

Deep Learning on Graphs

— CNN, RNN and GNN

Huan Ling

University of Toronto & Vector Institute & Nvidia Research Lab

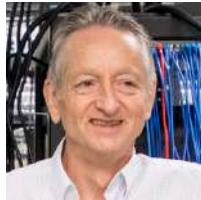
Toronto 9th/Oct

About

- The Vector Institute is an independent, not-for-profit entity dedicated to research in artificial intelligence with a focus on excellence in machine learning and deep learning.
- Vector launched in 2017 with support from the Government of Ontario, Government of Canada, and the private sector.



Researchers



Geoffrey Hinton
Chief Scientific Advisor



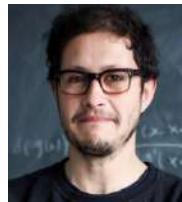
Richard Zemel
Research Director



Alán Aspuru-Guzik



Jimmy Ba



Juan Carrasquilla



David Duvenaud



Murat Erdogdu



Amir-massoud Farahmand



Sanja Fidler



David Fleet



Brendan Frey



Marzyeh Ghassemi



Anna Goldenberg



Roger Grosse



Alireza Makhzani



Quaid Morris



Sageev Oore



Pascal Poupart



Daniel Roy



Frank Rudzicz



Graham Taylor



Raquel Urtasun



Today

Deep Learning & Computer Vision on Graphs

Citation Network, Social Network

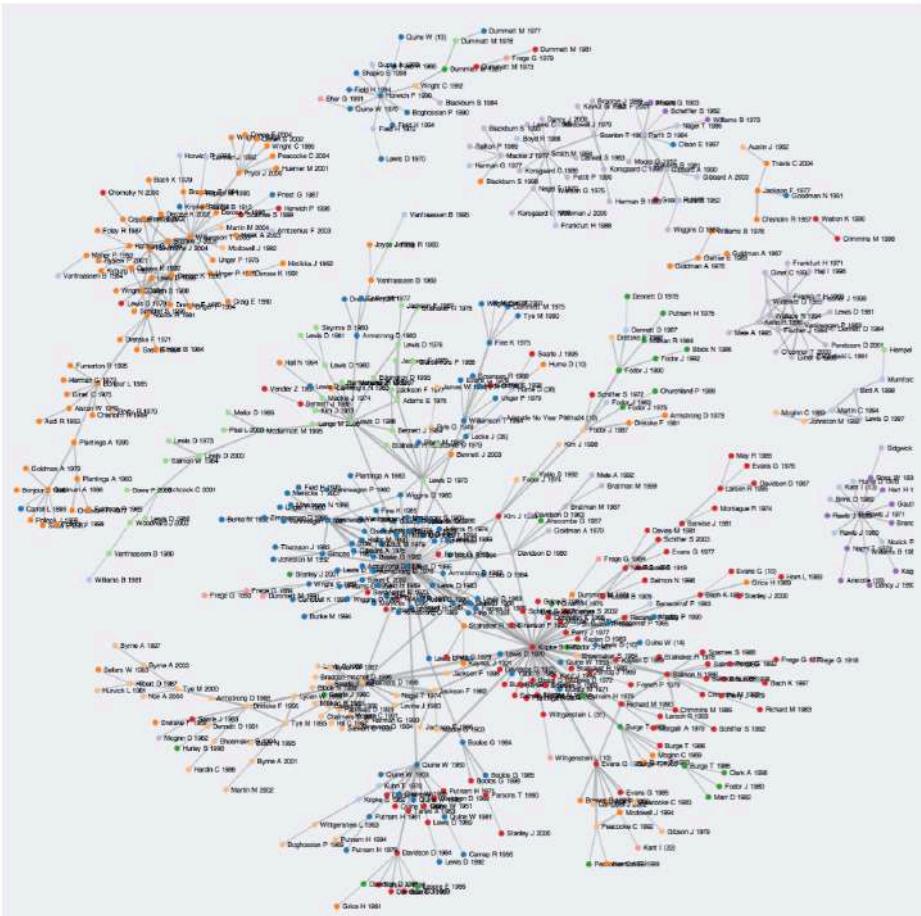


Figure: Citation network for Philosophy ¹

Image credit from Kieran Healy

Reinforcement Learning

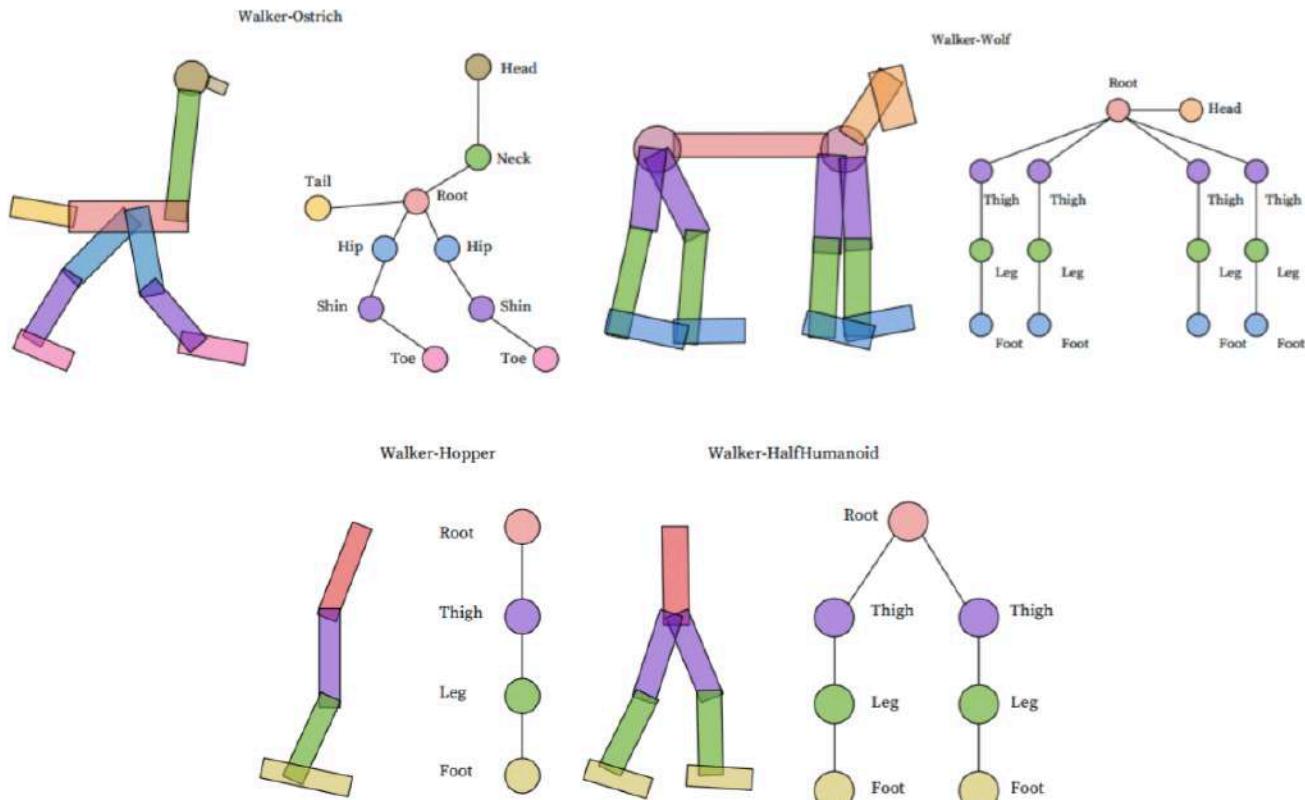
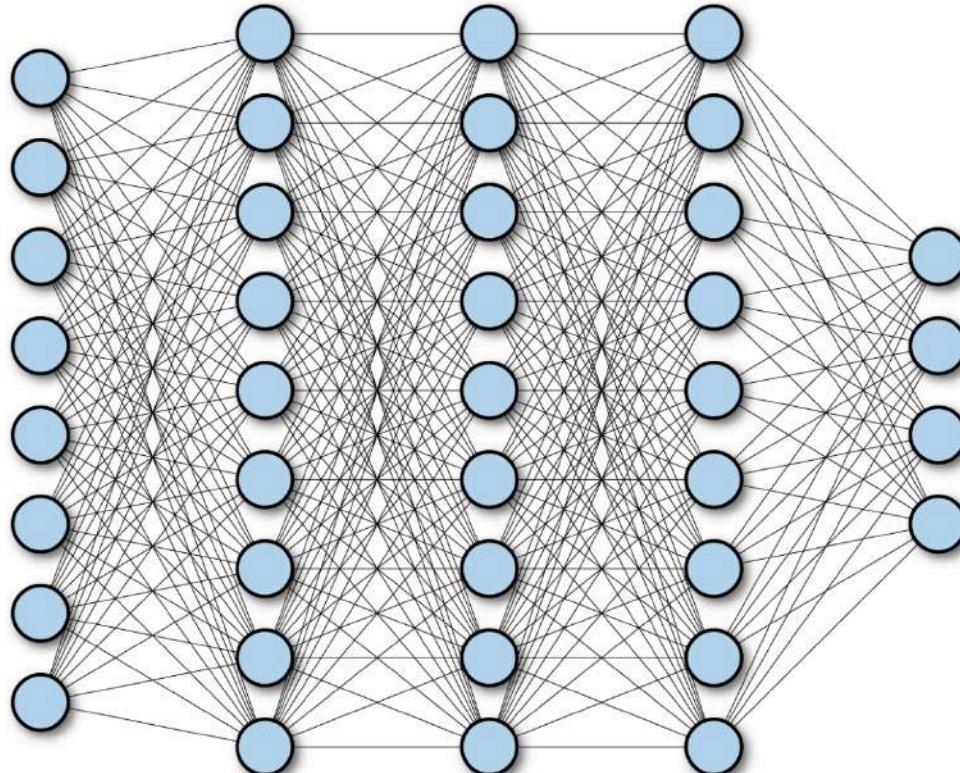


Figure: NerveNet ³

Skeleton as a graph

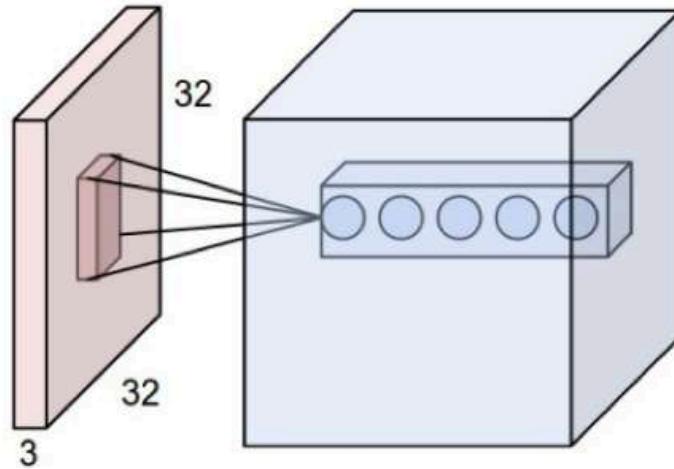
Image credit from (Wang et al., 2017)

Quick Review: Neural Networks



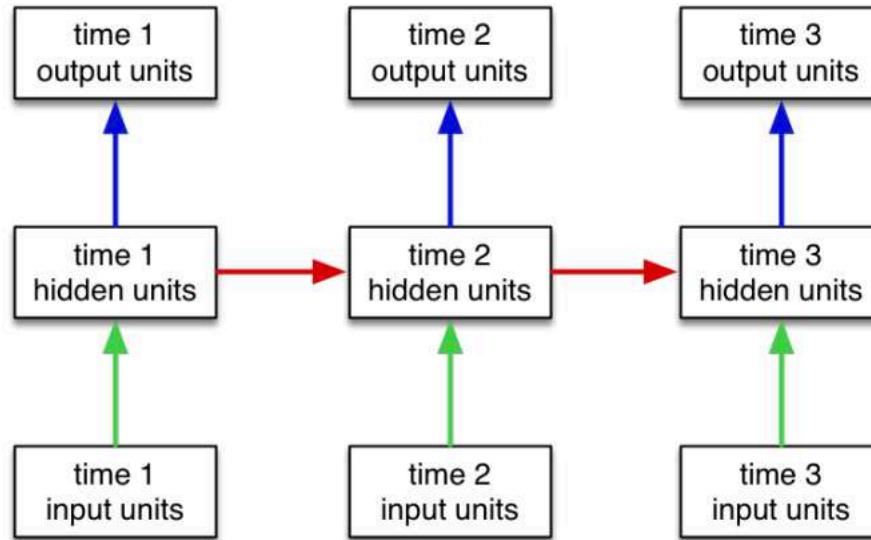
Fully connected neural networks

Quick Review: Neural Networks



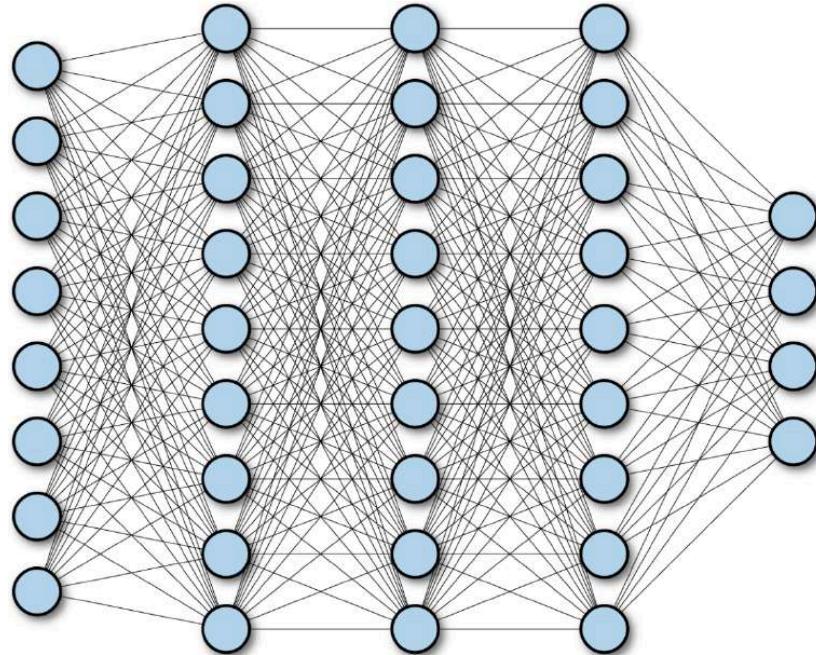
Convolutional neural network

Quick Review: Neural Networks



Recurrent neural nets

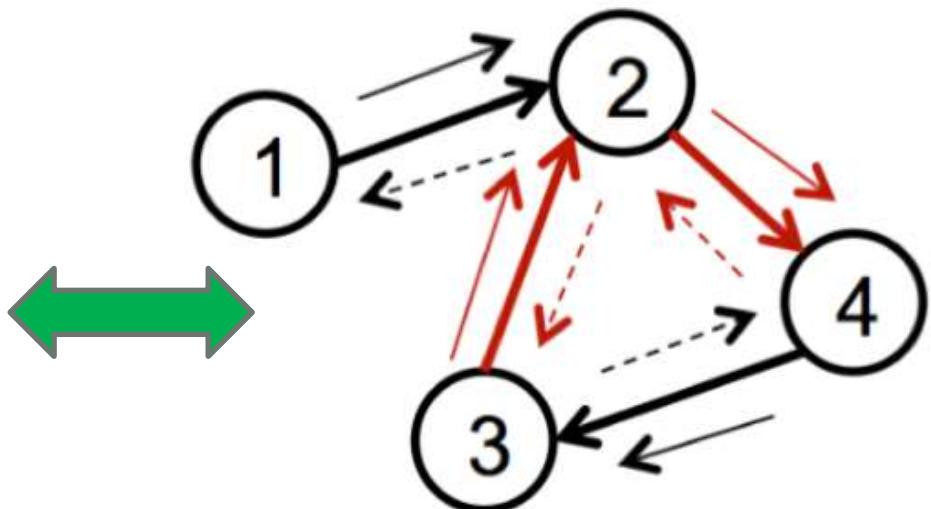
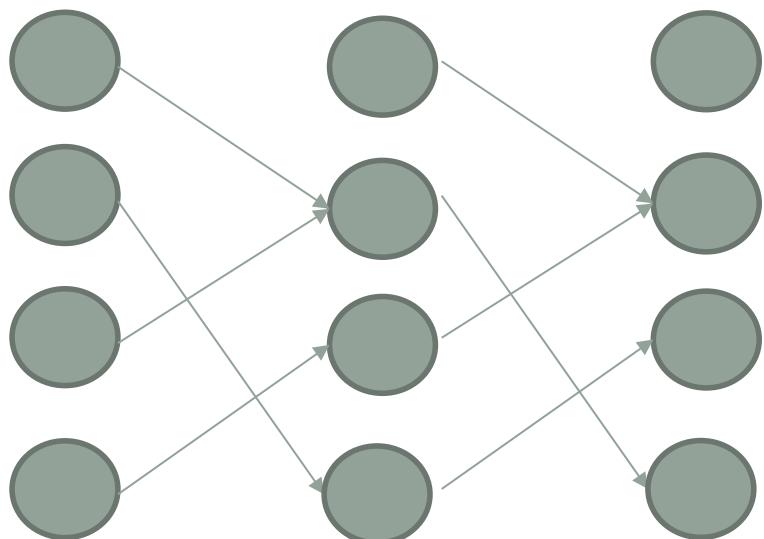
Quick Review: Neural Networks



**What if each node at input layer has its own semantic meaning?
(i.e. friendship in social network)**
What if we want our own link rules?

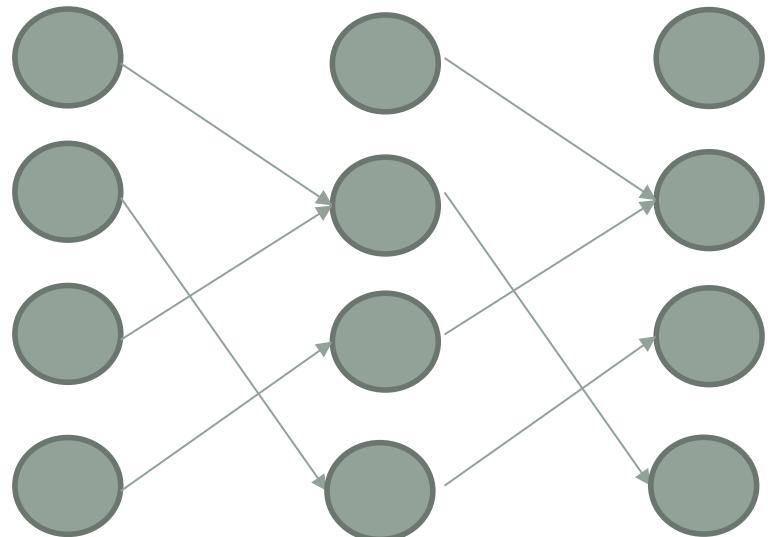
Neural Network on Graph

Define propagation by pre-defined rules



Graph Convolutional neural network

Aggregate node as CNN

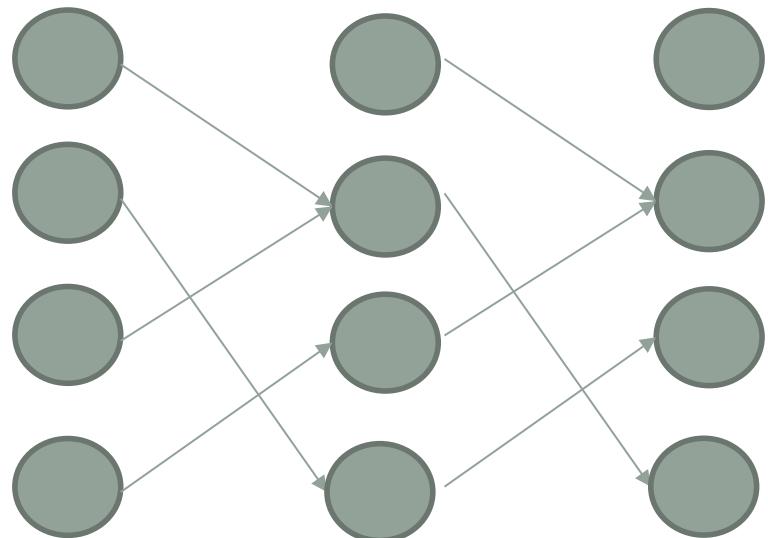


$N(p)$ is neighbourhood nodes for p
 l is time step

$$f_p^{l+1} = w_0 f_p^l + \sum_{q \in N(p)} w_1 f_q^l$$

Gated Graph Sequence Neural Networks

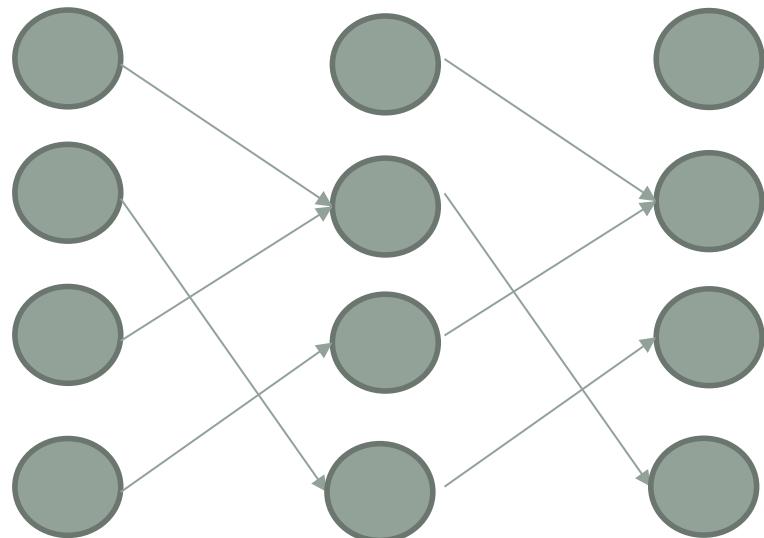
Aggregate node as RNN



$N(p)$ is neighbourhood nodes for p
 l is time step

$$f_p^{l+1} = w_0 f_p^l + \sum_{q \in N(p)} RNN(q)$$

Graph Neural Networks



Notes:

1. **GCN is more suitable for computer vision problem**
2. **GGNN has the sense of distance and time steps**

**All details are omitted.
Read reference for further details.**

Polygon Image Segmentation

Efficient Annotation of Segmentation Datasets with Polygon-RNN++

David Acuna^{* 1,3}

Huan Ling^{* 1,2}

Amlan Kar^{* 1,2}

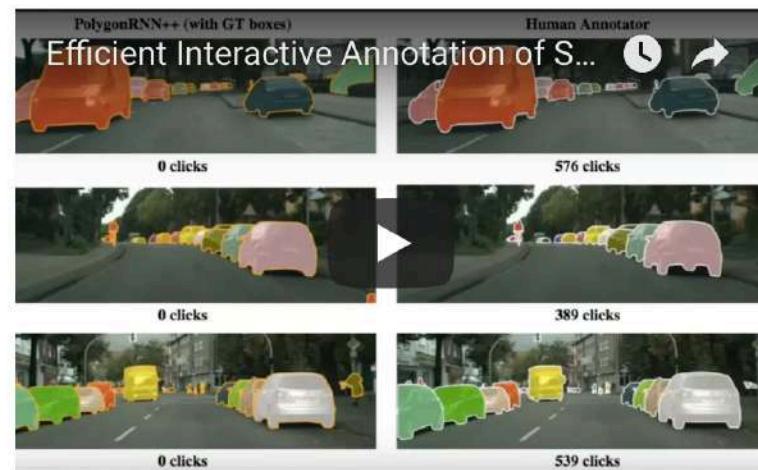
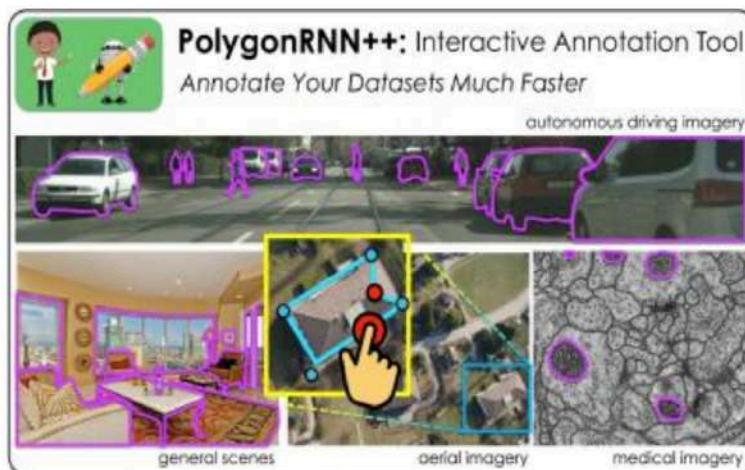
Sanja Fidler^{1,2}

¹University of Toronto

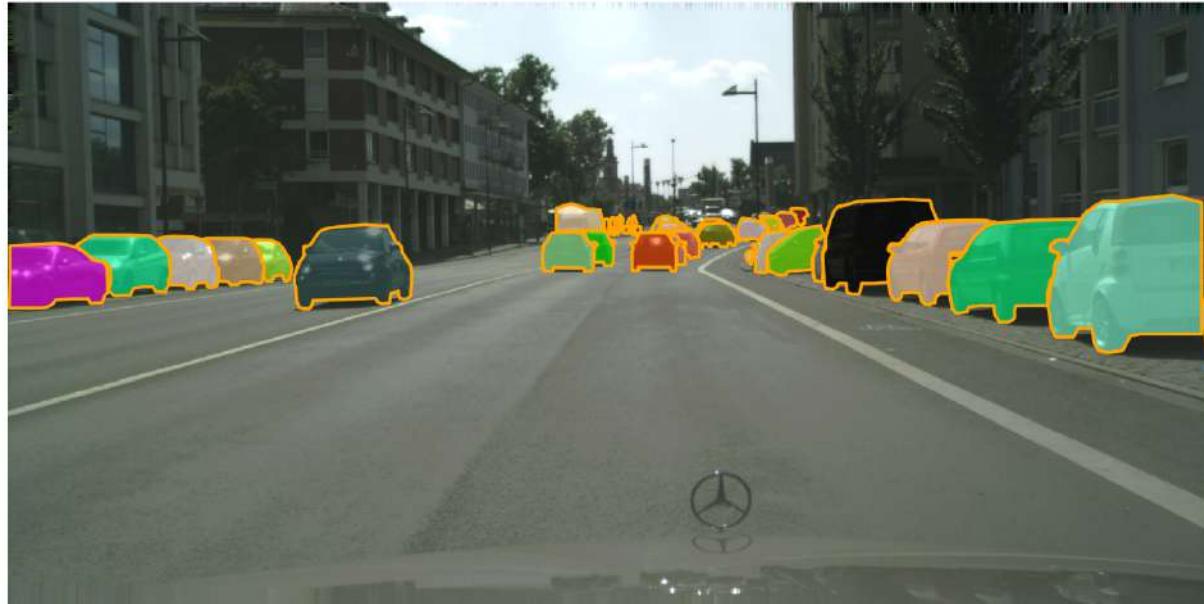
²Vector Institute

³NVIDIA[#]

CVPR, 2018



Polygon RNN



Why Polygon?

1. Human in the loop
2. Deformable

Polygon RNN

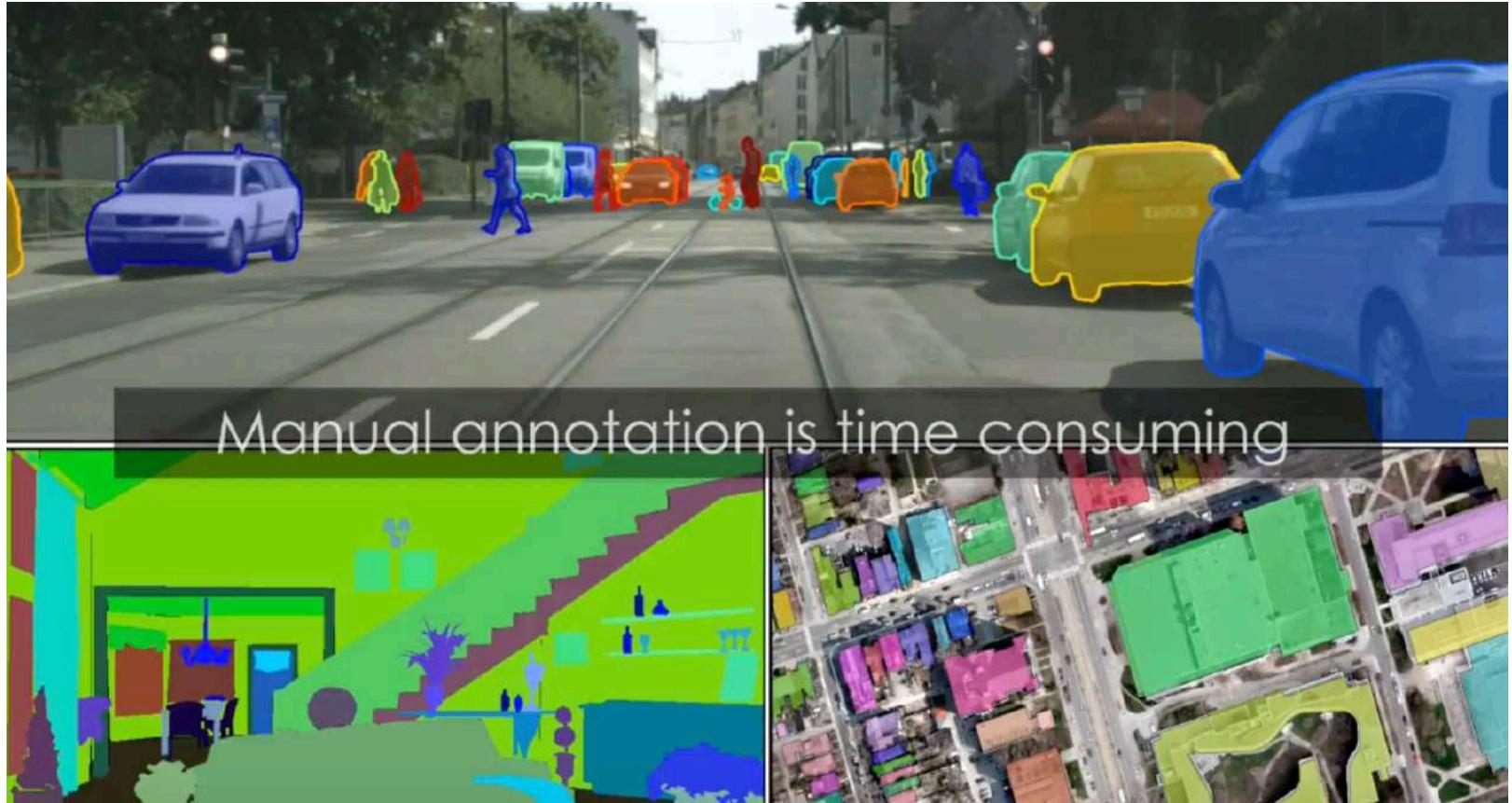


Why Polygon?

1. Human in the loop

2. Deformable

Polygon RNN : Bring human to the loop

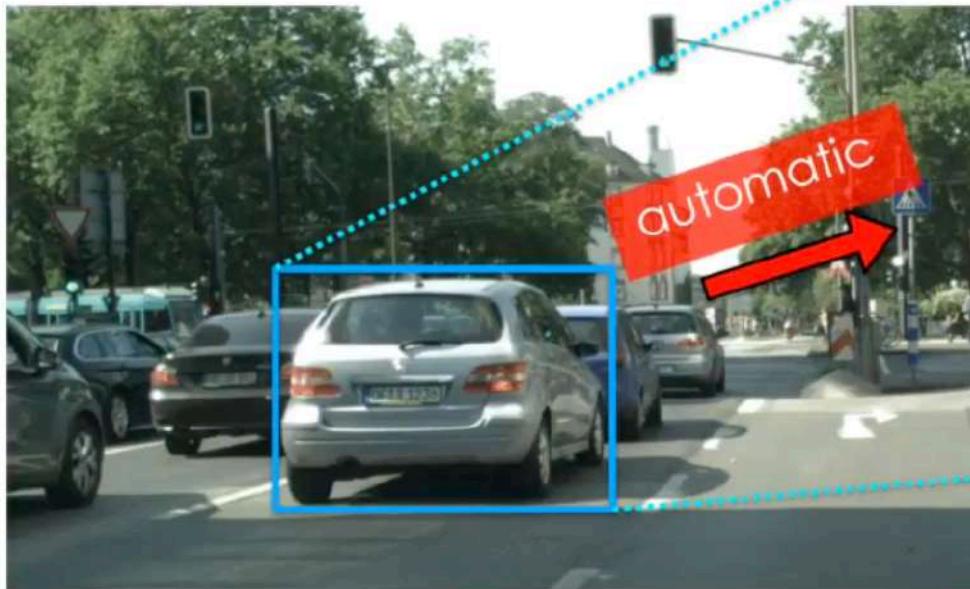


Polygon RNN : Bring human to the loop



Polygon-RNN++

Interactive Object Annotation Tool



Add box



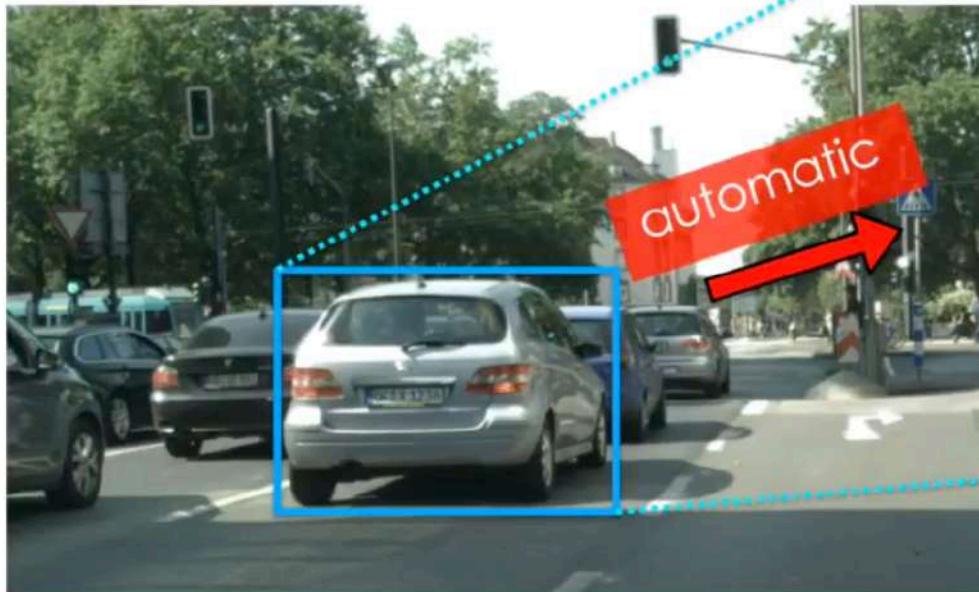
To correct the prediction, drag and drop a point

Polygon RNN : Bring human to the loop



Polygon-RNN++

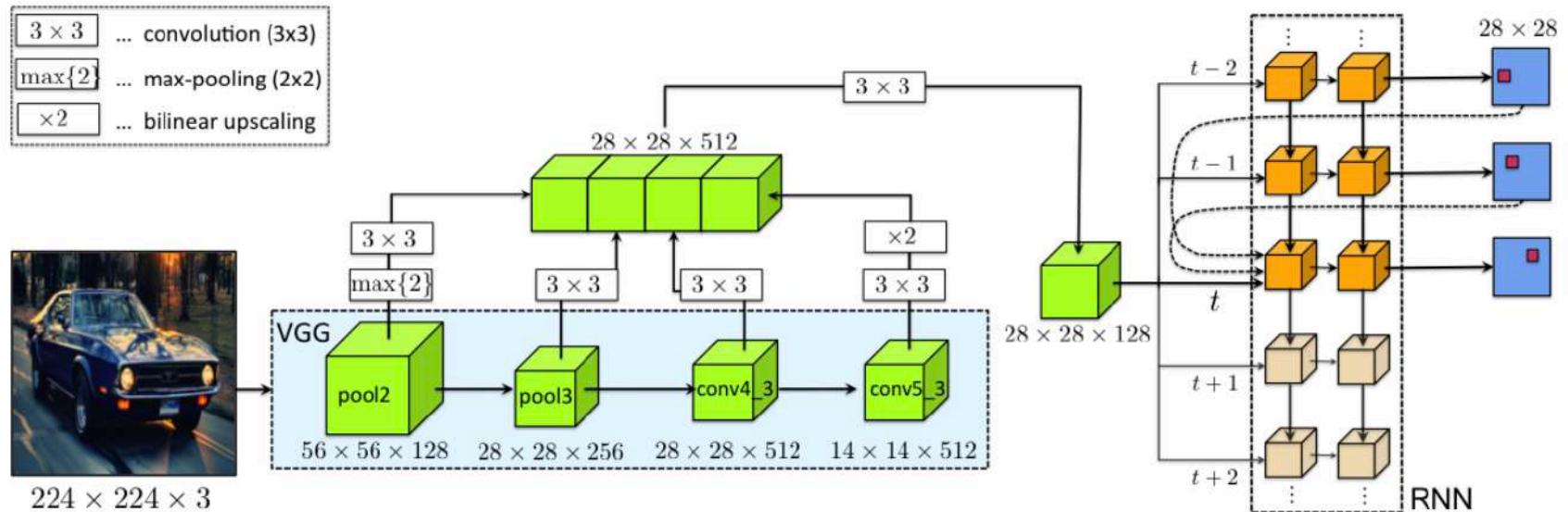
Interactive Object Annotation Tool



 Add box

 To correct the prediction, drag and drop a point

Polygon RNN : Bring human to the loop



Demo

PolygonRNN++

Interactive Object Annotation

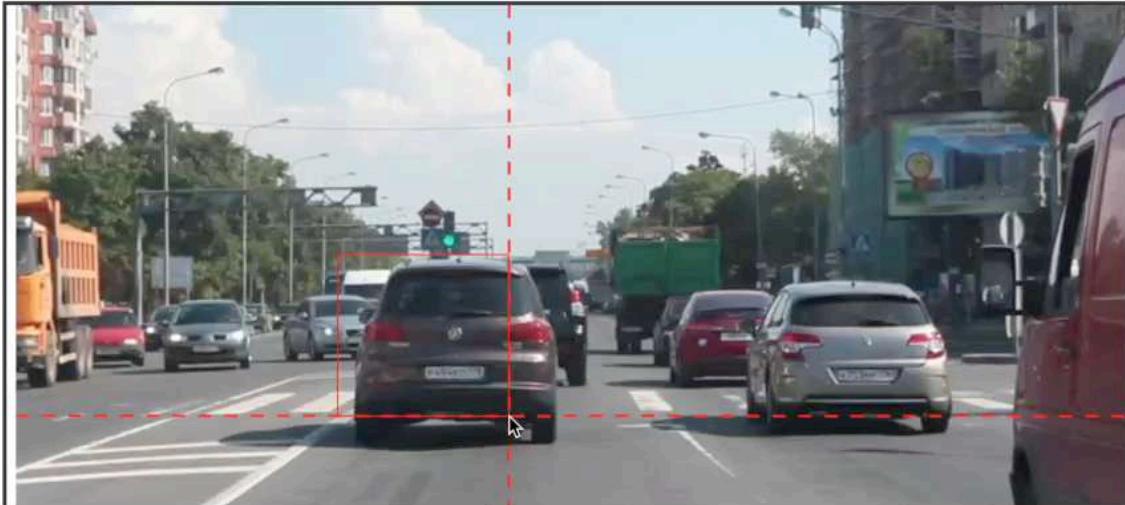
our AI assisted tool can help you annotate objects in images via polygons

Go ahead. Draw a box!

Enter Image URL

Submit URL Upload Local

- New Object (n)
- Finish Object (f)
- Discard Object (d/del)
- AI Smooth Poly (s)
- AI Assistance (a)
- Use fine polygon (g)

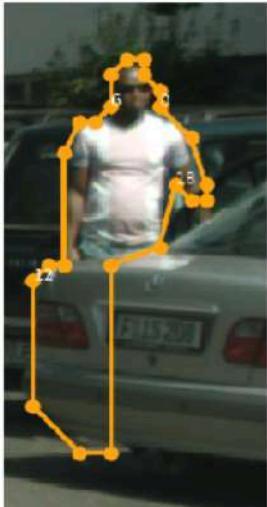


Thanks to NVIDIA for providing support in the form of GPUs for this demo.
We would also like to thank Masha Shugrina and Maxwell Fang for their help with the tool.
© University of Toronto

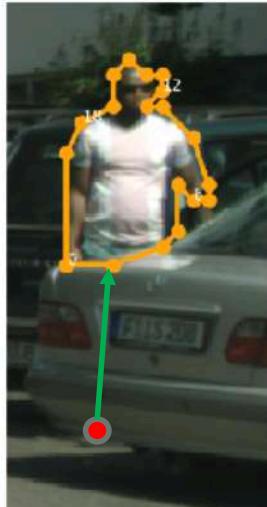
Polygon RNN : Bring human to the loop

Drag key point and redo inference from that point.

Automatic (0 clicks)
IoU:51.26



Interactive (1 clicks)
IoU:86.21



GT (39 clicks)
IoU:100



Automatic (0 clicks)
IoU:46.58



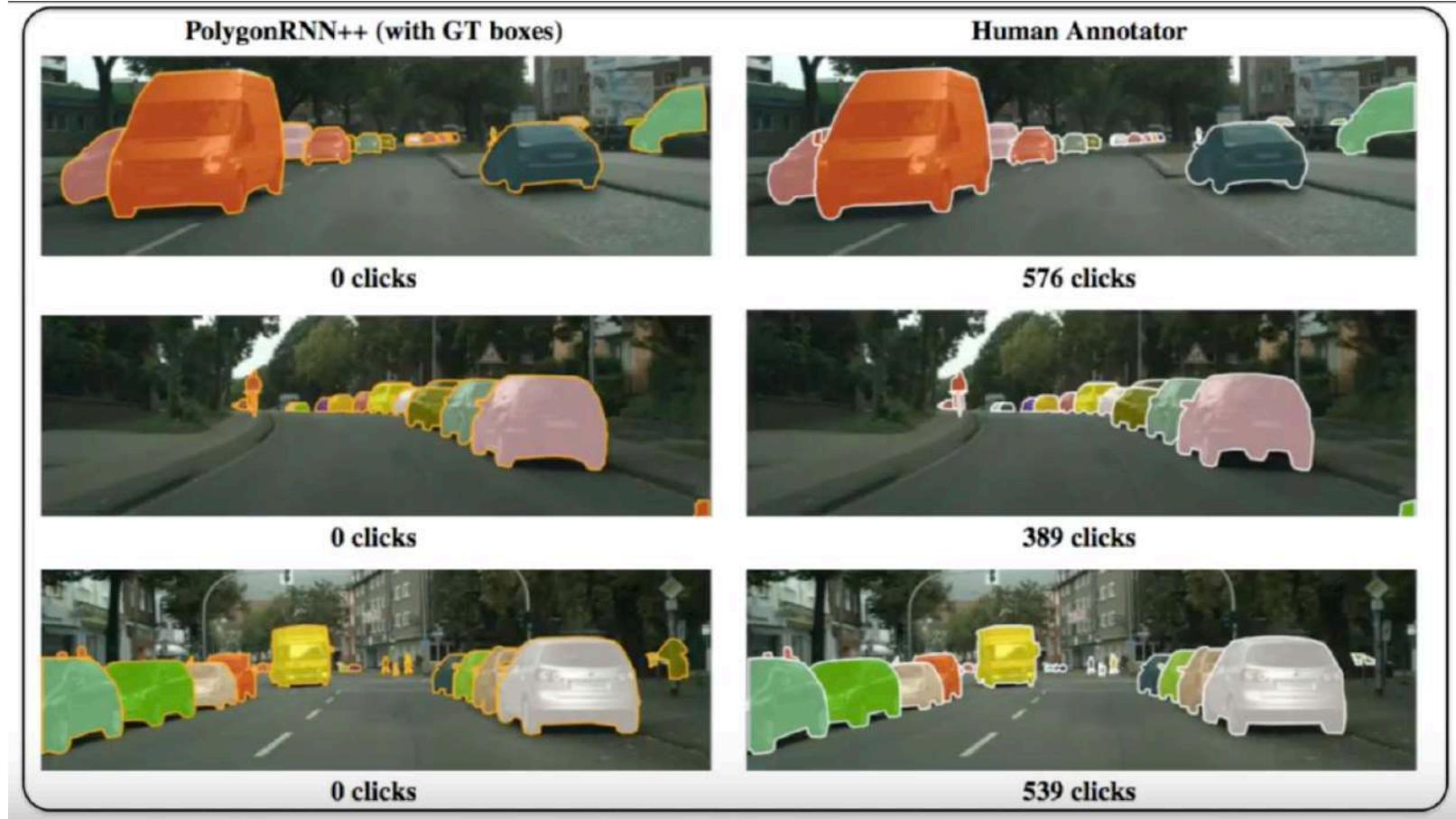
Interactive (3 clicks)
IoU:83.89



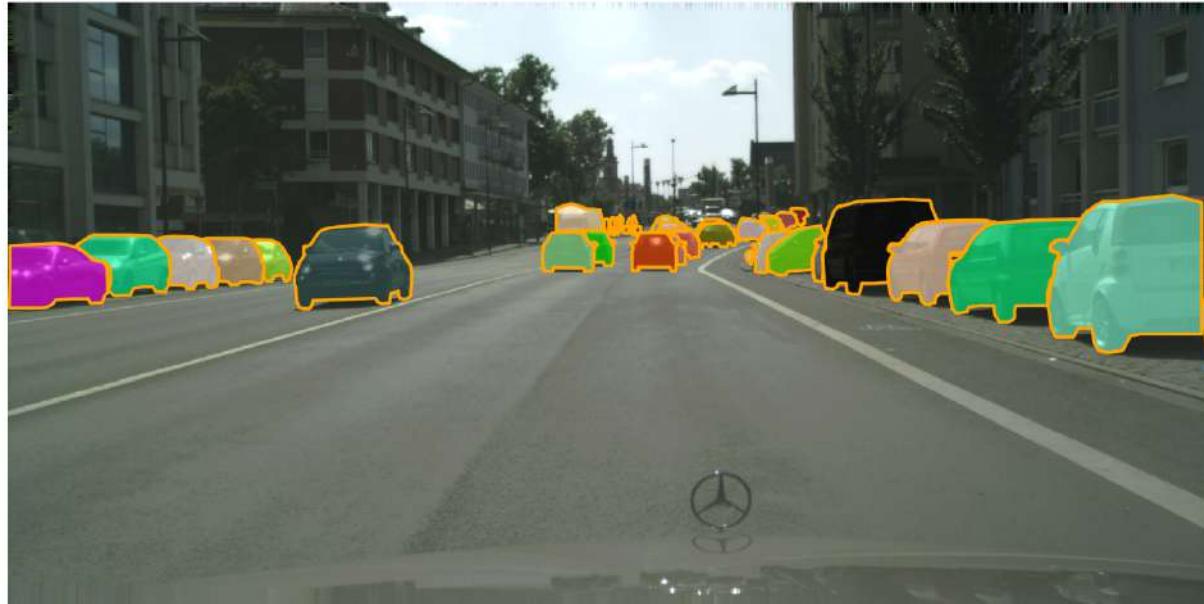
GT (30 clicks)
IoU:100



Polygon RNN : Bring human to the loop



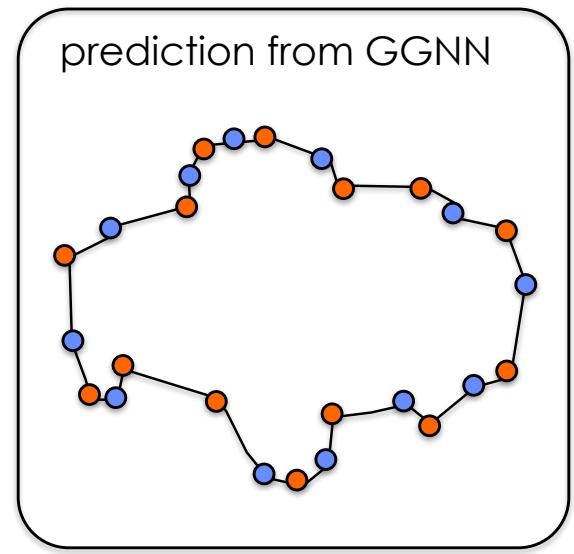
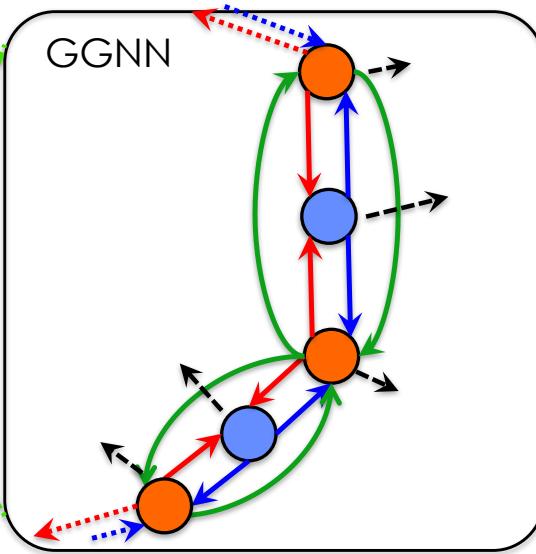
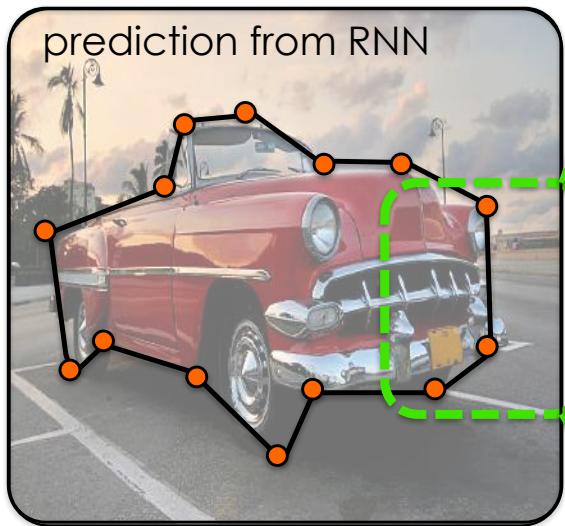
Polygon RNN++



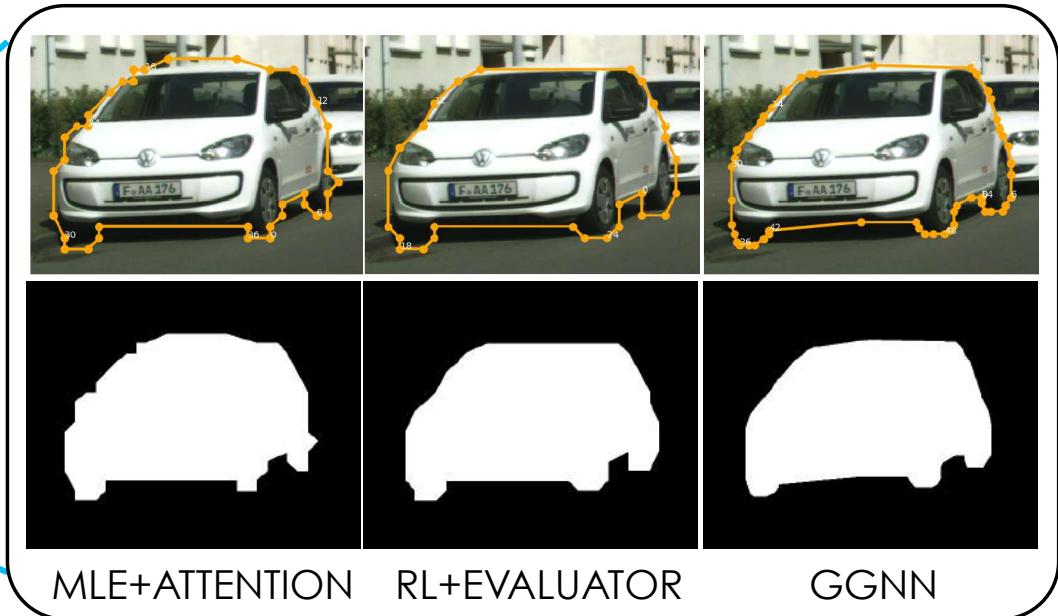
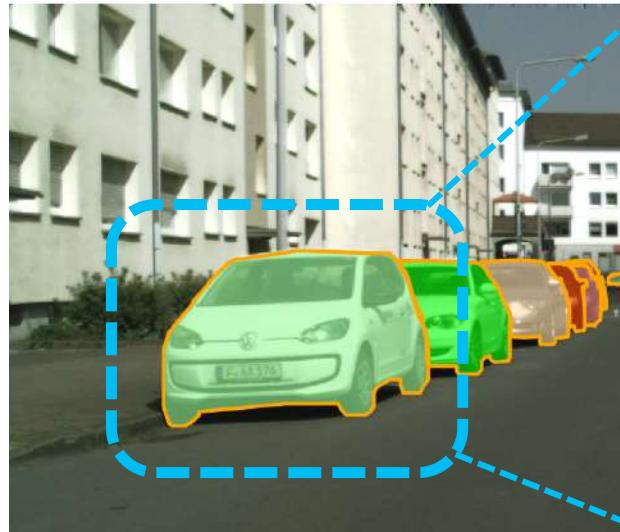
Why Polygon?

1. Human in the loop
2. **Deformable**

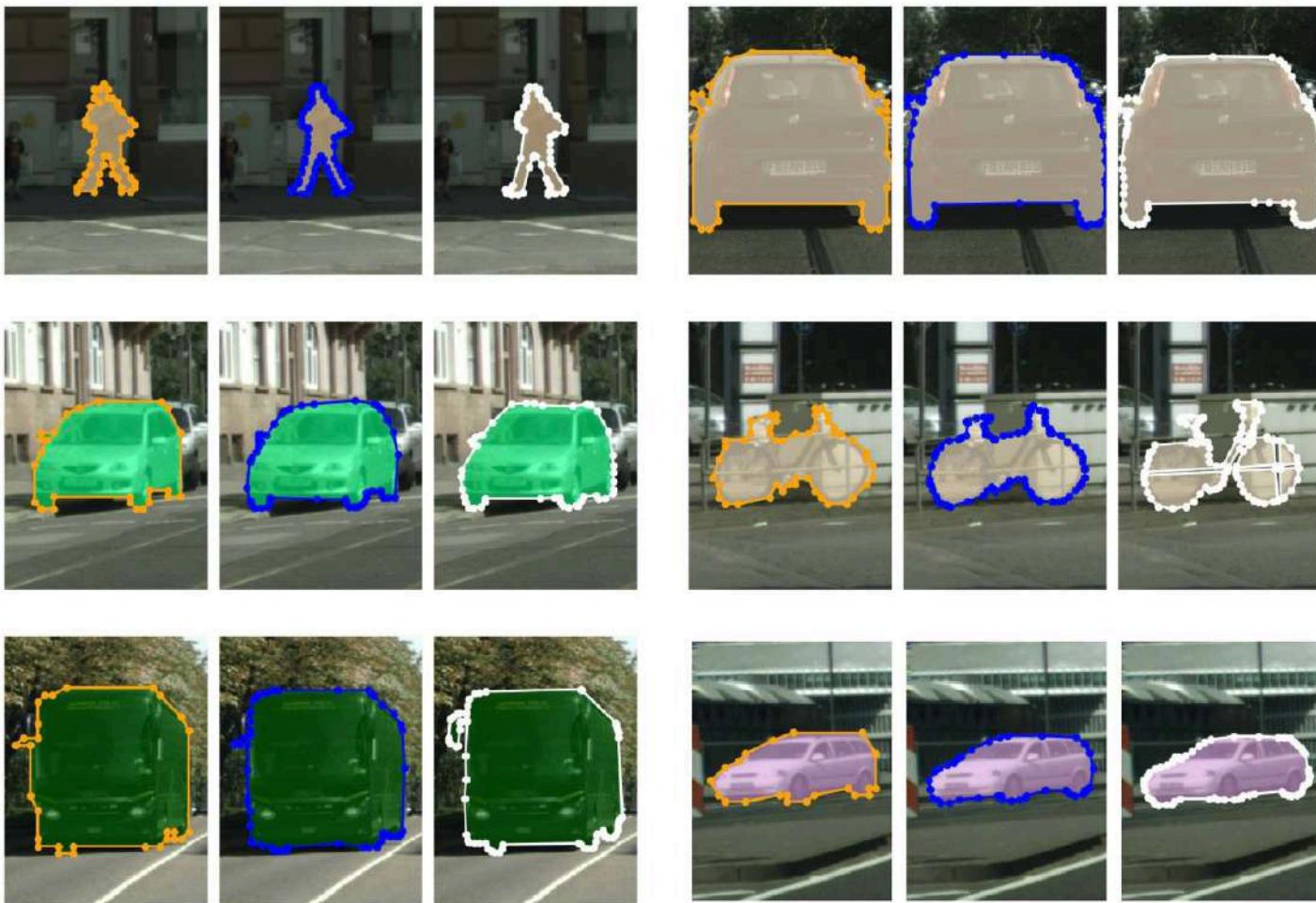
Polygon RNN++



Polygon RNN++



Polygon RNN++



Pixel2Mesh

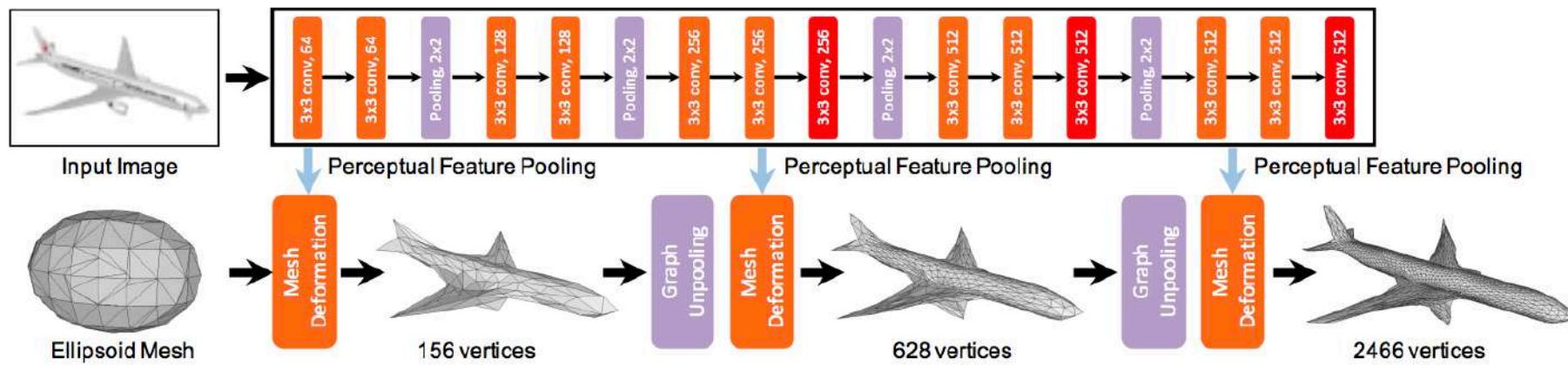
Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images

Nanyang Wang^{1*}, Yinda Zhang^{2*}, Zhuwen Li^{3*},
Yanwei Fu⁴, Wei Liu⁵, Yu-Gang Jiang^{1†}

¹Shanghai Key Lab of Intelligent Information Processing,
School of Computer Science, Fudan University

²Princeton University ³Intel Labs ⁴School of Data Science, Fudan University ⁵Tencent AI Lab
nywang16@fudan.edu.cn yindaz@cs.princeton.edu lzhuwen@gmail.com
yanweifu@fudan.edu.cn wl2223@columbia.edu ygj@fudan.edu.cn

Pixel2Mesh



Pixel2Mesh



3D Graph Neural Networks for RGBD Semantic Segmentation

3D Graph Neural Networks for RGBD Semantic Segmentation

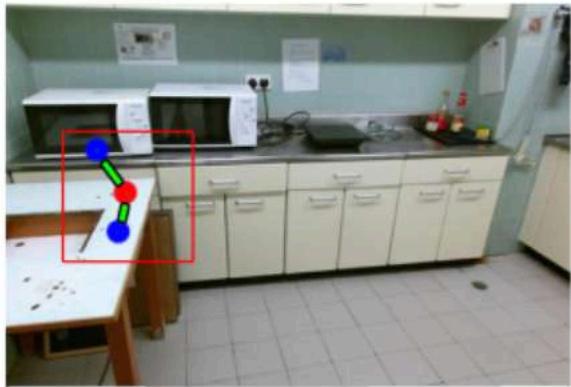
Xiaojuan Qi[†] Renjie Liao^{‡,§} Jiaya Jia^{†,ᵇ} Sanja Fidler[‡] Raquel Urtasun^{§,‡}

[†] The Chinese University of Hong Kong [‡] University of Toronto

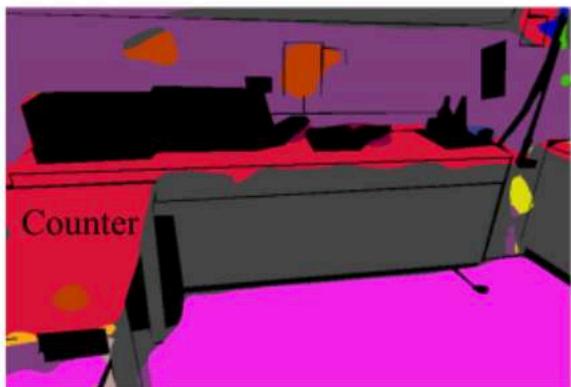
[§] Uber Advanced Technologies Group ^ᵇ Youtu Lab, Tencent

{xjqi, leo{jia}@cse.cuhk.edu.hk {rjliaoj, fidler, urtasun}@cs.toronto.edu

3D Graph Neural Networks for RGBD Semantic Segmentation



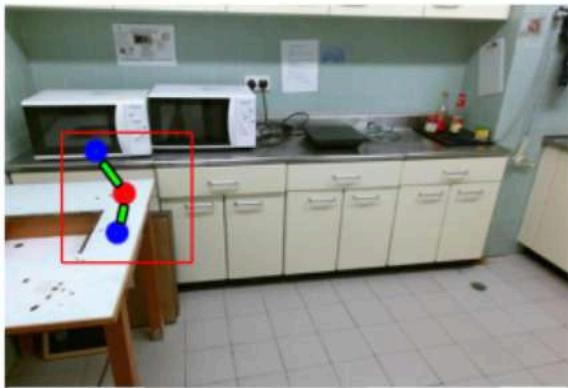
(a). 2D Image



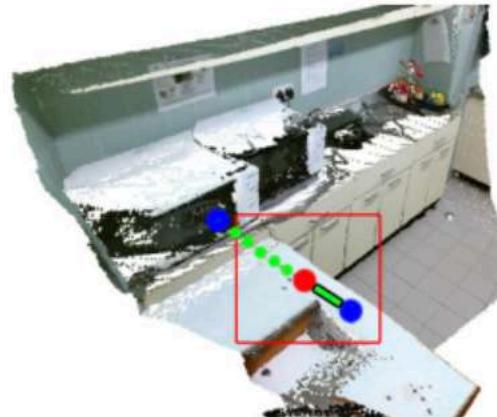
(c) 2D Prediction

1. We want to propagate information between nodes because nearby pixels are likely to be the same object.
2. We link pixels which are nearby by graph.
3. The link between top blue node and red middle node should not exist because they are actually not in the same surface.
4. How to solve this?
5. **RGBD 3D image & graph to help**

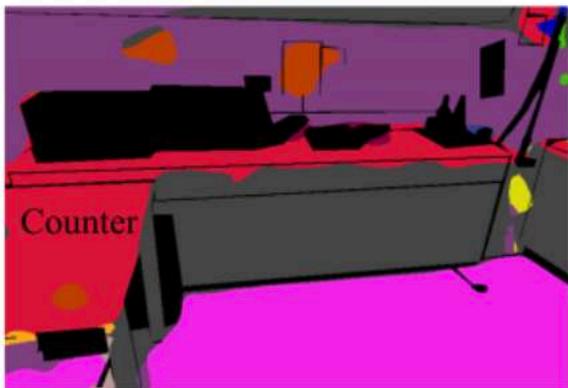
3D Graph Neural Networks for RGBD Semantic Segmentation



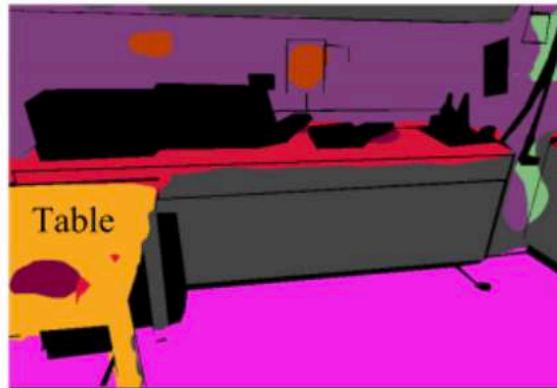
(a). 2D Image



(b) 3D Point Cloud



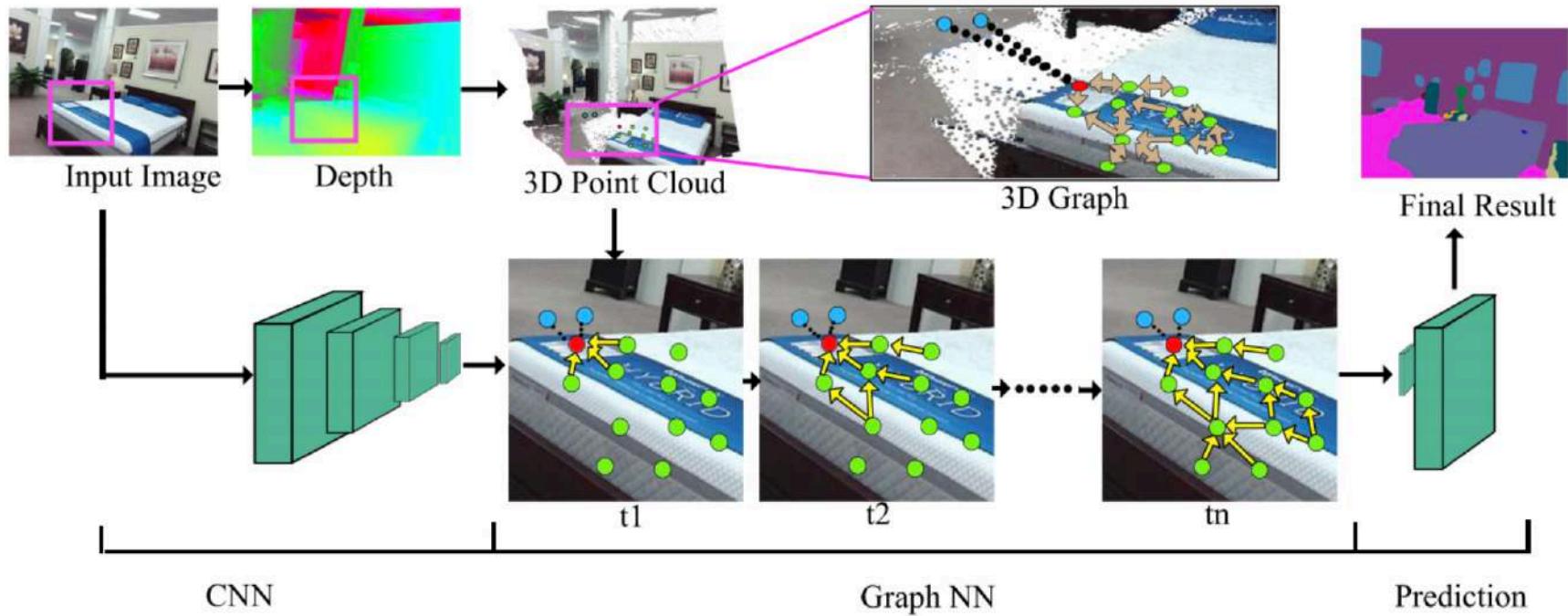
(c) 2D Prediction



(d) Ours (3D Prediction)

Dashed line means link exists in 2D image but not in 3D point cloud

3D Graph Neural Networks for RGBD Semantic Segmentation



References

1. Michaël Defferrard, Xavier Bresson and Pierre Vandergheynst. **Convolutional Neural Networks on Graphs with Fast Localized Spectral Filtering** <https://arxiv.org/pdf/1606.09375.pdf>
2. Thomas N. Kipf and Max Welling. **Semi-Supervised Classification with Graph Convolutional Networks** <https://arxiv.org/abs/1609.02907>
3. Yujia Li, Daniel Tarlow, Marc Brockschmidt and Richard Zemel. **Gated Graph Sequence Neural Networks** <https://arxiv.org/abs/1511.05493>
4. David Acuna ,Huan Ling ,Amlan Kar and Sanja Fidler. **Efficient Interactive Annotation of Segmentation Datasets with Polygon-RNN++** <https://arxiv.org/abs/1803.09693>
5. Lluis Castrejon ,Kaustav Kundu ,Raquel Urtasun and Sanja Fidler. **Annotating Object Instances with a Polygon-RNN** https://www.cs.toronto.edu/~urtasun/publications/castrejon_etal_cvpr17.pdf
6. Nanyang Wang , Yinda Zhang , Zhuwen Li , Yanwei Fu , Wei Liu and Yu-Gang Jiang. **Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images** <https://arxiv.org/pdf/1804.01654.pdf>
7. Xiaojuan Qi, Renjie Liao, Jiaya Jia, Sanja Fidler and Raquel Urtasun. **3D Graph Neural Networks for RGBD Semantic Segmentation**
http://www.cs.toronto.edu/~rjliaoj/papers/iccv_2017_3DGNN.pdf