

A novel reinforcement learning algorithm for virtual network embedding

A.Zamani

Supervised by: Dr. pourahmadi

Amirkabir University of Technology

Statistical Machine Learning, December 2018

Outline

- 1 Network modeling
- 2 Policy network
 - Feature extraction
 - convolutional layer
 - Softmax layer
 - Filter
- 3 Training and testing
 - Training
 - Testing
- 4 Reward
- 5 Evaluation

Network modeling

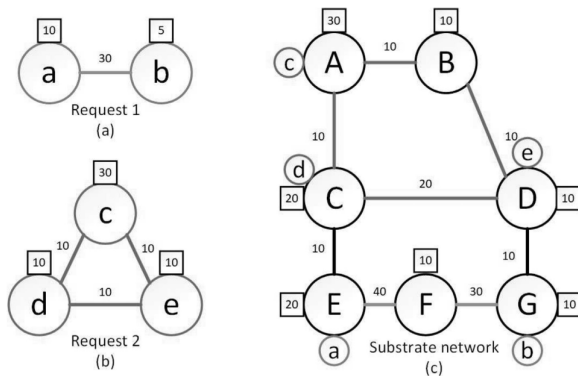


Figure: An example of virtual network embedding.

Network modeling

- Substrate network: $G^S = (N^S, L^S, A_N^S, A_L^S)$
- Request: $G^V = (N^V, L^V, C_N^V, C_L^V)$
- virtual network embedding process can be formulated as \rightarrow mapping G^V to $G^S : G^S(N^V, L^V) \rightarrow G^S(N', P')$ where $N' \subset N^S, P' \subset P^S$



Policy network

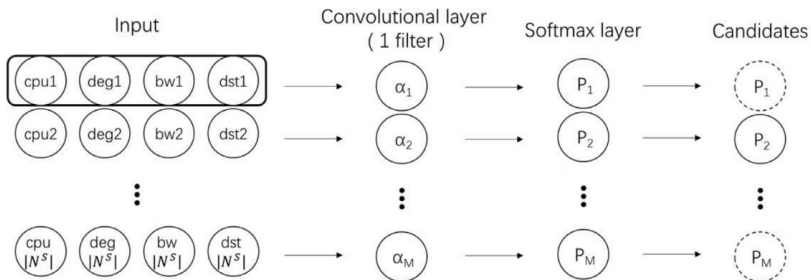


Figure: Policy network.

Feature extraction

- Computing capacity (CPU)
- Degree (DEG)
- Sum of bandwidth ($SUM^{(BW)}$)
 $\rightarrow SUM^{(BW)}(n^S) = \sum_{l^S \in L(n^S)} BW(l^S)$
- Average distance to other host nodes AVG^{DST}
 $\rightarrow AVG^{(DST)}(n^S) = \frac{\sum_{\hat{n}^S \in \hat{N}^S} DST(n^S, \hat{n}^S)}{|\hat{N}^S|+1}$
- feature vector $V_K \rightarrow$
 $V_K = (CPU(n_k^S), DEG(n_k^S), SUM^{(BW)}(n_k^S), AVG^{(DST)}(n_k^S))^T$
- feature matrix M_f
 $\rightarrow M_f = (v_1, v_2, \dots, v_{|N^S|})$



Feature extraction

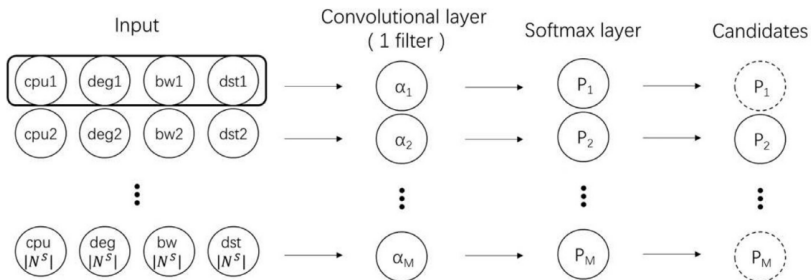
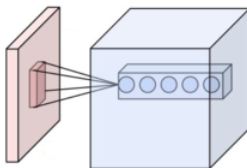


Figure: Policy network.

convolutional layer

- performs a convolution operation on the input
- produces a vector representing the available resources of each node

$$h_K^c = w.v_K + b$$



convolutional layer

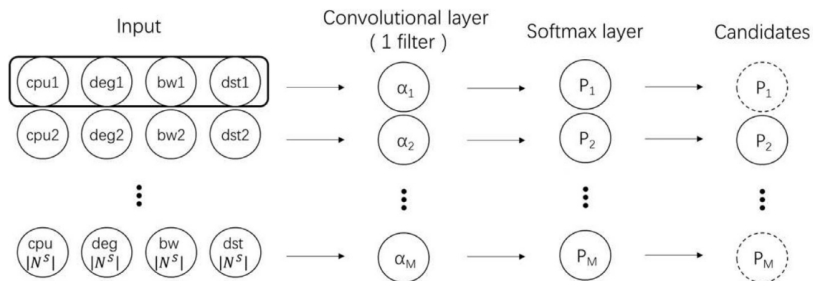
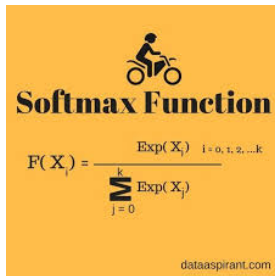


Figure: Policy network.

Softmax layer

- the n-dimensional vector into real values between 0 and 1 that add up to 1
- probability distribution over n different possible mappings

$$p_K = \frac{e^{h_K^c}}{\sum_i e^{h_K^c}}$$



Filter

- Some of the nodes are not able to host
- because they do not have enough computing resources
- add a filter to choose a set of candidate nodes with enough CPU capacities



Softmax & Filter

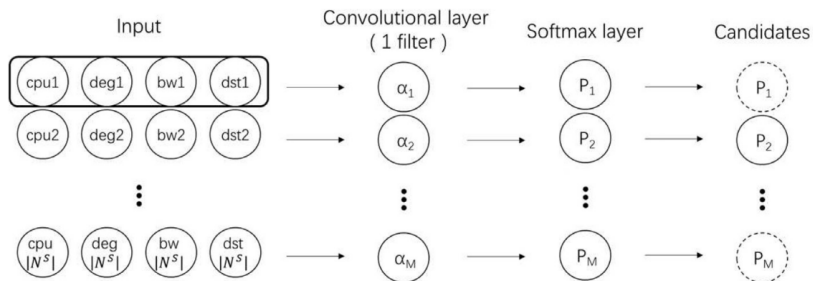


Figure: Policy network.

Training

- randomly initialize the parameters in the policy network
- cannot simply select the node with a maximal probability as the host
- exploration & exploitation
- sample from the set of available substrate nodes according to their probability
- select a node as the host



Training

- repeat this process until all the virtual nodes in a virtual request are assigned
- proceed to link mapping
- breadth-first search to find the shortest paths between each pair of nodes
- If no substrate node is available, the mapping fails
- in reinforcement learning, agent relies on reward signals to know if it is working properly



Training

- If we choose the i th node \rightarrow vector y filled with zeros except the i th position which is one
- Cross-entropy loss $\rightarrow L(y, P) = -\sum_i y_i \log(P_i)$
- use backpropagation to compute the gradients of parameters
- stack the gradients g_f
- $g = \alpha \cdot r \cdot g_f$



Testing

- greedy strategy



Copyright! Homemade-Preschool.com

Reward

- revenue of accepting a virtual network request

$$R(G^v, t, t_d) = t_d \cdot [\sum_{n^v \in N^v} CPU(n^v) + \sum_{l^v \in L^v} BW(l^v)]$$

- cost function: $C(G^v, t, t_d) = t_d \cdot [\sum_{l^v \in L^v} \sum_{l^s \in P'_{l^v}} BW(l^v)]$

- long-term average revenue: $\lim_{T \rightarrow \infty} \frac{\sum_{t=0}^T R(G^v, t, t_d)}{T}$

- long-term revenue to cost ratio: $\lim_{T \rightarrow \infty} \frac{\sum_{t=0}^T R(G^v, t, t_d)}{\sum_{t=0}^T C(G^v, t, t_d)}$



Evaluation

- network with 100 nodes and approximately 550 links
- capacity of every substrate node \rightarrow uniform distribution between 50 and 100
- bandwidth of every link \rightarrow uniform distribution between 20 and 50
- generated a number of virtual requests \rightarrow each with 210 virtual nodes
- computing capacity requirement of every virtual node \rightarrow uniform distribution between 0 and 50 units
- bandwidth requirement of every virtual link \rightarrow uniform distribution between 0 and 50 units
- 100 epochs
- gradient descent with a learning rate of 0.005



Evaluation

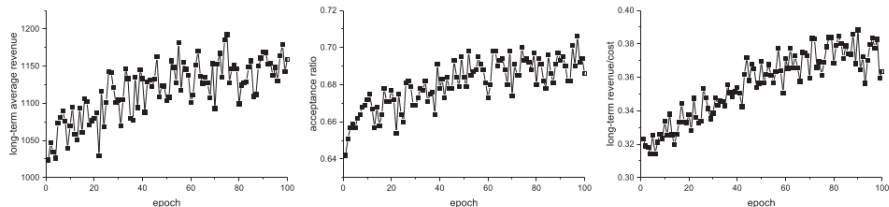


Figure: Performance on training set

Evaluation

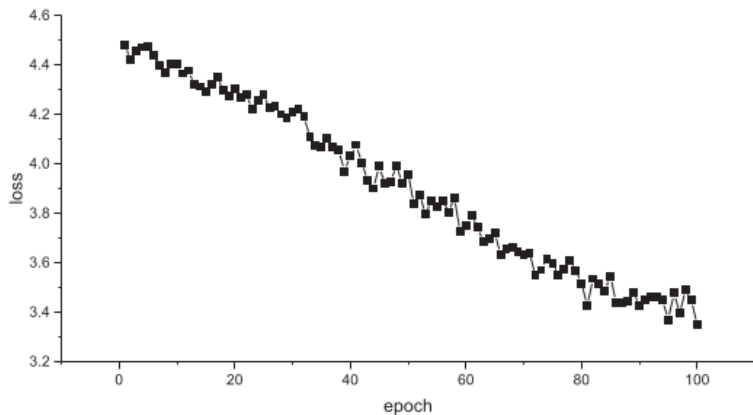


Figure: Loss on training set

Evaluation

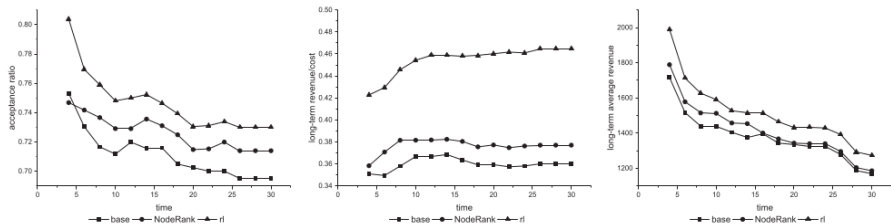


Figure: Performance on testing set

