To the Graduate Council:

I am submitting herewith a thesis written by Supriya Sarker entitled "Beacon: A Naturalistic Driving Dataset During Blackouts for Benchmarking Traffic Reconstruction and Control." I have examined the final paper copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Computer Engineering.

Weizi Li, Major Professor

We have read this thesis
and recommend its acceptance:

Jian Liu

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(Original signatures are on file with official student records.)

Beacon: A Naturalistic Driving Dataset During Blackouts for Benchmarking Traffic Reconstruction and Control

A Thesis Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Supriya Sarker

December 2024

This thesis is dedicated to my beloved parents for their love, endless support, encouragement and sacrifices.

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First and foremost, I express my deepest gratitude to the Almighty for bestowing His blessings on me and giving me the ability to accomplish this work successfully.

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"Without data, you're just another person with an opinion." — W. Edwards Deming

Abstract

The **Beacon** study provides insights into urban traffic dynamics during blackouts through the analysis of naturalistic driving data from two intersections in Memphis, TN. We reconstructed the proposed dataset **Beacon** in three different traffic settings which are (i) unsignalized, (ii) signalized, and (iii) mixed traffic control. We investigate the behavior of traffic at different intersections during traffic light blackout using **Beacon** dataset. Besides, our findings demonstrate the potential benefits of integrating robot vehicles for traffic management under these conditions, particularly in high-volume conditions. Moreover, the reconstruction of various traffic conditions such as unsignalized, signalized, and mixed showcases the usefulness of **Beacon** dataset while also revealing areas for improvement in modeling approaches. Our future work will focus on improving traffic simulation accuracy and expanding the dataset for broader applications, enhancing urban traffic resilience.

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Chapter 1

Introduction

1.1 Introduction

The field of transportation is experiencing a profound transformation, largely driven by the advent of self-driving vehicles. This revolution extends beyond mere technological innovation; it promises to redefine the entire landscape of mobility, safety, and urban planning. These rapid advancements in autonomous driving rely heavily on extensive datasets, which help autonomous driving systems be robust and reliable in complex driving environments (Liu et al., 2024). Autonomous vehicles (AV) are equipped with sophisticated sensors and powered by artificial intelligence (AI) and machine learning algorithms. These systems are designed to replace human drivers and enhance overall efficiency. However, despite these advancements, autonomous vehicles are not yet fully capable of eliminating accidents associated with human error. Incidents involving major companies like Tesla, Uber, and Waymo have underscored the persistent challenges and limitations of AI technologies, particularly in complex, real-world driving scenarios. The architecture of autonomous driving technology typically encompasses three main modules: environmental perception, decision making, and motion control (Schwarting et al., 2018), (Paden et al., 2016).

The decision-making module, in particular, plays a crucial role, akin to a driver's brain, and its effectiveness is vital for safe vehicle operation (Wang et al., 2024).

In recent years, there has been a significant increase in the quality and variety of autonomous driving datasets. The motivation for this enhancement is twofold. Firstly, improved datasets facilitate the development of more accurate and sophisticated algorithms capable of handling a wider range of driving scenarios. Secondly, these datasets serve as a foundational component for researchers and engineers to innovate and refine autonomous driving technologies. By expanding the scope and diversity of these datasets, the field can accelerate the advancement of autonomous vehicle capabilities, ultimately leading to safer and more reliable systems.

Modern urban infrastructure, especially in densely populated areas, is increasingly vulnerable to disruptions caused by extreme weather events and other factors. These disturbances often lead to significant power outages, incapacitating critical urban systems, with traffic control mechanisms being notably affected (Press, 2022). Traffic lights, the backbone of urban traffic management, rely entirely on electricity. Thus, their failure during blackouts leads to increased congestion and accident risks, especially at intersections. These critical nodes, crucial for multi-directional traffic flow, are also hotspots for over 45% of U.S. traffic crashes (Choi, 2010). During blackouts, intersections can remain without control for extended periods and cause widespread gridlock to a city (Winck, 2022; Ramirez, 2022).

To address these challenges and develop effective traffic management solutions for blackout scenarios, comprehensive datasets representing real-world traffic behavior during power outages are essential. However, capturing such a dataset is rare, as orchestrating a controlled blackout for data collection is impractical and potentially unsafe, making naturally occurring events the only feasible, though infrequent, opportunities for gathering this type of data.

In response to this critical need, we introduce **Beacon**, a dataset containing four hours of traffic dynamics during peak periods including midday and afternoon, captured during a blackout in Memphis, TN, USA. **Beacon** provides detailed traffic movements at two real-world intersections (Fig. 1.1), offering information such as timing, origin, and destination lanes for each vehicle navigation the intersections. This naturalistic driving dataset presents a unique opportunity to study and analyze traffic behavior under unsignalized conditions.

We reconstruct the intersection in three different types of traffic control - (i) unsignalized traffic control, (ii) signalized traffic control, and (iii) mixed traffic control as a showcase of the usage of the dataset and create benchmark for traffic reconstruction and control with **Beacon** dataset. This benchmarking will help to analyze the traffic light blackouts and to implement further control situation to handle blackouts efficiently. Therefore, in this thesis, we outline the processes of data collection, extraction, and reconstruction, and provide in-depth examination of the traffic dynamics at these intersections. Through this detailed analysis and reconstruction, we aim to contribute insights to the development of more resilient urban traffic systems that function during power disruption. In chapter 1, we discuss types of data depending on the collection process, the role of datasets in transportation research, key challenges, the purpose of the thesis, motivation, contributions made in the thesis, and outline of the thesis.

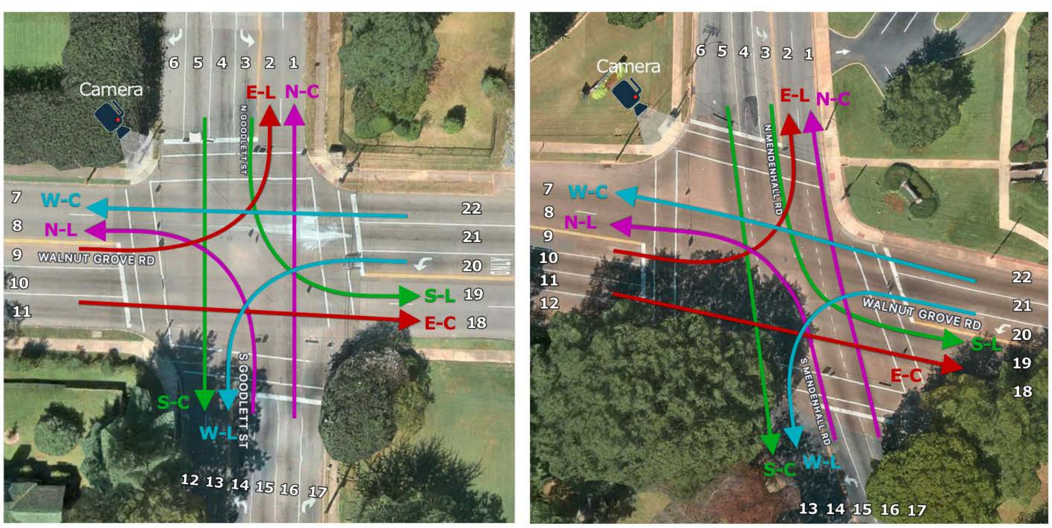


Figure 1.1: Satellite views of the GWG and WGM intersections

1.2 Types of Traffic Data Collection Process

Considering the method of data collection, the traffic dataset can be categorized into three major classes: (i) Onboard dataset, (ii) Vehicle-to-Everything (V2X) dataset, and (iii) Unmanned Aerial Vehicle (UAV) dataset.

- Onboard dataset: This dataset is gathered from sensors and systems installed directly on vehicles. It typically includes data related to the vehicle's internal environment and its interaction with the road, such as speed, acceleration, GPS location, and internal vehicle diagnostics. Data from dashboard cameras, GPS trackers, or onboard sensors like radar, LiDAR, and ultrasonic sensors are examples of onboard datasets. Onboard datasets are crucial for vehicle performance analysis, navigation, autonomous driving systems, and real-time traffic management.

- Vehicle-to-Everything (V2X) dataset: V2X datasets come from communication between vehicles and external systems, such as other vehicles (Vehicle-to-Vehicle or V2V), infrastructure (Vehicle-to-Infrastructure or V2I), pedestrians (Vehicle-to-Pedestrian or V2P), and networks (Vehicle-to-Network or V2N). Some examples of V2X datasets are data exchanged between vehicles for collision avoidance, signals from traffic lights, or communication with cloud-based systems for real-time navigation updates. V2X datasets are essential for enhancing road safety, enabling autonomous driving, optimizing traffic flow, and improving smart city infrastructure.

- Unmanned Aerial Vehicle dataset: This dataset is collected via drones or UAVs, which capture traffic data from a bird's-eye view. UAVs are often equipped with cameras and sensors to monitor traffic patterns, road conditions, or accidents in real-time. Aerial footage of traffic, road congestion data, or real-time accident monitoring are some examples of UAV dataset. UAV datasets are used for traffic surveillance, emergency response, urban planning, and providing a comprehensive overview of traffic flow over large areas.

1.3 Role of dataset in transportation research

Datasets play a pivotal role in transportation research, providing foundational insights and supporting advanced analytics that drive innovation and improvement in transportation systems.

- Traffic Management and Control: Datasets allow researchers and city planners to analyze traffic flow patterns and congestion points, enabling the design of more effective traffic control measures. Real-time data collection helps in adjusting traffic signals and signs to accommodate current traffic conditions, reducing congestion and improving traffic flow.

- Safety Enhancements: By studying accident data, researchers can identify high-risk areas and factors contributing to accidents, leading to targeted interventions like road redesigns or improved signage. Datasets can be used to predict where accidents are likely to occur, helping to proactively prevent them through changes in road design or traffic flow management.

- Infrastructure Planning and Development: Transportation datasets help in assessing the effectiveness of existing infrastructure and identifying the need for new projects like roads, bridges, or public transit options. Before implementing new transportation projects, datasets can be analyzed to predict their impact on current traffic systems and urban environments.

- Environmental Impact: Researchers use transportation data to study the environmental impact of traffic, such as emissions from vehicles, and to develop strategies to reduce pollution. Data-driven insights assist in planning more sustainable and environmentally friendly transportation options, like promoting electric vehicle use or enhancing public transport systems.

- Technological Advancements: Research on autonomous vehicle performance, interaction with human-driven vehicles, and integration into current traffic systems relies heavily on comprehensive datasets. Data integration from various transportation modes supports the development of smart city initiatives, enhancing connectivity and mobility within urban spaces.

1.4 Key challenges

In transportation research, while datasets are incredibly valuable, they also present several key challenges:

- Data Quality and Completeness: Data may be inaccurate due to sensor errors or incorrect data entry. Incomplete datasets can lead to biased analyses and inaccurate conclusions. Rapid changes in traffic patterns or infrastructure may render existing data obsolete.

- Data Integration and Standardization: Integrating data from different sources (like GPS, sensors, and manual surveys) can be challenging due to format inconsistencies. Lack of standardized data collection methods across different regions or systems complicates comparative analyses.

- Privacy and Security: Transportation data often includes personally identifiable information, raising privacy concerns. Ensuring the security of sensitive data against breaches is crucial but challenging.

- Scalability and Management: The sheer volume of data generated by transportation systems requires substantial storage and processing capabilities. Effective management tools and practices are necessary to handle, process, and analyze large datasets efficiently.

1.5 Purpose of the thesis

The purpose of this thesis on the Beacon dataset revolves around addressing the critical issues posed by traffic control system failures during power outages, particularly in urban environments. Some detailed objectives and goals of the thesis based on the dataset are:

- To Analyze Traffic Dynamics During Blackouts: The thesis aims to provide an in-depth analysis of how traffic behaves at unsignalized intersections during blackouts, a situation that leads to increased congestion and accident risks. This involves detailed observation and analysis of traffic patterns, vehicle trajectories, and density during these periods.

- To Benchmark Traffic Reconstruction and Control Techniques: Another central goal is to utilize the **Beacon** dataset to benchmark various traffic reconstruction techniques and control methods. By simulating different traffic control scenarios—unsignalized, signalized, and mixed to identify their performance under blackout conditions.

- To Develop Resilient Urban Traffic Systems: The ultimate purpose of this research is to contribute insights towards the development of more resilient urban traffic systems that can maintain functionality during power disruptions. This includes proposing improvements to traffic management strategies that can mitigate the adverse effects of blackouts on urban mobility.

- To Fill a Gap in Research: The **Beacon** dataset provides a unique opportunity to study naturalistic driving behaviors during blackouts, an area that has been seldom explored due to the difficulty in capturing such data. This thesis aims to fill this gap by offering new data and insights into an under-researched area of traffic management.

1.6 Motivation

The increasing frequency of power outages, often triggered by extreme weather events, disrupts urban traffic management, particularly at intersections, leading to severe congestion and heightened accident risks. Traditional traffic datasets rarely capture these blackout conditions, creating a significant gap in our ability to develop resilient traffic management strategies. This thesis leverages **Beacon** dataset, collected during actual blackouts, to study traffic dynamics in the absence of signalized controls. By analyzing this unique data, we aim to contribute to the development of more adaptive and resilient urban traffic systems that can effectively handle power disruptions.

1.7 Contribution of the thesis

This thesis introduces a detailed analysis of traffic dynamics during blackouts, utilizing the unique **Beacon** dataset to provide empirical insights rarely captured in other studies. It benchmarks and evaluates traffic control strategies under unsignalized, signalized, and mixed conditions during power outages, highlighting the strengths and weaknesses of current systems. By demonstrating the practical application of the dataset in simulating and understanding complex urban traffic scenarios, the research helps pave the way for the development of more robust traffic management solutions.

1.8 Thesis Outline

In the rest of this thesis, we present the details of our approach for preparation of Beacon dataset and usage of in different settings.

- Chapter 1 defines traffic dataset, the importance of dataset, and discusses various types of data collection processes.
- Chapter 2 reviews the literature of traffic datasets and the annotation process.

- Chapter 3 discusses the preparation of Beacon dataset.
- Chapter 4 discusses the experimental environment setup, and data analysis, and analyzes the results.
- Chapter 5 draws conclusions with some future recommendations.

1.9 Conclusion

This chapter discusses the significance of traffic datasets on transportation research and the purpose of the thesis with background and challenges. The motivation and contribution are clearly mentioned in this chapter. The research background on road safety and related literature review is done in the chapter 2.

Chapter 2

Literature Review

2.1 Introduction

Over the last decades, revolutionary development has been encountered in the traffic dataset. To solve the problem through traffic datasets researchers used various datasets in the field of transportation. In chapter 2 we aim to discuss the previously proposed and implemented traffic datasets for reconstruction purposes. Finally, we discuss elementary concepts of traffic dataset annotation methods.

2.2 Related work

2.2.1 Traffic reconstruction and control

(Sanchez et al., 2023) uses the Caltrans Performance Measurement System (PeMS) dataset, which provides sparse traffic data from sensors across California highways. To overcome data limitations, the authors propose a kernel-based traffic reconstruction method, simulating detailed vehicle trajectories to create a continuous, spatio-temporal traffic dataset. This method identifies SAG events by applying a kernel designed to detect speed oscillations and uses bootstrapping to quantify uncertainty, generating multiple traffic scenarios for robust detection. The approach enables precise identification of congestion "hotspots," offering insights to policymakers for targeted congestion interventions.

(Wang et al., 2018b) proposes a novel method called Temporal and Adaptive Spatial Constrained Low Rank (TAS-LR) for reconstructing missing traffic data. This method uses low-rank matrix factorization to analyze both spatial and temporal correlations within traffic data. Implementation involves decomposing the traffic matrix into two factor matrices, representing spatial features (road link characteristics) and temporal features (traffic patterns). The model leverages six real-world datasets, which include data from road links, speed, and volume metrics, making it adaptable to various traffic scenarios.

(Kataoka et al., 2014) proposes a method for reconstructing missing traffic data using Markov Random Field (MRF) modeling. The process involves using a Bayesian approach with MRFs to model the spatial dependencies in traffic data, estimating unobserved data by solving a system of equations via a mean-field method. The datasets include simulated road network data from Sendai, Japan, which reflects real traffic patterns.

(Bilotta and Nesi, 2021) proposes a traffic flow reconstruction model that addresses the indeterminacy in traffic distribution at junctions using a stochastic relaxation technique. The method involves solving a partial differential equation (PDE) for traffic flow and estimating traffic distribution at junctions by computing a Traffic Distribution Matrix (TDM) based on real-time sensor data.

(Qi et al., 2021) proposes a method for reconstructing vehicle trajectories on urban road networks using Automatic License Plate Recognition (ALPR) data. The implementation involves dividing vehicle trips based on travel time, generating candidate paths through an improved K-shortest-path (P-KSP) algorithm, and selecting the optimal trajectory using an auto-encoder model. The dataset comprises ALPR data from an urban network in Ningbo, China, with vehicle detection information.

(Feng et al., 2015) proposes a vehicle trajectory reconstruction method using Automatic Vehicle Identification (AVI) and traffic count data within a particle filter framework. The process combines spatial-temporal trajectory correction factors, such as path consistency, AVI measurability, travel time consistency, gravity flow model, and path-link flow matching, to estimate vehicle paths accurately. Implementation is tested on a simulated urban network in Beijing using VISSIM, with results showing high accuracy in both trajectory reconstruction and OD matrix estimation when AVI coverage is at least 50%.

(Bellini et al., 2018) proposes a traffic flow reconstruction method for urban areas using data from a limited number of fixed sensors. The method models traffic dynamics with differential equations and fluid dynamics on a city graph, estimating road segment capacities using stochastic learning. Implementation involves loading city graph data, updating sensor values, assigning weights to road segments, and iteratively calculating traffic density, which is then visually represented on a map. Using traffic sensor data from Florence, Italy, the model achieves around 75% accuracy, making it significant for real-time urban traffic monitoring.

(Bakowski and Radziszewski, 2021) analyzes changes in urban traffic parameters and noise levels before and after road reconstruction on a national road segment in Kielce, Poland. The study utilized traffic flow and noise data collected between 2011 and 2016, applying statistical and bootstrap methods to account for data gaps. Results showed that road reconstruction led to a decrease in noise levels despite a subsequent traffic increase. Using their proposed method the authors validated the Cnossos-EU noise model, aiding in assessing environmental impacts of urban roadworks.

(Čičić et al., 2020) proposes a method for reconstructing traffic states and controlling congestion using Connected Automated Vehicles (CAVs) as mobile sensors and actuators. The approach employs a model that simulates traffic flow using CAVs to measure local traffic density and act as controlled moving bottlenecks to dissipate stop-and-go waves. Simulated freeway data, based on the Cell Transmission Model

(CTM), demonstrates how subsets of CAVs can efficiently estimate traffic density and reduce congestion delay.

2.2.2 Datasets for traffic reconstruction

Another significance of traffic datasets is to facilitate simulators to deploy and validate to generate and analyze particular traffic scenarios. For mapping integration of AI and safety applications in traffic accident reconstruction (Shen et al., 2023) conducts a scientometric analysis on traffic collision scene reconstruction research from 2001 to 2021 using software tools like CiteSpace, VOSviewer, and SciMAT. (Li et al., 2024) introduces ScenarioNet, an open-source platform for large-scale traffic scenario simulation and modeling aimed at enhancing autonomous driving (AD) research. The proposed method collects traffic data from multiple real-world sources, including the Waymo(Sun et al., 2020), nuScenes(Caesar et al., 2020), and Argoverse(Chang et al., 2019) datasets, and standardizes it into a unified scenario description format. This data is then simulated in the MetaDrive(Li et al., 2022a) simulator, which supports tasks such as single-agent and multi-agent learning, AD stack testing, and scenario generation. By consolidating diverse traffic scenarios, ScenarioNet provides a comprehensive benchmark for AD safety evaluation, addressing challenges of data integration and cross-dataset scenario generation. The platform significantly improves AD system training by offering varied, realistic simulations for more robust and generalized learning.

2.3 Dataset Annotation

The effectiveness and dependability of autonomous driving algorithms depend significantly on not just the quantity of data, but also the quality of annotations. In this section, the method used for data annotation is initially discussed. Furthermore, key factors critical to ensuring the quality of annotations are analyzed. Various autonomous driving tasks necessitate distinct types of annotations. For instance, object detection tasks utilize bounding box labels for each instance, while segmentation relies on annotations at the pixel or point level. Meanwhile, trajectory prediction demands continuously labeled trajectories. Additionally, the annotation process can be divided into three categories: manual, semi-automatic, and fully automatic annotation. This section will provide an in-depth exploration of the different labeling strategies for these types of annotations.

2.3.1 Annotate Bounding Boxes

The accuracy of bounding box annotations critically influences the performance and reliability of perception systems, such as object detection in autonomous vehicles operating in real-world conditions. The annotation task typically involves marking images with rectangular boxes or delineating point clouds with cuboids to precisely identify objects of interest.

Labelme (Russell et al., 2008) is an earlier tool designed for image labeling specific to object detection. Yet, creating bounding boxes through professional annotators presents similar challenges to manual segmentation annotation. To address these issues, Wang et al. (Wang et al., 2018a) introduced a semi-automatic video labeling tool building on the VATIC (Vondrick et al., 2013) video annotation system. Additionally, Manikandan et al. (Manikandan and Ganesan, 2019) developed another automatic video annotation tool tailored for autonomous driving scenes. Notably, annotating bounding boxes at night poses greater difficulties than during the day, a challenge Schorkhuber et al. (Schörkhuber et al., 2021) tackled using a semi-automatic method that incorporates trajectory data.

Moving beyond 2D annotations, 3D bounding boxes provide more detailed spatial information, including the object's precise location, width, length, height, and orientation. Labeling with such detailed 3D annotations demands a more complex framework. Meng et al. (Meng et al., 2021) employed a two-stage weakly supervised learning approach, incorporating human-in-the-loop to label LiDAR point clouds. ViT-WSS3D (Zhang et al., 2023) created pseudo-bounding boxes by modeling the global interactions between LiDAR points and their corresponding weak labels. Apolloscape (Huang et al., 2018) utilized a labeling pipeline that includes separate branches for 3D and 2D annotations, addressing both static and moving objects. Furthermore, 3D BAT (Zimmer et al., 2019) developed a toolbox to support the generation of 2D and 3D labels in a semi-automatic fashion.

2.3.2 Annotate Segmentation Data

The goal of annotating segmentation data is to assign a label to each pixel in an image or each point in a LiDAR frame, identifying the object or region to which it belongs. In this process, all pixels or points associated with a particular object are labeled with the same class. Typically, in manual annotation, the annotator outlines the object and then fills or paints over the enclosed area. However, this method of creating pixel or point-level annotations is both costly and time-consuming.

To enhance the efficiency of the annotation process, numerous studies have developed methods that are fully or semi-automatic. Barnes et al. (Barnes et al., 2017) introduced a fully automatic approach using weakly supervised learning to segment drivable paths in images. Another semi-automatic method (Saleh et al., 2016) uses objectness priors to create segmentation masks, and further developments have extended this approach to include 20 different classes in (Petrovai et al., 2017). Polygon-RNN++ (Acuna et al., 2018) has developed an interactive segmentation tool that builds upon earlier concepts of (Castrejon et al., 2017). Rather than relying solely on image data, one study (Xie et al., 2016) explores the use of 3D information to assist in generating 2D image domain semantic segmentation annotations. For 3D data, a proposed image-assisted annotation pipeline facilitates the labeling process (Chen et al., 2019). Luo et al. (Luo et al., 2018) have adopted active learning techniques to select minimal points for creating a small training set, thereby reducing the need to label entire point cloud scenes comprehensively. Meanwhile, Liu et al. (Liu et al., 2022) have crafted an efficient framework using semi and weakly supervised learning methods to label outdoor point clouds, streamlining the annotation process significantly.

2.3.3 Annotate Trajectories

A trajectory is a sequence of points that outlines the movement of an object over time, encapsulating both spatial and temporal dimensions. In autonomous driving, labeling trajectory data involves marking the movement patterns of various entities within the driving environment, such as vehicles, pedestrians, and cyclists. This annotation process generally depends on results from object detection and tracking.

Historically, one of the earlier methods in trajectory annotation (Wang et al., 2011) involved online generation of actions for maneuvers, which were then incorporated into the trajectory data. Another approach (Moosavi et al., 2017) included a crowd-sourcing phase that was refined through a detailed expert aggregation process. Jarl et al. (Jarl et al., 2022) developed an active learning framework specifically for annotating driving trajectories, emphasizing the importance of accurately predicting pedestrian movements to enhance driving safety. Furthermore, Styles et al. (Styles et al., 2019) introduced a scalable machine-driven annotation scheme that allows for the annotation of pedestrian trajectories without requiring human intervention.

2.3.4 Annotate on Synthetic Data

Due to the costly and time-consuming nature of manual annotations on real-world data, synthetic data created through computer graphics and simulators offer a viable alternative. Synthetic data benefits from a controlled generation process, where the attributes of each object in the scene, such as position, size, and movement, are precisely known, allowing for automatic and accurate annotations.

Synthetic scenarios are crafted to replicate real-world conditions, including diverse objects, various landscapes, weather, and lighting variations. Choosing an appropriate simulation tool is essential to achieving realistic simulation outcomes. Earlier efforts like Torcs (Wymann et al., 2000) and DeepDriving (Chen et al., 2015) focused on simulating autonomous vehicles but did not incorporate multi-modality information or other dynamic objects like pedestrians. In contrast, open-source simulators like CARLA (Dosovitskiy et al., 2017), SUMO (Krajzewicz et al., 2012), and AirSim (Shah et al., 2018) have gained popularity for their transparency and flexibility, allowing users to modify the source code to meet specific research needs. Commercial tools such as NVIDIA's Drive Constellation, although powerful, may restrict user customization due to their closed-source nature.

Additionally, game engines like Grand Theft Auto 5 (GTA5) and Unity (Juliani et al., 2018) have also been employed to create synthetic autonomous driving data. Researchers have used the GTA5 engine to construct datasets (Richter et al., 2016, 2017), and Krahenbuhl et al. (Krähenbühl, 2018) introduced a real-time system utilizing multiple games for generating annotations for various AD tasks. Projects like SHIFT (Sun et al., 2022), CAOS (Hendrycks et al., 2019), FedBEVT (Song et al., 2023), and V2XSet (Xu et al., 2022) have been developed using the CARLA simulator, while V2X-Sim (Li et al., 2022b) explores the use of multiple simulators such as (Dosovitskiy et al., 2017; Krajzewicz et al., 2012) to create datasets for V2X perception tasks. Further, CODD (Arnold et al., 2021) leverages CARLA to generate 3D LiDAR point clouds for cooperative driving scenarios. Other research such as (Ros et al., 2016; Gaidon et al., 2016), (Cabon et al., 2020), (Saleh et al., 2018) utilizing the Unity platform has effectively produced synthetic datasets, showcasing the platform's utility in this field.

Chapter 3

Methodology

3.1 Introduction

Understanding of the traffic scene before beginning of any data collection process from it or before utilizing the dataset is significantly valuable to realize the significance of particular dataset. Besides, knowledge of dataset features of interest and data collection method are crucial to decide on whether to use a particular dataset. In section 3.2, we elaborately describe each features of Beacon and the process of data collection.

3.2 Description of Dataset

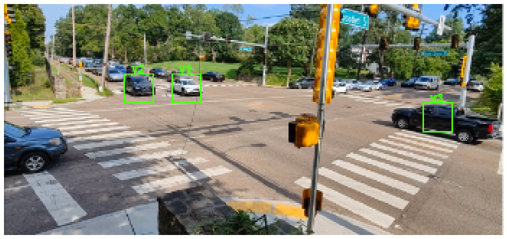
Our dataset contain three components of the traffic scene which are (i) human-driven vehicle (HV) which can be considered as object in any traffic scene (ii) start lane (iii) end location (iv) action. The components are dfined and elaborately described below:

- Timestep: The time of the video when the annotator saw a vehicle just started moving from the head of a lane which is in ”second:minutes” format. In order to simplify the format of time in video and to facilitate further processing and analysis we convert it to single value integer format. In this thesis, we denote timestep by t.

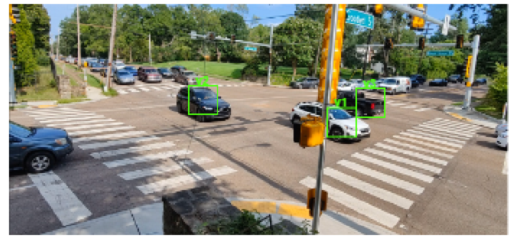
- Start Lane: The location of the human vehicle, HV at time $t - 1$ is called start lane, S_l. At time t, since only HV at the head of lane is going to cross the intersection we have considered it as our vehicle of interest for that time t. We have disregard other HVs which are arriving or waiting in the same lane, S_l but not crossing intersection.

- End Lane: The lane i.e., location of the HV after crossing the intersection and successfully reaching the next lane is called end lane, E_l.

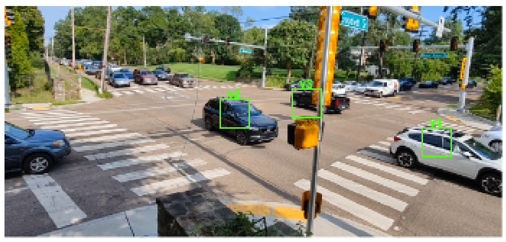
A pictorial presentation of the attributes of **Beacon** dataset and the way of collection from a traffic scenario is demonstrated in Figure 3.1. Figure 3.1(a) shows at timestep, t, three vehicles (let v1, v2, and v3) started moving from their individual start lane, S_l. Figure 1.1 shows the lane numbers, directions and camera position at the GWG and WGM intersections. So, the record of time, t and start lanes of v1, v2 and v3 are collected for the Beacon dataset. The direction of start lane of v1, v2 are facing towards the start lane of v3. The vehicles in non-facing directions have shown are waiting in Figure 3.1(b). At a later time, vehicles v1, v2, v3 are still crossing the intersection and heading towards their intended end lanes. In 3.1(c) we can see vehicle v1 has reached its end lane, e_l and v2 and v3 are still headed towards their end lanes, so the record of end lane of v1, v2, v3 have captured. Figure 3.1(d) shows, in a next moment, v2 left the intersection scene through its end lane while v3 is about to reach its end lane. As vehicles waiting in the no-facing directions realized v1, v2 and v3 have crossed the intersection successfully, they started to move and headed towards the intersection to cross. So, current time, t and start lanes are captured for v4, v5, v6. However, speed of the vehicles can't be captured because we collected the transition of vehicles from video captured by one single camera.



(a) At time t, v1, v2, v3 starts from start lane 22, 21, 10, respectively



(b) At a later time, v1, v2, v3 are crossing intersection



(c) v1 has successfully reached to end lane 8, v2, v3 are approaching to end lane 7, 19, respectively,

(d) At a later time, (for example, t+2), v3 almost reached end lane 19, v4, v5, v6, v7 has started moving from start lane 5, 17, 16, 15, respectively,

Figure 3.1: Collection of primary attributes of Beacon dataset from a traffic intersection scenario is shown.

3.3 Data Collection and Annotation

3.3.1 Location and Time

Our study focuses on traffic control during a blackout period in Memphis, TN, USA. Fig. 1.1 presents satellite views of the two intersections from where video data was collected: Walnut Grove-Goodlett Street (latitude: 35.131508, longitude: -89.925530) (left) and Walnut Grove-Mendenhall Road (latitude: 35.130825, longitude: -89.898503) (right). We use intuitive acronyms: GWG-N and GWG-AN for the scenarios in the Walnut Grove-Goodlett Street at noon (12:00 PM-1:00 PM) and afternoon (5:00 PM-6:00 PM), respectively. For Walnut Grove-Mendenhall Road scenario at noon (12:27 PM-1:27 PM) and afternoon (5:21 PM-6:21 PM), we use WGM-N and WGM-AN, respectively. The data collection was conducted on a weekday, capturing both midday and afternoon peak periods to provide a comprehensive view of traffic patterns under these circumstances.

3.3.2 Data Annotation Process

The quality of the dataset heavily depends on the quality of data labeling. **Beacon** dataset is annotated by a human annotator from collected traffic videos and later validated by two other human annotators. The age group of these human annotators ranges from 25 to 35 years.

3.4 Unsignalized Intersection Reconstruction

We utilize OpenStreetMap (OSM) (OpenStreetMap contributors, 2013) to select the specific area in Memphis, TN, USA that encompasses the the Walnut Grove-Goodlett and Walnut Grove-Mendenhall intersections. For traffic simulation, we employ SUMO (Simulation of Urban MObility) (Lopez et al., 2018). We utilize SUMO's NETCONVERT tool to transform the extracted OSM data into a .net.xml file, which is the standard network file format used by SUMO. During this conversion process, we pay particular attention to preserving the integrity and accuracy of road characteristics from the original OSM data. This includes ensuring correct lane numbers, intersection layouts, and road geometries. The resulting .net.xml file provides a detailed digital representation of the road network, serving as the basis for our traffic simulations.

We assigned integer numbers to lanes for each scenario for labeling convenience, as shown in Fig. 1.1. However, SUMO automatically assigns unique IDs to lanes in its network file. During data processing, we mapped our integer IDs to SUMO's IDs to accurately reconstruct traffic patterns. We get each vehicle's timestep when it is in the head of the start lane and start lane and end lane information from the Beacon dataset using TRACI and then add vehicles to the simulation. As the start lane and end lane of each vehicle together give us the route for that vehicle we imported the route information for each vehicle in the SUMO route files.

3.4.1 Correctness of the Unsignalized Reconstruction

To evaluate the accuracy of our traffic reconstruction, we compare the simulated traffic patterns with the observed data. Table 3.1 presents the results of this comparison across all four scenarios. We focus on three types of potential mismatches. Table 3.1 listed no mismatches of the start lane meaning all vehicles started from the lane that was supposed to start. We define each type of mismatch below:

- Timestep mismatch: Discrepancies in the timing of vehicle movements between the observed and simulated data.
- Start lane mismatch: Discrepancies in the starting lanes of vehicles entering the intersection.
- End lane mismatch: Discrepancies in the exit lanes of vehicles leaving the intersection.

Though vehicles' timestep information was imported simultaneously to the simulation from the **Beacon** dataset sometimes SUMO delayed generating some vehicles to the simulation. After crossing the intersections, some vehicles chose lanes different from the dataset's end lane. We suspect that these vehicles follow the free flow available in other lanes. Thus, a few timestep and end lane mismatches happened which was beyond our control.

Results show high accuracy for the Walnut Grove-Goodlett intersection, with mismatch rates of 0.41% and 1.93% for GWG-AN and GWG-N scenarios, respectively. The Walnut Grove-Mendenhall intersection exhibit higher mismatch rates (8.4% and 8.75%), primarily due to end mismatches, suggesting challenges in simulating more complex intersections under blackout conditions.

Table 3.1: Correctness of the reconstruction of unsignalized traffic scenarios from dataset

Scenario	Number of cars	Timestep mismatch	Start mismatch	End mismatch	Total mismatch	%
GWG-N	1962	38	0	0	38	1.93
GWG-AN	2452	10	0	0	10	0.41
WGM-N	2032	5	0	191	196	8.4
WGM-AN	2342	6	0	199	205	8.75

3.5 Signalized Intersection Reconstruction

Building upon our earlier work in extracting the road network from OpenStreetMap in section 3.4, we also reconstruct the four scenarios with traffic lights. The traffic light phases were extracted from videos captured from the same GWG and WGM intersections where traffic lights were activated.

3.5.1 Traffic Light Phase Implementation

For Walnut Grove-Goodlett intersection, we implement a fixed traffic phase timing for all four directions. In the x-axis and y-axis, we plotted time in seconds and directions, respectively. The phase for each direction over time is shown in Figure 3.2 (left). Each phase allocates green, yellow, and red lights to specific directions, ensuring orderly traffic flow. For Walnut Grove-Mendenhall intersection,illustrated in Figure 3.2 (right). This sequence follows a similar pattern of allocating green, yellow, and red lights to various directions, but with longer duration to accommodate different traffic patterns at this intersection.

3.5.2 Correctness of the Reconstruction

To validate our reconstruction, we compare simulated and observed data, as shown in Table 3.2. Since it is signalized reconstruction and vehicles may need to wait to cross

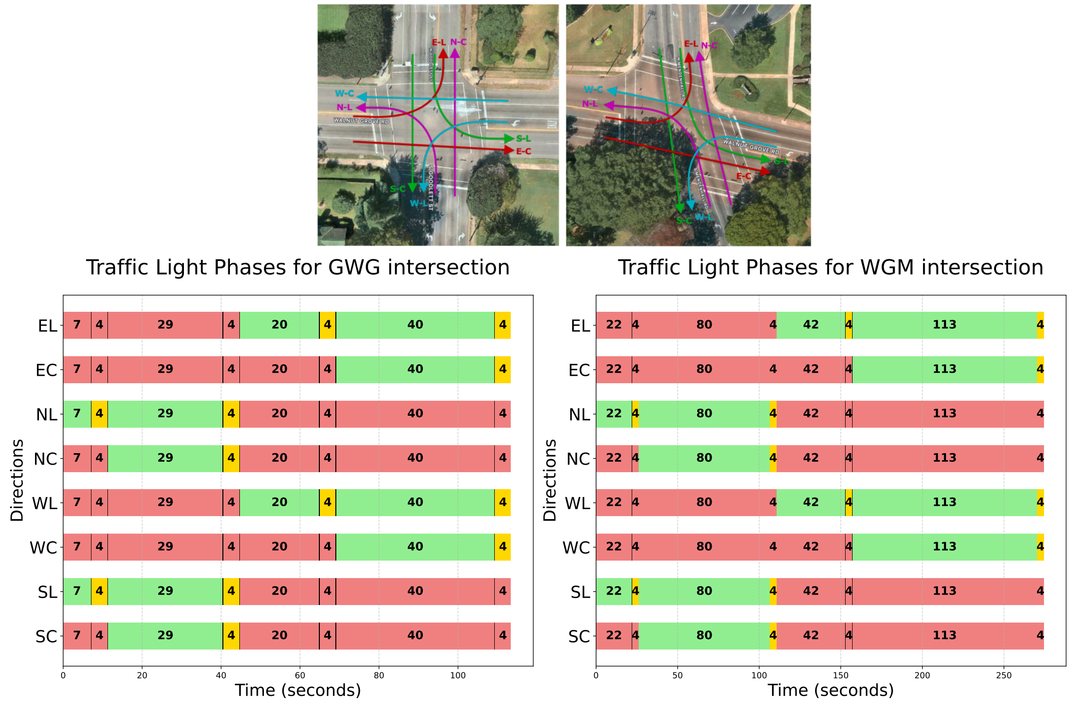


Figure 3.2: Traffic light phases for GWG and WGM intersection

the intersection, the timesteps may not match in simulation with the Beacon dataset. Results showed high accuracy for the Walnut Grove-Goodlett intersection (0.612% and 4.49% mismatch rates for noon and afternoon scenarios). The Walnut Grove-Mendenhall intersection had higher mismatch rates (14.13% and 15.77%), indicating challenges in simulating complex intersections under signalized conditions. The WGM intersection has more variation of actions which may make the scenes more complex.

3.6 Mixed Traffic Reconstruction and Control at Intersection

Mixed traffic control, where robot vehicles (RV) control surrounding robot vehicles and human-driven vehicles (HV) to accomplish some task (i.e. alleviate congestion), under unsignalized intersections has seen recent research. Existing work by (Wang et al., 2023) explores mixed traffic control at unsignalized, real-world intersections.

Given our data captures real-world traffic dynamics under unsignalized intersections, we use the framework by (Wang et al., 2023) to reconstruct our scenarios with mixed traffic.

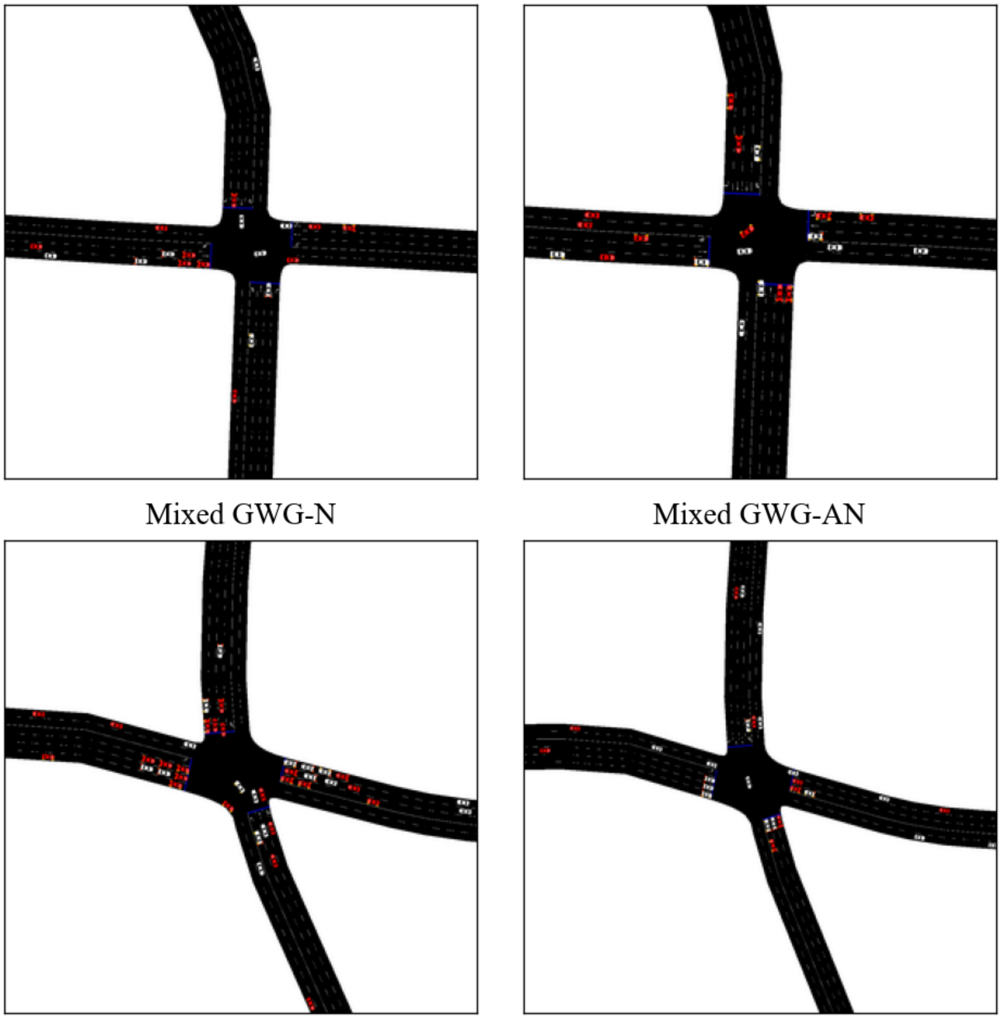
Figure 3.3 shows Beacon reconstructed under mixed traffic for GWG-N, GWG-AN, WGM-N and WGM-AN where red vehicles represent RVs and white vehicles represent HVs. Each scenario has 50% RV penetration rate, but any penetration rate in the range [0, 100] can be selected.

The results in Table 3.3 reveal that the effectiveness of RVs is highly dependent on the traffic volume. At the simpler Goodlett-Walnut Grove (GWG) intersection, RVs show limited benefits under normal traffic conditions, suggesting that traffic volumes haven't reached a threshold where RV coordination significantly outperforms human drivers. Conversely, at the more complex Walnut Grove-Mendenhall intersection, RVs demonstrate substantial improvements in wait times and travel times, particularly during high-traffic periods.

Another reason for the varying efficacy of RV is the complexity of the traffic scenes. GWG-N and GWG-AN show very flexible, safe, and less congested traffic scenes where HV outperforms RV control. On the other hand, at WGM-N and WGM-AN intersections diverse actions were performed which makes these two scenes very complex and needed for skillful control. Therefore, RV outperforms in these two traffic scenarios. We can not explicitly mention any impact of speed, acceleration, or declaration due to the absence of relevant information in our dataset.

Table 3.2: Correctness of the reconstruction of signalized traffic scenarios from dataset

Scenario	Number of cars	Start lane mismatch	End lane mismatch	Total mismatch	%
GWG-N	1961	0	12	12	0.612
GWG-AN	2135	0	96	96	4.49
WGM-N	2031	0	287	287	14.13
WGM-AN	2340	0	369	369	15.77



Mixed GWG-N | Mixed GWG-AN

Mixed WGM-N | Mixed WGM-AN

Figure 3.3: The figure shows all four scenarios using Beacon: (a) GWG-N(upper-left), (b)GWG-AN(upper-right), (c) WGM-N(lower-left), and (d) WGM-AN(lower-right) reconstructed with mixed traffic. The red vehicles are robot vehicles (RV), and the white vehicles are human-driven vehicles (HV). The RV penetration rate is 50%; however, the penetration rate can be adjusted to any percent in the range [0, 100]. Reconstructing Beacon under mixed traffic scenarios allows for mixed traffic control where RVs learn to take intelligent actions to improve traffic flow in the scenarios.

Table 3.3: Performance metrics for mixed traffic scenarios with varying RV penetration rates across four intersection scenarios

Scenario	Metric	HVs	RV Penetration Rate				
			20%	40%	60%	80%	100%
GWG-N	Wait Time (s)	**0.16**	0.19	0.27	0.44	0.47	0.41
	Travel Time (s)	**83.82**	84.38	84.79	86.08	86.25	86.22
	CO_2 Emissions (mg/s)	1642	1644	1640	1627	**1626**	1630
GWG-AN	Wait Time (s)	**0.78**	3.20	2.73	2.86	3.56	2.59
	Travel Time (s)	65.01	68.34	65.80	67.47	68.04	**64.61**
	CO_2 Emissions (mg/s)	3842	3405	3501	3424	**3350**	3529
WGM-N	Wait Time (s)	3.60	3.72	3.08	2.56	**1.52**	1.88
	Travel Time (s)	112.06	112.43	109.39	104.90	**99.72**	103.62
	CO_2 Emissions (mg/s)	1452	**1402**	1422	1443	1493	1470
WGM-AN	Wait Time (s)	16.21	2.11	1.71	1.98	1.72	**1.06**
	Travel Time (s)	127.36	98.86	98.16	100.44	99.00	**95.73**
	CO_2 Emissions (mg/s)	**1323**	1535	1537	1514	1527	1550

To further investigate the traffic volume threshold hypothesis, we conduct additional simulations at the Goodlett-Walnut Grove intersection, increasing the traffic demand at each direction from GWG-AN by 25% and 50%. Table 3.4 presents the results. With a 25% increase in demand, we observe that incorporating RVs reduces wait times by upto 82.6% and travel time by 10.3%. However, this improvement comes with a 7.2% increase in CO2 emissions. The benefits of RVs become even more pronounced with a 50% increase in traffic demand. RVs decrease the overall wait times by 47.1%, and travel times by 21.8%. As wait times decrease and throughput increases with higher RV penetration, we observe a corresponding increase in CO2 emissions. This is consistent with vehicles spending less time idling.

Table 3.4: Performance metrics for GWG intersection with increased traffic demand

Demand Increase	Metric	HVs	RV Penetration Rate				
			20%	40%	60%	80%	100%
25%	Wait Time (s)	6.48	7.81	4.15	2.33	**1.13**	3.06
	Travel Time (s)	95.53	97.14	91.48	88.44	**85.72**	90.47
	CO_2 Emissions (mg/s)	**1703**	1707	1759	1793	1825	1799
50%	Wait Time (s)	63.19	49.18	43.33	36.60	**33.47**	52.31
	Travel Time (s)	166.97	162.92	146.27	136.06	130.51	**129.39**
	CO_2 Emissions (mg/s)	**1440**	1489	1522	1565	1596	1864

3.7 Conclusion

In this section, we discuss details of dataset location, collection time, and environmental setting. we elaborately discussed the reconstruction of **Beacon** dataset in unsignalized, signlanized, and mixed traffic settings. We also compute the correctness and include relevant experimental details of each setting.

Chapter 4

Experimental Analysis

4.1 Introduction

In chapter 4 we discuss the data analysis of our proposed dataset.

4.2 Data Analysis

4.2.1 Traffic Demand Analysis

This section presents a comprehensive analysis of the traffic demand, vehicle trajectories, and traffic density across the four scenarios.

Table 4.1 presents the traffic demand for each scenario, broken down by direction. The data reveals significant variations in traffic volume and directional flow across different times and locations. The GWG intersection experiences the highest total demand during the afternoon peak (5:00-6:00 PM) with 2,453 vehicles. Conversely, the same intersection sees the lowest demand during midday (12:00-1:00 PM) with 1,983 vehicles.

Interestingly, directional patterns differ between the two intersections. At Walnut Grove-Goodlett intersection (Scenarios GWG-N and GWG-AN), eastbound traffic

Table 4.1: List of traffic demand

Intersection Scene	North-bound	South-bound	East-bound	West-bound	Total Demand
GWG-N	280	410	**685**	608	1983
GWG-AN	425	629	**794**	605	2453
WGM-N	403	434	527	**669**	2033
WGM-AN	494	523	625	**700**	2342

consistently dominates, while at Walnut Grove-Mendenhall intersection (Scenarios WGM-N and WGM-AN), westbound traffic is predominant.

4.2.2 Vehicle Trajectory Analysis

Figure 4.1, 4.2, 4.3, and 4.4 present transition matrices of lanes for each scenario, providing deeper insights into the traffic flow patterns. Figure 4.1 shows that lanes 11 to 18, 21 to 8, 22 to 7 and from 10 to 19 have the highest number of transitions indicating ST maneuver.

Figure 4.2 shows from lane 22 to lane 7, from lane 11 to lane 18, from lane 21 to lane 8, from lane 10 to lane 19, from lane 5 to lane 12 have the highest number of ST maneuvers. Figure 4.3 shows from lane 22 to lane 7, from lane 11 to lane 18, from lane 21 to lane 8, from lane 10 to lane 19 have the highest number of ST maneuvers. Figure 4.4 shows from lane 22 to lane 7, from lane 11 to lane 18, from lane 10 to lane 19, from lane 21 to lane 8, from 16 to 2 have the highest number of ST maneuvers.

Both intersections demonstrate strong east-west traffic flows along Walnut Grove Road, indicating its role as a major arterial route. At Walnut Grove-Goodlett intersection, the most significant movements during the afternoon peak are westbound (248 vehicles) and eastbound (228 vehicles) through movements. Walnut Grove-Mendenhall intersection exhibits more balanced east-west flows, with consistent high volumes in both directions throughout the day.

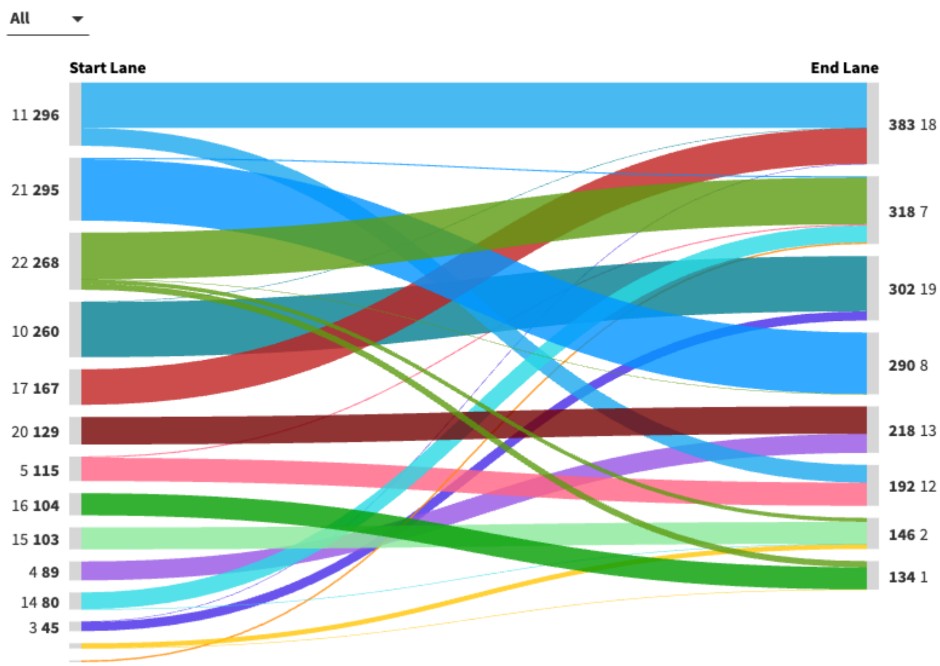


Figure 4.1: Transition from start lane to end lane in scenario GWG_N.

Turning behaviors at these intersections during the blackout reveal interesting patterns that vary by direction and location. At Walnut Grove-Goodlet intersection, we notice a strong preference for northbound right turns over left turns in both scenarios, while southbound left turns outnumber right turns. The pattern differs at Walnut Grove-Mendenhall intersection, where northbound left turns significantly surpasses right turns in both scenarios. These differences in turning preferences are likely linked to the surrounding road network, and the destinations accessible from each turn.

4.2.3 Traffic Density Analysis

Figure 4.5 presents the traffic density per minute over 60 minutes at four intersections, offering a more granular view of traffic patterns throughout the observation periods. In GWG intersection, at noon density ranges between 25 to 35 while the range increases which is 35 to 45 in the afternoon. In WGM intersection, at noon, the

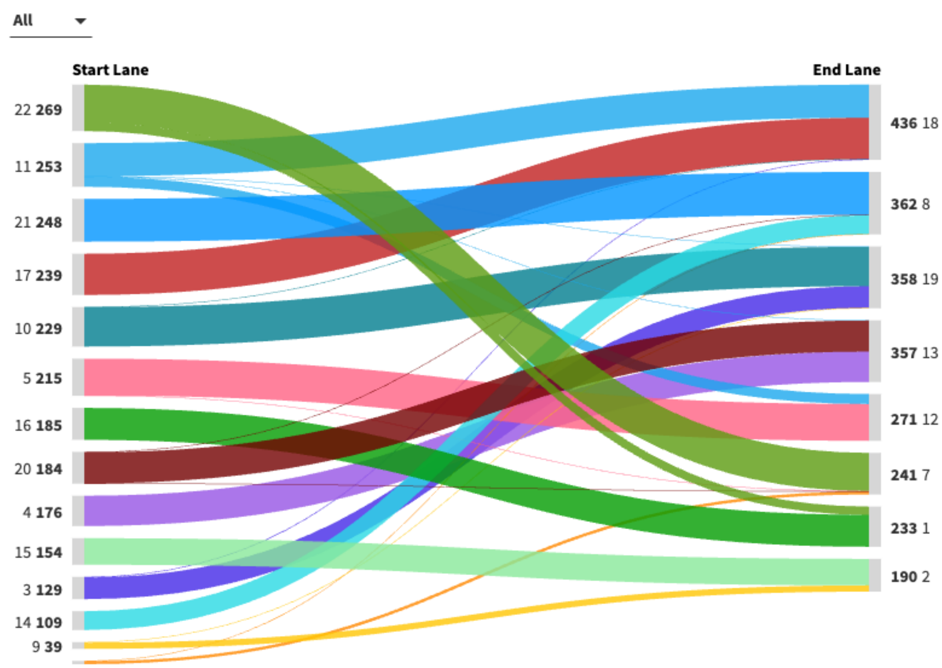


Figure 4.2: Transition from start lane to end lane in scenario GWG_AN.

density is high and stable compared to the afternoon data. At noon, density ranges from 35 to 45 while in the afternoon, density ranges from 35 to 42 with a high amount of fluctuation.

The erratic afternoon patterns at WGM intersection likely result from multiple factors interacting during the blackout. Without traffic signals, drivers must navigate the intersection independently, causing uneven traffic density. This effect is more pronounced during busy afternoons, which creates alternating periods of congestion and rapid clearance. Driver adaptation to unusual conditions, varying levels of caution and assertiveness, and the diverse mix of trip purposes typical of afternoon traffic could further contribute to the inconsistent flow.

Table 4.4, shows statistical analysis of density data that in GWG-N scene, the highest, lowest, and average traffic density is 43, 22, and 33.05, respectively which is lower than the highest, lowest, and average traffic density at GWG-AN which are 52, 30 and 40.87, respectively. For WGM-N scene, the highest traffic density is 50 which is a bit higher than that of WGM-AN i.e., 48. On the other hand, the lowest density

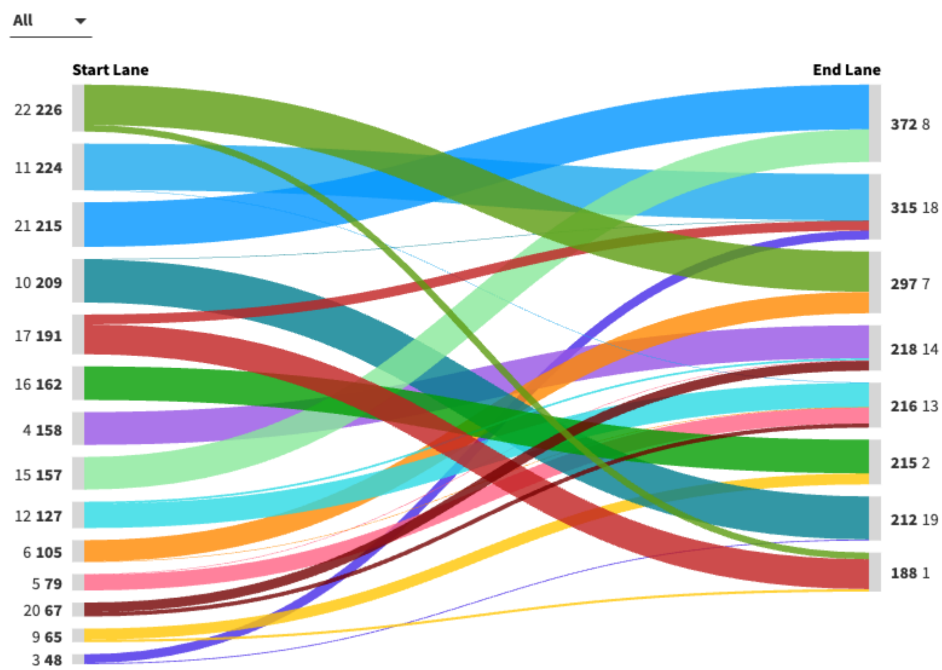


Figure 4.3: Transition from start lane to end lane in scenario WGM_N.

is lower i.e., 18 than that of WGM intersection's afternoon scene i.e., 30. The average traffic density is almost the same at noon and afternoon which are 39.12 and 39.15, respectively.

4.3 Human Driver Action Analysis

Because we collect the start lane, S_l, and end lane E_l for each moving vehicle at the head of S_l, the unique combination S_l and E_l indicates an action performed by the HV. Table 4.2 and 4.3 listed the actions performed by all HVs in GWG and WGN intersection, respectively. Since the actions are the same from a unique pair of S_l and E_l for a particular intersection independent of the time of the dataset collection GWG-N and GWG-AN scenes have the same list of actions. The same applies to WGM-N and WGM-AN scenes.

As at a particular timestep, multiple actions take place by multiple vehicles at the intersection when **Beacon** is applied to intersections other than GWG and

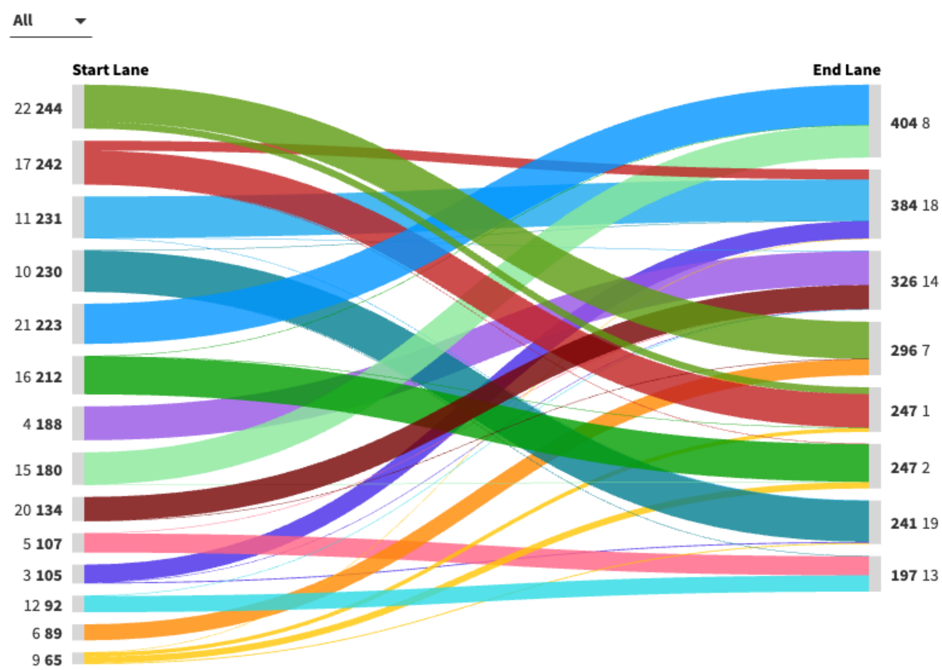


Figure 4.4: Transition from start lane to end lane in scenario WGM_AN.

WGM, carefully setting lane numbering is crucial. While setting the start lane and corresponding end lane numbers, we need to make sure of the action performed from the start and end lane too. We recommend setting the start and end lane in a way so that the start and end lane pair creates the same action or maneuver listed in Table 4.2 and 4.3. Otherwise, the combinations of actions that take place at a particular timestep may lead to collision events or violation of traffic rules.

In Figure 4.6, we demonstrate the distribution of various categories of actions across the dataset of four intersection scenes. We can see that straight-through (ST) is the most frequent action or maneuver performed by HVS in all four scenes. At GWG intersection, the right turn (RT) is the second-highest number of actions performed while at WGM intersection, the left turn (LT) is the second-highest of actions performed by HVs irrespective of the time of the day. We can find the associated start and end lanes in Table 4.2 and 4.3 for the intersection GWG and WGM, respectively.

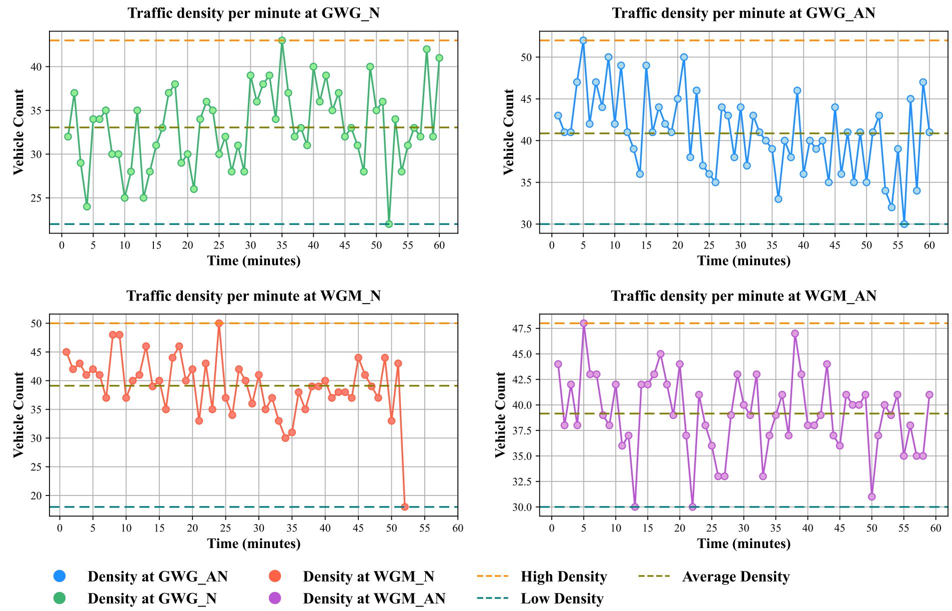


Figure 4.5: Traffic density per minute at four intersection scenes

4.4 Comparison with Benchmark Dataset

We compare the proposed **Beacon** dataset with previous datasets that were collected at intersections in urban areas. Table 4.5 listed three traffic datasets, their size, collected method, and weather, environment, specialty of the scenes. Other intersection datasets were collected from urban intersections and easily availability of urban intersections and having huge amounts of daily traffic density in the intersections the size of these datasets is much larger than **Beacon**.

Some datasets even did not mention the weather conditions of the collected scenes. However, we can see **Beacon** is the only dataset that has been collected from urban intersections during traffic light blackouts. Besides, **Beacon** has used the least amount of instruments to collect the dataset, which eventually results in the most cost-effective data. Besides, other traffic datasets were collected using a bunch of sensors, cameras, LiDAR which costs huge amount of money and installation efforts while **Beacon** is collected by one single camera for each set of data. Therefore, our datasets is the most cost-effective traffic dataset.

Table 4.2: List of actions performed by HVs at GWG-N and GWG-AN

Start Lane (S_l)	End Lane (E_l)	Action
21	8	ST
17	18	RT
10	19	ST
22	7	ST
5	12	ST
11	18	ST
16	1	ST
20	13	LT
4	13	ST
15	2	ST
3	19	LT
14	8	RT
11	12	RT
22	1	RT
9	2	LT
6	7	RT
3	18	ST
6	8	RT
11	19	ST
5	7	RT
16	2	ST
17	1	ST
11	13	RT
10	18	ST
20	12	LT
14	7	LT
22	2	RT
21	7	ST
22	8	ST
9	1	LT
20	8	ST
14	2	ST
19	13	LT
20	7	ST
20	9	ST
9	19	ST

Table 4.3: List of actions performed by HVs at WGM-N and WGM-AN

Start Lane (S_l)	End Lane (E_l)	Action
11	18	ST
21	8	ST
10	19	ST
22	7	ST
16	2	ST
4	14	ST
15	8	LT
17	1	ST
12	13	RT
6	7	RT
5	13	ST
9	2	LT
17	18	RT
20	14	LT
3	18	LT
22	1	RT
20	13	LT
9	1	LT
12	14	RT
3	19	LT
6	13	ST
5	14	ST
10	18	ST
3	14	ST
11	13	RT
5	15	ST
20	15	LT
20	7	ST
3	12	ST

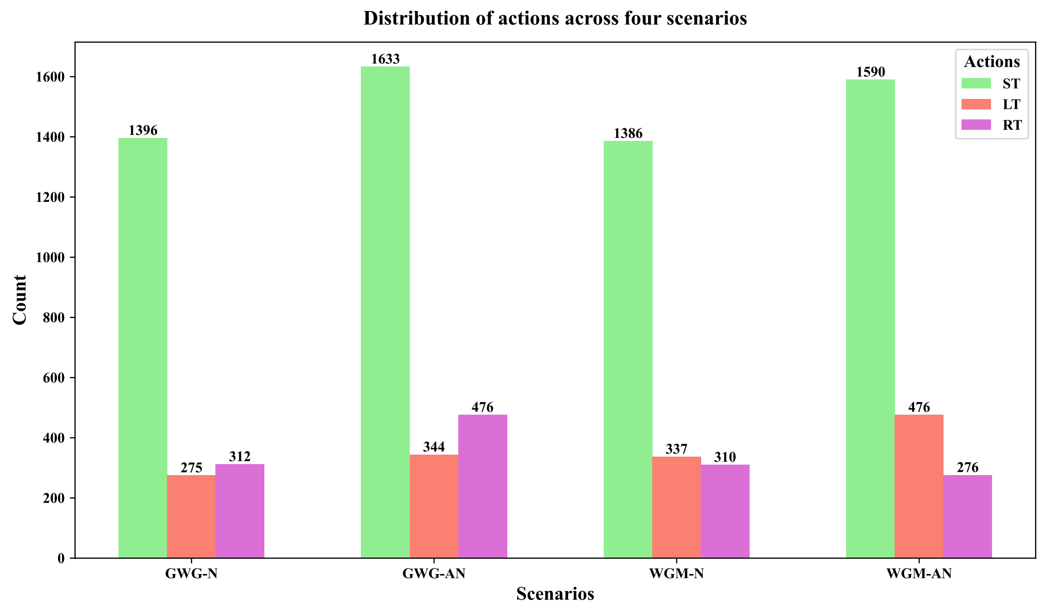


Figure 4.6: Distribution of actions across four scenarios

Table 4.4: Statistical analysis of traffic density per minute at four intersections

Scene	Highest density	Lowest density	Average density
GWG_N	43	22	33.05
GWG_AN	52	30	40.87
WGM_N	50	18	39.12
WGM_AN	48	30	39.15

Table 4.5: Comparison with other intersection datasets

Dataset	Size	Scene	Collection Method	Weather
INTERACTION (Wei, 2019)	110K trajectories	(un)signalized intersection	UAV, V2X	–
USyd (Zyner et al., 2019)	24K trajectories	5 intersections	onboard	–
V2X-Seq (Yu et al., 2023)	50K scenarios	28 urban intersections	V2X	–
Beacon	8811 vehicles	(un)signalized intersections	single camera	TL Blackout

Chapter 5

Conclusion

5.1 Conclusion and Future Work

The Beacon study provides insights into urban traffic dynamics during blackouts through the analysis of naturalistic driving data from two intersections in Memphis, TN. Our findings demonstrate the potential benefits of integrating robot vehicles for traffic management under these conditions, particularly in high-volume conditions. The reconstruction of various traffic conditions - unsignalized, signalized, and mixed - showcases the utility of Beacon while also revealing areas for improvement in modeling approaches. Future work will focus on improving traffic simulation accuracy and expanding the dataset for broader application, enhancing urban traffic resilience.

Bibliography

Acuna, D., Ling, H., Kar, A., and Fidler, S. (2018). Efficient interactive annotation of segmentation datasets with polygon-rnn++. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 859–868. 15

Arnold, E., Mozaffari, S., and Dianati, M. (2021). Fast and robust registration of partially overlapping point clouds. *IEEE Robotics and Automation Letters*, 7(2):1502–1509. 17

Bakowski, A. and Radziszewski, L. (2021). Measurements of urban traffic parameters before and after road reconstruction. *Open Engineering*, 11(1):365–376. 12

Barnes, D., Maddern, W., and Posner, I. (2017). Find your own way: Weakly-supervised segmentation of path proposals for urban autonomy. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pages 203–210. IEEE. 15

Bellini, P., Bilotta, S., Nesi, P., Paolucci, M., and Soderi, M. (2018). Wip: traffic flow reconstruction from scattered data. In *2018 IEEE International Conference on Smart Computing (SMARTCOMP)*, pages 264–266. IEEE. 12

Bilotta, S. and Nesi, P. (2021). Traffic flow reconstruction by solving indeterminacy on traffic distribution at junctions. *Future Generation Computer Systems*, 114:649–660. 11

Cabon, Y., Murray, N., and Humenberger, M. (2020). Virtual kitti 2. *arXiv preprint arXiv:2001.10773*. 17

Caesar, H., Bankiti, V., Lang, A. H., Vora, S., Liong, V. E., Xu, Q., Krishnan, A., Pan, Y., Baldan, G., and Beijbom, O. (2020). nuscenes: A multimodal dataset for autonomous driving. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 11621–11631. 13

Castrejon, L., Kundu, K., Urtasun, R., and Fidler, S. (2017). Annotating object instances with a polygon-rnn. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5230–5238. 15

Chang, M.-F., Lambert, J., Sangkloy, P., Singh, J., Bak, S., Hartnett, A., Wang, D., Carr, P., Lucey, S., Ramanan, D., et al. (2019). Argoverse: 3d tracking and forecasting with rich maps. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 8748–8757. 13

Chen, C., Seff, A., Kornhauser, A., and Xiao, J. (2015). Deepdriving: Learning affordance for direct perception in autonomous driving. In *Proceedings of the IEEE international conference on computer vision*, pages 2722–2730. 17

Chen, Z., Liao, Q., Wang, Z., Liu, Y., and Liu, M. (2019). Image detector based automatic 3d data labeling and training for vehicle detection on point cloud. In *2019 IEEE Intelligent Vehicles Symposium (IV)*, pages 1408–1413. IEEE. 15

Choi, E.-H. (2010). Crash factors in intersection-related crashes: An on-scene perspective. *National Highway Traffic Safety Administration, U.S. Department of Transportation*. 2

Čičić, M., Barreau, M., and Johansson, K. H. (2020). Numerical investigation of traffic state reconstruction and control using connected automated vehicles. In *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–6. IEEE. 12

Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., and Koltun, V. (2017). Carla: An open urban driving simulator. In *Conference on robot learning*, pages 1–16. PMLR. 17

Feng, Y., Sun, J., and Chen, P. (2015). Vehicle trajectory reconstruction using automatic vehicle identification and traffic count data. *Journal of advanced transportation*, 49(2):174–194. 12

Gaidon, A., Wang, Q., Cabon, Y., and Vig, E. (2016). Virtual worlds as proxy for multi-object tracking analysis. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4340–4349. 17

Hendrycks, D., Basart, S., Mazeika, M., Zou, A., Kwon, J., Mostajabi, M., Steinhardt, J., and Song, D. (2019). Scaling out-of-distribution detection for real-world settings. *arXiv preprint arXiv:1911.11132*. 17

Huang, X., Cheng, X., Geng, Q., Cao, B., Zhou, D., Wang, P., Lin, Y., and Yang, R. (2018). The apolloscape dataset for autonomous driving. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, pages 954–960. 15

Jarl, S., Aronsson, L., Rahrovani, S., and Chehreghani, M. H. (2022). Active learning of driving scenario trajectories. *Engineering Applications of Artificial Intelligence*, 113:104972. 16

Juliani, A., Berges, V.-P., Teng, E., Cohen, A., Harper, J., Elion, C., Goy, C., Gao, Y., Henry, H., Mattar, M., et al. (2018). Unity: A general platform for intelligent agents. *arXiv preprint arXiv:1809.02627*. 17

Kataoka, S., Yasuda, M., Furtlehner, C., and Tanaka, K. (2014). Traffic data reconstruction based on markov random field modeling. *Inverse Problems*, 30(2):025003. 11

Krähenbühl, P. (2018). Free supervision from video games. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2955–2964. 17

Krajzewicz, D., Erdmann, J., Behrisch, M., and Bieker, L. (2012). Recent development and applications of sumo-simulation of urban mobility. *International journal on advances in systems and measurements*, 5(3&4). 17

Li, Q., Peng, Z., Feng, L., Zhang, Q., Xue, Z., and Zhou, B. (2022a). Metadrive: Composing diverse driving scenarios for generalizable reinforcement learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 13

Li, Q., Peng, Z. M., Feng, L., Liu, Z., Duan, C., Mo, W., and Zhou, B. (2024). Scenarionet: Open-source platform for large-scale traffic scenario simulation and modeling. *Advances in neural information processing systems*, 36. 13

Li, Y., Ma, D., An, Z., Wang, Z., Zhong, Y., Chen, S., and Feng, C. (2022b). V2x-sim: Multi-agent collaborative perception dataset and benchmark for autonomous driving. *IEEE Robotics and Automation Letters*, 7(4):10914–10921. 17

Liu, M., Yurtsever, E., Fossaert, J., Zhou, X., Zimmer, W., Cui, Y., Zagar, B. L., and Knoll, A. C. (2024). A survey on autonomous driving datasets: Statistics, annotation quality, and a future outlook. *IEEE Transactions on Intelligent Vehicles*. 1

Liu, M., Zhou, Y., Qi, C. R., Gong, B., Su, H., and Anguelov, D. (2022). Less: Label-efficient semantic segmentation for lidar point clouds. In *European conference on computer vision*, pages 70–89. Springer. 16

Lopez, P. A., Behrisch, M., Bieker-Walz, L., Erdmann, J., Flötteröd, Y.-P., Hilbrich, R., Lücken, L., Rummel, J., Wagner, P., and Wießner, E. (2018). Microscopic traffic simulation using sumo. In *The 21st IEEE International Conference on Intelligent Transportation Systems*. IEEE. 21

Luo, H., Wang, C., Wen, C., Chen, Z., Zai, D., Yu, Y., and Li, J. (2018). Semantic labeling of mobile lidar point clouds via active learning and higher order mrf. *IEEE Transactions on Geoscience and Remote Sensing*, 56(7):3631–3644. 15

Manikandan, N. and Ganesan, K. (2019). Deep learning based automatic video annotation tool for self-driving car. *arXiv preprint arXiv:1904.12618*. 14

Meng, Q., Wang, W., Zhou, T., Shen, J., Jia, Y., and Van Gool, L. (2021). Towards a weakly supervised framework for 3d point cloud object detection and annotation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(8):4454–4468. 15

Moosavi, S., Omidvar-Tehrani, B., Craig, R. B., and Ramnath, R. (2017). Annotation of car trajectories based on driving patterns. *arXiv preprint arXiv:1705.05219*. 16

OpenStreetMap contributors (2013). Openstreetmap. `https://www.openstreetmap.org`. Accessed: 2023-03-25. 21

Paden, B., Čáp, M., Yong, S. Z., Yershov, D., and Frazzoli, E. (2016). A survey of motion planning and control techniques for self-driving urban vehicles. *IEEE Transactions on intelligent vehicles*, 1(1):33–55. 1

Petrovai, A., Costea, A. D., and Nedevschi, S. (2017). Semi-automatic image annotation of street scenes. In *2017 IEEE intelligent vehicles symposium (IV)*, pages 448–455. IEEE. 15

Press, A. (2022). Power still out to 50k customers, days after memphis storm. `https://www.usnews.com/news/best-states/tennessee/articles/2022-02-07/power-still-out-to-60k-customers-days-after-memphis-storm`. 2

Qi, X., Ji, Y., Li, W., and Zhang, S. (2021). Vehicle trajectory reconstruction on urban traffic network using automatic license plate recognition data. *IEEE Access*, 9:49110–49120. 11

Ramirez, R. (2022). Power outages are on the rise, led by texas, michigan and california. here's what's to blame. https://www.cnn.com/2022/09/14/us/power-outages-rising-extreme-weather-climate/index.html. 2

Richter, S. R., Hayder, Z., and Koltun, V. (2017). Playing for benchmarks. In *Proceedings of the IEEE international conference on computer vision*, pages 2213–2222. 17

Richter, S. R., Vineet, V., Roth, S., and Koltun, V. (2016). Playing for data: Ground truth from computer games. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part II 14*, pages 102–118. Springer. 17

Ros, G., Sellart, L., Materzynska, J., Vazquez, D., and Lopez, A. M. (2016). The synthia dataset: A large collection of synthetic images for semantic segmentation of urban scenes. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3234–3243. 17

Russell, B. C., Torralba, A., Murphy, K. P., and Freeman, W. T. (2008). Labelme: a database and web-based tool for image annotation. *International journal of computer vision*, 77:157–173. 14

Saleh, F., Aliakbarian, M. S., Salzmann, M., Petersson, L., Gould, S., and Alvarez, J. M. (2016). Built-in foreground/background prior for weakly-supervised semantic segmentation. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part VIII 14*, pages 413–432. Springer. 15

Saleh, F. S., Aliakbarian, M. S., Salzmann, M., Petersson, L., and Alvarez, J. M. (2018). Effective use of synthetic data for urban scene semantic segmentation. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 84–100. 17

Sanchez, E. R., Raghavan, S., and Wu, C. (2023). Data-driven traffic reconstruction and kernel methods for identifying stop-and-go congestion. *arXiv preprint arXiv:2312.03186*. 10

Schörkhuber, D., Groh, F., and Gelautz, M. (2021). Bounding box propagation for semi-automatic video annotation of nighttime driving scenes. In *2021 12th International Symposium on Image and Signal Processing and Analysis (ISPA)*, pages 131–137. IEEE. 14

Schwarting, W., Alonso-Mora, J., and Rus, D. (2018). Planning and decision-making for autonomous vehicles. *Annual Review of Control, Robotics, and Autonomous Systems*, 1(1):187–210. 1

Shah, S., Dey, D., Lovett, C., and Kapoor, A. (2018). Airsim: High-fidelity visual and physical simulation for autonomous vehicles. In *Field and Service Robotics: Results of the 11th International Conference*, pages 621–635. Springer. 17

Shen, Z., Ji, W., Yu, S., Cheng, G., Yuan, Q., Han, Z., Liu, H., and Yang, T. (2023). Mapping the knowledge of traffic collision reconstruction: A scientometric analysis in citespace, vosviewer, and scimat. *Science & Justice*, 63(1):19–37. 13

Song, R., Xu, R., Festag, A., Ma, J., and Knoll, A. (2023). Fedbevt: Federated learning bird's eye view perception transformer in road traffic systems. *IEEE Transactions on Intelligent Vehicles*. 17

Styles, O., Ross, A., and Sanchez, V. (2019). Forecasting pedestrian trajectory with machine-annotated training data. In *2019 IEEE Intelligent Vehicles Symposium (IV)*, pages 716–721. IEEE. 16

Sun, P., Kretzschmar, H., Dotiwalla, X., Chouard, A., Patnaik, V., Tsui, P., Guo, J., Zhou, Y., Chai, Y., Caine, B., et al. (2020). Scalability in perception for autonomous driving: Waymo open dataset. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 2446–2454. 13

Sun, T., Segu, M., Postels, J., Wang, Y., Van Gool, L., Schiele, B., Tombari, F., and Yu, F. (2022). Shift: a synthetic driving dataset for continuous multi-task domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 21371–21382. 17

Vondrick, C., Patterson, D., and Ramanan, D. (2013). Efficiently scaling up crowdsourced video annotation: A set of best practices for high quality, economical video labeling. *International journal of computer vision*, 101:184–204. 14

Wang, B.-L., King, C.-T., and Chu, H.-K. (2018a). A semi-automatic video labeling tool for autonomous driving based on multi-object detector and tracker. In *2018 sixth international symposium on computing and networking (CANDAR)*, pages 201–206. IEEE. 14

Wang, D., Li, W., Zhu, L., and Pan, J. (2023). Learning to control and coordinate hybrid traffic through robot vehicles at complex and unsignalized intersections. *arXiv preprint arXiv:2301.05294*. 24, 25

Wang, M., Ganjineh, T., and Rojas, R. (2011). Action annotated trajectory generation for autonomous maneuvers on structured road networks. In *The 5th International conference on automation, robotics and applications*, pages 67–72. IEEE. 16

Wang, Y., Han, Z., Xing, Y., Xu, S., and Wang, J. (2024). A survey on datasets for the decision making of autonomous vehicles. *IEEE Intelligent Transportation Systems Magazine*. 2

Wang, Y., Zhang, Y., Piao, X., Liu, H., and Zhang, K. (2018b). Traffic data reconstruction via adaptive spatial-temporal correlations. *IEEE Transactions on Intelligent Transportation Systems*, 20(4):1531–1543. 11

Wei, Z. (2019). Interaction dataset: an international, adversarial and cooperative motion dataset in interactive driving scenarios with semantic maps. *arXiv: 1910.03088*. 38

Winck, B. (2022). Get ready for blackouts from london to la, as the global energy crisis overwhelms grids and sends energy prices skyrocketing. https://www.businessinsider.com/global-europe-energy-crisis-power-electricity-outages-blackouts-energy-grid-2022-9. 2

Wymann, B., Espié, E., Guionneau, C., Dimitrakakis, C., Coulom, R., and Sumner, A. (2000). Torcs, the open racing car simulator. *Software available at http://torcs. sourceforge. net*, 4(6):2. 17

Xie, J., Kiefel, M., Sun, M.-T., and Geiger, A. (2016). Semantic instance annotation of street scenes by 3d to 2d label transfer. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 3688–3697. 15

Xu, R., Xiang, H., Tu, Z., Xia, X., Yang, M.-H., and Ma, J. (2022). V2x-vit: Vehicle-to-everything cooperative perception with vision transformer. In *European conference on computer vision*, pages 107–124. Springer. 17

Yu, H., Yang, W., Ruan, H., Yang, Z., Tang, Y., Gao, X., Hao, X., Shi, Y., Pan, Y., Sun, N., et al. (2023). V2x-seq: A large-scale sequential dataset for vehicle-infrastructure cooperative perception and forecasting. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 5486–5495. 38

Zhang, D., Liang, D., Zou, Z., Li, J., Ye, X., Liu, Z., Tan, X., and Bai, X. (2023). A simple vision transformer for weakly semi-supervised 3d object detection. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 8373–8383. 15

Zimmer, W., Rangesh, A., and Trivedi, M. (2019). 3d bat: A semi-automatic, web-based 3d annotation toolbox for full-surround, multi-modal data streams. In *2019 IEEE Intelligent Vehicles Symposium (IV)*, pages 1816–1821. IEEE. 15

Zyner, A., Worrall, S., and Nebot, E. (2019). Naturalistic driver intention and path prediction using recurrent neural networks. *IEEE transactions on intelligent transportation systems*, 21(4):1584–1594. 38

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