Dynamic Gated Graph Neural Networks for Scene Graph Generation

Mahmoud Khademi and Oliver Schulte

Department of Computing Science
Simon Fraser University
mkhademi@sfu.ca, oschulte@sfu.ca

Presented by Rui Zeng

Scene Graph Generation Task

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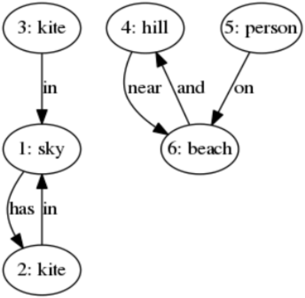
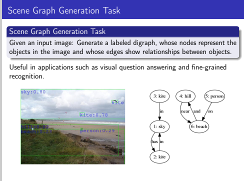
Given an input image: Generate a labeled digraph, whose nodes represent the objects in the image and whose edges show relationships between objects.

Useful in applications such as visual question answering and fine-grained recognition.



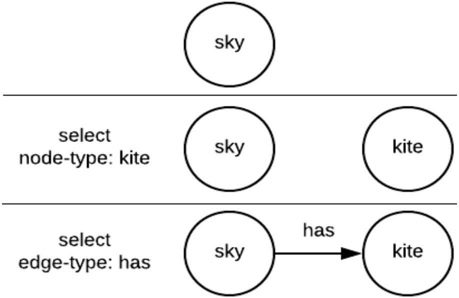


- A scene graph provides *scene understanding.*

D-GGNN: Reinforcement Learning for Scene Graph Generation

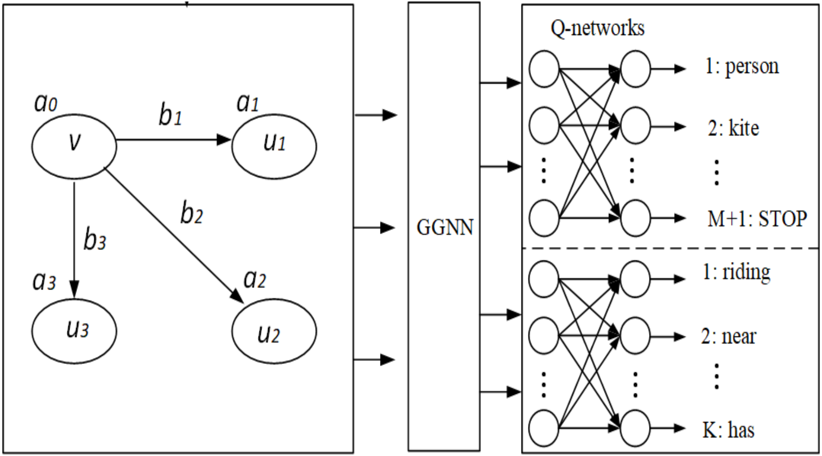
A scene graph generation algorithm needs to exploit visual contextual information.

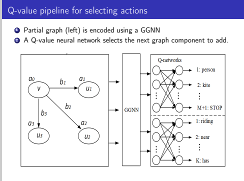
- State = (encoding of) partial graph
- Action = expands current graph
- Reward = agreement with ground truth



Q-value pipeline for selecting actions

1. Partial graph (left) is encoded using a GGNN
2. A Q-value neural network selects the next graph component to add.





- We use a standard object detector (Tensorflow API). The object detector produces objectness confidence scores. The graph construction starts with th highest-scoring object.
- Given an image and its candidate object bounding-boxes, we simultaneousl build the graph and assign node-types and edge-types to the nodes and edge in a Deep Q-Learning framework Mnih et al. [2013, 2015].
- The next slide explains more details.

Q-value network for selecting actions

State = Encoded Graph

- Feature vectors for each node v:
  - ResNet feature vector $\hat{\mathbf{x}}_v$
  - Node embedding $\mathbf{h}_v$, computed by GGNN Li et al. [2015].
    - Captures link information.
- Node feature vectors are combined using a soft attention mechanism that represents how important node v is for the next decision.

A Q-function takes as input a state s and an action a and outputs expected future reward $Q(s, a)$.

- Implemented by deep neural network
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- GGNN stands for Gated Graph Neural Net

Dataset

- The Visual Genome (VG) dataset 1.4 [Krishna et al., 2016] contains $108,077$ images. Annotations provide subject-predicate-object triples.
  - e.g. man-throwing-frisbee
- 5,000 images for hyperparameter validation, 5,000 for testing.
- Preprocessing:
  - `VG1.4-a` uses the most frequent 150 object categories and 50 predicates Xu et al. [2017].
  - `VG1.4-b` uses the most frequent 1750 object categories and 347 predicates.

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- Predicate = edge type.

Metrics (`VG1.4-a`)

The goal is to find ground truth relationship triplets (subject-predicate-object). Different input information = different tasks.

- Predicate classification (PRED-CLS): location and object categories are given.
- Scene graph classification (SG-CLS) task: location of objects are given.
- Scene graph generation (SG-GEN) task: only the image is given.
- Relationship phrase detection (REL-PHRASE-DET) and Relationship detection (REL-DET) are similar to SG-GEN, applied on VG1.4-b Liang et al. [2017].
- Metric is Top-K recall (`Rec@K`): the number of the ground-truth-triples hit in the top-K predictions in an image.

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- Predictions are ranked by the product of the objectness confidence scores an the Q-values of the selected predicates.
- We are following the evaluation methodology in previous papers.

Experimental Results

Model	PRED-CLS		SG-CLS		SG-GEN	
	R@50	R@100	R@50	R@100	R@50	R@100
Lu et al. [2016]	27.88	35.04	11.79	14.11	00.32	00.47
Xu et al. [2017]	44.75	53.08	21.72	24.38	03.44	04.24
D-GGNN (ours)	**46.85**	**55.63**	**23.80**	**26.78**	**06.36**	**07.54**

Table: VG1.4-a results for scene graph generation (SG-GEN). D-GGNN finds twice as many triplets as the previous state-of-the-art.

Model	REL-PHRASE-DET		REL-DET	
	R@100	R@50	R@100	R@50
CNN+RPN Simonyan and Zisserman [2014]	01.39	01.34	01.22	01.18
Faster R-CNN Ren et al. [2015]	02.25	02.19	-	-
CNN+TRPN Ren et al. [2015]	02.52	02.44	02.37	02.23
Lu et al. [2016]	10.23	09.55	07.96	06.01
VRL Liang et al. [2017]	16.09	14.36	13.34	12.57
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- For the VG1.4a dataset, the average number of ground-truth triplets in the images is 7.1.
- Results for VRL Liang 2017 are not available for VG1.4-a.

Conclusion

- Scene graph generation is an important part of scene understanding.
- We utilized a deep Reinforcement learning framework to sequentially generate a scene graph for an input image.
- New idea: entire partial graph is encoded as state information for RL.
  - A Gated Graph Neural Network computes node embeddings that capture relational information.
- We presented a generative deep architecture for graph-structured information from data sources (e.g. image, videos, text, program).
- Future Work: Evaluate in more applications, e.g. Visual Question Answering.
- We have a couple more scene graphs to show.

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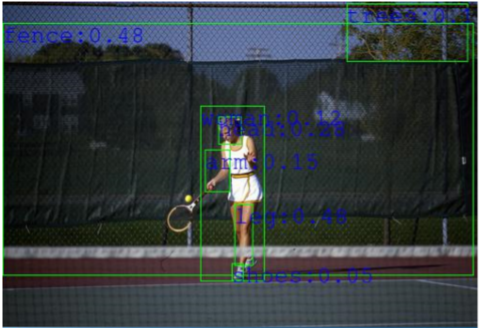
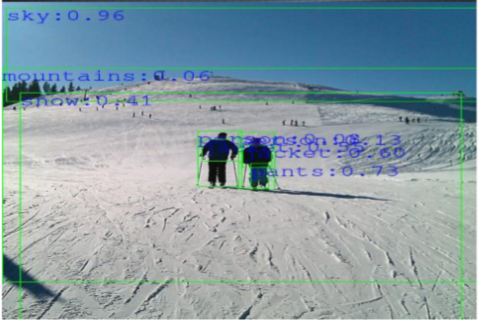
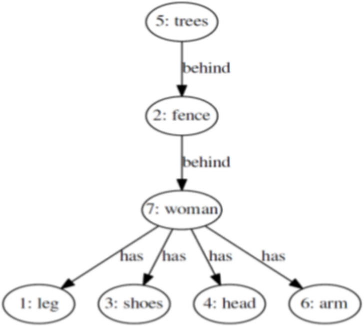
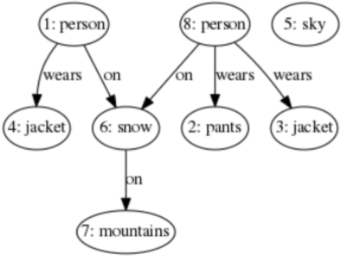
These are optional, it would be nice to leave the audience with pictures.

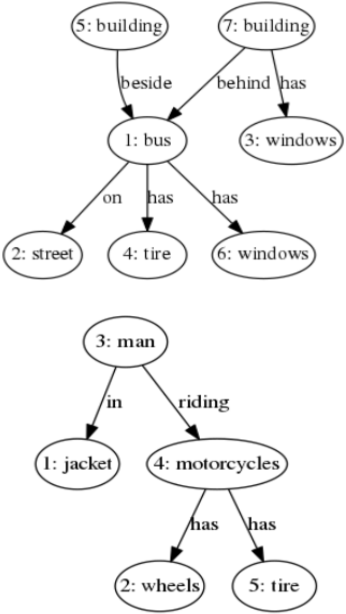

fence:0.48
arm:0.15
leg:0.48
shoes:0.05


sky:0.96
pants:0.73


5: trees
behind
2: fence
behind
7: woman
has
has
has
has
1: leg
3: shoes
4: head
6: arm


1: person
8: person
5: sky
wears
on
on
wears
wears
4: jacket
6: snow
2: pants
3: jacket
on
7: mountains


building:0.02
windows:0.04
windows:0.01
iPod
tire:0.28
man:0.75
wheels:0.02


5: building
7: building
beside
behind
has
1: bus
3: windows
on
has
has
2: street
4: tire
6: windows
3: man
in
riding
1: jacket
4: motorcycles
has
has
2: wheels
5: tire

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