



APPLYING ECONOMIC CONCEPTS TO BIG DATA TO DETERMINE THE FINANCIAL VALUE OF THE ORGANIZATION'S DATA AND ANALYTICS, AND UNDERSTANDING THE RAMIFICATIONS ON THE ORGANIZATIONS' FINANCIAL STATEMENTS AND IT OPERATIONS AND BUSINESS STRATEGIES

Abstract

Companies are contemplating the organizational and business challenges of accounting for data as a “corporate asset”. Data is now seen as a currency. This research paper deep dives into the economics of data and analytics and defines these analogies.

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Purpose of this Research Paper

The volume, variety and velocity of data may have changed over the past few years, but one thing hasn't changed – the value of the data to improve operational decision-making and power business strategies. This research paper will explore the following questions with respect to how do organizations maximize the economic and financial value of the organization's data and analytics:

- How does an organization identify and prioritize the business use cases upon which to focus its data and analytics initiatives?
- How does an organization determine the economic value of the data that supports the organization's business use cases?
- How does an organization create a framework that facilitates the capture and re-use of the organization's data and analytic assets?
- What is the role of the data lake, data governance, data quality and other data management disciplines in managing, protecting and enhancing the organization's data and analytic assets?

Abstract

The importance of data has changed over the years. Initially, data was just the “exhaust” from an organization's On-Line Transactional Process (OLTP) systems. However as the volume, variety and velocity of the data grew over the past few years, the economic value of data has been transformed by the big data phenomena ^[citation 1] that has enabled organizations to capture a broader, more granular and more real-time range of customer, product, operational and market interactions. Today, business leaders see data as a monetization opportunity, and their organizations are embracing data and analytics as the *intellectual capital* of the modern organization.

More and more companies are also contemplating the organizational and business challenges of accounting for data as a “corporate asset”. Data as an asset exhibits unusual characteristics when compared to other balance sheet assets (where *asset* is defined as property owned by a person or company, regarded as having value and available to meet debts, commitments, or legacies). Most assets depreciate with usage, however data **appreciates** or gains more value with usage; that is, the more the organization uses the data across more use cases, the more valuable, complete and accurate the data becomes. These same characteristics apply to analytics, where analytics is basically “data” that has been refined or “curated” into customer, product or operational insights.

This research paper will explore data as a form of currency. Most currencies are constrained to a one-to-one transactional relationship. For example, the economic value of a dollar is considered to be finite – the dollar can only be used to buy one item or service at a time. Same with the finite nature of a person as a person can only do one job at a time. However the economic value of data is not constrained by transactional limitations. Data as a currency exhibits a network (or multiplier) effect, where the same data can be used simultaneously across multiple business use cases thereby increasing its financial and economic value to the organization.

However, there are severe limitations in valuing data in the traditional balance sheet framework. It is important that firms identify a way to account for their data. Organizations also need a framework to address the “Rubik’s Cube” intellectual capital ^[citation 2] challenge regarding how to identify, align and prioritize the organization’s data and analytic investments. To address this challenge, this research paper will put forth the following:

1. A framework to facilitate the capture, refinement and sharing of the organization’s data and analytic assets, and
2. A process to help organizations prioritize where to invest their precious data and analytic resources.

It is our hope that this research paper will foster new ways for organizations to re-think how they value their data and analytics from an economic and financial perspective. The concepts covered in this research paper will provide a common vocabulary and approach that enables business leadership to collaborate with the IT and Data Science organizations on identifying and prioritizing the organization’s investments in data and analytics; to create a common *collaborative value creation* platform.

Section 1: Back to Basics

What is Data?

Data is a valuable commodity. Data is being produced at an ever-increasing rate. IBM research claims greater than 2.5 quintillion bytes of data is being generated every day and that by 2020 there will be over 44 trillion gigabytes of data available ^[citation 3]. Matt Aslett, Research Director for Data Platforms and Analytics Channel at 451 Research, predicts the total data market consisting of data platforms, database management and data analytics will double in size by 2019 ^[citation 4]. Big data and analytics are becoming a key differentiator for the banking and the financial services (BFSI) industry with nearly 71% firms using data and analytics for competitive advantage ^[citation 5]. The financial services sector is projected to grow their global big data spending at a CAGR of 25.5% over the period of 2014-2019 ^[citation 6]. A report from PWC also suggests that financial institutions are recognizing the power and influence of big data and analytics on their businesses. With 2.5 quintillion bytes of data generating daily, 62% of the financial services companies believe data is the source of a competitive edge ^[citation 7]. Moreover, companies are finding new ways to create and acquire consumer-generated content (CGC) via social media platforms. Facebook is generating 33 billion CGC per month, Twitter generating 15 billion CGC per month, and the content marketing player BazaarVoice generating 700 million of CGC per month ^[citation 8].

Data sources are not limited to only structured or relational databases. Data sources include web clickstreams, mobile data, blogs, news feeds and RSS feeds. Data sources include discussions in boardrooms, networking at conferences, events and symposiums, and even observations of a valet at a casino.

There is also a growing wealth of publicly available data such as traffic, weather, building permits, home values, local events, clinical studies, research grants, patent filings, economic reports, zip code demographics, job histories, job openings, college donations, state and city budgets, and crime reports.

Finally the Internet of Things (IoT) will unleash a tidal wave of machine-generated data. For example the iBeacon technology has the potential to dramatically expand the data captured during a customer's in-store retail experience. This technology allows smartphones to seamlessly interact with the physical sensors present in the store running on Bluetooth Low Energy (BLE) to determine your precise location – to determine which department you are in and at what products are you looking. Combining this data with your purchase data will enable retailers to design highly personalized loyalty programs and marketing campaigns.

Even though data is not a physical entity, data plays a critical role in determining an organization's financial valuation.

What is Analytics?

Analytics is defined as the systematic computational analysis of data. Analytics mine the growing wealth of internal and publicly available data to quantify operational and behavioral insights that can be used to improve the effectiveness and efficiency of the organization's **decisions**; decisions ranging from predicting store sales to predicting a sports team's efficiency based upon on-field player movements.

Analytics is the basis for fact-based decision making. A focus on optimizing decisions is critical to business success. According to a study by MIT Center of Digital Business ^[citation9], organizations driven by data-driven decisions had a 4% higher productivity and a 6% higher profitability.

Analytics encompasses a growing field of data science capabilities including statistics, mathematics, machine learning, predictive modeling, data mining, cognitive computing and artificial intelligence.

There are four categories of analytics that organizations need to consider:

- Descriptive: monitoring current state performance or results
- Diagnostic: understanding (quantifying) drivers of performances
- Predictive: forecasting likely outcomes
- Prescriptive: recommending actions for future decisions

Big Data Intellectual Capital “Rubik’s Cube” Challenge

Thomas A Stewart, the Executive Director of National Center for the Middle Market (NCMM) stated that intelligence becomes an asset only when it is *productive and creates something useful*. Organizations need a focal point that helps them to align and coordinate the organization's data and analytics to create something that is *productive and creates something useful*. Business **use cases** are that focal point and drive the alignment, coordination and optimization of the organization's data and analytic assets.

Business use cases are clusters of *decisions* around a common subject area. For example, a customer retention business use case would make decisions such as which customers are considered at-risk, which customers are worthy of retention efforts, which retention offers are most appropriate for which customers, what channels are the most appropriate for which customers, what relationships could be leveraged to enforce the messaging, when and how to follow up to those offers, etc.

Use cases, combined with data and analytics, form the three dimensions of the “Big Data Intellectual Capital Rubik’s Cube” solution”. Identifying, prioritizing and quantifying the business

use cases are key to effectively aligning and coordinating the organization's data and analytic assets and corresponding financial and human investments. If not aligned to the organization's key business use cases, then organizations may end up with missing or misaligned data, and ineffective or orphaned analytics that yield suboptimal (or even the wrong) business outcomes.

Data and Analytics: Building Competitive Differentiation

Data plays a pivotal role in defining competitive differentiation. But organizations need to understand where to invest their scarce data and analytic resources to drive competitive differentiation; organizations need to understand when to buy for competitive parity and when to build for competitive differentiation. For example, it is likely best to buy enterprise software packages – such as Enterprise Resource Planning (ERP), Customer Relation Management (CRM), Human Resources (HRMS), Sales Force Automation (SFA), Supply Chain Management (SCM) and Marketing Automation (MA) – that provide competitive parity. There is little business differentiation when all organizations are running the same enterprise software. However, leading companies are realizing that they can exploit data and analytics to build business differentiation such as optimizing key business processes, reducing security and compliance risk, uncovering new monetization opportunities and creating a more compelling customer and partner engagement. Examples of companies that are leveraging data and analytics to create competitive differentiation include:

- Google: PageRank® and Ad Serving
- Yahoo: Behavioral Targeting and Retargeting
- Facebook: Ad Serving and News Feed
- Apple: iTunes® Recommendations
- Netflix: Movie Recommendations
- Amazon: “Customers Who Bought This Item”, 1-Click® ordering and Supply Chain & Logistics
- Walmart: Demand Forecasting, Supply Chain Logistics and Retail Link®
- Procter & Gamble: Brand and Category Management
- Federal Express Critical Inventory Logistics
- American Express and Visa: Fraud Detection
- GE: Asset Optimization and Operations Optimization (Predix®)

Digital-first companies such as Google, Netflix, Facebook, and Amazon understand how to exploit their data and analytics to power business success. These organizations also understand how to account for the value of data and analytics on their financial statements. For example, when Facebook launched its 2012 IPO, it highlighted the financial value of data on the company's balance sheet. A unique user was worth \$4 to Facebook and the aggregated value of the data that the company collected on each unique user was valued on Facebook's balance sheet at nearly \$6.6 billion ^[citation 10].

Many organizations have started recognizing the need to account for the value of their data. According to a study by SAS in January 2016, nearly 20% of the large firms in the UK have started accounting for the value of their data. With the advent of Internet of Things, they estimated the total value of data and analytics from 2015 to 2020 to be nearly £322 Billion. In addition, they estimate the equivalent benefit of the data and the Internet of Things to be around £46 Billion, approximately 2.1% of their GDP ^[citation 11]. In another example, AT&T in 2011 accounted for their customer relationships at nearly \$2.7 billion on their balance sheet ^[citation 12].

The economic value of data and analytics is also becoming an important consideration during mergers. Neilson Holdings quoted “customer-related intangibles” worth \$271 million on their

balance sheet post acquisition of the radio audience tracker Arbitron Inc. [citation 13]. When it comes to the economic valuation of data, the numbers are staggering. McKinsey Global institutes estimates the potential economic valuation of data at nearly \$3 trillion, while the Warsar Institute of Economics projects it to be €205 billion annually to the European Union [citation 14].

Section 2: Economics 101

To help organizations properly account for the value of their data and analytics, organizations need to understand some basic economic concepts. Let's start the conversation with a definition:

Data Economics: The science of human choice and behaviors with respect to the production, distribution and consumption of scarce data and analytic resources.

Economic concepts are built around the law of supply and demand. The law of supply and demand rationalizes the interaction between the supply of a resource and the demand for that resource, and the subsequent effect that the law of supply and demand has on price.

There are other basic economic concepts that can be applied to help organization's prioritize the production, distribution and consumption of the organization's scarce data and analytic resources. Let's review these economic concepts and see how they could impact the economic value of an organization's data and analytic assets.

Scarcity

Scarcity refers to limitations; insufficient resources, goods, or capabilities to achieve the desired ends. Figuring out ways to make the best use of scarce resources or find alternatives is fundamental to economics [citation 15].

Scarcity is the heart of the economics discussion and ties directly to the law of supply and demand. Organizations have a limited pool of human and financial resources to fulfill select tasks. By the same token, organizations have a limited pool of data and analytic resources. Consequently, organizations need to factor scarcity into their decisions by prioritizing their data and analytic resources against the most appropriate business use cases.

To address the data and analytics scarcity issue, organizations need to acquire and/or develop additional analytic capabilities. This includes hiring additional data science resources, expanding the training of existing business analysts, hiring analytic consultants, and acquiring analytic tools and methodologies. But even with the acquisition of additional analytic resources, there will always be more demand than supply. How the organization prioritizes their analytic resources against an ever-increasing demand will be pivotal in determining organizational success or failure.

Postponement Theory

Postponement is a decision to postpone a decision. Postponement can occur as one party seeks to either gain additional information about the decision or to delay the decision seeking better terms from the other party.

Postponement theory is a factor if postponement is due to "insufficient" data from which to draw insights to improve the probability of making a "better" decision. Also, the critical nature of the decision – and the associated Type I and Type II risks and costs – also plays an important factor in making a postponement decision.

In order to facilitate a postponement decision, organizations need to understand the following data and analytic factors:

- What is the estimated effectiveness of the current decision?
- What data *might* be needed to improve the effectiveness of that decision?
- How much more accurate can the decision be made given these new data sources and additional data science time?
- What is the cost of the data versus the projected financial return from improvement in decision effectiveness?
- What are the risks and liabilities associated with Type I/Type II errors (i.e., costs associated with making the wrong decision)? See “[Understanding Type I and Type II Errors](#)” for more details on Type I/Type II errors.

Efficiency

Efficiency is a relationship between ends and means. When we call a situation inefficient, we are stating that we could achieve the desired ends with less means, or that the means employed could produce more of the ends desired.

To improve operational efficiency, organizations need to first create metrics against which to measure the effectiveness of that operational process. With the ability to measure current performance, operational discrepancies can be flagged, analyzed to understand (quantify) the variables that cause the discrepancy (predictive analytics) and then create recommended actions (prescriptive analytics).

Also, the aggregation of the operational insights (i.e., customer usage behaviors and product performance patterns aggregated across all customer and business constituents) gained from efficiency improvement can lead to new monetization opportunities. For example, organizations could create benchmark, share, and index calculations that their customers and partners could use to measure their own efficiencies vis-à-vis others. Organizations could capture the best practices across their aggregated customers and partners in order to provide recommendations on how those customers and partners could improve operational efficiencies.

Economic Multiplier

Economic Multiplier is defined as an economic effect where an increase in spending produces an increase in national income and consumption greater than the initial amount. The multiplier is thus, a ratio of change in income over investment ^[citation 16]:

$$k = \Delta Y / \Delta I$$

Where:

k = the economic multiplier

ΔY = change in income

ΔI = change in investment

The Multiplier Effect was developed by J.M. Keynes to explain the relationship between investments and outcomes in an economy. The essence of the multiplier is that the total *increase* in outcomes (e.g., income, gross national product, employment) is greater (or multiplies) the original *increase* in investment. The multiplier effect emphasizes how

investments in acquiring new data and developing new analytics algorithms can drive a magnitude increase in economic value of the organizations data and analytics.

For example, in the early 1980s, Consumer Packaged Goods (CPG) Manufacturers such as Procter & Gamble, Kraft, Unilever and General Mills drove their marketing strategies based on the Neilson bi-monthly audit data (6 observations per year per market). However with the advent of Point of Sale (POS) scanner data, these organizations were able to leverage the same POS data across multiple use cases including demand planning, supply chain optimization, procurement, pricing, category management, and trade promotion effectiveness. That is, CPG Manufacturers paid for the acquisition of the POS data once, but the value of the POS data was *multiplied* several times by using the POS data across multiple use cases.

Price Elasticity

Price elasticity of demand is the quantitative measure of consumer behavior that indicates the quantity of demand of a product or service depending on its increase or decrease in price [citation 17].

Demand and price normally share an inverse relation and hence, the price elasticity of demand is typically negative. Price elasticity of demand can be calculated by the percent change in the quantity demanded by the percent change in price. It is expressed by the formula:

$$\eta = (Q_1 - Q_0) \div (Q_1 - Q_0) / (P_1 - P_0) \div (P_1 + P_0)$$

where:

η = price elasticity of demand

Q_0 = initial quantity demanded that exists at price P_0

Q_1 = new quantity demanded at price P_1

Data science resources seem almost price inelastic – the demand for these resources is only marginally affected by an increase in price of these resources. This price inelasticity is due to the financial return on investment (ROI) that these analytic resources are yielding when applied to critical business use cases. The demand for analytic resources will only grow as organizations become more proficient at capturing, refining and re-using the data and analytics across the organization.

Capital

Capital is an already produced durable or non-durable product, solution or service, or any non-financial asset that is used in production of these goods and services.

Adam Smith, the pioneer of modern economics, defined capital as "that part of a man's stock which he expects to afford him revenue"[citation 18] or to put it another way, "to provide a revenue stream." Adam Smith's definition is especially relevant given the opportunity to leverage data and analytics to "provide a revenue stream" in four ways:

- Driving the on-going optimization of key business processes (e.g., reducing fraud by 3% annually, increasing customer retention 2.5% annually)
- Reducing exposure to risk through management of security, compliance, regulations, and governance; avoiding security breaches, litigation, fines, theft etc. to build customer trust while ensuring business continuity and availability.
- Uncovering new revenue opportunities through superior customer, product and operational insights that can identify unmet customer, partner and market needs

- Delivering a more compelling, more prescriptive customer experience that both increases customer satisfaction and advocacy, but also increases the organization's success in recommending new products and services to the highest potential customers and prospects

Section 3: Impact of Economics on Data

In this section, we will explore some broad economic concepts and ascertain their applicability on determining the economic value of an organization's data and analytics.

Theory #1: Data as an Asset

Traditional assets include both financial assets (stocks, bonds) as well as physical assets (equipment, vehicles, buildings). However, traditional assets suffer from two limitations:

- Assets are constrained by transactional limitations; that is, they cannot be used simultaneously across multiple use cases just as a person can only do one job at a time, a doctor can only perform one surgery at a time; an airplane can only fly one route at a time.
- Assets depreciate with usage; the more that you use the assets, the more the asset wears out.

However, data as well as analytics¹ do not suffer from transactional limitations. Data and analytics do not depreciate with usage, and in fact, appreciate with usage as the data and the analytics become more complete and accurate. This makes data and analytics powerful assets in which to invest.

Theory #2: Data as Currency

Currency is defined as an item that can be used as a medium of exchange and represents quantifiable financial value. Currency is the medium for purchasing goods or services. But data and analytics do not suffer from transactional limitations, which makes them power currencies in which to invest.

And to expand upon the "data as currency" concept, an organization only has to "pay" once for that data (where "pay" is either building an application to capture that data or acquiring the data from a third-party source), but the same data can be used simultaneously across multiple use cases at no extra cost.

One example of using data as currency is the Adhar card ^[citation 19] – India's Unique Identification ID (UID) program that creates an exhaustive database of every Indian citizen – right from the gender identification, place and date of birth, address to its current coordinates. The government is using this data as its currency to micromanage the different demographics sections in the country, identify areas having chunks of population, analyzing the current state of these areas, forecasting the finances involved in the development and betterment of these areas and verifying it with the census data to have accurate records.

¹ Analytics can be defined as the curation or refinement of data into actionable analytic insights such as scores, predictive indicators or business rules. Curation is the process of gathering information relevant to a particular topic or area of interest;

https://en.wikipedia.org/wiki/Content_curation

Theory #3: Data as Monetization

When examining 23andMe and Genentech, a Forbes report quoted that the data assets owned by 23andMe generated roughly \$80 million of revenue by selling nearly 800,000 DNA kits ^[citation 20]. Furthermore, 23andMe has granted permission to each of its customer to use this data for research purposes, the permission that Genentech forecasts will deliver another \$60 million of potential revenue.

Most organizations are discovering that one does not monetize the data by directly selling the data, but organizations actually monetize the *insights* buried in the data (i.e., customer purchase behaviors, product performance tendencies, new market demands, cyber security prevention) to uncover unmet customer and market needs that are the basis for new products, services, channels, and markets.

Section 4: Creating the Collaborative Value Creation Framework

Data and analytics are powerful assets in which to invest, but organizations struggle to assign these intangible assets their appropriate economic value. Assigning the appropriate value to these digital assets is important if organizations want to maximize their economic impact, and optimize organizational investments in data and analytics.

Organizations need a framework – what we will call the *collaborative value creation* platform – that maximizes the economic value of data and analytic assets across the organization. This framework requires:

1. Identifying and prioritizing highest potential business use cases
2. Building analytic profiles to facilitate analytics capture and re-use
3. Identifying and prioritizing the data sources loaded into the data lake

Step 1 – Prioritizing Business Use Cases

To quantify the value of these intangible data and analytic assets, we need to find a basis point around which the organization can establish the *prudent value* of the data and analytics. We will use the organization's key business use cases (e.g., acquiring more customers, reducing customer churn, improving the quality of care, improving customer satisfaction, reducing cyber security risks, reducing maintenance costs) and the financial value of these use cases to establish that *prudent value*.

EMC Dell uses the [Prioritization Matrix](#) to ensure that business leadership is focused on the most appropriate use cases (see Figure 4.1).

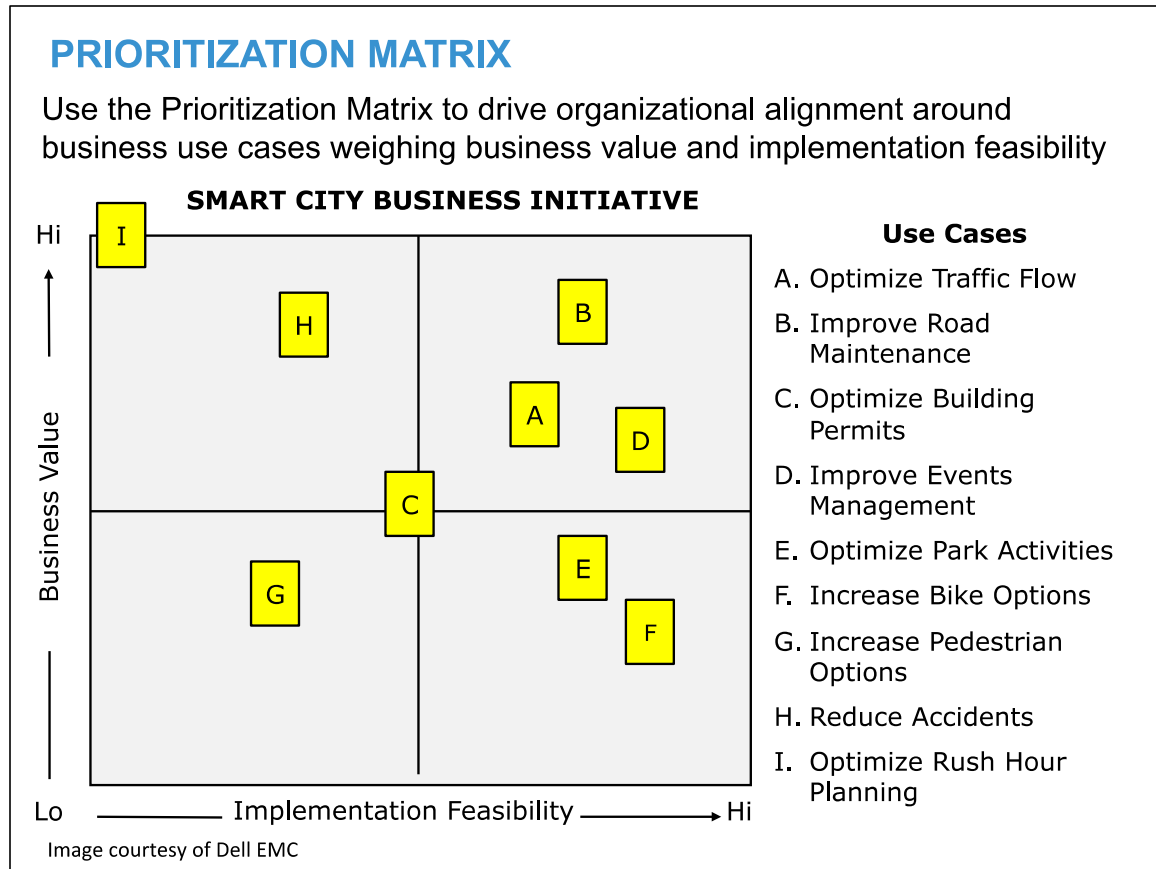


Figure 4.1: Prioritization Matrix

The Prioritization Matrix facilitates the discussion and debate between Business and IT stakeholders in identifying the “right” use cases upon which to focus the organization’s data and analytic resources – those use cases with both meaningful business value and reasonable feasibility of successful implementation.

Step 2: Role of Analytic Profiles

Even organizations advanced with substantial advanced analytic capabilities suffer from “orphaned analytics” ^[citation 21], analytics that address a one-time business need but are not “operationalized” or re-used across multiple use cases. The capture, refinement and reuse of the analytics can be addressed using a framework called an **Analytic Profile** ^[citation 22].

Applying predictive and prescriptive algorithms against the organization’s internal and external data sources yields analytic insights. Analytic Profiles capture those analytic insights in an organized and re-usable fashion. An Analytic Profile consists of metrics, predictive indicators, segments, scores, business rules and analytic (behavioral and performance) insights that provide a snapshot into the behaviors, preferences, propensities, inclinations, tendencies, interests, associations and affiliations at the level of the individual entity such as customers, patients, students, athletes, jet engines, cars, locomotives, CAT scanners, and wind turbines (see Figure 4.2).

ANALYTIC PROFILES: CUSTOMER

Analytic Profiles are structures that standardize the collection and re-application of analytics about Business Entities across multiple use cases

Traditional Data	Customer X Analytic Profile				Non-traditional Data
	Customer X Analytic Profile	NCE Score	Var	Trend	
<ul style="list-style-type: none"> • Purchases • Product Preferences • Add-on Preferences • Drink Preferences • Visit Frequency • Visit Recency • Visit Monetary • Market Basket • Group Size • Coupons • Consumer Comments • Store Manager Notes 	Demographic segments 3.2	92	1.85	▲	<ul style="list-style-type: none"> • Social Media Posts • Home Value • Employment history • Job Change Frequency • Job Change Recency • Industry certifications • Industry awards • Social Media Connections • Education degrees • Rank of college • College donations • Volunteer activities • Parking tickets
	Behavioral segments 3.1	67	3.25	▼	
	Loyalty Index 2.0	82	2.25	▲	
	Frequency Index 1.0	65	1.90	▼	
	Recency Index 1.0	92	1.89	▼	
	Lifetime Value Calc 1.0	99	1.05	▲	
	Event Propensity 1.0	14	1.74		
	Promotion Propensity 1.1	02	1.15		
	Advocacy Propensity 2.1	08	1.20		
	Attrition Propensity 1.2	09	1.25		

Image courtesy of Dell EMC

Figure 4.2: Analytics Profiles of Customer (Image courtesy of Dell EMC)

Analytic Profiles enforce discipline in the capture and re-use of key analytics insights. Analytic Profiles, coupled with a focus on the highest priority business use cases, ensure that the analytics are not developed in isolation; but that the analytics is re-usable across multiple use cases.

The lack of an operational framework for capturing and sharing the analytics can lead to:

- Inefficient use of data engineering and data science resources
- Analytics projects unattached to high level strategic initiatives
- Limited organizational learning opportunities
- Difficulty gaining organizational buy-in for investments in analytic technologies, resources, and skillsets
- Difficult to build credibility as a trusted advisor
- Lack of re-usable assets to make future use cases more cost efficient

Creating an operational framework for the capture, refinement and re-use of the organization's analytic assets enables:

- Leveraging analytic insights about key business entities across business functions such as marketing, operations, product development, sales, etc.
- Developing benchmarks that over time contribute to the optimization of future decisions.
- Developing repeatable analytic processes to accelerate the adoption of analytics within your organization.

- Justifying investment in analytics tools and data scientists to further increase the economic value of your data.
- Extending the value of your analytic efforts by making your analytics consumable to other business stakeholders.
- Gaining a better understand of what data you “don’t have” but “could have.”

Analytic Profiles help organization to prioritize and align data science resources to create actionable insights that can be re-used across the organization to optimize key business use cases, reduce cyber security risks, uncover new monetization opportunities and provide a more compelling, more prescriptive customer and partner experience.

Step 3 - Role of the Data Lake

A data lake is a data structure that holds large amounts of structured and unstructured data in its native format i.e., no schema is required to load data into the data lake. Unlike a data warehouse where the data is stored in a pre-defined relational structure, data in the data lake is stored as-is, in its native format. The ability to rapidly ingest, index, and catalog new data sources is critical in supporting the “fail fast / learn faster” data science efforts to identify variables and metrics that are better predictors of performance.

The data lake needs to treat data as a corporate asset by providing data services such as data provisioning, data governance, data quality, metadata management, security and privacy. If these supporting data services are not provided, the probability of deriving incorrect insights is increased potentially leading to suboptimal decisions or even wrong decisions. In this data and analytics renaissance, it is essential that the data in the data lake is reliable, relevant, accessible and secured.

Since the data lake can house any data in any format at any level of granularity; the challenge is to ensure that the data lake doesn’t become a dumping ground for the organization’s data and transformed into a “data swamp.” Consequently, organizations need a thoughtful process for building the data lake one business use case at a time.

As a result, the data lake becomes the organization’s “collaborative value creation” platform by facilitating the capture, refinement and re-use of the organization’s data and analytic assets (using a key-value store for your Analytic Profiles) across multiple business use cases (see Figure 4.3).

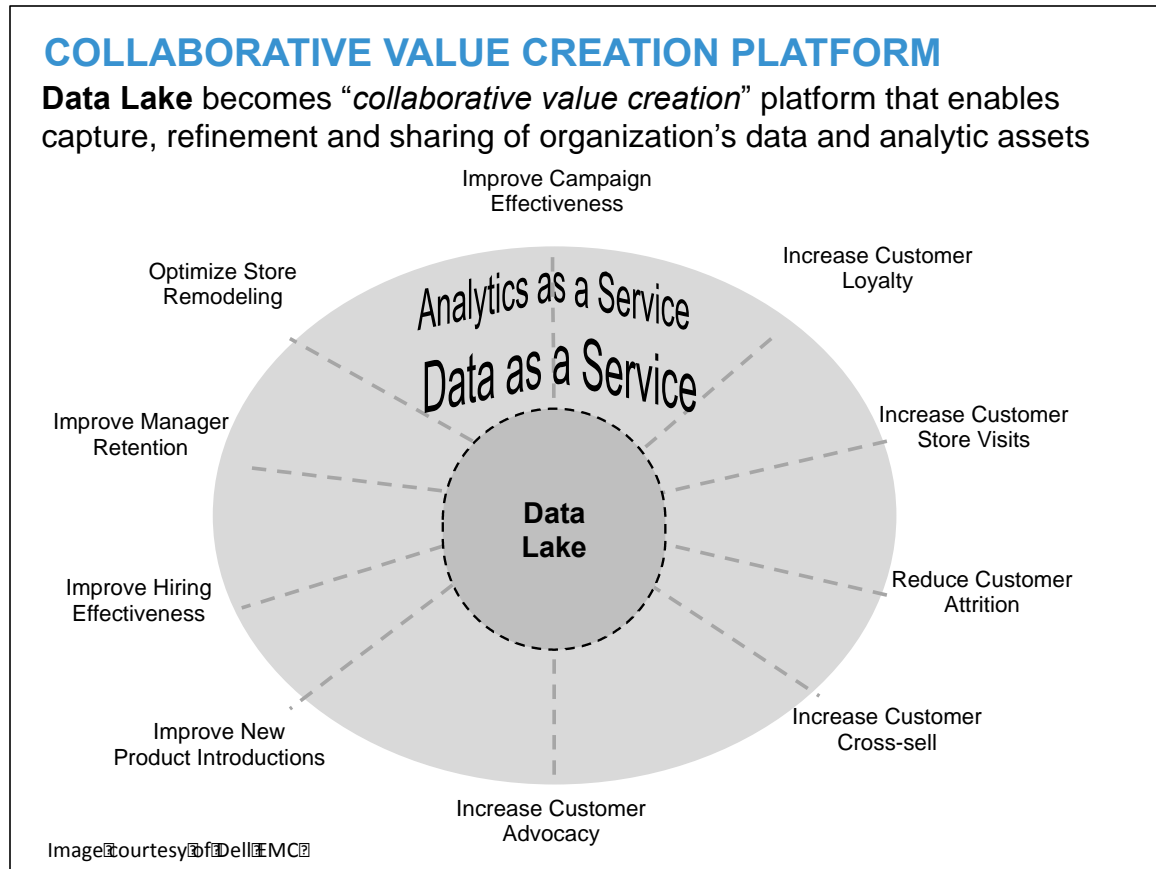


Figure 4.3: Data Lake = Collaborative Value Creation Platform

The data lake supports the data science processes of refining the data into actionable analytics to create financial or economic value. In other words, the data lake is a powerful data architecture that exploits the economics of big data.

Section 5: Chipotle Use Case

We will now apply the framework and supporting process outlined in this paper to a real-world organization. We selected a public company so that we could use publicly available data to demonstrate the paper’s concepts. The company that we selected was Chipotle Mexican Grill Inc. [citation 23].

Chipotle is an American chain of fast casual restaurants in the United States, United Kingdom, Canada, Germany, and France, specializing in tacos and burritos. Founded in the early 1990s in Colorado, Chipotle became one of the fastest growing food chains across the United States and then internationally that is currently trading on the New York Stock Exchange.

Step 1: Identify a Targeted Business Initiative

A **Business Initiative** is a cross-functional plan or program that is typically 9 to 12 months in duration, with well-defined financial or business metrics. One of the business initiatives highlighted in Chipotle’s 2012 annual report was increasing same store sales.

“Last year we opened 183 restaurants, grew our revenue by 20.3% to \$2.73 billion, and saw comparable restaurant sales grow 7.1% for the year. Our restaurant-level margins were among

the highest in the industry at 27.1%. We are pleased with our performance, and anticipate continued growth and success.”

Source: [Chipotle 2012 Annual Report](#)

This goal of increasing same store sales by 7% will be the business initiative upon which we will apply our data valuation framework and processes.

Step 2: Estimate Financial Value of the Business Initiative

First, we need to calculate the financial value of the targeted business initiative. The process of calculating the financial value of the targeted business initiative should be a straightforward financial accounting exercise. Table 1 provides an estimate of the financial value of Chipotle’s “Increase same store sales 7%” business initiative.

Targeted Business Initiative	
Increase Same Store Sales by 7%	
Chipotle Sales (\$ M)	\$ 2,731,224
Number of Stores	1,410
Average Store Sales (\$M)	\$ 1,937
7% increase in Avg. Store Sales (\$M)	\$ 2,073
Annual Impact (\$M)	\$ 191,186

Table 5.1: Calculate Financial Value of Targeted Business Initiative

Step 3: Identify Supporting Business Use Cases

The next step is to identify the use cases that support the targeted “increase same store sales” business initiative. We conduct interviews and envisioning exercises to identify the use cases across the different business stakeholders (i.e., store operations, procurement, marketing, product development, finance). For Chipotle “increase same store sales”, we identified the following use cases:

- Increase store traffic via local events marketing
- Increase store traffic via customer loyalty program
- Increase shopping bag revenue
- Increase corporate catering
- Increase non-corporate catering
- Improve promotional effectiveness
- Improve new product introductions

Step 4: Estimate Financial Value of Each Use Case

Next, we estimate the financial value of each use case identified in Step 3. To estimate the financial value of each use case, each impacted business function creates a financial scenario for that use case; that is, each use case will have different financial scenarios tied to the number of business functions impacted by the targeted business initiative. For the use case “Increase Store Traffic via Local Events Marketing,” we create three financial scenarios for the three impacted business functions of Field Marketing, Store Operations and Product Development.

- **Field Marketing** (Scenario #1) created a scenario that estimates the incremental revenue generated from designing localized pamphlets and brochures for local events yielding a financial estimate of \$62M. The figure below shows the old and new customers and their order type during the local event (See Figure 5.1):

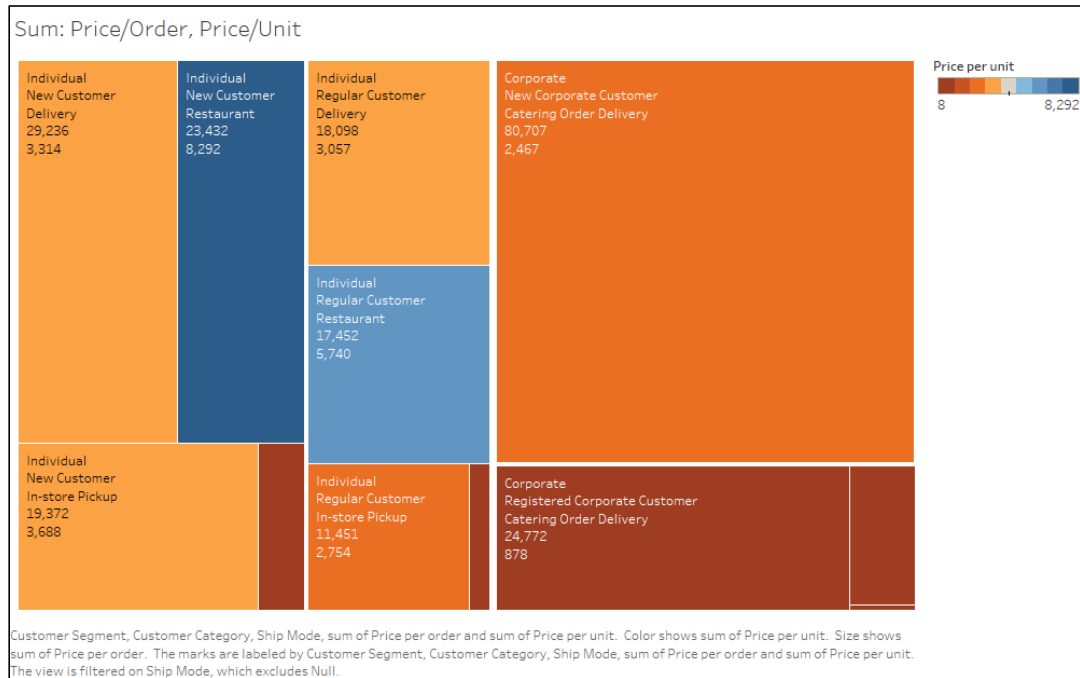


Figure 5.1: Customer Segment and Order Shipment Mode

The figure below shows the Pareto chart showing the percentage of customers driving the revenues for Chipotle (See Figure 5.2):

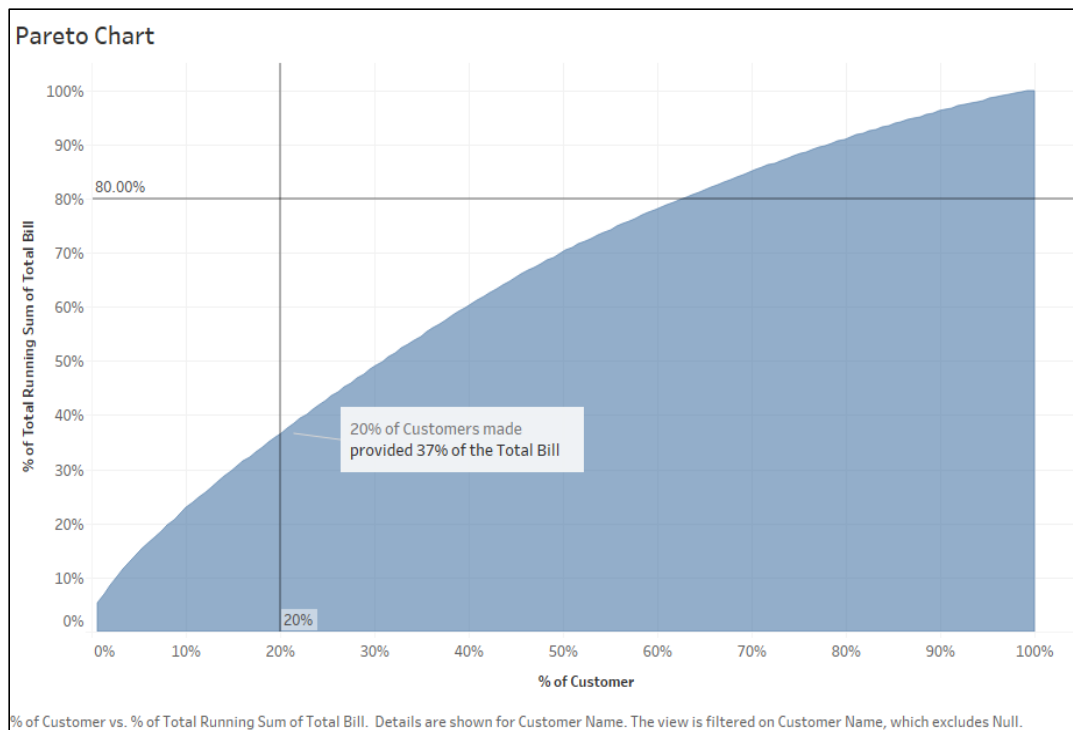


Figure 5.2: Pareto Chart

Assumptions	Values
Number of local event days per year per store (Note: events can cover multiple days)	50
Average Number of event attendees per day per store	525
Incremental Conversion Rate (customers coming to store who would not have otherwise come)	15.0%
Net New Customer Visits annually per store	3,938
Average Transaction Size	\$ 11.25
Totally Number of Stores	1,410
Incremental Annual Revenue Impact (\$M)	\$ 62.5

Table 5.2: Scenario #1 - Field Marketing

- **Store Operations** (Scenario #2) created a scenario for co-branded, holiday events to be executed by local store management (Christmas event with the New York Times). The Store Operations team created a monthly forecast of product demand based upon historical seasonal and holiday product sales, and used the monthly forecast to determine the ideal seasons and holidays in which to run their co-branded events (see Figure 5.3).

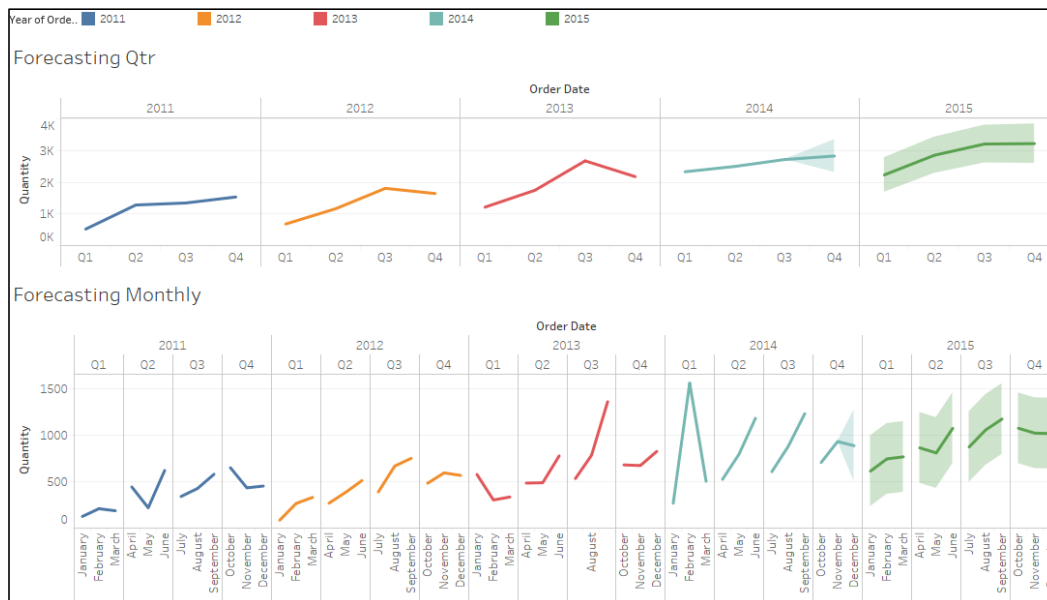


Figure 5.3: Monthly Store Demand Forecast

The resulting financial model yields a financial estimate of \$54M (see Table 5.3).

Assumptions	Values
Number of local event days per year per store during holidays (Note: can events cover multiple days)	65
Average Number of event attendees per day per store	700
Incremental Conversion Rate (customers coming to store who would not have otherwise come)	16.0%
Net New Customer Visits per store	7,280
Average Transaction Size	\$11.25
Number of Stores	1,410
Wages to Temporary Employees (\$M)	\$9.5
Wages to Permanent Employees (\$M)	\$20.0
Extra utilities costs - additional equipment, space, accessories, packaging and logistics (\$M)	\$30.0
Payments to vendors (\$M)	\$1.0
Incremental Annual Revenue Impact (\$M)	\$55.0

Table 5.3: Scenario #1 - Store Operations

The figure below shows the shipping cost incurred for delivery different customer orders:

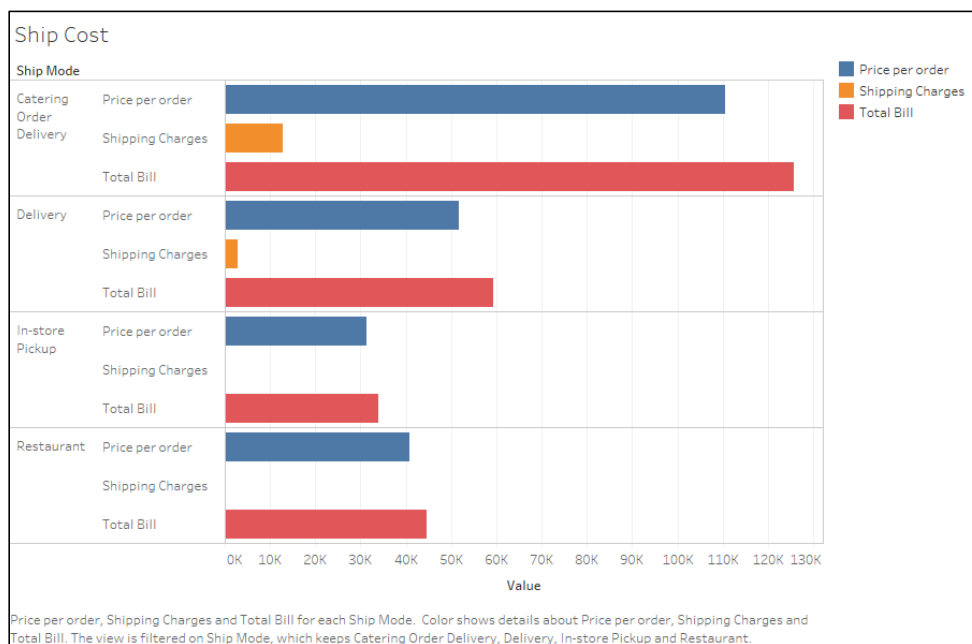


Figure 5.4: Shipping charges for each ship mode

- **Product Development** (Scenario #3) created an “eat on the run” product scenario targeting Chipotle customers who have a greater propensity of attending local events around the store yielding a financial estimate of \$44M.

Assumptions	Values
Number of local event days per year per store (Note: some events cover multiple days)	50
Average Number of event attendees per day per store	625
Incremental Conversion Rate (customers coming to store who would not have otherwise come)	15.0%
Net New Customer Visits per store	4,688
Average Transaction Size	\$11.25
Number of Stores	1,410
Purchase of new inventory (\$M)	\$9.0
Purchase of bags, cutlery and other misc. items (\$M)	\$6.0
Purchase of new equipment for product development (\$M)	\$14.0
Expense on media promotions (\$M)	\$0.5
Incremental Annual Revenue Impact (\$M)	\$44.9

Table 5.4: Scenario #3 - Product Development

The Product Development team created a quarterly forecast of product demand based upon historical seasonal and holiday product sales, and used the quarterly forecast to determine the ideal seasons and holidays in which to run their co-branded events (see Figure 5.5).

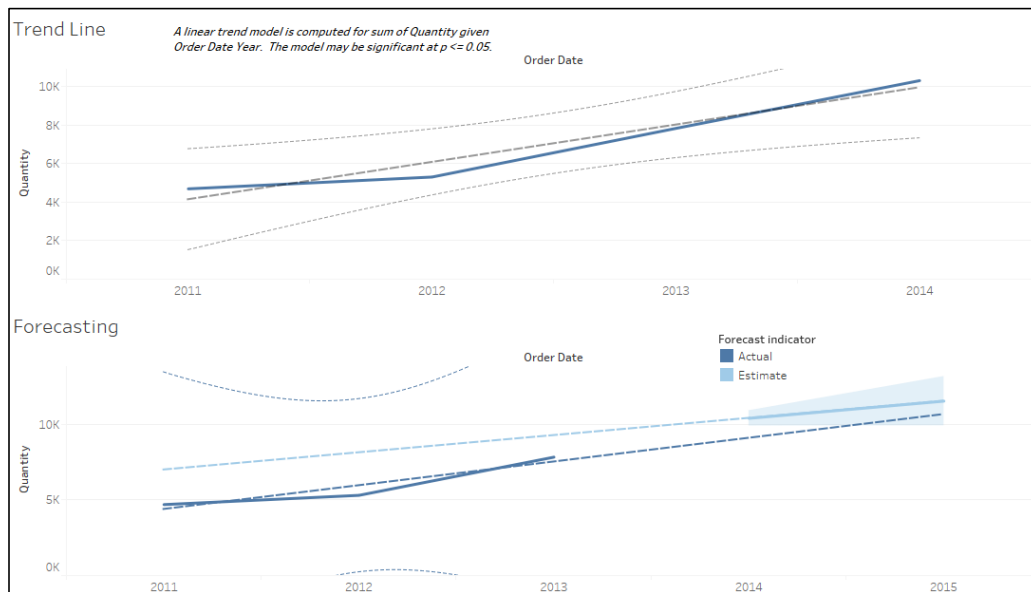


Figure 5.5: Monthly Store Demand Forecast

The business stakeholders would then collaborate to evaluate the different scenarios and select the most appropriate scenario (the scenario with proper match of financial value and execution feasibility). The financial value of the selected scenario would then be used as the basis for the financial value of that use case. In the Chipotle “Increase Same Store Sales via Local Events Marketing” use case, we chose Scenario #1 (Field Marketing) with estimated financial value of \$62M.

After repeating the scenario creation, evaluation and selection process for each use case, we end up with the following financial value for each use case (see Table 5.5).

Business Initiative: Increase Same Store Sales by 7%							
(Estimated Value of Business Initiative: \$191M annually)							
Use Cases							
Data Sources	Increase Store Traffic via local events marketing	Increase Store Traffic via Loyalty Program	Increase Shopping bag Revenue	Increase Corporate Catering Revenue	Increase Non-Corporate Catering Revenue	Improve New Product Introduction Effectiveness	Improve Promotional Effectiveness
Financial Value (\$M)	\$ 62.0	\$ 56.0	\$ 26.0	\$ 24.0	\$ 14.0	\$ 18.0	\$ 27.0
Field Marketing	\$62.0	\$25.0	\$26.0	\$8.0	\$10.0	\$14.0	\$18.0
Store Ops	\$55.0	\$42.0	\$18.0	\$24.0	\$14.0	\$9.0	\$16.0
Product Dev	\$45.0	\$24.0	\$12.0	\$8.0	\$8.0	\$18.0	\$22.0
Corp Marketing	\$50.0	\$56.0	\$22.0	\$10	\$8.0	\$12.0	\$27.0
Procurement	\$22.0	\$0.0	\$12.0	\$0.0	\$0.0	\$8.0	\$6.0

Table 5.5: Financial Value of Business Function Scenarios for each Use Case

Step 5: Estimate the Value of the Supporting Data

The next step is to estimate the value of the supporting data sources. We have each business stakeholder rate the relative value of each data source with respect to each use case; that is, how important is data source #1 to use case #1, how important is data source #1 to use case #1, etc. One can use a rating scale of 0 to 4, 0 to 10, or 0 to 100, but the finer the granularity of the data rankings, the more precise the data valuation determination (see Table 5.6).

Business Initiative: Increase Same Store Sales by 7% (Estimated Value of Business Initiative: \$191M annually)							
Use Cases							
Data Sources	Increase Store Traffic via local events marketing	Increase Store Traffic via Loyalty Program	Increase Shopping bag Revenue	Increase Corporate Catering Revenue	Increase Non-Corporate Catering Revenue	Improve New Product Introduction Effectiveness	Improve Promotional Effectiveness
Financial Value (\$M)	\$ 62.0	\$ 56.0	\$ 26.0	\$ 24.0	\$ 14.0	\$ 18.0	\$ 27.0
POS Transactions	4	4	3	2	2	3	4
Market Baskets	4	4	4	2	2	3	4
Local Demographics	3	3	2	4	4	2	2
Traffic	2	1	1	1	1	1	1
Weather	3	1	1	1	1	1	1
Local Events	4	1	1	0	0	1	4

Table 5.6: Assess Relative Impact of Data Sources – Assess (Weigh) relative value of each data source vis-à-vis each use case (Scale of 0 to 4)

Next, we calculate the value of each data source vis-à-vis each use cases. One can make the formula as sophisticated as required, as long as the business stakeholders understand the rationale for the formula. Below is the formula used for this paper:

$$D5/D\$11 \times D\$4$$

Where:

- D5 is the relative rank of the data source vis-à-vis the use case (column D)
- D\$11 is the sum of the data source rankings for the use case in column D
- D\$4 is the value of the use case in column D

This is a very simple formula, but if explaining the formula confuses the business stakeholders, then they will have little confidence in the results of the exercise. Consequently, err on the side of keeping the formula simple and understandable.

Finally, the data source values are summed across the use cases to get an aggregated value calculation (see table 5.7).

Key Business Initiative: Increase Same Store Sales by 7% (Estimated value of Business Initiative: \$ 191M Annually)								
Use Cases								
Data Sources	Increase Store Traffic via local events mktg	Increase Store Traffic via Loyalty Program	Increase Shopping bag Revenue	Increase Corporate Catering Revenue	Increase Non-Corporate Catering Revenue	Improve New Product Intro Effectiveness	Improve Promotion Effectiveness	Value of Data across all use cases
Financial Value (\$M)	\$ 62.0	\$ 56.0	\$ 26.0	\$ 24.0	\$ 14.0	\$ 18.0	\$ 27.0	
POS Transactions	\$ 12.4	\$ 16.0	\$ 6.50	\$ 4.80	\$ 2.80	\$ 4.90	\$ 6.80	\$ 47.40
Market Baskets	\$ 12.4	\$ 16.0	\$ 8.70	\$ 4.80	\$ 2.80	\$ 4.90	\$ 6.80	\$ 49.60
Local Demographics	\$ 9.30	\$ 4.0	\$ 4.30	\$ 9.60	\$ 5.60	\$ 3.30	\$ 3.40	\$ 44.10
Traffic	\$ 6.20	\$ 4.0	\$ 2.20	\$ 2.40	\$ 1.40	\$ 1.60	\$ 1.70	\$ 17.80
Weather	\$ 9.30	\$ 4.0	\$ 2.20	\$ 2.40	\$ 1.40	\$ 1.60	\$ 1.70	\$ 20.90
Local Events	\$ 12.40	\$ 4.0	\$ 2.20	\$ 0.00	\$ 0.00	\$ 1.60	\$ 6.80	\$ 20.20

Table 5.7: Aggregated Financial Value of Each Data Sources across All Use Cases

Step 6: Identify and Capture Analytics

The final step is to use the Analytic Profiles to identify and capture the analytics that support each use case. While the analytic results can take many forms (e.g., segments, clusters, business rules, predictive indicators), we will use the analytic concept of scores as a practical way to create analytic insights.

Scores are a rating system that aids in comparisons, performance tracking and decision-making. Scores are used to predict the likelihood of certain actions or outcomes. For example, the FICO score measures the likelihood of a borrower repaying their loan ^[citation 21]. Scores are actionable, analytic-based measures that support the key decisions your organization is trying to make.

Identifying and capturing the analytics is a 3 step process:

1. We first list the **decisions** needed to support the targeted Use Case (“Increase store traffic via local events marketing”).
2. Next, we identify or brainstorm the **recommendations** that need to be developed to support the decisions. A recommendation is a suggestion or proposal, developed using prescriptive analytics, as to the best course of action.
3. Finally, we identify the **scores**, and the metrics that comprise the score, that support the recommendations and decisions.

For the Chipotle “Increase Store Traffic via Local Marketing Events” use case, we identified three potential scores:

- a. **Local Economic Potential Score:** which measures the economic potential of the area around the store including demographics, house values, unemployment rate, average income levels and other economic variables.
- b. **Local Vitality Score:** which measures the amount of activity or “life” around the store such as proximity of schools, shopping malls, movie theatres, parking lots, business parks, and local event (sporting and entertainment) locations.
- c. **Local Sourcing Potential:** which measures the feasibility of getting the necessary organic food items to support the local event marketing, and includes variables such as number

of local suppliers, proximity to the stores, supplier reliability, and supplier quality and supplier production capacity.

Table 5.8 brings the Decisions, Recommendations and Scores process together.

Decisions		Recommendations	Scores/Metrics
Use Case: Increase Same Store Sales via Local Event Marketing			
Store Staffing	<ul style="list-style-type: none"> • How many people to staff during the local event? • What skills to staff for store as well as promotions? • When to staff based upon the local event? • How to measure the temporary and permanent staff performance? 	Local Economic Potential Score <ul style="list-style-type: none"> • Local demographics • Local economic variables • Local home values • Local unemployment rate • Change in number of nearby university students 	
Store Inventory	<ul style="list-style-type: none"> • How much food inventory to order for the local event? • How much utensils inventory to order for the local event? • What would be the minimum quantity of each food item to reorder? • What would be the storage plan for surplus inventory? 	Local Vitality Score <ul style="list-style-type: none"> • Mile from high schools • Miles from junior high schools • Miles from malls • Miles from local sports venues • Miles from college sports venues • Local sporting events • Local entertainment events • Other local events (Farmers Market) 	
Local Events Promotions	<ul style="list-style-type: none"> • Which local events to sponsor? • How much marketing funds to allocate to the local event? • What types of promotions to offer for local events? • Pricing of menu specifically for the local events with respect to the local competition? 	Local Sourcing Potential <ul style="list-style-type: none"> • Number of local suppliers • Miles from stores • Supplier production capacity • Supplier quality • Supplier reliability • Delivery feasibility 	
Supply Chain	<ul style="list-style-type: none"> • Where to acquire additional inventory in case of over-run? • Who would be the vendors for reorder procurement? • How to set the quality control of the new vendors? 		

Table 5.8: Mapping Analytic Scores to Recommendations to Decisions

See the following for more details on the role of scores and the Decisions-to-Recommendations-to-Scores mapping process:

- [Thinking Like A Data Scientist Part III: The Role of Scores](#)
- [Chief Data Officer Toolkit: Leading the Digital Business Transformation – Part II](#)

The end result is an Analytic Profile for each Chipotle store that captures the analytic results across all the use cases (see Table 5.9).

Chipotle Store 00134	NCE	Beta	Trend
Local Economic Potential Score 2.1	92	1.85	▲
Local Vitality Score 1.4	67	3.25	▼
Demographic Segments 3.2	82	2.25	▲
Behavioral Segments 3.1	65	1.90	▼
Store Traffic Score 1.0	92	1.89	▼
Store Remodel Score 1.0	55	2.75	▼
Store Loyalty Index 2.0	98	1.35	▲
Store Customer Satisfaction	88	1.74	▼
Vendor Reliability Score	99	1.10	▲
Store Employee Satisfaction Score	78	2.65	▼

Table 5.9: Chipotle Store Analytic Profile

The analytic results captured in the Analytic Profile are now ready to be refined and shared across other use cases, increasing the economic value of the analytic results and addressing the “orphaned analytics” issue.

Step 7: Putting Analytics into Action

One example of how to leverage the accumulation of store specific analytic insights is calculating the potential value of each store. Instead of using traditional transactional measures such as monthly revenues, profits, and average basket size to create a store value calculation, we could use the below calculation to *predict* the value of each store leveraging the Economic Potential, Local Vitality and Local Sourcing Potential scores:

[Predicted Store Value] = f [Current Store Value], [Local Economic Potential], [Local Viability], [Local Sourcing Potential]

Where:

- Current Store Value includes factors such as purchase history, returns, product margins, and customer frequency, recency, and monetary (RFM) variables

- Local Economic Potential includes factors such as local demographics, economy, employment rate, home values, real estate rental and leasing values
- Local Vitality includes factors such as proximity to business offices, educational institutions, shopping malls, and number of sporting and entertainment events
- Local Sourcing Potential includes factors such as number of local suppliers, distance from the stores, supplier quality ratings and supplier production capacity
- Maximum Store Value combines Current Store Value with Local Economic Potential, Local Vitality and Local Sourcing Potential scores to create a Predicted Store Value

As a result, investments across product development, store operations, sales and marketing could be optimized against those stores with the highest, untapped potential (see Figure 5.6).

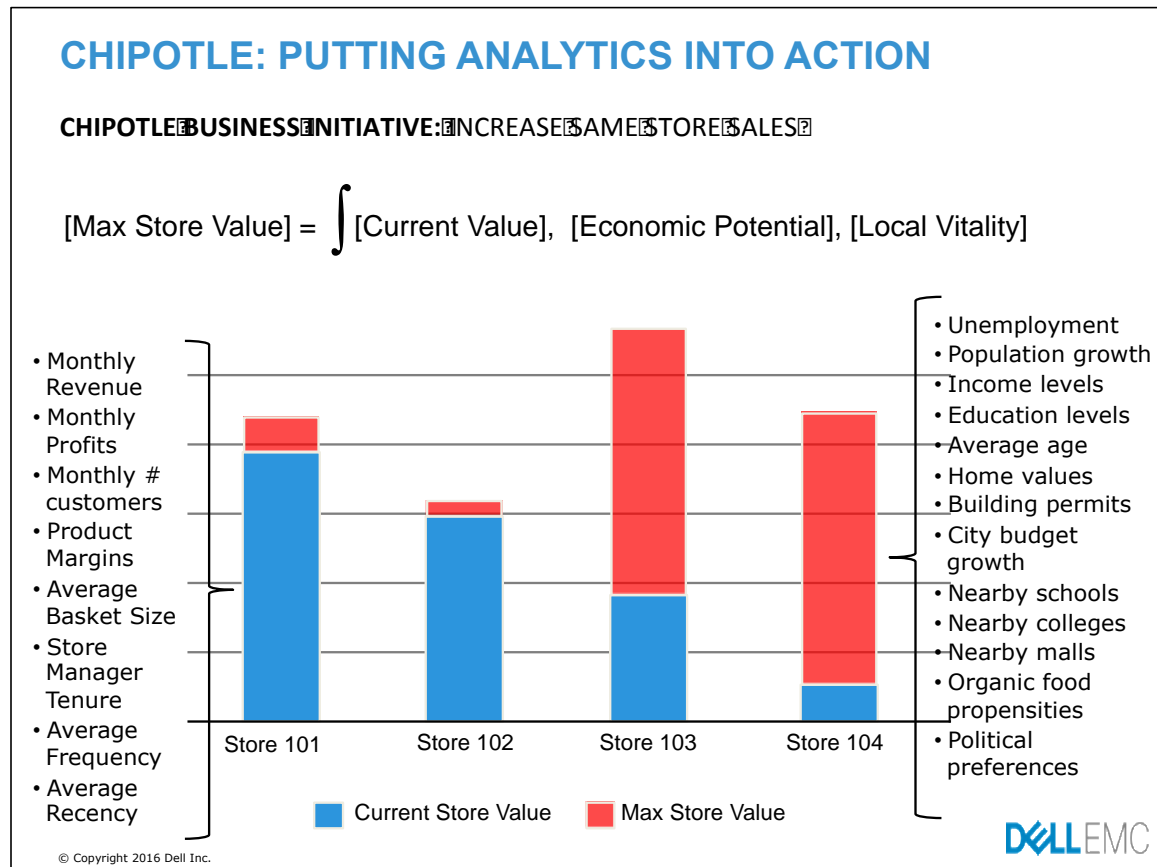


Figure 5.6: Leveraging Pre-existing Scores to Predict Store Value

The purpose of the Section 5 exercise using the Chipotle case study was to make the framework and supporting processes for determining the economic value of data come to life. While one lacks the space in a research paper to drill into the Financial Accounting concepts necessary to estimate the financial value of each use case, it is the hope of the authors that we provided enough of a structure so that business executives disciplined in economics and financial accounting can build upon the models and concepts.

Data is the New Oil

Let's conclude our research paper with a fun mental exercise. Crude oil was the catalyst for much of the industrial and social advancements enjoyed today. Oil is not only being used as a fuel for the retail and commercial vehicles like cars and trucks, it is also critical in making farm fertilizers, plastics, detergents, cosmetics, and nylon clothing.

It is said that data is analogous to crude oil; that "data is the new oil." Clive Humby first presented this analogy at the Association of National Advertisers (ANA), Senior Marketers Summit at Kellogg School in 2006 ^[citation 24]. Let's expand upon the "data is the new oil" analogy.

Oil is a source of *potential energy*, but is of limited use in its raw form. Oil is refined into fuel that has 5x to 7x the *potential energy* than crude oil, but is still only *potential energy* at this point. However, the *kinetic energy* of oil is not realized until the fuel is burned through combustion to either provide electricity or power vehicles.

Similarly in the big data world, data is like crude oil with *potential value* but is of limited economic value in its raw form. Data is refined with analytics that has more *potential value* in the form of customer, product and operational insights. However the *kinetic value* of data is not realized until the analytics are "put into motion" to optimize key business processes, uncover new monetization opportunities or create a more compelling customer engagement.

Summary

A Balance Sheet is a snapshot of an organization's financial health and assets. For the modern organization, data and analytics are assets that need to be accounted for as part of an organization's *financial health and assets*. For example, the Dutch data security firm DigiNotar went bankrupt in 2011 ^[citation 25], as it couldn't, ironically, protect its data from being hacked. Another example is the security breach of Washington State Apple Health ^[citation 26] in 2016 that affected 91,000 Medicaid clients, leading to the following press release:

"Employment terminated for individuals involved in data breach; notifying the appropriate federal officials for further investigation and potential criminal review"

Yes, data has economic value.

As organizations seek to leverage data and analytics to power their business models and improve operational and strategic decision-making, organizations need to manage and account for data and analytics as corporate assets. Data and analytics will become the primary economic driver in many organizations that seek to optimize key business process, reduce security and compliance risks, uncover new monetization opportunities, and create a more compelling user experience.

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