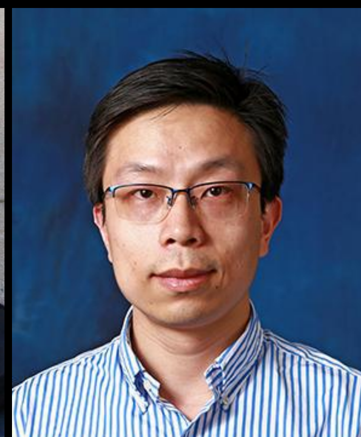
3D Graph Neural Networks for RGBD Semantic Segmentation

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Depth Sensors

Microsoft Kinect

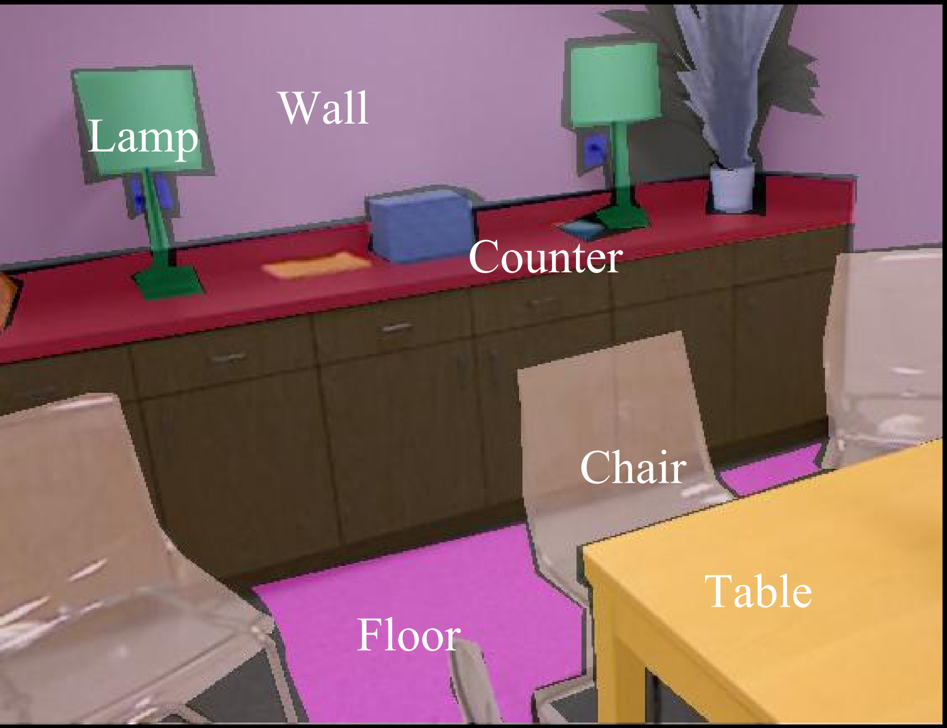
Intel RealSense

Depth information available

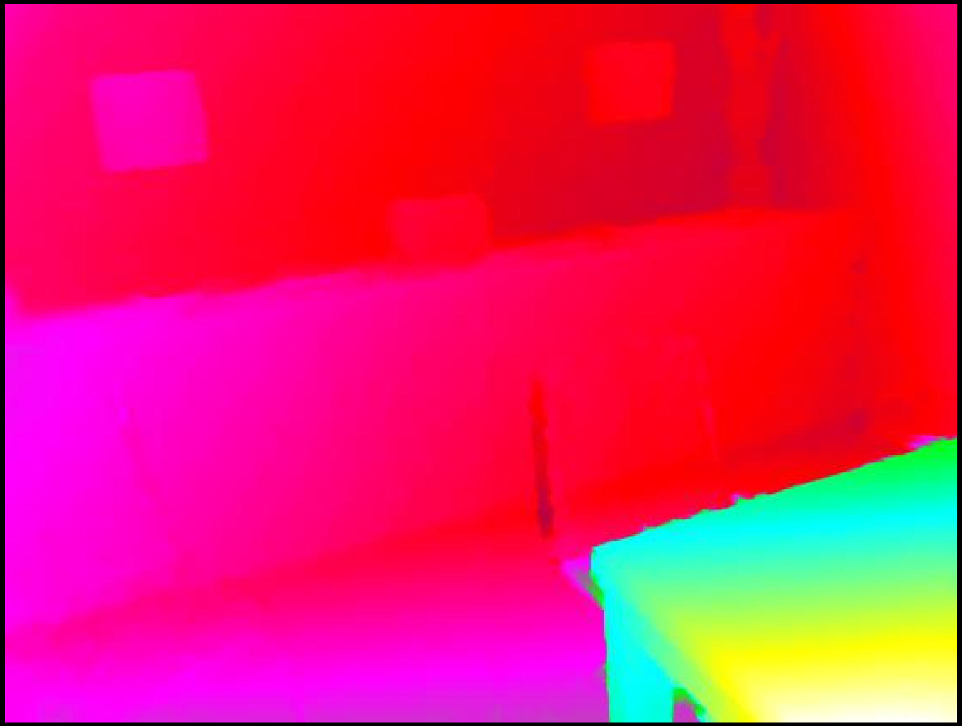
Dual Camera Smartphone

Dual Camera UAV

Problem



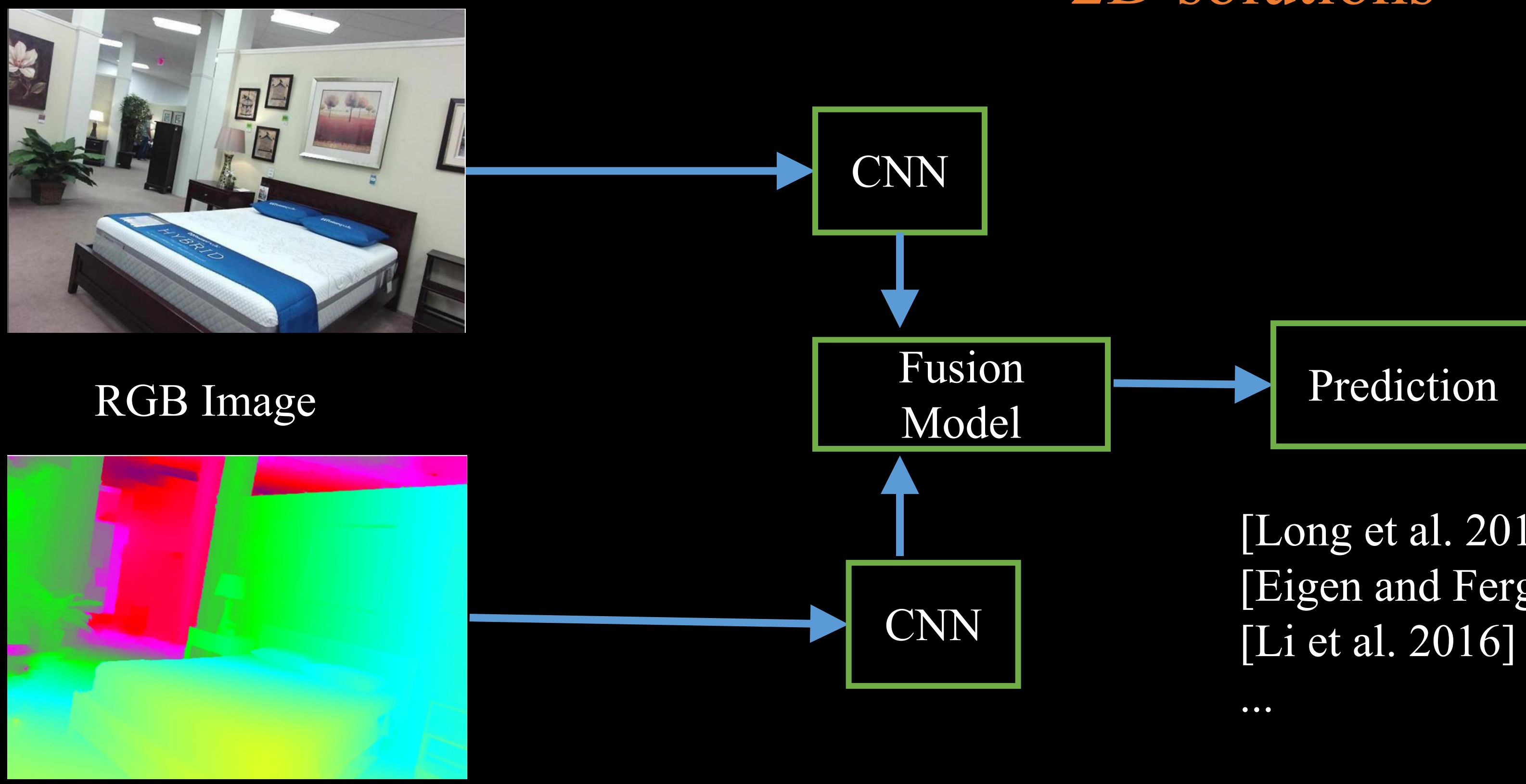
Segmentation map



Depth Image

Previous Approaches

2D solutions

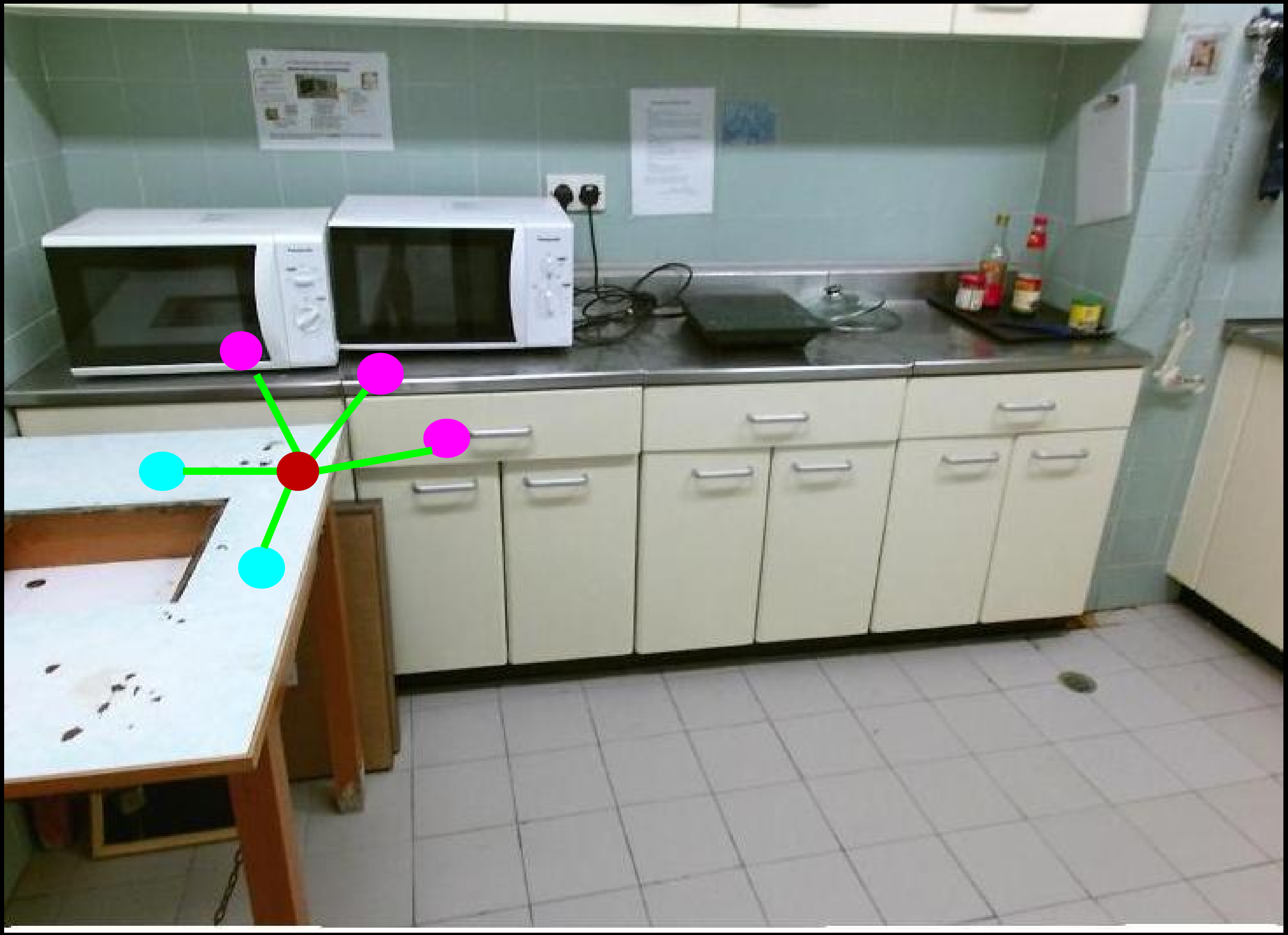


RGB Image

Depth Image

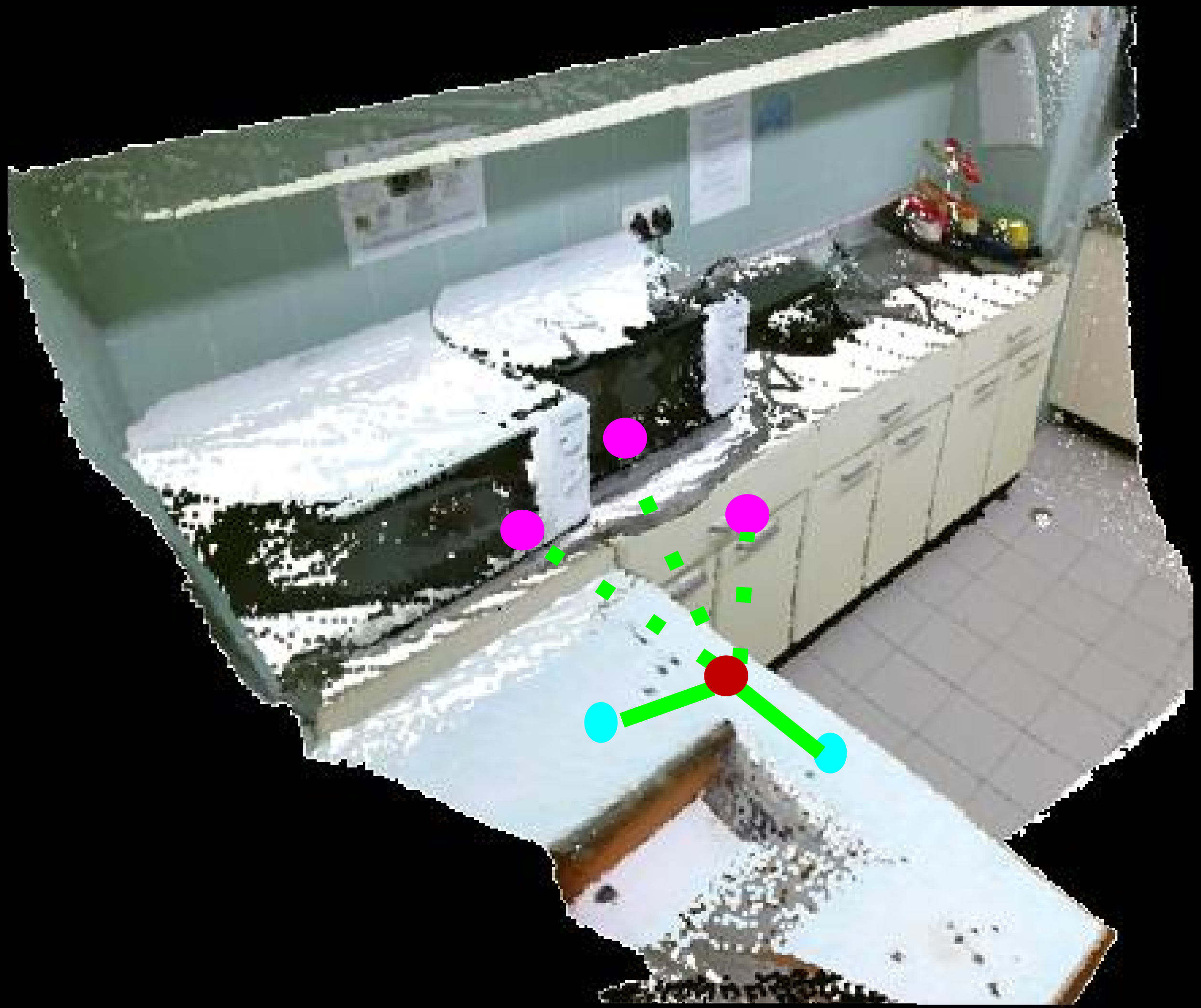
[Long et al. 2015]
[Eigen and Fergus 2015]
[Li et al. 2016]
...

Motivation



2D Image

Motivation

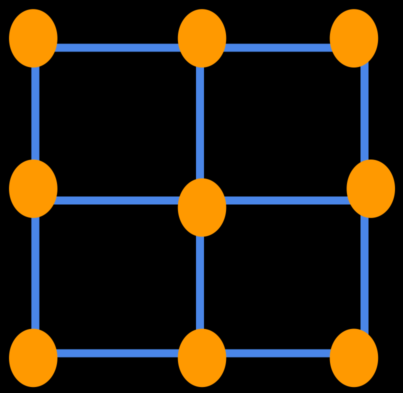


3D Point Cloud

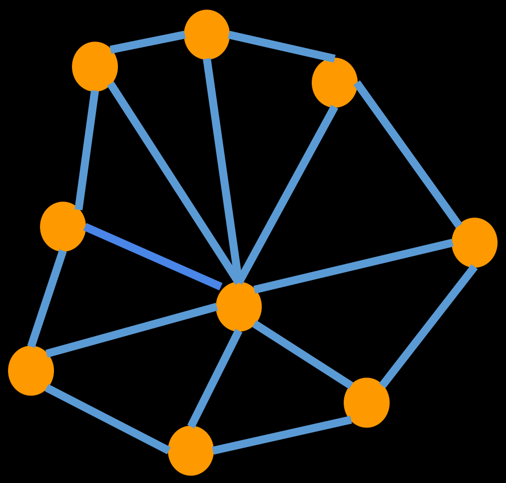
- Accurate Context
- 3D Geometry

Challenge

3D Point Cloud is non-uniformly structured data



Grid structured data



Non-uniform structured data

Solutions

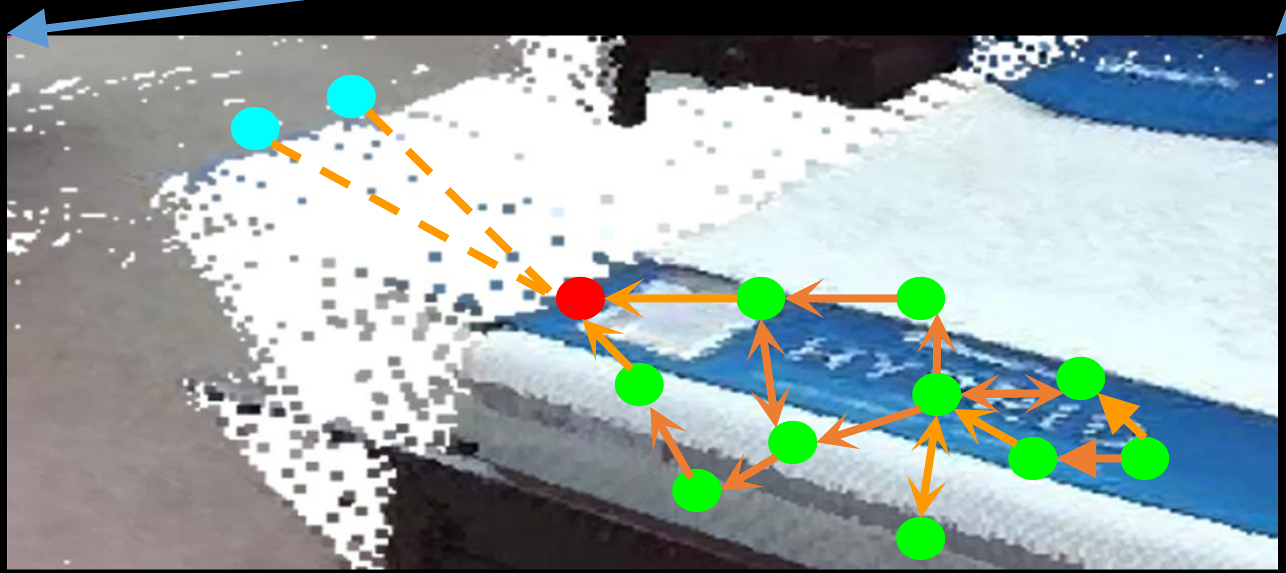
3D Graph Neural Networks

3D Graph Neural Networks (3DGNN)

- Graph Construction
- Propagation Model

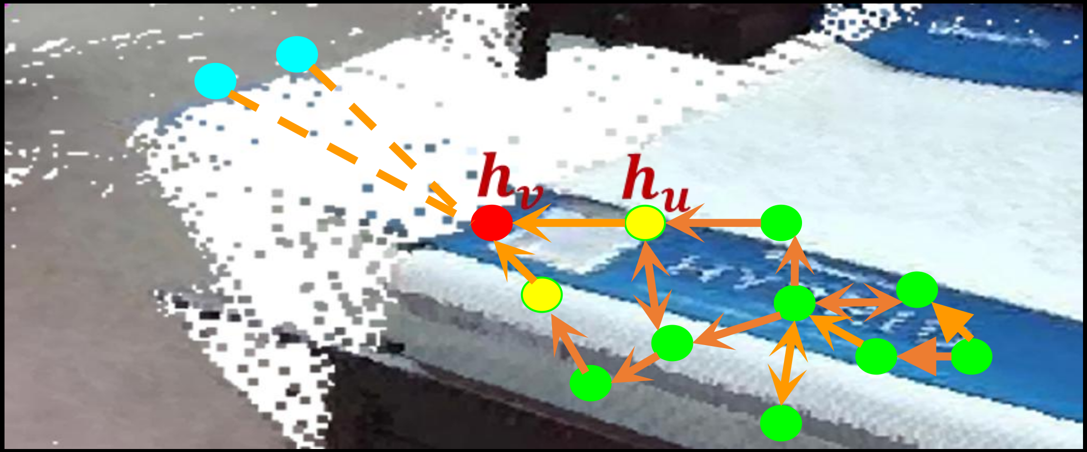
3DGNN: Graph Construction

- Graph Construction
  - ➢ Node: each point in the cloud
  - ➢ Edge: directed edge



3DGNN: Propagation Model

- Node v is associated with a state vector: h_v.
- The state vector is recurrently updated based on its history state and messages from its neighbor .



3DGNN: Propagation Model

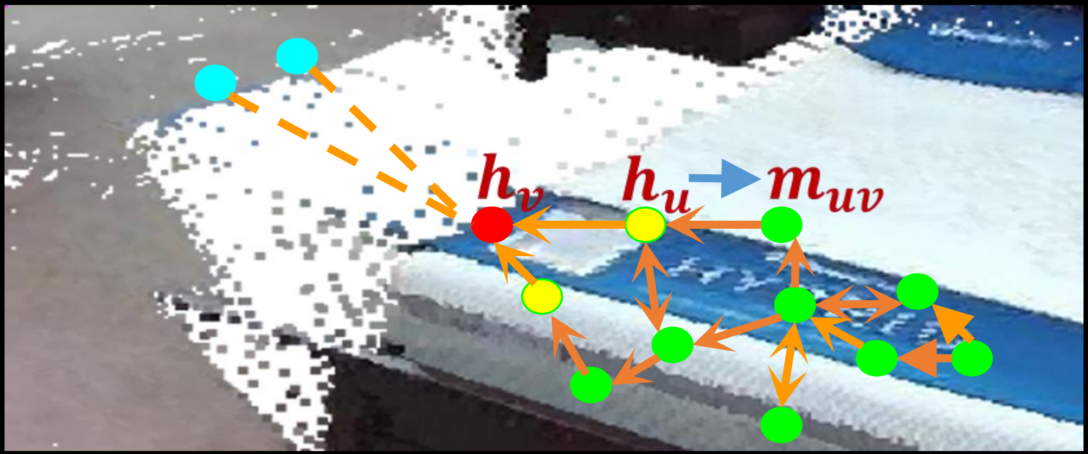
- In each block, we perform:
  - Message computation
  - Message aggregation
  - Node state update

3DGNN: Message Computation

- Step 1: For each directed edge (u, v), the message is:

$$m_{uv} = g_{uv}(h_u)$$

g_{uv}: a message function (an identity mapping in our case).

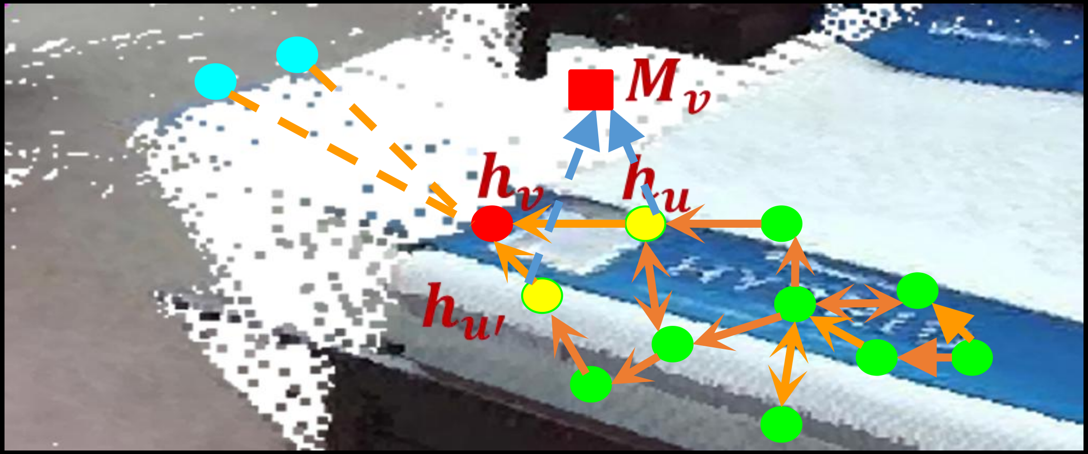


3DGNN: Message Aggregation

- Step 2: Each node v aggregates messages from its neighbors Ω_v:

$$M_v = q\{m_{uv} | u \in \Omega_v\}$$

q: aggregation function (average in our case)

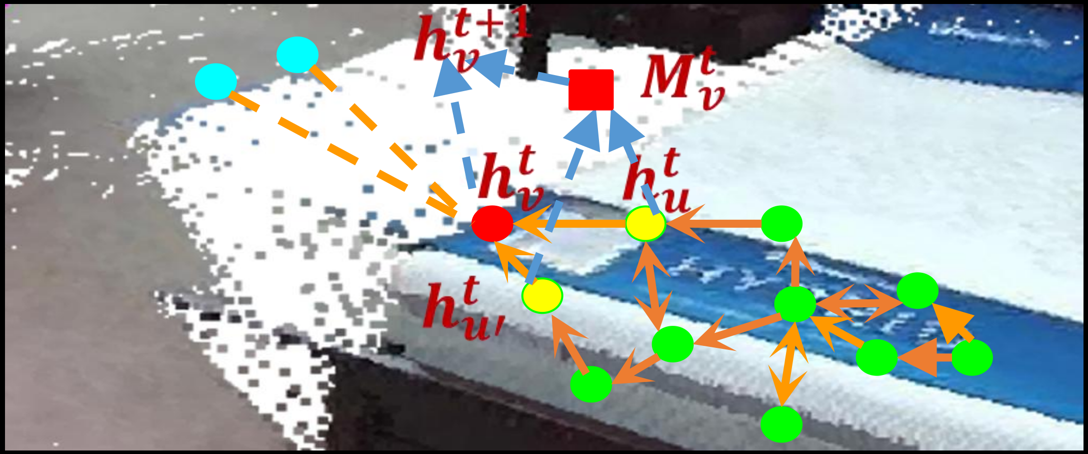


3DGNN: Node State Update

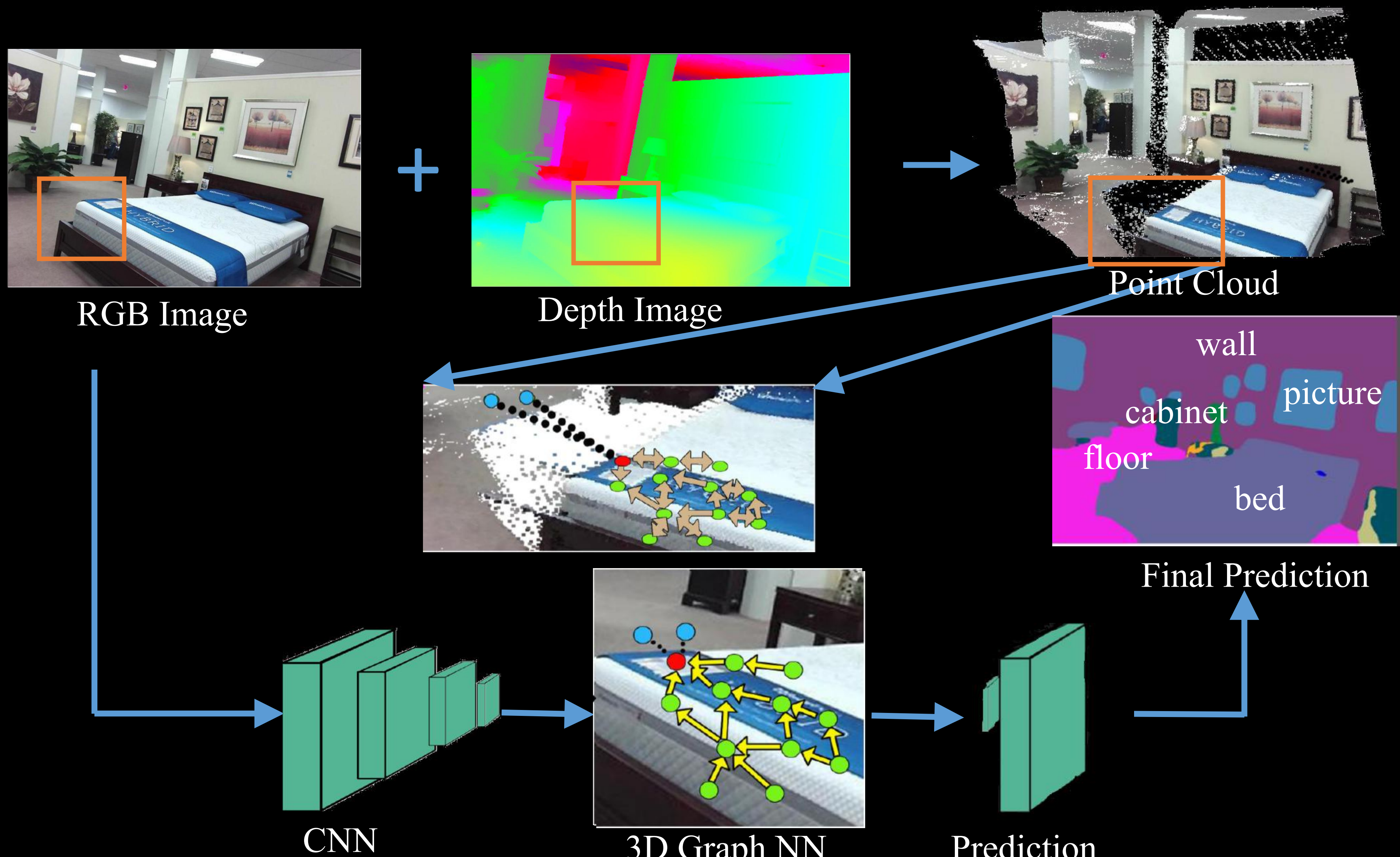
- Step 3: Update state of node v:

$$h_v^{t+1} = f(M_v^t, h_v^t)$$

f: update function (MLP with ReLu in our case)



Model Overview



Generalization of Existing Models

❖ 3D GNN to PointNet

- Graph structure → fully connected with self loop
- Message function → identity function
- Aggregation function → max pooling

❖ 3D GNN to RNN/LSTM

- Graph structure → chain structure

Generalization of Existing Models

❖ MRF Inference

$$Q(y_i) = \frac{1}{Z_i}\{-\phi_u(y_i) - \sum_{j\in\Omega_i} E_{Q(y_i)}[\phi_p(y_j, y_i)]\}$$

❖ Graphical Neural Network Interpretation

- Message function → $E_{Q(y_i)}[\phi_p(y_j, y_i)]$
- Aggregation function → Negation summation
- Update function → Softmax

Quantitative Experimental Results

Evaluation

[Gupta et al. 2014]	28.6	35.1
[Eigen an Fergus 2015]	34.1	45.1
3DGNN (VGG)	**41.7**	**55.4**

NYUD2 test set under 40 classes setting

Evaluation

[Song et al. 2014]	-	36.3
[Li et al. 2016]	-	48.1
	42.3	54.6
3DGNN (ResNet101)	**45.9**	**57.0**

SUN-RGBD test set

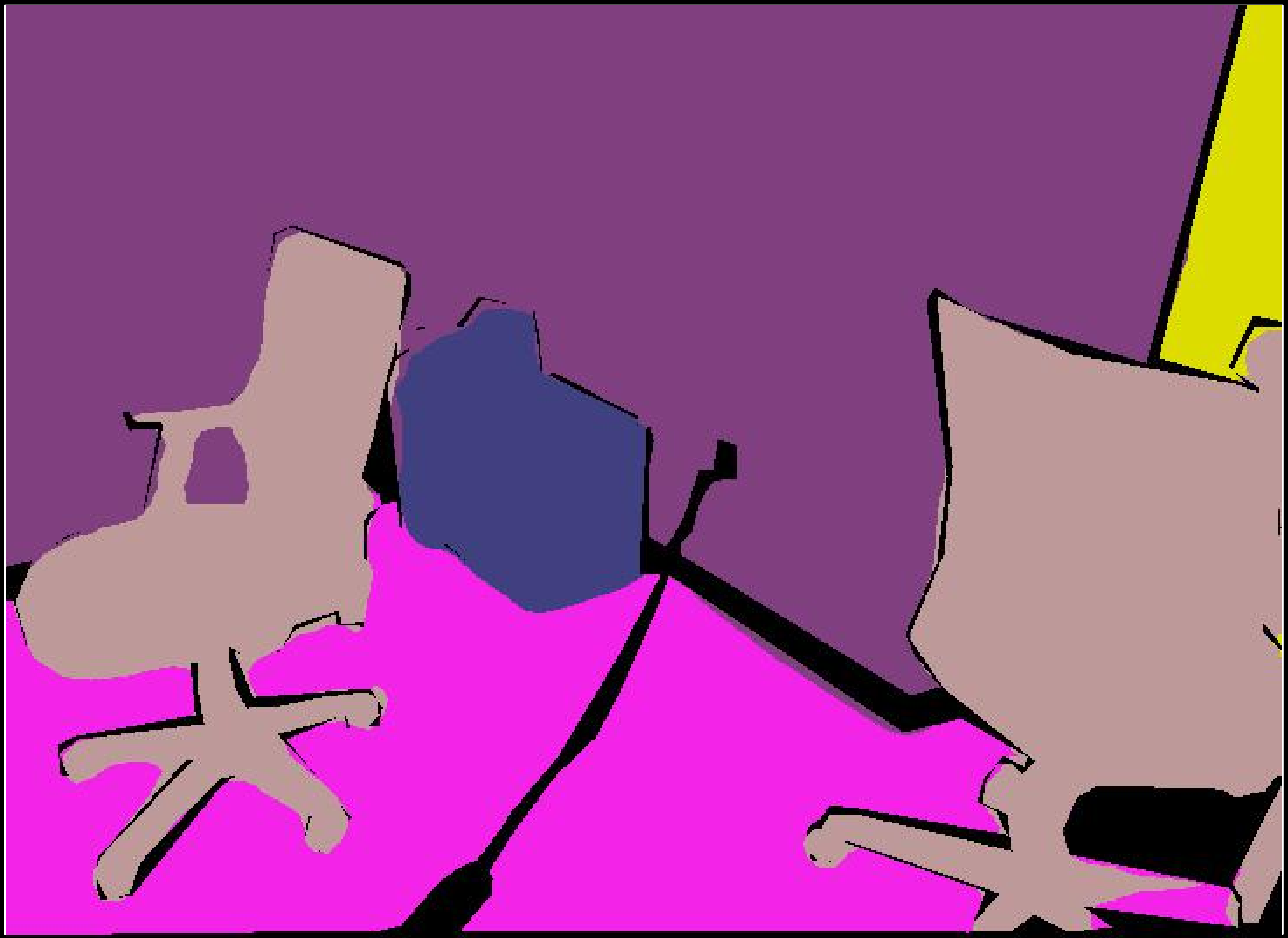
Ablation Study

- Effectiveness of 3D Graph Neural Network

NYUD2-40	Unary CNN	37.1	51.0
	3D GNN	**39.9**	**54.0**
	2D GNN	38.9	50.3
	3D GNN	**40.2**	**52.5**

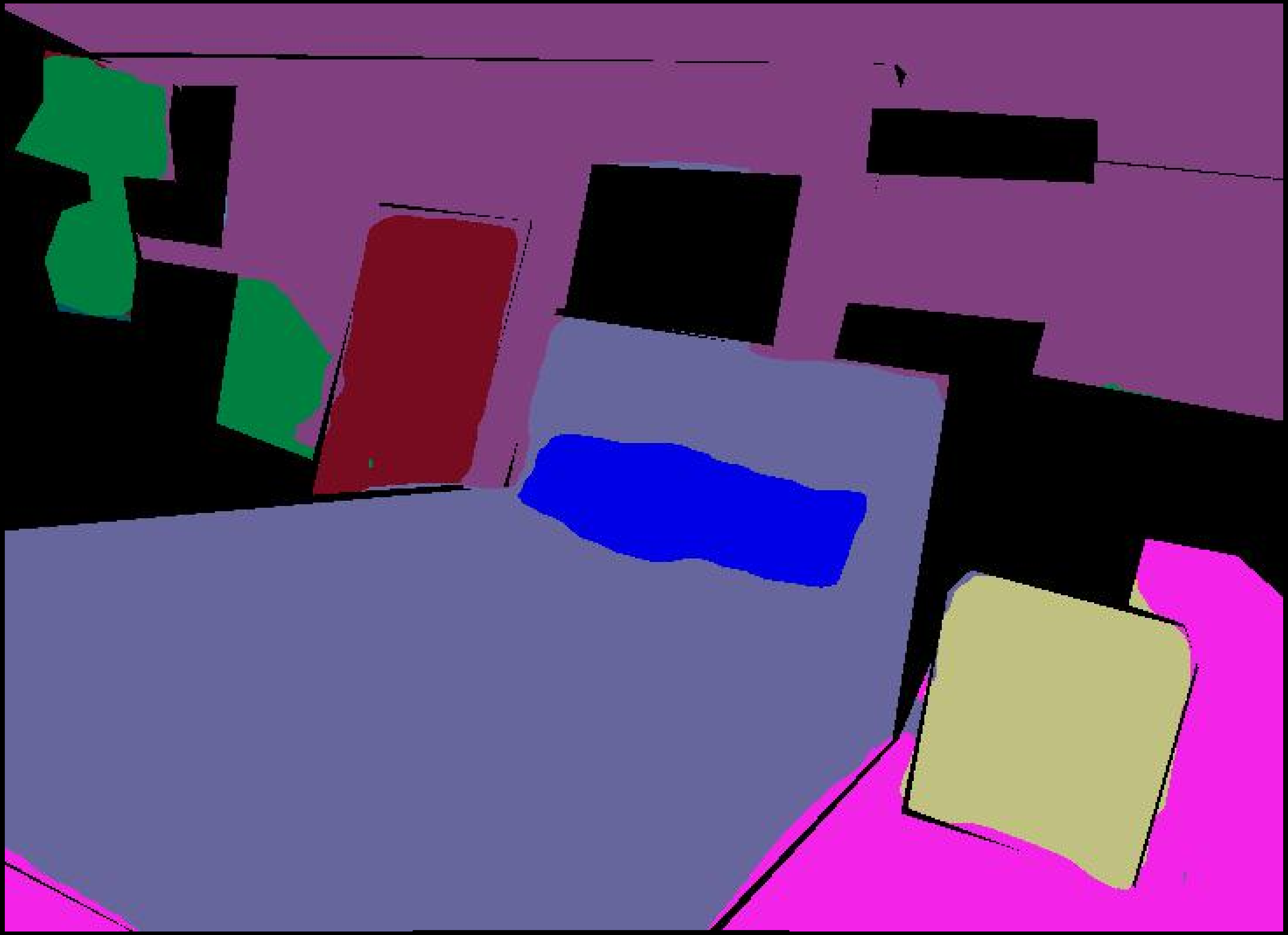
Qualitative Experimental Results

Visual Results



3DGNN

Visual Results



3DGNN

Visual Results

3DGNN

Conclusion

- **3DGNN** is a general framework for modeling RGBD data.

- **3DGNN** achieves state-of-the-art performance on RGBD semantic segmentation.

Thank You!

Image 2D (Resnet-101) 3DGNN