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Pattern classification driven enhancements for human-in-the-loop decision support systems

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ABSTRACT

Data mining has been a key technology in the warranty sector for mass manufacturers to understand and improve product quality, reliability and durability. Cost savings is an important aspect of business which calls for processes that are error proof. Pattern classification methods applied to the diagnostic data could help build error proof processes by improving the diagnostic technology. In this paper we present a case study from the automotive warranty and service domain involving a human-in-the-loop decision support system (HIL-DSS). The automotive manufacturers offer warranties on products, made of parts from different suppliers, and rely on a dealer network to assess warranty claims. The dealers use diagnostic equipment manufactured by third parties and also draw on their own expertise. In addition, a subject matter expert (SME) assesses these collective decisions to distinguish between inaccurate diagnoses by the dealers or an inadequate decision algorithm in the diagnostic equipment. Altogether this makes a comprehensive HIL-DSS. The proposed methodology continuously learns from collective decision making systems, enhances the diagnostic equipment, adds to the knowledge of dealers and minimizes the SME involvement in the review process of the overall system. Improving the diagnostic equipment helps in better warranty servicing, whereas improvements in the human expert knowledge help prevent field error and avoid customer dissatisfaction due to improper fault diagnosis.

1. Introduction

There are different kinds of decision support systems (DSS) — model driven, communication driven, data driven, document driven and knowledge driven [23]. Knowledge is gathered over time. It plays a crucial role in the decision making process. There are many ways of designing the DSS, namely — to incorporate all the possible factors under consideration which in real life can make the system very complicated. Realistically, only quantifiable factors can be easily incorporated into the DSS and there is less possibility for the DSS to learn new information and update automatically. This suggests the DSS' limitations and incompleteness. Human experts on the other hand, can learn and use the knowledge gained to make decisions even based on factors that cannot be easily incorporated algorithmically. For instance, let us consider a scenario where human experts use limited/incomplete DSS to make actionable decisions but not blindly follow them, i.e. the humans use their expertise on top of the DSS to make the final decision. This limited/incomplete DSS plus the human expertise (which can be a representation of a knowledge driven DSS) forms a comprehensive system that we call a human-in-the-loop decision support system (HIL-DSS). Decisions made this way are quite common in real life setup, e.g. warranty and service domain and air traffic management [28].

In this paper, we will demonstrate the enhancements to the HIL-DSS using the warranty and service domain as an example. The warranty space is a complex and sensitive structure in the view of the manufacturer because it needs special handling to take into account the customer priority first and still maintain profitability. In such a case, there are several factors that need to be considered while designing the DSS. As an illustration, if we consider the automotive warranty domain, manufacturers define service procedures, provide diagnostic testing tools and train the dealers to provide service support to the customers. In modern vehicles, many diagnostic sensors are also inbuilt in the car to comply with government regulations [2]. These regulations are focused towards customer safety and environmental concerns. For parts like battery, air conditioning system and others, manufacturers depend either on built-in sensors [32] or on commercial testing equipment. For the latter, manufacturers choose testers [8,19] that satisfy their criteria and provide requirements to the tester-OEM (original equipment manufacturer) to adapt them to suit their needs. These testers are then deployed in the field and dealer technicians are instructed to take appropriate action as per the tester outcomes. In the process,

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diagnostic data measured by the testers pertaining to repairs performed by the dealer technicians are mandatorily collected as part of the warranty claims. With high warranty costs, the manufacturers are apprehensive about many of the claims but they are restrained towards actions. The reason is two-fold — 1) the nature and large volume of claims that they cannot verify; and 2) the lack of adequate proof to back their apprehension. The incorrect/incomplete data provided by the dealers towards the claims usually adds to the confusion. More importantly, the manufacturer too may not know about all the factors that need to be collected in order to assess the correctness of the diagnosis and take subsequent action on every claim. Needless to say, understanding the completeness of the data collection is a continuous learning process.

Fig. 1, shows the current HIL-DSS used in the automotive warranty space. The various components involved in the HIL-DSS are described as follows:

- Scenario: The vehicle encounters a problem that requires it to be brought to the dealer for repair. A "scenario" is a representation of the failure.
- DSS: The diagnostic tester is the DSS used by the dealer for the assessment of the failed component in a given scenario.
- Human expert: The dealer technician, or the human expert, takes the liberty to take appropriate action based on his/her experience and does not rely entirely on the tester outcome. Although, the decisions through the human expertise and knowledge are expected to enhance the DSS, it also leaves an opportunity for field errors to prevail.
- Subject matter expert: Humans with in-depth knowledge of the domain. These subject matter experts (SMEs) are capable of reviewing decisions made by the DSS or the human expert and recommend enhancements/improvements in the two (human knowledge or diagnostic tester algorithm).

Here it is important to stress the difference between the human experts and the subject matter experts. Human experts are part of the dealer network and make decisions on every scenario, while subject matter experts are part of the manufacturers who review those decisions made by the DSS and the human experts on a conditional basis.

In the current setup, both the DSS and the human expert can benefit from the decisions made by the SME. However, the large volume of claims prohibits a comprehensive SME review. In this paper, we present a novel approach based on pattern-classification to — 1) continuously learn from collective decision making systems; 2) enhance the limited/incomplete DSS; 3) add to the knowledge of human expertise; and 4) minimize the SME involvement in the review process of the overall system. A detailed description of various steps involved in our methodology is presented in Sections 4 and 6.

In brief, though the manufacturers provide requirements to the tester-OEM and the tester is modified to suit them, in the real world, the algorithm of the tester is not shared because of intellectual property issues. The absence of the tester algorithm adds to the difficulty of the subject matter experts in assessing the correctness of the claim outcomes. To overcome this, we fuse the tester outcomes

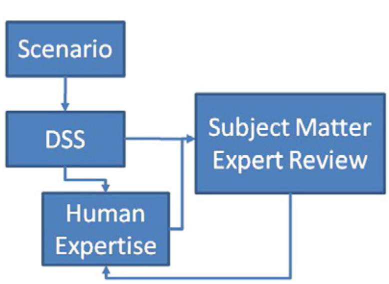

Fig. 1. The current human-in-the-loop DSS used in automotive warranty space.

with the human decisions and assume high confidence on the decisions being correct when they match. Pattern classification techniques [6,25] can be used to learn the underlying model from this agreement data. Outcomes from the learnt model on the disagreement data enables the manufacturers to (through a process of SME review):

1. Request modification of current DSS algorithm or inclusion of new features to enhance the limited/incomplete DSS.
2. Train the human experts using the knowledge gained from this learning for better field decision making.

To emphasize, the SME involvement in the overall process is reduced significantly as s/he is required to assess only the disagreement scenarios. The rest of the paper will focus on elaborating the methodology and present results based on a case study from the automotive domain. It is organized as follows. The following section discusses the motivation for this work, followed by a discussion on the related literature in Section 3 that the work builds on. Section 4 describes the proposed methodology for pattern classification driven enhancements for HIL-DSS. Section 5 describes an automotive warranty space case study in detail. Following this, the results are discussed in Section 6 and conclusions are drawn.

2. Motivation

Warranty is an integral part of any product these days. For "specialty products" which undergo a lot of scrutiny by the customers before the purchase [1], warranty assumes even greater importance. Better warranty signals better product quality and provides assurance to the customers. This drives manufacturers to follow the mantra of quality, reliability and durability. In spite of extensive testing, failures do happen (in accordance to the product reliability) and warranty provides coverage against these failures for a specified amount of time/usage.

Product reliability is influenced by decisions made during the design and manufacturing phase of the product life-cycle [20,21]. In a domain such as automotive, the product reliability is dependent on various parts obtained from different suppliers, and warranty coverage is based on individual reliability information for the supplied parts. When a vehicle comes for a repair, the importance of proper diagnosis of the part failure cannot be over-emphasized. It is crucial for the following reasons:

1. It enables better warranty servicing, thereby results in customer satisfaction. It further enhances the brand image of the product.
2. It keeps the warranty cost low by avoiding repetitive failures.
3. It provides the manufacturer the crucial failure data to learn and adapt its warranty strategy.

While diagnosing a part failure there can potentially be two kinds of errors:

False negatives — Failure to diagnose faulty part. Diagnosing faults efficiently by keeping false negatives minimal is a crucial part of service performance. These have a negative influence on the brand image which impacts sales and revenue due to customer dissatisfaction.

False positives — Erroneous classification of a good part as faulty. False positives add to the warranty cost and product wastage results in environmental damage.

The limitations in the diagnostic procedure result in false negatives. False positives, however, may have other reasons – firstly, to keep the service performance high in the eyes of the customer, the diagnostic thresholds that qualify a part as faulty are set relatively wide, meaning – a few good parts are also diagnosed faulty and