

## Chapter 2

# Analytics Domain Context

The Analytics Domain defined in the previous chapter introduces functions which, while not entirely new, are debuting in the context of Business analytics. Each of these functions is discussed in detail in subsequent chapters, but before one understands what is “in the box” of each of these functions, it is essential to understand the interplay of forces in the Analytics Domain that enables success in the domain.

Much like a shopping list of raw materials does not make a gourmet meal, a strategy of building capabilities in the six functions of the Analytics Domain without understanding the driving factors behind them will not work.

The unifying notion base of the Analytics Domain is that Decision Makers use analytics to make Rational Decisions in response to various Decision Needs.

Let us dwell on that for a minute ... business entities (through their agents, the Decision Makers) are constantly faced with situations that require them to make decisions. These situations occur at various levels of operations and are defined as Decision Needs. Analytics help business entities make data driven (rational) decisions in response to every decision need that may arise.

### Rational Decisions

The fundamental objective of analytics is to help people to make and execute rational decisions, defined as being Data Driven, Transparent, Verifiable and Robust.

- **Data Driven:** based on facts that can be verified and assumptions that can be criticized.
- **Transparent:** uses decision-making criteria that are clearly defined (such as costs, benefits, risks, etc.).
- **Verifiable:** resulting from a decision-making model that connects the proposed options to the decision criteria, and a method that assists in choosing the right

- option. The choice can be verified, based on the data, to be as good as or better than other alternatives brought up in the model.
- **Robust:** tested to remove biases that creep in, such as not considering all the criteria or options, calculation errors, presentation biases, etc. This also requires a feedback loop—to watch for the results and help change the selected course as well as the decision-making process.

- The benefits of rational decision making are
- Better decisions and focused actions that get desired results.
  - Faster and cheaper decision making processes by taking a scientific approach to decision-making.
  - Continuous learning and adapting the decision making processes to make decisions better, faster, and cheaper. The process becomes closed-loop and self-correcting.
  - Empowerment: with scalable closed-loop and self-correcting (learning) decision making processes, more people can be empowered to make decisions.
  - Organizational intelligence: as people learn to take rational decisions, they are said to act more intelligently, and the organization as a whole can be seen to act more intelligently to set and pursue its objectives. The organization can be said to be informed, controlled, responsive, and adaptive.

Decision Needs and Decision Layers

Business entities are called upon to make decisions at various levels that have varying impact periods, scale and scope. People easily recognize Strategic and Tactical decisions (otherwise referred to as Long-Term and Short-Term decisions). We find that it is useful to classify decision needs into four “Layers” based primarily on the scale in which the decision is executed and the degrees of freedom that the decision maker has at his/her disposal (Fig. 2.1).

DECISION LAYERS	NETWORK	Used to set vision & strategy, no constraints other than strategic intent
	CAPABILITIES	Used to create the capabilities demanded by the strategy, constrained by strategy
	CONTROL SYSTEM	Used to align resources to workloads, constrained by capacity & strategy
	WORKFLOW	Used to execute the workloads, constrained by the schedule & allocation

Fig. 2.1 Decision layers

**Workflow Layer**—These are the decisions that need to be taken as you work. The human decision is generally guided by rules and backed by expertise acquired through training and experience. Systems-driven decisions, such as pricing or discounting, can be of any complexity. Execution-layer decisions occur very frequently and are easily handled by systems that use a set of rules to make the decision.

Real-time analytics are commonplace—they are used whenever we must respond on an immediate basis, for instance to dispatch a police cruiser, to manage concrete-mix trucks, to control a refinery, or to fight a battle. Factory floors have a long history of real time control systems called Supervisory Control and Data Acquisition (SCADA), some of them integrated with Manufacturing Execution Systems (MES) that provide near-real-time visibility into the factory and the tools needed to control the machinery. IT Network Management systems such as HP *OpenView* or CA *Unicenter* track the state of a network and provide tools to manage it. More recently the IT departments have started to mine log files soon after an event is logged so that they can provide visibility to a different data-set, and companies such as Splunk provide commercial tools to do this. Call centers deploy voice analysis software that can run while the customer is on the line to help the call center agent make better decisions, call centers also use tools that can generate offers and pricing “on demand” (i.e., we can run a pricing or discounting algorithm while the customer is on the call).

- **Process decisions** are confined to what the assigned person can do with the work at hand, in the context of a process or procedure that constrains the possible paths and outcomes. The analyses required to support process execution decisions are embedded as rules for people to follow (put into training and procedure-manuals), and as code in automated systems. For example in an airline ticket-booking process, a person works with a system to make the booking. A multi-carrier system such as [Travelocity.com](http://Travelocity.com) will get the options, other underlying systems will determine routes and prices, and the person booking the ticket selects from the carriers, prices, routes, and seats available. In a customer service process, a call center agent can assess the customer’s concerns and address them in several ways, including the option to offer discounts, coupons, or escalate (transfer) a customer request to a higher level instead of addressing it at the current level, etc.
- **Assignment and dispatch decisions** occur when the next step in the process can be assigned (or dispatched) to someone else or to a different branch of the process. This provides a way to decide who will do what—as a way to manage inspection, specialization, or overloads (by switching work out of a work-center that is swamped).
- **Alerting decisions** are needed to identify events and to trigger alerts, such as when a project incurs an unexpected cost increase, a shipment is delayed, an important customer lodges a serious complaint, or a key employee takes ill. People need to know what to look for and whom to notify. e.g., we can set an alert to watch for excessively long queues in the checkout lines of a grocery store and a controller (human or machine) can make a decision to open another counter.

**Control Systems Layer**—In this layer resources are allocated to workloads in order to get results such as revenue maximization, delivery to meet or beat the committed deadline, etc. Control decisions assign resources to workloads while constrained by the capacity and availability of the resources, such as: which person should work on which project, which orders are released for production by which work-center, etc. Analyses required to support control occur once and are re-used many times, often in a highly-automated system that guides the decision-makers. This requires the use of an analytical model that aligns strategy, planning, control and execution, and the quality of the model can be verified every time a work-assignment is done—whether well or poorly. This layer is also, at times referred to as the **Schedule Layer**, since a lot of decisions that happen here have to do with a broad Scheduling problem as seen in traditional manufacturing and operations research.

**Capability Layer**—These decisions are used to change capacity and set targets, and are constrained by the organization's strategy. At this layer, we deal with making plans, assessing the plan to the reality as the data becomes available (e.g., tracking order-bookings against the quarterly plan), and evolving the plan as needed. These decisions are taken by experienced planners supported by a few repeatable and process-driven analyses that may be automated (such as an order book view that includes plan, committed, and forecasted orders) as well as with ad-hoc analyses conducted on request. Planning analyses are often entirely done using tools such as Microsoft Excel; though systems do exist that successfully grapple with the problems of automating these fast-evolving and people-dependent workloads (e.g., Hyperion Planning or Adaptive Planning for budgeting and forecasting). Planning decisions are taken in conjunction with assessments to address needs such as to increase the team capacity (size) when you plan for or encounter an ongoing increase in demand or to drive the actions needed to realize value from a new system by de-commissioning the old system.

**Network Layer**—Also referred to as a Strategy Layer. There are few constraints at this layer other than those an organization imposes on itself, such as deciding to focus on margins as opposed to revenues or to reduce environmental impact. These decisions are taken with long time-frames and large impacts and require in-depth analyses that are generally ad hoc and conducted on request.

Of these, we give special prominence to the Control Systems Layer as the primary target for analytics modeling. That is because this layer requires models that include knowledge of the other layers in order to function: effective scheduling requires us to implement the network (strategy), capabilities (capacities and plans), and workflow (execution) models. Network and capability layer models need to get feedback from lower layers, but do not need to model the scheduling and processes. Workflow models, on the other hand, are constrained by higher layers but the demands of rapid execution generally preclude the use of complex models and simulations in this layer. So we can use Control Systems models as the central model that feeds all other models.

By their very nature and time horizon, Network and Capabilities decisions involve parameters for which data may not be readily available. These decisions

often involve making several gross assumptions that can never be guaranteed to be of high enough fidelity to support “data driven” decision making in the true sense of the word. Here the use of “model driven” analytics is commonplace—models are used to rationally explore the decision space, and we leverage minimal data or assumptions to help with the exploration and decision-making.

On the flip side, Workflow decisions tend to be so constrained that the spectrum of options to choose from is very narrow. In such a scenario, the deviation of effects between good and bad decisions is minimal and hence leaves little room for analytics to make a “big impact”. Though there is a lot of interest in leveraging real-time situational visibility leading to improved business outcomes, a lot of the benefits come from simple decision models that can be run in near-real-time. As control systems models evolve and become faster to run, some of them become available to guide Workflow decisions ... but even so the modeling complexity and speed has to be tackled in the Control Systems layer.

*The concept of decision layers can be a little confusing to begin with, but one needs to understand that which layer a decision belongs in is driven by the situation that calls for that decision (the Decision Need) more than the decision itself.*

*A common theme in recent years is the outsourcing of “non-critical” business processes to vendors who specialize in exactly those skills and processes.*

*An organization could choose to outsource IT to a specialist vendor and choose to focus its energies on core competencies of the business. This is a strategic decision that is taken at the **Network** layer, and such decisions are binding over multiple years of time horizon.*

*In some cases, an organization could enter into partial outsourcing agreements with vendors to provide contract staff as needed. This allows the organization to acquire a “variable capacity” capability since these contract vendors can be brought on or off very easily. This is a decision at the **Capability** layer.*

*When an organization is faced with a very short term resource crunch, or is in need of highly specialized skills for a short order of time, consultants are engaged to provide specific services. This is a decision to outsource work that is taken at the **Control System** layer. These decisions are usually the result of being unable to “schedule” the right resource internally to complete the task.*

*In other cases, an organization could chose to outsource work on a “task-by-task” basis to partners who have been identified through a decision in the capacity layer. While the capacity is available, it is called upon as needed though a decision in the **Workflow** layer.*

As the example above illustrates, a decision can exist in various layers based on the primary objective or **need** that prompted that decision.

**Proactive** decision needs arise as a way to set and drive policies. These needs arise in strategy review sessions in which the organization sets/revisits its purpose, vision, mission, and plan, or on an ad-hoc basis as needed. During strategic reviews we recheck the strategic intent, assess the environment, assess our standing and progress, and look for warning signs (e.g., a reduction in subscriber renewals that can signal a market shift). Proactive events generate decision needs that cascade down from the strategy layer to the execution layer—a change in strategy has to be incorporated in the capacity which reflects in scheduling and finally in the day-to-day execution.

**Reactive** decision needs arise when your alarm system flags an alert. Such alerts drive decisions that constantly align execution to policy. These decisions have to be made fast so as to not impede execution and their effects can migrate up the decision-making stack from the execution layer to the strategy layer. We propose that all such decision needs should be addressed first in the Control Systems layer to enable speed as well as strategic alignment. For example a large batch of goods in a factory is rejected and has to be reworked, which changes the schedule for the impacted factory and the ripple spreads to other factories that must re-plan, and then the impact on the revenue and margin projections at the strategy level has to be re-assessed.

**Adaptive** decision needs refer to the ability of an organization to sense external and unexpected events and to incorporate their effects adaptively. These events are of diverse nature: a huge tsunami hits Japan, a new tax law is enacted in China, an influential blog post reviles your customer service, etc. These decision needs are difficult to address, because it may not be apparent as to which decision layers need to respond, or how.

Regardless of the need that prompts a decision, the decision need is propagated through the decision layers. Decisions in higher layers have an impact on operations at the lower decision layers, since decisions at the lower layers are constrained by the decisions made that the higher layers. Similarly, decisions made at the lower layers are propagated upwards for consideration in making subsequent decisions. The interplay between decision needs and decision layers is illustrated below (Fig. 2.2).

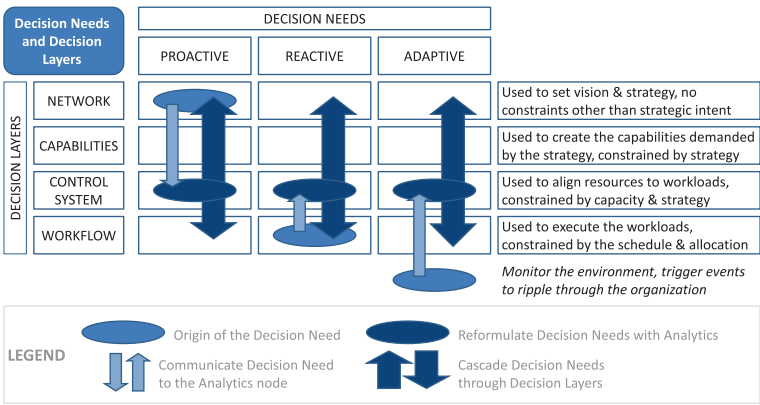


Fig. 2.2 Decision layers and decision needs

This formulation of decision needs is an evolution of Systems 3, 4, and 5 in the Viable System Model<sup>1</sup> proposed by Stafford Beer: System 3 that performs internal monitoring and coordination, System 4 that senses the external environment and assesses what changes are needed, and System 5 that is used to set strategy and policies for the organization. In our formulation, all three Systems share the same analytical model that aligns strategy, planning, control and execution at the Control Systems Layer that provides for the required level of detail and variety.

The decision framework laid out in this chapter is applicable at all the four decision layers, and identifying the layer of decision need origination is the critical first step in leveraging the framework. We will discuss the details of each of the analytics domain functions and their relationship to the decision layer in detail in subsequent chapters, but it is essential that the reader understand the concepts of decision layers before diving into the implementation of the analytics domain functions.

## Models: Connecting Decision Needs to Analytics

Reality is complex, and cause-effect chains are intricately networked. To address the need for rational decisions, we create “model” to help us arrive at the best decisions. These models incorporate selected aspects and perspectives of the problem—the model needs to be as simple as possible and only have as much complexity as is required to help make the decision.

**Network models** are used to make decisions that connect market or ecosystem needs to the workflows and capabilities required to address the need. Such models address aspects such as products (new product introduction, end-of-life, refresh, etc.), customers (segmentation, lifetime value, attrition, retention, etc.) distribution channels, and pricing. The focus is on finding and addressing market needs to achieve strategic goals such as profit, revenue, breadth-of-service, etc. Such models are used when the Decision Need has its roots in the Network Layer. The ecosystem typically consists of entities that are engaged in an end-to-end business process.<sup>2</sup>

**Capability models** are “introspective” in that, they seek to assist decisions internal to the organization. Such models treat market and business constraints as a “given”. These models are used to run, set-up, or evolve the capability in line with the business needs, and focus on efficient design and operation. Examples include product delivery capabilities (factories, warehouses, supply-chains etc.), service delivery capabilities, manpower planning, customer facing capabilities, offering design and development (R&D) capabilities, etc. These types of models serve a Decision Need originating in the Capability Layer.

---

<sup>1</sup> [http://en.wikipedia.org/wiki/Viable\\_system\\_model](http://en.wikipedia.org/wiki/Viable_system_model).

<sup>2</sup> Brache AP and Rummler GA (1990) Improving performance: how to manage the white space on the organization chart. Jossey-Bass, San Francisco

**Control Systems models** address the need to change, and they come in these types:

1. Optimization Systems Models are used where we can design, build, execute and trust the analytics required to make optimal choices. In operation, these models are often semi-automated and may even be fully automated.
2. Value Improvement Models are used when we can build analyses and compare options but it is not possible to definitively optimize the recommendations. These models enable the search for options, learning by modeling, comparing options, and learning in the modeling process.
3. Learning-by-Experiment Models are used to systematically improve by the process of experimentation. One process is to run controlled experiments in which we scientifically design and conduct experiments. In the second, we use the naturally occurring diversity around us to serve as “natural experiments” that we can analyze. In both cases we must leverage the results to continuously improve.
4. Learning-by-Asking Models are survey or feedback instruments that are used to guide decision making.
5. Expertise Models are used to learn from the history of input, decision, and outcome data records to help guide current decisions. In many cases, this learning model can be encoded in machine-learning algorithms.

**Workflow models** are used to observe and govern processes, manage dispatch, and generate alerts.

What is interesting in such a classification of models is that on first glance they share a lot of commonality. For instance, a Pricing model could potentially be classified under any of the four layers listed above. Why then, this attempt at classifying models? On deeper inspection, it becomes clear that the *objectives* or decisions driven by the model are, in fact very different. This difference stems from the Decision Layer where the Decision Need originated.

- Pricing as an “Ecosystem Model” provides pricing answers: “How will my market-share shift with a price movement?” “How will a price position affect my Brand position?” “What kind of response can I anticipate from the competition to my price move?” “How much of a demand/revenue lift can I expect for a given price move?” This is the view from outside—Pricing as a “black box”.
- Pricing in the “Capability Model” would address a very different set of questions: “Do we have the resources to build, operate, and evolve pricing models for the organization?” “What does it cost for us to have a pricing capability?” This is the view taken from the inside—Pricing as a “white box” set of people, tools, and methods, who require offices, computers, electricity, coffee, etc.
- Pricing in the “Control Systems Model” would be used to design and monitor the pricing capability. This is the view taken by the analytics practitioner who is building the “brains” of the organization to help it think and evolve systematically.



- Pricing in the “Workflow Model” would be used to provide prices to customers within the process of making the sale, and recording if the result was a sale-closed, lost, or negotiated-down.

What is critical is that “Pricing models” have varying levels of complexity, methodology and data needs depending on which decision layer each resides in, which in turn is governed by the layer in which the Decision Need originated. An understanding of the decision layers then becomes an essential aspect of building a model that is appropriate to the needs that it seeks to address. More often than not, excellent models are discarded or disregarded owing to a fundamental disconnect in understanding the layer of play.

## Stakeholders

Decisions will directly affect some people, and ripple through to affect others. These people (e.g., employees, suppliers, distributors, customers, etc.) collectively represent the stakeholders in the decision. All stakeholders may not be directly involved in the decision making process, but we need to take care to include them. In many cases, if we don’t consider these stakeholders we may be unable to execute the decision. These stakeholders may ask “what’s in it for me?” and refuse to act in alignment with the decision if they do not perceive their interests are taken into consideration.

The people who make and execute decisions are the most visible stakeholders in the decision making process. These stakeholders carry the responsibility of rational decision making, and need to prepare themselves for their role. However, help is at hand and they can call upon the support structure of “advisors” or “helpers” to assist them.

Those who help or advise in the decision making process often belong to staff organizations such as IT or analytics. They carry the responsibility of developing the capabilities needed to provide effective assistance to the decision makers. People filling this need are generally referred to as “Business Analysts” in most organizations today, but often lose sight of the advisory role they are supposed to play.

## Roles: Connecting Stakeholders to Analytics

As outlined above, there are three roles in decision making: decision maker, advisor, and analyst.

**Decision maker:** the responsibility and accountability for rational decision making rests with the “decision maker” who is expected to take decisions and also to drive the culture of rational decision making. This “decision maker” is a leader,

because with leadership comes the responsibility to own and make the decisions for the organization's direction, strategy, and day-to-day execution. Leaders may autocratically make the decisions themselves or democratically enable a set of people to come to a decision, but this is a matter of leadership structure, and does not dilute the leader's responsibility and accountability for rational decision making.

Decision-making roles are often shared between different people, so as to improve the quality of the decision, improve buy-in, or as a system of checks and balances.

**Advisor:** in many organizations, the “decision maker” or “leader” is provided with advice to help her/him come to a rational decision. We use the term “advisor” to denote the role of the person or team that provides the advice.

Splitting the role of advisor across different teams generally results in clashing analyses: e.g., the Sales and Finance departments may come up with different analyses to measure the return on a sales campaign. It is best to make it the role of one advisor to incorporate different perspectives within a single decision making context.

**Analyst:** advisors can be supported by a set of analysts who work with the advisor, or conduct the analysis on their own. Analysts can support the advisor, or the advisor can be an analyst too (the same person can play both roles).

The analyst role is often split across organizations such as analytics, IT and staff organizations such as Operations teams, and with good effect, as it enables focus and cultivates technical depth in different analytics functions. This depth can be leveraged by the advisor, and is often needed. Analysts can balance their depth and breadth based on exposure, experience, and education, possibly leading up to deeper expertise as analysts, to advisory roles, or to decision-making positions in staff or line-of-business teams.

Business Analytics

A Practitioner's Guide

Saxena, R.; Srinivasan, A.

2013, XII, 164 p., Hardcover

ISBN: 978-1-4614-6079-4