FADACS: A Few-shot Adversarial Domain Adaptation Architecture for Context-Aware Parking Availability Sensing

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ABSTRACT
The existing research on parking availability sensing mainly relies on extensive contextual and historical information. In practice, it is challenging to have such information available as it requires continuous collection of sensory signals. In this paper, we design an end-to-end transfer learning framework for parking availability sensing to predict the parking occupancy in areas where the parking data is insufficient to feed into data-hungry models. This framework overcomes two main challenges: 1) many real-world cases cannot provide enough data for most existing data-driven models. 2) it is difficult to merge sensor data and heterogeneous contextual information due to the differing urban fabric and spatial characteristics. Our work adopts a widely-used concept called adversarial domain adaptation to predict the parking occupancy in an area without abundant sensor data by leveraging data from other areas with similar features. In this paper, we utilise more than 35 million parking data records from sensors placed in two different cities, one is a city centre, and another one is a coastal tourist town. We also utilise heterogeneous spatio-temporal contextual information from external resources including weather and point of interests. We quantify the strength of our proposed framework in different cases and compare it to the existing data-driven approaches. The results show that the proposed framework outperforms existing methods and also provide a few valuable insights for parking availability prediction.

KEYWORDS
transfer learning, parking availability, sensor networks

1 INTRODUCTION
Parking availability sensing plays a vital role in urban planning and city management [24, 37]. According to a recent study, drivers spend more than 100,000 hours per year in looking for parking their cars [27]. Moreover, seeking for available parking can lead to severe traffic congestion and air pollution [9]. Hence, effective parking availability sensing can help drivers find a vacant parking spot. This also helps government to take appropriate measure by understanding the utilisation of parking facilities and provide more on-street parking lot in the areas with high parking demand.

Parking dynamics have been studied in many research domains. In recent times, two types of sensing systems (i.e. explicit and implicit) have been used to infer parking availability around the cities. The explicit sensing systems take a direct approach to measure the parking occupancy through physical sensors such as underground sensors, RFID sensors, and monitoring cameras. In contrast, implicit sensing systems use an indirect approach to measure parking occupancy, e.g., through the sensing of contextual information such as weather, the number of restaurants and office building nearby, and density of public transportation stops [34].

Most existing data-driven solutions heavily rely on the long-term and historical data which is not always available in the real-world scenarios [23]. In recent times, several works leverage the transfer learning techniques to estimate the traffic in areas without much historical data [31, 32]. However, domain shift and unsupervised learning remain as two main challenges in these parameter transferring models. Another common challenge is that most of the existing works focus on the temporal dependency of the contextual information and parking records. However, spatial dependency also plays a key role in parking occupancy because the status of a parking spot is highly correlated with nearby parking slots. For example,
drivers tend to park in a spacious space rather than a narrow space since crowded parking spaces is likely to rise the parking difficulty, and they also prefer a low occupancy area because of the Nash equilibrium [10]. Therefore, considering both spatial and temporal dependency is essential to parking occupancy prediction problem.

Adding to the above challenges is the highly diverse feature space in the source and the target domain when the sensor data are collected from two really different cities. This paper, in particular, presents a challenge that is often present when sensors in the different cities are deployed by local authorities and the data are collected by different agencies, capturing local contextual information that is pertinent to the local urban fabrics with their specific characteristics. In this paper, the source city is the city centre of an Australian state’s capital with its Central Business Districts (CBD) areas, and the target city is a little coastal town mainly populated by retirees and is very popular with tourists, in particular when the weather is clear. Hence, the parking patterns across the two regions are highly diverse and may not be directly transferable.

To overcome the challenges of integration of spatial dependency and temporal dependency and shared features extraction, we design a domain adaptation architecture called FADACS which can learn the parking occupancy with much historical parking data by utilising contextual sensor and parking sensor data from other areas. We use the idea from computer vision area [30] and incorporate with meta sensing technologies. Specifically, we propose a generative adversarial networks-convolutional long short term memory model for parking occupancy prediction by combining generating ability of generative adversarial networks (GAN) and spatio-temporal forecasting ability of convolutional long short term memory (ConvLSTM). Compared to existing transfer learning models such as parameter transferring models [31], GAN-based transfer learning work can easily learn the shared features of source domain (Where historical data is available and rich) and target domain (where we would like to predict the parking occupancy with no historical parking data) using adversarial learning mechanism, and it does not need historical data from target area. Additionally, ConvLSTM model applies the convolution operations on the spatial domain and recurrent layers to the temporal domain [31]. We embed such model into our adversarial learning framework and test it on two different real-world parking dataset with contextual information. The experimental results show that our proposed model outperforms other existing transfer learning models. We also show that the contextual information has a significant influence on the prediction accuracy. In particular, the contributions of this paper are as follows:

- To our best knowledge, We are the first to propose a GAN-based spatio-temporal transfer learning framework to predict the parking occupancy in areas without historical parking records by utilising parking data from other areas and contextual information. We compare our proposed model with traditional transfer learning model which only take temporal information into consideration and state-of-the-art works such as ConvLSTM which consider both spatial and temporal information but only use parameter transferring approach to learn the distribution from the source domain. The experiments validate that our work which incorporates both spatial information and temporal information and leverages the GAN-based transfer learning framework can improve the parking prediction accuracy.

- We conduct an in-depth analysis of contextual factors which have potential influences on parking occupancy in different regions. We conduct the quantitative investigation on parking sensing by both implicit and explicit ways. Our study found insights on the contextual factors that have potential influence on parking occupancy.

The rest of the paper is organised as follows. Section 2 describes relevant works in parking sensing area and transfer learning area. Section 3 introduces parking and contextual information dataset. Section 4 shows our data preprocessing pipeline. Section 5 illustrate our proposed framework. Section 6 provides experimental results, followed by conclusion in Section 7.

2 RELATED WORK

Parking prediction: Parking availability predictions, which can be treated as one of the time-series issues, are appropriate for many methods. Yu et al.[36] verify the effectiveness of making real-time parking availability prediction using time series model. They establish a variant of the autoregressive integrated moving average (ARIMA) model to predict remaining berth in an underground parking lot at Xinjie Kou in Nanjing, China. Pfügler et al. [22] make a detailed analysis of the importance of publicly available information. The authors train a neural network (NN) model based on contextual features solely, and it shows that the prediction made without the historical parking data could be very effective and the three most common information: time, location and weather have the greatest impact compare to all other features. Except the linear methods, Chu et al. [21] adopt the backpropagation neural network (BPNN) model proposed by Haviluddin et al. [8] on available parking spaces data collected in Xi’an, China. BPNN makes a nonlinear mapping between inputs and outputs, and the results show that it can generate effective predictions for parking lots with different capacities. Shao et al. [25] further utilise a large real-world parking spaces dataset in Melbourne, Australia and train a long short-term memory (LSTM) model on that dataset. Results are quite promising.

Domain transfer learning: Since most of the machine learning models assume that the overall of training and test data are IID (independent and identical distributed), which is not always the case in the real world [20]. One major drawback causing by this issue is that the test data which comes from a shifted distribution mostly will lead to an unexpected performance drop. Except for the traditional approach, which is to build a new model and retrain that model, transfer learning is widely used to overcome this problem due to its better performance and efficiency. Transfer learning enables us to learn knowledge from the source domain upfront and apply that knowledge to a new, relative data or target domain. Transfer learning has also developed different areas such as lifelong learning [28] and multitask learning [2] and transductive transfer learning [1].

Pan and Yang [20] considered transductive transfer learning is similar to domain adaptation, which has the ability to transfer the knowledge from the labelled source domain to unlabelled target domain. Generative Adversarial Networks (GANs) [6] since 2014
has become one of the hottest concepts in the field of artificial intelligence. Ganin et al. [4] first added adversarial mechanism into domain adaptation and propose a new framework called DANN (Domain-Adversarial Neural Network). The objective of this method is to generate features which contribute most to classification while making the discriminator unable to determine the source of those samples. In addition to mapping source and target domain into the same feature space, fine-tuning is another area of transfer learning, which is a process to reuse the training model into a second similar task and also is a simple method to transfer knowledge. Yosinski et al. [35] first demonstrated the transferability of features from a neural network. Since then, fine-tuning has been widely used in multiple areas. Google BERT [3] is considered as a milestone in NLP, which comprises a pre-training stage and a fine-tuning stage. Similarly, to detect pathological brain in magnetic resonance images (MRI), the authors of [11] achieved higher performance by using parameter-transfer learning based on pre-trained AlexNet model. Besides the improved performance and the reduced training time, another advantage of the fine-tuning is that it can counter the over-fitting problem, which usually occurs on small datasets. Facing ‘cold-start’ problem on expanding market into a new city, Guo et al. [7] gives a new framework, called CityTransfer, which could learn the knowledge of inter-city and intra-city, based on collaborative filtering. One of the latest work applied few shot learning technique in sensing area is proposed by Gong et al. [5]. They learn the behaviours of each user only with a few samples using transfer learning technique. However, they did not apply the model to spatio-temporal data and contextual information.

In this paper, due to the lack of historical data on the target domain, we choose to approach the problem with domain adaptation, allowing transfer of knowledge from the source domain to the target domain.

3 DATA

The two cities that are being investigated in this research are the City of Melbourne and the town of Rye. Both are in the state of Victoria, Australia. Melbourne is the capital city of Victoria. The municipality of Melbourne, with an estimated of 178,955 residents [12], has nearly 1 million people on average per day, visiting the municipality for work, education, and travel or tourism. On the other hand, Rye is a little coastal town, part of the Mornington Peninsula Shire municipality. Rye has a population of approximately 8,416 in the 2016 census and is located about 100km from the City of Melbourne and the town of Rye. Both are in the state of Victoria. The time range of this data is from 17th Nov 2019 to 20th Feb 2020 and spatially spread in 7 sectors. Details can also be found in Table 1, and an example of the status for those parking slots is shown in Fig 1.

3.1 Melbourne on-street Parking Data

Paying relative data is from the City of Melbourne Open Data [13]. We use the following data sets:

- On-street Car Parking Sensor Data 2017 [17]
- On-street Parking Bays [19]
- On-street Parking Bay Sensors [18]

In this section, we will use the name Parking Sensor Data, Polygon Data and Location Data to represent each of the above datasets.

3.1.1 Parking Sensor Data. The Parking Sensor Data has 35.9 million records of 2017 on-street car parking in Melbourne Vic, containing 35 areas, 5044 sensor devices and 4695 parking slots. The reason of inconsistency of the sensor devices and parking slots is that if a sensor device needs to be removed for faulty, low battery and upgrade the firmware, then a new sensor device with different id will be replaced. In addition, Open data mentioned that these are streaming data. Namely, no matter whether the parking slot is occupied or not, each sensor will run the whole day and is continuously generated records. If the parking slot is occupied, the corresponding sensor will record the arrival time and departure time. Otherwise, during some periods, the sensor will automatically record the times and label it as non-occupied. Additionally, every midnight all sensors will do the record and restart recording again. The detailed format of Parking Sensor Data is shown in Table 1.

3.1.2 Polygon Data. There are 24074 records in this dataset, including all parking slots in the Melbourne area. Each record contains a series of locations that define the actual boundary of a parking slot. Although each polygon has its unique parking bay Id, only a small portion of them have a sensor built-in with a street marker Id that could link to the parking data mentioned above.

3.1.3 Location Data. Since the polygon data contains the boundary of all parking slots no matter whether they have its dedicated sensor or not. In this paper, we also used another data called Location Data that contains a single longitude-latitude tuple for each parking slot which could eliminate ambiguous distance calculation.

According to the recommendation from the City of Melbourne Open Data Platform [13], Location data and Polygon data should be joined by Street Marker Id.

3.2 Rye Data

This data is collected by the Mornington Peninsula Shire which includes 179288 records cross 527 devices or parking slots in Rye, Victoria. The time range of this data is from 17th Nov 2019 to 20th Feb 2020 and spatially spread in 7 sectors. Details can also be found in Table 1, and an example of the status for those parking slots is shown in Fig 1.

3.3 Point of Interest

The Point of Interest (POI) data of Melbourne coming from the City of Melbourne’s Open Data Platform [13] under project CLUE (Census of Land Use and Employment). It records comprehensive information about land use and updated frequently. We choose three sub-datasets that covers most of the possible POI categories that related to parking prediction:

- Bars and pubs, with patron capacity [14]

All the datasets used in this system come from the following platforms: the City of Melbourne Open Data [13], Time and Date AS [29], Google Map API, and a proprietary Mornington Peninsula Shire data platform.
Table 1: Comparison of the format for both Parking Data used in this paper

| Column         | Dataset | Description                                                                 |
|----------------|---------|-----------------------------------------------------------------------------|
|                | Melbourne | Rye                                                                 |
| Device Id      | √        | The unique id for the parking sensors.                                    |
| Arrival Time   | √        | Date and time that sensor detected a vehicle located over it.              |
| Departure Time | √        | Date and time that sensor detected a vehicle no longer located over it.    |
| Duration       | √        | Time difference between arrival time and departure time events, measured in seconds. |
| Overstay Duration | ×     | Time that a vehicle overstay, measured in seconds                          |
| In Violation   | √        | Boolean value, indicate whether the parking event is violation or not.     |
| Street Name    | √        | Name for the street of sector that a sensor locates                        |
| Street Id      | √        | An unique Id for streets.                                                  |
| Street Marker  | ×        | An unique Id for each parking slot                                         |
| Device Name    | ×        | Name for each device.                                                      |
| Sign/Restriction | √   | Parking rule/sign in effect at the time of the parking event.              |
| Longitude      | √        | The longitude of the parking sensor.                                       |
| Latitude       | √        | The latitude of the parking sensor.                                        |

Figure 1: The location and status example of parking slots located in Rye. The green ones indicate available slots while the grey ones stand for the slots that currently occupied.

- Cafes and restaurants, with seating capacity [15]
- Landmarks and places of interest, including schools, theatres, health services, sports facilities, places of worship, galleries and museums [16]

3.3.1 Bars data and Cafes data. The first two datasets record all business establishments for pubs, bars, cafes and restaurants. The data collection of this part starts in 2002 and updated annually. We combine them due to their similar structure, after filtering out the data in 2017, we get 263 and 3563 records, respectively. Each record contains the trading name for that business establishment, an street address and a coordinate which can be pinned point on the map.

3.3.2 Landmarks and places of interest. The structure of the last dataset, landmarks and places of interest, is different from the other two, which only have 242 records with coordinate information and theme information. There are 49 themes such as hostel, cinema, library and casino.

3.4 Weather Data

Weather data of two places are both collected from Time and Date AS [29]. We gathered the weather data for both Melbourne and Mornington according to the time range of the data we gathered from those two places, respectively. Detailed columns used in this paper are shown below:

- Time: The specific time with the weather information
• Temp: The temperature in Celsius scale
• Weather: There are 29 different types of conditions, for example, 'Broken clouds', 'Clear', etc. Data in this column is the combination of weather conditions.
• Wind: The wind speed measured in km per hour
• Barometer: The barometer in Millibar Pressure Unit

4 DATA PRE-PROCESSING

4.1 Matching the Parking Slot with its location
The first important step in pre-processing is to match all parking slots with the correct location coordinate. We decide to use the StreetId as the primary key for matching since the DeviceId of a parking slot could be changed. For parking slots in the Melbourne area, we join the three aforementioned files on the StreetMarker column. If the location coordinate is missing for a parking slot, it will be filled with the centre of its polygon. To ensure the validity of this method, we have proved that all existing location values fall into their corresponding polygon boundary. For parking slots in the Mornington Peninsula, there is no need for further operation since all slots have a corresponding location coordinate.

4.2 Parking Slot Area Grouping
In this paper, instead of the individual parking slot, we decide to use the parking lot as the base unit in our experiments. The parking lot is a cluster of parking slots which fall into the same locality and share the same parking restriction rule. The size of a parking lot is relatively small due to its definition mentioned above. By grouping them together, we switch the objective of the model from predicting whether a given parking slot is occupied or not at a certain timestep to the occupancy rate of a group of parking slots. Since the status of a single parking slot can be noisy, this approach simplifies the problem while still maintaining the original goal of parking availability sensing.

4.2.1 Melbourne Data. Since each parking lot are considered as the base unit in later stages, we first need to ensure that a consistent parking rule is shared within this lot. Due to some reasons such as construction, the rule could be changed during this period. The parking rules for October, November and December 2017 are replaced with the whole-year rules. We then create an initial grouping which groups those spatially connected slots according to their polygon boundaries. However, this initial grouping result which uses the geometric information solely still needs improvements. As shown in Figure 2a, some of the parking slots are not under the same parking lot, although they are close to each other and having the same parking restriction. Based on this finding, we perform the grouping operation based on three criteria: connection, distance and rules. Namely, if the spatially connected, they will be clustered into the same lot. For those that are not connected, if they have the same parking restriction and the distance between them is under a threshold, they will also be put into the same lot. To calculate this threshold, we select a specific area and set the value as the sum of mean connection distance and 1.5 times its standard deviation. The example grouping result is shown in Figure 2b, and we cluster all 4192 parking slots located in the Melbourne data into 912 separate parking lots.

4.2.2 Rye Data. It is much simpler to cluster parking slots for Rye dataset. Although there is no polygon information in that dataset, each parking slot in the Rye Parking dataset has a coordinate with consistent parking restriction information. We first group the data by the sector and rule information to reduce complexity. For each group in the same sector with the same rule, we check the distance for the distance between two neighbour groups, if the distance is smaller than the threshold that we use in the Melbourne dataset, we combine them and get a larger group.

4.3 Occupancy Rate Calculation
In order to extract the occupancy of a parking lot at a given time, we remove the records that have no vehicle presented or belong to one of the following anomalies:
• DurationSeconds is non-positive which is usually caused by a faulty sensor;
• ArrivalTime and DepartureTime are both at midnight exactly;
• DepartureTime is past the midnight of the ArrivalTime;
• The records overlapping with other records which could be caused by other unexpected interference.

We eliminate over half of the Parking data in this cleaning process. Then, we slice the data every 1 and 5 minutes and calculate the occupancy of each parking lot at that time.

4.4 Contextual Features
Based on the POI and Weather dataset that we collect, we calculate the a series of contextual features which is shown in Table 2.

Since the weather condition is a categorical feature, and normal weather may not has a significant impact, we create a binary indicator for the presence of extreme weather condition ('Dust-storm', 'Extremely hot', 'Fog', 'Hail', 'Haze', 'Heavy rain' or 'Storm'). Then, we match each sample with the most recent weather record to get the temperature, humidity, extreme weather and barometer features.

For the Point Of Interest features, we consider that the total number of POIs and the number of opening POIs within a given distance may have a higher impact on the occupancy of parking lots. Since if there are many restaurants around a parking lot, this lot should be more popular during mealtime and have a lower occupancy rate at other periods.

There are a total of 4068 POIs in Melbourne, after aggregating all three aforementioned datasets. To crawl the opening hours for all those places, we use two Google Map APIs: Place Search and Place Details. The former one provides a place_id for each place which is used for searching the details in the latter one. We crawl the opening hours for POIs in both Melbourne and Rye, and we get a result involves totally 50 of POIs within eight different sub-categories.

For a given parking lot at a specific date-time, we first calculate the distance between all POIs and this parking lot, then we extract the features based on the opening info retrieved in the former stage. We also record its minimum distance to an opening or any POI.

After the extraction, we apply an ANOVA (Analysis of variance) test on both datasets. As shown in Table 3 and 4, the Pearson Correlation Coefficient of the same feature tends to have a contradicting
impact. Surprisingly, some contextual features have a opposite correlation with prediction occupancy in Melbourne CBD dataset and Rye dataset. For example, humidity has a negative correlation with parking occupancy in Melbourne city but has a positive correlation in Rye area. This reflects the possible shift in the data distributions of those two datasets, hence proving the need for introducing a domain transfer learning method in this situation.

5 FADACS ARCHITECTURE

The traditional method for transfer learning is fine-tuning, which first loads a pre-trained parameter from other tasks and then retrain them on the new domain/task. However, one issue that needs to be faced in real-world usage is that most of the task only has few or no historical data at all. According to [4], Tzeng et al. [30] propose a general architecture for adversarial domain adaption named Adversarial Discriminative Domain Adaption (ADDA). This new framework used in ADDA combines a discriminative model, untie weight sharing and GAN loss together, which shows a promising performance on unsupervised transfer learning. Compare to other domain adaptation methods, ADDA introduces the adversarial mechanism which trains an encoder to translate the features from the target domain to the latent space shared by both the source and target domain. Meanwhile, a discriminator is trained simultaneously to distinguish the origin of each latent code.

In this paper, we adopt the original ADDA framework, which is initially used for image classification task and modify it to make it applicable for our time-series prediction problem. We use $X^s$ and $X^t$ to denote source and target domain features. $Y^s$ denotes occupancy rate of parking lots from the source domain. $M^s(X^s)$ donates source mapping/encoder and $M^t(X^t)$ is about target mapping. The regression model is represented as $F$ while $D$ stands for the discriminator. The architecture we use in this paper is shown in Figure 3, and it comprises the three following stages.

The first part is the pre-training step to learn a source encoder $M^s(X^s)$ and a regression model based on the source domain data. Similar to an auto-encoder structure, the encoder here learns a mapping the source domain to a latent space. On the other hand, the regressor learns to decode features from this latent space and make a prediction on top of that. We use ConvLSTM (Convolutional Long-Short Term Memory) proposed in [33] as the encoder, which shows a good performance on spatio-temporal data. Extending on a common LSTM unit, matrix multiplication is replaced by convolution operation at each gate in the LSTM cell. The key equations of ConvLSTM are shown in equation 1 below, where ‘*’ denotes the convolution operator and ‘◦’ denotes the Hadamard product:
Figure 3: FADACS Domain Adaptation Architecture

Table 2: The detailed description of the contextual features that we used in this paper.

| Feature Name           | Description                                                                 |
|------------------------|-----------------------------------------------------------------------------|
| num_of_open_poi 1.0    | Number of Open POI within 0.5 KM nearby.                                    |
| num_of_open_poi 0.5    | Number of Open POI within 1.0 KM nearby.                                    |
| Temp                   | The temperature degree in Celsius.                                          |
| Hour                   | The hour of the day.                                                        |
| Wind                   | The wind speed.                                                             |
| num_of_poi 0.5         | Number of POI within 0.5 KM nearby.                                         |
| Day Of Week            | The ordinal of the day in the whole week.                                   |
| num_of_poi 1.0         | Number of POI within 1.0 KM nearby.                                         |
| availability           | Whether this parking lot is currently available.                            |
| Day Of Month           | The ordinal of the month in the whole year.                                 |
| Barometer              | The barometer value.                                                       |
| Extreme_weather        | An binary indicator for extreme weather.                                    |
| min_dis 1.0            | The Shortest distance of POI nearby within 1.0 KM.                          |
| min_dis 0.5            | The Shortest distance of POI nearby within 0.5 KM.                          |
| Humidity               | The humidity value.                                                        |

Next step is an adversarial adaptation, which is to learn a target encoder $M_t(X^t)$ so that the discriminator $D$ cannot distinguish the origin of that sample. By fixing source encoder parameter, the adversarial loss is used to minimise the distance of the mapping between source and target domain: $M^s(X^s)$ and $M^t(X^t)$ and maximise the discriminator loss.

$$
\min_{D} \mathcal{L}_{adv}(X^s, X^t, M^s, M^t) = \\
- \mathbb{E}_{x^s} \log D(M^s(x^s)) - \mathbb{E}_{x^t} \log (1 - D(M^t(x^t))) \tag{2}
$$

$$
\min_{M^t} \mathcal{L}_{adv}(X^s, X^t, D) = \\
- \mathbb{E}_{x^t} \log D(M^t(x^t))
$$

In the final stage, we assemble the learned target encoder $M_t(X^t)$ and regression model $F$ together, and use data from the target domain to test its performance. The regressor should be able to generate quality prediction since the latent features from the target domain is overlapping with the ones from the source domain after the previous adaptation stage.

6 EXPERIMENTS

6.1 Experimental Settings

We conduct all of our experiments on a Linux Server (CPU: Intel Xeon Gold 6132 CPU @ 2.60GHz - 56 cores, GPU: NVIDIA Quadro GP100). In order to find the best parameters, we use a parallel grid search strategy that utilises all cores in this Linux cluster. As stated in the Data Pre-processing section, we use 5 minutes as the basic interval between records. Besides, each sample contains features from the recent 30 minutes (i.e. 6 data points for each sample), and the tasks are to predict the parking occupancy rate in the next 5, 15 and 30 minutes (the next 1, 3, 6 timesteps). Two parking sensor datasets collected from Melbourne, Victoria and Rye, Victoria are used. The former one covers a whole year time period (2017), while the second one has a time range from 17th Nov 2019 to 20th Feb 2020. That reflects the big difference in both spatial and temporal domain which makes it difficult to apply the transfer learning method.
| Features      | Pearson Correlation Coefficient | F Value   | p-Value |
|---------------|----------------------------------|-----------|---------|
| num_of_openpoi 1.0 | 0.34                             | 51742.63  | 0       |
| num_of_openpoi 0.5  | 0.33                             | 48513.95  | 0       |
| Temp           | 0.23                             | 21622.33  | 0       |
| Hour           | 0.16                             | 9896.81   | 0       |
| Wind           | 0.13                             | 6871.60   | 0       |
| num_of_poi 0.5  | 0.09                             | 3356.62   | 0       |
| DayOfWeek      | 0.07                             | 2063.57   | 0       |
| num_of_poi 1.0  | 0.05                             | 1149.31   | 1.48e-251 |
| availability   | 0.02                             | 108.92    | 1.70e-25 |
| DayOfYear      | 0.01                             | 78.61     | 7.60e-19 |
| Barometer      | -0.01                            | 22.81     | 1.79e-06 |
| Extreme_weather | -0.03                           | 273.92    | 6.13e-62 |
| min_dis 1.0    | -0.04                            | 570.99    | 4.22e-126 |
| min_dis 0.5    | -0.04                            | 570.99    | 4.22e-126 |
| Humidity       | -0.25                            | 26409.49  | 0       |

| Features      | Pearson Correlation Coefficient | F Value   | p-Value |
|---------------|----------------------------------|-----------|---------|
| Humidity      | 0.19                             | 9247.09   | 0       |
| DayOfYear     | 0.11                             | 3032.63   | 0       |
| Barometer     | 0.06                             | 913.98    | 2.08e-200 |
| availability  | 0.02                             | 118.98    | 1.07e-27 |
| num_of_poi 1.0 | 0.00                            | 5.66      | 1.74e-02 |
| num_of_poi 0.5 | -0.03                           | 245.34    | 2.86e    |
| DayOfWeek     | 0.07                             | 771.68    | 1.41e-169 |
| Wind          | 0.07                             | 1165.69   | 6.82e-255 |
| Hour          | 0.07                             | 1139.34   | 3.41e-249 |
| min_dis 1.0   | 0.12                             | 3487.51   | 0       |
| min_dis 0.5   | 0.12                             | 3487.51   | 0       |
| Temp          | 0.24                             | 14862.64  | 0       |
| num_of_openpoi 0.5 | -0.30                         | 24221.17  | 0       |
| num_of_openpoi 1.0 | -0.32                         | 27946.25  | 0       |
| Extreme_weather | nan                              | nan      | nan     |

6.1.1 Evaluation Metric. In this paper, Mean Absolute Errors (MAE) and Root Mean Squared Errors (RMSE) are used to evaluate the effectiveness of different models. Except for the adversarial adaption stage, all models are trained using RMSE as its loss function.

6.1.2 Baseline Models. For FADACS, we implement two variants:
- ADDA (MLP): using MLP (Multi-Layer Perceptron) as the encoder to learn the mapping from the source/target domain to the latent space.
- ADDA (ConvLSTM): using ConvLSTM as the encoder to learn the mapping from the source/target domain to the latent space. The intention here is to extract better latent features using ConvLSTM since the problem here is a spatial-temporal prediction problem.

We compare FADACS with the following baselines:
- HA (Historical Average): using the mean of historical data as the prediction of the future data.
- MLP: (Multilayer Perceptron): a feed-forward neural networks which is widely used in function approximation and general regression problems. It also relies on the feature extraction and is data hungry. It cannot distinguish temporal features and spatial features.
- LSTM (Long-Short Term Memory): a recurrent based method that is wide-used in many time-series prediction tasks [25].
Table 5: Performance comparison with full parking data before domain adaptation

| Model   | MAE (5/15/30 mins) | RMSE (5/15/30 mins) |
|---------|--------------------|---------------------|
| HA      | 0.0600             | 0.1219              |
| MLP     | 0.0895 / 0.1188    | 0.0988 / 0.1456 / 0.1771 |
| LSTM    | 0.0942 / 0.1443 / 0.1765 |
| ConvLSTM| **0.0374 / 0.0677 / 0.1005** | **0.0894 / 0.1402 / 0.1714** |

Table 6: Performance comparison with only 6 days parking data and domain adaptation (MelbCity -> Rye)

| Model   | MAE (5/15/30 mins) | RMSE (5/15/30 mins) |
|---------|--------------------|---------------------|
| ConvLSTM| 0.0607 / 0.1091 / 0.1385 | 0.1222 / 0.1680 / 0.2003 |
| LSTM    | 0.0829 / 0.1035 / 0.1273 | 0.1261 / 0.1695 / 0.1998 |
| ADDA(MLP)| 0.0845 / 0.1151 / 0.1774 | 0.1187 / 0.1616 / 0.2434 |
| FADACS  | **0.0470 / 0.1216 / 0.1694** | **0.0813 / 0.1739 / 0.2229** |

But it only focuses on the temporal domain. Therefore, if the spatial domain also plays an important role, its performance will be limited.

- ConvLSTM: a state-of-the-art methods used in transfer learning area that can utilise features from both spatial and temporal domain [31].

We conduct two sets of experiments based on the aforementioned baselines. The first experiment is the basic parking occupancy prediction experiment. In the first experiment, all models are trained and validated using data from the Rye dataset. This experiment mainly show the performance of existing method to parking prediction problem. For the transfer learning part, we apply our refined ADDA architecture on data from Melbourne and Rye to evaluate its performance. Namely, we choose the Melbourne data as the source domain and the Rye data as the target domain since the Melbourne dataset is much richer. Besides, we also train an LSTM model and a ConvLSTM model on the source domain and test their performance on the Rye data in this experiment.

6.2 Experimental Results

In the first experiment, we compare a couple of existing approaches to predict the parking occupancy. We select four classic approach here: HA, MLP, LSTM and ConvLSTM. HA is a basic statistical method to estimate the parking occupancy based on the historical data by averaging them. The strength of this method is that HA can catch the periodical pattern of parking occupancy. However, it does not consider spatial dependency, temporal dependency and hidden trends in the data. Compared to HA, MLP can automatically explore the trends of the parking occupancy even though it also does not consider the spatio-temporal dependency. LSTM can predict the parking occupancy by leveraging the temporal dependency of the historical data which is the essential to time-series data prediction. However, as we mentioned in the introduction, the parking sensing not only relies on the temporal dependency but also relevant to the spatial dependency. ConvLSTM can integrate spatial and temporal features into one simple end-to-end model and Table 5 also validates our assumption. In Table 5, ConvLSTM outperforms other classic parking prediction approach for all prediction horizons. LSTM outperforms the second since it consider the temporal dependency but not spatial dependency. MLP performs better than HA but lose the match to LSTM and ConvLSTM. This result suggests us that both spatial and temporal dependency play a role in the parking occupancy prediction, and the temporal dependency seems more important since the gap between the LSTM and MLP is much smaller than MLP and other approaches.

The first experiment shows that ConvLSTM perform the best in parking sensing. Then, we conduct a few-shot transfer learning test to validate the effectiveness of our proposed transfer learning model with a few training samples from the target domain. Most machine learning techniques require thousands of examples to achieve good performance in parking prediction. The goal of few-shot learning is to achieve acceptable accuracy in parking sensing with a few training examples in target domain. We compare our model to four classic approaches used in spatio-temporal transfer learning area: LSTM with parameter transfer, ConvLSTM with parameter transfer, ADDA with MLP and our propose architecture. The first and second model are based on parameter transfer framework, which transfer the parameters trained in the source domain to the target domain. ADDA with MLP and our proposed architecture are GAN-based transfer learning framework. Table 6 shows that our approach perform the best. The ConvLSTM with parameter transfer perform better than LSTM with parameter transfer, and the ADDA with MLP perform the worst. This result validates our claim that both spatial and temporal dependency are significantly important in parking occupancy prediction, and adversarial learning is a good at learning the shared feature spaces. Additionally, it again validates that the importance of each component should be temporal dependency, spatial dependency and domain adaption.

In summary, we have conducted two experiments with Melbourne CBD parking data, Rye parking data and multiple contextual features. The experimental results show that our approach which integrates spatial information, temporal information and domain adaptation outperform other baselines. It also shows the importance of each component in predict parking occupancy in target domain by leveraging source domain historical data and contextual information.
7 CONCLUSION

In this paper, we use both implicit sensing and explicit sensing approaches to predict the parking occupancy in two different cities. We propose a GAN-based ConvLSTM transfer learning framework to sense the parking occupancy in a new area with few historical parking data. We also qualitatively analyse the correlation between the contextual information and parking occupancy with ten million level real-world datasets. We compare our proposed model with the state-of-the-art spatio-temporal transfer learning approach, and the experimental results show that our proposed model can solve both significant challenges: spatial and temporal information integration and contextual information shared feature extraction.

Our framework can be easily extend to other cities and other spatio-temporal sensors datasets as long as the data is graph-based and spatial correlated on which our model relies on. In the future, we would like to investigate other data sources such as traffic and human mobile. We also will apply our proposed framework to other graph-based sensor data sensing problems.

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