

Learning from 3D Data for Image Interpretation

Martial Hebert

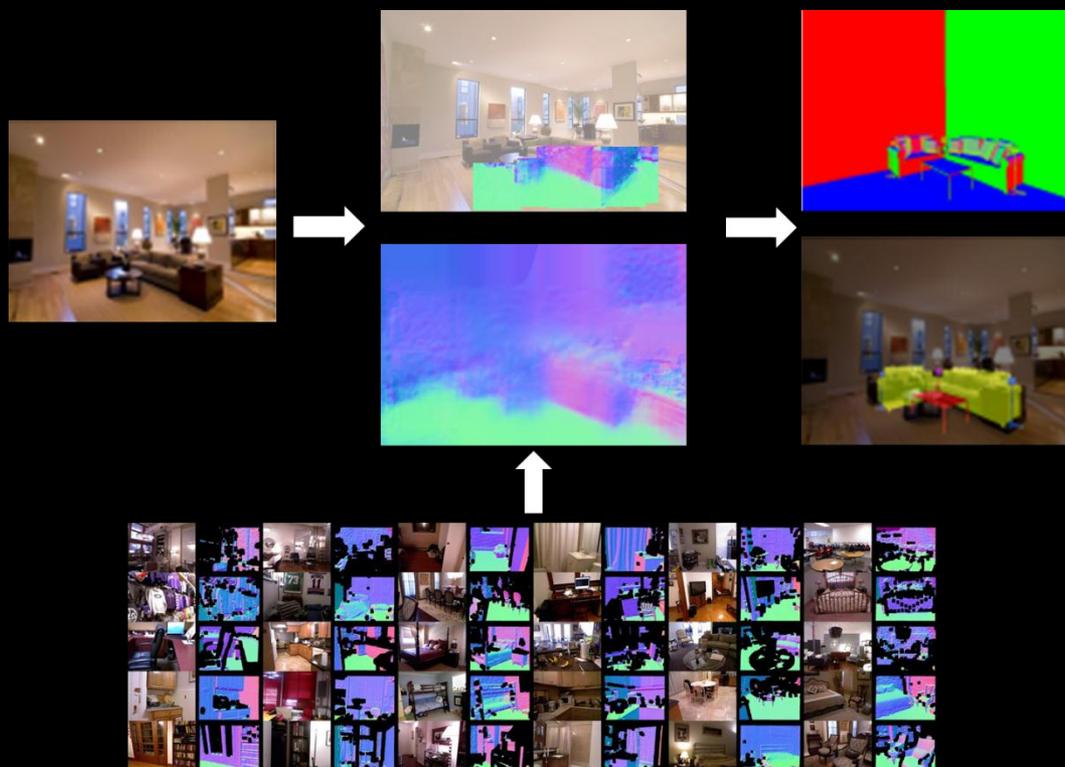
Abhinav Gupta

David Fouhey, Adrien Matricon, Wajahat Hussain



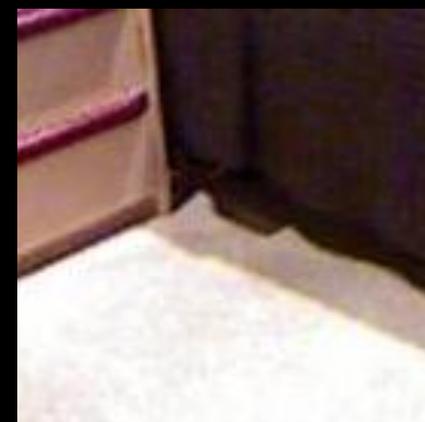
Slides adapted from David Fouhey

- Mid-level primitives learned from image+3D can be used to transfer geometric information?
- Geometric reasoning can use this local evidence to produce a consistent geometric interpretation?



Pattern Repetition

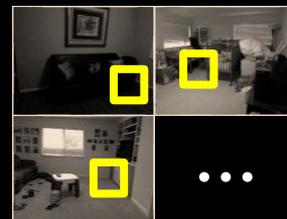
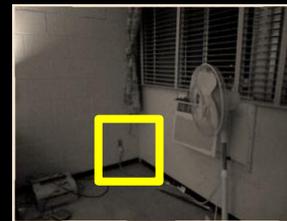
Common patterns correspond to common geometric configurations



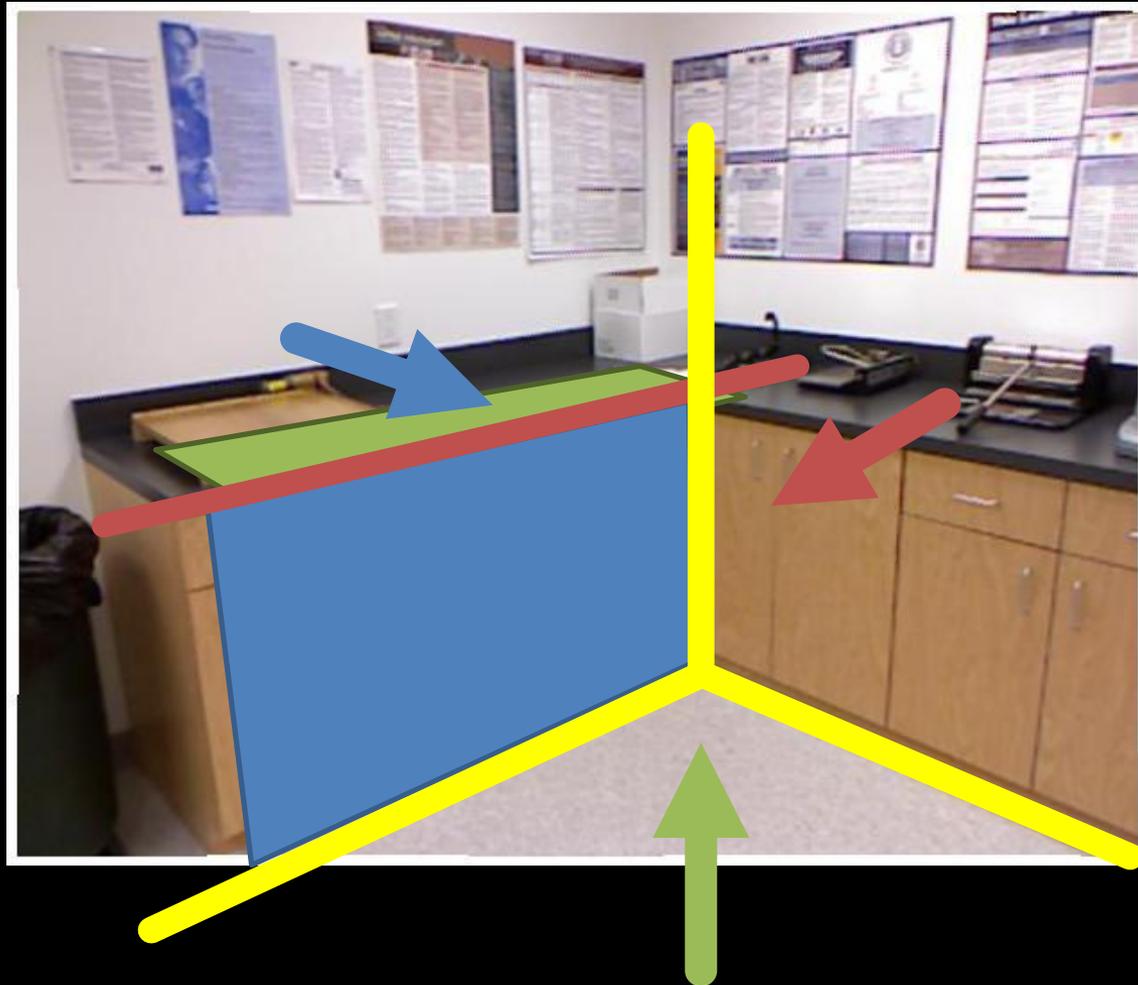
Pattern Repetition



Pattern Repetition

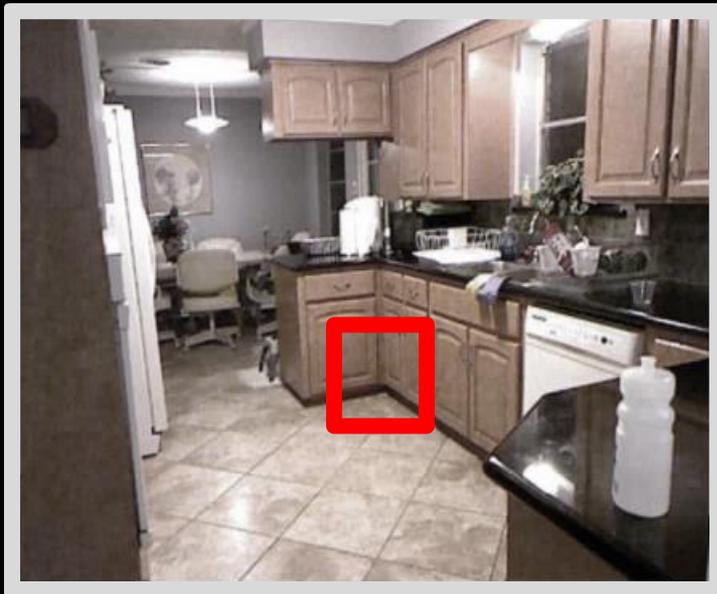
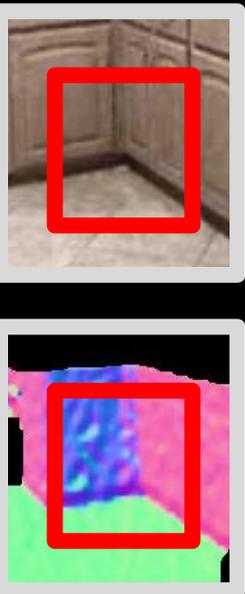


Physical/Geometric Constraints



Primitives

Visually
Discriminative



Image

Geometrically
Informative



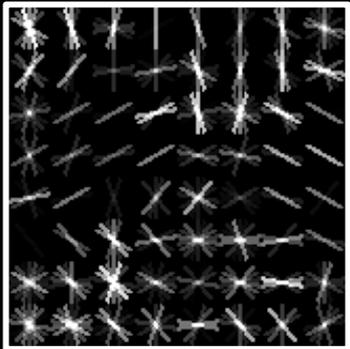
Surface Normals

Geometric configurations from large-scale RGBD data.

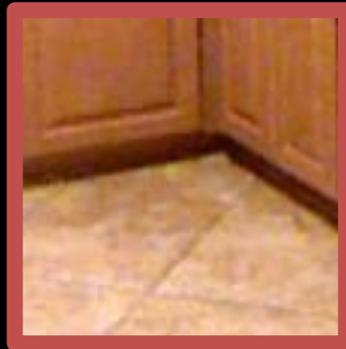


Representation

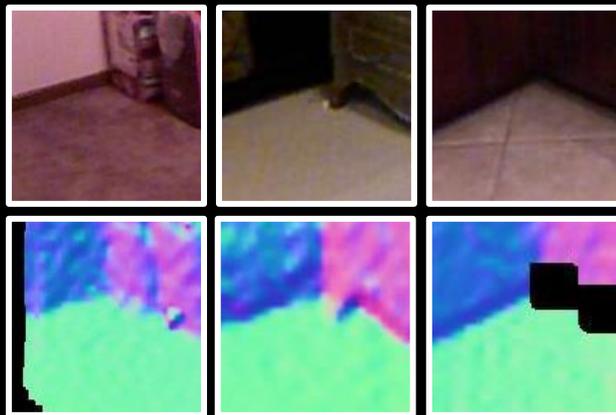
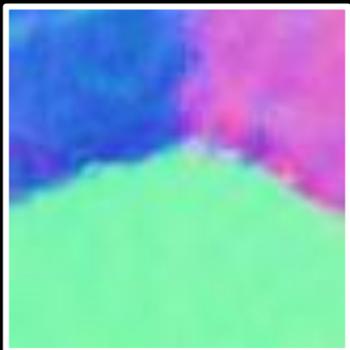
Detector

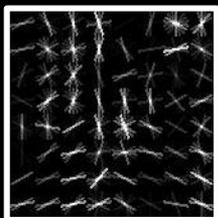
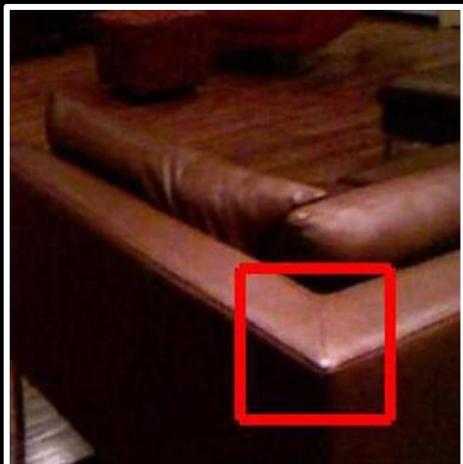
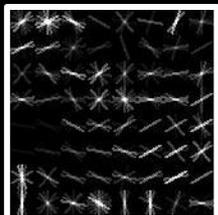


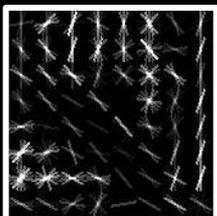
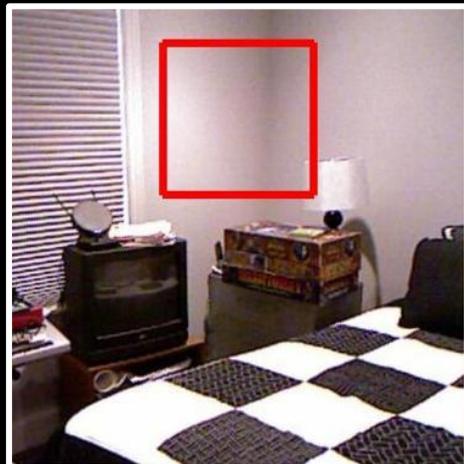
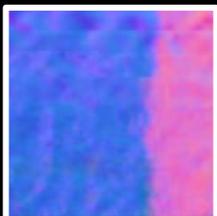
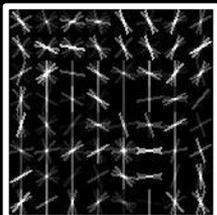
Instances

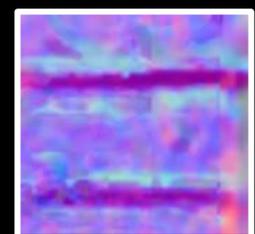
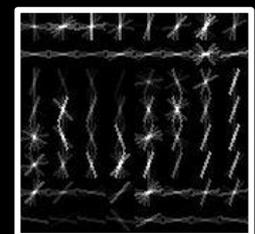
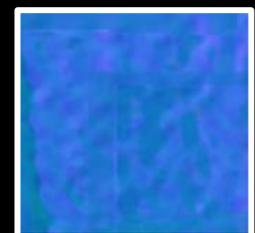
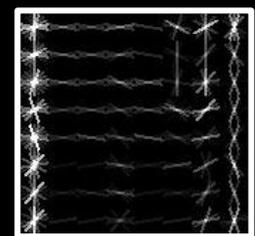


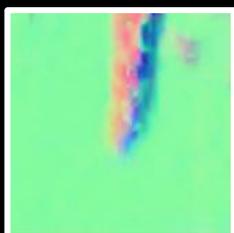
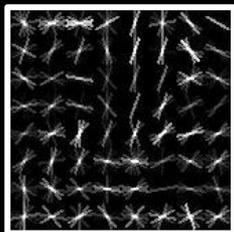
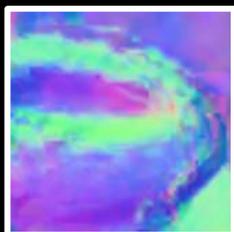
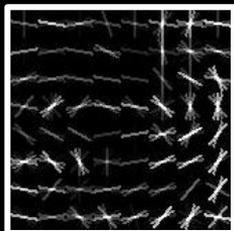
Canonical Form











Representation

Detector



Instances



Canonical Form



W

Representation

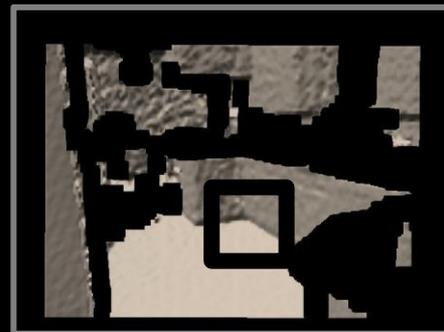
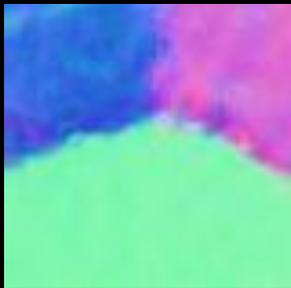
Detector



Instances



Canonical Form



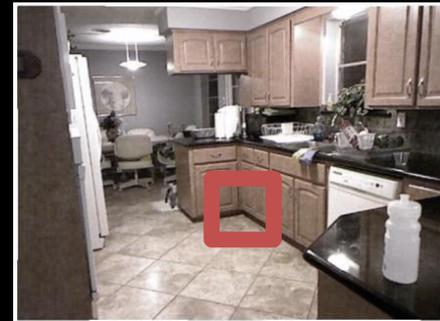
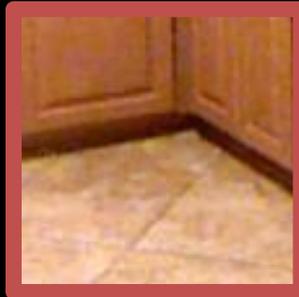
N

Representation

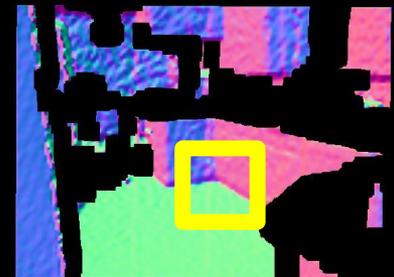
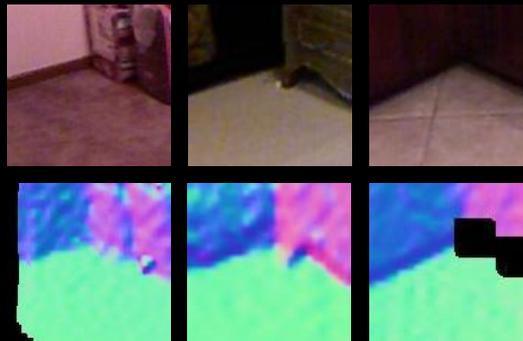
Detector



Instances



Canonical Form



Y

Learning Primitives

$$\min_{y, w, N} R(w) + \sum_i c_1 y_i \Delta(N, x_i^G) + c_2 L(w, N, x_i^A, y_i)$$

Primitive

Patch

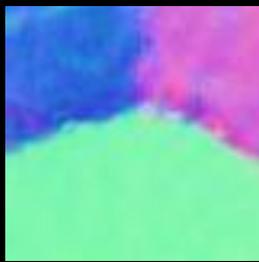
w

N

y

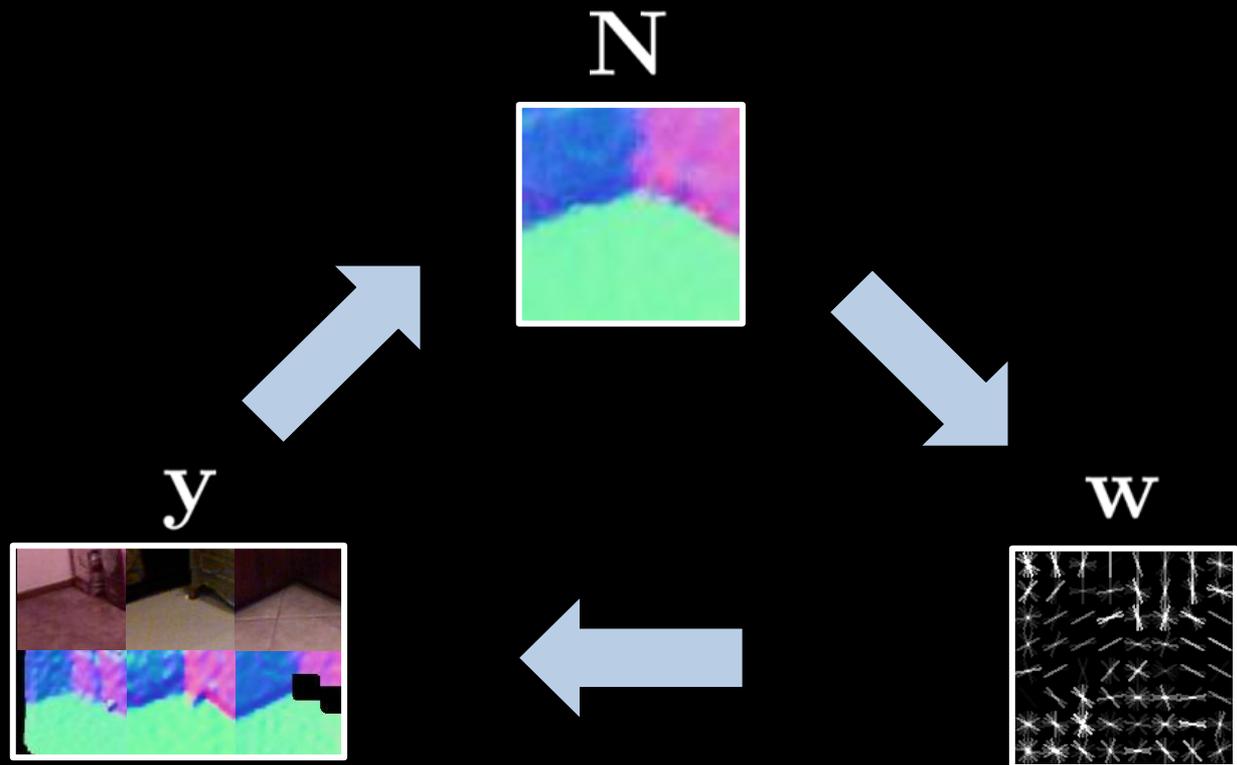
x_i^A

x_i^G



Learning Primitives

Approach: iterative procedure

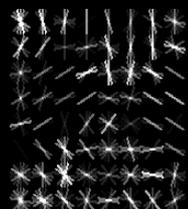


Learning Primitives

$$N \quad \text{[Image]} = \text{Avg} \left(\text{[Image]} \quad \text{[Image]} \quad \text{[Image]} \right)$$



y

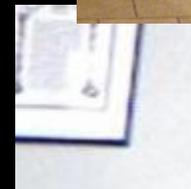
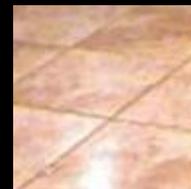
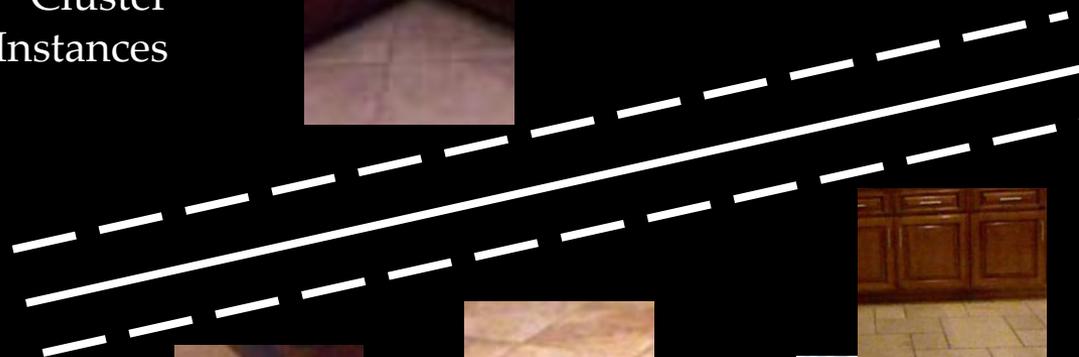
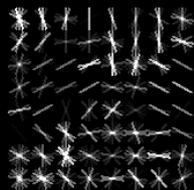


w

Learning Primitives



Cluster
Instances



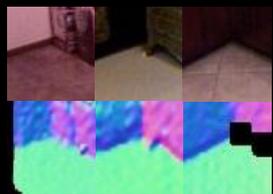
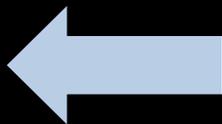
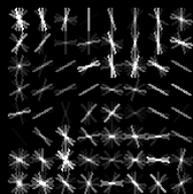
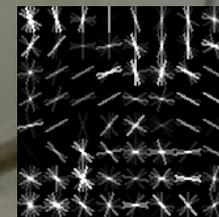
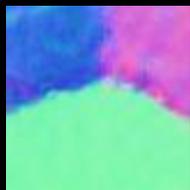
Patches
Geometrically
Dissimilar to N



y

Learning Primitives

N



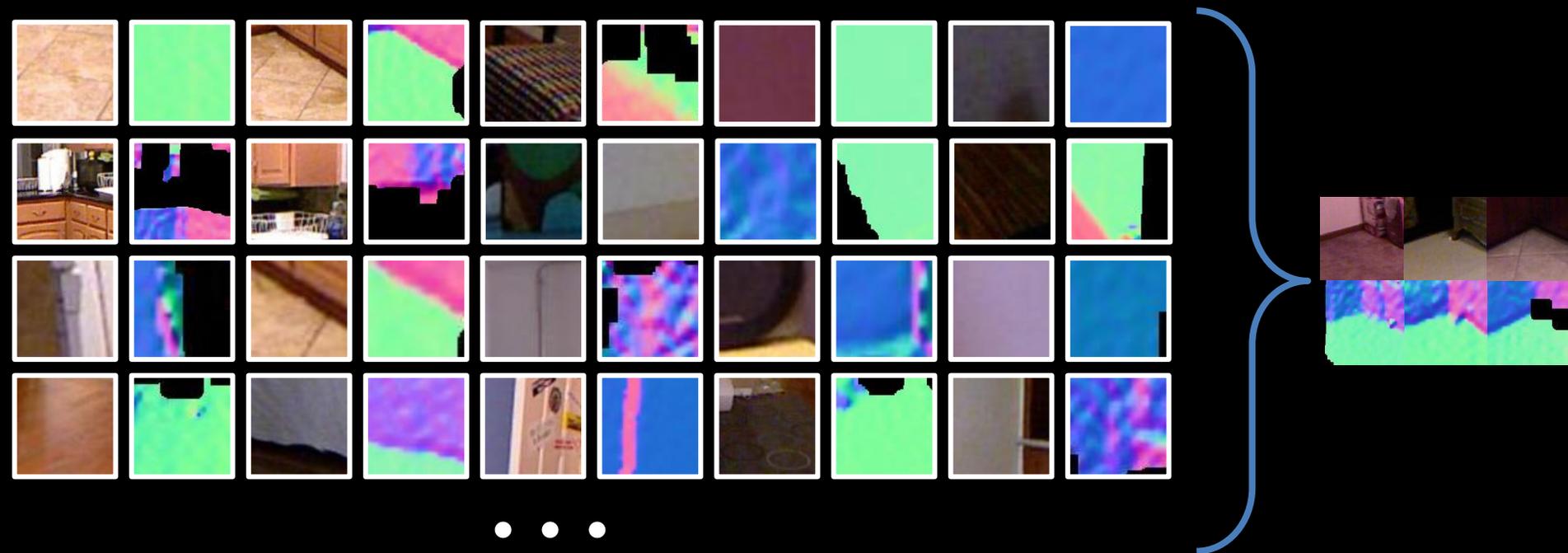
y

w



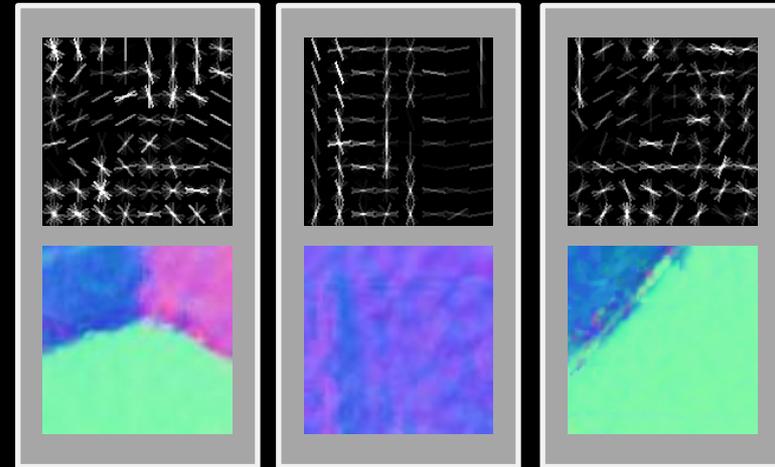
Learning Primitives

Initialize y by clustering sampled patches



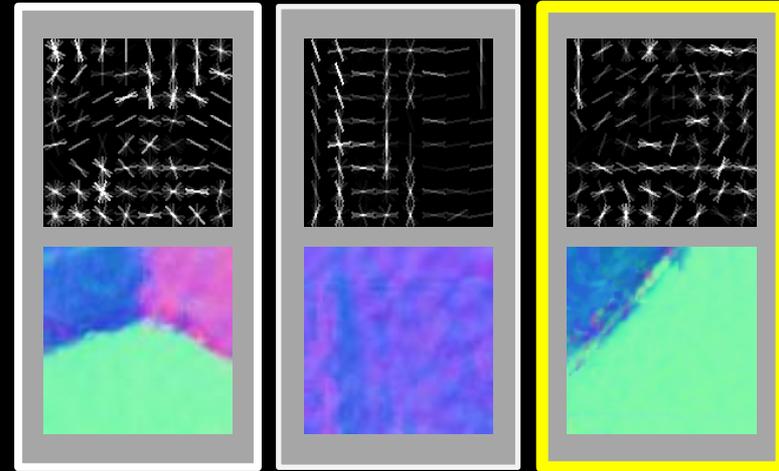
Inference

Sparse Transfer



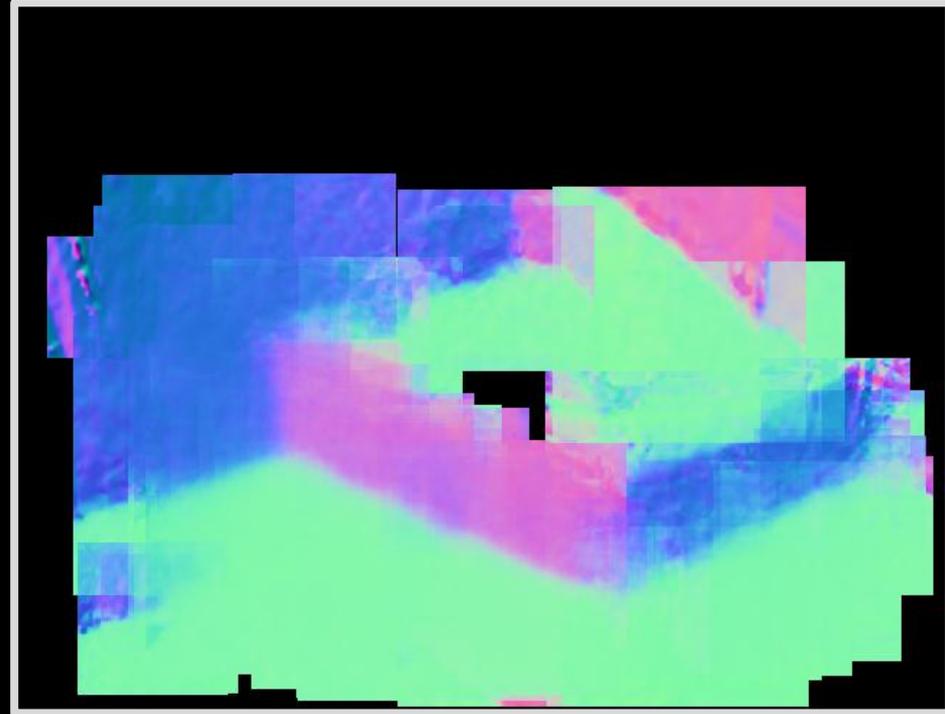
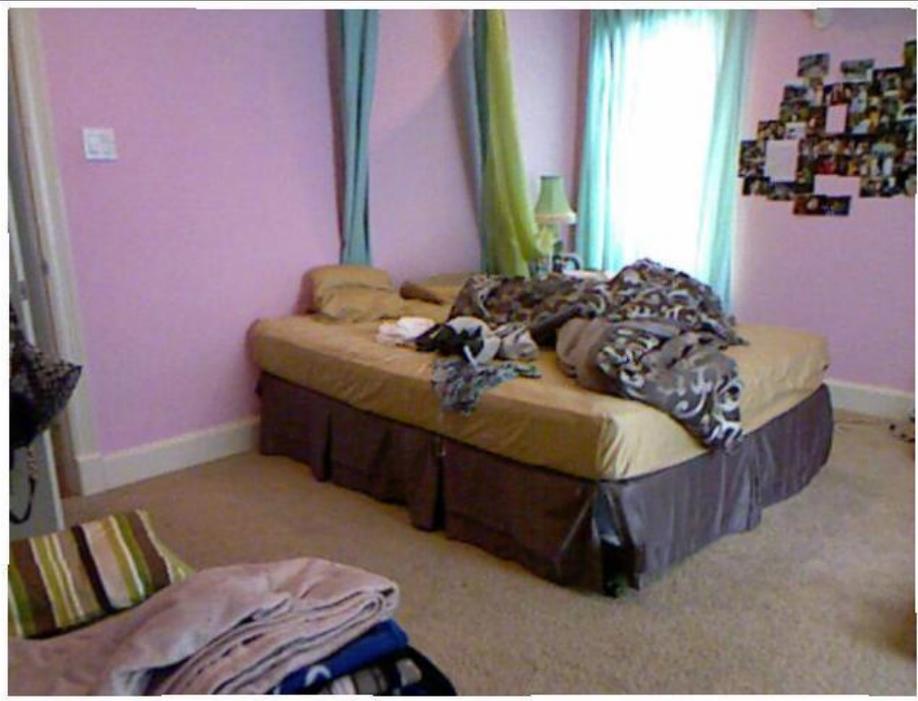
Inference

Sparse Transfer



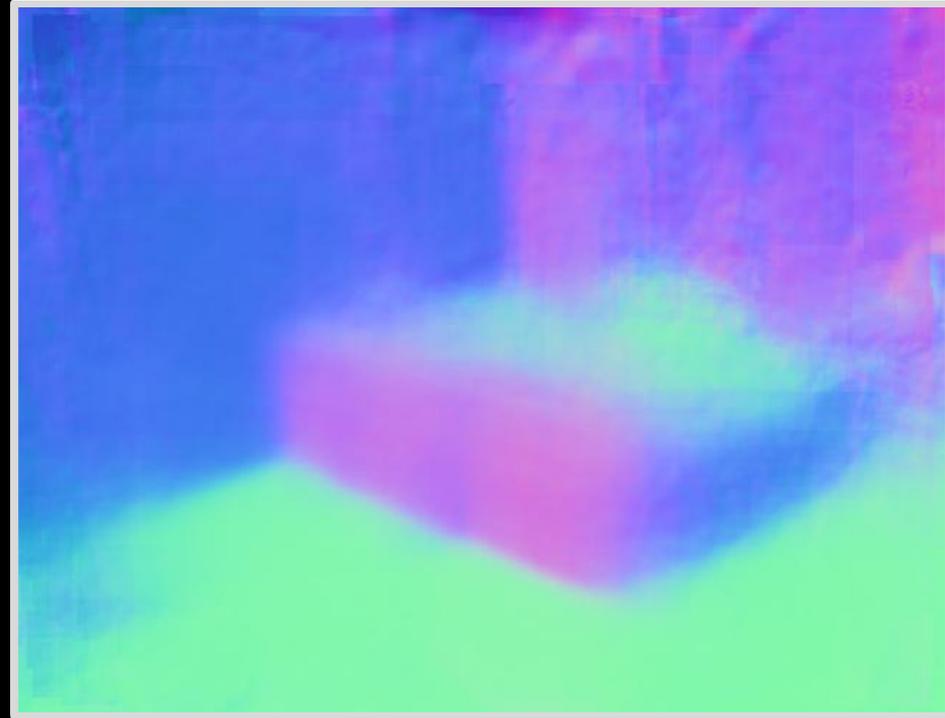
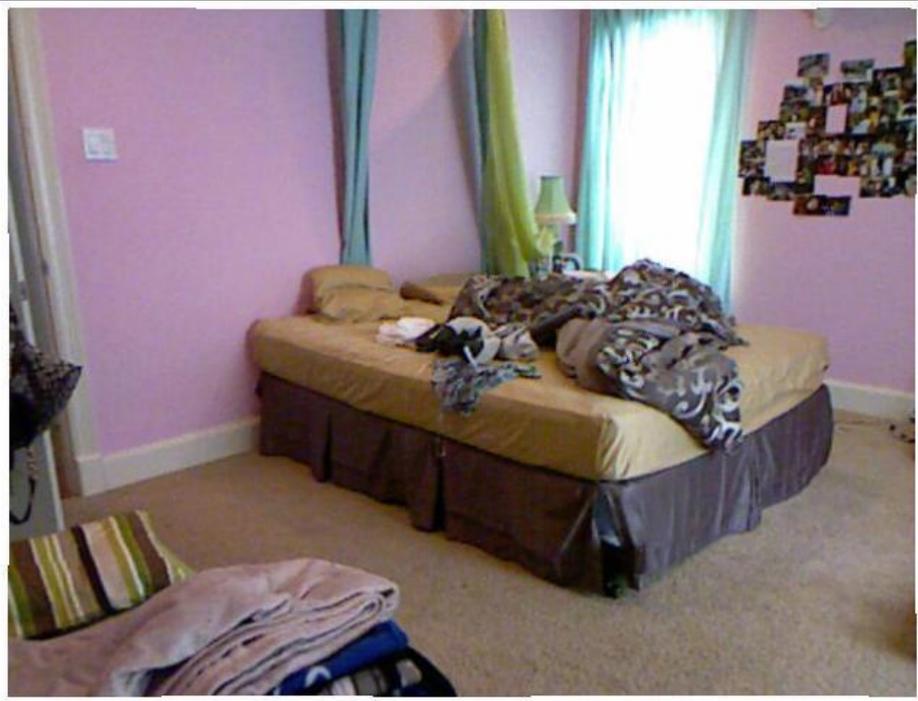
Inference

Sparse Transfer

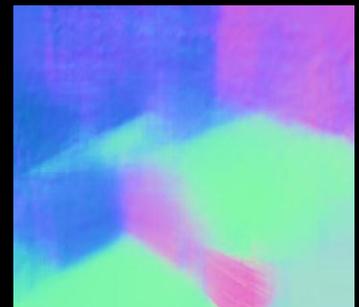
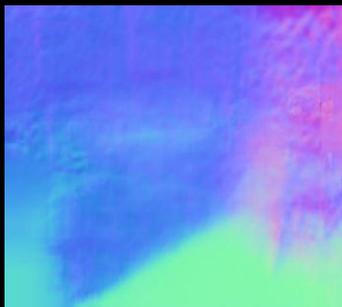
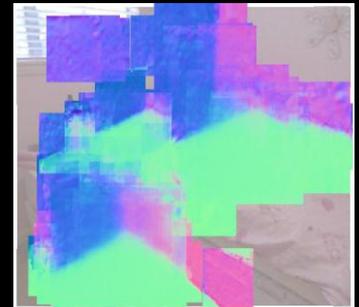
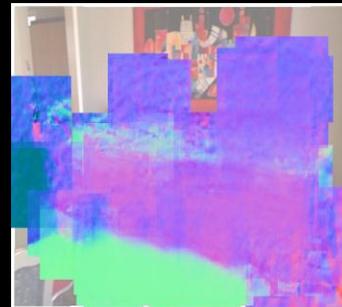
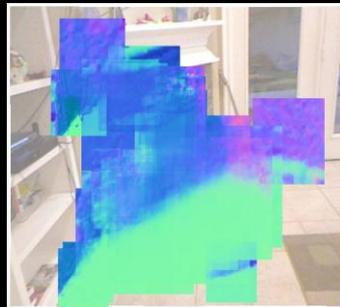
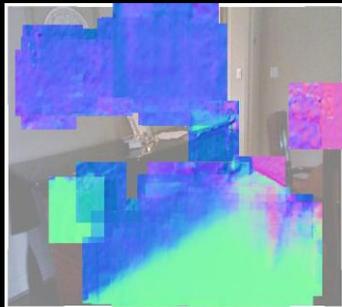
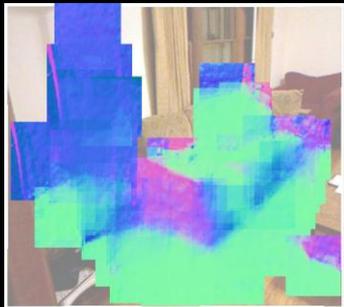


Inference

Dense Transfer

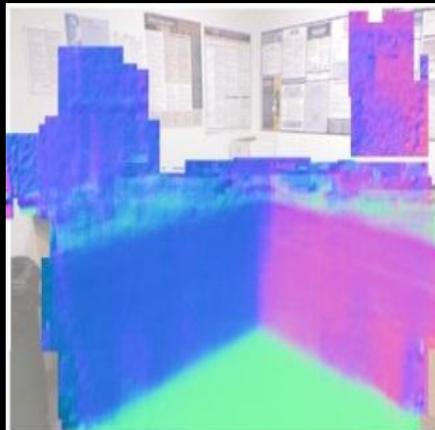


Sample Results – Qualitative



Confidences

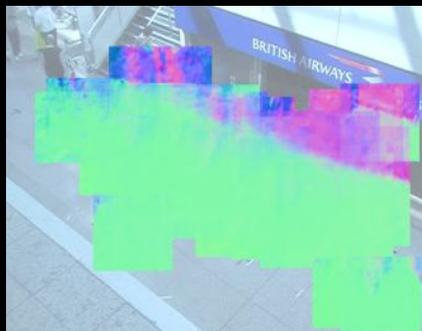
Most
Confident
Result



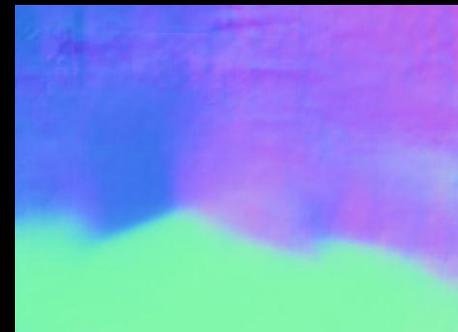
Least
Confident
Result



Cross-dataset

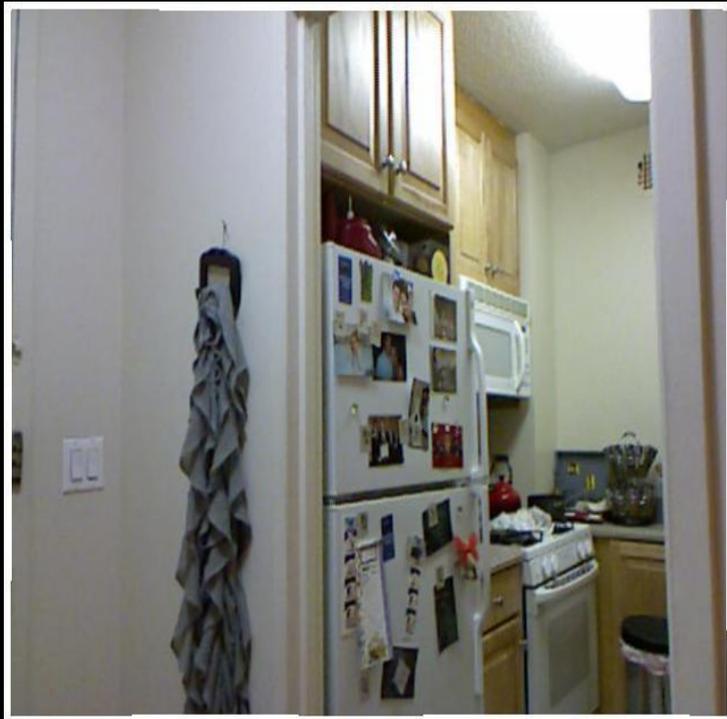


PETS



B3DO

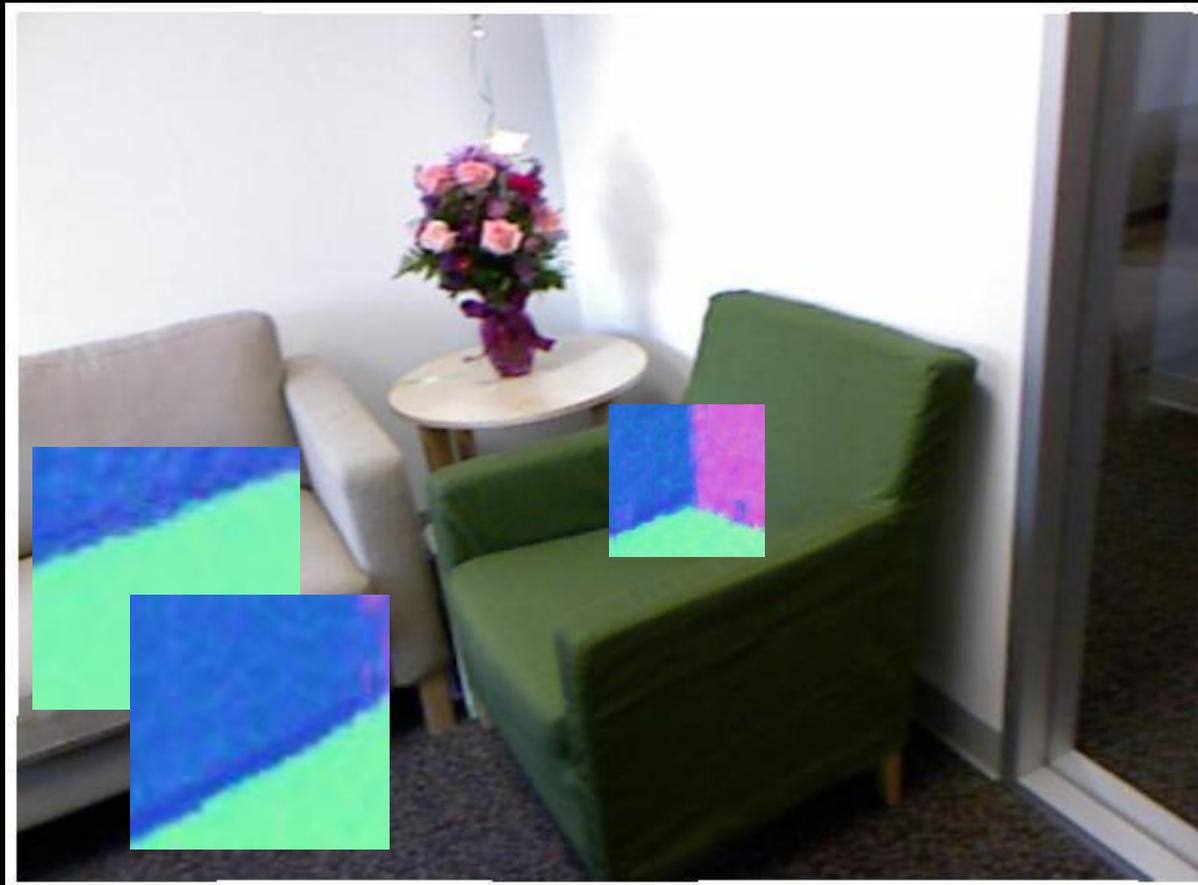
Failures



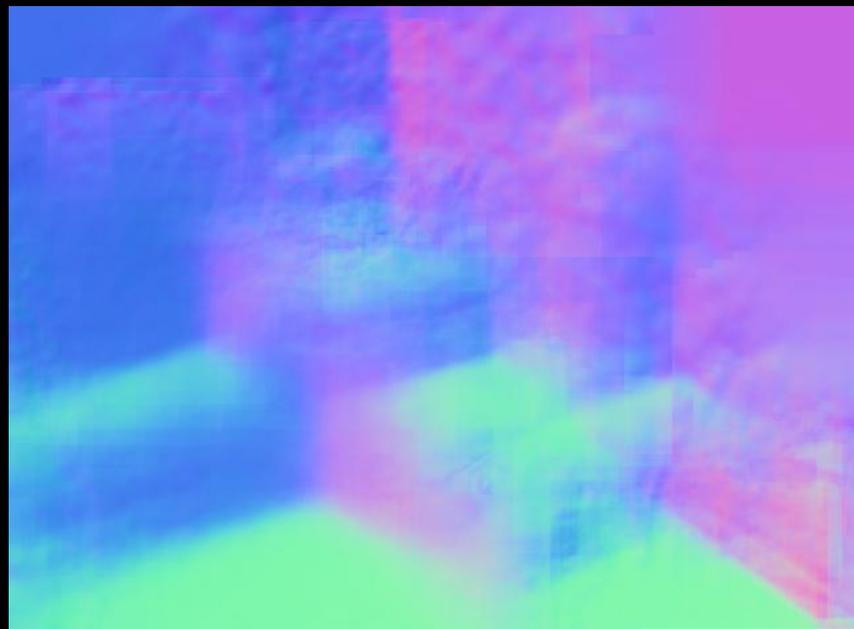
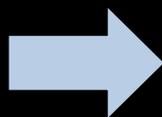
	Summary Stats (⁰) (Lower Better)			% Good Pixels (Higher Better)		
	Mean	Median	RMSE	11.25 ⁰	22.5 ⁰	30 ⁰
3D Primitives	<u>33.0</u>	<u>28.3</u>	<u>40.0</u>	<u>18.8</u>	<u>40.7</u>	<u>52.4</u>
Singh et al.	35.0	32.4	40.6	11.2	32.1	45.8
Karsch et al.	40.8	37.8	46.9	7.9	25.8	38.2
Hoiem et al.	41.2	34.8	49.3	9.0	31.7	43.9
Saxena et al.	47.1	42.3	56.3	11.2	28.0	37.4
RF + Dense SIFT	36.0	33.4	41.7	11.4	31.1	44.2

Using geometric and physical
constraints

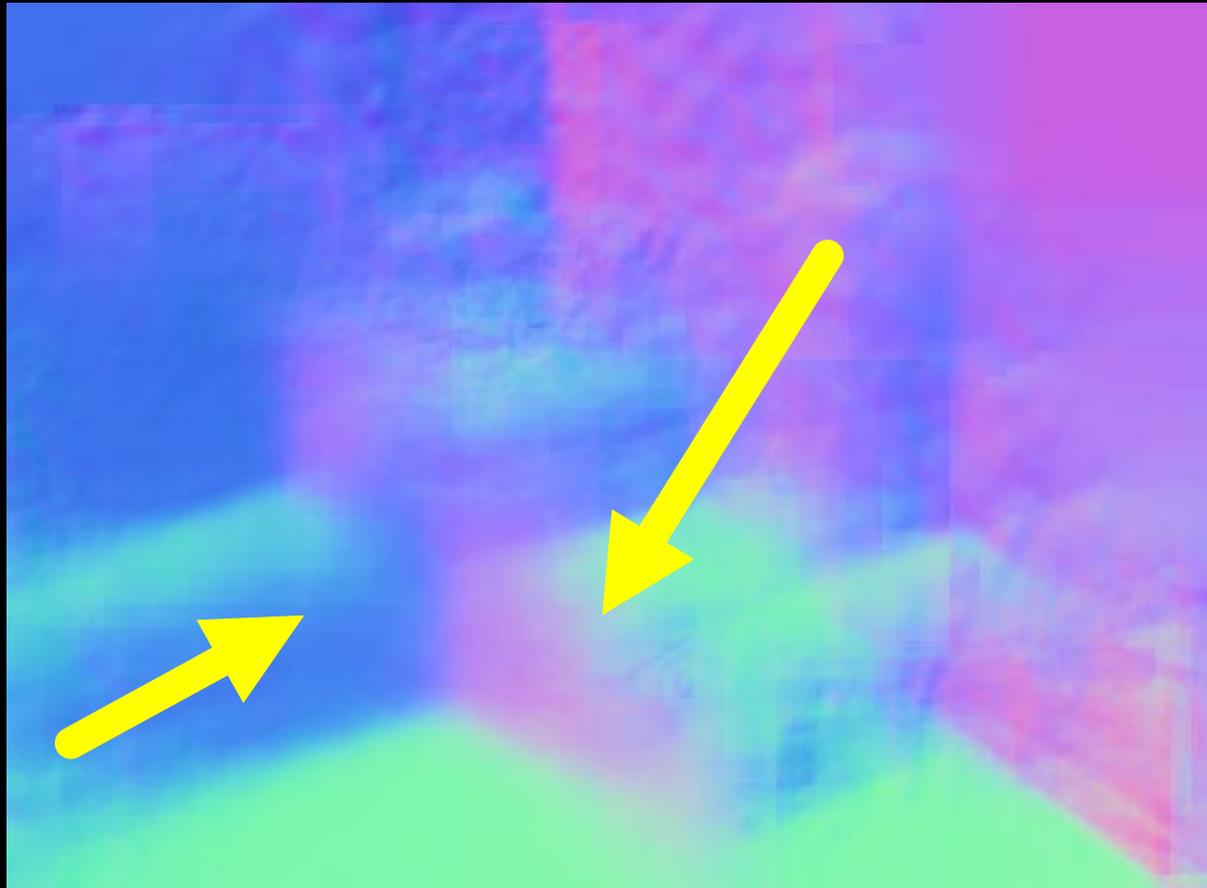
The Story So Far (Sparse)



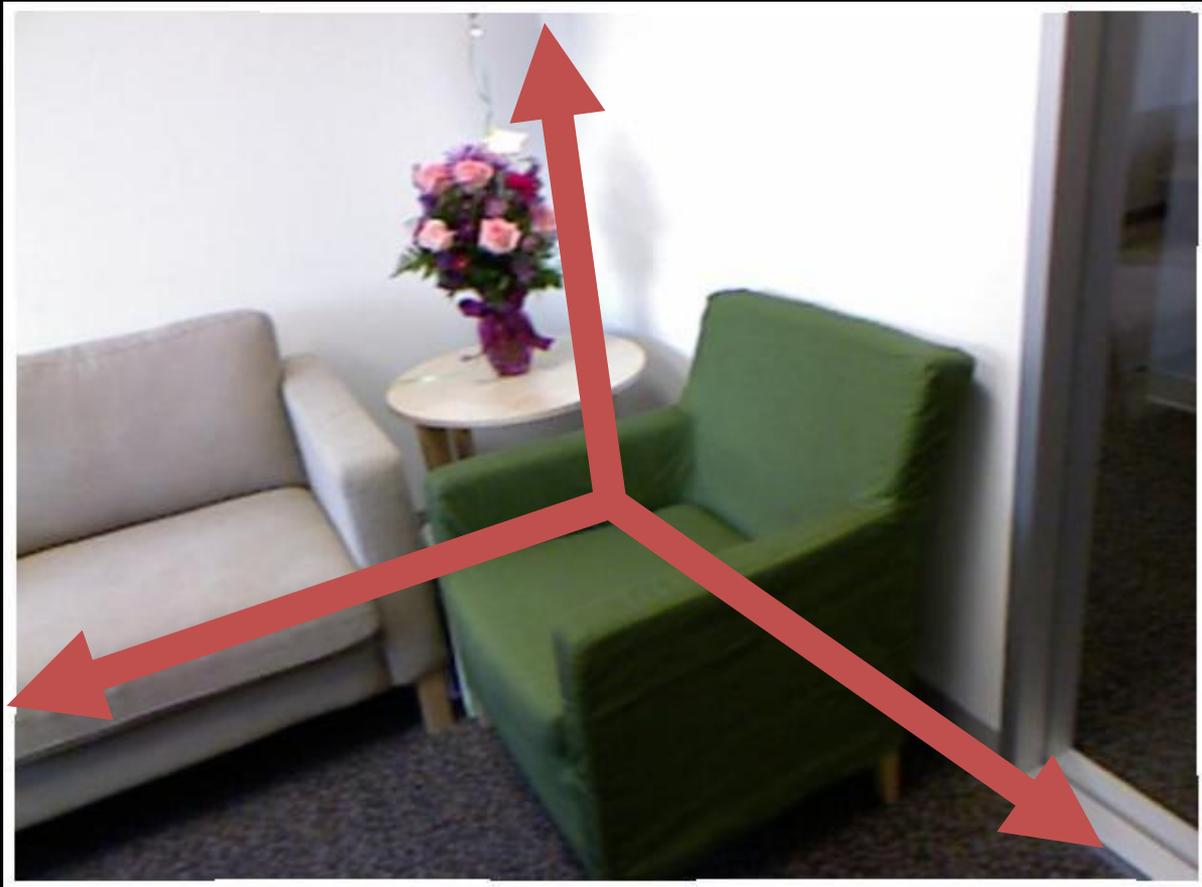
The Story So Far (Dense)



The Story So Far



Adding Physical/Geometric Constraints



Adding Physical/Geometric Constraints

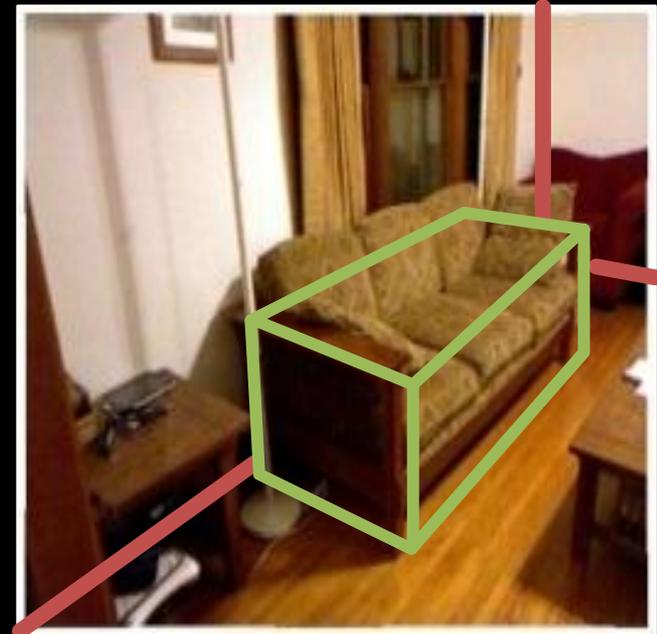


Past Physical Constraints



Camera-in-a-box

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

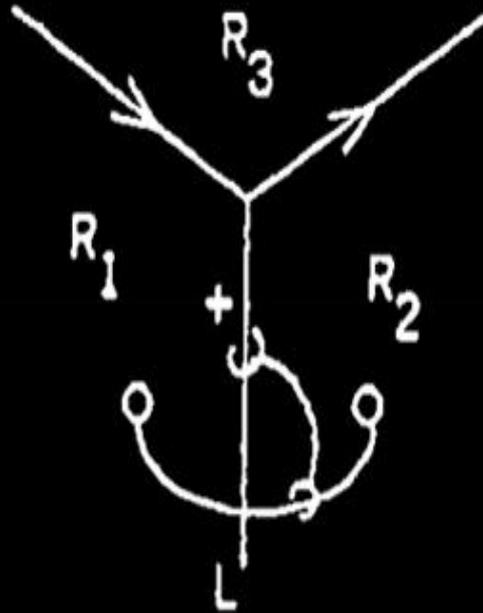


Top-down Cuboid

Lee et al. 2010, Gupta et al. 2010,
Xiao et al. 2012, etc.

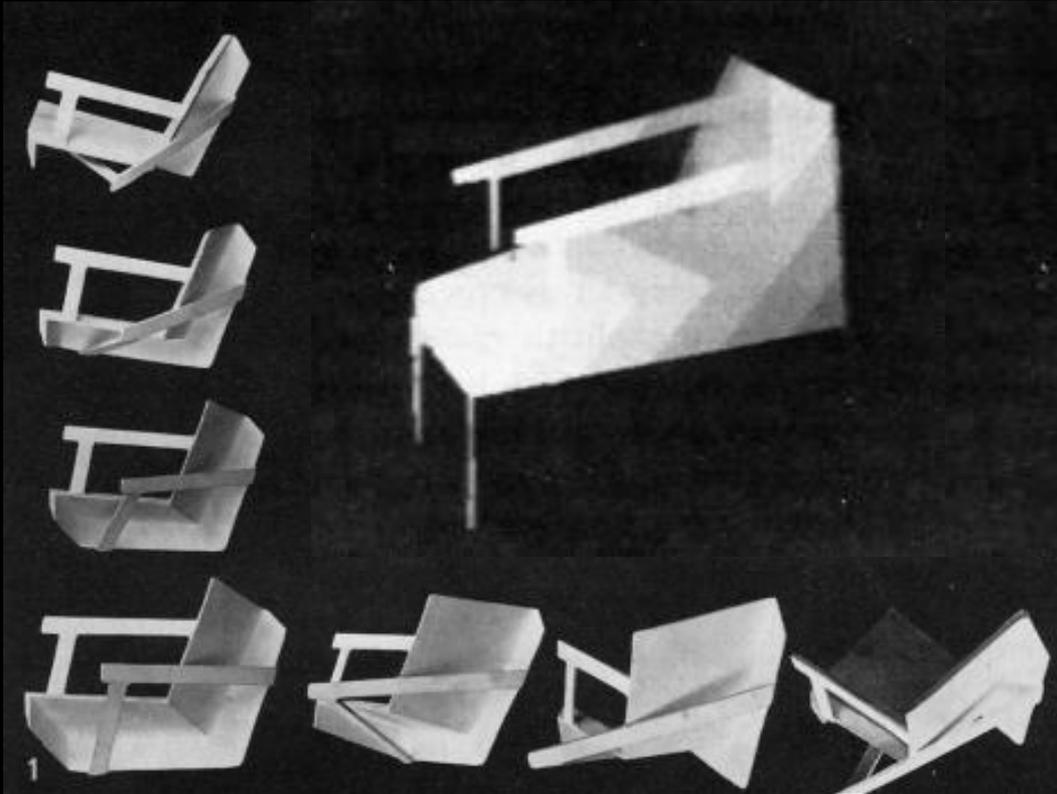
Digression: Inspiration from the past....

Kanade's Origami World, 1978

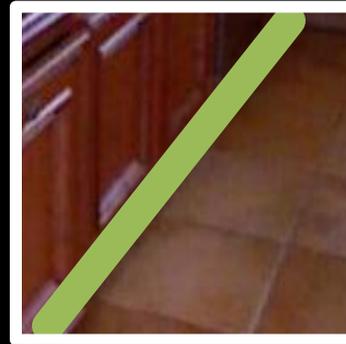
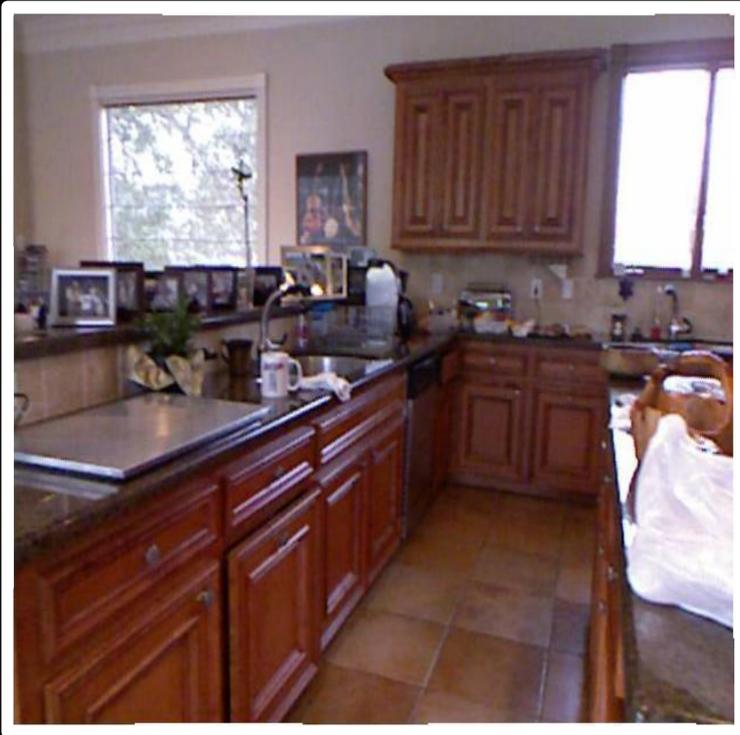


From the past....

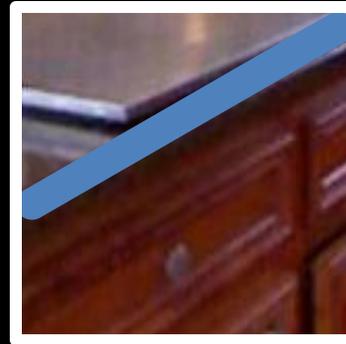
- Kanade's chair... (Artificial Intelligence, 1981)



Edges between surfaces

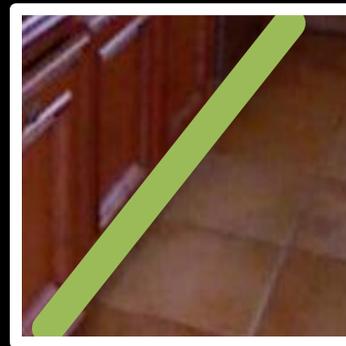
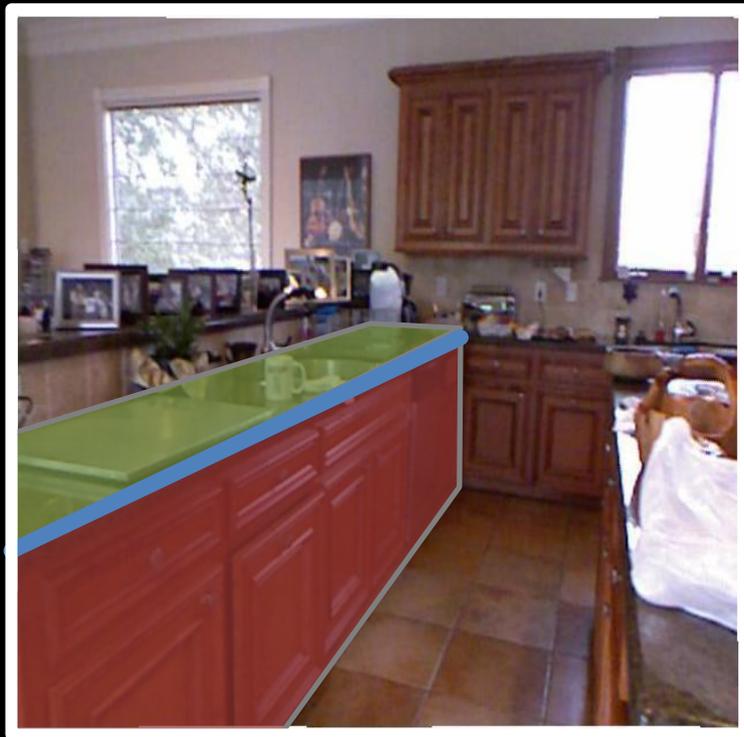


Concave
(-)

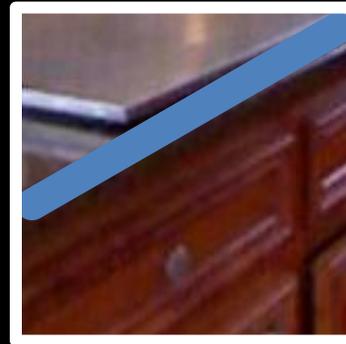


Convex
(+)

Edges between surfaces



Concave
(-)



Convex
(+)

Parameterization

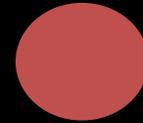
vp_1



vp_2



vp_3



Parameterization

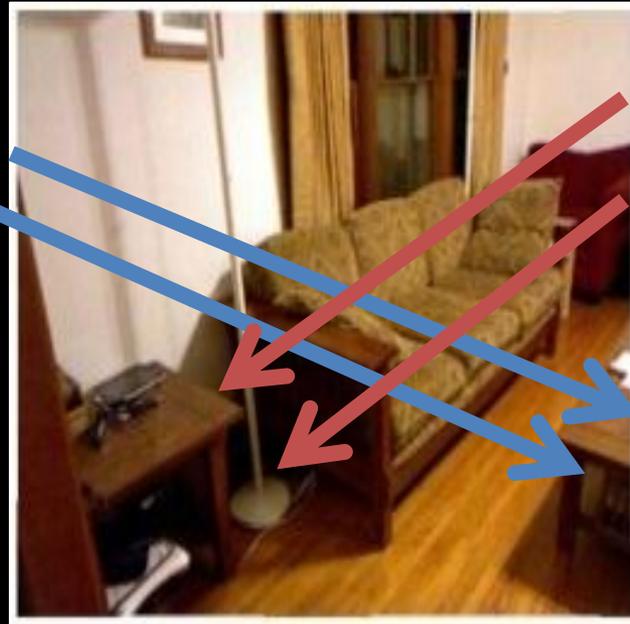
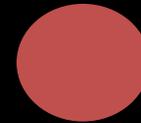
vp_1



vp_2



vp_3



Parameterization

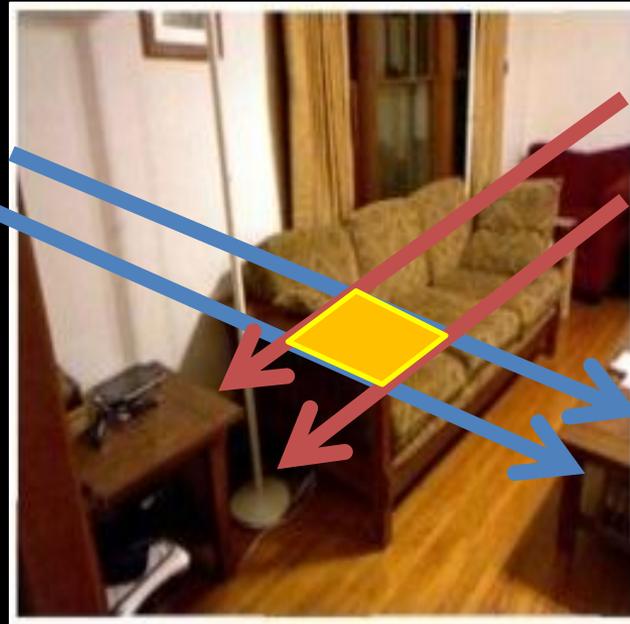
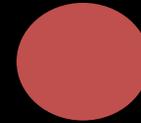
vp_1



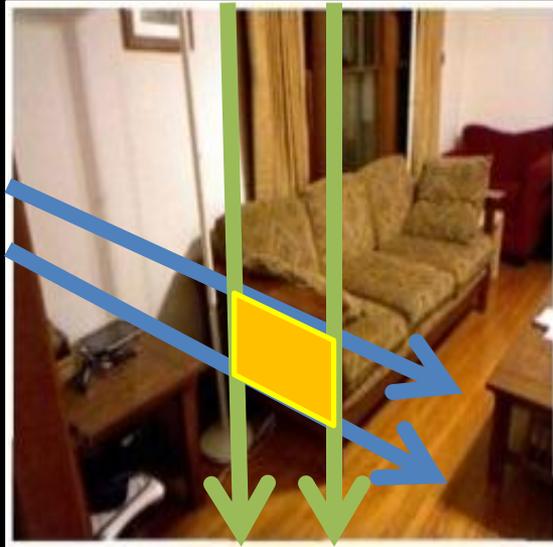
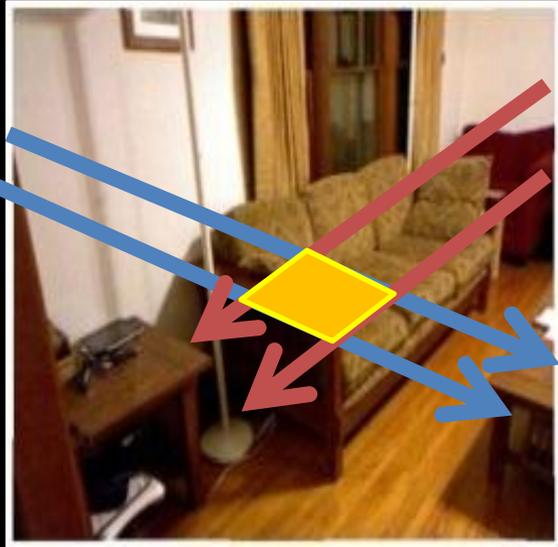
vp_2



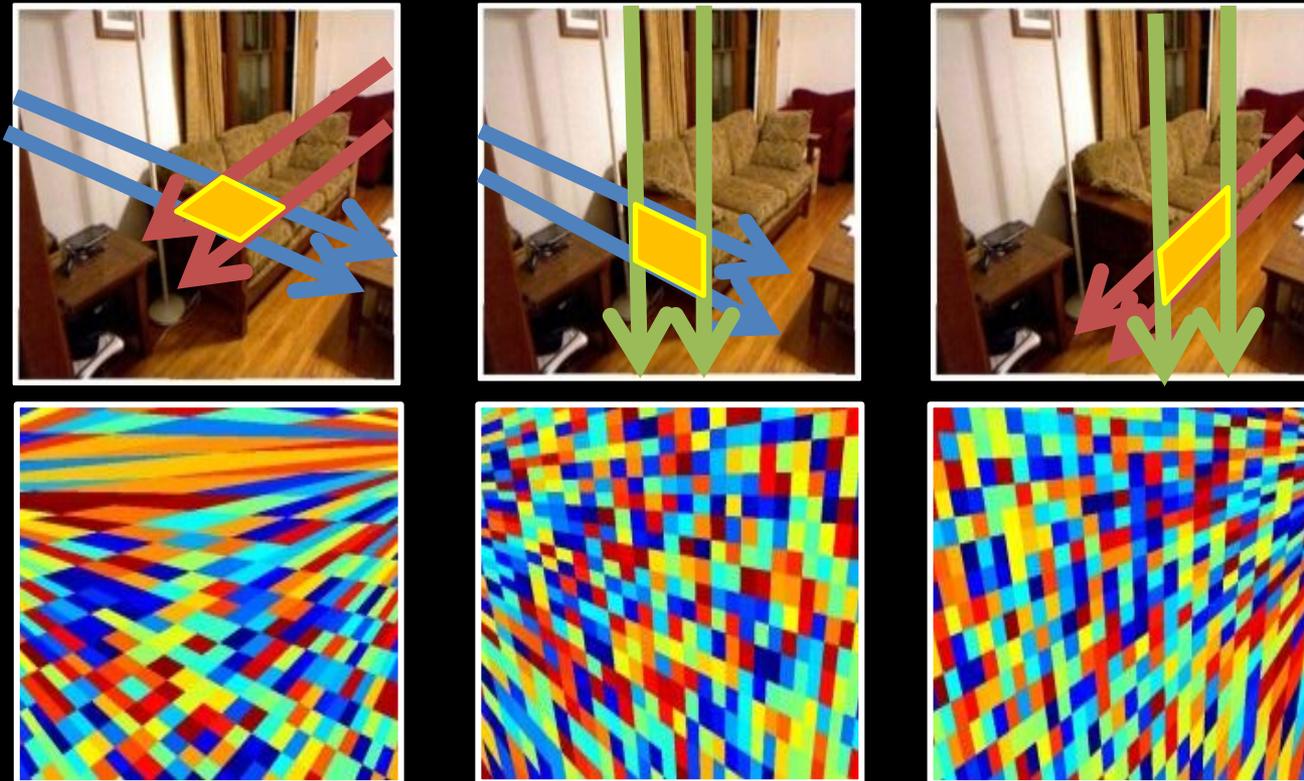
vp_3



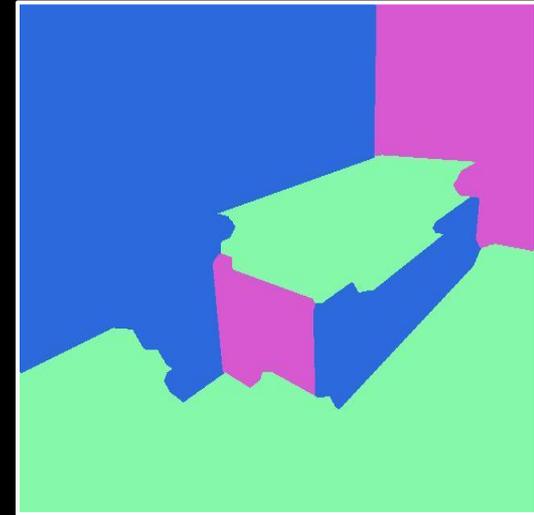
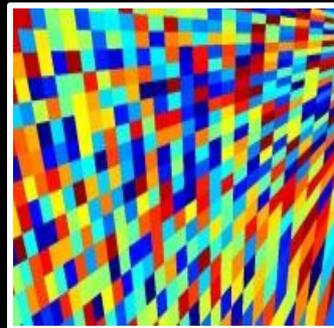
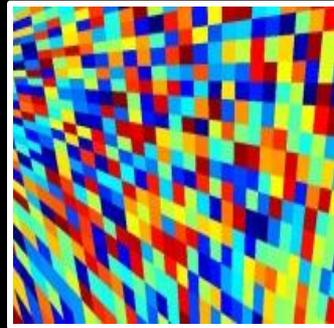
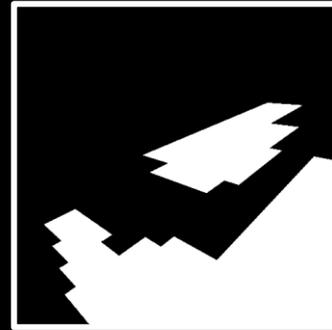
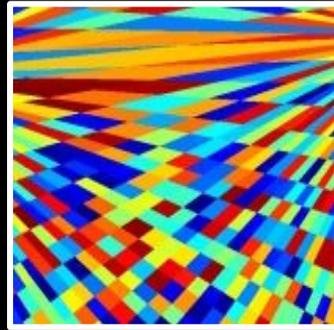
Parameterization



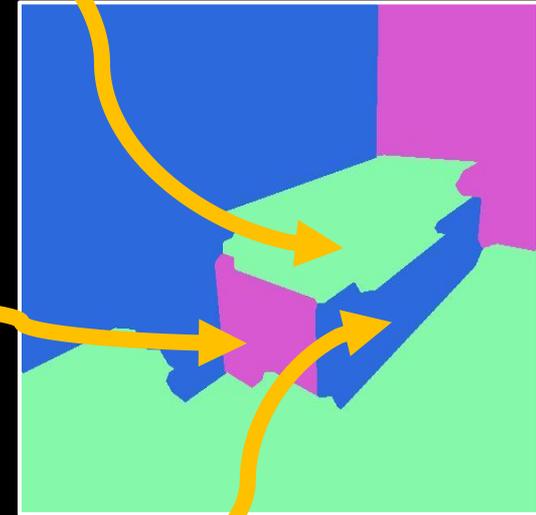
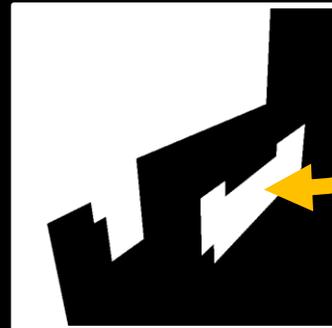
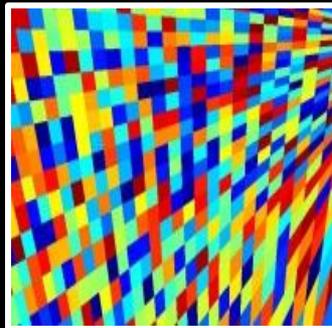
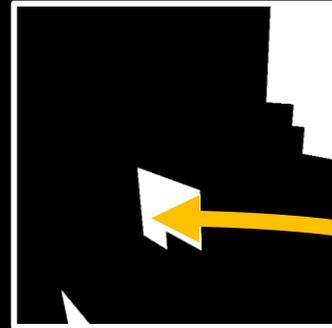
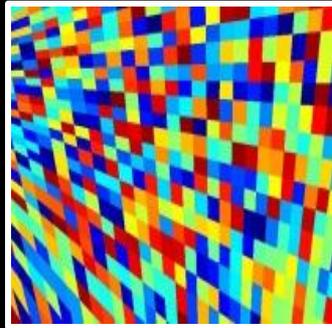
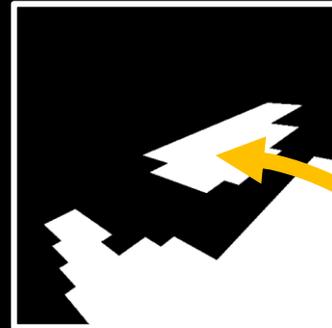
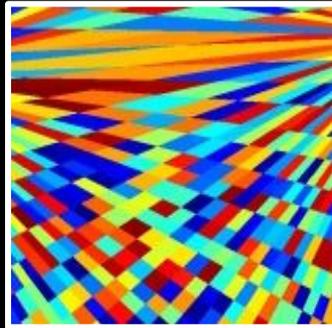
Parameterization



Parameterization

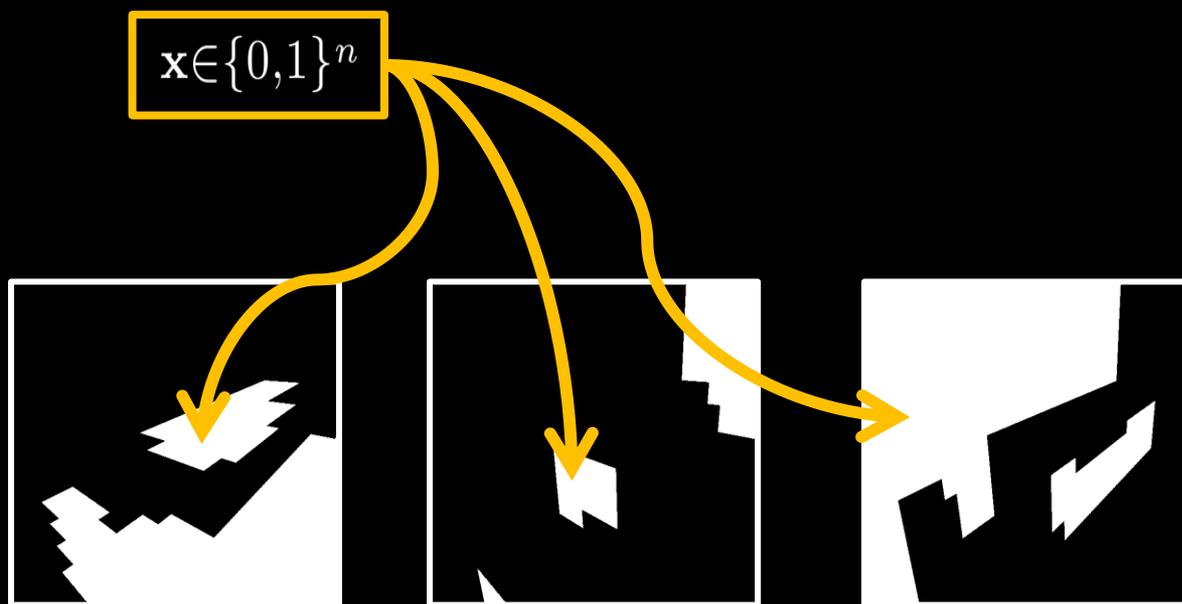


Parameterization



Labeling

x_i : is cell i on?



Formulation

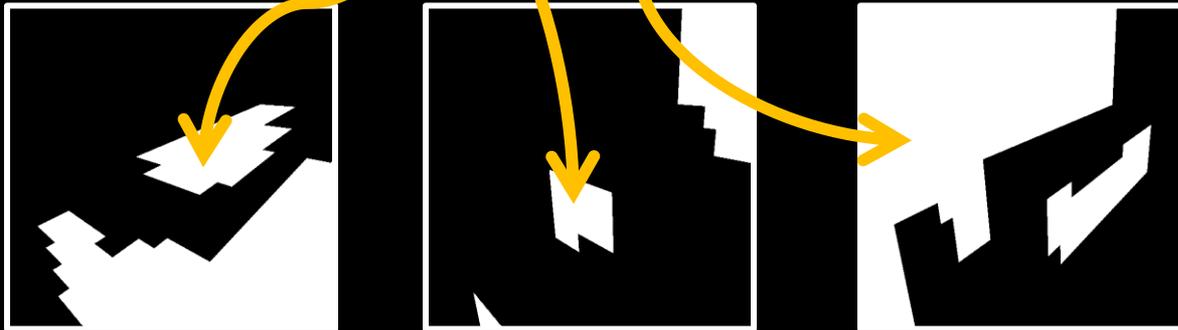
$$\arg \max_{\mathbf{x} \in \{0,1\}^n} \mathbf{c}^T \mathbf{x} + \mathbf{x}^T \mathbf{H} \mathbf{x} \quad \text{s.t.} \quad \mathbf{A} \mathbf{x} \leq \mathbf{1}$$

Variable

x_i : is cell i on?

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

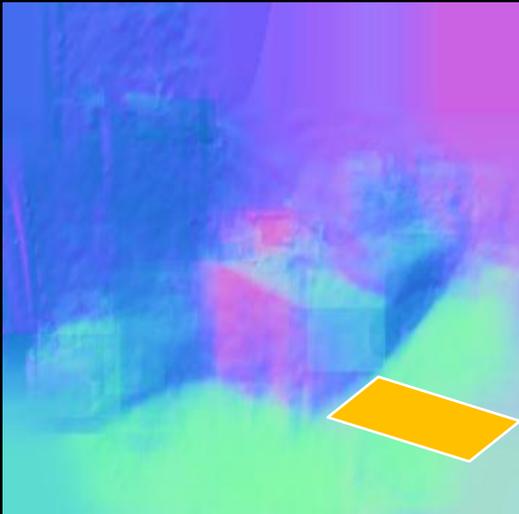
$\mathbf{x} \in \{0,1\}^n$



Unary Potentials

C_i : should cell i be on?

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



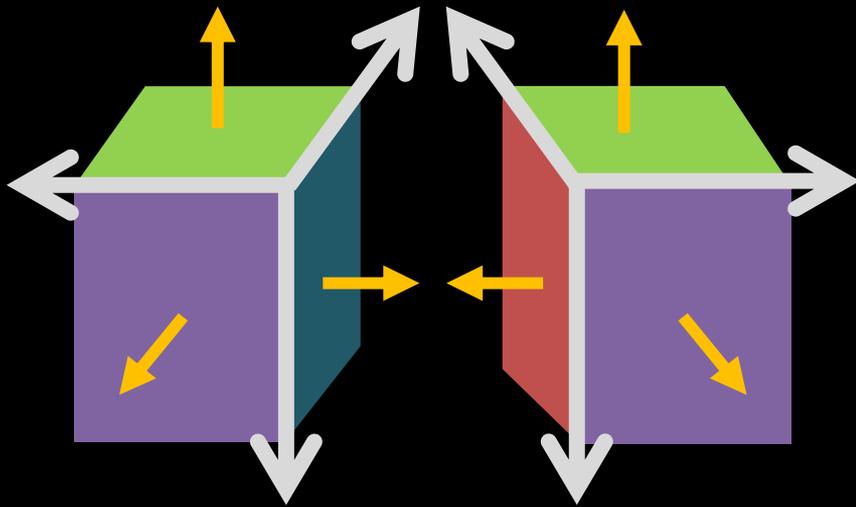
Binary Potentials

$H_{i,j}$: should cells i and j both be on?

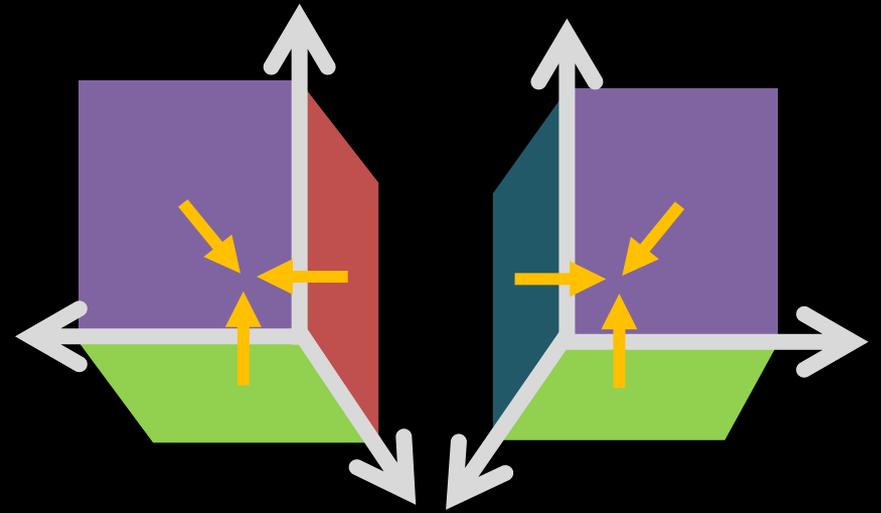
$$\arg \max_{\mathbf{x} \in \{0,1\}^n} \mathbf{c}^T \mathbf{x} + \mathbf{x}^T \mathbf{H} \mathbf{x} \quad \text{s.t.} \quad \mathbf{A} \mathbf{x} \leq \mathbf{1}$$

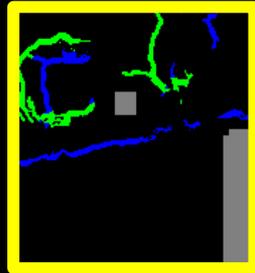
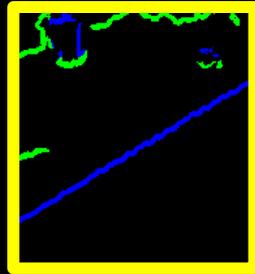
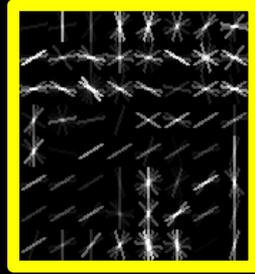
Binary Potentials

Convex (+)

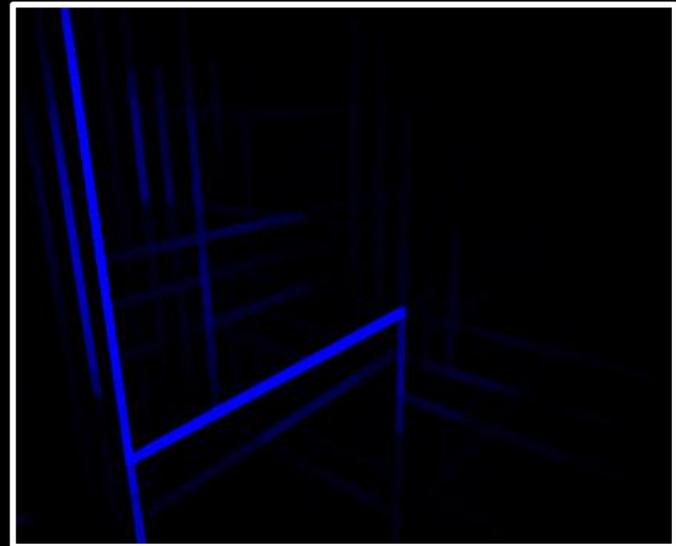
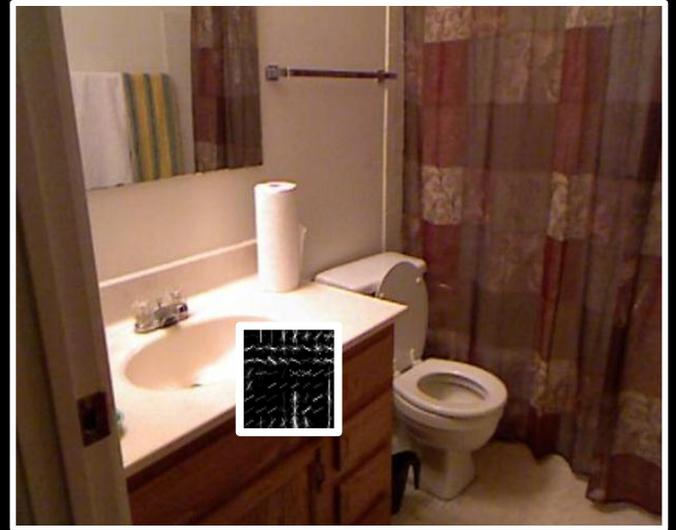
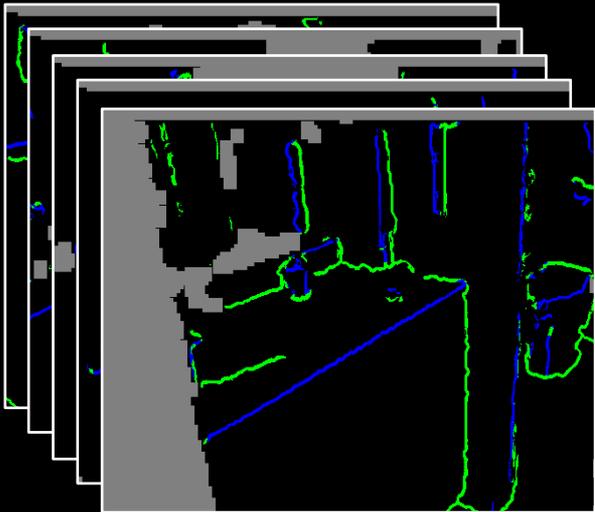


Concave (-)



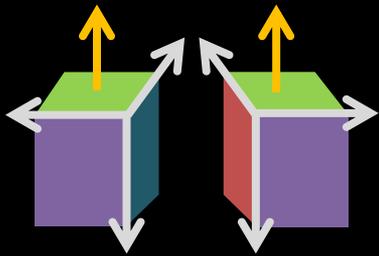


⋮

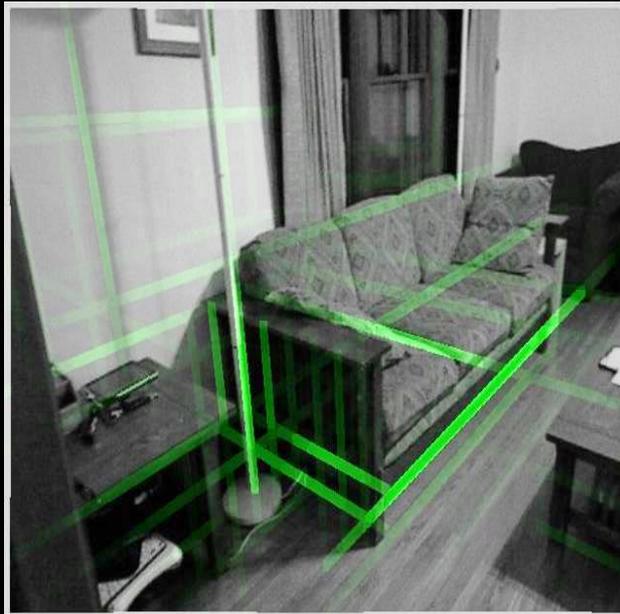
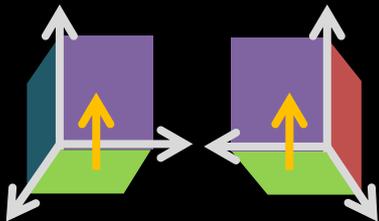


Binary Potentials

Convex (+)



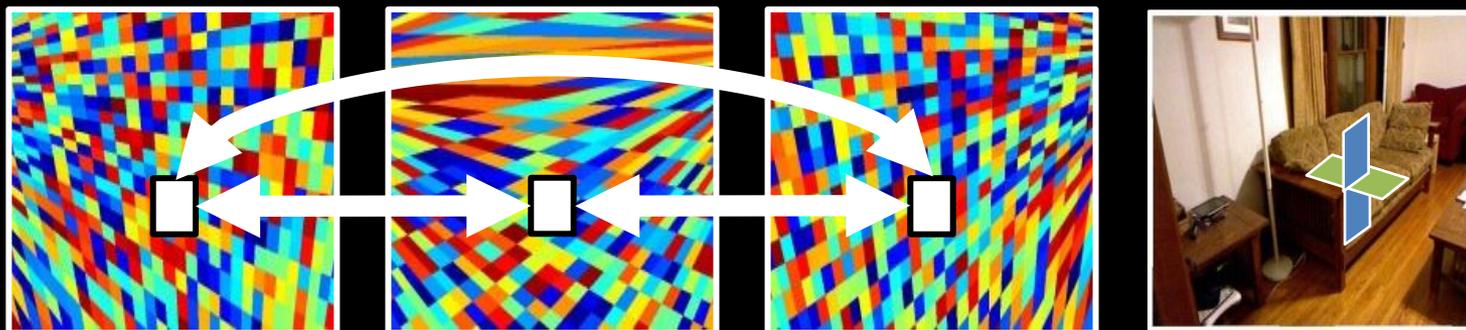
Concave (-)



Constraints

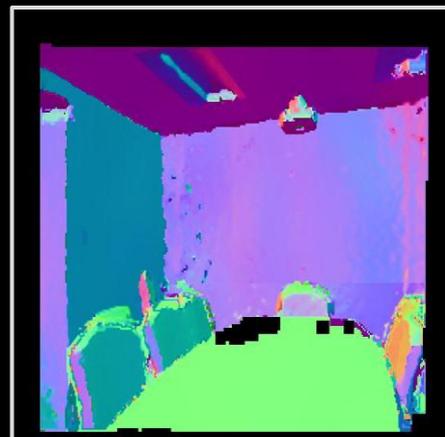
What configurations are forbidden?

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





Input



Ground Truth



3D Primitives



Projected 3D Primitives

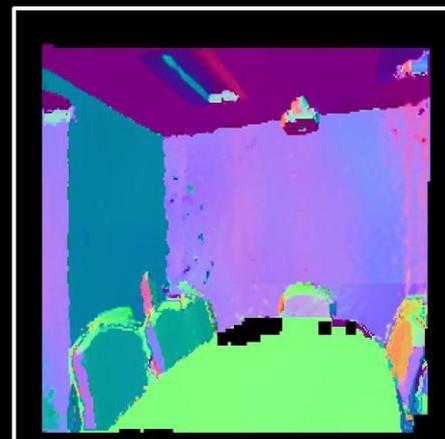


Proposed

Qualitative Results



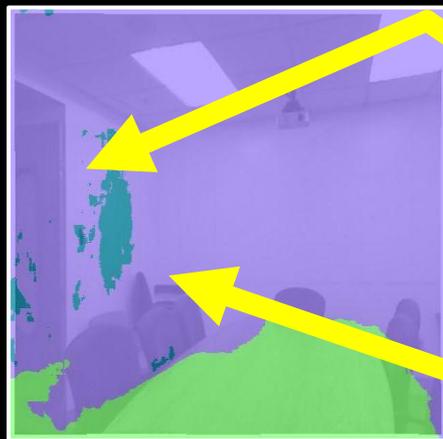
Input



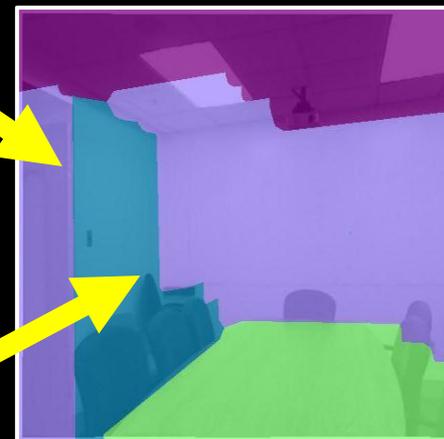
Ground Truth



3D Primitives



Projected 3D Primitives



Proposed



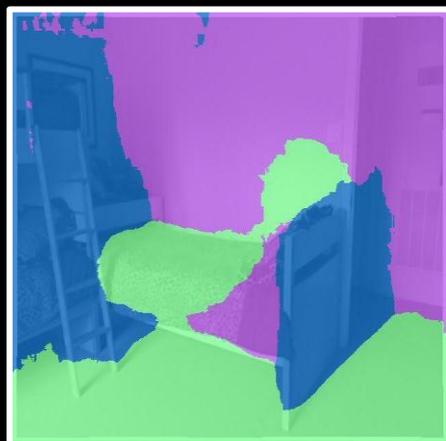
Input



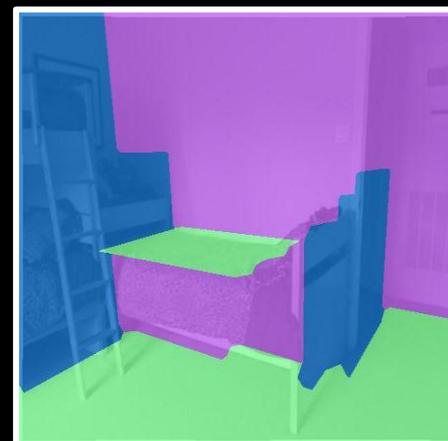
Ground Truth



3D Primitives



Projected 3D Primitives

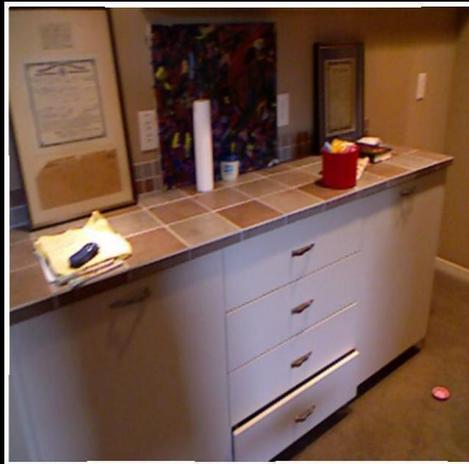


Proposed

Random Qualitative Results

3D Primitives

Proposed

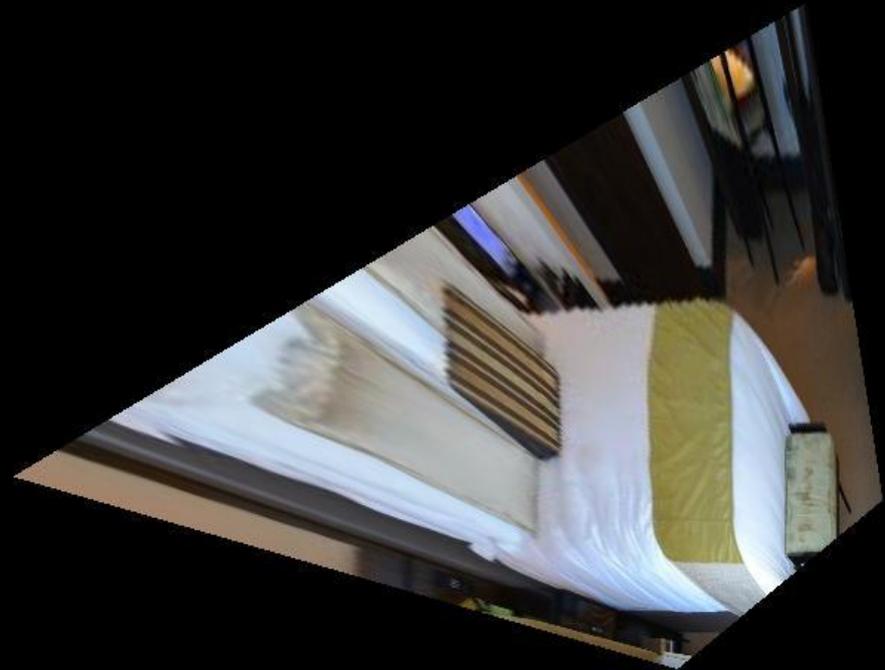


Quantitative Results

	Summary Stats (⁰) (Lower Better)			% Good Pixels (Higher Better)		
	Mean	Median	RMSE	11.25 ⁰	22.5 ⁰	30 ⁰
Proposed	<u>37.5</u>	<u>17.2</u>	<u>53.2</u>	<u>41.9</u>	<u>53.9</u>	<u>58.0</u>
3D Primitives	38.5	19.0	54.2	41.7	52.4	56.3
Hedau et al.	43.2	24.8	59.4	39.1	48.8	52.3
Lee et al.	47.6	43.4	60.6	28.1	39.7	43.9
Karsch et al.	46.6	43.0	53.6	5.4	19.9	31.5
Hoiem et al.	45.6	38.2	55.1	8.6	30.5	41.0



Style vs. structure?

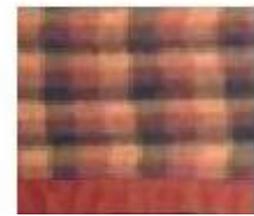


Tenenbaum & Freeman. Separating Style and Content with Bilinear Models. Neural Computation. 2000.

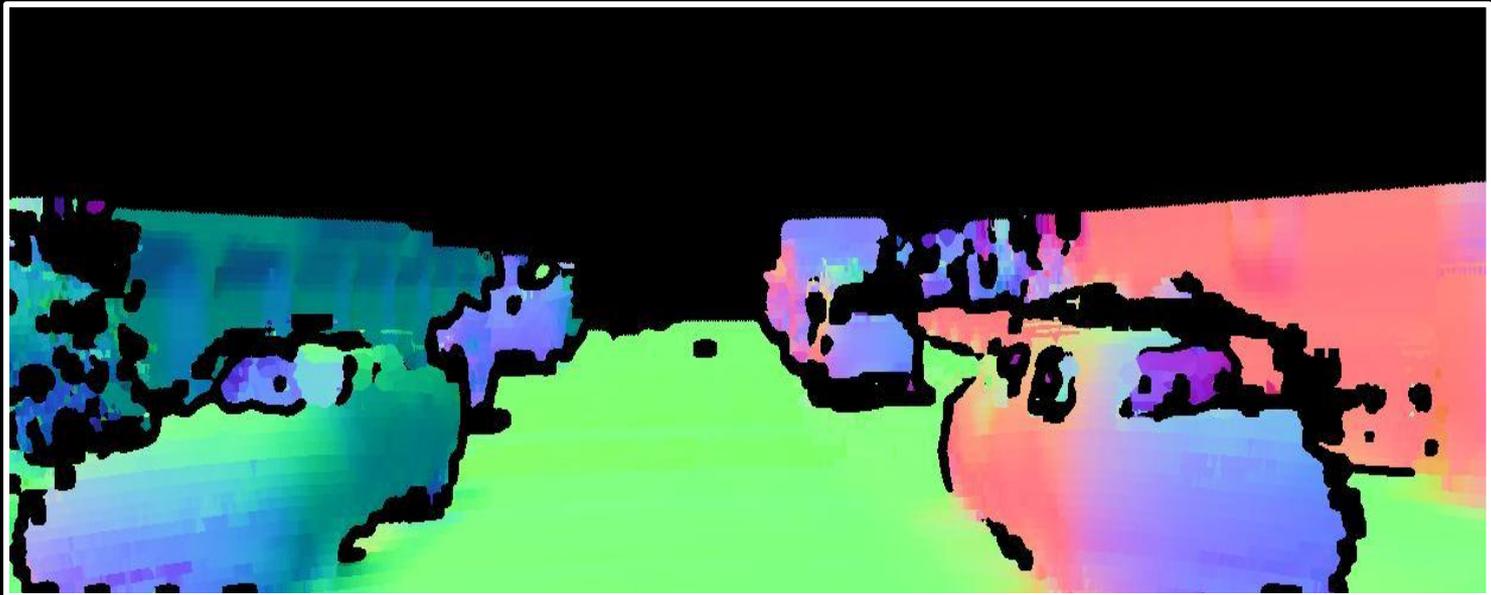
Casablanca Hotel, New York







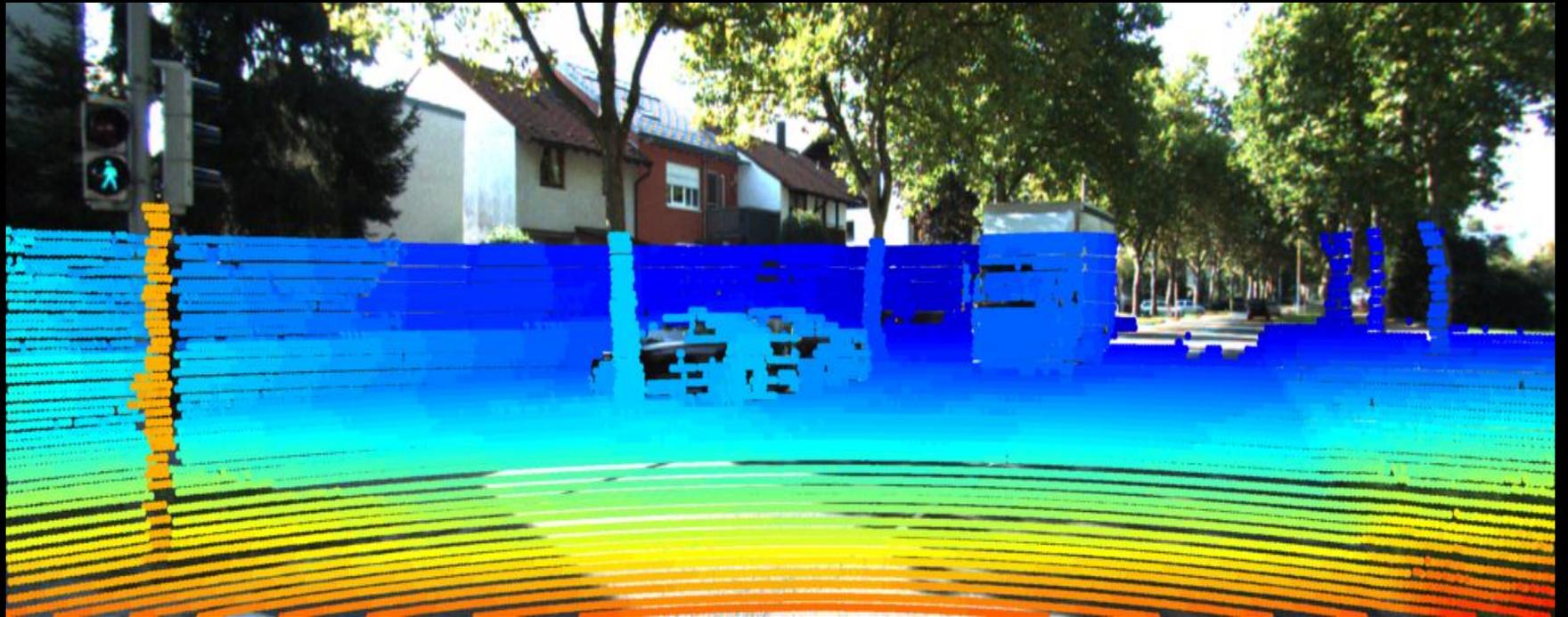
More general environments?



KITTI Dataset: Geiger, Lenz, Urtasun, '12

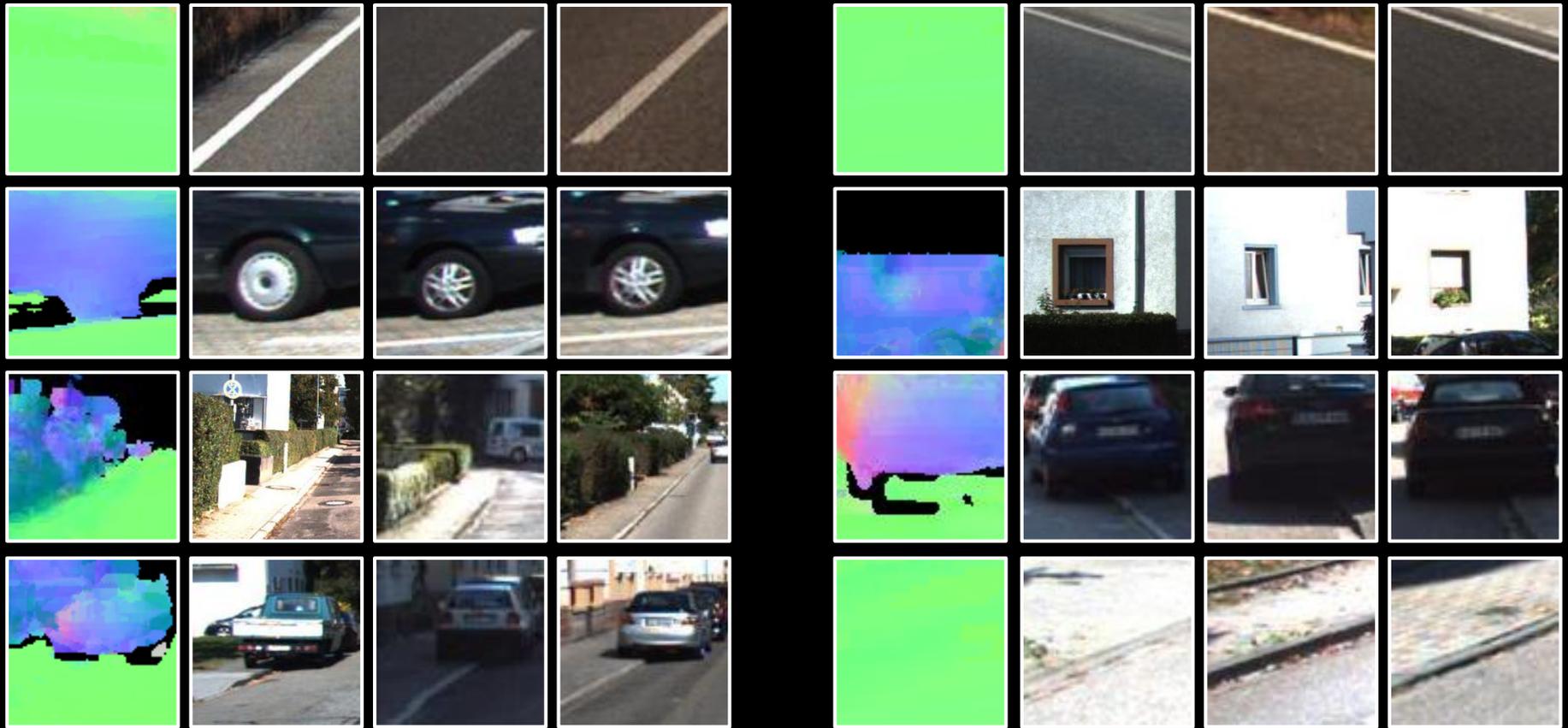


- Large regions without surface interpretation
- Fewer linear/planar structures to anchor
- Irregular distribution of 3D training data

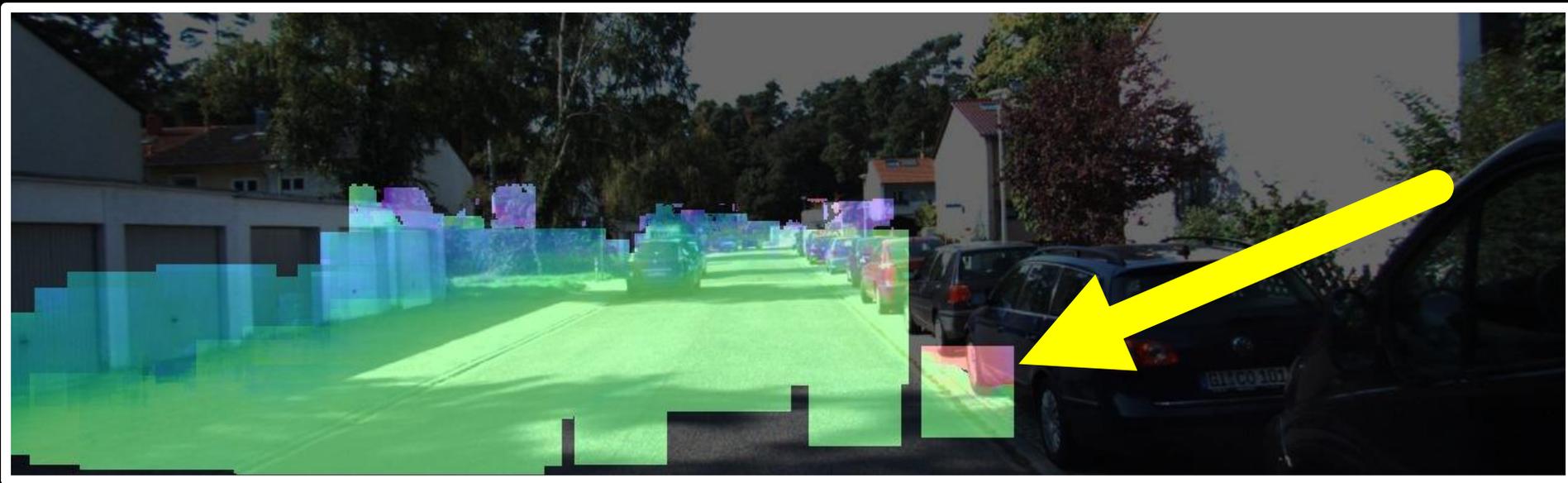




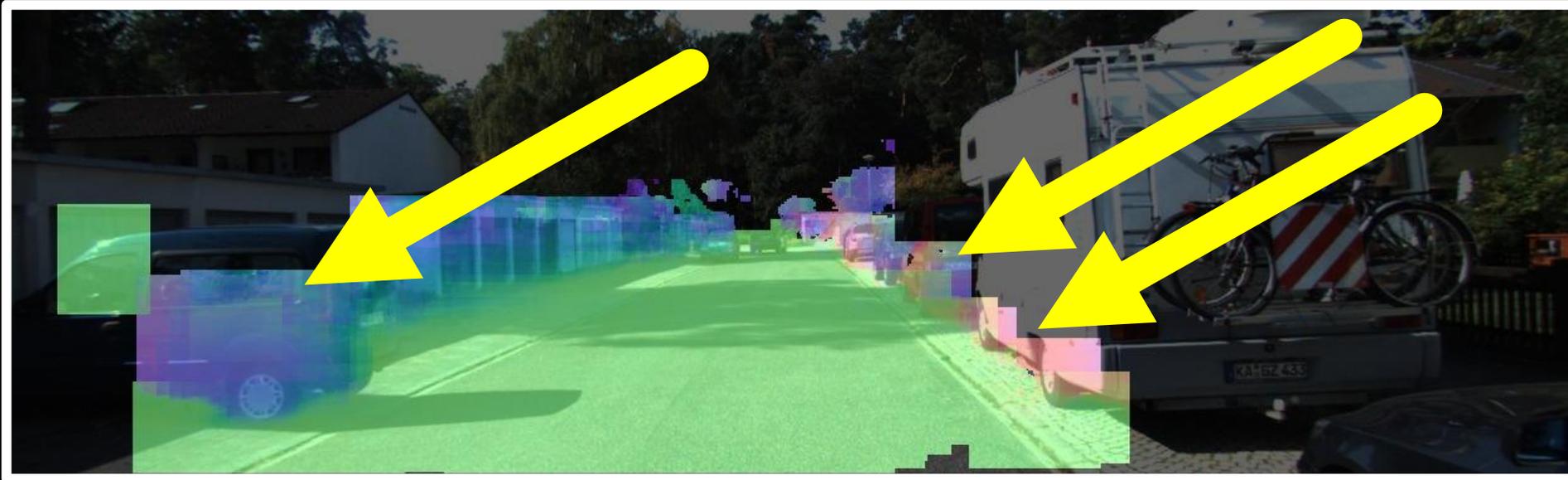
Discovered Primitives (Examples)

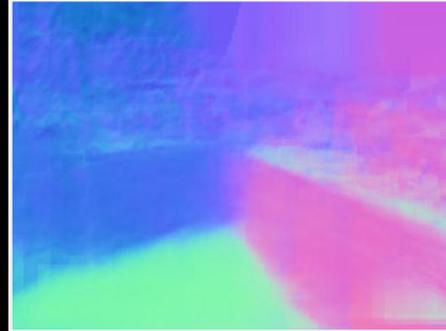
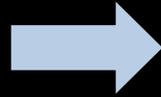


Contact points



Object surfaces + Contact points





Next:

Better reasoning

Semantic information

Less structured environments

Evaluation

Applications

Data-Driven 3D Primitives For Single-Image Understanding, Fouhey, Gupta, Hebert, In ICCV 2013.

Unfolding an Indoor Origami World, Fouhey, Gupta, Hebert, In ECCV 2014.

- Harvested from tripadvisor.com

Countries	8	USA, Japan, London, Germany, Canada, Australia, Thailand, Indonesia
Cities	> 10	New York, London, Berlin, Sydney, Tokyo, Las Vegas, San Francisco etc.
Chains	~ 5	Hilton, Marriott, Intercontinental, Sheraton, Best Western etc.



Sheraton Los Angeles



Meritan Apartments Sydney



Le Champlain Quebec

Project digression.....

CENTER FOR 
MISSING & EXPLOITED
CHILDREN


18
YEARS OF
HOPE

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Missing Children

Child Sexual Exploitation

- [CyberTipline](#)
- [Child Victim Identification](#)
- [Sex Offender Tracking](#)
- [Child Sex Trafficking](#)
- [Voluntary Industry Initiatives](#)
- [International Collaboration](#)
- [Success Stories](#)
- [FAQ](#)

Child Safety & Prevention

Law Enforcement Training

Victim & Family Support

CyberTipline

The CyberTipline® receives leads and tips regarding suspected crimes of sexual exploitation committed against children. More than 2.3 million reports of suspected child sexual exploitation have been made to the CyberTipline between 1998 and March 2014.

If you have information regarding possible child sexual exploitation, report it to the CyberTipline.

[MAKE A CYBERTIPLINE REPORT](#)

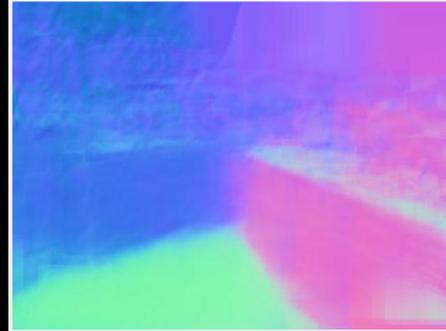
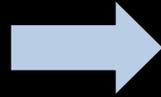
Purpose and function



**CYBER
TIPLINE**
www.cybertipline.com
1-800-843-5678

The CyberTipline is operated in partnership with the FBI, Immigration and Customs Enforcement, U.S. Postal Inspection Service, U.S. Secret Service, military criminal investigative organizations, U.S. Department of Justice, Internet Crimes Against Children Task Force program, as well as other state and local law enforcement agencies. Reports to the CyberTipline are made by the

**Safety starts
with NetSmartz**



Next:

Better reasoning

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Less structured environments

Evaluation

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Unfolding an Indoor Origami World, Fouhey, Gupta, Hebert, In ECCV 2014.

Results – Quantitative

