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OBJECT-AWARE GUIDANCE FOR AUTONOMOUS SCENE RECONSTRUCTION

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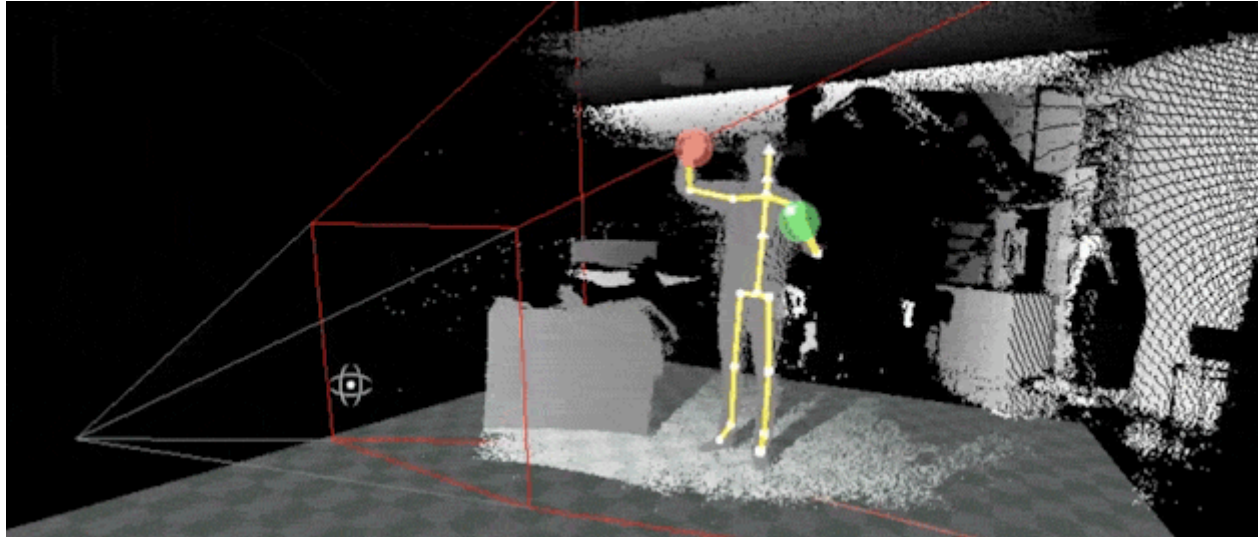




Photography & Recording Encouraged

Background

- Commodity RGB-D sensors



Microsoft Kinect



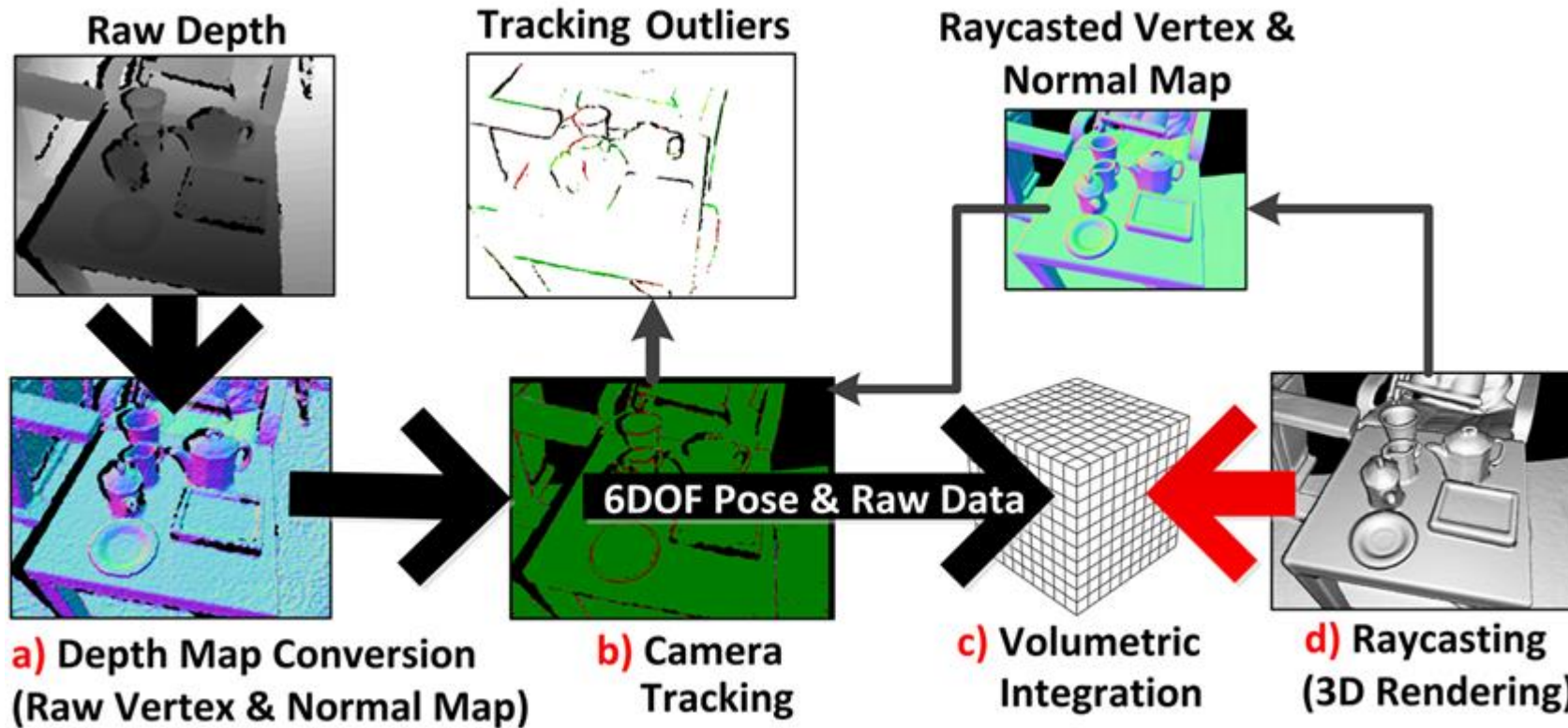
PrimeSense



Intel RealSense

Background

- RGB-D sensor allows real-time reconstruction

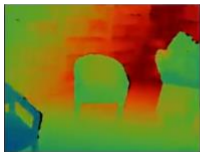


KinectFusion
[Izadi et al. 2011]

Background

- Other real-time reconstruction methods

Input Depth



Input RGB



Bookshop



Phong Shaded



Shaded with Voxel Colors

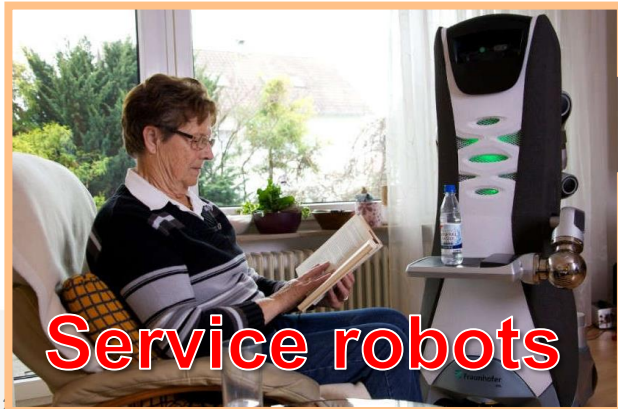
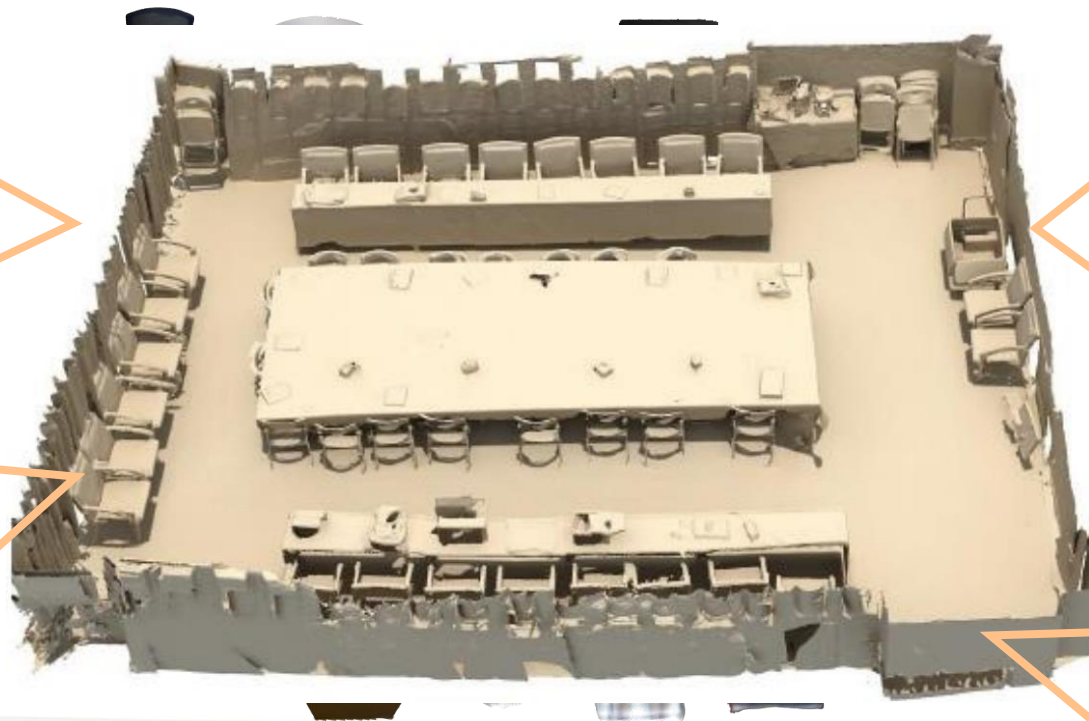
Voxel Hashing
[Nießner et al. 2013]



ElasticFusion
[Whelan et al. 2015]

Background

- Indoor scene reconstruction -> **3D object models**



Background

- Human scanning is a laborious task [Kim et al. 2013]

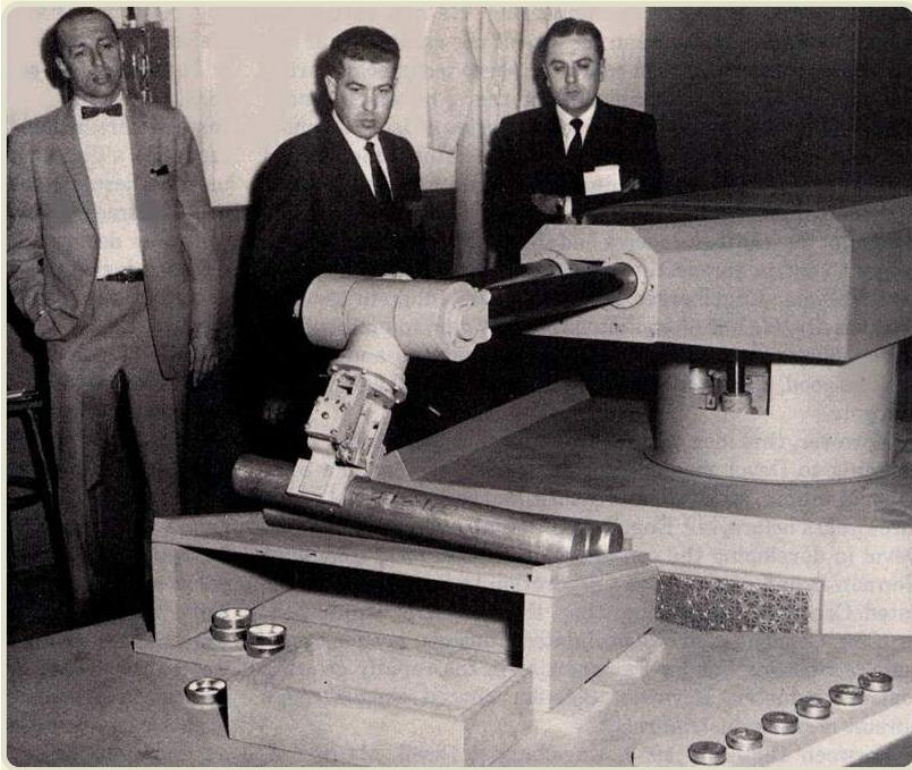
Time
consuming



Inaccurate
scanning

Background

- Modern robots are more and more reliable and controllable.



Unimation, 1958



Fetch, 2015

Motivation: Autoscanning with Robots

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Never feel
tired

Automatic

Stable and
precise



Existing Works: Single Objects

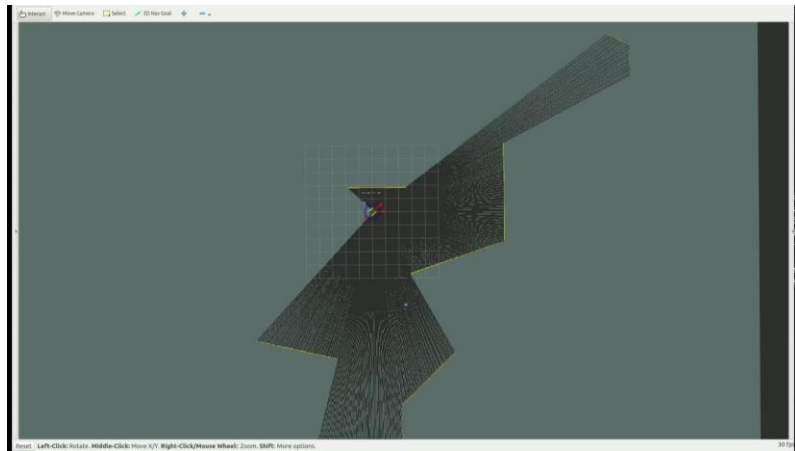
- High quality scanning and reconstruction of single object [Wu et al. 2014]



Existing Works: Unknown Scenes

- Two pass scene reconstruction and understanding.
- Can only use **low-level** information in first exploration pass.

First Pass



frontier-based exploration
[Yamauchi et al. 1997]

Second Pass



exploration & reconstruction
[Xu et al. 2017]

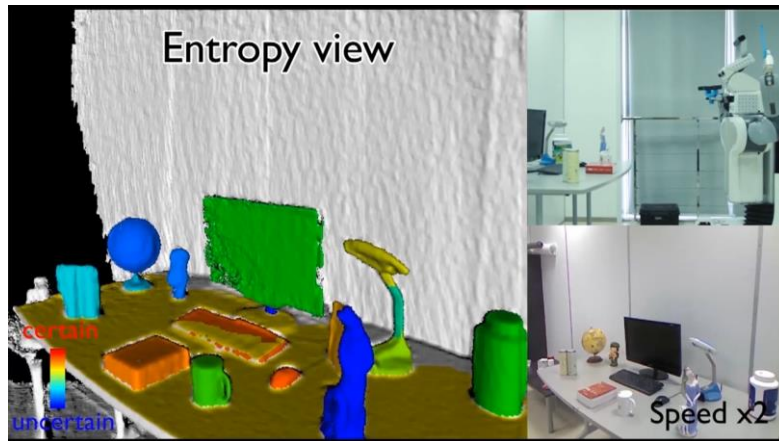


segmentation & recognition
[Nan et al. 2012]

Existing Works: Unknown Scenes

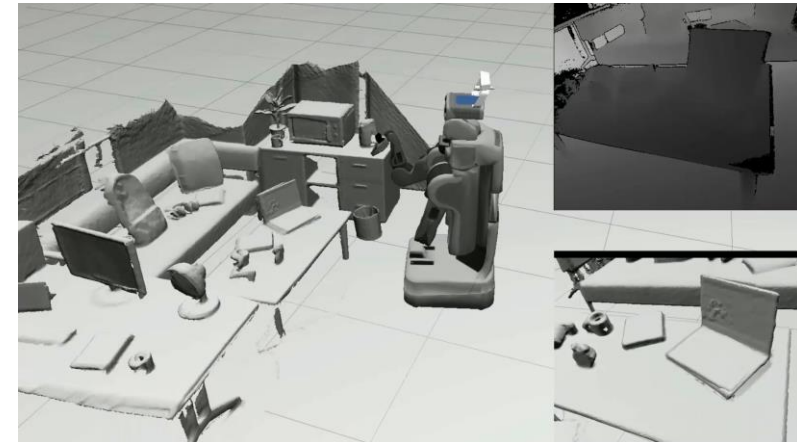
- Two pass scene reconstruction and understanding.
- Can only use **low-level** information in first exploration pass.

First Pass



reconstruction & segmentation
[Xu et al. 2015]

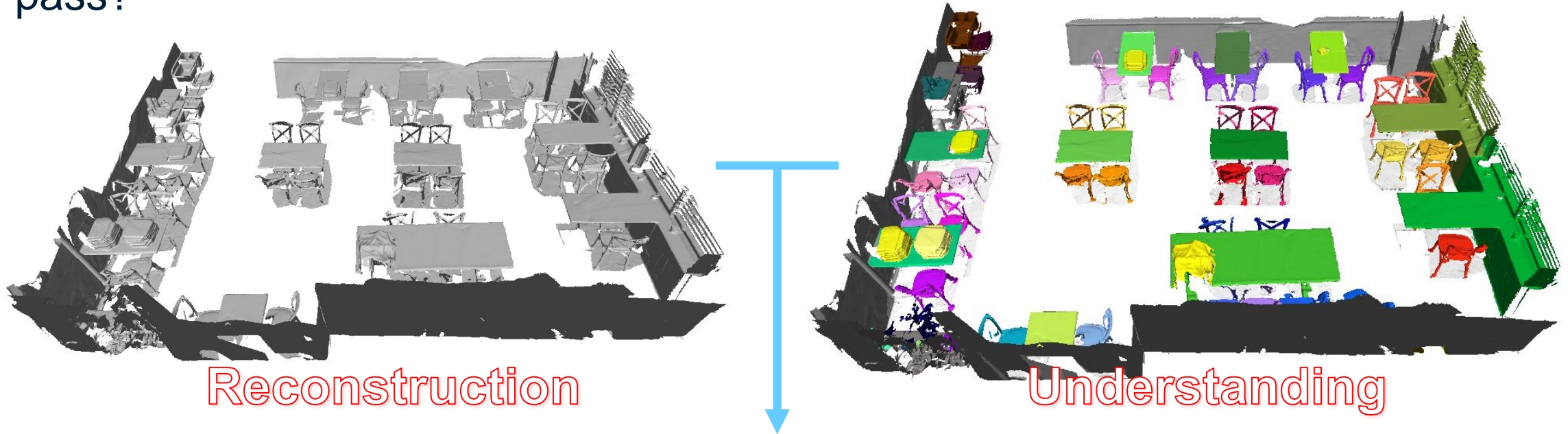
Second Pass



object recognition
[Xu et al. 2016]

The Main Challenge

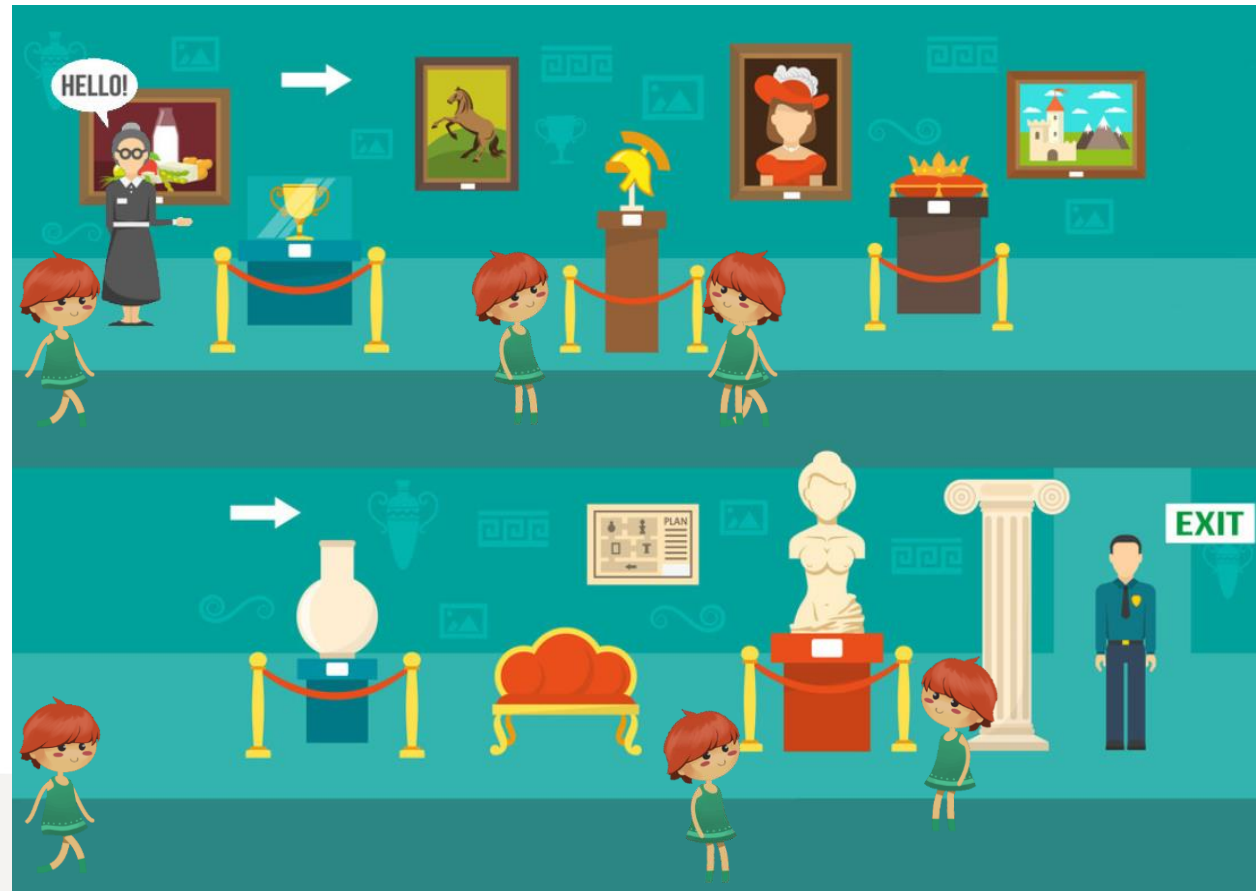
- How to automatically achieve scene reconstruction and understanding in one pass?



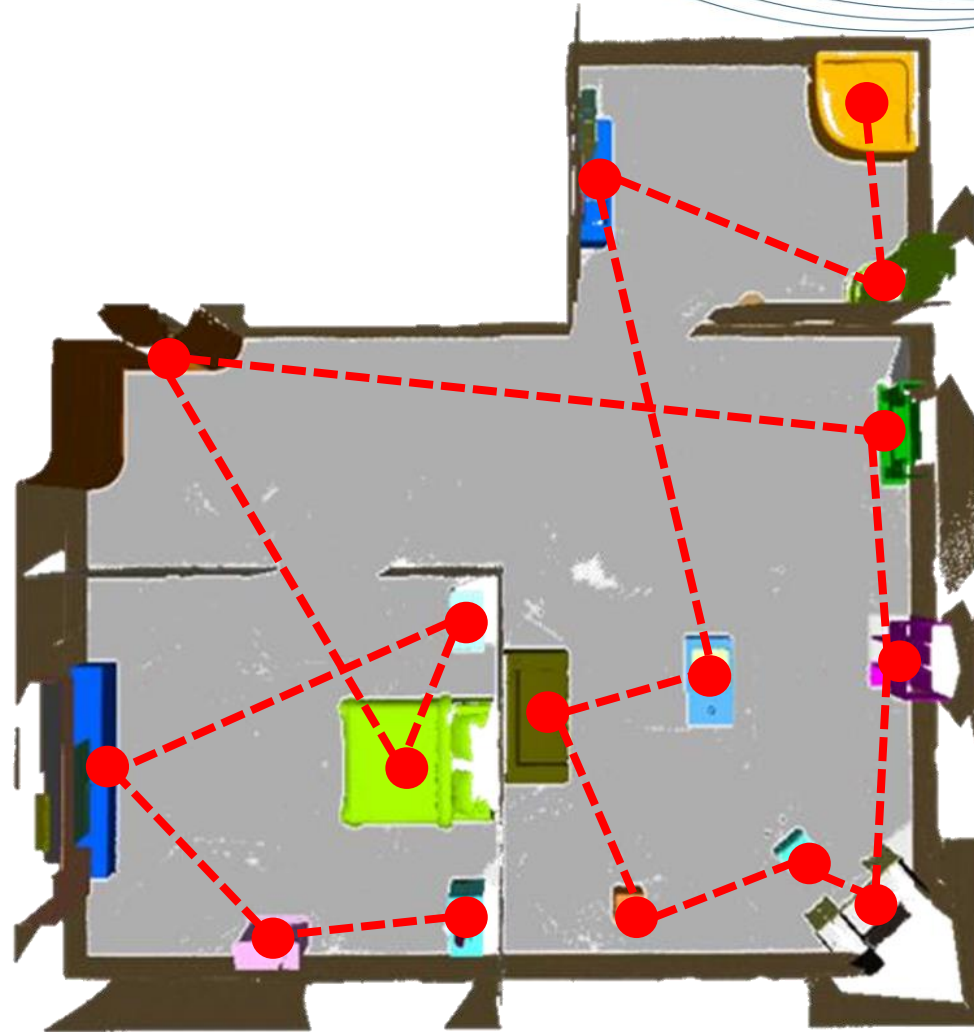
One pass?

Motivation

- Human explore unknown scenes **object by object!**



Our Solution



- **Key idea:** using recognized **objects** as a **guidance** map

We need to



One navigation

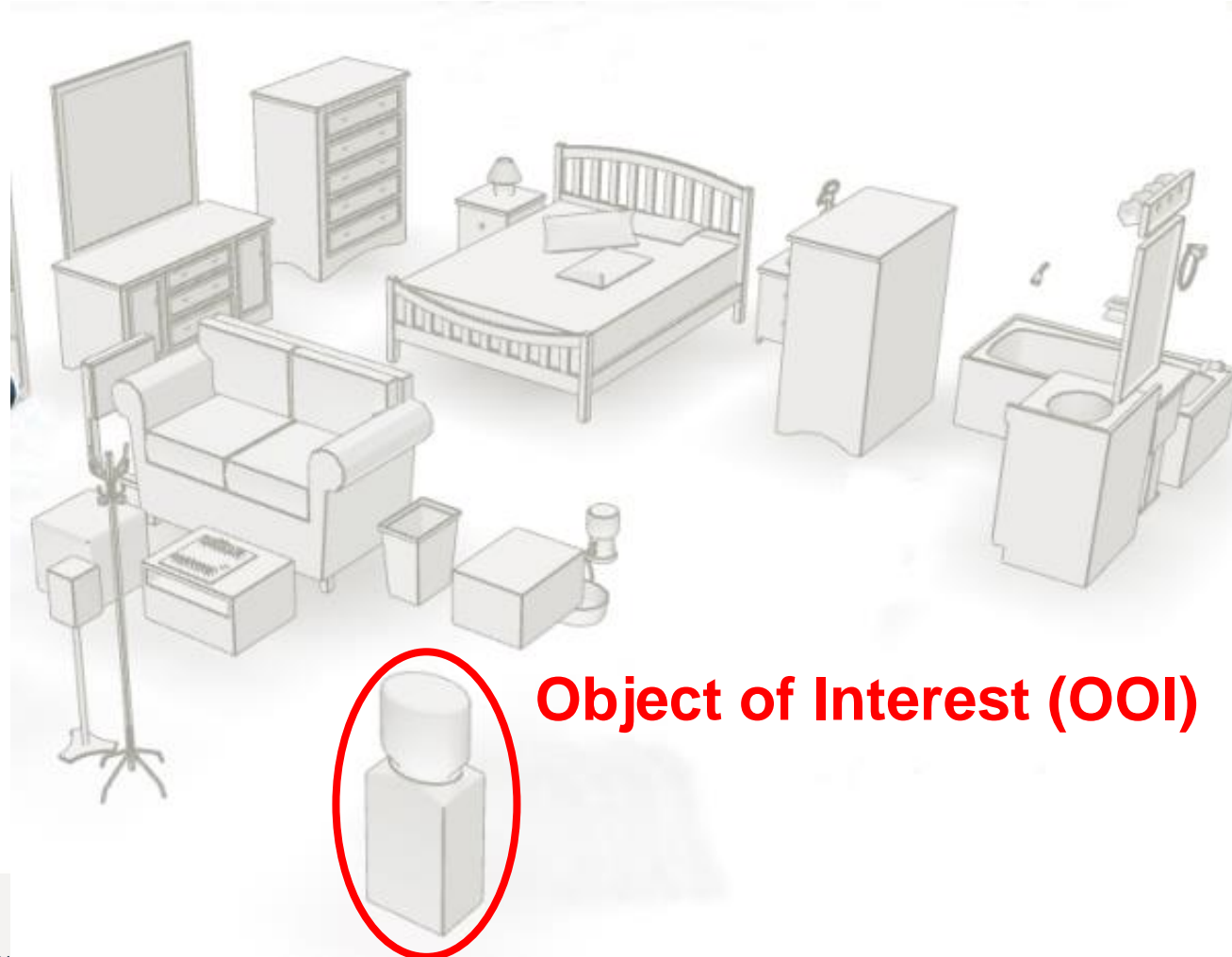
Automatic

Scene Understanding

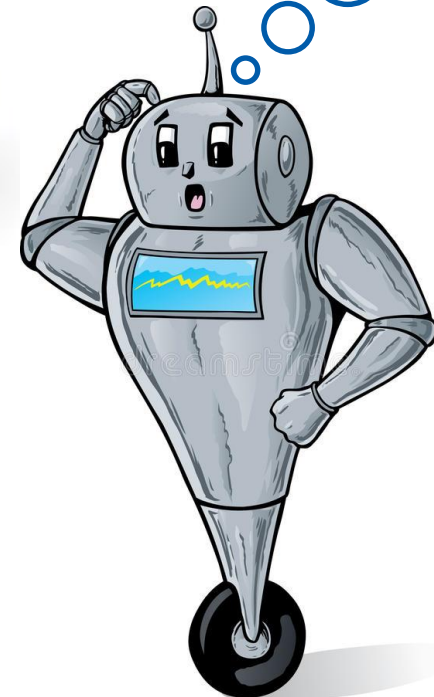
A grid of 50 small images of various chairs, arranged in a 5x10 grid. Each image is labeled with the chair's name, such as Eames chair, Butterfly chair, Bean chair, etc. The word "Recognition" is overlaid in red text.

Phase 1: The Next Best Object Problem

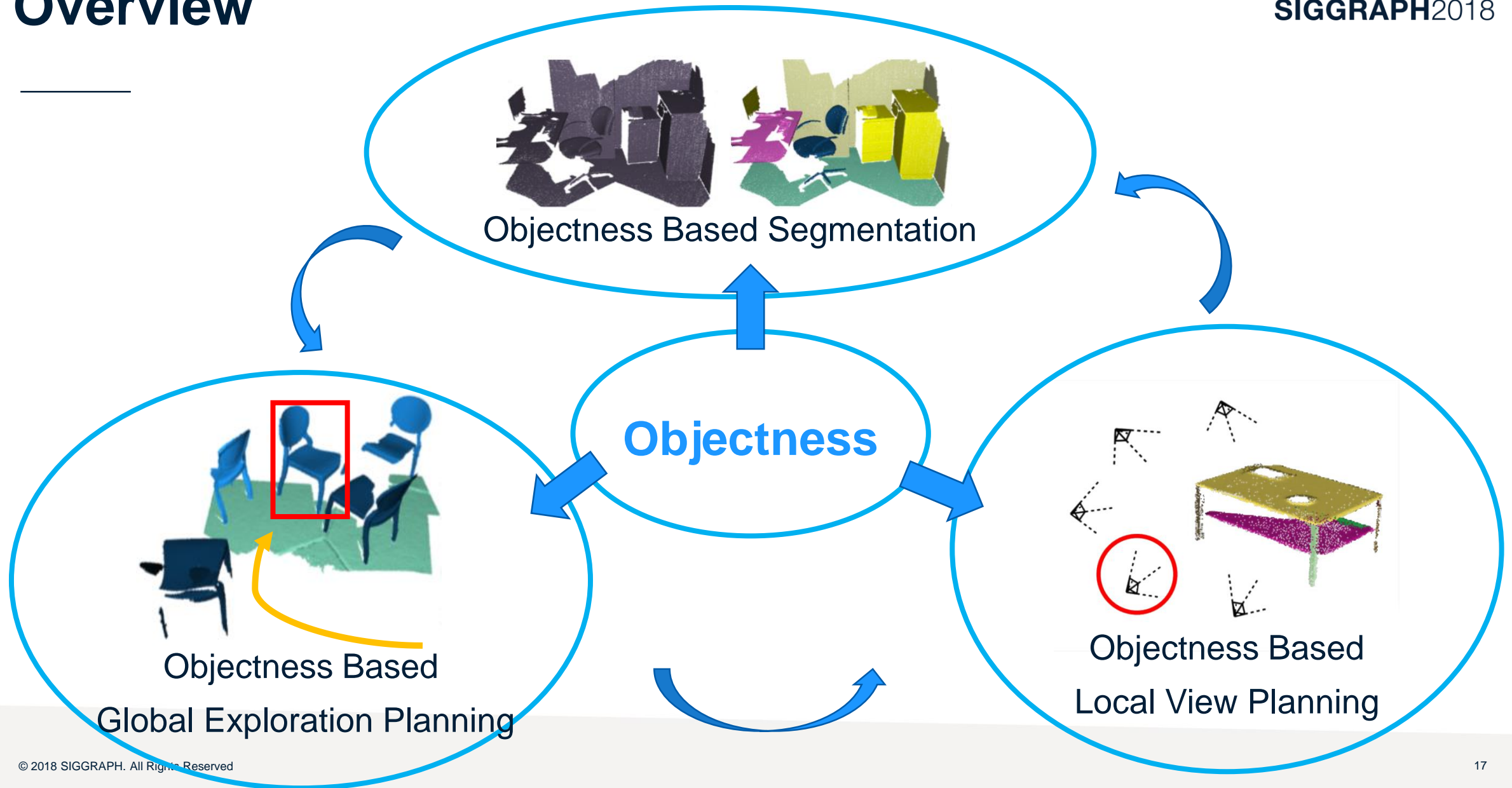
Which object should I scan next?



Object of Interest (OOI)

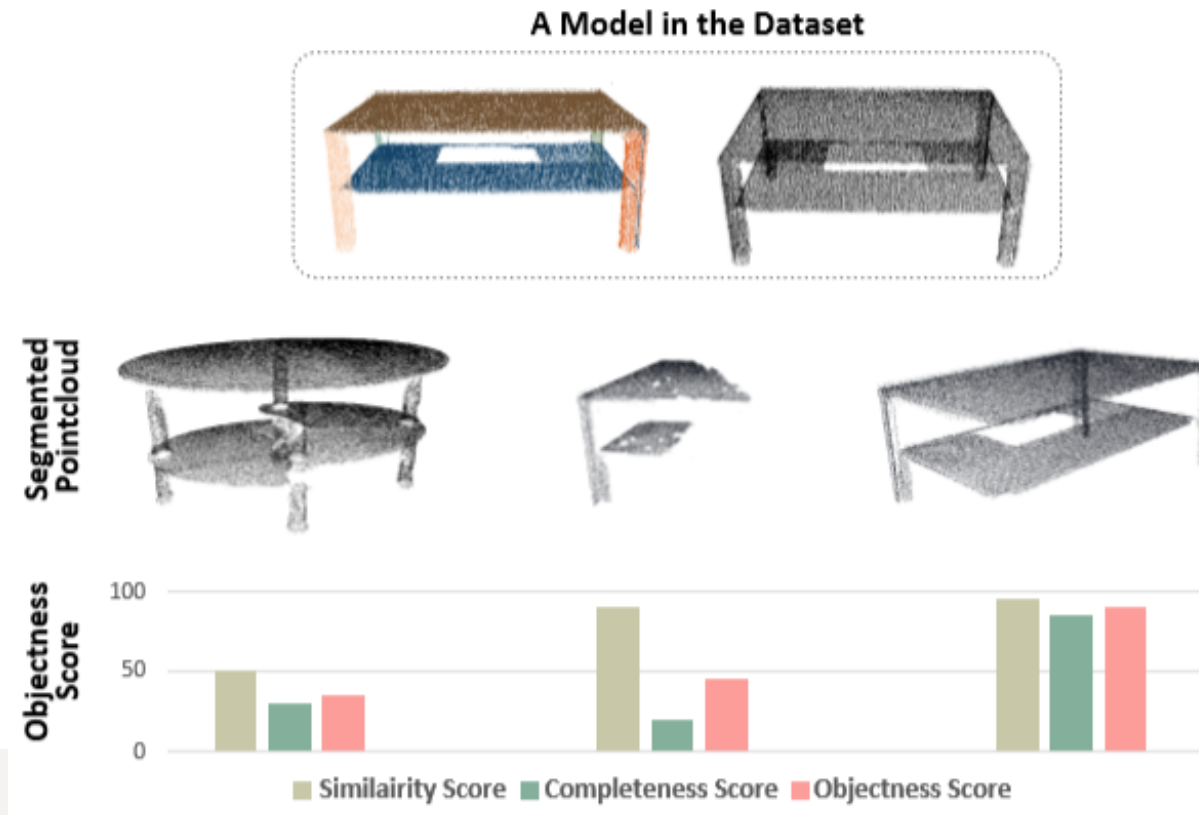


Overview

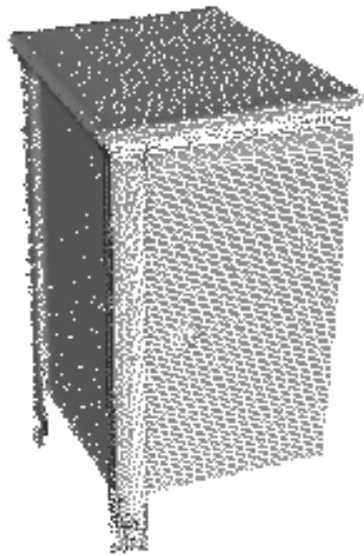


Model-Driven Objectness

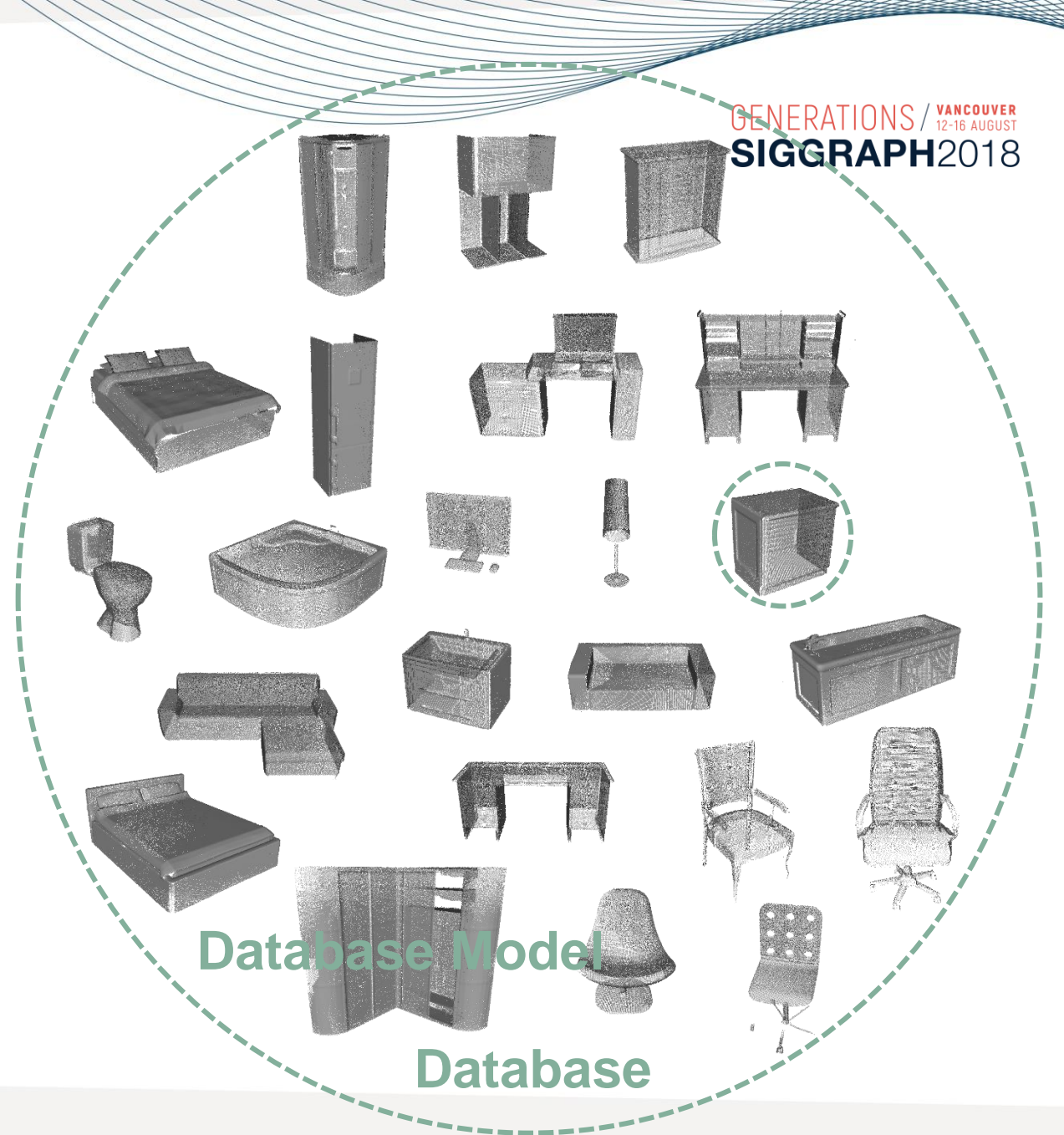
- Objectness should measure both similarity and completeness



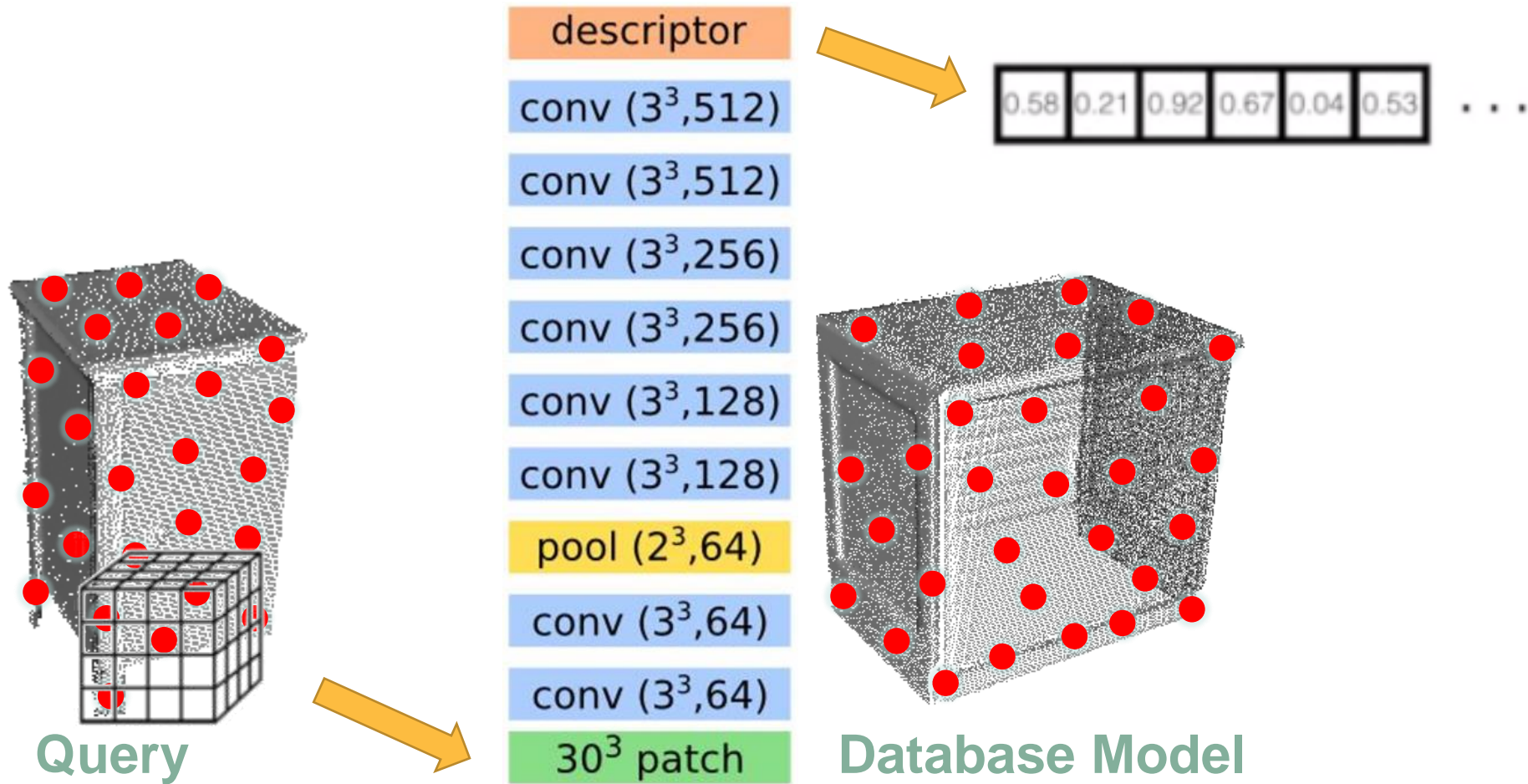
Partial Matching



Query

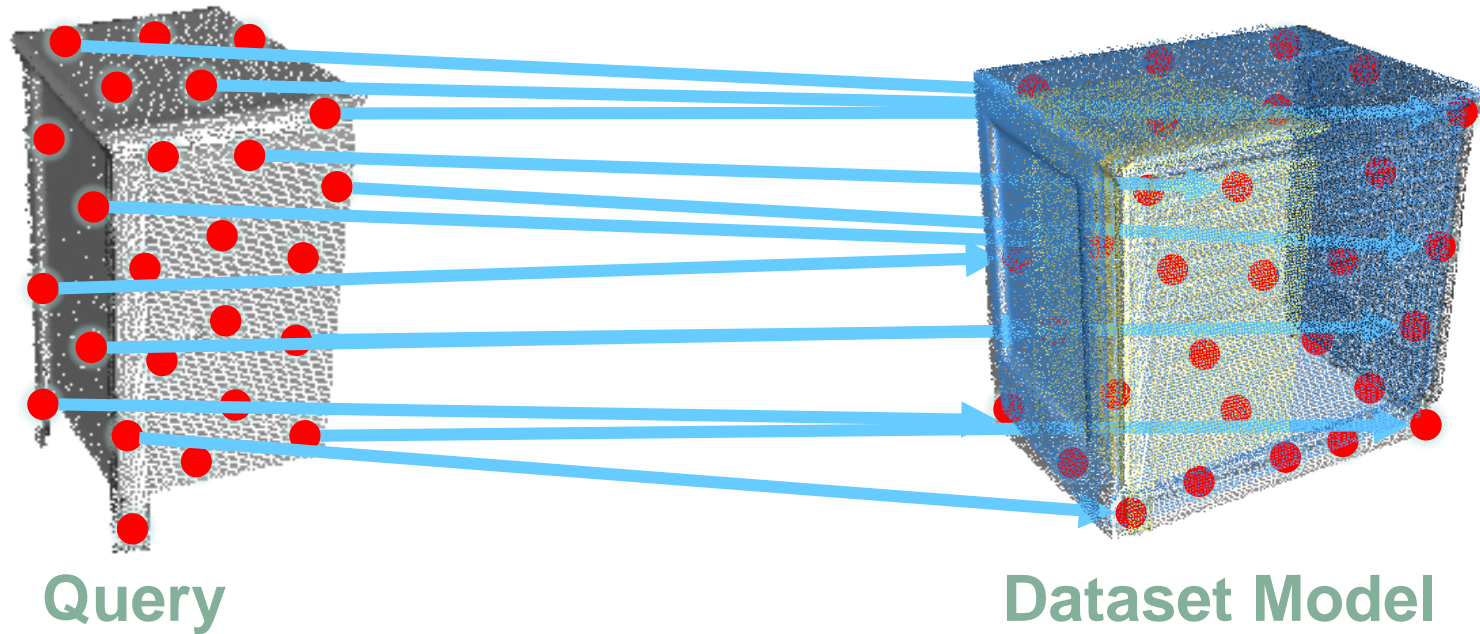


Partial Matching



3DMatch [Zeng et al. 2016]

Partial Matching



Model-Driven Objectness

$$d(X, Y) = \frac{1}{n_p} \sum_{i=1}^{n_p} d(x_i, Y)$$

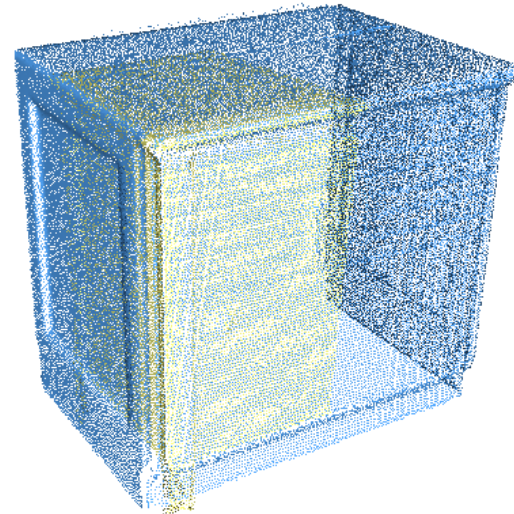
$$d(x_i, Y) = \min_{j=1, \dots, n_p} \|x_i - y_j\|^2$$

$$\underline{O(c, m)} = \exp \left[-\frac{1}{\underline{Diag(c)}} (\underline{d(c, m)} + \underline{d(m, c)})^{\frac{1}{2}} \right]$$

Objectness

Similarity

Completeness

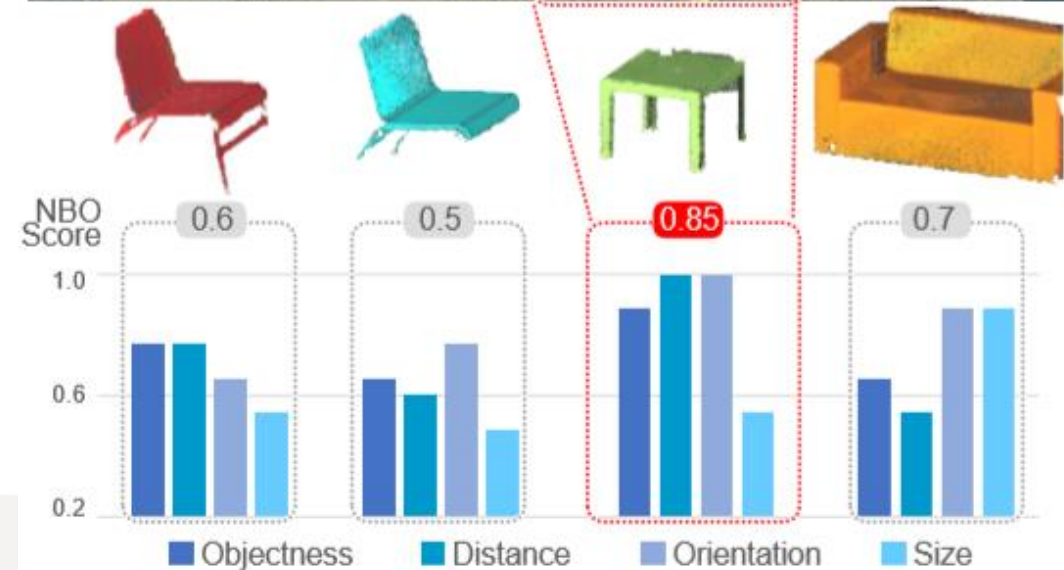
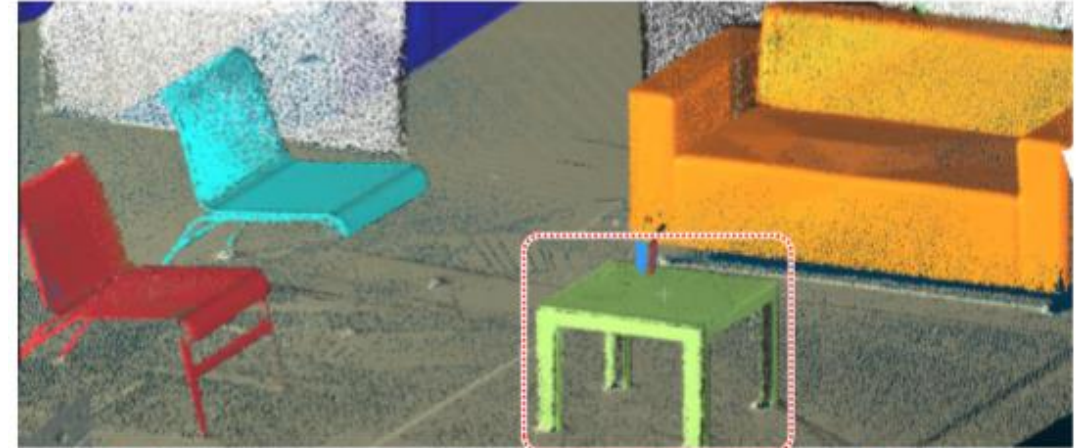


Next Best Object

Objectness

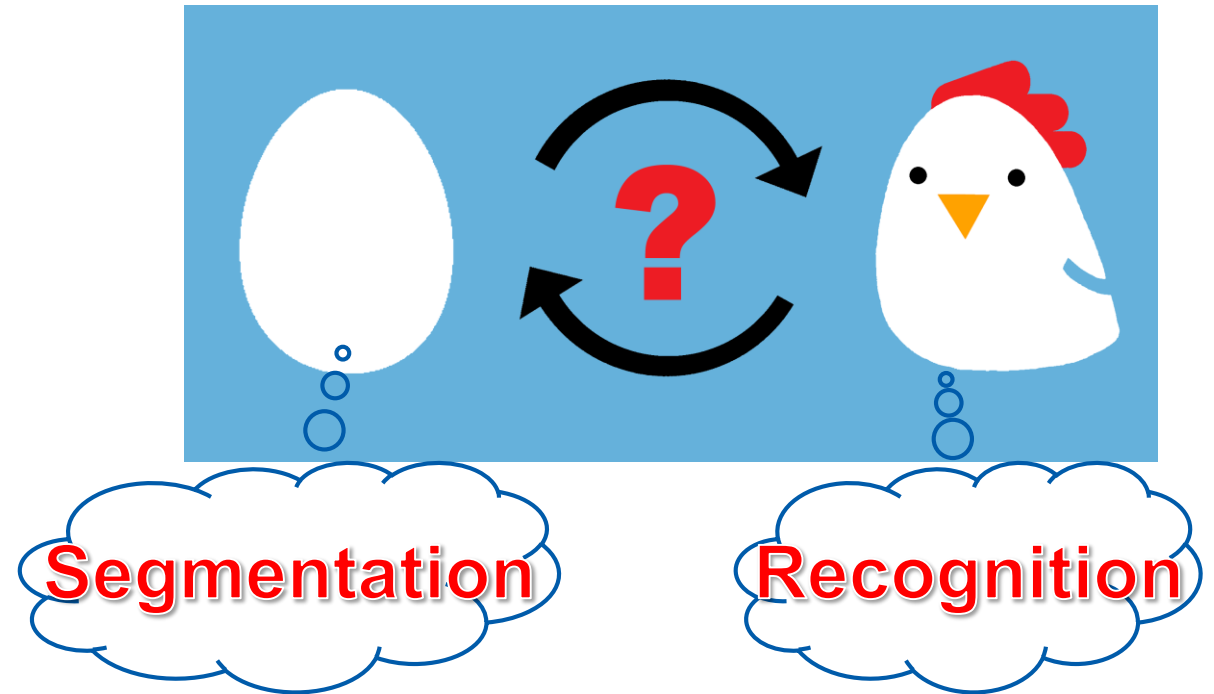
$$\gamma = \arg \max_{r \in \mathcal{R}} O(r) + S(r)$$

$$S(r) = \underbrace{w_z S_z(r)}_{\text{Distance}} + \underbrace{w_e S_e(r)}_{\text{Orientation}} + \underbrace{w_d S_d(r)}_{\text{Size}}$$



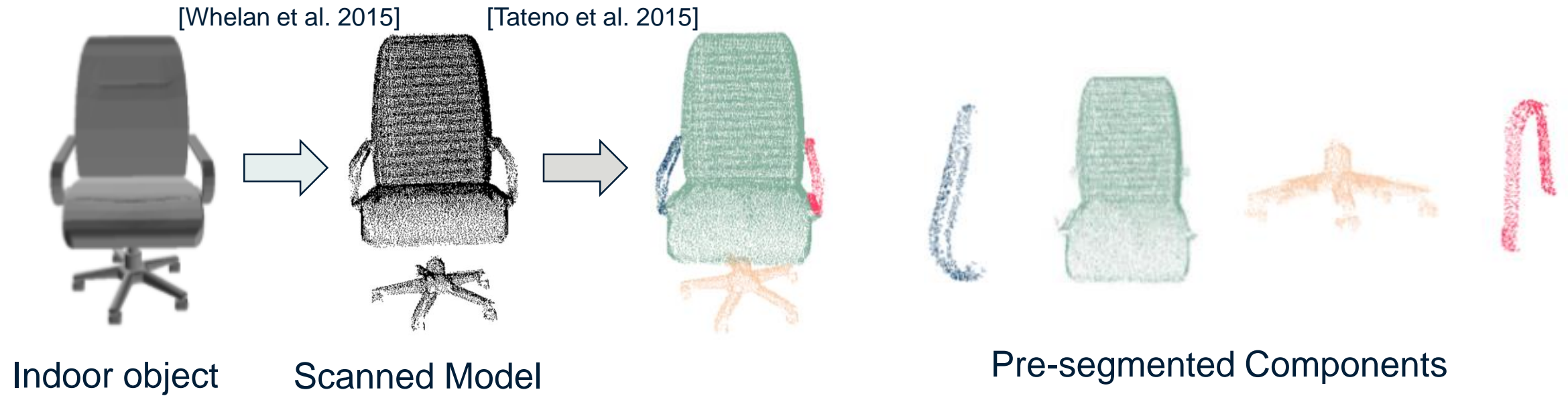
Technical Challenge

- How to segment and recognize objects during reconstruction?



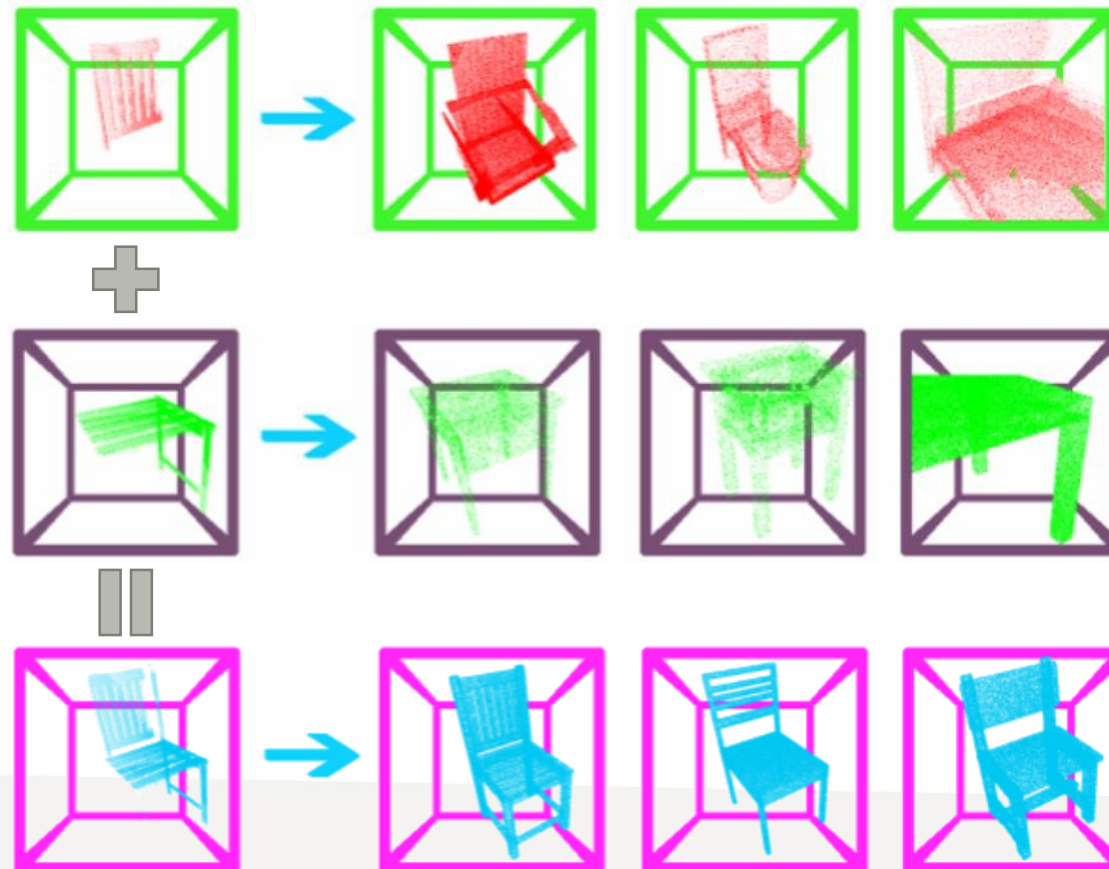
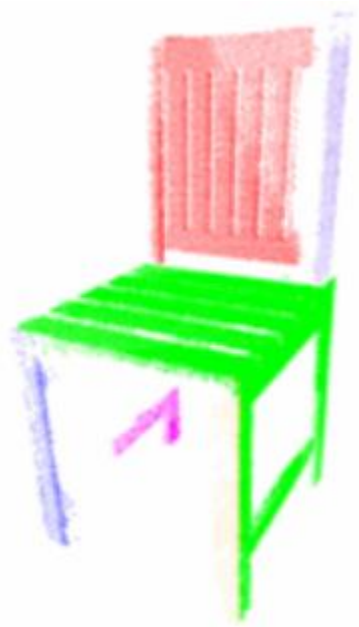
Recognition and segmentation constitute a *chicken-egg* problem

Pre-segmentation

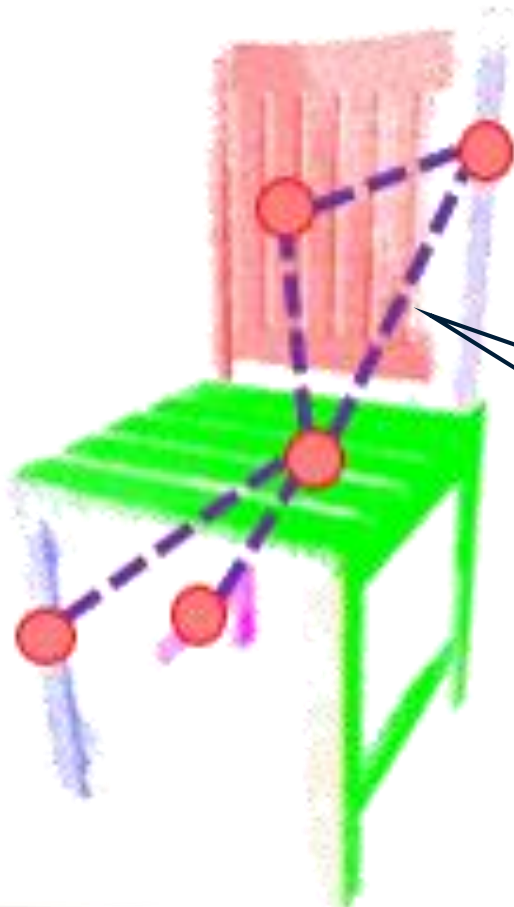


Post-segmentation

- Couples segmentation and recognition in the same optimization



Post-segmentation



$$E_D(l_c) = \min_{m \in M(c), l_c = L(m)} (1 - O(c, m))$$



$$E_S(l_c, l_d) = \begin{cases} \max_{m \in M(c \cup d)} O(c \cup d, m), & \text{if } l_c \neq l_d \\ 0, & \text{if } l_c = l_d \end{cases}$$

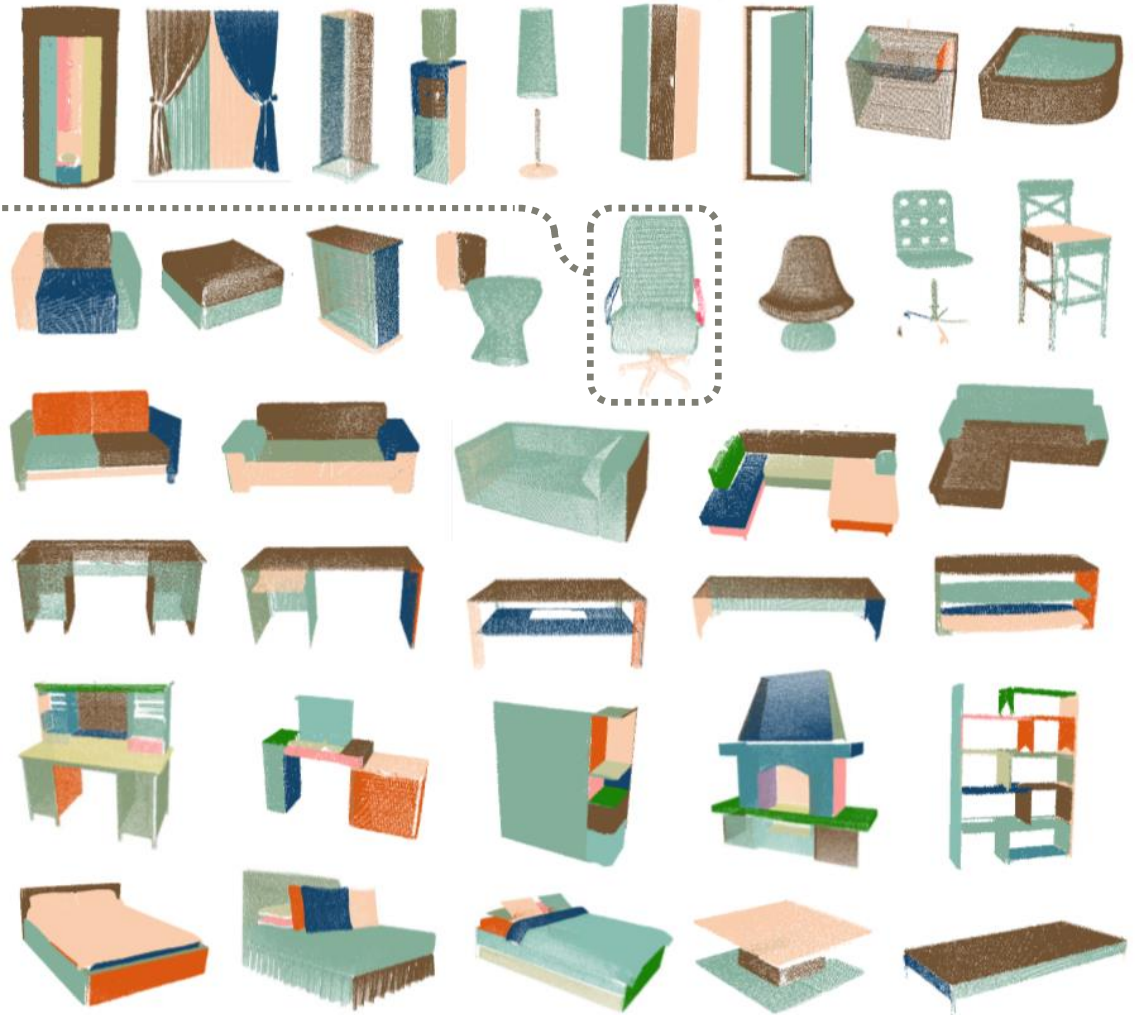
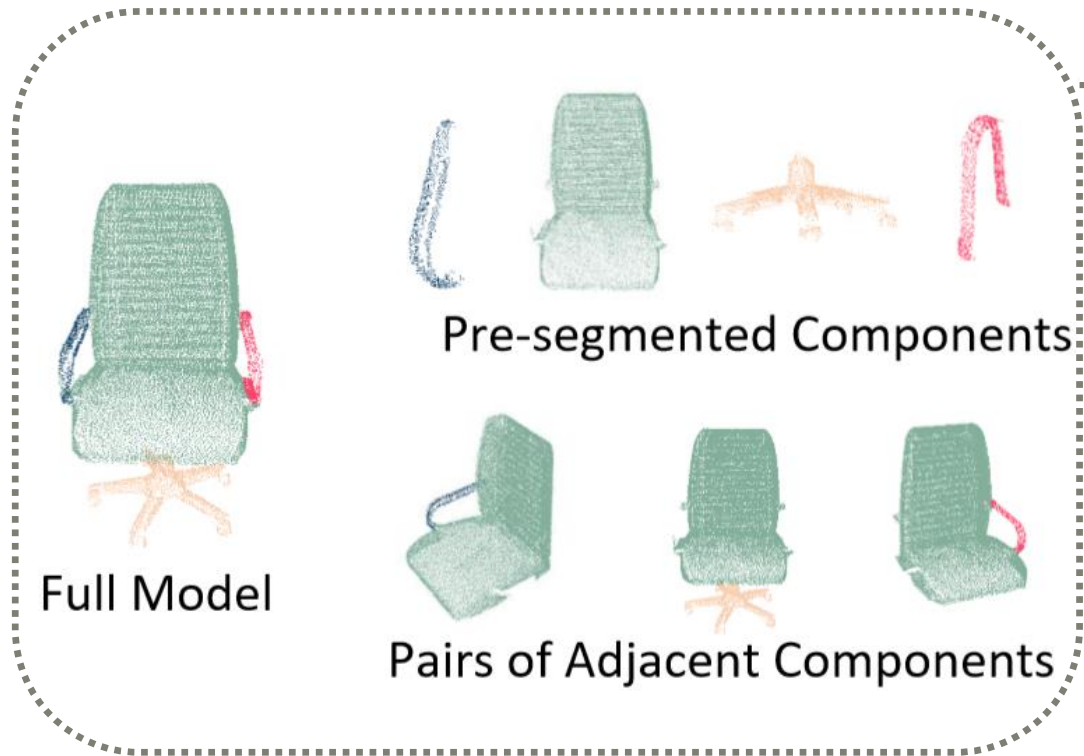


$$\min_{L=\{l_c\}} E(L) = \sum_{c \in \mathcal{V}_c} E_D(l_c) + \sum_{(c,d) \in \mathcal{E}_c} E_S(l_c, l_d)$$

Post-segmentation Results



Database Construction



Database Construction

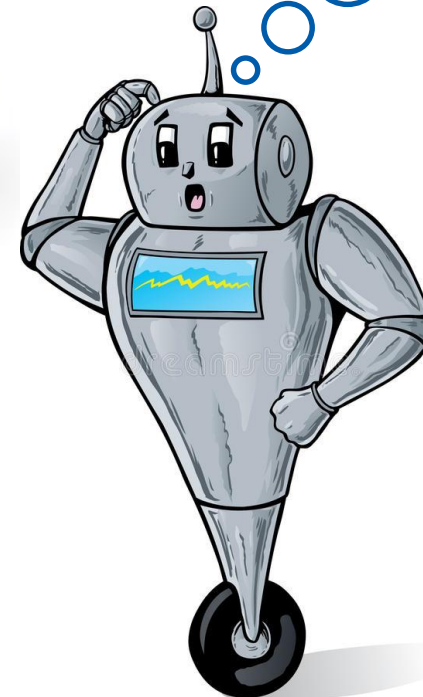
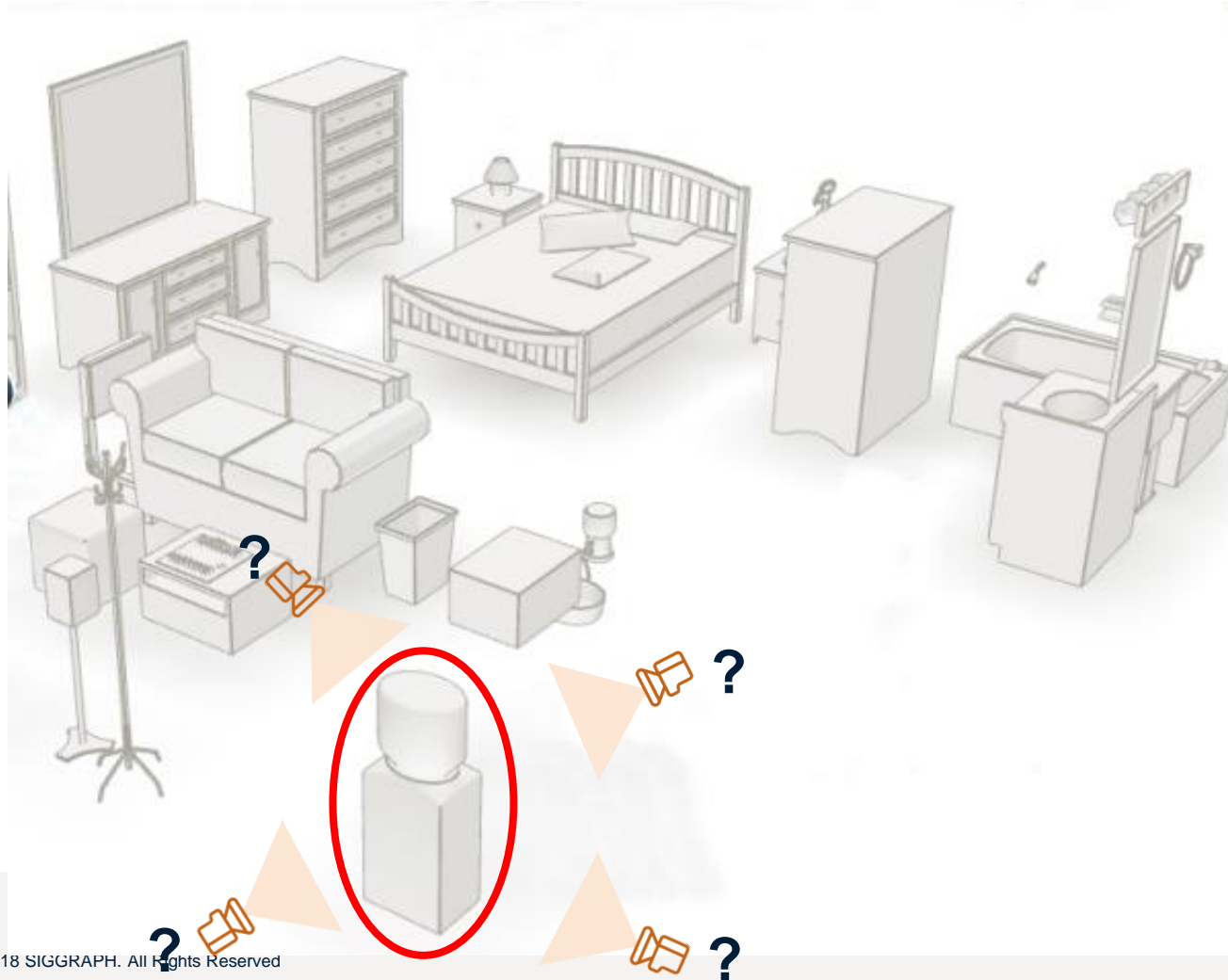
Two advantages:

- Decrease the difference between CAD model and scanned model
- Segmented components & component pairs can make retrieval **easier**

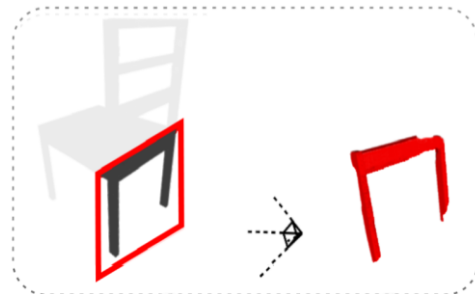


Phase 2: The Next Best View Problem

Which view of the OOI
should I scan next?



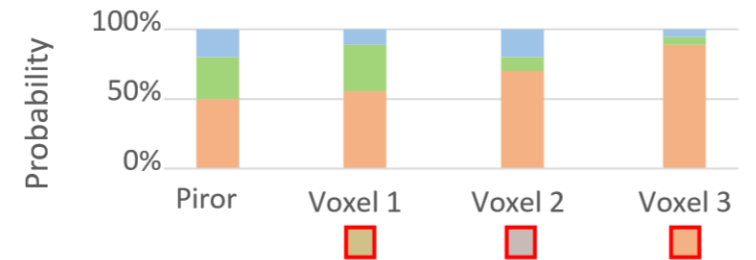
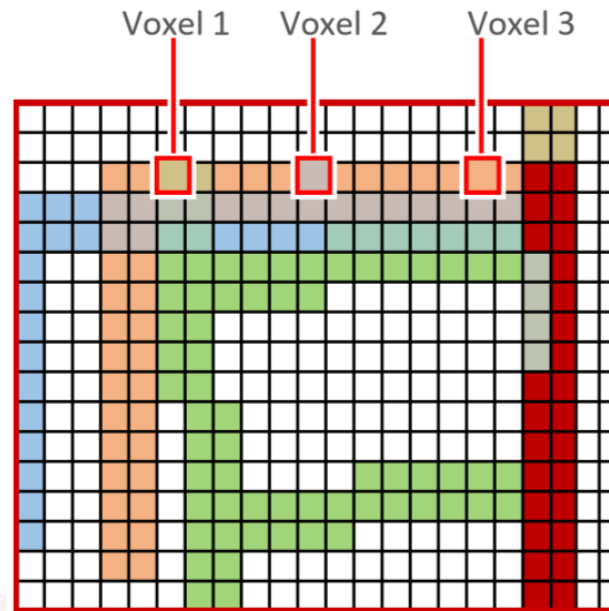
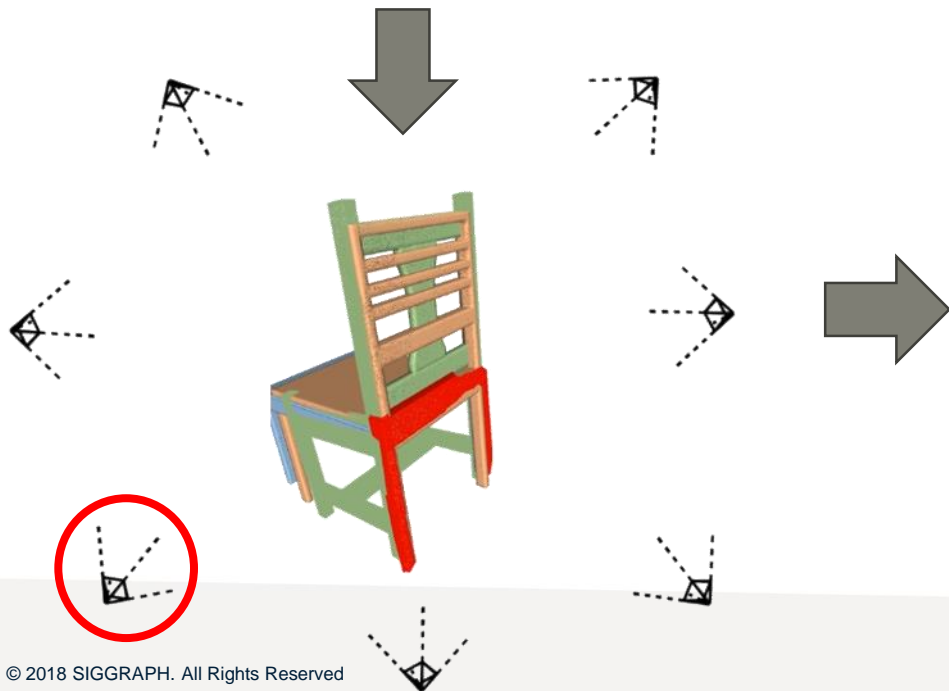
Next Best View



Maximal conditional information gain

$$\max_{j=1, \dots, n_v} G^j = \sum_{i=1}^{n_s} p(m_i) G^j(m_i)$$

$$\sum_{x \in \Delta} (H(x) - H(x|m_i))$$





Evaluation

- Virtual scene dataset



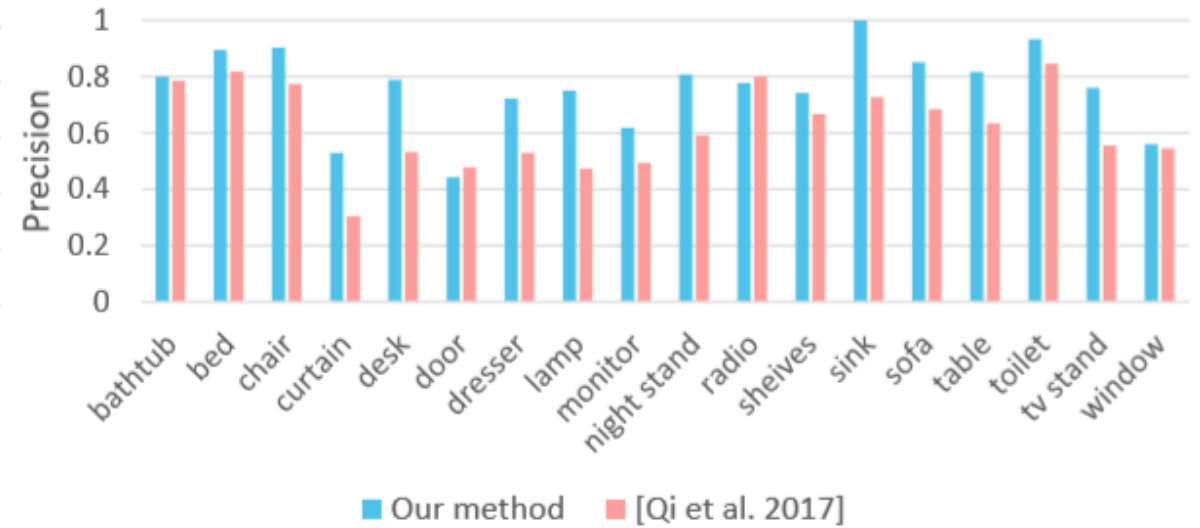
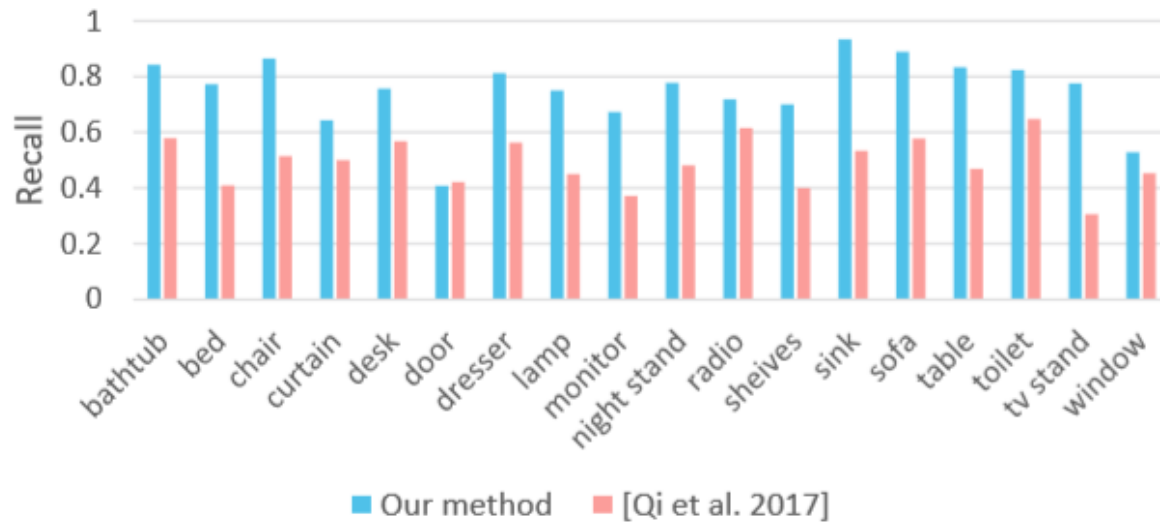
SUNCG (66 scenes)



ScanNet (38 scenes)

Comparison

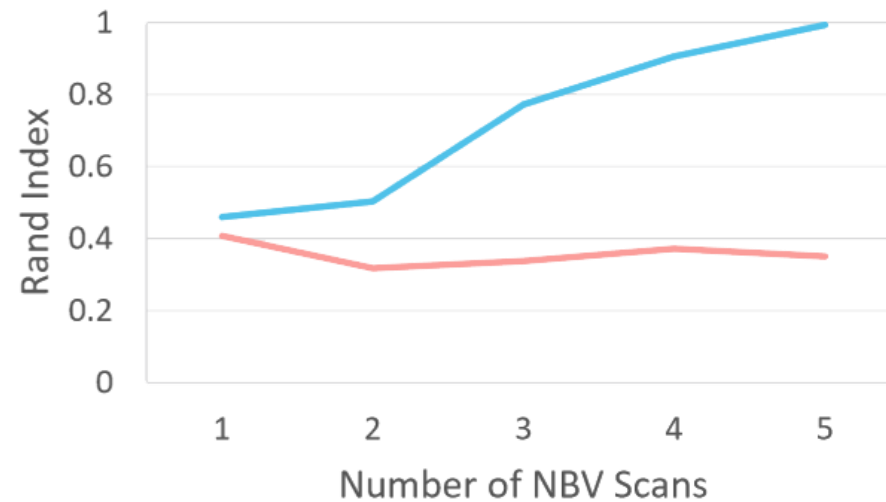
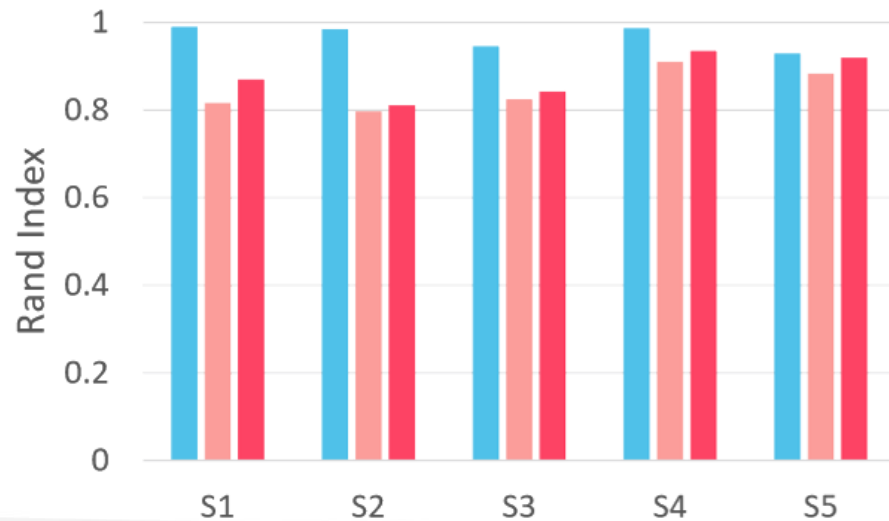
- Comparing object recognition with PointNet++ [Qi et al. 2017]



Comparison

- Comparing Rand Index of segmentation

$$RI(S_1, S_2) = \binom{2}{n}^{-1} \sum_{i,j,i < j} [C_{ij}P_{ij} + (1 - C_{ij})(1 - P_{ij})],$$

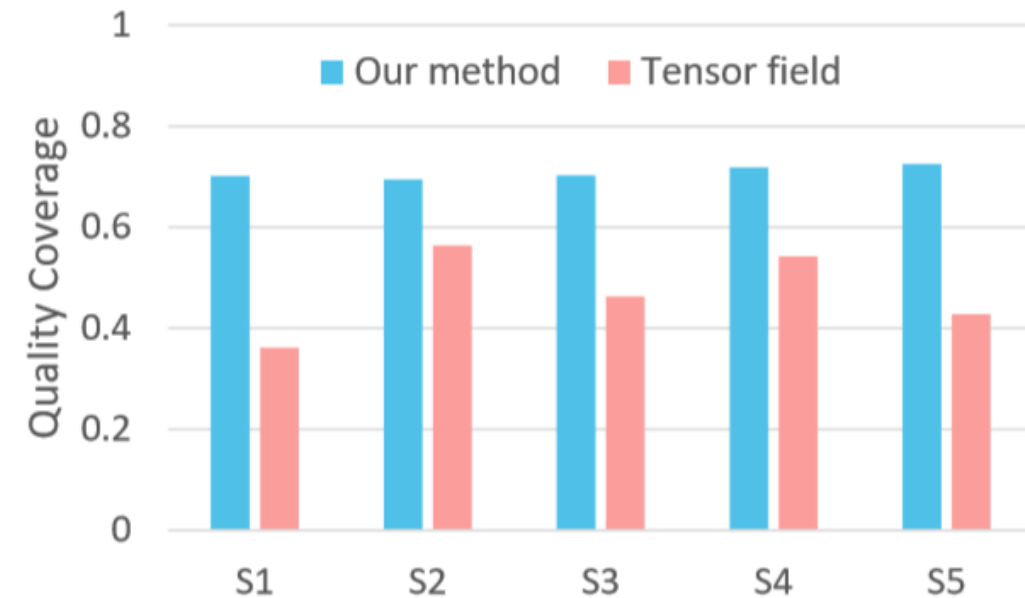
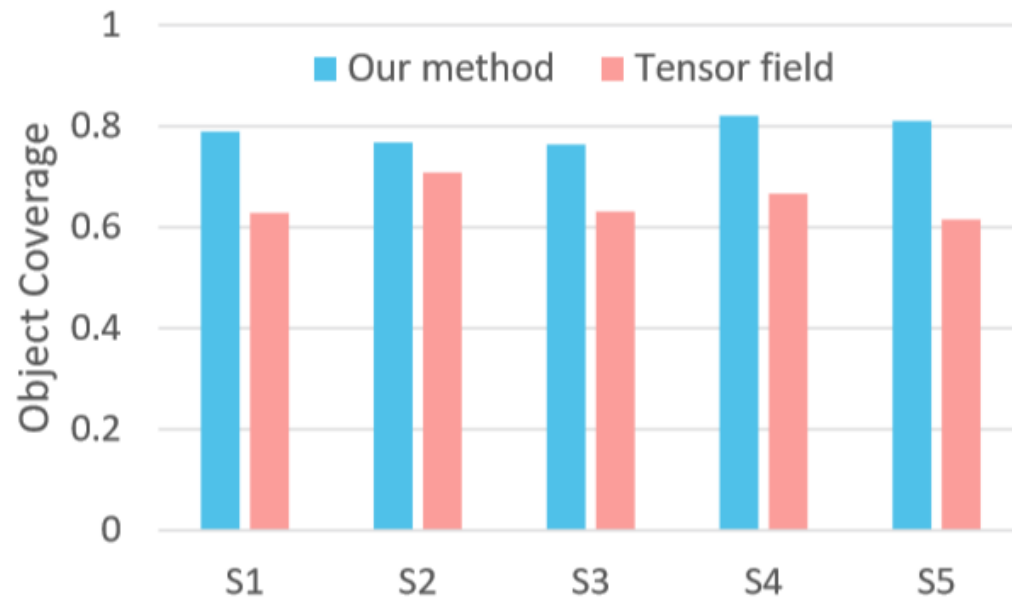


■ Our method ■ [Tateno et al. 2015] ■ [Qi et al. 2017]

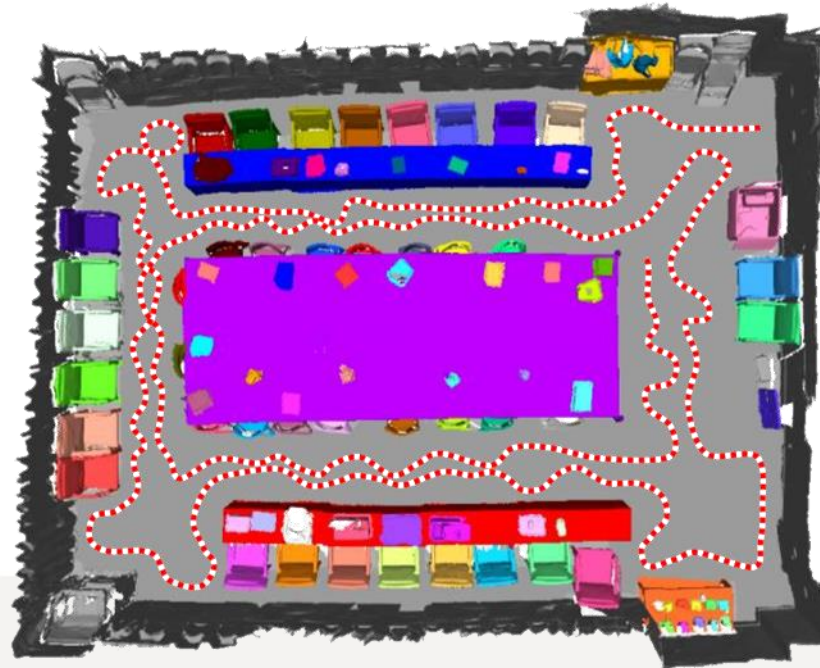
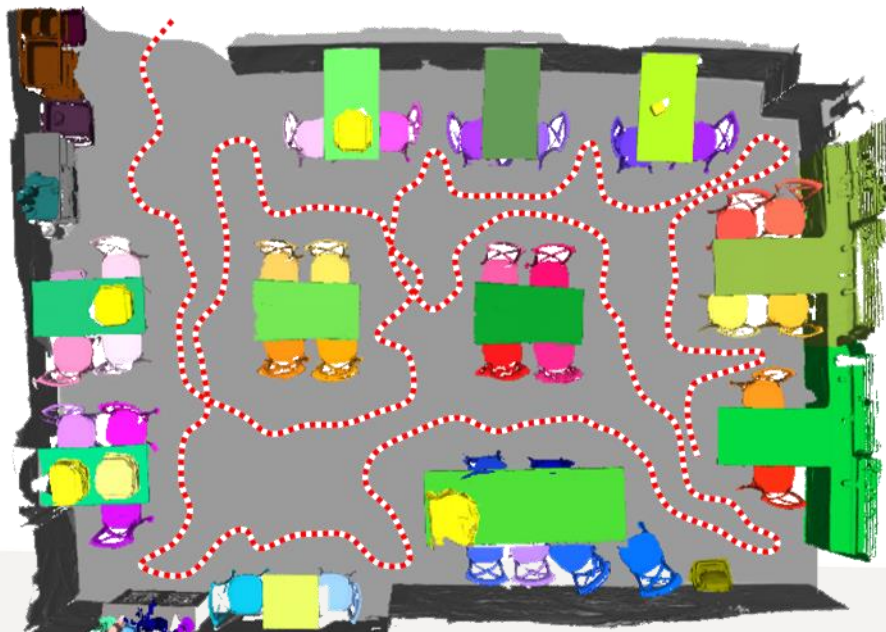
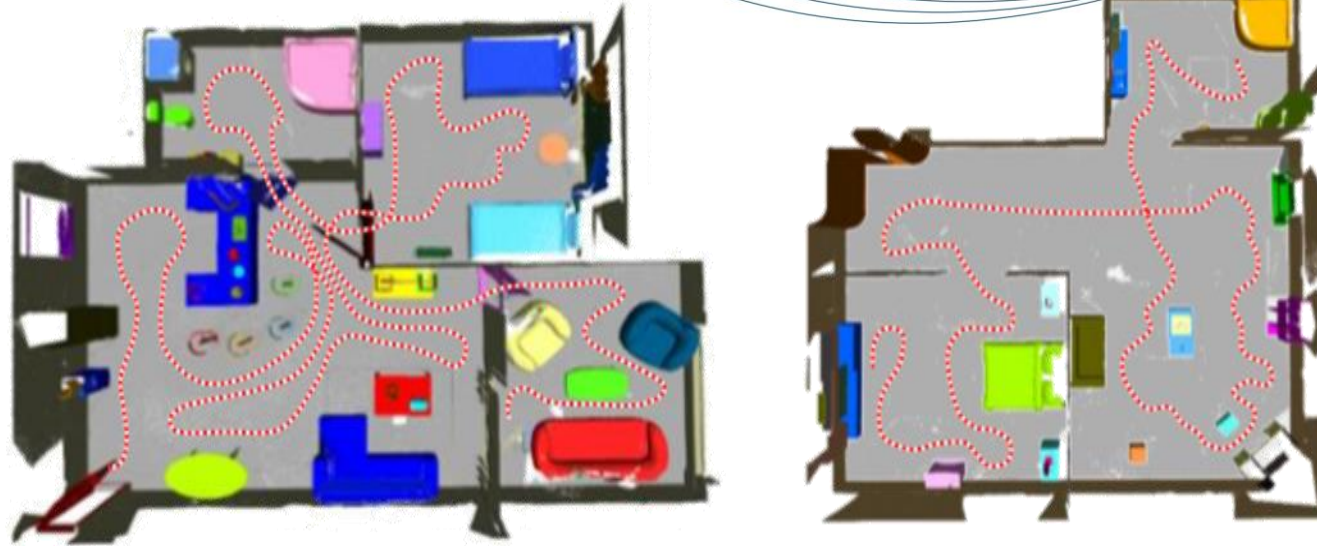
— Our method — [Tateno et al. 2015]

Comparison

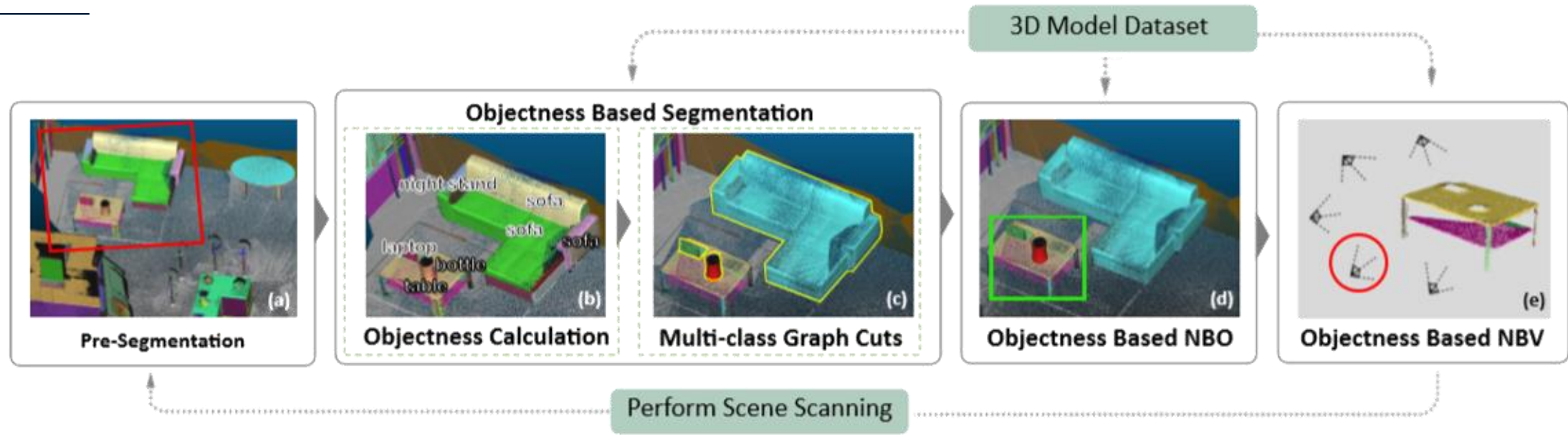
- Comparing object coverage rate and quality against tensor field guided autoscanning [Xu et al. 2017]



More Results



Conclusion



Key techniques:

- Objectness based segmentation
 - Pre-segmentation
 - Post-segmentation
- Objectness based reconstruction
 - The next best object (NBO)
 - The next best view (NBV)

Limitations

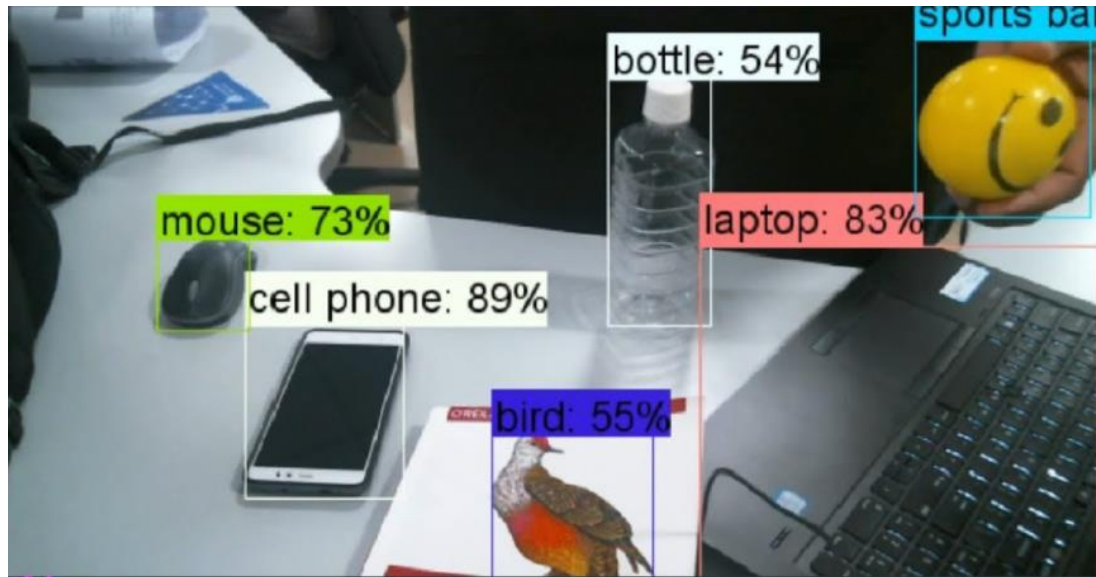


No similar models



Cluttered scenes

Future Works



Combine image-based method



Driverless car with LiDAR



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Thank you for your attention !

Data and code are available:

<http://kevinkaixu.net/projects/nbo.html>

Comparison

- Comparing object coverage rate and quality against tensor field guided autoscanning [Xu et al. 2017]

$$R_{\text{cover}} = \frac{1}{|\mathcal{V}_S|} \int_{v \in \mathcal{V}_S} \delta_{\text{detect}}(v) \cdot \delta_{\text{vis}}(v),$$

$$Q_{\text{cover}} = \frac{1}{|\mathcal{V}_S|} \int_{v \in \mathcal{V}_S} \delta_{\text{detect}}(v) \cdot \delta_{\text{vis}}(v) \cdot q(v),$$

Depth noise



Time Table

| Category | Total | Navigate | Segment | NBO | NBV |
|------------------|-------|----------|---------|-----|-----|
| Bedroom (V) | 47.8 | 24.1 | 20.1 | 2.0 | 1.6 |
| Living room (V) | 57.0 | 30.4 | 22.2 | 2.3 | 2.1 |
| Kitchen (V) | 37.5 | 16.2 | 17.6 | 2.0 | 1.7 |
| Bathroom (V) | 29.5 | 14.8 | 12.2 | 1.3 | 1.2 |
| Office (V) | 40.8 | 21.3 | 16.0 | 1.9 | 1.6 |
| Meeting room (R) | 101.4 | 62.3 | 32.4 | 3.6 | 3.1 |
| Resting room (R) | 78.5 | 47.9 | 25.4 | 2.9 | 2.3 |
| Office (R) | 94.7 | 56.9 | 30.3 | 4.2 | 3.3 |

Robot

