Bringing Clarity to Data Science Projects with Decision Modeling: A Case Study

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The Big Ideas

- A central analytics team benefits from using decision modeling to focus their efforts and build a shared understanding with their business clients.
- Decision modeling, even done in a rudimentary way, can revive projects that have lost their purpose.
- The simple diagrams built through decision modeling can bring clarity to problems long thought difficult.
- Decision modelers can start providing value even with a small training investment.

Introduction

This organization is a global leader in information technology. Like many large companies, it has teams focusing on data science in organizations like marketing, engineering, supply chain, and IT. They also have a centralized business intelligence and analytics capability, shared across internal operations.

The operations organization supports customer service, supply chain, information technology, and employee services such as facilities, payroll, and procurement.

Business Problem and Implications

The central data science team provides analytics services for groups in operations that cannot afford a full-time analyst, let alone an entire team. The team manager believes that analysts benefit from collaboration with other analysts and that analytic projects benefit from having more than one analyst. A team of analysts can utilize multiple skills and multiple problem-solving perspectives.

A central approach to providing analysts for projects presents challenges for both the data science team and the internal business client:

- Business clients are often making use of data science or predictive analytics for the first time, whereas the analysts have spent years developing their analytic skills and vocabulary. This means the business clients have no mental framework to connect their business problem and work environment to the analytic specialists.
- Because they support multiple business clients, the analysts often have little direct experience with the specifics of the business problem they are being asked to solve.

The team uses a technique called decision modeling to drive a conversation that bridges this gap.

Introduction to the Practice and Why It Is Important

Decision modeling helps the data science team and their business client build a shared understanding of
the problem or opportunity. Starting the conversation by talking about decisions rather than the data or analytic techniques to be used avoids overwhelming the business client with technical details. It also helps the data science team avoid jumping to conclusions about the analytic problem to be solved.

The analysts in the data science team have found that it is common for their business clients, even those who are experienced in using analytics, to frame a problem that is not actually the problem the group really needs to solve. For example, the business client may believe they need a model that predicts whether or not a service contract will be renewed, when what they really need to know is how to help the sales team prioritize renewal opportunities.

When the data science team accepts a poorly defined analytic problem, they may develop an accurate predictive model, but one that addresses the wrong problem. It will have no bearing on the decisions that affect an objective or measure that the business wants to improve. Worse yet, neither the analysts nor the business partner will understand what went wrong.

Decision modeling allows the teams to understand the context around a decision, including the objectives or metrics that are affected by the decision, the organizations that affect and are affected by the decision, and what input data, knowledge sources, and other decisions are needed to make the decision. An iterative approach to the decision modeling process enables the teams to develop a model that is recognizable (even if aspirational) to the business client and that can be interpreted for analytic requirement-gathering by the data science team.

**CRISP-DM and Decision Modeling**

The data science team uses the CRISP-DM methodology (Cross-Industry Standard Process for Data Mining) in analytic projects. This methodology provides a framework for consistent yet flexible deliverables in six iterative project phases: 1) Business Understanding, 2) Data Understanding, 3) Data Preparation, 4) Model Preparation, 5) Model Evaluation, and 6) Deployment. The methodology is described in detail in *CRISP-DM 1.0, Step-By-Step Data Mining Guide*.¹

Figure 1. Phases of the CRISP-DM reference model.

¹ Chapman, Pete (NCR), Clinton, Julian (SPSS), Kerber, Randy (NCR), Khabaza, Thomas (SPSS), Reinartz, Thomas (DaimlerChrysler), Shearer, Colin (SPSS), and Wirth, Rüdiger (DaimlerChrysler). “CRISP-DM 1.0, Step-By-Step Data Mining guide.” SPSS Inc. 1999, 2000.
The data science team considers decision modeling a key part of the Business Understanding phase of CRISP-DM. Business leaders who are interested in learning more about the practice of decision modeling as a part of CRISP-DM can find more detail in the research brief, “Framing Requirements for Predictive Analytic Projects with Decision Modeling.” The data science team has used decision modeling with increasing success to clarify and improve their business understanding in analytic projects.

**Applications of Decision Modeling to Solve Business Problems**

**Problem 1 - Service Contract Renewal Opportunity Analysis**

In one of its earliest applications of the decision modeling process, the data science team worked with a sales support team charged with increasing renewals of technical support service contracts. The business client originally requested a model to predict whether or not customers would renew certain service contracts, much like a phone company’s churn model.

When the data science team provided the insights requested, it quickly became clear that this information was not very useful to the decision-makers, who mistrusted the source of insights. The business client asked for additional information explaining why each contract would or would not be renewed (which predictive variables influenced the prediction and to what degree). Not surprisingly, attempts at providing rationale were not much more satisfying to the decision-makers, and the engagement started to lose focus.

Another problem the business client team had was a tendency to pursue and/or be distracted by “shiny objects,” any new directions or techniques that sounded interesting but didn’t necessarily lead to better results. The data science team had a difficult time articulating how these different directions were distracting from the primary goal.

It was then that the team was first introduced to decision modeling. After an extremely brief overview of the principles, the data science team project lead created a rough illustration; in retrospect, it was a mix of an influence diagram, a process map, and a decision model.

![Diagram](image.png)

*Figure 2. The team recognized that this simple model was flawed as a decision model, yet it was successfully used as a tool to focus the team and business client on the core analytic requirements.*

Though it was imperfect, the diagram proved extremely valuable to the joint effort. It gave the business client a much clearer vision of where a predictive model could take it and how it could be iteratively built up to improve as more information sources and knowledge sources were brought in. At the same time, it became clear to the data science team that the decision-makers really needed

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something different from a churn model: Instead, they needed a way to prioritize selling opportunities so they could maximize successful customer calls. The team then created a set of propensity scores that could be used to develop a prioritization framework for the decision-makers.

**Problem 2 - Cost Allocation**

A later use of the decision modeling methodology involved analyzing an element of the cost of providing warranty service. The business client was concerned that this cost was beginning to accelerate beyond acceptable levels. It was aware that the costs were increasing because the organizations that drove the costs were not being held accountable to the increases, but it was unable to allocate the costs correctly due to process complexity. It engaged the data science team to perform an analysis, explaining that there were over a dozen different data sources, none of which aligned with the others. The business client doubted that the problem could be resolved.

After several false starts — which led to some interesting insights but not to the solution to the problem — two data science team members diagrammed the decision, including all the input data sources. This led to a closer look at the sources, which allowed the team to see that the many disparate data sources actually originated from just two different sources. These could be reconciled using a bridging process that worked to allocate nearly all the costs to the correct organization that drove that cost.

The decision diagram, while still not being used quite as intended, allowed the team to provide clarity that the business client and all the affected organizations could agree on. This provided a resolution to an allocation problem that had never been fully addressed before.

Following these two successes, the data science team began to recognize the potential for decision modeling to save time and avoid frustrating iterations due to faulty business understanding. They sought training in decision modeling and started to practice decision-oriented business understanding if not always formal modeling and diagramming. As the team adopted this...
practice, engagements became easier, more streamlined and much less dramatic than in the past, rarely needing to be revived from near defeat.

**Problem 3 - Lead Size Prediction for Automated Leads**

One of the roles the data science team plays involves support and coaching for an internal data science training and certification program. This program allows the company to identify internal employees interested in data science and then provide a core data science certification for these internal hires.

One data science team member coached a group of five employees through the program. The program culminated in capstone projects selected from proposals from across the company. One of the five trainees is a demand-generation manager in the marketing organization. His team had created a way to automate marketing lead qualification, but they did not have an effective estimate of lead size that the sales agent could reliably use for lead prioritization. The trainees decided they would use sales lead data in conjunction with historical marketing leads to develop a predicted marketing lead size.

The team member quickly taught her group the high-level principles of decision modeling; they spent several days of their allotted seven weeks interviewing subject-matter experts in marketing and sales to understand marketing lead size in context of the decisions that were made in the sales and marketing processes. Puzzled at first, the trainees soon realized they were gaining a deeper understanding of the business that would keep them focused on the marketing organization’s ultimate goals. The trainees developed the model just to the point where they could understand their analytic problem within the context of the larger organization’s needs, and determine their requirements.

![Diagram](image)

**Figure 4.** Having created a simple model of the decisions made in this area, the trainees could quickly understand what was needed in their prediction model.

**Lessons Learned**

The data science team finds that it is using decision modeling more and more as they learn the technique and see its power to clarify and focus projects. They admit that they are still learning the discipline. For instance, sometimes they don’t think to hold a decision modeling session until later in the project as there is a natural impatience for both business partner and analyst to rush into solving problems and that is hard to overcome. The team is working on ways to mitigate the hastiness and make it more natural to bring in decision modeling at the start of each project.
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The value the team has experienced in these three examples is clear. They believe that without decision modeling’s influence to rally and focus key stakeholders, they would not have been able to successfully complete the opportunity prioritization project, the cost allocation project, or the lead size estimation project. In the case of the opportunity prioritization project, once implemented, decision-makers will be able to prioritize their opportunities and see a sizable annual uplift for the service contract renewal business. The warranty cost elements can now be allocated at a line item level, enabling complete traceability of spend. As for the automated leads program, marketing is now preparing to implement the model, which will allow them to markedly increase sales adoption of these leads.

The data science team is beginning to use the method earlier in the process instead of as a last resort to save a failing project. They are convinced that the practice will be one of the factors that drives their ability to complete many more projects and bring the company more value, faster, with the same small team. However, once they start using the technique for every project up front rather than waiting to see if a project needs it to regain focus, they can no longer be certain when decision modeling prevents failure or excessive iterations. In fact, they have successfully completed projects in the past without using the technique (though decision-oriented thinking is a touchpoint for the whole team).

Opportunities for Decision Modeling

As the data science team matures in its use of decision modeling, they are looking to expand their use of the technique. In addition to using decision modeling to focus their efforts on the right business questions, they are also using it as one of several tools for harnessing the strength of their diverse team. By using consistent processes such as CRISP-DM and decision modeling, they bridge the gap not only between analysts and business clients but also between analysts with different expertise, experience levels, and functional business knowledge. They are able to share their progress with each other and more easily pass the baton between team leads. Ultimately, this allows the data science team to share a broader skill set with the business client without the lengthy ramp-up time for new project team members.

As word spreads about the value they are bringing, the data science team is increasingly being approached by internal business clients who think they might benefit from analytics but are not sure how or where to begin. The data science team provides them with a new service: one-day solutions, in which they facilitate a simplified decision modeling session that brings the business clients together with other stakeholders and analytic team members. The business clients typically leave these sessions enthusiastic and clear on their next steps.

The data science team has also influenced other groups to invest in training managers in decision modeling. When managers are able to think about their scope in the context of decisions, they will be able to formulate their needs in a way that will help them work much more effectively with their analysts.

Checklist

- Examine your organization’s portfolio for analytics projects that are stagnating, or functions in your organization that might benefit from integrating analytics and decision management.
Learn more about CRISP-DM and decision modeling (papers listed above, online courses, books).

Hold one-day (or half-day) decision modeling sessions with stakeholders to understand their decision space and kick off.

Decision modeling sessions can be held with one or two stakeholders, with a small but broad set of people affected by the decisions, or by yourself and then validated by those who are affected.

**References**

- Chapman, Pete (NCR), Clinton, Julian (SPSS), Kerber, Randy (NCR), Khabaza, Thomas (SPSS), Reinartz, Thomas (DaimlerChrysler), Shearer, Colin (SPSS), and Wirth, Rüdiger (DaimlerChrysler). “CRISP-DM 1.0, Step-By-Step Data Mining guide.” SPSS Inc. 1999, 2000.


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