# Human-Centric Autonomous Driving Based on a Two-Stage Machine Learning Algorithm

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***Abstract*—This paper presents a human-centric autonomous driving system, which is based on a two-stage machine learning algorithm. In particular, driving perception and human features are integrated to develop human-centric autonomous vehicles. Hence, we propose two-stage machine learning algorithms to identify the driver features such as age, location, sense, etc. We consider both online and offline learning to construct a two-stage distribution model and determine the relationship between the driver features and its cluster. The simulation results show the performance of the proposed two-stage learning algorithms in terms of a driver's feature training performance.**

***Index Terms*—Human-centric, autonomous driving, machine learning, online and offline learning.**

## I. Introduction

Autonomous vehicle (AV) industries and researchers are investigating to enhance the road safety and performance of the autonomous driving systems [1], [2]. In contrast, human-centric applications such as virtual and augmented reality are key technology to future wireless communications. Due to the the different behaviour between AV and human driver, one road user cannot easy predict the intention of other road users. To integrate the AV and human driver's intention, a machine learning tool can offer a benefit from the feature-based dataset of human driver.

Recently, a joint user-centric stretegy of SmartCockpit is investigated by Amazon and Stellantis [3]. In [3], the manufacture companies were integrated AV with driver's digital twin to create personalized in-vehicle experiences leveraging artificial intelligence (AI) for entertainment, voice-assistance navigation, maintenance, e-commerce, and payment services. A human-centric vision called iNEXT proposed by BMW [4]. In iNEXT, an AI and electrification strategy is used to make highly automated, emotion-free and fully-connected vehicles.

In this paper, we propose a two-stage learning algorithm to further learn human driver features such as behavior, sense, age, emotion, and physical state. The computer simulation show the performance of the proposed two-stage learning algorithms in terms of a driver's feature training performance.

## II. System Model

We consider a downlink multiuser vehicular MIMO communication systems with driver's in the loop and a single base station (BS) serving a set $\mathcal{D}$ of $K$ user vehicles and a set $\mathcal{V}$ of Uu modules, where $k = \mathcal{D} \bigcup \mathcal{V}$. A blocked PC5 link is depicted in Fig 1 of the system model. Through Uu link, one user vehicle driver can respond to the other user vehicle driver. The received data rate for each user vehicle is given by

$$y_k(z_{k,j}) = B \sum_{j}^{K} z_{k,j} \log_2 \left(1 + \frac{p_{k,j} h_{k,j}}{\sigma^2}\right), \tag{1}$$

where $\sigma^2 = N_0 B$ is the noise power, $N_0$ denotes the power spectral density of noise and B denotes the bandwidth, $p_{k,j}$ is the transmitted power between the user $k$ and the BS over resource block $j$, $\mathbf{z}$ is a random binary vector, in which a particular element $z_{k,j} \in \{0, 1\}$. Hence, $\mathbf{z}$ is represented a mode indicator for the output of the offline learning.

## III. Proposed Two-Stage Machine Learning Algorithm

Let a dataset matrix $\mathbf{S} \in \mathbb{R}^{K \times d}$, where $\mathbf{s}_i = \text{vec}\{\mathbf{S}\} \in \mathbb{R}^d$ is one sample data vector and the the elements of $\mathbf{s}_i$ are driver's features $d$. Hence, the modified data matrix $\mathbf{X} \in \mathbb{R}^{n \times (d+1)}$ is given by

$$\mathbf{X} = \begin{bmatrix} s_1^T & \alpha_1 \\ \vdots & \vdots \\ s_K^T & \alpha_K \end{bmatrix}, \tag{2}$$

where $\mathbf{x}_k \in \mathbb{R}^{d+1}$ is a modified data vector with driver's response time $\alpha_k$ at $k$-th user vehicle. The probability distribution of $\mathbf{x}_k$ for the offline learning is given by [5]

$$p(\mathbf{x}_k) = \sum_{l}^{L} \pi_l \Omega\left(\mathbf{x}_k | \boldsymbol{\eta}_l, \boldsymbol{\Sigma}_l\right), \tag{3}$$

where $\Omega\left(\mathbf{x}_k | \boldsymbol{\eta}_l, \boldsymbol{\Sigma}_l\right)$ is the probability density function for mode $l$ of driver response, $\boldsymbol{\Sigma}_l$ denotes the covariance matrix and $\boldsymbol{\eta}_l$ represents the mean vector. Let each data vector $\mathbf{x}_k$ is labeled by $l(\mathbf{x}_k)$ and the target vector $\mathbf{r} = [l(\mathbf{x}_1) \ldots l(\mathbf{x}_K)]^T$ where the operator $(\cdot)$ is called transpose. Therefore, the label data $l(\mathbf{x}_k) = \arg\max_l y_k(z_l)$, where the responsibility for mode $l$ is given by

$$y_k(z_l) = \frac{\pi_l \Omega\left(\mathbf{x}_k | \boldsymbol{\eta}_l, \boldsymbol{\Sigma}_l\right)}{\sum_{j=1}^{L} \pi_j \Omega\left(\mathbf{x}_k | \boldsymbol{\eta}_j, \boldsymbol{\Sigma}_j\right)}. \tag{4}$$

Now we make a train data pair $(\mathbf{S}, \mathbf{r})$ where the output of offline learning step $\mathbf{r}$ is applied for the online training. Therefore, the online prediction function $f$ is given by

$$f = \arg\min_{\hat{f}} \mathcal{L}\left(l(x_k), \hat{f}(s_i)\right), \tag{5}$$

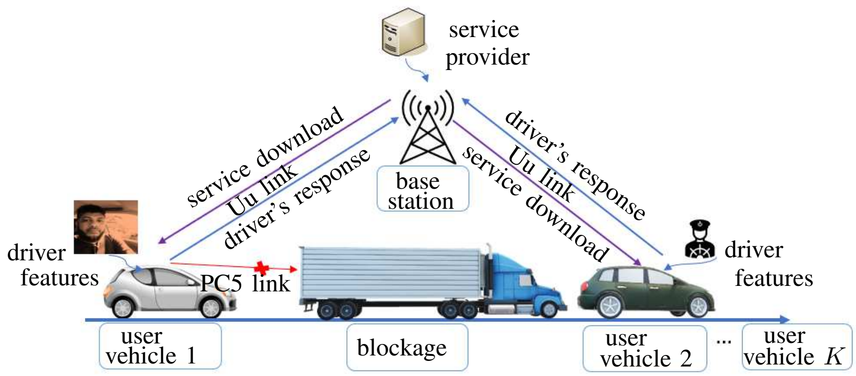


Fig. 1. System model is illustrated a human-centric autonomous driving scenarios.

where the operator $\mathcal{L}(\cdot)$ denotes the loss-function.

## IV. Result and Discussion

In this section, we compare the proposed two-stage learning algorithm in terms of a driver's feature training performance

**Algorithm 1** Proposed Two-Stage Learning Algorithm

**Input parameters:** $x_k = [s_k \ \ \alpha_k]$, $k = 1, 2, \ldots, N$

**Output:** $f$, $\pi_l$, $\eta_l$, $\Lambda_l$ where $l = 1, 2, \ldots, L$

**Begin:** Apply offline expected-maximization algorithm to $x_k$ and search $\pi_l$, $\eta_l$, $\Lambda_l$, $y_i(z_l)$, $l = 1, 2, \ldots, L$, and $k = 1, 2, \ldots, K$.

**for** $k = 1, 2, \ldots, K$, **do**

Search $l(\mathbf{x}_k) = \arg\max_l y_k(z_l)$.

**end for**

Pass $\mathbf{r}$ to the online learning algorithm

Search $f = \arg\min_{\hat{f}} \mathcal{L}\{l(x_k), \hat{f}(s_k)\}$.

**Output** $f$, $\pi_l$, $\eta_l$, $\Lambda_l$ where $l = 1, 2, \ldots, L$.

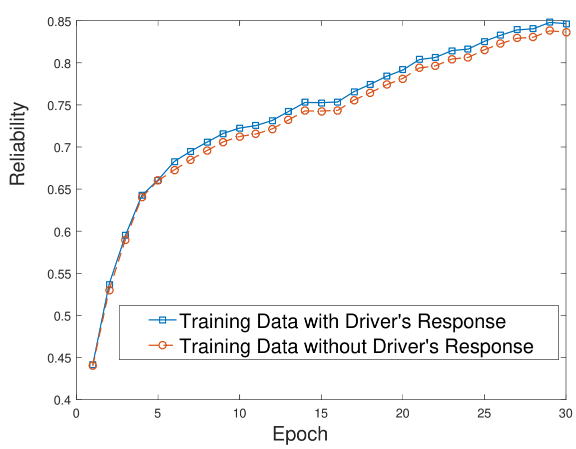


Fig. 2. Reliability performance of the two user vehicles.

via computer simulations. The signal-to-noise-ratio (SNR) is defined as $\gamma = \frac{|p_{k,j} h_{k,j}|^2}{\sigma_z^2}$. For data generation, we consider $\sigma^2 = N_0 + 10\log_{10} B$, $N_0 = -174$dBm/Hz, the bandwidth $B = 10$MHz and the transmit power $\mathbf{p} = 1$ Watt. For online training, we use a pair $(\mathbf{S}, \mathbf{r})$, which contains the modified features of driver.

Fig. 2 shows the reliability for the two-user vehicles with two drivers. We observed that the target training reliability is about $85\%$ and the data training performance is almost $3\%$ with the driver's response. The reliability performance gap is low due to the large response time of the driver as well as an inefficient dataset.

## V. Conclusion

In this paper, we proposed a two-stage learning algorithm for performing a human-centric autonomous driving. With the proposed two-stage algorithm, the learning performance is about $3\%$ due to the driver's large response time. Therefore, the proposed learning algorithm can be extended further analysis to the real-time scenarios with low response time, which will be pursued in future works.


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