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A Text Analytics Framework for Performance Assessment and Weakness Detection From Online Reviews

Amit Singh, Indian Institute of Technology Jodhpur, India*
Mamata Jenamani, Indian Institute of Technology, Kharagpur, India
Jitesh Thakkar, National Rail and Transportation Institute, Vadodara, India
Yogesh K. Dwivedi, Swansea University, UK

ABSTRACT

The present research proposes a framework that integrates aspect-level sentiment analysis with multi-criteria decision making (TOPSIS) and control charts to uncover hidden quality patterns. While sentiment analysis quantifies consumer opinions corresponding to various product features, TOPSIS uses the sentiment scores to rank manufacturers based on their relative performance. Finally, U and P control charts assist in discovering the weak aspects and corresponding attributes. To extract aspect-level sentiments from reviews, the authors developed the ontology of passenger cars and designed a heuristic that connects the opinion-bearing texts to the exact automobile attribute. The proposed framework was applied to a review dataset collected from a well-known car portal in India. Considering five manufacturers from the mid-size car segment, the authors identified the weakest and discovered the aspects and attributes responsible for its perceived weakness.

KEYWORDS

Artificial Intelligence, Automobile Industry, Consumer Review, Control Charts, Defect Discovery, Ranking, Reviews, Sentiment Analysis, Text Mining, TOPSIS, User-Generated Content, Weakness Detection

INTRODUCTION

Products such as automobiles may have both safety and performance defects. Government regulations and exposure to severe brand-value and financial losses compel manufacturers to be pro-active in detecting and eradicating safety defects. Traditionally, safety defects are identified through process improvement tools and service center feedbacks. Such approaches not only suffer from high cost, and incomprehensiveness; their applicability is limited in the case of performance defects (Law et al., 2017; Liu et al., 2018). In this regard, massive product review data generated from the web has turned out to be an important source to comprehend user experiences, reactions, and perceptions. While prospective consumers use them to analyse the peers' experience with the product, the organizations mine it to identify user requirements and expectations (Singh et al., 2020). However, it is beyond

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human cognition to scan the available reviews manually, summarize them, and use them for sensible decision making.

In this regard, artificial intelligence in general (Dwivedi et al., 2019; Grover et al., 2019; Dwivedi et al., 2020 Stieglitz et al., 2020) and sentiment analysis (SA) in particular has emerged as a tool to mine information from text. Its usefulness is well tested and validated in domains such as product promotions and marketing (Ting et al., 2014), demand and sales forecasting (Archak et al., 2011; Chong et al., 2017; Geva et al., 2013; Hou et al., 2017; Zhang et al., 2020), supply-chain performance evaluation (Swain & Cao, 2019), and product quality assessment (Abrahams et al., 2015; Law et al., 2017). Specifically, it assists the businesses in decision making in automotive industry (Abrahams et al., 2012, 2013, 2015; Gruss et al., 2018) electronic products (Abrahams et al., 2015), dishwasher appliances (Law et al., 2017), body wash products (Zhang et al., 2012), entertainment industry (Chintagunta et al., 2010; Yang & Chao, 2015) travel industry (Chang & Chen, 2019; Choi & Lee, 2017; Sann, & Lai, 2020), and the toy industry (Winkler et al., 2016; Saumya et al., 2019). However, there has been almost no effort to connect these results with traditional quality-control tools with which the manufacturing community is acquainted. Moreover, most of such studies focus on document or sentence level. More recently, aspect-level sentiment analysis (ASLSA) has emerged as a tool to identify product defects, more precisely targeting specific attributes and context (Schouten & Frasincar, 2016). In this research, the authors have contributed to this growing field by proposing an integrated automobile-defect detection framework that connects ASLSA with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and traditional quality-control tools. The framework answers following research questions:

RQ1: What are the important product features, which customers frequently discuss in online reviews?
RQ2: How feature level consumer sentiments be used to quantify manufacturers' perceived performance rating?
RQ2: Are review embedded consumer sentiments useful in discovering products' perceived weakness?

The proposed framework consists of three phases. In *Phase-I*, the authors extract attribute-level consumer sentiments indices for specific car aspects. The authors define aspects with various systems and subsystems of a car, and attributes to the more specific parts, features, or service of the system under consideration. For example, regarding *EXTERIOR* as an aspect, the authors can consider *bumper* as an underlying attribute. In *Phase-II*, the TOPSIS, a multi-criteria decision-making tool, compare extracted sentiments to compute manufacturers' relative performance index. Traditionally, TOPSIS requires inputs from experts. In this research, expert inputs are replaced by the sentiments scores mined from reviews. In this phase, the authors compute a performance score for each manufacturer based on overall consumer perception, from which a manufacturer could find its perceived performance in the market. In *Phase-III*, the authors use control charts, the *U*-chart at the aspect level, and the *P*-chart at the attribute level, to discover the reasons for performance degradation. This discovery gives the manufacturer an opportunity to identify the reasons for consumer dissatisfaction and take action accordingly. The authors apply the framework to a review dataset from a car portal in India, compare the manufacturers within a car segment, and identify the worst-performing manufacturer. In addition, the authors delve into the data to find the reasons for performance degradation.

The contributions of this research are as follows. *First*, the authors have proposed a passenger car aspect ontology consisting of 16 aspects at the system level and 15 at the subsystem level. *Second*, a heuristic for attribute-level sentiment index generation has been proposed, which differs from contemporary approaches such as (Hu & Liu, 2004; Moghaddam & Ester, 2010), in the way opinion-bearing words are connected to the exact target attribute. Specifically, the proposed heuristic splits the sentences with more than one attribute into a number of sub-sentences, each containing one attribute and corresponding sentiment phrases. The proposed heuristic has also been vetted using human annotators. *Third*, to the authors' best knowledge, the this is the first attempt to integrate