Real-Time Taxi Demand Forecast Using Wireless Network Data

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Background

Taxi drivers' problem

I pretended to be a new driver,
I heard about drivers' problems

- Listened from taxi drivers
  - **Fresh drivers:**
    don't have enough knowledge
  - **Experienced Drivers:**
    After the delivery, They'd like to return to a familiar place from an unfamiliar place

Drivers can't drive efficiently because they don't have enough knowledge about the area demand

By using real-time population statistics data, can we estimate the future taxi demand?

Objective

Taxi demand prediction

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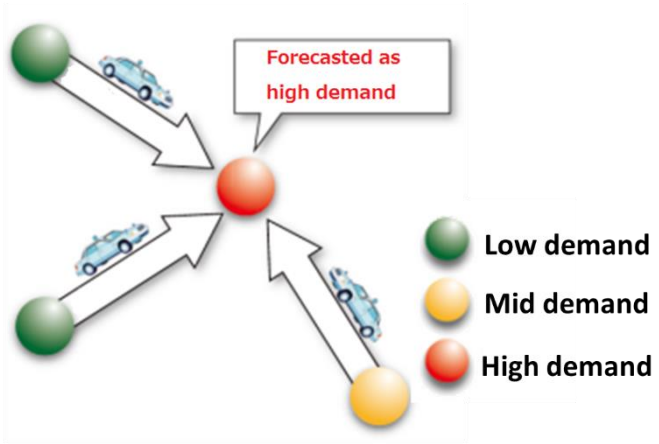
Future taxi demand prediction

For improving the efficiency of taxi drivers,

Forecast based driving



Problem:
Is it possible to predict highly accurately with combination of Real-time population and taxi navigation data?

Approach：
Future demand forecast based on Deep Learning using Taxi service data and DoCoMo's "real-time population data“

Movie

About Real-time population

Real-time population

Population dynamics data using docomo's mobile phone network mechanism. Periodically grasped mobile phones location in each area of each cellular base About 60M subscribers' data. Estimate the population in Japan all over the country 30 minutes before every 10minutes with a 500m grid.

Such data is owned only docomo in Japan
We want operator partners' in other countries!

Operation data

基地局#1、日時:
090-XXXX-XXXX、男性,
5.43.10.11生、……

Elimination of personal identity

Data cannot identify individuals

基地局#1、日時:
男性,40歳台、……

Estimate real population by Considering docomos' share rate in each area

Estimated population

(40歳台男性)

75人	120人	30人
90人	135人	105人
45人	60人	6人

Confidentialize small area

Real time population

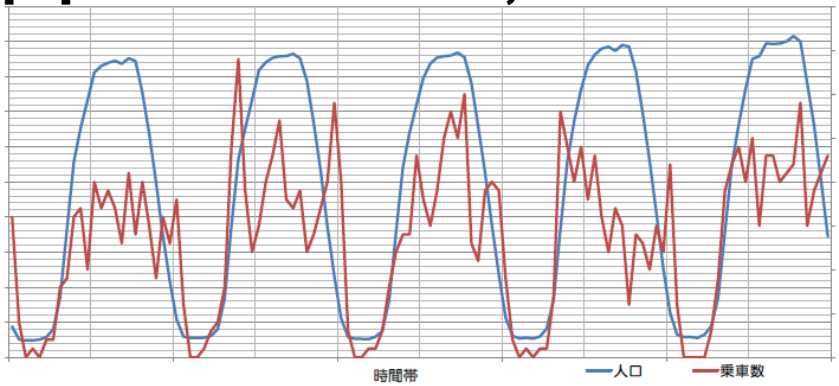
(40歳台男性)

75人	120人	30人
90人	135人	105人
45人	60人	—

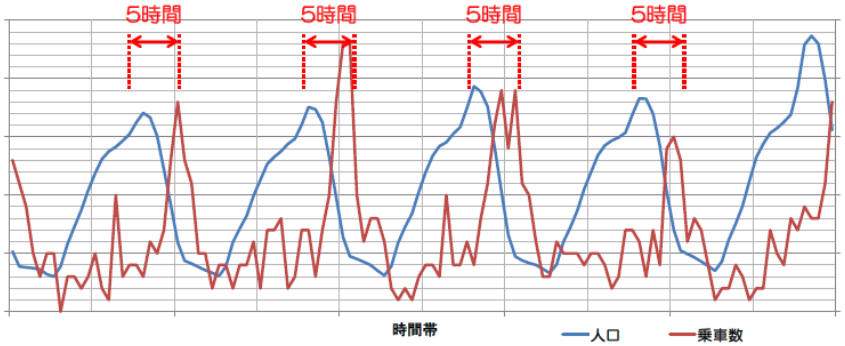
Preliminary verification of population and taxi usage 1

[Point A] Taxi boarding transition is synchronized with population transition

(As the population increases, the number of rides increases, and as the population decreases, the number of rides will decrease)

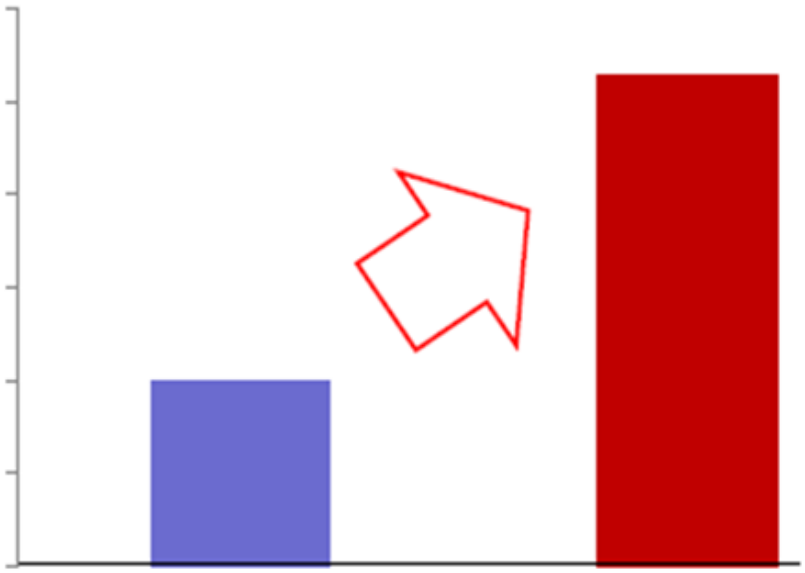


[Point B] Taxi boading transition is synchronized with population transition 5 hours delay



Preliminary verification of population and taxi usage 2

- **When and where population gathered more than usual,**
- **There is a possibility that the passenger acquisition rate is high and the demand can be found based on the population**



Average **Higher population**

Passenger Acquisition Rate

$$\text{Passenger Acquisition Rate} = \frac{\text{Taxi num who get passengers}}{\text{Number of empty taxi}}$$

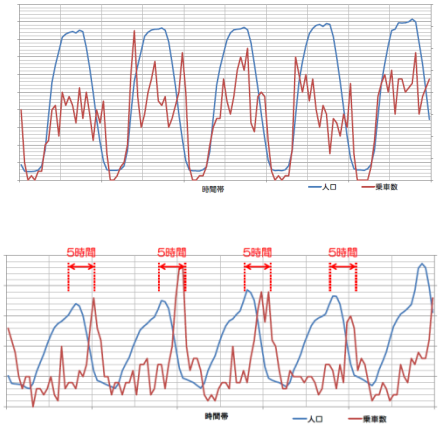
*** Per grid / per 30min**

Passenger Acquisition Rate

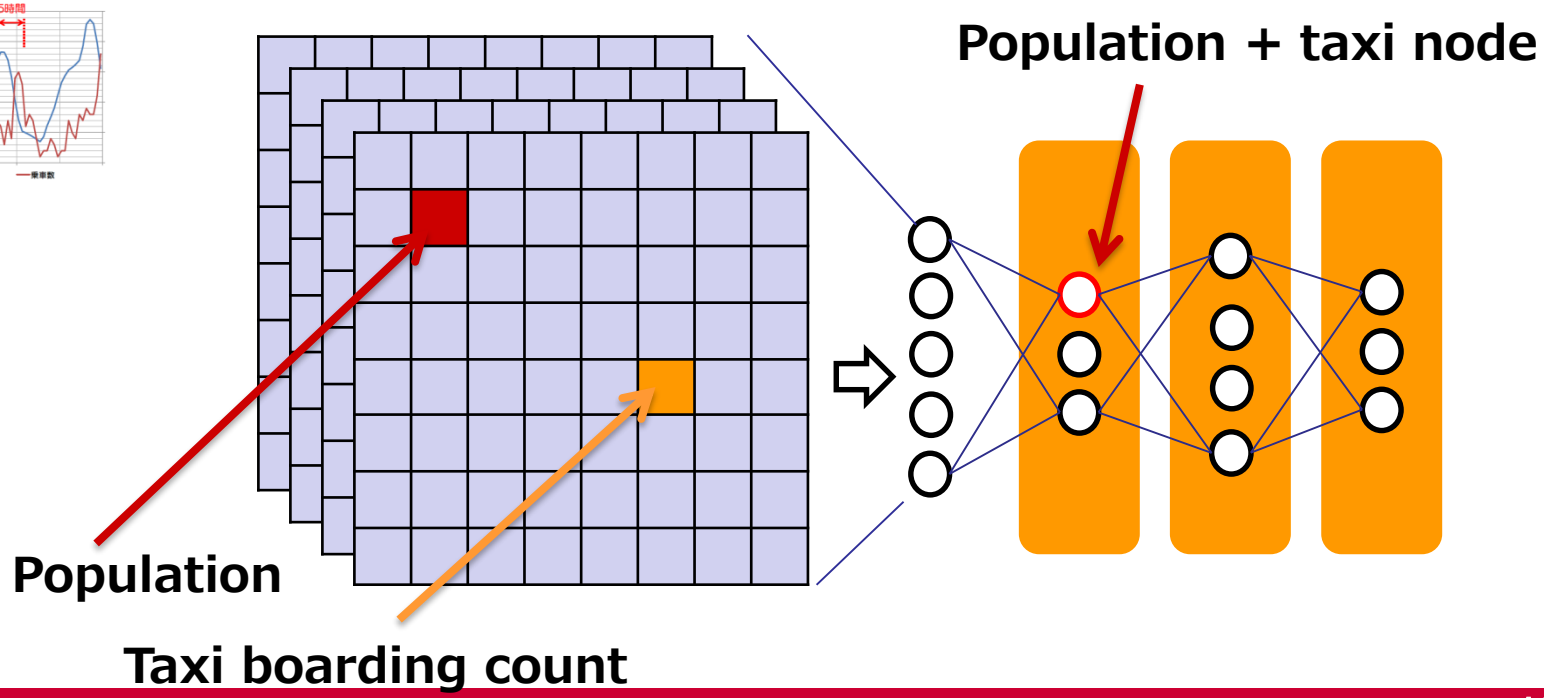
Approach

Demand forecast by Deep Learning

- **Abstraction of the correlation between features by Deep Neural Network**
  - Generate high dimensional features
  - Even when the correlation between data is not clear, high dimensional abstraction can be done

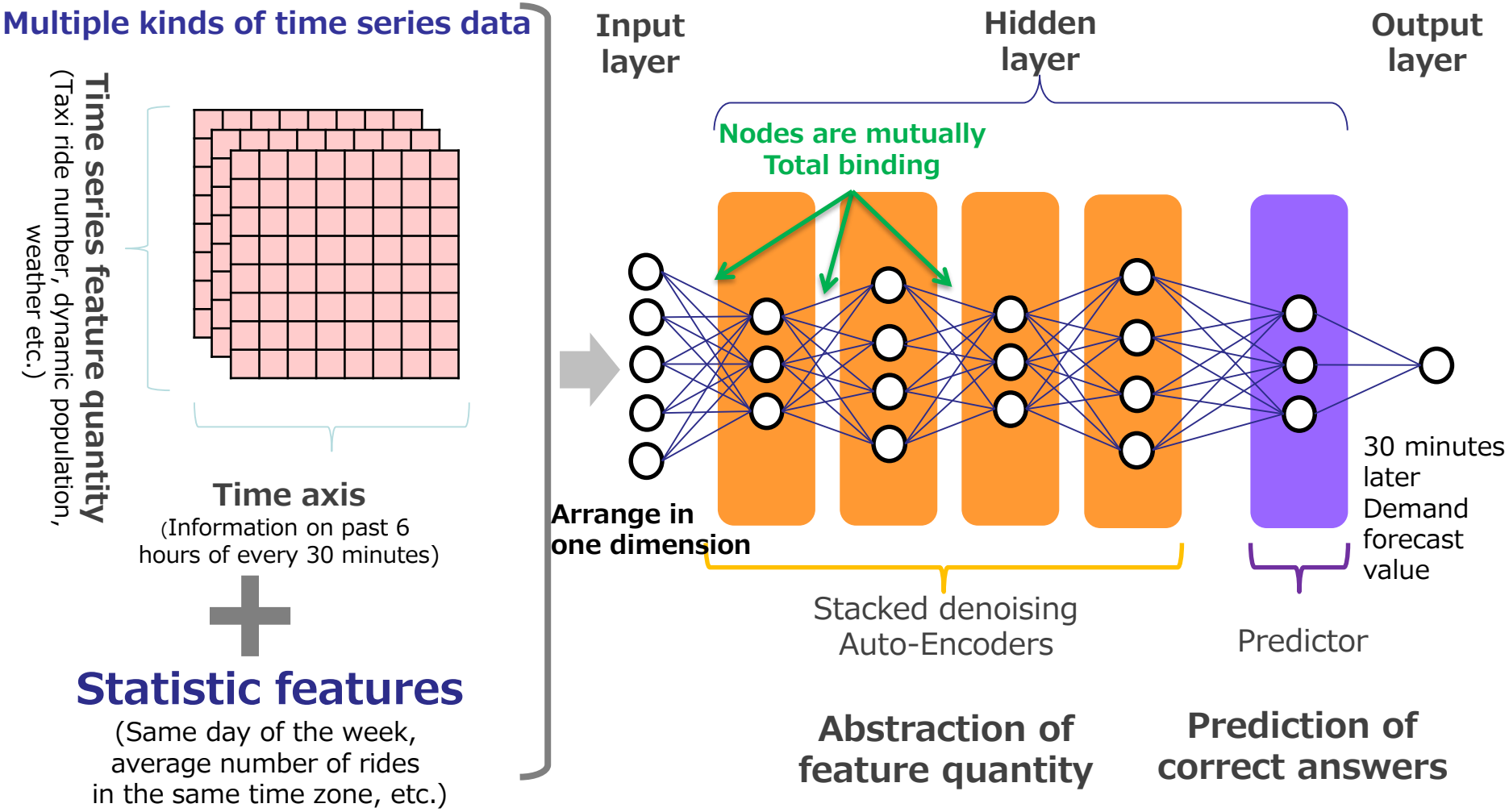


Depending on the characteristics of each area, the relationship between the population and the taxi that is synchronized but shifted could be expressed with DNN



Proposed method： SdA based learning

- **Enter time series / statistics data into Stacked denoising Autoencoders(SdA)**
- **Regression prediction in the final layer using abstracted feature quantities**



- **Target: Taxi ride number 30 minutes later**
- **Input:**
  - Population・rainfall・taxi data up to 6 hours ago at 30 minute intervals from target time …
  - Population, rainfall, and taxi data one day ago …
  - Population・rainfall・taxi data one week ago …

Data obtained for a certain grid

	Population data			weather data	Taxi data	
Time period	A	B	…	Rain amount	Drop off counts	Get on counts
2015-08-02 10:10	3197	2912		0	2	0
2015-08-02 10:40	2589	2343		0	1	6
2015-08-02 11:10	2308	2080		0	6	3
2015-08-02 11:40	2182	1842		4.1	2	1
2015-08-02 12:10	2102	1690		3.5	0	0
…	…	…	…	…	…	…
2015-08-02 15:10	1698	392		0	0	2
2015-08-02 15:40	1750	320		0	1	0
2015-08-02 16:10	1834	234		0	3	2

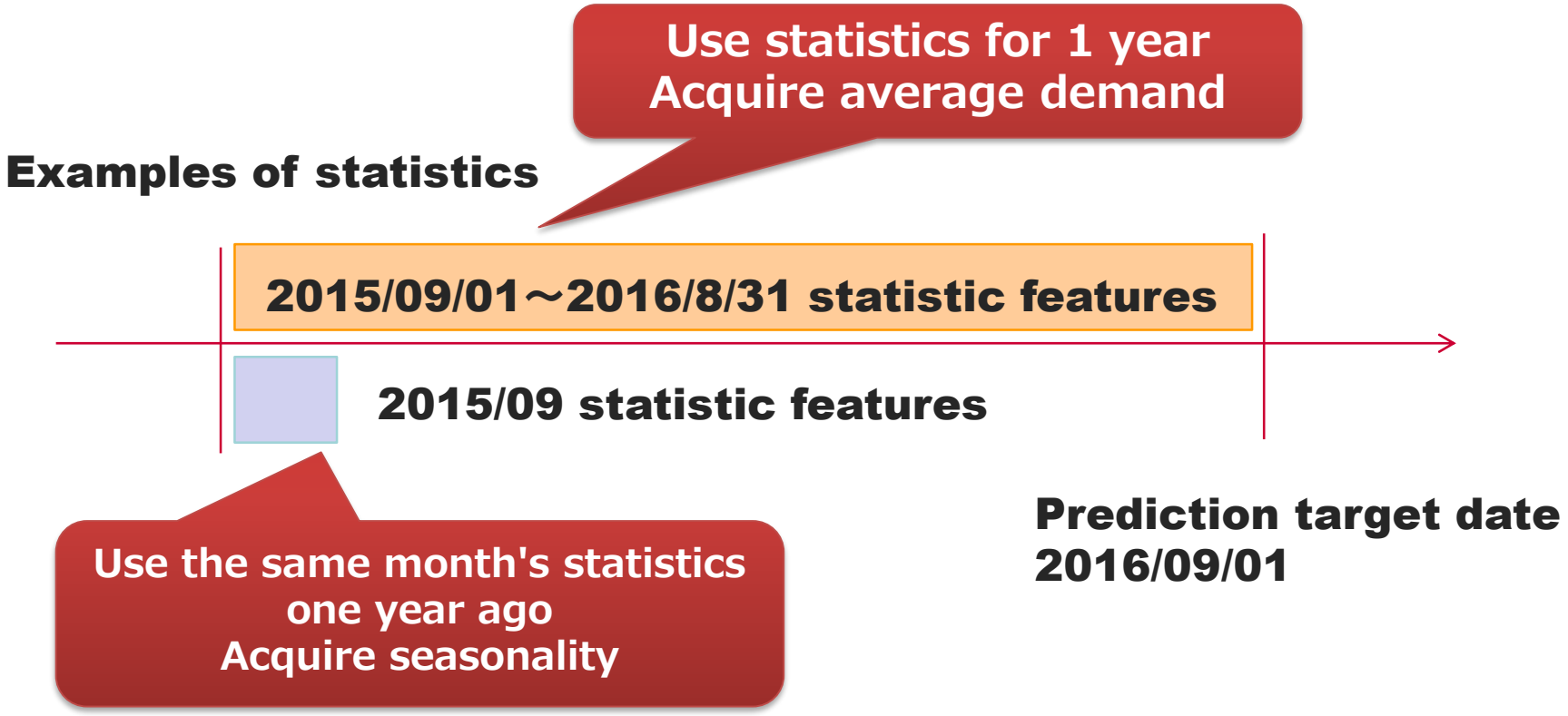
Explanatory variable
(input data)

In the past
6 hours data

Target variable
(What to forecast)

Creation of statistic features

- **For each taxi / population, various statistics are designed as feature quantities in order to capture long-term and short-term trends**
  - Statisticize the average value, maximum value, minimum value, total of the same day of week and the same time zone
  - Use statistics for one year and statistics one year ago

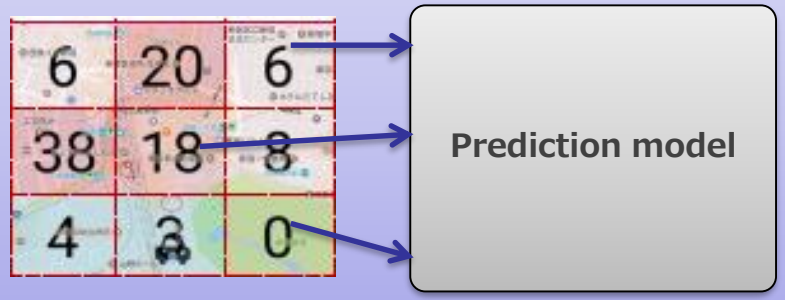


Two kinds of predictive model design

- **In the proposed method, all meshes are predicted with a single model**
  - **By adding a large amount of data at multiple points It can utilize "data of other places similar to each other"**

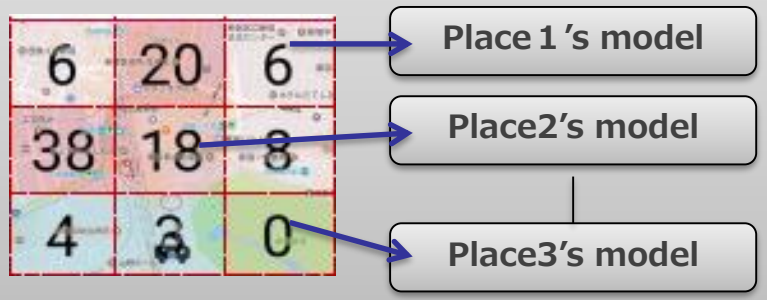
Create a single predictive model as a whole (Proposed method)

- Generalized performance is high because it uses data of all places
- Robust against noise



Create different forecast models for each location

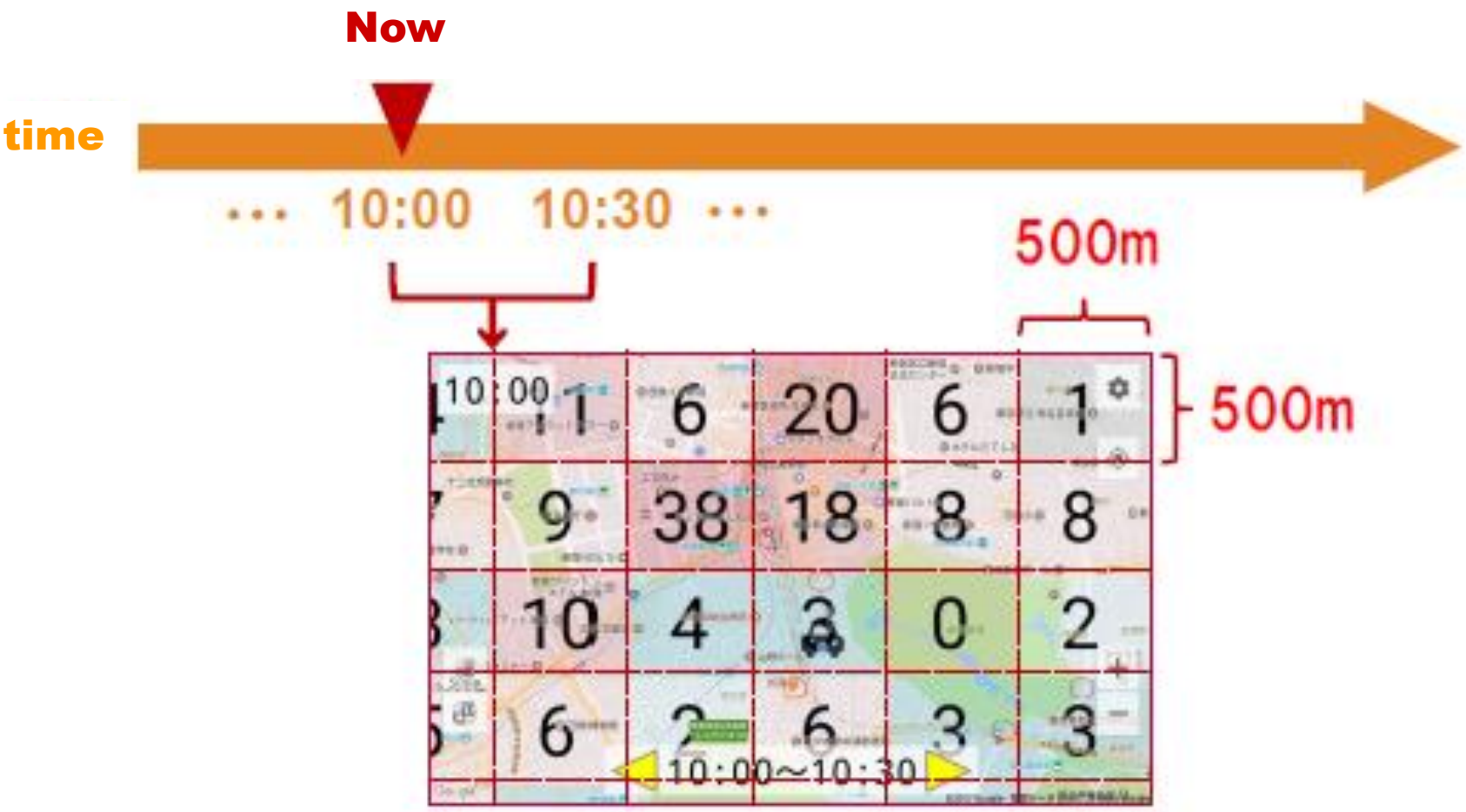
- Effective in a unique place such as a place where there are extremely a lot of people
- it is sensitive to noise



Experiment

Evaluation experiment: Problem setting

Based on the past data, estimate the accuracy of taxi boarding number every 500 minutes for every 500 m grid every 30 minutes and evaluate accuracy



Evaluation experiment: Precondition

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1. **Taxi data: Operation data in Tokyo**
2. **Population data: Real-time demographic data**
3. **Weather data: National synthetic radar data**

- **Learning data period: April 1, 2016 - August 31, 2016**
- **Evaluation data period: September 1, 2016 - September 14, 2016**
- **Target area: Tokyo 23 wards + Musashino city + Mitaka city**

Data type		
Taxi data	Car num	4425 units
	Resolution	GPS accuracy
	Acquisition frequency	Per 5～10 sec
Population data	Resolution	500m
	Acquisition frequency	Per 10 min
Weather data	Resolution	250m
	Acquisition frequency	Per 10 min

Convert to Last 30 min / 500 m Boarding or dropoff number count data

Conversion to Last 30 minutes / Total for every 500 m

Evaluation experiment: Setting of neural network

- **Hyper parameter search by random search is performed using Python's Hyperopt**
  - **For each experiment, 1000 model creation**

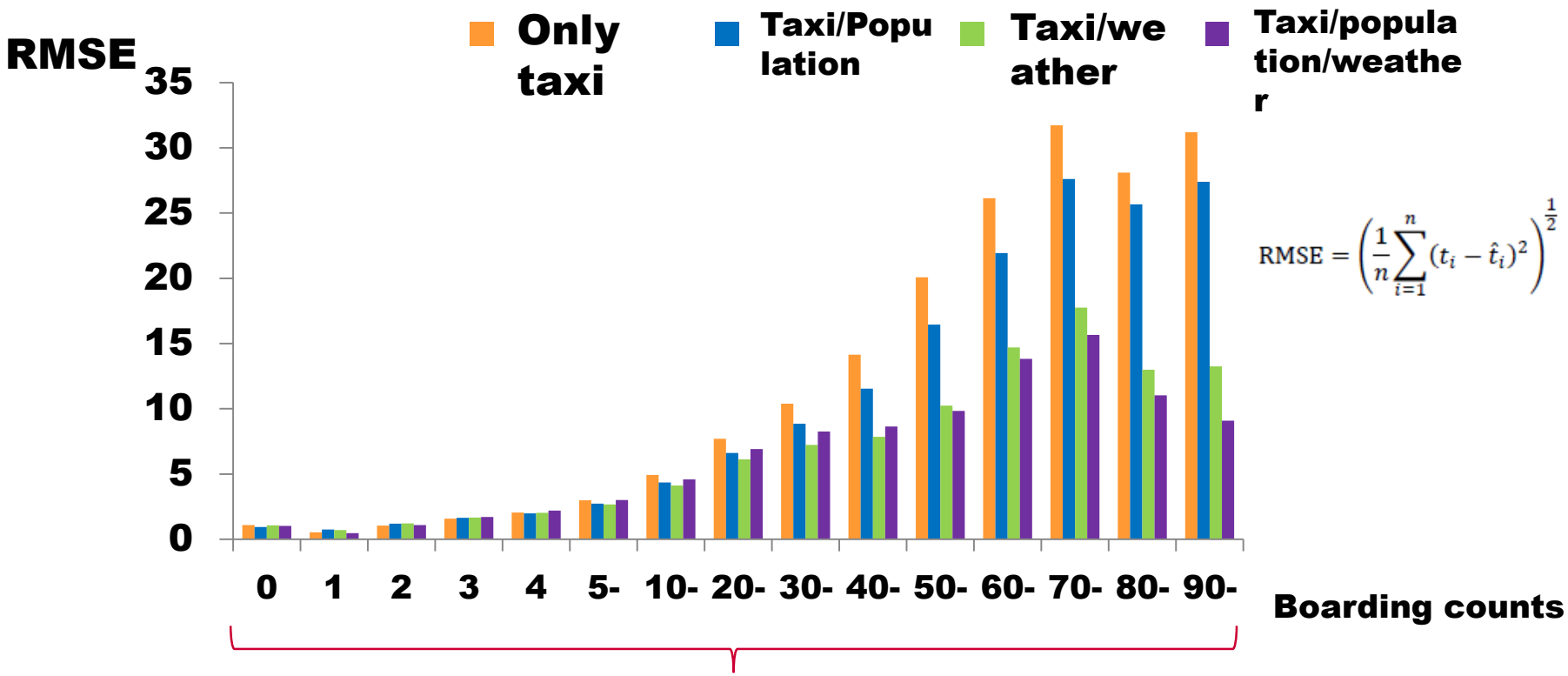
- **The activation function is ReLU**
- **Using Batch Normalization**
- **The optimization function is Adam**

Hyper parameters	Search space
Denoising Autoencoder's Noise coefficient	$0 \leq q_D \leq 0.2$
Sparse Autoencoder's Regularization factor	$0 \leq \rho \leq 0.02$
Dropout ratio	$0.3 \leq \varepsilon \leq 0.7$
Batch size	$50 \leq \mathrm{BS} \leq 200$
Unit counts	$10 \leq \mathrm{N} \leq 1000$

Evaluation results for each input feature quantity

Evaluate prediction accuracy by the 4-layer network
Perform learning by changing data

About 1st to 14th September 2016, every 10 minutes
We predicted the sum of the number of times of riding in the Tokyo metropolitan area 500 meters for 30 minutes,
Evaluate error from correct answer



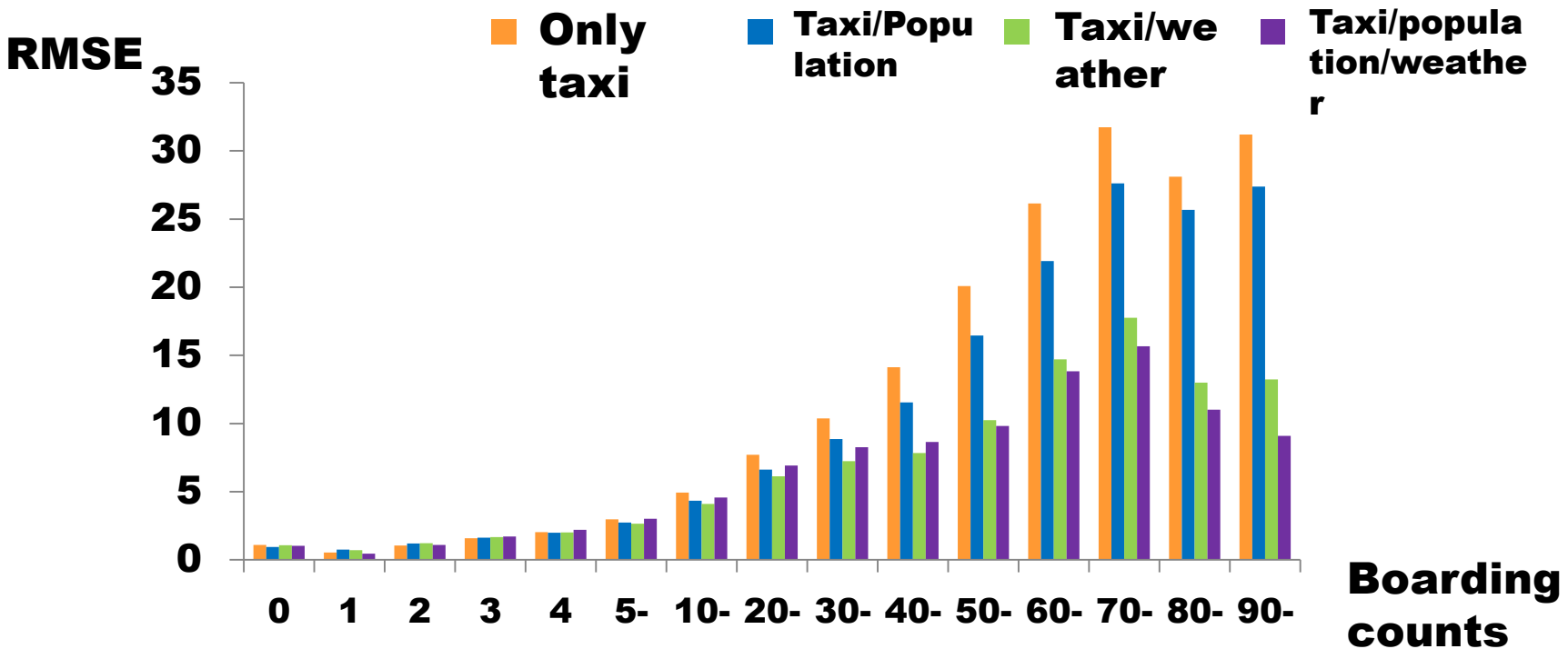
$$\mathrm{RMSE} = \left(\frac{1}{n}\sum_{i=1}^{n}(t_i - \hat{t}_i)^2\right)^{\frac{1}{2}}$$

Each 500 m mesh / 30 minutes, stratified by the number of total boarding

Evaluation results for each input feature quantity

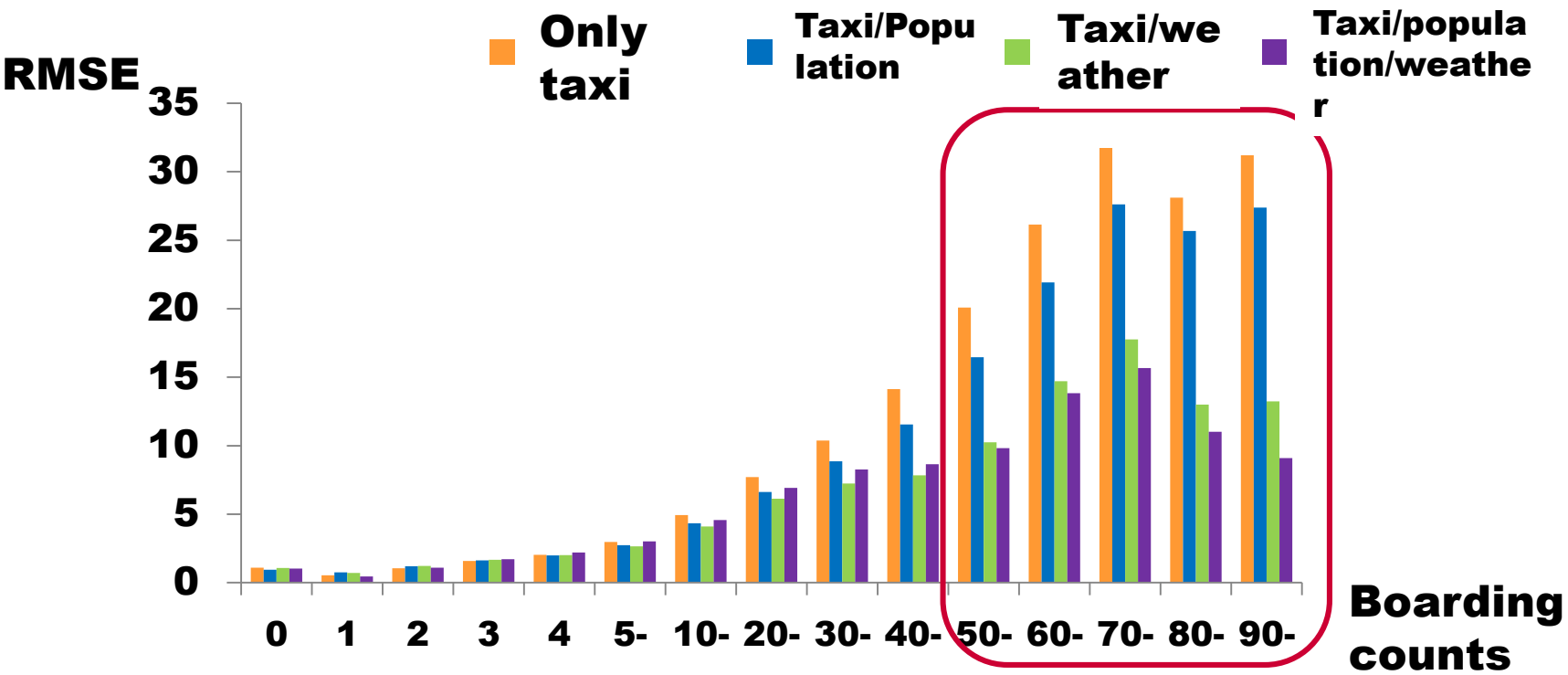
Compared to only taxi data
Improved accuracy by adding population and rainfall as a whole

Rainfall is working well,
Learning period: Since rain hardly fell during the evaluation period against rainy seasons from April to August,
Was the information "did not rain" work?



Evaluation results for each input feature quantity

In the place / time zone of the boarding record 50 to 90,
When population is added, great accuracy improvement can be expected

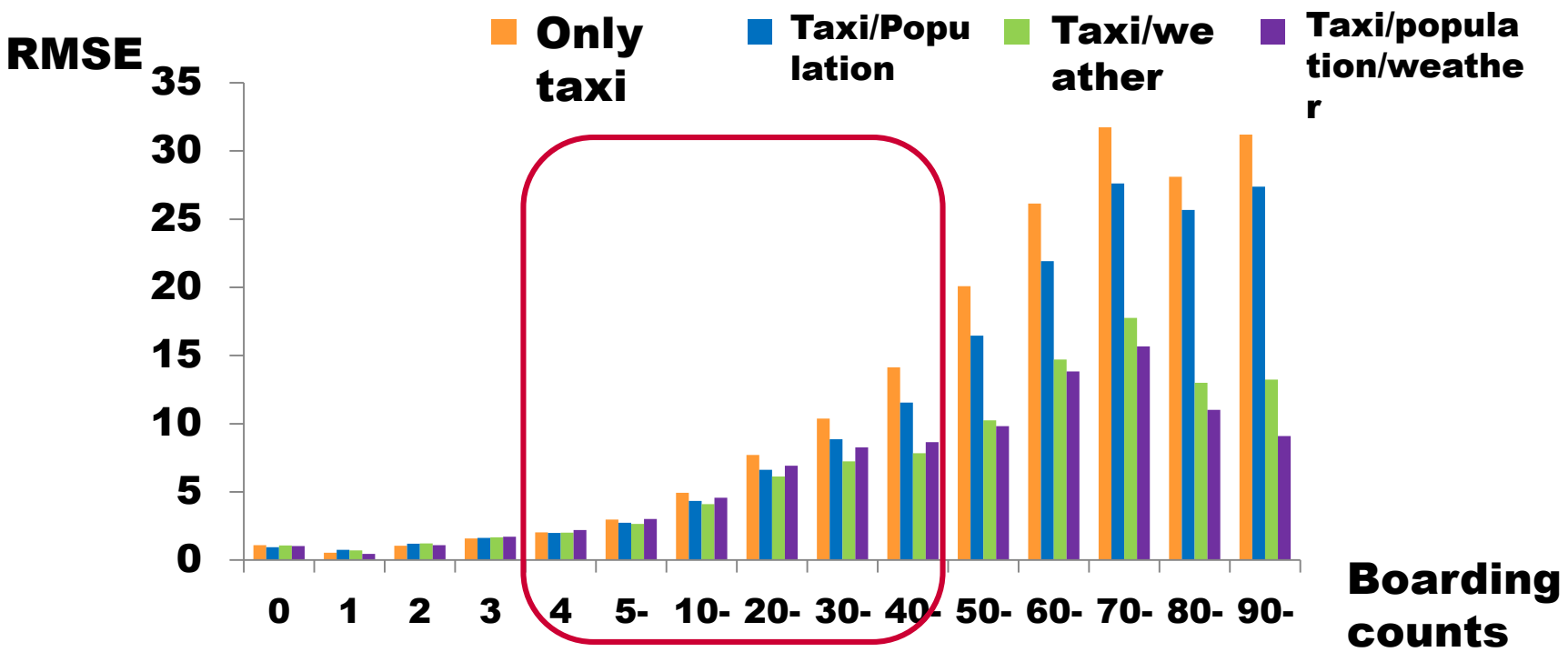


Evaluation results for each input feature quantity

In the place / time zone of the boarding record 4 to 40, using population data, accuracy improved but slightly reversed when adding rainfall data

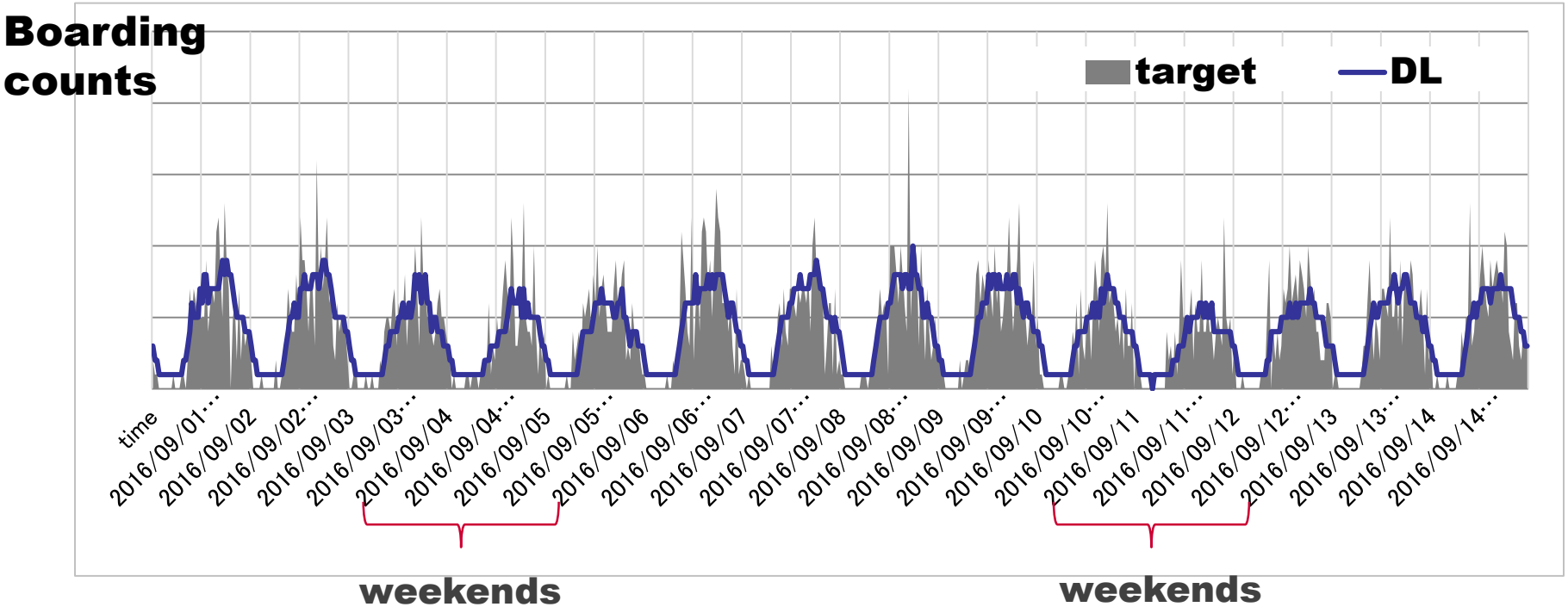
Possible Factors:

- **The influence of the population greatly affects where the demand is high?**
- **The model with population has not been converged yet?**



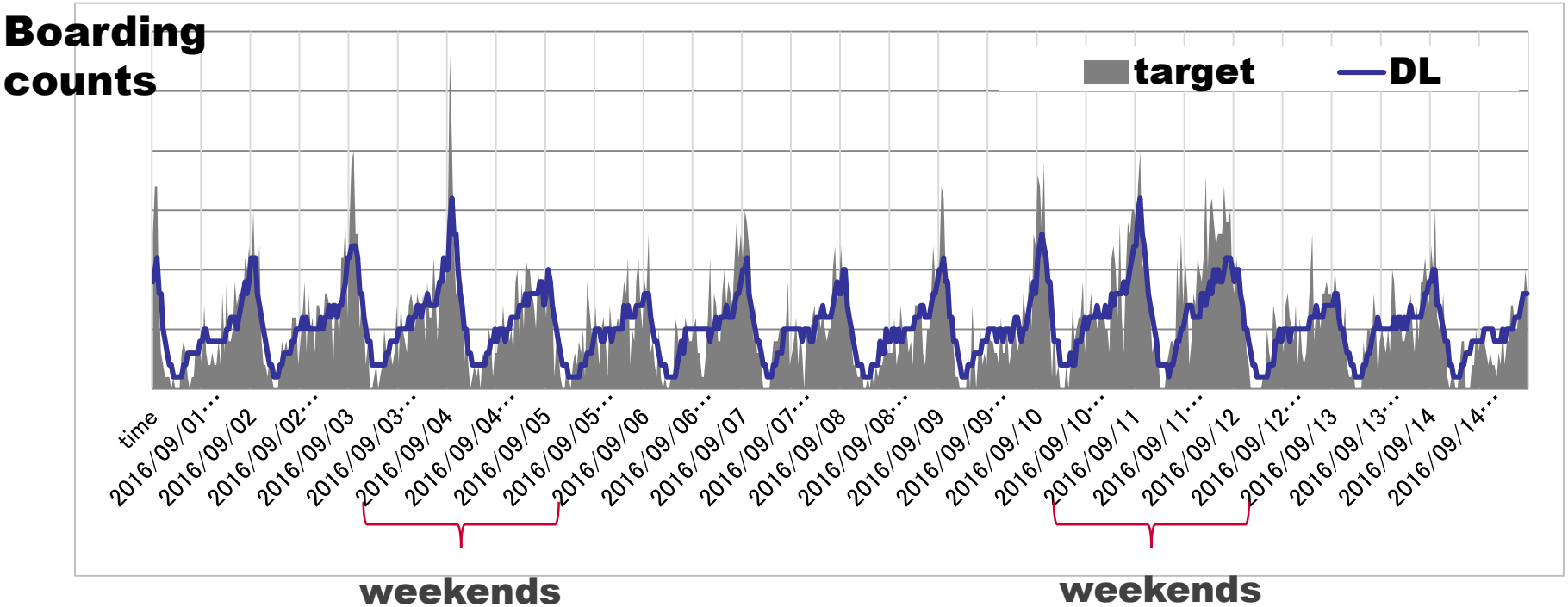
Prediction example: Around Hamamatsucho

- Deep learning models accurate events



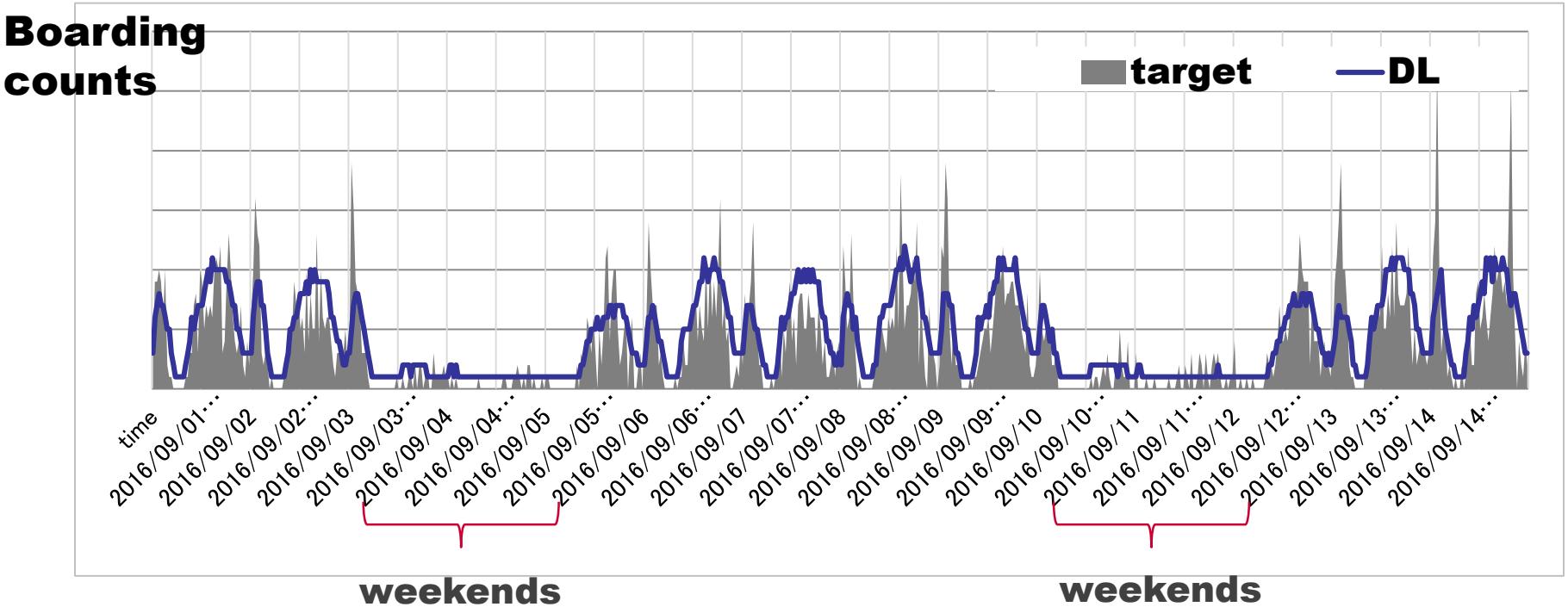
Prediction example: Around Kamata station

- Working relatively well
- Sometimes it is impossible to follow the extreme peak



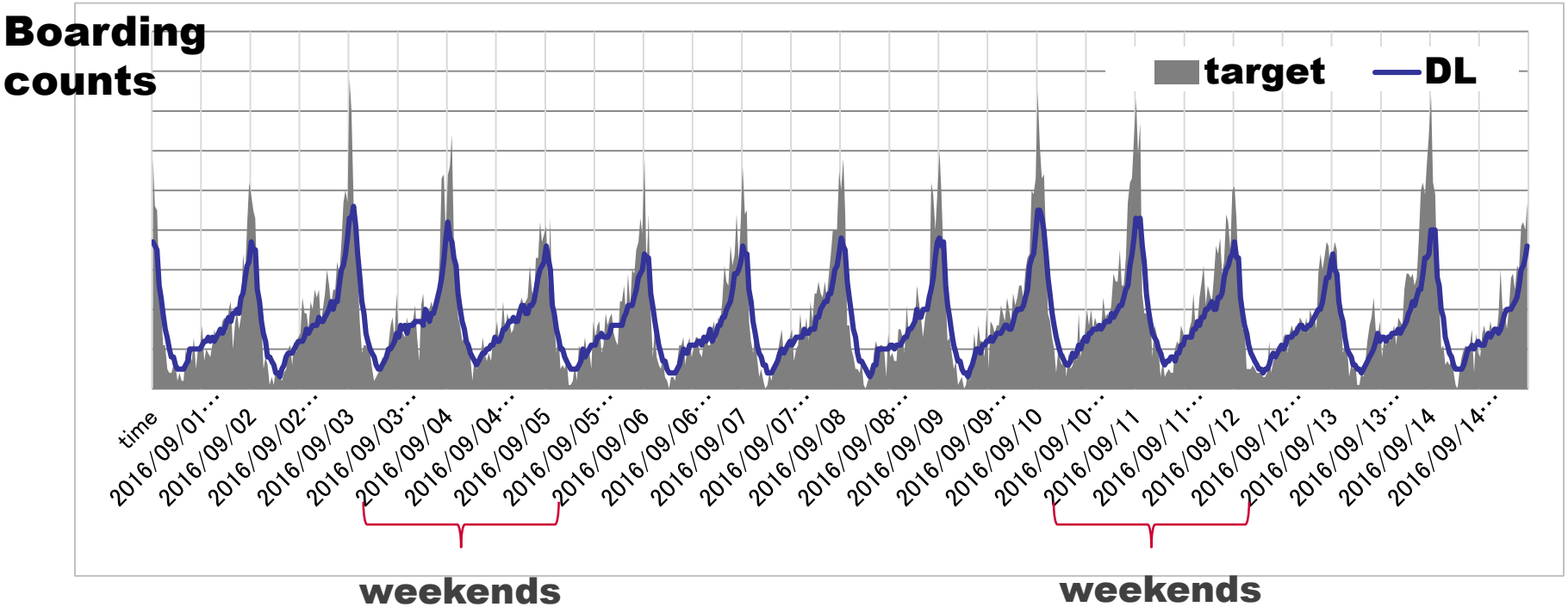
Prediction example: Near Toranomon · Hibiya Park

- It is comparatively well predictable
- We can consider the difference for each day of the week



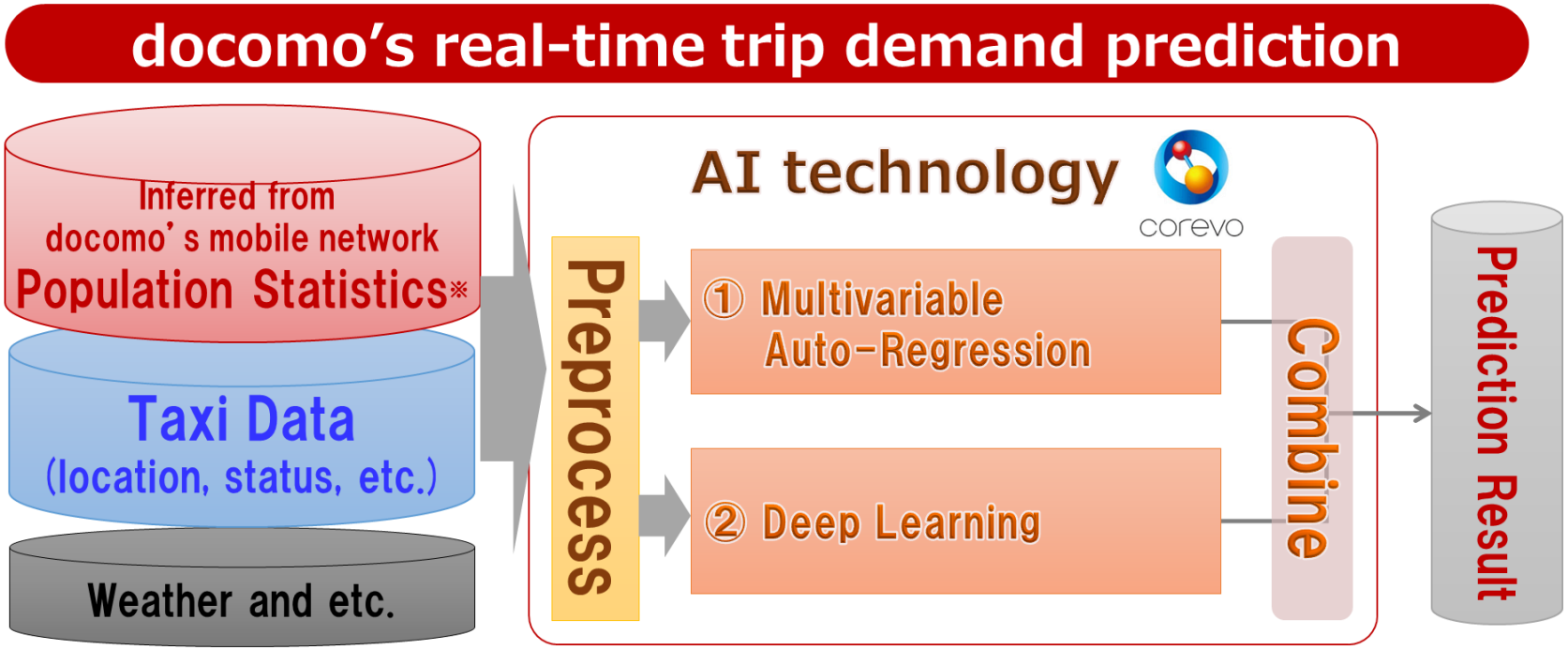
Prediction example: Tokyo station ~ Yurakucho

- Although the overall trend is caught, prediction looks downward at the peak



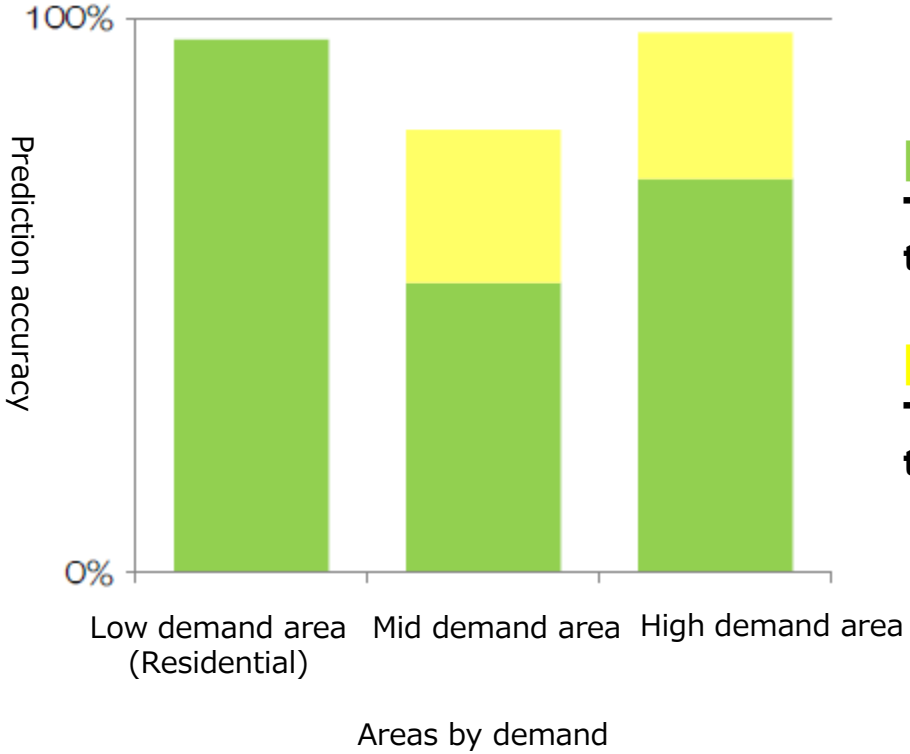
Demonstration experiment

- Online estimation uses docomo's cloud
  - Update once every 10 minutes, predict future ride demand for 30 minutes



Prediction accuracy: 92.9%

- High prediction accuracy is achieved especially in high demand area and low demand area
- Tackle further improvement in accuracy in the future



Correct
The predicted value is within the actual value ± 20% or within ± 1 unit

Quasi-correct
The predicted value is within the actual value ± 50%

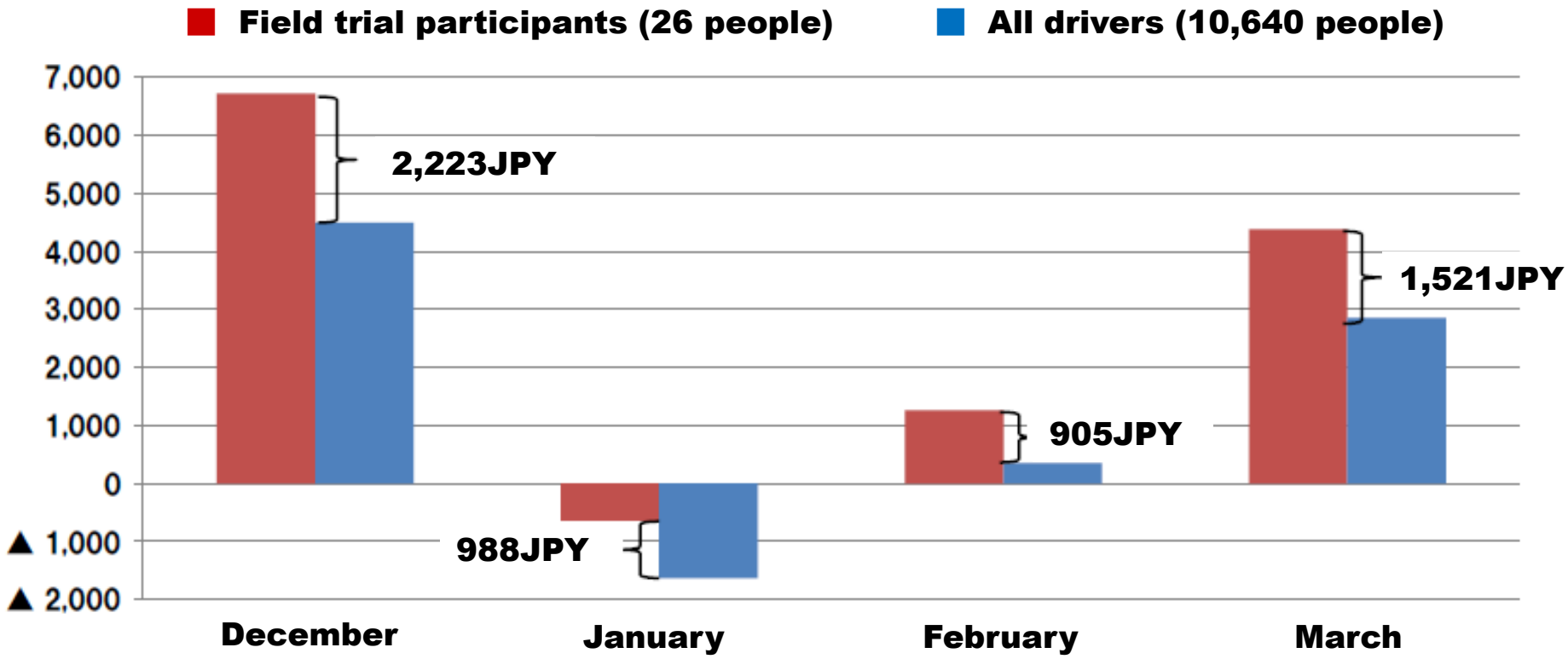
Result of sales of field demonstration

docomo

Increase sales of participants in field trials for the entire period of demonstration experiment

Average sales improvement is 1,409 JPY per driver per day (1,409 JPY ≈ 13.16 USD)

Sales result per driver per day
Sales results for December and March based on November (pre-experiment)



Commercial version released on February 15th, 2018 in Tokyo and Nagoya, Japan

東京無線タクシー

For 1,350 taxis

つばめグループ

For 1,150 taxis

Summary

■ Summary

- Taxi future demand prediction using SdA
- Confirm that prediction accuracy improves in high demand place / time zone by using population data
- Verification test realizes accuracy of 92.9%
- Confirmed sales improvement of 1,409 yen average per day per person

■ Future works

- Adding data: Using event information
- Realization of deeper learning algorithm with higher precision
  - Full utilization of DGX-1!

Thank you