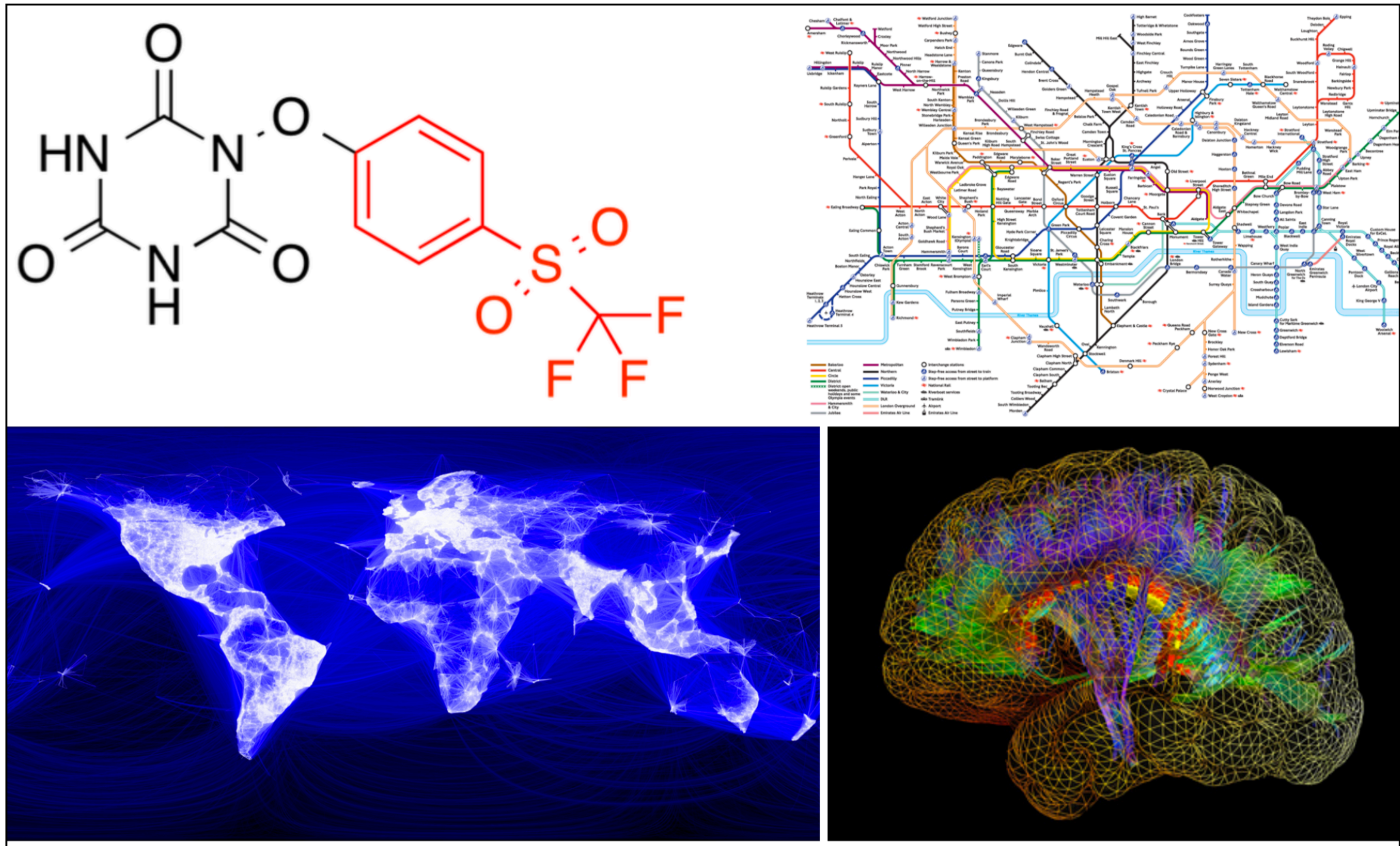


Constrained Graph Variational Autoencoders for Molecule Design

Станислав Рыбин, 151

Graph-structured inputs



Motivating examples of graph-structured inputs: molecular networks, transportation networks, social networks and brain connectome networks.

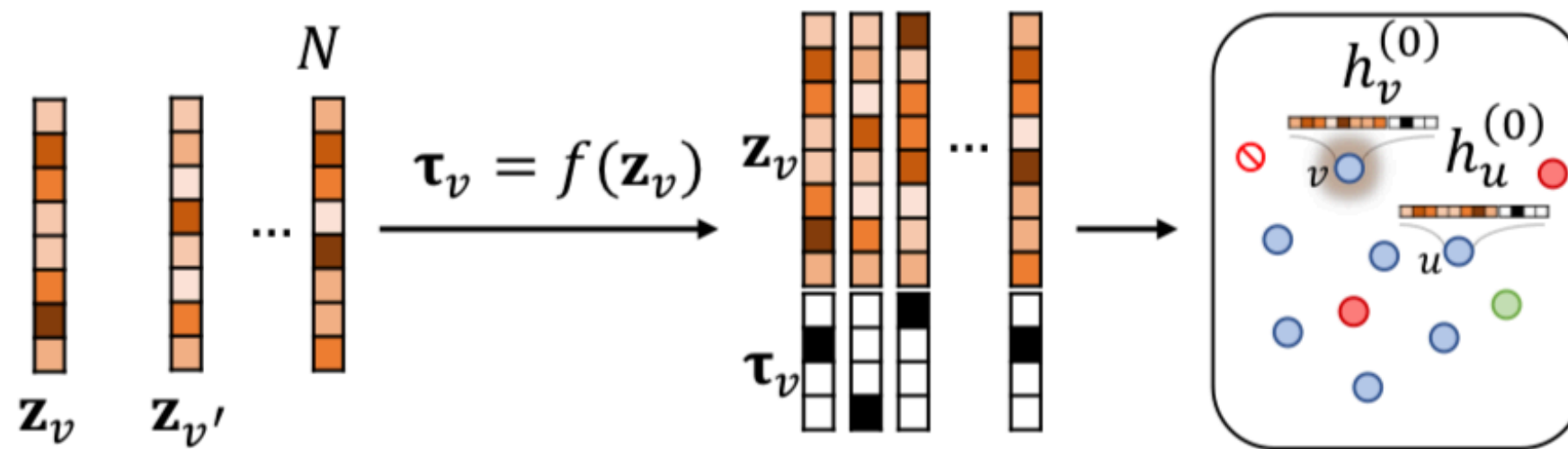
Three classes of graph generation models

- **Uncorrelated generation** - ignores the correlations & models the existence and label of each edge with *independent* random variables
- **Sequential generation** - factor the distribution into a *sequence* of discrete decisions in a graph construction trace
- **New class (our model)** - the learned component is conditioned only on the current state of generation and not on the arbitrarily chosen path to that state

Generative model

- Stages:
 1. Node Initialization
 2. Node Update
 3. Edge selection & labelling
 4. Termination

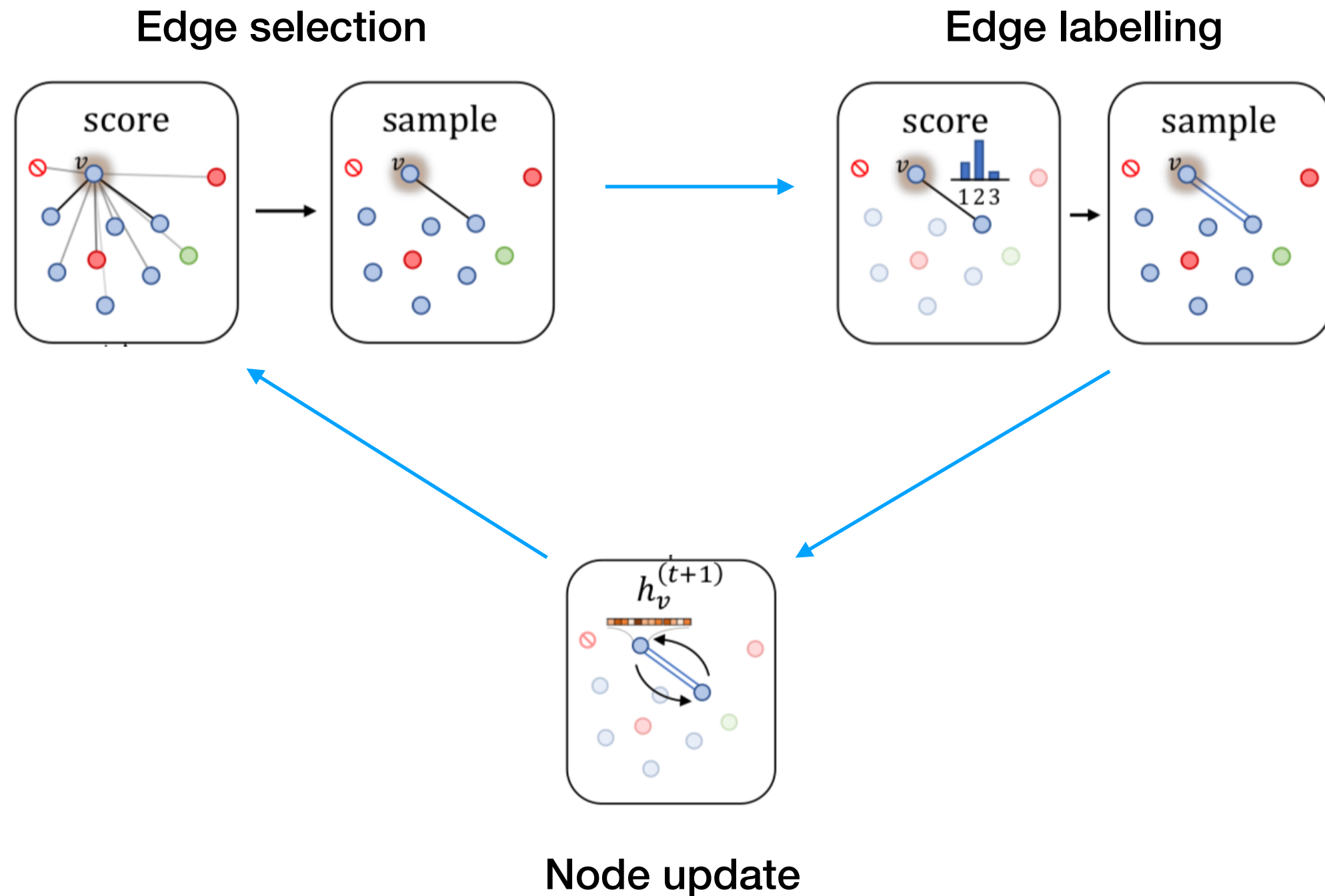
Node Initialization



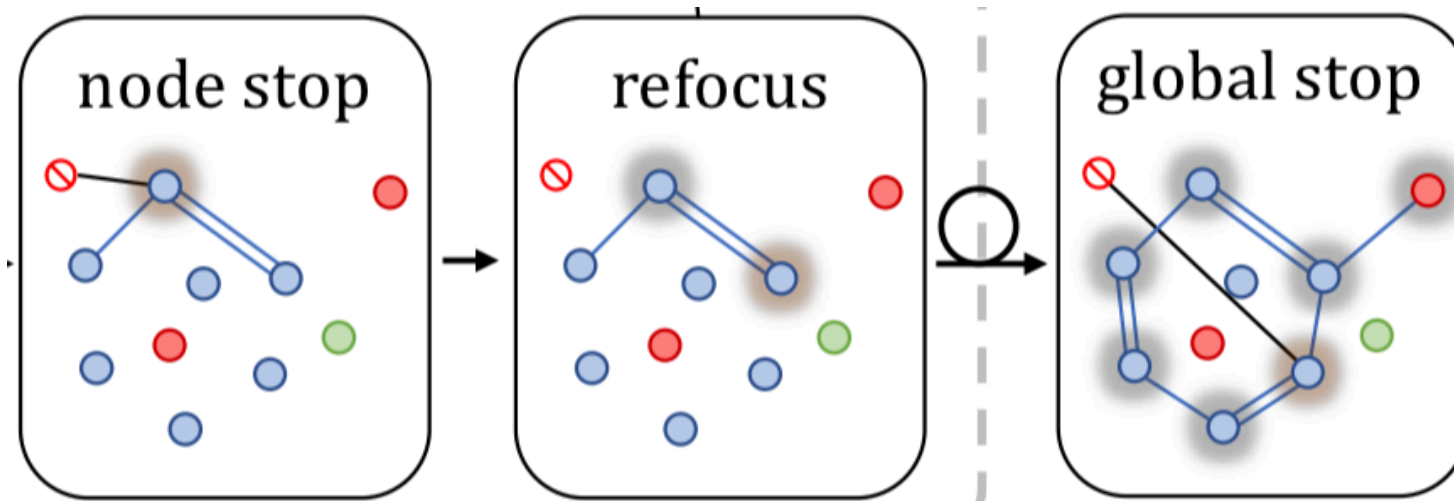
Generative model

- Generation of edges between nodes proceeds using two decision functions: **focus** and **expand**
 1. **Focus** function chooses a focus node to visit
 2. **Expand** function chooses edges to add from the focus node.

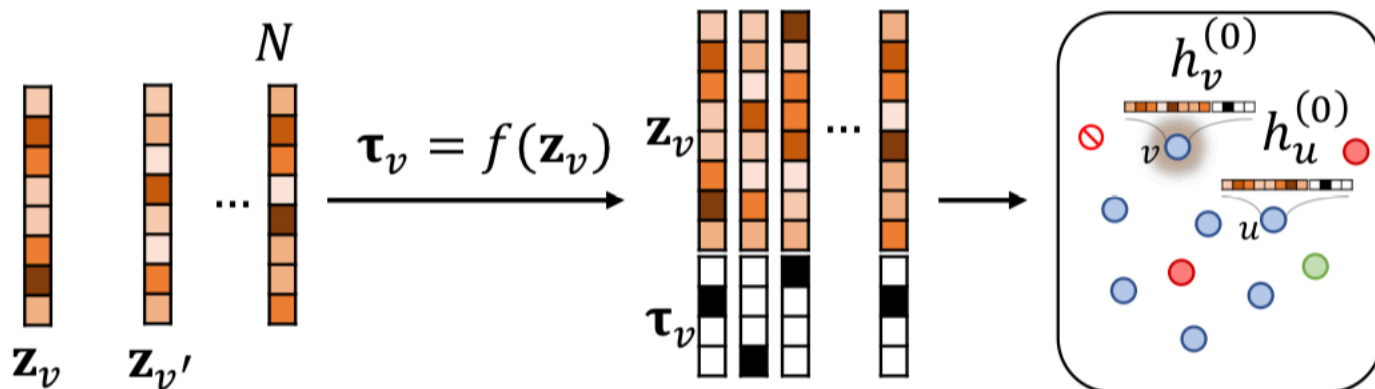
Node Update & Edge selection & labelling



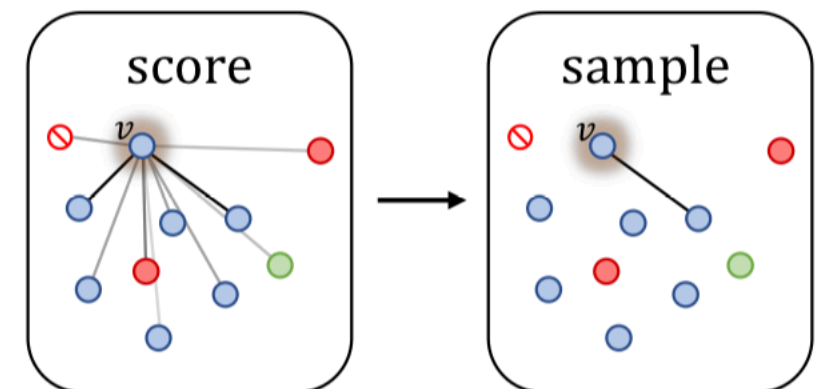
Termination



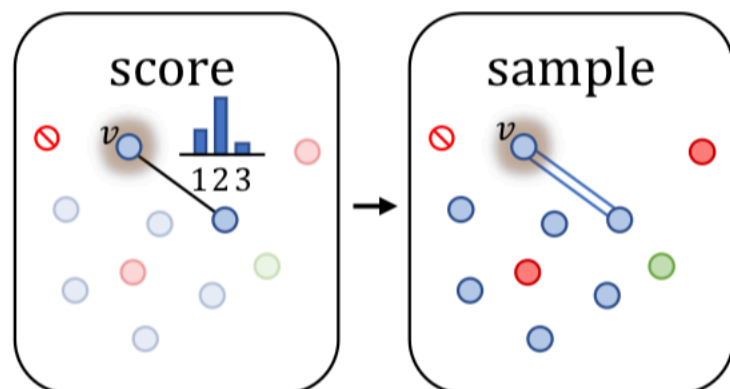
Node Initialization



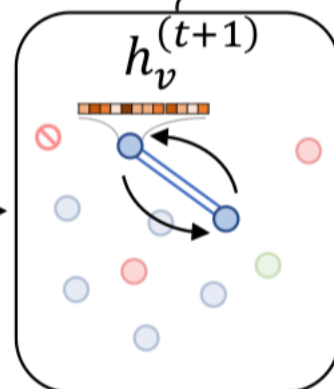
Edge Selection



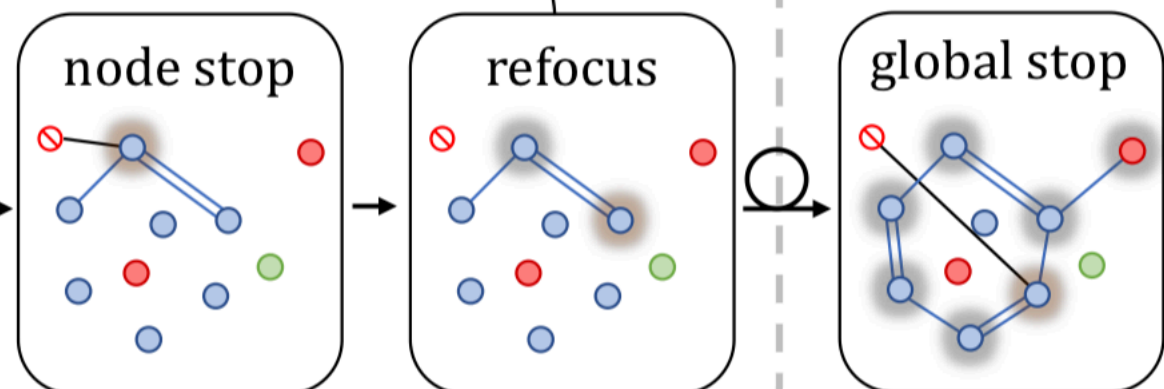
Edge Labelling



Node Update



Termination



$L_\ell(\phi)$

Training the Generative model

- Encoder
- Decoder
- Node Initialization

$$p(\mathcal{G}^{(0)} \mid \mathbf{z}) = \sum_{\mathcal{P}} p(\tau = \mathcal{P}(\tau^*) \mid \mathbf{z}) > \prod_v p(\tau_v = \tau_v^* \mid \mathbf{z}_v).$$

- Edge Selection and Labelling

- $$\log p(\pi \mid \mathcal{G}^{(0)}) = \sum_{(t,v,\epsilon) \in \pi} \left\{ \log p(v \mid \pi, t) + \log p(\epsilon \mid \mathcal{G}^{(t-1)}, v) \right\}$$

Application: Molecule Generation

- Datasets: QM9, ZINC, CEPDB

