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Pattern Recognition for Curb Usage

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16. Abstract

The increasing use of transportation network companies and delivery services has transformed the utilization of curb space, resulting in a lack of parking and contributing to congestion. No systematic method exists for identifying curb usage patterns, but emerging machine learning technologies and low-tech data sources, such as dashboard cameras mounted on vehicles that routinely travel the area, have the potential of monitoring curb usage. To demonstrate how video data can be used to recognize usage patterns, we conducted a case study on Bancroft Way in Berkeley, CA. The project collected video footage with GPS data from a dashboard camera installed on a shuttle bus that circles the area. We trained a machine learning model to recognize different types of delivery vehicles in the data images, and then used the model to visualize curbside usage trends. The findings include identifying hot spots, analyzing arrival patterns by delivery vehicle type, detecting bus lane blockage, and assessing the impact of parking on traffic flow. The proof-of-concept study demonstrated that machine learning techniques, when coupled with affordable hardware like a dashboard camera, can reveal curb usage patterns. The data can be used to efficiently manage curb space, facilitate goods movement, improve traffic flow, and enhance safety.

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Pattern Recognition for Curb Usage

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Executive Summary

Executive Summary

The increasing use of transportation network companies and delivery services has transformed the use of curb space, resulting in a lack of parking and contributing to congestion. No systematic method for identifying curb usage patterns exists, but emerging machine learning technologies and low-tech data sources, such as dashboard cameras mounted on vehicles that routinely travel the area, have the potential of monitoring usage. The collected video footage can be used to build a comprehensive traffic dataset to identify parking trends, busy areas, and curb usage patterns. Using neural networks for automated vehicle recognition and classification reduces the need for manual data analysis.

To demonstrate how video data can be used to recognize usage patterns, this report presents a case study conducted on Bancroft Way in Berkeley, CA. The project collected over a thousand hours of dashboard camera footage and developed a neural network for vehicle classification. The camera, installed on a shuttle bus that circles the area, generates a video file every minute that captures the road ahead, GPS geographic data, and the speed at which the bus is traveling. We used the GPS information to filter out frames that do not contain pertinent information. We trained a machine learning model to recognize different types of delivery vehicles in the data images, such as Amazon, FedEx, and UPS, and then used the model to visualize curbside usage trends. The findings include identifying hot spots, analyzing arrival patterns by delivery vehicle type, detecting bus lane blockage, and assessing the impact of parking on traffic flow.

The project's success demonstrated the potential of using affordable dashboard cameras combined with machine learning for monitoring curb usage patterns. Cities can use the data collected to efficiently manage curb space, facilitate goods movement, improve traffic flow, and enhance safety. The proposed information system can provide real-time insights and recommendations to commuters through mobility apps, leading to better utilization of curb space and reduced congestion.

This proof-of-concept project can be enhanced by adding cameras to other bus routes to expand the data collection, incorporating other machine learning models for feature extraction, implementing license plate recognition, and developing an interactive web application for user-friendly access to the data.

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Introduction

Curb space is increasingly becoming a dynamic interface between people and vehicles, and its stationary use as a place to park is waning. This transformation is fueled in part by people's increasing reliance on transportation network companies, such as Uber and Lyft, and on delivery services for food and consumer products. The curb space is also an important interface for bikeways, bus lanes, street vendors (for example, food trucks), and paratransit picking up and dropping off passengers with disabilities. These various demands are causing parking deficits, resulting in illegal parking and excessive cruising for spaces. In addition, with the absence of a present law enforcement system, commercial vehicles, due to the brief nature of their parking needs, can find it expedient to double-park or occupy a bus lane, causing traffic disturbance, congestion, and hazardous situations. Various curb management models involving dynamic parking pricing [1,2], parking reservations [3,4], or operation time partitioning have been developed to improve curb utilization, but implementing an adequate control policy requires extensive parking analysis to identify area-specific curb characteristics, spatiotemporal demand distributions, common reasons for congestion, and other parameters.

Human-related data collection methods, such as surveys and questionnaires conducted by logistics companies, can provide sensitivity toward various parking control policies [5,6], drivers' preferences for different delivery strategies [7], and individual agencies' interest for further curb management implementation. However, this approach is subjective because the analysis of the data is usually geared toward structuring public opinion rather than understanding parking patterns. Therefore, these data collection methods must be accompanied by more substantial and precise monitoring methods to build a comprehensive parking model of the network.

One such method commonly used for curbside analysis involves static surveillance cameras installed on urban streets. Surveillance cameras often have a high video resolution that can capture distinctive vehicle characteristics, such as license plate numbers, for law enforcement purposes or vehicle tracking. However, this approach can monitor only a limited area and has high maintenance costs. In addition, locations worth monitoring might not be known ahead of time.

This project aimed to avoid these issues by using dashboard cameras in vehicles to build an extensive traffic dataset comprising thousands of hours of video recordings from multiple angles across a large region to identify parking trends, busy areas, and curb usage patterns. The camera's dashboard position allows us to visualize and analyze the direct impact that parking inefficiencies have on traffic agents. Although the completeness of the data depends on the penetration rate of the vehicles supplying camera footage, even infrequent monitoring of a particular area, as demonstrated in this project, can be sufficient for a thorough analysis. Compared to static cameras, this solution is flexible, inexpensive, and scalable.

Several companies have attempted to develop a monitoring system for curb management purposes. One of these companies is Coord, which used augmented reality technology to capture the physical attributes of a scanned curb. However, the proposed technology was unable to provide real-time data or recognize moving objects, such as pedestrians and vehicles. Moreover, data collection needed to be done manually via the mobile app, which can be problematic for large and dense areas. Another company, Fehr and Peers, collaborated with various transportation authorities to study street-specific curb activity and analyze the data gathered. Their method involved static video and photo cameras and manual processing of the data, which does not scale well. In addition, Fehr and Peers relied on Uber's data regarding their pick-up and drop-off patterns, which has a limited application for the analysis of other commercial vehicles' behavior.

In this project, we developed a curb monitoring model based on single-source dashboard camera footage. To eliminate inefficient manual data analysis, we developed a neural network to recognize and classify delivery vehicles. Further curb activity pattern identification was performed on the labeled and structured datasets provided by the neural network. To test our approach, we conducted a case study of the southern periphery of the UC Berkeley campus on Bancroft Way. Bancroft Way is a microcosm for the increasingly multifaceted use of curb space in an urban area. In the absence of available curb space, delivery vehicles that serve the campus and nearby businesses and TNCs often double-park or park illegally in a red zone. The vehicles block bus stops, forcing buses to go around them and stop farther downstream, creating inconveniences for passengers, including those with special needs, as well as causing hazards, and adding to congestion.

Bancroft Way Case Study

To evaluate curbside activity, the monitoring method must be implemented in a busy street setting with a high demand for curb usage. Bancroft Way on the southern side of the UC Berkeley campus (Figure 1) fits this description. Numerous local businesses and university administrative buildings, and an Amazon drop-off location, make Bancroft Way a popular destination for delivery and freight trucks. High parking demand coupled with limited curbside availability results in frequent parking violations, including double-parking and bus lane occupation (Figure 2). The absence of curb monitoring and managing systems makes it currently impossible to improve the parking situation.

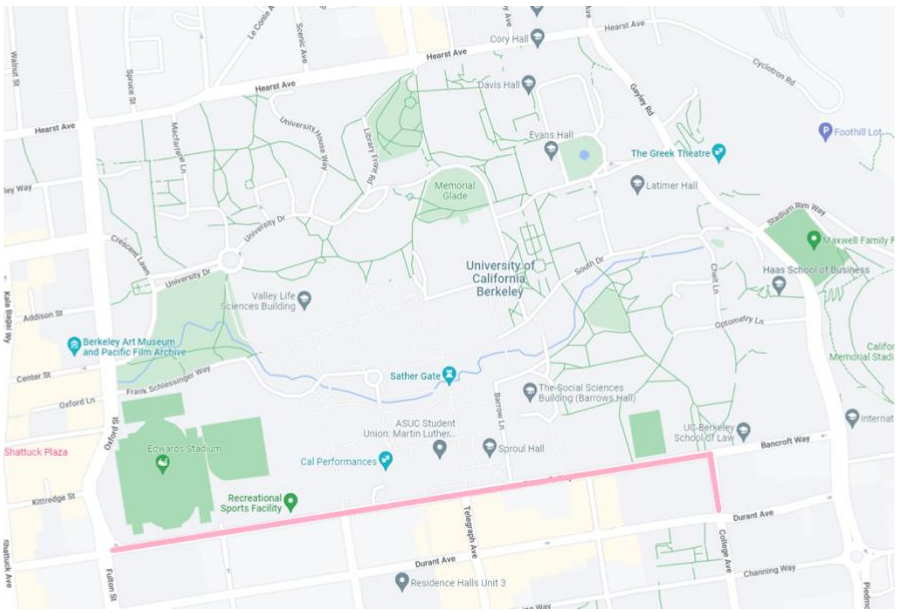

Figure 1. Monitored segment of Bancroft Way on the southern side of the UC Berkeley campus (highlighted in pink)

Figure 2. A dashboard camera image of Bancroft Way with the left and right lanes blocked by delivery trucks, creating a bottleneck

We first needed to establish reliable day-to-day curbside activity monitoring on Bancroft Way. In collaboration with the Berkeley Parking and Transportation Department, we were given access to a Bear Transit Perimeter shuttle bus (Figure 3), which cruises the campus between 7:30 a.m. and 7:30 p.m. daily (except for weekends). The circulation period is approximately 30 minutes, which might be a limiting factor for some types of activity analysis, such as parking duration identification. However, in subsequent sections we demonstrate the sufficiency of the collected data for the recognition of many important behavioral patterns. The project was conducted over the course of eight months, which resulted in over a thousand hours of dashcam video footage from different points of the campus periphery, including several hundreds of hours of Bancroft Way recordings specifically.

Figure 3. Dashboard camera installed on a Bear Transit shuttle bus served as a single data collection source for the model

Training the Model

To analyze the behavior of delivery trucks, it is important to distinguish them from other types of vehicles on the dashboard camera recordings. Each video sample must be independently processed to identify whether it contains valuable information. Manual analysis of data produced by a single camera is laborious and is not feasible for a network of dashboard cameras—the long-term application envisioned for this project. Therefore, vehicle recognition and classification must be automated to achieve the required performance level. In this project, we focused on a neural network approach based on the YOLOv5 framework. According to a recent study [8], the You Only Look Once (YOLO) object detection framework is reliable for identifying traffic objects even in congested traffic situations, which meets our requirements.

Accurate classification of specific traffic objects requires extensive neural network training and tuning. Because we could not find a pretrained machine learning solution for various types of delivery truck identification, we trained our own neural network to classify different vehicles. The accuracy of a neural network depends on the size and quality of the training dataset. A large number of high-resolution images with clear labeling is essential for efficient training. Another challenge was that datasets reflecting various types of delivery vehicles are not publicly available. All transportation-related datasets can identify trucks as a separate vehicle type, but they do not distinguish their company affiliation. Therefore, for the training and validation purposes we created a labeled dataset consisting of images extracted from the collected dashboard camera footage.

To find a video frame containing an object of interest requires viewing and analyzing many recordings, which is time-consuming. To simplify the process, we used the BDD100K [9] public dataset, developed by UC Berkeley researchers, to filter out video clips that do not contain any type of truck. We also trained another, more general machine learning model capable of recognizing trucks and selected corresponding footage for further manual review.

After training our YOLOv5 model on the custom dataset, we were able to run the remaining dashcam footage through the neural network, processing it frame by frame, to classify vehicles caught on the video. Each identified vehicle is outlined by a bounding box (Figure 4) that reflects its relative location in the frame. The size and position of a bounding box are important parameters for correlating the distance to the object and its position on a street. In addition to the model-generated data, dashcam video clips include the date, time, GPS coordinates, and the speed of the vehicle carrying the dashcam (a Bear Transit bus in our case). By combining the vehicle classifications from the neural network with the camera-generated information, we were able to build a comprehensive dataset with the corresponding spatiotemporal characteristics and bus speed measurements for curbside activity analysis. The GPS coordinates also helped us to extract only Bancroft-related video clips for analysis.

Figure 4. The bounding box includes the object's label and confidence level

Analysis Objectives

A key objective of our curb monitoring model is to identify "hot spots"—busy street regions with a high traffic density, a large number of delivery vehicles, and a high demand for parking. When management resources are limited, hot spots should have the highest priority for parking management. Using the classification dataset, along with the spatial (GPS coordinates) and temporal (date and time) detection characteristics, it is possible to accurately determine the busy locations via data point clustering. In most cases, hot spots are temporary and can be easily recognized only within a limited period of time (during rush hour, a grocery store's scheduled delivery times, etc.). On rare occasions, however, the location remains congested for a major part of the day, calling for more detailed monitoring and analysis.

Another component of the delivery vehicle behavioral analysis is trucks' arrival pattern recognition. Filtering by the model-generated labels, we can derive spatiotemporal detection distributions for each particular type of delivery vehicle (Amazon, UPS, FedEx, etc.). Depending on the arrival tendency for different hours within a day or different days within a week, it is possible to predict the future demand distribution and anticipate potential congestion. Furthermore, the arrival patterns for a particular company can provide valuable insights about their internal delivery policies. The detailed detection information enables us to identify periods of time with sparse arrivals and low parking demand, which can be useful information for curb reallocation by time of day.

Another feature detected by our model is the relative parking position of each delivery vehicle on the road (left curb, right curb). Of particular interest is recognizing whether a delivery truck occupies a bus lane or bus stop. The bounding boxes constructed by the object classification model are capable of providing the required estimations. Depending on the location of the box relative to the central vertical of the frame, we were able to approximate the detected vehicle's position with respect to a bus. Because buses tend to use the special dedicated lane (usually rightmost lane), detecting a truck to the right of the bus almost certainly suggests illegal bus lane occupation (Figure 4). To verify the accuracy of the result, additional manual analysis can be applied. This information is valuable for analyzing repeated violations on a company-to-company basis. Moreover, detecting bus lane occupation allows for a thorough investigation of the impact that these parking choices have on traffic progression and bus speed profiles.

Lastly, we are interested in analyzing the impact that different parking patterns have on traffic flow. One of the metadata parameters provided by the dashboard camera is the instantaneous speed of the bus, which can serve as an accurate representation of traffic progression. However, the delay in camera speed measurements was too high, causing discrepancy with the ground truth. Therefore, we developed a different approach using GPS coordinates. Instead of computing the current speed of the bus, we derived the average velocity within the specific road segments (Figure 5). The breaking points for the segments were chosen based on the locations of the bus stops and the hot spots. To avoid data corruption by long stopping delays, we kept the bus stops out of the segments. To capture the impact of the hot spots on the velocity profiles, we kept them in the segments. By combining the detection data with the average speed calculations, it was possible to analyze how the parking behavior of a particular delivery vehicle affects the actual traffic propagation.

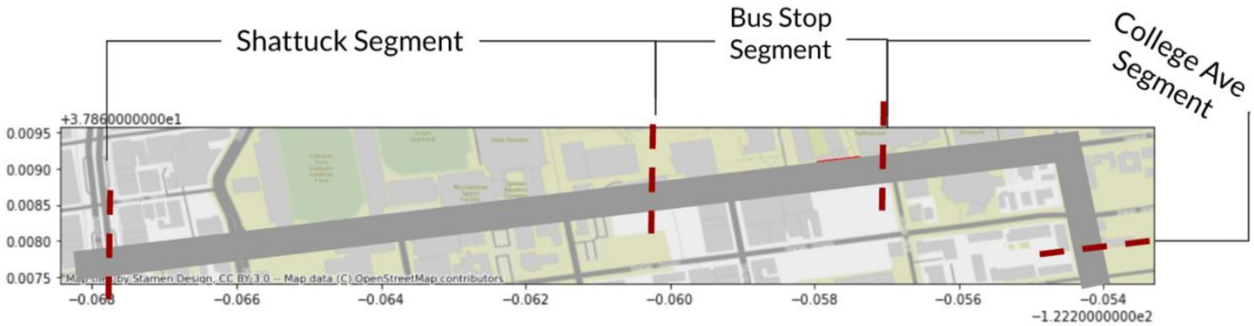

Figure 5. Bancroft Way segmentation for average bus speed computation using GPS coordinates and travel time

Results

In this section we demonstrate the application of our curb monitoring model on Bancroft Way. The parking trends and patterns derived by the data analysis algorithms corroborate traffic observations.

Detecting Hot Spots

First, we focused on hot spot identification based on the delivery truck detection data. After creating the heatmap covering all the occurrences across all the considered delivery truck types, we identified that the busiest location on Bancroft Way is between Bowditch Street and Barrow Lane (Figure 6). This area is close to many local businesses and several university buildings, all of which require frequent deliveries. A large number of available parking spots makes this location an easy and convenient parking destination.

Another busy area is between Barrow Lane and Telegraph Avenue. This is the closest parking street segment to the Amazon drop-off location, which also has a convenient road pocket on the right side of the road, allowing the parked vehicles to stay out of traffic's way and avoid flow disturbance.

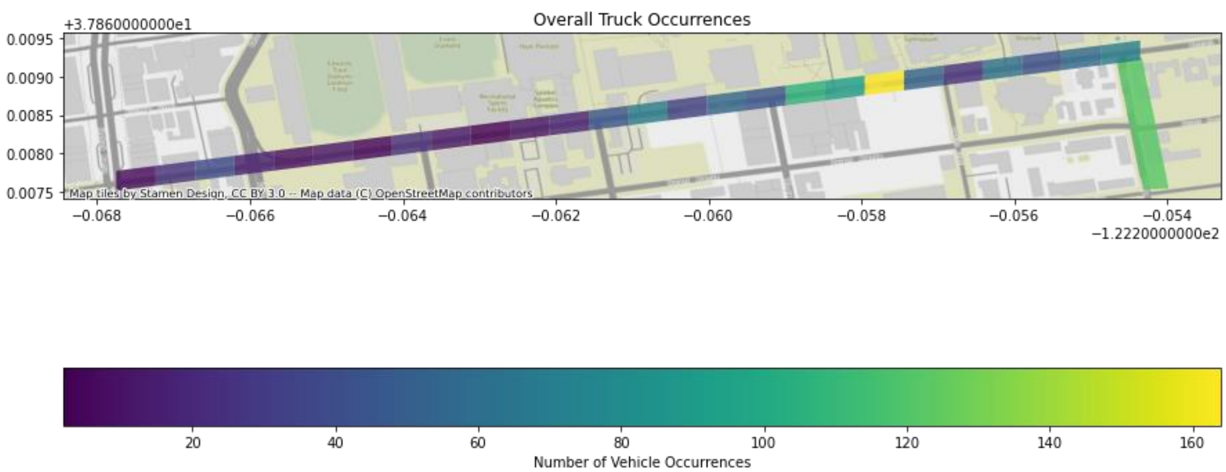

Figure 6. Heatmap of delivery vehicle detections on Bancroft Way, with the most-dense area (hot spot) located between the intersections of Telegraph Avenue and Bowditch Street

The third busy area is around the intersection of Bancroft Way and College Avenue, which also provides access to multiple campus buildings. Nearby cafes and housing contribute to the high frequency of delivery vehicles.

All three locations were reported to be problematic by bus drivers and the Transportation Department, which is now corroborated by the analysis results.

Temporal Distribution of Delivery Activity

The analysis revealed hourly and daily delivery trends on Bancroft Way. First, we focused on the vehicle arrival patterns during different hours of a day. Because the Bear Transit bus has a fixed operation schedule (7:30 a.m.–7:30 p.m.), only that period is considered in our analysis. As shown in Figure 7, UPS and Amazon delivery trucks have similar detection distributions that peak around 11 a.m. to noon and gradually decrease toward the end of the day. FedEx vehicles, on the other hand, tend to complete their deliveries earlier in the morning, between 9 a.m. and 11 a.m., with the last delivery spike at around 11 a.m.

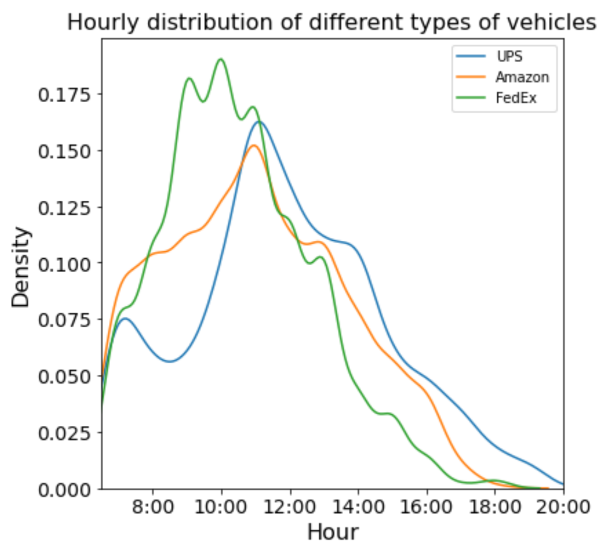

Figure 7. Hourly distribution for Amazon, FedEx, and UPS delivery vehicles

The day-to-day delivery trends compiled in Figure 8 show that FedEx and UPS have somewhat uniform arrival distributions among the different weekdays. A slightly different result is observed for Amazon vehicles. Approximately half of Amazon's weekly detections fall on Thursdays and Fridays. One possible reason for this uneven pattern could be related to the proximity of the Amazon drop-off location. To optimize the utilization of delivery trucks, Amazon might schedule picking up the returned packages from the drop-off location on the last two weekdays and shift the arrival frequency accordingly.

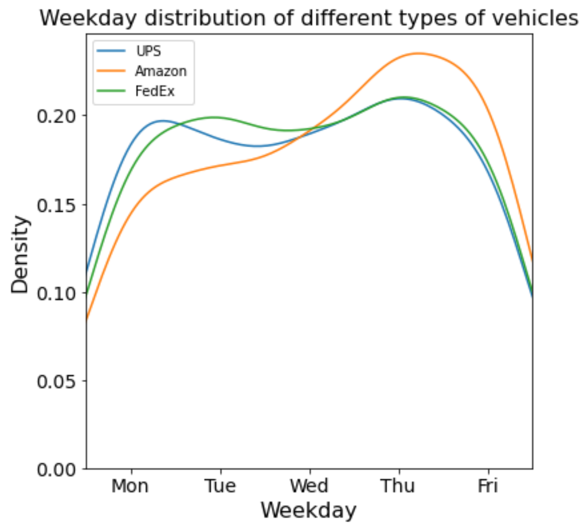

Figure 8. Weekly distribution for Amazon, FedEx, and UPS delivery vehicles

Delivery Trucks' Effect on Bus Speed

To analyze the impact of delivery vehicles on the average speed of the bus carrying the dashboard camera, we compared the velocity changes on the three segments of Bancroft Way with and without truck detections. The data summarized in Figure 9 does not reveal significant slowdowns caused by delivery vehicles—the biggest difference we could measure is under three miles per hour. However, manual review of the video clips revealed that the delivery vehicles' impact on the average bus speed is overwhelmed by the delays caused by pedestrian traffic. To isolate the correlation between the parking patterns and the traffic propagation, further analysis is required.

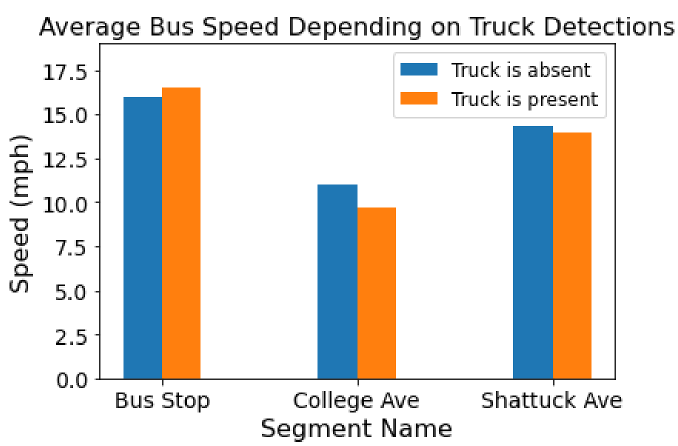

Figure 9. Impact of the delivery vehicle detection on the average bus speed conducted at the College Avenue, Bus Stop, and Shattuck Avenue segments

Bus Lane Occupation

The last analysis performed on the data was to detect occurrences of bus lane occupation by delivery vehicles, which can potentially cause traffic disruption and safety hazards because the bus has to leave its dedicated lane. According to the statistical breakdown from the data (Figure 10), FedEx trucks are the most frequently detected delivery vehicles in the bus lane by a large margin.

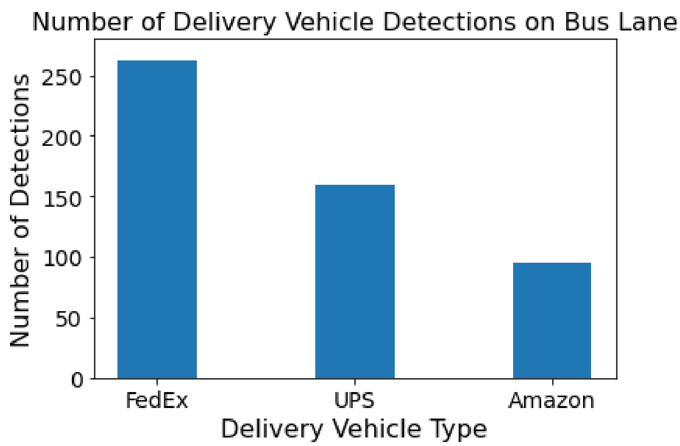

Figure 10. Bus lane occupation for Amazon, FedEx, and UPS delivery vehicles

It is important to note that this analysis does not necessarily indicate a large number of violations by delivery vehicles. Bus lane occupation estimation is probably the most uncertain algorithm considered in this study. First, having only one data source, which monitors each location for a brief period, we are unable to identify whether a particular vehicle is in motion or parked. Therefore, detecting a delivery truck on the right side of the video frame does not necessarily indicate a parking violation. Second, the assumption that the bus travels only in the bus lane whenever it is available is questionable and might cause false violation detections. For example, when the bus chooses the leftmost lane, any vehicle on the right would be considered occupying the bus lane. Lastly, not every road segment has a dedicated bus lane, which makes the bus lane violation physically impossible at this location. Further model development is required to improve the proposed analysis method.

Data Accessibility

To make the data readily accessible for further analyses, we developed four application programming interfaces (APIs) that return queried data that was produced via the YOLO model. The purpose and design of these APIs were influenced by our data analysis findings and the interests of the UC Berkeley Parking and Transportation Department.

The four APIs provide the following information:

- A list of detected vehicles along with the frame name, video name, and bounding box of where the vehicles were detected in the frame based on query parameters, such as time period and GPS position range
- The average calculated speed in a day on all three Bancroft Way segments during a specified time period
- The number of vehicles detected for each vehicle label in the model during a specified time period
- A downloaded version of a specific video of interest

Conclusions

The scope of this project can be expanded in several directions. For example, with minimal effort, we could increase the amount of data collected by adding more cameras and bus routes. Doing so would increase the accuracy of the model as well as the reliability of the data.

We could also add other machine learning models to the current setup to extract more features, such as the ability to identify if a vehicle is parked. This feature requires more effort to label parked cars and train the models. To assist the authorities in penalizing violators, this feature could also be supplemented with the ability to recognize the license plates of the parked vehicles. However, to implement this feature requires increasing the camera resolution.

We could further implement the current setup by tracking the vehicles over different frames to understand a vehicle's activity. We could use this to create a simple feature that determines whether a vehicle is parked or in motion.

An interactive, user-friendly web application would make the data more accessible. Currently, we only have APIs that return the detection results from the model. A web application could display a map and allow users to interact with different parts of the road and view results based on their needs.

This project's proof-of-concept study demonstrates that machine learning techniques, when coupled with affordable hardware like dashboard cameras, can reveal curb usage patterns. It shows the potential for large-scale deployment by cities that want to use curb usage data for facilitating freight and goods movement while avoiding disruptions to traffic flow. Cities can use the data to match demand to supply with efficient and nimble management of the curb space. Potential management strategies include dynamic allocation of curb space over the day, week, and year, for example, allowing food trucks to use red zones at lunch time to serve both public and commercial interests. Cities can also deploy real-time bidding options to enable delivery companies to reserve curb space at certain times of day.

In addition to assisting commercial activity and goods movement, the proposed information system can be used to improve traffic flow and safety. The data collection and analysis system provides the ability to identify hot spots in real time and how and when curb activity disrupts traffic flow, limits public access to bikeways and bus stops, and causes safety hazards. Active curb management can preempt such hazards.

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