

Factoring Scenes into 3D Structure and Style

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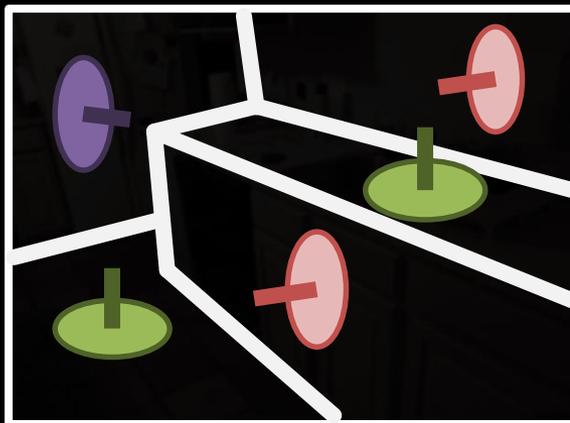


Image



3D Structure

What surfaces are where /
Underlying scene geometry



Style

Viewpoint-independent/
canonical texture
(fronto-parallel)



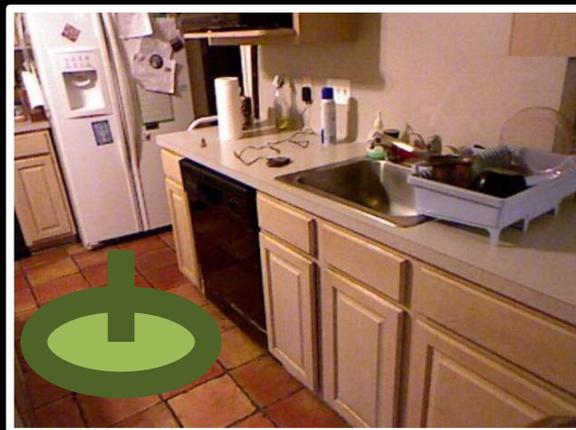
Example

Image



=

3D Structure



x

Style



You See...



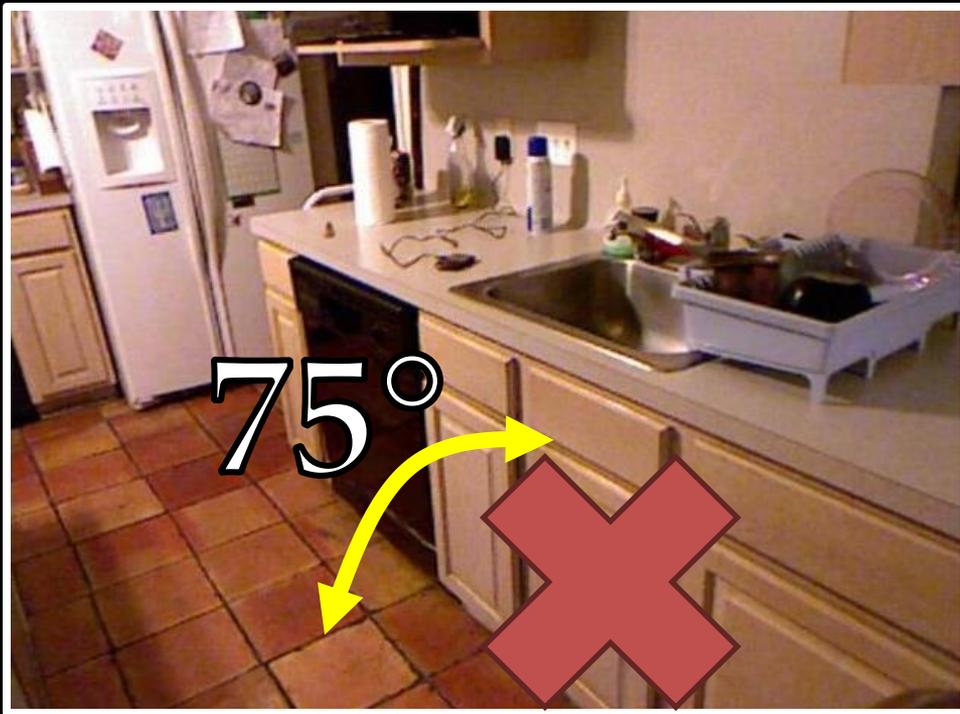
Unfortunately...



Why Can We Solve It?

Not all factorizations are equally likely!

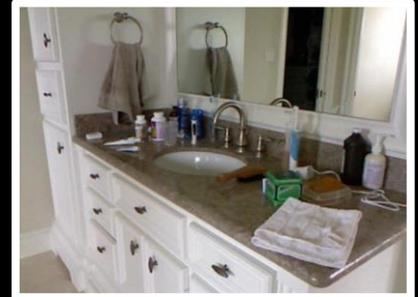
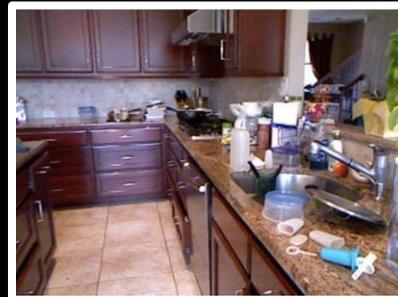
3D Structure



Style



Why Can We Solve It?



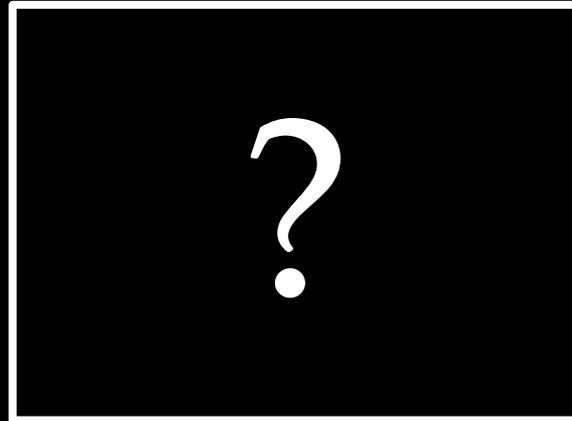
The Problem

Image



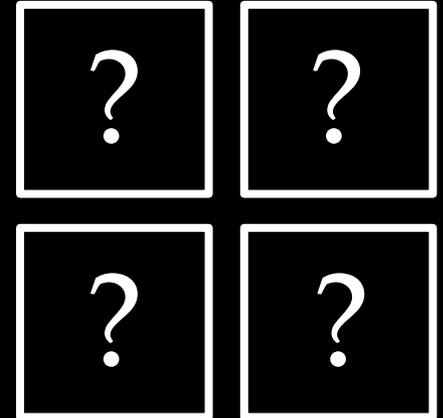
=

3D Structure



x

Style

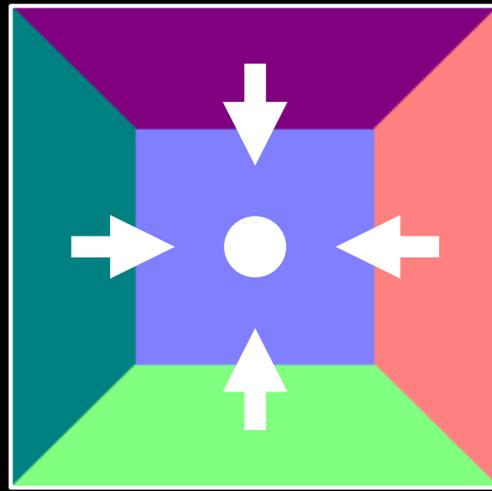


Representations/Visualization

3D Structure



Sample
Room



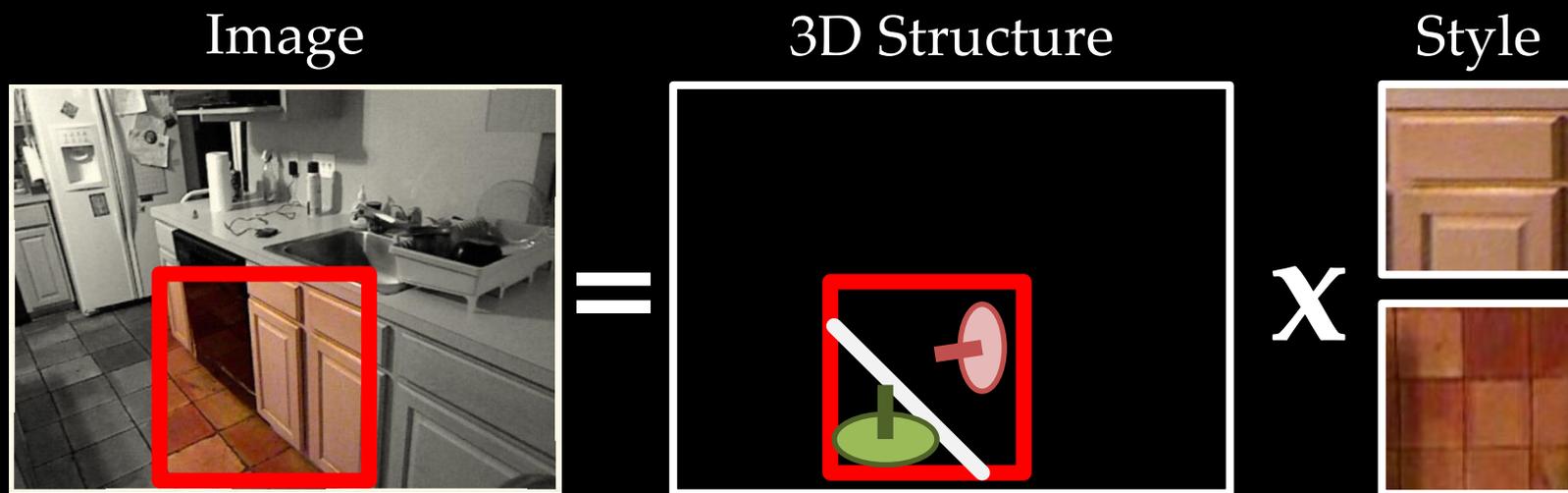
Surface Normal
Legend

Style



Contributions

Our First Contribution



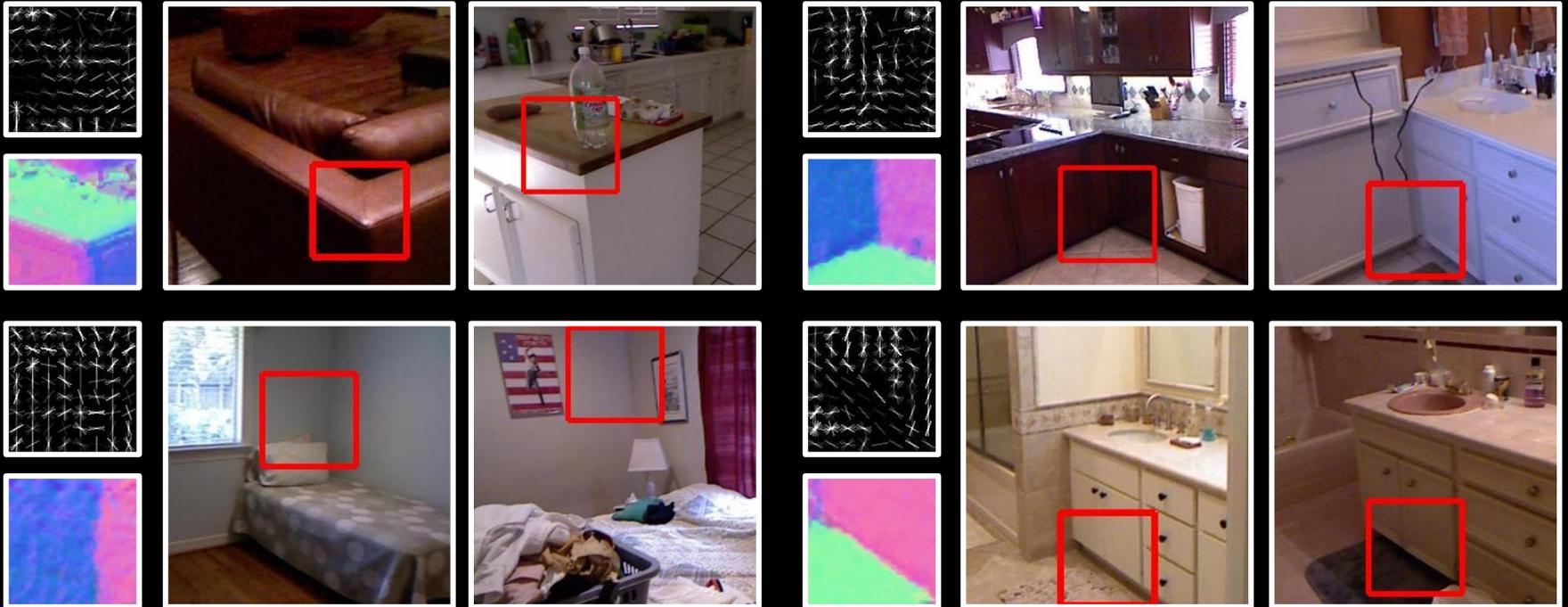
Data-Driven 3D Primitives for Single Image Understanding.
Fouhey, Gupta, Hebert. In ICCV '13.

Supervised Approach



Data-Driven 3D Primitives for Single Image Understanding.
Fouhey, Gupta, Hebert. In ICCV '13.

Supervised Approach



Data-Driven 3D Primitives for Single Image Understanding.
Fouhey, Gupta, Hebert. In ICCV '13.

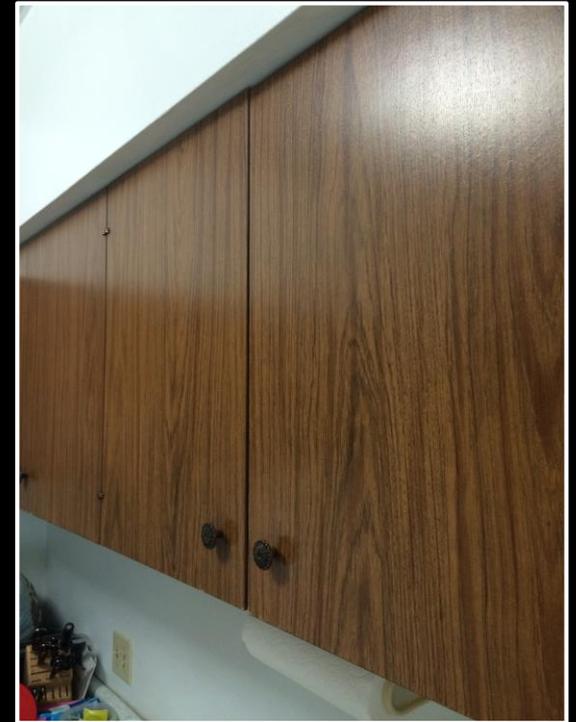
Supervised Approach



Data-Driven 3D Primitives for Single Image Understanding.
Fouhey, Gupta, Hebert. In ICCV '13.

Issue #1 – Data

Wasteful: no cross-viewpoint sharing



Solution

Explicit factorization via style elements:
cross-viewpoint and *do not require training data*

Style Element



Detections



Single Image 3D Without a Single 3D Image.
Fouhey, Hussain, Gupta, Hebert. In ICCV '15.

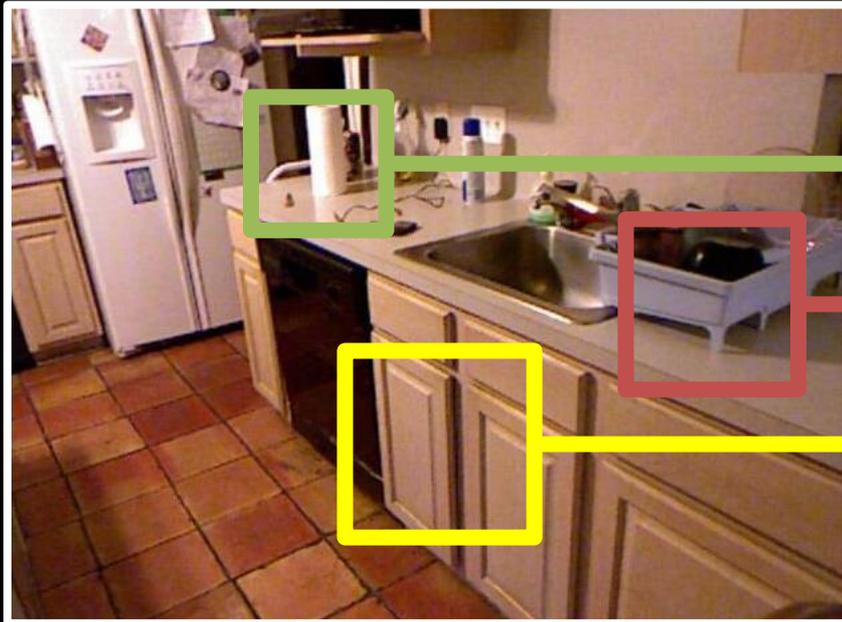
Issue #2

When do we apply domain knowledge/constraints?



Solution

Higher-order Shape Properties



“Cylindrical”

“Point Contact”

“Planar”

3D Shape Attributes.

Fouhey, Gupta, Zisserman. In CVPR '16.

Issue #3

World is much more constrained than per-pixel but more detailed than global properties.



Solution

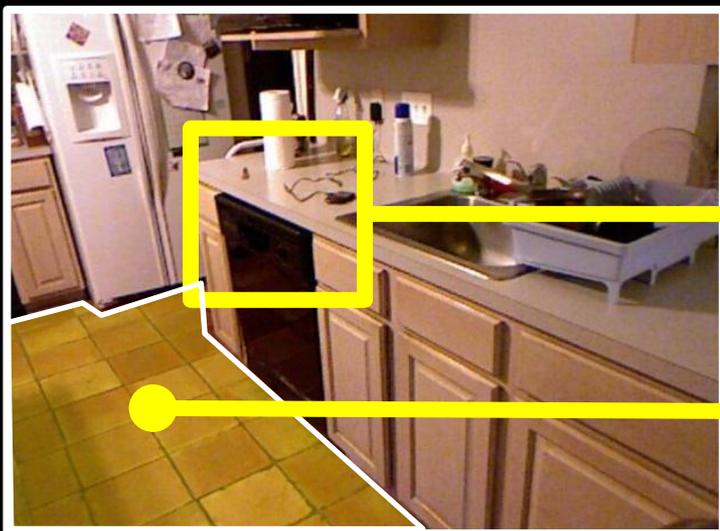
Mid-level constraints, discrete scene parses



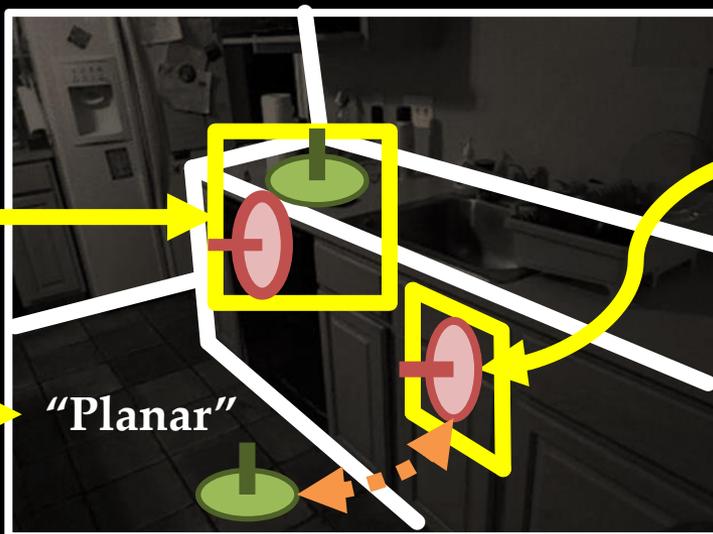
Unfolding an Indoor Origami World.
Fouhey, Gupta, Hebert. In ECCV '14.

Dissertation Contributions

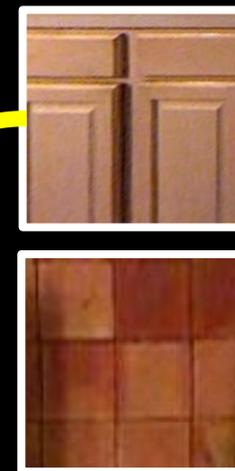
Image (3D Structure x Style)



3D Structure



Style



1. Local image-based cues

2. Local style-based cues

5. Data-driven dense normal estimation as a scene understanding task

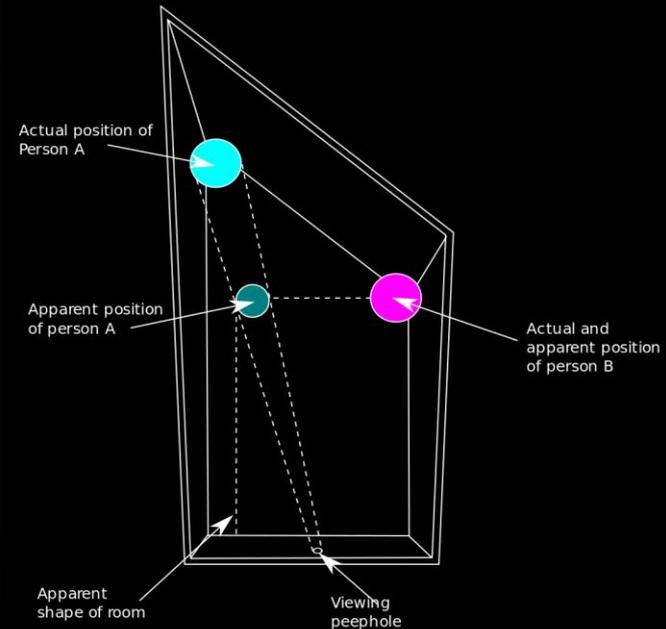
3. Cues for higher-order 3D structure

4. Constraints on 3D structure

RELATED WORK

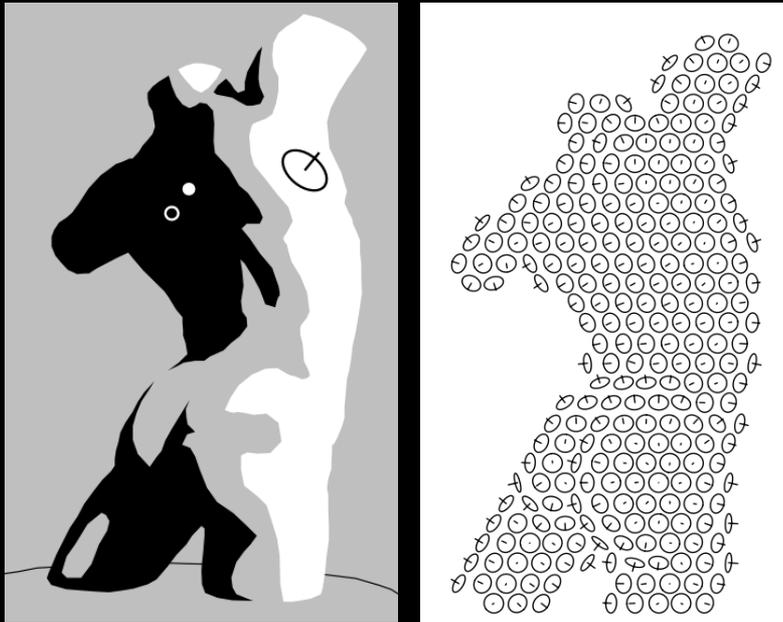
Human Vision

- Monocular cues are integral to “normal” vision
- Monocular can override binocular: monocular illusions persist under binocular conditions



Human Vision

Higher order properties are *not* obtained from depthmaps



“It is rather unlikely that the attitudes [i.e., normals] are derived from a pictorial depthmap”

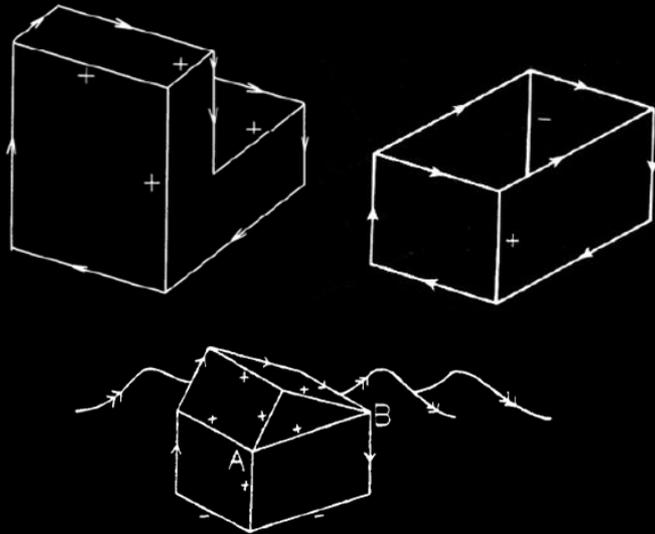
-Koenderink, van Doorn, Kappers '96

“Judgements about the curvature of local surface patches were too precise to be based on a symbolic representation of surface orientation ”

-Johnston and Passamore, '93

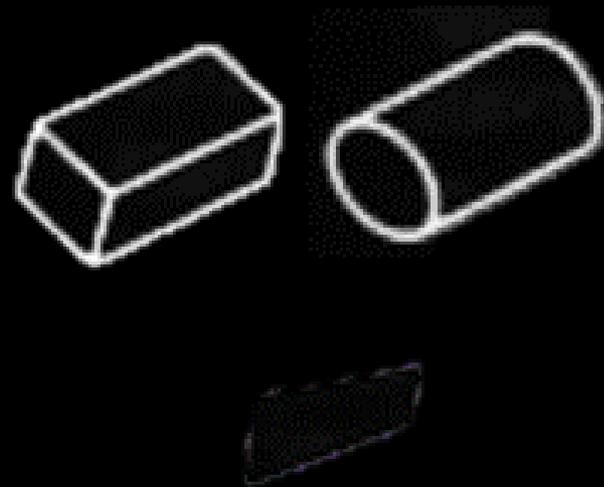
Recovering 3D Structure

Line-Based Primitives



Roberts 1963, Guzman 1968, Huffman 1971, Clowes 1971, Waltz, 1975, Kanade 1980, Sugihara 1986, Malik 1987, etc.

Volumetric Primitives

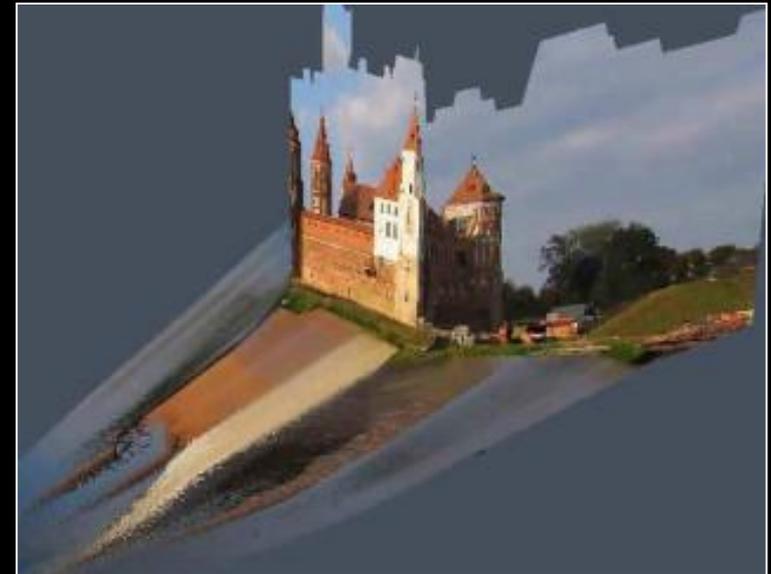


Binford 1971, Brooks 1979, Biederman 1987, etc.

Recovering 3D Structure

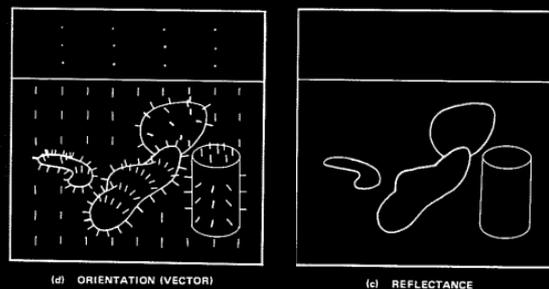


Hoiem et al., 2005
Qualitative Orientation



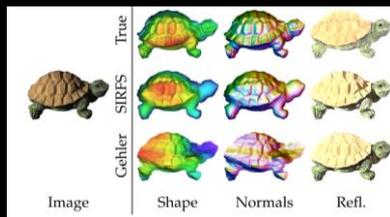
Saxena et al., 2005
Quantitative Depth

Image Factorization



Barrow and Tenenbaum 1978

Shape-from-X

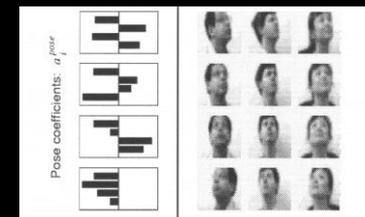


Tappen et al., 2002,
2006, Grosse et al.
2009, Barron et al.
2012, etc.



Malik et al. 1997,
Criminisi et al., 2000,
Forsyth 2002,
Zhang et al. 2014, etc.

Content & Style



Tenenbaum et al., 1997

Elgammal et al. 2004, Wang et
al., 2007, Pirsiavash 2009, etc.

SURFACE NORMALS

Surface Normals

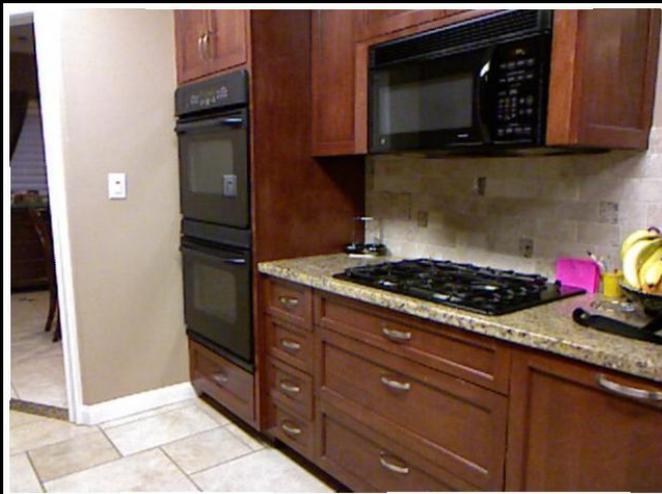
Quantitative Orientation



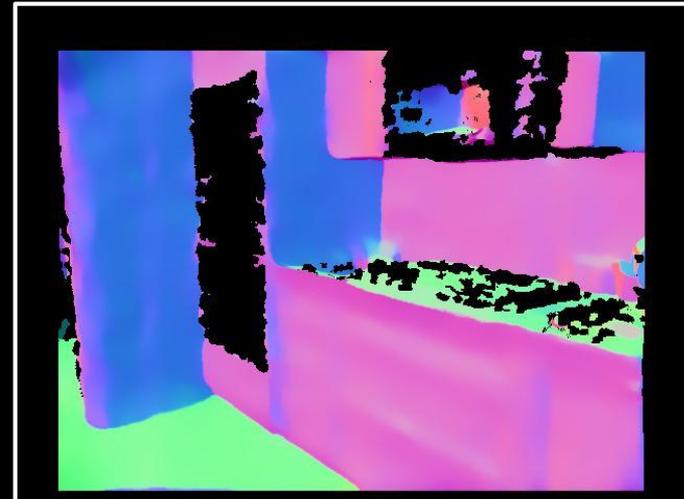
$$\begin{bmatrix} 0.82 \\ -0.21 \\ 0.53 \end{bmatrix}$$



Obtaining Normals



Color Image



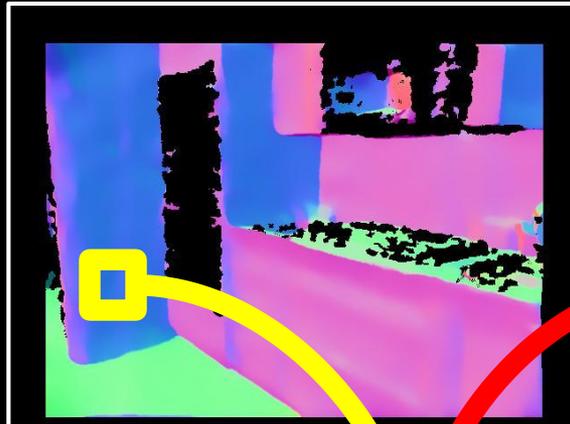
Normals

Evaluating Normals

Input

GT

Prediction



Aggregate over the entire dataset, compute:
 $\text{mean}(\mathbf{E})$, $\text{median}(\mathbf{E})$, $\text{sqrt}(\text{mean}(\mathbf{E}))$,
 $\text{mean}(\mathbf{E} < t)$, $t = 11.25, 22.5, 30$

Why Normals?

- Direct modeling produces better results
- Observable from perspective cues as opposed to scaling
- Fewer ambiguities than depth

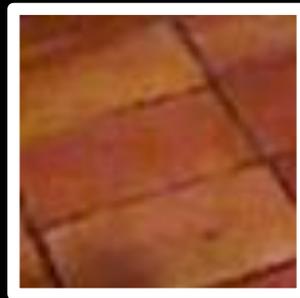
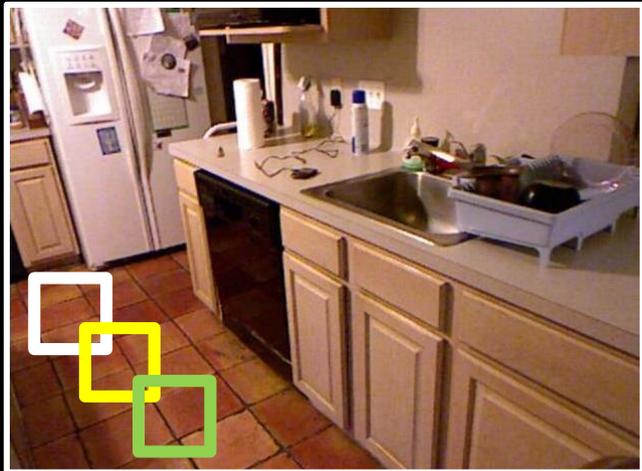
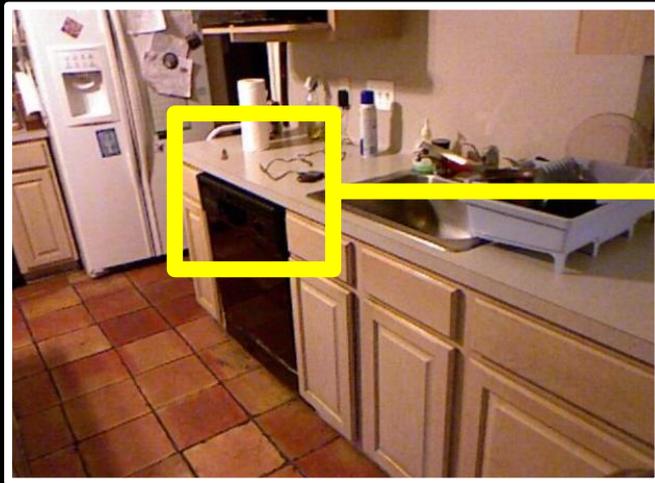
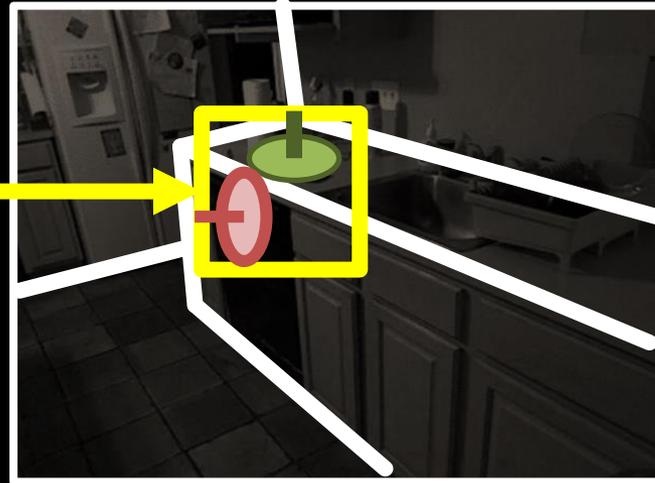


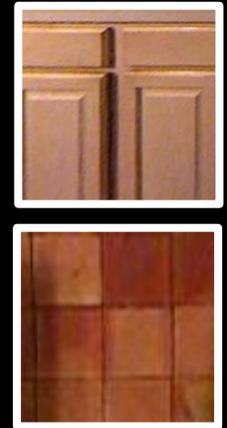
Image (3D Structure x Style)



3D Structure



Style



Local image-based cues

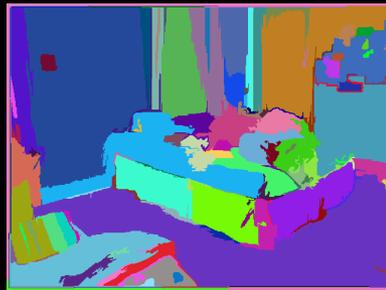
DATA-DRIVEN 3D PRIMITIVES

Previous Primitives



Lines + Planes

Kanade 1981,
Sugihara 1986,
Liebowitz et al. 1998,
Criminisi et al. 1999,
Lee et al., 2009, etc.



Segments

Hoiem et al. 2005,
Saxena et al. 2005,
Ramalingam et al.
2008, etc.



Rooms

Hedau et al. 2009,
Flint et al. 2010,
Flint et al. 2011,
Satkin et al. 2012,
Schwing et al. 2012,
etc.



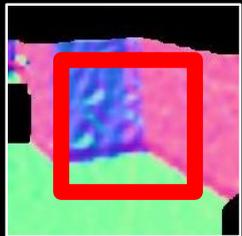
Cuboids

Lee et al. 2010,
Gupta et al. 2010,
Gupta et al. 2011,
Xiao et al. 2012,
Schwing et al. 2013
etc.

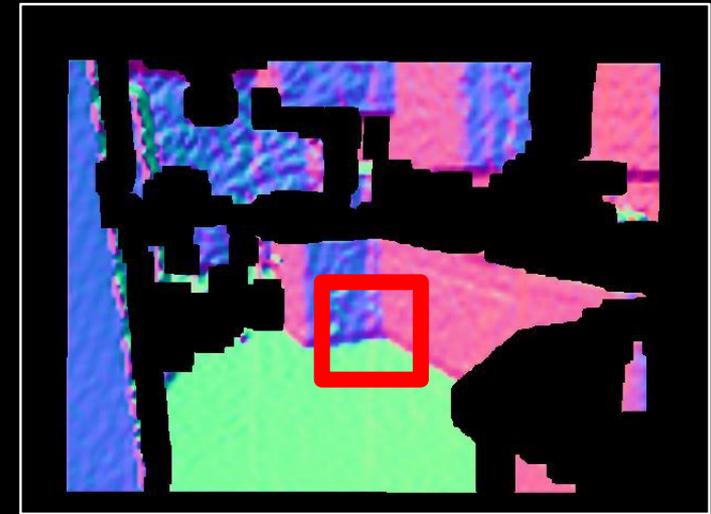
Objective

Visually
Discriminative

Geometrically
Informative



Image

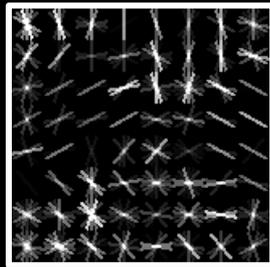


Surface Normals

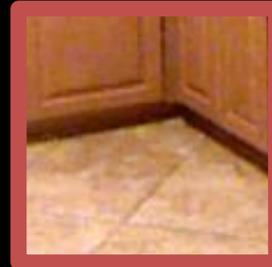
Similar ideas presented concurrently at ICCV '13:
Owens et al., Shape Anchors for Data-Driven Multi-view Reconstruction
Dollar et al., Structured Forests for Fast Edge Detection ;

Representation

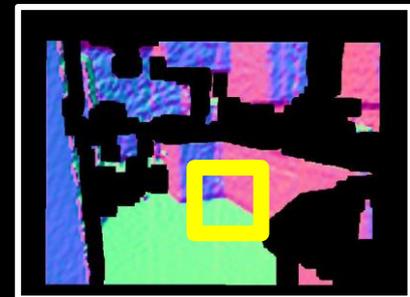
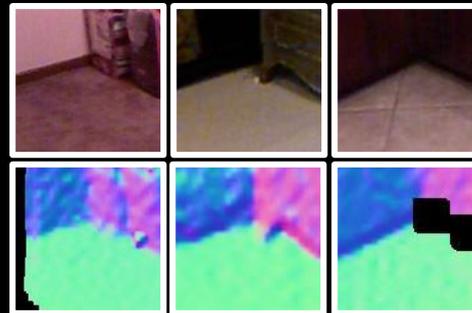
Detector



Instances

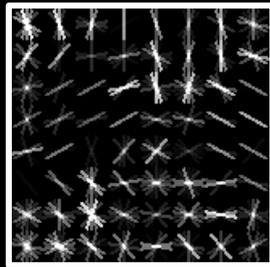


Canonical Form



Representation

Detector

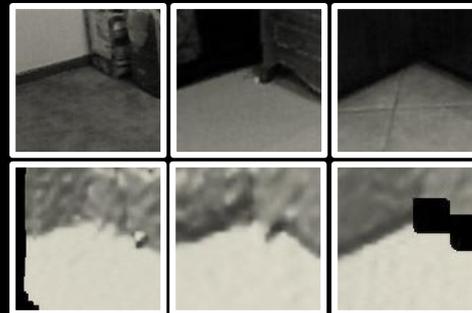


Instances



W

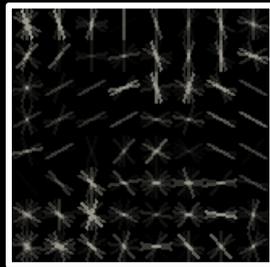
Canonical Form



Representation

N

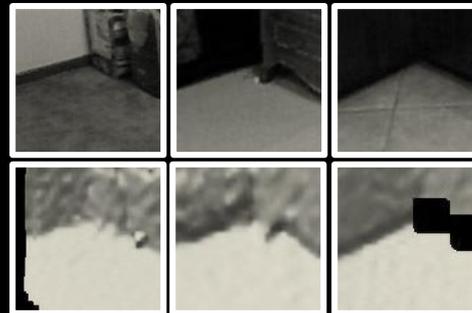
Detector



Instances



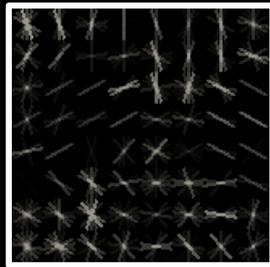
Canonical Form



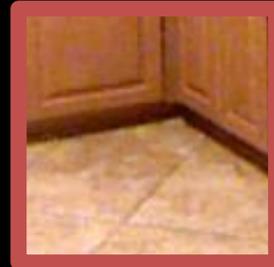
Representation

y

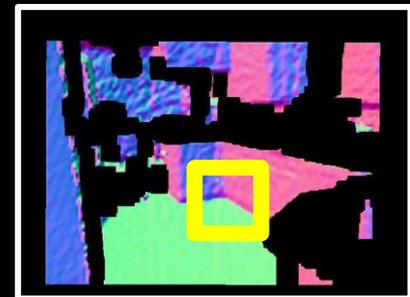
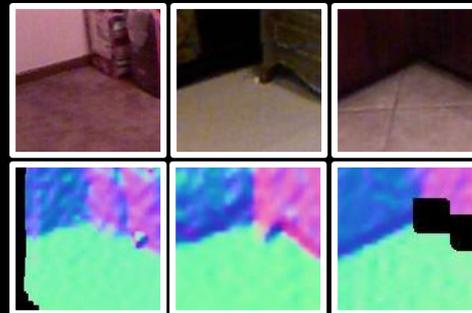
Detector



Instances



Canonical Form



Objective

$$\min_{\mathbf{y}, \mathbf{w}, \mathbf{N}} R(\mathbf{w}) + \sum_{i=1}^m \left[c_2 L(\mathbf{w}, \mathbf{N}, \mathbf{x}_i^A, y_i) + c_1 y_i \Delta(\mathbf{N}, \mathbf{x}_i^G) \right]$$

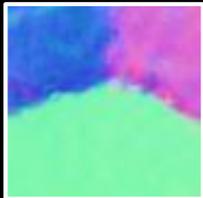
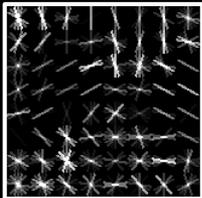
s.t. $|\mathbf{y}|_1 \geq c$

Primitive

\mathbf{w}

\mathbf{N}

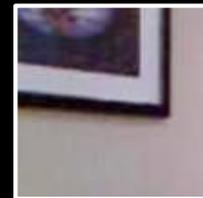
\mathbf{y}



Patch

\mathbf{x}_i^A

\mathbf{x}_i^G



Objective

Regularized classifier; loss for labels determined by geometry

$$\min_{\mathbf{y}, \mathbf{w}, \mathbf{N}} R(\mathbf{w}) + \sum_{i=1}^m \left[c_2 L(\mathbf{w}, \mathbf{N}, \mathbf{x}_i^A, y_i) + c_1 y_i \Delta(\mathbf{N}, \mathbf{x}_i^G) \right]$$

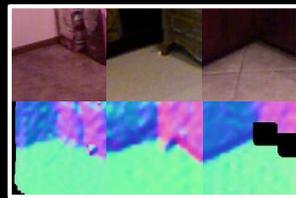
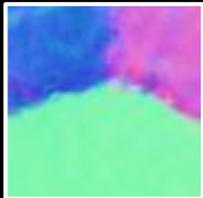
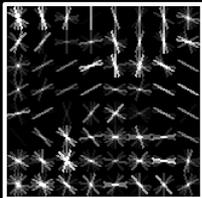
s.t. $|\mathbf{y}|_1 \geq c$

Primitive

\mathbf{w}

\mathbf{N}

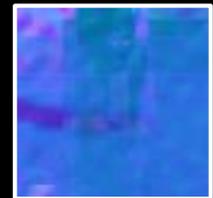
\mathbf{y}



Patch

\mathbf{x}_i^A

\mathbf{x}_i^G



Objective

Minimize intra-cluster
geometric distance

$$\min_{\mathbf{y}, \mathbf{w}, \mathbf{N}} R(\mathbf{w}) + \sum_{i=1}^m \left[c_2 L(\mathbf{w}, \mathbf{N}, \mathbf{x}_i^A, y_i) + c_1 y_i \Delta(\mathbf{N}, \mathbf{x}_i^G) \right]$$

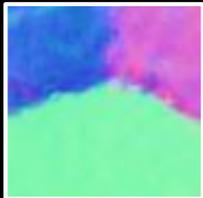
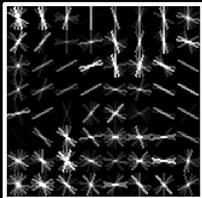
s.t. $|\mathbf{y}|_1 \geq c$

Primitive

\mathbf{w}

\mathbf{N}

\mathbf{y}



Patch

\mathbf{x}_i^A

\mathbf{x}_i^G



Objective

Solve with an approach similar to
block-coordinate descent

$$\min_{\mathbf{y}, \mathbf{w}, \mathbf{N}} R(\mathbf{w}) + \sum_{i=1}^m \left[c_2 L(\mathbf{w}, \mathbf{N}, \mathbf{x}_i^A, y_i) + c_1 y_i \Delta(\mathbf{N}, \mathbf{x}_i^G) \right]$$

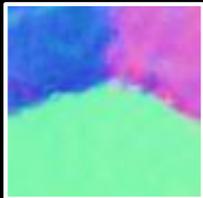
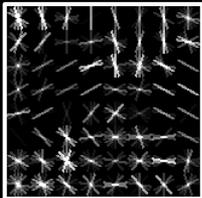
s.t. $|\mathbf{y}|_1 \geq c$

Primitive

\mathbf{w}

\mathbf{N}

\mathbf{y}



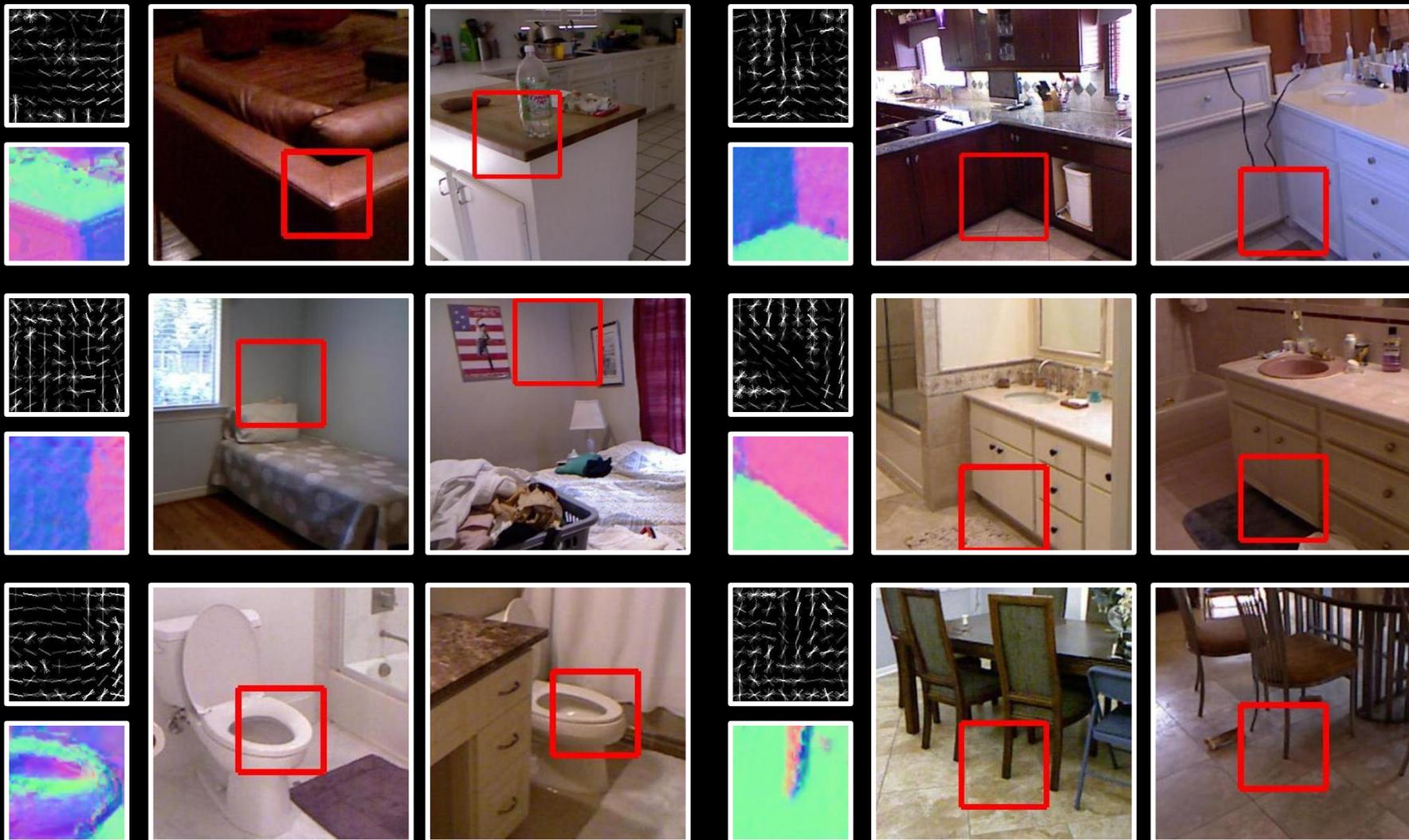
Patch

\mathbf{x}_i^A

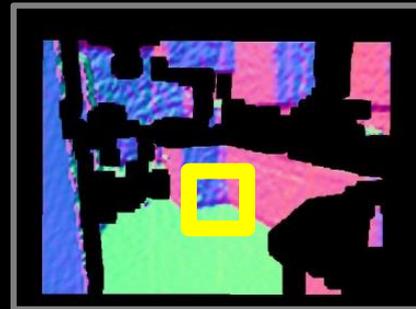
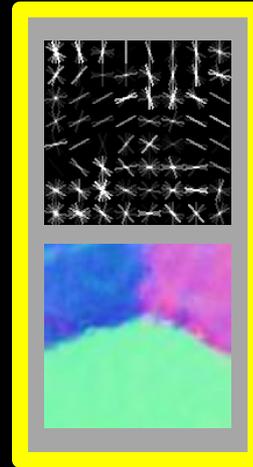
\mathbf{x}_i^G



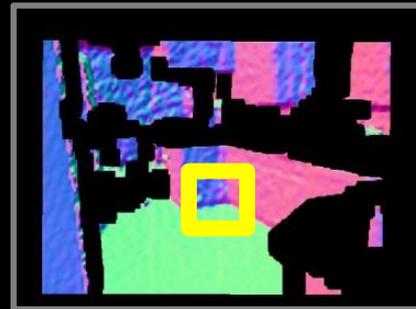
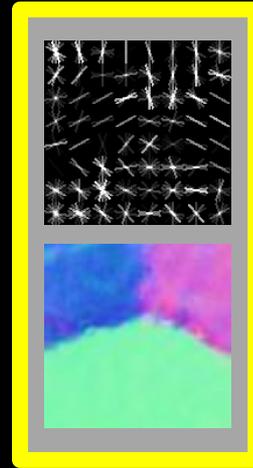
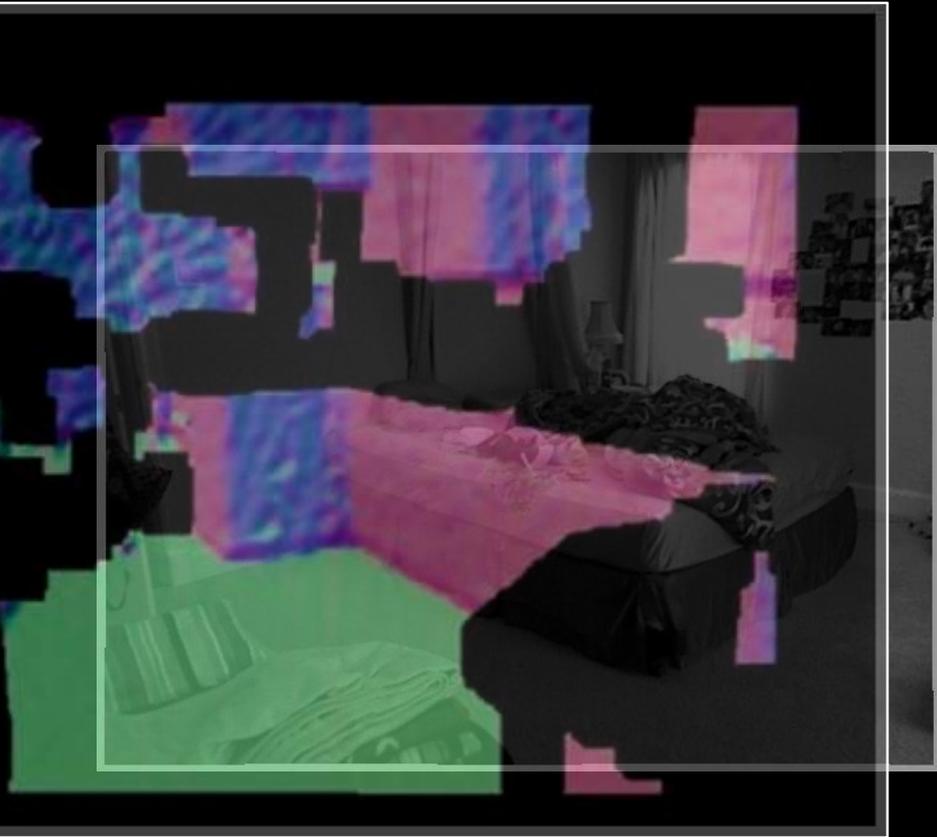
Learned Primitives



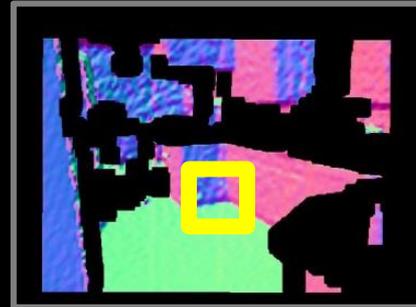
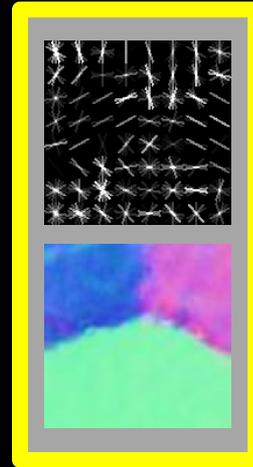
Interpretation from Primitives



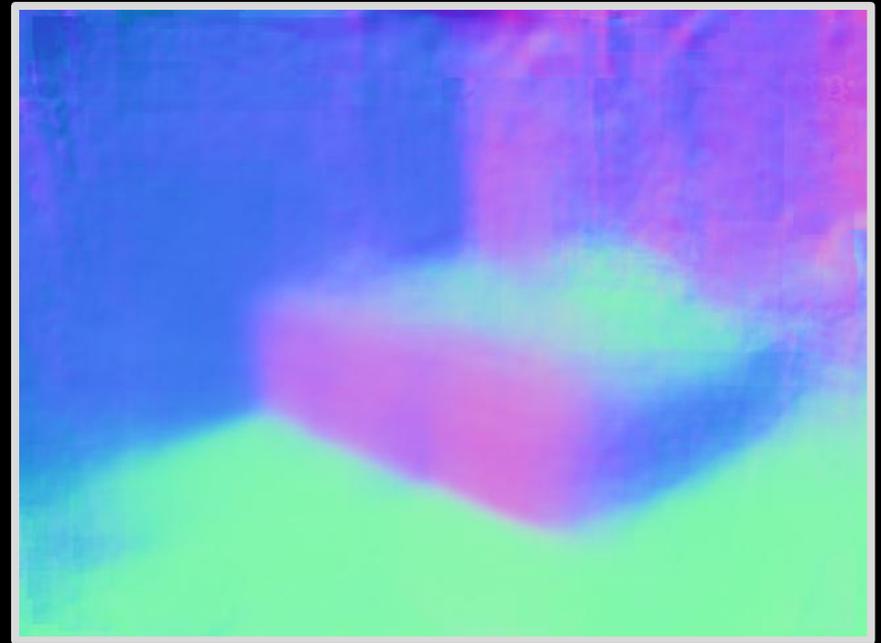
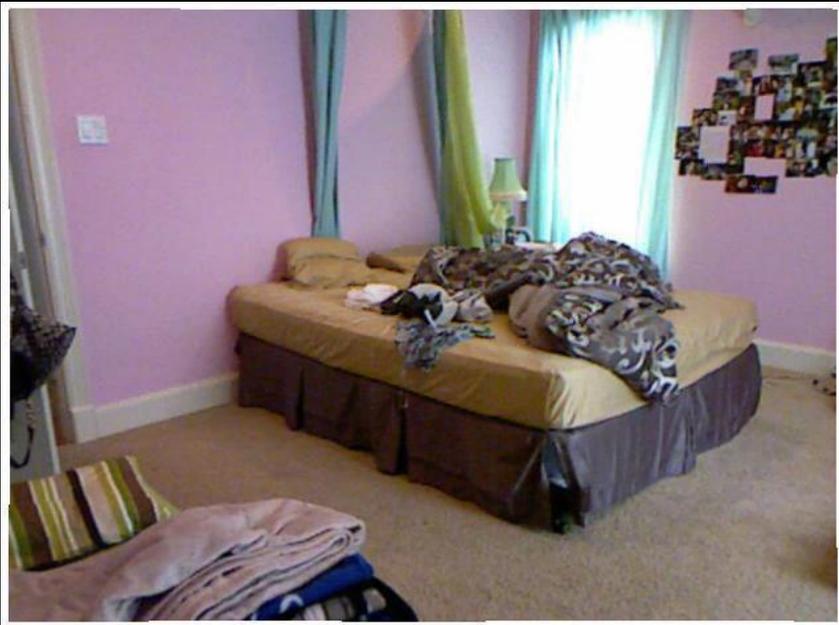
Interpretation from Primitives



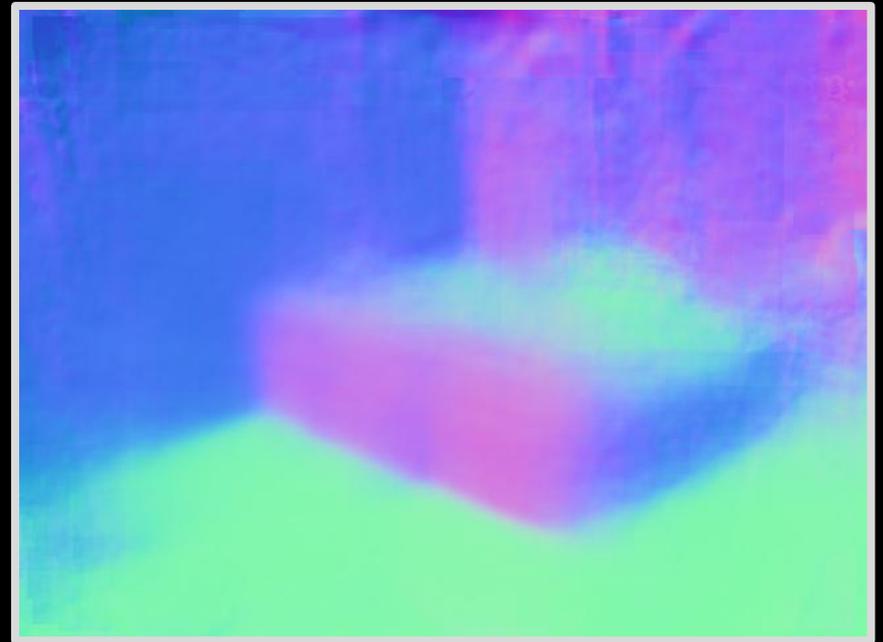
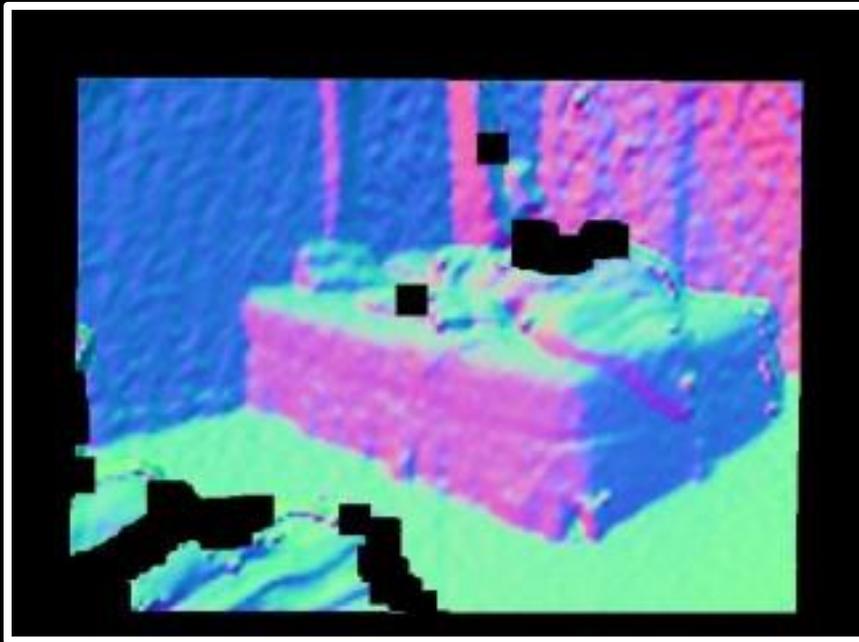
Interpretation from Primitives



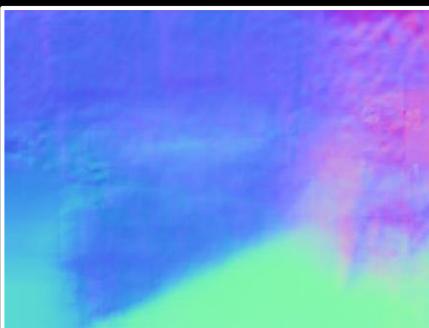
Interpretation from Primitives



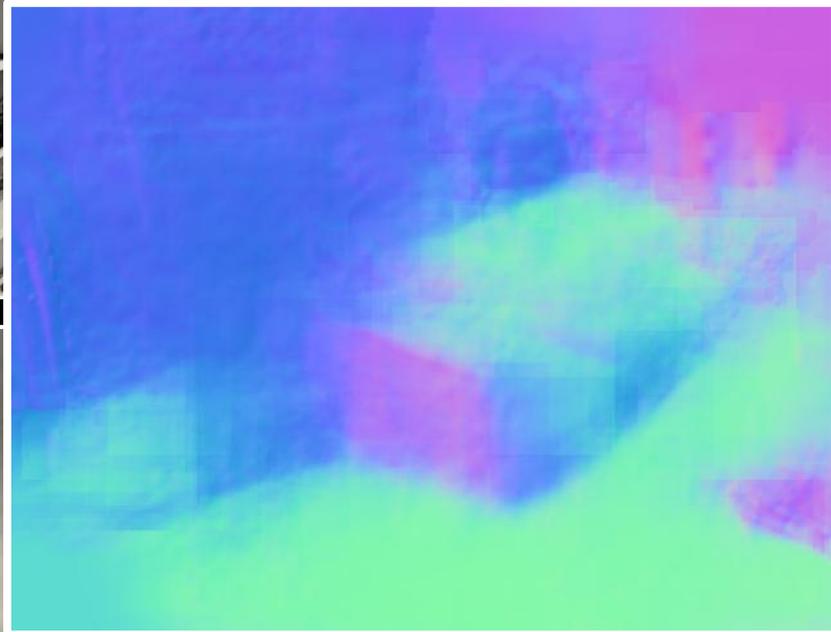
Interpretation from Primitives



Interpretation from Primitives



Interpretation from Primitives



Results – Quantitative

	Summary Stats (°) (Lower Better)			% Good Pixels (Higher Better)		
	Mean	Median	RMSE	11.25°	22.5°	30°
3DP	<u>34.2</u>	<u>30.0</u>	<u>41.4</u>	<u>18.6</u>	<u>38.6</u>	<u>49.9</u>
Karsch et al.	40.7	37.8	46.9	8.1	25.9	38.2
Saxena et al.	48.0	43.1	57.0	10.7	27.0	36.3
Hoiem et al.	41.2	35.1	49.2	9.0	31.2	43.5
RF+SIFT	36.0	33.4	41.7	11.4	31.4	44.5

Karsch et al., ECCV 2012; Hoiem et al., ICCV 2005; Saxena et al. NIPS 2005
Fouhey, Gupta, Hebert, ICCV '13.

Issues

Pure memorization: no sharing between views



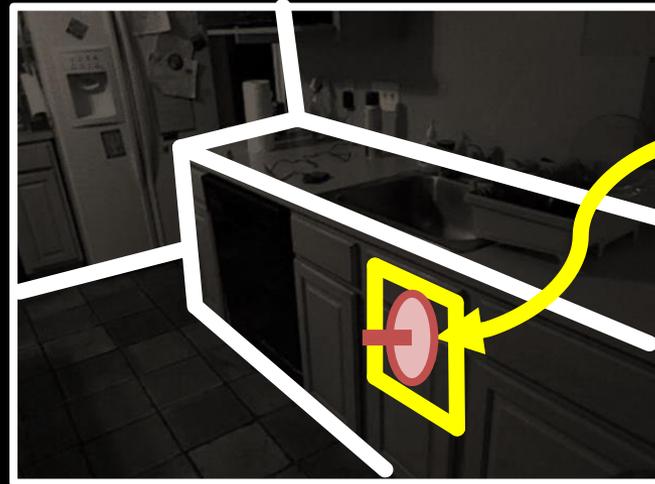
Learning requires a specialized sensor



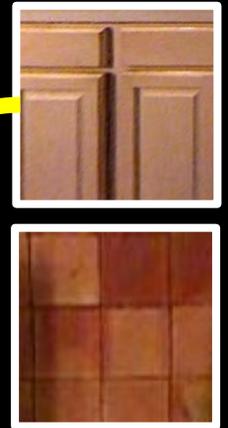
Image (3D Structure x Style)



3D Structure



Style



Local style-based cues

STYLE ELEMENTS

A Different Idea

These are easy
to get in bulk



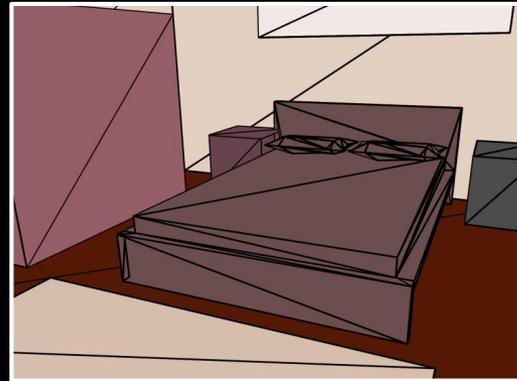
Image



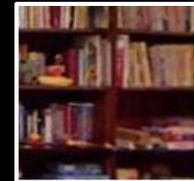
We can put
priors on this



3D Structure



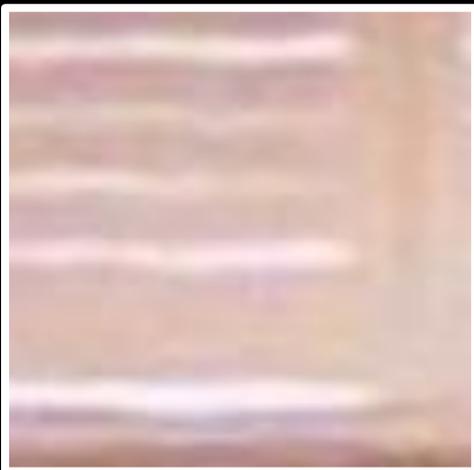
Style



=

x

Style Elements



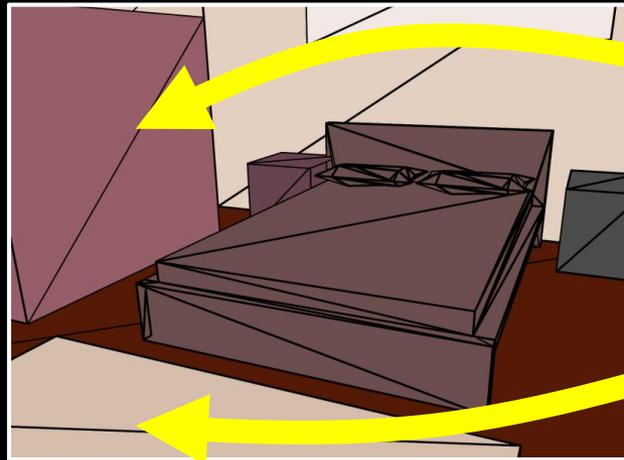
Factorization

Image



=

3D Structure



\times

Style

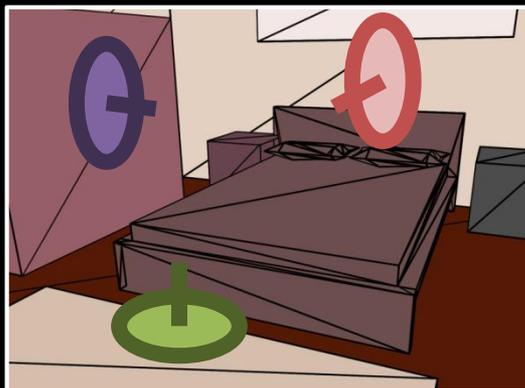


Solving for Style

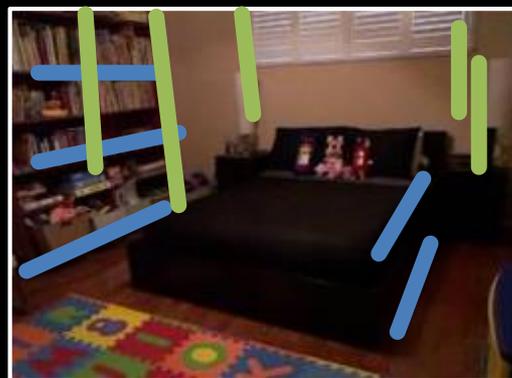
Image



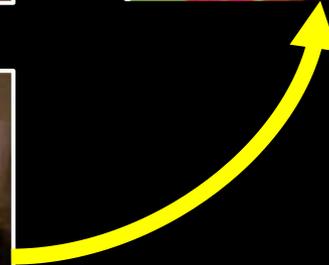
3D Structure



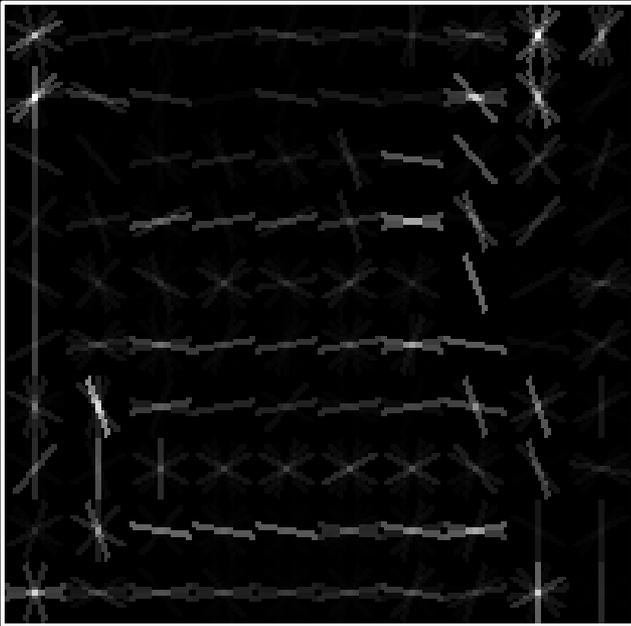
Style



Vanishing Points



Solving for 3D Structure

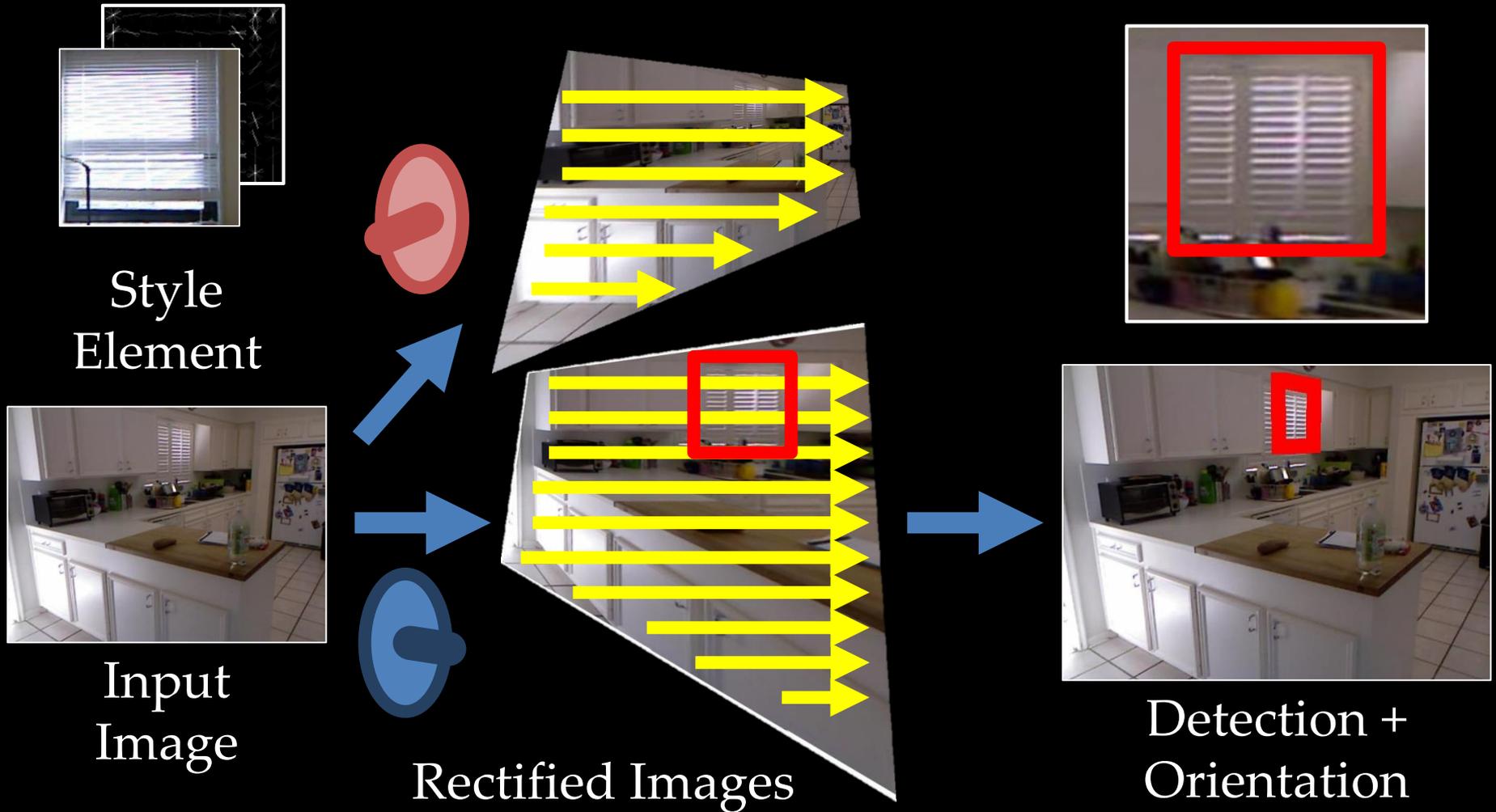


Style
Element



Input
Image

Solving for 3D Structure



Solving for 3D Structure over a Dataset



Style
Element



Set of Images



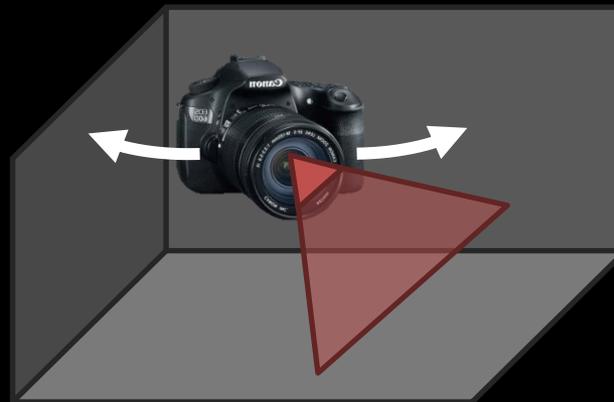
Detection +
Orientation

2 Key Assumptions

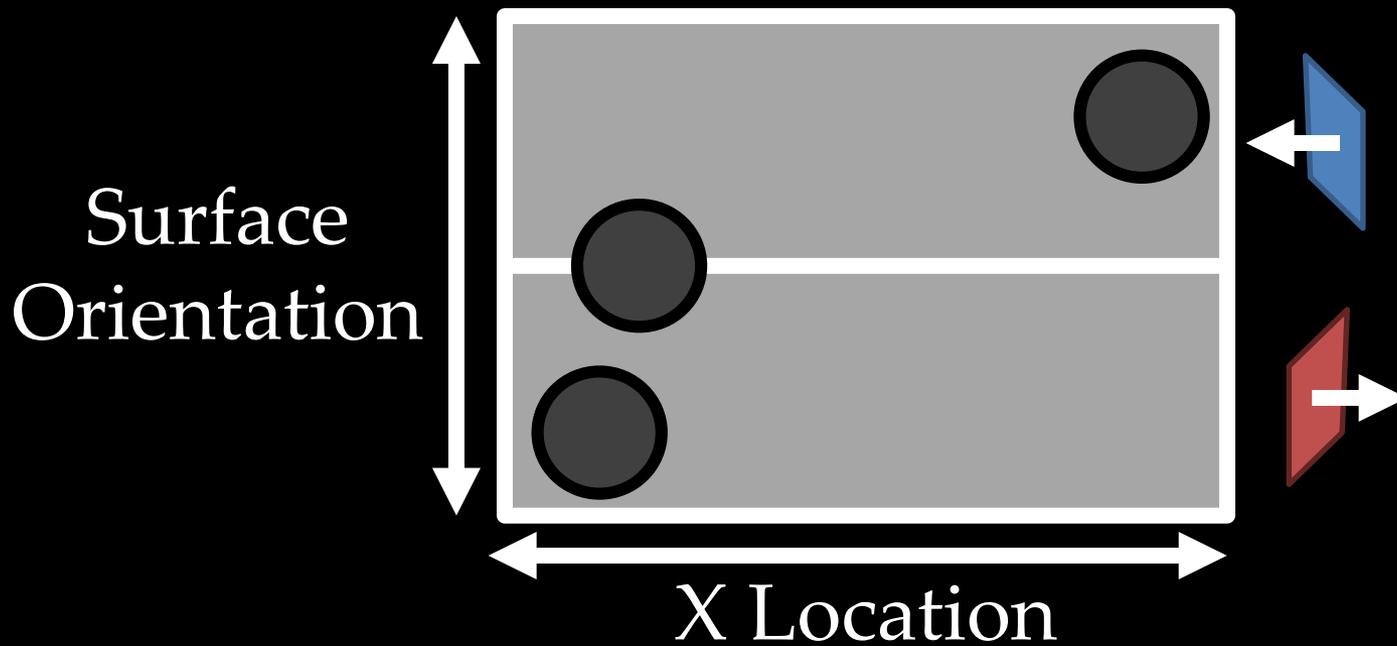
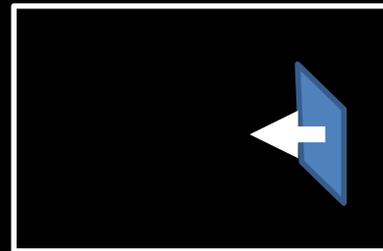
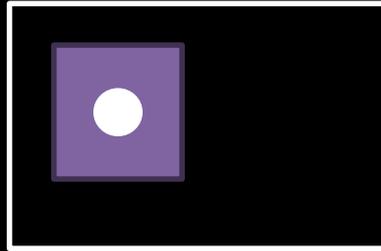
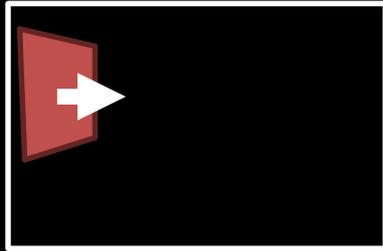
Style and 3D structure are independent



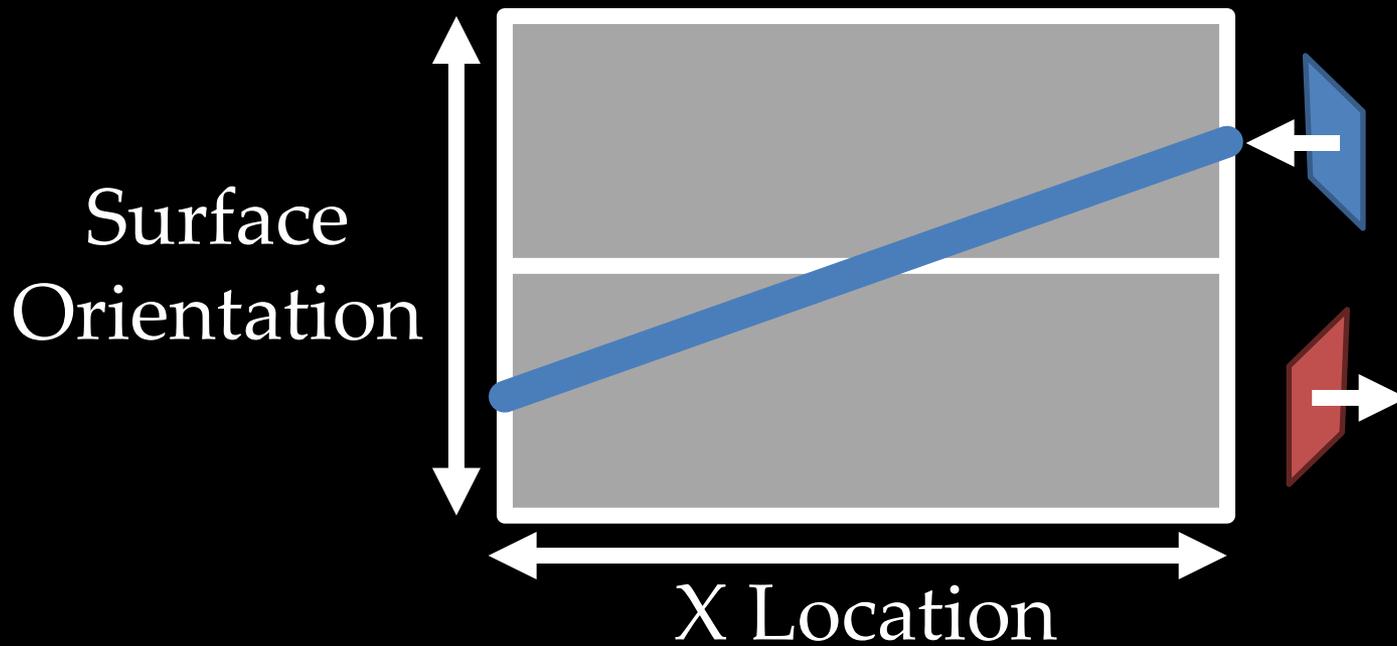
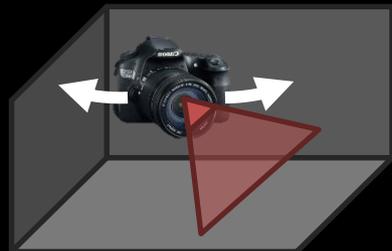
On average, 3D structure is a box



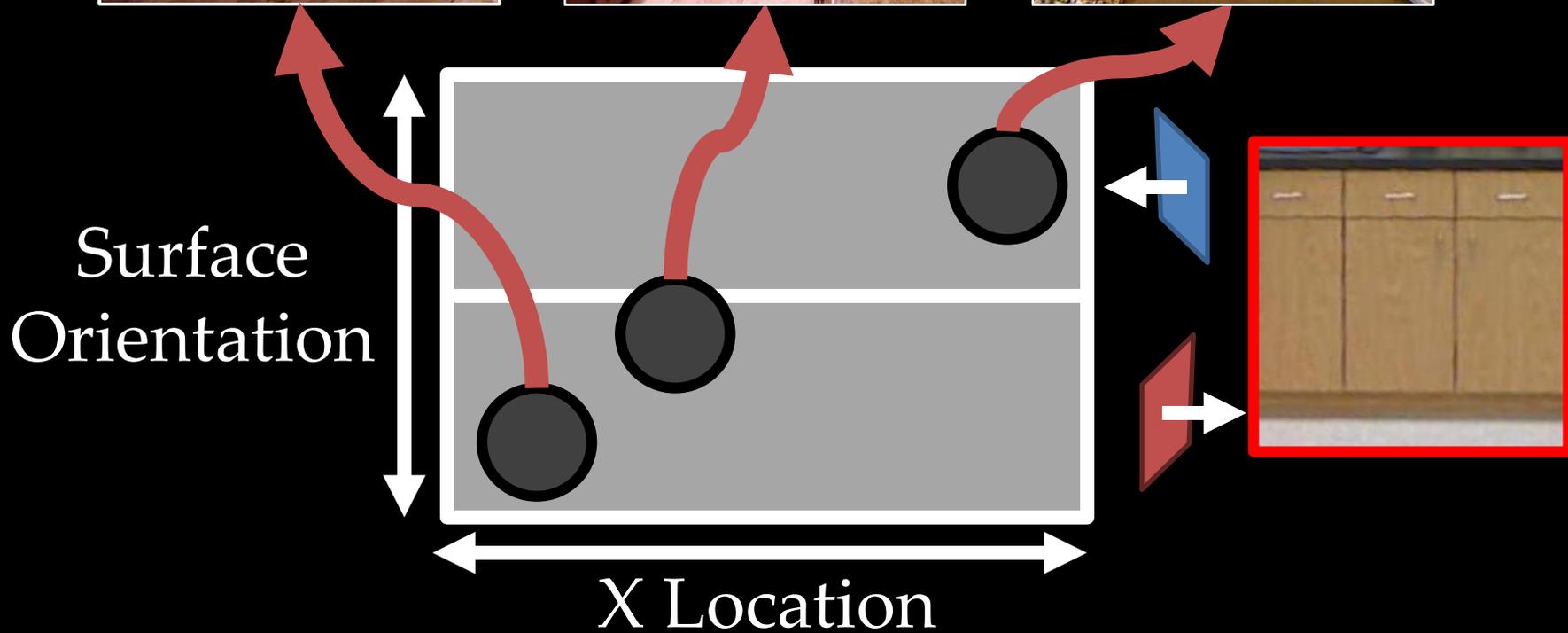
Plotting Detections



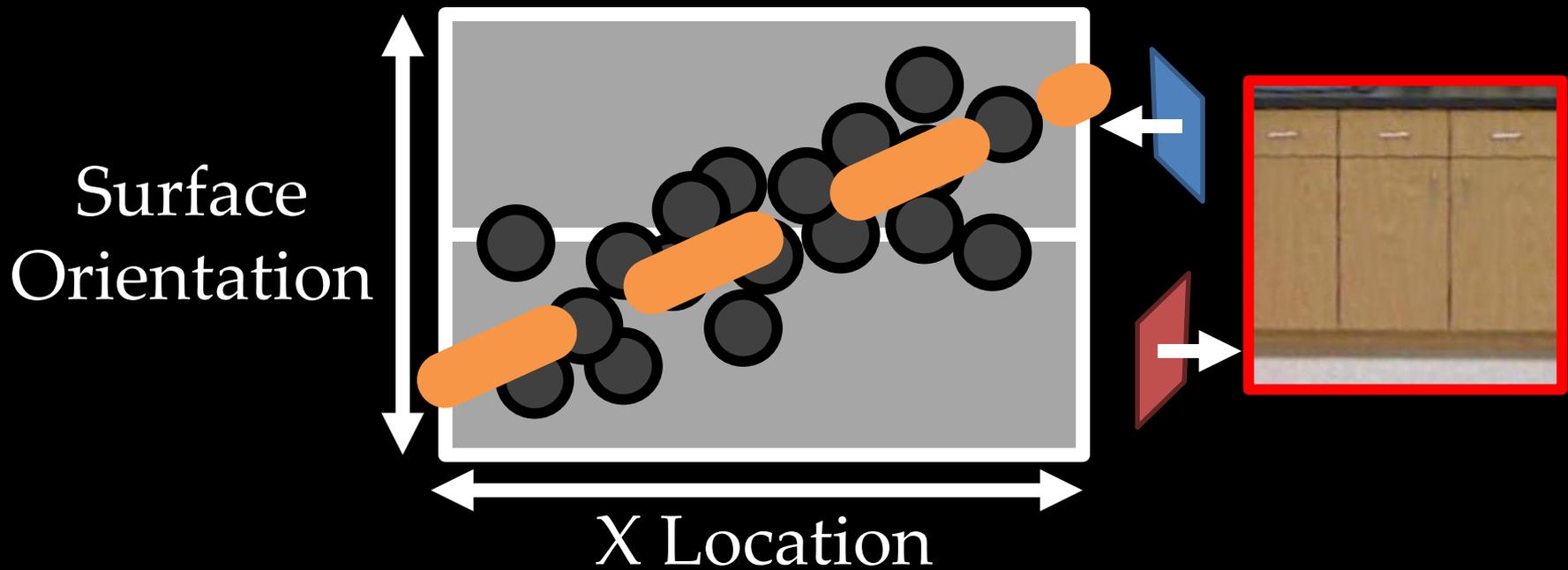
Box Assumption



Verifying Style Elements



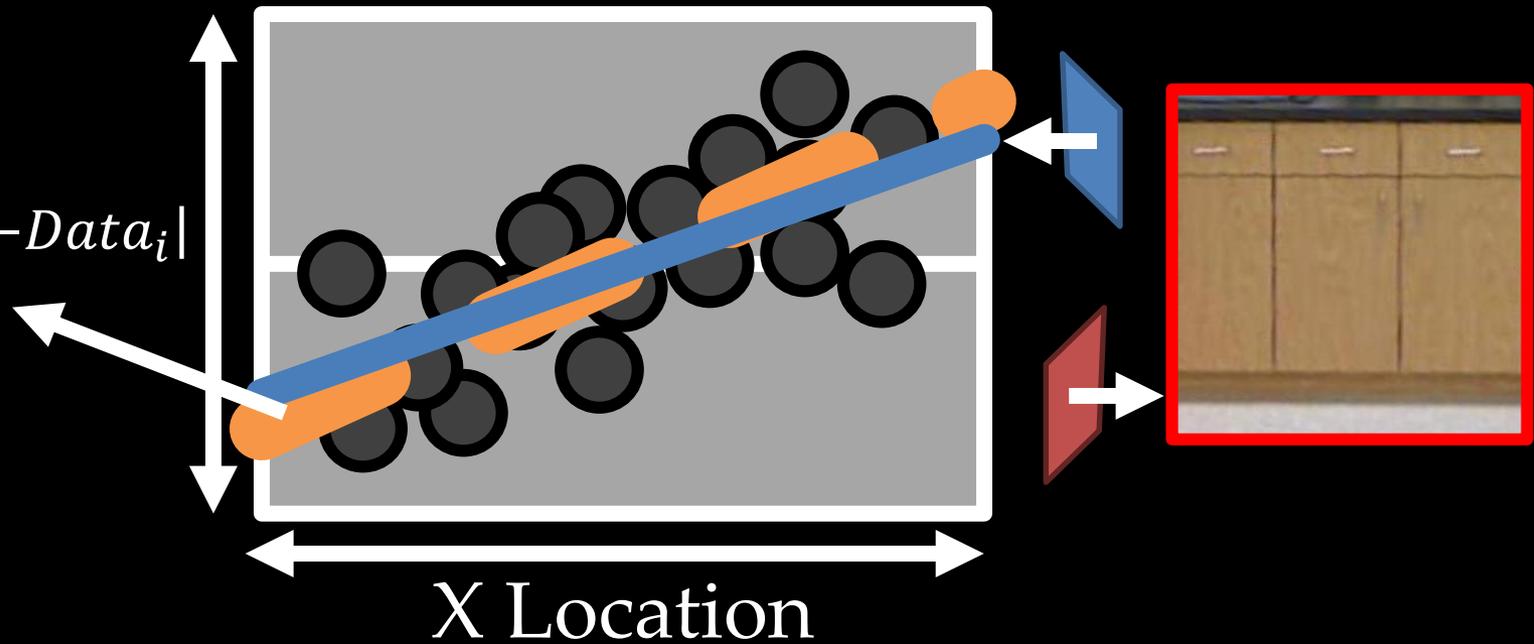
Verifying Style Elements



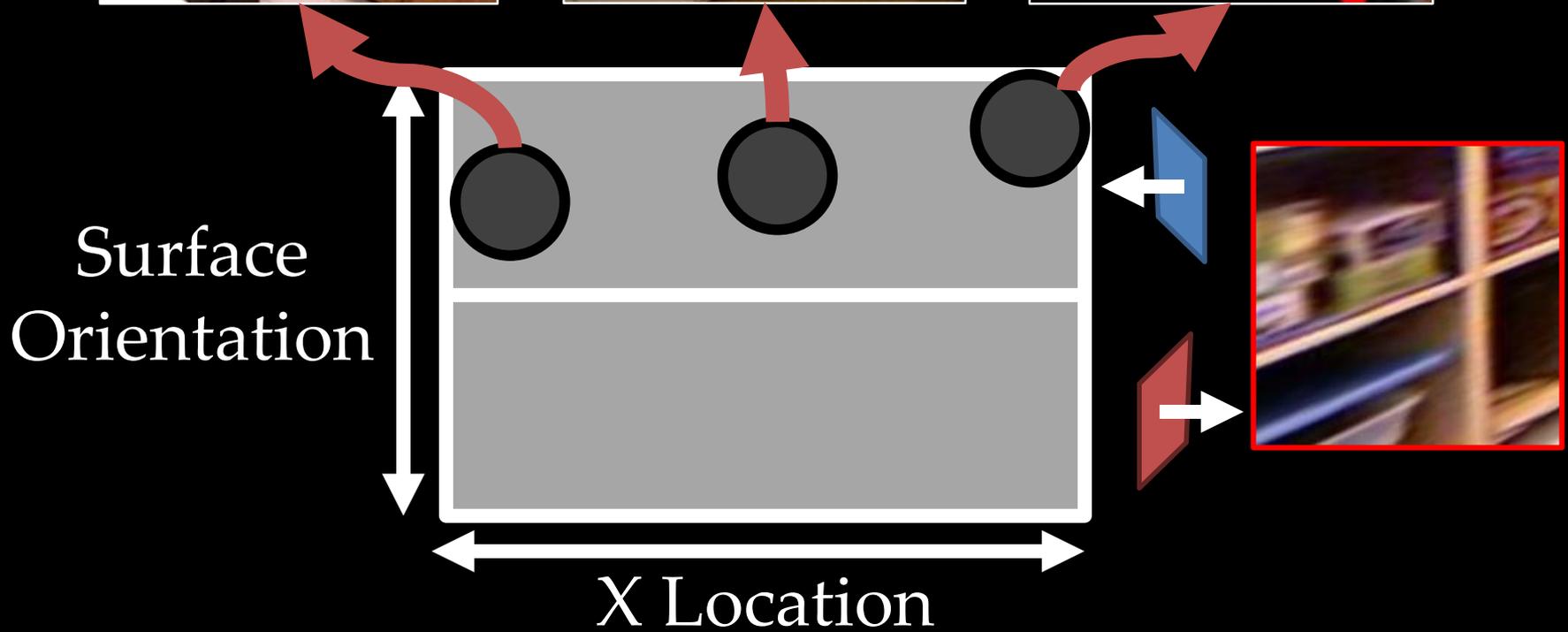
Verifying Style Elements



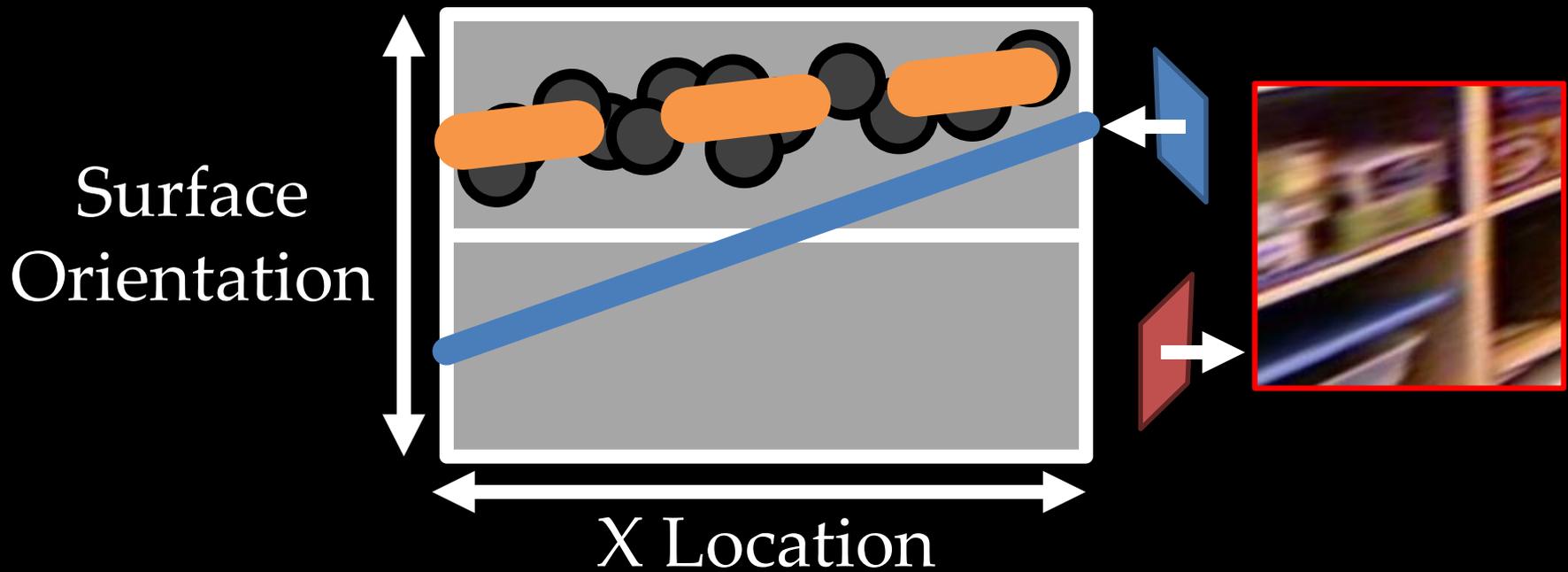
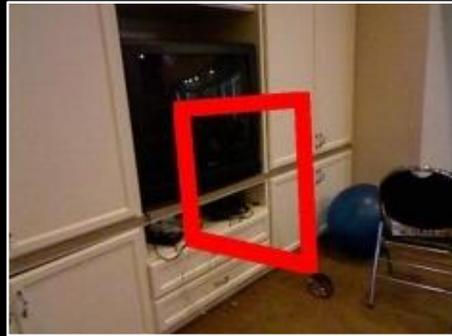
$$\sum_{i=1}^W |Prior_i - Data_i|$$



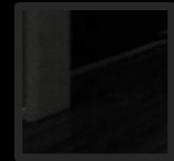
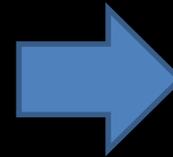
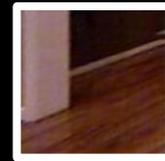
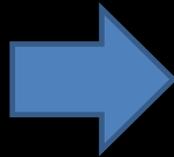
Verifying Style Elements



Verifying Style Elements



Hypothesize and Verify Pipeline



...

Discovered Style Elements

Vertical

Element

Detections



Element

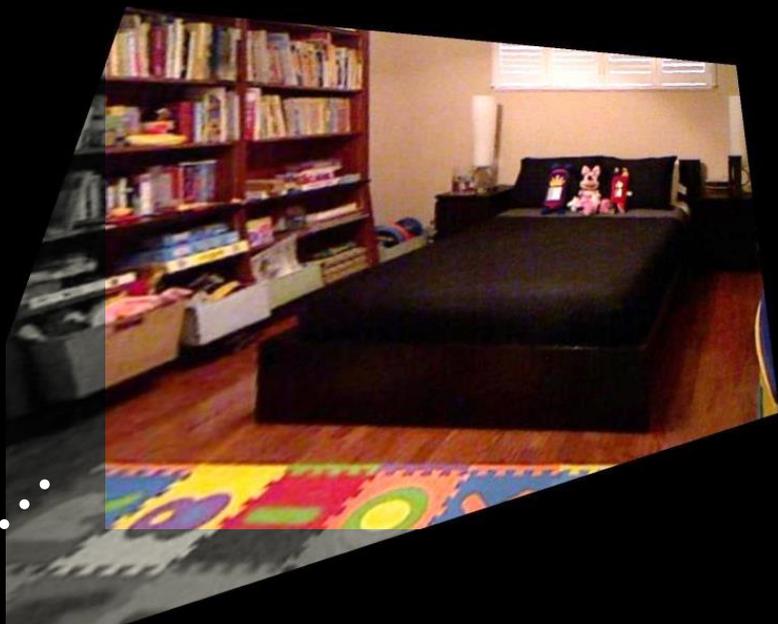
Detections



Horizontal



Interpreting



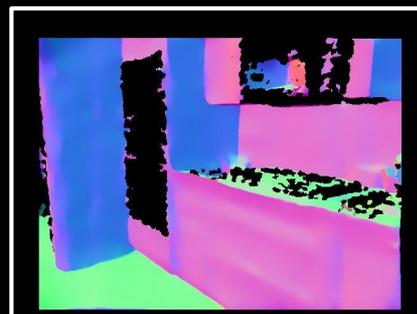
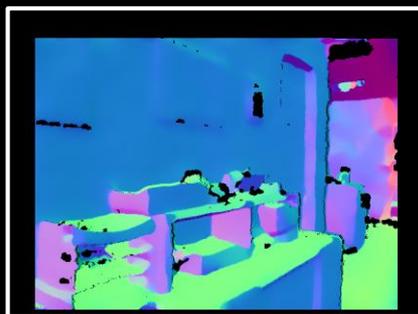
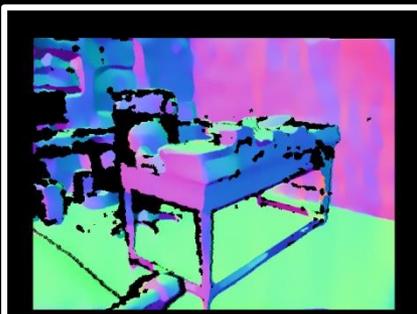
...

Results

Input



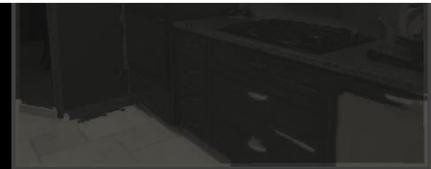
GT



Output



Results



Output

Quantitative Results

	<u>All Pixels</u>	<u>Vertical</u>		
	(Lower Better)	(Higher Better)		
	Median Error	Pixels < 11.25°	Pixels < 30°	Pixels < 30°
Style Elements	21.7°	36.8%	55.4%	59.7%
3DP	19.2°	39.2%	57.8%	58.8%
Origami World	17.9°	40.5%	58.9%	
Disc. Coding	23.5°	27.7%	58.7%	

Scaling Up To The World

RGBD Datasets

Internet Images



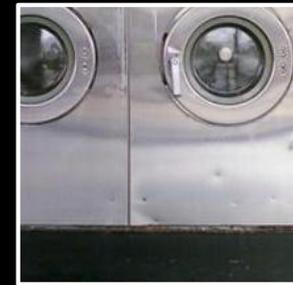
Results on Internet Images

Automatically Discovered Style Elements

Supermarket



Laundromat



Museum

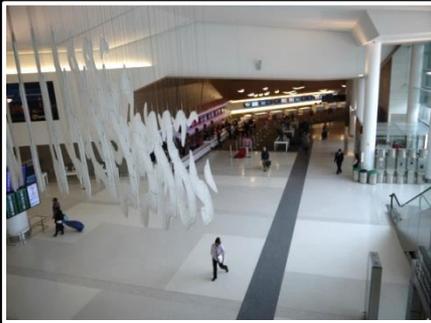


Locker Room



Quantitative Results

10 categories from Places-205 Dataset
Images sparsely manually annotated



Pixels < 30 Degrees

3DP
Style Elements



The Story So Far

Unconstrained Outputs



Constrained Outputs



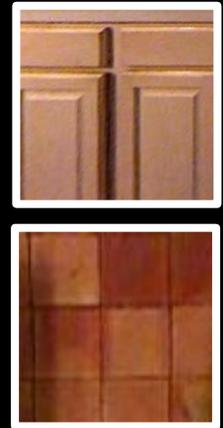
Image (3D Structure x Style)



3D Structure



Style



Cues for higher-order 3D structure

3D SHAPE ATTRIBUTES

Goal: 3D Shape Attributes



Not Planar

Smooth surface

1 point of contact

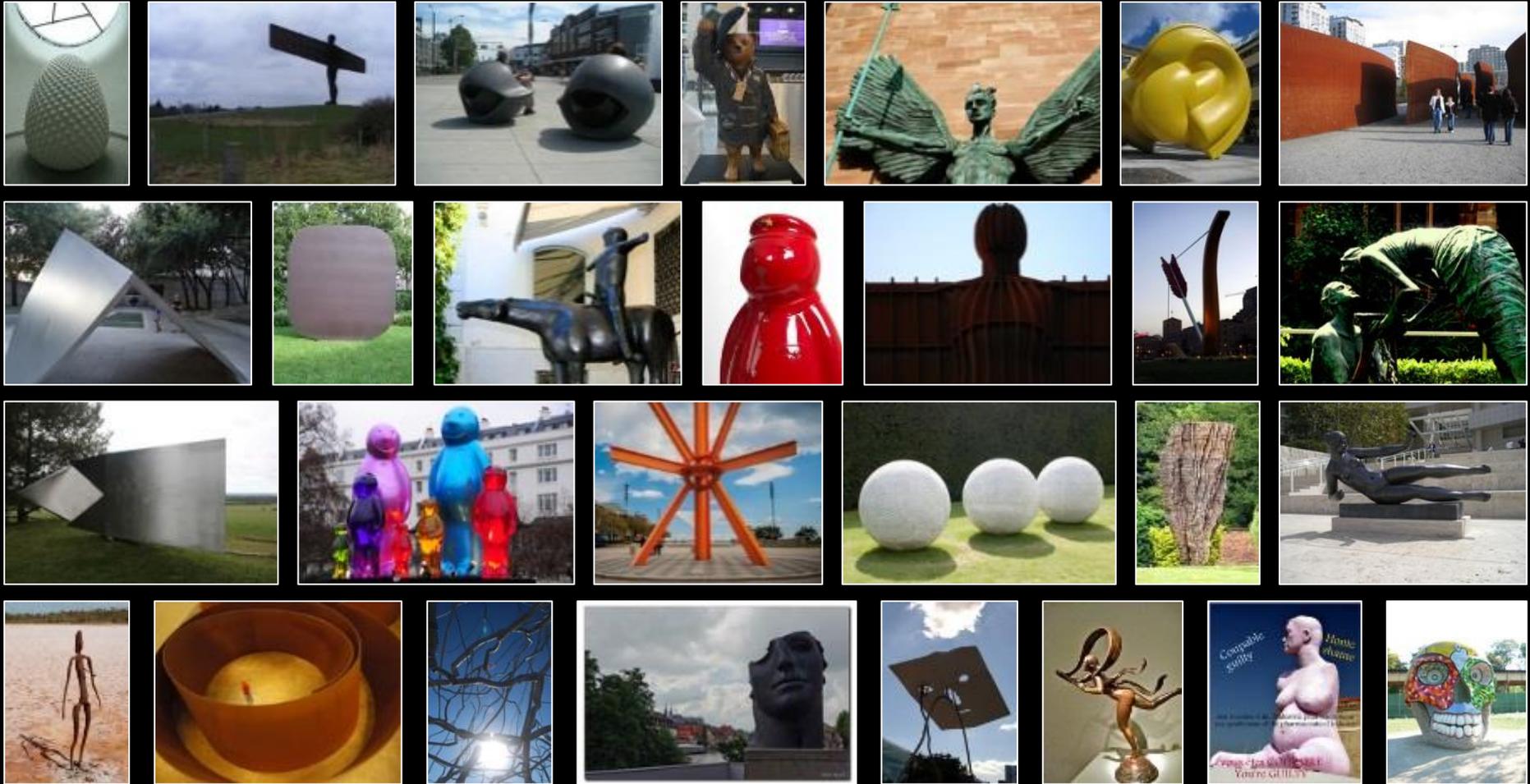
Not point contact

Has Hole

Not thin structures

...

Data

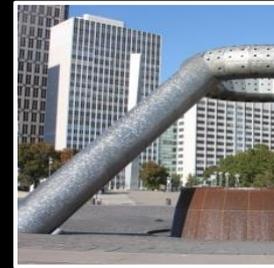


3D Shape Attributes

Curvature
(4 Total)



Planar
Surfaces



Cylindrical
Surfaces

Contact
(2 Total)



Point or
Line

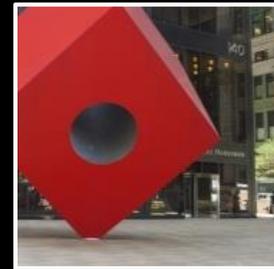


Multiple

Occupancy
(6 Total)



Thin
Structures



Has
Hole

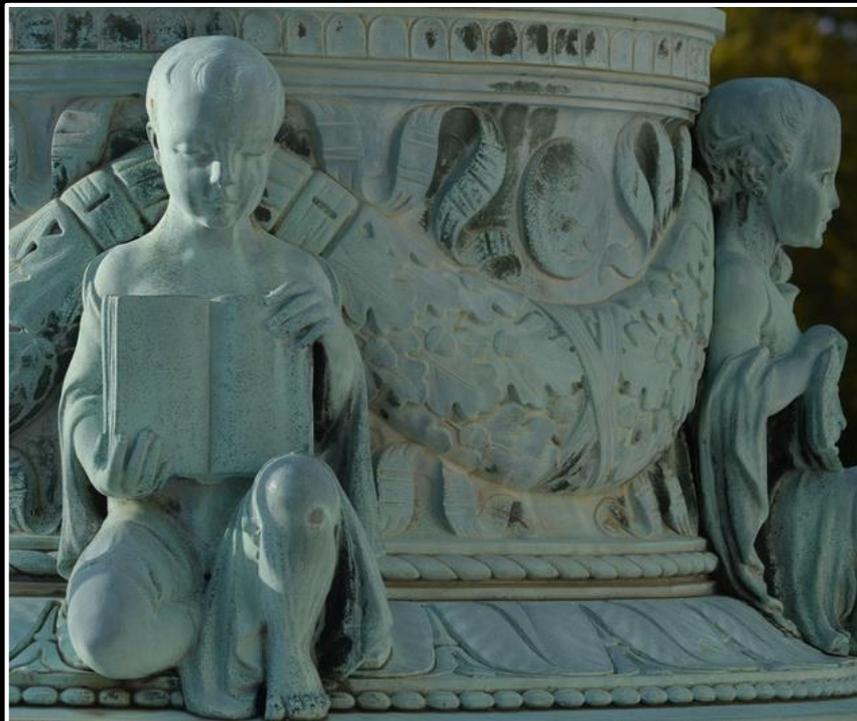
Examples

Positives: Has Planar Surfaces



Examples

Negatives: Has Planar Surfaces



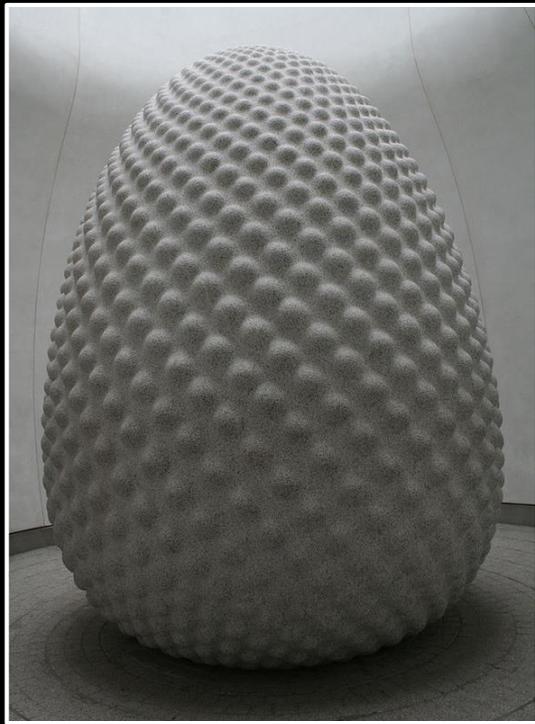
Examples

Positives: Has Point/Line Contact



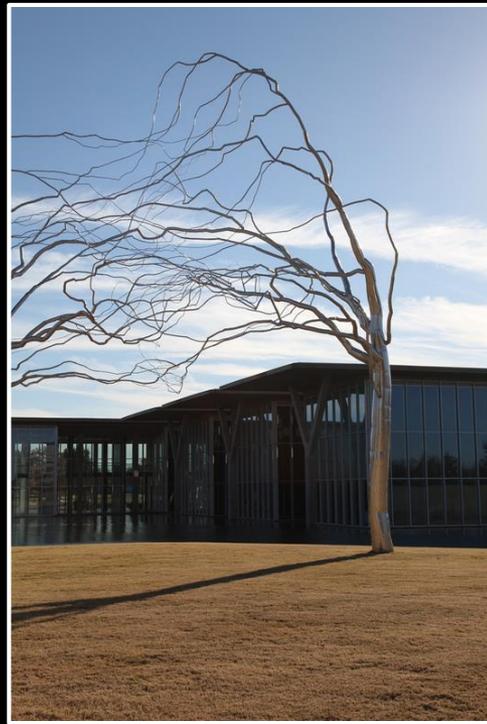
Examples

Negatives: Has Point/Line Contact



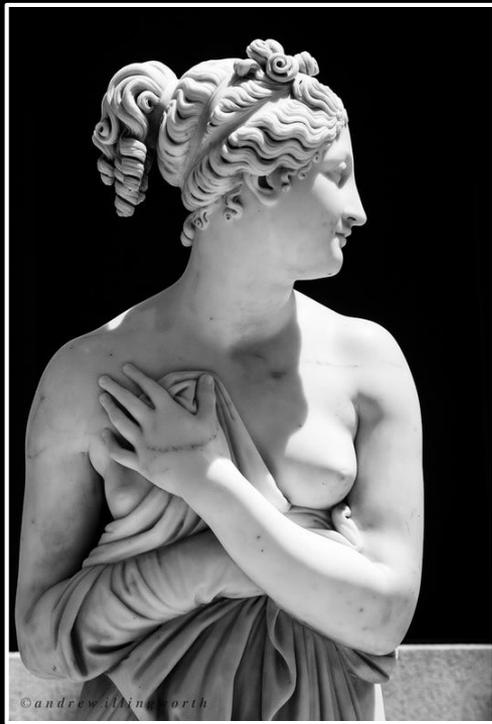
Examples

Positives: Has Thin Structures



Examples

Negatives: Has Thin Structures



Data

London



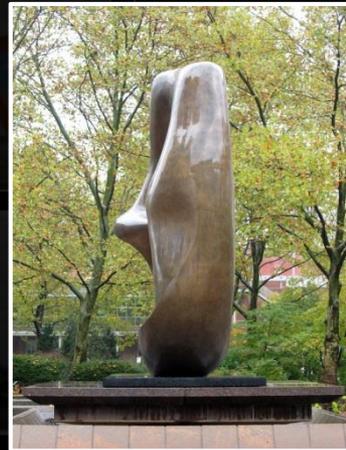
Malaga



Yorkshire



Princeton



Columbus

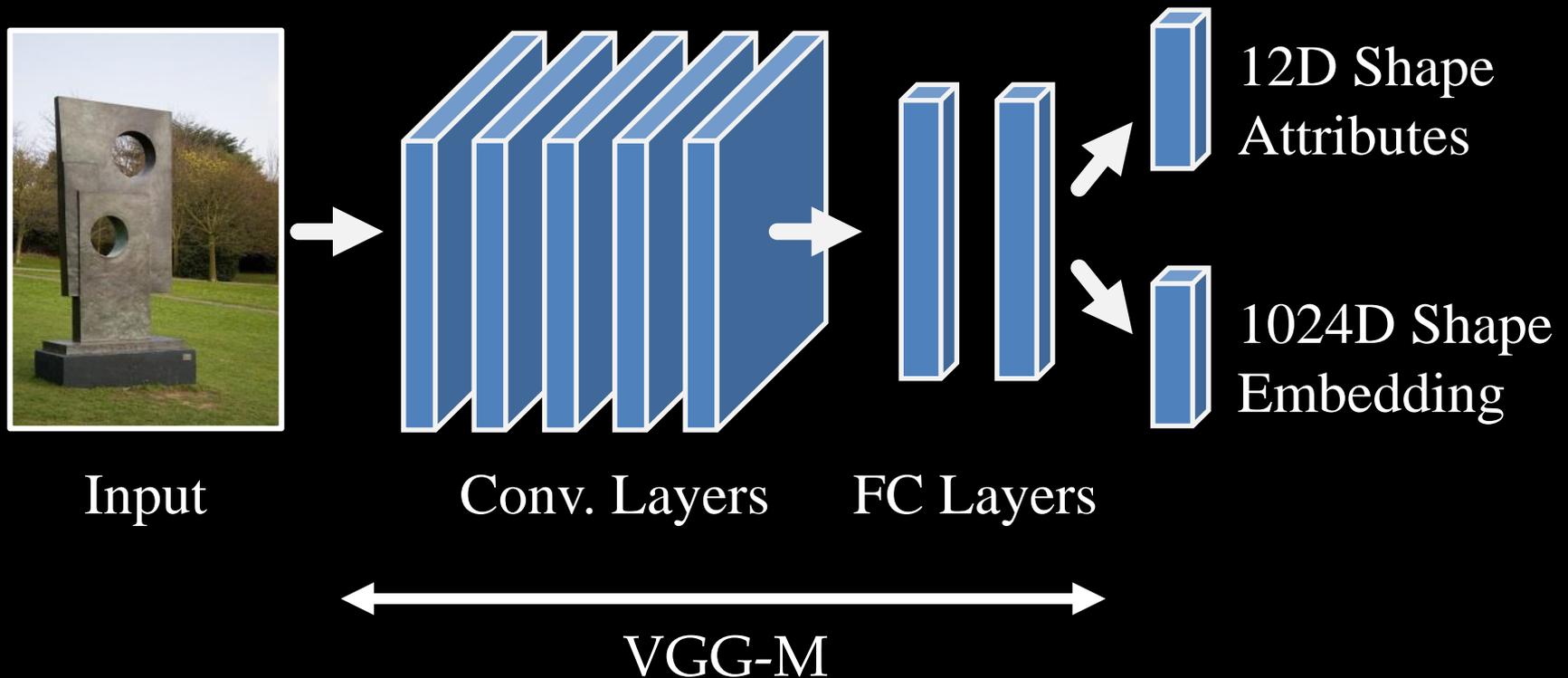


Toronto

Data



Learning To Predict



Triplet loss as in Schults and Joachims '04, Schroff et al. '14, Wang et al. '15, Parkhi et al. '15

Qualitative Results

Most

Point/Line Contact

Least



...



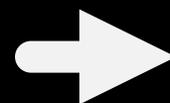
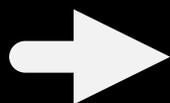
Rough Surface



...



Indirect Baselines



Planar = Yes
Holes = Yes

...

2+ Contacts = No

...

- SIRFS (Barron et al. '15)
- CNN (Eigen et al. '14)

- KDES+SVM (Bo et al. '11)
- HHA+CNN (Gupta et al. '14)

Quantitative Results

Criterion: mean AUC of ROC.

Eigen '14		Barron '15		End-to-end
KDES	HHA	KDES	HHA	
58.5	61.2	59.4	62.5	<u>72.3</u>

PASCAL VOC Results

Most



...

Planarity



Least

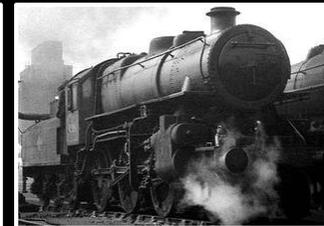


Most



...

Planarity



Least



PASCAL VOC Results

Most

Rough Surface

Least



...



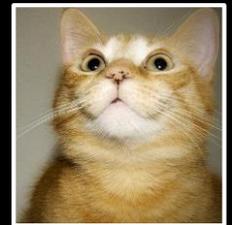
Most

Point/Line Contact

Least



...



The Story So Far

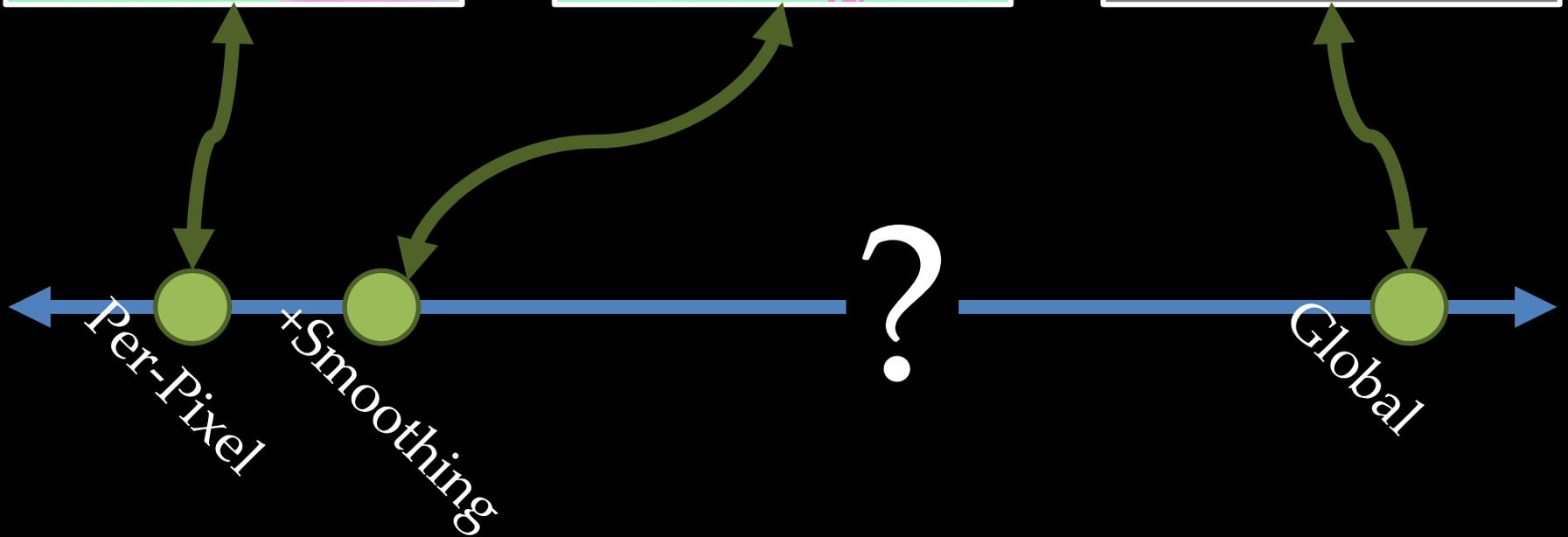
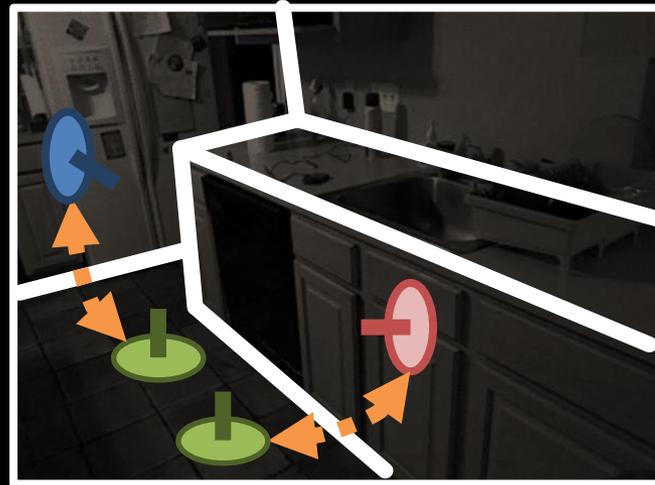


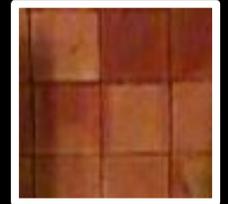
Image (3D Structure x Style)



3D Structure



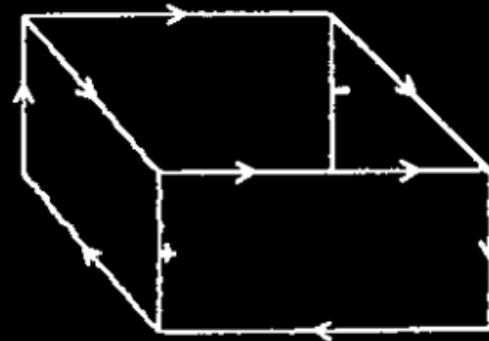
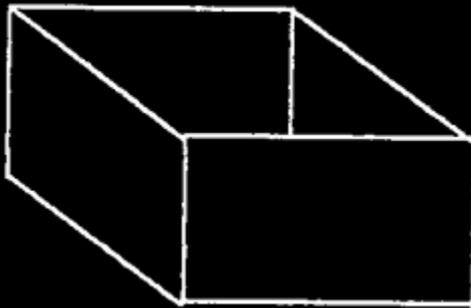
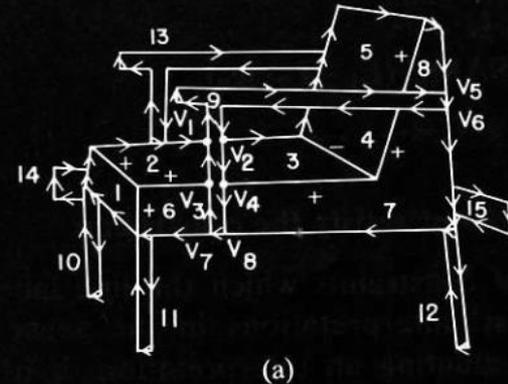
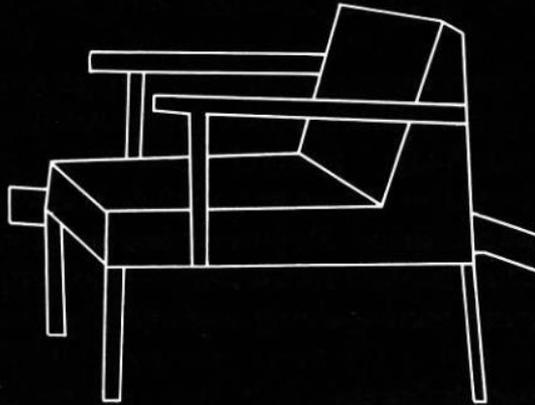
Style



Mid-level constraints on 3D Structure

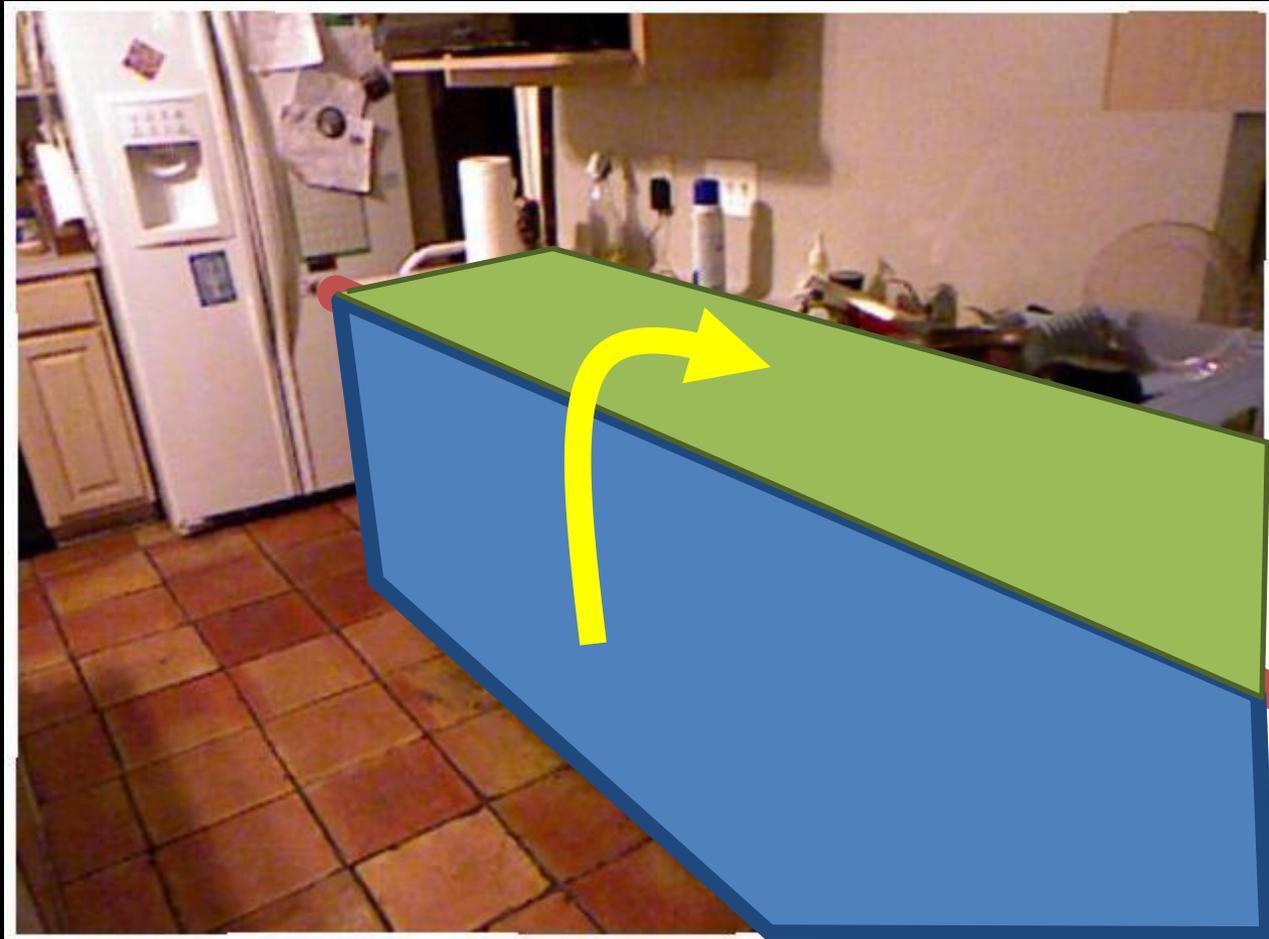
CONSTRAINTS ON 3D STRUCTURE

Mid-level in the Past



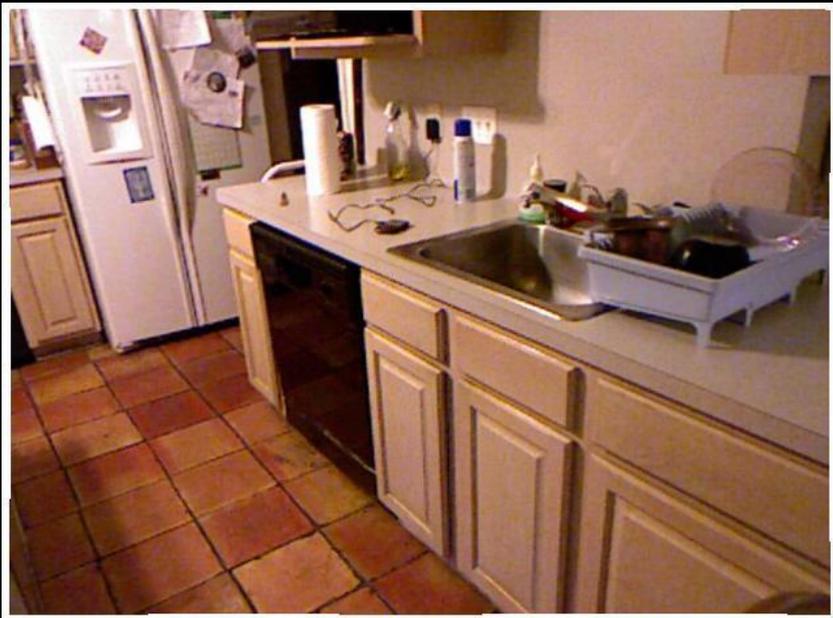
Huffman 71, Clowes 71, Kanade 80, 81 Sugihara 86, Malik 87, etc.

Our Mid-Level Constraints



Our Output

Input:
Single Image



Output:
Discrete Scene Parse



Parameterization

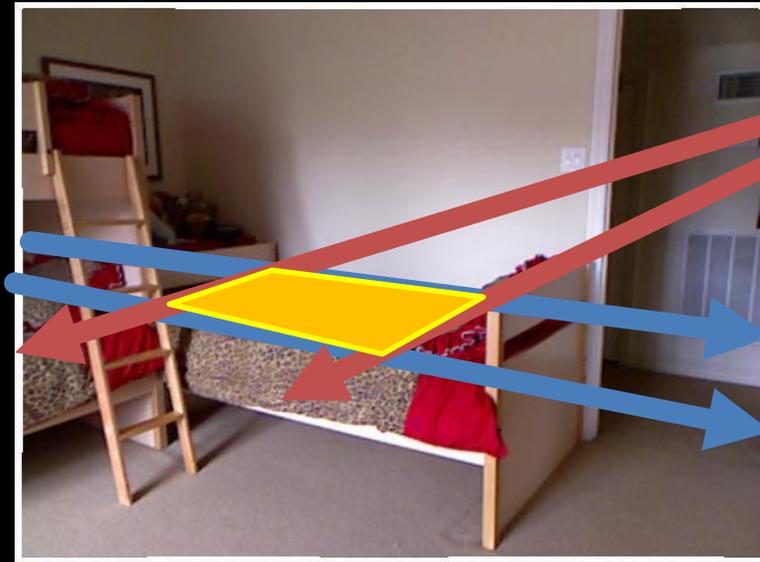


Parameterization

vp_2 ●

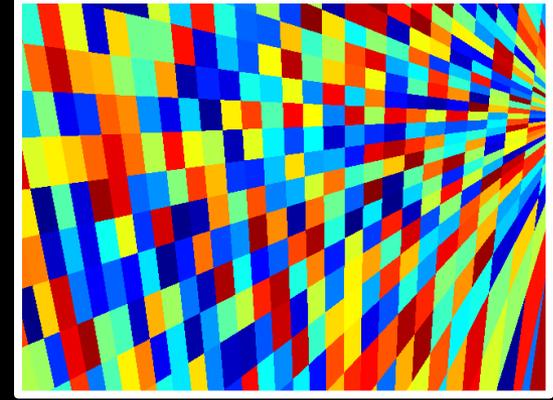
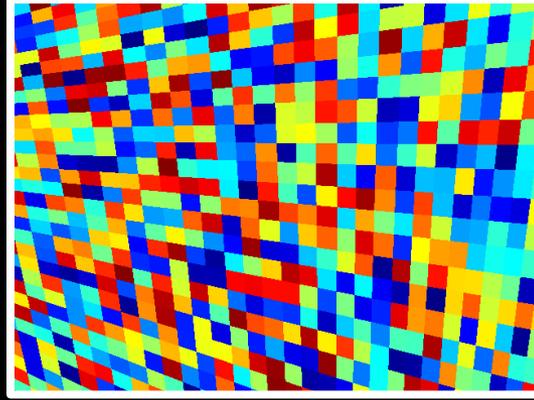
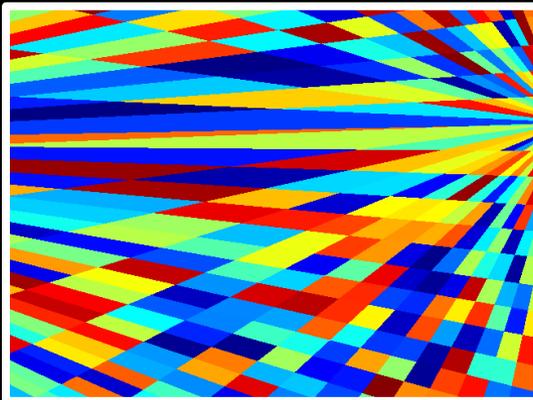
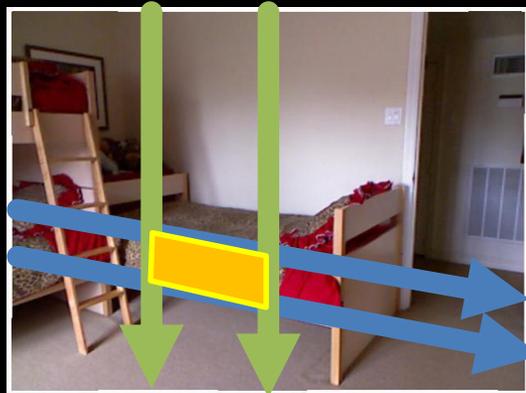
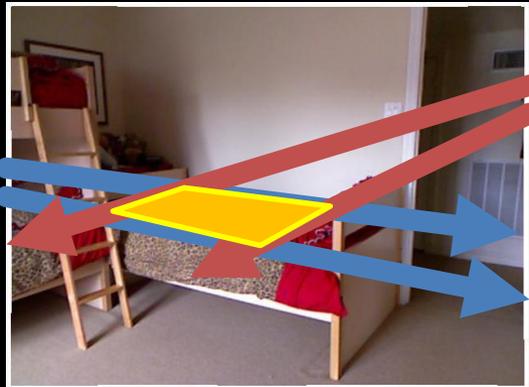
vp_3 ●

vp_1 ●

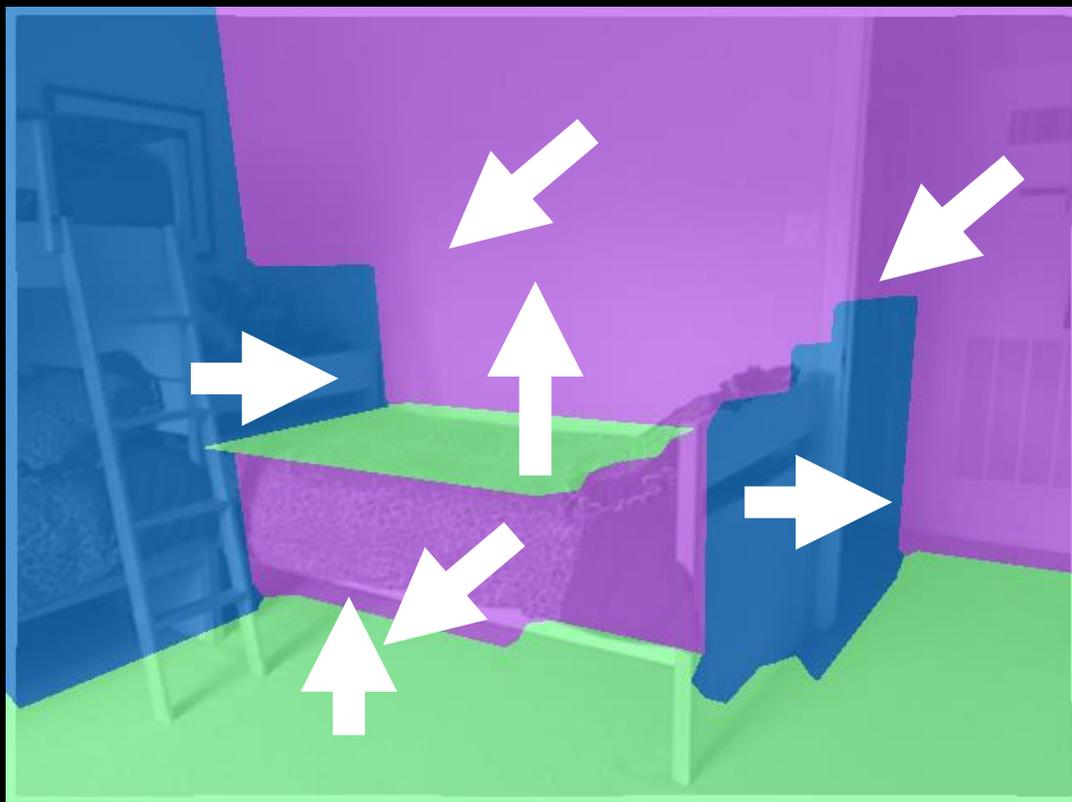


Parameterization

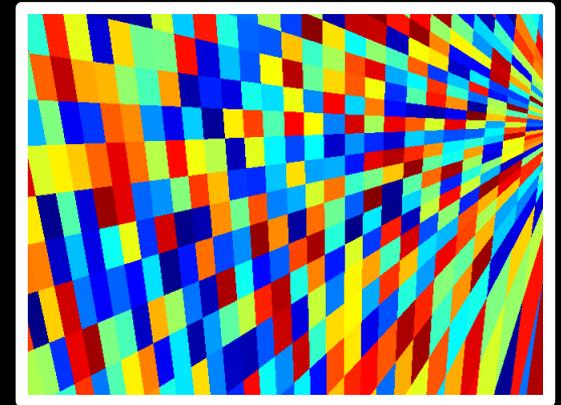
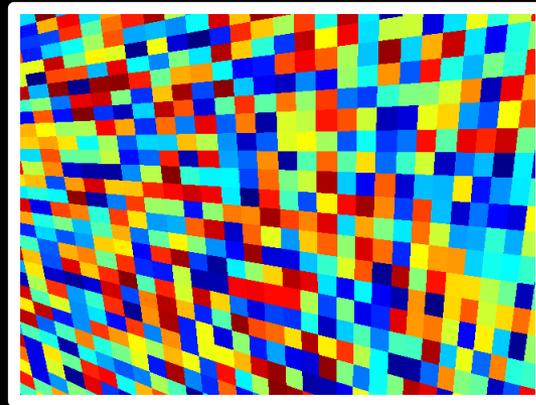
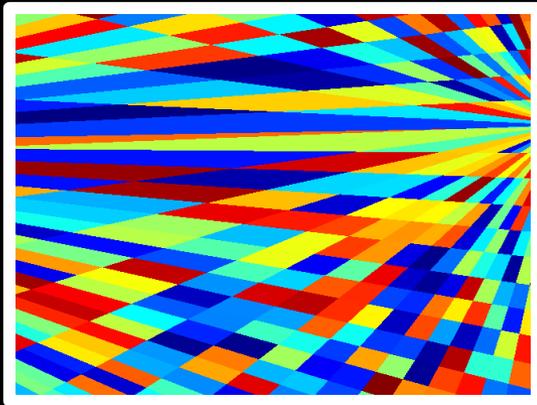
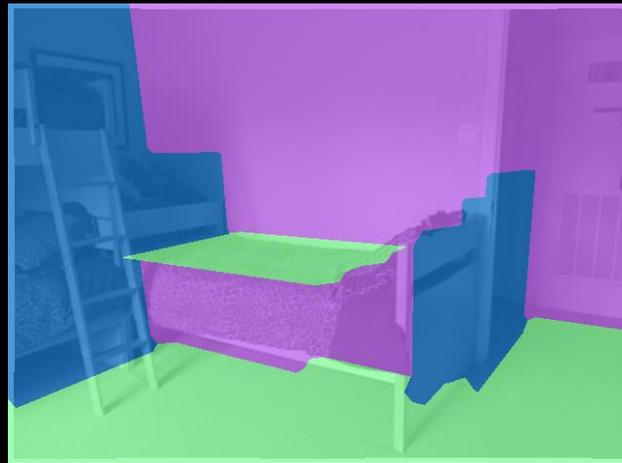
Two VPs give grid cell



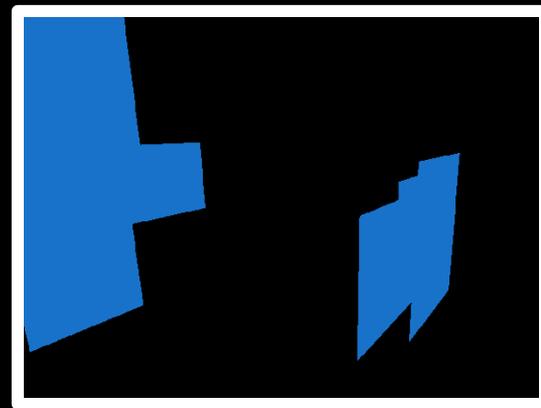
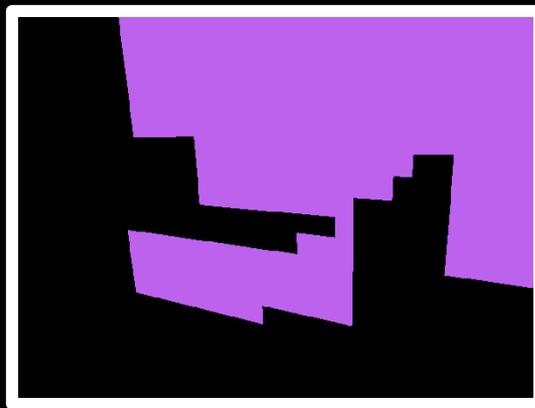
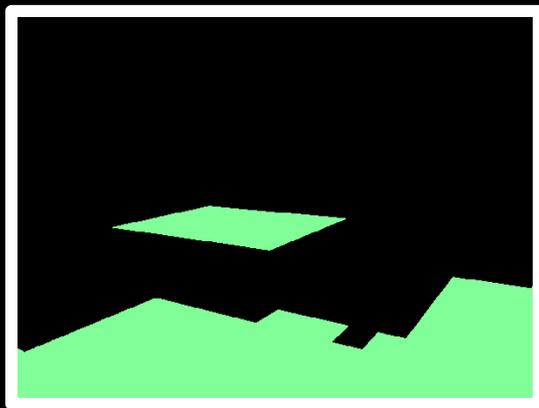
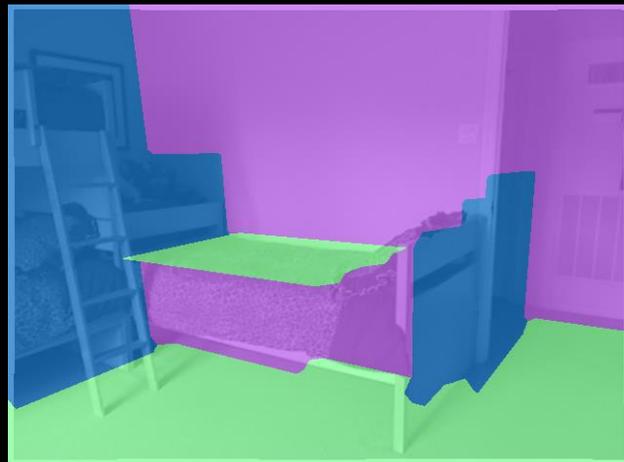
Encoding Surface Normals



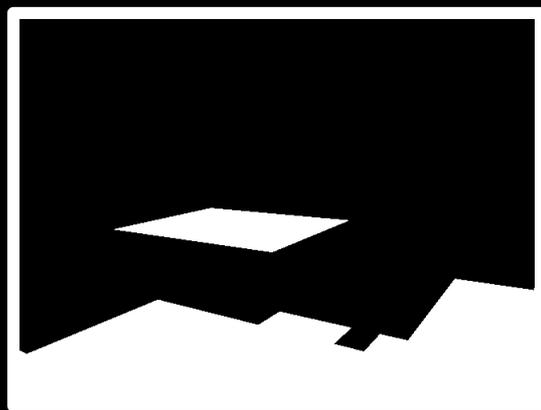
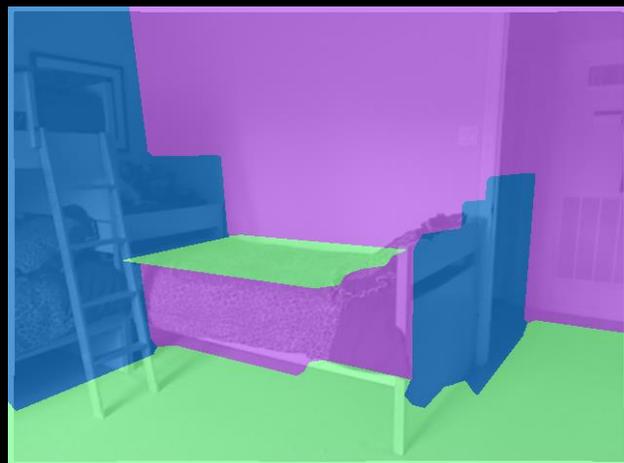
Encoding Surface Normals



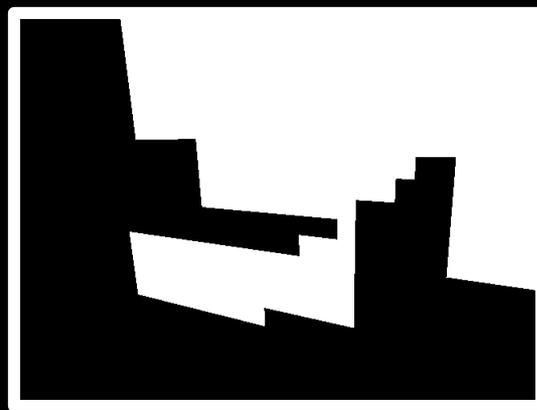
Encoding Surface Normals



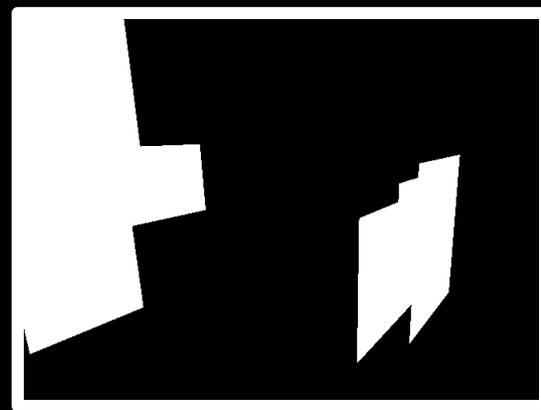
Encoding Surface Normals



x_1, \dots, x_{400}



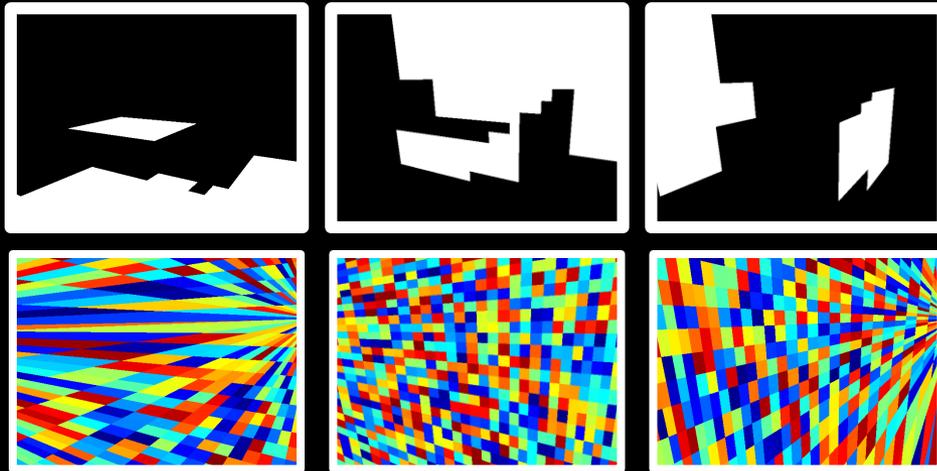
x_{401}, \dots, x_{800}



x_{801}, \dots, x_{1200}

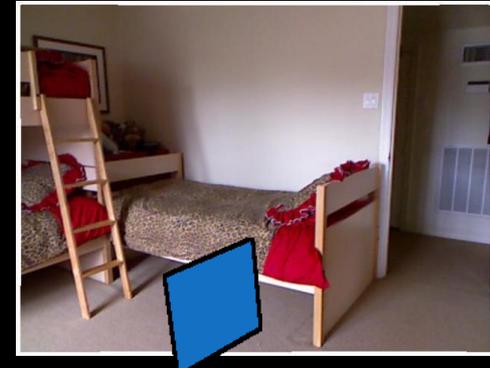
Formulation

$$\arg \max_{\mathbf{x} \in \{0,1\}^n} \mathbf{c}^T \mathbf{x} + \mathbf{x}^T \mathbf{H} \mathbf{x} \quad \text{s.t.} \quad \mathbf{A} \mathbf{x} \leq \mathbf{1}$$



Constraints

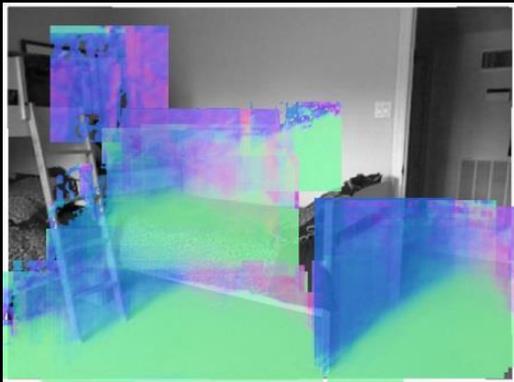
$$\arg \max_{\mathbf{x} \in \{0,1\}^n} \mathbf{c}^T \mathbf{x} + \mathbf{x}^T \mathbf{H} \mathbf{x} \quad \text{s.t.} \quad \mathbf{A} \mathbf{x} \leq \mathbf{1}$$



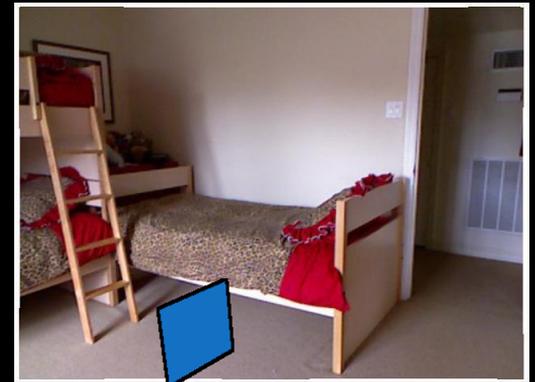
Unaries

$$\arg \max_{\mathbf{x} \in \{0,1\}^n} \mathbf{c}^T \mathbf{x} + \mathbf{x}^T \mathbf{H} \mathbf{x} \quad \text{s.t.} \quad \mathbf{A} \mathbf{x} \leq \mathbf{1}$$

Unaries



High c



Low c

Unary Evidence:
(1) 3DP
(2) Room Box Fitting

Binaries

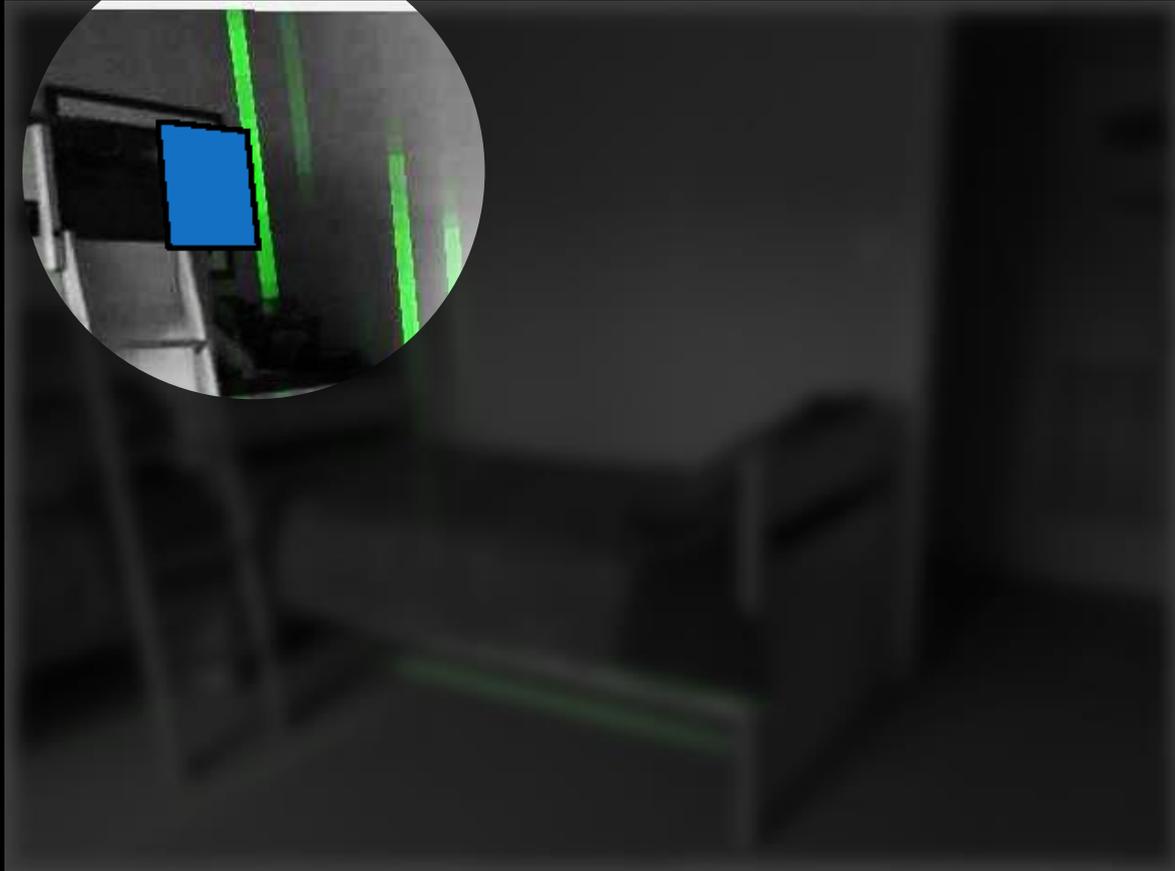
$$\arg \max_{\mathbf{x} \in \{0,1\}^n} \mathbf{c}^T \mathbf{x} + \mathbf{x}^T \mathbf{H} \mathbf{x} \quad \text{s.t.} \quad \mathbf{A} \mathbf{x} \leq \mathbf{1}$$

Convex/Concave Constraints



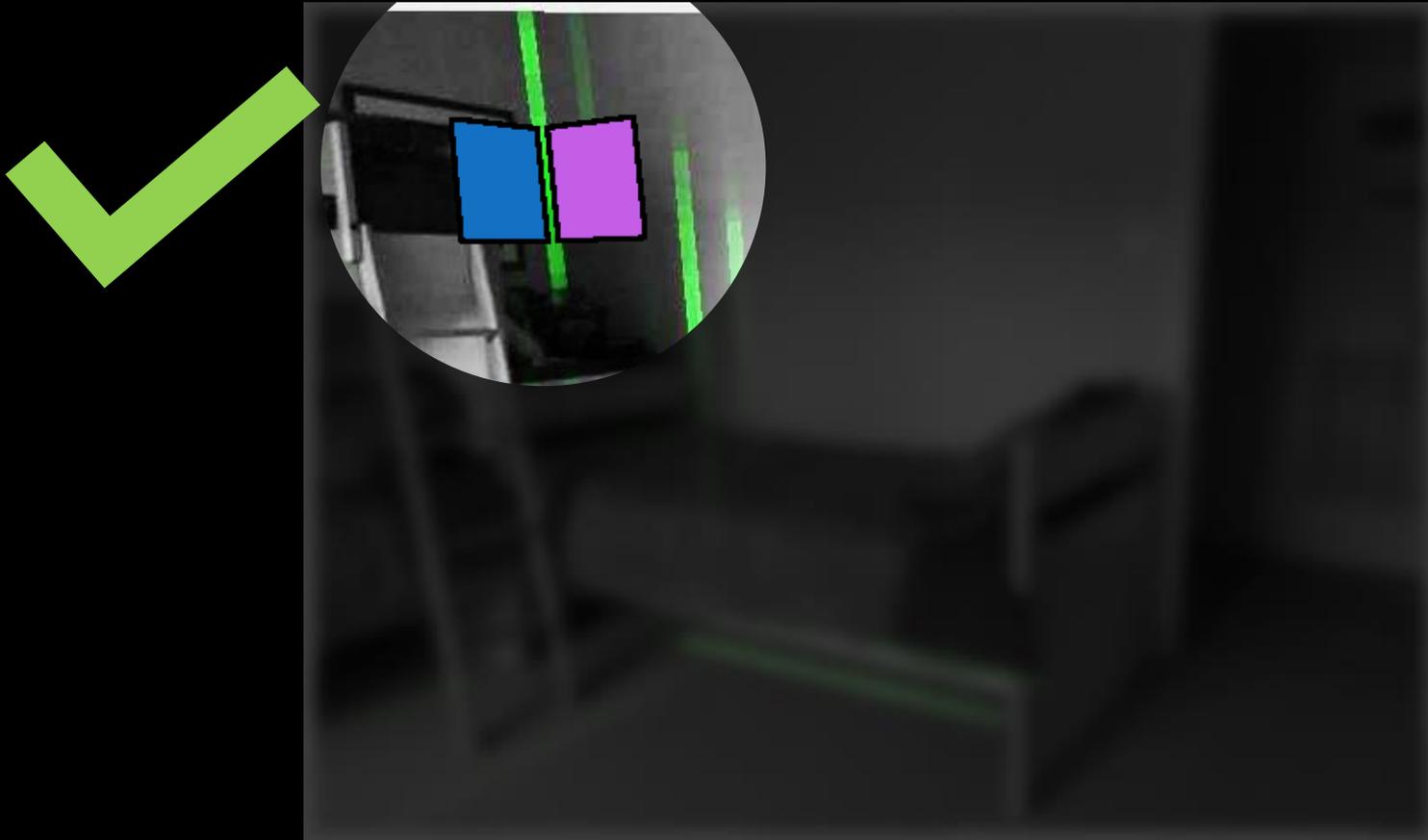
Detected Concave (-)

Convex/Concave Constraints



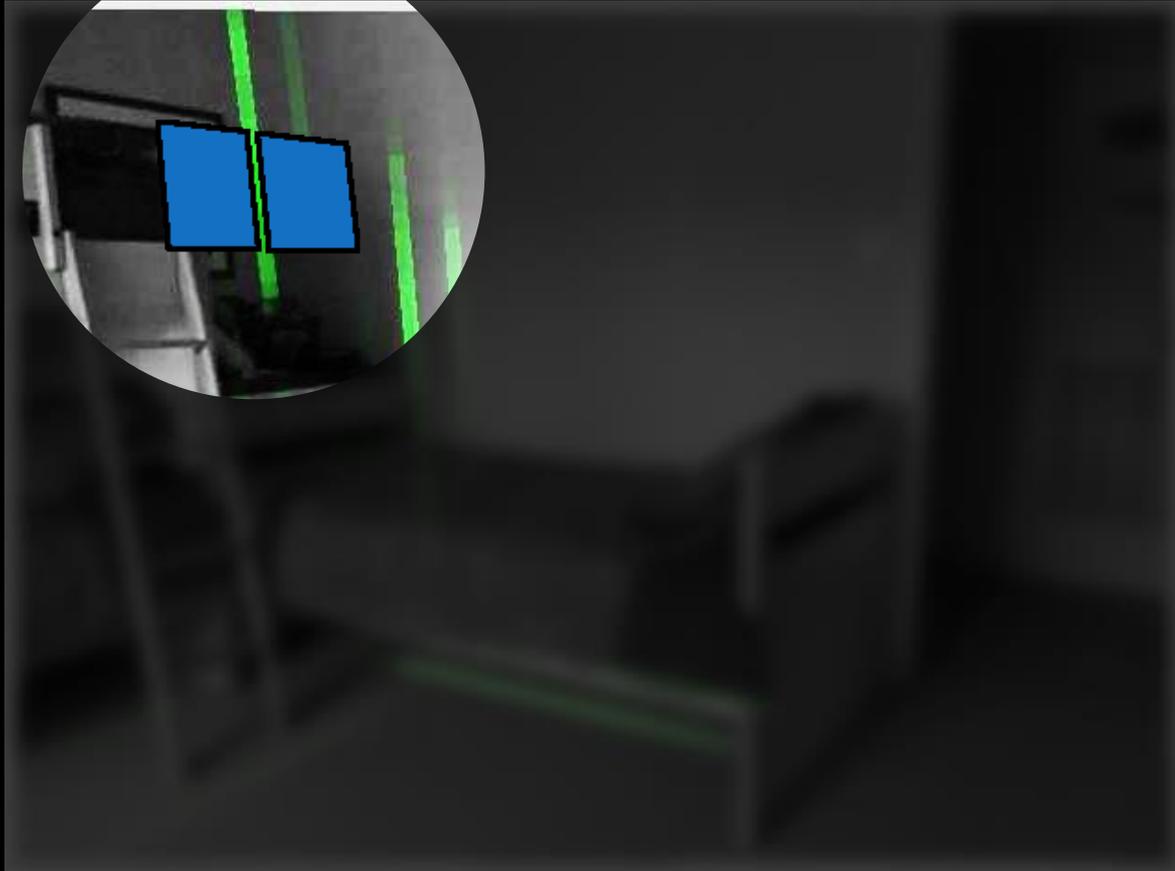
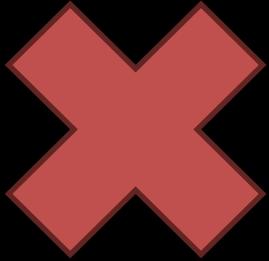
Detected Concave (-)

Convex/Concave Constraints



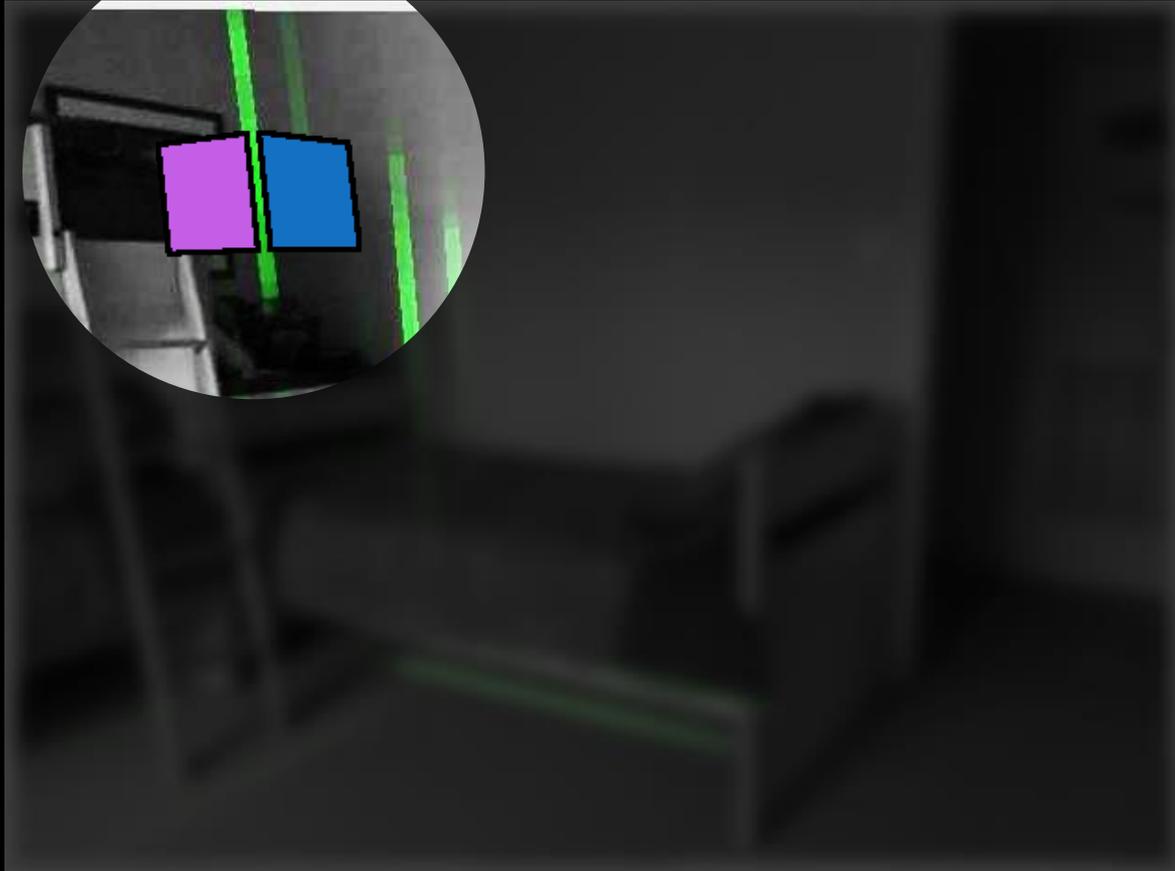
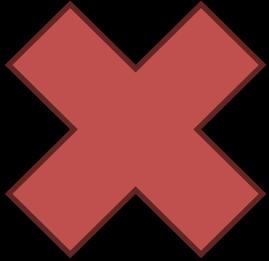
Detected Concave (-)

Convex/Concave Constraints



Detected Concave (-)

Convex/Concave Constraints

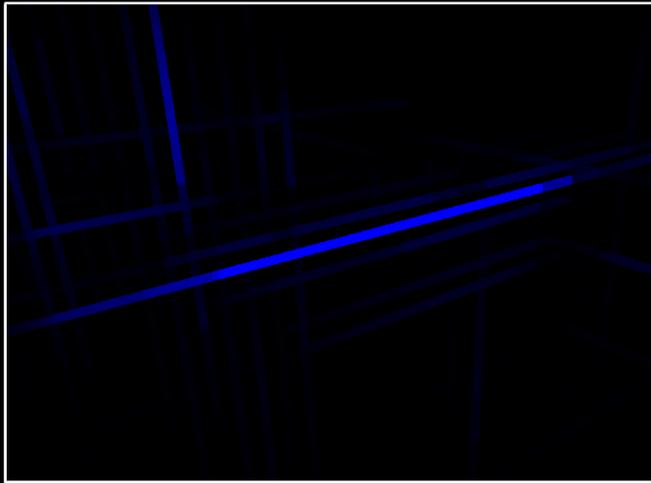


Detected Concave (-)

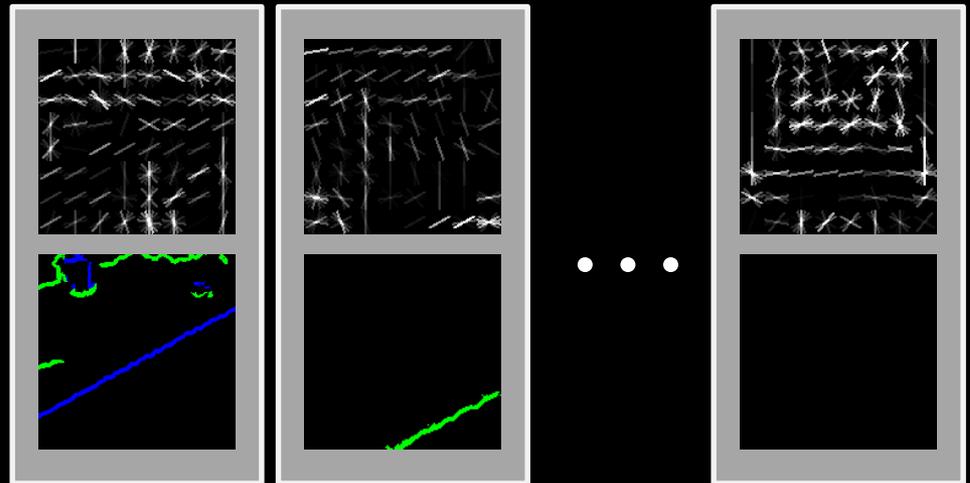
Detecting Convex/Concave

Use 3DP to Transfer Convex/Concave

Input

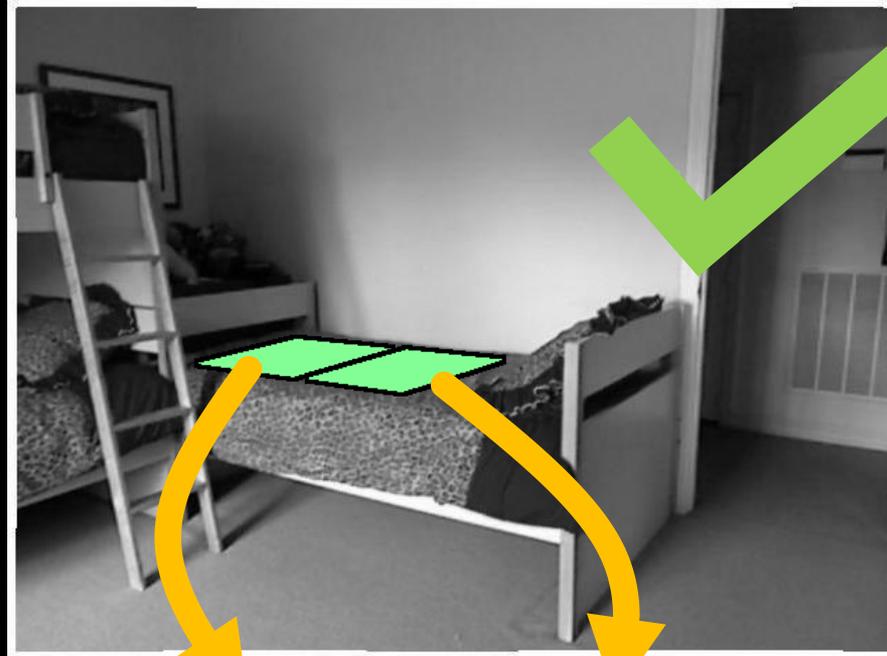


3D Primitive Bank



Ground-Truth Discontinuities similar to Gupta, Arbelaez, Malik, 2013
3DP from Fouhey, Gupta, Hebert, 2013

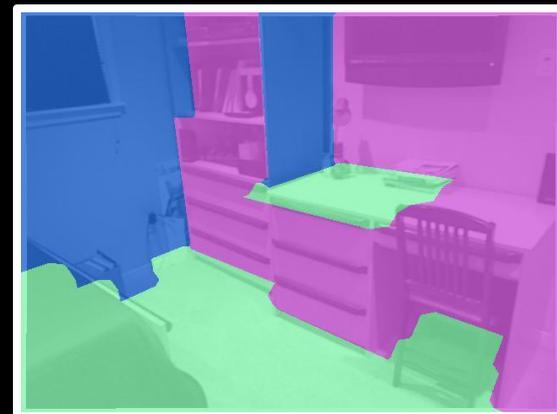
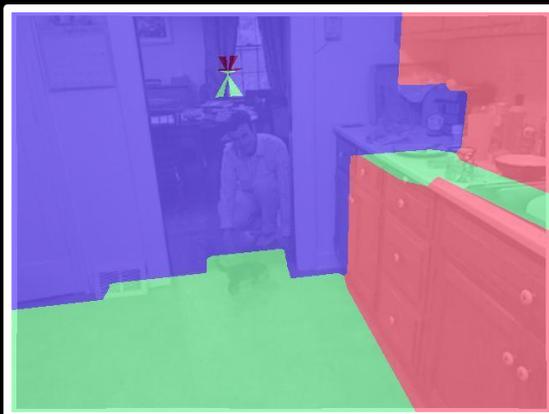
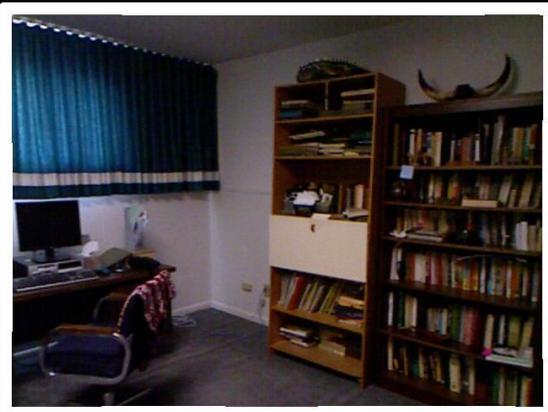
Smoothness



Solving the Model

$$\arg \max_{\mathbf{x} \in \{0,1\}^n} \mathbf{c}^T \mathbf{x} + \mathbf{x}^T \mathbf{H} \mathbf{x} \quad \text{s.t.} \quad \mathbf{A} \mathbf{x} \leq \mathbf{1}$$

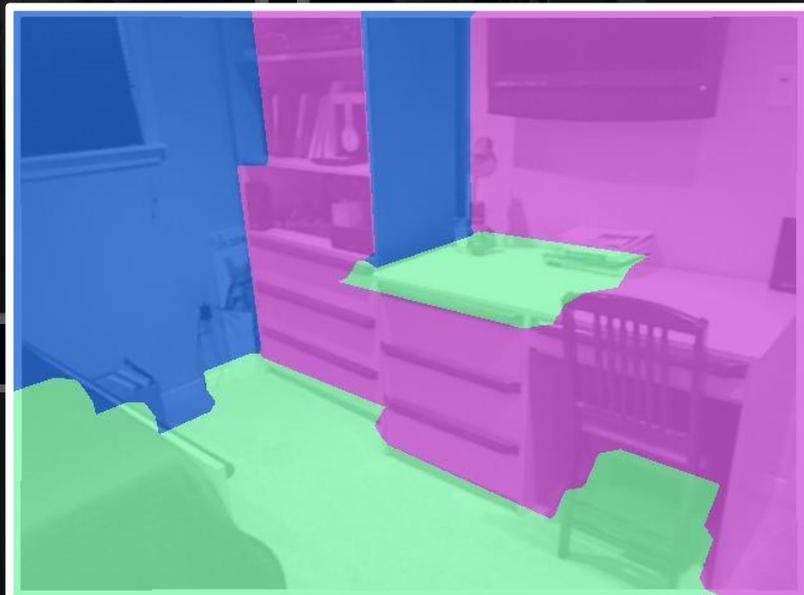
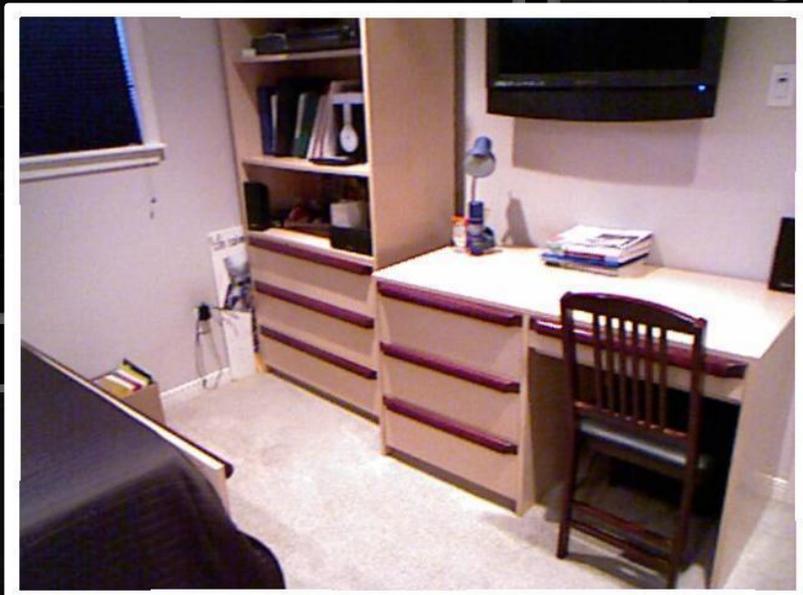
Qualitative Results



Qualitative Results



Qualitative Results



Results – Quantitative

	Summary Stats (°) (Lower Better)		% Good Pixels (Higher Better)		
	Mean	Median	11.25°	22.5°	30°
Proposed	35.2	<u>17.9</u>	<u>40.5</u>	<u>54.1</u>	<u>58.9</u>
3DP	36.3	19.2	39.2	52.9	57.8
Ladicky '14	<u>33.5</u>	23.1	27.7	49.0	58.7

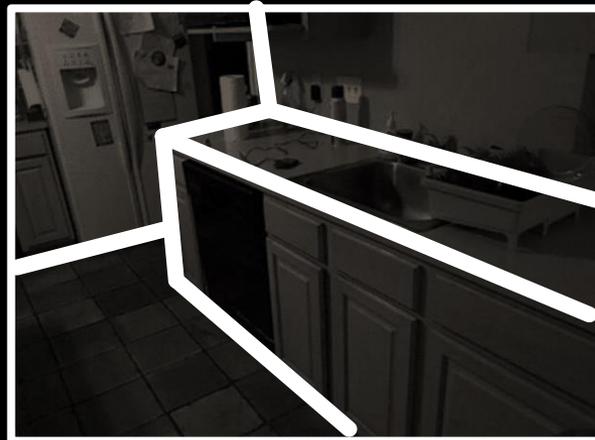
CONCLUSIONS & FUTURE WORK

Today

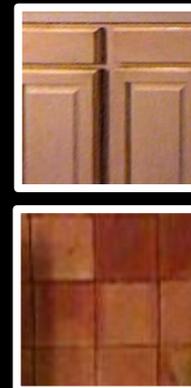
Image (3D Structure x Style)



3D Structure

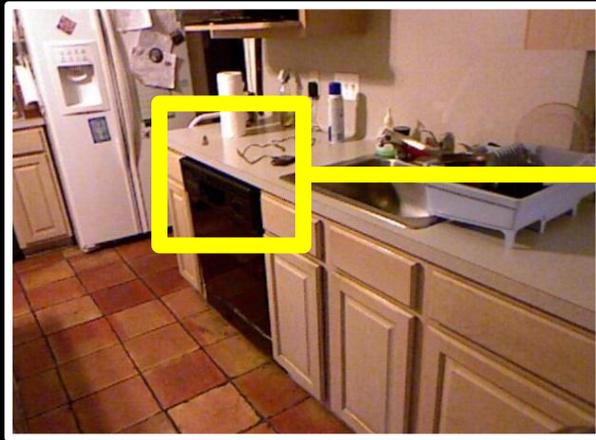


Style

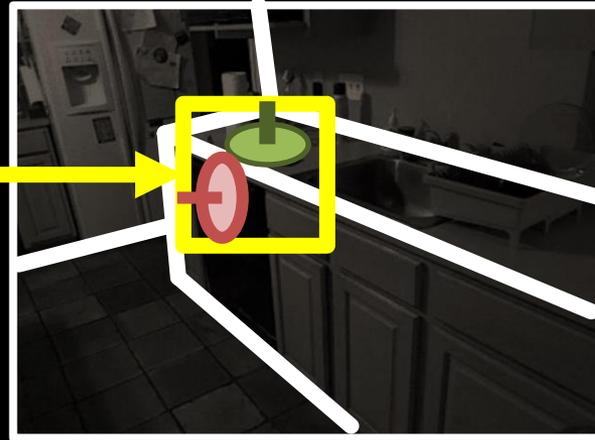


Today

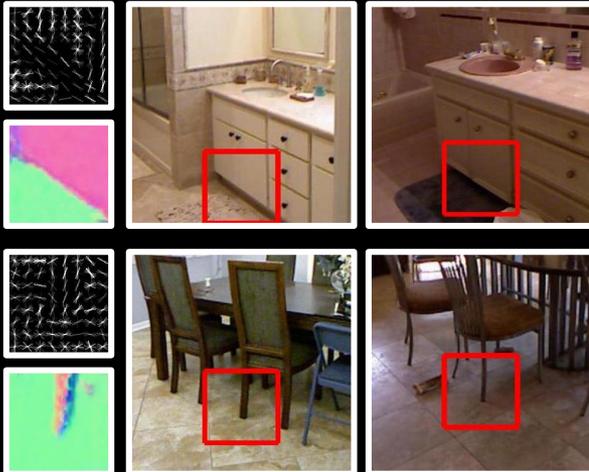
Image (3D Structure x Style)



3D Structure



Style

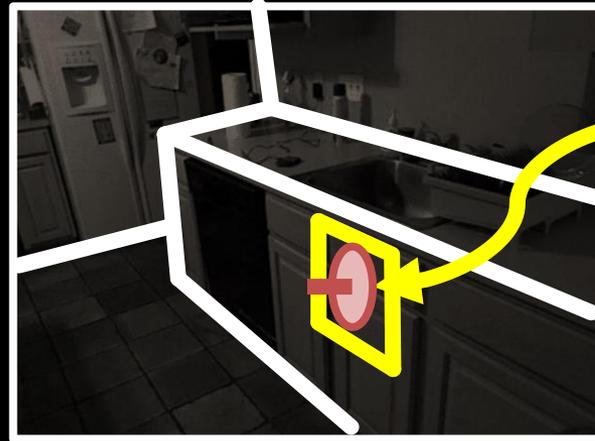


Today

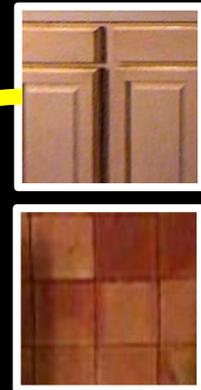
Image (3D Structure x Style)



3D Structure



Style



Today

Image (3D Structure x Style)



3D Structure



Style



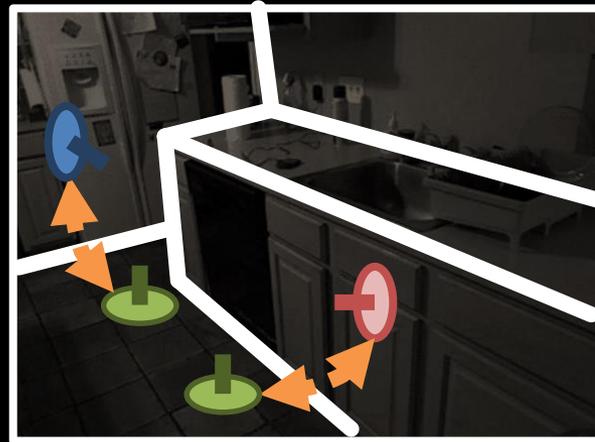
Planar	✓
Non-Planar	✗
Cylindrical	✗
Rough Surf	✗
Pnt/L. Contact	✓
Mult. Contact	✓
Empty	✗
Mult. Pieces	✓
Holes	✓
Thin	✓
Mirror Sym.	✓
Cubic Aspect	✗

Today

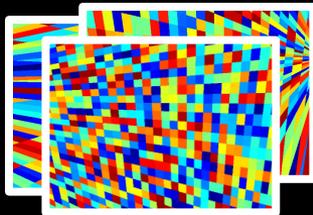
Image (3D Structure x Style)



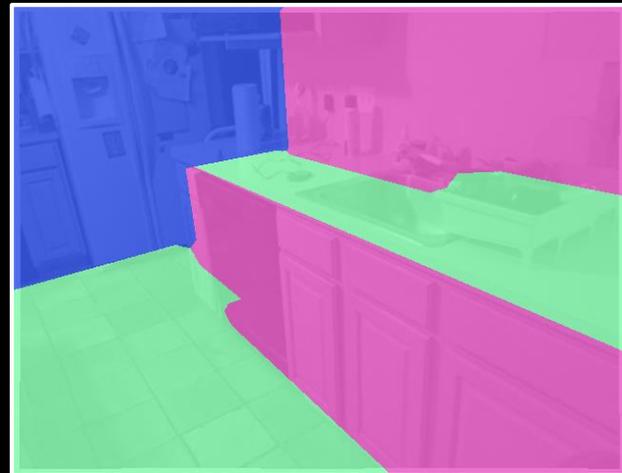
3D Structure



Style

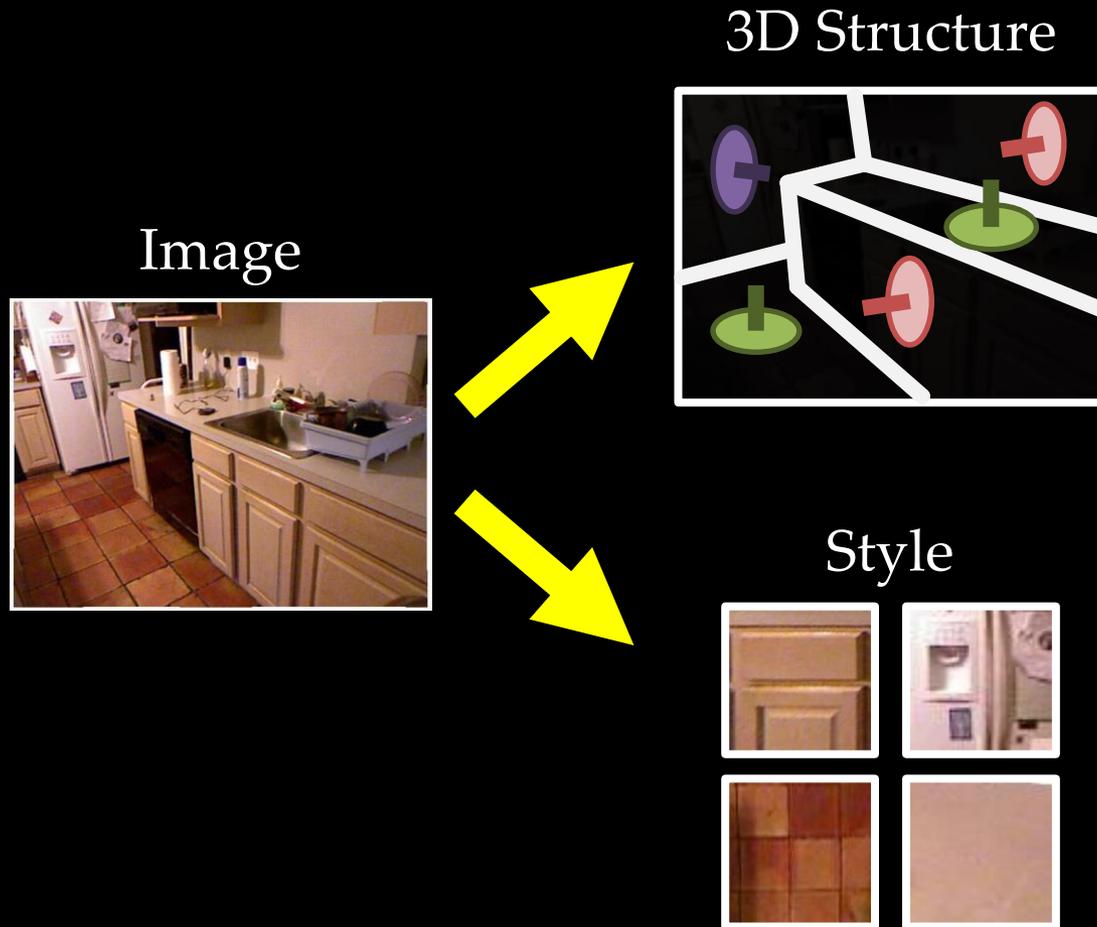


$$\begin{aligned} & \arg \max_{\mathbf{x} \in \{0,1\}^n} \mathbf{c}^T \mathbf{x} + \mathbf{x}^T \mathbf{H} \mathbf{x} \\ & \text{s.t. } \mathbf{A} \mathbf{x} \leq \mathbf{1} \end{aligned}$$

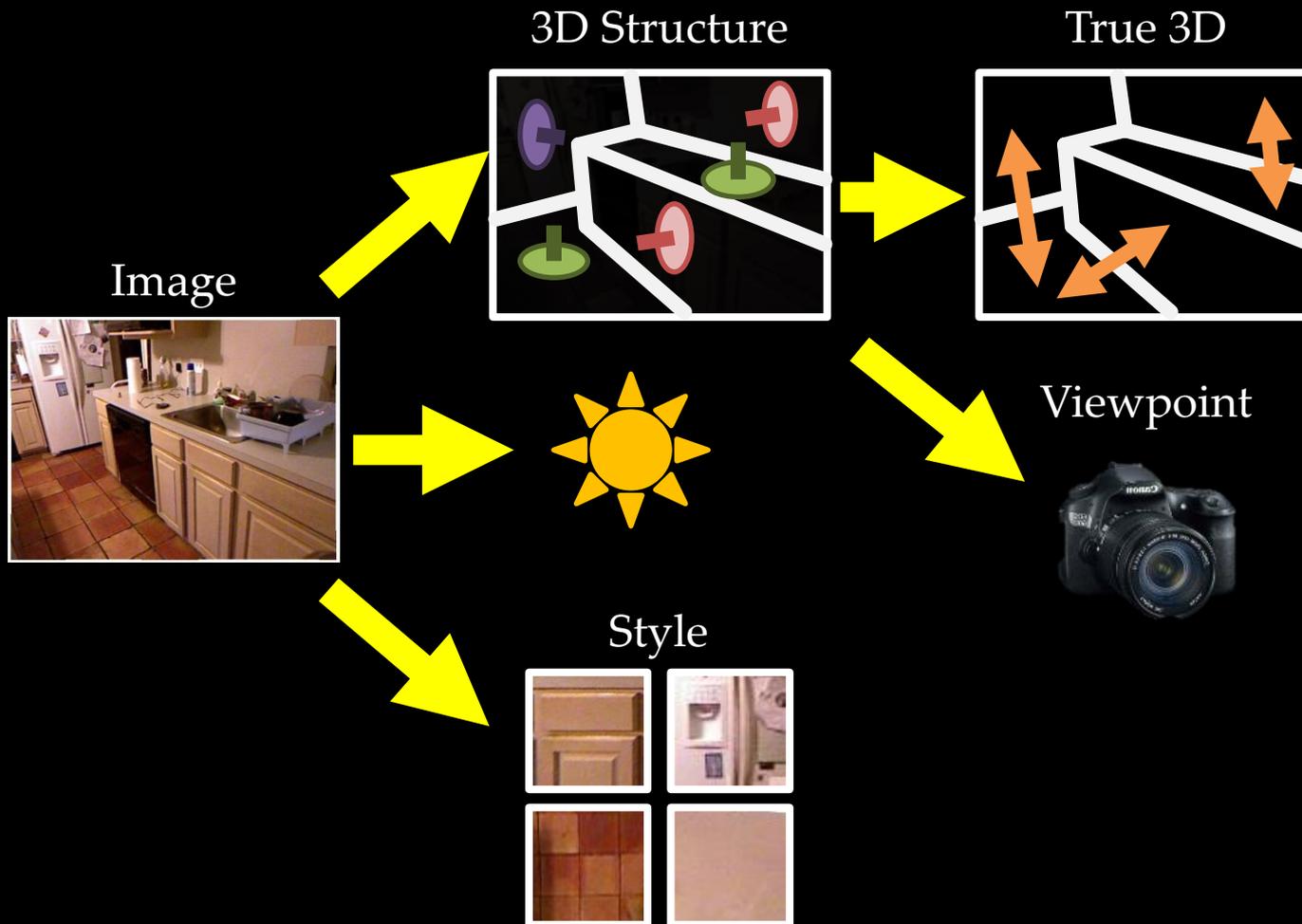


Future Work

Further Factorization

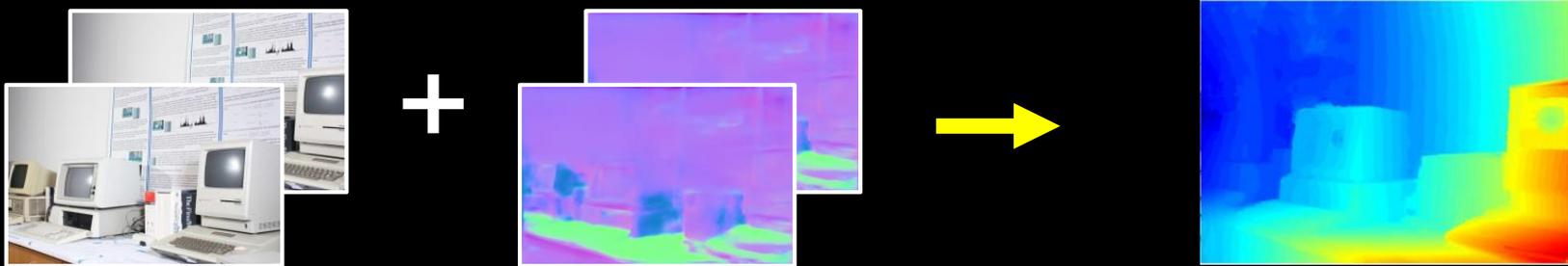


Further Factorization



Reuniting 3Ds (Multiview)

Monocular and multi-view cues

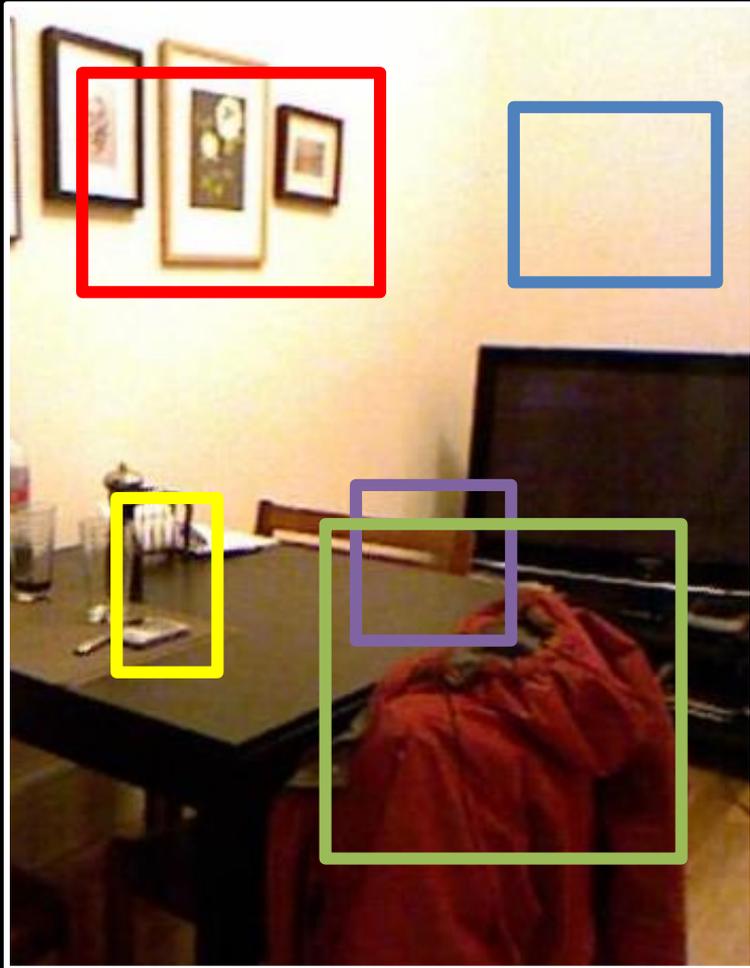


Supervised and unsupervised models

RGBD

RGB

Reuniting 3Ds (Single View)



Texture

Top-down

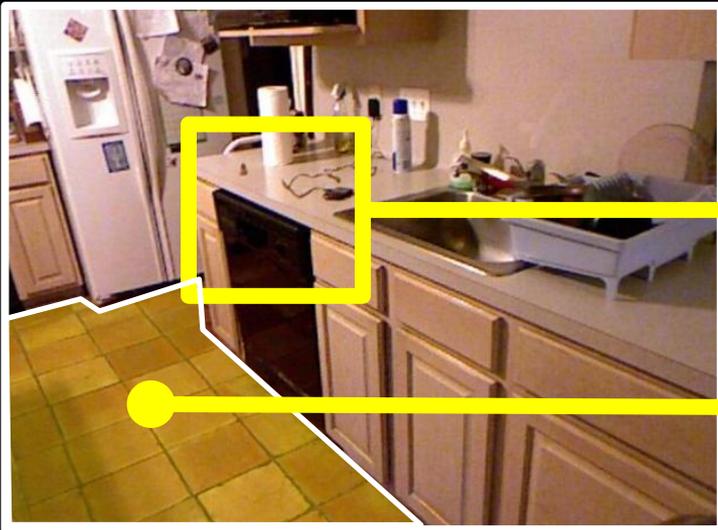
Occlusion

Shading

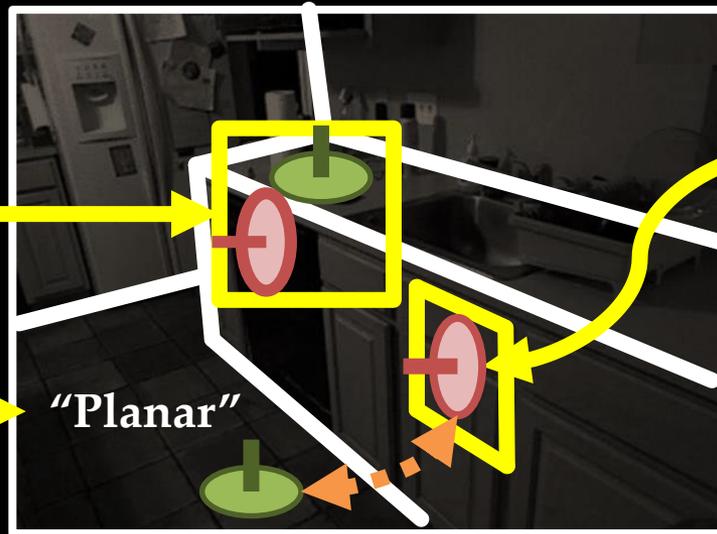
Semantics

Thank you

Image (3D Structure x Style)



3D Structure



Style

