

Graph Convolutional Policy Network for Goal-Directed Molecular Graph Generation

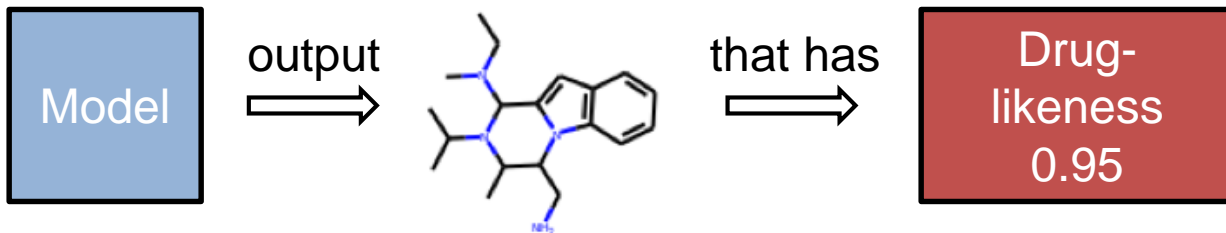
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Motivation

- Question:
 - Can we learn a model that can generate **valid** and **realistic** molecules with **high value** of a given chemical property?
 - **Valid, Realistic, High scores**



Goal-Directed Graph Generation

- Generating graphs that:
 - Optimize given objectives (High scores)
 - E.g., drug-likeness (black box)
 - Obey underlying rules (Valid)
 - E.g., chemical valency
 - Are learned from examples (Realistic)
 - E.g., Imitating a molecule graph dataset

Existing Approaches

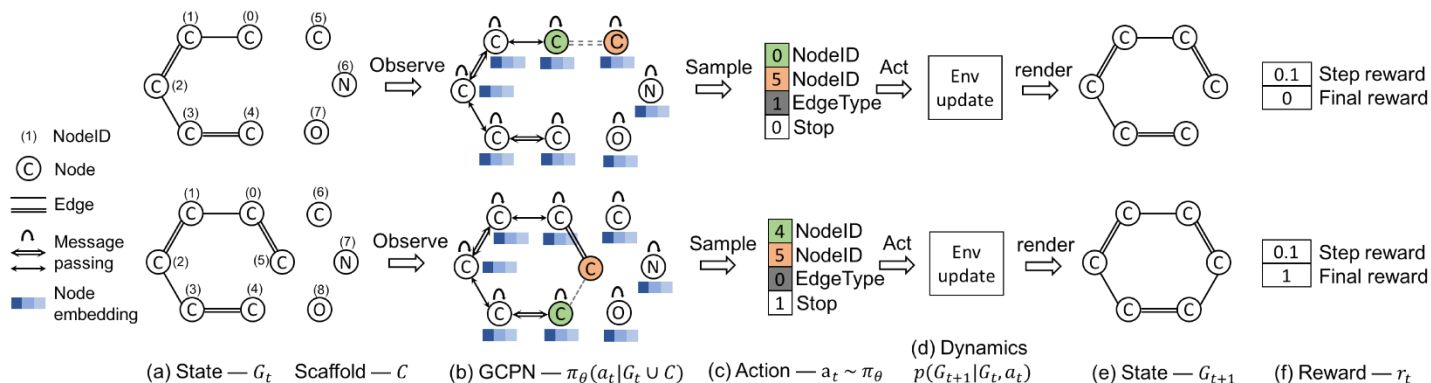
- String representations + RL [Guimaraes et al, 2017]
 - “CCN(C)C1C2=CC3=C(C=CC=C3)N2C(CN)C”
 - Very likely to generate invalid strings
- Learned VAE-based vector representations + Bayesian optimization [Jin et al, 2018]
 - Depends on latent space, hand-coded decoder rules

GCPN

- Our Approach: Graph representation + RL
 - Graph representation enables validity check in each state transition (Valid)
 - Reinforcement learning optimizes intermediate and final rewards (High scores)
 - Adversarial training imitates examples in given datasets (Realistic)

GCPN

Graph convolutional policy network (GCPN)



(1) Compute node embedding

$$H^{(l+1)} = \text{AGG}(\text{ReLU}(\{\tilde{D}_i^{-\frac{1}{2}} \tilde{E}_i \tilde{D}_i^{-\frac{1}{2}} H^{(l)} W_i^{(l)}\}, \forall i \in (1, \dots, b)))$$

(2) Predict edge, edge type and stop token

(3) Optimize using PPO

Results

- Generating graphs from scratch:
 - Over 60% higher scores

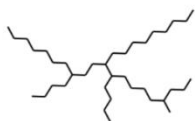
Table 1: Comparison of the top 3 property scores of generated molecules found by each model.

Method	Penalized logP				QED			
	1st	2nd	3rd	Validity	1st	2nd	3rd	Validity
ZINC	4.52	4.30	4.23	100.0%	0.948	0.948	0.948	100.0%
ORGAN	3.63	3.49	3.44	0.4%	0.896	0.824	0.820	2.2%
JT-VAE	5.30	4.93	4.49	100.0%	0.925	0.911	0.910	100.0%
GCPN	7.98	7.85	7.80	100.0%	0.948	0.947	0.946	100.0%

- Modifying existing graphs:
 - Over 180% higher scores improvement

Results

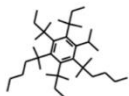
■ Visualization



7.98



7.48



7.12



23.88*

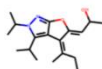
(a) Penalized logP optimization



0.948



0.945

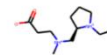


0.944

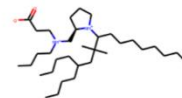


0.941

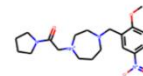
(b) QED optimization



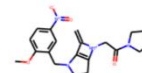
-8.32



-0.71



-5.55



-1.78

(c) Constrained optimization of penalized logP

Results

- https://github.com/bowenliu16/rl_graph_generation



- Come to poster AB#140 for more results!