Building Energy Efficient Traffic Congestion Prediction System

Speaker

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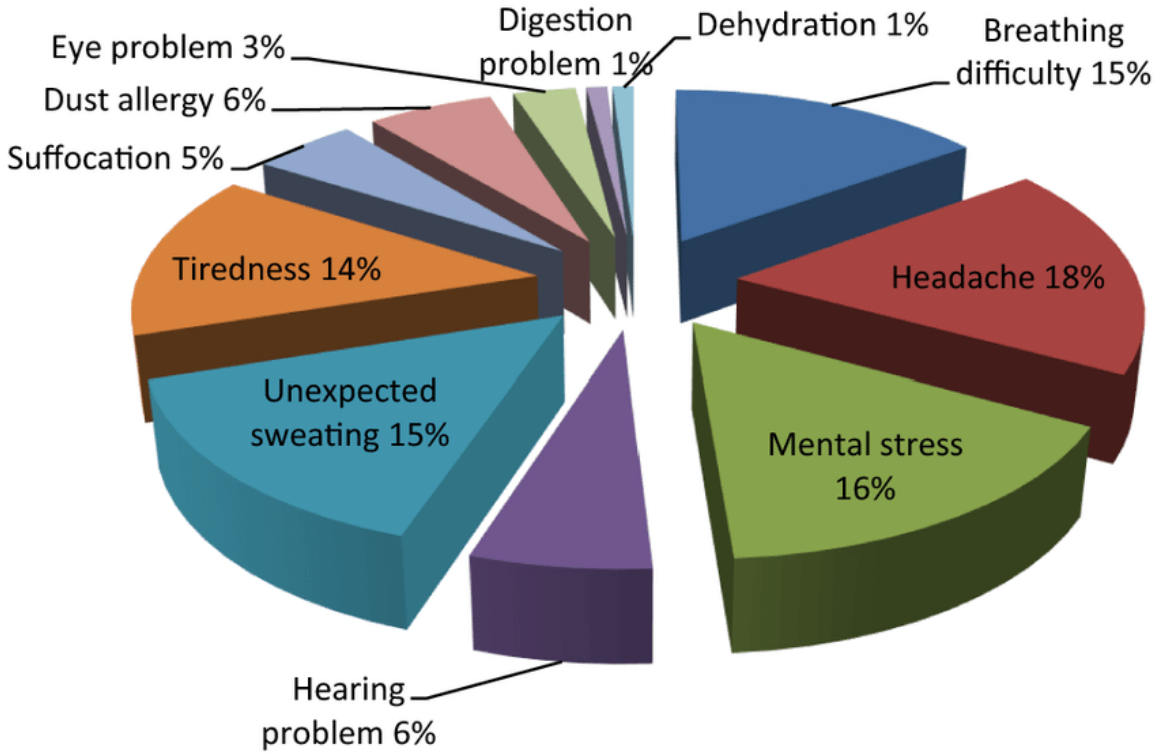
Outline

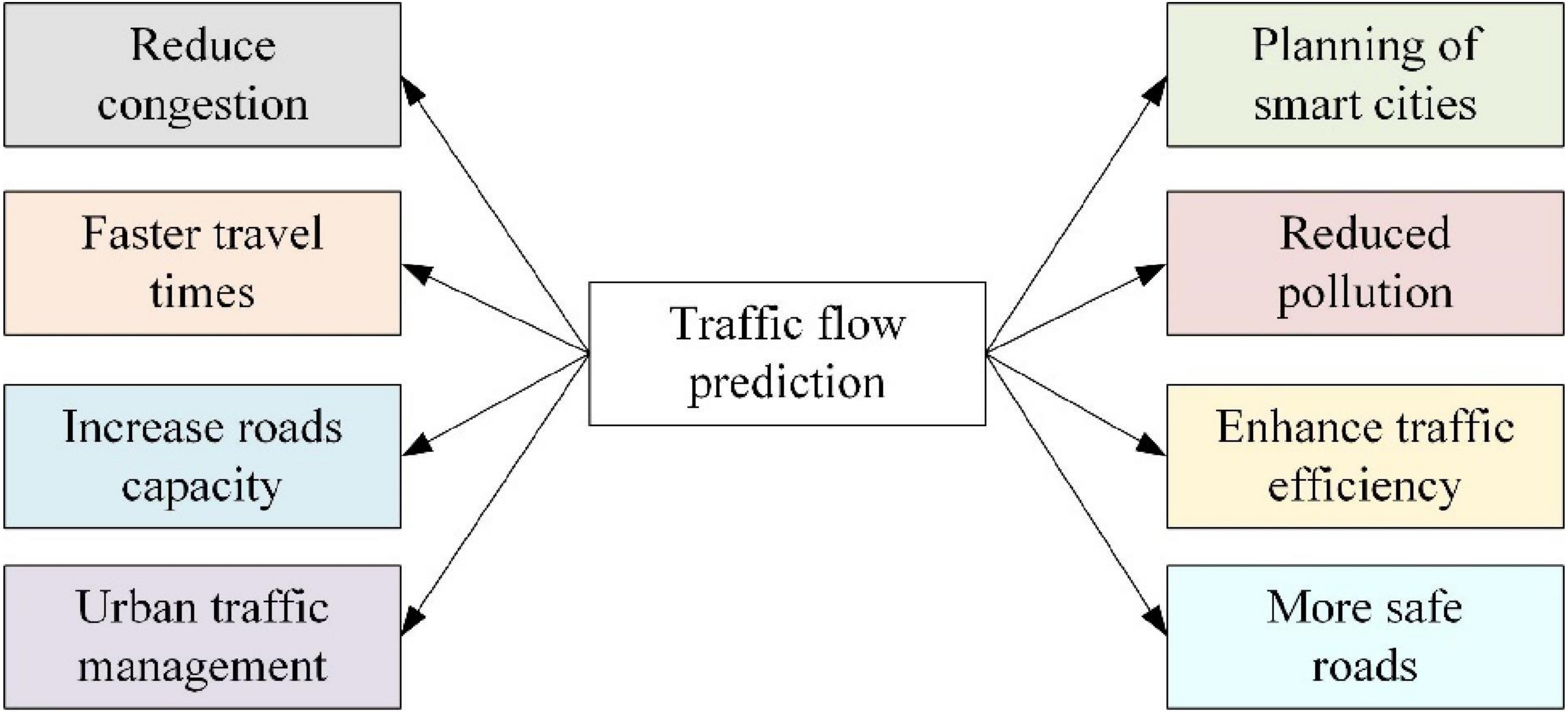
- Importance of Predicting Traffic Congestion
- Problem Definition
- Related Work
- Limitations
- Current Progress
- Future Work

Importance

- Traffic Congestion Prediction Systems (TCPS) are crucial to
  - Achieve Sustainable Developmental Goals (SDGs)
  - Reduce loss of life
  - Improve health
  - Faster travel
  - Reduce pollution
  - Reduce transportation costs



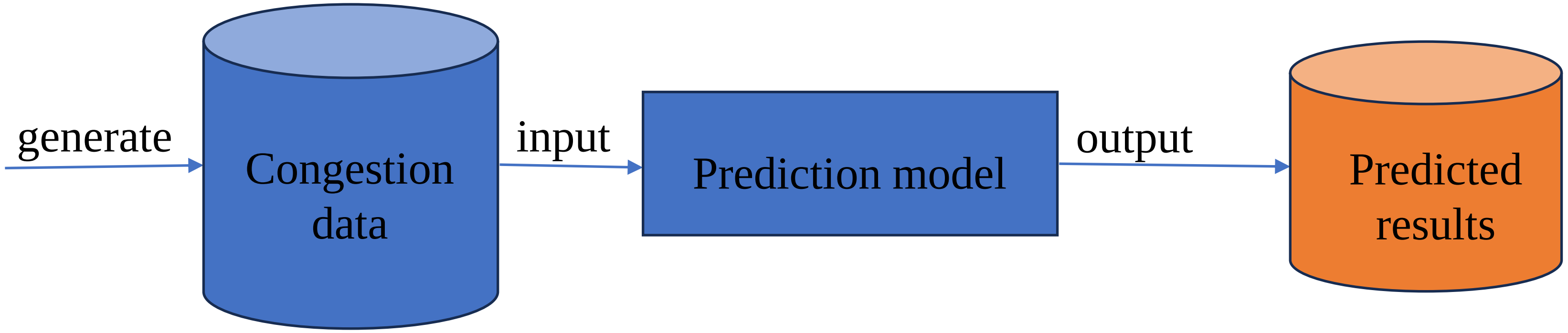
Applications



Problem Definition

- From the historical congestion data of a large transportation network, predict the future traffic congestion effectively.
  - Low Error values
  - Fast results

Large scale transportation network



Related Work

S.No	Author Name	Year	Methodology	Model	Dataset	Result	Limitation
1	Ismail Abiodun Sulaimon et al.	2021	Traffic-Related Air Pollutant (TRAP) Prediction using Big Data and Machine Learning	Extra Trees Regressor, Hist Gradient Boosting Regressor	Meteorological data	Extra Trees Regressor-93% Hist Gradient Boosting Regressor – 92%	Performance is nothing close to the best performing ML algorithm in this category
2	Moe Myint Mo et al.	2023	Measuring Traffic Congestion Based on the Taxi Operations of Traditional and On-Demand Taxis in Yangon	Aggregated model	Collection of GPS Data	The result shows that the "traditional taxis" stay in one place longer than the "on demand taxis."	It is difficult to validate the occupied, vacant, intersection, and waiting times.
3	Wei Cheng et al.	2022	Combination predicting model of traffic congestion index in weekdays based on Light GBM-GRU	Gated Recurrent Unit	Gaia Open Dataset	An accuracy of more than 90%	The limitation of collection technology makes the lack of traffic characteristics, which leads to the error of prediction.
4	Navin Ranjan et al.	2021	Large-Scale Road Network Congestion Pattern Analysis and Prediction Using Deep Convolutional Autoencoder	Convolution Autoencoder	dataset from Seoul city	GRU – 98.32%	we remove the data from some particular day due to missing data caused by an error or failure of the web crawling program

Related Work

S.No	Author Name	Year	Methodology	Model	Dataset	Result	Limitation
5	Honglei Ren et al.	2018	A Deep Learning Approach to the Citywide Traffic Accident Risk Prediction	LSTM Model	Big traffic accident data	LSTM - 90.3%	One limitation of these works is that, they did not incorporate several importance factors such as traffic flow, weather condition, air quality into their model.
6	Chantakarn Pholpol et al.	2021	Traffic Congestion Prediction using Deep Reinforcement Learning in Vehicular Ad-Hoc Networks (VANETS)	Reinforcement Learning	Road Traffic Data	Reinforcement Learning – 95%	VANET itself has a limitation and also lack of flexibility to find the congested route and to reroute to the alternative paths.
7	Mahmuda Akhtar et al.	2021	A Review of Traffic Congestion Prediction Using Artificial Intelligence	Hidden Markov Model	Stationary data and Probe data	HMM – 82%	No study has provided any reasonable logic on selecting the membership function, which is a significant limitation of fuzzy logic models.
8	Kadda Beghdad bey et al.	2024	Improving Road Traffic Speed Prediction Using Data Augmentation: A Deep Generative Models-based Approach	Deep Generative Model	Road Traffic Dataset	Deep Generative Model – 87%	Traffic datasets are often small

Limitations of Existing Studies

- Existing ML/DL models are based on single task learning:
  - build model for each road segment independently
  - Limited ability to share knowledge across related tasks or road segments

- Problems of Single Task Learning
  - Overfitting
  - High Computational Cost
  - Scalability Issues

- Proposed Solution: Multi-Task Learning

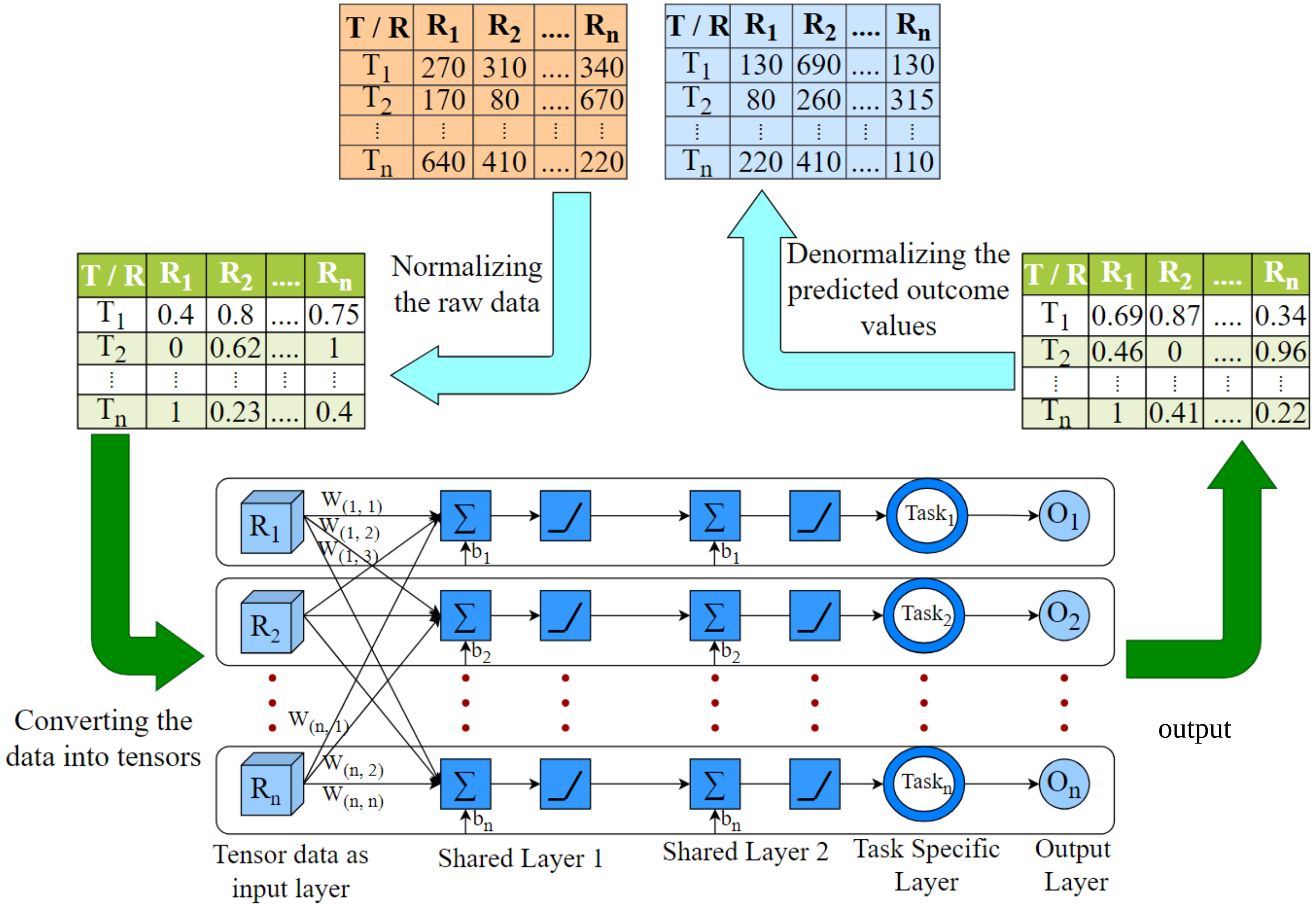
Proposed Multi-Task Learning Model

MTL uses shared information across multiple tasks to improve performance.

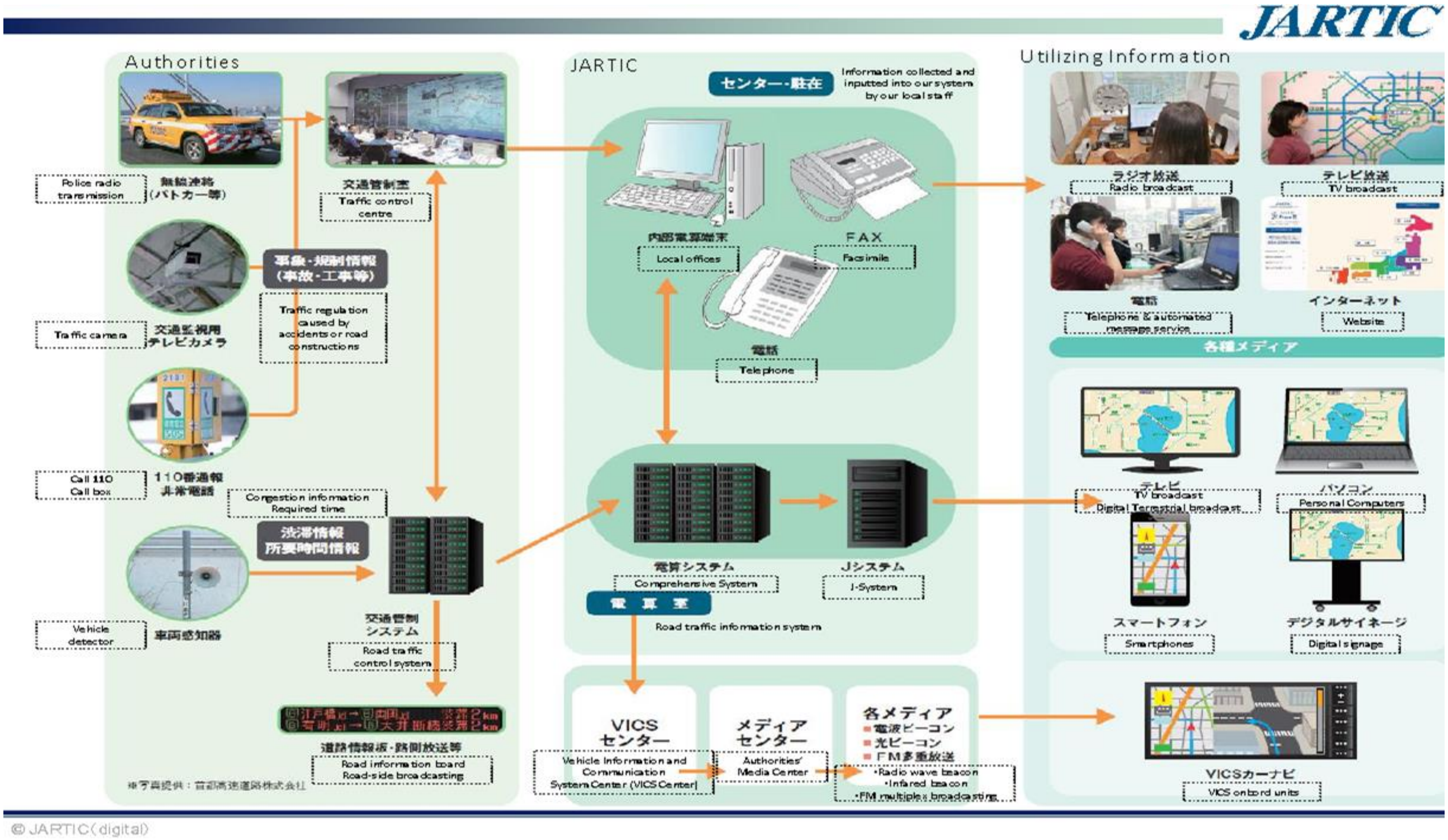
Input: Tensor data of normalized traffic congestion lengths.

Layers:

- Two shared hidden layers with Linear + ReLU activation.
- Task-specific layers generating predictions for each road segment.
- Output layer for normalized predictions.



About JARTIC system

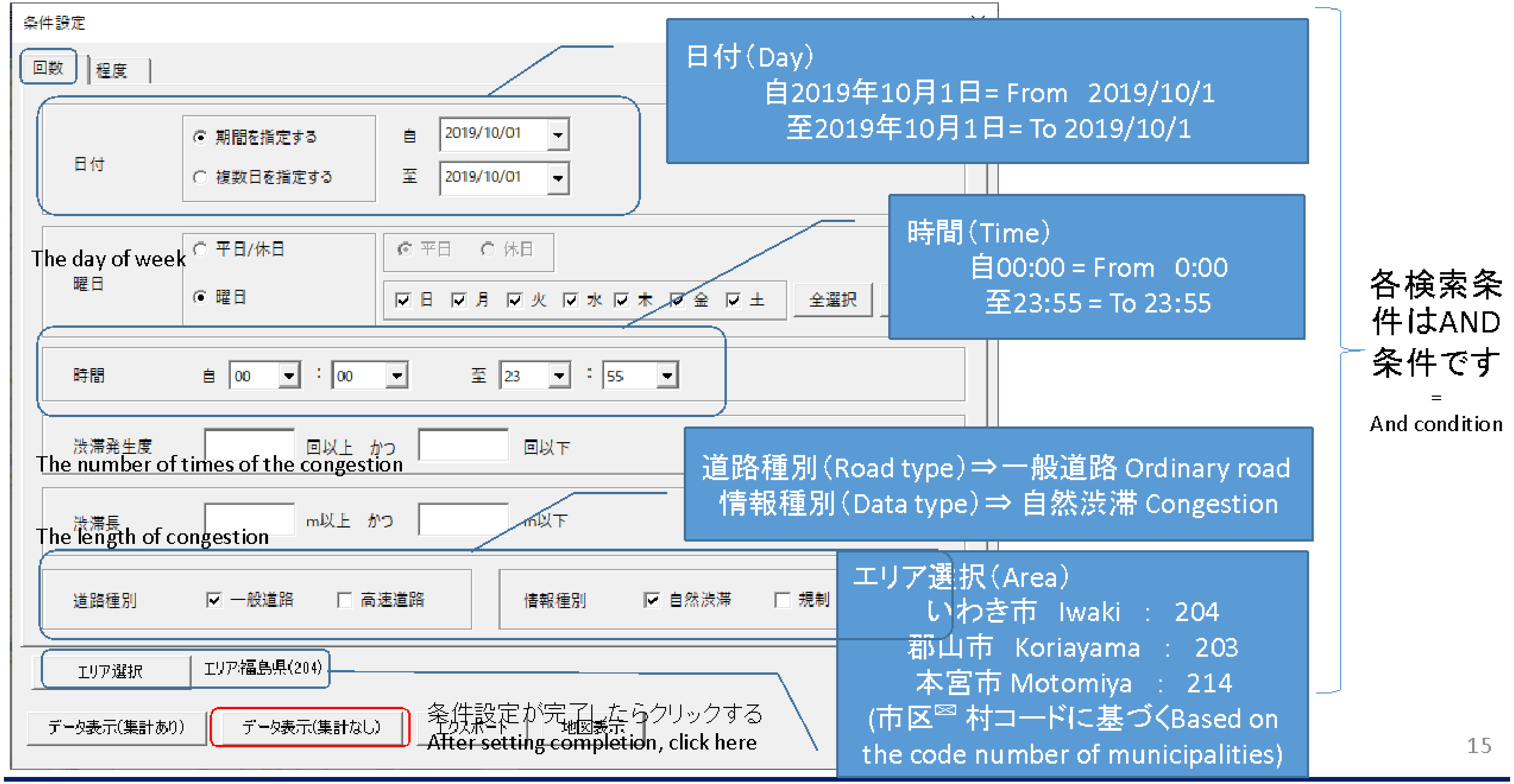


System usage example

To search total amount of congestion for 288 cycle (0:00, 0:05, ･･･ ,23:55) in Iwaki on 1-Oct-2019, setting the setting screen as in the below drawing.

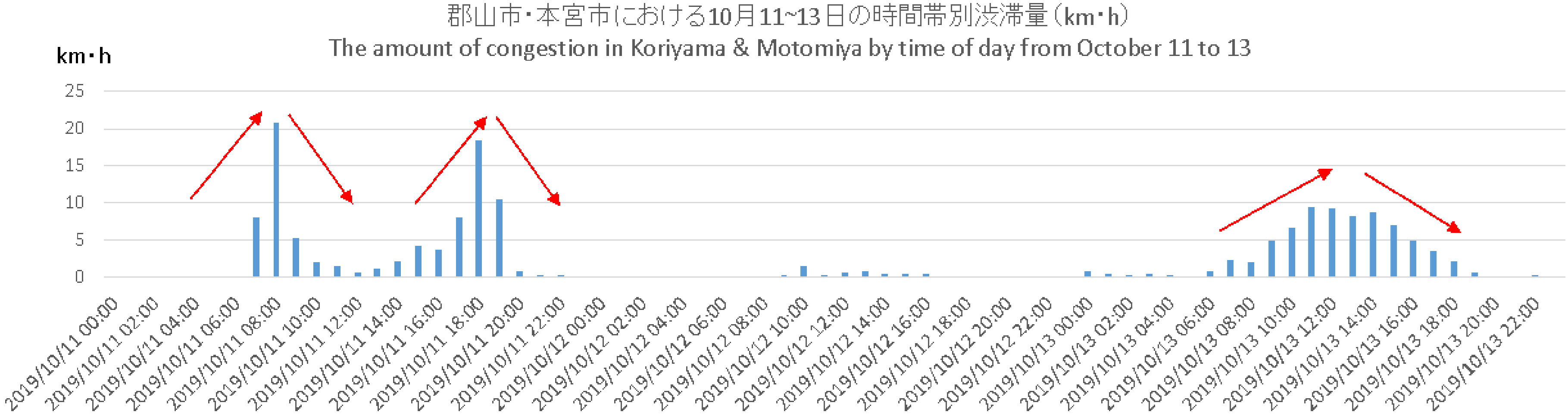
※渋滞量… 渋滞の規模を表す指標。渋滞長× 渋滞発￭時間で￭める

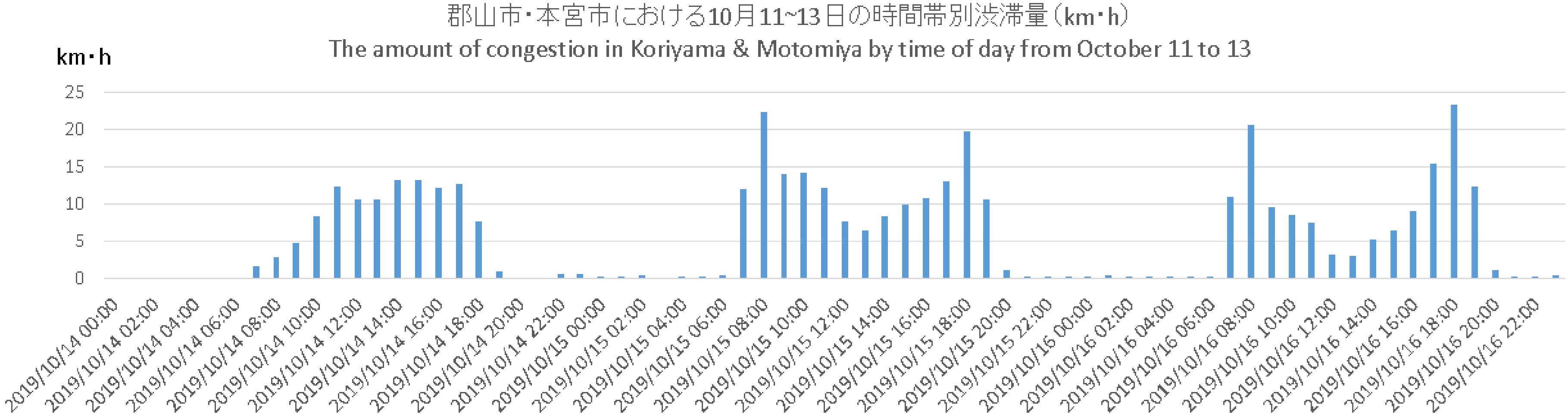
※Amount of congestion… An index expressing the scale of congestion, multiplying the length of congesiton and duration time of congestion



System usage example

The graph below shows the change over time about the total amount of congestion in Koriyama city and Motomiya city at each time of day from Oct 11 to 16 in 2019.

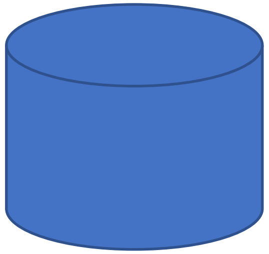




Real Time Data Collection

(a) Road sensor network of Fukushima prefecture

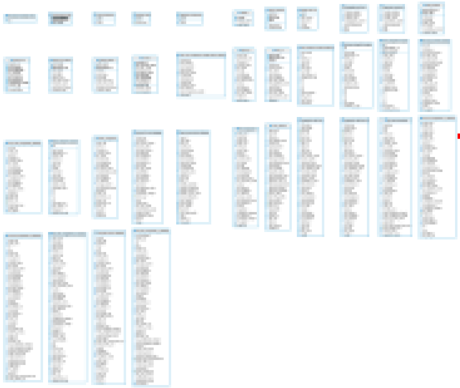
generates



104 K rows

(b) 5 min. interval traffic congestion data

storage

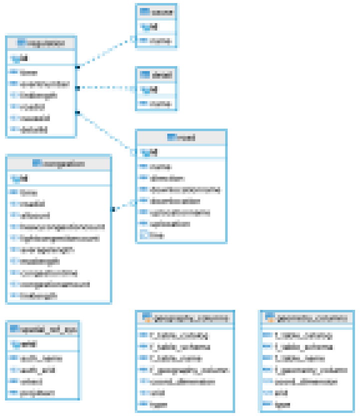


(c) JARTIC schema

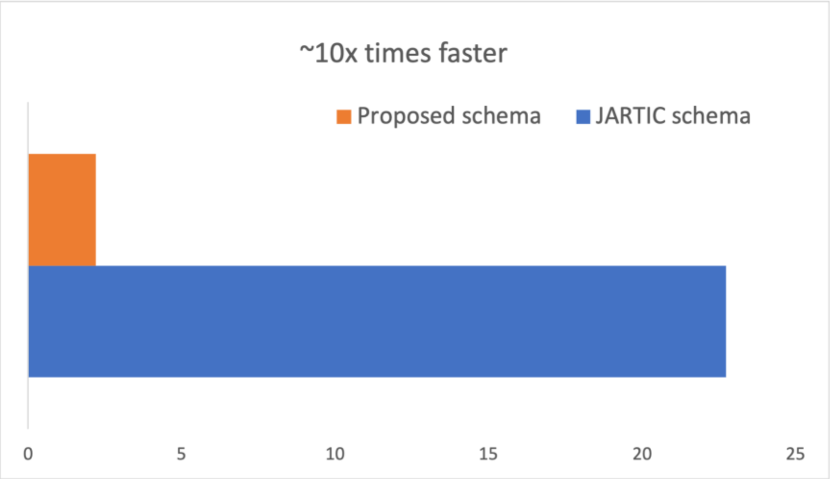
Issue

(d) Slow and cannot handle big data app requirements

Our Solution



Performance evaluation

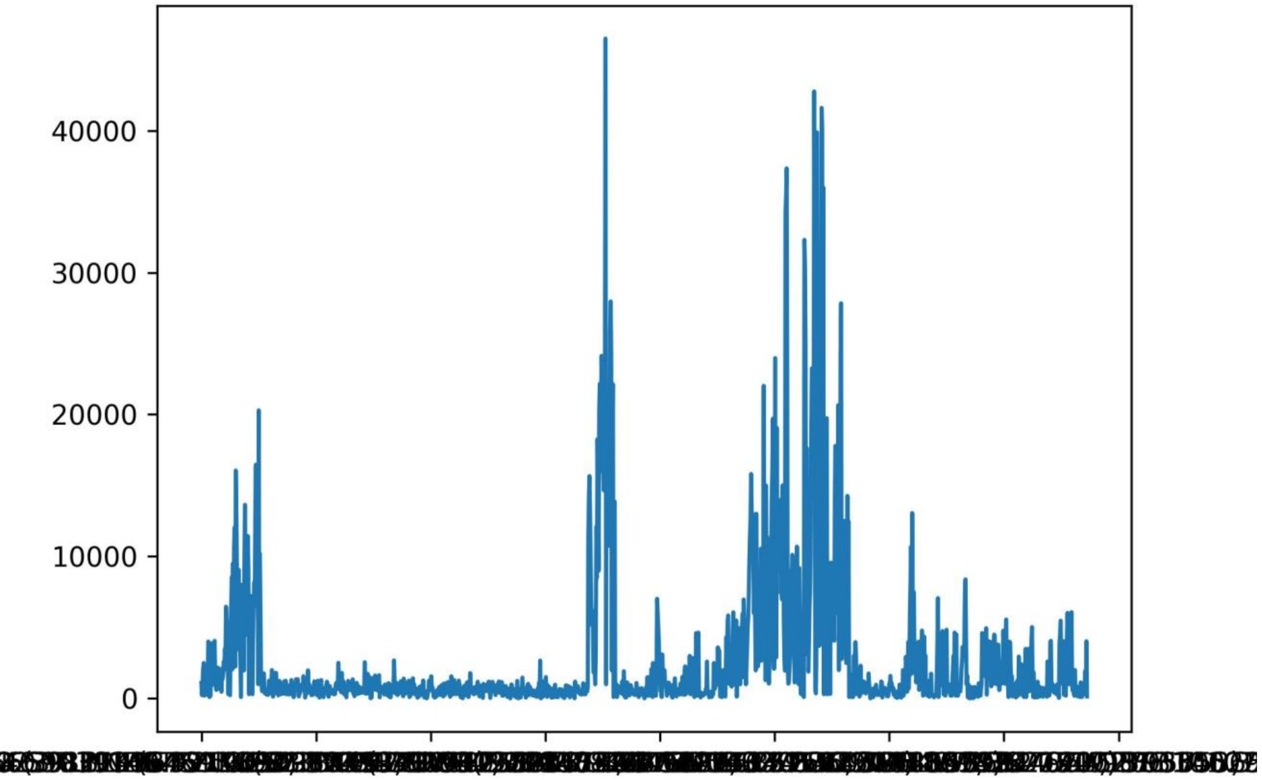


(f) Transactional databases for machine learning tasks can be generated 10 times faster

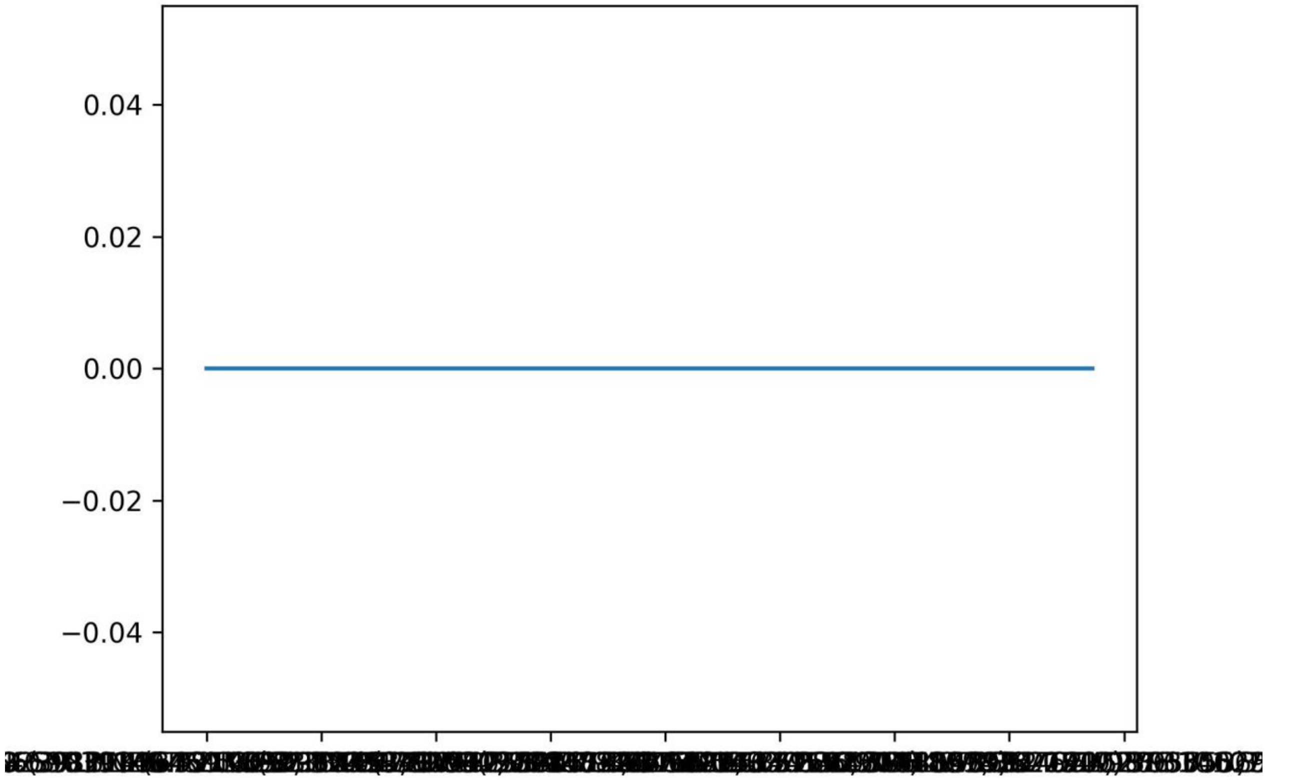
benefits

(g) Faster discovery of competitive information in big data at low cost. Our AI system was able to predict traffic congestion in Fukushima with an accuracy of 83.5%

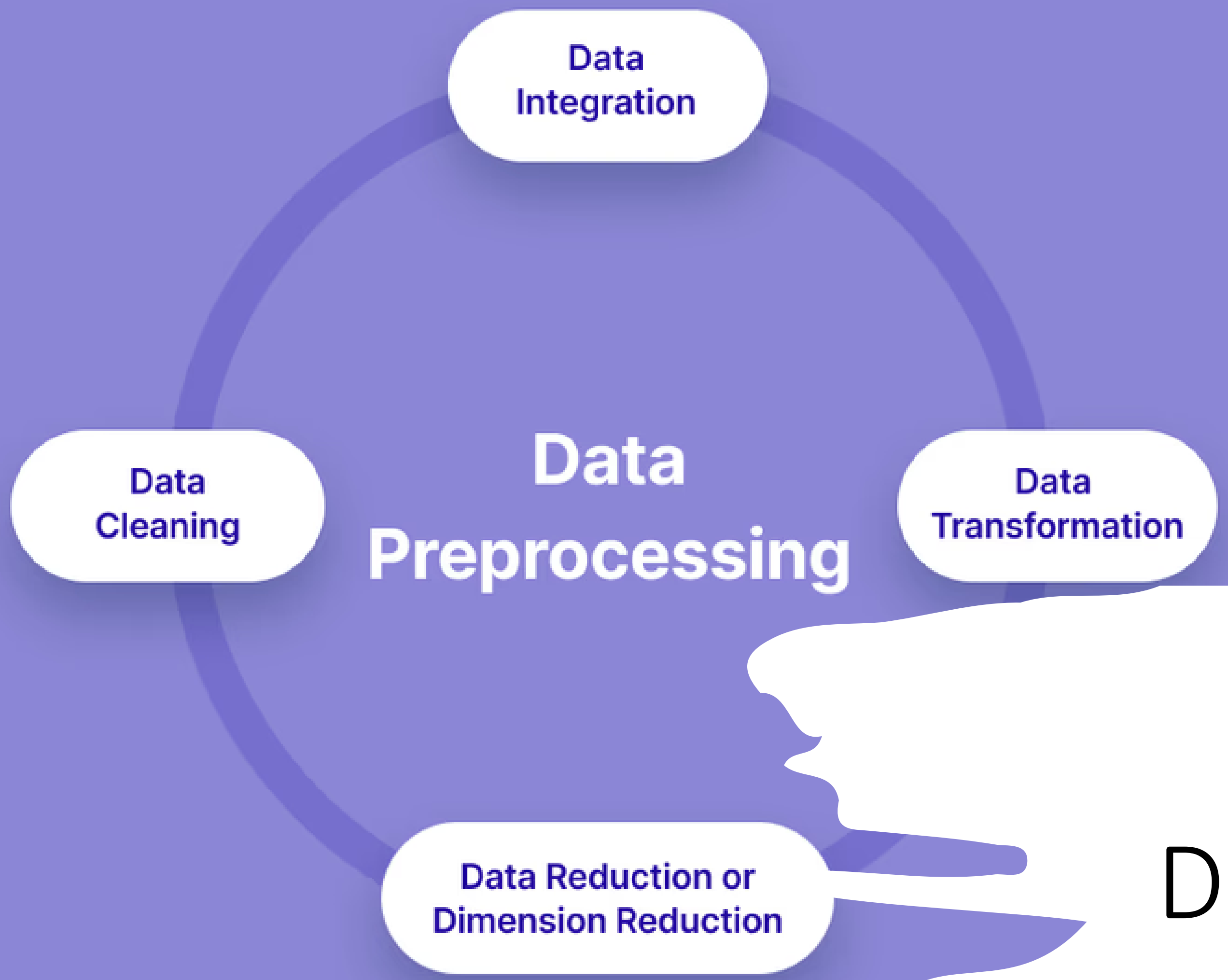
Outliers Identification in Dataset:

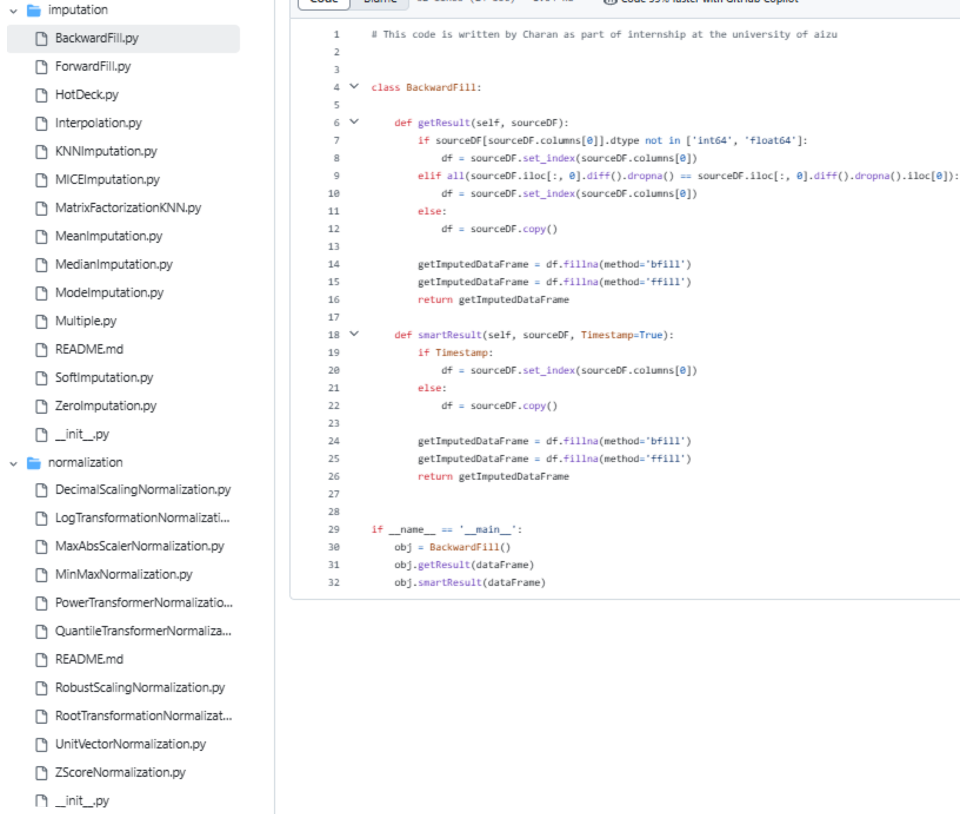


Maximum value in each column



Minimum value in each column





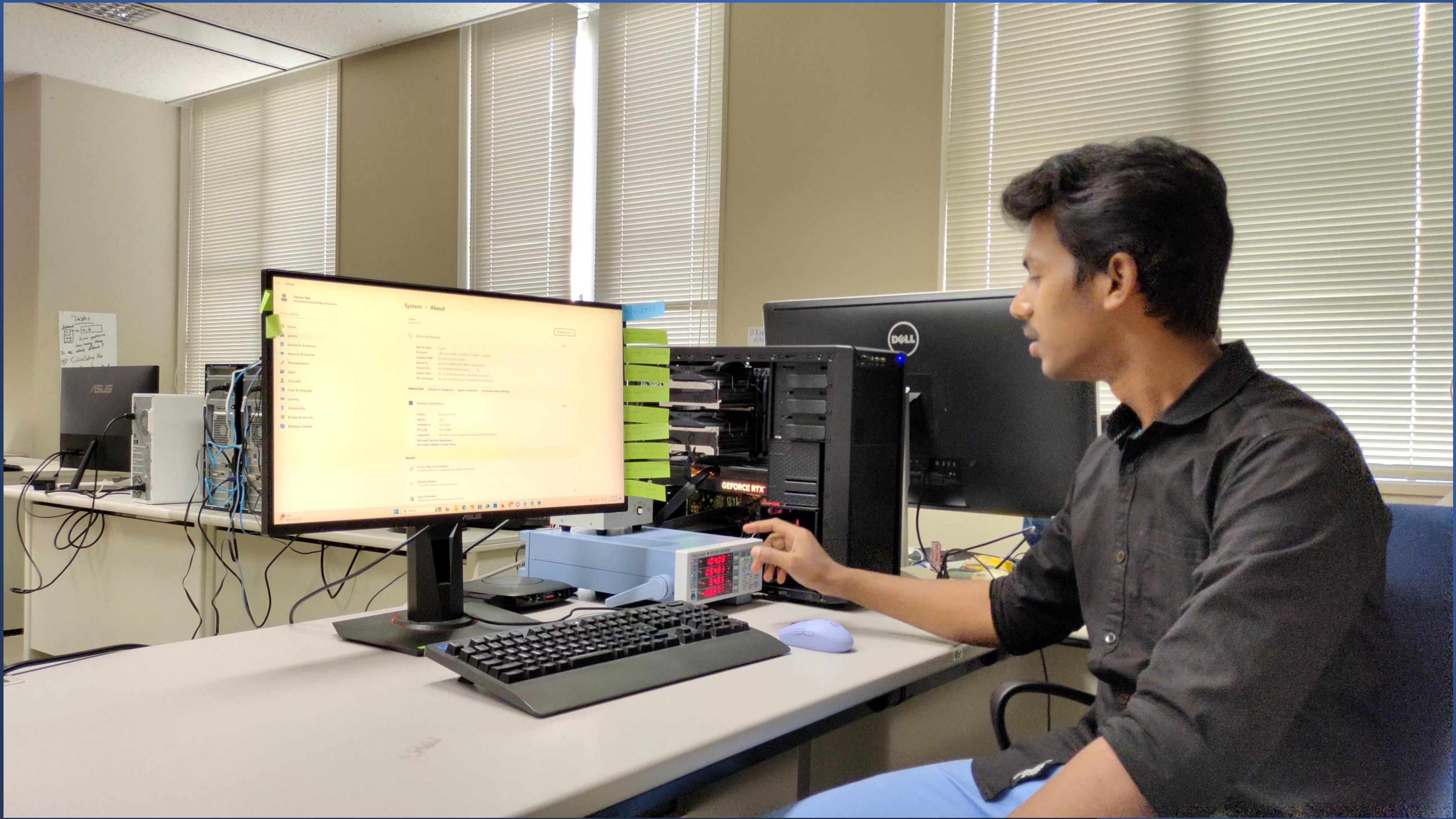
Data Preprocessing:

Imputation and Normalization

Experimental Setup

Power Calculation device: Yokogawa WT310EH Digital Power Meter

Edition	Windows 11 Pro
Processor	13th Gen Intel(R) Core(TM) i5-13400F 2.50 GHz
Installed RAM	64.0 GB
System type	64-bit operating system
Shared GPU	32 GB
SSD	2TB
Required Internet	Minimum 100 MBPS


System › About
GEFORCE RTX

Problem Statement:

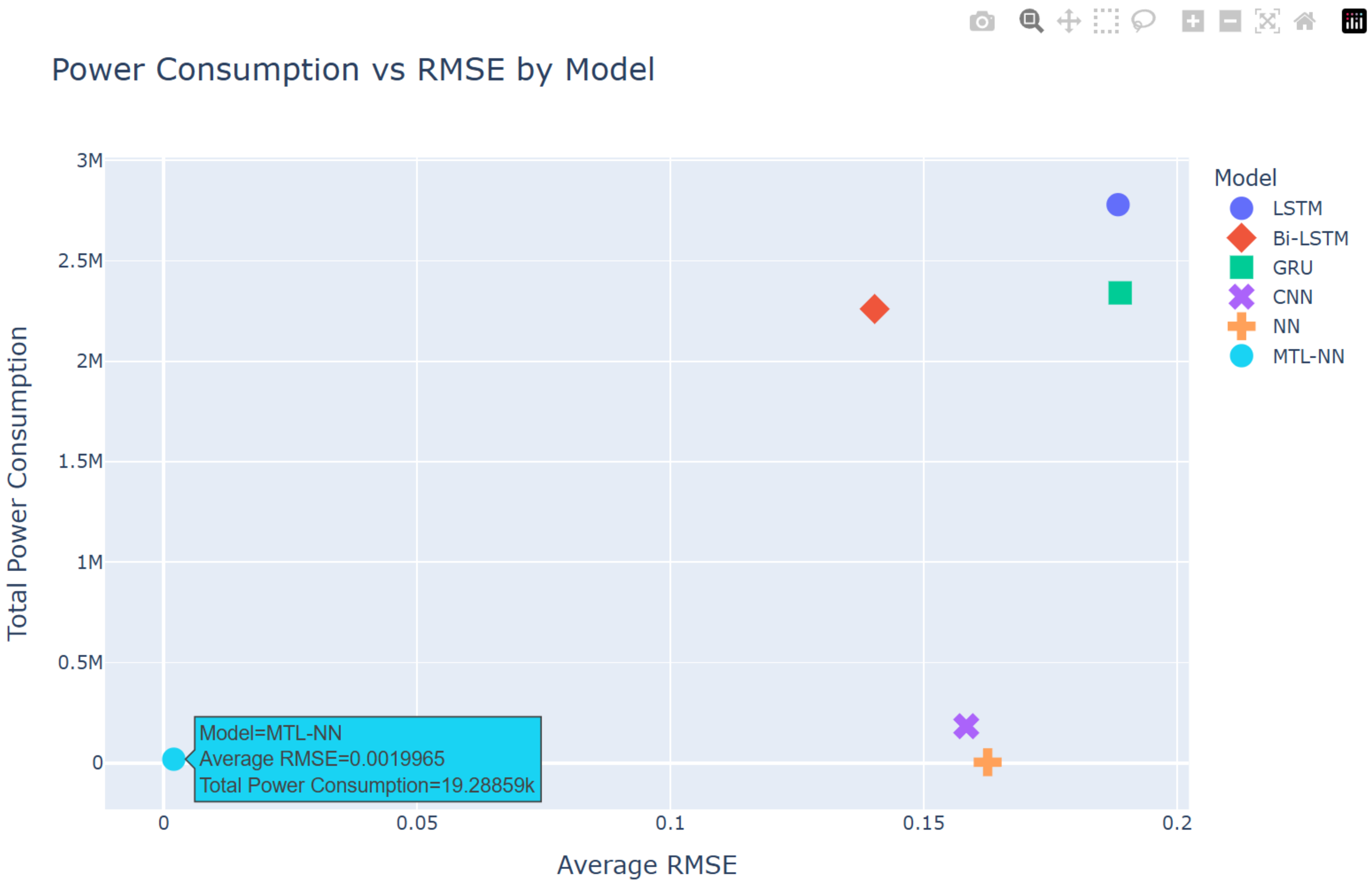
- Traditional models predict congestion independently for each road segment, which is inefficient for large networks.
- We need an energy-efficient, scalable system that accurately forecasts traffic across multiple road segments.

Objectives:

- ➢ Predict traffic congestion for large-scale road networks.
- ➢ Improve prediction accuracy using shared information across tasks.
- ➢ Develop a model with reduced computation time, memory and power consumption.
- ➢ **Novelty:** Use of shared and task-specific layers for different road segments.

Results:

	Model	Average_RMSE	Average_MAE	Aveerage_R2	Total_Time	Total_Memory	Total_Power_Consumption
0	LSTM	0.188374	0.087861	0.244536	5948.2	240.9800	2780044.50
1	Bi-LSTM	0.140328	0.064542	0.626795	4,543.90	350.5700	2260605.70
2	GRU	0.188786	0.105214	0.435177	4,578	260.7200	2340839.20
3	CNN	0.158414	0.083124	0.697999	395.66	238.3800	183652.39
4	NN	0.162634	0.082682	0.481399	4.6	86.7500	4461.43
5	MTL-NN	0.001997	0.000801	0.999880	27.4368	0.0009	19288.59


Power Consumption vs RMSE by Model
Total Power Consumption
Average RMSE
3M
2.5M
2M
1.5M
1M
0.5M
0
0
0.05
0.1
0.15
0.2
Model
LSTM
Bi-LSTM
GRU
CNN
NN
MTL-NN
Model=MTL-NN
Average RMSE=0.0019965
Total Power Consumption=19.28859k

Our Route Recommender System

私たちのルート推奨システム

Road congestion data
道路渋滞情報

Road Network
道路網

Google Geocoding and Routes
Googleのジオコーディングとルート

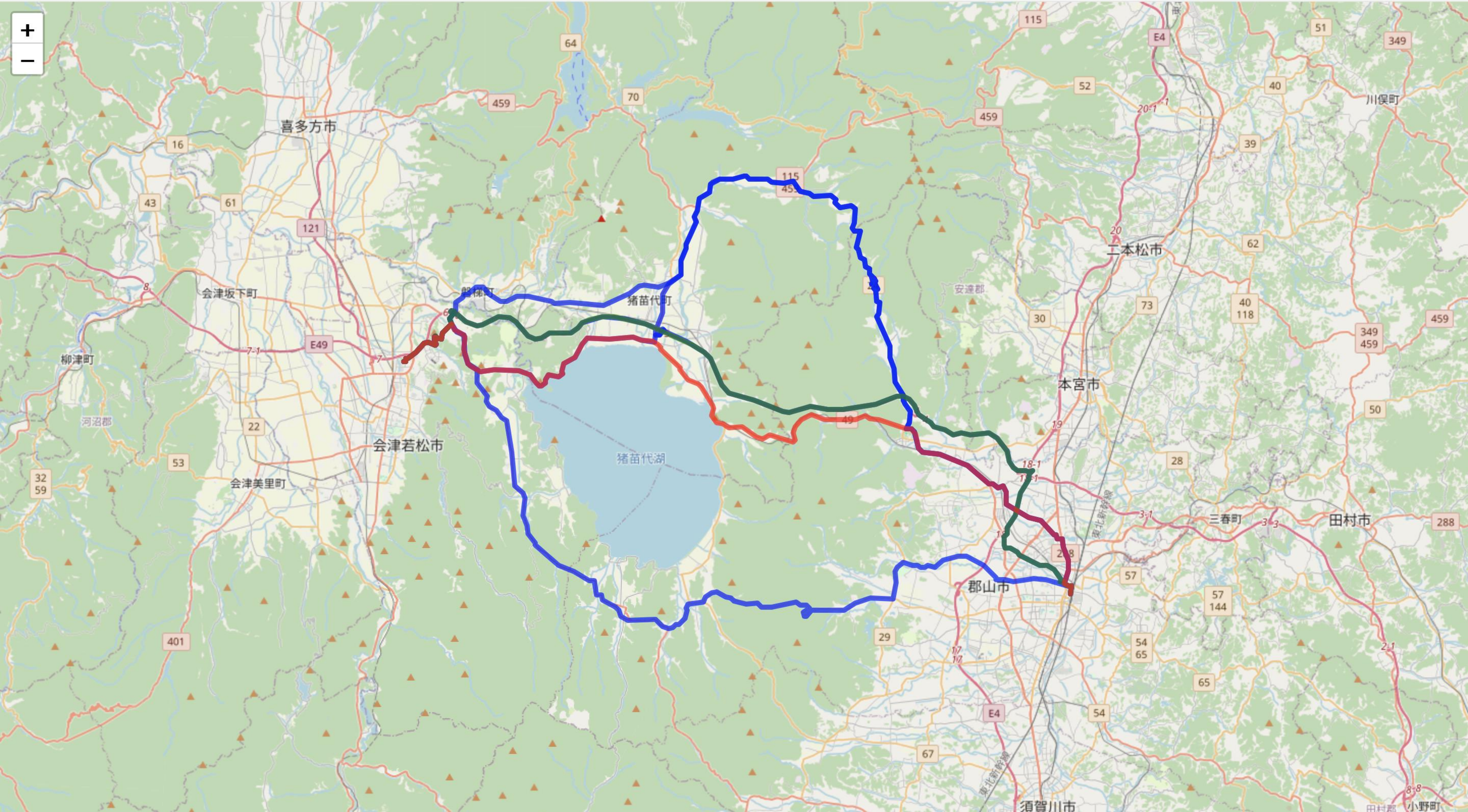
Yahoo! Weather data
Yahoo!の気象情報

Wind & Pollution
風と公害

$$\int (Congestion, RoadLayouts, Routes, Weather, WindSpeed, Pollution)$$

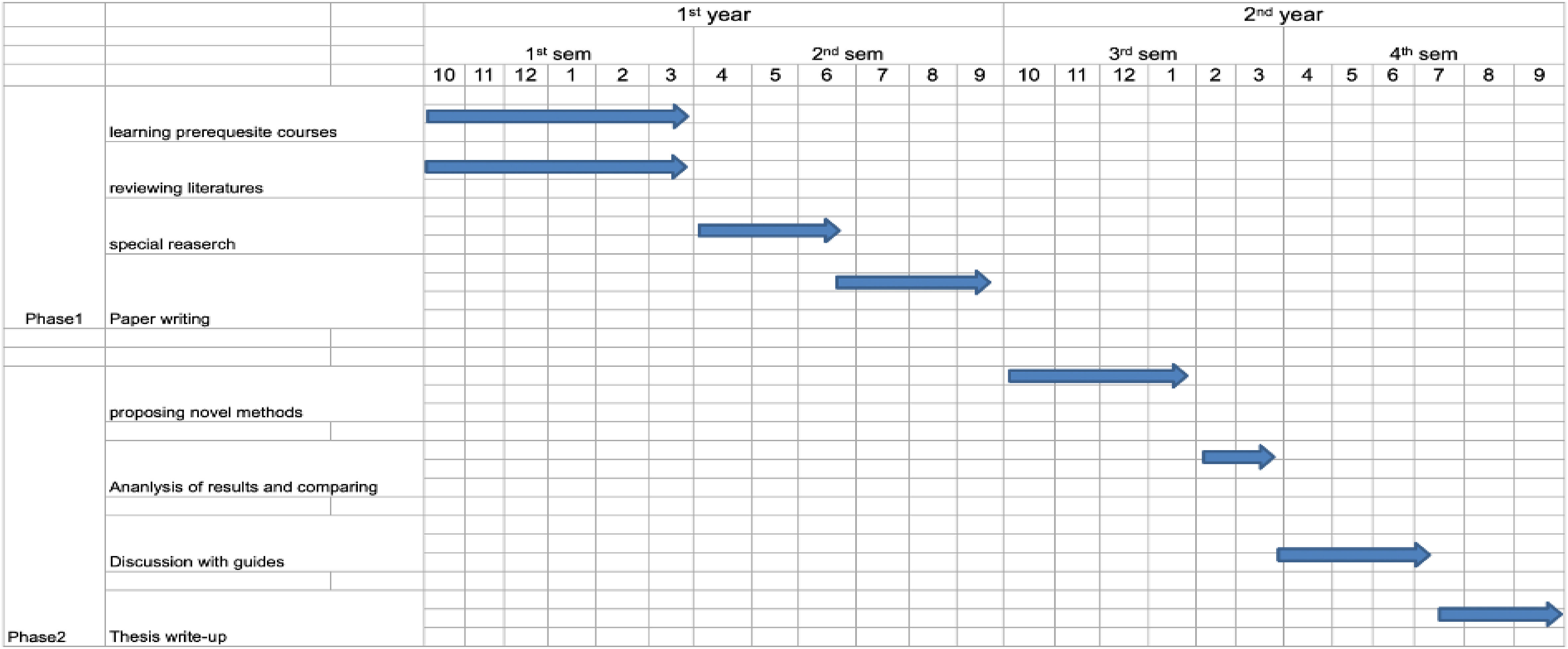
Recommends Route with minimal human driving

人の運転を最小限に抑えたルートを推奨



喜多方市
会津坂下町
柳津町
河沼郡
会津若松市
会津美里町
磐梯町
猪苗代町
猪苗代湖
安達郡
二本松市
本宮市
川俣町
三春町
田村市
郡山市
須賀川市

Schedule



1st year
2nd year
1st sem
2nd sem
3rd sem
4th sem
10 11 12 1 2 3 4 5 6 7 8 9 10 11 12 1 2 3 4 5 6 7 8 9
learning prerequesite courses
reviewing literatures
special reaserch
Paper writing
Phase1
proposing novel methods
Ananlysis of results and comparing
Discussion with guides
Thesis write-up
Phase2


Any Questions

THANK YOU!