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Profit optimization in service-oriented data market: A Stackelberg game approach

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HIGHLIGHTS

- The economic aspect of service-oriented data market is investigated.
- A Stackelberg game is proposed to model the interactions.
- We derive the equilibrium pricing and corresponding demands.
- We reveals the effects of user's utility and provider's cost on optimal strategy.

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ABSTRACT

Deep learning has drawn a lot of attention recently. It is successful in a variety of applications from natural language processing to autonomous vehicle control. A main difference from traditional learning is that deep learning learns the representations of the data, i.e., the features, via greedy layer-wise pre-training. The characteristics of deep learning promotes it as a power tool to mine the data from Internet of Vehicles (IoV). The paper focuses on the economic aspect of IoV and investigates deep learning enabled IoV market for data trading and processing. The economic model of IoV consists of three side: the data provider, the service provider, and the user. The data provider collects the data for the user. The user buys the raw data. The data is further processed by the service provider, who provides the learned features for the user to obtain some profit. To optimize the profit of three-sided participators, a Stackelberg game is proposed to model the interactions among them. We derive the equilibrium pricing mechanism of the providers and corresponding demands of the users. The existence and the uniqueness of the equilibrium strategies are proved. Our analysis reveals that the strategy of each participator is related to the utility of the user and the data/service provider's cost. To the best of our knowledge, this is the first time that the data provider and the service provider directly interact with the user in the data market.

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1. Introduction

With the rapid development of wireless communication, mobile computing, sensor techniques, and mobile social networking, many objects in our daily lives are interconnected through the Internet. The past few years have witnessed the proliferation of Internet of Things (IoT) paradigm [1–5]. Via smartphones, diverse sensors/actuators, Radio Frequency IDentification (RFID) tags, an enormous amount of data from different aspects and sectors is generated everyday. For instance, it is reported Google approximately processes 20,000 TB data and Flicker approximately generates about 3.6 TB data everyday [6]. It is expected that by 2020, the total amount of data worldwide will reach 35 ZB [7].

The services offered by IoT paradigm highly depend on the available data. However, approximately 90% of the generated data is unstructured [8]. The multimedia data collected from the Internet and mobile devices is a typical example of this unstructured data [6]. Fully utilizing the collected data to generate commercial value is a huge challenge in many scenarios [9]. Many data preprocessing and machine learning methods are proposed to extract useful information from the data. Machine learning technology enables many aspects of modern people's life, including web search, recommendation systems, natural language understanding as well as social networking [10–15]. Machine learning facilitates many services to Internet of Vehicles (IoV) [16]. With the aid of multiple sensors deployed in vehicles and roads, cloud platforms collect traffic information and current status from the vehicles [17]. Via data analysis and prediction, drivers are provided by accurate travel time estimation to improve their driving plans [18]. Indeed, by carefully mining the datasets from the IoV, there are many services that can be provided to the drivers, even if the same

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Table 1
The details of ResNet with different depths. All the results are cited from [28].

Depth	Parameters	Test error (%)
20	0.27M	8.75
32	0.46M	7.51
56	0.85M	6.97
110	1.7M	6.43

dataset are used. The possible services include: autonomous vehicle control, traffic event detection, traffic situation prediction, parking lot management, driving plan making [19–21].

We characterize the entities involved in the paradigm as three parts: data providers, service providers, and service users. Data providers are those devices generating raw data. They can be cameras, sensors, smartphones, and so on. Service providers collect the raw data from data providers. The raw data is processed and analyzed by service providers via learning models. Based on various purposes, various services are offered to service users. For example, service providers may provide extracted features from the raw data to service users, or they directly provide the predicting results to service users. Therefore, service providers provide platforms for the interactions between data providers and service users.

Participating in such service scenarios is a cost task for both data providers and service providers. On one hand, it consumes data providers' resources, such as battery, computing power and so on. In some scenarios, data providers are facing the problem of privacy leakage if the sensing data involves their private information [22]. For example, by submitting the images from specified scenarios, the providers expose their habits and preferences. In the IoV scenarios, uploading traffic information also reveals the locations of the vehicles.

On the other hand, extracting useful information consumes service providers' energy power, computing power and so on. A complicated learning model has the potential to discover intricate structures in the input data and offer better services. A larger amount of data also helps to improve the learning accuracy. However, the complicated model with more learning data requires more computation power and memory storage. Therefore, data providers and service providers are not interested in these tasks unless they receive satisfying rewards from service users to cover their participating costs.

From the perspective of service users, they obtain gains by purchasing data analysis services from the service provider [23]. The service quality is related to the amount of raw data bought from data providers, as well as the machine learning models used by service providers. For example, as the size of available training set on MNIST [24] and CIFAR-10 [25] datasets increases, prediction performance is improved [26]. But a service user has to pay for the data. There is a tradeoff between the amount of raw data a service user buys and the service quality the user gets. Meanwhile, different learning models offer various service quality. Table 1 lists the details of ResNet with different depths on CIFAR-10 dataset. It shows that as the neural network goes deeper, the test error decreases. However, the total number of model parameters and FLOPs are also increasing. In some cases there is strong correlation between the computation a model requires and the accuracy it achieves [27]. Therefore, there is a tradeoff among service users, data providers, and service providers.

To address the aforementioned issues, in the paper we focus on the economics of IoT/IoV, which is an under-investigated issue, especially when the computation cost of service providers is involved. We investigate two critical questions: (1) How much data should service users buy from data providers to satisfy their requirements? (2) What are the best prices that service providers and data providers charge service users for their services?

The above questions are significantly important in the economic scenario. We develop a game-theoretical economic framework to model the interactions among three parties. We consider a monopolistic scenario, i.e., there is one data provider, one service provider, and one service user, as the scenario is fundamental for the market. We model the interaction as a two-stage Stackelberg game. In the first stage, there is a non-cooperative game where the data provider and the service provider decide the price of the data and the service. Then in the second stage, the service user determines its demands of service units and data units to maximize its profit. We assume this scenario is a pricing market with complete information: each participator in the game has the complete knowledge of all the participator in the market. Then the Nash equilibrium of each subgame is derived. We also conduct extensive experiments to reveal the best price of the providers, the best demand of the user, as well as the profit of the participators.

The paper is organized as follows. Section 2 describes the related work, including deep learning and data pricing mechanisms. Section 3 presents the market model and formulates the optimal problem. Then the optimal pricing mechanism is discussed in Section 4. Section 5 presents some numerical results. Conclusion is drawn in Section 6.

2. Related work

2.1. Deep learning

Although the concept of "neural networks" has a long history, the past few years have witnessed an upsurge of research interest in deep neural networks. In 2006, Hinton et al. proposed a greedy layer-wise unsupervised training strategy for Deep Belief Networks [29]. The method overcame the issue that gradient-based optimization with random initialization may get stuck in poor solutions [30]. The work showed that the nonlinear, distributed representations in the deep hidden layers are high-level abstractions of the input. It is possible to interpret these representations and generate images from them. The success of greedy layer-wise unsupervised training strategy evoked the new wave of neural networks research. The term "Deep Learning" was coined in the year. Later in 2012, the group led by Hinton won the ImageNet classification benchmark, which is considered as a standard competition in computer vision community. The group achieved 15.3% top-5 test error rate, compared to 26.2% achieved by other standard machine learning methods. The winner, i.e., "AlexNet", consists of five convolutional layers and three fully-connected layers. The work stimulated huge public interests in deep learning research. Since then, an enormous amount of research effort has been going into deep neural networks worldwide.

The success of deep learning can be attributed to many factors. The convolutional neural network (CNN) is an essential factor among them. CNN is not new, which can be traced back to the 1980s [31]. By composing multiple nonlinear transformations on the original inputs, the representations are learned. This is a distinct pattern that deep learning differs from the traditional learning: the features of the data are learned by the greedy layer-wise unsupervised training manner. The low-level features are firstly extracted and then high-level features are obtained by multiple nonlinear transformations. The high-level features are more abstract and discriminative. AlexNet inspires many subsequent deep neural networks, such as Network-in-network [32], VGGNets [33], GoogLeNet [34], Highway [35], ResNets [28], DenseNet [36]. The neural networks are also going deeper. AlexNet has 8 layers, while Highway, ResNets, DenseNet all surpass 100 layers.

The deep neural networks are proposed for tasks in computer vision at the beginning, such as image classification and object detection. Currently, deep neural networks based technologies have already achieved significant success in a large number of applications with good performance, including speech recognition, natural language processing, web search, autonomous mobile robots, self-driving cars, drug discovery and genomics.

2.2. Pricing the data

There have been existing efforts to combine data analysis models with economic mechanisms [37]. The pricing is an effective means of coordination between the service provider and the service user. In the digital market, the service providers make profits via offering various services to the service users. The service users are willing to pay for the services of interest and get certain utilities from them. A well-developed digital market is in the context of Internet. Internet service providers (ISPs) offer their subscribers wired and/or wireless connectivity and bandwidth.

The basic goal of pricing is to incentivize users to adjust their demands so as to maximize the overall resource utilization. The resource utilization could be the profits of providers, the utilities of users, and capacity usage. Generally speaking, the pricing schemes could be classified into two different categories: static pricing and dynamic pricing, depending on resource condition, usage flexibility [38]. The pricing schemes could be further divided into three pricing schemes: usage-based, service-based, time-dependent [39]. These pricing schemes are successfully adopted in the field of wireless resource allocation [40,41,39], Internet resource allocation [42].

However, the significant role that pricing can play is beyond the area of Internet service. Recently, pricing the data in IoT has received attention due to the fact that IoT continues to thrive. There is plenty of literature on data and service trading [43–48]. [49] presents a survey of big data market. Unlike that of Internet, the market for trading data and service adopts the *pay-as-you-go* scheme to charge the users. In [45,50–53], machine learning based data trading in IoT is discussed. However, in [50,51] the users pay at a fixed-fee, while [45,52,53] ignore the costs of service providers.

Our work is similar to the work in [50–52]. However, in [50,51] the data is bought by the service provider and the user pays a fixed service fee to the service provider. The providers' cost is not considered in [52]. Besides, the users in our market interact with the data provider and service provider directly. The service provider then processes the data from the data provider per user's request.

3. Market model and problem description

In the paper we consider the following scenario. A certain dataset is bought by a mobile user from the data provider. The mobile user cannot support the computation requirement of machine learning model due to limited energy and computing capacity. Therefore, the service provider is engaged in the market and extracts the features from the dataset for the user. Then the user can use the learning representations for further tasks. In other cases, there are some other kinds of data services, such as financial crisis prediction, stock price prediction, traffic status prediction.

There are three kinds of participants: one data provider, one service provider, and one service user. Fig. 1 shows the pricing model considered in the paper. The data provider collects the raw data by sensing the environments, taking photos, detecting human's activities. The service provider processes the raw data and provides different services to service users. In the paper the service provider extracts best features from the raw data according to users' requests. The service user buys the raw data from the data provider and buys data analysis service from the service provider to process the raw data. We assume each request from the service user is independent. The data provider collects the raw data and

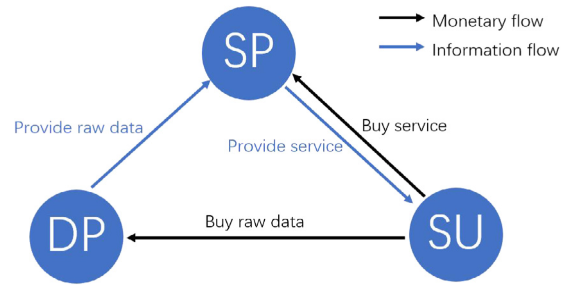

Fig. 1. Basic market relation among the DP, SP, and SUs.

the service provider processes the data according to each request from the service user. The raw data and the data analysis services cannot be reused. In order to focus on the data trading, we ignore the communication cost. Table 3 lists related notations used in the paper.

The data provider collects the raw data for further usage. The raw data can be classified into three classes: crowdsensing data, social networking data, sensing data [44]. In IoV, data can be provided by different on-board sensors, such as RADAR, GPS, video cameras, as well as sensors monitoring vehicle's status, fatigue detector and sleep detector monitoring driver's activities [54,55]. Driver's mobile phones also belong to common data source. In the scenario, the vehicle, including all on-board devices, is considered as a data provider.

The data provider encapsulates the data into data units. Each data unit represents a data sample, carrying the complete semantics. An example of the data unit is an image with the size of 32×32 in CIFAR-10 dataset [25]. The service user buys the raw data in terms of the data unit. Thus, the service provider processes the data based on the data unit. The maximum data units that a data provider can provide is N.

No matter where the data comes, it consumes the data provider's resource. The resource can be in terms of battery, computing power, memory space, time and so on. The cost goes up in proportion to the amount of the data unit. To simplify the analysis, the cost function $c^i_{DP}(n_i)$ is assumed to be linear increasing function of the data unit. This kind of cost functions is widely used in mobile crowdsensing/crowdsourcing [56,48], cloud computing [57], Internet of things [50], as well as Internet service [58]. Based on the analysis, the cost function of the data provider is defined as:

$$c^i_{DP}(n_i) = c_{du} \cdot n_i \tag{1}$$

where n_i is the amount of data units that the service user i buys, and c_{du} is the cost of per data unit.

The data provider also decides the price of per data unit, denoted as p_{du}. Therefore, via selling the sensing data, the profit of the data provider is

$$p_{DP}(n_i) = p_{du} \cdot n_i - c^i_{DP}(n_i) \tag{2}$$

$$s.t. \quad n_i, p_{du} > 0 \tag{3}$$

If positive profit can be obtained, the data provider is willing to collect the data. From the perspective of the data provider, the problem of profit maximization is formulated as: P_{DP}:

$$max \sum_n (p_{du} \cdot n_i - c^i_{DP}(n_i)) \tag{4}$$

The service provider processes the raw data and provides various data services to the service users. They can be cloud platforms, data centers, and computing clusters [59]. There are some available service platform: Google Cloud Machine Learning [60], Amazon's

Predictive Analytics with AWS [61], and Microsoft's Azure Machine Learning [62].

The service provider plays a significant role in the market. From the perspective of the service provider, several steps are required to process the raw data, including: identifying the learning task, collecting and cleaning the data for training, engineering data features for predicting, experimenting with different models and parameters to optimize the accuracy, embedding the resulting learned system for further operations [63]. In these steps, feature engineering is important. The performance of machine learning methods heavily depends on the features of the dataset [64]. In traditional machine learning field, constructing a machine learning is labor-intensive. Domain experts are required to design a feature extractor to transform the raw data into a suitable representation or feature vector [65]. Much attention is paid to the design of data preprocessing and data transformation for a better representation. The service provider uses deep learning models to process data. A distinct pattern of deep learning that distinguishes it from traditional learning methods is that the representations of the data are learned by neural networks [66]. The idea of greedy layer-wise unsupervised pretraining are used to extract features, from low-level representations into high-level representations. The important deep learning models include Network-in-Network [32], VGG Nets [33], GoogLeNet [34], Highway Nets [35], ResNet [28], DenseNet [36].

In our experiments we found that the learned representations determine the predicting performance. For instance, we obtain the inputs of the softmax layers from these neural networks. Then these learned features are used as the inputs of classifiers. The performance of these one-layer networks is similar to the performance of the original neural networks. It is found that, to some extent, the predicting accuracy of deep learning models is proportional to network size [33,67]. However, more connections and parameters are introduced by increasing the size of neural networks, which results in the high demands of memory storage and computation requirement. To obtain better services, the service users have to pay higher price.

Each service provider charges the service user for a service unit at the price of p_{su}. The resource demand of a service user i, denoted as r_i, depends on the choice of learning model, which further determines the service performance partly. The cost function of the service provider has the same characteristics with that of the data provider. When a service provider provides r_i service units to user i, the cost function is given by:

$$c^i_{SP}(r_i) = c_{su} \cdot r_i \tag{5}$$

where c_{su} is the cost of per service unit.

The interactions between the service provider and the service user i is to decide r_i by controlling p_{su}. Therefore, if a service user enters the market and decides to buy r_i service units, the profit of the service provider for the user is:

$$p_{SP}(r_i) = p_{su} \cdot r_i - c^i_{SP}(r_i) \tag{6}$$

$$s.t. \quad r_i, p_{su} > 0 \tag{7}$$

The service capacity of the service provider is constrained by limited-resource. From the perspective of the whole market, the profit maximization of the service provider can be formulated as: P_{SP}:

$$max \sum_n (r_i \cdot p_{su} - c^i_{SP}(r_i)) \tag{8}$$

$$s.t. \quad \sum_n r_i \le R_{SP} \tag{9}$$

Let us consider the service user now. The service user buy the raw data from the data provider and the data analysis from the service provider. Each service user obtains gain from both providers. Therefore, the service quality, e.g., the satisfaction rate of the user, is defined as a utility function of the service user. It consists of two parts:

Table 2
The performance of ResNet20 and ResNet56 with different training data size. The results of 50000/10000 split are cited from [28].

Training size	Testing size	ResNet20 (%)	ResNet56 (%)
10000	10000	18.01	16.11
40000	10000	8.89	8.38
50000	10000	8.75	6.97

$$u^i_{SU} = \theta(r_i) + \delta(n_i) \tag{10}$$

where $\theta(r_i)$ is the willing-to-pay-service function of user i, and $\delta(n_i)$ is the utility function of user i obtained from the raw data. In order to obtain the gain with the data, we conduct some experiments. The standard CIFAR-10 dataset is with a training set of 50,000 samples and a testing set of 10,000 samples [25]. We further randomly choose 10,000 samples and 40,000 samples from the original training set as new training sets. Then ResNet20 and ResNet56 are trained on the new datasets and tested on the original testing dataset. Table 2 shows the results. Therefore, the utility function is monotonically increasing and has a diminishing marginal utility of the amount of data units. We define the function as:

$$\delta(n_i) = a^i_1 \cdot \ln(1 + a^i_2 \cdot n_i) \tag{11}$$

$$s.t. \quad n_i, a^i_1, a^i_2 > 0 \tag{12}$$

where a^i_1 and a^i_2 are performance-related parameters of user i.

The willingness of a user depends on the learning performance. We previously has discussed that the high-quality learning models usually require more computation and storage resources, as Table 1 shows. We define the willing-to-pay service function $\theta(r_i)$ of user i as:

$$\theta(r_i) = b^i_1 \cdot \ln(1 + b^i_2 \cdot r_i) \tag{13}$$

$$s.t. \quad r_i, b^i_1, b^i_2 > 0 \tag{14}$$

where b^i_1 and b^i_2 are performance-related parameters of user i.

The function is also monotonically increasing and has a diminishing marginal utility of the service unit. It is coincident with the results in Table 1. From Table 2 we conclude that in the scenario with fewer training data (i.e., 40000/10000 setting), the service user could improve the learning performance by demanding more service units (ResNet56 with 40000/10000 compared with ResNet20 with 50000/10000). It shows that the learning performance is determined by both the service provider and the data provider. Therefore, the utility function of the service user is defined by the two parts. The two functions satisfy the following conditions:

- $\theta'(\cdot) > 0$ and $\delta'(\cdot) > 0$: The functions are monotonically increasing;
- $\theta''(\cdot) < 0$ and $\delta''(\cdot) < 0$: The functions have diminishing marginal utilities.

Each service user has to buy the raw data from the data provider and the service from the service provider. The profit of the service user i is:

$$p^i_{SU}(n_i, r_i) = u^i_{SU} - r_i \cdot p_{su} - n_i \cdot p_{du} \tag{15}$$

From the perspective of each service user, the profit-optimal problem can be formulated as: P^i_{SU}:

$$max \quad p^i_{SU}(n_i, r_i) \tag{16}$$

Table 3
Related notations used in the paper.

Notation	Description
p_{du}	Price of per data unit
c_{du}	Cost of per data unit
n_i	Amount of data units that service user i buys
p_{DP}	Profit function of data provider
p_{su}	Price of per service unit
c_{su}	Cost of per service unit
$c^i_{SP}(r_i)$	Cost of service provider due to user i's request
r_i	Amount of service units that service user i buys
R_{SP}	The service capacity that service provider can provide
p_{SP}	Profit function of service provider
a^i_1, a^i_2	Performance-related parameters of user i on data unit
b^i_1, b^i_2	Performance-related parameters of user i on service unit

4. Optimal pricing mechanism

The interactions among three parties are controlled by adjusting the data price and the service price so that the data provider and the service provider are able to maximize their profit. Meanwhile, the service user can determine the amount of service units and data units to optimize the profit. We can formulate the economic scenario as a Stackelberg game [68]. The Stackberg game often arises in user-provider interactions where the optimal actions are closely related to the pricing strategies. In standard model of Stackelberg game, there is a leader and several followers. The leader sets a price strategically, and the followers decide how much resource to buy based on leader's price. In the proposed game, there are two leaders, i.e., the service provider and the data provider. The participating service user is the follower. We consider the game as a variant of the Stackelberg game. The prices of service units and data units directly impact the demand of the service user. Thus, we model the scenario as a two-stage game. In first stage, there is a non-cooperative game where the service provider and the data provider determine their prices. In second stage, the service user determine the demands of service units and data units to maximize the profit. The whole stages of the game can be described as follows:

- Stage I—Data provider side: The data provider is a leader in the Stackelberg game, who decides the optimal price p^*_{du} of per data unit:

$$\textit{Subgame} \quad G_{DP} : p^*_{du} = argmax \quad p_{DP} \tag{17}$$

- Stage I—Service provider side: The service provider is also a leader in the Stackelberg game, who decides the optimal price p^*_{sp} of per service unit:

$$\textit{Subgame} \quad G_{SU} : p^*_{sp} = argmax \quad p_{SP} \tag{18}$$

- Stage II—Service User side: Each service user acts as a follower in the game. Given p^*_{du} and p^*_{sp}, the user determines the demand n^*_i and r^*_i to maximize its profit. n^*_i and r^*_i are also the user's best response:

$$\textit{Subgame} \quad G_{SU} : (n^*_i, r^*_i) = argmax \quad p^i_{SU} \tag{19}$$

We consider stage I as subgame 1, and stage II as subgame 2.

The Stackelberg game is usually solved via backward induction to derive the sub-game perfect equilibrium [68–71]. At the equilibrium, each player maximizes its own profit, and no player has the incentive to change its strategy. In the following we discuss the equilibrium of each sub-game. We assume the game is a pricing scenario with complete information: each player in the game has the complete knowledge of all the players in the market. According to the definition of Subgame Perfect Nash Equilibrium (SPNE), SPNE is a strategy profile that achieves a Nash Equilibrium at every subgame [72].

4.1. Analysis

The prices of data unit and service unit directly impact the demands of service user. When the data provider/service provider varies the price p_{du}/p_{su}, the service user changes its demand n_i/r_i. To maximize its profit, the data provider/service provider set the price p^*_{du}/p^*_{su}.

Theorem 1. *When $a^i_1 \cdot a^i_2 > c_{du}e^2$ and $b^i_1 \cdot b^i_2 > c_{su}e^2$, then the unique Nash Equilibrium demand strategy (n^*_i, r^*_i) and the unique Nash Equilibrium pricing strategy (p^*_{du}, p^*_{su}) in the game exist. The unique NE in the game is:*

$$n^*_i = \frac{a^i_1}{\sqrt{a^i_1 a^i_2 c_{du}}} - \frac{1}{a^i_2} \tag{20}$$

$$r^*_i = \frac{b^i_1}{\sqrt{b^i_1 b^i_2 c_{su}}} - \frac{1}{b^i_2} \tag{21}$$

$$p^*_{du} = \sqrt{a^i_1 a^i_2 c_{du}} \tag{22}$$

$$p^*_{su} = \sqrt{b^i_1 b^i_2 c_{su}} \tag{23}$$

Proof. According to (15), the profit function of the service user i is:

$$p^i_{SU}(n_i, r_i) = a^i_1 \cdot \ln(1+a^i_2 \cdot n_i) + b^i_1 \cdot \ln(1+b^i_2 \cdot r_i) - r_i \cdot p_{su} - n_i \cdot p_{du} \tag{24}$$

By differentiating $p^i_{SU}(n_i, r_i)$ with respect to n_i and r_i, we have:

$$\frac{\partial p^i_{DU}(n_i, r_i)}{\partial n_i} = \frac{a^i_1 \cdot a^i_2}{1 + a^i_2 \cdot n_i} - p_{du} \tag{25}$$

$$\frac{\partial p^i_{SU}(n_i, r_i)}{\partial r_i} = \frac{b^i_1 \cdot b^i_2}{1 + b^i_2 \cdot n_i} - p_{su} \tag{26}$$

The second derivatives of $p^i_{SU}(n_i, r_i)$ with respect to n_i and r_i are:

$$\frac{\partial^2 p^i_{SU}(n_i, r_i)}{\partial n_i^2} = -\frac{a^i_1 \cdot (a^i_2)^2}{(1 + a^i_2 \cdot n_i)^2} \tag{27}$$

$$\frac{\partial^2 p^i_{SU}(n_i, r_i)}{\partial r_i^2} = -\frac{b^i_1 \cdot (b^i_2)^2}{(1 + b^i_2 \cdot r_i)^2} \tag{28}$$

If $\frac{\partial^2 p^i_{SU}(n_i,r_i)}{\partial n_i^2} < 0$, $\frac{\partial^2 p^i_{SU}(n_i,r_i)}{\partial r_i^2} < 0$, closed-form Nash Equilibrium demand strategy (n^*_i, r^*_i) exists. The second derivatives of $p^i_{SU}(n_i, r_i)$ are negative due to the fact that $a^i_1 > 0$ and $b^i_1 > 0$. Therefore, the NE demand strategy (n^*_i, r^*_i) in subgame 2 is:

$$n^*_i = \frac{a^i_1}{p_{du}} - \frac{1}{a^i_2} \tag{29}$$

$$r^*_i = \frac{b^i_1}{p_{su}} - \frac{1}{b^i_2} \tag{30}$$

Given (n^*_i, r^*_i), the service provider and the data provider set the price p^*_{du} and p^*_{sp} that is best response. Replacing the value of n^*_i and r^*_i from (29) and (30) in (2) and (6), we have:

$$p_{DP}(n_i) = a^i_1 - \frac{p_{du} - c_{du}}{a^i_2} - \frac{a^i_1 \cdot c_{du}}{p_{du}} \tag{31}$$

$$p_{SP}(r_i) = b^i_1 - \frac{p_{su} - c_{su}}{b^i_2} - \frac{b^i_1 \cdot c_{su}}{p_{su}} \tag{32}$$

It obviously satisfies the conditions that the second derivatives of $p_{DP}(n_i)$ and $p_{SP}(R_i)$ with respect to p_{du} and p_{su} respectively are negative:

$$\frac{\partial^2 p_{DP}(n_i)}{\partial p_{du}^2} = -\frac{2c_{du} \cdot a_1^i}{p_{du}^3} \tag{33}$$

$$\frac{\partial^2 p_{SP}(r_i)}{\partial p_{su}^2} = -\frac{2c_{su} \cdot b_1^i}{p_{su}^3} \tag{34}$$

As the first derivatives of $p_{DP}(n_i)$ and $p_{SP}(R_i)$ with respect to p_{du} and p_{su} have only one positive solution, a unique NE exits in stage I, i.e.,

$$p_{du}^* = \sqrt{a_1^i a_2^i c_{du}} \tag{35}$$

$$p_{su}^* = \sqrt{b_1^i b_2^i c_{su}} \tag{36}$$

At NE, the pricing strategy satisfies p_{du}^* and p_{su}^*. Note that closed-form solutions of (n_i^*, r_i^*) have to satisfy $n_i^* > 0$ and $r_i^* > 0$. We derive $n_i^* > 0$ and $r_i^* > 0$ now. Replacing the value of p_{du}^* and p_{su}^* from (35) and (36) in (29) and (30), we have:

$$n_i^* = \frac{a_1^i}{\sqrt{a_1^i a_2^i c_{du}}} - \frac{1}{a_2^i} > 0 \tag{37}$$

$$r_i^* = \frac{b_1^i}{\sqrt{b_1^i a_2^i c_{su}}} - \frac{1}{b_2^i} > 0 \tag{38}$$

Thus, we must have

$$a_1^i \cdot a_2^i > c_{du} \tag{39}$$

$$b_1^i \cdot b_2^i > c_{su} \tag{40}$$

Meanwhile, only when the service user, the data provider and the service provider can obtain positive profit, they are willing to participate the market. At SPNE, the profit of each participator is:

$$\begin{aligned} p_{SU}^{i*}(n_i^*, r_i^*) &= a_1^i \ln(1 + a_2^i n_i^*) + b_1^i \ln(1 + b_2^i r_i^*) - r_i^* p_{su}^* - n_i^* p_{du}^* \\ &= a_1^i (\ln \sqrt{\frac{a_1^i a_2^i}{c_{du}}} - 1) + b_1^i (\ln \sqrt{\frac{b_1^i b_2^i}{c_{su}}} - 1) \end{aligned} \tag{41}$$

$$\begin{aligned} p_{DP}^*(n_i^*) &= a_1^i - \frac{p_{du}^* - c_{du}}{a_2^i} - \frac{a_1^i \cdot c_{du}}{p_{du}^*} \\ &= a_1^i + \frac{c_{du}}{a_2^i} - 2\sqrt{\frac{a_1^i \cdot c_{du}}{a_2^i}} \end{aligned} \tag{42}$$

$$\begin{aligned} p_{SP}^*(r_i^*) &= b_1^i - \frac{p_{su}^* - c_{su}}{b_2^i} - \frac{b_1^i \cdot c_{su}}{p_{su}^*} \\ &= b_1^i + \frac{c_{su}}{b_2^i} - 2\sqrt{\frac{b_1^i \cdot c_{su}}{b_2^i}} \end{aligned} \tag{43}$$

In the market, the profit has to satisfy $p_{SU}^{i*}(n_i^*, r_i^*) > 0, p_{DP}^*(n_i^*) > 0, p_{SP}^*(r_i^*) > 0$. Meanwhile, each service user is willing to buy the goods only when it can obtain positive profit from corresponding provider. Each term of $p_{SU}^{i*}(n_i^*, r_i^*)$ should be positive. Therefore, from (41)–(43) we have:

$$\begin{cases} a_1^i \cdot a_2^i > c_{du} e^2 \\ b_1^i \cdot b_2^i > c_{su} e^2 \\ a_1^i \cdot a_2^i \neq c_{du} \\ b_1^i \cdot b_2^i \neq c_{su} \end{cases} \tag{44}$$

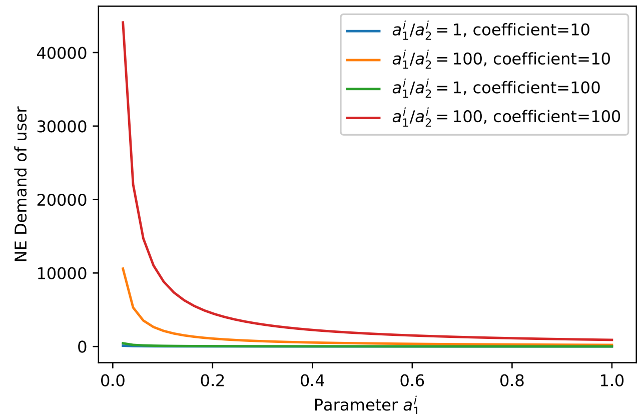

Fig. 2. Optimal demand of data unit under varied parameters. The coefficient is the ratio $a_1^i a_2^i / c_{du}$.

Combining the condition (44) with (39), (40), SPNE exits only when:

$$\begin{cases} a_1^i \cdot a_2^i > c_{du} e^2 \\ b_1^i \cdot b_2^i > c_{su} e^2 \end{cases} \tag{45}$$

In the case, the result follows.

From the above analysis it is concluded that the service user's utility function plays a significant role in the scenario. In the perfect information game, the parameters of the user's utility function and the unit cost of the provider jointly determine user's demands and participator's profit. In the following we will show their relationships via various experiments.

5. Numerical results

We conduct experiments to numerically evaluate the demand, the profit of the user, as well as the price and the profit of the data provider. We examine the performance under varied parameters. As the game is symmetrical design, i.e., the service provider and the data provider have the same form of the profit function, in the following we focus on the performance of the data provider. The service provider can obtain similar results.[1]

The user's demand n_i^* decreases as a_1^i increases, as Fig. 2 shows. The ratio a_1^i/a_2^i impacts the demand heavily. When a_1^i/a_2^i increases, the gain obtained by single data unit diminishes. In order to maximize its profit, the user has to buy more data. However, if the cost of per data unit of data provider is high, the user can obtain its NE point by shrinking the demand to minimize the user's cost.

Unlike the results in Fig. 2, the provider's price p_{du}^* increases as parameters a_1^i of user's utility function increases, as Fig. 3 shows. When a_1^i increases, the user's utility also increases when the same amount of raw data is bought. The user prefers to buy fewer data. To maintain a reasonable profit, the rise in price happens. Intuitively, the higher cost of per data unit increases provider's cost. Thus, the provider set a higher price to achieve the NE.

Fig. 4 reveals the relation between the NE price p_{du}^* of data unit and the NE demand n_i^* of service user. In the experiment $a_1^i a_2^i / c_{du} = 10$. Since the price quoted by the data provider

[1] The heterogeneity of the service providers (data provider) can be determined by the specified parameters. When we derive the Nash Equilibrium of the proposed game-theoretical framework, we use the completed information, which is a common-used assumption in related work. In the case, the Nash Equilibrium points can be achieved no matter what utility functions the participators choose, as the knowledge is available by the participators. Therefore, the market model be applied to the market where they are heterogeneous.

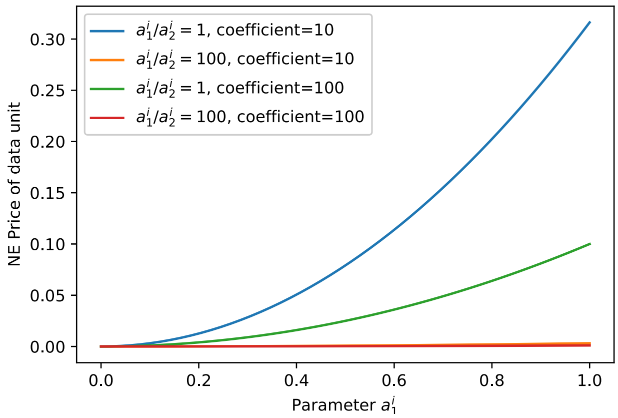

Fig. 3. Optimal price of data unit under varied parameters. The coefficient is the ratio $a_1^i a_2^i / c_{du}$.

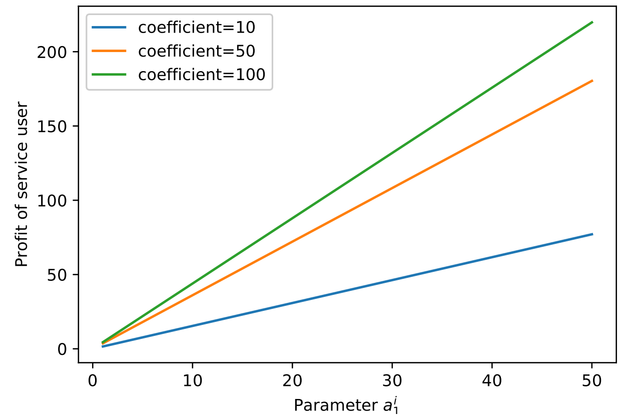

Fig. 6. Optimal profit of user under varied optimal price of data unit. The coefficient is the ratio $a_1^i a_2^i / c_{du}$, and $a_1^i / a_2^i = 1$.

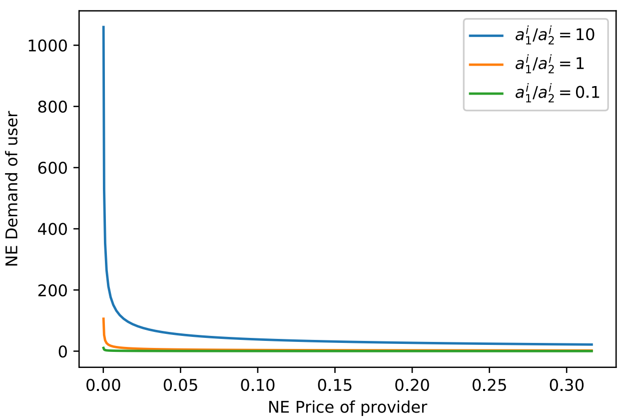

Fig. 4. Optimal demand of data unit under varied optimal price of data unit. The coefficient ratio $a_1^i a_2^i / c_{du} = 10$.

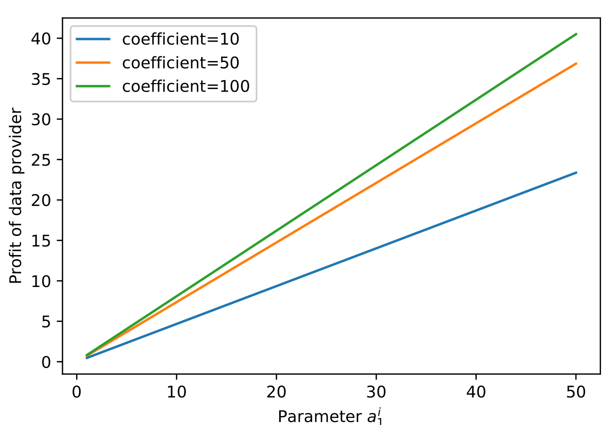

Fig. 5. Optimal profit of data provider from each user under varied parameters. The coefficient is the ratio $a_1^i a_2^i / c_{du}$, and $a_1^i / a_2^i = 1$.

increases, the demand decreases quickly. The demand becomes stable when the price $p_{du}^* > 0.05$.

Fig. 5 shows the profit of the data provider and Fig. 6 shows the profit of the service user. Note that the user's profit in Fig. 6 is the total profit that is obtained from the data provider and the service provider. It is found that both the user and the provider obtain an increasing profit as parameter a_1^i increases. Since a bigger a_1^i leads to a higher utility of the user. The user is willing to buy more data to maximize its profit. The provider also obtain the benefits as the user can tolerate higher prices due to bigger utility parameters. If the cost of per data unit that the data provider consumes is minimized, the provider and the user can improve their profit. Both Figs. 5 and 6 support the results.

6. Conclusion

IoV generate a lot of data every data. However, data does not equal to information. How to extract useful information from the data is a challenging task. Deep learning succeeds in many applications recently. It shows its power in learning the representations of the raw data. In the paper we study deep learning enabled IoV services. The economic aspect of IoV data is investigated. We consider the scenario where the data provider, the service provider and the user are responsible for generating the raw data, providing the data service via deep learning models, and buying the data and the service, respectively. As each participator wants to maximize its own profit, they have conflicted interests. A game theoretical framework is proposed to characterize the interaction among these participators. Specially, the proposed Stackelberg game consists of two stage. In the first stage, there is a non-cooperative game where the data provider and the service provider decide the price of the data and the service. In the second stage, the user determines the demand of service units and data units to maximize the profit. Via game-theoretical analysis, we show that the proposed game-theoretical framework drives each participator to choose the equilibrium strategy. Therefore, the optimal profit is achieved.

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