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Fixing shelf out-of-stock with signals in point-of-sale data

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A R T I C L E I N F O

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A B S T R A C T

Shelf out-of-stock (*OOS*) is a salient problem that causes non-trivial profit loss in retailing. To tackle shelf-OOS that plagues customers, retailers, and suppliers, we develop a decision support model for managers who aim to fix the recurring issue of shelf-OOS through data-driven audits. Specifically, we propose a point-of-sale (POS) data analytics approach and use consecutive zero sales observations in POS data as signals to develop an optimal audit policy. The proposed model considers relevant cost factors, conditional probability of shelf-OOS, and conditional expectation of shelf-OOS duration. We then analyze the impact of relevant cost factors, stochastic transition from non-OOS to *OOS*, zero sale probability of the underlying demand, managers' perceived *OOS* likelihood, and even random fixes of shelf-OOS on optimal decisions. We also uncover interesting dynamics between decisions, costs, and probability estimates. After analyzing model behaviors, we perform extensive simulations to validate the economic utility of the proposed data-driven audits, which can be a cost-efficient complement to existing shelf inventory control. We further outline implementation details for the sake of model validation. Particularly, we use Bayesian inference and Markov chain Monte Carlo to develop an estimation framework that ensures all model parameters are empirically grounded. We conclude by articulating practical and theoretical implications of our data-driven audit policy design for retail managers.

1. Introduction

The retail store is the last mile of supply chain management and error-free store execution ensures that the collective efforts of the whole supply chain pay off. Store execution primarily involves moving goods from the backroom to the shelves such that products are available to end consumers (Zondag & Ferrin, 2014). However, in-store logistics are highly labor-extensive and hence store execution is prone to various errors such as shrinkage, misplacement, and faulty transactions (Chuang & Oliva, 2015). Among documented symptoms of poor store execution, shelf out-of-stock (shelf-OOS) is a major problem and refers to the case that an item is in-store (e.g., misplaced or stored in the backroom) but it is unavailable to customers (Papakiriakopoulos, Pramatari, & Doukidis, 2009; Ton & Raman, 2010). The retail giant Walmart recently admitted to a shelf-OOS problem and predicted a $3 billion opportunity in filling in empty shelves caused by ineffective auditing and re-shelving operations (Dudley, 2014). Walmart even issued an urgent memo that demands store managers to improve grocery performance, which was seriously compromised by non-negligible shelf-OOS ratios (Greenhouse & Tabuchi, 2014).

To solve the shelf-OOS problem that plagues end customers, downstream retailers, and upstream suppliers, store managers oftentimes ask store employees to perform shelf audits and fill inventory on the shelf. The timing of shelf audits hence has substantial influence on product availability, customer satisfaction, and sales performance (Aastrup & Kotzab, 2010). Therefore, numerous cost-minimization policies have been proposed to assist shelf audit decisions. However, those policies often have one/multiple partially observed state variables (e.g., number of periods or transactions since last audit, shelf inventory level), which may undermine their practical applicability. In this study, we propose a point-of-sale (POS) data analytics approach to shelf audit policy design. Our decision support model is independent of any particular type of shelf inventory replenishment policies and exclusively based on POS data. Being widely available, POS data is reflective of customer demand subject to erroneous store execution. Some retailers have strived to estimate *OOS* rates from POS data (Gruen & Corsten, 2008). In the age of data analytics, this data-driven modeling choice is deliberate and ensures that the proposed policy is easy-to-implement.

Specifically, we keep track of unlikely events (probabilistic anomalies) in POS or scanned sales data as departures from normal operations and initiate an intervention in a cost-efficient way. In the context of retail operations, z signals, i.e., consecutive zero sales in POS data, are deemed as probabilistic anomalies and strong indicators of shelf-OOS. The use of consecutive zero sales as signals to trigger shelf audits has been proven useful in prior

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studies (Chuang, Oliva, & Liu, 2016; Fisher & Raman, 2010). Some manufacturers even infer that if a key item has no selling records during a time interval, chances are that the item is not on the retail shelf (Zondag & Ferrin, 2014). In this paper, we develop data-driven models that explicitly account for the fact that an observed zero sale for an item might be attributed to its underlying demand variation or caused by shelf-OOS. Given the realization of z signals, we derive the conditional probability of shelf-OOS and the conditional expectation of shelf-OOS duration. The derivation considers underlying drivers of observed zero sales, accounts for managers' estimate of *OOS* likelihood, and serves as the core of our data-driven audit policy.

Even though it is possible to include extra state variables such as system inventory records in the model, inventory records in the retail sector are largely erroneous (DeHoratius & Raman, 2008). The proposed policy focuses on maintaining shelf inventory availability and avoids the use of shelf inventory as a state variable, which requires retailers to differentiate shelf inventory records from backroom inventory records. Doing so would increase data requirements and data collection efforts. In fact, data errors are too common to lead to poor decisions as decision makers do not know how much inventory they actually have (Cachon, 2012). Even the item-level RFID does not guarantee full inventory visibility as tag readers (that are imperfect) would result in erroneous shelf inventory records. However, without detecting shelf-OOS caused by execution errors such as shrinkage and misplacement, retailers will not be able to replenish empty shelves and mitigate lost sales even when the backroom capacity is sufficient.

All the afore-mentioned issues create challenges for operations researchers to develop simplistic yet applicable audit policies. Hence, for practical considerations we design the audit policy exclusively based on z signals (i.e., consecutive zero sales) that are distribution-free and fully observable in POS data. After deriving the audit policy, our analysis enables retail managers to better understand the impact of probabilistic factors – stochastic transition from non-*OOS* to *OOS*, zero sale probability of underlying demand, and managers' perceived *OOS* likelihood – on audit decisions. We also uncover interesting interactions between the probabilistic factors and other factors (e.g., sales potential, cost). Further, we conduct simulation experiments to show the applicability and validate the utility of the POS data analytics approach. Extensive simulations uncover scenarios where data-driven shelf audits can effectively improve cost performance and complement existing shelf control systems that are prone to unobservable shelf stock loss. Particularly, simulation results suggest that when demand (and hence shrinkage) rates increase, shelf audits driven by z signals enable retailers to achieve significantly lower system costs.

While our paper is not the first in the literature that proposes decision support models for retail shelf audits, our study contributes to retail operations in two major ways. First, in line with Fisher and Raman (2010) and Chuang et al. (2016), we use the number of consecutive periods of zero sales as the state variable in our model. We improve their work by explicitly accounting for potential causes (i.e., demand variation or shelf-OOS) of realized zero sales, relevant cost factors, and intrinsic sales potential. Moreover, we incorporate the rarely studied random fixes into our model. This non-trivial relaxation of modeling assumptions reveals intricate dynamics of policy behaviors that are attributed to the chance of random fixes and carry important implications for shelf audit decision-making processes. By doing so, we come up with a probabilistic audit policy that is cost-sensitive and more comprehensive. Second, our POS data analytics approach avoids peculiar assumptions and utilizes scanned sales observations that are readily available to retailers. We further develop estimation techniques for key model parameters using maximum likelihood approaches and Bayesian inference with Markov chain Monte Carlo methods. The nature of Bayesian update also addresses the potentially non-stationary transition matrices in our models. Unlike studies that propose decision support models without showing how to estimate model parameters, our estimation framework ensures that audit decisions are empirically grounded.

The rest of the paper is organized as follows. Section 2 provides a succinct summary of relevant literature. Section 3 presents the design of a POS data-driven shelf audit policy and analyzes behaviors of the proposed policy. Section 4 incorporates random fixes of shelf-OOS into our policy design and sheds light on the impact of random fixes on audit decisions. Section 5 reports a simulation study that quantifies the cost-effectiveness of the proposed model. Section 6 presents primary tasks involved in model validation and estimation. We conclude by discussing key implications of our modeling effort.

2. Related literature

Inventory audits are deemed effective for elevating inventory integrity and product availability, both of which lead to better services and sales (Chuang et al., 2016). Prior studies have developed various *cost-minimization* decision support models under different types of inventory operations. Despite their differences in assumptions and settings, the common objective of those models is to determine the *optimal timing* of inventory audits. Given a re-stocking policy, Iglehart and Morey (1972) propose a cycle-count model that determines frequency and depth of inventory audits. In a similar vein, Kumar and Arora (1992) and Sandoh and Shimamoto (2001), develop models to find optimal frequencies of stock audits based on exponential inter-arrival time of inventory errors. Moving beyond optimal cycle-counting, Kok and Shang (2007) propose a joint audit and replenishment policy. While afore-mentioned studies model errors that cause *OOS* as random variables, DeHoratius, Mersereau, and Schrage (2008) take a step forward and apply Bayesian inference to construct probability distributions of inventory level. Using Bayesian inventory records, they develop an inventory audit policy based on expected value of perfect information. Different from above studies on the timing of *internal* audits (from retailers' perspectives), Chuang (2015) develops a periodic inventory audit policy for *external* service providers, who (unlike retailers) have limited/no access to inventory/sales information except audit reports. Quantifying the impact of unobserved human errors on optimal audit timing also distinguishes his model from others.

Nearly all foregoing studies on audit policy design do not differentiate store-OOS from the focal issue shelf-OOS in our study. Store-OOS (i.e., zero inventory holdings in both backroom and shelf) requires placing orderings to upstream suppliers, whereas shelf-OOS is more related to in-store logistics (Chuang et al., 2016). Also, prior literature tends to view inventory level as a whole. However, in the retailing sector, store inventories for SKUs are typically composed of backroom and shelf inventories. Most retailers keep track of their inventories at the store level (i.e., the sum of backroom and shelf), but do not know the exact amount of items on the shelf (Condea, Thiesse, & Fleisch, 2012). Consequently, it is common for "freezing" to take place in error-prone store operations (Kang & Gershwin, 2005). That is, even though retailers have abundant backroom inventory, they fail to detect shelf-OOS based on z signals and fill empty shelves before the next auditing and shelving. Our model is unique in that it is designed as a complement to retailers' existing shelf inventory audit and replenishment (rather than store-level inventory governed by automatic store replenishment). The POS data-driven audit initiatives are aimed to mitigate the "freezing", such that on-shelf availability can be maximized and lost sales can be reduced.

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