Representation and Reuse of Design Knowledge: An Application for Sales Call Support

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Abstract. This paper presents a Bayesian network representation of the function-behavior-structure (FBS) framework [10], which is used to guide salespersons through conceptual design tasks in lead qualification situations. After we outline the lead qualification situation and state the need of design support for salespersons, a review of the related works shows the necessity for a knowledge representation, which explicitly addresses the uncertainty of design decisions. In the remainder we propose a representation, which is capable of this, and close with an application example for sales call support.

Keywords: Knowledge modelling, Bayesian networks, design computing, conceptual design, lead qualification, function-behavior-structure framework.

1 Introduction

Increasing customer-oriented project delivery and implementation has been recognized as an important change in the context of organizational buying (B-to-B) [13]. For industries that offer customized solutions, fluid less structured knowledge is important for getting a shared understanding between customers and vendors. Typical examples of highly customer-oriented projects are office fit-out projects, as they may have an substantial impact on the customer's business operations [20]. They deal with the design and construction of the scenery and settings of office accommodation, aligned with the customer's very own aims, needs, structure and identity [2]. In the very first project phase, called lead qualification, the sales force is required to evaluate the readiness, willingness, and ability of a customer to buy an offer. With increasing customer-orientation this changes to a consultative "solution selling" task [18], demanding creative problem-solving skills [26], or in other terms conceptual designing experience. In this paper we propose a computational representation of office design knowledge and a method for knowledge reuse, to efficiently guide salespersons through the conceptual design processes in lead qualification situations for office fit-out projects.

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2 Problem Statement and Approach

Lead qualification can be conceptualized as a principal-agent situation, where the vendor delegates the tasks carried out in lead qualification to a salesperson (cf. [4]). The beginning of lead qualification is characterized by an information asymmetry that reflects a situation in which the company has insufficient information about what the lead (potential customer) desires [25]. The salesperson acts as an intermediator establishing a form of corporate communication between lead and vendor to reduce information asymmetry. This is mostly done iteratively in several sales calls with representatives of the lead. The salesperson uses the meetings to identify problems of the lead that can be solved by the vendor's goods and services. These perceptions are then reported back to the vendor where the information is used to evaluate the chances for business, and, if necessary, prepare adequate offerings. Since the accuracy of these perceptions depends only on the salesperson himself, his individual performance critically determines the outcome of the vendor's consultancy efforts [12,22].

A crucial issue in this setting is given by salespersons asking the wrong questions, i.e. they fail to gather right information in sales calls and thus miss important business opportunities. Following the notion that a solution is not only a mere consequence of a stated problem but also helps to (re-)structure a problem [6], salespersons should be aware of possible solutions to efficiently interview leads about their business needs. This in turn requires sophisticated conceptual design knowledge considering the characteristics of a solution (cf. [24]).

Our approach is to provide mechanisms to formalize the required design knowledge and reuse it by means of a dynamic questionnaire that will adapt to the current lead qualification situation when provided with answers. Considering the information that has already been gathered on the lead, the design knowledge is used to estimate a current state of the problem/solution space as seen from the vendor's point of view. Given this estimation we highlight those questions that are most insightful in the current situation. The answers provided by the salesperson are then used to restructure the problem/solution space and in consequence highlight consecutive questions. Embedded in an information system (IS) the questionnaire will guide the salesperson's preparations for sales calls.

3 Related Work

To the best of our knowledge, there exist no systems that explicitly support the lead qualification for office fit-out projects. But viewing the problem from a lead's perspective there have been several approaches that deal with the problem of contractor pre-qualification, i.e. the screening for capable vendors (cf. [8]). Furthermore, looking at the domain of project tendering, which can be seen as a downstream process to lead qualification, different decision support systems have been proposed to assist the vendor in estimating whether it is feasible or not to tender, the so called bid/no-bid problem (cf. [17]). Both are formulated as classification problems trying to measure the fitting of the lead's problems with the vendor's problem solving capabilities. But reconsidering the solution selling aspect, an adequate model for lead-qualification should not only allow for classifying different states of the problem/solution space but also be capable of generating this space.

A promising modeling approach comes from the field of design research: Functional concept ontologies provide a holistic view on the problem/solution space and may be used to assist people to deal with the complexity of conceptual design [3]. For a comprehensive review see [9]. The (situated) function-behavior-structure (FBS) framework [10] seems especially appropriate, as it focusses on the design object generation processes and intrinsically supports the notion of demands and offers. Even though the authors do not propose a formalized methodology to decompose the functions or to associate the functions with behaviors and structure [9], other works implemented computational representations of the FBS framework. In [15] a UML class diagram scheme of the FBS model is used to represent the interrelations of processes, products, resources and external effects in product life-cycles. [5] took a similar entity-relationship approach and provided an ontological FBS representation for conceptual design. Other approaches of functional concept ontologies have been implemented by means of some notion of a state transition system (e.g. [11]), where the state space provides a configurational description of the design object. Further, models for designing are defined to put constraints on the operations carried out in the state space, i.e. state transitions and production/association rules for design object entities (e.g. [27,28]).

However, none of these models provide a formal mechanism to specifically address the uncertainty of a design decision. Common theories of the management of uncertainty in design decisions are reviewed in [19]. The authors suggest probability theory as an appropriate approach, given the premise that probabilities for the outcomes of different design decisions can be defined from data (objective probability) or judgement (subjective probability). I.e. relevant design concepts are conceived as random variables, which define a state space whose realizations are more or less probable with respect to the objective frequency of past observations or to the subjective beliefs of an individual. Bayesian networks (BN) provide a well known conceptual framework to integrate multiple random variables to form a dependency network of conditional probabilities. These conditional probabilities are often used to express casual relations between concepts [21], likewise the associations inherent in a FBS model. Beside more general applications for information retrieval [7] BNs have been applied for design reasoning [16,23].

The idea of reasoning from a functional concept ontology defined in form of a BN shouldn't be seen as counterintuitive to the idea of case-based reasoning (CBR) [1], but as "soft computing" component in the technology stack for hybrid intelligent (design) systems (cf. [29]). In fact it can be used to implement the retrieve, reuse, revise and retain steps, as shown in [1]. Their BN-based CBR implementation not only considers experience from previous cases by using data mining (objective probabilities). It also integrates human generated design beliefs defined in domain ontologies (subjective probabilities).

In the remainder of the paper we present a novel BN-approach to operationalize the FBS framework, specially designed to cope with the uncertainty inherent in the vendor's view on the problem/solution space.

4 Representation of Office Design Knowledge

In the FBS framework a design object is described by (ranges of) values for three sets of variables, which define the problem/solution space (cf. [10]): Function (F) variables "describe the teleology of the object, i.e. what it is for" [10]. To cast this notion of Function in to the domain of office fit-out projects one should consider the project's value proposition. From the lead's perspective two factors contribute to this value proposition, the generation of benefits (e.g. flexibility to deal with changes in staff personnel, or represent corporate image) and the avoidance of costs (e.g. reduce vacancy rates, or lower operating costs) (cf. [2]). Structure (S) variables describe the components used for implementation. Regarding an office fit-out project this includes all goods, such as furniture and other interior elements, as well as services, like design, construction and project management, provided to the lead. Behavior (B) variables have a special role as they provide links between Function and Structure variables. Behavior variables are conceptualized as observable attributes that are exhibited by a solution (e.g. storage capability, adjustability of workplaces, degree of privacy). These variables hold two values (or ranges of values). Beside the value that is derived from a given Structure (Bs) representing the vendor's offer, they may also have an expected value (Be) representing the Behaviors demanded by the lead. The latter is derived from the defined Function variables. In this sense the FBS framework provides an integrated view on design objects, combining the problem and solution domain to form a combined space. The act of designing can be represented as a set of operations modifying this space by adding or removing variables and assigning (ranges of) values to the variables.

As mentioned the FBS framework is represented as BN to facilitate its computational use. BNs are instantiated to define the problem/solution space of a specific lead qualification situation. Instantiations are generated upon a predefined template called the FBS Network Template (FBS-NT), which encodes the vendor's design knowledge by means of conditional probabilities. Since BNs are generative probability models, we can compute estimates for all variables in the problem/solution space via Bayesian inference. These probability estimates are conceptualized as a vendor's guess of the problem/solution space given his design knowledge.

In a FBS-NT (cf. Def. 1) Functions, Behaviors and Structures are represented as random variables, which define the nodes of a directed acyclic graph (DAG). All random variables are discrete to simplify the computation of the Bayesian inference later on. Their states define the possible configurations of the problem/solution space. Connections between these variables are defined as conditional probability distributions represented by the graph's edges. Possible relations are $F \rightarrow B$ (Function expects Behavior) and $S \rightarrow B$ (Structure exhibits

Behavior) as well as relations denoting implications within a variable group, i.e. $F \rightarrow F$, $B \rightarrow B$ and $S \rightarrow S$. Further all variables are assigned to a distinct aspect of the problem/solution space (e.g. Project, Business, Office, User), termed Perspective. A Perspective may be related to other Perspectives to express dependencies like "Users can be related to Offices".

Definition 1 (FBS Network Template). Let $G = (U, E)$ be a directed acyclic graph (DAG), and let $\mathbf{X} = (X_u)_{u \in U}$ be a set of random variables indexed by nodes U, and let $P(\mathbf{X})$ be the joint probability over all variables with edges E representing the conditional dependencies, and let $G_{Pers} = (V_{Pers}, E_{Pers})$ be an undirected graph with nodes V_{Pers} representing Perspectives and edges E_{Pers} expressing *canBeRelatedTo* relations among the Perspectives, then $(\mathbf{X}, G_{Pers})$ is a FBS Network Template (FBS-NT), given the properties:

Partitioning. Every variable $X \in \mathbf{X}$ is assigned to a Perspective $v \in V_{Pers}$ with $inPerspective : \mathbf{X} \rightarrow V_{Pers}$.

Variables. Let Ω_X be a set of possible states for a discrete random variable X, then:
- Every Function is defined as $F : \Omega_F \rightarrow [0,1] \in \mathbf{F}, \mathbf{X}$.
- Every Behavior is defined as $B : \Omega_B \rightarrow [0,1] \in \mathbf{B}, \mathbf{X}$.
- Every Structure is defined as $S : \Omega_S \rightarrow [0,1] \in \mathbf{S}, \mathbf{X}$.

Factorization. Preserving the DAG property of G the joint probability $P(\mathbf{X})$ may be arbitrarily factorized with conditional probabilities $P(X \mid Pa(X))$ of the following types, where $Pa(X)$ is the set of parents of X:
- $X \in \mathbf{F}$ and $Pa(X) \subseteq \mathbf{F} \setminus X$ (Function implicates Function)
- $X \in \mathbf{B}$ and $Pa(X) \subseteq \mathbf{F}$ (Function expects Behavior)
- $X \in \mathbf{B}$ and $Pa(X) \subseteq \mathbf{B} \setminus X$ (Behavior implicates Behavior)
- $X \in \mathbf{B}$ and $Pa(X) \subseteq \mathbf{S}$ (Structure exhibits Behavior)
- $X \in \mathbf{S}$ and $Pa(X) \subseteq \mathbf{S} \setminus X$ (Structure implicates Structure)

The formalized design knowledge provided by a FBS-NT is used to instantiate a FBS Bayesian Network (FBS-BN, cf. Def. 2) for a specific lead qualification situation (cf. Fig. 1). The Perspectives of the FBS-NT frame the possibilities for instantiation. In a FBS-BN there may be multiple instances of these Perspectives, called Views. Every View stands for a complete duplicate of a Perspective's variables and their assigned relations, given a slight difference: All variables in B are represented twice in an FBS-BN, i.e. Be variables stand for the expected value of a Behavior, and Bs variables represent the value derived from Structure. Further additional Bc nodes are used to compare the Be and Bs values to measure their match. By defining $P(Bc = true | Be = Bs) \stackrel{\text{def}}{=} 1$ and 0 for all other cases we rigidly couple the problem and the solution space. By means of Bayesian inference, this property allows us to select a Structure that fits a defined Function or vice versa discover the Functions that are provided by a given Structure.

Definition 2 (FBS Bayesian Network). Let $G' = (U', E')$ be a directed acyclic graph (DAG), and let $\mathbf{X}' = (X'_{u'})_{u' \in U'}$ be a set of random variables

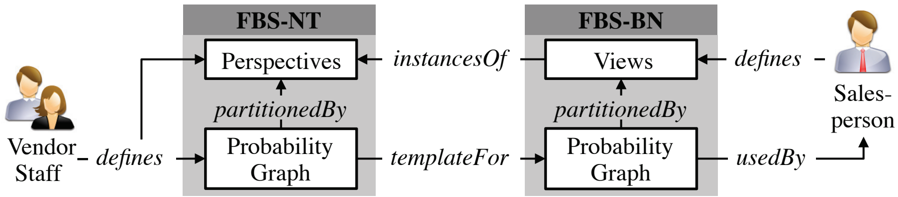

Fig. 1. Instantiation Concept

indexed by nodes U', and let $P(\mathbf{X}')$ be the joint probability over all variables with edges E' representing the conditional dependencies, and let $G_{View} = (V_{View}, E_{View})$ be an undirected graph with nodes V_{View} representing Views and edges E_{View} expressing *isRelatedTo* relations among the Views, then $(\mathbf{X}', G_{View})$ is a FBS Bayesian Network (FBS-BN) with respect to a FBS-NT $(\mathbf{X}, G_{Pers})$, given the properties:

Partitioning. Every variable $X' \in \mathbf{X}'$ is assigned to a View $v' \in V_{View}$ with $\mathit{inView} : \mathbf{X}' \rightarrow V_{View}$.

Instantiation. Every View $v' \in V_{View}$ is assigned to a Perspective $v \in V_{Pers}$ with $\mathit{instanceOf} : V_{View} \rightarrow V_{Pers}$.

Variables. For every View $v' \in V_{View}$ with $\mathit{instanceOf}(v') = v$:

– There is a random variable $F' \in \mathbf{F}', \mathbf{X}'$ with $\mathit{inView}(F') = v'$, where F' is a duplicate of the FBS-NT's Function F with $\mathit{inPerspective}(F) = v$.

– There are two random variables $Be \in \mathbf{B}e, \mathbf{X}'$ and $Bs \in \mathbf{B}s, \mathbf{X}'$ with $\mathit{inView}(Be) = v'$, $\mathit{inView}(Bs) = v'$, where Be and Bs are duplicates of the FBS-NT's Behavior B with $\mathit{inPerspective}(B) = v$. Further there is an extra random variable $Bc : \{true, false\} \rightarrow [0, 1] \in \mathbf{X}'$ with $\mathit{inView}(Bc) = v'$ and $P(Bc \mid Be, Bs)$, where $Bc = true$ denotes a match and $Bc = false$ denotes a mismatch of Be and Bs.

– There is a random variable $S' \in \mathbf{S}', \mathbf{X}'$ with $\mathit{inView}(S') = v'$, where S' is a duplicate of the FBS-NT's Structure S with $\mathit{inPerspective}(S) = v$.

Factorization. Given a conditional dependency $P(X \mid Pa(X))$ in $P(\mathbf{X})$, let $A_{X \cup Pa(X)} = \{v_1, \ldots, v_n\}$ be the set of mutually distinct Perspectives of variables $X \cup Pa(X)$, and let $A'_{X \cup Pa(X)} = \{(v'_1, \ldots, v'_n) \mid \mathit{instanceOf}(v'_1) = v_1, \ldots, \mathit{instanceOf}(v'_n) = v_n \quad v_i \in A_{X \cup Pa(X)}\}$ be the set of all possible corresponding View tuples (n-ary Cartesian product), there are duplicates $P(X' \mid Pa(X'))$ of the FBS-NT's $P(X \mid Pa(X))$ of the following types for every tuple $(v'_1, \ldots, v'_n)$ in $A'_{X \cup Pa(X)}$ that forms a path in G_{View}:

- $X' \in \mathbf{F}'$ and $Pa(X') \subseteq \mathbf{F}' \setminus X'$ (Function implicates Function)
- $X' \in \mathbf{B}e$ and $Pa(X') \subseteq \mathbf{F}'$ (Function expects Behavior)
- $X' \in \mathbf{B}e$ and $Pa(X') \subseteq \mathbf{B}e \setminus X'$ (Behavior implicates Behavior)
- $X' \in \mathbf{B}s$ and $Pa(X') \subseteq \mathbf{B}s \setminus X'$ (Behavior implicates Behavior)
- $X' \in \mathbf{B}s$ and $Pa(X') \subseteq \mathbf{S}'$ (Structure exhibits Behavior)
- $X' \in \mathbf{S}'$ and $Pa(X') \subseteq \mathbf{S}' \setminus X'$ (Structure implicates Structure)

Table 1. Concepts of the FBS-NT

Type	**Perspective**	**Name**	**States**
Function	Office	Being Flexible	Important, Unimportant
	User	Being Efficient	Important, Unimportant
Behavior	Office	Adjustability	High, Low
		Enclosure	High, Low
	User	Distractions	High, Low
		Quiet Work	Plenty, Moderate
Structure	Office	Layout	Open-Plan Office, Cell Office
	Office	Partitions	Cubicle, Acoustic Curtain, Solid Walls

5 Application for Sales Call Support

Consider the following example of our domain of interest: Flexibility in dealing with office changes, e.g. staff churn, is a frequent requirement in office fit-out projects. "Organisations are constantly required to deal with change, so office facilities need to be designed to be flexible to adapt to future changes" [2]. An open-plan office layout may offer the required adaptability. But the type of office layout may also influence the occupant's efficiency. Depending on their work type occupants need a distraction-free environment for doing concentrated quiet work. "An acceptable acoustic environment may be achieved in an open-plan setting for some of those behaviour patterns, but not all" [20]. An office designer may address this by providing a proper enclosure, such as solid walls or noise reducing curtains, to those workspaces that have high demands on acoustic privacy.

To formalize this knowledge in an FBS-NT we first define the problem/solution space, by providing a set of Function, Behavior and Structure variables and assign these to Perspectives as shown in Table 1. Building on the defined variables we connect the problem and solution parts with conditional probabilities. In the same manner as depicted in Table 2, we encode the following statements as probability tables: $P(B_1 \mid F_1)$ to be flexible with respect to future changes, an office should be highly adjustable; $P(B_3 \mid F_2)$ to work efficient, users should not be distracted; $P(B_1 \mid S_1)$ open-plan offices are highly adjustable, while cell offices are rather rigid; $P(B_2 \mid S_1, S_2)$ given an open-plan office, acoustic curtains provide a better enclosure than cubicles, and solid walls provide the best enclosure, but these are only available in cell offices; $P(B_3 \mid B_2, B_4)$ if a user group has a high amount of quiet work to do, but has not a sufficiently enclosed workspace, distractions will be high.

Now imagine a lead qualification situation where the lead requires the new office to accommodate two user groups with different needs in doing quiet work, e.g. a project management and a software engineering department. The instantiated FBS-BN is shown in Fig. 2. While users of the software engineering group spend most of their time with concentrated computer work, project managers are more concerned with communicative acts, like meetings and phone calls (cf. [20]). Given that both flexibility and efficiency are important goals for the lead,

Table 2. Encoding of "to be flexible with respect to future changes, an office should be highly adjustable" as probability table

Being Flexible F_1	**Adjustability** B_1	**Probability** $P(B_1 \mid F_1)$
Important	High	1.0
Important	Low	0.0
Unimportant	High	0.5
Unimportant	Low	0.5

the preferable solution would be to have an open-plan office with acoustic curtains. Bayesian inference on the FBS-BN will exactly express this in terms of a higher probability for the state Acoustic Curtain of variable Partitions $P(S_2^{v'_1} =$ Acoustic Curtain), if we set the probabilities to 1 for Being Flexible $P(F_1^{v'_1} =$ Important), and Being Efficient $P(F_2^{v'_2} =$ Important), $P(F_2^{v'_3} =$ Important), and Quiet Work $P(Be_4^{v'_2} =$ Moderate), $P(Be_4^{v'_3} =$ Plenty), and 0 in all other cases. These probabilities represent answers given to the questionnaire.

To highlight those variables that are important in determining the problem/solution space but have not been answered yet, we use a scoring function based on the inferred probabilities. We define a measure of uncertainty $S[P(X)]$ as the Kullback-Leibler divergence [14] of $P(X)$ with respect to a discrete uniform distribution of the same size n and normalize it to $[-1, 0]$:

$$S\left[P\left(X\right)\right] \stackrel{\text{def}}{=} \left(\sum_x P\left(X=x\right)\left(\log P\left(X=x\right)-\log\tfrac{1}{n}\right)\right)/\log\tfrac{1}{n}$$

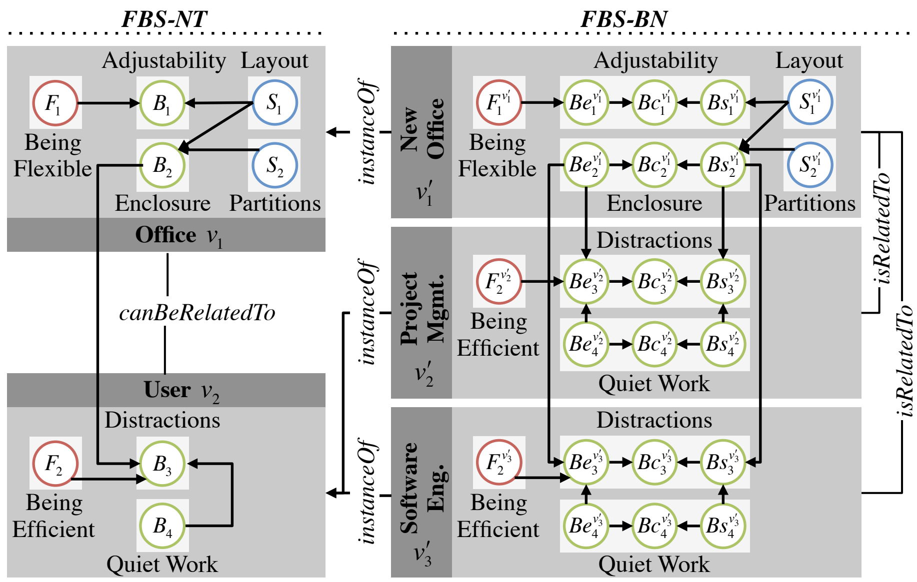

Fig. 2. Instantiation Example

This score is high (close to 0) if the inferred probabilities of X show a high ambiguity and are close to the uniform distribution, i.e. the variable's state is unknown and should be assessed by the salesperson. By rating all variables $X \in \mathbf{F}' \cup \mathbf{B}e \cup \mathbf{S}'$ with $S[P(X)]$ we can generate a ranked list of concepts. Questions that ask for these concepts are then presented to salesperson in form of a questionnaire, specifically highlighting higher rated concepts.

6 Conclusions and Future Work

We have presented a computational representation of the FBS framework, which specifically addresses the uncertainty inherent in the vendor's perceptions of a lead's demands. It is used to assist lead qualification by highlighting requirements and solution components that should come to speak in sales calls.

Currently we are integrating this representation in an prototype application, that resembles a questionnaire for sales call preparation. We expect this system to have a positive effect on a salesperson's performance in lead qualification situations, and look forward to test this assumption empirically.

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