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# 3D Attention-Driven Depth Acquisition for Object Identification

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[SA2016.SIGGRAPH.ORG](http://SA2016.SIGGRAPH.ORG)

# Background & motivation

- Robotic indoor scene modeling



Perception on object

# Background & motivation

- Indoor environments acquisition and modeling

Dense Reconstruction



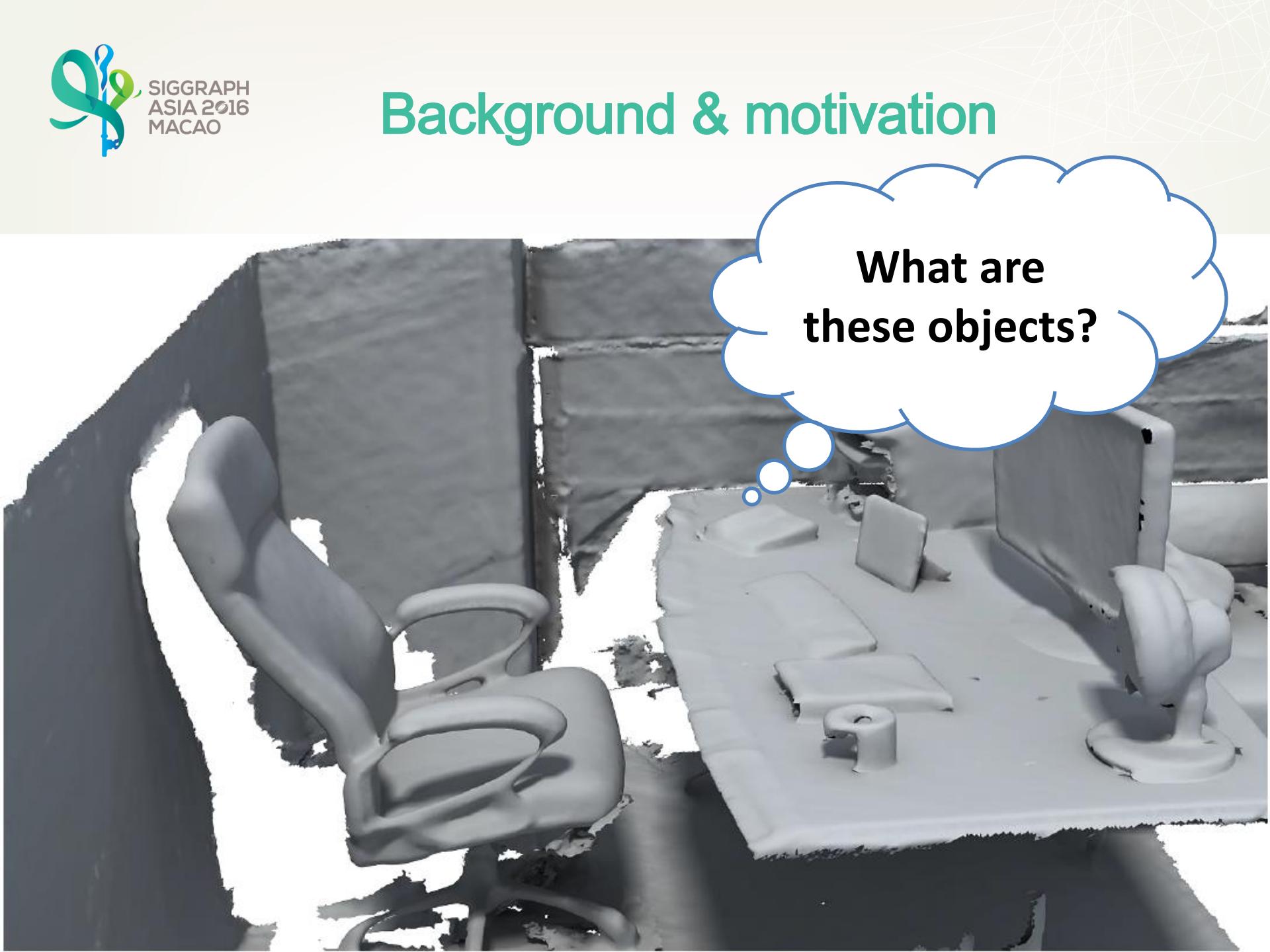
[Niemann et al. 2013]

Object Extraction



[Xu et al. 2015]

# Background & motivation



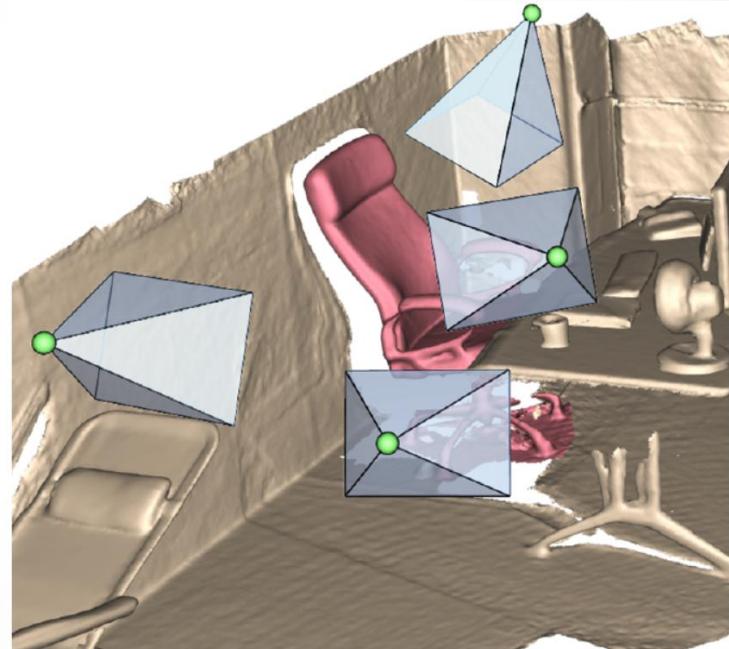
What are  
these objects?

3D shape database

	airplane	airplane	airplane	airplane	bomber	fighter	airliner	straight wing
basket,handbasket(2,11)								
bath,tub,bathing tub,bath,tub(0,856)								
bed(13,233)								
bench(7,1813)								
bicycle,bike,wheel,cycle(0,59)								
birdhouse(0,73)								
boot,shoe(0,452)								
bottle(0,498)								
bowl(1,186)								
bus,autobus,coach,charabanc,double-decker(0,11)								
cabinet(9,1571)								
camera,photographic camera(4,113)								
can,tin,tin can(2,108)								
cap(4,56)								
car,auto,automobile,machine,motorcart(0,11)								
chair(23,6778)								
clock(3,651)								
computer keyboard,keypad(0,65)								

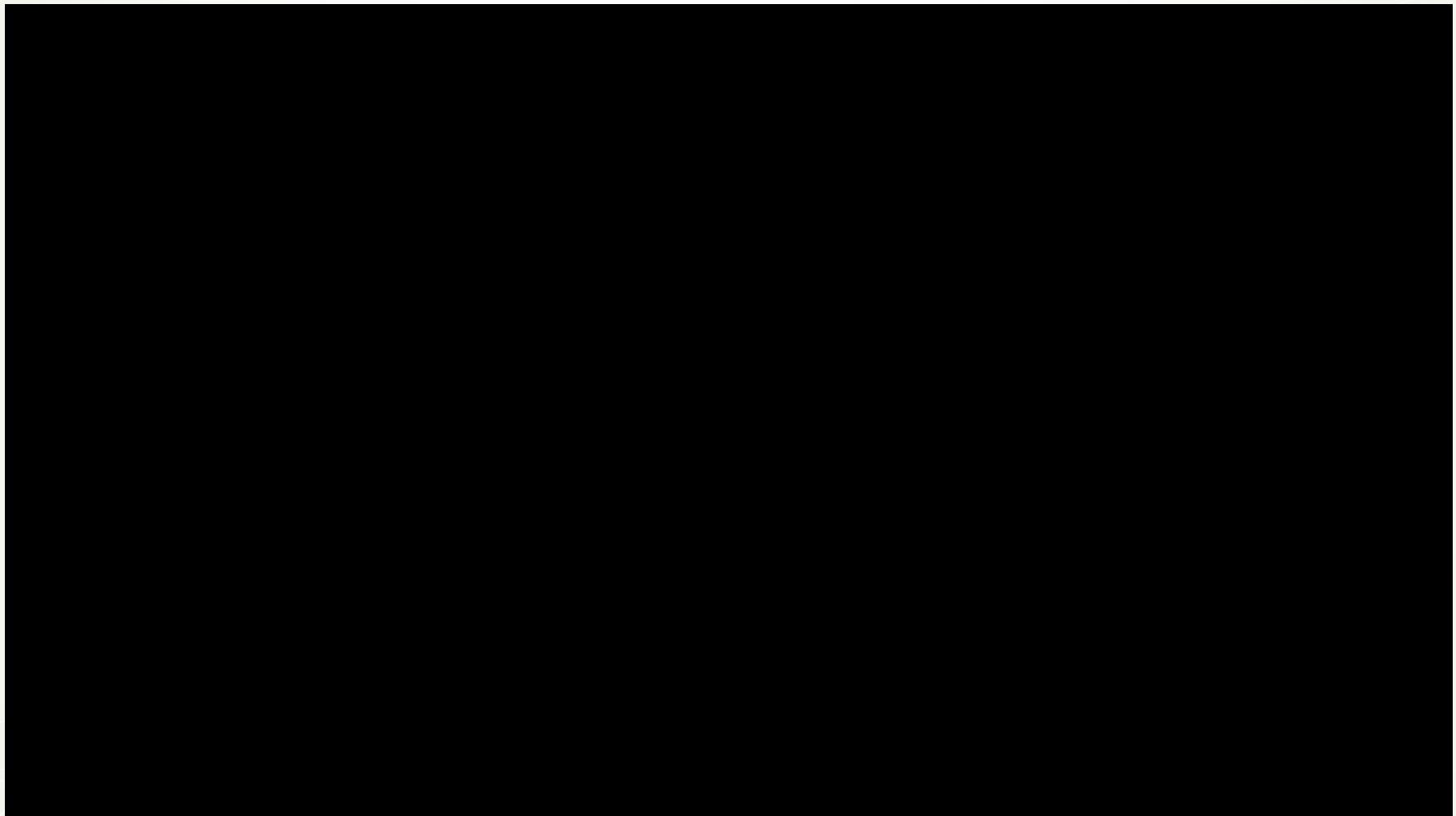
Object recognition

# Active object recognition





# Active object recognition



# Problem setting

- A robot actively acquires new observations to gradually increase the confidence of object recognition
- Two key components:

## Object classification

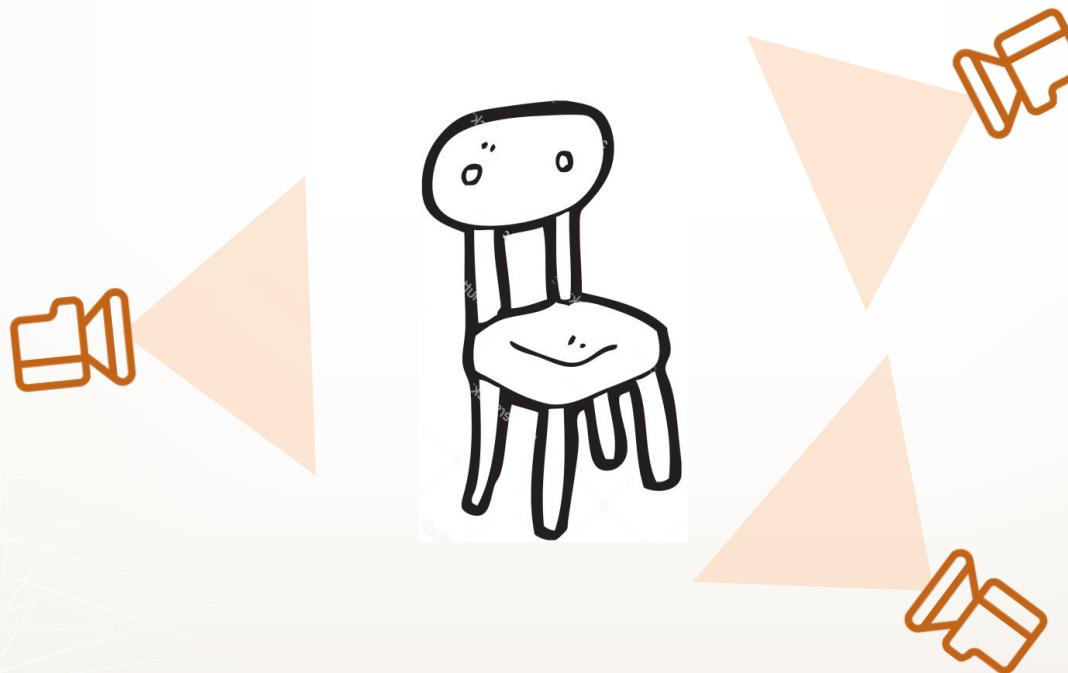
Estimate object class based on so far acquired observations

## View planning

Predict the Next-Best-View to maximize its information gain

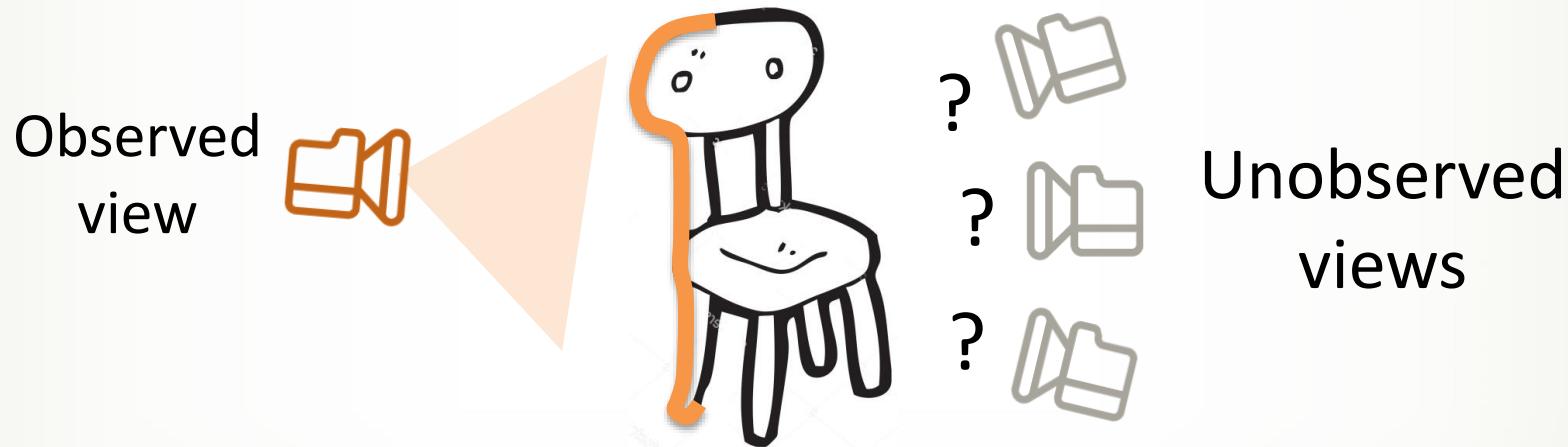
# The main challenge

- Observation is partial and progressive
  - Shape description/matching with partial data is hard
  - Observations from varying views



# The main challenge

- Observation is partial and progressive
  - View planning



How can you know which view is better without knowing its observation?

# The main challenge

- Real indoor scenes are often cluttered
  - Degrade recognition accuracy
  - Invalidate the off-line learned viewing policy





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# Related work

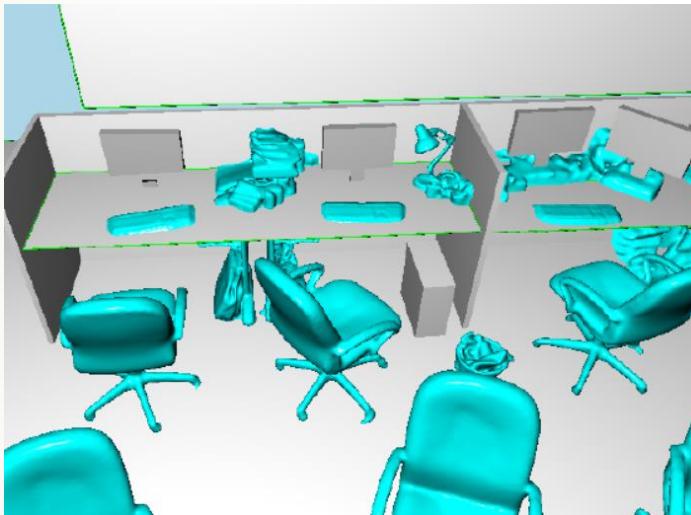
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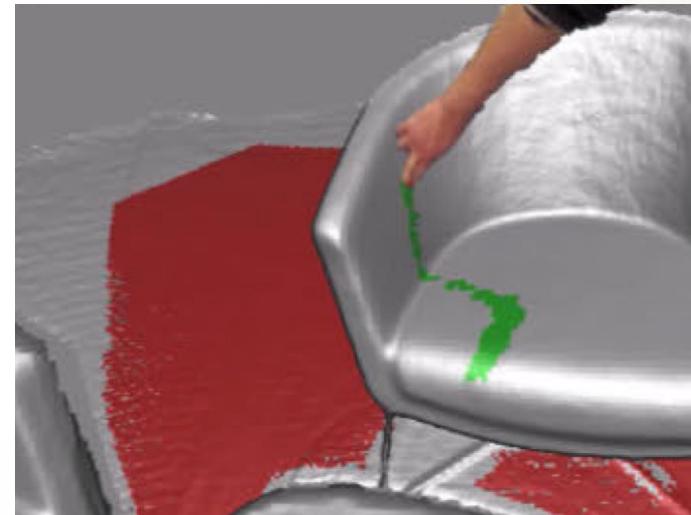
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## Related work

- **Online scene analysis and modeling**



Plane/Object Extraction  
[Zhang et al. 2014]



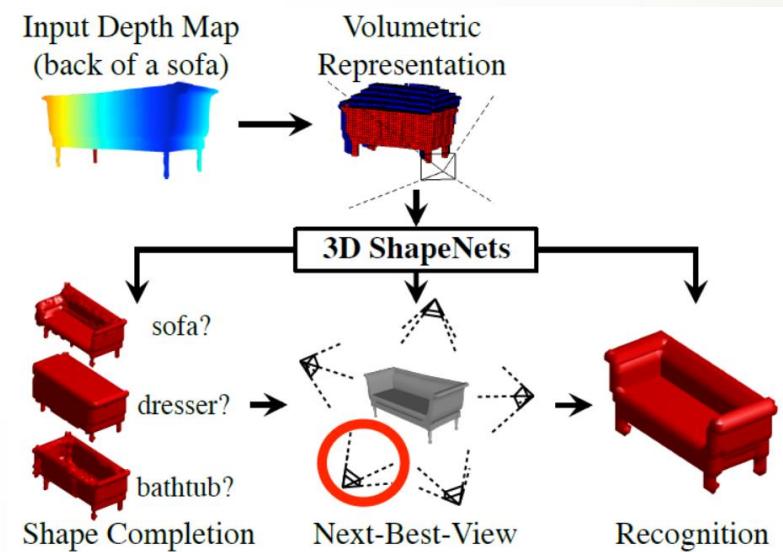
SemanticPaint  
[Valentin et al. 2015]

# Related work

- Active reconstruction and recognition



Next-best-view for reconstruction  
[Wu et al. 2014]



Next-best-view for recognition  
[Wu et al. 2015]



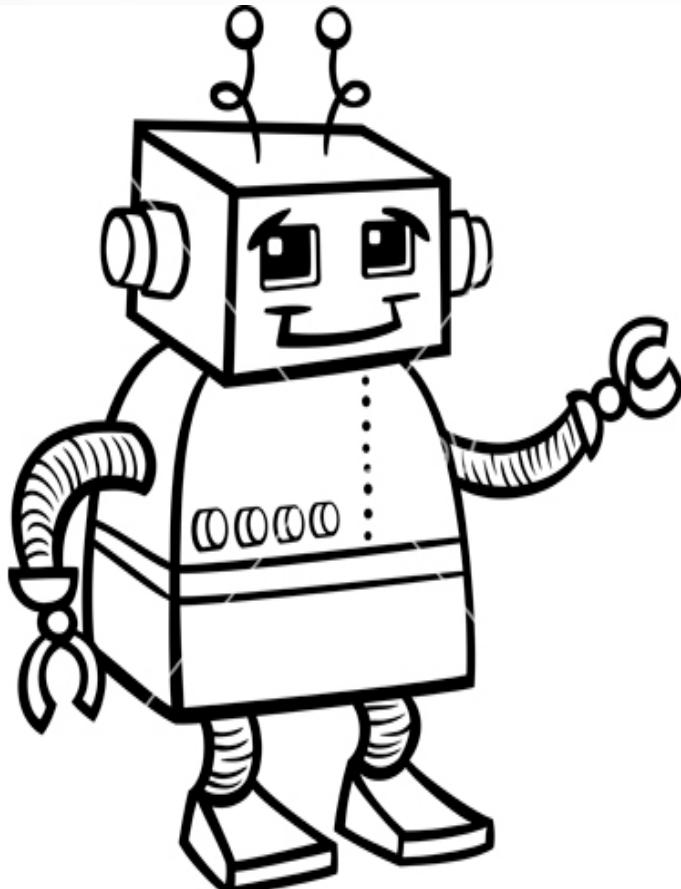
# Method

[SA2016.SIGGRAPH.ORG](http://SA2016.SIGGRAPH.ORG)

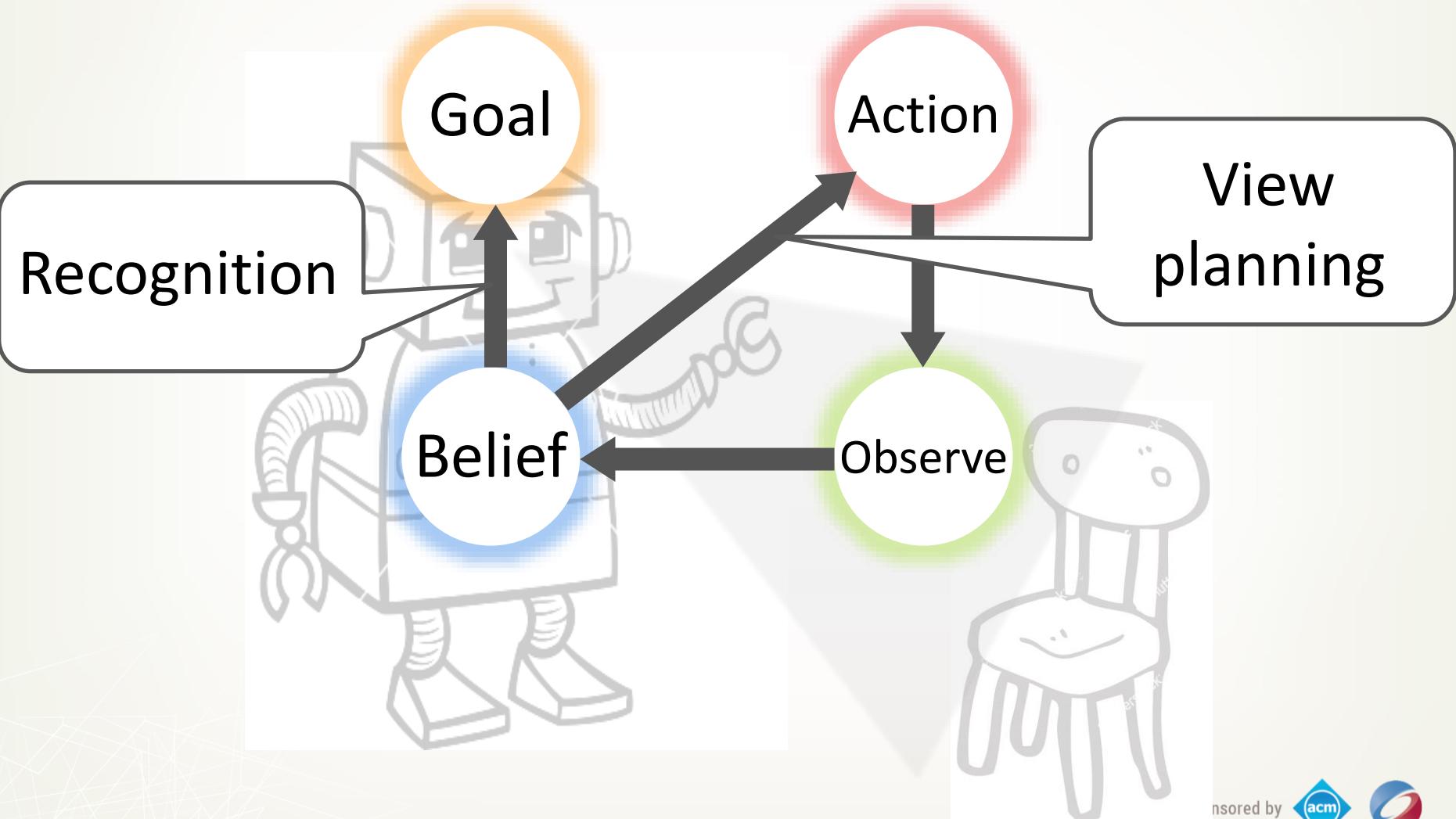
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# The general framework



# The general framework

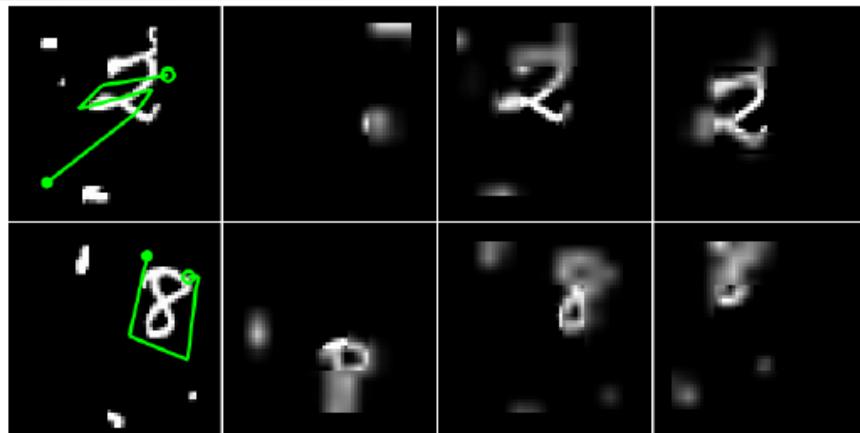


# An attentional formulation

“Humans *focus attention selectively on parts* of the visual space to acquire information when and where it is needed, and combine information from different fixations over time to build up an *internal representation* of the scene”

## ***Internal representation***

Ronald Rensink



Hand-writing recognition  
[Mnih et al. 2014]

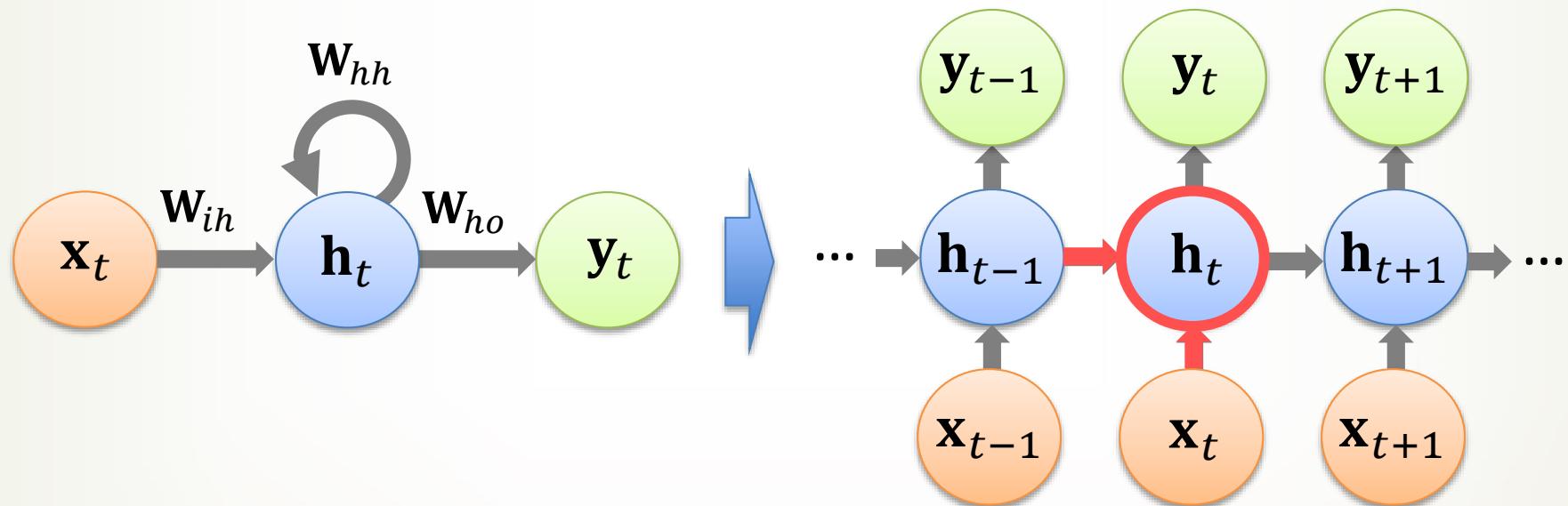


A woman is throwing a frisbee in a park.

Image caption generation  
[Xu et al. 2015]

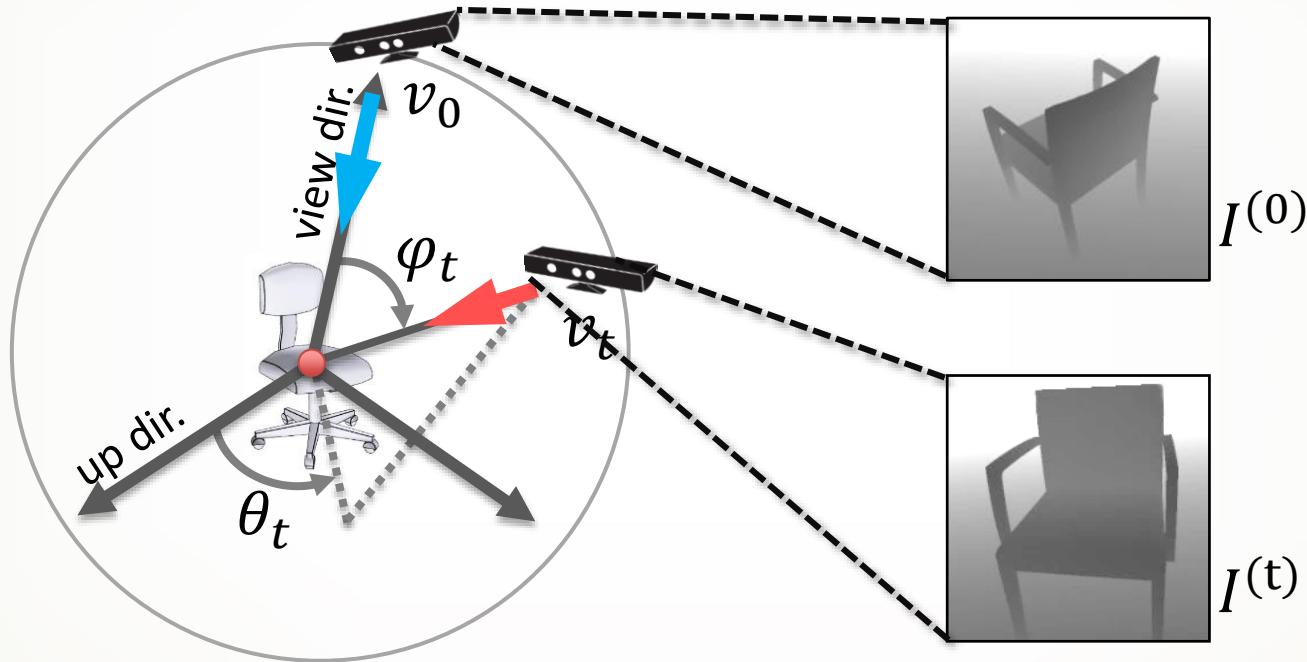
# Recurrent Attention Model

- Recurrent Neural Networks (RNN)



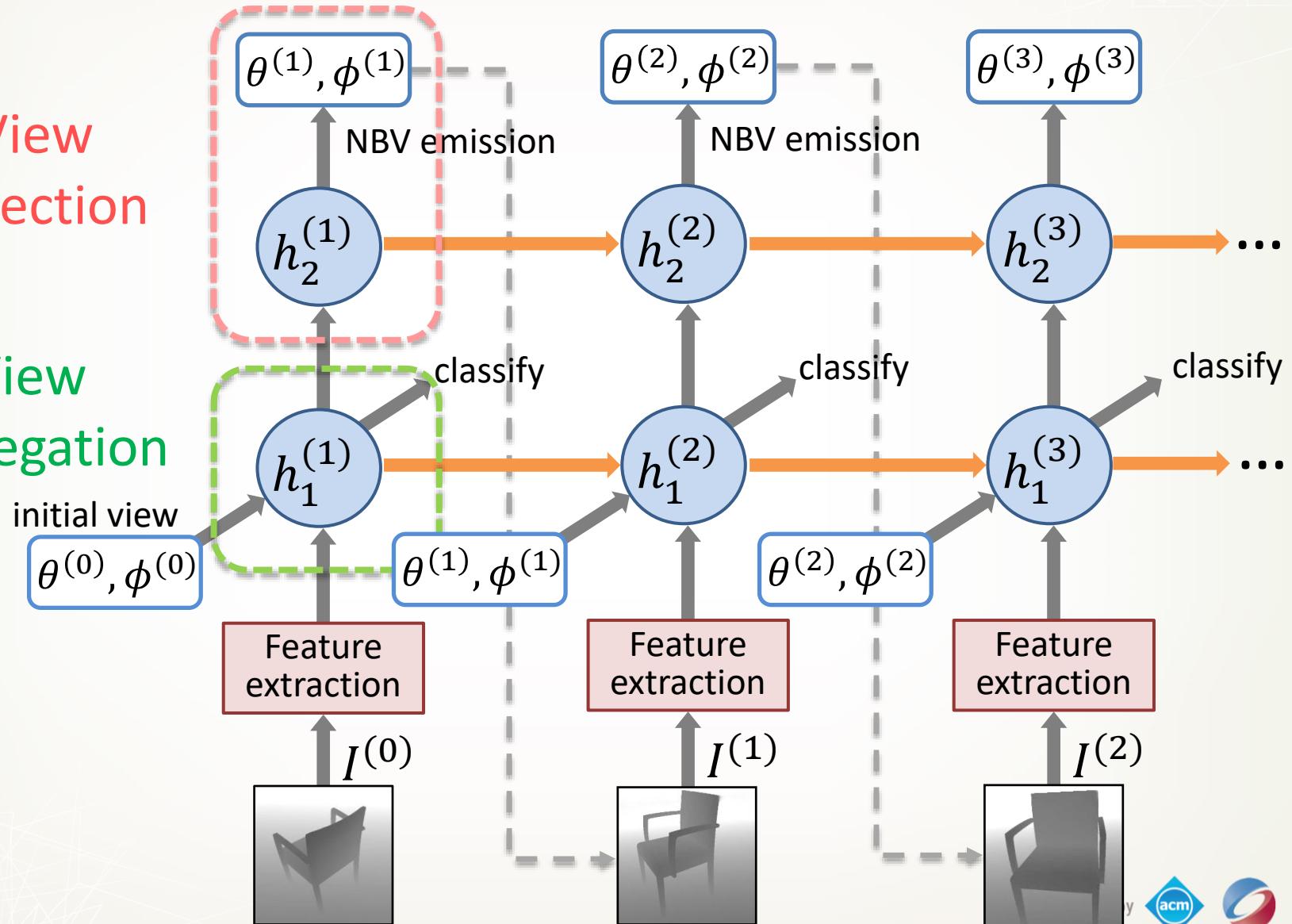
***Aggregate information***

# View-based observation

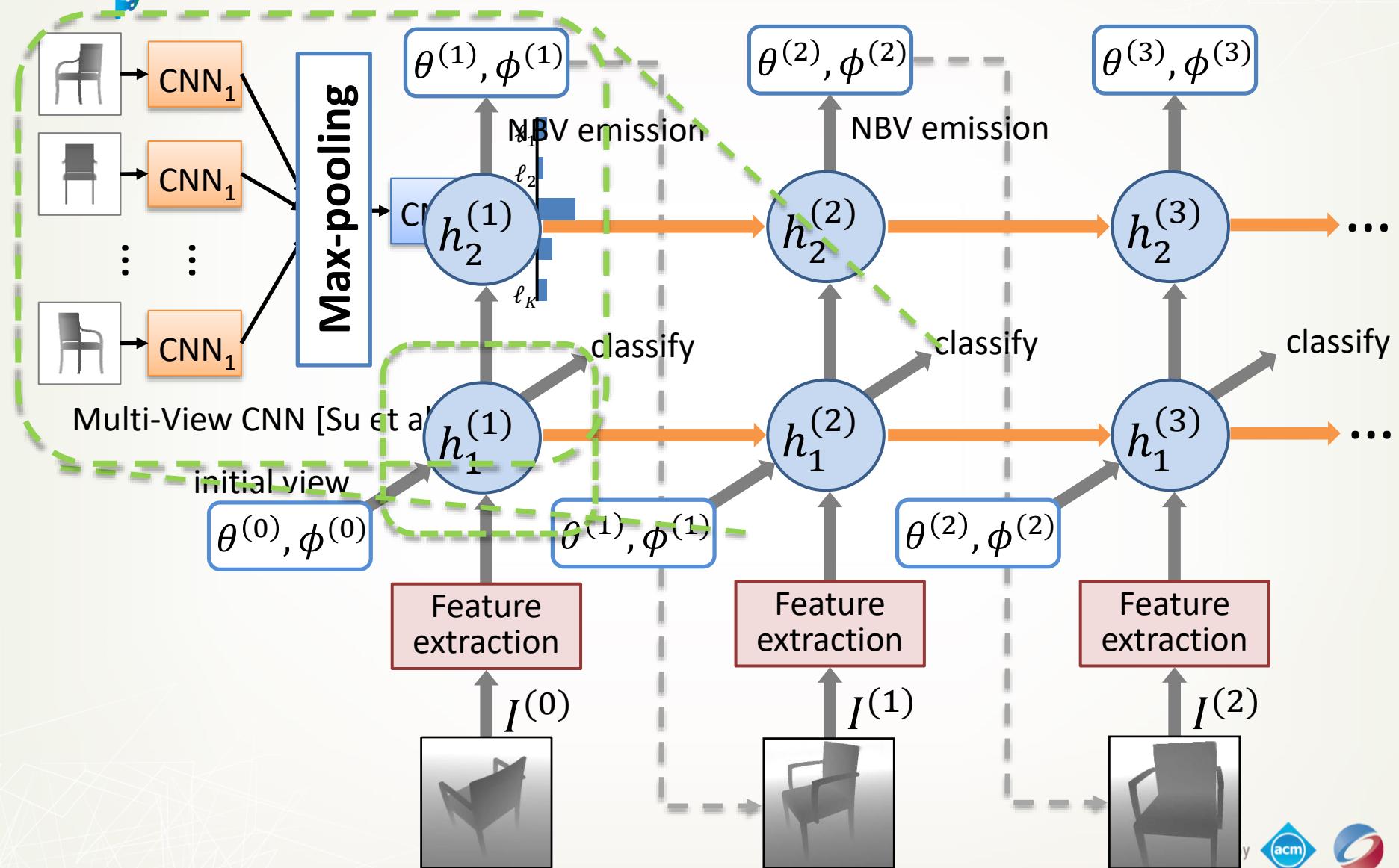


# 3D Recurrent Attention Model

View selection  
View aggregation



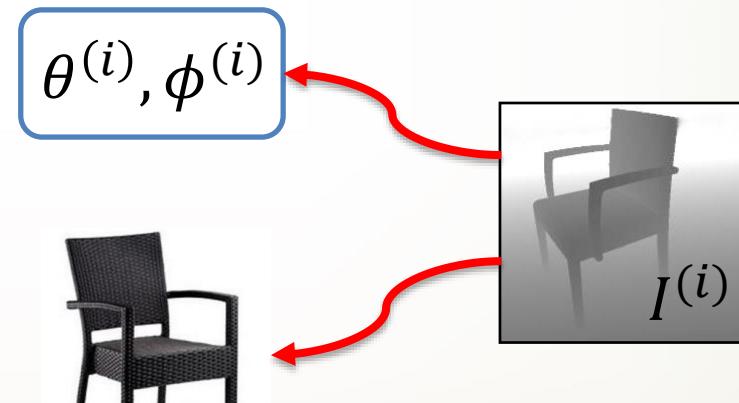
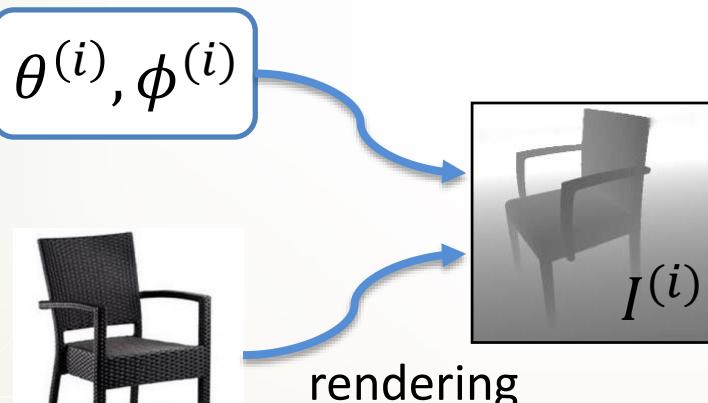
# 3D Recurrent Attention Model



# Network training

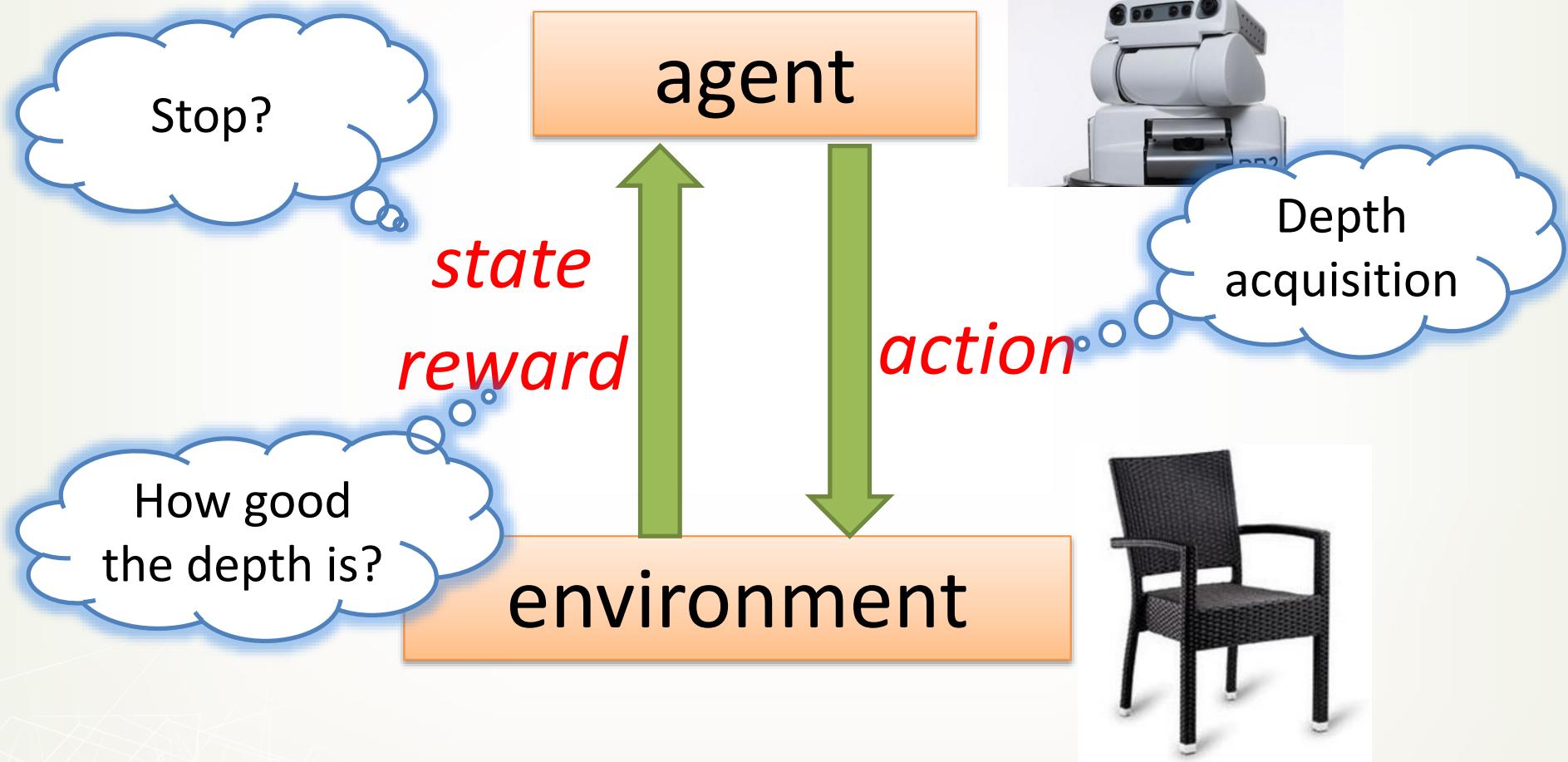


Reinforcement learning



Indifferentiable

# Reinforcement learning



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# Reward

$$r_t = H_t(p_t, \bar{p}) + I_t(p_t, p_{t-1}) - C_t$$



prediction  
accuracy



information  
gain

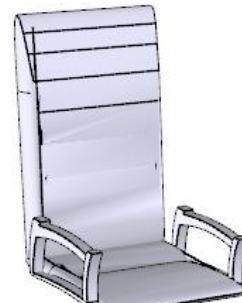


movement  
cost

# Part-level attention



occlusion



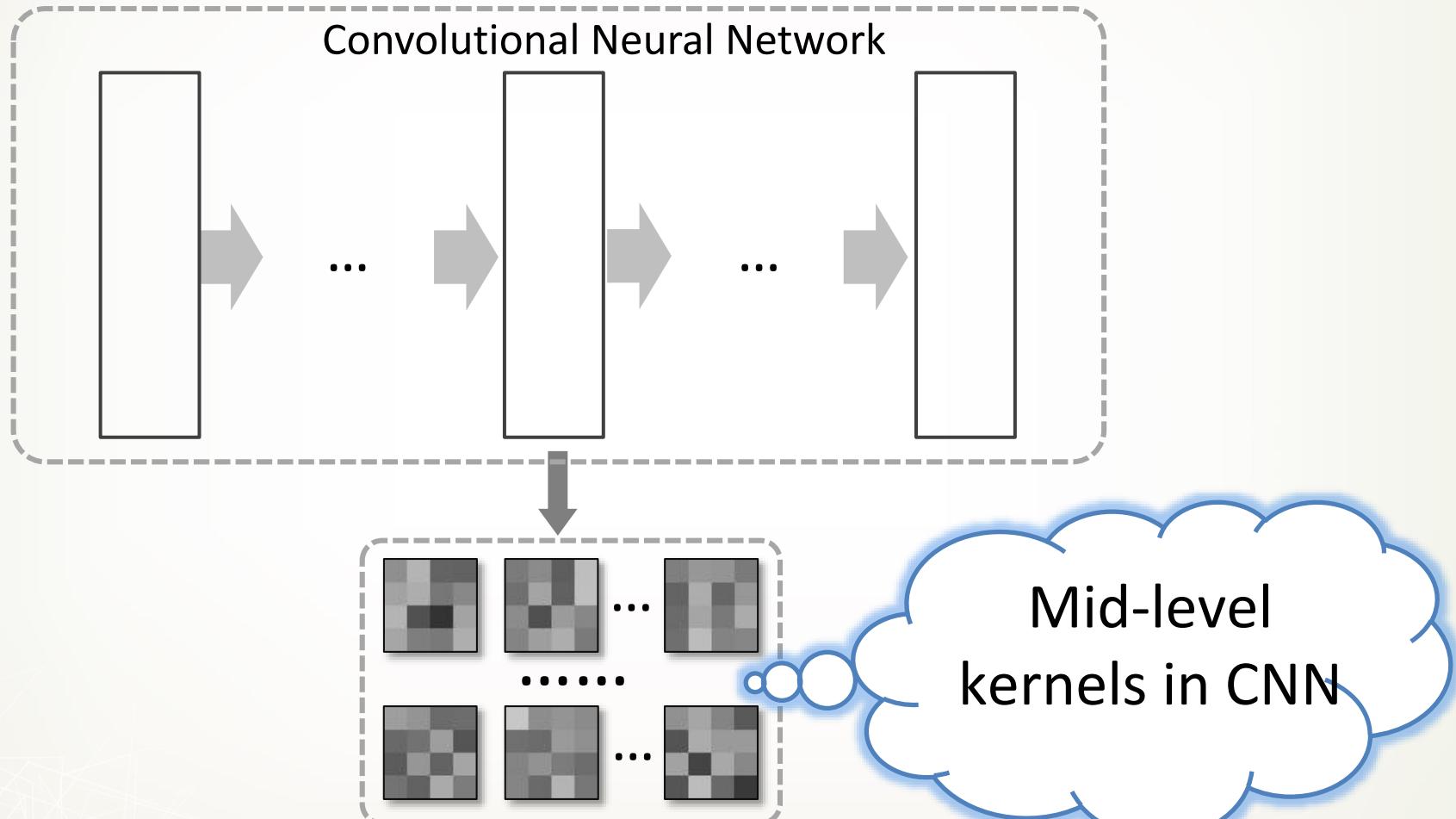
*Informative parts*

How to distinguish these two chairs?

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# Attention extraction

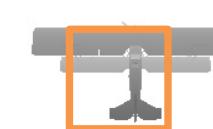
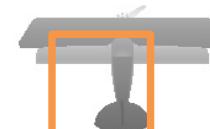
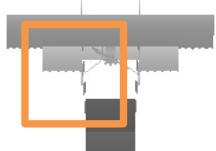


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# Attention extraction

One wing





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# Results and evaluation

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# Database

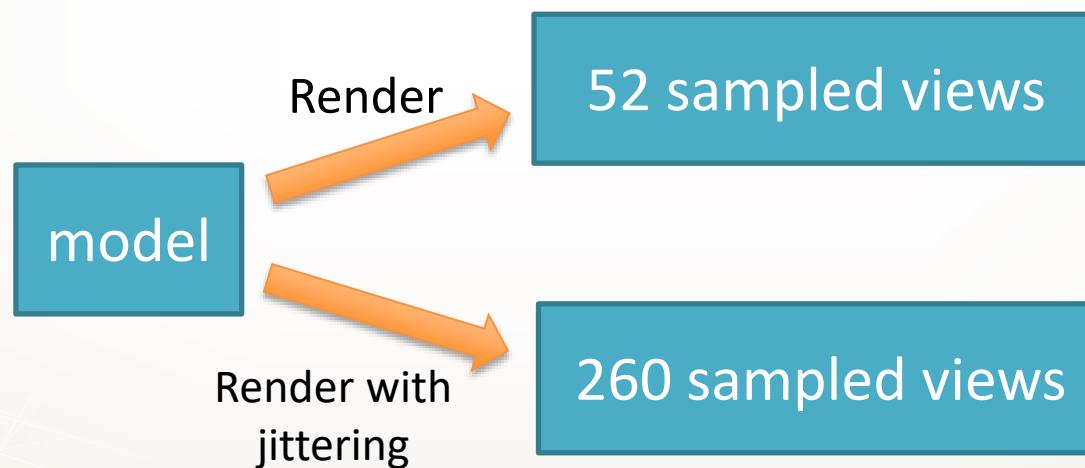


57,452 models  
57 categories



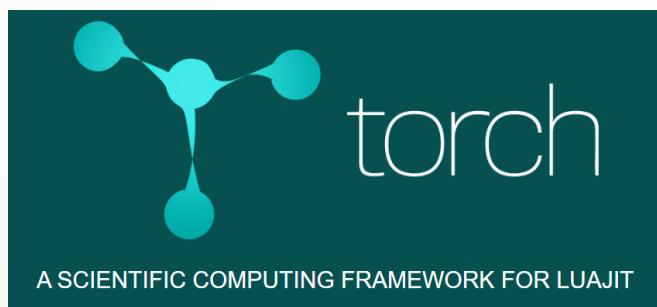
PRINCETON  
MODELNET

12,311 models  
40 categories



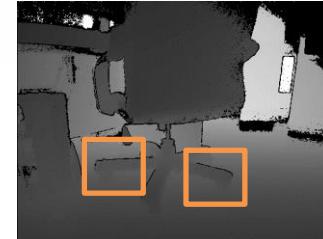
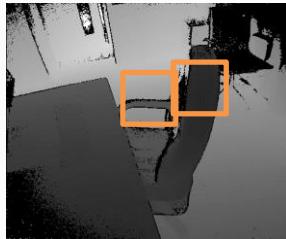
# Timing

Database	MV-RNN train	MV-RNN test
ShapeNet	49 hr.	0.1 sec.
ModelNet40	22 hr.	0.1 sec.

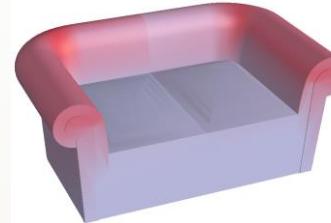
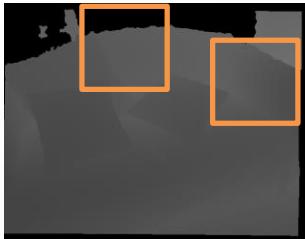
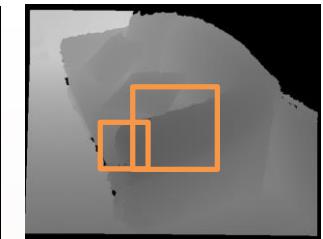
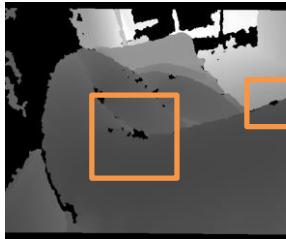


# Visualization of attentions

Part-level attention



View sequence



View sequence



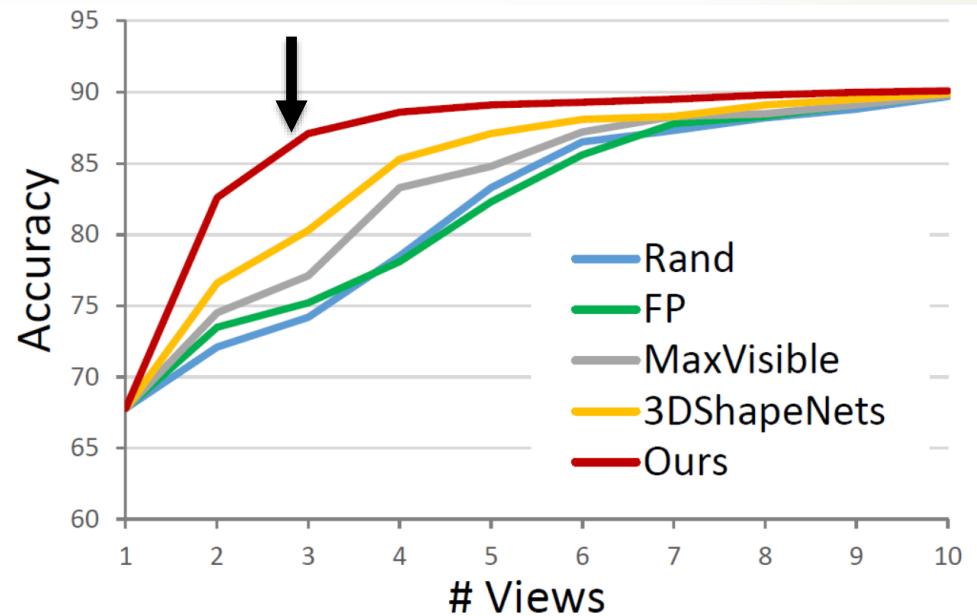
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# NBV estimation

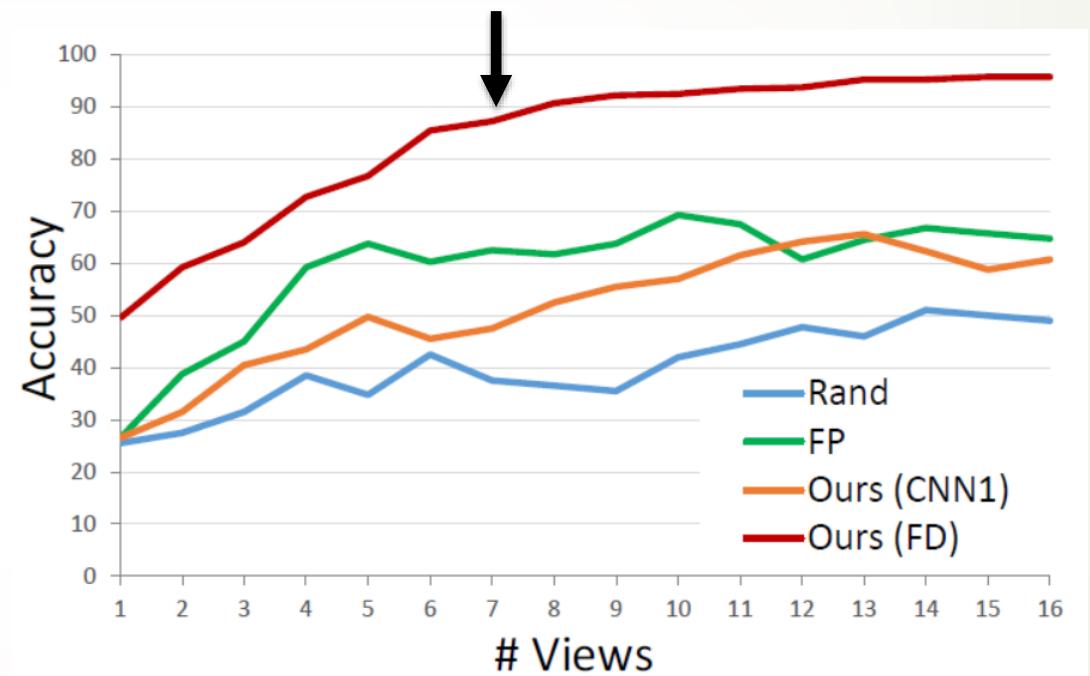


40 classes



## Classification Accuracy

# NBV estimation under occlusion



Classification Accuracy

# Results on real scenes



# Results on real scenes

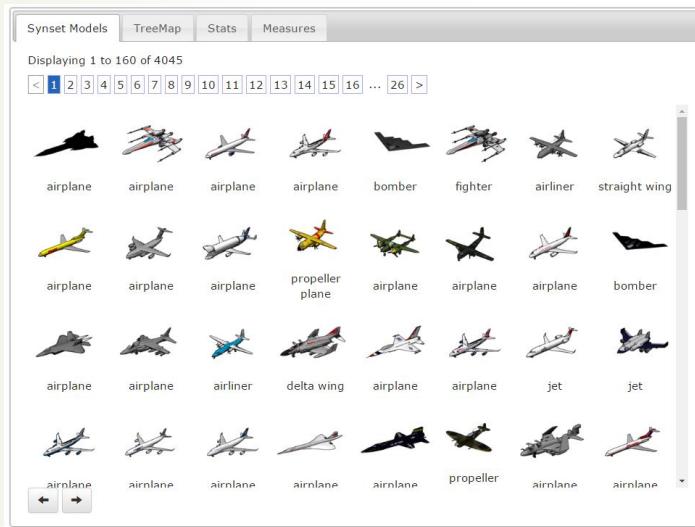


# Results on real scenes



# Limitations

- Recognizable objects
- No contextual information



# Future works: Multi-modal recognition

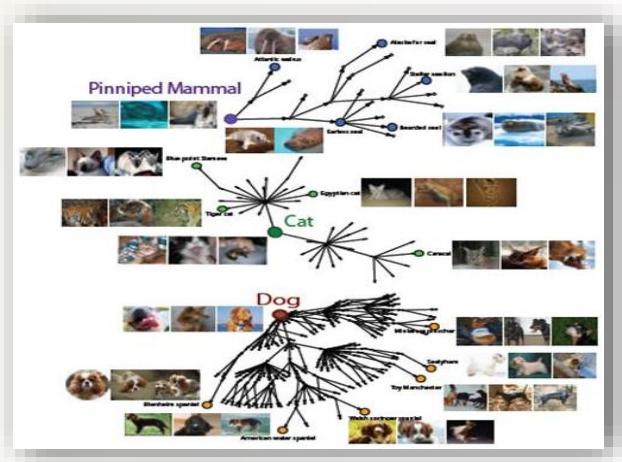
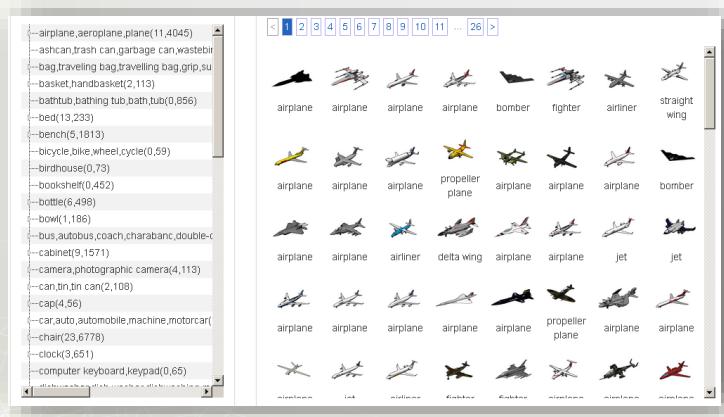


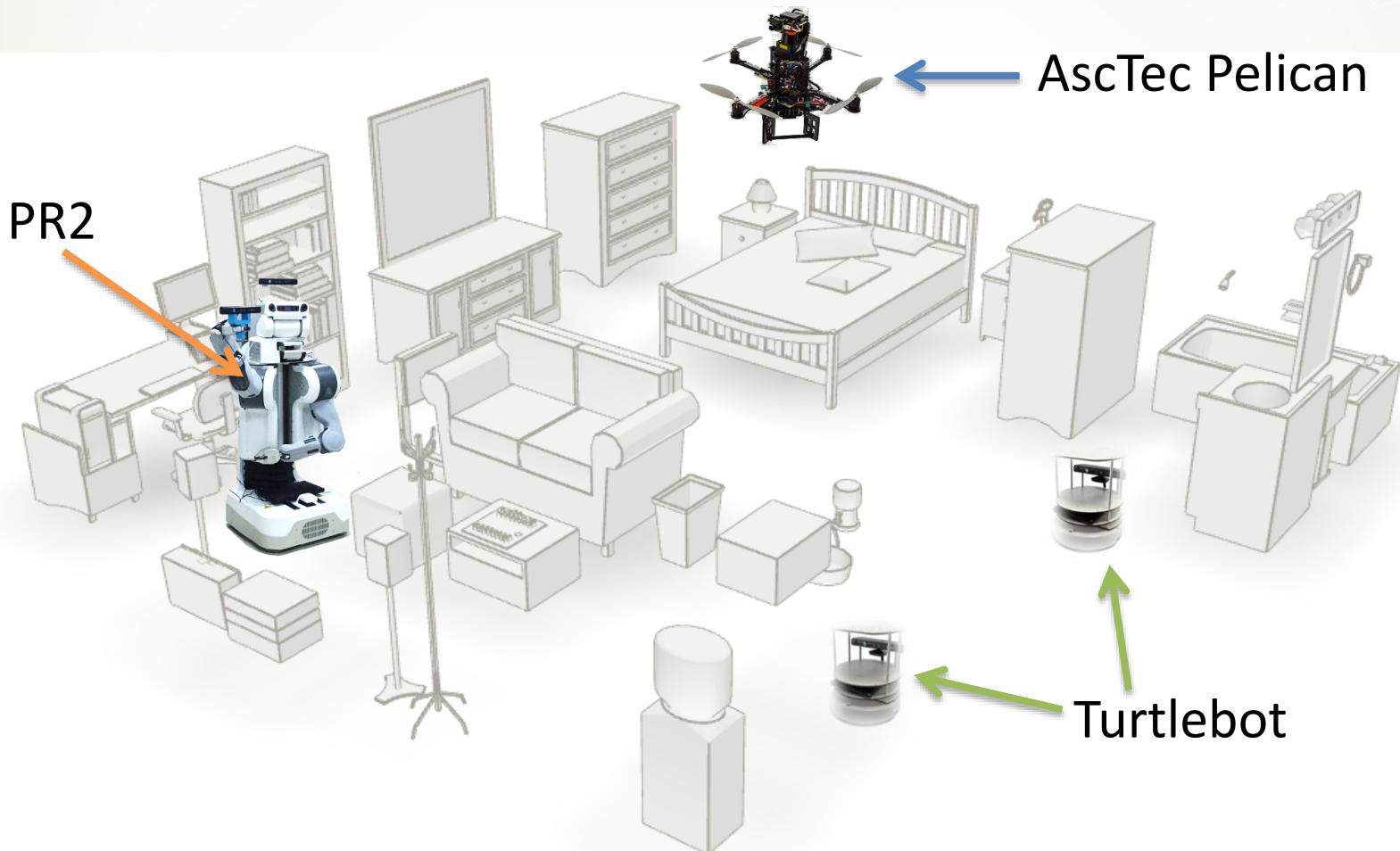
Image database



Shape database

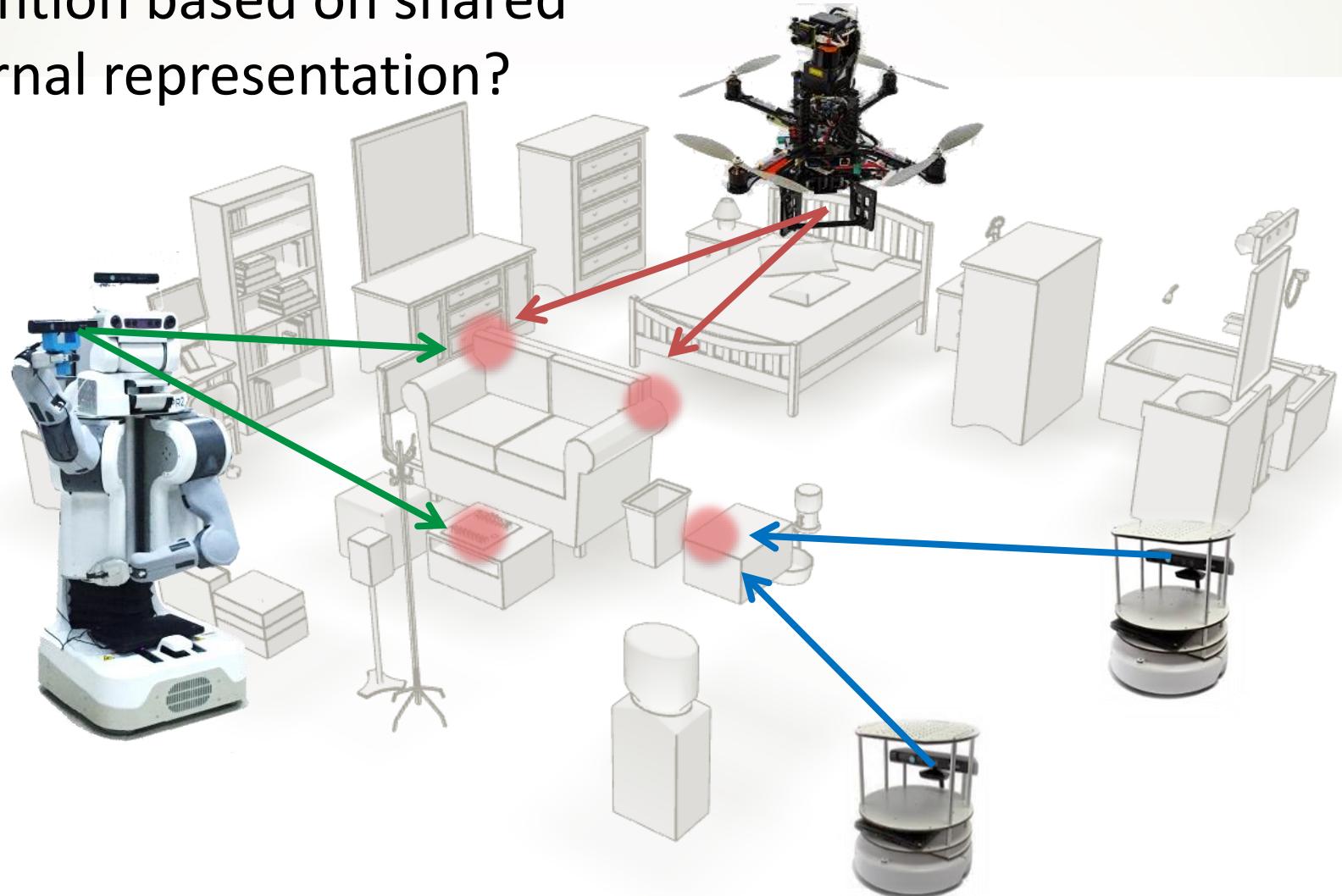


# Future: Multi-robot scene reconstruction & understanding



# Future: Multi-robot attention model

Attention based on shared internal representation?





# Thank you Q & A



More details: [kevinkaixu.net](http://kevinkaixu.net) & [yifeishi.net](http://yifeishi.net)

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