A Framework for Optimising Business Rules

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Abstract. There has been significant growth in the number of business intelligence platforms that support and execute business rules since the late 1990s that shows no signs of abating. This paper examines the question of how to optimize business rules that can support rather than replace the human decision maker. It presents a novel framework to combine data (including decisions and actual outcomes), a business rules engine and the human judge. Preliminary results, on real data, suggest that about 80% of cases could be determined by a rules engine with an overall increase in gross profit of about 2%.

Keywords: Business intelligence · Business rules · Analytics · Optimisation · Decision support · Services · Productivity

1 Introduction

According to Gartner, Business intelligence (BI) is an umbrella term that includes the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance [1]. A more comprehensive definition is: Business intelligence systems combine operational data with analytical tools to present complex and competitive information to planners and decision makers. The objective is to improve the timeliness and quality of inputs to the decision process [2]. Business rules are very common within industry, particularly the service sector. They enable consistent decision making by individuals and a degree of automation using business rules engines. Expertise and experience can be codified and used by a large number of less expect and less experience staff.

There is a natural relationship between BI and business rules. Whilst planners and decision makers use the insights directly, we can use the same insights to influence the behaviour of others of the business through the business rules that they adhere to.

This paper addresses a challenge in the services sector: that of finding a set of business rules that maximises the expected value to an organization. For example, in customer qualification (do we want to do business with this customer), segmentation (what do we want to offer this customer) and claims management, where we need to balance the wants and needs of the customer, and the profitability and reputation of the organisation.

The following section reviews relevant literature and compares and contrasts research the related field of business process optimization. In Sect. 3 we provide a

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definition of the problem. The framework is defined in Sect. 4 and in Sect. 5 we discuss its application. Preliminary results are described in Sect. 6.

2 Literature Review

Business rules deal with variability and uncertainty. Customers are different; outcomes are often uncertain. Yet we need consistency: if two customers meet a certain criterion for acceptance, then they should both be accepted. In the last 20 years or so there has been an increase in computerisation that enables not only consistency but monitoring, enforcement and flexibility [3]. These software systems, called business rules engines, enable organisations to build and maintain sophisticated sets of rules that can control and monitor many thousands of staff and millions of transactions, in real-time. They also enable rules to be changed to reflect changes in business circumstances. But while business rules deliver consistency, they do not automatically deliver efficiency or maximise customer service or revenue. For further information see [4].

Business processes are also important to both the services and manufacturing sectors. This is particularly important in manufacturing as many important parts of the business are about processing physical items rather than information and rules themselves are not sufficient [5]. The human resources and physical resources which are used, both cost money. This has naturally led to the concept of business process optimisation where the sequencing of tasks, allocation of tasks to machines, etc., are planned to minimise costs and/or maximise revenue [6]. Indeed manufacturing often goes a lot further and uses optimisation and forecasting techniques to maximise profit based on variable demand and anticipated demand in quite sophisticated ways [7].

Optimisation in the services sector is not so well advanced. Two notable exceptions are staff rostering [8] and supply chain optimisation [9]. Rostering is widely used for the purposes of having the right number of people (and no more than is necessary) with the right skills, in the right place at the right time. This is motivated by cost reduction, because people costs are very significant in the services sector. Supply chain optimisation is about tasks, such as supply, storage and distribution, the allocation of resources to tasks, and the order that tasks are performed.

There are significant potential economic benefits in optimising the operation of the services sector through optimal business rules, and increasing the productivity of the services sector has been identified as key challenge/opportunity [10].

So, broadly speaking, an organisation may have right number of people, with the right skills, all doing the same thing (in the same situation) by using the same business rules. But could it do better, and serve its customers better by optimising business rules?

Business rules are part of business processes, and it is important to understand the difference between them, and their respective optimisation. A business process is a collection of related, structured activities or tasks that produce a specific service or product (serve a particular goal) for a particular customer or customers. [11] Business process optimisation is considered as the problem of constructing feasible business process designs with optimum attribute values such as duration and cost [12].

A business rule is a rule that defines or constrains some aspect of business and always resolves to either true or false. Business rules are intended to assert business structure or to control or influence the behaviour of the business [13]. Our definition of BPR is: Business rules optimisation is about finding that set of business rules that maximises the expected net contribution to the organisation that uses them.

Business rules research has, up to now, focussed on the following areas:

- The efficient construction of business rules from expert knowledge [14, 15] or other data sources [16],
- The creation [17, 18], organisation [19], deployment [20] or integration [21] of business rules
- The impact or use of business rules [22–25]
- How they enforce policies [26]

There is one reference [27] that considers rules and optimisation, but in the context of rules working with optimisation (linear programming, etc.) to provide decision support; each case or situation is dealt with by rules and optimisation with a separate optimisation calculation carried out each time. We are looking at the ability to optimise the rules (in advance) so that they get the best outcome every time, without further optimisation being required.

There is a large body of research on Business Process Optimisation (BPO). A Google Scholar search for business process optimisation/optimization on 13/12/16 yielded 2502 results.

BPO research focusses predominately on the processes required to produce an outcome at minimum time and/or cost, and the way that tasks and activities are structured (ordering, linkage, etc.). In almost all cases in the literature, rules (where cases or components are directed one way or the other) are not considered.

Research on Business Rule Optimisation is limited. A Google Scholar search for business rule optimization/optimisation on 13/12/16 yielded 6 results [28, 29] relate to the interactions between participants in a communication channel (such as telephone calls or social media). [30] is about fraud prevention. [31] concerns the development of constraint based search techniques and [32] is about simulation of social economic systems within a city. Only [33] presents the problem, albeit at a very basic level. We believe that BRO represents and new area of research that is different too, yet complements, the established area of BPO.

3 Problem Definition

Examples of business rules include decisions around accepting new customers [34], paying insurance claims [35], and treating patients in hospital.

Rules provide consistency and enable organisations to employ less experienced and expensive staff to deal with variability and uncertainty. There has been significant growth in the number of software platforms that support and execute business rules since the late 1990s that shows no signs of abating [36].

Whilst business rules provide consistency and a degree of automation, there is always the question of whether they are, in some sense, correct. In the context of most organisations, correct means that the result of their consistent application is to maximise profit, minimise cost or some other key performance indicator (KPI).

In this research we propose to create a framework capable of constructing optimal business rules including important issues such as what is optimisation in this context, what information should we use to drive them, how we should construct them and how we integrate human judgement?

Many examples of business rules can be identified, ranging from commercial (deciding on a loan application or insurance claim, approving expenditure, etc.), to social such as medical diagnosis and assessing issues around child protection.

The basic idea is that we can use a computer (a business rules engine or machine) in conjunction with a human judge to make decisions. This is important; we are not seeking to eliminate the human judge as a matter of principal, we are merely using him or her when it make economic sense.

They have some concepts and features in common:

- There is a subject or CASE
- The CLASS of a CASE is an unknown variable
- We are required to make a DETERMINATION for each CASE
- Each CASE has ATTRIBUTES, features or cues that are apparent
- The ATTRIBUTES are random binary, integer and real variables
- The ATTRIBUTES cannot be assumed to be independent of each other
- It is possible to make a DETERMINATION on the CASE by observing the ATTRIBUTES
- This DETERMINATION may be made by a HUMAN judge or MACHINE
- There are BUSINESS RULES for the MACHINE
- The BUSINESS RULES are interpreted by the MACHINE, which processes each case and decides upon it or refers it to a HUMAN
- The HUMAN has some freedom to use their judgement, as well as the BUSINESS RULES, to make a DETERMINATION
- For the organisation, which is one of the STAKEHOLDERS, there are monetary consequences from both correct and incorrect DETERMINATIONS.

Table of Examples

Application	Loan approval	Child protection	Medical diagnosis
CASE	Loan applicant	Child of interest	Patient
CLASS	Good Bad	Abused At risk Not at risk	Healthy Diseased
DETERMINATION	Accept Reject	Do nothing Monitor Act	Do nothing Tests Treat
ATTRIBUTES	Credit score	Parents	Symptoms

(*continued*)

(*continued*)

Application	Loan approval	Child protection	Medical diagnosis
	Income Security	History Observations	Test results
BUSINESS RULES	Credit policy	Statute	Medical procedure
MACHINE	Application website	Triage	Screening test
Output from MACHINE	Accept, Reject or Refer	No case, Low priority, High priority	Negative, Positive (refer)
HUMAN JUDGE	Underwriter	Social worker	Doctor

In the cases above, the MACHINE takes one or more of the ATTRIBUTES as input and performs logical operations on the ATTRIBUTES to make a DETERMINATION on a CASE. One of the DETERMINATIONS is refer to the HUMAN JUDGE. In the loan approval application, certain CASES will be rejected automatically, others will be automatically accepted and the rest referred.

Organisations utilise processes to structure activities directed towards their objectives. Naturally an organisation may have many objectives, sometimes related to the different stakeholders in the organisation.

The activities of an organisation can be broken down into tasks, and each task requires different resources such as people, equipment, machines and time.

In this paper we consider organisations whose customers request a service. The particular objective we address is optimising the choice of which customers to accept and which to reject.

We examine the process which serves this objective: *the customer selection process*.

The outcomes of the process are (1) a set of customers (CASES) accepted (2) a set of customers who withdraw from the process (3) a total benefit from the customers served, and (4) an opportunity cost associated with the customers who are not served either because they dropped out, or because they were not selected. The process also has a cost (5) arising from the resources consumed in its component activities.

If the benefits (3) and the costs (4) and (5) can be quantified, the process is optimised when (3) – ((4) + (5)) has been maximised. In all cases we need to classify the customer (or case) as accurately as possible whilst minimising the cost of classification, the opportunity cost of rejecting a customer that we should accept and the liability of accepting a customer we should not have accepted. There are also consideration around abandoned transactions; making the customer experience more onerous by asking for too much information can results in otherwise potentially valuable customer giving upon the process. In addition we have to recognise that financial services providers have levels of engagement including on-line, customer service agents and experts, such as underwriters, each of which bring different costs and expertise to the problems.

A similar problem that can be addressed in the same way is one of approvals, particularly for purchases or commencement of a contract, where different levels of staff have different approval levels. If a purchase/project is above a particular level, it needs to go to a more senior member of staff.

For the pilot application we considered the problem of loan approval. There were 6 data items requested:

– Credit score (which is a composite of other variables including credit history) (FICO)
– Loan amount
– Debt to income (DTI)
– Years of employment (EMP)
– State
– Postcode

The complete objective function is:
(total good applications × (1 – AR) – good cases rejected) × potential profit
– cost of bad cases accepted × potential loss
– cost of determination

where AR is the abandonment rate which is a function of the amount of information requested.

For the purposes of the pilot we can assume that potential profit and potential loss are related to the size of the loan. The processing costs are a function of the amount of information, for example a familiarisation time and a time proportional to the amount of information.

4 Discussion

The customer selection process essentially involves two major subprocesses: an initial automated filtering of the customers, possibly followed by a final selection carried out by a human expert. In practice the number and availability of the experts is somewhat inflexible, so the allocation of resource to the second subprocess cannot readily be changed. Consequently the first, filtering, subprocess must adapt its outcomes: forwarding a narrower band of customers to the second process on some days to avoid overloading the experts.

In order to tackle the overall goal of optimising the customer selection process, the BRO framework must consequently address both automated and human decision-making.

To meet the overall objective of optimising the customer selection process, this research must address some traditional business process optimisation questions: resources and throughput of different activities, incurring certain resource costs and yielding certain value. It must also address issues in automated decision-making, such as decision-tree optimisation, but in the context of a decision-making process that includes delegation to a human expert. Thirdly it must address issues in human decision-making: what is the effect, on speed and accuracy of human decision-making, of sending them only the most difficult cases as opposed to a broader spread of cases? The final issue relates to the different stakeholders of the organisation. Is it important never to reject a "good" customer who might have benefitted from the service? Or is it important to process ALL the customers within a certain time? Or is it simply required to maximize the profit margin?

What we are seeking to understand is *how business rules and the process of their application can be designed and optimised, to maximise their net contribution to the business that uses them*. In this context optimisation includes:

- Costs (reduction)
- Compliance (with regulations)
- Customer service (maintain or improve)

There are different types of rules, but they share some common features:

- Humans can make decisions on their own
- The rules can help them
- Some of the rules can be executed by machine

What we are looking at comprises essentially three things

- What can the machine do, and what rules should they execute?
- How do we optimise such rules?
- How can we create a framework where humans and machine contribute to maximise net benefit?

5 The Framework

There are a number of considerations with the customer selection process that need to be addressed.

Firstly, that we have to decide on the information that we collect and analyse. Information collection may be relatively cheap and painless for the organisation; the customer either fills in a form or goes on-line and does all the work. But analysing the information may not be so cheap; if we can use a computer, costs are low; if we need to use a human to make the decision, costs can be high. In addition, there is evidence that asking for too much information can result in abandoned transactions; the customer simply gives up [37]. Whilst each piece of information will have an impact on the accuracy of the classification, it will also have an impact of the processing cost and abandonment rate. We are seeking that (minimal) subset that gives us the best expected profit. This is known as the feature selection problem in machine learning [38].

Unfortunately this is not a straightforward process. Until we define the rules we don't know how the outcome of the processing, and we cannot define the rules until we know what information we require to process. So in order to address the information question we need some way to approximate the processing step.

The second challenge is to model human judgement challenge is to model human judgement. There is a lot of research into this question in the field of psychology. The LENS model [39] has been applied to many problems involving judgement, such as medical diagnosis. Based on past performance, we can fit a model for any human judge and compare their judgement against 3 other quantities; the model of their judgement, a model of the outcome and the actual outcome. From that we can estimate their judgement on any particular case in the future. The original LENS model is linear but there are obvious extensions using polynomial regression and classifications techniques, such as decision trees [40].

The third challenge is how to build the rules, which are executed essentially for free by a computer. There are several ways to do this, for example decision trees or rule learning [41]. The subtlety in our case is that the decision is three ways; accept, reject and refer (to the human decision maker).

The final challenge is to incorporate the business rule engine (the computer) with the human judge. The key issue here is that we have to compare probabilities for each end point of the rules (the leaves of the decision tree). If we take the output of the rule we know the probability that any case will be good is determined during the build, based on the training data. Conversely, if we give the case to the human judge we can estimate their accuracy (using the judgement model) and determine is the extra cost is justified by increased discrimination or classification accuracy.

6 Preliminary Results

We tested the basic framework described with a subset of a large data set [42]. We examined the resource allocation problem, which is how many cases should be given to the human judge. For reasons of simplicity we assume that the human judge is 100% accurate; we have data on outcomes as well and this will be addressed later. We also assume that the potential profit (of taking on a good customer) and loss (from taking on a bad customer) are equal to 50% of the average loan value. These numbers are simple inputs and can easily be varied.

Initial analysis showed that the address attributes (State and Postcode) and Loan Amount did not add any value. A simple 5 level decision tree was built using the WEKA Workbench [43] with the remainder of the attributes. This is shown below:

```
FICO < 802.5
|  EMP < 0.75 : 0 (236800/649) [118014/306]
|  EMP >= 0.75
|  |  DTI < 24.99
|  |  |  DTI < 4.05 : 0 (25206/344) [12687/190]
|  |  |  DTI >= 4.05
|  |  |  |  FICO < 751.5 : 0 (44825/4009) [22450/1906]
|  |  |  |  FICO >= 751.5
|  |  |  |  |  FICO < 752.5 : 1 (520/126) [256/49]
|  |  |  |  |  FICO >= 752.5 : 0 (3716/911) [1760/445]
|  |  DTI >= 24.99 : 0 (30260/28) [15403/26]
FICO >= 802.5
|  FICO < 819.5
|  |  FICO < 803.5
|  |  |  DTI < 2.54
|  |  |  |  DTI < 0.39 : 0 (17/2) [9/4]
|  |  |  |  DTI >= 0.39 : 1 (60/27) [30/11]
|  |  |  DTI >= 2.54
|  |  |  |  DTI < 30.02 : 1 (905/27) [486/27]
|  |  |  |  DTI >= 30.02 : 0 (14/0) [8/0]
|  |  FICO >= 803.5 : 0 (864/0) [429/0]
|  FICO >= 819.5
|  |  FICO < 835
|  |  |  FICO < 820.5 : 1 (952/23) [508/6]
|  |  |  FICO >= 820.5 : 0 (40/0) [25/0]
|  |  FICO >= 835 : 1 (10491/2) [5271/2]
```

At each (of the 14) leaves of the tree we have information on the type of node (0 = bad, 1 = good) and the composition of that node (#correct, #incorrect) and the numbers in square brackets are the validation set. For example, on the first leaf we test for FICO < 802.5 and then EMP < 0.75. We determine that the node is bad with 236800 correctly classified (as bad) and 649 incorrectly classified. The problem now is to determine whether it is worth giving these cases to a human judge, and incurring a cost, or simply rejecting all of them automatically and accepting the cost of rejecting a relatively small number of good cases.

If we set the cost of a determination at 0.5% of the average loan, we find that it is optimal to assign 77% of the cases to the rules engine, and the gross profit increases by 1.8% over that obtained by using the human judge on all cases (shown below). With a determination cost of 0.25% of the average loan value, the allocation remains the same, with an increase in gross profit of 0.6%. The break-even point is reached when the cost of a determination is 0.134% of the average loan value. The profit figures below are $1,000's.

	Optimal case load		Profit
Leaf	Machine	Human	Increase
1	355769	0	15616
2	0	38427	0
3	0	73190	0
4	0	951	0
5	0	6832	0
6	45717	0	2419
7	0	32	0
8	0	128	0
9	0	1445	0
10	22	0	1
11	1293	0	78
12	0	1489	0
13	65	0	4
14	15768	0	910
Total	418634	122494	19028
	77.36%	22.64%	1.81%

The diagram shows that if we take the machine determination for leaf 1, the net saving over giving the cases to the human judge is $15,616,000. The same applies to leaves 6, 10, 11, 13 and 14. For the remainder, it is better to give the case to the human, with no net saving.

7 Conclusion

Business rules are widely used with industry yet there is virtually no research around how to create rules that in some sense optimise the expected value of their application. Conversely Business Process Optimisation (BPO) has been widely researched. There are similarities but also some essential differences. We have defined the concept of Business Rules Optimisation (BRO) in the context of their use in the services sector and created the representative example of customer selection. The framework we have developed employs ideas and techniques from machine learning and psychology, and is complementary to BPO. The frame work cannot be applied linearly as there are elements of iteration. But for each step within the framework we have identified useful techniques that could be applied to answer the key questions such as:

- What information do we ask for?
- How do we model human judgement?

– How do we build the rules?
– How do we incorporate a rules engine with a human decision maker?
– How do we modify the rules when caseload changes?

The potential of this approach is considerable. BPO has developed and created an industry without considering the impact that rules have on processes with variability and uncertainty. BRO has the potential to extend the application of optimisation to many more processes. In further work we plan to implement and validate the framework for a large credit assessment data set [38] that includes accepted and rejected customers, and outcomes. We will also consider human judgement and the ability to modify rules in real-time as the caseload changes.

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