A Procedure to Estimate Relations in a Balanced Scorecard

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Abstract. A Balanced Scorecard is more than a business model because it moves performance measurement to performance management. It consists of performance indicators which are inter-related. Some relations are hard to find, like soft skills. We propose a procedure to fully specify these relations. Three types of relationships are considered. For the function types inverse functions exist. Each equation can be solved uniquely for variables at the right hand side. By generating noisy data in a Monte Carlo simulation, we can specify function type and estimate the related parameters. An example illustrates our procedure and the corresponding results.

1 Related work

Indicator systems are appropriate instruments to define business targets and to measure management indicators together. Such a system should not be just a system of hard indicators; it should be used as a system with control in which one can bring hard indicators and management visions together.

In the beginning of the 90's Johnson and Kaplan (1987) published the idea how to bring a company's strategy and used indicators together. This system, also known as Balanced Scorecards (BSC), is developed until now.

The relationships between those indicators are hard to find. According to Marr (2004), companies understand better their business if they visualise relations between available indicators. However, some indicators influence each other in cause and effect relations which increases the validity of these indicators. Unusually, compared to a study of Ittner et al (2003) and Marr (2004) 46% of questioned companies do not or are not able to visualise cause-and-effect relations of indicators.

Several approaches try to solve the existing shortcomings.

A possible way to model fuzzy relations in a BSC is described in Nissen (2006). Nevertheless, this leads to restrictions in the variable domains.

Blumenberg et al (2006) concentrate on Bayesian Belief Networks (BBN) and try to predict value chain figures and enhanced corporate learning. The weakness of this prediction method is that it does not contain any loops which BSCs may contain. Loops within BSCs must be removed if BBN are used to predict causes and effects in BSCs.

Banker et al (2004) suggest calculating trade-offs between indicators. The weakness of this solution is that they concentrate on one financial and three nonfinancial performance indicators and try to derive management decisions.

A totally different way of predicting relations in BSCs is the usage of system dynamics. System Dynamics is usually used to simulate complex dynamic systems (Forrester (1961)). Various publications exist of how to combine these indicators with dynamics systems to predict economic scenarios in a company, e.g. Akkermans et al (2002). In contrast to these approaches we concentrate on existing performance indicators and try to predict relationships between these indicators instead of predicting economic scenarios. It is similar to the methods of system identification. In contrast, our approach calculates in a more flexible way all models within the described model classes (see section 3).

2 Balanced scorecards

”If you can’t measure it, you can’t manage it” (Kaplan and Norton (1996), p. 21). With this sentence the BSC inventors Kaplan and Norton made a statement which describes a common problem in the industry: you can not manage a company if you don’t have performance indicators to manage and control your company.Kaplan and Norton presented the BSC – a management tool for bringing the current state of the business and the strategy of the company together. It is a result of previous indicator systems. Nevertheless, a BSC is more than a business system (Friedag & Schmidt 2004). Kaplan & Norton (2004) emphasise this in their further development of Strategy Maps.

However, what are these performance indicators and how can you measure it. PreiSSner (2002) divides the functionality of indicators into four topics: operationalisation (”indicators should be able to reach your goal”), animation (”a frequent measurement gives you the possibility to recognise important changes”), demand (”it can be used as control input”) and control (”it can be used to control the actual value”). Nonetheless, we understand an indicator as defined in (Lachnit 1979).

But before a decision is made which indicator is added to the BSC and the corresponding perspective the importance of the indicator has to be evaluated. Kaplan & Norton divide indicators additionally into hard and soft, short and long-term objectives. They also consider cause and effect relations. The three main aspects are: 1. All indicators that do not make sense are not worthwhile being included into a BSC; 2. While building a BSC, a company should differentiate between performance and result indicators; 3. All non-monetary values should influence monetary values. Based on these indicators we are now able to build up a complete system of indicators which turns into or influences each other and seeks a measurement for one of the following four perspectives: (1) Financial Perspective to reflect the financial performance like the return on investment; (2) Customer Perspective to summarize all indicators of the customer/company relationships; (3) Business Process Perspective to give an overview about key business processes; (4) Learning and Growth Perspective which measures the company's learning curve.

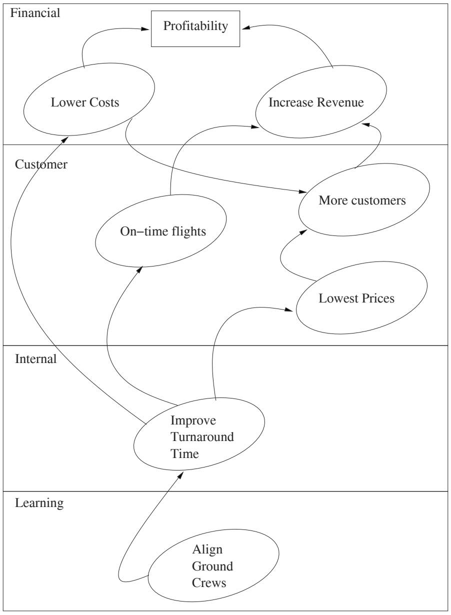

Fig. 1. BSC Example of a domestic airline

By splitting a company into four different views the management of a company gets the chance of a quick overview. The management can focus on its strategic goal and is able to react in time. They are able to connect qualitative performance indicators with one or all business indicators. Moreover the construction of an adequate equation system might be impossible.
Nevertheless the relations between indicators should be elaborated and an approximation of the relations of these indicators should be considered. In this case multivariate density estimation is an appropriate tool for modeling the relations of the business. Figure 1 shows a simple BSC of an airline company. Profitability is the main figure of interest but additionally seven more variables are useful for managing the company. Each arc visualizes the cause and effect relations. This example is taken from "The Balanced Scorecard Institute"[1].

[1] www.balancedscorecard.org

3 Model

To quantify the relationships in a given data set different methods for parameter estimation are used. Measurement errors within the data set are allowed, but these errors are assumed to have a mean value of zero. For each indicator within the data set no missing data is assumed. To quantify the relationships correctly it is further assumed that intermediate results are included in the data set. Otherwise the relationships will not be covered. Heteroscedasticity as well as autocorrelations of the data is not considered.

3.1 Relationships, estimations and algorithm

In our procedure three different types of relationships are investigated. The first two function types are unknown because the operators linking the variables are unknown:

$$z = f(x,y) = x \otimes y \tag{1}$$

where $\otimes$ represent an addition or a multiplication operator. The third type includes a parametric type of real valued function:

$$y = f_\theta(x) = \begin{cases} p & x \le a \\ \frac{c}{1+e^{-d\cdot(x-g)}} + h & a < x \le b \\ q & x > b \end{cases} \tag{2}$$

with $\theta = (abcdgh)$ and $p = \frac{c}{1+e^{-d\cdot(a-g)}} + h$ and $q = \frac{c}{1+e^{-d\cdot(b-g)}} + h$. Note, that all three function types are assumed to be separable, i.e. uniquely solvable for x or y in 1 and x in 2. Thus forward and backward calculations in the system of indicators are possible. As a data set is tested independently with respect to the described function types a Ŝidàk correction has to be applied (cf. Abdi (2007)).

Additive relationships between three indicators ($Y = X_1 + X_2$) are detected via multiple regression. The model is:

$$Y = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + u \tag{3}$$

where $u \sim N(0,\sigma^2)$. The relationship is accepted if level of significance of all explanatory variables is high and $\beta_0 = 0$, $\beta_1 = 1$ and $\beta_2 = 1$. The multiplicative relationship $Y = X_1 \cdot X_2$ is detected by the regression model:

$$Y = \beta_0 + \beta_1 \cdot Z + u \text{ with } Z = X_1 \cdot X_2, u \sim N(0,\sigma^2). \tag{4}$$

The relationship is accepted if the level of significance of the explanatory variable is high and $\beta_0 = 0$ and $\beta_1 = 1$. The nonlinear relationship between two indicators according to equation 2 is detected by parameter estimation based on nonlinear regression:

$$Y = \frac{c}{1+e^{-d\cdot(X-g)}} + h + u \quad \forall a < x \le b; u \sim N(0,\sigma^2). \tag{5}$$

In a first step the indicators are extracted from a business database, files or tools like excel spreadsheets. The number of extracted indicators is denoted by n. In the second step all possible relationships have to be evaluated. For the multiple regression scenario $\frac{n!}{3!\cdot(n-3)!}$ cases are relevant. Testing multiplicative relationships demands $\frac{n!}{2\cdot(n-3)!}$ test cases. The nonlinear regression needs to be performed $\frac{n!}{(n-2)!}$ times. All regressions are performed in R. The univariate and the multivariate linear regression are performed with the `lm` function from the R-base stats package. The nonlinear regression is fitted by the `nls` function in the stats package and the level of significance is evaluated. If additionally the estimated parameter values are in given boundaries the relationship is accepted.

The pseudo code of the the complete environment is given in algorithm 3.1.

Algorithm 1 Estimation Procedure

Require: data matrix $data[M_{t\times n}]$ with t observations for n indicators
significance level, boundaries for parameter

Ensure: detected relationships between indicators

```
for i = 1 to n − 2 AND j = i + 1 to n − 1 AND k = j + 1 to n do
  estimation by lm(data[,i]   data[,j] + data[,k])
  if significant AND parameter estimates within boundaries then
    Relationship "Addition" found
  end if
end for
for i = 1 to n AND j = 1 to n − 1 AND k = j + 1 to n do
  if i != j AND i != k then
    set Z := data[,j] · data[,k]
    estimation by lm(data[,i]   Z)
    if significant AND parameter estimates within boundaries then
      Relationship "Multiplication" found
    end if
  end if
end for
for i = 1 to n AND j = 1 to n do
  if i != j then
    estimation by nls(data[,j]   c/(1+exp(-d+g*data[,i])) + h)
    if significant then
      "Nonlinear Relationship" found
    end if
  end if
end for
```

4 Case study

For our case study we create an artificial model with 16 indicators and 12 relationships, see Fig. 2. It includes typical cases of the real world.

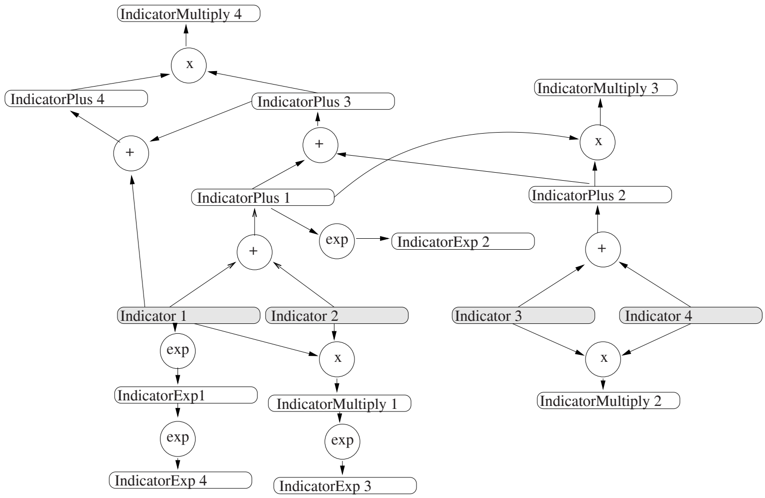

Fig. 2. Artificial Example

Indicators 1-4 are independently and randomly distributed. In Fig. 2 they are displayed in grey and represent the basic input for the simulated BSC system. All other indicators are either functional dependent on two indicators related by an addition or multiplication or functional dependent on an indicator according to equation 2. Some of these indicators effect other quantities or represent leaf nodes in the BSC model graph, cf. Fig. 2. Based on the fact that indicators may not be precisely measured we add noise to some indicators, see Tab. 1. Note, that IndicatorPlus4 has a skewed added noise whereas the remaining added noise is symmetrical.

In our case study we hide all given relationships and try to identify them, cf. section 3.

Table 1. Indicator Distributions and Noise

Indicator	Distribution	Indicator	added Noise	Indicator	Noise
Indicator1	$N(100, 10^2)$	IndicatorPlus1	$N(0,1)$	IndicatorExp1	$N(0,1)$
Indicator2	$N(40, 2^2)$	IndicatorPlus4	$E(1)-1$	IndicatorExp4	$U(-1,1)$
Indicator3	$U(-10,10)$	IndicatorMultiply1	$N(0,1)$		
Indicator4	$E(2)$	IndicatorMultiply4	$U(-1,1)$		

5 Results

The case study runs in three different stages: with 1k, 10k, and 100k randomly distributed data. The results are similar and can be classified into four cases: (1) if a relation exists and it was found (displayed black in Fig. 3), (2) if a relation was found but does not exist (displayed with a pattern in Fig. 3) (error of the second kind), (3) if no relation was found but one exists in the model (displayed white in Fig. 3) (error of the first kind), and (4) if no relation exists and no one was found. Additionally the results have been split according to the operator class (see Tab. 2).

Table 2. Identification Results

Observations	1k			10k			100k		
	+	*	Exp	+	*	Exp	+	*	Exp
(2)	0	3	27	0	5	48	0	2	49
(3)	1	0	3	1	0	3	1	0	3
	560	1680	240	560	1680	240	560	1680	240

Hence, Tab. 2 shows that the results for all experiments are similar for the operators addition and multiplication. For non-linear regression, relationships could not be discovered properly.

The additive relation of IndicatorPlus4 was the only non-detective relation, see observation (3) in Tab. 2. This is caused by the fact that the indicator has an added noise which is skewed. In such a case the identification is not possible.

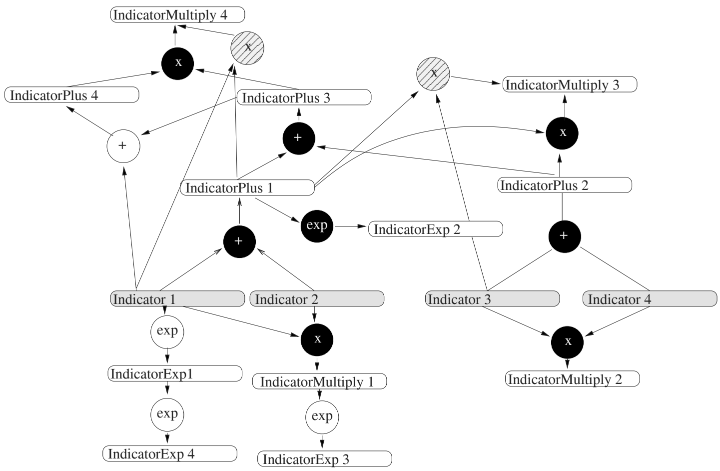

Fig. 3. Results of the Artificial Example for 100k observations

6 Conclusion and outlook

Traditional regression analysis allows estimating the cause and effect dependencies within a profit seeking organization. Univariate and multivariate linear regression exhibit the best results whereas skewed noise in the variables destroys the possibility to detect these relationships.

Non-linear regression has a high error output due to the fact that optimization has to be applied and starting values are not always at hand. The results from the non-linear regression should only be carefully taken into account.

In future work we try to improve our results while removing indicators for which we calculate a nearly 100% secure relationship. Additionally we plan to work on real data which also includes the possibility of missing data for indicators. Research aims at creating a company's BSC with relevant business figures while looking only at a company's indicator system.

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