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Decision Support

Analyzing operational risk-reward trade-offs for start-ups

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ABSTRACT

In many managerial situations it is important to consider both risk and reward simultaneously. This is a challenging task using standard techniques that are applied for solving sequential stochastic optimization problems since these techniques are designed to consider only one objective at a time—either maximizing reward or minimizing risk. In applications such as operational decisions for start-ups, this can be particularly restricting, since managers need to make trade-offs between profitability driven growth and the risk of bankruptcy. We extend in several ways prior work that has addressed the inventory issue for start-ups to minimize the risk of bankruptcy. The primary contribution of this paper is to present a novel approach to track mean as well as variance of a set of policies in a dynamic stochastic programming model and using the mean-variance solutions in a simple heuristic for creating efficient risk-reward frontiers. This is a challenging task from an implementation standpoint, since this requires carrying information on both risk and reward simultaneously for each state, which standard stochastic programming solution methods are not designed to do. We also illustrate the use of our methodology in a richer model of start-up operations where, in addition to inventory issues, advertising decisions are also considered.

1. Introduction

Start-ups are critical to the economic well-being of a nation. They are newly created firms that are in a phase of development and growth. Often start-ups act as incubators of new technology and innovation. They also contribute immensely in job creation. According to data from the Kauffman Foundation and the US Census Bureau (Weitekamp & Pruitt, 2009), without the jobs start-ups create, yearly employment growth would be negative. However, the startling reality about start-ups is that more than 50 percent of all new ventures fail within the first five years of inception (Shane, 2008, 2012; US Bureau of Labor Statistics, 2010). Start-ups often lack vital resources and have to compete against established companies for market share. These capital-constrained firms face challenges that are quite distinct. Thus, it is imperative to identify strategies that assist these start-ups in sustaining their growth endeavors.

Archibald, Thomas, Bates, and Johnston (2002) addressed the inventory issue for start-ups, and the importance of synchronizing inventory decisions with cash on hand to avoid bankruptcy. In this paper, we extend this work in several ways. We focus on two other extremely important operational issues for a start-up, namely the importance of risk-reward tradeoffs, and the need for them to consider both inventory and advertising decisions simultaneously. Most models in literature optimize for one decision alone—either maximize reward (most models) or minimize bankruptcy risk (as done by Archibald et al., 2002). Considering risk and reward simultaneously makes solving these problems by techniques used for solving sequential stochastic optimization problems very difficult. Modeling the problems using mathematical programming in the standard portfolio optimization way of minimizing risk subject to some level of reward is also not practical here because these dynamic and stochastic problems can become extremely large very quickly as there could be innumerable states traversed by the problem based on the actions sets and probability branches. In any real-life problem involving several stages with considerable number of possible actions and probability branches at any stage, the problem size grows exponentially. Therefore, the primary contribution of this paper is to present a simple way of tracking both risk and reward in a stochastic programming framework and creating efficient frontiers based on the risk-reward solutions. This is a challenging task from an implementation standpoint, since this requires carrying information on both risk and reward for each state, and standard solution methodologies such as dynamic programming carry only one piece of information, either risk or reward on the basis of which the functional value is computed. The extension of Archibald et al. (2002) to include consideration of advertising is an important secondary contribution.

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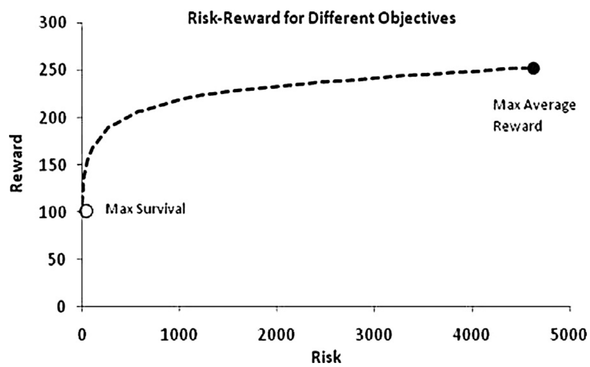

Fig. 1. Risk-return for optimal policies under different objectives.

Risk exposure is a critical aspect of start-up operations. For start-ups the risk of bankruptcy is a reality. Without strong financial controls supplementing growth, start-ups often lose their foundation and are left on shaky grounds. Often managers tend to focus just on the expected returns of a set of decisions ignoring the associated risks. It is critical to look beyond the expected returns of a set of decisions and weigh the variability induced by the outcomes. Maximizing profits can lead to outcomes with high variability that can be unacceptable to a risk-sensitive decision maker. On the other hand, being too conservative can also be dangerous for the profitability of the firm. Archibald et al. (2002) hypothesize that start-ups maximize the probability of their survival rather than their profitability. Survival is no doubt an important objective for a start-up. However, maximizing survival probability might be too conservative from the start-up's perspective and it might forego certain growth opportunities which can hurt the firm adversely. In our analysis, we focus not only on the expected profitability of the optimal inventory and advertising decisions but also explore the risks involved in those decisions.

We define risk as the variability associated with the outcomes of each of the policies and measure risk by the variance of the possible outcomes. Variance of the outcomes about the expected value is a widely used measure of risk in portfolio theory. Variance is used by investors to measure the risk of a portfolio of stocks. Portfolios of financial instruments are chosen to minimize the variance of the returns subject to a level of expected return or vice versa to maximize expected return subject to a level of variance of the return. This paradigm was first introduced by Markowitz's (1952, 1959) mean-variance analysis for which contribution he was honored with the Nobel Prize in Economics. In Fig. 1, we present the risk-reward associated with the optimal policies of a start-up under both maximizing profitability and maximizing survival probability. As expected the risk for a start-up that maximizes survival probability (Archibald et al., 2002) is lower but at the same time the expected return is also much less. On the other hand, if the start-up maximizes its profitability, the expected return increases but it exposes the firm to greater risks. From a start-up's point of view, it is important to measure and perceive the risks associated with any managerial decision rather than focus on just the expected return. Based on their risk tolerance managers might be interested in policies that expose the firm to less risk compared to the risks involved in a policy that maximizes expected reward. Therefore, decisions that result in the efficient risk-reward frontier are extremely beneficial to risk-sensitive managers.

In this paper, we present a heuristic that utilizes the information about the variance of a set of decisions and provides a mechanism to construct efficient mean-variance curves. In Fig. 1, the dotted line is the risk-reward frontier obtained by implementing our heuristic. The main theoretical contributions of this paper are three-fold. Firstly, we propose a methodology for tracking the variance of the possible outcomes at each stage and state of a multi-period stochastic program. We call our methodology *Variance-Retentive Stochastic Programming (Variance-Retentive SP)*. At each state in the Variance-Retentive SP, we capture the risk and reward for each action given the probability of reaching any state in the next period for which the risk and reward is known. Secondly, our proposed Variance-Retentive SP provides a methodology for solving stochastic programming problems where the optimization is done over two metrics, mean and variance, instead of the usual one. Thirdly, given the popularity of efficient frontier approaches in finance, we develop a heuristic to identify such mean-variance frontiers in the startup context using our Variance-Retentive SP. We also specify the limitations of this heuristic to problems where the action space is limited.

Our heuristic is easy to use and gives managers a useful tool with which they can figure out a set of decisions that maximizes profit at different levels of risk. In a standard finite-horizon stochastic programming problem, information about the expected reward of a set of decisions is carried along and is used to solve the problem by backward or forward induction. In our proposed Variance-Retentive SP we carry information about the variance of a set of decisions in addition to expected rewards and this information about the variance is used in selecting the optimal actions. The risk-reward solutions obtained by solving the Variance-Retentive SP are used in our heuristic to obtain mean-variance efficient frontiers.

Next we illustrate the utility of ascertaining the variance of a set of outcomes in a stochastic dynamic setting through a small numerical example.

Motivating example: Consider a simple two-period stochastic programming model shown in Fig. 2, where the rectangles are decision nodes and the circles are probability nodes (with probabilities shown on the arcs). The possible actions at the decision nodes are denoted by a_{ij}. The terminal rewards are shown in parenthesis in the rectangles on the far right. There are exactly 16 sample paths in this problem, and each has a risk and reward, resulting in an expected reward and variance.

Fig. 3 presents the efficient risk-reward frontier based on the solutions of this simple problem. The variance of the possible outcomes for a policy is calculated using Eq. (5), which is derived later in Section 4. The maximum expected reward in this problem is 19, with a variance of 425. This solution lies on the efficient frontier; however this solution may be unacceptable to a risk-sensitive decision-maker for whom the variance of 425 units may be too risky. The solutions having variance of 336 and expected reward of 17, variance of 127 and expected reward of 11 and variance of 0 and expected reward of 2 are the other solutions that are on the efficient frontier whereas solutions with variance 756 and expected reward of 3 or variance of 887 and expected reward of 5 are not on the efficient frontier. The solutions on this efficient frontier provide the maximum expected reward at different levels of variance. So depending on their risk tolerance, managers can pick policies that provide them solutions on this frontier assuring them maximum expected rewards at different levels of variance or risk.

Algorithms such as the critical line method introduced by Markowitz (1952, 1959) are used for the identification of the optimal mean-variance portfolios. These algorithms work by solving quadratic or non-linear programs when the investment horizon is of one period. However, in a dynamic stochastic programming setting we require decisions that are spread over different time-periods. Rather than a one-shot model as is solved through critical line algorithm, dynamic stochastic programs sequentially determine the optimal set of actions taking into consideration the impact of present actions on future rewards. The problem size of these stochastic programs grows exponentially with innumerable state spaces and actions. Converting these multi-period stochastic problems into quadratic or non-linear programs becomes computationally complex and intractable. In addition, as state space and probability intervals increase it is impossible to enumerate all the sample paths and then trace out the efficient frontier because the policy table and the