Network Traffic Prediction based on Diffusion Convolutional Recurrent Neural Networks

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Introduction

- Increasing complexity of modern telecom networks

Predicting traffic load on network

-> Effectively pre-dispose resource-allocation strategies

(e.g. incoming congestion event)

Introduction

None of the existing methods explicitely considers the **topological information** of the network

-> ML designed graph-based structures emerged recently

use filters **suitable for graphs** to capture hidden patterns among nodes

[11],[12] generalize CNNs for graph processing and node classification

[3] proposed the diffusion convolution operator and build ML algorithms

=> used to perform traffic forecasting on road traffic in [3], [13]

[3] Y. Li, R. Yu, C. Shahabi, and Y. Liu, "Diffusion convolutional recurrent neural network: Data-driven traffic forecasting," 2018.
[11] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," *arXiv preprint arXiv:1609.02907*, 2016.
[12] M.Defferrard,X.Bresson,andP.Vandergheynst,"Convolutionalneural networks on graphs with fast localized spectral filtering," in *Advances in Neural Information Processing Systems*, 2016, pp. 3844–3852.
[13] X. Wang, C. Chen, Y. Min, J. He, B. Yang, and Y. Zhang, "Efficient metropolitan traffic prediction based on graph recurrent neural network," arXiv preprint arXiv:1811.00740, 2018.

Introduction

None of the existing methods explicitely considers the **topological information** of the network

-> ML designed graph-based structures emerged recently

use the **same methodology** to forecast the load

use filters **suitable for graphs** to capture hidden patterns among nodes

on the links of a telecommunication network

[11],[12] generalize CNNs for graph processing and node classification

[3] proposed the diffusion convolution operator and build ML algorithms

=> used to perform traffic forecasting on road traffic in [3], [13]

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Research Objectives

Use Diffusion Convolutional Recurrent Neural Network (**DCRNN**)

- Predict the load on network links given historical records of traffic loads
- focusing on **predicting traffic loads** and considering **topological information**

Dataset

- Consider backbone Abilene network
  - Available topology and trace of real traffic crossing
    (topology characterized by 12 nodes and 30 unidirectional links)
  - Slots of 5mins, from 01,03,2004 to 10,09,2004
- Window size : 1hour
- Grouped together in sequences of 10 vectors
- Obtained 30X30 adjacency matrix

Model Architecture

- DCRNN
  - Sequence-to-sequence deep learning architecture
  - Consists of encoder and decoder

  - Input
    - Topologic traffic load data (30X30 matrix)
  - Output
    - Traffic load at time t+1 (30)

Model Architecture

Encoder

- Mapping between input and fixed-sized encoding vector

Decoder

- How to map encoding vector to output sequence

Layer

- Composed of DCGRU(Diffusion Convolutional Gated Recurrent Unit)

DCRNN composed of 2 Layers with 4DCGRU units each

Experiment

- Evaluation Metric

    1. MAPE (Mean Absolute Percentage Error)
    2. MAE (Mean Absolute Error)
    3. Root Mean Squared Error (RMSE)
    4. Convergence Epoch
    5. Convergence Time

Experiment

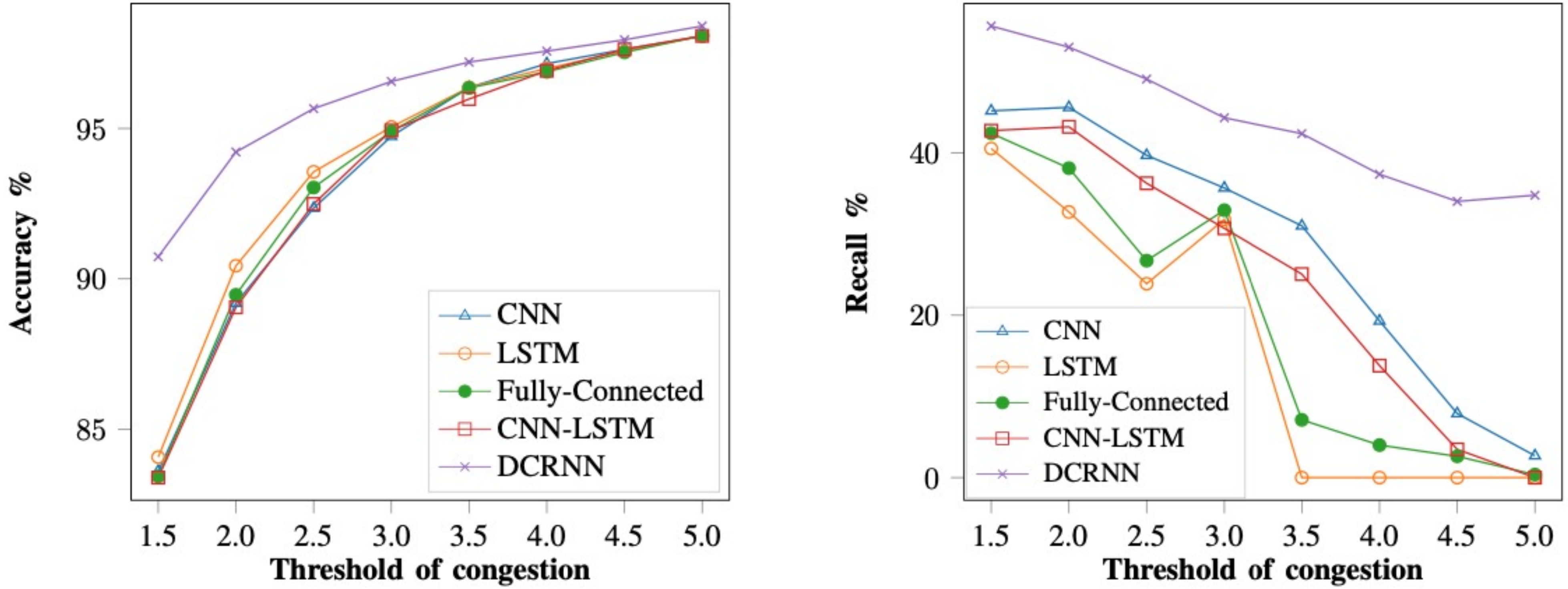
- Compare with
  - LSTM-based network
  - CNN-based network
  - CNN-LSTM-based network
  - Fully-Connected Neural Network

Experiment

TABLE I
COMPARISON OF THE DEEP LEARNING ARCHITECTURES CONSIDERING THEIR ABILITY TO PERFORM THE FORECAST OF THE NEXT TRAFFIC LOAD

	MAPE	MAE (Mbit/s)	RMSE (Mbit/s)	Convergence Epoch	Convergence Time (sec)
DCRNN	**43.2%**	**92.5**	**497.1**	225	525.1
LSTM	210.34%	142.43	525.21	**87**	19.83
CNN	234.75%	121.32	506.55	252	9.82
CNN-LSTM	248.16%	127.18	512.91	240	5.76
Fully-Connected	220.75%	138.24	522.65	201	**3.14**

Result



(a) *Accuracy of the effectiveness to detect a congestion event*

(b) *Recall of the effectiveness to detect a congestion event*

Fig. 1. Comparison of all the methods considering the ability to detect a congestion event in terms of Accuracy and Recall

Result

TABLE III
COMPARISON OF THE DEEP LEARNING ARCHITECTURES CONSIDERING THEIR ABILITY TO DETECT A CONGESTION EVENT WHEN THRESHOLD FACTOR $\alpha = 3$

	TP	TN	FP	FN	Accuracy	Precision	Recall	F-score
DCRNN	**1,97**	**94,70**	**0,93**	**2,40**	**96,67**	**67,93**	**45,01**	**54.14**
LSTM	1,14	93,64	1,92	3,03	95,05	42,37	31,80	36,33
CNN	1,58	93,15	2,40	2,85	94,74	41.86	35,67	37,85
CNN-LSTM	1,36	93,57	1,98	3,08	94,93	40,71	30.70	34,93
Fully-Connected	1,15	93,44	2.11	0.029	94,91	41,31	32,94	36,45

Conclusion

- This research employs DCRNN to predict the next traffic load
- DCRNN focuses on both traffic load characteristics and the topological relations
  (i.e., whether the links are connected or not).
- DCRNN demonstrates significant improvements in forecasting

ML approaches designed to capture both event properties and network structure can greatly benefit event prediction in telecom networks