GNNet Challenge 1st place solution

Bruno Klaus de Aquino Afonso

PaRaNA - Pattern Recognition and Network Analysis group

Federal University of São Paulo (UNIFESP) - Brazil

1) Generalization on larger graphs

Possible approaches to predicting network delay

	Fast Enough?	Has top tier performance?	Generalizes to larger graphs?
Analytical	✓	✗	✓
Packet simulators	✗(prohibited)	✓	✓
RouteNet	✓	✓	✗
Proposed solution	✓	✓	✓

Table 1: Types of approaches

How can we generalize to larger graphs?

— We know that **the Analytic/Queueing Theory (QT) baseline is able to generalize well** to larger graphs

— We want features that are **invariant** w.r.t. to graph size. The baseline prediction is certainly that...

— Use Graph Neural Networks to **fine-tune** the baseline prediction

How can we generalize to larger graphs?

Raw path, link features:
Bad generalization

Raw features, divided by average number of packets generated (`p_AvgPktsLambda`):
Better generalization

Baseline features (path, link level prediction):
Best generalization

2) Model Architecture and Implementation

Implementation

- **Implemented from scratch in Pytorch + PyG**
  - Input had to be converted to **.pt** files

- **Two message-passing models:**
  - **Model 1:** Really big and takes longer to train
  - **Model 2:** Way smaller and achieves similar results
  - **Final submission:** Average of both!

Elements present in our model

- **Entities:**
  - Paths
  - Links
  - Nodes **(Model 1 only!)**
- **Types of Messages:**
  - Path-To-Link, Link-To-Path
  - Edge-To-Node, Node-To-Edge **(Model 1 only!)**
  - Path-To-Node, Node-To-Path **(Model 1 only!)**

Possible approaches to predicting network delay

Fixed Columns (contains initial features):

$$\mathbf{X}_P, \mathbf{X}_L, \mathbf{X}_N$$

Hidden state columns:

$$\mathbf{X}_{Ph}, \mathbf{X}_{Lh}, \mathbf{X}_{Nh}$$

Architectural differences v RouteNet

- Use **Graph Convolutional GRU** for Link-To-Path message passing
  - Links ordered according to path traversal

- The rest of the message passing uses **Graph Attention (GAT)** convolutions

- **Baseline features** are also kept unchanged during message passing rounds

Architectural differences

- **MLPs before and after** message passing
- Get **Link-level** predictions (avg. utilization), then:

$$\mathtt{delayLink}(i) = \mathtt{avg\_utilization}_i \times (\mathtt{queue\_size}_i / \mathtt{link\_capacity}_i)$$

$$\mathtt{pathDelay} \approx \sum_{i=0}^{\mathtt{n\_links}} \mathtt{delayLink}(i)$$

Algorithm 2 Model 2 (submitted on September 29th)

Require: $\boldsymbol{X}$ = `Concatenate([`$\boldsymbol{X}_P, \boldsymbol{X}_{Ph}, \boldsymbol{X}_L, \boldsymbol{X}_{Lh}, \boldsymbol{X}_N, \boldsymbol{X}_{Nh}$`],axis=1)`
Require: `baseline_path`, `baseline_link`: baseline predictions
Require: $\boldsymbol{E}$: network topology
Require: `NUM_iterations`: number of message-passing iterations

```
E_lp_list ← SeparateEdgeTimeSteps(E_LP)
X ← MLP_1(X, E_LN)
for 0 ≤ i < NUM_ITERATIONS do
                                                    ▷ Paths receive messages
    H ← None
    for 0 ≤ k < E_lp_list.length do
        H ← (GConvGRU_{0,link_to_path}(X, H, E_lp_list[k]))
    end for
    X_Ph ← LeakyRELU(H/(E_lp_list.length))
    (X_Ph)[:, 0:baseline_path.shape[1]] ← baseline_path
                                                    ▷ Links receive messages
    X_Lh ← LeakyRELU(Conv_{i,path_to_link}(X, E_PL))
    (X_Lh)[:, 0:baseline_link.shape[1]] ← baseline_link
end for
L ← Concatenate(X_L, X_Lh)
L ← Sigmoid(MLP_2(L))                   ▷ Predicts average queue utilization
return GetPathDelay(L, E_LP)                        ▷ Obtains per-path-delay
```

Full report:
https://github.com/brunoklaus/PARANA-GNNChallenge/blob/main/GNNET_2021_report.pdf

	# of hidden input columns	**MLP_1**	**MLP_2**
Model 1	$\boldsymbol{X}_{Ph}$:64 $\boldsymbol{X}_{Lh}$:64 $\boldsymbol{X}_{Nh}$:64	Seq(Linear(128), LeakyRELU(), Linear(inp_dim), LeakyRELU())	Seq(Linear(512), LeakyRELU(), Linear(512), LeakyRELU(), Linear(1))
Model 2	$\boldsymbol{X}_{Ph}$:8 $\boldsymbol{X}_{Lh}$:8	Seq(Linear(128), LeakyRELU(), Linear(inp_dim), LeakyRELU())	Seq(Linear(128), LeakyRELU(), Linear(32), LeakyRELU(), Linear(1))

	Baseline iterations	**Message passing iterations**
Model 1	5	3
Model 2	3	3

3) Results

Results

	Val. 1	Val. 2	Val. 3	Test
Model 1 (Sep 22nd)	2.71	1.33	1.65	1.45
Model 2 (Sep 29th)	3.61	1.17	1.55	1.45
(Model 1+ Model 2)/2	—	—	—	1.27
Baseline	12.10	9.18	9.51	?
Model 1 w/o baseline	—	—	—	22.58

-Also, using raw path/link metrics only and without division lead to >100% MAPE

-Using Baseline makes huge difference! (~5th to 1st place)

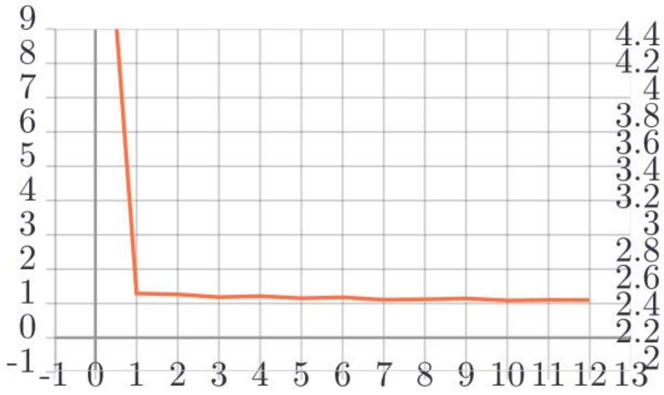

Figure 1: Training set

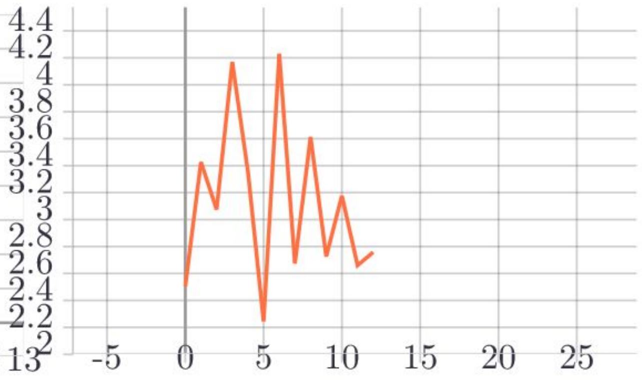

Figure 2: Validation set #1

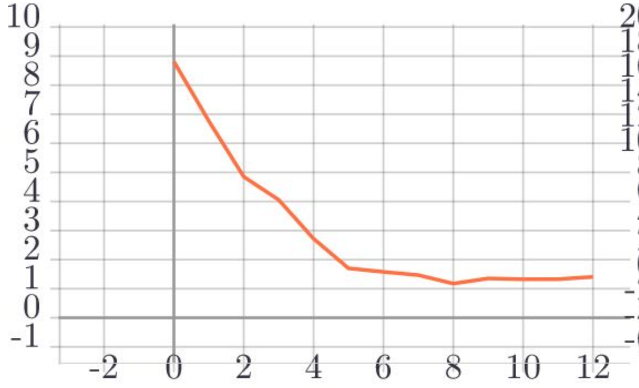

Figure 3: Validation set #2

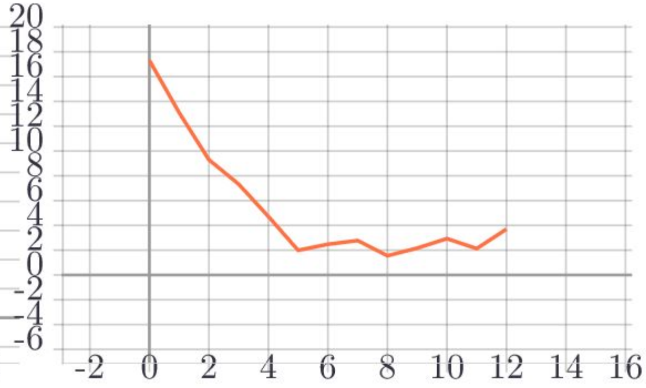

Figure 4: Validation set #3

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Thanks!

Any questions?

You can find me at:

- bruno.klaus@unifesp.br