

# Berlin V2X: A Machine Learning Dataset from Multiple Vehicles and Radio Access Technologies

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**Abstract**—The evolution of wireless communications into 6G and beyond is expected to rely on new machine learning (ML)-based capabilities. These can enable proactive decisions and actions from wireless-network components to sustain quality-of-service (QoS) and user experience. Moreover, new use cases in the area of vehicular and industrial communications will emerge. Specifically in the area of vehicle communication, vehicle-to-everything (V2X) schemes will benefit strongly from such advances. With this in mind, we have conducted a detailed measurement campaign that paves the way to a plethora of diverse ML-based studies. The resulting datasets offer GPS-located wireless measurements across diverse urban environments for both cellular (with two different operators) and sidelink radio access technologies, thus enabling a variety of different studies towards V2X. The datasets are labeled and sampled with a high time resolution. Furthermore, we make the data publicly available with all the necessary information to support the onboarding of new researchers. We provide an initial analysis of the data showing some of the challenges that ML needs to overcome and the features that ML can leverage, as well as some hints at potential research studies.

**Index Terms**—Dataset, V2X, LTE, sidelink, machine learning, QoS prediction, drive tests, automotive connectivity

## I. INTRODUCTION

Vehicle-to-everything (V2X) communication has a great potential to improve road safety, traffic efficiency, reduce congestions, and minimize energy consumption and emissions. It includes modalities such as vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-network (V2N) and vehicle-to-pedestrian (V2P) communication, and thus enables several cooperative intelligent transport systems (C-ITS) use cases such as collision warning, emergency vehicle warning, road works warning, cooperative lane change, platooning, and many others [2] [3]. These use cases have diverse network requirements in terms of latency, throughput, etc., and often

require a certain level of quality-of-service (QoS) to function optimally. In order to fulfill these QoS requirements, it might be necessary to predict the network behavior. To that end, various machine learning (ML) algorithms have been proposed [4].

Predicting QoS [5] is a complex task since many different characteristics across different network layers can be targeted as QoS, e.g., received power in the physical layer or throughput in the application layer. There are multiple research works on these topics [6–8]. However, one common theme across the majority of these works is the lack of a curated dataset capturing both vehicle data and wireless network data that is readily available to the research community. Vehicle datasets focused on mobility traces using global positioning system (GPS) and other sensor data are more common. In [9], a taxonomy to classify the open-source mobility traces based on data source, data collection methodology, and the mobility mode is presented.

Datasets capturing both vehicle and network data require time, effort, and equipment to collect data samples in different vehicular environments such as cities, highways, rural roads, or a combination of them. In [10], Boban et al. carried out a measurement campaign in Munich, Germany to predict uplink (UL) throughput for V2X scenarios such as tele-operated driving (ToD) and local dynamic map update. The MOVESET dataset [11] presents a sensor package, based on correlated sensor readings with measurements of cellular and dedicated short-range communication (DSRC), to help independent research groups create their own datasets. Another measurement campaign [12] has been conducted on the interstate and rural highways in Bozeman, USA. The gatech/vehicular dataset [13] presents collected data for short-range communication between vehicles, other vehicles, and roadside stations. In [14], Cruz et al. carried out a measurement campaign in Porto, Portugal [15] to improve the localization performance based on information from smartphone sensors and V2V communication. In [16], Torres-Figueroa et al. verified the performance of the available long-term evolution (LTE) networks to deploy C-ITS

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applications safely. The measurement campaign was carried out in Munich, Germany for three different mobile network operators (MNOs) with a focus on QoS with respect to end-to-end (E2E) delays. In [17], Mikami et al. verified the dynamic mode switching for 5G NR-V2X sidelink communication for a vehicle platoon moving in and out of coverage on the Shin-Tomei expressway in Japan.

Previous datasets have been captured by conducting measurement campaigns in either an urban or a highway setting. Our dataset [1] fills this gap in the literature with measurements from diverse vehicular environments mixing urban and highway scenarios. The dataset also includes network data from two different MNOs, which in turn can be used to assess whether the same ML models can adapt from one LTE network to another. Moreover, our dataset provides high-resolution data for both cellular and sidelink communication, as well as metadata for weather and traffic conditions.

The remainder of the paper is organized as follows. Section II explains the measurement campaign conducted in different vehicular environments in Berlin, Germany. Section III provides a first analysis of the captured dataset. Section IV outlines the potential studies and, finally, a conclusion is given in Section V.

## II. MEASUREMENT CAMPAIGN

Our data has been collected from drive tests around West Berlin along the route shown in Figure 1. This route contains a segment through the narrow *residential* streets in the district of Wilmersdorf, broader *avenues* in Charlottenburg and the central Tiergarten *park*, and the westernmost segment of the urban *highway* A100, between Hohenzollerndamm and Kaiserdamm, which also includes a short *tunnel* beneath Rathenauplatz. The whole route stretches over 17.2 km and a single drive round takes approximately 45 min on a weekday morning.

Within three days, we have driven 17 clockwise rounds along the measurement route with up to four cars following one of two driving modes:

- 1) Platoon: All vehicles in a convoy with fixed ordering (11 rounds).
- 2) 2x2: Two pairs of vehicles driving approximately 1.5 km to 3 km apart (6 rounds).

We have measured two radio access technologies (RATs) simultaneously:

- 1) Cellular: A dedicated measurement equipment (DME) in each car exchanged data with a server over LTE and collected related measurements. The server was located in a data center in Berlin, and we used the public LTE network from two different MNOs on frequency bands between 700 MHz and 2.7 GHz. Two cars connected to Vodafone’s network and the other two to Deutsche Telekom. In the remainder of the paper, we alias them arbitrarily as operator 1 and 2 to shift the focus away from an explicit MNO comparison.
- 2) Sidelink: Each car was also equipped with the software-defined radio (SDR) platform described in [18], which

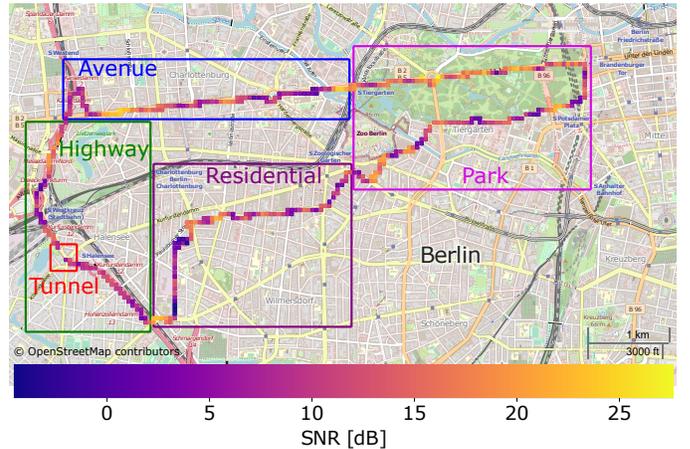


Fig. 1: Measurement route in Berlin with SNR heatmap for operator 1. The different urban environments are highlighted.

acted as a sidelink user equipment (UE) according to 3rd Generation Partnership Project (3GPP) Release 14.

For the cellular measurements, we reused the methodology from [19], specifically the DME with the same modem, antenna, and GPS receiver. Also, the same applications including MobileInsight, Tcpdump and Iperf were used for data collection and generation. We considered low datarate scenarios at 400 kbit/s both for uplink (UL) and downlink (DL) to obtain meaningful delay measurements, and performed experiments at 75 Mbit/s UL and 350 Mbit/s DL to capture the maximum achievable throughput. In each round, we assigned a specific UL/DL profile to each car and labeled the transmission with a unique port to ease data preprocessing.

On the other hand, the sidelink data was collected according to the following operation regimes:

- S1) Cooperative awareness messages (CAM) of length 69 bytes at a packet transmission rate of 20 Hz and modulation and coding scheme (MCS) 8 using two sub-channels (6 rounds).
- S2) Collective perception messages (CPM) of length 1000 bytes (including IP header and payload) at a rate of 50 Hz with MCS 12 using ten sub-channels (5 rounds).

In both cases, we used the frequency band of 5.9 GHz and blind hybrid automatic repeat request (HARQ).

Besides the wireless data, we also captured the cars’ GPS information and side information including traffic conditions and weather. Table I provides an overview of the captured data from different sources with corresponding sampling intervals.

## III. DATA ANALYSIS

Here, we provide a preliminary analysis of the dataset with a focus on its diversity over geographical areas, operators, and devices. The heatmap in Figure 1 already hints at some variation in the PHY characteristics along the route. This effect is confirmed by the datarate distribution for the different measurement areas and operators in Figure 2. There, we can notice some similarities between operators, e.g., for the

TABLE I: Overview of the captured dataset

Data category	Source	Tool	Sampling interval	Features
Cellular	DMEs	MobileInsight	10 ms	Physical layer (PHY): SNR, RSRP, RSRQ, RSSI
			20 ms	Physical shared channels: assigned resource blocks, transport block size, MCS
	Server	Ping	1 s	Radio resource control (RRC): cell identity, DL/UL frequency, DL/UL bandwidth
		Iperf	1 s	Delay
Sidelink	SDR platforms	TCPdump	Event-based	DL datarate, jitter
Position	GPS		1 s	UL datarate, jitter
Side information	Internet database	HERE API	5 min	Traffic jam factor
		DarkSky	1 h	Cloud cover, humidity, precipitation intensity/probability, temperature, wind speed

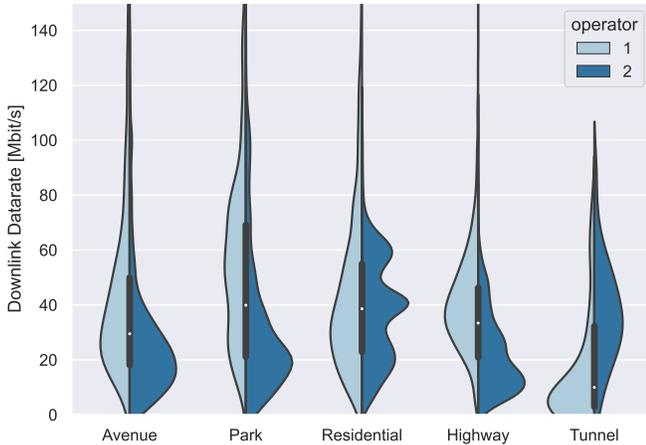


Fig. 2: Violin plots of downlink datarate for different areas.

avenue and the residential area. This might be attributed to some extent to the characteristics of the specific radio environment and perhaps some reusing of the same sites from the operators, which is a common strategy to reduce the cost of building and maintaining the infrastructure. In other areas, such as the highway, the datarate distributions seem to concentrate on disparate regions for each operator. Finally, the multimodal character of some distributions likely arises from the aggregation of two devices per operator.

We continue with the study of the correlation between features from both operators in Figure 3. For each operator, we see that the PHY features (most prominently the signal-to-noise ratio (SNR)) have a strong correlation with the DL datarate. For the UL datarate, the signal-strength type of PHY features (reference signal received power (RSRP) and received signal strength indicator (RSSI)) achieve the largest correlation, especially for operator 1. This discrepancy in UL and DL is expected, since SNR is measured in the downlink. The delay shows a weak correlation with PHY features, thus one should consider additional information for latency prediction. A look into the cross-operator region of the matrix reveals a modest correlation, most notably for RSRP and RSSI. This, again, may be due to site reuse across operators.

In Figure 4, we show the datarate and connected cell identity at different positions in the round for operator 1 along a route

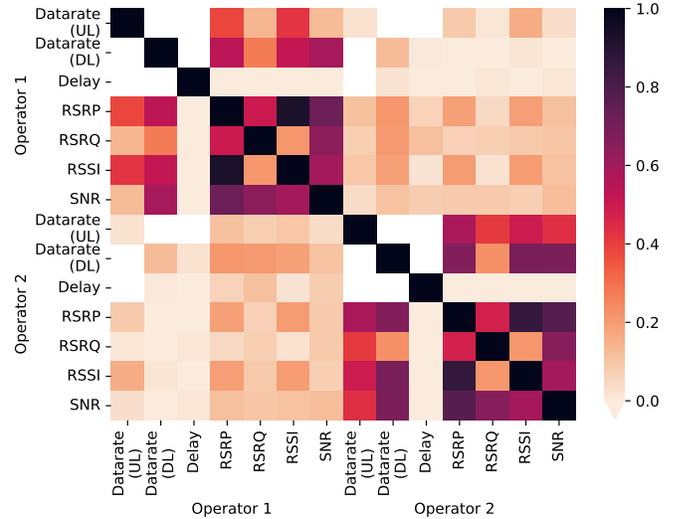


Fig. 3: Correlation matrix for 2 devices from 2 operators.

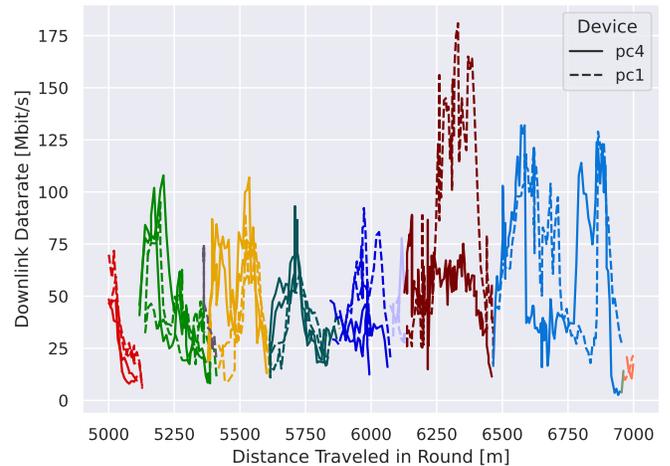


Fig. 4: Extract of downlink datarate along the round for operator 1. Color corresponds to cell identity.

segment of 2 km within the residential area. It can be clearly observed that both devices switch at roughly the same location to the same cells and the achievable datarates are lowest close to the handover points. We have observed that this consistency

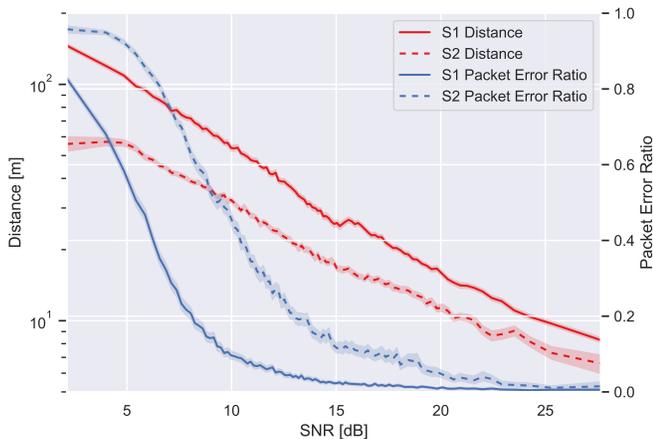


Fig. 5: Relation of distance and sidelink PER with SNR. Several links have been combined for each line.

in cell connectivity does not hold for operator 2 along the same route segment due to the fact that both devices use different frequency bands and thus have different cells available.

The GPS and sidelink measurements allow us to investigate the practical link range for different transmission modes as a relation between distance and packet error ratio (PER), which is mediated by the SNR (cf. Figure 5). From a first exploration of Figure 6, one can estimate the link range as no more than 80m and 30m for scenarios S1 and S2 defined in Section II, respectively, and select transmission parameters accordingly for the considered use case. Here, one should note that the employed HARQ mechanism provides extra tolerance to PER.

Due to the SDR-based setup, the sidelink experiences some hardware-related effects. Specifically, the transition of the power amplifier from transmission (TX) to reception (RX) injects residual TX power in the adjacent RX frames, which leads to SNR degradation and a higher PER. This holds true for all UEs, but the so-called SyncRef UE is most affected due to its periodic transmission of synchronization sequences. As a result, we have observed a different behavior of the links to/from the SyncRef UE for the curves in Figures 5 and 6, which consequently have been omitted from said figures.

#### IV. POTENTIAL STUDIES

The high correlation between datarate and PHY features, as shown in Figure 3, provides a good starting point for ML-based QoS prediction, which can be posed as various tasks thanks to the measurement framework. The captured cellular dataset also allows a comparison between two cellular networks deployed in the metropolis of Berlin from two different MNOs. The understanding of the similarity between the two networks can contribute to previously conducted work in the area [20]. Moreover, the presented similarities already hint that ML models can be reused, alleviating to some extent the need for recollecting data between MNOs. The modest cross-correlation in Figure 3 calls for recent transfer learning techniques to bridge the gap between operators and devices.

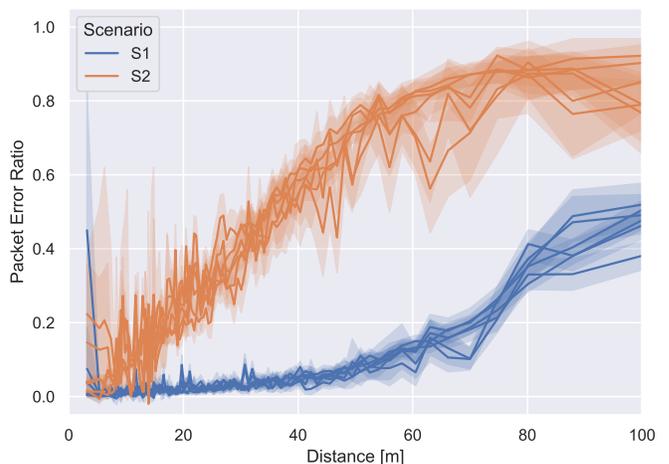


Fig. 6: Relation of distance and PER with 95 % confidence interval. Each line represents the sidelink between two UEs.

The provided measurements may also be used to correct and calibrate simulations, which in turn can provide pre-training data for ML models before their deployment in a commercial network. Finally, such ML-based prediction tasks can be thought of as an enabler for an increasingly proactive radio resource management (RRM), which leverages predictions to react to upcoming changes in the wireless environment.

Moving on to sidelink communication, an interesting ML research question is the estimation of PER from the distance between devices. Figure 6 hints at a good estimation capability across a wide selection of links from 5 m to 80 m. Outside this range, GPS data does not provide enough accuracy for smaller distances and the data becomes unreliable for greater distances as PER approaches 1. This relation clearly depends on settings such as packet rate or bandwidth, which is manifested by the differences between scenarios S1 and S2.

Finally, the inclusion of both cellular and sidelink data can help to test link selection strategies in a multi-RAT context.

#### V. CONCLUSION

In this paper, we present a complex dataset [1] containing GPS-located sidelink and cellular measurements from several devices, operators, and urban areas. This enables not only multi-RAT QoS prediction but also transfer learning studies across different setups.

For the sidelink, the dataset provides insight into the achievable link range for two different settings. Furthermore, we have observed that the relations between distance, SNR, and PER are consistent across several different links, which implies a good basis for ML-based QoS predictors in the sidelink.

Testing ML algorithms in such diverse scenarios can greatly increase confidence in ML applicability for wireless vehicular communications. In particular, model fine-tuning via online and transfer learning or domain adaptation can potentially reduce costly data collection procedures and thus improve ML adoption. The provided datasets allow extensive testing of

the above-mentioned ideas. Moreover, our preliminary analysis shows that the metropolitan area data is quite rich in dynamics and correlation patterns across operators and geographical areas, hence being a microcosmos to study many phenomena that are seen also in non-metropolitan setups.

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