On Advancing the Field of Organizational Diagnosis based on Insights from Entropy
Motivating the Need for Constructional Models

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Abstract: In this paper, we explore how the field of organizational diagnosis can benefit from lessons learned from entropy reduction in other fields. In an organizational context, entropy is related to the lack of knowledge concerning the way of how management-level KPIs (observable system macrostate) are brought about by operational elements (which are considered to be the causing microstate). Because of this lack of knowledge, the goal and scope of projects to remedy problematic KPIs cannot be determined unambiguously. Organizational diagnosis aims to further the insight in these decisions by providing conceptual models to find causal explanations between observations and their causes. In related fields, reduction of entropy is achieved by introducing and analyzing structure in a system, which is described in a constructional perspective. However, we will show in this paper that many diagnostic approaches do not support this constructional perspective adequately.

1 INTRODUCTION

Contemporary markets are characterized by volatility, both on the demand side as a result of changing customer preferences, as on the supply side as a result of mergers and takeovers. Therefore, the competitive environment of organizations is changing at a rapid pace. Consequently, organizations need to be able to react quickly to observed business performance issues in order to satisfy customer expectations. In order to be able to detect these issues, management often defines key performance indicators (KPIs) which capture relevant scores on various criteria. When a problematic KPI is observed, projects can be initiated to remedy the issue, and adapt the organization to its changing environment. However, the influencing factors of KPIs are often diverse and complex. As a result, it is not straightforward to define the concrete scope of such projects to achieve effective improvement of problematic KPI values. Various authors argue that it is indeed naive to expect that simple measures can provide insight in organizations which are complex and variable (Sitkin et al., 1994).

The field of organizational diagnosis attempts to provide conceptual models to find causal explanations of unwanted observations (Harrison, 1994). Such unwanted observations can be indicated by problematic KPIs. Without adequate understanding of the root causes of a problem, decision makers cannot efficiently remedy that problem (Senge, 1990). Consequently, the field of organizational diagnosis is very relevant in this context. However, it is still faced with significant challenges. First, the inherent complexity of organizations makes the diagnosing activity extremely challenging. Various authors suggest that the search for cause and effect relations in an operational organization is very difficult (Harrison, 1994; Harry, 1988). Second, organizational diagnosis depends largely on heuristics. One can expect a different diagnosis from a novice or an experienced diagnostician. In order to better teach or develop methods for performing organizational diagnosis, a more systematic approach is required.

The lack of a systematic approach and the difficulty of handling complexity indicate the need for a clear theoretical basis to approach these issues. A theoretical basis clarifies the concepts which are needed to explain how complexity can be dealt with, and allows to introduce prescriptive elements in a diagnosis approach. While the selection of a certain theoretical basis invariantly results in a focus on certain dimensions, and neglects others, we believe that a relevant theoretical basis can make significant contributions to an immature field. Therefore, we explore the use of the theoretical concept of entropy as defined in the field of thermodynamics in order to gain more insight

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in the field of organizational diagnosis. Entropy has already been applied in a wide variety of fields. Insight in dealing with entropy has already matured in those fields. Therefore, the field of organizational diagnosis can progress based on lessons learned from these fields. According to some research methodologies, such as design science, the application of proven solutions in new research fields is the way towards scientific progress (Hevner and Chatterjee, 2010).

This paper is structured as follows. First, we introduce the field of organizational diagnosis in Section 2. We then explore the entropy concept and the reduction of entropy in Section 3. In Section 4, we apply the concept of entropy on the field of organizational diagnosis. Finally, we summarize our conclusions and the contribution of this paper in Section 5.

2 ORGANIZATIONAL DIAGNOSIS

In organizational diagnosis consultants, managers or researchers use conceptual models to find causal explanations of observed and unwanted effects (Alderfer, 2010). A diagnostician works beyond an observational role since he attempts to explain why certain issues occur. He formulates questions (e.g., why are five percent of the produced products defective?) and aims to formulate adequate answers. When an enterprise diagnostician understands a problematic situation, a hypothesis can be formulated to explain how an observed issue can originate. Then, evidence needs to be gathered to confirm or falsify this hypothesis. Based on evidence, the hypothesis can be rejected or refined through an iterative process (Alderfer, 2010).

A popular approach used for diagnosing is Lean Six Sigma (LSS). LSS applies a specific analytic thinking pattern to support the problem solving performed by the diagnostician (de Mast and Bisgaard, 2007). According to this pattern, the analytic mind oscillates between on the one hand the theories, hypotheses, conjectures, ideas one has in mind (i.e., the interpretative world) and on the other hand the observations, measurements, experimental results empirically retrieved from the real world (i.e., the factual world) (Box and Liu, 1999). The pattern is graphically represented in Figure 1. The oscillation in this pattern can start from any of both worlds. It could for example start with an hypothesis one has in mind and the gathering of facts to justify it. These discovered facts might influence the hypothesis, which then again needs to be justified with new facts. However, the process can also start by observing facts from which a hypothesis is built, which is then justified by new facts

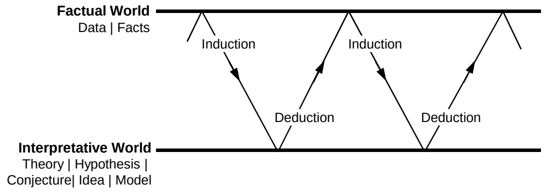

Figure 1: Learning by iteration between data and models.

until a satisfactory hypothesis has been formulated. This is called sawtooth thinking, i.e., the repeated alternation of discovery and justification in which we develop causal explanations (de Mast and Bisgaard, 2007).

Based on this sawtooth-thinking pattern, a wide variety of causal explanations, formulated as hypotheses, can be gathered. In LSS, a so-called *logic filter* is used to select the most important causal explanations when faced with a business performance problem (Harry, 1988). The application of the logic filter is organized in iterative optimization cycles. Each cycle uses a specific collection of tools and techniques to guide an applicant to the vital key correlations between influence variables and business performance outcome variables. However, no theoretical basis is provided to select or evaluate these tools and techniques. We do not claim that this indicates that these tools and techniques are lacking or insufficient. Instead, we believe that a theoretical evaluation can indicate more improvements in a structured way. Therefore, the goal of this paper is to assess whether these tools and techniques can be improved based on insights from the theoretical concept of entropy.

3 THEORETICAL FRAMEWORK: ENTROPY

In this section, we introduce entropy as a theoretical basis to interpret the current diagnosis approaches such as LSS and to analyze how they can be improved. In Section 3.1, we introduce the entropy concept and its definition. In Section 3.2, we explore how entropy is controlled in different fields. Based on this insight, we will be able to formulate improvements for organizational diagnosis approaches.

3.1 Defining Entropy

Entropy as expressed in the second law of thermodynamics is considered to be a fundamental principle. There are many versions of this law, but they all have the same intent. Mathematical derivations of the entropy principle start in general from a formula describing the number of possible combinations. In statistical thermodynamics, entropy was defined by Boltzmann in 1872 as the number of possible microstates corresponding to the same macrostate (Boltzmann, 1995). The aim is to understand and to interpret the externally observable and measurable macroscopic properties of materials — the macrostate — in terms of the properties of the constituent parts — the microstate — and the interactions between these parts. In Boltzmann's definition, entropy is a measure of the number of possible microstates of a system, consistent with its macrostate. Mathematically, the entropy of a particular macrostate (S) is equal to the Boltzmann constant (k_B) times the natural logarithm of the number of microstates corresponding to that macrostate ($ln\Omega$).

$$S = k_B ln\Omega \qquad (1)$$

In thermodynamics, examples of properties related to such a macrostate are the temperature, pressure, or volume of gas in a containment. The studied gas containment consists of a collection of molecules. The observed values of this macrostate are brought about by a certain arrangement of these molecules. However, many different arrangements could result in a certain macrostate: therefore, one cannot be sure of the exact arrangement of molecules represented by a single macrostate. The number of arrangements which can correspond to a single macrostate is the number of microstates referred to in the formula above. This notion of entropy can be seen as a measure of our lack of knowledge about a system.

This definition of entropy can be further clarified by the example of a set of 100 coins, each of which is either heads up or tails up. The macrostate is specified by the total number of heads and tails, whereas the microstate is specified by the possible configuration of the facings of each individual coin. For the macrostate of 100 heads or 100 tails, there is exactly one possible configuration, so our knowledge about the system is complete. At the opposite extreme, the macrostate which gives us the least knowledge about the system consists of 50 heads and 50 tails in any order, for which there are 10^{92} possible microstates (Wikipedia, 2011a). It is clear that the entropy is extremely large in the latter case because we have no knowledge of the internals of the system.

3.2 On Controlling Entropy

A common way of dealing with entropy, is to increase the *structure* or the knowledge of the internals of the system. Consider the coin example. The entropy in this example can be reduced when we add structure to the studied system. Suppose we would have 10 groups of 10 coins, each with 5 heads and 5 tails, the number of possible microstates would only be 2520 (Wikipedia, 2011a). Consequently, the entropy for this system would be much lower. Structure can be used to control entropy, in the sense that by allowing less interaction between the constituing components, a lower number of valid combinations are possible. This leads to less uncertainty concerning the actual microstate configuration.

In complex systems, one has to consider that structure needs to be applied to the constituent parts of the system, not on the macrostate measurement. In the example of the gas container, it is clear that it would not make sense to make more detailed temperature measurements. This would be an example of a more precise macrostate measurement. Instead, the lacking knowledge refers to the characteristics of the individual molecules. Consequently, it is important to be able to distinguish between the nature of the macrostate and microstate. In systems theory, such a distinction is made between the functional and constructional perspective of a system (Weinberg, 1975; Gero and Kannengiesser, 2004). The constructional perspective describes the composition of a system. In a constructional perspective, the different subsystems of which a system consists and their relations (i.e., how do the different subsystems cooperate) are described. In contrast, the functional perspective describes what a system does or what its function is, i.e., how it is perceived by its environment. In a functional perspective, the input variables (i.e., what does the system need in order to perform its functionality?), transfer functions (i.e., what does the system do with its input?) and output variables (i.e., what does the system deliver after performing its functionality?) are described. In order to reduce entropy, the structure of a system needs to be studied from a *constructional perspective*.

Models from a functional or constructional perspective are different in nature (Dietz, 2006). Models created from a functional perspective are called black-box models. These models only depict the input and output parameters by means of an interface, describing the way how the system interacts with its environment. Consequently, the user of the system does not need to know any details about the inner workings of the system. Put differently, the complexity of the system internals is hidden in these models. Models created from a constructional perspective are called white-box models. These models depict the different components of which the system consists, and the way these components work together. Each of these components can be considered to be a subsystem. Consequently, each component can be regarded as a system on its own and can therefore be described using a functional (i.e., black-box) or constructional (i.e., white-box) model. However, this alternation between black-box and white-box models should be clearly distinguished from merely adding detail to existing models. As argued by Dietz, additional detail within a single perspective can be added by performing functional or constructional decomposition (Dietz, 2006). However, functional decomposition, which elaborates on a certain model from a functional perspective, cannot be used to obtain a constructional model. As discussed, it is in the constructional perspective that the structure of a system is described. Consequently, reducing entropy requires a constructional perspective. As a result, a functional decomposition cannot be used to reduce entropy, since the required structure cannot be applied in this perspective.

4 APPLYING INSIGHTS FROM ENTROPY ON ORGANIZATIONAL DIAGNOSIS

The concept of entropy already received attention in management literature. Various authors applied it to the organizational level:

- First, entropy is considered to be a measure for waste in organizational processes. Originally, entropy was a term to describe the loss of useful energy of mechanic devices such as heat engines when converting energy to work. Several authors argue that waste in organizational processes can be described similarly (Katz and Kahn, 1978).
- Second, entropy is used as a measure of uncertainty with regard to a random variable in information theory (Shannon, 1948). The so-called Shannon entropy quantifies the expected value of a specific instance of the random variable. For example, a coin toss of a fair coin (i.e., a coin toss which has an exact 50% chance of resulting in head) has an entropy of 1 bit (Wikipedia, 2011b). If the coin is not fair, the entropy will be lower since one can expect a certain value to occur more. In other words, the uncertainty of the outcome has been reduced. The entropy of a coin toss with a double-sided coin is zero.
- Third, entropy has been proposed as a measure of industry concentration (Horowitz, 1970) and corporate diversification (Jacquemin and Berry, 1979; Palepu, 1985). In a concentrated industry, entropy is considered to be low. The higher the entropy, the greater the uncertaintenty will be with which one can predict which firm will gain the preference of a random buyer.
- Fourth, Janow has studied organizations and productivity based on entropy (Janow, 2004). Janow concluded that entropy offered an interesting means to explain why organizations tend to become gradually more slow in their decisionmaking processes, as well as lose productivity over time.

While the interpretation of entropy in the first type is related to waste, the interpretation of entropy in the second, third and fourth types are related to uncertainty. We will follow the latter interpretation of entropy. For our purpose, entropy can be interpreted as a measure of the number of microstates consistent with a given macrostate. In an organization, a KPI can be considered to be such a macrostate. However, when the influencing factors of this KPI are not known, many different microstates can be relevant for the values of this macrostate. Consequently, the entropy is considered to be high.

By itself, the interpretation of KPIs as a macrostate with high entropy does not contribute much to the field of organizational diagnosis. However, we can now analyze how other fields achieve a reduction of entropy, and compare their approach to the current practice of organizational diagnosis. In Section 3.2, we argued that a constructional perspective is required to reduce entropy. Organizational measurements such as KPIs are defined in relation to the behaviour of the organization in its environment, and are therefore mostly described from a functional perspective.

When insight is needed in problematic KPIs, most approaches only propose to use functional decomposition. Consider an analysis of the return on equity (RoE) according to the strategic profit model. The RoE is defined as the net income divided by the average stockholder assets. The strategic profit model proposes the DuPont formula, which breaks the RoE down into operation efficiency (Net Income divided by Sales), asset use efficiency (Sales divided by Total Assets), and financial leverage (Total Assets divided by Average Stockholder Assets).

$$RoE = \frac{NetInc.}{Sales} * \frac{Sales}{TotalAss.} * \frac{TotalAssets}{Avg.Stckh.Ass.}$$

However, such a decomposition does not coincide with the constructional model of an organization.

Such a model will likely exist of, amongst others, the different products. Consider a lacking product feature as a negative impact on the sales of the organization. In the DuPont formula, such aspects will impact both the operation efficiency and asset use efficiency. Consequently, it will be very hard to arrive at a correct and precise analysis of the cause of the declining ROE by using functional decomposition. Moreover, other terms can easily be added to the DuPont formula, or a completely different decomposition can be made. As a result, different analysts will arrive at different conclusions. Based on constructional models, a more objective analysis can be made (Dietz, 2006). Therefore, we expect the integration of constructional models in organizational diagnosis approaches. However, different shortcomings with regard to this expectation can be observed.

First, many causal diagrams only focus on creating finer grained black-box models. Put differently, they decompose a big black box into smaller black boxes. However, they do not consider the relevance of including constructional mechanisms. As a result, these organizational diagnosis approaches limit themselves to functional decomposition, and exhibit similar shortcomings as described in the example above. For example, Russo describes how Causal Loops Diagramming (CLD) can be used to specify correlation relations between variables (Russo, 2008). However, such approaches are only considered to be able to predict the behavior of organizations, not to explain the observed phenomenon (Craver, 2006). Moreover, Woodward argues that such approaches may even fall short when used for predicting behavior (Woodward, 2005): without constructional knowledge, it is not possible to foresee the "conditions under which those relations might change or fail to hold altogether".

Second, certain approaches seem to propose to include constructional elements in the functional decomposition in order to claim causality. By including constructional elements, a direct relationship between observed functional elements and constructional elements can be made. Craver calls such models "mechanism sketches" (Craver, 2006). Mechanism sketches are incomplete models of a mechanism, which "characterize some parts, activities, and features of the mechanism's organization, but [which have] gaps" (Craver, 2006). With regard to this approach, several reservations can be made.

- It has been argued that functional and constructional models are different in nature (Dietz, 2006). Consequently, different modeling constructs need to be used, which makes a model harder to interpret.
- Modeling the functional variables of an organization would already result in an enormous amount of variables (Ettema, 2011). Adding additional variables will result in increasing complexity, which makes the models harder to manage and interpret.
- Adding constructional elements in an ad-hoc manner fails to identify dependencies between various constructional elements.
- Craver argues that the missing gaps in such mechanism sketches can function as "veil for a failure of understanding" (Craver, 2006).

Third, approaches which explicitly incorporate a constructive perspective, and separate it from behavorial observations, do not offer any support on how to model or select such a constructive perspective. For example, we discussed the sawtooth thinking approach in LSS (see Figure 1). In this approach, the behavioral measurements belong to the factual world, while a constructional model would belong to the interpretative world. However, no guidance to identify relevant constructional elements is available: cause and effect thinking in LSS is supposed to be performed through "brainstorming" (Ettema, 2011).

This analysis shows that, in order to deal with the presented complexity, current diagnosis approaches (1) only consider functional decomposition, or (2) include constructional elements partially, or (3) include explicitly constructional models, but do not provide guidelines on how to construct them. Based on this classification, it can be concluded that it is useful to develop a method, based on a current organizational diagnosis approach, which explicitly includes a concrete approach for constructing constructional models (such as, for example, Enterprise Ontology (Dietz, 2006)).

5 CONCLUSIONS

In the introduction, we started by positioning two issues in the field of organizational diagnosis. We can summarize the contributions of this paper with regard to these issues. First, the inherent complexity of organizations makes diagnosing challenging. In regard to this issue, this paper makes a contribution by using the concept of entropy to interpret the origin of this complexity. Moreover, the paper shows how entropy can be controlled based on insights from related fields. We identified the presence of structure in the constructional perspective to be primordial in controlling entropy. Consequently, a diagnosing approach which attempts to address this complexity should explicitly incorporate a constructional perspective. Second, no systematic approach is currently available to perform organizational diagnosis. In order to demonstrate this point we argued that current diagnosis approaches do not adequately incorporate the explicit usage of constructional models. We believe that the thorough application of engineering concepts such as entropy in organizational research is important to further the scientific field described in the Enterprise Engineering Manifesto (Dietz, 2010). Therefore, such a method would indeed further the field of organizational diagnosis.

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