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Learning a board Balanced Scorecard to improve corporate performance

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ABSTRACT

The objective of this paper is to demonstrate how the boosting approach can be used to define a data-driven board Balanced Scorecard (BSC) with applications to S&P 500 companies. Using Adaboost, we can generate *alternating decision trees* (ADTs) that explain the relationship between corporate governance variables, and firm performance.
We also propose an algorithm to build a representative ADT based on cross-validation experiments. The representative ADT selects the most important indicators for the board BSC. As a final result, we propose a partially automated strategic planning system combining Adaboost with the board BSC for board-level or investment decisions.

1. Introduction

Kaplan and Norton [20] introduced the Balanced Scorecard (BSC) as a management system that helps organizations define their vision and strategy, and translate them into specific actions. The BSC provides feedback on internal business processes, performance, and market conditions in order to review the strategy and future plans [21–24,28]. Large U.S. companies, such as General Electric and Federal Express, and non-profit and public organizations have implemented the BSC approach [2,36].

The strategy of an organization, its main objectives, and its key business drivers define the indicators of the BSC. However, the choice of indicators is, in general, highly subjective and is often driven by company management or industry practices. Youngblood and Collins [39] describe a method based on indicators using multi-attribute utility theory. Clinton et al. [6] base their method on Analytic Hierarchy Process; nevertheless, these methods still require a mix of quantitative measures with a qualitative evaluation by managers or experts.

The main objective of this paper is to adapt a machine learning method, such as Adaboost, to define the core variables and the structure of the board BSC. The criterion used to design the board BSC is the firm performance. We compare the predictive capacity of Adaboost with several other algorithms such as logistic regression, and other decision trees.

The rest of the paper is organized as follows: Section 2 presents the basic concepts of a board BSC; Section 3 presents the methods used in this paper; Section 4 introduces the data and variables used in this research; Section 5 explains in detail our experiments; Section 6 presents the results of our forecast; Section 7 examines the results and the transformation of a representative ADT to a board BSC, and Section 8 presents the conclusions.

2. The Balanced Scorecard

The BSC suggests that an organization should be evaluated from four perspectives:

1. *The financial perspective* emphasizes the long-term objectives of the company in terms of revenue growth and productivity improvement. The financial objectives should be the final goals for the other perspectives.
2. *The customer perspective* emphasizes the lifetime relationship and service delivery with clients.
3. *The internal process perspective* focuses on the use of client information to sell new products and services according to their needs.
4. *The learning and growth perspective* is the foundation of the BSC. This perspective looks at the motivation, training, and capacity to innovate that employees need in order to implement new strategies.

The BSC is generally implemented at the corporate, business unit, and individual level. A missing element in these BSC implementations is the corporate governance dimension. In response to the recent

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corporate scandals in the U.S., several organizations and researchers have proposed corporate governance scorecards. Gompers et al. [14] use 24 different provisions related to takeover defense and shareholder rights to create a governance index. They show that a trading strategy based on this index outperforms the market. Standard & Poor's Governance Services [32] have developed a method which combines macro and micro variables and uses qualitative and quantitative analysis.[1] The German Society of Financial Analysts [33] and to some extent Standard & Poor's, use a qualitative framework based on "best practices" and require a lengthy due diligence process for each company under study, while the one proposed by Gompers et al. [14] is purely quantitative. Besides these corporate governance scorecards which emphasize corporate governance scoring, Kaplan and Nagel [19] proposed the creation of a board BSC that includes corporate governance variables and is oriented to strategic planning at the board level.

According to Kaplan and Nagel [19] an effective BSC program should include three parts:

1. *An enterprise BSC* that presents the company strategy, with detailed description of objectives, performance measures, targets, and initiatives to be implemented by the CEO and managers throughout the organization. The enterprise BSC also becomes a powerful tool for the directors to monitor the implementation of the corporate strategy.
2. *A board BSC* which defines its strategic contribution, includes the data necessary for the board operation, and offers an instrument to monitor the structure and performance of the board and its committees. Epstein and Roy [9,10] explain the importance of the board BSC as an instrument to monitor and implement the best-practices of corporate governance, and also as a mechanism for stakeholders to evaluate the board of directors.The enterprise BSC and the board BSC share the same financial objectives because the final role of the board and senior managers is to maximize the long-term return to shareholders. Additionally, an important element that differentiates the board BSC from the enterprise BSC is the perspective of "stakeholder" instead of "consumer". The reason to include the "stakeholder" perspective is that the stakeholders–such as shareholders, senior managers and financial analysts–are the consumers or clients of the board of directors. As a result, one of the key roles of the board is its responsibility to evaluate and motivate the senior management team.
3. *An executive BSC* allows the board of directors and the compensation committee to evaluate the performance of the top managers of the organization.

There is no theoretical support to indicate the selection and optimal combination of organizational variables such as executive compensation and insider ownership in a board BSC. Moreover, these variables may change from industry to industry and from country to country. Therefore a system that is able to recognize the optimal combination and mechanism that connects these variables, would contribute significantly to an efficient planning process.

The main hypothesis evaluated in this paper is the following: The definition of a board BSC can be partially automated[2] through a machine learning method such as boosting if this method is adapted to: a) select the most important variables, b) forecast corporate performance, c) establish the relationship among the relevant variables, d) define the minimum target (threshold) that each variable should have to contribute to a sufficient corporate performance, and e) build a board strategy map and a board BSC using the identified variables.

We evaluate this hypothesis as follows:

1. Select a group of well-known accounting and corporate governance variables that affect corporate performance.
2. Evaluate the capacity of Adaboost, logistic regression, single tree using boosting, and boosting decision stumps[3] for forecasting, variable selection, identification of relationships among variables, and definition of a minimum (maximum) threshold for each variable. We choose the algorithm with the best forecasting results and, thus, capable of selecting the most important variables, and establish how these variables interact to explain corporate performance.
3. Evaluate if the variables selected in the previous step can be converted into objectives in order to build a board strategy map.
4. Evaluate if the objectives defined in the previous step can be converted into indicators to build a board BSC.

The next section introduces the main methods that are used in this paper.

3. Methods

This section introduces two main forecasting approaches: logistic regression and boosting. In both cases, the training set consists of pairs $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_m, y_m)$ where $\mathbf{x}_i$ corresponds to the vector of features or variables of an instance i and belongs to the instance space X, and y_i is the binary label to be predicted of an instance i and belongs to the label set Y. For this paper, we assume $Y = \{0, 1\}$ because we are trying to evaluate if each firm under study is a low-middle (0) or high performance company (1). The features are the accounting and corporate governance variables described in Section 4.1 and we refer to them in a generic way as the vector $\mathbf{x}$.

3.1. Logistic regression

The logistic regression models [15] the posterior probabilities of Y using linear regression in the observed features $\mathbf{x}$. As in this paper the label set Y is binary, the model is specified in terms of the following log–odds ratio:

$$\log\frac{\Pr(Y=1|X=x_i)}{\Pr(Y=0|X=x)} = \alpha + \beta_T x.$$

3.2. Boosting

Adaboost is a general discriminative learning algorithm invented by Freund and Schapire [12]. The basic idea of Adaboost is to repeatedly apply a simple learning algorithm, called the *weak* or *base* learner,[4] to different weightings of the same training set. In its simplest form, Adaboost is intended for binary prediction problems. A *weighting* of the training examples is an assignment of a non-negative real value w_i to each example $(\mathbf{x}_i, y_i)$.

On iteration t of the boosting process, the weak learner is applied to the training sample with a set of weights $w_1^t, \ldots, w_m^t$ and produces a prediction rule h_t that maps $\mathbf{x}$ to $\{0, 1\}$. The requirement on the weak learner is for $h_t(x)$ to have a small but significant correlation with the example labels y when measured using the *current weighting of the examples*. After the rule h_t is generated, the example weights are changed so that the weak predictions $h_t(x)$ and the labels y are

[1] Even though the Standard & Poor's corporate governance scoring has been very successful in emerging markets, Standard & Poor's corporate governance services decided to pull out of the U.S. market in September 2005.

[2] For the presentation of a fully automated enterprise modeling system and its application to electronic commerce see Refs. [3,4].

[3] Boosting decision stumps algorithm is the boosting algorithm that uses decision stumps as the weak learner.

[4] Intuitively, a weak learner is an algorithm with a performance at least slightly better than random guessing.