Edge-Aware Graph Attention Network for Ratio of Edge-User Estimation in Mobile Networks

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Abstract

Estimating the Ratio of Edge-Users (REU) is an important issue in mobile networks, as it helps the subsequent adjustment of loads in different cells. However, existing approaches usually determine the REU manually, which are experience-dependent and labor-intensive, and thus the estimated REU might be imprecise. Considering the inherited graph structure of mobile networks, in this paper, we utilize a graph-based deep learning method for automatic REU estimation, where the practical cells are deemed as nodes and the load switchings among them constitute edges. Concretely, Graph Attention Network (GAT) is employed as the backbone of our method due to its impressive generalizability in dealing with networked data. Nevertheless, conventional GAT cannot make full use of the information in mobile networks, since it only incorporates node features to infer the pairwise importance and conduct graph convolutions, while the edge features that are actually critical in our problem are disregarded. To accommodate this issue, we propose an Edge-Aware Graph Attention Network (EAGAT), which is able to fuse the node features and edge features for REU estimation. Extensive experimental results on two real-world mobile network datasets demonstrate the superiority of our EAGAT approach to several state-of-the-art methods.

Motivation

- **Background**

I. Our task is to estimate the Ratio of Edge-Users (REU) in mobile networks.
II. We aim to use a machine learning technique to adaptively estimate or predict the REU.
III. Note that the mobile network naturally contains a graph structure, we employ the GCN as the backbone.
IV. The graph edges and their features also play a critical role in determining the REU in mobile networks

- **Prior work**

✓ Spectral-Based Graph Convolution
✓ Spatial-Based Graph Convolution
✓ Edge-based Graph Convolution

Both Spectral-Based Graph Convolution and Spatial-Based Graph Convolution can not process the graph with edge attribute. There are some preliminary researches on learning with a graph with edge features. But the edge features are merely utilized as a binary indication of whether there is a connection between the two nodes.

The Algorithm

Algorithm 1 Edge-Aware Graph Convolution Process of EA-GAT

Input: Input node features $\mathbf{H}$; Input edge features $\mathbf{E}$; Neighborhood $\mathcal{N}$;

// Calculate the attention coefficients
for $i = 1, 2, \ldots, N$ **do**
  for $j = 1, 2, \ldots, N$ **do**
    Obtain α_{ij} according to Eq. (8);
    Obtain $\mathbf{A}_{ij}$ according to Eq. (9);
  end for
end for
// Perform graph convolution
for $l = 1, 2, \ldots, L-1$ **do**
  Obtain $\mathbf{H}^{(l)}$ according to Eq. (11);
end for
Calculate the network output according to Eq. (12);

Output: Network output $\hat{\mathbf{y}}$.

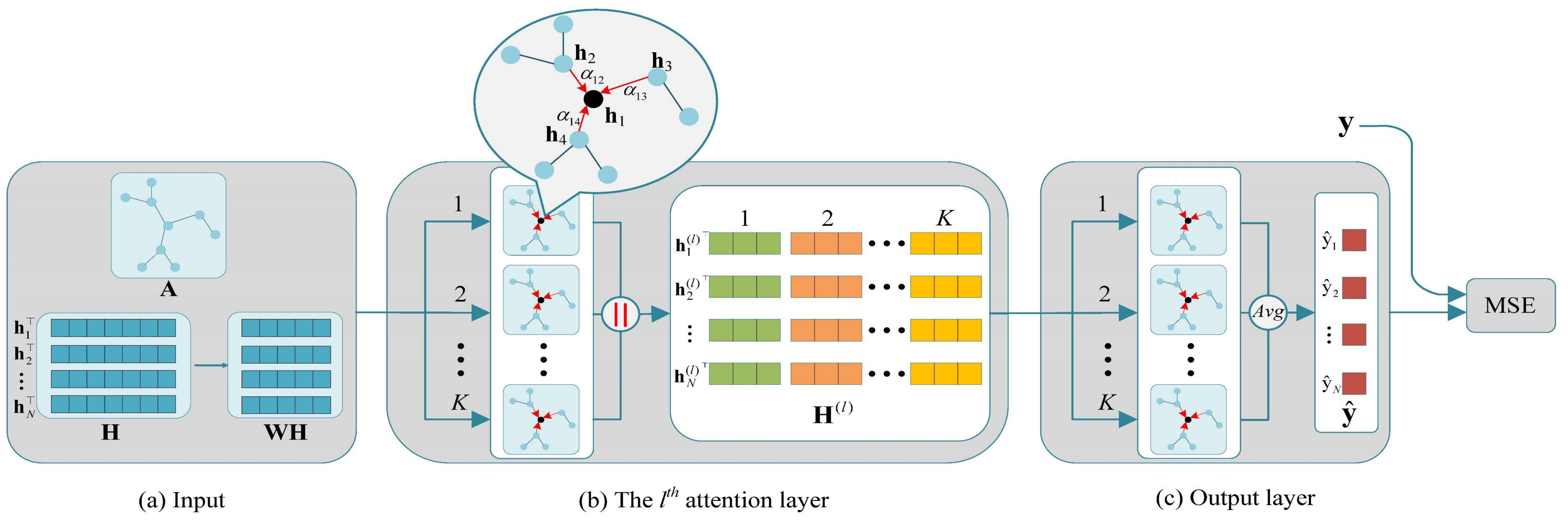
Algorithm 2 Proposed EAGAT for REU Estimating

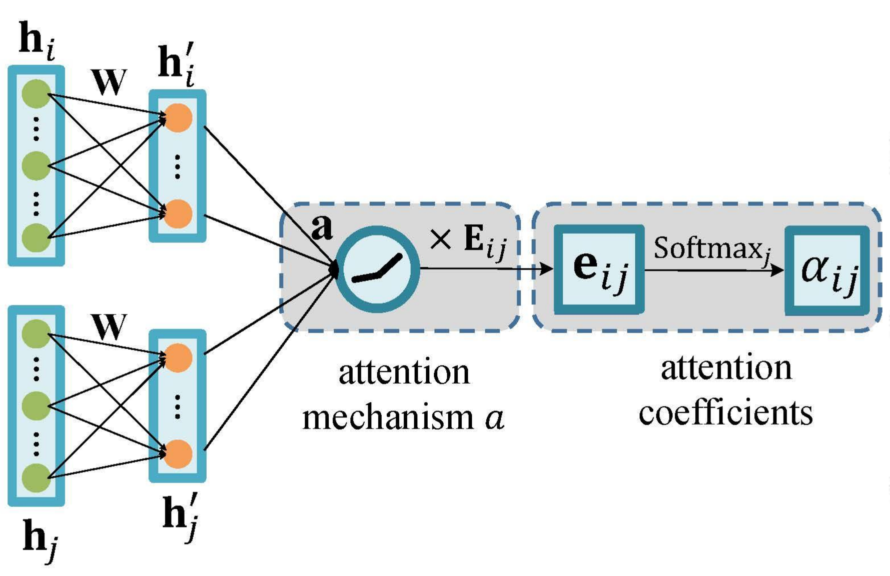
Input: Input Graph with $\mathbf{H}$ and $\mathbf{E}$; Neighborhood $\mathcal{N}$; number of iterations T; learning rate η; number of graph convolutional layers L; number of attention heads K;

// Train the model
for $i = 1, 2, \ldots, T$ **do**
  Conduct EAGAT by Algorithm 1;
  Calculate the error term according to Eq. (13), and update the weight matrices $\mathbf{W}^k_{(l)} (1 \le l \ge L, 1 \le k \ge K)$ using full-batch gradient descent;
end for
Conduct prediction by Algorithm 1;

Output: REU prediction for each node in the graph.

Our Model





$$e_{ij} = a(\mathbf{W}\mathbf{h}_i, \mathbf{W}\mathbf{h}_j) \times \mathbf{E}_{ij}$$

$$\alpha_{ij} = \mathrm{softmax}_j(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(e_{ik})}$$

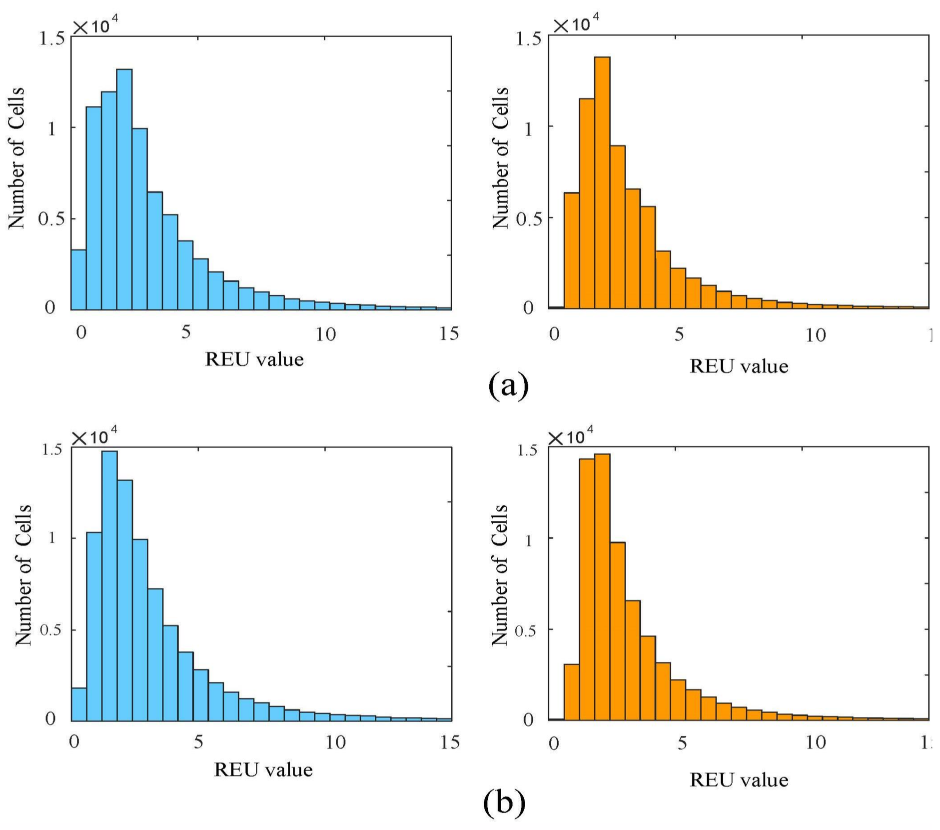
$$\alpha_{ij} = \frac{\exp(\mathrm{LeakyRelu}(\mathbf{a}^\top [\mathbf{W}\mathbf{h}_i || \mathbf{W}\mathbf{h}_j]) \times \mathbf{E}_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(\mathrm{LeakyRelu}(\mathbf{a}^\top [\mathbf{W}\mathbf{h}_i || \mathbf{W}\mathbf{h}_k]) \times \mathbf{E}_{ik})}$$

Experimental Results

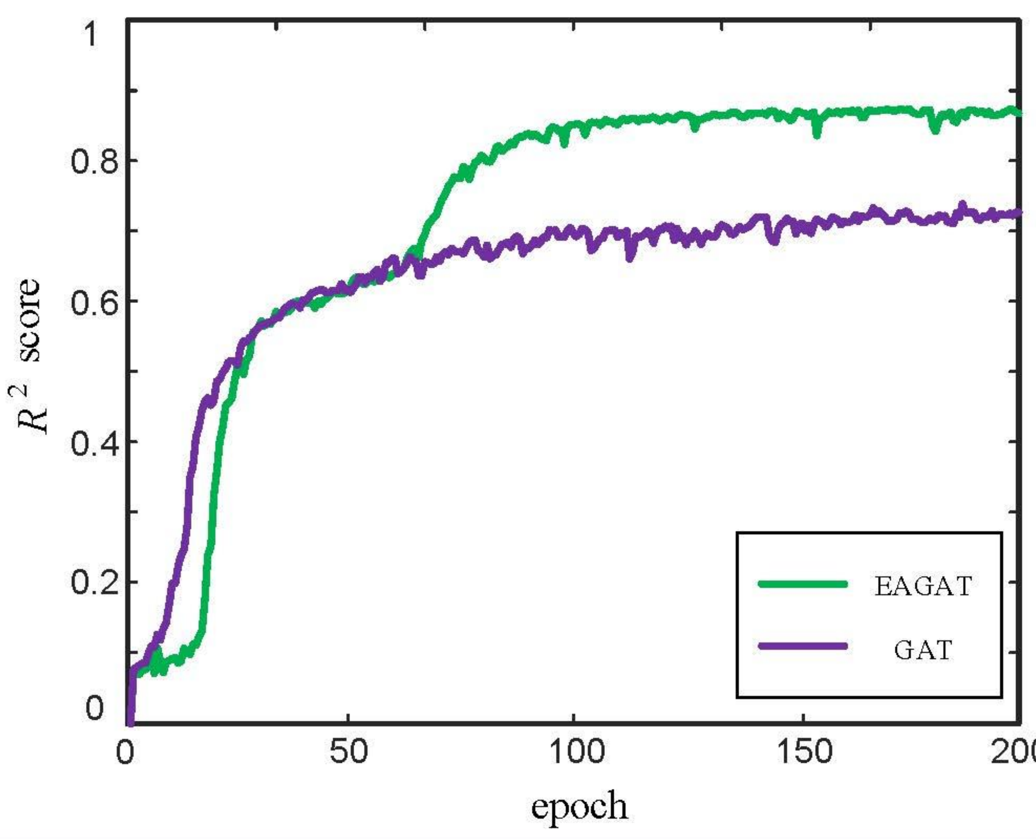
- **Regression Result**

Model	*Mobile_Spring*	*Mobile_Summer*
MLP [48]	0.602 ± 0.007	0.614 ± 0.006
RF [49]	0.610 ± 0.008	0.618 ± 0.007
GraphSAGE [23]	0.702 ± 0.010	0.712 ± 0.011
GAT [15]	0.721 ± 0.007	0.734 ± 0.013
EGNN [29]	0.733 ± 0.008	0.745 ± 0.009
EAGAT	$\mathbf{0.880 \pm 0.010}$	$\mathbf{0.891 \pm 0.008}$

- **Distribution**



- **Ablation study**



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