
MAP583

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Introduction

- Two discussions
 - **Stability** : train a network and test it on another dataset
=> Generate new datasets on CPUs
 - **Performance** : modify the laplacian positional embedding (lap_pos_enc)
=> Train new networks on GPUs

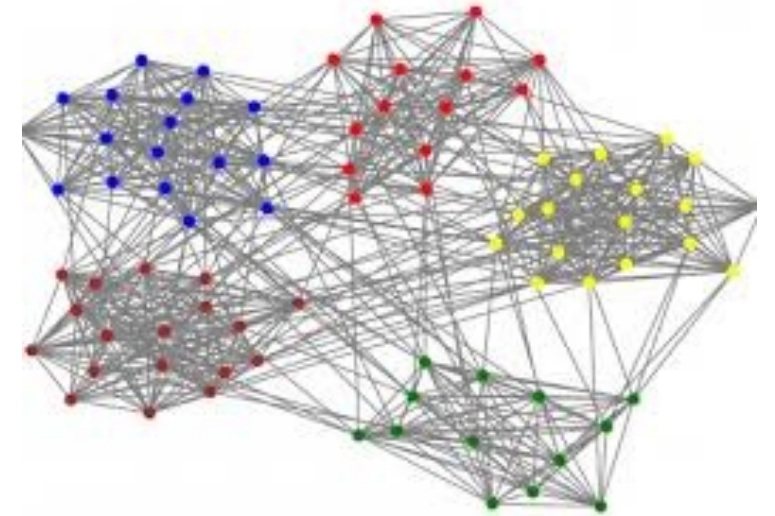
| GPU | Our experiments | Paper's experiments |
|------------------|-----------------------------------|---------------------------------|
| Material | 1 Nvidia Quatro 4000 8Go (~1000€) | 4 Nvidia 1080Ti 11Go (~4x1000€) |
| Epochs | 80 max | 1000 max |
| Computation time | 5h max per experiment | 24h max per experiment |

| Matériel CPU | Datasets created | Computation time/dataset |
|-----------------------------|------------------|--------------------------|
| 2 Intel Xeon E-2174 3.80GHz | 5 | 5h |

Table 2: presentation of the CPU and computation time

I-a\ Stability: the PATTERN dataset

- 5 communities are generated with the same probabilities for each block
- We add a 6th community with a different extra-link probability
- Communities' average size is 20
- The goal is to classify the dataset and find which individuals belong to the 6th community

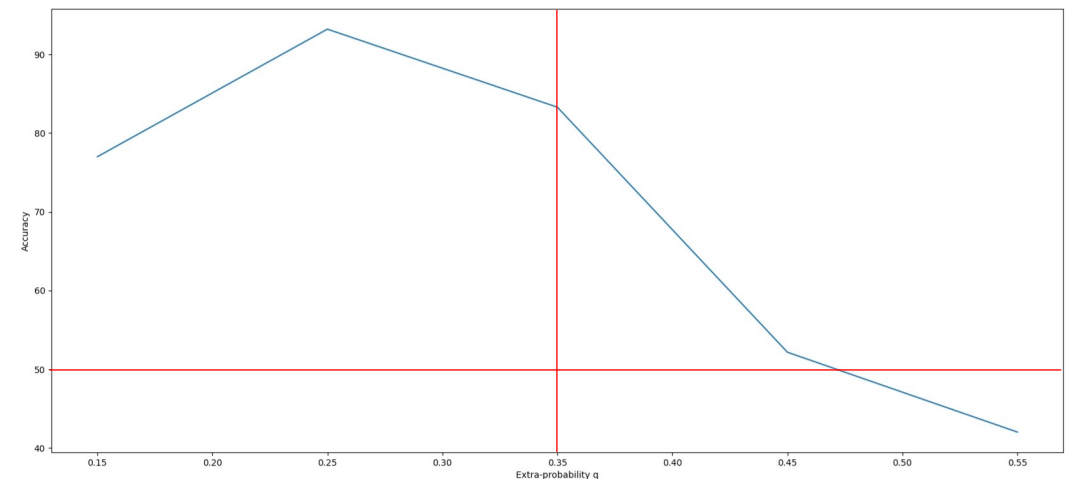


PATTERN: The graph pattern recognition task, presented in [75], aims at finding a fixed graph pattern P embedded in larger graphs G of variable sizes. For all data, we generate graphs G with 5 communities with sizes randomly selected between $[5, 35]$. The SBM of each community is $p = 0.5, q = 0.35$, and the node features on G are generated with a uniform random distribution with a vocabulary of size 3, *i.e.* $\{0, 1, 2\}$. We randomly generate 100 patterns P composed of 20 nodes with intra-probability $p_P = 0.5$ and extra-probability $q_P = 0.5$ (*i.e.*, 50% of nodes in P are connected to G). The node features for P are also generated as a random signal with values $\{0, 1, 2\}$. The graphs are of sizes 44-188 nodes. The output node labels have value 1 if the node belongs to P and value 0 if it is in G .

I-b\ Stabilité : faire varier q

- When $q < 0.35$, it's easier at first to find the different community
- However, when $|q_{extra} - q|$ is big, the model starts to lose accuracy.
- The 20 epochs model seems to generalize better than the 80 epochs one.

| q | Model 20 epochs | Model 80 epochs |
|-----------------------|-----------------|-----------------|
| 0.15 | <u>77.0046</u> | 69.1981 |
| 0.25 | <u>93.2172</u> | 92.2461 |
| 0.35 (original model) | 83.2934 | <u>84.7762</u> |
| 0.45 | <u>52.1648</u> | 51.5637 |
| 0.55 | <u>42.0210</u> | 41.8587 |



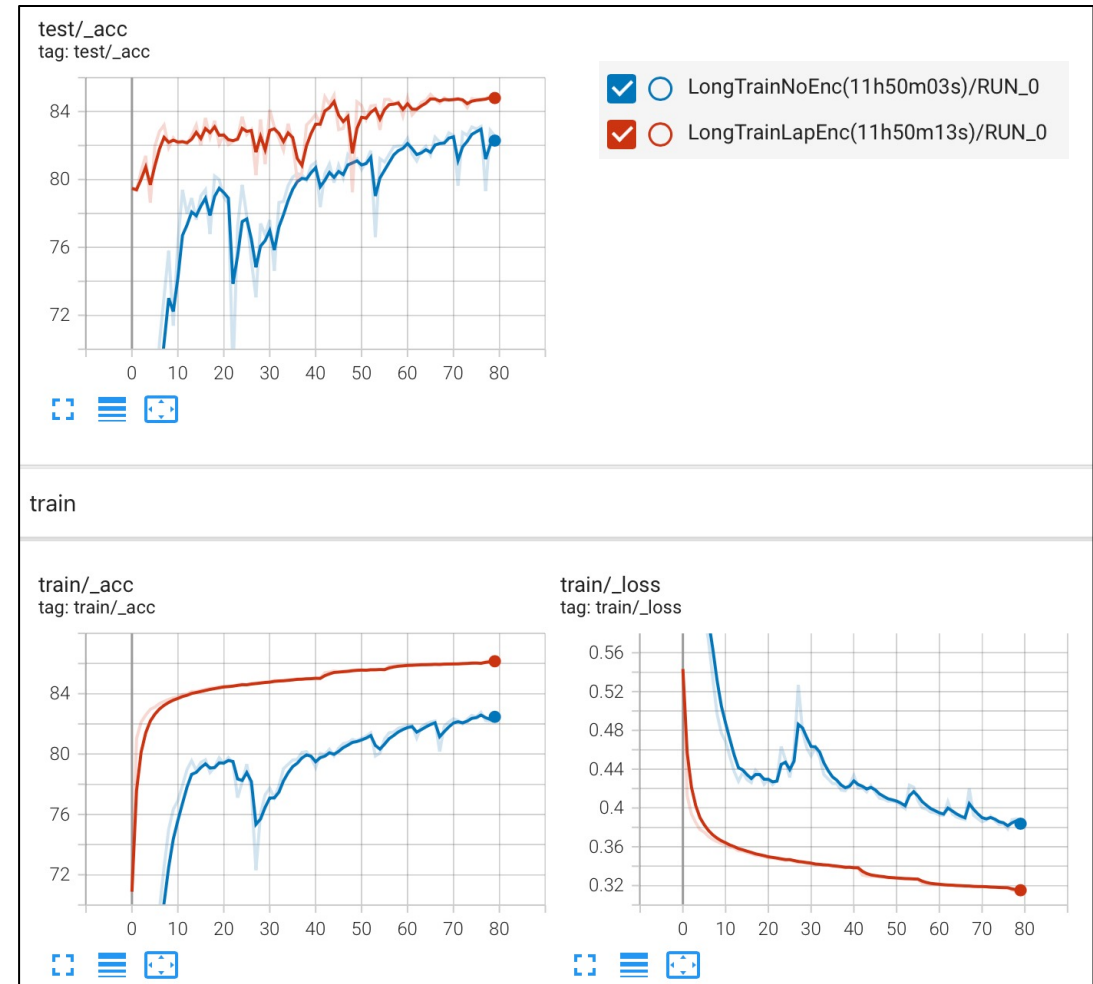
I-c\ Stability: size of the dataset

- As we could expect, the bigger the graph, the harder it is for the model
- The 20 epochs model seems to generalize better than the 80 epochs one

| Communities sizes | Model 20 epochs | Model 80 epochs |
|-------------------------------------|-----------------------|-----------------------|
| Uniform between 5 and 35 (original) | 83.2934 | <u>84.7762</u> |
| Uniform between 35 and 65 | <u>68.4562</u> | 65.9456 |
| Uniform between 65 and 95 | <u>39.8145</u> | 33.6427 |

2-a\ Performance – With or without embedding ?

- Much faster and precise training with the embedding.
- The gap is smaller and smaller with training
- About 20% accuracy gap for the first epoch.



2-b\ Performance – Exponential factors

- Exponential: give more weight to smaller eigenvalues :

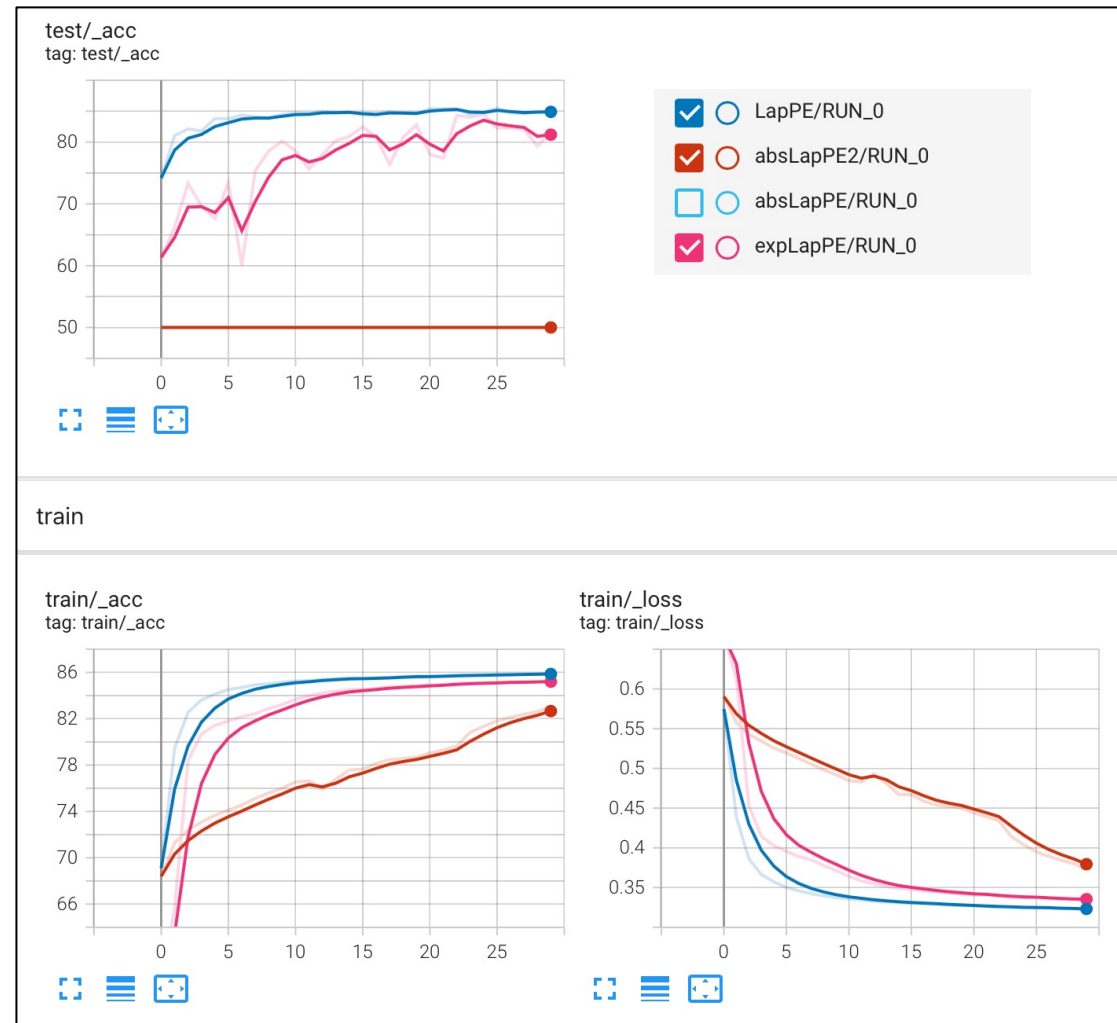
$$(U_1, \dots, U_n) \Leftarrow (U_1 \exp^{-|\lambda_1|}, \dots, U_n \exp^{-|\lambda_n|})$$

- Absolute value: increase sign symmetry:

$$(U_1, \dots, U_n) \Leftarrow (|U_1|, \dots, |U_n|)$$

2-b\ Performance - Exponential factors

- Results:



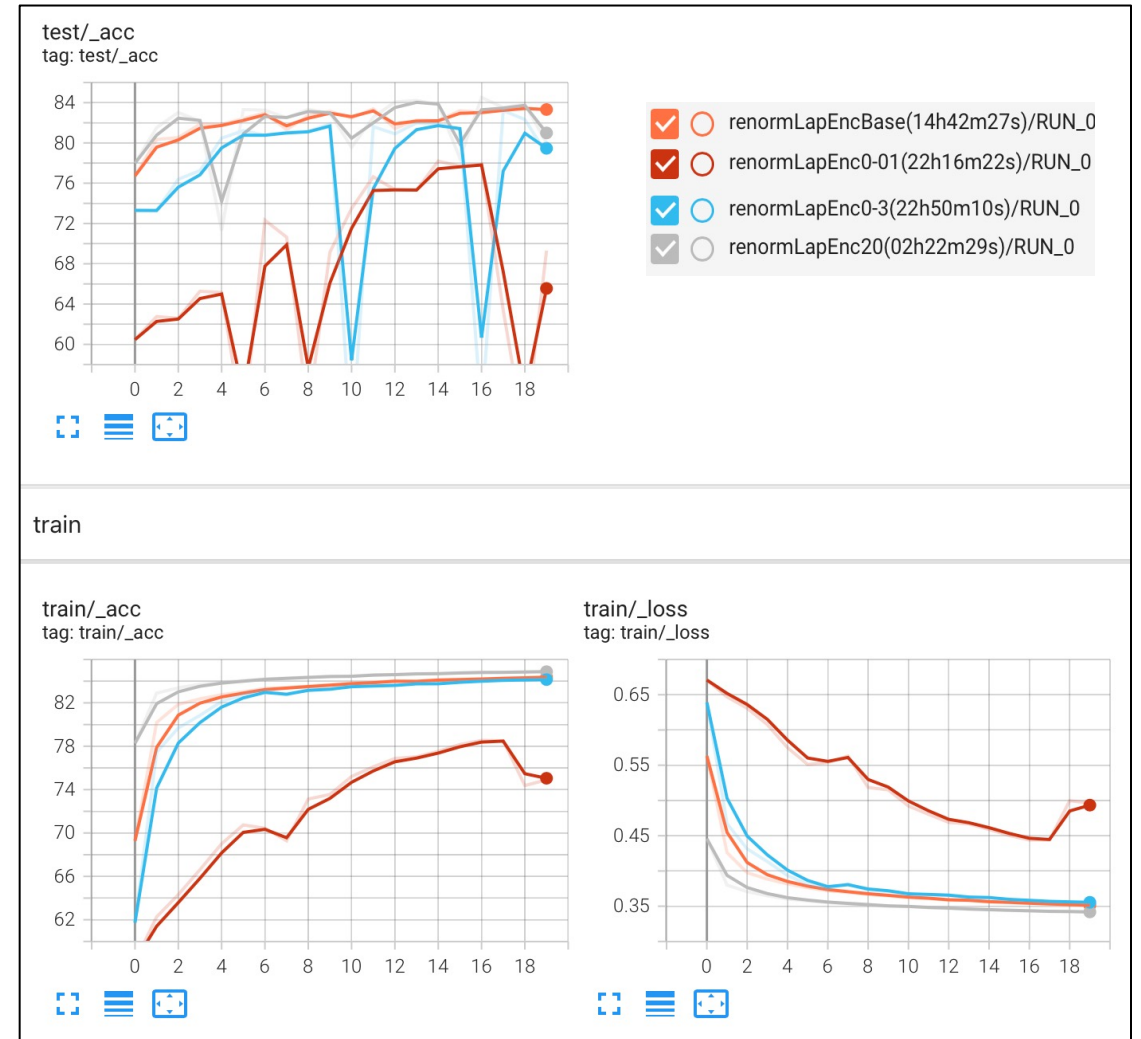
2-c\ Performance - Homothety

- Homothety :

$$(U_1, \dots, U_n) \Leftarrow h \times (U_1, \dots, U_n)$$

- In theory: no change due to the neural network

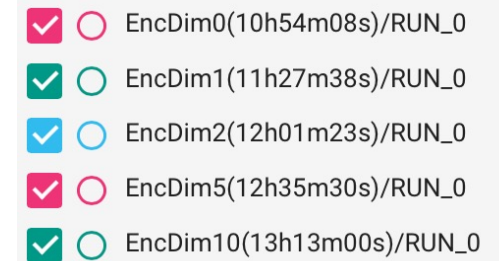
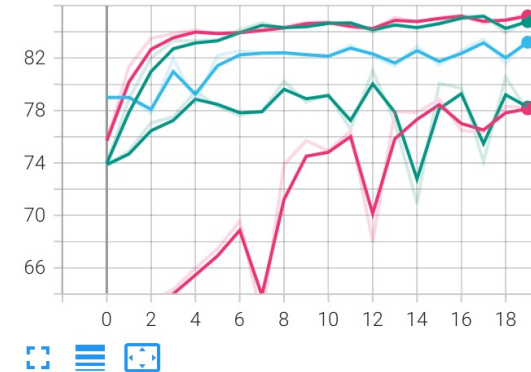
- In practice: difference since the signal is harder for the network to pick up information



2-d\ Performance - Dimension

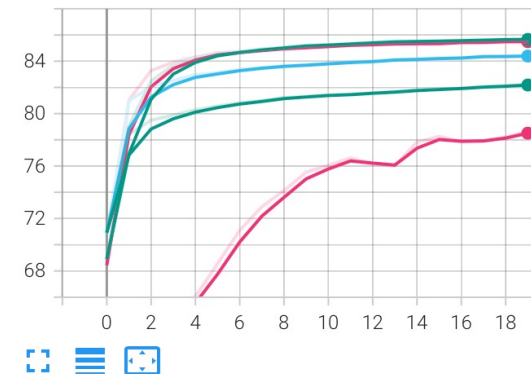
- The code of the paper uses the $k=2$ smallest eigenvalues of the Laplacian by default.
- Better performances can be achieved with $k=5$ in the long run. Few changes for $k>5$.

test/_acc
tag: test/_acc

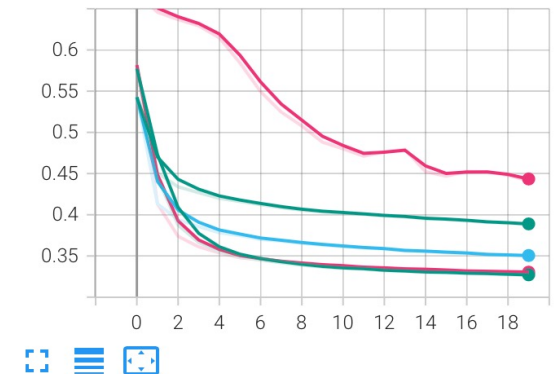


train

train/_acc
tag: train/_acc



train/_loss
tag: train/_loss





Thank you !

