Faculdade de Computação

Programa de Pós-Graduação em Ciência da Computação

Universidade Federal de Uberlândia

A Mobile Traffic Predictor Enhanced by Neighboring Transportation Data (MTP-NT)

Patrick Luiz de Araújo

Defesa de dissertação de mestrado em 21/11/2023

Contents

Introduction

5 billion

5G subscribers in 2028

19 GB/month

Data per month, per smartphone in 2028

100 exabytes

Data per quarter in 2028

Fonte: Ericsson Mobility Report, November 2022

Introduction

To

Allocate the maximum amount of users

Optimize network operability

Reach 5G QoS/QoE metrics[1]

- **1ms latency**
- **low energy consumption**
- **High coverage**

New 5G networks will count on

Core Network (CN) based on Virtual Network Functions (VNF) over a Network Function Virtualization (NFV)[2] topology

Use Machine Learning (ML) and other predictive tools

- **Intelligent caching in network edge**
- **Cloud computing optimization**

[1] AGIWAL, M.; ROY, A.; SAXENA, N. Next generation 5g wireless networks: A comprehensive survey. IEEE Communications Surveys Tutorials, v. 18, n. 3, p. 1617–1655, 2016.
[2] Sun, Y. et al. Application of machine learning in wireless networks: Key techniques and open issues. IEEE Communications Surveys Tutorials, v. 21, n. 4, p. 3072–3108, 2019.

Introduction

AI models advantages

- **Rely on historical data[1,2,3]**
- **Can be less complex than conventional approaches[4]**
- **Robust patterns and best overall performance[5]**

[1] Wang, X. et al. Spatio-temporal analysis and prediction of cellular traffic in metropolis. In: 2017 IEEE 25th International Conference on Network Protocols (ICNP). [S.l.: s.n.], 2017. p. 1–10
[2] Wang, J. et al. Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach. In: IEEE INFOCOM 2017 - IEEE Conference on Computer Communications. [S.l.: s.n.], 2017. p. 1–9.
[3] CHEN, X. et al. Analyzing and modeling spatio-temporal dependence of cellular traffic at city scale. In: 2015 IEEE International Conference on Communications (ICC). [S.l.: s.n.], 2015. p. 3585–3591.
[4] SUN, H. et al. Learning to optimize: Training deep neural networks for wireless resource management. In: 2017 IEEE 18th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC). [S.l.: s.n.], 2017. p. 1–6.
[5] Sun, Y. et al. Application of machine learning in wireless networks: Key techniques and open issues. IEEE Communications Surveys Tutorials, v. 21, n. 4, p. 3072–3108, 2019.

Introduction

Mobile Traffic Predictor Enhanced by Neighboring Transportation Data (MTP-NT)

Is a

Machine Learning model

That

Helps the scheduler to better optimize the computational and/or radio resources

By

Providing a reliable network traffic prediction

Mobile Traffic Predictor Enhanced by Neighboring Transportation Data **MTP-NT**

City of Milan Dataset[1]

- **Network usage**
- **Geolocalized tweets**
- **Weather**
- **Electricity**
- **News**

[1] Barlacchi, G. et al. A multi-source dataset of urban life in the city of milan and [illegible]he province of trentino. Sci Data 2, [illegible]5.)

Mobile Traffic Predictor Enhanced by Neighboring Transportation Data MTP-NT

City of Milan Dataset[1]

- Network usage
- Geolocalized tweets
- Weather
- Electricity
- News

Scalable public transport and neighboring data

Open source

[1] Barlacchi, G. et al. A multi-source dataset of urban life in the city of milan and the province of trentino. Sci Data 2,

Mobile Traffic Predictor Enhanced by Neighboring Transportation Data MTP-NT

City of Milan Dataset[1]

- Network usage
- Geolocalized tweets
- Weather
- Electricity
- News

Scalable public transport and neighboring data

Open source

Lightweight, adaptable and highly performant

[1] Barlacchi, G. et al. A multi-source dataset of urban life in the city of milan and he province of trentino. Sci Data 2,

Mobile Traffic Predictor Enhanced by Neighboring Transportation Data MTP-NT

City of Milan Dataset[1]

- Network usage
- Geolocalized tweets
- Weather
- Electricity
- News

Scalable public transport and neighboring data

Open source

Lightweight, adaptable and highly performant

State-of-art performance

[1] Barlacchi, G. et al. A multi-source dataset of urban life in the city of milan and the province of trentino. Sci Data 2, [illegible]5)

Contents

Related work

Characterization

Metrics and mathematical characteristics of network usage

Prediction

Mathematical models to predict network traffic

Characterization – Xu

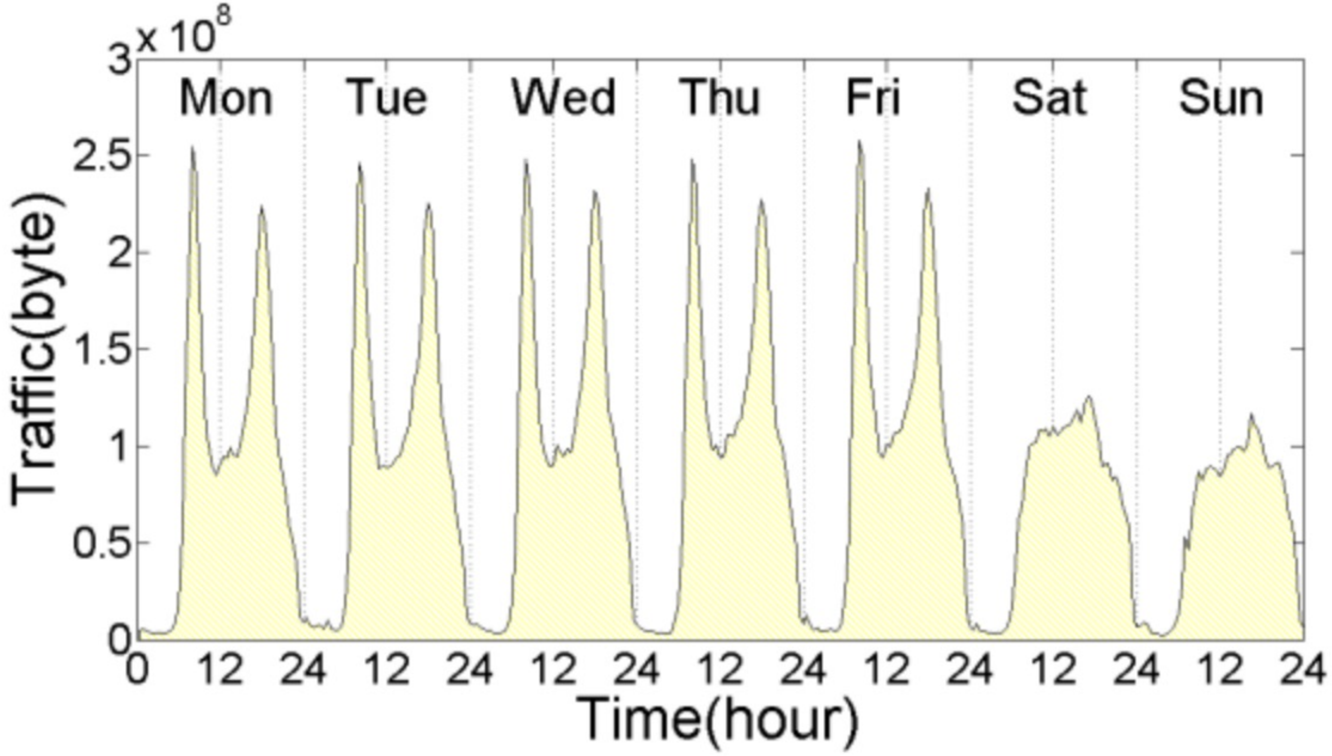
Characteristics of traffic: temporal and frequency

Grouping of regions based on network usage patterns

- **Residential**
- **Transport**
- **Office**
- **Entertainment**
- **Comprehensive areas**

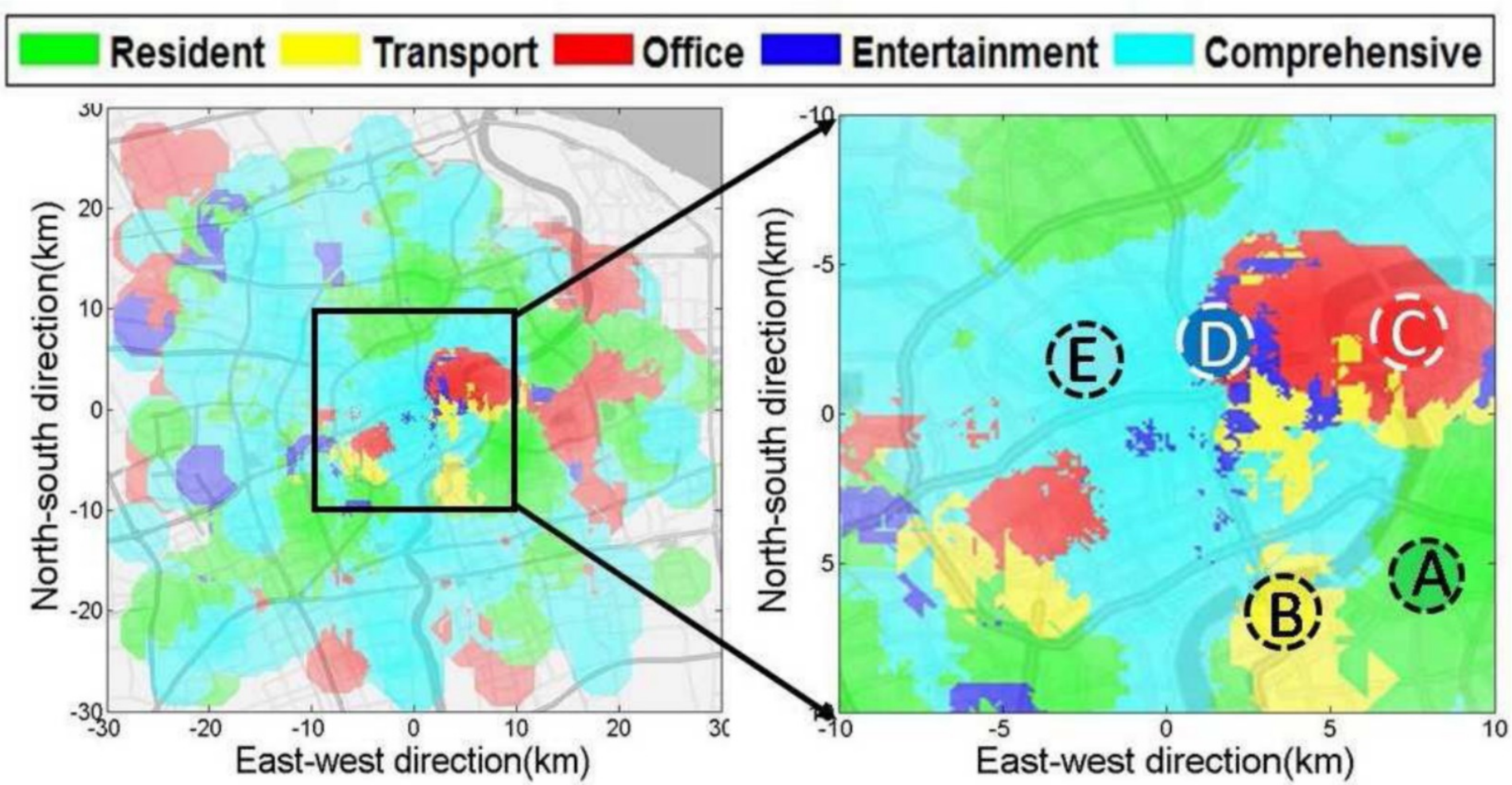
Human labelling of some regions to generalization

Characterization – Xu



Source: Xu, F. et al. **Understanding mobile traffic patterns of large scale cellular towers in urban environment**. IEEE/ACM Transactions on Networking, v. 25, n. 2, p. 1147–1161, 2017.

Characterization – Xu



Source: Xu, F. et al. **Understanding mobile traffic patterns of large scale cellular towers in urban environment**. IEEE/ACM Transactions on Networking, v. 25, n. 2, p. 1147–1161, 2017.

Characterization – Wang 2015

380,000 Base Stations (BSs) in Shanghai

August 1 – August 31, 2014

10 minute samples of each Base Station (BS)

1.96 billion entries; 28PB (92TB per day, 7GB per BS on average)

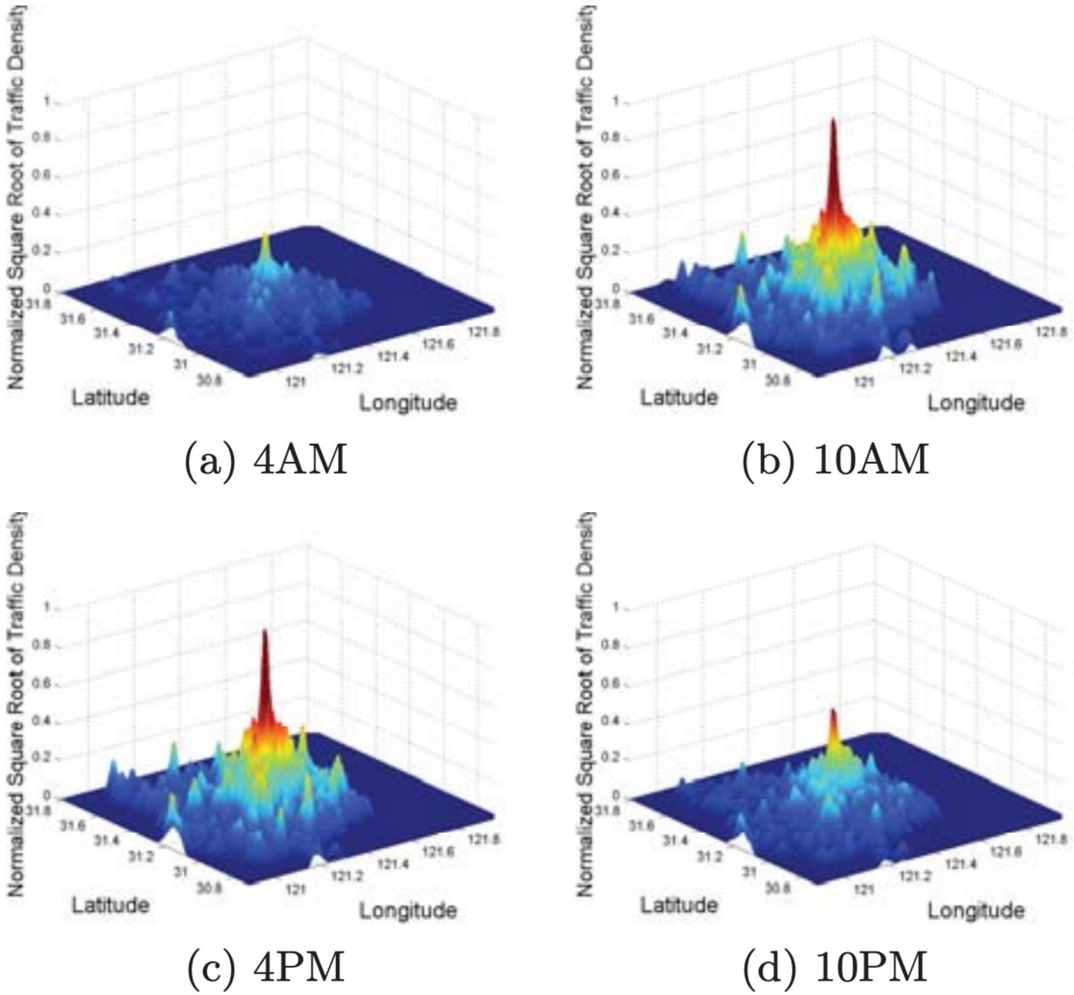
Source: WANG, H. et al. **Characterizing the spatio-temporal inhomogeneity of mobile traffic in large-scale cellular data networks**. In: Proceedings of the 7th International Workshop on Hot Topics in Planet-Scale MObile Computing and Online Social NeTworking. New York, NY, USA: Association for Computing Machinery, 2015. (HOTPOST ’15), p. 19–24. ISBN 9781450335171. Disponível em: <https://doi.org/10.1145/2757513.2757518>.

Characterization – Wang 2015

Findings

Spatial and temporal distribution of network traffic highly concentrated

Source: WANG, H. et al. **Characterizing the spatio-temporal inhomogeneity of mobile traffic in large-scale cellular data networks**. In: Proceedings of the 7th International Workshop on Hot Topics in Planet-Scale MObile Computing and Online Social NeTworking. New York, NY, USA: Association for Computing Machinery, 2015. (HOTPOST ’15), p. 19–24. ISBN 9781450335171. Disponível em: <https://doi.org/10.1145/2757513.2757518>.

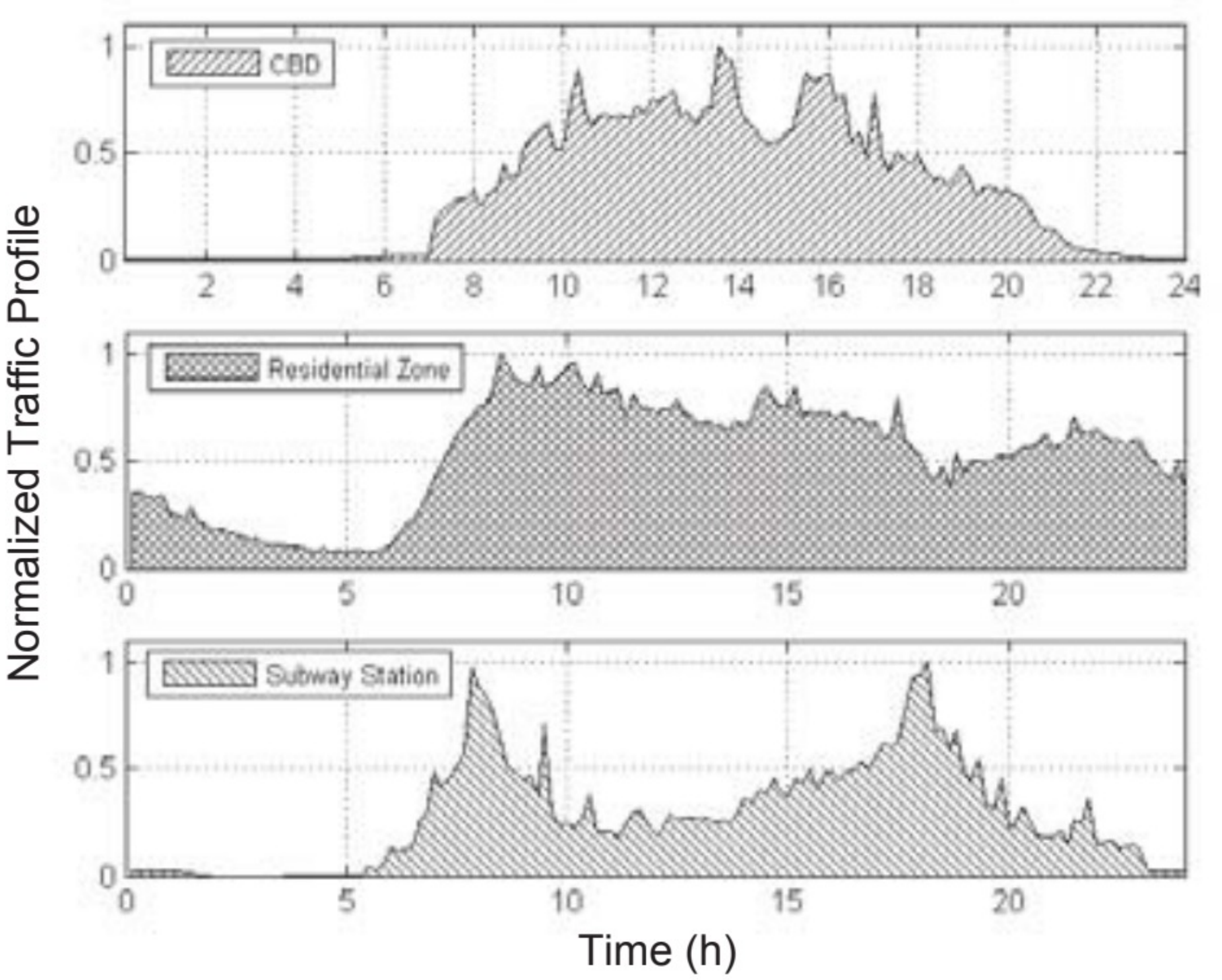


(a) 4AM (b) 10AM (c) 4PM (d) 10PM

Characterization – Wang 2015

Findings

Irregular usage depending on the urban ecology



Source: WANG, H. et al. **Characterizing the spatio-temporal inhomogeneity of mobile traffic in large-scale cellular data networks**. In: Proceedings of the 7th International Workshop on Hot Topics in Planet-Scale MObile Computing and Online Social NeTworking. New York, NY, USA: Association for Computing Machinery, 2015. (HOTPOST '15), p. 19–24. ISBN 9781450335171. Disponível em: <https://doi.org/10.1145/2757513.2757518>.

Characterization – Gotzner

Network traffic in Berlin

May 1996 – August 1997

Findings

- **Traffic concentrated in city centre**
- **Congestions in peak hours**
- **Network resources not fully used in other points**
- **The infrastructure reaches the maximum capacity before all processing power request**

Source: Gotzner, U.; Rathgeber, R. **Spatial traffic distribution in cellular networks**. In: VTC'98. 48th IEEE Vehicular Technology Conference. Pathway to Global Wireless Revolution (Cat. No.98CH36151). [S.l.: s.n.], 1998. v. 3, p. 1994–1998 vol.3.

Network Traffic Prediction

Pure Time Series Function (TSF) and Non-TSF problem[1]

1989

1991

2017

2021

AutoRegressive Moving Average (ARIMA) and Neural Network model training with Simulated Annealing (SA)[7]

In-tower and inter-tower traffic analysis through a Graph Neural Network (GNN)[6]

Recurrent Neural Network and usage of global + local autoencoders[5]

MLP to network traffic forecasting[4]

Single Layer Perceptron (SLP) to traffic perdiction[3]

Multi Layer Perceptrion (MLP) to traffic perdiction[2]

[1] BOUTABA, R. et al. A comprehensive survey on machine learning for networking: evolution, applications and research opportunities. Journal of Internet Services and Applications, Springer, v. 9, n. 1, p. 1–99, 2018.

[2] CYBENKO, G. Approximation by superpositions of a sigmoidal function. Mathematics of control, signals and systems, Springer, v. 2, n. 4, p. 303–314, 1989.[3] Funahashi, 1989

[4] HORNIK, K. Approximation capabilities of multilayer feedforward networks. Neural networks, Elsevier, v. 4, n. 2, p. 251–257, 1991.[5] Wang, 2017a

[5] FUNAHASHI, K.-I. On the approximate realization of continuous mappings by neural networks. Neural networks, Elsevier, v. 2, n. 3, p. 183–192, 1989.

[6] Wang, X. et al. Spatio-temporal analysis and prediction of cellular traffic in metropolis. In: 2017 IEEE 25th International Conference on Network Protocols (ICNP). [S.l.: s.n.], 2017. p. 1–10.

[7] YANG, H. et al. A network traffic forecasting method based on sa optimized arima–bp neural network. Computer Networks, v. 193, p. 108102, 2021. ISSN 1389-1286. Disponível em: <https://www.sciencedirect.com/science/article/pii/ S1389128621001821>.

Prediction – Wang 2017a

2844 Base Stations (BSs) in Suzhou

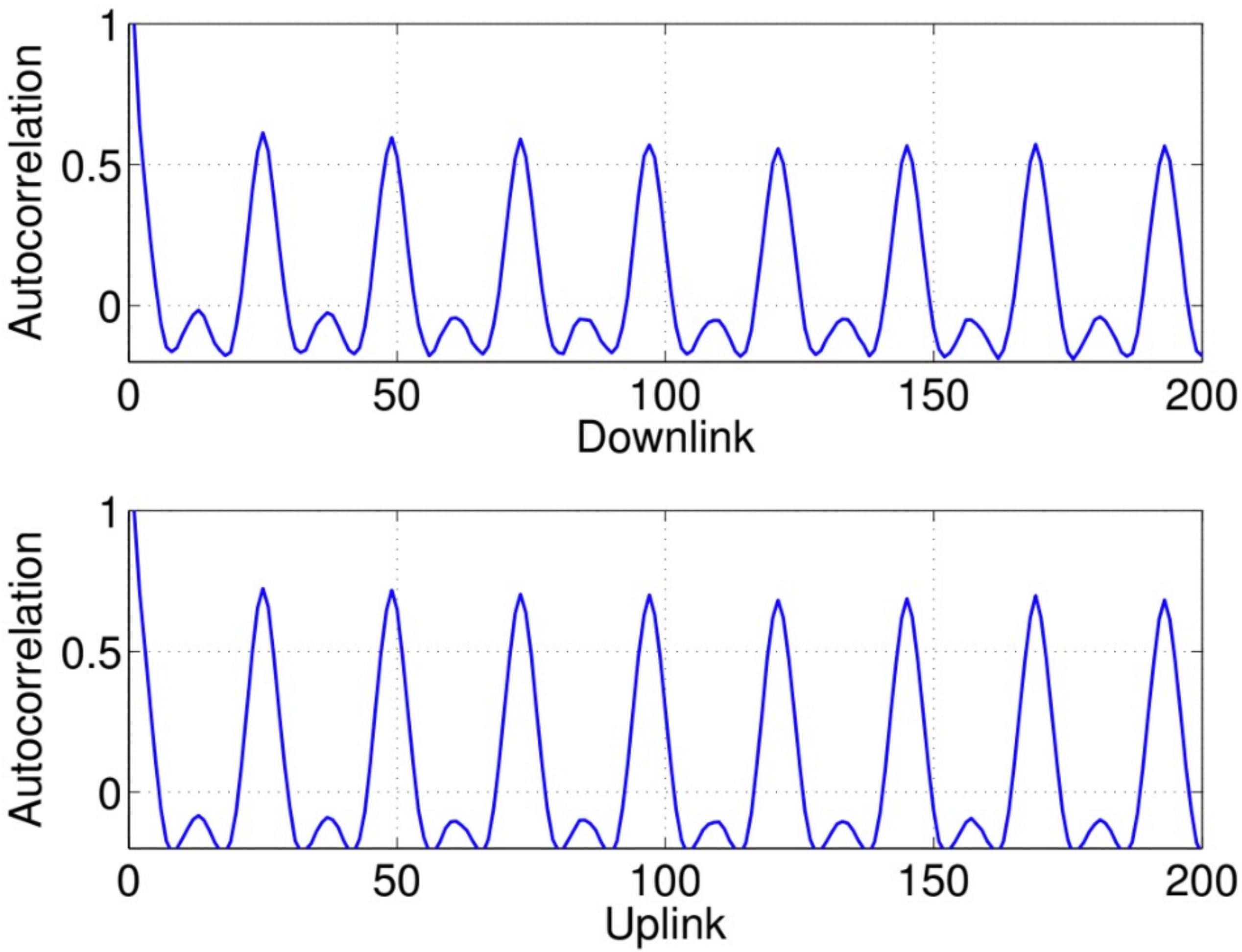
$500m^2$x $500m^2$

Uses the neighborhood concept

LSTM Cells paired with Global and Local Autoencoders

Source: Wang, J. et al. Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach. In: **IEEE INFOCOM 2017 - IEEE Conference on Computer Communications**. [S.l.: s.n.], 2017. p .1–9.

Prediction – Wang 2017a



Source: Wang, J. et al. Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach. In: **IEEE INFOCOM 2017 - IEEE Conference on Computer Communications**. [S.l.: s.n.], 2017. p. 1–9.

Prediction – Wang 2017a

Table 1 – Spatial correlation of a arrange of 7 BSs

	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6	Cell 7
Cell 1	1.000	0.167	0.435	0.130	0.040	0.341	0.307
Cell 2	0.396	1.000	0.338	0.129	0.084	0.310	0.222
Cell 3	0.345	0.541	1.000	0.159	0.162	0.697	0.536
Cell 4	0.437	0.439	0.458	1.000	0.104	0.131	0.114
Cell 5	0.360	0.471	0.492	0.508	1.000	0.163	0.080
Cell 6	0.286	0.491	0.550	0.432	0.535	1.000	0.603
Cell 7	0.284	0.506	0.526	0.459	0.535	0.577	1.000

Source: Wang, J. et al. Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach. In: **IEEE INFOCOM 2017 - IEEE Conference on Computer Communications**. [S.l.: s.n.], 2017. p. 1–9.

Prediction – Wang 2017a

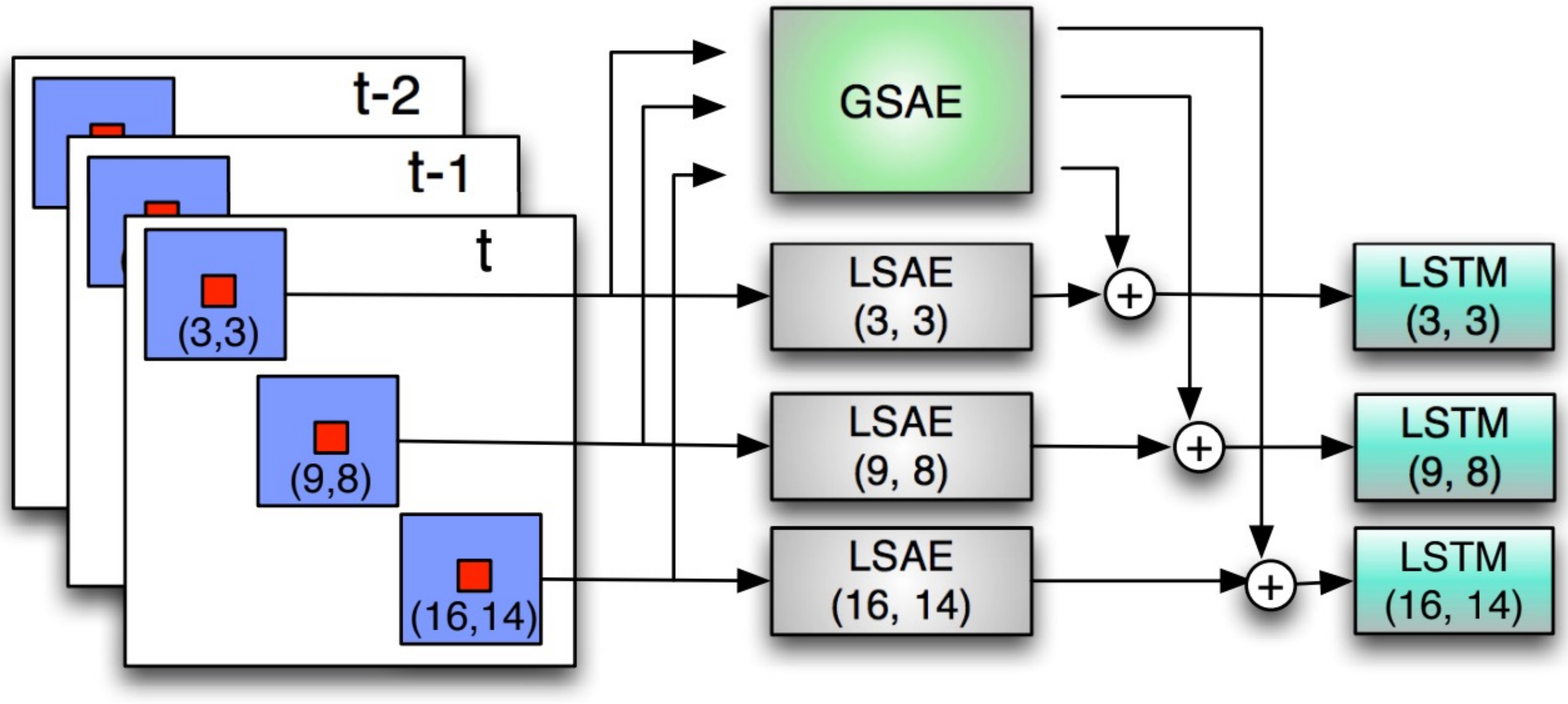
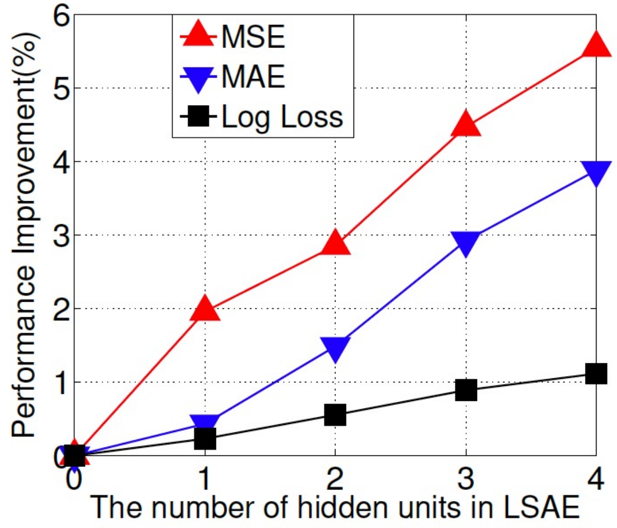


Fig. 3. The proposed deep learning model

Source: Wang, J. et al. Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach. In: **IEEE INFOCOM 2017 - IEEE Conference on Computer Communications**. [S.l.: s.n.], 2017. p. 1–9.

Prediction – Wang 2017a



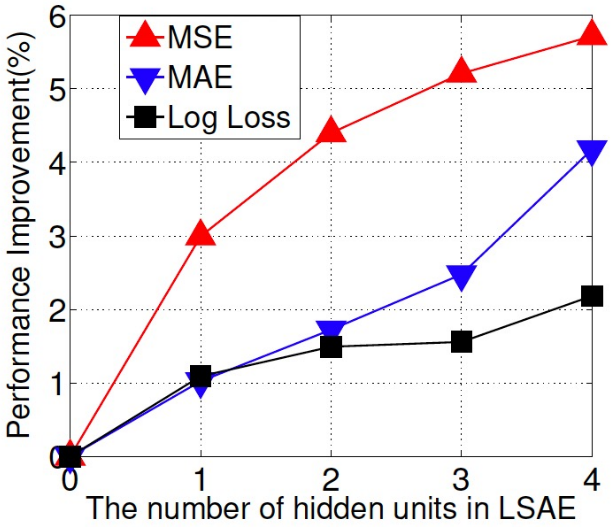


Fig. 13. Prediction performance improvement (Top: Downlink, Bottom: Uplink)

Source: Wang, J. et al. Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach. In: **IEEE INFOCOM 2017 - IEEE Conference on Computer Communications**. [S.l.: s.n.], 2017. p. 1–9.

Related work – Wang 2017b

5929 Base Stations (BSs), 1.5 million users

In-tower and inter-tower traffic

Source: Wang, X. et al. Spatio-temporal analysis and prediction of cellular traffic in metropolis. In: **2017 IEEE 25th International Conference on Network Protocols (ICNP)**. [S.l.: s.n.], 2017. p. 1–10.

Related work – Wang 2017b

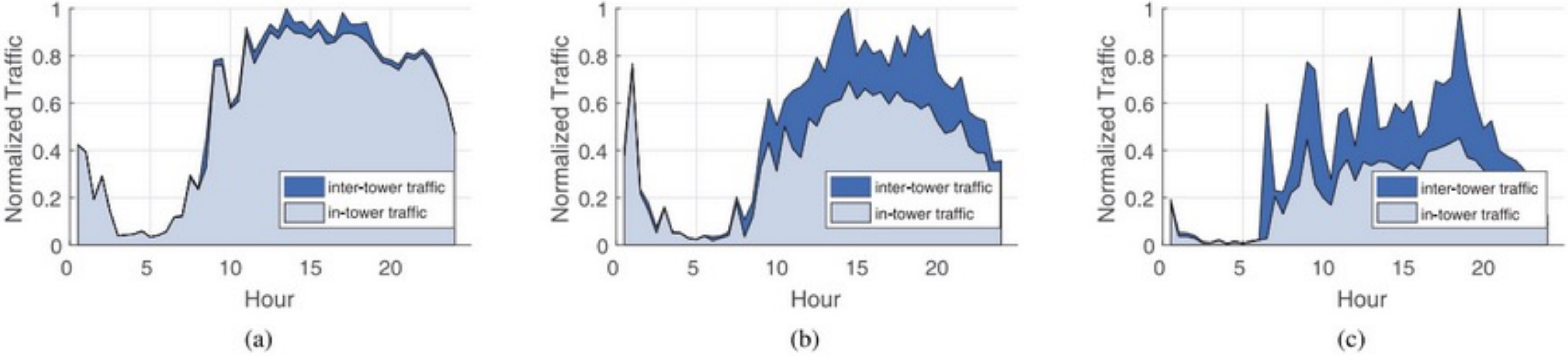
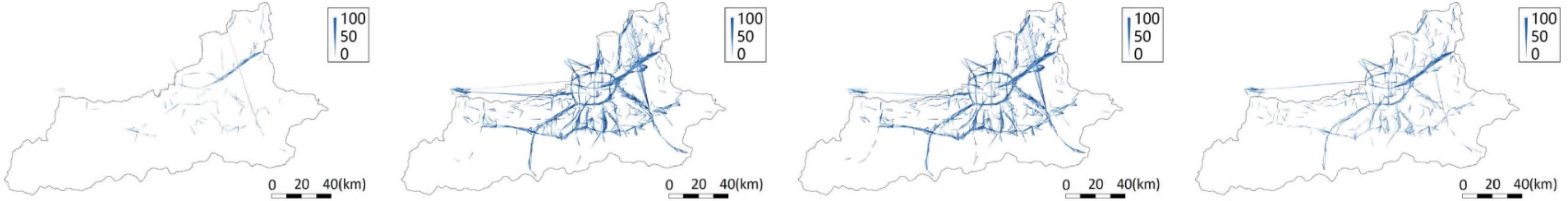


Fig. 5. An illustration of three typical in-tower and inter-tower cell tower data traffic characteristics. (a) In-tower traffic dominant, collected from a cell tower in a residential area; (b) inter-tower traffic consistently notable during the daytime, collected from a cell tower in a shopping mall; and (c) inter-tower traffic surges at certain times, collected from a cell tower in a transit station.

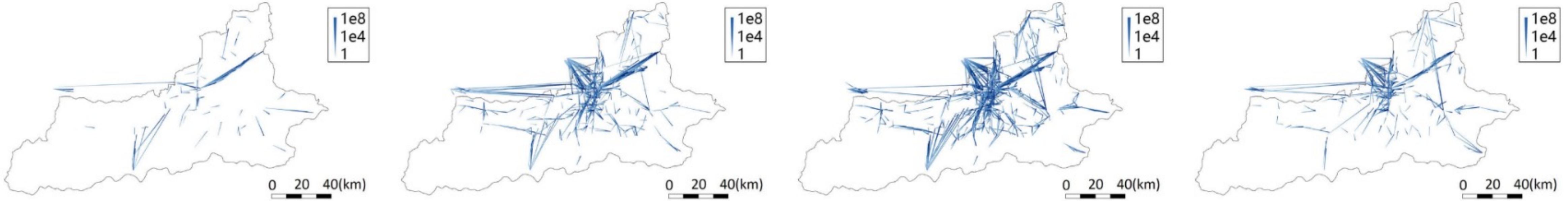
Source: Wang, X. et al. Spatio-temporal analysis and prediction of cellular traffic in metropolis. In: **2017 IEEE 25th International Conference on Network Protocols (ICNP)**. [S.l.: s.n.], 2017. p. 1–10.

Related work – Wang 2017b



(a) 04:00 (b) 10:00 (c) 16:00 (d) 00:00

Fig. 7. Distribution of user mobility at different times of a day. An edge with gradient color from white to dark blue represents the direction of user mobility between a pair of cell towers. The line width of the edge shows the intensity of user mobility.



(a) 04:00 (b) 10:00 (c) 16:00 (d) 00:00

Fig. 8. Distribution of inter-tower traffic volume at different times of the same day. The line width of each edge represents the volume of inter-tower traffic between a pair of cell towers, aggregated by half an hour.

Source: Wang, X. et al. Spatio-temporal analysis and prediction of cellular traffic in metropolis. In: **2017 IEEE 25th International Conference on Network Protocols (ICNP)**. [S.l.: s.n.], 2017. p. 1–10.

Related work – Summary

Ref.	LSTM	Time series	Grid arrange	Neighborhood concept	Spatial modelling	Residual/aperiodic events	Network traffic consumption characterization
Wang et al., 2015							✓
Wang et al., 2017a	✓		✓	✓	✓		
Wang et al., 2017b		✓		✓	✓	✓	
YANG et al., 2021		✓					
Gotzner; Rathgeber, 1998							✓
BOUTABA et al., 2018							✓

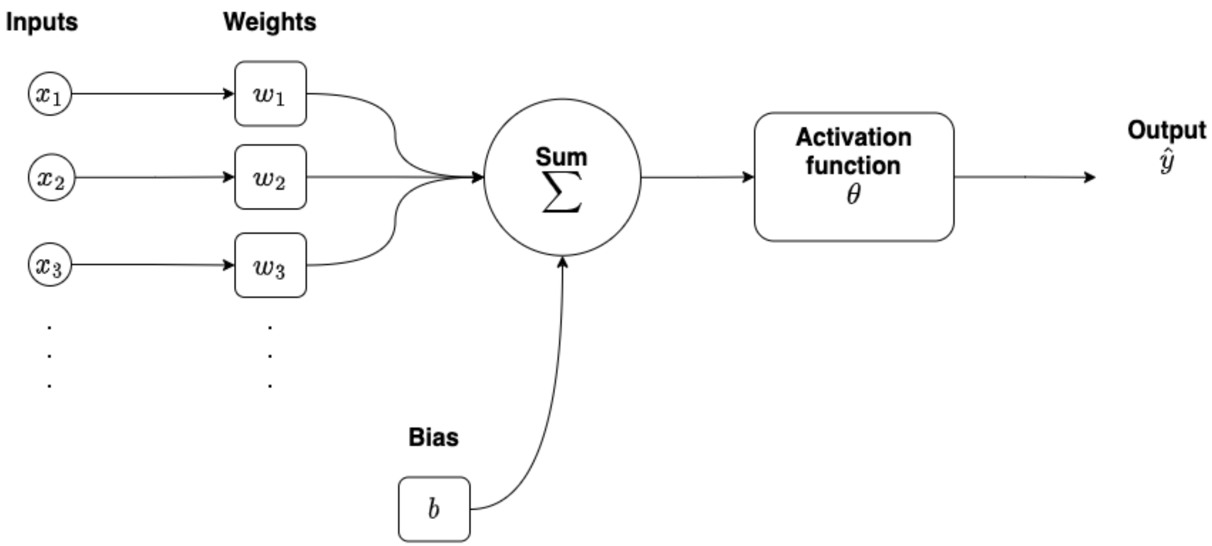
Contents

Theoretical fundamentation – Neural networks development and training

$$Z = X \times W + b$$

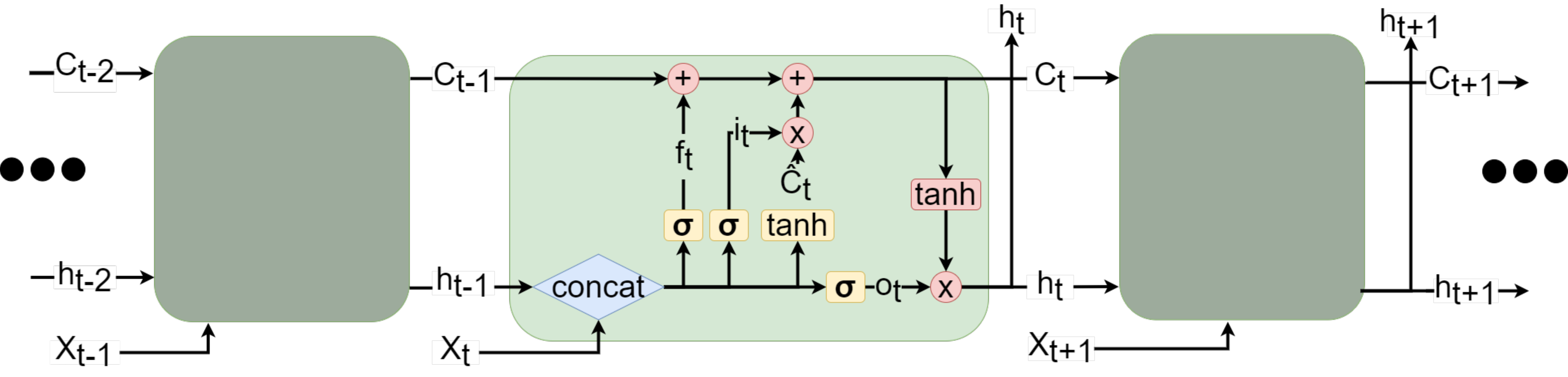
$$\hat{Y} = \theta(Z)$$

Common activation functions:
- Sigmoid: output between 0 and 1;
- Hyperbolic tangent: output -1 and 1;
- Rectified Linear Unit (ReLU)



Source: the author

Theoretical fundamentation – LSTM



Source: the author

Theoretical fundamentation – Feature selection

Mainly used to dimensionality reduction

Pearson correlation coefficient

- **Between -1 and 1**
- **Strength of the relationship between two variables**

f-value

Distance based algorithm
- **All transport regions inside 20 Moore distance***

***Later explained**

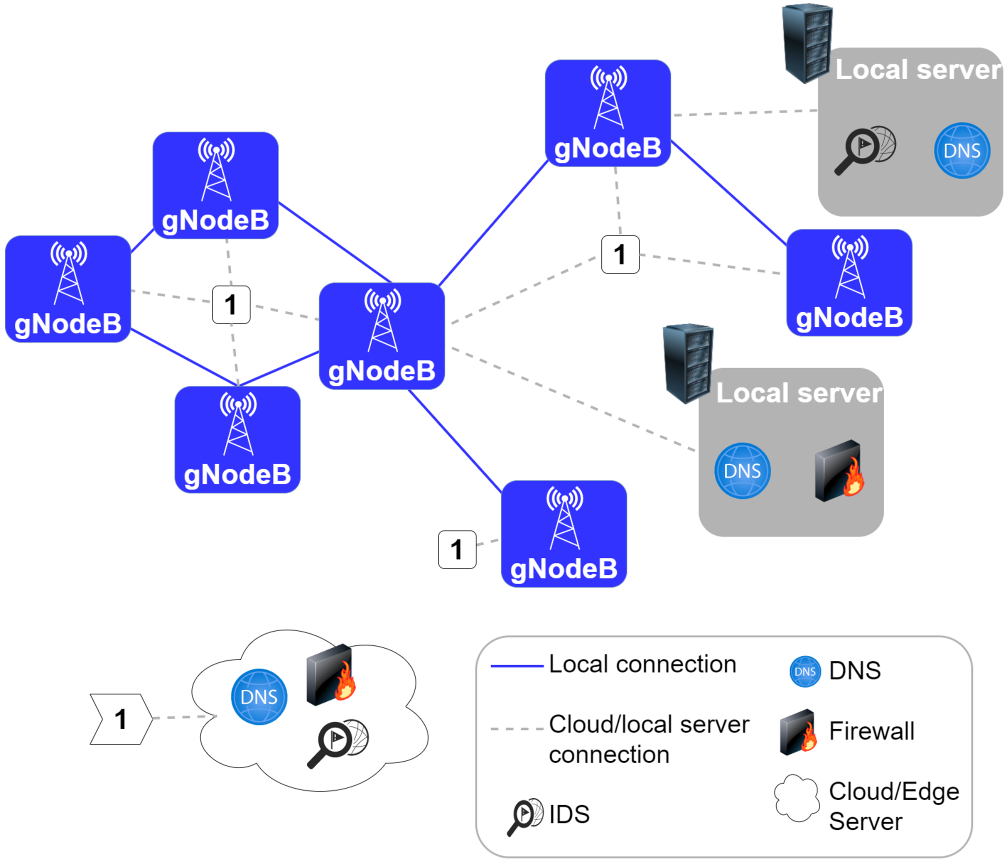
Contents

Preliminaries on data Collection for MTP-NT – The predictive model in the 5G Infrastructure

Hardware middleboxes become software functions

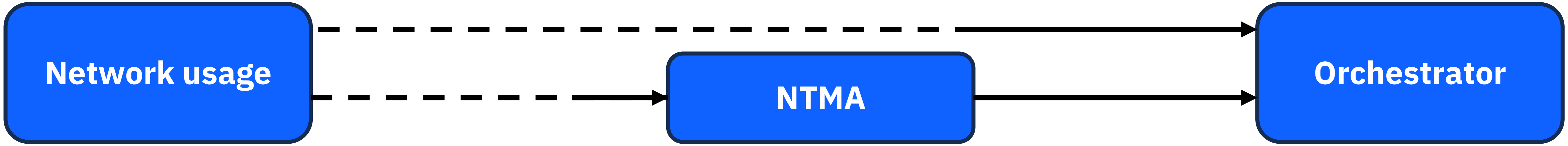
Rely on dedicated hardware and/or cloud

Preliminaries on data Collection for MTP-NT – The predictive model in the 5G Infrastructure



Source: the author

Preliminaries on data Collection for MTP-NT – The predictive model in the 5G Infrastructure



Problems

- **Volume**
- **Velocity**

Network Traffic Monitoring and Analysis

Also a NFV

Problems

- **Volume**
- **Velocity**

Preliminaries on data Collection for MTP-NT – The predictive model in the 5G Infrastructure

How does it flow?

How to store?

Is there a open standard?

Preliminaries on data Collection for MTP-NT – Data flow

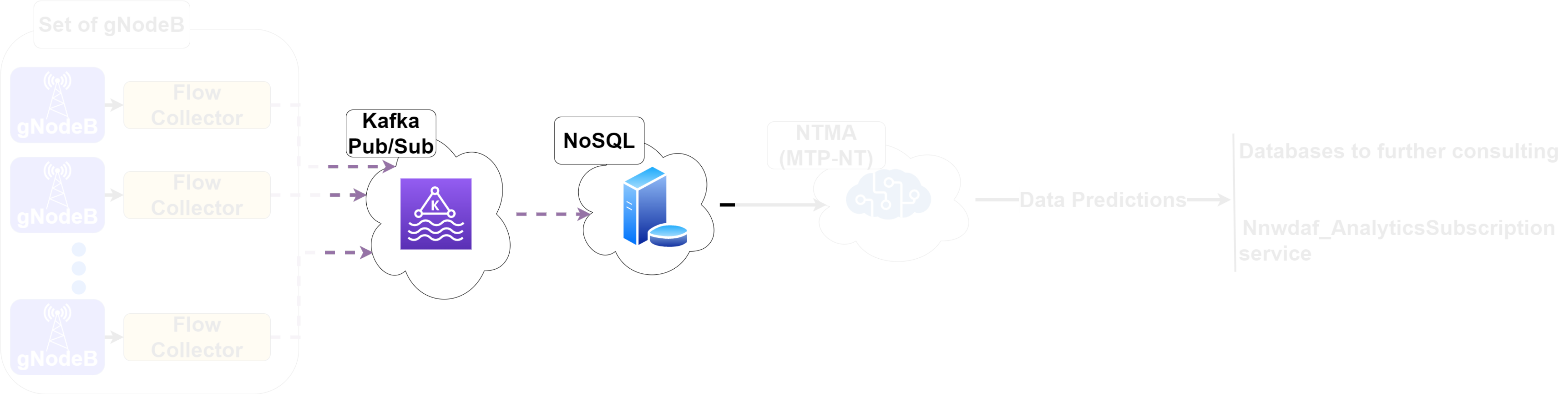
Flow collectors/Network exporters and collectors

Radio Access Network (RAN) layer

Network Data Analytics Function (NWDAF)[1]

[1] 3GPP. Architecture enhancements for 5G System (5GS) to support network data analytics services. [S.l.], 2022. Version 17.5.0. Disponível em: <<https://portal.3gpp.org/desktopmodules/Specifications/SpecificationDetails.aspx?specificationId=3579>>.

Preliminaries on data Collection for MTP-NT – Data flow



NoSQL[1,2]

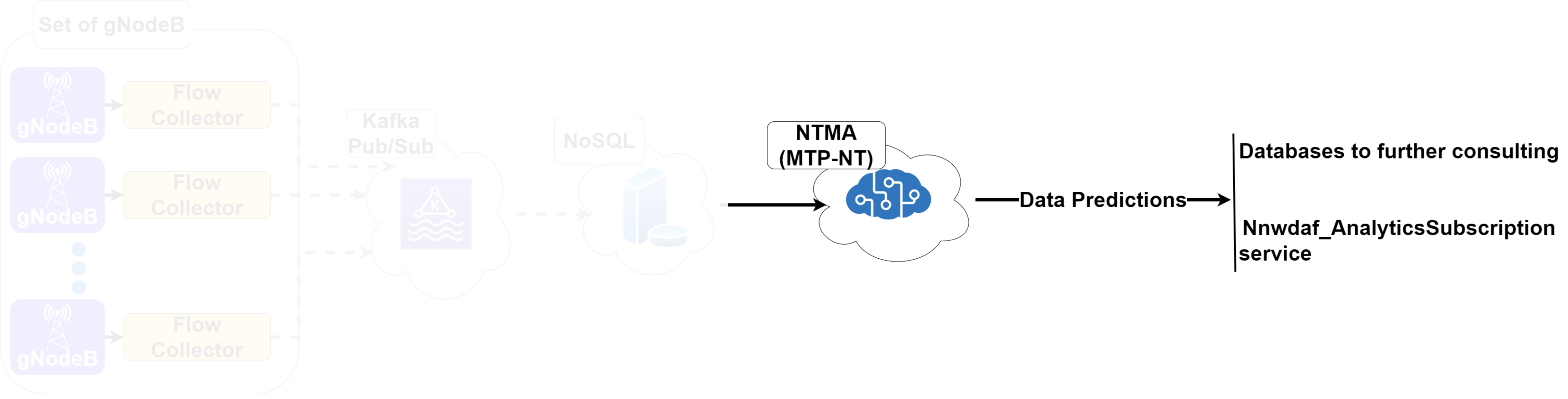
Less performance penalties with large datasets

Popular open source solutions

[1] HAN, J. et al. Survey on nosql database. In: IEEE. 2011 6th international conference on pervasive computing and applications. [S.l.], 2011. p. 363–366.

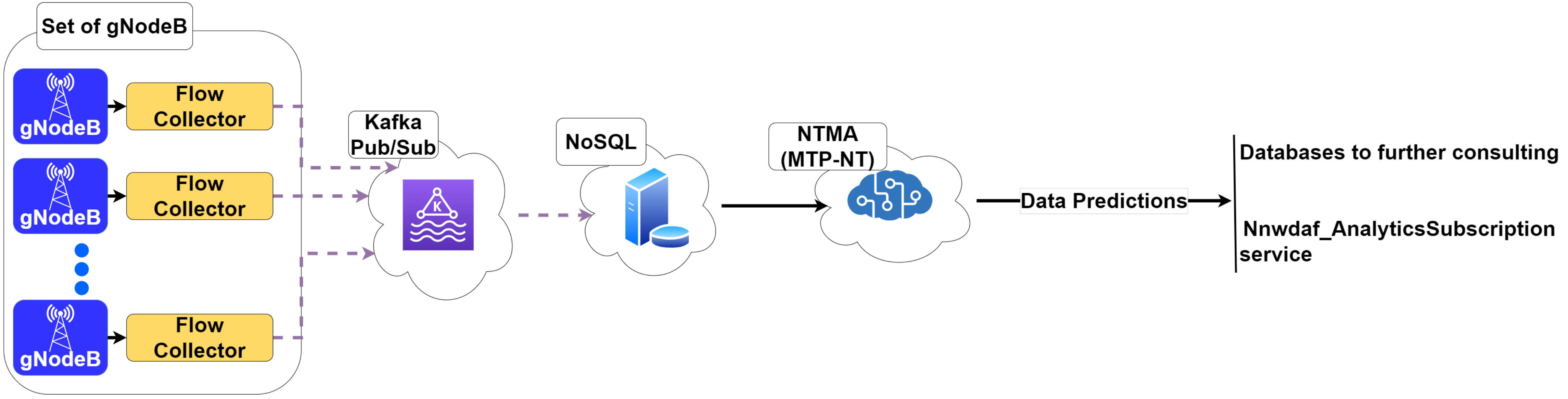
[2] D'ALCONZO, A. et al. A survey on big data for network traffic monitoring and analysis. IEEE Transactions on Network and Service Management, IEEE, v. 16, n. 3, p. 800–813, 2019.

Preliminaries on data Collection for MTP-NT – Data flow



The data is pulled by the MTP-NT, which can be seen as a NTMA

Preliminaries on data Collection for MTP-NT – Data flow



Source: the author

Preliminaries on data Collection for MTP-NT – Dataset used in this work

Database to Milan and Trento from November 1st to December 31st of 2013[1]

1. **Grid (Telecom Italia)**
2. **Social Pulse (Spazio Dati, DEIB)**
3. **Telecommunications (Telecom Italia)**
4. **Precipitations (Metereotrentino, ARPA)**
5. **Weather (ARPA)**
6. **Electricity (SET Distribuizione SPA)**
7. **News (Citynews)**

[1] Barlacchi, G. et al. A multi-source dataset of urban life in the city of milan and the province of trentino. Sci Data 2, 2015.

Preliminaries on data Collection for MTP-NT – Dataset used in this work

Telecommunications dataset from Milan

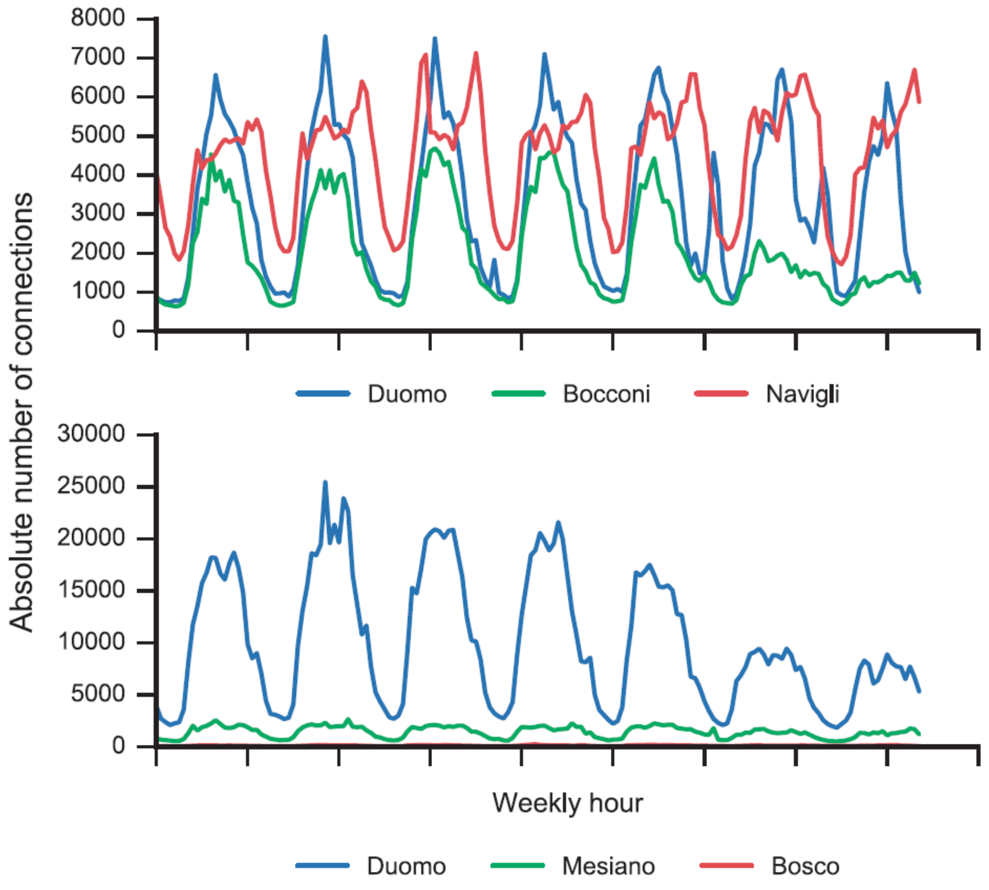
- **10,000 zonal regions in a 100x100 regular grid**
- **Each regions is a square of 0.06km^2**
- **One log at every 10 minutes in every region**
- **Call Detail Records (CDRs)**
  - **Every time an user initiates or ends a network connection;**
  - **For a given connection, an additional CDR is generated every 15 additional minutes of connection or if the user transfers more than 5MB over the internet;**
  - **Other origins as SMS and calls, but this information is not used in this work.**

Preliminaries on data Collection for MTP-NT – Dataset used in this work

Anonymization of data

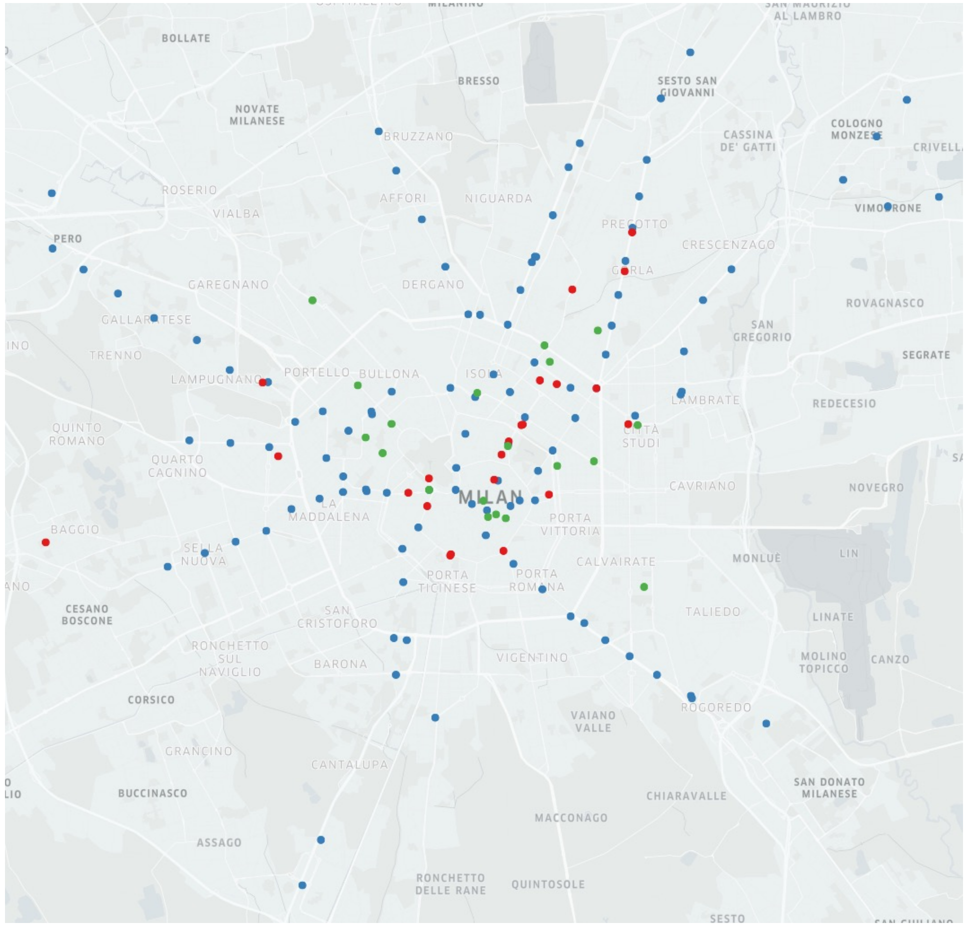
- **GDPR compliant**
- **Protects the real infrastructure capabilities**
- **Each parameter f is multiplied by a anonymization constant k_f**

Preliminaries on data Collection for MTP-NT – Dataset used in this work



Source: Barlacchi

Preliminaries on data Collection for MTP-NT – Dataset used in this work



Source: the author

Contents

Framework structure and fundamentation – Mathematical formalization of MTP-NT operations

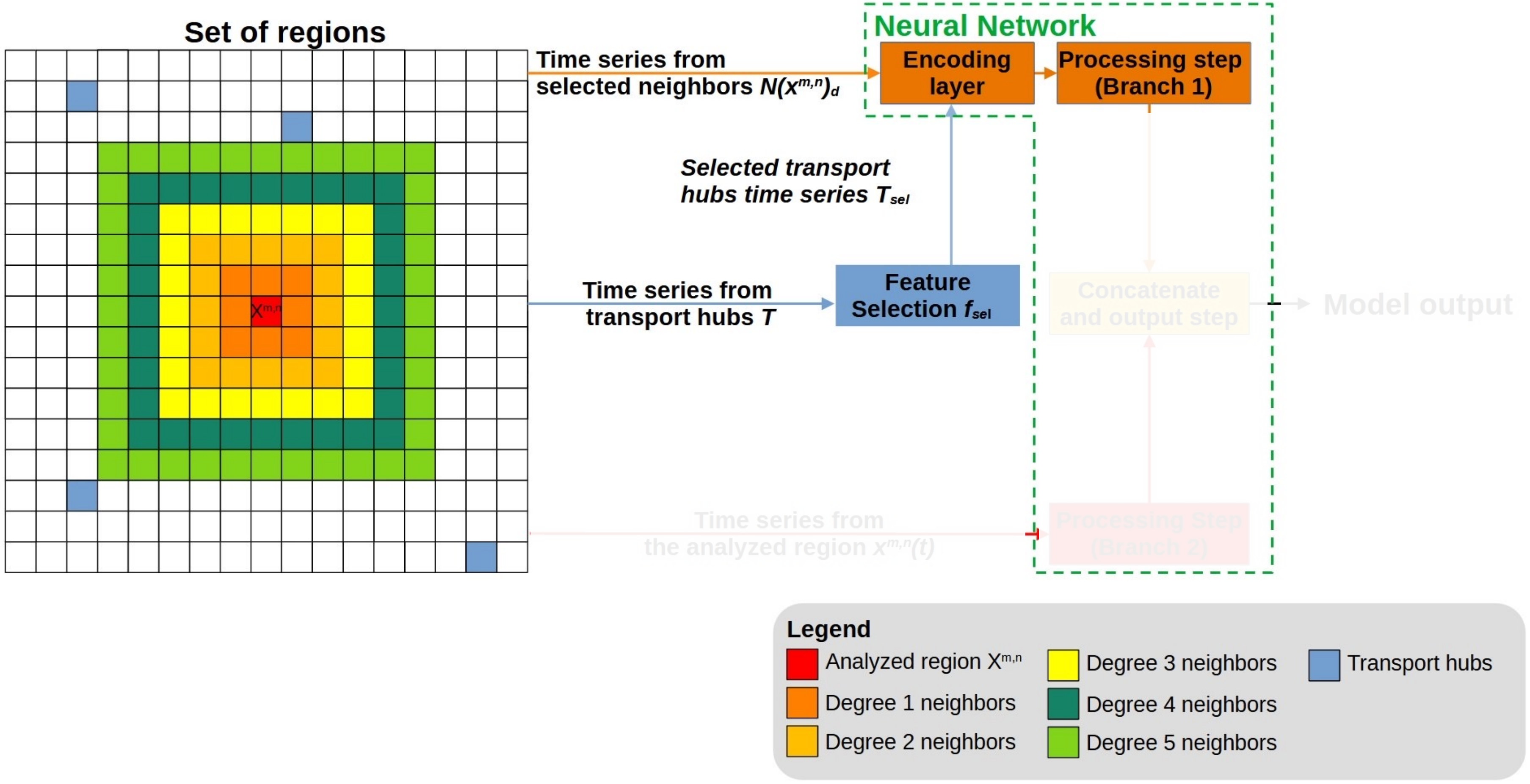
MTP-NT inputs

Time series from the analyzed region

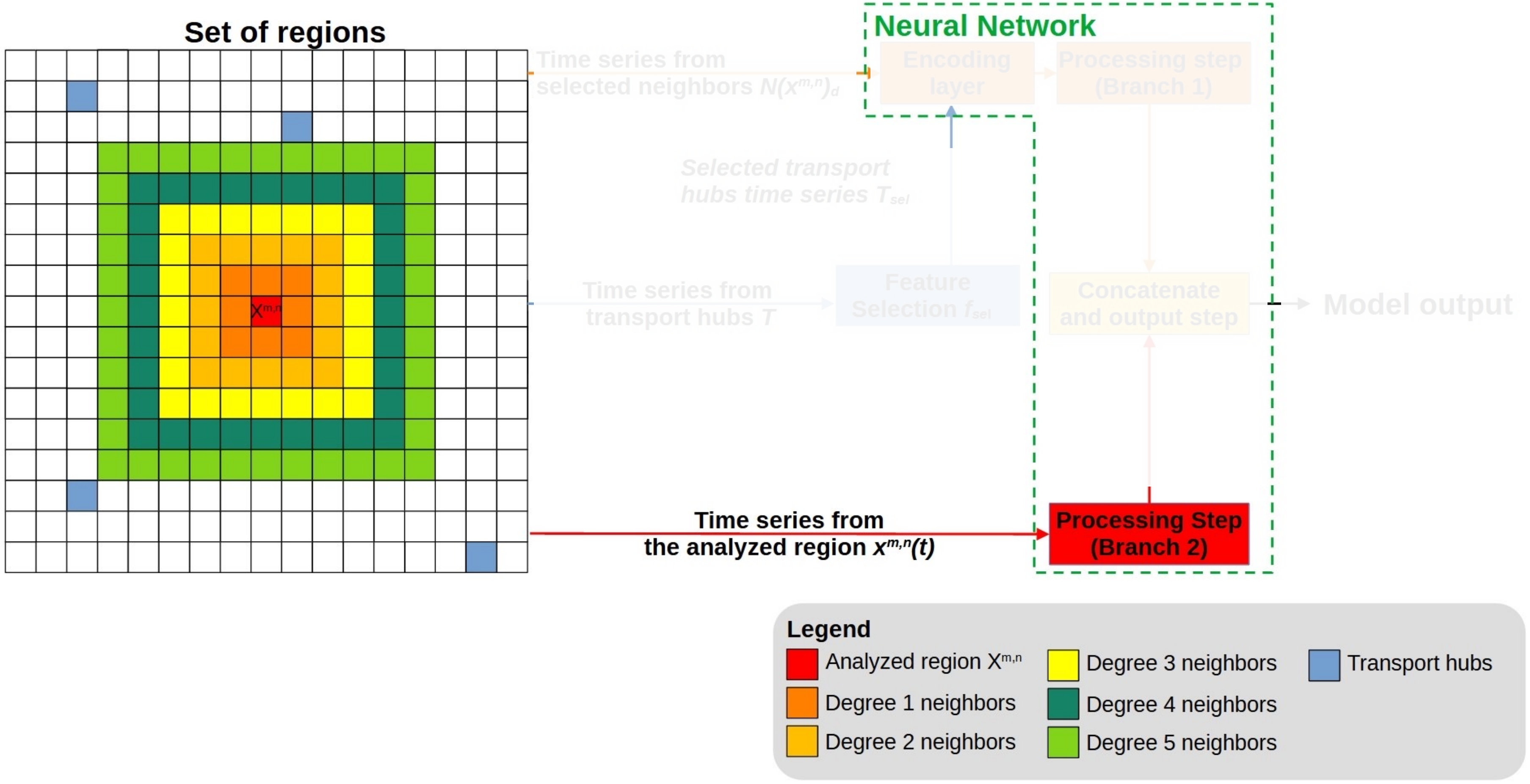
Time series from selected neighbors

Time series from transport hubs

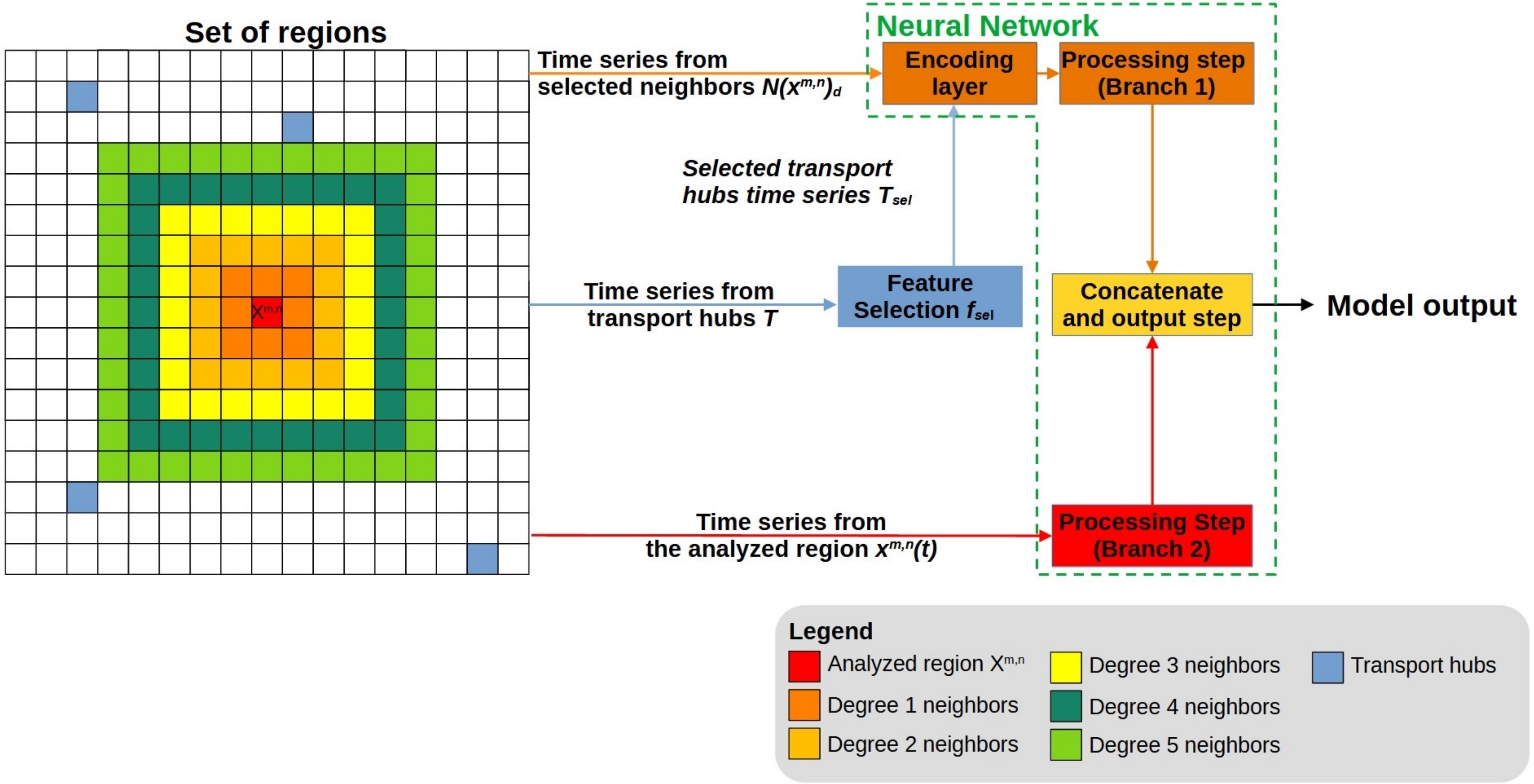
Framework structure and fundamentation – Mathematical formalization of MTP-NT operations



Framework structure and fundamentation – Mathematical formalization of MTP-NT operations



Framework structure and fundamentation – Mathematical formalization of MTP-NT operations

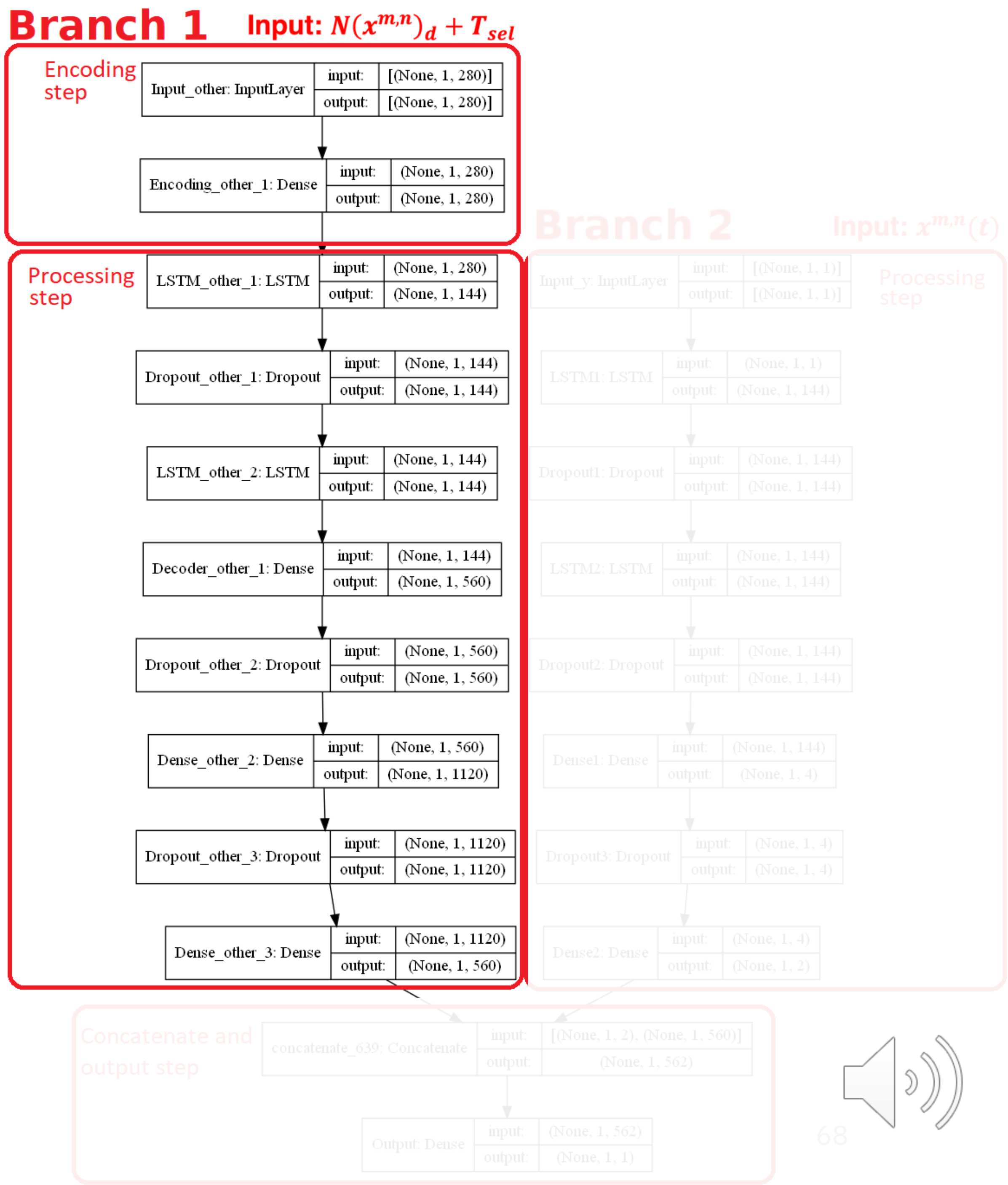


Source: the author

MTP-NT's framework architecture

Branch 1

1. **Decode the input and begin the compression**
   $Input\_other$; $Encoding\_other\_1$
2. **Temporal relations**
   $LSTM\_other\_1$; $Dropout\_other\_1$
3. **Temporal relations**
   $LSTM\_other\_2$; $Decoder\_other\_1$; $Dropout\_other\_2$
4. **General purpose correlations and reduce overfitting**
   $Dense\_other\_2$; $Dropout\_other\_3$
5. **Concatenation of Branches**
   $Dense\_other\_3$



MTP-NT’s framework architecture

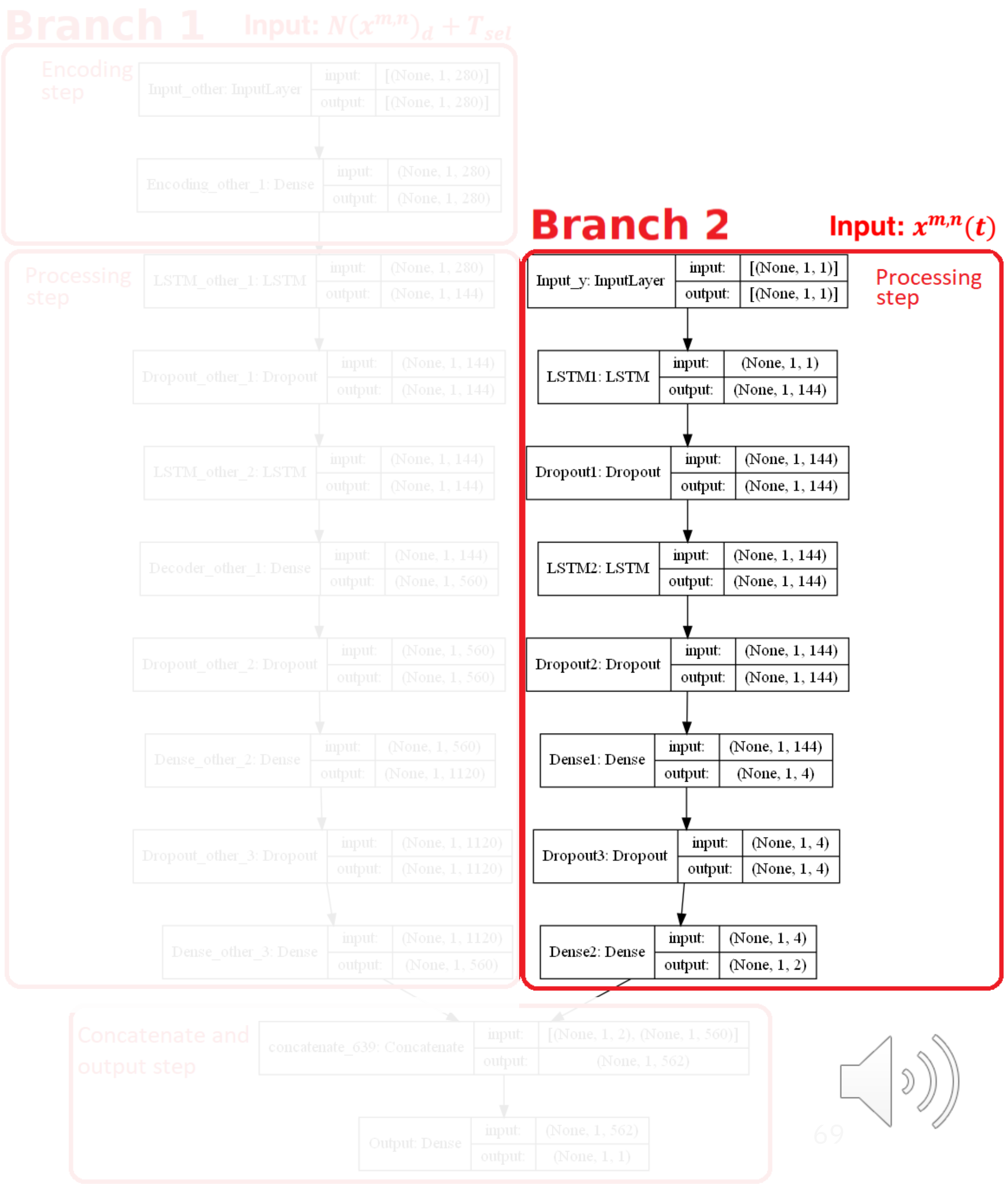
Branch 2

1. **Input layer**
   $Input\_y$

2. **Temporal relations**
   $LSTM1$; $Dropout1$
   $LSTM2$;$Dropout2$

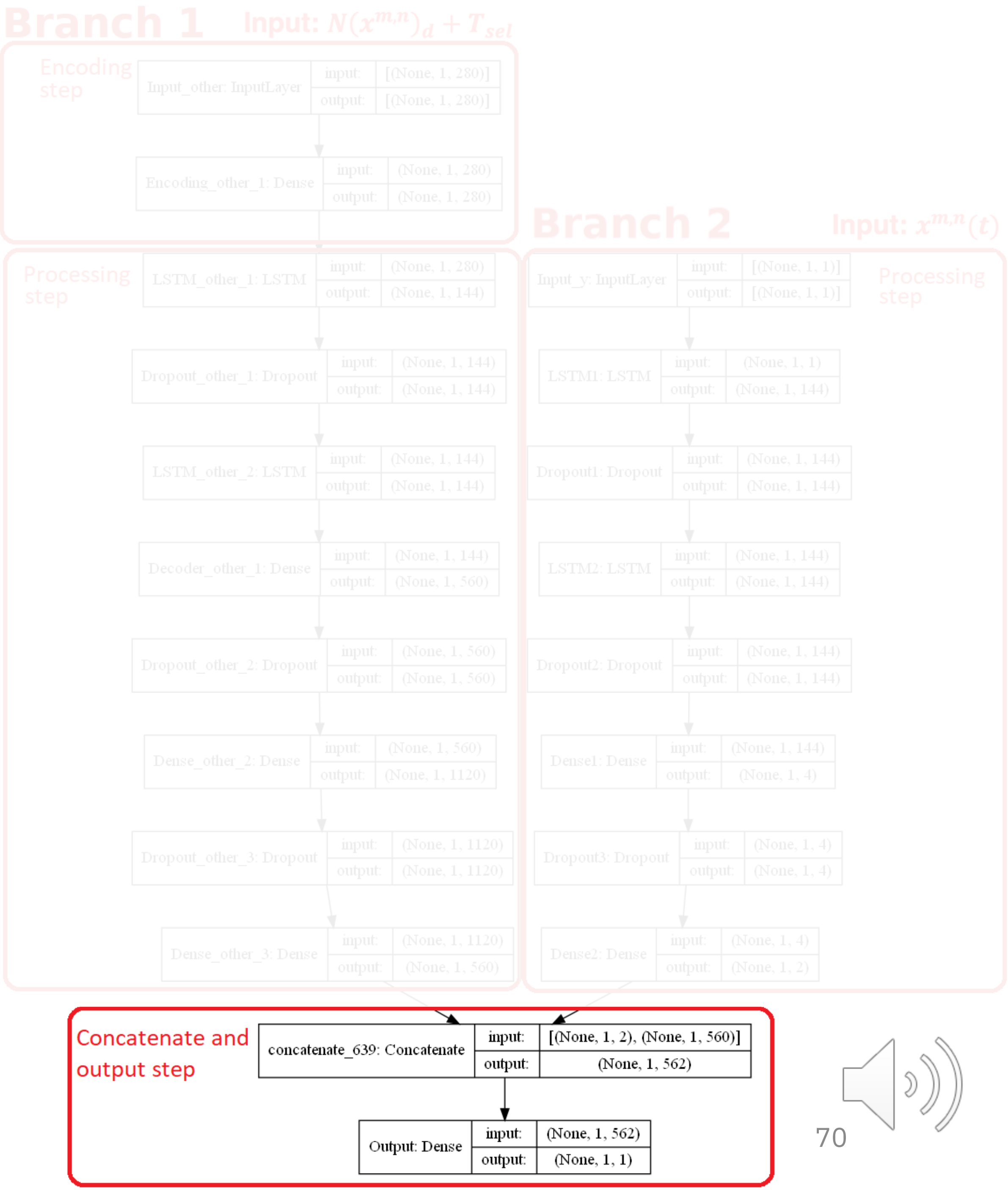
3. **General purpose correlations and reduce overfitting**
   $Dense1$
   $Dropout3$; $Dense2$

4. **Concatenation of Branches**
   $Dense2$

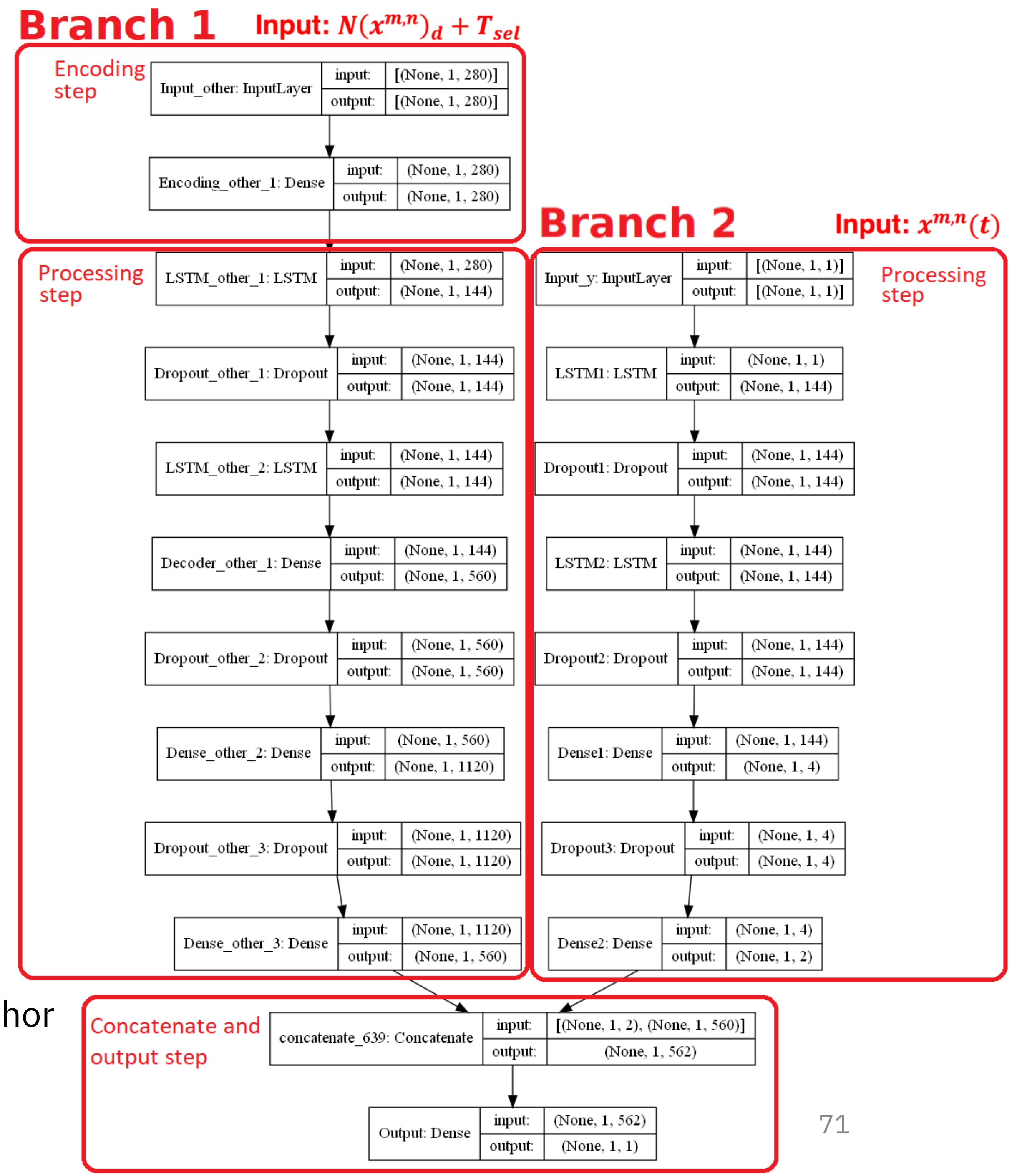


MTP-NT’s framework architecture

Concatenate and output step



MTP-NT's framework architecture



Source: the author

Contents

Experimental results - Setup

Moore regions: 1; 1~2; 1~3; ... ; 1~5

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- **Pearson correlation coeficient**
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- **With transport hubs**
- **Without transport hubs**

Experimental results - Setup

Moore regions: 1; 1~2; 1~3; ... ; 1~5

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Variations

- **With transport hubs**
- **Without transport hubs**

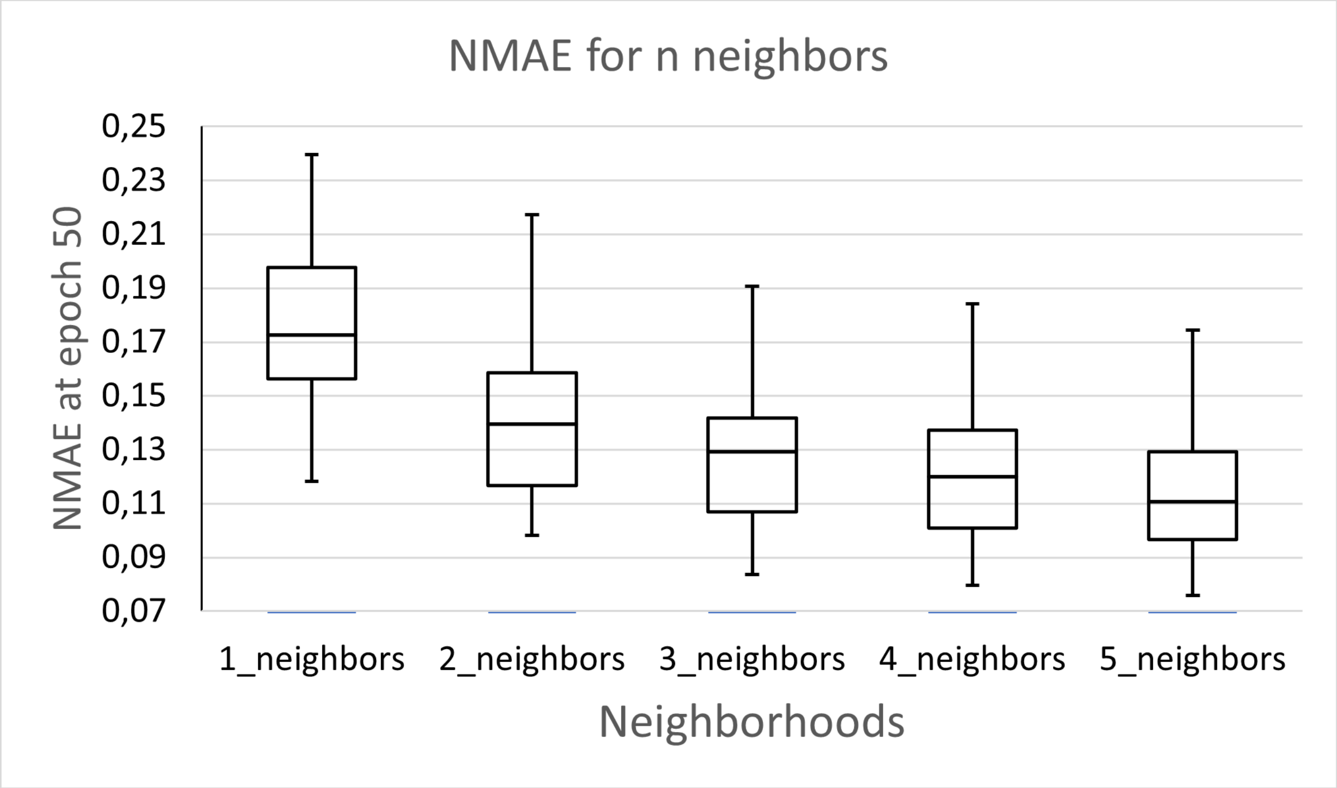
Plus: dataset compiled in 1-hour samples

Experimental results - Setup

Evaluation metric

$$NMAE(y, \hat{y}) = \frac{\sum |\hat{y} - y|}{\sum y} \tag{12}$$

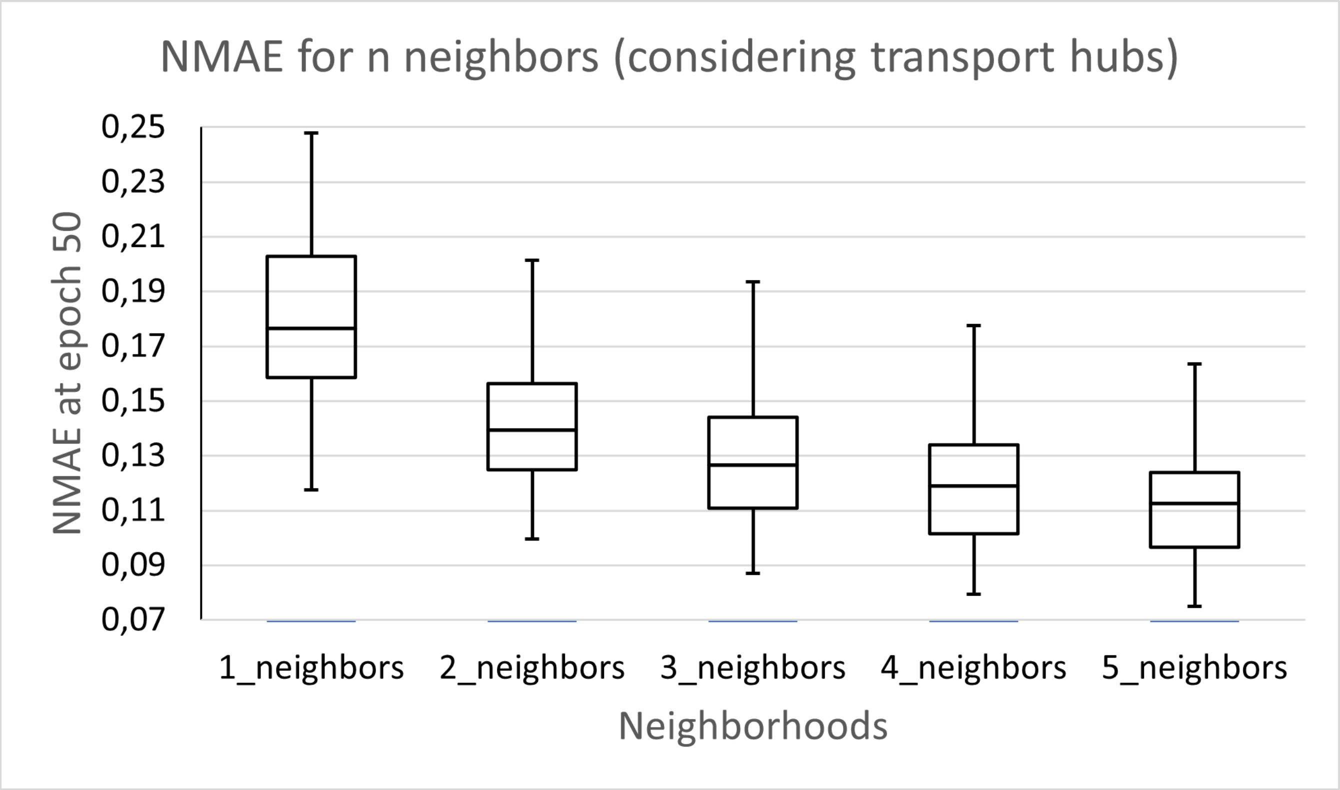
Experimental results - Results



Source: the author

Descendent error

Experimental results - Results

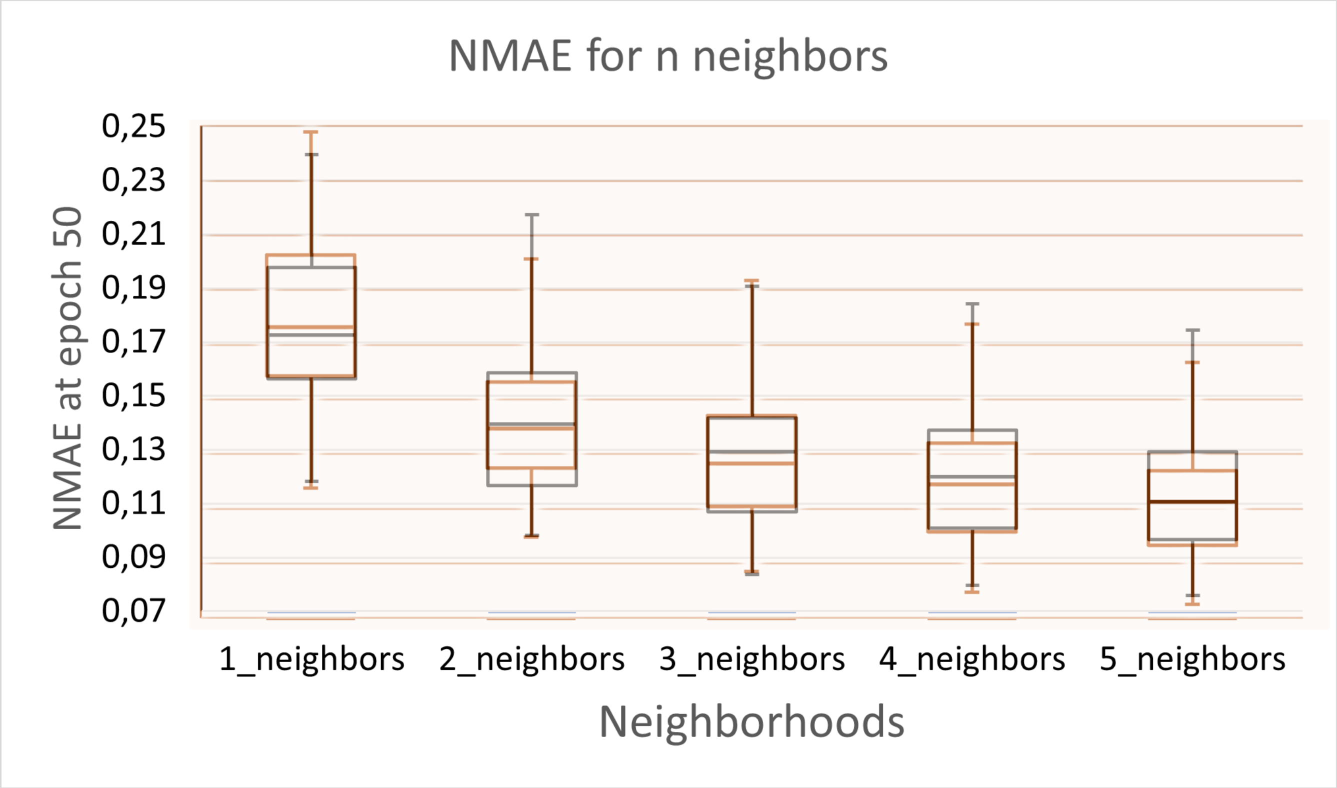


Source: the author

Better overall performance, specially in:

- **Outliers**
- **Lower Moore distance models**

Experimental results - Results



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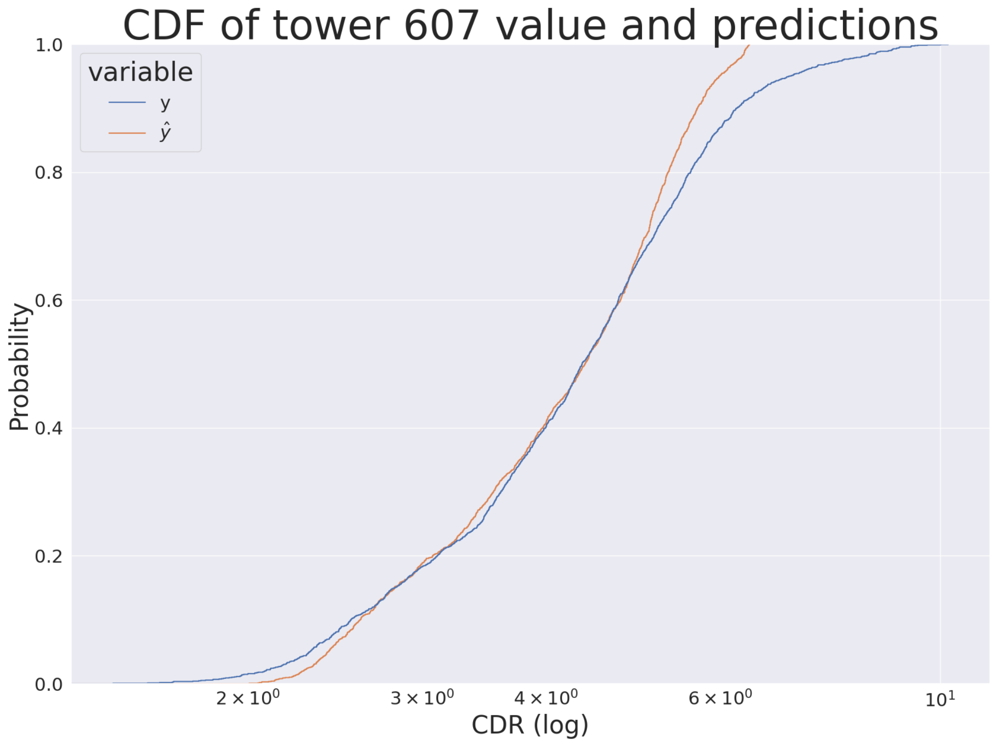


Source: the author

Considerations of transport hubs

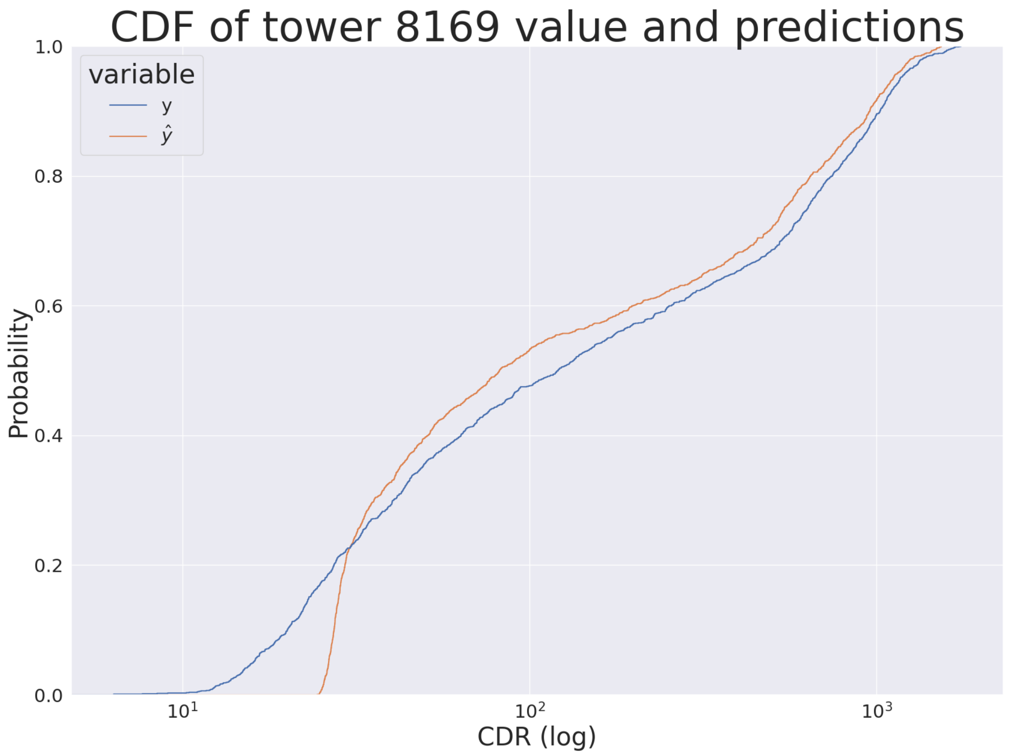
- **Can be important to anticipate fast changing demand from non-seasonal events[1]**
- **More important in central regions of the city**

Region 607 (near Vigano)

- **Normal tests:** $NMAE = 12\%$
- **Transport hubs tests:** $NMAE = 11\%$

[1] Wang, J. et al. Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach. In: IEEE INFOCOM 2017 - IEEE Conference on Computer Communications. [S.l.: s.n.], 2017. p. 1–9.

Experimental results - Results



Source: the author

Considerations of transport hubs

- **Can be important to anticipate fast changing demand from non-seasonal events[1]**
- **More important in central regions of the city**

Region 8169 (mall near Parco Nord Milano)

- **Normal tests:** $\boldsymbol{NMAE = 13\%}$
- **Transport hubs tests:** $\boldsymbol{NMAE = 11\%}$

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Experimental results - Results

How can MTP-NT perform in a different scenario?

Table 6 – NMAE in tests with 10-minute and 1-hour observations, varying the usage of transport hubs.

Window size	NMAE with transport data	NMAE without transport data
10 minutes	0.1120	0.1100
1 hour	0.1355	0.1441

Source: the author

Experimental results – Execution Time Evaluation

Growth of regions with the maximum Moore distance d considered

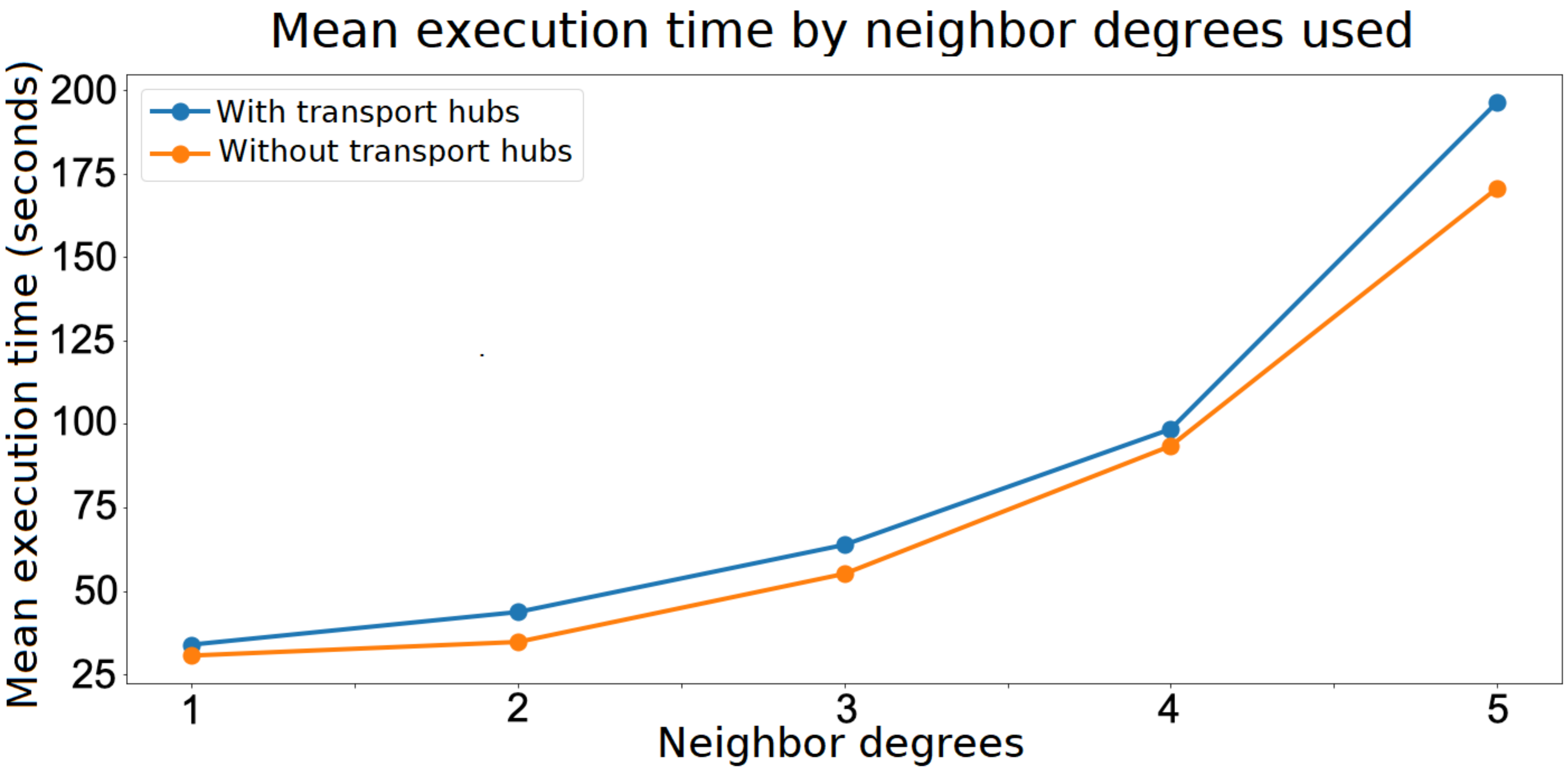
$$N_d = N_{d+1} + 8(d+1)$$

Table 5 – Number of regions and data samples in a 24 hour interval with increasing neighborhoods.

Neighborhoods	1	2	3	4	5
Total regions	9	25	49	81	121
Samples in 24 hours	1,296	3,600	7,056	11,664	17,424

Source: the author

Experimental results – Execution Time Evaluation



Source: the author

Experimental results – Performance Analysis

Closed datasets and models – How to compare different studies?

Experimental results – Performance Analysis

Closed datasets and models – How to compare different studies?

Answer: Benchmark your proposal against widely known models

- **ARIMA**
- **HW**
- **Prophet**
- **LSTM model**

Experimental results – Performance Analysis

Auto Regressive Integrated Moving Average - ARIMA

- **Autoregression: self correlation (p)**

$$Y_t = \beta_1 + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \dots + \Phi_p Y_{t-p}$$

- **Integration: stationary time series (d)**

$$Z_t = Y_{t+1} - Y_t \qquad \dots d = 1$$
$$Q_t = Z_{t+1} - Z_t \qquad \dots d = 2$$
$$\dots$$

- **Moving Average: relation between error of previous samples and the actual (q)**

$$Y_t = \beta_2 + \omega_1 \varepsilon_{t-1} + \omega_2 \varepsilon_{t-2} + \dots + \omega_q \varepsilon_{t-q} + \varepsilon_t$$

Experimental results – Performance Analysis

Auto Regressive Integrated Moving Average – ARIMA

Best model: p=36;d=1;q=0

Experimental results – Performance Analysis

Holt-Winters (HW) model: aditive trend

Prophet: daily and weenkly seazonality

LSTM model

- **Standard scaler**
- **128-cell LSTM layer + Dropout (10%)**
- **128-cell LSTM layer + Dropout (10%)**
- **Dense layer**

Experimental results – Performance Analysis

Table 6 – NMAE among different benchmarking techniques in Distributed, Core and Event tests.

	Distributed test	Core test	Event test
ARIMA	51.00	65.03	60.014
HW	11.78	9.34	15.16
LSTM	57.03	54.35	67.06
Prophet	61.00	94.66	178.65
MTP-NT	**11.47**	**8.22**	**11.62**

Source: the author

Experimental results – Performance Analysis

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Source: the author

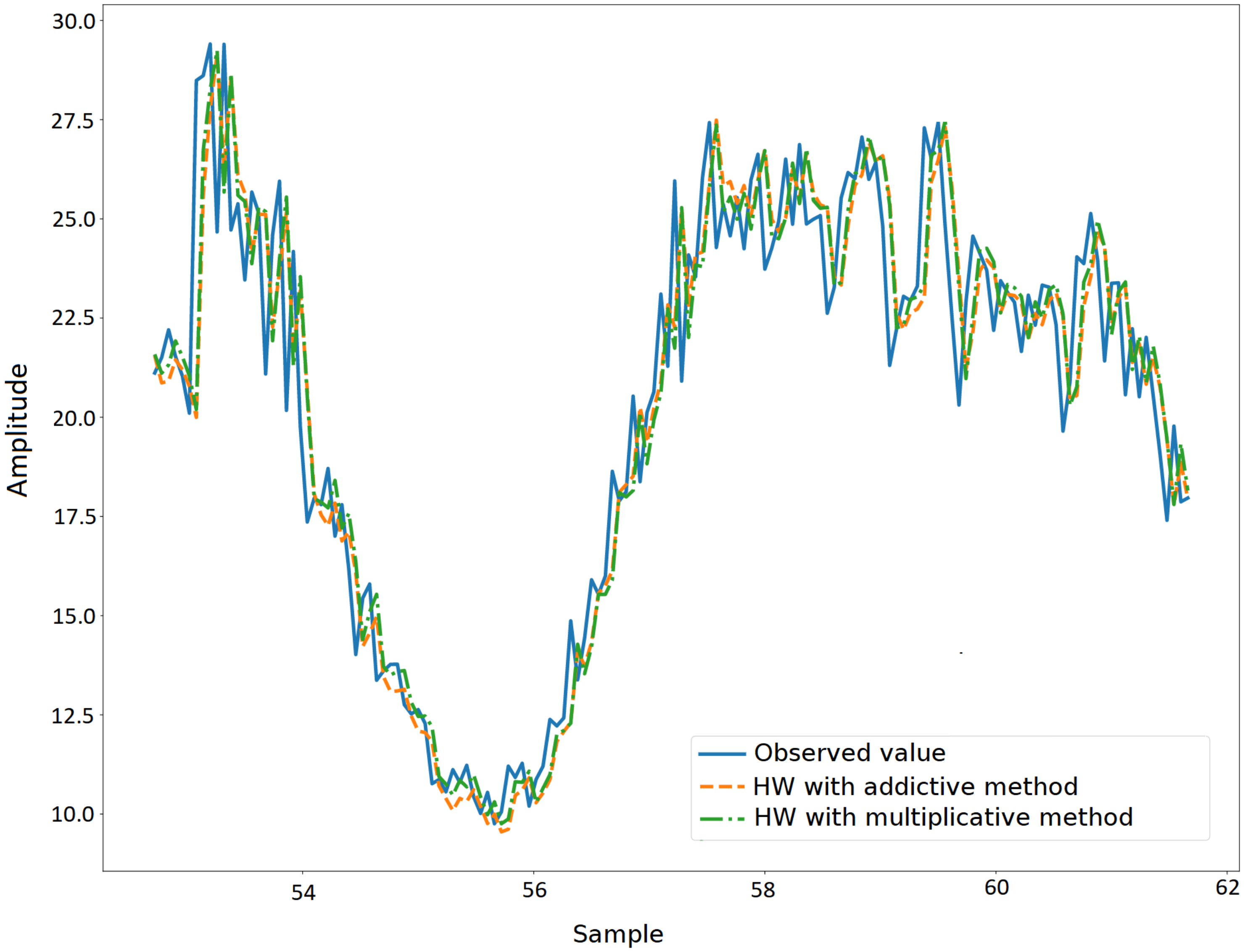
(Wang 2017b) 45% drop in error compared to LSTM

MTP-NT: 77%

(Wang 2017b) 62% drop in error compared to HW

MTP-NT: similar

Experimental results – Performance Analysis



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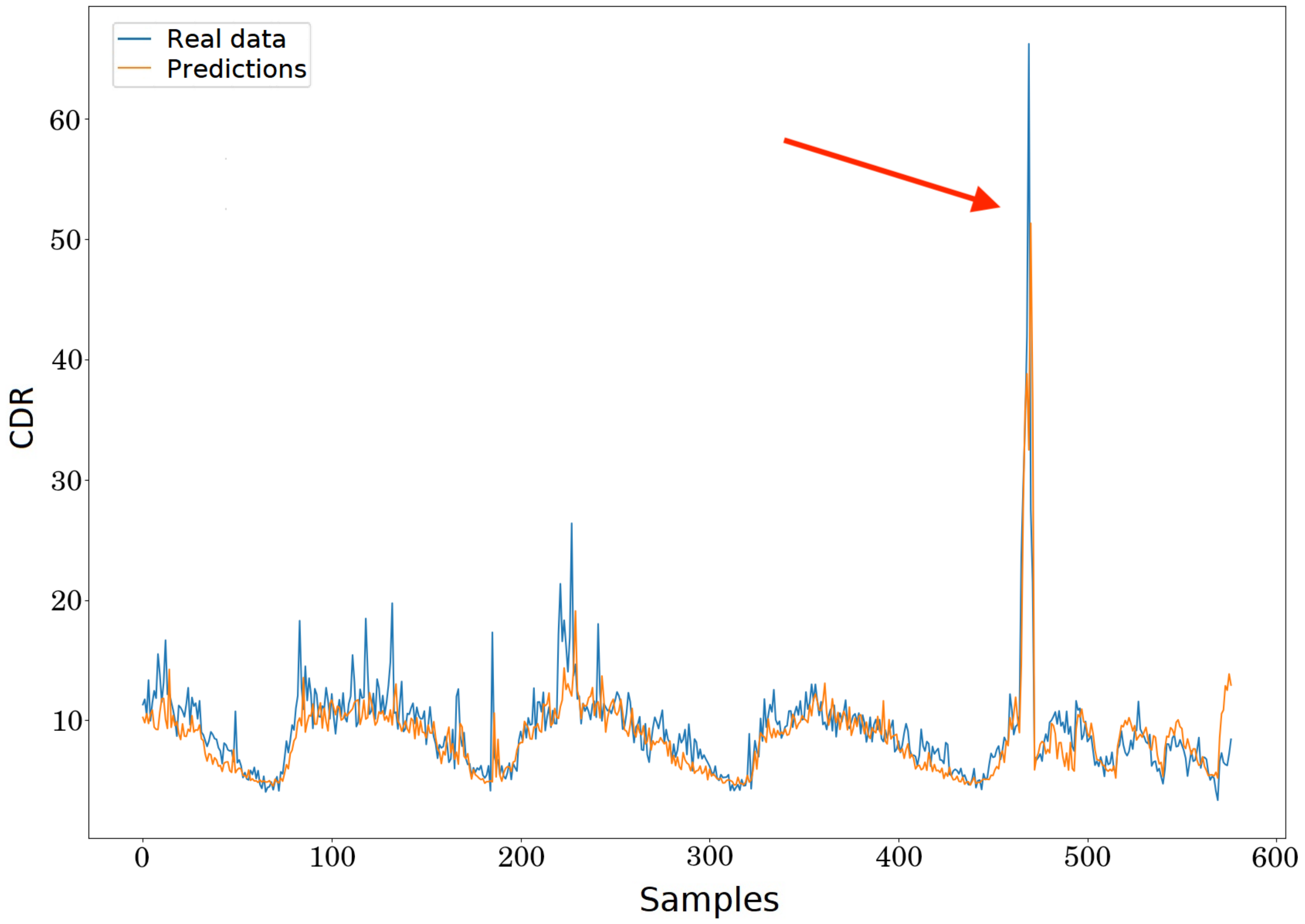

Contents

Scenario in 5G

Data driven technologies in mobile networks

Large urban centers

- Dynamic scenarios
- Patterns and irregular factors
- Strict QoS/QoE metrics

Cloud based architecture; 3GPP architecture purposal

GDPR and other major privacy policies

MTP-NT

Public transport hubs

As a way to bring new information to the model

Improve the coverage of aperiodic events

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Future work

More neighborhoods

Heavier models

GPUs and other advancements make cloud computing cheaper

Multi-region model

MTP-NT compiles a single region at a time

A new multi-region architecture can be better

Faculdade de Computação

Universidade Federal de Uberlândia

Thanks!

A Mobile Traffic Predictor Enhanced by Neighboring Transportation Data (MTP-NT)

Patrick Luiz de Araújo

patrick@ufu.br

Prof. Dr. Rafael Pasquini

rafael.pasquini@ufu.br

Prof. Dr. Murillo Guimarães Carneiro

mgcarneiro@ufu