



Research Note

A framework for evaluating the analytic maturity of an organization

Robert L. Grossman^{a,b,*}^a University of Chicago, United States^b Open Data Group Inc., United States

ARTICLE INFO

Keywords:

Analytic maturity
 Deploying analytic models
 Analytic operations
 Analytic governance
 Analytic infrastructure

ABSTRACT

We introduce a framework called the Analytic Processes Maturity Model (APMM) for evaluating the analytic maturity of an organization. The APMM identifies analytic-related processes in six key process areas: i) building analytic models; ii) deploying analytic models; iii) managing and operating analytic infrastructure; iv) protecting analytic assets through appropriate policies and procedures; v) operating an analytic governance structure; and vi) identifying analytic opportunities, making decisions, and allocating resources based upon an analytic strategy. Based upon the maturity of these processes, the APMM divides organizations into five maturity levels: 1) organizations that can build reports; 2) organizations that can build and deploy models; 3) organizations that have repeatable processes for building and deploying analytics; 4) organizations that have consistent enterprise-wide processes for analytics; and 5) enterprises whose analytics is strategy driven. The APMM is broadly based upon the Capability Maturity Model that is the basis for measuring the maturity of processes for developing software.

1. Introduction

It is rare today for an organization to develop software that is critical to its products, services or operations without a software methodology being used; on the other hand, it is relatively common for an organization to build analytic models that are critical to its products, services or operations without using any analytic methodology.

We introduce a framework for evaluating the analytic maturity of an organization that consists of assigning an *Analytic Maturity Level or AML* score from 1 to 5. The higher the score the more likely that the organization's processes for building and deploying analytic models will result in analytic models that: i) that are statistically valid and are completed according to schedule; ii) can be deployed into an organization's products, services or operations; and, iii) meet the organization's goals for the model.

The framework is based on common challenges that organizations face when developing and deploying analytic models:

- Problems obtaining the data necessary for building models.
- Problems deploying models into an organization's products, services and operational systems.
- Problems quantifying the business value generated by models.
- Deployed models do not bring the business value that was expected.
- A lack of repeatability when building models.
- A lack of repeatability when deploying models.

- A lack of repeatability when testing and evaluating models.
- Difficulty integrating different models developed across an organization to meet the requirements of the organization as a whole.

There are also several common confusions that organizations face:

1. Not understanding the difference between reports generated from data and models built from data.
2. Not understanding the difference between models built from data and business rules.
3. Not understanding the difference between the *outputs* of models and the *actions* and *business processes* required so that products, services and operations achieve a desired business goal.

The greater the analytic maturity of an organization, the more likely that it is for an organization to meet these challenges and not face these confusions.

We note that there is no standard terminology yet in the discipline of analytics. For some time, the first confusion above has been described as the difference between reports (or business intelligence reporting) and predictive models. More recently, developing reports from data that summarize the data has been called descriptive analytics, while the term predictive analytics has been used when statistical models are built from data, especially when these are used to make predictions about future events. Recently, the term prescriptive

* Correspondence to: Center for Data Intensive Science – KCB D 10142, University of Chicago, 900 East 57 Street, Chicago, IL 60637, United States.
 E-mail address: robert.grossman@uchicago.edu.

analytics has begun to be used when the outputs of predictive models are used to derive actions that have business value (which is related to confusion 3 above). Prescriptive analytics has also been used more generally when optimization and related techniques are applied to the outputs of predictive models.

It may be helpful to look at the framework introduced here for evaluating the analytic maturity of an organization from the viewpoint of information or knowledge management. At a high level, one can think of analytics as using data to build models and then deploying the models within an organization's products, services or internal processes to achieve a desired outcome, such as increased revenue, higher retention, lower costs or reduced risks. If we think of knowledge management as the process of capturing, distributing, and effectively using knowledge, then the analytic framework described here relates to knowledge and practices around analytic models, including not only building and deploying them, but also related strategic, governance, security, privacy and risk issues. In the broader context of information management, the framework involves the information management required to manage the data and model assets associated with building, deploying and evaluating models.

2. Background

2.1. Analytic models, infrastructure and operations

The framework introduced here is based upon a few basic concepts: analytic models, analytic infrastructure and analytic operations. We describe each of these in turn. In addition, the framework specializes more general processes related to strategy, IT governance, and security and compliance to those specifically focused on analytics. We use the terms: analytic strategy, analytic governance, and analytic security and compliance for these specializations. See Fig. 1.

2.1.1. Analytic models

By analytic models we mean statistical or data mining models that are empirically derived from data using generally accepted statistical methodologies.¹ For simplicity, we generally use the term *model* below instead of *analytic model*. In contrast to model, we use the term *rule* to refer to a manually derived “if-then” statement that sets a variable or take a specified action based upon the “if” clause of the statement. Although some models can be described by one or more if-then statements, the essential difference is that with models statistical algorithms are used to create the if-then statements while with rules humans manually create rules.

2.1.2. Analytic infrastructure

Analytic infrastructure refers to the software components, software services, applications and platforms for managing data, processing data, producing analytic models, and using analytic models to generate business value through taking actions, making recommendations, and generating alerts (Grossman, 2009).

2.1.3. Analytic operations

Analytic operations refers to the various processes that result in the outputs of analytic models being used to make decisions and to take actions relevant to the business or enterprise, such as increasing revenues, decreasing costs, or improving operations. Analytic operations ensure that the results of analytic models are integrating into an organization's products, services and operations.

¹ We borrow this terminology from the Fair Credit Reporting Act (FCRA), codified at 15 U.S.C. Section 1681 et seq., which requires a credit model to be “empirically derived, demonstrably and statistically sound.”

2.1.4. Analytic strategy

Although there is an extensive literature on strategy and there are several articles that stress the importance of analytic strategy, we have not found a commonly accepted definition of analytic strategy. For the purposes of the APMM, we define *analytic strategy* as the long term decisions an organization makes about how it uses its data to take actions that satisfies its organizational vision and mission; specifically, the selection of analytic opportunities by an organization and the integration of its analytic operations, analytic infrastructure and analytic models to achieve its mission and vision.

Note that this definition is modeled on a standard definition of corporate strategy, which is sometimes defined as “Strategy is the direction and scope of an organization over the long-term: which achieves advantage for the organization through its configuration of resources within a challenging environment, to meet the needs of markets and to fulfill stakeholder expectations” (Johnson, Scholes, & Whittington, 2017).

2.1.5. Analytic governance

As with strategy, although there is a large literature on IT governance, there is no commonly accepted definition of analytic governance. A common definition of IT governance is (Brown & Grant, 2005): 1) Ensure that the investments in IT generate business value. 2) Mitigate the risks that are associated with IT. 3) Operate in such a way as to make good long-term decisions with accountability and traceability to those funding IT resources, those developing and supporting IT resources, and those using IT resources. This suggests that the goals of Analytic Governance should include:

1. Ensure that good long-term decisions about analytics are reached and that investments in analytics generate business value.
2. Operate in such a way that data, derived data and analytic products are protected and managed in a secure and compliant fashion.
3. Operate in such a way as to make sure that there is accountability, transparency, and traceability to those funding analytic resources, to those developing and supporting analytic resources, and to those making use of analytic resources.
4. Provide an organization structure to ensure that the necessary analytic resources are available; that data is available to those building analytic models; that analytic models can be deployed; that the impact of analytic models is quantified and tracked; and that data, derived data and data products are managed in a secure and compliant fashion.

2.2. Building and deploying models

In general, models do not generate value for an organization until they are deployed. They can be deployed into products, into services, or to improve operations. For this reason, it is helpful when evaluating the analytic maturity of an organization's processes to be aware of certain choices when building models.

Usually, a modeling group using statistical or other specialized applications develops an analytic model. Once the model is developed, the IT group deploys the model into the appropriate product, service or operational system. Since they are two environments (the modeling environment and the deployment environment) and two teams (the modeling team and the IT team), it is important that there be an efficient mechanism for moving the models between the environments. There are a few common approaches:

1. The same application may be used in both environments. This approach is sometimes used but not very often since applications that are designed to be used by modelers are not in general designed to be deployed into operational systems.
2. The model may be applied to data in the development environment to produce a table of outputs, which are then loaded into a database

Download English Version:

<https://daneshyari.com/en/article/5110707>

Download Persian Version:

<https://daneshyari.com/article/5110707>

[Daneshyari.com](https://daneshyari.com)