Towards Identifying Business Value Patterns

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Abstract. Patterns are known from Software Engineering, and earlier from building construction to capture well-accepted design knowledge. We explore a pattern elicitation method, based on the PattCar method, to find business value models. We use the field of Big Data advertisements business models to explore our approach.

1 Introduction

Following Alexander [1], a pattern can be considered as an accepted problem-solution pair that can be re-used over and over again. Although Alexander's work on patterns stems from building architecture, patterns are also frequently used in software engineering (see e.g. [2]). Often occurring design problems (e.g. a list of items) are combined with broadly accepted solutions (e.g. a linked list).

For a number of years, there exist modeling languages to represent business models, such as the Business Model Canvas (BMC) [3], the Resource Event Agent (REA) ontology [4], and the e^3*value* ontology [5]. This gives the language to develop patterns for business models; being business models that work. For e^3*value* , there patterns have already utilized for fraud detection and prevention [6].

This paper proposes an approach to identify e^3*value* patterns. The approach is based on PattCaR [7]. PattCar is a step wise approach to identify business process patterns. Obviously, there is a difference with e^3*value* , as the e^3*value* ontology abstracts away from how business process are actually performed, and instead focuses on the economic value produced, exchanged, and transferred.

We use the domain of 'Big data' to explore the adapted PattCar approach for pattern elicitation, and more specifically, we focus on the advertisement driven business models of Big Data.

This paper is structured as follows. In Sec. 2 we present our PattCar grounded approach to construct business model patterns. Sec. 3 explains one of the found Big Data business model patterns. Finally, Sec. 4 provides a short discussion.

2 Constructing Business Value Model Patterns

Traditionally, a pattern has the following structure: name (used for lookup), context (the environment problem and solution occurs in), problem, and solution(s) [2]. The 'problem' slot in the pattern structure does not really reflect the actual use of business value model patterns, as this is more opportunity driven. Consequently, we replace the 'problem' slot by a 'goal' slot, stating what a network (or individual companies) would like to achieve by applying the pattern.

For describing the solution part of a pattern, which is effectively a business model fragment, we use the e^3*value* modeling language. In short, the e^3*value* graphical modeling language represents a business model as a network of enterprises and end users, exchanging things of *economic value* with each other. For more information on e^3*value* , the reader is referred to [5];

Secura and Loucopoulos [7] suggest an approach, named PattCaR, to ease and guide the capturing and reuse of patterns in a business domain. The PattCaR methodology consists of six basic activities: (1) define the domain and analyze context, (2) define the domain core processes and vocabulary, (3) describe the sub domains in terms of existing generic business processes, (4) develop the sub domain enterprise models for the n businesses, (5) define patterns for each sub domain, and (6) organize and interrelate patterns [7]. Note that PattCar has a focus on business processes, whereas our interest is in business value models. This results in the following approach.

Step 1 Define domain and analyze context. For the field of Big Data advertising, we first do a literature and web survey (see [8]).

Step 2 Define domain vocabulary. The domain vocabulary is a concise handbook of precise definitions for significant terminology in the domain of business value models representation. We use the e^3*value* ontology [5] for this purpose, since this ontology provides an accepted terminology for expressing networked business value models.

Step 3 Describe sub domains. A terminology should be proposed to characterize the sub domain adequately, here the sub domain of Big Data..

Step 4 Develop the sub domain business value models for selected cases. For a number of cases found in the literature and on the web, we construct individual business value models based on publicly available information. Thus results in a number of business value models for enterprises: Barclays, Uber, ABN Amro, Rabobank, Mastercard, Weve, ING, Twitter, BDEX, and TomTom. Note that most these of enterprises are active as financial service providers. We expect that this biases the patterns.

Step 5 Definition of the patterns by doing a commonality/variability analysis and a synthesis of the results. In this step, the business models found in the previous steps are analyzed for overlap and differences.

Step 6 Identify patterns. We model the e^3*value* pattern based on models of the cases, which are classified as 'common' based on the common-variability analysis.

Step 7 Internal validation. We have added to the PattCar approach an additional step, with the aim to early validate the patterns. During this last step, we re-model the studied cases (see step 4), but now with the help of the found patterns. The aim of this step is to check whether the patterns can be used for model construction at all. As a result, all individual cases could be modeled by using one or more patterns, plus obviously case specific additions.

3 Big data value patterns

Given that the steps 5, 6 and 7 of our PattCar grounded approach enable us to define, identify and validate patterns, in this section we only report on these steps. The context (step 1) of Big Data is obtained by literature and web search. To express networked business models (step 2), we employ e^3*value* . To identify the sub domains (step 3), here in Big Data advertising, we use a classification of Big business model types by Ray Wang [9] (see Fig. 1. first column). Finally, the models for the individual cases (step 4) can be found in [8].

Fig. 1. Classification of Big Data business model cases

Big Data Business Cases Ray Wang (2012)	BDBC1 Barclays	BDBC2 Uber	BDBC3 ABN	BDBC4 Rabo	BDBC5 Master	BDBC6 Weve	BDBC7 ING	BDBC8 Twitter	BDBC9 BDEX	BDBC10 TomTom
Information-based differentiation										
1. Creating new service offerings	×	×	×	×	×	×	×	×	×	×
2. Satisfy customers	×	×	×	×	×	×	×	×	×	×
3. Providing contextual relevance	×	×	×	×	×	×	×	×	×	×
Information-based brokering										
4. Selling raw information	×	×	×	×	✔	×	✔	×	✔	✔
5. Delivering insights & analysis	✔	×	✔	✔	✔	×	×	×	✔	×
6. Providing benchmarking	×	×	×	×	×	×	×	×	×	×
Information-based delivery networks										
7. Fostering marketplaces	×	×	×	×	×	×	×	×	✔	×
8. Driving deal making	✔	✔	✔	✔	✔	✔	×	✔	×	×
9. Enabling advertising	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔

Commonality/variability analysis. Figure 1 shows the individual Big Data cases classified according to the typology of Wang. Check marks indicate that a business case can be considered as an example of the Wang business model type.

To discover clusters and consequently identify patterns, we do an commonality-variability analysis.

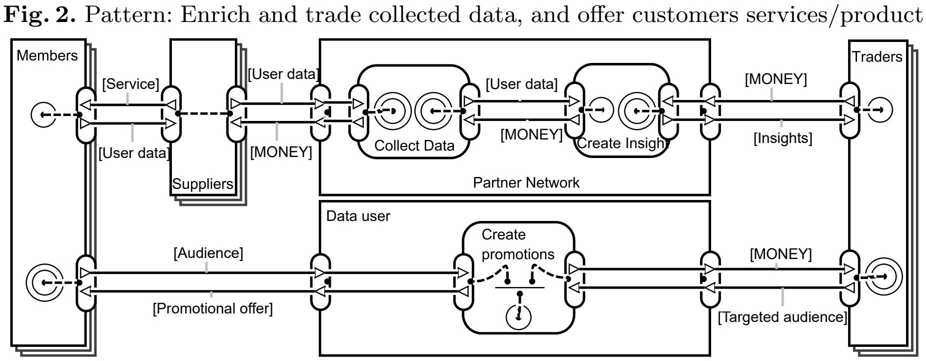
The clustering criterion consist of a combination of the check marks and similarities Big Data business cases have regarding the coverage of the business model types. The cluster is required to have a minimum of one business model type that covers at least two Big Data business cases.

Three clusters were identified, which are color-coded to be distinctive in the classification framework: Enrich and Trade collected data, Information broker, Data insights and analysis as a service

Pattern identification. Next, we present only one of the three identified patterns due to space restrictions.

Element	**Description**
Pattern:	Enrich and trade collected data, and offer customers services/products
Goal:	Initially, build a large customer base, Receive additional revenues as the customer base grows by selling the obtained data, Give customer base easy access to a wider selection of offerings they might interested in, Allow partnerships to generate new offerings with discount or additional services.
Solution:	A Supplier (e.g. Twitter) of a service or product offers a platform to its Members (e.g. to exchange tweets). A Partner (e.g. Datalogix) aggregates, exchanges, and enriches usage data of the Supplier into insights, which are sold to interested parties (Traders). Finally, a Data User (e.g. Nestle) uses data from the Traders to create promotions to Members of the original service supplier (Twitter).
Model:	see Fig. 2.
Evidence:	case 2, 4, 8

Fig. 2. Pattern: Enrich and trade collected data, and offer customers services/product



Internal validity. We have re-modeled the cases on which the patterns are based, but this time by using the found patterns. We were able to use the patterns to model the cases. We also invited two companies, not part of the cases to construct the patterns, to model their Big Data business model by using the patterns. The patterns were experienced as useful for model construction, but due to space considerations, we can not report on these cases in more detail.

4 Discussion

We have proposed an approach to construct business model patterns, as well as way to represent these.

For the construction process, we have to rely on existing business models that are proven to be successful. This is often a problem, as companies are not keen to expose their business model to outside world, specifically if these companies obtain (early) competitive advantage.

With respect to the representation of business model patterns, we use e^3*value* to specify the 'solution' part in a model-based way. Ideally, the 'problem' part (in our case the opportunities) should also be represented by models. We feel that the traditional goal oriented approaches (e.g. i-star) are not really suitable for this purpose, as they do not include the concept of *commercial opportunity.* Future work therefore would be to develop an ontology about commercial opportunity.

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