

Towards modelling operational risk in service networks ¹

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Abstract: The application potential of probabilistic relational models (PRM) for the analysis of operational risks is presented. We explain some basic commonalities of current approaches to PRM and their relevance to the analysis of operational risks. Possible extensions of the methodological approach to risk analysis in complex service networks are discussed.

Keywords: Markov random fields, Operational risk

1. Introduction

In statistical models for operational risk, we often need to combine information from multiple sample spaces. An example would be to build a model combining

- observations related to failures of a technical or general service component
- observations related to customer contract related data, like customer claims in the scope of a service contract.

Both classes of observations can be described by suitable theoretical distributions whose parameters can be estimated given actual empirical data. Typically, failure probabilities can be assessed using distributions from reliability theory, while customer claims will follow some loss sizes distribution that is typically taken from one of the "fat tail" distribution families like the Weibull distribution.

In conventional risk analysis, combination of these distributions can be done using convolution in order to estimate losses as they accumulate over time.

In the present service provider scenario, however, the combination of the information from both data sets, is more complicated, since we actually need to take into account the service providers who are operating the technical components and also appear as contracting party in customer service contracts. This implies that only component failures that fall in the service domain of a given service contract can be the possible causes of certain customer claims. This dependency can be formulated conveniently using relational algebra like in database modelling (see below).

As a consequence, for an integrated statistical model of both sample spaces contributing to operational risk we may not combine the sampling spaces for both observation classes by considering a suitably extended product space. Rather, we need to have a language in which we can declare the constraint on possible dependencies between observations and perform computations of parameter estimates in accordance with the real data at hand.

This requirement for a relational modelling enabled formulation of observation based variable dependency has been noted in several fields of applications, notably bioinformatics, web link analysis, natural language based information extraction. As a consequence,

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the new field of probabilistic relational modelling and learning is being established by a network of cooperating groups, see Getoor and Taskar (2007).

In section 2. we present the basic approach to handling models for risk on entities linked by relationships, and in section 3. we explore the basic ideas of extending the approach to service networks.

2. Relational Models for Variable Dependencies in multi-entity Observations

We provide here a short overview of the state of the art in PRM (probabilistic relational models). PRM are closely related to Markov random fields, but the approach to defining variables and estimating parameters is different from conventional applications. A similar view on PRM can be obtained departing from Bayesian networks – these can be seen as single-entity PRMs. Therefore, the PRM approach nicely specializes to conventional and well known methods for statistical analysis.

Several approaches related to PRM with essentially the same basic assumptions have been published, they build on

- using an entity relationship model (ERM) for encoding the relational dependencies like in Getoor *et al.* (2007)
- using a suitable subset of first order logic (FOL) and model-theoretic semantics to describe entities, attributes and dependencies like in Kersting and De Raedt (2007)
- combining ERM and FOL assertions for capturing constraints like in the Directed Acyclic Probabilistic Entity Relationship approach (DAPER) in Heckerman *et al.* (2007)

The key idea behind all approaches is that we define an explicit formal data theory in a *declarative* way. This theory contains non-logical (factual) axioms about entity classes, their generic relationships and attribute classes. In a statistical setting, the attributes correspond to random variables. The theory has models in terms of real-world scenarios allowing for experiments. These experiments consist of drawing samples of entities interpreting the entity classes. These entities obey the relationships as stated in theory about relationship classes. What we observe is the values of the attributes corresponding to the attribute classes in the theory.

Continuing with the example of the introduction, the theory would contain axioms like the following examples for defining attributes of entities –

1. A customer has a unique economic activity code (taken from the business taxonomy NACE)
2. A service has a unique service domain code (taken from the service taxonomy UN-SPSC)
3. A service contract has a validity time interval.

In addition, the theory would contain axioms capturing relationships between entities like the following examples –

1. Each customer claim refers to one service contract.
2. Each service contract is owned by one service provider.
3. Each service is using some specific service components.

4. A service component is owned by a service operator.
5. The service provider is service operator of at least one service in each contract owned.

For the sake of brevity, we leave out the exercise to write these statements in FOL. A convenient way to do this is to use either a logic programming language like PROLOG or an ontology language like the web ontology language OWL, see Motik *et al.* (2006). The latter approach is taken in the EU MUSING project.

A real world scenario that is a model of this theory would be given by virtual network operator (VNO) in the telecommunications industry. The operator is owner of some services (like network routers and switches) but may subcontract other services like customer invoicing. The VNO acts as service provider to different enterprises with different service needs. A scenario related to this example analysed in the MUSING project by the Libero Lenti Laboratory at Pavia University together with Kenett Preminger Associates, a Tel Aviv based consultancy, for a large VNO in Israel.

A key result of the PRM approaches in all variants is that under very mild conditions all scenarios that are models (in the model-theoretic sense) of a formal data theory as explained yield variable dependencies equivalent to a Bayesian network or to a Markov random field. Effectively, the formal theory is just a concise way to specify a class of such networks or random fields. However, it should be noted that the interpretation of the theory changes with entity additions or removals from the scenario – fixed scenarios are also often referred to as skeletons related to a formal data theory, see Heckerman *et al.* (2007). To put it briefly, we obtain a skeleton-specific Markov random field.

The main difference of this setup compared to traditional multivariate sampling is that – due to our underlying theory – we have *systematically incomplete observations*. This is a simple consequence of the constraints stated in the theory about the entity relationships. As a matter of fact, with each change in the skeleton we obtain different observable configurations.

In practical terms, the consequence of systematically incomplete observations is that counts etc from samples are *not sufficient statistics* by themselves, they rather provide information only about a specific model (in the sense of model-theoretic semantics) of the underlying axiomatic theory of entities and relationships. This is fundamentally different from (single-entity) Bayesian networks, where we assume either a full data set for training or a partial data set for evidence propagation and inferencing across the network. As a consequence, for each scenario or skeleton we can only update those parameters of network components represented in the skeleton. We are, however, in general not interested in a skeleton-specific model – in the example, the VNO would not want to assess risks only for a certain configuration of service contracts engaging certain components and relating to certain customers. He/she might rather be interested in assessing claim density for customers with specific economic activities, or failure density related to service contracts employing a given class of components.

In order to build a model addressing these questions that go beyond a specific scenario, we need to estimate parameters for a skeleton-independent model from observations taken on one or more skeletons. Fortunately, this can conveniently be done by using the EM-algorithm.

3. Outlook – Towards Operational Risk Models for Service Networks

An interesting aspect of multi-Entity based statistical models is that they can be generalized to large networks of entities. While in an entity-relationship model we typically think of an operative database in an enterprise with a limited number of tables and foreign-key relationships, the reality in today's networked economics tends towards complex networks of business operations in digital business ecosystems (DBE).

We are just beginning to understand the structure of such systems, certainly the modelling of operational risk in these systems will be of prime importance. The main goal is to determine key vulnerabilities of DBE by analysis of the risks each partner has and combining these analyses to yield a realistic overall risk model. A general approach to this task is outlined in the following paragraphs.

Let us assume at a fairly generic level that a DBE can be modelled as a directed graph with nodes corresponding to service providers or service consumers and links corresponding to service contracts. The graph need not be acyclic since a service consumer can act as a provider in a feed-back loop to the service operator. Actually, in customer-relationship management, this is even a quite common pattern. Figure 1 depicts an example based on a purely theoretical assumption of connectivity. Now, in such a service network, the types of risk as distinguished in Basel Committee on Banking Supervision (2006) can be analyzed (with a slight re-interpretation of the notion of credit risk) –

market risk – to be operationalized as competition density of providers addressing the same customers with similar service needs

operational risk – operationalized as described in section 2. for downstream customers, extending the skeleton to a full provider/consumer network

credit risk – operationalized as probability of service defaults (not necessarily measured by financial indicators) occurring upstream in the service network

We are currently evaluating applications of these general considerations to real service networks together with several service engineering research groups.

4. Conclusion

This contribution shows a novel application area for probabilistic relational models in the analysis of operational risks. We also presented a possible extension of the approach to complex service networks as they are characterizing the highly connected and distributed business interrelationships of today's and future globalized economic activities.

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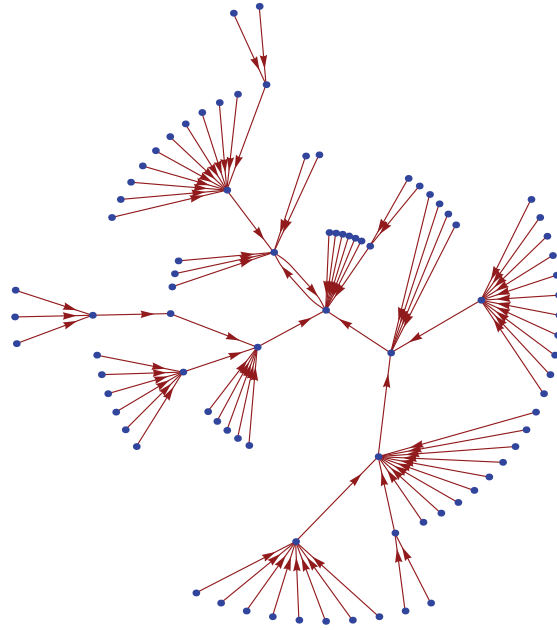


Figure 1: An example of a directed graph depicting a service network governed by Poisson distributed connectivity.

References

- Basel Committee on Banking Supervision (2006) International convergence of capital measurement and capital standards: A revised framework - comprehensive version, Technical report, Bank for International Settlements.
- Getoor L., Friedman N., Koller D., Pfeffer A. and Taskar B. (2007) Probabilistic relational models, in: *Introduction to Statistical Relational Learning*, Getoor L. and Taskar B., eds., 129–174.
- Getoor L. and Taskar B. (Eds.) (2007) *Introduction to Statistical Relational Learning*, Massachusetts Institute of Technology, MIT Press, Cambridge, MA.
- Heckerman D., Meck C. and Koller D. (2007) Probabilistic entity-relationship models, prms, and plate models, in: Getoor and Taskar (2007), 201–238.
- Kersting K. and De Raedt L. (2007) Bayesian logic programming: Theory and tool, in: Getoor and Taskar (2007), 291–322.
- Motik B., Patel-Schneider P. and Horrocks I. (2006) Owl 1.1 web ontology language structural specification and functional-style syntax.