BLECE: BLE-based Crowdedness Estimation Method for Restaurants and Public Facilities

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***Abstract*—The crowdedness in various places in the city, such as public transportation, restaurants, and public facilities, is high-demand information for not only general people but also municipalities and companies. However, it is not easy to acquire comprehensive data because existing services of crowdedness measurement separately collect and provide data in different ways, although there are many services. This study aims to establish the universal method of crowdedness estimation, which is robust to various environments, by scanning BLE (Bluetooth Low Energy) signals emitted from mobile devices owned by general people. In this paper, we focus on restaurants and public facilities with different types, conditions, and sizes and propose a method of crowdedness estimation by fusing data obtained from other numbers of BLE scanners depending on each space. As a result, we confirmed that models trained with the same feature set for each space show a practical performance. Additionally, we explore the technical challenges when implementing the system in a new space through detailed analysis.**

***Index Terms*—Smart City, IoT, Crowdedness Estimation, Bluetooth Low Energy**

I. Introduction

The level of crowdedness at various places in an urban environment is one of the most anxious information for people visiting and staying in a city. This demand covers a wide range of places including public transportation, restaurants, and public facilities. From the perspective of the whole society, there is also a need to preserve cities safe and comfortable for all by leveling congestion (i.e., avoiding excessive crowding in public spaces). From both perspectives, it is essential to know the level of crowdedness across various places.

In recent years, various congestion estimation methods have been studied. For example, methods using GPS logs from smartphones [1], [2], cameras and LiDAR [3]–[8], smartphone-equipped sensors [9]–[11], and radio waves such as Wi-Fi and BLE [12]–[20] have been proposed. Some of these methods are commercialized as actual services. However, existing congestion measurement services collect data and provide information in different ways at different locations and by other providers, making it difficult for users to obtain crowdedness information across various places.

This study aims to establish a universal crowdedness estimation method independent of location and environment. To achieve this aim, we are exploring a technique based on scanning BLE (Bluetooth Low Energy) signals, which are emitted from smartphones and other electronic devices, from the environmental side, and estimating the level of crowdedness using the data of the received signals. In recent years, people have tended to bring/wear/use multiple devices such as smartphones, smartwatches, smart tags, and smart locks. These devices communicate via BLE when exchanging data in most cases. Hence, we can assume that people usually turn on the BLE of their devices. So far, we have proposed a method for estimating the number of passengers in a car of public transportation, namely fixed-route buses, and trains, and have confirmed the effectiveness of the method [15], [16].

In this paper, we focus on the crowdedness in closed spaces such as restaurants and public facilities, which differs from the target of our previous work. Compared with previous work, people can enter and leave the space anytime for indoor spaces. Hence, the problem of increasing the number of addresses will be expected to arise. We created the in-the-wild datasets for around 10 days in actual restaurants and public facilities, which have different types, conditions, and sizes (four locations in total) by using other numbers of BLE scanners. Then, we built and evaluated a crowdedness estimation model. The results showed that our model built for each space using XGBoost Regressor performs with the mean absolute error (MAE) of 4.89, the mean absolute percentage error (MAPE) of 84.0%, and the root mean square error (RMSE) of 6.34 in the worst case. These results indicate that a certain crowdedness level can be estimated by using a model with common features. Additionally, we explore the technical challenges when implementing the system in a new space through detailed analysis.

Our contribution is three-fold:

1) we proposed a BLE-based crowdedness estimation method for public facilities and restaurants based on fusing data from a different number of BLE scanners,
2) we evaluated the performance of the proposed method with in-the-wild datasets in four public spaces which have different types, conditions, and sizes, and
3) we provided a discussion of the technical challenges when distributing the proposed method to a new space through detailed analysis.

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II. Related Work

Research on crowdedness estimation in public spaces has been tackled for various spaces, with various approaches. Here, we explain them categorized into three groups: urban spaces (i.e., wide areas of the city), mobility spaces (e.g., public transportation), and indoor/outdoor spaces (e.g., public facilities, restaurants). In the following, a literature review of related studies and the position of this study will be provided.

A. Crowdedness Estimation in Urban Spaces

Several telecommunication companies provide crowdedness information of the city by using their customer's connection status. There are several services, Yahoo! Map Congestion Radar [1] provided by Yahoo Japan and Kompreno [2] by Agoop. These services collect and visualize location information using GPS-equipped mobile devices such as smartphones, with permission from users of applications provided by each company. These services estimate the population at a certain mesh, such as 125m or 250m square, but it is difficult to derive the degree of crowdedness in a specific space.

In the research area of computer vision, estimating crowdedness and people flow by image analysis using cameras is getting attention for a long time [3], [4]. Sindagi *et al.* [3] proposed a method for estimating crowd density and count by fusing multiple CNN components which incorporate global and local contextual information of a crowd image. Liu *et al.* [4] proposed an end-to-end trainable deep architecture, named Context-Aware Network, that combines the features obtained from multiple receptive field sizes for counting people in crowded scenes.

B. Crowdedness Estimation in Mobility Spaces

The methods for estimating the crowdedness using cameras installed inside a car of public transportation are proposed [5], [6]. Song *et al.* [5] proposed a system for counting the number of passengers using images from surveillance cameras. Although these approaches directly recognize images of people to be observed and thus enable estimation with relatively high accuracy, the installation and analysis of cameras are likely to create restrictions on the locations where they can be installed from the viewpoint of social acceptability.

The methods using radio waves, such as Wi-Fi and BLE, are also proposed [12]–[16]. Handte *et al.* [12] proposed a method for estimating the number of passengers on routed busses by counting the number of MAC addresses of passengers' mobile devices that connect to the Wi-Fi access point equipped with a bus car. Hydayat *et al.* [13] used GPS and Wi-Fi scanner which detects MAC addresses of individual bus passengers, for estimating the number of passengers. Maekawa *et al.* [14] proposed a method based on scanning surrounding Bluetooth signals by the passengers' smartphones. In our previous work [15], [16], we proposed a method for estimating crowdedness on buses and trains by scanning BLE signals emitted from passengers' mobile devices using scanners in the environment and building models with the signal reception strength and its combinations.

C. Crowdedness Estimation in Indoor/Outdoor Spaces

There are studies and services using the technology of laser imaging, detection, and ranging (LiDAR). Yamaguchi *et al.* [7] proposed a LiDAR-based estimation method of individuals' and human crowds' locations and behavior, named Hitonavi. SICK AG [8] provides a system for counting the number of people who leave or enter an area by using 3D-LiDAR.

Also, the methods using several sensors equipped on mobile devices are proposed [9]–[11]. Kannan *et al.* [9] proposed participatory crowdedness estimation system where sound signal emitted from a smartphone is received by another user's smartphone, and its acoustic characteristics is analyzed. Nishimura *et al.* [10] proposed a method for estimating the smoothness of pedestrian flows using accelerometer data and ambient sound data collected by smartphones. Moustafa *et al.* [11] proposed crowdedness estimation method in railway stations using motion sensors of a smartphone for analyzing passenger's behavior and the microphone for capturing ambient sound characteristics.

The crowdedness estimation methods using Wi-Fi and BLE are also studied [17]–[19]. Umeki *et al.* [17] used the BLE emitter and receiver for counting people who pass through between devices, by observing the RSSI fluctuation caused by people. Weppner *et al.* [18] proposed the people density estimation method by using people's mobile devices for scanning neighbor BLE devices. Takahashi *et al.* [19] combines an overhead camera and a Wi-Fi scanner that detects probe requests from people's mobile devices for estimating crowdedness of bus stations.

D. Position of this study

As mentioned above, although there have been many studies on crowdedness estimation, there has not been sufficient verification of its applicability to different environments. This study aims to establish a universal crowdedness estimation method that can be applied across various public spaces, including mobility and indoor/outdoor spaces. The purpose of this paper is to evaluate and discuss whether crowdedness estimation is feasible in indoor spaces, especially restaurants and public facilities with different conditions, by applying the method proposed by the authors previously [15], [16] which uses BLE scanners placed in the environment.

III. Data collection

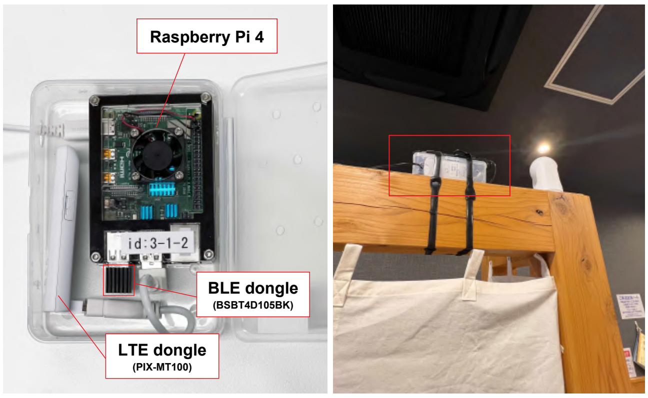
A. Data collection system

For data collection, a device with the same functionality as those used in previous studies by the authors [15], [16] will be used (hereafter referred to as BLECE node). The setup of the device and its installation example are shown in Figure 1. The BLECE node operates based on the Raspberry Pi 4 Model B, and BLE data acquired using a Bluetooth 4.0+EDR/LE Class 1 compatible USB adapter (BUFFALO, BSBT4D105BK) will be uploaded to a cloud server via mobile network using LTE compatible USB dongle (PIXELA, PIX-MT100).

TABLE I: Overview of target spaces and collected data

Space ID	Type of space	Capacity	Shape of space	# of BLECE nodes	Label data collection method	# of Label data samples	Data collection period *g
A *a	Cafe	25	Square	1	SurvCam*e	556	Dec. 15, 2021 – Mar. 15, 2022
B *b	Restaurant	50	Square	1	SurvCam*e	895	Dec. 23, 2021 – Mar. 15, 2022
C *c	Restaurant	50	Rectangle	2	SurvCam*e	1398	Nov. 24, 2021 – Mar. 15, 2022
D *d	City Library	-	L-shaped	3	Manual*f	316	Jan. 5, 2022 – Mar. 29, 2022

*a nijiiro*cafe (cafe & restaurant), https://nijiirocafe.com/ *b Tonmasa (Japanese pork cutlet restaurant), https://tonmasa.com/
*c Marukatsu Ikoma (Japanese pork cutlet restaurant), https://marukatsu912.com/ *d Ikoma City Library, https://lib.city.ikoma.lg.jp/
*e A surveillance camera is placed at entrance. *f A person in charge manually counts number of people.
*g In this paper, we used nondeletional and continuous 10 days data from data collection period for building models.



(a) Setup of BLECE node (b) Installation example of BLECE node

Fig. 1: Overview of BLECE node

B. Overview of target spaces and collected data

In order to verify the possibility of estimating congestion in public facilities and restaurants of different types, conditions, and sizes, the fixed spaces shown in Table I were used for data collection. This study was approved by the Ethical Review Committee for Research Involving Human Subjects at Nara Institute of Science and Technology (Approval No.: 2020-I-16).

As shown in Table I, the target spaces A–D have different business types and capacities, and shapes of space. The required number of BLECE nodes placed differs based on these conditions. Figure 2 shows the shape and seating arrangement of each space, as well as the placement of BLECE nodes and entrance/exit cameras (the red ◆ indicates the location of BLECE nodes and the green ▲ indicates the location of surveillance cameras). For example, three BLECE nodes have been placed in space D because it is a city library in front of a main station and has a large area and the floor plan is L-shaped. The data collected are timestamps, the Bluetooth Device Address (hereinafter referred to as BD address) of each scanned device, and the received signal strength (RSSI) of the BLE. Since this study is targeting indoor spaces, information specific to mobility spaces, such as location information and route numbers, which have been utilized in previous studies [15], [16], are excluded. The BLE scan interval is 15 seconds (10 seconds for scanning and 5 seconds for sending data and waiting time). To reduce installation costs, we tolerate

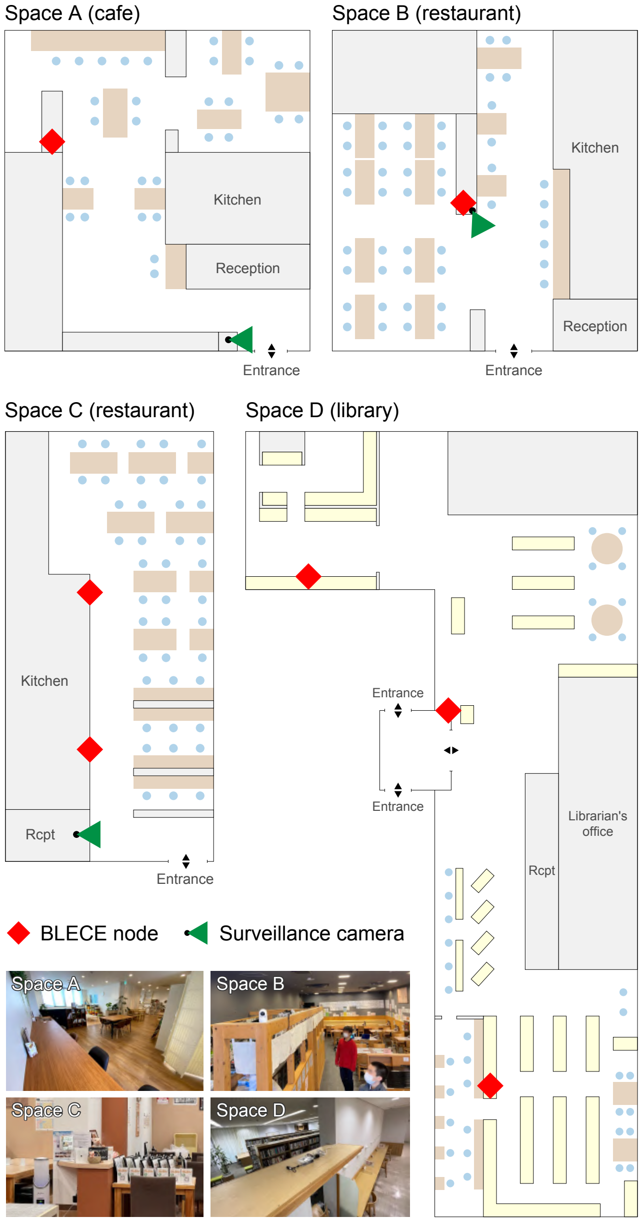


Fig. 2: Floor plan of each target space, locations of BLECE nodes and surveillance cameras, and photos of each target space. Note that the scale and aspect ratio of space and the location of tables and seats are not precise necessarily.

that each BLECE node does not synchronize the timing of scanning BLE devices.

The label data of crowdedness, i.e., the number of people staying in space at a certain moment, has been collected in different ways depending on the requests from the managers of each space. In spaces A, B, and C, a surveillance camera (equivalent to the BLECE node configuration with the addition of a Raspberry Pi Camera Module) was installed at the entrances and exits of the spaces. Then, label data every five minutes were acquired by performing posterior annotation through counting manually. The difference in the number of label data samples for each space is due to the different opening hours. An example of the installation of a surveillance camera and an example of the captured images are shown in Figure 3. When installing the surveillance cameras, the data collection has been conducted in consideration of the privacy of general people, referring to the Camera Image Utilization Guidebook Ver. 2.0 [21] formulated by the Ministry of Economy, Trade and Industry (METI), the Ministry of Internal Affairs and Communications (MIC), and IoT Acceleration Consortium (ITAC). Specifically, captured movies taken by surveillance camera have been processed on the edge side so that specific individuals cannot be identified, and the notice of this experiment has been provided through the authors' website [1] and posters put in each space during the data collection periods (from one month before starting to ending of the experiment). In space D, an investigator staying in the space has patrolled periodically (about once every 15 minutes) the space and collects the label data by visually counting the number of people.

The data collection period is shown in Table I. Due to a technical problem, there are several missing data, hence, in the following sections, we used non-deletional and continuous 10 days data of each space (Spaces A, B, and C: January 19 to February 3, 2022; Space D: March 15 to March 29, 2022).

IV. Crowdedness Estimation Model

Using the datasets collected in the previous section, we evaluate the feasibility of estimating crowdedness in various indoor spaces.

A. Preprocessing

In this paper, the number of BLECE nodes differs due to the different space sizes of target spaces A to D. Therefore, as a preprocessing step, the data scanned by multiple BLECE nodes are integrated and converted into a format that is independent of the number of BLECE nodes. As mentioned above, the BLECE nodes perform BLE scans with a measurement cycle of 15 seconds, but the acquisition timing among the BLECE nodes is asynchronous because the scans are initiated at arbitrary timings.

The data integration procedure is as follows. First, the most recent N samples before time t of the label data are obtained for each BLECE node, and the pairs of data to be integrated are determined by considering the time-adjacent data as having been obtained at the same time. Next, the union set (OR) of the BD addresses in the data to be integrated will be taken. For duplicate data that are caused by a device being scanned by more than one BLECE node, the one with the highest RSSI (stronger signal) is retained. This process is equivalent to a virtual superposition to the same location of BLECE nodes that are actually installed in different locations.

[1] https://www.iopt.jp/exp/blece-vol1

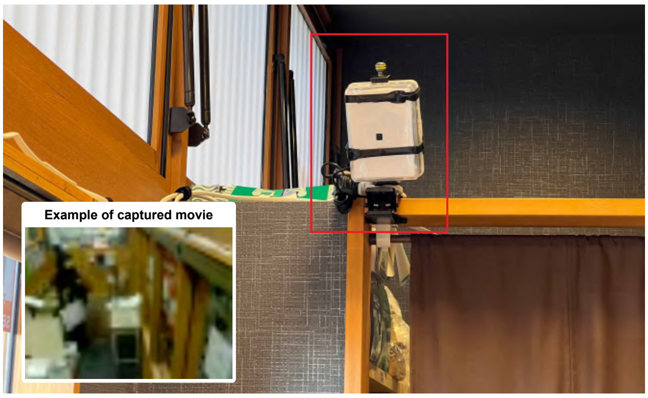


Fig. 3: Installation example of surveillance camera

B. Feature extraction

BLE signals can not be scanned from all devices in the space at any given time, but only when the device sends a BLE advertising packet while the BLECE node is performing a scan (10 seconds in the BLECE node configuration in this paper, as mentioned above). Also, if the number of devices in the space is large, scan omissions may occur. Therefore, it is necessary to mitigate these effects by providing the model with features based on multiple samples of data. On the other hand, many of the devices currently in the markets incorporate an algorithm that irregularly randomizes BD addresses to protect the privacy of the owner. In other words, there is a risk of an unnecessary increase in the number of BD addresses if the samples used for calculating features of estimation models are taken from too long time range. In mobility spaces such as fixed-routed buses, people do not move in and out of spaces while driving between bus stops. Our previous method utilize this condition as a cue that the person was staying in the space. In contrast, people can enter and leave the space at any time for indoor spaces such as a restaurant, hence, the problem of increasing the number of addresses will be expected to arise.

In order to construct a model that does not depend on the location or environment while taking into account the conditions specific to an indoor space, we employ additional features derived by varying the range (time width) of past sample acquisitions. Table II shows a list of features and their details. Since it is supposed that the number and demographics of visitors in restaurants and public facilities will be changed depending on the time of day and the day of the week, we also employed features of the hour (time of day) and is_weekday (weekday flag). In total, 42 features are extracted.

TABLE II: List of features

Feature name[*a]	Details
all_num_Tsec	Total number of devices (BD addresses) scanned in the past T seconds.
unique_num_Tsec	Total number of unique devices (BD addresses) scanned in the past T seconds.
unique_ratio_Tsec	Percentage of unique devices among BD addresses scanned in the past T seconds (ratio of unique number and total number).
unique_num_Tsec_Sdb	Total number of unique devices whose RSSI is more than threshold S among BD addresses scanned in the past T seconds.
hour	Time of day (0–23)
is_weekday	Weekday flag (weekday: 1, weekend/holiday: 0)

[*a] T indicates the time range (15, 30, 45, 60 seconds) over which past samples are referenced, and S indicates the threshold (-60 to -90 dB, in 5 dB increments) when referring to samples with high RSSI values.

C. Evaluation and results

We built a crowdedness estimation model using the extracted features for each space and evaluated them. Three types of machine learning models were used: SVR (Support Vector Regressor, RBF kernel), RFR (Random Forest Regressor), and XGBR (XGBoost Regressor). The hyperparameters of each model were optimized by GridSearchCV in scikit-learn. To evaluate the models, leave-one-day-out cross-validation was used, and MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), and RMSE (Root Mean Squared Error) were used as evaluation indices.

The evaluation results are shown in Table III. Overall, the model constructed by XGBR showed relatively high performance. For Space A, the range of the number of people visiting this space is too small within the data set collected in this paper (maximum label data was 12 people), hence, we will exclude Space A in the subsequent analysis and discussion.

The results of the model constructed by XGBR for spaces B, C, and D (scatter plots of the label data and estimated data) are shown in Figure 4. The scatter plots show that each estimation model captures the general trend in the crowdedness of the space. Also, we have confirmed the performance of the models did not differ significantly for different numbers of BLECE nodes. In Spaces B and C, both cases show large errors in MAPE of 51.9% and 58.1%, respectively. This might be due to the fact that there were many samples with a small number of people (less than 10 people) in the data set, as can be seen from Figure 4a and Figure 4b.

Next, the feature importance (top 20 features) of the models constructed by XGBR for the spaces B, C, and D are shown in Figure 5a, 5b, and 5c, respectively. The results show that the most promising BLE-related features are the total number of BD addresses in the most recent sample (all_num_15sec), the percentage of unique BD addresses in a wide time range (unique_ratio_Tsec, range of $T = 30 - 60$sec), and the number of uniques BD addresses with strong signal strength in a narrow time range (unique_num_Tsec_Sdb, range of $T = 15 - 30$sec and $S > -70$db). For the total number of BD addresses and the number of unique BD addresses, the data in the short term and/or data with strong signal strength tend to contribute effectively because they directly and roughly reflect the number of people. In contrast, for the percentage of unique BD addresses, the data in the long term tend to contribute effectively because they could explain how fluid the location is. These indicate that it is effective to provide features with different time ranges which are newly employed in this paper. Also, the time of day was shown to be a strong cue.

TABLE III: Evaluation results of crowdedness estimation model for each space

Space ID	Model	MAE (# of people)	MAPE (%)	RMSE (# of people)
A	SVR	1.36	61.1	1.97
	RFR	1.44	71.2	2.01
	XGBR	1.49	69.6	2.06
B	SVR	3.97	91.0	5.40
	RFR	3.75	90.0	5.00
	XGBR	3.61	84.0	4.59
C	SVR	4.51	80.1	6.15
	RFR	4.09	77.5	5.59
	XGBR	4.04	70.9	5.62
D	SVR	5.47	27.5	6.99
	RFR	4.91	25.5	6.33
	XGBR	4.89	24.0	6.34

V. Conclusion

This study aims to realize a method for estimating the crowdedness in various spaces including mobility spaces and indoor/outdoor spaces based on the BLE signals emitted from mobile devices such as smartphones owned by general people. In this paper, we build and evaluate crowdedness estimation models for four indoor spaces (restaurants and public facilities) with different types, conditions, and space sizes. As a result, it was shown that the models built for each space using common features achieve a certain level of crowdedness estimation performance regardless of the different numbers of BLECE nodes. However, we also confirmed the performance of congestion estimation is not yet enough when the number of people in the space is less than 10 people. In the future, we will explore more effective data integration methods and feature extraction methods to improve performance and realize a universal crowdedness estimation method.

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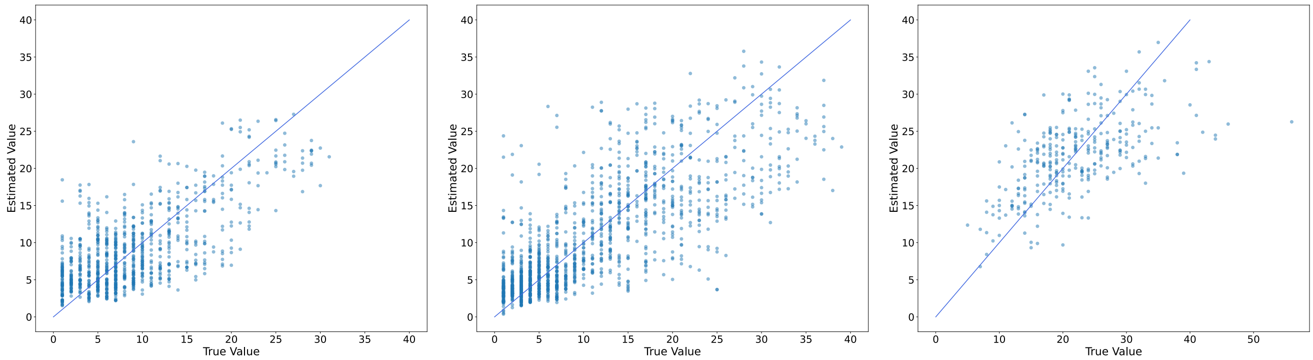
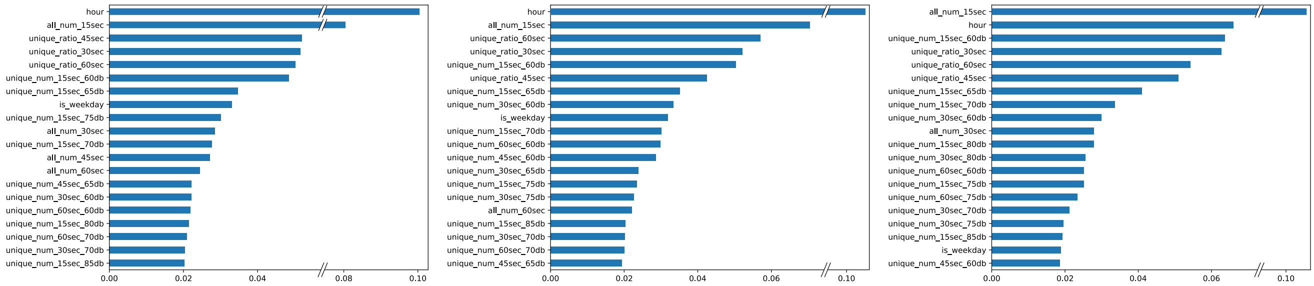


(a) Space B (b) Space C (c) Space D

Fig. 4: Evaluation result of crowdedness estimation model with XGBR



(a) Space B (b) Space C (c) Space D

Fig. 5: Top 20 important features for crowdedness estimation model with XGBR

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