A Procedure to Estimate Relation in a Balanced Scorecard

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Abstract. A balanced scorecard (BSC) 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 will be 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 MC simulation we can specify function type and estimate the respected parameters. An example will illustrate our procedure and the corresponding results.

1 Related Work

Indicator systems are becoming more and more appropriate instruments to formulate business targets and management measurements together. These system should not be only a system of hard indications; it should be used as a system with automatic control in which you can bring hard indicators and management visions together. Due to falling prices in storage systems companies store more and more information about their available indicators. Resulting into a flood of indicators company's loose the big picture which indicators influences each other which destroys the plan, finding practical indicators to fulfil a managements vision.

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

But the relationships between these indicators are hard to find. Compared to Marr (2004) companies understand better their business when they visualise relations between available indicators. But some indicators influence each other in cause and effect relations which reduces the validity of these indicators. Some indicators will be found hypothetically which assails these connections with doubts. 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 relations between indicator causes and effects.

Different approaches try to solve these existing shortcomings. Due to the fact that variables are described as crisp, stochastic or fuzzy data an arithmetically equation system can deliver unknown variables. A possible way to model fuzzy relations in a BSC is described in Nissen (2006). But 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 it does not contain any loops which BSCs may contain. Loops within BSCs must be removed if BBN are sued to predict the cause and effect in BSCs.

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

A totally different way of predicting relations in BSCs is the usage of system dynamics. Normally system dynamics are used to simulate complex or dynamic systems (Forrester (1961)). With the combination of indicators various publications exists 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.

2 Balanced Scorecards

"If you can't measure it, you can't manage it" (Kaplan and Norton (1996), p. 21). With this sentence the Balanced Scorecard (BSC) inventors Robert S. Kaplan and David P. 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. With the BSC Kaplan and Norton represented 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. But a BSC is more than a business system (Friedag & Schmidt 2004). Kaplan & Norton (2004) emphasise this in their further development of Strategy Maps.

But 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 you decide which indicators you use to build up your BSC and the corresponding perspectives you have to look onto the importance of the indicators. Kaplan & Norton divide indicators additionally into hard and softer objectives, short and long-term objectives. Kaplan & Norton also consider about cause and effect. The three main aspects are that: 1. all indicators which does not make sense are not valuable to be included in the BSC, 2. while building a BSC, a company should be differentiated between performance and result indicators and 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 sum 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.

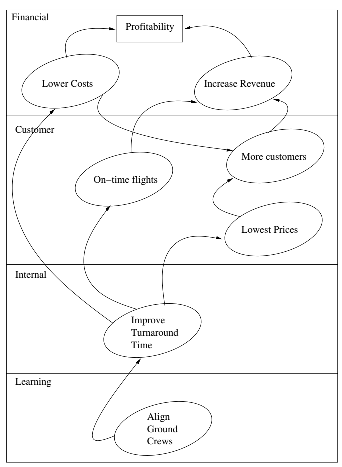

Fig. 1. BSC Example of a domestic airline

By splitting a company into four different views the management of a company gets the chance to have a quick overview over the main perspectives of their company and divide these into usable and unnecessary layers. The management can focus onto their strategic goal they are responsible for and are able to react in time. They are able to connect qualitative performance indicators with one or all business indicators. Also 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. For this case multidimensional estimation like multivariate density estimation is an appropriate tool for modelling the relations of the business

3 Model

To quantify the relationships in a given data set different methods for parameter estimation are used. The data set is presumed to be free of manipulation although measurement errors can be inherited. But these errors are assumed with 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.

3.1 Relationships, estimations and algorithm

In our procedure three different relationships are investigated. The first two function types f are unknown with respect to operators linking the values like:

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

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

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

with restrictions on p and q. Note, that all three function types are separable. So forward and backward calculations in the system of indicators are possible. Testing the data set for the described function types is done by independent tests. So 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:

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

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 within ($Y = X_1 \cdot X_2$) is detected by the regression model:

$$Y = \beta_0 + \beta_1 \cdot Z \text{ with } Z = X_1 \cdot X_2 \tag{4}$$

The relationship is accepted if 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 5 is detected with estimation by the nonlinear regression:

$$Y = \frac{c}{1 + e^{-d\cdot(X-g)}} + h \tag{5}$$

The relationship is accepted if level of significance of the explanatory variable is high.

The data sets of indicators can be taken from business databases, files or tools like excel spreadsheets. In a first step the indicators are extracted. The number of extracted indicators will be denoted by n. In the next step all possible relationships are listed. For the multiple regression scenario $\frac{n!}{3!\cdot(n-3)!}$ cases have to be evaluated. Testing multiplicative relationships demands $\frac{n!}{2\cdot(n-3)!}$ test cases. The nonlinear regression needs to be $\frac{n!}{(n-2)!}$ times performed.

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. The level of significance is evaluated and if additionally the estimated parameters are in given boundaries the relationship is accepted.

The pseudo code of the the complete environment is given in algorithm 1. Note that different programming languages are used for the implementation.

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
Extract indicator information
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 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 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 which simulates 16 indicators and its relationships to each other, see Fig. 2. Four of them are independent random distributed vectors which are displayed in grey and represent the basic input for the simulated BSC system. All other indicators are the result of two indicators, done by an addition, multiplication or exponential function. That's why each of these operators has two inputs resulting into one output. Partly these indicators effect new calculations or represent a final state in our simulated BSC.

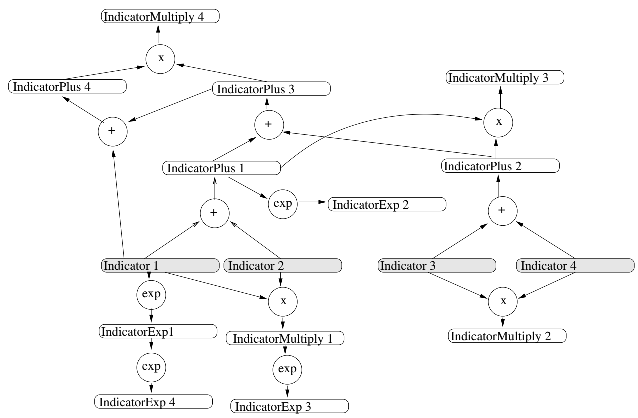

Fig. 2. Artificial Example

Based on the fact indicators can also be manipulated in a company some are influenced by noise, see Table. 1. For our case study we hide all relationships and try to recover all relationships as shown in section 3.

Table 1. Indicator Distributions and Noise

Indicator	Distribution	Indicator	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 run in three different stages: with 1k, 10k, and 100k randomly distributed data. All showed similar results and can be classified into (1) if a relation exists and it was found (displayed black in Fig. 4), (4) if no relation exists and no one was found, (2) if a relation was calculated but no one exists (displayed with a pattern in Fig. 4), and (3) if no relation was calculated but one exists in the model (displayed white in Fig. 4). Additionally the results have been split into each operators (see Fig. 3).

Obser–vations	1k			10k			100k		
	+	*	Exp	+	*	Exp	+	*	Exp
(1)	3	4	1	3	4	1	3	4	1
(2)	0	3	27	0	5	48	0	2	49
(3)	1	0	3	1	0	3	1	0	3
(4)	556	1673	209	556	1671	188	556	1674	187
	560	1680	240	560	1680	240	560	1680	240

Fig. 3. Classification Results

Hence, Fig. 3 shows that the results for all stages are similar for the operators addition and multiplication. Also the relationships of the indicator which has been destroyed by noise and simulates fraud data could not be discovered in all stages. For non-linear regression, relationships could not be discovered properly.

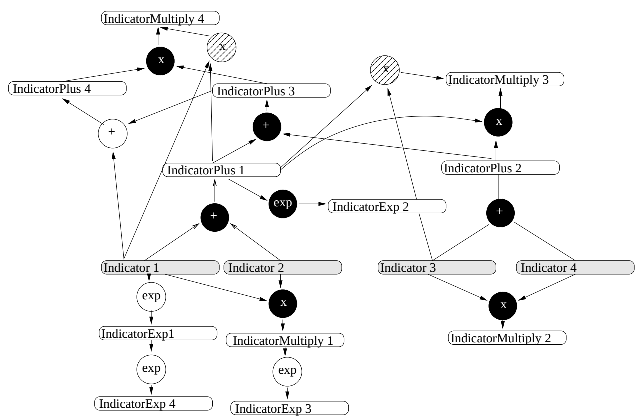

Fig. 4. Results of the Artificial Example for 100k observations

6 Conclusion and Outlook

Traditional regression analysis gives the possibility to estimate the cause and effect for a profit seeking organisation. Univariate and multivariate linear regression have best results whereas skewed noise destroys the possibility to estimate relations. A further advantage of additive and multiplicative relationship detection is error detection. If the relations are known these relations have to be revealed with our methods. Otherwise the data inherits errors that might occur due to theft and infidelity.

Non-linear regression has a high error output due to the fact that optimisation has to be done and automatic starting values are not always suitable. The results from the non-linear regression should only be carefully taken into implication.

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. All research results are planned to flow into the idea of creating a company's BSC with relevant business driver only while looking at the relationships of a company's indicator system.

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Keywords

Balanced Scorecard, Parameter Estimation