WHITE PAPER

Phases of Predictive Analytics Maturity

> Understanding the phases on the way to efficiency

Introduction

Insurers have come a long way in their use of predictive analytics to deliver better business outcomes. Guidewire has found that insurers typically progress through several phases on their way to becoming efficient. In this white paper, we introduce a predictive analytics maturity model, discuss the typical issues insurers face in each phase, and recommend best practices for an efficient and agile approach.

The Big Picture

Predictive analytics involves building models to predict future results. It's much more than looking at historical data to understand past results (often called "descriptive analytics" or "business intelligence"). Predicting the future involves separating random events from predictable patterns and requires well-grounded mathematical techniques.

Insurers have come a long way in their use of predictive analytics. Based on the attempts we've seen insurers make over time, we can identify three phases through which insurers have typically progressed. By describing these phases, we want to help insurers more clearly identify their current efforts and desired direction. However, it's not necessary to progress through these phases sequentially.

Phase Zero: Getting Started

In this phase, insurers understand that they should be "doing predictive analytics" but are not quite sure what this means. It is characterized by a lack of experience or expertise on the topic—which makes it difficult to even ask the right questions. As a result, the relevant question at this point is how to get the required expertise. Seek advice and make a plan with the end goal in mind.

Phase One: Single-Model Thinking

This phase is characterized by a narrow vision that only asks what is required to get a single model in production. Historically, this phase was necessary because insurers were new to the issues surrounding the building and implementation of models.

Pricing was typically the focus as a first use case because it was impactful and possible to complete. Insurers typically either contracted with consultants to provide these models or hired (or re-purposed) people with the skillsets required to build predictive models. Implementation of these models relied on providing the specifications to an IT department so that they could program the changes.

Phase Two: Expanding the Single-Model Approach

After building their first model, many insurers realized that they needed a more expansive vision to realize the potential of predictive analytics. However, because many of them had existing predictive modelers, this vision was oriented around expanding the scope of existing analytics teams.

Phase Two is characterized by the understanding that insurance data can inform many insurance processes—pricing, of course, but also insurance operations (Whom to renew? Whom to inspect? How to handle audits?) and claims operations (Which claims need attention? Can we fast-track straightforward claims?). In Phase Two, insurers attempt to meet these needs by expanding the solutions of Phase One.

Most insurers with established analytics teams are in Phase Two, which relies on a team of talented and experienced predictive modelers. Issues with Phase Two include:

- Increasing investment: Expanding the Phase One approach to multiple models requires scaling up the investment in individuals who are experienced in predictive modeling.
- Increasing impact of legacy systems: Solutions for extracting and transforming data that worked for specific predictive models may not scale into an efficient framework for the future, exacerbating the cost required to expand.
- Increasing "key-person risk": As specific, talented individuals build customized models, the risk associated with those people leaving the group (to another company or another unit of the insurer) increases accordingly.
- Operationalized models require maintenance over time: While new challenges excite the talented predictive modelers in the existing group, it's still necessary to make sure that operationalized models remain efficient and are rebuilt when necessary.
- Use cases beyond pricing require new analytical techniques: Although this seems like a straightforward statement, the introduction of new analytical techniques impacts the skills that are required of those in the predictive analytics group and, more importantly, impacts the implementation of the predictive models.

- Implementation of predictive models becomes hugely important: As new techniques are used, the complexity of model rules generally increases to a point where it's infeasible to expect an IT department to program the model based on specifications. New approaches are required in this phase.

Because these issues have become well known, insurers and the vendors who supply their predictive analytics software have been working to solve them. In particular, automated creation of a predictive model's structure is now typical, and the use of API calls to access those predictive models is standard. This solves the technical complexity issues associated with the plethora of techniques now being used. However, most solutions to this problem still miss the fact that business solutions often need more than just the technical predictive model.

One underappreciated issue is the increasing burden of model management. Think of this as a general enterprise risk management (ERM) task: do you know how many models are used in production business processes, including which business processes and which version of the model? Keeping track of this information and auditing it periodically are key to minimizing model risk.

Phase Three: Building an Efficient and Agile Approach to Analytics

Phase Three is all about taking a comprehensive view of predictive analytics and the associated tasks. Rather than trying to extend previous approaches, Phase Three reverts to the fundamentals:

- Not all predictive analytics tasks are new and unexplored. The most efficient resources should be used for each problem to be solved.
- Operationalizing predictive models can be a standardized process that leverages software solutions rather than individual expertise.
- Getting the most out of insurance data in some cases requires creative approaches to new problems.

- Keeping track of "model risk" is a legitimate ERM task. Insurers should be able to catalogue all production models—from data used to modeling choices to implementation procedures.

When viewed as a whole, the advantages of platform approaches that standardize the process of building, implementing, and maintaining predictive models become obvious. Insurers still need talented individuals who can create new solutions to novel problems, but most insurance processes do not require this level of expertise. Something like the 80/20 rule plays out here.

Predictive analytics platforms encourage the sharing of knowledge across predictive modelers and the recording of choices for auditing purposes. Coherent platforms that integrate data, model building, and deployment in one place increase the efficiency of an insurer's predictive analytics efforts, as well as reducing "key-person" risk through a shared platform.

While predictive analytics holds tremendous potential to transform insurer operations, the efficiency of these efforts should not be overlooked. Predictive analytics platforms that encourage uniform standards and processes will be key in making insurers competitive in their marketplaces.

Guidewire's approach to predictive analytics in insurance has been designed with the big picture in mind. See the blog series Guidewire's Approach to Predictive Analytics for more information.