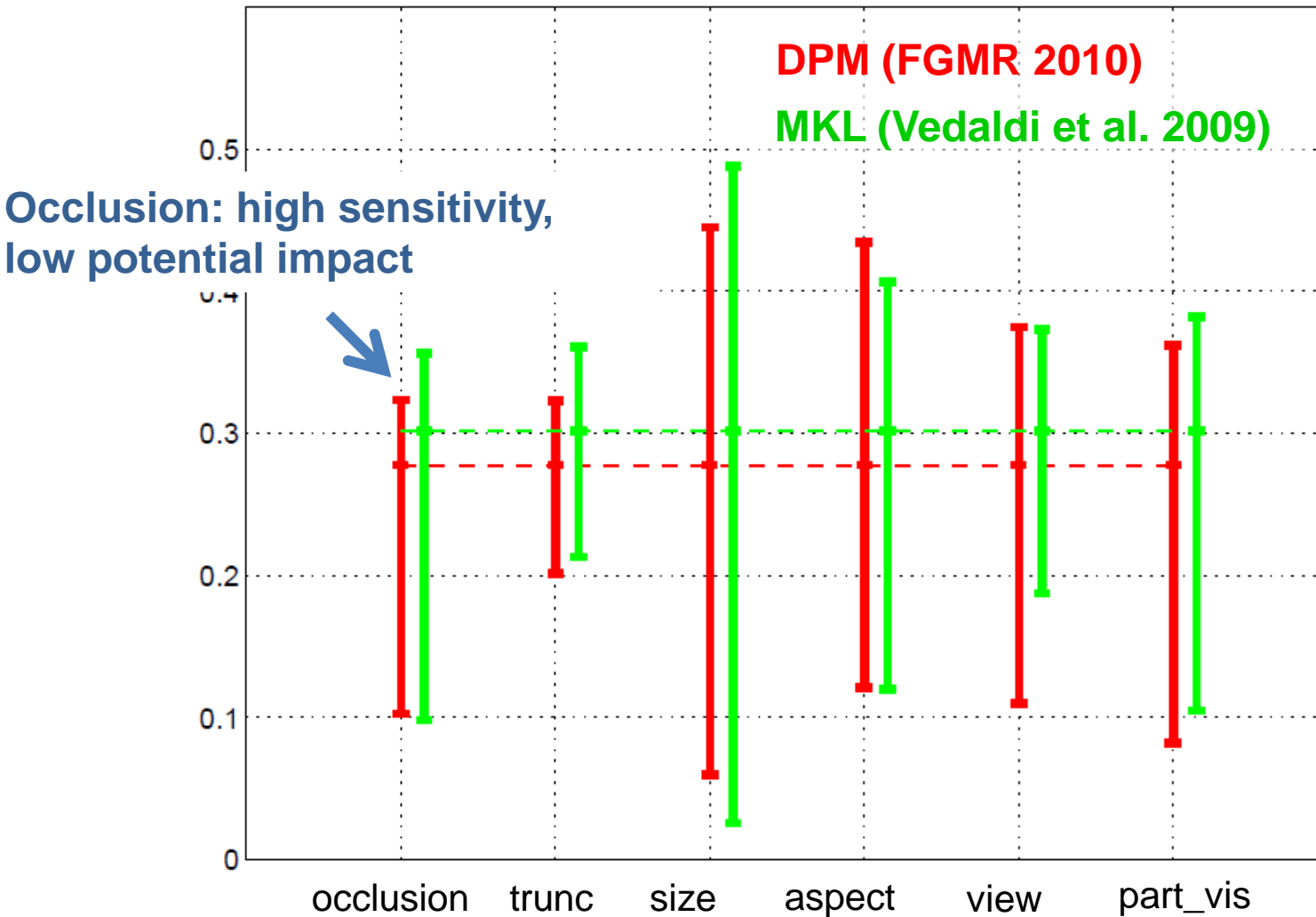
Summarizing Detector Performance

Best, Average, Worst Case



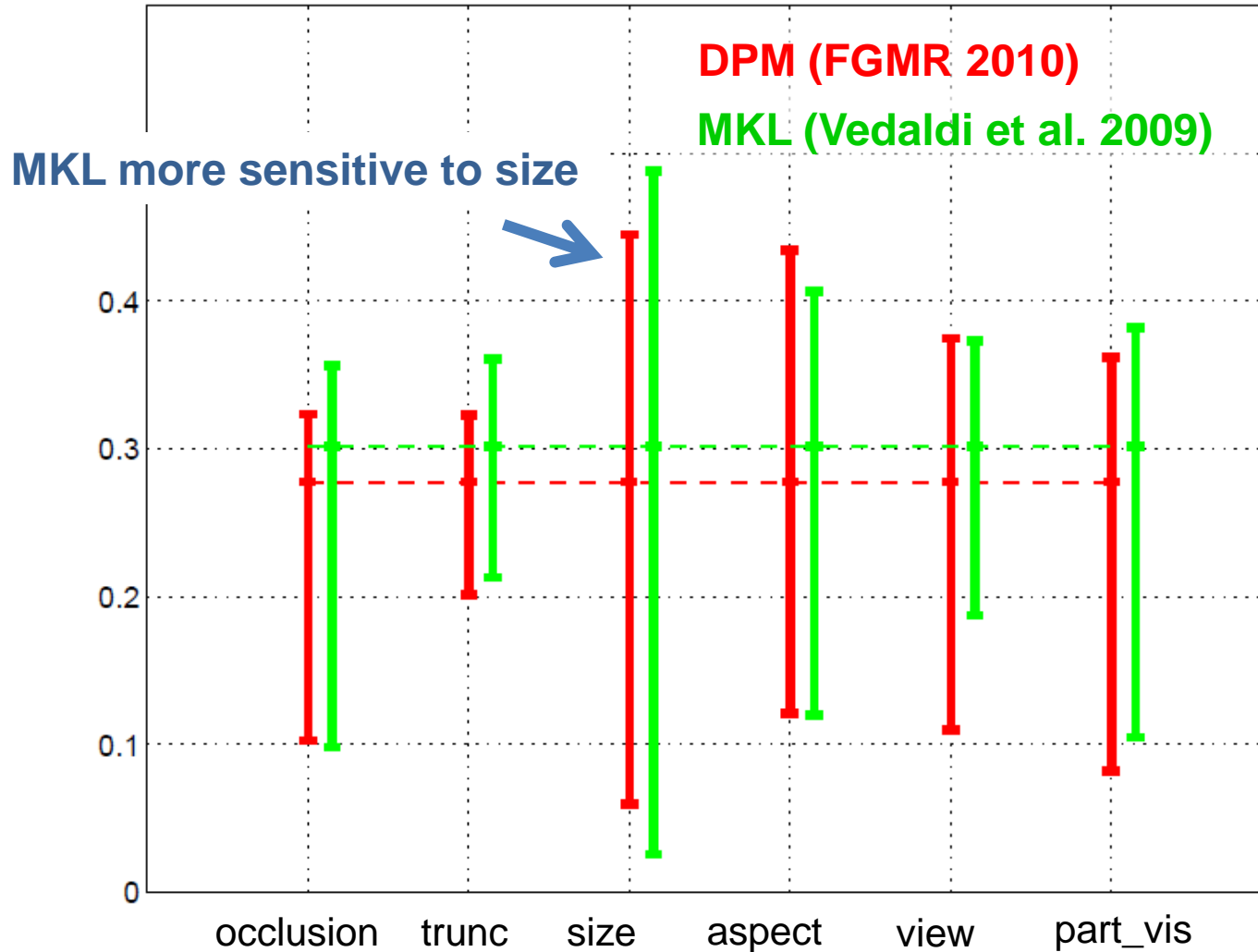
Summarizing Detector Performance

Best, Average, Worst Case



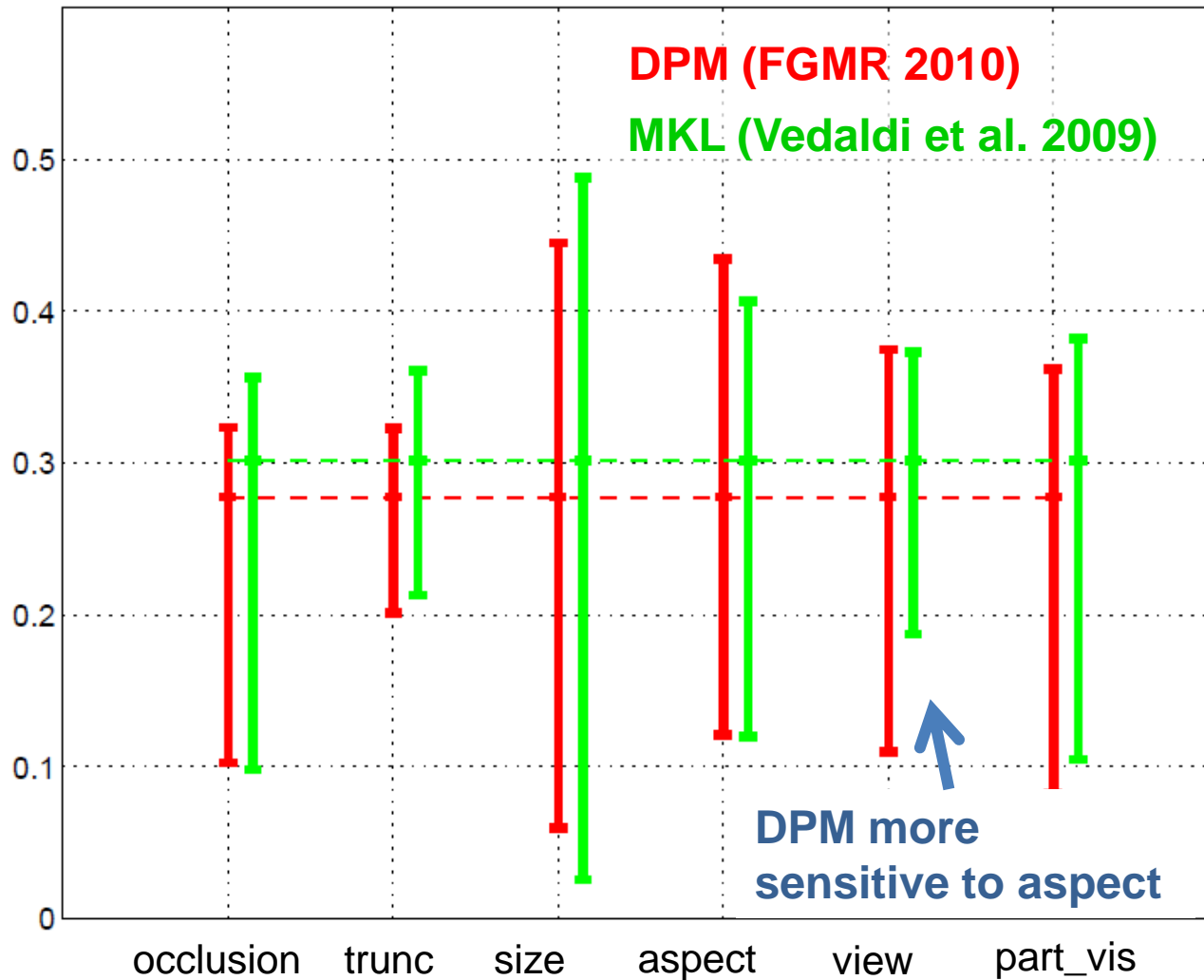
Summarizing Detector Performance

Best, Average, Worst Case



Summarizing Detector Performance

Best, Average, Worst Case

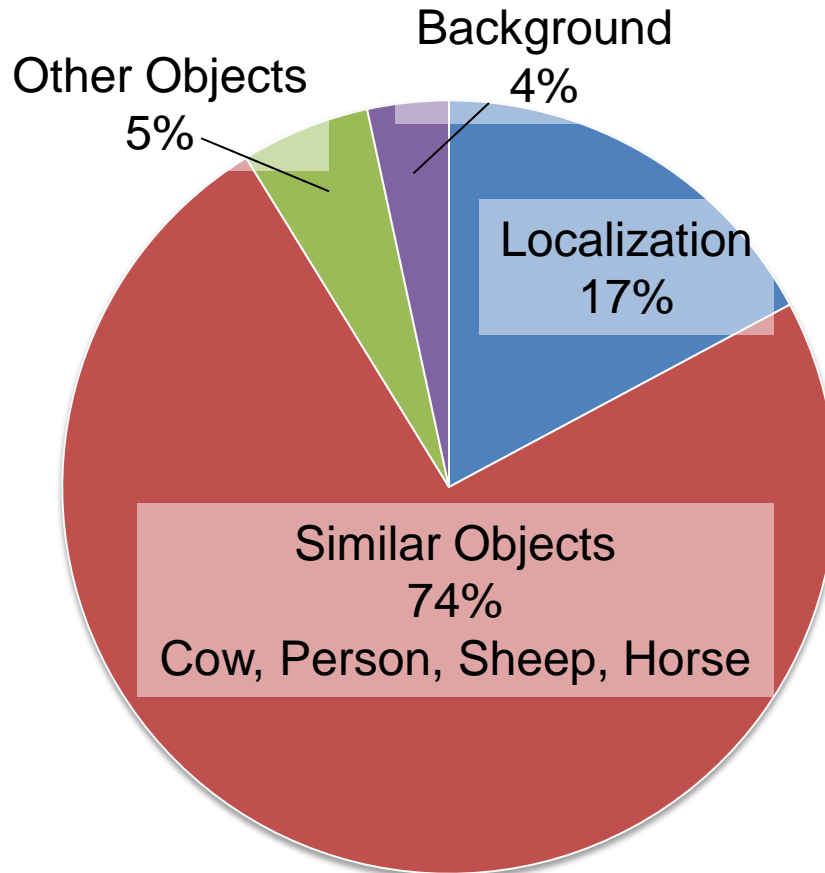


Conclusions

- Most errors that detectors make are reasonable
 - Localization error and confusion with similar objects
 - Misdetection of occluded or small objects
- Large improvements in specific areas (e.g., remove all background FPs or robustness to occlusion) has small impact in overall AP
 - More specific analysis should be standard
- Our code and annotations are available online
 - Automatic generation of analysis summary from standard annotations

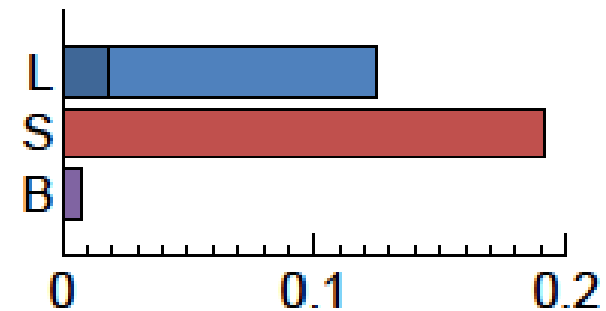
Thank you!

**Top Dog
False
Positives**



AP = 0.17

**Impact of
Removing/Fixing FPs**



Top 5 FP

