**DECISION
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Analytics Teams: 5 Things You Need to Know Before You Deploy Your Model

Many Analytics and Data Science teams have experience with building what seems like a great model – valid, predictive, powerful – only to see disappointing or even non-existent business impact. Models are not deployed, or take so long to deploy their accuracy is lost. Deployed models are not used or not used very effectively. And models age in place, degrading and dragging down performance.

What can you do? Make sure you can answer these 5 questions before deploying your model:

1 Does the model evaluate well against business objectives?

CRISP-DM, The Cross Industry Standard Process for Data Mining, is the most widely used approach to analytic projects. Once the data analysis and model development are complete, the model needs to be evaluated. Making sure the results are good enough and that these results match the original intent is critical. If models don't evaluate successfully then the project is back to square one.

Many analytics or data science teams evaluate their models only in statistical or modeling terms. Yet analytic models can pass these mathematical checks without helping solve the business problem. A good analytical model is one that helps the business get better results. Successful analytic teams minimize the white space between analytic success and business success, evaluating their models against business drivers as well as analytic ones.

2 Who's using the model, to decide what, where and how?

Sometimes it is clear from the business objectives of the project and its scope alone exactly how the analytic will be used. More often, though, it is not. The reality is that without a clear business understanding — who is going to use the analytic model and what decision they are trying to make with it — it is often impossible to tell if an analytic will be successful. Also, the degree to which the decision is automated, where it is being automated, or the way it will be presented to a human decision-maker all matter too.

A decision model using the graphical Decision Model and Notation (DMN) standard developed as part of the Business Understanding step in CRISP-DM focuses the analytic effort and builds a shared understanding with your business partners, helping ensure you can effectively deploy your analytic to solve the target business problem or improve the target decision.

3   What will it take to make the model actionable?

AI, machine learning, and predictive analytic models let you peer into the future and can help you make better decisions. But having a predictive analytic model is not the same as making a better decision. Your predictive analytics must be made actionable to add business value.

DMN decision models outline how your predictive analytics can be made actionable. Decision models show all the elements of your decision, not just the analytic ones. Other elements of the decision model represent the policies and regulations that constrain decision-making or define score cut-offs and appropriate actions that are based on your analytics. The decision model makes it clear exactly what needs to be deployed to improve decision-making.

4   What's the plan for capturing and analyzing data about model effectiveness?

Analytic and data science teams perform a lot of testing and analysis of the likely results of an analytic before it is deployed. But once it gets deployed, it starts to interact with real people, real organizations, real transactions. The actual results probably won't exactly match your expectations. And use of the model changes behavior which can mean that, for instance, fraudsters or loyal customers change their behavior.

Before a model is deployed, it is essential that you know what data you are going to collect about the model, about the decisions made with the model and about the business results arising from those decisions. Only if you can collect this data and tie it together can you really see if your model is effective in business terms.

5   When do we need to revisit the model to make sure it is still effective?

Once the model is deployed, working and being tracked you are still not done. Models age and degrade. As the world changes and new data is collected, the accuracy of your model can drop and its business value lessen, even reverse. Making sure you have a plan to revisit your models, to check their performance periodically, to manage your AI, machine learning, and analytic portfolio is critical to long-term success and business value.

What Next?

The best way to succeed with your analytic deployment is with decision modeling. Decision modeling delivers three key benefits:

▸ Decision modeling using the Decision Model and Notation (DMN) standard gives you a clear sense of the decision-making your AI, machine learning or analytic is meant to improve, helping you evaluate it and put it in context.

▸ Decision models define what it will take to make your analytic actionable, making it clear exactly what needs to be deployed to improve decision-making.

▸ Continuous improvement, experimentation and analytic model management ensure your analytic will be successful for the long haul. Decision models set up the framework you need to collect and analyze data about your model's performance and its business impact.

Decision Modeling is a powerful complement to analytic methodologies like CRISP-DM. A decision model built using the Decision Model and Notation (DMN) standard provides much needed clarity of business impact and orchestrates your analytic as part of your overall business environment.

Learn More

Here are a few ways to learn more or get started with decision modeling:

▸ Try decision modeling by downloading our white paper Framing Analytic Requirements.

▸ Learn more about our DMN Decision Modeling for Analytics Teams engagement. We have extensive experience helping analytics teams quickly and efficiently adopt decision modeling and integrate it into their approach.

So, 5 Things You Need to Know Before You Deploy:

1. Does the model evaluate well against business objectives?
2. Who's using the model, to decide what, where and how?
3. What will it take to make the model prescriptive not just predictive?
4. What's the plan for capturing and analyzing data about model effectiveness?
5. When do we need to revisit the model to make sure it is still effective?