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Good drivers pay less: A study of usage-based vehicle insurance models

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ABSTRACT

Usage-based insurance (UBI) has been attracting more and more attention; however, two open research questions are how behavioral data of drivers affects driving risk and how driver behavior should affect UBI pricing schemas. This paper proposes a driver risk classification model to evaluate the risk level of drivers based on in-car sensor data. A Behavior-centric Vehicle Insurance Pricing model (BVIP) and a vehicle premium calculation prototype are developed in this paper. Based on empirical data, our research results show that BVIP achieves better accuracy in terms of risk-level classification and the prototype achieves good performance in terms of effectiveness and usability.

1. Introduction

In recent years, a noticeable trend of data-driven business service in vehicle insurance and transportation industry is Usage-Based Insurance (UBI). Numerous business opportunities and service modes are created because companies could get access to individual behavior data (Miah et al., 2017). Vehicle insurance pricing (premium) is known as the amount of money that an insurant must pay for an insurance policy of vehicle travel. Basing premiums on "how much you drive", UBI premium would be transferred from annual costs to variable charges such as miles and other driving behavior variables. It allows an insurance company to accurately target discounts at careful drivers and charge more aggressive customers an appropriately higher amount based directly on how much the vehicles are driven during the lifetime of an insurance policy (policy term). Information Technology (IT) provides facilities for collecting instantaneous driving data and calculating various driving indicators through on-board diagnostics (OBD) and online vehicle network platform (Baecke and Bocca, 2017; Baek and Jang, 2015). The real-time vehicle related parameters and driving information data can be uploaded by OBD to the vehicle network platform. Specifically, IT extends the individual vehicle insurance pricing indicators from traditional factors (e.g., age, gender and auto purchase price) to new driving factors like mileage-per-trip and driver habits. Such an approach changes the existing business model of vehicle insurance that lower-risk drivers pay less and higher-risk drivers pay more for their auto insurance (Litman, 2005).

UBI is now changing the incumbent business model of vehicle insurance. Traditional insurance and actuarial science has estimated individuals' driving risk based on driver-related personal information. Studies showed that demographic variables (such as age, gender) and personalities have significant impacts on driving risk and insurance pricing (Guo and Fang, 2013; Litman, 2005; Miyajima et al., 2007). However, driving behaviors are also powerful predictors for assessing individual driving risk. Automobile insurance companies have been trying for years to convince customers to pay premiums based on their driving behavior; however

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such programs are still not widely used. According to Boulton's report, people have questions like "Does the pricing model of UBI lower premiums logically?" "Will premiums increase if insurance companies know too much about them?" (Boulton, 2013). Therefore, insurers and researchers are still trying to find an appropriate path for UBI. Currently, basic usage-based premiums are calculated by dividing existing premiums by *pay as you drive* and *pay how you drive*, offered by Metromile and Progressive companies, respectively. These two insurance programs have emerged in the US, and a couple of case studies have examined these models for premiums. For instance, Desyllas and his colleagues discuss an example of how firms can profit from business model innovation using the prominent case of PAYD auto insurance (Desyllas and Sako, 2013). Unfortunately, few statistics are provided in these studies that identify factors associated with individual driving risk and help predict high-risk drivers. In prior papers, most of the chosen driving features (e.g., demographic data, mileage and time) were too general to capture driving risk. In fact, companies have been trying to collect and take advantage of big data in the changing and competitive business environment (Jukić et al., 2015). For UBI research, much of the available influential vehicle sensor data and indicators are still unemployed.

The **key research question** in this research is *how to utilize massive behavior data to offer assistance for making personalized UBI pricing strategy*. It is noted that factors of personalized driving behavior are strongly correlated with the driver's traffic accident rate. Hence, a novel behavior-centric insurance model should be developed and applied to complete UBI studies as Paefgen et al. (2013) indicated in his research.

Nevertheless, how to develop a personalized vehicle premium model according to the driving behavior data is one of the open research issues for UBI research. To fill this research gap, this research proposes a behavior-centric pricing mechanism for vehicle insurance and strives to develop novel features for UBI pricing. One important advancement of this study is to utilize supervised machine-learning approach to train the risk-level classification model with relevant sensor features and extend the existing research scope of usage-based insurance by designing a differential behavior-centric pricing mechanism based on in-car sensor data. The study also adds practical insights on UBI business via a down-to-earth demonstration. The premium calculation prototype shows potential practical value for organizations and companies to exploit UBI related business.

This study is organized as follows. In Section 2, we review the literature on user behavior variables, risk-level classification models and insuring pricing methods. A behavior-centric vehicle insurance pricing model is proposed in Section 3. Section 4 describes a prototype for vehicle premium calculation. The validity of the risk-level classification model and the prototype are evaluated in Section 5. Section 6 summarizes contributions of this study and outlines future work.

2. Literature review

2.1. Development of UBI premium strategies

Conventional vehicle insurance premium is established through an actuarial rating. Insurance companies use actuarial science to quantify the risks based on the policyholder's basic information such as type of car owned, age and gender (Azzopardi and Cortis, 2013). The conventional vehicle insurance is inefficient and inequitable because it ignores the differential driving behavior of drivers. Drivers who are similar in age, gender and automobile price may pay nearly the same premiums no matter how and how often they drive.

Usage-based insurance premium as a business pricing strategy was first introduced in 1994 at Progressive. The built-in telematics devices with GPS enabled tracking vehicle routing and emergency response. Progressive modeled premiums by combining factors of speed, location, mileage and time when driving occurred (Desyllas and Sako, 2013). The new usage-based model offered various benefits to both customers and insurers. Past studies proposed variant forms of usage-based premium options. Paefgen et al. (2013) treated mileage as a most important rating factor into the insurance premium model. It is the simplest option to implement but is constrained by the weight that can be placed on self-reported mileage estimates. Around that time, another method, *Pay-at-the-Pump* (Sugarman, 1994), funded basic insurance coverage through a surcharge (about 50 cents per gallon) on fuel sales (Litman, 2007). Efficient management of fuel sales is a critical issue in vehicle related industry (Suzuki, 2009). However, this model is less popular nowadays because the payments of this model are only based on vehicle fuel consumption and do not incorporate risk factors into the existing premium option. A premium model called *Per-Mile Premiums (PMP)* (Butler, 1993; Ferreira and Minikel, 2012) changes the unit of exposure from the vehicle year to the vehicle miles or kilometers. Drivers should pay their insurance premium based on the distance they drive. The mileage-based *PMP model* significantly improves actuarial accuracy since odometer audits provide more accurate mileage data than the self-reported methods. Prior studies showed that *PMP* has a different financial impact on different customer segments. *PMP* provides significant consumer savings, particularly to younger drivers and lower income households. *Per-Minute Premiums* is a similar approach. It uses a small electronic device to calculate the minutes of vehicle operation as the unit of exposure (Litman, 2007). The Per-Minute model allows insurance premium rates to vary by time of day. For instance, if drivers avoid peak-period travel, they can reduce their insurance premiums. So drivers can adjust their driving patterns in order to receive an extra incentive. Another method is called *GPS-Based Pricing* (Bomberg et al., 2009). It calculates insurance premiums based on when and where driving occurs. An in-car sensor installed on the vehicle could track the related rating factors. In this case, users can monitor their driving pattern using GPS data or vehicle routing systems (Santos et al., 2011), and insurers can improve the accuracy of their insurance premiums with such data.

The most recent approach is *Pay-How-You-Drive* premium. It has already been recognized as the most promising differentiated commercial vehicle insurance premium strategy in UBI (Nai et al., 2016). Because the premium is calculated based on driving patterns, the Pay-How-You-Drive vehicle premiums become more personalized. Therefore, driving behavior indicators have drawn many researchers' attention, such as speed violations (Lahrmann et al., 2012), experience (Aseervatham et al., 2016) and driving time