

3D Object Detection and Pose Estimation

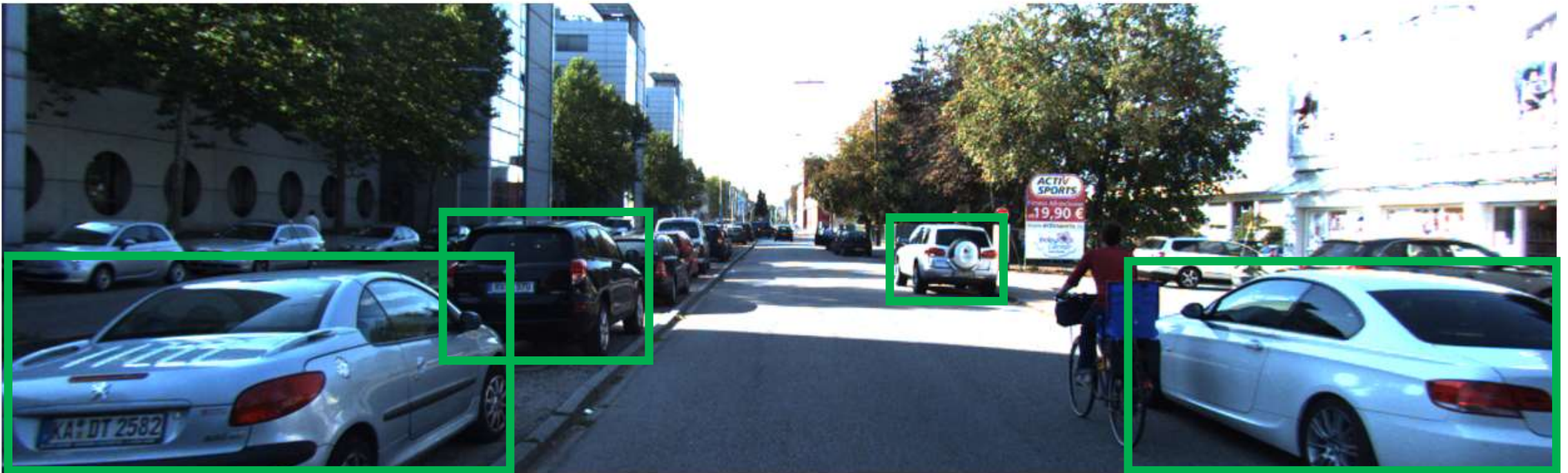
Yu Xiang

University of Michigan

1st Workshop on Recovering 6D Object Pose

12/17/2015

2D Object Detection



2D detection is NOT enough!

Applications that need 3D Object Detection



Autonomous Driving



Robotics

Any application that interacts with the 3D world!



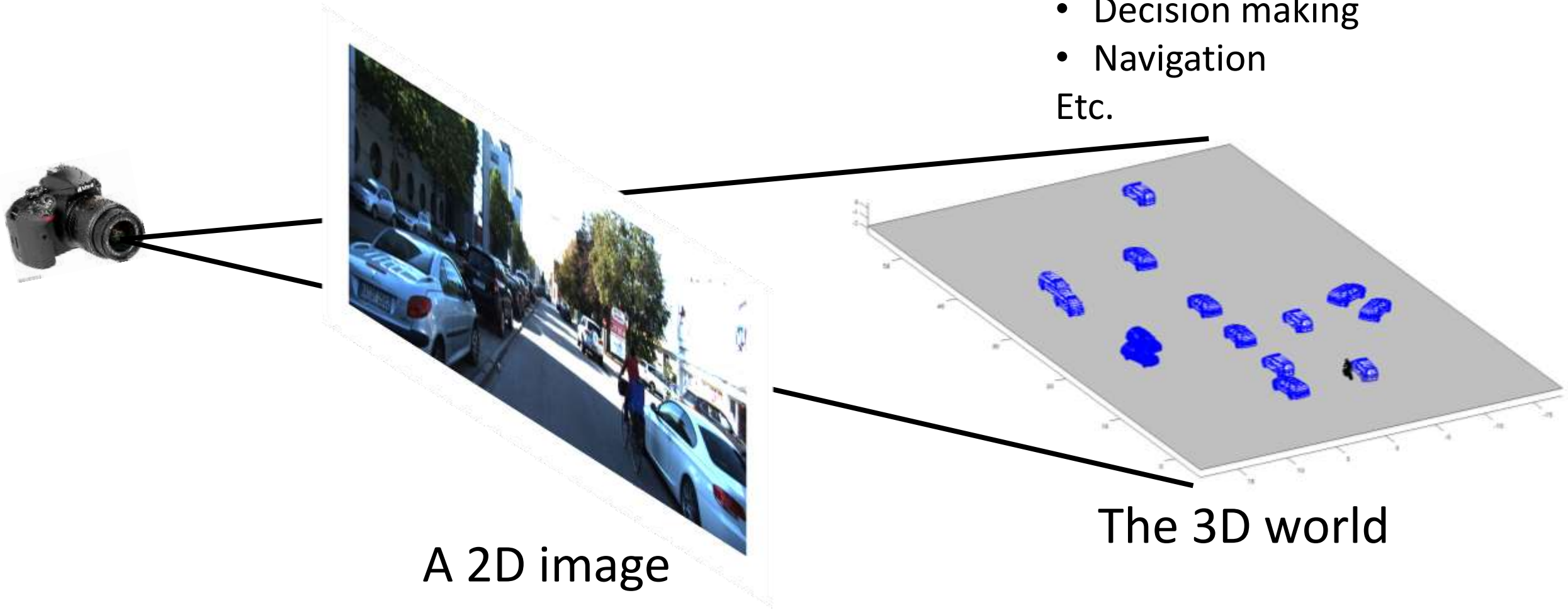
Virtual Reality



Gaming

Goal: Infer the 3D World

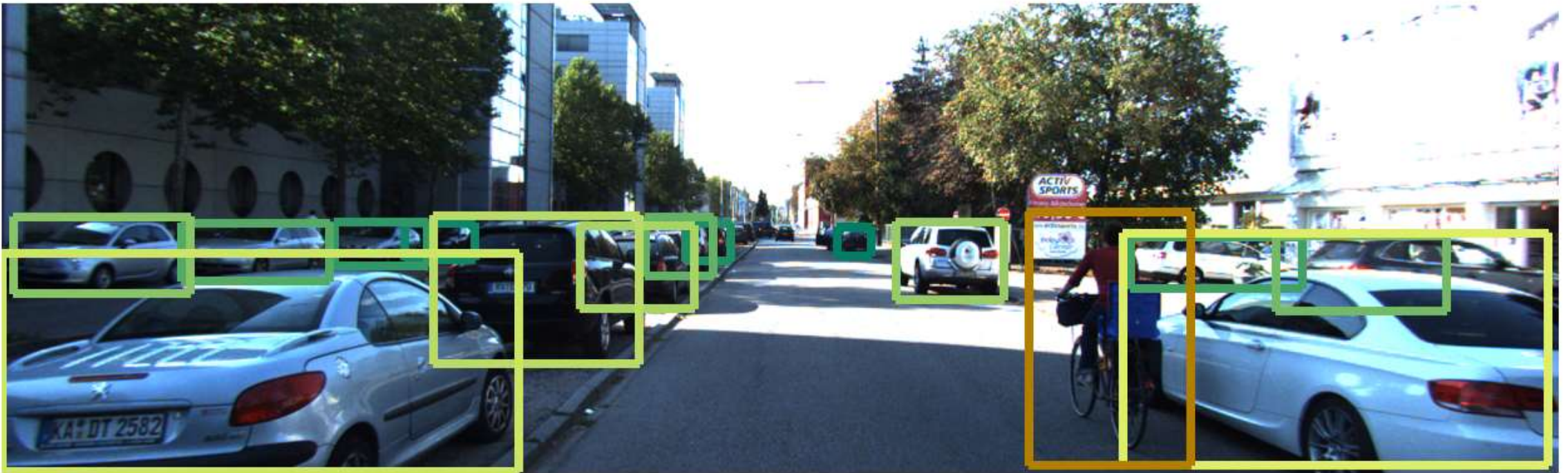
- Interaction
 - Control
 - Decision making
 - Navigation
- Etc.



Our Work: 2D Object Detection



Our Work: 2D Object Detection



Our Work: 2D Object Segmentation



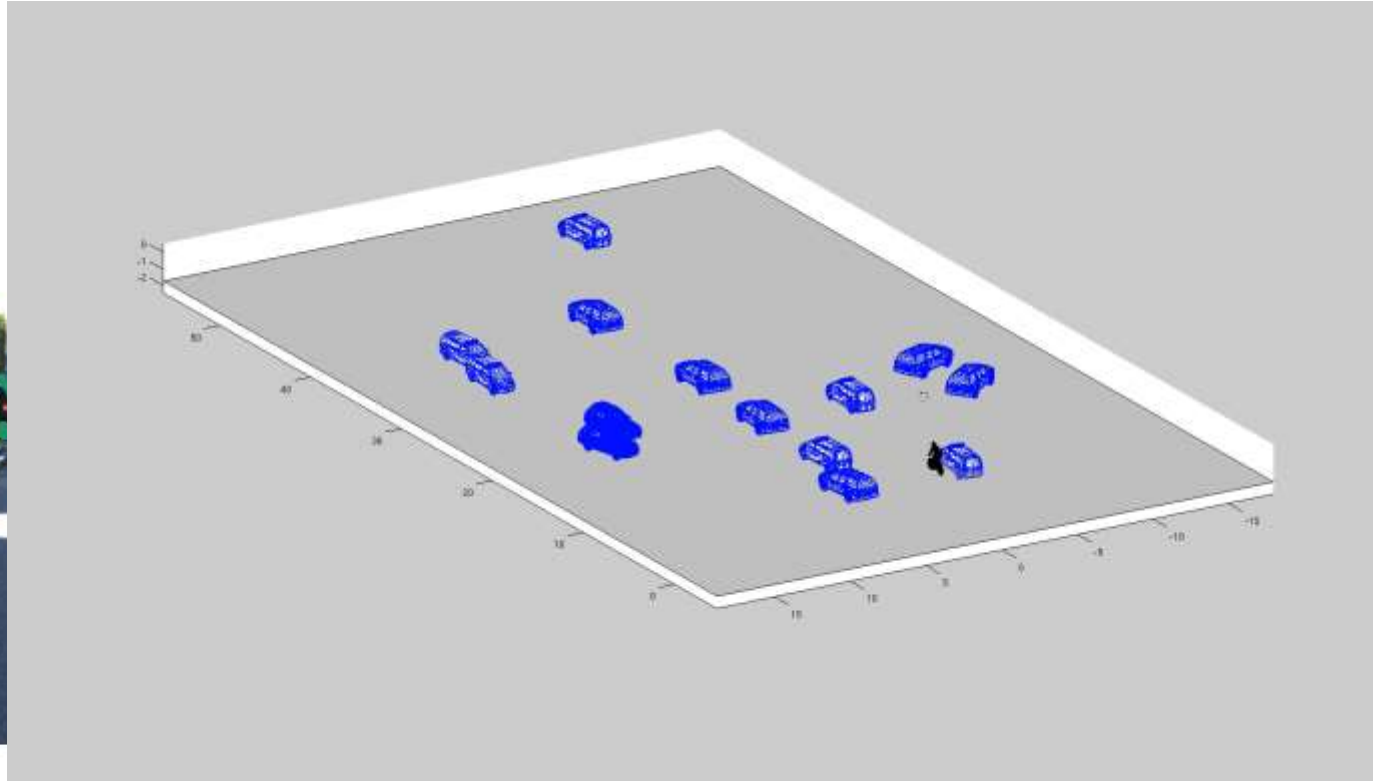
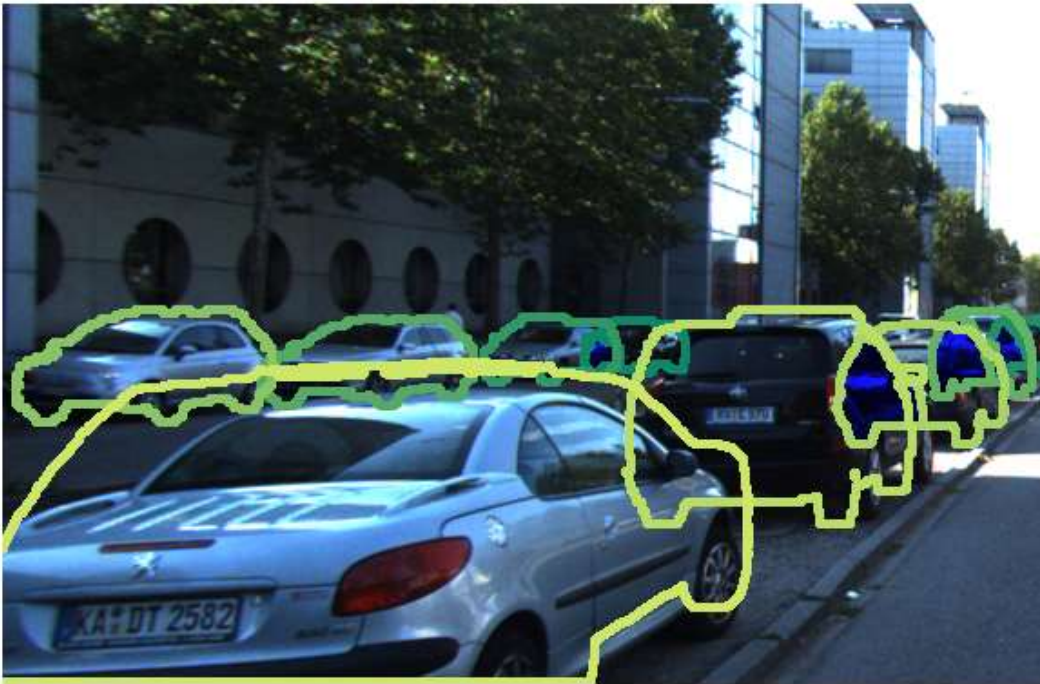
Our Work: Occlusion Reasoning



Our Work: Occlusion Reasoning



Our Work: 3D Localization

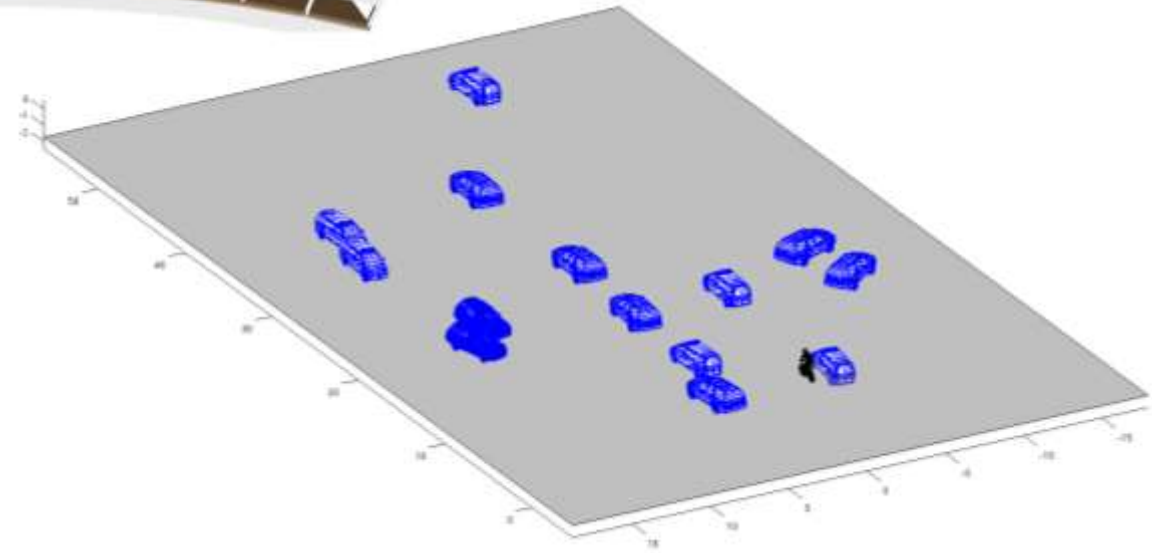
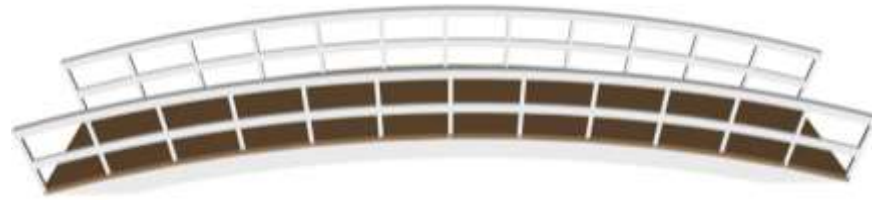


Contribution: 3D Object Representations

3D Object Representation

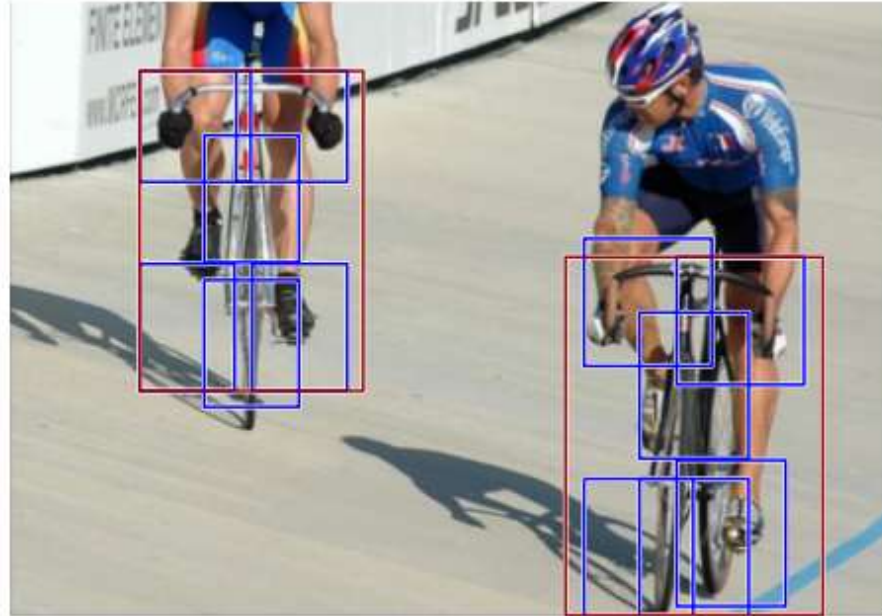


A 2D image



The 3D world

Related Work: 2D Object Representations



Deformable part model
Felzenszwalb et al., TPAMI'10

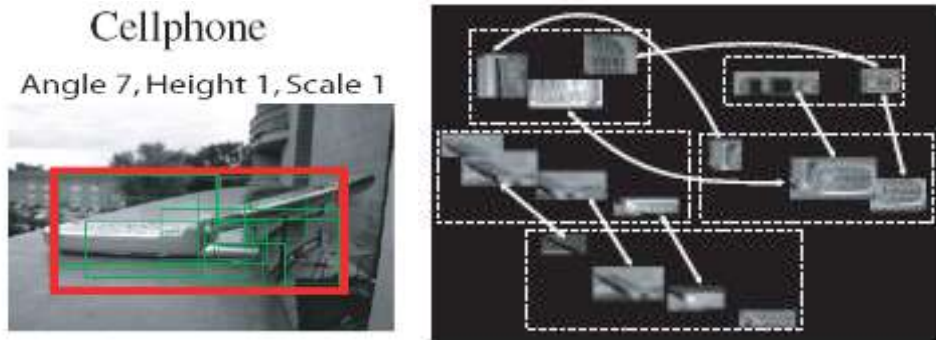
- ✓ 2D detection
- ✗ 3D pose
- ✗ Occlusion
- ✗ 3D location

- Viola & Jones, IJCV'01
- Fergus et al., CVPR'03
- Leibe et al., ECCVW'04
- Hoiem et al., CVPR'06

- Vedaldi et al., ICCV'09
- Maji & Malik, CVPR'09
- Felzenszwalb et al., TPAMI'10
- Malisiewicz et al., ICCV'11

- Divvala et al., ECCVW'12
- Dolla'ar et al., TPAMI'14
- Etc.

Related Work: 2.5D Object Representations

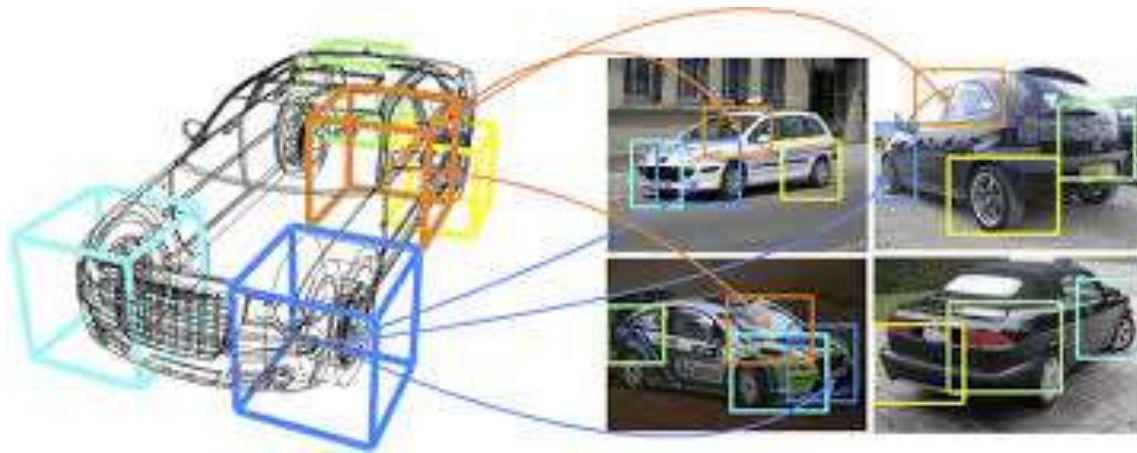


Savarese & Fei-Fei ICCV'07

- ✓ 2D detection
- ✓ 3D pose
- ✗ Occlusion
- ✗ 3D location

- Thomas et al., CVPR'06
- Savarese & Fei-Fei ICCV'07
- Kushal et al., CVPR'07
- Su et al., ICCV'09
- Sun et al., CVPR'10
- Etc.

Related Work: 3D Object Representations



3DDPM

Pepik et al., CVPR'12

- ✓ 2D detection
- ✓ 3D pose
- ✗ Occlusion
- ✗ 3D location

- Yan et al., ICCV'07
- Hoiem et al., CVPR'07
- Liebelt et al., CVPR'08, 10
- Glasner et al. ICCV'11

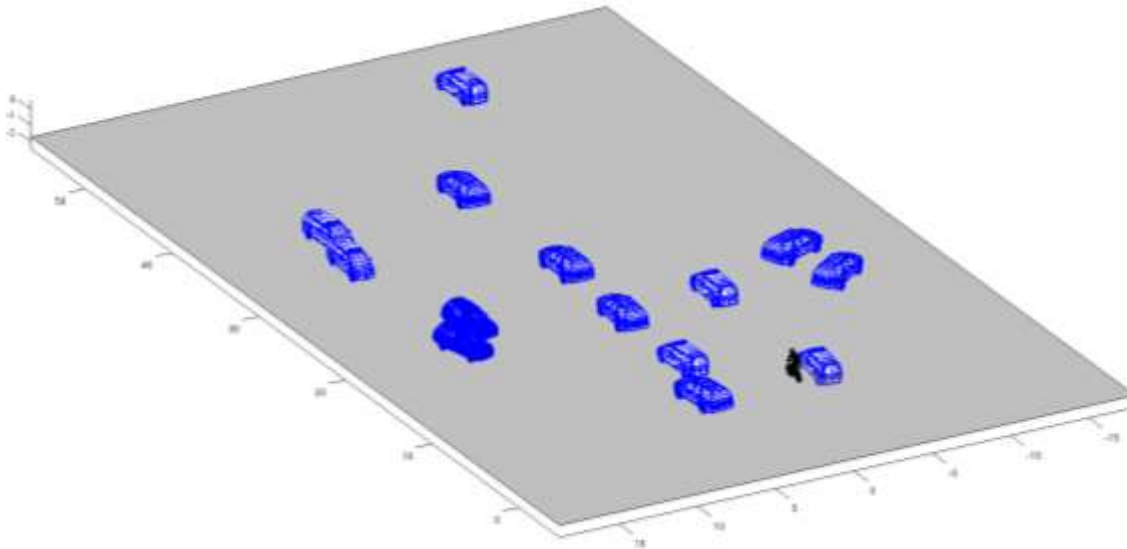
- Pepik et al., CVPR'12
- Xiang & Savarese, CVPR'12
- Hejrati & Ramanan, NIPS'12
- Fidler et al., NIPS'12

Etc

Contribution: 3D Object Representations



- ✓ 2D detection
- ✓ 3D pose
- ✓ Occlusion
- ✓ 3D location



Outline

- 3D Aspect Part Representation
- 3D Aspectlet Representation
- 3D Voxel Pattern Representation
- Conclusion and Future Work

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- **3D Aspect Part Representation**
- 3D Aspectlet Representation
- 3D Voxel Pattern Representation
- Conclusion and Future Work

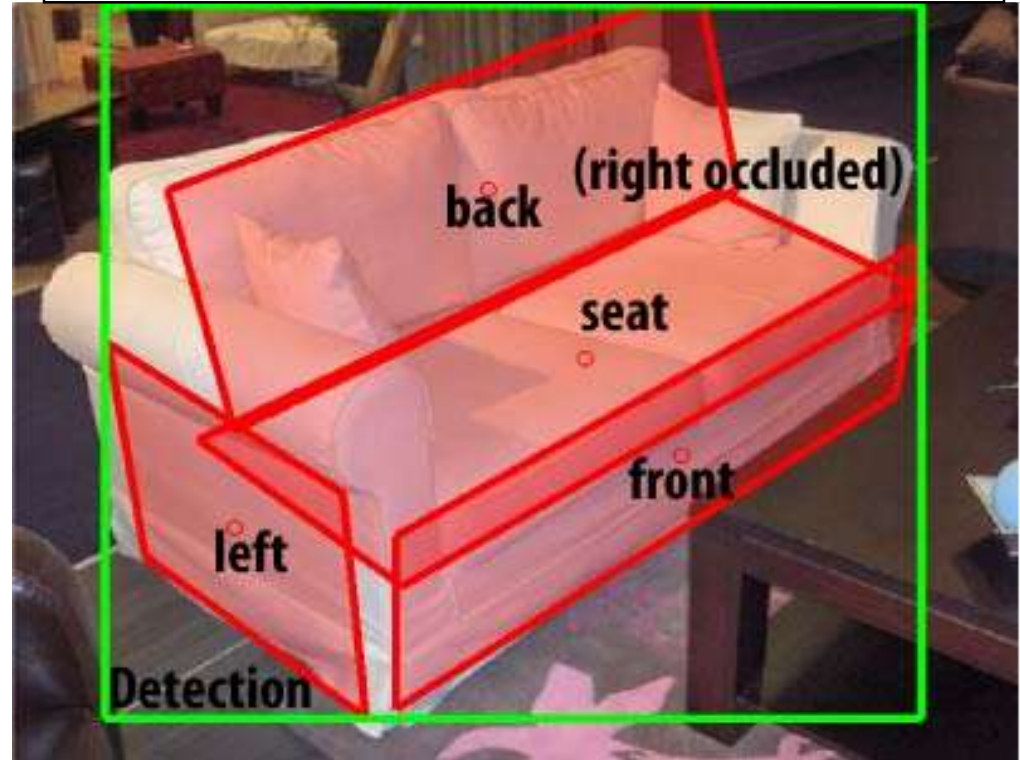
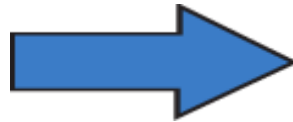
3D Aspect Part Representation

Viewpoint Variation



3D Aspect Part Representation

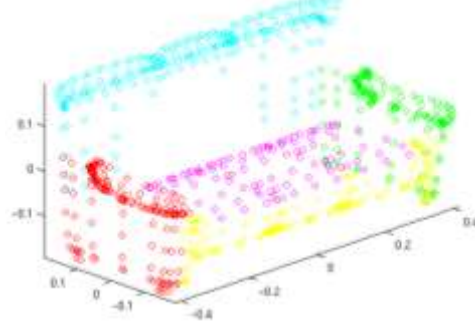
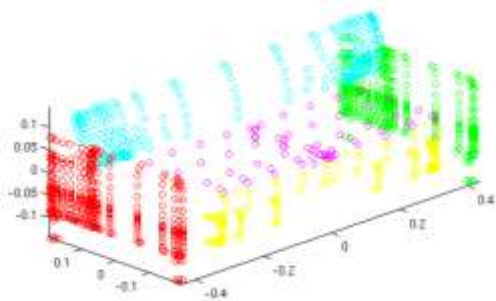
Viewpoint: Azimuth 315°,
Elevation 30°, Distance 2



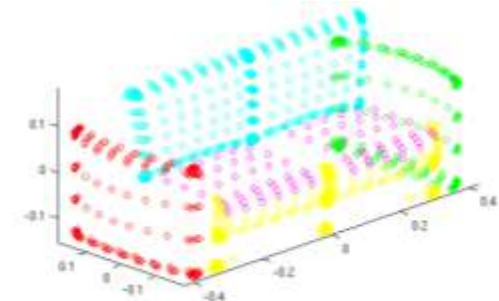
3D Aspect Parts from 3D CAD Models



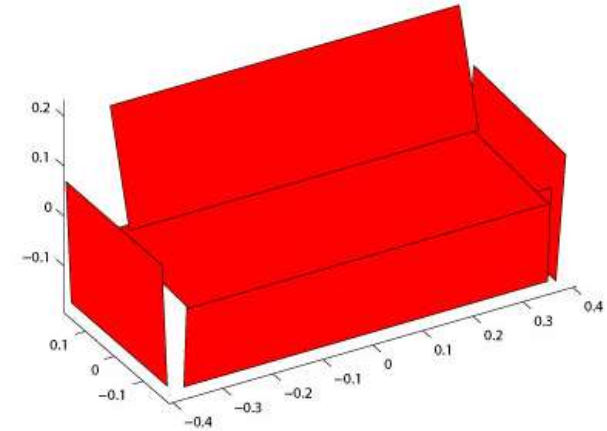
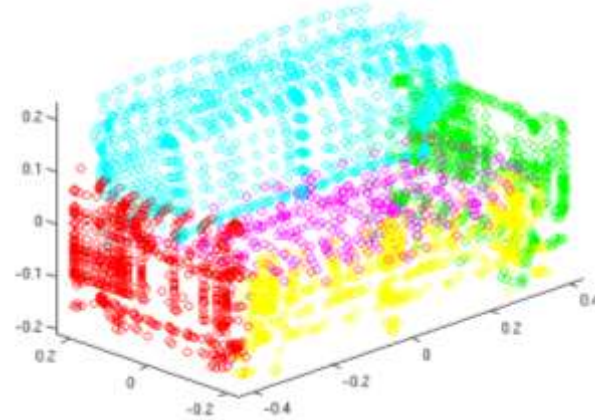
...



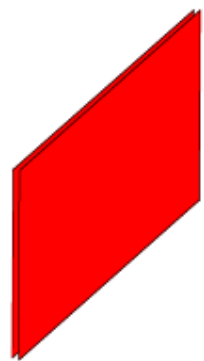
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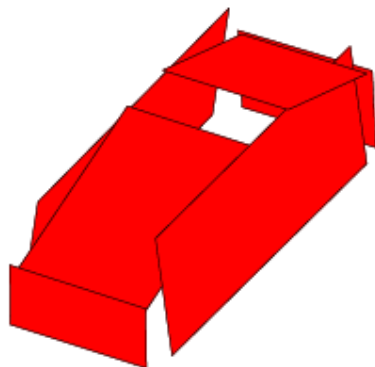
Mean Shape



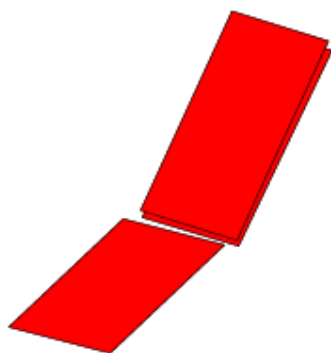
3D Aspect Part Representation



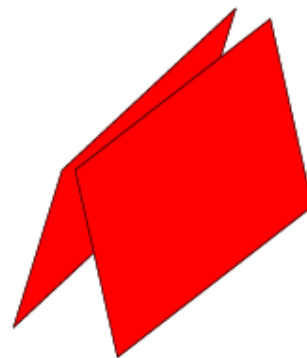
Bicycle



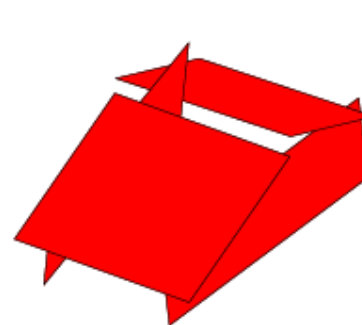
Car



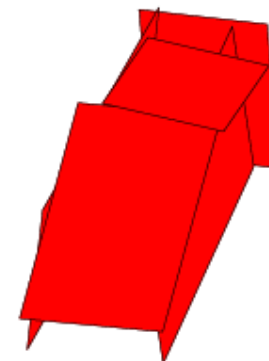
Cellphone



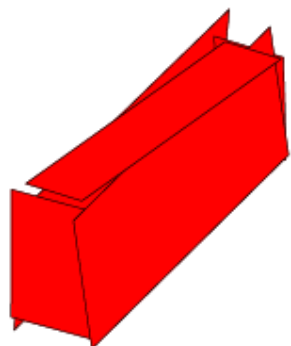
Iron



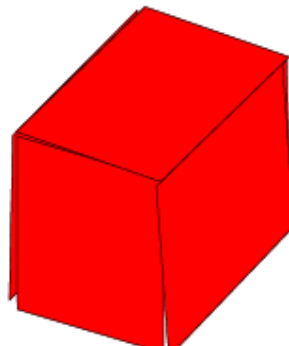
Mouse



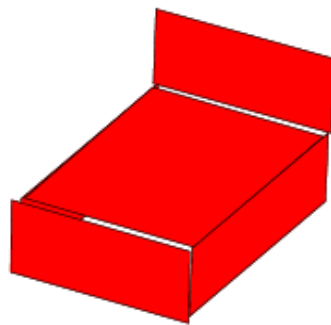
Shoe



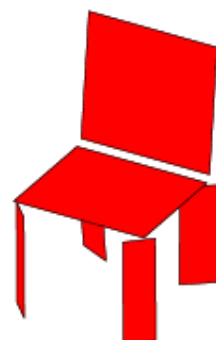
Stapler



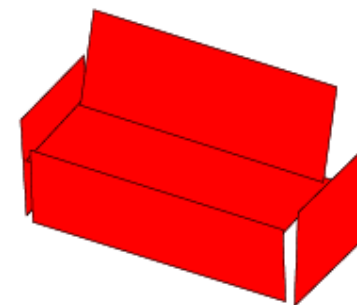
Toaster



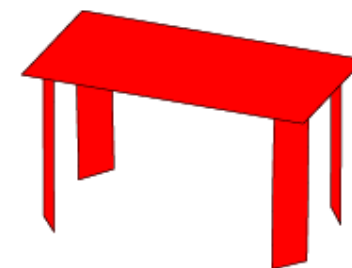
Bed



Chair



Sofa

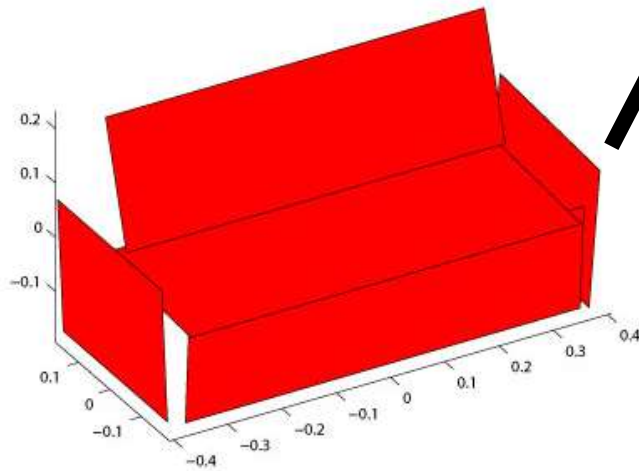


Table

Aspect Layout Model



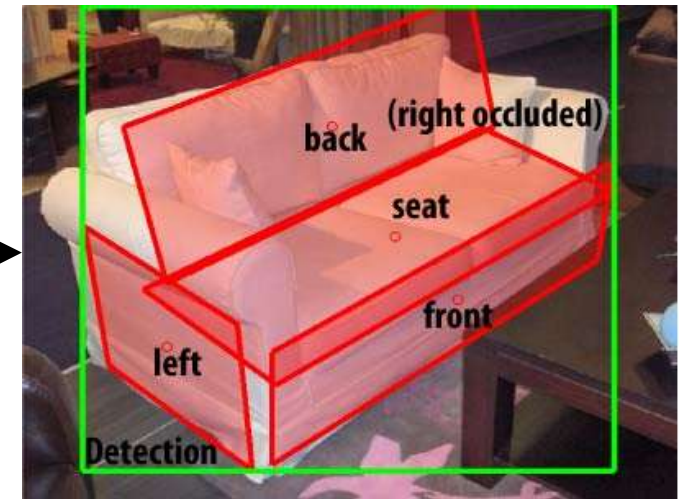
An input image



3D aspect part representation

Aspect
Layout
Model

Viewpoint: Azimuth 315° ,
Elevation 30° , Distance 2

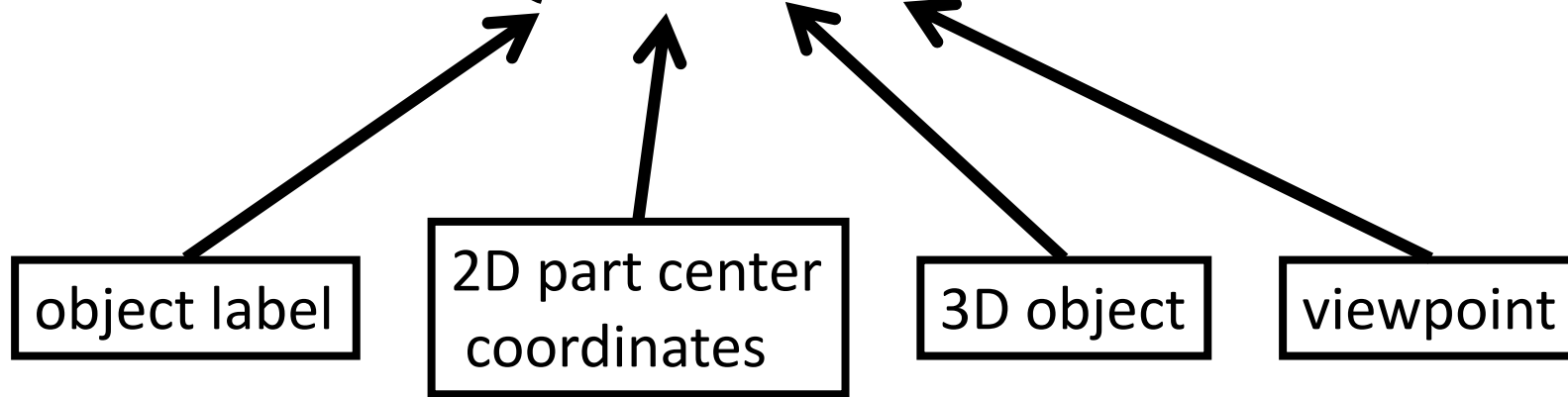


Output

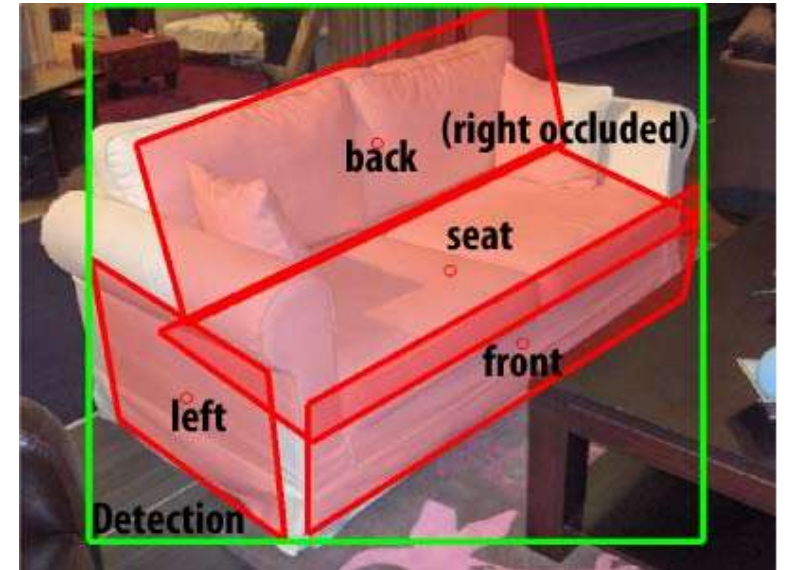
Aspect Layout Model

- Posterior distribution

$$P(Y, L, O, V | I) \propto \exp(E(Y, L, O, V, I))$$



$$L = (\mathbf{l}_1, \dots, \mathbf{l}_n), \mathbf{l}_i = (x_i, y_i)$$



Aspect Layout Model

- Energy function

$$E(Y, L, O, V, I) = \begin{cases} \sum_i V_1(\mathbf{l}_i, O, V, I) + \sum_{(i,j)} V_2(\mathbf{l}_i, \mathbf{l}_j, O, V), & \text{if } Y = +1 \\ 0, & \text{if } Y = -1 \end{cases}$$

The diagram illustrates the components of the energy function. Two boxes at the bottom, labeled "unary potential" and "pairwise potential", have arrows pointing upwards to the terms $\sum_i V_1(\mathbf{l}_i, O, V, I)$ and $\sum_{(i,j)} V_2(\mathbf{l}_i, \mathbf{l}_j, O, V)$ respectively in the equation above.

Aspect Layout Model

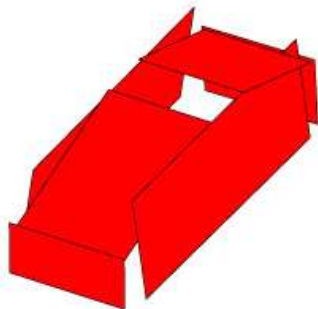
- Unary potential

The diagram illustrates the unary potential $V_1(\mathbf{l}_i, O, V, I)$ with three annotated components:

- part template**: An arrow points from this box to the term $\mathbf{w}_i^T$ in the equation.
- feature vector**: An arrow points from this box to the term $\phi(\mathbf{l}_i, O, V, I)$ in the equation.
- self-occlusion weight**: An arrow points from this box to the term α_i in the equation.

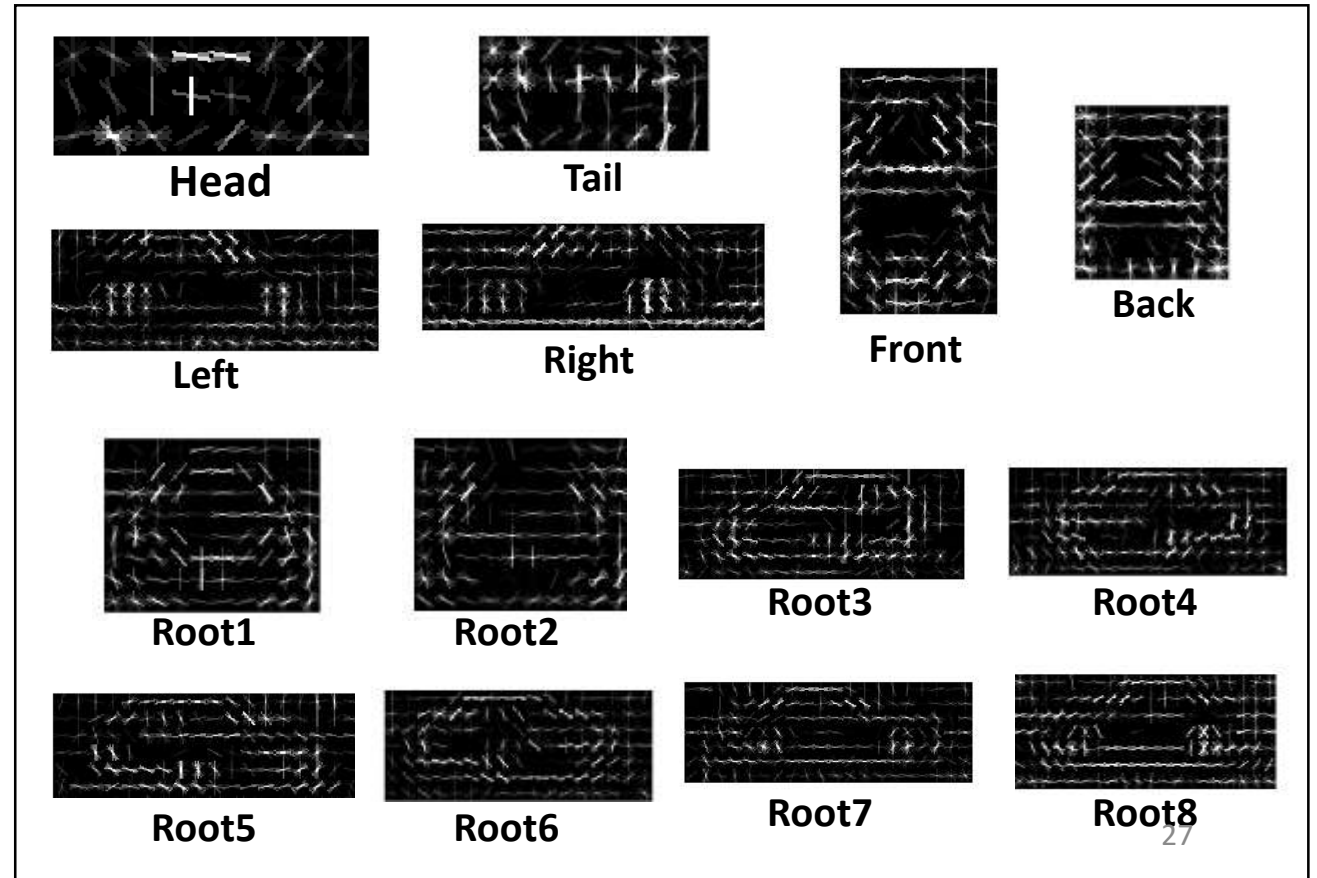
$$V_1(\mathbf{l}_i, O, V, I) = \begin{cases} \mathbf{w}_i^T \phi(\mathbf{l}_i, O, V, I), & \text{if unoccluded} \\ \alpha_i, & \text{if self-occluded} \end{cases}$$

Aspect Layout Model



Car

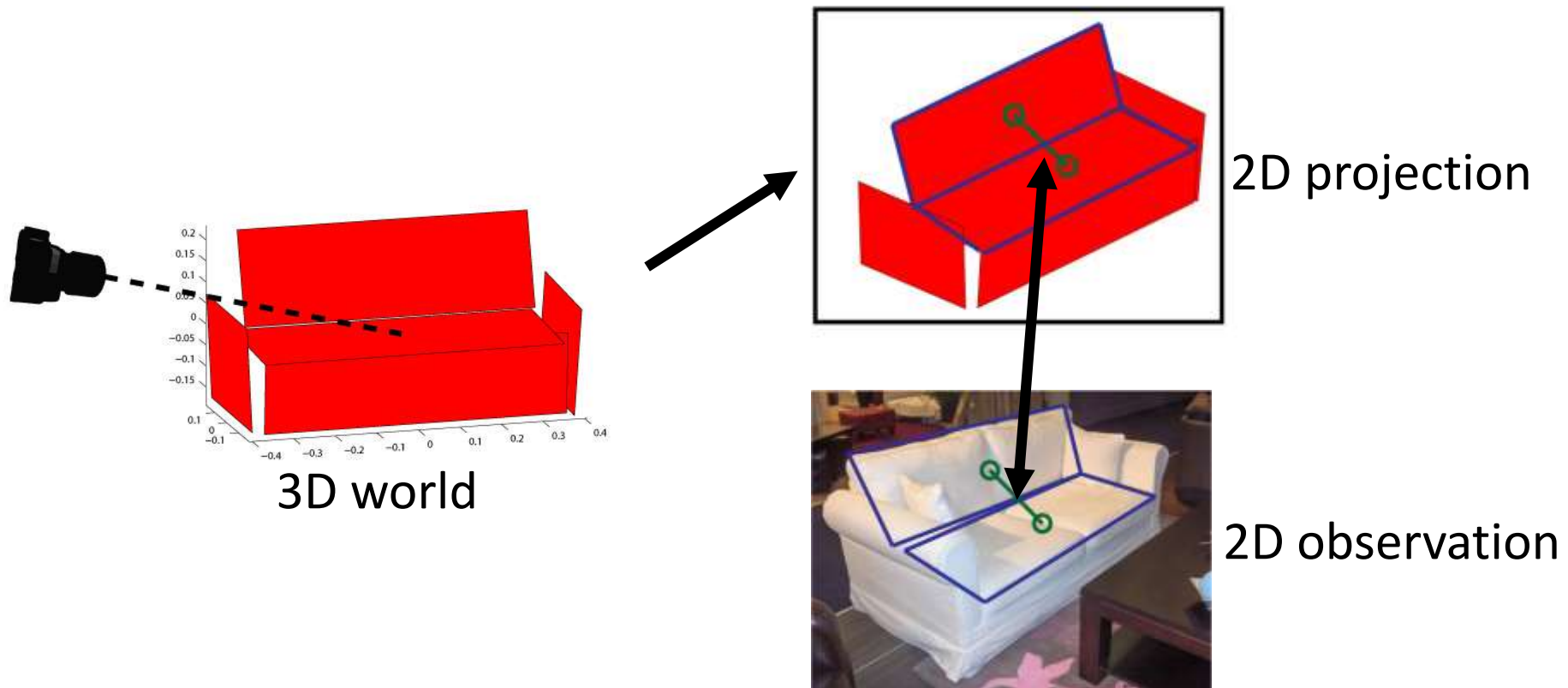
$$V_1(\mathbf{l}_i, O, V, I) = \begin{cases} \mathbf{w}_i^T \phi(\mathbf{l}_i, O, V, I), & \text{if unoccluded} \\ \alpha_i, & \text{if occluded} \end{cases}$$



Aspect Layout Model

- Pairwise potential

$$V_2(\mathbf{l}_i, \mathbf{l}_j, O, V) = -w_x (x_i - x_j + d_{ij,O,V} \cos(\theta_{ij,O,V}))^2 - w_y (y_i - y_j + d_{ij,O,V} \sin(\theta_{ij,O,V}))^2$$



Aspect Layout Model

- Training with Structural SVM [1]

$$\min_{\theta} \frac{1}{2} \|\theta\|^2 + \lambda \sum_{t=1}^N \left[\max_{Y,L,O,V} [\theta^T \Psi_{t,Y,L,O,V} + \Delta_{t,Y,L,O,V}] - \theta^T \Psi_{t,Y^t,L^t,O^t,V^t} \right]$$

- Inference $(Y^*, L^*, O^*, V^*) = \arg \max_{Y,L,O,V} E(Y, L, O, V, I | \theta)$
 - Loop over discretized viewpoints
 - Run Belief Propagation [2] under each viewpoint to predict part locations

[1] I. Tsochantaridis, T. Hofmann, T. Joachims and Y. Altun. Support vector machine learning for interdependent and structured output spaces. In ICML, 2004.

[2] J. S. Yedidia, W. T. Freeman, and Y. Weiss. Understanding belief propagation and its generalizations. In Exploring artificial intelligence in the new millennium, 2003.

Aspect Layout Model

- Best results upon publication in pose estimation and 3D part estimation

Cars from 3D Object dataset [Savarese & Fei-Fei ICCV'07]	Method	Ours	[1]	[2]	[3]	[4]	[5]	[6]
	Viewpoint (cars)	93.4%	85.4	85.3	81	70	67	48.5

Cars from EPFL dataset [Ozuysal et al. CVPR'09]	Method	Ours	Ours - baseline	DPM [7]	[8]
	Viewpoint (cars)	64.8%	58.1	56.6	41.6

Chairs, tables, sofas and beds from IMAGE NET [Deng et al. CVPR'09]	Method	Ours	Ours - baseline	DPM [7]
	Viewpoint	63.4%	34.0	49.5

[1] N. Payet and S. Todorovic. From contours to 3d object detection and pose estimation. In ICCV, 2011.

[2] D. Glasner, M. Galun, S. Alpert, R. Basri, and G. Shakhnarovich. Viewpoint-aware object detection and pose estimation. In ICCV, 2011.

[3] M. Stark, M. Goesele, and B. Schiele. Back to the future: Learning shape models from 3d cad data. In BMVC, 2010.

[4] J. Liebelt and C. Schmid. Multi-view object class detection with a 3D geometric model. In CVPR, 2010.

[5] H. Su, M. Sun, L. Fei-Fei, and S. Savarese. Learning a dense multiview representation for detection, viewpoint classification. In ICCV, 2009.

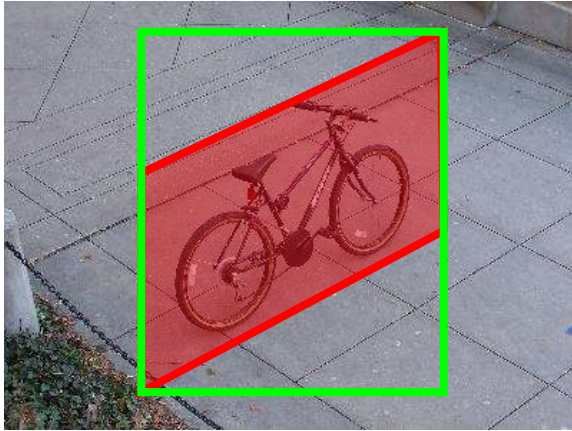
[6] M. Arie-Nachimson and R. Basri. Constructing implicit 3d shape models for pose estimation. In ICCV, 2009.

[7] P. Felzenszwalb, R. Girshick, D. McAllester, and D. Ramanan. Object detection with discriminatively trained part-based models. TPAMI, 2010.

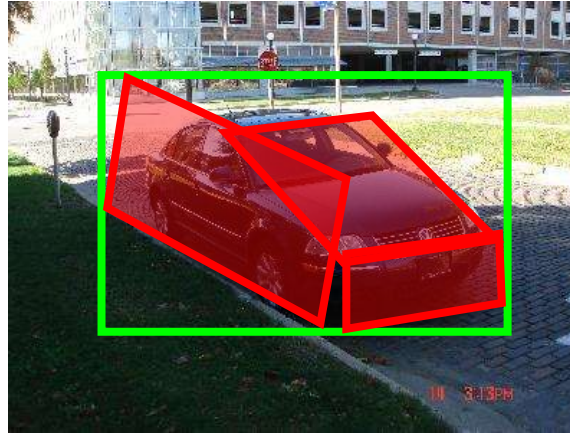
[8] M. Ozuysal, V. Lepetit, and P. Fua. Pose estimation for category specific multiview object localization. In CVPR, 2009.

Aspect Layout Model

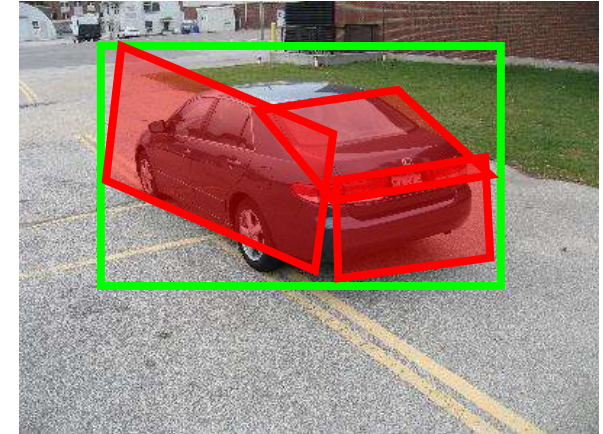
Prediction: $a=225$, $e=30$, $d=7$



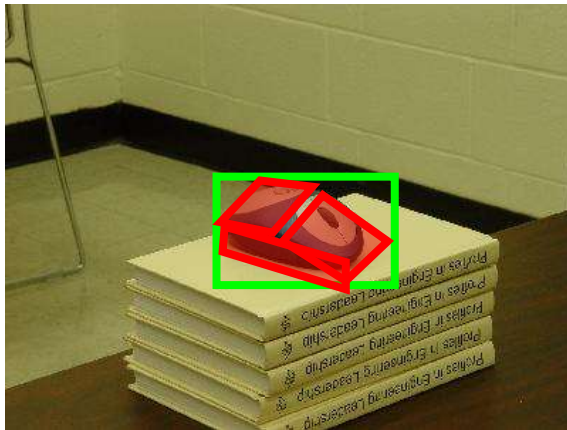
Prediction: $a=330$, $e=15$, $d=7$



Prediction: $a=150$, $e=15$, $d=7$



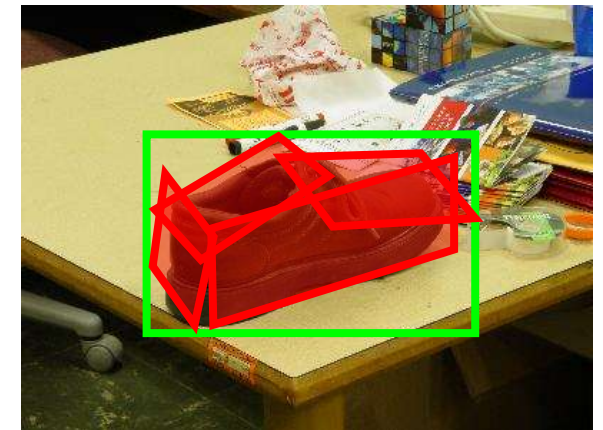
Prediction: $a=300$, $e=45$, $d=23$



Prediction: $a=45$, $e=90$, $d=5$



Prediction: $a=240$, $e=45$, $d=11$

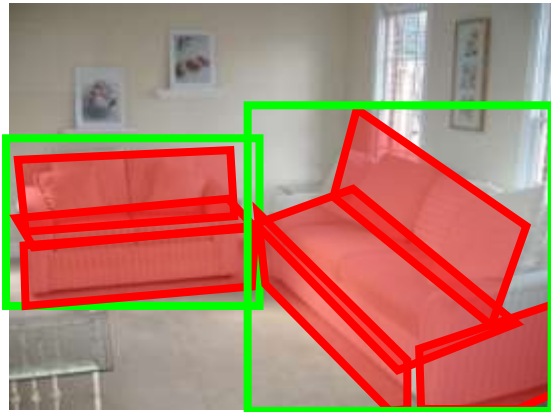


Aspect Layout Model

Prediction: $a=30, e=15, d=2.5$



Prediction: $a=345, e=15, d=3.5$
 $a=60, e=30, d=2.5$



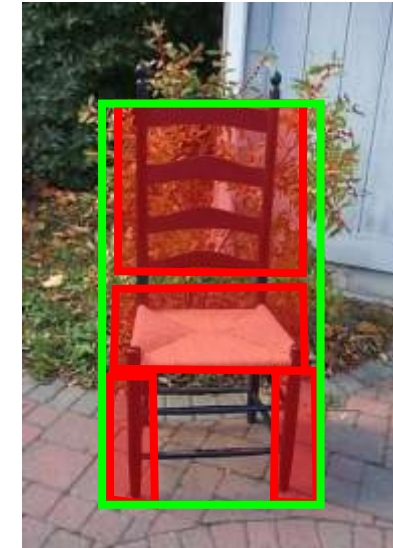
Prediction: $a=0, e=15, d=1.5$



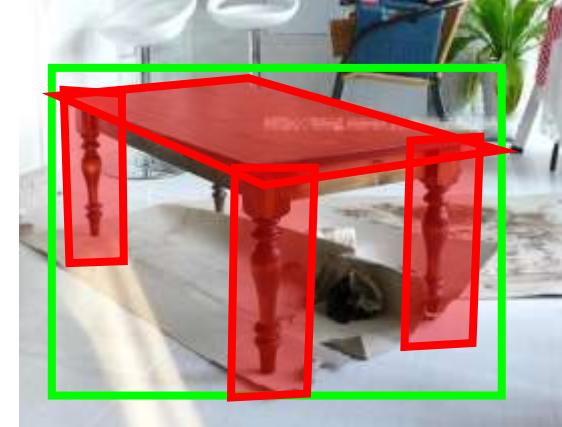
Prediction: $a=315, e=30, d=2$



Prediction: $a=0, e=30, d=7$



Prediction: $a=60, e=15, d=2$

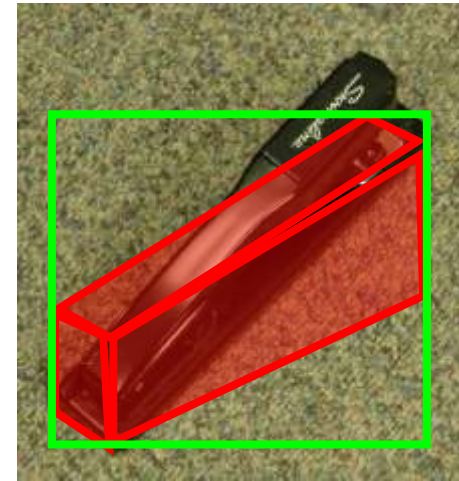


Wrong examples

Prediction: $a=45$, $e=15$, $d=1.5$



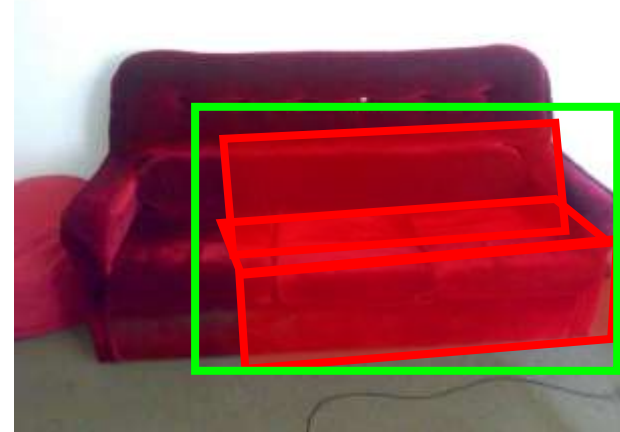
Prediction: $a=225$, $e=30$, $d=7$



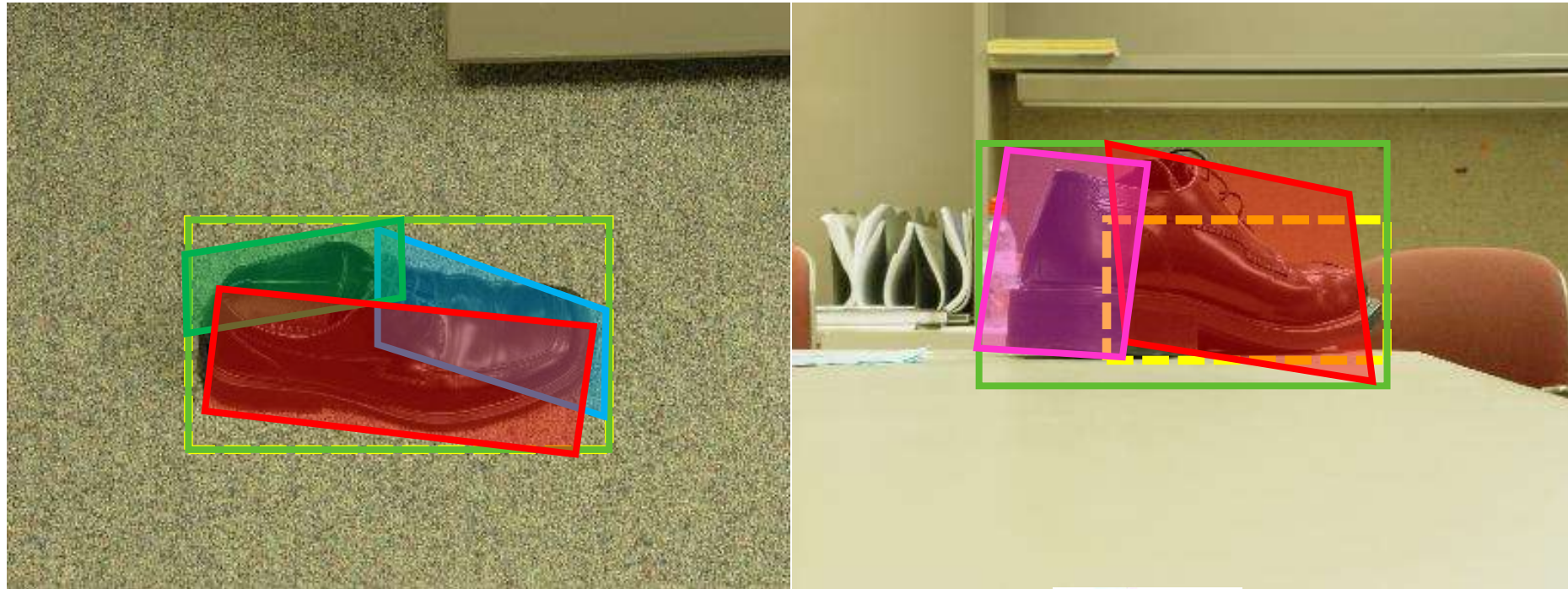
Prediction: $a=0$, $e=30$, $d=7$



Prediction: $a=345$, $e=15$, $d=2.5$



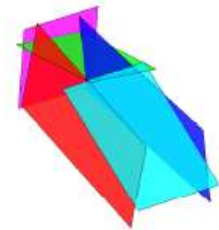
Application I: Object Co-detection with 3D Aspect Parts



Single Image Detector

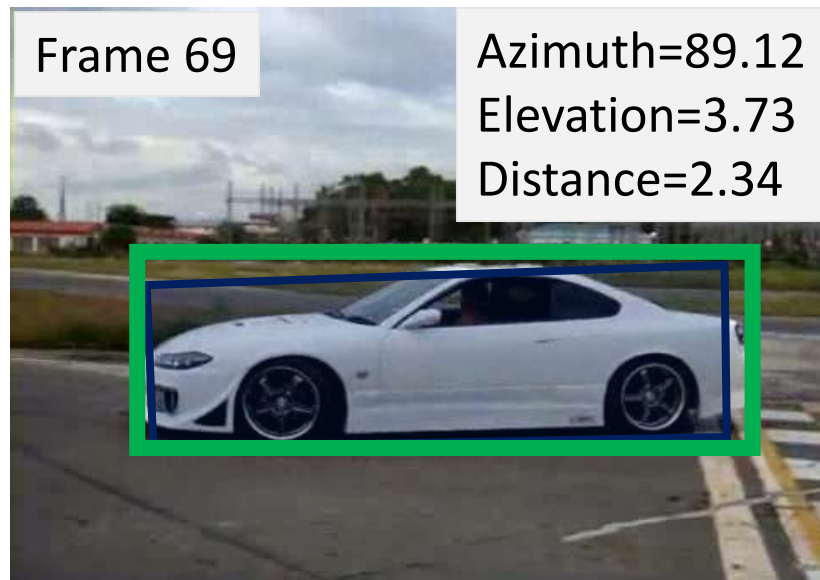
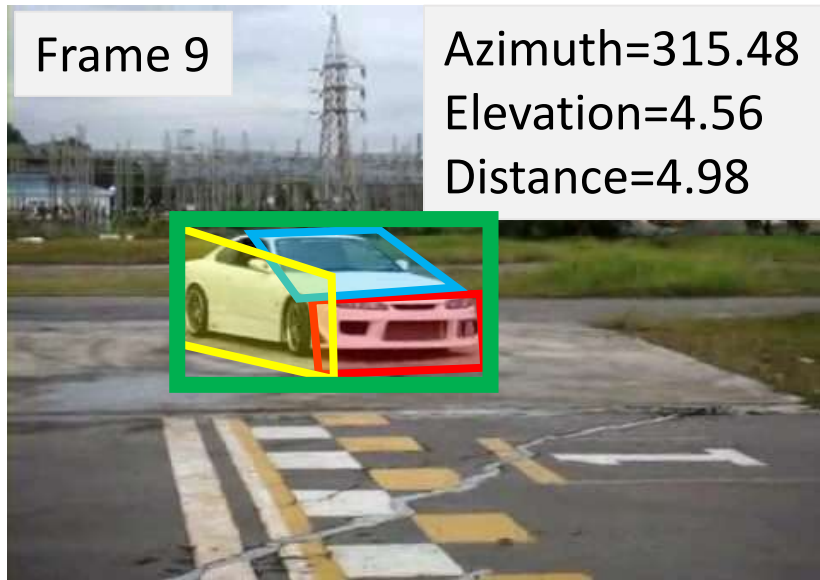


Co-detector

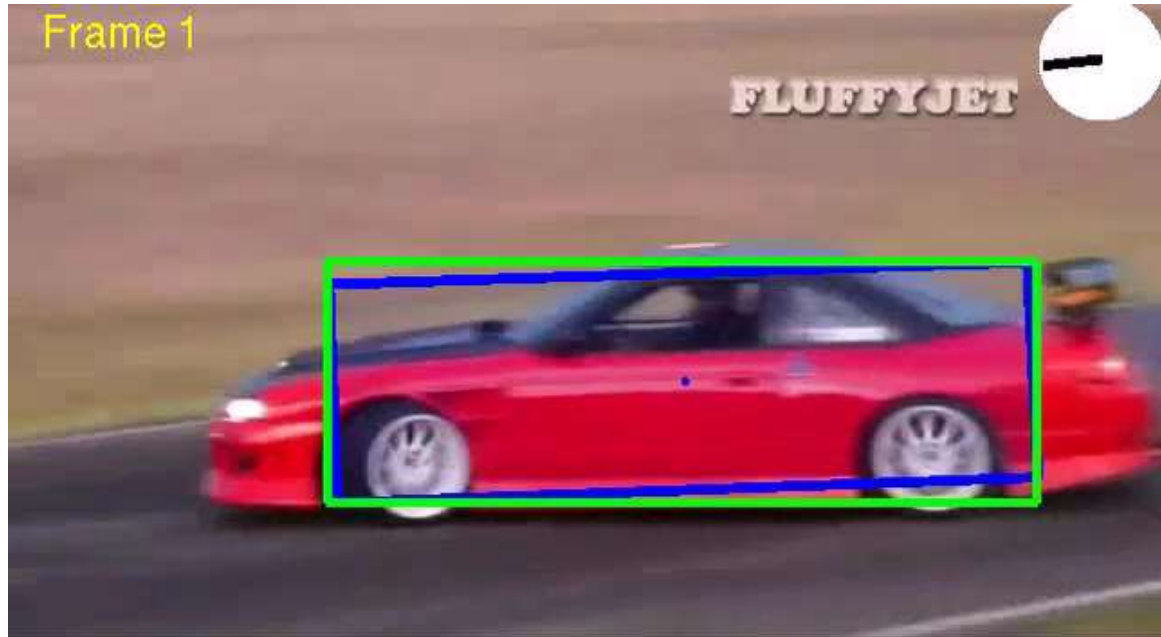


Shoe model

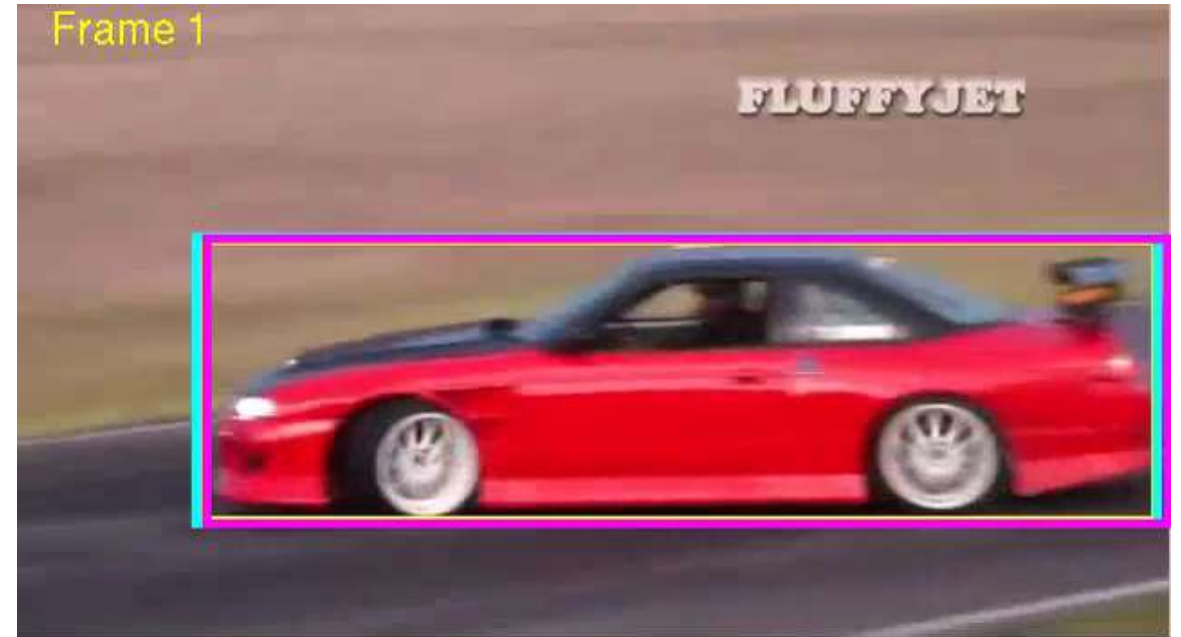
Application II: Multiview Object Tracking with 3D Aspect Parts



Application II: Multiview Object Tracking with 3D Aspect Parts



Ours: Multiview tracker



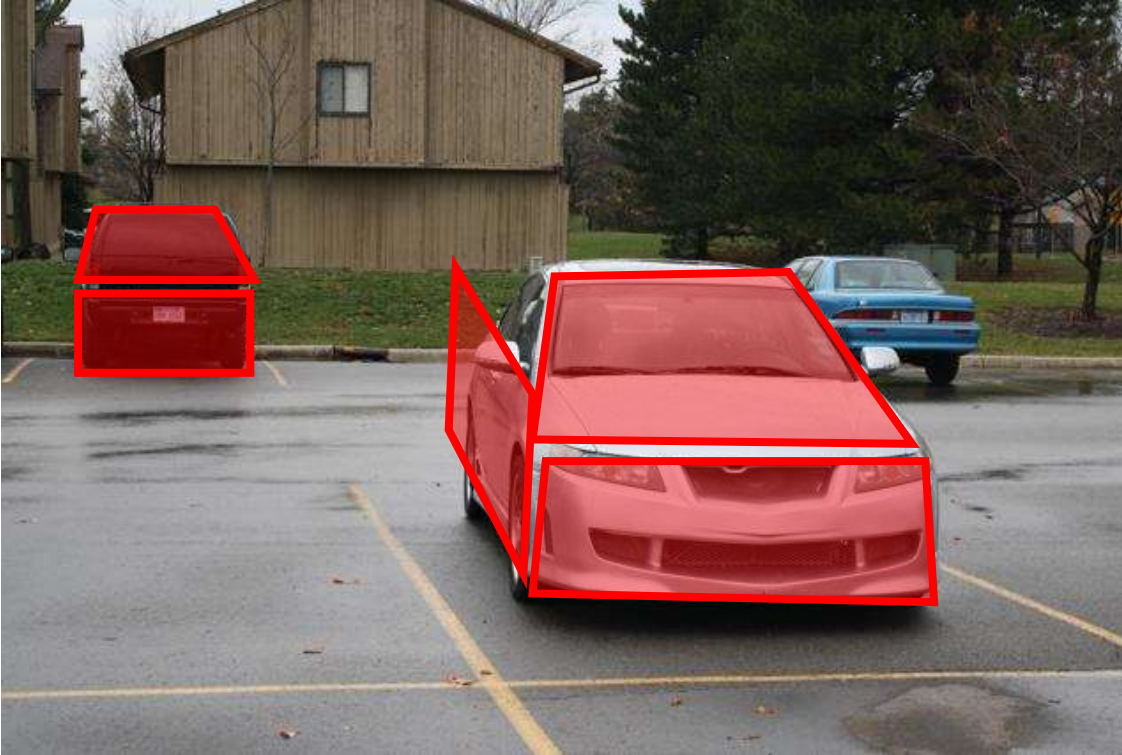
— MIL — L1 — TLD — Struct

- [MIL] Babenko, B., Yang, M.H., Belongie, S.: Robust object tracking with online multiple instance learning. TPAMI, 2011.
- [L1] Bao, C., Wu, Y., Ling, H., Ji, H.: Real time robust l1 tracker using accelerated proximal gradient approach. In CVPR, 2012.
- [TLD] Kalal, Z., Mikolajczyk, K., Matas, J.: Tracking-learning-detection. TPAMI, 2012.
- [Struct] Hare, S., Saari, A., Torr, P.H.: Struck: Structured output tracking with kernels. In ICCV, 2011.

Outline

- 3D Aspect Part Representation
- **3D Aspectlet Representation**
- 3D Voxel Pattern Representation
- Conclusion and Future Work

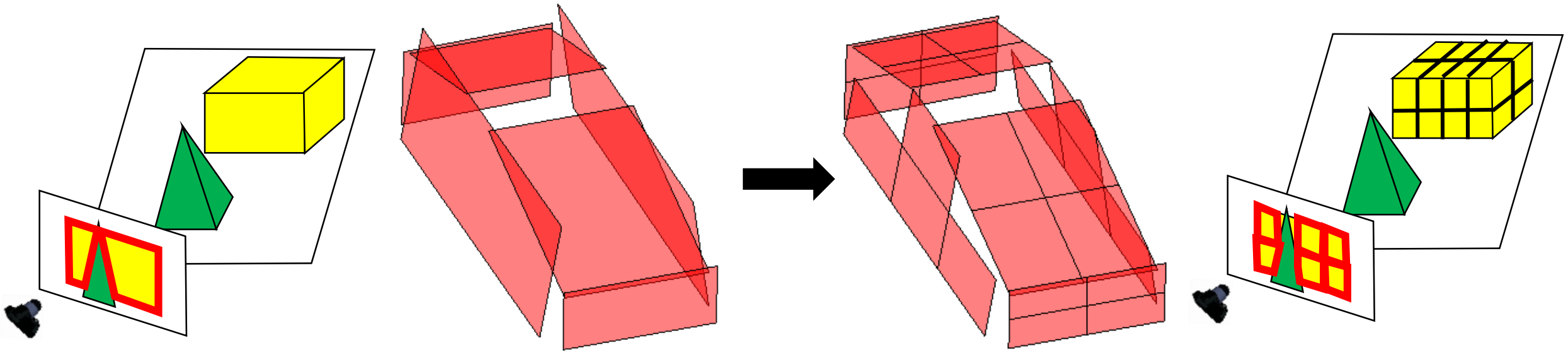
Occlusion in Object Recognition



?

Occlusion changes the appearances of objects.

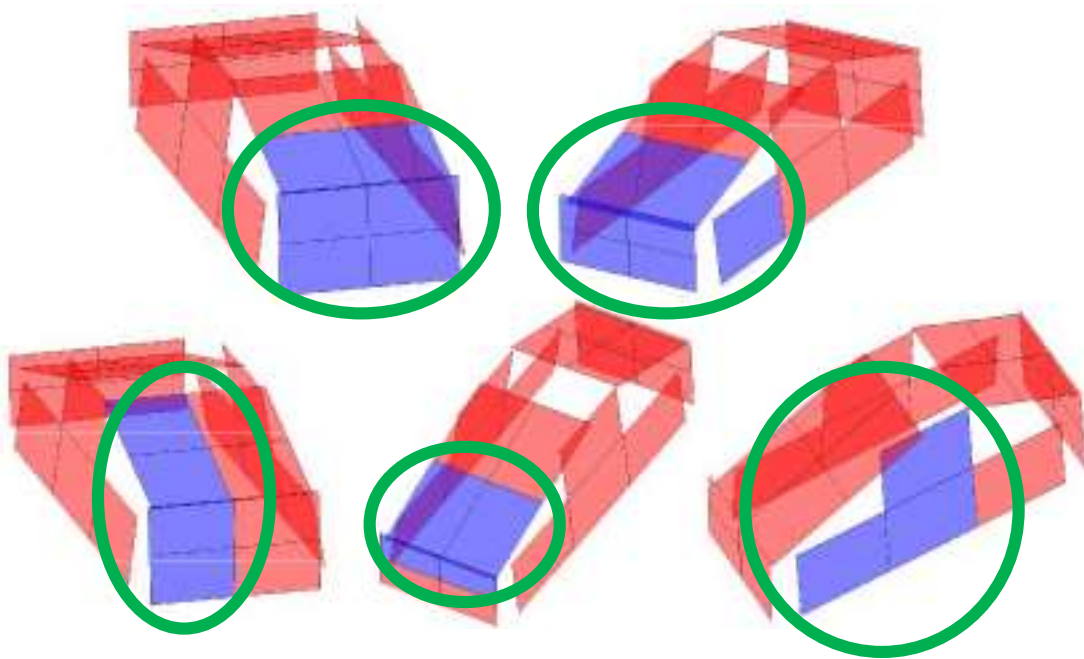
3D Aspectlet Representation



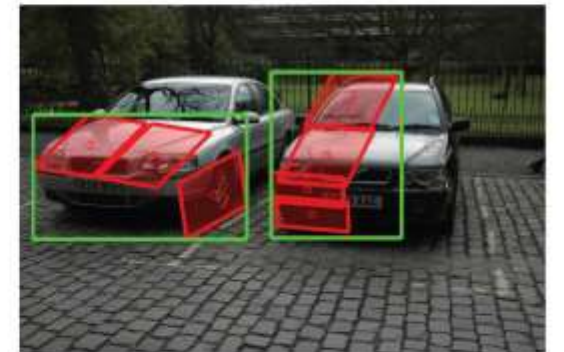
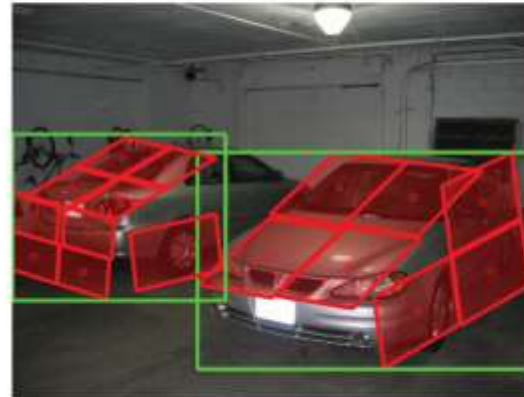
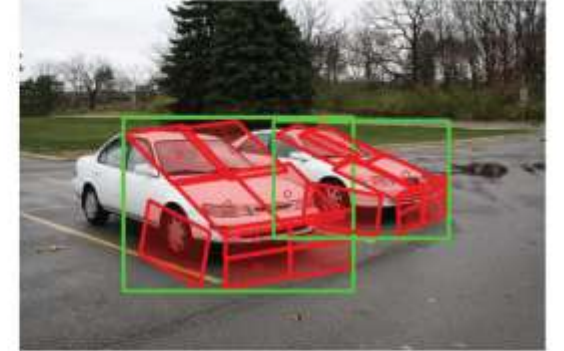
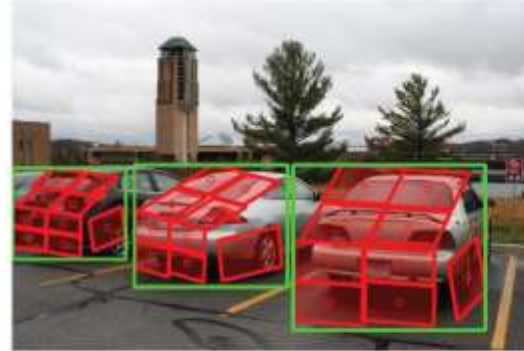
3D Aspect Parts

Atomic 3D Aspect Parts

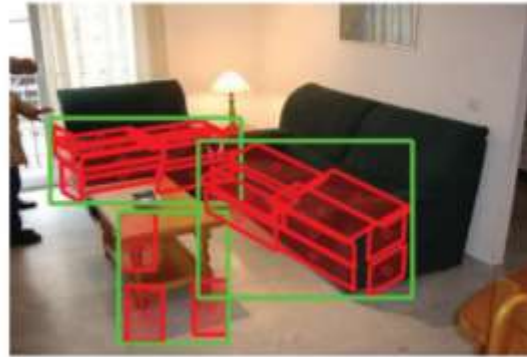
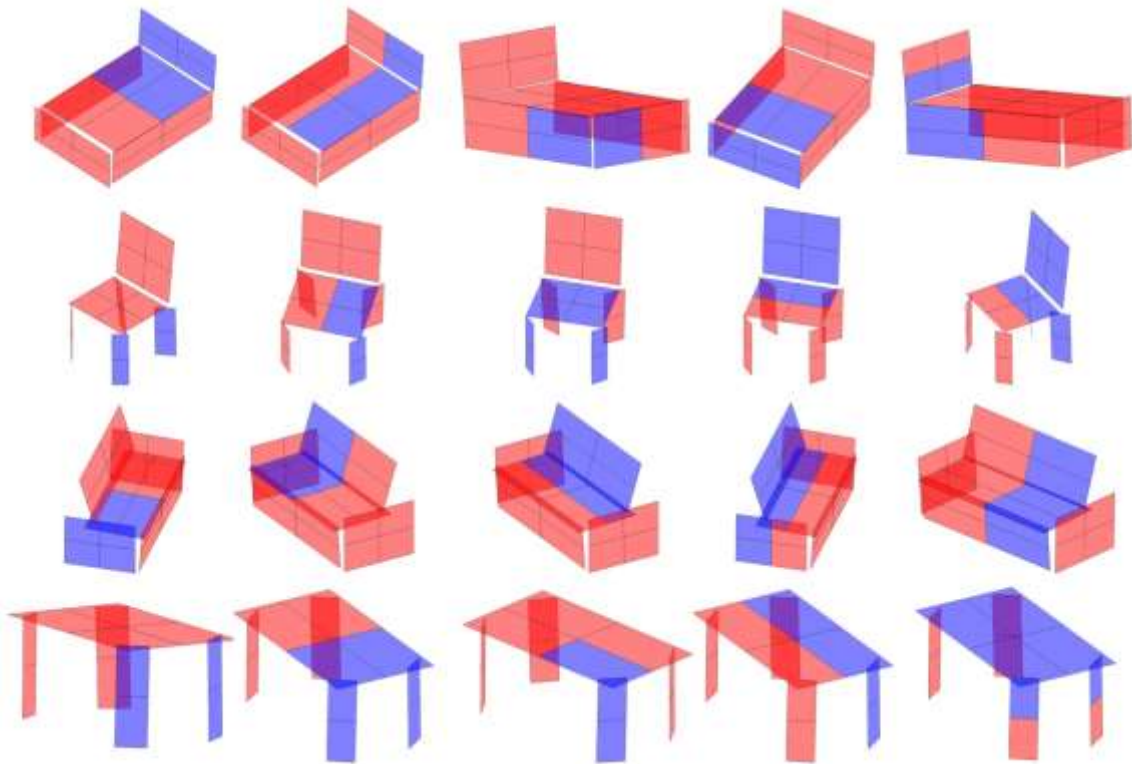
3D Aspectlet Representation



3D Aspectlets



3D Aspectlet Representation



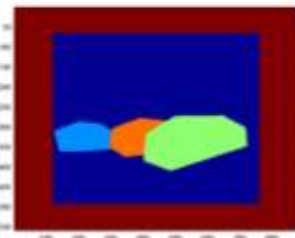
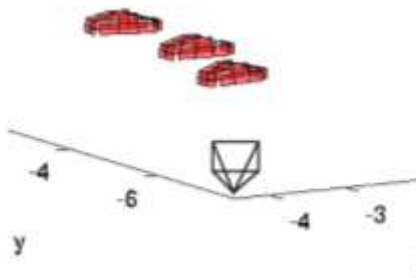
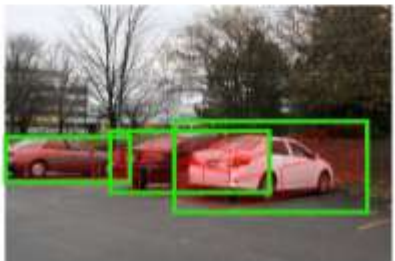
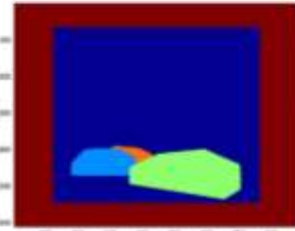
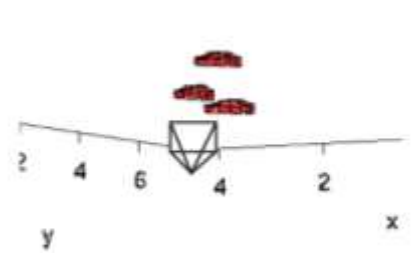
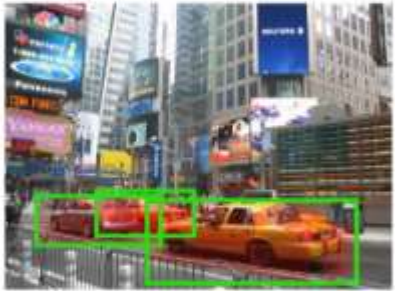
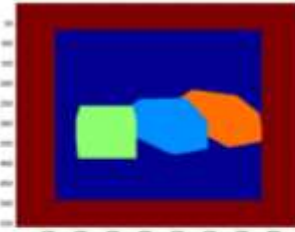
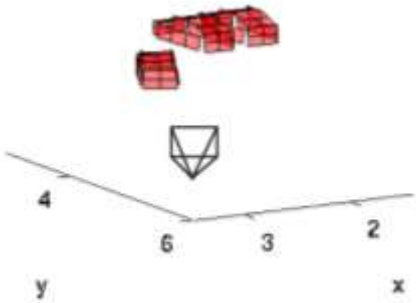
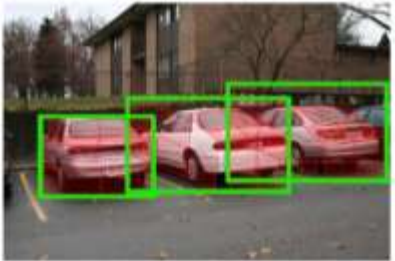
Object Detection Experiments

Dataset	Outdoor-scene			Indoor-scene		
% occlusion	< 0.3	0.3 – 0.6	> 0.6	<0.2	0.2-0.4	>0.4
# images	66	68	66	77	111	112
ALM [1]	72.3	42.9	35.5	38.5	25.0	20.2
DPM [2]	75.9	58.6	44.6	38.0	22.9	21.9
Ours 3D Aspectlets	80.2	63.3	52.9	45.9	34.5	28.0

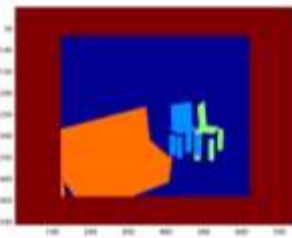
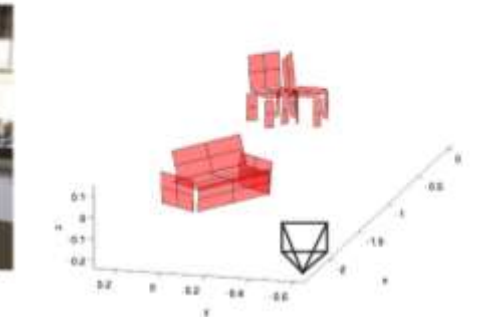
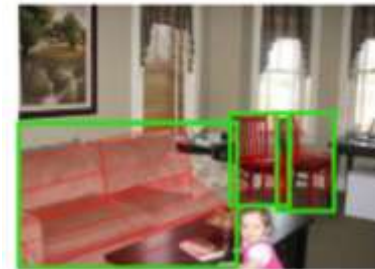
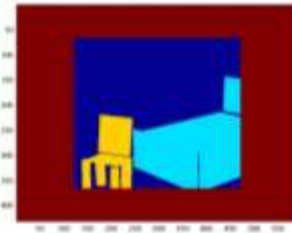
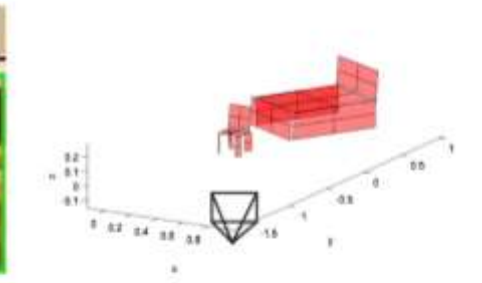
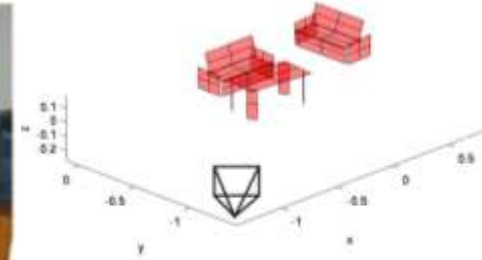
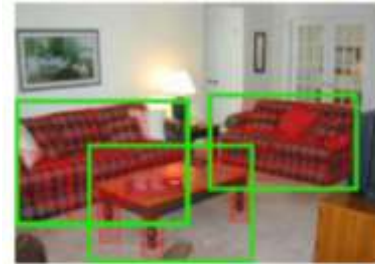
[1] Y. Xiang and S. Savarese. Estimating the aspect layout of object categories. In CVPR, 2012.

[2] P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan. Object detection with discriminatively trained part-based models. TPAMI, 2010.

Object Detection Experiments



Outdoor Scenes

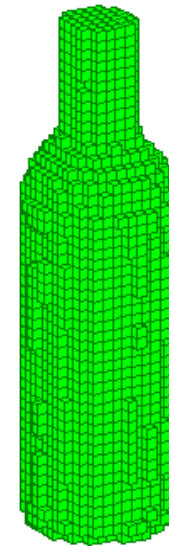
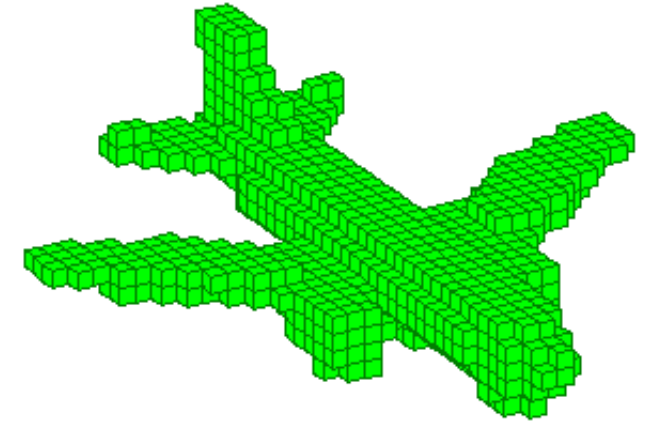


Indoor Scenes

Outline

- 3D Aspect Part Representation
- 3D Aspectlet Representation
- **3D Voxel Pattern Representation**
- Conclusion and Future Work

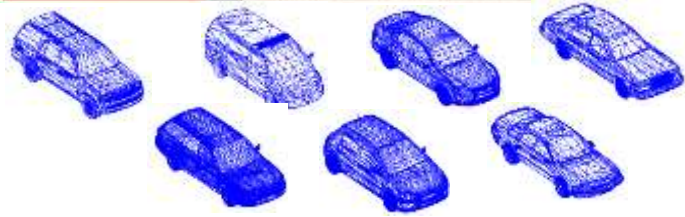
What are the 3D aspect parts for aeroplane and bottle?



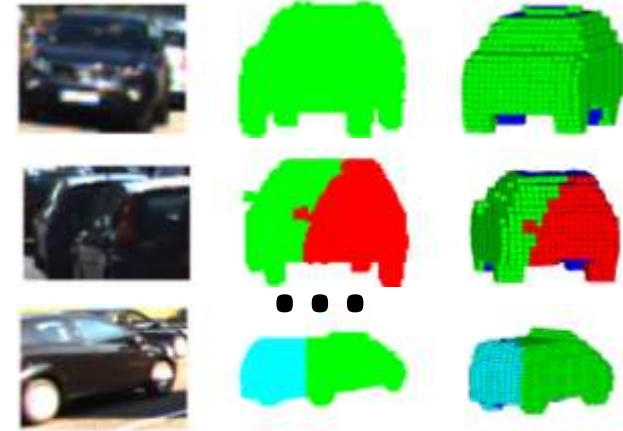
Data-Driven 3D Voxel Patterns



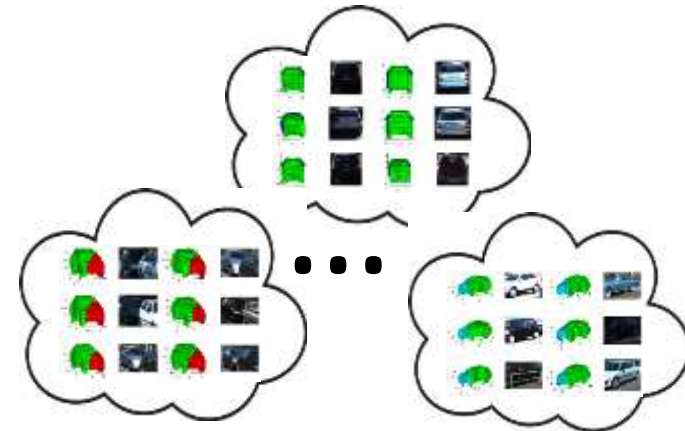
Training Pipeline Overview



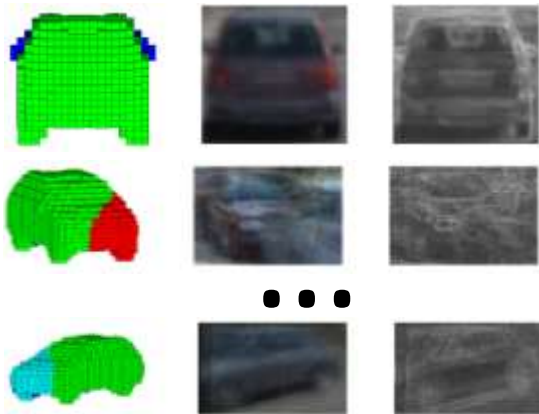
1. Align 2D images with 3D CAD models



2. 3D voxel exemplars

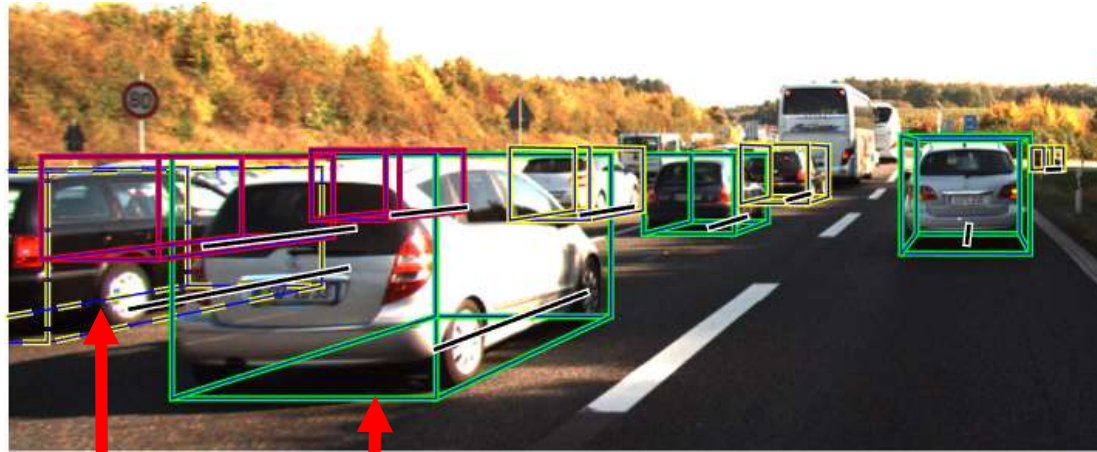


3. 3D voxel patterns

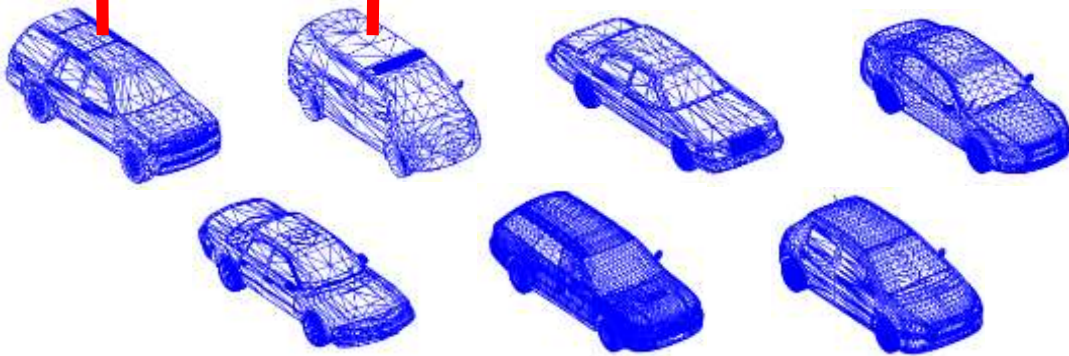


4. Training 3D voxel pattern detectors

1. Align 2D Images with 3D CAD Models



3D annotations ...



3D CAD models

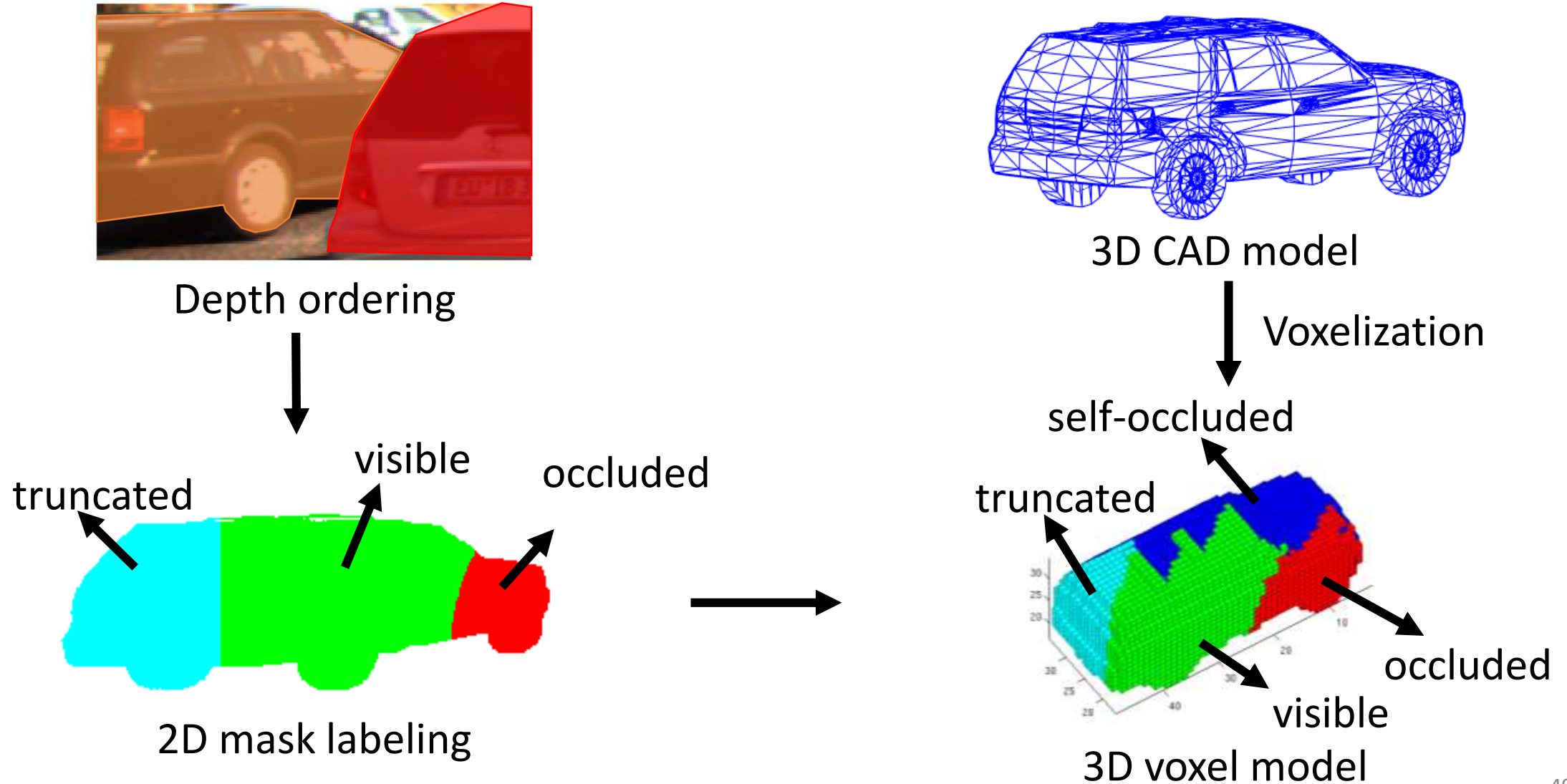


Project of 3D CAD models



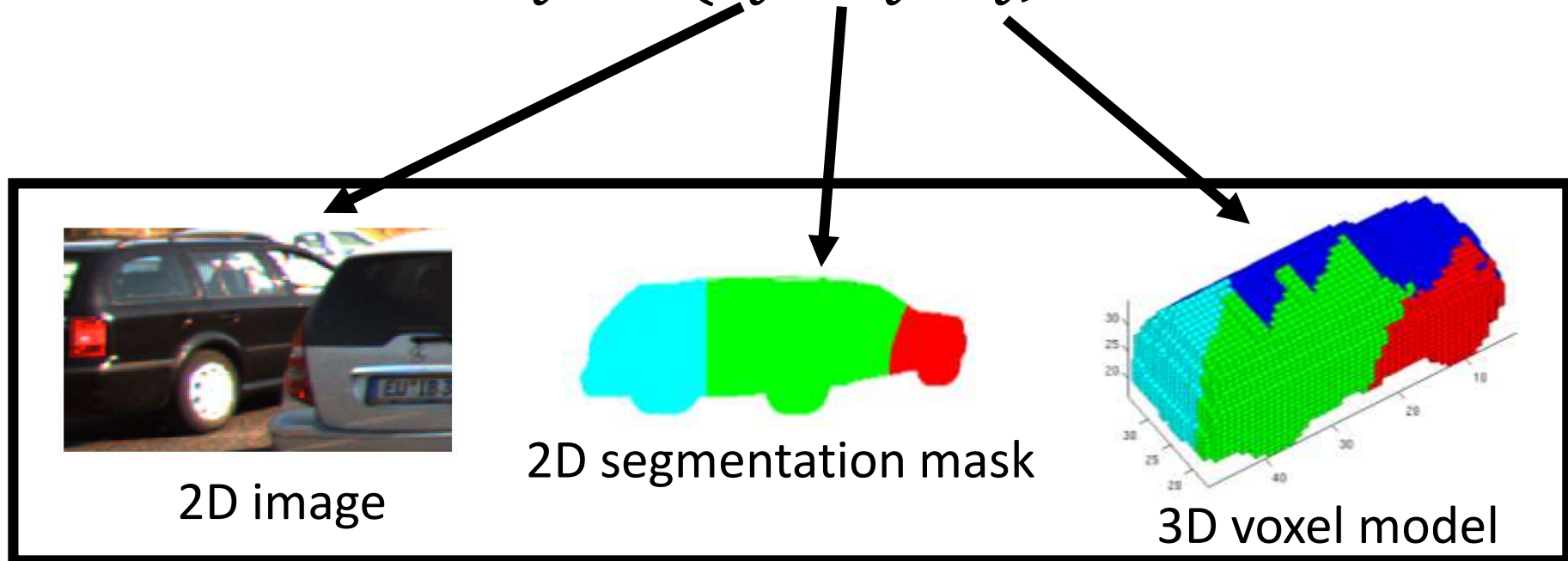
Depth ordering

2. Building 3D Voxel Exemplars



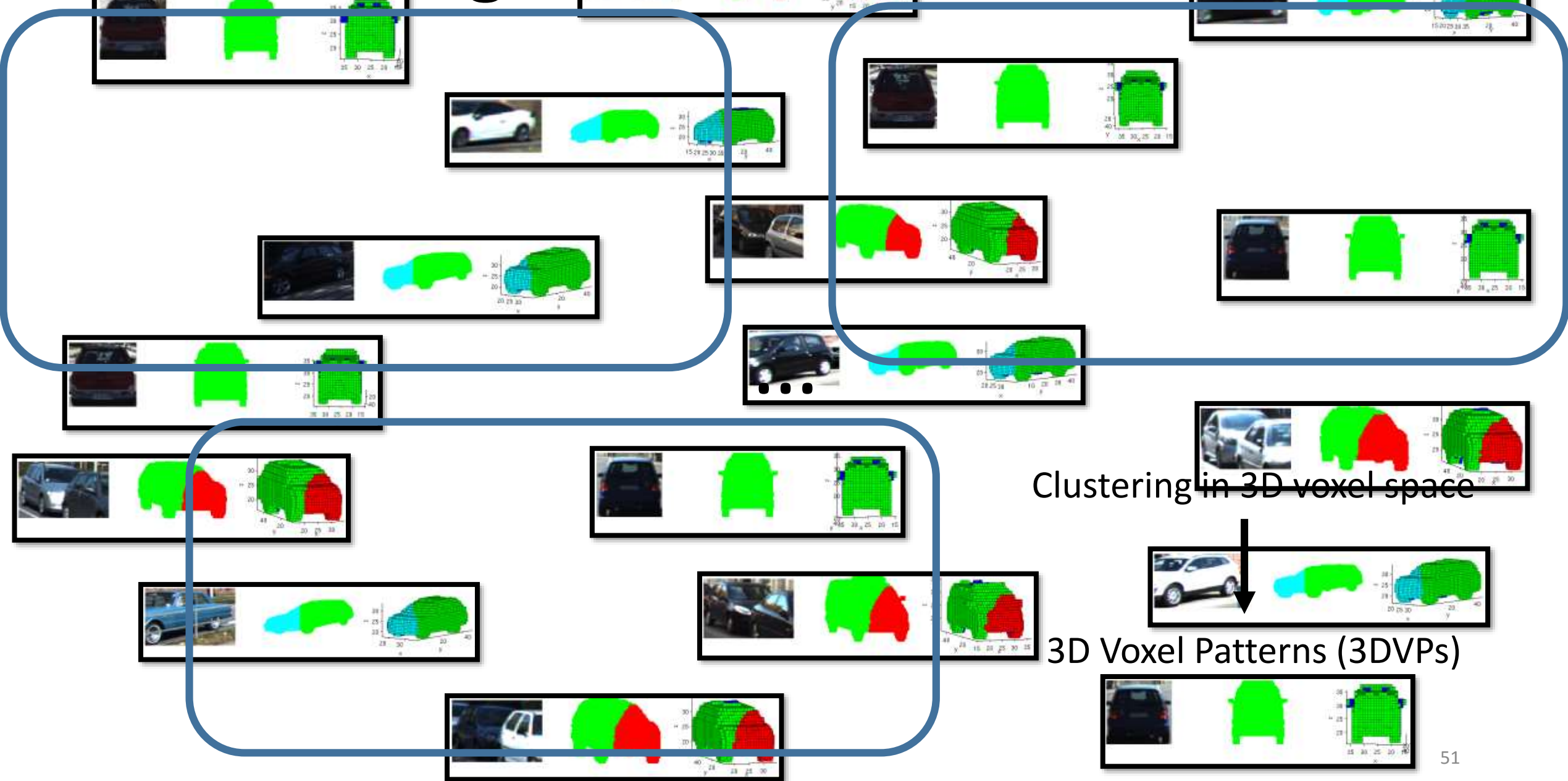
2. Building 3D Voxel Exemplars

A 3D voxel exemplar $E_i = (I_i, M_i, V_i)$

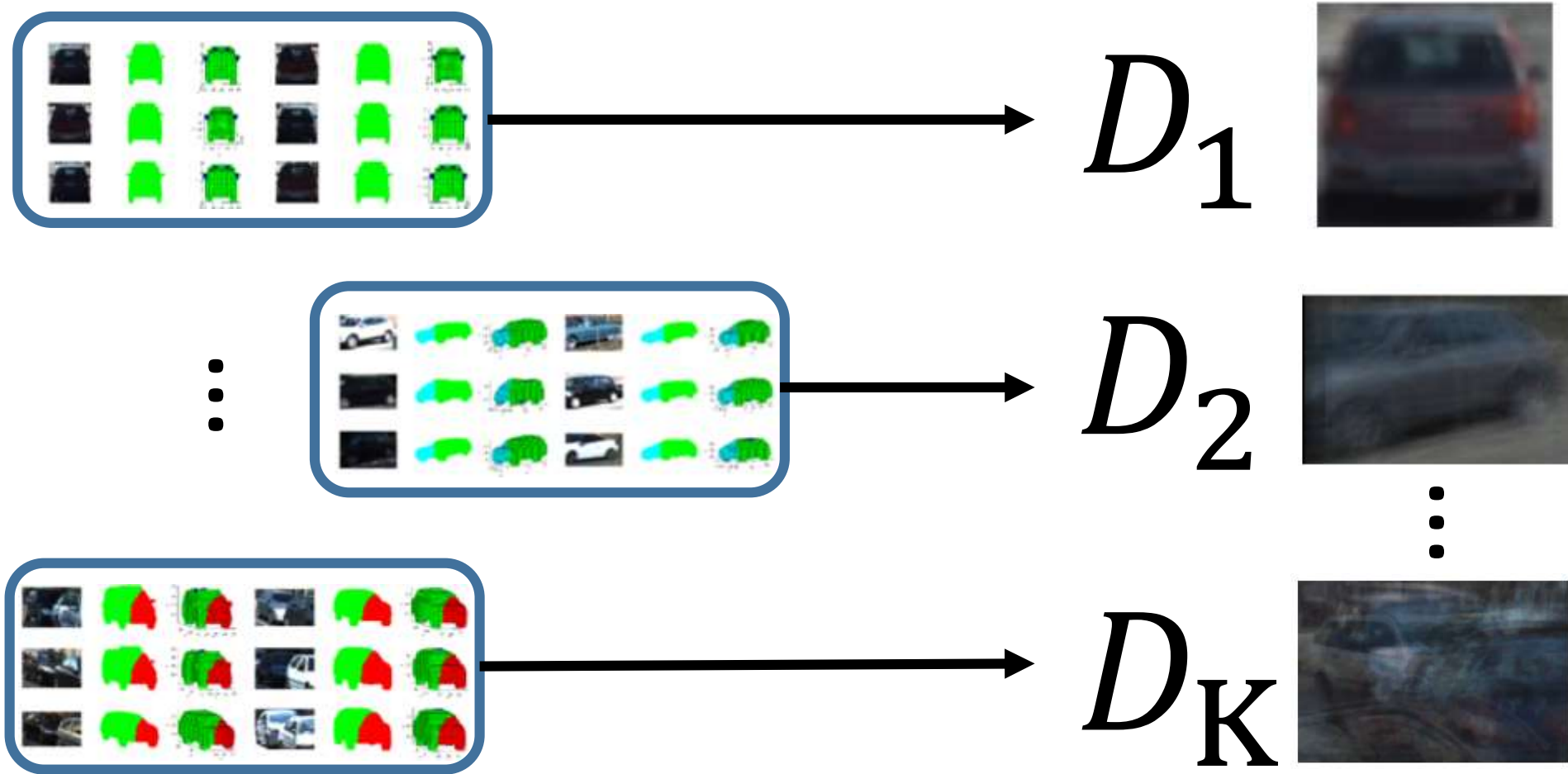


3D Voxel Exemplars

3. Discovering 3D Voxel Patterns

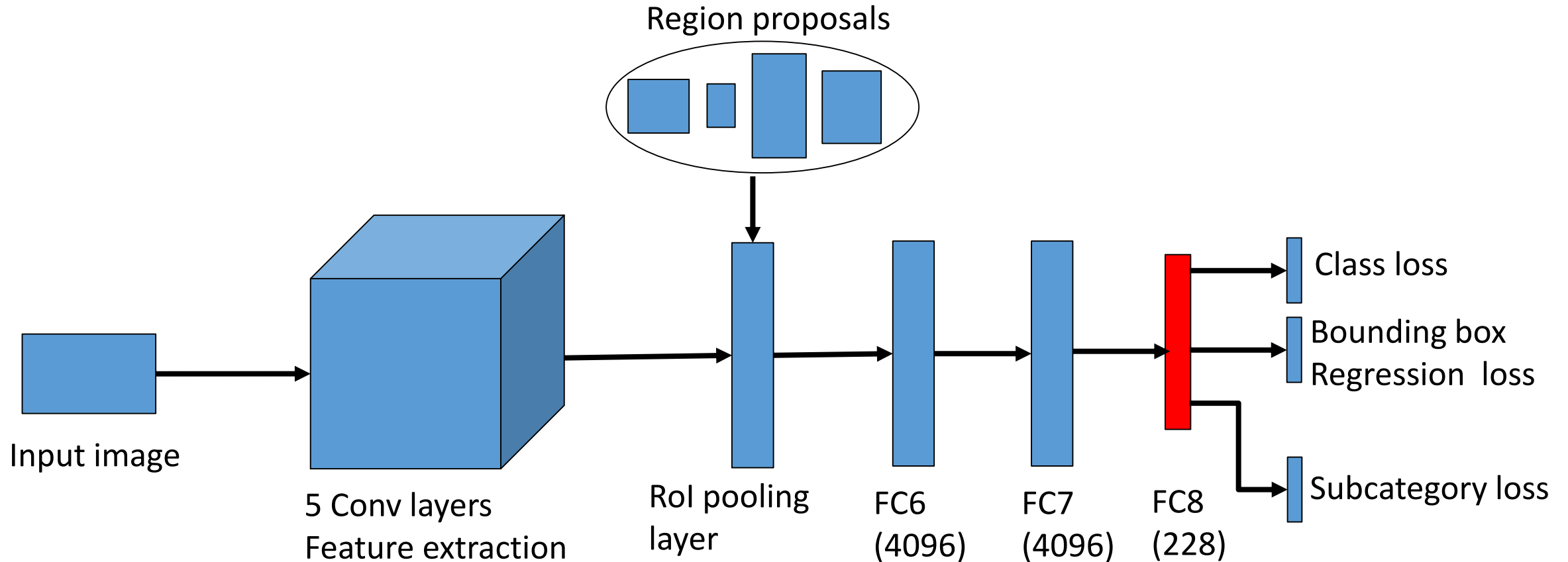


4. Training 3D Voxel Pattern detectors



- Train a ACF detector for each 3DVP.

4. Training 3D Voxel Pattern detectors



- Train a Convolutional Neural Network (CNN) for 3DVPs.

Under review

Testing Pipeline Overview



Input 2D image

1. Apply 3DVP detectors



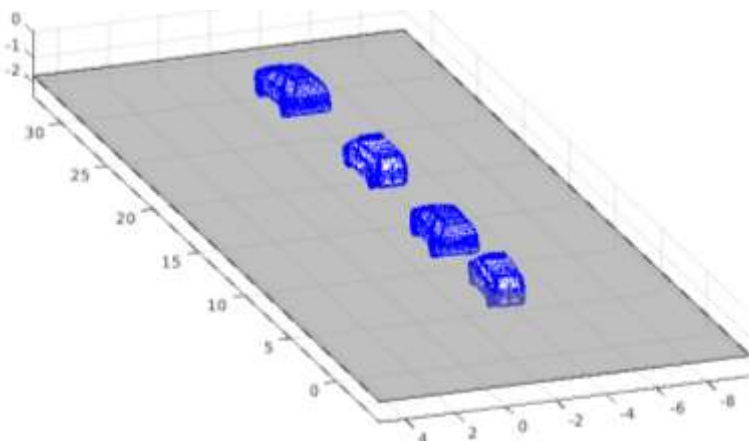
2D detection

2. Transfer meta-data
3. Occlusion reasoning



2D segmentation

4. Backproject to 3D

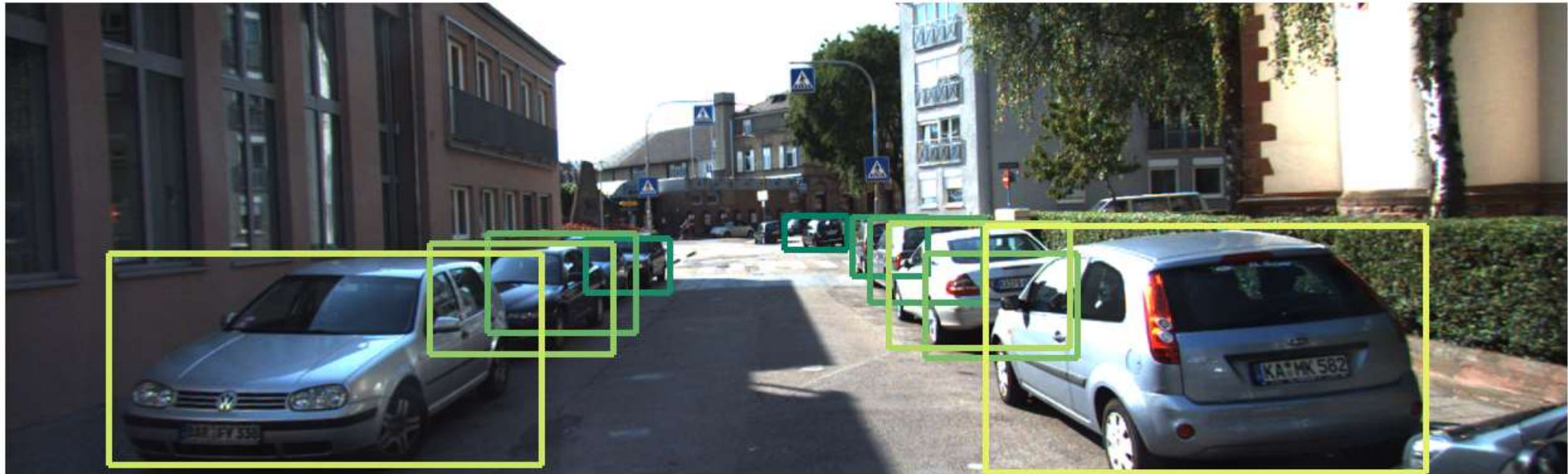


3D localization

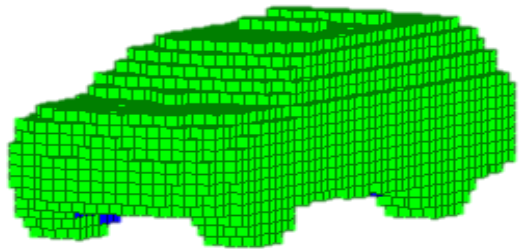
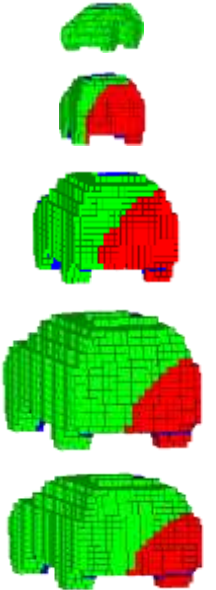
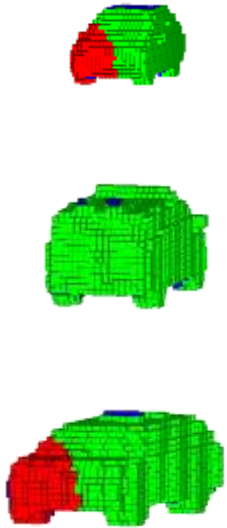
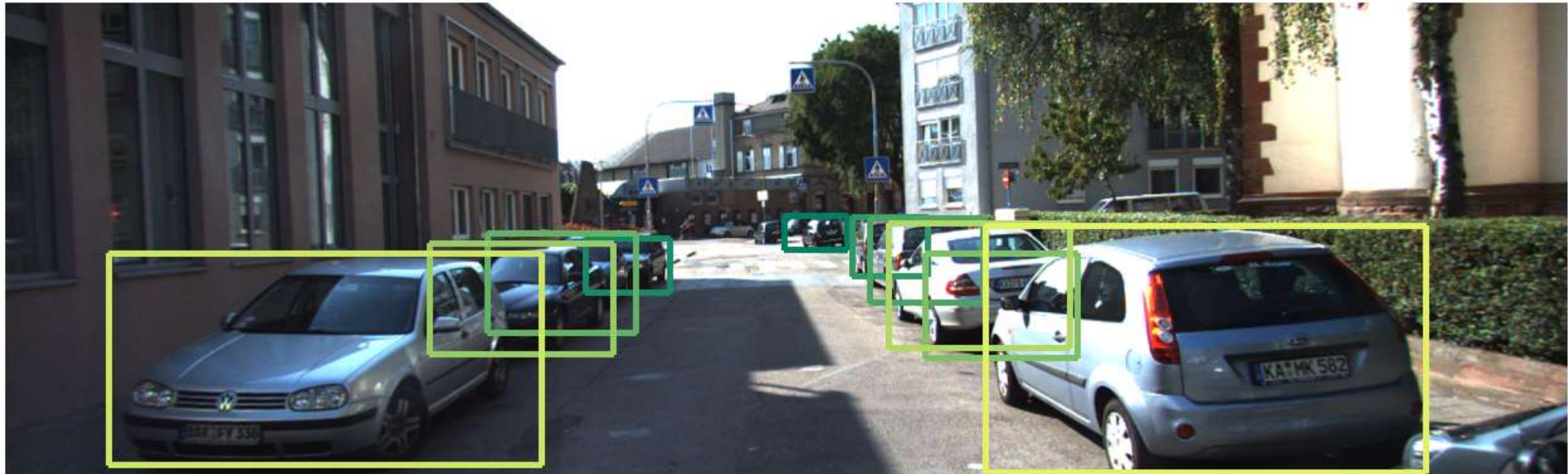
1. Apply 3DVP Detectors



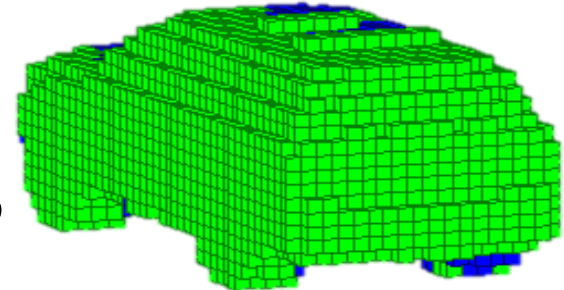
1. Apply 3DVP Detectors



2. Transfer Meta-Data



3D Voxel Patterns



2. Transfer Meta-Data



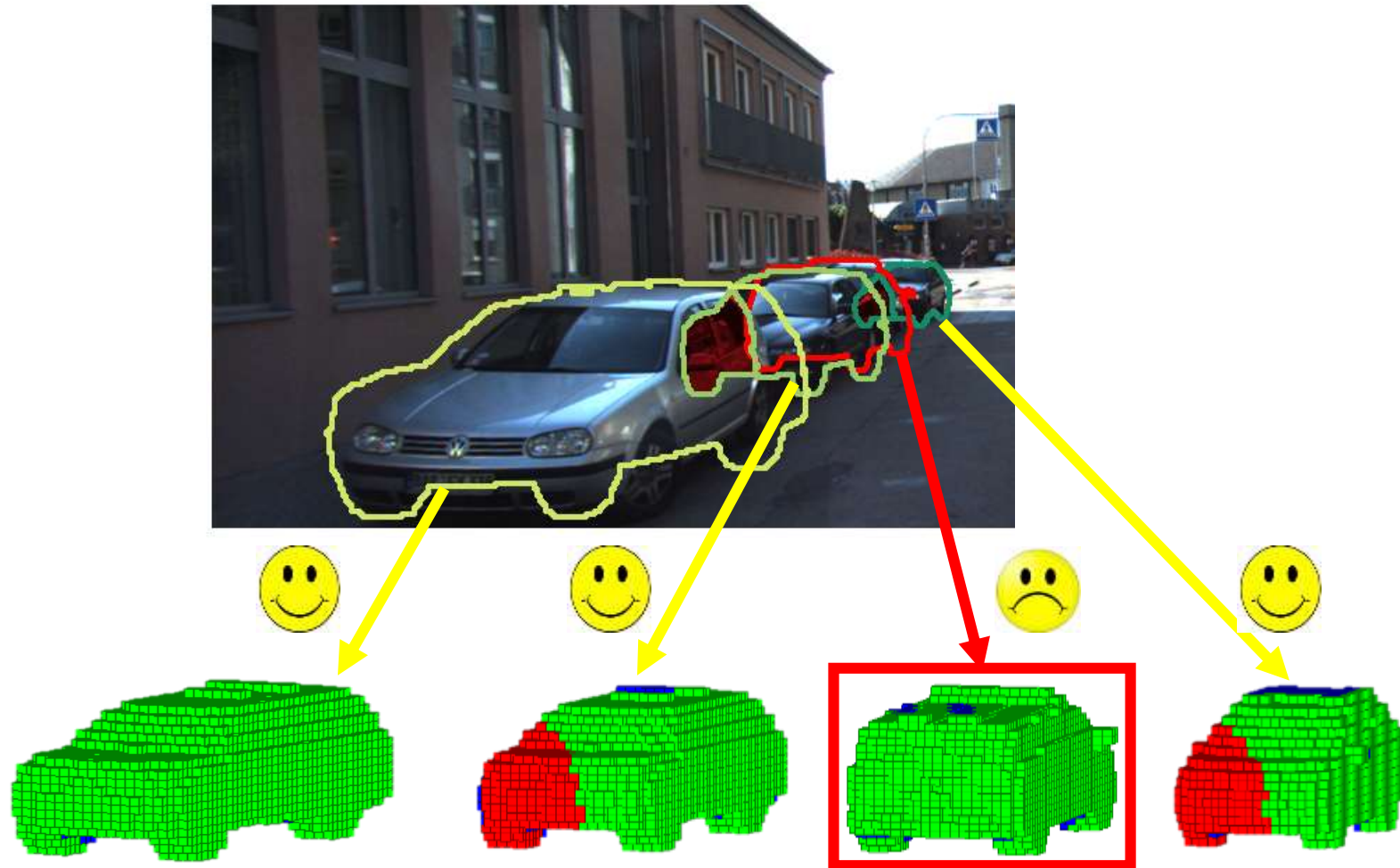
3. Occlusion Reasoning

Occlusion reasoning: find a set of visibility-compatible detections

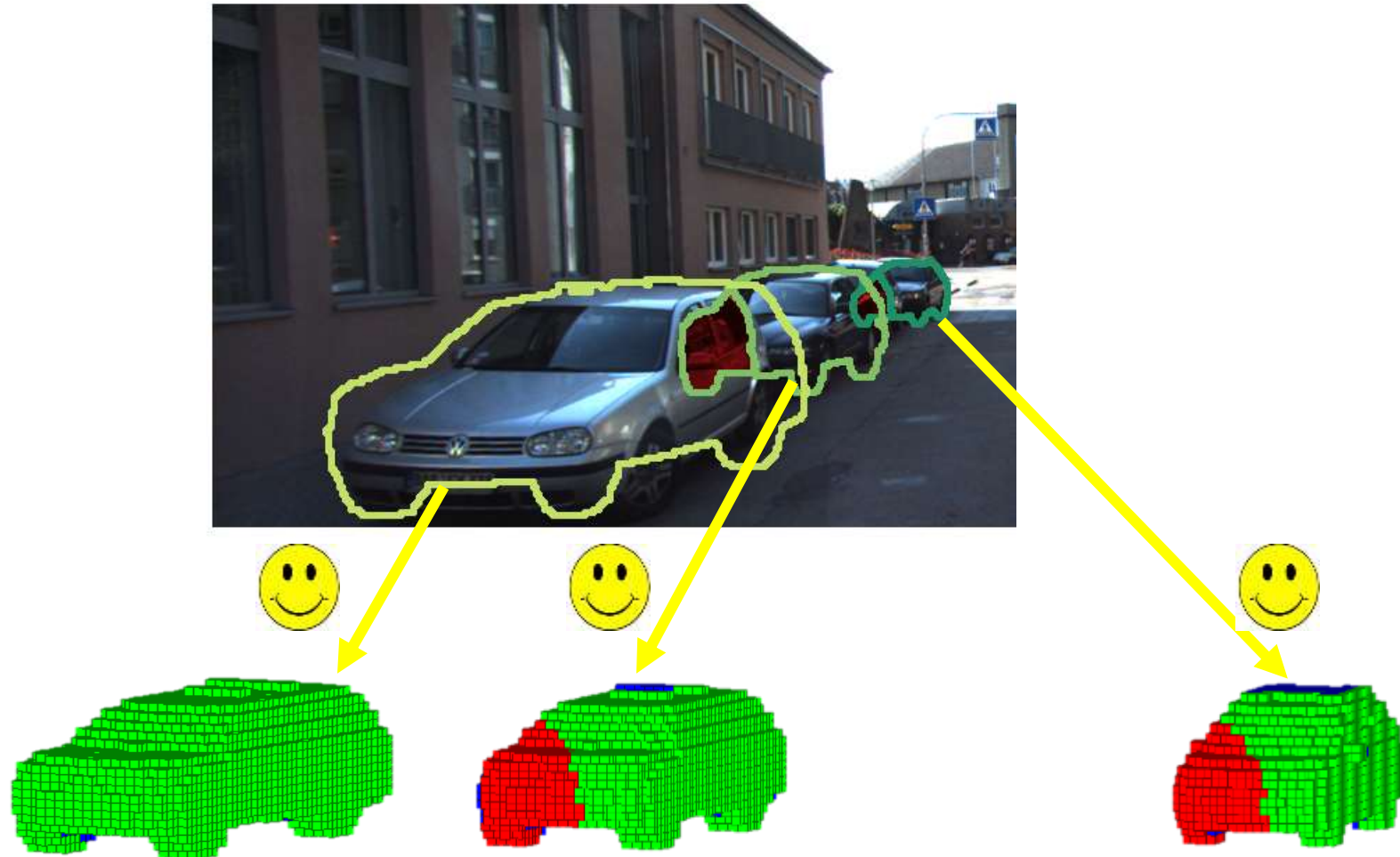


$$E = \sum_i (\psi_{\text{detection_score}} + \psi_{\text{truncation}}) + \sum_{ij} \psi_{\text{occlusion}}$$

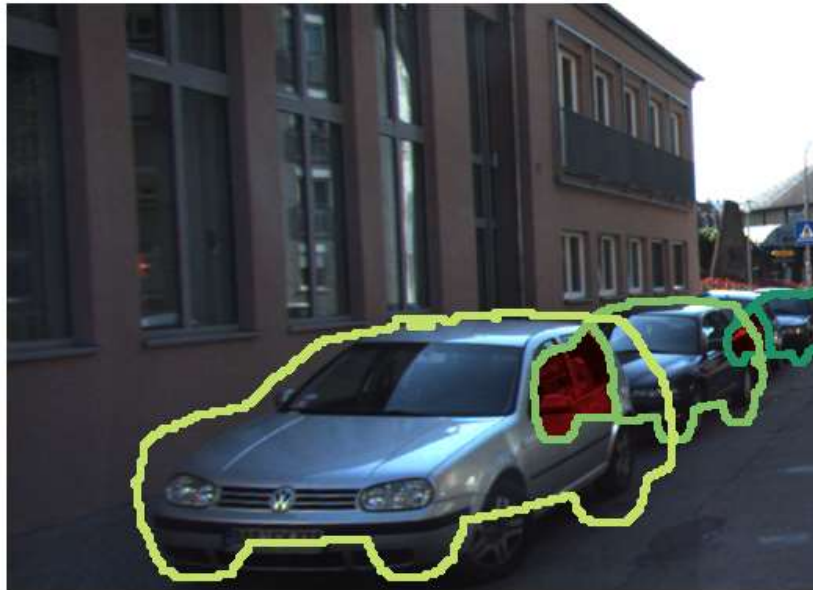
3. Occlusion Reasoning



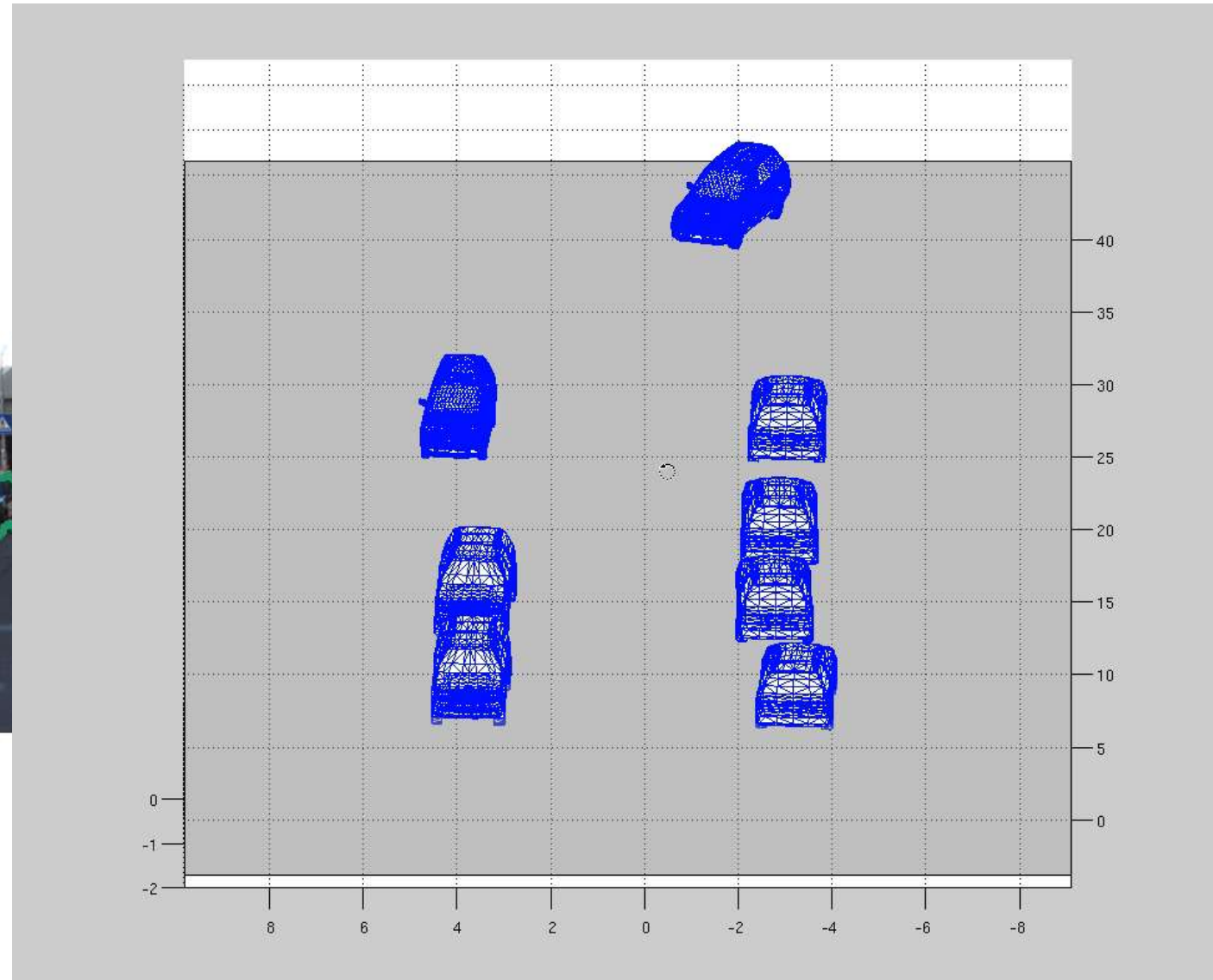
3. Occlusion Reasoning



4. 3D Localization



Backprojection



Car Detection and Orientation Estimation on KITTI

	Object Detection (AP)				Object Detection and Orientation estimation (AOS)		
Method	Easy	Moderate	Hard		Easy	Moderate	Hard
ACF [1]	55.89	54.77	42.98		N/A	N/A	N/A
DPM [2]	68.02	56.48	44.18		67.27	55.77	43.59
DPM-VOC+VP [3]	74.95	64.71	48.76		72.28	61.84	46.54
OC-DPM [4]	74.94	65.95	53.86		73.50	64.42	52.40
SubCat [5]	84.14	75.46	59.71		83.41	74.42	58.83
Regionlets [6]	84.75	76.45	59.70		N/A	N/A	N/A
AOG [7]	84.80	75.94	60.70		33.79	30.77	24.75
Ours 3DVP	84.81	73.02	63.22		84.31	71.99	62.11

[1] P. Dollár, R. Appel, S. Belongie, and P. Perona. Fast feature pyramids for object detection. TPAMI, 2014.

[2] P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan. Object detection with discriminatively trained part-based models. TPAMI, 2010.

[3] B. Pepik, M. Stark, P. Gehler, and B. Schiele. Multi-view and 3d deformable part models. TPAMI, 2015.

[4] B. Pepik, M. Stark, P. Gehler, and B. Schiele. Occlusion patterns for object class detection. In CVPR, 2013.

[5] E. Ohn-Bar and M. M. Trivedi. Learning to detect vehicles by clustering appearance patterns. T-ITS, 2015.

[6] X. Wang, M. Yang, S. Zhu, and Y. Lin. Regionlets for generic object detection. In ICCV, 2013.

[7] B. Li, T. Wu, and S.-C. Zhu. Integrating context and occlusion for car detection by hierarchical and-or model. In ECCV, 2014.

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- [1] P. Dollár, R. Appel, S. Belongie, and P. Perona. Fast feature pyramids for object detection. TPAMI, 2014.
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- [4] B. Pepik, M. Stark, P. Gehler, and B. Schiele. Occlusion patterns for object class detection. In CVPR, 2013.
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Ours CNN	90.74	88.55	77.95		90.49	87.88	77.10

[1] P. Dollár, R. Appel, S. Belongie, and P. Perona. Fast feature pyramids for object detection. TPAMI, 2014.

[2] P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan. Object detection with discriminatively trained part-based models. TPAMI, 2010.

[3] B. Pepik, M. Stark, P. Gehler, and B. Schiele. Multi-view and 3d deformable part models. TPAMI, 2015.

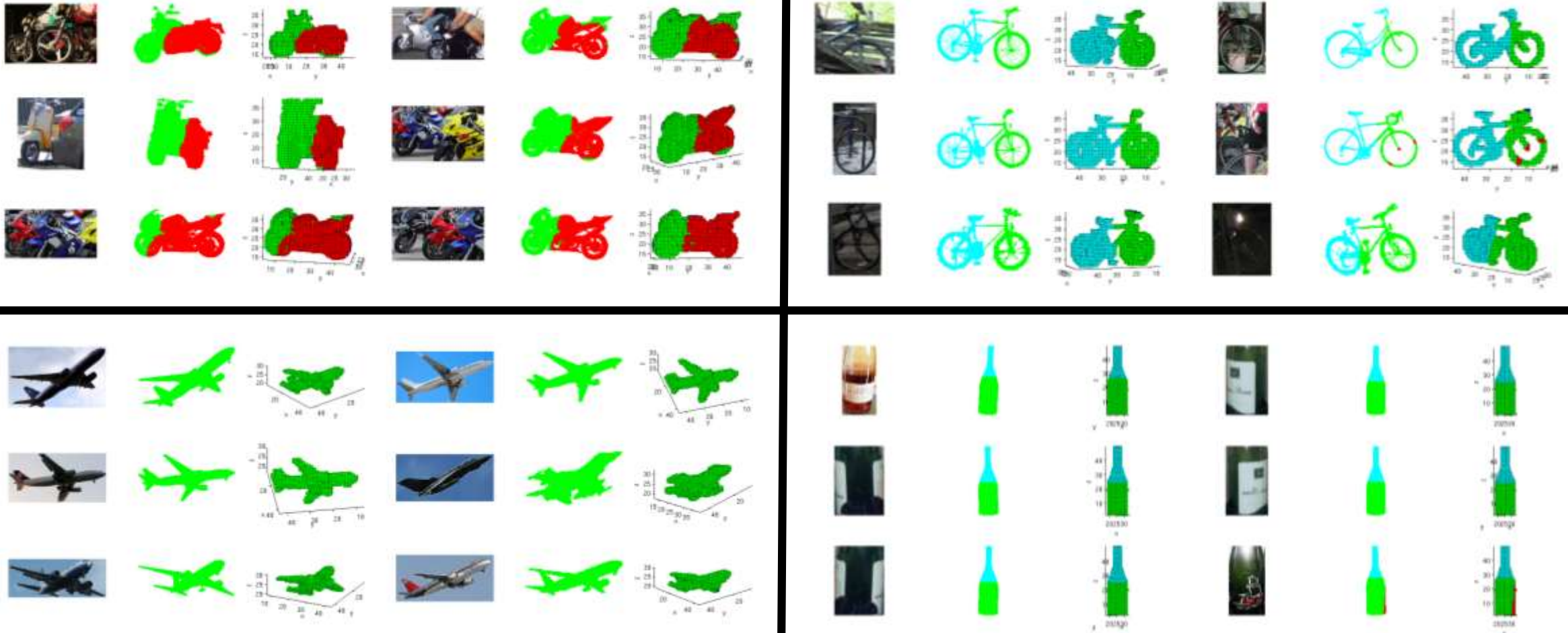
[4] B. Pepik, M. Stark, P. Gehler, and B. Schiele. Occlusion patterns for object class detection. In CVPR, 2013.

[5] E. Ohn-Bar and M. M. Trivedi. Learning to detect vehicles by clustering appearance patterns. T-ITS, 2015.

[6] X. Wang, M. Yang, S. Zhu, and Y. Lin. Regionlets for generic object detection. In ICCV, 2013.

[7] B. Li, T. Wu, and S.-C. Zhu. Integrating context and occlusion for car detection by hierarchical and-or model. In ECCV, 2014.

3D Voxel Patterns from PASCAL3D+ [1]



12 Rigid Categories

Detection and Pose Estimation on PASCAL3D+

Method	Detection (AP)
DPM [1]	29.6
R-CNN [2]	56.9
Ours CNN	60.7

Method	4 Views (AVP)	8 Views (AVP)	16 Views (AVP)	24 Views (AVP)
VDPM [3]	19.5	18.7	15.6	12.1
DPM-VOC+VP [4]	24.5	22.2	17.9	14.4
Ours CNN	47.5	31.9	24.5	19.3

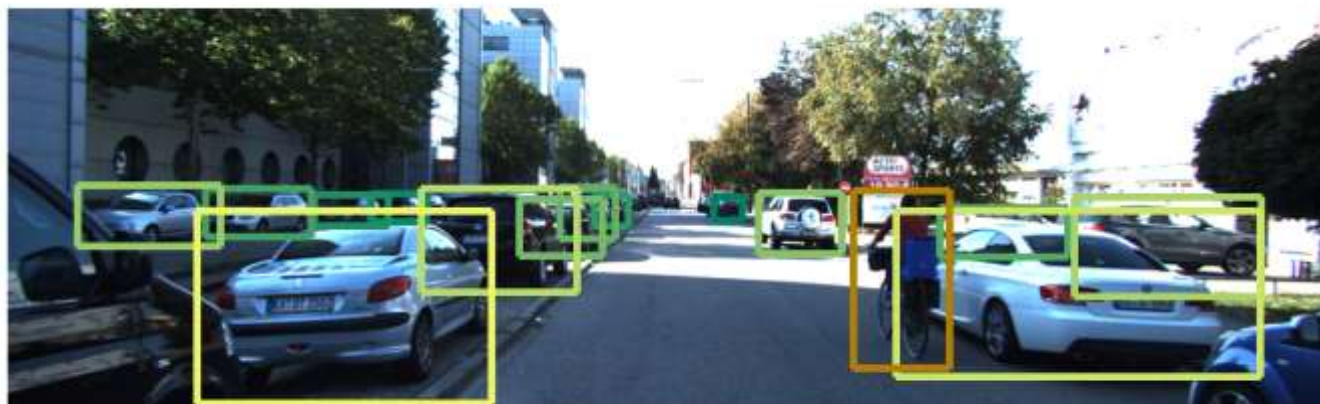
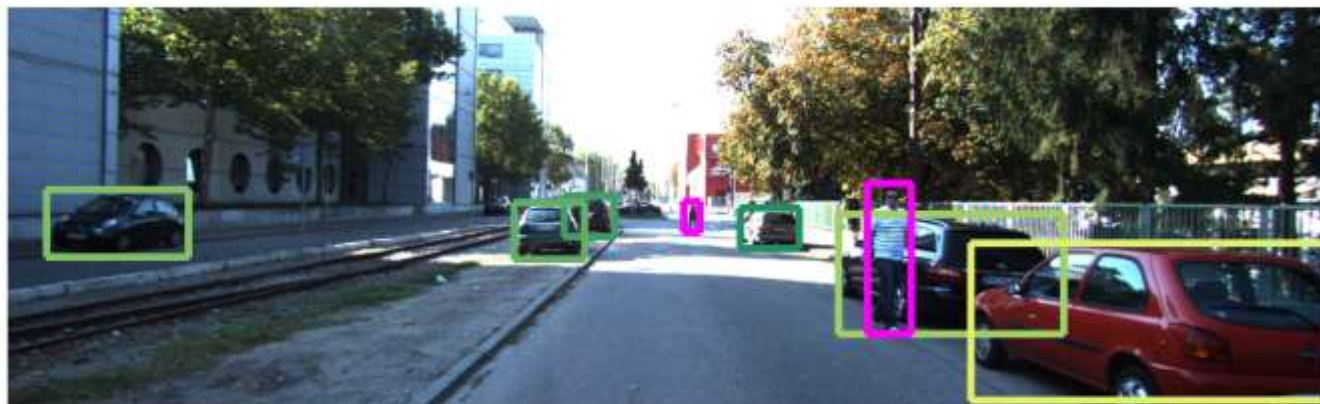
[1] P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan. Object detection with discriminatively trained part-based models. TPAMI, 2010.

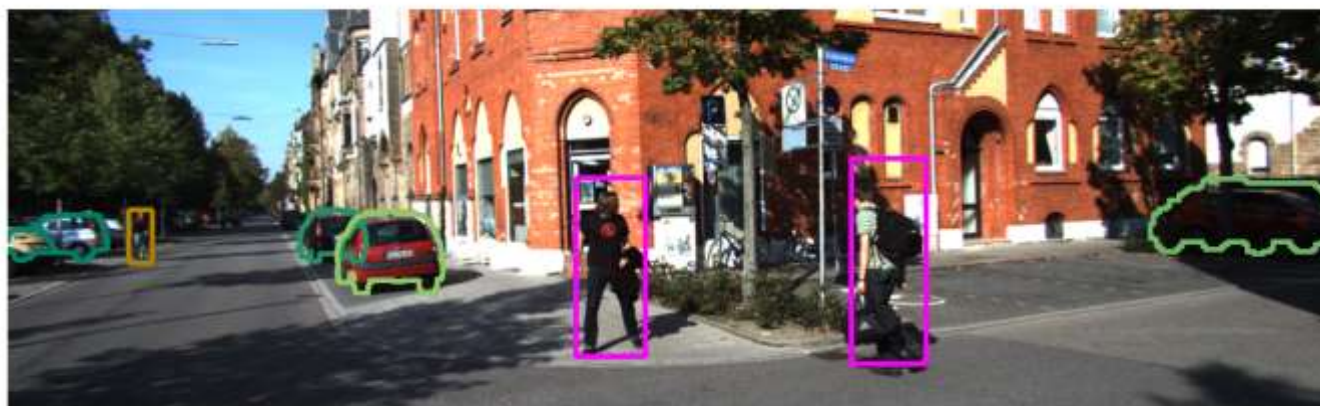
[2] R. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. arXiv preprint arXiv:1311.2524, 2013.

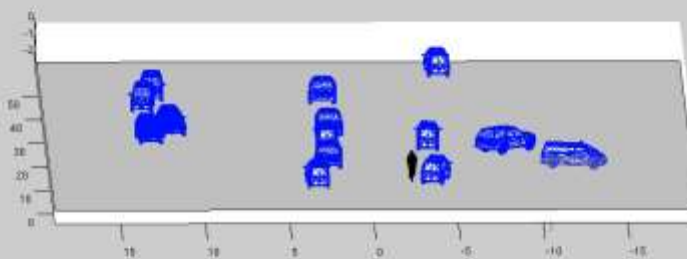
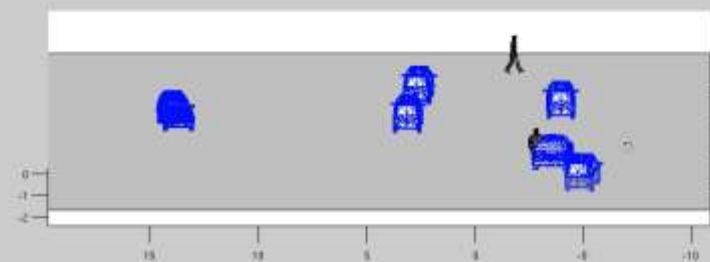
[3] Y. Xiang, R. Mottaghi, and S. Savarese. Beyond pascal: A benchmark for 3d object detection in the wild. In WACV, 2014.

[4] B. Pepik, M. Stark, P. Gehler, and B. Schiele. Multi-view and 3d deformable part models. TPAMI, 2015.



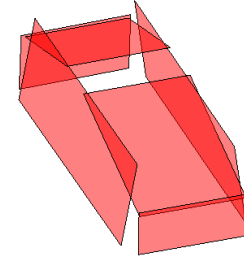




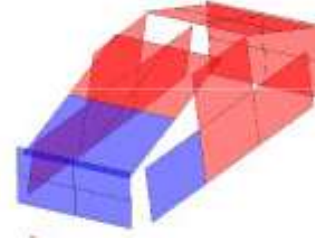


Conclusion

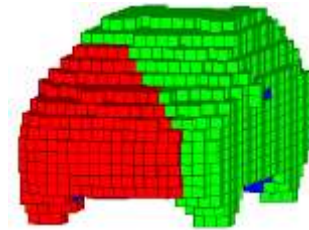
- 3D aspect part representation



- 3D aspectlet representation



- 3D voxel pattern representation



Open Questions

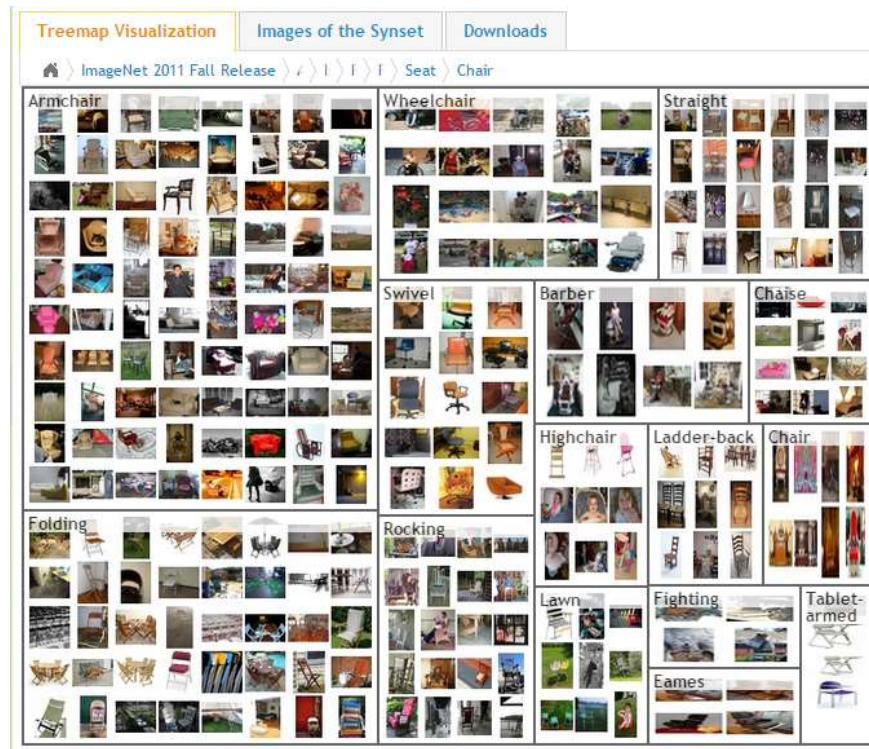
- How to scale up and benchmark 3D object recognition and scene understanding?
- How to combine deep learning with 3D representations for recognition?
- How to utilize videos and unlabeled data for 3D recognition?
- How to interact with the 3D world (affordance, action, decision)?

Ongoing Work

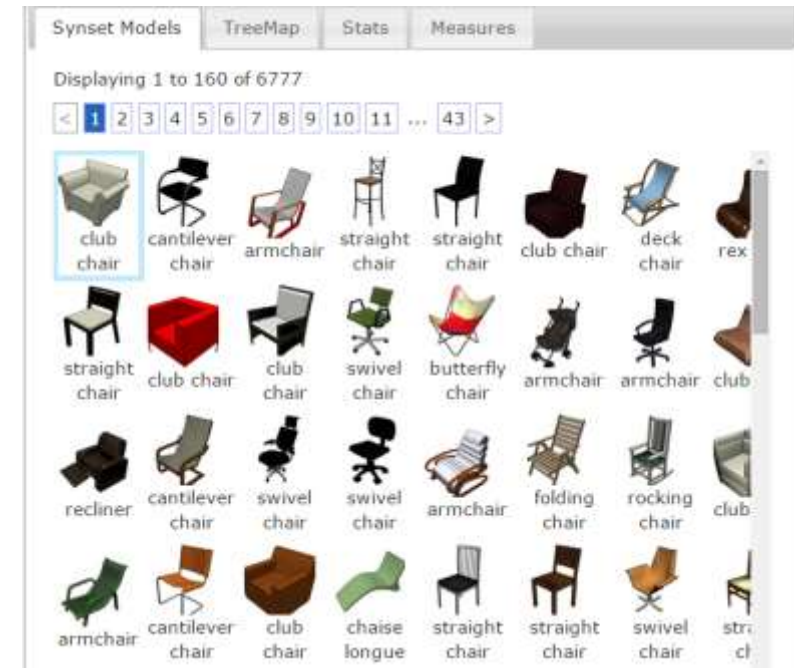
- A large scale dataset for 3D object recognition with 100 categories

ashtray	coffee_maker	fork	microphone	rifle	stove	bicycle
backpack	comb	guitar	microwave	road_pole	suitcase	boat
basket	computer	hair_dryer	mouse	satellite_dish	teapot	bottle
bed	cup	hammer	paintbrush	scissors	telephone	bus
bench	desk_lamp	headphone	pan	screwdriver	toaster	car
blackboard	dishwasher	helmet	pen	shoe	toilet	chair
bookshelf	door	iron	pencil	shovel	toothbrush	diningtable
bucket	eraser	jar	piano	sign	trash_bin	motorbike
cabinet	eyeglasses	kettle	pillow	skate	trophy	sofa
calculator	fan	key	plate	skateboard	tub	train
camera	faucet	keyboard	pot	slipper	vending_machine	tvmonitor
can	filing_cabinet	knife	printer	speaker	washing_machine	
cap	fire_extinguisher	laptop	racket	spoon	watch	
cellphone	fish_tank	lighter	refrigerator	stapler	wheelchair	
clock	flashlight	mailbox	remote_control	stove	aeroplane	

Ongoing Work



Images from ImageNet [1]



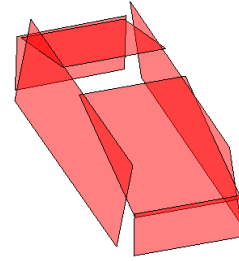
3D CAD models from ShapeNet [2]

[1] J. Deng, W. Dong, R. Socher, L.J. Li, K. Li and L. Fei-Fei. ImageNet: A Large-Scale Hierarchical Image Database. In CVPR'09.

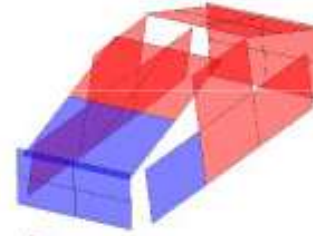
[2] ShapeNet. <http://shapenet.cs.stanford.edu/>

Conclusion

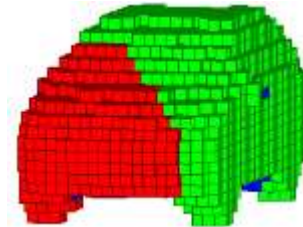
- 3D aspect part representation



- 3D aspectlet representation



- 3D voxel pattern representation



Thank you!

