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GENERATING BUSINESS VALUE THROUGH SIMULATION AND DATA SCIENCE

Bipin Chadha

VP Data Science
CSAA Insurance Group
5353 W Bell Rd
Glendale, AZ 85308, USA

ABSTRACT

One of the key challenges that businesses are facing is how to leverage the emerging tools and methods of data science to improve their business performance. Although there are many examples of the use of data science/machine learning techniques in specific sectors and in the areas of games, it is often not easy to translate that success in other sectors or use cases. We have had great success in achieving business value for many use cases by using data science techniques in combination with operations research techniques such as simulation and optimization. In this paper we will go over several case studies that show how simulation and optimization helps in overcoming many of the challenges associated with data science techniques. The methodology we use is easily extended to a wide range of industries and use cases and enables an organization to improve its decision making and generate business value.

1 MODELING METHODOLOGY

Many organizations are successfully generating business value via the emerging data science techniques. While some use cases are pretty straightforward, there are many use cases where it is not obvious that a machine learning model will generate business value or produce something actionable. Primary reason for this is that most machine learning models are focused on narrowly defined problems, and the model results in a prediction. This prediction in turn needs to be turned into an action or intervention (Figure 1).

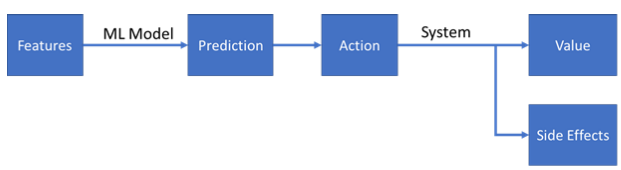

Figure 1: Prediction to value.

Many times this transformation from prediction to action is trivial, but many times a non-trivial transformation is required. Sometimes the prediction goes to a decision maker, who then determines appropriate action. This action is then applied to a system that ultimately generates value. Often, this also results in side effects that are typically ignored in analyses. It is interesting to note that typical machine learning methods take you from features in data to a prediction. Remaining flow is typically manual and somewhat ad-hoc. In our experience the rest of the flow shown in figure 1 can make the difference between a successful or an unsuccessful model. Interestingly this is where simulation methods play a critical role in guiding what action should be taken to maximize value and minimize harmful side effects.

This is achieved by creating a broader system level simulation of the system. The machine learning model that is developed for predictions is then embedded inside the simulation. The overall system is then simulated many times to understand the outcomes based on various action options. The results can then be analyzed to understand the short term and long term impacts in terms of value metrics as well as any side effects. The names and data have been obfuscated to protect proprietary information.

2 CASE STUDIES

First case study involves an end to end product acquisition process (Figure 2). The model was built to address capacity problems after a demand shock. Traditional efforts to address these problems were not effective and a model based approach was employed to understand the problem and address these challenges. The demand was modeled via time series forecasting methods, and other external factors such as GDP were modeled by fitting a distribution to historical GDP data. The process was modeled using the system dynamics modeling method and it captured the process flow as well as causal factors that drove key aspects of the process. The causal relationships were characterized by collecting data and then fitting simple linear regression models. The model was then calibrated with historical data and was found to represent past behavior very well to the point that the stakeholders were comfortable with the results. The model was then run to understand key dynamics of the problem. Several alternative staffing scenarios and process improvement scenarios were analyzed to determine the best course of action. The selected course of action helped stabilize the process and also helped prevent an overstaffing situation that would have emerged six months later after the backlog had been worked off. The model also highlighted that the root of the problem was not the operational process (which is where everyone was focused), but the fact that the forecasting models of demand were not very good and it took a long time to hire and train the staff.

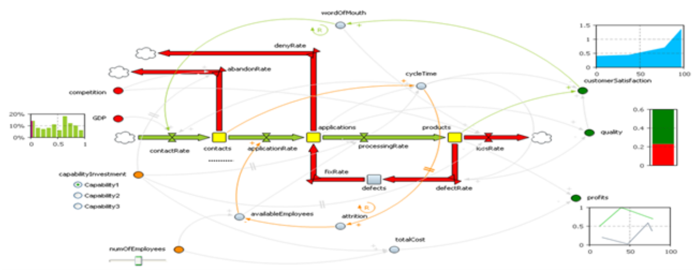

Figure 2: Product acquisition process.

Second case study involves the strategic planning process of an organization. During strategic planning several decisions are made and new initiatives are launched. While a lot of discussion takes place and some analysis is done, it is often not enough to reduce the risk of failure, and strategic failures can be very costly to an organization. To address this challenge, we developed a system level strategic simulation model that modeled the entire market of tens of millions of potential customers. The model was built at an individual level using Agent Based Modeling methodology. Data was analyzed and several individualized behavior models were developed to predict how a person behaves under certain circumstances. These data science models were really simple linear regression models or logistic regression models, but a large number of these models were built quickly and using automatic modeling methods. These models were then used to give behaviors to modeled agents in the agent based model. This model was then calibrated by running it on past year's data. The results were then validated with stakeholders to ensure accuracy and credibility. This model was then used to play out many scenarios to arrive at optimal decisions. The model results showed that targeting a different mix of customer segments provided a better mix of results for key performance indicators than what was favored. The results also showed that although the original proposal did better in the short term, it left the organization more vulnerable in the long term. The model therefore allowed the organization to make decisions that were non intuitive, but better in the long term.

REFERENCES

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