Intelligent Sampling System for Connected Vehicle Big Data

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Abstract: The impact of connected vehicle big data on the automotive industry is significant. Big data offers data scientists the opportunity to explore and analyze vehicle features and their usage thoroughly to assist in optimizing existing designs or offer new features. However, the downside of big data is its associated cost. While storage tends to be cheap, data transmission and computational resources are not. Specifically, for connected vehicle data, even when unstructured data is excluded, the data size can still increase by several terabytes a day if one is not careful about what data to collect. Therefore, it is advisable to apply methods which help avoiding collecting redundant data to reduce the computation cost. Furthermore, some data scientists may be tempted to calculate "exact" metrics when the data is available, partly because applying statistical methods can be tedious, which can exhaust the computational resources. In this paper we argue that intelligent sampling systems which centralize the sampling methods and domain knowledge are required for connected vehicle big data. We also present our system which assists interested parties in performing analytics and provide two case studies to demonstrate the benefits of the system.

1 INTRODUCTION

As connected vehicles become more mainstream, the demand for acquiring and accessing connected vehicle data has been increasing. Even though a vehicle equipped with few cameras has the potential to generate terabytes of data each day, as of today, only few megabytes of structured data are sent over the air to the cloud due to the relatively large cost of data transmission. Larger volumes of data are usually sent over WIFI if the vehicle is configured to connect to the owner's network, which is usually not the case. Nevertheless, with millions of vehicles present on the road, and due to the increment of connected vehicle features, the data size will grow at a minimum of polynomial rate, as will be shown later. With this data growth, reliance on sampling techniques will become important to efficiently build models. More discussion on the role of sampling in big data can be found in (Albattah, 2016).

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In general, obtaining data from a vehicle has the following challenges. Transmission cost, bandwidth limitations, storage, computational costs, and administrative costs such as adhering to regulations, managing access, etc. Using today's technologies, engineers can put data request orders to specify the signals that must be collected (Rocci et al., 2021). In many cases, different requests can specify common signals and thus creating data duplication in the cloud. Furthermore, the data request owners may not be aware of additional related signals which may be of interest. Vehicle signal specification standard (COVESA, 2024) attempts to mitigate this problem and provide a common language for signals. While this covers the "common" signals used, each Original Equipment Manufacturer (OEM) has plethora of other architecture specific signals. Different vehicle types can have different vehicle architectures, and for the same vehicle type, its architecture can vary among model years. Therefore, identifying which signals are needed for a representative study is not trivial since the signals can vary between model years and can vary between vehicles having the same model year.

Another challenge arises in determining how much data to collect and from how many vehicles.

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Engineers and data scientists are tempted to collect "as much data as possible" which can be costly, or for simplicity, they may sample from arbitrarily selected vehicles. They usually do not have all the knowledge about the general demographics, geographical similarities, vehicle configurations, etc. as these change over time. Therefore, it is important to have a centralized system which assists in collecting the proper amount data from the required signals sampled correctly. Otherwise, studies or machine learning models can be biased and under-perform, as can be shown in (Hasanin et al., 2019) and (Johnson and Khoshgoftaar, 2020).

To solve this problem, we developed an intelligent sampling system for connected vehicle feature analytics which combines connected vehicles domain knowledge and analytical results with data sampling techniques, while balancing the budget with the desired statistical significance whenever possible. It assists the users in determining which signals to use, sampling technique, and in choosing a sample suitable for their studies while meeting their budget constraints.

This paper is organized as follows. Section 2 describes common technologies used in vehicles, and motivates the need for an intelligent sampling system. Section 3 describes our system architecture and components. Section 4 demonstrates using the system for analyzing feature usage on different types of roads. Section 5 describes a case which models fuel consumption as a function of tire pressure. Section 6 concludes the paper.

2 BACKGROUND

Big data challenges related to our work have been known for several years, even before cloud solutions became powerful. As computational power improved, data collection also increased, and therefore, these challenges remain. An obvious approach to deal with the computational burden created by big data is sampling. What is not obvious is how to perform the sampling. For example, in (Casamayor-Pujol et al., 2023), the authors designed a scalable "Intelligent Sampling" method to assist in scheduling workloads in large scale heterogeneous computing continuum. This, of course, is abstracted from the end users who are interested in building models, which serves as a suitable example of an intelligent sampling system. A comprehensive list of sampling techniques is found in (Djouzi et al., 2023). Some of these methods are very well known. We review some of the fairly recent methods in adaptive sampling. In (John and Langley, 1996), the authors introduced a progressive sampling method and the concept of "Probably Close Enough" (PCE). The idea behind PCE is to obtain a good enough sample such that it is very unlikely to improve a mining algorithm any further by using the entire dataset. The authors discussed static versus dynamic sampling and their work aims to deal with big data efficiently. In (Satyanarayana, 2014), the authors proposed Generalized Dynamic Adaptive Sampling (GDAS), an adaptive sampling technique to tackle the limitations in progressive sampling, listed in their work. In (Djouzi et al., 2022), the authors proposed a new adaptive sampling method, Subsampled Double Bootstrap GDAS (SDBGDAS) method, which is an improvement over GDAS (Satyanarayana, 2014) method, which allows the scaling of adaptive methods to big data. In (Loyola R et al., 2016), various sampling methods are discussed and the authors propose a Smart Sampling and Incremental Function Learning Algorithm to find a Probably Approximately Correct Computation (PACC) regression model.

Other work, such as in (Zhang and Wang, 2021), (Ai et al., 2021), investigated methods to deal with distributed and massive data. The idea is to optimally select a distributed sub-data, for which summary statistics are calculated on the edge and sent to a central server or to build generalized linear models (GLM). Fuzzy methods are also proposed to reduce sample size such as in (He et al., 2015).

Whether simple random sampling techniques are used, or advanced methods, it is clear that challenges arise when dealing with big data, and good sampling techniques help address these challenges. As noted earlier, the data size of connected vehicle data in the cloud grows at least polynomially (ignoring any changes in regulations, consent agreements, etc.). A proof is offered here before proceeding to the next section.

2.1 Polynomial Growth of Connected Vehicle Data

To motivate the need for intelligent sampling systems, we first show that the data will grow at polynomial rate during the next few years. Let S_y be the number of connected vehicles sold in year y, and assume that $y_1 < y_2 \implies |S_{y_1}| < |S_{y_2}|$. In other words, the sales of connected vehicles each year are more than the previous year (unsaturated market). Note that we only consider connected vehicles. Therefore, the assumption $|S_{y_1}| <= |S_{y_2}|$ holds until almost all vehicles on the road are connected vehicles. Let d_i be the amount of data collected from model year y_i. Assuming d_i is proportional to S_{y_i}, we have $y_1 < y_2 \implies d_1 < d_2$, meaning, each new year we collect more data than the previous year. Under these assumptions, we now prove that the data size grows at least polynomially with the years.

Let I be an enumeration set of all years under which the assumptions hold. Let $\Delta_i = d_i - d_{i-1}$, the increment of collected data for year $y_i, i \in I$. For all the years, while the market is not saturated with connected vehicles, there exists a year for which the increment in data collection Δ_{min} is minimal.

Then

$$\sum_{i \in I} d_i = d_1 + d_2 + d_3 + \ldots \tag{1}$$

$$\sum_{i \in I} d_i = d_1 + d_1 + \Delta_2 + d_2 + \Delta_3 + d_3 + \Delta_4 + \ldots \tag{2}$$

$$\tag{3}$$

But

$$d_{i+1} > d_i + \Delta_{min} > d_{i-1} + 2\Delta_{min} \tag{4}$$

Therefore

$$\sum_{i \in I} d_i \geq d_1 + d_1 + \Delta_{min} + d_1 + 2\Delta_{min} + d_1 + 3\Delta_{min} \ldots \tag{5}$$

$$\sum_{i \in I} d_i \geq |I| d_1 + \sum_{i \in I} i\Delta_{min} \tag{6}$$

Letting $N = |I|$, the number of included years, then the partial increment of data $\Delta(N)$ at year N from year y_1 is

$$\Delta(n) = \sum_{n=1}^{N} n\Delta_{min} \tag{7}$$

$$\Delta(n) = \Delta_{min} \frac{N(N+1)}{2} \tag{8}$$

Hence, the data size grows with the years, following at least a polynomial of order 2. □

Therefore, it is important to build a system which efficiently selects a representative samples to handle the large amount of actual and expected data. For example, the systems described in (Makke and Gusikhin, 2018) and (Tran et al., 2024) will require less data to build the desired models and to update them on a regular basis, which makes the cost of "live" services feasible.

3 SYSTEM DESCRIPTION

To address the issues listed above we propose a system which assists in performing "Connected Vehicle Feature Analytics" defined below, by combining sampling techniques with domain knowledge retrieval, while simultaneously considering any known system or budget constraint.

Definition 3.1. *Connected Vehicle Feature Analytics (CVFA) refers to the analysis of the performance and usage of the vehicle features within the vehicle population. The objective is to generate actionable insights for engineering, marketing and product development, leveraging connected vehicle technology, domain knowledge, and data science.*

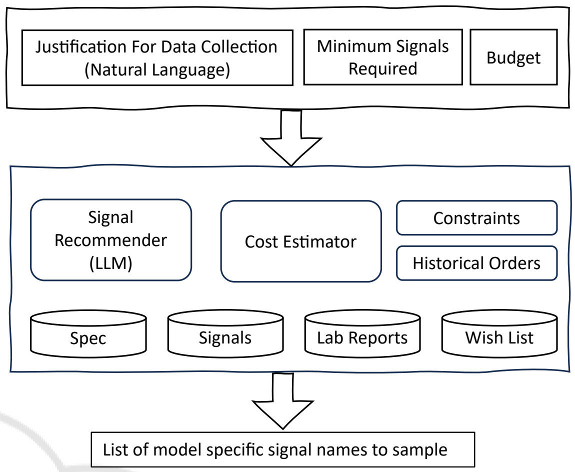


Figure 1: Architecture of Signal Recommender.

In comparison to "connected services", features such as remote start from mobile phone and prognostics, which are tailored to individual vehicles, are not CVFA since CVFA focuses on the broader trends.

The proposed system is divided into two main components. The first is the Signal Recommender component which focuses on assisting the users with choosing the correct signals for their studies while adhering to any system or business constraints. The second is the Intelligent Data Collection component which, once signals are known, assists the users in sampling the data sources using one of the many sampling techniques. These components are discussed in details below.

3.1 Signal Recommender

The architecture for the Signal Recommender is shown in Figure 1. The user starts by describing the use case using natural language. This step is required before the data collection is approved to ensure that privacy rules and regulations are met, and that the proposed use case fits within the driver's consent agreement. The user of the system also selects the signals of interest by their "standard" name such as VSS (COVESA, 2024). This is important because the actual signal names can change based on the vehicle architecture. For example, an 8 bits temperature signal on CAN bus may have a suffix of "_8", but on vehicles with Automotive Ethernet (IEEE Standards Association, 2015), it may be 16 bits. The user may not know which model year this change took effect. The user also specifies a budget which can be approximated as dollars per megabytes of data.

This information, along with vehicle specification documents, network signal specifications, relevant lab reports, and historical data collection orders are fed into a signal recommender. This can be either a classical recommender based on knowledge databases such as vehicle ontology, or it can be implemented with the assistance of a Large Language Model (LLM) (OpenAI, 2023), (Google, 2023). We find that an LLM can easily recommend possible relevant signals when such information is provided. The LLM has the advantage of being able to read the use case justification to understand the issue and match that with other documents using Retrieval Augmented Generation (RAG) techniques to identify other possible signals.

The cost estimator looks up the type of signal and its specification and provides a cost estimate for adding that signal to the study. For example, a Door Switch signal is an event driven signal where as a transmission output speed is an analog signal that can be collected at around $10Hz$. Ambient temperature is available at $1Hz$ but the signal does not have to be collected at that rate unless a specific study related to the performance of the sensor is required.

The constraints block imposes any constraints on the system, such as no more than 10 Mb can be transferred from vehicles with 3G connection, and no more than 50 Mb can be transferred from vehicles with 4G connections. This is important because at any point in time, there are vehicles of different ages and technologies on the road. Usually, it suffices to choose a specific model year for the study, but in some cases a study can span different model years such as when investigating tire pressure, general vehicle usage, etc.

The output of this component is a list of signals to sample along with the desired sample rate, and this list is an input to the next component.

3.2 Signal Sampling and Collection

The Signal Sampling and Collection component comprehensively analyze driving characteristics, vehicle attributes, and demographic data to determine the appropriate sampling size and type, as shown in Figure 2. More dimensions are available and additional ones can be added over time, such as the study shown in Section 4. The selection of these set of factors is entirely dependent on the objective of data collection. By integrating these key factors, the system aims to generate a sample that is not only statistically significant in size but also representative of the wider population.

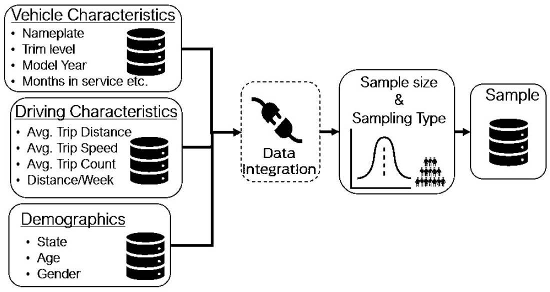


Figure 2: Architecture of Signal Sampling and Collection.

3.3 Sample Size

In the case of connected vehicles it's nearly impossible to collect data from all the vehicles and hence the population size is unknown. There are difference approaches to estimate the sample size based on the distribution of selected continuous and discrete sampling parameters. For continuous sampling parameters like average trip distance and given the population is unknown, the sample size is estimated (Nanjundeswaraswamy and Divakara, 2021) by,

$$n_c = Z^2 max\left(\frac{\sigma_1^2}{e_1^2}, \frac{\sigma_2^2}{e_2^2}, \frac{\sigma_3^2}{e_3^2} \ldots\ldots \frac{\sigma_n^2}{e_n^2}\right)$$

Z: Z – statistic value for the required confidence level
σ^2: Variability of the sampling parameter
e: Maximum allowable error

For discrete sampling parameters like model year of vehicle and given the population is unknown, the sample size is estimated (Louangrath, 2019) by,

$$n_d = Z^2 max\left(\frac{p_1^2 q_1^2}{e_1^2}, \frac{p_2^2 q_2^2}{e_2^2}, \frac{p_3^2 q_3^2}{e_3^2} \ldots\ldots \frac{p_n^2 q_n^2}{e_n^2}\right)$$

Z: Z – statistic value for the required confidence level
p: Proportion of the class in the sampling variable
q = (1-p)
e: Maximum allowable error.

The overall sample size for the study with a combination of continuous and discrete sampling parameters has been chosen as the maximum of the estimated individual sample sizes.

$$n_o = max(n_c, n_d)$$

n_c : minimum sample size required to account for the variability in continuous sampling attributes.
n_d: minimum sample size required to account for the variability in discrete sampling attributes

Thus, the maximum allowable error and confidence level can be traded off with the available budget before data is collected.

3.4 Sampling Type

Strata 1	Strata 2	Strata 3	Strata 4
Fast , Long Trips, California	Slow, Medium Trips, Michigan	Medium Speed, Short Trips, Arizona	Fast, Short Trips, Texas
N=200 (n=40)	N=500 (n=100)	N=300 (n=60)	N=500 (n=100)

Figure 3: Stratified Random Sampling.

Selecting a sample that represents the population is as important as collecting data from statistically significant sample size. Once the sample size is estimated, it is important to identify a set of vehicles that represent the distribution of the targeted population, and the sampling methodology depending on objective of the study (Elfil and Negida, 2016). We find that 'Stratified Random Sampling' method is effective as it balances the complexity of sampling with the intended use of data, since in most cases all subjects in the targeted population have equal chances to be selected. Otherwise, we choose non-probabilistic sampling - "Judgmental Sampling".

Stratified sampling is a probabilistic sampling method which is based on dividing a population into strata of homogeneous members, and members of the sample are selected randomly from these strata. For example, if we want to collect data to study usage of washer fluid, it is important to select driving characteristics that have high correlation with washer fluid usage like average trip speed, average trip duration and state in which vehicle is being driven. The entire population is divided into homogeneous strata and samples would be picked from each strata proportionately as shown in Figure 3. Population(N)=1500, Sample Size (n) = 300, and Strata Multiplier = 0.2 ($\frac{n}{N}$).

This methodology would ensure that data is representing the population and sample size is statistically significant.

As more strata are discovered, their descriptions and sample sizes are added to our system, exposed to the LLM, thus allowing future users to select from these strata, and thus allowing the system capability to naturally grow with time.

3.5 Logical Grouping of Events

In addition to sampling data from the vehicles, the system is setup to sample from existing connected vehicle data. Millions of vehicles on the road sending at least a Megabyte of data a week raises challenges in managing the collected data. Even if querying the entire data set is possible, that can be very expensive. Therefore, it is important to store the data in a form that can be sampled correctly based on different needs. Logically, the data is partitioned using event Ids as shown in Figure 4. When the controller sending the data boots up, it generates a unique identification number by hashing its VIN and a randomly generated number. Figure 4 shows an example of these events, some of which are disjointed such as "Drive Mode" and "Park mode", and some of which are hierarchical such as "Ignition Id" and "Drive Cycle Id". Then, as an example, suppose there is also an "Abs Id", an event indicating an anti-lock braking system actuation event. The sampling can be limited to grab data from all data which have "Ignition Id" that has at least 1 "Abs Id" event. Furthermore, the sampling can be performed so that (1) Either data is sampled randomly from the set of all data which has in its "Ignition Id" event at least one "Abs Id" event, (2) or sample a small subset of "Ignition Id" events which have at least one "Abs Id" event, and then for each sample "Ignition Id", grab all its data. This is important if the data leading to an event is important, and must be complete. Note that the LLM plays an important role here if the users of the system do not know the details on when the signal is available. For example, it may be trivial that cruise control is only available when "Drive Cycle Id" is present, but the user of the system may not know that there is a "Drive Cycle Id" for use, especially when there are many other event identification numbers present. The specification of the tagging system are fed into the LLM which then recommends to the users to limit the sampling to the events tagged with "Drive Cycle Id". In addition to the case studies that will be discussed in this paper, other examples which use this system can be found in (Beyel et al., 2024) and (Beyel. et al., 2023).

4 CASE STUDY 1: GEO-SPECIAL FEATURE USAGE

Consider the following scenario. An OEM needs to conduct a study on how a specific feature is used on different roads. In order to do that, the OEM must analyze how many kilometers a vehicle spends on different types of roads. Here, the type of roads are as defined by Open Street Map (OSM) (Open Street Map, 2024). Suppose also that the data is already collected at a rate of 1 sample every 30 seconds (a constraint) as described in the previous section. To determine how man kilometers on average vehicles drive on each type of road, GPS coordinates, vehicle speed and vehicle type are needed. Then, for every 30 seconds, and a speed sample v_i we estimate total kilometers driven to be

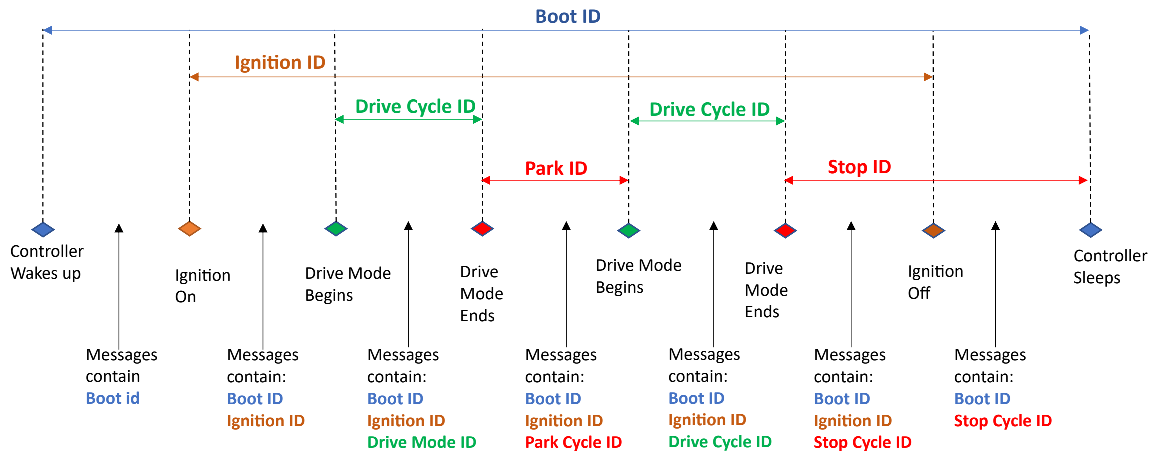


Figure 4: Data is tagged with various event identification numbers to make sampling more efficient.

$$Km_{total} = \sum_i v_i \times 0.0083\text{h} \quad (9)$$

Equation (9) works as long as all the samples $i \in I$ are chosen, where I is the set of all measurements of vehicle speed. However, millions of data points can exist at every 30 seconds interval, and performing Geo-special queries to map each GPS recording to the nearest road type is computationally expensive. Therefore, sampling is required.

Remark: Note that the experiments conducted can be repeated for each Strata (vehicle type). The results shown here, however, are for the entire dataset for confidentiality reasons.

To demonstrate the effectiveness of sampling connecting vehicle data, two experiments are performed. In the first experiment, 0.01% of the data over a year (3 Million points), and in the other, around 0.00005% of the data over year (around 10k data points). Bootstrap method is used, and each experiment is repeated 32 times, and the mean and standard deviation are averaged over the 32 trials.

Table 1 shows the distribution of kilometers driven per Open Street Map road type. The road type is chosen to be the closest match on OSM within 100 meters to the logged GPS coordinates. Table 2 shows that when 3 million samples where used, the standard deviation was every small. When the sample size is reduced to 10k, the standard deviation increased. However, as shown in Table 3, the percentage change between using 3 million samples and 10k samples is negligible. It is worth noting that the query duration dropped from around 2 hours to around 5 minutes.

In this case study, the signals were trivial to identify, and the study was straight forward. The component shown in Figure 2 is still used, except the sampling is performed on already existing data.

Remark: Running the query on the entire data set would time out after 2 hours, and it was not possible to obtain the metrics from the entire data set. The larger set (3 million samples) was heuristically setup so that the query finishes in approximately 2 hours before the query terminates.

Table 1: Mean % of the trials measuring kilometers driven on different road types using different sample sizes.

Road Type	% (3M Samples)	% (10k Samples)
Motorway	23.92	24.1
MW Junction	3.97	3.88
MW Link	10.75	11.1
Trunk	5.3	5.05
Trunk Link	0.92	0.85
Primary	9.71	9.83
Secondary	10.34	10.18
Tertiary	9.69	9.9
Others	25.38	25.11

5 CASE STUDY 2: IMPACT OF TIRE PRESSURE ON FUEL ECONOMY

In this study, we are interested to find the relation between tire pressure and fuel economy. Using the LLM, we find that tire pressure signals and fuel economy signals are common across wide range of vehicle older vehicle and all recent vehicles. Furthermore, from the CAN Database, the LLM identified that not all the signals have the same unit (depending on the architecture and the country). The data size is in the order of tens of terabytes. Although this is not a problem at all for Big-Query, an organization may throttle the consumption of computational resources per user

Table 2: Standard deviation of the trials shown in Table 1. Smaller data sets are still accurate.

Road Type	(3M Samples)	(10k Samples)
Motorway	0.02	2.37
MW Junction	0.01	0.29
MW Link	0.01	0.48
Trunk	0.01	0.37
Trunk Link	0.01	0.09
Primary	0.01	0.64
Secondary	0.01	0.51
Tertiary	0.01	0.49
Others	0.02	1.1

Table 3: Difference between the results using different sample sizes.

Road Type	% Difference
Motorway	-0.01
MW Junction	0.02
MW Link	-0.03
Trunk	0.05
Trunk Link	0.08
Primary	-0.01
Secondary	0.02
Tertiary	-0.02
Others	0.01

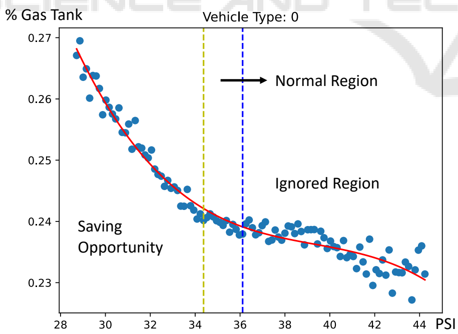
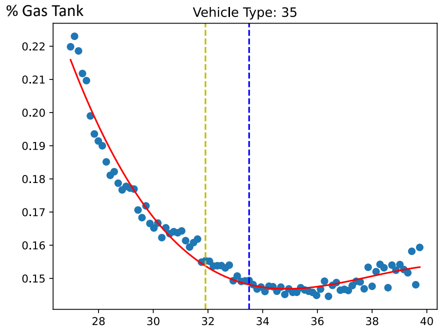
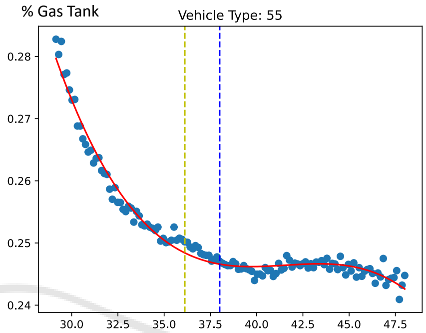


Figure 5: Example of fuel consumption as a function of tire pressure for an arbitrary vehicle type.

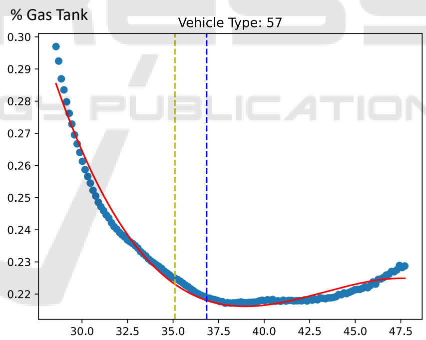
to prevent cost runaway. Therefore, sampling the data is desired. For each of the vehicle types identified under "Vehicle Characteristics" in Figure 2, 5% of the data is sampled. The maximum reported "Fuel Level" for each vehicle type is considered to be a full tank at 100%, and then all fuel level measurements are normalized by that maximum for each vehicle type. For each trip with "Ignition Id" present, the first and last tire pressure measurements from all 4 tires are taken and averaged (average of 8 measurements). The average tire pressure is assumed to be the tire pressure for the trip, converted to PSI. The x-axis in Figure 5 represents the average tire pressure for each trip. The x-axis is quantized by steps of 0.2 PSI, so that each two consecutive integer PSI measurements on the x-axis constitute 5 bins.



(a) Heavy Vehicle.



(b) Medium Vehicle.



(c) Light Vehicle.

Figure 6: Graphs showing the performance of 3 classes of vehicles. The area on the left of the dashed line is common. The area on the right side of the lines is ignored.

For all trips with fuel level at the beginning of the trip larger than fuel level at the end of the trip (ignores trips where refueling occurs), the difference between the initial and final fuel levels is taken and normalized by the maximum measurement. This value represents how much fuel percentage the trip consumed. All trip percentages in the same x-axis bin are averaged. We then arrive to the graph shown in Figure 5. The two dashed vertical lines in the middle of the graph indicate the region considered "normal". The region to the left of the lines represent fuel saving opportunities.

The dots on the graph show how much percentage of the fuel tank on average a trip consumes at a given tire pressure. As expected, lower tire pressures result in reduced fuel economy. The data gives insight into how much, in practice, this is occurring. This data can be used to compare the fuel consumption of customers who use a mobile application which notifies them about low tire pressure, and those who don't. We exclude that result for confidentiality reasons.

The region to the right of the dashed lines is ignored for the following reasons. Although better fuel economy can be achieved, tire wear can become an issue. Also, the reported tire pressure can be influenced by the weight of the vehicle (which is more obvious in trucks). The study is concerned with how much fuel saving can be achieved if customers avoid the left region.

The red line is a fitting of a cubic polynomial, which we found to best fit the data for almost all vehicle types. This makes it possible to make predictions on how much fuel is wasted when tire pressure is low.

Note that although this study is simple in principle, having tens or hundreds of such models updating on regular basis can be expensive unless sampling is used. Furthermore, it is tedious to track changes at the vehicle level without using automated methods such as an LLM, which is another justification to use an intelligent sampling system.

6 CONCLUSION

In research paper, we explored some of the challenges associated with the management and analysis of big data, emphasizing the crucial role of data sampling strategies. Given the vast amount of data generated daily, data scientists often encounter difficulties due to cost constraints and insufficient knowledge about the underlying implementation. This complexity is made even more challenging due to the diverse architectures of data sources, such as vehicles with unique signal names or constraints.

To address these challenges, we propose a system designed to aid data scientists in the data collection and sampling process. This system is engineered to handle the intricacies of big data, offering a straightforward and statistically robust approach for data sampling. One of the key innovations highlighted in our discussion is the utilization of recent advancements in large language models. These models play a pivotal role in simplifying the complexity associated with managing different data sources. Moreover, we discussed a tagging technique to improve the efficiency of data sampling for the data stored in the cloud. By implementing such tagging mechanism, our system facilitates more precise and efficient data sampling processes.

We also provided concrete examples to illustrate how effective sampling methodologies can lead to the extraction of accurate and meaningful insights from large datasets. Through the provided case studies, we demonstrate the significant performance improvements achieved by adopting our proposed system.

As a result, this paper demonstrates the necessity of an advanced data sampling system for any large-scale organization experiencing rapid data growth. Such a system is vital for ensuring that data scientists can derive valuable insights in a timely and efficient manner.

CONFLICT OF INTEREST

The authors of this paper declare that they have no conflict of interest in relation to this work.

REFERENCES

Ai, M., Yu, J., Zhang, H., and Wang, H. (2021). Optimal subsampling algorithms for big data regressions. *Statistica Sinica*, 31(2):361–390.

Albattah, W. (2016). The role of sampling in big data analysis. pages 1–5.

Beyel., H., Makke., O., Yuan., F., Gusikhin., O., and van der Aalst., W. (2023). Analyzing cyber-physical systems in cars: A case study. In *Proceedings of the 12th International Conference on Data Science, Technology and Applications - DATA*, pages 195–204. INSTICC, SciTePress.

Beyel, H. H., Makke, O., Gusikhin, O., and van der Aalst, W. M. P. (2024). Analyzing behavior in cyber-physical systems in connected vehicles: A case study. In De Weerdt, J. and Pufahl, L., editors, *Business Process Management Workshops*, pages 92–104, Cham. Springer Nature Switzerland.

Casamayor-Pujol, V., Morichetta, A., and Nastic, S. (2023). Intelligent sampling: A novel approach to optimize workload scheduling in large-scale heterogeneous computing continuum. pages 140–149.

COVESA (2024). COVESA Vehicle Signal Specification. https://github.com/COVESA/vehicle_signal_specification. Accessed on 4/3/2024.

Djouzi, K., Beghdad-Bey, K., and Amamra, A. (2022). A new adaptive sampling algorithm for big data classification. *Journal of Computational Science*, 61:101653.

Djouzi, K., Beghdad Bey, K., and Amamra, A. (2023). Big data sampling techniques: A state-of-the-art survey.

Elfil, M. and Negida, A. (2016). Sampling methods in clinical research; an educational review. *EMERGENCY*, 4.

Google (2023). Gemini pro. url https://gemini.google.com/.

Hasanin, T., Khoshgoftaar, T. M., Leevy, J. L., and Bauder, R. A. (2019). Severely imbalanced big data challenges: investigating data sampling approaches. *Journal of Big Data*, 6:107.

He, Q., Wang, H., Zhuang, F., Shang, T., and Shi, Z. (2015). Parallel sampling from big data with uncertainty distribution. *Fuzzy Sets and Systems*, 258:117–133. Special issue: Uncertainty in Learning from Big Data.

IEEE Standards Association (2015). IEEE Standard for Ethernet Amendment 1: Physical Layer Specifications and Management Parameters for 100 Mb/s Operation Over a Single Balanced Twisted Pair Cable (100BASE-T1). Technical Report IEEE 802.3bw, IEEE.

John, G. and Langley, P. (1996). Static versus dynamic sampling for data mining. In *Proc. of the 2nd International Conference on Knowledge Discovery and Data Mining*, pages 367–370. Accessed on 4/3/2024.

Johnson, J. and Khoshgoftaar, T. (2020). The effects of data sampling with deep learning and highly imbalanced big data. *Information Systems Frontiers*, 22.

Louangrath, P. (2019). Sample size calculation for continuous and discrete data. *International Journal of Research & Methodology in Social Science*, 5(4):44–56.

Loyola R, D. G., Pedergnana, M., and Gimeno García, S. (2016). Smart sampling and incremental function learning for very large high dimensional data. *Neural Networks*, 78:75–87. Special Issue on "Neural Network Learning in Big Data".

Makke, O. and Gusikhin, O. (2018). Connected vehicle prognostics framework for dynamic systems. *Advances in Intelligent Systems and Computing*.

Nanjundeswaraswamy, D. and Divakara, S. (2021). Determination of sample size and sampling methods in applied research. *Proceedings on Engineering Sciences*, 3:25–32.

Open Street Map (2024). Open Street Map Highways. https://wiki.openstreetmap.org/wiki/Highways. Accessed on 4/3/2024.

OpenAI (2023). Chatgpt (mar 14 version). https://chat.openai.com/chat.

Rocci, B. M., Krozal, C., and Rockwell, M. A. (2021). Onboard data request approval management. U.S. Patent No. US 20210074083 A1.

Satyanarayana, A. (2014). Intelligent sampling for big data using bootstrap sampling and chebyshev inequality. In *2014 IEEE 27th Canadian Conference on Electrical and Computer Engineering (CCECE)*, pages 1–6.

Tran, T. B., Kolmanovsky, I., Biberstein, E., Makke, O., Tharayil, M., and Gusikhin, O. (2024). Effect of wind on electric vehicle energy consumption: Sensitivity analyses and implications for range estimation and optimal routing. *ACM Journal on Autonomous Transportation Systems*, 1(2):1–31.

Zhang, H. and Wang, H. (2021). Distributed subdata selection for big data via sampling-based approach. *Computational Statistics & Data Analysis*, 153:107072.