Toward a Better IPA Experience for a Connected Vehicle by Means of Usage Prediction

Osamu Masutani
Alliance Connected Vehicle
Nissan Motor Co., Inc.
Yokohama, Japan
o-masutani@mail.nissan.co.jp

Shungo Nemoto
Alliance Connected Vehicle
Nissan Motor Co., Inc.
Tokyo, Japan
nemoto-shungo@mail.nissan.co.jp

Yusuke Hideshima
Alliance Connected Vehicle
Nissan Motor Co., Inc.
Tokyo, Japan
y-hideshima@mail.nissan.co.jp

***Abstract*— Recently, a connected vehicle comes into wide use. A connected vehicle enables seamless access from outside of the vehicle. A user can easily control the vehicle remotely as if it is a home appliance device. IPA (Intelligent Personal Assistants) or smart speaker adoption is growing rapidly these years. We have already released an IPA application for remote control of a vehicle to enhance accessibility of our connected vehicle. Since the launch, we found significant drop of users from using application, which is reportedly caused by social or mental obstacles to use IPA in some researches. To mitigate these obstacles, we propose proactive suggestion by IPA. We apply a vehicle usage prediction model on our connected vehicle data. The prediction enable spontaneous suggestion by IPA, therefore the user doesn't need to speak wake-up word. In our model, firstly LDA automatically discover usage patterns and clustering method on the latent space. The result suggests some user segments which represent habitual vehicle usage. The prediction is performed by dynamic Bayesian networks for each user segment. An evaluation with actual service data confirms applicability of the prediction model and potential of IPA log itself can also assist vehicle usage prediction.**

Keywords—connected vehicles, IPA, activity prediction

I. Introduction

A connected vehicle is a widely accepted concept among modern vehicle technologies. A connected feature is one of important differentiator of a vehicle sold by most of automakers [3]. It enhances drivers convenience, safety and efficiency in a direct or an indirect way. A connected vehicle produce various valuable diverse data from GPS tracking data to vehicle health data. Many of transportation industries are interested in benefit of data generated from vehicles to develop advanced functionality such as autonomous driving or fleet management. On the other hand, connected vehicle data is also regarded as a activity log of the vehicle owner. Therefore, vehicle data analytics has potential to enhance applications such activity recommendation or smart home.

Smart phone applications for a vehicle such as remote security, parked car finder or car navigation are released from various application developers right after smart phone revolution initiated by Apple in 2007. Vehicle control features such as key-less entry, vehicle status monitor, remote vehicle operation (engine, air conditioner) have been also provided by most of automakers through their branded smart phone applications [1]. Nissan also have been provided a genuine companion applications which support remote door lock, remote air conditioner, remote status monitor and remote charge especially for top-selling EV Leaf [2]. The companion application mainly beneficial for a car owner during away from his car. Therefore usage of the application spans not limited to driving time. Smart device application for a vehicle virtually extend touch points to whole day life of car owners.

Voice activated IPA (intelligent personal assistant) or VPA (virtual personal assistant) quickly penetrated home mainly supported by a smart speaker such as Amazon Echo. IPA becomes one of popular smart devices especially for home use. IPA is taking a roll of home hub to access various assets of home such as lighting, air conditioner, audio visual system, intelligent sensors and so on. We provide Leaf skill for Amazon Alexa, which enables access to most of connected functionalities of Leaf. Its versatile functionalities and intuitive operation promote popularity of IPA in the home. However regardless of initial fever by geeks, it generally has issues of continuity of use because of its special characteristics such as difficulty of access or social embarrassment in some situations [7]. We found our skill also suffers discontinuity of usage. To mitigate these blockages, we propose a spontaneous suggestion from IPA. The suggestion or notification is like "Are you going to drive today ? How about turning on air conditioner before drive ?" in appropriate time in advance of actual drive time.

To realize such suggestions, we propose an activity prediction to trigger the suggestion at an appropriate timing. Our primary interest is driving activity which occurs regularly or irregularly in daily life. A user is assumed to receive a recommendation from Alexa in advance of a departure. A driving time of the user is predicted by his usage history using activity prediction by means of dynamic Bayesian networks [7]. A connected vehicle data such as a driving time and a charging time and also Alexa usage data are used. We evaluated predictability of a driving time with actual vehicle and Alexa data. The evaluation result confirms applicability of our prediction model and reveals importance of Alexa usage as an evidence. Usage of Alexa skill such as turning on air conditioner or start charging provides a good indication of a vehicle use after a certain duration of time.

II. Background

A. Connected vehicle and behavior anlaysis

Connected vehicle is fundamental in advanced car technologies which is represented as CASE (Connected, Autonomous, Sharing and Electrification). It is also an important enabler of smart environment such as a smart city, a smart transportation or a smart infrastructure [5]. The most of current connected vehicle experiences are inherited from telematics applications such as traffic information service, in-vehicle entertainment, connected safety or traveler assistance from early 90s. These services are implemented in a vehicle (on-board) and also outside of a vehicle (off-board) with a telecommunication. Earlier studies in intelligent transportation system or latest IoT ventures have proved that Vehicle to Infrastructure Integration (VII) yield synergic benefits for both inside and outside of vehicle.

Main applications of a connected vehicle are sensory and control of a vehicle in an environment [11]. A vehicle is regarded as one of devices in a smart environment. It has unique nature as a personal space, mobility, location awareness, physical and social restrictions, high energy usage and capacity, in contrast to generic IoT devices. Data from connected vehicles produce much values as a behavior data. GPS data is a typical vehicle usage data which is primary used as road traffic data. This is called as a floating car data (FCD) which actually is a crowd sourced traffic information. Vehicle usage data is important for development of a vehicle control, ADAS, autonomous driving, diagnostics. On the other hand, vehicle usage have also studied for long-term scenario; purchasing, ownership, annual mileage in terms of house hold economics.

Recently, usage of electric vehicle (EV) have been focused in studies of electric power management. A variety of approaches in power systems, energy and environmental analyses as well as power demand analysis are applied. Understanding EV charging behavior is important not only for vehicle battery management but also for home energy management system (HEMS). To understand EV usage among household activities become more important to optimizing smart home or smart energy system.

B. IPA

IPA is a concept that voice or natural language based computer agent to help users in a daily life. Voice activated IPA products like Siri, Google Assistant, Microsoft Cortana and Amazon Alexa are widely spread as a smart phone feature or stand-alone intelligent speakers (e.g. Amazon Echo and Google Home). Some popular IPAs have already introduced into in-vehicle equipment as Android Auto or Apple CarPlay..

Worldwide IPA wireless speaker market is forecast to reach $3.52 billion by 2021 according to Gartner, Inc. Contrarily, according to the consumer behavior report from the Verto Analytics, 70% of users will not continue to use the IPAs after the first introduction [7]. L. Zhao et al. stratified reasons of discontinuous usage of voice-Activated IPAs as perceived ambiguity, cognitive overload, privacy concern, social embarrassment and lack of integration. Cognitive overload or social embarrassment of IPA are caused by a nature of voice interaction.

These concerns might be eased by omitting wake-up word or a short cut features. However more fundamental solution is demanded. A proactive recommendation, which make users avoid lengthy activation utterance, might effectively reduce cognitive overload. Push notification in right timing will reduce an effort of operation. Such a proactive notification is already seen in non-voice IPAs such as Google now or Cortana. Such notification requires understanding of user behavior to make a prediction of a user activity or intention. We propose a usage prediction based on usage pattern analysis.

C. Usage prediction

A usage prediction of vehicle enables some applications in regard to potential usage of vehicle, drive preparation, destination recommendation or charge planning. Proactively asking potential usage of vehicle will enable smoother operation of vehicle.

A usage prediction become more important to enhance user experience in diverse services. Web usage mining have evolved in 90s to find usage pattern to explain how users reach to / leave from a web site. Various approaches of prediction of usage have been developed in mobile application which has not only virtual access log but also physical sensory data such as GPS, accelerometer. In IoT era, a usage prediction takes more primary role in human centric fabric of devices. Studies in smart house or smart buildings pay more attention about human behavior, compared to conventional facility control [11].

Various models are proposed as a usage model to predict user behaviors [7][8]. Time series analysis, state space model and dynamic Bayesian networks are have been applied to the prediction [9]. We employ dynamic Bayesian networks [10] to understand basic behavior and applicability of usage prediction in a connected vehicle context. With its white box and consistent probabilistic representation of Bayesian networks, we easily test an effect of a certain features into a model.

III. Fundamental observation

To confirm discontinuity problem of IPA usage, which is reported on [7], we observed drop rate of Alexa skill usage (Fig. 1). 65% of users left 3 months after last usage and 38% of users left 6 months after last usage. These values are not worse than reported in general IPA usage, however majority of early users surely have dropped.

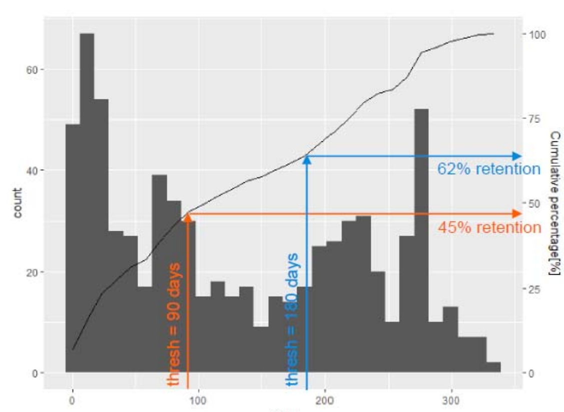


Fig. 1. Drop out behavior of current Alexa leaf skill users

We observed fundamental behavior of users of the vehicle who subscribes Alexa leaf skill. We found a significant relationship between remote control and vehicle usage. The one is a remote air conditioner (a/c) control short before vehicle usage. The other is charging control in a previous day of a vehicle usage. Typical usage behaviors of EV and IPA are visualized as Fig. 2. Driving (pink bar) in the morning and evening represents commute to the office. A user charges in the night when its necessary (yellow bar). These activity patterns are diverse by user characteristics such as commuter vehicle, less frequent users or holiday long traveler. An invocation of remote a/c (blue dot) tends to happen right before a driving time.

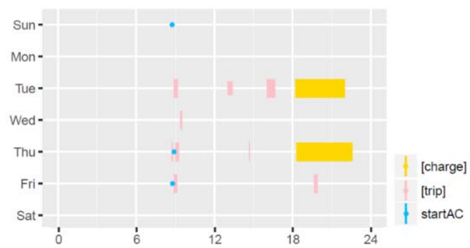


Fig. 2. Image of data sample of conneceted car and alexa data

A timing of remote a/c can considered as an apparent signal of driving. The observation reveals 53% (25/47) of a/c trigger are followed by actual driving in an hour. Average time to travel is 878 seconds if it is less than an hour (Fig. 3). This result indicates a/c turning on as a clue of higher likelihood of trip in a short term. A simple rule based automation such as a scenario; every time when user turns on a/c, then trigger some other actions such as contents download, garage door control and key control.

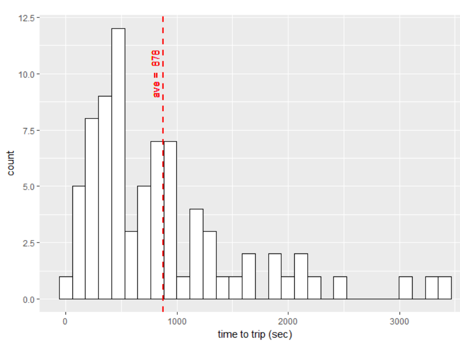


Fig. 3. Time to trip after Alexa AC control

A charging time is also a good clue of vehicle usage afterward. Our observation reveals 93% (981/1051) of a charge in the late night followed by trip in next morning (Fig. 5). Average time to trip from last charge is 5.94 hour (Fig. 4). Oppositely, 92% (623/671) of first trip in the morning have lead by charging in former 24 hours. Average time to trip from last charge start is 5.1 hour. Therefore charging behavior is regarded as strong indicator of highly possible use of vehicle in a following day. This long-term relationship between a preparation charge and a driving is possibly provide a good feature for vehicle usage prediction. Highly probable use of the vehicle next day will realize services like notification about predicted traffic condition next day, a notification of estimated departure time in conjunction with a scheduler or automatic parking lot reservation.

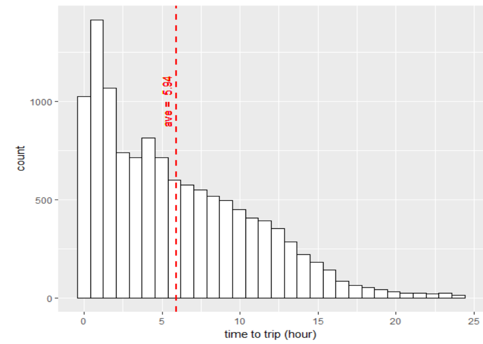


Fig. 4. Time to trip after charge

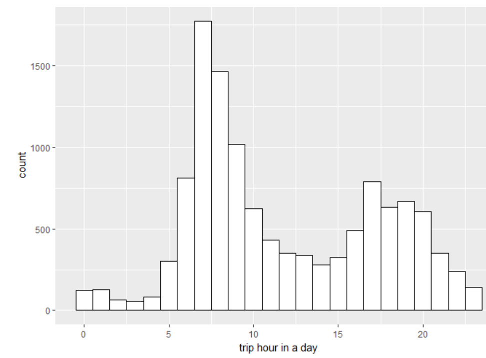


Fig. 5. Hour of first trip after charge

With these fundamental findings, we employ remote a/c and charging to predict daily usage of vehicles. We guess testing behavior or immaturity of Alexa skill of early adaptors introduce some noise into dataset. We expects more regular use of skills improve predictability.

IV. Methodologies

A. *User clustering*

The vehicle usage is diverse in user personality and purpose of vehicle use, such as commuter, commercial or leisure. We extracted typical user segments by use of clustering technique over temporal usage pattern. We aggregate dataset into weekday by hour matrix to represent average usage pattern (Fig. 2). The selected features, which are drive time and charge time and location attribute (home/office), are selected (4 dimension). LDA (Latent Dirichlet Allocation) is applied to factorize significant features in event pattern. Then we applied K-means clustering with cosine similarity to identify typical user clusters.

B. *Dynamic Bayesian networks*

We introduce dynamic Bayesian networks (DBNs) as a fundamental method of our usage prediction. Among prediction techniques in activity recognition, we firstly employ a simple model with directly observed graphical model without latent nodes. Because the dataset we currently obtained is less expressive about user behavior, we do not need to employ complex model. BNs have appropriate nature like probabilistically valid input and output, white box model which allows prior knowledge injection, combination of nominal and numerical variables and simultaneous inference of multiple variables.

A DBNs is a simple extension of BNs which has ability to model temporal sequence such as sensory time series or activity observation [8]. Contemporaneous or time-lagged dependency is seamlessly introduced into static BNs. DBNs can be seen as a generalization of some major technique for activity recognition such as Hidden Markov model [9]. We have introduced similar model of DBNs with former application to activity recognition [10].

Normal BNs are represented as conditional probability on parent variables based on conditional independence of each variables. Combinational probability on BNs described as bellow:

$$\mathrm{P}(\mathrm{X}_1, \dots, \mathrm{X}_n) = \prod_{i=1}^{n} (\mathrm{X}_i | Pa(\mathrm{X}_i))$$

DBNs are extension of parent variables to it is previous state. A simplest full observability style network is like follows:

$$\mathrm{P}(X_1^t, \dots, X_n^t) = \prod_{i=1}^{n} (X_i^t | Pa(X_i^t), Pa(X_i^{t-1}))$$

We introduced simple DBNs with some descendant nodes of current and former vehicle status. We employ target variable S_t as vehicle status. Moreover, descendant nodes are hour and weekday at time t and vehicle status and Alexa intent at time t-1. Therefore, data record with features is defined as a tuple: $(\mathrm{t}, S_t, h_t, w_t\, I_t)$ for each time t where

$S_t \in \{driving,\ charging, parking\}: status\ of\ vehicle$

$h_t \in \{1 \dots 24\}: hour\ in\ a\ day$

$w_t \in \{1 \dots 7\}: day\ in\ a\ week$

$g_t \in \{home, office, other\}: location$

$I_t \in \{start\ ac, charge\ other\}$: intent of Alexa at time t

Unrolled style of the network is shown as Fig. 6 This is a dynamic belief network style with multi stage delay.

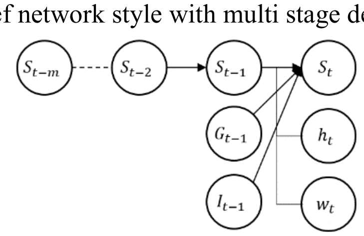


Fig. 6. DBNs model

C. System overview

We use a big data log analytics environment to prepare usage data from connected car and Alexa. Analytical data flow is shown as Fig. 7. Three kinds of prediction have performed with dynamic Bayesian networks. We preprocess raw data on Azure Data Lake store and MPP environment (Azure Data Lake Analytics). R and BayesServer which is a commercial Bayesian network workbench software have also used to build a behavior model. The model will be deployed prediction engine so that provides enhanced application such as Alexa skill or other applications.

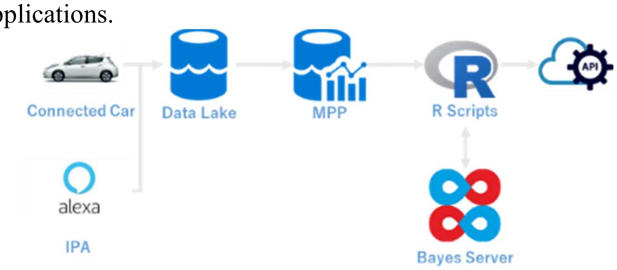


Fig. 7. Our analytics environment

V. Evaluation And Result

A. Data set

We collected data after launch of Alexa skill and connected vehicle data from November 2017. Connected vehicle data consist of timings of driving (trip) and charging. Alexa log is aggregated by Amazon Alexa API. Alexa log mainly consists of timestamp, intent type. These event data have been merged in hourly data with appropriate alignment.

TABLE I. Data Spec

Period	Hourly data from Jan 1, 2018 to Mar 31, 2018
# of vehicles	Up to 411 (depends of exam.)

B. User clustering

We composed week by hour matrix for each week for each user. Each data point has four mode, driving, charging, home and office, therefore 24*7*4 dimensional data is composed as a weekly usage pattern. A weekly usage pattern represents commuter pattern, leisure pattern and charge pattern. We extracted thirty dimensional latent feature vector after applying LDA as a dimension reduction. Then we applied clustering in the latent space. The result indicates typical Leaf user would be recognized as six types (Fig. 8).

Fig. 8 presents hourly usage as four modes (red: charge, purple: driving, blue: at home, green: at office). According to an average behavior pattern of each cluster we assume the characteristics for each user cluster as follows :

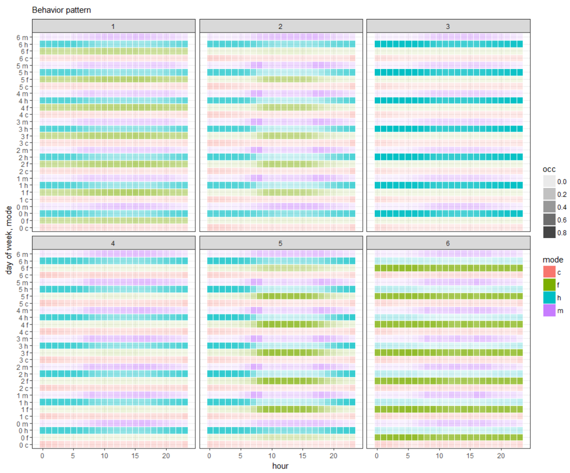


Fig. 8. Hour day activity matrix view for user clusters

cluster 1 : *private business user* who use their private car

cluster 2 : *partial commuter user* who sometimes use a car to drive to office

cluster 3 : *inactive private user* who is not often use a car

cluster 4 : *active private user* who relatively use a car than cluster 3

cluster 5 : *commuter user* who commute by a car more than cluster 2

cluster 6 : *commercial user*

Cluster statistics in Fig. 9 shows ratio of staying home and mobility.

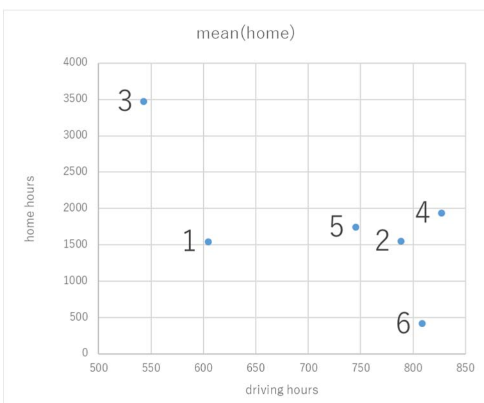


Fig. 9. Clusters mapping on driving hours and home hours

C. *Short term status prediction*

For many use cases, or scenarios in daily life, a short-term prediction is useful for activity recommendation. In this examination, an event of driving D of next one hour is predicted. We compose Bayesian networks to predict D by use of past status, hour in a day, day in a week. 4 models are examined to capture better configuration for the driving status prediction. Because opportunity of Alexa usage is smaller than entire connected car observation, we narrows dataset into the 144 dates only when Alexa a/c used.

Firstly we examined belief network only with observation variables. In this simple network, the model precision will be 60-70%. Existent of Alexa intent of remote a/c (I_t) improves driving event prediction significantly.

Model 1: $P(D_t | D_{t-1}, h_t)$

Model 2: $P(D_t | D_{t-1}, h_t, I_t)$

TABLE II. SHORT TERM PREDICTION RESULT (DBN)

	Accuracy	Precision($D_t = 1$)	Recall($D_t = 1$)
Model 1	84.5	68.5	22.6
Model 2	87.2	73.8	42.4

We also examined the network with a hidden variable S_t which has 6 latent status. A simple introduction of hidden variable improves a prediction significantly. And we confirmed improvement with intent for this model.

Model 3: $P(S_t | D_t), P(S_t | S_{t-1}, h_t)$

Model 4: $P(S_t | D_t), P(S_t | S_{t-1}, h_t, I_t)$

TABLE III. SHORT TERM PREDICTION RESULT (HMM)

	Accuracy	Precision($D_t = 1$)	Recall($D_t = 1$)
Model 3	84.8	71.4	23.6
Model 4	90.0	88.3	50.0

D. *Long term status prediction*

A charging behavior varies according to daily vehicle usage style. Recent model of commercial EV has enough capacity to drive up to 400km without stop for charge. Average state of charge (SOC) is more than half of maximum battery capacity. Therefore user doesn't need to charge every time they arrive at home. We assume manual charging behavior has some intention to prepare for coming long driving. We employ four hour time step to capture long term behavior. 3 HMM models are performed for this evaluation with or without charging feature and user cluster feature described in previous sector.

Model 1: $P(S_t | D_t)\ P(S_t | S_{t-1}, h_t, w_t)$

Model 2: $P(S_t | D_t)\ P(S_t | S_{t-1}, C_{t-1}, h_t, w_t)$

Model 3: $P(S_t | D_t)\ P(S_t | S_{t-1}, U, h_t, w_t)$

Model 4: $P(S_t | D_t)\ P(S_t | S_{t-1}, C_{t-1}, U, h_t, w_t)$

,where

We confirmed a charging event is a good clue of coming driving event in 4 – 8 hour later, recall raised in Model 2 from Model 1, and Model 4 from Model 3. And introduction of user cluster U is also improved recall in Model 3 from Model 1, Model 4 from Model 2. Introduction of U as a parent node of hidden state directly means the dedicated separate HMM models for each user cluster are trained and applied for prediction.

TABLE IV. LONG TERM PREDICTION RESULT

	Accuracy	Precision($D_t = 1$)	Recall($D_t = 1$)
Model 1	64.8	57.3	21.4
Model 2	77.1	66.8	44.2
Model 3	72.3	66.5	51.1
Model 4	72.3	64.3	57.2

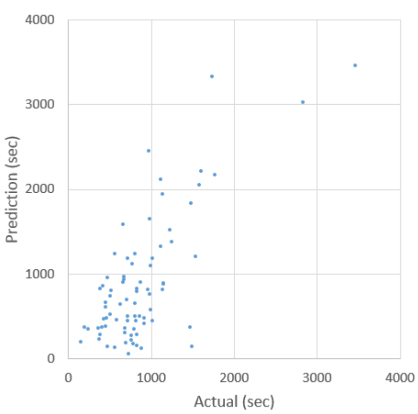
E. Prediction of time to drive

In some scenario these prediction with fixed duration is not enough. For example in driver preparation scenario, the system had better estimate time user might depart so that cool down or charge vehicle in appropriate timing. We examined DBNs which predict time span from call of Alexa intent to trip. Timing of Alexa operation will trigger the prediction, and estimated time span will used as parameter of various kind of services follows.

We employed DBNs model again to predict time to trip. The model is represented as follows:

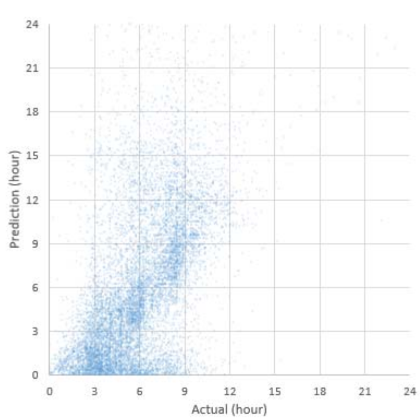
$$P(T_t \mid T_{t-1}, U, h_t, w_t)$$

where T_t is time to trip at t. An Experimental simulation result shows applicability of rough prediction of time to trip.



RMSE	497
MAE	375
R^2	0.54

Fig. 10. Time span prediction result (short term)



RMSE	4.07
MAE	2.95
R^2	0.31

Fig. 11. Time span prediction result (long term)

CONCLUSIOIN

We examined and evaluated applicability of a usage prediction on connected vehicle data with aid by IPA usage data. A probability of a user will drive or not in certain timing are predicted in short and long term future by dynamic Bayesian networks. Alexa usage of remote a/c or charge behavior can be regarded as good clue for future usage of vehicle.

In some of use cases, rule based method might work, for example notification or recommendation every time when Alexa is triggered. However that might cause other problem of IPA. A proactive reminder without any user operation makes total operation smoother than manual operation of IPA. In some scenario such as vehicle to grid, vehicle to home energy management, usage prediction is important to optimize battery utilization. These kind of vehicle infrastructure integration (VII) is also an important factor of smart environment system.

Our future works will introduce more detailed information such as other IPA usage or connected vehicle data such as drive destination. And we will apply various use cases around vehicle environment integration. In autonomous vehicle context, the intelligent engine with prediction of user behavior might pretend a clever chauffeur.

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